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Automatic Imagery Data Analysis for Proactive Computer-Based Workflow Management during Nuclear Power Plant Outages

Reactor Concepts Research Development and Demonstration (RDRD&D)

Pingbo Tang

Arizona State University

Collaborators

The Ohio State University

Alison Hahn, Federal POC

Shawn St. Germain, Technical POC

NEUP Nuclear Energy University Programs

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Final Report:

Automatic Imagery Data Analysis for Proactive Computer-Based Workflow Management during Nuclear Power Plant Outages

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By

Principal Investigator:	Dr. Pingbo Tang, Arizona State University
Co-Principal Investigator:	Dr. Alper Yilmaz, The Ohio State University
Co-Principal Investigator:	Dr. Nancy Cooke, Arizona State University
Collaborator:	Dr. Ronald Laurids Boring, Idaho National Laboratory
Collaborator:	Dr. Allan Chasey, Arizona State University
Collaborator:	Ms. Lisa Hogle, Arizona State University
Collaborator:	Mr. Timothy Vaughn, Arizona Public Service Company
Collaborator:	Mr. Samuel Jones, Arizona Public Service Company
DOE Technical Contact:	Mr. Shawn W. St. Germain, Idaho National Laboratory
Postdoctoral Researcher:	Dr. Ashish Gupta, The Ohio State University
Graduate Students:	Mr. Zhe Sun, Mr. Jiawei Chen, Ms. Yanyu Wang, Ms. Verica Buchanan, and Ms. Saliha Akca-Hobbins, Arizona State University Mr. Nima Ajam Gard, The Ohio State University

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Executive Summary

This report is being submitted for the task "Final Report" of DOE NEUP Project 15-8121 "Automatic Imagery Data Analysis for Proactive Computer-Based Workflow Management during Nuclear Power Plant Outages." Typical nuclear power plant (NPP) outages always involve thousands of maintenance and refueling activities and a large number of workers in limited workspaces, while having tight schedules and zero-tolerance for accidents. During an outage, thousands of workers will be working in various workspaces across the NPP. High outage costs and expensive delays (approximately 1.5 million dollars of loss per day of delay) in NPP maintenance demand tight outage schedules. In packed workspaces, an automatic system that monitors human behaviors in real-time and provides insights about current and pending schedule deviations from the plan is critical for ensuring: 1) effective collaboration among workers and worker teams from different trades; 2) less waste of time and resources due to the lack of situational awareness; and 3) proactive outage project control.

The overall goal of this project is to test the hypothesis that real-time imagery-based object tracking and spatial analysis, as well as human behavior modeling of outage participants, will significantly improve the efficiency of outage control while lowering the rates of accidents and incidents. Three objectives of this project are: 1) Establish real-time object tracking and spatiotemporal analysis methods that automatically assess the productivity of field activities and detect anomalous spatiotemporal relationships among activities that cause inefficiencies and risks; 2) Establish real-time human tracking and human factor modeling methods for automatically diagnosing unexpected actions of and interactions between outage participants, those which cause inefficient collaborations between Advanced Outage Control Center (AOCC), satellite outage centers, NPP workers, and maintenance service providers; and 3) Test the proposed automated object tracking, human behavior modeling, and spatiotemporal analysis methods in outage control case studies in order to characterize the effectiveness of automated imagery-data-driven methods in proactively improving the efficiency and safety of workflows in outage coordination and risk management.

Recent studies of detailed human behavior monitoring on construction sites have examined the potential of applying advanced computer vision algorithms in detecting and tracking anomalous workers (i.e., workers who do not wear hard hats or safety vests) for ensuring job site safety. Some studies of human factor studies revealed the importance of modeling detailed interactions between individuals within and across teams in better understanding the impact of human in proactive project control. Other studies in the construction domain have developed computational simulation frameworks that formalize detailed spatiotemporal interactions between tasks in order to simulate the impacts of individual tasks on the performance of workflows. While integrated analyses that combine human factor assessment, as well as image processing and simulation, are in demand for effective decision-making, limited studies have examined the potential of such integrated analyses in NPP outage control. This research project has examined an automatic outage monitoring and control system that integrates human factor analysis, computer vision techniques, and simulation methods in order to enable engineers to better understand the interactions between humans, resources, and workflows during outage processes. The project aims at providing NPP maintenance agencies insights into more efficient use of limited resources in extending the life of a nuclear plant, as well as reducing waste while ensuring sufficient generation of electricity. This study is significant for the safety of nuclear plants, sustainable electricity generation for livable communities, and cost savings for maintaining electricity infrastructures in the United States.

Contents

1 Introduction

In the United States, many nuclear power plants (NPPs) were built forty years ago [1], and they require regular maintenance. NPPs typically shutdown every eighteen or twenty-four months to refuel the reactor and execute repairs. Such processes are called "NPP outages." Such outages are among the most challenging projects because they involve a large number of maintenance and repair activities, with a busy schedule and zero-tolerance for accidents [2]. Also, these outages may require a significant supplemental workforce that consists of hundreds of contract personnel who are not permanent employees of the NPP and who are unfamiliar with the workspaces and procedures. The involvement of such contract personnel in outages significantly increases the workload of permanent employees of NPPs, who need to train, guide, monitor, and coordinate the work done by contract personnel, in addition to their regular work responsibilities. Interactions between permanent and contract personnel with diverse backgrounds and experiences also significantly increase the complexity of communication and information flows throughout outage procedures, thus raising the error rates and delays in field operations [3]–[6].

Human factors play critical roles in busy workspaces that have high safety and productivity requirements. Improper design of site layouts and workspaces can force the workers to waste time on acquiring materials and tools for completing their work. Moreover, cluttered site conditions and occlusions can influence the capabilities of workers in recognizing risks on job sites. When workers work simultaneously across multiple areas of a job site, their activities can rely on each other, or compete for limited workspaces and resources. Human-related issues, such as miscommunications between workers in crowded job sites, can cause unnecessary waiting of workers for collaboration activities or resources, or unexpected sharing of spaces and resources, all of which affect the productivity of scheduled tasks. Comprehending and diagnosing human-factor issues in outage processes and workspaces is thus crucial for proactive control of outage operations through timely adjustment of resource allocations, and for improving the design of outage workspaces and processes in order to provide long-term solutions. How to improve the situational awareness of project managers about the outage progress through state-of-the-art sensing technology and computational models becomes vital.

Effective outage control requires an effective exchange of workflow information between the "virtual" and "physical" worlds that represent as-planned outage workflows and actual real-time conditions of outage workflows, respectively. As shown in Figure 1, outage control requires updates of the virtual world on computers, based on field data from the physical world. Such updates lead to better situational awareness by outage managers for effective coordination of field operations. In order to achieve timely situational awareness of the outage progress and the impacts of human factors on outage performance, this research project investigators have developed an automatic video surveillance system that uses state-of-the-art computer vision algorithms. The developed system aims at monitoring workers' behaviors in an indoor workspace, captures unusual poses identified by the human factor studies, and sends out timely alerts for schedule updating and decision support. Many IT-based techniques have been used to generate real-time data for monitoring the location of construction entities across time, such as Radio Frequency Identification (RFID), Global Positioning Systems (GPS) and Ultra-Wideband (UWB). However, all these sensors require the installation of a sensor on each worker. This requirement hinders the application of these techniques in large-scale, congested construction sites where many entities need to be tagged. Computer vision-based tracking requires no tags on entities and can readily retrieve time, location, and action information of construction workers.

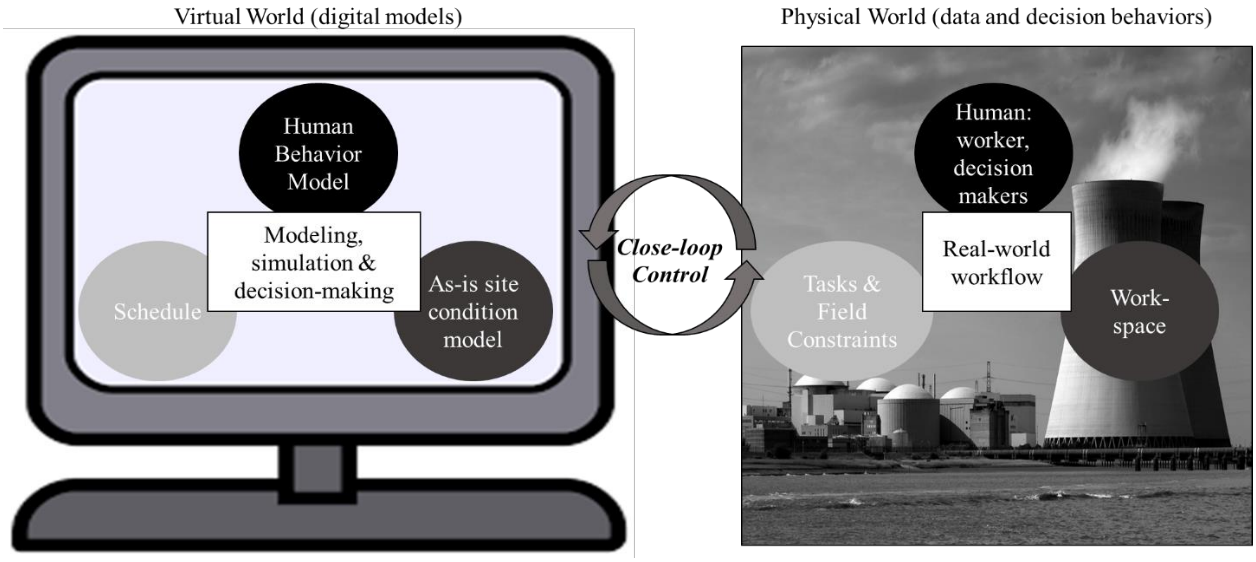

Figure 1. The overall framework of the project

In this research, the project investigators proposed a deep-learning-based, multi-worker tracking approach for the monitoring and analysis of waiting times of workers in nuclear power plants. How to assess the impacts of detected anomalous human behaviors on construction productivity is then necessary for precisely predicting and controlling the duration of outage workflows. The proposed human behavior monitoring system aims at not only capturing anomalous human behaviors, but also using knowledge about anomalous behaviors that deviate from as-planned behaviors in developing computation simulations that help diagnose those anomalies.

Modeling and simulating the uncertainties in NPP outages can help resolve the difficulties of assessing the impacts of uncertain factors (e.g., human behaviors) on outage productivities. Such modeling and simulation require detailed spatiotemporal information for quantitative assessment of the impact of field activities on field workflows. Unfortunately, current approaches to outage control rely heavily on tedious and error-prone manual inspections, which produce less-detailed field information and result in additional difficulties and higher costs in workflow monitoring. Some researchers tried to extract spatiotemporal interactions within workflows from historical data and documents. Unfortunately, most historical documents of NPP outages did not record detailed handoff (task transition) processes between tasks, and such human factors significantly influence handoff efficiency and workflow delays. As a result, people from both industry and the academy do not yet have a comprehensive understanding of how human factors influence tasks and handoffs in outages.

The simulation and modeling of the uncertainties and task handoffs in NPP outages are challenging considering the highly uncertain human behaviors (e.g., communications) during task handoffs that do not have formal representations in the scheduling methodology of project management. Uncertainties such as human communications during task handoffs and task-related anomalies are the main concerns. In this project, the project investigators examined methods for representing those human behaviors in computational simulations and developed a computational simulation platform that can accurately represent the impacts of human behaviors on outage workflow efficiency.

Overall, the developed simulation platform integrates the knowledge from past outages, human errors studied by human factor analyses, and anomalies captured by computer vision algorithms. The platform consists of two modules: the first is a human behavior module and the second is a workflow module. The human behavior modeling and analysis module developed by the project investigators brings insights about possible human errors in NPP outages and the impacts of the studied human behaviors on workflow performance. This module also uses the detected anomalous human behaviors (waiting, long and frequent communications) as inputs to the developed simulation model, as detailed in section 5.5.

The workflow module uses the documented outage schedule and inspection reports (*the physical world*) to model detailed spatiotemporal interactions between tasks in outage workflows in the simulation platform (*the virtual world*). Then, the task durations and human actions derived by the computer vision algorithms serve as inputs for the workflow module to profile the uncertainties within the workflows, including task durations and spatiotemporal interactions between two sequential tasks during handoffs. The human and workflow modules collectively support the development of a simulation platform that can simulate and assess the impacts of human behaviors and task anomalies on the productivity of various field workflows during an outage.

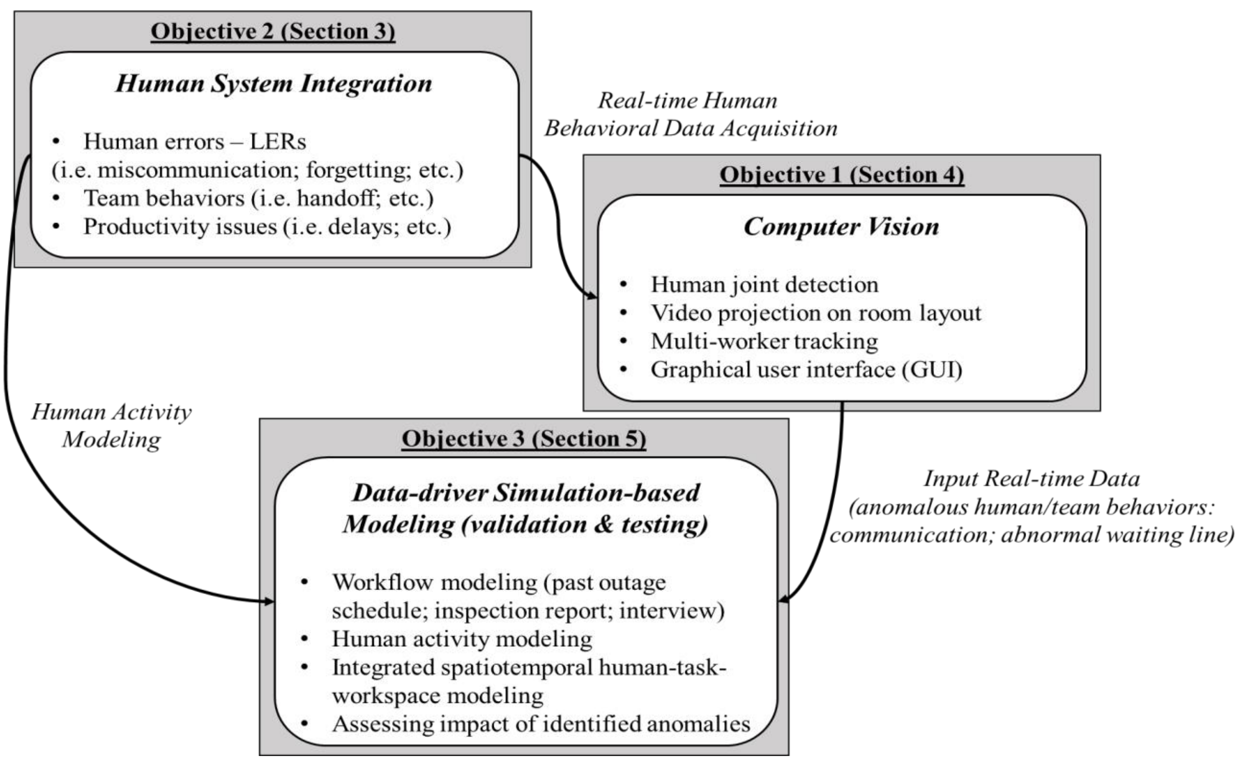

Figure 2. A detailed explanation of the framework

The project team used the developed computer vision algorithms and simulation platform to test the hypothesis that real-time, imagery-based object tracking and spatial analysis, as well as human behavior modeling of outage participants, will significantly improve the efficiency of outage control while lowering the rates of accidents and incidents. Figure 2 shows three specific objectives of this research and development project. As shown in Figure 2, the specific objectives of this research project include:

1) *Establish real-time object tracking and spatiotemporal analysis methods that automatically assess the productivity of field activities and detect anomalous spatiotemporal relationships among activities that cause inefficiencies and risks;*
2) *Establish real-time human tracking, spatiotemporal analysis methods, and human factor modeling methods for automatically diagnosing unexpected actions of and interactions between outage participants that cause inefficient collaborations between Advanced Outage Control Center (AOCC), satellite outage centers, NPP workers, and maintenance service providers;*
3) *Test the proposed automated object tracking, human behavior modeling, and spatiotemporal analysis methods in outage control case studies in order to characterize the effectiveness of automated imagery-data-driven methods in proactively improving the efficiency and safety of workflows in outage coordination and risk management.*

Sections 3 to 5 of this report describe research work relevant to the three objectives presented above. Overall, the developed automatic system in this project, which integrates human factor analysis, computer vision techniques, and simulation platform, is intended to assist engineers in better understanding the interactions between human, resource, and workflow that influence the productivity of outage processes. The principal disciplines involved in the project include: 1) human systems integration (section 3); 2) computer vision (section 4); and 3) computing for construction engineering and management (section 5). The impacts on the development of these three disciplines involved in the project include:

1) For the discipline of human systems engineering, this project is advancing the application of cognitive science and team behaviors in the domain of construction management. This project applies the theory of "team recognition" to help outage control center personnel in identifying problematic processes that cause difficulties for groups of workers to work together safely and efficiently. Additionally, the project integrates the synthesized findings of human factors in outage control to model detailed interactions between individuals within and across teams during NPP outages. The human modeling reveals how human issues (i.e., communication error) affect the outage control.
2) For the discipline of computer vision, this project advances the application of object tracking and action recognition in videos captured by cameras located in a workspace or task preparation space. The developed state-of-the-art computer vision algorithms help with monitoring anomalous human behaviors in workspaces during NPP outages.
3) For the discipline of construction engineering and management, this project further develops the theory of "safety design" and the theory of "lean construction." For the theory of "safety design," the project reviewed the literature about human factors that influence construction safety and synthesize knowledge about how to better design construction processes and job site layout to prevent workers from unsafe behaviors without having them go through tedious safety training. For the theory of "lean construction," this project synthesized sensor technologies that enable timely and detailed monitoring of the construction productivity and wasted time/resource/materials on job sites. Such synthesis is paving a path toward real-time efficiency diagnosis of construction processes and

workers as interconnected systems and mathematical modeling of "lean" practice that can proactively control waste in construction projects. Also, the project has developed a simulation platform based on the real outage workflow and the human interaction model and aimed at understanding the impact of human behaviors on outage workflows.

2 Literature review

In this project, the investigators synthesized the literature and tried to understand better the domain problems in NPP operation and maintenance (O&M), as well as the implementation issues of emerging technologies in helping improve the NPP O&M performance. Section 2.1 reviews details about the domain challenges in the current practice of NPP outage control. Section 2.2 focuses on summarizing research reports and published literature that examined various aspects of how human factors (i.e., handoff processes, communication errors, team cognition, and so on) influence field workflow performance. Section 2.3 focuses on synthesizing the literature and published open-source codes about real-time human detection and tracking technology for engineering management applications. The purpose is to better understand how computer vision could help monitor human behaviors in order to achieve proactive outage control. Section 2.4 focuses on summarizing existing literature involving uses of computational simulation techniques for predicting workflow failures, as well as the impact of human behaviors on workflow efficiency and safety in operation and management of civil infrastructures, such as NPPs.

2.1 NPP industries domain challenges

Managing NPP outages is difficult due to the large number of maintenance and refueling activities that need to be completed within a short period [3]. Coordinating hundreds of workers with various backgrounds also brings challenges to effective control of outages [7]. The variances of task durations and handoffs introduce a large number of uncertainties during the outage, which significantly increases the risks of delays [8]. Also, a significant portion of contract personnel involved during outages, who have limited knowledge and experiences in outage activities and environments, proves to be another concern. Also, the lack of familiarity with the outage decision contexts could also cause risks of miscommunications and errors in teamwork [9]. Effective and resilient outage control aims at reducing the duration of the tasks and handoffs, as well as the human error rates during handoffs, those errors which typically involve travel, communication, and unnecessary waiting of workers [10].

Furthermore, NPP outage projects are accelerated construction projects that operate under extremely tight schedules. Such schedules specify task durations with a 10-minutes accuracy, while variances of many tasks' durations could be longer than 10 minutes [11]. In this case, a better understanding of the detailed spatiotemporal interaction between tasks is critical for stabilizing the task sequences in leveled schedules and preventing abnormal schedule updates, both of which are often tricky for NPP outages [12]. Moreover, in packed schedules and workspaces, delays or mistakes often influence successor tasks and compromise the productivity and safety at large [13]. Being able to precisely predict and control uncertainties within the workflow can result in significant improvements in NPP outage performance regarding productivity and safety.

NPP outage performance relies on the communication and coordination among hundreds of outage participants within a complex organization and is thus hard to predict and control [14]. Thus the modeling and simulation of the coordination and communication processes during an outage is quite challenging.

The main challenges originate from the uncertainties about task durations and unpredictable events that trigger schedule updates, all of which often influence multiple outage participants and stakeholders. For instance, the approval of a work package due to an unexpected valve maintenance failure can involve multiple stakeholders in order to ensure safety [15]. More specifically, the process of executing a work package is as the following:

1) Workers need to initiate a new work request for replacing the broken valve;
2) A work package reviewer need to screen the work request;
3) A field planner and a scheduler need to work closely to create a work package and schedule additional tasks in the work package;
4) The supervisor needs to conduct a pre-implementation check once the work package has been created;
5) The supervisor will then need to hold a pre-job debrief to assign tasks to the worker teams;
6) The supervisor and the craftsmen need to measure and test the equipment, tools, and spare parts to get ready for the new work package;
7) The supervisor needs to issue the clearance to start the new work package;
8) The craftsmen will then perform work activities included in the new work package;
9) The supervisor needs to check the quality at the end of each particular section of the schedule (i.e., check the quality of the new valve when complete valve maintenance workflow) and to archive this work package.

Uncertainties within the nine-step process described above are difficult to represent using existing scheduling software tools. As a result, existing schedule tools hardly help to analyze the potential impacts of variances of task durations, human errors, and handoff processes; thus, analyzing such processes through advanced simulation techniques that can represent detailed information related to task executions becomes vital. In particular, communication between workers and the management team, the Outage Control Center (OCC) and supervisors, and supervisors and workers is a critical component for successful information exchanges. However, existing schedule software tools cannot integrate communication modeling into the schedule simulation to examine the impacts of communication errors on workflow efficiency.

One critical part of communication modeling is the representation of forms of communications that have pros and cons in different contexts. Three forms of communication modes can influence the efficiency of the coordination among multiple groups of engineers handing over their tasks. The researchers should model and analyze the impacts of these three forms of communication modes on field workflow performance. These communication modes are: 1) radio communications between people inside the containment; 2) telephone communications between people outside of the containment; and 3) face-to-face communications.

Out of the three forms of communication modes, face-to-face communication is the least preferred because it requires workers to leave their worksites, find the person to whom they need to communicate with, resolve the issues at hand, and then travel back to their worksites. Consequently, face-to-face communication is inefficient and results in significant work time loss. However, most workers and supervisors prefer face-to-face communication during handoffs because of the tradition of most engineering projects. In order to effectively and efficiently communicate during handoffs, craftsmen need to notify their supervisor at least an hour ahead of task completion. In turn, the supervisor will be able to notify OCC and initiate a “hot handoff.” A hot handoff allows workers for the successor tasks to statrt their preparation while the last task is on-going and will finish shortly. The workers can prepare tools and materials, get briefed, complete other necessary tasks (e.g., go through a Radiationn Protection Island, or RPI hereafter), travel to the worksite and arrive early so that they can immediately start the next task. In other words, as the current task is being finished by the previous work crew, the coming crew is being briefed. As soon as the old task is finished the new work crew starts working. Hence, there are generally no communication delays during “hot” handoffs.

The second least preferred communication mode is phone communication because workers and supervisors may need to locate a phone first before they can communicate with each other. Overall, radio communication is the fastest and preferred mode of communication. However, the variance in communication styles and effectiveness could still result in some delays. Modeling communication styles and various agencies and actions involved should consider numerous parameters for a reliable simulation in predicting how communication effects workflow performance and error rates. These parameters of communications include: 1) mode of communication (e.g., face-to-face, phone, and radio); 2) persons involved (e.g., OCC, supervisors, and workers); 3) familiarity with tasks (e.g., experienced/non-experienced workers); 4) types of handoffs (e.g., hot handoff); and 5) general communication style differences among personnel. Table 1 shows a synthesis of these communication parameters. More detailed discussions about these parameters are in subsection 2.2.

Another obstacle of useful handoff modeling is that current construction simulation tools have limited capability to precisely model the complicated spatiotemporal interactions between human factors, tasks, and resources so as to support accurate handoff modeling [16]. Currently, shutdown managers use a Gantt chart or PERT model to represent and analyze workflow schedules [10][11][17]. These workflow representations hardly represent how human behaviors influence task executions, as well as the complex interaction between different tasks and resources. Under the influence of handoffs, the task sequence in NPP outages is changing more frequently while widely used scheduling tools cannot effectively analyze task sequence updates and how uncertain human behaviors and field events influence task execution sequences. New simulation models are thus necessary to integrate representations of human behaviors (e.g., communications, mistakes in reporting, and executing tasks) and unexpected events into schedule analysis methods.

To model detailed spatiotemporal interactions between tasks during outages, the project investigators should consider the uncertainties of tasks’ durations, travels, and communications while modeling the detailed interactions. Unfortunately, current construction simulation software cannot model the uncertainties during handoffs--those caused by the changes in task sequences in “job-shop” schedules. The job-shop problem is a set of jobs on a set of machines, and each job has a specific operation order [18]. In dynamic job shop scheduling problems, jobs arrive continuously over time in the job shop manufacturing systems. Unknown task sequences in a job-shop workflow will lead to uncertainties about the traveling time and task preparation time because these processes are related to both the successor tasks and the predecessor tasks.

The knowledge gained through the review of outage documents and literature helped the project investigators understand better about the schedule updating challenges during NPP outages. On the other hand, a better understanding of these challenges motivated the project investigators to interview domain experts working for NPPs and request more specific information related to these challenges. Such information can help the project investigators to create advanced simulation models to address these challenges. The following sections sequentially present the findings from interviews with domain experts and outline the simulation model developed based on what the project investigators learned from these interviews, as well as the simulation results.

2.2 Human system integration

Modeling detailed interaction and communication between individuals is crucial for proactive outage control that reduces time waste and error rates in NPP workflows. This section focuses on summarizing research reports and published literature that examined various aspects of how human factors (i.e., handoff processes, communication errors, team cognition, and so on) influence field workflows. The focus is to synthesize the following elements: 1) background knowledge about handoff and communication analysis (subsection 2.2.1); 2) how various research studied communications of project participants from different perspectives (subsections 2.2.2, 2.2.3, 2.2.4, 2.2.5, 2.2.6, 2.2.7); and 3) how to model communication behaviors for predictive delay analysis of field workflows (subsection 2.2.8).

2.2.1 Background knowledge about handoff and communication analysis

Handoffs are transitional stages between tasks that usually involve travels between job sites, as well as communications between the management team and the workers in exchanging information on the status of the work [19]. Past studies examined two critical concepts related to the monitoring and control of handoffs between tasks: 1) handoff control; and 2) monitoring and responding to unexpected events (contingencies) during handoffs [20]. Effective handoff control aims at reducing the duration of and the error rates in handoffs that involve traveling, communication, and waiting behaviors of workers. Handoffs between tasks represent a large portion of overall activities in construction workflows and can significantly influence the project efficiency.

Furthermore, NPP outages often operate under tight schedules that have tasks that are tens of minutes long, so that the variances of handoff durations can be longer than the tasks themselves. In such cases, maintaining the as-planned task sequences is difficult [3]. Uncertainties during a typical NPP outage, such as frequent schedule updates due to contingencies (i.e., additional work caused by a valve found as broken during the work time), are also challenging for ensuring "resilient" outage control [15]. An effective method in helping to respond to contingencies and make appropriate decisions is thus critical. Moreover, in packed schedules and workspaces, delays or mistakes in handoffs could influence many tasks and compromise the productivity and safety at large. Being able to predict and control uncertainties within handoffs thus is critical for improving the efficiency of outages.

Handoff control and responding to contingencies necessarily influence each other. For example, complicated communications before multi-team approvals of one task consume most of the time of handoffs [19]. However, these communications about the work status reduce the risk of erroneously approving tasks without real-time field information. Such communication activities are necessary to help the management team diagnose anomalous field observations and proactively avoid accidents [21]. On the other hand, when the management team is seeking the best resolution of certain events, redundant resources (e.g., human, devices, and materials) and communications are necessary, but consequently make the durations of handoffs both lengthy and costly. Overall, resilient NPP outage control should both simultaneously increase the performance of handoffs and streamline processes of responding to contingencies through effectively managing human factors in field workflows.

Communication, as one of the most important processes during handoff, plays a significant role in affecting the information flow between individuals within and across groups during a typical outage. Previous studies about communication are mainly within the social science domain, and several parameters of communication have been extensively studied by social scientists. The following subsections synthesize those studies along two dimensions: 1) communication network patterns; and 2) characterization of communication links. Table 1 presents a synthesis of parameters of communication along these two dimensions, and list the subsections that provide a detailed review of the literature that discuss the parameters along these two dimensions.

Table 1. Parameters of communications studied in the past studies

Aspects of Communication	Properties	Example Values
Communication Network Patterns (Subsection 2.2.2, 2.2.3, and 2.2.4)	Communication network structure formed by nodes and links	Circle-pattern; Chain-pattern; Wheel-pattern; Y-pattern
	Multi-level indicators of communication complexity	Complexity levels of communications related to simple or complex tasks at different levels of engineering decision making (Abstraction Hierarchy Level (AHL) and Engineering Decision Level (EDL)
	Team-level indicators of communication patterns	Communication Measures (i.e., content; flow; timing)
Characterization of Links (Subsection 0, 0, and (1))	Communication channels	Face-to-face communication; radio device; mobile communication devices; social media; and so on.
	Timing and frequency of communication	Every 15 min; 15 min before the completion of the predecessor task; and so on.
	Ownership and accessibility of the links	Point-to-point link; Multipoint link; Broadcast link; and so on.
	Standardized language in communication	Standardized symbols and language for communication

2.2.2 Communication network patterns

Communication pattern is the structure of flows within an organization in the form of a circle, chain, wheel, or Y patterns that consists of at least two nodes and links (see Figure 3) [22]. Nodes in communication patterns are either a redistribution point or a communication endpoint [23]. Links in the communication patterns connect nodes used as a media for exchanging information [24]. For each communication pattern, positions at the center of the structure may hold a different degree of centralization. Some researchers have mentioned that with a high and localized centrality pattern, the organization will evolve more quickly and become more stable in its performance, and thus fewer mistakes during operations errors will occur due to miscommunication [22]. However, other researchers have found that the centralization of team communication will have negative impacts on its creativity [25]. With the number of team members in the inter-team communication network increases, the creative performance of the team will drop [26].

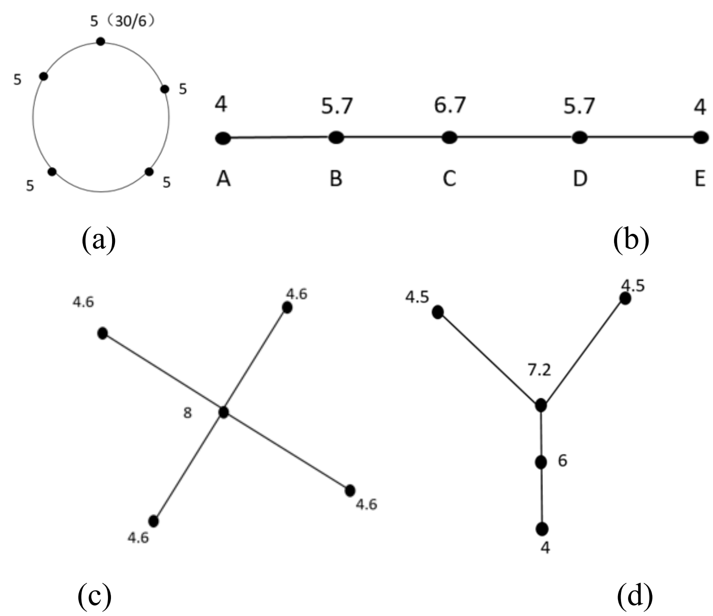

Figure 3. Communication Patterns in Task-Oriented Groups (Alex Bavelas, 1950)

(a) Circle-pattern; (b) Chain-pattern; (c) Wheel-pattern; (d) Y-pattern

Previous literature has determined methods to analyze communication patterns [23]. This research, however, reveals that people should first have a basic evaluation of the capability of a communication network in terms of fewer miscommunications. Specifically, people should know the sources of different types of information, and the communication options available when engineers and stakeholders are discussing and solving problems. The goal is to deliver the right information to the right people at the right time for timely and effective problem-solving.

2.2.3 Multi-level indicators of communication complexity

The complexity of communications not only refers to the number of hierarchy levels of a communication network but also indicates the complex levels of knowledge or information being delivered in the communication network [22]. Previous studies examined methods for measuring and improving the performance of communications during field coordination of workflows. The abstraction hierarchy level (AHL) and engineering decision level (EDL) in communication has been defined as measures to identify communication quality [27]. The conclusions indicate that the higher the abstraction level of communications, the lower the operators' performance will be, and the engineering decision level shows a similar relationship with the owner's performance. The abstraction hierarchy level has been divided into four subgroups, which are the component function level (CF), the system function level (SF), the process function level (PF), and the abstraction function level (AF) [28]. Since each level has a unique complexity in terms of content and a specific requirement, AF is the highest level due to the highest complexity among the abstraction hierarchy level, and CF is the lowest (the most straightforward).

As stated by Kim in [27] on page 3: "The abstraction hierarchy level (AHL) describes the levels of knowledge or information related to the problem space that should be considered to perform a response action described in procedures." Thus, different AHL may include different response actions based on different considerations. For example, the component functional level (CF) includes response actions, which can be performed with considerations of the function or status of a single component. System function level (SF) includes response actions that can be performed with considerations of the functions or status of more than two components. Process function level (PF) includes response actions that can be performed with considerations of the functions or status of more than two systems, and the abstraction function level (AF) includes response actions that can be performed with considerations of the functions or status of more than two processes.

Different from AHL, "An engineering decision level (EDL) describes the level of cognitive resources that are required to establish the decision criteria for response actions described in procedures" as stated in [27]. Considering the communication quality, a lower EDL makes it easier for the listener to have a better understanding of the information. On the other hand, a higher EDL may lead to a situation where there will have no criterion for decision making due to the high level of cognitive resource.

2.2.4 Team-level indicators of communication patterns

A team is a united but interdependent group of individuals (human or synthetic) with differing backgrounds, who plan, decide, perceive, design, solve problems, and act as an integrated system [29]. Measuring team communication processes is crucial to ensure good team performance during NPP outages [30]. Some previous studies investigated team-level indicators of communication patterns, called "communication measures," to quantify certain aspects of communications across teams of collaborators. Cooke [31] stated that "Teams perform cognitive activities such as making decisions and assessing situations as a unit." Whereas, team cognition is more reliant on the knowledge and skills of individuals who form the teams. Dozens of coordinating components are included in an existing team; however, communication measures at team-level are sometimes unstructured [32].

For communication analysis measure, Cooke et.al. have defined two types of measure types as shown as Table 2: 1) static and 2) dynamic measures.

Table 2. Classification of communication measures

Category	Content	Flow	Timing
Static	Avg. # of words, Latent Semantic Analysis, Communication Density	Following behavior (Dominance)	Avg. time of the following the behavior
Dynamic	Semantic, correlations, Latent Semantic Analysis Lag Coherence	Chain Master, Procedural Networks (PRONET), Transition analysis	Communication timing stability

Communication data analyses after the data collection have significant impact on the generation of communication measures for characterizing various team communication processes. The communication data analyses for dynamic and static measures are different. Dynamic measures require a summary analysis, which collapses communication across a relatively large interval of time in order to acquire average measures for the analyzed time period. The assumption in summary analysis is that a sequence of communication events is mostly random, such that the frequency, mean, or variability is the best estimate of communication behavior. The static data requires pattern analysis, which examines how communication pattern varies over time within a particular communication network.

2.2.5 Communication links

A communication link implements the communication channels and connects at least two nodes within the communication network [24]. Several types of links exist in the communication network, depending on the channels of communication and communication timings and frequency. For example, links can be in the forms/types of point-to-point, broadcast, or point-to-multipoint. A point-to-point link is a dedicated link that connects exactly two nodes in a communication network. A broadcast link connects two or more nodes in networks and supports a broadcast transmission where one node can transmit so that all other nodes can receive the same transmission. A point-to-multipoint link provides a type of communication where a distinct type of one-to-many connection provides multiple paths from a single location to multiple locations [33].

Also, communication links can have properties of the ownership and the accessibility of the link. A private link is a one that is either owned by a specific entity or one that is only accessible by a specific entity; however, a public link is a link that uses the public switched telephone network or other public utility or entity to provide the link and which may also be accessible by anyone. A specific entity or an individual can either own a private link or the access authority to a specific link. On the other hand, a public link uses the public switched telephone network or other public utility (or entity) to support communications. Public links are accessible to anyone within the network. Specifically, four types of link are determined according to the direction of the public links, including uplink, downlink, the forward link and reverse link (the return channel).

2.2.6 Communication channels

Communication channels are also part of the characters of the links in a communication network and are crucial for communication pattern analyses. Communication channels usually refer to either a physical transmission medium, such as a wire, or to a logical connection over a multiplexed medium, such as a radio channel. Different channel options, such as face-to-face, broadcast media, mobile, electronic, or written documents, are very commonly used in the patterns of communications [33]. All these channels are important within communication networks for handling different situations and related communication needs. For example, a face-to-face channel is more suitable for complex or emotionally charged messages; broadcast media can be used when serving the mass audience. Mobile communication channels work well for individual or small groups, while electronic communication channels, such as the internet, email, and social media, are commonly used for one-on-one, group, or mass communications. Moreover, measuring macro cognition is now a common area for researchers to measure team performance [31]. Four types of data are collected to measure the macro cognition in the past field works: audio, chat, email, and logged communication events.

(1) Audio data are records of verbal communications. The dimensions of the data consist of communication content (what was said), communication timing (who was talking and for how long) and sequential flow (who talks to whom or what communication events follow another).

(2) The chat communications consist of sequences of typed messages sent by team members. Two dimensions of data are collected: 1) the communication content and 2) message flow in the chat communications.

(3) As for using email to measure the macro cognition of teams, the message contents and message flows (who is sending, when, to whom, and when opened) are in the form of email-based communications.

(4) Logged communication event means that the log of specific events. The researchers used a technique in which trained observers monitor the communications for specific events by specific team members and the timestamp of the occurrence of events. Such communication monitoring captures a combination of communication content and information flow.

2.2.7 Standard language used in communication for effective event handling

Based on the reviewed literature, several communication techniques to improve the efficiency of response to unexpected events have been studied in the past. One communication technique is to establish standardized symbols and/or words of a natural language used by agents within the communication network. Such standardized communication language can help agents who are familiar with these symbols and words better understand each other so that rates of communication errors decrease. In other words, when an unexpected event happens, communication between inter-group agents will go through the entire network in the form of standardized symbols and/or words for more transparent and efficient communications [34].

Another communication technique is to create communication models that capture how backgrounds of communication participants influence the communication performance and then use such models to guide systematic improvement of communication systems and personnel. Some researchers found that human perception of their roles and their own experience will have a high impact on unexpected event identification and thus will influence communication negatively [35]. In short, a clear perception of their roles and some basic training will help participants of the communication improve the performance of an existing communication network.

2.2.8 Modeling the impacts of communications on workflow performance

Based on communication network analysis research, some researchers examined the impacts of communication behaviors of multiple groups of people on workflow performance, such as delays, stoppages of workflows, and collaboration failure rates. Complicated communications between all these organizational units are necessary for safety but will cause possible time waste [5]. For example, the OCC needs to have 30-minute meetings up to every three hours to know the as-is status of the outage progress and performance [36].

Other than communication errors, Bolton mentioned in his paper that erroneous human behavior is the primary factor in the failure of complex, safety-critical systems. An error-checking model has been created to be incorporated into larger formal system models automatically so that safety properties can be formally verified with a model checker [37]. As mentioned in [20], human-automation interaction (HAI) plays a significant role in the operation of safety-critical systems

[20]. Considering human nature, even though operation protocol does exist to make sure that an operator needs to follow to eliminate safety problems, the human operator could end up not precisely following the normative procedures. Hence, erroneous human behavior has always been a vital cause of operational failures.

Considering the checking process, three main parts are included in the framework shown in Figure 4 as 1) human error prediction, 2) translation, and 3) model checking [28]. Within the human error prediction part, the erroneous human behavior patterns can be determined by checking the normative human behavior model and the human-system interface model. As for the translation process, a single model will be created by combining the human-system interface model and the normative human behavior model that is readable for the model checker. In the last part, the verification process will examine the system properties (i.e., task relationship; a communication network; system reliability; and so on) from the specification and give reasonable verification results. Such formal modeling process has a broad usage in analyzing the impacts of human errors to the system and give a better explanation on how these errors will become a potential factor that leads to a system failure, such as delays, schedule changes, and reworks in NPP outages.

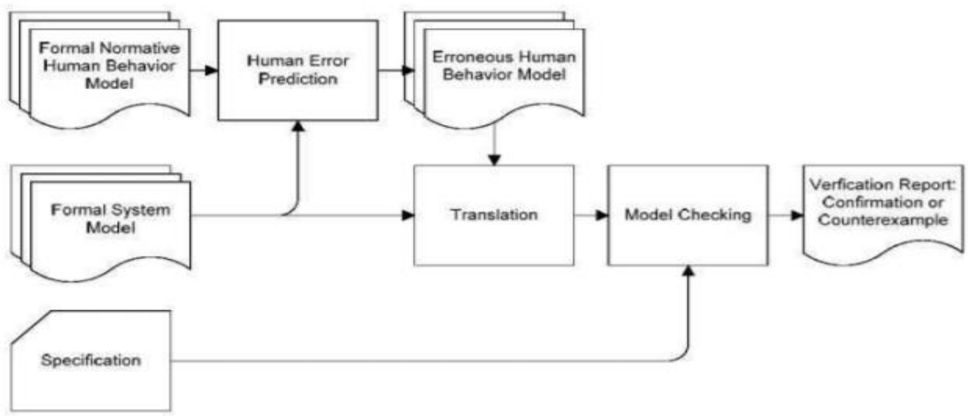

Figure 4. Human error and system failure prediction framework (Matthew L. Bolton, 2013)

2.3 Computer vision

Workflow surveillance is a major aspect in determining whether a project can be finished on time and on a budget [39]–[41]. Many researchers have attempted to develop an effective and timely method to manage workers' activity and thereby to improve productivity. Some researchers [40] used the data fusion of spatial-temporal and workers' posture data to monitor workers' activity. Many sensing and computational techniques have been used to generate real-time data on the location of construction entities across time, such as Radio Frequency Identification (RFID), Global Positioning Systems (GPS), and Ultra-Wideband (UWB) [39]. However, all these sensors require the installation of devices on workers and tag-based human tracking technologies are not suitable for NPP outages because NPP has restrictions on the devices that can be installed on the site and trackable tasks may cause confidentiality issues [20]. This requirement hinders the application of these contact sensors for workspace surveillance in large-scale, congested construction sites that have a large number of workers and objects to track.

In recent years, with the emergence of affordable video cameras and advance of computer vision techniques, an increasing number of industries have begun to set up cameras on sites for field surveillance. Computer vision-based tracking requires no tags on entities and can retrieve time, location, and action information of objects and workers. Multiple object tracking is a computer vision technology used to locate multiple objects, maintain the identity of the objects, and generate trajectories of different objects given an input video [42]. Multiple object tracking (MOT) has gained a good deal of research interests in recent years due to its academic and commercial potentials [42]. The information of objects generated from MOT can support further behavior analysis and action recognition.

In this research, the project investigators propose the deep-learning-based, multi-worker tracking approach for the monitoring and analysis of waiting times of workers in nuclear power plants. The specific focus is to monitor multiple workers moving in the RPI of a reactor under maintenance during the studied outage. The multi-worker tracking and waiting-time monitoring algorithm developed herein by the project investigators is aimed at automating outage workflow monitoring in order to address the challenges associated with manual monitoring and control of outage workflows. The algorithm can automatically derive the waiting times of workers across multiple areas of an outage job site. Such automation enables automatic comparison between the real-time and the as-planned workflows in these monitored areas in order to identify the deviations between as-designed and as-is workflow, while discovering anomalous waiting or other behaviors as early as possible to prevent delays. This algorithm could help reduce the uncertainties about the duration of the tasks in outage workflows and thus allow outage controllers to coordinate field operations and workflows based on high-quality, real-time information.

2.4 Simulation

Handoffs are transitional stages between tasks. Effective handoff control aims at reducing the duration of and the error rates in handoffs, which often involve traveling, communication, and waiting for workers. Handoffs between tasks involve a large portion of overall activities in construction workflows [1–3] and can thus significantly influence the project efficiency. Furthermore, NPP outage projects operate under extremely tight schedules, often refined to the extent of a 10-minute granularity while uncertainties of the handoff durations could be longer than some tasks or activities. In this case, maintaining the task sequences in leveled schedules is difficult for NPP outages [4].

Moreover, in packed schedules and workspaces, delays or mistakes in handoffs can influence many tasks and compromise the productivity and safety at large. Being able to precisely predict and control uncertainties within handoffs can lead to significantly improved productivity of NPP outages. One primary reason that aggravates the handoff performance in NPP outages is the complex organization of outage participants and processes [5]. The approval of each task involves multiple stakeholders to ensure safety. For example, an outage tasks should be confirmed by the following organizational units before the execution: 1) the outage control center, which determines whether the task is needed; 2) schedulers, who arrange the schedules of interconnected tasks; 3) maintenance shops, who arrange workforces for tasks; 4) the main control room staff, which configures the NPP according to the requirement of certain tasks; and 5) the work execution center, which inspects the site preparation for the safe execution of a given task. Complicated communications between all these organizational units are necessary for safety but will create long handoffs and possible time waste.

Precisely modeling and estimating the events influencing the handoff process will help predict and control the duration of future handoffs, thus significantly improving the productivity of NPP outages. The expected result from handoff modeling is to tell decision makers the next step to optimize the total workflow. However, the lack of a formal workflow model considering human behavior in handoffs impedes engineers and researchers from using a computer algorithm to assist in assessing handoff scenarios and schedule adjustment strategies. Handoff, even itself, is much more complicated to define and assess because the communication pattern and traveling pattern are always things that cannot be precisely modeled and simulated in the real world. For example, the communications--the ways people talk and/or chat--are variable and untraceable. Different people have different talking habits and speed, and all these factors are a matter of communication, leading to the complication of handoff simulation. So, for most construction simulation, planning, and scheduling, project managers chose not to consider complex handoff behaviors as a factor for analytical modeling but add buffer or contingencies between tasks in schedules. Buffering approaches are generally conservative to allow some waste of time.

Another obstacle of effective handoff modeling is that current construction simulation tools have limited capability to precisely model the detailed spatiotemporal relationship between human factors, tasks, and resources in support of accurate handoff modeling [6]. Currently, shutdown managers use a Gantt chart or PERT model to represent and manage the workflow (schedule). These workflow representations rarely consider the information of human behaviors, as well as the interaction between different tasks and resources, in representing handoffs in the workflow. When handoffs have unexpected waiting and communications that are longer than some tasks' durations, the task sequence in NPP outages could change frequently. Current scheduling tools can hardly model such task sequence changes due to handoff uncertainties. So this situation requires high quality and intelligent simulation tools to model the workflows with many handoffs between short tasks.

Precisely modeling handoffs require to model the uncertainties of the duration of the task, traveling, and communication. However, current construction simulation software cannot model the uncertainties during handoffs caused by the changing of a task sequence in job-shop scheduling problems. A job-shop scheduling problem is about how to handle a set of jobs that can be processed on a set of machines, and each job has a specific operation order [7]. In dynamic job shop scheduling problems, jobs arrive continuously over time in job shop manufacturing systems. Unknown task sequence in a job shop workflow will lead to the uncertainty of traveling time and task preparation time of workers for various tasks because these processes are related to both the successor task and the predecessor task.

The job shop scheduling problem is a combinatorial optimization problem as well as NP-hard and is one of the most typical and complex production scheduling problems [8,9]. Researchers developed different methods trying to solve the job shop scheduling problem [7–9]. Unfortunately, very few of these previous studies support real-time updating of the schedule according to the real-time progresses of tasks. Furthermore, the uncertainty of the duration of the tasks will greatly influence the performance of scheduling techniques. In brief, none of the current scheduling techniques have been applied to the real outage workflow management. Modeling task sequence changes based on agent-based simulation techniques can be the key to model handoffs for reducing the time wasted and error rate in NPP outage workflow, as detailed in section 5.5.

3 In-depth productivity and human behavior analysis in NPP outages

The project investigators completed in-depth productivity and human behavior analysis in NPP outages and listed the major research findings in the following sections. Specifically, section 3.1 synthesized the major findings of human errors and team collaboration issues in past NPP outages through reviewing Licensee Event Reports (LERs); section 3.2 revealed the impact of human errors and team cognition in NPP outages by conducting interviews with an expert from Arizona Public Service (APS) and reviewing past outage reports.

3.1 Human errors and team collaboration issues in NPP outages

3.1.1 Background of Licensee Event Reports (LERs) in NPP

Licensee Event Reports (LERs) are publicly available narrative reports filed by employees of NPPs that provide critical insight into plant operations and incidents. In some studies, LERs were used for mathematical risk estimations such as estimation of common-cause failure probability calculation [43], reliability analysis [44], and human reliability research [44].

Limited research has been conducted to use the LERs to understand human errors in the nuclear industry. For example, Svenson and Salo [44] used the LERs to analyze the time between when an error occurred and when it was detected and reported as an LER. According to this study, 10% of the incidents that occurred during outage control remained undetected for 100 weeks or longer. The results suggested that a higher number of LERs or error reports could be a sign of higher safety standards [45]. We propose that LERs can provide a rich source of data about anomalous events during NPP outages.

Teamwork is increasingly more necessary in accomplishing complex tasks that individuals cannot manage alone. NPP outage control is one of those tasks that require teamwork. Teams are a particular type of group for which members have different skills and perform different tasks in an interdependent manner[46]. In the case of NPP outage control, there are organizations or "teams of teams" that carry out both physical and cognitive tasks. The complexity of the task, systems, and human resources requires tight integration of teamwork.

The workload in NPPs requires high levels of cognitive skills. Prior research on team cognition in the main operation room of an NPP shows that challenging tasks can be completed by flexible[47], adaptive[32], and diverse teams[30]. The dynamic work environment of nuclear plants requires unique cognitive skills to cope with the demands[48].

In NPPs, human information processing relies on active knowledge-driven monitoring[48]. In order to complete a cognitively complex task in a high-risk environment, effective coordination and communication should be prevalent[48]. The distributed cognition of operators strongly depends on smooth information flow between team members so that they can synchronize team actions without sacrificing safety requirements[48].

Despite the attention given to studying teamwork in the main control room, no empirical study examines team interactions and team cognition during outage management and maintenance. Past studies have investigated the ergonomic aspects of outage control[49], the technological improvement of control centers[3], and the organizational structure of outage management[50]. Strict regulations require NPPs to document their operation details. However, previous studies provide limited analysis of events and accidents during outages, especially regarding team dynamics that are difficult to capture and comprehend. However, large numbers of LERs accumulated through decades contain rich information to be excavated and mined for addressing such difficulties.

3.1.2 Licensee Event Report (LER) Analysis

The project investigators extracted Licensee Event Report (LER) between 2006 and 2016 from the Nuclear Regulatory Commission (NRC) website. Based on a previous analysis, six keywords were selected to filter human-related error reports: "human error," "personal error," "cognitive error," "inadequate," "deficiency," "insufficient," "lack of." All nuclear power plants were included, and operation modes were limited to outage control management - Modes 2, 3, 4, 5 and 6. According to the initial search, 571 LERs were selected, 1) 158 LERs were excluded because of technical issues; 2) 372 Team Errors, 41 Individual Errors (Table 3).

Table 3. List of NPPs and LER counts

Name of NPP	LER Reports	Human Errors	Name of the NPP	LER Reports	Human Errors
Arkansas	6	6	McGuire	11	9
Beaver Valley	6	6	Millstone	8	7
Braidwood	5	3	Monticello	13	12
Browns Ferry	26	20	Nine Mile Point	6	4
Brunswick	10	9	North Anna	6	5
Byron	7	4	Oconee	5	5
Callaway	13	12	Oyster Creek	20	14
Calvert Cliffs	6	2	Palisades	4	2
Catawba	7	6	Palo Verde	27	19
Clinton	10	8	Peach Bottom	12	6
Columbia	6	6	Perry	6	5
Comanche Peak	4	3	Pilgrim	8	4
Cook	10	8	Point Beach	8	6
Cooper Station	8	8	Prairie Island	8	6
Crystal River	1	0	Quad Cities	8	3
Davis-Besse	10	7	River Bend	4	3
Diablo Canyon	9	7	Robinson	6	6
Dresden	13	7	Salem	6	5
Duane Arnold	7	5	San Onofre	11	7
Farley	8	6	Seabrook	3	3
Fermi	6	5	Sequoyah	4	3
FitzPatrick	8	7	South Texas	6	6
Fort Calhoun	40	38	St. Lucie	9	8
Ginna	5	5	Summer	4	2
Grand Gulf	3	2	Surry	2	0
Harris	8	6	Susquehanna	4	2
Hatch	21	14	Three Mile Island	1	0
Hope Creek	8	4	Turkey Point	20	16
Indian Point	17	15	Vermont Yankee	1	1
Kewaunee	11	8	Vogtle	4	4
LaSalle	4	3	Waterford	7	7
Limerick	6	4	Watts Bar	9	9
			Wolf Creek	16	12

LERs that were related to human errors were categorized based on operation modes. According to Figure 5, the highest number of human error was reported in Mode 5, Cold Shutdown. Next LERs that were related to individual human errors were excluded. Based on the root cause of the incidents, LERs were categorized into four main categories: 1-Team Error, 2-Procedural issues, 3-Organizational issues, and 4- Design issues. Table 4 shows the details of four categories. Figure 6 shows the results in the form of a Venn diagram.

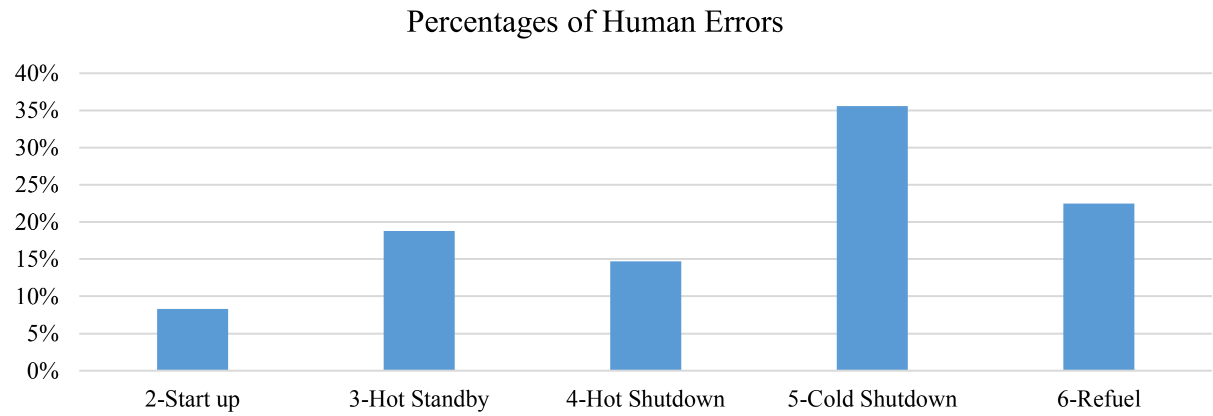

Figure 5. Percent of Human Error in different operation modes

Table 4. Four main reasons for team failures

Categories	**Keywords**
Team	Performance, control, questioning, communication, coordination, calculation, etc.
Procedural	Guidance, procedures, etc.
Organizational	Scheduling, planning, training, administration, briefing, documentation, work package, etc.
Design	Design

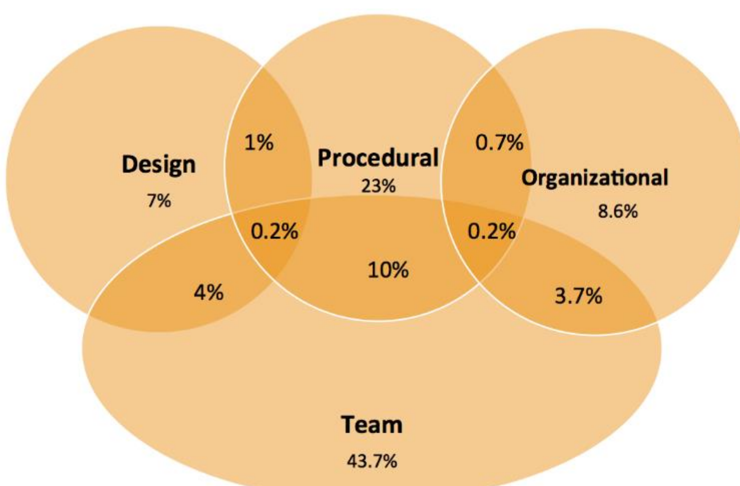

Figure 6. Venn diagram of the root cause of team errors

The results of the LER analysis show that 43.7% of the incidents are solely related to team cognition errors such as coordination, communication, team performance, and inadequate work quality. However, 56.3% of the team related incidents are related to a) procedural issues, b) organizational issues or c) design problems. For a better understanding of the nature of these errors, interviews with experts or outage control teams should be pursued. Results thus far indicate that teamwork is a significant issue that recurs in many LERs. Improvements in teamwork could increase overall system resilience.

3.2 Impact of human factors in NPP outages

3.2.1 Interview with APS plant manager

To better understand the real outage procedures and find out the most common delays caused during previous outages, the project investigators did a thorough interview with a plant manager working at PVNGS. In this section, the project investigator synthesizes the findings of common causes of delays in previous outages and the reasons for causing those delays through interviews.

3.2.1.1 Identify common delays occurring during NPP outages

To better understand delays occurring during NPP outages and common causes of delays, the project investigators interviewed a plant manager at Arizona Public Service (APS) to solicit his ideas about this research. According to the interview and the post-outage report (1R20), the project investigators have identified that the 1R20 outage was built to a 28-day schedule to meet a 30-day business goal. The actual completion time was 30 days and 18 hours. The outage process has nine time windows (sections) for different maintenance activities that have different purposes (see Table 5). Each window has a strict time limit that requires the teams and supervisors to follow the timelines and avoid delays. However, a 66-hour extension happened during the 1R20 outage. This 66-hour outage extension on the scheduled duration was the combined effects of the following elements:

1) Reactor Vessel and Core Barrel 10 Year Inspection (63.5 hours of delay occurred in Window #5);
2) Main Spray Isolation Valve (RCEV240) (19 hours of delay occurred in Window #8);
3) Fuel Movement and Additional Inspections (15.5 hours of delay occurred in Window #4 and Window #6);
4) Main Steam Isolation Valve Testing (7 hours of delay occurred in Window #9).

The project investigators studied the post-outage report of an outage - 1R20 (Unit 1, 20th Refueling Outage, Palo Verde Nuclear Generating Station) – to understand which windows (sections) during a typical outage often causing more delays. According to the post-outage report, significant delays in this outage are due to uncertainties in maintenance activities within Window #4 and Window #5 (see Table 5). Window #4 is the section where the NPP starts offloading and preparing for refueling of the core. The scheduled time window is 48.0 hours but achieved in 53.6 hours (5.6 hours over baseline). The delays within Window #4 is mainly due to the debris discovered on multiple fuel assemblies that need additional work to remove the debris, which is not a scheduled task in the as-planned schedule. Window #5 is the section that the NPP core needs to empty its vessel for refueling activities (Pressurized Water Reactor Group). The scheduled time window is 174.5 hours but achieved in 243.0 hours (68.5 hours above the baseline). The primary causes of delays within Window #5 are due to the malfunction of the reactor vessel inspection robot. The outage management team need to assign additional work packages to repair the inspection robot (multiple components replaced to include hydraulic pump, pressure relief valve, and manifold) and continue activities within Window #5.

Table 5. Delays during the studied outage - 1R20 (Unit 1, 20th Refueling Outage, Palo Verde Nuclear Generating Station)

Milestone/Activity	Timeline	Window Activity	Deviation (Hrs.)	Major Delays
PWROG 1: Offline to Mode 5	10/7/17	Shutdown/Cool down	-2.0	
PWROG 2: Mode 5 to Mode 6	10/7/17 – 10/11/17	Rx Disassembly to Rx Head Detention	-0.5	
PWROG 3: Mode 6 to Start Offload	10/11/17 – 10/13/17	Remove Rx Head/UGS Perform RFM PMs	-0.5	
PWROG 4: Start Offload to Offloaded	10/13/17 – 10/15/17	Core Offload	-5.6	Fuel Movement and Additional Inspections
PWROG 5: Reactor Vessel Empty	10/15/17 – 10/25/17	SG Maintenance and Reduced Volume Required Work	-68.5	Reactor Vessel and Core Barrel 10 Year Inspection
PWROG 6: Start Reload to Reloaded	10/25/17 – 10/28/17	Reload of 1st Fuel Assembly to Last Fuel Assembly and 2 Hours of Core Verification	-9.9	Fuel Movement and Additional Inspections
PWROG 7: Rx Reassembly to Mode 5	10/28/17 – 10/29/17	UGS Installation, CEA Coupling, Rx Head Install, and Tensioned	13.4	
PWROG 8: Mode 5 to Mode 4	10/29/17 – 11/3/17	RCS Fill and Vent, Draw PZR Bubble, Secure SDC, Start RCP's	-29.4	Main Spray Isolation Valve (RCEV240)
PWROG 9: Mode 4 to 1st Breaker Close	11/3/17 – 11/6/17	Plant Heat-up, Physics Testing, Plant Startup and Generator 1st Breaker Closure	-7.0	Main Steam Isolation Valve Testing
PWROG 10: Online to 100% Power	11/6/17 – 11/9/17	Power Escalation and At-Power Physics Testing	0.0	

*Please see the explanation of the abbreviations used in the above table. **(PWROG**: Pressurized water reactor owners' group; **CEA**: Control element assembly; Rx: Reactor; **RCS**: Reactor coolant system; **RCP**: Reactor coolant pump; **SDC**: Safety design criteria; **PZR**: Pressurizer; **UGS**: Upper guide structure)

3.2.1.2 Identify the causes of delays during NPP outages

According to the statement by the interviewed expert, tasks listed in the sections "Window #4" and "Window #5" have the largest variances per the outage schedule updating histories. This observation is true for many other outage projects across the whole nuclear industry [45]. Tasks within these two sections are mainly related to the main reactor and the main turbine system, which contain a large amount of work and complex task dependence relationships. In that case, a small delay in one task could propagate into a major extension on the overall outage duration.

"Discoveries" of new tasks during scheduled activities are the primary cause of delays during the outage. For example, the worker team needed to isolate a valve, so that maintenance could work on it. However, the worker team had difficulties when closing the isolated valve and ended up over-torquing the valve, which broke the valve. Over-torquing the valve caused an additional 18 hours of delay on the critical path due to the broken valve. In this case, the worker team needed to go to the OCC and reported that this valve was broken. The OCC then had to modify the work order; it took 6 hours to re-establish the work conditions. After that, the team needs to tag out the valve; then the worker team could continue replacing the valve once the work conditions were re-established. This additional work is an example of what drives task variance.

3.2.2 Past outage report analysis

The objective of the schedule analyses is to identify parts of an outage schedule that could provide sufficient repetitions of similar tasks and processes for estimating the variances of those tasks and processes. Such estimation of variances of tasks and processes is critical for developing a computer simulation of a section of an outage process to understand how the variance of tasks could induce risks of delays during the outage. That computer simulation of workflows can help engineers analyze that to what extent the variations in the duration of individual tasks can result in delays. Quantifying variances of task durations requires multiple observations of similar tasks repeated so that the project investigators can calculate the mean and variance of task durations. In other words, "sufficient data" means that the project investigators need to find a section of outage schedule that contains repetitions of similar tasks so that the investigators can obtain a variance and mean of the task duration, and then use a random number to represent the task duration in the simulation. Also, critical-path activities play a significant role in causing delays to the workflow. Identifying the part of the outage schedule that contains many critical-path activities is very important for the project investigators to understand better how delays in these activities will affect the overall duration of the entire workflow.

The authors used the following data 1) P6 schedule of 3R19; 2) one-day Post-Outage Report of 1R20, and 3) a Complete Outage Report of 1R20) for selecting part of the outage schedule for computer simulation modeling (please see Table 6 below).

Table 6. Data used for schedule analysis

Name of report	Outage	Time of outage	Data included
Primavera 6 (P6) Schedule	3R19 (Unit 3, 19th Refueling Outage, PVNGS	October 8, 2016 – November 8, 2016	As-planned mater schedule, task relationship
Post-Outage Report	1R20 (Unit 1, 20th Refueling Outage, PVNGS)	October 7, 2017 – November 6, 2017	Major delays, causes, Primary/Secondary window activities summary
Complete Outage Report	1R20 (Unit 1, 20th Refueling Outage, PVNGS)	October 7, 2017 – November 6, 2017	Total float, resource, actual task start/finish time

*PVNGS: Palo Verde Nuclear Generating Station

3.2.2.1 Identify critical activities in a previous outage

The complete outage report (as shown in Figure 7) contains much useful information such as the total float for each activity, the primary resource of certain activities, start/finish time, remaining duration. It also includes the "Breaker Open Variance," which represent the variance of the as-is schedule from the as-planned schedule. A "+" sign means the schedule has been speeding up, and a "-" sign means the schedule currently falls behind compare to the as-planned schedule. The "Last 24-Hr variance" in the complete outage report represent the variance a scheduled activity has changed in the last 24 hours. As for the red bars, it represents the graphical representation of the critical path, and the green bars represent the non-critical activities. Moreover, if two red bars (critical activities) occur simultaneously, this is when hot handoffs occur.

As shown in Table 7, the Primary & Safety Systems and the Secondary System contains the major amount of activities in the 3R19 outage and contains a significant amount of critical-path activities. It is crucial to look into the workflow and activities in this two system to better understand the detailed spatiotemporal interactions between tasks, and how uncertainties of these tasks will affect the overall duration of the entire schedule. By analyzing the previous outage schedule, the project investigators have identified that the Main Turbine system contains the most amount of critical-path activities and is more prone to cascading delays (see Table 7 and Table 8).

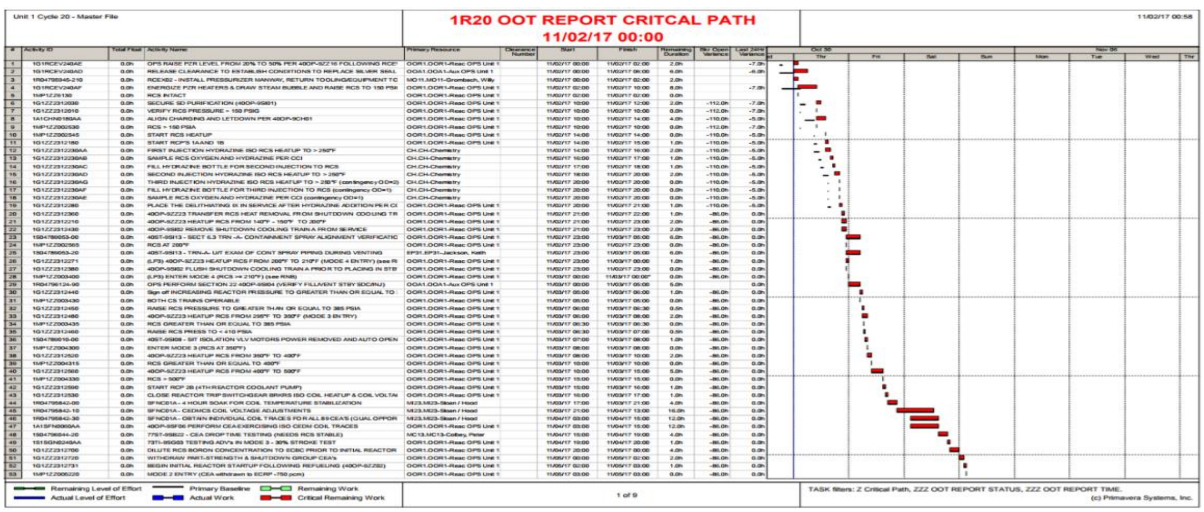

Figure 7. A complete outage report (November 2nd, 2017, 1R20)

Table 7. Distribution of activities on the critical path (3R19)

Major Systems	TOTAL	Critical-path Activities
Primary & Safety Systems	4386	86
Secondary Systems	4271	129
Electrical Systems	1743	5
Misc Activities & Non-Syntempo Reviewed Work	2581	2
Paragon Activities	65	0
Overview & WOG Activities	124	4
TOTAL	13170	226

Table 8. Distribution of activities on the critical path of Primary System (3R19)

SYS	System	# of Activities on Critical Path
CH	Chemical & Volume Control	3
FH	Fuel handling	2
MA	Main Generation	4
PC	Fuel Pool Cooling & Cleanup	1
RC	**Reactor Coolant**	**56**
RI	In-Core Instrumentation	2
SA	Engineered Safety Features	1
SB	Reactor protection	4
SE	Ex-Core Neutron Monitoring	1
SF	Reactor Control	5
SI	Safety Injection & Shutdown Cooling	4
ZZ	Civil Structures	3
	Total (Critical)	86

3.2.2.2 Identify common delays occurring during NPP outages

To better understand delays occurring during NPP outages and common causes of delays, the project investigators interviewed a plant manager at APS to solicit his ideas about the research work. According to the interview and the post-outage report (1R20), the project investigators have identified that the 1R20 outage was built to a 28-day schedule to meet a 30-day business goal. The actual completion time was 30 days and 18 hours. The outage was split into nine windows (sections) for different maintenance activities that have different purposes (see Table 5). Each window has a strict time limit that requires the teams and supervisors to follow the timelines and avoid delays. However, a 66-hour extension happened during the 1R20 outage.

The project investigators studied the post-outage report of an outage - 1R20 (Unit 1, 20th Refueling Outage, Palo Verde Nuclear Generating Station) – to understand which windows (sections) during a typical outage often cause more delays. According to the post-outage report, significant delays in this outage are due to uncertainties in maintenance activities within Window #4 and Window #5 (see Table 5). Window #4 is the section where the NPP starts offloading and preparing for refueling of the core. The scheduled time window is 48.0 hours but achieved in 53.6 hours (5.6 hours over baseline). The delays within Window #4 is mainly due to the debris discovered on multiple fuel assemblies that need additional work to remove the debris, which is not a scheduled task in the as-planned schedule. Window #5 is the section that the NPP core needs to empty its vessel for refueling activities (Pressurized Water Reactor Group). The scheduled time window is 174.5 hours but achieved in 243.0 hours (68.5 hours above the baseline). The primary causes of delays within Window #5 are due to the malfunction of the reactor vessel inspection robot. The outage management team need to assign additional work packages to repair the inspection robot (multiple components replaced to include hydraulic pump, pressure relief valve, and manifold) and continue activities within Window #5.

4 Computer vision algorithms for automatic human behavioral data acquisition and analysis

The project investigators have developed a multi-worker tracking algorithm that can use videos collected by one camera to locate locations of multiple workers in an indoor environment. Such indoor tracking of multiple workers is vital for identifying abnormally long waiting time in certain areas that form bottlenecks of outage workflows. Waiting time information in different areas of a space having multiple workers can help outage managers arrange their schedule and resources to avoid the time waste. One example is that the RPI of a nuclear reactor is a space that has multiple stations for preparing workers before they enter the reactor. Monitoring the waiting time at those stations in an RPI can help outage managers and supervisors to rearrange the resources available at each station or update the working schedules of their workers to avoid the long waiting times at some "bottleneck" stations. The following sections summarize the major research findings in the areas of: 1) how computer vision techniques can help monitor human behaviors and achieve proactive outage control (section 4.1); 2) details of the developed algorithms (section 4.2, section 4.3, and section4.4); 3) the design of Graphical User Interface (GUI) (section 4.5); and 4) the evaluation of the developed algorithms (section 4.6).

4.1 Overall framework

The computer vision algorithm developed and tested in this project has two unique technical features that are state-of-the-art: 1) only using one camera for 3D localization indoor, and 2) real-time tracking of multiple moving workers with significant occlusions in a crowded RPI. Only using one camera makes the multi-worker-tracking solution flexible in environments where limited spaces are available for installing surveillance cameras. Rather than the 2D frames of videos, single-camera 3D tracking enables localization of workers in the physical world when identifying areas that are too crowded and need the attention of the supervisors for mitigating the waiting through resource allocation and schedule updating. The main challenges include: 1) the loss of depth using a single camera for tracking, and 2) the difficulties of avoiding ID switch of tracked workers and losses of objects when occlusions occur in a crowded indoor environment.

The project investigators developed a novel approach that addresses the two challenges described above. This algorithm first uses a two-branch convolutional neural network to detect workers and their body joints. Instead of tracking the body joints in the image space, the algorithm transforms the detected joints onto virtual parallel planes called "Anthropometric Planes" in order to mitigate the loss of depth due to the use of only one camera (single-camera constraint). Based on anthropometric measures of an average American male, the algorithm generates a series of Anthropometric Planes along the vertical axis. The algorithm then uses a Kalman Filter to track the detected joints on these Anthropometric Planes. Finally, an uncertainty measure is introduced to reduce the number of ID switch and to handle missing joints.

The project investigators tested the developed multi-worker tracking algorithm to analyze representative video sections selected from a 24-hour video collected in the April 2017 outage of Palo Verde Nuclear Generating Station (PVNGS). The performance metrics used for these tests are the recall and precision of the waiting time calculated by the algorithm from the videos. The project investigators analyzed the cases where the algorithm failed and summarized the challenging scenarios for the algorithm to achieve precise waiting time monitoring of multiple workers in an RPI.

For timely and effective outage coordination at an NPP, efficient and effective monitoring and control of two types of tasks are critical: 1) non-wrench time activities (e.g., obtaining parts, tools or instructions, the travel associated with tasks), and 2) tasks that are near the critical path. Duration variations and no-wrench time associated with tasks near critical paths could cause critical path changes and unexpected delays. The first step for achieving such monitoring and control of non-wrench-time and near-critical-path activities is to automatically and precisely detect and track workers during each activity to estimate future non-wrench time and task variations, which will help with effective scheduling and decision making. In this research, the project investigators developed an automatic computer vision-based workflow monitoring approach and carried out the following performance analysis of this approach using video data collected at the April 2017 outage of PVNGS.

As shown in Figure 8, the research work presented in this report consists of four consequential steps. The first step is the detection of workers in video frames. The algorithm needs to detect workers in each frame and then match the detected workers in consecutive video frames. When many occlusions happened during the peak time of outage operations, workers are occluded by each other, and the video cannot show the entire body of workers. The project investigators used a 2D human pose predictor [3]. That human pose predictor takes an online video stream as inputs and predicts the poses of all people in the video. The algorithm can detect body parts of workers. For example, when some workers' left legs were occluded by other workers' bodies, the algorithm still can detect those workers' heads and arms.

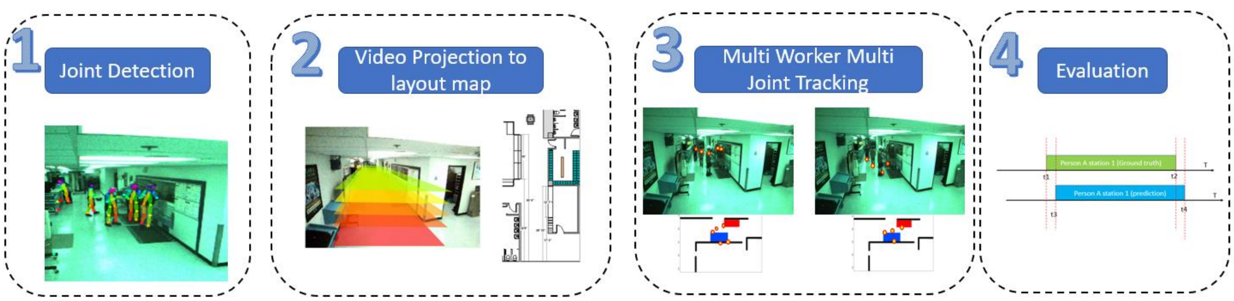

Figure 8. Overall Pipeline of the proposed worker tracking methodology

The second step of the algorithm is to build the projection relationship between the video frames and the layout map of the RPI. Only the videos having their coordinate system aligned with the layout map of the RPI can be useful for monitoring the exact locations of workers in RPI and relevant activities at certain locations in the RPI. The third step is called "multi worker multi-joint tracking." This step of the algorithm associates the detected body joints in different video frames with each other. For example, the tracking algorithm needs to link the head of worker 1 in frame 1 to the head of worker 1 in frame 2. The algorithm will similarly link other body parts across video frames. The last step of the research method presented in this report is the evaluation of the performance of the developed multi-worker tracking algorithm for monitoring activities of workers in an RPI. The computer vision algorithms could encounter various challenges in this real-time monitoring of activities in RPI, such as missing objects and losses of tracks because of occlusions. The research team reviewed all the collected videos and selected 14 video clips to assess the algorithm and report failures of the algorithm in various scenarios. The purpose is to synthesize these failure cases for pointing out future research directions.

4.2 Human joint detection

The algorithm needs to process the "spaces" of images and field maps for mapping the locations on video frames to locations on the layout map of the RPI. The first space processed by the algorithm for mapping the image space to the 2D trajectory in the space that represents the RPI room layout is the image space, represented by the symbol "I," where detections occur. Although the algorithm can build upon any frame-based pose estimation system, the project investigators used the top-down 2D human pose estimator due to its robust and near real-time detection performance [51]. A skeleton represents a person, and the joints within a skeleton represent joints of the human body accordingly. A two-branch network (Figure 9) takes an image as input [51]. The algorithm detects the body joints and connects limbs along with orientations of body parts through a refining process [51].

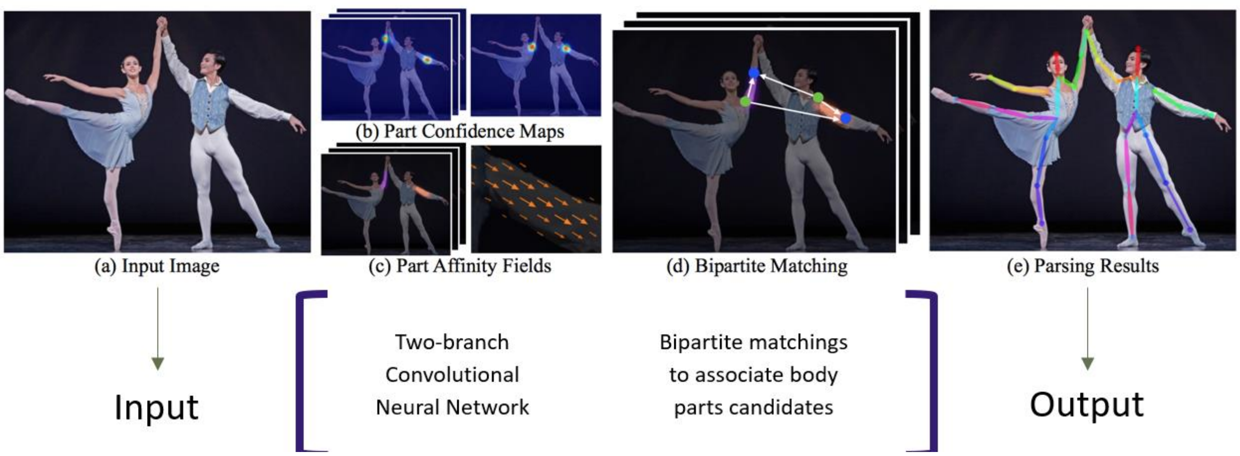

Figure 9. Joint Detection Architecture: Images are fed to VGG16, and generated feature maps are fed to a two-branch network. Branch 1 (top) finds the confidence map for a labeling a joint. Branch 2 (bottom) is in charge of estimating the orientation of the limb between two detected joints (pictures from [51]**)**

A graph matching algorithm is responsible for mixing and matching the body joints of a person [3]. Given the orientation and the limbs as the edge weights of the k−partite graph, and the labeled joints as the vertices of the graph, the matcher finds the joints that belong to a person [51]. However, since the detection randomly chooses an ID for a person in the video per frame, keeping track of the assigned ids of workers, when a person first appears in the scene, remains as a challenge. Furthermore, missing joints due to partial or complete occlusion or even just failing to detect a worker aggravate the situation. The outputs of this process of grouping the labeled joints into human skeletons are the inputs to a set of virtual planes created according to the anthropometric measures of a human [52].

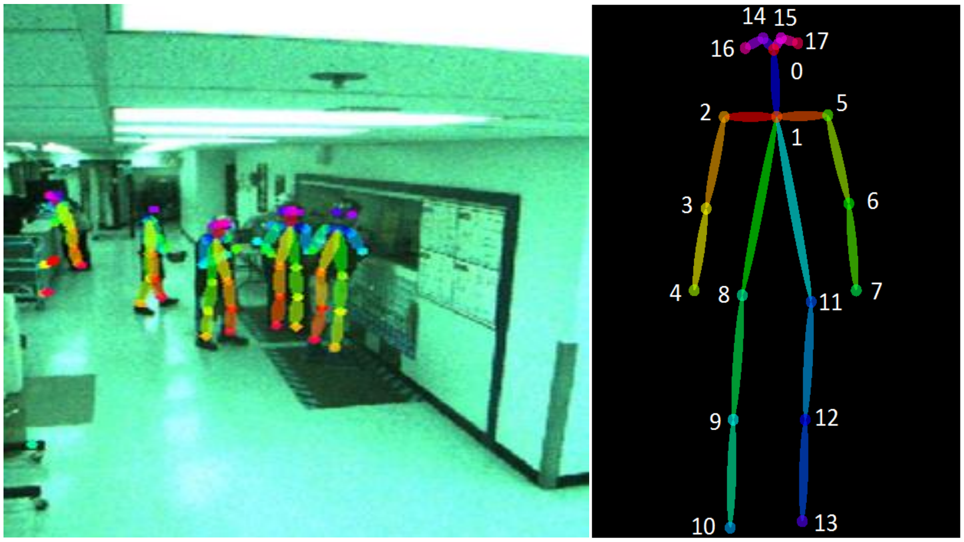

Figure 10. Body joint detection of workers

The project investigators used the COCO body model to finish the body joint detection of workers [51]. Figure 10 shows the joint detection results on video data collected in RPI. COCO body model can detect eighteen joins of each worker. Table 9 represents all the eighteen joint numbers and corresponding body parts.

Table 9. The joint number and corresponding body parts

Joint number	Body part
0	Nose
1	Neck
2	Right Shoulder
3	Right Elbow
4	Right Wrist
5	Left Shoulder
6	Left Elbow
7	Left Wrist
8	Right Hip
9	Right Knee
10	Right Ankle
11	Left Hip
12	Left Knee
13	Left Ankle
14	Right Eye
15	Left Eye
16	Right Ear
17	Left Ear

4.3 Video projection to layout map

Tracking body joints in video frames of a single camera are prone to inconsistent displacements due to challenges such as change of perspective, occlusion, lighting conditions, and so on [4]. A consistent tracking algorithm must be able to track a worker regardless of his or her position in an environment. Consider the case when a worker approaches a single fixed camera. As he or she gets closer to the camera, his or her displacement in the image space becomes larger and larger. In other words, the worker's velocity changes although in the object space he or she has a constant velocity of moving. Now, consider another worker who moves away from the same camera. The worker's displacement becomes smaller and smaller resulting in a lower velocity in the image space. There could be other workers walking across the room, running, standing still, and so on. These issues created by the loss of depth because only a single fixed camera is available and cause difficulties in reliably tracking objects that are moving and with non-linear relationships between the objects' locations and the appearances.

To overcome these issues, the project investigators propose to transform the detected body joints from the camera's image space into a set of virtual planes parallel to the floor of the RPI. The creation of anthropometric planes is inspired by the work of [5] where the researchers eliminated the use of camera calibration for shape reconstruction and instead adopt the silhouette images. The idea is to utilize a homograph transformation to generate virtual planes at the levels of all body joints, parallel to the horizontal plane of the ground of RPI.

Virtual planes are constructed through the following process:

1) Let a set of points, $X=\{x_1,x_2,\ldots,x_n\}$,n≥4, be located on a reference plane, π, defined in the object space O.
2) Define a transform, T(X, X_z)which elevates X to a new set of points, X_z, by $z \in R$ in the direction of π's normal. $X_z=\{x_1^{(z)}, x_2^{(z)},x_3^{(z)},\ldots,x_n^{(z)}\}$ are in the new plane, π_z which is parallel to π.

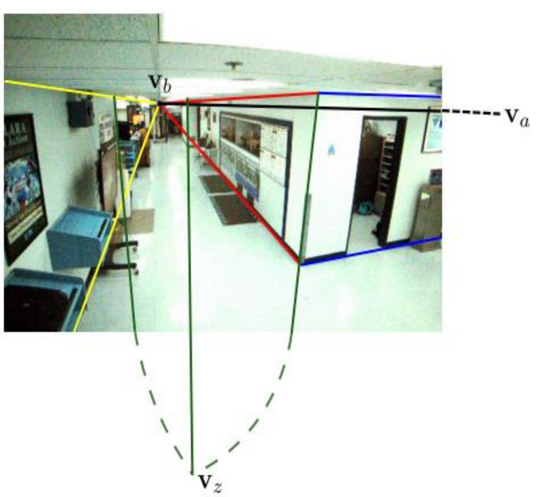

Figure 11. Vanishing Lines and Points: V_a and V_b are the vanishing points in the horizontal direction. V_z is the vanishing point in the vertical direction

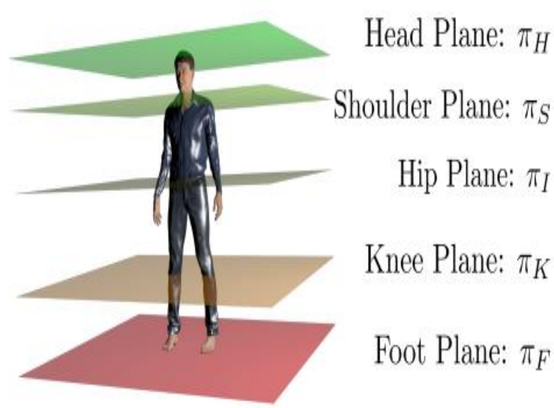

Figure 12. Anthropometric Planes for Human: body joints are tracked on their corresponding planes

3) Consider the set of lines, L, passing through all the pairs,(x_i, $x_i^{(z)}$), $i \in \{1,2,...,n\}$. In projective geometry, according to the definition of parallel lines, one can see that Li 's are parallel and intersecting in infinity.
4) Project the two sets of points, X and X_z, from the object space O to the image space I, and define X' and X_z' as their projections. It can be shown that the set of vanishing lines, L_v are the lines passing through X' and X_z', which intersect at the vanishing point, V_z (Figure 11).

The project investigators transformed the body joint detection results to the ground plane of RPI (Figure 13). For more detailed technical background please refer to [8]. As Figure 13 shows, the developed projection model transformed detection results of left ankle and right shoulder to the layout map of the RPI where video data collection occurred in April 2017. After the transformation, the managers can have a better view of which stations workers are waiting for in the RPI.

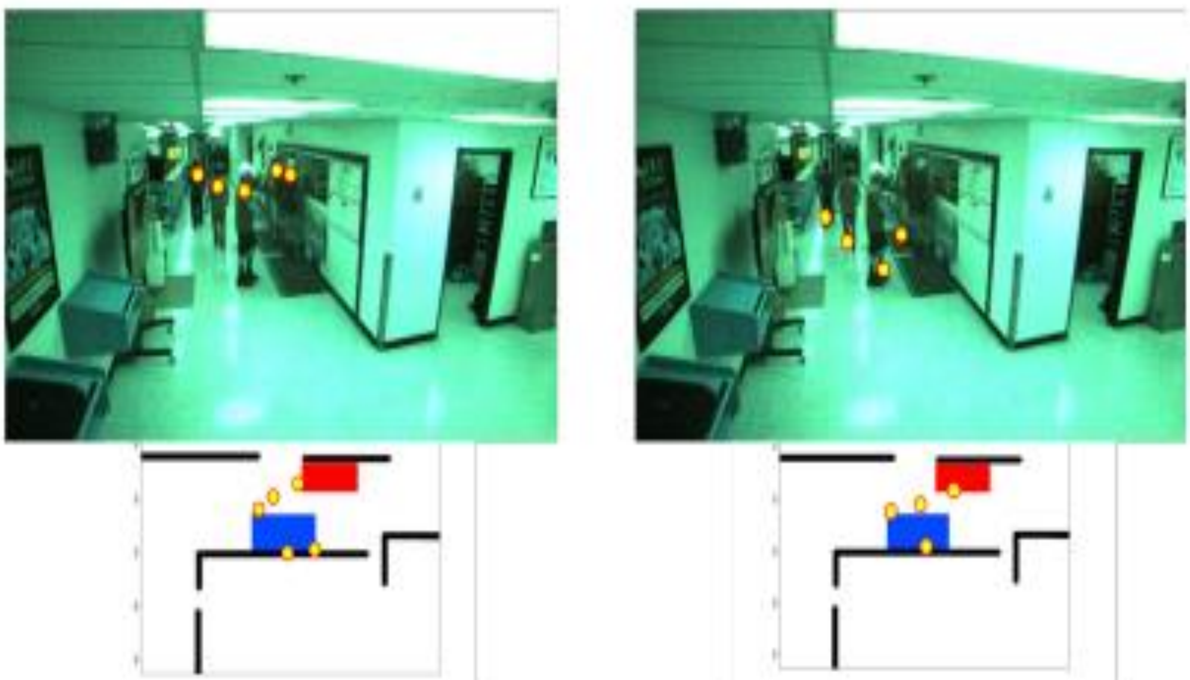

Figure 13. Detections on anthropometric planes: Not all the joints are detected

4.4 Multi-worker multi-joint tracking in the compact indoor workspace

This section defines necessary terms that help to formulate a multi-object tracking scheme, and technical details of an implementation of this scheme in this research. This multi-object tracking scheme consists of the following critical concepts and terms: object state, object appearance, object trajectory, and object tracking. The following paragraphs sequentially introduce these concepts and terms for presenting the technical implementation of the multi-object tracking algorithm developed in this project.

4.4.1 Object State

Object state is an indicator of joint visibility. In our algorithm, an object (worker's body) is comprised of eighteen body joints, for which the state is defined as its location if the joint is visible or labeled as occluded if the joint is not visible. Since the joints are being detected and labeled in the detection phase, we use the Hungarian algorithm to associate detected workers which are the same person in adjacent frames [52].

4.4.2 Object Appearance

Object appearance is the way an object is represented. At each frame, the object is represented as the mean value of all the observed or predicted locations of joints and an uncertainty region. An uncertainty region is defined by the standard deviation of all the locations of the joints for one worker.

4.4.3 Object Trajectory

The trajectory of the object is the history of the object written by its state and appearance in the image sequence. The trajectory is readily available by connecting the mean locations in the previous video frames.

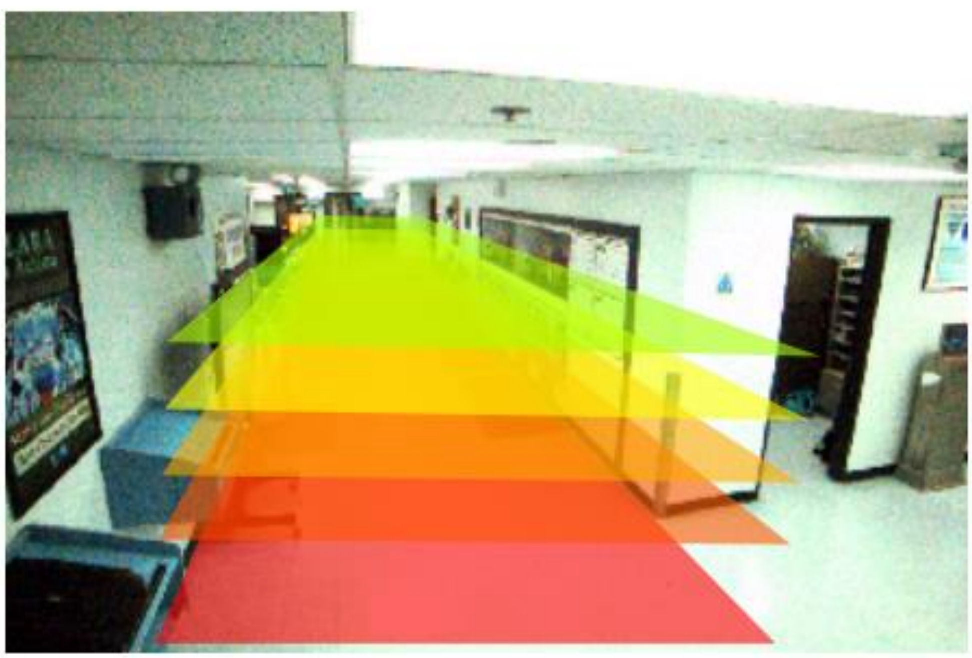

Figure 14. Anthropometric Planes: A new trajectory space for tracking joints of multiple people

4.4.4 Object Tracking

Based on the concepts presented above, object tracking is consistently detected and assign labels to workers. Given the body joint predictions grouped in the image space for the latest frame, the main task is to correctly find a person who corresponds to the same person in the previous frame.

The object trajectory for each joint will be transformed to the corresponding plane. These anthropometric planes, in fact, create a new space in which one can perform all the previous tracking methods. For this work, the researchers focus only on the Kalman Filter [53]. The Kalman Filter consistently adds detected joints for one person to his trajectory constructed over time. In the case of occlusion, the Kalman filter predicts a joint position in order to keep the trajectory consistent. ***Figure 15*** shows the results of the trajectories of tracked heads on the image and the trajectories of tracked heads on the layout map of the RPI.

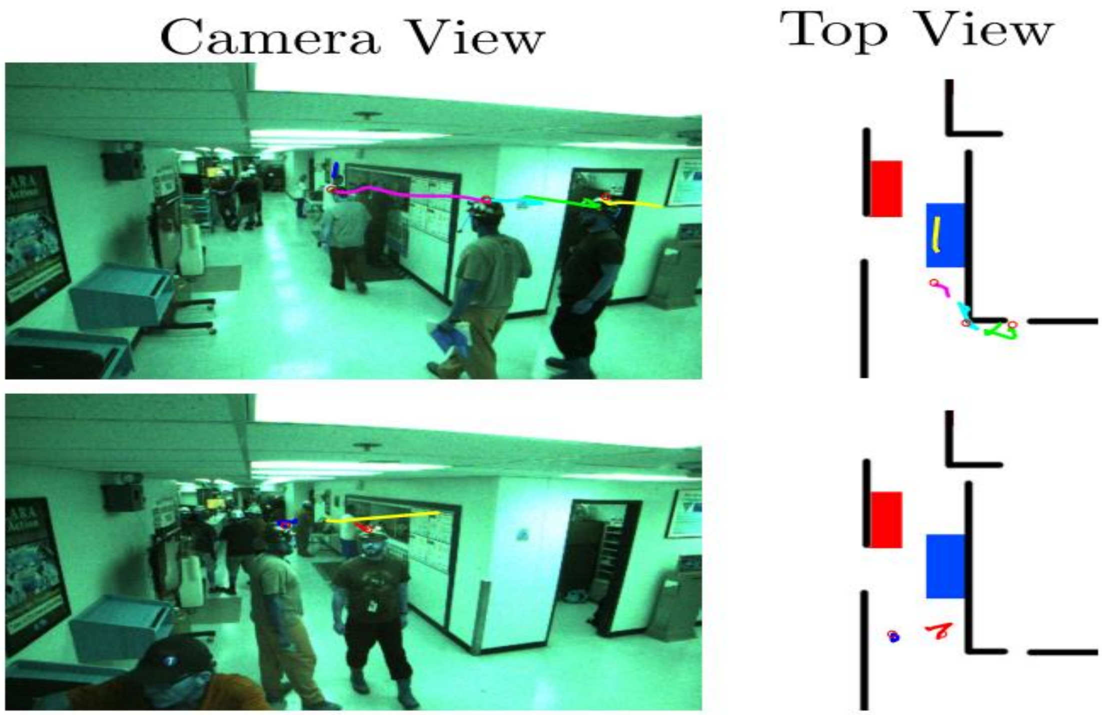

Figure 15. Tracking head in image space vs. tracking all points in layout map

4.5 Design of graphical user interface (GUI)

This section presents a graphical user interface (GUI) that enables engineers using the human-tracking algorithm for real-time visualizing of the tracking results without having to know technical details of the computer vision algorithms. This GUI is a type of user interface allows users to interact with electronic devices through graphical icons and visual indicators such as secondary notation, instead of text-based user interfaces, typed command labels, or text navigation. The GUI was designed to display multiple simultaneously tracked workers in an RPI. The aim is to identify the location and temporal duration of bottlenecks in the workflow.

This GUI can achieve real-time monitoring. There are two configurations that users need to complete through interacting with the GUI. The first configuration is to identify the area that users want to monitor. Figure 16 shows that the user can select the layout map of different rooms and select the areas the user wants to monitor. In Figure 16, the researchers used the layout map of RPI for testing and use a rectangular to highlight two stations to monitor.

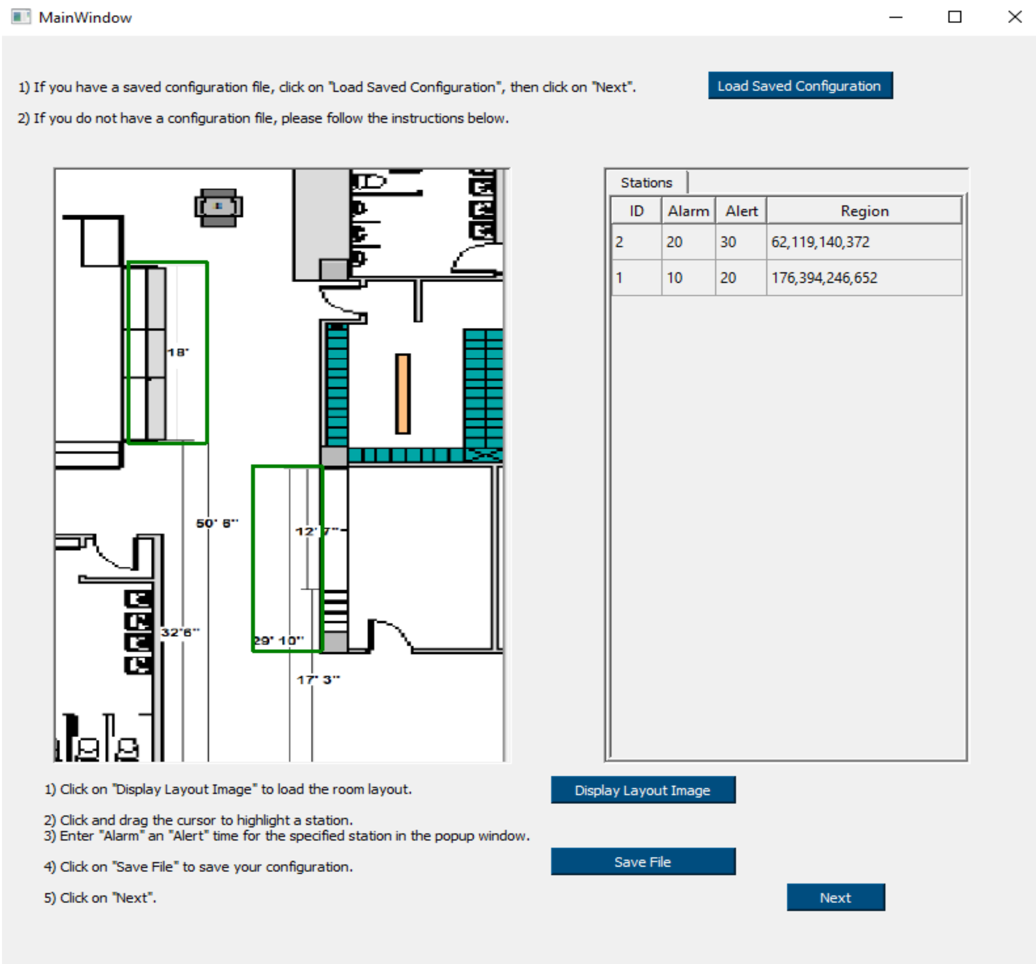

Figure 16. Select Areas user wants to monitor

The next configuration by the user is to choose the corresponding points in the layout map and video (Figure 17). This step serves to build the connection between the video and layout map. The user needs to

1) Press "Display Layout Image"
2) Press "Display Camera Image"
3) Click on four or more points in the left image.
4) Click on the corresponding points with the same order in the right image.
5) Press "Next"

The number of personnel at each station is monitored and recorded; therefore, workstation usage efficiency can be improved. This visualization of the computer vision system enables outage controllers to quickly identify the status of multiple stations and spot the bottlenecks. Figure 18 shows the detailed GUI design for visualizing the handoffs in the room. When a worker enters Station 1, the average waiting time will start counting until the worker finishes and moves on to Station 2. At that time, the total waiting time at Station 1 will freeze and the average waiting time at Station 2 will start counting until the worker is done at that station. Once the waiting time has exceeded the alert time limit shown on the left of Figure 18, based on the time exceed, an alert signal will be triggered and shown next to the station information on the right.

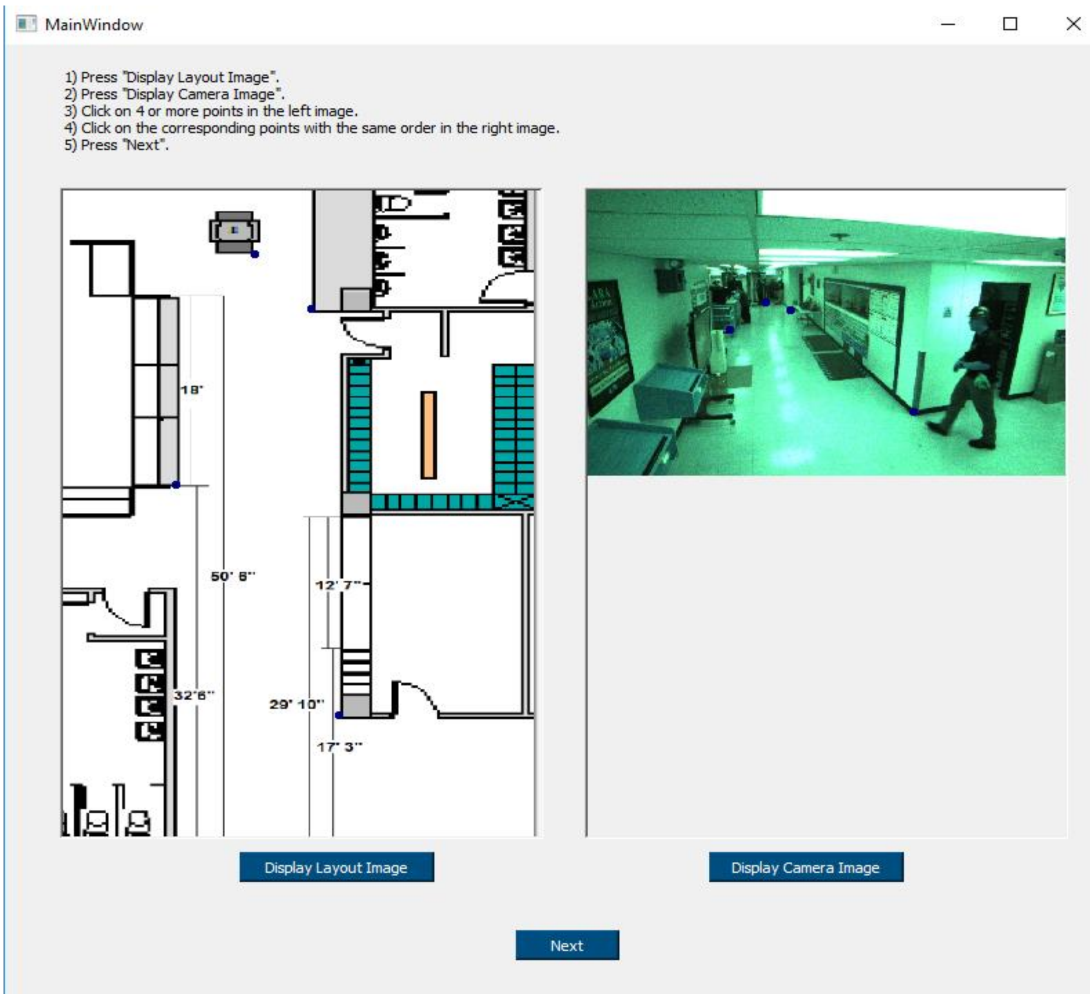

Figure 17. Build transformation between layout map and video

In this GUI, Station 1 and Station 2 have separate and different thresholds (alarming and alert times) with the time unit because the nature of the tasks at these two stations is different. Also, a total alert and alarming time in the "Summary Table" has been added. Until the worker has exited the station, his/her data will not be displayed. The program will be able to capture the average waiting time for each waiting at each station, as well as the waiting time in the RPI. Based on the information, the management team would be able to monitor the real situation within the RPI and make a decision.

Figure 18. Real-time monitoring and statistics output (Red cell indicates the time worker spent in the station exceeded the alert limits)

4.6 Evaluation of the developed algorithms

This section presents the testing results of the developed multi-object tracking algorithm. The main purpose is to assess the performance of the algorithm in terms of reliably monitoring the waiting time in the RPI for identifying bottlenecks in the indoor workflows. The process for this evaluation is as the following:

1) Select videos based on the five characteristics proposed above. The primary data sources we are going to test is RPI video data collected at the April 2017 outage of PVNGS. Each video clip contains 200-300 frames. The project investigators manual labeled the time when the workers waited in the Station 1 and 2 as the ground truth of the algorithm. Also, the researchers will manually annotate the video for the five labels including occlusion, number of workers, time resolution, and spatial resolution to describe the scenarios. For example, a selected video can be severely occluded, has nine people, time resolution is 30 fps, spatial resolution is 968*608.
2) Execute the algorithm for all the selected video and each video should generate the time workers waited in the Station 1 and 2.

3) Calculate the precision and recall of the waiting times generated by the developed multi-object tracking algorithm.

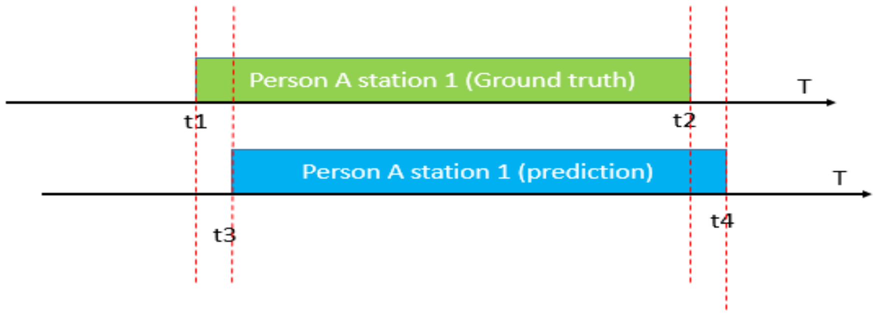

Figure 19. Example of performance evaluation

$$Recall = \frac{t2-t3}{t2-t1} \qquad Precision = \frac{t2-t3}{t4-t3} \qquad \textbf{Equation 1}$$

For the waiting time monitoring purpose, the authors designed two performance metrics: precision and recall. As Figure 9 and Equation 1 show, the green area in the time axis represents the real value of the time a person A stayed in station 1, while the blue area gives the value predicted by the computer vision algorithm. The researchers calculated the recall and precision of the multi-object tracking algorithm developed in this research. The recall means the percentage of the time predicted correctly by the computer vision algorithm among the real-time duration. The precision means among the duration of prediction, the percentage of the correct prediction.

Previous studies in the domain of computer vision assess the performance of multi-object tracking but did not provide scientific information needed for assessing the waiting time monitoring the performance of the algorithm developed in this research. Most researchers in the domain of computer science evaluate tracking performance by comparing the tracking results and the ground truth[54]. The ground truth of the objects of interests to track were manually labeled in the test videos. Then the tracking results from the proposed method were compared with the ground truths to calculate the tracking precision and spatial overlap. Tracking precision is measured by center location error, which is typically defined as the Euclidean distance between center locations of the objects and their corresponding ground truths in the videos. The unit of the distance is pixel [55]. The following paragraphs first present the experiment set up to collect the video data in RPI for testing the algorithm.The researchers showed the testing results and summarized the scenarios where the algorithm has low precision and recall.

4.6.1 Experiments Setup

The researchers put a camera in the RPI during the April 2017 outage of Palo Verde Nuclear Power Plant and collected 24-hour video data on Apr. 16th, 2017. The researchers used a laptop that was placed in the RPI. The researchers did not connect this laptop to PVNGS' computer network because the research development focuses on the computer vision methods without considering live streaming and real-time monitoring of the RPI. The video is used and will be used to test the capabilities of the human tracking algorithm, determine appropriate alarm settings, tune the algorithm that calculates predicted wait times, discriminate out those, not in the process, improve the user interface, etc. The following two sub-sections will introduce the verification results based on the 24-hour RPI video data. The research team used the data collected in RPI in April 2017 to test the algorithm.

4.6.2 Results

The researchers selected seven video clips to test the algorithm. Also, the researchers subsampled all the selected videos in order to test if the performance will be affected when lowering the video resolution. In total, the researchers had 14 video clips to evaluate the performance of the algorithm as listed in Table 10.

Table 10. Test results characterizing some workers, occlusion level, time resolution, and spatial resolution

ID	Frame number	The number of workers	Occlusion level	Time resolution	Spatial resolution	Average Precision	Average Recall
1	12780 - 12980	4-6	High	6	968*608	0.98	0.77
2	13860 - 13968	2-3	no	6	968*608	0.97	0.54
3	14112 - 14375	1-3	medium	6	968*608	1	0.99
4	23264 - 23364	1	no	6	968*608	0.32	0.1
5	23745 - 24005	1-3	no	6	968*608	1	0.15
6	32436 - 32604	1-3	no	6	968*608	0.70	0.58
7	36000 - 36214	1	no	6	968*608	1	0.61
8	12780 - 12980	4-6	High	6	600*600	0.5	0.17
9	13860 - 13968	2-3	no	6	600*600	0	0
10	14112 - 14375	1-3	medium	6	600*600	1	0.05
11	23264 - 23364	1	no	6	600*600	0.1	0.05
12	23745 - 24005	1-3	no	6	600*600	0.87	0.1
13	32436 - 32604	1-3	no	6	600*600	0.43	0.32
14	36000 - 36214	1	no	6	600*600	1	0.94
Average						0.70	0.38

For each video clip, the researchers calculated the precision and recall for every worker who showed up in that clip. The researchers used the average of the precision and recall of all the workers to represent the precision and recall of that video clip. As Table 10 shows, the algorithm can achieve good precision on the collected data, the average precision of the tested 14 videos is 0.70. The average precision means that the algorithm can calculate the waiting time of workers in stations at a 70% level. The average recall of the tested videos is 0.38. The average recall means the algorithm can track 38% of the time period when workers spent in stations.

Figure 20. ID switch due to inter-worker occlusion

From the tested results, the researchers identify the scenarios where the algorithms are likely to fail. The first scenario is that when irrelevant workers passed the station and occluded the workers. As Figure 20 shows, the algorithm assigned id 2 in the left image to the worker in the station. When the workers passed the station, the id 2 went to another person in the middle image. In the right image, id two was lost. This scenario is an example of id switch which causes the calculation of waiting time inaccurate.

Figure 21. False detection due to reflective objects (red circle the false detection, the algorithm detected one worker in the video, whereas there is no worker)

Another typical failure is a false detection. Sometimes the algorithms could detect more people than the number of workers in the video. Due to reflections of the mirror in the RPI room, the current state-of-art algorithm could give false detection of the worker which also makes the waiting time inaccurate. A similar problem could happen when there are reflective objects on the construction sites.

Figure 22. Occlusions due to the background obstacles. (The algorithm missed the worker at the left.)

The research team found the algorithm calculated the waiting time with low recall and precision when the background obstacles occluded the worker. Figure 22 shows that the algorithm missed the worker at the left of the scene because the wall occluded part of his body. Occlusion by the background obstacle happened frequently in real construction sites such as occlusion from excavator and wall.

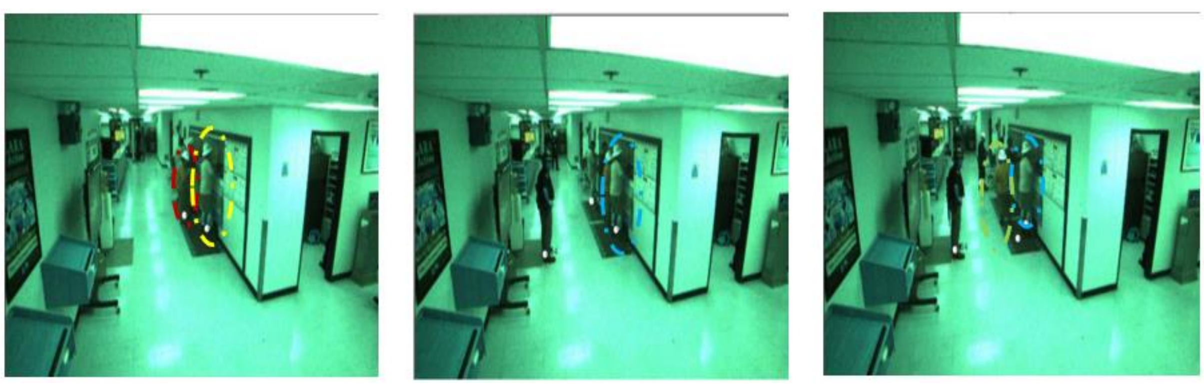

Figure 23. Missed objects due to workers merge and split

The researcher found another typical failure was that the algorithm missed the workers when they merge and split. As shown in Figure 23, in the left image, the two workers circled in red and yellow merge together at first. Then in the middle image, the algorithm considered them as a new object together. In the right image, when they split, the algorithm assigned a new identity to the two workers, which means the algorithm failed to track the worker continuously and assigned a new identity to the worker.

5 Data-driven simulation of detailed spatiotemporal human-task-workspace interactions within NPP outage workflows

The project investigators modeled spatiotemporal human-task-workspace interactions within NPP outage workflow by using detailed human factor and NPP operation knowledge introduced above (section 5.1). Then, the project investigators conducted a series of lab experiments with a focus on the following: 1) understanding the communication error during the lab experiments (section 5.2); 2) how an automatic communication system can help reduce the risks of communication errors in terms of delays (section 5.3); and 3) how an automatic communication system performs better than a human supervisor (section 5.4). Based on the data collected from the lab experiments about task duration variations and communication errors, the project investigators carried out computational simulations to study the impact of numerous uncertainties (i.e. task duration variations, human errors, handoff processes, etc.) to the productivities of the workflow and have tested numerous control strategies in terms of reducing the delays caused by workers and supervisors (section 5.5).

5.1 Modeling of detailed spatiotemporal human-task-workspace interactions within NPP outage workflows

This section presents research experiments for capturing and modeling communication behaviors of a group of workers during the handoffs between tasks in typical field workflows of an NPP outage. Extensive post-outage report analysis and interviews with industry experts helped the project investigators identify sections of turbine maintenance workflows as typical field workflows that are 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 project investigators used two typical sections of turbine maintenance schedules to create two test cases for carrying out lab experiments that simulate real handoffs for those field workflows (section 5.1.1). Those experiments helped the project investigators to capture communication data and behaviors of workers in the RPI, where the handoffs and waiting occur between tasks. The communication data and schedules of the workflows are the basis for the development of computational agent-based models that quantitatively simulate how human behaviors during handoffs influence the schedule updates and delays. Section 5.1.2 presents the computational agent-based model created based on lab experiment data and the schedule information used in these lab experiments. This section then analyzes the communication data collected in the lab experiments in order to comprehend and simulate how human errors influence the productivity of outage workflows.

5.1.1 Experiment designs for modeling and analyzing communication errors

5.1.1.1 Two basic plans for supporting the experiment design

The lab experiment design presented here has two objectives: 1) to model the detailed interactions between individuals in a turbine maintenance workflow during a typical NPP outage, and 2) to assess to what extent the variations of task durations and abnormal turnovers/handoffs will influence the field workflows.

Specifically, the experiment design aims at answering the following questions:

1. How do the handoffs in RPI affect the duration of the valve maintenance workflow?
2. By running this experiment multiple times (e.g., 20 times), would the team be able to estimate the uncertainty/variance of the duration of valve maintenance workflow?

3. What are the impacts of variation/uncertainty of valve maintenance to the delay risks of the entire outage? How could we use the valve maintenance experiment data to carry out a computational simulation to understand how uncertainties of vale maintenance influence the entire outage?
4. How do different communication protocols help reduce the delays in the workflow? What is the optimal time to inform the next worker team that the current task is about to finish?
5. How will the automated communication tools, such as an automatic schedule updating and notification software that automatically remind workers when they could start their work at the completion of predecessors, could help reduce the risks of delays?
6. How a computer vision algorithm could automatically analyze videos of handoff processes for identifying handoff anomalies? What is the accuracy of human detection and tracking algorithm? Could the algorithm automatically ignore reliably track waiting time of workers and correctly ignore people who will not influence the handoff efficiency (e.g., people who are walking nearby without participating in the handoffs)?

The indoor experiment includes two plans that consider different complexity of the schedule structures and workflows to understand how various communication protocols and related human factors influence the uncertainties and productivity of the studies schedules:

1) Plan A uses a *simple linear workflow* for *valve maintenance* to understand how different scenarios in the "RPI" (in this case, the lab for simulating the RPI indoor space) could affect the overall schedule duration and the possibilities of critical-path changes that could significantly influence resource allocations for controlling the critical tasks in the schedule;
2) Plan B uses a more *complex workflow* extracted from a previous outage schedule – Unit 3, 19th Refueling Outage, PVNGS (3R19) – for *turbine maintenance* during the outage, to understand how different scenarios (i.e. workers are following different moving sequences at stations) during the handoff processes in the indoor environment (in this case, the indoor lab space for simulating a tool pickup/return room) could affect the overall schedule duration and critical-path change.

Within the indoor environment (RPI for plan A; tool pick-up/return stations for Plan B), the project investigators set up four stations (station 1, station 2, station 3, and station 4) in the lab at the Polytechnical campus of Arizona State University (ASU). The videos collected were used to test how accurately the computer vision algorithm can estimate the waiting time at each station when workers have different moving patterns in the indoor workspace. The following sub-sections introduces detailed designs of the experiments for both Plan A and Plan B. Specific detailed designs include the design of the communications (section 5.1.1.2), and detailed indoor processes that can guide the participants of the lab experiments to complete the simulation of the indoor work processes of both Plan A and Plan B (section 5.1.1.3).

5.1.1.2 Communication design during the case study

A communication protocol is a set of rules defining the organization structures, timing, channel, and content of communication according to the information transition needs of a workflow. The communication protocols for both Plan A and Plan B generally defines a centralized communication network, the direction of the information flow and the timing of the communication. Both plan A and plan B involves a number of experiment participants. In plan A, the experiment needs participants to play the roles of supervisor, insulator, mechanics, and electrician (plan A). In Plan B, the experiment needs the participants to play the roles of supervisor, mechanic, welder, turbine operator (plan B) (see Figure 24).

Within this centralized communication protocol, each field worker (everyone except the supervisor, including insulators, mechanics, welders, turbine operators, and electricians) needs to report to the supervisor after his/her current tasks are done (or 15 minutes before task complete). This protocol enables the supervisor to have a better understanding of the task status on the field through communications with different workers.

The task of the supervisor is to communicate with other "field workers" (i.e., insulator, mechanics, and electrician) to manage the workflow by acquiring all task information according to the communication protocols. After task information has been collected from different workers, the supervisor will have a better understanding of the availabilities of tasks based on the as-planned schedule. The supervisor is then required to notify workers for all available tasks so that a worker is only allowed to start the next task after getting the permission from the supervisor.

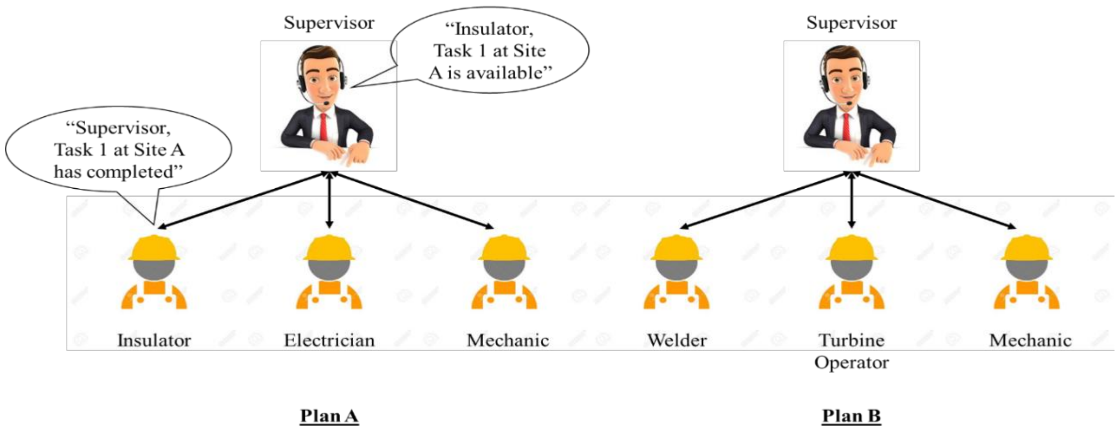

Figure 24. Communication activities for Plan A and Plan B

5.1.1.3 The indoor laboratory scene for the case study setup

Plan A: Simple linear schedule

By reviewing the schedule of previous outages (Unit 3, 19th Refueling Outage, PVNGS - 3R19; Unit 1, 20th Refueling Outage, PVNGS - 1R20), the investigators found that the outage process was split into nine windows (sections) for different maintenance activities that have different purposes (see Table 5). Each window has a strict time limit that requires the teams and supervisors to follow the timelines and avoid delays. However, a 66-hour extension happened during the 1R20 outage. This 66-hour outage extension on the scheduled duration was the combined effects of the following: Reactor Vessel and Core Barrel 10 Year Inspection (63.5 hours of delay occurred in Window #5); Main Spray Isolation Valve (RCEV240) (19 hours of delay occurred in Window #8); Fuel Movement and Additional Inspections (15.5 hours of delay occurred in Window #4 and Window #6); and Main Steam Isolation Valve Testing (7 hours of delay occurred in Window #9).

The project investigators studied the post-outage report of an outage - 1R20 (Unit 1, 20th Refueling Outage, Palo Verde Nuclear Generating Station) – to understand which windows (sections) during a typical outage often causing more delays. According to the post-outage report, significant delays in this outage are due to uncertainties in maintenance activities within Window #4 and Window #5 (see Table 5). Window #4 is the section where the NPP starts offloading and preparing for refueling of the core. The scheduled time window is 48.0 hours but achieved in 53.6 hours (5.6 hours over baseline). The delays within Window #4 is mainly due to the debris discovered on multiple fuel assemblies that need additional work to remove the debris, which is not a scheduled task in the as-planned schedule. Window #5 is the section that the NPP core needs to empty its vessel for refueling activities (Pressurized Water Reactor Group). The scheduled time window is 174.5 hours but achieved in 243.0 hours (68.5 hours above the baseline). The primary causes of delays within Window #5 are due to the malfunction of the reactor vessel inspection robot. The outage management team need to assign additional work packages to repair the inspection robot (multiple components replaced to include hydraulic pump, pressure relief valve, and manifold) and continue activities within Window #5.

According to the statement by the interviewed expert, tasks listed in the sections "Window #4" and "Window #5" have the largest variances per the outage schedule updating histories. This observation is true for many other outage projects across the whole nuclear industry [45]. Tasks within these two sections are mainly related to the main reactor and the main turbine system, which contain a large amount of work and complex task dependence relationships. In that case, a small delay in one task could propagate into a major extension on the overall outage duration. The project investigators thus decide to design the experiment to comprehend how handoff processes between tasks in valve maintenance workflows influence the productivity. The particular experimental design involves both computational simulations of field workflows and physical simulations of handoff processes. As shown in Figure 25 below, computational simulations of some field workflows helped the project investigators to create "virtual sites" that do not need actual executions of nuclear power plant operations. The lab space is a "physical site" that needs actual physical simulations of human behaviors in an indoor environment where handoffs occur.

The hybrid virtual-physical simulation shown in Figure 25 allowed the project investigators to understand how handoff influences a complete workflow that has some "virtual" tasks simulated on computers. The tasks simulated in the experiment are *valve maintenance* at two workspaces, "Site A" and "Site B", and the handoff processes occurring at the RPI.

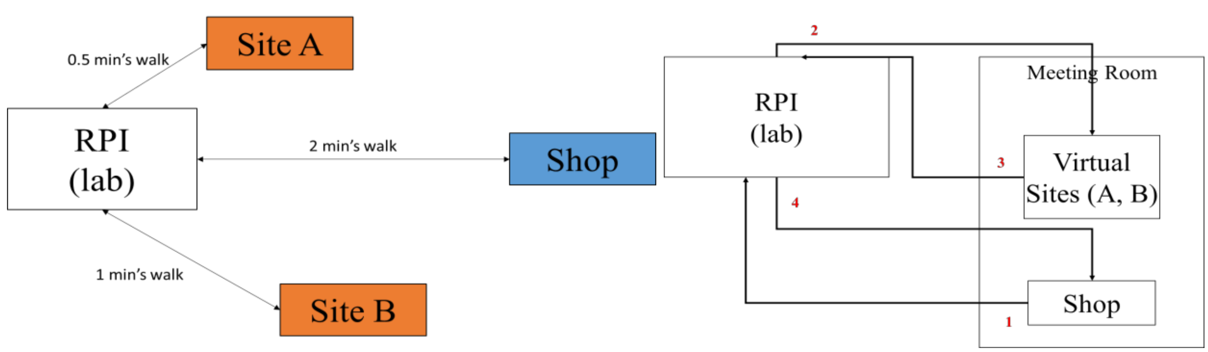

Figure 25. Layout map showing the distance between all three sites

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 them start their work at Site A. In addition, once a worker team complete 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.

Table 11 lists the tasks in the schedule of Plan A and the duration information. In the experiment, the project investigators scaled the duration of tasks to simulate the schedule with the duration much shorter than the actual outage processes simulated by the researchers. Column "Scaled Task Duration" in the table shows that scaled duration that is 10% of the actual duration.

Table 12 lists the stations in the RPI for workers to complete specific handoff tasks in the RPI, as well as specific time requirements for different types of workers to complete specific handoff tasks at those stations (different types of workers need different times at the same station due to the different needs of their work responsibilities). The time needed for handoff tasks also have scaled values for research experiments. In practice, when multiple workers are on the same station, workers should wait at the stations for others who are receiving the service. That waiting will be additional time on top of the time needed for completing the handoff tasks because even before starting the handoff tasks, the workers need to wait. The waiting time of workers who are going through the handoff processes in the 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 workflow caused by delayed valve maintenance. This experiment used the following schedule captured in the previous outage (see Figure 26 and Figure 27). Please see detailed RPI layout in Figure 28 and Figure 29.

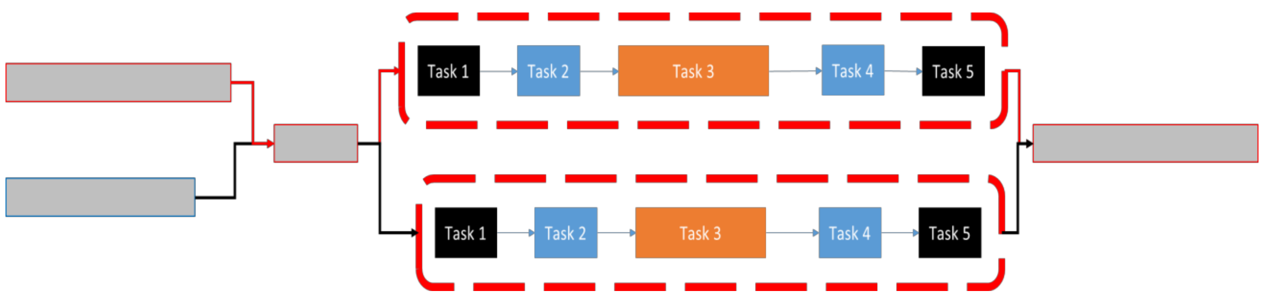

Figure 26. Section of the schedule

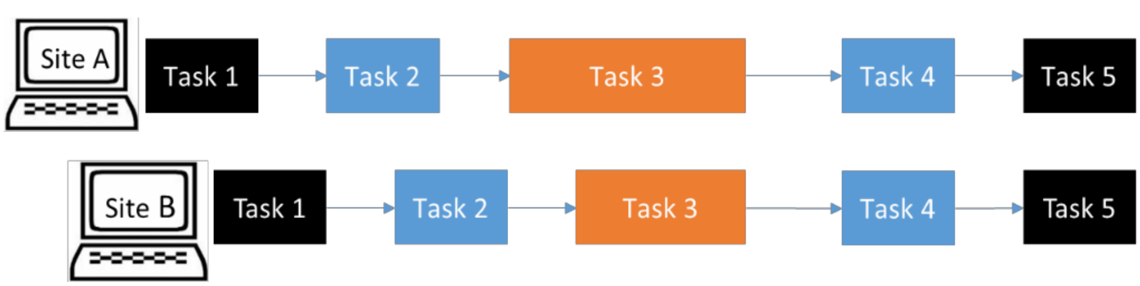

Figure 27. Valve maintenance workflow

Plan A - Handoff Workflows in the RPI

After reviewing data collected in past outages, the project investigators found out from the video collected from Palo Verde that workers might have different objectives when they enter the RPI, which will make the moving patterns of workers different. Also, the time for each worker team spent at the stations in RPI might be different. In order to test the capability of the computer vision algorithms for accurately estimating the waiting times of workers in the RPI, the project investigators asked different worker teams working on different work packages to follow different handoff processes in the lab. The purpose is to test how computer vision techniques could estimate the overall waiting time when the RPI have various people working on different things and visit the stations in different orders and with different time consumptions at those stations.

Table 11. Task Duration of valve maintenance workflow

Task #	Task name	Location	Resource	Planned Duration (min)	Scaled Task Duration (min)
Task 1	Remove insulation from the valve	Site A	Insulators	30	3
Task 2	De-term the motor operator	Site A	Electricians	45	4.5
Task 3	Perform valve maintenance	Site A	Mechanics	60	6
Task 4	Re-term the motor operator	Site A	Electricians	45	4.5
Task 5	Re-install the insulation	Site A	Insulators	30	3
Task 1	Remove insulation from the valve	Site B	Insulators	30	3
Task 2	De-term the motor operator	Site B	Electricians	45	4.5
Task 3	Perform valve maintenance	Site B	Mechanics	60	6
Task 4	Re-term the motor operator	Site B	Electricians	45	4.5
Task 5	Re-install the insulation	Site B	Insulators	40	3

Plan A - Uncertainties considered and simulated in the laboratory experiment

1. Uncertain task durations of maintenance tasks
   - The variance of maintenance task duration due to the insufficient knowledge and experience that a worker has while performing the scheduled maintenance activities.
2. RPI task duration
   - The variance of RPI task duration due to different natures of the work responsibilities of workers while a worker team spent at each station (e.g., the mechanical team might spend a long time on repairing activities at certain stations compared with other teams).
   - The different team might spend a different amount of time at the same station.
   - The same team might spend a different amount of time at the same station when they enter or leave the RPI.
3. Moving patterns
   - Different worker teams should follow different schedules in the RPI because of the different needs of their responsibilities (please see the details of moving patterns in the next section).

Table 12. Task information in RPI

Task name	Resource	Avg. Task Duration: enter/exit (minutes)	Scaled Task Duration (minutes)
RPI Station 1 (Dosimetry Checking)	Insulator	5/5	0.5/0.5
	Electrician	5/5	0.5/0.5
	Mechanic	5/5	0.5/0.5
RPI Station 2 (Pickup/drop-off tools)	Insulator	5/3	0.5/0.3
	Electrician	10/5	1/0.5
	Mechanic	15/5	1.5/0.5
RPI Station 3 (Technical Debrief)	Insulator	5/3	0.5/0.3
	Electrician	10/5	1/0.5
	Mechanic	15/5	1.5/0.5
RPI Station 4 (Check Available Work Packages)	Insulator	5/3	0.5/0.3
	Electrician	5/3	0.5/0.3
	Mechanic	5/3	0.5/0.3

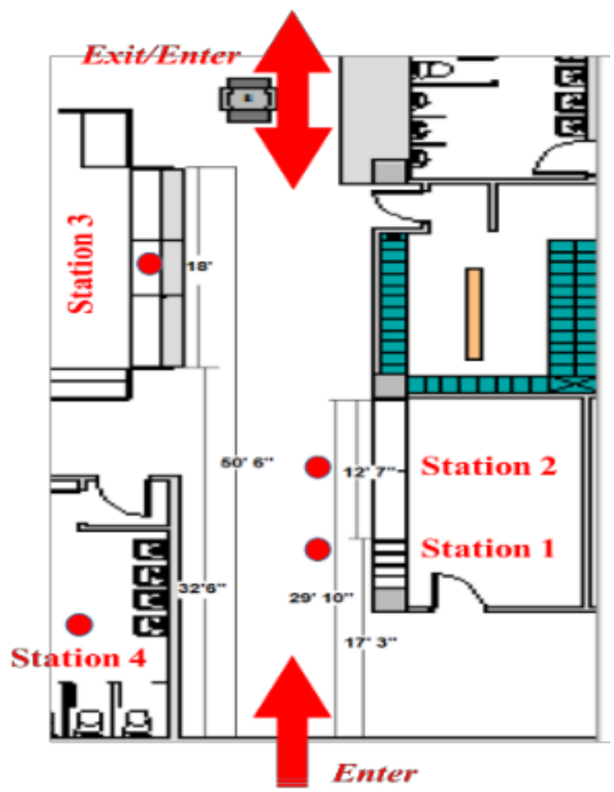

Figure 28. The RPI (indoor workspace) Layout

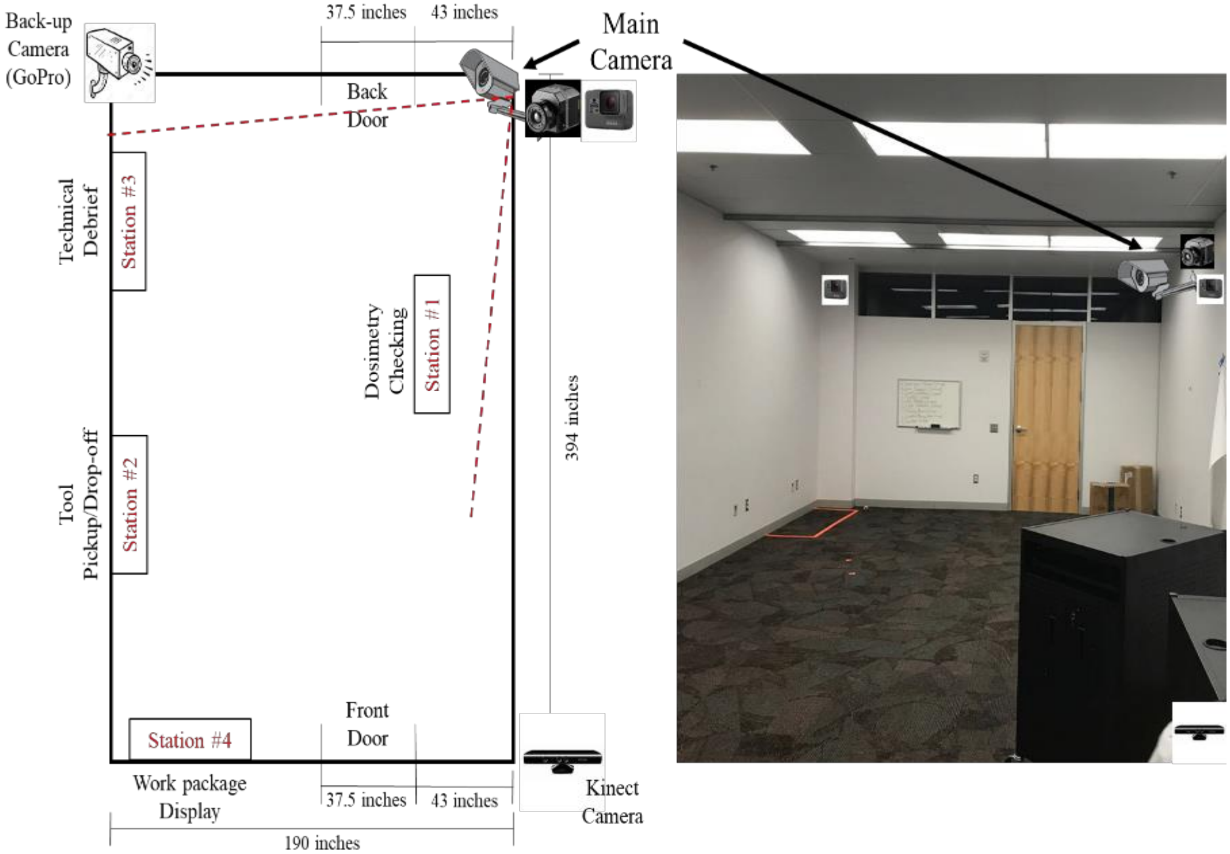

Figure 29. Lab layout (similar layout set up with RPI)

<u>Plan A - Moving patterns in RPI</u>

1. Enter the containment
   - *The Insulator Team*: (4, 1, 2, 3) Station 4 (Check available work packages) → Station 1 (dosimetry checking) → Station 2 (pickup ear plugs) → Station 3 (get technical debriefing) → enter containment
   - *The Electrician Team*: (4, 2, 1, 3) Station 4 (Check available work packages) → Station 2 (lock-up personal belongings) → Station 1 (dosimetry checking) → Station 3 (get technical debriefing) → enter containment
   - *The Mechanical Team*: (4, 2, 3) Station 4 (Check available work packages) → Station 2 (pickup tools) → Station 3 (get technical debriefing) → enter containment
2. Exit the containment
   - *The Insulator Team*: (1, 2, 4) exit from the containment → Station 1 (dosimetry checking) → Station 2 (drop-off ear plugs) → Station 4 (Check available work packages)
   - *The Electrician Team*: (1, 4) exit from the containment → Station 1 (dosimetry checking) → Station 4 (Check available work packages)
   - *The Mechanical Team*: (1, 2) exit from the containment → Station 1 (dosimetry checking) → Station 2 (drop-off tools)

Plan A - Personnel Set-up Information:

To test the capability of the designed computer vision algorithm for estimating the waiting time of groups of people in RPI, the project investigators created two cases: one with the fewer worker and one with more workers.

1. Case one: one worker for each worker team (4 in total; 1 supervisor included)
2. Case two: two workers for each worker team (briefing in the RPI could be individually or as a group) (7 in total)
3. For each case (few people/more people), the project investigators had irrelevant people show up in the indoor workspace to increase the difficulties of computer vision techniques in human detection and tracking, and test whether the algorithms could automatically ignore irrelevant people and correctly tracking the waiting time at different stations in the RPI.

Plan B - Turbine maintenance schedule (segment part of the schedule from P6 – 3R19)

The tasks simulated in the experiment are *turbine maintenance* at Site A (virtual site) and handoff processes in an indoor workspace (lab). All worker teams need to go through an indoor workspace for 1) checking available work packages; 2) getting technical debrief; and 3) picking up tools (e.g., earplugs) before them start their work at Site A. In addition, once a worker team complete a task, they need to 1) get back to indoor workspace for dosimetry checking; 2) drop off tools; and 3) check other available work packages (please see detailed task information Table 13 and Table 14, which list the maintenance task duration and RPI handoff task duration information). The waiting time during the handoff processes within the schedule of Plan B is thus crucial to 1) estimate the delays to the turbine maintenance activities at Site A caused by handoff in RPI and 2) estimate the delays of the entire outage workflow caused by delayed turbine maintenance. This experiment used the following schedule captured in the previous outage (see Figure 30 and Figure 31).

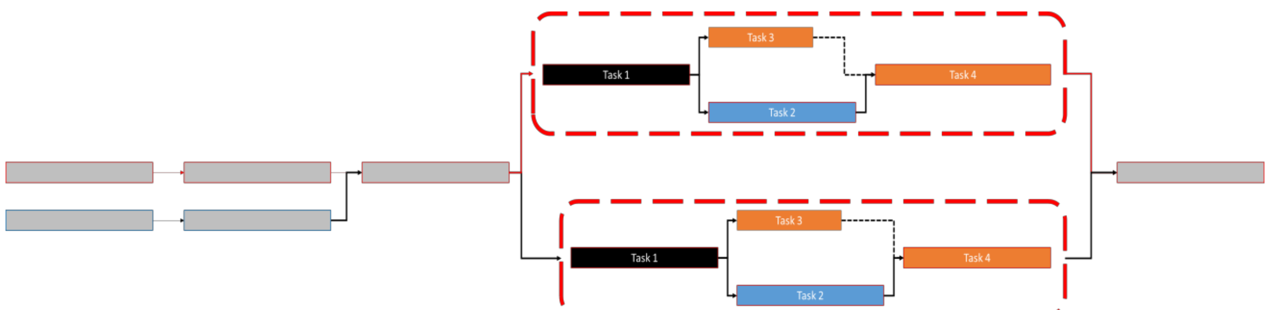

Figure 30. Section of the turbine maintenance schedule

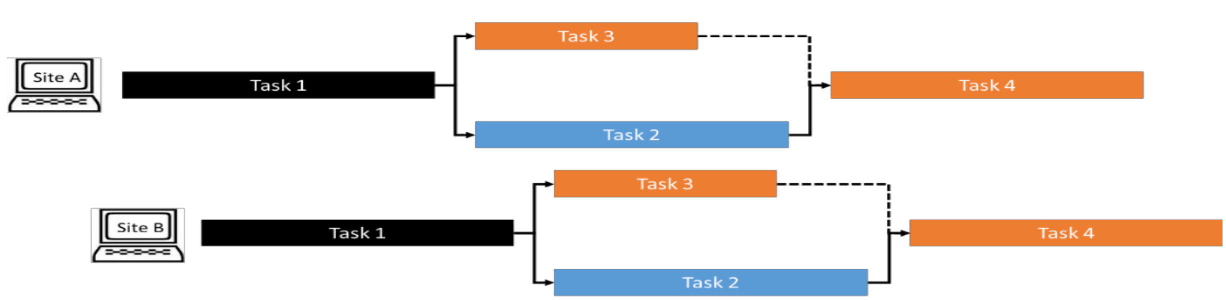

Figure 31. Turbine maintenance workflow

Table 13. Task information for the turbine maintenance workflow

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

Table 14. Task information in the indoor workspace for the handoff processes

Task name	Resource	Avg. Task Duration: enter/exit (minutes)	Scaled Task Duration (minutes)
Station 1 (Dosimetry Checking)	Mechanic	5/5	0.5/0.5
	Welder	5/5	0.5/0.5
	Turbine Operator	5/5	0.5/0.5
Station 2 (Pickup/drop-off tools)	Mechanic	5/3	0.5/0.3
	Welder	10/5	1/0.5
	Turbine Operator	15/5	1.5/0.5
Station 3 (Technical Debrief)	Mechanic	5/3	0.5/0.3
	Welder	10/5	1/0.5
	Turbine Operator	15/5	1.5/0.5
Station 4 (Check Available Work Packages)	Mechanic	5/3	0.5/0.3
	Welder	5/3	0.5/0.3
	Turbine Operator	5/3	0.5/0.3

<u>Plan B - Scenarios in the indoor workspace where handoff processes occur</u>

According to the practice of handoff processes between tasks, the project investigators found out from the video that workers might have different objectives before/after they start working on the scheduled tasks. Thus, different worker teams could have different moving patterns in the indoor workspace during handoff. Also, the time for each worker team spent at different stations might be different. The project investigators had different worker teams who were working on different work packages to follow different handoff processes in the lab. The 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.

<u>Plan B - Uncertainties considered and simulated in the laboratory experiment</u>

1. Uncertain task durations of maintenance tasks
   - The variance of maintenance task duration due to the insufficient knowledge and experience that a worker has while performing the scheduled maintenance activities.
2. RPI task duration
   - The variance of RPI task duration due to different natures of the work responsibilities of workers while a worker team spent at each station (e.g., the mechanical team might spend a long time on repairing activities at certain stations compared with other teams).
   - The different team might spend a different amount of time at the same station.
   - The same team might spend different time at same station when enter or leave into the workspace because of different technical needs of them at those stations.
3. Moving patterns
   - Different worker teams should follow different schedules in the RPI because of the different needs of their responsibilities (please see the details of moving patterns in the next section).

<u>Plan B - Moving patterns in the indoor workspace during handoff</u>

1. Enter the workspace
   - *The Mechanical Team*: (4, 1, 2, 3) Station 4 (Check available work packages) → Station 1 (dosimetry checking) → Station 2 (pickup ear plugs) → Station 3 (get technical debriefing) → enter containment
   - *The Welder Team*: (4, 2, 1, 3) Station 4 (Check available work packages) → Station 2 (lock-up personal belongings) → Station 1 (dosimetry checking) → Station 3 (get technical debriefing) → enter containment
   - *The Turbine Operator Team*: (4, 2, 3) Station 4 (Check available work packages) → Station 2 (pickup tools) → Station 3 (get technical debriefing) → enter the containment
2. Exit the workspace
   - *The Mechanical Team*: (1, 2, 4) exit from the containment → Station 1 (dosimetry checking) → Station 2 (drop-off ear plugs) → Station 4 (Check available work packages)
   - *The Welder Team*: (1, 4) exit from the containment → Station 1 (dosimetry checking) → Station 4 (Check available work packages)
   - *The Turbine Operator Team*: (1, 2) exit from the containment → Station 1 (dosimetry checking) → Station 2 (drop-off tools)

<u>Plan B - Personnel Set-up Information:</u>

To test the capability of the developed computer vision algorithms for estimating the waiting time of groups of people in RPI, the project investigators plan to create two cases: one with fewer worker and one with more workers who form teams for specific tasks.

1. Case one: one worker for each worker team (4 in total; 1 supervisor included)
2. Case two: two workers for each worker team (briefing at each station could be done individually or as a group) (7 in total)

3. For each case (few people/more people), we plan to have irrelevant people show up in the indoor workspace to increase the difficulties of computer vision techniques in human detection and tracking, and test whether the computer vision algorithms could correctly ignore irrelevant people in the RPI and correctly estimate the waiting time of workers in the handoff processes.

5.1.2 Computational simulation for predicting impacts of human factors on workflow performance

In this section, the project investigators aimed at developing computational models that can simulate how human factors influence the workflow performance, with a focus on process efficiency. These computational simulation efforts have two main branches: 1) an agent-based model for capturing how human factors influence handoff processes; 2) an analytical model that automatically prioritize on-going tasks for a supervisor to check the progress for ensuring timely workflow status monitoring and control. These two parts of the computational simulation collectively help engineers to analyze the detailed interactions between tasks and to understand better on the following questions:

1. How the variances of task duration affect the overall workflow duration (subsection 5.1.2.2);
2. How different communication protocols affect the delays of the workflow (subsection 5.1.2.3);
3. How proper progress monitoring strategies (proper prioritization of tasks for timely status checking during the outage) can help reduce delays in the workflow (subsection 5.1.2.4).

Good understanding of these questions can help engineers to study strategies of better control outage workflows, such as using the automatic communication system to improve communication efficiency and reduce communication errors in handoff processes. Actually, the computational simulation results guide the project investigators of this research to study how an automatic communication system could help reduce the risks of communication errors. The answer to that question leads to the research study that examines how an automatic communication system could help reduce uncertainties within handoff processes and what are the pros and cons of using such automation.

The proposed simulation model consists of a workflow module, a communication module, and a critical task identification module.

1) The workflow module represents the two workflows adopted in the designed experiments (Plan A: a linear schedule on the valve maintenance process; Plan B: a more complicated schedule on the turbine system maintenance process). The focus is to represent the detailed interactions between tasks in a workflow.
2) The communication module models the detailed interactions between individuals within and across groups (communications between the supervisor and the worker team).
3) The critical task identification module can identify the tasks that may cause workflow delays or critical path changes in dynamic NPP workflows.

5.1.2.1 Workflow scenario description

Figure 25 visualizes the entire as-designed workflow at Site A, Site B and RPI (indoor workspace). Please see Figure 27 and Figure 31for detailed visualization of task relationships. Blocks with the same color are tasks using the same resource that is part of, the same labor team (e.g., Insulators: black, Electricians: blue, Mechanics: orange). Tasks sharing the same team cannot be executed at the same time. In this research, the project investigators choose the simulation platform of Netlogo. In this model, the temporal scale is set as "10 seconds" as the minimum unit (one "click" in the simulation model indicate 10 seconds) of discrete time frames for simulating the outage processes, including both maintenance workflows and handoff processes.

5.1.2.2 Handoff process modeling

The project investigators also modeled the RPI process (handoff) within the workflow. The moving patterns designed indicates different worker teams follow different schedules in the RPI because of the different needs of their responsibilities. Each worker team needed to go through certain stations, with a designed moving pattern for briefing and tool pick-up for the scheduled tasks. The worker teams also needed to go through certain stations with a designed moving pattern for briefing and tool return once they complete their scheduled tasks (please see section 5.1.1.3 for a detailed explanation of moving patterns of different worker teams inside the indoor scene).

5.1.2.3 Human activity modeling

Human activity modeling defines the participants (workers, supervisor) involved in the outage processes and the required human activities (i.e. communications). A communication protocol is a set of rules defining the organization structures, timing, channel, and content of communication according to the information transition needs of a workflow. The communication protocols for both Plan A and Plan B generally defines a centralized communication network, the direction of the information flow and the timing of the communication. Both plan A and plan B involves a number of experiment participants. In plan A, the experiment needs participants to play the roles of supervisor, insulator, mechanics, and electrician (plan A). In Plan B, the experiment needs the participants to play the roles of supervisor, mechanic, welder, turbine operator (plan B).

Within this centralized communication protocol, each field worker (everyone except the supervisor, including insulators, mechanics, welders, turbine operators, and electricians) needs to report to the supervisor after his/her current tasks are done (or 15 minutes before task complete). This protocol enables the supervisor to have a better understanding of the task status on the field through communications with different workers.

The task of the supervisor is to communicate with other "field workers" (i.e., insulator, mechanics, and electrician) to manage the workflow by acquiring all task information according to the communication protocols. After task information has been collected from different workers, the supervisor will have a better understanding of the availabilities of tasks based on the as-planned schedule. The supervisor is then required to notify workers for all available tasks so that a worker is only allowed to start the next task after getting the permission from the supervisor.

<u>Worker agent</u>

The project investigators introduced the "worker" agent in the modeling to model human behaviors. In the current stage, the project investigators have modeled the worker as a team instead of different individuals. Each worker team can do the following things:

1. The worker agent can travel at a certain speed.
2. Each worker agent can do specific tasks according to the worker type. Specifically, in Plan A, the insulators can remove or re-install the insulation (Task 1 and Task 5). The electricians can de-term or re-term the motor operator (Task 2 and Task 4). The mechanics can do the maintenance work (Task 3). In Plan B, the mechanics can tension inner casing, closing doors

and heat shields (Task 1), the welders can use weld hood spray union lock tabs (Task 2), and the turbine operator can install cone extension and remove decking from casing (Task 3 and Task 4).

3. The worker agent can do self-check on the progress of their current task so that they can estimate the time left to complete the current task.
4. The worker agent can communicate with the supervisor about the progress of other tasks (e.g., the completion of the current task; the time left for the current task to be completed).
5. The worker agent can decide what to do next after they finish their current tasks based on the currently available tasks.

Based on these features of a worker agent, we can generate the "worker team" class. The "worker team" class defines a team composed of multiple workers collaborating on a particular task during NPP outages. The worker team class has the following attributes:

- Type - Each worker team has a type ranging from "insulators, electricians, and mechanics" (Plan A); "mechanics, welders, turbine operators" (Plan B). A different type of worker team can do different types of tasks.
- Location - Each worker team agent can travel between and work at different valves. The variable "Location (x, y)" can document the as-is coordinate of the worker team agent in the workspace within the evolving simulation model that simulates a changing job site.
- Current task - This attribute is tracking the current task a worker team agent is doing. This variable is updated when the agent "determines" which task to do next right before moving toward the valve where the current task takes place.
- Available tasks - This attribute represents a list of tasks that the worker team agent can do in the future.
- Status - The worker team agent has four statuses: 1) working, 2) communication, 3) traveling, and 4) waiting. At the start of the simulation, the status of every worker team is "waiting."

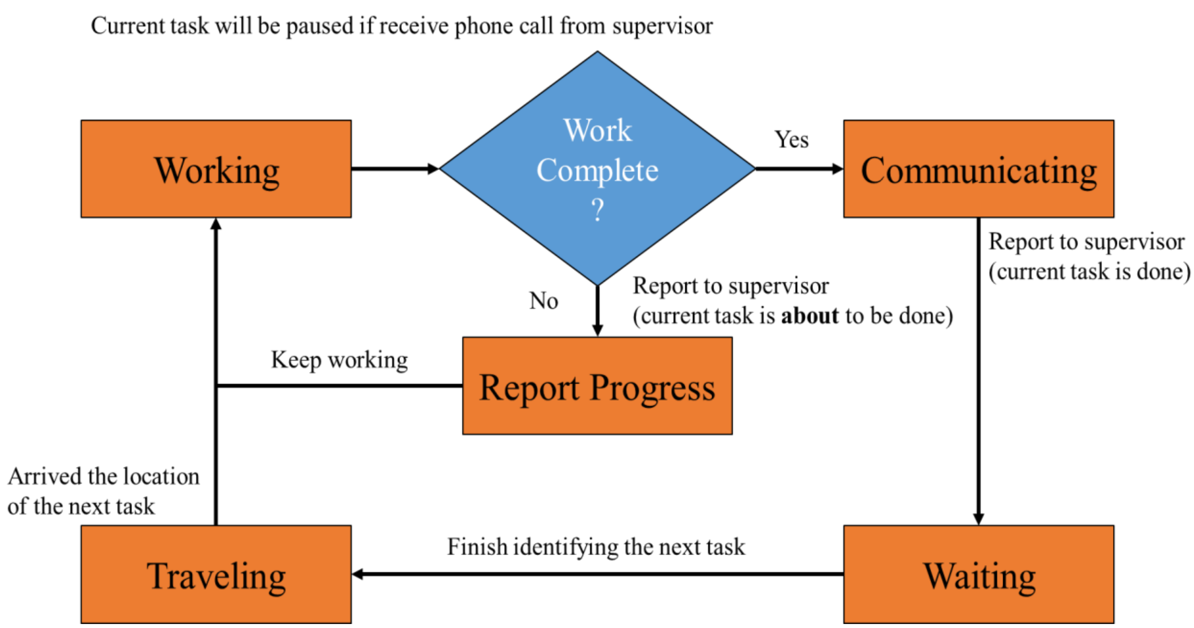

Figure 32. A status transition of a worker agent

Each worker team agent has three functions (see Figure 32).

- Travel - After the worker team identifies the "current task," it will move toward the location of the current task for step one. If the current location of the agent is the same as the location of "current task," the status of the worker team agent will transfer from "moving" to "working."
- Operations - When the worker agent is in status 2, the timer of the current task starts counting down. After the timer of the current task becomes zero, the status of the worker will become 3 (communicating), and the status of the valve will be changed according to the current task.
- Communication - When the worker team agent enters the communication status, the communication timer of this worker team starts to countdown. When the timer reaches zero, the supervisor will receive a message saying that the "current task" of the worker team is finished. Then the status of the worker team becomes waiting.

<u>Supervisor agent</u>
In this NPP outage scenario, the supervisor needs to 1) answer the phone calls from the worker team and record the information about the progress of the current tasks (e.g., the completion of the current task; the time left for the current task to be completed), and 2) inform the worker team that specific tasks are ready to be worked on after the supervisor receives a phone call reporting a finishing task.

Based on the behavior of the supervisor, we generate the supervisor agent, which has the following attributes:

- Status. The supervisor agent has two statuses: 1) communication, 2) waiting. At the start of the simulation, the status of the supervisor is waiting.
- Talking Object. This "talking to whom" agent will represent that who is the supervisor speaking with if the status of the supervisor is "communicating."

The supervisor agent has the following functions (see Figure 33).

- Receive a phone call: Once the worker agent calls the supervisor, the supervisor's status will become "communicating."
    1) Receive phone calls from worker agents about the completion of their current tasks;
    2) Receive phone calls from worker agents about the progress of their current tasks (when worker agent is about to complete their current task).
- Calling the successor agent
    1) Once the supervisor finishes answering the incoming phone-call from worker team A, the supervisor will check which task is available. Then the supervisor will "make a phone call" to inform the worker team agent B who is responsible for the successor task, which means B will add the successor task into the available list.
    2) Once the supervisor finishes answering the incoming phone-call from worker team A, the supervisor will check which task is available. Then the supervisor will "make a phone call" to inform the worker team agent B who is responsible for the successor task that they can prepare for the task and can only start working on that task once they receive another confirmation call.

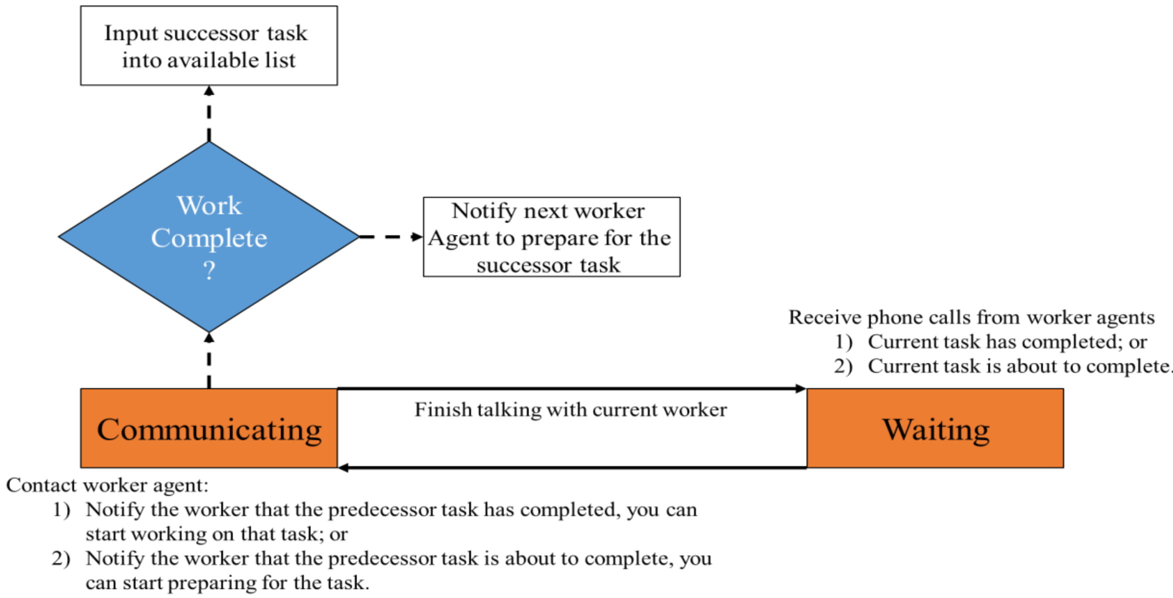

Figure 33. A status transition of supervisor agent

5.1.2.4 Critical task identification modeling

Early detection of workflow delays or critical path changes is challenging in busy NPP outage workflows. A first challenge is many tasks in NPP workflows. The outage management team needs to spend much labor and resource on monitoring the progress of all the tasks on critical paths. Also, sometimes the outage management team needs to monitor the progress of the non-critical-path tasks, because the accumulation of delays of non-critical-path tasks may cause the critical path to change and delay the entire workflow. Therefore, the lack of progress monitoring personnel and resource often exists in NPP outage projects. Another challenge is the long communication chain caused by the complex organization of outage participants and processes. According to the work presented in [11], when a worker finishes a task in an outage, he or she needs to *"...update the task status to his or her supervisor, who often updates an outage maintenance coordinator who then updates the Outage Control Center (OCC) outage maintenance manager who then updates the paper copy of the schedule*." When a worker finishes a task in an outage, he or she needs to "…update the task status to his or her supervisor, who often updates an outage maintenance coordinator who then updates the Outage Control Center (OCC) outage maintenance manager who then updates the paper copy of the schedule." The delays in this reporting chain 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 their statuses are updated as complete in the scheduling software.

In the domain of construction management, limited explorations focus on the theory of proactively identifying the probability of each task is delaying the workflow or causing critical path changes. To build such a theory, we borrowed the concept of Team Situation Awareness (TSA) from cognitive science domain, which describes the states of a team knowing what happened and what will happen. In the context of progress-monitoring, the TSA of the people working on workflow is the status of the management personnel being aware of the risks of workflow delay or critical path change caused by the potential delay of each task. This link between TSA theory and progress monitoring sheds lights on the early detection and resolve of workflow delays and critical path change. However, previous studies related to TSA have limited focus on quantitatively modeling and optimizing the information transmission processes in complex workflows. This research is trying to bridge the gap between the TSA theory and the need for evaluating the progress monitoring activities by quantitatively determining the risk of each task delaying the workflow or causing critical path, which leads to the timely answer of "which task to monitor" and "when to monitor" in busy, complex NPP outage workflows. Figure 34 shows the IDEF0 model of the proposed proactive progress monitoring method.

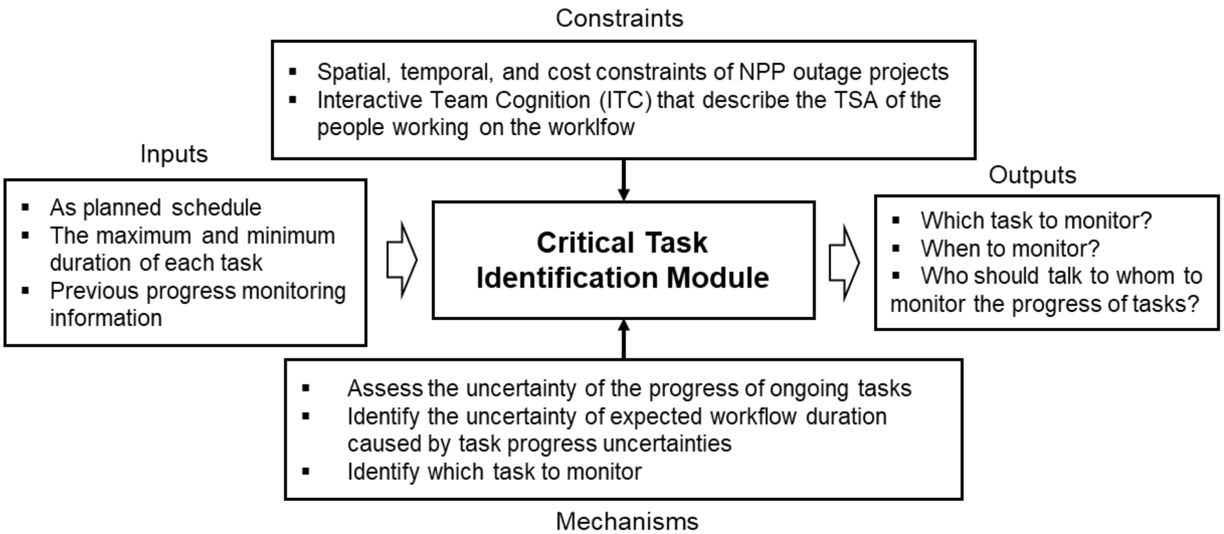

Figure 34. IDEF0 model the critical task identification module

The input of the proactive workflow progress monitoring method is the as planned workflow schedule, the maximum/minimum duration of each task, and the previous progress monitoring information. The constraints are the spatial, temporal, and cost constraints of NPP outage projects as well as the Interactive Team Cognition (ITC) theory that describes the TSA of the people working on the workflow. The output is the proactive progress monitoring plan: which task to monitor, when to monitor, and who should talk to whom to monitor the progress of tasks. Figure 35 visualizes the critical steps of proactive progress monitoring:

- Step 1 is to model the information need for workflow progress monitoring;
- Step 2 is to model the relationship between workflow progress and progress of individual tasks;
- Step 3 is to determine the communication protocol between team members for proactive progress monitoring.

These steps will help the decision-making about which task to monitor and when to monitor. The quantitative theory about such a task selection based on delaying risks is not available based on the literature review of the research team. This sub-section will introduce how to achieve these steps by modeling the information needs, the relationship between sub-goal and overall team goal, and the communication protocol.

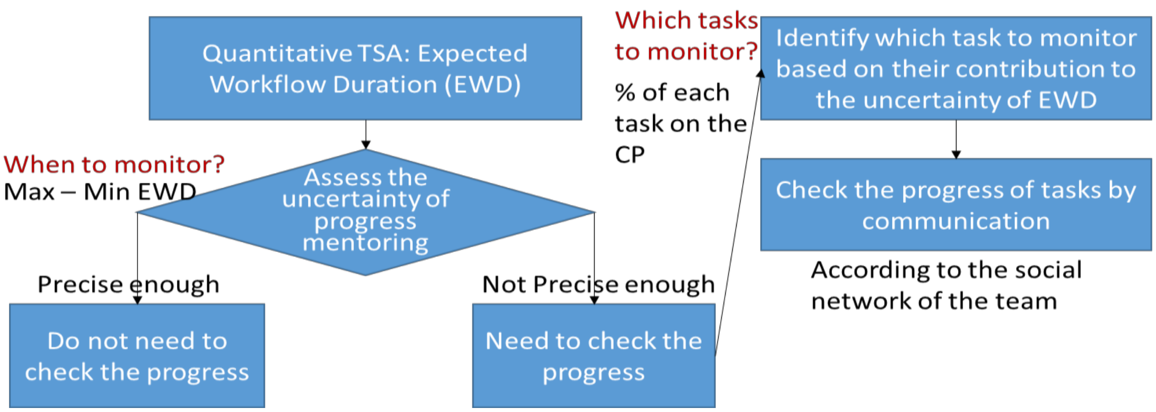

Figure 35. The framework of proactive progress monitoring

5.2 Communication analysis based on data collected in lab experiments

The project investigators analyzed the data collected in the lab experiments, with a focus on understanding the communication error during the lab experiments. Specifically, the project investigators examined how communication errors happened and affected the overall workflows.

5.2.1 Types of interactions in the case study

During the lab experiment, multiple communications are required for workers and supervisors to allow a fast information exchange during the experiment processes. As for the workers, they are required to acknowledge all message sent by the supervisor by saying "copy that." For example, workers need to acknowledge to the supervisor that they received the information about the tasks available for them to start their work. This communication is trying to help the supervisor know that the worker has received their messages. Another communication required for a worker is to send a notification to the supervisor about the progress of their work. In the lab experiment, the project investigators only ask the "participants" (workers) to send a notification about the completion of their tasks to the supervisor, so that the supervisor will know which task has been completed and decide which task would become available. Figure 36 shows the communication errors captured during the lab experiments. In the computer simulation, the project investigators modeled an additional function of the worker agents that represent the "reporting" behaviors of workers (i.e. report when current task is about 15 minutes to complete) for informing the supervisor to notify the next team to get ready for a task that will become available for the next team.

	Assignment						Acknowledgement				Report Complete				Ask if done	Call	Grand Total Interactions
Row Labels	Error	Correction	Correct	Error Rate	Correction Rate	Total	Error	Correct	Error Rate	Total	Error	Correct	Error Rate	Total	Correction	Error	Total
Supervisor -- Electrician			12	0%	0%	12											12
Supervisor -- Insulator	3	1	9	23%	8%	13									1		14
Supervisor -- Mechanic	1		7	13%	0%	8									1	2	11
Supervisor -- Turbine Operator		1	4	0%	20%	5											5
Supervisor -- Welder			2	0%	0%	2											2
Electrician -- Supervisor							1	18	5%	19		12	0%	12			31
Insulator -- Supervisor							6	13	32%	19	1	12	8%	13			32
Mechanic -- Supervisor							2	10	17%	12	1	7	13%	8			20
Turbine Operator -- Supervisor							3	2	60%	5		5	0%	5			10
Welder -- Supervisor							0	4	0%	4		2	0%	2			6
Grand Total	4	2	35	10%	5%	41	12	47	20%	59	2	37	5%	39	2	2	143

Figure 36. Summary of communication errors captured during lab experiments

As for the communication for supervisor, they will 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 supervisor are in the same communication channel, the supervisor is required to send out a notification to workers with targeted worker name and the task information (i.e., @insulator, task 1 at site A is available for you). Hence the worker will be notified there's a message relevant to his or her tasks.

During the lab experiments, additional information might occur because of human errors. For example, if a worker team forgot to report his progress, and the supervisor realized that he or she did not receive any information from that work for a long time. The supervisor could contact the worker and request updates on the tasks. Also, the supervisor might forget to send out notifications to workers about tasks available for them to work on. If a worker had been being idling for a very long time, he or she could contact the supervisor and request updates on the work packages that are matching their capability and available for them to work on at that particular time.

5.2.2 Communication errors captured during lab experiments

During the experiment, the project investigators found that the highest number of tasks were assigned to the Insulator and the highest number of errors occurred between the interactions of Supervisor and Insulator (see Figure 37). After interviewing the participants, the project investigators found that the reasons causing these communication errors might be related to the different workload between different workers. For example, the insulators having more tasks with longer task durations could commit more communication errors compared with electricians and mechanics who have lower workloads. Other factors could also influence the complexity of the contexts of workers, their workloads, and communication error rates: 1) complex network structures of the schedule could bring more frequent task changes and parallel tasks for particular workers (i.e., insulators need to take care of multiple tasks at the beginning and the end of the workflow); 2) the familiarity of the workers with the workflow could also influence error rates. Workers who are more familiar with the workflows could tolerate more tasks at the same time without committing any communication errors.

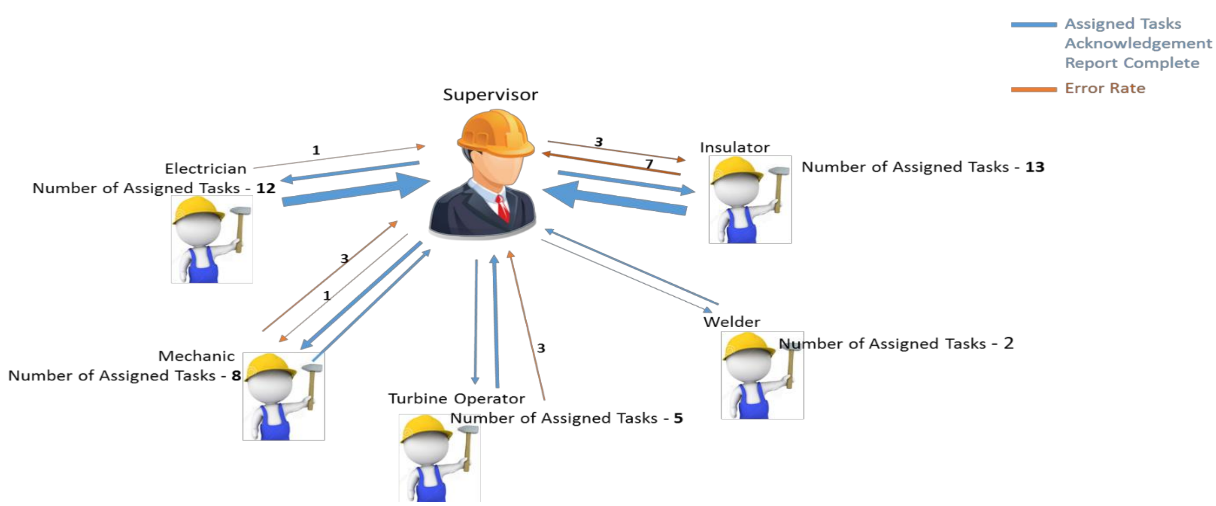

Figure 37. Overview of the communication errors

5.3 Develop an Automatic Communication System for Reducing Communication Errors

This section presents research work stimulated by findings of computational simulations about how to reduce communication errors for improved handoff efficiency. Based on the findings in the computational simulations presented above, the project investigators found that certain parts of the communication network could benefit from automated communication systems. For example, a scheduling system could automatically use the task completion information submitted by multiple workers to notify workers working on successor tasks automatically. Such automatic notification replaces the manual communications between the supervisor and workers and could reduce communication errors for improved process efficiency.

5.3.1 Hypothesis about how automatic communication system will reduce the risks of delays by reducing communication errors

Based on the previous analysis of communication data collected in the lab experiments presented above, the project investigators found that supervisors might be in a critical role during the workflow and the communication errors made by a supervisor can cause more risks to the workflow. The project investigators then decided to develop an automatic communication system and test whether such a system can help smooth the workflow by reducing risks of communication errors.

During the lab experiments presented above, the most frequent communication errors were lack of acknowledgment by the worker (e.g. "Copy that"); supervisor assigned tasks before workers were ready; workers fail to report that work is complete. However, the project investigators believe that automating the communication process could not only reduce communication errors and aid the supervisor in assigning tasks to the worker. Workers can also get an automatic notification about the information regarding available work orders. By implementing such an automatic communication system, the project investigators believe it can reduce delays caused by communication errors and keeping supervisors informed with automatic updates (see Figure 38).

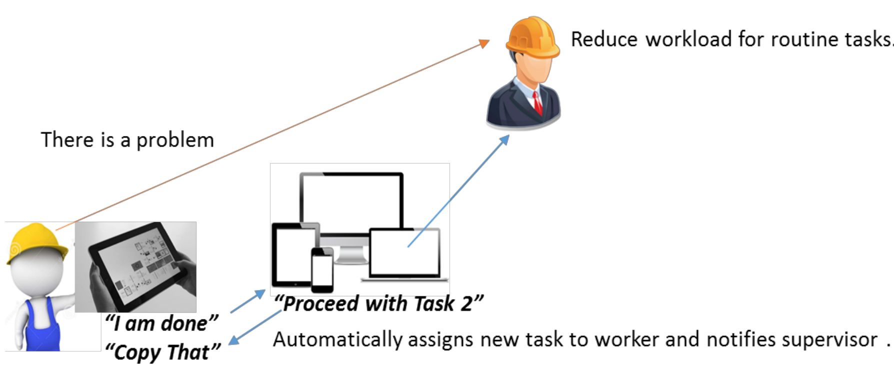

Figure 38. A prototype of automating the communication process

5.3.2 A detailed description of the developed automatic communication system

The first step is to create a blackboard table. The blackboard table includes information on all participants in the entire experimental phase, facilitating the logical construction of the sub-tables, and facilitating the experimental organization to view the progress of the experiment in real time. According to the experimental design, there are two working places, Site A and Site B. There are five tasks and three groups of participants. The actual participants in each group of experiments were three people, representing insulator, electrician, and mechanic. According to the above information, the summary table is designed as follows:

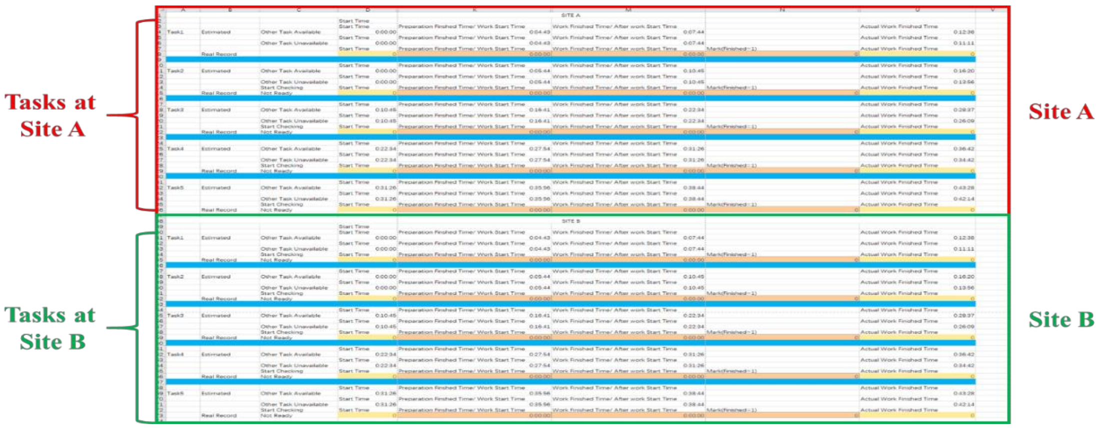

Figure 39. Layout in the excel sheet

According to the above information, the summary table is designed as shown in Figure 39. This table is divided into two parts from top to bottom, representing the work sites (Site A and Site B). Task 1 to Task 5 is performed sequentially at each work sites. Each Task has two-time recording parts. One is "Estimated Time," which is the time when the experiment designer expects each worker to prepare, start, and end. The other part is "Real Records." Data recorded in this section is the time records in the actual experiment about when the workers prepare, start, and end specific tasks.

After completing the blackboard table, the design of the sub-table is performed. Take the Insulator's work record table as an example; the following is displayed (see Figure 40):

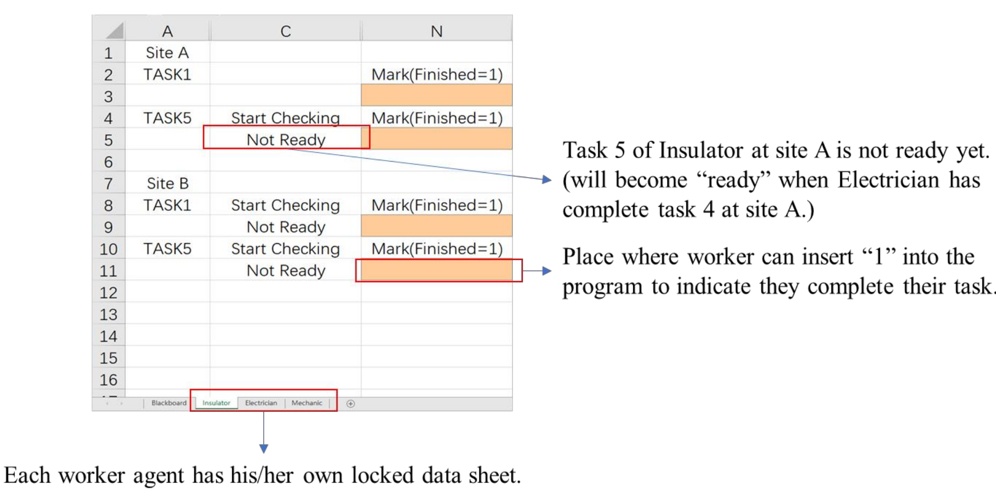

Figure 40. Task real-time status (insulator)

As with the master list, the table is also divided into Site A and Site B based on the work location. Work 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 performed. The last column is to record the completion of the work, workers are required to type "1" in the "Mark (Finished = 1)" cell to indicate if the work is completed. Through the built-in function, when the previous work is completed, the Start Checking part of the latter work can be automatically changed to the Ready state to notify the next worker to start work preparation. Electrician and Mechanic's tab design is similar to the Insulator's tab.

5.3.3 Description of how the automatic communication system works during a lab experiment

In order to enable the experimenter to share and edit the automatic communication system, the experimental designer decided to use Wechat as an experimental information delivery platform. Create three Wechat accounts, representing Insulator, Electrician, and Mechanic, and set up a group chat with the experimental designers, as shown in Figure 41.

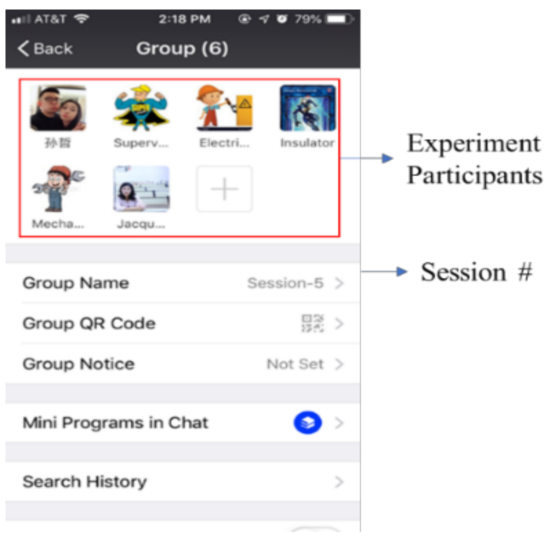

Figure 41. Group chat in Wechat

During the experiment, Insulator, Electrician, and Mechanic completed Tasks 1, 2, 3, 4, and 5 of Site A and Site B in sequence. The default work location starts with Site A, so Site A, Task 1 of Insulator does not need to be checked for work to begin. When the Insulator completes task 1 at Site A, he or she will enter "1" in the cell "N3" in his sheet to indicate that the work has completed. At this point, the status of task 1 at Site B will automatically change to the "Ready" state, and task 2 at Site B will also automatically display the "Ready" state as well (see Figure 42). By checking the updated excel sheet, workers will be automatically alerted that some tasks are available for them to be working on.

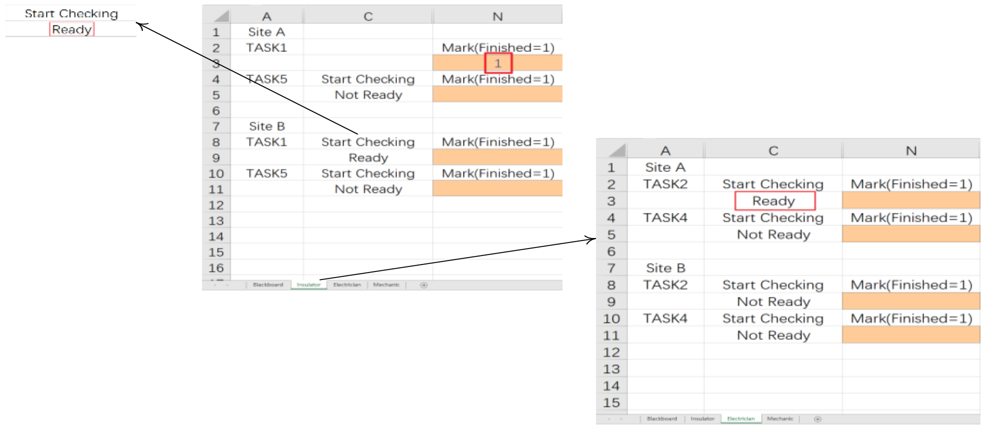

Figure 42. Status updating of task (insulator & electrician)

At this point, the Insulator can start the work of Site 1 of Site B. Electrician can start the work of Task 2 of Site A. After the Insulator reports to the Supervisor, the Supervisor instructs the Electrician to work. The process described above shows how to achieve automatic communication.

5.4 Performance evaluation between supervisor and automated communication system

To test the performance of the developed automatic communication system and compare the results with the performance of the workflow with the supervisor, the project investigators repeated the lab experiment. During the experiment, the project investigators used the valve maintenance workflow to conduct comparative lab experiments between workflow with and without a supervisor. The project investigators have run the experiment for 16 sessions in total (10 sessions of workflow that are replacing the supervisor with the developed automatic communication system; 6 sessions of workflow that are involved with a supervisor).

The project investigators hired participants from the Fulton School of Engineering at Arizona State University to join the experiments. Before each session of the experiment, the project investigators went through a 30-minutes training for all the participants involved in this session to get them familiar with the workflow and requirement. After each session, the project investigators asked each participant to fill out the NASA TLX questionnaire for the later analysis of the workload.

By comparing the performance of the workflow with and without a supervisor involved, since the use of automatic communication software can eliminate communication errors (no communication is required while using the automatic communication software), the project investigators tried to use the following metrics for the comparative study.

1. Overall workload duration and variance
2. Average task duration and variance
3. NASA TLX workload

5.4.1 Overall workflow performance

Table 15 and Table 16 indicate the average workflow duration between supervisor condition and automation system and the comparison of variance as well. Results show that the use of automatic communication system can significantly reduce the workflow duration and create less variance.

Tedious communication between supervisor and worker teams takes a good deal of effort and will increase the risks of communication errors. Delays could happen due to inappropriate communications, wrong information, late communications, misunderstanding, etc. Thus, an automatic communication system will help with reducing the risks of delays.

Table 15. Comparison of average workflow duration between supervisor condition and automation system

	Supervisor Condition (minutes)	Automation System (minutes)
Average	79.97	68.39

Table 16. Comparison of the standard deviation of workflow duration between supervisor condition and automation system

	Supervisor Condition	Automation System
Standard Deviation	10.29	8.70

5.4.2 Average and variances of task duration

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. The results are shown in Figure 43 and Figure 44. These results indicate that the use of an automatic communication system did not have significant impacts on the duration of executing individual tasks. There is no significant difference in the average task duration when comparing the workflows with a supervisor against those with an automatic communication system. In addition, the results also imply that the time wasted in the handoff and communication is significant and could be the main reason of delays.

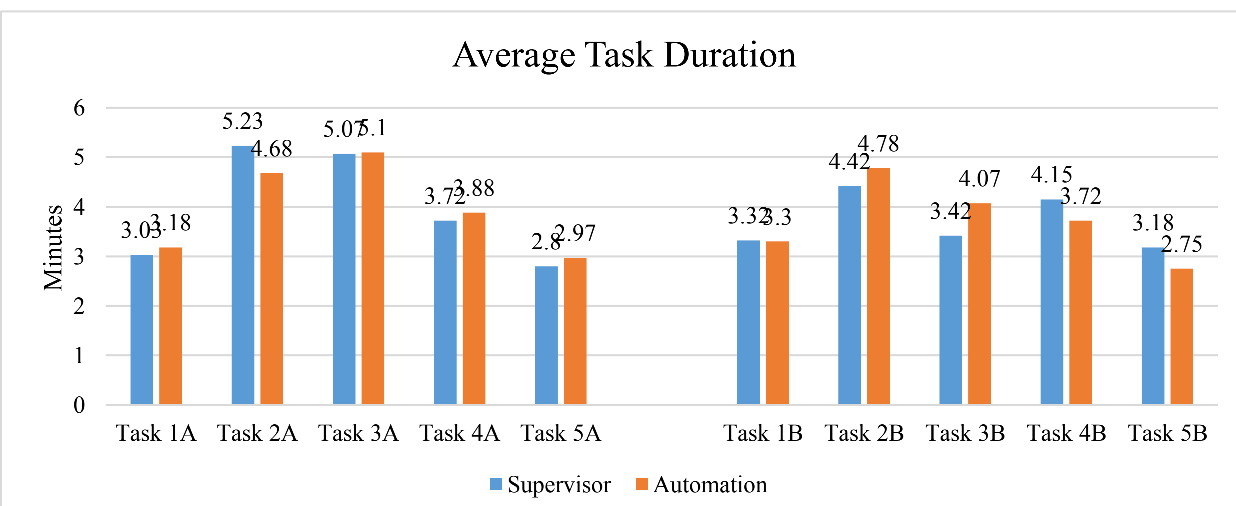

Figure 43. Comparison of average task durations between supervisor condition and automation system

Figure 44 indicates that the variances of tasks are quite different before and after using the automatic communication system. The variance of Task 2A, task 4A, task4B, and task 5B show that the variance of using automatic communication system is much higher than the case using a supervisor. The variance of Task 1B, task 2B, and 3B show that the variance of using a supervisor is much higher than the case using an automatic communication system. Those tasks where the supervisor show higher performance variances are those parts that have two workflows at two sites overlapping with each other so that the supervisor needs to pay attention to on-going works across two different sites. One possibility is that when two parallel processes at two different sites for two valves both have on-going tasks, the automated communication approach could better handle multiple parallel on-going tasks. Human supervisors could experience higher mental workload when handling multiple parallel on-going tasks, and possibly commit more errors and show more performance variances in coordinating tasks.

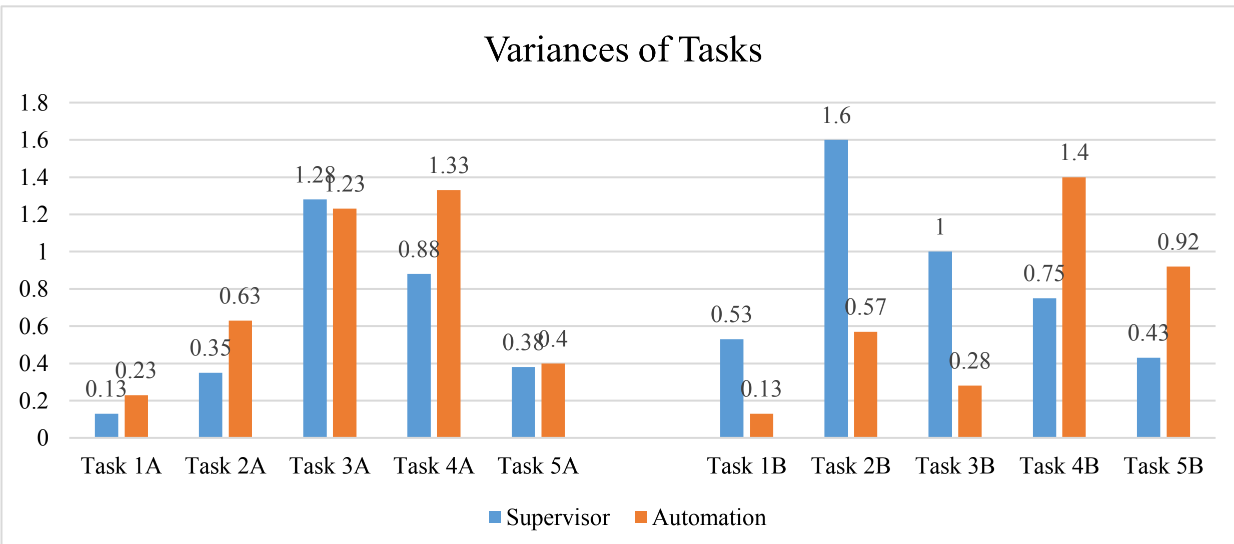

Figure 44. Comparison of variances of task between supervisor condition and automation system

5.4.3 NASA TLX workload comparison

The NASA TLX workload questionnaire (see Table 17) was distributed to all participants in order to better understand participants' cognitive demands during their tasks. Additionally, we were interested in whether the perceived workload between the two groups differed. That is, did the participants in the supervisor group condition perceive their workload differently than the participants in the automatic communication system group? Overall, the project investigators were interested in answering the following questions:

1. How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)?
2. How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred?

3. How did the experimental participants feel about the experiment among different emotional dimensions?

A two-sample t-test was conducted in order to compare the workload measures between the two groups. This comparison was conducted in order to understand whether the automatic communication system can reduce NPP outage workers' workload.

The two-sample t-test (95% CI) is one of the most commonly used tests. It is applied to compare whether the average difference between two groups is significant or if it is due instead to random chance. It helps to answer questions like whether the average success rate is higher after implementing a new tool than before. 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.

Table 17. NASA TLX questionnaire

Q1 How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)?		
The task was easy	1 2 3 4 5 6 7 8 9 10	The task was demanding
The task was simple	1 2 3 4 5 6 7 8 9 10	The task was complex
The task was forgiving	1 2 3 4 5 6 7 8 9 10	The task was exacting
The task was mentally effortless	1 2 3 4 5 6 7 8 9 10	The task was mentally difficult
Q2 How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred?		
The task was slow	1 2 3 4 5 6 7 8 9 10	The task was rapid
The task was leisurely	1 2 3 4 5 6 7 8 9 10	The task was frantic
Q3 How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)?		
Unsuccessful	1 2 3 4 5 6 7 8 9 10	Successful
Q4 Please rate the following emotional dimensions felt during the task.		
Insecure	1 2 3 4 5 6 7 8 9 10	Secure
Discouraged	1 2 3 4 5 6 7 8 9 10	Gratified
Irritated	1 2 3 4 5 6 7 8 9 10	Content
Stressed	1 2 3 4 5 6 7 8 9 10	Relaxed
Annoyed	1 2 3 4 5 6 7 8 9 10	Complacent

*For Q1, 1 means the participant felt the task was mentally easy; 10 means the participant felt the task was mentally demanding.

Figure 45 indicates the P-value calculated by comparing the mean values of each question in the NASA TLX questionnaire between the supervisor condition and the automatic communication system condition. The results show that there are statistically difference (p-value smaller than 0.5) between supervisor and automation condition when comparing whether the participants feel about the task is easy/demanding; simple/complex and discouraged/gratified. However, there are no significant differences between supervisor and automation condition when comparing whether the participants feel about the task is forgiving/exacting; mentally effortless/mentally difficult; slow/rapid; leisurely/frantic; unsuccessful/successful; insecure/secure; irritated/content; stressed/relaxed; and annoyed/complacent.

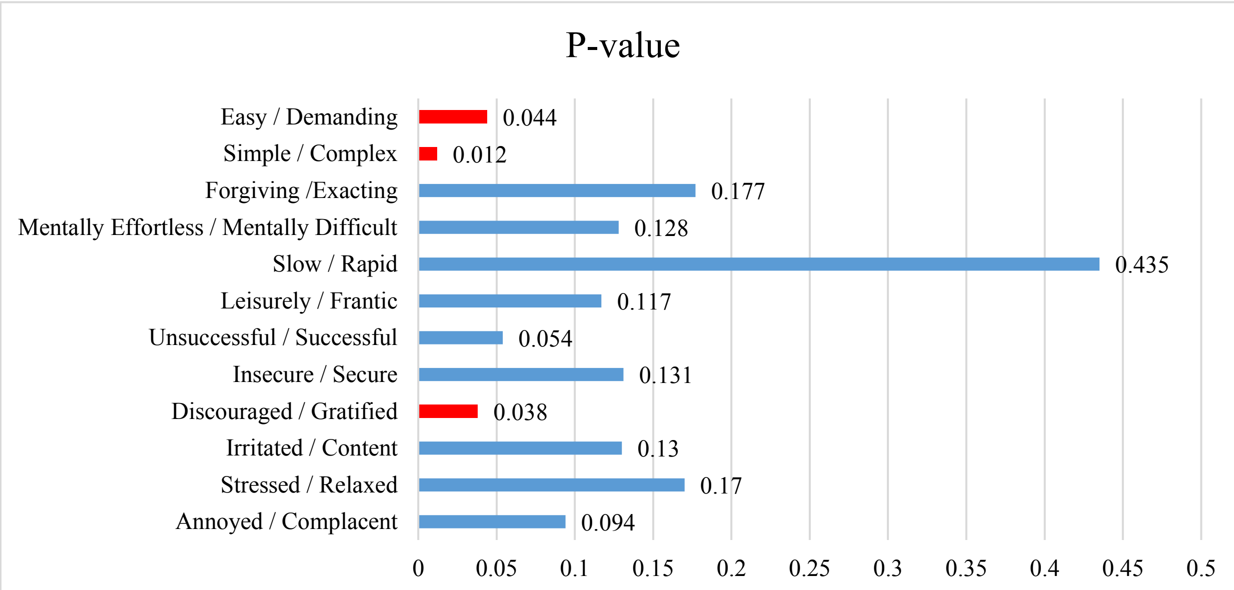

Figure 45. P-value of the factors in the NASA TLX

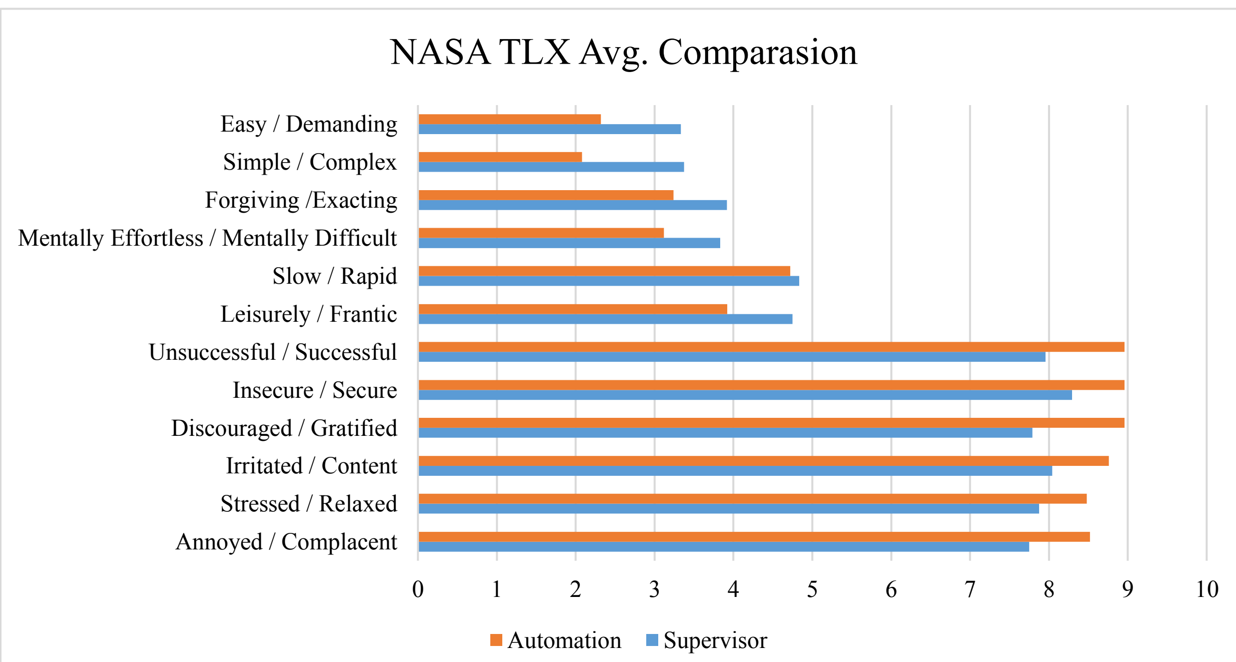

Figure 46. NASA TLX average comparison

Participants using the automatic communication system found the experimental tasks easier and simpler than participants who worked with a supervisor. These results seem to indicate that automating the communication process would lower the cognitive demands of NPP outage workers because the overall workflow process is simplified due to the elimination of the communication process. Additionally, participants using the automatic communication system were less discouraged and more gratified while performing the tasks than the participants who worked with a supervisor.

5.5 Simulation-based assessment of uncertainties and communication protocol optimization

This section presents research studies about how the numerous uncertainties affect the workflow productivity and possible adjustments of communication protocols based on findings from computational simulations and lab experimental studies (subsection 5.5.1 – impact of task duration variations; subsection 5.5.2 – impact of forgetting errors; subsection 5.5.3 – impact of communication errors, and subsection 5.5.4 – impact of handoff processes). This section presents an analysis of the task progress checking strategy generated by the analytical model for prioritizing tasks in terms of minimizing the uncertainties of workflow status and maximizing the situation awareness of the supervisor (subsection 5.5.5).

In this section, the project investigators aimed at developing an agent-based simulation model to simulate the detailed interactions between tasks and to understand better on the following questions:

1. How the variance of task duration affects the overall workflow duration;
2. How forgetting the errors of workers affects the overall workflow in terms of productivity (delays) and stability (schedule change);
3. How communication errors of workers affect the overall workflow in terms of productivity (delays) and stability (schedule change);
4. How different handoff processes and communication protocols affect the delays of the workflow;
5. How progress monitoring can help reduce delays in the workflow;

The proposed simulation model consists of a workflow module, a communication module, and a critical task identification module. The workflow module represents the two workflows adopted in the designed experiments (Plan A: a linear schedule on the valve maintenance process; Plan B: a more complicated schedule on the turbine system maintenance process). The focus is to represent the detailed interactions between tasks in a workflow. The communication module models the detailed interactions between individuals within and across groups (communications between the supervisor and the worker team). The critical task identification module can identify the tasks that may cause workflow delays or critical path changes in dynamic NPP workflows.

5.5.1 Impact of task uncertainties

According to the experiment results, the project investigators found that task duration variation was the primary cause of delays to the entire workflow. Also, poor human behaviors caused deviations of task durations. The designed experiments calculated the range of the as-planned task duration using average task duration and a standard deviation to determine which task deviates from the designed range. The highlighted durations of tasks were those that deviated from the range of the task duration and marked as delays. As shown in Table 18, Table 19 and Table 21 (Plan A), valve maintenance tasks scheduled for insulator team and electrician team are delayed at both Site A, and Site B. As shown in Table 20, the turbine maintenance tasks scheduled for the mechanical team and welder team are delayed at Site B.

For the designed experiments, all the participants received the same training about the experiment process and were strictly required to follow the as-planned task duration. However, the insulator team and the electrician team in Plan A (mechanical team and welder team in Plan B) might not have had a good understanding on the requirements for the experiments due to insufficient knowledge and experience for the experiments. Delays might occur and the productivity of the workflow would have been severely affected.

Table 18. Experiment results on 5-14-2018 First Round (Plan A, one worker/team)

	Worker Team	Start Time	End Time	As-is Duration	As-planed Duration
Task 1 (A)	Insulator	1:45:28 PM	1:48:50 PM	3:22	3:01
Task 2 (A)	Electrician	1:57:19 PM	2:02:40 PM	5:21	5:01
Task 3 (A)	Mechanic	2:11:34 PM	2:18:20 PM	6:46	5:53
Task 4 (A)	Electrician	2:28:41 PM	2:32:16 PM	3:35	3:32
Task 5 (A)	Insulator	2:39:40 PM	2:42:48 PM	3:08	2:48
Task 1 (B)	Insulator	1:56:18 PM	1:59:22 PM	3:04	3:10
Task 2 (B)	Electrician	2:10:24 PM	2:15:53 PM	5:29	4:58
Task 3 (B)	Mechanic	2:27:19 PM	2:32:40 PM	5:21	5:01
Task 4 (B)	Electrician	2:39:51 PM	2:44:40 PM	4:49	4:30
Task 5 (B)	Insulator	2:49:33 PM	2:52:52 PM	3:19	3:05

Table 19. Experiment results on 5-14-2018 Second Round (Plan A, one worker/team)

	Worker Team	Start Time	End Time	As-is Duration	As-planed Duration
Task 1 (A)	Insulator	3:26:40 PM	3:30:10 PM	3:30	3:01
Task 2 (A)	Electrician	3:37:50 PM	3:43:10 PM	5:20	5:01
Task 3 (A)	Mechanic	3:51:07 PM	3:57:31 PM	6:24	5:53
Task 4 (A)	Electrician	4:07:28 PM	4:11:00 PM	3:32	3:32
Task 5 (A)	Insulator	4:17:18 PM	4:20:30 PM	3:12	2:48
Task 1 (B)	Insulator	3:36:50 PM	3:40:20 PM	3:30	3:10
Task 2 (B)	Electrician	3:50:05 PM	3:55:25 PM	5:20	4:58
Task 3 (B)	Mechanic	4:05:55 PM	4:10:27 PM	4:28	5:01
Task 4 (B)	Electrician	4:19:22 PM	4:24:18 PM	4:56	4:30
Task 5 (B)	Insulator	4:30:15 PM	4:33:40 PM	3:25	3:05

Table 20. Experiment results on 5-23-2018 First Round (Plan B, one worker/team)

	Worker Team	Start Time	End Time	As-is Duration	As-planed Duration
Task 1 (A)	Mechanic	1:22:55 PM	1:27:10 PM	4:15	4:15
Task 2 (A)	Welder	1:34:40 PM	1:40:35 PM	5:55	5:55
Task 3 (A)	Turbine Operator	1:35:15 PM	1:39:30 PM	4:15	4:15
Task 4 (A)	Turbine Operator	1:46:18 PM	1:52:13 PM	5:55	5:55
Task 1 (B)	Mechanic	1:36:31 PM	1:41:33 PM	5:02	4:22
Task 2 (B)	Welder	1:49:27 PM	1:56:10 PM	6:43	6:31
Task 3 (B)	Turbine Operator	1:59:26 PM	2:03:46 PM	4:20	4:15
Task 4 (B)	Turbine Operator	2:10:21 PM	2:16:32 PM	6:11	6:20

Table 21. Experiment results on 5-14-2018 Second Round (Plan A, two workers/team)

	Worker Team	Start Time	End Time	As-is Duration	As-planed Duration
Task 1 (A)	Insulator	3:13:30 PM	3:16:31 PM	3:01	3:01
Task 2 (A)	Electrician	3:37:19 PM	3:42:20 PM	5:01	5:01
Task 3 (A)	Mechanic	3:41:25 PM	3:47:18 PM	5:53	5:53
Task 4 (A)	Electrician	3:50:55 PM	3:54:40 PM	3:45	3:32
Task 5 (A)	Insulator	4:00:25 PM	4:03:13 PM	2:48	2:48
Task 1 (B)	Insulator	3:23:51 PM	3:27:54 PM	4:03	3:10
Task 2 (B)	Electrician	3:38:13 PM	3:43:20 PM	5:07	4:58
Task 3 (B)	Mechanic	3:56:06 PM	4:00:51 PM	4:45	5:01
Task 4 (B)	Electrician	4:08:23 PM	4:13:08 PM	4:45	4:30
Task 5 (B)	Insulator	4:18:41 PM	4:21:46 PM	3:05	3:05

Baseline task duration

The fourth and the fifth column of Table 22 and Table 23 shows the average duration of and the standard deviation of each task in the simulation model A and B. The seventh row of Table 22 and Table 23 indicate the total duration workflow A and B in the simulation model.

Table 22. Workflow duration by running the simulation model (Plan A)

No.	Task name	Resource	Average Duration (min)	Standard Deviation
1	Remove the valve	Insulator	30	3
2	De-term the motor operator	Electrician	45	4.5
3	Perform valve maintenance	Mechanic	60	6
4	Re-term the motor operator	Electrician	45	4.5
5	Re-install the valve	Insulator	30	3
Total Duration			**11.57 (hours)**	

Table 23. Workflow duration by running the simulation model (Plan B)

No.	Task name	Resource	Average Duration (min)	Standard Deviation
1	Tension Inner Casing, Closing Doors & Heat Shields	Mechanic	45	4.5
2	Weld Hood Spray Union Lock Tabs	Welder	60	6
3	Install Cone Extension	Turbine Operator	45	4.5
4	Remove Decking from Around Casing	Turbine Operator	60	6
Total Duration			**10.53 (hour)**	

Delays captured during the lab experiments

The project investigators tried to understand the potential impact of the delays caused by individual tasks during the workflows. The last columns of Table 24 and Table 25 indicate the average delays captured during the lab experiments and the delays during simulation (duration in the lab experiments are scaled). Among the 1,000 runs of the simulation model, the average total duration of model A is 11.57 hours, and the average total duration of model B is 10.63 hours. Compare to the scheduled durations, model A has a delay of 0.29 hours (2.5%), and model B has a delay of 0.10 hours (1%).

Table 24. Average delays captured during Plan A experiments

	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%**	

The sensitivity of individual delays to the overall duration

According to the data collected from the experiments, uncertainties of task duration due to variations in people's behaviors is one of the main risk factors associated with delays. For instance, untrained workers may be inefficient and not knowledgeable enough to complete their tasks on time. Variation in communicating work status due to delayed updates or incomplete reporting can also cause substantial work delays. In order to better understand which tasks are more vulnerable in the workflow and which will cause more delays due to these uncertainties, the project investigators conducted a sensitivity analysis by calculating the delays and adding additional times during handoffs between tasks.

Table 25. Average delays captured during the Plan B experiment

	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%**	

As shown in Table 26, the "Delays" column indicates the delays to the overall workflow (Plan A) due to an extension of handoff on each task. For example, the project investigators added a 30-minute delay after the insulator finished task "AIR" due to the insulator forgetting to report to the supervisor that "AIR" has completed. That 30-minute delay eventually leads to a 30-minute delay to the overall schedule since "AIR" was a critical-path task.

Table 26. Delays while adding 30-minutes delay to each task (Plan A)

Site	**Task**	**Worker**	**As-planed Duration**	**Extended Duration**	**Total Duration (Hrs.)**	**Delays (Hrs.)**	**Percentage**
A	AIR	Insulator	30	60	12.07	0.5	4.32%
	AED	Electrician	45	75	12.09	0.52	4.49%
	AMM	Mechanic	60	90	12.21	0.64	5.53%
	AER	Electrician	45	75	12.07	0.5	4.32%
	AIC	Insulator	30	60	11.73	0.16	1.38%
B	BIR	Insulator	30	60	12.07	0.5	4.32%
	BED	Electrician	45	75	11.97	0.4	3.46%
	BMM	Mechanic	60	90	12.04	0.47	4.06%
	BER	Electrician	45	75	12.08	0.51	4.41%
	BIC	Insulator	30	60	12.07	0.5	4.32%

Table 26 shows that the task "AMM" is more vulnerable because the workflow is more sensitive to the delays of the handoffs involving "AMM" (0.64 hours, 5.53%). Delays on task "AIC" had the least impact on the overall workflow duration. Considering a 30-minute delay has been added to one of the tasks in the workflow, the extension on the task duration will not only affect the task itself but also affect the process in the RPI. If specific tasks got delayed, the probability of having scheduling conflicts between different crews while in the briefing process within RPI would increases. Additionally, the waiting time in the RPI will increase as well due to the conflicts, causing additional delays to the workflow. For example, additional waiting time might occur while task "AMM" got delayed because the tool returning process of the mechanical team might conflict with the tool pick-up process of the electrician team that is about to start on task "AER."

As shown in Table 27, the "Delays" column indicate the delays to the overall workflow (Plan B) due to an extension on each task. Obviously, "Task 4 (A)" is more vulnerable and the workflow is more sensitive to the delays on "Task 4 (A)" (0.99 hours, 9.31%). Delays on task "Task 2 (B)" has the least impact on the overall workflow duration.

Table 27 Delays while adding 30-minutes delay to each task (Plan B)

Site	Task	Worker	As-planed Duration	Extended Duration	Total Duration (Hrs.)	Delays (Hrs.)	Percentage
A	Task 1	Mechanic	45	75	11.12	0.49	4.61%
	Task 2	Welder	60	90	10.65	0.02	0.19%
	Task 3	Turbine Operator	45	75	11.19	0.56	5.27%
	Task 4	Turbine Operator	60	90	11.62	0.99	9.31%
B	Task 1	Mechanic	45	75	10.68	0.05	0.47%
	Task 2	Welder	60	90	10.63	0	0.00%
	Task 3	Turbine Operator	45	75	11.11	0.48	4.52%
	Task 4	Turbine Operator	60	90	11.1	0.47	4.42%

5.5.2 Impacts of forgetting errors

In this step, we first introduce the *Ebbinghaus Forgetting Curves* as a reference to model the probability of forgetting. The authors define the forgetting model in the simulation as a function of time describing that whether a worker can fully complete the required procedure, which means when the worker team receives the task information from the supervisor, the probability of forgetting certain steps in the procedure depends on when the worker team starts working on the successor task after they receive the information. If the time is too long since they receive the task information, they have a chance of forgetting certain steps in the required procedure, which will cause failure to complete the task, and rework will be needed. In this equation of forgetting, there are two parameters: A represent the pre-knowledge level of a person, and B represent the memory decay speed (B is larger mean memory decay faster). Figure 47 shows the most classical and common forgetting curves found in the literature for testing how forgetting happens on a different type of people (i.e. college student, a young worker, experienced professional, etc.), and how forgetting affects human behavior. Then, if a worker team forget to do certain step in the pump maintenance workflow, signals will be triggered in the control room, and the supervisor will be able to know which task needs to rework and assign rework task to the worker team, delays could happen due to rework.

$$P = Ae^{-Bt} \qquad \textbf{Equation 2}$$

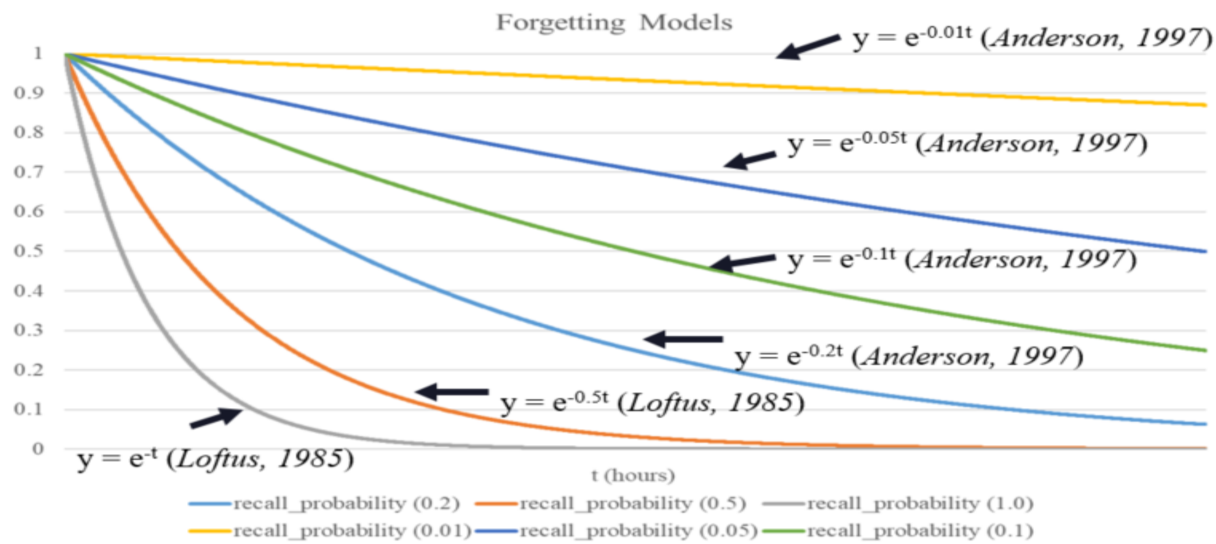

Figure 47. Existing forgetting curves tested in this study

Simulation-based communication protocol optimization

The project investigators designed a proactive follow-up protocol that asks the supervisor to follow up with workers by sending text notifications to every worker after issuing the task for a while. The purpose is to help remedy the forgotten information and mitigate the risks of delays caused by rework. The objective is to help the supervisor proactively monitor the entire workflow by checking the valve status, and follow-up with all worker teams when certain workers forget to do certain steps in the workflow during the outage. If a worker forgets certain steps during the workflow, the supervisor will help remind workers about the task information and procedures to complete certain tasks through text messages. The parameter in the follow-up module is the time interval between sending notifications. Therefore, we will be able to understand what is the optimal time interval to send text notifications based on different probabilities of forgetting when worker forget certain steps in the workflow.

This section shows the simulation results (see Table 28) to help illustrate how forgetting could cause delays to the workflow, and how different probability of forgetting will further influence the workflow duration. The results will quantify the relationship between probability of forgetting, workflow duration, and delays respectively.

Table 28. Delays Caused by Forgetting

Baseline Results				
As-planned Schedule (No forgetting)		The probability of Workflow Failure	Workflow Duration	Delays
		0%	595 min	0 min
Delays cases				
Forgetting Curve	Parameters	The probability of Workflow Failure	Workflow Duration	Delays
$P = Ae^{-Bt}$	*A = 1.0, B = 0.01*	14%	635 min	40 min
	A = 1.0, B = 0.05	51%	671 min	76 min
	A = 1.0, B = 0.1	71%	697 min	102 min
	A = 1.0, B = 0.2	80%	751 min	156 min
	A = 1.0, B = 0.5	96%	917 min	322 min
	A = 1.0, B = 1.0	98%	1001min	406 min

Impact of different forgetting curves on workflow duration

In the practice of NPP outage management, construction workers might have different education levels, background, and cognitive capability. Professionals might have higher memory capability on the required procedures due to their valuable experience, and contract personnel might not have that much experience in certain outage activities. In terms of different background of workers, people have different pre-knowledge level (A) and memory decay speed (B). In this study, the author assumes that all workers have the same pre-knowledge level but different memory decay speed. To mitigate the risks of forgetting, the nuclear industry needs a properly designed communication protocol to help reduce delays caused by forgetting. As shown in Table *28*, the authors have tested the impact of the workflow duration with different forgetting curves (see Figure 47) in terms of delay, trying to investigate what are the impacts to the workflow duration according to different forgetting curves. The results indicate that with the increased memory decay speed (B), the probability of failure workflows increased significantly, and the workflow duration as well. According to the results, depending on the different level of memory decay speed (B), the probability of workflow failure can range from 14% to 98%, and delays to the workflow can range from 40 minutes to 406 minutes. Therefore, an effective communication protocol (follow-up protocol) is highly desired, which can deal with all type of outage participants with different background and different memory capabilities.

Impacts of different follow-up intervals on workflow duration

The proposed simulation-based approach enables us to optimize the communication protocol considering the interaction between the probability of forgetting and delay of the workflow duration. In this study, the authors test two forgetting curves ($P = Ae^{-Bt}$, A= 1.0, B = 0.01; $P = Ae^{-Bt}$, A= 1.0, B = 0.05) in the simulation model and test the efficiency of using text messages to remind workers about task procedure. Results indicate that the duration of the workflow will extend to 635 minutes when introducing the probability of forgetting into the model ($P = Ae^{-Bt}$, A= 1.0, B = 0.01), which cause 40 minutes delay to compare to the workflow without considering the effect of forgetting. When introducing the probability of forgetting into the model with a higher memory decay speed ($P = Ae^{-Bt}$, A= 1.0, B = 0.05), the duration of the workflow will extend to 671 minutes, which causes 76 minutes delay to the workflow.

The simulation result (see Table 29 and Table 30) shows that with more frequent text notification sent by the supervisor to the worker can help reduce the delay caused by forgetting. Results indicate that with the memory decay speed becomes higher (B becomes higher), the probability of forgetting will increase faster over time, and the supervisor needs to send the text notification to workers to remedy task information more frequently. From the simulation outputs, since the supervisor might not be able to keep sending text notifications to all worker teams, we set the optimal time interval for sending text notification by a supervisor is every 30 minutes when B equals 0.01 and 0.05, and the delay to the workflow can be eliminated or reduced to 10 minutes respectively.

Table 29. Simulation Results (A=1, B=0.01)

Scenarios	Workflow Duration	Delay
No Forgetting, No Text Notifications	595 Min	N/A
Forgetting, No Text Notifications	635 Min	40 Min
Send out text notifications @ 120 Min	627 Min	32 Min
Send out text notifications @ 90 Min	619 Min	24 Min
Send out text notifications @ 60 Min	615 Min	20 Min
Send out text notifications @ 30 Min	595 Min	0 Min
Send out text notifications @ 0 Min	595 Min	0 Min

Table 30. Simulation Results (A=1, B=0.05)

Scenarios	Workflow Duration	Delay
No Forgetting, No Text Notifications	595 Min	N/A
Forgetting, No Text Notifications	671 Min	76 Min
Send out text notifications @ 120 Min	650 Min	55 Min
Send out text notifications @ 90 Min	641 Min	46 Min
Send out text notifications @ 60 Min	631 Min	46 Min
Send out text notifications @ 30 Min	605 Min	10 Min
Send out text notifications @ 0 Min	595 Min	0 Min

5.5.3 Impacts of communication errors

This research attempts to identify how human error can influence the stability of the workflow. Specifically, this simulation can quantify how possible forgetting to communicate with the supervisor will cause the entire workflow to fail.

In this simulation model, we assume that each worker team has a% chance to forget the report to the supervisor after they finished their current task. Also, the supervisor has b% chance to forget informing the team who is in charge of the successor task. According to the simulation model, if any mistake occurs the workflow will fail. Figure 48 shows the relationship between the chance of the entire workflow to fail and the human mistake rate. The simulation results show the following:

- 1% chance worker forget to report, and 1 % chance the supervisor forget to inform the next task: 22.7% runs are problematic.
- 2% chance worker forget to report, and 2 % chance the supervisor forget to inform the next task: 38.5% runs are problematic.
- If the worker and the supervisor have a 10% chance to forget communication, the workflow will have more than 80% chance to fail.

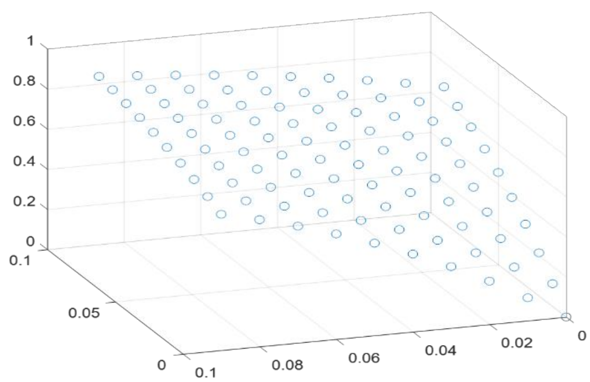

Figure 48. The relationship between error rate of worker/supervisor and the probability of the entire workflow to fail

Simulation-based communication protocol optimization for remedying communication errors

To start from a simple case, the communication in this workflow is centralized, which means a supervisor will organize the communication of the entire team. Three workers (i.e. the insulator, the mechanics, and the electrician) can only talk with the supervisor but are not allowed to talk with each other. Figure 49 visualizes the communication protocol between the workers and the supervisor. Without losing generality, the insulator should call the supervisor when he/she finished the first task in Site A (noted as A1) and report. After the talking on the phone with the insulator, the supervisor should call the electrician who is responsible for task A2 which is the successor of A1. After this phone call, the electrician will know that task A2 is ready for him/her to work on.

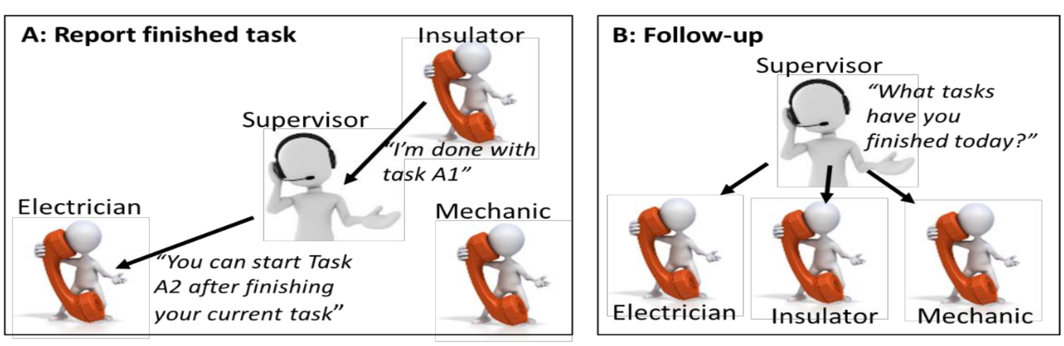

Figure 49. The communication protocol of the team

In order to mitigate the impacts of human errors, which can be the workers or the supervisor forgetting to make phone calls, Figure 49 visualizes the follow-up process in the communication protocol. At a certain amount of time interval, the supervisor will call all the workers asking about what tasks have been finished in all. In this way, all the information about the finished task can be recovered even if workers or the supervisor forget to communicate. Considering the reality of the communication pattern between the supervisor and workers, the information flow between people is mainly based on the current memory of a human. To achieve that in the simulation model, the author implemented two types of memory for both supervisor and workers, the temporal memory and comprehensive memory. As for the temporal memory part, the worker can remember the current task he/she has just finished, while the supervisor can remember the call from the worker reporting his/her task that just has been finished. As for the comprehensive memory, an information center stores a memory list that allows each person to share their memories to the public. With the help of an information center, the communication among large number of people could be easier. When communication happens, the information flow is based on the memory.

The simulation-based communication protocol optimization provides us a method to optimize the communication protocol considering human error rate, delay of the workflow duration, and the critical path change. The simulation result (shown in Table 31) shows that frequent status checking can help reduce the chance of critical path changing and mitigate the delay caused by human errors, but the communication time caused by frequent follow-up call will delay the entire workflow also. In order to balance the critical path change and delay of workflow duration considering different human error rate, the management team can set a threshold of "acceptable rate critical path change" and then choose the communication protocol that can minimize the workflow duration. For example, we can set the acceptable rate critical path change at 28% because it is the probability of critical path change in the baseline workflow without any human error or follow-up calls. Then we can choose the commutation protocol that satisfies this threshold and minimizes the workflow duration. Table 31 tells that the optimized follow-up call interval is 3.5 hours, 2 hours, and 1.5 hours (which are highlighted in yellow) when the human error rate is 1%, 2%, and 5%, respectively.

Table 31. Comparison of the probability of critical path change and workflow duration delay under different follow-up call interval and different human error rate

Error Rate	Index	0.5 hr.	1 hr.	1.5 hrs.	2 hrs.	2.5 hrs.	3 hrs.	3.5 hrs.
1%	Delay CP change	54.4 1.1%	30.7 5.6%	23.4 10.9%	20.0 20.1%	19.0 17.8%	20.0 20.6%	17.8 25.9%
2%	Delay CP change	56.2 1.1%	32.2 8.4%	27.5 12.1%	24.6 22.5%	24.7 22.2%	27.4 20.7%	25.1 31.3%
5%	Delay CP change	57.0 0.5%	37.7 8.2%	33.9 19.3%	34.2 27.6%	38.3 31.8%	41.2 29.7%	43.3 40.7%

5.5.4 Impacts of handoff processes

In the current communication protocol (see Figure 50), multiple communications are required for workers and supervisors to allow a fast information exchange during a workflow. As for the workers, they are required to acknowledge all messages sent by the supervisor by saying "copy that." 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.

As for the communication for supervisor, they will check the message sent by workers about their progress of work, and also send out as a notification to workers about tasks that are ready to be working on. Since all the workers and the supervisor are in the same communication channel, the supervisor is required to send out a notification to workers with a specified worker name and the task information (i.e. @insulator, task 1 at site A is available for you). Hence the worker will be notified there's a message for him/her.

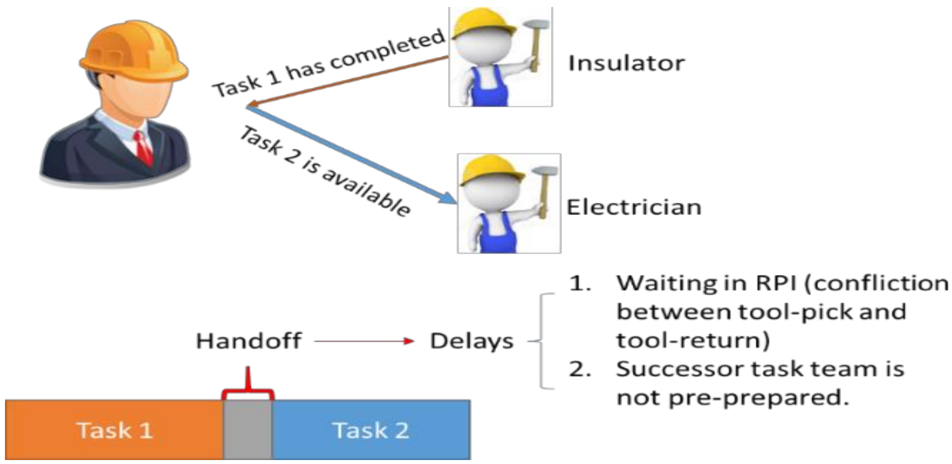

Figure 50. The current approach of hand-off

As for the optimized communication protocol, additional communications are required for the worker, who is to send a notification to the supervisor about the progress of their work. In the lab experiment, the project investigators only ask the "participants" (workers) to send a notification about the completion of their current tasks to the supervisor, so that the supervisor will know which task has been completed and decide which task can become available. In the computer simulation, the project investigators added another function to allow workers to report their progress of work so that the supervisor can ask the team who work for the successor task to get prepared.

The project investigators were also trying to model overlapped handoff and understand how the overlapped handoff can help reduce the risk of delays during an outage (Figure 51). Such overlapped handoffs could have different impacts on schedules of different network structures – the more parallel tasks in a schedule, the overlapped handoffs could get more people on different tasks in the RPI. One thing is that resources in the RPI are designed not to be shared, so 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 in the RPI. Since the waiting time is hard to estimate due to the variances of task duration in a workflow, reducing the time frame of the handoff through overlapping can create more spaces for accommodating task uncertainties. On the other hand, an overlapped handoff might create additional waiting time inside the RPI because both current and next tasks could go through the RPI. However, reduced handoffs could also increases the chance of shortening the overall workflow duration. Thus, the project investigators designed an "early-call" protocol that allows workers to report their progress of the current task (i.e. 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 send early messages to the workers working for the successor task and get prepared in the RPI in advance.

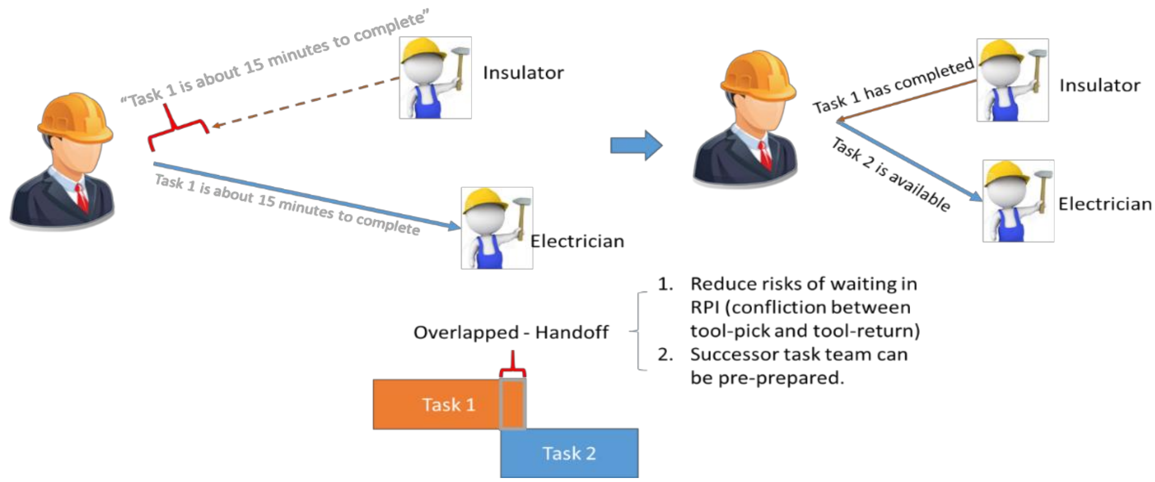

Figure 51. Overlapped handoff

The computer-based simulation results below indicate the delays reduced by a different type of "early-call." Since the shortest task has the duration of 30 minutes, the project investigators set the maximum time for an early call to the supervisor as 25 minutes. In the simulation, the project investigators tried to simulate the time for an early-call at 10 minutes, 15 minutes, 20 minutes, and 25 minutes. The results showing below indicate that for Plan A, worker calls 15 minutes and 20 minutes early to the supervisor, can reduce the most amount of delays (0.36 hrs, 3.1%) (see Table 32). As for Plan B, worker calls 15 minutes early to the supervisor can reduce the most amount of delays (0.33 hrs, 3.2%) (see Table 33).

Table 32. Plan A – Delays reduced by early-calls

Time of "head-up" Early Call	Workflow Duration (Hour)	Delays (+) (Hour)	% of Reduced Delays
Baseline	11.57	0	0
10 minutes	11.23	-0.34	2.9%
15 minutes	11.21	-0.36	3.1%
20 minutes	11.21	-0.36	3.1%
25 minutes	11.35	-0.22	1.9%

Table 33. Plan B – Delays reduced by early-calls

Time of "head-up" Early Call	Workflow Duration (Hour)	Delays (+) (Hour)	% of Reduced Delays
Baseline	10.41	0	0
10 minutes	10.26	-0.15	1.4%
15 minutes	10.08	-0.33	3.2%
20 minutes	10.28	-0.13	1.2%
25 minutes	10.30	-0.11	1.0%

5.5.5 Progress monitoring strategy comparison through simulations

Figure 52 compares the progress monitoring result of the different strategies. The project investigators still use estimated workflow duration as the performance function. The blue line shows the estimation of workflow duration under ideal progress monitoring approach, which means the supervisor can monitor all the on-going tasks in real time.

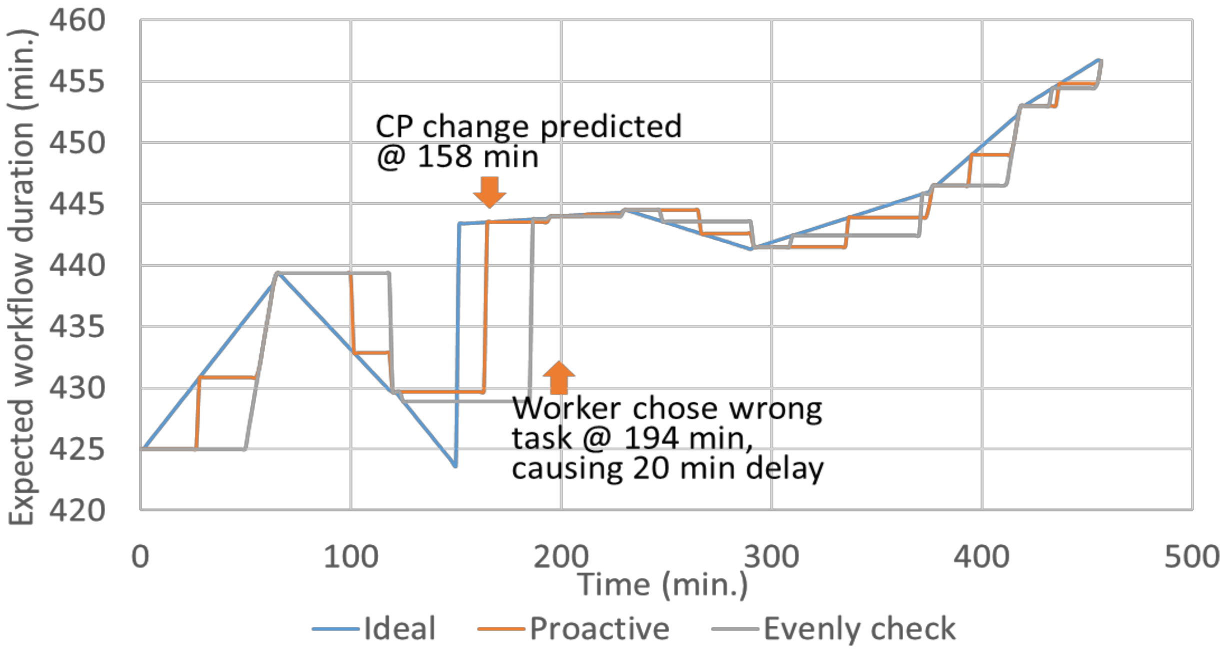

Figure 52. Compare different progress monitoring strategy

The orange line and the gray line visualize the estimation of workflow duration under resilient progress monitoring or only use workers' report of task finishing time. Figure 52 shows that the orange curve is much closer to the blue line compared to the gray line, which means the result of resilient progress monitoring is better than the progress monitoring result only based on workers' report of task finishing time.

The results presented above indicate that, with the proposed proactive progress monitoring method, the management team can predict the risk of critical path change 36 minutes before a worker making the wrong decision because he or she is choosing the following inappropriate task after finishing the current one. This risk of critical path change will cause 20 minutes' delay of the entire workflow. On the other hand, if the management team only focus on the progress of the tasks on the as-planned critical path, they will identify the mistake after the unreliable decision has caused the workflow delay. This result means the resilient progress monitoring method can proactively detect the potential critical path change and workflow delay to maintain the resilient management of NPP outage project.

6 Major research findings

6.1 Technical challenges of integrating computer vision, human systems engineering, and simulation for solving practical problems in NPP outages

The automatic system developed in this project integrates human factor analysis, computer vision techniques, and computational simulations to help engineers better understand the interactions between humans, resources, and workflow that influence the productivity of outage processes. The project investigators have encountered some technical challenges while integrating the human factor analysis, computer vision techniques, and simulation platforms for proactive outage control. The following paragraphs present these challenges from three perspectives: 1) the technical challenges of developing computer vision algorithms for automatically tracking outage workflows; 2) technical challenges related to the modeling of outage workflows influenced by human factors; and 3) challenges related to the assessment of the impacts of human factors on the productivity of outage workflows.

The focus of automatic video analysis and object tracking in this project is to enable automatic indoor handoff process monitoring (e.g., monitoring the handoff processes in an RPI) to better understand how critical handoffs influence workflow delays. Monitoring indoor handoff processes is relatively easy due to the controlled environment. Indoor monitoring and limits about the number of cameras for indoor monitoring pose unique challenges to the computer vision methods developed in this research. Specifically, the computer vision algorithm developed and tested in this project has two unique technical features in addressing the following technical needs and challenges: 1) only using one camera for 3D localization indoor, and 2) real-time tracking of multiple moving workers along with significant occlusions in a crowded RPI. Only using one camera makes the multi-worker-tracking solution flexible in environments where limited spaces are available for installing surveillance cameras. Single-camera 3D tracking enables localizations of workers in the physical world rather than on the 2D frames of videos in identifying crowded areas that need the attention of the supervisors for mitigating the waiting through resource allocation and schedule updating. More specific technical challenges include: 1) the loss of depth using a single camera for tracking, and 2) the difficulties of avoiding ID switch of tracked workers and losses of tracking of objects when occlusions occur in a crowded indoor environment.

Modeling the detailed interactions between human, task, and workspace by integrating the knowledge from human system engineering is also challenging. Modeling such human-task-workspace interactions is critical to better understand how the time waste and error rate during handoffs occurs in an NPP outage workflow. The challenges associated with this specific task are the difficulties of quantitatively defining “normal” interactions among individuals. Manuals used by OCC personnel and satellite outage centers specify procedures for various operations but lack details on the expected motions and interactions at “team” levels. Often the manuals define the coordination plan and roles of participants, while providing fewer details about expected human interactions and motions. Also, integrating the cognitive activities carried out by teams is challenging. In order to create a precisely model, the group interactions both physically and cognitively require consideration of team decision making based on the communication among all interdependent individuals within a group. Communications among team members are cognitive processes at the team level. Thus, an understanding of communication patterns can provide a deeper understanding of challenges associated with team cognition during handoffs. Capturing and modeling communication patterns can also be difficult in terms of capturing communication content and timing. Many of the methods such as manual transcription and coding of communications are time-consuming.

Quantitatively assessing the impact of numerous uncertainties such as human errors and task duration variations are also challenging. Some domain challenges in NPP outage control include frequent schedule updates due to contingencies (i.e., additional work caused by a valve found as broken during the work time), tedious team coordination and communication, and frequent human errors during field operations. These challenges are also related to human task interactions and unexpected events with human-in-the-loop. For example, contingencies such as discoveries of new tasks due to maintenance failures on scheduled tasks, unexpected structural defects on mechanical parts used during maintenance, or unexpected delays that occur while ordering new parts for maintenance can cause severe delays as well. All of these factors pose challenges to ensuring a "resilient" NPP outage control, which requires an approach that should rapidly and proactively respond to delays, errors, or unexpected tasks added during outages because of field discoveries. Unfortunately, current approaches of outage control rely heavily on tedious manual inspection. Such manual approach results in less-detailed job site information for effective monitoring and modeling of detailed spatiotemporal interactions among multiple workers and tasks. Current historical documents about the executed task durations during real NPP outage operations are not detailed enough, which brings significant challenges in estimating the variances of task durations of similar outage operation. Moreover, people from both the industry and academia do not yet have a comprehensive understanding of how numerous uncertainties such as the variances of task durations and unexpected human errors will affect the productivity of an outage.

6.2 Feasibility of the integrated analysis

The developed automated system shows the feasibility of integrating the human factor analysis, computer vision techniques, and simulation platforms for addressing the challenges described above. These methods have shown potential, both in one real outage and in a series of lab experiments, for helping engineers better understanding how numerous anomalies (i.e., human errors, task deviations, and so on) can be captured in the field and assess the impacts of the detected anomalies on outage workflows.

The project investigators developed a novel approach for effective anomaly-detection that addresses the challenges described above for real-time computer vision and video analysis of indoor handoffs. This algorithm first uses a two-branch convolutional neural network to detect workers and their body joints. Instead of tracking the body joints in the image space, the algorithm transforms the detected joints onto virtual parallel planes called "Anthropometric Planes" in order to mitigate the loss of depth due to the use of only one camera (single-camera constraint). The algorithm generates a series of Anthropometric Planes along the vertical axis, based on anthropometric measures of an average American male. The algorithm then uses a Kalman Filter to track the detected joints on these Anthropometric Planes. Finally, an uncertainty measure is introduced to reduce the number of ID switch and to handle missing joints.

The researchers also explored the modeling of the detailed interaction between individuals within and across groups by modeling the communication process within the workflow. In the computer-based simulation, the project investigators used agent-based modeling to calculate: 1) how the probability of human communication error will influence the probability of the failure of the entire workflow; 2) how the probability of forgetting error will influence the probability of the failure of the entire workflow; 3) how the task duration variations affect the workflow productivity; 4) how different communication protocols (i.e. “early-call” strategies) can help mitigate the risks of delays and communication errors between worker teams and the supervisor; and 5) how to identify tasks with high uncertainties in order to reduce delays of workflow.

Finally, the project investigators developed and tested the use of automatic communication system by replacing the supervisor. The purpose is to understand how the performance of an automatic communication system compared to a human supervisor. Results indicate that automating the communication process not only eliminates communication errors, but also streamlines the workflow by simplifying the overall process. Finally, workflow duration has been reduced greatly by introducing the automatic communication system.

7 Conclusion and future research

Timely capturing anomalous human behaviors and precisely estimating workflow duration is critical for maintaining productivity and safety in an NPP outage project. However, the uncertainties of human behaviors and tasks bring difficulties to precise estimation. Even experienced outage participants could hardly estimate the duration of each task precisely. However, NPP staff could spend more time and data collection resources to get the “real-time truth” on the tasks under highly uncertain environments and identify highly uncertain parts of schedules. Identifying highly-uncertain tasks in a workflow can guide the management team to allocate the resource better and achieve resilient NPP outage control. This research proposed an automatic system that integrates the state-of-the-art human tracking algorithms and agent-based simulation to identify anomalies in the field and assess the impacts of the detected anomalies on outage process productivity.

The developed computer vision methods can detect and track multiple workers in crowded indoor environments by using a single fixed camera. These computer vision methods combine a state-of-the-art human pose estimation method with a novel joint trajectory space representation. Transforming joints from the image space to the joint space significantly improve tracking performance where even a simple tracking algorithm such as the Kalman Filter along with a Hungarian algorithm is sufficient. The project investigators have selected the video sections of different complexities for testing the algorithms. Overall, the algorithm can calculate the waiting time of workers at the station with a precision of 70% and a recall of 38%. The project investigators categorized scenarios where multiple object tracking fails and found the major failures came from identity switching and false positive detection of workers in a mirror or on shiny surfaces. The project investigators synthesize the failures of the algorithms for guiding future research development. The future research will be analyzing the root causes of the failures to improve the multiple object tracking results in indoor applications.

The computer-based simulation results show that the variance of individual task duration and human errors play a significant role in affecting the overall duration of the workflow. The simulation and lab data analysis helped the project investigators to understand how early the supervisor should call the workers so as to mitigate the risks of delays, and how communication errors influenced the field workflows. The simulation results indicate that the algorithm developed by the research team has the potential to precisely monitor different types of handoffs in real outages. The analysis of the communication data collected during laboratory experiments for simulating turbine maintenance workflows, which are typical sections of NPP outage workflows, revealed the relationship between the numbers of tasks assigned, types of interactions, and error rates. Such communication data analyses pave the path toward the modeling of communication errors and team behaviors in the NPP outage workflows. All these simulation and communication data analysis results show the potential of proactively monitoring and controlling the productivity of the workflows in NPP outages.

This research also highlights some future research directions and the value of the research work for the broad scientific research community composed of construction and computer science researchers. For the construction research community, this research will form a framework to assess the reliability of multiple object tracking algorithms in deriving information used by field engineers. For the computer science community, this research identified the scenarios where state-of-art visual tracking algorithms fail to motivate the development of new algorithms.

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Appendix – I

(Manual of the developed Computer Vision prototype system)

1. Installation Guide

This software is written in C++ under window 10 system. This section provides details of the installation of the software and some key usages of this software. There are mainly six steps to configure the environment. All the steps have been tested on the researchers' computer. Section 1 introduces the steps that users need to finish to configure the environment for the software. Section 2 describes how to get the source code and run the code.

1.1. Installation of Visual Studio 2015

This software is developed under visual studio 2015.

Download Link: https://visualstudio.microsoft.com/vs/older-downloads/

- The first thing you have to do is to open the Visual Studio 2015 download page and click the Get it now button in the Visual Studio Preview.
- After you click the Get it now button, you will redirected to the Visual Studio Online Login page where you type your credentials there.
- Download and run the installer step by step.
- When the installation ends, you will see a "Visual Studio install has completed successfully" message.

1.2. Installation of Qt (version 5.10)

Qt is a cross-platform application development framework for desktop, embedded and mobile. The researchers use Qt to design the software and integrate the developed computer vision algorithm in a user-friendly way.

There are two ways to install Qt:

- Through the Qt Installers – downloads and installs Qt
- Through the Qt sources

The following link provides the guides to install Qt. Please note install Qt version 5.10 for Windows 10 system. A different version of Qt may cause problems.

1.3. Install Qt Visual Studio Tools

We need to install Qt visual studio tools to use the Qt framework in visual studio.

Launch Visual Studio, go to Tools -> Extensions and Updates -> Search Qt Visual Studio Tools (Figure 53)

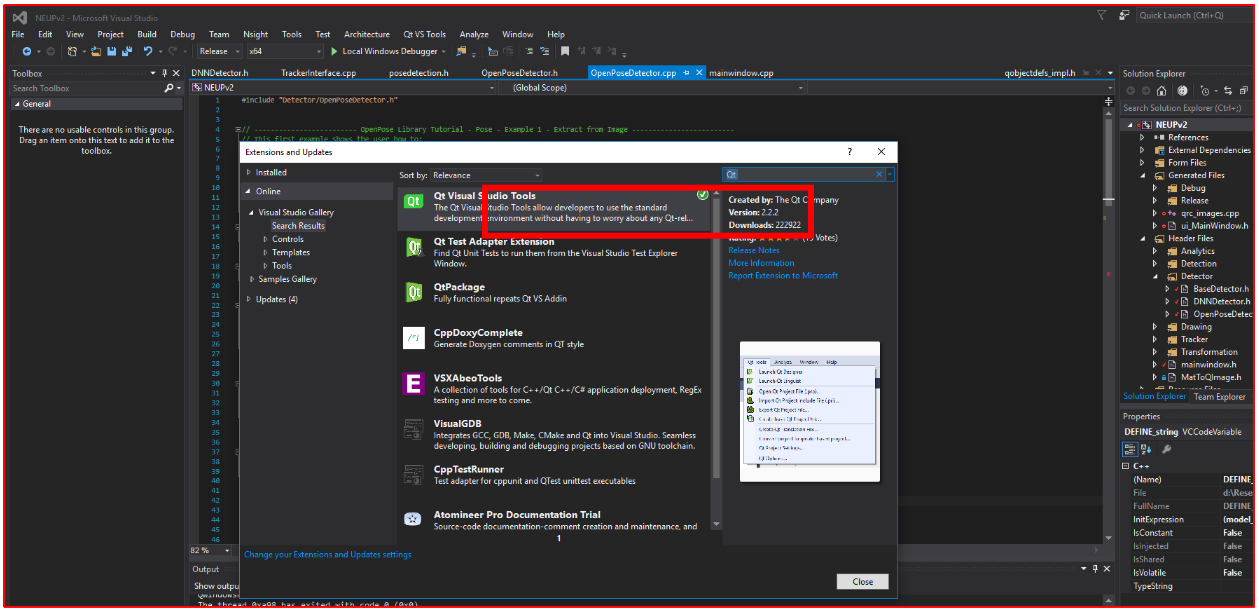


Figure 53 Install Qt Visual Studio Tools (Red box highlighted the search results of Qt Visual Studio Tools)

After the installation of Qt Visual Studio Tools, we need to set up the Qt versions for the Visual Studio. Go to Qt VS Tools – Qt Options – Add- find the qt 5.10 (Figure 54)

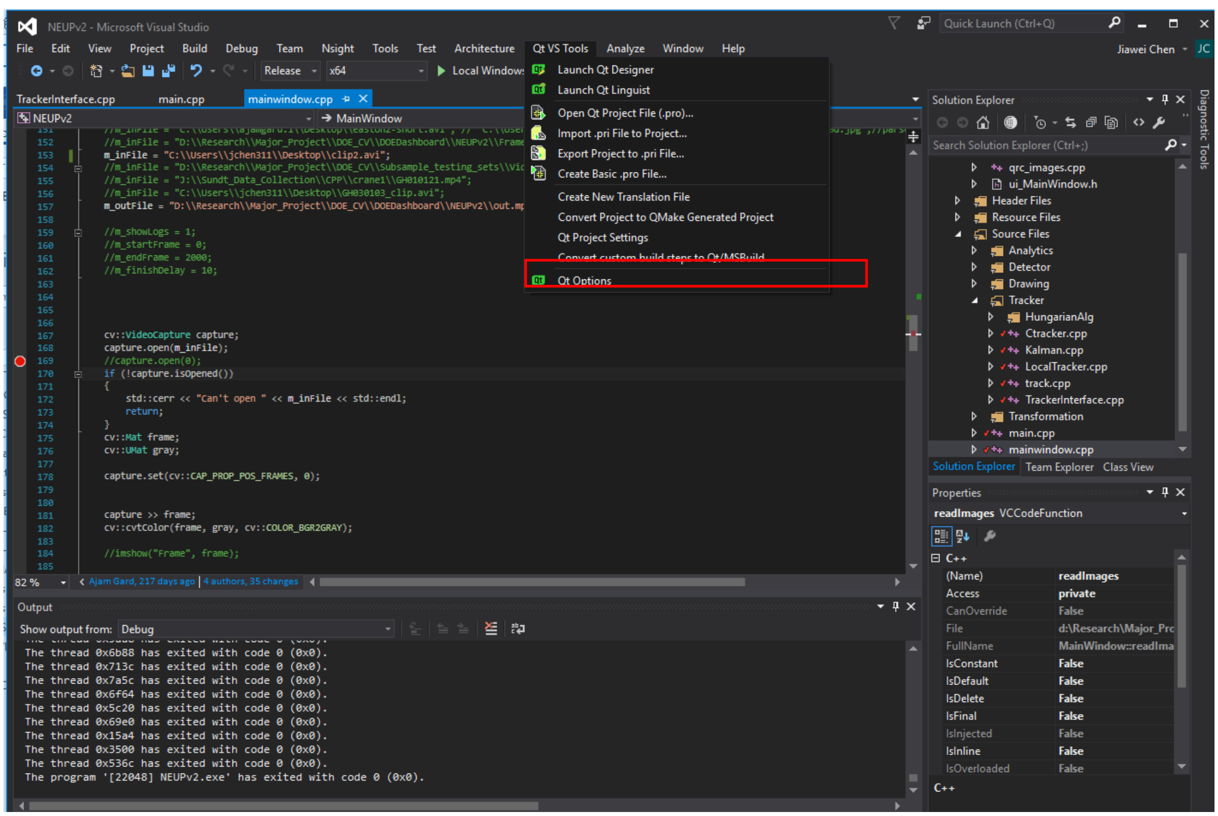


Figure 54 Set up Qt versions for Visual Studio

1.4. Installation of OpenCV 3.30

OpenCV (Open Source Computer Vision Library) is released under a BSD license and hence it's free for both academic and commercial use. It has C++, Python and Java interfaces and supports Windows, Linux, Mac OS, iOS and Android. OpenCV was designed for computational efficiency and with a strong focus on real-time applications. Written in optimized C/C++, the library can take advantage of multi-core processing. Enabled with OpenCL, it can take advantage of the hardware acceleration of the underlying heterogeneous compute platform. The researchers copied the link https://github.com/opencv/opencv/releases/download/3.3.0/opencv-3.3.0.exe

After downloading the file and install it to the desired folder you want.

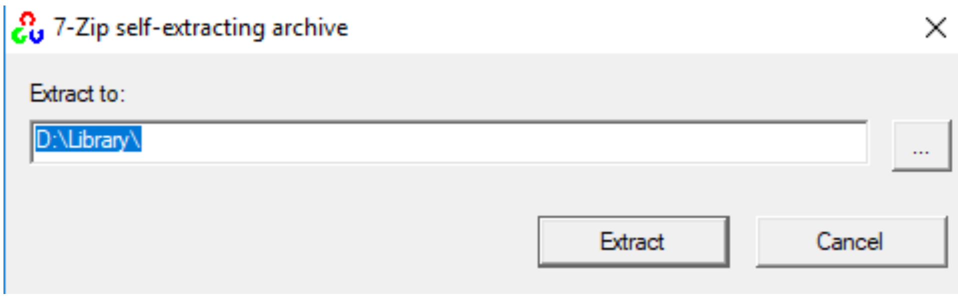


Figure 55 Installation of OpenCV

After installation of OpenCV, we need to set the path in system environment variables as OPENCV_DIR. Go to Control Panel-> System and Security-> System-> Advanced system settings

1.5. Installation of Cuda 8.0

Next, we need to install Cuda 8.0. Users need to go to https://developer.nvidia.com/cuda-80-ga2-download-archive and select Cuda 8.0 for windows. After download the file, the users need to unzip the downloaded file and open CUDA Setup Package as Figure 56. This installation is supposed to set the environment variable automatically. Until now, you are supposed to finish the installation of the software if you finish the previous steps successfully.

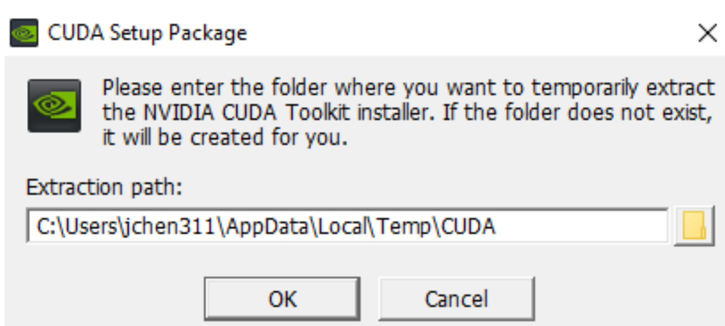


Figure 56 Installation of CUDA

2. Usage example of the Computer Vision system developed by the project investigators

After configuring the environment for the software. This section shows how to get and run the source code. There are some options for using this software that the user needs to customize in the source code.

2.1. Downloading the source code

The users can download the source code from this link:

- https://www.dropbox.com/s/yrmueld7743mjk8/DOEDashboard.7z?dl=0

After downloading the source code file, please unzip the file. Start the Visual studio and use the file->open->project to select the source code.

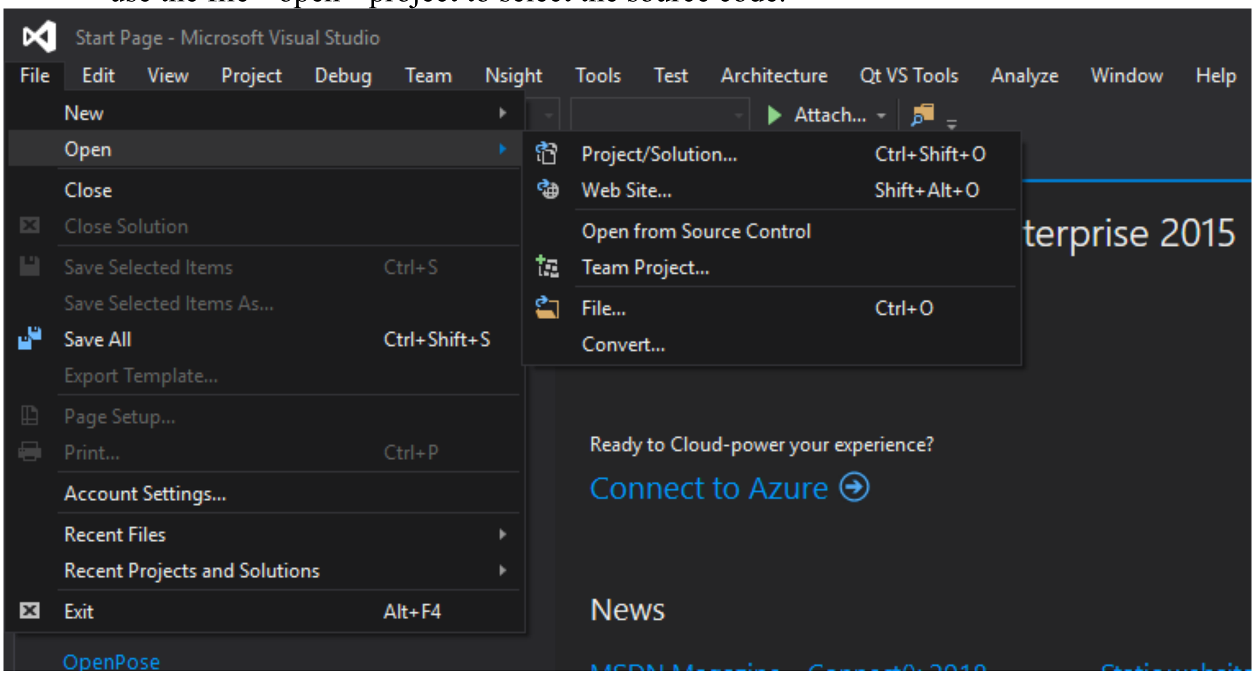


Figure 57 Import the source code to visual studio

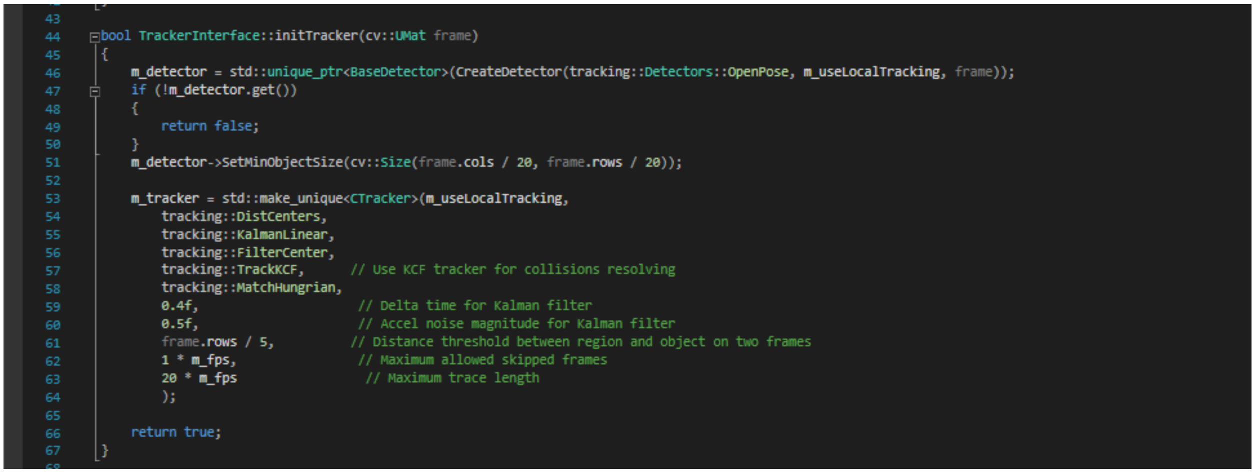
2.2. Setting up the input video data for the computer vision system

This software can achieve real-time monitoring, so the input can be real-time video. This software also supports the recorded videos and pictures. The user needs to adjust the path of the input files in "Mainwindow.cpp" file at line 15. "m_inFile" is the parameter to indicate the path of input data. Revise the m_inFile as the path of your desired input data. This software supports using real-time video from web camera as input , the user needs to change m_inFile at line 162 from to 0 or -1.

Figure 58 Input data of the software

2.3. Choosing the object detector of the computer vision algorithm

This software is developed to be extendible. The user can change the detection algorithm and tracker as they wish. In the TrackerInterface.cpp, line 46, change the detector from OpenPose to DNN or another detector.



```
43
44 bool TrackerInterface::initTracker(cv::UMat frame)
45 {
46     m_detector = std::unique_ptr<BaseDetector>(CreateDetector(tracking::Detectors::OpenPose, m_useLocalTracking, frame));
47     if (!m_detector.get())
48     {
49         return false;
50     }
51     m_detector->SetMinObjectSize(cv::Size(frame.cols / 20, frame.rows / 20));
52
53     m_tracker = std::make_unique<CTracker>(m_useLocalTracking,
54         tracking::DistCenters,
55         tracking::KalmanLinear,
56         tracking::FilterCenter,
57         tracking::TrackKCF,      // Use KCF tracker for collisions resolving
58         tracking::MatchHungrian,
59         0.4f,                     // Delta time for Kalman filter
60         0.5f,                     // Accel noise magnitude for Kalman filter
61         frame.rows / 5,          // Distance threshold between region and object on two frames
62         1 * m_fps,                // Maximum allowed skipped frames
63         20 * m_fps                 // Maximum trace length
64         );
65
66     return true;
67 }
```

Figure 59 Select different detectors for the tracking module.

2.4. Graphical user interface

This module contains a graphical user interface (GUI) that enable engineers using the human-tracking algorithm for real-time visualizing the tracking results without having to know technical details of the computer vision algorithms. This GUI is a type of user interface allows users to interact with electronic devices through graphical icons and visual indicators such as secondary notation, instead of text-based user interfaces, typed command labels, or text navigation. The GUI was designed to display multiple simultaneously tracked workers in an RPI. The aim is to identify the location and temporal duration of bottlenecks in the workflow.

This GUI can achieve real-time monitoring. There are two major configurations that users need to interact with the GUI. The first configuration is to identify the area that users want to monitor. Figure 60 shows that the user can select the layout map of different rooms and select the areas the user wants to monitor. In Figure 60, the researchers used the layout map of RPI for testing and use a rectangular to highlight two stations to monitor.

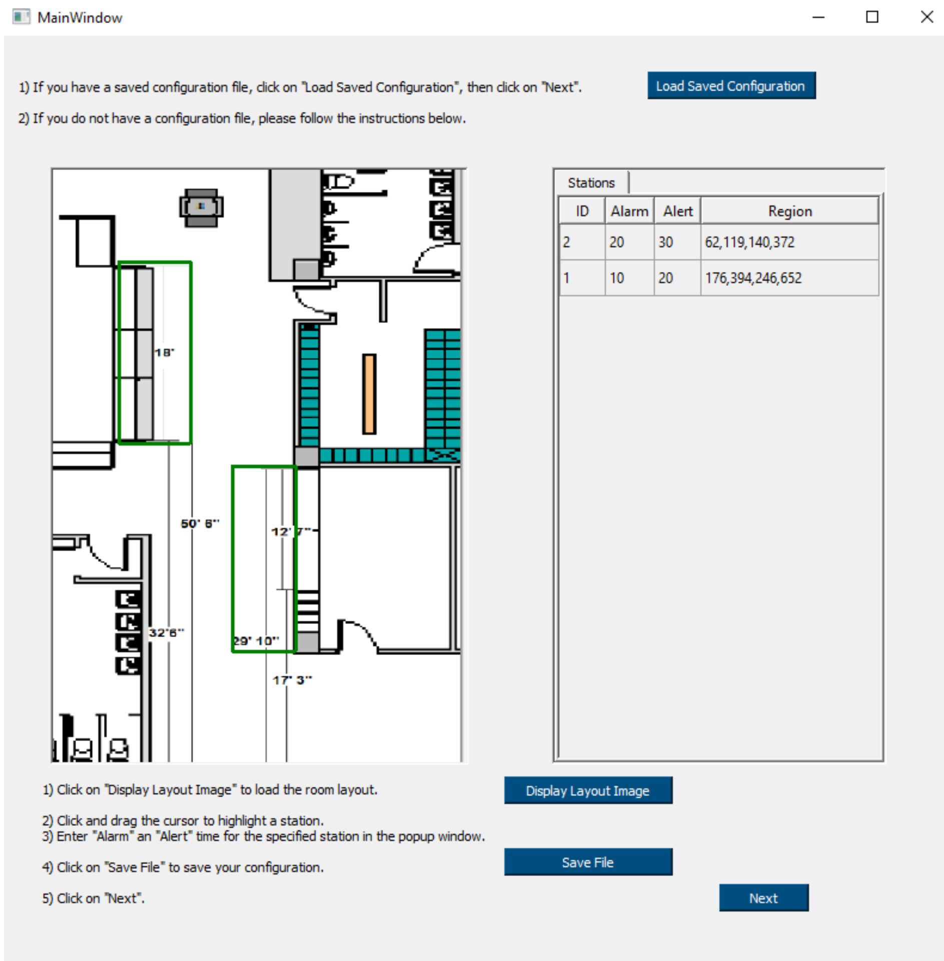


Figure 60 Select Areas user wants to monitor

The next configuration by the user is to choose the corresponding points in the layout map and video (Figure 61). This step serves to build the connection between the video and layout map. The user needs to

1) Press "Display Layout Image"
2) Press "Display Camera Image"
3) Click on four or more points in the left image.
4) Click on the corresponding points with the same order in the right image.
5) Press "Next"

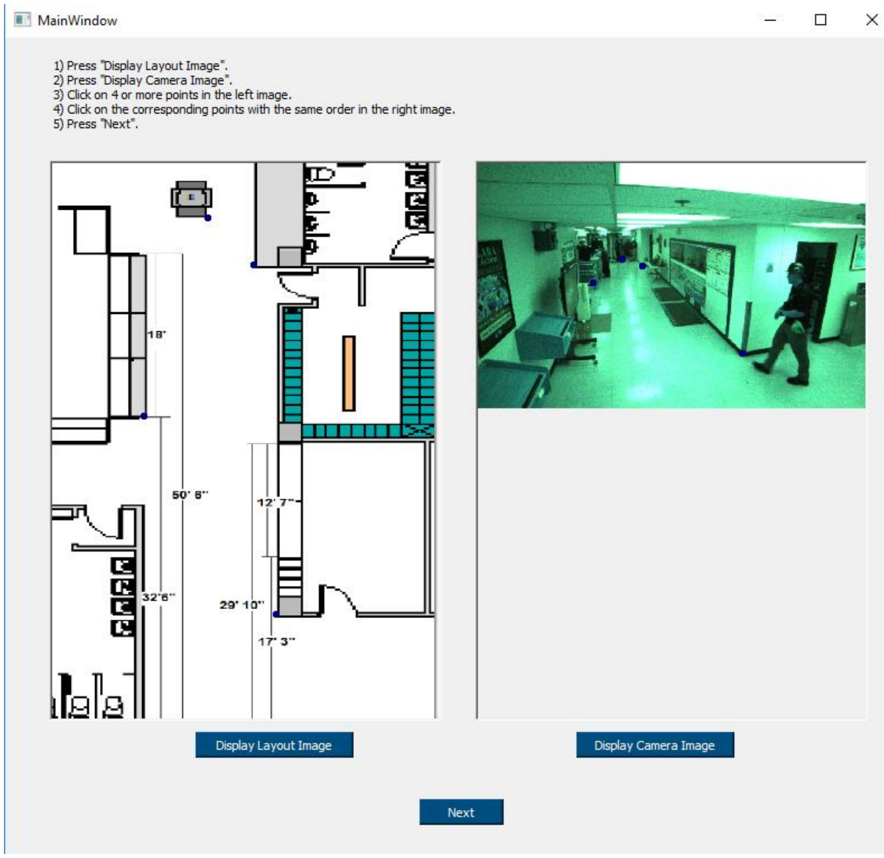


Figure 61 Build transformation between layout map and video

The number of personnel at each station is monitored and recorded; therefore, workstation usage efficiency can be improved. We can easily detect the status of every station within RPI to gain better control of the waiting queue. Figure 62 shows the detailed GUI design for visualizing the handoffs in the room. When a worker enters Station 1, the average waiting time will start counting until the worker finishes and moves on to Station 2. At that time, the total waiting time at Station 1 will become solid and the average waiting time at Station 2 will start counting until the worker is done at that station. Once the waiting time has exceeded the alert time limit shown on the left of Figure 62, based on the time exceed, an alert signal will be triggered and shown next to the station information on the right. In our GUI, Station 1 and Station 2 have separate different thresholds (alarming and alert times) with time unit because the nature of the tasks at these two stations is different. Also, a total alert and alarming time in the "Summary Table" has been added. Until the worker has exited the station, his/her data will not be displayed. The program will be able to capture the average waiting time for each waiting at each station, as well as the waiting time in the RPI. Based on the information, the management team would be able to monitor the real situation within the RPI and make a decision.

Figure 62 Real-time monitoring and statistics output (Red cell indicates the time worker spent in the station exceeded the alert limits)