Feature Extraction for Data-Driven Fault Detection in Nuclear Power Plants

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INTRODUCTION

Health monitoring of nuclear power plants (NPP) is one of the key issues addressed in nuclear energy safety research. The effects of health monitoring depend on the performance of sensors. Traditionally, sensor calibration is performed during each nuclear power plant refueling outage, which may not be cost effective [1]. On the other hand, in unusual circumstances, the normal calibration schedule may not be able to detect aggravation of hidden faults, which may result in a permanent damage of the plant components or a potentially catastrophic accident. Hence, there is a need for new technologies of health monitoring for NPPs, which can be pursued online during operation and without the need for installation of additional sensors.

Anomaly (i.e., deviation from the nominal condition) detection algorithms, built upon a data-driven statistical pattern recognition tool called symbolic dynamic filtering (SDF), have been developed and experimentally validated for real-time execution in different applications [2].

A major challenge in data-driven fault detection with degraded sensors is to satisfy the specified probabilities of false alarms and correct detections. The situation becomes worse if a controller relies on sensor signals as the feedback information to calculate the control inputs. To address this issue, tools of analytic redundancy have been traditionally used for sensor fault detection.

This paper presents a novel approach that investigates necessary developments and modifications of SDF to distinguish the effects of sensor degradation from those of actual system faults. The key idea is Pareto optimization of statistical feature extraction as a trade-off between the effects of sensor degradation and system fault signatures. Pareto (multi-objective) optimization has been used to identify a partitioning that is highly sensitive for detection of statistical information changes in the data and, at the same time, robust to sensor degradation.

PROBLEM STATEMENT & METHODOLOGY

Let a dynamical system (or plant) $\mathbb{P}$, equipped with a sensing system $\mathbb{S}$, be monitored to detect faults in $\mathbb{P}$. While $\mathbb{P}$ and $\mathbb{S}$ denote both the plant and its sensing system to be in nominal condition, $\widetilde{\mathbb{P}}$ and $\widetilde{\mathbb{S}}$ denote any possibly anomalous conditions of the plant and the sensing system, respectively. The objective of the fault detection algorithm is to detect whether the plant is in an anomalous condition or not, in spite of a degraded condition of the sensing system. Let $\mu(\widetilde{\mathbb{S}})$ and $\mu(\widetilde{\mathbb{P}})$ be the anomaly measure values for only degraded sensor condition $\widetilde{\mathbb{S}}$ or only plant fault condition $\widetilde{\mathbb{P}}$ respectively, whereas $\mu(\widetilde{\mathbb{P}}\widetilde{\mathbb{S}})$ is the anomaly measure in the presence of both conditions $\widetilde{\mathbb{P}}$ and $\widetilde{\mathbb{S}}$. In this context, the fault detection algorithm should achieve the following objectives:

- Minimization of $\mu(\widetilde{\mathbb{S}})$
- Maximization of $\mu(\widetilde{\mathbb{P}})$ and $\mu(\widetilde{\mathbb{P}}\widetilde{\mathbb{S}})$
- Satisfying the constraint $\left|\mu(\widetilde{\mathbb{P}}\widetilde{\mathbb{S}}) - \mu(\widetilde{\mathbb{P}})\right| < \delta$ where δ is the threshold.

The multi-objective anomaly detection optimization problem is realized as a partitioning problem. Among the plant fault conditions denoted by $\widetilde{\mathbb{P}}$, only the minimal fault that needs to be detected is considered for optimization of partitioning. The underlying assumption here is that for any partitioning, $\mu(\widetilde{\mathbb{P}}_{min}) \geq \mu(\widetilde{\mathbb{P}})$ for any $\widetilde{\mathbb{P}}$, where $\widetilde{\mathbb{P}}_{min}$ is the minimal plant fault that needs to be detected. Similarly, among the sensor degradation conditions denoted by $\widetilde{\mathbb{S}}$, only the maximal degradation that is allowable, is considered for optimization of partitioning. The underlying assumption here is that for any partitioning $\mathbb{B}$, $\mu(\widetilde{\mathbb{S}}_{max}) \geq \mu(\widetilde{\mathbb{S}})$ for any $\widetilde{\mathbb{S}}$, where $\widetilde{\mathbb{S}}_{max}$ is the maximal sensor degradation that is allowable.

The multi-objective optimization problem, described above, involves: (i) a two-dimensional objective space $\mathcal{O}$ that consists of the reward $\mu(\widetilde{\mathbb{P}}_{min})$ and the penalty $\mu(\widetilde{\mathbb{S}}_{max})$, and (ii) the space $\mathcal{P}$ of all possible partitions where the decisions are made. As a further simplification, it is assumed that the time series data is one-dimensional wherein a partition consisting of m cells (denoted by $\Lambda \triangleq m-1$). The reward and penalty values are dependent on a specific partition Λ and are denoted by $\mu_\Lambda(\widetilde{\mathbb{P}}_{min})$ and $\mu_\Lambda(\widetilde{\mathbb{S}}_{max})$ respectively. Hence, the optimal partitioning scheme involves an estimation of the elements of the partitioning Λ that minimizes $\mu_\Lambda(\widetilde{\mathbb{S}}_{max})$ and maximizes $\mu_\Lambda(\widetilde{\mathbb{P}}_{min})$.

A search-based Pareto optimization has been adopted, where the number of cells, m, of the partitioning Λ is first chosen. Then, using a suitable fine grid size depending on the data characteristics, the space of all possible partitioning $\mathcal{P}$ is explored and the positions in a partitioning are located in the two-dimensional objective space. The Pareto front is generated by identifying the non-dominated points in the objective space, as shown in Fig. 1. Results generated by maximum entropy partition (MEP) and uniform partitioning (UP) are also shown in Fig. 1. Finally, the Neyman-Pearson criterion is applied to choose the optimal partitioning Λ^* to have maximum reward for detecting minimal plant fault while not allowing the penalty due to detecting maximal sensor degradation to exceed a specified threshold, say ϵ. In other words, the optimal partitioning Λ^*according to the Neyman-Pearson criterion is the solution to the following constrained optimization problem:

$$\Lambda^* = \arg\max_{\Lambda} \mu_\Lambda(\widetilde{\mathbb{P}}_{min}) \text{ , such that } \mu_\Lambda(\widetilde{\mathbb{S}}_{max}) \leq \epsilon$$

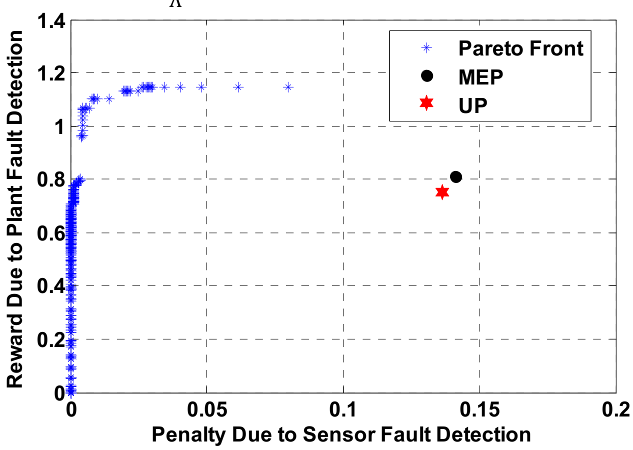

Fig. 1. Pareto front for partition optimization

SIMULATION VALIDATION ON IRIS TESTBED

The proposed methodology has been validated on the International Reactor Innovative and Secure (IRIS) testbed representing a modular pressurized water reactor.

Sensor degradation with changes in the sensor-noise variance is studied in this paper. Also, the reactor coolant pump (RCP) is chosen to be the location of a component level (plant) fault and the sensor *THL* (i.e. the hot-leg reactor coolant temperature sensor at RCP outlet) is chosen for fault detection in RCP.

Time series data have been collected from the *THL* sensors under persistent excitation of turbine output power load that have step profiles with the mean value of 0.99, fluctuations within ± 0.01 and frequency of 0.0025 Hz. The NPP simulation is conducted at a frequency of 10 Hz (i.e., inter-sample time of 0.1 sec).

In the IRIS testbed, the RCP is considered in nominal condition when no fault is injected, denoted as $\psi = 0\%$. Fault is injected into RCP by over-speeding its rotor. The result presented here considers degradation of RCP and the minimal fault that needs to be detected (i.e., $\widetilde{\mathbb{P}}_{min}$), corresponds to $\psi = 1\%$ of its measurement span. The sensor *THL* has an additive Gaussian random noise with variance 0.005% of its measurement span. The degradation in the sensor is realized as a change in the noise variance (σ_N^2) that range from 0.005% to 0.01%. Thus, the maximum allowable sensor degradation condition $\widetilde{\mathbb{S}}_{max}$ corresponds to $\sigma_N^2 = 0.01\%$ of the sensor's measurement span.

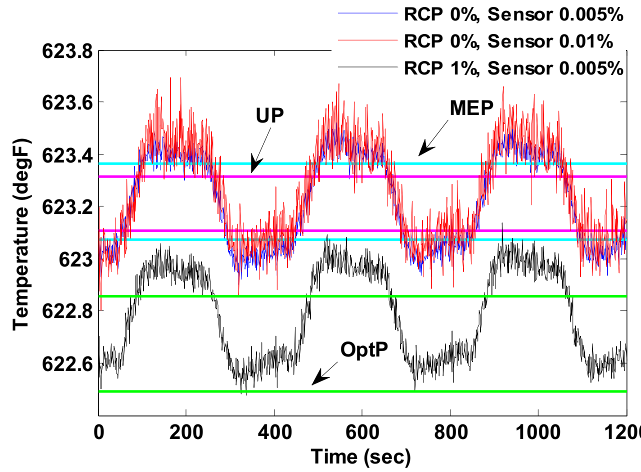

Fig. 2. Partitioning of time-series data space

Fig. 2 shows three types of partitioning on the time-series data that collected from sensor *THL* from different level of faulty conditions, i.e., $\psi = 0\%$, 1% and $\sigma_N^2 =$ 0.005%, 0.01%. Table I shows the results of anomaly measure with the three partition methods. It is seen that the optimal partitioning is not sensitive to noise. At the two noise levels with no plant fault condition, the anomaly measures are very close to 0. When a fault occurs (e.g. RCP overspeed by 1%), the anomaly measure becomes very high while the anomaly measures between two sensor noise levels are still close. For MEP and UP, the anomaly measure deviates from 0 even when there is no plant fault, and as sensor noise increases, the anomaly measure becomes large abruptly.

Table I. Anomaly Measure with Different Partitions

		$\sigma_N^2 = 0.005\%$	$\sigma_N^2 = 0.01\%$
Optimal Partition	$\psi = 0\%$	0.0005	0.0012
	$\psi = 1\%$	0.7755	0.7355
MEP	$\psi = 0\%$	0.0210	0.1412
	$\psi = 1\%$	0.8114	0.6996
UP	$\psi = 0\%$	0.0309	0.1363
	$\psi = 1\%$	0.7510	0.6992

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2. A. RAY, "Symbolic dynamic analysis of complex systems for anomaly detection," *Signal Processing*, Vol. **84**, No. **7**, pp. 1115-1130, 2004.