From predictive maintenance to predictive manufacturing

Big Data challenge for industry
Goal of the presentation

+ Summarize and situate POM2 results into the broader picture of the manufacturing industry
+ Link the project results to the future industrial trends
+ POM2 technologies can enable
  - development of self-aware, self-learning, self-adapting machines
  - the transition towards a predictive manufacturing industry
Towards the 4th industrial revolution

The first power loom, 1784
Towards the 4th industrial revolution

The first moving assembly line, 1913

The first power loom, 1784
Towards the 4th industrial revolution

The first power loom, 1784
The first moving assembly line, 1913
The first industrial robot, 1962
Towards the 4th industrial revolution

Cyber-physical systems

The first power loom, 1784

The first moving assembly line, 1913

The first industrial robot, 1962
What is Industry 4.0?

It is about making...
Technology behind the vision

+ Many technologies have already deeply transformed the industry

+ The time is ripe for the next transformation: a self-aware, self-learning, self-adapting industry
  - Extensive sensor networks → big data streams
  - Advanced modelling and predictive techniques

For details see: http://imscenter.net/industry-4-0-activities/publications
Het is me niet helemaal duidelijk hoe dit olijnt met de 4 revoluties

Wim Symens, 20-Mar-14
Industry generates big data and will do it even more in the future
Hier begrijp ik de boodschap niet zonder toelichting.
Wim Symens, 20-Mar-14
Big data challenges

<table>
<thead>
<tr>
<th>Volume</th>
<th>Velocity</th>
<th>Variety</th>
<th>Veracity</th>
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</thead>
<tbody>
<tr>
<td><strong>Data at rest</strong></td>
<td><strong>Data in motion</strong></td>
<td><strong>Data in many forms</strong></td>
<td><strong>Data in doubt</strong></td>
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<tr>
<td>Terabytes to exabytes of existing data to process</td>
<td>Streaming data, milliseconds to seconds to respond</td>
<td>Structured, unstructured, text and multimedia</td>
<td>Uncertainty due to data inconsistency and incompleteness, ambiguities, latency, deception and model approximations</td>
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Big data - volume

+ **What do the experts say?**
  - *Industry generates about a third of all data today,* and this is certainly going increase significantly in the future

+ **GENERATION: What was our experience within POM2 project**
  - 150 MB data set, covering data from 2007 to 2014, mostly temperature and pressure measurements
  - 250 MB data set, covering data collected between 2011 and 2013, temperature measurements from a large machine park
  - 400 MB data set, raw accelerometer data, 22 measurements of 10s each

+ **STORAGE: The data should be stored**
  - It can be used to keep improving the diagnostic and predictive models
  - Adapting, self-learning algorithms improve their performance using historic data
Big data - velocity

+ **Real-time data processing**
  - Large amounts of data have to be collected from many sensors
    - LOW DATA RATES: Temperature, pressure, current, voltage → 0.1 kbps
    - HIGH DATA RATES: Accelerometers → 1 Mbps
    - VERY HIGH DATA RATES: Images → 100 Mbps
  - The data needs to be analyzed, fused and results need to be generated in real time in order to drive fast control loops
    - Fast, distributed data processing is needed
Big data - variety

- **Typical situation in a company – data is recorded in many different databases, in multiple formats**
  - Process database – information about the process parameters: temperature, pressure, flows, events. Information recorded continuously or with a high frequency
    - Data types: simple continuous 1D signals (easy to compress, high sampling rate), discrete events
  - Maintenance database – vibrations, infra-red, ultrasound recordings.
    - Data types: complex fragmented 1D signals, images (difficult to compress, low sampling rate)
    - Data recorded periodically, weekly or monthly
  - Interventions database – textual information
    - Data types: discrete events
  - Financial database – records the costs and revenues
    - Data types: tables of discrete records
Big data - veracity

+ **Industrial databases have plenty of uncertainties**
  - Missing data
    - Communication failures, sensor failures, registration failures
  - Uncertain data
    - The equipment was down but the exact reason is unknown
  - Synchronization aspects
    - A maintenance event is registered in the interventions database but it is not synchronized with the process and maintenance databases
  - Sampling aspects
    - Signals are sampled with different rates (need to be interpolated and resampled)
  - Discretization aspects
    - Signals are uniformly discretize but not all values are equally important. Values close to critical values (like critical temperature) are more important and should be recorded with higher precision
Big data value

+ Valuable information can be extracted from existing industrial databases but shortcomings often reduce their informative value
  - In developing an automatic system manual labeling, especially of the ground truth, is essential, but it is often missing
    - Knowledge about the ground truth is necessary for training an automatic system
  - Components are often replaced too early, therefore failure data are missing (and they are essential to build reliable models)
  - Sensors are often kept to a minimum in number and sampling rate to save costs the absence of their information can have a negative effect on the accuracy of the models
POM2: a first step towards predictive manufacturing

- Predict Machine Availability
- Monitor Material Quality
- Optimal machine control
- Monitor Product Quality

Advanced Diagnostic and Predictive Models

Measurements
Monitor material quality

+ Steel cord machine use case
  - Quality of the raw material is unknown but it can be monitored

+ A feature based on wires ruptures count is developed and can be used to:
  - Identify improper machines settings (if only certain machines show a anomalous increase in wire rapture)
  - Decrease in the raw material quality (if the increase in wire raptures is measured on several machines)
Predictive machine availability

+ **Centrifuge use case**
  - Large number of signals were measured (>25)
  - Expert information was additionally processed and integrated
  - Maintenance actions integrated in the dataset
Results

- Vibration signal is predicted using a complex predictive model combining more than 30 features
- The model makes accurate predictions for the next 14 days
- The condition of the machine can be predicted and maintenance actions can be better planned.
Monitor product quality

+ **Case of the packaging machine**
  - Bad packages are identified and removed
  - Loss in product quality can be traded-off against losses due to maintenance
Optimal machine control
1st step - Static optimization of the energy consumption of the linear axis

+ Energy consumption of the linear axis has been optimized off-line using a multi-objective genetic algorithm
+ Machine settings, $v_{\text{max}}$ and $a_{\text{max}}$, have been adapted to minimize the energy consumed by the linear axis
+ The optimization used a consumption model of the robot
2nd step – run-time optimization of the energy consumption of the linear axis

Process has been optimized statically **but**

- Sub-optimal performance (“might perform better”)
- Shifting optimum ("Variations shift the optimum"): impurity of input batches, …
- Drifting optimum ("Optimum slowly shifts with time"): changes in friction, environmental conditions, wear-out

Track the optimum (shifting/drifting)

- Try and keep the response steady and acceptable over time

**Perform optimization without stopping the machine**

- Use data collected during normal operating conditions
2nd step – run-time optimization of the energy consumption of the linear axis

- Systematic search for a local optimum (minimum energy) based on a statistical local model of the system
- Quality can be traded-off for energy consumption
- Step towards a self-optimizing system

![Diagram showing optimization process](image)
The time of self-aware, self-learning, self-adapting computers

+ Computers move towards self-awareness
  - Ability to observe itself and optimize its behavior
  - Observe application behavior and optimize the application
  - Self-healing
  - Goal-oriented, while taking constraints into account
  - Efficient, use just enough resources to accomplish the task
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Next step in manufacturing – Self-aware, self-learning, self-adapting systems

- Materials will carry tags containing meta-information about their origin and the way they have been produced
- Machines will be self-aware of their condition and will detect
  - The type of product that is being made
  - Changes in the environmental conditions
  - Changes in the operating conditions (e.g. condition of the other machines in the production line)
- Machine will continuously adapt the settings themselves to optimize pre-defined performance criteria (e.g. energy consumption, product quality)
- Products will carry tags containing meta-information about the way they have been produced
Beyond POM2: Next step reach predictive manufacturing

- Self-aware machines
- Self-optimizing machine control
- Predictive Product Quality

Predictive material quality models

Measurements
- Material meta-data
- Predictive machine condition models
- Predictive process models
- Product meta-data

POM Prognostics for Optimal Maintenance, IWT-SBO-100031
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Final goal - Self-aware, self-learning, self-optimizing manufacturing

Self-aware machines
- Predictive machine condition models

Self-optimizing machine control
- Predictive process models

Predictive material quality
- Material meta-data

Predictive Product Quality
- Product meta-data