Technische Universiteit Eindhoven University of Technology

Big data in daily manufacturing operations

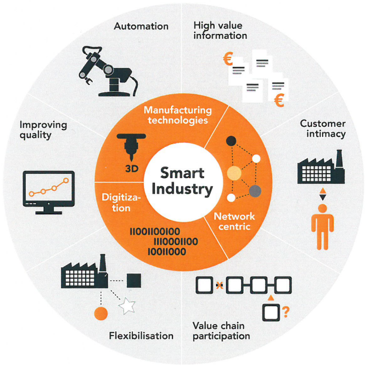
Ivo Adan

Joint work with

Tim Wilschut and Joep Stokkermans

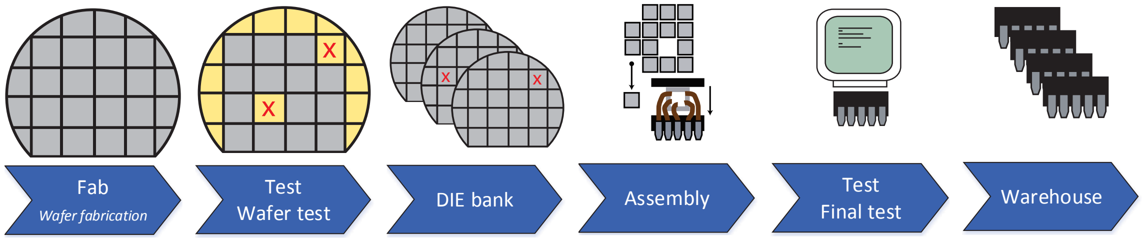
Big Data and Smart Industry

- ICT and robotization are changing the manufacturing industry: the fourth industrial revolution
- Internet of Things: Products, machines, factories, warehouses, customers are able to exchange information!
- Challenge: Fully exploit this network to improve processes and to develop innovative products and services!
- National initiative: Smart Industry



- This project is example of smart use of information

Semi-conductor manufacturing



Fab
- Furnace
- Implantation
- Deposition
- Stepper
- Etching
- Wetting

Test (Wafer test)
- Functional wafer test

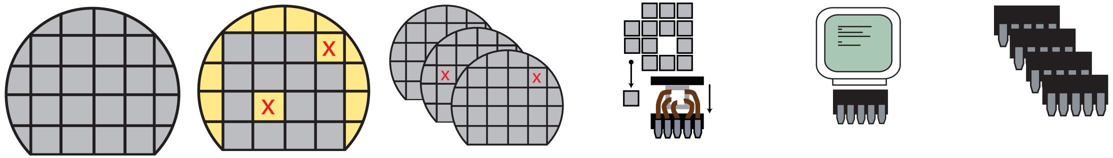
DIE bank
- Semi-finished goods on stock

Assembly
- Grinding
- Sawing
- Die bonding
- Wire bonding
- Molding
- Trim & form

Test (Final test)
- Final testing

Warehouse
- Finished goods on stock

Semi-conductor manufacturing



Fab – *Wafer fabrication*
- Furnace
- Implantation
- Deposition
- Stepper
- Etching
- Wetting

Test – Wafer test
- Functional wafer test

DIE bank
- Semi-finished goods on stock

Assembly
- Grinding
- Sawing
- Die bonding
- Wire bonding
- Molding
- Trim & form

Test – Final test
- Final testing

Warehouse
- Finished goods on stock

- Focus on die assembly (die bonding, wire bonding, molding)

NXP Assembly Plant in Guandong China

- Advanced Warning and data Collection System (AWACS) collects 26 GB's of data/day (100 Oxford dictionaries!)
- Is it possible to increase Overall Equipment Efficiency (OEE) by exploiting Big Data?

NXP Assembly Plant in Guandong China

- Production characteristics
  - High speed production: Thousands of products are produced per machine per hour
  - High volume production: Millions of products per day
- Due to scale of operations: Difficult to get a grasp of “What is happening?”
- Manually monitoring and processing data is labor intensive and inefficient
- Develop software tool to give clues to basic operational questions like:
  - How is production going?
  - Where is what attention required?
  - Which action has priority?
- To answer first two questions: Data should be filtered on dedicated metrics (OEE)
- To answer third question: Intelligent data mining is required (Fluid flow simulation model)

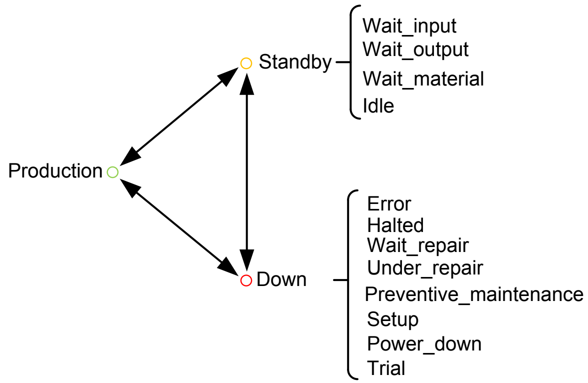
Project objectives

In order to support factory maintenance teams in prioritizing their activities

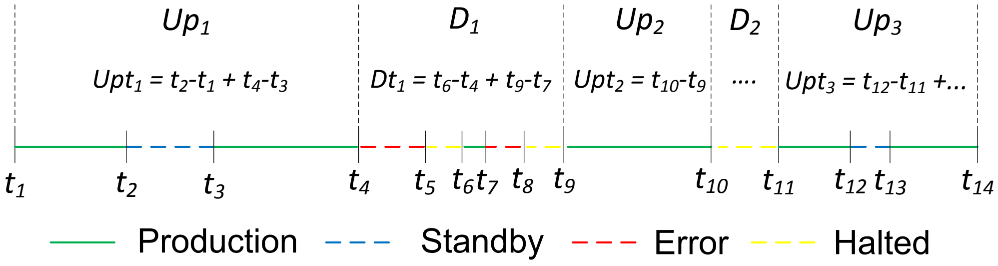
- Design and develop data analysis software for every day use in manufacturing operations
- Investigate the suitability of a fluid simulation model to conduct “what if” analysis, such as
    - What can be gained in terms of throughput if certain machine errors are solved?

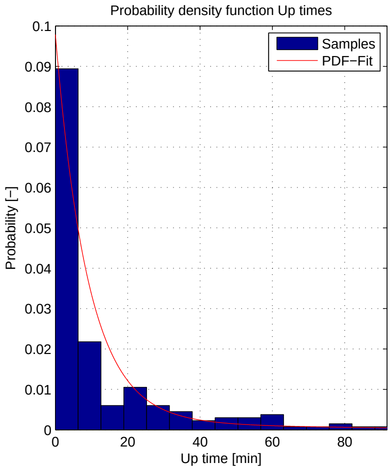
Data collection

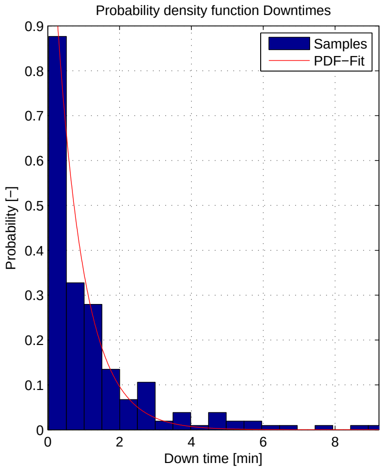
- AWACS collects state events of equipment with corresponding times stamps
- Machine states
  - Production: Machine is producing
  - Standy: Machine could be producing but is not
  - Down: Machine cannot produce



Machine up and down times







The software

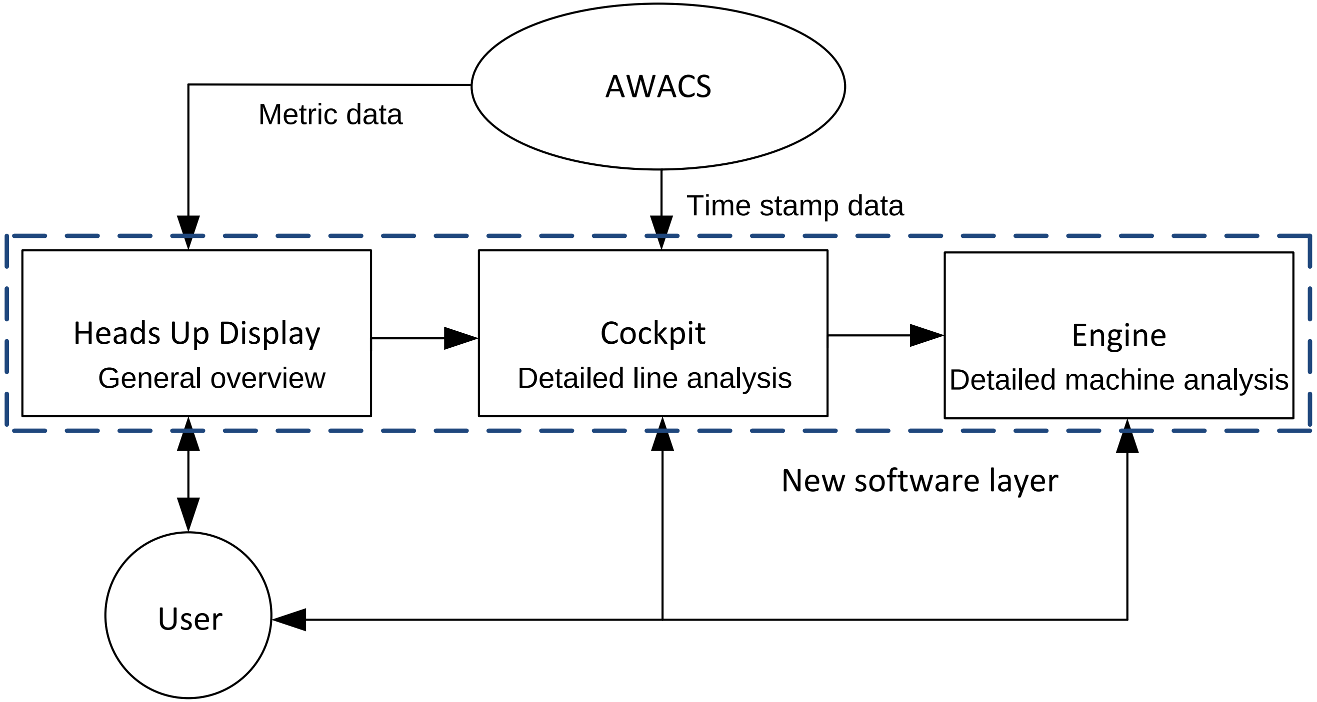
Three level Graphical User Interface since “different management levels require different information”

- Heads Up Display: General overview of complete production floor
  - How is production going?
  - Where is attention required?

  Target user group: Production managers, quality managers, maintenance managers
- Cockpit: Line analysis tool
  - What happened on this production line?
  - What should I do first?

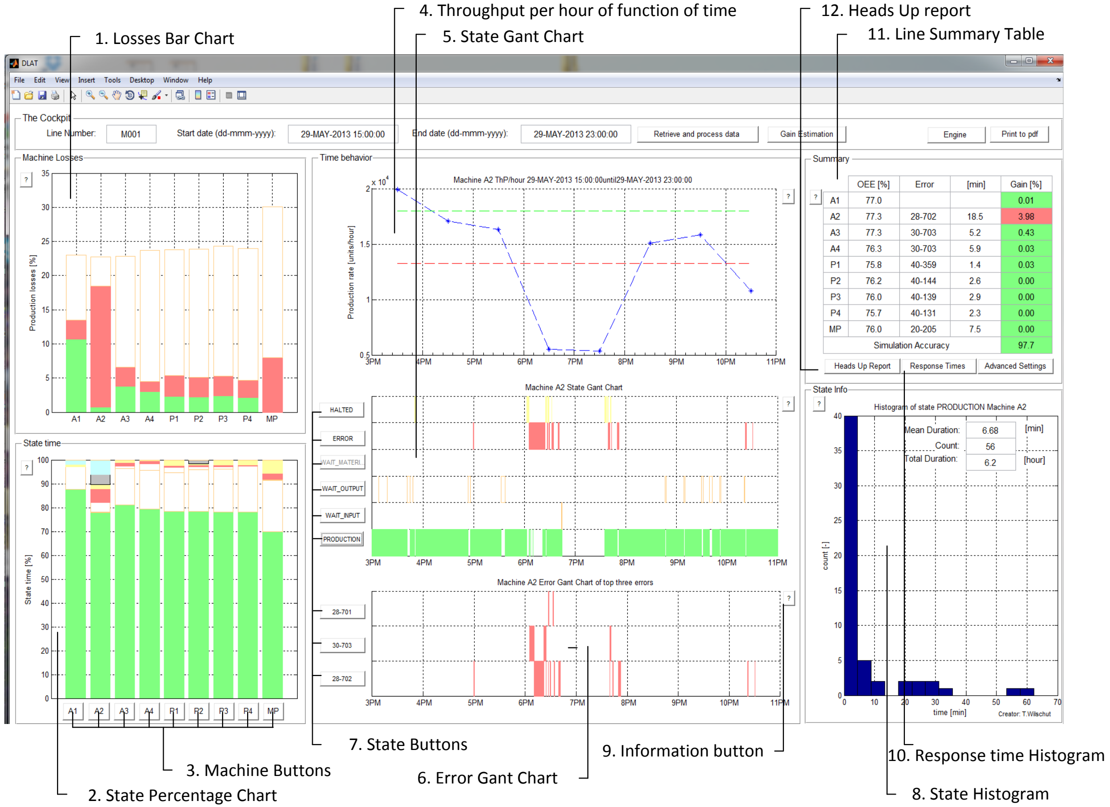
  Target user group: Production supervisors, maintenance supervisors
- Engine: Equipment specific information
  Target user group: Maintenance engineers, technicians

The software

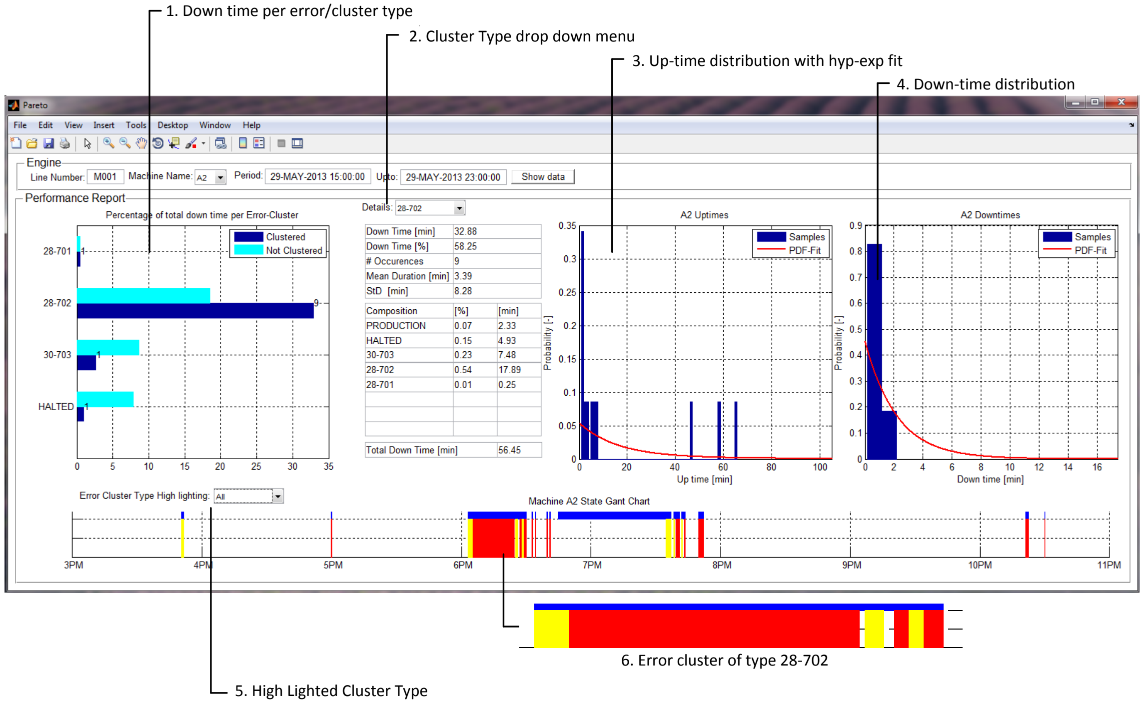


The software: Heads Up Display

The software: Cockpit

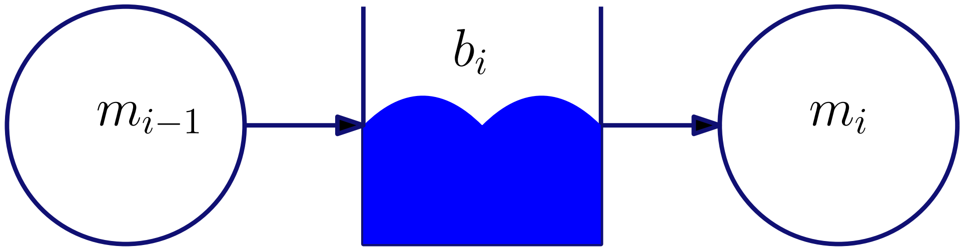


The software: Engine



Fluid flow simulation model

- Discrete flow of products through assembly line is modelled as continuous fluid flow
- Natural due to high production rates: products literally flow through equipment
- Production line consists of nine machines $m_1, \ldots, m_9$, in series separated by finite buffers $b_1, \ldots, b_8$



- Buffer content is continuous
- Machine states are discrete
- Machine up and down time distributions are fitted to data
- Model describes interactions between machines in the assembly line

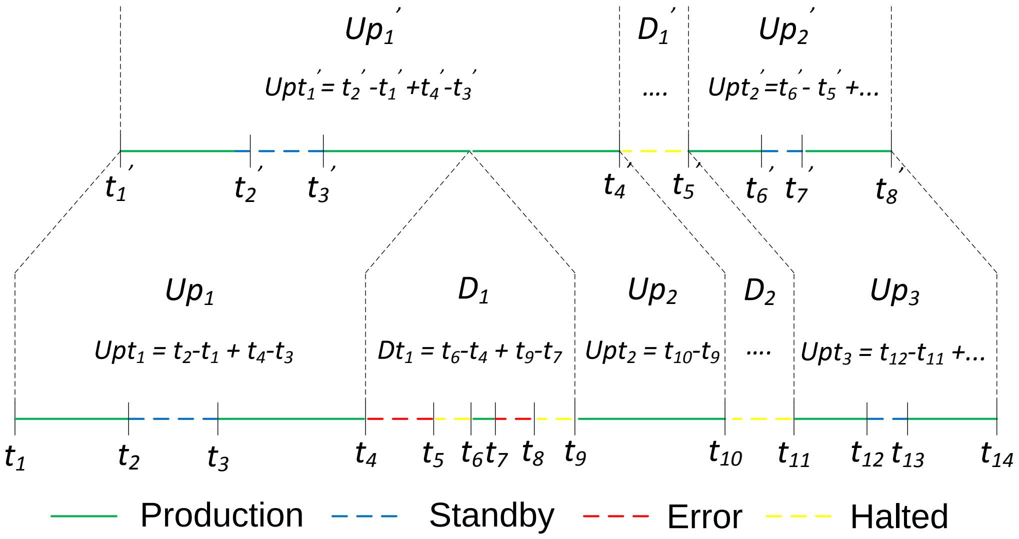
Validation of fluid flow simulation model

	Absolute Error [%]				
#Shifts	1	3	6	12	18
Data set 1	5.43	0.01	4.74	1.43	3.78
2	9.60	7.88	5.14	0.82	18.34
3	1.81	0.53	3.26	8.29	0.34
4	10.2	1.07	1.99	3.59	1.56
5	6.58	3.33	0.73	4.71	3.29
6	14.8	6.07	4.38	2.55	3.52
7	8.27	0.83	2.49	3.97	3.46
8	13.5	2.49	1.59	3.03	6.28
9	7.90	2.99	2.66	3.25	5.92
10	11.3	3.24	0.15	8.45	2.58
Average Error	8.93	2.84	2.72	4.01	4.91
Maximum Eror	14.8	7.88	5.14	8.45	18.3

- On average the simulation model has an accuracy $> 95\%$ if the data set is ≥ 3 shifts
- However, in the presence of rare events (such as long power downs) the simulation model is not accurate

Setting maintenance priorities

- Maintenance capacity is limited so priorities need to be set!
- Simulation model is used to help set these priorities
  - Estimate the effect of removing an error from the system in terms of throughput gain
  - Removing certain errors from the event list of a machine modifies both up and down times



Estimating throughput gain

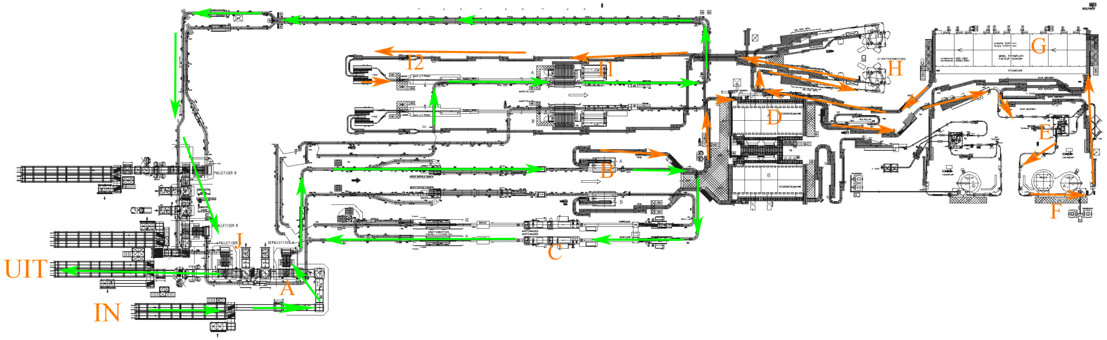
- Throughput gain is estimated by comparing “base simulation” with “what if” simulation

Date	17-04-13		19-04-13		28-04-13	
Machine	Error type	Gain [%]	Error type	Gain [%]	Error type	Gain [%]
1	28-702	0.11	40-702	0.02	28-552	0.00
2	30-709	0.18	40-702	0.06	30-703	0.00
3	30-34	0.07	40-703	0.05	30-703	0.14
4	28-702	0.22	40-703	0.04	30-703	0.00
5	40-144	0.14	40-145	0.04	40-351	0.00
6	40-145	0.05	40-356	0.61	40-135	1.91
7	40-359	0.04	40-135	1.10	40-144	1.93
8	40-139	1.74	40-356	0.88	40-144	0.00
9	20-165	0.06	20-177	0.16	20-177	0.00

- On different days different error-types are dominant

Conclusions and remarks

- Effective integration of data analysis and simulation
- Maintenance crew can better focus their attention and set priorities
- Fluid flow simulation model can accurately predict production line behavior
  - Fluid model has also been used for packaging lines at Heineken (line configuration)



  - Use chronological list of up and down time events as input to the simulation model
- Few percent increase in the Overall Equipment Efficiency within the first few months after implementation!