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Smart Manufacturing Machine Learning for Predictive Maintenance

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Analytics Platform

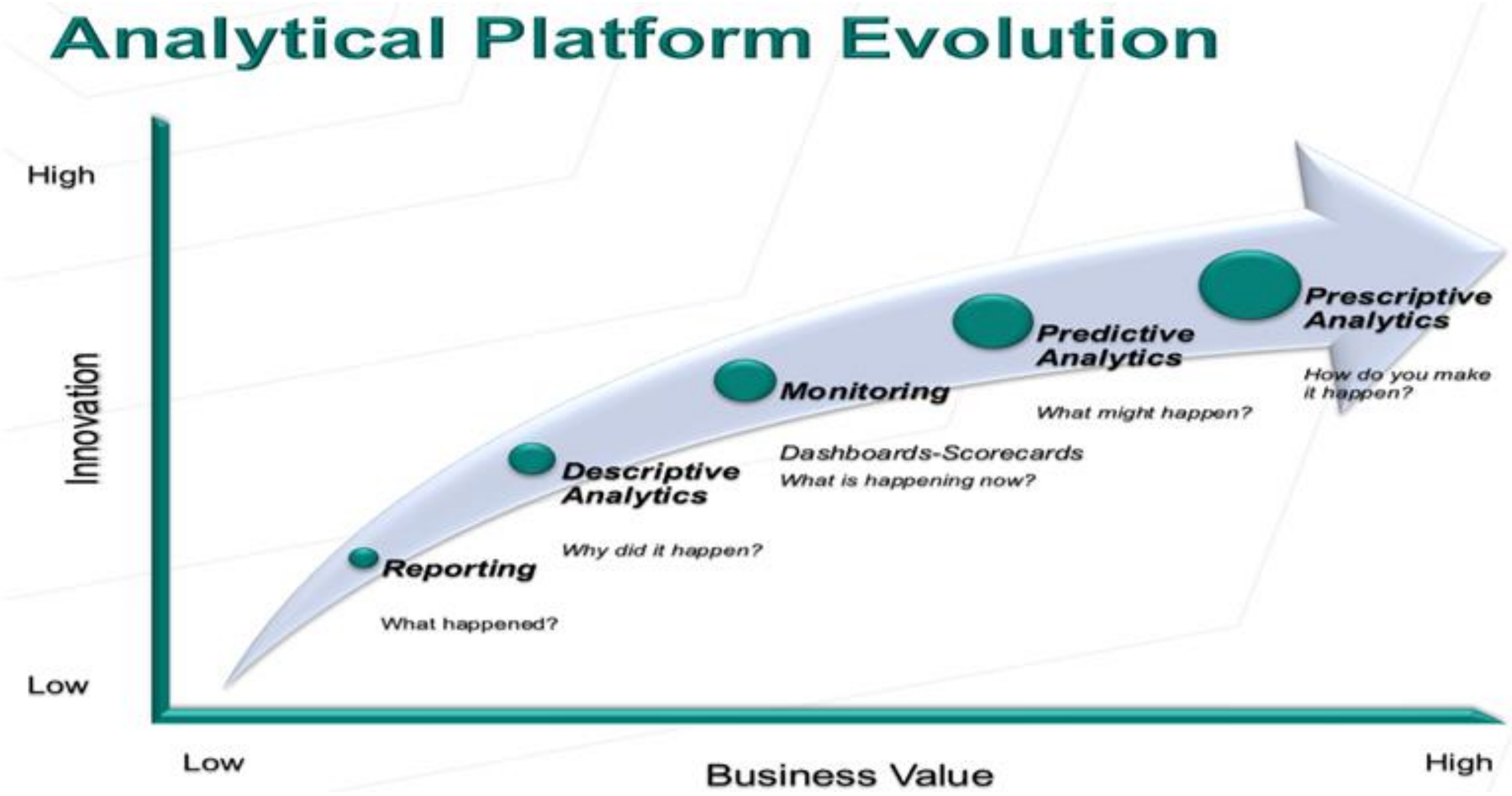


Image source: http://asi-solutions.com/2016/12/evolution-of-analytics-where-does-your-company-stand/

Machine Learning In Industrial IoT

XILINX aingura IIoT

Predictive Maintenance

No Unplanned Downtime

Anomaly Detection

Highest Quality

Optimal Efficiency

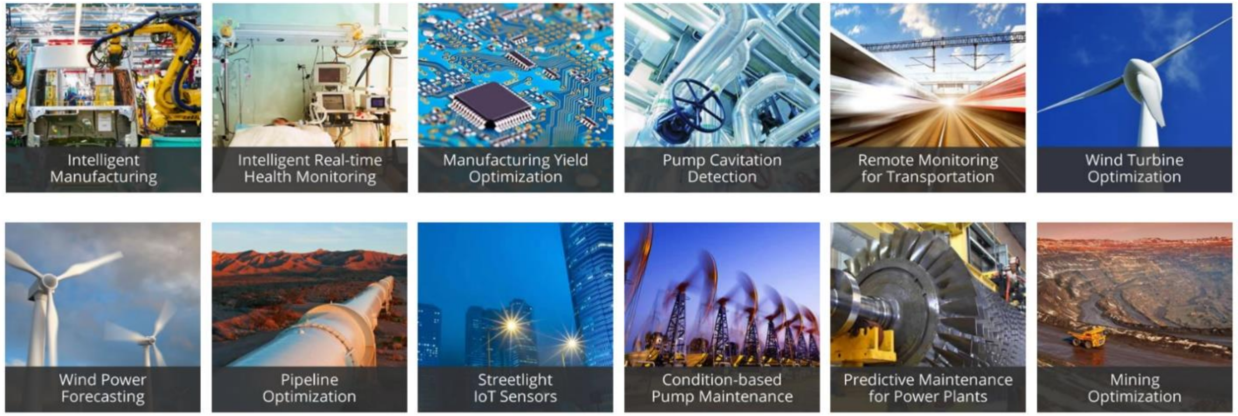
Peak Productivity

Autonomous Operation

Lowest Manufacturing Cost

Security and Safety

Secure Networking Protected Environment



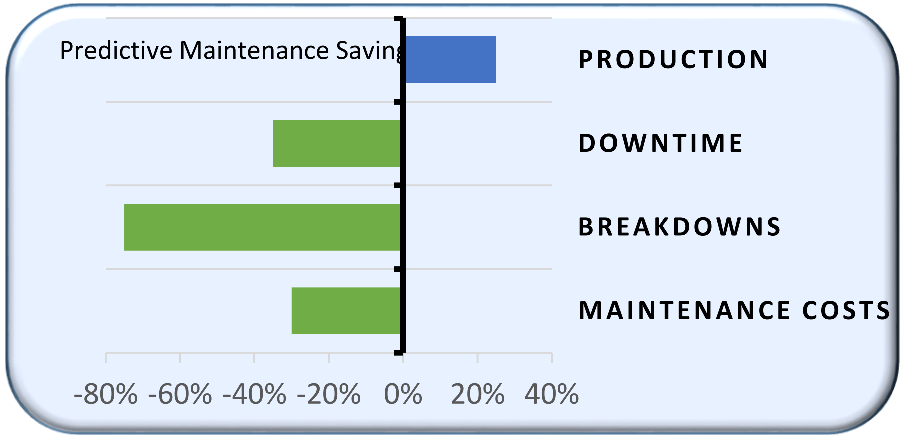
Machine Learning provides increased intelligence to the Industrial Internet of Things

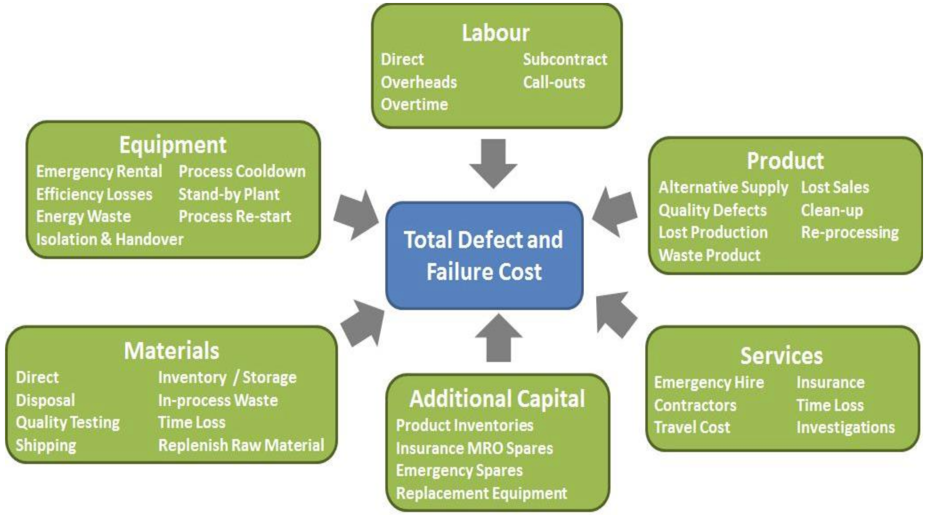
Image source: https://www.foghorn.io

Savings Potential –> Total Cost of Failure

Predictive Maintenance can provide significant savings

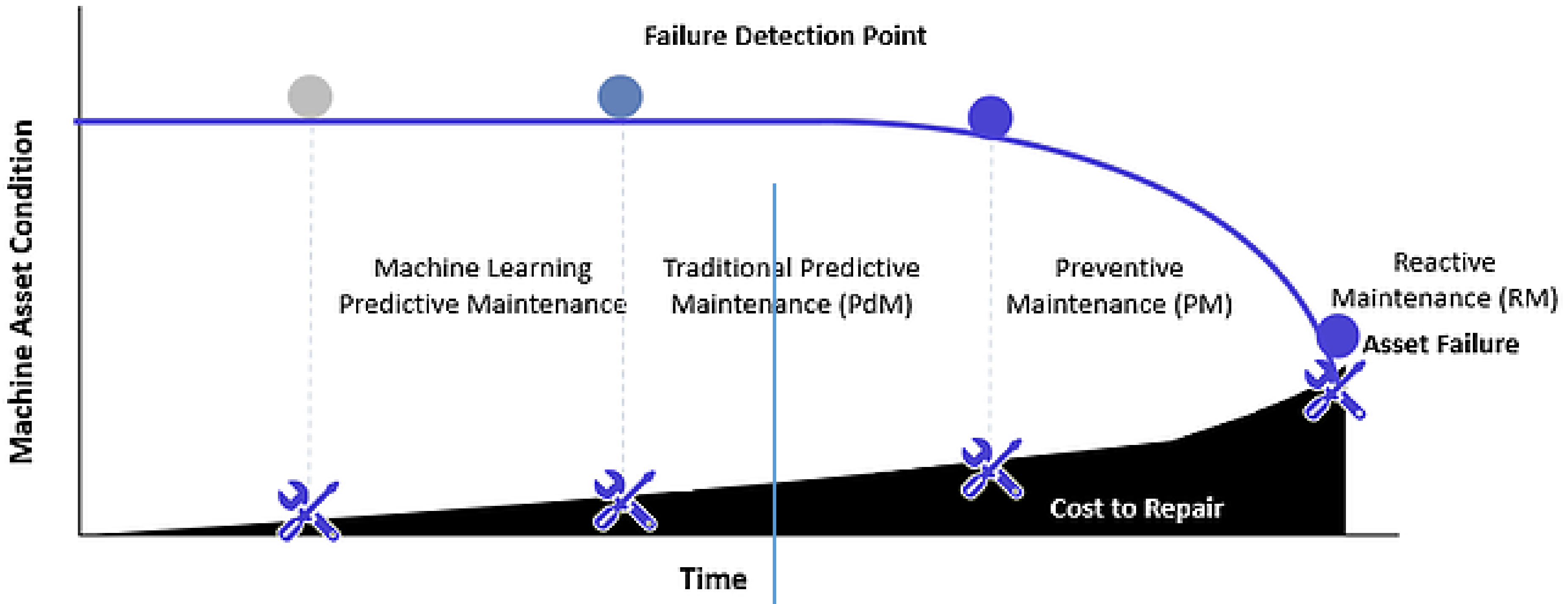
- **30 - 40 % over reactive maintenance and,**
- **8 - 12 % over preventive maintenance programs.**





Source: Mike Sandalini, "Defect and Failure True Costing"

Significant Savings Potential



Source: Mike Sandalini, "Defect and Failure True Costing"

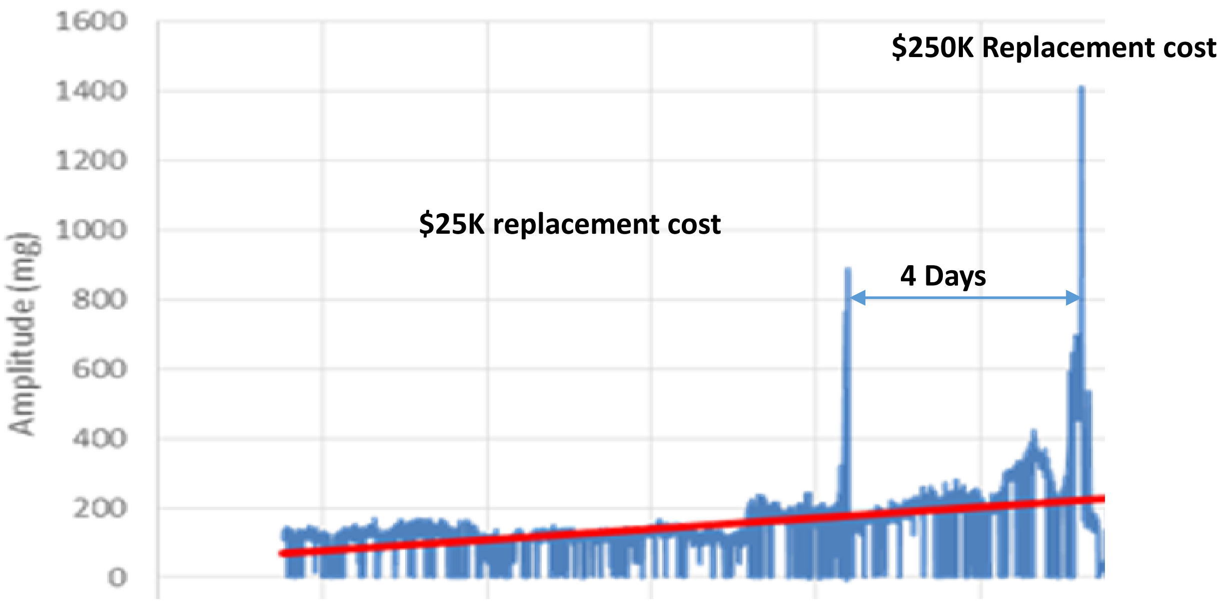
Image source: presenso

Predictive Maintenance market expected growth: $1,404.3 Million in 2016 to $4,904.0 Million by 2021, Compound Annual Growth Rate (CAGR) of 28.4%*

*Source: https://www.linkedin.com/pulse/20140814090436-13439787-the-business-case-for-predictive-plant-maintenance

Predictive Maintenance - Automotive Machine Tools Market

- **Early failure prediction can help reduce unplanned downtime reduction**
  Costs $50K+ per hour in high-productivity markets like automotive
- **Component failures signals can be measured and detected at early stage**
  Helps to avoid damage of other related/connected components



- **Machine learning-based monitoring systems can identify system inefficiencies**

A single line in production CN codes with slightly different parameters 2% loss in cycle time
Detection using machine learning techniques identified process anomalies.

Predictive Maintenance – Machine Learning for Early Prediction

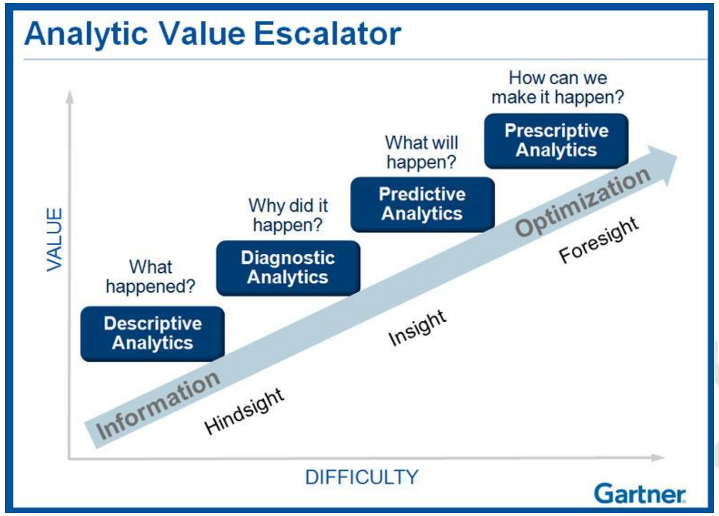
- **New machine learning-based solutions for efficient manufacturing:**

Machine learning-based tools used to increase detection rate and reduce occurrence value of High Risk Priority Numbers (RPN) for critical parts identified by machine tool's FMEA. This helps to reduce RPN increasing machine availability

- **Support early failure prediction**

Cross-multivariable/multicomponent degradation monitoring supported through real-time machine learning solutions. These solutions can run diagnostics tasks that can evolve to prognostic detection to reduce random failure

Note: 85% of failures are considered random lack of understanding the failure mechanism(s).



Market Opportunity

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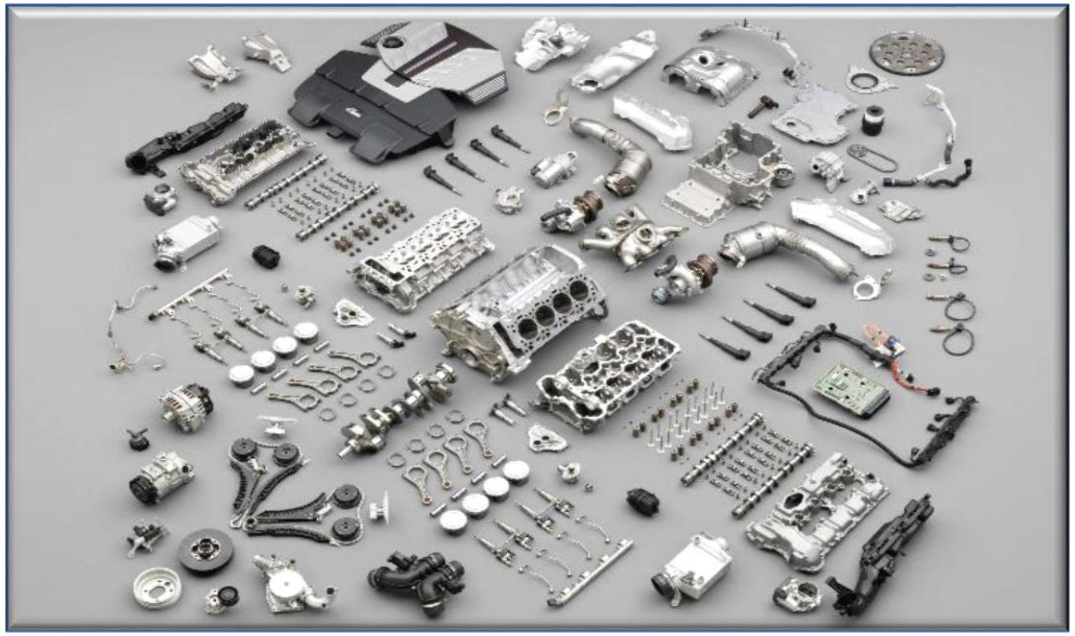
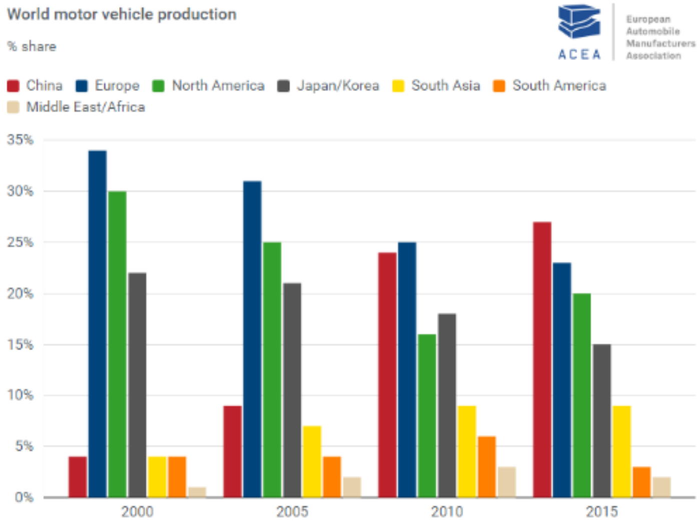


Automotive:
- 91.5 million motor vehicles were produced globally in 2015.
- ~ 250,000 motor vehicles produced per day.
- High-productivity machining of powertrain: >1,000 systems/day



Predictive Maintenance Potential
- Increase system availability through 8% reduction in unexpected downtimes.

Aingura IIoT Powered by Xilinx

Smart Factory Machine Learning Testbed

XILINX aingura IIoT

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HOME COMMITTEES INDUSTRIES RESOURCE HUB MEMBERSHIP MEMBERS AREA

SMART FACTORY MACHINE LEARNING FOR PREDICTIVE MAINTENANCE

SMART FACTORY MACHINE LEARNING FOR PM • TESTBEDS

Testbed in Action

CASE STUDY: VALUE OF PREDICTIVE MAINTENANCE

This case study exemplifies where Predictive Maintenance with Machine Learning would have avoided significant financial and production line delay in a high volume manufacturing system. Shortly after experiencing initial problems, an unknown degradation in system

FAST FACTS

MEMBER PARTICIPANTS:

Aingura IIoT, Xilinx

SUPPORTING COMPANIES INCLUDE:

aicas, Bosch Software Inno … nstruments, RTI, System View, Thingswise, T…

Industrial Internet Consortium Launches Smart Factory Machine Learning Testbed

NEEDHAM, Mass.--(Business Wire)--The Industrial Internet Consortium® (IIC™), the world' s leading organization transforming business and society by accelerating the adoption of the Industrial Internet of Things (IIoT), today announced the Smart Factory Machine Learning Testbed

Sep 18, 2017 17:08 UTC

MARKET SEGMENT:

Industrial Manufacturing

GOALS:

- Evaluate & validate Machine Learning techniques for Predictive Maintenance on high volume production machinery to deliver optimized system operation.
- Achieve increased uptime & improved energy efficiency utilizing Machine Learning techniques for advanced detection of system anomalies and fault conditions prior to failure.

CHALLENGE:

Today's methodology of Preventative Maintenance, taking machines offline on a regularly scheduled timeline is not cost efficient and does not necessarily ensure addressing the actual problems leading to system failure. Gaining accurate, actionable insight from the tremendous amount of data acquired in real-time, to understand key component anomalies during operation before system failure, for Predictive Maintenance is a daunting challenge. Furthermore, the root cause of over 80% of failures is not understood.

Smart Factory Machine Learning Predictive Maintenance Testbed

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Goals

- Evaluate & validate Machine Learning (ML) techniques for Predictive Maintenance (PM) on high volume production machinery to deliver optimized system operation
- Achieve increased uptime & improved energy efficiency utilizing ML techniques for advanced detection of system anomalies and fault conditions prior to failure

Participants

- Sponsors: Plethora IIoT: R&D of ML IP, Oberon system & applications with visualization
  Xilinx: All Programmable Technology, Connectivity IP, Security, Machine Learning framework and related IP

Phases

1) *Lab Development and Test*: Utilizes simulated data and degradation/fault conditions for ML exploration - Spain
   - Development / Exploratory phase: understand, implement & validate requirements for CNC Manufacturing system and preparation for pilot factory deployment
2) *Pilot Factory*: Initial Deployment in limited production facility - Spain - Etx-Tar CNC Manufacturing Facility
   - Field test in controlled facility – emphasis on PM and ML deployment on production manufacturing machines
3) *Production Facility*: Deployment of ML and real-time analytics in Automotive OEM facility – Confirmed -TBA
   - Deployment, validation of ML techniques on production CNC systems for optimized operation and energy efficiency

Smart Factory Machine Learning Testbed

Solution Overview

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Deployment Scenarios (OT)

Factory

Production Line

Manufacturing Cell

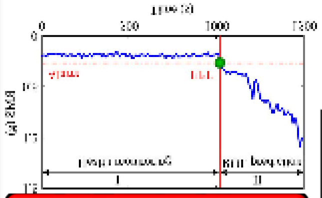
Machine

100011100
010110111
111000010

Data

Convergence (OT-IT)

- Time critical sensor fusion to synchronize data from different domains
- Feature (variables) subset selection to:
  - optimize data transmission and
  - improve algorithms performance.
- Machine Learning algorithms to:
  - leverage knowledge discovery and
  - failure prediction

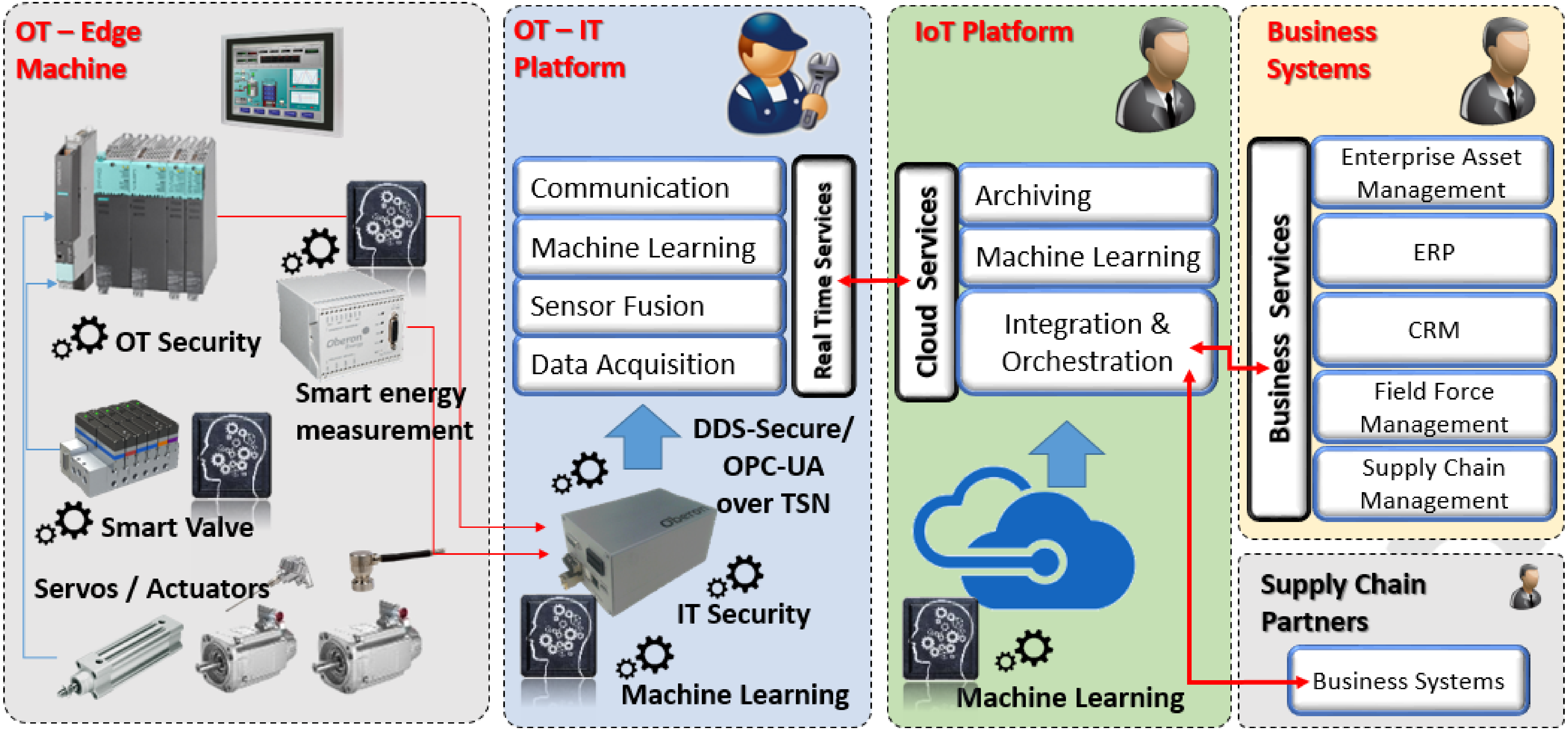


Information

Result (Actionable Insight)

- Machine Tool System
  - Component degradation pattern analysis
  - Machine behavior pattern
- Manufacturing cell
  - M2M interaction
  - Energy consumption patterns
- Production line
  - Energy optimization
  - Production line characterization
- Factory Production plant
  - Overall data aggregation
  - Availability optimization

Solution Overview



Solution – Service Stack Example

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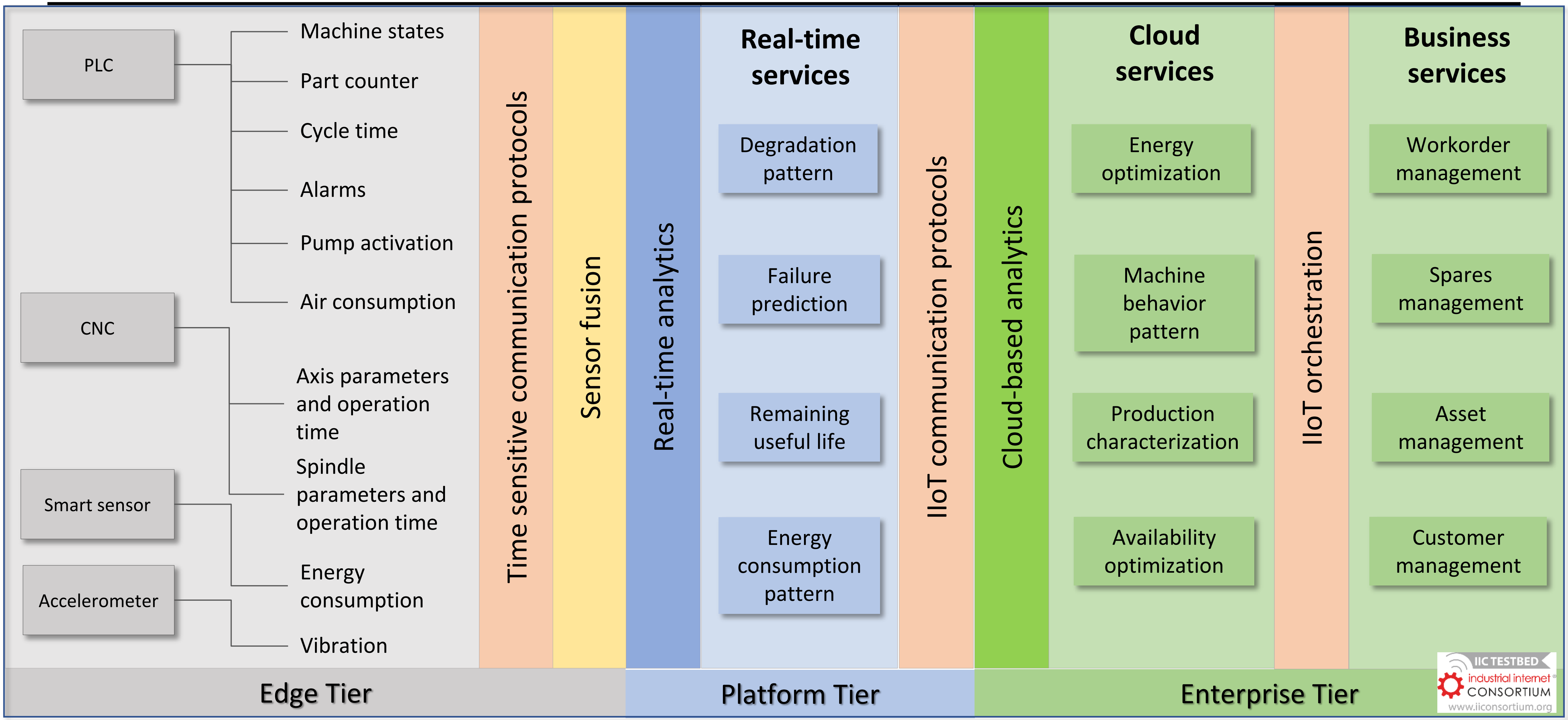
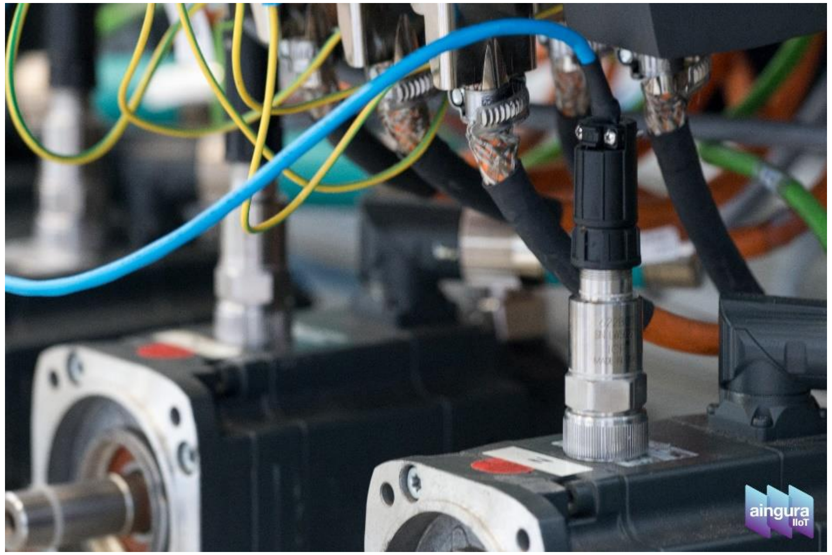


Edge Tier – Raw data



- Business (ERP, CRM, etc.)
  - Company name, address, etc
    - 20 variables
- Machine
  - PLC, CNC, sensors, actuators
    - 110.000 variables
- Sensors working on different domains
  - Different sampling times
    - Temperature: 0,01 samples/second
    - Angular velocity: 10 samples/second
    - Power consumption: 4.000 samples/second
    - Vibration+: 32.000 samples/second

Platform Tier - IIoT Programmable SoC

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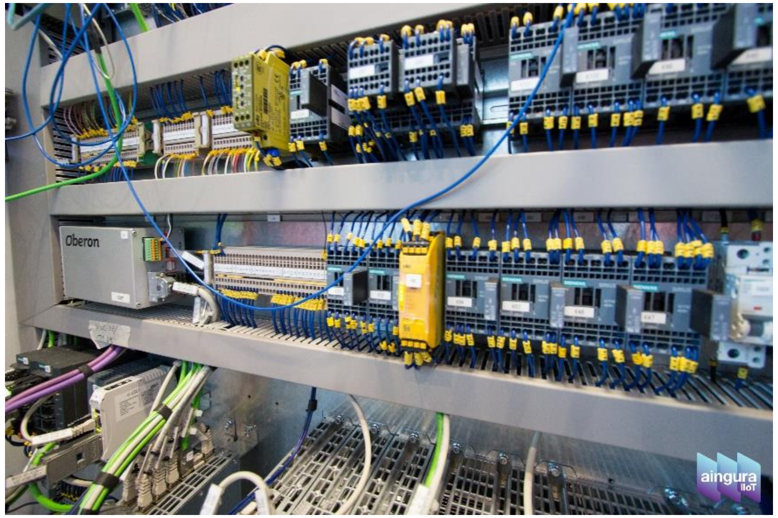
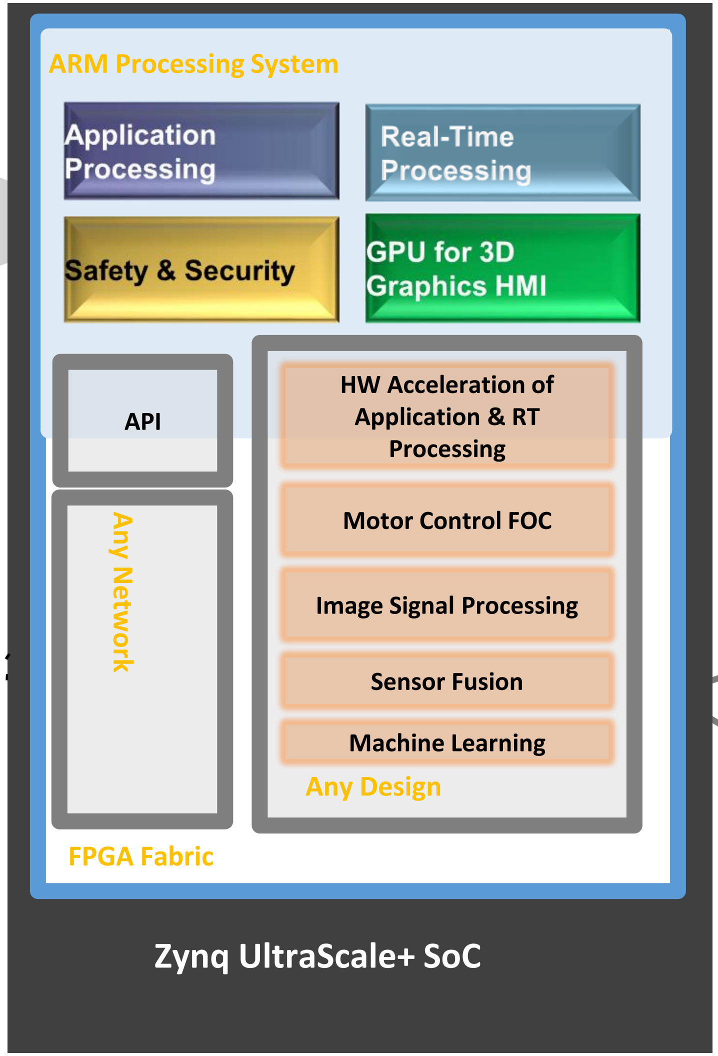


- Intelligent Gateway:
  - Zynq Programmable SOC (Xilinx)
    - Integrated ARM Processing System w/Programmable Logic
  - Tasks:
    - Sensor fusion:
      - Data acquisition from sensors, PLC and CNC.
      - Fuse data from multiple sensor domains
      - To impute data when different sampling rates
    - Feature subset selection:
      - Perform multivariate variable selection
    - Pre-processing
      - Filtering , FFT, etc
    - Processing
      - Perform on-line machine learning analytics

Platform Tier - IIoT Programmable SoC

Local Analytics Augmenting Cloud Services

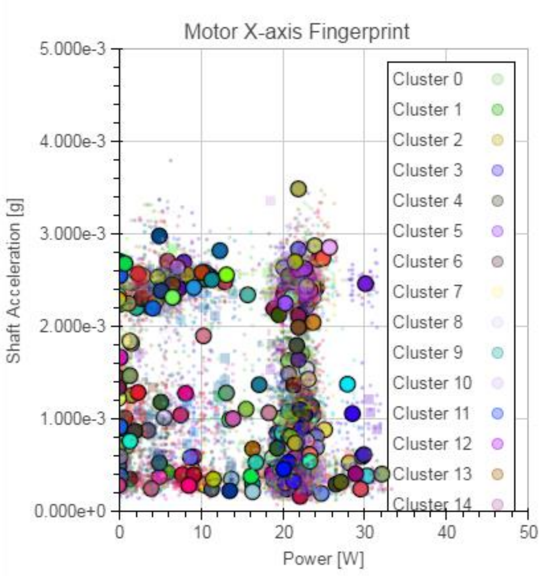
TSN IEEE 802.1

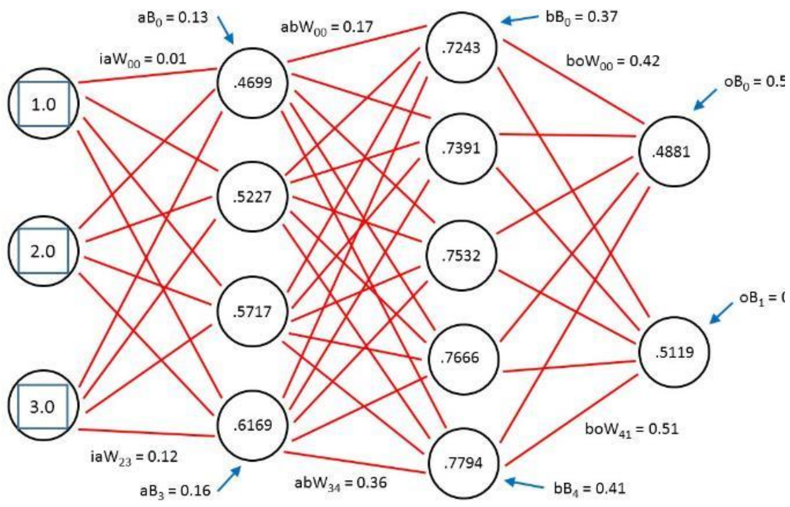


	Running function in SW	Running on FPGA	Running on optimized FPGA
Average Time (in ms)	5057.37	4208.65	257.65
Speed increase over SW	N/A	16.78%	94.91%

Enabling Secure, Safe, Synchronized, Autonomous Operation

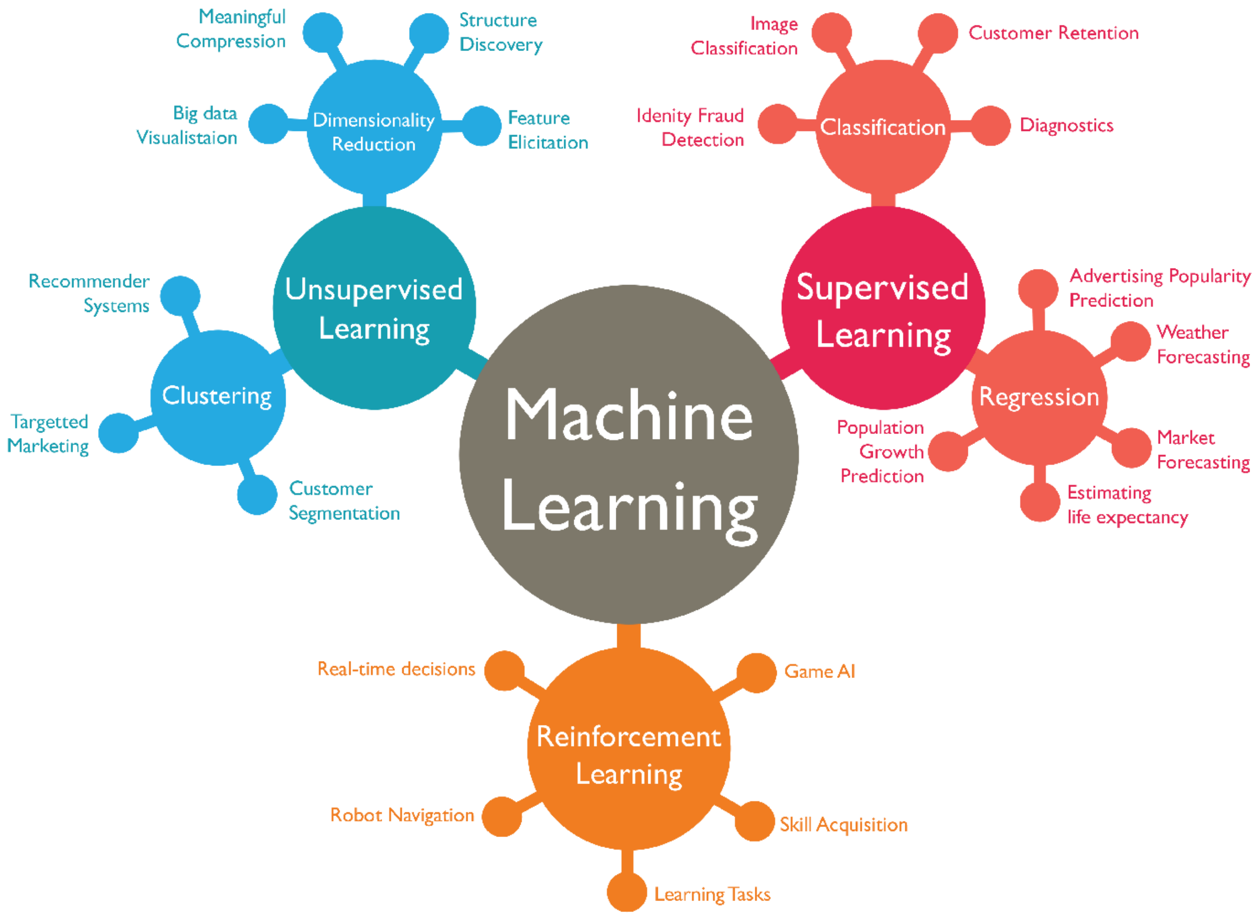
Platform Tier - Analysis





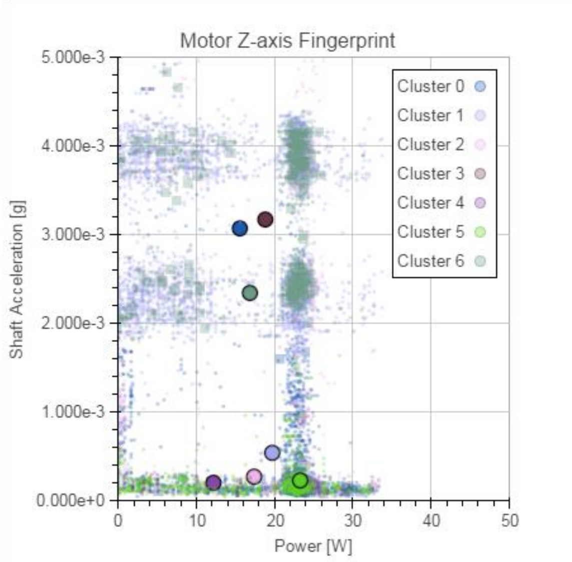
- Different approaches for data analysis
  - Visual Analytics
  - Traditional statistical tools
  - Artificial intelligence-based tools
    - Automatic learning
    - Deep Learning
    - Evolution of neural networks
- Method is transparent
  - Reduce adverse effects of noise
  - Illogical relationships
  - Control over system variations

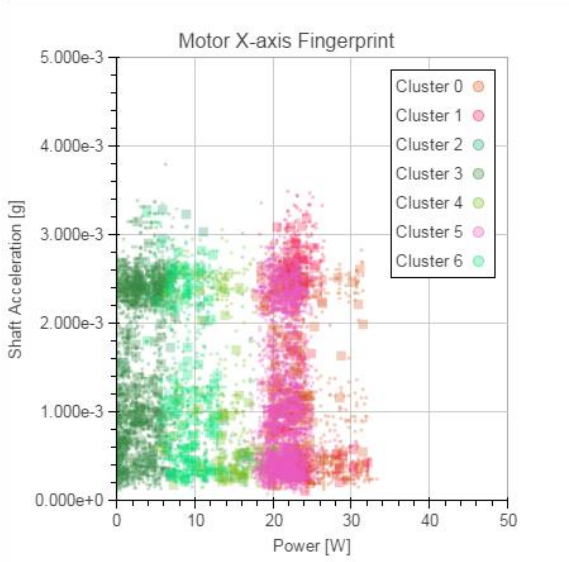
Platform Tier - Machine Learning Analysis

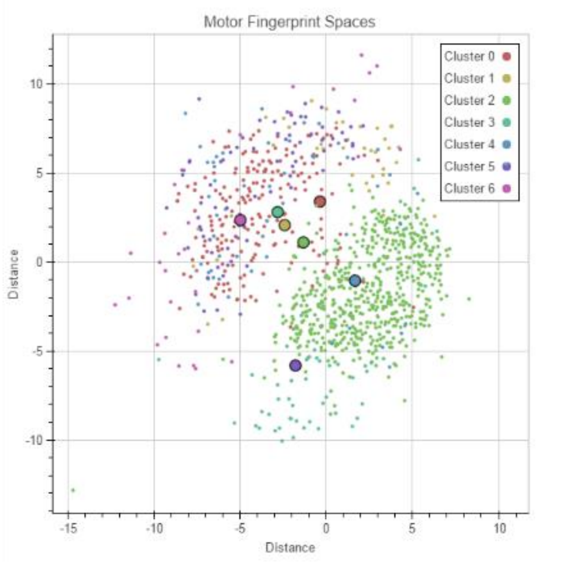


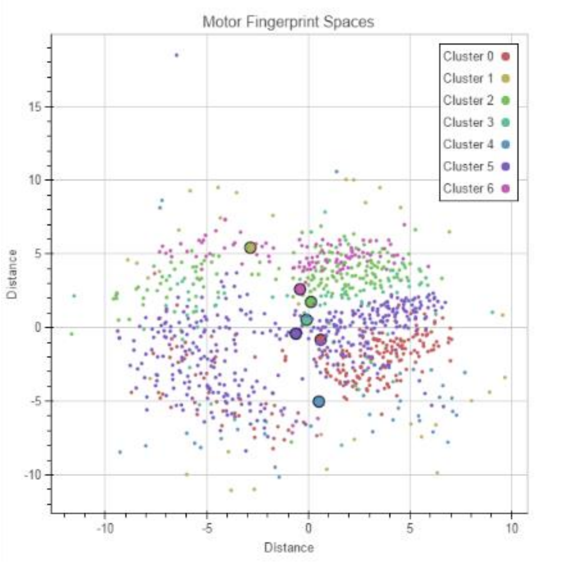
- Goal: Identify structural patterns in the data
  - Classify
  - Predict
  - Extract new knowledge
- Three types
  - Exploratory analysis
  - Descriptive modeling
  - Predictive modeling

Platform Tier – Static Machine Learning



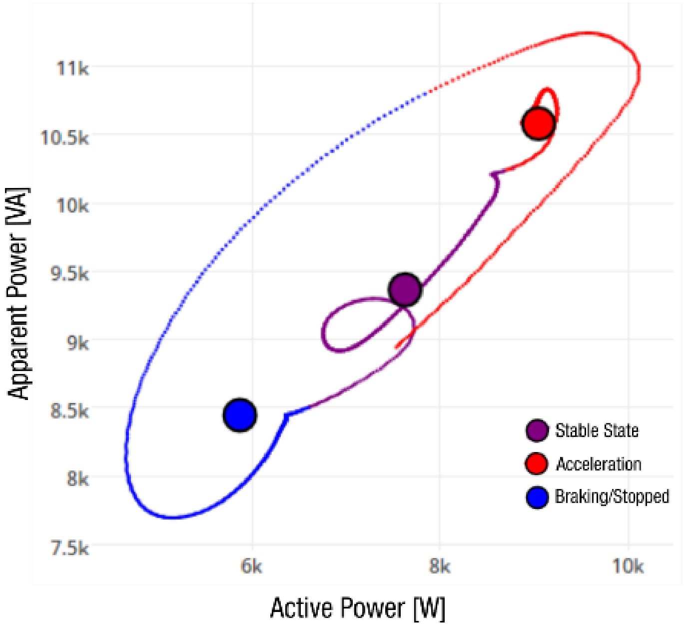


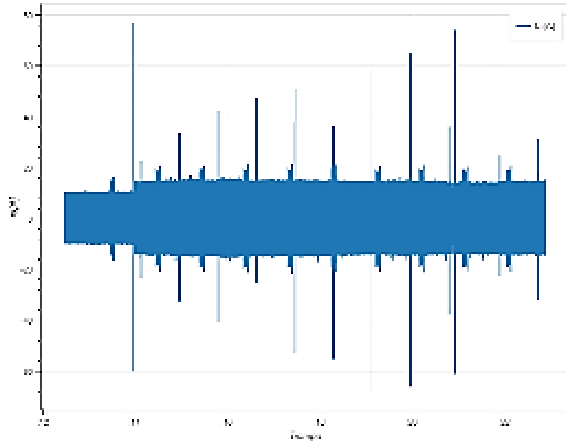




- Exploratory analysis
  - Explore in the data without clear idea
  - For small amounts of data, conventional visualization methods
  - For large amounts of data, dimensional reduction
- Example
  - Real Application on machine tool
  - Performance analysis of 3 servomotors
  - 13 variables per servo

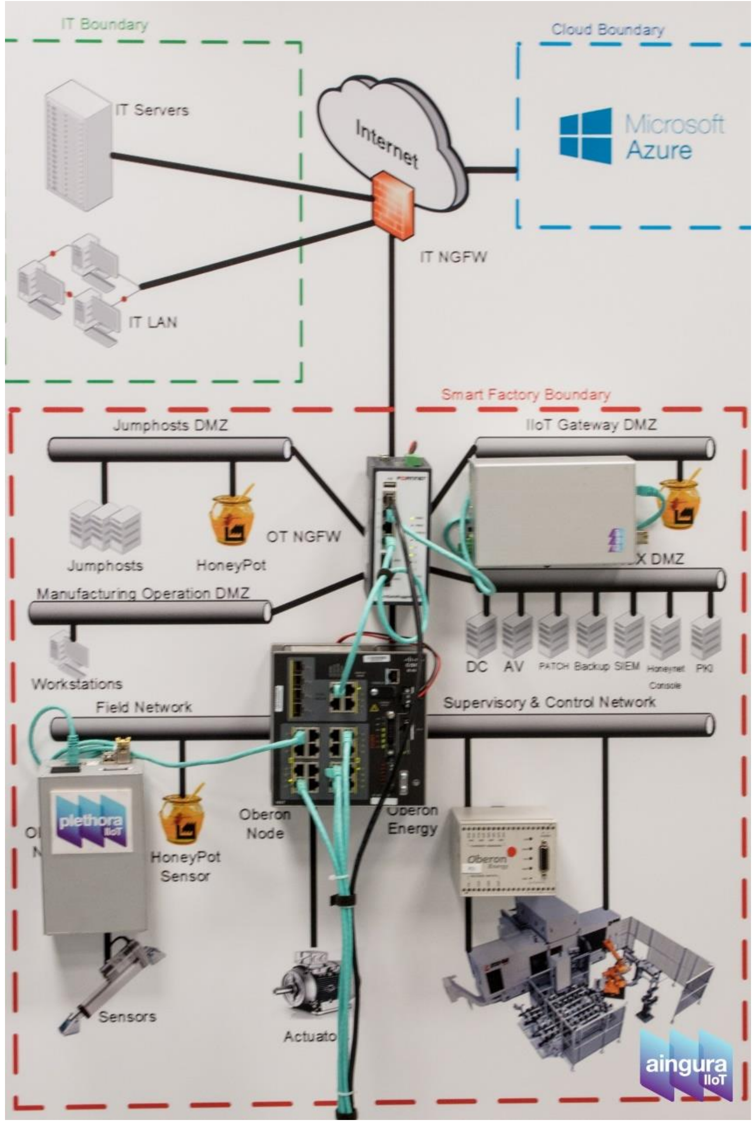
Platform Tier – Dynamic Machine Learning





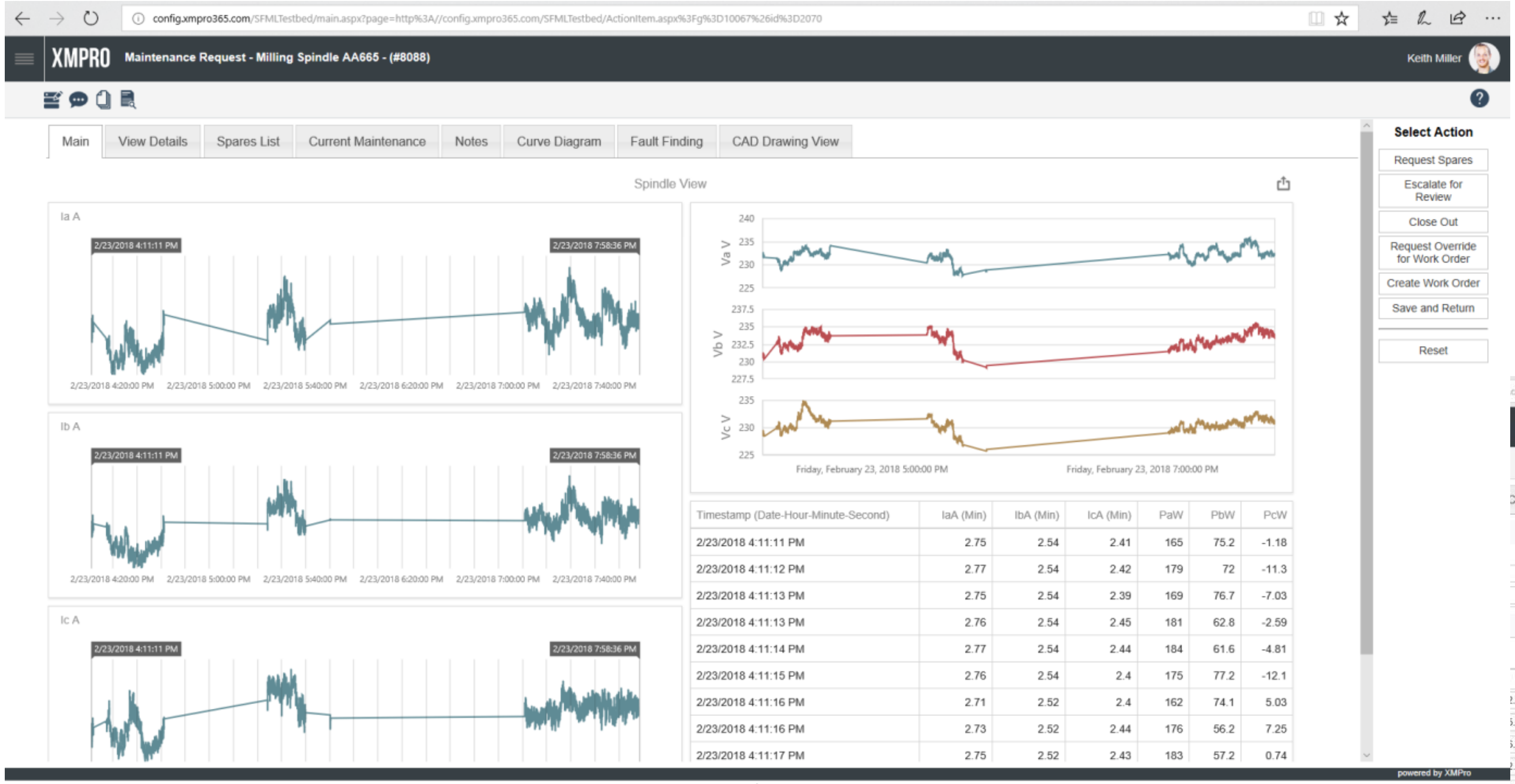
- Remaining useful life:
  - Machine Learning
    - Data stream analysis
  - There are not enough bad cases
    - Extremely unbalanced data → Novelty Detection
    - ML algorithm is measuring abnormal changes of the behavior pattern.
  - Detects early degradation that can affect the expected useful life.
    - Degradation can affect the expected service time.
    - It take data coming from the second stage to monitor anomalies.
    - Added value: early degradation measured using a multivariate approach.

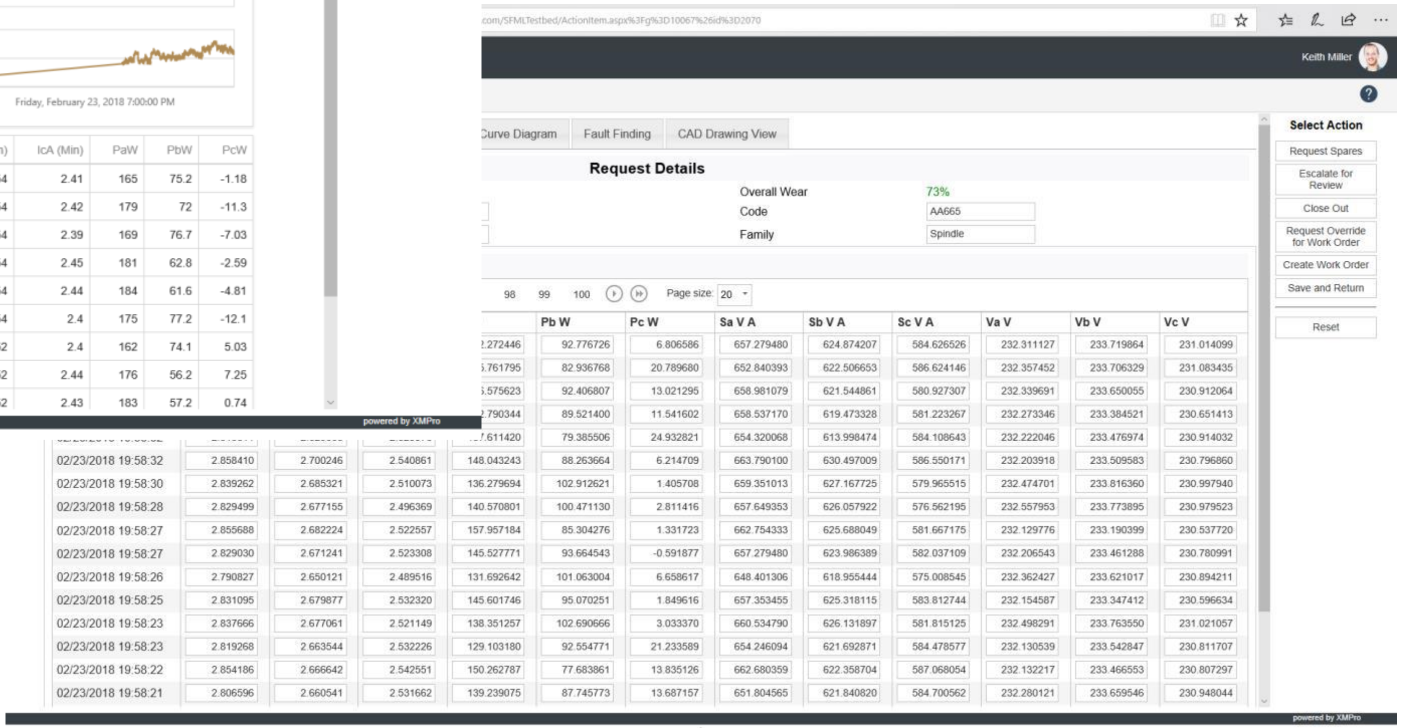
Cloud Tier - Services



- Microsoft-Azure
  - MQTT-based communication
  - USD 10 per 52 MB/h
  - Analytics & Business oriented
  - Transmission speed dependent
- GE Digital – Predix/APM
  - Communication based on OPC-UA
  - Industry-oriented
  - KPI developed for maintenance
- Ability to integrate
  - ERP, MES and other business services

Cloud Tiers – Business Services

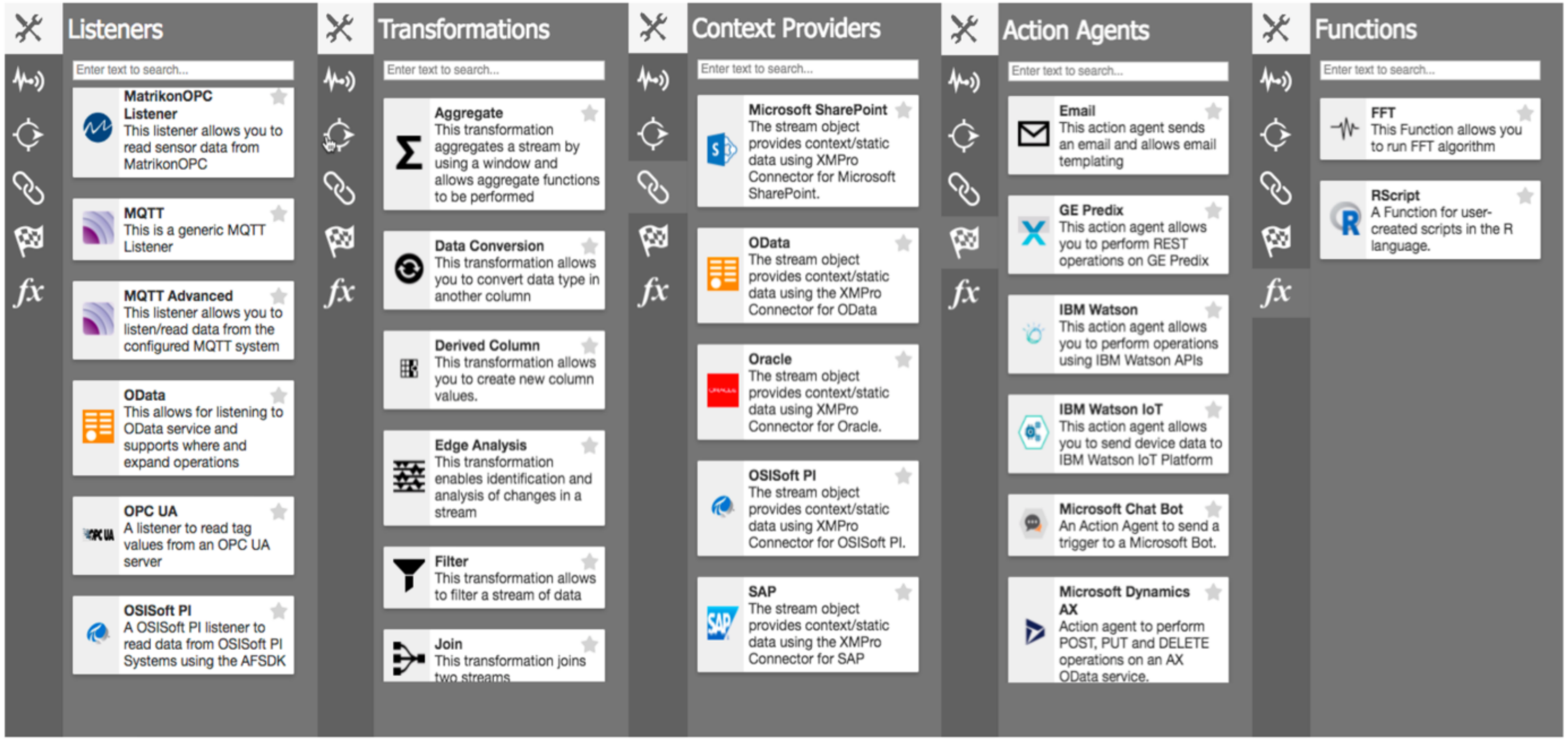




Cloud Tiers – Business Services

XMPRO

Extensible Integration Connectors



Testbed Usage Scenarios

Predictive Maintenance & Machine Learning

Machine-tool System

Identify Degradation
Behavior Pattern Measurement

Manufacturing Cell

Automation Interaction Behavior
M2M Energy Consumption Patterns

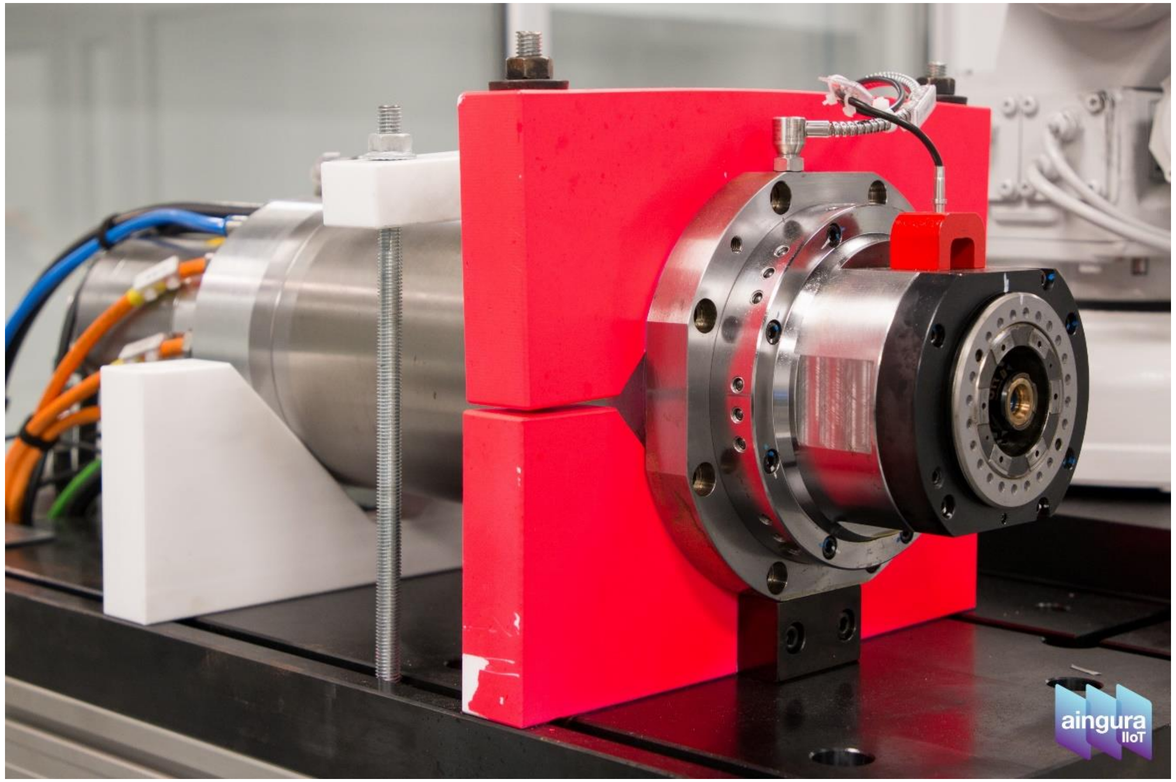
Production Line

Energy Consumption Behavior
Production Line Characterization

Factory Production

Overall Data Aggregation
Availability Optimization

Machine Tool – Spindle Critical Component



- Machine-tool for powertrain manufacturing
  - Cycle time 60 seconds
  - Utilization over 95%
- Spindle head – Key critical component
  - Power 10 kW
  - Primary function: Material removal
- Failure cost :
  - Costs USD 30,000 up to 250,000
  - Repair time: 5 working shifts
  - Impact: 200 direct jobs

Machine Tool – Spindle Critical Component

- Data acquisition and pre-processing
  - PLC variables: timestamp, in-cycle, dry-cycle
  - CNC variables: power, angular velocity, torque, temperature
  - Sampling rate: 10 Hz
  - 10 machining cycles (20 crankshafts)
  - More than 90.000 instances

Machine Tool – Spindle Critical Component

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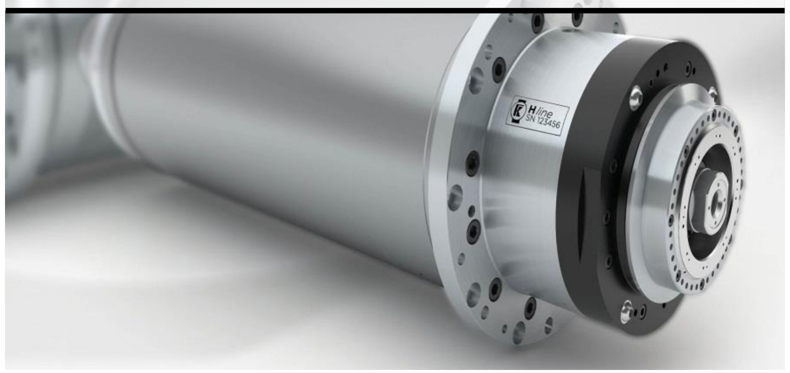
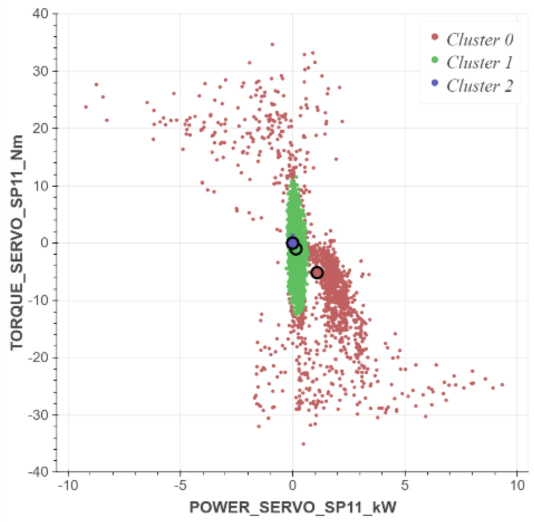
SPINDLES

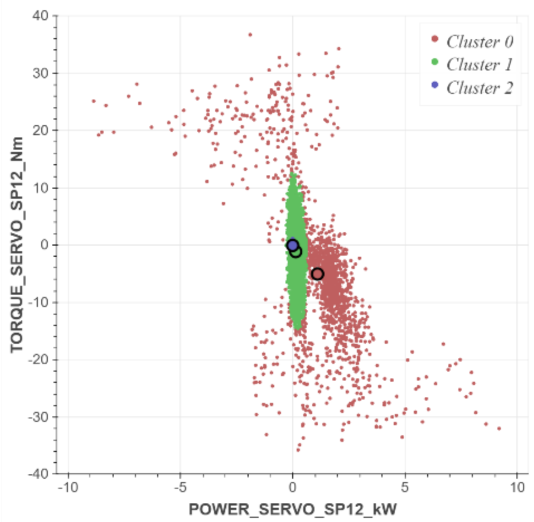


- ¿Vibration levels on the ball-bearings?
- ¿Temperature level on the ball-bearing?
- ¿Temperature level on the windings?
- ¿Tool engagement time?
- **¿General behavior of the spindle?**

- Descriptive analytics
  - **8 variables at the same time**
  - During as many cycles as possible
  - Looking for a behavior pattern
    - Given by “not obivous” variable correlations
- Objetive?
  - Define a behavior reference for a healthy spindle
  - Use the reference to detect deviations
    - Early degradation
- How?
  - Using clustering techniques

Machine Tool – Spindle Critical Component





- Understand Cluster Evolution:
  - Cluster shapes
  - (how the identified machining characteristics change over time)
  - Number of clusters (identify new machining characteristics).
- Gaussian mixtures
  - Provides new information about different states of the spindle
- Real-time operation:
  - Focus on upgrading CPS embedded electronics
  - Enable the algorithm acceleration using the Zynq Programmable SOC / FPGA

Community. Collaboration. Convergence.

Things are coming together.

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