Probing Facility Modeling and Anomaly Detection System through Simulation of Arbitrarily Complex Processes

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Background

- System for Process Anomaly Recognition and Corroboration (SPARC) is a framework for anomaly detection in the context of unmanned facility monitoring using unsupervised machine learning and stochastic process modeling.
- SPARC has domestic and international safeguards applications, adding an autonomous monitoring factor to nuclear material control. This supplements existing nuclear security methods without putting added strain on personnel.
- To validate this framework, a flexible simulation capability was created which models normal and anomalous behaviors in arbitrarily complex facilities.
- This simulated model, along with limited collected data from the Sanitary Effluent Reclamation Facility (SERF) will be fed into SPARC and probed for its anomaly detection capability.

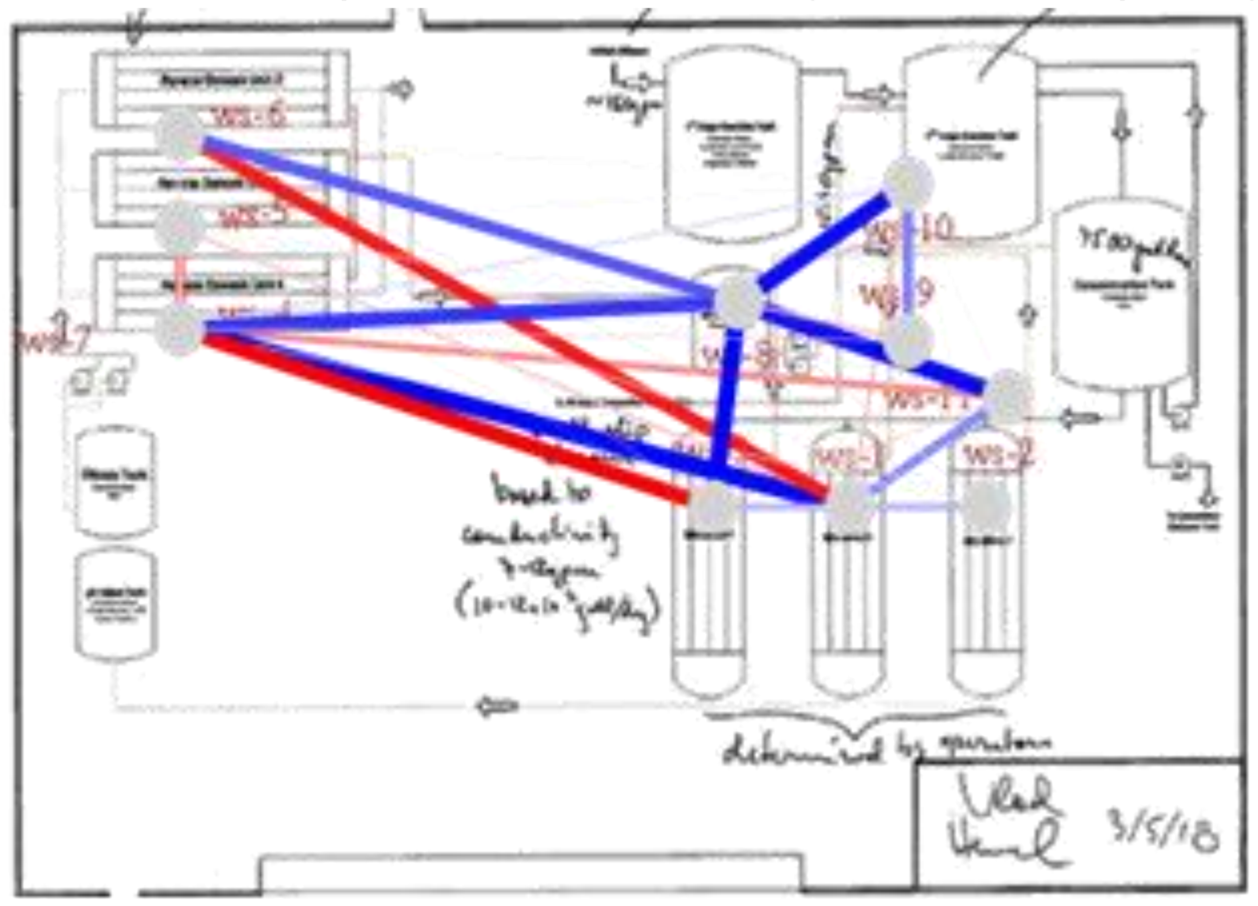


Figure 1. A schematic of the SERF overlaid with the learned Ising neural network. Blue edges represent positive relationships between nodes and red represent negative. The thickness of the edge represents the strength.

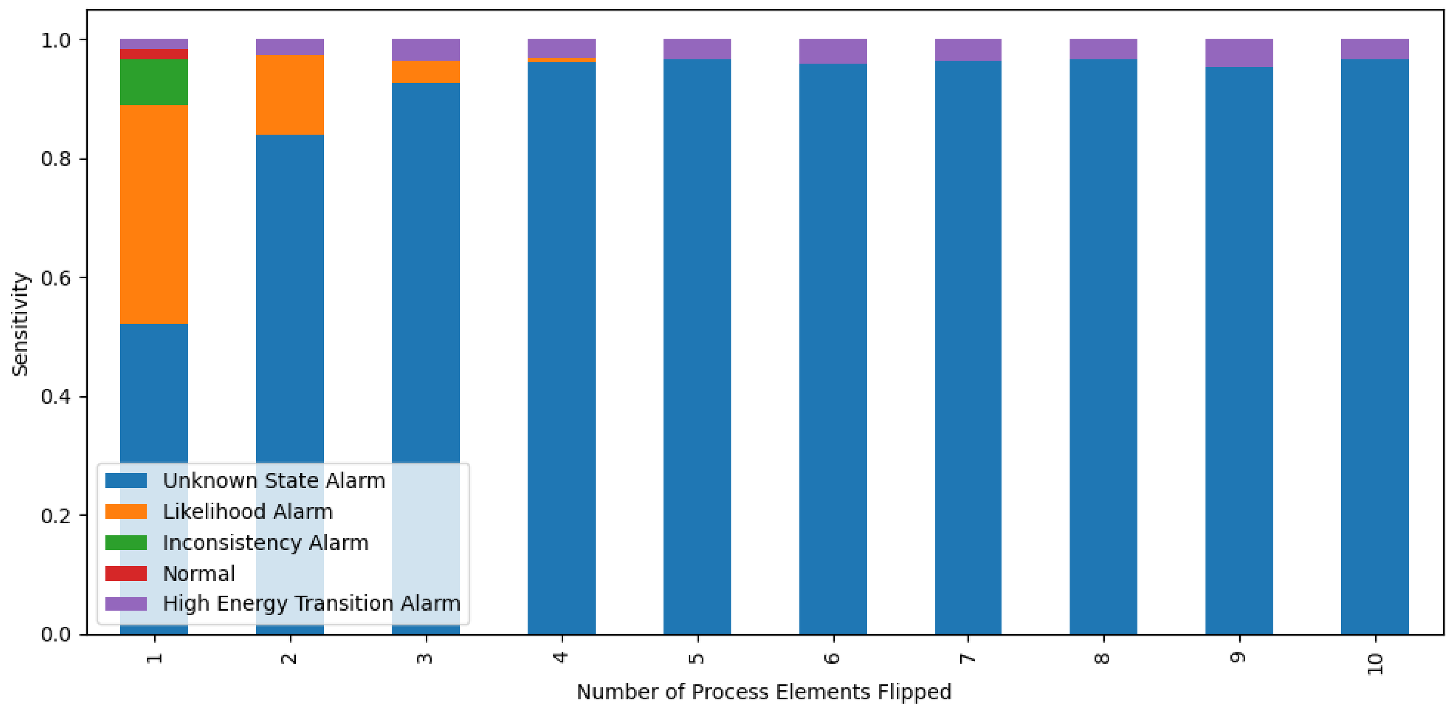


Figure 2. The sensitivity of SPARC to artificially injected anomalies into the collected data from SERF. Anomalies are created by flipping a varied number of process elements.

Validation with Empirical Data.

- Nonintrusive sensors measure process elements to provide a robust snapshot of a facility.
- Ising neural networks and Discrete-Time Markov Chains characterize the activity of a facility from learned dynamics.
- SPARC was initially trained on the data from SERF.
- Because of the limited data volume, a testing set was created by artificially injecting anomalies into the training set. This was done by flipping random process elements in the data for a random period.
- While this does not accurately represent what a real facility experiences, it is useful for initial testing of the anomaly detection systems.

Validation through Simulation

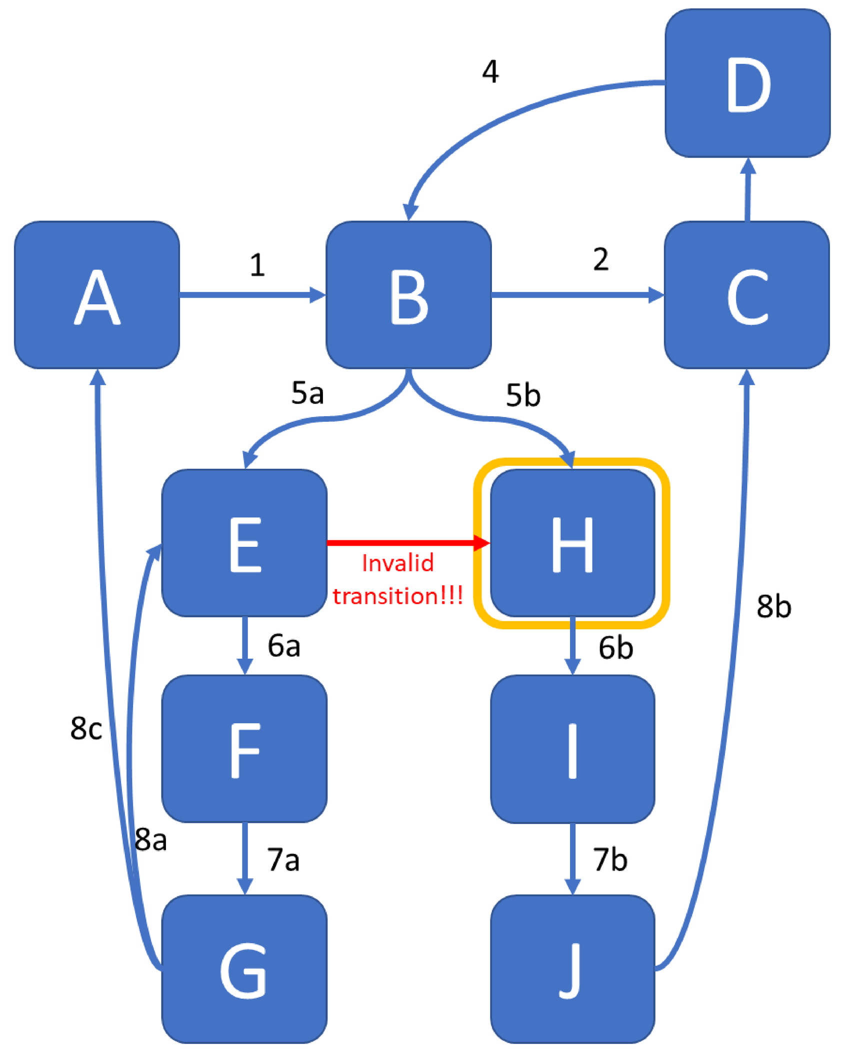
- To better classify how SPARC performs with realistic environment behavior, a simulated facility data will be used.
- This demonstrates SPARC's dynamic power to be trained and re-trained to profile any facility with varying processes.
  - The simulated space has nonidentical training/testing sets.
- Once trained, SPARC can detect anomalies such as invalid transitions between states, delayed or accelerated transitions, and invalid states. These anomalies correspond to unfamiliar processes occurring in the facility that should be alarmed.
- Sensitivity and specificity are important metrics to take into consideration when studying a binary classifier.
  - These highlight the anomaly detection picking up on correct trends as well as if the model makes errors in its classification.

Set Size: 2592000	Predicted Normal	Predicted Anomaly
Real Normal	2515046	76953

Table 1. Confusion matrix of SPARC's binary classification on testing data with no anomalies. Accuracy of 97.0%, false positive rate of 3.0%.

Set Size: 2592000	Predicted Normal	Predicted Anomaly
Real Normal	1870380	53889
Real Anomaly	9064	658663

Table 2. Confusion matrix of SPARC's binary classification on testing data with anomalies. Accuracy of 97.6%, false positive rate of 2.8%, false negative rate of 1.4%.



State	Duration	Trans	Trans P
A	5s	B	1
B	4s	C	1
C	3s	D	1
D	6s	B	1
B	2s	E	0.2
B	3s	H	0.8
E	3s	F	1
E	1s	H	0.5
F	5s	G	1
G	4s	E	1
G	2s	A	0.7
E	4s	END PROCESS	
H	2s	I	1
H	4s	I	0.5
I	6s	J	1
J	2s	C	1
C	6s	END PROCESS	

Figure 3. Network of simulated facility's connections with invalid transition (red) and delayed transition (yellow).

Table 3. The simulated facility's Discrete-Time Markov Chain with durations in each state. Invalid transition highlighted in red and delayed transition in yellow.

Results

- The results from the SERF data qualitatively showed SPARC was able to pick up on the artificially injected anomalies with relatively low false positive and false negative indications.
- With results from the simulation, SPARC's efficacy was quantified and emphasized its anomaly detection capability.
- In the data set with normal behavior, SPARC's accuracy was 97.0%. An error of 3.0% is from predicting phantom anomalies.
- In the set with anomalous behavior included, SPARC had an accuracy of 97.6%. When there was an error, SPARC is 98.6% likely to detect it. When there is no error, SPARC is only 2.8% likely to wrongly indicate an error. The sensitivity is 98.6% and the specificity is 92.4%.

Conclusion

- Machine learning and stochastic process modeling was successfully implemented for anomaly detection and facility monitoring towards nuclear safeguards applications.
- SPARC was shown to be effective in detecting anomalies in simulation and with real data.
- Detection rate was relatively high with a low false positive rate.

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