Reliability in the Age of Big Data

TNO - Jan Eite Bullema | ASQ CQE, ASQ CSSBB

29 NOVEMBER 2018
TECHNIEKHUYS
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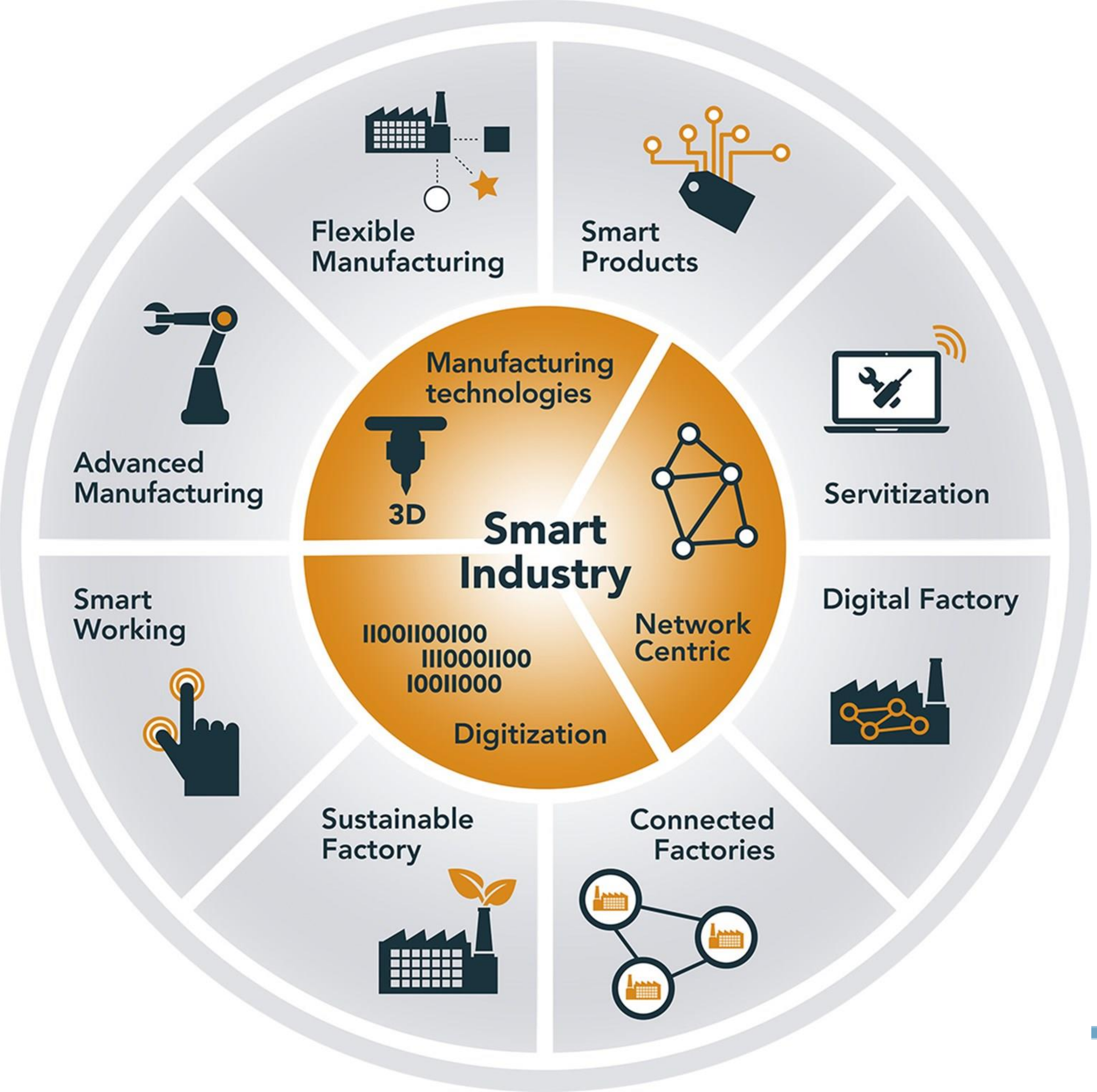
TOMORROW'S RELIABILITY

TNO innovation for life


Flexible Manufacturing
Smart Products
Servitization
Digital Factory
Connected Factories
Sustainable Factory
Smart Working
Advanced Manufacturing
Manufacturing technologies
3D
Smart Industry
Network Centric
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Digitization

Reliability in the Age of Big DATA

The nature of Big Data: **new types of data**

Opportunities of Big Data for Reliability: **new reliability methods**

New degradation models and application of Digital Twins

New types of covariates

Application of Machine Learning

Emergence of **new reliability applications**

New propositions: use based insurance, early warning warranty

The nature of Big Data: Many V's

Many V's (Variety, Volume, Veracity, Velocity, Value, Variability, Visualise)
brontobyte (10^{27}) = 1000 yottabyte (10^{24}) = 1000000 zettabyte (10^{21})

Big Data has often complex structures or is even totally unstructured
high speed sensor data, video, images, text, weather, environment, Email

Emergence of (Industrial) Internet of Things
2015: 15 billion iot sensors/devices 2025: 75 billion iot sensors/devices

https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/

Big data in Semicon Manufacturing Explosion in Generated Data

2004
1 FAB produces
1 Terabyte/day

→

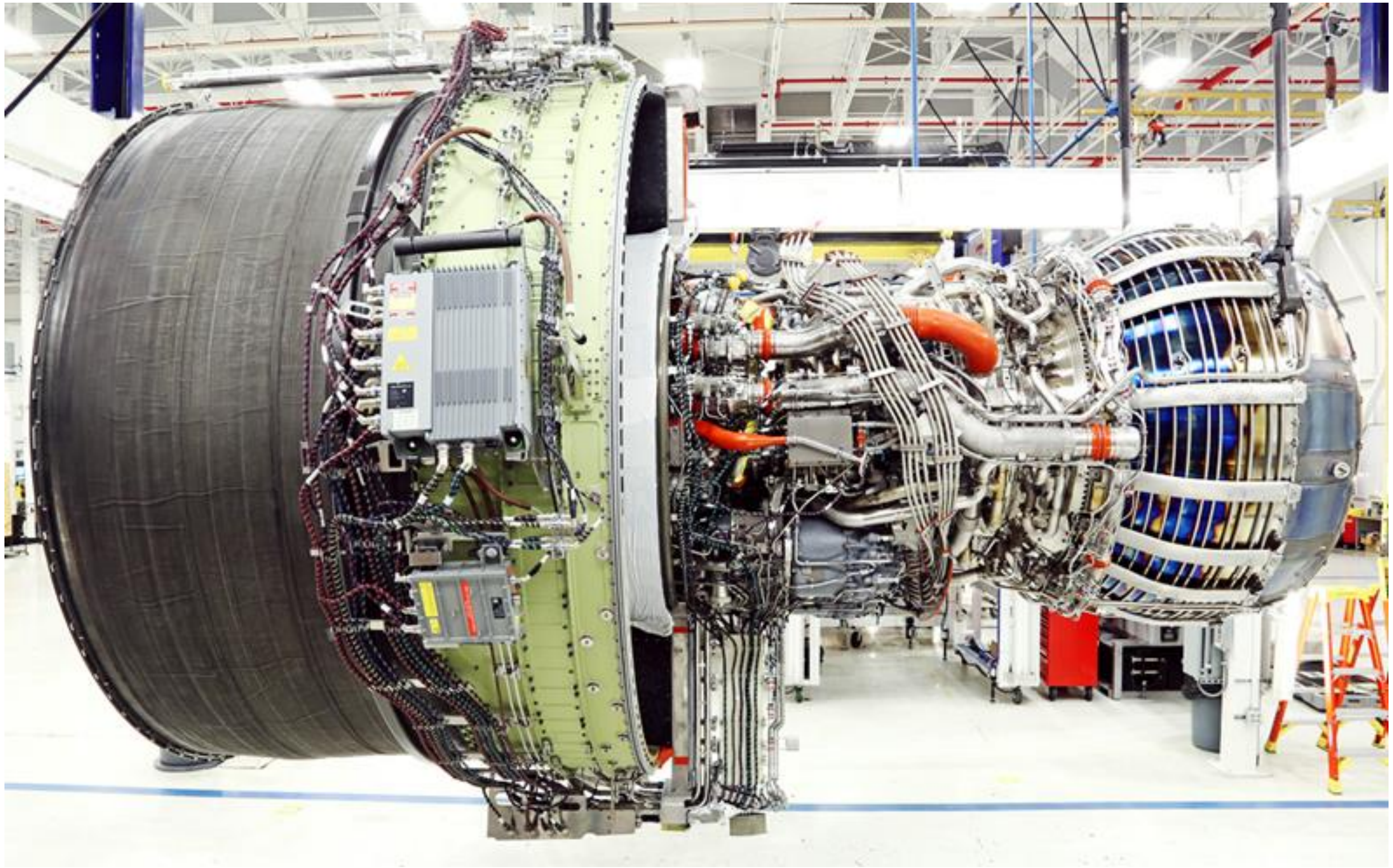
2014
1 FAB produces
1 Petabyte/day

→

2020
1 FAB
multiple
Petabytes/day

http://electroiq.com/blog/2014/09/the-semiconductor-industry-out-in-front-but-lagging-behind

Twin-engine aircraft with 12-hr. flight-time can produce up to 844 TB of data

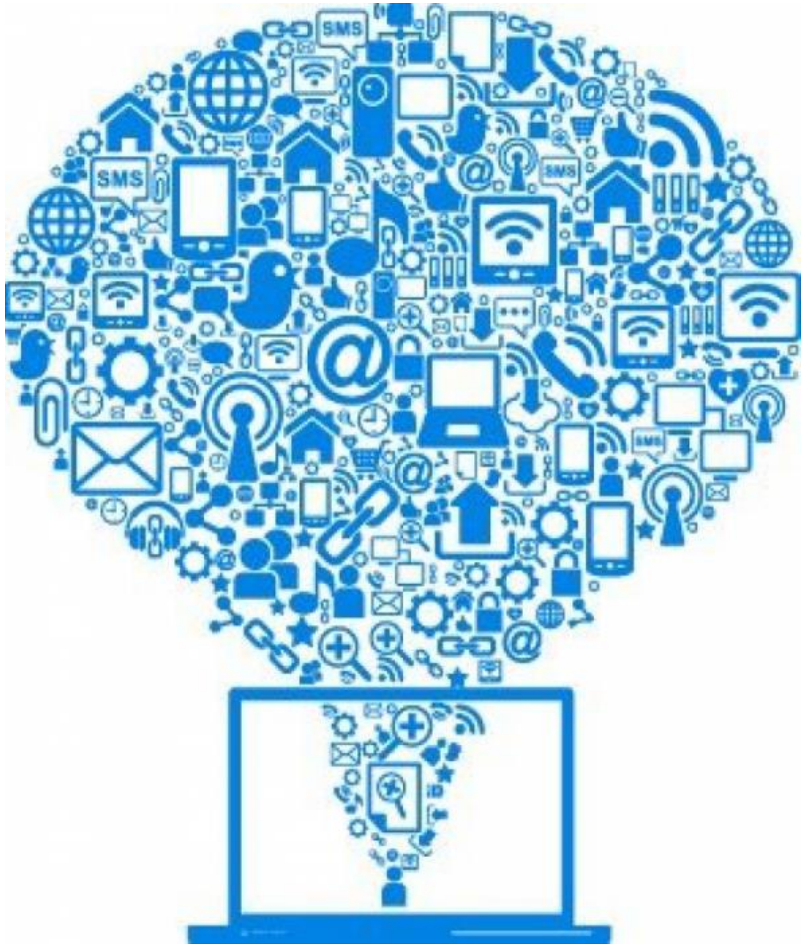


http://aviationweek.com/connected-aerospace/internet-aircraft-things-industry-set-be-transformed

Value Creation in Industry 4.0

Most value creation in implementation of Industry 4.0 will occur not by replacing equipment as in previous industrial revolutions, but by equipping existing equipment with sensors so that machines can be used more efficiently and productively

The nature of Big Data: new data types



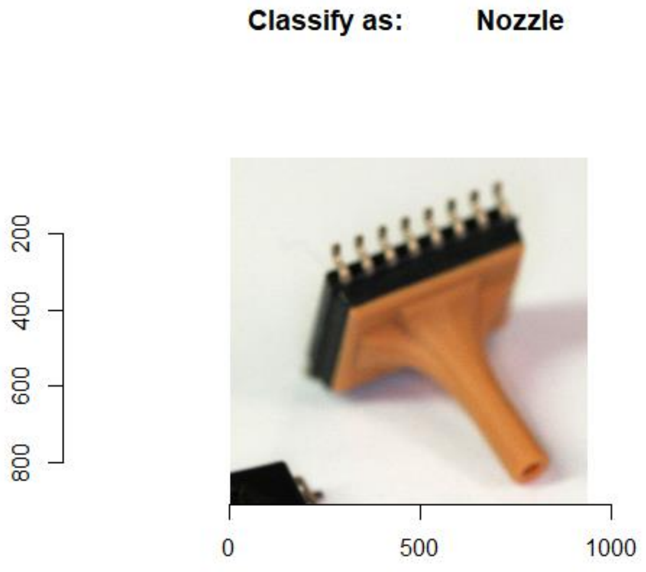
Multi variate time series date: e.*g. high speed multi-channel sensor data*

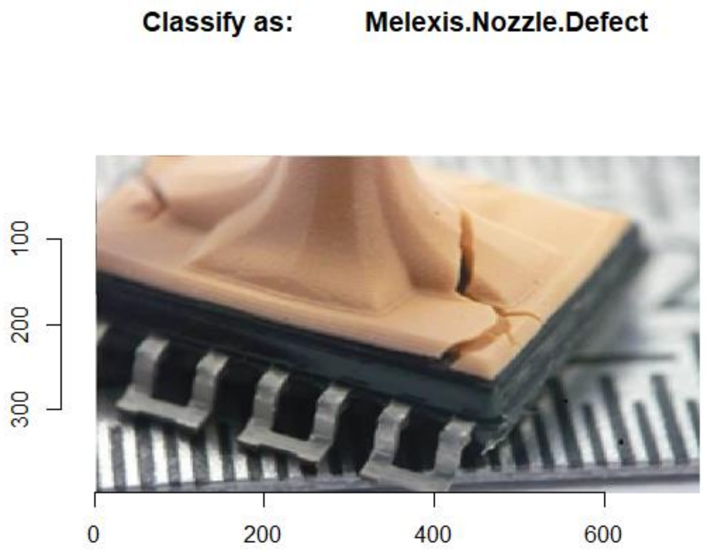
Functional Data: *e.g. functional curves, e.g. data from spectrometers*

Image Data / Video Streams: *e.g. camera image data or electron microscope image data*

Unstructured: *e.g. text, audio*

Example of New Data Types: images and Video Streams for defect classification





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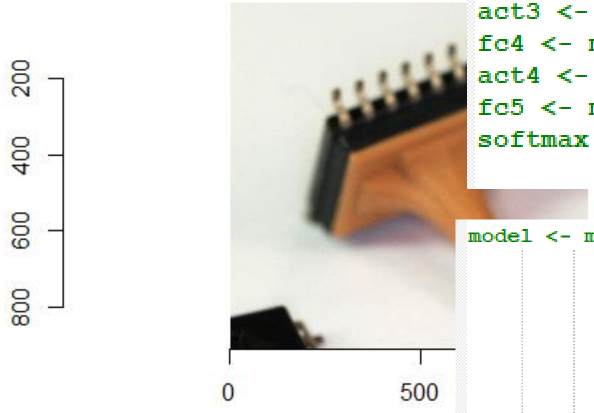
Example of New Data Types: images and Video Streams for defect classification

Classify as:

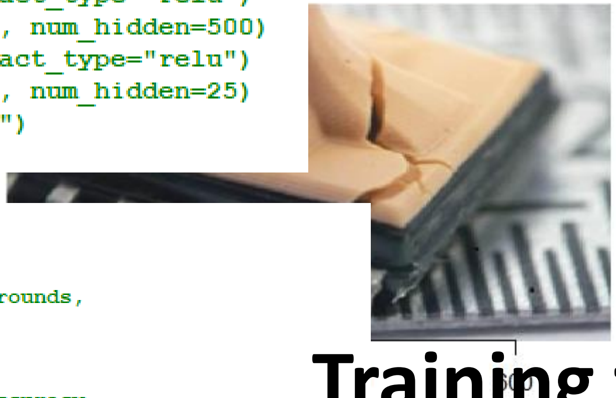



```
## set up the deep learning model

data <- mx.symbol.Variable("data")
fc1 <- mx.symbol.FullyConnected(data, name="fc1", num_hidden=250)
act1 <- mx.symbol.Activation(fc1, name="relu1", act_type="relu")
fc2 <- mx.symbol.FullyConnected(act1, name="fc2", num_hidden=500)
act2 <- mx.symbol.Activation(fc2, name="relu2", act_type="relu")
fc3 <- mx.symbol.FullyConnected(act2, name="fc3", num_hidden=1000)
act3 <- mx.symbol.Activation(fc3, name="relu3", act_type="relu")
fc4 <- mx.symbol.FullyConnected(act3, name="fc4", num_hidden=500)
act4 <- mx.symbol.Activation(fc4, name="relu4", act_type="relu")
fc5 <- mx.symbol.FullyConnected(act4, name="fc5", num_hidden=25)
softmax <- mx.symbol.SoftmaxOutput(fc5, name="sm")
```

lexis.Nozzle.Defect

Deep Learning Model



```
model <- mx.model.FeedForward.create(softmax,
                                     X=train.x,
                                     y=train.y,
                                     ctx=devices, num.round=rounds,
                                     array.batch.size=125,
                                     learning.rate=0.01,
                                     momentum=0.9,
                                     eval.metric=mx.metric.accuracy,
                                     initializer=mx.init.uniform(0.1),
                                     epoch.end.callback=mx.callback.log.train.metric(50))

print(proc.time() - tic)

preds <- predict(model, test.x)
dim(preds)
#preds
pred.label <-  max.col(t(preds)) - 1
```

Training the Model

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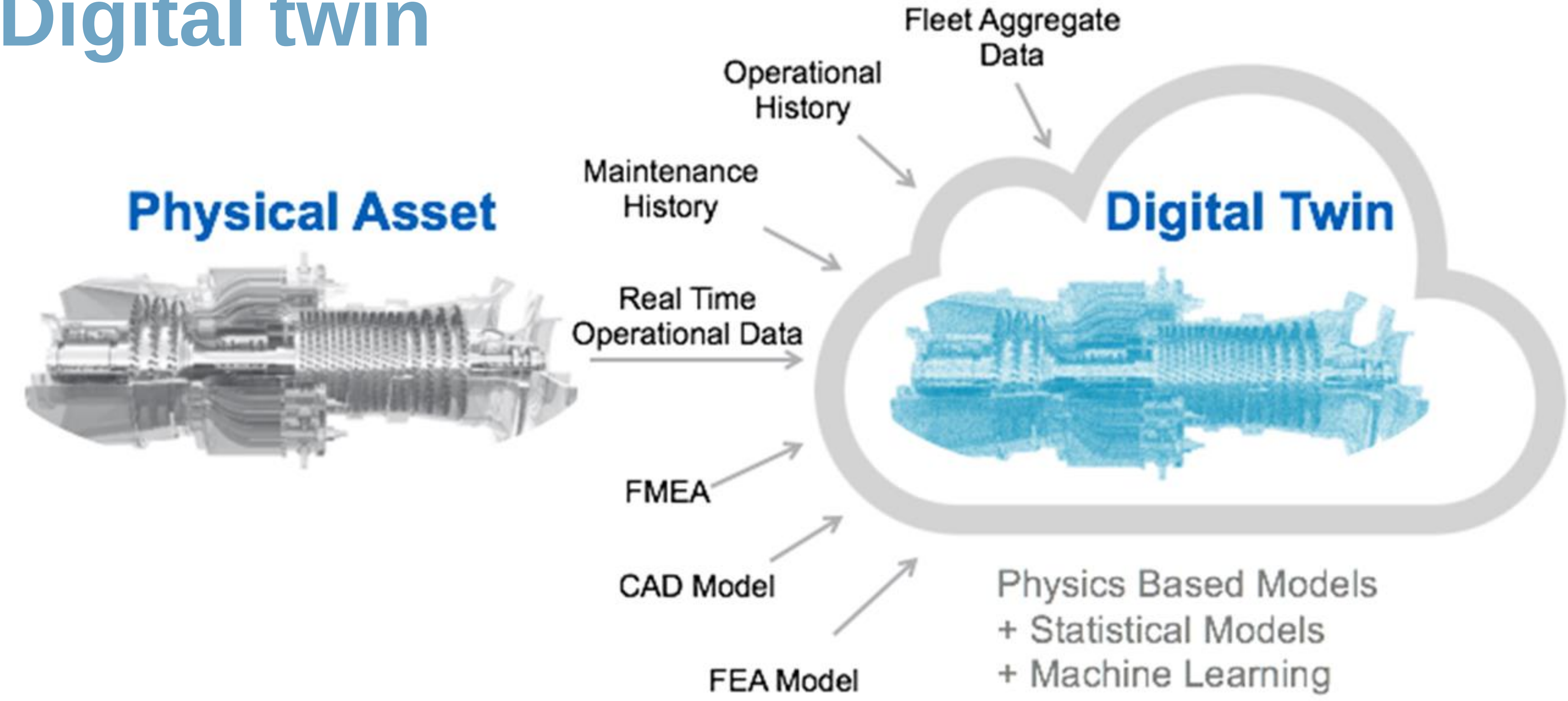
Example of New Data Types
Text Mining

Digital twin



https://www.capgemini.com/2018/08/digital-twin-physical-meets-digital-world/

Digital twin

Data Poor → Data Rich

Model

Complex
Multi-scale
Multi-physics
Modelling

Upscaling
Reduced-order
Modelling

Connect and transition to Data modelling

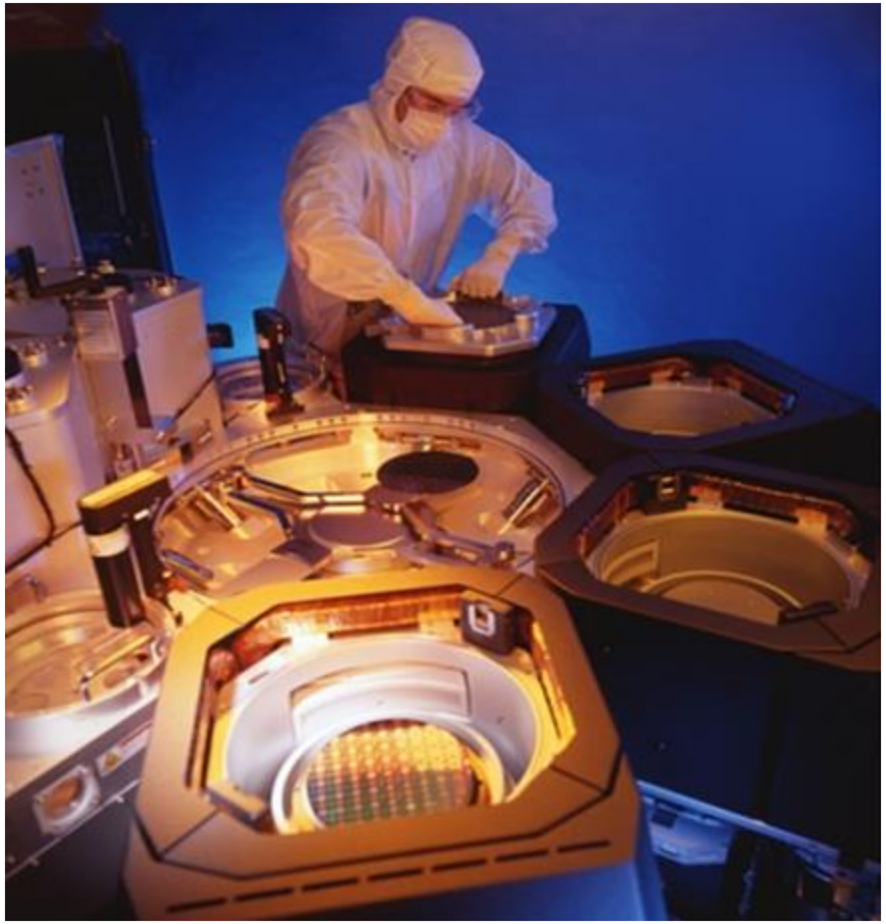
Big Data

Data Based Techniques / Data Analytics

Life Cycle

conception | prototype | deployment | evolution | maintenance | disposal

Predictive Maintenance: Improved Asset Utilization



Case: Deposition Tool

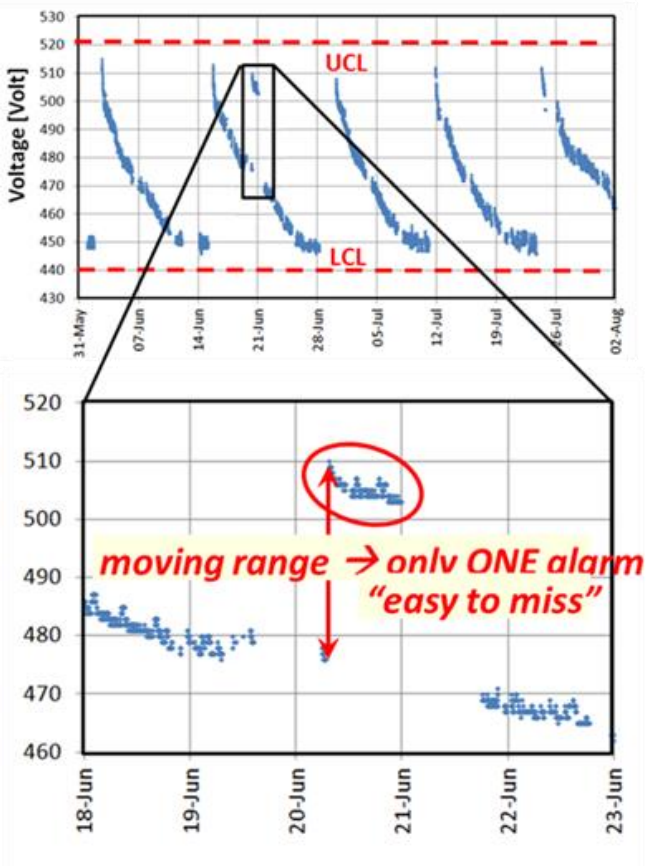
Applied Materials claims that a customer increased profits > $100,000 per chamber, per year using predictive maintenance modelling

Charlie Pappis, Optimizing Fab Through Data Analytics, Nano chip Fab Solutions, V9/ Issue 2/2014

Predictive Maintenance: Improved Asset Utilization

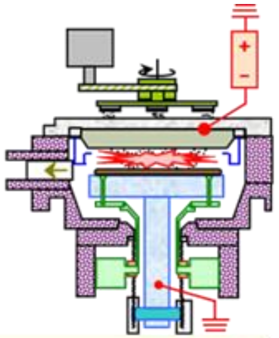
Jan Eite Bullema, How to make Big Data Productive in Semiconductor Manufacturing, 2016

Predictive Maintenance: Improved Asset Utilization



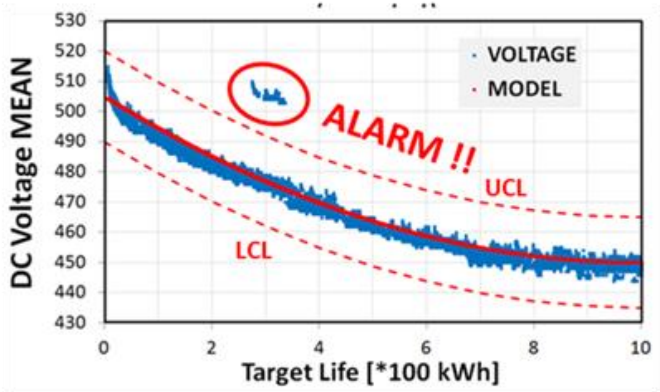
Incident 2004

- "electrical short" Alu heater
- "grounded" i.s.o. "floating"
- metal +10% too thick
- 311 wfrs affected



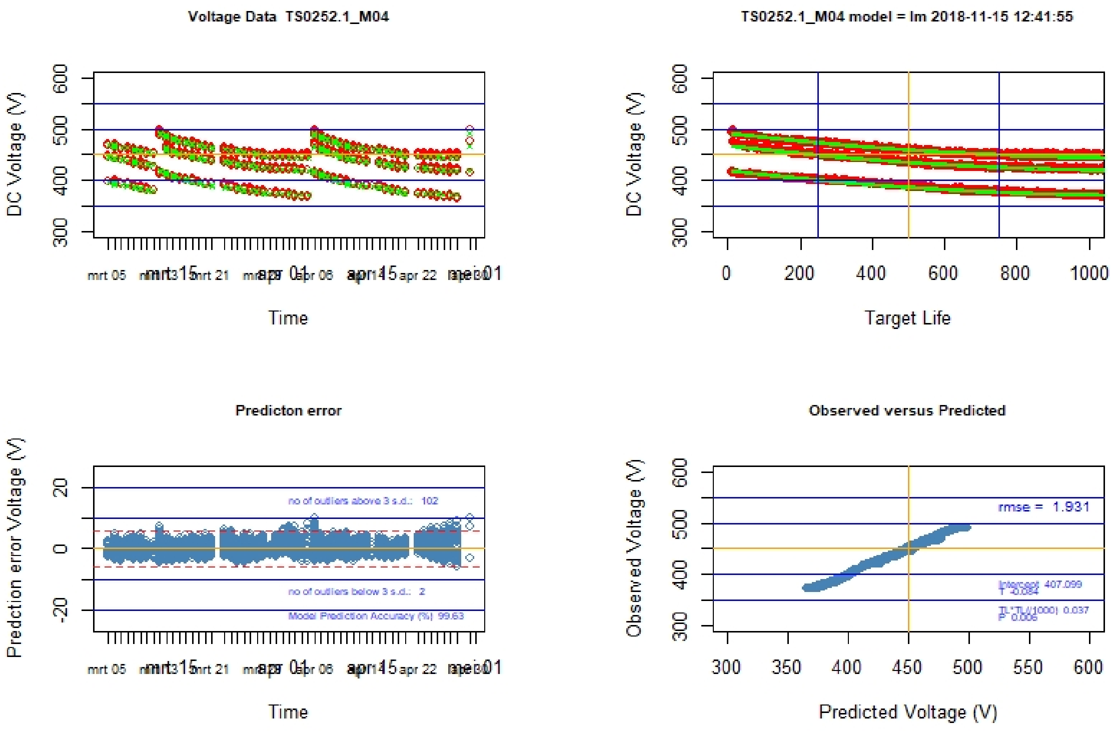
VISION for TOOL CONTROL

"narrow" control range around expected value



After a serious manufacturing Issue, control charts for deposition were adapted with a general model for sputtering Voltage

Predictive Maintenance: Improved Asset Utilization

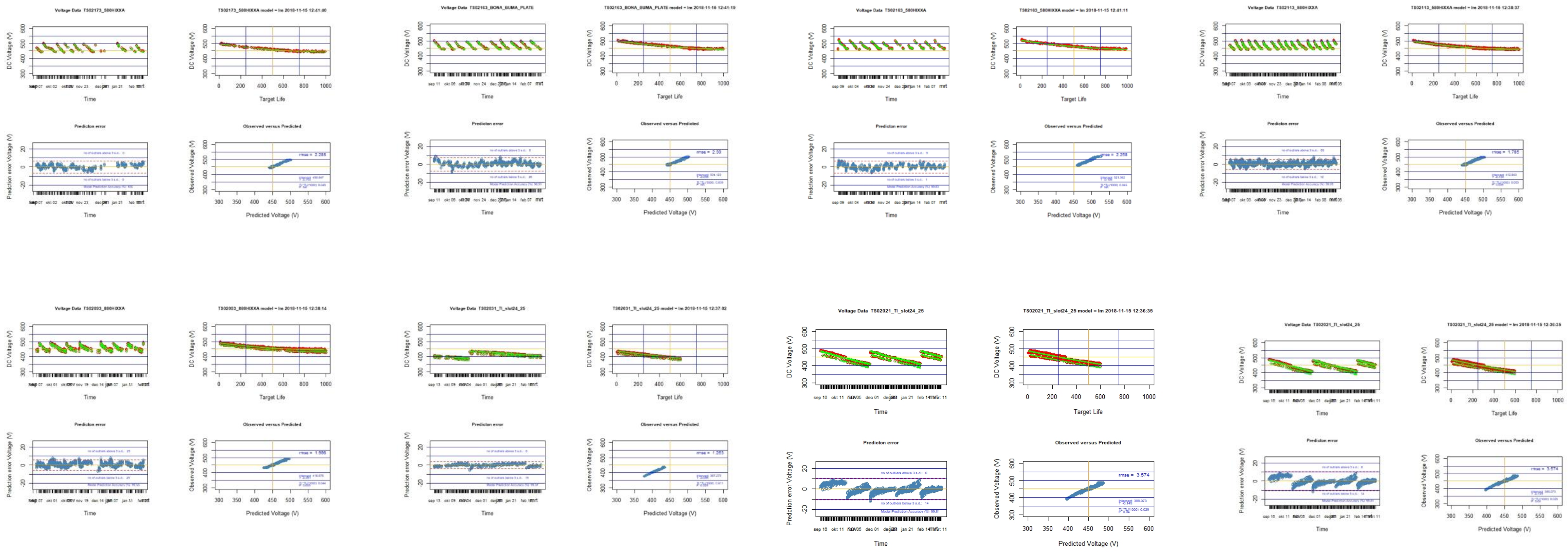


A new model was developed that predicts sputtering Voltage for 18 machines and 40 recipes

This model is 6 times better than the previous Voltage prediction model

The model gives additional information about machine status

Predictive Maintenance: Improved Asset Utilization



innovation for life

Jan Eite Bullema, How to make Big Data Productive in Semiconductor Manufacturing, 2016

CONCLUSION

Big Data technology leads to new types of data
high dimensional sensor data, images, functional curves, text messages

That lead to new statistical methods in reliability
functional data analysis, text mining, deep learning and image regression

That lead to higher levels of reliability and new propositions
use based insurance, use based warranty

Thank You for your Attention

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