Lessons Learned in Projecting the Monitoring of Nuclear Material Production into the Field

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Abstract

US national laboratories seek to use their own facilities to develop and test methods for monitoring of nuclear material production. As part of a recent monitoring effort, different aspects of edge computing were assessed, including approaches for remote data transmission, best practices for unattended systems and sensors, and system-level complementarity and redundancy. These approaches inadvertently received additional testing due to COVID19-related travel restrictions, which required the unattended operation of remote sensor networks for longer periods of time than had been previously tested. Here we report lessons learned and describe observed tradeoffs between different approaches.

Introduction

The Persistent DyNAMICS (Dynamic Nuclear Activity Monitoring through Intelligent Coordinated Sensing) project aims to develop and test edge computing methods for continuous measurement of activities involving nuclear material production. To this end, a range of sensors at were deployed at different facilities. These sensors were exposed to the environment for extended periods during which conditions of rain, lightning, snow, and wind all presented challenges. In addition to these standard challenges of projecting monitoring into the field, during COVID19-mandated travel restrictions, sensors could not be maintained by personnel from the laboratories at which they were developed and could only be physically accessed by personnel from the facility at which they were deployed. Personnel from those facilities were also constrained in their ability to access the site, which limited data retrieval and maintenance opportunities.

This paper presents an overview of the deployed monitoring system, a description of some of the specific challenges involved in deploying nuclear material monitoring equipment into the field, specific steps taken to improve our ability to monitor nuclear material production under conditions with substantially less human interaction than anticipated during original system development, and our observations of the impact of monitoring gaps on the ability to make inferences about nuclear material production.

Deployed Monitoring System

The monitoring system deployed under Persistent DyNAMICS has five main components:

1) Nuclear process knowledge. This process knowledge includes an understanding of the process flowsheets involved in the production of material at a given facility, as well as the locations within the facility at which different process steps occur. It is used to determine the available indicators for specific process activities and drives the placement of sensors in the testbed environment.
2) Edge computing nodes (Hamilton 2018) for turning timeseries data, such as vibration amplitudes, currents or voltages, or low frame rate video, into information. Here we use the term information to describe the meaning associated with the data (Zins 2007) (Ackoff 1989). An example would be using a sensor to collect video of a truck and using an edge

computing node to identify the truck. The identification, “truck”, is associated with metadata that captures collection time, collection location, and sensor characteristics and turned into a text message that can be transmitted from the edge node to other systems using low bandwidth communication.

3) Communication software and hardware for moving information from collection locations to remote sites for additional analysis.
4) Inference algorithms that use the information provided by edge computing devices as input features to generate labels for the state of nuclear material production at each testbed. In this paper, “inference” is the process by which a multi-state classification machine learning algorithm outputs a particular classification label as a function of input features. This inference process assumes that the machine learning algorithm has been previously trained (or created based on subject matter expertise). Inference approaches explored included a Dynamic Bayesian Network, XGBoost, and an ontological reasoner.
5) Real-time visualization tools that provide users with access to background information about the collection sites, as well as collected information from the edge sensors, and the derived inferences about the nuclear production activities at a given facility.

Challenges of Nuclear Material Monitoring

A key challenge in nuclear material production monitoring is to maintain sufficient sensor coverage to enable correct inference of facility states despite inevitable gaps in coverage from individual sensors/edge nodes. Individual sensors and nodes can fail to report data and information due to environmental effects (i.e., changing day/night light levels, dust/snow/fog/rain, extreme fluctuations in temperature, vibration, moisture levels, etc.), and hardware, network, and software errors. This challenge is even more difficult when deploying the monitoring into the field, where consistency in available power and network connections is typically lower and environmental effects are more frequent and extreme. These issues can be partially addressed by sensor redundancy, network redundancy, and diligent maintenance. However, sufficient levels of redundancy can be difficult to achieve within practical cost constraints and diligent maintenance is compromised when physical access is limited. Under these limitations, new approaches are required.

Lessons Learned

Edge Nodes

Edge nodes were small COTS computers (NVIDIA Jetson Nano/Xavier™ and Intel NUC ™) used to control and acquire data from directly attached sensors, calculate sensor-specific inferences and summary statistics, and communicate the results of local calculations to a central server (Edge computing 2023). Depending on deployment location, edge nodes used either local Wi-Fi or cellular modems to connect through a security firewall to the internet. Control servers were not physically located at the collection sites.

Communication

When collecting at testbeds, a traditional approach to ensure that collection systems (physical sensors, data acquisition hardware, analysis computers) are operating correctly is manual supervision. During the 2019-2023 COVID19 pandemic, restrictions on site visitation challenged this approach and required greater reliance on remote monitoring of sensor health. Sensors were connected to commercial, off-the-shelf (COTS) communication systems, using either Wi-Fi or cellular communications, depending on the rules and regulations at each test site. Figure 1 shows inexpensive communication systems that were adequate for project needs. The communication systems allowed sensor operators to remotely log into collection systems to verify system status.

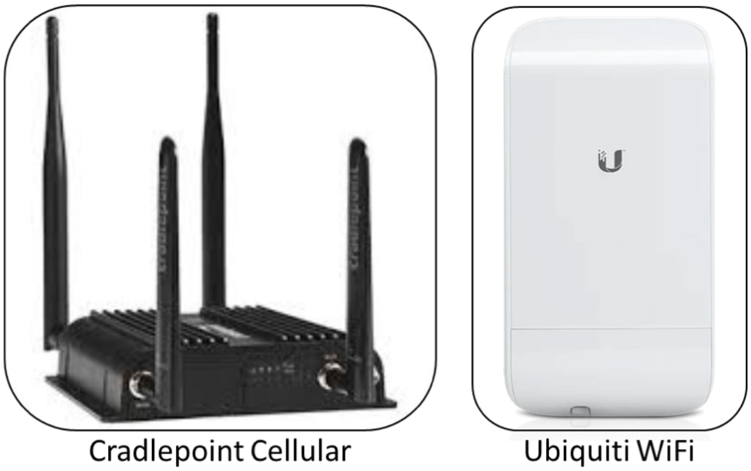

Figure 1. Examples of COTS communication systems used to provide remote access to sensors in the field.

Computation for data processing at the edge

Another traditional approach is to measure data using individual sensors and collect the results in locally attached storage devices (typically multi-terabyte hard drives). After days to weeks of sensor measurements, these storage devices (collectively containing TB of data) are then physically shipped to another location for analysis. When sensors can be maintained in good operational states, this is a viable approach; however, with sensors left unattended for extended periods, this approach can lead to substantial data loss, e.g., if/when hard drives fill up or if/when sensors are rendered inoperable due to power loss or environmental damage. In addition, the lengthy time delays between experiment and data analysis in traditional approaches can lead to the inadvertent generation of long periods of degraded data resulting from sensors that became detached from physical surfaces, blocked, misaligned, or otherwise compromised. In contrast, edge computing provides real-time messages describing sensor observations which enables physical errors to be corrected before the experiment is complete. An example of a data gap due to power loss is shown in Figure 2.

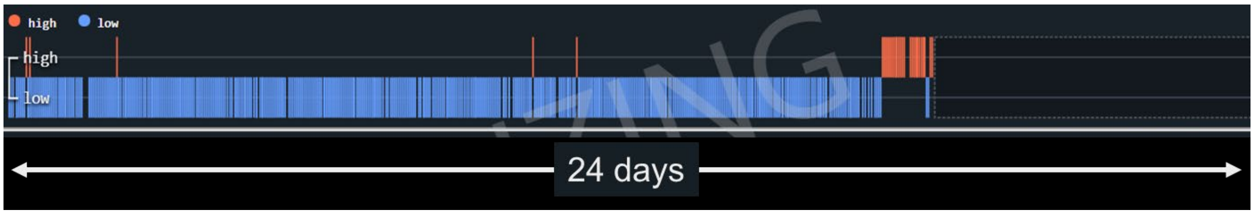

Figure 2. Information from a thermal sensor reported over a 24-day period. The edge processing summarized each measurement as "high" or "low" with respect to a pre-set threshold. At the end of the period shown, reporting from the sensor disappears for ~ 7 days due to a power outage. Knowing that the sensor had failed allowed deployment of personnel to the remote site for system maintenance. Note that the watermark indicates that the system was still in its "Initialization" state during the time period shown.

Data processing at the edge – that is, on a computational node either at, or physically near, the sensor – allows reporting of summary statistics that can reveal sensor degradation. This can be revealed by either anomalous values with respect to typical sensor performance or by anomalous values with respect to other sensors. For example, simple reporting of median absolute values for timeseries data can provide early warning of many failure modes. Figure 3 shows an example case in which anomalous values provided an indicator that a vibration sensor had become detached from its measurement surface.

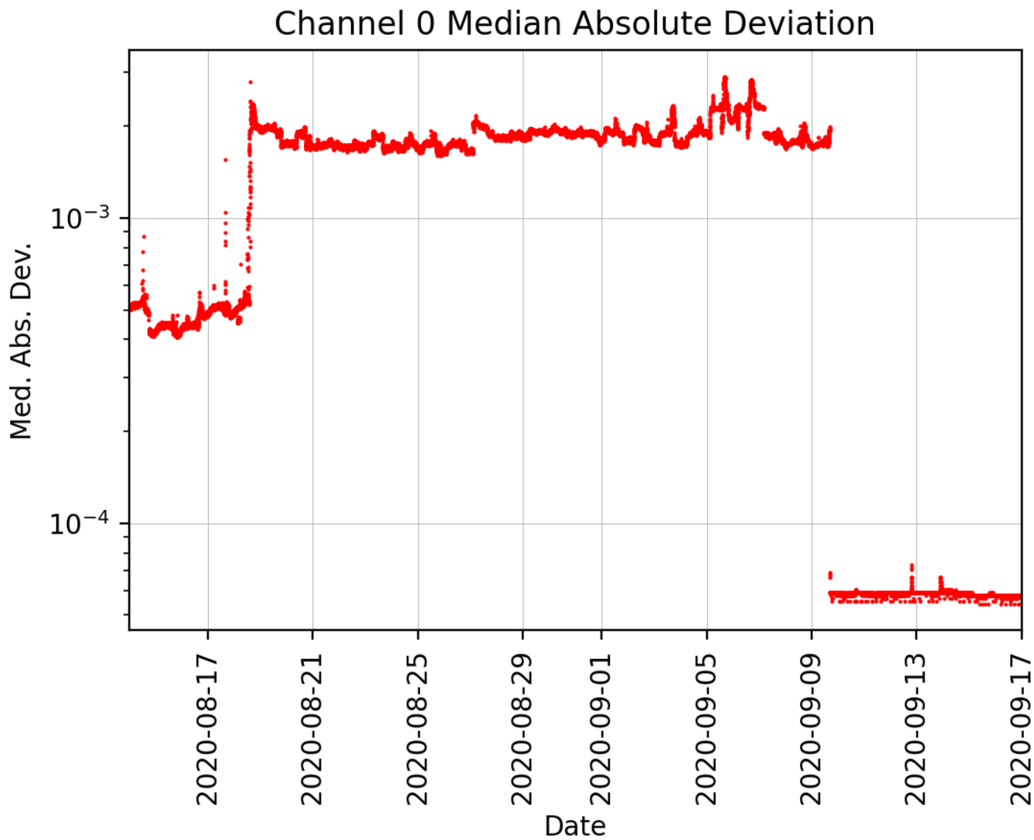

Figure 3. The median absolute deviation for the amplitude of timeseries data from an accelerometer reported over a 34-day period. The first 5 days show the noise baseline in the absence of facility activity. The next 21 days show the median absolute deviation of the vibration amplitudes during a time when the facility was active. The dramatic amplitude reduction in the final 7 days indicates that the accelerometer has detached from the measurement surface. Here, tracking of the summary statistics allows detection of the failure mode and deployment of personnel to the remote site for system maintenance.

Automated alerts and visualization tools

In the context of COVID19 pandemic restrictions, automated notification of the need for manual intervention was important, as no regular maintenance was being performed. The combination of data processing at the edge with networked communications enabled creation and delivery of automated alerts when sensors went off-line, as shown in Figure 2. In addition, evidence of the need for intervention was important for obtaining necessary permissions for site access. Summary statistics from edge processing were used as evidence of the need for sensor maintenance, as shown in Figure 3. In addition, presentation of the output of multiple information streams in context allowed for detection and remote diagnosis of more subtle anomalies in sensor behavior, as shown in Figure 4.

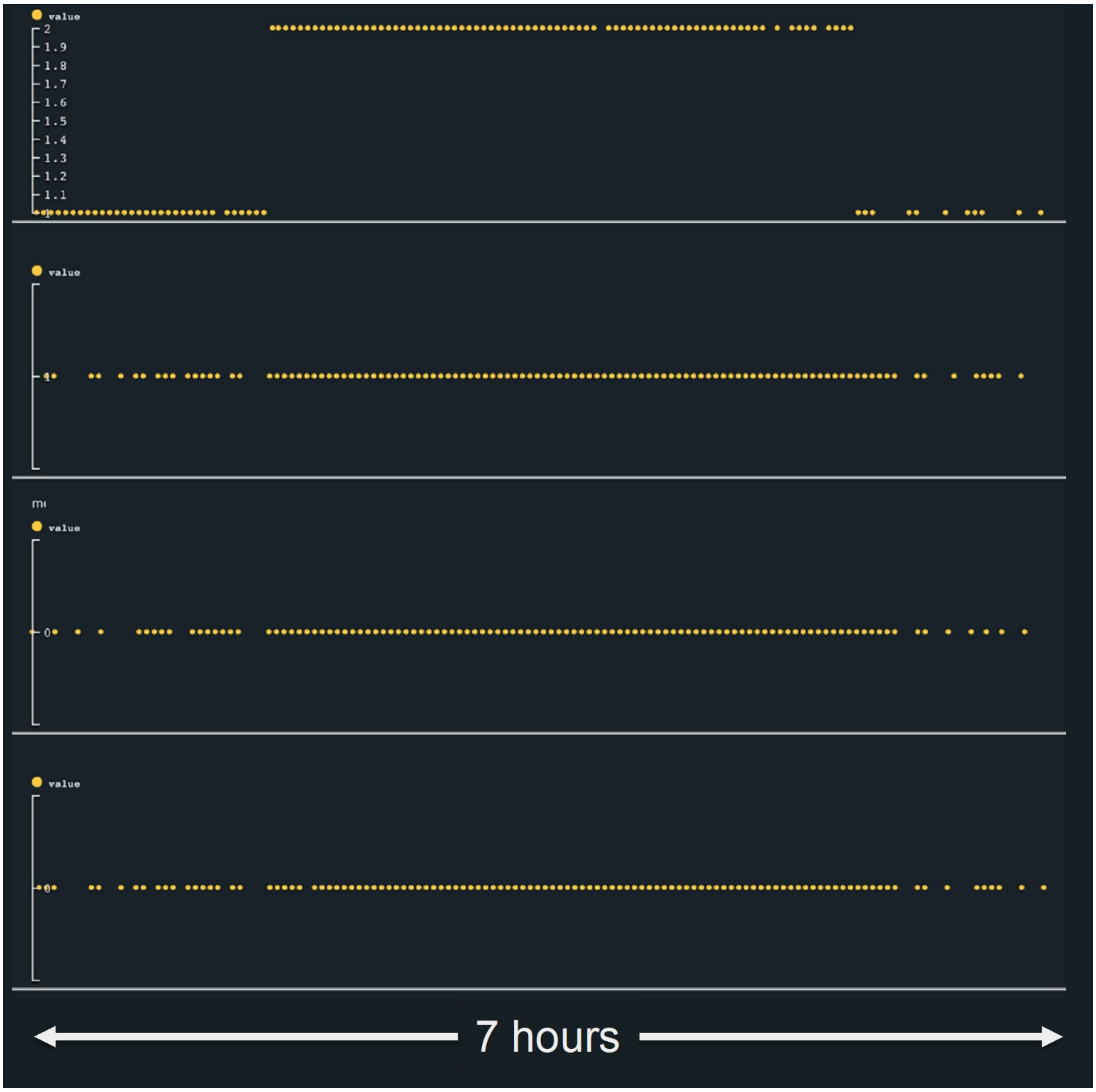

Figure 4. Panels show values of summary statistics from four different sensors over a seven-hour period. Comparison of summary statistics across the sensors shows that the reporting from the sensor in the top panel is inconsistent with the reporting from three other sensors during the middle of this period. Specifically, the other three sensors are reporting steady state behavior at the facility while the sensor in the top panel is reporting a change. Missing dots are due to intermittent cellular network connectivity. Investigation revealed that the sensor in the top panel was unplugged at the time of the observed change. Intervention allowed the sensor to be restored to the correct state in less than a day.

Confidence

As noted earlier, a key component of the deployed monitoring system is the inference component that monitors the state of material production activities at the testbed. Building end-user confidence in computational inference algorithms requires an understanding of the impact of missing information on the inference performance. Figure 5 shows an example of the real-time output of an edge sensor ("Appear") and the associated confidence probabilities in the multi-state inference of which material type is being processed at the test facility. The dashed orange lines indicate periods of missing or intermittent data and the associated impact on inference probabilities is show in the lower visualization track. These evaluations can be used to determine, for each information stream, the urgency of troubleshooting and repair.

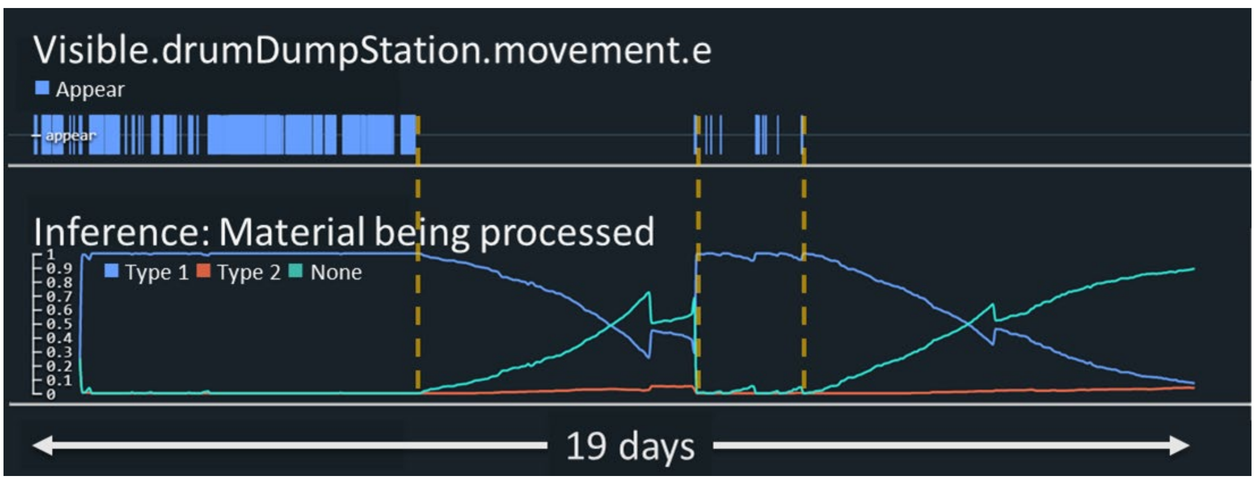

Figure 5. Top panel: Information reported from a visible camera when movement was detected in the area of the facility labeled as "drum dump station". Bottom panel: Probability assigned to three potential inferences about the material being processed in the facility. The inference result was obtained from a Dynamic Bayesian Network (DBN). While the inference relied on more than one input information stream, the result was significantly impacted by the information stream shown in the upper track. The inference clearly indicates processing of material type 1 during the time when the information stream reports frequently; however, starting at the first dashed vertical line, the probability that no material is being processed increases. The discontinuity between the first two vertical lines is caused by input from an information stream not shown. Between the second and third vertical lines, the rate of decay of the inference in the absence of new information, and rate of recovery when new information is provided, can be observed.

Conclusion

When projecting nuclear monitoring systems into the field, national laboratories have often relied on direct human oversight of collection systems. Due to COVID19 pandemic restrictions on travel and site access, system oversight had to be performed remotely and systems were unattended for longer periods of time than previously tested. This accelerated development and deployment of communication hardware, edge processing software, and visualization tools for monitoring and understanding system health in real time. In addition, the impact of collection gaps on the performance of inference tools was used to quantify the urgency of troubleshooting and repair for individual information sources. These advances not only improved our ability to deploy nuclear monitoring systems into the field during the COVID19 pandemic, but also inform the design and deployment of future collection systems. Continuous unattended remote monitoring systems have the potential to increase the effectiveness and efficiency of nuclear monitoring systems by reducing the number of times that personnel need to travel to a facility while still providing virtually continuous monitoring coverage and improving detection timeliness (Sanders, Liu and Shuler 2015).

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