

aingura

Actionable Insights Towards Competitiveness



Smart Manufacturing: Data-based actionable insights



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Javier Diaz IloT Team Leader



About Aingura IIoT



Aingura IloT



Our objective is to use data and domain knowledge to provide added value bringing competitiveness to the industry, at product and process level, through machine learning-based failure diagnosis, prognosis and energy efficiency actionable insights.



IIoTUse Case Example

45

40

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ZHANGJIAKOU

WUHAN CITY

TAIZHOU

SHANGHAI

LIUZHOU, GUANGXI

GUIYANG CITY

CHANGCHUN

BAODING CITY

BAOJI

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- Chinese automotive **OEMs**
 - More than 300 machines working
- None of the above are performing the same operation
- However, all of them are looking to:
 - minimize downtime \bigcirc
 - increase availability







• Product

- Powertrain crankshaft \cap
- Cycle time
 - 60 seconds 0
- Average production
 - 1.000 parts/day Ο
- Required availability 95%
 - \cap
- Problem
 - Large temperature gradients within Ο production facility
 - Reduced availability when machine Ο stopped by low temperature
 - Loss of precision Ο
 - Quality issues risk Ο
 - Machine stop could be up to 2 Ο hours per day
 - That is, more than 80 crankshafts 0 not produced.
 - A stop machine can costs around Ο \$50k per hour









Sampling rate

- Probe measurement: 240s
- Temperature: 80s

Number of variables

0 15

Main variables

- $\circ~$ X and Y tooltip position,
- 9 machine structure and fluids temperatures
- \circ Environment temperature.

Sampling time

- \circ 12 months
- Total dataset size o 2.4 GB





Machine Learning application

- Feature subset selection
 - Select the most relevant variables (sensors) that has influence on the tooltip position
- Multi-output regression
 - Find how variables influence on the tooltip position
 - Predict the tooltip position
 - Provide feedback to the compensation control at the CNC

• Results:

- \circ One part of the machine basement is the responsible for tooltip deviation
 - New machine materials are studied for further design improvement.
- Compensation of the CNC system is improved by this model

Outcome:

- \circ $\,$ To provide better knowledge from the machine to the designers
 - Direct impact the machine design in terms of materials used and their specification
- Dynamical compensation of machine-tool behavior during production
- An increase crankshaft quality in terms of tolerance variation during thermal changes and machine availability.
- An important increase in availability
 - Avoiding machine-tool stop until stable environmental temperature is reached.
- Saved downtime costs up to \$100k per day.



IIC Testbed: Smart Factory Machine Learning for Predictive Maintenance

SFMLTestbed





HOME

COMMITTEES INDUSTRIES MEMBERSHIP MEMBERS AREA

SMART FACTORY MACHINE LEARNING FOR PREDICTIVE MAINTENANCE

SMART FACTORY MACHINE LEARNING FOR PM . TESTBEDS

high volume production

izing Machine Learning techniques for advanced



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 IloT, Xilinx

SUPPORTING COMPANIES INCLUDE

Industrial Internet Consortium Launches Invusional Internet Consortium® (IICTM Smart Factory Nachine Learning Testbed Smart Factory Nachine Industrial Internet Consortium® (IICTM DHAM, Mass -- (Business Wire) - <u>The Industrial Internet Consortium</u>® (the world's leading organization transforming business and society) the world's leading organization transforming internet of Thinne UIII the works and the adomtion of the Industrial Internet of Thinne UIIII to acceleration the adomtion of the Industrial Internet of Thinne UIIII aicas, Bosch Software Innovations, GlobalSign, Infineon Tee the world's leading organization transforming business and society, by accelerating the adoption of the Industrial Internet of Things (IIOT), by today announced the Smart Factory Machine Learning Testhed Thingswise, Titanium Industrial Security, and XMP by accelerating the adoption of the Industrial Internet of Things (IIG) today announced the Smart Factory Machine Learning Testbed

MARKET SEGMENT

Industrial Manufacturing

GOALS:

- Evaluate & validate Machin machinery to deliver optimiz
- Achieve increased uptime & i. detection of system anomalies

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.

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Sep 18, 2017 17:08 UTC

RESOURCES

http://www.iiconsortium.org/smart-factory-machine-learning.htm

SFMLTestbed





• Phase 1: Lab Development and Test

Utilizes simulated data and degradation/fault conditions for ML exploration

• Phase 2: Pilot Factory

Initial Deployment in limited production facility – Etxe-Tar

Phase 3: Production Facility

Deployment of ML and real-time analytics in Automotive OEM facility

• Sponsors:

- Aingura IIoT
- Xilinx

• Supporting:

- \circ Aicas,
- Bosch Software Innovations,
- o GlobalSign,
- Infineon Technologies,
- o iVeia,
- o Microsoft,
- PFP Cybersecurity,
- o RTI,
- o Thingswise,
- Titanium Industrial Security, and
- o XMPro



Preliminary Public Results

Industrial Applications of Machine Learning



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Richard Soley, Executive Director, Industrial Internet Consortium (IC)

The Machine Learning techniques presented in this highly interest publication provide an excellent overview of key respectively. It is now shorts when replementing those fundamentally remeweld algorithms that are driving the Fourth Instateal Revolution. Using real word filt 2 optications, the block presents a clear description of remote higher and machine learning analytics technologies, where programmable logic and other handware technologies allow a contral prior in the data capsiation - employs, and transformation medimentations to make actionable minight mough with and the applications descripted in this local: Chestraph Freton, Series Treeters Industrial Tot, Scientific and Madrial Interest Unit. Xemes Treeters Industrial Tot, Scientific and Madrial

This bock 4th a cape in the current technological diverginances censiting in most externist and in-depth analysis of machine learning anteholds for externist appointions. It is very well written and capacitad with spin-jail focus a pottessional, researchers and pottes graduate students of bets industrial an intering and machine learning.¹ toos forms, Americal Review Roda (Islaminie:

Additional additionation of Machine Learning above how machine learning, and be appelled to address rule world problems in the touch robustion prodution, and provide the negative fixed learning and touch to address and the shall there are address to the server and products. The book introducble for both robustion and and community rule products. The book introducing the both robustion and the community products and products and the both robustion and and constant and the approximation and community and address the server and the server and the server include the address. The server address is the manuscharing on bogins and any server and approximation that the server address the server of point of view. It should be of a spacial internal to researchers interneted in weak world notation is problems. Deter & HalfCE Date Manage and Towards and Determined of the Control of the Contr

Alberto Onbechie

Concha Rielz:



Book details:

- Title: "Industrial Applications of Machine Learning"
- Series: Chapman & Hall/CRC Data Mining and Knowledge Discovery Series
- ISBN 9780815356226 CAT# K346412
- o CRC URL: <u>https://goo.gl/psf3Xi</u>
- o Table of Contents
 - 1. The Fourth Industrial Revolution
 - 2. Machine Learning
 - 3. Applications of Machine Learning in Industrial Sectors
 - 4. Component-Level Case Study: Remaining Useful Life of Bearings
 - 5. Machine-Level Case Study: Fingerprint of Industrial Motors
 - 6. Production-Level Case Study: Automated Visual Inspection of a Laser Process
 - 7. Distribution-Level Case Study: Forecasting of Air Freight Delays

Industrial Applications of Machine Learning







• Exploratory analysis

- \circ $\,$ Explore in the data without clear idea
- For small amounts of data, conventional visualization methods
- \circ For large amounts of data, dimensional reduction

• Example

- \circ Real Application on machine tool
- Performance analysis of 3 servomotors
- \circ 13 variables per servo
- 5 different algorithms:
 - Agglomerative hierarchical clustering
 - K-means clustering
 - Spectral clustering
 - Affinity propagation clustering
 - Gaussian mixture model clustering

Knowledge discovery with real data





Testing 3 different clustering algorithms to find new knowledge

- K-Means, agglomerative hierarchical, Gaussian mixture model.
- J. Diaz-Rozo, C. Bielza, and P. Larrañaga, "Machine learningbased CPS for clustering high throughput machining cycle conditions," *Procedia Manufacturing*, vol. 10, pp. 997–1008, 2017.

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 :
 - o Costs USD 30,000 up to 250,000
 - Repair time: 5 working shifts
 - Impact: 200 direct jobs

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

Gaussian-based Dynamic Probabilistic Clustering







0.8

0.4

GDPC is an algorithm developed by Aingura IIoT to measure component degradation

- J. Diaz-Rozo, C. Bielza, and P. Larrañaga, "Clustering 0 of Data Streams with Dynamic Gaussian Mixture Models. An IoT Application in Industrial Processes," IEEE Internet of Things Journal, 2018.
- https://doi.org/10.1109/JIOT.2018.2840129

Data stream analytics

- Able to perform analytics in Real-Time
- No need of data storage Ο
- Machine Learning at the edge
- Update the learnt model once the component degrades
 - Concept drift Ο

Edge Computing Node





Integrated modules for:

- Analog sensors
- High speed energy measurement
- \circ Vibration
- o Ethernet/switching
- \circ Storage
- Powered by Xilinx MPSoC Ultrascale+



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Edge computing deployment



There could be a need for computing power at the edge

- Traditional computing devices not suitable for industrial environments
- Large amounts of data to be pre-processed depending on application
- Complex algorithms to solve specific questions
- Extremely fast computing needs to provide actionable insights in Real-Time

Steps for industrial computing at the edge US Patent 10031500B1

"Device and system including multiple devices for supervision and control of machines in industrial installation"



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