U.S. DEPARTMENT OF ENERGY | Office of NUCLEAR ENERGY

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Big Data For Operation and Maintenance Cost Reduction

Advanced Sensors and Instrumentation Annual Webinar

November 6, 2019

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Project Overview

- Goal and Objective
  - This project will develop a first-of-a-kind framework for integrating Big Data capability into the daily activities of our current fleet of nuclear power plants.
- Participants (2019)
  - Carol Smidts, PI, Ohio State University
  - Marat Khafizov, Co-PI, Ohio State University
  - Hany Abdel-Khalik, Co-PI, Purdue University
  - Eric Helm, Co-PI, Framatome
  - Vaibhav Yadav, Co-PI, Idaho National Laboratory
  - Alexandra Zelaski, Collaborator, First Energy

Project Overview

- Schedule

Task	Finish Date
Identifying available data	1/31/2019
Knowledge extraction	11/30/2020
Building and reasoning with the domain ontology	11/30/2020
Developing plans	11/30/2020
Review and make decisions	3/31/2021
Prototype tool development	3/31/2021
Case study	9/30/2021

Accomplishments

- Milestone
  - Identifying available data (1/31/2019)
    - Visited nuclear power plant, and talked to their operation and maintenance staff
    - The data that will be used in the project include system configuration diagrams, free text reports (e.g. inspection, maintenance, testing), sensor data, and the PRA model
    - Due to export control issues, we are working with First Energy to sanitize the original data and use the sanitized data in the project

Accomplishments

- Research progress
  - Piping and Instrumentation Diagram (P&ID) object detection
    - Detect objects (e.g. valve, pump), text, and their relations in P&IDs
  - Bayesian analysis for component degradation model inference
    - Update model parameters with multi-source uncertain evidence
    - Will support component evolution prediction and hence maintenance optimization
  - Pump degradation classification
    - Classify different levels of pump degradation with sensor data
    - Will support real-time component state diagnostics

Accomplishments

- Component detection for Piping and Instrumentation Diagram (P&ID)
  - Purpose: to automatically develop the knowledge of components relations
  - P&IDs are the most commonly used engineering drawings to describe components and their relationships.
  - One of the most important inputs for data analysis in Nuclear Power Plants (NPP)
  - Traditional analysis extracts the information manually from the P&IDs, which usually takes large amounts of efforts and is error prone.

Accomplishments

- Component detection for Piping and Instrumentation Diagram (P&ID)
  - Detection Method

Data Preparation

- Data Source: DCD
- Data Grouping
- Label Images
- Data Augmentation
- Split Datasets

Detection

- Faster RCNN
- Hyperparameters Configuration
- Component Detection
- Text Detection

Association

- Map text to component
- Connect components to pipes

Accomplishments

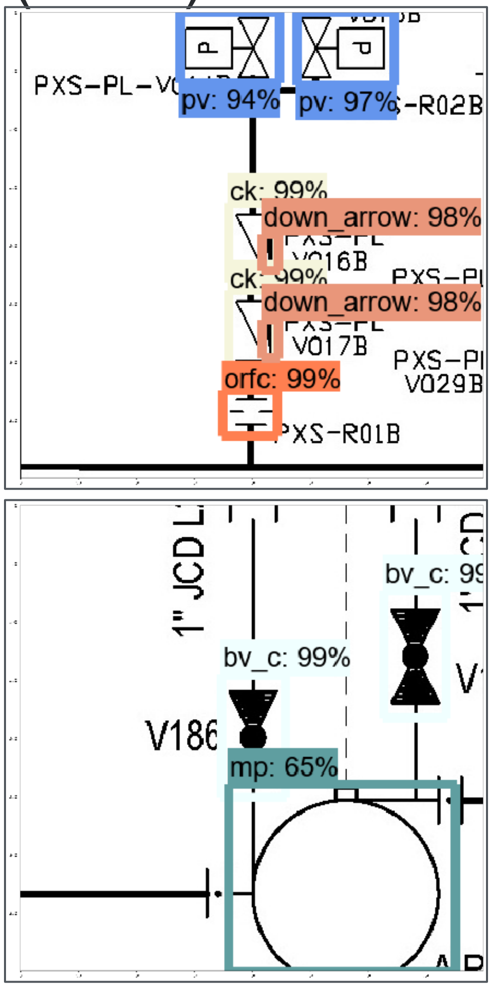
- Component detection for Piping and Instrumentation Diagram (P&ID)
  - Detection Results

Class #	Class Name	Precision (%)	Class #	Class Name	Precision (%)
1	butterfly Valve (open)	97.5	13	orifice	95.9
2	butterfly Valve (closed)	100	14	pneumatic valve (open)	99.6
3	ball valve (open)	99.7	15	pneumatic valve (closed)	100
4	ball valve (closed)	97.9	16	relief valve (open)	100
5	check valve	99.9	17	relief valve (closed)	98.8
6	flow control valve (open)	100	18	squib valve	100
7	flow control valve (closed)	100	19	solenoid valve (open)	100
8	heat exchanger	89.9	20	solenoid valve (closed)	100
9	manual valve	100	21	tank	74.5
10	motor pump	95.0	22	steam generator	98
11	motor valve (open)	93.8	23	pipe	92
12	motor valve (closed)	100			

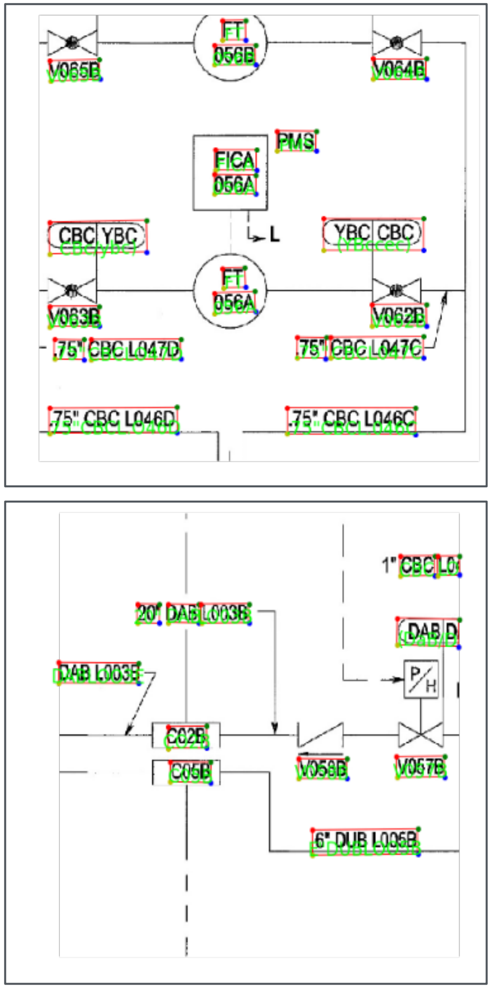
Accomplishments

- Component detection for Piping and Instrumentation Diagram (P&ID)

Component detection results



Text detection results

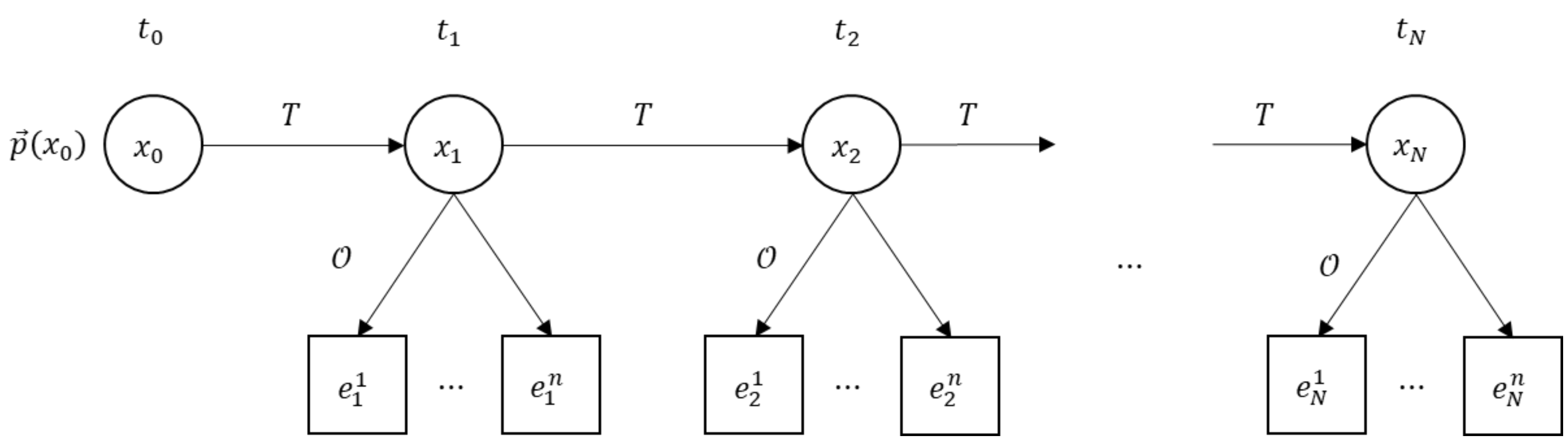


Accomplishments

- Component detection for Piping and Instrumentation Diagram (P&ID)
  – Several software modules were developed to facilitate data preparation and batch detection.
  – A paper regarding this research is being prepared.

Accomplishments

- Bayesian analysis for degradation model inference
  - We model component degradation and state observation as a hidden Markov process
    - The component can be in multiple states from normal to failed
    - The evidence can be from multiple sources and may be uncertain



t_0 - the time at the beginning
t_k - the time of the kth inspection
x_k- component state at t_k
T - transition intensity matrix
e_k^j - evidence from source j at t_k

$\mathcal{O}$ – observation probability
N – number of inspections
n – number of evidence sources
$\vec{p}(x_0)$ – the component state probability distribution at the beginning

Accomplishments

- Bayesian analysis for degradation model inference
  - Specifically, the component degradation can be modeled as

$$\frac{d\vec{p}(t)}{dt} = T\vec{p}(t),$$

where T is the transition intensity matrix,

$$T = \begin{bmatrix} -\sum_{j=2}^{m}\lambda_{1,j} & 0 & \cdots & 0 & 0 \\ \lambda_{1,2} & -\sum_{j=3}^{m}\lambda_{2,j} & \cdots & 0 & 0 \\ \lambda_{1,3} & \lambda_{2,3} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \lambda_{1,m} & \lambda_{2,m} & \cdots & \lambda_{m-1,m} & 0 \end{bmatrix}.$$

Accomplishments

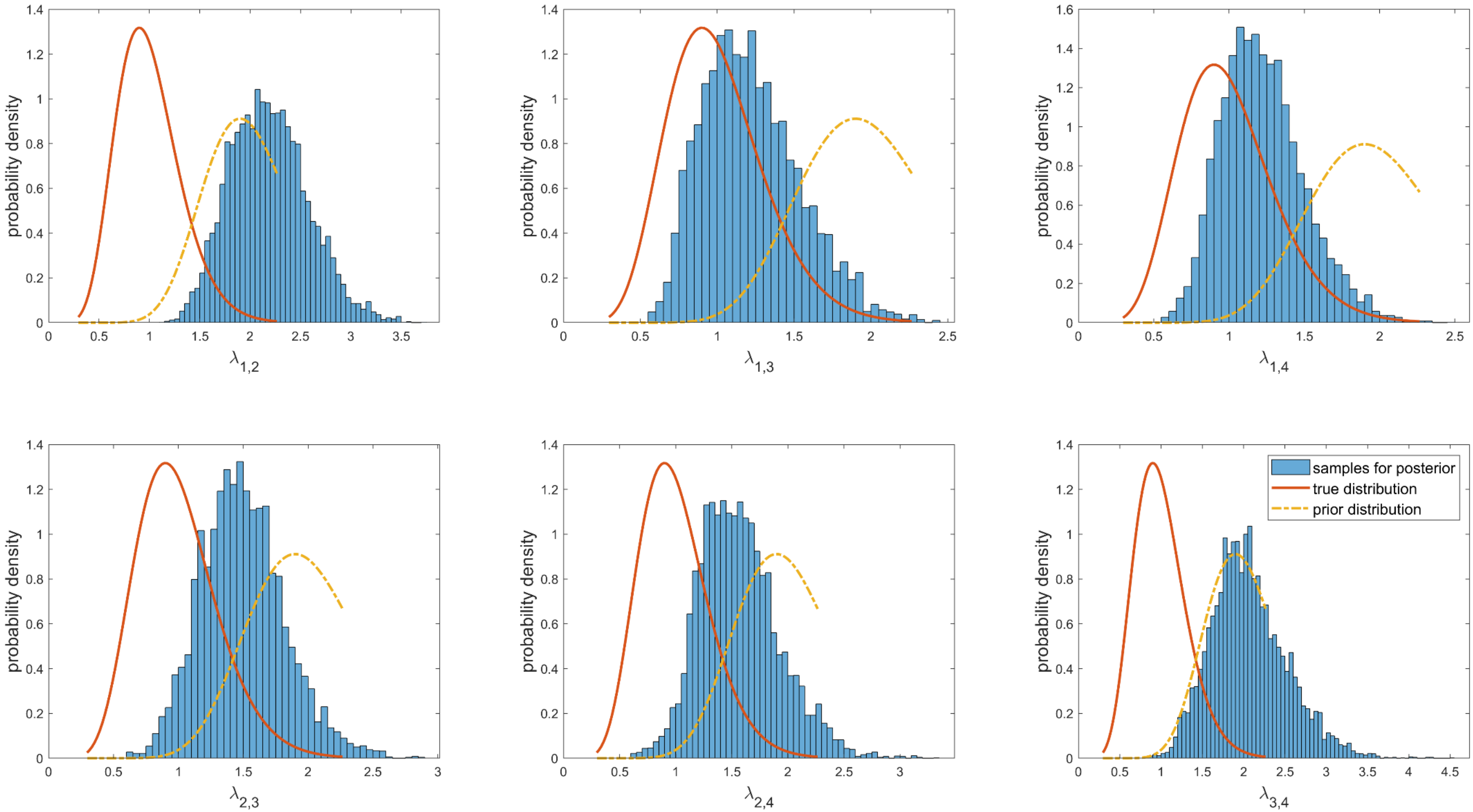
- Bayesian analysis for degradation model inference
  - We have some prior belief, $p(\lambda)$, about model parameters λ
  - We have collected evidence e from different sources
  - Then, the objective is the update our belief about model parameters using the collected evidence
  - In the Bayesian analysis formulation, this is to obtain

$$p(\lambda|e) = \frac{p(\lambda)p(e|\lambda)}{p(e)}.$$

    - $p(\lambda|e)$ - the posterior distribution of λ given evidence e
    - $p(e|\lambda)$ - likelihood function
  - For arbitrary prior distributions and likelihood functions, Markov chain Monte Carlo methods can be used to obtain the posterior distribution

Accomplishments

- Bayesian analysis for degradation model inference
  - A simple case study



Technology Impact

- The Big Data framework will allow plant management to leverage the rich data available in nuclear power plants to monitor plant state in a timely manner and optimize plant management while maintaining the risk at an acceptable level and reducing operation and maintenance cost significantly.
- This research extends the application of big data analytics to the nuclear energy sector. This will help identify and resolve unique challenges faced by this particular application, which will in turn supplement the base of knowledge and theory of big data analytics.

Conclusion

- The rapid development in computer vision enables us to use deep learning techniques to detect symbols in P&IDs with better precisions than ever before. The detection results are very promising.
- A Bayesian analysis framework for multi-state component degradation model parameter inference with multi-source uncertain evidence was developed, and demonstrated using a simple case study.
- A method for classifying different levels of pump degradation was developed.

Conclusion

- We have submitted two abstracts to the Big Data Analytics for Nuclear Power Plants special issue in Progress in Nuclear Energy and the Big Data for Nuclear Power Plants Workshop 2019
  - Component Detection in Piping and Instrumentation Diagrams of Nuclear Power Plants Based on Neural Networks
  - A Bayesian analysis framework for multi-state component degradation model parameter inference with multi-source uncertain evidence

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