To: United States Nuclear Regulatory Commission
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Subject: Role of Artificial Intelligence Tools in U.S. Commercial Nuclear Power Operations

Introduction

In this letter, Westinghouse Electric Company (WEC) provides input to the United States (US) Nuclear Regulatory Commission (NRC) request for comment on the role of artificial intelligence (AI) tools in US commercial nuclear power operations posted in the Federal Register (Vol. 86, No. 5), dated April 21, 2021. Since AI and Machine Learning (ML) are ever-expanding fields, it is challenging to achieve agreement on scope and utility for any single application, let alone drawing conclusions for an entire industry. As such, the opinions and evaluations presented in this letter represent those of the authors and may not reflect the common viewpoint for all of WEC. Some of the comments pertaining to the status in the nuclear industry are derived from industry journals, conferences, and conversations with utility engineers. As such, they will be provided without reference and should be considered as professional opinion.

The request for comment seeks to address the eleven issues that have been summarized in Table 1. For completeness, some of the text from NRC-2021-0048-0001 is repeated verbtim in Table 1. Broadly speaking, these eleven questions can be categorized into the general topics of status, benefits, and methods. For those questions addressed, an attempt will be made to address these general topics in addition to specifically answering the question.

Table 1
Summary of US NRC Request for Comment per Docket NRC-2021-0048

Discussion	The NRC is exploring the potential for advanced computational and predictive capabilities involving AI and ML in the various phases of nuclear power generation operational experience and plant management. The NRC is soliciting comments on the state of practice, benefits, and future trends related to the advanced computational tools and techniques in predictive reliability and predictive safety assessments in the commercial nuclear power industry.
Specific Request for Comment	The NRC requests comments from the public, the nuclear industry and other stakeholders, as well as other interested individuals and organizations. The focus of this request is to gather information that will provide the NRC staff with a better understanding of current usage and future trends in AI and ML in the commercial nuclear power industry.
Requested Information and Comments	AI and ML are emerging, analytical tools, which, if used properly, show promise in their ability to improve reactor safety, yet offer economic savings. The NRC requests comments on issues listed below in this solicitation to enhance the NRC's understanding of the short- and long-term applications of AI and ML in nuclear power industry operations and management, as well as potential pitfalls and challenges associated with their application. 1. What is status of the commercial nuclear power industry development or use of AI/ML tools to improve aspects of nuclear plant design, operations or maintenance or decommissioning? What tools are being used or developed? When are the tools currently under development expected to be put into use? (1) 2. What areas of commercial nuclear reactor operation and management will benefit the most, and the least, from the implementation of AI/ML? Possible examples include, but are not limited to, inspection support, incident response, power generation, cybersecurity, predictive maintenance, safety/risk assessment, system and component performance monitoring, operational/maintenance efficiency and shutdown management. (1) 3. What are the potential benefits to commercial nuclear power operations of incorporating AI/ML in terms of (a) design or operational automation, (b) preventive maintenance trending, and (c) improved reactor operations staff productivity? (1) 4. What AI/ML methods are either currently being used or will be in the near future in commercial nuclear plant management and operations? Example of possible AI/ML methods include, but are not limited to, artificial neural networks, decision trees, random forests, support vector machines, clustering algorithms, dimensionality reduction algorithms, data mining and content analytics tools, gaussian processes, Bayesian methods, natural language processing, and image digitization. (1) 5. What are the advantages or disadvantages of a high-level, top-down strategic goal for developing and implementing AI/ML across a wide spectrum of general applications versus an ad-hoc, case-by-case targeted approach? 6. With respect to AI/ML, what phase of technology adoption is the commercial nuclear power industry currently experiencing and why? The current technology adoption model characterizes phases into categories such as: the innovator phase, the early adopter phase, the early majority phase, the late majority phase, and the laggard phase. (1) 7. What challenges are involved in balancing the costs associated with the development and application of AI/ML tools, against plant operational and engineering benefits when integrating AI/ML into operational decision-making and workflow management? 8. What is the general level of AI/ML expertise in the commercial nuclear power industry (e.g. expert, well-versed/skilled, or beginner)? 9. How will AI/ML effect the commercial nuclear power industry in terms of efficiency, costs, and competitive positioning in comparison to other power generation sources? 10. Does AI/ML have the potential to improve the efficiency and/or effectiveness of nuclear regulatory oversight or otherwise affect regulatory costs associated with safety oversight? If so, in what ways? 11. AI/ML typically necessitates the creation, transfer and evaluation of very large amounts of data. What concerns, if any, exist regarding data security in relation to proprietary nuclear plant operating experience and design information that may be stored in remote, offsite networks? (1)

Notes:

1. Indicated questions are addressed in the subsections below within this letter. Other questions are not directly addressed based on the areas of expertise of the signees.

Acronyms about in both the nuclear industry and AI/ML community, and so the following defines the acronyms used within this letter:

Acronym	**Definition**
AI	Artificial Intelligence
CHF	Critical Heat Flux
DNB	Departure of Nucleate Boiling
DT	Digital Twin
FIV	Flow-Induced Vibration
GPR	Gaussian Process Regression
ML	Machine Learning
OED	Optimal Experimental Design
PIML	Physics-informed Machine Learning
PRA	Probabilistic Risk Assessment
R&D	Research and Development
ROM	Reduced Order Model
RUL	Remaining Useful Life
UQ	Uncertainty Quantification
V&V	Verification and Validation

Responses

It is not claimed that any of these subsections offer an exhaustive treatment of a particular topic, but rather a representative sampling of work happening in the industry.

1. **What is status of the commercial nuclear power industry development or use of AI/ML tools to improve aspects of nuclear plant design, operations or maintenance or decommissioning? What tools are being used or developed? When are the tools currently under development expected to be put into use?**

Question 1 asks the status, in terms of both content (i.e., the "what") and timing (i.e., the "when"), as AI/ML tools pertain to four aspects of a nuclear plant – design, operations, maintenance, and decommissioning. Table 2 provides a categorical response to this question with emphasis on work that WEC has been associated with in the recent years. This table effectively summarizes the status and scope for the aspects addressed.

Table 2
Content and Timing of AI/ML Work Pertinent to Design, Operations, Maintenance, and Decommissioning

Aspect of Nuclear Plant	What	When (2)
Design	Use of surrogate modeling to perform efficient global sensitivity analysis of structural dynamics and FIV models used for design qualification. [2,3]	Has been partially used to streamline design analysis process.
	OED for sensor placement. [4,5,6,7] (1)	Ongoing R&D topic, potential to impact new plant designs.
	ROM development for advanced reactor safety analysis. [10]	Commensurate with the pace of advanced reactor development.
Operations	Assessment of nuclear-specific phenomena, such as DNB or CHF via PIML; could eventually impact thermal margins. [9]	Ongoing R&D topic. Unlikely for PIML to impact plant operations for multiple years.
	ML-based emulation of fire hazard for PRA. [8]	May require approval of PRA methods with "dynamic" ties to physics-based modeling for adoption.
	Signal process of human movement data (i.e., footstep induced vibrations [17]) could complement plant physical security.	Would require R&D, and possibly regulatory document updating, to meaningful impact plant security protocols.
Maintenance	Prognostication of RUL using GPR. [14]	Multiple predictive maintenance software tools implementing similar methods, but adoption into maintenance policy requires high quality data.
	Signal processing of SG tube eddy current data, to inform maintenance timing and extent. [16]	Near-term impact the practice of SG tube eddy current analysis.
Decommissioning	Optimal layout of discrete objects [18], such as applied to loading of storage casks, could be approached using AL/ML methods.	Would require R&D to apply discrete object topology optimization methods to nuclear.

Notes:

1. While the Optimal Experimental Design (OED) problem directly impacts design (i.e., where to place a sensor), it ultimately provides value to both operations and maintenance, depending on the utility of the sensor.
2. Timing for full adoption of AI/ML methods depends largely on the extent to which credibility can be demonstrated, leveraging principles of V&V and UQ, such as described in [11].

As an industry, the design paradigm for new reactors incorporates AI/ML tools as part of a digital twin. Most of the new designs (i.e., small modular reactors, micro reactors, etc.) have advertised the development of a digital twin to facilitate the design process. In some cases, AI/ML could enable design optimization.

However, considering new reactors represents the 'future' of the commercial nuclear power industry. The current commercial nuclear power industry using AI/ML tools embedded in a digital twin of a system has provided a cost-effective predictive tool for monitoring plant systems. Several large US utilities employ AI/ML in a variety of cost-saving applications that range from predicting renewal energy load to the grid by using AI/ML to evaluate local weather conditions to reduction of 'paperwork' associated with repetitive form filling.

Largely, the AI/ML tools can be broadly grouped into two categories: Anomaly detection and machine learning. Each of these categories have a wide variety of nuance but can be distilled into relatively simple definitions. Anomaly detection monitors live data or computed results to identify instances of data that are not consistent with the previously defined statistical norm. Such tools can give operators and designers warnings of anomalies otherwise not perceptible by a human observer (i.e., something is not quite right and might require repair). In practice, anomalies are often 'spikes' in the data which show significant deviations from the expected values.

Machine learning is, in principle, akin to human learning: Teach the software (human) to find a pattern. Give an algorithm data and train itself to find patterns in the data. There are many algorithms used for AI/ML. Concretely, WEC has recently developed a tool that evaluates over ten regression-based AI/ML algorithms to find trends in the data and then select the optimal algorithm based on data-driven modeling validation metrics.

These functional patterns can then augment anomaly detection, as well as prognosticate future behavior based on the historical (or simulated) data. These types of predictive capabilities are very useful in determining remaining useful life of a component or structure, long term behavior of a system (maintenance related), and system optimization.

Finally, data does not have to be numeric. In fact, one of the largest demonstrated benefits of AI/ML in the nuclear power industry has been use of AI/ML coupled with text recognition (i.e., natural language processing). This powerful combination has allowed at least one utility to reduce a large amount of person-hours in effort by having software evaluate and process forms. Several organizations are looking into applying this textual AI/ML to improve their human performance and corrective actions processes.

2. What areas of commercial nuclear reactor operation and management will benefit the most, and the least, from the implementation of AI/ML? Possible examples include, but are not limited to, inspection support, incident response, power generation, cybersecurity, predictive maintenance, safety/risk assessment, system and component performance monitoring, operational/maintenance efficiency and shutdown management.

Most Benefical

Digital twins will play a vital role in facilitating the realization of AI/ML benefits throughout the nuclear power industry. The growing interest and maturity of digital twins, such as described generally in [12] and specifically to engineering dynamics in [13], offers potentially significant value in terms of bridging the "gap" between physical equipment and virtual simulations thereof, such as conceptually described in Figure 1 and Figure 2. Holistically speaking, a digital twin is a combination of live (and historical) plant data coupled with physics-based models. Properly constructed, a digital twin can incorporate AI/ML to emulate and predict future performance of a component, process, or system. Digital twins can incorporate any type of physics-based model (structural, fluids, radiation, neutronics, etc.) along with statistical evaluations that, when coupled to properly trained AI/ML create a powerful, living tool. It is a digital twin coupled with AI/ML that would provide the greatest potential benefit to the nuclear power industry.

Particularly from the standpoint of digital twins, ML/AI methods can reasonably be expected to offer at least two major contributions:

1. *Validity* → use of AI/ML methods to better understand differences between measurements, predictions, to calibrate and thus validate engineering models and simulations, perhaps building upon such methods as described in [15].
2. *Computational efficiency* → use of AI/ML methods to construct surrogate models (otherwise knowns as metamodels, reduced order models (ROMs), emulators[1]), such as described in [2,3] for dynamic design analyses, [9] for nuclear phenomenological modeling, or [8] for hazard analysis, for example.

[1] We recognize these terms are not completely synonymous, but that level of nuance is judged unnecessary for the discussion herein.

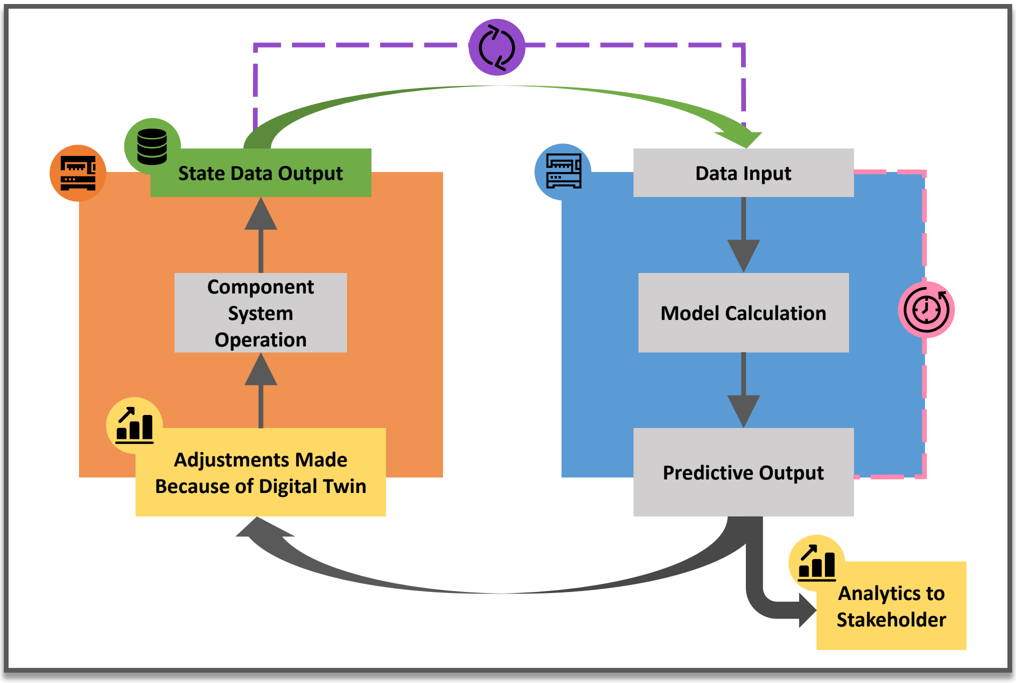

Figure 1 - Conceptual Illustration of Coupled Physical and Digital Twins

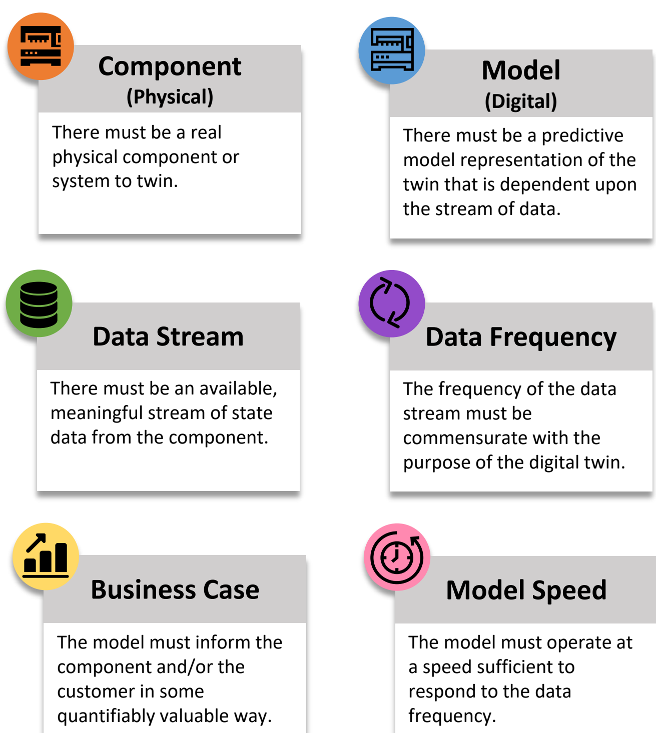

Figure 2 - Required Elements of Coupled Physical and Digital Twins

Least beneficial

While one could argue that no instance exists where judicious use of AI/ML tools would not provide some benefit to reactor operations and management, a business does have to perform a cost-benefit analysis. At least one major utility has stated that they see limited value from digital twins as applied to existing plants due to perceived upfront costs. In reality, this conclusion is probably correct for systems that are rarely used or at plants that are scheduled for retirement (if one neglect applications of AI/ML to decommissioning). Also, applying AI/ML to highly regulated activities (such as using such methods as [20] to more than supplement existing plant physical security protocols) would have a challenge to build a suitable business case since the business model might have to include costs related to regulatory concerns.

3. **What are the potential benefits to commercial nuclear power operations of incorporating AI/ML in terms of (a) design or operational automation, (b) preventive maintenance trending, and (c) improved reactor operations staff productivity?**

In regard to design, AI/ML coupled with other advanced tools (such as computational optimization software) offers promise to significantly reduce the time for a design cycle and potential reduce the amount of physical testing that needed to certify a future design. AI/ML can be coupled with existing and virtual test information to optimally locate measurement locations and can help define a minimum viable set of sensors needed to properly monitor a system. As a result, AI/ML can improve the cost competitiveness of new and existing designs.

Specific to the areas of predictive maintenance and system/component performance monitoring, Value of Information (VoI) analysis, such as described in [14], is envisioned to prove useful for appropriately scoping predictive maintenance activities, which arguably has potential to financially benefit operating nuclear plants.

Finally, AI/ML, coupled with other advanced tools such as a digital twin, can be used to optimize workforce productivity by identifying the most cost-effective methods for operator or maintenance actions, or potential security force patrols/allocations. In addition, AI/ML can be used to reduce or eliminate several human tasks performed during daily plant procedures (such as predicting when changes need to be made in a system rather than having an engineer physically check the system on a regular basis).

4. **What AI/ML methods are either currently being used or will be in the near future in commercial nuclear plant management and operations? Example of possible AI/ML methods include, but are not limited to, artificial neural networks, decision trees, random forests, support vector machines, clustering algorithms, dimensionality reduction algorithms, data mining and content analytics tools, gaussian processes, Bayesian methods, natural language processing, and image digitization.**

Question 4 lists many AI/ML methods. In Table 3, these methods are listed with known or potential applications in the nuclear power industry.

Table 3
AI/ML Methods and Precedent for use in Nuclear

Method [3][4]	**Precedent for use**
Artificial Neural Networks (ANN)	Ubiquitous across nearly all ML applications, and thus not detailed herein.
Decision Trees	Applications involving the use of these methods are not known to the authors of this document, without further research.
Random Forests	
Support Vector Machines (SVM)	Variant of SVM used for regression-based anomaly detection [18].
	Recent use of ANN to optimize in-house manufacturing process [5]
Clustering	Unsupervised clustering is being used in natural language processing (NLP) projects to group words and phrases from parts lists, work orders, documents, and corrective actions databases
Dimensionality Reduction	Proper Orthogonal Decomposition (POD) [1] used for reduced order modeling of reactor fluid dynamics [4]
	Fisher linear discriminant (FLD) analysis used for dimensionality reduction and classification for wind turbine monitoring [23].
Data Mining & Content Analytics	These methods are 'known' but posit these terms as ambiguous since both topics cover a wide range of applications. In the nuclear industry, 'data mining' is just beginning to be used to determine trends in equipment failure, equipment performance, and corrective action process. However, many of these 'data mining' applications utilize other methods listed in this table.
Gaussian Processes (GP) [2]	Surrogate modeling of reactor structure FIV [2,3].
Bayesian methods	Bayesian Belief Network (BBN) used for probabilistic approach to diagnostics [18].
Natural Language Processing (NLP)	Under consideration for various use cases, such as management of spare parts data. The nuclear industry has been incorporating more and more use of NLP in such activities such as form filling and process simplification.
Image Digitalization	Vision-based automatic crack detection for reactor internals [24]
	Potential applicability to visual inspections of rod cluster control assembly (RCCA) guide cards.

Notes:

1. For purposes of present discussion, considered equivalent to principal component analysis (PCA) or singular value decomposition (SVD).
2. Related to GP are generalized polynomial chaos (gPC) expansions, such as used for structural acoustics [22].
3. k-nearest neighbor (kNN) approach was used for metamodeling in [9].
4. Random data (i.e., vibration) analysis methods per [1], using such techniques as Fourier transforms, have been used extensively as a means of feature extraction, a necessary prerequisite for successful use of AI/ML.
5. Draft paper currently under review by ASME J. Verification, Validation, and Uncertainty Quantification.

6. **With respect to AI/ML, what phase of technology adoption is the commercial nuclear power industry currently experiencing and why? The current technology adoption model characterizes phases into categories such as: the innovator phase, the early adopter phase, the early majority phase, the late majority phase, and the laggard phase.**

For the nuclear vendors, AI/ML is just beginning to be adopted at a larger scale in design and analyses. Preventative maintenance has garnered focused emphasis (i.e., AI/ML to monitor and trend live/historical data), as well as use of AI/ML embedded in digital twins of portions of new reactor designs and existing reactor components/systems. These two broad areas of application have been identified as cost-effective methods to improve the products and hence potentially increase revenue.

For the nuclear power industry, AI/ML is being readily incorporated by the larger nuclear power utilities. Some of the larger utilities have been investing in AI/ML (tools, staff, and applications) for more than a decade. Smaller nuclear utilities are just beginning to apply AI/ML on a limited basis presumably due to the smaller financial resources when compared to the larger utilities.

11. **AI/ML typically necessitates the creation, transfer, and evaluation of very large amounts of data. What concerns, if any, exist regarding data security in relation to proprietary nuclear plant operating experience and design information that may be stored in remote, offsite networks?**

Working in a cloud environment entails transmission of data to a pseudo-shared environment. From a nuclear vendor perspective, care must be taken to not allow co-mingling of data between various data sources. This can be done through partitions (ideally) or could be enforced admistratively. However, the latter would leave open the possibility of accidental mixing of data sets. Additionally, key areas that need governance for the success of AI tools, yet sometimes require complex solutions, include security, privacy, export control compliance, and access needs.

Sincerely,

Signatures

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