Predictive Control of Interpersonal Communication Processes in Civil Infrastructure Systems Operations

by

Zhe Sun

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Graduate Supervisory Committee:

Pingbo Tang, Chair
Steven K. Ayer
Nancy J. Cooke
Yongming Liu

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ABSTRACT

Interpersonal communications during civil infrastructure systems operation and maintenance (CIS O&M) are processes for CIS O&M participants to exchange critical information. Poor communications that provide misleading information can jeopardize CIS O&M safety and efficiency. Previous studies suggest that communication contexts and features could be indicators of communication errors and relevant CIS O&M risks. However, challenges remain for reliable prediction of communication errors to ensure CIS O&M safety and efficiency. For example, existing studies lack a systematic summarization of risky contexts and features of communication processes for predicting communication errors. Limited studies examined quantitative methods for incorporating expert opinions as constraints for reliable communication error prediction. How to examine mitigation strategies (e.g., adjustments of communication protocols) for reducing communication-related CIS O&M risks is also challenging. The main reason is the lack of causal analysis about how various factors influence the occurrences and impacts of communication errors so that engineers lack the basis for intervention.

This dissertation presents a method that integrates Bayesian Network (BN) modeling and simulation for communication-related risk prediction and mitigation. The proposed method aims at tackling the three challenges mentioned above for ensuring CIS O&M safety and efficiency. The proposed method contains three parts: 1) Communication Data Collection and Error Detection – designing lab experiments for collecting communication data in CIS O&M workflows and using the collected data for identifying risky communication contexts and features; 2) Communication Error Classification and Prediction – encoding expert knowledge as constraints through BN

model updating to improve the accuracy of communication error prediction based on given communication contexts and features, and 3) Communication Risk Mitigation – carrying out simulations to adjust communication protocols for reducing communication-related CIS O&M risks.

This dissertation uses two CIS O&M case studies (air traffic control and NPP outages) to validate the proposed method. The results indicate that the proposed method can 1) identify risky communication contexts and features, 2) predict communication errors and CIS O&M risks, and 3) reduce CIS O&M risks triggered by communication errors. The author envisions that the proposed method will shed light on achieving predictive control of interpersonal communications in dynamic and complex CIS O&M.

DEDICATION

I dedicate this dissertation to my father and my mother, Qiang Sun, Ph.D., and Baoqin Duan, and my girlfriend, Qian Li, M.S., whose support for higher education motivated me to reach greater boundaries and take up higher challenges. I owe a lot to my parents and my girlfriend for their continuous support and belief in me.

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CHAPTER 1

INTRODUCTION

Civil infrastructure systems (CIS), such as transportation infrastructure, canal system networks, and power plants, require effective operations and maintenance (O&M) for providing vital services to surrounding communities. CIS O&M contains operational networks, which consist of human activities that interact with physical environments. Such operational networks are extremely vulnerable due to tedious interpersonal communication processes dominated by CIS O&M participants for achieving effective team coordination and collaboration. Interpersonal communications during CIS O&M are processes by which CIS O&M participants exchange information on field discoveries and schedule updates. Reliable and timely information exchanged through such communications are thus necessary to allow CIS O&M participants to make proper decisions and ensure CIS O&M safety and efficiency. An extensive study is thus indeed for revealing the causal relationships between interpersonal communications and the impacts on CIS O&M risks.

CIS O&M contains interwoven networks of sets of interconnected elements such as human activities and CIS O&M workflows. The human activity network specifies the behaviors of CIS O&M participants during task preparations and executions. The CIS O&M workflows specify the spatiotemporal relationships between tasks listed on the as-planned schedule. The interwoven relationships between human activities and CIS O&M workflows are vulnerable due to the large number of interconnected elements that interact in a way that is hard to predict and control. Despite well-designed procedures to carry out CIS O&M workflows, poor communications that provide misleading information could still ruin these procedures and threaten CIS O&M safety and efficiency. Timely recognizing the vulnerabilities of interpersonal communications is vital for preventing CIS O&M risks (Golparvar-Fard et al. 2009; Zhang et al. 2009).

Interpersonal communications during CIS O&M remain the main approach for exchanging data and information between CIS O&M participants by following well-designed communication protocols during task preparations and executions. Such protocol specifies the communication network structure, chains of communications, communication timing and frequency, and the use of standardized phraseologies. For example, nuclear power plant (NPP) outages require an outage control supervisor to communicate with multiple field workers to exchange field information (e.g., field discoveries, abnormal indicators) through radio transmissions (Sun et al. 2018a). All such communications require clear and accurate exchanges of information promptly. Despite well-designed communication protocols, communication errors still exist and cause delays during NPP outages. Such delays could easily accumulate that cause significant cost overrun of NPP outages.

Previous studies indicate that communication contexts and features could be indicators of communication errors during CIS O&M. Communication contexts refer to the environmental conditions when communication occurs during CIS O&M. For example, communication protocols during NPP outages require outage participants to communicate within a centralized communication network, in which field workers can only communicate with their supervisor individually. Besides, CIS O&M schedules that specify the spatiotemporal relationships between tasks could also affect communications. As the interconnectivity of a task (i.e., the number of connected tasks) increases, workers who work on such a task could make more communication errors due to the increased task interconnectivity.

Communication features refer to the distinctive aspects of communication networks and contents, which define the talking behaviors of CIS O&N participants. These features such as, message length, talking speed, timing, frequencies, patterns, and keywords are all features that compose communication contents. For example, interpersonal communications during air traffic control allow the air traffic controller (ATC) to communicate with pilots for exchanging directive information (i.e., clearance) (see Figure 1). ATCs may issue long clearances to pilots to guide aircraft arrivals and departures. Such long clearances contain numerous numerical information including heading directions, reduced speed, and decent altitude (Sun et al. 2018c). Even experienced pilots cannot percept and read-back such information correctly. Besides, meticulous ATCs can hardly discover all read-back errors while controlling numerous aircraft in the controlled airspace. Despite well-designed communication protocols, communication errors still exist and aggravate the challenge for keeping aircraft separated in a safe distance.

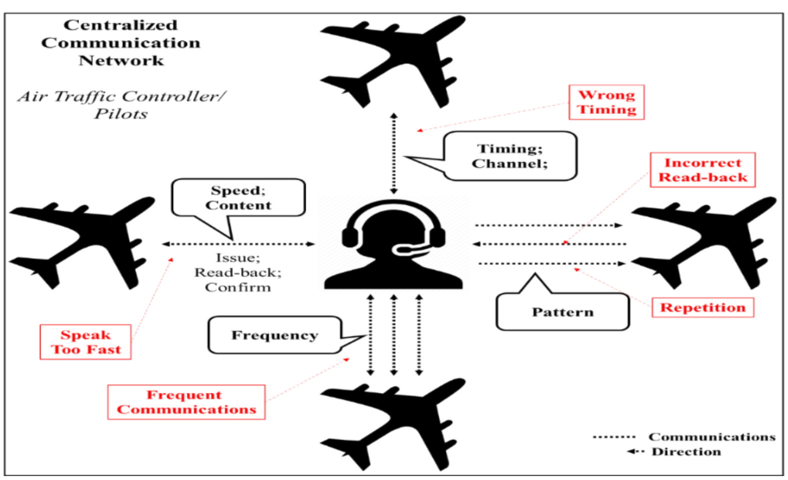

Figure 1. Communication Contexts and Features during Air Traffic Control Processes

It is thus necessary to develop resilience-based scientific tools for ensuring the CIS O&M safety and efficiency due to communication errors. Previous studies spent extensive efforts in the design of such tools for improving CIS O&M resilience, challenges still exist (Madni and Jackson 2009). Some studies focused on the design of system-level strategies (e.g., schedule updating, network optimization) for improving the CIS O&M resilience (Rodríguez-Sánchez and Vera Perea 2015; Zeng and Yang 2009; Zhang et al. 2017b). Studies in the human factors domain discovered anomalous human/team behaviors in CIS O&M through tedious lab experiments. However, these studies aim at understanding how human/team cognitions influence the safety and efficiency of CIS O&M but fell short of providing a quantitative assessment of the impacts of communication errors on CIS O&M safety and efficiency (Boring 2015; Cooke et al. 2004; Pan and Bolton 2015).

This dissertation aims to develop scientific tools for civil engineers to 1) identify risky communication contexts and features during CIS O&M workflows; 2) encode experts' opinions as constraints with field observations for reliable prediction of communication errors and CIS O&M risks, and 3) examine possible mitigation strategies in reducing delays caused by communication errors during CIS O&M. The author envisions the tools developed in this dissertation will form a foundation for advancing interpersonal communication prognosis in the domain of CIS O&M.

Motivating Cases

This section demonstrates two motivating cases of the proposed research. The first case study shows potential delays due to communication errors (e.g., late communication, wrong information) in a long chain of work package approval processes during NPP outages. The second case study demonstrates the safety risks (e.g., loss of separations, known as “LoS”) due to read-back errors during aircraft landing processes.

The two motivating cases demonstrate the need for more in-depth investigations of the impacts of interpersonal communications on the safety and efficiency of CIS O&M. The investigations should focus on the 1) identification of risky communication contexts and features during CIS O&M, 2) using the identified communication contexts and features for predicting communication errors and CIS O&M risks (e.g., delays, LoS), and 3) examining potential mitigation strategies for reducing impacts of communication errors on CIS O&M risks. Please see the detailed descriptions of the three case studies.

Case 1: Interpersonal communications in nuclear power plant outages

NPPs need routine shutdowns (known as “outages”) for maintenance and refueling activities that requires thousands of contract personnel to complete numerous maintenance and refueling tasks within 30 days (Sun et al. 2020; Zhang et al. 2018). Transitions between tasks (known as “handoff”) often involve highly uncertain activities, such as frequent transports of resources and labors between job sites, tedious interpersonal communications, and complex briefing and checking processes during NPP outages (Sun et al. 2020). The transitional nature of handoffs causes time and resource wastes due to the involvement of multiple groups of personnel and resource sharing problems. Despite well-developed training programs, contract personnel’s unaccustomedness of the working procedures and environments could still aggravate the risks of delays during handoffs.

Interpersonal communications during handoffs are time-consuming due to complicated organization structures and tedious operational processes (Petronas et al.

2016; Tang et al. 2016; Zhang et al. 2016b). For example, field discoveries require approvals of new work packages for resolving the discovered anomalies (e.g., broken pump). Such approval processes require confirmations from all stakeholders to confirm before executions of the new work packages (Germain et al. 2014). Communication protocol violations during such approval processes could trigger safety concerns during NPP outages (Akca 2020).

Tedious interpersonal communications in the chain of the approval process during NPP outages are necessary for ensuring safety while inducing time wastes and risks of communication errors (Akca 2020; Gorman et al. 2006). Hobbins et al. (Hobbins et al. 2016) claimed that 50% of human-related incidents during NPP outages are associated with communication errors. For example, a field worker requested a valve replacement after over-torquing a valve during a turbine maintenance workflow with a hectic schedule at the Palo Verde Nuclear Generating Station in 2018. The worker accidentally sent a request to the outage control center directly by bypassing the supervisor, who needs to verify the request. In the request, the worker used the wrong model number of the valve without meticulous verifications and only fond out until the requested valve was delivered. The worker ends up sending a second request by following the specified chain of communication, which caused an 8-hour-delay to the outage.

The example case above indicates that the wrong information (i.e., content) exchanged during communications and abnormal communication patterns resulted in delays during an NPP outage. Precise communications that follow the specified communication patterns are thus essential to avoid communication errors and delays. Furthermore, such delays on individual tasks often cause propagative delays to workflows with hectic schedules. Motivated by this case, this dissertation aims at revealing what communication contexts that influence the occurrences of communication errors and propagate to CIS O&M risks.

Case 2: Interpersonal communications in air traffic control

Air traffic control aims at keeping multiple aircraft separated in a safe distance. LoS occurs when the minimum distance between airborne aircraft are breached in either a vertical or horizontal plane within the controlled airspace (U.S. Department of Transportation 2013). The U.S. Federal Aviation Administration (FAA) has reported over one thousand LoS in 2018 (Federal Aviation Administration 2019). Most of LoS involved with communication issues between ATC and pilots and remains threatening to airspace safety (Gario et al. 2016). The Terminal Approach and Departure Control Facilities (TRACON) usually handle traffic in a 30 to 50 nautical mile radius from the airport for guiding aircraft arrivals and departures (Castle et al. 2010).

LoS occurs within TRACON controlled airspace occurs even more frequently due to the operational complexity within such airspace that requires tedious communications between ATC and pilots for coordinating air traffic flows (Castle et al. 2010). For example, operations within the TRACON airspace consist of tedious handling processes of aircraft arrival and departure. Despite the uses of Automatic Dependent Surveillance-Broadcast (ADS-B) in the NextGen (Castle et al. 2010), LoS still exists and jeopardizes the aviation safety (Bailey et al. 2005; Federal Aviation Administration 2015).

ATCs are responsible for safe and efficient coordination of air traffic, play vital roles in avoiding LoS (Skaltsas et al. 2013). Poor communications between ATCs and pilots could result in misinterpretations of the clearances on flying instructions. For example, two aircraft breached the horizontal separation minima near the Brisbane airport (Queensland, Australia) in 2016 due to an incorrect read-back of decent altitude from the pilot of Qantas Flight 652 (QF 652). The ATC issued a descending clearance to Qantas Flight 62 (QF 62) – "*Qantas flight sixty-two descending maintain twenty-five thousand*." However, the pilot of QF 652 mistook this clearance and gave an incorrect read-back – "*Descending maintain twenty thousand, Qantas flight six fifty-two*." The ATC did not recognize the incorrect read-back until the horizontal separation of two aircraft (QF 652 and QF 62) reached to 3.2 nautical miles (separation minima is five nautical miles).

Communication error between the ATC and pilots is one of the main contributors to most aviation accidents (Krivonos 2007; Shappell et al. 2007). Misunderstandings in communications can be hard to recognize and remain a critical threat to aviation safety (Elliott 2013; Immanuel and Candace 2013). Previous studies and historical records indicate that over 70% of all aviation accidents were involved with communication errors (Dao et al. 2011; Stelkens-Kobsch et al. 2015; Witowski 2018). Despite well-trained and experienced ATCs and pilots, miscommunications still occur and jeopardize the safety and efficiency of the aviation system (Molesworth and Estival 2015; Skaltsas et al. 2013).

The example case above indicates that incorrect content in the pilot's read-back lead to this LoS incident. Besides, the ignorance of the ATC on the pilot's incorrect read-back also contributes to the LoS. A follow-up investigation of this incident also suggests that the talking speed and radio congestions were contributing factors to this incident. Motivated by the above case, this dissertation will dedicate in revealing 1) what communication features that influence the communication error occurrences and 2) what communication errors are more likely to cause CIS O&M risks.

Problem Statement

The above motivating cases show that complex CIS O&M are extremely vulnerable due to numerous risky contextual factors and features of interpersonal communications during CIS O&M workflows. Challenges include: 1) lack of a synthesis of risky communication contexts and features during CIS O&M for predicting communication errors, 2) lack of methods to encode expert knowledge for reliable predictions of communication errors and CIS O&M risks based on the identified features and contextual factors extracted from limited communication data, and 3) lack of methods for using formalized representations to model communication behaviors in CIS O&M and examining different communication protocols in reducing risks of communication errors.

How to identify risky contextual factors and features of interpersonal communications for predicting communication errors is pivotal. Besides, assessing the CIS O&M risks of communication errors and examining potential mitigation strategies to ensure CIS O&M safety and efficiency is also important. This section synthesizes the efficiency and safety risks associated with interpersonal communications in practices of CIS O&M.

Efficiency issues in NPP outages due to interpersonal communications

Interpersonal communications during NPP outages follow an adequately designed communication protocol that defines the organization structures, timing, channel, and content of the communication. Improper communications during handoffs could accumulate non-value-added waiting times due to resource sharing issues and cause delays to the workflow (Kim et al. 2014). A “hot handoff” in practice means two sequential tasks overlap with each other that allows workers on the successor task can early start the preparation processes. Such “hot handoffs” are encouraged in the current

NPP practice to allow worker teams to prepare in advance and reduce delays. However, how to determine the best timing for allowing worker teams to start preparing for the successor tasks without causing unnecessary delays to remain as a challenge in the current practice. A better understanding of how delays arise that involve complex interactions between workers and multiple tasks is thus necessary for predicting delays due to different “early-call” strategies. Such prediction could help outage control centers prepare for delays and control field operations proactively for improved efficiency and safety.

Safety issues in air traffic control processes due to interpersonal communications

Reliable communications are also critical for ensuring the safety of air traffic operations. Tedious communications between ATCs and pilots during busy air traffic operations could incur risks unwanted event handling processes that trigger propagations of air traffic control inefficiencies and accidents (Molesworth and Estival 2015; Prinzo and Britton 1993). Communication errors between ATCs and pilots have contributed to a majority of LoS that trigger risks of fatal accidents (Elliott 2013; Immanuel and Candace 2013). A proactive air traffic control system is thus necessary. Establishing such a system requires a systematic characterization of communication errors to reveal how various communication arrangements and errors influence LoS during air traffic control operations. Such “know-how” can target the efforts of ATCs and pilots to the parts of communication processes and contents that influence LoS the most.

Summary of similarities of interpersonal communications in CIS O&M

Interpersonal communications during CIS O&M workflows and processes share some similarities. The nature of such similarities could introduce similar problems that trigger CIS O&M risks. Table 1 provides a summary of similarities of communication during NPP outages and air traffic operations. As shown in Table 1, communications during NPP outages and air traffic operations are similar in terms of network structure (e.g., centralized), communication channel (e.g., radio), communication direction (e.g., bi-direction), and content. The summary indicates that a comprehensive understanding of the communication processes in CIS O&M is important for ensuring safety and efficiency

Table 1. Similarities of Communications during NPP Outages and Air Traffic Operations

	NPP Outages	Air Traffic Operations
Structure	Centralized (supervisor); De-centralized	Centralized (ATC)
Channel	Face-to-face; Radio; Text Messages	Radio; DataLink (text)
Direction	Bi-directional; Multi-directional	Bi-directional
Content	Casual (task/site condition; field discoveries)	Standard Phraseology (call-sign; altitude)
Timing/ Frequency	After task completion; Emergent situation	Before all actions
Pattern	Report status; Assign tasks	Issue clearance; Read-back

Vision

The goal of this research is to establish a predictive control system that could identify vulnerable interpersonal communications during CIS O&M using communication features and contextual factors. Such a system aims to assess the impacts of communication errors on efficiency and safety and provide mitigation strategies in reducing the risks of communication errors on CIS O&M safety and efficiency.

The overall research question of this dissertation

How to capture communication errors and mitigate communication-related safety and efficiency risks during CIS O&M?

To answer this research question, the proposed study lists three steps in the overall research roadmap, 1) *Communication Data Collection and Error Detection* – designing a lab experiment for collecting communication data and identify communication errors; 2) *Communication Error Classification and Prediction* – establishing a constraint-based Bayesian Network (BN) model updating method that incorporates expert opinion as constraints for predicting communication errors and the associated risks, and 3) *Communication Risk Mitigation* – developing a computational agent-based simulation approach for examining mitigation strategies in reducing the delays due to communication errors. The author decomposes the overall research question into three sub research questions based on the "three-step" research roadmap (Figure 2).

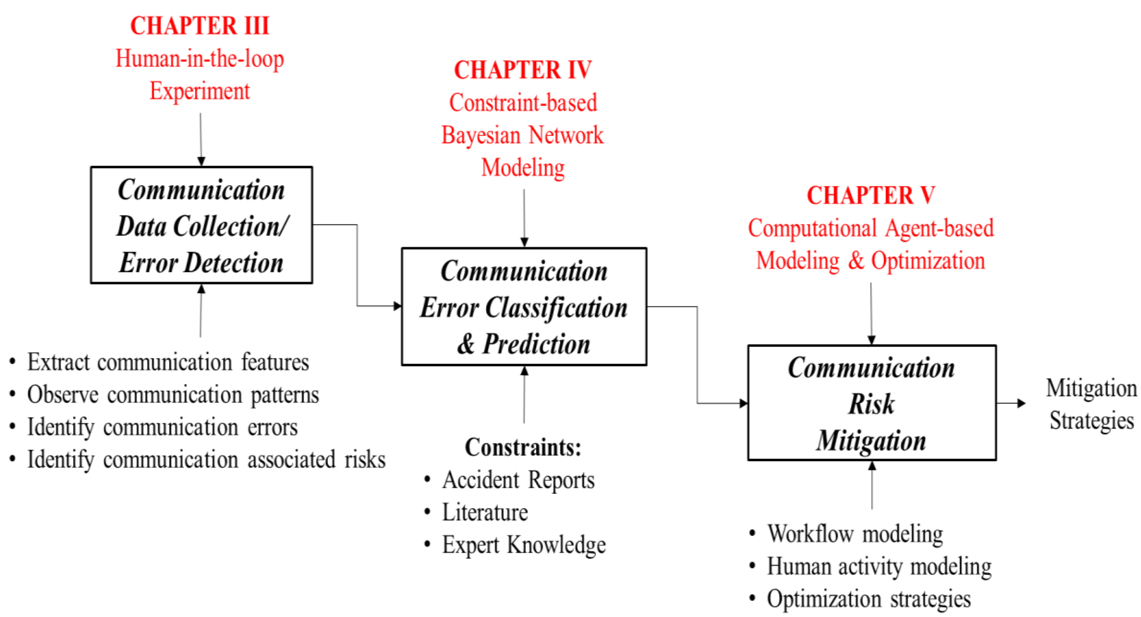

Figure 2. Overall Research Roadmap

Sub Research Question #1

What are the features and contextual factors that influence the occurrence and propagation of communication errors in CIS O&M?

Identifying features and contextual factors that influence the occurrence and propagation of communication errors is essential to ensure the efficiency and safety of civil infrastructure operations. To answer this sub-question, this dissertation aims at 1) reviewing previous accident reports for identifying abnormal communication processes and risky features and contexts in communications, and 2) designing lab experiments for collecting communication data using two cases.

The author first uses an NPP outage case to demonstrate how the proposed method could identify features and contexts that will influence the occurrence and propagation of communication errors in NPP outages through lab experiments. The designed lab experiment models the spatiotemporal relationship, and the human-resource relationship between tasks based on typical NPP outage maintenance workflow extracted from a previous outage schedule. The author recruits students from the Construction Engineering program at Arizona State University for participating in the experiments and collecting data. During experiments, the author observes the communication behaviors between participants and their performances. Such observations aim to identify risky contexts and features of the communication processes and understand the impact of communication errors on workflow delays.

The author then designs an experiment of using an air traffic control case for identifying features and contexts that will influence the occurrence and propagation of communication errors during air traffic control processes. The designed experiment is based on an aircraft approaching process controlled by the TRACON controller. The aircraft approach process includes adjusting flight directions, speed reductions, and descending altitudes through communications between the ATC and pilots. The author recruits a retired ATC and three student pilots from the Aviation Program for participating in the experiment and collecting data.

Sub Research Question #2

How to classify and predict communication errors by integrating field observations and experts' experience?

Classifying and predicting communication errors using contexts and features identified in the data collection section is critical for making timely corrective actions and ensuring the safety of civil infrastructure operations. However, a more accurate and reliable prediction demands an integrated use of field observations (observations in experiments) and experts' experience. To answer this sub-question, this dissertation aims at implementing a constraint-based Bayesian Network (BN) model updating method that uses experts' experiences as constraints for updating the conditional probabilities derived from field observations.

Specifically, the author first constructs two BN models based on the data collected in the two experiments. The author uses the constructed BN models for deriving 1) conditional probabilities of communication errors on contexts and features and 2) conditional probabilities of risks on communication errors. Then, the author uses the *Maximum-Entropy* method to encode experts' opinions into the BN for updating the posterior distributions derived from the data collected during lab experiments.

Sub Research Question #3

What communication protocols are optimal in mitigating delays caused by communication errors?

Mitigating risks of communication errors is vital for ensuring the efficiency of civil infrastructure operations. Optimizing communication protocols could potentially help streamline CIS O&M by reducing delays caused by communication errors. To answer this sub-question, this dissertation aims at developing a computational agent-based simulation approach for examining mitigation strategies in reducing delays due to communication errors. In the simulation model, the author introduced an “early-call” function, which allows a “hot handoff” during NPP outage for reducing delays.

The objective function of the optimization is to minimize the outage workflow duration. However, a fundamental understanding of 1) when to call, and 2) who to call is thus necessary for investigating optimal communication strategies in reducing delays. To validate this methodology, the author classified the tasks in a valve maintenance workflow based on 1) the number of links a task has, and 2) the position of the task in the workflow. Then the author examined the “early-call” function in reducing delays.

Research Objectives

Specifically, the objectives of the proposed research are:

(a) Review accident reports from multiple sources and literature to identify features and contextual factors that influence the occurrence and propagation of communication errors during CIS O&M and design lab experiments for capturing the identified anomalies (*Sub Research Question #1*; Chapter 3);

(b) Establish a constraint-based BN model updating method that can encode expert opinion as constraints on updating the conditional probabilities derived from the data collected during lab experiments for predicting communication errors (*Sub Research Question #2*; Chapter 4);

(c) Develop an agent-based simulation model for examining mitigation strategies in reducing impacts of communication errors on the delays of civil infrastructure operations (*Sub Research Question #3*; Chapter 5).

Dissertation Organization

The Introduction chapter of this dissertation provides a brief overview of the conducted research and identifies the potential of the research study using two strong motivation cases. This chapter also elaborates on the vision of the author based on the discussed research objectives. The overall dissertation provides specific research contributions that highlighted and discussed in the research vision section. The author concludes the dissertation by summarizing the entire research study, its contributions to the literature and briefly mentions the future research directions. The four chapters discussed between the Introduction and Conclusion chapter are being prepared to submit for publication as separate journal articles.

The following describes the outline of each chapter.

- Chapter 1 (INTRODUCTION) uses two strong motivation cases to demonstrate the practical problems of communication issues in CIS O&M. The author shows a "three-step" research roadmap to approach three listed sub research questions.
- Chapter 2 (A REVIEW OF INTERPERSONAL COMMUNICATIONS IN CIS O&M) synthesizes various communication-related studies for understanding the impacts of interpersonal communications on CIS O&M safety and efficiency. The significance of this review of the literature and CIS O&M accident/incident reports is to provide a basis for identifying risky communication contexts and features.
- Chapter 3 (COMMUNICATION DATA COLLECTION AND ERROR DETECTION) designs lab experiments for capturing abnormal interpersonal communications during CIS O&M. The author uses formal models for modeling detailed human-task-workspace interactions during typical workflows of CIS O&M.

The significance of the experiment design is to collect abundant human behavior data for comprehending human reliability on CIS O&M safety and efficiency.

- Chapter 4 (COMMUNICATION ERROR CLASSIFICATION AND PREDICTION THROUGH CONSTRAINT-BASED BAYESIAN NETWORK MODELING) introduces a constraint-based BN modeling method for predicting communication errors and CIS O&M risks. In particular, the BN method aims at 1) constructing a BN model based on the data collected from a series of lab experiments, 2) classifying and predicting communication errors and CIS O&M risks (LoS during air traffic control operations, delays during NPP outages) based on contexts and features of communication processes, and 3) using a *Maximum-Entropy* method to encode expert knowledge as constraints for improving the prediction accuracy of the BN model. The significance of this method is to incorporate expert knowledge for updating posterior distributions derived from the BN based on the data collected from lab experiments.
- Chapter 5 (COMMUNICATION RISK MITIGATION THROUGH COMPUTATIONAL AGENT-BASED MODELING AND OPTIMIZATION) demonstrates a developed computational simulation model of a CIS O&M workflow. The significance of the developed model is to incorporate human activities into conventional CIS O&M workflow modeling efforts. Besides, the developed model allows examinations of possible mitigation strategies in reducing CIS O&M workflow delays under numerous uncertainties.
- Chapter 6 (CONCLUSION AND FUTURE RESEARCH) concludes and summarizes the major contributions of this research. This chapter shows the future research directions for advancing the proposed research.

CHAPTER 2

A REVIEW OF INTERPERSONAL COMMUNICATIONS IN CIS O&M

CIS O&M requires effective team coordination and collaboration to ensure safety and efficiency. Such coordination and collaboration often involve tedious interpersonal communication processes for exchanging information of schedule updates or field discoveries. Communication errors arise and propagate during CIS O&M could result in delays and safety issues. For example, 80 percent of aviation accidents and incidents during air traffic operations were associated with communication errors (e.g., read-back error) between ATCs and pilots. Some of the accidents involve severe fatalities. Besides, late communications during NPP outages often lead to significant delays and financial losses. Moreover, inadequate information exchanged during interpersonal communications could cause severe damage to the civil infrastructure. For example, the Three Mile Island accident was due to miscommunications among field workers that cause the cooling system malfunction. Such loss of coolant accidents (LOCA) usually causes severe core damages and leads to radioactive contamination due to core meltdown. A better understanding of interpersonal communications is thus crucial for ensuring the efficiency and safety of civil infrastructure operations.

This section aims at synthesizing various research studies that examine the impacts of interpersonal communications on CIS O&M safety and efficiency. This synthesis provides a detailed review of the studied communication contexts and features (e.g., communication network, link). Such a synthesis forms a basis for the author 1) to identify risky communication contexts and features, and 2) to study how these risky communication contexts and features are associate with communication errors and CIS

O&M risks, and 3) to quantitatively assess the impacts of the interpersonal communications on the identified CIS O&M risks.

Contextual Factors and Features of Interpersonal Communications

CIS O&M requires coordinating groups of workers to complete thousands of tasks in complex workflows. Good teamwork is increasingly more necessary in accomplishing complex tasks that individuals cannot manage alone. Such teamwork demands all team members work together and make decisions. However, limited studies examined "good" teamwork in the contexts of CIS O&M. Communication, as one of the most important processes to increase team situation awareness, plays a significant role in affecting the information flow between individuals within and across teams. Previous studies about communication are mainly within the social science domain, and social scientists have extensively studied several parameters of communication. However, most of these studies fell short in providing a quantitative assessment of how combinations of communication parameters could result in communication errors.

The author has synthesized all communication-related studies along two dimensions: 1) communication network patterns; and 2) characterization of communication links. Table 2 presents a synthesis of parameters of communication along these two dimensions. For example, the structure of a communication network is formed by nodes and links. Most of these studies show that multiple communication features could have an impact on causing communication errors. However, how to quantitatively assess the impacts of communication errors on operational processes remain challenging. Besides, such a quantitative assessment is critical to guide developing better communication training for ensuring CIS safety and efficiency.

Table 2. Communications Parameters Studied in Previous Studies

Aspects of Communication	Properties	Example Values	References
Communication Network Patterns	Structure – network formed by nodes and links	Circle-pattern; Chain-pattern; Wheel-pattern	(Liao et al. 2014a; Park et al. 2012)
	Multi-level indicators of communication complexity	Complexity levels of communications (Abstraction Hierarchy Level and Engineering Decision Level)	(Cooke et al. 2017; Pan and Bolton 2015; Wang et al. 2016)
	Team-level indicators	Communication Measures (content; flow; timing)	(Cooke et al. 2005, 2013; Cooke and Gorman 2009)
Characterization of Links	Communication Channel	Face-to-face; Radio device; Mobile devices.	(Jara et al. 2014; Sites et al. 2016)
	Timing and Frequency of Communication	Every 15 min; "early-call"	(Kim et al. 2010; Liao et al. 2014a)
	Ownership and Accessibility of the Link	Point-to-point link; Multipoint link; Broadcast link	(Park et al. 2012)
	Standardized Language	Symbols and language for communication	(Guzman et al. 2002)

Many studies established methods for characterizing communication networks and identifying critical factors that influence communication errors and related team performance degradation. These studies considered communications as a network composed of nodes and links between nodes (Liao et al. 2014b; Wang et al. 2016). Nodes are people or teams linked by various communication channels or methods (Darwazeh et al. 2017; Liao et al. 2014a). Communication reliability analysis thus includes the characterization of the nodes, links, and the network structures that collectively achieve data and information sharing across people and teams for achieving real-time team situation awareness and effective teamwork (Dao et al. 2011).

At the node level, the human reliability studies mentioned in the previous section examined the cognition, decision, and execution reliability of human individuals (Wilke et al. 2014). At the link level, a series of "communication protocol" studies examined how various options of exchanging information between people and teams influence the success rates of transferring the information and data. Those factors include the technical methods or channels used for information exchange (Darwazeh et al. 2017), frequencies, and timing of communication along with the link (Smart and Shadbolt 2012), communication contents, and related coding or standardization efforts (Chierichetti et al. 2014; Tiferes et al. 2015), and confirmation and follow-up strategies for confirming the communication contents (Laakso et al. 2002).

At the network level, some studies investigated how network structures and dynamics-related factors influenced the real-time team situation awareness. Examples of communication network reliability studies examined ways of classifying topological structures of networks (Gillan et al. 1992; Wang et al. 2016), examining properties of data and information flows (Herrmann 2004), identifying the vulnerability of communication protocols and networks for ensuring the cyber-security of the communication networks (Jara et al. 2014) and assessing schedules and delays of communication networks (Mo 2007).

All these communication protocols and network studies have been advancing the understanding of communication reliability. Unfortunately, limited studies were on the impacts of communication errors on teamwork safety and efficiency during the collaborative operations in CIS O&M. Fundamental limitations lie in the lack of understanding about 1) what features and contexts that influence the occurrence and propagation of communication errors; 2) how to reliably predict communication errors using combinations of features and contexts; 3) what communication protocols are optimal in mitigating communication-related risks.

One challenge related to the communication issues is that technically it is infeasible to carry out a large number of teamwork simulations in various environmental conditions and changed facility conditions. Combinations of a large number of environmental factors need careful synthesis for designing human subject experiments that cover critical combinations that significantly influence team performance. Another possible approach could be using natural language processing, and machine learning algorithms that could automate the summarization of documented accidents in historical reports and experimental results documented by researchers to identify common factors and environmental conditions studied and critical knowledge gaps (Demner-Fushman et al. 2009; Zou et al. 2017). Further experiment design should build on such gap analysis using historical reports and academic literature.

A Synthesis of Impacts of Interpersonal Communications CIS O&M Safety and Efficiency

Reliable interpersonal communications require immediate attention and a clear understanding of the information exchanged for achieving more resilient CIS O&M (Boring 2009, 2010; Shi et al. 2019). Table 3 lists steps (e.g., cognition, decision-making, execution) in the communication processes with examples to demonstrate the complexity of such communications. Each step could induce risks of communication errors and affect CIS O&M safety and efficiency. For example, during air traffic control, the ATC is responsible for providing vocal directives such as flight directions, speed limit, and weather conditions to pilots during the take-off, en-route, and landing processes (Wang et al. 2016). Such air traffic operation requires the ATC and pilots to exchange real-time information using standard phraseologies through radio communications. A correct understanding of the exchanged information is critical to ensure safe air traffic control. Besides, both ATC and pilots also need to maintain situation awareness by continuously monitoring the radar or through visual checking (Dao et al. 2011; Demir et al. 2017). Decisions and executions such as aircraft turn-around reduce speed, and change flight directions are always required to make sure the minimum separation between aircraft and avoids LoS.

Table 3. Detailed Illustration of Communication Processes in CIS O&M

Human Cognitive Behaviors during Interpersonal Communications	Examples
Cognition	• Perception of the information received • Talking behaviors ❖ Talking speed ❖ Frequency ❖ Information volume
Decision-making	• Who to report for ❖ Field observations ❖ Abnormal indicators? • When to communicate?
Execution	• Initiate communications ❖ Phone call ❖ E-mail ❖ Message

Interpersonal communications during CIS O&M remain as a key approach for human individuals within and across the team to exchange field information and achieve better team situation awareness (Liao et al. 2014a). Poor communications always jeopardize the safety and efficiency of CIS O&M (Figure 3). Researchers can quantify team situation awareness as the deviations of the team’s knowledge and the actual conditions in the field

(Demir et al. 2017; Gorman et al. 2006). The communication reliability thus examines how the reliability of data or information exchanges during communications between human individuals or digital devices used by multiple people influence the team situation awareness (Lee et al. 2015; Park et al. 2012). Specifically, the communication reliability reveals how communication errors arise, propagate, and influence the safety and efficiency of the real-time operation and environmental condition information shared by all team members (Cooke et al. 2017; Sun et al. 2020).

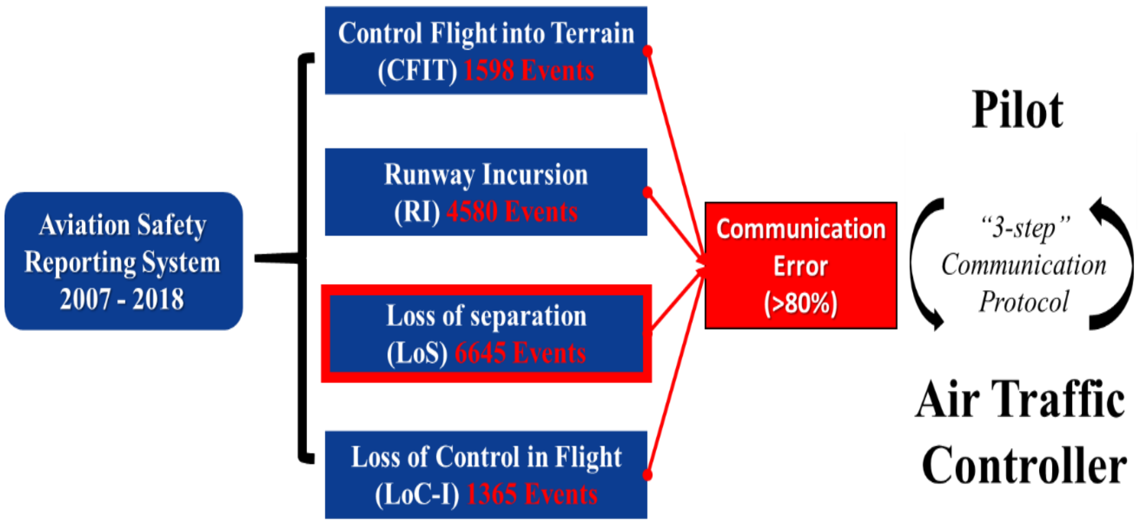

Figure 3. Impact of Communication Errors on Aviation Safety

Studying team communication reliability should examine how different communication protocols influence communication error occurrences and propagation. Communication protocols are rules that 1) define the structures of the communication network; and 2) specify the communication channel, frequency, timing, and standardized phraseologies used during communications (Sun et al. 2018b; Zhang et al. 2018). A typical communication protocol should answer three questions, 1) who to communicate within or across the team (e.g., team member, supervisor); 2) when to communicate (e.g., when the task completes; when the task is about to complete); 3) how to communicate (e.g., face-to-face; text message; email; phone call). All individuals are required to follow the specified communication protocols when exchanging field information.

Interestingly, even everyone strictly follows the protocol, communication errors still exist and jeopardize CIS O&M, which usually results in reworks, severe delays, and additional cost (Sambasivan and Soon 2007). A better understanding of the communication error propagation mechanisms during CIS O&M is thus necessary to ensure CIS O&M safety and efficiency. Such an understanding should address 1) how communication errors arise and propagate during CIS O&M; 2) how to assess and mitigate the impact of communication errors on CIS O&M safety and efficiency quantitatively; 3) how to validate the proposed mitigation strategies for reducing impacts of communication errors on CIS O&M.

CHAPTER 3

COMMUNICATION DATA COLLECTION AND ERROR DETECTION

Introduction

CIS O&M workflows usually involve coordinating a huge amount of tasks with extensive collaboration efforts among participants. Timely and effective interpersonal communications in CIS O&M are essential for ensuring safety and efficiency. Poor interpersonal communications between CIS O&M participants not only result in late deliveries of information during field operations but also propagate to severe CIS O&M risks and jeopardize CIS safety and efficiency. NPPs and airports are all critical CIS that could be vulnerable to delays or incidents. However, several challenges exist that prevent the safe and efficient CIS O&M, such as 1) lack of systematic summarization of risky linguistic and grammatical features for predicting communication deficiencies, and 2) lack of formalized representations of communication behaviors consist of linguistic and grammatical features for modeling communication behaviors within and across teams.

Achieving safe and efficient CIS O&M requires extensive data analytics to reveal the underlying problems. Such data analytics usually requires rich field data and historical records to serve as input for data analytics. Unfortunately, researchers from multiple domains start to collect human behavior data but only limited data are available for comprehending human behaviors on CIS O&M. Besides, data from NPP outages and air traffic control operations could be difficult to acquire due to 1) privacy issues, 2) cybersecurity concerns, and 3) union restrictions (a huge number of NPP workers and ATC participants are union workers). Moreover, comprehensive human-related dataset (e.g., communication behaviors) does not exist yet for researchers to study how interpersonal communications could jeopardize CIS O&M safety and efficiency. This section aims at design and carries out a series of lab experiments for capturing abnormal interpersonal communications during CIS O&M. The author uses a formal method for modeling detailed spatiotemporal human-task-workspace interactions during typical workflows of CIS O&M.

Handoff processes are transitions between tasks during CIS O&M. Such processes involve tool pick-up/drop-off activities, traveling between job sites, preparations for the next work orders, and tedious interpersonal communications for coordination and collaboration between multiple worker teams (Zhang et al. 2017a). Poor communications during handoffs could induce resources sharing problems that accumulate non-value-added waiting times and cause delays to the workflow (Kim et al. 2014). Figure 4 illustrates the waiting line at the shared tool pick-up/return and dosimetry checking area inside the radiation protection island (RPI) at an NPP. The outage manager should determine the best timing to call in worker teams to start handoffs. However, without real-time field information and properly designed communication protocols, even an experienced outage manager could hardly determine 1) which worker team should I call to start the handoff processes, and 2) when should I call the worker teams to start the handoff processes?.

Good communication protocols should always rely on the progress of CIS O&M workflow and field conditions to avoid non-value-added activities (e.g., non-essential travel, long waiting lines). A better understanding of delays arising and propagation mechanisms associate with dynamic human-physical interactions of CIS O&M are thus necessary for predicting delays under different communication protocols. Such prediction could support the outage manager to make a proper judgment on 1) when to call, and 2) who to call for reducing delays and achieving better NPP outage resilience.

Figure 4. Waiting Line in the Radiation Protection Island (RPI) during an NPP Outage

Besides, allocating workers and resources to monitoring a large number of tasks for ensuring safety and efficiency during NPP outages is challenging. Workers need to keep tracking the progress of all the tasks on the critical path to avoid delays (Yoo et al. 2016). Besides, workers also need to monitor the progress of the non-critical-path tasks to avoid critical-path change due to the accumulation of delays of non-critical-path tasks (Kim et al. 2014). However, such manual progress monitoring requires excessive human efforts, which are limited resources in NPP outages. Besides, the long communication chain caused by the complex organization of outage participants and tedious processes. Delays in such a communication process prevent the real-time updating of the overall outage schedule using the scheduling software directly to coordinate work because the tasks are completed long before the status updates as complete in the scheduling software.

Previous Research

Interpersonal communications in NPP outages

Operating and managing NPP outages is challenging due to the coordination and collaboration of a large number of outage personnel on thousands of maintenance and refueling activities within a short period and zero-tolerance for accidents (Hadavi 2008). Tedious refueling and maintenance tasks during NPP outages require workers to perform the scheduled tasks at the right time and place by strictly following outage procedures. However, workers can still forget certain steps specified in the procedure while performing the scheduled tasks and cause reworks (Pyy 2001).

Human and team cognition have played a critical role in affecting the efficiency and safety of CIS O&M (Promsorn et al. 2015). For example, previous studies have revealed that the forgetting, fatigue, and experience level of individuals can seriously affect workflow efficiency and safety during CIS O&M (Sun et al. 2018a). Besides, team behaviors (e.g., communication, situation awareness, culture) also contribute to many operational failures. Forgetting errors (known as "omission errors") is the most frequent human error in valve maintenance tasks and causes 14% of valve maintenance failures (Kim and Park 2012; Love and Li 2000; Neboyan and Lederman 1987; Pyy 2001). Besides, such errors always associate with additional costs due to reworks (Love and Li 2000).

Interpersonal communications in air traffic control operations

Air traffic control also involves complex operational processes that help to maintain minimum separation between aircraft while keeping orderly and expeditious air traffic flows (Sun et al. 2018c). Human factors during air traffic control have been proved to be one of the dominant factors that could jeopardize the airspace safety (Borghini et al. 2017; Chang and Wong 2012; Shappell et al. 2007). In particular, ATC-pilot communication studies have been studying risky communication features, such as message frequency and message complexity, as indicators of communication errors (Smith 2005). These risky communication features could raise concerns of communication errors that often arise in read-backs and confirmations during the information exchange processes between the ATC and pilots.

Communication monitoring and error detection alerts could be potentially useful to not only recognize erroneous communication behaviors but also minimize LoS during an air traffic control. Besides, communication classification is vital for formulating the basis for accurate detection of communication errors. Previous studies focused on identifying inconsistencies during ATC-pilot communications (Geacăr 2016; Immanuel and Candace 2013). Such error detection concentrates only on determining whether a mismatch occurred in the communications without quantifying the risks of such errors. Communication errors still exist and jeopardize the safety and efficiency of air traffic control operations.

Augmenting the existing ATC-pilot communication mechanisms is thus necessary through automatic recognition of communication errors and guidance for preventing propagated risks. Such augmentation requires 1) detailed aircraft approach process model with full consideration of ATC-pilot communications; 2) identifications of communications features that could potentially support the early detection of communication errors; 3) discovering trends of communication errors from historical data and propose a systematic classification method to classify communication errors.

Lab Experiment Design/Setup for Human Behavior Data Collection

The author carried out series of lab experiment for simulating 1) valve/turbine maintenance processes during NPP outages and 2) aircraft landing processes during TRACON operations and for collecting data of 1) communications between participants, 2) task information, 3) workflow duration, and 4) events of accidents/incidents.

Collecting human behavior data during valve/turbine maintenance processes

This section presents research experiments for modeling and capturing communication behaviors of outage participants (e.g., supervisor, workers) during valve/turbine maintenance workflows of NPP outages. The author conducted extensive post-outage report analysis and interviews with industry experts to identify sections of NPP outages as typical field workflows that have repetitive procedures close to critical paths of outage schedules. Such typical "repetitive near-critical-path field workflows" can frequently cause changes of critical paths, and uncertain handoffs within such field workflows can seriously influence the delays. The author found two typical workflows (valve maintenance and turbine maintenance) that always delay during NPP outages. These workflows associate with many handoffs ("transitions" between tasks) activities in the Radiation Protection Island (RPI) (in this case, the lab for simulating the RPI indoor space) that could induce risks of delays.

The lab experiment design (Figure 5) has two objectives: 1) modeling – to model the detailed interactions between individuals in a valve/turbine maintenance workflow during a typical NPP outage, 2) data collection – to capture abnormal human/team behaviors during such maintenance workflows, 3) to examine the performance of using the developed proactive communication system in reducing workflow delays, and 4) to serve as inputs for the computation simulation for examining the impact of abnormal human/team behaviors in complex scenarios and potential mitigation strategies in reducing delays.

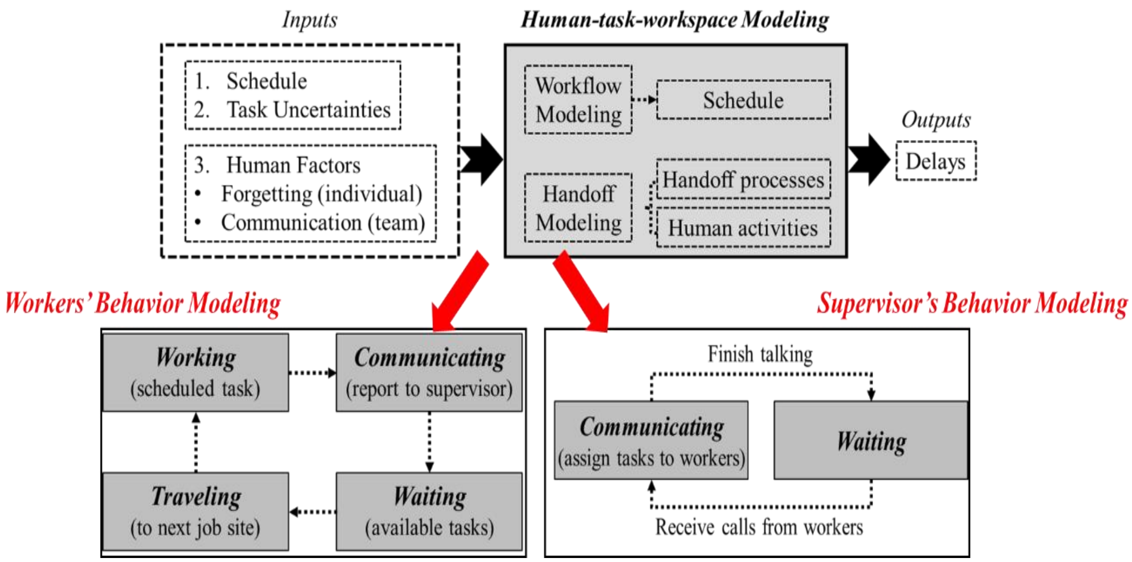

Figure 5. Experiment Design and Modeling of Workflows during NPP Outages

Workflow Modeling

Valve Maintenance Workflow – A Linear Schedule (Plan A)

The tasks simulated in the experiment are valve maintenance at Site A, Site B, and handoff at an indoor workspace. Maintenance of a valve at one job site requires five steps, 1) Remove the insulation from the valve; 2) De-term, the motor operator; 3) Perform valve maintenance; 4) Re-term the motor operator, and 5) Re-install the insulation. Figure 6 visualizes the entire as-designed workflow at Site A and Site B. Blocks with the same color are tasks using the same resource that is part of the same worker team (e.g., Insulator: black, Electrician: blue, Mechanic: orange). Tasks sharing the same worker team cannot be executed at the same time. Table 4 summarizes detailed task information and the associated uncertainties.

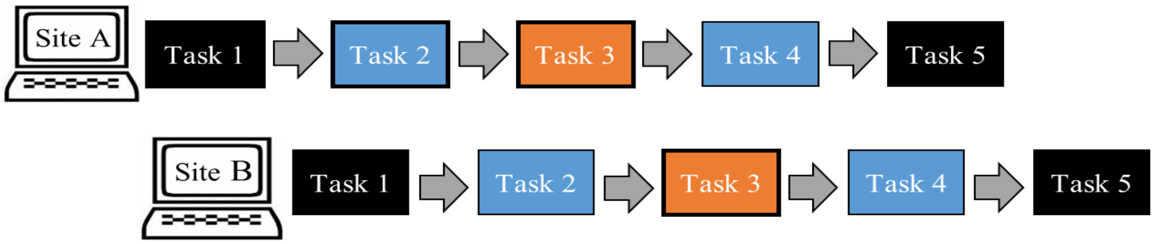

Figure 6. Valve Maintenance Workflow at Site A/B (Plan A)

Table 4. Task Information for the Valve Maintenance Workflow (Plan A)

Task #	Task Name	Location	Worker Team	Avg. Task Duration (min)	Scaled Task Duration (min)
Task 1	Remove the insulation from the valve	Site A/B	Insulators	30	3
Task 2	De-term, the motor operator		Electricians	45	4.5
Task 3	Perform valve maintenance		Mechanics	60	6
Task 4	Re-term the motor operator		Electricians	45	4.5
Task 5	Re-install the insulation		Insulators	30	3

Turbine Maintenance Workflow – A Non-Linear Schedule (Plan B)

The tasks simulated in the experiment are turbine maintenance at Site A, Site B, and handoff at an indoor workspace. Maintenance of a turbine at one job site requires four steps, 1) Tension Inner Casing, Closing Doors & Heat Shields; 2) Weld Hood Spray Union Lock Tabs; 3) Install Cone Extension, and 4) Remove Decking from Around Casing. Figure 7 visualizes the entire as-designed workflow at Site A and Site B. Blocks with the same color are tasks using the same worker team that is part of the same labor team (e.g., Mechanic: black, Welder: blue, Turbine Operator: orange). Tasks sharing the same worker team cannot be executed at the same time. Table 5 summarizes detailed task information and the associated uncertainties.

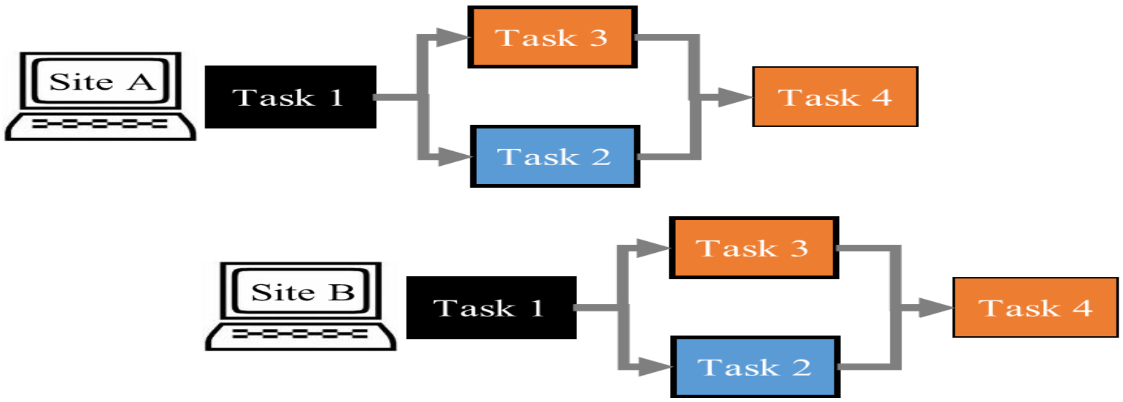

Figure 7. Turbine Maintenance Workflow at Site A/B (Plan B)

Table 5. Task Information for the Turbine Maintenance Workflow (Plan B)

Task #	Task name	Location	Worker Team	Planned Duration (min)	Scaled Task Duration (min)
Task 1	Tension Inner Casing, Closing Doors & Heat Shields	Site A/B	Mechanic	45	4.5
Task 2	Weld Hood Spray Union Lock Tabs		Welder	60	6
Task 3	Install Cone Extension		Turbine Operator	45	4.5
Task 4	Remove Decking from Around Casing		Turbine Operator	60	6

Handoff activities in the valve/turbine maintenance workflow

Handoffs are “transitions” between tasks during NPP outages. The indoor workspace (Figure 8) simulates the handoff processes inside the RPI. The designed indoor workspace aims to prepare worker teams for conducting scheduled tasks inside the containment. The handoff processes inside the indoor workspace include checking available work packages, dosimetry checking, getting technical debrief, picking up tools (e.g., earplugs). All worker teams need to go through a specific handoff process (different worker teams will have a different sequence of station visiting) in an indoor workspace to be ready to work inside the containment for valve maintenance.

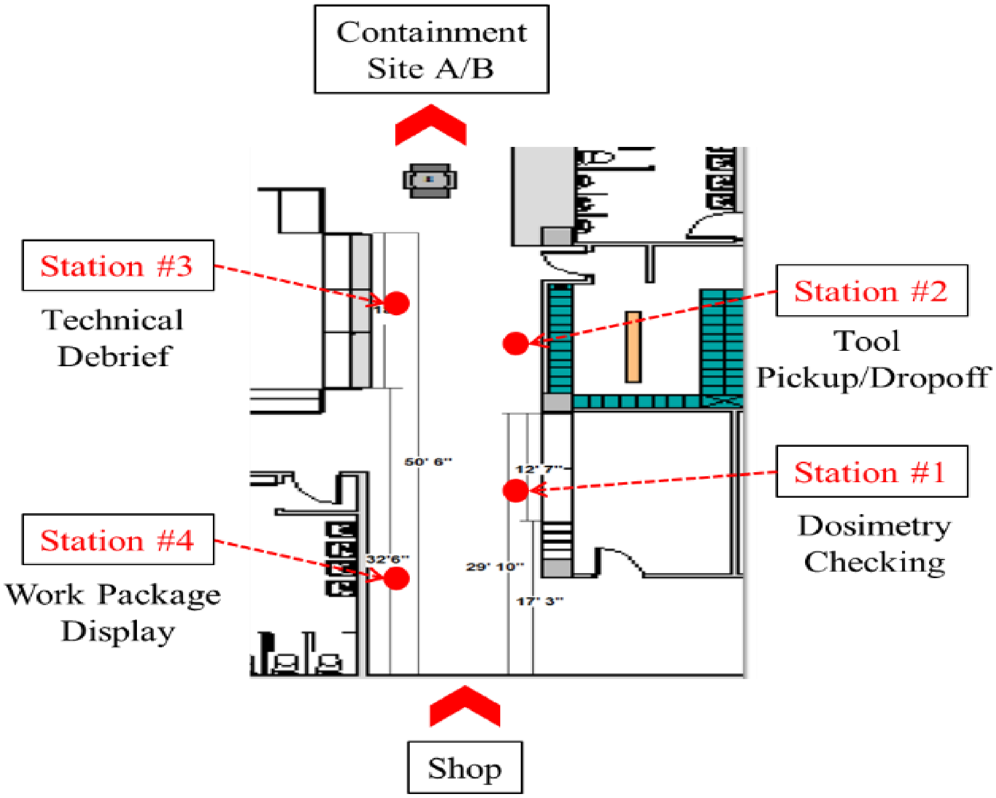

Figure 8. The Layout of the RPI at Palo Verde NPP Station

Within the indoor workspace, the author set up four stations (station 1, station 2, station 3, and station 4) in the lab at the Polytechnic campus of Arizona State University (ASU) for representing the workstations (Dosimetry Checking, Tool Pick-up/Drop-off, Technical Debrief, and Work Package Display) (Figure 9). All worker teams need to go through RPI for 1) checking available work packages, 2) getting the technical debrief, and 3) picking up tools (e.g., earplugs) before they start their work at Site A. Besides, once a worker team completes a task, they need to 1) get back to RPI for dosimetry checking; 2) dropping off tools, and 3) check other available work packages (see Table 11 and Table 12). The waiting time of RPI is thus essential to 1) estimate the delays to the valve maintenance activities at Site A caused by handoff in RPI and 2) estimate the delays of the entire outage workflow caused by delayed valve maintenance.

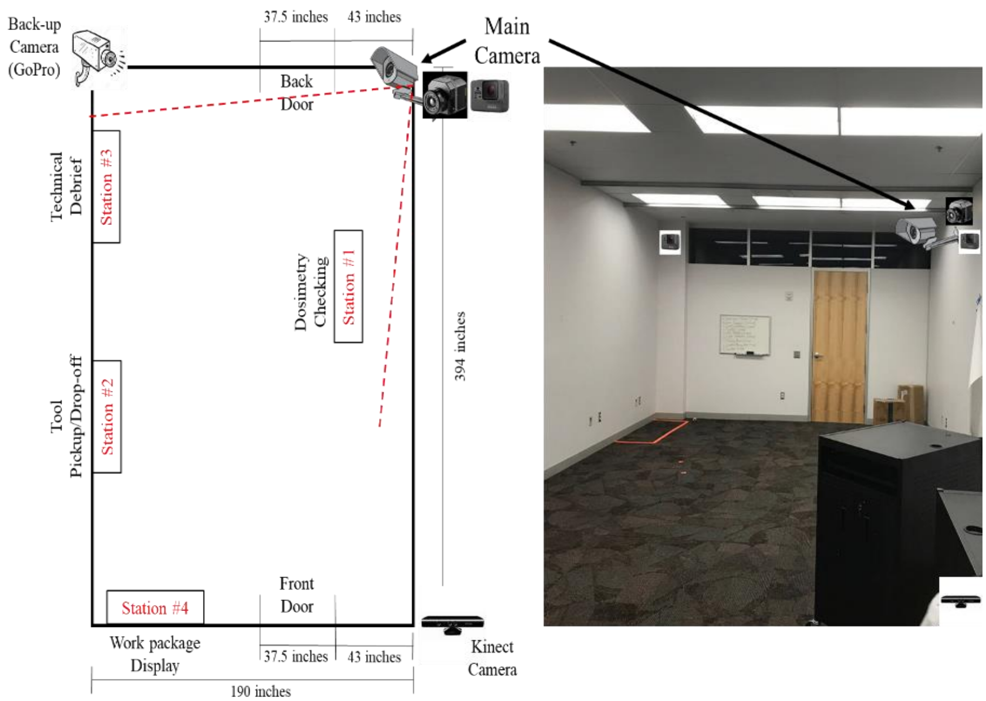

Figure 9. Lab Layout (Similar Layout with an RPI)

According to the real practice of handoff processes during NPP outages, worker teams may have different objectives when they enter into the indoor workspace. For example, the electricians are pick-up electrical tools and get debriefing about which motor need to be de-termed during valve maintenance. Thus, different worker teams could have different moving patterns in the indoor workspace during handoff. Besides, the time for each worker team spent at different stations might be different. The author asked different worker teams who were working on different work packages to follow different handoff processes in the lab. Another purpose is to test how the developed computer vision algorithms could estimate the overall waiting time even when different workers visit the indoor stations in different orders due to the nature of their tasks. Such waiting-time estimation for different types of workers mixed in a room is complex due to the interwoven workflows of task preparations of multiple workers in the RPI.

Table 6 and Table 7 illustrates all station visiting sequences of worker teams while entering or exiting the indoor workspace in Plan A and Plan B. Besides, once a worker team completes a task and travel back from the containment, they need to go through certain processes in the RPI for dosimetry checking, drop off tools, and check other available work packages. According to the practice of handoff processes between tasks, the author found out from the interview that workers might have different objectives before/after they start working on the scheduled tasks. Thus, different worker teams can have different moving patterns in the indoor workspace during handoff. Besides, the time for each worker team spent at different stations might be different. Table 8 and Table 9 indicates detailed handoff activity information for different worker teams in Plan A and Plan B.

Table 6. Handoff Processes in the Indoor Work Environment (Plan A)

Worker	Enter/Exist containment	Sequences of station visiting
Insulator	Enter	4 → 1 → 2 → 3
	Exit	1 → 2 → 4
Electrician	Enter	4 → 2 → 1 → 3
	Exit	1 → 4
Mechanic	Enter	4 → 2 → 3
	Exit	1 → 2

Table 7. Tasks during Handoff for Valve Maintenance (Plan A)

Task name	Station	Resource	Avg. task duration: Enter (min)	Avg. task duration: Exit (min)
Dosimetry checking	Station 1	Insulator/Electrician/Mechanic	5/5/NA	5/5/5
Pick-up/Drop-off tools	Station 2	Insulator/Electrician/Mechanic	5/10/15	3/NA/5
Technical debrief	Station 3	Insulator/Electrician/Mechanic	5/10/15	NA
Check work packages	Station 4	Insulator/Electrician/Mechanic	5/5/5	3/3/NA

Table 8. Handoff Processes in the Indoor Work Environment (Plan B)

Worker	Enter/Exist containment	Sequences of station visiting
Mechanic	Enter	4 → 1 → 2 → 3
	Exit	1 → 2 → 4
Welder	Enter	4 → 2 → 1 → 3
	Exit	1 → 4
Turbine Operator	Enter	4 → 2 → 3
	Exit	1 → 2

Table 9. Tasks during Handoff for Turbine Maintenance (Plan B)

Task name	Station	Resource	Avg. task duration: Enter (min)	Avg. task duration: Exit (min)
Dosimetry checking	Station 1	Mechanic/Welder/Turbine Operator	5/5/5	5/5/5
Pick-up/Drop-off tools	Station 2	Mechanic/Welder/Turbine Operator	5/10/15	3/5/5
Technical debrief	Station 3	Mechanic/Welder/Turbine Operator	5/10/15	3/5/5
Check work packages	Station 4	Mechanic/Welder/Turbine Operator	5/5/5	3/3/3

Human Activity Modeling

Worker teams and the supervisor need to communicate to exchange the as-is workflow information. The supervisor first needs to collect field information by communicating with all work teams and assign available tasks to corresponding teams based on the task availabilities. Worker teams can receive phone calls from the supervisor if tasks became available. The author introduced the “worker” and “supervisor” agents in human activity modeling to model the behaviors of the worker teams and the supervisor. In particular, the author modeled the communication behaviors for exchanging task information between two agents. Such information contains two parts: 1) the amount of all tasks in the workflow for a work team, technical details of the tasks, and general timing and resource needs; and 2) notifications on the completion of predecessors of the tasks assigned to a work team.

The communication behaviors in the model include 1) task completion notifications from workers to the supervisor, and 2) task available notifications from supervisor to workers. For the worker agent, each work team has four functions, namely, working, communicating, traveling, and waiting (see Figure 10). After that, the workers may enter into the working status to execute the scheduled task once they receive the notifications from the supervisor. When in working status, the timer of the current task starts counting down. After the timer of the current task becomes zero, the worker should switch to communicating status. The communicating status specifies the worker needs to report to the supervisor on the completeness of the current task so that the supervisor can mark complete on the task. When the worker enters the communicating status, the communication timer of this worker starts to countdown until the communication with the supervisor is over. After that, the status of the work team becomes waiting if no incoming calls from the supervisor. The worker will remain waiting status until he/she receives a phone call from the supervisor on the available work packages. The work can start to travel to different job sites or workstations at the same job site.

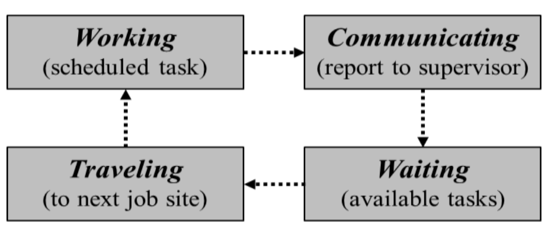

Figure 10. The Status Transition of the Worker Agent

In this NPP outage case, the supervisor agent should 1) answer the phone calls from the work team and record the information on the completed tasks and 2) inform the work team that specific tasks are ready to be worked on after the supervisor receives a phone call reporting a finished task (see Figure 11).

The supervisor will continue monitoring the progress of the workflow by acquiring field information from workers and check which task is available. After that, the supervisor will make a phone call to inform the worker agent who is responsible for the available task. If no tasks are available, then the supervisor will remain in the waiting status. At the beginning of the workflow, the supervisor is responsible for initiating the workflow by informing the workers that the first task is available, thereby enabling the workers to start working on the first task.

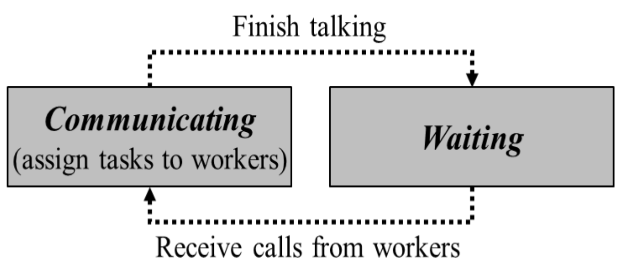

Figure 11. The Status Transition of the Supervisor Agent

Automated communication system module in valve/turbine maintenance workflow

The developed automatic communication system is based on group chat software – WeChat – installed on four iPods. The author then distributed the iPods to the experiment participants. The developed automated communication system includes information on all worker teams, facilitating the logical construction of the sub-tables, and facilitating the experimental organization to view the progress of the workflow in real-time. Figure 12 visualizes the group chatting interface that participants were using during the lab experiment. All NPP outage participants are required to send out voice messages within the group chat.

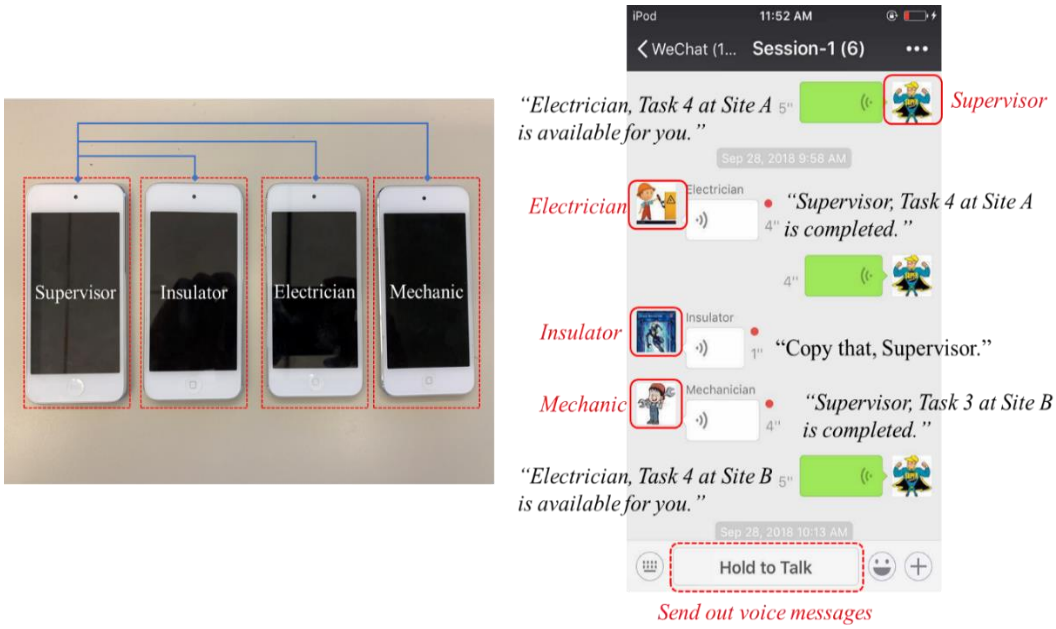

Figure 12. The User Interface of the Communication Software (WeChat)

The developed automated communication platform includes a master sheet for showing the overall workflow status and individual sheets for different worker teams to indicate specific tasks status (whether a task is available or not) (see Figure 13). As with the master list, the table is also divided into Site A and Site B based on the work location. Tasks are arranged in order of the work order of the staff in each workplace. For example, each Insulator needs to work on Task 1 and Task 5 in turn at each work location. Tasks 1, 2, 3, 4, and 5 all need to be performed in sequence, so each work task is followed by the Start Checking section, which provides information to the staff member whether the task can be achieved. The last column is to record the completion of the work, Mark (Finished = 1) means that if the work is completed, enter "1" in the highlighted area to mark the completion of the work. Through the built-in function, when the previous work is completed, the successor tasks will be automatically changed to the "Ready" state to notify the next worker to start work preparation.

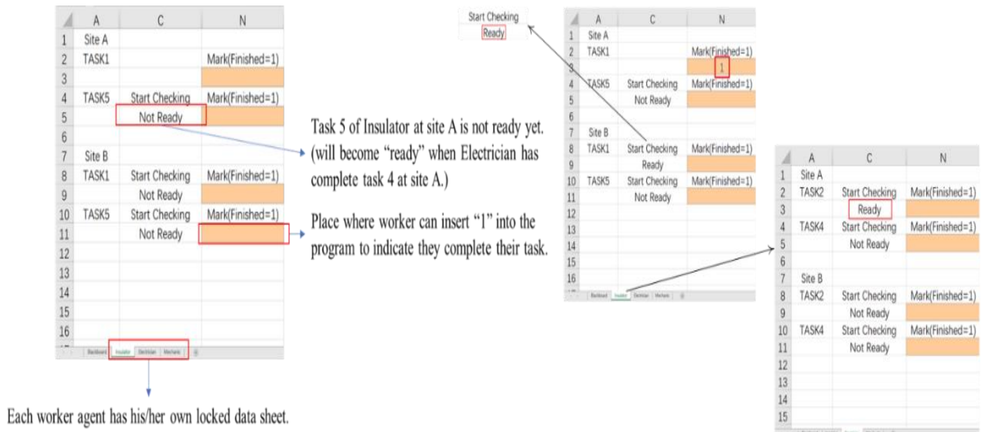

Figure 13. The Excel Table Developed for Automatic Communications

Collecting human behavior data during air traffic control of aircraft landing processes

The aircraft landing processes during the approach phase within the TRACON airspace involves tedious aircraft handling processes (e.g., adjust flight direction, reduce speed, and descend), which always require timely communications. However, limited data exist to fully understand the impacts of tedious communications and air traffic control safety and efficiency. The goal of this study is to understand how communication errors occur in the approach phase of aircraft and how these errors eventually lead to LoS through Human-in-the-loop (HITL) simulations. This study has three sub-objectives related to the overall goal. First, the author developed a process model for understanding how LoS arise during the aircraft approach phase by analyzing aviation accident reports. Second, the author conducted HITL simulations in the Phoenix (PHX) radar simulators (TRACON) for collecting communication data between ATCs and pilots and conduct detailed communication analysis. Third, the author established a Bayesian Network (BN) model based on the process model and features of communications derived from HITL to quantify the correlations between communication features, communication errors, and LoS. The overall framework of the proposed approach show in Figure 14.

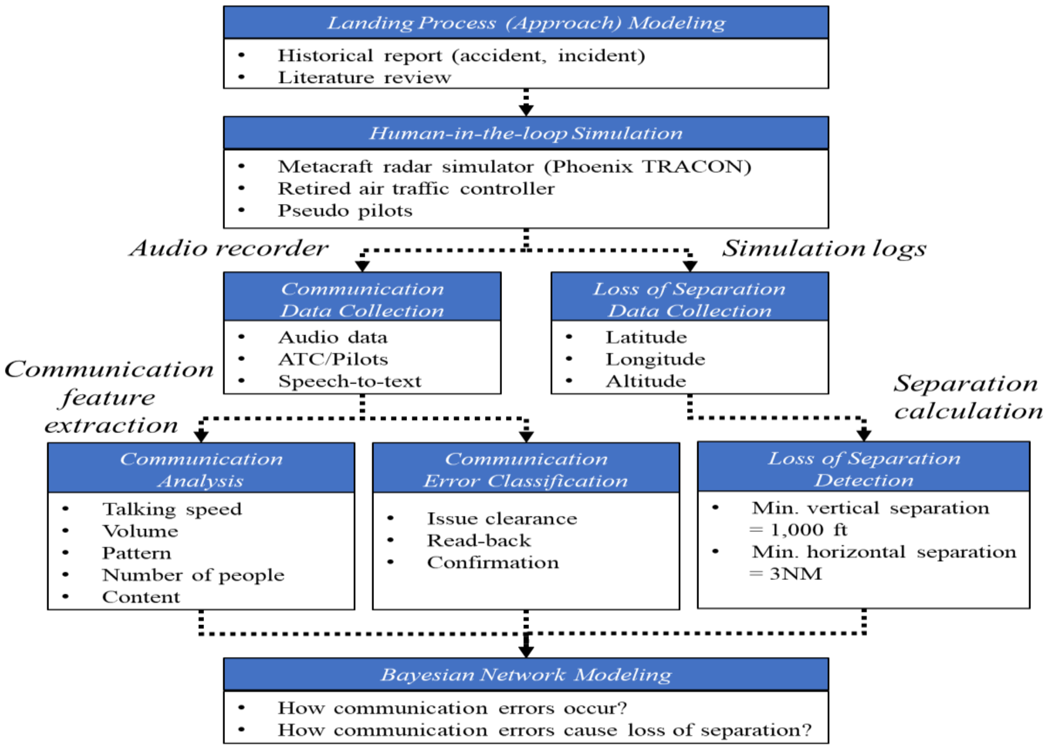

Figure 14. An Automatic Communication Error Detection Framework

Aircraft Landing Process Modeling

The author used a radar simulator (shown in Figure 15) to simulate air traffic control processes at the Phoenix (PHX) TRACON. The ATC at the PHX often handles arrival flows coming from the west (e.g., arrivals from San Francisco) or north. The author expanded the sector to include a second flow for aircraft coming from Tucson, El Paso, and México. The aircraft will follow the STAR flight procedure instrument flight rules (IFR) flight plan for approaching the destination airport. The author recruited a retired ATC with extensive TRACON experiences as the test subject to participate in the simulations for ensuring the reliability of the results. During the simulation, one ATC (station 1) must collaborate with three pseudo pilots (stations 5, 6, and 7) and provide instructions for 15 aircraft in the approach phase (each pseudo pilot will be flying four to six aircraft).

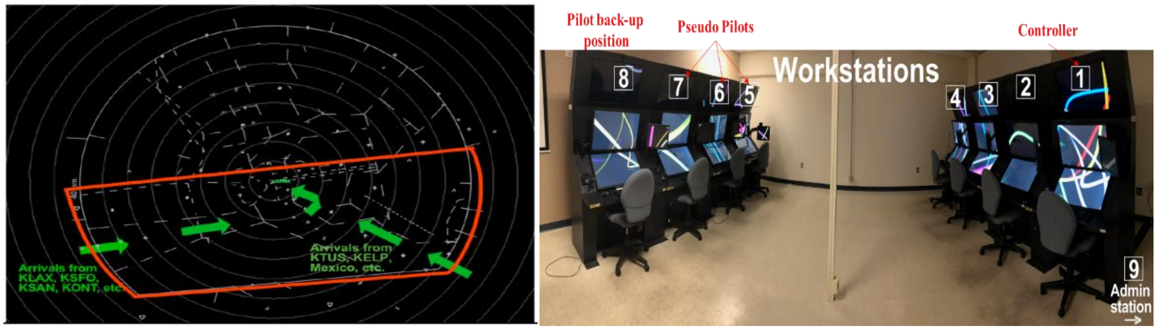

Figure 15. Experiment Environment at a Radar Simulator

According to the literature review, a typical landing process of an aircraft involves several phases (e.g., approach phase, landing on a runway, taxi). The HITL simulation focused on the approach phase, which is controlled by the TRACON (shown in Figure 16). TRACON controllers are responsible for guiding pilots to adjust flight direction, smoothly descend to specified altitudes, and reduce speed until the aircraft is handed over to the control tower for landing.

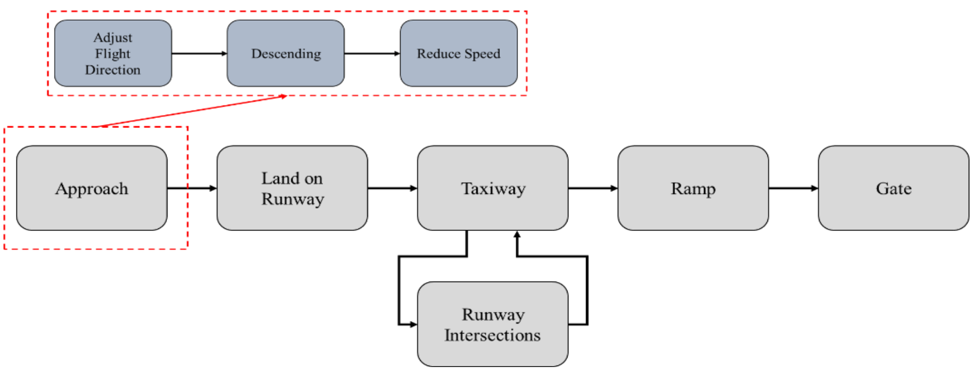

Figure 16. Landing Process used in the HITL Experiments

Human Activity Modeling (interpersonal communications between ATC and pilots)

First, the author collected accident reports related to communication errors in ATC-pilot communications and retrieve documented communication transcripts (or audio data) when accidents occurred. The author identified communication processes and specific error categories involved in the studied accidents and incidents. Then a process model has been created based on the standard terminal arrival route (STAR) flight procedure to represent how communication errors occurred and contributed inevitable accidents/incidents at different steps of the approach process per the reviewed accident reports.

Next, the author conducted HITL simulations to simulate the landing processes in TRACON airspaces, which involve a great number of communications between ATC and pilots. In this step, the author collected audio data and event log data during the simulation for detailed communication analysis to understand how communications affect the LoS (shown in Figure 17). The author used *IBM Watson Speech to Text* (IBM 2019) to automatically transcribe the collected audio files into text documents for both ATC and pilots. Such a tool takes recorded audio files as input and provides an output, which contains information of the speaker ("Speaker #" in the transcripts) and the content of a sentence. The author manually checked transcripts of all audio files for ensuring the accuracy of the transcription process. Then, the author used Natural Language Processing tools (e.g., *LinguaKit* and *Cortical.io*) (Numenta's HTM technology 2011; ProLNat@GE Group et al. 2018) to help extract communication features (e.g., number of words per message) automatically. The author also classified communication errors using data collected from HITL. Besides, the author recorded the simulation log data for recording the coordinates (latitude, longitude, and altitude) of each aircraft for calculating LoS according to FAA standards. The author then constructed a BN model based on the extracted communication parameters, classified communication errors, and LoS. The developed BN aims at deriving the conditional probabilities of communication errors based on multiple features and LoS caused by communication errors.

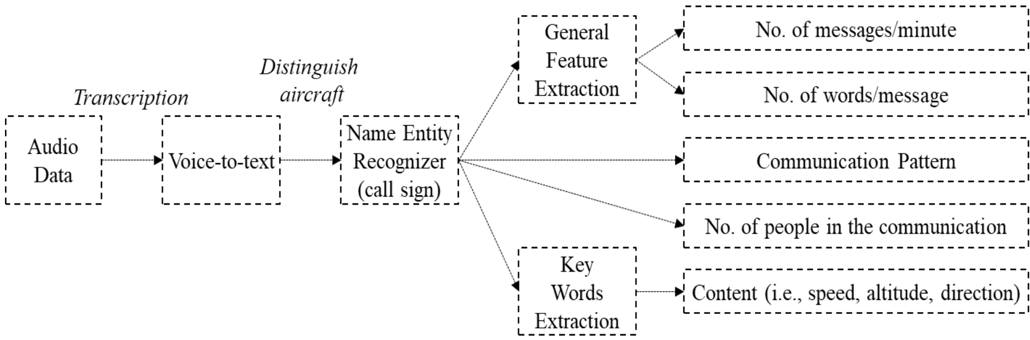

Figure 17. The Audio Data Processing Pipeline

Data Collection Results and Discussion

Collecting human behavior data during valve/turbine maintenance processes

In this section, the author presents results include 1) number of experiments conducted; 2) delays captured during experiments, and 3) comparative analysis between human and automatic communication system

Experiments carried out by the author and the recruited participants

The author used the valve/turbine maintenance workflow to conduct lab experiments between workflow with and without a supervisor. The author ran the experiment for 20 sessions in total (see Table). During the experiment, the author collected data from two aspects, 1) task relation data (individual task duration, overall workflow duration), and 2) human/team behavior data (e.g., human errors).

The author hired participants from the Fulton School of Engineering at Arizona State University to join the experiments. Before each session of the experiment, the author went through a 30-minutes training to all the participants involved in this session to get them to be familiar with the workflow and requirement. After each session, the author asked each participant to fill out the NASA TLX questionnaire for the later analysis of the workload. Figure 18 visualizes the scenarios during one session of the experiment with the supervisor involved. The captured images indicate that workers were having tedious voice communications with the supervisor and cause waiting lines and propagative delays. Table 10 summarized all lab experiments carried out.

Table 10. Number of Lab Experiments Carried Out

Schedule Types	Communication Methods	
	Supervisor	Automatic System
Valve Maintenance Workflow – Plan A	8 sessions	10 sessions
Turbine Maintenance Workflow – Plan B	1 session	1 session

Delays captured during valve/turbine workflows

The author carried out a series of lab experiments with participants recruited from the construction engineering program at Arizona State University. All participants have profound knowledge about the construction schedule and were provided with training sessions to get familiar with the experiments. The experiment was set up based on the established spatial and temporal relationship between tasks in the outage workflow (Figure 6 and Figure 7) and the human behavior models (Figure 10 and Figure 11). The supervisor will coordinate with three workers (insulator, electrician, and mechanic) to complete five tasks at two job sites (Table 4 and Table 5). Besides, all workers have to go through RPI for completing the handoff activities (Figure 9, Table 6, Table 7, Table 8, and Table 9). Each task will have an as-planned task duration that requires the participant to follow (participants will use the timer provided to count the time for their tasks).

However, different behaviors of participants will create variations to the as-planned task duration and cause delays. Besides, such delays could be critical if the successor tasks are on the critical path of the schedule. According to the as-planned schedule, the author derived the critical path of this workflow to better interpret the delays captured during the experiments. According to the experiment results, the author found that participants may not be able to complete the task by following the as-planned task duration, and such variation was the primary cause of delays in the entire workflow. The author then recorded all delays found during the experiments compare to the as-planned task duration and incorporated these delays into the simulation model to simulate the impact of task duration variations.

The author tried to understand the potential impact of the delays caused by individual tasks during the workflows. The last columns of Table 11 and Table 12 indicate the average delays captured during the lab experiments and the delays during the simulation (duration in the lab experiments are scaled). The average total duration of is 11.57 hours of Plan A. Compare to the scheduled duration, the delay is 0.29 hours (2.5%). The average total duration of is 10.63 hours of Plan B. Compare to the scheduled duration, the delay is 0.10 hours (1%).

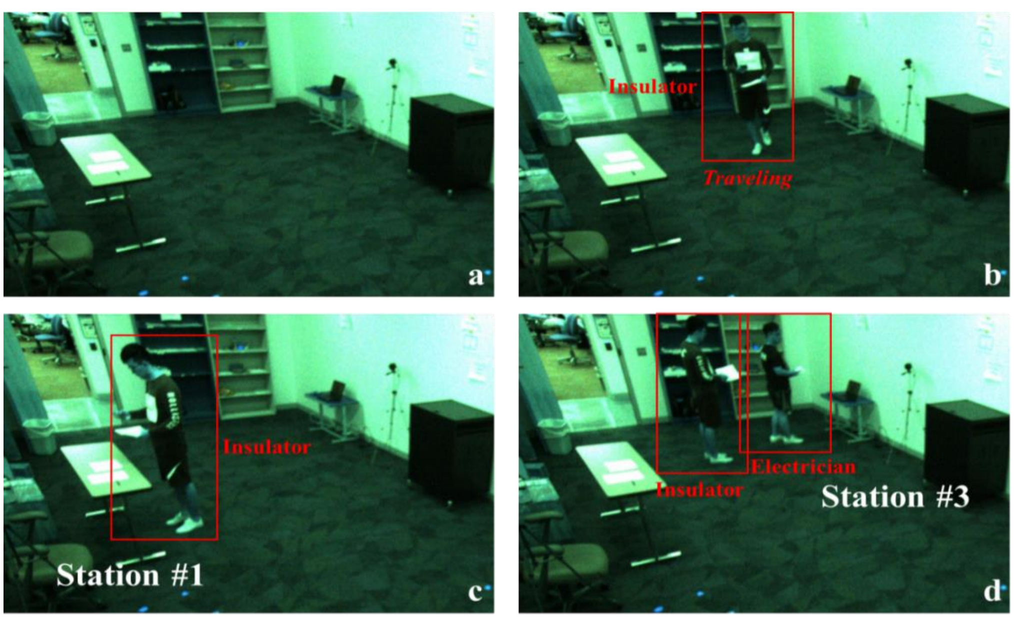

Figure 18. Images Captured during Lab Experiments

Table 11. Average Delays Captured during Lab Experiments (Plan A)

	Worker Team	As-planed Duration (min)	**Avg. Delay (min)**	**Delays in Simulation (min)**
Task 1 (Site A)	Insulator	3	0:25	4:10
Task 2 (Site A)	Electrician	4.5	0:20	3:20
Task 3 (Site A)	Mechanic	6	0	0
Task 4 (Site A)	Electrician	4.5	0	0
Task 5 (Site A)	Insulator	6	0	0
Task 1 (Site B)	Insulator	3	0:37	6:10
Task 2 (Site B)	Electrician	4.5	0:21	3:30
Task 3 (Site B)	Mechanic	6	0	0
Task 4 (Site B)	Electrician	4.5	0	0
Task 5 (Site B)	Insulator	6	0:20	3:20
Total Duration			**11.86 (hour)**	
Delay			**0.29 (hour) 2.5%**	

Table 12. Average Delays Captured during Lab Experiments (Plan B)

	Worker Team	As-planed Duration (min)	Avg. Delay (min)	Delays in Simulation (min)
Task 1 (Site A)	Mechanic	4.5	0	0
Task 2 (Site A)	Welder	6	0	0
Task 3 (Site A)	Turbine Operator	4.5	0	0
Task 4 (Site A)	Turbine Operator	6	0	0
Task 1 (Site B)	Mechanic	4.5	0:40	6:40
Task 2 (Site B)	Welder	6	0:12	2:00
Task 3 (Site B)	Turbine Operator	4.5	0	0
Task 4 (Site B)	Turbine Operator	6	0	0
Total Duration			**10.63 (hour)**	
Delay			**0.10 (hour) 1%**	

Comparative analysis between human and automatic communication system

Results indicate the average workflow duration of supervisor condition and automation system are 79.97 minutes and 68.39 minutes (Plan A). Hence, the use of an automatic communication system can significantly reduce workflow duration. Tedious communication between supervisor and worker teams takes a lot of effort and will increase the risks of communication errors. Three types of communication errors have been observed during the data collection. Type 1 (late communication) communication errors resulted in the late information exchanged between the supervisor and workers that directly induce delays. Type 2 (wrong information) and Type 3 (missing information) communication errors may require examinations of incorrect or incomplete information and cause additional communications that accumulate delays. Delays could happen due to these communication errors. Thus, an automatic communication system will help with reducing the risks of delays.

By investigating the detailed information of the workflow, average, and variances of individual task duration are critical to understanding which task and which worker is more comfortable while using the automatic communication system and can perform better. Results (see Figure 19) indicate that whether the use of an automatic communication system, the impact on individual tasks is minimum. There is no significant difference in the average task duration when compare the workflow with and without a supervisor. The results also indicate that the time wasted in the communication process is significant and becomes one of the major causes of causing delays.

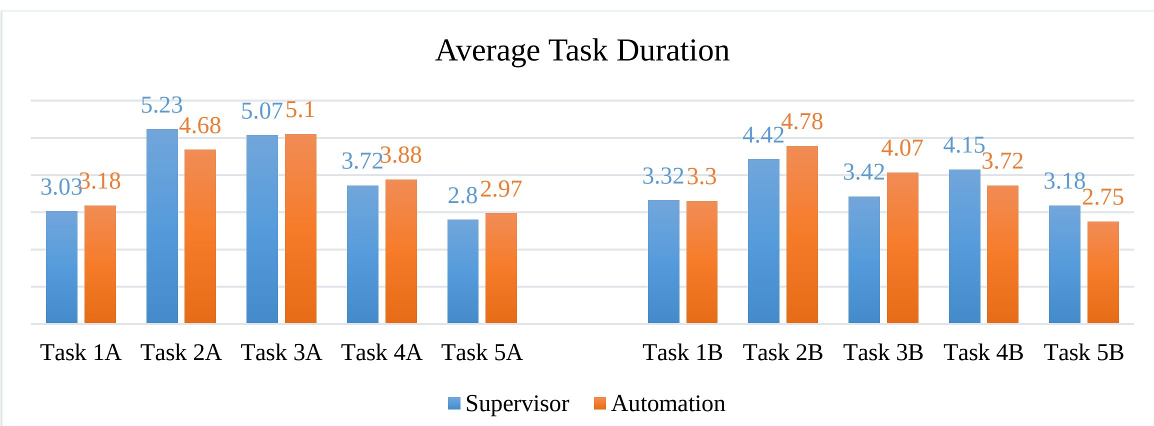

Figure 19. Comparison of Average Task Durations between Supervisor Condition and Automation System (Plan A)

Figure 20 indicates that the variances of tasks are quite different while implementing the automatic communication system. The variance of Task 2A, task 4A, task4B, and task 5B show that the variance of using an automated communication system is much higher than using a supervisor. The variance of Task 1B, task 2B, and 3B show that the variation of using a supervisor is much higher than using an automatic communication system. Such result findings indicate that the adaptabilities of individuals on an automated system are different. The workload of a worker could arise due to the use of an automated system at independence that has aroused without help from a supervisor in a workflow. Worker teams that are working on tasks (i.e., Task 2A, Task 4A) that have more correlated sequential tasks tend to rely more on the supervision of a supervisor, and their performances are more stable. Automated technologies could induce risks by creating a distraction to worker teams, who have to pay more attention to the use of such technologies. However, worker teams who work on tasks at the final stage of a workflow might feel comfortable with such technologies as few tasks were left in the workflow.

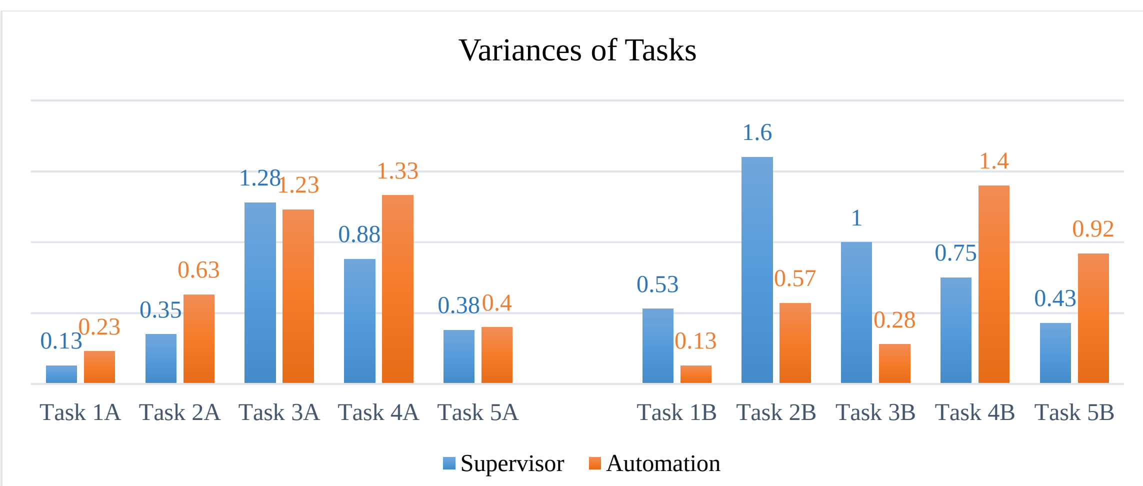

Figure 20. Comparison of Variances of Task between Supervisor Condition and Automation System (Plan A)

To better understand the adaptability of using such an automation system, the author distributed the NASA TLX workload questionnaire to all participants to understand participants' cognitive demands during their tasks better. Additionally, the author was interested in whether the perceived workload between the two groups differed. The author conducted a two-sample t-test to compare the workload measures between the two groups. The two-sample t-test (95% CI) is one of the most commonly used tests. The test is applied to compare whether the average difference between the two groups is significant or if it is due instead to random chance. The test helps to answer questions like whether the average success rate is higher after implementing a new tool than before.

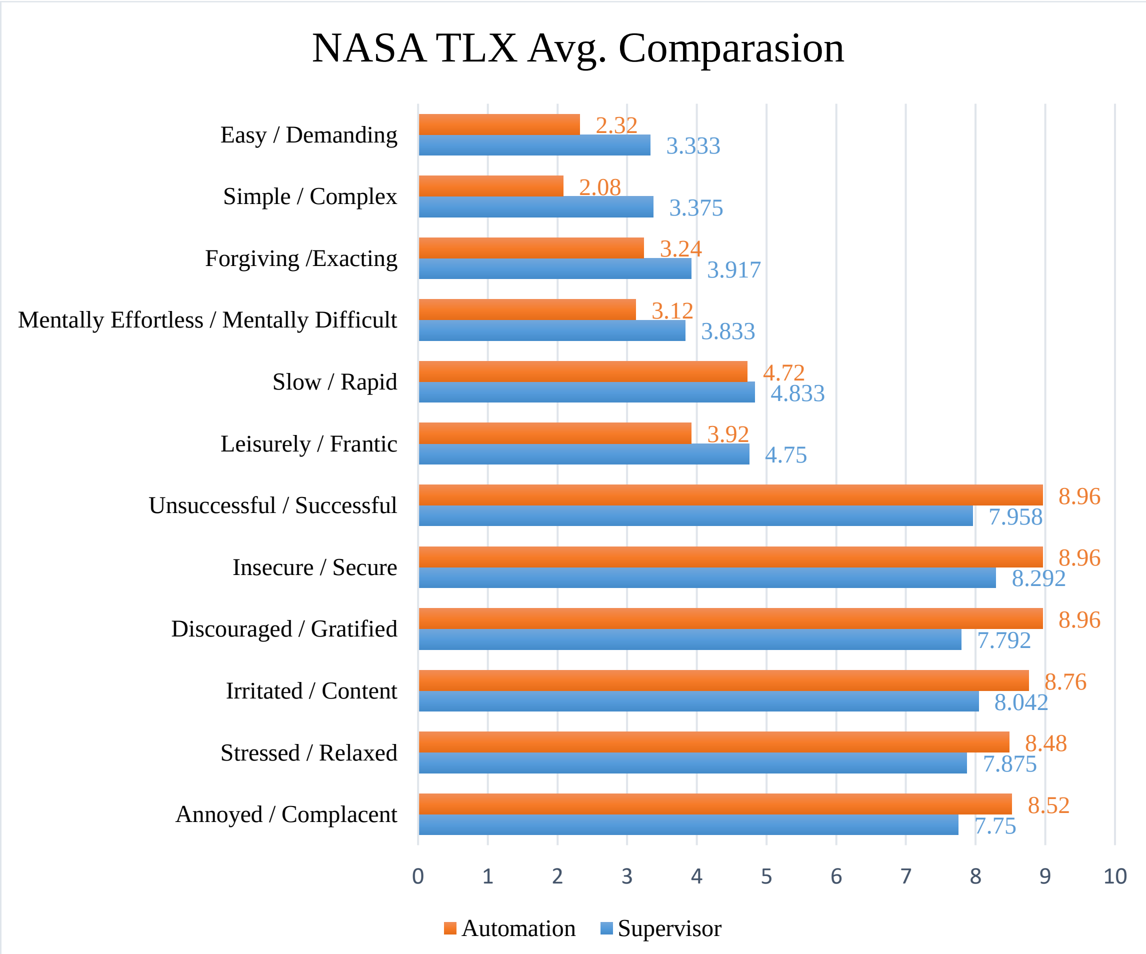

Figure 21. NASA TLX Mean Comparison

In the t-test, the P-value, or calculated probability, is the probability of finding the observed, or more extreme results when the null hypothesis (H_0) of a study question is true. The results show that there are statistical differences (p-value smaller than 0.05) between the supervisor and automation group condition in the rating of easy/demanding, simple/complex, and discouraged/gratified. Results (see Figure 21) show that participants using the automatic communication system found the experimental tasks more comfortable and more straightforward than participants who worked with a supervisor. These results indicate that automating the communication process would lower the cognitive demands of NPP outage workers.

Collecting human behavior data during air traffic control of aircraft landing processes

In this section, the author presents results include 1) communication feature analysis, 2) communication error classification, and 3) detection of LoS.

Detailed communication feature analysis

The author conducted the communication analysis at two levels: communication process structures and features of communication content. The communication process structures contain two types of information, the number of people on the radio and the communication patterns between people within the communication network. 95.8% of communications in the simulation occurred only between ATC and one pilot for exchanging information. Only 4.2% of communications contain interruptions from another pilot when the ATC is talking with a pilot. For example, the communication between ATC and FDX 971 was interrupted by SWA3277 at 14:09.5 when the ATC is assigning heading direction to FDX 971. The interruption resulted in additional communications between ATC and FDX 971 to clarify the required heading direction.

Table 13. Communication Patterns Observed from the HITL Experiments

Patterns	Explanations	Examples
A-P-A (85.42 %)	ATC issues correct clearances; pilot provides correct read-back; ATC confirms the read-back.	**ATC**: "*Alaska four sixty-seven descending maintain six thousand*." **ASA 467**: "*Dropdown to six thousand Alaska four sixty-seven*."
	The pilot requests ATC to repeat the clearance.	**ATC**: "*Envoy twenty-three fifty flies in zero niner zero descending maintain four thousand, contact approach one two zero point niner*." **ENY 2350**: "C*ould you repeat that, please*?" **ATC**: "*Sure. Envoy twenty-three fifty flight in zero niner zero maintain four thousand, contact approach one two zero point niner*."
A-P-A-P (11.46%)	ATC issues correct clearances; Pilot provides incorrect read-back; ATC makes corrections.	**ATC**: "*Southwest seven forty-three fly in zero seven zero speed one seven zero*." **SWA 743**: "*Roger, heading zero seven zero speed two one zero Southwest seven forty-three*." **ATC**: "*Southwest seven forty-three speed one seven zero*." **SWA 743**: "*Sorry, one seven zero Southwest seven forty-three*."
A-A-P (2.08 %)	ATC issues incorrect clearances with self-correction.	**ATC**: "*Speed bird two eighty-one heavy flight in zero seven zero maintain six thousand*." **ATC**: "*Speed bird two eighty-one heavy descending maintain five thousand*." **BAW 281**: "*Roger, descending maintain five thousand speed bird two eighty-one*."
A-P-P-A-P (1.04 %)	ATC issues long clearance; The pilot provides incomplete read-back and asks for a repeat of the clearance.	**ATC**: "*FedEx nine seventy-one heavy your assigned altitude is one zero thousand*." **FDX 971**: "*Our altitude is….but…*" **FDX 971**: "*Can you repeat that…FedEx nine seven one?*" **ATC**: "*Southwest, correction, FedEx nine seventy-one make your altitude to eight thousand*." **FDX 971**: "*Making altitude eight thousand FedEx nine seventy-one*."

For the communication patterns, ATC and pilots are required to follow standard procedures to exchange information during air traffic operations. ATC (A) needs to issue

(I) clear clearances to pilots (P) with specific instructions for guiding pilots to avoid LoS. Pilots (P) should provide prompt responses to the ATC’s clearance with a full read-back (R) on the clearance. ATC (A) then needs to confirm (C) the read-back to ensure that the pilot has a clear understanding of that clearance. An improper read-back from a pilot or missed confirmation from an ATC could induce risks of misunderstanding on the clearance. Such erroneous communication patterns could thus be indicators for predicting communication errors. For example, according to the communication data collected in the HITL simulation, 11.46 percent of communications are in a pattern “A-P-A-P.” Such communications usually involve repeated communications due to in-correct read-back or misunderstanding of the clearance (see Table 13).

Communication during air traffic control processes may involve abundant uses of numerous numerical information. Certain communication contents during communications could also lead to misunderstandings. For instance, FAA has specified that numbers (e.g., altitude, speed) contained in a clearance shall be spoken by separating the digits preceding the word "thousand” (e.g., “maintain altitude at one zero thousand”). Communications involve descent altitude, speed reduction, and heading direction always involve the use of numbers.

Results (see Table 14) indicate 18.75 percent of communications involves descent altitude during the aircraft landing processes, 10.42 percent of communications involve with speed reduction, 39.58 percent of communications with adjustment of heading direction (adjust the heading angle), and 31.5 percent of communications that ATC provides instructions that require pilots to comply with assigned descend altitude, speed reduction, and direction adjustment in one single clearance.

Table 14. Communication Content Discovered from the HITL Experiments

Communication Content	Explanation	Example
Descent Altitude (18.75%)	The ATC provides instruction for pilots to descend or maintain at a certain altitude.	**ATC**: "*Southwest thirty-two seventy-seven descending maintain one zero thousand*."
Reduce Speed (10.42%)	The ATC provides instruction for pilots to reduce the speed to prepare for landing.	**ATC**: "*Southwest seven forty-three flight in zero seven zero speed one seven zero*."
Adjust Heading Direction (39.58%)	The ATC provides instruction for pilots to adjust their heading direction to prepare for landing.	**ATC**: "*Southwest seven forty-three turn right, heading one one zero*."
All Information (Descent Altitude, Reduce Speed, Adjust Heading Direction) (31.5%)	The ATC provides instructions that require pilots to comply with assigned descend altitude, speed reduction, and direction adjustment at the same time.	**ATC**: "*Southwest seven forty-three fly in one zero, reduce speed to two one zero, descending maintain one zero thousand.*"

Communication error analysis

As for the communication error classification, the author classified the communication error according to the "three-step" communication protocol (I-R-C) (Risser 2005). There are eight total possibilities of communication errors, as shown in the table. A cross mark indicates the error while a checkmark indicates the correction of certain steps. For instance, 16.67 percent (Type 5) of communications involve incorrect read-back by the pilot with no confirmation or correction by the ATC (see Table 15). One example of such read-back errors is that the pilot of SWA 743 read-back (SWA 743: "Roger, reduce speed to one one zero.") the speed information incorrectly compare to the clearance issued by the ATC (ATC: "Southwest seven forty-three fly in one one zero reduce speed to two one zero."). Results also suggest that most communication errors (Type 5 and Type 6) involve read-back issues between the ATC and pilots.

Table 15. Communication Errors

Errors	Type	Explanations	Examples
$I^{x}R^{x}C^{x}$	E_1 (2.08%)	ATC issues incorrect clearance → incorrect read-back → uncorrected	**ATC**: "*UPS four forty-seven heavy fly in one zero zero contact approach one zero point niner*." (should contact approach one two zero point niner) **UPS 447**: "*Going to two niner zero UPS four forty-seven*."
$I^{x}R^{x}C^{\surd}$	E_2 (0.00%)	ATC issues incorrect clearance → incorrect read-back → ATC correction	N/A
$I^{x}R^{\surd}C^{x}$	E_3 (2.08%)	ATC issues incorrect clearance → correct read-back → unconfirmed	**ATC**: "*Air shuttle four sixty-seven turn right heading zero niner zero contact approach one two zero point niner*." **ASA 467**: "*Heading zero niner zero one two zero point niner for Alaska four sixty-seven thanks*."
$I^{x}R^{\surd}C^{\surd}$	E_4 (0.00%)	ATC issues incorrect clearance → correct read-back → ATC confirmed	N/A
$I^{\surd}R^{x}C^{x}$	E_5 (16.67%)	ATC issues correct clearance → Incorrect read-back → uncorrected	**ATC**: "*Southwest seven forty-three fly in one one zero reduce speed to two one zero*." **SWA 743**: "*Roger, reduce speed to one one zero*."
$I^{\surd}R^{x}C^{\surd}$	E_6 (3.13%)	ATC issues correct clearance → Incorrect read-back → ATC correction	**ATC**: "*American two fifty-four speed two one zero heading three zero zero*." **AAL 254**: "*Speed two one zero knots heading three four zero American two fifty-four*." **ATC**: "*American two fifty-four heading three zero zero*."
$I^{\surd}R^{\surd}C^{x}$	E_7 (0.00%)	ATC issues correct clearance → correct read-back → unconfirmed	N/A
$I^{\surd}R^{\surd}C^{\surd}$	E_8 (76.04%)	All communications are correct	**ATC**: "*UPS four forty-seven heavy turn left heading two seven zero*." **UPS 447**: "*Turn left two seven zero UPS four forty-seven*."

*N/A: The collected data does not contain this type of communication errors.

Loss of separation

An LoS between aircraft occurs whenever predefined separation minima in controlled airspace are breached. Minimum separation standards for airspace are specified by air traffic service (ATS) authorities, based on ICAO standards. For airspace between the surface (FL000) and 29,000 ft. (FL290), the minimum vertical separation is 1,000 ft. and the horizontal separation is 3 NM. Due to the irregularity in the surface of the earth, only a few methods are widely used to calculate the ellipsoidal distance between two coordinates. The author used the spherical law of cosines and *Haversine* formulas to calculate the distance between two aircraft by assuming that the earth is spherical. The formulas below illustrate how the author computed the distances between aircraft.

$$\boldsymbol{\alpha = sin^2\left(\frac{\varphi_1 - \varphi_2}{2}\right) + cos\varphi_1 * cos\varphi_2 * sin^2\left(\frac{\lambda_1 - \lambda_2}{2}\right)} \tag{1}$$

$$\boldsymbol{c = 2 * \alpha tan2(\sqrt{\alpha}, \sqrt{1 - \alpha})} \tag{2}$$

$$\boldsymbol{d = R * c} \tag{3}$$

Where $\boldsymbol{\varphi}$ is latitude, $\boldsymbol{\lambda}$ is longitude, R is earth's radius (mean radius = 6,371 km), d is the distance between two aircraft.

Results in Table 16 show six LoS occurred within a 25-minute simulation. For instance, an LoS occurred at 13:04.3 that Speed Bird 281 and Alaska 467 due to the wrong heading direction of BAW281. At 15:14.4, an LoS occurred between SWA3277 and AAL561. The pilot of AAL561 read-back incorrectly about the descend altitude and entered the incorrect horizontal airspace that assigned to SWA3277 and causes LoS. In addition, AAL254 has been involved in multiple breaches that occurred in the session that due to its communication errors, such as incorrect read-backs about the speed reduction, descending altitude, or heading direction.

Table 16. LoS Occurred in the HITL Experiments

Time Stamp	Traffic Density within the Airspace	Pair of Aircraft that breach the Separation Minima		Communication Issues
13:04.3	4 aircraft	BAW 281	ASA 467	Speed Bird 281: missed heading direction in read-back
15:14.4	6 aircraft	NAX 994	AAL254	American 254: incorrect speed in read-back
19:19.6	4 aircraft	SWA 3277	AAL 561	American 561: incorrect descend altitude in read-back
19:39.6	4 aircraft	NAX 994	AAL 254	American 254: missed heading direction and descending altitude in read-back
20:54.6	4 aircraft	AAL 8921	NAX 994	No. messages/minute is greater than average.
23:44.8	3 aircraft	SWA 743	AAL 254	American 254: missed heading direction and descending altitude in read-back

The results indicate that even with only a few aircraft present in the TRACON controlled airspace during their approach phase, LoS still occurs due to communication errors. For example, when LoS occurs between SWA743 and AAL254 at 23:44.8, only 3 aircraft presented in the airspace, and two of them breached the separation minima. Besides, the author expanded the Phoenix terminal section in the simulation by adding a second arrival flow of aircraft coming from Tucson, El Paso, and México. Such expansion will increase the difficulty and workload of ATC when handling two arrival flows. Moreover, three pseudo pilots must communicate with ATC and control 15 aircraft, which causes additional workload of pilots and lead to a high frequency of LoS.

Conclusion

Timely capturing anomalous human behaviors for estimating workflow duration and risk assessment is essential for ensuring CIS O&M safety and efficiency. However, the uncertainties of communication errors bring significant challenges to achieve a precise estimation and reliable assessments. Even experienced CIS O&M participants could hardly provide reliable assessments on the CIS O&M condition based on tedious field observations. However, CIS O&M participants allocate more resources and spend more data collection efforts to reveal risky parts of CIS O&M processes. Identifying such risky CIS O&M processes can thus provide guidance to the CIS O&M management team to achieve resilient NPP outage control. Collecting such human behavior data could help reveal 1) what communication features are more likely to cause communication errors and 2) what communication behaviors are more likely to cause CIS O&M risks.

CHAPTER 4

COMMUNICATION ERROR CLASSIFICATION AND PREDICTION THROUGH CONSTRAINT-BASED BAYESIAN NETWORK MODELING

Introduction

Accurate and effective interpersonal communications between the CIS O&M participants are crucial for ensuring safety and efficiency. For example, communications between pilots and ATCs are critical to ensuring safe coordination during air traffic control processes. ATCs need to communicate with pilots through radio to provide instructions or clearances regarding altitudes, speeds, weather, and air traffic conditions (Immanuel and Candace 2013). ATC/Pilot communications also need to employ read-back/hear-back procedures for ensuring that the information could be properly understood. Several challenges still exist and prevent the safe and efficient CIS O&M, such as 1) lack of comprehensive characterization of the communication errors in making team decisions under a dynamic work environment of CIS O&M., and 2) lack of comprehensive characterization of the impacts of communication errors in changing decision contexts on teamwork performance.

Communication errors have been identified as one of the most common human errors and are threatening the safety and efficiency of the nuclear and aviation industries (Geacăr 2016; Molesworth and Estival 2015; Wu et al. 2017). For example, communications during NPP outages usually involves exchanging task completion status, field observations, abnormal indicators in the NPP outage control room, and assignment of additional work packages. However, communication errors always cause severe delays during NPP outages and result in significant cost overrun. Unfortunately, limited studies have revealed such communication error propagation processes and quantitatively assess the impacts of communication errors on the safety and efficiency of CIS O&M.

Existing studies of accidents/incidents during CIS O&M focus on detailed process modeling of complex CIS O&M processes to simulate possible patterns that deviate from the specified procedures (Graziano et al. 2016). Previous studies examined text mining algorithms for automatic communication error detection using communication transcripts (Chierichetti et al. 2014; Johnson et al. 2013; Skaltsas et al. 2013). Some studies synthesized communication errors during NPP outages (Kim et al. 2007). Limited studies have quantitatively assessed how communication issues arise, and trigger propagated CIS O&M risks. An effective control system that can reduce such risks by detecting erroneous communications could be beneficial for safe CIS O&M.

The overall goal of this section is to 1) understand how communication contexts and features affect the occurrences of communication errors in two CIS O&M processes and 2) how communication errors lead to workflow delays and safety risks. The proposed constraint-based BN Modeling method focuses on 1) constructing a BN model based on the data collected from the lab experiments, 2) using the developed BN model for predicting communication errors and CIS O&M risks (LoS, delays); and 3) using the *Maximum-Entropy* method to encode expert knowledge as constraints to update the posterior distributions derived based on lab experiments data and improve the prediction accuracy of the BN model.

Previous Research

Previous research on the accidents/incidents during CIS O&M focused on two questions (i) what are the contributing factors that cause the miscommunications and the

CIS O&M risks; (ii) what are the accident occurrence processes. Most studies use the Fault Tree Model or Event Tree Model to quantify the causal relationship between contextual factors and communication errors in certain aviation accident scenarios (e.g., runway incursion) (Lower et al. 2016). Some studies synthesized factors that cause various of CIS O&M accidents. Some studies showed that a safety ontology-based framework could help to formalize the safety management knowledge (Zhang et al. 2014). El-Gohary has developed a set of construction ontologies to better understand the processes of project development (El-Gohary and El-Diraby 2010). These previous studies show the potential of using process models along with BN learning methods for synthesizing mechanisms about how accidents occurred during CIS O&M.

A recent study tried to establish methods to predict the likelihood of structure defect based on field observations through constraint-based Bayesian Entropy Network (BEN) modeling (Wang and Liu 2020). The study requires quantifiable knowledge or experience to be used as constraints to update the BN model to achieve reliable prediction. This section presents a constraint-based Bayesian Network (BN) modeling approach that first create process models for showing processes of air traffic control that gradually lead to LoS during aircraft landing processing. A Bayesian network-learning algorithm then uses this process model and the data collected during lab experiments to generate a BN that captures histories about how various contextual and human factors influence the probabilities of certain events and miscommunications that lead to LoS. Then the author used the knowledge and opinion solicited from the domain expert as constraints to update the posterior distribution of the developed BN for achieving better prediction accuracy of communication errors and associated CIS O&M risks.

The goal of this study is to understand how communication errors occur in the CIS O&M workflow by using two cases. The valve maintenance workflow case during NPP outage is to reveal how communication errors arise and cause delays to the workflow. The aircraft landing case in air traffic control is to reveal how communication errors arise and cause LoS between aircraft.

Research Methodology

BN modeling is an ideal statistical tool for taking an event that occurred and predicting the likelihood of any one of several possible successor events. In this case, the BN model used the data from the lab simulation and quantitatively assessed 1) the conditional probabilities of communication errors in certain types of communications; and 2) the conditional probabilities of safety (LoS) and efficiency (delays) due to different types of communication errors. The goal of this section is to understand how communication errors occur during CIS O&M and how these errors eventually lead to safety and efficiency concerns.

To achieve the goal, the four sub-objectives are 1) Data collection from human-in-the-loop experiments; 2) Synthesizing historical records (e.g., aviation accident reports, NPP outage inspection reports) from multiple sources (NTSB database, ASRS database) for better understating the occurrence of communication errors and propagated risks; 3) Establish a BN model based on the collected data to predict the CIS O&M risks, and 4) Synthesize knowledge from domain experts as constraints on updating the developed BN for achieving better prediction accuracy. This section presents a BN modeling approach with a focus on 1) modeling of delays of a valve maintenance workflow during NPP outages and how communication errors arise and result in delays; and 2) modeling LoS that occur during aircraft landing process and how different factors contribute to the accident occurrences.

Bayesian Network (BN) Modeling based on historical records and data collected in lab experiments

The proposed BN modeling approach aims at 1) predicting communication errors during valve maintenance workflow and aircraft landing process for given communication contexts and features; 2) predicting delays caused by communication errors during valve maintenance workflow in NPP outages, and 3) predicting LoS caused by communication errors during the aircraft landing process.

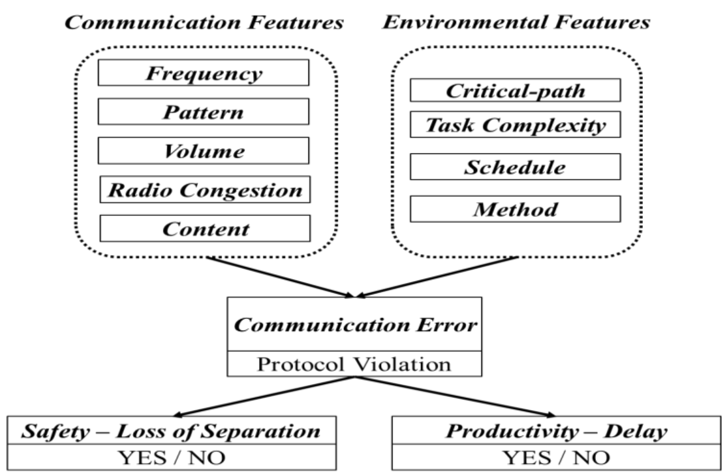

Figure 22. Constraint-based Bayesian Network (BN) Model Updating Method

The proposed method consists of three steps (Figure 22). The first step is to collect accident/incident reports of valve maintenance workflow and aircraft landing process that involved with communication errors from the multiple data sources. This step aims at revealing the causal relationships between contextual factors, communication errors, and delays or LoS. The second step is to extract information from the collected data during the lab experiment (i.e., communication features, environmental conditions). The third step is to classify the types of communication error based on the protocol violations. The author then constructed a BN model to represent how anomalous events arise and propagate that lead to different types of communication errors and lead to delays or LoS. The model provides the capability to quantify risks by calculating the probabilistic dependence between anomalies represented in the BN.

The *Maximum-Entropy* (ME) method is an alternative method to update the posterior distribution (conditional probabilities) derived from conventional BN by integrating the expert knowledge as constraints (Wang et al. 2018). The ME method aims at maximizing the entropy term under constraints so that the updated probability distribution, which best represents the current state of knowledge (Guan et al. 2012). The form of entropy term is defined as the negative of *Kullback-Leibler* (KL) divergence between the updated conditional probability distribution $P'(\theta|x)$ and the original conditional probability distribution $P(\theta|x)$. Where θ represents the predicted events (e.g., communication errors), and x represents the given condition.

$$\boldsymbol{S[P', P] = -\iint_{X\times\Theta} P'(\theta|x)\log\frac{P'(\theta|x)}{P(\theta|x)}\,dx\,d\theta} \qquad \textbf{(1)}$$

While maximizing entropy, the author introduced two constraints 1) normalization constraint (Wang and Liu 2020); and 2) mean constraint (Giffin and Caticha 2007). The normalization constraint specifies that the integral of the probability function over the domain is unity. The mean constraint uses the expectation value of the $(\theta|x)$ to encode the expert opinion or knowledge solicited from experienced field engineers.

$$\boldsymbol{\sum_{k=1}^{n} P'(\theta|x)_k = \iint_{X\times\Theta} P'(\theta|x)\,dx\,d\theta = 1} \qquad \textbf{(2)}$$

$$\boldsymbol{E(\theta|x) = \sum_{k=1}^{n} P'(\theta|x)_k(\theta|x)_k = \iint_{X\times\Theta} P'(\theta|x)(\theta|x)\,dx\,d\theta = M} \qquad \textbf{(3)}$$

To maximize the entropy under these two constraints, the author used the *Lagrange* method to derive the optimal solution of $P'(\theta|x)$.

$$\boldsymbol{\mathcal{L} = S + \alpha\left[\iint_{X\times\Theta} P'(\theta|x)\, dx\, d\theta - 1\right] + \beta\left[\iint_{X\times\Theta} P'(\theta|x)(\theta|x)\, dx\, d\theta - M\right]} \quad \textbf{(4)}$$

$$\boldsymbol{P'(\theta|x) = P(\theta|x)e^{-1+\alpha+\beta(\theta|x)}} \quad \textbf{(5)}$$

Where α and β are the Lagrangian multipliers.

From the above equation, it is evident that the result from the ME method has an additional exponential term added to the Bayes' rule. The exponential term represents the additional expert opinion or knowledge that encoded in the BN as constraints.

Validation

BN constructed using the data collected during lab experiments of an NPP outage workflow

The author constructed a BN model by using the schedule features, communication errors, and delays captured during the lab experiments of the valve/turbine maintenance workflows during NPP outages (Figure 23) (Section "*Collecting human behavior data during valve/turbine maintenance processes*" provides detailed information about the workflow). The features (Table 17) selected are based on extensive literature review and expert opinion that all such features have a great impact on causing communication errors and lead to delays during outages. The overall goal of this BN is trying to understand the cause of delays due to communication errors by answering four questions, 1) is the task in critical-path; 2) is the task has too many connected tasks; 3) is the task in a linear or complex schedule, and 3) how the worker communicate during valve/turbine maintenance workflow.

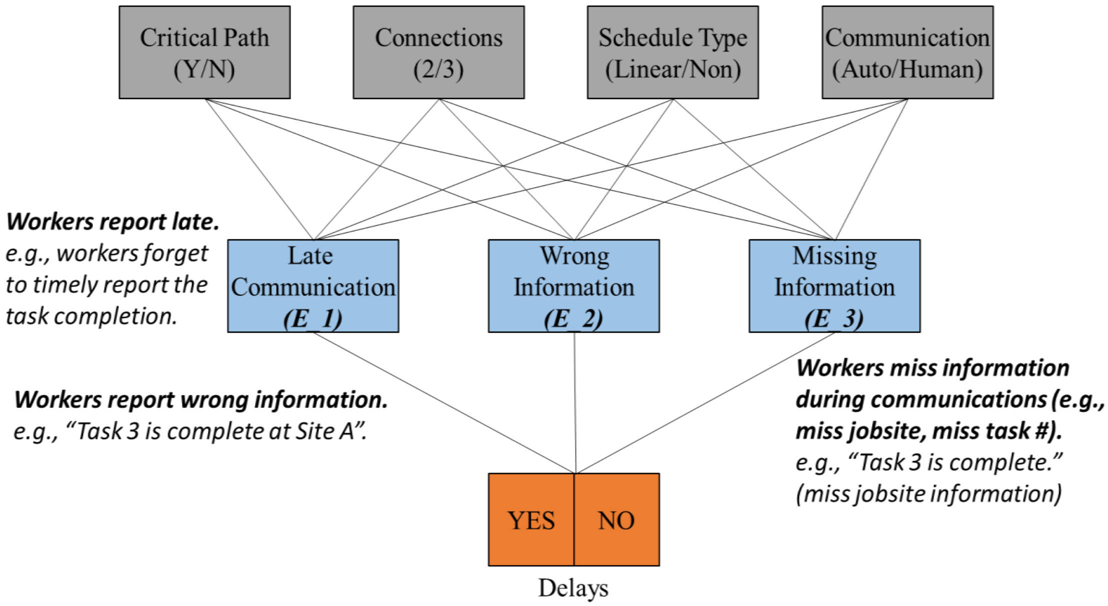

Figure 23. BN Modeling for Predicting Communication Errors and Delays during NPP Outages

Table 17. Explanations of Communication Features

Features	Symbol	Variables	
Critical Path	**a**	Yes ($\mathbf{a^0}$)	No ($\mathbf{a^1}$)
# of Connected Tasks	**b**	2 ($\mathbf{b^0}$)	3 ($\mathbf{b^1}$)
Schedule Type	**c**	Linear ($\mathbf{c^0}$)	Non-linear ($\mathbf{c^1}$)
Communication Method	**d**	Automation ($\mathbf{d^0}$)	Supervisor ($\mathbf{d^1}$)

Table 18. Conditional Probabilities of Communication Errors (E) on Communication Features (a, b, c, and d)

	(E_1)	(E_2)	(E_3)	TOTAL
$a^0b^0c^0d^0$	**0.67**	**0.33**	0	1.0
$a^0b^0c^1d^0$	**1.00**	0	0	1.0
$a^0b^0c^0d^1$	**0.72**	**0.14**	**0.14**	1.0
$a^0b^0c^1d^1$	**1.00**	0	0	1.0
$a^0b^1c^0d^0$	**0.60**	**0.40**	0	1.0
$a^0b^1c^1d^0$	**1.00**	0	0	1.0
$a^0b^1c^0d^1$	**0.56**	**0.13**	**0.31**	1.0
$a^1b^0c^0d^0$	**1.00**	0	0	1.0
$a^1b^0c^0d^1$	**0.89**	0	**0.11**	1.0
$a^1b^0c^1d^1$	**1.00**	0	0	1.0
$a^1b^1c^0d^0$	**1.00**	0	0	1.0
$a^1b^1c^0d^1$	**1.00**	0	0	1.0
$a^1b^1c^1d^1$	**1.00**	0	0	1.0

The above results indicate that when the workers are working on critical-path activities, the workers and the supervisor committed more communication errors in all three categories (E_1, E_2, and E_3) compared with workers working on non-critical path activities. The reason could be that critical-path activities tend to pose more stringent time limits so that workers could have less time for ensuring the timeliness and content correctness. Besides, the workers made fewer communicating errors (E_1, E_2, and E_3) when communicating through the automatic communication system. The reason could be the workers only need to input task completion status into the automatic communication system, which can automatically update the task availability information based on inputs from workers. Using such technology may potentially reduce communication errors that often occur during verbal communications.

As for the impacts of communication errors on workflow delays, results (Table 19) indicate that type 2 and type 3 communication errors caused higher probabilities of delays. The observations also indicate all communication errors result in workflow delays in different manners. For example, Type 1 communication errors resulted in the late information exchanged between the supervisor and workers that directly induce delays. Type 2 and Type 3 communication errors may require examinations of incorrect or incomplete information and cause additional communications that accumulate delays. For example, the human supervisor has to double-check with all collected information to make sure certain tasks are available based on the as-is condition of the workflow. Besides, the workers may go to the wrong job site to find out the information they received from the “supervisor” is incorrect. All such communication errors lead to a significant amount of non-value-added travels, waiting, and delays.

Table 19. Conditional probabilities of Delays on Communication Errors (E)

Delay in Communication Errors	Probability of Delay
P (Delay | E_1)	0.670
P (Delay | E_2)	1.000
P (Delay | E_3)	0.875

Constraints synthesized from expert opinion and literature

The author conducted a series of interviews with experienced NPP outage engineers and through literature review to acquire additional knowledge about the human error-related outage delays based on their field experiences. Then the author encoded these rules into the BN as constraints to update the conditional probabilities for predicting the causes based on field observations.

1) When the task is on a critical path, the workers are more likely to make type 2 communication errors.
2) Traditional interpersonal communications between supervisors and workers are more likely to cause type 2 communication errors.

BN constructed using the data collected during lab experiments of air traffic control of aircraft landing processes

The author constructed a BN model by using the data collected in the lab experiments of air traffic control of the aircraft landing process. The data includes communication features, communication errors, and LoS that occurred during the aircraft approach phase in the landing process (Figure 24). The features (Table 20.) selected are based on extensive literature review and expert opinion that all such features have a great impact on causing communication errors and LoS. The goal of this BN is trying to understand how communication errors arise and lead to LoS.

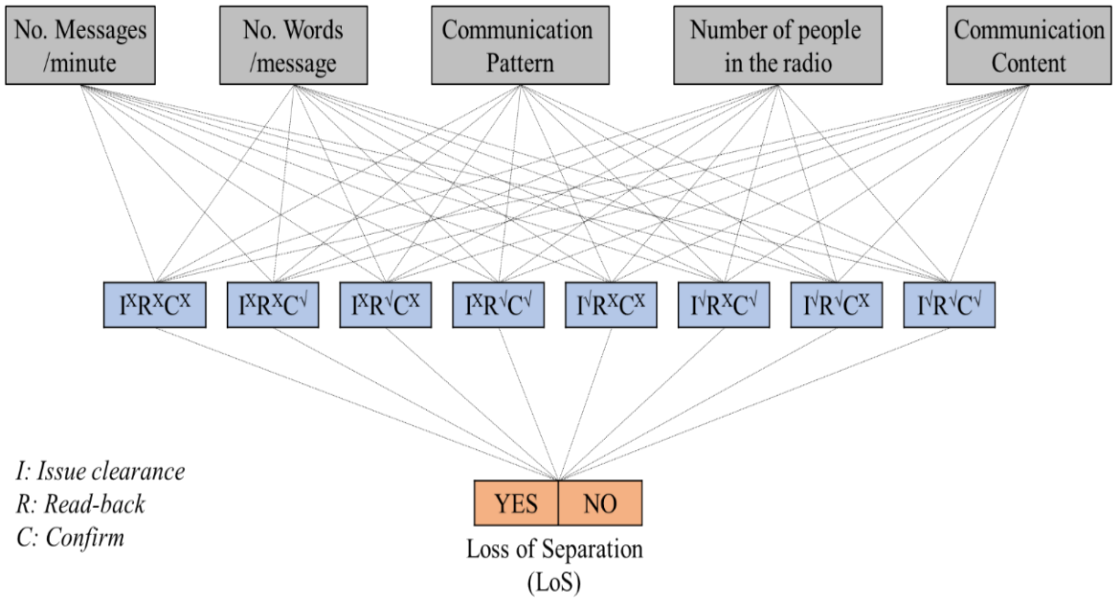

Figure 24. BN Modeling for Predicting Communication Errors and LoS

This section summarizes the research findings. Table 20 provides detailed explanations of symbols of communication features derived from the communication data collected during lab experiments. Table 21 and Table 22 illustrate the probabilistic relationships 1) between different communication errors and different combinations of communication features and 2) between LoS and communication errors.

Table 20. Explanations of Communication Features

Features	Symbol	Variables			
# of Messages/Minute	**a**	< Avg. ($\mathbf{a^0}$)		> Avg. ($\mathbf{a^1}$)	
# of words/Message	**b**	< Avg. ($\mathbf{b^0}$)		> Avg. ($\mathbf{b^1}$)	
Pattern	**c**	APA ($\mathbf{c^0}$)	APAP ($\mathbf{c^1}$)	AAP ($\mathbf{c^2}$)	APPAP ($\mathbf{c^3}$)
# of People	**d**	2 ($\mathbf{d^0}$)		3 ($\mathbf{d^1}$)	
Content	**e**	Descend ($\mathbf{e^0}$)	Speed ($\mathbf{e^1}$)	Direction ($\mathbf{e^2}$)	ALL ($\mathbf{e^3}$)

Table 21 illustrates the probabilistic relationship between communication errors and combinations of communication features. Each issuance of clearance shows a combination of communication features and one type of communication error. For instance, Type 3 (E_3) communication error will have 20 percent probability to occur when the ATC-pilots communication satisfies the following conditions ($a^0b^0c^0d^0e^0$): 1) the No. messages per minutes smaller than the average (12.87); 2) the No. words per message smaller than the average (13.03); 3) the communication pattern is "A-P-A"; 4) only two people are in the communication channel, and 5) the communication is related to descend altitude.

Table 21. Conditional Probabilities of Communication Errors (E) on Communication Features (a, b, c, d, and e)

	(E_3)	(E_5)	(E_6)	(E_8)	TOTAL
$a^0b^0c^0d^0e^0$	**0.2**	**0.2**	0	**0.6**	1.0
$a^0b^1c^0d^0e^0$	0	**0.5**	0	**0.5**	1.0
$a^0b^1c^0d^0e^1$	0	**0.5**	0	**0.5**	1.0
$a^0b^1c^0d^0e^2$	**0.1**	**0.1**	0	**0.8**	1.0
$a^0b^1c^0d^0e^3$	0	**0.33**	0	**0.67**	1.0
$a^0b^1c^1d^0e^3$	0	**0.33**	0	**0.67**	1.0
$a^1b^0c^0d^0e^1$	0	**0.17**	0	**0.83**	1.0
$a^1b^0c^1d^0e^2$	0	0	**0.5**	**0.5**	1.0
$a^1b^0c^1d^0e^3$	0	0	**0.5**	**0.5**	1.0

Table 22 illustrates the probabilistic relationship between LoS and eight types of communication errors. Results indicate that LoS is more likely to occur when the E_5 and E_6 communication errors occur. Both errors involve incorrect read-backs of pilots during the aircraft approach phase. Results indicate with a correction from the ATC (E_6), more communications are needed to make sure the pilot can fully understand the correct clearance.

However, as ATC-pilot communication is time-sensitive, excessive communications will delay the pilot's reaction to the clearance and increase risks of LoS. Results also indicate a 13.7 percent probability of LoS when no communication error occurred but rather involves high talking frequency and large information volume. The major findings are that incorrect pilots' read-backs are implicated with a majority of LoS when ATC does not correct the in-correct read-backs from pilots.

Table 22. Conditional Probabilities of LoS on Communication Errors (E)

LoS on Communication Errors	Probability of LoS
P (LoS | E_1)	0
P (LoS | E_2)	0
P (LoS | E_3)	0
P (LoS | E_4)	0
P (LoS | E_5)	**0.250**
P (LoS | E_6)	**0.333**
P (LoS | E_7)	0
P (LoS | E_8)	**0.137**

Constraints synthesized from expert opinion and literature

The author conducted interviews with experienced ATCs and through literature review to acquire additional knowledge about the aircraft landing processes in the TRACON airspace based on their field experiences. Then the author encoded these rules into the BN as constraints to update the conditional probabilities for predicting the causes based on field observations. Since all the variables are categorical nodes, integer values are assigned accordingly.

1) When the clearance issued by the ATC contains too much information, pilots are more likely to read-back the clearance incorrectly;
2) When there are many people in the radio channel, ATC is more likely to issue incorrect clearance and cause incorrect read-back from pilots;
3) When the communication pattern is "A-P-A-P", ATC is more likely correcting the read-back error from the pilot;

4) When the communication is too frequent, ATC is more likely to forget to confirm the read-back from the pilot.

Discussions

The author has examined and cross-validated the proposed framework using the data collected from the lab experiments with the ground truth obtained through interviews with engineers who have a profound experience with NPP outage control and air traffic control processes. The prediction results (see Table 23) show that the constraint-based BN provides higher accuracy compare to the conventional BN with only limited data sources. Although the accuracy is still not satisfactory yet partially due to the limited number of data collected, the constraint-based BN model shows substantial improvement compared with the classical Bayesian method.

Using communication contexts and features for predicting communication errors is crucial to ensure CIS O&M safety and efficiency. The established quantitative relationship between communication features and errors has the potential of aiding ATCs for timely detection and the faster reaction to erroneous communications. Specifically, implementing the developed algorithms into existing ATC-pilot communication auxiliaries (e.g., Data Comm) could help generate alerts about erroneous communications.

On the other hand, the current communication practices of TRACON training programs may also benefit from the developed algorithms. For instance, existing training programs may improve the ATC-pilot communication practices by incorporating more communication regulations (e.g., using fewer words for clearances; speak slowly and clearly; using standard phraseologies). Implementing such specified communication practices into the TRACON training programs may increase the ATCs' situation awareness of good communication practices and reduce risks of having erroneous communications that could lead to LoS.

Table 23. Classification Accuracy Improvement of the Constraint-based BN Model

BN Model	Training/Testing	Communication Error Prediction	
		NPP Outage	Air Traffic Control
Conventional BN Model	50:50	64.2857%	70.8333%
	70:30	64.7059%	75.8621%
	85:15	77.7778%	78.5714%
Constraint-based BN Model	50:50	75.0000%	79.1667%
	70:30	76.4706%	89.6552%
	85:15	88.8889%	85.7142%

Results indicate the proposed method could help predict the probabilities of LoS when certain communication errors occur. However, due to the limited data collected, the quantitative relationship derived in this study still requires further improvement through advanced statistical approaches. These approaches could increase the reliability of the developed BN model by introducing engineering knowledge as constraints for updating the probability distribution when dealing with a small dataset. The derived results could be essential for ATC training in the TRACON training programs as ATC could get additional alerts from the algorithm that LoS will occur, and they need to put more attention on certain aircraft.

Conclusion

Results indicate the proposed method is capable of integrating observations and domain knowledge to achieve reliable estimation on the efficiency and safety during NPP outages and air traffic control. The limitations of the proposed method remain. The main reasons behind the limited accuracy of the BN model could be 1) manually summarizing engineering “rules” from historical documents is time-consuming, and 2) human errors during CIS O&M are always case-by-case and might not be the same. Future directions of this research could focus on 1) integrating advanced machine learning algorithms for processing imbalanced dataset, 2) integrating more engineering knowledge as constraints into the BN model for improving the reliability of the correlation model, and 3) expand the proposed framework to fully consider data inconsistencies when conflict information exists among multiple data sources.

CHAPTER 5

COMMUNICATION RISK MITIGATION THROUGH COMPUTATIONAL AGENT-BASED MODELING AND OPTIMIZATION

Introduction

Handoffs between scheduled tasks during NPP outages are time-consuming and error-prone. Such handoffs typically involve travels between job sites and communications between the management team and workers to exchange information on the task status (Zhang et al., 2017). Human and team cognition during handoffs could accumulate delays during NPP outages (see Figure 25). However, the outage manager could hardly track and analyze the time consumption caused by late communication and wrong information exchanged during handoffs (i.e., waiting time caused by late communication on available tasks). Thus, late communications and wrong information exchanged during communications could interrupt outage workflows by causing rework and results in severe delays (Sun et al., 2018b). An improved understanding of how delays arise during handoffs are necessary and crucial to predict delays for the outage workflow.

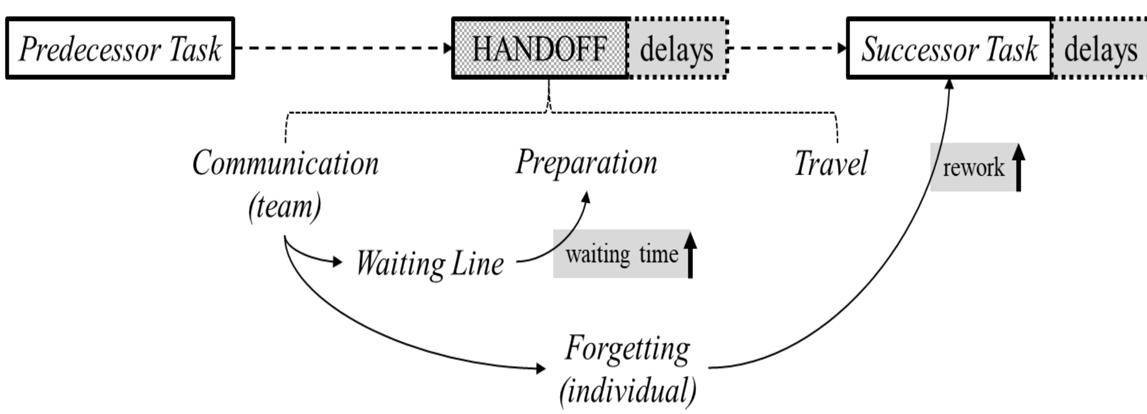

Figure 25. Framework for Assessing the Impact of Cognitive and Communication Factor on Workflow Delays

Several challenges impede the existing scheduling, and process simulation tools fail in diagnosing handoff management issues that cause delays in accelerated CIS O&M (Wang et al., 2018). Current construction scheduling tools only include as-planned tasks in CIS O&M workflows without considering handoffs between tasks (Zhang et al., 2017). Furthermore, these tools entail difficulty in representing a communication network along with the schedule network (Rozinat et al., 2009). Moreover, the use of conventional simulation tools is even more difficult in representing uncertain communication behaviors and analyzing its impact on workflow delays.

The majority scheduling software only simulates a fixed sequence of tasks in a pre-defined CIS O&M schedule. Frequent schedule changes/updates that often arise due to uncertainties are difficult to formalize into representations in the existing scheduling software. The limitations of schedule modeling and simulation tools prevent the mathematical modeling of handoffs in the workflow. Moreover, engineers and researchers are impeded from simulating the potential impact of communication errors on workflow efficiency and determining optimized scheduling strategies.

NPP outages desire a more resilient outage control system for reducing delays. Such a system should automatically identify human errors or unexpected discoveries during field operations to avoid delays. Given the complexity of the interwoven relationships between the workflow and interpersonal communication processes between outage participants. Agent-based simulation modeling is a powerful tool to simulate uncertainties and predict changes in task sequences and efficiency variations in outage workflows (Zhang et al., 2002; Lu, 2003). The author developed a simulation model to examine the impact of communication behaviors on NPP outage delays.

The developed simulation platform consists of 1) a workflow model based on a previous NPP outage schedule, 2) a developed handoff model according to the handoff process observed during NPP outages, and 3) a developed simulation-based communication protocol optimization approach for reducing delays caused by communication errors. In particular, the workflow model specifies the spatiotemporal relationships between tasks of the outage workflow. Such relationships specify the precedence relationship between tasks, locations, and random task durations that follow uniform distributions. The developed handoff model represents human activities (i.e., travel, communication) that fills in the gap between the connected tasks.

Previous Research

Advanced technologies and properly designed communication protocols are crucial for predictive outage control that reduces the time wastes and error rates in the NPP workflows. This section focuses on summarizing research reports and published literature that 1) advanced technologies in NPP outage control, and 2) the use of simulation for examining control strategies on workflow efficiency. The focus is to synthesize the background knowledge about the current practice in NPP outage control for identifying knowledge gaps.

Advanced technologies in NPP outage control

NPP outages are complex and challenging projects due to a large number of maintenance and refueling activities that need to be completed in a short period (Germain et al. 2013). All tasks conducted in an NPP are guided by well-designed procedures to help ensure the safety and efficiency of NPP operations (Oxstrand and Blanc 2017). The paper-based procedures are widely used during NPP operations (Oxstrand and Blanc

2017). Recent interest in using advanced systems has aroused for improving NPP outage safety and efficiency by automating the operational procedures during NPP outages (i.e., initiation of work request) (Germain 2015; Rashdan et al. 2015).

Advance outage control center (AOCC) implemented in the current practice of NPP outage control enables real-time work status updates from automated tools tracking individual workers' workflows (i.e., Computer-Based Procedures, CBPs, and Automated Work Packages, AWPs) (Zhang et al. 2017a). Previous studies have demonstrated the potential of using CBPs for increasing NPP operation efficiency and safety (Le Blanc and Oxstrand 2012; Oxstrand and Blanc 2017). Other studies have examined the effectiveness of using AWPs among field workers and supervisors for exchanging updated information on work packages according to the dynamic NPP conditions (Rashdan et al. 2015; Rashdan and Agarwal 2016; Rashdan and Oxstrand 2017). Unfortunately, these advanced tools provide limited capability of predicting delays due to communication errors. Besides, a properly designed communication protocol is missing in these advanced tools.

Simulation for examining control strategies on workflow efficiency

Construction simulation is the science of developing and experimenting with computer-based representations of construction systems to understand their underlying behavior (AbouRizk 2010). However, on many occasions, existing project scheduling methods failed to provide a precise depiction of the dynamic project conditions and its real behaviors. Using computer simulation tools, the overall logic relationships of various activities during CIS O&M can be represented by formalized representations. Such representations include the changing states of a physical facility and the resources (workforce, tools) involved in carrying out the work.

Existing construction simulation tools have limited capability to precisely model the complicated spatiotemporal interactions between human, tasks, and resources to support risk assessment. Currently, project managers use a Gantt chart or PERT model to represent and analyze workflows (Alzraiee et al. 2015). These workflow representations could hardly describe how human behaviors influence task executions as well as the complex interaction between different tasks and resources. New simulation models are thus necessary to integrate representations of human behaviors, and unexpected events into schedule analysis methods.

Research Methodology

This study proposed a novel control system for smoothing the communication processes and reduce outage delays. The system includes an automated communication platform with proactive communication protocols to reduce the risks of communication errors. The author developed an automated communication system through lab experiments and computational simulations. Specifically, the author has examined 1) the performance and reliability when using advanced technologies during NPP outage control, and 2) the performance of developed "early-call" strategies in reducing delays. The developed proactive control system hence can provide two control strategies that can be implemented into the practice of NPP outage control and resolve the efficiency issues. The first control strategy is to use an automatic communication system to notify workers automatically about the completion of relevant tasks so that the supervisor does not need to inform workers and avoid communication errors manually. The second control strategy is to adopt an "early call" strategy that needs supervisors to call the workers of following tasks in advance before the completion of a task.

In general, the proposed simulation-based model input the as-planned schedule and uncertainties found from the interview and documented historical records, and calculate the delays caused by the identified uncertainties. The proposed model represents and simulates the detailed spatiotemporal interaction between tasks (e.g., processor and successor task relationships) and human resources (e.g., management team and work teams). These relationships are constraints that determine how the detailed spatiotemporal interaction between tasks and human occur within the workflow model. Moreover, the model represents information flows across multiple teams in a centralized communication network.

The proposed simulation-based modeling method (see Figure 26) integrates a workflow model based on the NPP outage schedule and a developed handoff model according to the handoff process observed from the field. The workflow model aims to represent the detailed interactions among tasks in an accelerated construction workflow. However, the handoff model simulates detailed human activities during handoff processes (i.e., communication, travel, and wait). The developed handoff model represents detailed interactions among individuals within and across groups (communications between the supervisor and worker teams).

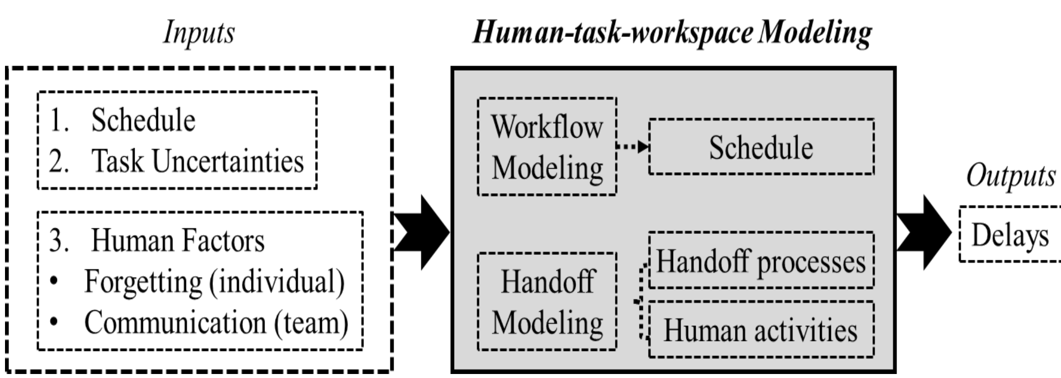

Figure 26. Overall Methodology

Scenario 1: Assessing the influence of late communications on a valve maintenance workflow during an NPP outage

This section presents a simulation model based on a valve maintenance workflow (Plan A) for the main turbine system maintenance operations. The developed model includes the developed handoff model for assessing the impact of late communications on workflow delays (Section "*Collecting human behavior data during valve/turbine maintenance processesCollecting human behavior data during valve/turbine maintenance processes*" provides detailed information about the workflow). Valve maintenance is a critical activity that needs worker teams to enter the containment for conducting maintenance activities. Moreover, worker teams need additional handoff activities (i.e., technical briefing, dosimetry checking, tool pick-up/return, and check available work package) in the radiation protection island before and after the scheduled tasks. However, the RPI is a compact place where different workstations should be shared among all work teams (i.e., work teams cannot pick-up tools if another worker team has already occupied the tool pick-up station). Thus, communications between supervisor and worker teams are important to deliver the message and avoid additional waiting times during handoff. The author introduced a substantially comprehensive handoff model to evaluate how late communication affects the handoff processes and eventually lead to workflow delays. Figure 27 visualizes the overall workflow for this scenario. In this scenario, worker teams have to go through the indoor workspace and complete the handoff processes to get prepared for the valve maintenance activities at Sites A and B.

The tasks simulated in the experiment are valve maintenance at Sites A and B and handoff at an indoor workspace. Figure 6 visualizes the entire as-designed workflow at

Sites A, and B. Blocks with the same color are the tasks using the same worker team (i.e., insulator—black; electrician—blue; mechanic—orange). Tasks sharing the same team cannot be executed simultaneously. The detailed task information is presented in Figure 6 and Table 4.

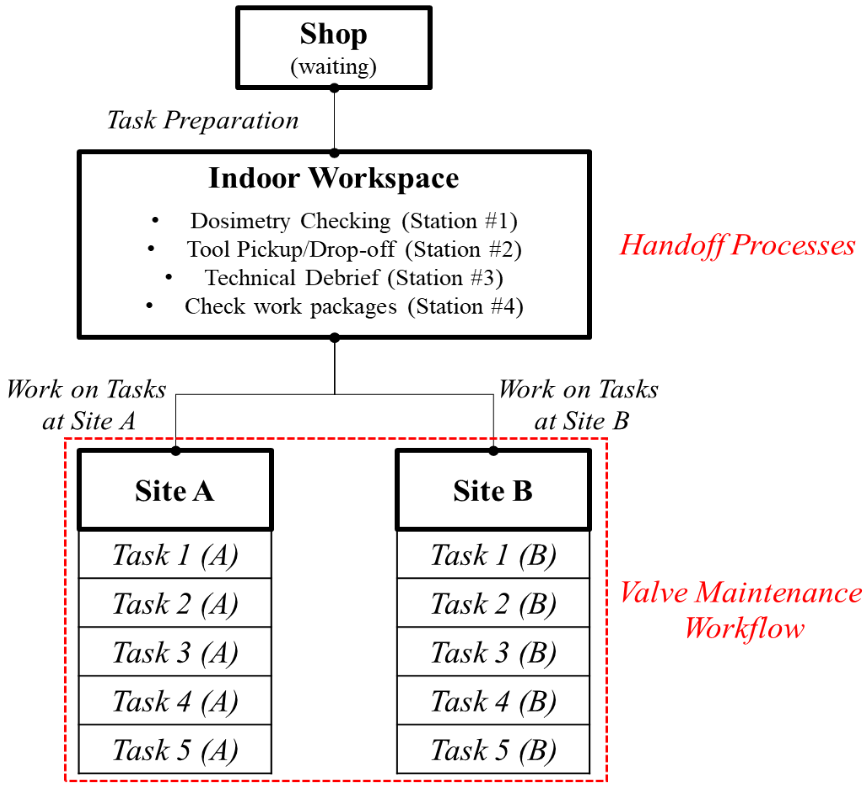

Figure 27. The Overall Workflow for Scenario 1

The indoor workspace (see Figure 28) simulates the handoff processes within the radiation protection island and prepare worker teams for working within the containment. Such handoff processes include checking available work packages, dosimetry checking, getting technical debrief, and picking up tools (e.g., earplugs). All worker teams should go through a specific handoff process in an indoor workspace to be ready to work inside the containment for valve maintenance. Table 6 illustrates all sequences of station visiting for work teams while entering or exiting the indoor workspace.

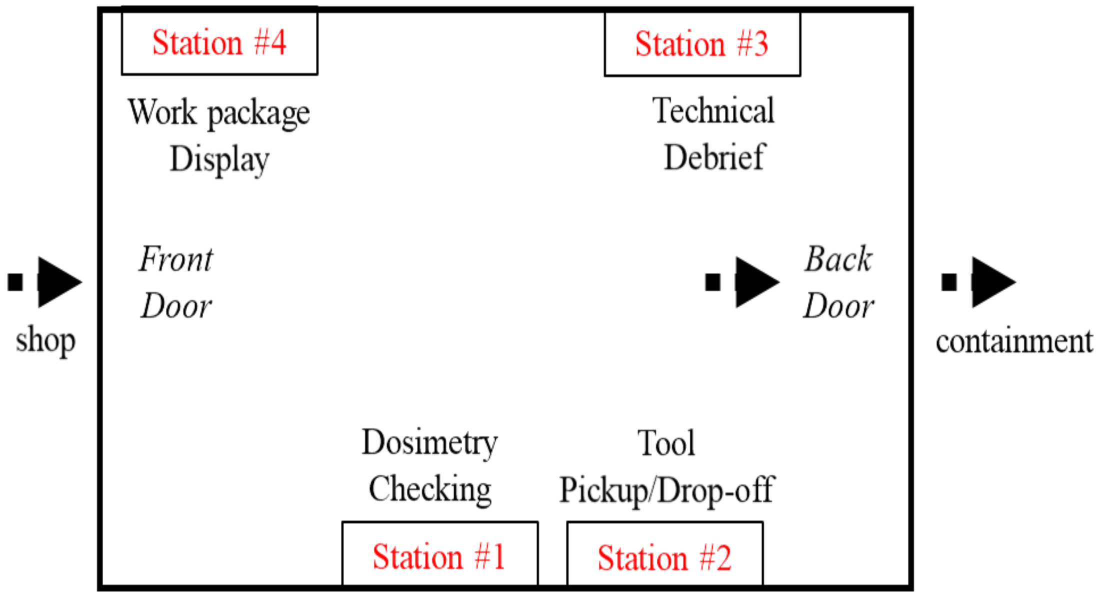

Figure 28. Indoor Workspace Setup for Handoff Processes

Once a worker team completes a task and travel back from the containment, all team members should go through certain processes in the RPI for dosimetry checking, drop off tools, and check other available work packages. According to the practice of handoff processes among tasks, the author found out from the interview that workers might have different objectives before/after they start working on scheduled tasks. Thus, different worker teams may have different moving patterns in the indoor workspace during handoff. For example, the insulator typically goes to Station 4 first to check the work packages; then goes to Station 1 for dosimetry checking; pick-up their tools at Station 2; and goes to Station 3 for technical debrief before they enter into the containment. However, the mechanic does not need to go to Station 1 for dosimetry checking before entering the containment. The time that each work team spends at different stations may also be different from one another. Table 7 presents detailed handoff activity information for different worker teams.

Communication during handoffs can be challenging. Worker teams may forget to report to the supervisor on the completion of current tasks, thereby causing delays. The observations indicate that three major types of uncertainties involved during the handoffs and caused late communications between the supervisor and workers. For example, workers may miss the voice message from the supervisor and do not realize an available work package for them to work on. Moreover, the supervisor could send out the available task information late to the workers of the successor tasks when the supervisor is simultaneously coordinating several tasks with different workers.

In this scenario, the author has simulated the late report of workers for assessing its impacts on workflow delays. The author modeled the late report by modifying the communication function of the worker agent. Accordingly, workers are allowed to report the completion of their tasks after a certain time once they complete certain tasks. This modification will set up a specified timer and ask workers to report to the supervisor for the task completion when the countdown of the timer reaches zero. In this case, the workers will be able to report to the supervisor when they are either traveling, waiting, or in the handoff processes in the indoor workspace.

Scenario 2: Assessing the influence of automatic "early-call" protocol in reducing workflow delays

This section presents a simulation model based on a valve maintenance workflow (Plan A) for the main turbine system maintenance operations. The model includes the developed handoff model for examining the "early-call" protocol in reducing workflow delays (Section "*Collecting human behavior data during valve/turbine maintenance processes*" provides detailed information about the workflow). The communication protocols for the valve maintenance workflow generally defines a centralized communication network, the direction of the information flow, and the timing of the communication. In the developed simulation model, two agents play the leading roles for representing human behaviors of different types of participants of the handoff and maintenance processes. The worker agent captures the behaviors of workers who carry out tasks in the field. The supervisor agent captures behaviors of supervisors who are communicating across multiple teams and coordinate the works of various workers and the works related to other teams' tasks.

In the current practice, typical handoffs occur between the predecessor task and the successor task. Such handoffs usually involve communication, travel activities, and waiting time. However, such handoffs could induce severe delays when the "float" between tasks is limited. "Hot handoff" allows the worker teams to pre-prepare their successor tasks in advance to avoid delays, especially when the task is on the critical path. The author then modeled an overlapped handoff ("hot handoff"), which allows the "early-call" strategies to help mitigate the risks of delays (see Figure 29). The author is trying to understand how such a "hot handoff" can help reduce the risk of delays during an outage workflow.

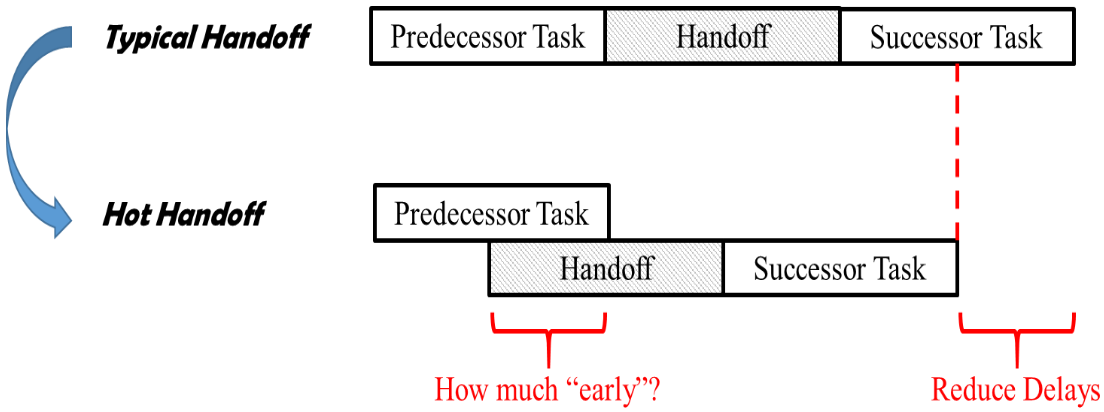

Figure 29. "Hot handoff" Modeled in the Simulation

In the current communication protocol (see Figure 30), multiple communications are required for workers and supervisors to allow a fast information exchange during a workflow. Workers are required to acknowledge all messages sent by the supervisor. For example, workers need to acknowledge to the supervisor that they receive the available task information. This communication is trying to help the supervisor know that the worker has successfully received their message. The supervisor will regularly check the message sent by workers about their progress of work, and send out a notification to workers about tasks that are ready to be working on. Since all the workers and the supervisor are on the same communication channel, the supervisor is required to send out a notification to workers with specified worker names and the task information (i.e., @insulator, task 1 at site A is available for you). Hence, the worker will be notified that there is a message for him/her.

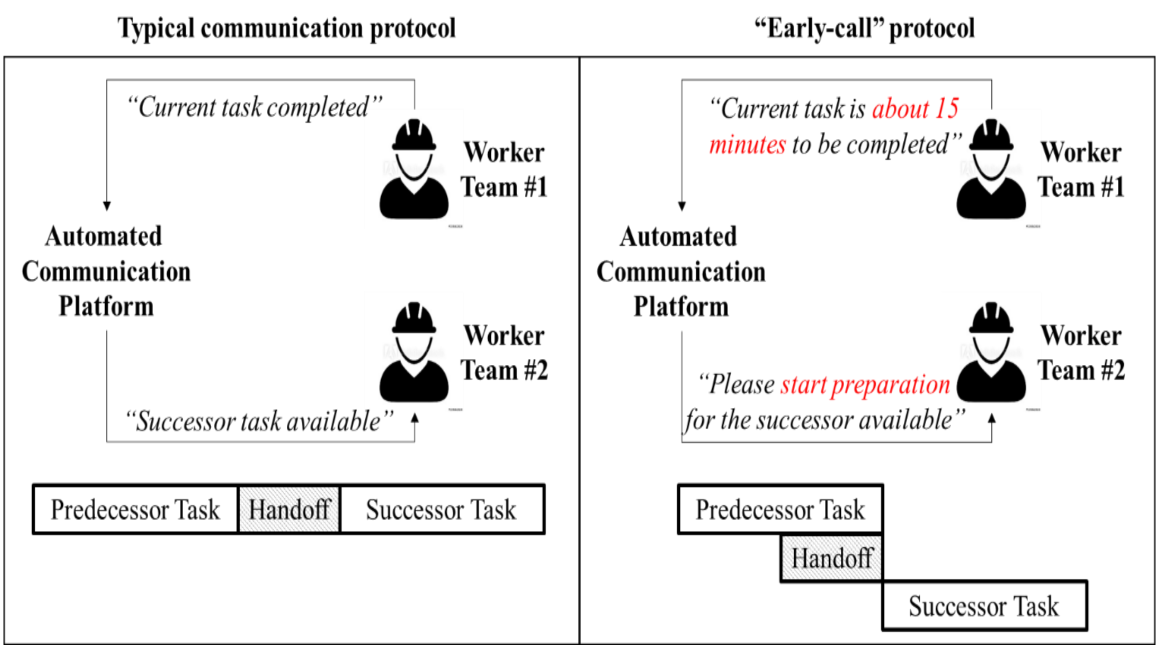

Figure 30. Improved Communication Protocol with "Early-call"

The designed "early-call" protocol allows workers to report their current task progress early (e.g., the worker can call 15 minutes ahead of time to notify the supervisor that they are about to complete the current task). Thus, the supervisor can ask the worker team who work for the successor task to start preparations. As for the optimized communication protocol, additional communications are required for the worker, which is to send a notification to the supervisor about the progress of their work. In the lab experiment, the author required the worker teams to send a notification about the completion of their current tasks to the supervisor so that the supervisor will know which task has completed and decide which task can become available. In the computer simulation, the author added another function to allow workers to report their work progress so that the supervisor can notify the successor task team to get prepared.

Validation

Impact of late communication during handoffs on workflow delays

Late communications can accumulate time wastes and cause severe delays to the handoff processes. For example, given that handoff processes involve traveling, communications, and task preparation activities (e.g., tool pick-up/return, technical briefing, security checking), late communication would cause conflicts between workers in resource sharing (e.g., different workers may simultaneously come to a station for tool pick-up) and result in delays. Moreover, a scheduled task on the critical path has zero-tolerance of delays during the handoff process. To better understand how late communication affects the workflow delays, the author 1) conducted 20 trials of laboratory experiments using the developed workflow and handoff model to capture workers' late-report behaviors (i.e., the worker reports the completion of each task late to the supervisor); and 2) conducted computational simulations to simulate how such late-report behaviors affect overall workflow delays. The author hired participants from the construction management program of Arizona State University and provided detailed training on the experiment. During the experiment, the author observed and captured the late-report behaviors by the participants (Table 24).

Table 24. Late-report Captured during the Lab Experiments

Task	Worker	Late report (delayed time: min)	Trial
Task 1 (A)	Insulator	2.6	2
Task 3 (A)	Mechanic	1.5	2
Task 4 (A)	Electrician	1.8	7
Task 1 (A)	Insulator	0.5	12
Task 3 (B)	Mechanic	3.0	14
Task 4 (A)	Electrician	1.2	18
Task 1 (B)	Insulator	0.8	18

According to the field observations, the captured average delays caused by late-report can be up to 30 minutes (durations in the laboratory experiment are scaled back ten times). After that, the author simulated a 30-min late-report during the handoff process in the simulation model. For example, a 30-min late-report behavior is simulated after the insulator finished Task 1 (A) due to the insulator forgetting to report to the supervisor that Task 1 (A) has completed. That 30-min late-report behavior eventually leads to a nearly 30-min delay to the overall schedule because Task 1 (A) was a critical-path task.

Table 25 shows that Task 4 (B) is more vulnerable because the workflow is more sensitive to the delays of handoff (30 min, 5.28%). Delays on Task 5 at Sites A and B had the least impact on the overall workflow duration. Given that a 30-min late-report has been added to one of the tasks in the workflow, the extension on the task duration will affect the actual task and the handoff process of other tasks. In particular, the supervisor will receive the field information late owing to the late-report and cause delays to the successor task. Such late-report behaviors may also cause extended occupation on a certain station during the handoff processes by having a phone call.

Table 25. The Sensitivity of the 30-min Late-report of Each Task

Site	Task	Worker	As-planed task duration (min)	Late report (min)	Workflow delays (min)	Probability
A	Task 1	Insulator	30	30	29	5.10%
	Task 2	Electrician	45		16	2.82%
	Task 3	Mechanic	60		9	1.58%
	Task 4	Electrician	45		17	2.99%
	Task 5	Insulator	30		0	0%
B	Task 1	Insulator	30		9	1.58%
	Task 2	Electrician	45		2	0.35%
	Task 3	Mechanic	60		18	3.17%
	Task 4	Electrician	45		30	5.28%
	Task 5	Insulator	30		0	0%

The extended occupation on the shared stations will eventually cause additional waiting time for other workers who are waiting to use the station. If specific tasks are delayed, then the probability of having conflicts among different work teams while in the handoff process would increase. The waiting time during handoff will also increase owing to the conflict, thereby causing additional delays to the workflow. For example, additional waiting times may occur, while Task 4 (B) is delayed. The reason is that the tool returning process of the electrician team may conflict with the tool pick-up process of the insulator team that is about to start on Task 5 (B).

Assessing developed automatic "early-call" protocol in reducing workflow delays

To validate the proposed "early-call" strategies in reducing workflow delays, the author created several scenarios according to the characteristics of the individual tasks and different "early-call" strategies. For example, a task that has more links to other tasks may need more attention, and "early-call" strategies might be more effective in reducing delays in such tasks. Besides, tasks with more successor tasks could also be critical since delays of such tasks could lead to the late start of all linked successor tasks. Thus, the author first classified the tasks in the valve maintenance workflow (see Figure 6) into four types (Figure 31) based on 1) the number of connections (links); and 2) configurations of the predecessor/successor tasks. Then, given the shorted task duration is 30 minutes, the author set the maximum time for an early call to the supervisor as 25 minutes. In the simulation, the author simulated the time for an early-call at 10 minutes, 15 minutes, 20 minutes, and 25 minutes. In the end, the author ran the simulation depending on the task types and "early-call" strategies to validate how the "early-call" protocols performed within different tasks in the valve maintenance schedule.

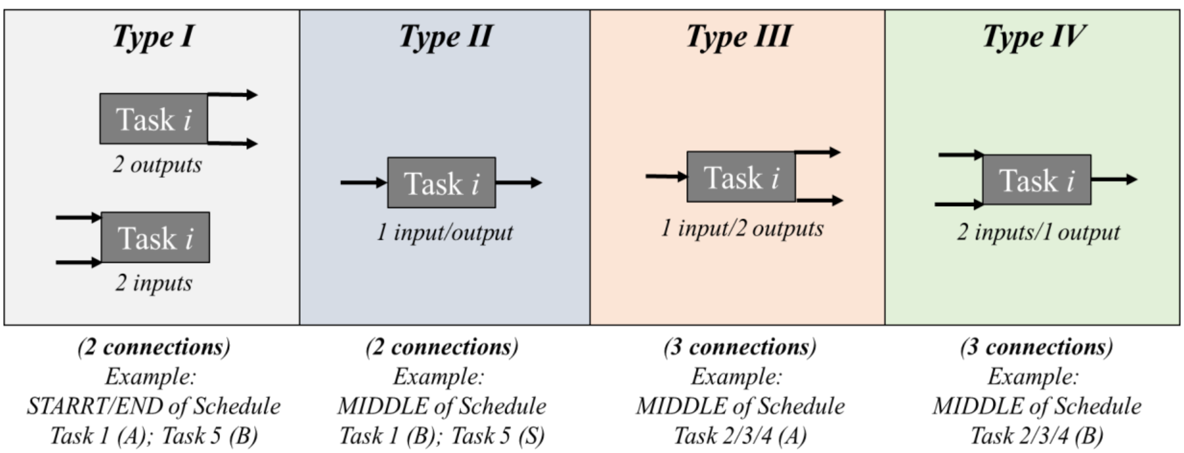

Figure 31. Task Classifications

Simulation results (Table 26) indicate that "early-call" strategies worked for most of the tasks in the valve maintenance workflow in reducing delays up to 28.8 minutes. For Type I tasks, since Task 1 (A) is the start of the schedule, "early-call" on this task only means an early start of the workflow and does not contribute to reducing delays.

However, for Task 5 (B), which is the last task in the workflow, calling 10/15 minutes early will even cause more delays to the workflow. Results indicate that for Type I tasks, the more early the supervisor notifies the worker team, the more delays can be reduced. The author found out that calling the insulator when the current task (Task 4B) is about to complete in 10 to 15 minutes resulted in additional travel time for the insulator and conflicts in the indoor workspace. Specifically, the start times for Type I tasks depend on the end times of both predecessor tasks. However, if a large deviation exists between the end times for predecessor tasks, workers for Type I tasks will have to get back to the shop and wait until further notice. Calling early allows the workers to stay at the job site and wait instead of going back to the shop, which add more travel time.

For Type II tasks, which are typical tasks that have one predecessor and one successor task, the "early-call" strategies can reduce delays up to 10 minutes. However, it is clear to see that such tasks are not sensitive to different "early-call" strategies. The author found out that Type II tasks are close to the start and the end of the workflow, where only a few workers are occupying the resources in the indoor workspace. Thus, workers for Type II tasks can smoothly go through the handoff processes without conflict with other workers and start the task in time. Such smooth handoff processes are the main reason that contributes to reducing delays.

For Type III tasks, which contain one predecessor task and two successor tasks, results indicate that the more early that workers are notified about the task, the more delays can be reduced. The author found out that any delays to Type III tasks could be disasters since the two successor tasks could be affected and aggravate the delays to the workflow. An "early-call" to Type III tasks allows the workers to pre-prepare the tasks and get ready for the task immediately. Besides, an aggressive “early-call” (i.e., calling 25 minutes early) allow buffers for any conflicts, which the worker team might encounter during the resource sharing processes in the indoor workspace.

Table 26. Delays Reduced by “Early-calls” in the Valve Maintenance Workflow

	Task	10 minutes	15 minutes	20 minutes	25 minutes
Type I	Task 1 (A) Task 5 (B)	-10.2 minutes	- 4.8 minutes	4.2 minutes	11.4 minutes
Type II	Task 1 (B); Task 5 (A)	10.2 minutes	10..8 minutes	7.2 minutes	9.6 minutes
Type III	Task 2 (A); Task 3 (A); Task 4 (A)	15.6 minutes	20.4 minutes	28.2 minutes	28.8 minutes
Type IV	Task 2 (B); Task 3 (B); Task 4 (B)	26.4 minutes	23.4 minutes	20.4 minutes	17.4 minutes

For Type IV tasks, which contains two predecessor tasks and one successor task, results indicate that calling too early might not be necessary. Similarly, the start time for Type IV tasks also depends on the end times of both predecessor tasks. However, unlike Type I and Type II tasks that are close to the start/end of the workflow, Type IV tasks are in the middle of the schedule. Besides, workers on such tasks usually stay at the job site for getting ready for the tasks. Since the indoor workspace is a “hot” area during the middle of the workflow where resource-sharing processes could induce workflow delays. Calling too early could result in unnecessary conflicts during the handoff processes in the indoor workspace and cause delays to other tasks.

The author used the developed “early-call” model to test the optimal time to call-in worker teams for early preparation for the successor tasks and reduce delays. However, such overlapped handoffs due to the “early-call” strategy could have different impacts on schedules given the different task characteristics. One thing is that resources during handoff are designed not to be shared – one station can only serve one worker at a time. In that way, overlapped handoffs will get more workers waiting at some stations for workers already using that resource during handoff. Since the waiting time is hard to estimate due to the variances of task duration in a workflow, reducing the handoff duration through overlapping can create more spaces for accommodating task uncertainties. On the other hand, given different task characteristics, tasks with more links to other tasks, and those tasks in the middle of the schedule require more attention. Calling early to some tasks might not be necessary but rather create conflicts during the handoff processes. Thus, the developed simulation-based method could help evaluate to what extent the “early-call” protocol can help reduce workflow delays under different circumstances.

Discussions

The proposed handoff modeling resolved the primary concerns in detailed workflow modeling to understand the impact of human factors on workflow efficiency. In particular, the developed simulation platform has integrated communication and traveling activities into an interwoven workflow for revealing the impact of late communication on workflow delays. Such a simulation platform represents the detailed interactions among human, workspace, and tasks, and serves as a powerful tool to simulate human and task-related uncertainties. By using the developed simulation platform, users will be able to predict changes in task sequences and efficiency variations in a workflow. The author envisions that the extensions of the developed simulation platform could 1) benefit the project manager to better assess potential delays and economic losses; 2) assist the project scheduler in updating the schedule accordingly based on the simulation results (i.e., find an optimal slot to insert new tasks); 3) help examine optimal communication protocols to ensure efficient communication between project participants (i.e., supervisors, workers); and 4) help develop better training programs that prepare workers with sufficient knowledge for scheduled tasks.

The developed simulation platform could also be useful for outage control and other types of project schedule analysis where communications during handoffs between tasks cause main delays. For example, the developed handoff modeling platform could help simulate the communication between ATCs and pilots during air traffic controls to assess and predict the delays and accidents (i.e., runway incursion, LoS) in air traffic operations. Moreover, bridge inspection requires the cognitive capabilities of an engineer to recognize structure defects and describe in detail to ensure that the management team has a proper understanding of the bridge condition. Misunderstandings or misinterpretations of the inspection results could lead to the improper design of maintenance strategies during bridge maintenance. The developed platform could also serve to help estimate the potential failures of field inspection operations.

Conclusion

Precise estimations of workflow durations are critical to maintain the safety and efficiency of NPP outages. However, numerous uncertainties of tasks and human behaviors bring significant challenges to achieve precise estimations of workflow durations. However, identifying the list of vulnerable tasks in the as-planned schedule can guide the management team to allocate resources better during the planning phase of the outage. Such improved resource allocation can thus help to achieving resilient NPP outage control. According to the simulation results, task deviations and delays during handoffs of certain tasks play a significant role in affecting the overall duration of the workflow. The result also shows that the proposed handoff modeling can provide a reliable reference to improve the monitoring strategies in outage workflows.

The research findings indicate that the detailed interactions among tasks, individuals, and resources are significant concerns that cause delays during outages. Hence, reducing the time wasted and error rates caused by uncertainties (e.g., communication error, time for communication, travel activities) in the schedule maintenance workflows and handoff processes are critical to ensure the on-time completion of outages. The author used the developed simulation platform to 1) examine whether additional communication can help increase workers' familiarity with tasks, and 2) examine whether the early-call during handoff process could reduce delays (supervisor will call work team 15 min ahead of time, according to the as-planned schedule, to inform the work team that his/her successor task is about to finish).

This study explores the potential of implementing an automated communication system with proactive communication protocols to help reduce delays during outage workflows. An automated communication system was developed and examined that such a system could significantly reduce delays caused by redundant communications and avoid delays due to miscommunications. The author also modeled the "early-call" strategy to mitigate the risks of delays by shortening the handoff processes and providing additional supervision to critical tasks. The simulation results about the "early-call" strategy indicate the reduced delays in workflows compared with manual communication about task completions and random progress checking. All these simulation and communication data analysis results show the potential of proactively monitor and control the efficiency of the workflows in NPP outages through automation and simulation.

CHAPTER 6

CONCLUSION AND FUTURE RESEARCH

Summary of Research Contributions

CIS requires safe and effective O&M, which involves significant human efforts. The reliability of interpersonal communication processes during CIS O&M is the key for the assurance of safety and efficiency. Poor interpersonal communication behaviors during CIS O&M could induce delays and safety concerns. Previous studies fell short in providing quantitative representations of to formalize numerous categories of communication reliability issues during CIS O&M and assess the impacts on CIS O&M safety and efficiency. This study proposed a predictive control method for 1) identifying risky communication contexts and features, 2) using the identified risky communication contexts and features for predicting communication errors and CIS O&M risks, and 3) examining mitigation strategies to reduce the CIS O&M risks due to communication errors.

Precise estimation of CIS O&M workflow duration and reliable prognosis of CIS O&M risks are extremely important to maintain the safety and efficiency of CIS O&M. However, numerous task-related uncertainties and abnormal human behaviors become obstacles for effective and reliable CIS O&M risk prognostics. Such prognostics require excessive human efforts and resources for 1) discovering vulnerable sections of CIS O&M, and 2) resolving the identified risks to ensure CIS O&M safety and efficiency. Thus, identifying a list of vulnerable tasks with high uncertainties during the planning phase of CIS O&M can guide the management team to better allocate resources and improve CIS O&M resilience.

In the NPP outage case, the author first identified the risky communication contexts and features based on an extensive review of NPP accident reports and literature. Then the author uses a constraint-based BN model expert knowledge encoded for predicting communication errors and delays for given communication contexts and features. The author then proposed an agent-based simulation platform based on a typical NPP outage schedule. Simulation results indicate that the significance of different "early-call" strategies heavily depends on the task characteristics (e.g., number of links, location within the schedule). For example, applying "early-call" strategies on tasks with more links can reduce more delays. Such findings provide a basis for the management team of NPP outages to refine their existing communication protocols by better allocating the managing efforts on critical tasks.

In the air traffic control case, the author first identified the risky communication contexts and features based on an extensive review of air traffic control accident reports and literature. Then the author used a constraint-based BN model expert knowledge encoded for predicting communication errors and LoS for given communication contexts and features. The proposed method aims at supporting automatic communication error detection through 1) aircraft landing process modeling, 2) communication error classification, and 3) speech recognition for communication data analytics. Major findings show that the incorrectness of pilots' read-backs contributes to most LoS. The ATC should correct the in-correct read-backs from pilots to avoid LoS.

Limitations

The proposed method provides the potential for identifying risky communication contexts and features based on literature and accident reports. Using this method, the author would be able to identify these risky communication contexts and features while processing the audio communication data and use the identified contexts and features for predicting communication errors through Bayesian Network modeling. The simulation model then allows examining potential mitigation strategies in reducing the impacts of communication errors on CIS O&M safety and productivity. The proposed method has been validated using two cases. However, as the contribution of the proposed method would be methodological, limitations still exist and require more data collection efforts and data analysis for further validating the proposed method in more complex CIS O&M scenarios.

Limitations of the proposed method still exist as the communication behaviors of CIS O&M participants vary in different CIS O&M scenarios. How to implement the proposed method in other CIS O&M scenarios is still challenging. For example, the author only identified a list of risky communication contexts and features in the context of NPP outage and air traffic control environments. These identified risky communication contexts and features might not be the same in other CIS O&M scenarios (e.g., building construction projects). A systematic summarization of risky linguistic and grammatical features in numerous CIS O&M scenarios for predicting communication errors is necessary but challenging. Some studies have examined automatic text processing methods for extracting causal factors and features of risky events and from a huge amount of accident reports (Chokor et al. 2016; Tixier et al. 2016). Other studies examined automatic speech recognition methods detecting communication errors (Johnson et al. 2013; Kopald et al. 2013; Krajewski et al. 2008). These studies could support the automatic summarization of risky linguistic and grammatical features from communication data collected in various CIS O&M scenarios.

On the other hand, the communication behaviors modeled in this dissertation only consider the two-way communications between CIS O&M participants. For example, the communication behaviors in the NPP outage case only consider the two-way communications between the supervisor and the workers. However, communication behaviors may vary under different CIS O&M scenarios. For example, informal communications through phone calls or text messages may be used among workers in typical construction projects to exchange information. Such communication may not have a specific protocol to specify 1) when to call, and 2) who to call. It is necessary to consider a formal method to model various communication behaviors in different contexts. However, establishing formalized representations of communication behaviors for modeling such communication behaviors within and across teams in various CIS O&M contexts is challenging. Some studies have synthesized the communication behaviors in different CIS O&M scenarios (Abdel-Monem and Hegazy 2013; Lee and Doran 2017; Liao et al. 2014b; Pan and Bolton 2015). The communication behaviors synthesized could help to form a basis for establishing formalized representations of communication behavior.

Besides, different CIS O&M workflows may have different requirements and face various challenges. In this dissertation, one of the impacts of communication errors on CIS O&M safety and efficiency is delays. Specifically, NPP outages are extremely sensitive to such delays, which could result in huge financial costs. However, the minute-level delays might not be sensitive to building construction projects compare to NPP outages (e.g., building construction projects may only concern about delays in months). It is thus necessary to consider the impacts of communication errors on different CIS O&M workflows by tailoring the proposed method. Some studies have studies the impacts of communication behaviors on the safety and efficiency of various CIS O&M scenarios (Lee and Doran 2017; Sambasivan and Soon 2007; Skaltsas et al. 2013). These studies could help to establish a comprehensive characterization of the impacts of communication errors in various CIS O&M scenarios. Such a comprehensive characterization could then help future modeling efforts for examining the impacts of communication errors on CIS O&M safety and efficiency.

Future Research Directions

Communication issue during CIS O&M is only one aspect of the human reliability challenge that will affect CIS O&M safety and efficiency. Human reliability contains three aspects of systems reliability that collectively consider a balance between time for processes and the time limits posed by the development of natural or engineering processes. Specifically, the three aspects of systems reliability are 1) Human-Physical reliability (HP), 2) Human-Human reliability (HH), and 3) Human-Cyber reliability (HC). While this dissertation aims at addressing the challenges in the HH aspect (communication) of human reliability issues in CIS O&M, the other two human reliability aspects need to be addressed accordingly as well. These three human-related reliability issues involve interwoven interactions between human, cyber, and physical elements of CIS O&M, which pose challenges to state-of-the-art data analytics techniques and mathematical models.

The interwoven interactions between workers and teams during cognition, decision-making, and task execution activities are elements that form the CIS O&M processes. When these elements of CIS O&M processes demand more time and result in processes that exceed the time needed for preventing specific incidents or accidents, the systems enter into an unsafe state. A better understanding of these human-cyber-physical interactions is critical for reducing the impacts of uncertain human factors on the safety and efficiency of CIS O&M (Boring 2009, 2010; Shi et al. 2019). Future directions of this dissertation will focus on addressing the challenges in the HP and HC aspects of human reliability to ensure CIS O&M safety and efficiency.

Future Research Directions (I) – Human-Physical Reliability for Ensuring CIS O&M Safety and Efficiency

Human-physical (HP) reliability refers to human reliability during the engagement with the physical environment of CIS O&M. Human cognitive and task execution behaviors are critical to ensure the safety and efficiency of CIS O&M; inappropriate behaviors could lead to operation errors and result in severe damage to the physical infrastructure (e.g., NPPs) (French et al. 2011). This section summarizes three aspects of HP-reliability issues based on the three-stage process (Patterson et al. 2009). Specifically, such three-stage process includes 1) cognition – perceptions of human individuals when collecting data and information from physical environments; 2) decision-making – choice selections of human individuals based on the available information about the states of tasks and environments, and the knowledge and experiences of human individuals; 3) physical process execution – actions carried out by human individuals on physical environments.

The human cognition stage of field workers involves the perception of the raw data from the physical environment (i.e., workspace), such as the physical objects (e.g., valve, pumps, wires, machinery), and workspace layout (Alvarenga and e Melo 2019). Existing studies focused on 1) effective workspace layout design, 2) process modeling of workflows 3) object detection using computer vision techniques, and 4) leveraging human senses for ensuring the safety and efficiency of CIS O&M (AbouRizk and Hajjar 2011; Luo et al.

2019; Zhang et al. 2016a). These studies captured field operation anomalies (e.g., abnormal human cognitive and task execution behaviors, the wrong object moving patterns) by checking the compliance of the specified operation procedures. Besides, studies on human senses (e.g., visual, audio, smell) identified the root cause of fault, such as human olfactory, auditory, and tactile senses (e.g., the smell of the leaking gas, sounds of equipment vibrations) (Purarjomandlangrudi and Nourbakhsh 2013). However, few studies provide quantitative assessments of the impacts of human cognition on HP reliability during CIS O&M.

The decision-making stage of field workers often can be knowledge-based and related to specific operation goals. Some studies developed process models to investigate the mechanisms behind the field workers' decision-making processes during extreme events (Lu and Sy 2009). Other studies focused on enhancing the field workers' knowledge and skills by utilizing advanced technologies to improve the training methods (Weick 1989). Some more recent studies examined the use of electroencephalogram (EEG) to investigate the influence of information perception on human individual's decision making (Cha and Lee 2019). Nevertheless, how to predict the decision-making mechanisms of field workers in the dynamic operation process is challenging (Alvarenga and e Melo 2019).

The execution stage of field workers involves the actions applied to the physical environment to ensure the safety and efficiency of the CIS O&M (Kontogiannis and Malakis 2009). Such execution reliability could greatly affect the physical environment. For example, the large number of similar instruments and devices densely located in the mechanical rooms of NPPs raise significant difficulties for field workers to identify the correct instruments to operate (Preischl and Hellmich 2013, 2016). Some researchers adopted augmented reality that provides operation procedures and animation information to improve the human operation reliability in dynamic changing workspaces, such as mechanical rooms of NPPs (Palmarini et al. 2018). However, field workers still make mistakes while conducting schedule tasks and raise elevated risks.

Overall, existing studies conducted extensive explorations of many aspects of the reliability of human individuals. However, limited studies provided 1) quantitatively assessment on the impacts of HP reliability (e.g., cognition, decision-making, and execution) on the CIS O&M safety and efficiency in the changing environments and facilities; 2) a systematic characterization of smell, taste, self-motion, temperature, and humidity sensing performance of workers and the impacts of anomalous human sense performance on the CIS O&M safety and efficiency in diverse environments encountered in civil engineering projects, and 3) a systematic approach based on historical training data with full environmental condition records for better designing personalized operator training for mitigating the risks of HP reliability in highly demanding tasks in working environments that change rapidly and influence team performance.

Future studies should focus on conducting an extensive review of existing cognitive analyses and informal interviews with domain experts for synthesizing numerous categories of human errors during CIS O&M. Besides, future studies should aim to establish formal representations to create mathematical models of interwoven relationships in the human-cyber-physical systems for examining the impacts of human behaviors on CIS O&M safety and efficiency under various CIS O&M scenarios. Moreover, future studies should collect more human behavior data to study the performance of teams of human individuals in various decision contexts.

Future Research Directions (II) – Human-Cyber Reliability for Ensuring CIS O&M Safety and Efficiency

Deriving information from a tremendous amount of data to support decision-making is critical to ensure the safety and efficiency of CIS O&M. Human-Cyber (HC) reliability refers to the reliability issues of the data analysis processes with a human in the loop during CIS O&M. Previous data analysis reliability studies capture how various factors influence the quality of information derived from the data. Such data analysis usually involves sequential three stages that gradually derive various information from raw data sources (e.g., indicators on the digital information displays, images, historical records): 1) data pre-processing (Lopes et al. 2017), 2) data processing (Sun et al. 2019a), and 3) data interpretation (Reiman and Oedewald 2006; Sun et al. 2019b).

With human-in-the-loop of data analysis processes, inappropriate selections of algorithms and parameters (e.g., poor subsampling methods) during the data pre-processing and data processing stages could result in missing critical data (Chen et al. 2017). Besides, interpreting the data into information for decision-making may also heavily subject to domain knowledge and experience. How to better understand the impacts of human cognitive behaviors in the data analysis processes on HC reliability is thus necessary to ensure CIS O&M safety and efficiency.

The HC reliability issues of control operators in typical control room operations involve the interactions with the data from digital information displays, such as the control objects (e.g., valves, pumps, water tank), indicators (e.g., temperature, pressure, coolant flow rate), and alarms (Alvarenga and e Melo 2019). Human errors occur frequently due to the high proximity of similar control instruments located closely on the digital control panel (Smidts et al. 1997). Besides, high repeatability of control actions while switching between multiple tasks creates obstacles for control operators to stay focus on the task (Braver et al. 2003; Goffaux et al. 2006; Sohn and Anderson 2001).

For example, control operators are required to execute a plant cool-down protocol in a Loss-of-coolant-accident (LOCA) event during NPP operations (Pettersson et al. 2009; Terrani et al. 2014). The control operators have to continuously monitor and maintain the reactor temperature and pressure of the reactor. Omitting in the temperature checking could occur and cause LOCA response failures. Previous studies focus on establishing contingency procedures and better training programs in responding to NPP accidents (Kaplan et al. 2013; Kim et al. 2010). However, limited studies examined the impacts of such omission errors on NPP safety and efficiency quantitatively.

Information visualization during the control process during CIS O&M is also critical and affects the cognitive behaviors of control operators. Previous cognition studies on information visualization research focus on improving the delivery of information to information or data users in a way that minimizes human individuals' mental workloads and misunderstandings. Some studies focused on designing a better information visualization system, which enables human individuals to perceive information quicker and more precisely (Hogenboom et al. 2020; Jia et al. 2013). Recent efforts in the NPP industry focus on the implementation of advanced NPP outage control centers to enable real-time work status updates (Zhang et al. 2017a). Compare with the paper-based and computer-based procedure that widely used in the current NPP control, the automatic work packages are effective in exchanging information on plant conditions, resource status, and user progress (Rashdan et al. 2015; Rashdan and Agarwal 2016;

Rashdan and Oxstrand 2017). However, few studies provide a quantitative assessment of the impacts of excessive amounts of digital information delivered on such advanced control tools on HC reliability during CIS O&M.

Future studies should focus on 1) conducting data collections of human-in-the-loop simulations comprehending such processes in highly uncertain CIS O&M scenarios, 2) developing human-in-the-loop data analysis workflows for examining data analysis reliability due to data analysts' behaviors (e.g., algorithm selection, parameter setup), and 3) developing and testing data analytic methods for encoding physics/experiences from human knowledge and data with field observations to improve data analysis reliability.

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