CHALMERS
UNIVERSITY OF TECHNOLOGY

DIGITALIZATION IN PRODUCTION AND MAINTENANCE

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CHALLENGES AND OPPORTUNITIES

Need for a clear strategy to implement digitalization solutions

Cost of production disturbance ~106 Bn SEK

OEE of industrial equipment ~50 %

PRODUCTION SERVICE & MAINTENANCE SYSTEMS

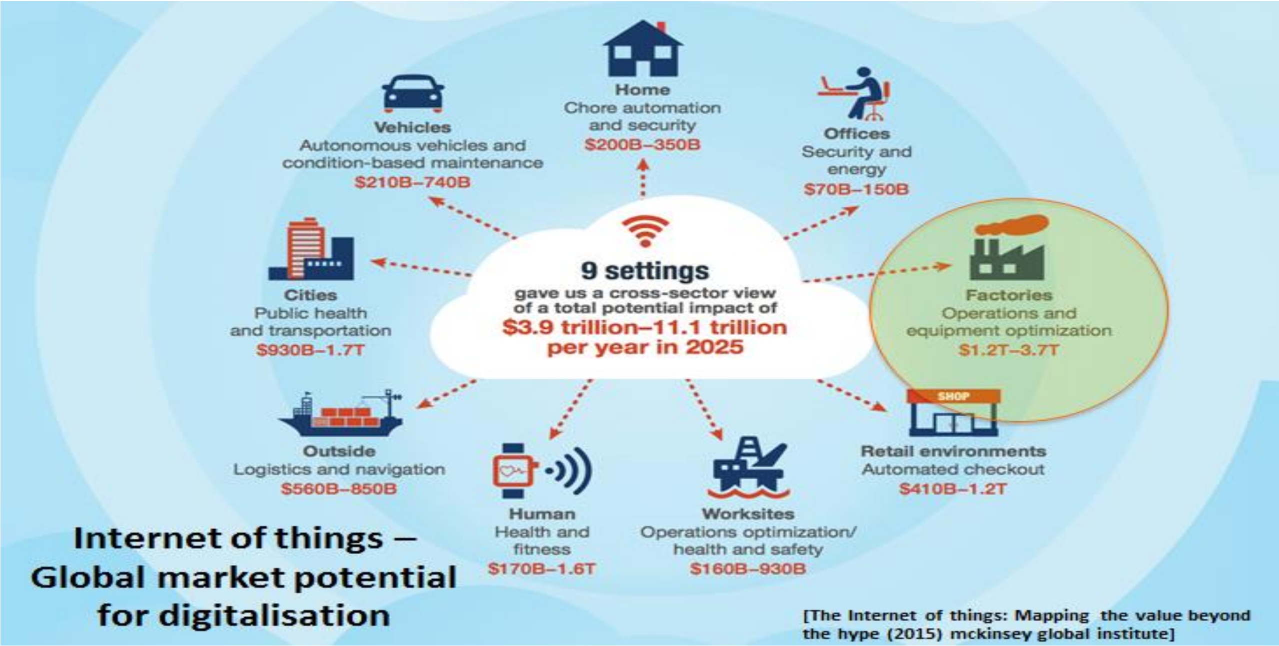
Sets the agenda for Smart Maintenance

Data-driven decisions, human capital, internal and external integration

The link between maintenance and production

Together with industry

Potential


Home
Chore automation and security
$200B–350B
Vehicles
Autonomous vehicles and condition-based maintenance
$210B–740B
Offices
Security and energy
$70B–150B
Cities
Public health and transportation
$930B–1.7T
9 settings
gave us a cross-sector view of a total potential impact of
$3.9 trillion–11.1 trillion per year in 2025
Factories
Operations and equipment optimization
$1.2T–3.7T
SHOP
Outside
Logistics and navigation
$560B–850B
Retail environments
Automated checkout
$410B–1.2T
Human
Health and fitness
$170B–1.6T
Worksites
Operations optimization/ health and safety
$160B–930B
Internet of things – Global market potential for digitalisation
[The Internet of things: Mapping the value beyond the hype (2015) mckinsey global institute]

”Industrie 4.0”

”Smart Industri”

“Smart Manufacturing”

”Robot Revolution”

“Smart Factory”

”Made in China 2025”

”Digital Single Market”

POTENTIAL WITH MODERN MAINTENANCE

Highest-ranked use cases, based on survey responses	Use case type	Impact	Data richness
Predict failure and recommend proactive maintenance for production and moving equipment	Predictive maintenance	1.3	1.0
Optimize complex manufacturing process in real time—determine where to dedicate resources to reduce bottlenecks and cycle time	Operations/logistics optimization (real time)	1.1	1.0
Predict future demand trends and potential constraints in supply chain	Forecasting	0.8	0.7
Identify design problems in pre-production to reduce ramp-up time to maximum output (i.e., yield ramp)	Predictive analytics	0.6	0.3
Identify root causes for low product yield (e.g., tool-/die-specific issues) in manufacturing	Discover new trends/ anomalies	0.5	0.7

[McKinsey, 2016]

IS SWEDISH INDUSTRY SMART?

	90's *(Ljungberg 1998)*	2006-2012 *(Ylipää et al.)*
Planned stops	5%	6,6%
Unplanned stops	12%	9,6%
Set-ups	8%	11,5%
Availability	80%	78,9%
Utilization	77%	80,2%
Quality	99%	96,9%
OEE	***55%***	***51,5%***

DATA-DRIVEN MAINTENANCE

Reactive maintenance
- Wait and repair

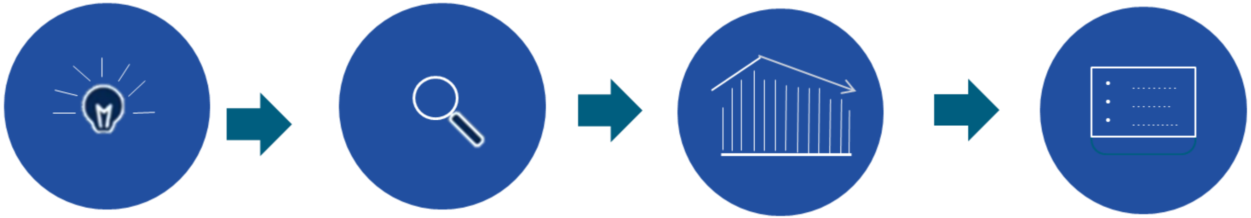
Preventive maintenance
- Continuous service

Predictive maintenance
- Service on predicted problems
- Machine learning

Self-coordinating maintenance
- Service when optimal from the entire system
- AI on combined data

DATA ANALYTICS IN MAINTENANCE

Descriptive | Diagnostic | Predictive | Prescriptive



Descriptive: Description of what has already happened

Diagnostic: Exploration of meaningful information

Predictive: Prediction of future outcomes based on historical data

Prescriptive: Recommendations on predictive model output

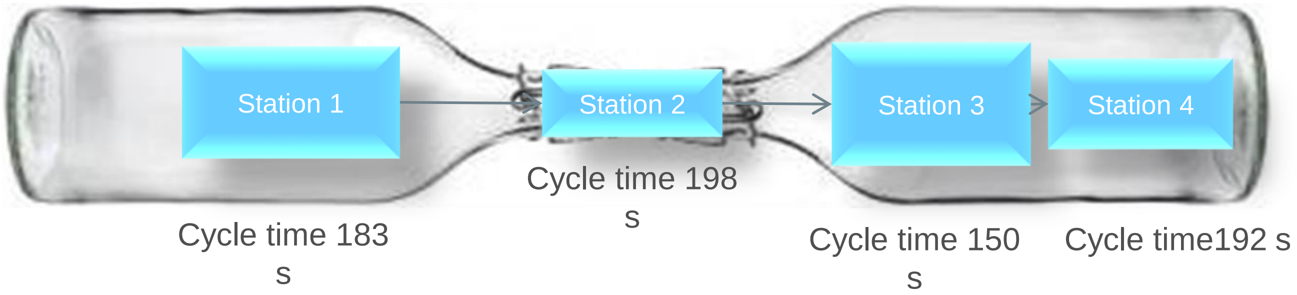
Descriptive: What happened?

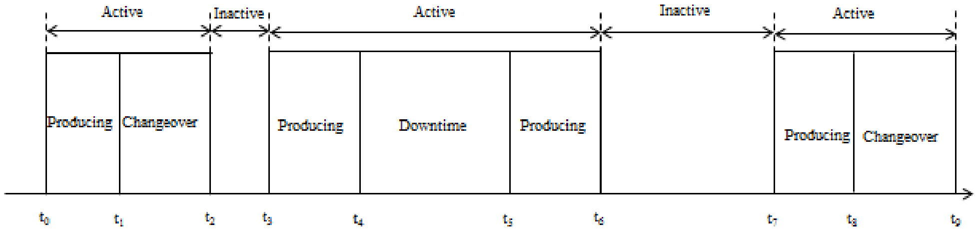
Diagnostic: Why did it happen?

Predictive: What will happen?

Prescriptive: What should I do?

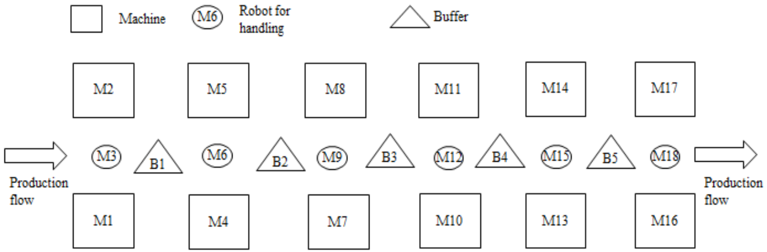
EXAMPLE FROM MANUFACTURING



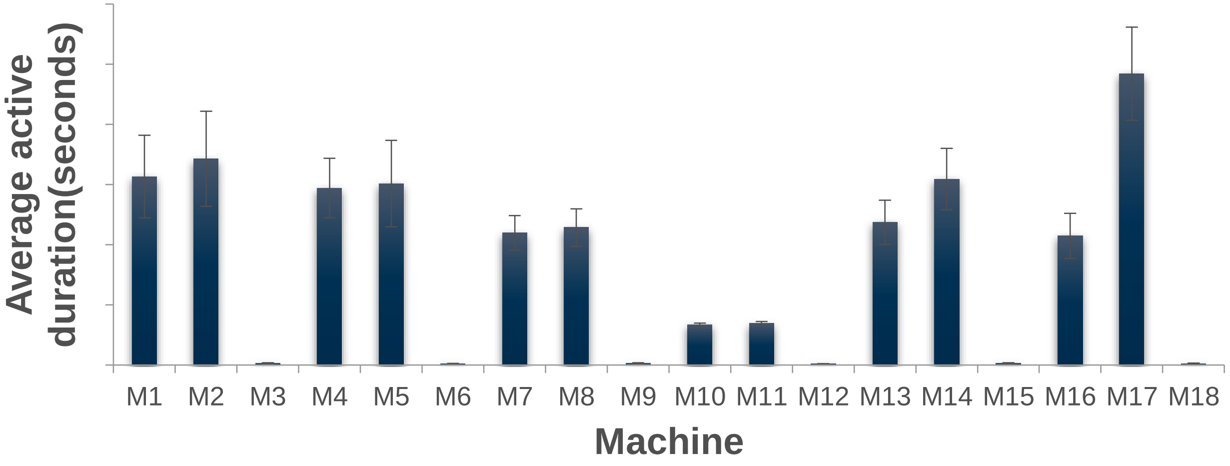


MES EXAMPLE

Production Area	Work Area	Date with Time	State of the machine
Line 1	M1	01-09-2014 06:28:02	Not Active
Line 1	M1	01-09-2014 06:28:25	Comlink Up
Line 1	M1	01-09-2014 06:29:20	Not Active
Line 1	M1	01-09-2014 06:29:34	Waiting
Line 1	M1	01-09-2014 06:29:34	Waiting
Line 1	M1	01-09-2014 06:42:46	Producing

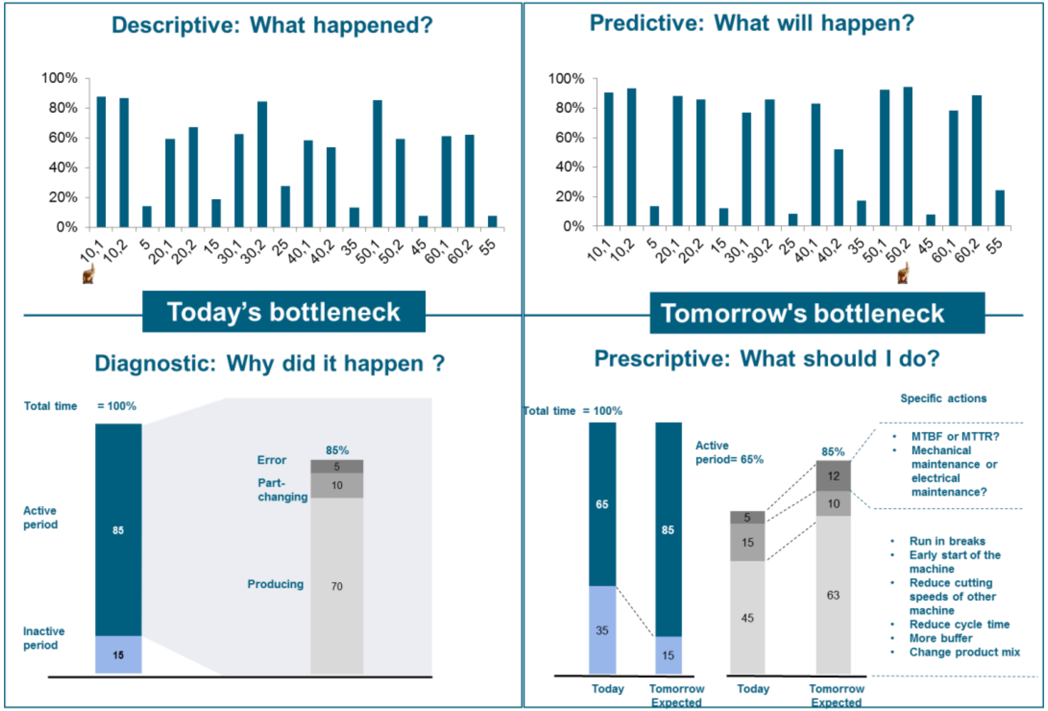


EXAMPLE FROM A SERIAL PRODUCTION LINE



- M17 is a primary bottleneck
- M2 could also be a primary bottleneck
- M17 and possibly M2 should be prioritized in maintenance and improvements

ANOTHER AUTOMOTIVE EXAMPLE WITH ALL STAGES



Example: Shifting bottlenecks algorithm implementation

Background

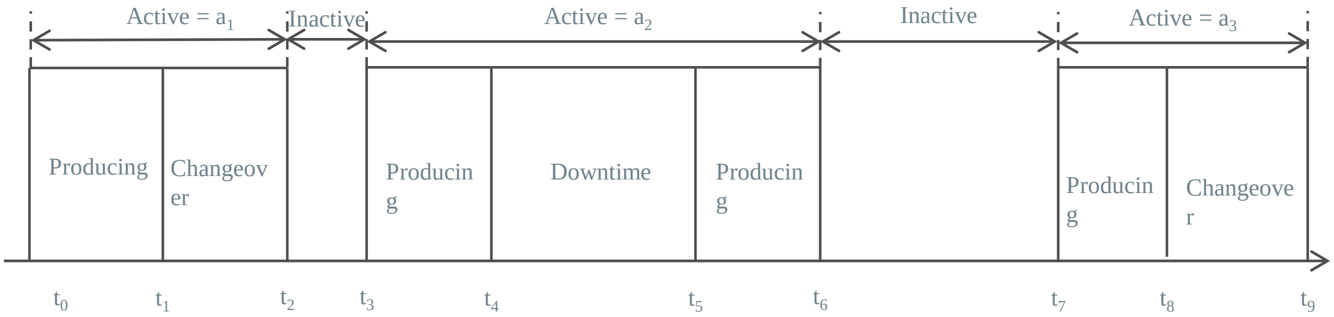
- Manufacturing companies collect a lot of machine data – Consequence of digitalisation
- Production and maintenance engineers wanted to explore how AI could make,
  - Faster decisions
  - Better decisions
  - Confident decisions

Background

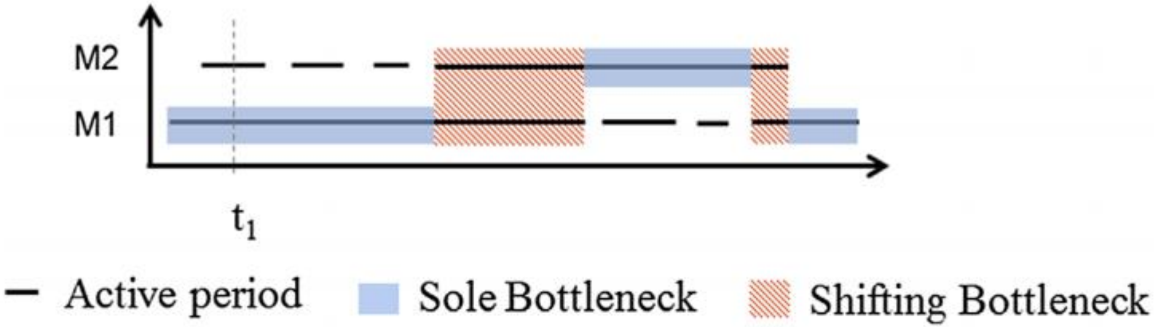
- Have to detect the bottlenecks from machine data
  - In real-time
  - Detect the shifting patterns in the bottlenecks

Shifting bottleneck detection method by Toyota Company

Concept and Approach



Method



Example : Shifting bottlenecks algorithm implementation

Flow of Analysis

Data → Data pre-processing → Algorithm development

Data

- Event log data that has time stamps and event descriptions

Data pre-processing

- Sampling every second
- Active/Inactive state coded as 1/0

Algorithm development

- Dynamic programming
- Recursive loops

Impact

- Help maintenance and production engineers to prioritise improvement activities
- Produce more products within the same scheduled hours
- Lower costs

Example : Shifting bottlenecks algorithm implementation

Step 1: State accumulation transformation

A

$$\begin{bmatrix} 0&0&1&1&1&0&1&1&1&1 \\ 1&1&1&0&1&1&1&1&0&0 \\ 0&0&0&1&0&1&0&1&1&1 \end{bmatrix}$$

State Accumulation →

B

$$\begin{bmatrix} 0&0&1&2&3&0&1&2&3&4 \\ 1&2&3&0&1&2&3&4&0&0 \\ 0&0&0&1&0&1&0&1&2&3 \end{bmatrix}$$

Current bottleneck

Step 2: Potentials bottleneck detection transformation

B

$$\begin{bmatrix} 0&0&1&2&3&0&1&2&3&4 \\ 1&2&3&0&1&2&3&4&0&0 \\ 0&0&0&1&0&1&0&1&2&3 \end{bmatrix}$$

Potential bottlenecks detection →

C

$$\begin{bmatrix} 0&0&1&1&1&0&1&1&1&1 \\ 1&1&1&0&1&1&1&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

Potential bottlenecks

Step 3: Shifting bottlenecks transformation

C

$$\begin{bmatrix} 0&0&1&1&1&0&1&1&1&1 \\ 1&1&1&0&1&1&1&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

Shifting bottlenecks →

D

$$\begin{bmatrix} 0&0&1&0&1&0&1&1&0&0 \\ 0&0&1&0&1&0&1&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

Shifting bottlenecks

Step 4: Finding sole bottlenecks

C - D = E

$$\begin{bmatrix} 0&0&1&1&1&0&1&1&1&1 \\ 1&1&1&0&1&1&1&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0 \end{bmatrix} - \begin{bmatrix} 0&0&1&0&1&0&1&1&0&0 \\ 0&0&1&0&1&0&1&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0 \end{bmatrix} = \begin{bmatrix} 0&0&0&1&0&0&0&0&1&1 \\ 1&1&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

PRESCRIPTIVE MAINTENACE

Systems level (MES-data)

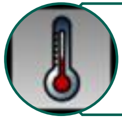
Real-time observation and prediction of bottlenecks and critical resources

Systems level (MES-data)

Prioritize improvements and maintenance on future needs in critical resources

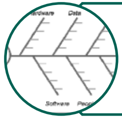
Equipment level (MES-data)

Real-time analysis and prediction of trends in failure frequencies and repair times



Sensor level

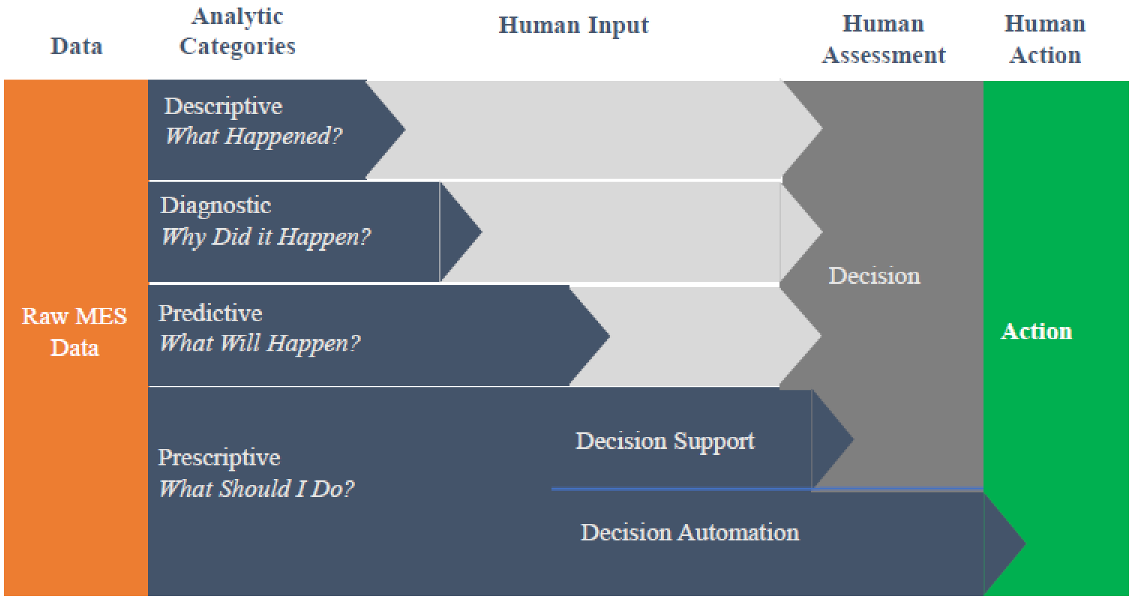
Detect patterns in alarm and sensor data



Combined MES and sensor level

Identify and predict root causes

AUTOMATED DECISION SUPPORT



SUMMIT – SMART MAINTENANCE TESTBED

- ❑ Algorithm development for Smart Maintenance
- ❑ Collaboration between data scientists, process experts, and maintenance researchers
- ❑ Evaluation of existing data sets and collection of new data
- ❑ Test of commercial software packages

- ✓ Scania - case
- ✓ Volvo Cars - case
- ✓ SSAB - case
- ✓ Preem - case
- ✓ Göteborg Energi - case
- ✓ Microsoft – software
- ✓ Siemens – software
- ✓ Sigma - integration
- ✓ KTH – case and analysis
- ✓ Fraunhofer Chalmers Center – algorithms
- ✓ Chalmers – project management and algorithms

Virtual Development Lab - Chalmers

PRODUKTION2030

Med stöd från: VINNOVA Energimyndigheten formas STRATEGISKA INNOVATIONSPROGRAM

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