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In-Depth Analysis of Nuclear Data Flow Using Graph Theory and the Technology, Organization, People Model Through the Application of Betweenness Centrality Measure and Community Detection

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ABSTRACT

This study addresses the significant challenges faced by the nuclear industry in managing complex information systems, where traditional approaches often result in inefficiencies, inconsistencies, and inaccuracies that can have serious consequences for plant performance. By applying graph theory to the analysis of nuclear data flow and integrating the concept of Human System Integration (HSI) through the Technology Organization People (TOP) model, this research proposes an innovative methodology for optimizing data management and improving efficiency in nuclear facilities throughout their lifecycle. The TOP model provides a comprehensive framework that considers technological, organizational, and social aspects of complex systems, providing a holistic approach to understanding interactions within the information system. Through the application of graph theory methods such as betweenness centrality measure and community detection, this study aims to identify critical nodes and group similar nodes that share common data transmission characteristics, ultimately facilitating more informed data management decisions and data flow optimization. The results demonstrate the potential of this approach to address the complex information management challenges faced by the nuclear industry, with implications for improving the performance and efficiency of nuclear facilities.

Keywords: Digital transformation, Data management, Graph theory, Human systems integration, Complex information systems, Nuclear industry

INTRODUCTION

Nuclear power plants are complex systems that generate energy through controlled nuclear fission reactions (Jayakrishna et al., 2016). Managing these systems requires a deep understanding of their design, operation, and maintenance throughout their lifecycle (IAEA, 2015). This involves coordinating multiple stakeholders, managing diverse activities, and leveraging various technologies to ensure safe and efficient operations. The integration of digital technologies has become essential in enhancing the efficiency and performance of nuclear facilities, particularly during the operational phase (Vu and Hartley, 2022).

Digital transformation has accelerated productivity growth and economic outcomes in recent years (Hao et al., 2024). However, the adoption of digital technologies within the nuclear sector is hampered by the intricate nature of its stakeholders, supply chain, and activities. The traditional approaches to managing data often result in inefficiencies, inconsistencies, and inaccuracies, which can have severe consequences on the performance of nuclear facilities (Vu et al., 2022). Furthermore, the exponential growth of complex information systems has created substantial challenges in data management within the nuclear sector.

To address these critical issues, this study proposes the application of graph theory and the Technology-Organization-People (TOP) model to analyze nuclear data flow and integrate human system integration (HSI). The TOP model is a comprehensive framework that considers the technological, organizational, and social aspects of complex systems, providing a holistic approach to understanding interactions within the information system (Jayakrishna et al., 2016).

To effectively represent and analyze the complex interactions among system components, this study employs two graph theory-based methods:

- Betweenness Centrality Measure: This method is used to identify critical nodes within the data network that are most central or influential in terms of data flow. By highlighting these key components involved in data transmission, we can gain insights into the underlying structure and dynamics of the nuclear data flow.
- Community detection: This method is used to group similar nodes within the data network that share common data transmission characteristics, thereby facilitating insight into the underlying structure and dynamics of the nuclear data flow.

The findings of this study will demonstrate the potential of this innovative methodology for addressing the challenges faced by the nuclear industry in managing nuclear complex information systems. The results will underscore the significance of integrating human factors into data management and provide a framework for enhancing the efficiency of nuclear facilities throughout their lifecycle. This study contributes to the development of more effective strategies for managing complex information systems within the nuclear sector, with implications for enhancing the performance and efficiency of nuclear facilities.

LITERATURE REVIEW

The Complexity of Data Management in the Nuclear Industry

Managing data in the nuclear sector is a complex task due to the interdependent systems nature of the field (Jayakrishna et al., 2016). The data generated within a nuclear plant comes from a multitude of interconnected subsystems, including reactor sensors, cooling loop controls, turbines, radiation monitors, and organizational units such as engineering and operations teams. Each of these systems generates disparate types of data, including real-time sensor data, logs, control signals, and operational data, among others (Hao et al., 2024). Furthermore, the process of mapping and managing the interactions, propagation, and impacts of this data on other parts of the system can become highly complex due to the significant dependencies and propagation of data involved (Nath et al., 2020).

Another factor contributing to the complexity of this issue is the nature of the data, which is characterized by three key attributes: volume, velocity, and variety (Jayakrishna et al., 2016). Nuclear power plants generate a substantial quantity of real-time data from sensors and control systems. They also produce a significant amount of data related to facilities lifecycles, fuel lifecycles, etc. The processing of this continuous stream of data in an efficient manner while ensuring accurate lineage tracking will necessitate the implementation of a meticulous optimization strategy (Nath et al., 2020). The data may also be presented in a variety of formats, including structured sensor logs, unstructured maintenance reports, time-series data from control loops, design change management, or even manual operator inputs.

Furthermore, it is essential to address the issue of fault tolerance and error propagation, which can result in erroneous data (Vu et al., 2022). Errors in sensor readings, calculation errors in data processing, or incorrect operator inputs can propagate through the system, potentially leading to suboptimal decision-making or safety risks. This complexity underscores the need for a comprehensive approach to managing data in the nuclear sector.

Graph Theory and Its Applications

A graph theory approach employs a diagrammatic representation of the entire system, delineating its constituent subsystems and their interactions. This approach facilitates a comprehensive understanding of the system, particularly in comparison to other methodologies such as the analytical hierarchy process, which can prove overwhelming in this context. Additionally, these diagrammatic representations can be readily transformed into matrix format, such as an adjacency matrix or incidence matrix representation (Van Steen, 2010), which can be utilized for mathematical computations that are not feasible with other diagrammatic representations, including flowcharts, cause-and-effect diagrams, and so forth (Jayakrishna et al., 2016). The application of graph theory has already been demonstrated in the dynamic description of systems, including electrochemical systems (Dao and McPhee, 2011). In such cases, the number of equations representing the system has been reduced significantly, thereby reducing the overall complexity compared to the original model. Graph theory models have been developed to assess the performance and interrelationship between the sustainability enablers within an organization, to identify a set of sustainability enablers and attributes that impact a manufacturing organization (Jayakrishna et al., 2016). Furthermore, graph theory models have been applied to an Indian industry with the objective of evaluating total quality management parameters. This parameter enabled the industry to be assessed and ranked for a given period using a logical and rational procedure (Kulkarni, 2005).

The application of graph theory-based methods, including betweenness centrality and community detection, has been widely adopted in various fields to analyze and cluster complex networks. Research has demonstrated the effectiveness of these methods in various contexts, such as point-set correspondence matching (Carcassoni et al., 2002), distributed cluster management for dynamic publish/subscribe systems (Tariq et al., 2012) and graph partitioning for water distribution systems (Han et al., 2017). In addition, studies have explored the integration of graph theory with machine learning techniques to improve clustering efficiency (Liu et al., 2015) and scalability. The use of betweenness centrality measures and clustering coefficients has also been extended to identify initial seed sets for network coverage (Saxena et al., 2023). Collectively, these contributions highlight the versatility and effectiveness of graph theory-based methods in tackling complex network analysis and clustering tasks.

Human System Integration Framework

Digital transformation has been accompanied by many technological advances that provide significant opportunities to improve flexibility, efficiency, and human well-being, but also increase complexity and the lack of a comprehensive view of the behavior of autonomous agents. This leads to questions of acceptance, understanding or adaptation between humans and systems. Human System Integration announces itself as an approach to deal with the different changes to bring this digital transformation the most suitable.

HSI can be defined as a transdisciplinary field that combines systems engineering, human factors, ergonomics, information technology, and sector specific applications such as aerospace, healthcare, and energy. It focuses on integrating technology, organizations, and people throughout the entire life cycle of complex sociotechnical systems. Unlike traditional usability approaches, HIS involves considering human and organizational factors early in the design and development processes (Boy, 2023).

It is relevant to point out that it has become an essential topic in the development of digital transformation towards the industry 4.0 and its projection into Industry 5.0 where people's roles and responsibilities must be at the center of sociotechnical organizations (Pacaux-Lemoine and Flemisch, 2021).

Under the HIS approach, the TOP model supports design and development teams in the rationalization of interdependencies between technology, organizations, and people in which a system is considered as a representation of a natural or artificial entity.

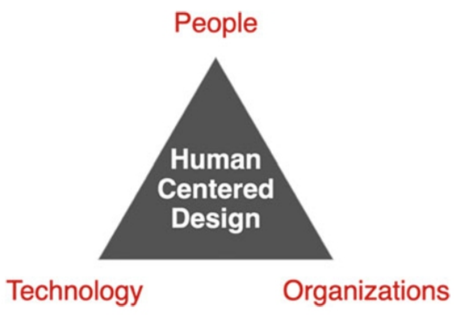

Figure 1: TOP model under HSI approach. Adapted from Guy 2023.

Synthetic Data Generation

The use of real-world data from the nuclear industry is limited by confidentiality and the need to protect assets. Thus, another part of the proposed methodology is the use of synthetic data. The latter has received significant attention in various areas, including healthcare and question answering corpora. In Abay et al. (2018), a privacy-preserving synthetic data release method using deep learning was introduced, highlighting the importance of protecting sensitive information. Also, the generation of synthetic question-answer corpora was introduced by combining question generation and answer extraction models, ensuring roundtrip consistency. In addition, an evaluation of different approaches to generate synthetic patient data was introduced, including probabilistic models and generative adversarial neural networks, addressing the challenge of limited availability of real patient data for research purposes (Goncalves et al., 2020).

Overall, the literature on synthetic data generation showcases the importance of privacy preservation, utility evaluation, and the development of innovative methods for generating synthetic data across various domains.

METHODOLOGY

This study adopts a multidisciplinary approach to address the complexities of data management in the nuclear power plant's information systems leveraging mainly synthetic data generation, graph theory and Human System Integration (HSI) through the TOP model. The methodology is divided into several steps:

Data Sources and Data Transformers Identification Based on the TOP Model

The first step of the methodology entails the identification and cataloging of all data sources and data transformers within the system. This process is guided by the TOP model, which emphasizes a comprehensive understanding of the systemâŁ™s architecture through an analysis of its three constituent components: Technology (T), Organizational structure (O), and People (P). A comprehensive examination of the system's architecture is conducted to delineate the interactions and dependencies between these three elements. This permits a holistic view of the interconnections between technological systems, organizational processes, and human actors. Technology components are modeled through digital systems and physical sensors that generate and process data. The organizational structure is represented by the various departments and teams responsible for data management and decision-making.Human factors are captured by observing operator actions and their influence on data generation and flow. This first step enables the creation of an initial real-life operational dataset.

Synthetic Data Generation

The second step in our methodology involves generating synthetic data that accurately reflects the complex interactions within the nuclear facility. This is achieved through a process that begins with the real-life operational dataset previously explained, which forms the basis for extrapolation using the nuclear-oriented Large Language Model (LLM), SPARK (NuclearnAI, 2024). The LLM model is specifically designed to generate new elements that conform to the same dataset structure, thereby enriching and expanding the original dataset. Following this, expert knowledge is applied to evaluate the various generated elements, as well as their relationships with one another. This allows for the creation of a comprehensive and meaningful dataset that simulates the complex interactions within the nuclear systemâŁ™s information environment.

Graph Conversion and Visualization

The input data is converted into a graph that enables to model complex relationships between different entities. A force-directed layout algorithm (such as Spring or Fruchterman-Rheingold) is used to visualize the graph in a 2D space, where nodes represent individual data sources and transformers, and edges indicate the direction of data flow between them. This graphical representation serves as a visual backbone for our analysis: where the dependencies lie, and how changes in one part of the system affect others.

Graph Based Methods for Analysis of the Nuclear Data Graph

We utilize two complementary methods to uncover the underlying structure of data flow. Betweenness Centrality measure: we calculate the betweenness centrality for each node in the graph. This measure quantifies the extent to which a node lies on the shortest paths connecting other nodes and is commonly used to identify influential or “central” nodes in a network. Here, we interpret the betweenness centrality as a distribution of workload among different nodes, reflecting their relative importance in facilitating information flow and coordination within the nuclear facility.

$$c_B(u) = \sum_{x \neq y} \frac{|S_{(x,u,y)}|}{|S_{(x,y)}|} \tag{1}$$

where:

- $c_B(u)$ is the betweenness centrality of node u
- $S_(x, y)$ is the set of shortest paths between two nodes x and y
- $S_(x, u, y)$ is the number of those paths that pass through the node u.

A higher betweenness centrality score indicates a greater potential for a node to control or influence communication and flow within the graph. It can highlight nodes that serve as crucial intermediaries in a network structure, potentially identifying bottlenecks in information or data flow.

Community detection using Louvain algorithm with modularity maximization: To identify the clusters or communities within the graph, we employ the Louvain algorithm with modularity maximization as the objective function (Dugué et al., 2015). This approach ensures that the detected clusters are well structured connected and have a high degree of internal cohesion, while also exhibiting low inter-cluster connectivity. To enhance reproducibility, we use an integer random seed for the algorithm. The resulting community structure is used to gain insights into the functional organization of the nuclear facility. The modularity for direct graphs (Dugué et al., 2015) can be expressed as follows:

$$Q_d = \frac{1}{m} \sum_{i,j} \left(A_{ij} - \frac{d_i^{in} d_j^{out}}{m} \right) \delta \left(c_i, c_j \right) \tag{2}$$

Where A_{ij} represents the existence of an arc between i and j, and d_i^{in} (resp. d_j^{out}) stand for the in-degree (resp. out-degree) of i. The algorithm continues as there exists a move that produces a gain of modularity. It can be expressed as follows:

$$\Delta Q_d = \frac{d_i^C}{m} - \left(\frac{d_i^{out} \cdot \Sigma_{tot}^{in} + d_i^{in} \cdot \Sigma_{tot}^{out}}{m^2} \right) \tag{3}$$

where Σ_{tot}^{in} (resp. Σ_{tot}^{out}) denotes the number of in-going (resp. out-going) arcs incident to community C.

RESULTS

The synthetic data simulates the operations of a nuclear facility by capturing the intricate interplay between technological systems and human roles. It represents a complex and highly integrated information environment, where sensor systems continuously collect data from temperature sensors, pressure monitors, level gauges, and radiation detectors. This data feeds into the facility's control systems, including reactor controllers, cooling unit managers, and power loop regulators, which coordinate essential processes to ensure smooth operation.

To maintain the facility's integrity, an Automated Maintenance System performs routine tasks efficiently, while a Data Management System stores, processes, and analyzes the vast data generated. High-Performance Computing (HPC) clusters are employed to conduct advanced calculations that support optimization of energy production and resource management. The facility infrastructure includes critical components such as radiation monitoring equipment, cooling systems, turbines, generators, backup power units, and heat exchangers, all of which work in unison to maintain operational stability.

Table 1: Example table of synthetically generated data showing the different TOP elements and their data flows.

Source	Destination	Source Type	Destination Type	Data Flow
Automation technology Team	Operational Engineer	organization	people	Automation system operational data
Design Engineering Unit	Upper-Level Technical Preparation Unit	organization	organization	Equipment maintenance procedure
Design Engineering Unit	Upper-Level Technical Preparation Unit	organization	organization	Design Configuration Modification
IT Support Team	Waste Management Technician	organization	people	IT systems for waste tracking and management
Operational Engineer	Safety Officer	people	people	Operational safety requirements

In emergency scenarios, a robust Emergency Response System is activated, mobilizing multidisciplinary teams to manage the situation. These teams include Maintenance and Repair units that address equipment failures, Safety Officers who ensure personnel safety, and Quality Control Specialists who verify that all repairs meet regulatory standards. The Project Manager oversees the entire response, coordinating efforts and resources across teams. Supporting this effort, the Radiation Protection Team minimizes exposure risks using specialized protocols and equipment, while the Emergency Response Coordinator ensures efficient communication and collaboration among stakeholders.

Additional specialized roles strengthen operational readiness. The Equipment Management Team handles critical hardware, while the Data Management Team ensures the availability and integrity of information. The Thermal Management Team addresses cooling issues, and the Power Dispatcher maintains a stable energy supply. The Nuclear Fuel Management Team is responsible for the safe handling of fuel rods, guided by strict radiation protocols. Technical support is provided by IT Support and Automation Technology Teams, along with Data Analysts and Design Engineers who provide real-time insights and technical solutions during crises.

The facility also benefits from robust support and oversight functions. The Safety and Compliance Department monitors adherence to regulations, while the Training and Development Center ensures all personnel are properly prepared for emergencies. Waste Management personnel safely handle and dispose of hazardous materials, and Digital Twin technology provides virtual models of systems to enable simulation and performance optimization. The Upper-Level Technical Unit and Environmental Monitoring Technicians offer technical support and track environmental safety parameters throughout a crisis.

As operations scale, SCADA systems offer real-time monitoring and control capabilities, while the Supply Chain Management Unit ensures timely delivery of critical resources. Meanwhile, the Research and Development Department drives innovation, working to improve system efficiency, reduce waste, and enhance overall facility performance.

Subsequently the data can be converted into a graph.

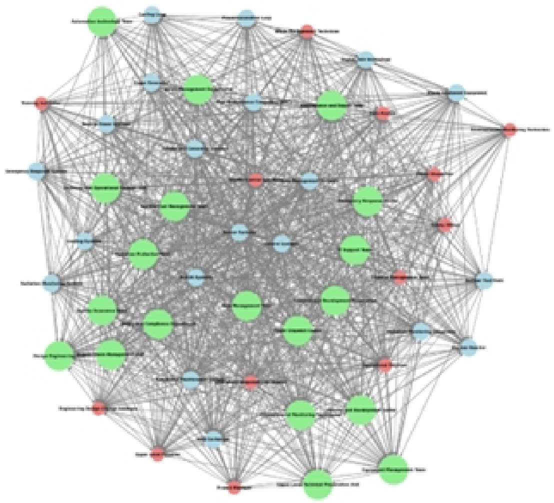

Figure 2: Graph visualization of the nuclear complex information system highlighting the different TOP elements: organizations (green nodes), technology (blue nodes) and people (red nodes).

Figure 2 shows the visualization of the graph representing the nuclear complex system information, highlighting the different TOP elements interacting. Then, the community detection algorithm and betweenness centrality analysis are performed. After applying the Louvain clustering algorithm, we found four different clusters or communities:

Cluster 1: Includes nodes such as “Data Management Systems”, “Supply Chain Management Unit”, “Design Engineering Unit”, “Safety and Compliance Department”, “Waste Management Department”, “Nuclear Fuel Rods”, “Cooling Loop”, representing the heart of fission management related to the fuel life cycle, within a safety compliant industrial activity. This cluster may indicate a high degree of data centralization, with most data flowing through these systems. The presence of ‘Supply Chain Management Unit’ suggests that this cluster may be connected to external data sources.

Cluster 2 includes nodes like ‘Automated Maintenance Systems’, ‘Sensor Systems’, ‘Control Systems’, ‘Cooling Systems’, ‘Turbine and Generator Systems’, ‘Backup Power Systems’. These systems are primarily responsible for monitoring, controlling, and maintaining the operational performance of various equipment within the nuclear facility. This cluster may indicate a high degree of control over the operational aspects of the facility. The presence of ‘Sensor Systems’ suggests that this cluster might be connected to data from various sources and a global involvement of I&C systems.

Cluster 3 appears to be the hub of data-driven decision-making within the nuclear facility, with nodes such as “High-Performance Computing (HPC)”, “Data Management Team”, “Equipment Management Team”, and “Project Manager” indicating a focus on analyzing and processing large amounts of data in real-time, as well as in non-real time. The presence of HPC resources suggests advanced computational capabilities for analyzing large datasets and optimizing processes.

Cluster 4 includes nodes like ‘Radiation Monitoring System’, ‘Emergency Response System’, ‘Heat Exchanger’, ‘Steam Generator’, ‘Power Generation Loop’, ‘Emergency Response Center’, ‘Power Dispatch Center’, primarily responsible for ensuring the safe and efficient operation of the nuclear facility. The presence of ‘Emergency Response System’ suggests that this cluster may be connected to critical response scenarios.

The data flow structures identified in each cluster can be expressed as follows:

- Data centralization in Cluster 1
- Control over operational aspects in Cluster 2
- Data-driven decision-making in Cluster 3
- Safety and operational efficiency in Cluster 4

The betweenness centrality distribution reveals a nuanced landscape, where most nodes exhibit moderate influence, while a select few have significantly higher scores. In particular, Control Systems (70.9), Sensor Systems (69.1), Automated Maintenance Systems (31.1), High-Performance Computing (HPC) (23.8), Quality Control Specialist (45.4) and Data Management Systems (45.2) stand out as key nodes with high betweenness centrality values, highlighting their crucial roles in facilitating information flow across different clusters. The high betweenness centrality values are concentrated in Cluster 4: Safety and operational efficiency, where nodes like Power Dispatch Center (23) also exhibit moderate high scores, suggesting that Cluster 4 plays an important role in connecting different parts of the network and ensuring safety and operational efficiency. In addition, Quality Control Specialist appears to be bridging Cluster 3: Data-driven decision-making with Cluster 4, while Data Management Systems and High-Performance Computing facilitate connections between Cluster 1: Data centralization and Cluster 3. Automated Maintenance Systems seems to be connecting Cluster 4 with Cluster 2: Control over operational aspects, enabling efficient maintenance planning and execution.

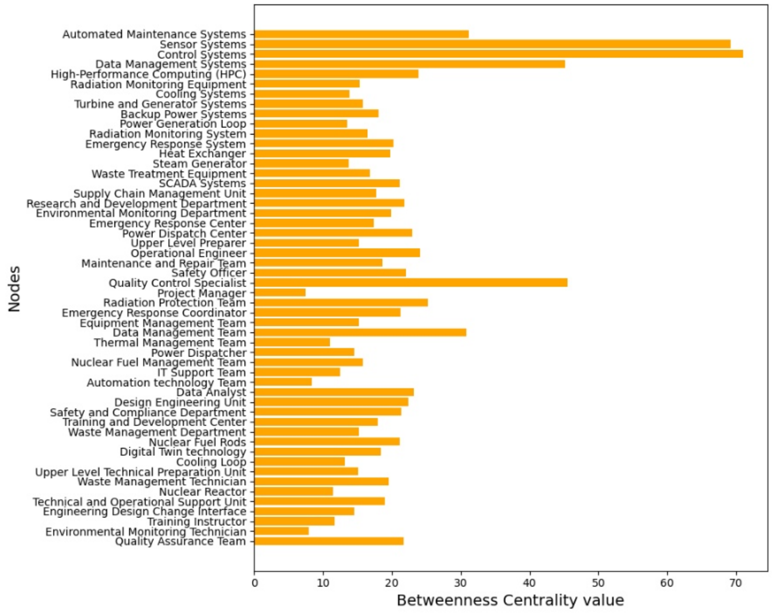

Figure 3: Betweenness centrality distribution for all the nuclear system information nodes.

The high influence of these nodes suggests that they are critical to ensuring the efficient operation of critical systems, making informed decisions, and maintaining safety and operational efficiency across different clusters.

CONCLUSION

This study addresses the significant challenges faced by the nuclear industry in managing complex information systems, where traditional approaches often result in inefficiencies, inconsistencies, and inaccuracies that can have consequences for plant performance. Building on our analysis of synthetic generated data, to overcome the nuclear industry limitations of confidentiality and the need to protect assets, using graph theory-based methods, we demonstrate the potential of this approach to address the complex information management challenges faced by the nuclear industry.

The application of betweenness centrality measures and community detection has revealed a nuanced landscape of critical nodes and connections within the nuclear facility's information system. Our results show that select nodes, including Control Systems, Sensor Systems, Automated Maintenance Systems, High-Performance Computing, Quality Control Specialist, Data Management Systems, and Backup Power Systems, exhibit high influence in facilitating information flow across different clusters, particularly within Cluster 4: Safety and operational efficiency. This suggests that these nodes play a crucial role in ensuring the efficient operation of critical systems, making informed decisions, and maintaining safety and operational efficiency, with Control Systems and Sensor Systems standing out as key nodes with the highest betweenness centrality values. Furthermore, our clustering analysis reveals that Cluster 4 is heavily connected to other clusters, indicating its crucial role in connecting different parts of the network and ensuring overall system performance. The high-betweenness centrality values within this cluster suggest a critical importance of these nodes in facilitating information flow and decision-making processes, ultimately contributing to improved safety and operational efficiency. However, if nodes exhibiting high values of betweenness centrality are not well handled they may become bottlenecks into the network.

Moreover, our analysis highlights the importance of considering human factors in system information management through the Technology Organization People (TOP) model. By integrating the TOP model with graph theory-based methods, we provide a comprehensive framework for understanding interactions within the information system, considering technological, organizational, and social aspects of complex systems. Our findings demonstrate that this approach can facilitate more informed data management decisions and data flow optimization, ultimately improving the performance and efficiency of nuclear facilities.

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