Smart Manufacturing
Machine Learning for
Predictive Maintenance

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Machine Learning provides increased intelligence to the Industrial Internet of Things

Machine Learning In Industrial IoT

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

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

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

Image source: presenso

Source: Mike Sandalini, “Defect and Failure True Costing”
- 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.
- **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

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.
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

Deployment Scenarios (OT)
- Factory
- Production Line
- Manufacturing Cell
- Machine

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

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

#### Edge Tier
- **PLC**
  - Machine states
  - Part counter
  - Cycle time
  - Alarms
  - Pump activation
  - Air consumption
- **CNC**
  - Axis parameters and operation time
  - Spindle parameters and operation time
- **Smart sensor**
  - Energy consumption
- **Accelerometer**
  - Vibration

#### Platform Tier
- **Time sensitive communication protocols**
- **Sensor fusion**
- **Real-time analytics**
- **Real-time services**
  - Degradation pattern
  - Failure prediction
  - Remaining useful life
  - Energy consumption pattern

#### Enterprise Tier
- **Cloud services**
  - Energy optimization
  - Machine behavior pattern
  - Production characterization
  - Availability optimization
- **IoT orchestration**
  - Workorder management
  - Spares management
  - Asset management
  - Customer management

#### Business services
- **IIoT orchestration**
- **Edge Tier**
- **Platform Tier**
- **Enterprise Tier**
Edge Tier – Raw data

• Business (ERP, CRM, etc.)
  o Company name, address, etc
    ▪ 20 variables

• Machine
  o PLC, CNC, sensors, actuators
    ▪ 110,000 variables

• Sensors working on different domains
  o Different sampling times
    ▪ Temperature: 0.01 samples/second
    ▪ Angular velocity: 10 samples/second
    ▪ Power consumption: 4,000 samples/second
    ▪ Vibration+: 32,000 samples/second
• **Intelligent Gateway:**
  o Zynq Programmable SOC (Xilinx)
    ▪ Integrated ARM Processing System
      w/Programmable Logic
  o 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

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
Extensible Integration Connectors

Listeners:
- Matrion OPC Listener
- MQTT Listener
- MQTT Advanced Listener
- OData
- OPC UA
- OSIsoft PI

Transformations:
- Aggregator
- Data Conversion
- Derived Column
- Edge Analysis
- Filter
- Join

Context Providers:
- Microsoft SharePoint
- OData
- Oracle
- OSIsoft PI
- SAP

Action Agents:
- Email
- GE Predix
- IBM Watson
- IBM Watson IoT
- Microsoft Chat Bot
- Microsoft Dynamics AX

Functions:
- FFT
- Rscript
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
  o PLC variables: timestamp, in-cycle, dry-cycle
  o CNC variables: power, angular velocity, torque, temperature
  o Sampling rate: 10 Hz
  o 10 machining cycles (20 crankshafts)
  o More than 90,000 instances
Machine Tool – Spindle Critical Component

¿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
  o 8 variables at the same time
  o During as many cycles as possible
  o Looking for a behavior pattern
    ▪ Given by “not obvious” variable correlations

• Objective?
  o Define a behavior reference for a healthy spindle
  o Use the reference to detect deviations
    ▪ Early degradation

• How?
  o Using clustering techniques
• Understand Cluster Evolution:
  o Cluster shapes
  o (how the identified machining characteristics change over time)
  o Number of clusters (identify new machining characteristics).

• Gaussian mixtures
  o Provides new information about different states of the spindle

• Real-time operation:
  o Focus on upgrading CPS embedded electronics
  o Enable the algorithm acceleration using the Zynq Programmable SOC / FPGA

Things are coming together.

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