

Machinery Predictive Analytics and Decision Making

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DecisionIQ: Founders



Andrew Lewis
Founder, CEO

- MBA, University of Chicago
- BS, Aerospace Engineering, Georgia Tech

Successful Engineer/Entrepreneur Technology Enabled Products & Businesses



Apple Clone License / High Performance Computing



F-16 New Supersonic Cruise Wing



Nagi Gebraeel, PhD
Co-Founder, Chief Data Scientist

- Professor, Industrial Engineering, Georgia Tech
- MS, PhD, Industrial Engineering, Purdue University



Background

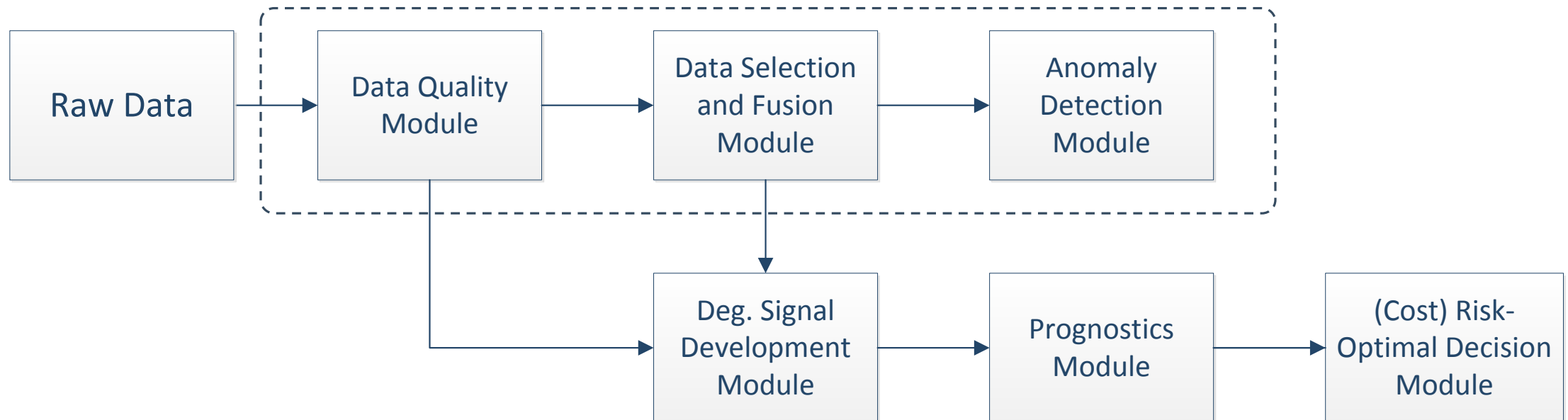
- DecisionIQ is an Atlanta-based startup company specialized in equipment predictive analytics and asset management.
- DecisionIQ is commercializing state-of-the-art research in this space that has been developed at Georgia Tech.
- Unique aspect of the DecisionIQ platform:
 - *Seamless integration between reliability engineering, sensor-based and optimization models for real-time decision-making for maintenance, operations, and (spare parts) supply chain.*

Balancing Flexibility and Scalability

- DecisionIQ is home to APDP:
Adaptive Predictive Analytics Development Platform
- APDP was developed on the basis of an **assemble-to-order** deployable analytics platforms
 - *Enables rapid development of custom-built analytic solutions that meet unique customer needs*
 - *Balances flexibility provided by customized solutions while ensuring scalability and ease of deployment that comes with one-size-fits-all solutions*

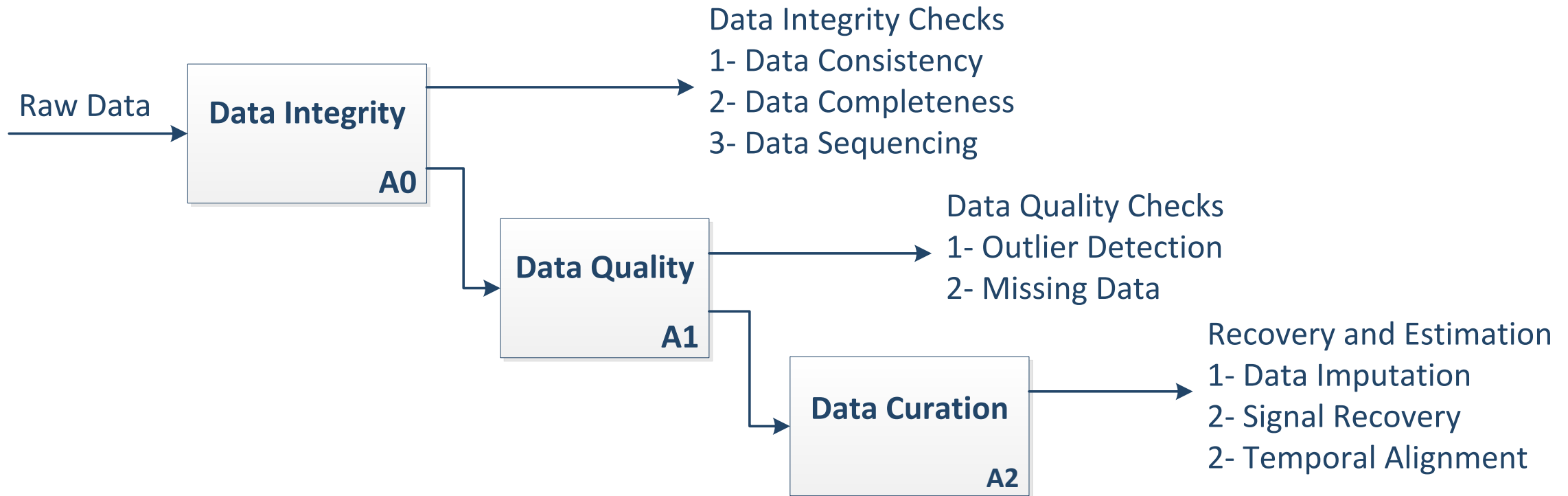
Platform Overview

- APDP consists of six modules
- Modules used for the SNC Monitoring Challenge are highlighted below



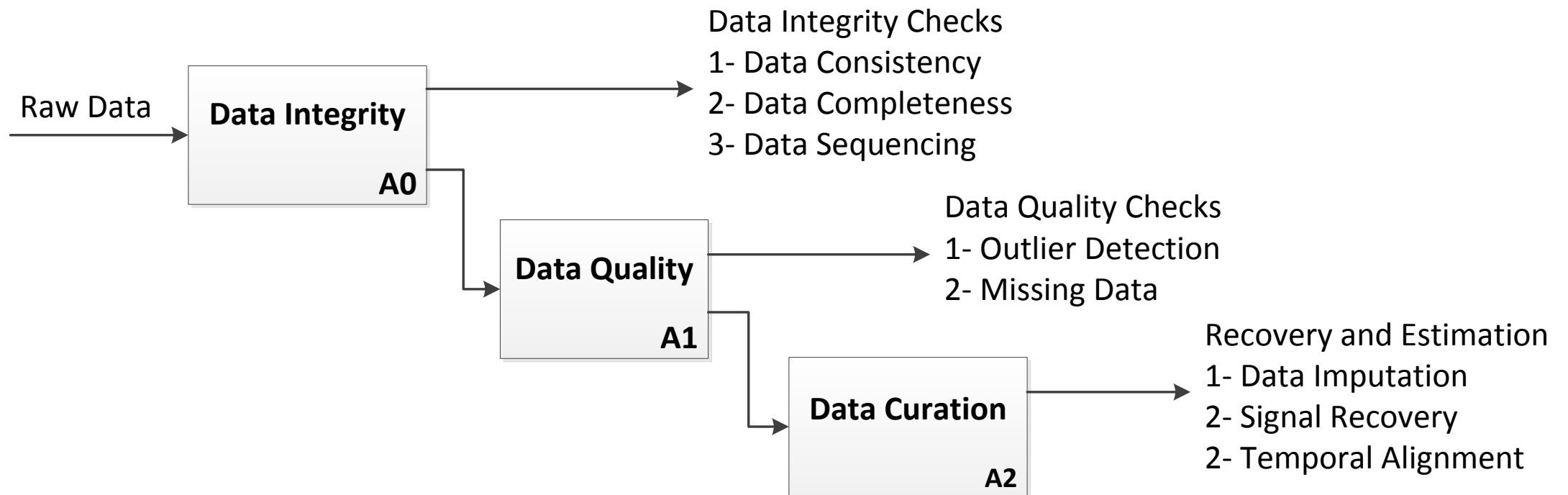
Data Quality Module

- DQM is where data quality and integrity checks are applied and data curation tasks are performed.



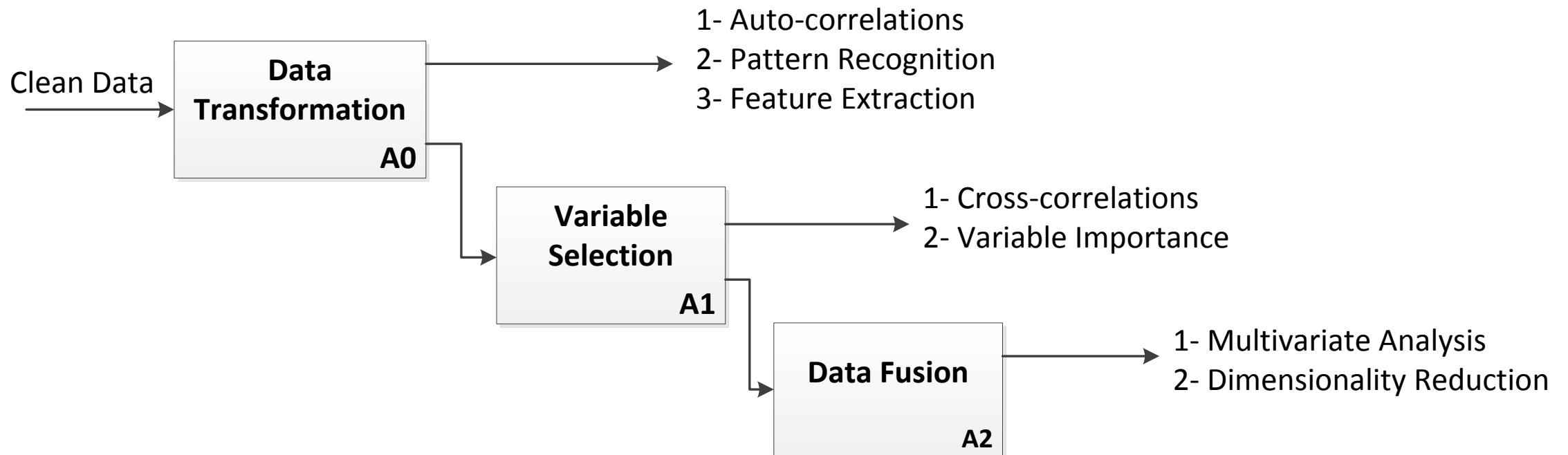
Data Quality Module

- Data Quality plays a primary role in the effectiveness of diagnostic or prognostic techniques. **DQM** is where data quality and integrity checks are applied, and data curation tasks are performed.*



Variable Selection and Data Fusion Module

- *Variable Selection identifies the most informative data variables, and adaptively eliminating redundant variables.*
- *Data Fusion intelligently combines different variables to enable multivariate analysis.*

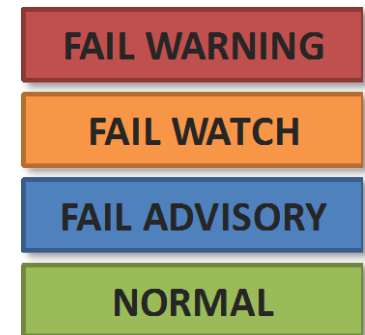
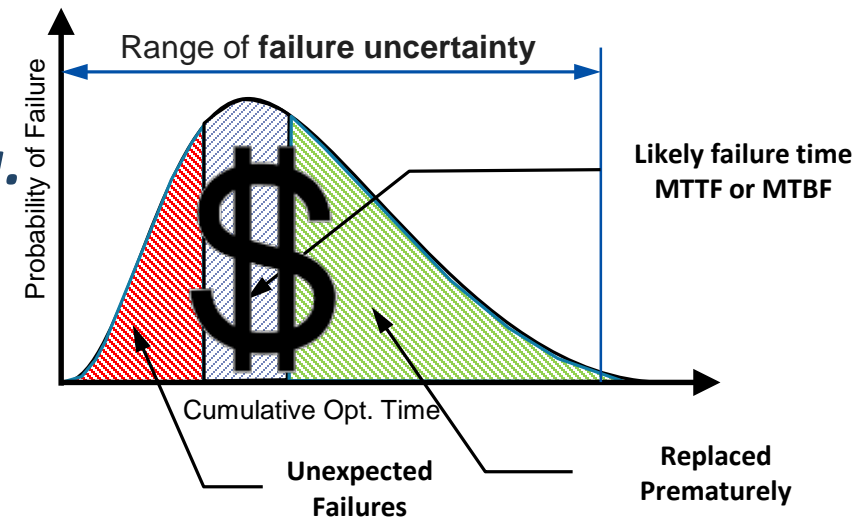


Anomaly Detection Module

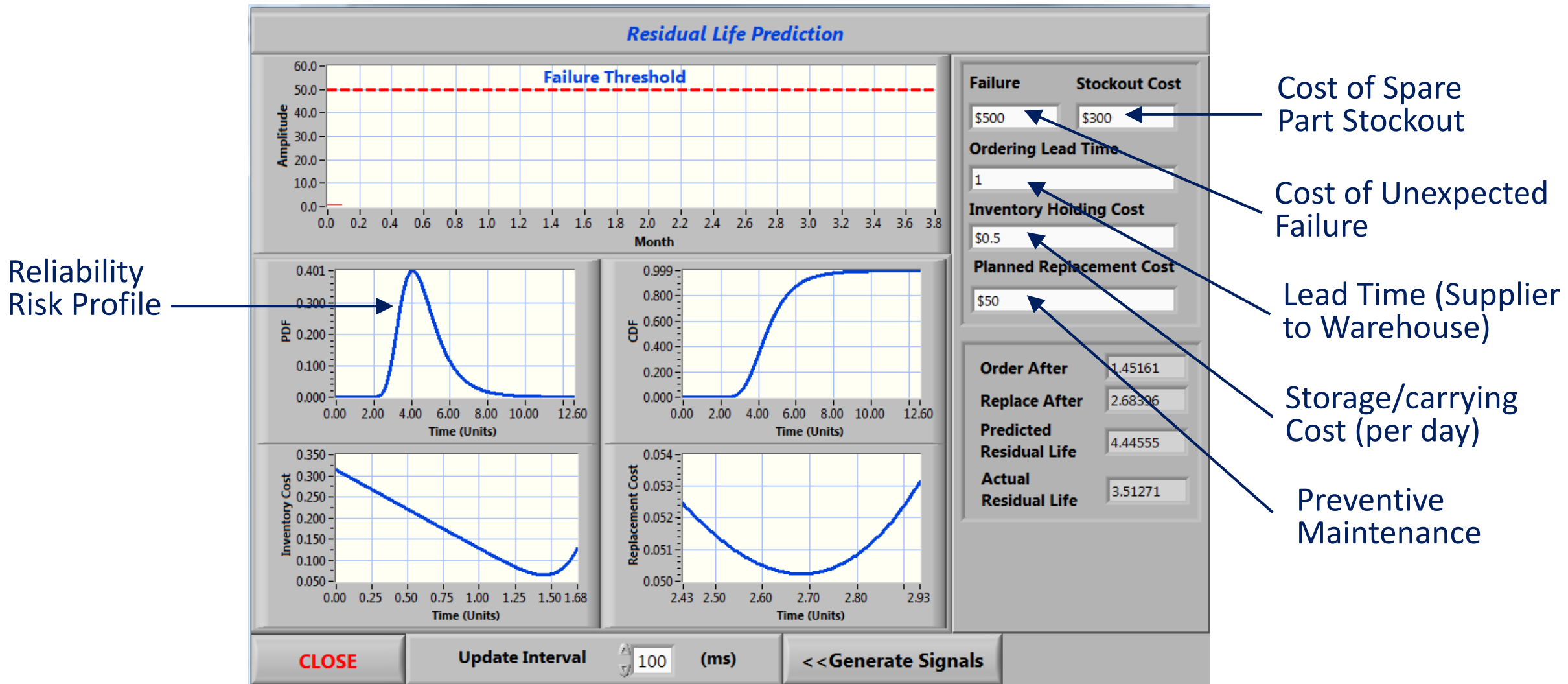
- *Classical anomaly detection algorithms are often plagued with false alarms.*
- ***Individual Sensor Monitoring*** : A sensor has about a 0.27% chance of generating a false alarm. If 50 sensors are monitored individually (each with 0.27% false alarm rate), the actual false alarm rate jumps to about 14%.
- ***Fusion-Based Sensor Monitoring***: Controls false alarm rates but masks any diagnostics capability.
- *Our ADM module, employs an Ensemble Anomaly Detection Approach where we leverage the strengths of a suite of algorithms that allow us to control the low false rates while simultaneously providing diagnostic capabilities*

Prognostics Module: Combining Reliability & Condition Monitoring

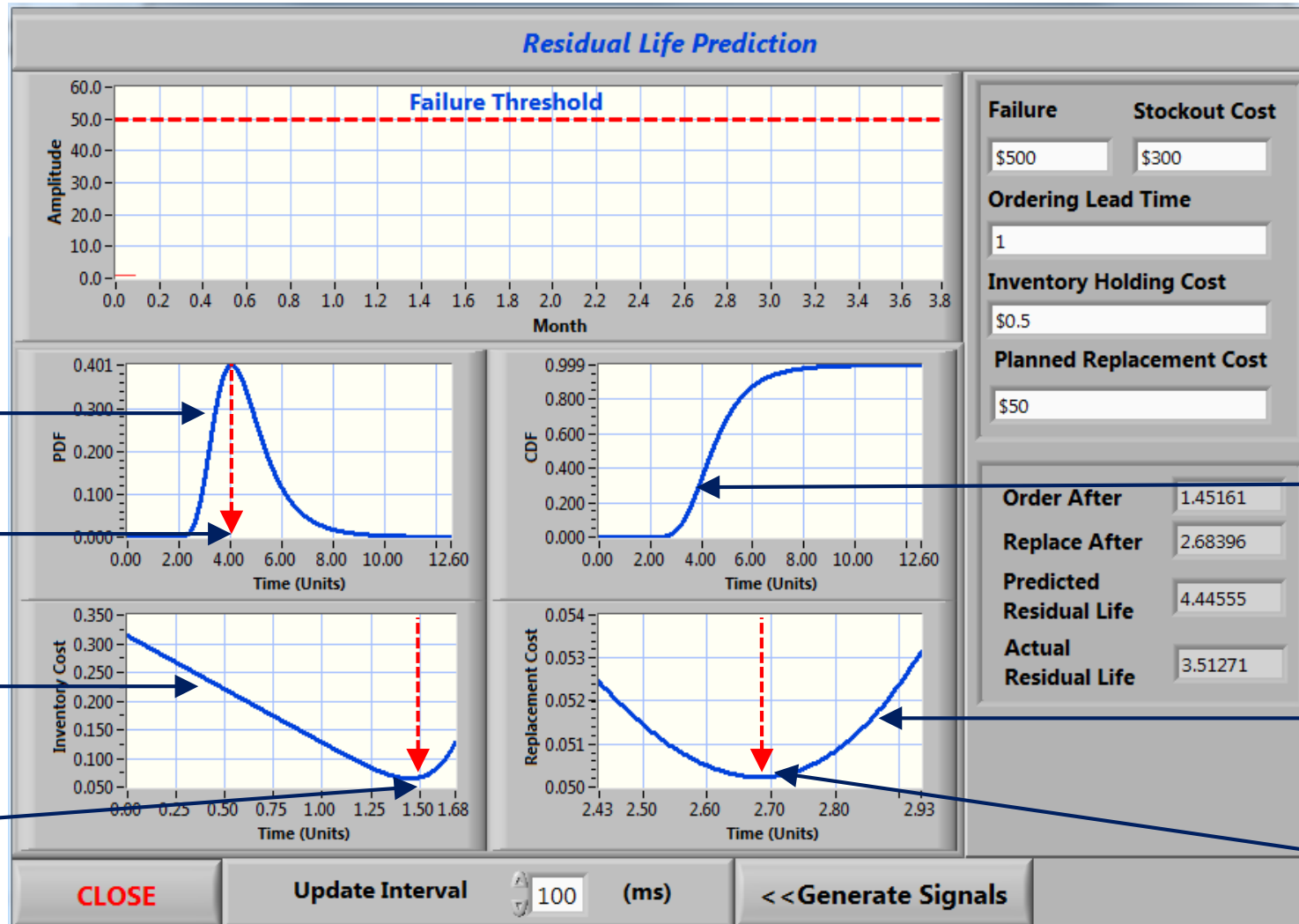
- *Our Prognostics module combine the **best of both worlds**.*
- ***What is achievable using Reliability Analysis cannot be accomplished by Condition Monitoring.***
 - Quantifying Failure Uncertainty
 - Managing and Monetizing risk
 - Strategic Planning and Decision Making (PMs)
- ***What is achievable using Condition Monitoring cannot be accomplished using Reliability analysis.***
 - Visibility into the asset health
 - Fault Detection and Diagnostics



Example: Starting with Reliability Data



Example



Reliability Risk Profile

MTTF

Spare Part Inventory Cost Function

Optimal Spare Part Ordering Time (1.5 mons)

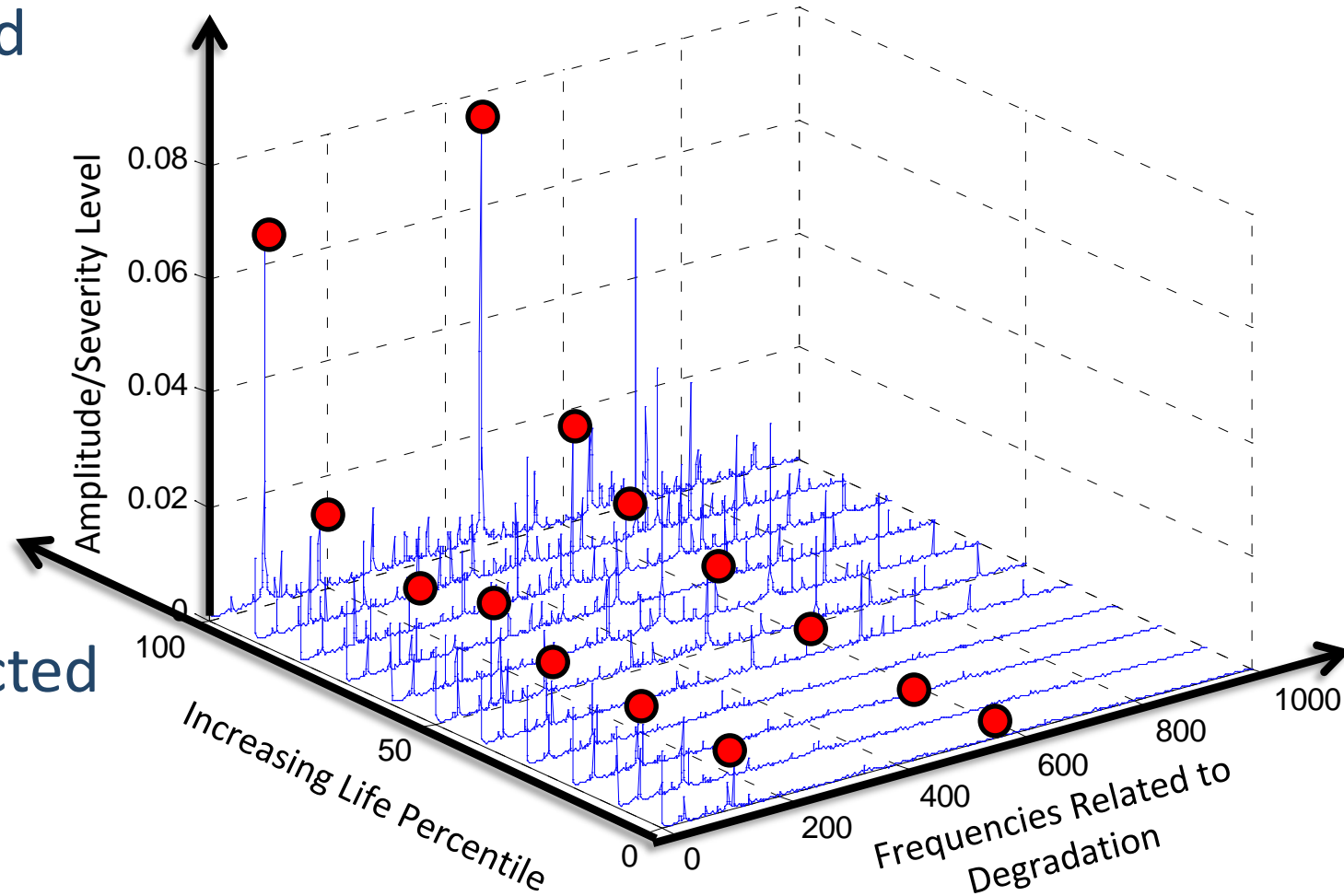
Probability Distribution

Repair/Replacement Cost Function

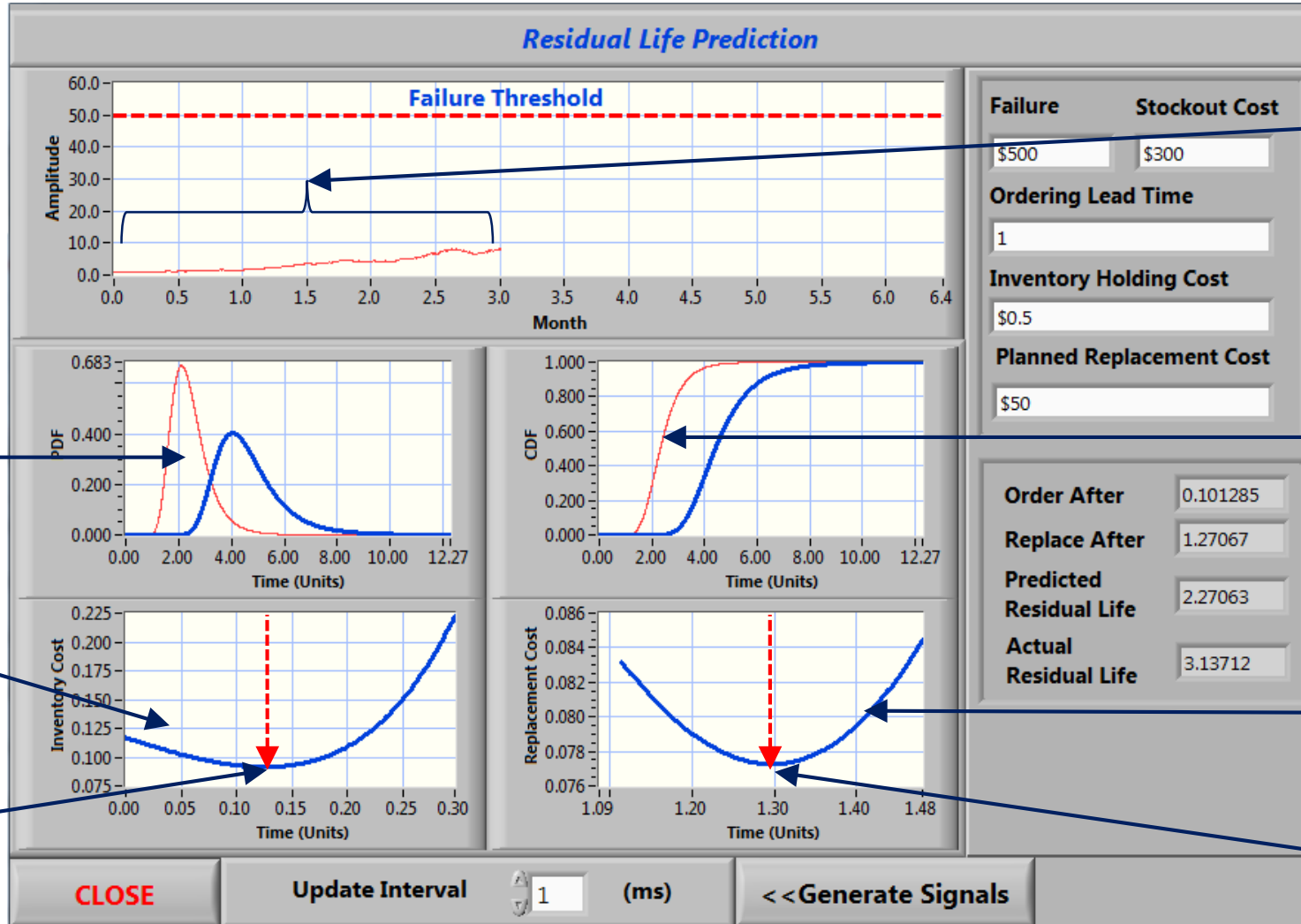
Optimal Repair or Replacement Time (2.7 mons.)

Example of Condition monitoring data

- Vibration signatures acquired as the asset/equipment progresses over its life cycle.
- The figure shows post-processed vibration data at different life percentiles of the equipment.
- Fault-specific features extracted in real-time (red dots) and modeled over time.



Example with CM Data



Real-time Condition Monitoring Data

Updated Risk Profile (Remaining Life)

Updated Probability Distribution

Updated Spare Part Inventory Cost Function

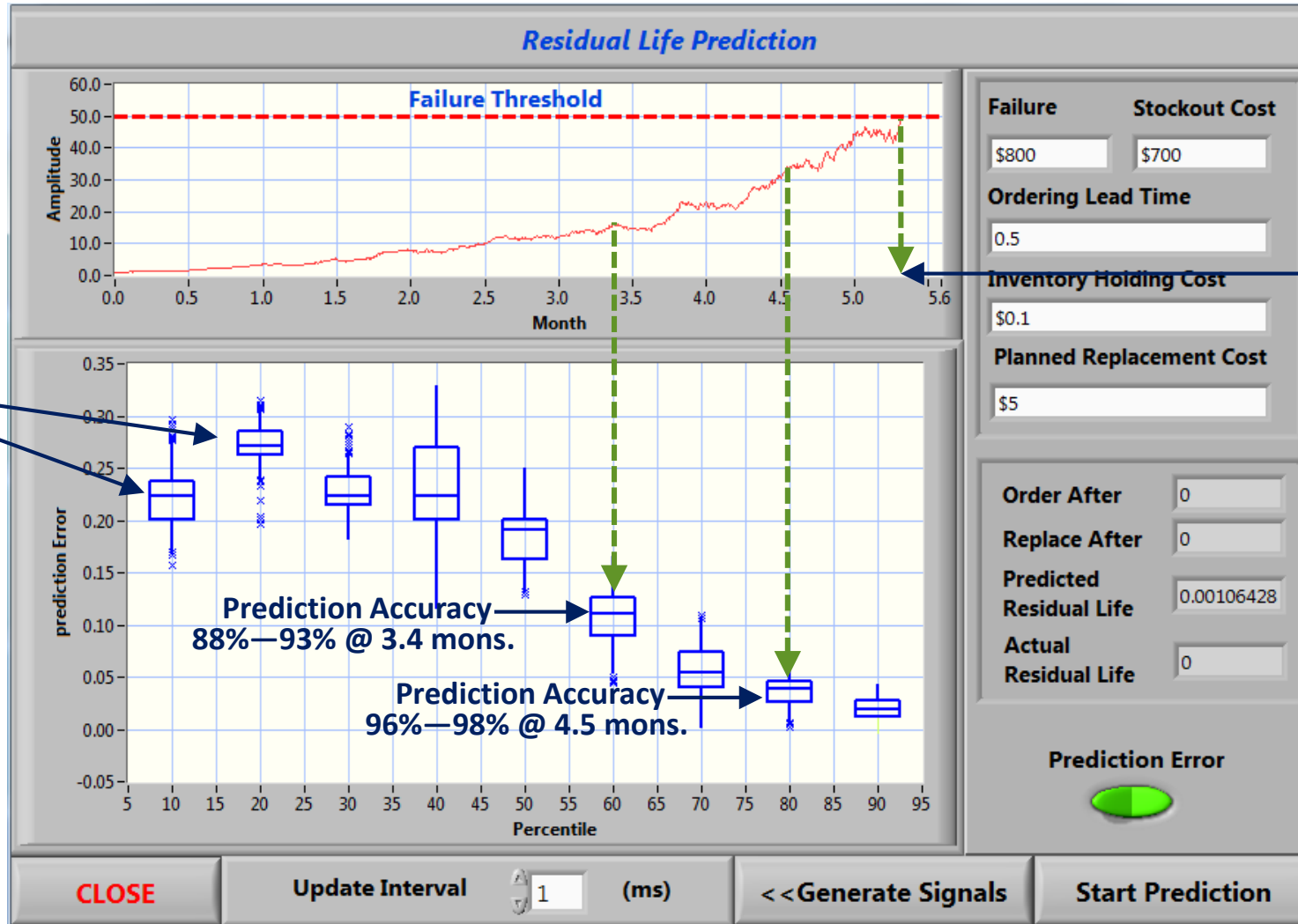
Updated Replace. Cost Function

Optimal Spare Ordering Time (1 week)

Optimal Repair or Replacement Time (1.3 mons.)

Prediction Accuracy

Early Prediction are based on Reliability Prediction Accuracy 69%—78% @ 0—1 month.



Actual Lifetime (5.5 mons.)

Thank you

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