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Human-centered automation for resilient nuclear power plant outage control

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ABSTRACT

Nuclear power plant (NPP) outages are challenging construction projects. Delays in NPP outage processes can cause significant economic losses. In typical NPP outages, extremely busy outage schedules, large crew sizes, dynamic workspaces and zero tolerance of accidents pose challenges to ensuring the resilience of outage control, which should rapidly and proactively respond to delays, errors, or unexpected tasks added during outages. Two mutually interacting practical problems impede NPPs from achieving such resilient outage control: 1) how to control errors and wastes effectively during the “handoffs” between tasks, and 2) how to respond to numerous contingencies in NPP outage workflows in a responsive and proactive manner. A resilient NPP outage control system should address these two practical problems through “Human-Centered Automation (HCA),” which is improving the control process automation while fully considering human factors. Previous studies examined two categories of technologies that potentially enable HCA in outage control: 1) computational modeling and simulation methods for predicting states of field operations and workflows; 2) data collection and processing methods for capturing the reality and thus providing feedback to computational models. Unfortunately, limited studies systematically synthesize technological challenges related to these practical problems and underlying HCA principles.

This paper identifies the domain requirements, challenges, and potential solutions of achieving the HCA system that effectively supports resilient NPP outage control. This proposed system aims at significantly improving the performance of handoff monitoring/control and responding to contingencies during the outage. Firstly, the authors identified information acquisition and modeling challenges of achieving human-center automation for outage control. The rest of the paper then synthesizes potential techniques available in the domains of computer science, cognitive science, system science, and construction engineering that can potentially address these challenges. The authors concluded this literature and technological review with a research roadmap for achieving HCA in construction.

1. Introduction

In the United States, many nuclear power plants (NPPs) were built forty years ago [1] and require regular maintenance. NPPs typically shut down every eighteen to twenty-four months to refuel the reactors and execute repairs. Such processes are called “NPP outages.” NPP outages are challenging because they require coordinating thousands of activities in short time periods with an average time frame of thirty to forty days [2]. Moreover, most NPP outages require supplemental workforces that consist of hundreds of contract personnel who are not permanent employees of the NPP and are not familiar with the workspaces and procedures that vary from one NPP to another. The presence of such contract personnel in outages significantly increases the workload of permanent NPP employees, who train, guide, monitor, and coordinate the work done by contract personnel in conjunction with their regular work responsibilities. Interactions between permanent and contract personnel with diverse backgrounds also significantly increase the complexity of communication and information flow

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throughout outages procedures, thereby increase the error rates and delays in field operations [3–6].

Other challenges that cause delays, schedule overruns, and escalating costs in NPP outage projects include highly uncertain and frequently updated schedule due to contingencies (e.g., discoveries of hidden structural defects during field operations), multi-group coordination and communication, frequent changes of nuclear facility states, and highly uncertain human behaviors on job sites [7–11]. Unfortunately, any delays in the NPP outage processes will cause significant economic losses. For instance, a one-day delay can lead to one to two million dollars loss for the electric power company. All these factors pose challenges to ensuring "resilient" NPP outage control, which requires an approach that should rapidly and proactively respond to delays, errors, or unexpected tasks added during outages. In other words, a resilient outage control should reduce outage's cost, duration, labor, and accident rates by "*proactively and adequately adapt to perturbations and changes in the real world given finite resources and time*" [12].

In NPP outages, two practical problems are causing main difficulties related to the vision of "resilient outage control." The first practical problem is about how to control the efficiency and error rates of handoffs, which are the transitional stages between tasks. Handoffs involve highly uncertain activities, such as transports of resources and labors, inter-person and human-computer communications, field preparation, mobilization, and waiting. Transitional nature of handoffs causes time and resource wastes, incidents or accidents due to the involvement of multiple groups of workers and complex spatiotemporal interactions between space and resource needs of tasks, and decision difficulties under uncertainties. The second practical problem is how to respond to many contingencies in NPP outages so that workflows can quickly recover from interruptions and incidents due to field discoveries. In NPP outages, about 15% of tasks are "discovered" in the field because many problems could be unapparent due to the uncertainties about the field conditions and resource availability. Uncertainties about the field conditions and resource availability combined with the need to incorporate additional work adds extra stain to NPP outage control because workflows, workspaces and large crew sizes must be quickly adjusted and reconfigured.

Human factors play important roles in the two practical problems described above [1,13–15], while in current practice, outage management teams have been struggling with the manual management of the behaviors of field workers [3,16,17]. With experienced outage managers retiring, manual analysis of human factors in uncertain and dynamic environments of outages will challenge new generations of engineers in the coming decades. Specifically, 38% of the nuclear industry workforce will be eligible for retirement by 2018 [18] while young engineers still lack experience in real outages. In such a context, the Human-Centered Automation (HCA) techniques can be critical for assisting new generations of engineers in outage control [19–21]. These automation techniques help better managing human factors by enhancing situation awareness (SA) while reducing workloads, developing a communication protocol across outage participants, and building predictive models of human behaviors in various contexts. Researchers and field engineers have been working on examining various automation technologies to improve the information acquisition and modeling of human factors in NPP outages to enable HCA and resilient outage control [22–25]. These efforts revealed potentials of HCA techniques, but the lack of a comprehensive review of HCA for supporting resilient outage control impede researchers and engineers from approaching HCA in an outage with a systematically-designed research map.

This paper presents an extensive review of literature related to HCA for resilient NPP outage control. The aim is to establish a research roadmap that systematically incorporates human factors into the loop of automated outage control and synthesize technological gaps against domain requirements for such incorporation. The authors summarized nuclear plant operation documents and past studies to identify the information requirements and process automation needs and then reviewed related computational modeling and data collection/processing techniques that have the potential of addressing such needs. The focus is on data and modeling technologies that could address effective handoff monitoring/control and contingencies handling during outages, as those are practical bottlenecks. Such discussions will lead to the identification of technological gaps and fundamental scientific questions about HCA in construction, as well as technical tools necessary for answering those questions. Such tools include as artificial intelligence techniques that enable "self-learning human systems" that can automatically adjust systems design and automatically recommend continuous improvements of outage processes based on historical data.

The organization of the remaining parts of the paper is: Section 2 introduces the motivation of this review by presenting the two practical problems of achieving resilient NPP outage in detail, summarizing human factors in outages, and explaining why human factors are the key to achieving resilient outage control. Section 3 summarizes latest outage control practice and the data and modeling barriers to achieving HCA for resilient outage control. Section 4 synthesizes various technologies that have the potential of addressing the identified challenges of HCA in outage control. Section 5 presented the resulted research roadmap and then conclude.

2. Motivation: practical problems in resilient outage control

This section motivates HCA for resilient outage control. In this context, "resilient" outage control system refers to the ability to quickly recover from errors, delays, interruptions, and changes in schedules to achieve as-planned project productivity and safety [12,26]. The nuclear industry has developed a variety of technologies to improve the resilience, productivity, and safety of outages. For example, daily reports recording the progress and guiding resource allocations are prepared before daily meetings and distributed widely through outage information systems accessible to outage participants. In addition, performance metrics for different outage procedures exist to quantify and diagnose the performances of past and on-going outages [27]. However, these approaches of outage control are mostly manual, tedious and error-prone. Two mutually interacting practical problems are main barriers to resilient outage control: 1) handoff control, and 2) responding to contingencies. Sections 2.1–2.3 introduce these two problems in detail. Based on such introduction, Section 2.4 synthesizes how the human factors influence the outage performance, and why HCA is critical for achieving resilient outage control.

2.1. Practical problem one: handoff monitoring and control

Handoffs are transitional stages between tasks. Effective handoff control aims at reducing the durations 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 [28–30], and can significantly influence the project efficiency. Furthermore, NPP outages often operate under tight schedules that have a 10-minute granularity such that uncertainties of handoff durations could be longer than some task durations. In such cases, maintaining the as-planned task sequences is difficult [31]. Moreover, in packed schedules and workspaces, delays or mistakes in handoffs could propagate to many tasks and compromise the productivity and safety at large [32]. Being able to predict and control uncertainties within handoffs thus are critical for improving the efficiency of outages.

Besides tight schedules and large crew sizes, two other factors further exacerbate handoff problems in NPP outages. The first factor is relevant to the uncertainties of human behaviors in outages. NPP personnel are complex agents working in complex sociotechnical systems, and "their activities will not always follow some deterministic mechanism" [27]. Furthermore, NPP outages often need to involve external contractors to perform maintenance activities or render specialized services for the sake of resource availability, specialization, and cost efficiency. However, external personnel could be unfamiliar with certain NPP environments and procedures compared to long-term NPP employees. Relatively high incident/error rates of external contractors could cause reworks, delays, extra communications, and training efforts. Overall, uncertainties and errors associated external contractors are difficult to predict and control.

The second factor is the complicated organization of outage participants and processes [3]. 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 timing and relationship between tasks; 3) maintenance shops, who coordinate workforces for tasks; 4) the main control room staff, which configures the NPP according to tasks' requirements; 5) the work execution center, which inspects the site preparation for safe execution of tasks. Complex communications across all these organizational units are necessary for safety but will create long handoffs and possible time wastes.

2.2. Practical problem two: responding to contingencies

The second practical problem is how to respond to numerous contingencies in NPP outage workflows. Contingencies in outages include errors, accidents, tasks discovered during the field work, and other unexpected events in outages. NPP outages have been triggering nation-wide concerns and motivating multiple efforts in evaluating risks of nuclear plants to assist proper handling of critical contingencies occurring during nuclear plant outages [13]. The high probability of identifying new tasks during outages brings uncertainties to the schedules and field workflows. Moreover, complicated workflows and tight schedules of outages could magnify the impacts of errors or incidents during handoffs. Therefore, techniques that help respond to contingencies should reduce the uncertainties in outage workflows and enable resilient outage control.

To achieve proactive responding to contingencies, the nuclear industry has been trying to examine all possible procedures that could occur during outages and design protocols to address various events and alleviate the consequences of these events [33]. However, some events are hardly predictable so that human interventions are necessary. The cognitive flexibility of experienced NPP personnel will take over the control when automation or pre-defined reaction procedures fail. For example, control room crews would not thoughtlessly follow the procedures, but to consider the actual situation and remain alerted to the appropriateness of the procedures in contexts [34]. With many experienced outage managers retiring, manual analysis of human factors in uncertain and dynamic environments will challenge new generations of engineers who are taking over NPP maintenance work. HCA technologies are thus necessary to enable the transition from rule/experience-based decision making to data-based decision making to aid new generations of outage coordinators and get them prepared for the upcoming shortage of outage experiences.

2.3. Interactions between two practical problems challenging resilient outage control

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

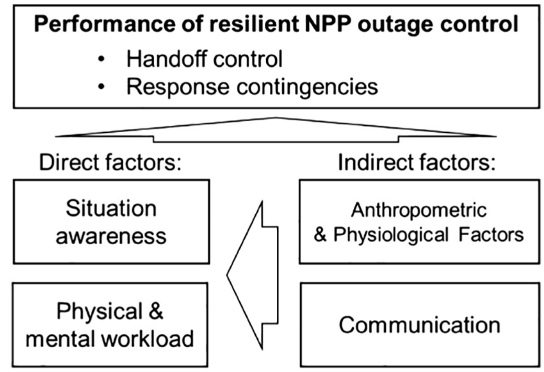

Fig. 1. Human factors that influence the performance of resilient NPP outage control.

2.4. Human factors in NPP outages influencing the practical problems

The performance of handoff control and responding to contingencies involve significant human interventions. As a result, both practical problems described in Section 2 will be greatly influenced by human factors. Direct human factors are SA, physical and mental workload (PMW) whereas indirect factors consist of anthropometric and physiological (APF) factors as well as communication [35]. Fig. 1 shows the relationship between the human factors, handoff control, contingencies and effective outage control.

The first direct factor SA is "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status shortly" [36]. Human operators with good SA can properly assess the situation and take timely actions accordingly. Appropriate SA helps operators make a better decision according to the field conditions. SA is especially crucial in the highly dynamic NPP outage projects because things can change from a normal operating status to an unexpected one in a short time (tens of minutes). The second direct factor physical and mental workload (PMW) is a measurement of both physical and mental demands on a person [4,37]. All tasks require some variations of physical and mental effort; however, the degree to which these two are needed can vary significantly depending on the task. Moreover, a greater need for one will influence the other. That is, an operator completing tasks that necessitate high physical demands can become cognitively overloaded even with a relative small mental task [38]. Overall, having to maintain a high SA increases the mental workload of an operator which can negatively influence personnel task performance [36]. The best task performance will be achieved when the related personnel can adapt to the fluctuations of PMW while maintaining an appropriate SA.

Two indirect factors, APF, and communication, can influence the performance of outage control through influencing operators' SA and PMW. For example, operator's inability to perceive field changes (maintain appropriate SA) may be directly tied to physiological factors such as poor vision, hearing, or directional sensing. Hence, the workload may be unnecessarily high because the operator needs to divert additional resources (attention and working memory) to compensate for not being able to see, for example. Communication, the other indirect factor, plays an important role in maintaining appropriate SA [39]. For instance, through communication, various outage participants coordinate the workflow design and implement changes necessary. Communication is also a means to push-and-pull information up the chain of command from outage decision makers to field supervisors, to workers and vice versa, allowing individuals to stay connected to others and perceive changes (due to updates). Good information flow and communication protocol design could enable high SA while reducing the mental workload of outage participants.

The four human factors described above collectively influence the performance of teams of human individuals in handoff control and responding to contingencies. First, the ability to achieve effective handoffs is influenced by human factors such as maintaining appropriate SA. For only with the appropriate perception of status can outage participants aggregate the situation and assess change before communicating them through needed channels. However, communication can become cumbersome and complicated due to the sheer volume of updates and personnel thus creating delays in handoffs. Moreover, ineffective communication could increase workload due to missed information or redundant status updates. Thus, researchers should assess and model various information flows and its propagation to ensure optimal SA, reduce PMW, and enable time-efficient information exchanges during handoffs.

Additionally, human factors will influence the response and performance to contingencies. For instance, human operators can recover from system errors [27] when the pre-defined procedures do not cover all possible emergencies. However, proper reactions to contingencies require a newly formed SA based on present situations deviating from predefined cases. Therefore, human interventions on pre-defined procedures should be considered together with the operators' experiences and SA, along with the flexibility that interventions allow on the system's configuration [40]. Likewise, the workload will influence the effectiveness and efficiency of responding to contingencies because PMW is highly related to the reaction time and error rate of humans [41]. Finally, different communication patterns will result in different information propagation time, affecting the timeliness and accuracy of responding to contingencies.

3. HCA for outage control: state-of-the-art and challenges

This section defines HCA for outage control, examines state-of-the-art of HCA techniques for the outage in practice, thereby identify challenges that impede NPP managers from resilient outage control. Fig. 2 illustrates the relationship between the goal of resilient outage control, human factors, and HCA. An HCA-based outage control system could improve the SA and reduce PMW of people in outages through automation technologies to automatically acquire important information and aiding the decision-makers in carrying out project control actions (e.g., resource allocation adjustments). The purpose of HCA is to improve the efficiency and effectiveness of handoff control and to respond to contingencies. Overall, according to the literature and technology review of the authors, state-of-the-art outage control technologies still have difficulties in addressing the following domain needs:

- *Information acquisition challenges*: How to automatically collect human factor data using sensor technology that provides sufficient detail in both, spatial and temporal, domains to support the decision making process?
- *Modeling challenges*: How to generate and model the appropriate abstraction of the real-world human factors to enable human-in-the-loop decision making?

The rest of this section will define the HCA concept (Section 3.1), AOCC and AWP methods as state-of-the-art HCA methods (Section 3.2), human-related information and modeling needs not currently addressed by AOCC and AWP (Sections 3.3 and 3.4). Such discussions are critical for guiding further exploration into technologies not yet introduced into outage control domain, discussed in Section 4.

3.1. Defining HCA for outage control

Achieving a higher degree of automation for resilient outage control is a general trend [18], but HCA techniques are undeveloped in outage control due to the less mature computing hardware and software systems used in this domain. The authors start by defining HCA in outage control by synthesizing relevant automation techniques on three aspects of construction project control, which has similar challenges as outage control [42]:

- "*Task*" aspect involves the work that humans need to do according to certain standards, sequences, and time. For example, automatic scheduling is a typical automation technique for the task aspect.
- "*Workspace*" aspect focuses on managing non-human objects and spaces, i.e. facilities, materials, and building elements. Automation techniques on this aspect include automated workspace data collection, site layout design, and crane planning through various sensors such as laser scanners.
- "*Human*" aspect refers to methods related to managing performance and behaviors of human individuals and organizations involved in the project, including workers, foremen, and management staff.

Fig. 3 visualizes a framework of HCA for resilient NPP outage control. An HCA-based outage control system is a system which automatically acquires human factor information and support decision-making considering the interactions between human, workspace, and tasks through human-in-the-loop modeling and simulation. In this system, sensing techniques capture actual workflow status including tasks, workspace, and human factor information to build an information model that contain sufficient information about site conditions, progress, and environments [43]. Next, simulation and decision-making technologies can be used to generate feedback and modify workflow to achieve optimal operations during the outage. Currently, many automation technologies potentially useful for outage control are focusing on the use of scheduling software, database, and Office Suites (e.g., Microsoft Excel, OneNote) [3–6]. However, only a few automation technologies focusing on human factors are invented and applied in the domain of construction and outages. More specifically, limited studies were on considering human aspect in the two practical problems described above - handoff issues and responding to contingencies that need significant amounts of human interventions, so that human performance monitoring and robust design of work processes that can effectively avoid or handle human errors becomes the bottleneck.

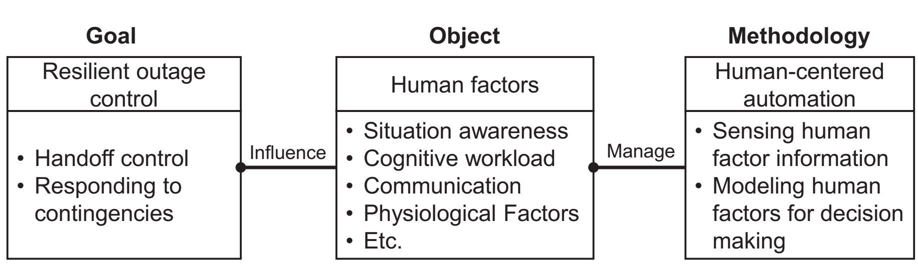

Fig. 2. IDEF1x model that depicts the overall concept of HCA

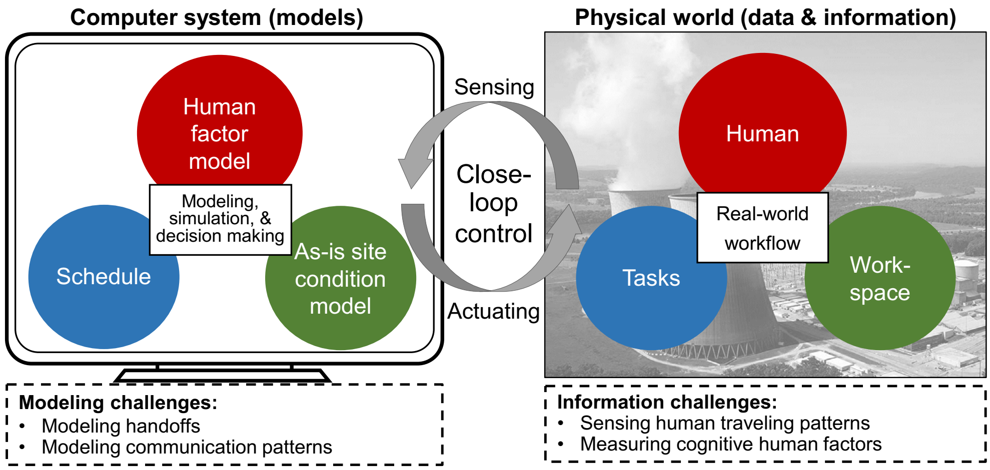

Fig. 3. Information and models of NPP outage control.

3.2. State-of-the-art human-centered approaches in NPP outage control

Previous explorations in the domain of automated NPP outage control aimed at applying state-of-the-art data collection and automated decision-making techniques at both the macro and micro level for improved productivity and state awareness of human individuals involved in outages [3]. The resulted HCA approaches thus also can be found at the macro level, in the form of Advanced Outage Control Center (AOCC), and at the micro level, in the form of Automatic Work Packages (AWP). Fig. 4 uses an analogy to illustrate the roles of AWP and AOCC in outage control. This analogy is between the functions of outage control and the nervous system of a human. Specifically, the AOCC, a temporary headquarter, serves as the "brain" of the outage project. AOCC receives updates from department representatives involved in the outage and coordinates different work groups concerning schedule, cost, task performance, and safety [3]. The function of the supervisors is similar to the spinal cord, which is to receive the updated, higher-level scheduling information, manage field workers' tasks, and report tasks' progress and any anomalies to the AOCC. Supervisors also coordinate with each other to modify as-planned schedules when needed. Currently, limited technologies are specifically developed to aid the micro decision-makings of the supervisors. Lastly, AWP, which serves as the "peripheral nervous," is used to reduce error rates of the field workers by providing detailed checklists for every task, step-by-step and collecting as-is work status information from field workers. Sections 3.2.1 and 3.2.2 will introduce AOCC and procedures in detail, respectively.

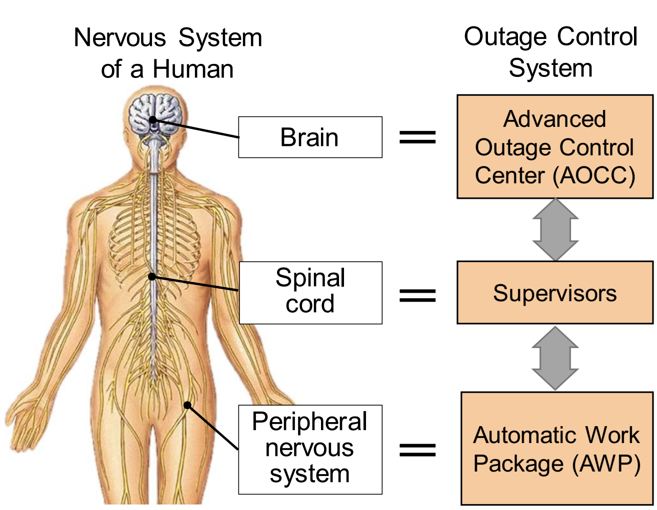

Fig. 4. The analogy between outage control and human nervous system.

3.2.1. Outage control center (OCC) and advanced outage control center (AOCC)

An outage control center (OCC) is the temporary command center for executing NPP refueling outages while an Advanced Outage Control Center (AOCC) is an advanced version of OCC tested in certain NPPs, where modern information technologies are applied to improve people's communication. NPP outage control requires a high-level management technique focusing on the big pictures, which includes collecting work status of the whole project, quick responding to contingencies, and streamlining the tasks of different departments to avoid spatio-temporal conflicts. The close collaboration and communication between different groups will resolve the difficulties brought by many maintenance and repair activities, large crew sizes, and extremely short project durations in outage control. Due to this vast amount of communication required during the outage the OCC is staffed twenty-four-seven.

Many current OCCs are not taking advantage of available information technologies to improve the communication and decision-making process, shown in Fig. 5(A). Currently, many OCCs are using paper-form schedules and work orders forms to share the plant status information. The use of automation technology has the potential to reduce the need for face-to-face meetings, save time, and increase data accessibility. Moreover, richer data availability could increase the level of comprehension about complex problems. Overall, an advanced OCC (AOCC) shown in Fig. 5(B) can improve OCC on three aspects [44,45]:

Information inflow: AOCC enables real-time work status updates from automated tools tracking individual workers' workflows (i.e. Computer-Based Procedures, CBPs, and Automated Work Packages, AWPs). Also, video stream data can be utilized to enrich the spatial-temporal detail of as-is workflows for monitoring jobsites and workflow statuses.

Real-Time Collaboration and communication: Instead of having face-to-face meetings around the traditional whiteboard, NPP staff in AOCC could use multi-touch boards and high-quality audio and video conferencing equipment. These advanced information technologies would enable the staff to simultaneously work on complex problems from different locations by sharing notes, pictures, diagrams, and schedule information. Also, collaboration software (e.g. Microsoft OneNote) can be used to disseminate information to staff using desktop computers and tablets in any location, onsite or off, guiding discussions, enabling collaborations, and aiding in documentation.

Decision making: AOCC is aiming at integrating the information from AWPs to the real-time scheduling monitoring. An electronic record of the discussions supported by collaboration and communication

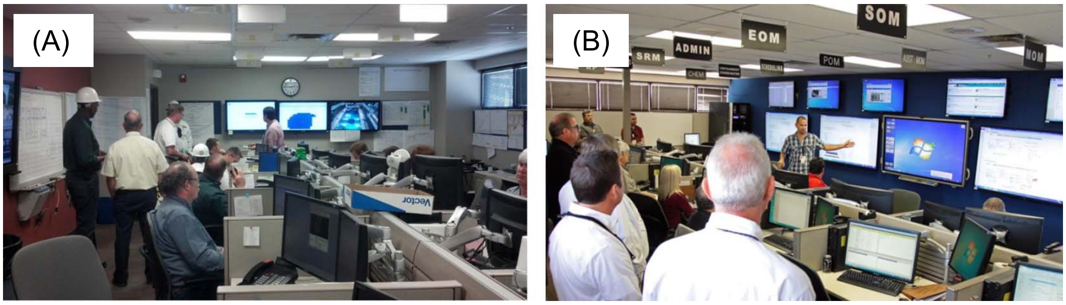

Fig. 5. Traditional OCC (A) vs. AOCC (B).

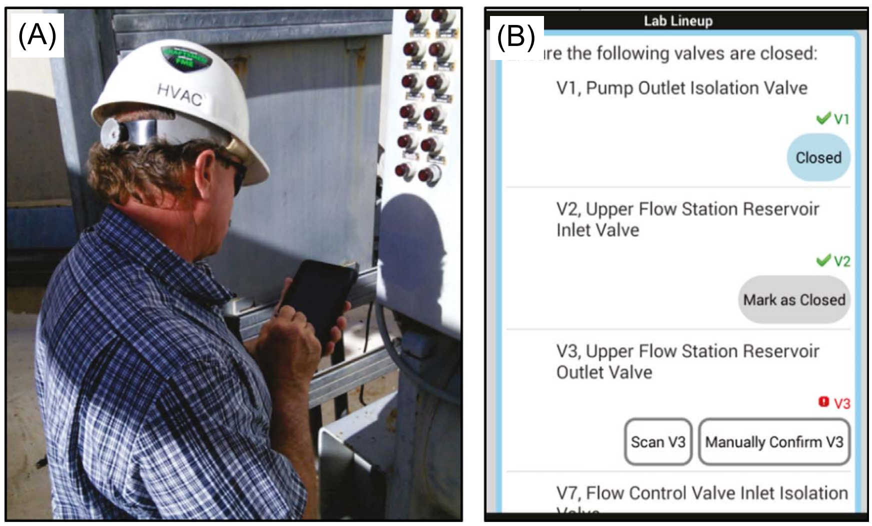

Fig. 6. (A) An HVAC engineer is using AWP to guide his work; (B) example UI of AWP on a cell phone. This system is guiding the work procedures of the user.

technologies will also help knowledge management of the information for better decision making.

3.2.2. Automatic work package (AWP)

Automatic Work Package (AWP) is an automation technique that supports micro-level management and control of outage tasks (shown in Fig. 6). As an emerging alternative to manual paper works, AWP technology could potentially increase reliability, efficiency, and safety at the plant by reducing operator workload and reducing the rates of human errors [46]. A work package is a compilation of documents including a work order, work instructions, and any other supporting references/materials (for example, drawings, vendor manuals, weld process sheets, safety analysis, permits). The work order is a document describing what tasks are needed, while the work instruction provides information for the work to be yet completed. With thousands of entries and transcriptions generated during an outage, a moderate to high error propensity exists.

In a current operating fleet of NPPs, the work management process uses paper-based work packages, which are typically bulky, cumbersome, and error-prone. First, printed work packages are expensive, wasteful and overwhelming to transport to and from the job site increasing the amount of contaminated waste generated. Moreover, the paper-based work packages rely on human performance to correctly obtain the plant information, enter it into the documents, complete the steps of the process in the right sequence, and ultimately validate that correct results have been obtained [47]. For example, field workers may have calculation errors, omit steps, apply wrong equations, or commit rounding errors while executing work orders associated with the paper process. The complexity of these activities and the sheer bulk of the paperwork often cause errors that result in rework, delays and even latent nuclear safety issues. The functionality of AWP minimizes such human errors. Overall, AWP system enables the workers to track their tasks on a hand-held electronic device (e.g. tablets or smartphones), and the general requirements state that AWPs should [47]:

- Guide operators through the logical sequence of the procedure.
- Ease the burden of place-keeping for the operator.
- Make the action steps distinguishable from information gathering steps.
- Alert operator about dependencies between steps.
- Ease the burden of correct component verification for the operator.
- Ease the identification and support assessment of the expected conditions and the expected plant and equipment response.
- Include functionality that improves the communication.
- Automatically populate the procedure with values from previous logs.
- Automatically acquire of as-is workflow data.

3.2.3. Limitations of the state-of-the-art HCA approaches

Both AOCC and AWP are trying to achieve resilient outage control considering the needs about process automation and managing human factors in outage personnel, aiming at improving the performance of individual workers and various teams involved in outages. AOCC improves the SA of management personnel while reducing their mental workload by enabling them to communicate in a convenient, informative way using modern information technologies. AWP, on the other hand, is focusing on guiding the field workers through the complicated tasks and track their work status in real time, which also helps improve the field worker's SA and reduce their MW.

However, AOCC and AWP still could not fully satisfy the needs of resilient outage control. The nuclear industry needs “a monitoring system that incorporates a systematic review of actual results and compares these with expectations established by objectives" [48]. Specifically, HCA in outages needs the further support of 1) timely, detailed workflow information involving human factors (e.g.: who are working on which task? Any jam at certain bottleneck areas? Any people made mistakes? Any task behind schedule?); and 2) advanced decision-making methods to control ubiquitous handoffs and emergencies caused by contingencies in NPP outage workflows, especially technologies that help the supervisors make minor decisions which are not required to report to OCC (e.g. How many supervisors/inspectors/representatives are needed in different circumstances to improve the efficiency of communication? If a task is delayed, could the supervisor of this task communicate with other supervisors and make small changes to the schedule or he/she should report to the OCC? How to coordinate with other supervisors to allocate the resource if a new task is identified? In different cases, how could OCC judge who should be responsible for not finishing the tasks on schedule, the scheduler of the management team?). Hence, NPP outages need to address challenges by using automated systems to acquire the following information: as-is position, task progress, SA, PMW of outage personnel. Additionally, modeling challenges need to be addressed to support AOCC and supervisors to achieve better decision making about scheduling, resource allocation, human behavior regulation, and communication strategy when facing anomalies caused by handoffs and contingencies in complicated NPP outage workflows. The following sections will discuss these information acquisition challenges and modeling challenges in detail.

3.3. Information acquisition challenges that impede HCA in NPP outage control

Collecting human factor information in field outage workflows is the first step of resilient workflow control. Besides the work status information provided by AWP, HCA needs to automatically acquire traveling pattern and cognitive human factor information, which is challenging but important for resilient outage control. Sections 3.3.1 and 3.3.2 will discuss in detail how traveling pattern information and human cognitive factors can help improving the performance of handoff control and responding to contingencies yet difficult to acquire.

3.3.1. Sensing traveling patterns of human individuals across job sites

To reduce time loss and errors during handoffs the management team needs more information than just starting and end time for each task (currently provided by AWP). The traveling pattern of field workers is a major part of handoffs. Hence, automatic sensing of field workers' traveling patterns can provide managers with accurate status updates and enhance their overall SA. For instance, managers can be alerted of congested areas such as waiting in long lines to receive briefings or at radiation checkpoints. Knowing to incorporate the delays caused by long lines into their daily schedules and handoff procedures can lead to more accurate schedules in the long run.

However, numerous challenges exist in capturing traveling pattern information of field workers. First, the areas inside nuclear plants and reactors in most cases blocks the use of many wireless technologies to track humans, including the Global Positioning System (GPS) signal; Second, the complicated environment and busy jobsite are challenging for identifying and tracking individuals, especially for tracking the traveling pattern of a crowd. Third, the large NPP site cannot be fully covered by the sensing technologies so that the sensor allocation problem will compromise the sensing result. Lastly, privacy issue arises from monitoring workers 24/7. Hence, tracking technology should be anonymous. That is, counting the individuals standing in line without specifically identifying 'who' it is.

3.3.2. Measuring human cognitive factors

Two important cognitive human factors for resilient NPP outage control are SA and mental workload (MW). However, currently, neither the AOCC nor AWP system is capable of monitoring these while the physical workload of field workers could be tracked by AWP. Operators need appropriate levels of SA and MW to perform as expected and react to unanticipated events. Furthermore, measuring SA and MW of NPP outage personnel enable better decision making and human autonomy when pre-defined construct cannot cover the contingencies [37]. Therefore, developing early warning systems based on inappropriate operator's SA or MW within a task can first, alert the operator and second, suggest appropriate actions to be taken. For instance, the warning system may signal severe cognitive overload of an operator, and at the same time, suggest a break, alert immediate supervisors or directly notify the AOCC. Additional resources can be diverted to aid this operator sooner rather than later. However, it is naturally difficult to measure these two cognitive human factors because there are no physical signals that sensors can capture. As a result, researchers developed various techniques to enable the effective and efficient measurement of SA and MW. Measuring SA has also been an important topic in numerous domains including the military, aviation, and healthcare [40,49,50]. The purpose of valid and reliable measurement of individual and team SA is to prevent the degrading of SA throughout the workflow. Researchers summarize six categories of SA measurement methods [49]:

- *Freeze probe techniques*: a task is randomly paused, and the status of the task is "frozen" when the participant's SA is measured through a set of SA queries regarding the current situation. Though, it is almost impossible to "freeze" a task in highly busy outage workflows without compromising the performance.
- *Real-time probe techniques*: the participants (operators) respond to queries at certain time points during task executions. The main issue is that the queries can interfere with the task execution and reduce the productivity.
- *Subjective rating techniques*: subjective-rating techniques are typically administered post-trial, wherein the participants rate their SA once tasks are completed. However, this method may not be capable of reliably measuring team SA in a collaborative environment when both, humans and computer systems work together.
- *Observer-rating techniques*: a subject matter expert (SME) observes participants performing the task and then provides an assessment/rating of each participant's SA. This method is most commonly used in field tasks because it is non-intrusive, but results can vary because the observer may exhibit biases.
- *Performance measures*: this method indirectly measures participant's SA by assessing the performance of task execution. However, the relationship between task execution and SA can be task- and context- specific and could be not deterministic.
- *Process Indices* (Eye Tracker): process indices involve recording the processes that the participants use to develop SA during the task under analysis. Conversely, the use of an eye-tracking device in the NPP outage workflow is difficult if not impossible.

Some methods for measuring MW are similar to the ones measuring SA. For instance, *performance measure* and *subjective ratings* can be applied to assess both SA and MW. Other means of measuring MW is through *physiological measures* because MW significantly affects various physiological indices, such as heart rate, heart rate variability, blood pressure (systolic pressure and diastolic pressure), parasympathetic/sympathetic ratio (LF/HF ratio), eye blink frequency and eye blink duration [4,51]. Thus far, researchers have been working on measuring NPP control room operators' MW by using a combination of subjective ratings and physiological measures [4,37,51]. However, the NPP control room is a fairly stable environment, and operators' physiological information is relatively easy to measure, but this does not apply to the more complex NPP outage workspaces involving more physical activities.

Overall, measurement of SA and MW is mostly based on manual

Table 1
Summary of information acquisition challenges.

Information acquisition challenges	Beneficial to handoff control?	Beneficial to responding to contingencies?	Why challenging?
Traveling pattern of human [7–11,46,47]	Reduce uncertainty during handoffs.	Assist operators during transition times.	Complex workspace and human behavior in NPP outages.
Cognitive human factor information [4,37,40,49–51]	Ability to understand the current state and project actions needing to be taken.	Proactively estimating the task performance based on SA and MW enables better anticipation and decision-making during contingencies.	Current sensors are not capable of directly measuring human cognitive factors.

work coupled with intrusiveness and ineffectiveness. Human factor information acquisition achieves sensor-based automation in some instances and only to some extent, but better sensing technologies and fundamental theory on measuring SA and MW in various environments and tasks are needed. Table 1 summarizes the identified information acquisition challenges for HCA in outage control.

3.4. Human-related modeling challenges that impede HCA in NPP outages

Modeling is another important part of HCA for resilient outage control. Modeling techniques enable simulation and analysis, both of which can result in earlier identification of design defects than prototyping [43]. Although many modeling technologies have been applied to the nuclear industry (e.g. Building Information Modeling, smart grid modeling), human-factor-related functions and processes in resilient outage control are still difficult to be modeled and simulated, which brings challenges to effective decision making for outage control. Current outage control approach lacks the systematical understanding about handoffs and communication patterns, which impede the effective handoff control and responding to contingencies. Sections 3.4.1 and 3.4.2 will introduce how modeling handoffs and communication patterns will contribute resilient outage control and why they are challenging.

3.4.1. Modeling handoffs

Precisely modeling and estimating the events influencing the handoff process will help predict and control the duration of future handoffs and thus, significantly improve the productivity of NPP outages. The goal of handoff modeling is to inform the decision maker so they can better prepare and anticipate the next step. However, the lack of a formal workflow model considering human behavior in handoffs impedes engineers and researchers from using a computer algorithm to assist engineers in assessing the handoff scenarios and schedule adjustment strategies. Handoffs are difficult to model and simulate precisely because communication and traveling patterns are not predetermined. In particular, speech can vary greatly due to speed, pattern, accent, content, etc. Therefore, most construction simulation, planning, and scheduling project managers may not want to consider modeling communication patterns.

Another obstacle of effective handoff modeling is that current construction simulation tools have limited capability to accurately model the detailed spatiotemporal relationship between human factors, tasks, and resources to support handoff modeling [52]. Currently, shutdown managers use Gantt chart or PERT model to represent and manage the workflow (schedule). These workflow representations cannot incorporate the vast amount of information from human behaviors, interactions between different tasks, workflows, and handoffs.

3.4.2. Modeling communication patterns

Facing the complex scenarios of handoffs and contingencies in NPP outages, operators need to precisely determine what information needs to be delivered to whom, at what time, with what detail and frequency [53]. Additionally, operators must choose appropriate communication channels to deliver their messages, and at the same time, maintain their own SA [3,54,55]. Hence, communication, routine and non-routine, serves to aid others in forming SA and maintaining and updating one's own. Ideally, appropriate SA results in a reduction of MW because operators that are aware of arising issues can adjust their work accordingly. However, outdated communication processes can have exactly the opposite effect – decreasing SA and increasing MW [44]. For instance, if operators spent an excessive amount of time and resources to get their messages across then they will need to exert additional mental resources while diverting attention to the message delivery instead of their work. At the same time, today's communication process in NPP employs outdated technologies [3]. These outdated technologies should be updated to reduce the negative effect on the operators' SA and MW. However, improving these communication processes needs to be accomplished by more than random trial-and-error strategies because this would further deteriorate the current communication paradigm and cause greater deficiencies in communication. Thus, communication pattern modeling should describe information flow between various individuals as well as teams. Mathematical representations of different communication flow patterns (e.g. hierarchical compared to open) and various channels of distribution (e.g. face-to-face, phone call, email, OneNote) could be used to design the best communication strategies and information propagation resulting in more resilient outage control.

In turn, elements in communication pattern modeling need to include objects, organization topology, frequency, communication channel, and type of information shared. Additional elements that need to be considered is an understanding of which individuals are consulted when problems arise and how information exchanges vary depending on scenarios (e.g. routine updates compared to emergency notifications). Furthermore, parameters such as talk frequency and durations of a conversation need to be built into the model. Then, accurate representation of communication through modeling can aid in uncovering patterns of interactions and identify key people. Optimal communication channels (face-to-face, phone calls, emails) could also be determined and recommended. For example, face-to-face is suitable for complex or emotion involved messages while broadcast media can be used when information needs to be delivered to a mass audience. Table 2 summarizes the identified modeling challenges for HCA in outage control.

4. Potentials to address the challenges to resilient NPP outage control: information acquisition and modeling technologies

Although challenges related to information acquisition and modeling exists in achieving HCA in outages, many techniques that have not been applied in NPP outages are potentially helpful in addressing these challenges mentioned above. The authors broadly explore various techniques developed in the domains of computer science, human factor and ergonomics, construction engineering, system science, and nuclear industry to find potential solutions to these challenges. Finally, we identified the following techniques from the literature as potentially useful for supporting resilient outage control. For the information acquisition challenges, computer-vision-based human tracking (Section 4.1.1) can provide human traveling pattern information, and natural language processing (Section 4.1.2) can aid the measurement of

Table 2
Summary of modeling challenges.

Modeling challenges	Why beneficial to handoff control?	Why beneficial to responding to contingencies?	Why challenging?
Modeling handoffs [1–5,7–11,48,52]	Provide decision-making support systems during handoffs.	Support operators during complex and time-sensitive decision-making processes.	Current construction modeling tools cannot model all complicated processes of NPP outage workflows (including unexpected and random discoveries during outage work).
Modeling communication patterns [3,44,53–55]	Enable optimization of communication strategies and recommend appropriate communication channels for handoffs.	Enable optimization of communication during responding to contingencies.	Current tools cannot model the vast and varied amount of communication in real-time to support outage control.

cognitive factors as well as automatically analyzing operational histories of past NPP outages. In addition, wearable devices (Section 4.1.3) can improve the performance of both information acquisitions. For the modeling challenges, the combination uses of Petri-net (Section 4.2.1), EAST analysis (Section 4.2.2), and Human reliability analysis (Section 4.2.3) can show the potential of the precisely model and analysis handoffs and communication patterns. The rest of this section will review these potentials to draw a practical research roadmap toward the goal of HCA for resilient outage control.

4.1. Information acquisition technologies for HCA in outage control

4.1.1. Human tracking

Human tracking is using sensing technologies to automatically capture the trajectory of moving people, which can address the challenges of capturing the human traveling pattern information in the complicated NPP outage environment. Available human tracking can be divided into two categories: computer-vison based and tag-based tracking. Tag-based human tracking utilizes the trackable devices attached to the human body, which includes RFID, Wi-Fi, global navigation satellite system (GNSS), etc. RFID technology is a well-implemented technology mainly for tracking equipment. The accuracy of human tracking can achieve meter level [56,57]. However, tag-based human tracking technologies are not suitable for NPP outages because of three reasons: 1) GNSS does not function in indoor and underground environments. Assisted GNSS (A-GNSS) extends GNSS to indoors, but it is limited and unreliable. On the other hand, the performance other tag-based tracking technologies might not satisfy the sub-meter-level tracking need of NPP outage workflow; 2) NPP have restrictions on the devices which can be installed on the site, so that the signal field supporting the tag-based tracking might not be available; 3) trackable tasks may cause confidential issues, which is rejected by the labor union.

Meanwhile, computer vision technology can detect the presence/absence of objects as well as their trajectories, which can provide useful information about the motion of workers on the construction jobsite [58–62]. Using data fusion of worker's position and upper body postures along with the jobsite environment information, computer-vision-based approaches can capture the positions activity types of field workers in real time [62,63]. The work activity information is used to perform automatic work sampling to facilitate real-time productivity assessment. Computer-vision-based human tracking may also enable the detection of abnormal human behaviors in workspaces. Using these technologies to detect anomalous behavior of field workers can help anticipate accidents or delays in workflow. Researchers are focusing on using computer vision technologies to identify individuals whose behaviors are different from the majority [64–68].

However, challenges exist in achieving computer-vision-based human tracking. Current NPP outage supports videos and image as data inputs. However, these imagery sensors cannot be allocated everywhere across the NPP. Also, the data transition rate is limited by the restricted strength of Wi-Fi signal used in NPP. As a result, to achieve real-time human behavior inspection, a sensor allocation technology and new research focusing on the trade-off between data size and tracking performance is needed to reduce data collected while keeping all the needed information [69,70].

4.1.2. Natural language processing

Natural language processing (NLP) is a subfield of artificial intelligence that aims to use natural language text making it understandable to computers so that it is processed in a human-like manner [71]. As already mentioned in Section 3.3.2, most cognitive measures used to determine SA and MW are survey-based and require direct input from the test takers. Unfortunately, requiring any additional tasks from the already over-worked operator may cause interruptions of on-going work. Besides interrupting the operator, manual assessments are also tedious and error-prone. Furthermore, achieving timely, reliable, and comprehensive assessment of field personnel's SA and MW in dynamic NPP outages is nearly impossible. NPL has the potential to simplify this measurement process by enabling automatic assessment of the test takers' SA and MW through simple, but effective oral assessments and in turn, reducing management's workload and interruption caused by cognitive factor measurements [72].

Additionally, NLP can help achieve the automated extraction of rich, semantic information from the documentation of various events during the operation and maintenance of nuclear plants (e.g. the Licensee Event Report system established by Idaho National Lab [73–76]) for supporting the analysis of nuclear power plant incidents, such as technical problems, personnel errors, safety violation, inadequate procedure, radioactive leak, or supervision issues. Automated analysis of documentations can assist in understanding dynamic team processes, such as team cognition during outages, thereby provide insights and information about complex team skills to improve team SA and reduce team MW. Furthermore, this automated analysis can suggest ideal interventions target cognitive underpinnings of team performance, such as training programs and technological support systems to increase team effectiveness [77,78].

4.1.3. Wearable devices

Wearable devices are clothing and accessories incorporating computer and advanced electronic technologies that can sense multiple information and exchange data with a server, an operator or other devices. Embedded with multiple sensors, wearable devices can measure multiple indices of human behaviors, such as movements, heart rate, body temperature, along with the capability of communication between people wearing the devices [79–83].

Wearable devices could help acquiring the human traveling pattern information. The accelerometer is the standard configuration in most wearable devices. Together with gyroscope it can form an inertial measuring unit (IMU) which can sense the trajectory of its user independently, the precision and accuracy of which can support simple travel pattern recognition, such as step counting, running/walking recognition, etc. [80].

The wearable device could also support the measurement of cognitive factors because cognitive factors could be inferred from measuring physiological factors, such as heart rate, blood pressure, and electroencephalography (EEG) [37,38,82,83]. Wearable devices can enable the real-time acquisition of such physiological information to support automatic cognitive factor monitoring.

4.2. Modeling technologies

4.2.1. Petri net

As mentioned Section 3.4.1, current construction modeling and simulation tools are not able to represent the uncertainties and randomness in NPP outage workflows caused by deterministic human factors in handoffs. The lack of a formal workflow model considering human behavior in handoffs impedes engineers and researchers from using a computer algorithm to assist engineers in assessing the handoff scenarios and schedule adjustment strategies [52]. A more powerful tool is needed to mathematically model the NPP outage workflow including not only the tasks but also the information flow, traveling, and waiting behaviors.

Petri Net is a powerful discrete-event modeling tool to model human workflows and to represent the interactions between tasks and resources [84]. Its intuitive graphical representation and powerful algebraic formulation enable the researchers to simulate and analyze how human factors influence the duration and error rate of the handoffs between tasks. In this approach, the authors use a Colored Petri Net (CPN) to simulate how the proficiency and SA of the workers will influence a selected workflow in an NPP outage project [85–88].

4.2.2. Event analysis of systemic teamwork (EAST) framework

Event Analysis of Systemic Teamwork (EAST) framework is an analytic methodology that has the potential of meeting the challenges of managing large, complex, and dynamic systems that require the management infrastructure of command, control, communications, computers, and intelligence (C4i) [49]. Currently, there is no mature theory of commanding and controlling such a system because of the informational complexity and ongoing technological evolution embedded in such a system [89,90]. EAST shows its potential by integrating various levels of human factor analysis to provide a macro-ergonomic view of a system from the perspective of teamwork. This method assesses social networks, information flow, and tasks to make the interdependencies of socio-technical systems more explicit. Thus, complexity is reduced to a manageable level in which interactions between sub-systems can be explored and their boundaries examined.

The EAST method consists of three layers [89]. The first layer is the data collection layer. Structured data collection methodologies are required to extract meaningful data from an NPP outage scenario. For instance, activity sampling involves monitoring actual behavior in the field. This method provides a means of relating the timing of actions to specific locations, decisions made, actors involved, and context of the situation. Another data collection method used in EAST is the critical decision method (CDM) which focuses on capturing the cognitive activities of people during certain events, especially unexpected ones. Typical questions used in CDM are [89]: “What were your specific goals at the various decision points?” and “Are there situations in which your decision would have turned out differently?” and “Were you at any time reminded of previous experiences in which a different decision was made?” The data collection procedure used in EAST can be cumbersome due to the time required to monitor real life events, interview subject-matter experts, and administer questionnaires. The human tracking and NLP technologies mentioned in Section 4.1 have the potential to facilitate EAST data collection.

After acquiring the data about as-is cognitive activities during an outage scenario, the analysis method, Layer 2 of EAST, will generate the “who, when, where, what, and how” information [89]. The analysis method first identifies the actors in the scenario, the type of tasks being performed, the temporal structure of tasks, and task locations (geographic location). Special attention is given to ‘who talks to whom’ (flow of information), the frequency of information exchanges, and what communication medium is used (i.e. communications technology). The next step is Layer 3 in which data from Layer 1 (activity sampling, CDM) and Layer 2 (who, when, where, what, and how) is integrated into graphical forms. For example, the output of Layer 3 consists of two types of graphical representations: scenario process charts and propositional networks. The scenario process charts are the main summary representation of EAST that describes activities related to all human and non-human elements in the scenario. This includes a temporal overview of tasks, communications, and links between agents. In the second part of Layer 3, a propositional network is used to model knowledge in any given scenario and provide ways to represent the team's, as well as, an individual's situation awareness.

To sum up, EAST is a descriptive form of modeling that facilitates understanding of the sociotechnical system. Social network analysis parameters can be applied to each of these networks in order to gain a better understanding of potential system overloads, bottlenecks, and inefficiencies. Additionally, it can highlight communication patterns to inform central actors within the entire system or sub-systems. Furthermore, task relationships and interdependencies can be identified. The EAST method may, therefore, provide insight into the outage control system by identifying system bottlenecks and interdependencies. In turn, these data can be used to inform human reliability analysis (HRA) and the design of technological or process interventions.

4.2.3. Human reliability analysis (HRA)

HRA is a powerful tool for assessing the impacts and risks of potential human errors in a workflow, which is helpful to reduce human errors during handoffs. An HRA method will analyze the probability of human actions being successful in a task or scenario, which is helpful in preventing a potential accident scenario from leading to core damage in a nuclear power plant or another form of major accident) [91,92].

There are dozens of different HRA methods [93], leading to many variations in how HRAs are conducted, such as Technique for Human Error Rate Prediction (THERP) [94] and Cognitive reliability and error analysis method (CREAM) [95]. However, the general HRA process is similar. In an activity or a cluster of human activities, a human reliability analyst will identify the possible human errors and their human error probabilities (HEPs), which is called nominal HEPs. Then a human reliability analyst will choose the appropriate performance shaping factor (PSFs) to modify the selected HEPs according to the as-is activities, tasks, or scenarios so that the calculated conditional HEPs will reflect the likelihood of certain human errors more precisely. Finally, the probability of successfully running a workflow will be calculated based on the conditional HEP of each activity in the workflow and the spatial/temporal/logical relationship between these activities.

However, three drawbacks exist in traditional or static HRA when applied to nuclear industry, especially in outage control projects. First, the deterministic of the error type when choosing the appropriate HEP and PSF is based on the experience of the analyst, which is not reliable. Second, the identification of HEP and PSF is based on a static, as-designed scenario or workflow, so that the result might not accrete because of the contingencies during NPP outage workflows [96]. Third, most HEP currently used cannot be measured directly, so that the validation of the effectiveness current HRA method is somewhat questionable [97].

Therefore, the resilient NPP outage control calls for a new HEP framework that relies on 1) a solid qualitative data collection and qualitative data analysis (such data could come from EAST analysis mentioned in Section 4.2.2), 2) dynamic modeling and simulating the as-is scenario, and 3) the cognitive model of both the actors in the scenario and the analyst itself. Such framework could choose the appropriate task types and PSFs and a traceable rationale to be documented concerning why specific selections were made and providing clear solutions to redress high-risk tasks identified during the analysis to improve the performance of HRA. Table 3 summarizes the technologies that have the potential of addressing these challenges of achieving HCA in NPP outages.

Table 3
Technologies that can address the domain challenges.

Category	Technology	Explanation	Addressing which challenge
Information acquisition technologies	Human tracking [58–70]	Capture the trajectories of moving people	Traveling pattern of field workers
	Natural language processing [71–78]	A technology enabling computers to derive meaning from human or natural language input	Cognitive human factor information
	Wearable devices [79–83]	Clothing and accessories incorporating computer and advanced electronic technologies that sense multiple information and exchange data with a manufacturer, operator, and other connected devices.	Traveling pattern of field workers; cognitive human factor information
Modeling technologies	Petri net [84–88]	A mathematical modeling language for the description of distributed systems, such as discrete-event workflows.	Handoff modeling, communication pattern modeling
	EAST analysis [89,90]	Describe the scenarios in a workflow using social network, task network, and information network to better analyze the communication activities	Communication pattern modeling
	Human reliability analysis [91–94]	Analyze the probability of human actions being successful in a task or scenario	Handoff modeling, communication pattern modeling

5. Research road map: toward human-in-the-loop cyber-physical systems for resilient NPP outage control

A Cyber-Physical System (CPS) is a mechanism that the physical world is controlled or monitored by computer-based algorithms, tightly integrated with the Internet and human users [98,99]. In a CPS, computers monitor and control physical processes, usually with feedback loops, where physical processes affect computation processes and vice versa. Domain applications of CPS include automotive systems, manufacturing, medical devices, etc. [100]. In recent years, researchers proposed the concept of "Human-in-the-Loop Cyber-Physical Systems (HiLCPSs)," which is defined as "*a loop involving a human, an embedded system (the cyber component), and the physical environment wherein the embedded system augments a human's interaction with the physical world*" [99]. In HiLCPSs, the sensors and computer systems monitor human activities (both cognitive and physical) and translate the sensory measurements into close-loop control signals to aid and modify the interaction between human and other components in the physical world [101]. HiLCPS combined with Building Information Modeling (BIM) enables activity-level construction site planning that has the potential to gradually achieve proactive improvements of operational and construction safety in NPP outages [63].

The vision of CPS in outage control is to optimize human-automation interactive decision making and achieve the following: 1) the performances of tasks will be automatically tracked in detail with abundant human factor information; 2) outage schedules will be automatically updated and adjusted while human intervention is fully supported in order to mitigate the impacts of delays, errors, or field discoveries; 3) detailed as-is workflow information including human factors can be restored in supporting data-based decision making for future needs. Furthermore, artificial intelligence techniques, such as statistical learning methods, integrated into HiLCPS for continuously improvements of the system based on learning from historical data and documents [102–105]. In the future, the authors expect that computers would be able to automate more decision-making and control mechanisms, so that release human operators and decision makers to conduct more detailed diagnosis of projects and outage control strategies. Smarter computers and algorithms also should be able to enable automatic learning from human-computer interaction histories to recommend better human-computer interaction interfaces [106,107].

Despite of significant progress into CPS and HiLCPS technology in recent years, building a reliable, self-learning HiLCPS for a complex system such as NPP outage control is still difficult because of three challenges [98–101]: 1) sensing and modeling techniques for each system need to be developed specifically based on the domain needs, which is not yet supported by mature computational and data science [100]; 2) traditional data analysis tools are unable to cope with the complexity of CPS or adequately predict system behavior [99]; 3) integrations of knowledges from different domains (e.g. computer science, mechanical & civil engineering, management science, and phycology science) are difficult to achieve for a reliable HiLCPS because of the natural complexity and uncertainty of human behaviors and physical processes [98,101]. Fully addressing these challenges requires the breakthroughs in computer science, cognitive science, and system science. Therefore, the practical step forward toward HiLCPS is to address the identified information acquisition and modeling challenges to precisely monitor the as-is workflow, to comprehend and optimize the decision-making processes. A further step toward HiLCPS will be to build comprehensive outage databases with detailed human behavior historical data that provide a solid foundation for future self-learning systems that support resilient NPP outage control. Based on this overall concept of self-learning HiLCPS, the authors propose a research roadmap that highlights researches that further examine the technologies discussed in previous sections to solve the challenges of achieving the HiLCPS of NPP outage control:

Multimedia data analytics for handoff monitoring and diagnosis [58–66,69–72,74,75,77,78]: A handoff monitoring system enables the tracking of multiple people and the communication activities during the bottleneck handoffs in the NPP environment using videos, audio, project documents and field notes. These techniques form methods to support the identification of abnormal situation and the estimation of waiting time in the monitored handoffs.

Real-time cognitive task analysis based on communication analysis [71,72,74,75,77,78,89,90]: This analysis method uses NLP to automatically assess operators' attention, SA, and MW following the EAST framework. The results from such assessment can aid human operators during the decision-making and problem-solving process. NLP has the potential to enable automatic assessment of the field personnel' SA and MW through simple, but effective oral assessments and reducing management team's workload and interruption caused by cognitive factor measurements [72].

Human-in-the-loop simulation and decision-making for handoff control [84–88]: a human-in-the-loop modeling method based on Colored Petri net (CPN) can mathematically represent the duration of tasks and handoffs under the influence of different communication patterns between people. In the simulation model, the handoffs between tasks will be influenced by the collective effects of the communication process, the traveling between different locations and waiting times. Such study would lead to the identification of optimal communication patterns and outage workspace & process design with minimum time waste and error rate in handoffs within outage projects.

A dynamic HRA system for NPP outage scenarios [91–94]: The proposed HRA system will integrate the data and analysis result from EAST analysis and dynamically simulate the future workflow based on the as-is activities happened in the outage scenario. The human-in-the-loop simulation and decision-making and EAST will provide a better estimation of HEPs and PSFs.

A human-centered Cyber-physical system for outage control [98–104,106,107]: An integrated sensing, modeling, and decision-making platform enables dynamic scheduling and resource allocation through real-time workflow capturing considering human factors and automatic deviation identification from the as-planned workflows. This system will also help NPP outage control achieve a space-efficient historical database of as-is workflow based on the sensing and modeling techniques mentioned above.

6. Conclusion

This paper presents a synthesis of domain requirements, technical challenges, and available automatic data collection and information modeling techniques in order to reveal the potential and needs of an HCA system in achieving resilient nuclear power plant (NPP) outage control. After reviewing the practical problems of NPP outage control, the authors identified two practical problems critical in resilient NPP outage control: handoff process control and proactively responding to contingencies. To address these practical problems, this paper proposes HCA for resilient outage control for resilient NPP outage control. The major findings include:

- An HCA system should be able to automatically collect human factor information and make decisions considering the interactions between human, workspace, and tasks through human-in-the-loop modeling and simulation.
- In the nuclear and construction industries, previously efforts have been made focusing on the automation techniques related to tasks and workspaces. Therefore, considering human factors including SA, physical and mental workload, communication, and anthropometric and physiological factors is the current focus of developing the proposed HCA system for NPP outage control.
- A research roadmap developed by the authors indicates that the challenges related to information acquisition and modeling lie between current outage control approaches and the proposed HCA approach. Existing techniques could potentially address these challenges, and a research roadmap can guide the future researches in identifying HCA technologies and motivating relevant technology explorations.
- The roadmap reveals the needs for future investigations into "Multimedia data analytics for handoff monitoring and diagnosis" through utilizing the state-of-the-art sensing and modeling techniques.
- The proposed research roadmap highlights "real-time cognitive task analysis based on communication analysis" as another promising area, which needs the development of natural language processing technology with higher performance and new theories describing the complex team skills.
- "Human-in-the-Loop Cyber-physical system" is a critical research question about achieving the proposed HCA for resilient NPP outage control, calling for the advance of cognitive science, computer science, system science and a deeper understanding of the complex and dynamic scenario in NPP outages.

Overall, the HCA system and various techniques synthesized in this paper should also be potentially beneficial for automated control of other shutdown projects, such as the turnaround of petrochemical plants, shutdown maintenance of other types of power plants and water supply system, and fast bridge maintained and construction on highways. In order to achieve HCA in the control of other shutdown projects, researchers need to 1) define handoffs and describe the handoff scenarios considering the interaction of "human, task, and workspace"; 2) identify key features of potential contingencies (e.g. types, frequencies, potential harms, and pre-defined responses); and 3) profiling human activities within workflows in those projects.

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References

[1] R.L. Lloyd, A Survey of Crane Operating Experience at US Nuclear Power Plants From 1968 Through 2002 (Report No. NUREG-1774), US Nuclear Regulatory Commission, Washington, DC, USA, 2003.
[2] N. Spring, Nuclear outage operational excellence: the US nuclear fleet faces a tough outage schedule this fall, but there are ways to manage scarce resources, Power Eng. 113 (2009) 48–51.
[3] S.W.St. Germain, R.K. Farris, A.M. Whaley, H.D. Medema, D.I. Gertman, Guidelines for Implementation of an Advanced Outage Control Center to Improve Outage Coordination, Problem Resolution, and Outage Risk Management, Idaho Falls, ID, (United States), 2014, http://dx.doi.org/10.2172/1168631.
[4] S.L. Hwang, Y.J. Yau, Y.T. Lin, J.H. Chen, T.H. Huang, T.C. Yenn, C.C. Hsu, Predicting work performance in nuclear power plants, Saf. Sci. 46 (2008) 1115–1124, http://dx.doi.org/10.1016/j.ssci.2007.06.005.
[5] Z. Ghazali, M. Halib, Towards an alternative organizational structure for plant turnaround maintenance: an experience of PETRONAS gas Berhad, Malaysia, Eur. J. Soc. Sci. 26 (2011) 40–48.
[6] C.C. Obiajunwa, C.C. Obiajunwa, A framework for the evaluation of turnaround maintenance projects, J. Qual. Maint. Eng. 18 (2012) 368–383, http://dx.doi.org/10.1108/13552511211281543.
[7] K. Le Blanc, J. Oxstrand, Computer-based Procedures for Field Workers in Nuclear Power Plants: Development of a Model of Procedure Usage and Identification of Requirements, (2012), http://dx.doi.org/10.2172/1047193.
[8] J. Hinze, Practices that influence safety performance on power plant outages, Pract. Period. Struct. Des. Constr. 10 (2005) 190–194, http://dx.doi.org/10.1061/(ASCE)1084-0680(2005)10:3(190).
[9] P. Muganyi, C. Mbohwa, Process improvement for power plant turnaround planning and management, Int. J. Archit. Eng. Constr. 3 (2014), http://dx.doi.org/10.7492/IJAEC.2014.014.
[10] I. Utne, L. Thuestad, K. Finbak, T. Anders, I. Utne, T.A. Thorstensen, Shutdown Preparedness in Oil and Gas Production, (2012), http://dx.doi.org/10.1108/13552511211244193.
[11] A. Hameed, F. Khan, S. Ahmed, A Risk-based Methodology to Estimate Shutdown Interval Considering System Availability, 34 (2015), http://dx.doi.org/10.1002/prs.
[12] A.M. Madni, S. Jackson, Towards a conceptual framework for resilience engineering, IEEE Syst. J. 3 (2009) 181–191, http://dx.doi.org/10.1109/JSYST.2009.2017397.
[13] US Nuclear Regulatory Commission, Shutdown and Low-Power Operation at Commercial Nuclear Power Plants in the United States (Report No. NUREG-1449), Washington, DC, USA, (1993).
[14] J. Brewer, S. Hendrickson, S. Cooper, R. Boring, Human Reliability Analysis-informed Insights on Cask Drops (Report No. NUREG/CR-7016, SAND2010-8463P), U.S. Nuclear Regulatory Commission, Washington, DC, USA, 2011.
[15] J.W. Garrett, J. Teizer, Human factors analysis classification system relating to human error awareness taxonomy in construction safety, J. Constr. Eng. Manag. 135 (2009) 754–763, http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000034.
[16] J.H. Oxstrand, K.L. Le Blanc, A.D. Bly, H.D. Medema, W.O. Hill, CBP for Field Workers – Results and Insights From Three Usability and Interface Design Evaluations, Idaho Falls, ID, (United States), (2015), http://dx.doi.org/10.2172/1245689.
[17] J. Oxstrand, K. Le Blanc, A. Bly, Light Water Reactor Sustainability Program: Computer-Based Procedures for Field Activities: Results From Three Evaluations at Nuclear Power Plants, Idaho Falls, ID (United States), (2014), http://dx.doi.org/10.2172/1168650.
[18] C. Goldman, M.C. Fuller, E. Stuart, J.S. Peters, M. McRae, N. Albers, S. Lutzenhiser, M. Spahic, Energy Efficiency Services Sector: Workforce Size and Expectations for Growth, Berkeley, CA (United States), (2010), http://dx.doi.org/10.2172/992489.
[19] P. Pyy, K. Laakso, L. Reiman, A study on human errors related to NPP maintenance activities, Proc. 1997 IEEE Sixth Conf. Hum. Factors Power Plants, 1997. Global Perspect. Hum. Factors Power Gener., IEEE, 1998, pp. 12/23–12/28, , http://dx.doi.org/10.1109/HFPP.1997.624871.
[20] C.E. Billings, Aviation Automation: The Search for a Human-centered Approach, Lawrence Erlbaum Associates Publishers, Mahwah, NJ, USA, 1997.
[21] M.A. Goodrich, E.R. Boer, Designing human-centered automation: trade-offs in collision avoidance system design, IEEE Trans. Intell. Transp. Syst. 1 (2000) 40–54, http://dx.doi.org/10.1109/6979.869020.
[22] C.C. Obiajunwa, C.C. Obiajunwa, Skills for the management of turnaround maintenance projects, J. Qual. Maint. Eng. (2013), http://dx.doi.org/10.1108/13552511311304483.
[23] M.F. Siu, M. Lu, S. Abourizk, V. Tidder, Improving sophistication and representation of skilled labor schedules on plant shutdown and maintenance projects, Proc. 13th Int. Conf. Constr. Appl. Virtual Real., London, UK, 2013.

[24] S.O. Duffuaa, M.A.A. Ben Daya, Turnaround maintenance in petrochemical industry: practices and suggested improvements, J. Qual. Maint. Eng. 10 (2004) 184–190, http://dx.doi.org/10.1108/13552510410553235.
[25] S. Pokharel, J. (Roger) Jiao, Turn-around maintenance management in a processing industry, J. Qual. Maint. Eng. 14 (2008) 109–122, http://dx.doi.org/10.1108/13552510810877638.
[26] P. Carayon, P. Hancock, N. Leveson, I. Noy, L. Sznelwar, G. van Hootegem, Advancing a sociotechnical systems approach to workplace safety - developing the conceptual framework, Ergonomics 139 (2015) 1–17, http://dx.doi.org/10.1080/00140139.2015.1015623.
[27] P.V.R. De Carvalho, Ergonomic field studies in a nuclear power plant control room, Prog. Nucl. Energy 48 (2006) 51–69, http://dx.doi.org/10.1016/j.pnucene.2005.04.001.
[28] T. Cheng, J. Teizer, Real-time resource location data collection and visualization technology for construction safety and activity monitoring applications, Autom. Constr. 34 (2013) 3–15, http://dx.doi.org/10.1016/j.autcon.2012.10.017.
[29] X. Hu, N. Cui, E. Demeulemeester, L. Bie, Incorporation of activity sensitivity measures into buffer management to manage project schedule risk, Eur. J. Oper. Res. 249 (2016) 717–727, http://dx.doi.org/10.1016/j.ejor.2015.08.066.
[30] M.C. Gouett, C.T. Haas, F. Asce, P.M. Goodrum, M. Asce, C.H. Caldas, M. Asce, Activity Analysis for Direct-work Rate Improvement in Construction, 137 (2011), pp. 1117–1124, http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000375.
[31] M.F.F. Siu, M. Lu, S. Abourizk, Bi-level project simulation methodology to integrate superintendent and project manager in decision making: shutdown/turnaround applications, Proc. - Winter Simul. Conf. 2015–Janua, 2015, pp. 3353–3364, , http://dx.doi.org/10.1109/WSC.2014.7020169.
[32] M.M. Cowing, M. Elisabeth Paté-Cornell, P.W. Glynn, Dynamic modeling of the tradeoff between productivity and safety in critical engineering systems, Reliab. Eng. Syst. Saf. 86 (2004) 269–284, http://dx.doi.org/10.1016/j.ress.2004.02.003.
[33] P.V.R. Carvalho, I.L. Dos Santos, M.C.R. Vidal, Safety implications of cultural and cognitive issues in nuclear power plant operation, Appl. Ergon. 37 (2006) 211–223, http://dx.doi.org/10.1016/j.apergo.2005.03.004.
[34] H. Broberg, M. Hildebrandt, S. Massaiu, P.Ø.Ø. Braarud, A simulator experiment investigating the effects of masked indicators in a NPP emergency control task: scenario and design, Proc. Hum. Factors Ergon. Soc. Annu. Meet, 2008, pp. 1728–1732, , http://dx.doi.org/10.1177/154193120805202108.
[35] J. O'Hara, Human Factors Engineering Program Review Model, Washington, DC, USA, (2004), http://dx.doi.org/10.2172/10173655.
[36] M.R. Endsley, Toward a theory of situation awareness in dynamic systems, Hum. Factors J. Hum. Factors Ergon. Soc. 37 (1995) 32–64, http://dx.doi.org/10.1518/001872095779049543.
[37] S.L. Hwang, G.F. Liang, J.T. Lin, Y.J. Yau, T.C. Yenn, C.C. Hsu, C.F. Chuang, A real-time warning model for teamwork performance and system safety in nuclear power plants, Saf. Sci. 47 (2009) 425–435, http://dx.doi.org/10.1016/j.ssci.2008.07.011.
[38] J. Chen, X. Song, Z. Lin, Revealing the “invisible gorilla” in construction: estimating construction safety through mental workload assessment, Autom. Constr. 63 (2016) 173–183, http://dx.doi.org/10.1016/j.autcon.2015.12.018.
[39] M. Demir, N.J. McNeese, N.J. Cooke, Team situation awareness within the context of human-autonomy teaming, Cogn. Syst. Res. (2016), http://dx.doi.org/10.1016/j.cogsys.2016.11.003.
[40] M.R. Endsley, Situation awareness misconceptions and misunderstandings, J. Cogn. Eng. Decis. Mak. 9 (2015) 4–32, http://dx.doi.org/10.1177/1555343415572631.
[41] H. Makishita, K. Matsunaga, Differences of drivers' reaction times according to age and mental workload, Accid. Anal. Prev. 40 (2008) 567–575, http://dx.doi.org/10.1016/j.aap.2007.08.012.
[42] T.S. Abdelhamid, J.G. Everett, Identifying root causes of construction accidents, J. Constr. Eng. Manag. 126 (2000) 52–60, http://dx.doi.org/10.1061/(ASCE)0733-9364(2000)126:1(52).
[43] P. Derler, E.A. Lee, A.S. Vincentelli, Modeling cyber–physical systems, Proc. IEEE 100 (2012) 13–28, http://dx.doi.org/10.1109/JPROC.2011.2160929.
[44] S.St. Germain, K. Thomas, R. Farris, J. Joe, Status Report on the Development of Micro-scheduling Software for the Advanced Outage Control Center Project, Idaho Falls, ID (United States), (2014), http://dx.doi.org/10.2172/1169244.
[45] S.St. Germain, R. Farris, Benchmark Report on Key Outage Attributes: An Analysis of Outage Improvement Opportunities and Priorities, Idaho Falls, ID (United States), (2014), http://dx.doi.org/10.2172/1212134.
[46] K. Le Blanc, J. Oxstrand, D.E. Carolinas, Model of procedure usage – results from a qualitative study to inform design of computer-based procedures, Proc. Seventh Am. Nucl. Soc. Int. Top. Meet. Nucl. Plant Instrumentation, Control Human-Machine Interface Technol. NPIC & HMIT 2012, 2012, pp. 2027–2038.
[47] V. Agarwal, J.H. Oxstrand, K.L. Le Blanc, Automated Work Packages Architecture: An Initial set of Human Factors and Instrumentation and Controls Requirements, Idaho Falls, ID (United States), (2014), http://dx.doi.org/10.2172/1213619.
[48] International Atomic Energy Agency, Indicators for Management of Planned Outages in Nuclear Power Plants (Report No. IAEA-TECDOC-1490), International Atomic Energy Agency, Vienna, Austria, 2006.
[49] P. Salmon, N. Stanton, G. Walker, D. Green, Situation awareness measurement: a review of applicability for C4i environments, Appl. Ergon. 37 (2006) 225–238, http://dx.doi.org/10.1016/j.apergo.2005.02.001.
[50] J.C. Gorman, N.J. Cooke, J.L. Winner, Measuring team situation awareness in decentralized command and control environments, Ergonomics 49 (2006) 1312–1325, http://dx.doi.org/10.1080/00140130600612788.
[51] M.W. Demas, N. Lau, C.E. Elks, Advancing human performance assessment capabilities for integrated system validation – a human-in-the-loop experiment, Proc. 9th Int. Conf. Nucl. Plant Instrumentation, Control Human-machine Interface Technol. (NPIC HMIT 2015), Charlotte, NC, USA, 2015, pp. 1051–1064.
[52] J.C. Martinez, P.G. Ioannou, General-purpose systems for effective construction simulation, J. Constr. Eng. Manag. 125 (1999) 265–276, http://dx.doi.org/10.1061/(ASCE)0733-9364(1999)125:4(265).
[53] Gregory Weatherby, Advanced Outage and Control Center: Strategies for Nuclear Plant Outage Work Status Capabilities, (2012), http://dx.doi.org/10.2172/1056003.
[54] J. Abraham, T. Kannampallil, V.L. Patel, A systematic review of the literature on the evaluation of handoff tools: implications for research and practice, J. Am. Med. Inform. Assoc. 21 (2012) 154–162, http://dx.doi.org/10.1136/amiajnl-2012-001351.
[55] N.J. Cooke, J.C. Gorman, Interaction-based measures of cognitive systems, J. Cogn. Eng. Decis. Mak. 3 (2009) 27–46, http://dx.doi.org/10.1518/155534309X433302.
[56] A. Montaser, O. Moselhi, RFID indoor location identification for construction projects, Autom. Constr. 39 (2014) 167–179, http://dx.doi.org/10.1016/j.autcon.2013.06.012.
[57] N. Li, B. Becerik-Gerber, Performance-based evaluation of RFID-based indoor location sensing solutions for the built environment, Adv. Eng. Inform. 25 (2011) 535–546, http://dx.doi.org/10.1016/j.aei.2011.02.004.
[58] J. Seo, S. Han, S. Lee, H. Kim, Computer vision techniques for construction safety and health monitoring, Adv. Eng. Inform. 29 (2015) 239–251, http://dx.doi.org/10.1016/j.aei.2015.02.001.
[59] R. Zaurin, F.N. Catbas, Computer vision oriented framework for structural health monitoring of bridges, Proc. 25th Int. Modal Anal. Conf. (IMAC), Society for Experimental Mechanics (SEM), Orlando, FL, 2007.
[60] K. Sato, J.K. Aggarwal, Temporal spatio-velocity transform and its application to tracking and interaction, Comput. Vis. Image Underst. 96 (2004) 100–128, http://dx.doi.org/10.1016/j.cviu.2004.02.003.
[61] C. Koch, K. Georgieva, V. Kasireddy, B. Akinci, P. Fieguth, A review on computer vision based defect detection and condition assessment of concrete and asphalt civil infrastructure, Adv. Eng. Inform. 29 (2015) 196–210, http://dx.doi.org/10.1016/j.aei.2015.01.008.
[62] J.M. Chaquet, E.J. Carmona, A. Fernandez-Caballero, A survey of video datasets for human action and activity recognition, Comput. Vis. Image Underst. 117 (2013) 633–659, http://dx.doi.org/10.1016/j.cviu.2013.01.013.
[63] T. Cheng, J. Teizer, G.C. Migliaccio, U.C. Gatti, Automated task-level activity analysis through fusion of real time location sensors and worker's thoracic posture data, Autom. Constr. 29 (2013) 24–39, http://dx.doi.org/10.1016/j.autcon.2012.08.003.
[64] V. Chandola, A. Banerjee, V. Kumar, R. Kandhari, V. Chandola, A. Banerjee, V. Kumar, R. Kandhari, Anomaly detection, ACM Comput. Surv. 41 (2009) 1–58, http://dx.doi.org/10.1145/1541880.1541882.
[65] L. Kratz, K. Nishino, Anomaly detection in extremely crowded scenes using spatio-temporal motion pattern models, 2009 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work. CVPR Work, 2009 2009, pp. 1446–1453, , http://dx.doi.org/10.1109/CVPRW.2009.5206771.
[66] A. Patcha, J.M. Park, An overview of anomaly detection techniques: existing solutions and latest technological trends, Comput. Netw. 51 (2007) 3448–3470, http://dx.doi.org/10.1016/j.comnet.2007.02.001.
[67] C. Zhang, P. Tang, A. Yilmaz, N. Cooke, A. Chasey, S. Jones, Automatic crane-related workflow control for nuclear plant outages through computer vision and simulation, Int. Symp. Autom. Robot. Constr. (ISARC), Auburn, AL, 2016.
[68] P. Tang, C. Zhang, A. Yilmaz, N. Cooke, Automatic Imagery Data Analysis for Diagnosing Human Factors in the Outage of a Nuclear Plant, Lect. Notes Comput. Sci. - Digit. Hum. Model. Appl. Heal. Safety, Ergon. Risk Manag, (2016), p. 9745.
[69] J.R. Spletzer, C.J. Taylor, Dynamic sensor planning and control for optimally tracking targets, Int. J. Robot. Res. 22 (2003) 7–20, http://dx.doi.org/10.1177/0278364903022001002.
[70] K.A. Tarabanis, P.K. Allen, R.Y. Tsai, A survey of sensor planning in computer vision, IEEE Trans. Robot. Autom. 11 (1995) 86–104, http://dx.doi.org/10.1109/70.345940.
[71] S. Dutta, Knowledge processing and applied artificial intelligence, Knowl. Process. Appl. Artif. Intell. (1993) 165–196, http://dx.doi.org/10.1016/B978-0-7506-1612-6.50016-X.
[72] S. Verma, S. Vieweg, W.J. Corvey, L. Palen, J.H. Martin, M. Palmer, A. Schram, K.M. Anderson, Natural language processing to the rescue? Extracting “situational awareness” tweets during mass emergency, Proc. Fifth Int. AAAI Conf. Weblogs Soc. Media, 2011, pp. 385–392.
[73] S. Hobbins, N.J. Cooke, P. Tang, Analyzing licensee event reports for improved teamwork and nuclear power plant safety during outages, 22nd Occup. Heal. Week Knowledge-based Networks, Worldw. Connect. Glob. Work, Corporación de Salud Ocupacional y Ambiental, Medellin, Colombia, 2016.
[74] I. Salo, O. Svenson, Mental causal models of incidents communicated in licensee event reports in a process industry, Cogn. Tech. Work 5 (2003) 211–217, http://dx.doi.org/10.1007/s10111-003-0121-3.
[75] D.I. Gertman, H.S. Blackman, L.N. Haney, K.S. Seidler, H.A. Hahn, INTENT: a method for estimating human error probabilities for decisionbased errors, Reliab. Eng. Syst. Saf. 35 (1992) 127–136, http://dx.doi.org/10.1016/0951-8320(92)90032-G.
[76] J.A. Schroeder, G.R. Bower, Initiating Event Rates at U.S. Nuclear Power Plants. 1988–2013, Idaho Falls, ID (United States), (2014), http://dx.doi.org/10.2172/1149013.
[77] N.J. Cooke, E. Salas, P.A. Kiekel, B. Bell, Advances in measuring team cognition, Team Cogn. Underst. Factors That Drive Process Performance, 2004, pp. 83–106, ,

http://dx.doi.org/10.1037/10690–005.
[78] A. Zouaq, An overview of shallow and deep natural language processing for ontology learning, Ontol. Learn. Knowl. Discov. Using Web, IGI Global, 2011, pp. 16–37, , http://dx.doi.org/10.4018/978-1-60960-625-1.ch002.
[79] M. Billinghurst, T. Starner, Wearable devices: new ways to manage information, Computer (Long. Beach. Calif). 32 (1999) 57–64, http://dx.doi.org/10.1109/2.738305.
[80] D. Son, J. Lee, S. Qiao, R. Ghaffari, J. Kim, J.E. Lee, C. Song, S.J. Kim, D.J. Lee, S.W. Jun, S. Yang, M. Park, J. Shin, K. Do, M. Lee, K. Kang, C.S. Hwang, N. Lu, T. Hyeon, D.-H. Kim, Multifunctional wearable devices for diagnosis and therapy of movement disorders, Nat. Nanotechnol. 9 (2014) 397–404, http://dx.doi.org/10.1038/nnano.2014.38.
[81] C. MA, B. HA, V. KG, P. MS, M.A. Case, H.A. Burwick, K.G. Volpp, M.S. Patel, Accuracy of smartphone applications and wearable devices for tracking physical activity data, J. Am. Med. Assoc. 313 (2015) 625, http://dx.doi.org/10.1001/jama.2014.17841.
[82] W. Gao, S. Emaminejad, H.Y.Y. Nyein, S. Challa, K. Chen, A. Peck, H.M. Fahad, H. Ota, H. Shiraki, D. Kiriya, D.-H. Lien, G.A. Brooks, R.W. Davis, A. Javey, Fully integrated wearable sensor arrays for multiplexed in situ perspiration analysis, Nature 529 (2016) 509–514, http://dx.doi.org/10.1038/nature16521.
[83] M. Rehman, C. Liew, T. Wah, J. Shuja, B. Daghighi, Mining personal data using smartphones and wearable devices: a survey, Sensors 15 (2015) 4430–4469, http://dx.doi.org/10.3390/s150204430.
[84] M. Zhou, Modeling, analysis, simulation, scheduling, and control of semiconductor manufacturing systems: a Petri net approach, IEEE Trans. Semicond. Manuf. 11 (1998) 333–357, http://dx.doi.org/10.1109/66.705370.
[85] W.M.P. Van Der Aalst, The application of Petri nets to workflow management, J. Circuits, Syst. Comput. 8 (1998) 21–66, http://dx.doi.org/10.1142/S0218126698000043.
[86] S. Wang, C. Wang, M. Zhou, Design of optimal monitor-based supervisors for a class of petri netswith uncontrollable transitions, IEEE Trans. Syst. Man Cybern. Part A Syst. Humans 43 (2013) 1248–1255, http://dx.doi.org/10.1109/TSMC.2012.2235427.
[87] S. Biruk, P. Jaśkowski, Simulation modelling construction project with repetitive tasks using Petri nets theory, J. Bus. Econ. Manag. 9 (2008) 219–226, http://dx.doi.org/10.3846/1611-1699.2008.9.219-226.
[88] S. Liu, Y. Fan, Workflow performance analysis and simulation based on multi-dimensional workflow net, Comput. Ind. 65 (2014) 333–344, http://dx.doi.org/10.1016/j.compind.2013.12.002.
[89] G.H. Walker, H. Gibson, N.A. Stanton, C. Baber, P. Salmon, D. Green, Event Analysis of Systemic Teamwork (EAST): a novel integration of ergonomics methods to analyse C4i activity, Ergonomics 49 (2006) 1345–1369, http://dx.doi.org/10.1080/00140130600612846.
[90] P.M. Salmon, M.G. Lenne, G.H. Walker, N.A. Stanton, A. Filtness, Using the Event Analysis of Systemic Teamwork (EAST) to explore conflicts between different road user groups when making right hand turns at urban intersections, Ergonomics 57 (2014) 1628–1642, http://dx.doi.org/10.1080/00140139.2014.945491.
[91] R.L. Boring, M. Rasmussen, M. Rasmussen, GOMS-HRA: a method for treating subtasks in dynamic human reliability analysis, Proc. ESREL2016, Glasgow, Scotland, September 25–29, 2016, 2016.
[92] R.L. Boring, Fifty years of THERP and human reliability analysis, Proc. Probabilistic Saf. Assess. Manag. Eur. Saf. Reliab. Conf. (PSAM 11 ESREL 2012), Helsinki, Finland, 2012.
[93] B. Kirwan, Human error identification in human reliability assessment. Part 1: overview of approaches, Appl. Ergon. 23 (1992) 299–318, http://dx.doi.org/10.1016/0003-6870(92)90292-4.
[94] A.D. Swain, H.E. Guttmann, Handbook of Human-reliability Analysis With Emphasis on Nuclear Power Plant Applications. Final Report, Albuquerque, NM, and Livermore, CA (United States), (1983), http://dx.doi.org/10.2172/5752058.
[95] E. Hollnagel, Cognitive Reliability and Error Analysis Method (CREAM), Elsevier, Amsterdam, Netherlands, 1998.
[96] R.L. Boring, Dynamic human reliability analysis: benefits and challenges of simulating human performance, Eur. Saf. Reliab. Conf. (ESREL 2007), Stavanger, Norway, June 25–27, 2007, pp. 1043–1050.
[97] R.L. Boring, J.C. Joe, D. Mandelli, Human Performance Modeling for Dynamic Human Reliability Analysis, (2015), pp. 223–234, http://dx.doi.org/10.1007/978-3-319-21073-5_23.
[98] E.A. Lee, The past, present and future of cyber-physical systems: a focus on models, Sensors (Switzerland) 15 (2015) 4837–4869, http://dx.doi.org/10.3390/s150304837.
[99] G. Schirner, D. Erdogmus, K. Chowdhury, T. Padir, The future of human-in-the-loop cyber-physical systems, Computer (Long. Beach. Calif.) 46 (2013) 36–45, http://dx.doi.org/10.1109/MC.2012.428.
[100] E.A. Lee, Cyber physical systems: design challenges, Isorc 2008 11th IEEE Symp. Object/component/service-oriented Real-time Distrib. Comput. - Proc, 2008, pp. 363–369, , http://dx.doi.org/10.1109/ISORC.2008.25.
[101] S. Munir, J.A. Stankovic, C.-J.M. Liang, S. Lin, Cyber physical system challenges for human-in-the-loop control, 8th Int. Work. Feed. Comput., USENIX, San Jose, CA, June 24–28, 2013.
[102] R.S. Michalski, J.G. Carbonell, T.M. Mitchell, Machine Learning: An Artificial Intelligence Approach, Springer Science & Business Media, New York, NY, USA, 2013.
[103] L. Deng, D. Yu, Deep learning: methods and applications, found. Trends®, Signal Process. 7 (2014) 197–387, http://dx.doi.org/10.1561/2000000039.
[104] J. Schmidhuber, Deep learning in neural networks: an overview, Neural Netw. 61 (2015) 85–117, http://dx.doi.org/10.1016/j.neunet.2014.09.003.
[105] B. Liu, Y. Shen, W. Zhang, X. Chen, X. Wang, An interval-valued intuitionistic fuzzy principal component analysis model-based method for complex multi-attribute large-group decision-making, Eur. J. Oper. Res. 245 (2015) 209–225, http://dx.doi.org/10.1016/j.ejor.2015.02.025.
[106] W. van der Aalst, T. Weijters, L. Maruster, Workflow mining: discovering process models from event logs, IEEE Trans. Knowl. Data Eng. 16 (2004) 1128–1142, http://dx.doi.org/10.1109/TKDE.2004.47.
[107] J. Herbst, A Machine Learning Approach to Workflow Management, (2000), pp. 183–194, http://dx.doi.org/10.1007/3-540-45164-1_19.