UNIVERSITÄT DUISBURG ESSEN
Offen im Denken

Hochschule Kempten
University of Applied Sciences

Forschungszentrum Allgäu (FZA)

Prediction based component and process optimization

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AMAP Colloquium, Aachen, December 15th, 2016

Background

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Specialized Area Foundry Technology

Werkstoffprüfung & Prozessmonitoring

Process monitoring and process analysis
Predictive Manufacturing

Institute of Metallurgy
and Metalforming

Chair of Mathematics for Engineers

Machine Learning
Predictive Analytics

EIDOdata

Agenda

Motivation

What is knowledge?

Prediction-based processes

Model building

Risk factors in the foundry process

Challenges

Prospects and possibilities / examples

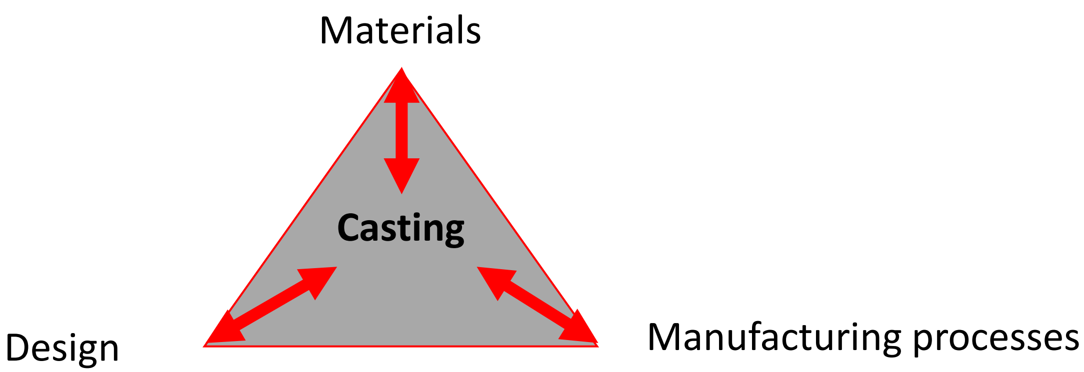
Conclusion

Motivation

Process understanding ⇨ Basis for improving Process:

To know, for what (objective) something happen, by what means and how

(with which settings and with what results)

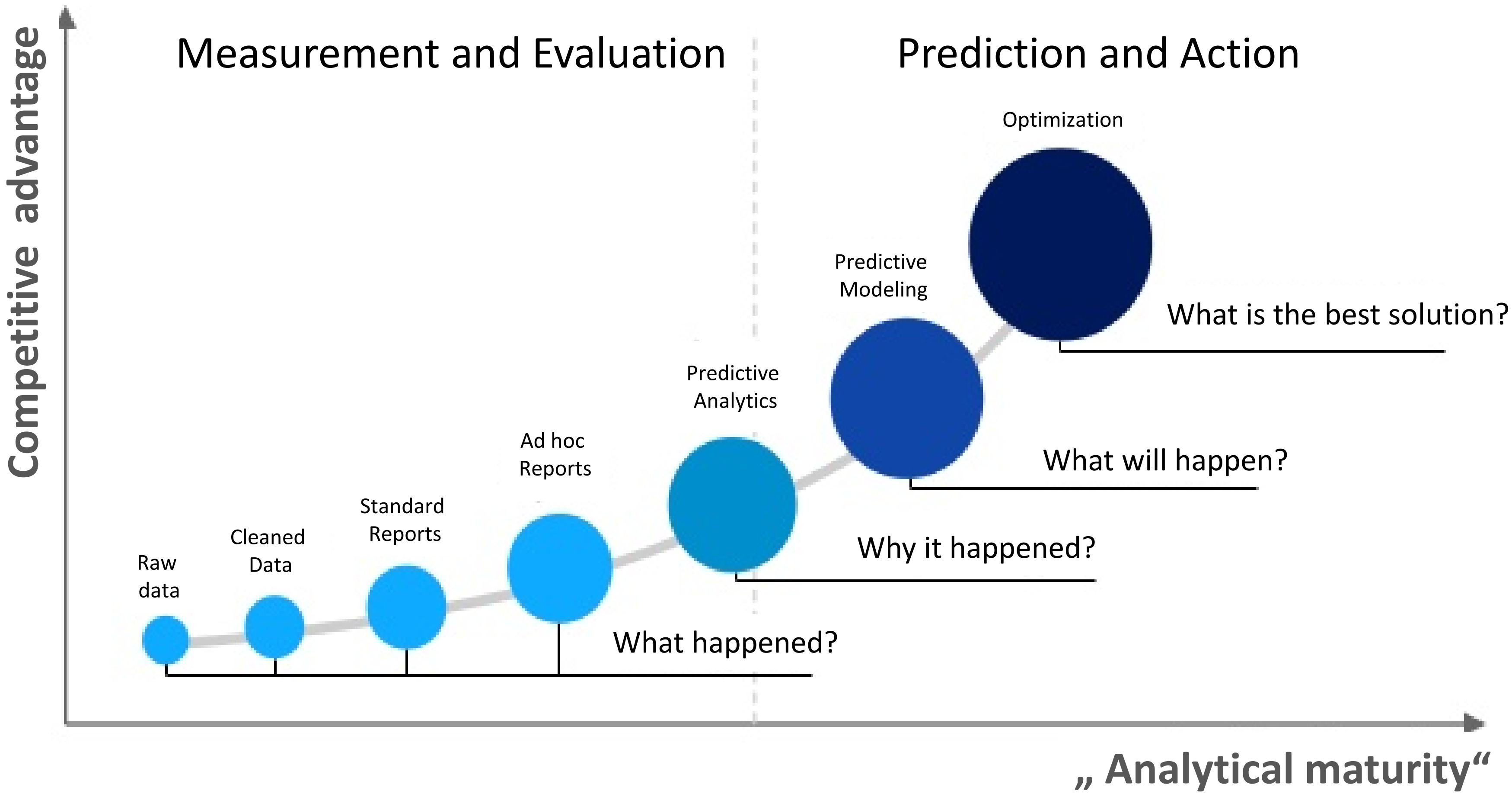


The requirements for the development and production of casting parts are complex and closely linked

Empirical development- and optimization methods can no longer cope with the required complexity

D. Hartmann, VDG-VDMA Gespräch 2005, Zukunftsfähigkeit durch Erhöhung der Fertigungsflexibilität

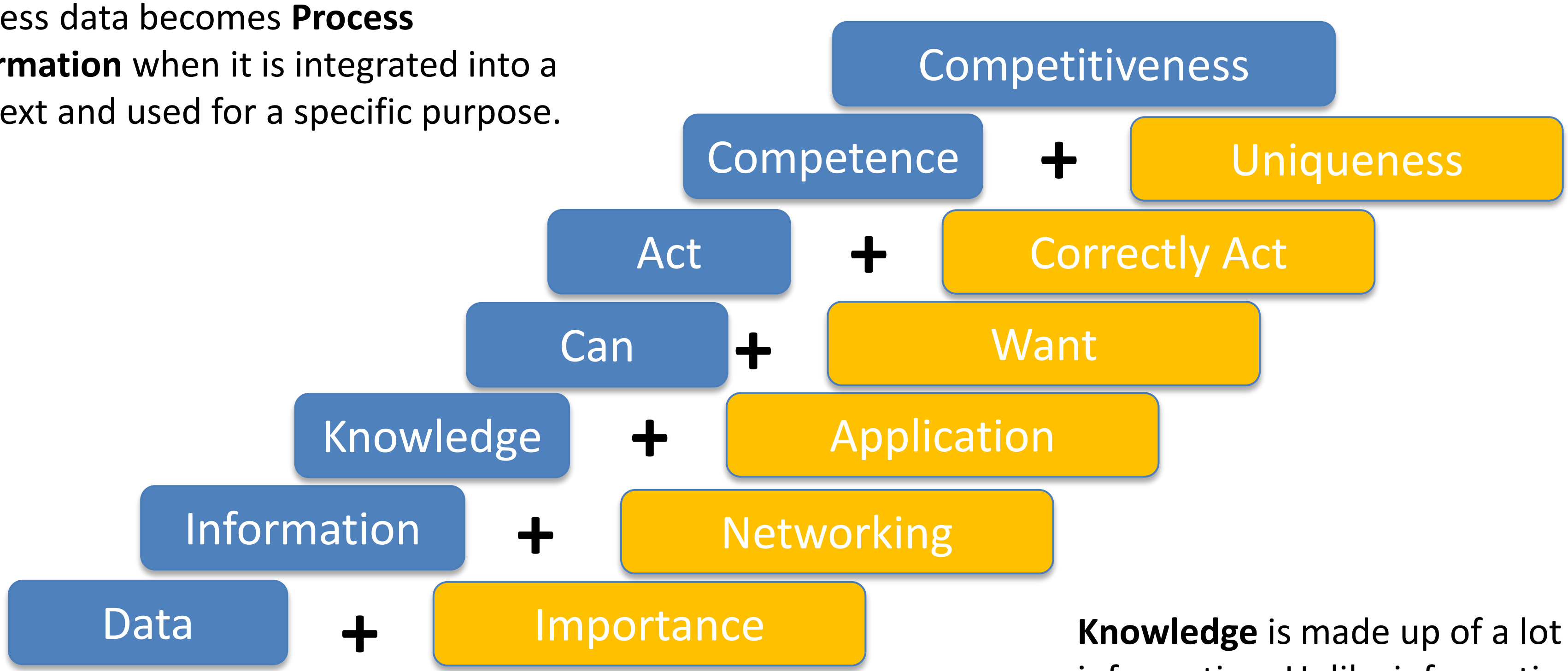
Motivation



Competitive advantage
Measurement and Evaluation
Prediction and Action
Optimization
Predictive
Modeling
What is the best solution?
Predictive
Analytics
What will happen?
Ad hoc
Reports
Standard
Reports
Why it happened?
Cleaned
Data
Raw
data
What happened?
„ Analytical maturity“

From Data to Information production and Knowledge generation

Process data becomes **Process information** when it is integrated into a context and used for a specific purpose.



Nach: http://qib.f-bb.de/wissensmanagement/thema/wissen/wissenstreppe.rsys

Relevant information forms the basis for decisions and becomes an important operational resource.

Knowledge is made up of a lot of data and information. Unlike information, knowledge is action-oriented: It is created by combining different information on action patterns and thus leads to practical, everyday applications.

Process knowledge

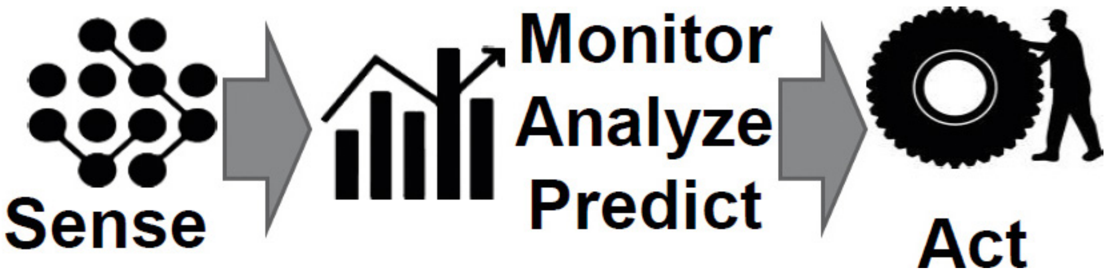
Explicit knowledge is documented knowledge that is available to others, e.g. In the form of Measurements, Data, work Instructions, documented Procedures, Reports or Drawings.

Implicit knowledge exists in the form of Patterns and Relationships in data. Or as a skill and experience in the minds of employees.
It is difficult to grasp, store, divide, and distribute.
Implicit knowledge occupies a far greater share of corporate knowledge, Experience, Routine and Abilities of the employees.

Implicit knowledge is difficult to develop, to make available, to store, divide and distribute.

Prediction-based Process control

With the implicit knowledge contained therein, data is a Capital, which should be used consistently to Optimize Processes!



Measure by means of Sensors (Sense), but: "**Measuring** serves the classification and not the understanding and recognition!

Creating knowledge: Monitor, Analyze, and Predict **Working patterns**? (Monitor, Analyze, Predict)

Evaluation enables Solutions: Taking and implementing measures (Act)

Prediction-based Process control

Datamining and Process intelligence		Predictive Analytics	Prescriptive Analytics
What happened?	Why?	Predictive Modelling	What should be done?
„Realtime“-data	Pattern		AUTOMATED DECISIONS

Influence on process and Product quality / Production result

Recognition of Patterns and governing laws from / to data (Process settings, Operating variables, Input size, machines, ERP systems)

Application by learning phase to unknown instances

Predictive Analytics (Event, Damage, Behavioral prediction)

(Recommender systems recommendations for action)
Process control

Data driven vs. Analytical Models

Monitoring of complex processes in the process industry

Complete Process = Sum of diverse sub-processes	Complex, non-linear, discontinuous and highly crosslinked Process chains	Interactive Process parameters and influencing variables	Very large data volumes – Big data situation

Operators' requirements regarding economic operation:

- Online monitoring and evaluation of the process state
- Detect creeping errors (quality, maintenance planning, ...)
- Detailed information on error localization and elimination
- Application-oriented representation of the diagnostic information

Data driven vs. Analytical Models

- In model-based Diagnostics, the deviation between measured and modeled Process variables is used as a distinctive measure.

- Analytical Process models are not always suitable for online monitoring of complex processes because:
  - They do not allow a holistic Process description,
  - Detailed expert knowledge of the plant must be assumed,
  - Modeling by experimental System analysis is very complex.

Data driven vs. Analytical models

Data-driven process models recognize the individual "fingerprints":

- allow a holistic Online-process diagnosis,
- are obtained from the running process data by the use of machine learning methods,
- the running plant operation is not disturbed during the learning process,
- require no detailed expert knowledge (in on-line operation!)
- prediction of the target quantity on the basis of measured influencing variables,
- choice of the influencing variables is not restricted, since statistical methods are used universally,
- extremely large or extremely complex Data sets, which can no longer be processed manually, can be systematically searched using predictive analytics.

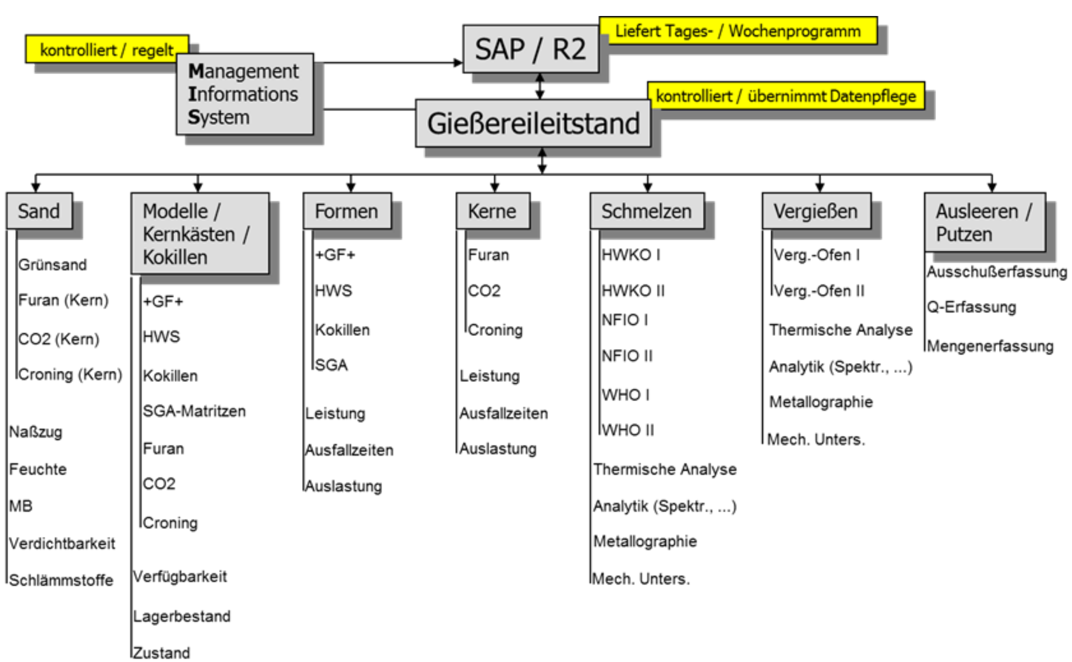
Conduction to Foundry Production Processes
Risk factors

Complete Process = Sum of diverse sub-processes

Complex, non-linear, discontinuous and highly crosslinked Process chains

Interactive Process parameters and influencing variables

Very large data volumes – Big data situation



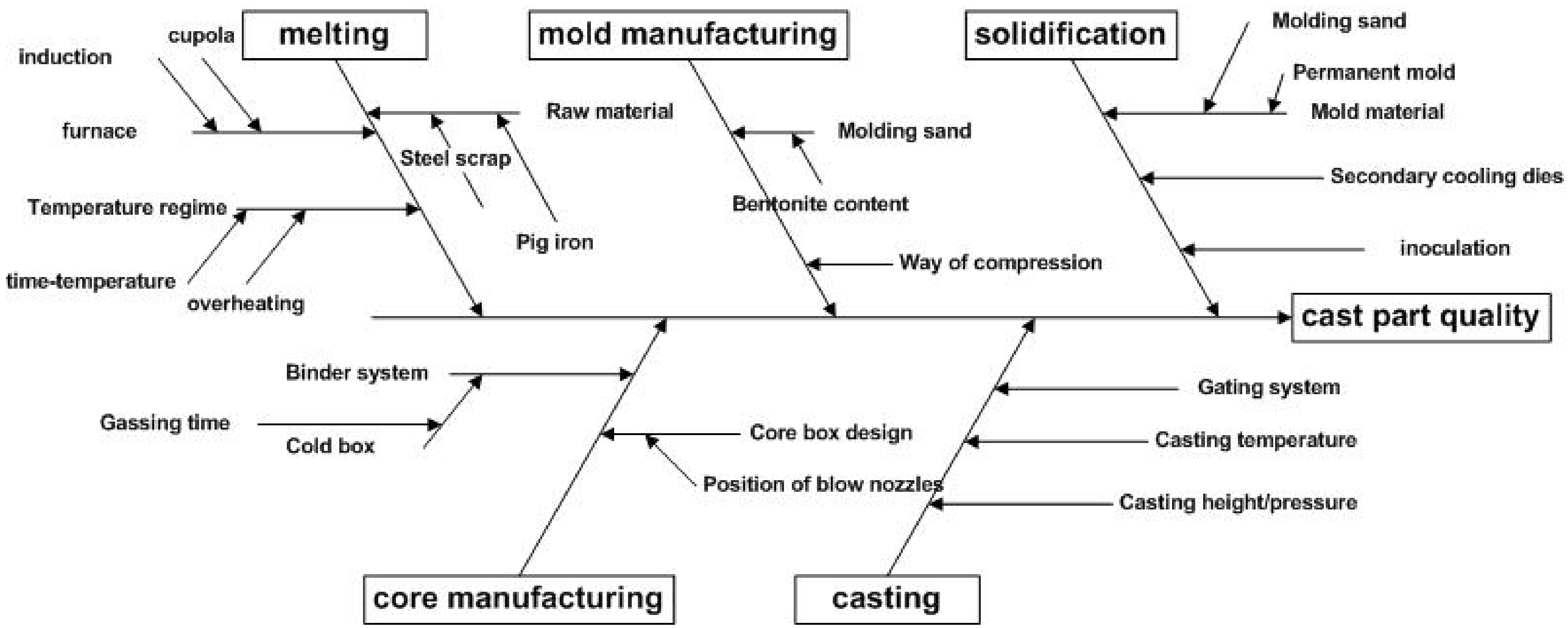
Data collection methods

Relevant data

Real-time measurement

Foundry production

Risk: Digitisability of complex processes



- Different sub-processes
- A wide range of individual process parameters
- Individual parameter control
- Interdependencies and interactions between process parameters
- Process control without in-situ consideration of interdependencies

Foundry production

Risk: Process control and Process optimization

Process control and Process optimization

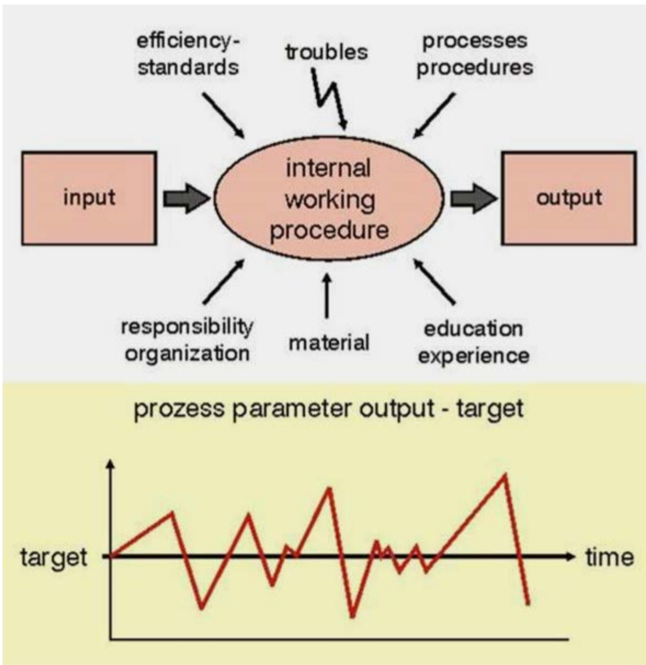
Process simulation	Complex partial process control	Empirical analysis and experience	Static process control
"Simulated control targets" are often not stably and robustly reached	The boundary conditions are regarded as given or not taken into account		

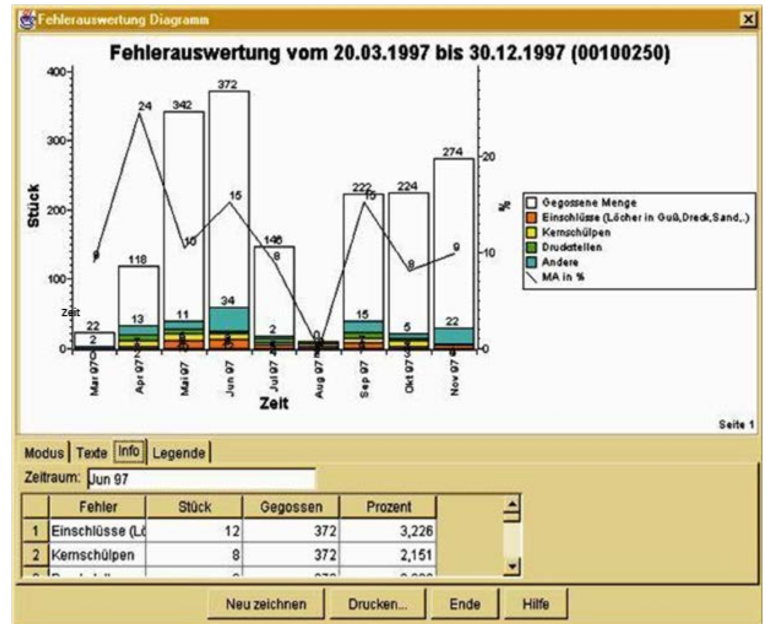
Predictions of expected control targets are usually based on the compliance with individual process limit values.

Interactions are not considered.

Foundry production

Risk: "static" process control





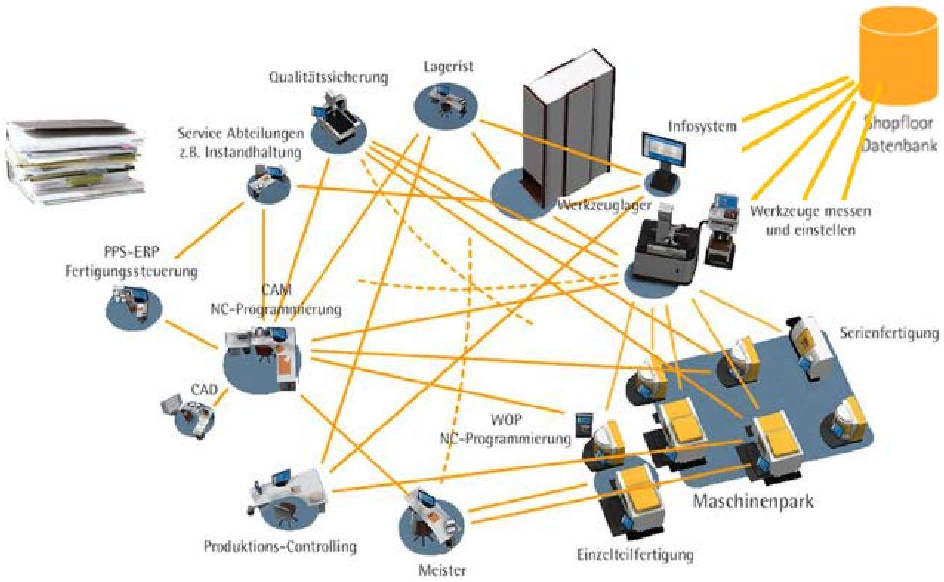
Unexpected errors and unexpected rejections

The usual data analysis is no longer up-to-date

Effective data analysis is costly, costs time and investment

Foundry production

Risk: Data collection and consolidation

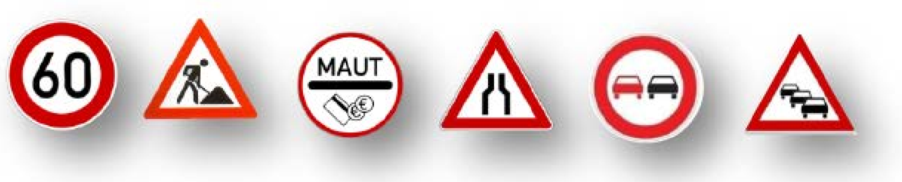


This is Reality in many Process Industries

The integration and consolidation of the data must be guaranteed because they are constantly changing and the content often comes from quite different sources.

The pure data must be converted into useful, context-related information.

The employees have to be supported by the IT, so that they can act properly.



J. Hofmann, Maschinenfabrik Reinhausen GmbH, Entwicklungspfad zu Industrie 4.0 über MES am Bsp. Fertigung, Symposium Gießerei 4.0, Bad Dürkheim, 19.11.2015

Prediction based Foundry production

Risk: Data quality

Completeness: Is the set of functionally independent variables complete in the sense that the independent can predict the dependent variable (s) well. By increasing additional independent variables, the “Prediction quality" can often be significantly improved.

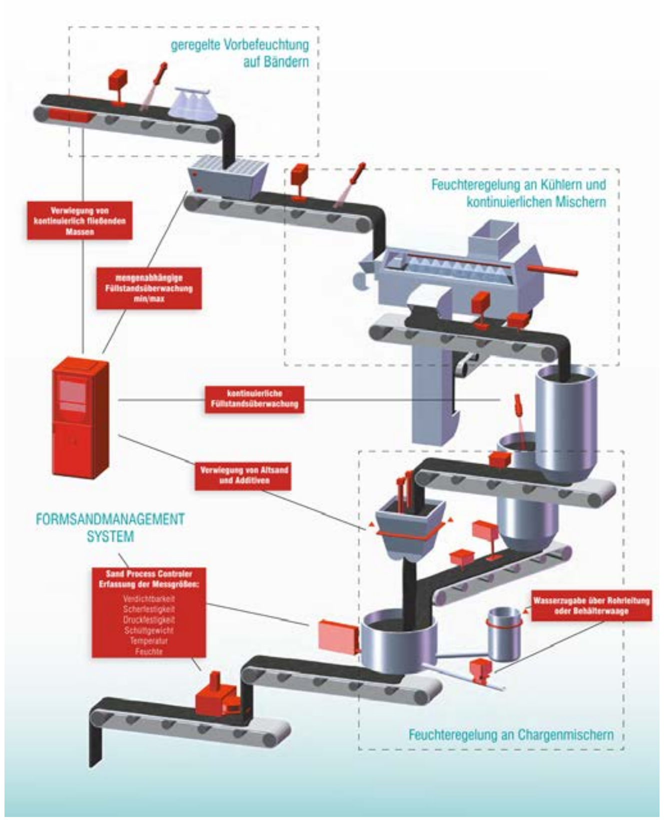
Data volume: A higher data volume ("event frequency"), usually ensures higher prediction accuracies

Complex correlations: If functionally independent variables are correlated (not only linear), the measurement of their isolated influence on the functionally dependent variable is made more difficult. A variable, which is correlated with another variable, measures in part the influence of the other variables. This so-called *Multicollinearity* can be eliminated or reduced by different methods.

Prediction based Foundry production

Challenges

- Robust sensor concepts
- Definition of relevant measuring locations
- Clear data consolidation structures
- Integrability of existing structures
- Parts traceability



http://sensor-control.de/giesserei/

Prediction based Foundry production

Challenges

- Commitment to “self-renewal”
- Realization of facility, ingenuity and expedition
- Adequate staff structures
- Qualified Employees
- Training and qualification
- Acceptance of change from empirical statistical process control to systemic data / knowledge-based process management with intelligent assistance systems
- Acceptance of machine learning methods (see Process simulation)
- Intensive Networking / Cooperation with Service providers

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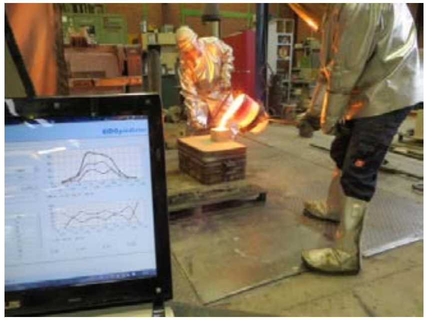
Prediction-based Foundry production

What *"actually only"* missing,

are ways and means,

- to consolidate our Data,
- as far as possible in real time to capture, evaluate and ad-hoc to use.



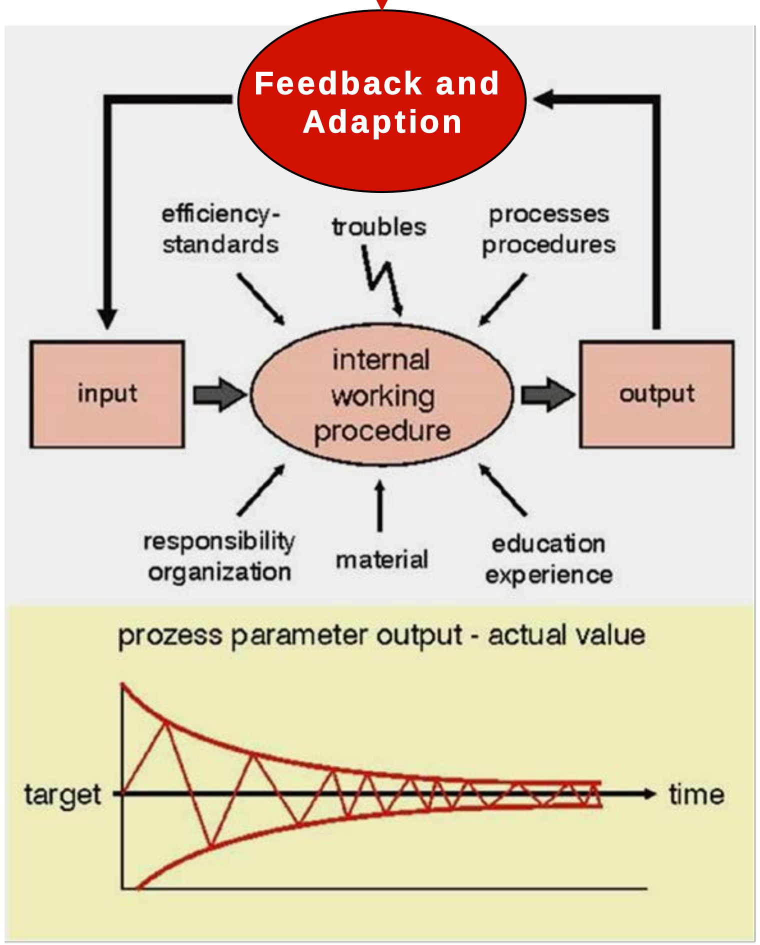
to optimize Production processes through Automation and Predictions.

Applied machine learning is the next logical development step:
The generation of (data) knowledge and the use of the gained experience

- Analysis of complex data sets based on automatically created models
- Learning from the results of the Analysis
- Use of this knowledge for optimization.

Prediction-based Foundry production

- ❐ Deviations between targets and actual values are continuously reduced
- ❐ Target controlled continuous adaption of input and output parameters
- ❐ Permanent feedback between output and input parameters
- ❐ Continuous improvements of process constraints



Knowledge based permanent in situ parameter evaluation

Prediction based Manufacturing processes

Example of Steel production and Steel processing

Intelligent data-driven Models
for Predicting the Final state at the BOF converter, Dillinger Hütte

- Increased steel production by reducing the post-blowing rate and the overblowing rate.
- Reduction of Process costs (eg. energy) and inputs (eg. oxygen, heating media, coolant).
- Reduction in the wear of the converter lining.
- Increasing the steel output from the converter.
- Reduction of personnel costs.

Improved hit accuracy at the tap temperature of 5° C results in a **Saving potential of around € 0.5 million per year** through a reduction in the heating means and the post-blowing rate [at a steel production of 2 Million t/a]

Hans-Jürgen Odenthal, Mike Löpke, Jochen Schlüter, Norbert Uebber, SMS Siemag AG
Pressetag: 3. Juli 2014, SMS Siemag AG in Hilchenbach; Thema: Data Mining / Industrie 4.0 – Vorhersage und Steuerung von Prozessen

Intelligent data-driven Models for Predicting the Final state at the BOF converter

The target values are

- the tap temperature T,
- the carbon content [%C] of the Melt,
- the phosphorus content [%P] of the Melt
- and the iron content (%Fe) of the Slag

to the oxygen bladder end point.

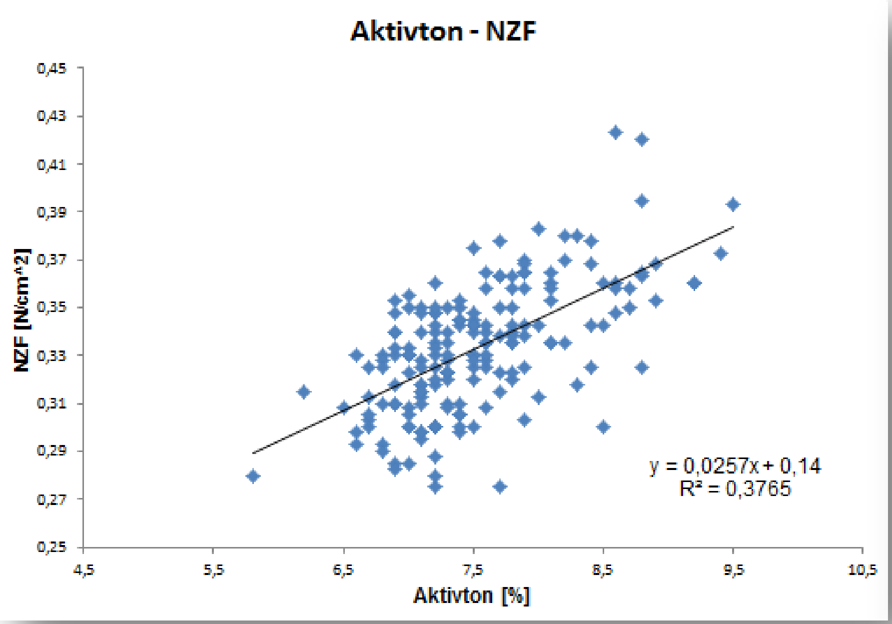
90 **static Process variables**, such as
Cast iron weight, Scrap weight, Pig iron analysis, Converter age and Lance age, Events, such as, for example the time and amount of the heating means (Ferro-Silicon - FeSi) and Coolant (Ore, Dolomite).

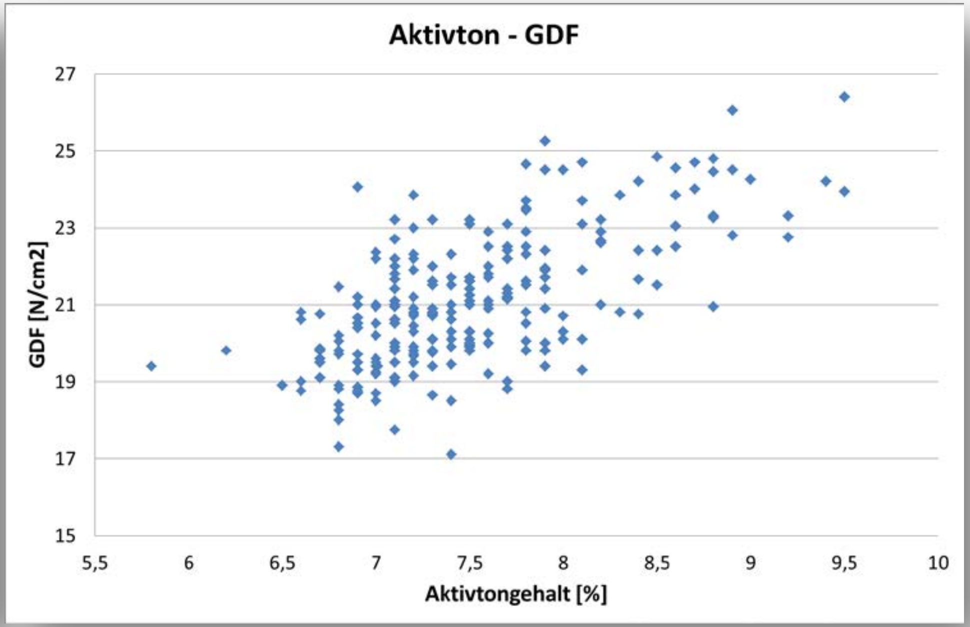
36 **dynamic Process variables** such as Exhaust gas composition (CO, CO2, O2), Cooling water volume, Cooling water temperature, further Sensors from the fields of Vibration, Sound and Optics: 3D-Acceleration sensor on the Lance, a microphone at the Converter mouth and a Radiation pyrometer for Monitoring the Exhaust gas flame

Prediction with Process models

Molding sand control

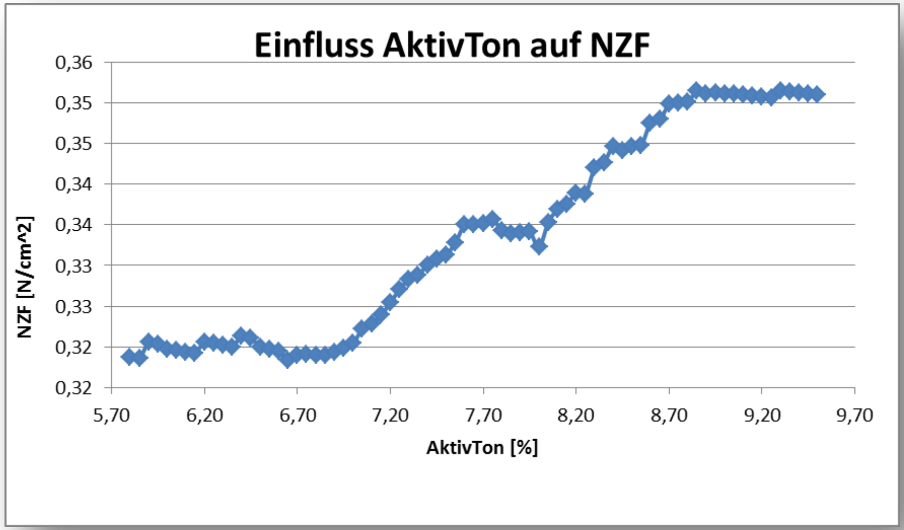
Simple linear correlations of the Control variables Active tone and C with the wet-Strength (NZF). These dependencies are also slightly linearly correlated.

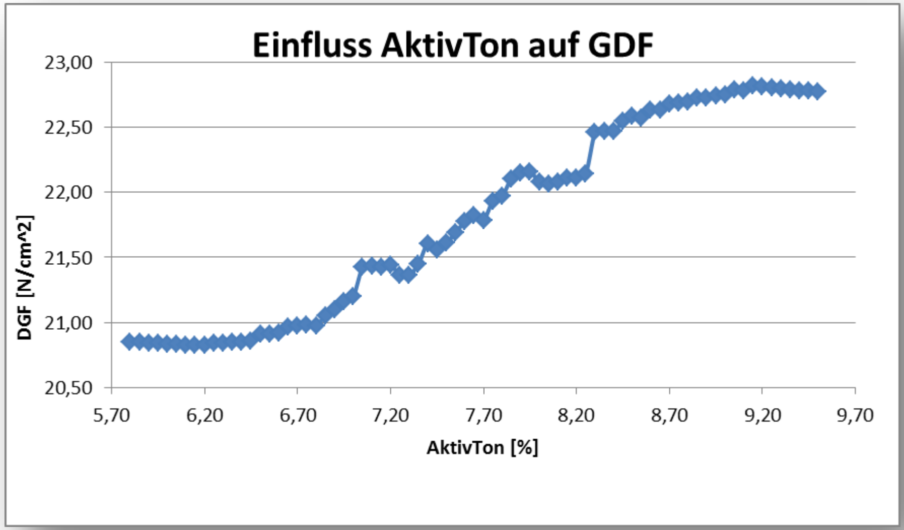




Prediction with Process models
Molding sand control

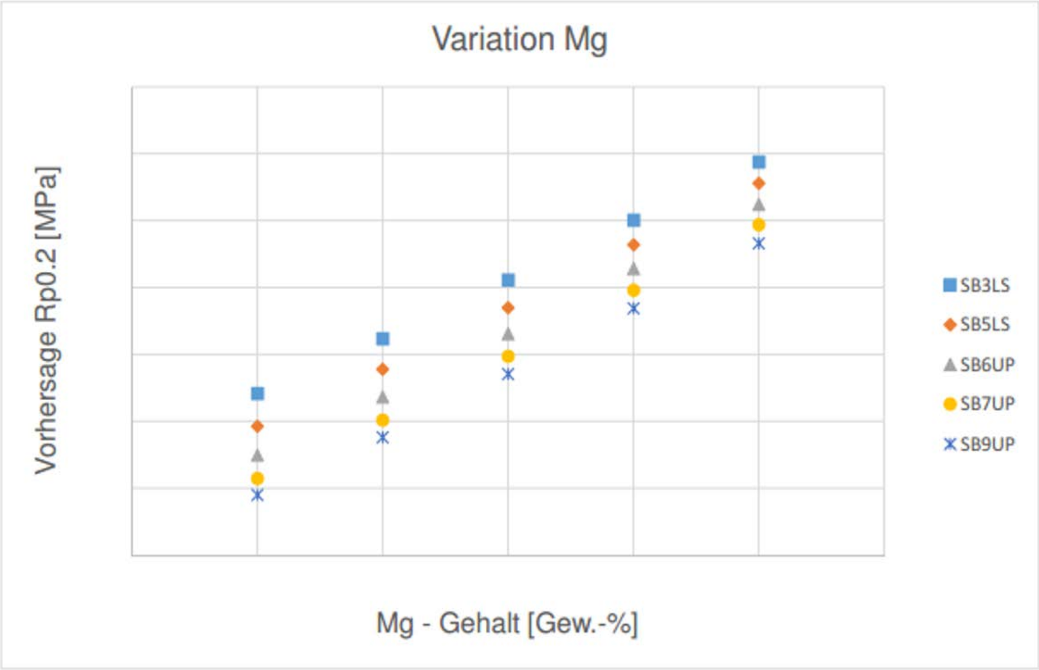
Consideration of all Control variables: Active tone (= var.), H_2O, C, SSG, Mean grain size (KG) (all const, Median), gives clear Correlation

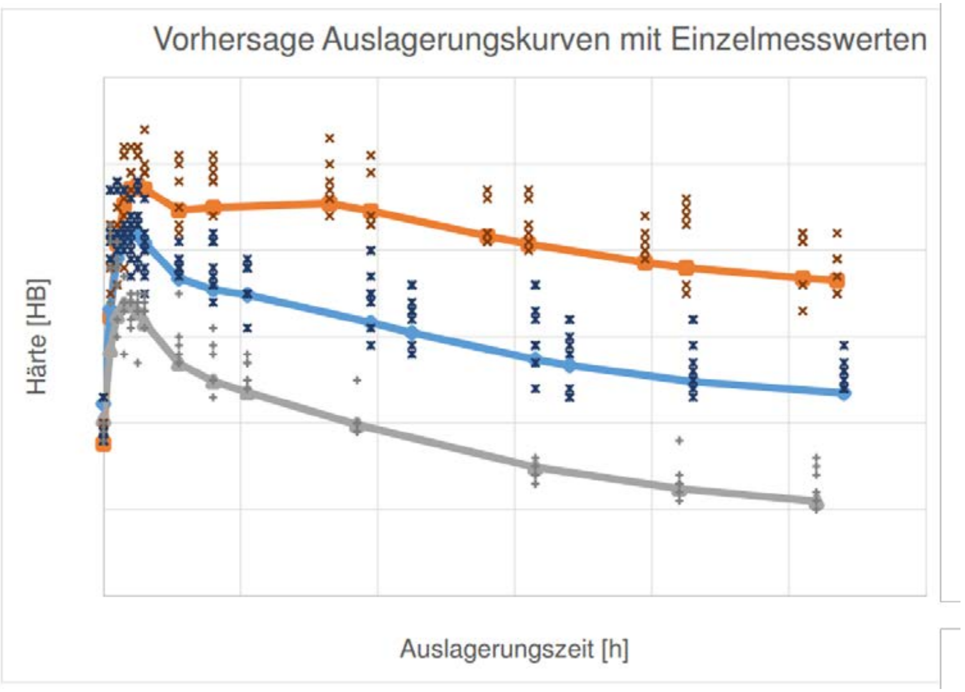




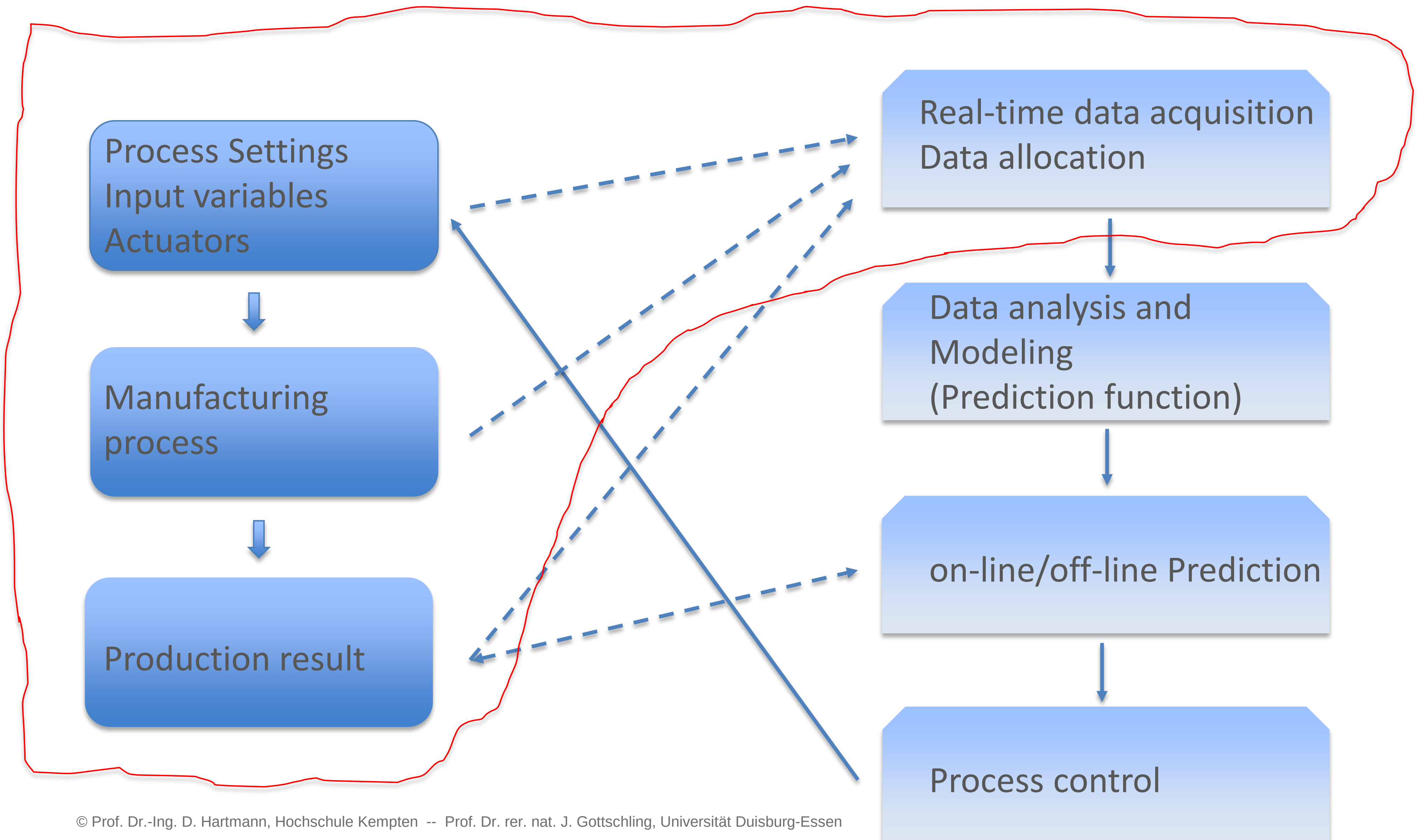
Prediction with Process models

Precipitation hardening of AlSi8Cu3-components





Prediction based Manufacturing processes



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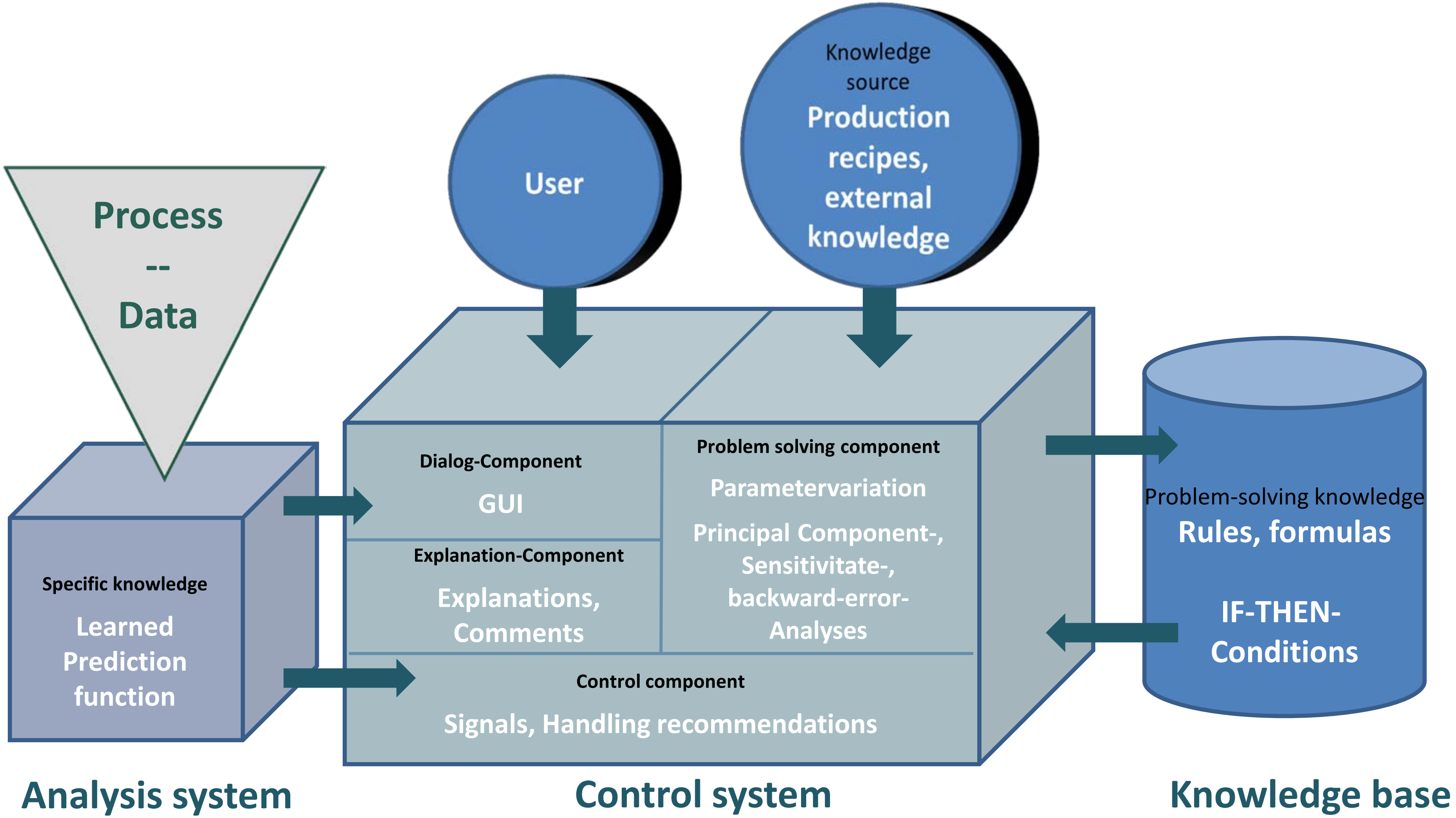
Dynamic Process control



Technical and economic opportunities

- Effective and efficient Fault analysis
- Forward-looking, adaptive Process management
- Potential for Process optimization
- Potential for Cost optimization
- Production flexibility
- Energy and Resource-efficient processes
- Comprehensive traceability

Conclusion

Intelligent use of data cannot close down foundries. "Predictive analytics" opens up new ways and approaches for Process planning, Process analysis, Process optimization and Process control.

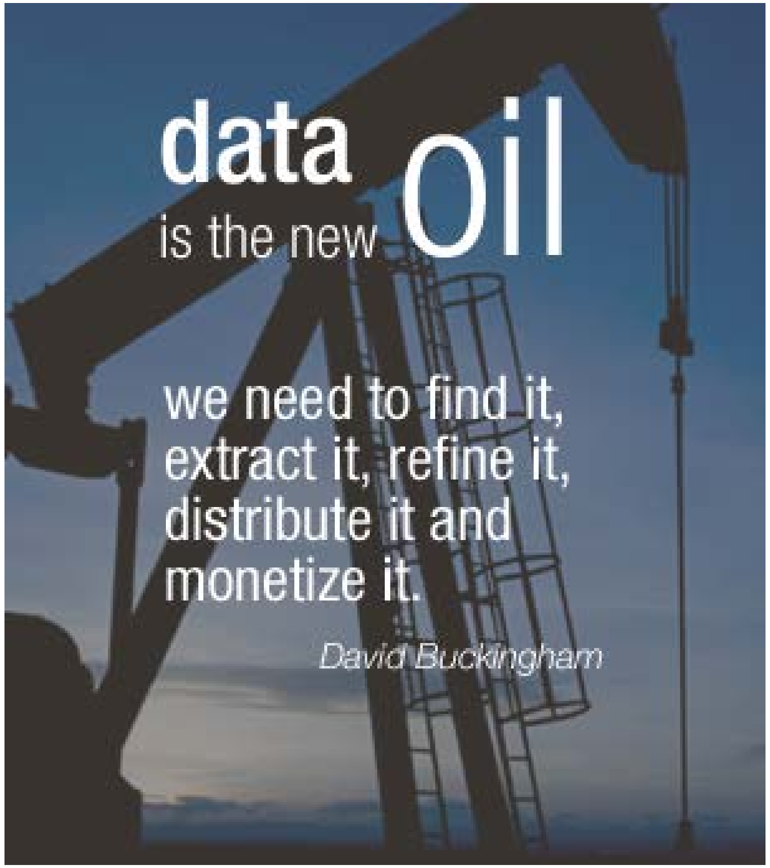
In the technical field of foundries, there is often a considerable need for innovation in the process data collection and the traceability of these data.

The requirements for the analysis of data are determined by the requirements to generate effectively usable knowledge and to make it retrievable at any time.

Adaptation of the analysis algorithms and methodology to the specific requirements of a foundry production.

"Predictive analytics" opens up new approaches and approaches for process planning, process analysis, process optimization and process control.

This is then “Predictive manufacturing".


data
is the new oil
we need to find it,
extract it, refine it,
distribute it and
monetize it.
David Buckingham