SPATIO-TEMPORAL SOCIO-TECHNICAL RISK ANALYSIS METHODOLOGY FOR EMERGENCY RESPONSE

Ha Bui[1], Justin Pence[1], Zahra Mohaghegh[1], Ernie Kee[1]

[1] *Department of Nuclear, Plasma, and Radiological Engineering, University of Illinois at Urbana-Champaign, Urbana, Illinois, U.S., 61801, habui2@illinois.edu, jpence2@illinois.edu, zahra13@illinois.edu, erniekee@illinois.edu*

The Socio-Technical Risk Analysis (SoTeRiA) framework is a theoretical causal model that integrates both the social aspects (e.g., safety culture) and the structural features (e.g., safety practices) of an organization with the Probabilistic Risk Assessment (PRA) scenarios of the associated technical system. The original scope of SoTeRiA was limited to one organization (e.g., one Nuclear Power Plant; NPP), while in Emergency Response (ER), multiple organizations (e.g., the plant, offsite response organizations and regulatory agencies) and their interactions with the population are important; therefore, the authors have expanded the scope of SoTeRiA. In addition, their focus has been on the development of a ***S****patio-****T****emporal* ***So****cio-****Te****chnical* ***Ri****sk* ***A****nalysis (****ST-SoTeRiA****) methodology to quantify the expanded, macro-level SoTeRiA framework. This paper reports on the status of on-going research regarding the foundations and dimensions of the ST-SoTeRiA methodology; the first approach to explicitly incorporate the spatial dimension (in addition to the temporal aspect) into the simulation of socio-technical failure mechanisms connected with PRA logic. This paper first analyzes the incorporation of time and space in existing PRA models in order to determine which aspects of existing PRA have the potential to be utilized or advanced by* ***ST-SoTeRiA****. In the new methodology, time-dependent conditional probabilities required for executing the PRA logic would be estimated by running a spatio-temporal probabilistic simulation module, which includes the following technologies: (a) Geographic Information Systems (GIS), (b) System Dynamics (SD), (c) Bayesian Belief Network (BBN), (d) Agent-Based Modeling (ABM), (e) Data Analysis, (f) Uncertainty Analysis, and (g) Initiating Event Modeling. The estimated risk from this methodology can provide input for risk-informed decision making in order to identify and rank the most critical spatio-temporal risk-contributing factors with respect to their undesirable consequences in ER scenarios.*

I. INTRODUCTION

Probabilistic Risk Assessment (PRA) is a systematic risk methodology and a key pillar of safety policy setting and regulation for the U.S. Nuclear Regulatory Commission (NRC), under the title of Risk-Informed Regulatory Framework.[1] PRA for the nuclear industry originated in academia[2] and its application has been extended to other high-consequence industries such as aviation,[3] space,[4] oil and gas.[5] For a nuclear power plant (NPP), PRA provides three levels of risk information including system risk information (Level 1 PRA), containment risk information (Level 2 PRA), and population and environmental risk information (Level 3 PRA). Among these levels, risk-informed emergency response (ER), which evolves during the phase of Level 3 PRA, is one area that had a slow progress and still needs to be adequately addressed.[6, 7] An unfortunate indicator showing this slow progress is that more than 30 years after the Three Mile Island (TMI) accident, findings such as "*insufficient implementation of the emergency plan*", "*ill-defined delineation of responsibilities*", and "*insufficient collection, sharing, and dissemination of information*"[8] emerged from the more recent investigations of Fukushima,[9] showing strong parallels to the previous issues at TMI. While there are some differences in the offsite response practices between Japan and the U.S., lessons learned from the Fukushima disaster can and should be used to improve Emergency Preparedness, Planning and Response (EPPR) in the U.S. and abroad.[10] Nuclear disasters such as Fukushima,[8, 10] Chernobyl,[11, 12] etc., that emerged from the dynamic interactions of social and technical contributing factors[13-17] have made it clear that integrating physical and social causes of failure into a cohesive modeling framework is critical to prevent undesirable consequences of large-scale technological accidents. Over the past decade, the Socio-Technical Risk Analysis (SoTeRiA)[18-23] theoretical causal framework was developed to incorporate underlying social and organizational mechanisms into the PRA of complex technological systems.[19, 22] Organizational factors such as organizational culture, climate, leadership, structure, and human resource practices are widely recognized as key contributors to some of the world's worst accidents.[24-26] SoTeRiA is a theoretical causal framework that explicitly integrates both the social aspects (e.g., safety culture; Node 8 in Figure 1) and the structural features (e.g., safety practices; Node 7 in Figure 1) of organizations with technical system PRA models (i.e., Node 1 in Figure 1). SoTeRiA was performed mainly for the scope of one organization (e.g., a nuclear power plant) and its system-level physical consequences (e.g., core damage). Therefore, the authors have been expanding the scope of SoTeRiA to cover the interrelated high-level theoretical dimensions of Population Evacuation, Offsite Response Organizations (e.g., first responders/ fire and police departments), and Critical Public Infrastructure (e.g., medical facilities, transportation networks) involved in ER scenarios. Figure 1 shows the current status of the macro-level constructs being added (i.e., Nodes 17 to 21 in Figure 1) to the original SoTeRiA (i.e., Nodes 1 16 in Figure 1). References[19, 22] provide additional details.

The original quantification methodology[19, 22] of SoTeRiA that was developed for the scope of one organization, by integrating System Dynamics (SD) and the Bayesian Belief Network (BBN) with the PRA logic, was temporal but not "spatial". ER is not only associated with socio-technical failure phenomena, but is also spatial and temporal. At the macro level, time and space associated with social actions and inter-organizational performance are critical in providing more accurate risk estimations in population response modeling.[27] The current incorporation of social and organizational factors into the existing Level 3 PRA tool used by the Nuclear Regulatory Commission (NRC) to support the emergency response, namely MELCOR Accident Consequence Code System, Version 2 (MACCS2), is neither location specific nor explicit.[28] Therefore, the authors have focused on the development of a ***Spatio-Temporal Socio-Technical Risk Analysis (ST-SoTeRiA)** methodology*[29] in order to quantify the macro-level SoTeRiA causal framework (Figure 1) for ER modeling. ST-SoTeRiA is an integrated PRA methodology (i.e., an integration of a simulation platform with PRA logic) that *explicitly* incorporates location-specific and temporal socio-technical factors into a temporal PRA logic.

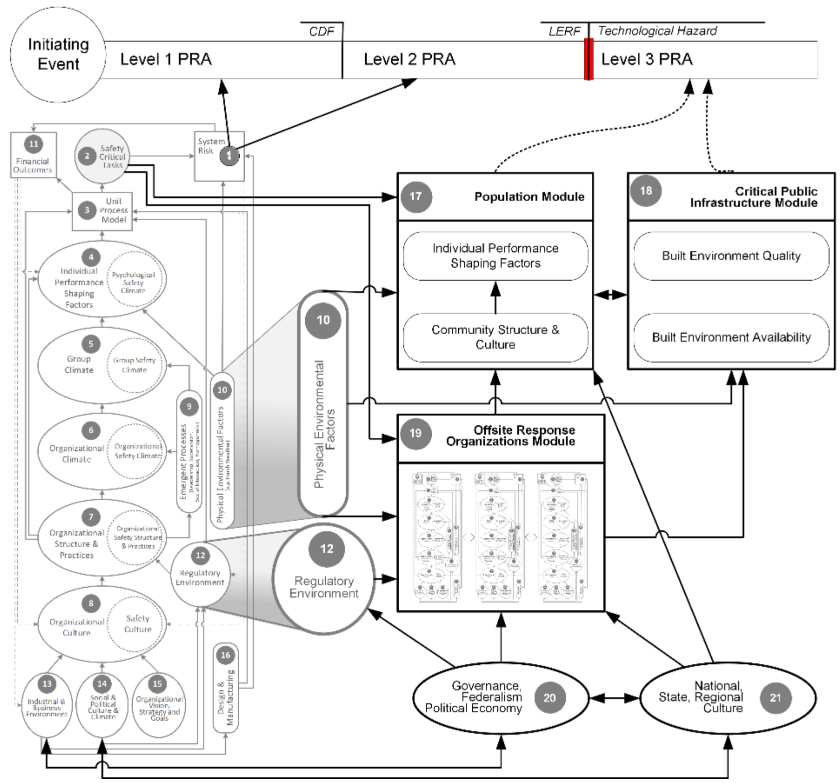

Fig. 1. Expanded Macro-level SoTeRiA Framework for Emergency Response

This paper reports on the current status of the development of this methodology. In order to justify model selection for ***ST-SoTeRiA***, Section II analyzes and categorizes the current status of incorporations of time and space in existing PRA models. Section III summarizes how those dimensions have been advanced in the ***ST-SoTeRiA*** methodological structure.

II. CATEGORIZATION OF THE INCORPORATION OF TIME AND SPACE IN PRA

This section analyzes and categorizes the incorporation of time and space in PRA models. The purpose is to determine which aspects of PRA methodologies have the potential to be utilized or advanced in the **ST-SoTeRiA** methodology (to be explained in Section III) for ER applications. The PRA has two fundamental dimensions: (A) generation of the sequence of events (i.e., accident scenarios) and (B) estimation of failure probabilities associated with those events. In this section, we analyze the incorporation of time and space with respect to these two dimensions and within the existing PRA models.

II.A. Implicit vs. Explicit Incorporation of Time in Generation of the Sequence of Events in PRA

The authors categorized the generation of sequence of events in PRA into three types: (i) *Implicit-time models*, (ii) *Explicit discrete-time models*, and (iii) *Explicit continuous-time models*. Type (i), which refers to the Event Trees (ETs) in the classical PRA where events are sorted in a logical order predetermined (by the analyst) and the analysis is based on a few thermal-hydraulic calculations which are chosen for the most conservative/limiting cases (by the analyst). ETs in classical PRA rely on the "implicit" incorporation of time without providing an exact timing of an event sequence.[30] This leads to a limited evaluation of the effects of the variability of system and operator responses. In dynamic systems, their responses to initial perturbations evolve over time as system components interact with each other and with the environment. With regards to modeling the sequence of events, applying the classical ET methodology for dynamic systems has shown critical structural limitations[31]: a) Variations in the ordering of top event successes and failures do not affect the final outcome of a scenario and its likelihood; b) Variations in event timing do not affect scenario outcomes or frequencies (as long as these variations are not large enough to change "failures" to "successes", or vice versa). *The explicit time methods in type (ii) and type (iii)* refer to dynamic PRA methodologies, also referred to as Simulation-based PRA, that are being developed in such a way that timing and sequence of system responses following an initiating event are determined by time-dependent models of system evolution (e.g., RELAP, MELCOR, TRACE, etc.), where Dynamic Event Trees (DET) branching conditions are selected by the analyst.[32] Time in DETs is enhanced, to be either continuously or discretely "*explicit*" according to the dynamic PRA methodology being used. The difference between the methods of type (ii) and those of type (iii) is whether the branching is considered at a discrete or continuous time, respectively. Examples of discrete-time methods are DYLAM,[33] DETAM,[34] ADS,[35] MCDET,[36] SimPRA,[37-39] ADAPT,[40] SCAIS,[41] and RAVEN,[42, 43] while some representatives for continuous-time methods are continuous event tree (CET)[44] and continuous cell-to-cell-mapping technique (CCCMT).[45] Currently, applications of continuous-time methods for realistic systems have been limited due to the computationally intensive nature of the methodologies and the need to develop algorithms specific to the system under consideration,[46] whereas many of the DET methodologies have adopted discrete-time methods.[32] "Space" cannot directly be considered in the "models of sequence of events (scenarios)" in PRA and instead is related to the supportive models for estimation of failure probabilities associated with the events in the PRA scenarios. This topic is discussed in Section (II.B.)

II.B. Implicit vs. Explicit Incorporation of Time and Space in Estimation of Event Failure Probabilities in PRA

Estimation of probabilities associated with the basic and/or top events in PRA has advanced from "implicit" to "explicit" modeling of failure mechanisms. Based on an analysis by the authors, as these models (i.e. models for hardware failure, human errors or software faults) advance from implicit to explicit models of underlying failure mechanisms, the incorporation of time and space in these models has become more "explicit". As a result, the authors categorized these models into three types: *Type (1) Models informed solely by data, Type (2) Models informed by performance influencing factors, and Type (3) Models based on probabilistic simulation of deterministic failure phenomena*.

Models in Type (1) do not take into account "why" and "how" the failures occur. Time and space are both "implicitly" considered in these models due to the fact that the models are solely based on statistical data and/or expert judgment. Time-to-failure and failure-on-demand models that are widely used to provide hardware component probabilities in FTs or ETs in PRA are examples of Type (1) models. It is the nature of those time-to-failure and failure-on-demand models that time is masking every physical process, and explicit representation of the physical variables is absent. Time is, therefore, implicitly incorporated in these models. Regarding space, FTs are used in PRA to implicitly consider location based on how components and systems function, and how they are coupled. FTs also provide a visualization of component to system relationships, without a direct connection to a geographic or axial location.

Models in Type (2) are more explicit in depicting the underlying failure mechanisms compared to the models solely informed by data. Performance influencing factors that inform these models are either physical variables (e.g., temperature, pressure, etc.) or human performance shaping factors (stress, training, etc.) or software failure parameters, rather than the mere passage of time (as in time-to-failure models in Type (1)). These models have been developed with some degree of knowledge and understanding of the processes and mechanisms that induce failures and errors; hence, are able to answer not only the question of *what* failures may occur, but also the question of *why* those failures may occur. However, it was either that the science of underlying failure mechanisms was not clear well enough or the required computing capabilities for modeling the underlying physics were not readily available that prevented the models in this type from depicting the underlying phenomena explicitly or thoroughly answering the question of how the failures may occur. Time and space incorporated in the models of this group are still implicit as these two dimensions are not explicitly considered in the governing equations being used in the models. However, these models generate a relationship between failure probabilities and their underlying physical or technical parameters that are associated with time and space. Therefore, these models are closer to explicit than Type (1) with respect to incorporation of time and space. Under Type (2) models, engineering correlations and probabilistic physics-of-failure models[47] (e.g., stress-strength model, damage-endurance model) are being widely used for modeling hardware component performance and estimating the associated failure probabilities in both classical PRA and dynamic PRA contexts. For example, the stress-strength model[47] is used for modeling failure of passive components (e.g., steam generators, condensers, containment, pipes, etc.) in PRA.[48, 49] With respect to human error estimation, both the first- and second-generation HRA models[50] are representatives of Type (2) because they are considering the performance-shaping factors that contribute, to some extent, "why" a human error would occur.

Models in Type (3) refer to probabilistic simulation of underlying deterministic failure phenomena. Simulation methods in risk and reliability applications have been proposed for several decades; however, the availability of advanced spatio-temporal simulation tools have been limited mostly due to the lack of required computational resources and immature understanding of the underlying physical and social failure mechanisms. Zio[51] noted that "…simulation appears to be the only feasible approach to quantitatively capture the realistic aspects of the multi-state system stochastic behavior." These models are usually based on a set of differential equations in which time and/or space are explicitly treated. With those characteristics, the models in this type can adequately provide insights for PRA in terms of the failures that may occur, why they may occur and how the failures progress. In addition, the scope and scale of spatial modeling (micro, meso, and macro) has been considered in this category.

Recent advancements in supercomputing technologies have allowed an increased use of simulation techniques in modeling complex and dynamic phenomena and estimating their associated failure probabilities. With respect to underlying physical phenomena, there have been recent PRA studies associated with models in Type (3). For example, an integrated PRA (i.e., integration of simulation models with PRA logic) has been developed by the authors for the risk-informed resolution of Generic Safety Issue 191 (GSI-191).[52-55] As another example, the authors utilized the integrated PRA approach for fire PRA, [56, 57] where the computational fluid dynamics (CFD) model of physical fire phenomena (using Fire Dynamic Simulator; FDS[58]) has been used and integrated with PRA logic to account for the location-specific and time-dependent behavior of fire and fire-induced effects (e.g., thermal radiation, high temperature gas, smoke density) on equipment and electrical cables, as well as to obtain time-dependent probability distribution of target damage induced by fire (when combining the sampling method and the fire simulation code). Another example regarding the benefit of advanced mechanistic models in connection with PRA may also be found in efforts[59, 60] in which flooding and tsunami phenomena have been modeled using physics-based 3D simulation tools. These models demonstrate an explicit incorporation of time and space into PRA through the integration of underlying physical failure phenomena into the PRA logic.

With respect to human and social failure mechanisms, simulation-based Human Reliability Analysis (HRA) methods[59, 61] are example of Type (3) models since they explicitly incorporate time to model dynamic operator performance utilizing cognitive-based HRA models. However, there has not yet been any explicit consideration of spatial dimensions in these simulation-based HRA models. With respect to organizational failure mechanisms, the integrated PRA approach[62, 63] developed by the authors that combines System Dynamics (SD) and Bayesian Belief network (BBN) with classical PRA logic techniques is an example of Type (3) models. This approach was temporal and not spatial, and now is being advanced in ST-SoTeRiA (to be explained in Section III) to become spatio-temporal. The integrated PRA approach for organizational failure mechanism[62, 63] was originally developed for level 1 PRA. The current incorporation of social factors into the existing Level 3 PRA tool used by the U.S. NRC, MACCS2, is neither location specific nor explicit.[28] The proposed ST-SoTeRiA methodology in this research explicitly incorporates the spatial dimension (in addition to the temporal aspect) into the simulation of socio-technical failure mechanisms connected with PRA logic to be utilized for emergency response applications.

III. SPACIO-TEMPORAL SOCIO-TECHNICAL RISK ANALYSIS METHODOLOGY

The ST-SoTeRiA methodology (Figure 2) is an advancement of integrated PRA approaches, developed by the authors (e.g., for GSI-191,[52-55] for organizational factors,[64, 65] and for fire PRA[56, 57]), in order to quantify the macro-level SoTeRiA (Figure 1) for ER applications. In this methodology, with respect to "generation of sequence of events" (explained in Section II.A.), discrete-time DET (DDET) is selected to explicitly incorporate time. With respect to "estimation of failure probabilities" (explained in Section II.B.) associated with the events in risk scenario, ST-SoTeRiA is in Type (3) where probabilistic spatio-temporal simulation of underlying phenomena is integrated with PRA logic. In this proposed approach, time-dependent conditional probabilities required for executing the temporal PRA logic would be estimated by running the *spatio-temporal probabilistic simulations module* in Figure 2, which includes the following elements: (a) Geographic Information Systems (GIS), (b) System Dynamics (SD), (c) Bayesian Belief Network (BBN), (d) Agent-Based Modeling (ABM), (e) Data Analysis, (f) Uncertainty Analysis, and (g) Initiating Event/ Hazard Modeling. The following sub-sections explains the current status of development of the ST-SoTeRiA methodology.

III.A. Discrete Dynamic Event Trees & their Interfaces with Spatio-Temporal Probabilistic Simulation Module in ST-SoTeRiA

In the ST-SoTeRiA framework, DET logic (shown on the top of Figure 2) is used to develop the sequence of events of emergency response scenarios at each point of time and location, given the occurrence of an Initiating Event (IE). As an example of a DET scenario following a nuclear accident, the sequence of potential events include: Information Release (Event A in DET in Figure 2), Population Awareness of the occurrence of the accident (Event B in DET in Figure 2), Population Action with respect to subsequent hazards (Event C in DET in Figure 2), Responder Availability (Event D in DET Figure 2), Responder Action (Event E in DET Figure 2), and the availability of Critical Public Infrastructure (Event F in DET in Figure 2). For simplicity, the DET in Figure 2 does not include all possible branches of the Tree.

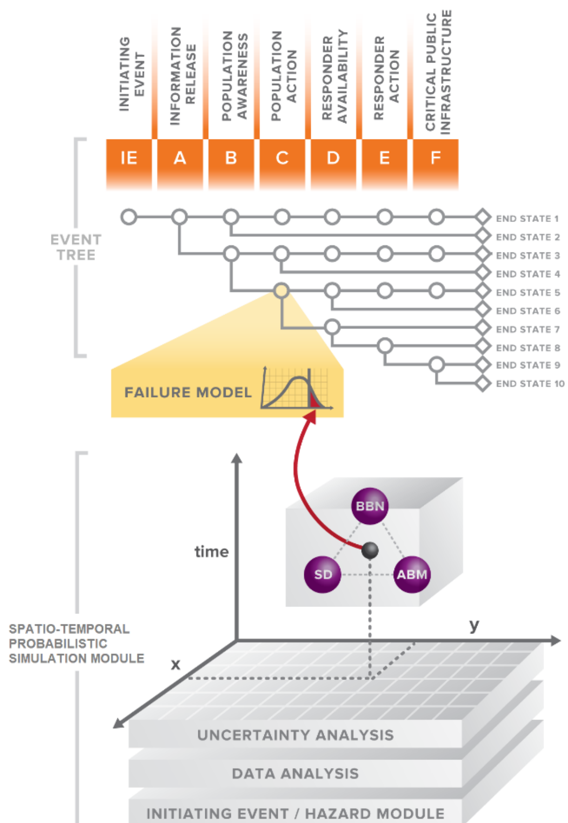

Fig. 2. Spatio-Temporal Socio-Technical Risk Analysis (ST-SoTeRiA) Methodology

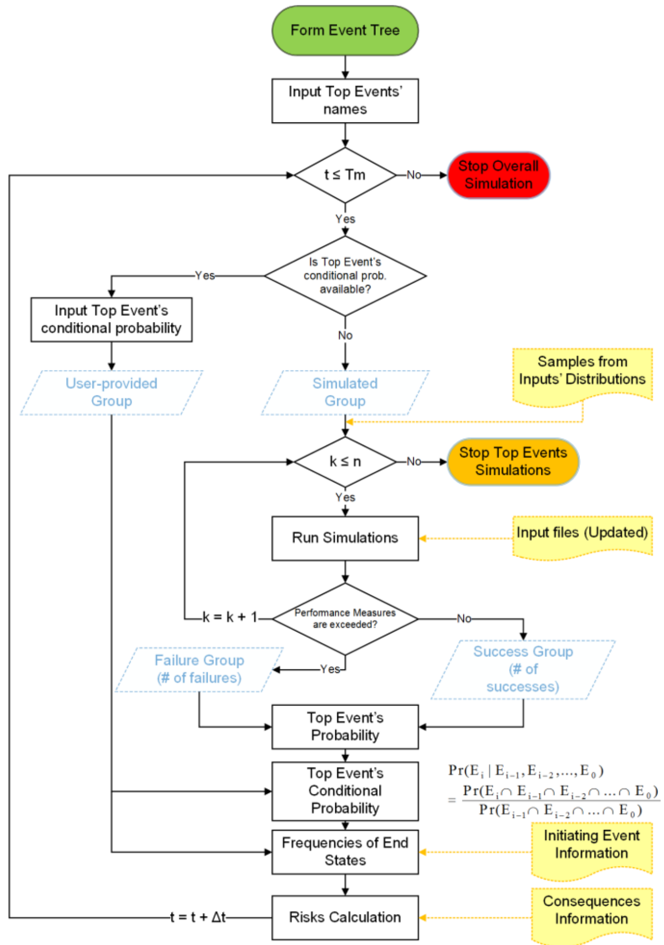

Fig. 3. High-Level Algorithm for Interface of DET & Spatio-Temporal Probabilistic Simulations Module

In order to estimate risk at each location and at each point in time, the DET logic quantification is used to estimate the frequency of failure of all potential scenarios associated with each point in time and location. For example, for scenario *i* (e.g., with end state # 8 in Figure 2), the frequency of failure (associated with the failures of events A, B, C, and D) can be calculated as follows:

$$f_{ij} = IE_{ij} \times \Pr(A_{ij} \mid IE_{ij}) \times \Pr(B_{ij} \mid A_{ij}, IE_{ij}) \times \Pr(C_{ij} \mid B_{ij}, A_{ij}, IE_{ij}) \times \Pr(D_{ij} \mid C_{ij}, B_{ij}, A_{ij}, IE_{ij}) \qquad \text{(Eq. 1)}$$

where:

f_{ij} = Frequency of failure associated with scenario i at Latitude j, Longitude j, and Time j;

IE_{ij} = Frequency of the accident associated with scenario i and at Latitude j, Longitude j, and Time j;

A_{ij} = Probability of failure of Event A associated with scenario i, at Latitude j, Longitude j, and Time j;

$\Pr(A_{ij} \mid IE_{ij})$ = Conditional probability of failure of Event A given the occurrence of the accident (initiating event), associated with scenario i and at Latitude j, Longitude j, and Time j;

$\Pr(B_{ij} \mid A_{ij}, IE_{ij})$ = Conditional probability of failure of Event B given occurrence of the accident (initiating event) and occurrence of failure for Event A, associated with scenario *i* and at Latitude j, Longitude j, and Time j;

The other conditional probabilities in the DET follow the same definition format. These conditional probabilities will be estimated by running the *Spatio-Temporal Probabilistic Simulation Module* (shown at the bottom of Figure 2). Since there are multiple potential scenarios of failure associated with location j and time j, the total frequency of failure at j is the summation of frequency of failure scenarios and is a function of location, time, and the "structure of DETs" (explicitly guided by the *Spatio-Temporal Probabilistic Simulations Module*).

Figure 3 demonstrates the high-level algorithm developed for running the interface between the DETs and the Spatio-Temporal Probabilistic Simulations Module. The high-level algorithm is a logic controller for sequencing simulations and managing the dynamic elements of each model. The algorithm schedules the calculation of conditional probabilities at each time step, while managing the spatial attribute data of the input and the output. In the ST-SoTeRiA methodology, each top event on the DET can be modeled using a simulation. Failure of a top event can be determined if some "performance measure" associated with that top event exceeds designated preset threshold criteria. To propagate the uncertainty associated with the input parameters, key input parameters to the simulation are sampled from their uncertainty distributions using an advanced sampling technique. The simulation is then run with each set of input parameters to develop the empirical probability distribution function representing the uncertainty in key physical/social performance measures, and outcomes are grouped into success or failure states. The logic controller (Figure 3) also allows simultaneous running of multiple simulations, when probability of multiple top events failing together is of interest. In such a way, it is possible to compute the multiple system failure probabilities due to some common cause using the output from the simulation-based model of underlying mechanisms. Then the conditional probabilities of top events can be calculated at each time point that, in turn, allows for computing the time-dependent frequency of each event sequence in the DET. By having this frequency and finding the undesirable consequences associated with each failure scenario, risk associated with each location and time for that scenario can be determined. Future publications will report on the ongoing effort by the authors regarding the critical aspects of interface between PRA logic and the Spatio-Temporal Probabilistic Simulations Module such as (a) spatio-temporal treatment of Common Cause Failures (CCFs) and (b) generation of probabilities considering time-dependent and time-independent failure thresholds. Examples of time-independent performance measures of interest in physical phenomena include component stress load, temperature, and pressure. In emergency response in order to overcome the challenge of lacking explicit damage models when dealing with human and organizational failures, time (e.g., failure to perform some action within a period of time, time to evacuation) is utilized as a surrogate for performance measures. The issues associated with CCFs and time-independent failure thresholds have been partially covered in the Fire PRA research[57] by the authors.

III.B. Spatio-Temporal Probabilistic Simulation Module in ST-SoTeRiA

As Figure 2 demonstrates, in the ST-SoTeRiA methodology, the probabilities required for executing PRA logic are estimated by running a spatio-temporal probabilistic simulation, which is a Geographic Information Systems (GIS)-based platform integrating the deterministic simulation methods (e.g., System Dynamics (SD) and Agent-Based Modeling (ABM)) with probabilistic techniques (e.g., Bayesian Belief Network (BBN)) in a spatial environment. Uncertainty propagation is essential for making the deterministic elements of the ST-SoTeRiA platform probabilistic and for generating probabilities to be passed onto the PRA logic. The proposed methodology will require the use of state-of-the-art big data analytics for two reasons: (i) a large volume of data related to geographic and spatial information, which will be operationalized in the GIS platform, along with high-performance sampling and uncertainty analysis and (ii) the heterogeneous nature of data dealing with unstructured social information, which will be extracted and operationalized utilizing data analytic techniques such as text mining (the heterogeneous type of big data analysis for SoTeRiA is related to another on-going research[65, 66] by the authors).

Integrating System Dynamics (SD) and Bayesian Belief Network (BBN): Due to the nature of socio-technical performance models, the integration of SD and BBN (SD-BBN)[63] is necessary for ST-SoTeRiA. Mohaghegh has demonstrated this integrated modeling approach in applications for aviation maintenance performance modeling.[63] BBN can establish explicit probabilistic relations among elements of the model, where objective data are lacking and use of expert opinion is necessary. This, of course, is very important for the quantification of emergency response models that deal with the soft nature of human and organizational factors. However, BBN alone is inadequate for representing dynamic aspects such as feedback loops and delays. Therefore, the combination of SD with BBN empowers BBN with dynamic features.[63] For Top Events A (Information Release), B (Population Awareness), and E (Responder Action) in Figure 2, BBN and SD are candidate techniques for quantification. Information Release performance can be modeled as a function of multi-organizational coordination and preparedness. The quality of an organization's capabilities of disseminating information can be derived from expert opinion given for each unique hazard type. Quality estimates can be based on empirical evidence of messaging during a historical event, the utilization of media, or the ability to communicate with stakeholders in unfolding scenarios during emergency scenarios. BBN will help operationalize the soft nature of population data, providing a connection to demographic information and providing a surrogate for estimating preparedness in the event of a specific hazard. Several factors used to estimate a Social Vulnerability Index can be included in population awareness modeling to derive a likelihood of vulnerable populations having access to the necessary tools and information in order to take appropriate actions.[67-71] Responder Action can be considered from an individual organization performance perspective, as well as from an inter-organizational performance perspective. The initial quantification of BBN and SD for Responder Actions can come from an empirical data collection of training evaluations for each specific category of hazard and multi-hazard scenario, as well as from expert elicitation. Expert opinion in BBN models will provide insight into the real-world experience of inter-organizational performance, which will be enhanced by SD for the explicit incorporation of feedback and delay caused by miscommunications and improper training among organizations.[72, 73]

Integrating Geographic Information System (GIS) and Agent-Based Modeling (ABM) Techniques: The commonality between all emergency response elements is the shared spatial dimension. In the proposed methodology, the Geographic Information System (GIS) will be the spatial simulation platform for combining SD-BBN, Agent-Based Modeling (ABM) and PRA logic (DETs). ABMs can be directly linked with GIS and have been used for modeling socio-technical systems,[74] organizational mechanisms,[75] individual decision making,[76] urban dynamics,[77] critical infrastructure,[78] emergency response,[79] and transportation.[80] In this research, the plan is to utilize the existing Planning and Operations Language for Agent-based Regional Integrated Simulation (POLARIS) tool,[81, 82] combined with the GIS-based tool, Transportation Analysis Simulation System (TRANSIMS) traffic micro-system code, for evacuation simulation. The open source TRANSIMS code can simulate individual travelers, their routes, and modes (car, public transit, or walking) to calculate traffic patterns on the basis of the "microscopic interactions between individual vehicles and detailed street network features".[83] Although spatial dependencies are important for risk analysis,[84] and GIS tools have been considered for determining the effects of multi-hazards (e.g., using seismic loss estimates from FEMA HAZUS-MH),[85] GIS and ABM have not yet been integrated with PRA logic, and will be added for the first time in the ST-SoTeRiA methodology. An ABM-GIS module for Population Action (Event C in Figure 2) will be used to simulate the effects of offsite response organization actions on the estimated consequences. The ST-SoTeRiA methodology will change the paradigm of conventional evacuation modeling for emergency modeling by increasing the behavioral realism of population action.

IV. CONCLUDING REMARKS

The expanded, macro-level SoTeRiA framework (Figure 1) has been advanced from its original, SoTeRiA, to take into account complex interactions between multiple organizations and the population, which are significant during ER situations. This paper reports on the status of the on-going research regarding the foundations and dimensions of the ***S**patio-**T**emporal **So**cio-**Te**chnical **Ri**sk **A**nalysis (**ST-SoTeRiA**)* methodology, which is used to operationalize and quantify the expanded macro-level SoTeRiA framework. The ST-SoTeRiA methodology is the first in taking an approach to explicitly incorporate the spatial dimension (in addition to the temporal aspect) into the simulation of socio-technical failure mechanisms connected with PRA logic. A categorization to address the status of incorporation of time and space in existing PRA models has been developed to help justify model selection for ST-SoTeRiA. Discussions and examples given in Section III have shown that ST-SoTeRiA has the capability to incorporate simulations of underlying physical and social failure mechanisms into PRA logic while also advancing the explicit incorporation of time and space in its structure. As ER is not only associated with socio-technical failure phenomena but also a spatial and temporal one, ST-SoTeRiA provides the best-suited technique to tackle ER modeling. Future publications reports on the advancement of the execution of this methodology and its implementation for ER contexts. The estimated risk from this methodology can provide input for risk-informed decision making in order to identify and rank the most critical spatio-temporal risk-contributing factors with respect to their undesirable consequences in ER scenarios.

ACKNOWLEDGMENTS
This material is based upon work supported by the National Science Foundation under Grant No. 1535167. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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