



APRIL 2019

The Autonomous Industrial Plant – Future of Process Engineering, Operations and Maintenance

Plenary at IFAC DYCOPS 2019 in Florianópolis, Brazil, 25 April 2019

Alf Isaksson, ABB Corporate Research, Västerås, Sweden



The world is changing at unprecedented speed

Technology influences the future of how we...

...power



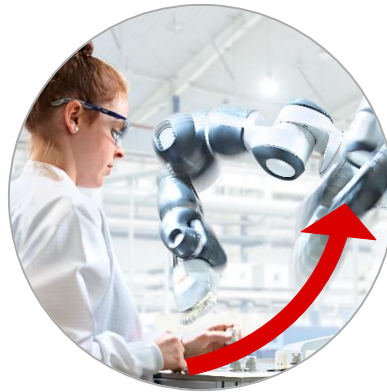
>\$4 tn of renewable investment

...produce



+300% industrial IoT¹ devices installed

...work



+300% robot sales

...live



+1 bn people in cities

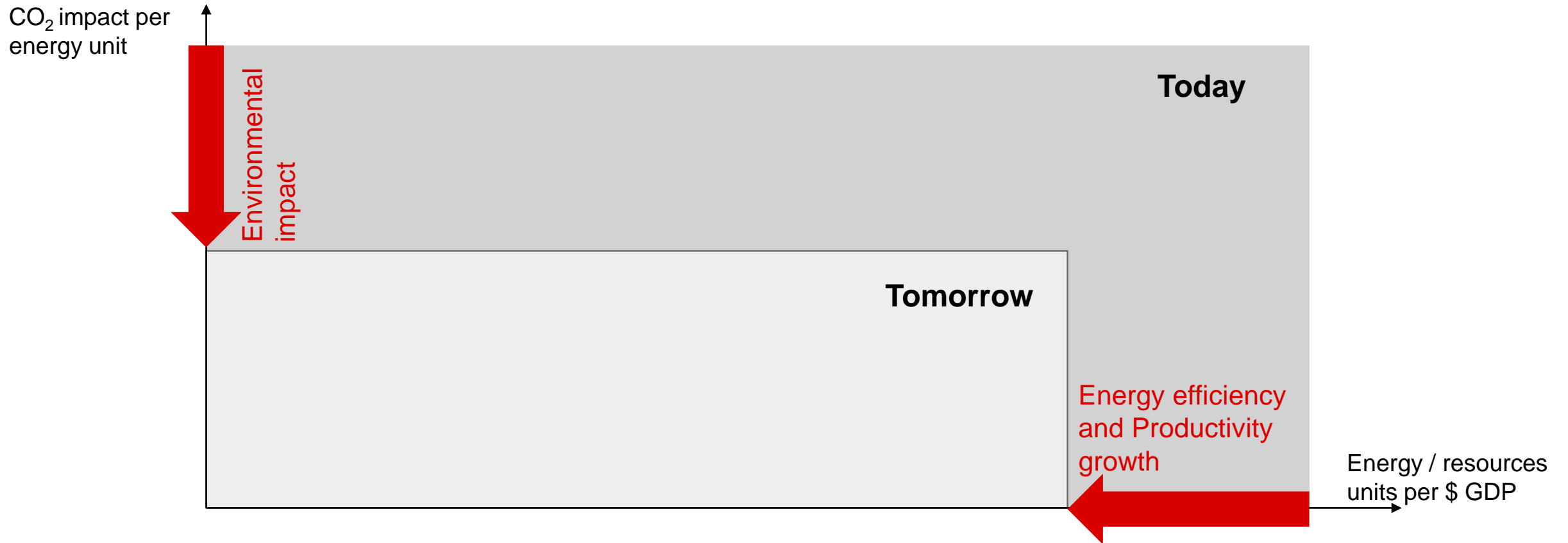
...move



~30% CAGR² for EV³ sales

Key challenge: decoupling economic growth from environmental impact

Two key levers: Increasing Productivity/Efficiency and lowering carbon footprint



Outline

Facts about ABB

Future Automation

Integration of power and automation

The modelling complexity

Modular Automation

AI for Manufacturing Industries

Transition into Autonomous Systems

Conclusions

The new ABB



Pioneering technology leader in digital industries

~\$410 bn market

~\$29 bn revenues

34%

Asia, Middle East and Africa

31%

Americas

35%

Europe

~110,000 employees

R&D at ABB – facts and figures



\$1.5 bn

Annual investment



9,500+

Scientists and Technologists



10 countries

with major R&D Centers

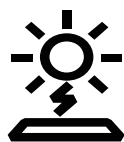


5 Analytics Solutions Centers (ASCs) bring analytics-based solutions to our customers



>100

University collaborations



20 active Startup investments

5 Venture funds



15

Strategic Partnerships



>10,000 patent families
40% of patents related to digital portfolio



Revolutions that are changing the industry

Digitalization, emobility, automation, and robotization

Energy revolution



Utilities

The fourth industrial revolution



Industry

eMobility revolution



Transport & Infrastructure

ABB Ability™: brings industry leading digital solutions to our customers

210+ ABB Ability™ solutions

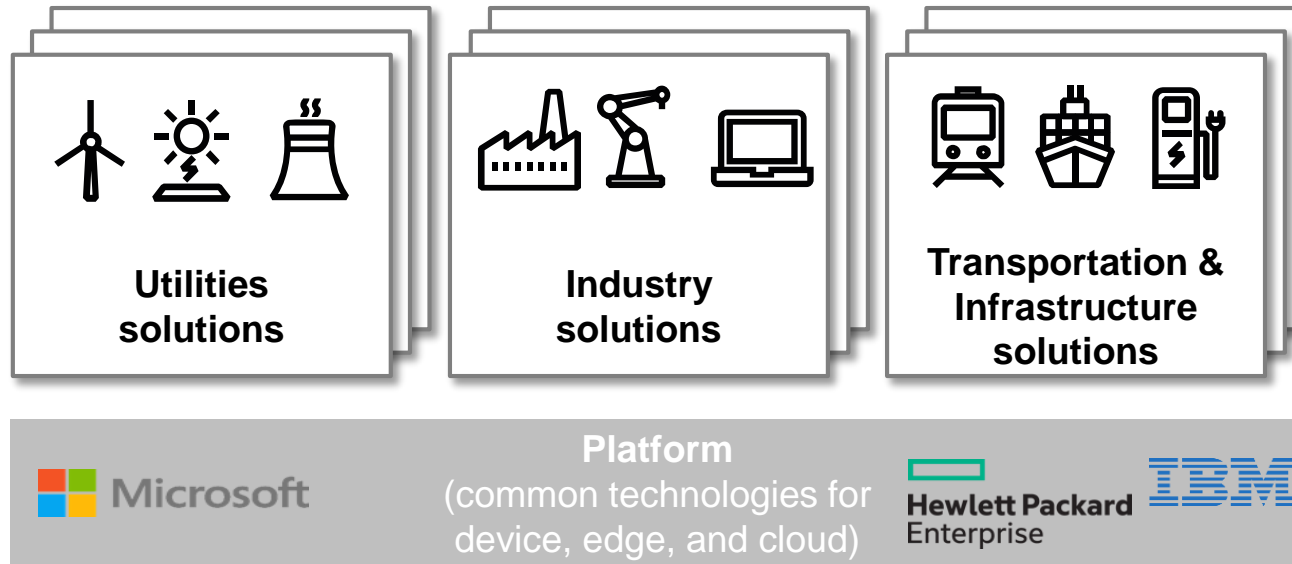


ABB Ability™

What

Delivers customer value (safety, uptime, speed, yield...) with AI based solutions

How

Provides ABB with efficiency and scale through AI
Our customers own their data and IP

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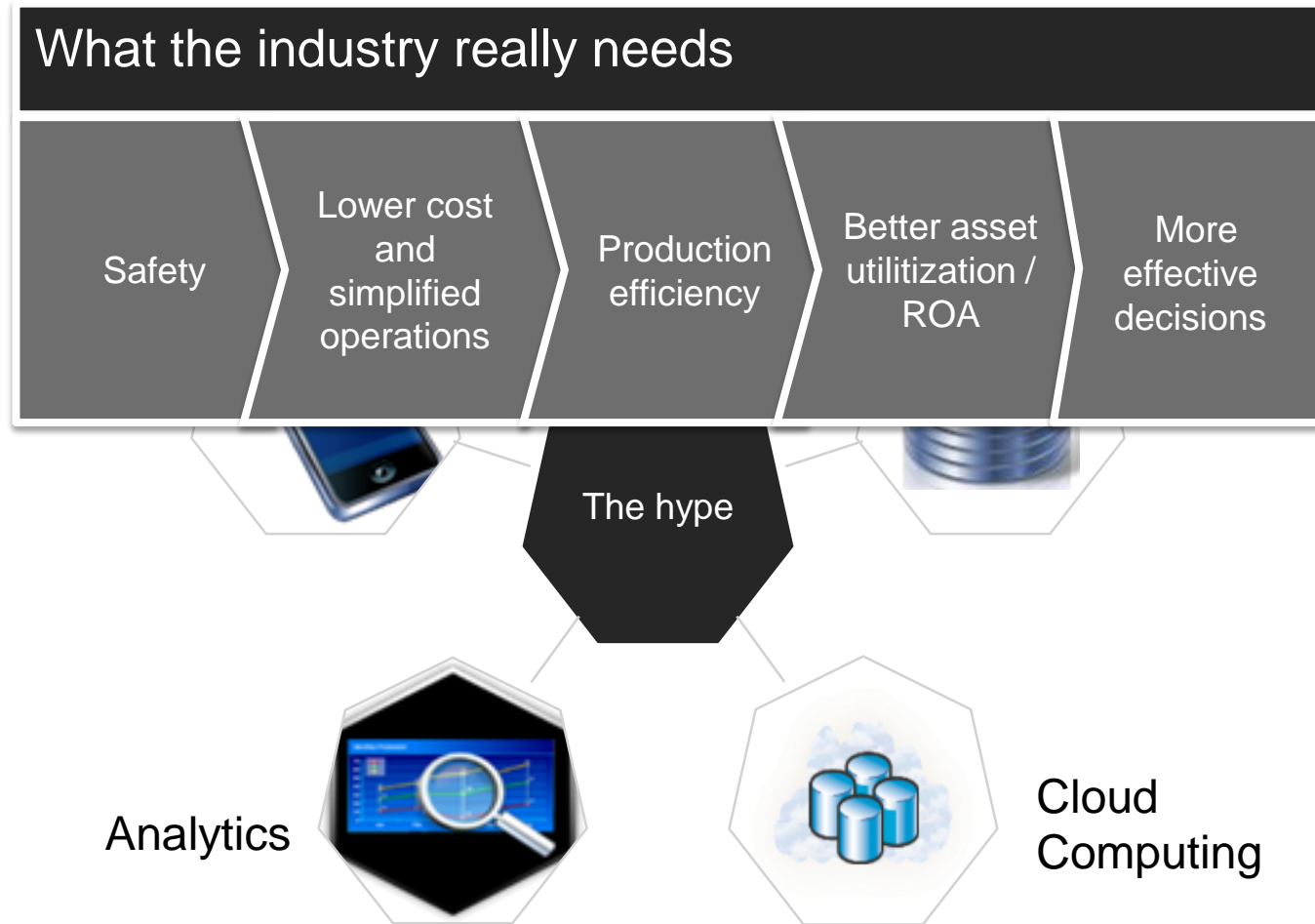
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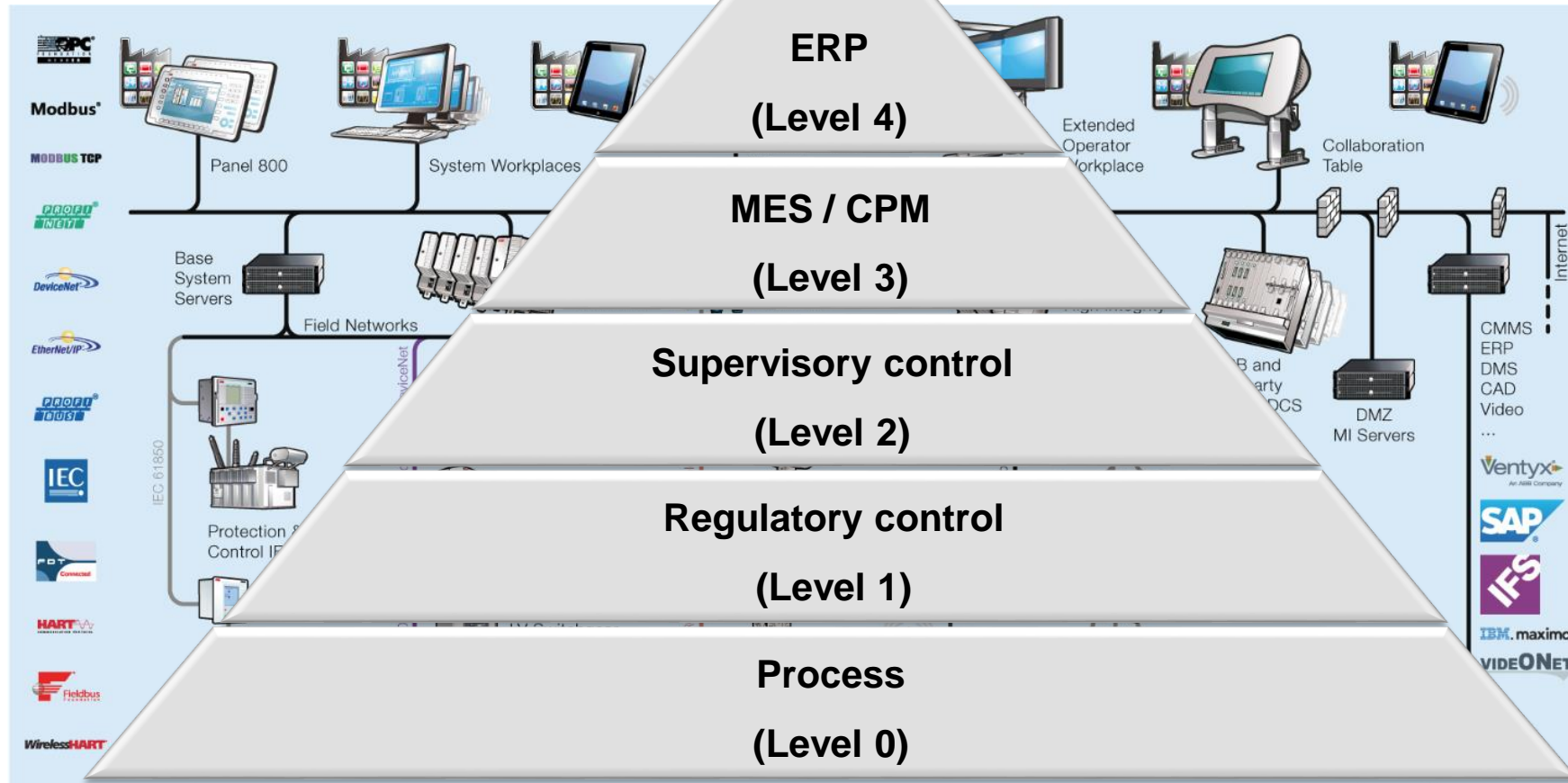
Market Trends

The Five Major Trends that Manufacturers Must Follow



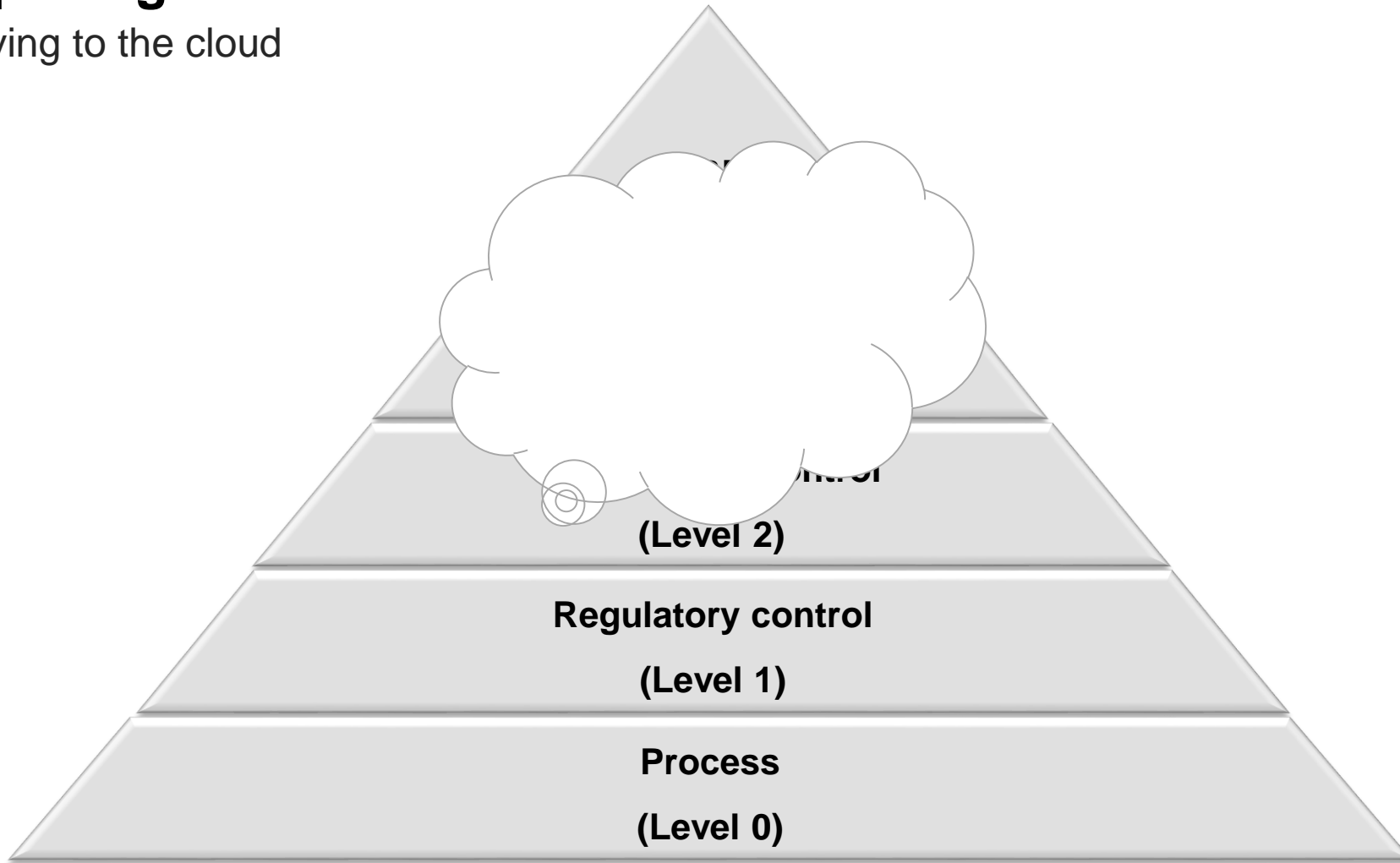
Today's automation systems

Automation Network and Hierarchy



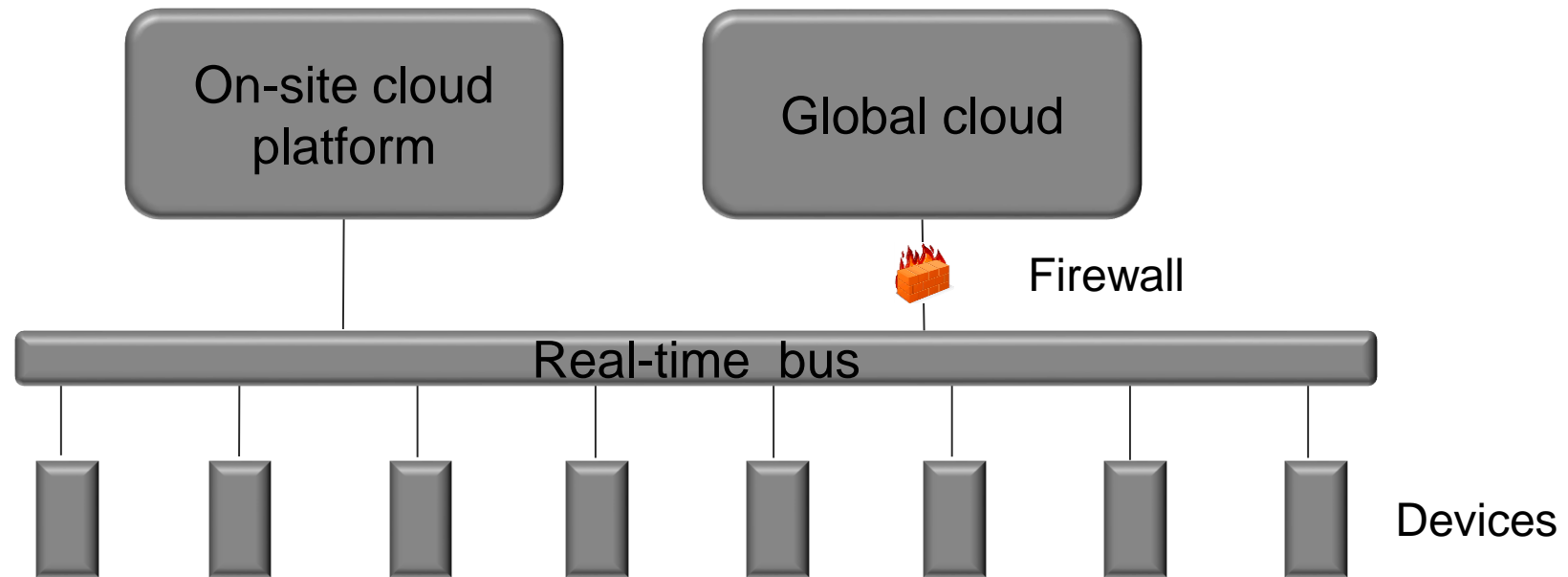
What is happening next?

Upper levels moving to the cloud



Future automation system architecture

Trade-off between edge and cloud



OPTIMAX® PowerFit

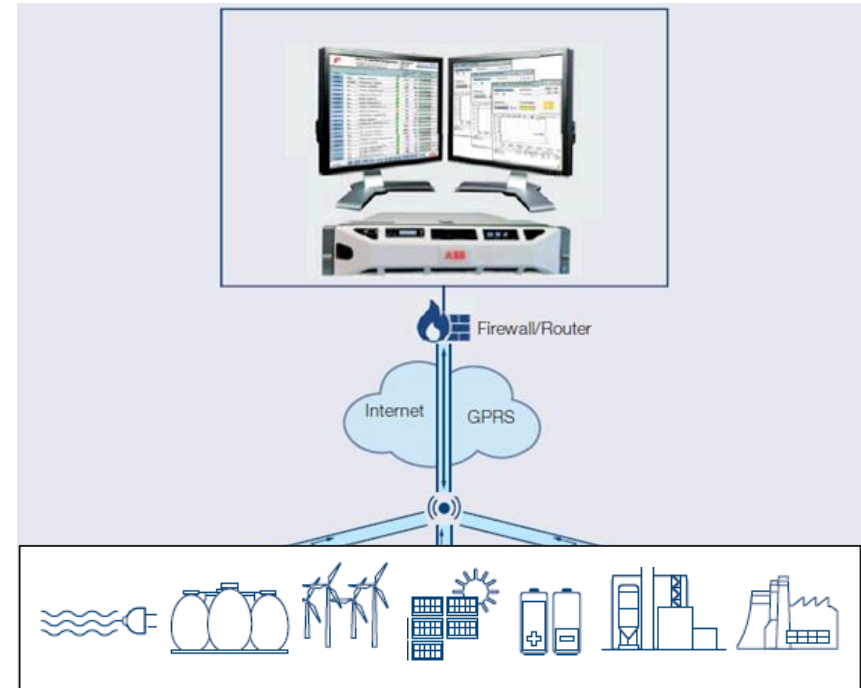
Optimizing control of Virtual Power Pools

Task

- Aggregate many small production units and treat them like one big power plant
- Exploit multiple forms of energy (e.g. el and heat) and storages

Solution

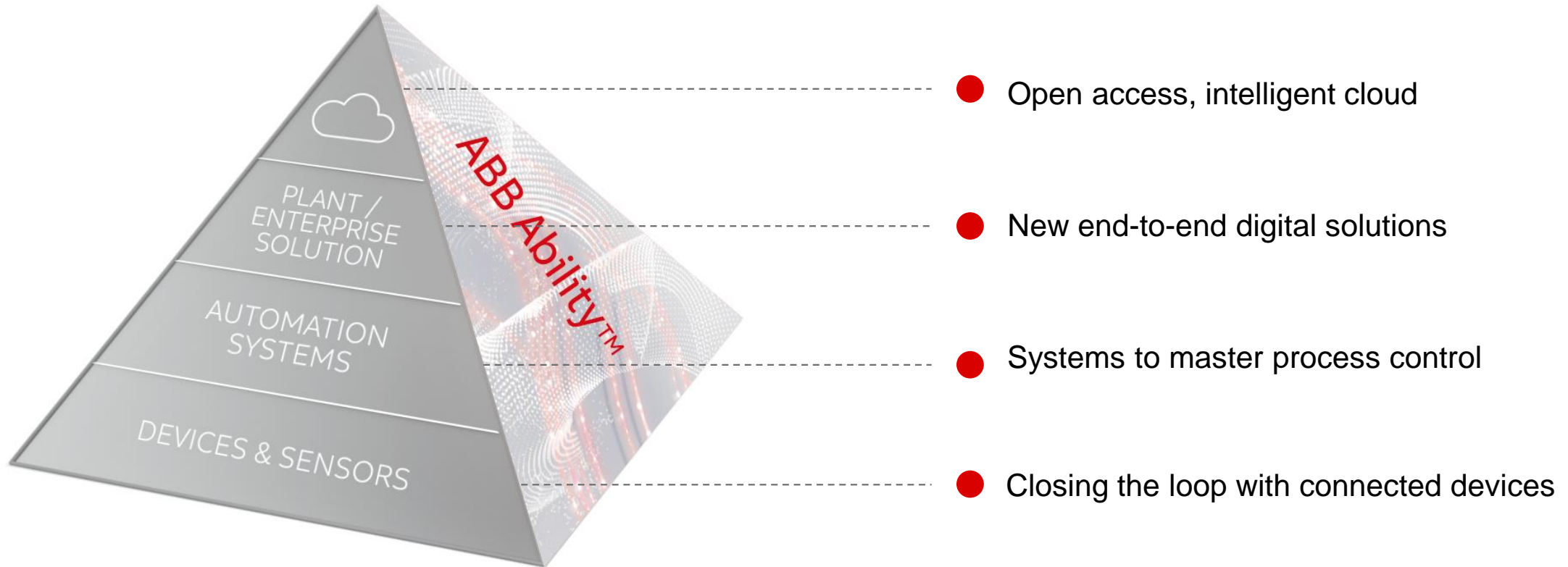
- Build overall plant model (exploiting Modelica multi-physics)
- Formulate optimizing control task as mathematical program
- Online optimization of set points and plant schedules



Digitalization enables the interconnection of power generation, consumption, storage and production

ABB Ability™

Industry-leading digital solutions built on a common set of standard technologies



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End of Isolated Solutions

Balancing Between Control Systems



Energy availability and pricing
(smart grids)

Grid control



Industrial demand-side management



Production Management
(Planning & Scheduling,
APC, Analytics, ...)



Integration of scheduling and control



Process variations, e.g. quality,
yield, disturbances (DCS)

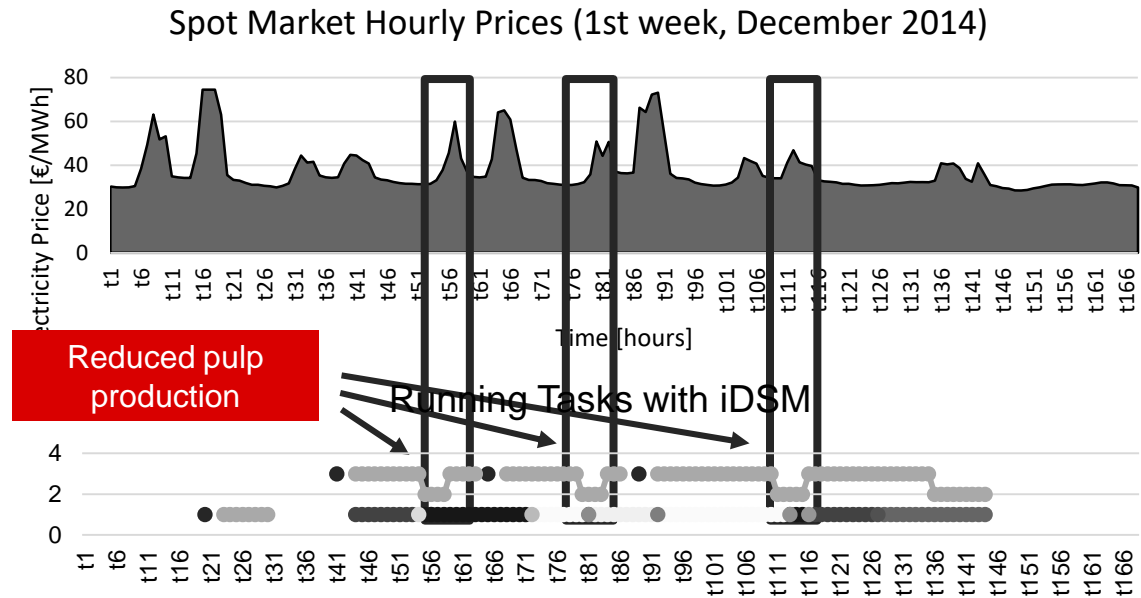
Process control

Industrial demand side management in pulp & paper

Coordination of production planning and energy management

Mechanical pulp production

- Thermo-mechanical pulp (TMP) production is highly integrated with other parts of paper plant
- Most energy consuming production steps are moved **to low cost times**
- Paper output of plant is **not reduced**



Industrial demand side management in pulp & paper

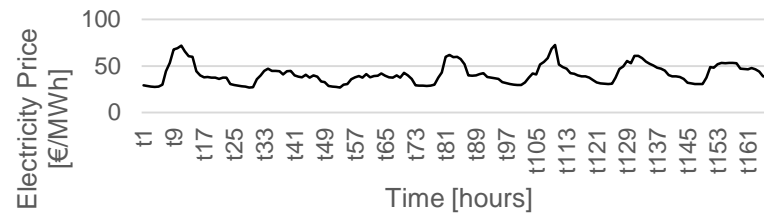
Evaluating market opportunities for thermo mechanical pulping (TMP) mills

Case study with TMP mill

- Real world plant and production data of a Nordic paper mill
- Different scenarios evaluated

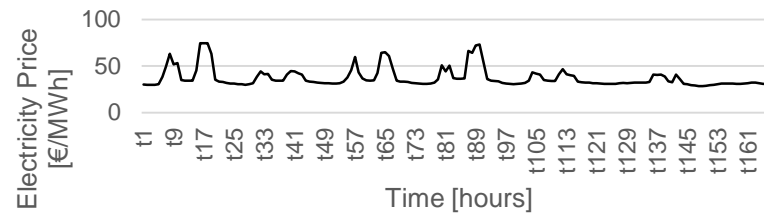
Scenario	Energy cost	Allowed pulp storage levels
S0	No	20%-80%
S1	Yes	20%-80%
S2	Yes	5%-95%

Spot Market Hourly Prices (1st week, August 2014)



	No. of starts	Savings
S0	8	0%
S1	24	6%
S2	26	5%

Spot Market Hourly Prices (1st week, December 2014)



	No. of starts	Savings
S0	7	0%
S1	34	4%
S2	33	4%

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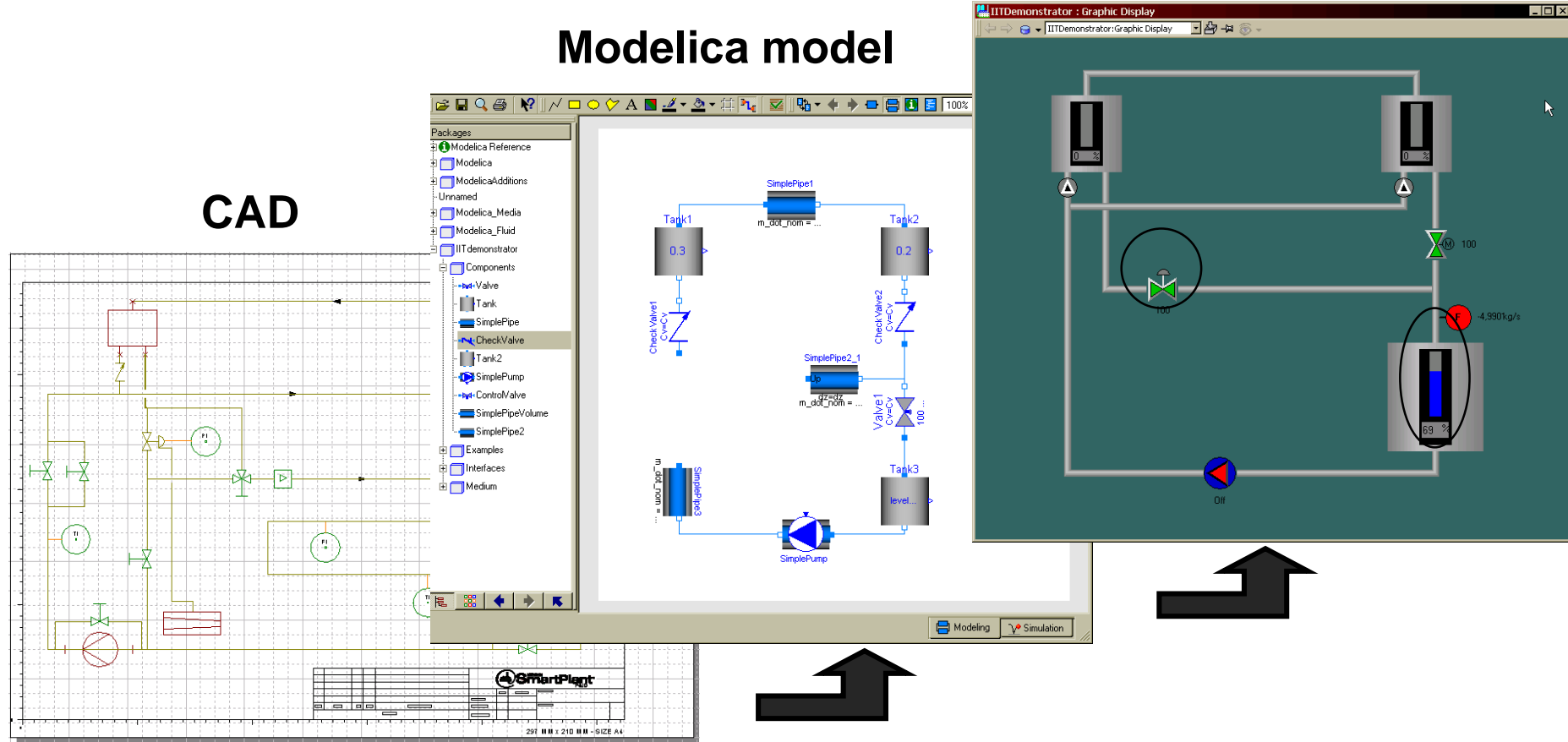
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Modelling vision – Automation of automation

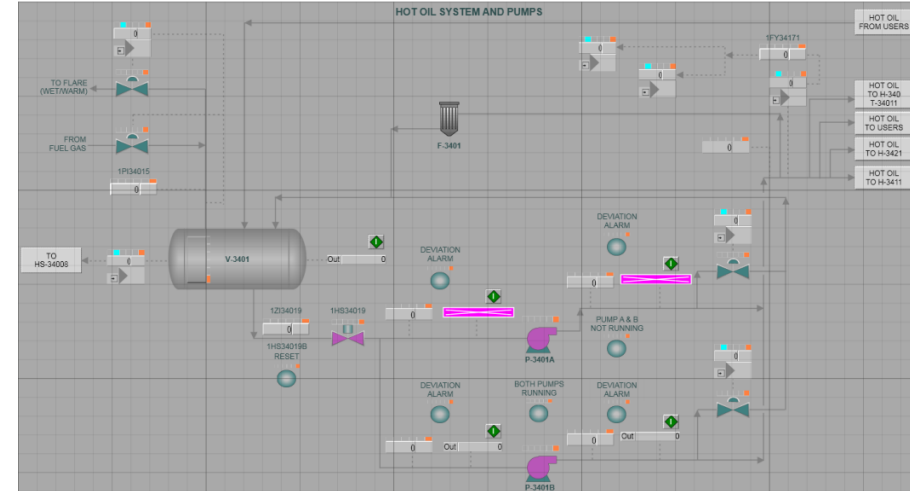
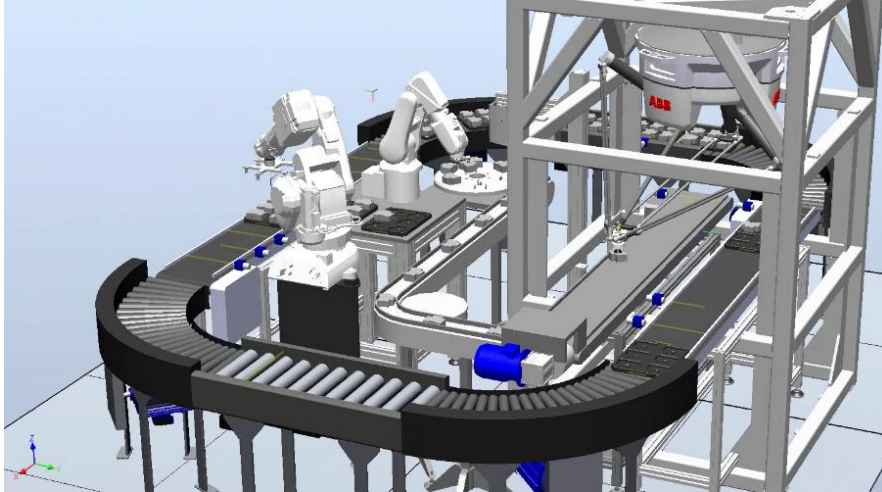
Automatically generate models for control and optimization from CAD

Process graphics in 800xA



Virtual commissioning

Commissioning using a (simulated) virtual reality



Manufacturing: Mechanical objects up to cells, lines, incl. 2D or 3D simulation are coupled with automation systems (hardware or software in the loop)

Process automation more difficult due to lack of easily available process models. Currently piloting simulation models derived from P&I diagram to be used for FAT.

Learning models from historic data

Finding intervals that are useful for modelling

- Original method for system identification using single input – single output data
- Less than 5 % of normal operating data found useful for identification
- Implementation in ABB Ability™ Manufacturing Operations Management (MOM) for MIMO process data
- Can (historic) data be used also for applications learning decision models rather than process models? For example
 - Alarm management
 - Production scheduling
 - Supply-chain optimization



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Modular Automation

Background - Why Modular Plants?

Market situation and challenges

- Highly competitive
- Volatile markets
- Shorter product lifecycle required faster time-to-market.

Challenges in process industries

- Flexible, but efficient, modular plant concepts.
- Short time span between development and production.
- Numbering-up instead scale-up



Modular Automation

Targeted industries

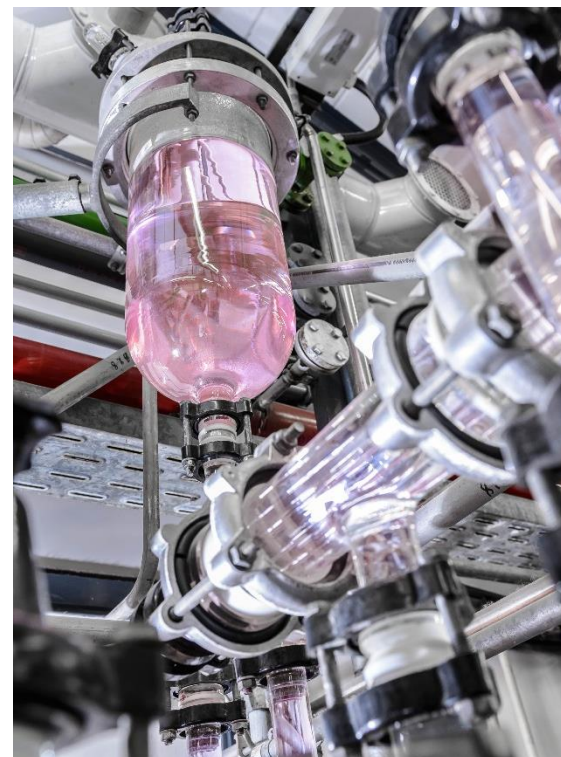
Pharmaceutical industries



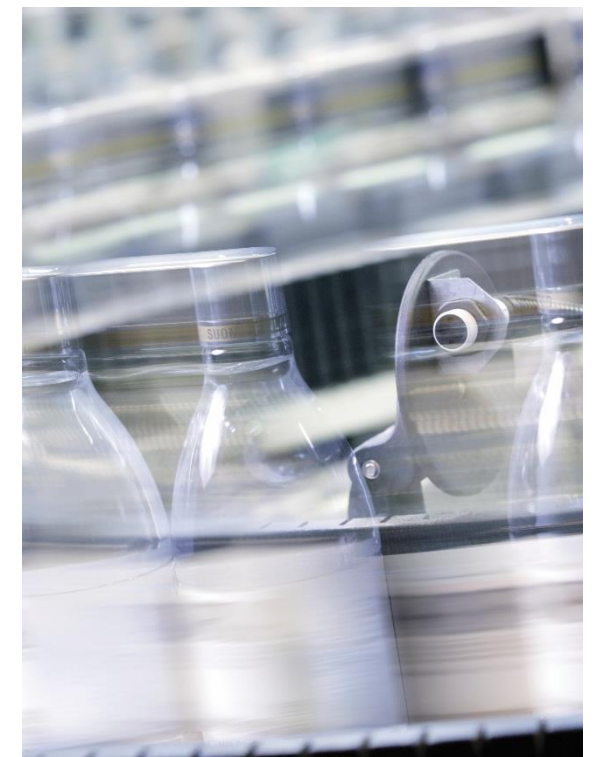
Biotech industries



Fine chemical industries



Food and Beverage



Pilot project since 2014

Together with Bayer, INVITE, Helmut-Schmidt University and TU Dresden



Source: Achema 2018

- Several modules engineered using our prototype „Module Designer“ and „Orchestration Designer“ with Freelance controller for modules and System 800xA as supervisory control system
- First demonstrated at ACHEMA Fair in Frankfurt June 2018

Concepts on:

- System architecture
- Module configuration
- Module integration into an orchestration system
- Automatic generation of operation and orchestration environment
- Operator workplace

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Definitions of Artificial Intelligence

Many different definitions available

Working definition:

"AI is the science of making machines do things that require intelligence if done by men"
(Minsky, 1968)

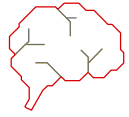

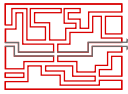

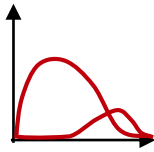

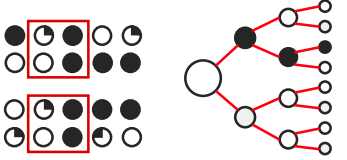
Neglected alternatives:

- A: 1: A branch of computer science dealing with the simulation of intelligent behavior in computers
 2: The capability of a machine to imitate intelligent human behavior (Meriam Webster)
- B: "Artificial Intelligence is the study of mental faculties through the use of computational models" (Charniak, McDermott Introduction to Artificial Intelligence, 1985)
- C: (In this view), the problem of AI is to describe and build agents that receive percepts from the environment and perform actions. (Russel, Norvig, Artificial Intelligence, A Modern Approach, 1995)

There is not one definition and no clear and generally agreed structuring of the field!

Branches of Artificial Intelligence

Overview of our structuring

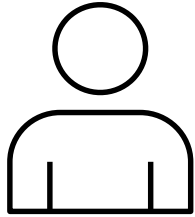
<p>Knowledge & Inference </p> <p>Emulate expert decisions and expert behavior</p> <p>Pre-Requisites: Capturing expert knowledge, Contextual-knowledge</p>	<p>Problem Solving </p> <p>Find solutions automatically for problems like packing problems or design tasks</p> <p>Pre-Requisites: Precise problem definition, heavy modeling task</p>	<p>State & Action Planning </p> <p>Find a good or optimal sequence of actions to reach a predefined goal</p> <p>Pre-Requisites: Modelling of planning problem</p>	<p>Natural Language Processing </p> <p>Interpret & process human natural languages for computer-human interaction</p> <p>Pre-Requisites: Signal processing, semantics or lots of data</p>
<p>Learning Probabilities </p> <p>Derive probability distributions from data for predictions & risk analysis</p> <p>Pre-Requisites: Prior experiences, informative data</p>	<p>Machine Perception </p> <p>Deduce real world aspects by using sensor input information</p> <p>Pre-Requisites: Data models, good quality sensing, dealing with uncertainty</p>	<p>Machine Learning </p> <p>Create the ability to perform tasks without explicitly programming a machine</p> <p>Pre-Requisites: Computation power, amount of data, good models, labeled data</p>	

The branches of AI are not independent and have many overlaps

AI – a paradigm shift in ease of installation and use of robots

From programming to teaching and learning

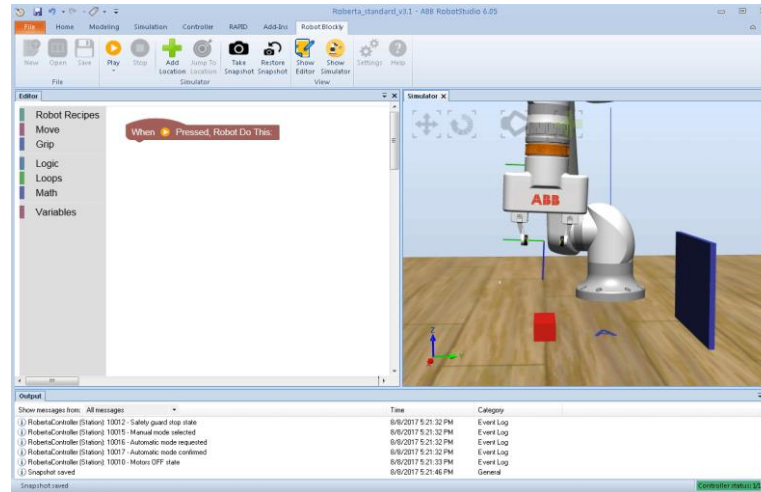
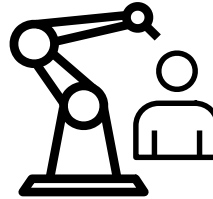
Yesterday: **programming**



```
//Defining single location in RAPID
```

```
CONST robtarget  
rb_Location1:=[[471.90028601, -  
160.550088443, 259.855061587],  
[0.0196845700059949, 0.999779442304461, -  
0.00713127900217168, 0.00165206200050307],  
[-1, -1, 1, 0], [9000000000, 9000000000,  
9000000000, 9000000000, 9000000000,  
9000000000]];
```

Today: **teaching**



Tomorrow: **learning**



Mainstream AI going beyond image recognition

First it was all games and fun

1997 IBM Deep Blue – Kasparov

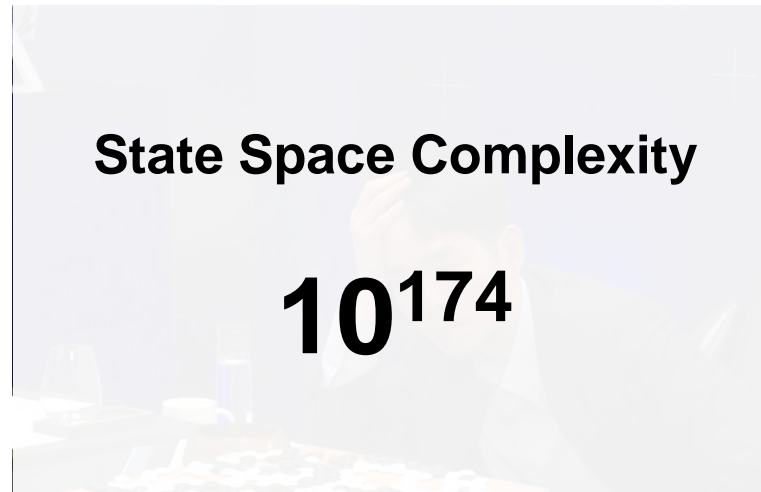
Result: 3½-2½



- Thousands of **rules and heuristics**
- Handcrafted by strong **human players**
- Try to account for every eventuality

2016 Google AlphaGo – Lee Sedol

Result: 4-1



- Knows nothing except basic rules
- Learns by **Self-Play** against itself
- Highly dynamic, “**unconventional**” style

2019 Google AlphaStar – “MaNa”¹

Result: 5-0



- Raw data fed to a deep neural network
- 1st learned from footage of human games
- 2nd played against a league of AI players

Complexity of the industrial reality

Life isn't playing a game

Well defined rules and limited states in games



Unlimited states in reality¹

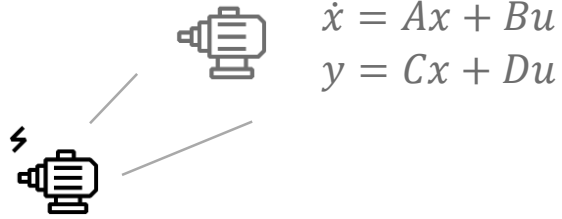


Moving from a closed world to reality requires Industrial AI

Industrial AI addressing the complexity in industrial reality

Combining domain knowledge with data

Know (foresight)



Domain knowledge

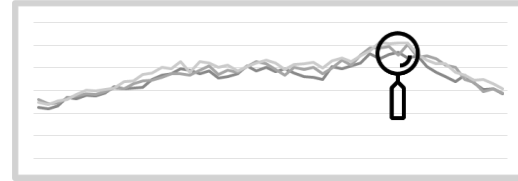
First principles models and simulation

- Described, but not yet observed

Safety, control and optimization

- Engineered well-defined solutions

Observe (hindsight)



Data science

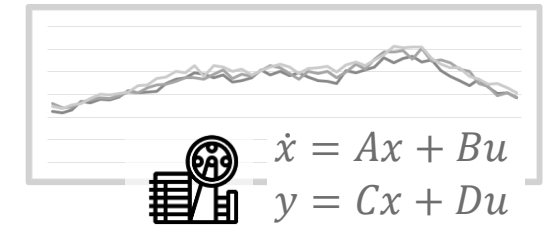
Data driven models

- Observed, but not a priori described

Industrial AI

- Complex scenarios

Combined approach



Build on what is known

Safely avoid known dangers

Explore the unknown through data analysis and simulation to increase flexibility

Industrial AI needs a combination of domain and data expertise to be successful

Example: Remaining Useful Lifetime of Azipod® Bearings

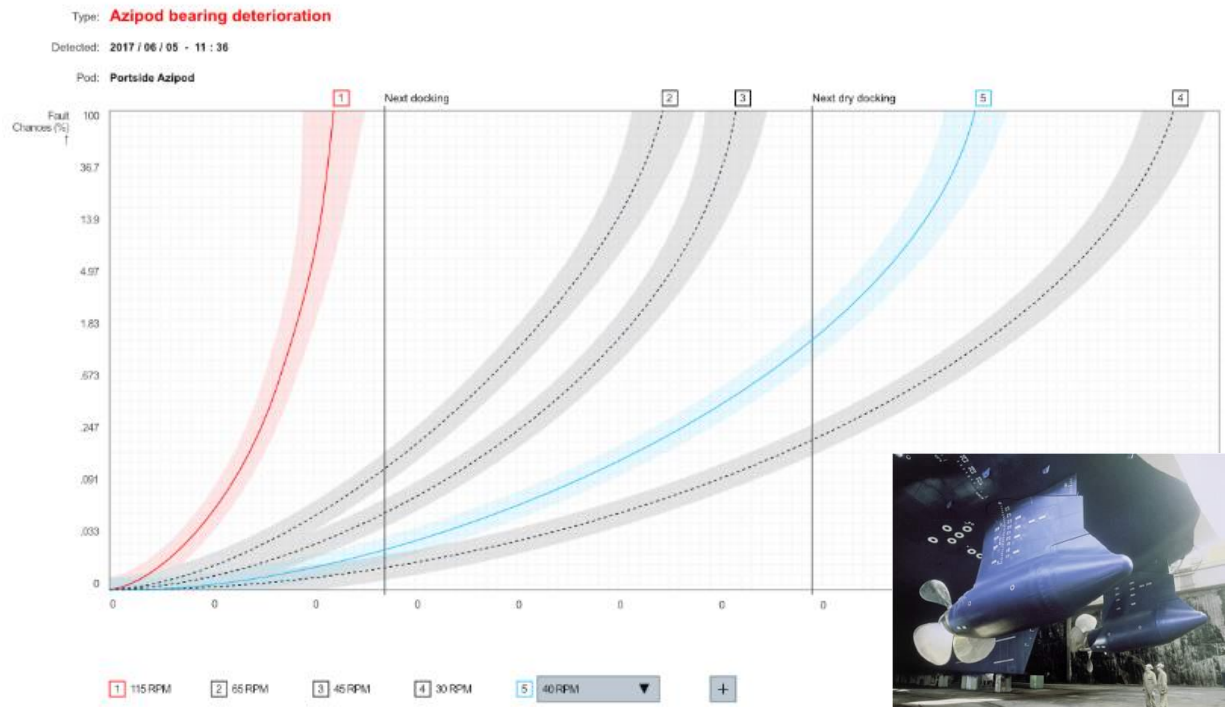
Prescriptive service solution for marine application

Can we estimate and prolong the lifetime of an asset?

An accurate estimate of remaining useful life (RUL) for the critical component, i.e. Azipod® bearing, enables to avoid unplanned stop and maximize reliability.

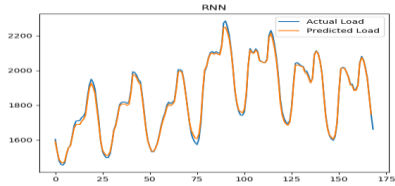
- Early detection of bearing faults based on signal processing and physical models, using the resonance as well as bearing fault frequencies
- Estimation of a degradation vector based on machine learning using condition monitoring signals
- Lifetime model predicting the RUL of the Azipod® bearing as a function of operational condition (physical model) and estimated degradation vector (data driven)
- Use of the estimated RUL for an optimal maintenance planning through adaptation of operational condition

LIFETIME ESTIMATION



Machine Learning / Artificial Intelligence Projects in ABB Corporate Research

Overview



Distributed Energy Resource (DER) forecasting



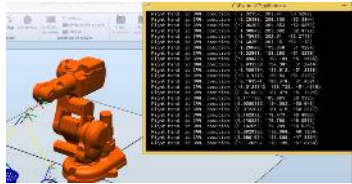
Improved yield in grinding circuit operation



Cloud tracking – prediction of the power output from a solar PV park



Artificial Intelligence supported building automation



Integration of machine learning frameworks into Robot Studio



Anomaly detection of robotic paint system



Motor failure prediction using data analytics and machine learning



Optimized multi-compressor efficiency



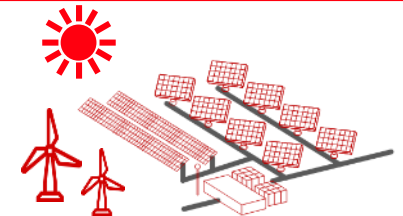
Increased uptime by advanced Alarm management



Preventive maintenance of wind turbines



Foaming prediction to prevent plant shutdowns



Increased PV plant uptime

Glimpse into the future

AI Assistants as unified interface to advanced analytics



Connected with ML Services

Proactive Assistance

Graph-based Dialogs for Analytics

AI assistant connected to machine learning services

Proactively approaching user with relevant information

Unified user experience with natural-language interfaces for all algorithmic functionality

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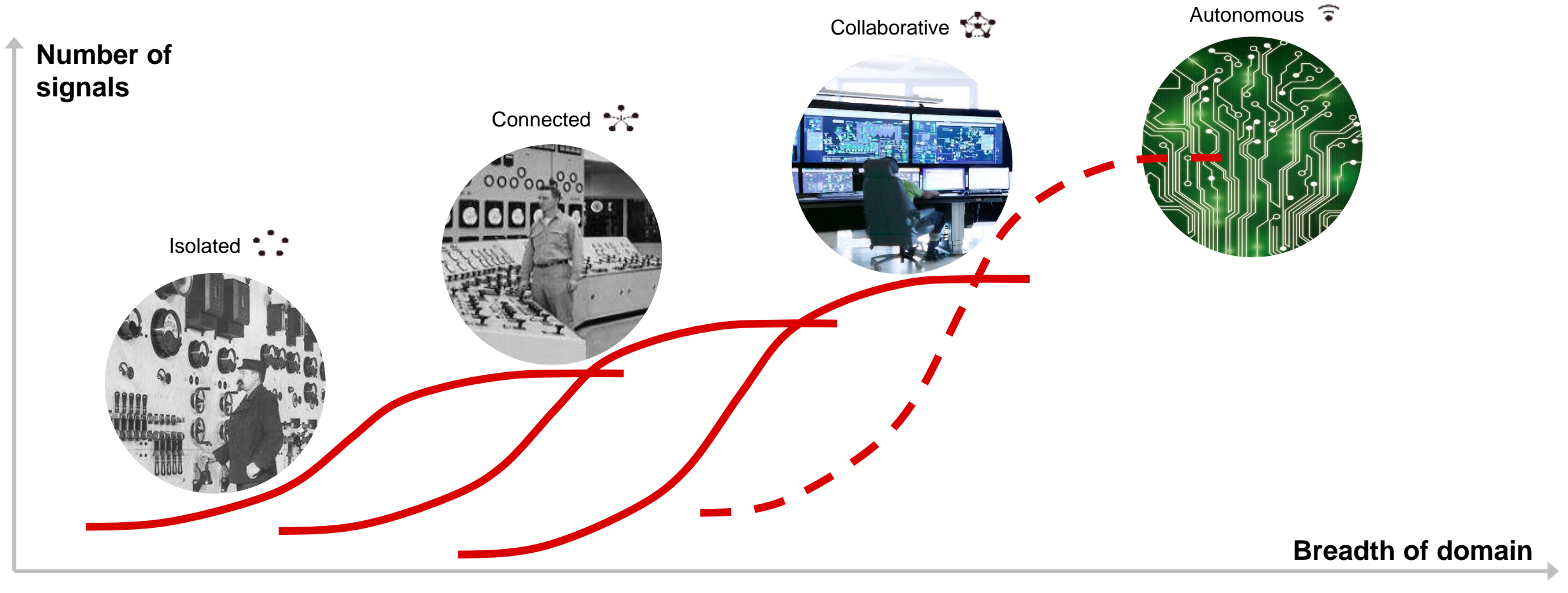
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Conclusions

Industrial automation has progressed for more than one century

Broader application space, going beyond classical control, move towards autonomous



What do we mean by an Autonomous System?

Definition



Systems that [without manual intervention] can change their behavior in response to unanticipated events during operation are called “autonomous”

Autonomous Systems David P. Watson and David H. Scheidt at John Hopkins Applied Physics Laboratory

Remote Control and Autonomous Systems

Examples from other Industries

Airplanes/Drones (Military)



General Atomics MQ-9

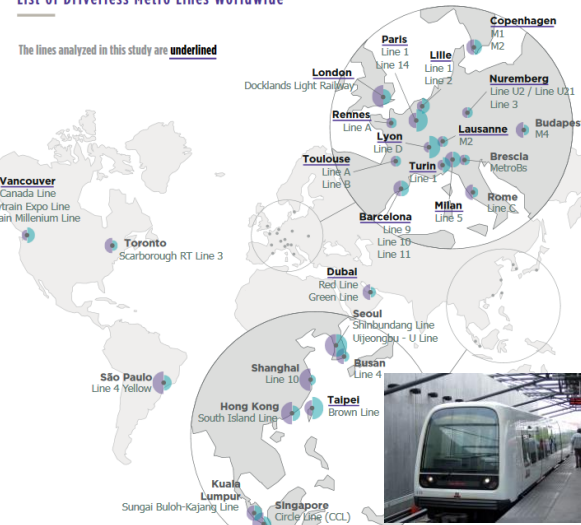


IAI Heron

Driverless metros

List of Driverless Metro Lines Worldwide

The lines analyzed in this study are underlined



Sources: Wavestone research and analysis, UN data, UITP

Warehouse robots



Amazon Robotics
(formerly Kiva Systems)

Cars
























Google's self-driving car

Autonomous Systems are appearing in various industries


Levels of autonomy

Definition from the Society of Automotive Engineers (SAE)

For on-road vehicles

		 Human driver	 Automated system		
		Steering and acceleration/deceleration	Monitoring of driving environment	Fallback when automation fails	Automated system is in control
Human driver monitors the road	0 NO AUTOMATION				N/A
	1 DRIVER ASSISTANCE				SOME DRIVING MODES
	2 PARTIAL AUTOMATION				SOME DRIVING MODES
Automated driving system monitors the road	3 CONDITIONAL AUTOMATION				SOME DRIVING MODES
	4 HIGH AUTOMATION				SOME DRIVING MODES
	5 FULL AUTOMATION				

Source: SAE International

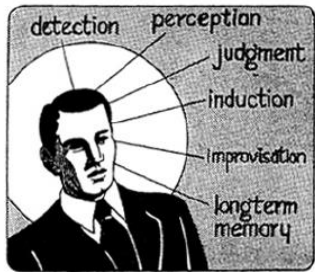


Academic origins of levels of autonomy

Decades of research leading up to the SAE 0..5 scale

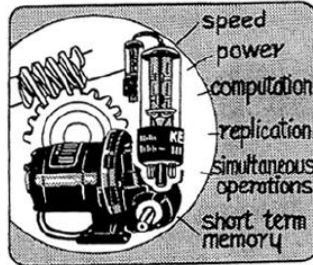
Function Allocation (1951)

Humans Surpass Machines in the:



- Ability to detect small amounts of visual or acoustic energy
- Ability to perceive patterns of light or sound
- Ability to improvise and use flexible procedures
- Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time
- Ability to reason inductively
- Ability to exercise judgment

Machines Surpass Humans in the:



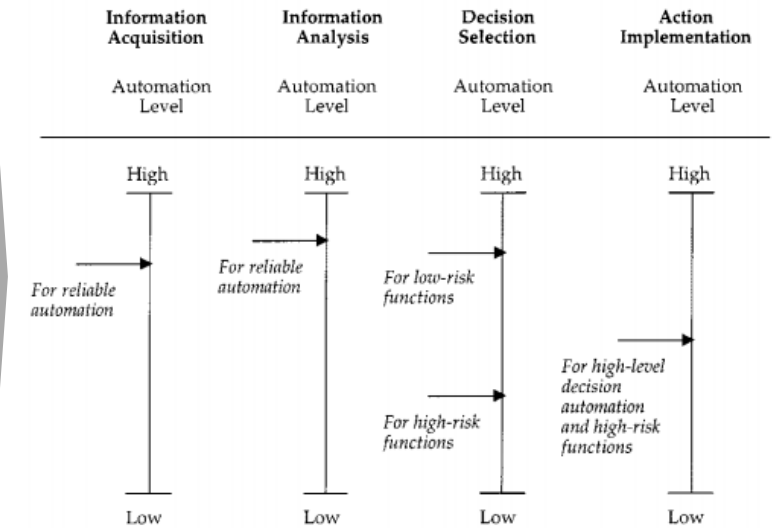
- Ability to respond quickly to control signals, and to apply great force smoothly and precisely
- Ability to perform repetitive, routine tasks
- Ability to store information briefly and then to erase it completely
- Ability to reason deductively, including computational ability
- Ability to handle highly complex operations, i.e., to do many different things at once.

Methods for Function Allocation

Level of Automation (1978)

1. The computer offers no assistance: human must take all decision and actions.
2. The computer offers a complete set of decision/action alternatives, or
3. narrows the selection down to a few, or
4. suggests one alternative, and
5. executes that suggestion if the human approves, or
6. allows the human a restricted time to veto before automatic execution, or
7. executes automatically, then necessarily informs humans, and
8. informs the human only if asked, or
9. informs the human only if it, the computer, decides to.
10. The computer decides everything and acts autonomously, ignoring the human.

Levels & Stages of Automation (2000)



Parasuraman, Sheridan, & Wickens (2000)
(2600+ citations)

Moving towards autonomous industries

Increasing the level of autonomy

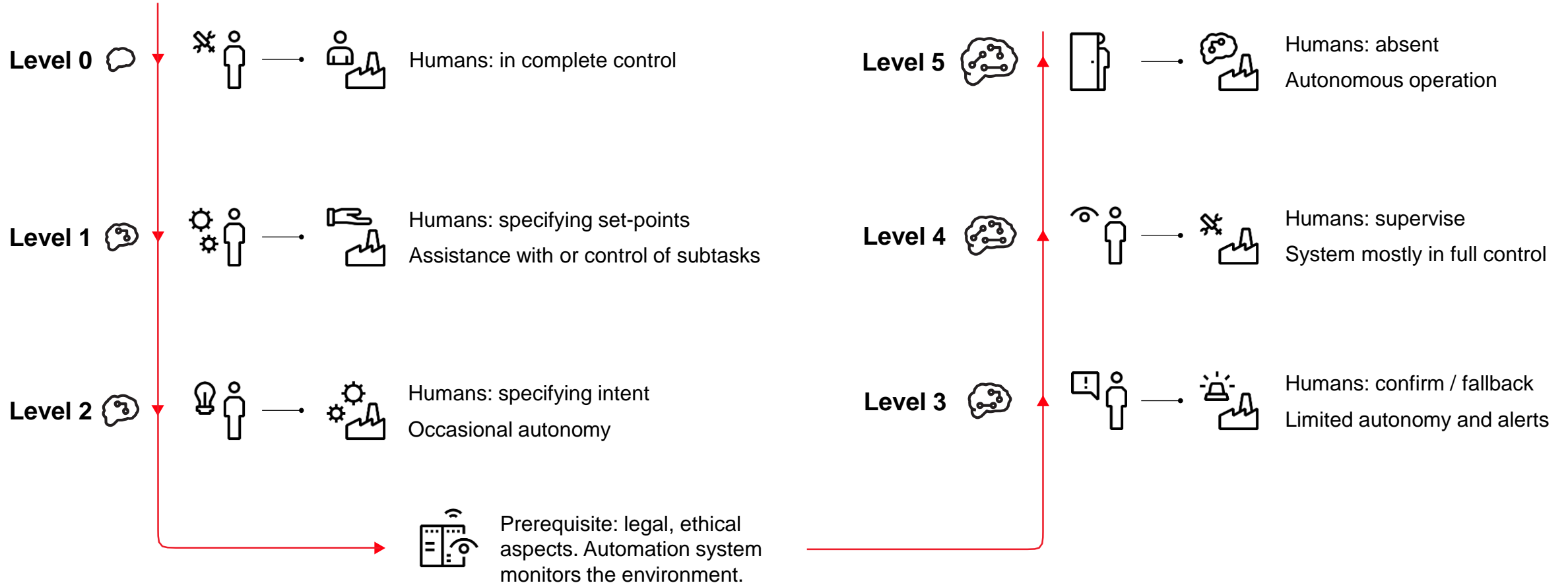
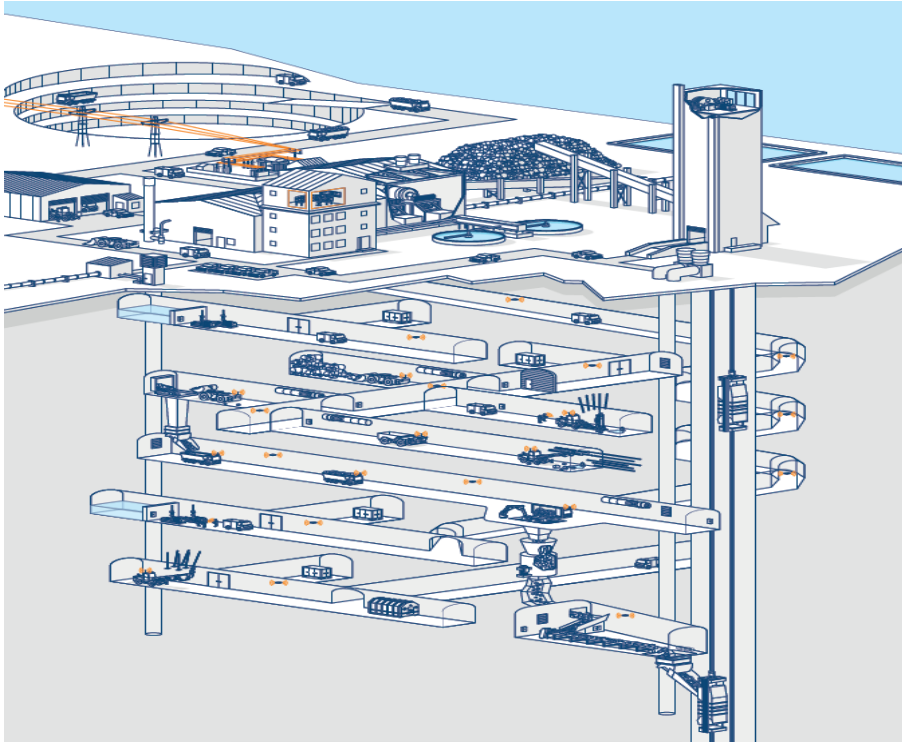


ABB Application Example – Mining

Future underground mine will possibly be fully autonomous with no people underground



Swedish mining companies – Boliden and LKAB – are world leaders in automation

Comparison of “our world” with automotive

Why it is not as easy with the process domain as with automotive



Life cycle phase	Operation	Life cycle phase	Operations*, possibly others too
Autonomous key feature	Driving	Autonomous key feature	Control room operation, field operation, process optimization, production scheduling
Human role(s)	Driver	Human role(s)	Control room and field operator, process engineer, dispatcher, ...
# tasks / set points	Low: speed, lane position	# tasks / set points	High: dozens to hundreds
# of artifacts	Medium: ECUs, sensors, valves, ...	# of artifacts	High: I/Os, controllers, valves, pumps, compressors,...
Homogeneity of tasks	High: each driver can drive every car	Homogeneity of tasks	Low: Operators cannot (easily) be switched between plants

Autonomous plant / factory

Autonomous key features for lifecycle phase operations (work in progress)

	Definition – Plant/Factory	Control Room Operation	Field Operation / Maintenance	Planning and Scheduling
0	No Autonomy: Humans carry out all necessary operations without assistance	Manual control of all assets. No support by automation system.	All field operator tasks executed by humans.	Manual development of plans and the corresponding schedule.
1	Operations Assistance: Automation system provides decision support for necessary operations by remote / digital assistance. Humans always responsible.	Automation of control loops during steady - state. Manual startup and shutdown of the plant. Manual execution of transitions. Alarm based notification.	Automation system notifies humans about field activities. Some tasks are automated , e.g. operating valves.	ERP plan creation on human request. Human decides when and how to execute the plans and adapts plans.
2	Automation system is in control in certain situations on request (humans pull support, e.g. for plant startup). Humans always responsible.	Automation system assisted plant startup, transition, steady-state, and shutdown. Manual fault correction supported by decision support system.	System guided field operation tasks. Humans get instructions what to do and when by decision support system.	Adaptations of plans to current situations by operator request.
3	Automation system is in control in certain situations. Plant actively alerts to issues and proposes solutions. Humans confirm.	Automated plant shutdown, startup and transition, on human request. Automatic correction of known deviations. Decision support for unexpected/unknown faults.	Most tasks required for standard operations are automated, like shutdown, startup and transition phases. Number of humans in the field heavily reduced.	Continuous feedback and re-planning in case of production deviations.
4	Autonomous operations in certain situations: automation system has full control in these situations, humans supervise actions.	Autonomous control in certain situations with automatic fault and deviation correction and avoidance.	Almost human free field operation. Only human field operation in exceptional situations.	Continuous autonomous planning and scheduling without user interaction. Detection of production deviations and re-planning. Manual schedule release.
5	Full autonomous operation in all situations. Humans may be completely absent.	Full autonomous control, fault correction and avoidance in all situations. No human supervision required.	Full autonomous field operation, no manual actions in the field necessary. No humans remain in the plant.	Autonomous development and execution of plans and schedules. Autonomous re-planning in case of production deviations. No human interaction.

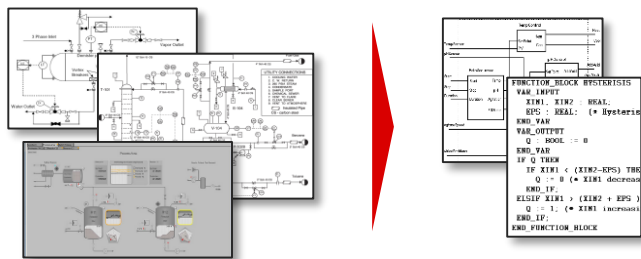
Future of Autonomous Plants

Scenario Overview



Efficient Engineering: intent-based automation

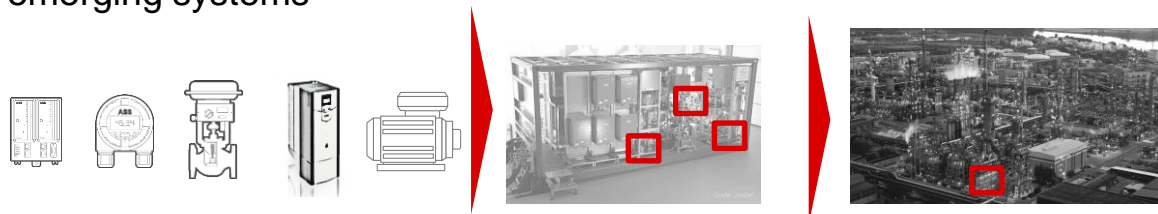
Automatically turn process to automation design and simulation



Rapid Commissioning and Reconfiguration: plug & produce for complex systems



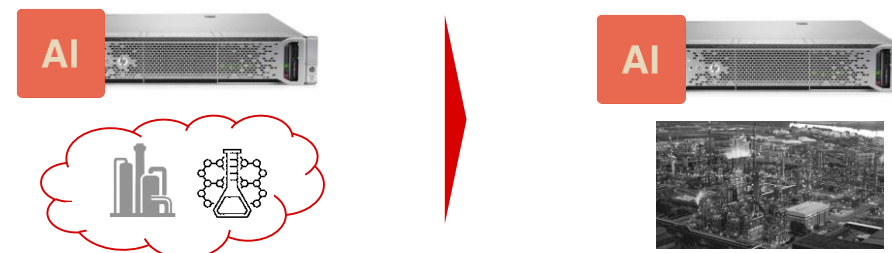
Self-integration and -configuration of components, automated testing, emerging systems



Efficient, Continuous Operation: decision-making AI



AI running operations as “world’s best operator”, trained on high-fidelity simulations; move beyond AI assistants



Example: optimize brownfield plant

- Increase availability: 100% available plant
- Increase productivity: from 85% to 95%
- Highest quality and security desired
- Rapid upgrade free of side-effects



The transition to autonomous systems in industry

Value proposition of autonomy



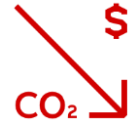
Handle increasing complexity of Industrie 4.0 systems



Lot size one production



Higher productivity / yield and increased quality



Lower cost and energy consumption



Improved worker health & amplify human potential



Bring out and accelerating new innovations



Enable new business models and value propositions



Opportunities currently not imagined at all

Outline

Facts about ABB

Future Automation

Integration of power and automation

The modelling complexity

Modular Automation

AI for Manufacturing Industries

Transition into Autonomous Systems

Conclusions

Conclusions

Autonomy needed along entire lifecycle of manufacturing

- First applications of Autonomous Systems in autonomous transport/vehicles (cars, metros and for ABB e.g. mining, cranes, ships and logistics)
- Standard for autonomy levels already in place for autonomous driving and emerging for shipping
- ABB is now looking at autonomy also for industrial plants
- AI and Machine Learning are key enabling technologies for Autonomous Systems
- In ABB, we have a long tradition of Machine Learning, especially for Condition Monitoring
- Industrial AI and autonomy will need combination of modelling and data based learning



Value proposition always most important consideration

Towards autonomous operations: Let's build a bridge into this future



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ABB