Industrial AI-Augmented Predictive Analytics for Highly-Connected and Complex Industrial Systems

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Founding Director

NSF I/UCRC on Intelligent Maintenance Systems (IMS)

&

Industrial AI Center

Univ. of Cincinnati

1

Outline

- Introduction of IMS Center
- Issues of Uncertainty, Variability, and Data Quality
- Examples in High-Volume Manufacturing, Semiconduc Mfg, EVs, and Wind Turbines

2

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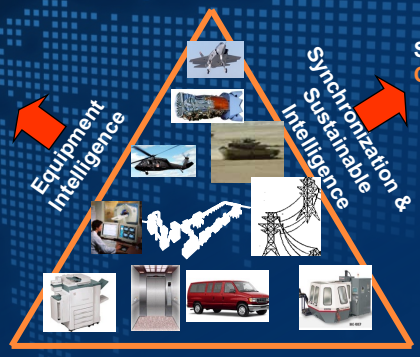
3

Motivation of Intelligent Maintenance Systems (IMS) in 2000



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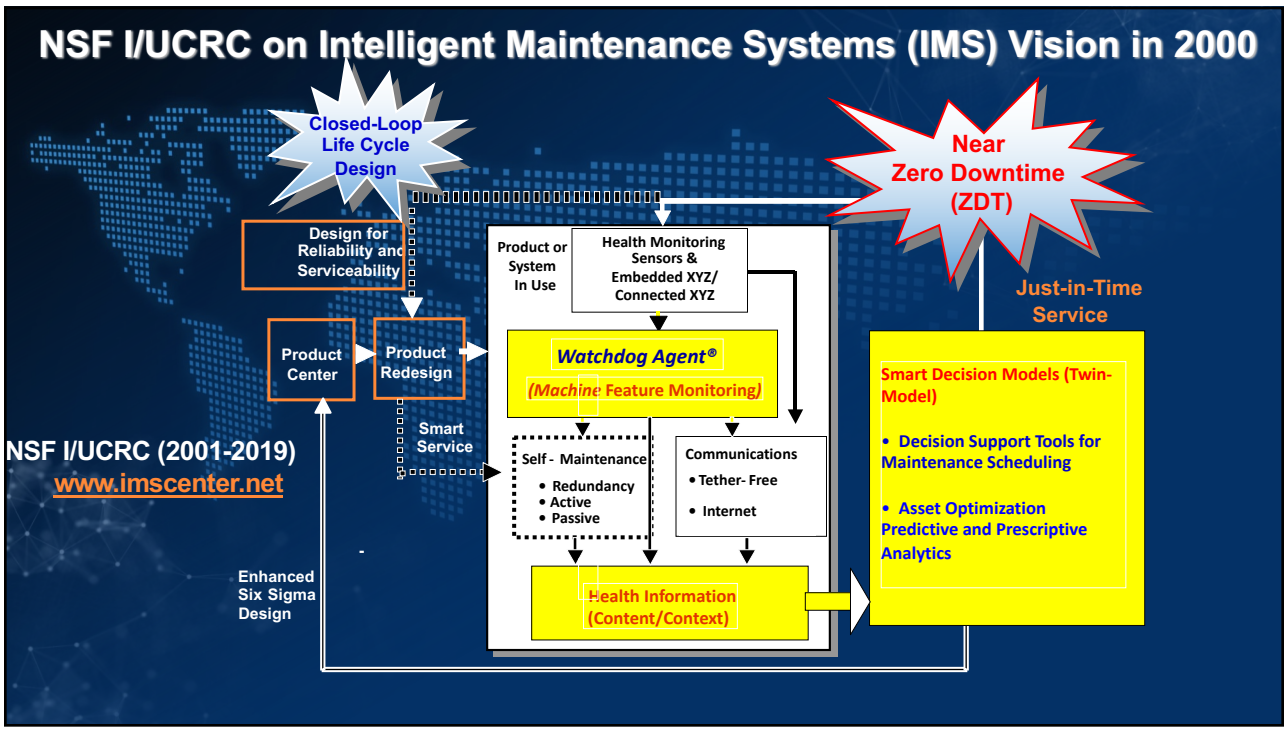
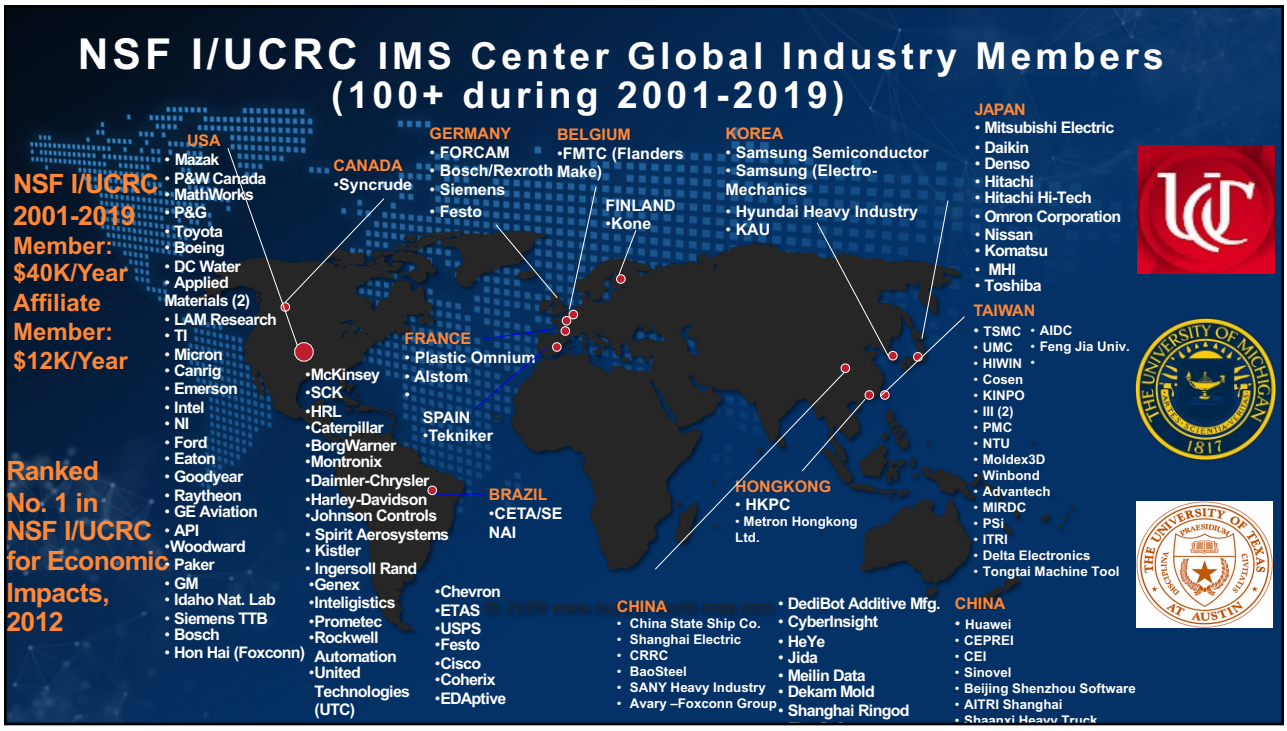
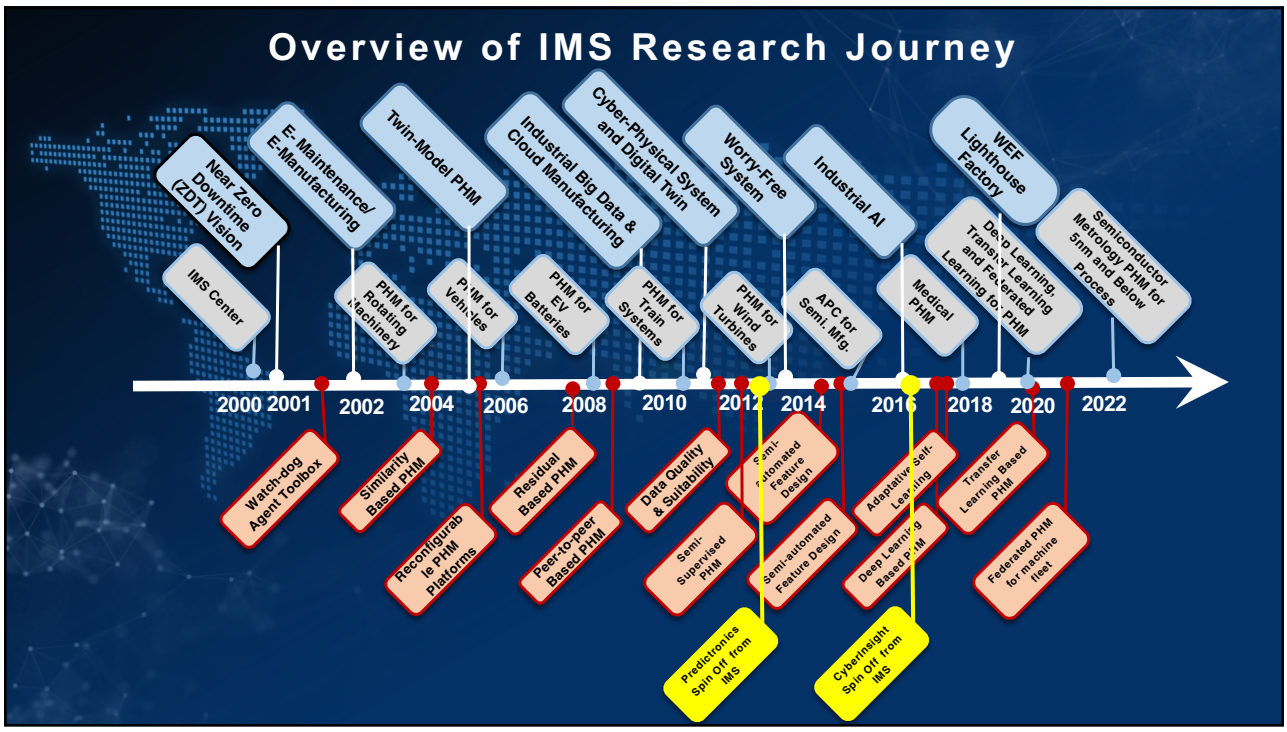

NSF I/UCRC on Intelligent Maintenance Systems (IMS) Vision in 2000
Closed-Loop Life Cycle Design
Near Zero Downtime (ZDT)
Design for Reliability and Serviceability
Product Center
Product Redesign
Smart Service
Product or System In Use
Health Monitoring Sensors & Embedded XYZ/ Connected XYZ
Watchdog Agent®
(Machine Feature Monitoring)
Self - Maintenance
• Redundancy
• Active
• Passive
Communications
• Tether- Free
• Internet
Health Information (Content/Context)
Just-in-Time Service
Smart Decision Models (Twin-Model)
• Decision Support Tools for Maintenance Scheduling
• Asset Optimization Predictive and Prescriptive Analytics
Enhanced Six Sigma Design
NSF I/UCRC (2001-2019)
www.imscenter.net

5


NSF I/UCRC IMS Center Global Industry Members
(100+ during 2001-2019)
NSF I/UCRC 2001-2019 Member: $40K/Year
Affiliate Member: $12K/Year
Ranked No. 1 in NSF I/UCRC for Economic Impacts, 2012
USA
• Mazak
• P&W Canada
• MathWorks
• P&G
• Toyota
• Boeing
• DC Water
• Applied Materials (2)
• LAM Research
• TI
• Micron
• Canrig
• Emerson
• Intel
• NI
• Ford
• Eaton
• Goodyear
• Raytheon
• GE Aviation
• API
•Woodward
• Paker
• GM
• Idaho Nat. Lab
• Siemens TTB
• Bosch
• Hon Hai (Foxconn)
CANADA
•Syncrude
GERMANY
• FORCAM
• Bosch/Rexroth
• Siemens
• Festo
BELGIUM
•FMTC (Flanders Make)
FINLAND
•Kone
KOREA
• Samsung Semiconductor
• Samsung (Electro-Mechanics
• Hyundai Heavy Industry
• KAU
JAPAN
• Mitsubishi Electric
• Daikin
• Denso
• Hitachi
• Hitachi Hi-Tech
• Omron Corporation
• Nissan
• Komatsu
• MHI
• Toshiba
TAIWAN
• TSMC • AIDC
• UMC • Feng Jia Univ.
• HIWIN •
• Cosen
• KINPO
• III (2)
• PMC
• NTU
• Moldex3D
• Winbond
• Advantech
• MIRDC
• PSi
• ITRI
• Delta Electronics
• Tongtai Machine Tool
FRANCE
• Plastic Omnium
• Alstom
•
SPAIN
•Tekniker
•McKinsey
•SCK
•HRL
•Caterpillar
•BorgWarner
•Montronix
•Daimler-Chrysler
•Harley-Davidson
•Johnson Controls
• Spirit Aerosystems
• Kistler
• Ingersoll Rand
•Genex
•Inteligistics
•Prometec
•Rockwell Automation
•United Technologies (UTC)
BRAZIL
•CETA/SENAI
•Chevron
•ETAS
•USPS
•Festo
•Cisco
•Coherix
•EDAptive
HONGKONG
• HKPC
• Metron Hongkong Ltd.
CHINA
• China State Ship Co.
• Shanghai Electric
• CRRC
• BaoSteel
• SANY Heavy Industry
• Avary –Foxconn Group
• DediBot Additive Mfg.
• CyberInsight
• HeYe
• Jida
• Meilin Data
• Dekam Mold
• Shanghai Ringod
CHINA
• Huawei
• CEPREI
• CEI
• Sinovel
• Beijing Shenzhou Software
• AITRI Shanghai
• Shaanxi Heavy Truck

6



7

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8

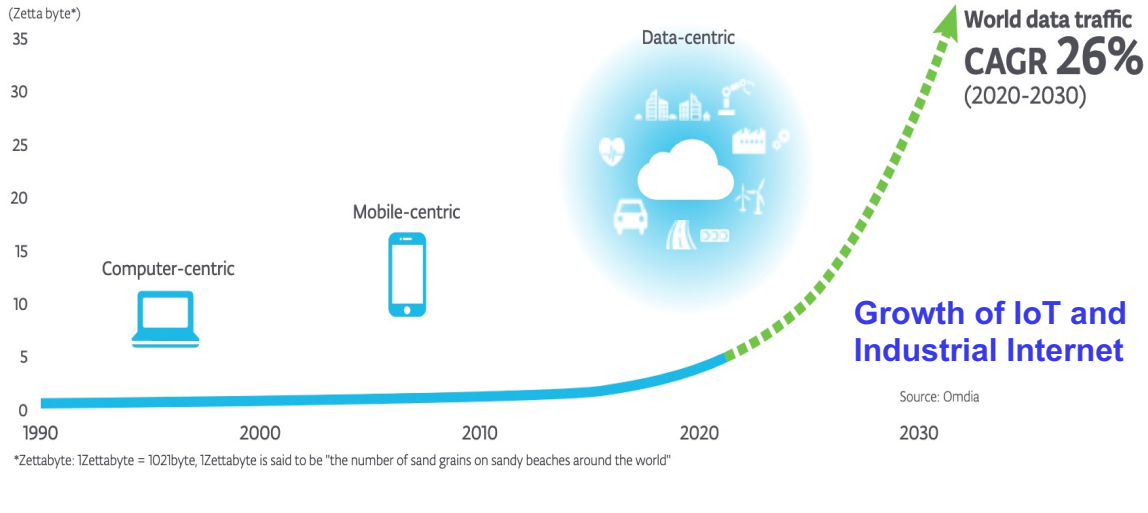
Issues and Opportunities in Productivity

	Visible	Invisible
Avoid	Utilize New Knowledge/ Technologies For Value-added Improvement	Value Creation using Smarter Information For Unknown Knowledge
Solve	Problem Solving Through Continuous Improvement and Standard Work	Utilize New Methods/ Techniques to Solve The Unknown Problems

Jay Lee, Book on Industrial AI, Springer, 2020

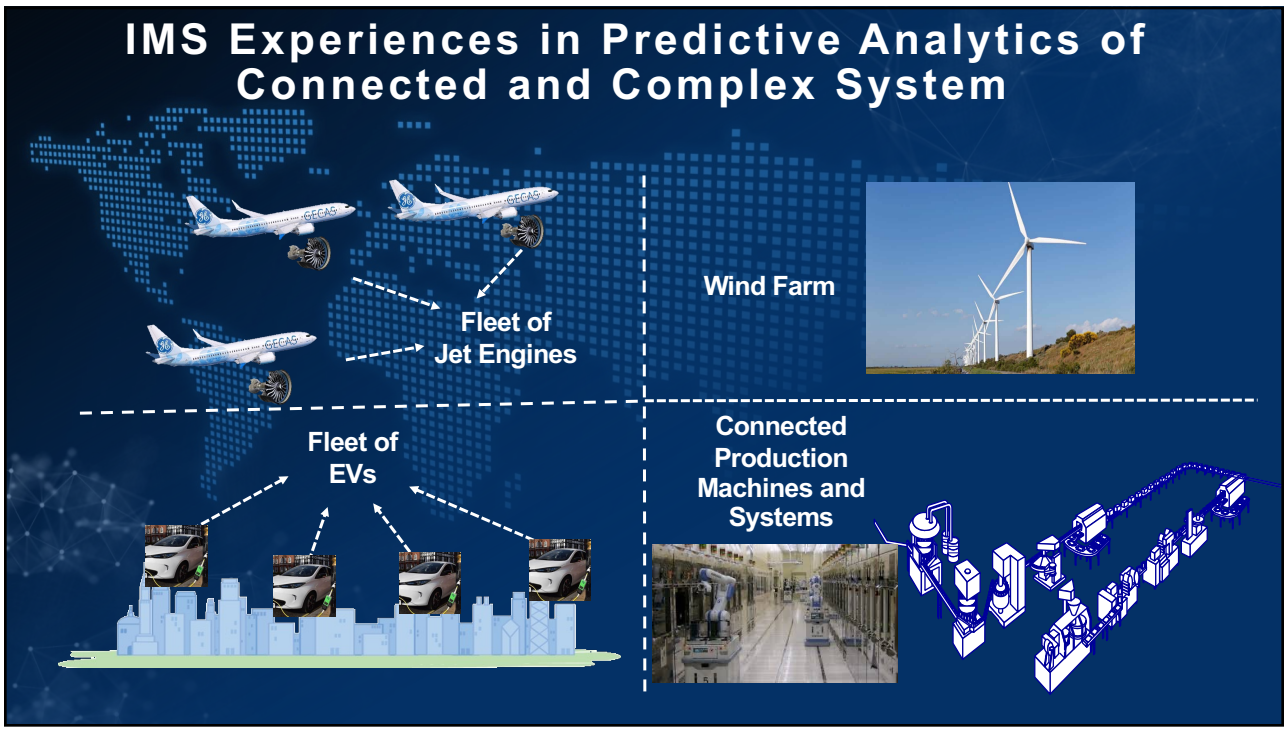
9

Trends of Connected Systems and Data Driven Economy

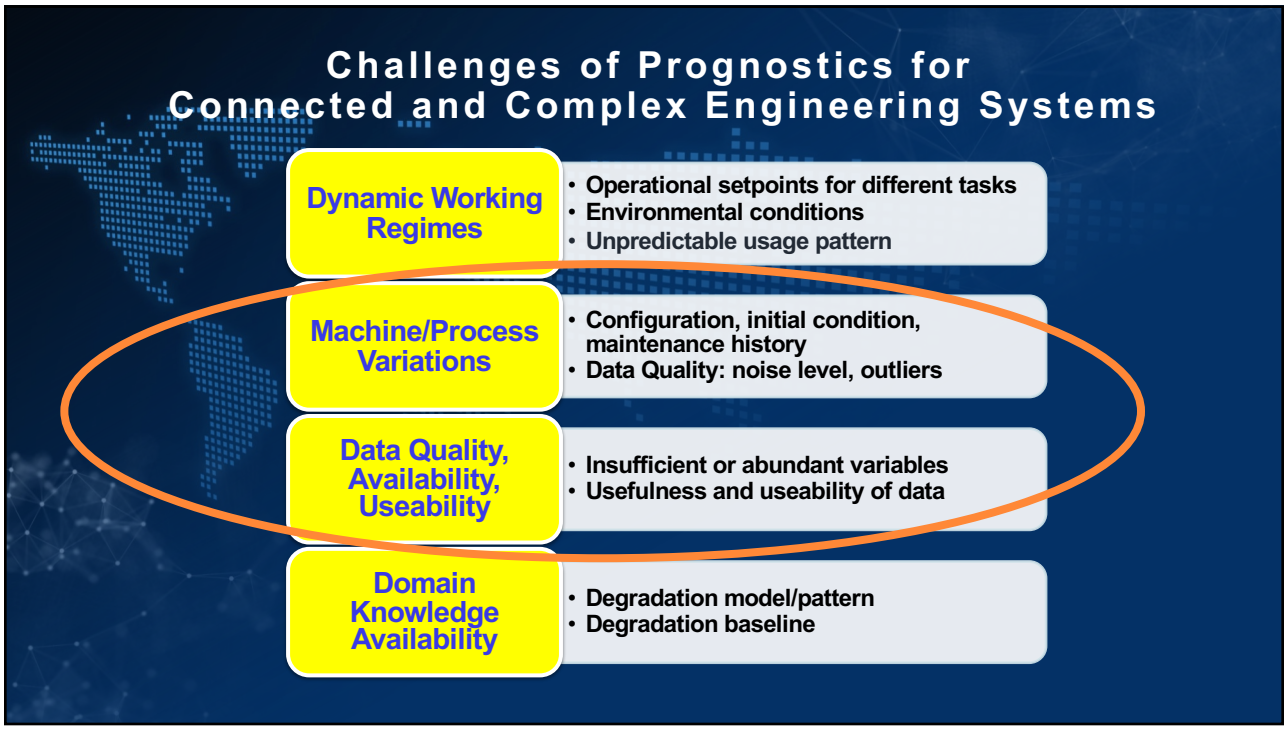


Reference: Tokyo Electron Ltd. (TEL)

10

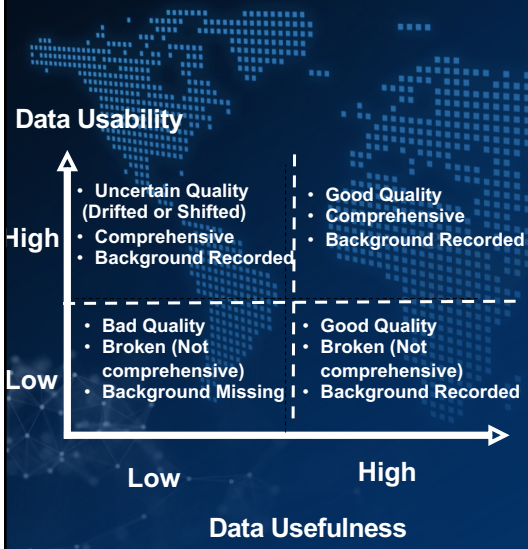

IMS Experiences in Predictive Analytics of Connected and Complex System
Fleet of Jet Engines
Wind Farm
Fleet of EVs
Connected Production Machines and Systems

11

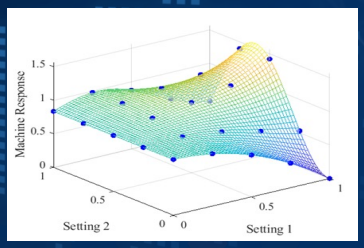

Challenges of Prognostics for Connected and Complex Engineering Systems
Dynamic Working Regimes
• Operational setpoints for different tasks
• Environmental conditions
• Unpredictable usage pattern
Machine/Process Variations
• Configuration, initial condition, maintenance history
• Data Quality: noise level, outliers
Data Quality, Availability, Useability
• Insufficient or abundant variables
• Usefulness and useability of data
Domain Knowledge Availability
• Degradation model/pattern
• Degradation baseline

12

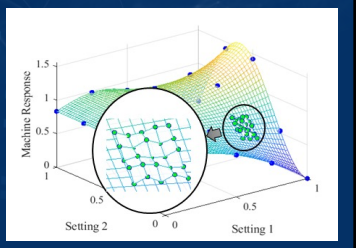
Data Issues in Variability & Uncertainty



Reference Source



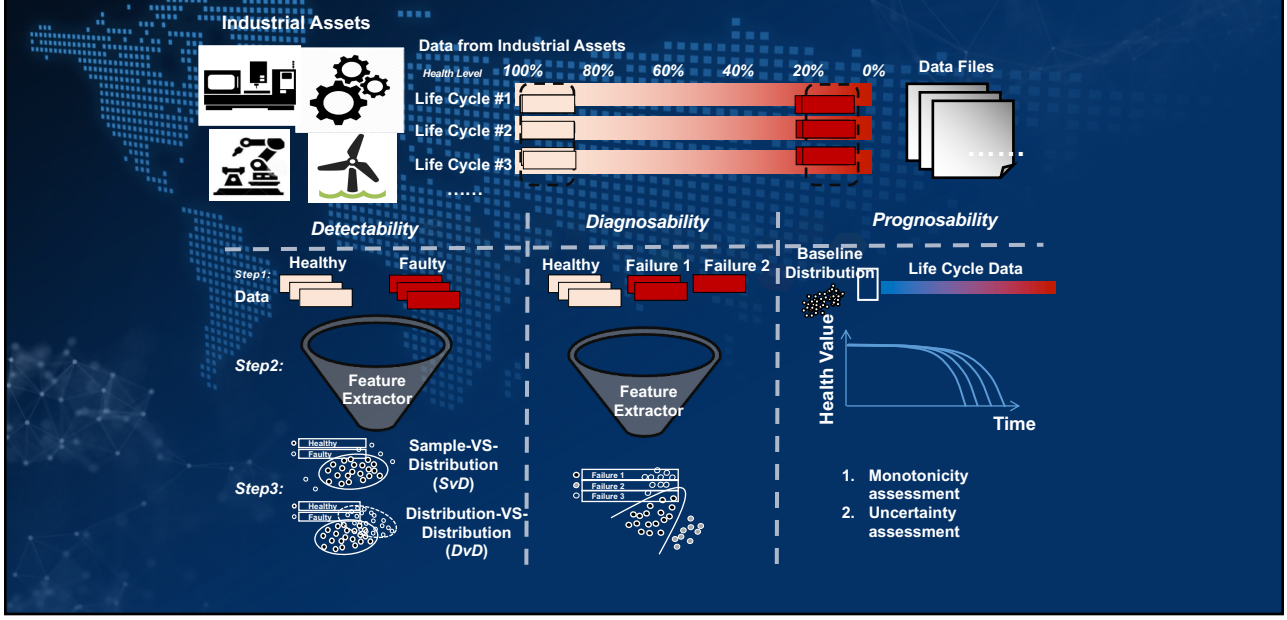
Target Source



Source	Reference Source	Target Source
Data Quantity	✓ High Volume	✓ Low Volume
Data Quality	✓ High quality	✓ Dynamic ✓ Time-restricted ✓ Drifted / Shifted ✓ Noisy
Data Representativeness	✓ Comprehensive	✓ Local ✓ High variation
Data Availability	✓ High availability	✓ Low availability

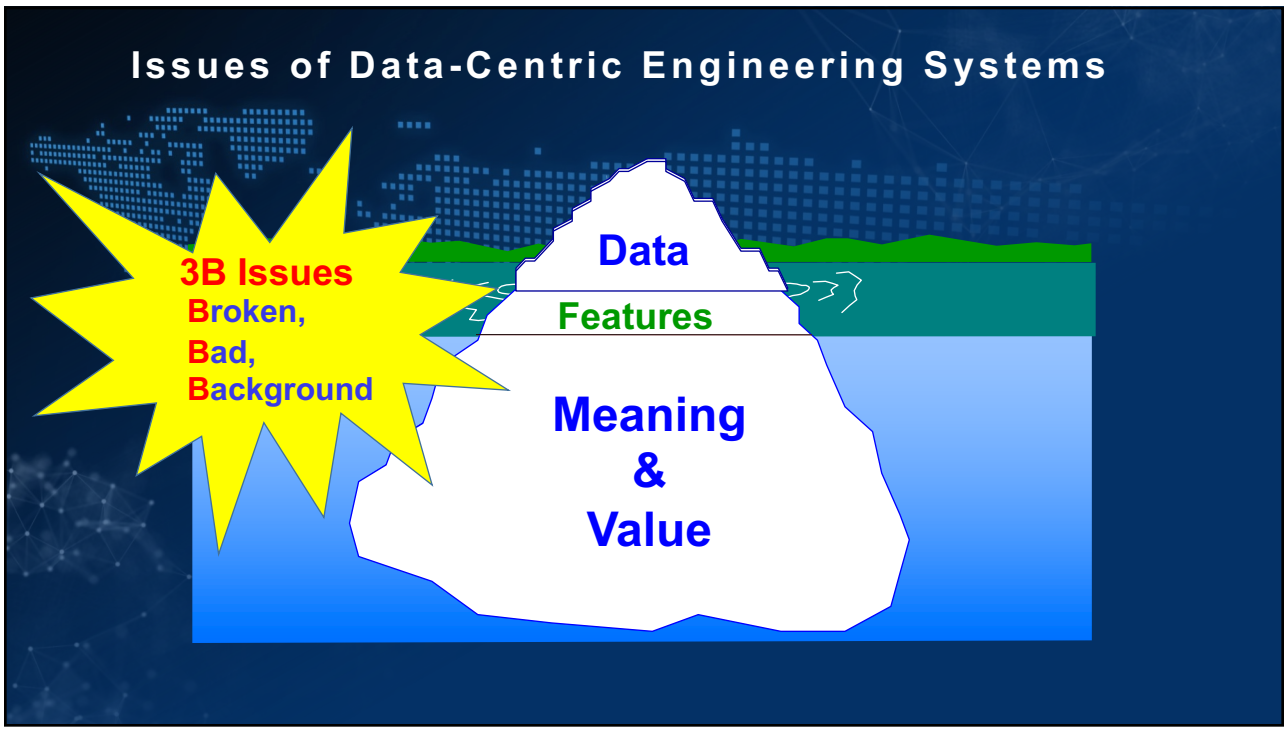
13

Data Evaluation for Predictive Analytics



14

Issues of Data-Centric Engineering Systems



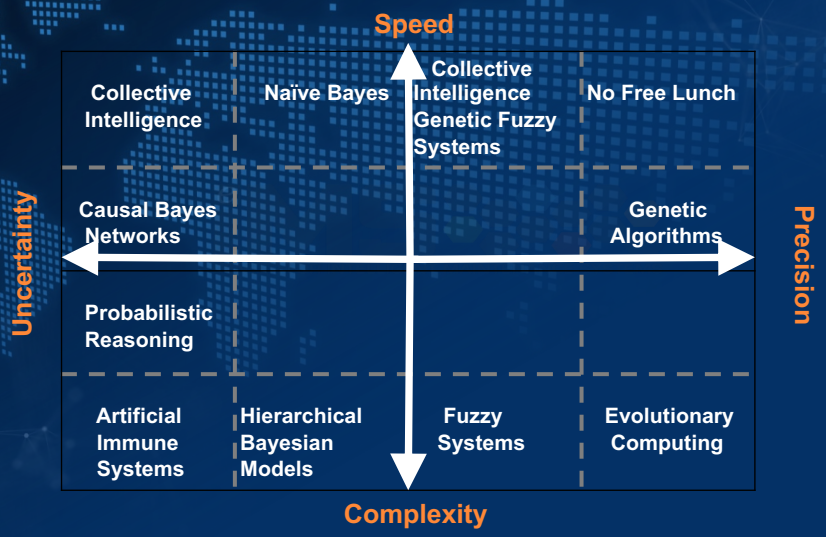
15

AI and Industrial AI

- AI is a *cognitive science* with rich research in the areas of imaging analysis & machine vision, natural language processing, robotics, and machine learning, etc. AI has been perceived as a black art and often lacks of compelling evidence to convince industry that these techniques will work repeatedly and consistently with a sound return on investment
- Industrial AI, is a *systematic discipline* which focuses on developing, validating and deploying various machine learning algorithms systemically and rapidly for industrial applications with sustainable performance.

16

Challenges in Using the Right Tools for the Right Applications



17

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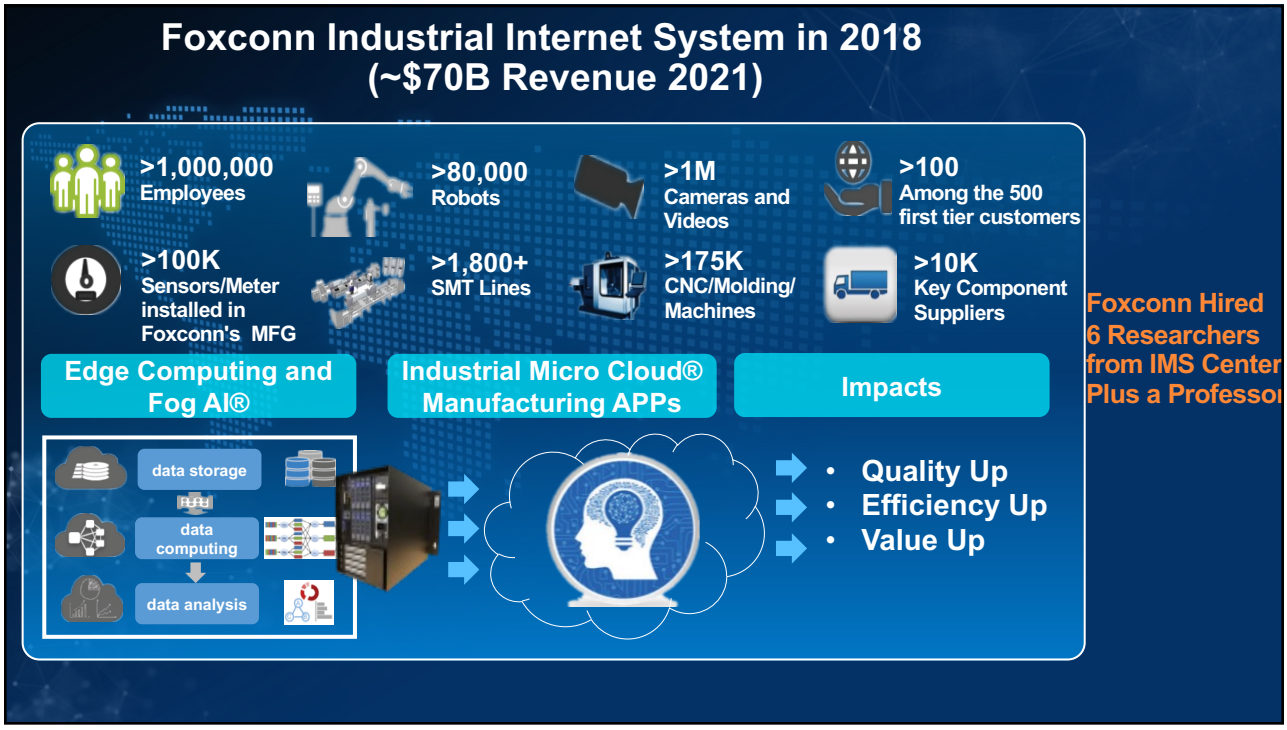
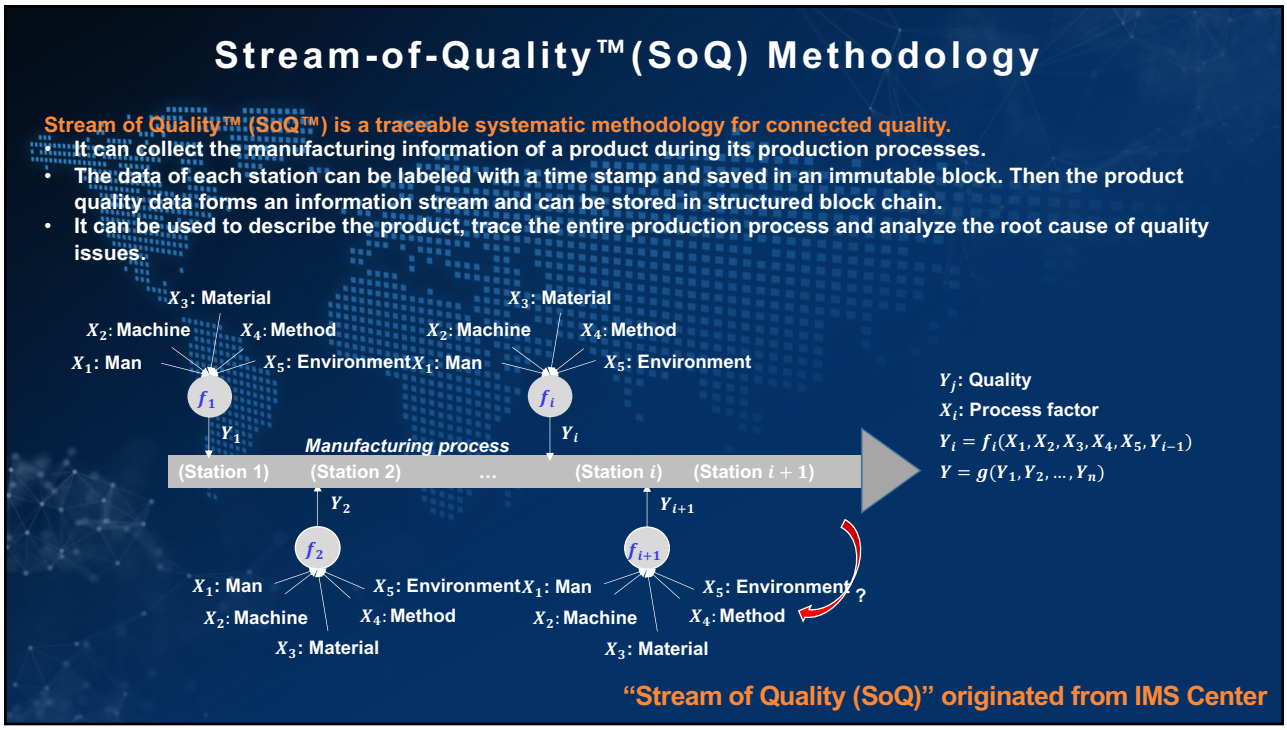
18


Foxconn Industrial Internet System in 2018
(~$70B Revenue 2021)
>1,000,000
Employees
>80,000
Robots
>1M
Cameras and
Videos
>100
Among the 500
first tier customers
>100K
Sensors/Meter
installed in
Foxconn's MFG
>1,800+
SMT Lines
>175K
CNC/Molding/
Machines
>10K
Key Component
Suppliers
Edge Computing and
Fog AI®
Industrial Micro Cloud®
Manufacturing APPs
Impacts
data storage
data
computing
data analysis
Quality Up
Efficiency Up
Value Up
Foxconn Hired
6 Researchers
from IMS Center
Plus a Professor

19


Stream-of-Quality™(SoQ) Methodology
Stream of Quality™ (SoQ™) is a traceable systematic methodology for connected quality.
It can collect the manufacturing information of a product during its production processes.
The data of each station can be labeled with a time stamp and saved in an immutable block. Then the product quality data forms an information stream and can be stored in structured block chain.
It can be used to describe the product, trace the entire production process and analyze the root cause of quality issues.
X_3: Material
X_2: Machine
X_4: Method
X_1: Man
X_5: Environment
f_1
Y_1
f_i
Y_i
Manufacturing process
(Station 1)
(Station 2)
...
(Station i)
(Station $i+1$)
Y_2
Y_{i+1}
f_2
f_{i+1}
?
Y_j: Quality
X_i: Process factor
$Y_i = f_i(X_1, X_2, X_3, X_4, X_5, Y_{i-1})$
$Y = g(Y_1, Y_2, \ldots, Y_n)$
"Stream of Quality (SoQ)" originated from IMS Center

20

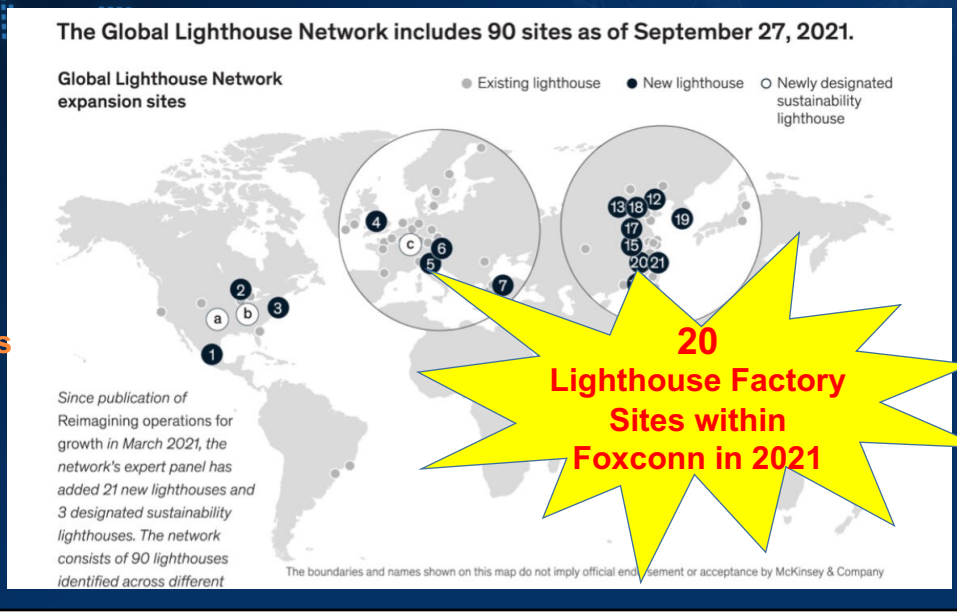
Foxconn Received 2019 World Economic Forum (WEF) Lighthouse Factory Award

21

WEF Lighthouse Factory Networks (103 Sites As of March 2022)

Top WEF Lighthouse Sites:

- Foxconn 5 sites
- J&J 7 sites
- P&G 4 sites
- Schneider 4 sites
- Siemens 2 sites
- Unilever 3sites



22

Predictive Metrology for Yield Enhancement in Next-Generation (5nm/3nm/1nm) Semiconductor Manufacturing

Event Name
Event Details

23

Intel Plans to Build Two More Fabs in Columbus, OH (as of 1/19/22)

Changing Global Supply Chains

The complexity and capital intensity of semiconductor development and the need for high volume production have resulted in high degrees of industry agglomeration in just a few key regions worldwide. The U.S. remains the global leader for semiconductor design and R&D, and U.S. firms still account for nearly 50% of global chip sales. However, the U.S. accounts for just 13% of global chip manufacturing, down from 37% in 1990.[vi] This includes 19% of silicon wafers produced for discrete, analog and optoelectronics and sensors (DAO) and just 5% of wafers produced for memory.[vii] More than 80% of production now occurs in Asia — specifically China, Taiwan and South Korea. Furthermore, all leading-edge chips, those with 10-nanometer (nm) transistors and smaller ones essential for emerging technology, are only produced in South Korea and Taiwan.[viii]

Rising geopolitical tension and the effects of the COVID-19 pandemic have highlighted vulnerabilities and national security concerns around existing supply chains. It is estimated there are currently more than 50 points across the semiconductor supply chain where a single region holds more than 65% of the global market share [ix] — meaning a single point of failure in the chain could have global catastrophic outcomes. Consequently, there is growing interest by governments, consumers and firms in the diversification of manufacturing supply chains outside of Asia. As more producers consider expanding operations in North America and Europe, Greater Phoenix will remain a top contender due to its thriving semiconductor ecosystem driven by proximity to west-coast technology hubs, coastal ports of entry and the massive North American microelectronics consumer base.

Market share of domestic firms and wafer fabrication capacity in major global semiconductor exporters. (2019)

24

3nm Race in 2022

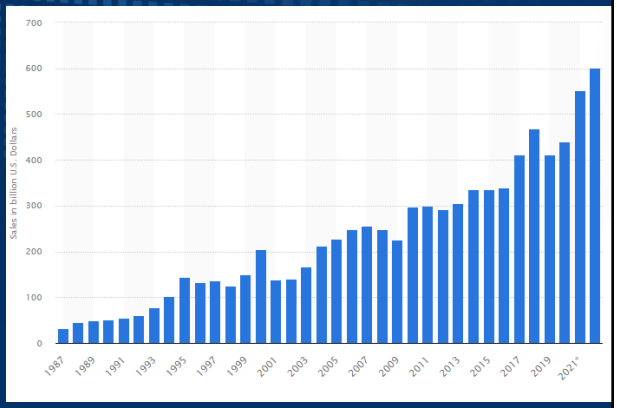
- TSMC and Samsung are the only foundry players that make chips using 5nm process node
- TSMC 3nm Value Proposition vs 5nm

Speed Improvement at Same Power	Power Reduction at Same Speed	Logic Density	SRAM Density	Analog Density
10~15%	25~30%	~1.7x	~1.2X	~1.1x

(image credit: TSMC)

- TSMC will plan high volume production of 3nm process in Q3 or Q4 in 2022; Samsung plans to start mass production using 3nm process node in 2022.
- New transistors and materials (FinFET vs GaaFET), new EUV scanner, new atomic layer deposition, metrology and inspection, yield improvement, packaging will be the key technical challenges for 3nm and beyond

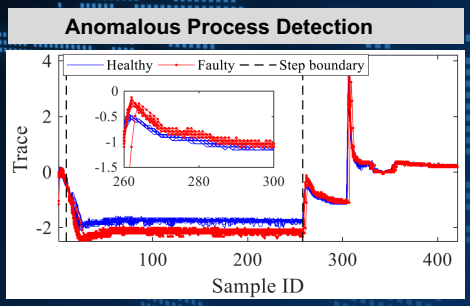
Semiconductor market size worldwide (in billion U.S. dollars)

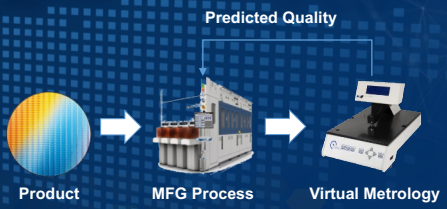


Source: Statista

25

Data-Driven Process Metrology for Yield Enhancement in Semiconductor Manufacturing Process





Predictive Maintenance

Process Optimization

Merits of Data-Driven Solutions:

- (Near) Real-Time Computation and Optimization
- Cost-Effective
- Short Development Cycle

Major Challenges:
Variations and uncertainties in the manufacturing processes.

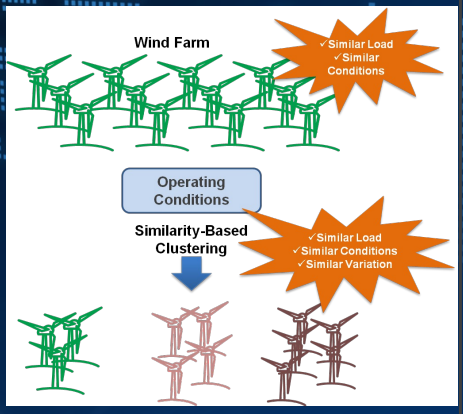
26

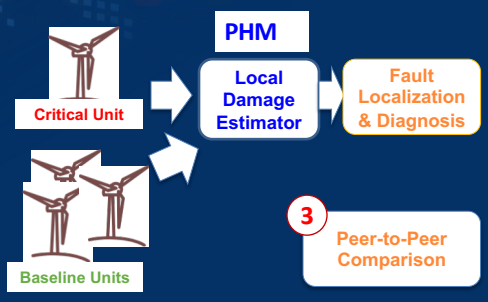
Energy—Wind Farm

27

Similarity-based PHM Approach

Turbine-to-Turbine Prognostics for Wind Farms



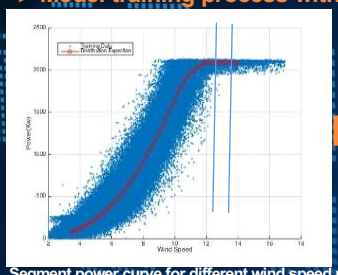


U.S. Patent US 8924162 B2

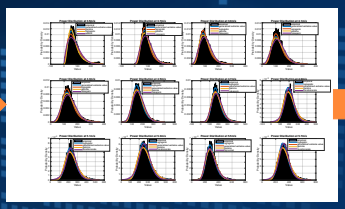
28

Time-Machine Based Health Analysis

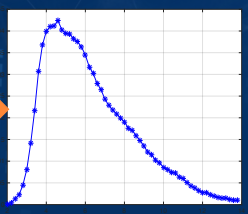
► Model training process with baseline data:



Segment power curve for different wind speed regimes

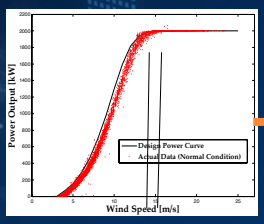


Calculate the distribution model of power at each wind speed and save as baseline mode



Calculate the frequency of wind speed as weight for final CV output

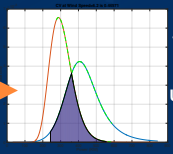
■ Model application process with real-time data



Sort data by wind speed regimes

Feature Buffer	
Wind Speed	Sample Size
3m/s	87
3.2m/s	61
3.4m/s	11
....	....
6.2m/s	102
6.4m/s	77
....	....

Fit distribution model when data is enough

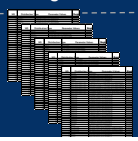


Variation Assessment

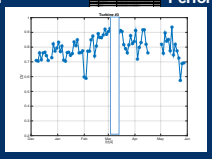
Update the variation part in current model

Update turbine health value

Time-machine of model variation



Performance model at time t



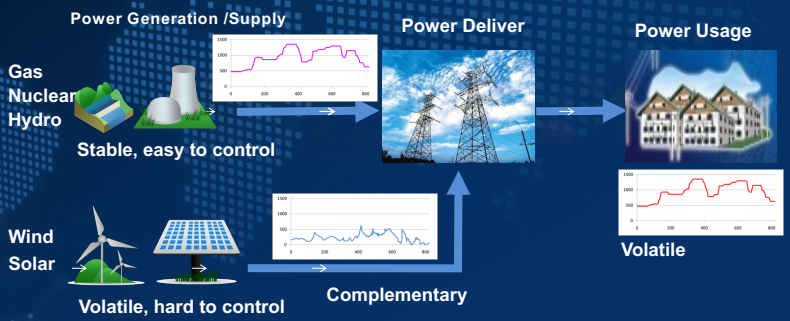
abnormality detected

Calculate the Health Value

Wind Speed Prediction for Power Optimization

Current wind speed/power prediction (WSP) concentrate on average wind speed and its high frequency components, and the prediction interval are basically limited to short-term prediction (less 1 hour ahead) due to the limit of prediction algorithms.

Current WSP relies on time series prediction model that will give much higher prediction error for long-term prediction, which are extremely dangerous for power grid frequency stabilization.



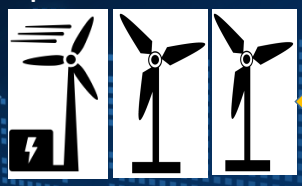
In order to match power supply/need, wind power needs to be predicted at least 4 hours ahead so that traditional power generator can have enough time adjusting the total supply to make power grid stable and safe

Wind Speed Prediction

Background:

Uncertainty
Inconsistency

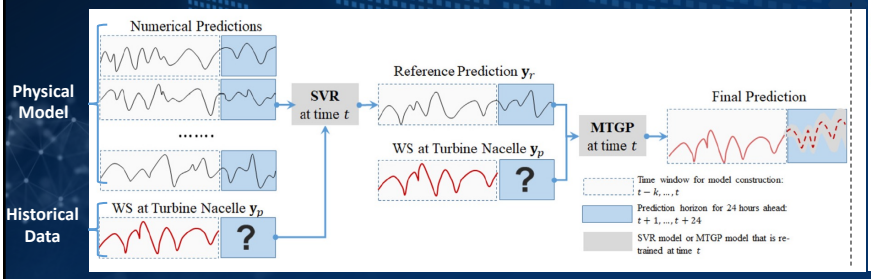
Operation & Maintenance



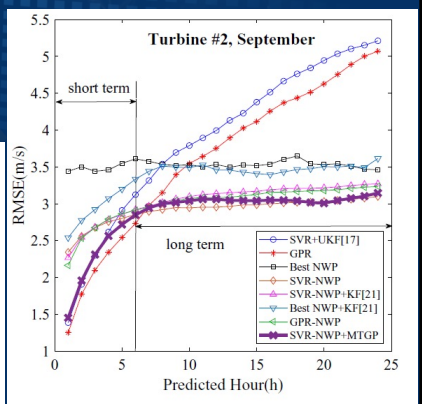
Wind Power Generation

Wind Speed Prediction

Methodology:



Results:

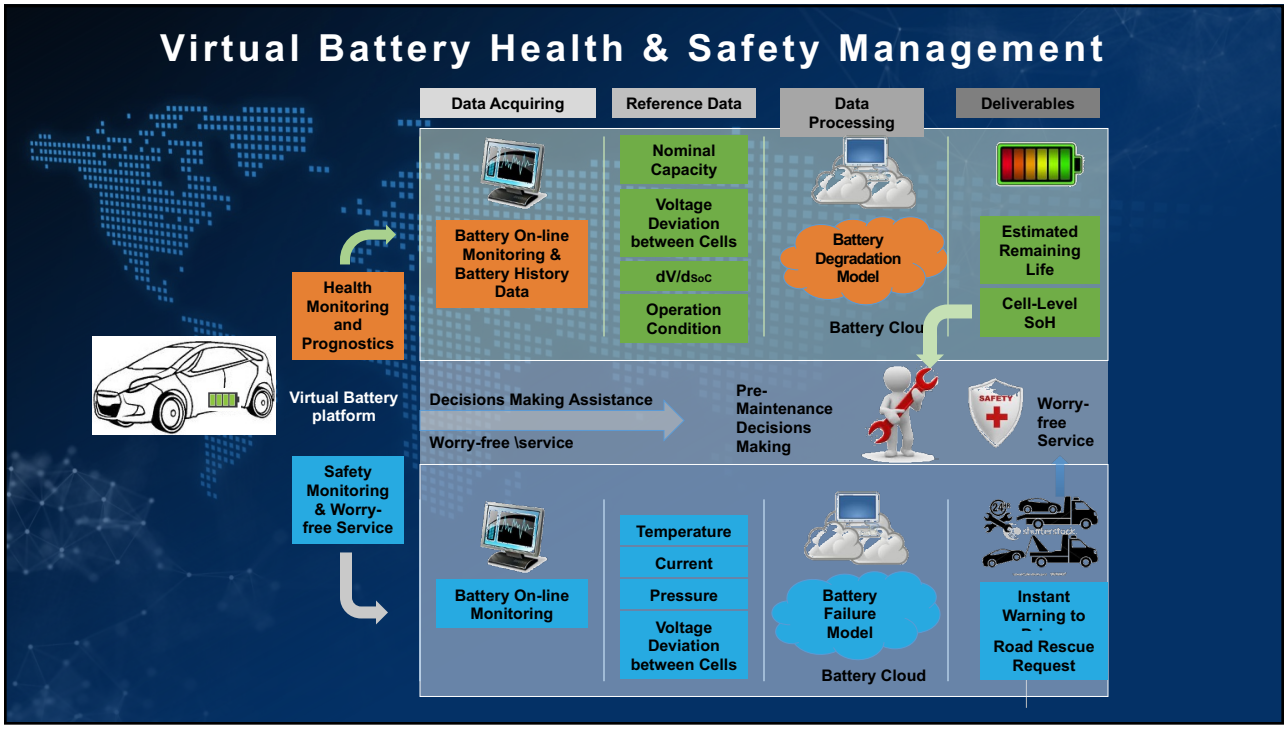


[1] Haoshu, Cai, Xiaodong Jia, Jianshe Feng, Wenzhe Li, Yuan-Ming Hsu, and Jay Lee. "Gaussian Process Regression for numerical wind speed prediction enhancement." *Renewable Energy* 146 (2020): 2112-2123.

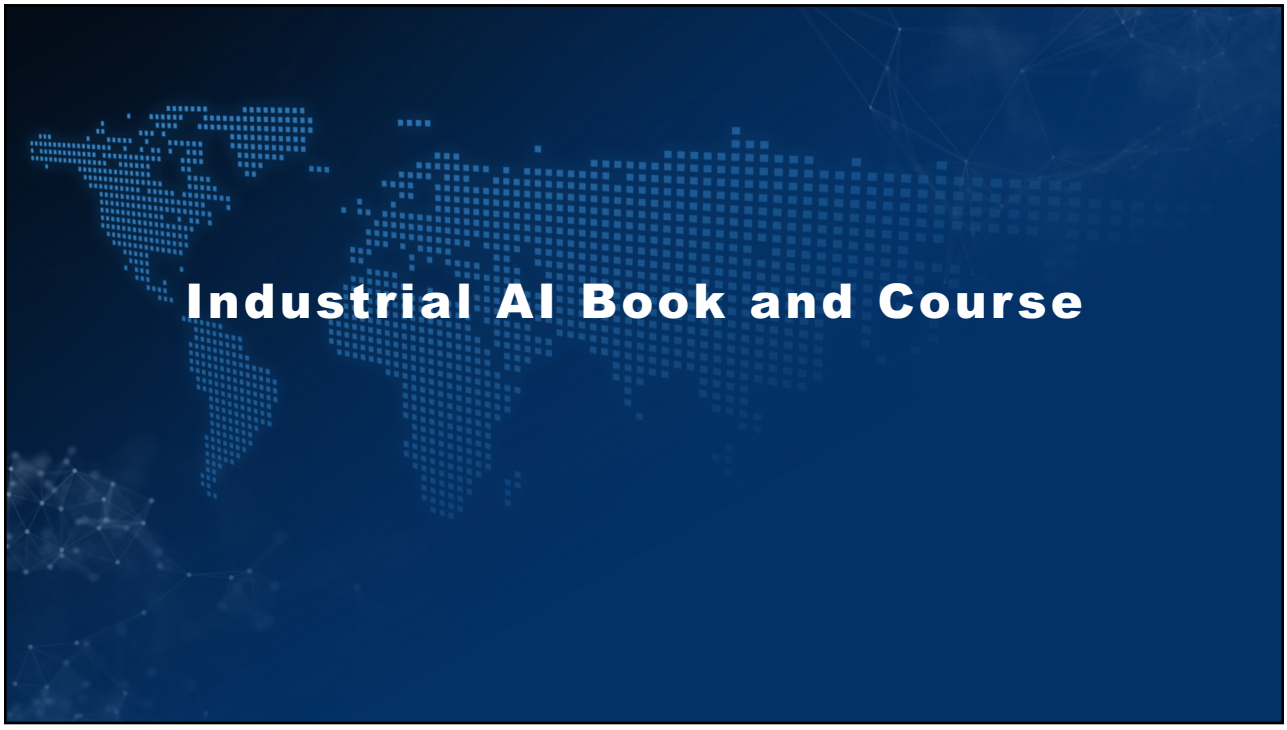
31

EV Battery Analytics and Mobility AI

32

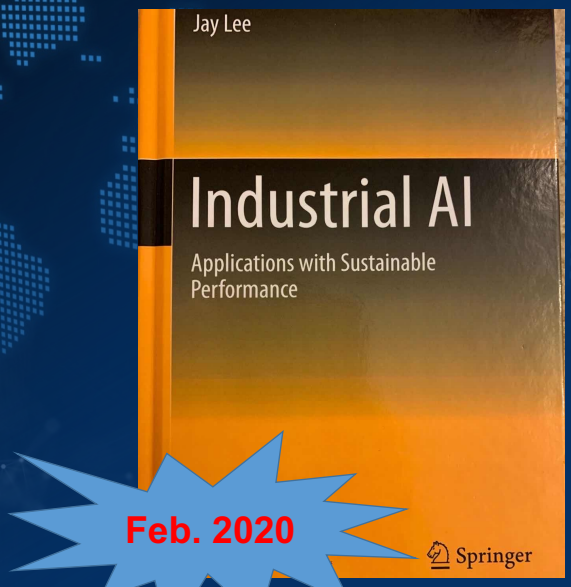

Virtual Battery Health & Safety Management
Data Acquiring
Reference Data
Data Processing
Deliverables
Nominal Capacity
Voltage Deviation between Cells
dV/dSoC
Operation Condition
Battery On-line Monitoring & Battery History Data
Battery Degradation Model
Estimated Remaining Life
Cell-Level SoH
Health Monitoring and Prognostics
Virtual Battery platform
Decisions Making Assistance
Worry-free \service
Pre-Maintenance Decisions Making
Worry-free Service
Safety Monitoring & Worry-free Service
Temperature
Current
Pressure
Voltage Deviation between Cells
Battery On-line Monitoring
Battery Failure Model
Battery Cloud
Instant Warning to
Road Rescue Request

33


Industrial AI Book and Course

34

"Industrial AI" Book



Feb. 2020

35

More Information See

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36