SPATIO-TEMPORAL SOCIO-TECHNICAL RISK ANALYSIS METHODOLOGY: AN APPLICATION IN EMERGENCY RESPONSE

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This paper reports on the status of on-going research regarding the development of a Spatio-Temporal Socio-Technical Risk Analysis (ST-SoTeRiA) methodology for Emergency Response (ER) modeling. ST-SoTeRiA is an approach to explicitly incorporate spatial and temporal dimensions, while connected with Probabilistic Risk Assessment (PRA) logic, into the simulation of socio-technical failure mechanisms. The probabilities required for executing PRA are estimated by running a spatio-temporal platform that integrates deterministic simulation methods with probabilistic techniques. In this paper, a case study for fire ER demonstrates one of the building blocks of the ST-SoTeRiA methodology in which Agent-Based Modeling (ABM) technique is combined with physical hazard progression simulation in a shared Geographic Information System (GIS)-based spatial platform, as an input to PRA scenarios. A multi-method coupling between physical progression models and human response models in a spatio-temporal platform is essential to: (i) better characterize dynamic behaviors in ER, given location-specific hazards, (ii) better account for uncertainty, and (iii) better inform decision making in ER contexts.

I. INTRODUCTION

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 results, as part of the regulatory framework, provide a risk-importance ranking to more efficiently allocate resources for inspections, maintenance, operation, design and regulation.[2] For a nuclear power plant (NPP), PRA provides three levels of risk information including system risk (Level 1 PRA), containment risk (Level 2 PRA), and population and environmental risk (Level 3 PRA). Recent research and applications of PRA have mainly focused on Levels 1 and 2. Meanwhile, in Level 3 analysis, risk-informed ER is one area that has not been adequately addressed and where progress has been slow.[3, 4] Currently, ER oversight is performance-based (not risk-informed), which means that the standards and requirements for ER are prescribed without sufficient empirical data, comprehensive theory or methodologies that can justify the risk importance of one factor over another. This approach may not only create costly requirements to maintain all elements of ER for industry and the regulator, but also may eliminate the opportunity to implement highly-localized safety performance goals, thereby limiting progress in ER policy making.[4] The lack of explicit incorporation of location-specific social, political, and community information in PRA models restricts the realism in risk estimates associated with highly complex socio-technical systems. To overcome these challenges, ER models should be advanced to: *(i) explicitly account for risk-contributing socio-technical factors;* and *(ii) explicitly account for spatial and temporal variations of those important socio-technical factors, which consequently affect the evolution of risk*. To achieve these two goals, recent efforts by the authors have been focused on the development of **(A)** a macro-level Socio-Technical Risk Analysis (SoTeRiA) theoretical causal framework[5] and **(B)** an associated methodology[6] (i.e., ST-SoTeRiA) to operationalize and quantify the theoretical framework for ER modeling and applications. Reporting the current status of the ST-SoTeRiA methodology is the focus of this paper.

Nuclear disasters, such as Fukushima[7, 8] and Chernobyl,[9, 10] emerged from the dynamic interactions of social and technical contributing factors,[11-15] making 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. 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.[16-18] Over the past decade, to incorporate underlying social and organizational mechanisms into the PRA of complex technological systems,[19-24] the SoTeRiA theoretical causal framework has been developed and is constantly being enhanced. SoTeRiA is a theoretical causal framework that explicitly integrates both the social aspects (e.g., safety culture) and the structural features (e.g., safety practices) of organizations into a technical system PRA model.[5, 22] SoTeRiA was developed mainly for the scope of one organization (e.g., an NPP) and its system-level physical consequences (e.g., core damage). In ER contexts, however, multiple organizations (e.g., the plant, offsite organizations and regulatory agencies) and the offsite population are all involved in a dynamic, macro-scale environment. It is, therefore, important to capture the dynamic interactions among these regional system components. Recently, the authors of this paper have been expanding the scope of the SoTeRiA causal framework (Fig. 1) to a macro level to include 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. For additional details on the macro-level constructs being added to the original SoTeRiA, readers are referred to Pence et al.[5], as the explanation of this theoretical framework is not the focus of the current paper.

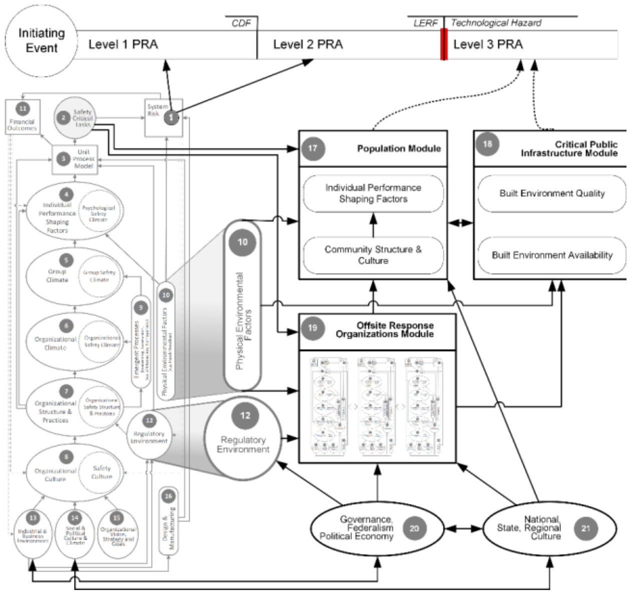

Fig. 1. Expanded macro-level SoTeRiA framework for Emergency Response

ER phenomena not only have characteristics of a socio-technical system; they are also spatially and temporally dependent. At the macro (i.e., regional) level, time and space associated with social actions and inter-organizational performance are critical in providing more accurate risk estimations in population response modeling.[25, 26] The current inclusion of social and organizational factors in the existing Level 3 PRA tool used by the U.S. Nuclear Regulatory Commission (U.S. NRC), namely MELCOR Accident Consequence Code System, Version 2 (MACCS2)[27] is not location-specific, explicit or dynamic.[28] In an effort to depict the socio-technical phenomena associated with time and space and to quantify the expanded SoTeRiA framework (Fig. 1), the authors have been developing an ST-SoTeRiA methodology (Fig. 2) that is capable of explicitly incorporating location- and time-specific socio-technical factors into PRA logic. Section II summarizes the foundations of the ST-SoTeRiA methodology and the status in the development of this methodology, specifically addressing the integration of Agent Based Modeling (ABM) –Geographic Information System (GIS) and physical progression models in ST-SoTeRiA; Section III introduces a case study for fire ER to demonstrate this integration in ST-SoTeRiA; Section IV provides conclusions and discusses future work.

II. CURRENT PROGRESS ON DEVELOPING ST-SOTERIA METHODOLOGY

In PRA, the temporal dimension has been improved and is being explicitly considered in simulation-based techniques.[29-31] The spatial dimension, however, is still implicitly considered. Though the consideration of space has very recently been expanded to be explicit for physical phenomena,[32-37] it has not yet been developed for socio-technical mechanisms. ST-SoTeRiA is the first approach to explicitly incorporate, while being connected to PRA logic, the spatial dimension (in addition to the temporal aspect) into socio-technical risk analysis. The original quantification methodology of SoTeRiA was developed for the scope of one organization by integrating System Dynamics (SD) and the Bayesian Belief Network (BBN) in PRA logic.[20, 23] This integrated methodology was temporal but not spatial.

II.A. The ST-SoTeRiA Methodology

In general, 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. Current PRA practice in the nuclear industry utilizes the static Event Tree/Fault Tree (ET/FT) approach with reliability data to address these two dimensions. This static approach has disadvantages, however, such as (i) the exact timing/sequence of events is not explicitly accounted for in the structure of the ET, and (ii) the status and behavior of the system lack influence on the likelihood of the top events. To overcome these limitations, a series of Dynamic PRA methodologies (also referred to as Simulation-based PRA) that employ time-dependent simulation for modeling system elements (e.g., hardware, software, human actions) have been developed over the last three decades.[38] As the static ET/FT approach has been widely used in the nuclear industry for forty years, the transition to fully-dynamic PRA requires a significant amount of effort and resources, making it impractical in the short term. Recently, the authors have made efforts toward the development of an integrated PRA (I-PRA) that can combine classical PRA with the dynamic progression of physical failure mechanisms[32, 34, 39-41] while utilizing the existing plant-specific PRA at NPPs.

In the I-PRA methodology, simulation-based methods have been used to estimate the probability of basic events in the plant-specific PRA. The ST-SoTeRiA methodology has been built upon the I-PRA framework and is advanced to allow for an explicit incorporation of time and space in the underlying phenomena of PRA basic events as well as for an explicit incorporation of time in PRA scenarios. The estimation of probabilities associated with the basic and/or top events in PRA has been advanced from an "implicit" to "explicit" modeling of underlying failure mechanisms.[6] As these models (i.e., models for hardware failure, human error or software fault) advance from implicit to explicit, the spatial and temporal dimensions are those which are being enhanced.[6] With an increased use of advanced simulation models in PRA, the temporal and spatial insights gained from simulation results help provide more realistic probabilities of basic events, and consequently, provide a more accurate estimate of risk as a function of time and space. Therefore, a multi-level integration of simulation environments with PRA has been advanced in the ST-SoTeRiA methodology. Fig. 2 shows a schematic structure of the ST-SoTeRiA methodology tailored for an ER modeling application.[6]

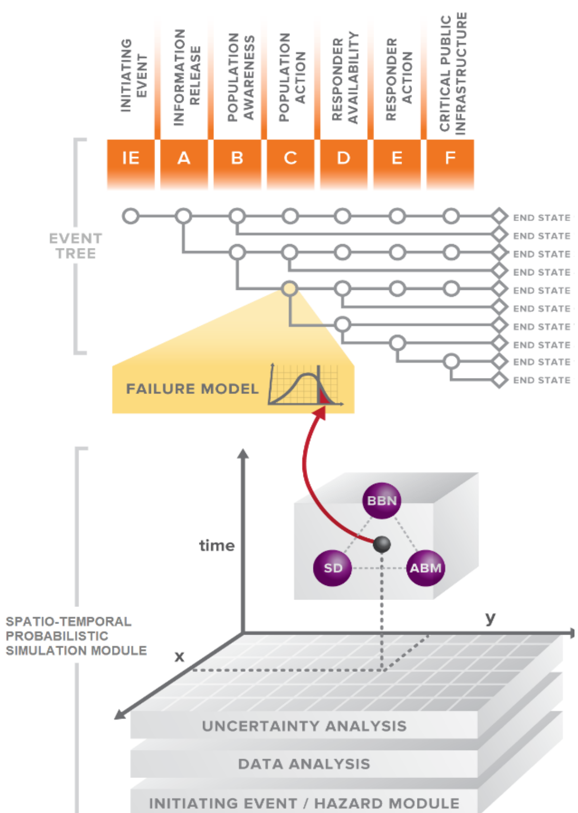

Fig. 2. Schematic Representation of Spatio-Temporal SoTeRiA Methodology for Emergency Response

In this methodology, with respect to the "generation of sequence of events", the Discrete-time Dynamic Event Tree (DDET) is selected to develop event sequences for ER scenarios at each point of time and location, given the occurrence of an Initiating Event (IE), such as radiation release from a severe accident at an NPP. With respect to the "estimation of failure probabilities" associated with the events in the risk scenarios (i.e., in DDET), the spatio-temporal probabilistic simulation of underlying phenomena is integrated with PRA logic. Time-dependent conditional probabilities required for executing the temporal PRA logic are estimated by running the *spatio-temporal probabilistic simulations module*, which is a GIS-based platform integrating the deterministic simulation methods (e.g., SD, ABM) with probabilistic techniques (e.g., 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 to the PRA logic. In order to estimate risk at each location and at each point in time, DDET quantification logic is used to estimate the frequency of failure of all potential scenarios associated with each point in time and space.[6]

Due to the nature of socio-technical performance models, the integration of SD and BBN (SD-BBN)[42] is necessary for ST-SoTeRiA. Mohaghegh has demonstrated this integrated modeling approach in applications for aviation maintenance performance.[42] BBN can establish explicit probabilistic relations among elements of the model when objective data are lacking and the use of expert opinion is necessary. This, of course, is very important for the quantification of ER 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.[42]

The commonality among all ER elements is the shared spatial dimension. In the ST-SoTeRiA methodology, GIS will be the spatial platform for combining SD-BBN, ABM, and PRA logic. Agent-based models can be directly linked with GIS and have been used for modeling socio-technical systems,[43] organizational mechanisms,[44] individual decision making,[45] urban dynamics,[46] critical infrastructure,[47] emergency response,[48] and transportation.[49] Although spatial dependencies are important for risk analysis,[50] and GIS tools have been considered for determining the effects of multi-hazards (e.g., using seismic loss estimates from FEMA HAZUS-MH[51]), the combination of GIS and ABM has not yet been integrated with PRA logic. More details on the ST-SoTeRiA methodology and its quantification algorithm can be found in Bui et al.[6] Sub-section II.B elaborates on the incorporation of ABM-GIS and the integration of ABM-GIS with physical progression models into ST-SoTeRiA. Section III explains this integration using a fire emergency response case study. Future work will expand the case study to implement and demonstrate the entire structure of the ST-SoTeRiA methodology for ER modeling.

II.B. Incorporation of ABM-GIS and Physical Progression Models in ST-SoTeRiA

ABM is a bottom-up modeling approach that originated in the late 1940s from the domain of Complex Adaptive Systems.[52] Due to limitations in computational resources, it did not receive much attention among academic researchers until the 1990s. Some examples of agent-based models that became popular are Conway's "Game of Life" model,[53] and Thomas Schelling's model of segregation.[54] Applications of ABM in industry started since early 2000s and then became popular in various fields, e.g., ecology, biology, economics, social sciences, human behavior and movement. The purpose of this paper is not to include a comprehensive review of agent-based models across the wide spectrum of disciplines, but rather to explore the benefits of incorporating ABM-GIS and physical progression models in PRA, and specifically, in the ST-SoTeRiA methodology.

A model is an abstracted description of a process, an object, or an event that exaggerates certain aspects at the expense of others.[52] Based on the level of abstraction (e.g., low, medium, high) a model can be developed to represent a socio-technical system at micro level (e.g., operational level), meso level (e.g., tactical level), or macro level (e.g., strategic level). The combination of models with various levels of abstractions, utilizing diverse modeling methods (e.g., DDET, SD, ABM) in a unified platform (e.g., ST-SoTeRiA), can be referred to as a multi-method, multi-level modeling technique. In a socio-technical system, DDET and SD can be used at system level (e.g., organizational and multi-organizational levels) while ABM is an individual-level (or individual-centric) modeling method. ABM starts with an element of the system (i.e., an individual), then describes individual (agent) behaviors, timing, decisions, and interactions with other agents in the system and the surrounding environment. An agent can be defined by its states and behaviors and normally possesses extended capabilities such as rules for decision making, autonomy, cooperation (e.g., communication, perception, action, etc.), memory, learning, vision, sensing, mobility, etc. While basic decision rules enable agents to interact with other agents and with the environment, additional higher-order/ global rules are needed (i.e., for changing the basic rule assumptions) if the agents are required to learn and adapt their behaviors accordingly. With set rules and simulation runs, global system behaviors emerge out of the concurrent behaviors of the individuals.

The main principle of ABM is to create an artificial population of agents and let them interact with each other and with the environment.[55] With that, it is possible to explore a landscape of outcomes that are more likely to emerge and others that are less likely to emerge, but are still possible. This type of outcome is referred to as the emergent behavior, adaptive behavior or "surprise behavior" of the socio-technical system since it was not expected. In agent-based models, this type of phenomena is also seen at the level of aggregate stocks and flows (as in SD models). By running many simulations, emergent behaviors can be explored in terms of patterns over time, patterns over space, and patterns over networks, etc. From that perspective, ABM allows for experimenting to understand how a socio-technical system can transition to a certain end state, or how influencing factors can be controlled to keep the system away from undesirable outcomes. Agent-based models are typically stochastic (this contrasts with SD models) to capture the nature of those interactions (e.g., social influences between human agents in the system) that are modeled. Stochasticity in socio-technical modeling provides a way to observe variability in simulation results to gain insight into the variability seen (or expected) in real-world data. The degree of uncertainty associated with the simulation results can be investigated by running many simulations; however, there is a high computational demand tradeoff.

In risk analysis, the use of ABM-GIS has increased in the last decade, but its connection with PRA logic and Human Reliability Analysis (HRA) has been limited. Even integrating ABM with GIS is no trivial task, especially when the amount of agents increases and GIS data become more complicated.[56, 57] In the early 2000s, there were studies that tried to couple both GIS and ABM in a single framework;[58-61] however, most of them considered only static geographic data (i.e., landscape of the environment), not the dynamic geographic data (i.e., temporal changes in the environment). Instead, these models focused more on behaviors of the agents and their interactions with each other. In the last decade, with advancements in GIS, several studies[57, 62-64] have been made to boost the communication of temporal information between agent-based models and geospatial modules. These studies relied on a temporal series of spatially-registered "snapshots" for visualization of agent-based models within GIS.[57] Moreover, none of these studies connected ABM-GIS with PRA.

In modeling ER, however, the authors believe that an ABM-GIS approach can combine PRA logic with human and organizational performance dynamics and HRA to establish a powerful tool for socio-technical risk analysis. Additionally, in dealing with emergency situations where the physical environment rapidly changes and significantly affects the system (e.g., the evolution of a disaster and its influence on a large-scale socio-technical system), it is required to have a separate physical model connected to ABM and GIS to account for the spatio-temporal evolution of a hazard. For instance, in the context of ER, the progression of hazard is dynamic, and the performance of first responders plays a significant role in disaster management, e.g., in preventing and mitigating the progression of hazard and reducing the magnitude of damage to human and property. Because only limited data is available from real accidents, computer simulation has been used as an effective approach for understanding the performance of first responders during emergency situations[48, 62, 63] and for assessing how complicated interactions, i.e., interactions among the responders and between the responders and the environment that is continually changing over the course of the disaster, would affect their performance. The combination of ABM with GIS can capture the behavior of spatially-aware agents and the temporal agent-to-agent interactions, but requires additional models for agent-to-environment interactions. This requires a physical progression model (e.g., Consolidated Model of Fire and Smoke Transport (CFAST),[65] MACCS2), which captures the spatio-temporal evolution of the hazard (e.g., fire, radiological release), and prepares it for integration with the ABM-GIS so that the influence of hazard progression on agent behavior (e.g., performance of first responders, movement of evacuees, etc.) can be captured. In fact, most of the phenomena in ER, as well as the behaviors among individuals, groups, organizations and inter-organizational entities (e.g., population, first responders, organizations, etc.) are spatially and temporally dependent on the evolution of the disaster. Therefore, the combination of GIS-ABM with a physical progression model is essential for ER modeling.

There are three types of connections between the ABM and the physical progression model[57]: location-based, time-based, and entity-based. The most practical approach for large-scale applications is the location-based approach,[57] which relies on a temporal series of spatially-registered "snapshots" to capture space-time information within a GIS model. The ST-SoTeRiA methodology adopts this approach and utilizes a temporal-raster (grid) to store multiple values of the changing environment for each "cell". The simulation data from this combined model (i.e., ABM-GIS and physical progression model) can be used for estimating several quantities in PRA, such as the probabilities of basic events in the PRA model and human error probabilities in HRA). More details on this will be discussed in the following sections.

III. CASE STUDY: FIRE EMERGENCY RESPONSE

To demonstrate the concept of incorporating ABM-GIS and physical progression of the disaster for the ST-SoTeRiA methodology, a case study of fire brigade ER at an NPP was developed. Some of the authors of this paper have developed an I-PRA framework for Fire PRA at NPPs in which an interface of fire brigade action and fire progression is modeled using a data-driven approach.[66, 67] This case study further advances the spatio-temporal modeling of fire brigade behaviors by using ABM-GIS, interfaced with the outputs of CFAST (i.e., the fire progression model).

One of the ultimate goals of this ST-SoTeRiA research is to model ER scenarios given the occurrence of, for example, a radiation release from a severe accident at an NPP (as illustrated in Fig. 2). This task would require the model to encompass various spatial scales (i.e., micro, meso, and macro). The case study developed in this paper, however, is the first step in developing that multi-scale model, and therefore, starts with the micro-scale context. Specifically, in this micro-scale model, the fire is assumed to occur in a switchgear room inside an Electrical Auxiliary Building in a referenced NPP. We assumed this unusual event would not lead to an alert level requiring the Offsite Emergency Response Organization to be activated. Meso-scale (e.g., entire-site level) and macro-scale (e.g., regional level) case studies will be addressed in future work. Safety-related equipment in the room (e.g., relay panels, switch panels, cables, etc.) could be damaged by the fire, which would have the potential to negatively influence the safe shutdown of the plant. It is assumed that automatic fire suppression systems are not available and that the situation requires the onsite fire brigade to take action. Fig. 3 demonstrates the phases involved in the fire brigade ER actions that are developed utilizing the procedures at a referenced plant[68] (with a zoomed-in view showing the search algorithm for the fire search phase).

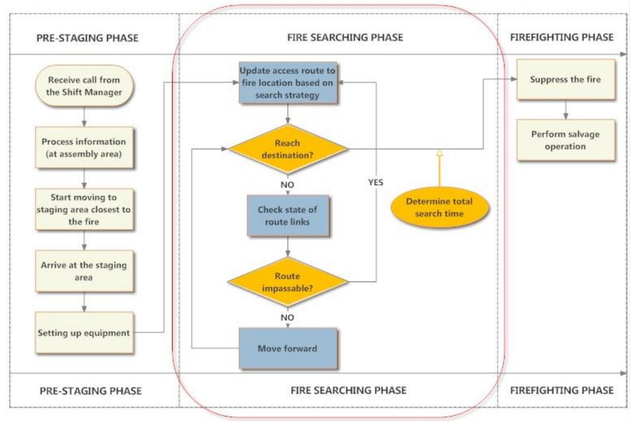

Fig. 3. Typical Fire Brigade Emergency Response Phases at a Referenced NPP

III.A. Model Structure

CFAST software,[65] a two-zone fire model developed by the National Institute of Standards and Technology (NIST) to solve physical governing equations (i.e., mass balance, energy conservation) numerically and to predict time evolution of gaseous species concentration (e.g., CO, CO_2), smoke spread, and hot gas layer temperature, is used to model the fire progression inside the room.

An agent-based model is developed in the NetLogo toolkit[69] to model the fire search performed by the fire brigade. In this context, 'fire search' is the process of the fire brigade locating the fire source in the fire compartment. NetLogo is capable of building large, complex, and multi-level agent-based models for simulating complex socio-technical systems. Commonly used GIS data formats from ESRI (i.e., shape files for vector-based data and .asc files for raster-based data) are directly supported in NetLogo, creating a compatible integration of GIS and ABM.

Fig. 4 provides a schematic overview showing how ABM, GIS and CFAST are connected in this case study. Simulated spatio-temporal data on fire-induced conditions (e.g., hot gas layer temperature, smoke density) are captured with CFAST and fed into the agent-based model to represent the dynamically changing environment in the room. The agent-based model is designed to study the performance of the fire brigade in locating the fire source, considering the dynamic interactions between the fire brigade and the changing environment. GIS provides a shared geographic map of the room and facilitates the connection between the CFAST outputs and adaptive agent-based models. Ideally, the connection between the fire progression model and the ABM model as shown in this figure should be two-way, i.e., performance of the fire brigade does influence the fire progression and this influence needs to be captured. However, in this case study, we did not consider this aspect as the fire search operation itself is less likely to affect the fire progression captured in the CFAST outputs. Other collaborators of the authors' research team have preliminarily explored this angle when the study involves fire suppression activities.[70]

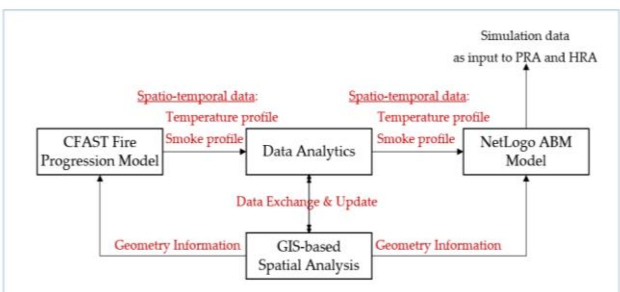

Fig. 4. Schematic Interrelations among CFAST, GIS, and ABM Models

Direct output from this combined model may include more realistic estimates of time to locate the fire (performed by the fire brigade) and explicitly estimated relationships between time to locate the fire and fire brigade starting time. This simulation data can be used for estimating several elements of the PRA model while providing meaningful insights on performance shaping factors (e.g., time available, time pressure, etc.), which are important for HRA. Indirect output from this combined model includes insights that can also be used in improving current ER practices. The Monte Carlo method is used to study the uncertainty associated with the simulation results. Details are discussed in Section IV.

III.B. Model Settings

For simplicity, while maintaining the important characteristics that are required to demonstrate ST-SoTeRiA concepts, the following assumptions have been made when constructing this case study:

- The Fire Brigade is called out by the Shift Manager (in the Main Control Room) at the beginning of the pre-staging phase.
- The fire brigade is available and well-equipped.
- The agent-based model focuses only on the Fire Search phase, i.e., starting when the fire brigade enters the room and ending when the fire location is identified.
- Responding time window for the fire brigade (i.e., until the fire brigade enters the room and begins its activity) is between 5 minutes and 25 minutes.
- There are no evacuees in this emergency.
- Only one firefighter is included in the NetLogo model. This type of situation would require two firefighters to enter the room, and together, attempt (with proper equipment) to locate the fire. Interactions between them are quite limited (each carrying different equipment), so this can be simplified and reduced to one agent in the NetLogo model.
- Temperature and smoke profiles are updated into the NetLogo model every 5 seconds.
- The fire is assumed to have ignited from one of the 4 cabinets located inside the 15×15 (m×m) room.

Fig. 5 shows the profile of the fire input to CFAST.

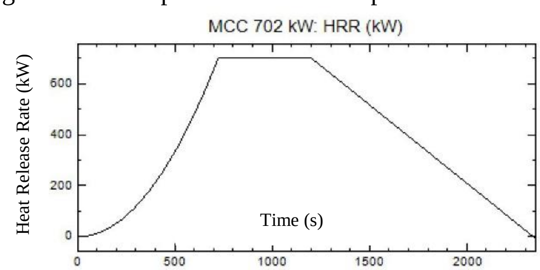

Fig. 5. Heat Release Rate Curve of the Input Fire

Regarding the NetLogo model, there are multiple decisions to be made by the firefighter (agent) during the search for the fire location. The decisions are affected by the variables as summarized in Table I.

Table I. Decision Making Points and Affecting Variables

Decisions	Variables	Value
Initiate fire search	Start time	300 – 1500 (s)
Locate fire	Visibility in smoke	Visibility (m)
	Sensing heat	Temperature (ºC)
Select route	Room familiarity	Yes/No
	Updated memory	Memory list
Avoid obstacles	Visibility in smoke	Visibility (m)
Change speed	Visibility in smoke	Visibility (m)
	Movement ability	0.3 – 1.4 (m/s)

In this case study, the visibility in smoke changes due to smoke density (optical density). An empirical correlation[71] is used for estimating the visibility, V (m) based on the smoke (optical) density, C_s (1/m):

$$V = k\frac{1}{C_s}$$

In this empirical correlation, k is almost constant and ranges from 5 – 10 for a light-emitting sign.[71] We chose k = 8 for this case study.

There have been studies to address the impacts of smoke density on walking speed in evacuation.[71] These studies relied heavily on empirical data though there was an apparent lack of data for building this correlation.[72] Within the scope of this case study, however, and with regards to the firefighter's walking speed in smoke, we adopted the following empirical correlation[71] with an assumption that minimum and maximum walking speeds are 0.3 m/s and 1.4 m/s, respectively.

$$Wsmoke\ (m/s) = -0.1364 \times \ln(C_s) + 0.6423$$

where *Wsmoke* is the walking speed in smoke-filled environment.

Another dynamic value that can affect the performance of the agent in this case study is the familiarity with the room. For simplicity, this case study assumes that the agent is either fully aware or completely unaware of the ventilation setting inside the room. Fig. 6 shows an example of the NetLogo simulation environment.

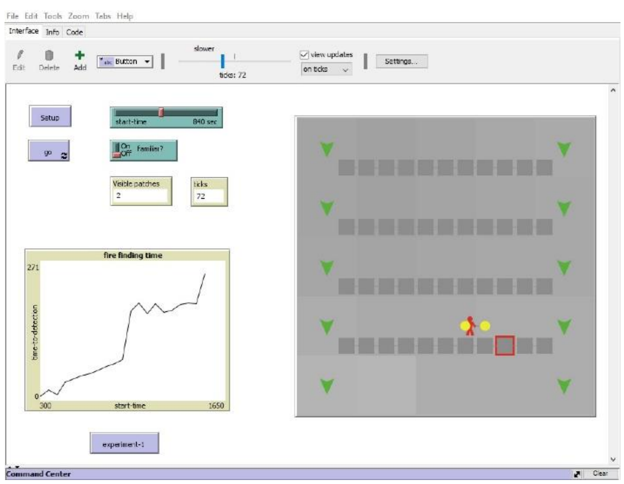

Fig. 6. Example of Simulation Execution

III.C. Simulation Results

The effects of changes in the fire brigade starting time on the time to locate the fire are tested based on the model settings discussed in the previous sub-section and are shown in Fig. 7.

In both cases, the agent starts the search from the entrance door that is located at the upper left corner of the room, as shown in Fig. 6. First, the agent is asked to perform an overall check for each cabinet row (separated by the 4 lines of cabinets), observing density - storing the information in 'memory'. As the agent reaches the far end of the room, a decision is made to go back to the row with the highest smoke density. This is determined based on the information in the updateable. After arriving at the row with the highest smoke density, a thorough check is performed by walking along the row. If the agent does not find the fire in that row, a decision must be made as to whether to go left or right at the end of the row. If the agent is familiar with the room setting (i.e., the ventilation system setting), the best decision would be to go against the direction of air movement (as smoke travels downwind) to look for the fire. But, if the agent is not familiar with the room setting, the agent will randomly pick another row to continue with the thorough search. This process continues until the agent locates the fire.

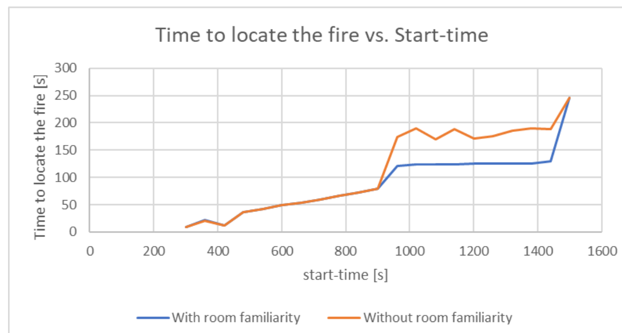

Fig. 7. Simulation Results

When the agent is completely unaware of the ventilation system setting inside the room, the time to locate the fire slightly increases when the start-time is less than 900 seconds, then almost doubles when the start-time is 960 seconds. The time to locate the fire then fluctuates to around 180 seconds even though the agent begins the search later than 960 seconds into the fire. This is because, when the agent is able to start the search early, the smoke density is still low during the overall check. Hence, visibility is good and the agent is able to see the fire from a greater distance. When the agent begins the search at a later time, the smoke has already filled the room and has reduced visibility. In this case, the agent has to move very close to the fire source in order to locate it. The fluctuation observed seems to emerge from the stochasticity in decision-making - whether to turn left or right after the first thorough check.

When the agent is fully aware of the room setting, the pattern in the relationship between time to locate the fire and start-time is similar to the previous case. When the start-time is less than 900 seconds, the time to locate the fire is the same as in the case of being unaware. However, in the interval where the start-time is between 960 seconds and 1440 seconds, the time to locate the fire remains stable at about 125 seconds, which is about two thirds of what is observed in the unaware case. This stability is due to the lack of stochasticity in the agent's decision-making process since the agent in this case has more knowledge of the current situation. It is worth emphasizing that in both cases, the patterns are similar. These patterns can be considered as emergent behavior of the system that results from the interactions between the agent and the spatio-temporal evolution of the fire hazard. When more complexities are added to the model (e.g., increasing the number of agents, considering multiple fire locations, etc.), it is expected that new phenomena will be observed.

IV. CONCLUSION AND FUTURE WORK

The ST-SoTeRiA methodology is developed to quantify the macro-level SoTeRiA theoretical causal framework (Fig. 1), which allows for explicit consideration of social and organizational factors that significantly affect the evolution of the socio-technical phenomena in Emergency Response (ER). This paper reports on the status of ST-SoTeRiA, more specifically, on the development of one of its building blocks, i.e., the integration of an Agent-Based Modeling (ABM) - Geographic Information System (GIS) module with a physical hazard progression model. With this integration, the ST-SoTeRiA methodology can change the paradigm of conventional responder models in ER modeling by increasing the behavioral realism of responder action. This integration is essential for ER modeling as it explicitly accounts for: (i) risk-contributing socio-technical factors; and (ii) spatial and temporal variations of those important socio-technical factors, which consequently affect the spatio-temporal socio-technical system risk.

The integration of ABM-GIS with a physical hazard progression model has been demonstrated in this paper by a case study that provides a limited-scope demonstration of micro-spatial emergency responder performance in a fire scenario. In the case study, the Consolidated Model of Fire and Smoke Transport (CFAST) is utilized to depict the fire progression phenomena. The simulation results in the case study emphasize the importance of communicating spatio-temporal information between the agent-based model and the hazard progression model in obtaining emergent behavior estimations for the complex socio-technical system. The ABM environment provides the opportunity to vary many model parameters to observe how the parameters may influence the outcomes of the simulation.

Simulation data can also help improve the current PRA techniques in several ways. In the current Fire PRA,[73] manual fire detection and suppression are addressed by data-driven approaches, where the human error rates and times to action are estimated based on empirical data, including historical fire records and fire drill reports. In existing Fire PRA, the interactions of the plant crew with fire progression are addressed in an "implicit" way, by using the competition between two separately computed time quantities for "time to target damage" and "time to fire suppression". The authors of this paper are working on utilizing simulation data from such ABM-GIS-CFAST approach to provide more realistic estimates of the time to manual detection. The case study in this work demonstrates the importance of training, drills, and familiarization with fire compartments to improve performance and reduce fire search time. This approach provides opportunities for enhancing decision making strategies for locating hazards in industrial settings, and improving firefighter training through cost-effective simulation-based training methods. This modeling approach, when successfully connected to a thermal-hydraulic code, can also help improve success criteria (e.g., time window for operator action, firefighter action, etc.) used in PRA. In the Integrated-PRA and ST-SoTeRiA methodologies, simulation results produce a key performance measure of interest (i.e., time to detection) that, when compared with threshold criteria, results in a failure probability of a basic event (e.g., human fails to detect the hazard) in the PRA logic.

Future work will also expand the implementation of the ST-SoTeRiA methodology for integrating multi-scale simulations of complex ER phenomena following severe accidents. Three types of modules will be developed: (1) Micro, (2) Meso, and (3) Macro, which will be nested into one framework capable of generating multi-faceted risk criteria for key performance measures of interest (e.g., time to evacuation, health consequences, etc.).

1. Micro-spatial models will include site-specific emergency responder performance, given the type of hazard and built environment through HRA approaches (e.g., fire brigade at an industrial site) that can be generically applied across multiple sites.

2. Meso-spatial modules will consider entire-site models for inter-organizational cooperation for larger hazards, including dispatch logistics, communication networks, and staging location availability.

3. Macro-spatial modules will serve as regional network models for sequencing and scheduling micro and meso models, while also providing urban dynamics of population movement through transportation networks and the tracking of hazard evolution across modules (e.g., plume dispersion).

Outputs from the ST-SoTeRiA methodology can be utilized in the multi-faceted risk-informed decision making method, proposed in previous work,[5] to improve the ER regulation in several ways, including: identifying potential deficiencies in programmatic features of ER, providing valuable information for risk management, training, resource allocation for preparedness, and real-time response efforts, in order to protect workers, the public and the environment from undesirable consequences.

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