

NEW SCIENCE AND INNOVATION BREAKTHROUGHS IN AI/ML/ DATA SCIENCE FOR RAILROAD PREDICTIVE & PRESCRIPTIVE MAINTENANCE

AI STATISTICAL MACHINE LEARNING FOR IOT PROGNOSTIC APPLICATIONS



Advanced Pattern Recognition – AI-MSET, is a nonlinear, nonparametric machine learning method that was originally developed at the US DoE's Argonne National Laboratory in the 1990's for prognostic anomaly detection in commercial nuclear plants, NASA, commercial aviation, advanced manufacturing, and business-critical industrial applications.

- Earliest Detection of anomalous behavior in noisy dynamic s/w & integrated s/w-h/w systems, mathematically proven in peer-reviewed scientific publications with real signals across many commercial & defense industries
- Ultra-low False and Missed Alarms probabilities (FAP/MAP). Proven FAPs for safety-critical and mission-critical implementations of One in 10^{**5} over 10,000 hours of operation.
- AI-MSET attains high sensitivity for detecting subtle anomalies in noisy or even chaotic time series metrics, but with ultra-low false- and missed-alarm probabilities, making this technology an ideal AI algorithm for early-warning predictive and prescriptive maintenance.

AI-MSET beats* all conventional forms of ML, including Neural Nets, Support Vector Machines, Kernel Regression, and GE Predix's Asset Performance Management (APM).

- (*"Beats"* = Lowest false/missed alarm probabilities, highest prognostic accuracy, earliest (mathematically proven) detection of incipient anomalies,
- Lowest compute cost, scales to highest #Signals x Sampling Rates, lowest latencies for massive "big data" applications)

ADVANCED PATTERN RECOGNITION

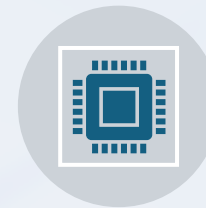


TNP has extensive experience using versions of MSET for business-critical assets in data centers and other industries, where MSET is integrated with various pre-processing, post-processing, and optimal training/tuning algorithms so that TNP's AI-MSET is more robust to low resolution sensors, data acquisition limitations, missing values in time series signatures, intermittent spurious anomalies, signal-asynchrony issues in large-scale datacenter and industrial applications, etc.

- Signal Inferencing
- Reliability/Quality Testing
- Remaining Useful Life (RUL) Estimation
- Autonomous Tuning/Training/Optimization
- Auxiliary AI-MSET & SPRT Innovations

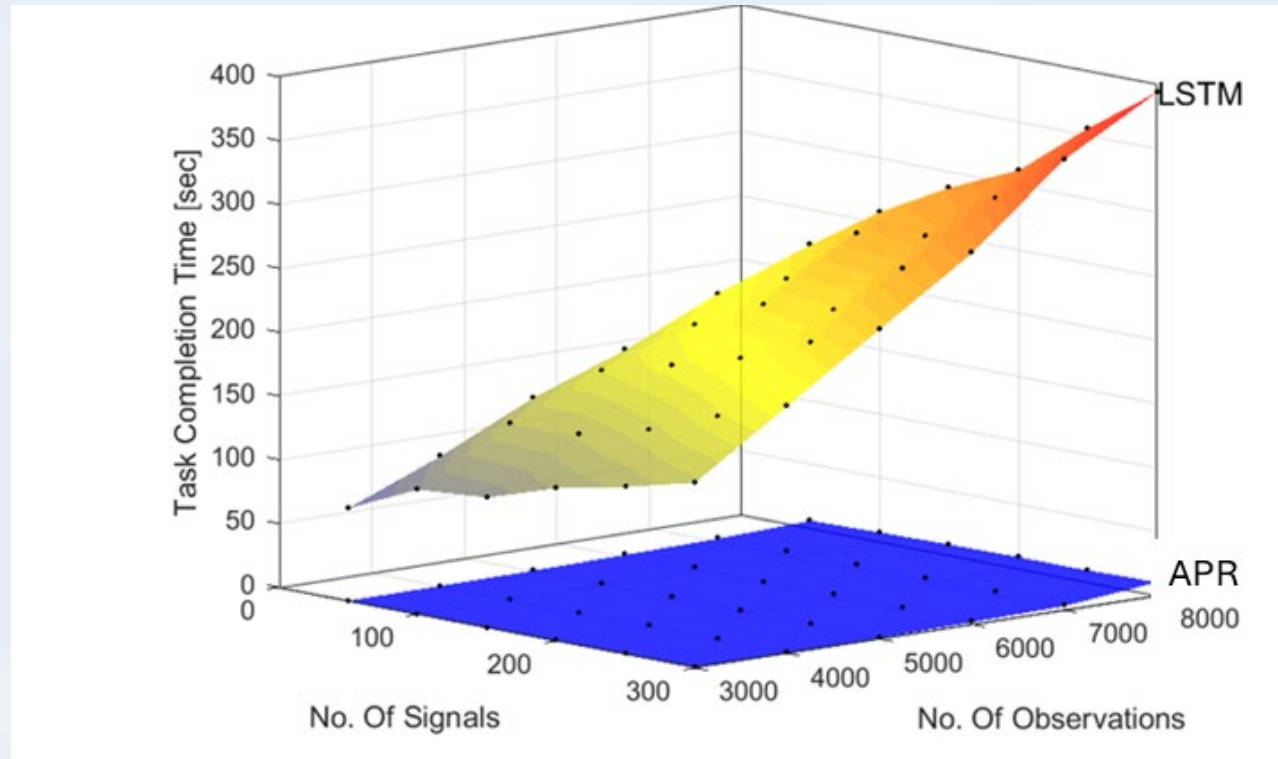


Conventional and competitive ML techniques such as Neural Networks (including LSTMs used in AWS and Azure) do not parallelize on any CPUs or GPU because of the stochastic optimization of the weights.



AI-MSET is a deterministic mathematical algorithm that parallelizes naturally on all modern multi-core, multi-thread CPUs and GPUs, attaining unprecedented speed-up factors, ultra-high throughputs for cloud and EDGE streaming anomaly detection, and ultra-low latencies.

ADVANCED PATTERN RECOGNITION



Illustrates a comparison between the compute cost of LSTM relative to AI-MSET, measured in time to task completion as the problem size is increased incrementally in both dimensions.

AI-MSET HAS 2-3 ORDERS OF MAGNITUDE SPEEDUP FOR BIG-DATA USE CASES WITH LOTS OF SIGNALS AND SENSORS (Thousands +) AND/OR HIGH OR VERY HIGH SAMPLING RATES (kHz +), VERSUS COMPETITIVE NEURAL NETWORKS

AI-MSET Competitive Differentiation Note:

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STATISTICAL M/L FOR IOT PROGNOSTIC APPLICATIONS



MSET SUCCESSFUL USE CASES AND HISTORY



Approved by the U.S. Nuclear Regulatory Commission for all instrumentation in commercial nuclear plants.

Today, in use by 100% of the US Reactors and most of the 450 Commercial Reactors world-wide.

APPROVED BY THE US NUCLEAR REGULATORY COMMISSION FOR ALL INSTRUMENTATION IN COMMERCIAL NUCLEAR PLANTS. TODAY, IN USE BY ALL 93 US REACTORS AND MOST OF THE ~450 COMMERCIAL REACTORS WORLD-WIDE.



“Big Data” AI Prognostics. Earlier versions of MSET were used extensively for "massive data" streaming ML prognostics long before any other industry.

AI-MSET was originally developed for commercial nuclear plants. One \$12B Reactor has about 3,400 sensors. One Oracle M9 Server has 4,000+ sensors inside. Today, a typical data center has over 20,000 servers. A medium sized Cloud data center has more than 1,000,000 sensors.

Oracle started developing Big Data MSET-based IT System Prognostics 20 years ago scaling to million-sensor fleets of assets long ago.

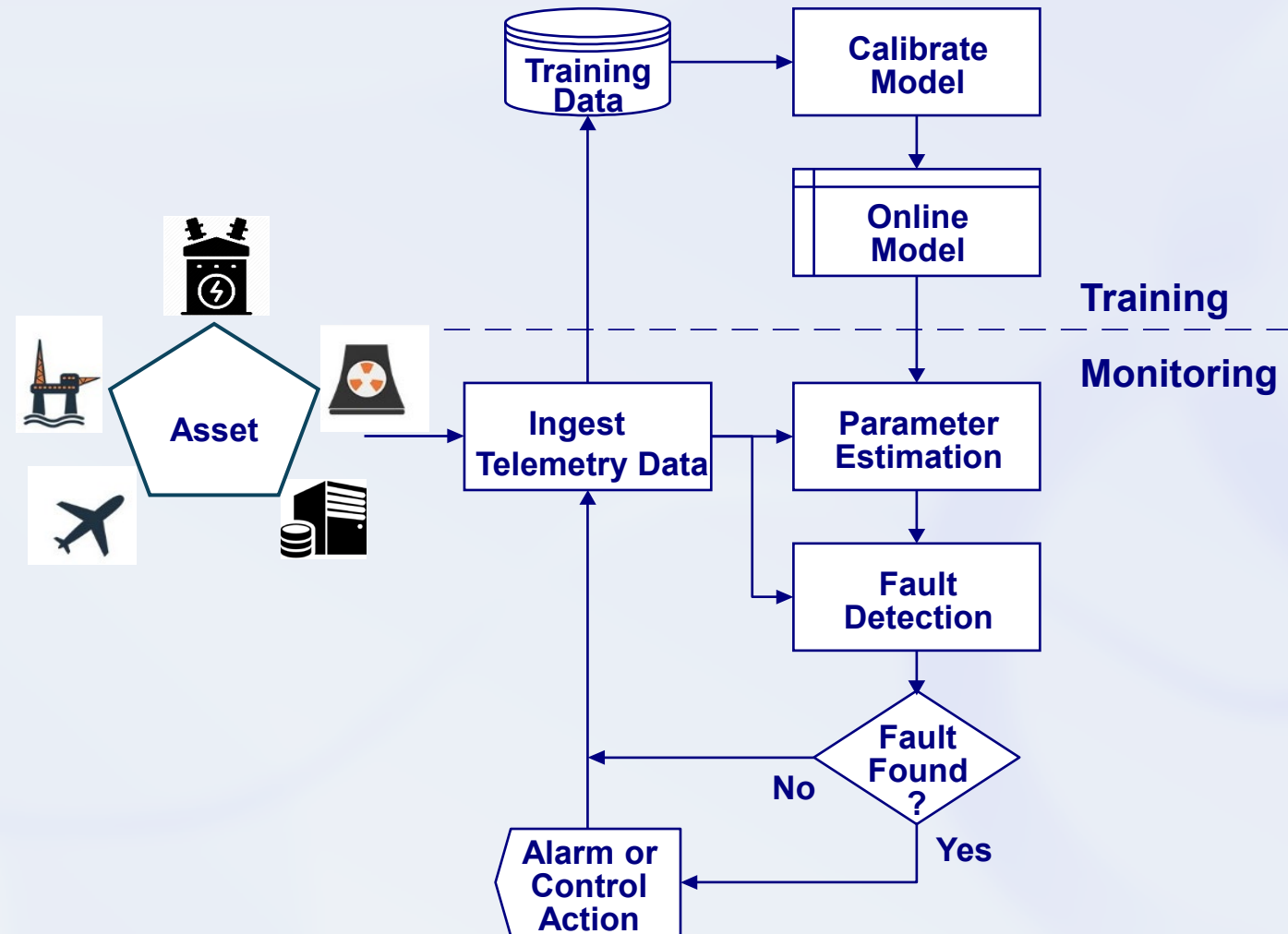
AI STATISTICAL MACHINE LEARNING FOR IOT PROGNOSTIC APPLICATIONS

- Non-linear, non-parametric ML for prognostic anomaly detection
- Detects subtle anomalies, even in noisy or chaotic time series metrics
- Ultra low false-alarm and missed-alarm probabilities
- Ideal AI algorithm for dense-sensor and/or high sampling-rate prognostics



ADVANCED PATTERN RECOGNITION

- AI-MSET model is trained by operating telemetry data
- AI-MSET estimate is produced for each new telemetry observation
- AI-MSET alarms when estimated and observed data statistically disagree



ADVANCED PATTERN RECOGNITION TOOLS FOR PROGNOSTIC CYBER SECURITY ANOMALY DISCOVERY WITH PROVABLE-LOWEST FALSE-ALARM RATES

Sequential Probability Ratio Test (SPRT) *For Stationary Time Series*

Advanced pattern recognition technique for high sensitivity anomaly discovery in noisy time-series signals. Developers proved in refereed journals that the SPRT provides the earliest mathematically possible annunciation of subtle incipient faults in noisy process variables, and with the lowest probability of false or missed alarms

Advanced Pattern Recognition (AI-MSET) *For Dynamic Time Series*

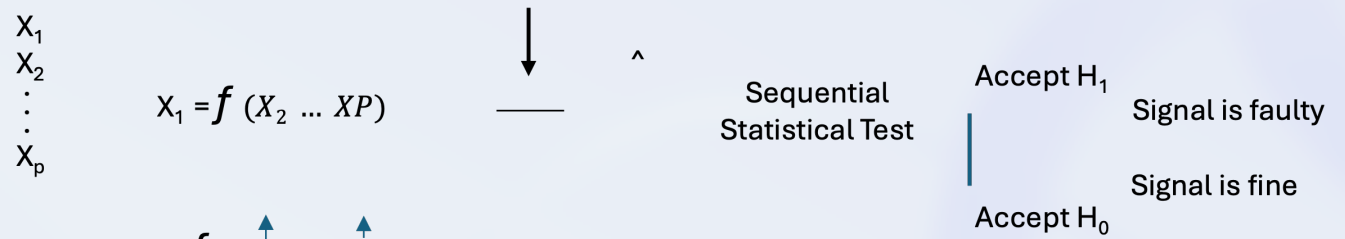
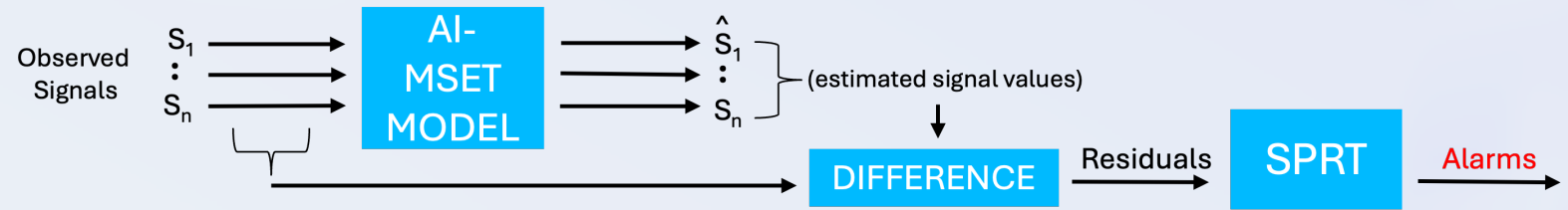
Online model-based fault detection and identification

AI-MSET predicts what each process should be on the basis of learned correlations among all process variables

AI-MSET incorporates the SPRT to monitor the residuals between the actual observations and the estimates MSET predicts on the basis of correlated variables (cross correlation and autocorrelation vs historical measurements)

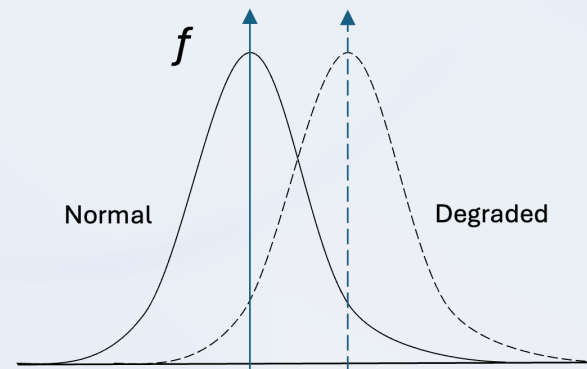
SPRT (SEQUENTIAL PROBABILITY RATIO TEST)

1. Sequential binary-hypothesis test compares likelihood of observations coming from reference distribution (H_0) vs degraded distribution (H_1)
2. Empirically learns reference distribution H_0 and uses as baseline for system



Sequential test for residual signals is based upon two hypotheses:

Where the μ is the mean of the distribution under test and the M is a preset alarm threshold.

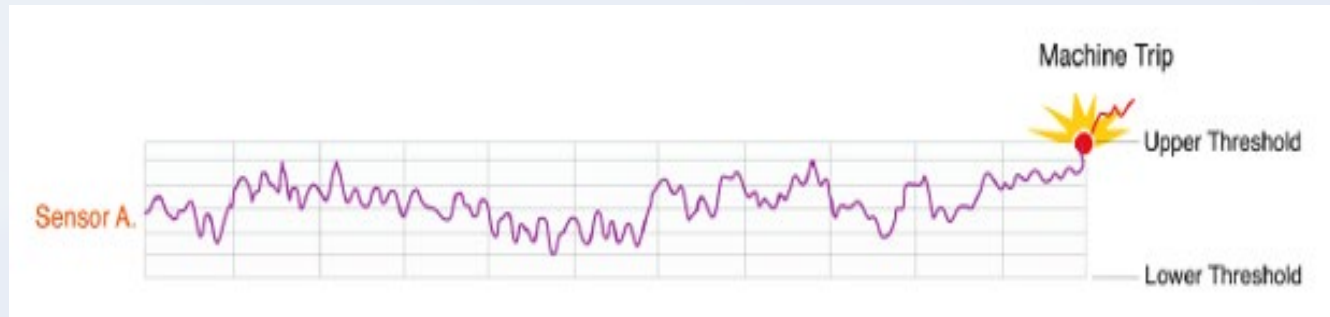


Unlike threshold limit tests, SPRT detects shifts in noise distributions. This breaks the "sea-saw" effect between sensitivity and false alarms inherent in conventional monitoring approaches.

TYPES OF PHYSICAL SENSORS AI-MSET ALGORITHMS WORK WELL WITH:

- Electrical (current, voltage, power)
- All types of thermal transducers, FBG optical thermometry, Pixelated infrared 2D thermography
- All physical transducers used in SCADA and Switch & Control Systems
- **Tri-axis accelerometers (using TNP's AI-MSET-based super-fast vibrational-resonance-spectrometry)**
- Tachometers, proximity-transducers for rotating shafts
- All types of fluid flow sensors, including venturi-flow sensors, pressure transmitters and pressure transducers
- HFCT (High Frequency Current Transformers)
- Ambient environmental sensors automatically extracted and synchronized with rolling stock internal telemetry, from NOAA weather feeds (RH, Temperature, wind speed, pressure, rate of change of P, rate of precipitation, etc.)
- Time-Domain Reflectometry (TDR)
- Compression sensors for hydraulic and pneumatic flow systems
- UHF (Ultra High Frequency) Sensors
- **Acoustic sensors (using TNP's "acoustic resonance spectrometry") for high-accuracy incipient fault prognostics in mechanical, electromechanical, and hydraulic systems from inexpensive directional acoustic sensors)**
- FMC (Flexible Magnetic Coupler) Sensors

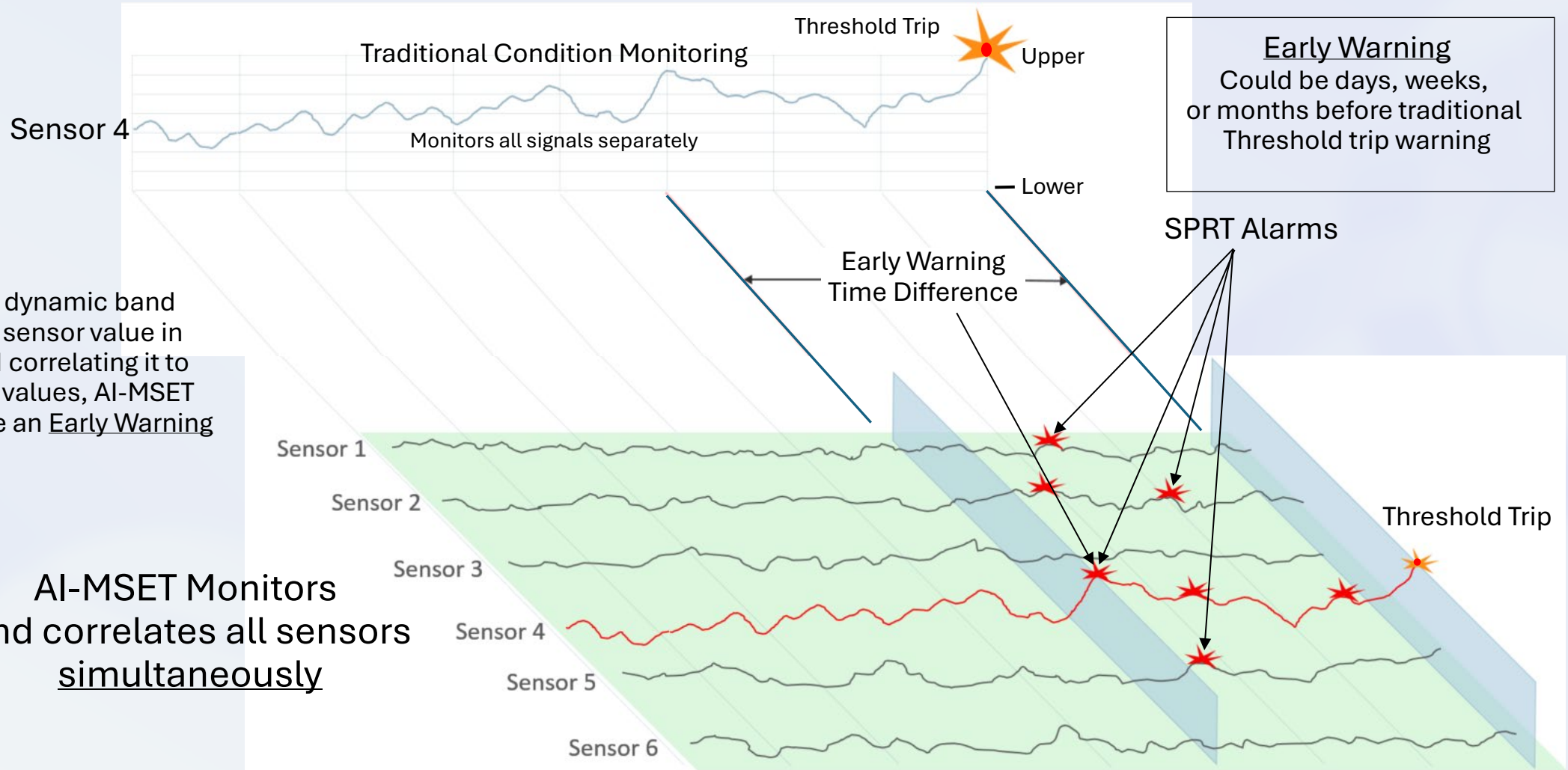
Traditional threshold-based prognostic approaches may use Machine Learning to distill down and coalesce important metrics for distinguishing between “normal” and “anomalous” behavior, but ultimately metrics are being compared against a threshold:



The endemic problem with threshold limit tests is the “sea saw” effect between false alarms and missed alarms.

If the user wants to get earlier warnings for developing problems and “squeezes” the thresholds closer to the means, we get spurious trips and high false alarm rates. If the user wants to avoid costly false alarms and moves the thresholds further away from the distribution means, then the assets can be severely degraded (or failed/crashed) before any alerts are generated.

ADVANCED PATTERN RECOGNITION

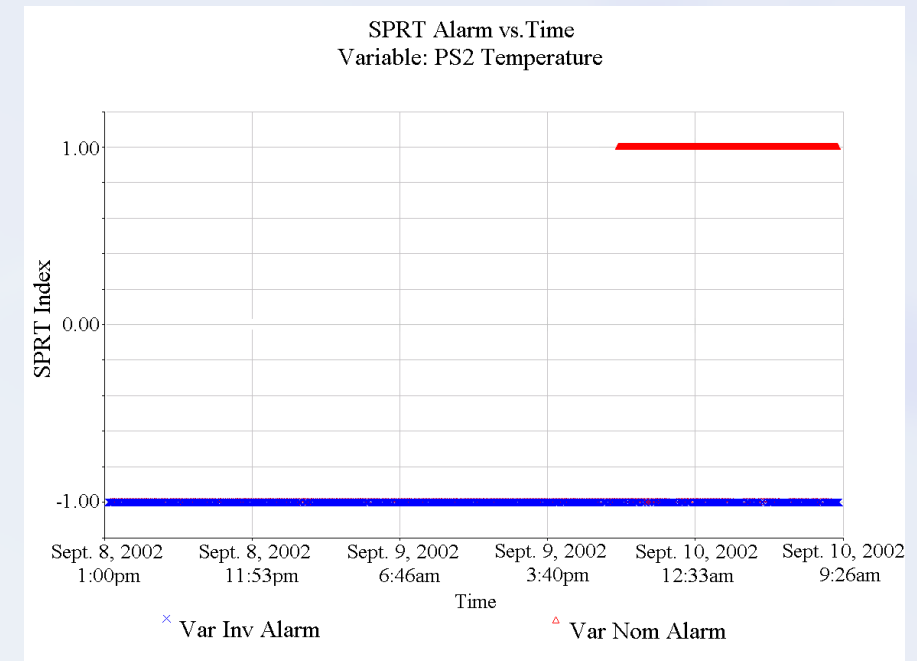
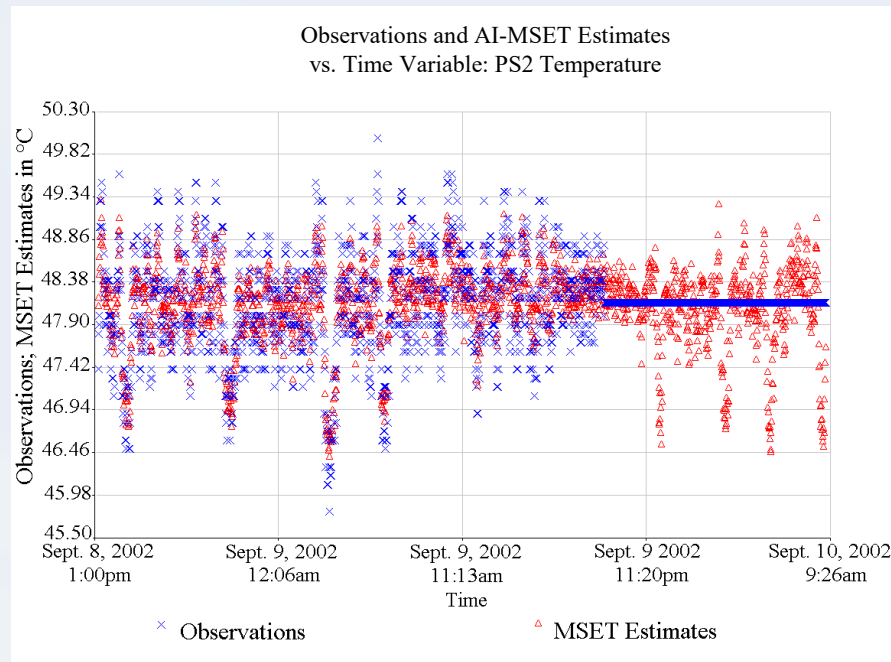


Inferential Sensing

INFERENCE SENSORS via AI-MSET

Physical sensors can fail. In many cases, the physical sensors have a shorter Mean Time Between Failure than the assets the sensors are supposed to protect. With AI-MSET, if a physical sensor fails or degrades in service, AI-MSET can mask the sensor signal and swap in the highly accurate AI-MSET estimate (red variable in figure). Immediate SPRT alarms observed.

AI-MSET disambiguates between sensor degradation mechanisms and degradation in IoT assets/processes



AI-MSET DISAMBIGUATES BETWEEN SENSOR DISTURBANCES AND ANOMALIES IN CRITICAL ASSETS

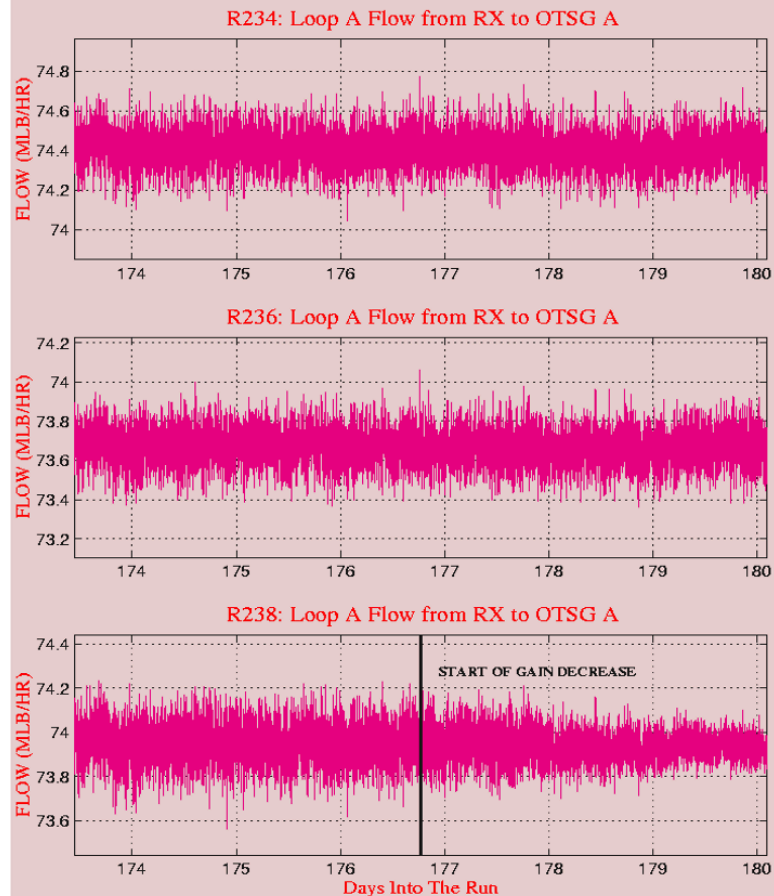
Sensors often have a shorter mean-time-between-failure (MTBF) than the assets the sensors are supposed to protect
TPN's AI-MSET detects all types of sensor de-calibration bias and sensor degradation modes

AI-MSET provides signal validation and sensor-operability validation. Subsequent system/process anomaly detection operations are then performed on fully validated signals.

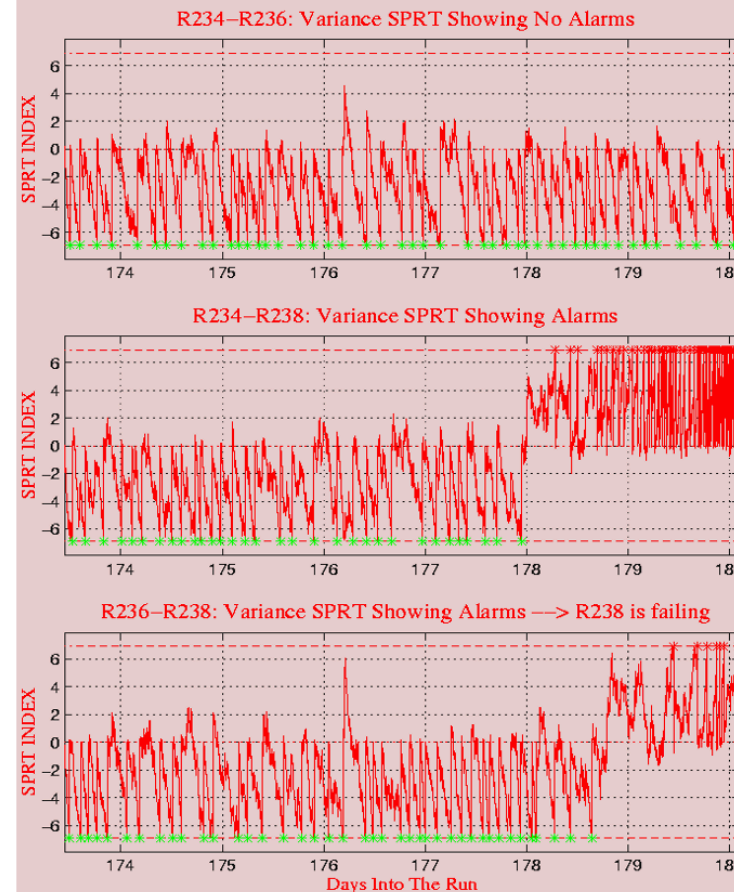
- High-end servers can contain hundreds (sometimes thousands) of physical transducers (distributed Temperature sensors, voltages, currents, and fan speeds) that protect the system by detecting when a parameter is out of bounds.
- When a sensor failure is detected, AI-MSET swaps out the degraded sensor signal, and swaps in an “analytical estimate” of the physical variable, called an "inferential sensor". This analytical estimate can be used indefinitely, or until the board containing the failed sensor needs to be replaced for other reasons.
- No longer have to shut down a \$1M critical asset to discover a \$5 Temperature sensor is drifting out of calibration.

ADVANCED PATTERN RECOGNITION

Linearly Decreasing Gain Factor Failure Detection



Variance SPRT Detects the Gain Factor Failure in R238



Sensor “Loss-of-Gain” failures lead to costly outages in Utility, Oil & Gas, Railroads, Avionics, and other industrial IoT applications, and to loss of lives in safety-critical applications.

Thresholds cannot catch this sensor degradation mode.

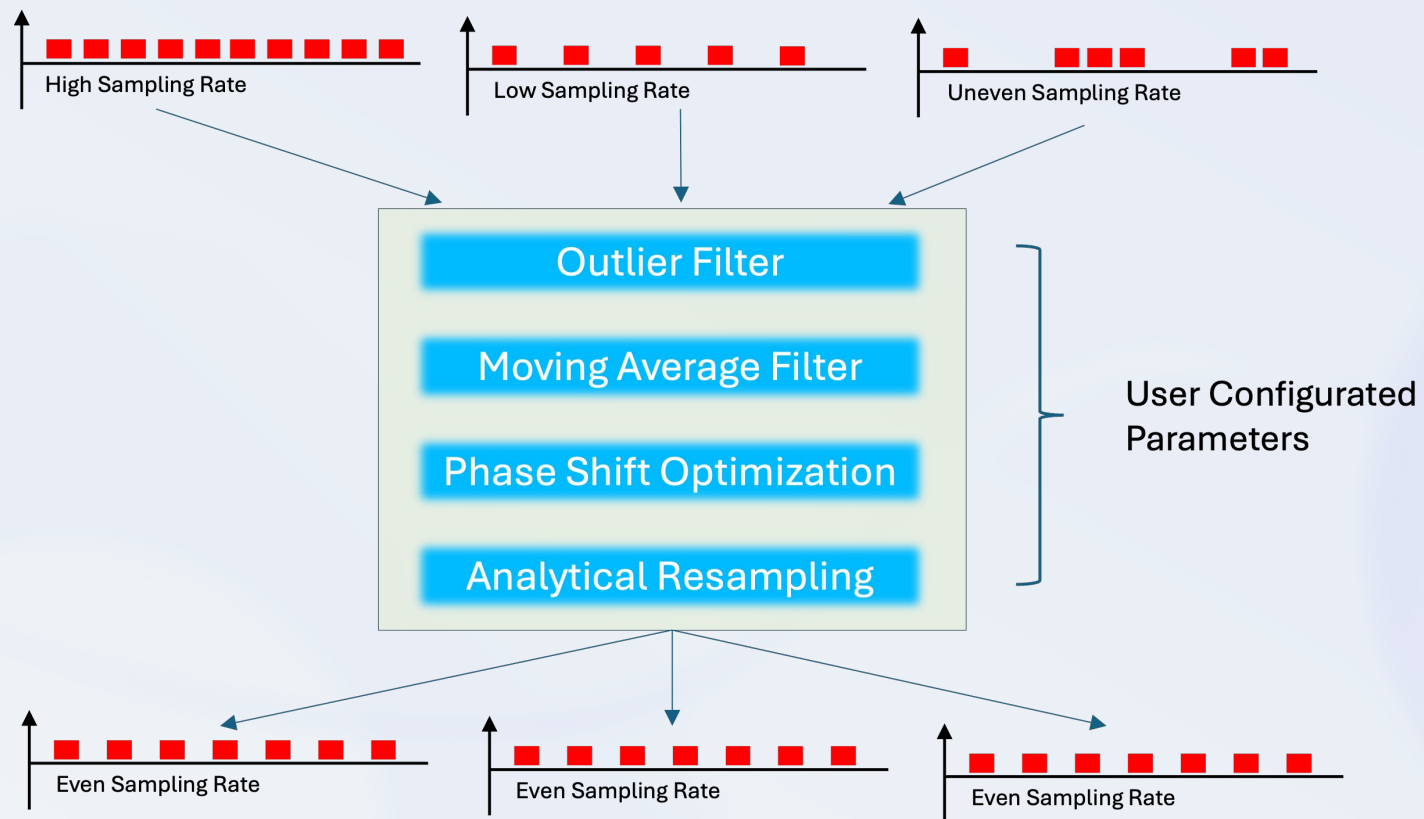
AI-MSET detects this degradation mode with very high accuracy, no false alarms.

CHALLENGES FOR CONVENTIONAL AI/ML ALGORITHMS FOR PROGNOSTICS WITH RAIL ROADS AND OTHER INDUSTRIES, (e.g., Neural Nets, SVMs, AAKR, Linear Regression, etc.)

- Low resolution sensors, Quantized sensor signals
- Variable sampling rates for sensor signals (slower, faster, uneven)
- Missing values in time series signatures
- Robustness to intermittent spurious sensor anomalies
- Signal-asynchrony issues, Clock miss-match issues in large-scale IoT applications
- Assets are fine but sensors drifting out of calibration

Analytical Resampling Process

ESSENTIAL FOR MULTI-SIGNAL DIAGNOSTICS/PROGNOSTICS



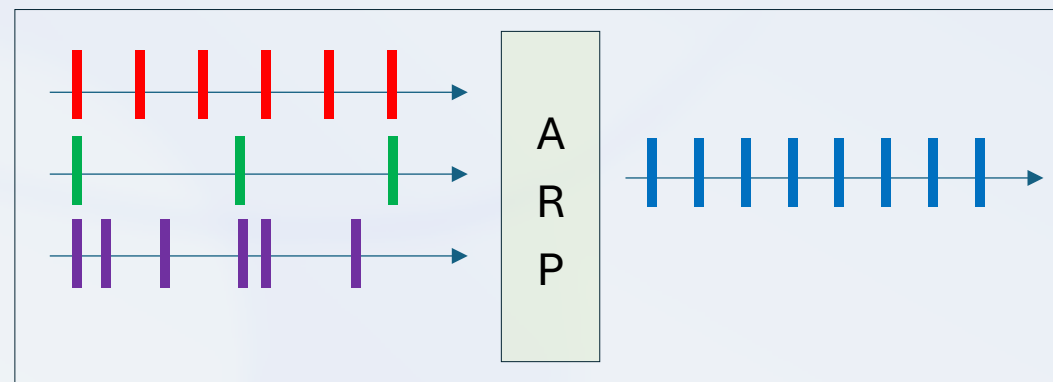
INTELLIGENT RESAMPLING PERFORMANCE

Telemetry streams originate with differing sampling rates

- ARP uses interpolation-based up-sampling/down-sampling methods to generate uniform sampling intervals for all telemetry time series
- It is very commonly the case that the four primary sources of telemetry signatures to be used in prognostic security originate from clocks that are significantly out of sync

Asynchronies from Clock Mismatch Issues

- Clock mismatch issues will cause almost all time-series Machine Learning algorithms to fail prognostic functional requirement criteria
- ARP performs real-time “adaptive empirical synchronization”



TNP's Analytical Resampling Process (ARP)

The various telemetry streams originate with differing sampling rates:

- ARP uses interpolation-based up-sampling/down-sampling methods to generate uniform sampling intervals for all telemetry time series

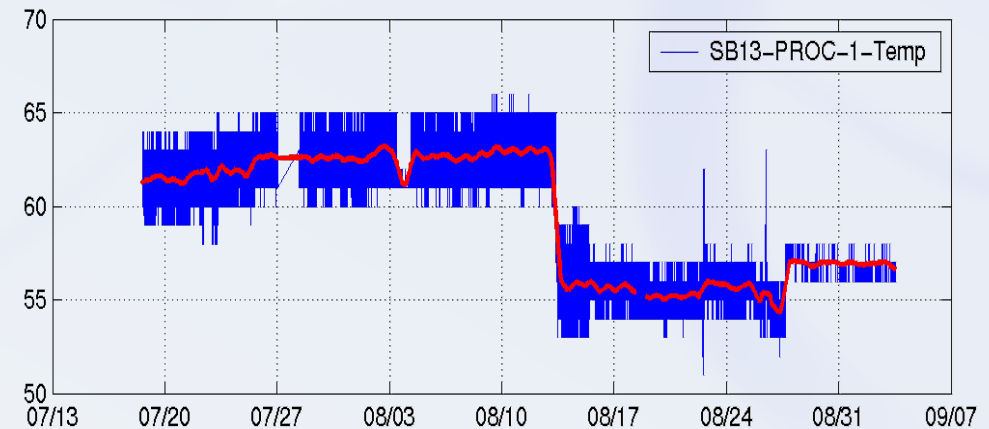
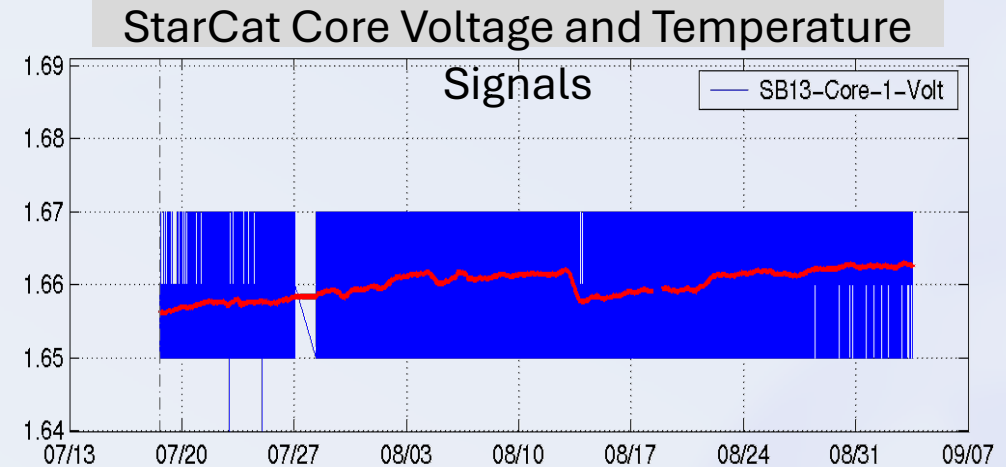
Asynchronies from Clock Mismatch Issues:

- It is very commonly the case for O&G, manufacturing, railroads, etc., that distributed Data Acquisition Modules (DAQs), that the primary sources of telemetry signatures used in prognostics originate from clocks that are significantly out of sync
- Clock mismatch issues will cause almost all time-series Machine Learning (ML) algorithms to fail Prognostic Functional Requirement criteria. [Low prognostic sensitivity, high false-alarm and missed-alarm probabilities (FAPs & MAPs)]
- ARP performs real-time “adaptive empirical synchronization” at front end of AI-MSET

DeQuantize

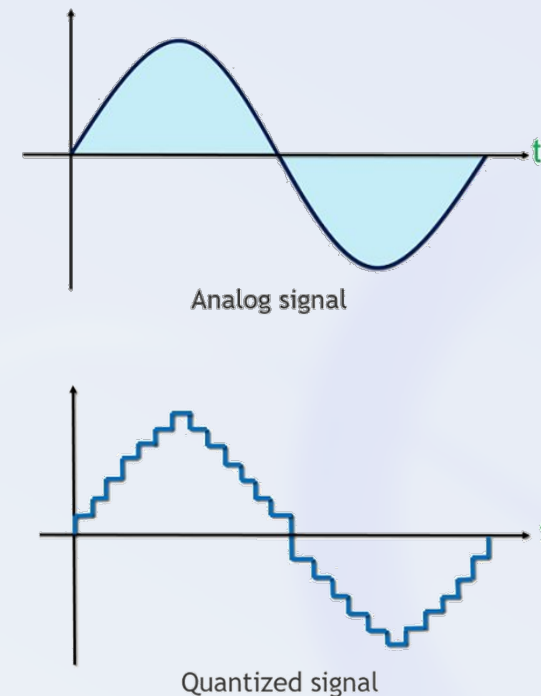
DEQUANTIZE PERFORMANCE

- Drastic difference between the quantized sensor readings (blue) and the genuine signal characteristics (red) on both signals
- The global trend and local dynamics were missing in the quantized signals
- The UnQuantize algorithm reveals the true characteristics of the two signals, benefiting the downstream anomaly detection tasks



URNS LOW-RESOLUTION INPUT SIGNALS INTO HIGH-ACCURACY OUTPUT SIGNALS

- Many industries (including railroads and locomotive manufacturers) use 8-bit Analog/Digital conversion chips for physical sensors
- As a result of low-bit resolution, physical variables are severely quantized.
- Machine Learning algorithms can't discern small variations in the quantized telemetry signals that could precede component degradation or system failure



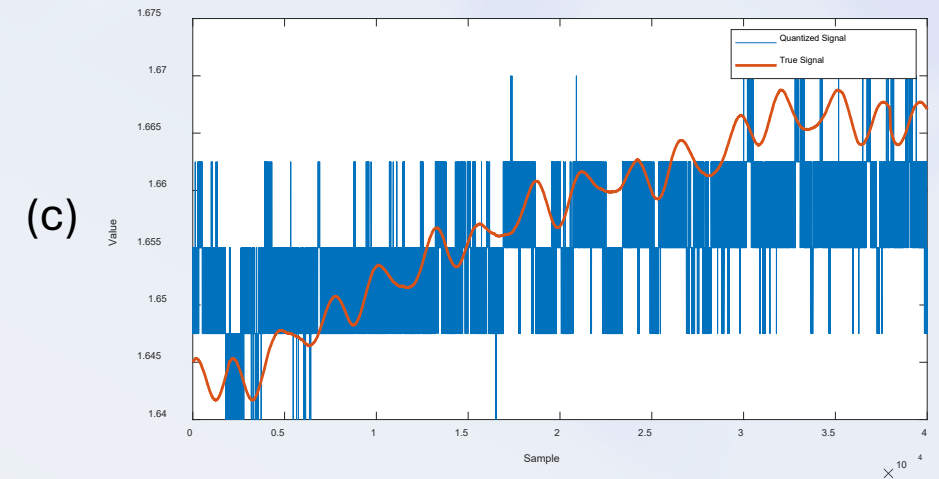
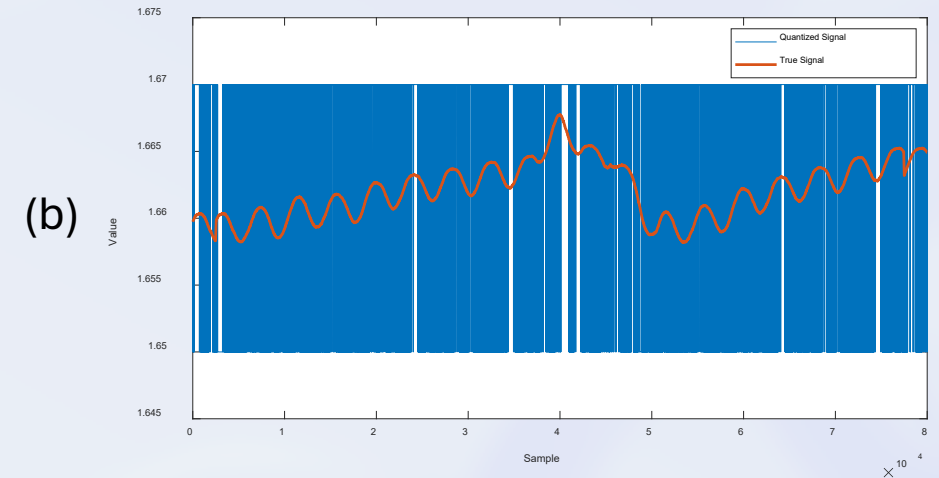
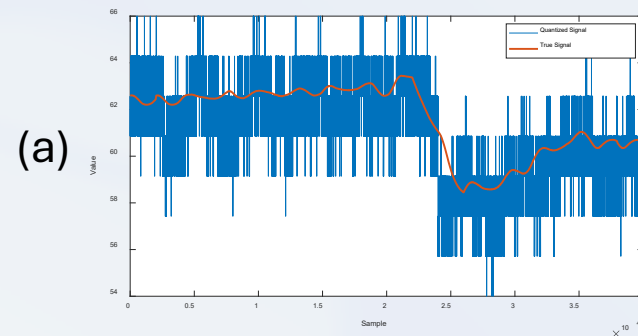
SIGNAL QUANTIZATION EXAMPLES

- Three examples of quantized signals with 8-bit A/D chips (blue) vs. true signals (i.e., high-resolution) with 16-bit A/D chips (red)

(a): a voltage signal with level-2 quantization consisting of 2 oscillating values

(b & c): Temperature and voltage signals with QL=4 quantization

- The non-linear trends and dynamics were absent in the quantized signals



QUANTIZED SIGNALS

Raw telemetry signals in many industries are quantized by low-resolution A/D chips.

In the example at right, the voltage signal is quantized to 10 mV “buckets” because of 8-bit A/D chips.

“DeQuantize” algorithm (Upstream of AI-MSET) reveals that this signal is slowly drifting due to a degrading interconnect.

