

Sequential Uncertainty Modeling for Unfolding Phenomena (SUM-UP) method for estimating probabilities of events specific to Level 2 MUPRA

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Abstract: During the Fukushima Daiichi Nuclear Power Plant accident, various events that affected accident mitigation across multiple units—hereafter referred to as multi-unit (MU) events—occurred. Examples of MU events include resource conflicts due to shared equipment and interruptions of outdoor work caused by elevated radiation levels and/or hydrogen explosions. Such MU events can hinder or even prevent mitigation actions for multiple units and therefore need to be incorporated into probabilistic risk assessment (PRA) to quantify site-level risk.

We have been developing a Level 1 multi-unit PRA (MUPRA) methodology, including techniques to evaluate MU events relevant to Level 1 PRA. To extend this framework to Level 2 MUPRA, it is necessary to consider a new class of MU events (L2 MU events) that interrupt or prevent mitigation actions due to phenomena occurring primarily after the loss of containment integrity. In conventional Level 2 single-unit PRA, assessments have largely focused on containment failure within an individual unit, and L2 MU events, which occur after containment failure, have not been explicitly addressed.

This study proposes an evaluation framework for L2 MU events that enables probabilistic assessment under current technological limitations. In particular, we propose a Sequential Uncertainty Modeling for Unfolding Phenomena (SUM-UP) method to systematically propagate uncertainty while accounting for the key characteristics of L2 MU events—namely, that they consist of cascading phenomena and may involve phenomena for which analytical methods and knowledge differ in maturity.

1. INTRODUCTION

The Fukushima Daiichi Nuclear Power Plant (1F) accident highlighted the importance of events that can influence accident mitigation across multiple units rather than within a single unit alone. These events, referred to here as multi-unit (MU) events, include, for example, conflicts in the allocation of shared equipment and constraints on outdoor operations caused by elevated radiation levels and/or hydrogen explosions. By affecting several units concurrently, MU events may compromise the implementation of mitigation measures and, in some cases, render them infeasible.

Following the 1F accident, international organizations and research institutions across various countries have been conducting research on probabilistic risk assessments (PRA) for multiple units (hereinafter referred to as MUPRA) [1][2][3]. In response to growing research needs, we are currently developing evaluation methods for Level 1 MUPRA. As part of this effort, we have established evaluation methods for various MU events—including resource conflicts due to shared equipment, loss of function in shared equipment, common-cause failures between structures, systems, and components (SSCs) in different units, and the impact on human behavior under MU accident conditions—as a means of assessing scenarios specific to MU accidents [4].

In the 1F accident, Level 2 MUPRA-specific events (hereinafter referred to as “L2 MU events”) have occurred due to events following the loss of containment vessel (PCV) function, which have affected other units. For example, “damage to portable equipment caused by debris scattered during an explosion of flammable gas in the building” has been observed. An L2 MU event is an event that, occurring after the loss of PCV function, affects the occurrence or mitigation of accidents in other units; it consists of

multiple cascading events driven by different dominant phenomena. L2 MU events also had a significant impact on accident mitigation during the 1F accident. Since they are considered important for understanding MU risk, L2 MU events need to be considered in Level 2 MUPRA.

Conventional Level 2 single-unit PRA (SUPRA) typically limits accident sequence analysis to the progression leading to the loss of PCV function in the target unit, and therefore does not explicitly address L2 MU events. Although MUPRA has been investigated in earlier studies, established methodologies for evaluating L2 MU events are still lacking. The accumulation of technical knowledge and the development of analytical methods for such evaluations remain insufficient, and event-specific techniques have not yet been established for some phenomena and events that constitute L2 MU events.

This study therefore proposes a framework for evaluating L2 MU events that enables the estimation of event probabilities and their distributions under current methodological limitations, including cases in which the relevant analyses have different levels of technical maturity. In particular, we propose the Sequential Uncertainty Modeling for Unfolding Phenomena (SUM-UP) method as a phenomenon analysis technique for systematically treating diverse uncertainties while reflecting the specific characteristics of L2 MU events. The method enables both point estimation and uncertainty analysis of L2 MU event probabilities.

2. L2 MU EVENTS

2.1. Definition

An L2 MU event is defined as a series of events caused by physicochemical phenomena occurring after the loss of PCV function, the effects of which propagate to cause damage to SSCs in other units and/or impact mitigation actions. Since an L2 MU event occurs between different units that are separated and operated independently, it requires an intermediary event or phenomenon. Consequently, it is characterized by three elements: the initiating phenomenon (causative event), the events that occur as a result (consequential events), and the mechanism of propagation (propagation mode) (**Figure 1**).

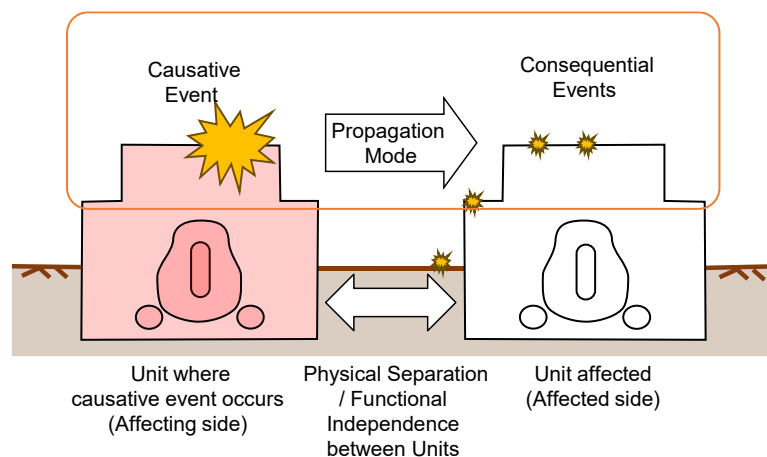


Figure 1 Elements of an L2 MU event (causative event, propagation mode, and consequential event)

Causative Event: It refers to the event that causes an L2 MU event. For example, in the case of an L2 MU event such as “damage to an alternative water injection line caused by debris scattered during a hydrogen explosion,” the “hydrogen explosion” would be the causative event.

Propagation Mode: The mode of action by which a causative event triggers a consequential event is named the propagation mode. For example, in the case of the L2 MU event “damage to an alternative water injection line caused by debris scattered during a hydrogen explosion,” “scattered debris” corresponds to this.

Consequential Event: A consequential event is an event that is resulted by a causative event. For example, in the L2 MU event “damage to an alternative water injection line caused by debris scattered during a hydrogen explosion,” “damage to the alternative water injection line” corresponds to this.

2.2. Characteristics

The definition implies several characteristics of L2 MU events that are important for their evaluation.

Sequential structure of constituent events: An L2 MU event is not a single isolated phenomenon, but a sequence of constituent events. A causative event generates an effect, the effect is transmitted through a propagation mode, and a consequential event occurs in another unit or in site-level mitigation activities. Therefore, the evaluation needs to treat the L2 MU event as a chain of causally connected events.

Heterogeneity in dominant phenomena and technical maturity: The dominant phenomena and the maturity of available evaluation methods may differ among the constituent events. For example, a single L2 MU event may involve combustion, structural damage, debris scattering, radiological effects, or impacts on mitigation actions. Some of these phenomena may be evaluated using established analysis methods or empirical correlations, whereas others may require simplified models or engineering judgment.

Dependencies among parameters and constituent events: Dependencies may exist among the parameters used in the evaluation. Outputs from an upstream constituent event can become inputs to downstream events, and several parameters may share common physical quantities, assumptions, or data. These dependencies should be retained when uncertainties are propagated through the sequence.

These characteristics should be reflected in the response analysis performed within the L2 MU event evaluation framework described in Section 3.

3. EVALUATION FRAMEWORK OF L2 MU EVENTS

The units in which the causative event and the consequential event occur are classified as the affecting side and the affected side, respectively. Assuming that the accident sequences of each unit are basically evaluated separately, considering the causative event and the consequential event independently is expected to lead to effective modeling.

When separating the probabilities of the causative event and the consequential event in the context of L2 MU events, considering the cause and effect relationship, the probability of L2 MU event can be expressed as follows:

$$P(\text{Causative event}) \times P(\text{Consequential event}|\text{Causative event})$$

where $P(\text{Causative event})$ is the probability of a causative event, and $P(\text{Consequential event} | \text{Causative event})$ is the conditional probability of a consequential event given that the causative event has occurred.

It should be noted that L2 MU events are broadly classified into events where the occurrence of the consequential event is almost certain if the causative event occurs, and events where the consequential event occurs with a certain probability; in this study, these are referred to as deterministic and probabilistic consequential events, respectively. The following discussion focuses on the probabilistic case.

The consequential event occurs when the intensity of the impact (s) exceeds the strength of the consequential event at the location and time where the subject of the consequential event exists. Here, the intensity of the impact (s) caused by the causative event follows a probability distribution due to the timing and scale of the causative event itself, as well as uncertainties in the process by which the impact occurs. Furthermore, even for a given intensity of impact (s), the occurrence of the consequential event follows a probability distribution due to variations in the resilience of the affected entity to that

impact (Figure 2-2). This approach is similar to the methodology used in fragility analysis for seismic PRA, where fragility (the probability of failure due to an earthquake) is estimated from the distributions of response and capacity [5]. Following this approach, the intensity of the impact at the location and time where the affected entity exists due to the causative event is referred to as the “response,” the resilience of the affected entity against the impact is referred to as the “capacity,” and the indicator of this impact intensity is referred to as the “damage assessment indicator.”

Based on the above approach, the conditional probability of a consequential event given a causative event i can be expressed as follows.

$$P(\text{Consequential event}|\text{Causative event } i) = \int P(\text{Consequential event}|s)P(s|\text{Causative event } i)ds \quad (1)$$

where the various probabilities are defined as follows.

- $P(\text{Consequential event}|\text{Causative event } i)$: The conditional probability of the consequential event given the occurrence of the causative event i
- $P(s|\text{Causative event } i)$: Distribution of the conditional probability of the causative event given the intensity of its impact (probability density function)
- $P(\text{Consequential event}|s)$: Distribution of the conditional probability of the consequential event given the intensity of the impact (probability density function)

The conditional probability of the consequential event can be estimated by calculating the probability that the capacity is below the response (Figure 2). Note that the estimated probability is a single value.

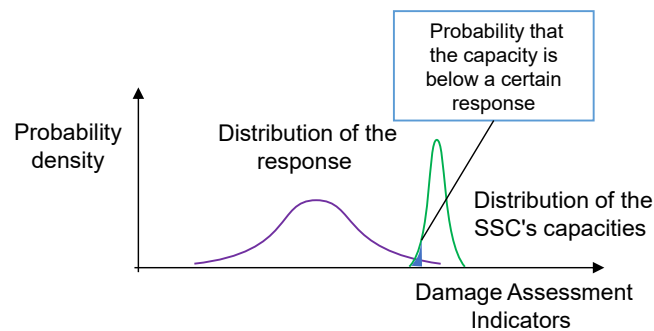
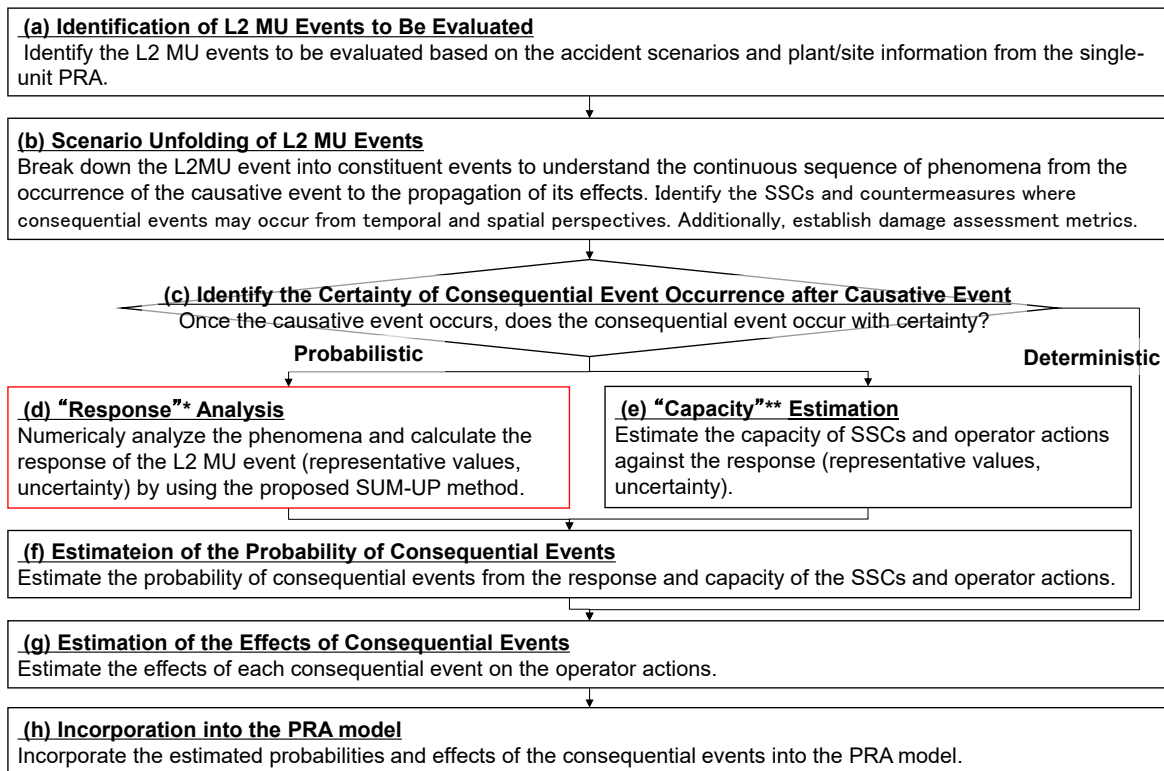


Figure 2: Illustration of the probability estimation of a consequential event

Based on the fundamental concepts outlined above, this study proposes an L2 MU event evaluation framework consisting of eight steps (Figure 3).

First, the L2 MU event to be evaluated is identified (Step (a)), and then the scenario for the L2 MU event is unfolded to identify the constituent events (Step (b)). In the L2 MU event evaluation framework, the evaluation steps differs depending on whether the occurrence of the consequential event following the causative event is deterministic or probabilistic (Step (c)). If the occurrence is probabilistic, the conditional probability of the consequential event given the occurrence of the causative event is estimated. The response of SSCs and mitigation actions to the phenomenon (Step (d)) and the capacity of SSCs to withstand the response (Step (e)) are estimated, and the conditional probability of the consequential event is estimated by comparing the response and the capacity (Step (f)). Since deterministic consequential events always occur when the causal event occurs, the probability of the consequential event is 1. Finally, the effectiveness of L2MU events in mitigating accidents at consequential event occurrence units is evaluated (Step (g)) and incorporated into the multi-unit PRA model (Step (h)).

Among the eight steps, the response analysis in Step (d) is the main methodological challenge because L2 MU events consist of cascading phenomena with possibly heterogeneous technical maturity as explained in Section 2.2. Therefore, this paper focuses on Step (d) and proposes the SUM-UP method.



*Indicates the severity of the phenomenon's impact, corresponding to the “response” in the fragility analysis.

**Indicates the SSC's resistance to the phenomenon's impact, corresponding to the “capacity” in the fragility analysis.

Figure 3 Procedures for the L2 MU event probability estimation framework

4. RESPONSE ANALYSIS USING THE SUM-UP METHOD

This chapter describes the SUM-UP method, newly developed for application to the response analysis in Step (d). In Step (d), we perform an analysis based on the evaluation scenario for those L2 MU events identified in Step (a) that cause probabilistic consequential events, and estimate the distribution of responses.

As described in Section 2.2, L2 MU events are characterized by sequentially unfolding constituent events, heterogeneous dominant phenomena and technical maturity, and dependencies among parameters. In the response analysis of L2 MU events, we need to consider these evaluation characteristics.

In addition to them, in PRA, uncertainty analysis is sometimes required in addition to point estimation. Therefore, in the assessment of L2MU events and the associated response analysis, both epistemic and aleatory uncertainties need to be systematically addressed to enable both point estimation and uncertainty analysis.

Moreover, the evaluation effort should be commensurate with the risk significance of the target events. Experience from the 1F accident suggests that L2 MU events as a whole include event groups that are important from the perspective of MU risk. However, not every individual L2 MU event is necessarily risk-significant. It is therefore not practical to allocate excessive resources to detailed evaluations of events that have limited risk relevance, particularly in scenarios with inherently low frequencies.

Taking these requirements into account, this study proposes the SUM-UP method (Sequential Uncertainty Modeling for Unfolding Phenomena) as a response analysis technique. The SUM-UP method systematically evaluates and propagates the uncertainty inherent in each event within a scenario

where multiple constituent events unfold sequentially. This method can perform probability estimation even when events have different levels of evaluation maturity or exhibit interdependencies.

4.1. Overview of the SUM-UP Method

The SUM-UP method has the following two key features:

- By representing both detailed phenomenon analyses and engineering judgments as simple functional forms, it provides a unified way to describe how variations in input parameters are transformed into variations in output parameters for each constituent event.
- By distinguishing between aleatory and epistemic uncertainties and propagating them in stages, it enables point estimation and uncertainty analysis.

Figure 4 shows an overview of the SUM-UP method procedure. The first two steps are used to estimate the response distribution for point estimation, whereas the third step is used to generate a set of response distributions for uncertainty analysis.

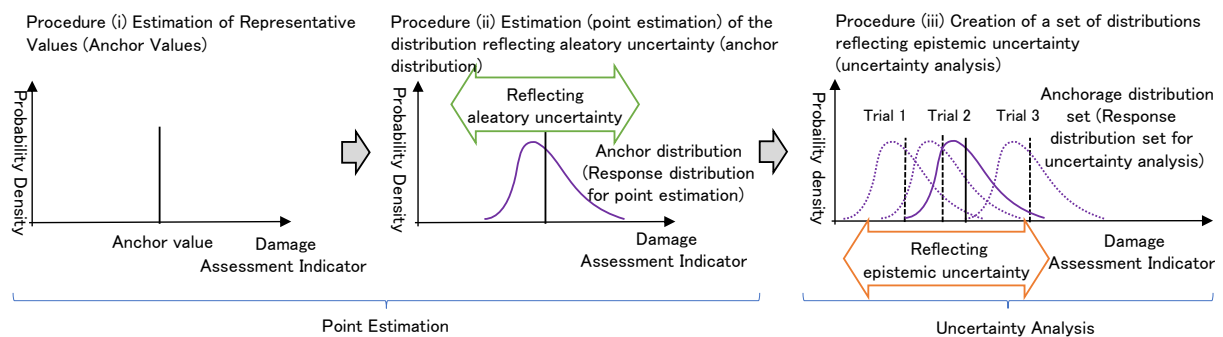


Figure 4 Overview of the SUM-UP Method Procedure

- Procedure (i). Based on the representative values of each input parameter (hereinafter referred to as “anchor values”), estimate the anchor values of the damage assessment indicator;
- Procedure (ii). Sample the aleatory uncertainty of the input parameters to obtain the response distribution of the damage assessment indicators for point estimation. This distribution is hereafter referred to as the anchor distribution. In this step, dependencies among the input parameters are also taken into account.

Procedure (ii) is performed by propagating aleatory uncertainty through the constituent events. Based on the anchor values estimated in procedure (i), estimation models are selected or developed for each constituent event. Monte Carlo samples reflecting aleatory uncertainty are then sequentially propagated through the constituent events, and the anchor distribution is obtained from the final constituent event (see **Figure 5**).

For uncertainty analysis, epistemic uncertainty is assumed to affect the location of the anchor distribution, while the distributional shape reflecting aleatory uncertainty is retained. Based on this assumption, procedure (iii) generates an anchorage distribution set by translating the anchor distribution according to sampled epistemic uncertainty.

- Procedure (iii). Using the sample set obtained as the anchor distribution in procedure (ii), generate a set of shifted distributions as the response distribution set for uncertainty analysis. This set is hereafter referred to as the anchorage distribution set.

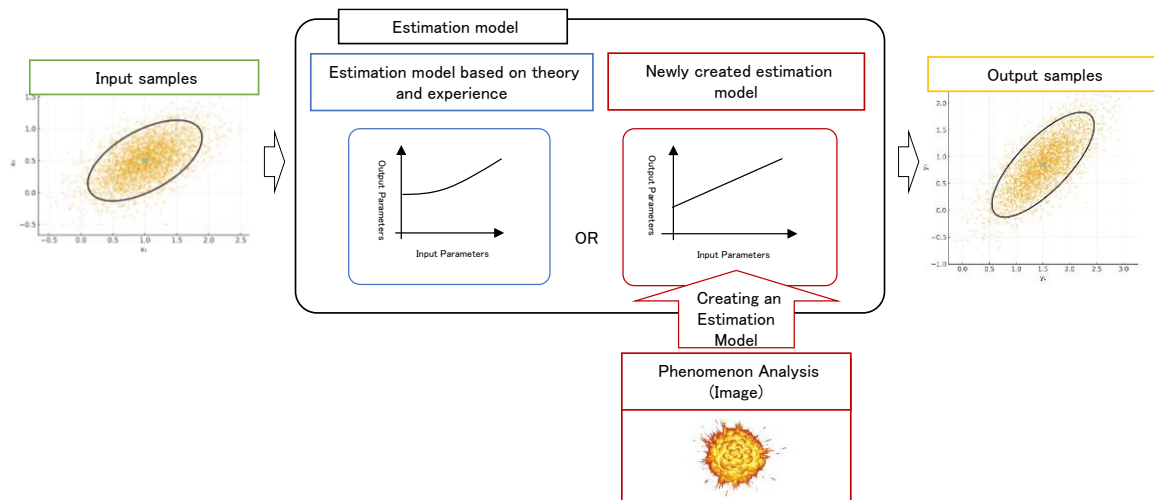


Figure 5 Illustration of how input parameter samples are converted to output parameter samples through the estimation model

4.2. Estimation of the Response Distribution (Anchor Distribution) for Point Estimation

We derive an anchor distribution to reflect the aleatory uncertainty of each input parameter, propagate uncertainty using an estimation model, and estimate the point estimate for the probability of the consequence event. The process of deriving this distribution consists of the following three steps:

- I. Conducting a base case analysis (analysis of anchor values)
- II. Selecting and developing an estimation model
- III. Propagating aleatory uncertainty via Monte Carlo sampling

Details are explained in the following sections.

4.2.1 Base Case Analysis

For each constituent event, a base case analysis is performed to calculate the anchor values of the relevant output parameters. The analysis uses the representative values of the specified input parameters, together with the anchor values propagated from preceding constituent events when applicable. The resulting output anchor values serve as reference points for estimating the anchor distribution in the subsequent steps. The anchor value of the damage assessment indicator is obtained from the output parameters of the final constituent event.

4.2.2 Selection / Development of Estimation Model

In Monte Carlo sampling, running detailed simulations for every sampled case can be computationally expensive. To reduce the computational burden, estimation models are selected or developed to approximate the responses of constituent events. In this study, an estimation model is defined as a mathematical model that represents a constituent event for a given input–output parameter relationship. Existing empirical correlations or experimentally derived formulas may be used when available; otherwise, a new estimation model must be developed.

From the perspective of the level of detail used to simulate the phenomena, an estimation model should ideally be developed after characterizing how the output parameters vary over a sufficiently wide range of input-parameter combinations. This would require simulations for many cases. However, such an approach is not compatible with the SUM-UP method’s policy of adopting the simplest possible modelling approach so that diverse estimation methods can be accommodated. Therefore, the SUM-UP

method is designed to remain applicable even when simulations are available only for the base case and engineering-judgement-based estimations need to be applied in uncertainty propagation.

Specifically, the method assumes that the effects of individual input parameters on the output parameters can be treated independently and neglects interaction effects among the input parameters. This assumption simplifies the relationship between input and output parameters and enables the development of an estimation model even when the available simulation cases are limited.

The estimation model is expressed in mathematical form. Consider the effect of input parameters $x_1, \dots, x_i, \dots, x_k$ on output parameters y_j . Let $\Delta x_1, \dots, \Delta x_i, \dots, \Delta x_k$ and Δy_j denote the deviation from the base case. The input-output relationship is then expressed as follows.

$\Delta y_j = f_{j 1}(\Delta x_1) + f_{j 2}(\Delta x_2) + \dots + f_{j k}(\Delta x_k) = \sum_{i=1}^k f_{j i}(\Delta x_i)$	(2)
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Based on the input–output formulation described above, the estimation model is developed using either of two approaches: a simulation-based approach or an engineering-judgment-based approach. These approaches are described below.

Development of Estimation Models Based on Simulation

The development of estimation models based on simulation offers a high degree of flexibility and allows for the estimation of nonlinear models. To develop an estimation model through simulation, one must first define the type of model to be estimated. This involves specifying the functional form of the model (e.g., linear, polynomial, exponential). These assumptions regarding the model are determined through trial and error, taking into account factors such as comparisons of errors between models and consistency with the upper and lower limits of possible values.

Note, however, that these assumptions are subject to constraints regarding the number of simulations that can be performed for the target input parameters. Additionally, the uncertainty propagation is based on the difference from the anchor value; therefore, the function representing the estimated model must necessarily pass through the base case, which serves as the anchor value.

Development of Estimation Models Based on Engineering Judgment

For input parameters for which estimation models cannot be developed through simulation, models are developed using methods based on engineering judgment. Due to ease of explanation and data constraints, we assume the estimation model is linear and estimate its slope based on engineering judgment. In this method, the relative sensitivity coefficient is utilized to evaluate, from an engineering perspective, the impact of variations in input parameters on the output.

The relative sensitivity coefficient is an indicator that numerically represents the extent to which a variation in a given input parameter affects the output parameter; it is a dimensionless value derived to standardize variations caused by units, scales, and other factors. The relative sensitivity coefficient of an input parameter with respect to the output parameter is defined by the following equation.

$S_{j i} = \left. \frac{\partial y_j}{\partial x_i} \times \frac{x_i}{y_j} \right _{base\ case}$	(3)
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Here, the relative sensitivity coefficient represents the local sensitivity around the base case (anchor value).

By assuming that the input-output relationship is linear, the correction term can be determined using the relative sensitivity coefficient. Under the assumption, Equation (3) can be rearranged to give

$$\Delta y_{j|i} = S_{j|i} \frac{y_j}{x_i} \times \Delta x_i |_{base\ case} \quad (4)$$

where Δx_i represents the difference from the base case for the input parameter, and $\Delta y_{j|i}$ represents the change to output parameter y_j in the corresponding Δx_i . Given the input deviation Δx_i , the base-case values of x_i and y_j , and the relative sensitivity coefficient, the resulting output change $\Delta y_{j|i}$ can be calculated using Equation (4). The total output change is then estimated by summing the contributions from all input parameters, as shown in Equation (5).

$$\Delta y_j = \sum_i^k \Delta y_{j|i} = \sum_{i=1}^k S_{j|i} \frac{y_j}{x_i} \Delta x_i |_{base\ case} \quad (5)$$

Next, we explain the method for determining the relative sensitivity coefficient. Regarding the interpretation of the magnitude of the relative sensitivity coefficient, Reference [6] proposes an indicator for classifying the contributions of each factor when evaluating the impact of urbanization and land-use changes on the risk of agricultural land flooding.

Table 1 provides simplified coefficient values used in this study for engineering-judgment-based estimation. The values are not intended to represent universal thresholds; rather, they are assigned as practical representative values corresponding to high, intermediate, and low degrees of influence, referring to the qualitative interpretation of sensitivity coefficients in Reference [6]. A relative sensitivity coefficient of 1.0 indicates a one-to-one relative response, in which the output changes by the same relative magnitude as the input. Smaller coefficients represent attenuated responses; for example, coefficients of 0.2 and 0.05 correspond to output changes equal to 20% and 5% of the input change, respectively.

Table 1 Proposed Guidelines for Setting Relative Sensitivity Coefficients for Aleatory Uncertainties in Input Parameters

Importance (Degree of impact)	Estimation of relative sensitivity coefficient, S
High	$S = 1.0$
Intermediate	$S = 0.2$
Low	$S = 0.05$

Existing knowledge from constituent event analyses can be used as a reference when assessing the importance, or degree of impact, of input parameters on the output. For example, if there are prior studies analyzing similar phenomena, the sensitivity analysis results presented therein can be referenced. Referring the PIRT (Phenomena Identification and Ranking Table) is also an option (e.g., Reference [7]). This is a method developed for safety analysis of nuclear power plants and code development to identify and rank important phenomena and the parameters that influence them.

The relative sensitivity coefficients for the target input parameters can then be assigned based on the assessed importance level and the guidelines in **Table 1**. By substituting the determined relative sensitivity coefficients into Equation (5), the aleatory uncertainty associated with the input parameters can be assigned to the output parameters.

4.2.3 Propagation of Aleatory Uncertainty via Monte Carlo Sampling

Monte Carlo sampling is used to generate input samples reflecting aleatory uncertainty. Samples are propagated sequentially among the constituent events, and the anchor distribution is calculated based on the results from the final constituent event.

First, the distributions and anchor values of the input parameters are estimated. Then, input samples are generated via Monte Carlo sampling according to the specified distributions and anchor values of the input parameters.

Next, the samples generated for the input parameters are converted into samples of the output parameters using the estimated model. A diagram illustrating this conversion is shown in **Figure 5**.

Based on Equation (2), the mathematical expression is formulated as follows. For the m -th input sample set, let $\Delta x_1^{(m)}, \dots, \Delta x_i^{(m)}, \dots, \Delta x_k^{(m)}$ denote the deviations of the input parameters from the base case. The estimation model, $\Delta y_j = \sum_{i=1}^k f_{j|i}(\Delta x_i)$, is then used to estimate the corresponding deviation in the j -th output parameter. The m -th sample value of the output parameter, $y_j^{(m)}$, is calculated using the following equation.

$y_j^{(m)} = y_j _{base\ case} + \Delta y_j = y_j _{base\ case} + \sum_i^k f_{j i}(\Delta x_i^{(m)})$	(6)
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The output parameters of a constituent event are used as input parameters for the subsequent constituent event. To account for dependencies between parameters, the sample set of output parameters obtained from the estimation model is retained without altering the set, and the sample set reflecting the correlations between output parameters is used as the input parameters for the subsequent constituent event. Thereafter, the operations starting from the estimation of input parameters described in Section 4.2.1 - 4.2.3 are repeated for each constituent event until the final constituent event.

As explained in Section 3, the probability of the consequential events of the L2 MU event is calculated by comparing the response and the capacity. For this comparison, the response and the capacity must be expressed in terms of the same damage assessment indicator. The damage assessment indicator for the response is calculated based on the output parameters of the final constituent event.

4.3. Estimation of the Response Distributions (Anchorage Distribution Set) for Uncertainty Analysis

This section describes how the SUM-UP method generates a set of response distributions by incorporating epistemic uncertainty. The output of this uncertainty analysis is an anchorage distribution set, which represents the uncertainty in the response distribution. The uncertainty in the consequential-event probability can then be evaluated by comparing each response distribution in this set with the corresponding capacity distribution, following the response-capacity framework described in Section 3.

Mathematically, the calculation is performed by sampling epistemic uncertainty, $\epsilon^{(n)}$, from $\epsilon \sim N(0, \sigma_{D,u}^2)$, and adding the same sampled value to all samples in the anchor distribution, $(d^{(1)}, \dots, d^{(m)}, \dots, d^{(M)})$. This yields a shifted anchor distribution, $(d^{(1)} + \epsilon^{(n)}, \dots, d^{(m)} + \epsilon^{(n)}, \dots, d^{(M)} + \epsilon^{(n)})$. By repeating this operation for the epistemic uncertainty samples, $(\epsilon^{(1)}, \dots, \epsilon^{(n)}, \dots, \epsilon^{(N)})$, an anchorage distribution set is obtained.

This anchorage distribution set can then be used to evaluate the uncertainty in the consequential-event probability. Specifically, each shifted response distribution is compared with the capacity distribution, and the corresponding consequential-event probability is calculated. Repeating this calculation for all shifted distributions yields a sample distribution of the consequential-event probability, $(P^{(1)}, \dots, P^{(n)}, \dots, P^{(N)})$.

In the following, epistemic uncertainty is assumed to follow a normal distribution. This assumption is based on the Central Limit Theorem, under the interpretation that the epistemic uncertainty considered here represents the aggregate effect of multiple independent uncertainty sources.

We handle epistemic uncertainty according to the following two types:

- Epistemic uncertainty associated with input parameters
- Epistemic uncertainty associated with the estimation model of the constituent events

4.3.1 Assigning Epistemic Uncertainty Associated with Input Parameters to Anchor Distribution

If input parameters possess epistemic uncertainty, or if there is aleatory uncertainty that could not be reflected in the point estimation, these factors shall be incorporated into the assessment as epistemic uncertainty during the estimation of response distribution uncertainty (uncertainty analysis).

By calculating the relative sensitivity coefficient of the uncertainty factor p_i (in this section, the anchor value of input parameter i) with respect to the damage assessment indicator (hereinafter referred to as the global relative sensitivity coefficient), the standard deviation of the uncertainty factor σ_{p_i} can be aggregated according to the following equation, and the epistemic uncertainty to be evaluated can be calculated.

$$\sigma_{D,u} \approx \sqrt{\sum_i \left(S_{D|i} \frac{D}{p_i} \sigma_{p_i,u} \Big|_{base\ case} \right)^2} \quad (7)$$

The aggregated uncertainty is defined as the variation in the anchor values of the response damage assessment indicators. Specifically, we sample a random variable with a mean of 0 and a distribution with a given variance $\sigma^2_{D,u}$, and then shift the anchor distribution by the amount corresponding to the variation in the sample values representing the epistemic uncertainty.

The epistemic uncertainty associated with an input parameter is given when the parameter's anchor value and uncertainty (standard deviation) are known. For epistemic uncertainty, we apply a simplified uncertainty estimation method based on the concept of relative sensitivity coefficients proposed in Section 4.2.2. The global relative sensitivity coefficient $S_{D|i}$ of a parameter p_i can be calculated if the relative sensitivity coefficients for each of the chained constituent events are known. If needed, the global relative sensitivity coefficient can be assigned by engineering judgment using the same criteria as for aleatory uncertainty.

4.3.2 Assigning Epistemic Uncertainty Associated with Estimation Models to Anchor Distribution

We consider the case where the epistemic uncertainty associated with the estimation model of structural event analysis is reflected in the response damage assessment indicator. When using Equation (7), in addition to the relative sensitivity coefficient, we need to estimate the uncertainty of the estimation model and the anchor value. However, quantitatively determining these values are challenging. Therefore, to reduce the number of unknowns and facilitate engineering judgment, we use the following equation based on the coefficient of variation, $CV_{p_i} = \sigma_{p_i}/p_i|_{base\ case}$.

$$\Delta\sigma_{D,u} \approx \sqrt{\left(S_{D|p_i} D \cdot CV_{p_i} \Big|_{base\ case} \right)^2} \quad (8)$$

We consider guidelines for simplifying the setting of CV. Based on the interpretations of the magnitude of the CV in prior studies [8][9], this study proposes the simplified guidelines shown in **Table 2** for assigning the coefficient of variation for epistemic uncertainty associated with constituent event analysis.

Table 2 Proposed Guidelines for Setting Coefficients of Variation in Constituent Event Estimation Models

Accuracy of estimation model	Estimation of coefficient of variation, CV_x
High	$CV_x = 0.1$
Intermediate	$CV_x = 0.2$
Low	$CV_x = 0.3$

Next, set the global relative sensitivity coefficient. To do so, use the method described in Section 4.3.1. With the above steps completed, the response in terms of the damage assessment indicator D , the coefficient of variation representing the relative magnitude of uncertainty CV_{p_i} , and the global relative sensitivity coefficient $S_{D|p_i}$ have been set. Using Equation (8), we can now calculate the standard deviation representing the uncertainty $\sigma_{D,u}$.

5. CONCLUSION

To account for L2 MU events in MUPRA, we proposed an evaluation framework and developed the Sequential Uncertainty Modeling for Unfolding Phenomena (SUM-UP) method as its core component. The SUM-UP method enables probabilistic estimation by incorporating uncertainty according to the maturity of the phenomenon analysis while accounting for dependencies among constituent events. This approach may also provide a practical basis beyond L2 MU event evaluations for estimating event probabilities even when some constituent phenomena are supported only by immature analytical methods.

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