A dynamic Bayesian network-based emergency decision-making framework highlighting emergency propagations: Illustrated using the Fukushima nuclear accidents and the Covid-19 pandemic

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Abstract
When facing public emergencies, human societies need to make decisions rapidly in order to mitigate the problems. However, this process can be difficult due to complexity of the emergency scenarios and lack of systematic methods for analyzing them. In the work reported here, we develop a framework based upon dynamic Bayesian networks in order to simulate emergency scenarios and support corresponding decisions. In this framework, we highlight the importance of emergency propagation, which is a critical factor often ignored by decisionmakers. We illustrate that failure of considering emergency propagation can lead to suboptimal mitigation strategies. By incorporating this critical factor, our framework enables decisionmakers to identify optimal response strategies minimizing emergency impacts. Scenarios developed from two public emergencies: the 2011 Fukushima nuclear power plant accidents and the Covid-19 pandemic, are utilized to illustrate the framework in this paper. Capabilities of the framework in supporting decision making in both events illustrate its generality and adaptability when dealing with complex real-world situations. Our analysis results reveal many similarities between these two seemingly distinct events. This indicates that seemingly unrelated emergencies can share many common features beyond their idiosyncratic characteristics. Valuable mitigation insights can be obtained by analyzing a broad range of past emergencies systematically.

KEYWORDS
Covid-19 pandemic, decision support, emergency preparedness, Fukushima nuclear accidents, risk propagation

1 INTRODUCTION

When a public emergency occurs, human societies need to determine mitigation strategies in a timely manner in order to control the overall situation. However, this can be difficult due to the complexity of the problems and interdependency of multiple factors. Such problems occurred during the 2011 Fukushima nuclear power plant accidents (Fukushima accidents) as well as the 2020 Covid-19 pandemic. During the Fukushima accidents, four nuclear reactors experienced different degrees of damage due to lack of systematic planning of the whole nuclear power plant restoration process (Cai & Golay, 2020a). During the Covid-19 pandemic, virus spread between different regions challenged the safety of the whole community due to lack of inter-regional collaboration. Therefore, when making public emergency decisions, in addition to focusing upon localized problems, it is critical to develop systematic understanding of the whole picture.

Emergency response is a field that has been widely studied (Huang et al., 2021) classifies emergency response activities into three phases: pre-event, in-event and post-event. Among them, emergency response during events is extremely
challenging due to psychological and technical reasons. In these processes, decisionmakers need to collect and process a large amount of highly uncertain information under high pressure and harsh environmental conditions (Aven, 2016). Moreover, the dynamic nature of emergencies imposes additional difficulties in anticipating potential future progresses of emergency scenarios (Sanderson et al., 2020). Given these challenges, incorporating all relevant information into response decisions is important yet difficult for decisionmakers.

The importance of incorporating as many relevant factors as possible has been widely recognized. Zio (Zio, 2018) emphasizes the importance of managing risks in a systematic way considering all potential progresses of emergencies. Zio (Zio, 2016) elaborates the value of considering all interdependencies of systems when formulating emergency risk scenarios. Son et al. (Son et al., 2020) highlights the importance of developing integrated decision support systems incorporating all relevant information. In light of these recognitions, a variety of methods, including case-based reasoning (Feng & Xiang-Yang, 2018; Shimin et al., 2007; D. Wang et al., 2020), network methods (Buzna et al., 2006; Helbing et al., 2006; Li & Chen, 2014; Ouyang et al., 2008), and the fuzzy decision methods (Camasta et al., 2015; Hao et al., 2018; Peng et al., 2019) have been utilized in analyzing and mitigating emergency risks. Even though they all made valuable contributions to this problem, an important factor, emergency propagation between multiple entities and its effect upon mitigation strategies, has been neglected by previous researchers.

Traditional risk management mostly focus upon a single entity. For nuclear accident, studies focus upon a single nuclear reactor (Fleming, 2005; Modarres et al., 2017; United States Nuclear Regulatory Commission, 2003). For Covid, studies focus upon a single, predefined region (Block et al., 2020; R. Li et al., 2020; Zhang et al., 2019). However, emergency propagation between different nuclear reactors or different regions, which act as a critical risk factor, has not been researched. Past research upon general emergency propagation mostly focuses upon propagation mechanisms (Chen et al., 2019; Deng et al., 2018; N. Feng et al., 2014; Garvey et al., 2015; P. Wang et al., 2021). Few studies have revealed the effects of emergency propagation upon response decisions. In our work, we focus upon this point and reveal that failure of incorporating emergency propagation leads to suboptimal mitigation strategies and unnecessary losses. In this work, a decision-making framework based upon dynamic Bayesian networks (DBNs) is proposed to support emergency decisions. Event propagation between different entities is highlighted in our framework to provide more accurate analysis of potential emergency scenarios. DBN is selected in our framework due to its capabilities of representing complex and dynamic interactions between different factors in emergencies (Khazad et al., 2011; Mkrtchyan et al., 2015; Weber et al., 2012). This enables us to dynamically model emergency propagation between multiple entities and anticipate their effects upon future progresses of emergency scenarios. Moreover, the capabilities of DBN in handling uncertainties (Iqbal et al., 2015; Langseth & Portinale, 2007; Lee et al., 2008) make it suitable to deal with emergency mitigation problems, which often occur under highly uncertain environments (Aven, 2016).

Scenarios developed from two real-world emergencies: the 2011 Fukushima Nuclear Accidents and the 2020 Covid-19 pandemic are discussed in this work to illustrate the utilization of the framework. These two seemingly unrelated events are selected to illustrate the generality and adaptability of the proposed framework. Moreover, we found that these two events face common challenges due to the nature of public emergencies beyond their idiosyncratic characteristics. The common challenges analyzed in this work are listed in Table 1 below. By developing parallel analysis of the events and comparing corresponding insights, we can understand some fundamental aspects of public emergencies and provide guidance applicable to future events in general. Importance of learning from past experiences has been widely recognized by the emergency management community (Hoffmann & Muttarak, 2017; Salama et al., 2004; Tsui, 2013). Our work illustrates that in addition to learning from past emergencies in a similar field, one can learn valuable lessons from seemingly unrelated emergencies. This enables the research community and decisionmakers to obtain insights that cannot be revealed by solely focusing upon emergencies in a single field.

Interactions between various factors of a public emergency can be complex. During the Fukushima accidents, failure of a single reactor unit propagated to neighboring units according to interviews with engineers involved in its mitigation (Cai & Golay, 2020a). A similar situation occurs in the Covid-19 pandemic since the virus can spread between different regions. Moreover, interactions between emergency status and human activities can be complex as well. During the Fukushima accidents, nuclear system status could be changed by implementing restoration activities. Site personnel could also adjust their activities based upon latest perceived nuclear system status. In the Covid-19 case, the severity of the pandemic could be controlled by implementing behavior restrictions. Humans may also change their behaviors when they believe that the pandemic is less severe.

When a public emergency occurs, it can be difficult to respond to it in a timely fashion, especially when it imposes novel challenges beyond the experiences of human societies. Such delays can degrade the effects of implemented response strategies. During the Fukushima accidents, functional restoration delays imposed great challenge to mitigation activities (Cai & Golay, 2020a). For the Covid-19 pandemic, delays of contact tracing, diagnosis, and laboratory results can decrease the effectiveness of corresponding activities (Kretzschmar et al., 2020; Mögling et al., 2020; Rong et al., 2020). Moreover, only focusing upon decreasing response delay at a single nuclear reactor unit or a single region is not sufficient due to potential emergency propagation. Therefore, response delay is an important factor needing to be considered systematically when dealing with public emergencies.
2 | DISCUSSIONS OF THE 2011 FUKUSHIMA NUCLEAR POWER PLANT ACCIDENT

2.1 | Modeling structure for the Fukushima accidents

In this section, Fukushima accidents scenarios are analyzed using the proposed framework. The models used are plausible ones based upon interviews with Tokyo Electric Power Company (TEPCO) staff who worked on stabilizing the Fukushima nuclear power plants after the Tohoku earthquake and tsunami. Figure 1 illustrates the structure of the DBN utilized for analysis of the Fukushima accidents. In this work, a nuclear power plant having two reactor units is selected as the analysis object. The figure only illustrates the modeling structure for Unit 1 (Unit 2 follows the same structure).

In this paper, we focus upon explaining high-level modeling assumptions that are applicable to public emergencies in general. Technical details related to the Fukushima accidents and nuclear power plants are available in Cai and Golay (2020b, 2021). Baseline assumptions for modeling parameters employed in this work are presented in Appendix 1 Table A1. All scenarios presented in this Section utilize the parameters in the table unless otherwise specified.

We choose to expand the graph in time to decouple various feedback effects. In Figure 1, green nodes represent system status at the current time, $t$, while blue nodes represent system status at a previous time, $t - dt$. Feedback effects between human restoration activities and system status are implicitly encoded by the dependency of a system’s status upon its status at a previous time step. The feedback effects between system diagnosis outcomes, as represented by gray nodes, and its status are decoupled in time as well. As shown in the graph, system status at time, $t - dt$, affects corresponding diagnosis outcomes at the same time, which in turn affects the system’s status at the end of the next time step, $t$. Detailed explanation of the nodes and their dependencies are given in Appendix 2.

In addition to dependencies within a single nuclear reactor unit described in Figure 1, interactions between multiple nuclear reactor units at the same site is another problem worth emphasizing. According to interviews with TEPCO engineers involved in Fukushima accidents mitigation, such interactions imposed great challenges to response decisions.
EMERGENCY DECISION FRAMEWORK INCLUDING PROPAGATION

**FIGURE 1** Time dependent modeling graph for interactions between reactor systems and human activities

**FIGURE 2** Interactions among two nuclear reactor units at the same site

(Cai & Golay, 2020a). Figure 2 illustrates the interactions between the two nuclear reactor units considered in this section. Such interactions are represented by edges between systems and structures of different reactor units. In this work, in addition to intra-unit interdependencies, DC power and portable reactor cooling restorations are also assumed to be vulnerable to reactor building failure at the neighboring units as occurred during the Fukushima accidents (Cai & Golay, 2020a). This dependency is expanded in time to decouple potential feedback effects between the two units. When solving the Bayesian network, both intra-unit dependencies encoded in Figure 1, and inter-unit dependencies encoded in Figure 2 would be considered in our model.

Integrating the dependencies described in Figures 1 and 2, we obtain a complete DBN model that can be utilized to simulate the status of all systems at all time steps given a specific set of site conditions as input. Figure 3 below represents the output of the DBN defining the status of reactor cores, internal energy, cooling status, and reactor buildings for one specific scenario. In this work, we focus upon maximizing long-term success probabilities of nuclear reactor cores. Thus, we extract and summarize the status of nuclear reactor cores when time goes to infinity. Running multiple iterations and summarizing reactor core status in all these simulations using the Monte Carlo method, we
can obtain the success probability of nuclear reactor cores under a specific set of site conditions. Varying input site conditions and analyzing resulted reactor core success probabilities, we can determine the conditions maximizing success probabilities and corresponding mitigation strategies. In this way, decisionmakers can identify optimal response strategies maximizing overall benefits.

2.2 Analysis of the Fukushima accidents response strategies

2.2.1 Fukushima accidents restoration delay problem

When a nuclear reactor loses normal cooling capabilities, the reactor core will heat up (due to fission product decay) and fail if cooling capabilities are not restored in time. Therefore, it is important to implement restoration activities in a timely fashion. This problem is more complex when multiple reactor units need to be protected. When it is difficult to proceed with restoration tasks at all reactor units in parallel, decisionmakers tend to devote most of their efforts to the reactor unit in the most urgent condition, as during the Fukushima accidents (Cai & Golay, 2020a). However, this is not always the best strategy due to the interdependencies between different reactor units, as illustrated in the analysis shown in this section.

In the scenarios analyzed in this section, restoration delay of nuclear reactor Unit 1 is kept at zero. The restoration delay for nuclear reactor Unit 2 is varied in order to analyze its effects upon both units. Figure 4(A) and (B) displays the effects of Unit 2 restoration delay upon success probabilities of two units, with and without incorporating inter-unit failure propagation, respectively. As shown in Figure 4(A), where inter-unit failure propagation is correctly considered, the increase of Unit 2 restoration delay not only decreases its own success probability, but also decreases the other unit’s (Unit 1’s) success probability. In this case, even though Unit 1 has no restoration delay, failure of Unit 2 can propagate to Unit 1 and degrade its safety. Therefore, it is not sufficient to focus upon a single reactor unit in order to protect its integrity. However, if inter-unit accident propagation is not correctly considered, as shown in Figure 4(B), decisionmakers may mistakenly believe that Unit 1’s success probabilities are not affected by restoration delays at other units. As a result, decisionmakers may fail to properly coordinate restoration tasks at multiple nuclear reactors. This can lead to unnecessary losses in real-world emergencies. During the Fukushima accidents, mitigation focus shifted from one reactor unit to another consecutively due to lack of systematic coordination between them. Long restoration delays at reactor units not being prioritized negatively affected safety of all nuclear reactor units at the site (Cai & Golay, 2020a). In addition to qualitatively revealing this effect, our framework also quantifies the effects of Unit 2 response delays.
2.2.2 Fukushima accidents resource distribution problem

When resources are insufficient to support restoration work at all reactors units in parallel, the most tempting decision would be that of allocating all of them to the unit in the most urgent condition, as decisionmakers did during the Fukushima accidents (Cai & Golay, 2020a). However, as illustrated in this section, this may not be the best choice given the interdependency between multiple reactor units.

Figure 5(A) and (B) displays the effects of resource distribution on site success probabilities, with and without incorporating inter-unit accident propagation, respectively. In these scenarios, the operator population is very few relative to the needs as displayed in Table A1. Therefore, two reactor units need to compete for the limited human resource. The x-axis represents the resource fraction allocated to Unit 1, increasing its resource fraction decreases resources allocated to Unit 2 since resource fractions of both units sum to unity. An optimal resource distribution exists that maximizes the success probabilities of any single unit as well as of both units.
As shown in Figure 5(A), where inter-unit accident propagation is properly considered, even if one wants to maximize the success probability of a single reactor unit, allocating all resources to it is not optimal. Devoting all resources to a single reactor unit would leave the other one unattended and having a high failure probability. The failure could propagate back to the unit getting all resources, and thus decrease its success probability. Such effects could remain unnoticed if decisionmakers were to employ localized views and only focus upon a single reactor unit, as illustrated in Figure 5(B). If decisionmakers fail to consider inter-unit propagation, they may wrongly determine that allocating all resources to a single nuclear reactor would maximize its success probability. As a result, they may fail to systematically coordinate restoration activities at multiple reactors and formulate suboptimal mitigation strategies. In addition to qualitatively revealing the importance of properly allocating resources among multiple reactors, our framework quantitatively identifies the optimal resource distribution for each reactor unit. As a result, corresponding response decisions can be made more accurately. Analyses of the Covid-19 pandemic reveal similar results as discussed in Section 3.2.2.

2.2.3 Fukushima accidents bottleneck task identification problem

During the Fukushima accidents, multiple challenging problems, including resource shortages and false system status diagnosis, needed to be solved to mitigate the situation (Cai & Golay, 2020a). However, solving each of the problems can require large efforts. Therefore, decisionmakers need to identify and prioritize the bottleneck restoration task to mitigate the accidents most effectively. To achieve this, candidate restoration tasks need to be compared based upon their effects in improving site success probabilities. This could be difficult without a systematic method to analyze the whole situation. In this section, we illustrate the capability of our framework in supporting such decision-making problems.

To quantitatively compare the effects of increasing human resource and decreasing false diagnosis rate, we conduct sensitivity analysis of the two factors jointly. Figure 6 presents site success probabilities under various combinations of the two factors. Even though success probabilities increase with decreased false diagnosis rates under all operator populations, low diagnosis accuracy is not always the bottleneck problem most seriously challenging the site safety. For example, when the human resource level is low (5 operators for each task), site success probability is below 0.1 even if no false diagnosis exists. In such scenarios, increasing human resource level is the bottleneck problem needing to be prioritized. If site decisionmakers focus upon nonbottleneck problems, it would be very difficult to substantially improve the site safety. Therefore, identifying the bottleneck problem in emergency decision making is very important because it determines the high-level direction of all mitigation tasks. Our framework is capable of providing decision-making guidance for such problems given its capability of quantitatively analyzing joint effects of multiple restoration tasks. Similar results are also revealed in the Covid-19 pandemic as discussed in Section 3.2.3.

3 DISCUSSIONS OF THE COVID-19 PANDEMIC

3.1 Modeling structure for the Covid-19 pandemic

In this section, the proposed framework is illustrated using scenarios adapted from the Covid-19 pandemic. In order to illustrate the interactions between neighboring regions during the Covid-19 pandemic, New York (NY) and New Jersey (NJ) states in the United States are selected as illustrative examples due to their vicinity and high transportation volume between them. Figure 7 presents the DBN structure for NY, the graph for NJ follows a similar structure. Similar to the Fukushima case, the modeling graph is expanded in time in order to decouple potential feedback effects. In this section, response strategies are compared based upon their effects on cumulative fatality number when the pandemic ends. Detailed modeling assumptions are available in Appendix 3.

Two categories of strategies have been implemented in order to control the Covid-19 pandemic: preventive strategies (Güner et al., 2020; Joshi & Mehendale, 2021; Molnar et al., 2021; Sharma et al., 2021) curbing the spread of the virus and medical strategies (Adhikari et al., 2021; Janiaud et al., 2021; Mohamed et al., 2021; Putman et al., 2021) treating infected individuals. In this work, we mainly focus upon the effects of preventive strategies upon severity of the pandemic. Joshi and Mehendale (2021) provide a reasonably complete list of potential preventive strategies. These strategies fall into the

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2 The two states are only selected as illustrative examples. Similar analysis can be conducted on any vicinity regions.
following categories: mask wearing, social distance, vaccination, and environmental disinfection. In this work, all strategies except for environmental disinfection are incorporated in our models. This treatment is sufficient for our purpose since environmental disinfection can be incorporated into the model by adding a multiplier representing its preventive effects, similar to the way that mask wearing and social distance have been modeled.

Detailed explanations of the nodes and their interactions in Figure 7 are available in Appendix 4. In Figure 7, the feedback effects between human activities and pandemic status are encoded by the dependency of mask wearing and social distance upon the number of perceived Covid-19 cases. Detailed assumptions for this dependency are available in Appendix A3.2. Presumably, more restrictions are implemented when the pandemic is serious. Restrictions can be relaxed when the pandemic is in a stable state. Moreover, the perceived case numbers can deviate from the actual situation due to test errors. In addition to mask wearing and social distancing, case tracking, and vaccine availability can also limit virus spread. Case tracking levels depend upon the number of tests, because only confirmed cases can potentially be tracked. In additional to activities inside the state, virus spread in NY can also be affected by the pandemic status in the neighboring state: NJ. Figure 8 illustrates the virus spread mechanism considered between them.

The major virus spreading mechanism considered in this work between NY and NJ states is by populations commuting between the two states. According to United States Census Bureau (n.d.-a) around half a million people commute daily between them. A severe pandemic in any single state could propagate to the other due to their close connections. This is consistent with the actual situation during the first few months of the pandemic when both states suffered. In this work, we assume that 1000 and 500 people are infected by the virus at NY and NJ, respectively. The virus could spread either way when in the later stage of simulated scenarios.

Utilizing the graph structure represented in Figure 7 and the modeling assumptions described in Appendix 3, Covid cases and fatality numbers at both states for all time steps can be obtained by solving the DBN. In this work, we focus upon the cumulative Covid fatality number of the two states when the pandemic ends. Extracting this information from DBN simulation results and varying the input hyper parameters corresponding to response strategies, decision makers can understand the value of alternative response strategies and identify the ones minimizing the losses caused by the pandemic.

### 3.2 Analysis of the Covid-19 pandemic response strategies

#### 3.2.1 Covid-19 pandemic response delay problem

When responding to the Covid-19 pandemic, decision-makers at each region tend to focus upon decreasing their own response delays. However, delays in the neighboring region can also challenge its safety due to the existence of inter-regional virus spread. Such effects would remain unnoticed without systematic analysis of the pandemic status involving multiple regions. In this section, we illustrate this phenomenon using delays of testing and behavior restrictions at NY and NJ as examples.

Figure 9 shows the effects of the NJ response delay on the total fatality number of the two states, with and without considering interstate virus transmission. In both the scenarios, the NY response delay is set to zero. As shown in the Figure 9(A), when inter-state virus transmission is incorporated into the model, even though there is no delay at NY, its fatality number increases with increased delays at the

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3 In this work, we focus upon the cumulative fatality number until the pandemic is fully controlled.
neighboring state. This indicates that it is not sufficient to protect a single state by only decreasing its own response delay. On the contrary, if one fails to consider interstate virus transmission, as shown in Figure 9(B), NY decisionmakers can falsely believe that coordination between neighboring regions is unnecessary since the NY fatality number is not affected by NJ response delays. This illustrates the importance of considering emergency propagation in real-world scenarios. Failure of doing so can lead to overly optimistic estimation of emergency scenario results and suboptimal mitigation decisions. In addition to qualitatively revealing such vulnerabilities, our framework can quantify such effects. This can better support response decisions given the nonlinear relationship between fatality numbers and response delays.

### 3.2.2 Covid-19 pandemic resource distribution problem

This section explores resource distribution problem for the Covid-19 pandemic using mask resources as an example. Other resources like medical resources and human resources can be modeled following the same logic. In this work, we assume that wearing masks could decrease virus spread by as much as 70%. However, that effect depends upon the availability of masks. In the scenario discussed in this section, we assume that 20% of people in each state have access to their own masks originally. We focus upon the problem of distributing additional mask supplies when they become available. A similar situation occurred when the hospital ship Comfort arrived at the New York region in order to help treat Covid-19 patients (LaGrone, n.d.). The ship could have chosen to dock in NY or in NJ to provide additional medical resources to the corresponding state. Two states compete for the limited resources since docking the ship at one state would decrease the amounts of benefits provided to the other state.

Figure 10 presents the effects of mask resource distribution upon fatality numbers, with and without considering interstate virus transmission. The x-axis corresponds to

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4 In this scenario, we assume that additional mask supplies covering 1.4 million population are available.

5 All response delays are set to zero in this scenario to eliminate their effects.
3.2.3 Covid-19 pandemic bottleneck task identification problem

During the Covid-19 pandemic, multiple tasks need to be accomplished. How to prioritize between them is an important problem determining the effectiveness of response strategies. Focusing upon other problems instead of the bottleneck ones could lead to waste of resources since they are not the key factors limiting the severity of the pandemic. This section explores this problem using increasing clinical test accuracy and improving contact tracing rate as illustrative examples. False negative clinical tests where infectious individuals are missed could impose great challenges upon pandemic mitigation (Arevalo-Rodriguez et al., 2020), because it is unlikely to track or impose any behavior restrictions upon unidentified individuals. Even if infectious individuals are identified, their contact rate could still be high if no behavior restriction is imposed upon them. In this work, we assume that an infectious individual will not infect others only if he/she is both detected and tracked. Any behavior restriction, including self-quarantine, that can limit the contact rate of infectious individuals is considered a form of tracking.

Figure 11 presents the joint effects of the two factors upon fatality numbers. As shown in the figure, even though

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Footnote: For all scenarios in this section, we consider a situation where delays are zero, and 20% of population have access to masks.
decreasing test error can generally decrease fatality numbers, the benefits provided by it depends upon case tracking fraction. When no case is tracked, improving test accuracy cannot decrease fatality numbers since no behavior restriction is implemented upon the detected individuals. In such cases, increasing case track fraction is the bottleneck problem needing to be prioritized. On the contrary, if test error is high (0.9), fatality numbers are high even if most of the cases are tracked. Thus, more efforts should be devoted to decreasing test rate. Identifying and focusing upon the bottleneck problem can mitigate the pandemic most effectively. The capability of our framework in quantifying such effects can be practically useful as well. According to Arevalo-Rodríguez et al. (2020), most studies report false negative rates ranging between 0.018 and 0.33, which is not particularly high if a sufficient number of individuals are tracked based upon the results in Figure 11. Therefore, in the regions where few cases are tracked, tracking more cases can contribute greatly to controlling the pandemic.

4 | CONCLUSIONS
In this work, we propose a DBN-based emergency decision-making framework incorporating event propagation between multiple entities. The proposed framework is illustrated using the Fukushima accidents and the Covid-19 pandemic scenarios. By comparing scenarios with and without incorporating emergency propagation, we illustrate that failure of incorporating this factor can lead to erroneous mitigation insights and suboptimal mitigation strategies. As discussed in Section 1, this is a point that has not been focused upon by previous researchers. Based upon our analysis results and reflection of mitigation strategies implemented in practice, we propose high-level mitigation suggestions that can be utilized for all emergencies facing challenges similar to those discussed in this work. By conducting parallel analysis of the Fukushima accidents and the Covid-19 pandemic, we illustrate that seemingly distinct emergency events can face common challenges and share common features despite their idiosyncratic characteristics. This expands the potential emergency candidates that decisionmakers can learn from. Emergencies from a specific field can be scarce, learning from a broad range of seemingly unrelated events can provide valuable insights for decision makers. Utilization of our framework in the two relatively distinct events illustrates the generality and adaptability of the framework. Applying the proposed framework to future emergencies can support high-quality response decisions when human societies face significant challenges unexpectedly.

ACKNOWLEDGMENT
The Fukushima related research project is funded by Tokyo Electric Power Company.

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How to cite this article: Cai, Y., & Golay, M. W. (2023). A dynamic Bayesian network-based emergency decision-making framework highlighting emergency propagations: Illustrated using the Fukushima nuclear accidents and the Covid-19 pandemic. *Risk Analysis*, 43, 480–497. https://doi.org/10.1111/risa.13928
APPENDIX 1
Baseline parameters utilized in the Fukushima scenarios

**TABLE A1** Baseline parameter assumptions for the Fukushima scenarios

| Assumptions category                  | Assumptions          | Unit 1        | Unit 2        |
|---------------------------------------|----------------------|---------------|---------------|
| Thermal hydraulic condition           | Initial internal energy (MJ) | $4 \times 10^5$ |               |
|                                       | Core failure threshold (MJ)   | $1.6 \times 10^6$ |               |
|                                       | Decay power (MW)             | 33            | 24.75         |
|                                       | Portable Cooling Power if Restored (MW) | 33            |               |
| Restoration workload for each task (man × hour) |                         | 40            |               |
| Total site operators for each task    | 10                    |               |               |
| Resource distribution among two units | 50%                   | 50%           |               |

APPENDIX 2
Description of Bayesian network nodes for Fukushima nuclear accident analysis (Figure 1)

**TABLE A2** Explanation of Bayesian network nodes for Figure 1

| Node category          | Node name                              | Node description                                                                 | Relationship with parent nodes                                                                 |
|------------------------|----------------------------------------|----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| Site conditions (white node) | Unit 1 Resource, delay, and system false diagnosis rates | This node describes site conditions that will affect restoration tasks of all systems. | Site conditions are input as hyperparameters in the model to analyze their effects upon accident scenarios. |
| System status at the end of a previous time $t - dt$. Utilized as the initial status for the current time $t$ (blue nodes) | Unit 1 Containment Venting time $t - dt$ | Status of Containment at a previous time $t - dt$ | Initial status of a system at the next time step is the output of the system status of the DBN from the previous time step. For example, suppose that status of DC system at the end of time step $t = 1$ is success. Then, at the beginning of time step $t = 2$, its initial status would be success. All other systems follow the same logic. |
|                        | Unit 1 DC Status time $t - dt$          | Status of DC power at a previous time $t - dt$                                  |                                                                                                |
|                        | Unit 1 Depressurization time $t - dt$   | Status of depressurization function at a previous time $t - dt$                 |                                                                                                |
|                        | Unit 1 Portable cooling time $t - dt$   | Status of portable cooling at a previous time $t - dt$                          |                                                                                                |
|                        | Unit 1 Internal energy time $t - dt$    | Nuclear reactor internal energy at a previous time $t - dt$                     |                                                                                                |
|                        | Unit 1 Core status time $t - dt$       | Nuclear reactor core status at a previous time $t - dt$                         |                                                                                                |
|                        | Unit 1 Containment time $t - dt$       | Nuclear reactor containment status at a previous time $t - dt$                 |                                                                                                |
|                        | Unit 1 Reactor building time $t - dt$   | Nuclear reactor building status at a previous time $t - dt$                    |                                                                                                |

(Continues)
| Node category | Node name | Node description | Relationship with parent nodes |
|---------------|-----------|------------------|-------------------------------|
| Diagnosis result of systems (gray nodes) | Unit 1 Venting diagnosis time \( t - dt \) | Diagnosis result of containment venting system at the end of the previous time \( t - dt \) | Diagnosis result of a system depends upon its own status and the status of DC power. When DC power is unavailable, false diagnosis rate can be higher than the cases where it’s available. |
| | Unit 1 DC diagnosis time \( t - dt \) | Diagnosis result of DC system at the end of the previous time \( t - dt \) | |
| | Unit 1 Depressurization diagnosis time \( t - dt \) | Diagnosis result of Depressurization system at the end of the previous time \( t - dt \) | |
| | Unit 1 Portable cooling diagnosis time \( t - dt \) | Diagnosis result of portable cooling system at the end of the previous time \( t - dt \) | |
| Status of systems at the end of the current time step \( t \) (green nodes) | Unit 1 DC Status time \( t \) | DC power status at the end of current time step \( t \) | Status of DC system depends upon its status at the previous time step, its diagnosis result and site conditions. Diagnosis result determines site personnel’s understanding of the system status. This determines whether the system can be properly restored if needed, and determines whether site personnel would utilize the system to provide necessary functions if possible. Site conditions determine the speed at which the system can be restored in case it is damaged. The logic follows for all other systems. |
| | Unit 1 Containment venting time \( t \) | Containment venting status at the end of current time step \( t \) | Status of containment venting depends upon its status at the previous time step, its diagnosis result, site conditions, and the availability of DC power. DC power can decrease the workload needed to implement containment venting. |
| | Unit 1 Depressurization time \( t \) | Depressurization function status at the end of current time step \( t \) | Status of depressurization function depends upon its status at the previous time step, its diagnosis result, site conditions and the availability of DC power. DC power can decrease the workload needed to implement depressurization function. |
| | Unit 1 Portable cooling time \( t \) | Portable cooling system status at the end of current time step \( t \) | Status of portable cooling system depends upon its status at the previous time step, its diagnosis result, site conditions, and the status of depressurization. Due to design features of nuclear systems, the portable cooling system can only function properly when depressurization is successful. |
| | Unit 1 Internal energy time \( t \) | Nuclear reactor internal energy at the end of current time step \( t \) | Internal energy of the nuclear reactor at the end of time \( t \) depends upon its internal energy at the previous time step and the status of portable cooling. Portable cooling can remove heat from the reactor and decrease its internal energy |
| | Unit 1 Core status time \( t \) | Nuclear reactor core status at the end of current time step \( t \) | Nuclear reactor core status depends upon its status at the previous time step and its internal energy. Reactor core would fail if its internal energy exceeds a certain threshold |
| | Unit 1 Containment time \( t \) | Nuclear reactor containment status at the end of current time step \( t \) | Nuclear reactor containment status depends upon its status at the previous time step, the status of reactor core, and the status of containment venting. Failure of reactor core could lead to failure of the containment if containment venting is not implemented successfully. |
| | Unit 1 Reactor building time \( t \) | Nuclear reactor building status at the end of current time step \( t \) | The status of the reactor building depends upon its status at the previous time step and the status of containment. Failure of nuclear reactor containment can lead to failure of reactor building. |
TABLE A3  Variables utilized in the modified SIR model (Equation A1) 

| Variable     | Definition                                                                 |
|--------------|-----------------------------------------------------------------------------|
| S, I, I_nt, R| S: susceptive population  
|              | I: infectious population being tracked  
|              | I_nt: infectious population not tracked  
|              | R: removed population                                                       |
| m_m, m_d    | m_m: multiplier representing preventive effect of mask wearing  
|              | m_d: multiplier representing preventive effect of social distance           |
| β           | Infectious rate without any preventive method                               |
| N           | Population of the state                                                     |
| I'_nt, N'_nt, N_c | I'_nt: infectious population not tracked at the neighboring state  
|              | N'_nt: total population at the neighboring state  
|              | N_c: commute population between the two states                              |
| f_t         | Fraction of infectious individuals being tracked                            |
| γ_v, γ_r, γ_d | γ_v: immunization rate by vaccine  
|              | γ_r: recovery rate  
|              | γ_d: death rate                                                             |

APPENDIX 3: DESCRIPTION OF EPIDEMIC MODELS UTILIZED IN THIS WORK

A3.1 Summary of Epidemic Models
In this work, a modified version of susceptible-infected-recovered (SIR) (Harko et al., 2014) model is utilized to describe the epidemiology features of the Covid-19. The population are divided into three compartments: susceptive individuals (S), infectious (I) individuals, and removed (R) individuals. The modified model for a single state is presented in Equation A1, while corresponding variables and their definitions are presented in Table A3. All variables listed in the table are time dependent.

\[
\frac{dS}{dt} = -\frac{m_m m_d \beta S}{N} \left( I_{nt} + I'_{nt} N'_c \right) - \gamma_v S \\
\frac{dI}{dt} = f_t \frac{m_m m_d \beta S}{N} \left( I_{nt} + I'_{nt} N'_c \right) - \gamma_r I - \gamma_d I \\
\frac{dI_{nt}}{dt} = (1 - f_t) \frac{m_m m_d \beta S}{N} \left( I_{nt} + I'_{nt} N'_c \right) - \gamma_r I_{nt} - \gamma_d I_{nt} \\
\frac{dR}{dt} = \gamma_r I + \gamma_d I + \gamma_r I_{nt} + \gamma_d I_{nt}
\]  

(A1)

As shown in Equation A1, susceptive individuals can either be infected or immunized. Mask wearing and social distance can change the actual infection rate. Infectious individuals commuting from neighboring state can also infect susceptive individuals. We assume that only infectious individuals not being tracked can infect other people. Infectious individuals, no matter whether being tracked or not, can be removed if they are recovered or dead.

A3.2 Effects of confirmed case upon behavior restrictions
Behavior restrictions including mask wearing and social distance can be implemented or relaxed based upon the pandemic severity. In this work, we assume that these methods are implemented for 90 days initially. Later, they are adjusted based upon the number of confirmed Covid-19 cases. Figure A1 illustrates the model utilized in this work to describe the implementation and relaxation of behavior restrictions. When perceived Covid-19 cases in NY consecutively increase for $\Delta t_{impose}$ days, the behavior restrictions are implemented for $\Delta t_{restrict}$ days in order to control the pandemic.\(^7\) After that, the behavior restrictions are lifted. This assumption is consistent with the actual case. New York city started Phase 1 reopen in early June 2020 (Cuomo, n.d.-a), which was around 90 days since a disaster emergency was declared in early March 2020 (Cuomo, n.d.-b). Later in July 2020, New York Governor Andrew Cuomo indicated that the reopening could rollback to an earlier phase if the Covid-19

\(^7\) In this work, $\Delta t_{impose}$ and $\Delta t_{restrict}$ are set to be 14 and 30 days, respectively.
FIGURE A1  Behavior restrictions implementation based upon perceived Covid-19 cases in NY

TABLE A4  Determination method of parameters utilized in this work

| Variable | Determination Method |
|----------|----------------------|
| $m_{i0}$, $m_d$ | $m_{i0} = 1 - \min(1, \frac{\text{mask amount}}{N}) \times 0.7$  
$m_d = 0.4$ |
| $\beta$ | 0.63 (R. Li et al., 2020) |
| $N$, $N_c$ |  
NY population: $\sim$19 million (United States Census Bureau, n.d.-c)  
NJ population: $\sim$9 million (United States Census Bureau, n.d.-b)  
Commute population between NY and NJ: 543,903 (United States Census Bureau, n.d.-a) |
| $f_t$ | $f_t$ depends upon three parameters:  
• fraction of infectious cases being tested, 0.2 in this work (Matrajt & Leung, 2020).  
• test false negative probability, default value 0.25  
• fraction of confirmed case being tracked, default value 0.2 |
| $\gamma_v$, $\gamma_r$, $\gamma_d$ |  
$\gamma_v$: available after day 270, immunized 75% of susceptible population every 180 days  
$\gamma_r = \frac{\beta}{R_0} \times (1 - \text{death fraction})$, $R_0 = 2.3$, death fraction = 0.148 (Liu et al., 2020, Ji et al., 2020)  
$\gamma_d = \frac{\beta}{R_0} \times \text{death fraction}$ |

situation were to get worse (Borter, n.d.). The dependency of behavior restrictions upon the pandemic status is captured by our model.

A3. 3 Determination of modeling parameters

\[8 \leq 9 \leq n\]

\(^*\)This number is the weighted average of documented and un-documented patients infection rate in R. Li et al. (2020).

\(^*\)Vaccine available time and effectiveness are based upon our assumption.
### APPENDIX 4
Description of Bayesian network nodes for Covid-19 analysis (Figure 7)

**TABLE A5** Explanation of Bayesian network nodes for Figure 7

| Node category | Node name | Node description | Relationship with parent nodes |
|---------------|-----------|------------------|---------------------------------|
| New Jersey (NJ) case number (yellow node) | NJ actual cases time $t - dt$ | Actual Covid cases in NJ at the end of the previous time step $t - dt$ | Case count of NJ depends upon its own response strategies. Figure 7 only provides a detailed DBN structure for NY state, NJ state follows the same logic. |
| New York (NY) status at the end of the previous time step $t - dt$ (blue nodes). These nodes act as initial conditions for the simulation of the current time step | NY perceived cases time $t - dt$ | Perceived Covid cases in the NY state at the end of the previous time step $t - dt$ | Nodes in this category inherit their values from the DBN simulation results at the previous time step. |
| New York (NY) status at the end of the current time step $t$ (green nodes) | NY actual cases time $t - dt$ | Actual Covid cases in the NY state at the end of the previous time step, $t - dt$ | |
| New York (NY) status at the end of the current time step $t$ (green nodes) | NY test number time $t$ | Number of Covid patients being tested at the current time $t$ | In this work, we assume that a constant fraction of Covid cases is tested. This fraction is treated as a hyper parameter being input to the model. Detailed assumption is available in Appendix A3.3 |
| | NY case track number, time $t$ | Number of Covid cases being tracked at the current time $t$ | Number of Covid cases being tracked depends upon the number of cases being tested. Only cases that are tested positive can potentially be tracked. |
| | NY mask wearing, social distance time $t$ | Status of mask wearing and social distance at the current time $t$ | Human behavior including mask wearing and social distance depends upon perceived cases. Detailed assumption is available in Appendix A3.2 |
| | NY vaccine availability, time $t$ | Vaccine availability status at the current time $t$ | Availability of vaccine over time is treated as a hyper parameter being input to the model. Detailed assumption is available in Appendix A3.3 |
| | NY virus spread time $t$ | Virus spread status at the current time $t$ | Spread of the virus depends upon virus spread status at the previous time step and multiple curbing activities including case tracking, mask wearing, social distance and vaccine availabilities. Moreover, virus spread of NY can be affected by case count in NJ due to interstate virus transmission. Detailed epidemic models utilized in this work is available in Appendix A3.1. |
| | NY test error time $t$ | Covid test error at the current time $t$ | Test error rate is treated as a hyper parameter input to the model. |
| | NY actual cases time $t$ | Actual Covid cases at the current time $t$ | The actual Covid case count depends upon virus spread status at the same time |
| | NY perceived cases time $t$ | Perceived Covid cases at the current time $t$ | Perceived Covid cases depends upon the actual case, test number and test error rate. False test results would lead to discrepancy between perceived cases and actual cases. |
| | NY fatality number time $t$ | Covid fatality number at the current time $t$ | Fatality number depends upon actual Covid cases. Detailed epidemic models utilized in this work is available in Appendix A3.1. |