



Advanced Sensors and Instrumentation

## Advanced Online Monitoring and Diagnostic Technologies for Nuclear Plant Management, Operation, and Maintenance

Advanced Sensors and Instrumentation (ASI) Annual Program Webinar October 24 – 27, 2022

### Daniel G. Cole, Ph.D., P.E.

University of Pittsburgh, Pittsburgh, Pennsylvania

## Goal: To develop and demonstrate advanced online monitoring to better manage nuclear plant assets, operation, and maintenance





Heng Ban (Pitt)



Vivek Agarwal (INL)

Integrating condition monitoring, supply chain analytics, and decision making, we can improve asset-management for nuclear O&M



This research provides an integrated approach for long-term decision-making for plant operation

Utilities would be better able to manage plant O&M

Minimize staffing levels with real financial impact.

The asset management analysis will support decision-making for

- SSC replacement and asset management
- supply chain, resource availability, and outage planning
- license extension for long-term operation

By better accounting for obsolescence and replacement in financial decision-making, utilities can optimize costs.

The proposed technology can be applied to different reactor designs or fuel cycle applications.

### The objective is to extract contact force at the radial key using neutron-noise data



The interaction of the core-barrel and radial key is a feedback process. We can link known vibration models with data to estimate the contact force model.



## Machine learning and Kalman filter approaches struggle to estimate contact force behavior for a PWR's internals





7

## The accuracy of each method's parameter estimates depends on the dataset

Dataset	Contact Parameter	True Value	ML Estimate	KF Estimate	Ratio of ML Est. to Truth	Ratio of KF Est. to Truth
Case 1	α	100	268	487	2.68	4.87
	β	10.0	5.18	70.6	0.518	7.06
Case 2	α	31.6 164 480		480	5.19	15.2
	β	316	10.0	69.7	0.0316	0.221
Case 3	α	490 100 665		665	0.204	1.36
	β	70.0	3.83	108	0.0547	1.54
Case 4	α	660	178	718	0.270	1.09
	β	110	3.83	125	0.0348	1.14

# Using deep reinforcement learning, we can train a decision-maker to reduce overall costs



#### **Deep Reinforcement Learning (DRL):**

- Two major components:
  - Environment
  - Agent (decision-maker)
- Learns through trial-and-error
- Maximizes expected long-term reward

#### Go (Google DeepMind)

Agent

Policy,  $\pi(s, a)$ 

Environment

POMDP





Action,  $a_t$ 



## The circulating water system (CWS) pump reliability and maintenance are the environment



## The generalized renewal process model fits the repairable system data better than MTBF

#### **Generalized Repair Process (GRP)**



Parameter	$\mathbf{RP}$	NHPP	GRP (Type II)
$\lambda$	0.1724	0.0800	0.0780
eta	1.38	1.71	1.80
q	0	1	0.642
Log-likelihood	-38.22	-37.08	-36.90

### Mean Cumulative Number of Events



The last part of the environment is creating the observation vector, actions, and rewards

#### **Observations**

<b>┌</b> 1.	Phase
2.	Degradation
Component $-3$ .	Virtual age
4.	In_repair (flag)
<b>└</b> 5.	In_replace (flag)
┌ 6.	Number of inventory
Inventory $\neg$ 7.	Leadtime
L 8.	Inventory (flag)
<b>∽ 9</b> .	In_outage (flag)
Outage - 10	. Time to next outage
L 11	. Time to startup

#### <u>Actions</u>

Action	Maintenance	Inventory
1	Do nothing	Do nothing
2	Do nothing	Order spare
3	Repair	Do nothing
4	Repair	Order spare
5	Replace	Do nothing
6	Replace	Order spare

#### **Rewards**

•	Forgone revenue	=	\$3,127
•	Hourly labor	=	\$100
•	Hourly materials	=	\$333
•	<b>Replacement cost</b>	=	\$500,000

## A trained neural network model can react to changes in the component condition, optimizing long-term rewards



Condition monitoring can be challenging, and success can be problem dependent. Preliminary results for decision-making show that significant savings could be achieved.



Daniel Cole University of Pittsburgh



**Ryan Spangler** 



Manyu Kapuria





**Robert Lois** 



**Nicholas Harn** 







