1-1-2023

Application of Artificial Intelligence in Detection and Mitigation of Human Factor Errors in Nuclear Power Plants: A Review

Meenu Sethu
San Jose State University

Bhavya Kotla
San Jose State University

Darrell Russell
The University of Tennessee, Knoxville

Mahboubeh Madadi
San Jose State University, mahboubeh.madadi@sjsu.edu

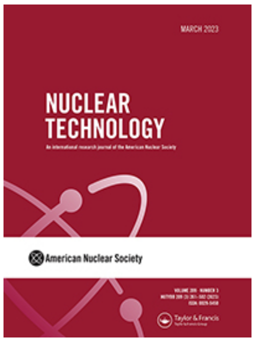
Nesar Ahmed Titu
The University of Tennessee, Knoxville

See next page for additional authors

Recommended Citation

Meenu Sethu, Bhavya Kotla, Darrell Russell, Mahboubeh Madadi, Nesar Ahmed Titu, Jamie Baalis Coble, Ronald L. Boring, Klaus Blache, Vivek Agarwal, Vaibhav Yadav, and Anahita Khojandi. "Application of Artificial Intelligence in Detection and Mitigation of Human Factor Errors in Nuclear Power Plants: A Review" *Nuclear Technology* (2023): 276-294. https://doi.org/10.1080/00295450.2022.2067461

Meenu Sethu, Bhavya Kotla, Darrell Russell, Mahboubeh Madadi, Nesar Ahmed Titu, Jamie Baalis Coble, Ronald L. Boring, Klaus Blache, Vivek Agarwal, Vaibhav Yadav, and Anahita Khojandi



Nuclear Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/unct20

Application of Artificial Intelligence in Detection and Mitigation of Human Factor Errors in Nuclear Power Plants: A Review

Meenu Sethu, Bhavya Kotla, Darrell Russell, Mahboubeh Madadi, Nesar Ahmed Titu, Jamie Baalis Coble, Ronald L. Boring, Klaus Blache, Vivek Agarwal, Vaibhav Yadav & Anahita Khojandi

To cite this article: Meenu Sethu, Bhavya Kotla, Darrell Russell, Mahboubeh Madadi, Nesar Ahmed Titu, Jamie Baalis Coble, Ronald L. Boring, Klaus Blache, Vivek Agarwal, Vaibhav Yadav & Anahita Khojandi (2023) Application of Artificial Intelligence in Detection and Mitigation of Human Factor Errors in Nuclear Power Plants: A Review, Nuclear Technology, 209:3, 276-294, DOI: 10.1080/00295450.2022.2067461

To link to this article: https://doi.org/10.1080/00295450.2022.2067461

NUCLEAR TECHNOLOGY · VOLUME 209 · 276–294 · MARCH 2023

DOI: https://doi.org/10.1080/00295450.2022.2067461

Check for updates

Critical Review

Application of Artificial Intelligence in Detection and Mitigation of Human Factor Errors in Nuclear Power Plants: A Review

Meenu Sethu,[a] Bhavya Kotla,[a] Darrell Russell,[b] Mahboubeh Madadi,[a*] Nesar Ahmed Titu,[b] Jamie Baalis Coble,[b] Ronald L. Boring,[c] Klaus Blache,[b] Vivek Agarwal,[c] Vaibhav Yadav,[c] and Anahita Khojandi[b]

[a]*San Jose State University, One Washington Square, San Jose, California 95192-0069*
[b]*The University of Tennessee, Knoxville, Tennessee 37996*
[c]*Idaho National Laboratory, P.O. Box 1625, Idaho Falls, Idaho 83415-3840*

Received January 27, 2022
Accepted for Publication April 13, 2022

Abstract — *Human factors and ergonomics have played an essential role in increasing the safety and performance of operators in the nuclear energy industry. In this critical review, we examine how artificial intelligence (AI) technologies can be leveraged to mitigate human errors, thereby improving the safety and performance of operators in nuclear power plants (NPPs). First, we discuss the various causes of human errors in NPPs. Next, we examine the ways in which AI has been introduced to and incorporated into different types of operator support systems to mitigate these human errors. We specifically examine (1) operator support systems, including decision support systems, (2) sensor fault detection systems, (3) operation validation systems, (4) operator monitoring systems, (5) autonomous control systems, (6) predictive maintenance systems, (7) automated text analysis systems, and (8) safety assessment systems. Finally, we provide some of the shortcomings of the existing AI technologies and discuss the challenges still ahead for their further adoption and implementation to provide future research directions.*

Keywords — *Human factors, human errors, nuclear power plants, artificial intelligence, operator support systems.*

Note — *Some figures may be in color only in the electronic version.*

I. INTRODUCTION

Human errors in safety-critical systems, such as nuclear power plants (NPPs), have been an important topic of research in the field of human factors. The Three Mile Island and Chernobyl accidents sparked interest in nuclear safety around the world. These accidents revealed that plant operators may not always adequately handle and process the large volume of information and that the high workload and stress during abnormal events can severely affect their performance. In fact, it is reported that human errors accounted for 40% of the failures during startup and shutdown operation from 1997 to 2017 at NPPs in Korea because of the operator burden arising from monitoring hundreds of parameters for an extended period.[1] A 1985 U.S. Nuclear Regulatory Commission (NRC) study showed that upward of 65% of commercial nuclear system failures involve human error.[2] Human-caused accidents remain rare, and most human errors do not have an impact on plant safety. Nonetheless, human errors can result in downtime for plants as systems are reset or repaired and root cause analyses are performed to ensure continued safe operations.

The analysis of incidents in the nuclear industry over the past few decades has spawned a great deal of research

*E-mail: mahboubeh.madadi@sjsu.edu

into the critical role played by human factors in ensuring low human error rates and maintaining the reliability of NPPs. Recent developments in digital technology and information technology and ergonomics have accelerated digitization and design innovation in the nuclear industry. Specifically, the involvement of human factors in the design of NPPs has gained considerable attention. Traditional alarm systems and many analog instruments and displays have already been replaced by more recent digitized systems. Many operator support systems have been created to assist operators in evaluating conditions, providing computerized procedures, and regulating their operations in response to changing circumstances. Beyond operation, human errors related to maintenance and modifications also have a significant influence on plant safety.[2–5]

Although NPPs have become increasingly digital over the years, the design of digital solutions has not always been optimized to simplify the work of operators. There is a need to build "intelligent" operator support systems that can accurately assess the safety status of the NPP in real time and realize intelligent human-machine interaction. Specifically, such smart systems should assist operators in making mission-critical decisions and performing timely actions to reduce the risk in the operational safety of NPPs.

Artificial intelligence (AI) technology has the potential to bring this kind of intelligence and revolutionize this important industry. Artificial intelligence can be defined as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chances of success.[6] In recent decades, AI, and especially deep learning, which is a machine learning method based on artificial neural networks (ANNs), has made considerable progress.[7] Modern AI-powered systems such as smart devices, mobile phones, and virtual assistants are ubiquitous today. With the development and popularity of AI, many researchers have considered how this technology could be applied to NPPs to reduce errors overall (not just human errors), provide useful guidance to operators, and help them make accurate and rapid decisions while ensuring and potentially enhancing the safety of nuclear energy production.

This work reviews the common human errors in the operation and maintenance of NPPs and explores the role AI technology can play in mitigating the risk of human failures and improving the performance of NPPs.

II. BACKGROUND

Human reliability analysis (HRA) is the study of human contributions to human error and the quantification of human error (e.g., rates, probabilities) for use in overall risk models. Historically, human factors and human reliability have diverged, whereby human factors engineering has tended to focus on understanding factors that influence human performance in sociotechnical systems to improve the design of those systems, while HRA has tended to focus on safety and risk factors, including as-built systems like existing nuclear facilities.[8] These two fields converge with the introduction of new analytical tools such as AI. Traditional HRA uses worksheets and subject matter experts to predict the factors that will contribute to human errors. This approach depends on the subjectivity of analysts and can result in considerable inter-analyst variability. The advent of AI techniques in HRA promises the opportunity to minimize such subjectivity and provide a more consistent tool for HRA. Additionally, where the causes of human error are identified, AI can provide technology to assist operators in preventing and mitigating errors.

II.A. Causes of Human Error

Human performance is the product of the context in which the human operates. While humans have some tendencies to commit errors even in the most positive contexts, such error is considered random. Some contexts, however, clearly drive success or failure. In HRA, the systematic review of these contexts is treated through performance shaping factors (PSFs), also referred to as performance influencing factors and common performance characteristics in different parts of the research community.

The earliest HRA method, the Technique for Human Error Rate Prediction[9] (THERP) captures most contexts as predefined scenarios. The analyst matches scenarios under analysis to these predefined scenarios in THERP. This process proves somewhat limited because the predefined scenarios are not extensible, resulting in a degree of force fitting. THERP has limited coverage of PSFs to cover operator stress and experience levels, which serve as modifiers on the nominal human error probability levels extracted from scenario matching. Descendants of THERP, like the Standard Plant Analysis Risk–Human Reliability Analysis (SPAR-H) method,[10] expand the process to let PSFs cover most of the context without scenario matching. SPAR-H features a list of eight PSFs: Available Time, Stress/Stressors, Complexity, Experience/Training, Procedures, Ergonomics/Human–Machine Interface, Fitness for Duty, and Work Processes. The SPAR-H analyst assigns a level for each PSF, resulting in a positive effect, neutral or nominal effect, or a negative effect on performance. The subjective level of the PSF influence translates to a multiplier on a nominal human error probability.

A proliferation of HRA methods to cover different applications and contexts results in an ever-growing list of possible PSFs. While HRA methods are mostly grounded in their specific and fixed sets of PSFs, the impression across methods is that no single HRA method covers all possible PSFs. Efforts to standardize the list of relevant PSFs have emerged. NUREG-1792, "Good Practices for Implementing Human Reliability Analysis,"[11] provides a standard list of 15 PSFs to cover human actions in response to plant upset conditions:

1. applicability and suitability of training and experience
2. suitability of relevant procedures and administrative controls
3. availability and clarity of instrumentation
4. time available and time required to complete the action
5. the complexity of required diagnosis and response
6. workload, time pressure, and stress
7. team/crew dynamics and crew characteristics
8. available staffing and resources
9. ergonomic quality of human-system interface (HSI)
10. environment in which the action needs to be performed
11. accessibility and operability of equipment to be manipulated
12. need for special tools
13. communications
14. special fitness needs
15. consideration of "realistic" accident sequence diversions and deviations (e.g., extraneous alarms, failed instruments, outside discussions).

This list was not meant to be exhaustive, but rather the minimum set of factors to consider in an HRA. While the list includes nearly double the number of PSFs as SPAR-H, treatment of the PSFs could easily be cross walked across most HRA methods. In the case of SPAR-H, for example, a single PSF covers multiple elements that are treated as separate PSFs in NUREG-1792.

NUREG/CR-4862 (Ref. 12) presents the cognitive environment simulation modeling tool that can be used to investigate what situations and factors lead to intention failures, what actions follow from intention failures (e.g., errors of omission, errors of commission), the ability to recover from errors or additional machine failures, and the effects of changes in the NPP person-machine system.

Realizing that contextual nuances provide for an almost infinite number of possible PSFs, efforts have been undertaken to develop PSF categories that could frame broad influences while allowing more nuanced explorations within individual HRA methods. Groth and Mosleh[13] reviewd available HRA databases to identify PSFs in use and developed a Bayesian Belief Network of the interactions between PSFs. The optimal number of categories to maintain orthogonality is five, as follows: (1) organizational factors related to training, corrective action, safety culture, and management activities; (2) team factors related to communications, direct supervision, team coordination, and team cohesion; (3) personal factors related to cognitive attention, physical and psychological abilities, morale and motivation, knowledge and experience, skills, familiarity, and biases; (4) situational factors related to external environment, hardware and software, conditioning events, task-specific factors, and decision making; and (5) machine design factors such as the HSI and system responses.

III. TYPES OF HUMAN ERROR

Just as there are a multitude of PSFs to catalog the causes of errors, there are numerous ways of classifying the types of human error. For example, popular error taxonomies suggest that there are errors of omission and commission,[9] reflecting actions skipped or done in addition to required tasks, respectively. Another taxonomy suggests an error may be considered a slip, lapse, mistake, or circumvention.[14] Errors may occur leading up to an event (pre initiators), causing the event (initiating events), or in responding to the event (post initiators).[11] Errors may be latent or active, meaning they have a delayed or immediate effect.[14] And errors may occur for all activities involving the nuclear facility, from the design, fabrication, and installation phases; to operations activities, involving control room and field operators; to emergency operations; to maintenance activities; to decommissioning.

The cognitive basis of human errors described in Whaley et al.[15] anchors different causes and types of errors according to macro-cognitive functions. Macro-cognitive functions represent the basic processes of human mental activity, covering different stages: detecting and noticing, in which sensory information is taken into the human; sense making and understanding, in which this information is imbued with meaning; decision making, in which courses of action or inaction are determined; action, in which decisions are turned into behaviors; and teamwork, which complements the other stages by providing supplemental people to perform each stage and relay information between each other. Each macro-cognitive function presents unique opportunities for errors. For example, key information and cues may be missed by not being perceived, not being attended to, or being misperceived. This early-stage cognitive error affects subsequent stages and can lead to incorrect sense making and understanding, decision making, and actions. PSFs, such as the quality of the information or workload, set the context for detecting and noticing, and poor PSFs may prime an increased likelihood of error.

Fortunately, human errors rarely rise to have significant consequences at plants. Plants are designed with redundancies such that no single-point failure leads to an accident. Likewise, human activities feature checks and balances, from second-checker personnel to catch errors, to procedure checks for correct performance of tasks, to hardware safety systems to prevent unintended effects of human errors. The purpose of AI tools to support operations is therefore not specifically to address safety concerns but rather to assist operators in day-to-day operations at the plant and to provide additional defense in depth during potential upset conditions. Artificial intelligence–based systems at NPPs foremost help ensure efficiency, ease of use, and reliability of operations. They may in some cases reinforce safety practices to provide even greater safety margins at NPPs.

IV. MITIGATING HUMAN ERRORS USING AI

To reduce the consequences of human errors in NPPs, many efforts have been made to develop advanced operator support systems, such as decision support systems, sensor fault detection systems, operation validation systems, operator monitoring systems, autonomous control systems, predictive maintenance systems, automated text analysis systems, and safety assessment systems. Of particular interest is the use of AI technologies to ensure safe and reliable operation of a NPP. In this section, we examine the various AI-based methods that have been investigated in the literature to mitigate human errors in NPPs.

IV.A. Decision Support Systems

The use of smart support systems to assist operators' decision-making ability has been widely researched in the past few decades. A well-designed decision support system must aid the cognitive process of operators and allow for convenient main control room (MCR) operation. This is particularly important during abnormal transient and process disturbances in NPPs where operators need to assess the current situations promptly and accurately. A typical alarm system in an MCR has a thousand or more alarms in addition to displays of analog data. In the event of an emergency, such as a loss-of-coolant accident or a feedwater line break, hundreds of alarms occur simultaneously. This causes information overload and stress on operators, severely affecting their decision-making ability.

A fault diagnosis system is a type of decision support system whose objective is to make the task of fault diagnosis easier and reduce possibilities of human errors. Operators often need to perform high mental workload activities in the first few minutes after a fault occurrence. The information overload and time pressure under these emergency conditions cause stress, thereby severely affecting the operators' decision-making ability when it is required the most. Fault diagnostic systems ease the workload of operators by quickly suggesting likely faults based on the probability of occurrence and provide accident-related information.

Various methods based on AI have been proposed to build smart decision support systems for fault diagnostics (which include transient detection for many reactor conditions/states) and accident prediction in NPPs. The range of AI techniques studied spans from knowledge-based methods, such as expert systems, to more advanced and sophisticated data-driven algorithms such as ANNs, support vector machines (SVMs), and genetic algorithms.[16–22]

Artificial neural networks have been one of the most popular AI modeling techniques for fault diagnostics and transient analysis in nuclear plants.[16,23–31] For instance, Mo et al.[16] and Lee et al.[23] propose a fault diagnosis and advisory system based on dynamic neural networks, which are a type of multilayer perceptron (MLP) neural network to enhance operators' decision-making ability and reduce their mental workload. Mo et al.[16] use a two-level classifier architecture for fault diagnosis. The first level classifier recognizes the type of transient, and consequently, the second level classifier performs fault location detection and severity prediction, providing detailed accident information. Lee et al.[23] improve upon this fault diagnostic system using two parallel neural networks, consisting of a modified dynamic neural network and a dynamic neuro-fuzzy network. The two networks perform independent fault diagnosis using different inputs to generate a more reliable output variable. Based on the diagnosis results, a computerized procedure search system selects an appropriate operating procedure necessary to manage the current situation so that operators' omission errors can be considerably reduced.

With the recent advances in neural network architecture and training procedures in the past decade, the effectiveness of deep learning–based models as a powerful feature extractor to perform high-accuracy prediction has come a long way. Many research works have explored the use of deep learning–based systems for the nuclear accident identification problem.[32–36] Santos et al.-[32] demonstrate the performance of a deep rectifier neural network that can identify many operational situations quickly and with high accuracy rates under reasonable training times. Zhang et al.[33] propose a modified long short-term memory (LSTM) neural network, an improved version of the recurrent neural network, to identify abnormal or false pressurizer water levels (PWLs) in pressurized water reactors. Specifically, by modifying the loss function to include a cost-sensitive weighting factor, the LSTM model can overcome the issue of time-shifting correlations and example imbalance in PWL prediction. Such identification of the pressurizers' real water levels can reduce the difficulty of the operation and reduce the probability of human errors. Yang and Kim[34] develop an accident diagnosis algorithm using LSTM that allows for longer time dependencies in the input data to be modeled. Choi and Lee[35] propose an automated diagnosis algorithm in emergency situations using a gated recurrent unit-decay model, an evolution over the LSTM model, to better handle missing data from faulty sensor measurements. Yang and Kim[36] develop an accident diagnosis algorithm for the startup mode of NPPs wherein anomalies are harder to detect because of the several operation modes during startup.

Accurate and rapid identification of fault status is of premier importance to reduce human error under pressure and to guarantee the safe and reliable operation of an NPP. The accuracy of neural network–based fault diagnosis methods is shown to improve by applying principal component analysis for dimensionality reduction and noise filtering of the plant data in the prediagnostic stage.[25,26] To recognize malfunctions in a timely manner, Yu and Liu[24] evaluate a real-time fault diagnosis method using a two-stage neural network architecture. The first ANN performs a rapid prediagnosis while the second ANN verifies the diagnosis and makes it more accurate. Using this two-stage neural network architecture, the method can not only diagnose the learned faults accurately with a low pretermission rate, but also identify unlearned faults under different operating conditions in real time. Ming et al.[25] study a similar two-step hybrid approach for fault diagnosis wherein first a multiflow model (MFM) localizes the fault, and then an ANN performs deep accurate diagnosis upon verifying the MFM result. The knowledge-based MFM method improves the understandability of diagnostic processes and results while the ANN enhances the success rate of identification.

Many studies suggest AI approaches to diagnose potential accident scenarios; however, if an unknown (or untrained) accident scenario is presented, the performance of supervised approaches tends to deteriorate. To address these concerns, Yang et al.[30] develop an accident diagnosis algorithm including the "don't know" response using LSTM neural networks and an auto encoder novelty detection function. Pinheiro et al.[31] augment state-of-the-art deep learning–based systems for the nuclear accident identification problem with novelty detection and demonstrate outstanding performance in terms of correct "don't know" classifications.

Besides ANNs, some studies have explored support vector–based models, namely SVM classifier and support vector regressor, for fault identification and detailed accident information.[17,37–39] Evolutionary algorithms, such as genetic algorithms, have also been reported to work robustly in terms of fault diagnosis.[18,19]

Beyond accurate fault identification and diagnosis, ANNs have also been used in the context of diagnosis error and uncertainty estimation in nuclear plants.[20,27,40] The prediction error/uncertainty, estimated using an auxiliary neural network, allows plant operators to examine the credibility of the fault diagnosis and thereby make reliable decisions in a timely manner.

While most research on decision support systems is based on modern machine learning algorithms, several intelligent operator support systems that adopted knowledge-based systems (KBSs) have been reported in the literature.[21,22,29,41–43] The most popular knowledge-based AI system is an expert system. An expert system is an AI program that emulates the decision-making ability of a human expert. Uhrig[21] provides a survey of the different potential applications of expert systems in nuclear plants to reduce operator error and increase plant safety, reliability, and efficiency. Varde et al.[44] implement a hybrid expert system combining the advantages of ANNs and KBSs to enhance the decision-making ability of the operator while coping with operational requirements, particularly during abnormal conditions. In this study, the ANN monitors the reactor's safety status while the KBS module performs the fault diagnosis and procedure generation. Uhrig and Tsoukalas[29] discuss the use of an expert system that has a neural network in its knowledge base, called a connectionist expert system, for identification of transients in NPPs that yielded great benefits in terms of speed, robustness, and knowledge acquisition. Further, they report the robust performance of hybrid neuro-fuzzy approaches that couple a rule-based expert system with pretrained ANNs using fuzzy logic in the presence of noise.

Operator information/cognitive overload and lack of knowledge are major contributing factors to nuclear accidents. As such, expert support systems have the potential to reduce operator error in NPPs (Ref. 45). For instance, Mampaey et al.[46] discuss the problem of operator stress and information overload that arise from using written procedures in post-accident situations and propose an expert system that can act as a truly dynamic task scheduler, rather than a conventional computerized procedure display to minimize operator omission errors in NPPs.

Recent research by Hanna et al.[22] demonstrates the use of a novel declarative AI approach, namely, Answer Set Programming, to represent the qualitative knowledge of the NPP in the form of logic rules. The represented knowledge is structured to form a reasoning-based operator support system and is shown to be capable of diagnosing faults, informing the operator of different scenarios and consequences, and generating recommended control actions.

IV.B. Sensor Fault Detection Systems

Sensors are used to measure a range of parameters (e.g., temperature, pressure, flow, fluid level, radiation) in NPPs and are one of the essential sources of data. Most automated and human-initiated decisions are based in whole or in part on these data, so it is important to ensure the reliability of the sensor and the accuracy of sensor readings. Incorrect sensor data could lead to incorrect decision making by humans or by automation systems. Human errors may also occur from operators misdiagnosing an accident and taking actions based on fault plant parameter measurements. Sensor failure detection is thus an extremely useful component of process control systems where an unchecked failure can be expensive and potentially dangerous.

A study by Uhrig[47] reports the use of probabilistic neural networks to diagnose instrument failures in NPPs. When a sensor begins to drift, the values predicted by the trained neural network and the observed plant parameters start to differ. By monitoring these deviations, a drift or instrumentation system failure can be identified. Uhrig and Tsoukalas[29] survey an adaptive neural fuzzy inference system that uses fuzzy logic and the sequential probability ratio test (SPRT) for sensor fault detection. The system not only detects the fault but also isolates the channel in which the fault has occurred. Zvaljevski and Gross[48] implement a combination of multivariate state estimation technique kernel with the SVM method to demonstrate superior sensor fault detection and generalization properties. Shaheryar et al.[49] develop a denoised auto-associative sensor model based on deep learning to overcome the poor regularization and robustness issues that plague auto-associative neural network–based empirical sensor models.

While various online monitoring techniques have been developed to monitor the state of sensors during normal NPP operations,[29,47–49] they are inappropriate in emergency situations where the plant parameters undergo complex and nonlinear changes because of the reactor core trip.[48–51] Choi and Lee[52,53] construct an abnormal sensor detection system for NPPs using an LSTM-based machine learning model adopting a consistency index. The use of consistency index labeling makes it possible to detect sensor error immediately and locate the sensor where the error occurred. Yoo et al.[37] develop an auto-associative kernel regression model and SPRT to diagnose instrument failures in severe accident scenarios in NPPs.

Several data-driven AI methods have been researched and proposed for fault diagnosis in the nuclear field. However, for real applications, the developed fault identification systems need to be robust to sensor anomalies such as sensor faults and noise. Choi and Lee[54] develop a sensor fault-tolerant accident diagnosis system that can be applied during abnormal situations and startup and shutdown operations of NPPs, as well as other industries requiring process parameter–based reactions sensitive to sensor faults. The authors develop an iterative random forest–based regression model and a recurrent neural network (RNN)–based gated recurrent unit with decay model and demonstrate that the proposed approach successfully recovers the degradation in the performance from sensor errors.[54]

IV.C. Operation Validation System

An operation validation system is an advisory system used to supervise and validate operator actions in NPPs.

Operation validation systems provide two important functions for the operators: validating operator actions and performing an effects analysis of the proposed actions. By providing these functions to validate operator actions in the control panel, operator commission errors that may arise in high stress emergency situations can be effectively reduced.

Neural networks have been used to model the effects analysis of operator actions and reduce the error of commission in NPPs (Refs. 23, 55 through 58). Lee et al.[23] and Mo et al.[55] propose an operation validation system that evaluates each operator action and simulates possible outcomes using ANNs. The system provides both qualitative and quantitative effects analysis of operator actions. Based on the predictions, suggestions/warnings are provided to operators to mitigate human errors during operation in emergency scenarios. Operators can examine the possible outcomes of their expected actions and accordingly choose to confirm or cancel their actions. Similarly, Bae et al.[58] propose a recursive strategy that employs an ANN as its prediction model to predict the future trends of important plant parameters to determine whether a performed action is an error or not. In this study, two types of ANNs, namely, MLP and LSTM networks, are compared against their usefulness in detecting and recovering human errors in emergency situations in NPPs. It is observed that the future trends of plant parameters are quite accurately predicted through the LSTM model. Ahn et al.[56] suggest an unsafe acts detection system based on colored petri nets (CPNs) and deep neural networks to determine if an operator action is an error and discover its effect on the plant integrity. The proposed system reduces human error in the MCR by reducing the mental workload and enhancing the operators' situational awareness.

Ahn and Lee[57] propose a procedural compliance check (PCC) system based on CPN modeling and neural networks. The CPN model converts the NPP emergency operating procedures to modeling language and is used in situations where no decisions or only simple decisions are needed. In situations where it is difficult to implement rule-based answers, such as continuous observation of changes in the trends of a parameter, a deep learning algorithm is employed to assist with complex decision making. A procedure incompliance is judged when an operator action is inconsistent with the response planning as predicted by the system. The PCC system proposed can help reduce procedural violations and human error, and therefore reduce the human error probability in emergency operating situations.

IV.D. Operator Monitoring System

Operators' fitness for duty (FFD), defined as the physical and mental ability of operators to safely perform their duties, has been highlighted as one of the primary reasons for human error in industrial and nuclear accidents.[14,59,60] For instance, the NRC has published the requirements for FFD programs in nuclear facilities in the Code of Federal Regulations (CFR), namely, 10 CFR 26 (Ref. 61). In order to remain compliant with 10 CFR 26, NPP licensees have implemented FFD management programs that address operators' physical fitness, drug and alcohol testing, fatigue management, and psychological testing.[62] However, these systems have been far from effective in practice.[63] Many elements of the program involve tests that are subjective and infrequent (only once or twice a year) and pre-access or are conducted as one-time events and thus can play only a supplemental role. A continuous operator monitoring system can hence overcome many of the challenges of existing FFD approaches.

There have been a few notable works to objectively estimate operator performance to reduce human error and enhance human performance.[64–67] Jo et al.[64] propose a facial expression–based performance estimation system using an LSTM network. The system processes the operators' facial images as they perform nuclear accident diagnosis tasks and provides an immediate analysis of their performance unobtrusively. Findings from this study are consistent with previous research that shows emotion-related facial expressions reflect biological responses to performance-impairing stress.[68]

Several studies have investigated the feasibility of using bio-monitoring systems to predict and thereby minimize the risk of human error at nuclear facilities.[65–67] A study by Suh and Yim[66] shows the potential of a machine learning–based approach to monitor a worker's FFD status using bio-signals. The FFD statuses considered include psychoactive substance use (alcohol use), psychological status (depression, stress, anxiety), and physiological status (sleep deprivation). The important bio-signal markers of FFD are selected based on a multivariate analysis of variance and are fed to a multiclass and binary-class SVM classifier to achieve fast identification of a potential at-risk worker. In a different study by Kim et al.,[67] electroencephalography (EEG) and eye movement signals are used to remotely measure operator attention levels in real time and provide feedback to supervisors. Specifically, the study demonstrated that, with a few EEG and eye movement features, the presence or absence of human attention can be classified with up to 90% accuracy using the k-nearest neighbor and SVM classification models. Along the same lines, Zhang et al.[69] propose the use of wearable device sensors for real-time acquisition of physiological information to support automatic cognitive factor monitoring using data mining algorithms.[70,71] The use of such intelligent bio-signal-based fitness and attention monitoring systems can thus help prevent human errors and enhance human performance in NPP MCRs.

The safe operation of an NPP can be further ensured through proper coordination and teamwork among the MCR operators.[72] This is particularly important in the digital technology–based MCR environments where a lack of personal interactions and communications may reduce the performance of a team.[73,74] Kim et al.[74] suggest quantitative indicators for estimating the implicit intentions of reactor operators to mitigate such concerns. Specifically, they propose an SVM-based classifier to classify implicit intentions of agreement and disagreement. The classification is based on EEG data measured from operators while they performed operational tasks using soft controls. The proposed indicators support peer checks and concurrent/independent verifications to help diagnose and prevent human errors through enhanced operator communications.

Besides the use of wearable devices for operator monitoring, Zhang et al.[69] suggest the use of natural language processing (NLP) and computer vision technologies to monitor operator cognitive factors for reducing human errors in NPPs. NLP technology can enable the automatic assessment of an operator's situational awareness and mental workload through oral assessments. NLP simplifies the measurement process by reducing the workload and interruption caused by traditional survey-based cognitive measures. Moreover, through automated extraction of rich, semantic knowledge from the record of different events during the operation and maintenance in NPPs, NLP can aid in understanding complex team processes (e.g., team cognition). The insights gained therein can improve the team's situational awareness and reduce their mental workload. Computer vision-based human tracking can be used to detect the anomalous behavior of field workers in NPPs, which in turn can help anticipate and avoid accidents. Further, the automatic sensing of operator traveling patterns can reduce time loss and errors during handoffs and enhance the management team's situational awareness by keeping them informed.

IV.E. Autonomous Control Systems

An autonomous control system has the power for self-governance in performing control functions.[75] Such a system is composed of hardware and software that can execute the requisite control function over extended periods without human intervention. By removing humans from the control loop, autonomous operation algorithms can reduce operator burden and the potential for human errors in NPPs.

Autonomous control systems in the nuclear industry have relied on classical proportional-integral-derivative (PID) controllers. The optimal control strategy in Edwards et al.[76] uses state feedback–assisted control along with a classical controller to achieve optimal reactor performance over a wide range of operational scenarios. The work demonstrated that state feedback–assisted control more effectively accommodated for plant modeling errors and disturbances than did a conventional controller. Many AI-based methods, such as neural networks, fuzzy logic, genetic algorithms, and expert systems, have already been applied in order to move toward a higher level of automation.[1,21,77–83]

Ramaswamy et al.[82] and Liu and Chan[80] expand the application of classical controllers to include anticipatory control strategies using a neuro-fuzzy approach. Basher and Neal[81] survey the industry status and practices on autonomous systems for nuclear reactor control and operations. This survey highlights the potential for increased plant safety and reduces the cost of operation. Specifically, they posit that a higher degree of autonomy in control of complex systems such as NPPs is more easily achievable through the integration of conventional control methods with intelligent components, such as fuzzy logic, neural networks, genetic algorithms, and expert systems. They investigate the feasibility of such integration in different aspects of reactor operations, such as reactor startup, shutdown in emergency situations, fault detection and diagnosis, nuclear reactor alarm processing and diagnosis, and reactor load-following operations, to name a few.

Uhrig[21] outlines the use of expert systems for monitoring and control of NPPs. Such control expert systems take an action (e.g., opening a valve) automatically upon identifying a discrepancy from monitoring the plant over time. Lee and Kim[78] develop an autonomous algorithm based on deep learning to control the safety systems of an NPP. The algorithm performs system analysis on power plant systems and achieves a high degree of automation for the nine safety functions of NPPs. RNNs, a type of ANN with feedback connections typically used for time series monitoring and predictions, have also been proposed for building automated control systems.[77–79] Lee et al.[77] suggest an autonomous control algorithm for NPP safety systems using an LSTM and a function-based hierarchical framework (FHF). The FHF models the safety goals, functions, systems, and components in the NPP. The hierarchical structure is then transformed into an LSTM network that controls the safety functions. The automated algorithms are shown to respond to accidents faster than automatic plus human control. Similarly, Boroushaki et al.[79] design an online intelligent reactor core controller for load-following operations of NPPs using RNNs and fuzzy logic systems.

In addition to normal operating conditions, fully autonomous control systems that reduce human involvement in plant operations during transient and emergency situations have great potential in preventing human errors.[83–87] Kim et al.[87] present a conceptual design for a plant-wide autonomous operation system based on deep learning that can perform the control functions needed for the emergency operation of an NPP with reduced human intervention. Yang and Kim[34] demonstrate the feasibility of accident diagnosis and correct response under startup operations using autonomous control with an LSTM neural network and functional requirement analysis (FRA). The neural network ensures the safe operation (by performing both accident diagnosis and protection control) while the FRA is performed to define the goal, functions, processes, systems, and components for protection control. Similarly, Kim et al.[83] propose a framework to develop an LSTM-based control system to avoid human errors during startups and shutdowns in NPPs.

Although such intelligent control systems automate most of the NPP operations, there are some situations, e.g., when a critical decision needs to be made by an operator or the autonomous system cannot manage the situation, when an operator's intervention is required. Autonomous control systems that do not correctly provision the HSI make it more difficult to detect and recover from errors and challenge the human's ability to maintain awareness of the NPP operation modes. NUREG-0700, "Human-System Interface Design Review Guidelines," provides the human factors guidelines for physical and functional characteristics of HSI design for the various levels of automation.[88] The prototype autonomous emergency operation system by Kim et al.[87] considers the human (operator)-autonomous system interaction as one of the key design features of the system and lay out high-level requirements to tackle the widely known human factors–related automation issues that are discussed in further detail in Sec. IV.

IV.F. Predictive Maintenance Systems

Maintenance of equipment in optimal condition is required to provide improved availability and reliability in NPP facilities. Monitoring and early detection of emergent problems from faulty equipment are crucial for operational safety and performance improvement. However, performing such routine preventive and corrective maintenance can significantly increase operating expenses. Performing corrective and predictive maintenance of NPP systems, structures, and components can alleviate this problem.

A deviation from normal operating circumstances can be caused by a single component failure or several faults in many components. It can be difficult for an operator to detect such problems and locate the problematic equipment in a timely manner, especially if the problem develops slowly. NPPs have effectively implemented preventive and corrective maintenance strategies over several decades; however, these strategies are proving to be cost prohibitive and labor intensive, which challenges the economic stability of the current fleet in competitive energy markets. To address these challenges, plants are transitioning to a predictive maintenance strategy that utilizes data collected from permanently installed sensors and from periodic inspection activities. Advanced data analytics and machine learning approaches can automate fault detection and diagnosis and prediction of remaining useful life. This, combined with automated work package generation, can optimize resource allocation and maximize plant asset availability while minimizing the possibility of potential human errors in both maintenance planning and maintenance execution.

Step-up transformers are a high-value asset that is crucial to export energy from an NPP to the grid. Aizpurua et al.[89] present a novel transformer lifetime estimation approach integrating uncertainty modeling, data-driven forecasting models, and model-based experimental models to increase the prediction accuracy in a Bayesian particle filtering framework. The use of gradient-boosting algorithms for forecasting showed the best prediction performance. The proposed approach enables the modeling of these dynamic contexts accurately while accounting for uncertainties.

Tsoukalas[90] develops an intelligent prognostics methodology for predicting aging effects impacting the long-term performance of nuclear components and systems. The approach is particularly suitable for predicting the performance of nuclear reactor systems that have low failure probabilities. Such components and systems are often perceived as peripheral to the reactor and are left somewhat unattended. An ANN-based intelligent agent monitoring framework is developed and studied using test cases. Similarly, Ahsan and Hassan[91] build an automatic fault prediction system to be used for fault monitoring using decision tree and ANN algorithms. Gohel et al.[92] develop an advanced predictive maintenance analytics system for nuclear infrastructure using machine learning algorithms to ensure efficient and secure operations. SVM and logistic regression models are used to perform the prediction. Specifically, the likelihood of a component failure in a given cycle and the chances of the component failure in the next *n* cycles are estimated and the results are contrasted with prior work.

IV.G. Automated Text Analysis Systems

The nuclear power industry has many licensee-generated event reports. A comprehensive analysis of these reports could yield useful information for enhancing NPP operation and safety. However, the reports' free text structure makes such analysis difficult and time consuming. To this end, several automated analysis approaches based on NLP techniques have been proposed.[69,93–95]

Zhang et al.[69] discuss the use of NLP to achieve the automated extraction of rich, semantic information from the documentation of various events during the operation and maintenance of NPPs. Such automated systems can support the analysis of NPP personnel errors, safety violations, inadequate procedures, or supervision issues. Furthermore, such systems can assist in comprehending dynamic team processes, like team cognition during outages, providing insights and information on complex team skills to increase team situational awareness and minimize mental fatigue and even identify optimal interventions.

A preliminary study by Zhao et al.[93] investigates the feasibility and provides the basis for developing an automated tool for analyzing text-based event reports. The study aims at identifying causal relationships between events described in the report in the NRC Licensee Event Report (LER) database. To this end, a list of keywords that indicate causal relationships is first identified from examining a set of sample reports. These keywords are then considered together with part of speech tagging and dependency parsing of a sentence using state-of-the-art NLP techniques to identify the causal and consequent events in the sentence. In a related work, Zhao et al.[94] propose the use of a rule-based expert system that can identify over 86% of the causal relationships in the test data automatically. The proposed methods are foreseen to be used in a number of areas, such as the analysis of PSFs and reconstruction of the scenario in an event.

Pence et al.[95] advance "sociotechnical" risk analysis by explicitly incorporating organizational factors into probabilistic risk assessments (PRAs) and quantifying them using data analytic techniques. By integrating text mining for the measurement of organizational factors and PRAs, useful features are extracted from unstructured free text data and an SVM classifier is used to estimate the probability of having "training deficiency" as one of the causes of reported events. The methodology is applied to a case study on a set of LERs from the database to demonstrate the efficacy of the text mining step.

IV.H. Safety Assessment

When designing a NPP, stringent design requirements are imposed to ensure that all components can withstand abnormal operating conditions. Severe weather, seismic activity, or extreme heat and pressure may occur as a result of an accident at the facility. This method of designing a plant and its components that includes requirements and safety margins to account for anticipated abnormal conditions is called deterministic safety analysis. Starting in the 1980s, PRAs (also called probabilistic safety assessment) was established as a way to calculate the risk that arises from the interplay of equipment failure and human error. PRA models analyze the overall risk to a nuclear power station under abnormal conditions using probabilities. PRAs assist operators in gaining a better understanding of each NPP and identifying areas where safety can be improved.

Kim and Seong[96] develop a new safety evaluation methodology for NPPs by adopting the concept of an early warning score from the medical field. The proposed methodology overcomes the challenges in existing methodologies, such as PRAs or safety performance indicators, by handling cases that are not included in the model and enables real-time safety evaluation.

Abrishami et al.[97] study the use of Bayesian networks to improve the performance of Success Likelihood Index Models (SLIMs), one of the widely used deterministic techniques in HRA to handle uncertainty arising from experts' opinions and insufficient data. The proposed BN-SLIM model considers uncertainty associated with the rates of PSFs using probability distributions and can provide a better estimation of human error probability by considering conditional dependencies resulting from common PSFs. The probability updating feature of the BN-SLIM can be used to determine which PSFs are most responsible for human failure events. To obtain more accurate and realistic results of PRAs, it is necessary to reflect more complete dynamics of NPPs. Kim et al.[98] propose a fast-running model using deep learning techniques to obtain plausible accident scenarios while reducing the resources required to conduct a full PRA. The proposed method can reduce uncertainty in PRAs and contribute a key technique to dynamic PRAs.

V. DISCUSSION

Several studies performed over the years indicate that the occurrence of human error is an important factor in NPP safety-related incidents and effective operations and maintenance. Many traditional decision-making systems and data intelligence functions based on static models and algorithms have been developed to aid operators' cognitive activities. Although such systems have made great progress, they are often limited in their impact when dealing with complex decision-making environments and the rapidly increasing volume and complexity of data.[99] For instance, Hsieh et al.[100] develop a decision support system based on a deterministic computer program and a database for abnormal operating environments in NPPs. However, the system state combination created by dynamic and complicated parameter changes can quickly make the size of this database impractical to manage and eventually lead to unpredictable system states and faults.

Although the concept of automated control systems in NPPs has been around for decades, the degree of automation in safety functions is still low, and operator intervention remains a crucial part of the control system. Extensions to traditional PID-based automated and anticipatory control strategies have been proposed to advance the operation of NPPs and reduce the reliance on human actions.[82] However, an effective fully autonomous system is still far from practical implementation in the nuclear industry. Moreover, insufficient automation also exists in other aspects apart from safety functions, such as power control, where traditional control methods are dominant.[101]

As described in the previous section, AI technology can overcome many of these challenges of traditional operator support systems. The infusion of AI in direct support systems, such as intelligent advisors, alarm systems, fault diagnostic systems, and operation validation systems, can aid plant operators in situation assessment and response planning and implementation. Artificial intelligence–powered fitness monitoring systems that continuously track worker wellbeing and safety assessment systems are crucial to building a safe environment. Predictive maintenance systems and sensor fault detection systems are required to monitor and detect emergent problems early on to ensure the operational safety and performance improvement of NPPs. Automated text analysis systems that extract rich semantic information from the event reports during the operation and maintenance of NPPs yield useful information for enhancing NPP operation and safety. Figure 1 summarizes the different smart support systems discussed in the literature and the various AI technologies used therein.

Artificial intelligence–based systems also have their limitations. While recent years have seen significant advances in AI technologies, there has been growing discussion about the scalability, explainability, and trustworthiness of these AI technologies, and why a particular decision was reached.[102,103] Starter and Billings[104] explain how autonomous systems may sometimes create surprises for operators when they confront unpredictable and difficult-to-understand system behavior in the context of ongoing operations. Building explainable AI systems is of paramount importance, especially for mission-critical applications such as NPP outage management. Further, the performance of any AI system depends heavily on the data used to train and evaluate the system. With the information security and protection measures of NPPs still in their infancy,[105,106] one needs to be wary of new threats and challenges to data and cybersecurity. For instance, the electrical systems in NPPs in use today lack effective protection measures and their information security protection capabilities are weak.[106] It is also worth noting that the inferences drawn from previous studies about the usefulness of AI technology in reducing human errors are based on controlled experiments or nuclear event simulations and their practical implementation in NPPs is yet to be achieved.

While AI-enabled digital systems have the capability to enhance plant automation and automate error-prone and tedious activities, plant designers must decide what to automate and how to integrate operator interaction with automation to utilize these systems to their fullest potential. Novel approaches are thus needed to optimize the overall plant performance by allocating functions between operators and autonomous systems based on their strengths and weaknesses and designing HSIs that support human-automation interaction.

The interactions between human and autonomous systems are crucial to the plant system's performance and reliability. Several human factors–related issues regarding the human-autonomous system interaction have been addressed in the literature.[87,104,107,108] Starter and Billings[104] describe how a considerable number of unanticipated problems and failures are related for the most part to breakdowns in the interaction between human operators and automated systems and explain the principles and benefits of a human-centered rather than a technology-centered approach to the design of

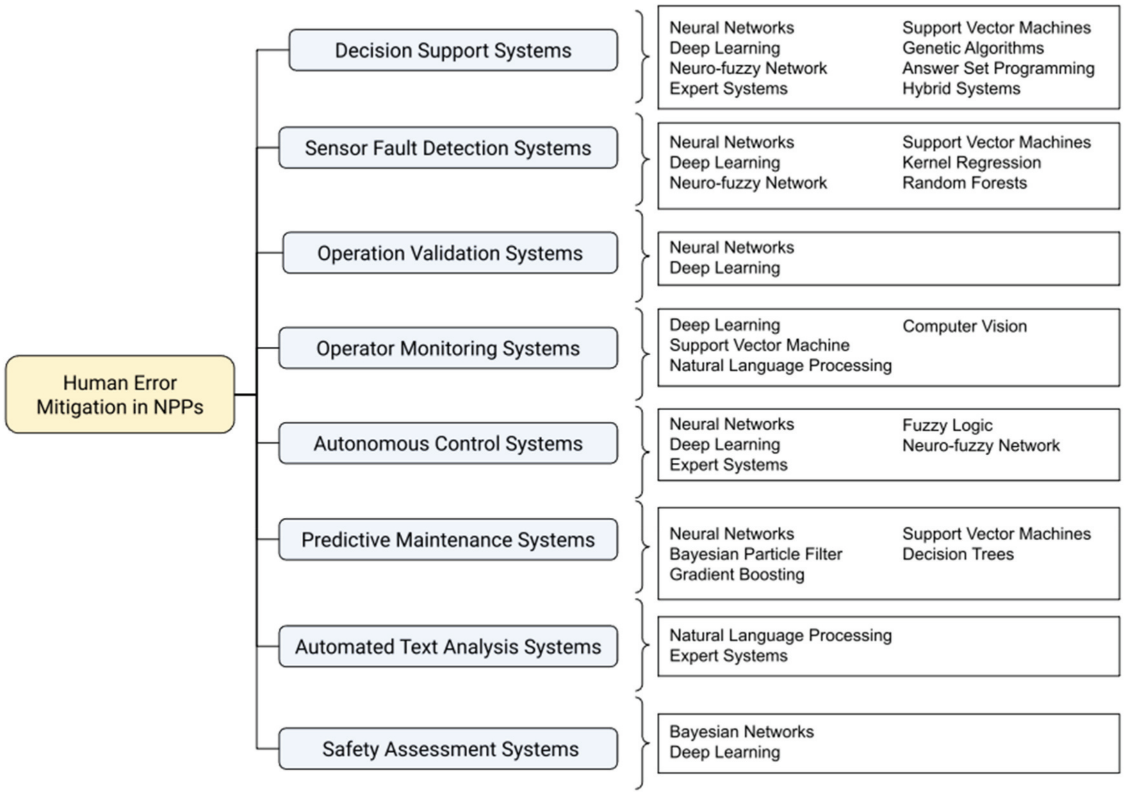


Fig. 1. Summary of different intelligent support systems and AI technologies used to mitigate human factor errors in NPPs.

automated systems. O'Hara[107] presents guidelines for the design of interfaces that enhance the ability of operators to monitor and supervise automation and facilitate greater cooperation between human and autonomous agents. O'Hara[107] also describes a qualitative methodology that can be used to allocate functions to automatic systems, plant operators, or to some combination of the two based on the relative role of humans and automation. Similarly, O'Hara and Higgins[109] develop a general guideline for human-automation interactions. Kim and Park[110] list considerations for designing HSIs using previous research of human-computer interactions or human-robot interactions. Specifically, they consider task allocation and the five attributes of human-automation interactions to optimize the performance of the joint human-automation system based on Goodrich and Schultz,[111] namely, autonomy and interaction, information exchanges, team structure, adaptation, learning and training, and shape of the task.

Kim et al.[87] discuss human-autonomous system interaction as one of the key design features of an advanced support system and describe three key human factors issues: (1) out-of-the-loop (OOTL) unfamiliarity wherein a lack of understanding of autonomous behavior can result in difficulties for human operators when they take over control of the operation, (2) the tendency of designers to create multimodal systems that possess increased complexity and longer time constant feedback loops, and (3) the critical decision authority, especially in relation to safety, assigned to autonomous systems. Kaber and Endsley[112] also discuss the critical issue of OOTL performance in fully autonomous systems. Operators of highly automated systems are often separated from direct, real-time control of the system, whether it is determining if process control intervention is required, noticing a critical system event, or approving or rejecting the actions of an automated control system. OOTL performance is associated with many negative consequences, such as reduced vigilance (operator failure to observe system changes), complacency (human over-trust in computers), loss of situation awareness (because of poor system observability), and operator skill decay. These consequences have been found to impact human performance under both normal and abnormal operating conditions, with a greater effect on the latter.[113] This causes major problems with operators' capacity to perform their role when working together with autonomous systems. Kaber and Endsley[112] present a level of automation taxonomy to ameliorate OOTL performance problems. Using this framework, they identify optimal combinations of human and computer control of various system functions, such as monitoring, planning, and option selection and implementation, that produce improvements in system performance under intermediate levels. Results on its utility in a dynamic control task indicated decreases in the number of system processes/tasks overlooked by operators. These enhancements are expected to be relevant to general process control systems and could result in cost savings due to increased operational safety.

Traditional computer-based procedures and AI-powered portable devices can also play a key role in improving the plant work management process, thereby increasing operator productivity and decreasing cost. Rashdan et al.[114] and Rashdan and Agarwal[115] propose an automated work package (AWP) technology to improve the plant work management process in a manner that increases efficiency while reducing human error. AWP uses plant condition, resources status, and user progress to adaptively drive the work process using the information acquired from various systems of a NPP and incorporates several advanced instrumentation and control technologies along with modern human factors techniques.

Beyond building smart operator support systems, AI technology can also be leveraged to build improved indirect operator support systems. These include intelligent HSIs that support rich interactions, advanced display systems and information systems to improve the operators' perceptions and awareness abilities for monitoring and detection activities.

There is also vast potential for cross knowledge transfer from other sectors and industries, including oil and gas, healthcare, aviation, and manufacturing industries, that have adopted and implemented AI technologies to mitigate human errors. Particularly, in the case of the healthcare industry, AI helps in detecting and mitigating preventable medical errors. The most common and costly types of measurable or preventable medical errors in the United States in 2008 were postoperative infection ($3.4 billion); pressure ulcer ($3.3 billion); a mechanical complication of noncardiac device, implant, or graft ($1.1 billion); and post-laminectomy syndrome ($1 billion), accounting for almost half of all estimated medical error–associated costs that year.[116,117] To combat these, AI-based support systems could help physicians decide what treatment to provide patients, taking into account vast amounts of data and finding patterns that doctors might normally miss, especially in high-stress environments. Some of the AI models that are already in practice include hospital computerized physician order entry for medication ordering errors,[118] image analysis in radiology and dermatology, and deep learning histopathology for identifying metastatic breast cancer.[119]

Another industry where machine learning methodologies are proving to be useful is the aviation industry. Human errors are recognized to be the primary or secondary cause of most residual accidents or incidents in the aviation industry.[120] Errors like a controlled flight into terrain and loss of control remain the predominant causes of loss of life in aviation worldwide, making humans one of the weak links in aircraft safety.[121] Here, AI proves to be useful in mitigating errors. The already useful applications in practice can be seen in augmenting drone technology for flight accuracy, building smart cockpits for safety, and intelligent maintenance schedules to detect and track possible faults.[122]

Despite existing challenges, AI has immense potential to speed technological development in nuclear fields by seizing opportunities and borrowing ideas from different sectors and industries. As mentioned by Mikhail Chudakov, International Atomic Energy Agency Deputy Director General and Head of the Department of Nuclear Energy:

> In order to be competitive, as well as integrated into the mix of modern energy systems, nuclear power plants – in addition to being safe, secure and reliable – also need to be economical and efficient.[123]

Although almost all subsectors of the nuclear energy industry have implementations of AI, there still remains the need for standardization and cooperation. Accepting a set of internationally acceptable standards enables even wider adoption of AI with the potential of developing from the current standards. Given that AI depends on data availability and quality, as more curated data are available, it will be easier for algorithms to identify patterns in certain phenomena and thus make better predictions. Therefore, international cooperation to obtain, develop, maintain, and analyze global data with the help of AI in various nuclear fields is key to accelerating technological development and realizing the full potential of AI (Ref. 123). Along with this, collaboration across different disciplines to establish common knowledge-sharing platforms to coordinate and support partnerships between cross-domain researchers for the development of guidelines related to regulations, education, and training in AI will enable researchers from around the world to share experience, knowledge, and good practices.[123]

VI. CONCLUSION

Human errors have been identified as the major cause of safety-related incidents in the nuclear industry. Although some NPPs have been digitized after decades of use, many NPPs still use traditional operation and control methods, decreasing the operational performance and increasing the risk of accidents. Developing advanced operator support systems that leverage the latest advancements in AI technology can enhance operations, potentially leading to additional benefits for overall plant safety and reliability. This critical review provides a deep insight via literature review and critical analysis into the potential of AI technology to mitigate human errors and their consequences in NPPs. While the incidence of human errors leading to events at NPPs is rare, the advent of AI technology increases the safety margin on plants and paves the way to introduce AI-based concepts of operation into future plants.

The causes for human error occurrences in NPP activities are introduced and their classification is provided. A thorough review of the different types of operator support systems, namely, decision support systems, sensor fault detection systems, operation validation systems, operator monitoring systems, autonomous control systems, autonomous control systems, predictive maintenance systems, automated text analysis systems, and safety assessment systems, and how researchers have integrated AI technologies into NPPs is presented. Through the various research studies, the application of AI technologies to assist plant operators in diagnosing faults quicker and making mission-critical decisions for continued safe operation of the plant is discussed. Such intelligent operator support systems will pave the way for the safe, economic, reliable, and efficient operation of NPPs in years to come.

Acknowledgments

This work of authorship was prepared as an account of work sponsored by the U.S. Department of Energy, an agency of the U.S. government, under grant no. DE-NE0008978 to the University of Tennessee-Knoxville. The authors would also like to thank Erica Christine Swift and Stephen Lamar Farlett for their insights in study design. Neither the U.S. government, nor any agency thereof, nor any of their employees makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights.

Disclosure Statement

No potential conflict of interest was reported by the authors.

ORCID

Mahboubeh Madadi http://orcid.org/0000-0002-2787-722X
Jamie Baalis Coble http://orcid.org/0000-0002-0736-673X
Ronald L. Boring http://orcid.org/0000-0001-5460-9610
Vivek Agarwal http://orcid.org/0000-0003-1334-0509
Anahita Khojandi http://orcid.org/0000-0001-6818-2048

References

1. J. M. KIM and S. J. LEE, "Framework to Develop Artificial Intelligent Autonomous Operating System for Nuclear Power Plants," *Int. Conf. Human Interface Manage. Info.*, **8**, 508 (2018).
2. T. RYAN, "The Human Factor in Operation and Maintenance of Complex High-Reliability Systems," *Sym. Maintain Aerospace Syst.*, **21**, 5064 (1989).
3. I. SALO and O. SVENSSON, "Human Factors in Maintenance: Development and Research in Swedish Nuclear Power Plants," *Swedish Nucl. Power Inspectorate* (2001).
4. M. SHEIKHALISHAHI, L. PINTELON, and A. AZADEH, "Human Factors in Maintenance: A Review," *J. Qual. Maint. Eng.*, **22**, *3*, 218 (2016). https://doi.org/10.1108/JQME-12-2015-0064
5. G. MOMIN, R. PANCHAL, and D. LIU, "Case Study: Enhancing Human Reliability with Artificial Intelligence and Augmented Reality Tools for Nuclear Maintenance," *ASME Power Conference*, Lake Buena Vista, Florida, June 24–28, 2018.
6. S. RUSSELL and P. NORVIG, *Artificial Intelligence: A Modern Approach*, 3rd ed., Pearson Education, Inc., Upper Saddle River; New Jersey (2009).
7. Y. LECUN, Y. BENGIO, and G. HINTON, "Deep Learning," *Nature*, **521**, 7553, 436 (2015). https://doi.org/10.1038/nature14539
8. R. L. BORING and A. BYE, "Bridging Human Factors and Human Reliability Analysis," *Proc. 52nd Annual Meeting of the Human Factors and Ergonomics Society*, **52**, 733 (2008).
9. A. D. SWAIN and H. E. GUTTMANN, "Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications," U.S. Nuclear Regulatory Commission (1983).
10. D. GERTMAN et al., "The Spar-H Method," U.S. Nuclear Regulatory Commission (2005).

11. A. KOLACZKOWSKI et al., “Good Practices for Implementing Human Reliability Analysis (HRA),” U.S. Nuclear Regulatory Commission (2005).

12. D. D. WOODS and E. M. ROTH, “Cognitive Environment Simulation: An Artificial Intelligence System for Human Performance Assessment: Cognitive Reliability Analysis Technique,” Westinghouse Res. Dev. Center (1987).

13. K. GROTH and A. MOSLEH, “A Data-Informed Model of Performance Shaping Factors for Use in Human Reliability Analysis,” University of Maryland, Department of Mechanical Engineering (2009).

14. J. REASON, *Human Error*, Cambridge University Press, Cambridge, United Kingdom (1990).

15. A. M. WHALEY et al., “Cognitive Basis for Human Reliability Analysis,” U.S. Nuclear Regulatory Commission (2016).

16. K. MO, S. J. LEE, and P. H. SEONG, “A Dynamic Neural Network Aggregation Model for Transient Diagnosis in Nuclear Power Plants,” *Prog. Nucl. Energy*, **49**, *3*, 262 (2007). https://doi.org/10.1016/j.pnucene.2007.01.002

17. C. M. ROCCO and E. ZIO, “A Support Vector Machine Integrated System for the Classification of Operation Anomalies in Nuclear Components and Systems,” *Reliab. Eng. Syst. Saf.*, **92**, *5*, 593 (2007). https://doi.org/10.1016/j.ress.2006.02.003

18. Z. YANGPING, Z. BINGQUAN, and W. DONGXIN, “Application of Genetic Algorithms to Fault Diagnosis in Nuclear Power Plants,” *Reliab. Eng. Syst. Saf.*, **67**, *3* (2000).

19. V. H. C. PINHEIRO and R. SCHIRRU, “Genetic Program-ming Applied to the Identification of Accidents of a PWR Nuclear Power Plant,” *Ann. Nucl. Energy*, **124**, 335 (2019). https://doi.org/10.1016/j.anucene.2018.09.039

20. K. KIM and E. B. BARTLETT, “Error Prediction for a Nuclear Power Plant Fault-Diagnostic Advisor Using Neural Networks,” *Nucl. Technol.*, **108**, *2*, 283 (1994). https://doi.org/10.13182/NT94-A35035

21. R. E. UHRIG, “Use of Expert Systems in Nuclear Power Plants,” Oak Ridge National Laboratory (1989).

22. B. HANNA, T. C. SON, and N. DINH, “Ai-Guided Reasoning-based Operator Support System for the Nuclear Power Plant Management,” *Ann. Nucl. Energy*, **154**, *C*, 108079 (2021). https://doi.org/10.1016/j.anucene.2020.108079

23. S. J. LEE, K. MO, and P. H. SEONG, “Development of an Integrated Decision Support System to Aid the Cognitive Activities of Operations in Main Control Rooms of Nuclear Power Plants,” *Proc. IEEE Symp. Computational Intelligence in Multi-criteria Decision-Making*, **146**, 703 (2007).

24. R. YU and F. LIU, “An Online Fault Diagnosis Method for Nuclear Power Plant Based on Combined Artificial Neural Network,” *Proc. Asia-Pacific Power and Energy Engineering Conf., 1*, Institute of Electrical and Electronics Engineers (2010).

25. Y. MING et al., “A Hybrid Approach for Fault Diagnosis Based on Multilevel Flow Models and Artificial Neural Network,” presented at the Int. Conf. on Computational Intelligence for Modelling Control and Automation and Int. Conf. on Intelligent Agents Web Tech. and Int. Commerce, Sydney, New South Wales, Australia, November 29–December 1, 2006.

26. A. AYODEJI, Y. K. LIU, and H. XIA, “Knowledge Base Operator Support System for Nuclear Power Plant Fault Diagnosis,” *Prog. Nucl. Energy*, **105**, 42 (2018). https://doi.org/10.1016/j.pnucene.2017.12.013

27. K. KIM, “An Artificial Neutral Network Fault-Diagnostic Adviser for a Nuclear Power Plant with Error Prediction” (1992).

28. T. V. SANTOSH et al., “Diagnostic System for Identification of Accident Scenarios in Nuclear Power Plants Using Artificial Neural Networks,” *Reliab. Eng. Syst. Saf.*, **94**, *3*, 759 (2009). https://doi.org/10.1016/j.ress.2008.08.005

29. R. E. UHRIG and L. H. TSOUKALAS, “Soft Computing Technologies in Nuclear Engineering Applications,” *Prog. Nucl. Energy*, **34**, *1*, 13 (1999). https://doi.org/10.1016/S0149-1970(97)00109-1

30. J. YANG, S. LEE, and J. KIM, “Nuclear Power Plant Accident Diagnosis Algorithm Including Novelty Detection Function Using LSTM,” *Proc. Int. Conf. Applied Human Factors and Ergonomics*, **965**, 644, Washington, DC, July 24–28, 2019, p. 644 (2019).

31. V. H. C. PINHEIRO et al., “Nuclear Power Plant Accident Identification System with “Don’t Know” Response Capability: Novel Deep Learning-Based Approaches,” *Ann. Nucl. Energy*, **137**, 107111 (2020). https://doi.org/10.1016/j.anucene.2019.107111

32. M. C. SANTOS et al., “Deep Rectifier Neural Network Applied to the Accident Identification Problem in a PWR Nuclear Power Plant,” *Ann. Nucl. Energy*, **133**, 400 (2019). https://doi.org/10.1016/j.anucene.2019.05.039

33. J. ZHANG et al., “Application of Cost-Sensitive LSTM in Water Level Prediction for Nuclear Reactor Pressurizer,” *Nucl. Eng. Technol.*, **52**, *7*, 1429 (2020). https://doi.org/10.1016/j.net.2019.12.025

34. J. YANG and J. KIM, “An Accident Diagnosis Algorithm Using Long Short-Term Memory,” *Nucl. Eng. Technol.*, **50**, *4*, 582 (2018). https://doi.org/10.1016/j.net.2018.03.010

35. J. CHOI and S. J. LEE, "Strategy for the Accident Diagnosis in Sensor Error States," *Trans. Korean Nuclear Soc.*, **20**, 20 (2020).

36. J. YANG and J. KIM, "Accident Diagnosis Algorithm During the Startup Operation Using LSTM," *Proc. of the Korean Nuclear Society 2019 Spring Mtg.*, Daejeon, Korea, May 23–24, 2019.

37. K. H. YOO et al., "Smart Support System for Diagnosing Severe Accidents in Nuclear Power Plants," *Nucl. Eng. Technol.*, **50**, *4*, 562 (2018). https://doi.org/10.1016/j.net.2018.03.007

38. C. GOTTLIEB, V. ARZHANOV, and W. GUDOWSKI, "Feasibility Study on Transient Identification in Nuclear Power Plants Using Support Vector Machines," *Nucl. Technol.*, **155**, *1*, 67 (2006). https://doi.org/10.13182/NT06-A3746

39. H. WANG et al., "A Hybrid Fault Diagnosis Methodology with Support Vector Machine and Improved Particle Swarm Optimization for Nuclear Power Plants," *ISA Trans.*, **95**, *5*, 358 (2019). https://doi.org/10.1016/j.isatra.2019.05.016

40. K. KIM and E. B. BARTLETT, "Nuclear Power Plant Fault Diagnosis Using Neural Networks with Error Estimation by Series Association," *IEEE Trans. Nucl. Sci.*, **43**, 2373 (1996).

41. B. K. HAJEK and D. W. MILLER, *Installation and Evaluation of a Nuclear Power Plant Operator Advisor Based on Artificial Intelligence Technology*, Ohio State University (1989).

42. J. S. WU, G. E. APOSTOLAKIS, and D. OKRENT, "Probabilistic Risk Assessment and Intelligent Decision Support Systems," *Nucl. Eng. Des.*, **113**, *2*, 269 (1989). https://doi.org/10.1016/0029-5493(89)90078-2

43. Y. TAKIZAWA et al., "An Intelligent Man-Machine System for Future Nuclear Power Plants," *Nucl. Technol.*, **107**, *1*, 72 (1994). https://doi.org/10.13182/NT94-A34999

44. P. V. VARDE, S. SANKAR, and A. K. VERMA, "An Operator Support System for Research Reactor Operations and Fault Diagnosis Through a Connectionist Framework and PSA Based Knowledge Systems," *Reliab. Eng. Syst. Saf.*, **60**, *1*, 53 (1998). https://doi.org/10.1016/S0951-8320(97)00154-3

45. C. VENKATESH and K. SUBRAMANIUM, "A Knowledge Based Operator Support System for Emergency Conditions in Nuclear Power Plants," *Proc. Conf. On AI Applications in Physical Sciences*, **534**, F3.1, Bhabha Atomic Research Centre, Bombay, India (1992).

46. L. MAMPAEY et al., *Artificial Intelligence and Other Innovative Computer Applications in the Nuclear Industry*, 1st ed., Springer, Boston, Massachusetts (1988).

47. R. E. UHRIG, "Use of Neural Networks in Nuclear Power Plants," *ISA Trans.*, **32**, *2*, 139 (1993). https://doi.org/10.1016/0019-0578(93)90036-V

48. N. ZVALJEVSKI and K. C. GROSS, "Sensor Fault Detection in Nuclear Power Plants Using Multivariate State Estimation Technique and Support Vector Machines," Argonne National Laboratory (2000).

49. A. SHAHERYAR et al., "A Denoising Based Autoassociative Model for Robust Sensor Monitoring in Nuclear Power Plants," *Sci. Technol. Nucl. Ins.*, **2016**, 1 (2016). https://doi.org/10.1155/2016/9746948

50. J. GARVEY et al., "Validation of On-line Monitoring Techniques to Nuclear Plant Data," *Nucl. Eng. Technol.*, **39**, *2*, 133 (2007). https://doi.org/10.5516/NET.2007.39.2.133

51. J. B. COBLE et al., "A Review of Sensor Calibration Monitoring for Calibration Interval Extension in Nuclear Power Plants," Pacific Northwest National Laboratory (2012).

52. J. CHOI and S. J. LEE, "Consistency Index-based Sensor Fault Detection System for Nuclear Power Plant Emergency Situations Using an LSTM Network," *Sensors*, **20**, *6*, 1651 (2020).

53. J. CHOI and S. J. LEE, "Abnormal Sensor Detection Using Consistency Index in Accident Situation," presented at the Korean Nuclear Society Autumn Mtg., Goyang, Korea, February 9–14, 2019.

54. J. CHOI and S. J. LEE, "A Sensor Fault-Tolerant Accident Diagnosis System," *Sensors*, **20**, *20*, 5839 (2020). https://doi.org/10.3390/s20205839

55. K. MO, S. J. LEE, and P. H. SEONG, "A Neural Network Based Operation Guidance System for Procedure Presentation and Operation Validation in Nuclear Power Plants," *Ann. Nucl. Energy*, **34**, *10*, 813 (2007). https://doi.org/10.1016/j.anucene.2007.04.008

56. J. AHN, J. BAE, and S. J. LEE, "A Human Error Detection System in Nuclear Power Plant Operations," Proc. 11th Nuclear Plant Instrumentation Control Human-Machine Interface Technologies, NPIC HMIT, Orlando, Florida, February 9–14, 2019.

57. J. AHN and S. J. LEE, "Deep Learning-based Procedure Compliance Check System for Nuclear Power Plant Emergency Operation," *Nucl. Eng. Des.*, **370**, *15*, 110868 (2020). https://doi.org/10.1016/j.nucengdes.2020.110868

58. J. BAE, J. AHN, and S. J. LEE, "Comparison of Multilayer Perceptron and Long Short-Term Memory for Plant Parameter Trend Prediction," *Nucl. Technol.*, **206**, *7*, 951 (2020). https://doi.org/10.1080/00295450.2019.1693215

59. M. MARIANA, T. R. SAHRONI, and T. GUSTIYANA, "Fatigue and Human Errors Analysis in Petrochemical and Oil and Gas Plant's Operation," presented at the 8th Annual Int. Conf. on Industrial Engineering and Operations Management, Bandun, Indonesia, March 6–8, 2018.

60. J. A. YEOW et al., "Effects of Stress, Repetition, Fatigue and Work Environment on Human Error in Manufacturing Industries," *J. Appl. Sci.*, **14**, 24 (2014). https://doi.org/10.3923/jas.2014.3464.3471

61. "Fitness for Duty Programs," *Federal Register*, **73**, *62*, 16965 (2008).

62. M. C. BARNES et al., "Fitness for Duty in the Nuclear Power Industry: A Review of Technical Issues," U.S. Nuclear Regulatory. Commission (1988).

63. C. WESTRA et al., "Fitness for Duty in the Nuclear Power Industry," U.S. Nuclear Regulatory Commission (1994).

64. C. W. JO, Y. H. CHAE, and P. H. SEONG, "Performance Estimation Using Deep Learning Based Facial Expression Analysis," presented at the Korean Nuclear Society Virtual Spring Mtg., July 9–10, 2020.

65. J. H. KIM, Y. SUH, and M. S. YIM, "An Investigation of Human Error Identification Based on Bio-monitoring System (EEG and ECG Analysis)," *Proc. 9th Int. Conf. on Applied Human Factors and Ergonomics*, p. 145, Springer Int. Publishing (2018).

66. Y. A. SUH and M. S. YIM, "A Worker's Fitness-for-Duty Status Identification Based on Biosignals to Reduce Human Error in Nuclear Power Plants," *Nucl. Technol.*, **206**, *12*, 1840 (2020). https://doi.org/10.1080/00295450.2020.1731405

67. J. H. KIM et al., "Biosignal Based Attention Monitoring to Support Nuclear Operator Safety-Relevant Tasks," *Front. Comput. Neurosci.*, **14** (2020). https://doi.org/10.3389/fncom.2020.596531

68. D. F. DINGES et al., "Optical Computer Recognition of Facial Expressions Associated with Stress Induced by Performance Demands," *Aviation SPace Environ. Med.*, **76**, *6*, B172 (2005).

69. C. ZHANG et al., "Human-Centered Automation for Resilient Nuclear Power Plant Outage Control," *Autom. Constr.*, **14**, 179 (2017).

70. S. L. HWANG et al., "A Real-Time Warning Model for Teamwork Performance and System Safety in Nuclear Power Plants," *Saf. Sci.*, **47**, *3*, 425 (2009). https://doi.org/10.1016/j.ssci.2008.07.011

71. C. S. LIEW et al., "Mining Personal Data Using Smartphones and Wearable Devices: A Survey," *Sensors*, **15**, *2*, 4430 (2015).

72. S. KIM, J. PARK, and Y. J. KIM, "Some Insights About the Characteristics of Communications Observed from the Off-Normal Conditions of Nuclear Power Plants," *Hum. Factors Ergon. Manuf. Serv. Ind.*, **21**, *4*, 361 (2011). https://doi.org/10.1002/hfm.20270

73. S. W. LEE et al., "Measuring Situation Awareness of Operating Team in Different Main Control Room Environments of Nuclear Power Plants," *Nucl. Eng. Technol.*, **48**, *1*, 153 (2016). https://doi.org/10.1016/j.net.2015.09.008

74. J. H. KIM et al., "Electroencephalography-Based Intention Monitoring to Support Nuclear Operators' Communications for Safety-Relevant Tasks," *Nucl. Technol.*, **207**, *11*, 1753 (2021). https://doi.org/10.1080/00295450.2020.1837583

75. P. J. ANTSAKLIS, K. M. PASSINO, and S. J. WANG, "An Introduction to Autonomous Control Systems," *IEEE Control Sytem Magaz.*, **11**, *4*, 5 (1991).

76. R. M. EDWARDS, K. Y. LEE, and A. RAY, "Robust Optimal Control of Nuclear Reactors and Power Plants," *Nucl. Technol.*, **98**, *2*, 137 (1992). https://doi.org/10.13182/NT92-A34669

77. D. LEE, P. H. SEONG, and J. KIM, "Autonomous Operation Algorithm for Safety Systems of Nuclear Power Plants by Using Long Short-Term Memory and Function-based Hierarchical Framework," *Ann. Nucl. Energy*, **119**, 287 (2018). https://doi.org/10.1016/j.anucene.2018.05.020

78. D. LEE and J. KIM, "Autonomous Algorithm for Safety Systems of the Nuclear Power Plant by Using the Deep Learning," *Int. Conf. on Applied Human Factors and Ergonomics*, **599**, 72 (2017).

79. M. BOROUSHAKI et al., "An Intelligent Nuclear Reactor Core Controller for Load Following Operations, Using Recurrent Neural Networks and Fuzzy Systems," *Ann. Nucl. Energy*, **30**, *1*, 63 (2003). https://doi.org/10.1016/S0306-4549(02)00047-6

80. X. J. LIU and C. W. CHAN, "Neuro-Fuzzy Generalized Predictive Control of Boiler Steam Temperature," *IEEE Trans. Energy Convers.*, **21**, *4*, 900 (2006). https://doi.org/10.1109/TEC.2005.853758

81. H. BASHER and J. S. NEAL, "Autonomous Control of Nuclear Power Plants," Oak Ridge National Laboratory (2003).

82. P. RAMASWAMY, R. M. EDWARDS, and K. Y. LEE, "Fuzzy Logic Controller for Nuclear Power Plant," *Proc. 2nd Int. Forum on Applications of Neural Networks to Power Systems*, 35, IFAC Proceedings Volumes, Institute of Electrical and Electronics Engineers (1992).

83. H. KIM et al., "Study on Automation System for Startup and Shutdown Mode Using Artificial Intelligence," *Proc. Korean Nuclear Society*, **50**, *40* (2018).

84. S. S. CHOI, S. H. CHANG, and D. H. LEE, "Automating Strategies of Emergency Operation for Optimal Shutdown in Pressurized Water Reactors," *IEEE Trans. Nucl. Sci.*, **45**, *1*, 17 (1998).

85. D. LEE and J. KIM, "Autonomous Algorithm for Start-up Operation of Nuclear Power Plants by Using LSTM," *Proc. Int. Conf. on Appl. Human Factors Ergonomics*, **787**, 465 (2018).

86. J. YANG, D. LEE, and J. KIM, "Accident Diagnosis and Autonomous Control of Safety Functions During the Startup Operation of Nuclear Power Plants Using LSTM," *Proc. Int. Conf. on Applied Human Factors and Ergonomics*, **787**, 488 (2018).

87. J. KIM et al., "Conceptual Design of Autonomous Emergency Operation System for Nuclear Power Plants and Its Prototype," *Nucl. Eng. Technol.*, **52**, *2*, 308 (2020).

88. J. M. O'HARA, "Human-System Interface Design Review Guidelines," U.S. Nuclear Regulatory Commission (1996).

89. J. I. AIZPURUA et al., "Adaptive Power Transformer Lifetime Predictions Through Machine Learning and Uncertainty Modeling in Nuclear Power Plants," *IEEE Trans. Ind. Electron.*, **66**, *6*, 4726 (2018).

90. L. TSOUKALAS, "Intelligent Component Monitoring for Nuclear Power Plants," Purdue University (2010).

91. S. N. AHSAN and S. A. HASSAN, "Machine Learning Based Fault Prediction System for the Primary Heat Transport System of CANDU Type Pressurized Heavy Water Reactor," presented at the Int. Conf. on Open Source Systems and Technologies, Lahore, Pakistan, December 16–18, 2013.

92. H. A. GOHEL et al., "Predictive Maintenance Architecture Development for Nuclear Infrastructure Using Machine Learning," *Nucl. Eng. Technol.*, **52**, *7*, 1436 (2020). https://doi.org/10.1016/j.net.2019.12.029

93. Y. ZHAO, X. DIAO, and C. SMIDTS, "Preliminary Study of Automated Analysis of Nuclear Power Plant Event Reports Based on Natural Language Processing Techniques," The Ohio State University, Department of Mechanical and Aerospace Engineering (2018).

94. Y. ZHAO et al., "Automated Identification of Causal Relationships in Nuclear Power Plant Event Reports," *Nucl. Technol.*, **205**, *8*, 1021–1034 (2019). https://doi.org/10.1080/00295450.2019.1580967

95. J. PENCE et al., "Data-Theoretic Approach for Socio-Technical Risk Analysis: Text Mining Licensee Event Reports of U.S. Nuclear Power Plants," *Saf. Sci.*, **124**, 104574 (2020). https://doi.org/10.1016/j.ssci.2019.104574

96. S. G. KIM and P. H. SEONG, "Development of Nuclear Power Plant Safety Evaluation Method for the Automation Algorithm Application," *Proc. Korean Nuclear Society 2016 Autumn Meeting*, Kyungju, Korea, October 26–28, 2016.

97. S. ABRISHAMI et al., "BN-SLIM: A Bayesian Network Methodology for Human Reliability Assessment Based on Success Likelihood Index Method (Slim)," *Reliab. Eng. Syst. Saf.*, **193**, 106647 (2020). https://doi.org/10.1016/j.ress.2019.106647

98. H. KIM, J. CHO, and J. PARK, "Application of a Deep Learning Technique to the Development of a Fast Accident Scenario Identifier," *IEEE Access*, **8**, 177363 (2020).

99. M. MA et al., "Data and Decision Intelligence for Human-in-the-Loop Cyber-Physical Systems: Reference Model, Recent Progresses and Challenges," *J. Signal Process. Syst.*, **90**, *8*, 1167 (2018). https://doi.org/10.1007/s11265-017-1304-0

100. M. HSIEH et al., "A Decision Support System for Identifying Abnormal Operating Procedures in a Nuclear Power Plant," *Nucl. Eng. Des.*, **249**, 413 (2012). https://doi.org/10.1016/j.nucengdes.2012.04.009

101. F. R. ISKANDAR and P. I. WAHYONO, "Design of Power Control System for Automatic Operation of the Kartini Reactor," *J. Phys. Conf. Ser.*, **1436**, *1*, 012066 (2020).

102. A. RUBEL, *The Black Box Society: The Secret Algorithms that Control Money and Information*, p. 320, Harvard University Press, Cambridge, Massachusetts (2016).

103. F. EMMERT-STREIB, O. YLI-HARJA, and M. DEHMER, "Explainable Artificial Intelligence and Machine Learning: A Reality Rooted in Perspective," *WIREs Data Mining Knowl. Discovery*, **10**, *6*, El368:1 (2020).

104. F. B. STARTER, D. D. WOODS, and C. E. BILLINGS, *Handbook of Human Factors and Ergonomics*, 2nd ed., John Wiley & Sons, Inc., Hoboken, New Jersey (1997).

105. J. LI et al., "Research and Suggestion on Information Secuity of Nuclear Power Plant," *Nucl Sci Eng.*, **36**, *6*, 803 (2016).

106. C. CUI et al., "Research on Information Security of Electrical Systems in the Whole Life Cycle of Nuclear Power Plant," *Network Security Technol Appl.*, **4**, 297 (2018).

107. J. O'HARA, "Guidance for the Design and Use of Automation in Nuclear Power Plants," *Electric Power Research Institute* (2005).

108. J. M. O'HARA and S. FLEGER, "Adaptive Automation: Potential for Improving Human-Automation Team Performance," presented at the Regulatory Information Conf., North Bethesda, Maryland, March 13–15, 2018.

109. J. M. O'HARA and J. C. HIGGINS, "Human-System Interfaces to Automatic Systems: Review Guidance and Technical Basis," U.S. Nuclear Regulatory Commission (2010).

110. Y. KIM and J. PARK, "Envisioning Human-Automation Interactions for Responding Emergency Situations of NPPs: A Viewpoint for Human-Computer Interaction," *Trans. Korean Nuclear Society Autumn Mtg.*, Yeosu, Korea, October 25, 2018.

111. M. A. GOODRICH and A. C. SCHULTZ, "Human-Robot Interaction: A Survey," *Foundations and Trends in Human-Computer Interaction*, **1**, *3*, 203 (2007). https://doi.org/10.1561/1100000005

112. D. B. KABER and M. R. ENDSLEY, "Out-of-the-Loop Performance Problems and the Use of Intermediate Levels of Automation for Improved Control System Functioning and Safety," *Process Saf. Prog.*, **16**, *3*, 126 (1997). https://doi.org/10.1002/prs.680160304

113. M. R. ENDSLEY, "Level of Automation Effects on Performance, Situation Awareness and Workload in a Dynamic Control Task," *Ergonomics*, **42**, *3*, 462 (1999). https://doi.org/10.1080/001401399185595

114. A. AL-RASHDAN, J. OXSTRAND, and V. AGARWAL, "Automated Work Packages: Capabilities of the Future," *Nucl. Technol.*, **202**, 2 (2018). https://doi.org/10.1080/00295450.2017.1406774

115. A. AL-RASHDAN and V. AGARWAL, "A Data Model for Nuclear Power Plant Work Packages," *Nucl. Technol.*, **205**, *8*, 1053 (2019).

116. M. PAREDES, "Can Artificial Intelligence Help Reduce Human Medical Errors? Two Examples from ICUS in the US and Peru," Techpolicy Institute (2021).

117. J. VANDEN. BOS et al., "The $17.1 Billion Problem: The Annual Cost of Measurable Medical Errors," *Health Affairs*, **30**, *4*, 596 (2011).

118. R. KOPPEL et al., "Role of Computerized Physician Order Entry Systems in Facilitating Medication Errors," *Jama*, **293**, *10*, 1197 (2005). https://doi.org/10.1001/jama.293.10.1197

119. D. D. MILLER and E. W. BROWN, "Artificial Intelligence in Medical Practice: The Question to the Answer?," *Am. J. Med.*, **131**, *2*, 129 (2018). https://doi.org/10.1016/j.amjmed.2017.10.035

120. X. ZHANG and S. MAHADEVAN, "Ensemble Machine Learning Models for Aviation Incident Risk Prediction," *Decision Support System.*, **116**, 48 (2019). https://doi.org/10.1016/j.dss.2018.10.009

121. Z. XU and J. H. SALEH, "Machine Learning for Reliability Engineering and Safety Applications: Review of Current Status and Future Opportunities," *Reliab. Eng. Syst. Saf.*, **211**, 107530 (2021). https://doi.org/10.1016/j.ress.2021.107530

122. J. OEHLING and D. J. BARRY, "Using Machine Learning Methods in Airline Flight Data Monitoring to Generate New Operational Safety Knowledge from Existing Data," *Saf. Sci.*, **114**, 89 (2019). https://doi.org/10.1016/j.ssci.2018.12.018

123. N. WATSON and A. PEEVA, "Nuclear Sector Is Capitaliz-ing on Opportunities in Artificial Intelligence, ITU-IAEA Events Hear," International Atomic Energy Agency (2021).