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The Spatial Dimension in Human Reliability Analysis

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Traditional static human reliability analysis (HRA) methods focus on producing human error probabilities based on qualitative insights derived from operating context such as performance shaping factors (PSF). Especially for field operations outside the control room, travel time between two locations largely determines how long it takes to complete tasks, which in turn affects the success likelihood of the task. While most HRA methods consider required or available time as a PSF, they do not adequately account for spatial dimensions that influence time. This paper outlines the importance of the spatial dimension for HRA. Location affects the availability of tools, the workload of the operator, and the complexity of the task. The need to travel from one location to another can considerably change the context of the task and even has implications for error dependency. This paper outlines considerations for location and movement and presents use cases to explore how spatial HRA could be treated for balance-of-plant and main control room tasks. The spatial dimension complements recent developments in dynamic HRA. Dynamic HRA, which uses simulation techniques to model human performance, implies primarily a temporal dimension. Dynamic HRA captures the evolution of an event over time; however, dynamic HRA is incomplete without consideration of location. Spatial HRA is part of a broader approach joined with dynamic HRA that is called computation-based HRA (CoBHRA).

Keywords: human reliability analysis, computational risk assessment, dynamic, spatial, location, movement

1. Dynamic Human Reliability Analysis

Conventional, so-called "static" human reliability analysis (HRA) uses paper or software worksheets to capture key aspects of the operational context and quantify the human error probability (HEP). Each scenario or human failure event (HFE) must be analyzed manually, typically as part of a broader overall probabilistic safety assessment (PSA). The advent of dynamic HRA approaches has automated the analysis process, allowing exploration of multiple scenarios and what-if explorations using Monte Carlo simulation methods. Much of the emphasis in dynamic HRA is on the time-course of the scenario, namely exploring how changes in the flow of operations can impact the scenario outcomes. For example, a scenario might explore if an operator of a nuclear power plant initiates safety injection in a timely manner following a reactor trip. A conventional, static HRA would explore the likelihood of the HFE surrounding safety injection—a necessary activity for shutting down the plant and maintaining adequate cooling. Safety injection would be captured as a necessary branch point in an event tree, with the probability of success or failure of the activity affecting subsequent downstream outcomes. In contrast, dynamic HRA might model different time windows for initiating safety injection. The event tree can take many possible timelines, allowing exploration of delayed safety injection. The outcome is not simply binary failure or success of safety injection but rather when that success or failure to initiate safety injection occurred.

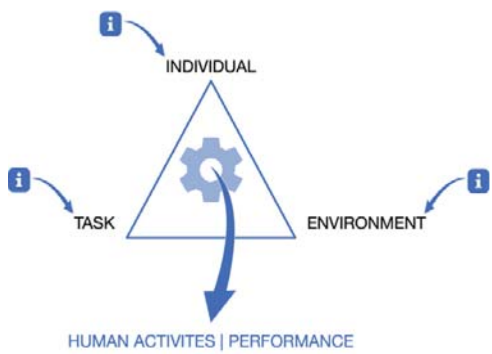

Fig. 1. Functional modules used in the HUNTER HRA method.

Recent work on developing the Human Unimodel for Nuclear Technology to Enhance Reliability (HUNTER; Boring et al., 2022) has shown the utility of dynamic HRA in terms of considering the temporal dimension of human activities. While conventional HRA produces HEPs, HUNTER is able to generate additional quantitative outputs such as task time duration. HUNTER works by coupling a virtual operator model (i.e., a digital human twin) with a virtual plant model (i.e., a simulator or digital twin). HUNTER juxtaposes individual, environment, and task modules, corresponding to operator, plant, and procedures, respectively (see Figure 1). The tight coupling of the operator and plant models allows exploration of the nuances of how events unfold through the feedback loop of an operator action and a plant response, leading to further operator responses, leading to changes in the plant states, and so on (see Figure 2).

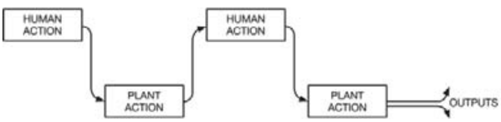

Fig. 2. Tight coupling and interactive feedback loop of operator and plant in HUNTER.

In accounting for the interplay between the human and the plant, an accurate estimate of time can be produced. The importance of time has been understood from early time reliability methods of HRA, since one of the ultimate measures of successful or failed events is whether or not required actions can be completed within a specific time window. This time window is a reflection of changing plant states (e.g., slow core heat decay without sufficient cooling), which may lead to an escalation of the event, including core damage in rare cases. Plant parameters like core temperature evolve in a fashion to where there is a threshold of damage. The time window reflects when that threshold is crossed and provides an upper limit on how long the human may take to complete certain actions. Dynamic HRA methods like HUNTER provide a simulation capable of estimating the duration of tasks and determining when safety time thresholds are crossed. Human error, in such cases, is not just the probability that the operator fails to complete a task; it is also the time it takes to complete tasks vs. the time available.

Table 1. GOMS-HRA task level primitives.

Primitive	Description
A_C	Performing required physical actions on the control boards
A_F	Performing required physical actions in the field
C_C	Looking for required information on the control boards
C_F	Looking for required information in the field
R_C	Obtaining required information on the control boards
R_F	Obtaining required information in the field
I_P	Producing verbal or written instructions
I_R	Receiving verbal or written instructions
S_S	Selecting or setting a value on the control boards
S_F	Selecting or setting a value in the field
D_P	Making a decision based on procedures
D_W	Making a decision without available procedures
W	Waiting

HUNTER decomposes procedure tasks into task level primitives (TLPs) according to the Goals-Operator-Method-Selection rules (GOMS)-HRA method (Boring and Rasmussen, 2016; see Table 1). Where applicable, the TLPs feature separate primitives for control room and field operations. For example, the *Check* (C) TLP can be divided into checking functions within the control room (C_C) or in the field (C_F). These TLPs follow a typical information processing framework adopted in cognitive psychology (Boring et al., 2018) as depicted in Figure 3, representing the most basic human activities delineated as sensation or perception, cognition or decision making, and behavior activities. Each of the TLPs also has associated task level errors (Boring, Ulrich, and Rasmussen, 2018), which identify the most likely types of errors to occur for each activity. The TLPs are mapped to nominal HEPs derived from static HRA methods. Additionally, the TLPs for control room activities feature timing data derived from simulator studies (Ulrich et al., 2017; see Table 2). Using nominal HEPs and timing data for the TLPs allows HUNTER to produce both HEP and duration outputs.

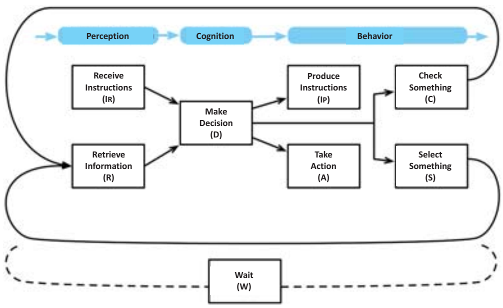

Fig. 3. Cognitive model of GOMS-HRA task level primitives.

Table 2. GOMS-HRA task level primitive timing.

Task Level Primitive	5th %tile	Time (seconds)	95th %tile
A_C	1.32	18.75	65.26
C_C	2.44	11.41	29.88
D_P	2.62	51	152.78
I_P	3.35	15.56	40.66
I_R	1.47	10.59	31.84
R_C	3.08	9.81	21.90
S_C	3.01	34.48	115.57
W	1.79	14.28	113.61

2. Computation-Based HRA

HUNTER has been framed as a computation-based HRA (CoBHRA) approach (Rasmussen and Boring, 2016), which is the human-centered aspect of computational risk assessment (CRA; Sezen et al., 2019). CRA and CoBHRA make heavy use of computational tools like simulation and simulators to model plant or human performance. These tools may make use of multiple model codes in parallel, e.g., HUNTER makes use of both a virtual operator and a simulator to represent the nuclear power plant. With multiple codes, there is also the opportunity to consider different aspects of risk than has been the case in historical applications of PSA and HRA. Some of the roadmap issues for CRA to tackle include temporal, spatial, mechanistic, and topological—related to timing, location, physics, and complexity issues, respectively (see Figure 4). Within CoBHRA, mechanistic issues might be considered *psychological* rather than physical phenomena.

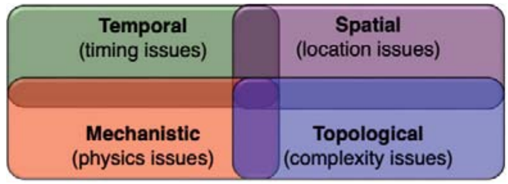

Fig. 4. New facets of risk possible with computational risk assessment (Courtesy of Curtis Smith).

The potential for CoBHRA can be framed by considering the interrogative *wh*-words in English, including who, what, when, why, and how (Koutsoudas, 1968). Conventional static HRA can be considered to answer *who* and *what* as qualitative elements and *how often* as the quantitative element. As discussed in the previous section of this paper, dynamic HRA addresses temporal concerns—*when* and *how long*—that were not previously adequately considered in static HRA. HUNTER is now beginning to consider the next facet of CRA, namely spatial HRA, which addresses *where* human actions occur.

3. Spatial HRA

Spatial HRA (not to be confused with space HRA for galactic applications) is the consideration of locations and distances in the determination of human error likelihoods. For many tasks, humans are not stationary, and the only way to model the true risk of their activities is to consider location and changes in location relative to emerging hazards. While it is possible to consider spatial aspects of risk in static HRA, mobility and corresponding changes in risk are best reflected in dynamic HRA.

To understand spatial HRA within HUNTER, consider the three main modules implemented in HUNTER—individual, environment, and task. Spatial HRA allows a way to account for the relative placement of the individual relative to the environment in which they are working. The task accounts for the interplay between the individual and environment and any changes in location. For example, if the main control room calls a field operator (i.e., the individual) to check a pressure level on a local indicator in the turbine building (i.e., the environment), the task involves walking from the current location where the phone is located to the indicator, checking the level, and returning to the phone to report back the value. These three tasks can actually be broken into considerably more detail in a task analysis, including the sub-process of walking between two locations. Dynamic HRA requires a time course to account for the time spent waiting for the remote reading, something not fully covered in simple TLPs like checking in the field (C_F) or waiting (W). Any activity involving a change in location must account for the distance traveled to give a reasonable time estimate. Similarly, any activity involving a change in location introduces new opportunities for human error in the chain of activities. Moreover, those opportunities for human error may change throughout the journey, as the hazards and error traps vary at different locations.

Spatial HRA is influenced by movement factors, including:

- Distance between point A and point B
- Directional changes that may complicate or slow movement
- Navigational ease or difficulty that affect mental workload
- Topographical changes requiring climbing or descending
- Terrain considerations like characteristics of the surface being traversed or obstructions
- Load while moving such as when carrying objects or wearing personal protective gear
- Mobility restrictions such as personal protective gear or weather factors like snow or flooding
- Method of travel such as walking vs. driving a vehicle
- Personnel factors like injury or fatigue.

Currently, the HUNTER development team is cataloguing these features and determining how to implement them within an HRA framework. A novel Movement (M) TLP is being mapped, with an output function related to the distance traveled and factors that affect the efficacy of that travel. In most cases, there is a direct relationship between movement and duration of a task. New task level errors for M are being modeled and validated. The movement factors listed above have similarities to performance shaping factors to help increase the accuracy of the Movement TLP.

In addition to characterizing *where* actions take place, spatial HRA may also address aspects of *who* is performing actions. Current HRA methods tend to consider the crew as a single analysis unit, especially in control room operations. Indeed, the crew acts in concert to monitor and control the plant, but each member of the crew has slightly different responsibilities. The responsibilities are also reflected spatially. For example, the control room supervisor oversees the reactor operators and typically assumes a stationary role that provides an overview at all times. The operator at the controls is typically responsible for the primary side related to reactivity and cooling, while the balance-of-plant operator is typically responsible for the secondary side related to electricity generation. In traditional stand-at-the-boards control rooms, these two reactor operators will move within specific parts of the control room related to their sphere of control. Thus, the task of changing reactor power will involve geographically distinct locations and personnel than changing electricity generation. By accounting for location and movement, spatial HRA has the potential to consider individuals within a crew.

One lesson learned from the ongoing HUNTER implementation is that dynamic HRA brings tradeoffs. Dynamic HRA, in relying on computational tools, affords greater realism and greater opportunity to consider multiple possible courses of action. However, dynamic HRA can be considerably harder to model than its simpler worksheet-based methods. A dynamic simulation models human tasks at the procedure step or even finer level of analysis, and interactions with plant simulators or simulations must also be considered. Such level of detail is costly and time-consuming to model, at least initially, creating a considerable barrier to using dynamic HRA. One goal of HUNTER has been to make a simplified approach for dynamic HRA, meaning it strives to be easier to use than some antecedent approaches. Even with an emphasis on ease of modeling, HUNTER is considerably harder to model than static HRA methods. For analyses that require this level of granularity or consideration of what-if modeling that cannot be accomplished as easily with static HRA, developing dynamic HRA models is worthwhile. The same can be said of pending spatial HRA modeling—many HRAs simply do not require consideration of spatial factors. Where there is no benefit to spatial risk considerations, there is no need for spatial HRA. In the next sections, I will discuss two use cases for spatial HRA and suggest some benefits for pursuing research to develop a framework for spatial HRA in HUNTER.

4. Spatial HRA Use Cases

4.1. Balance of Plant

As an initial use case, consider the prospect of a field worker at a nuclear power plant needing to walk the space between an outbuilding where backup pumps are stored and a connection area on the exterior of the containment area of the plant. For the present purposes, assume the distance is 100 meters (m) or 328 feet (ft) as the crow flies. This distance is hypothetical and does not represent any actual plant geometry. Assuming an unobstructed direct path and normal gait, the field operator would be able to walk between the two facilities at a normal to brisk pace around 1.5 meters per second (m/s), 5.4 kilometers per hour (km/h), or 3.4 miles per hour (mph), give or take 20% (Bohannon, 1997), resulting in a total travel time of 150 s or 2½ minutes (min). This would present as the optimal case. Degradations to performance can occur through:

- Rough or uneven terrain, which can slow walking due to a shortened gait. Downey et al. (2022) found that rough terrain increased travel speeds up to 15%. In our example, the travel time would increase, with total walking time up to 172 s. Changing from sidewalk to uneven terrains resulted in metabolic energy expenditure increases up to 22.5%, suggesting quicker fatigue and a slower pace over time (Kowalsky et al., 2021).
- Slippery terrain such as caused by storms, which can actually decrease the walking speed but increase the fall rate due to reduced friction. Chang et al. (2017) found travel time would decrease up to 21%, potentially reducing the total time to 118 s. However, any reduction in time is lost if a fall occurs, which takes time to recover and may result in injury. Additionally, slippery surfaces do not provide sufficient friction coefficients for carrying or moving heavy objects.
- Walking speed in water such as caused by flooding, which can decrease speed up to 22% for ankle-deep water, 44% for knee-deep water, and 63% for waist-deep water (Dias, Rahman, and Zaiter, 2021). The overall walking time would now be up to 245 s, more than a minute and a half longer than without flooding.
- Load while carrying a cart with the pump, which results in a progressive decrease in walking speed as a function of the weight of the cart relative to the individual's body weight. Research on carrying luggage, for example, (Ali et al., 2018) found up to a 13% reduction in walking speed with a light load, resulting in transit time of 170 s in the present example. However, heavier loads also result in higher metabolic cost, resulting in increased fatigue, shorter travel distances, and slowed travel speeds over time (e.g., Knapik et al., 2004).
- Fatigue such as caused by other factors described in this section or as the accumulation of multiple walking tasks over time, which slows walking speed and increases the rate of missteps and falls. Li et al. (2022) found an average 22% reduction in walking speed due to fatigue, resulting in a total walking time up to 183 s for the 100 m distance.
- Obstructions such as debris following a natural disaster, which forces an alternate route and increases distance and time. For example, a single 2 m circumference object in the direct path could easily result in a 6 m circumnavigation, increasing time 9 s even without time to assess and route plan.

Multiple factors could compound the distance and/or time required for the route, but a clear model of additive effects does not currently exist. Increases in distance and duration are also likely to increase fatigue, which further slows gait or, in extreme cases, results in the inability to complete the entirety of the prescribed walking distance.

While the effects of slowing gait may seem minor (e.g., a 30% overall increase in time walking is only 45 s for the 100 m distance), it is reasonable to expect that many scenarios would involve multiple shuttles between the two facilities, resulting in multiple minutes worth of degradation in travel time. In the case of a plant upset involving critical time windows to complete remediations, such delays could prove risk significant. A failure to model distance for field operations clearly overlooks an important source of risk uncertainty.

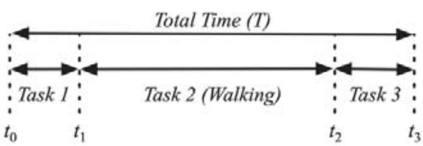

Fig. 5. Task time windows.

Figure 5 illustrates the relationship between performing activities at the first facility (e.g., getting pumps), walking between facilities (e.g., carrying parts to be connected), and performing activities at the second facility (e.g., attaching pumps). We will arbitrarily assume that in the present example, the plant allows 30 minutes to complete the task safely, after which the safety of the plant is compromised. If we assume 5 minutes to collect parts at the first facility and 10 minutes to install when they are at the second facility, this allows a total of 15 minutes (900 s) of walking time between the two facilities.

Table 3 illustrates the duration of walking depending on the speed of walking and the number of times the individual travels between the two facilities. Any transfer between facilities that exceeds the available time window of 900 s is flagged in red. With a slow gait attributable to any of the factors described above, even a single transfer may not be possible within the available time window. This flags a potential failure of the activity, or denotes the need to assign additional personnel to assist with the task in the given time. Fortunately, in most plants, there is not the need for repeatedly walking back and forth across large distances to accomplish a task. Still, this made-up example helps illustrate the importance that distance traveled between two locations can affect the success or failure of a task.

Table 3. Walking transfers at different speeds.

		Number of Walking Transfers Between Facilities (100 m)				
		1	**2**	**3**	**4**	**5**
	1.8	55.6	111.1	166.7	222.2	277.8
	1.7	58.8	117.6	176.5	235.3	294.1
	1.6	62.5	125.0	187.5	250.0	312.5
	1.5	66.7	133.3	200.0	266.7	333.3
	1.4	71.4	142.9	214.3	285.7	357.1
	1.3	76.9	153.8	230.8	307.7	384.6
	1.2	83.3	166.7	250.0	333.3	416.7
	1.1	90.9	181.8	272.7	363.6	454.5
Walking Speed (m/s)	**1**	100.0	200.0	300.0	400.0	500.0
	0.9	111.1	222.2	333.3	444.4	555.6
	0.8	125.0	250.0	375.0	500.0	625.0
	0.7	142.9	285.7	428.6	571.4	714.3
	0.6	166.7	333.3	500.0	666.7	833.3
	0.5	200.0	400.0	600.0	800.0	1000.0
	0.4	250.0	500.0	750.0	1000.0	1250.0
	0.3	333.3	666.7	1000.0	1333.3	1666.7
	0.2	500.0	1000.0	1500.0	2000.0	2500.0
	0.1	1000.0	2000.0	3000.0	4000.0	5000.0

4.2. Main Control Room

The main control room of a nuclear power plant is a self-contained environment with relatively short distances travelled due to small dimensions. Nonetheless, in legacy reactors with analog human-machine interfaces, indicators and controls are distributed across multiple panels, necessitating some travel for the operators at the boards. Analog control rooms largely feature operation at the boards, requiring the reactor operators to walk between panels. Monitoring and control tasks that fall within a common system will require little walking once the operators are at the correct panel, but plantwide activities with several systems involve travel across the control room. Such activities may be referred to as "operator ping-ponging" when the operator traverses one end of the control room to another. Monitoring may involve less travel, as indicators can—depending on the design—be read at some distance. Controls, however, must be operated within arm's length, requiring walking to the appropriate panel to be able to reach the controls. Figure 6 provides an historic illustration of the walking patterns of two reactor operators during a plant upset condition using an L-shaped control room (Seminara et al., 1976).

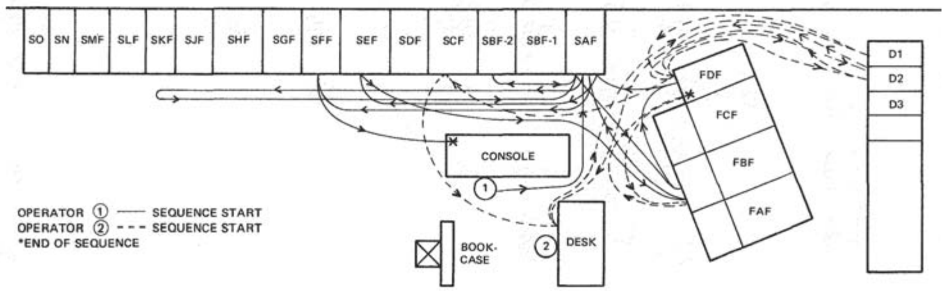

Fig. 6. Reactor operator movements in a main control room (Seminara et al., 1976).

The distances travelled are smaller in a control room than in most field operations. Moreover, roles are shared between multiple reactor operators, whereby the control room supervisor will generally direct the operator closest to a particular panel to carry out those specific activities. Still, as noted in Figure 6, if each panel represents approximately 1 to 1.5 m, walking the boards may easily represent dozens of meters of walking. Additionally, there is the distance and time associated with scanning the panels for relevant indicators. Work by Kovesdi et al. (2017) indicates that for analog indicators and controls, the average visual fixation is 0.38 s, with an average scan path duration of 21.28 s, corresponding to 18,648 pixels per scan (i.e., approximately 396 inches or 1,006 cm using a 47 pixels per inch display). Vicente et al. (2001) note that digital control rooms consolidate information into screens instead of displaying all information simultaneously. The distance travelled becomes one of navigating through different layers of information spread across different windows or screens Kovesdi et al. note shorter visual fixation times for digital interfaces (0.29 s) but with a longer scan path duration (42.48 s) and scan path length (27,851 pixels, 592 inches, and 1,503 cm).

The important takeaway message is that distance is both a measure of physical distance traveled in moving across control panels and visual scan distance for indicators and controls on those panels. Additionally, fixation or dwell time must be factored into the overall time, since dwell time corresponds to time not moving but rather identifying important information and making decisions. Dwell time is a measure of cognitive effort, which can be seen symbolically as the mental distance to make sense and process information. Newer digital technologies, which consolidate information into a few displays, nest information across different windows. Distance is a measure of the number of steps required to navigate to different pieces of required information (i.e., clicking through menu choices to drill down to the right screen) plus the scan time to find the required indicator or control once the appropriate screen is identified. This notional definition of distance within the control room may be captured by Equation 1:

$$d = w + l + k + n \quad (1)$$

where d is the multidimensional distance, w is walking distance, l is looking or scanning, k is knowledge-related such as understanding and decision making, and n is navigation distance. Each element of distance may be transformed into a time measure, but a generalized form is not available, and each parameter must currently be considered according to context. An eventual generalized transformation function from distance to time is planned in HUNTER but not currently implemented.

5. Discussion

This paper has introduced the topic of spatial HRA and provided preliminary ideas into how spatial considerations can be incorporated into the HUNTER dynamic HRA tool. Of course, there remain many unanswered topics that require further research as spatial HRA is matured into a useful concept within HRA. Research is ongoing within the HUNTER project to explore the following aspects of spatial HRA:

- The relationship between dynamic and spatial HRA

- The need for new TLPs within GOMS-HRA to account for movement between locations
- Performance shaping factors that increase duration or error rates during movement
- New error types for location or movement
- Additional use cases, including those outside nuclear power such as transportation, which may see even greater benefits of incorporating spatial HRA
- The ability to interface HUNTER with three-dimensional models like virtual reality
- The need for new sources of empirical HRA data to inform spatial HRA
- Identification of risk applications that explicitly need spatial HRA models
- Optimization strategies and guidance for performing spatial HRA
- Use of spatial HRA beyond HUNTER.

Spatial HRA remains a novel concept, and much research remains to be done beyond this introduction.

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