Commentary on Use of Model-Augmented Data Analytics for Improved Operational Efficiency of Nuclear Power Plants

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Abstract: Machine learning and data science have the potential for improving the operational efficiency and productivity of the current fleet of light water reactors. However, to date, the nuclear industry has not leveraged recent advances in these fields. This paper provides commentary on the potential advantages and challenges of using recent advances in data analytics and probabilistic modeling techniques that support mixed inference application. This paper proposes an initial, high-level machine-learning-derived framework for integrating nuclear plant data streams in near-real time for improved diagnostics, online risk-management, and decision-making. This paper also outlines several challenges that must be overcome before realizing the benefits of machine learning and data science for improving nuclear power plant operations.

Keywords: big data, data analytics, operations, efficiency.

1. INTRODUCTION

The United States Department of Energy (DOE) has identified several research and development topical areas of relevance to ensuring that nuclear power remains a viable component of the U.S. energy portfolio. In particular, DOE has identified the need for information technologies that provide an enhanced understanding of plant operating conditions as well as a need for research products that support state-of-the-art NPP safety analysis and yield new insights regarding plant safety and operational margins [1].

Machine learning and data science, particularly big data analytics, have the potential for improving the operational efficiency and productivity of the current fleet of light water reactors (LWRs) [2]. Big data generally includes information whose size, type, diversity, or complexity goes beyond the capabilities of individual analysts to manage and process. Big data analytics leverages this information to identify insights that would not be available using more conventional analytical approaches. As such, recent advances in data science and artificial intelligence provide an excellent opportunity to develop tools that integrate heterogeneous, high-volume information streams in innovative, novel, and powerful ways.

Moreover, opportunities exist to go beyond analysis of big data. In particular, additional potential may be realized by coupling these big data approaches with probabilistic and mechanistic models capable of capturing the relationships and dependencies between processes that generate data. This can be leveraged to provide useful insights to inform plant operations and enable better decision-making. To date, the nuclear industry has not fully leveraged recent advances in these fields. In this paper, we offer commentary and propose ways to leverage advances in machine learning and data science for nuclear plant applications.

2. NUCLEAR POWER PLANT INFORMATION STREAMS

Nuclear power plant operations generate a large volume and variety of information streams. Some of these data streams fall into the category of online, real-time monitoring of a large number of systems. For example, plant instrumentation systems utilize sensors to monitor and provide information on diverse quantities such temperatures, vibrations, water levels, pressures, valve positions, and radiation levels in major systems, structures, and components (SSC) of the reactor system and balance of plant. Plant control systems are then used as part of a feedback loop to control system performance based on information from these instruments. In existing nuclear facilities, many instruments and sensors are linked to plant monitoring and control systems via physical cables and wiring. However, opportunities exist to further instrument nuclear plant structures, systems, and components using wireless sensor arrays. These arrays can be used to augment and replace existing wired sensors or to monitor quantities that were previously not measured. Use of wireless technologies can potentially provide plant information at lower costs than would be required when installing wired sensors (e.g., because extensive wiring is not needed). In addition, wireless sensors do not require new cable trays and penetrations (which may create fire, flood, or other vulnerabilities), can be installed in areas with limited space, and can be more easily replaced or moved. The notion of using wireless sensor arrays for monitoring nuclear plant operations has been discussed for over a decade in relation to activities such as plant monitoring and aging management (e.g., [3], [4]). In addition, wireless sensors are being increasingly employed in monitoring of other types of engineered systems outside of the nuclear industry (e.g., structural health monitoring applications involving buildings and bridges as well as systems used to monitor and control industrial processes).

Plant instruments and sensors are not the only source of real-time plant information streams. Additional information is available from the plant computer and main control room, which provides information on the status of major systems and critical safety functions. Additional relevant information streams may also come from offsite (e.g., information on the status of offsite power sources). Valuable insights may also be gleaned from plant operational and maintenance information such as that contained in maintenance logs, outage reports, and corrective action program entries.

In addition to online information, it is useful to consider the insights that may be obtained from the extensive offline data sources generated by the nuclear industry. This includes industry operating experience as captured in databases and reports from the U.S. Nuclear Regulatory Commission (NRC) reactor operational experience database [5], event notification reports [6], and Licensee Event Reports [7], and as well as industry maintenance, inspection, and reliability data. Additional information about human performance in control rooms can be obtained by capturing information from simulator-based operator training and detailed control room operations experiments [8] conducted in facilities such as the OECD Halden Reactor Project, KAERI, or the Idaho National Lab.

In addition to these traditional data sources, valuable insights may be obtained by considering the data generated by the extensive modeling and computational capabilities developed for the nuclear industry. System simulation tools such as RELAP, MAPP, MELCOR, and MACCS provide detailed scientific insight into the underlying physics and system interactions. Additional powerful computational tools exist for specific phenomena, such as behavior of nuclear fuels (BISON) and reactor physics (MAMMOTH).

3. APPLICATION OF BIG DATA TO IMPROVE OPERATIONAL EFFICIENCY

These data streams provide a valuable source of information that can be leveraged to develop information and insights that may not be apparent using traditional data analysis techniques focused on single data types. While machine learning and data science provide an opportunity to improve upon existing practices, there are several challenges that must be overcome before realizing the benefits of machine learning and data science for improving NPP operations. These challenges include the need to: (1) ***process*** the disparate plant data streams that are available to NPP decision makers in near-real time, (2) ***integrate*** disparate information streams with existing knowledge of plant operations and response, and (3) ***transform*** complex, integrated information into a product that is useful to plant operators and supports robust decision-making.

4. AUGMENTING BIG DATA WITH MODELS

Similar to the risk-informed (rather than risk-based) approach utilized by the nuclear industry,* a framework utilizing data analytics for nuclear plant operations and decision-making should be ***data-informed*** (rather than data-based). This means that information must processed, integrated, and transformed within a broader decision-making framework that balances operational efficiency and productivity with the safety expectations and regulatory requirements of the nuclear industry.

The authors envision that there are three fundamental components to a framework for leveraging big data for improved plant operations. This framework is shown in Figure 1. First, the aforementioned disparate information streams (four of which are illustrated in Figure 1) must be compiled, processed, and integrated into a common data architecture. Then, through use of data analytics on individual or sets of information streams, it is possible to identify trends and potential indicators related to plant status and operation, component status and performance, and other plant metrics of relevance. The final aspect of the framework is a collection of online status visualization and decision support tools designed to provide decision makers with understandable and actionable information derived from the data.

Even more powerful insights may be garnered by coupling information from data streams with probabilistic models that are integrated with plant process and mechanistic models discussed in Section 2. In doing this, it becomes possible to perform more complex reasoning tasks such as diagnosing potential causes of changes in SSC status via multi-directional probabilistic inference (e.g., see [10], [11]). Multi-directional inference encompasses three classes of inference: forward inference, backward inference, and inter-causal inference. Under forward inference (also referred to as predictive inference or causal reasoning), available information (observations) about a cause are used to make updated predictions or inferences about an effect. For example, using forward inference, an observation about vibration in the pump (e.g., from a sensor mounted on the pump) may be used to "forward update" beliefs about the probability that the component has failed (or in an unacceptably degraded state) and thus the probability that an annunciator will be seen in the main control room (MCR), including possibilities for annunciator errors. Under backward inference (also referred to as diagnostic inference or reasoning), information (observations) about an effect are used to update beliefs about a cause. Returning to previous example, using backward inference, an observation that an annunciator has been seen in the MCR can be used to make inferences about whether the pump is actually failed (versus an erroneous indicator) as well as inferences the probable cause of the failure (e.g., excessive vibration, power fault. or overheating). This is referred to as backward inference because information flows in the opposite direction of the causal relationship. This type of inference is particularly useful in scenarios in which latent causes cannot be readily observed; these types of scenarios are prevalent in existing nuclear power plants. Finally, inter-causal inference (reasoning) allows inferences to be made between causes when there is a common effect [12]. Returning to the previous example and supposing that an inspection has confirmed that the pump has failed, inter-causal inference would allow observations about whether the pump has experienced excess vibration (e.g., based on processing information from a mounted sensor) to be used to update beliefs about the probability of other the other causes that may not be readily observable due to lack or failure of sensors.

All NPPs in the U.S. have dedicated significant resources to developing plant probabilistic risk assessments (PRAs). These plant PRAs provide a valuable tool for understanding SSCs reliability, relationships, and dependencies as well as their importance to plant safety. As a result, additional benefit can be achieved by integrating data fusion tools with existing PRAs to support online risk

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* The United States nuclear industry is regulated under a risk-informed regulatory approach that considers probabilistic assessment with conventional deterministic concepts such as defense-in-depth and maintenance of safety margins [9].

assessment and management via probabilistic updating and multi-directional inference (e.g., using other tools available from the machine learning sector such as Bayesian networks).

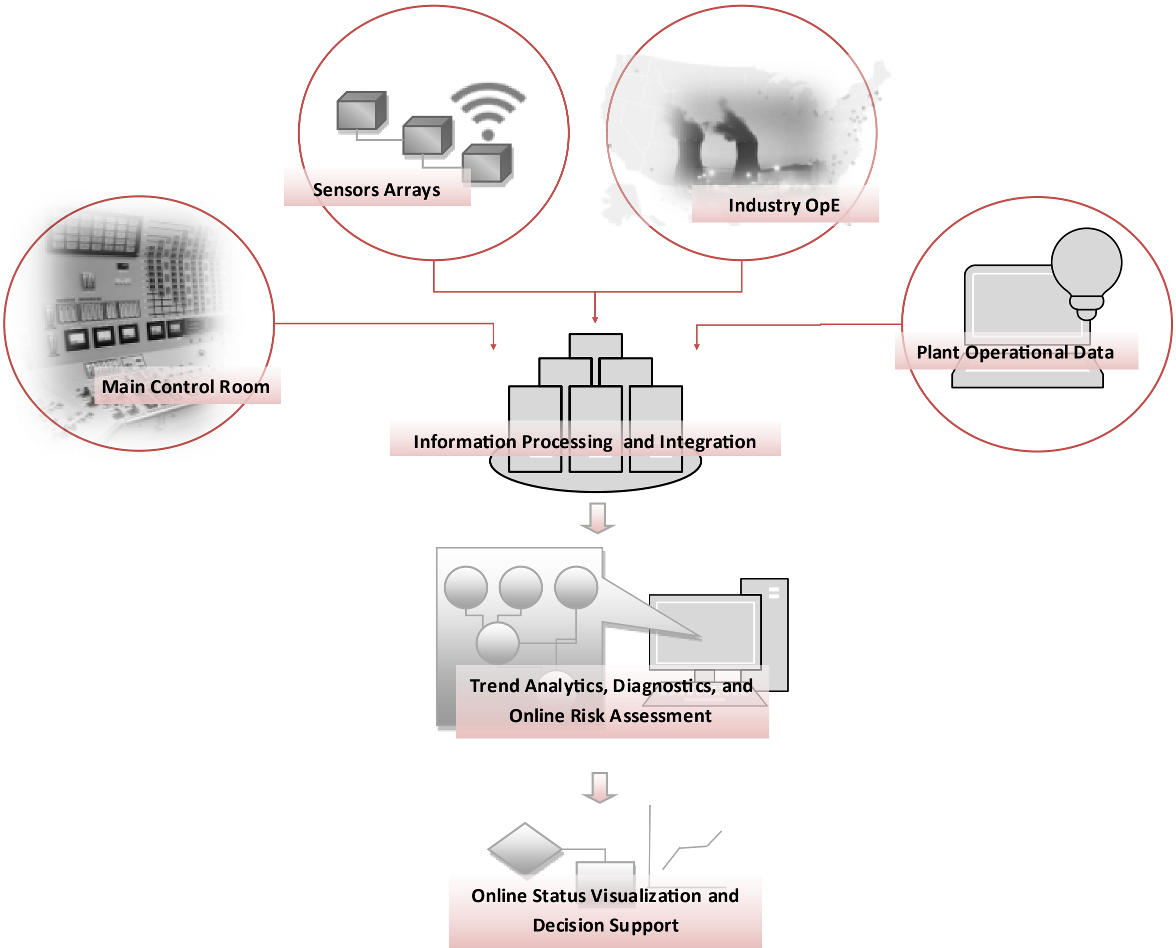

Figure 1: Proposed Framework for Model-Based Data Analytics

5. CONCLUSION

Recent advances in machine learning and data science have the potential for improving the operational efficiency and productivity of NPPs. In particular, these advances provide a valuable opportunity to develop tools that can integrate heterogeneous, high-volume information streams in innovative, novel, and powerful ways to provide useful insights to inform plant operations and enable better decision-making. However, to date, the nuclear industry has not truly realized the benefits on these advances. The commentary provided in this paper proposes that the industry should alter this existing paradigm and leverage tools to process, integrate, and transforming disparate nuclear plant information streams to support improved plant operations and decision-making. The authors envision that the aforementioned information, data, models, and methods would be integrated within a broader risk-informed decision-framework that facilitates online status visualization and incorporates operational cost information to support more efficient and economical decision-making while maintaining overall plant safety.

Table of Abbreviations

DOE	Department of Energy
LWR	Light water reactors
NPP	Nuclear power plants
SSC	Structure, system, and component
MCR	Main control room

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