Human Reliability Analysis for Human-Induced Common-Cause Failures

Yuta Yanada[a], Kanoko Nishiono[a], Tingting Cheng[b], Ali Mosleh[b]
[a] Nuclear Regulation Authority, Tokyo, Japan,
yanada_yuta_g8v@nra.go.jp, nishiono_kanoko_yg4@nra.go.jp
[b] The B. John Garrick Institute for the Risk Sciences, University of California, Los Angeles, California, USA, tingtingc@ucla.edu, mosleh@ucla.edu

Abstract: Common-cause failures (CCFs) are events in which multiple redundant pieces of equipment, or multiple components or systems, fail simultaneously or in a correlated manner due to a single common cause. CCFs are an important consideration in probabilistic risk assessment (PRA) for evaluating realistic risk. Conventional PRA has focused primarily on hardware-induced CCFs; however, in recent years, increasing attention has been paid to the impact of human-induced CCFs associated with maintenance and inspection activities on core damage risk. In order to address such human-induced CCFs, it is effective to conduct human reliability analysis (HRA) that explicitly considers CCFs.
In this study, a human error probability (HEP) quantification incorporating human-induced CCFs was conducted based on an actual incident that occurred at a nuclear power plant in Japan. The analysis scenario consisted of a series of human tasks involved in maintenance work in which similar tasks were repeatedly performed. Using Phoenix, an HRA method developed by UCLA, HEPs were calculated both with and without consideration of human-induced CCFs. By comparing the two results, the applicability of Phoenix's dependency analysis method to human-induced CCFs was examined. The results confirmed that the HEP with dependency considered changed very little compared with the HEP without dependency considered. This is thought to be because the scenario has a structure in which the process proceeds to a subsequent task only when the preceding task is successful, and the overall failure is determined as soon as any one of the tasks fails. As a result, the effect of dependency is limited to the success path.

1. INTRODUCTION

Common-cause failures (CCFs) are events in which multiple redundant items of equipment, or multiple components or systems, fail simultaneously or in a correlated manner due to a single common cause. CCFs are an important consideration in probabilistic risk assessment (PRA) for evaluating realistic risk, because they can cause the simultaneous loss of safety functions, even in safety systems whose reliability has been enhanced through redundancy and diversity[1]. Although conventional PRA has primarily focused on hardware-induced CCFs, increasing attention has recently been given to the impact of human-induced CCFs arising from maintenance and inspection activities on core damage risk. Human-induced CCFs may remain latent as potential failure causes common to multiple tasks and become manifest as operational abnormalities only when the tasks are performed. Such failures may therefore contribute to the simultaneous loss of safety functions. Major contributing factors identified to date include inadequate planning, insufficient knowledge, design deficiencies, and deviations from procedures. The OECD/NEA ICDE topical report [2] indicates that experience related to pre-initiator human failure events (HFEs), which may act as common causes, can provide useful information for improving human reliability analysis (HRA) in PRA models. It also points out that many aspects of dependency as a common cause are not normally modeled in HRA. At the same time, although both the dependencies captured by HRA and those revealed through operating experience should be incorporated into PRA, doing so raises the issue of double counting. Accordingly, a consistent framework for integrating human-induced CCFs into PRA/HRA remains an open challenge.

To address this issue, this study does not introduce human-induced CCFs as separate independent events in HRA; instead, it represents human-induced CCFs by using the dependency-analysis framework embedded in an existing HRA method. A human error probability (HEP) analysis incorporating human-induced CCFs was performed based on an actual incident at a nuclear power plant in Japan. The analysis scenario consisted of a sequence of human tasks in maintenance work involving repeated execution of similar tasks. Phoenix [3][4], an HRA method developed by UCLA, was used in the analysis. Using Phoenix's dependency-analysis function, the common causes of human-induced CCFs were treated as performance influencing factors (PIFs), and human-induced CCFs were modeled through dependencies mediated by these PIFs. Specifically, HEPs were quantified for cases with and without consideration of human-induced CCFs, and the results were compared to examine the applicability of Phoenix's dependency-analysis method to human-induced CCFs.

2. METHODOLOGY FOR INCORPORATING HUMAN-INDUCED CCF

Human-induced CCFs refer to phenomena in which multiple HFEs occur due to shared common causes. These common causes of human-induced CCFs correspond to PIFs in HRA. Therefore, in order to incorporate human-induced CCFs into HRA, it is necessary to devise an appropriate way of defining PIFs within the HRA framework. Accordingly, this study examines whether HEP analysis that accounts for human-induced CCFs can be achieved by using the dependency analysis function of Phoenix, an HRA method developed by UCLA, and by defining PIFs that affect multiple HFEs in a common manner across those HFEs.

In the trial analysis conducted in this study, an incident that actually occurred at a nuclear power plant in Japan was adopted as the analysis scenario, and a series of human processes associated with a reactor trip event caused by human error during equipment maintenance was analyzed. For the evaluation of human-induced CCFs, Phoenix's dependency analysis was applied, and dependencies among the PIFs representing common causes were incorporated into the model. The selection of PIFs to which dependency was assigned was based on factors identified through the cause analysis of the event as well as on measures subsequently implemented to prevent recurrence. Section 2.1 presents the approach for incorporating human-induced CCFs into Phoenix, Section 2.2 outlines the accident scenario adopted for the trial analysis, and Section 2.3 describes the assumptions and conditions used in the analysis.

2.1. Phoenix HRA methodology

Phoenix provides a framework for identifying HFEs in accident scenarios, modeling operational sequences, classifying human errors, and quantifying HEPs through PIFs [3,4]. A notable feature of Phoenix is that it represents the relationships between PIFs and crew failure modes (CFMs) using a Bayesian belief network (BBN), thereby enabling the effects of PIFs on HEP to be reflected on the basis of a causal model consistent with the scenario context. Phoenix was adopted in this study because it enables the common cause of human-induced CCFs to be organized and evaluated as PIFs, making it possible to explicitly analyze the causal relationships between common PIFs to multiple HFEs and the occurrence of each HFE. This makes it possible to incorporate common cause of human-induced CCFs into the model as PIFs and to estimate HEP while accounting for human-induced CCFs by treating inter-HFE dependencies through those PIFs.

2.2. Dependency Analysis Methodology in Phoenix

Figure 1 illustrates the concept of the dependency analysis method in Phoenix using an example [5]. In the upper part of Figure 1, a scenario is considered in which HFE2 is performed as a recovery action following the failure of HFE1, and crew response trees (CRTs) are constructed for each HFE. In CRT HFE1, shown on the left side of the upper part of Figure 1, Critical Task (CT) A is identified. In CRT HFE2, shown on the right side of the upper part of Figure 1, CT B, CT C, and CT D are identified. If CT B succeeds, the process proceeds to CT C, whereas if CT B fails, it proceeds to CT D. Failure of either CT C or CT D results in the occurrence of HFE2. In CRT HFE1, shown on the left side of the second row of Figure 1, CFM A1 is assigned to CT A, and PIF1 and PIF2 are assigned as its associated PIFs. In contrast, CFM B1 and CFM B2 are assigned to CT B, as shown on the right side of the second row, and CFM D1 is assigned to CT D. As a result of assigning the corresponding PIFs to CFM A1, CFM B1, CFM B2, and CFM D1, PIF1 is defined as a common PIF for CFM A1, CFM B1, and CFM D1.

As shown in the lower part of Figure 1, when an analysis is conducted without considering dependency, the common PIF1 is treated as an independent element in each case. In contrast, when dependency is taken into account, multiple CFMs are linked through the common PIF, PIF1, and its influence is updated by Bayesian updating according to event progression. In this example, three time steps are defined: the first time step addresses HFE1; the second time step addresses CT B after the failure of HFE1; and the third time step addresses CT D after the failure of both HFE1 and CT B. From the second time step onward, conditional probabilities are evaluated using the failure of preceding tasks as evidence. For example, failure of CT A propagates to the subsequent CFM B1 through PIF1, thereby increasing the influence of PIF1 on CFM B1.

Phoenix classifies dependency into three categories [6,7]. The first is sequential dependency, the second is static causal dependency, and the third is dynamic causal dependency. Sequential dependency corresponds to the connection between EF1 and the initiating event (IE) of CRT HFE2 in Figure 1. It is modeled through the CRT structure, and the end state corresponding to failure of the recovery action HFE B following failure of HFE A reflects both the failure of HFE A and the failure of HFE B. Static causal dependency corresponds to the relationships between PIF1 and each CFM at the second and third time steps in Figure 1. Under this type of dependency, common PIFs affecting multiple CFMs are defined in common, and dependency is considered by propagating evidence of the success or failure of preceding tasks to subsequent CFMs through those common PIFs. The common PIFs under static causal dependency are static PIFs whose states do not change over time, such as the human-system interface (HSI) and procedures; however, their degradation probabilities for the downstream HFE can be updated due to the observed upstream HFE. In addition, dynamic causal dependency refers to when the upstream HFE is observed, the PIFs affecting the downstream HFE are changed, which means the upstream outcome modifies the future context in which the downstream human task is performed [7].

When performing quantitative evaluation with the Phoenix HRA tool, the user can select whether dependency is turned on or off. Sequential dependency is considered under either setting. By contrast, when dependency mode is turned on, static and dynamic causal dependencies are additionally taken into account, and the HEP value changes as the influence of PIFs on CFMs increases or decreases through conditional probabilities updated by Bayesian updating [4]. In conventional dependency analysis methods based on the joint HEP concept, the failure probability of the next action increases according to the degree of dependency as a result of the failure of the preceding action. In contrast, Phoenix's dependency analysis based on Bayesian updating can reflect not only the effect of failure of the preceding action, but also changes in the failure probability of the subsequent action when the preceding action succeeds. Specifically, when the preceding action fails, the influence of common PIFs on the CFMs becomes greater, whereas when the preceding action succeeds, the influence of those common PIFs on the CFMs becomes smaller.

The common causes underlying human-induced CCFs can be represented as PIFs that affect multiple CFMs, such as the HSI and procedures. This is conceptually compatible with static causal dependency in Phoenix. In other words, by positioning the common causes of human-induced CCFs as PIFs and modeling them as common PIFs, it is considered possible to estimate HEP while accounting for human-induced CCFs. Accordingly, in this study, Phoenix's dependency analysis method was applied to calculate HEPs both with and without consideration of human-induced CCFs. By comparing the two, the applicability of Phoenix's dependency analysis method to human-induced CCFs was examined. In this study, the analysis incorporating human-induced CCFs focused on static causal dependency, one of the three types of dependency defined in Phoenix.

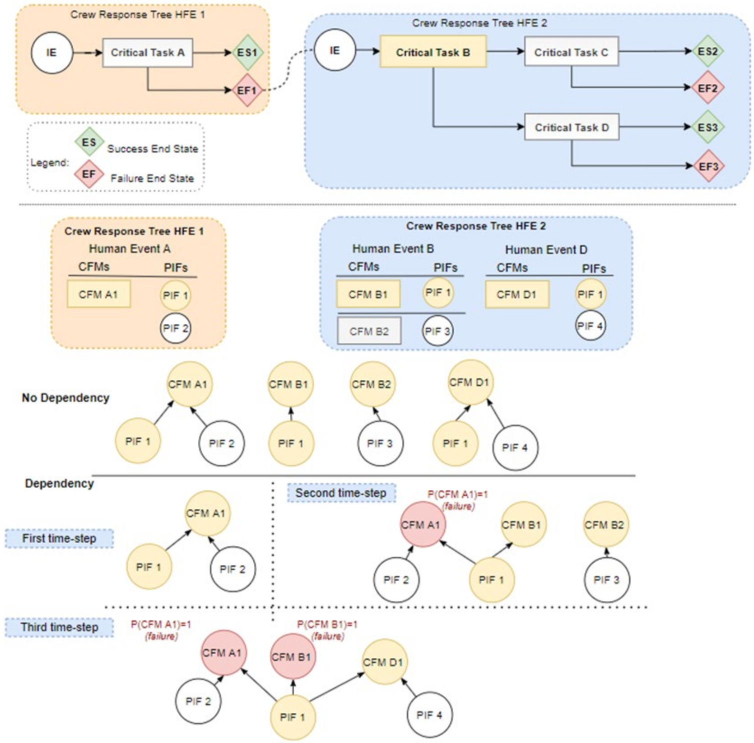

Figure 1. Overview of static dependency analysis in Phoenix HRA [5]

3. CASE STUDY

3.1. Accident Scenario

3.1.1. Overview of the Event

In this study, we estimated the HEP while taking human-induced CCFs into account, using an actual incident that have occurred at a nuclear power plants in Japan. This event involved an automatic reactor trip at an adjacent operating unit, caused by the inadvertent isolation of the current transformer (CT) circuit of that operating unit during protective relay inspection work for a unit undergoing a periodic inspection. Figure 2 shows the sequence of work operations for CT isolation in the A and B trains, viewed from above [8]. The event occurred at the step-up transformer protective relay panel, where the inadvertent isolation of the CT circuit led to generator trip, turbine trip, and ultimately automatic reactor shutdown.

3.1.2. Plant Conditions and Work Activities at the Time of the Event

At the time of the incident, Unit 1 was in a periodic inspection outage, while Unit 2 was operating at rated power. At Unit 1, as part of the periodic inspection of the step-up transformer, an inspection of the step-up transformer protection relay (percentage differential relay) was being conducted. This task required isolation operations of the CT circuits connected to the percentage differential relay at the step-up transformer protection relay panel.
The work was carried out by two personnel from the department responsible, with one serving in a supervisory role and the other primarily performing the operational actions.

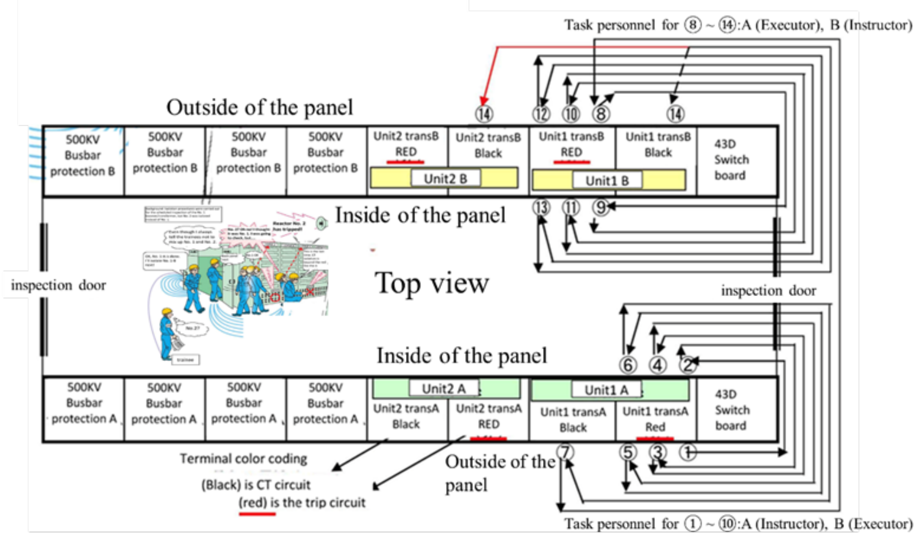

Figure 2. CT Isolation Workflow Overview (A/B Trains) [8]

3.1.3. Work Procedures and Event Scenario

A CT is designed to convert a large primary current into a smaller secondary current, which is supplied to relays and instruments for protection and measurement. Under normal conditions, the CT secondary current circuit is connected to the relay side. During inspection activities, however, the CT secondary side is short-circuited and isolated from the relay side. If a CT circuit were to become open, a high voltage could be induced on the secondary side, posing a risk of damage to instruments and other equipment. Therefore, the work procedures are designed to prevent the CT circuit from becoming open.

First, the A train work was performed. The A train work required multiple actions, including operation of trip terminals installed on the exterior surface of the panel as well as switch operations inside the panel. Accordingly, the worker proceeded with the task while moving back and forth between the outside and inside of the panel a total of three times. The A train work was carried out with the less-experienced worker (Crew B) acting as the operator, while the experienced worker (Crew A) performed checking activities with reference to the checklist prepared for the A train work. Finally, the CT terminals located to the left of the trip terminals on the exterior surface of the panel were operated, and The work steps indicated as 1–7 in Figure 2 were completed. Subsequently, The work steps indicated as 8–14 in Figure 2 was conducted.

For the B train work, the roles were reversed from those in the A train work: Crew A acted as the operator, while Crew B stood nearby and performed checks with reference to the checklist for train B. The B train work step 14 in Figure 2, although the CT terminals of Unit 1, B train should have been operated, insufficient confirmation of the unit was made. As a result, the workers mistakenly moved to the adjacent panel on the right and operated the CT terminals of Unit 2, B train. Due to this operation, the CT circuit of Unit 2 was isolated, multiple circuit breakers opened, and a loss of power to the normal bus occurred. Consequently, the generator of Unit 2 automatically tripped, followed by automatic trips of the turbine and the reactor.

3.2. Analytical Assumptions

3.2.1. PIFs Based on Results of the Licensee's Cause Analysis

The nuclear power plant incident selected for the preliminary analysis in this study was not caused by a single operational error; rather, it was a human-related event that resulted from the overlapping influence of underlying factors, including work procedures, the working environment, operators' cognitive characteristics, and managerial factors. According to the accident cause analysis [8] conducted by the licensee, one of the primary PIFs to this incident was the poor discriminability of control panels by unit and system, attributable to deficiencies in the layout of the relay panels. As a consequence, this layout may have induced perceptual errors on the part of the operator. Based on the results of this cause analysis, the present analysis considered the PIFs related to HSI and resources.

3.2.2 Potential PIFs Not Identified in the Licensee's Cause Analysis

This section analyzed potential PIFs that may not have been fully captured by the licensee's analysis alone, from the perspectives of task characteristics, the work environment, and the work organization. The factors extracted and identified through this analysis are described below.

In the B-train work, the task was performed consecutively right after the completion of the A-train work. In addition, similar to the A-train work, the task involved repeated back-and-forth movements between the inside and outside of the panel, resulting in operational behavior that closely resembled that of the A-train work. Consequently, it is considered likely that the operators transitioned to the next operation while retaining the mental image of the immediately preceding task. This may have led to (i) an assumption that "the same actions as in the A-train work would suffice," and (ii) reduced attention to physical movement between panels, rendering the confirmation of the unit with less attention. Therefore, in this study, inattention, workload, and cognitive bias were considered as PIFs for this task.

With regard to the A-train work, the operational actions were performed by a less-experienced worker, while an experienced worker supervised and conducted checks with reference to the procedure. Accordingly, lack of task experience is considered as a PIF for the A-train work. In contrast, during the B-train work, the roles of the two workers were reversed: the experienced worker performed the operation, while the less-experienced worker was responsible for checking and verification using the procedure. Although the roles of operator and checker were formally separated in the B-train work, the checker had limited experience with the task, while the operator was highly experienced. As a result, the checking activity may have remained superficial, and an independent reconfirmation (cross-check) of the target unit may not have been adequately performed. This is also considered to be a factor that prevented the erroneous operation from being detected and corrected in advance. Therefore, team composition and inappropriate role allocation were considered as PIFs for this task.

Furthermore, the procedure did not explicitly include a step requiring confirmation of the target unit prior to performing the operation. This omission is also considered to have contributed to the operation being performed on the incorrect unit. Accordingly, procedure quality was taken into account as a PIF.

3.2.3 PIFs Considered in the Case Study and Corresponding Phoenix PIFs

Based on the results of the licensee's cause analysis presented in Section 3.2.1 and the analysis of PIFs discussed in Section 3.2.2, the PIFs defined for the case study in this research and their corresponding PIFs in Phoenix are summarized in Table 1. In Phoenix HRA, PIFs are specified by answering a set of questionnaires prepared for each PIFs category [4]. Accordingly, we organized the mapping by identifying the questionnaire items relevant to the human error factors determined in Sections 3.2.1 and 3.2.2.

Table 1. PIFs defined in the case study and their corresponding Phoenix PIFs

PIFs Based on the Licensee Report	PIFs for the Case Study
Visibility of unit identification markings	HSI
Layout of the work location	Resource
Inattention	Knowledge Abilities
Lack of experience with the task	Knowledge Abilities
Workload	Task Load
Cognitive bias	Bias
Team composition and inappropriate role allocation	Team Effectiveness
Absence of safety-significant instructions in the procedure	Procedure

3.3 Analytical Conditions and models

Based on the accident scenario described in Section 3.1 and the analytical assumptions presented in Section 3.2, an HRA model was developed using the Phoenix method. Figure 3 shows the Master Event Sequence Diagram (Master ESD). The Master ESD represents the event progression as a scenario, depending on the success or failure of each major task. In addition, Table 2 shows Critical Functions (CFs) of Master ESD. As illustrated in Figure 3 and Table 2, the scenario consists of a total of 17 CFs. These CFs are broadly divided into three phases: preparation of inspection (CF1), the CT isolation operation phase for the A train conducted for transformer inspection (CF2-CF9), and the CT isolation operation phase for the B train (CF10-CF17). During the CT isolation operation phase, after repeating the in-cabinet and out-of-cabinet operations on the trip terminals three times, the procedure then transitions to operations on the CT terminals. Each panel operation consists of two steps: selecting the panel to be operated and executing the operation. An error in panel selection leads to a Reactor Trip, whereas an error in executing the operation leads to a Failure of Inspection.

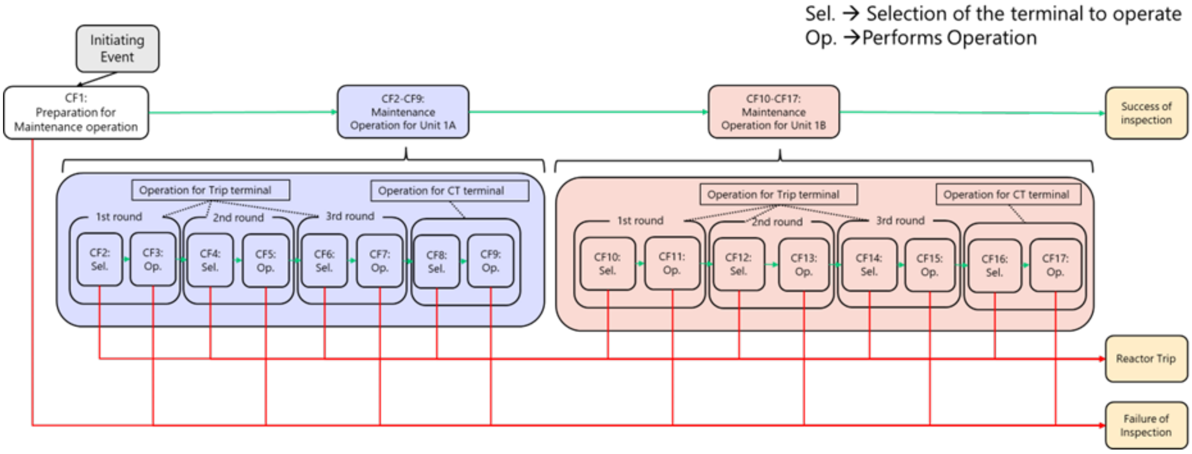

Figure 3. Master ESD for case study

Table 2: Critical Function of Master ESD

CF No.	Description
CF1	Preparation for periodic inspection for Unit 1
CF2	Unit1A-1st round-Selection of Trip Terminals for Unit 1A
CF3	Unit1A-1st round-Operate trip terminals (in)outside of the panel
CF4	Unit1A-2nd round-Selection of Trip Terminals for Unit 1A
CF5	Unit1A-2nd round-Operate trip terminals (in)outside of the panel
CF6	Unit1A-3rd round-Selection of Trip Terminals for Unit 1A
CF7	Unit1A-3rd round-Operate trip terminals (in)outside of the panel
CF8	Selection of Trip Terminals for Unit 1A CT terminal
CF9	Unit1A-Operate CT terminal outside of the panel
CF10	Unit1B-1st round-Selection of Trip Terminals for Unit 1B
CF11	Unit1B-1st round-Operate trip terminals (in)outside of the panel
CF12	Unit1B-2nd round-Selection of Trip Terminals for Unit 1B
CF13	Unit1B-2nd round-Operate trip terminals (in)outside of the panel
CF14	Unit1B-3rd round-Selection of Trip Terminals for Unit 1B
CF15	Unit1B-3rd round-Operate trip terminals (in)outside of the panel
CF16	Selection of Trip Terminals for Unit 1B CT terminal
CF17	Operate CT terminal outside of the panel for Unit 1B

In addition, Figure 4 and 5 present two examples of CRTs representing CFs downstream in Figure 3. Figure 4 shows the CRT of the CFs related to accurately selecting the panel to be operated. Specifically, after the occurrence of the Initiating Event, if the indicator needed for the crew to recognize the correct target panel is available, the sequence transitions to BP_D2. If the indicator is not available, it proceeds to EF_4. At BP_E2, if the crew selects the correct panel to operate, the sequence proceeds to ES_5; if the crew selects the wrong panel, it proceeds to EF_5. ES_5 represents success of the CF and transitions to the Initiating Event of the subsequent CF, i.e., the CF associated with executing the panel operation. EF_4 and EF_5 represent failure of the CF and cause a trip of Unit 2's generator during power operation, resulting in a reactor trip. Figure 5 shows the CRT of the CFs related to accurately executing the panel operation. Specifically, following the occurrence of the Initiating Event, the sequence proceeds to ES_3 if the crew can correctly carry out the panel operating procedure; otherwise, it proceeds to EF_6. ES_3 represents success of the CF and transitions to the Initiating Event of the subsequent CF. EF_6 represents failure of the CF and results in a Failure of Inspection.

Based on the task analyses presented in Figure 3, 4, and 5, the PIFs considered in the present case study and their relationships with the corresponding CFMs in each CRT are summarized in Table 3. In addition, Figure 6 illustrates the relationship between the PIFs and the CFs for which dependencies are introduced when dependency is considered. The common causes of human-induced CCFs that commonly affect the operations in both train A and B trains were considered HSI and Procedure. HSI was treated as common PIF for the CFs related to panel selection, whereas Procedure was treated as common PIF for the CFs related to panel operation. In addition, PIFs that commonly affect the operations within each train, were considered Knowledge and Abilities for A train operations, and Knowledge and Abilities as well as Team Effectiveness for B train operations. For Knowledge and Abilities, the groups were separated in consideration of the fact that Crew B performed the A train operations and Crew A performed the B train operations. Specifically, in Figure 6, Operator A's Knowledge and Abilities and Team Effectiveness are linked to CF1 (preparation for inspection) following the occurrence of the Initiating Event. Furthermore, Task Load due to repeating similar operations was considered for both A train and B train operations, specifically for the repeated operations from the third iteration onward.

As shown in Table 3 and Figure 6, HSI, Procedure, Knowledge and Abilities, Team Effectiveness, and Task Load are PIFs that commonly affect multiple CFs. Therefore, these PIFs were selected as common cause of human-induced CCFs, and dependencies were introduced among the related CFs.

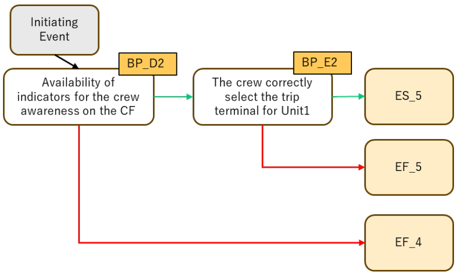

Figure 4. CRT for CFs related to selecting the terminals for operation (CF2, CF4, CF6, CF8, CF10, CF12, CF14, CF16)

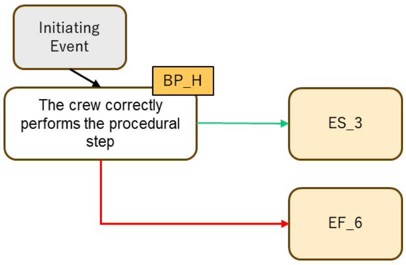

Figure 5. CRT for CFs related to operating terminals (CF3, CF5, CF7, CF9, CF11, CF13, CF15, CF17)

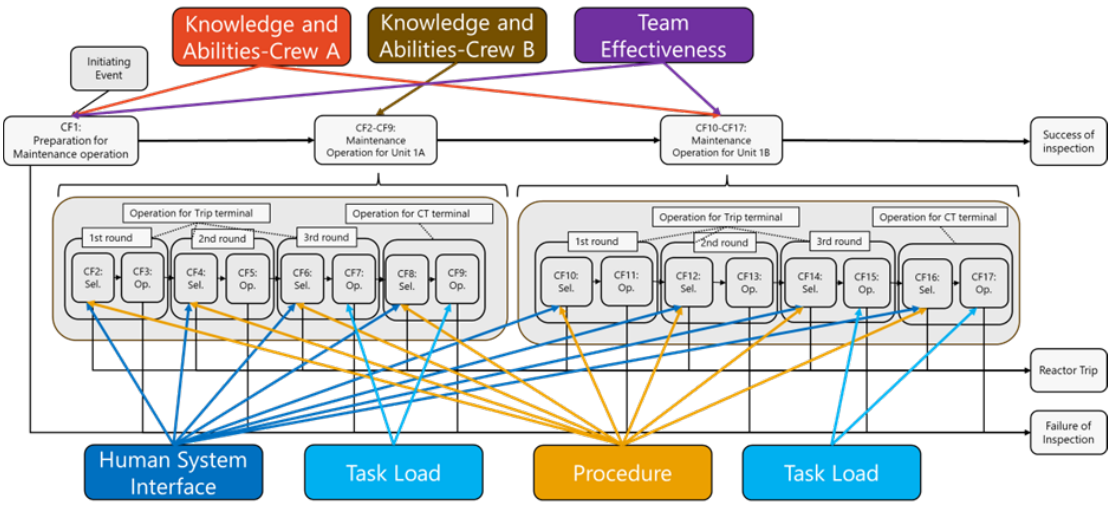

Figure 6. PIFs for which dependencies are considered and the corresponding CFs

Table 3. CFM corresponding to CT-related CFs and PIFs in each CRT

PIF/PIF level	CRT Branch Point	CFM	Relevant CFs	Description
HSI /0.667	The crew correctly select the trip terminal for Unit1	Action on Wrong component	CF2, CF4, CF6, CF8, CF10, CF12, CF14, CF16	Because the unit identification markings on the panels were common across all panels, the CFs related to panel selection share a common PIFs.
Resource /0.333	The crew correctly select the trip terminal for Unit1	Action on Wrong component	CF16	The layout structure was such that it was prone to inducing errors in panel selection in CF16.
Knowledge and Abilities for Crew A /0.25	The crew correctly select the trip terminal for Unit1	Action on Wrong component	CF1, CF10, CF11, CF12, CF13, CF14, CF15, CF16, CF17	In the series of operations for the B train, a potential lack of attention by Crew A, attributable to their high level of task familiarity, was considered.
	The crew correctly performs the procedural step	Incorrect Operation of component		
Knowledge and Abilities for Crew B /0.25	The crew correctly select the trip terminal for Unit1	Action on Wrong component	CF2, CF3, CF4, CF5, CF6, CF7, CF8, CF9	In the series of operations for the A train, insufficient task experience of Crew B was considered.
	The crew correctly performs the procedural step	Incorrect Operation of component		
Task Load /0.375	The crew correctly performs the procedural step	Incorrect Operation of component	CF7, CF9, CF15, CF17	Increased workload due to the continuation of repetitive tasks and the large number of procedural steps was considered.
Bias /0.333	The crew correctly select the trip terminal for Unit1	Action on Wrong component	CF16	It was considered that an assumption existed that “performing the same actions as in the A-train work would be sufficient.”
Team Effectiveness /0.214	The crew correctly select the trip terminal for Unit1	Action on Wrong component	CF1, CF10, CF11, CF12, CF13, CF14, CF15, CF16, CF17	In the series of operations for the B train, the work was not sufficiently supervised due to an inappropriate team composition.
	The crew correctly performs the procedural step	Incorrect Operation of component		
Procedure /0.7	The crew correctly select the trip terminal for Unit1	Action on Wrong component	CF2, CF4, CF6, CF8, CF10, CF12, CF14, CF16	When selecting the panel, the procedure did not include a step requiring confirmation of the target unit.

4. IMPACT OF DEPENDENCY ON HEP IN PHOENIX ANALYSIS

Based on the analysis conditions defined in Section 3.3, HEPs were estimated using Phoenix for the case in which dependencies were considered, and the results were compared with the HEPs obtained without considering dependencies. Figure 7 shows the occurrence probabilities of each end state in the Master ESD. The vertical axis represents the end states, and the horizontal axis represents the HEP. Additionally, the probabilities evaluated with dependency taken into account are indicated by dots, whereas the other series represents probabilities evaluated without considering dependency.

As shown in Figure 7, no substantial differences were observed in the probabilities of the two failure end states defined in the Master ESD even when dependencies were taken into account. This result can be attributed to the structure of the analysis scenario: a transition to a subsequent CF occurs only upon the success of the preceding CF, and once a failure occurs in any CF, no subsequent CF exists. Consequently, inter-CF dependency is restricted to effects conditioned on “success of the preceding CF.” Under this structure, the Bayesian update reduced the influence of the dependency factors and the five PIFs specified as human-induced CCF factors, HSI, Procedure, Knowledge and Abilities, Team Effectiveness, and Task Load, on the associated CFMs. As a result, the human error probability decreased after incorporating dependency. However, the reason the change in HEP was minimal is presumably that, during the Bayesian update, one data point should have been removed from the referenced dataset due to the success of the preceding operation. In practice, the number of referenced data points changed by only one before and after the update, and this small change in sample size is expected to have resulted in no substantial shift in the updated HEP.

Figure 8 shows the rate of change in the HEP for each CFs in the Master ESD, comparing the cases before and after accounting for dependency and human-induced CCFs. The vertical axis represents the HEP change rate, and the horizontal axis represents the CFs name. The probability of changes in HEP related to preparation of operation and terminal selection is indicated by diagonal hatching, whereas the other shows data related to the operation. No change was observed for CF2–9 between the two cases.
For CF2-9, no change was observed before and after incorporating dependency effects. This is most likely because CF2-9 did not share any common PIF with the immediately preceding operation, CF1, and therefore was not affected by the Bayesian update associated with dependency modeling (see Figure 6).

In contrast, for CF1 and CF10–CF17, incorporating dependency and human-induced CCFs resulted in a reduction in HEP. Specifically, for the CFs related to selecting terminals for operating (CF10, CF12, CF14, and CF16), the decrease was on the order of a few percent, whereas for the CFs related to executing operations on the target terminals (CF11, CF13, CF15, and CF17), a reduction of approximately 10% in HEP was observed. As described above, the fact that all change rates exhibited a downward trend can be attributed to the assumption that each operation involved only success dependency. Under this setting, the Bayesian update reduced the extent to which the PIFs influence the CFMs. In addition, the overall decrease in CF10–17 is likely because of Knowledge and Abilities and Team Effectiveness for Crew A, which are shared with CF1. The reason is considered that the common PIF specified in this analysis—namely “Team Effectiveness” and “Knowledge and Abilities” associated with Crew B—were influenced primarily through the success-side behavior.

In contrast, in scenarios where recovery actions are introduced after a preceding task failure, Bayesian updating in the BBN can propagate the failure evidence from the preceding task to subsequent tasks via the PIFs. This allows the latent common-cause degraded state to be updated and potentially reflected in the HEPs of the subsequent tasks.

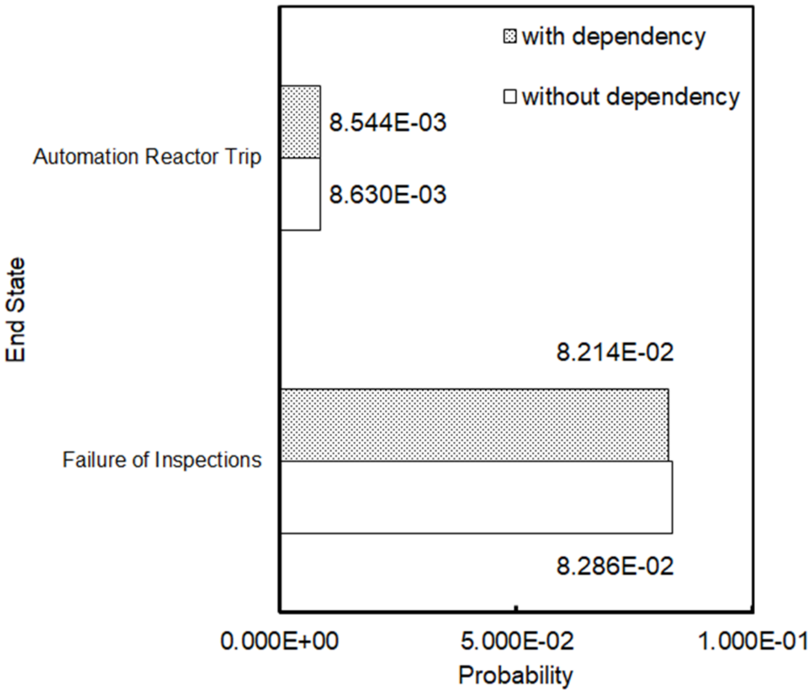

Figure 7. HEP of end states with/without dependency

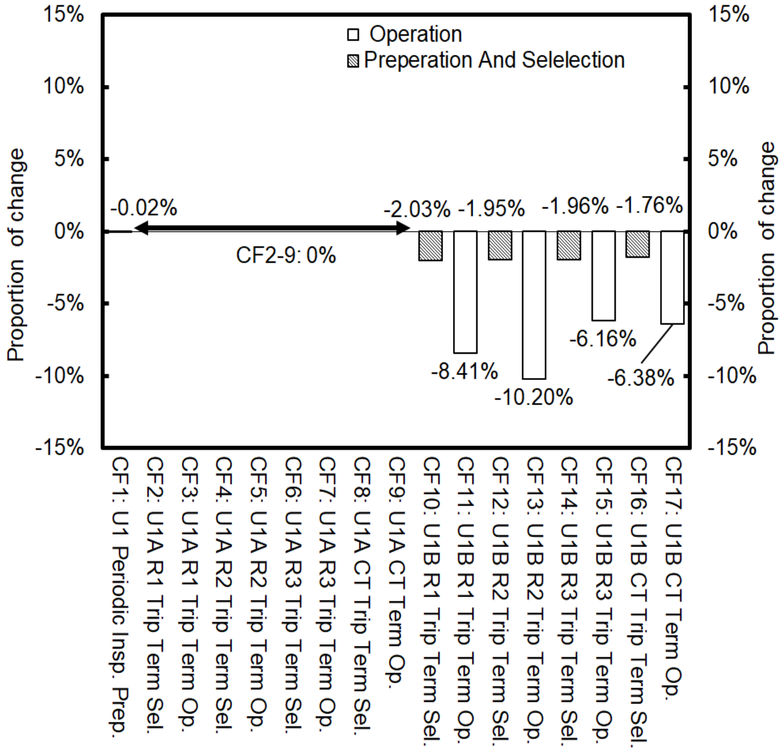

Figure 8. Rates of change in the HEP of each CFs relative to the case without dependency
[CF1: Performs by Crew A and B, CF2-9: Performs by Crew B, CF10-17: Performs by Crew A]

5. CONCLUDING REMARKS

Using the dependency analysis method based on BBNs implemented in Phoenix, a trial HEP analysis was conducted for a trouble scenario related to periodic inspection operations that actually occurred at an operating nuclear power plant. In the analysis, to represent the effects of human-induced CCFs, PIFs corresponding to common causes were shared across multiple CFs, and dependencies were modeled using Phoenix's static causal dependency concept. The results showed that the HEPs estimated with dependency consideration were almost unchanged compared with those estimated without considering dependencies. This is attributed to the structure of the scenario, in which progression to subsequent tasks occurs only when the preceding task is successful, and failure is determined at the point where any task fails. As a result, the influence of dependency is limited to the success side of task execution.

In contrast, in scenarios that include recovery actions following the failure of a preceding task, Bayesian updating allows information on the preceding task failure to propagate to subsequent tasks via common PIFs. Thus, Phoenix's dependency analysis function is considered capable of supporting HEP calculation that accounts for human-indued CCFs by propagating the success or failure of a preceding task to subsequent tasks across successive HFEs.

As a future challenge, it will be necessary to further examine the applicability of Phoenix dependency analysis to human-induced CCFs by conducting additional trial analyses using models that explicitly incorporate a framework of dynamic dependency, in which PIF states change over time due to factors such as workload and stress, as well as failure-oriented dependency (for example, scenarios involving recovery actions after failure).

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