Final Report for (Project 18-15346) Big Data For Operation and Maintenance Cost Reduction

Prepared by

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1 Introduction

The purpose of this research is to develop a first-of-a-kind framework for integrating Big Data capability into the daily activities of our current fleet of nuclear power plants. Big Data is traditionally defined as data sets with high volume, velocity, and heterogeneity, and the existing Big Data analytics capabilities are now widely popular in fields such as finance, weather, e-commerce, healthcare and sports. In the nuclear industry, while the volume and velocity of data may present computational challenges for existing analytics capabilities, data heterogeneity are seen to present the major challenge. This research project mainly focuses on incorporating the wide range of data heterogeneities in nuclear power plants into an integrated Big Data Analytics capability. The primary end-product of this project is a Big Data framework that is capable of dealing with the large volume and heterogeneity of the data found in nuclear power plants to extract timely and valuable information on equipment performance. The framework can generate system insights that are actionable relations between measurable impacts and the corresponding maintenance action plans and enable optimization of plant operation and maintenance based on the extracted information. The developed framework is capable of handling heterogeneous data including both image data and time-series sensor data.

Specifically, this developed framework includes the following components. The first component is an overarching maintenance ontology (see Section 2) which includes system insights required by maintenance optimization. The maintenance ontology interacts with other components in the developed framework. The second component (see Section 3) handles Piping & Instrumentation Diagram (P&ID) data. It can be used to extract system components and their relations automatically from the P&IDs. This extracted information is stored in the first component, i.e., maintenance ontology, and is also used as input to the third component (see Section 4), i.e., a tool for generating the fault tree for the corresponding system. The generated fault tree in turn is stored in the ontology for assessing risk that is used as a criterion in maintenance policy optimization. The fourth component (see Section 6) is a tool for inferring the parameters in the Markov degradation model for a nuclear system. It uses basic information from the ontology. The fifth component (see Section 8) is a tool for assessing the degradation level using sensor measurement data, for example, pressure, flowrate. This tool can be used for determining corrective maintenance actions. The results obtained from components four and five are returned to the ontology. The sixth component of the framework (see Section 10) is a tool for optimizing the maintenance policy for a nuclear system of interest. It takes certain basic information from the ontology, e.g., costs of maintenance actions and system failures, as input, and returns the optimal maintenance policy to the ontology. This tool can be used for determining predictive maintenance actions.

A set of experiments have also been conducted to verify the algorithms developed in this project for nuclear system degradation monitoring. The experiments are based on four solenoid valves, similar to the ones used in nuclear power plants (see Section 7). The analyses based on the experimental data using two algorithms, i.e., the Randomized Window Decomposition (RWD) algorithm and the particle filtering algorithm, and the results are provided in Sections 8 and 9, respectively.

The Big Data framework developed in this project can be used as a support tool in daily activities of plant operation and maintenance and will reduce current costs while maintaining or improving safety levels. Overall, the project will not only benefit existing reactors, however it will open new frontiers to realize the long overdue value of Big Data Analytics in the nuclear sphere.

2 Maintenance Ontology

The maintenance ontology is a superset of concepts and constraints regarding maintenance activities applied to industrial systems, modeling and recording important factors (e.g., failure rate, cost, etc.) during system operations and outages. The framework provides information to answer the competency questions[1], such as what the most efficient applicable maintenance activities are to lower the risks of the target system/component, what the most critical component or sub-component of the target system/component is by considering maintenance costs and times, what the maintenance activities that can be removed are without increasing risks, etc.

The development of the proposed maintenance ontology follows the principles of development of ontologies with seven steps[2]. 1) Determine the domain and scope of the ontology. 2) Consider reusing existing ontologies. 3) Enumerate important terms in the ontology. 4) Define the classes and the class hierarchy. 5) Define the properties of classes. 6) Define the facets of the properties. 7) Create instances.

The final maintenance ontology includes six views that categorize the ontological concepts, their properties, and related axioms. These views include a) Component View, which models the structures of systems and components (SSC); b) Failure View, which contains the failure modes and their causes; c) Maintenance Activity View, which includes maintenance activities, goals, maintenance strategies, etc.; e) Monitoring View, which defines sensors, measures, alarms; f) Risk View, which defines risk assessment methods, hazards, the severity of consequences; g) Decision-Making View, which defines decision-making criteria and calls decision-making algorithms.

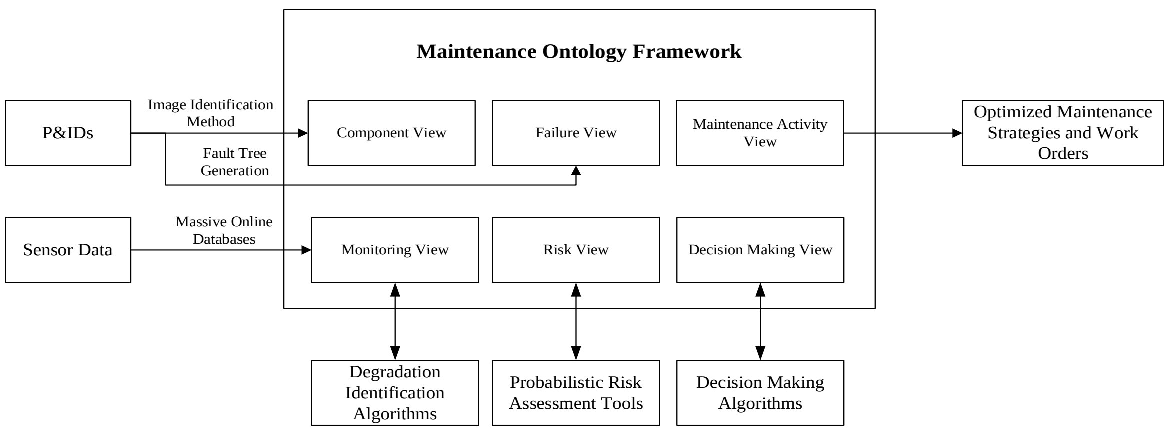

Figure 1 Overview of relations between the maintenance ontology framework and external elements

The maintenance ontology framework is the center of information required by maintenance optimization. Figure 1 illustrates the essential views of the maintenance ontology framework with their related external tools or elements. In detail, the component view utilizes the P&IDs of the target system to extract system components and their relations by applying image identification methods. The failure view can obtain the fault trees for the target system by employing the fault tree generation method. The monitoring view reads data from massive online databases for the real-time data sampled by sensors during the system operation. Meanwhile, the monitoring view transfers the sampled data to degradation identification tools for discovering the state of system components, which can be nominal or degraded. Based on the discovered states, the risk view can evaluate the potential risks of the target system by interacting with external Probabilistic Risk Assessment (PRA) tools. Finally, based on the predicted risks and the available

[1] Grüninger M, Fox MS, Gruninger M. Methodology for the Design and Evaluation of Ontologies. Int Jt Conf Artif Intel (IJCAI95), Work Basic Ontol Issues Knowl Shar 1995:1–10.

[2] Noy N, Mcguinness DL. Ontology Development 101: A guide to creating your first ontology. Sustain 2017;9:1–25. https://doi.org/10.3390/su9122317.

maintenance activities (provided by the maintenance activity view), the decision-making view calls predefined decision-making algorithms to select the optimal maintenance strategy and establish the corresponding work orders.

Further details on this research can be found in Appendix A.

3 P&ID Information Extraction

This work is presented in a detailed manner in the paper titled "Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks." The paper has been published in the journal of Progress in Nuclear Energy as a copyrighted document[3]. Please refer to this paper for more details.

Piping and Instrumentation Diagrams (P&IDs) are one of the most commonly used drawings to describe components and their relationships in nuclear power plants. P&IDs constitute an important data source in various applications. They provide the necessary information to understand the basic structure of a plant in safety analysis and operation and maintenance decision-making. To use P&IDs, the first step is to extract the information from these diagrams. Specifically, such information includes the components in a P&ID, the type, location, and description of each component, and the relations between the components. Traditionally, P&IDs are manually examined by human analysts to extract such information. This process is time-consuming and also error-prone. Recent advances in machine learning, in particular computer vision, provide unique opportunities to make this process automatic. In this research, we investigated automatic information extraction from P&IDs for nuclear power plants based on machine learning techniques.

The method we developed consists of three components. The first component is objection detection. It identifies the type and location of each component in a P&ID, for example, a motor valve and a bounding box that locates the valve. The second component is text detection. It identifies the text that describes each component, for example, the identification number of a motor valve. The third component is component connection. It builds a library that describes the relations between the components, for example, which components are connected to a pipe.

Object detection is the main component of the method and is realized based on a machine learning technique called faster region-based convolutional neural networks (FRCNN)[4]. A FRCNN model is comprised of two major parts. The first part is a backbone and a regional proposal network (RPN). The backbone is simply a convolutional neural network. In this research, we used ResNet-50[5]. It takes an original image as input and outputs the feature map for this image. The backbone is connected to the RPN. The RPN is used to generate a number of regional proposals, or regions of interest. A regional proposal is simply a bounding box that may be an object we are interested in. The regional proposals are then used as inputs to the head of the FRCNN model to finally classify an object and identify its location. The head is also a neural network. It uses a box-classification layer to identify the class of the objects and a box-regression layer to determine the coordinates of the objects. Though well-trained FRCNN models for common objects (e.g., cats, dogs) exist, there is no such model for P&IDs. Therefore, in this research, we retrained existing models for common objects to adapt them to P&IDs.

Text detection is realized based on a natural language processing technique called SegLink[6]. The basic idea of SegLink is to break down the long text into two smaller pieces and then combine the detection results of the two smaller pieces to obtain the detection for the original text. The detection result is in the form of letters in the original text and a bounding box for the location of the text. Well-trained SegLink models exist, but these models are only applicable to horizontal text. These models were not intended for vertical

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[3] Gao, W., Zhao, Y. and Smidts, C., 2020. Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks. *Progress in Nuclear Energy*, *128*, p.103491.

[4] Ren, S., He, K., Girshick, R. and Sun, J., 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems* (pp. 91-99).

[5] He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

[6] Shi, B., Bai, X. and Belongie, S., 2017. Detecting oriented text in natural images by linking segments. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 2550-2558).

or upside-down text, which often appears in P&IDs. This problem is addressed by first rotating the original image three times, then performing text detection using an existing SegLink model, and lastly combining the detection results of all four images. The idea is that the horizontal text would appear in at least one of the four images.

Object detection and text detection result in bounding boxes for both objects and text. Based on this result, we can then identify the relations between the objects and text and connect all these single pieces. This can be simply done by checking whether two bounding boxes overlap with each other. If two bounding boxes overlap with each other, we connect the corresponding object or text. This information is stored in a library. This library is a list of dictionaries. We set the key of each dictionary to be each pipe and a nested dictionary to be the value of each dictionary. The nested dictionary is a list of components that are connected to each pipe. It also contains information about the class and text description of each component. Each dictionary can also have an inlet value and outlet value, corresponding to the upstream pipe and downstream pipe, if any.

Due to proprietary restrictions, we demonstrated the proposed method on publicly available data. Specifically, we used 68 P&IDs in the AP1000 design control documents[7]. Since we need to retain the FRCNN model, we need to prepare the training dataset. Specifically, we need to label the components in the P&IDs and create the bounding box for each component. Compared with regular object detection in computer vision, this dataset is relatively small. To increase this dataset, we have introduced a number of augmentation techniques, including resizing, rotation, and cropping of the original images. These measures helped us to increase the dataset to 8608 images. We labeled these images and split these images into three datasets: 7756 images for training, 428 images for validation, and 424 images for testing. There are 27 classes in total in the dataset. The performance of the model is measured using average precision (AP), which is a combination of precision and recall. Precision is the ratio of true positive to the sum of true positive and false positive. Recall is the ratio of true positive to the sum of true positive and false negative. Average precision is the area under the recall-precision curve. In the application to the AP1000 P&IDs, we were able to achieve a mean AP over small components of 95.29%, a mean AP over large components of 98%, and a mean AP over thin components of 92%. We have also performed sensitivity analysis to identify factors that may affect the training time and performance of the model, for example, the scaling factors and optimization algorithm. For component connection, our method successfully mapped text to components in 117 out of 120 cases, and components to pipes in all 319 cases.

Further details on this research can be found in Appendix B.

[7] Westinghouse Electric Company LLC, 2011. AP1000 Design Control Document No. APP-GW-GL-700, Rev. 19 (downloaded from the NRC website).

4 Fault Tree Generation

This work is presented in a detailed manner in the paper titled "Fault Tree Generation from P&IDs Using Deep Learning." The paper has been published in the International Topical Meeting on Probabilistic Safety Assessment and Analysis 2021 (PSA 2021) as a copyrighted document[8]. Please refer to this paper for more details.

Fault tree generation is an inference-based method for directly extracting system structure information from the Piping and Instrumentation diagrams (P&IDs) using the deep learning technique presented in Section 3 and to construct the fault tree for the target system automatically. To check the consistency of the generated fault trees, an algorithm based on Boolean logic expressions and logical reductions is developed. The proposed method reduces the amount of effort required in the manual extraction of the information from the P&IDs and reduces potential human errors that may occur during fault tree constructions.

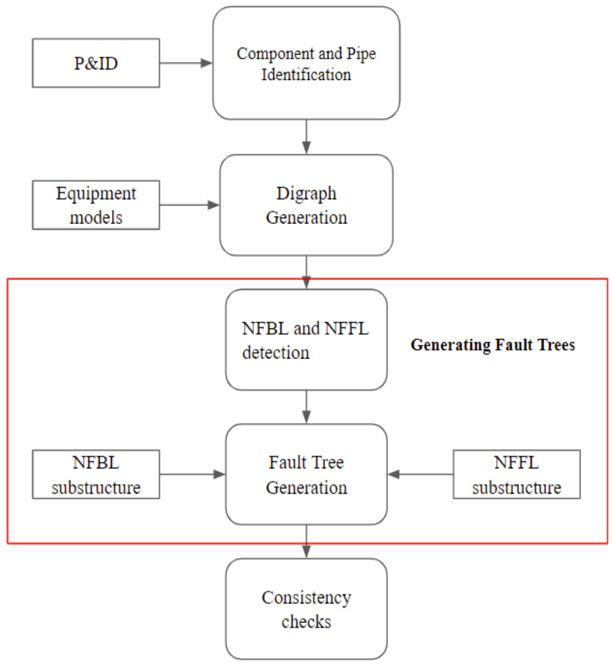

Figure 2 Fault Tree Construction Process[8]

The method for generating a fault tree from the P&ID diagrams can be broken down into various phases. Figure 2 displays the critical phases involved in the proposed method, including the process for negative feedback loops (NFBL) or negative feedforward loops (NFFL) detection, which widely exist in modern control systems and complicate the inference process for fault tree construction. The mentioned phases are detailed below.

Component and Pipe Identification reads the P&ID, identifies different components, and models the relationship between them. This task reuses the F-RCNN based object detection model developed in previous research[9] to classify and localize different components and their connections from the P&IDs (see Section 3).

Digraph Generation models the interactions between the process variables in the form of digraphs.

Fault Tree Generation uses predefined equipment models and templates to automatically infer the fault tree structure.

- **Detecting Control Loops** is an essential step to identify the Negative Feedback Loops (NFBL) and Negative Feedforward Loops (NFFL) in the target system. A cycle detection algorithm using depth-first search (DFS) with a recursion stack is developed to detect NFBLs. Another DFS based algorithm is used to find NFFLs.

[8] Thik, J., Diao, X., Vaddi, P.K., and Smidts, C., 2021. Fault Tree Generation from P&IDs Using Deep Learning. International Topical Meeting on Probabilistic Safety Assessment and Analysis 2021 (PSA 2021).

[9] Gao W, Zhao Y, Smidts C. Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks. Prog Nucl Energy 2020;128. https://doi.org/10.1016/j.pnucene.2020.103491.

- The **Fault Tree Generation** process builds the fault trees for NFBLs and NFFLs by applying predefined templates[10] to the target system. The templates include the deviations (aka a disturbance) of the process variables controlled by NFBLs and NFFLs, which is generally caused by the disturbance that propagates through loop paths while the controller failed to cancel that disturbance.

The **Consistency Checks** step uses the Boolean logic reduction method to detect contradictions and simplify fault tree structures. This is implemented by first reducing the leaf nodes of the generated fault tree using Boolean reduction functions provided by programming languages, and then using the reduced partial tree as a result and moving up the fault tree structure. If the result of such reduction is "False", it indicates that there is an inconsistency detected, and the branch involving that particular event should not be developed further.

Further details on this research can be found in Appendix C.

[10] Lapp SA, Powers GJ. Computer-aided synthesis of fault-trees. IEEE Trans Reliab 1977;26:2–13.

5 Randomized Window Decomposition and Its Application on Degradation Problems

As the industrial control system embraces the digital age, the rapid increase of available sensor data has prompted the development of modern condition monitoring techniques to realize many benefits, including predictive maintenance, anomaly, or degradation detection, etc., to improve efficiency, promote safety, and optimize economy. To exploit this data availability, a category of condition monitoring methods, known as data-driven techniques, has emerged at the same time as the rising digitalization. Data-driven methods are able to process raw sensor data in search of patterns and to extract features without the inclusion of first-principle models. Therefore data-driven methods have been widely adopted. Specifically, data-driven methods extract patterns contained in the raw data, which can be recognized as dominant/regular patterns and residuals, denoted as low-order components (LOCs) and high order components (HOCs) respectively, borrowing the terminology from linear algebra. The regular pattern represents the structured variations in the data, considered to represent normal behavior and the remaining residuals are usually considered as uncertainties or noises. For example, the LOCs can manifest as a linear or a certain type of trend, while the HOCs may manifest as higher-order terms or noise. Studies focusing on employing LOCs for condition monitoring or anomaly detection have been conducted for abrupt state changes[11,12,13,14], such as components failures, accidents or patterned anomalies, and have been proved to be effective. On the other hand, the LOCs may not be effective for the detection of subtle state changes /minor anomalies until a critical threshold is reached[15], such as components degradation/aging. To address this issue, HOCs that are usually omitted in the learning process, can be employed to capture subtle variations. One implementation of this idea with adaptation to the condition monitoring of a system or its components is randomized window decomposition (RWD). RWD gathers snapshots of sensor readings into a matrix and decomposes this matrix into LOCs and HOCs, based on which a series of features can be constructed. Then a feature selection and feature fusion can be conducted per application to amplify the subtle discrepancy resulting from the component degradation. Here in this project, equipped with labeled data from different stages of valve degradation, RWD serves as an analysis tool to provide a metric to quantify the valve degradation together with the hydraulic condition degradation.

Further details can be found in Appendix D.

[11] W. Wang, F. di Maio, and E. Zio, “A Non-Parametric Cumulative Sum Approach for Online Diagnostics of Cyber Attacks to Nuclear Power Plants”, In *Resilience of Cyber-Physical Systems* (pp. 195-228). Springer, Cham.

[12] Shannon L. Eggers, “Adapting Anomaly Detection Techniques for Online Intrusion Detection in Nuclear Facilities,” 2018.

[13] H. L. Gawand, A. K. Bhattacharjee, and K. Roy, “Securing a Cyber Physical System in Nuclear Power Plants Using Least Square Approximation and Computational Geometric Approach,” *Nuclear Engineering and Technology*, vol. 49, no. 3, pp. 484–494, 2017, doi: 10.1016/j.net.2016.10.009.

[14] F. Zhang and J. B. Coble, “Robust localized cyber-attack detection for key equipment in nuclear power plants,” *Progress in Nuclear Energy*, vol. 128, no. July, p. 103446, 2020, doi: 10.1016/j.pnucene.2020.103446.

[15] R. L. Boring, K. D. Thomas, T. A. Ulrich, and R. T. Lew, “Computerized Operator Support Systems to Aid Decision Making in Nuclear Power Plants,” *Procedia Manufacturing*, vol. 3, no. Ahfe, pp. 5261–5268, 2015, doi: 10.1016/j.promfg.2015.07.604.

6 Nuclear Power Plant System Degradation Model Parameter Inference

This work is presented in a detailed manner in the paper titled "Sequential Bayesian inference of transition rates in the hidden Markov model for multi-state system degradation." The paper has been published in the journal of Reliability Engineering & System Safety as a copyrighted document[16]. Please refer to this paper for more details.

A better understanding of nuclear power plant system degradation certainly can improve decision-making in maintenance. A mismatch between the system degradation model and the actual system degradation may lead to off-optimal decisions, for example, too early overhaul when the system is still operating in an excellent condition or too late repair when the system actually has degraded severely. The latter case will result in system failure and the consequence may be costly. In contrast to binary states usually considered in reliability engineering, a nuclear system may undergo different levels of degradation before system failure. Markov models have been widely used to describe such multi-state degradation behavior. Specifically, the transition rates in the transition matrix in a Markov model describe quantitatively how a system degrades from the operating state through various degradation states to the failure state. Also note that a system is usually partially observable. That is, there is no way of observing the actual state directly, but we can use sensors to infer the actual system state. All these aspects amount to a hidden Markov model for partially observable multi-state system degradation. The objective is then to infer the transition matrix in the Markov chain based on observations.

Traditionally, there are two main classes of methods for transition rate inference. The first group of methods is based on the frequentist view and obtains a point estimate of each transition rate based on, for example, maximum likelihood estimation. The second group of methods is based on the Bayesian view and obtains the posterior distribution of the transition rates. The advantage of the second group over the first group is that it provides an easy way to model the uncertainty in the inference. Bayesian methods have been applied to transition rate inference in various areas. They rely on the prior distribution of the transition rates and the likelihood function to obtain the posterior distribution of the transition rates. In general, it is hard to obtain the closed form solution of the posterior distribution. In this case, approximate methods, for example, Markov chain Monte Carlo methods, can be used to draw samples from the posterior distribution.

In existing applications, Bayesian methods have been used in a batch-processing fashion. That is, the inference of transition rates is performed based on a fixed set of observations. Note that in real applications, such observations would be collected sequentially. With more observations, the computation time in the Bayesian analysis increases almost linearly. This is a major limitation of existing batch-processing Bayesian methods.

In this research, we proposed a novel Bayesian method for inferring transition rates in a hidden Markov model. The most promising feature of this new method is that it can be performed sequentially as observations are collected sequentially. In this way, the computation time remains almost constant every time the Bayesian analysis is performed. This significantly reduces the computation time compared with batch-processing methods, where the computation time increases almost linearly with the number of observations. It also shows advantages over existing sequential Monte Carlo or particle filtering algorithms in reducing the space of parameters to be inferred.

We have performed a case study to demonstrate this sequential Bayesian algorithm using a pump system used in nuclear power plants. Besides the operating and failure states, we consider two degradation states in modeling pump degradation, i.e., moderately degraded and severely degraded. In the hidden Markov model, there are six unknown transition rates, corresponding to transitions from less degraded states to

[16] Zhao, Y., Gao, W. and Smidts, C., 2021. Sequential Bayesian inference of transition rates in the hidden Markov model for multi-state system degradation. *Reliability Engineering & System Safety*, *214*, p.107662.

more degraded states. We generated synthetic data in the case study since a real-world dataset is unavailable. Specifically, we set true values for the transition rates and performed Monte Carlo simulation to obtain system state transition trajectories and observations. The result of the sequential Bayesian analysis shows that the posterior distributions of all six transition rates become closer to their true values. This result is also verified by the result obtained based on the Metropolis-Hastings algorithm, which however is performed in a batch-processing fashion.

Further details on this research can be found in Appendix E.

7 Experiment and Data Collection

In this research project, our team has developed a set of algorithms for nuclear power plant system degradation monitoring and degradation model identification. A set of experiments involving solenoid operated proportional flow control valves were developed and useful experimental data were collected to test and validate these algorithms. Initially, spring degradation and damage of the rubber seal were the two modes of component degradation considered. However, during the experiments, it was also discovered that rust formed in the valves got washed away by the flow and was deposited in the filters which resulted in the deterioration of the performance of the system through a reduction in flowrate. As discussed in the design of experiments in Appendix F, the valves were operated continuously at maximum power in 3hrs sessions, followed by a step test i.e., a short test in which the valve input power was increased in increments of 2% from 0% to 100% and then reduced back to 0%. A manual inspection was performed on two valves at the end of every session in which, the valves were disassembled, the valve dimensions along with weight were measured, and reassembled. In addition, a photography based setup was used to measure the plunger stroke length at varying levels of input power.

The experiments were performed for a total of 32 sessions and the collected sensor measurements of flowrate, pressure, input current to the valves in each session, and the spring compression values measured at the end of every session were used to validate our proposed methods.

Further details on the experiment design and implementation, and data collection can be found in Appendix F. Analyses using the algorithms developed in this research project are performed and are introduced in Sections 8 and 9, respectively.

8 Randomized Window Decomposition for Valve Degradation Monitoring

Valve degradation or hydraulic condition deterioration problems usually manifest themselves as a gradual presence of decreased mechanical performance, including the loss of flow rate control, increased flow friction or insensitive response to actuators, etc. To identify the valve aging/degradation stages, representing a gradual change of component condition, one needs to detect subtle variations in the behavior of the loop in which the valve is located. In this section, a feature engineering method, randomized window decomposition (RWD) is used. RWD was originally proposed for subtle anomaly detection problems, showing that the system behavior under normal operation can be effectively characterized using certain features that can amplify the difference between the normal and subtly falsified data. Given the gradual state variation in degradation problems, RWD is adopted to characterize, identify, and quantify the degradation of the loop condition, especially the valve degradation. The rationale behind RWD is to construct features from both dominant and non dominant components of the signals being observed, denoted as low-order components (LOCs) and high-order components (HOCs) respectively. While abrupt changes may be identified using the LOCs alone, subtle changes to the data, such as degradations, are often hidden in the HOCs or in the fused features obtained from LOCs and HOCs. This screening of features is based on their sensitivity to variations; for example, pure noise or the dominant components that do not reflect the subtle variations will be omitted. This feature screening can pinpoint a series of feature candidates, and then enable further engineering-oriented analysis, such as classification, regression, or dimensionality reduction, etc.

In this project, two types of experiments are conducted to investigate the valve conditions:

(1) fully open sessions, in which the valves are fully opened for three hours to degrade the valves;

(2) step test sessions, in which the actuator of the valves is applied as a series of step functions to capture the valve characteristics after the 3-hour degradation that occurred during the fully open session.

For each type of experiment, an initial session is conducted to record the undegraded valve state.

The data from each fully open session is shown as a cloud of points representing the experimental uncertainty bounds. This cloud is then condensed to its mean for the measurements in the session. After completing this data processing for all datasets, linear analysis is applied to identify the flowrate control capability of each valve. Flowrate control capability represents an important indicator of valve degradation. For the step test experiment, the valve behaviors are recorded as time series. The RWD approach is applied on the initial step test data to extract features that characterize the valve behavior in pristine condition, and the features constructed from other sessions represent data associated to progressively increasing degradation levels. The discrepancies between the features from the initial step test and the subsequent step tests are calculated as another indicator/measure/metric for the valve degradation. The RWD results together with the causes of degradation in each session are analyzed to determine the evolution of the degradation when it originates from the loop or from the valve conditions respectively.

The results from the fully open session indicate the overall hydraulic conditions, including the valve degradation and the loop condition degradation. The results from the step test show that the RWD can outline the overall degradation behaviors. Further analysis shows that the filter change works as a more dominant factor for the improvement of the overall hydraulic condition than the valve aging; the valve degradation evolutions can be identified via features extracted by RWD.

Further details on this research can be found in Appendix G.

9 Valve Degradation Monitoring Using Experimental Data

In this section, we study the problem of valve degradation monitoring based on physics-informed stochastic degradation models and collected experimental data (see Section 7). This problem can be resolved via three steps: step 1, build a stochastic model for valve degradation; step 2, estimate the unknown parameters in the degradation model; and step 3, perform valve degradation monitoring based on the identified degradation model and collected experimental data.

We consider two types of valve degradation modes. The first degradation mode is rust growth in a valve. An increased amount of rust in a valve will degrade the performance of the filter in the water loop of the valve, which in turn affects the flowrate and pressure in the loop. The second degradation mode is the degradation of the spring in a valve. Increased spring degradation will affect the length of move of the plunger in a valve, or in other words, the opening of the valve, given the same amount of actuation current input to the valve.

An overview of the modeling of the two types of degradation modes is presented in the two illustrations in Figure 4. In Figure 4, X_1 and X_2 denote the amount of rust and spring degradation level, respectively. λ_1 and λ_2 denote the degradation rates for the types of degradation modes. The variables at the top of the two illustrations denote the measurements collected in the experiment. The illustrations in Figure 4 also describe the dependencies between the variables. For example, the left illustration indicates that the amount of rust at the current time in a valve is dependent on the amount at the previous time step as well as the current degradation rate. The models presented in Figure 4 are also capable of describing the probabilistic relations between the variables. For example, given a degradation level of the spring, i.e., X_2, there may be uncertainty in the measurement H.

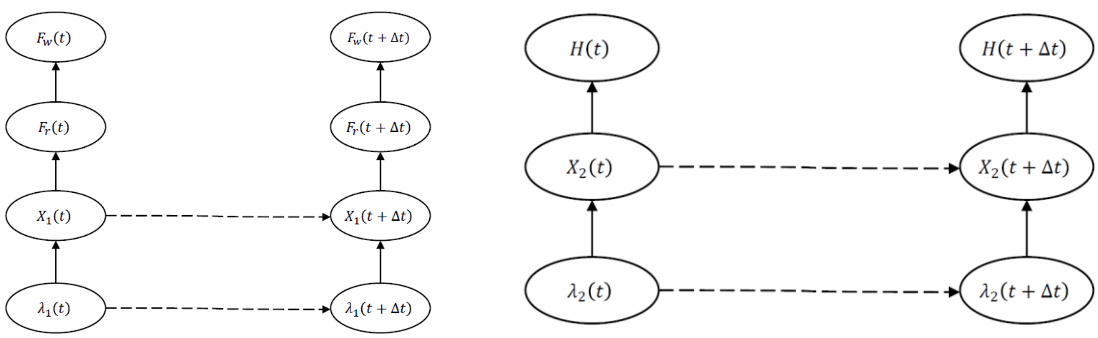

Figure 3. Overview of the modeling of rust growth (left) and spring degradation (right).

Certain parameters in the models for the two degradation modes that describe the probabilistic relations between variables may be unknown. So the second step in the research is to estimate the unknown parameters in each of the two degradation model using collected experimental data. Maximum likelihood estimates of the model parameters are considered in this research. Since closed forms of the maximum likelihood estimates usually do not exist, in this research we resort to approximate methods. Specifically, an expectation-maximization algorithm is designed to obtain the maximum likelihood estimates of the unknown model parameters.

Once the degradation model for each type of degradation mode is identified, then collected experimental data can be used to infer the degradation state, i.e., the amount of rust or the spring degradation level. A Bayesian algorithm, specifically a particle filtering algorithm is designed to achieve this. This algorithm is adapted from the one proposed in Section 6. The major change is to account for the continuous variables considered in this section rather than discrete variables considered in Section 6. In this algorithm, a number of sequences of samples of the degradation variables are drawn and each sequence of samples is assigned a weight that reflects the likelihood of measurements conditional on the sample values. Some of the inference results are presented in Figure 5.

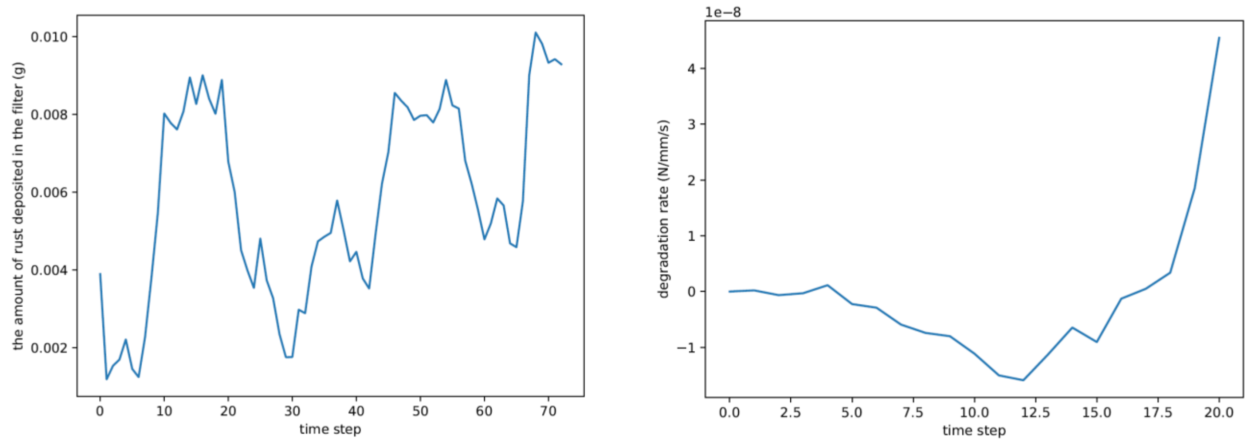

Figure 4. Inference results for the amount of rust (left) and spring degration level (right).

Further details on this research can be found in Appendix H.

10 Reinforcement Learning for Maintenance Optimization

This work is presented in a detailed manner in the paper titled "Reinforcement learning for adaptive maintenance policy optimization under imperfect knowledge of system degradation and partial observability of system states." The paper was submitted to the journal of Reliability Engineering & System Safety as a copyrighted document[17]. Please refer to this paper for more details.

In Sections 6-9, we proposed a set of algorithms for nuclear power plant system degradation monitoring and verified the algorithms using experimental data. Once the inference of the degradation level of a specific system is obtained, the remaining task to improve the maintenance program for nuclear systems based on the inference so that their maintenance expense is reduced. This fits into the larger effort in the nuclear industry to improve the economic competitiveness of nuclear energy compared to other energy sources, for example, natural gas.

The maintenance program for a nuclear system is largely dependent on the reliability model of the concerned nuclear system, or in other words, our knowledge of the nuclear system degradation process. In such maintenance programs, the trade-off between the cost of maintenance actions and the cost due to current and future system failures is considered. In current practices, the maintenance of a nuclear system is usually based on generic information of the system degradation process and is performed periodically. To improve the maintenance program for a nuclear system, one key step is to improve the knowledge of the system degradation process. The large set of system monitoring and inspection data collected in nuclear power plants provides a great opportunity to achieve this.

In the research introduced in this section, we propose a reinforcement learning method to address the maintenance optimization problem for nuclear systems with a Markov degradation process. This reinforcement learning method builds on the sequential Bayesian algorithm proposed in Section 6. The reinforcement learning approach consists of two components: learning and planning. Using sequentially collected monitoring or inspection data for a nuclear system, the learning component improves the knowledge of the system degradation process in terms of the probability distributions of the transition rates in the Markov degradation model based on sequential Bayesian inference. Compared with other Bayesian inference methods used in the field of maintenance optimization, the proposed one only relies on the immediate past inference result and the newly collected monitoring or inspection data. So the proposed sequential Bayesian inference algorithm can be performed in a sequential fashion, which is more computationally efficient. Using the updated transition rates, the maintenance policy optimization problem is then formulated as a partially observable Markov decision problem, and the planning component computes the optimal maintenance policy that maximizes the expected cumulative reward, or in other words, minimizes the expected cumulative cost. Such an optimal maintenance policy specifies, for example, whether the concerned nuclear system should be repaired or whether the system should be inspected in the next time step. The proposed reinforcement learning method iterates between the learning component and the planning component: the learning component provides the basis for the planning component, and the planning component collects necessary data for the learning component. It is also worth noting that in contrast to current practices of periodic maintenance, the proposed reinforcement learning method is adaptive since it adapts the maintenance policy based on the updated knowledge of the system degradation process. As a result, the overall maintenance cost can be reduced.

The proposed method is illustrated using a numerical example with repair and inspection maintenance actions. Part of the results is presented in Figure 6. The result shows that as more observations are collected, the learning component progressively learns the true system degradation process, and the planning

[17] Zhao, Y. and Smidts, C., 2021. Reinforcement learning for adaptive maintenance policy optimization under imperfect knowledge of system degradation and partial observability of system states. Submitted to *Reliability Engineering & System Safety*.

component adjusts the optimal maintenance policy accordingly as well, which leads to increased reward (decreased maintenance cost).

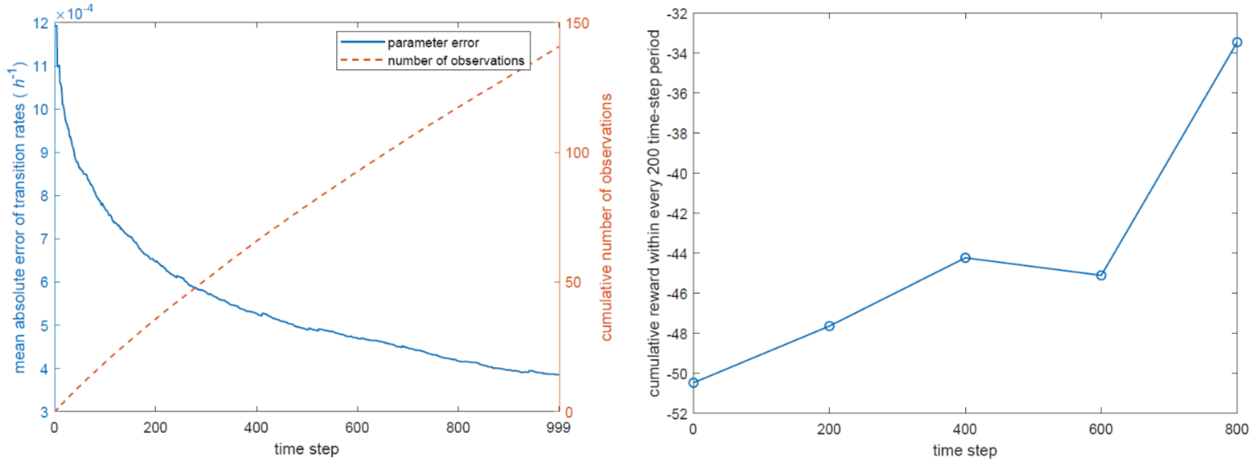

Figure 5. Part of the results for the reinforcement learning method.

Further details on this research can be found in Appendix I.

11 Conclusion and Future Work

This research developed a Big Data framework for integrating information about the daily activities of nuclear power plants to enable optimization of plant operation and maintenance based on the extracted information. Several tools, including the one for extracting component and structural information from P&IDs, the one automatically generating fault trees, and the one optimizing maintenance activities based on reinforcement learning technology were developed. The developed framework is verified using a solenoid valve.

The original contributions made in this project include: 1) development of a maintenance ontology that serves as an information management center and interacts with other constituent algorithms in the Big Data framework; 2) development of a neural network model for automated information extraction from Piping & Instrumentation Diagrams; 3) development of a Bayesian inference algorithm that can be performed in a sequential fashion and more computationally efficient; 4) development of a reinforcement learning algorithm for maintenance policy optimization that updates the degradation model and the maintenance policy for a concerned system concurrently; and 5) design and implementation of experiments to verify the algorithms developed in this project.

Future research in the following areas is expected to further improve the developed Big Data framework.

1. In the future, application interfaces for automating the interaction between the maintenance ontology and other tools developed in the Big Data framework should be developed.
2. For Piping & Instrumentation Diagram information extraction, methods for reducing the training time for building the neural network model and methods for incorporating a priori information in determining the relationships between detected nuclear components will be investigated.
3. For the fault tree generation, the use of multivalued logic solvers will be incorporated in future iterations of the research. Additionally, one of the limitations that only two variables can be considered at a time to generate the rules of the digraph should be solved.
4. For the sequential Bayesian inference algorithm, further research on parameter inference for more complex degradation models, for example, semi-Markov models, is warranted. Applications to larger sets of real-world data from nuclear power plants are also expected.
5. For the reinforcement learning algorithm, currently the focus is on one single system. In the future, research on joint optimization of maintenance actions for interdependent systems is warranted and is expected to lead to further reduction of maintenance cost.
6. For the overall Big Data framework, it is useful to apply the framework in a nuclear power plant, gather feedback from such uses, and improve the framework accordingly based on the feedback.
7. For the randomized window decomposition (RWD) algorithm, in this research the feature extraction focuses on a single or two variable(s), which may not be effective or efficient for a more complex system, such as a nuclear reactor or power plant. Therefore, a sophisticated version of RWD will be developed to adapt to complex models by extracting features across multiple sensors. Also, the metric of feature screening is based on the variation sensitivity, accomplished manually given a few variables of interest, which will not be feasible for complex models. To address that, an algorithm for automatic selection of the variation-sensitive features will be developed as well.

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Publications

Journal publications

1. Zhao, Y., Gao, W. and Smidts, C., 2021. Sequential Bayesian inference of transition rates in the hidden Markov model for multi-state system degradation. *Reliability Engineering & System Safety*, *214*, p.107662.
2. Gao, W., Zhao, Y. and Smidts, C., 2020. Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks. *Progress in Nuclear Energy*, *128*, p.103491.
3. Li, Y., Abdel-Khalik, H.S., Brunett, A.J., Jennings, E., Mui, T. and Hu, R., 2021. ROM-Based Surrogate Systems Modeling of EBR-II. *Nuclear Science and Engineering*, *195*(5), pp.520-537.
4. Zhao, Y., Smidts, C. Reinforcement learning for adaptive maintenance policy optimization under imperfect knowledge of system degradation and partial observability of system states. Submitted to *Reliability Engineering & System Safety* (under revision)

Conference publications

1. Thik, J., Diao, X., Vaddi, P.K., and Smidts, C., 2021. Fault Tree Generation from P&IDs Using Deep Learning. International Topical Meeting on Probabilistic Safety Assessment and Analysis 2021 (PSA 2021).
2. Sundaram, A., Li, Y. and Abdel-Khalik, H.S., 2021. A Multi-Level Feature Extraction and Denoising Approach to Detect Subtle Variations in Industrial Control Systems. The International Conference on Mathematics and Computational Methods Applied to Nuclear Science and Engineering (Mathematics & Computation (M&C) 2021).

Thesis

1. Thik, J., 2021. Fault Tree Generation from P&IDs Using Deep Learning, Master's thesis.

Presentations

1. "A Bayesian Analysis Framework for Multi-state Component Degradation Model Parameter Inference with Multi-source Uncertain Evidence," Big Data for Nuclear Power Plants Workshop 2019, December 10, 2019, Columbus, OH, USA. (Yunfei Zhao)
2. "Neural Network Based Component Detection in Piping and Instrumentation Diagrams for Nuclear Power Plants," Big Data for Nuclear Power Plants Workshop 2019, December 10, 2019, Columbus, OH, USA. (Wei Gao)

Appendix A. Maintenance Ontology

The paper for this research is being prepared.

Appendix B. P&ID Information Extraction

This work is presented in a detailed manner in the paper titled "Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks." The paper has been published in the journal of Progress in Nuclear Energy as a copyrighted document. Please refer to this paper for more details.

Appendix C. Fault Tree Generation

This work is presented in a detailed manner in the paper titled "Fault Tree Generation from P&IDs Using Deep Learning." The paper has been published in the International Topical Meeting on Probabilistic Safety Assessment and Analysis 2021 (PSA 2021) as a copyrighted document. Please refer to this paper for more details.

Appendix D. Randomized Window Decomposition and Its Application on Degradation Problems

This work is presented in a detailed manner in the paper titled "Real-time Monitoring for Detection of Adversarial Subtle Process Variations." The paper has been published in Nuclear Science and Engineering as a copyrighted document. Please refer to this paper for more details.

Appendix E. Nuclear Power Plant System Degradation Model Parameter Inference

This work is presented in a detailed manner in the paper titled "Sequential Bayesian inference of transition rates in the hidden Markov model for multi-state system degradation." The paper has been published in the journal of Reliability Engineering & System Safety as a copyrighted document. Please refer to this paper for more details.

Appendix F. Experiment and Data Collection

The paper for this research is being prepared.

Appendix G. Randomized Window Decomposition for Valve Degradation Monitoring

The paper for this research is being prepared.

Appendix H. Valve Degradation Monitoring Using Experimental Data

The paper for this research is being prepared.

Appendix I. Reinforcement Learning for Maintenance Optimization

This work is presented in a detailed manner in the paper titled "Reinforcement learning for adaptive maintenance policy optimization under imperfect knowledge of system degradation and partial observability of system states." The paper was submitted to the journal of Reliability Engineering & System Safety as a copyrighted document. Please refer to this paper for more details.