Panel on INTELLI/InManEnt/ICWMC

Smart Components and Smart Models in Intelligent Manufacturing Environments



InManEnt 2016 – International Symposium on Intelligent Manufacturing Environments November 13 – 17, 2016 – Barcelona, Spain

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Smart Components and Smart Models in Intelligent Manufacturing Environments

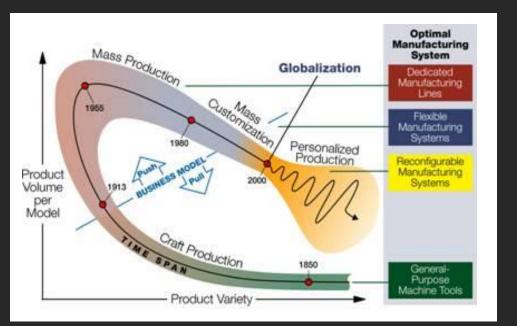
Moderator: Gil Gonçalves

Panelists

- Norbert Link
 - Institute of Computational Engineering at IAF, Karlsruhe University of Applied Sciences, Germany
- Leo van Moergestel
 - HU Utrecht University of Applied Sciences, The Netherlands
- Gil Gonçalves
 - Institute for Systems and Robotics, Faculty of Engineering, University of Porto, Portugal

Smart Components and Smart Models in Intelligent Manufacturing Environments

Companies are subject to constant changes in their operational environment (new regulations, economic up/downturns, environmental issues, technological innovation, competition and customer trends)



Challenges for industry

More demanding specifications Small lots and one-of-a-kind Material re-use and zero-waste Quality/performance after ramp-up Huge amounts of data

Smart Components and Smart Models in Intelligent Manufacturing Environments

Responding to continuous and most of the times disruptive changes, demands for reconfigurability, flexibility, adaptability and agility (new technological trends)



Smart Components and Smart Models in Intelligent Manufacturing Environments

– Leo van Moergestel: End-user driven manufacturing as a way to prevent waste and overproduction.

– Gil Gonçalves: Smart Components as agility enablers in modern manufacturing environments.

- Norbert Link: Can we rely on machine-learning powered smart components in critical applications?

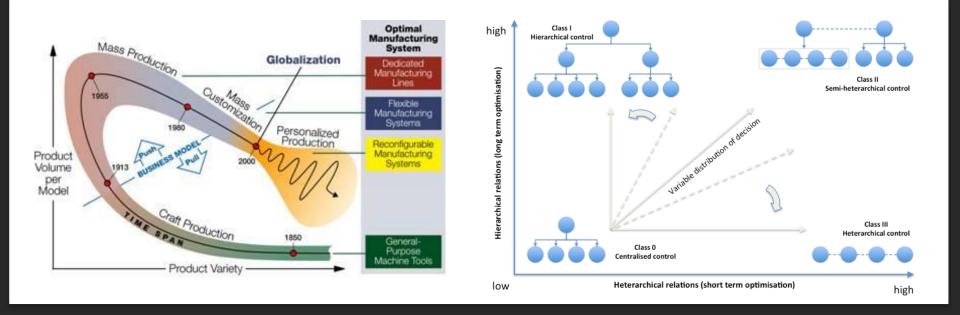
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Smart Components and Smart Models in Intelligent Manufacturing Environments

Smart Components as agility enablers in modern manufacturing environments Gil Gonçalves, University of Porto



InManEnt 2016 – International Symposium on Intelligent Manufacturing Environments November 13 – 17, 2016 – Barcelona, Spain In personalised production, control systems need to manage product variability and disturbances, and to implement agility, flexibility and reactivity.



Facing these challenges requires highly flexible, intelligent and self-adaptive production systems, equipment and control systems, which can react to continuously changing demand, can be smoothly brought into operation, and can extend equipment life cycle.









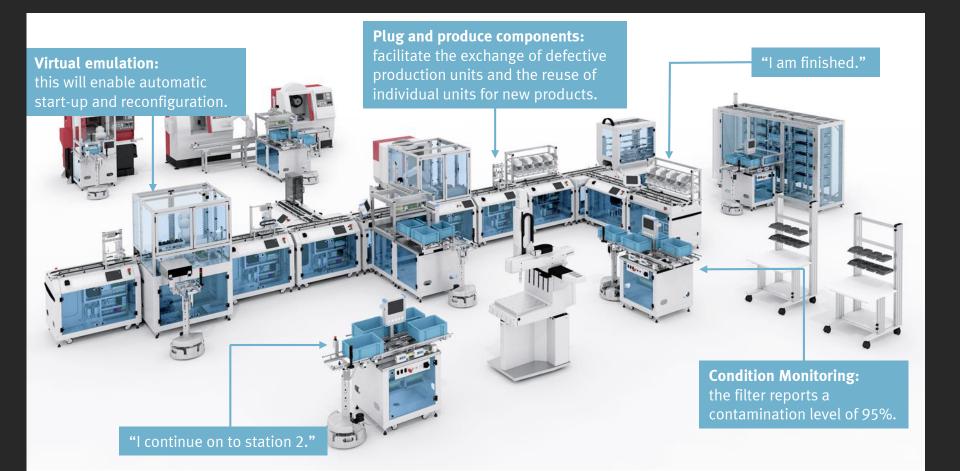




Different manufacturing environments

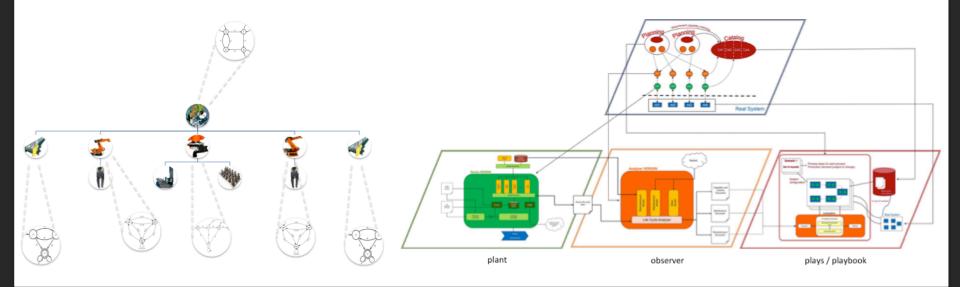
Smart Components as agility enablers in modern manufacturing environments.

Networked production systems and smart components



Multiple solutions analysed during the design phase of the production system (off-line mode).

Reaction to "change events" can be based on a selection of the most adequate configuration amongst the existing ones (selection of the most adequate play from a playbook).



During the running phase (on-line mode), new configurations can be added and obsolete configurations removed (learning process).

Dynamic configuration repository (playbook).

Summary of the "Smart Components and Smart Models" panel

"Smart Components and Smart Models" make new production paradigms – more efficient and greener – possible!

- End-user driven manufacturing might prevent waste and overproduction.
- Produce what the user wants and not what might be easier to produce.
- Embedded intelligence in the products will help to increase the re-use.
- Smart Components are agility enablers in modern manufacturing environments.
- Reconfiguration and adaptation to exogenous conditions.
- Arrangement of smart components make networked production systems possible.
- Standards, new business models, and new skill sets are needed.
- Main barrier to machine-learning powered smart components in critical applications is trust.
- One single wrong control model can produce millions of failure-prone safety relevant parts.
- Countermeasures (Convex cost function, robust estimators, controlled and adequate sampling, ...) fallback strategies and risks versus probability analysis are needed.

But present also many challenges related with new knowledge based approaches and life cycle sustainability of products, processes and systems.

"CAN WE RELY ON MACHINE-LEARNING POWERED SMART COMPONENTS IN CRITICAL APPLICATIONS?"

Panel on INTELLI/InManEnt/ICWMC, Norbert Link

The Fifth International Conference on Intelligent Systems and Applications

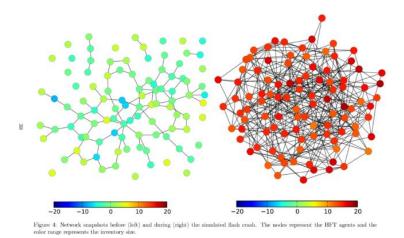
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Prominent Failure Cases

2010 Flash Crash

United States trillion-dollar[2] stock market crash, which started at 2:32 p.m. EDT and lasted for approximately 36 minutes.

High Frequency Trader Agents



By Ryanrhymes - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=33458889

Network snapshots before (left) and during (right) the simulated flash crash. The last 400 transactions in the order-book are plotted by connecting the HFT agents who transact with each other. The node color indicates the inventory size of the HFT agent. When the market operates normally (left subplot), almost all of the HFT agents are in control of their inventory (greenish color). In crash period (right), most of the HFT agents gain large inventories (red) and the network is highly interconnected: over 85 percent of the transactions are HFT-HFT.

Prominent Failure Cases

Tesla Fatal Autopilot Crash

Tesla Model S struck a big rig while traveling on a divided highway in central Florida, and speculated that the Tesla Autopilot system had failed to intervene in time to prevent the collision.

http://www.latimes.com/business/autos/la-fi-hy-autopilot-photo-20160726-snap-story.html



National Transportation Safety Board

Some Critical Applications

- Driver Asistance and Self-Driving Vehicles
 - Situation Recognition
 - Situation Prediction
 - Optimal Strategy
- Network Balancing (Power, Communiation)
- Stock Exchange Trading Agents
- Medical Diagnosis
- Credibility Assessment
- Industrial Production
 One single wrong control model can produce millions of failureprone safety relevant parts.

Discussion Starter

- Reasons for Failures of Models from Machine Learning
 - Buried in Machine Learning Principles
 - · Learning probability models from samples
 - Probability: Intrinsic Uncertainty
 - Representativeness of samples
 - · Learning decision surfaces from samples
 - · Learning regression models from samples
 - Dedicated to Specific Technologies
 - · Robustness of estimation (cost function): Cost function, support vectors
 - Under-determination in Deep Learning ...
- Countermeasures

Convex cost function, robust estimators, controlled and adequate sampling, ...

Fallback Strategies

Consideration of failure probability -> "safe strategy", if too high

- Risks versus Chances
- Conclusions ???

End-user involvement in manufacturing

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Mass production 1(2)



Mass production 2(2)



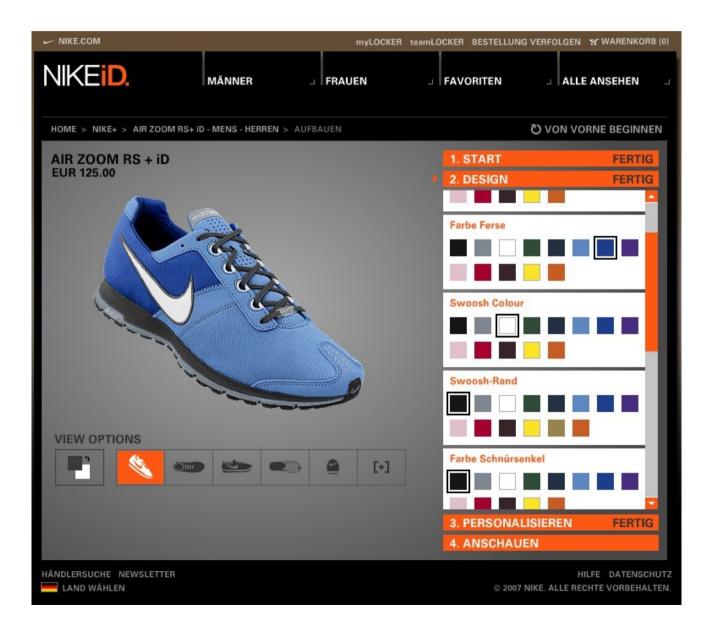
Personalizing 1(3)



Personalizing 2(3)



Personalizing 3(3)



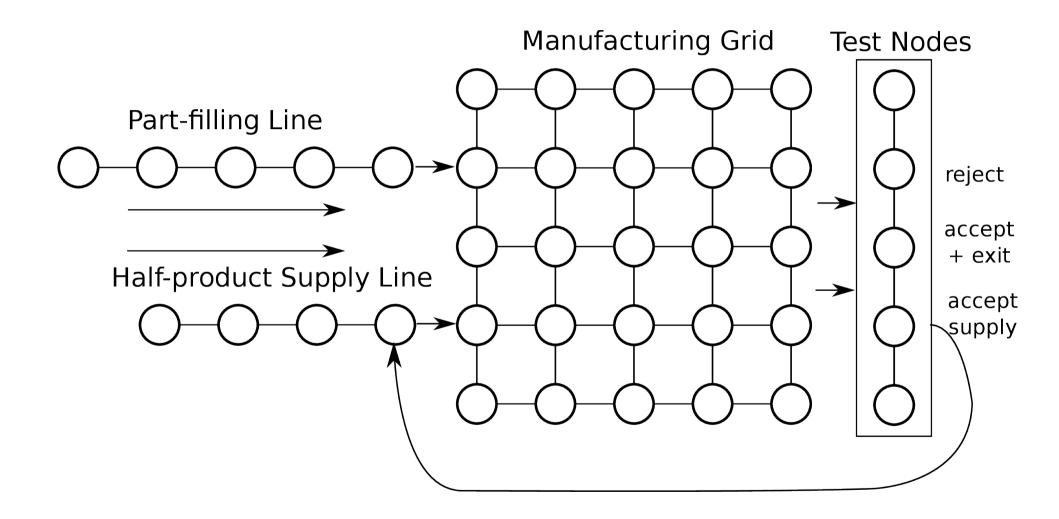
Make your own design / product

- Internet, new technologies for user interaction
- 3D-printing
- Agile manufacturing
- Reconfigurable machines

Our research on grid manufacturing

- Offering an agile production infrastructure
- Based on equiplets and agent technology

Production Logistics / Transport



Demo movies

- Equiplets
- https://www.youtube.com/watch?v=W3BepRkuzeg
- Grid manufacturing
- https://www.youtube.com/watch?v=IdVAUdZKwvI