Development of a Dynamic Cognitive Modeling Architecture of Human Reliability Simulation using the Rancor Microworld Simulator

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Abstract: Human error is regarded as the largest contributor to plant safety. Even with careful selection and training human performance can vary between operators and even within operators. Despite decades of advancement Human reliability analysis (HRA) primarily relies on experts to perform subjective analyses of tasks and subtasks to estimate performance shaping factors (PSFs). These PSFs are then used to estimate human error probabilities (HEP). The subjective analysis is also prone to error, bias, and requires the experts to accurately understand the task complexity and time constraints. During operations the conditions can be highly dynamic and the conditions may not match those envisioned during the HRA. Dynamic HRA aims at estimating HEPs *on-the-fly* based on dynamically estimated *PSFs*. Here we describe the development of a cognitive modeling architecture for dynamic HRA and the use of Rancor for model development and validation.

1. INTRODUCTION

Nuclear power plants are among the most complex systems built by humans. Automation and control systems are improving but plants are still highly dependent on skilled and knowledgeable operators to monitor plant health, operate plant systems, and detect, diagnose, and respond to abnormal events. Key to the safe operation of plants is probability safety analysis (PSA) which aims at estimating the causes and frequencies of faults. Because human operators are critical components in these engineered systems we must understand and be able to estimate human performance to conduct valid PSA. Adding to the challenge of undertaking this research is the reality that psychological research in human error is incredibly difficult. As human error is, by definition, an unintentional act, the development of experiments which can reliably control specific performance shaping factors (PSFs) and elicit a consistent unintentional error is a large obstacle to empirical work in this field and would require thousands of repetitions.

1.1. Cognitive Modeling

Here we develop a model based dynamic HRA method to estimate human error probabilities using integrated modeling of plants and computational cognitive modeling to capture the specific nuances of human decision-making and error in these situations. Cognitive modeling is a computational method for representing a mechanistic model of what is known of human cognition in a manner which allows the model to perform in a way like that of a human participant. Cognitive modeling has not been a broad topic of interest for HRA, generally, but there are significant advantages to using cognitive modeling rather than the other traditional methods. One critical advantage of cognitive modeling is the ability to represent the functions of human cognition and decision making more closely. Currently HRA analysts make subjective determinations about the potential for human error and the impacts of various PSFs. These subjective determinations are then aggregated to form an HEP for the task or subtask. The process is time consuming and labor intensive as it requires manually decomposing and rating tasks. Utilizing a cognitive model coupled to plant models that can provide a basis for external PSFs like time-pressure and complexity allows analysts to run the virtual human operator through tasks many times and collect general performance data that is more aligned with known operations of decision making, thus making the HRA more grounded in the reality of human performance than subjective estimates. Cognitive modeling can also serve to simulate many of the different mental capabilities that humans possess. For example, the full ACT-R (Adaptive Control of Thought—Rational) implementation can simulate memory, attention, visual perception, motor functions, and more. Some modeling applications may require only some of these functions, but they are there if needed.

Using cognitive modeling to explore human error is a somewhat novel application of cognitive models. Many applications of cognitive modeling study specific tasks or application spaces such as process control microworlds [1] or cybersecurity detection [2]. As such, human error was a component of the overall process in that an unsuccessful run made a mistake or incorrect judgment somewhere in the model. Some efforts have been made to establish and capture performance effects in cognitive modeling because of fatigue [3, 4]. These efforts are valuable to this project to provide a means of modeling the impacts of fatigue on human performance. By defining and formalizing dynamic PSFs and their impacts on cognitive processing we can more readily evaluate the probability of human error occurrence. This information could be used to redesign operations, invest in additional technologies, processes, and resources to make them more resilient to human error.

While HRA is the primary discipline or term being used here, the true goal of this effort is a more accurate accounting and modeling of human error. Specifically, cognitive modeling enables a greater understanding of the various likelihoods as well as the impact of the numerous factors which impact our decision-making. Aspects of human cognition and error have been captured conceptually [5, 6, 7] but in capturing this more specific information system, designers can make decisions around how to make systems more resilient to human error as well as highlight more fragile operating circumstances.

1.2. Full-Scope vs. Reduced Order Models

Significant effort has been put into the development of high-fidelity thermohydraulic modeling for nuclear power and process control generally. Plants utilize full-scope simulators for engineering and training purposes. While not perfect, they tend to accurately represent the physical configuration and control systems of plants with a high degree of fidelity. These models are complex and can require several years to fully develop and validate. While the complexity provides higher fidelity it also increases the difficulty of understanding how the simulators function from a technical perspective and modifying the models has a steep learning curve that requires learning boutique development environments. Full-scope simulator models also contain several thousand or even tens of thousands of parameters. Much time and effort is required to find parameters of interest and the complexity and shear number and interaction of parameters increases the difficulty of coupling models to other models or hardware in the loop processes.

High-fidelity full-scope nuclear power plant simulator models can be challenging to use for a variety of reasons. First, they can be expensive to develop and maintain. Second, they can require a lot of computing resources to run, which can make them difficult to use for real-time training or for large-scale studies. Finally, they can be complex to use, requiring a deep understanding of the nuclear power plant system being simulated.

Yet another disadvantage of full-scope simulators are also not optimized for speed, and even with modern multi-core workstations conducting Monte Carlo simulations with 10s of thousands or 100s of thousands of runs is not logistically feasible. Obtaining full-scope simulator models with source code can also be challenging, and even when used for academic research purposes the full-scope simulators may come with restrictions on use and restrictions on sharing derived products. Despite these challenges full-scope simulators are valuable feats of technological achievement and their roles in engineering, training, and safety should not be overlooked. However, for many tasks simpler models and tools such as the Rancor Microworld Nuclear Power Plant Simulator (Rancor) can over high value solutions across a variety of problem domains.

Reduced order models (ROMs) are simplified engineering models that validate particular aspects (e.g. steady state performance) against physical systems or higher fidelity models. They can then be utilized within their validated envelopes for gaining insights into engineered systems. ROMs address the complexity and coupling disadvantages of full-scope models due to their simplified nature. In the human factors domain an analogous problem exists with full-scope simulators. The simulators represent all of the sub-systems and components in physical plants and licensed operators go through years of training to operate these plants competently. Licensed operators are a finite and expensive commodity for laboratory human reliability studies to the extent that obtaining statistically useful error probability rates is not feasible.

1.3. The Rancor Nuclear Power Plant Microworld Simulator

Reduced-order models are particularly beneficial for integrative nuclear power engineering because they allow for the simulation of complex systems while reducing the computational burden. Here we utilize the Rancor Microworld.

The Rancor was jointly developed by Idaho National Laboratory and the University of Idaho to investigate attention and situation awareness with novice operator. It has subsequently been used to design and validate the concept of operations, procedures, and interface design of an integrated energy system for nuclear power. A shortcoming of the Rancor was that the simulation model was only accessible through a graphical user interface. Here we describe how the simulation model of Rancor has been extracted and made accessible to a variety of platforms and applications by modularizing the model to a .NET core library that can be utilized from .NET compatible environments including Visual Studio and Unity3d.

The model has also been ported to Python with the ability to load initial conditions, and trigger faults. Integrating it with the Human Unimodel for Nuclear Technology to Enhance Reliability (HUNTER) will enable dynamic human reliability simulations. The fidelity of Rancor is limited compared to full-scope simulators or even simplified educational/training simulators. However, the tradeoff is performance, with yet-to-be-optimized code running 100x the speed of full-scope simulators. Furthermore, the simplicity and flexibility of Rancor is favorable to proof-of-concept testing for HUNTER. Dynamic human reliability simulation fundamentally requires a model with a deterministic fault tree, the ability to specify the probability of faults and accept human control actions, and the ability to conduct enough simulation runs to capture the fault tree.

The Rancor python model meets these specifications. In this manner the Rancor model can capture theoretical principles of dynamic human reliability analysis (DHRA) ahead of more lengthy and complex integration with higher fidelity models that more precisely capture the temporal and failure dynamics of nuclear power systems.

2. DYNAMIC HRA COGNITIVE MODELING ARCHITECTURE

Operators are critical to safe and reliable plant operations. Human reliability analysis has developed means of estimating human error rates based on PSFs. Here we aim to develop an cognitive modeling architecture of human operators that can dynamically model human errors based on conditional factors like time pressure and situation complexity.

Operators of nuclear power plants are tasked with monitoring plant conditions during normal operations and identifying and diagnosing abnormal plant conditions. Operators must have a deep understanding of how plant systems function and interact with one another. Nuclear power plants have thousands of indications that operators must use to determine the current state of the plant. Interpreting these indications is also dependent on the current objectives and state of the plant. For example, during startup many parameters would be considered outside normal operating conditions. Operators spend a great deal of time training to learn how to interpret various normal and abnormal plant conditions and develop automated responses to particular events. For example, after a reactor trip an operator will check and verify a handful of other parameters within a few seconds without any additional prompting or referencing of procedures.

A barrier to modeling in general is the "Black Box Problem." Models can be trained to provide the appropriate responses to a set of inputs but understanding how and why the models yield their trained responses is not always easy. Models can get the right answer for the wrong reasons, which can lead to non-generalizability when they encounter new conditions. Here our goal is to use cognitive modeling as a backbone for our operator model. A key distinction is that the cognitive model is mechanistic. It processes information in a manner that is consistent with our understanding of cognitive science. The cognitive science is based off of a corpus of human performance data and neuro-imaging.

Perhaps the key challenge for this current work is complexity scaling. Cognitive modeling primarily exists in the domain of basic research as a tool for hypothesis driven modeling for understanding particular aspects of cognition such as language processing, sensation and perception, decision-making, memory, etcetera. To develop models, human participants conduct hundreds to thousands of short stimulus/response trials with a high degree of external control. These tasks could be described as "toy problems" where the parameter space and decision space are relatively simple compared to a main control room of a nuclear power plant.

Here we describe a cognitive modeling architecture for nuclear process control. The architecture uses ACT-R's declarative memory processing and the relevant parameters related to that model within the PyIBL library. The architecture scaffolds declarative memory with a heuristic control loop based on our experience with how operators perform monitoring and control tasks in a nuclear control room. During steady-state operations operators are said to "walk the boards." This describes physically traversing the control room and scanning indications to gain situational awareness of the current state and direction of the plant. Main control rooms contain thousands of indications, but operators do not divide their attention between indications equally. Some indicators provide higher informational value compared to others. This pattern of attention has been observed across dozens of operators, operating both digital and analog systems, during normal and abnormal conditions (see Figure 1).

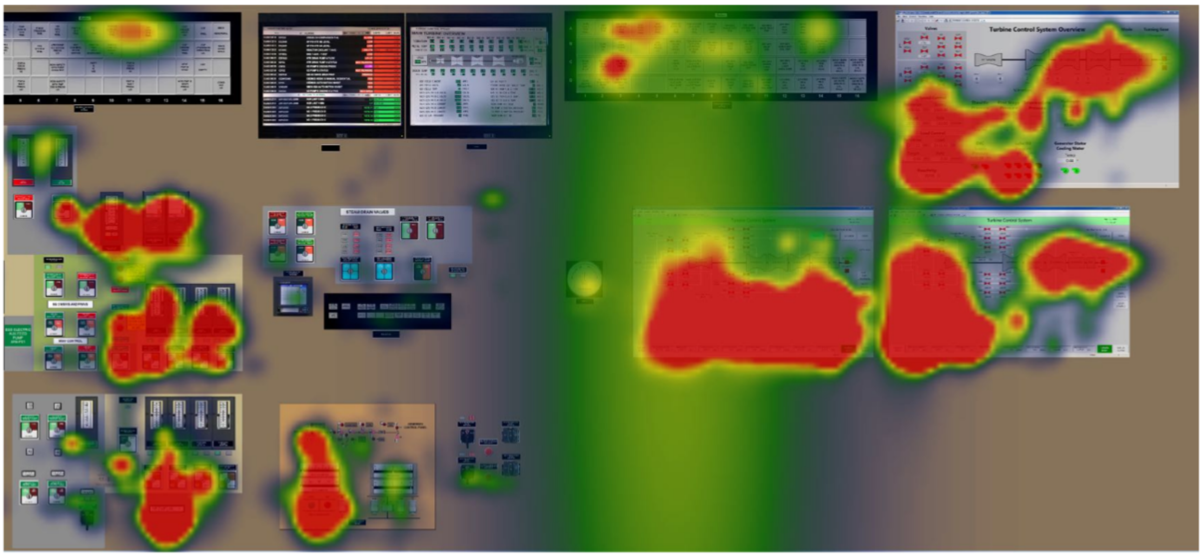

Figure 1. Heat map of an operator eye-tracking in a hybrid control room with digital and analog indications.

Another key aspect of the model structure is the notion of operator archetypes. A critical component of nuclear power operations and critical infrastructure is that operators are highly trained and exhibit a high level of expertise in the relevant tasks. To reflect this in the cognitive model, archetypes will be constructed to represent a reactor operator, trainee operator, and senior operator, as examples. These archetypes will also contain the core parameters for the cognitive model like utility, threshold, and more which then pass through the PSF module to the cognitive model, as shown in Figure 2. These agent archetypes will simplify model performance by allowing the selection of specific agent types to explore error likelihoods across these known expertise and training differences. The agent archetypes can be serialized and packaged for reuse in other cognitive model instances.

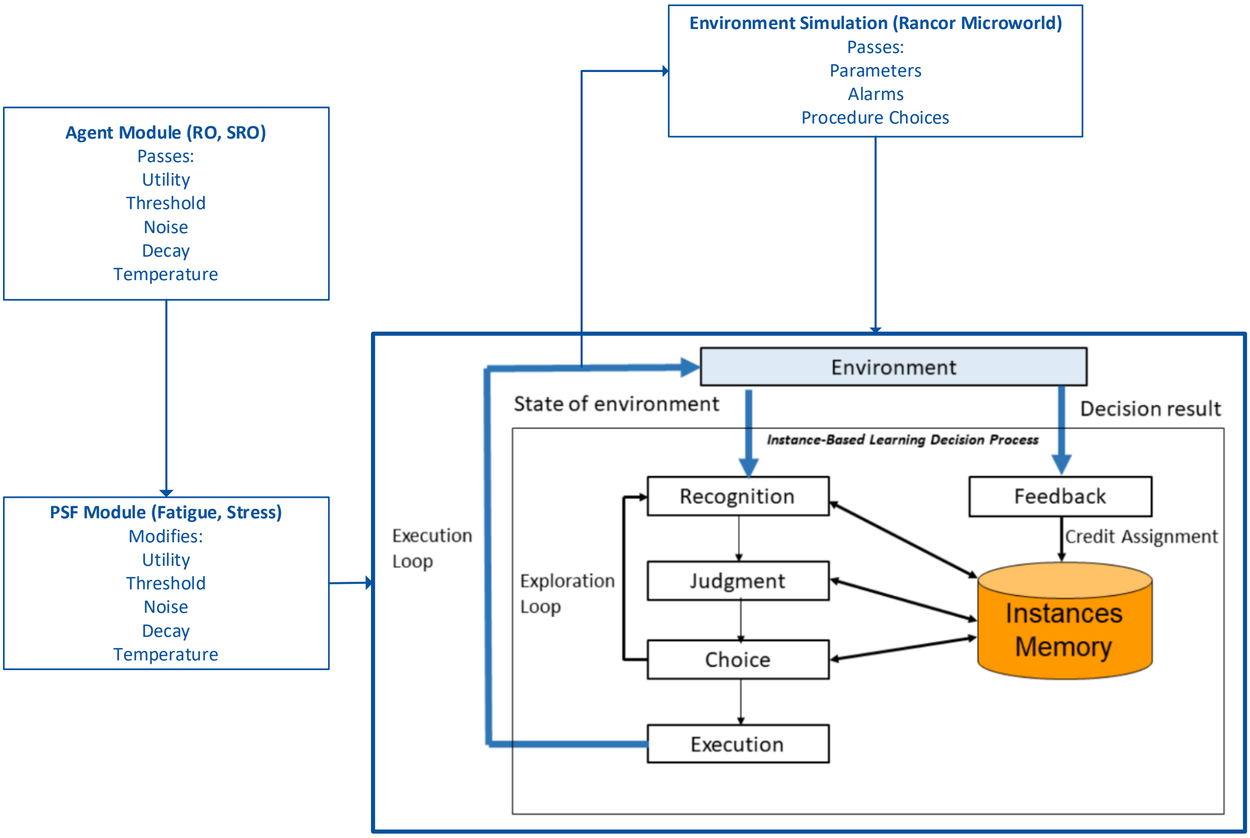

Figure 2. Cognitive Model Architecture

Operators are also explicitly trained to use redundant indications while operating. For example, if the reactor scrams, operators will routinely check reactivity and control rod positions within a few seconds of a trip. They are also conditioned to investigate indications that are inconsistent with their experience or mental model of the plant. Operators could be described as building a high-level chunked representation of the plant. For example, when debriefed operators can describe plant evolutions with a surprising amount of detail where many of the details are likely filled in from their experience with the plant and not direct recollection of events.

The cognitive modeling architecture we envision is capable of scanning non-orthogonal plant parameters to maintain a high-level representation of the current state of the plant. This high-level representation is available for retrieving decisions related to specific alarm conditions. For example, if the reactor is online and an alarm trips, an action could be required. However, if the reactor is offline no action could be required. In addition, alarm prioritization may be required. In some circumstances a particular alarm could warrant a particular action, unless a more critical alarm is also annunciating.

2.1. Cognitive Model Framework Selection

Many different cognitive architectures have been developed, generally stemming from the ACT-R framework [9], and have been applied in many different instances or applications. ACT-R is one of the original cognitive architectures and is also considered one of the most thorough systems, with modules for motor cognition and perception. However, this leads to ACT-R being a relatively complex and hefty architecture to use and may not be completely suitable for rapid exploration of different cognitive modeling applications [10]. ACT-R has a significant learning curve, and more research is needed to better understand the capabilities and whether the components are necessary for our use case. Additionally, there are some concerns that the original software. As our model is focused on decision-making in an unstructured task there is not as much of a need for the motor or sensory modules for the purposes of this effort, so the focus is on the memory modules and action execution.

In response to ACT-R's popularity and complexity there was increased interest in modeling dynamic decision-making processes. As discussed, much of ACT-R is external to this core cognitive process however the modules which capture aspects of memory and how decision-making relies on past experience are extremely relevant to this goal. This led to the creation of a Python module which contains an implementation of the declarative memory model from ACT-R but enables rapid development of models and decision-making experiments by those not already familiar with LISP and ACT-R [10]. has specific benefits in the way it handles memory aspects and how memories are encoded. Traditionally, models are trained on a set-aside data set to teach the model what to do or, in this case, what the model knows. This can be a time-consuming process and, in some cases, may be impossible due to an absence of human performance data sets in process control and nuclear. PyACTUp specifically includes a method for defining memory objects as needed. This sidesteps the need to train up memories with the data sets and allows research teams to define the key memory concepts that the model will require to execute the decision-making tasks. This makes it a good candidate for initial model development and testing.

The structure of the Instance-based Learning Theory (IBLT) and the subsequent modeling library (PyIBL) [10, 11, 1] was selected as a good candidate for this application. IBLT has been used to model many different aspects of dynamic decision making in a variety of mission critical and high-risk industries [12, 2, 1] and has also been coupled with microworld environments to explore specific processes or systems. Microworld usage has also been a focus of human performance and HRA research at the Idaho National Laboratory in recent years, and has proven to be an incredibly valuable resource to designing, evaluating, and testing specific conditions or applications of nuclear power operations and operator performance [13, 14, 15, 16, 17, 18]. As such, the implementation of an IBLT-based cognitive architecture could enable the integration of some microworld instantiations which have already shown promise in nuclear power and HRA.

Many of the aspects of IBLT are captured in Gonzalez's initial description of the architecture [11]. PyIBL uses PyACTUp's memory model [9] which captures specific calculations such as memory decay and retrieval probabilities. The memory model stores experience and the 'world state' representations along with their utility. The IBLT model can then explore if specific world state parameters match any *instance* in the memory store and execute the decision appropriately. The model will allow for partial matching and blending of specific instances and parameter sets to maximize utility while enabling researchers to explore imperfect data or unique instances.

IBLT is conceptualized as an agent, and multiple agent instances or agent types can be used to capture specific agent-based characteristics such as variations in training or experience. This will provide a means for representing training and experience PSFs as these agent types will necessarily have separate memory stores which reflect those traits. Fundamentally, many cognitive models perform decision calculations based on a final assessment of matching and decision values compared to a defined utility function. This will enable research teams to explore different utility functions for specific applications or circumstances, which will develop additional depth in the model's functionality.

2.2. Initial Cognitive Modeling Development

Preliminary efforts examined alarm to response mappings with PyACTup declarative memory models. The simplest one-to-one alarm to response mappings were easy to train even with moderate levels of accuracy (as low as 45%) during training. We also found that manipulating decision accuracy in the training dataset and the number of training repetitions can be used to control the performance of the model (model experience and training PSFs). However, as the parameter space increases where multiple parameter states encode the appropriate response the number of training repetitions grows exponentially. A model with 5 actionable responses encoded in 5 alarms with 5 distractor alarms required on the order of 1,000,000 training repetitions per actionable alarm to yield accurate retrieval responses.

For this reason, we found it desirable to use multiple hierarchical declarative memory models. One model is dedicated to the high-level (overview) awareness of the plant. And other second tier models are dedicated to specific sub-tasks that involved looking at subsets of model parameters with an overall awareness of the plant. For example, to effectively control steam generator (SG) level only a small subset of plant parameters are needed. A smaller declarative memory model can be built around this parameter space to effectively control SG level and respond to SG alarms. In the current preliminary model, the alarms are explicitly coded to trigger these second-tier declarative memory models. In essence, the alarms trigger an orienting response to address the alarm. In future models this could likely be replaced by another cognitive memory model that determines which second tier model should be ran given the current state and alarm space.

Nuclear power operations are highly proceduralized, and one of the most critical tasks of an operator is to identify conditions that require operator intervention and matching the conditions to the appropriate action (oftentimes this is entry into the appropriate procedure after carrying out "immediate actions" from memory). In the cognitive architecture, alarms trigger declarative memory models trained to determine the appropriate response to the alarm.

2.3. Continuous Parameter Discretization

Another key challenge to the use of cognitive modeling is that many of the indications used by operators are continuous parameters like temperatures, pressures, flows, and levels that are constantly changing over time. However, cognitive modeling frameworks like ACT-R are developed to recognize un-ranked discrete states. Here we devise discretization maps to transform continuous variables from the Rancor Microworld [18] environment to discrete states that can be used to train declarative memory modules. The discretization is based on their operational relevance to the plant (as determined by the developer of the Rancor Microworld model who is also the cognitive modeler; See Table 1). For instance, steam generator level is discretized as unknown (N/A), low (< 40%), normal (40% - 60%), or high (>60%). In addition, the derivative of plant parameters is discretized as unknown (N/A), decreasing, stable, or increasing. Table 1 lists additional discretization schemes for Rancor parameter types. Ideally, these discrete states would be learned in an unsupervised manner. However, here the goal is to build the architecture and then use the architecture as a scaffold for future refinements.

Table 1. Rancor Microworld Parameter Discretization Schemes

Parameter Type	Discretization
Alarm	N/A, False, True
Reactivity	N/A, Offline (0%), Online (0% - 100%), Over-Power (100%-102.5%), Over Trip Threshold (>102.5%)
Pump State	N/A, Off, On
SG Level	N/A, Low (<40%), Normal (40%-60%), High (60%)
Valve	N/A, Closed (0%), Open (>0%)
Latched	N/A, Not Latched, Latched

2.4. Hierarchical Cognitive Modeling

PyIBL (agent-based instance-based learning model that uses PyACTup) has been used to build a two layer hierarchical model capable of identifying plant mode and responses to control steam generator levels. The plant mode identification is encoded by six plant parameters and 3 distractor parameters.

The parameters are defined as known or unknown. The model is trained by randomly generating synthetic data across the parameter space with a defined accuracy rate or 90% correct identification.

It has been found that increasing the number of distractor variables and states significantly increases the number of repetitions required to train the model. This has an interesting theoretical implication that much of operating is learning what parameters are relevant in the given context and what parameters can be safely ignored.

The second layer of the model learned the appropriate responses to manually maintain SG levels in the Rancor Microworld as shown in Table 2.

This two-stage cognitive modelling architecture proves the concept that declarative memory models can be trained to recognize plant conditions and to select appropriate actions. The model also demonstrates that the architecture is scalable by training additional models for specific plant and control circumstances.

Table 2 Parameters and responses needed to manually control SG levels in Rancor

plant mode	alarm high sg	alarm low sg	SG A level	SG B level	Δ SG A level	Δ SG B level	response	comments
Shutdown	*	*	*	*	*	*	None	
*	*	*	*	*	*	*	determine plant mode	low SA
Online/ Startup	*	*	normal	*	↑	*	↓CV A	ahead of alarm
Online/ Startup	*	*	high	*	↑	*	↓CV A	after alarm
Online/ Startup	*	*	high	*	~	*	↓CV A	way after alarm
Online/ Startup	*	*	*	normal	*	↑	↓CV B	ahead of alarm
Online/ Startup	*	*	*	high	*	↑	↓CV B	after alarm
Online/ Startup	*	*	*	high	*	~	↓CV B	way after alarm
Online/ Startup	*	*	normal	*	↓	*	↑CV A	ahead of alarm
Online/ Startup	*	*	low	*	↓	*	↑CV A	after alarm
Online/ Startup	*	*	low	*	~	*	↑CV A	way after alarm
Online/ Startup	*	*	*	normal	*	↓	↑CV B	ahead of alarm
Online/ Startup	*	*	*	low	*	↓	↑CV B	after alarm
Online/ Startup	*	*	*	low	*	~	↑CV B	way after alarm
Online/ Startup	True	*	None	None	None	None	investigate high	low SA
Online/ Startup	*	True	None	None	None	None	investigate low	low SA

3. CONCLUSIONS AND NEXT STEPS

The functionality of PyIBL/PyACTup to learn discretized states from the Rancor Microworld has been proven. From here we need to fully train declarative models and link them together in a common model framework. We have also validated that it is possible to serialize PyACTup memory instances to Python pickle files and deserialize them back to Python objects. This will allow virtual operators to be saved and loaded for Monte-Carlo testing. As a proof-of-concept exercise we plan on linking the operator model to manually control SG levels. Another interesting finding from the modeling thus far is that situational awareness can roughly be inferred by the operator's current awareness of the parameter space and their response (see the comments column of Table 2). When the operator is paying attention to the parameters, they should be able to form control actions ahead of setpoint alarm thresholds being reached.

An end goal of this work is to tie cognitive modeling to the HUNTER model. HUNTER is designed to represent and carry-out procedures in a manner consistent with human operators. To reach this goal we must first build a cognitive model that is capable of monitoring plant parameters and forming responses to changing conditions and dynamic performance shaping factors in a manner consistent with human operators. To reach this goal we are using the reduced order Rancor Microworld Nuclear Power Plant Simulator. The simulator represents the major systems of a pressurized water reactor but in a simplistic fashion. The simulator has alarms and abnormal operating procedures modeled after real nuclear power plant operations. Validation comparisons between novice and expert operators have been conducted with the Rancor Microworld and we a large volume of simulator and operator logs to available to aid in training and validating cognitive models. For these reasons the Rancor Microworld is being used to develop a proof-of-concept for the cognitive modeling architecture. The system complexity is a magnitude order greater than paradigms typically used by ACT-R experiments but is still simple enough that the training and model spaces can be deconstructed to understand how the model is functioning.
To be applicable as a HRA tool for nuclear power we would like to use cognitive modeling for specific full-scale simulators that contain thousands of parameters and at least an order of magnitude more complex than Rancor. An outstanding challenge is to determine 1) if and how cognitive models can be trained in an automated fashion, or 2) how the findings from the cognitive modeling can be generalized to traditional HRA analysis. One steppingstone to fully dynamic integrated cognitive model HRA could be using cognitive modeling to better understand how PSFs can be integrated to produce HEPs. A cognitive model with PSF implementation could allow analysts to explore different levels of PSFs and determine if there are 'tipping points' where the error is increased dramatically at a certain level of PSF impact, and similarly when error likelihood flattens out. As most human performance follows a logarithmic form it is possible that these will be seen.

There remain some large challenges in this effort as well. As discussed throughout this report, there are known behavioral changes with the presence of PSFs, however there is a deficit of examples of how these affect core cognitive parameters that can be instantiated within a cognitive model's parameters. Much of the research on fatigue and other impacts on cognitive modeling is completed in a trial-and-error fashion as modelers adjust parameters on the fly and compare to known psychological research studies on the factors of impact to see when the model roughly aligns with performance shown in the research. Then it is assumed that the model which most closely approximates real world performance contains the most likely parameter manipulations. While this has been completed for fatigue, it remains to be completed for stress and other PSFs. This is a challenge but also a future opportunity to explore existing psychological research on human performance and work to replicate that performance in the cognitive model.

In conclusion, the initial drive for this research was to better understand and quantify the probabilities of human error in a way which more closely aligns with what is known about cognitive performance. Many other HRA methods use expert ratings or subjective analyst determinations to identify the probabilities, however many are not well grounded in known psychological principles and thus do not demonstrate the levels of ecological validity and realistic performance that is important in these critical infrastructure domains. It is our contention that an HRA method which utilizes a mechanistic model of cognition relying on known and demonstrated human performance decrements is the best path forward for HRA research.

References

[1] Gonzalez, C., Dana, J., Koshino, H., & Just, M. (2005). The framing effect and risky decisions: Examining cognitive functions with fMRI. J. Econ. Psychol., 26(1), 1-20. doi:10.1016/j.joep.2004.08.004
[2] Dutt, V., Ahn, Y.-S., & Gonzalez, C. (2013). Cyber situation awareness: modeling detection of cyber attacks with instance-based learning theory. Hum. Factors, 55(3), 605-618. doi:10.1177/0018720812464045
[3] Gunzelmann, G., Gross, J. B., Gluck, K. A., & Dinges, D. F. (2009). Sleep deprivation and sustained attention performance: Integrating mathematical and cognitive modeling. Cognitive science, 33(5), 880-910.
[4] Gunzelmann, G., Moore, L. R., Gluck, K. A., Van Dongen, H., & Dinges, D. F. (2011). Fatigue in sustained attention: Generalizing mechanisms for time awake to time on task.
[5] Rasmussen, J. (1980). Notes on Human Error Analysis and Prediction. In G. Apostolakis, S. Garribba, & G. Volta (Eds.), Synthesis and Analysis Methods for Safety and Reliability Studies (pp. 357-389). Boston, MA: Springer US.
[6] Rasmussen, J. (1983). Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models. IEEE Trans. Syst. Man Cybern., SMC-13(3), 257-266. doi:10.1109/TSMC.1983.6313160
[7] Reason, J. (1990). Human Error: Cambridge University Press.
[8] Anderson, J. R., Matessa, M., & Lebiere, C. (1997). ACT-R: A theory of higher level cognition and its relation to visual attention. Human–Computer. Retrieved from https://www.tandfonline.com/doi/abs/10.1207/s15327051hci1204_5
[9] Reitter, D., & Lebiere, C. (2010). Accountable modeling in ACT-UP, a scalable, rapid-prototyping ACT-R implementation. Paper presented at the Proceedings of the 10th international conference on cognitive modeling (iccm).
[10] Gonzalez, C., & Dutt, V. (2011). Instance-based learning: integrating sampling and repeated decisions from experience. Psychol. Rev., 118(4), 523-551. doi:10.1037/a0024558
[11] Gonzalez, C., Lerch, J. F., & Lebiere, C. (2003). Instance-based learning in dynamic decision making. Cogn. Sci., 27(4), 591-635. doi:10.1207/s15516709cog2704_2
[12] Ben-Asher, N., & Gonzalez, C. (2015). Effects of cyber security knowledge on attack detection. Comput. Human Behav., 48, 51-61. doi:10.1016/j.chb.2015.01.039
[13] Boring, R., Kelly, D., Smidts, C., Mosleh, A., & Dyre, B. (2012). Microworlds, simulators, and simulation: Framework for a benchmark of human reliability data sources. Retrieved from https://inldigitallibrary.inl.gov/sites/sti/sti/5680970.pdf
[14] Boring, R., Ulrich, T., Lew, R., & Skogstad, M. R. (2019). Human reliability studies with microworld simulators. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.
[15] Lew, R., Ulrich, T. A., & Boring, R. L. (2020). Rancor Hybrid Energy System Microworld. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.
[16] Lew, R., Ulrich, T. A., Boring, R. L., & Werner, S. (2017). Applications of the rancor microworld nuclear power plant simulator. Paper presented at the 2017 Resilience Week (RWS).

[17] Ulrich, T. A., Boring, R. L., & Mandelli, D. Using Microworlds to Support Dynamic Human Reliability Analysis. Proceedings of PSAM 14-Probabilistic Safety Assessment and Management, 16-21. Retrieved from http://www.iapsam.org/psam14/proceedings/paper/paper_57_1.pdf
[18] Ulrich, T. A., Lew, R., Werner, S., & Boring, R. L. (2017). Rancor: A gamified microworld nuclear power plant simulation for engineering psychology research and process control applications. Proc. Hum. Factors Ergon. Soc. Annu. Meet., 61(1), 398-402. doi:10.1177/1541931213601582