Winter School on Knowledge Technologies for Complex Business Environments

Dealing with Complexity in Manufacturing Systems

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INTRODUCTION

- Manufacturing of products and goods for general, industrial and personal use is becoming the most important activity in the world.
- Generation of quality of life for citizens and contribution to the continuous growth of wealth as well as power and position of a state depend decisively on superior results of manufacturing activities in individual countries.
- This value and jobs creating activity deserves strong and continuous endeavor of all actors of the modern society to ensure prosperity, better life and sustainable development.
- These cognitions make research in manufacturing even more exiting and put research efforts and contributions in a new perspective.

PART 1: COMPLEXITY IN MANUFACTURING

WHY STUDYING COMPLEXITY IN MANUFACTURING SYSTEMS?

- Modern manufacturing organizations are operating in an uncertain and ever-changing environment.
- They are subjected to opportunities and constraints of the global market, cooperating and competing at the same time.
- While operating in an environment full of disturbances, the main challenge is how to ensure a stable and deterministic delivery of products even though the demand is of stochastic nature.
- These are the issues related to complexity and, in order to better cope with them, demand
    (1) better understanding of complexity phenomenon,
    (2) ability of measuring complexity,
    (3) development of knowledge for better control of complexity.

REFERENCES OF THE RESEARCH GROUP AT THE UNIVERSITY OF LJUBLJANA ON COMPLEXITY ISSUES

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DEFINITION OF COMPLEXITY

- The word complexity is derived from the Latin word *complexus* which signifies *entwined* or *encircled*.
- Complexity is a property of systems which are composed of many elements interacting in a nontrivial fashion.
- The interactions between the elements spur patterns or structures which can be detected by external observers but are not obvious from the observation of individual interactions or individual elements.
- New properties *emerge* from the system

DEFINITION OF COMPLEXITY IN ENGINEERING

- NP Suh defines four types of complexity in engineering.
  - Time-independent real complexity is the measure of uncertainty of achieving the functional requirements.
  - Time-independent imaginary complexity is defined as uncertainty which arises because of the designer's lack of knowledge and understanding of a specific design itself.
  - Time-dependent combinatorial complexity is the complexity that increases as a function of time due to a continued expansion in the number of possible combinations. It is a consequence of the unpredictability of the future.
  - Time-dependent periodic complexity, on the other hand, only exists in a finite time period. Thus, the number of possible combinations is limited.

TO REDUCE OR NOT TO REDUCE COMPLEXITY?

- Suh argues that complexity of engineered systems should be reduced at all times to make the system robust, stable, and reliable.
- Van Eijnatten, Putnik and Sluga however, disagree with this reductionist approach, especially when considering generation of novelty. They argue that complexity should be nurtured, not reduced, in manufacturing system design and development. Only this allows for true-novelty creation.
- It seems that this apparent discrepancy originates from two sources. Firstly, complexity has a different meaning in different sub domains, such as design, control, etc. Secondly, there is a lack of quantitative definitions for complexity. Still, some characteristics of complexity are common to all sub domains.

DEFINITION OF COMPLEXITY IN MANUFACTURING SYSTEMS

- Peklenik identifies five key characteristics of complexity in manufacturing systems:
    (1) the absence of formal mathematical descriptions,
    (2) stochastic properties of elements,
    (3) intolerance to control,
    (4) non stationary element behaviours, and
    (5) irreproducibility of measurements.
- The absence of formal mathematical descriptions is perhaps the most characteristic property of complex systems. Still, if a complex system is to be controlled, some sort of a mathematical model must be devised. But, since models are specific to a system or a phenomenon, a general approach towards complex systems control is difficult to formulate.

COMPLEXITY ISSUE IN MANUFACTURING SYSTEMS

- Complexity has been identified as a ubiquitous and ever increasing property of manufacturing systems.
- Modern manufacturing systems are widely perceived as complex.
- Their socio-techno-economical nature is the source of nontrivial interactions resulting in emergent behaviours.
- The cause and effect relationships are not clear, especially when they involve human decisions.
- Accurately capturing the nonlinearities and consequent bifurcations or symmetry breakings is extremely difficult.

DRIVERS OF COMPLEXITY IN MANUFACTURING SYSTEMS

- Outside drivers - features of today's markets:
  - global competition
  - abrupt behavior
  - uncertain environment
  - interdependence risks
  - hard-to-determine causal relations
- Inside drivers - management issues:
  - incompleteness of information
  - limited knowledge
  - insufficient understanding of complexity

THE BASIC PROBLEM OF MANUFACTURING

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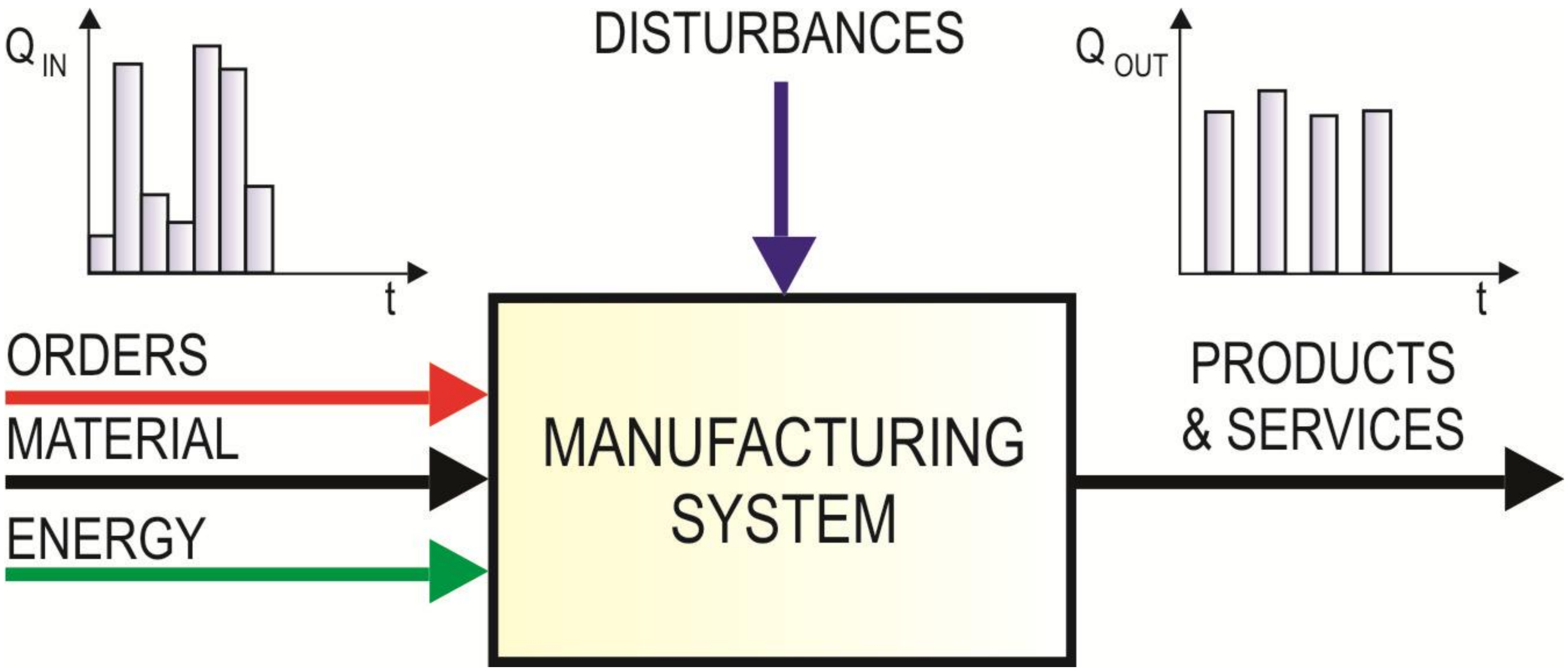
- **How to effectively create value by converting random inputs into deterministic outputs?**



CLASSIC APPROACH TO SOLVING OF THE PROBLEM

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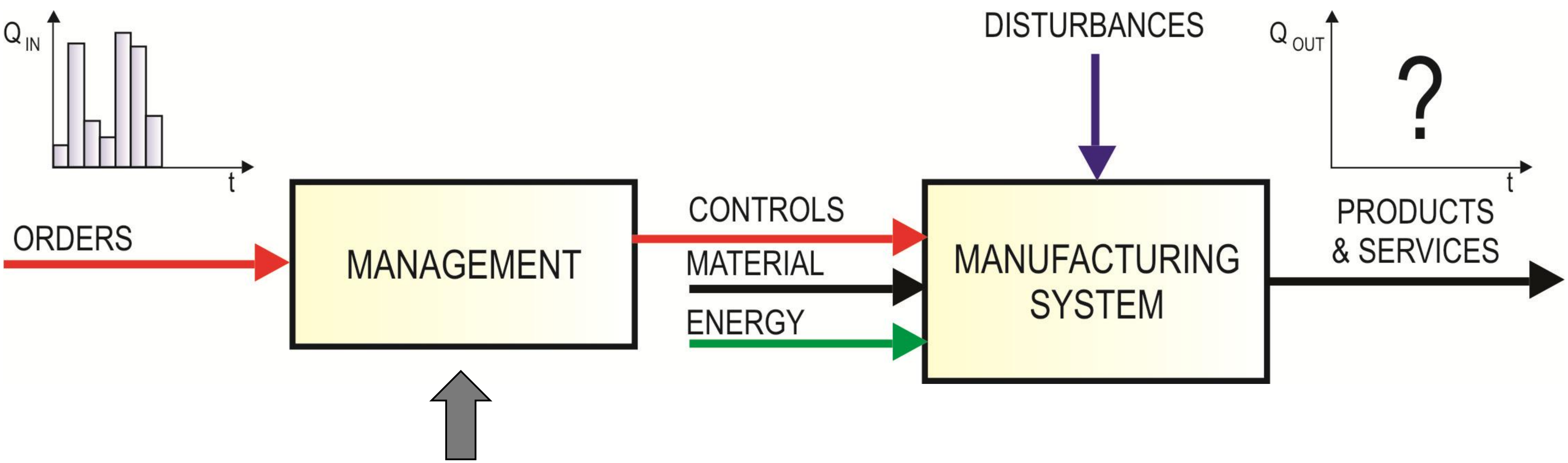
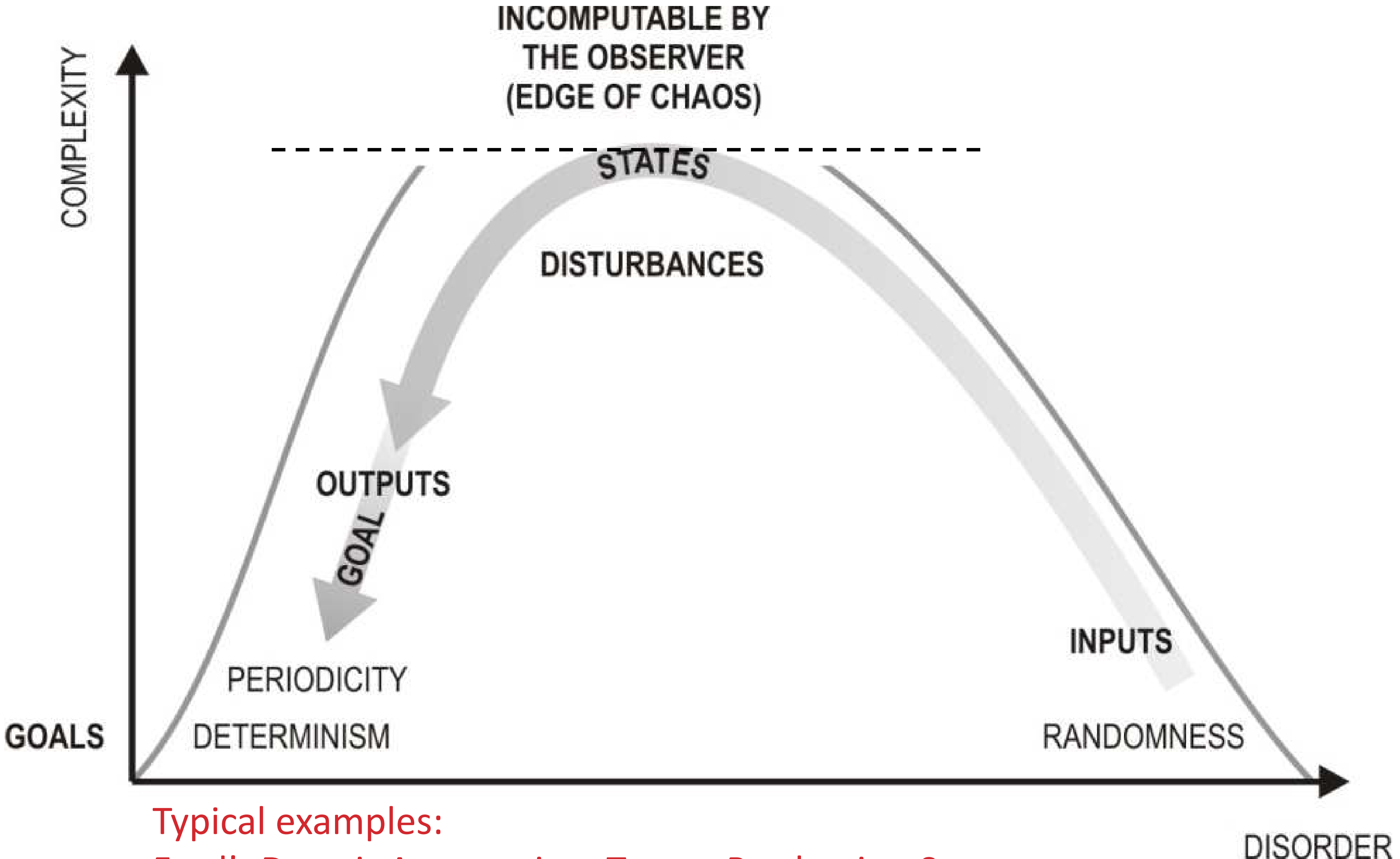
Open loop control

Is it successful?



Applied principles of Scientific Management:
planning & division of tasks and operations

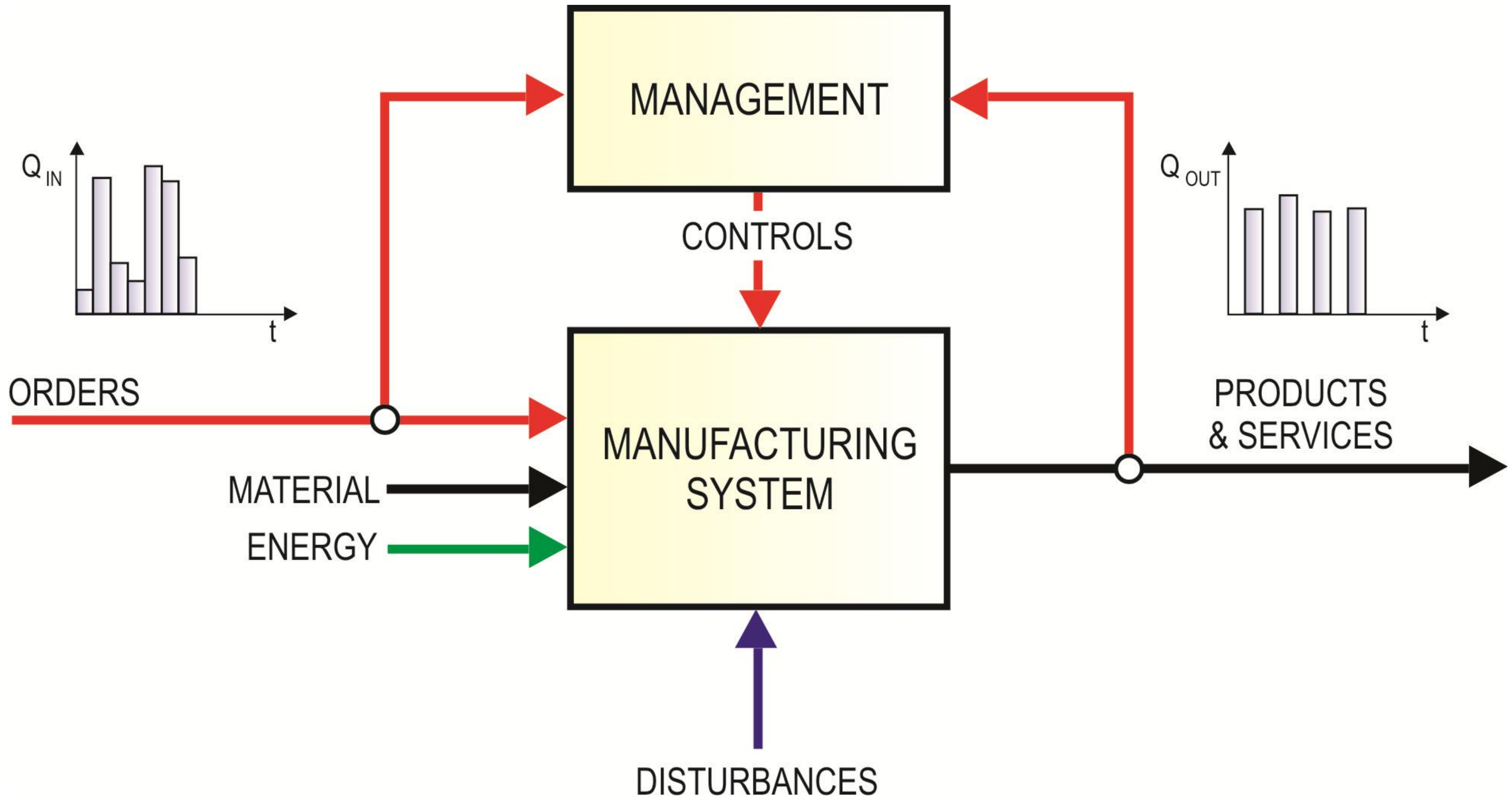
COMPLEXITY CURVE FROM THE CONTROL PROBLEM PERSPECTIVE



Typical examples:
Ford's Detroit Automation, Toyota Production System

MODERN APPROACH TO CONTROL IN MANUFACTURING

Goal oriented, closed loop



IS COMPLEXITY A NIGHTMARE OR A CHALLENGE ?

- Many customer complains and warranty issues as well as a lot of stress and many headaches of managers in manufacturing can be attributed to complexity issues .
- The actors usually even do not recognize that causes may lie in the complexity.
- Therefore, we need better understanding and in depth knowledge about this phenomenon.
- And those who will be able to recognize, understand, assess and manage complexity to those the future will belong.

PART 2: A METHOD FOR ASSESSING OPERATIONAL COMPLEXITY

MANUFACTURING COMPLEXITY RESEARCH

- Two fundamental types of complexity have been identified:
  - structural (static)
  - operational (dynamic)
- Current state of manufacturing complexity metrics research:
  - ad-hoc metrics
  - metrics based on uncertainty – Shannon entropy from information theory
  - metrics based on nonlinear dynamics approaches

MANUFACTURING COMPLEXITY RESEARCH (CONT.)

- However:
  - operational complexity still relatively poorly researched
  - usually related to uncertainty of schedule
- Is uncertainty really the basis of complexity?
  - uncertainty is always to a degree subjective
- Complexity science offers new approaches.
- Computational mechanics theory hypothesizes that complexity is not related to uncertainty, but to **difficulty of prediction**.

COMPUTATIONAL MECHANICS: INTRODUCTION

- Computational mechanics [Shalizi 2001] addresses:
  - patterns
  - structure
  - organisation
- It provides an information-theoretic method for finding **optimal causal models of stochastic processes**. In essence, it shows – from either empirical data or a probabilistic description of behaviour – how to infer a model of the hidden process that generated the observed behaviour.
- Computational mechanics is concerned with symbolic dynamics – signals of discrete symbols assigned to discrete time steps.

COMPUTATIONAL MECHANICS: BASICS

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- Consider a symbolic sequence

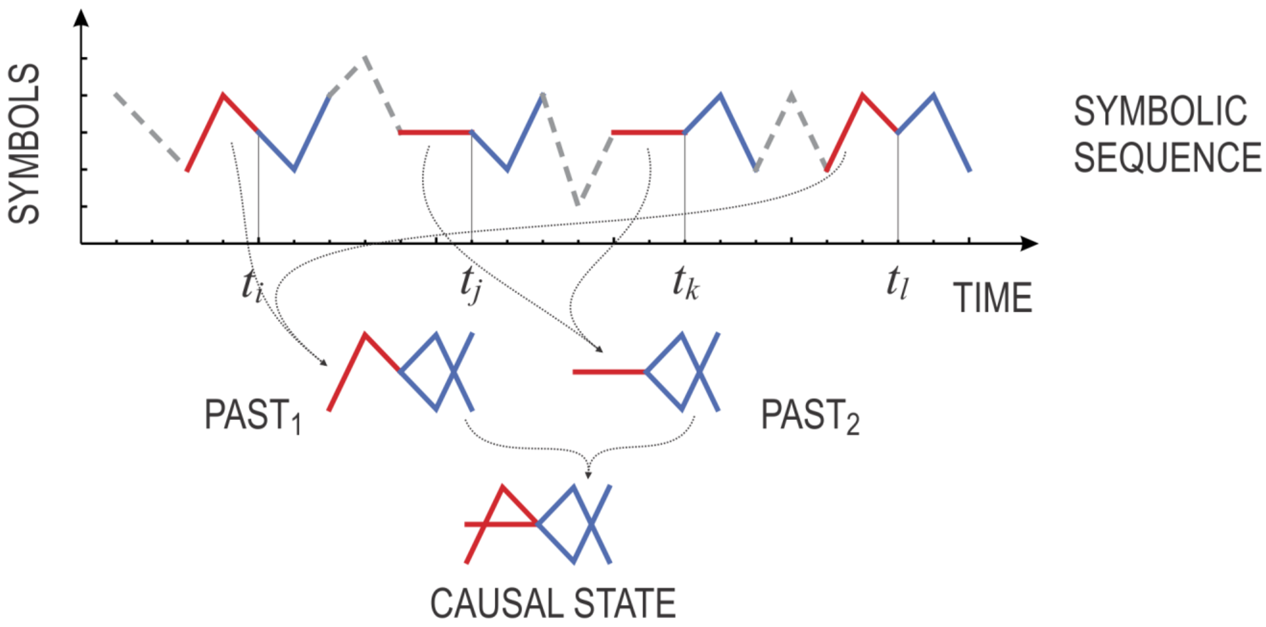
$$\overleftrightarrow{S} = \cdots S_{-1} S_0 S_1 S_2 \cdots \qquad (1)$$

- consisting of random variables S_i, where each S_i may take a symbol s_i drawn from an alphabet, a finite countable set A of size k.
- At any time t, the sequence can be divided into a past $\overleftarrow{S}$ and a future $\overrightarrow{S}$
- A causal state is then defined as a set of pasts that have the same distribution of conditional probabilities for all possible futures. Formally, causal states are members of the range of the function ε, which maps from histories to sets of histories:

$$\varepsilon\left(\overleftarrow{s}\right) = \{\overleftarrow{s}' \mid P(\overrightarrow{S} = \overrightarrow{s} \mid \overleftarrow{S} = \overleftarrow{s}) = P(\overrightarrow{S} = \overrightarrow{s} \mid \overleftarrow{S} = \overleftarrow{s}'), \text{ for all } \overrightarrow{s} \in \overrightarrow{S},\ \overleftarrow{s}' \in \overleftarrow{S}\} \qquad (2)$$

CAUSAL STATED

- Each causal state S_i is defined by its index *i*, a set of pasts $\{\overleftarrow{s} \in S_i\}$, and a conditional distribution over futures $P(\vec{S} \mid \overleftarrow{s}), \overleftarrow{s} \in S_i$.



ε-MACHINES

- A causal state and the next observed symbol define a new causal state. Therefore, transitions exist between causal states.
- Moreover, a causal state defines the probability of the next observed value (future sequence of length 1):

$$T_{ij}^{(s)} \equiv P\left(S' = S_j, \vec{S}^1 = s \middle| S = S_i\right) \tag{3}$$

- $T_{ij}^{(s)}$ is the probability of the process creating symbol *s* when moving from causal state S_i to S_j.
- Together, causal states and transition probabilities define an automaton called **ε-machine**.
- ε-machines are unique and maximally efficient models.

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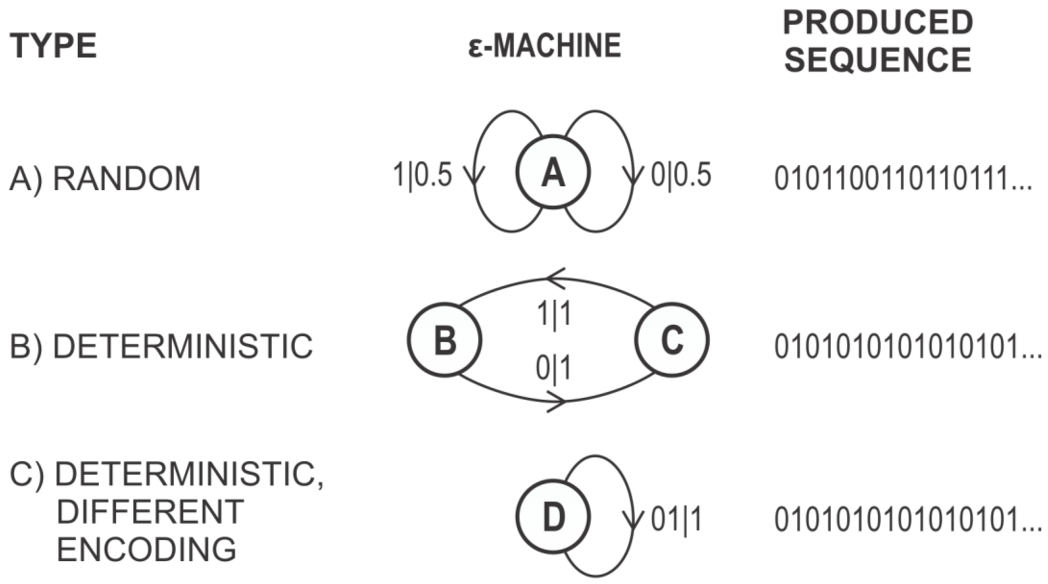
ε-MACHINES EXAMPLES



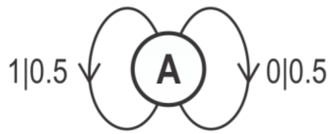
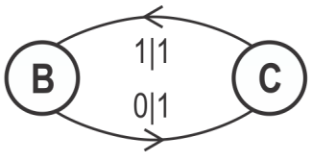
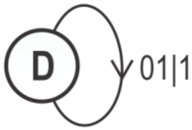
STATISTICAL COMPLEXITY

- Statistical complexity C_μ is defined as the Shannon entropy over the distribution of causal states. $P(S_i)$ denotes the probability of the ε-machine being in state S_i.

$$C_\mu = -\sum_{S_i \in S} P(S_i)\log_2 P(S_i) \tag{4}$$

- Statistical complexity C_μ is the **average amount of historical memory stored in the process**, in the units of bits.
- In a complex process, more information about the past is stored internally.
- Prediction therefore requires more information and is, in turn, more difficult.

EXAMPLE STATISTICAL COMPLEXITIES

TYPE	ε-MACHINE	PRODUCED SEQUENCE	STATISTICAL COMPLEXITY
A) RANDOM		0101100110110111...	0
B) DETERMINISTIC		0101010101010101...	1
C) DETERMINISTIC, DIFFERENT ENCODING		0101010101010101...	0

EXCESS ENTROPY AND EFFICIENCY OF PREDICTION

- Statistical complexity is an upper bound of excess entropy *E*, which is the mutual information of the process' past and future.

$$E = I(\overleftarrow{S}, \overrightarrow{S}) \leq C_\mu \quad (5)$$

- This allows for another interpretation:
  - The memory needed to perform an optimal prediction is greater or equal to the amount of information that the past provides about the future.
- In computational mechanics, a metric is proposed that helps guide the selection of the appropriate observation level. This metric is termed 'efficiency of prediction' (*e*) and is calculated as a ratio between excess entropy and statistical complexity.

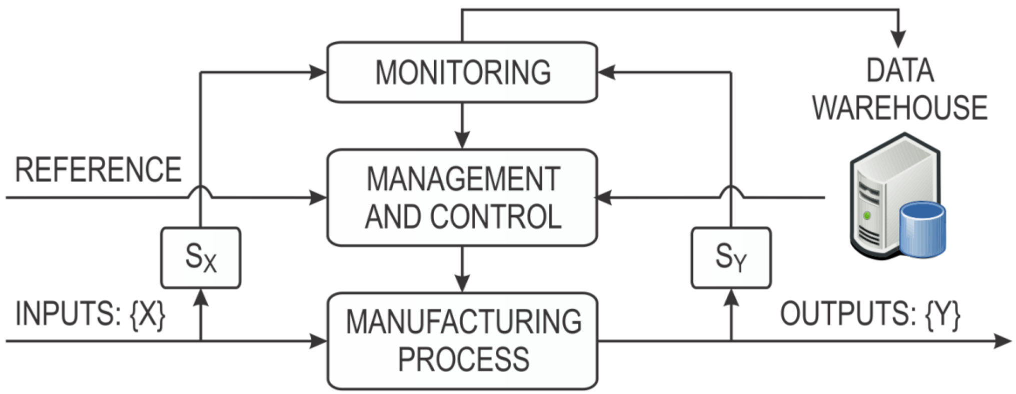
$$e = \frac{E}{C_\mu} \quad (6)$$

COMPUTATIONAL MECHANICS: SUMMARY

- The computational mechanics approach has a number of features that make it suitable for complexity analysis of manufacturing systems:
  - prediction centred
  - can be used without an underlying model
- To apply computational mechanics to manufacturing systems, a method is needed.

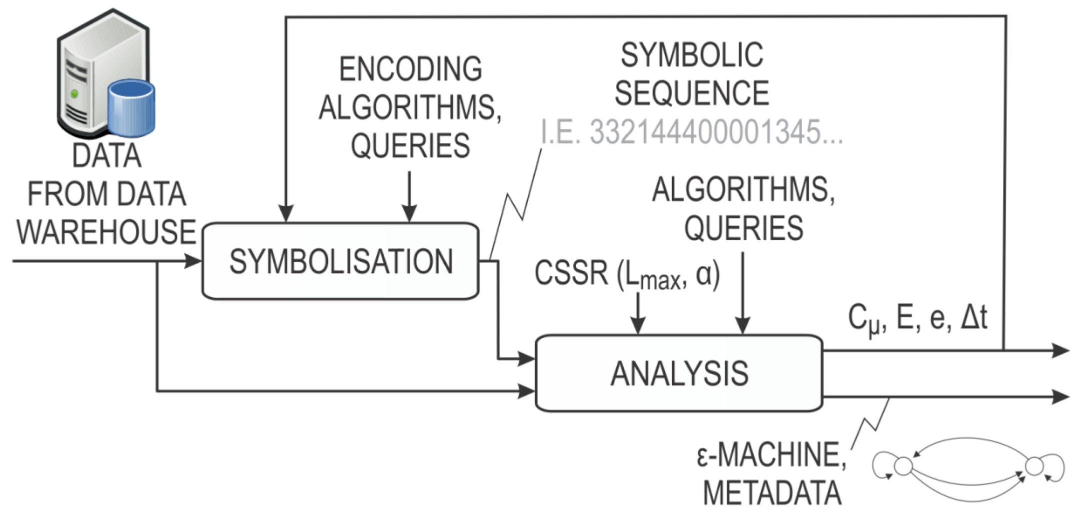
COMPLEXITY ASSESSMENT METHOD

- How can operational complexity be calculated from the observation of a manufacturing process?
- Information about inputs and outputs is saved in a data warehouse.



COMPLEXITY ASSESSMENT METHOD

- Symbolisation:
  - Δt – time interval
  - encoding function
- Analysis:
  - creation of ε-machines with CSSR algorithm [Shalizi 2004]
  - calculation of statistical complexity, excess entropy, and efficiency of prediction
- Symbolisation and analysis form a feedback loop:
  - Δt evaluation in light of efficiency of prediction



CASE STUDY: INTRODUCTION

- The method is applied in a case study of real industrial data.
- Case study overview:
  - serial production, 24h/day, 3 shifts
  - data acquired for 5 work centres (WC) over 24 months (October 2007 – October 2009)
  - 4 centres identical, 5th slightly different – all interchangeable
  - during the period, ~350,000 pieces were produced on average per work centre
  - production made use of a total of 75 different tools
- The acquired data contains information about each process cycle:
  - the WC,
  - the tool,
  - the time of production,
  - several process parameters.

CASE STUDY: METHOD

- Chosen time interval $\Delta t = 240$ s ($L_{max} = 6$). This was suggested by an analysis of the efficiency of prediction for different time intervals.

- The number of produced pieces during the time interval (between 0 and 5) is the basis for the encoding.

- Example symbolic sequence:
  - …332144400001345310000000041013454444344024434112544 4122332130341143144544451444034534444444444414444445 …

CASE STUDY: CHARACTERISTIC RESULTS

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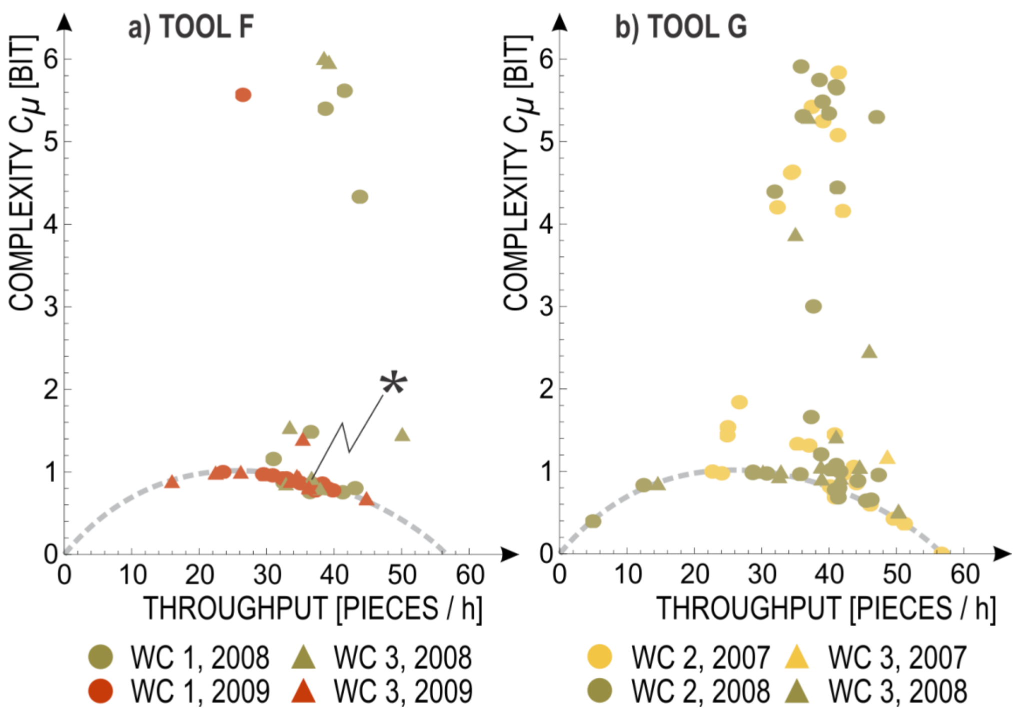
- C_μ(throughput) in relation to WC, tool, year of production, and lot. 'lot' is used to describe a period of continuous work.



Relation between complexity and throughput for 2 different tools

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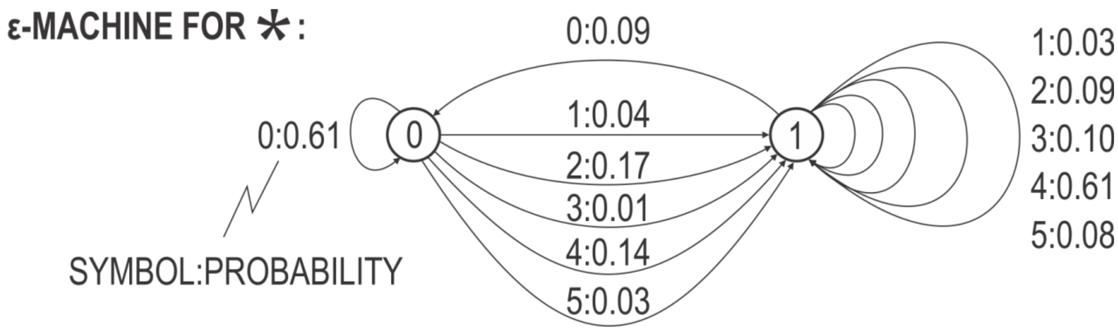
CASE STUDY: CHARACTERISTIC RESULTS (CONT.)

- Complexity value interpretation:
  - 1 bit – 2 levels: producing / not producing;

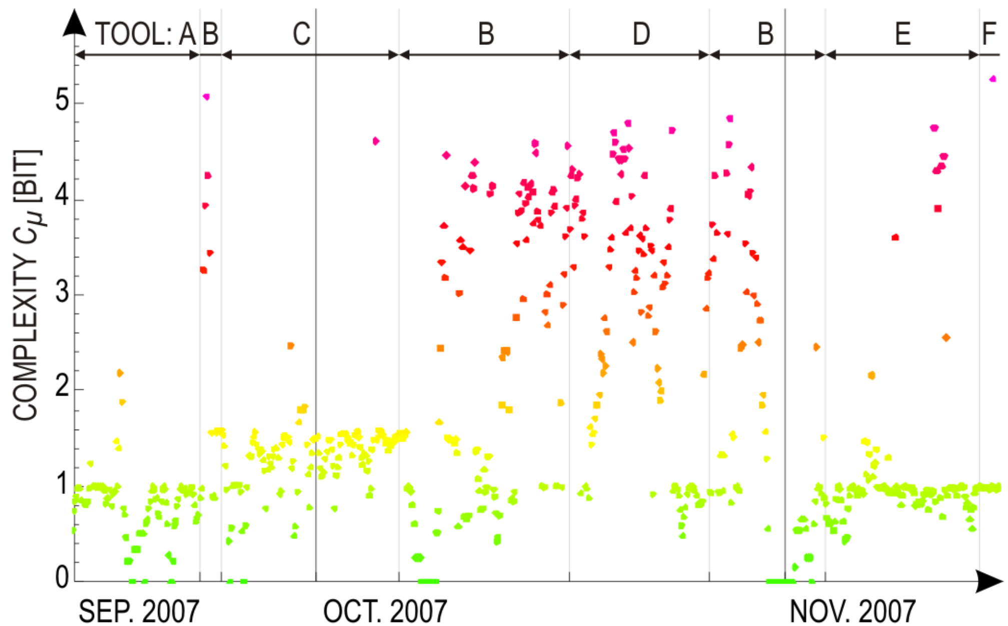


ε-machine for complexity of ~1bit

- Complexity is 1 bit for the vast majority of lots from year 2009. As shown by a preliminary analysis of the data, this may be the result of a significant decline in orders, which is itself a consequence of the global recession.

CASE STUDY: CHARACTERISTIC RESULTS (CONT.)

- Complexity of outputs of WC 1 as a function of time, starting from the beginning of data acquisition for the WC. The complexity is calculated for a time window of 256 sequential time intervals.
- Complexity levels are influenced by the tool used, being ~1 bit for tools A, E, and F, ~1.5 bit for tool C, and higher for tools B and D.



Relation between complexity and time for WC 1.

CONCLUSIONS

- The computational mechanics approach towards complexity is based on the hypothesis that the harder a process is to predict, the more complex it is.
- The developed method for complexity assessment in manufacturing systems not only quantifies complexity in a meaningful way, but also elaborates why a process is complex through analysis of the generated ε-machine.
- The results of the case study show that the prevalent factor in operational complexity is the tool used. This implies that the tool geometry and the consequent process knowledge and management are important factors and should be targeted in order to reduce complexity.

CONCLUSIONS (CONT.)

- As seen from the relation between the complexity and the throughput, complexity should be lowered, but not in a way that would decrease the throughput. An important result is that complexity of 1 bit or less can be achieved, signifying that the best predictive description in this type of production is statistical. This can increase the management’s confidence in statistical forecasts.
- In contrast to the tool, the work centre was not found to be a factor in this case. As the work centres were identical, this implies that the effect of different operators is best described statistically and thus has no direct influence on complexity.
- As a further research step, an analysis of the connection between structural and operational complexity needs to be performed, focusing on the influence of tool geometry and process management on complexity.

PART 3: LEARNING LOOP IN A DIE CASTING WORK SYSTEM

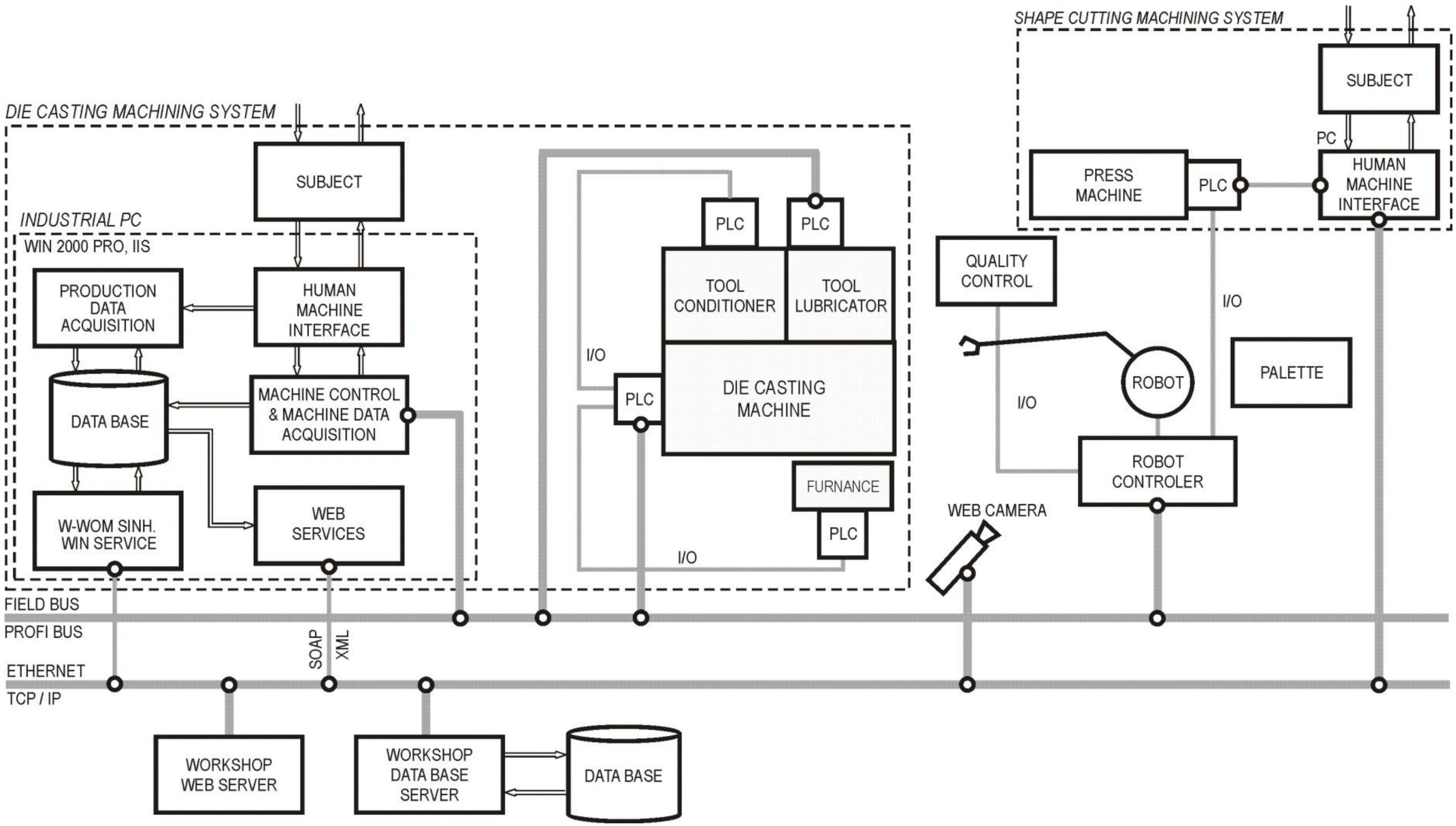
INTRODUCTION

- Advantages of collaborative business forms lie, among other, in sharing of information, knowledge, resources, competencies and risks.
- Knowledge is recognized as a major success factor for competitiveness and growth and is becoming one of the major assets in the modern global economy.
- Manufacturing data collected during operations contain valuable information and knowledge that could be integrated within the manufacturing system to improve decision making and enhance productivity.
- Knowledge discovery in databases (KDD) and data mining (DM) have become extremely important tools in realizing the objective of intelligent and automated data analysis.

KNOWLEDGE DISCOVERY AND DATA MINING

- Knowledge discovery process is defined as a nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data.
- Data mining is a particular step in the process of knowledge discovery, involving application of specific algorithms for extracting patterns (models) from data.
- The aim of data mining is to make sense of large amounts of mostly unsupervised data, in a particular domain.
- The additional steps in the knowledge discovery process, such as data preparation, data cleaning, data selection, incorporation of appropriate prior knowledge and proper interpretation of the results of mining, ensure that useful knowledge is derived from data.

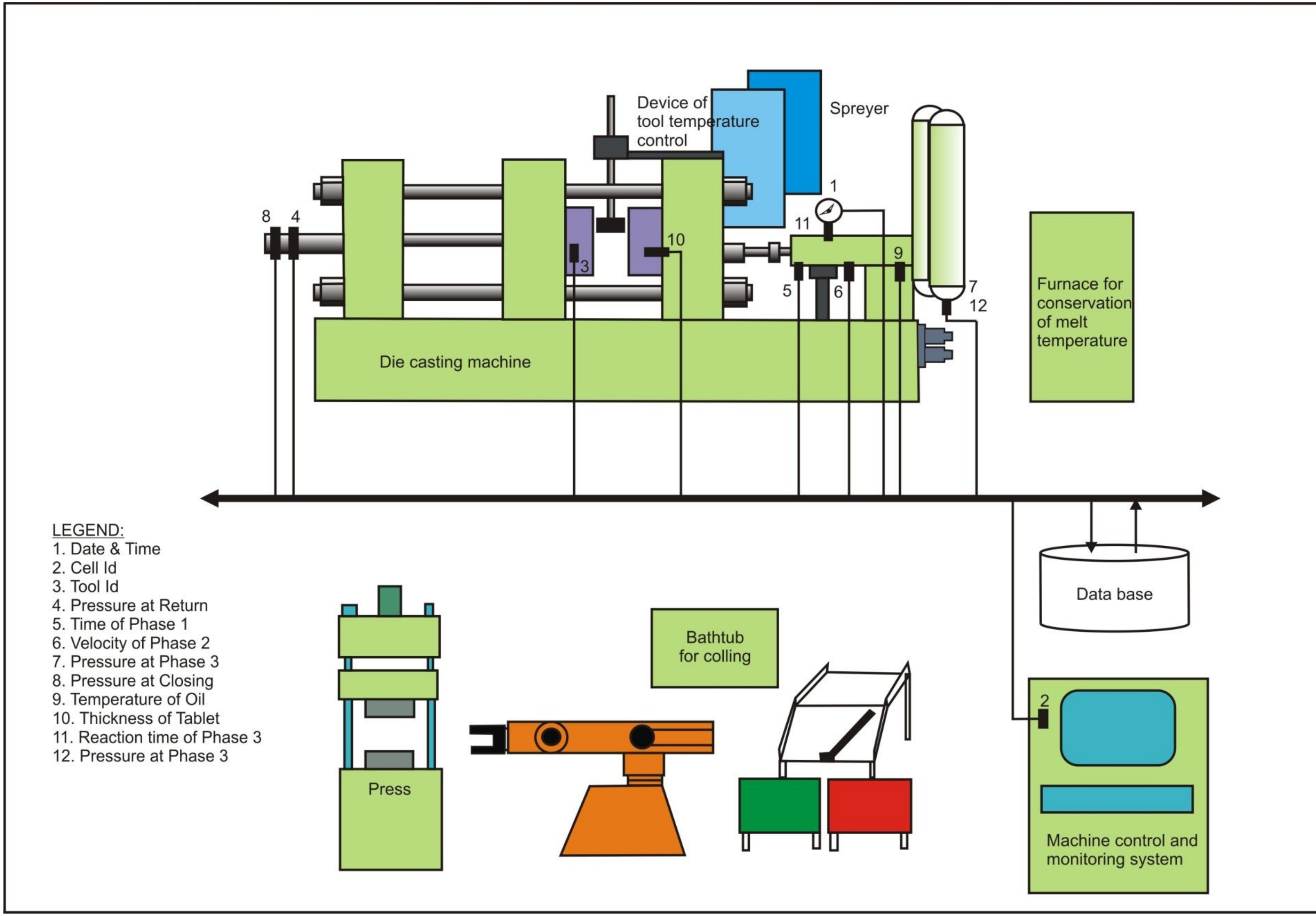
COCAST



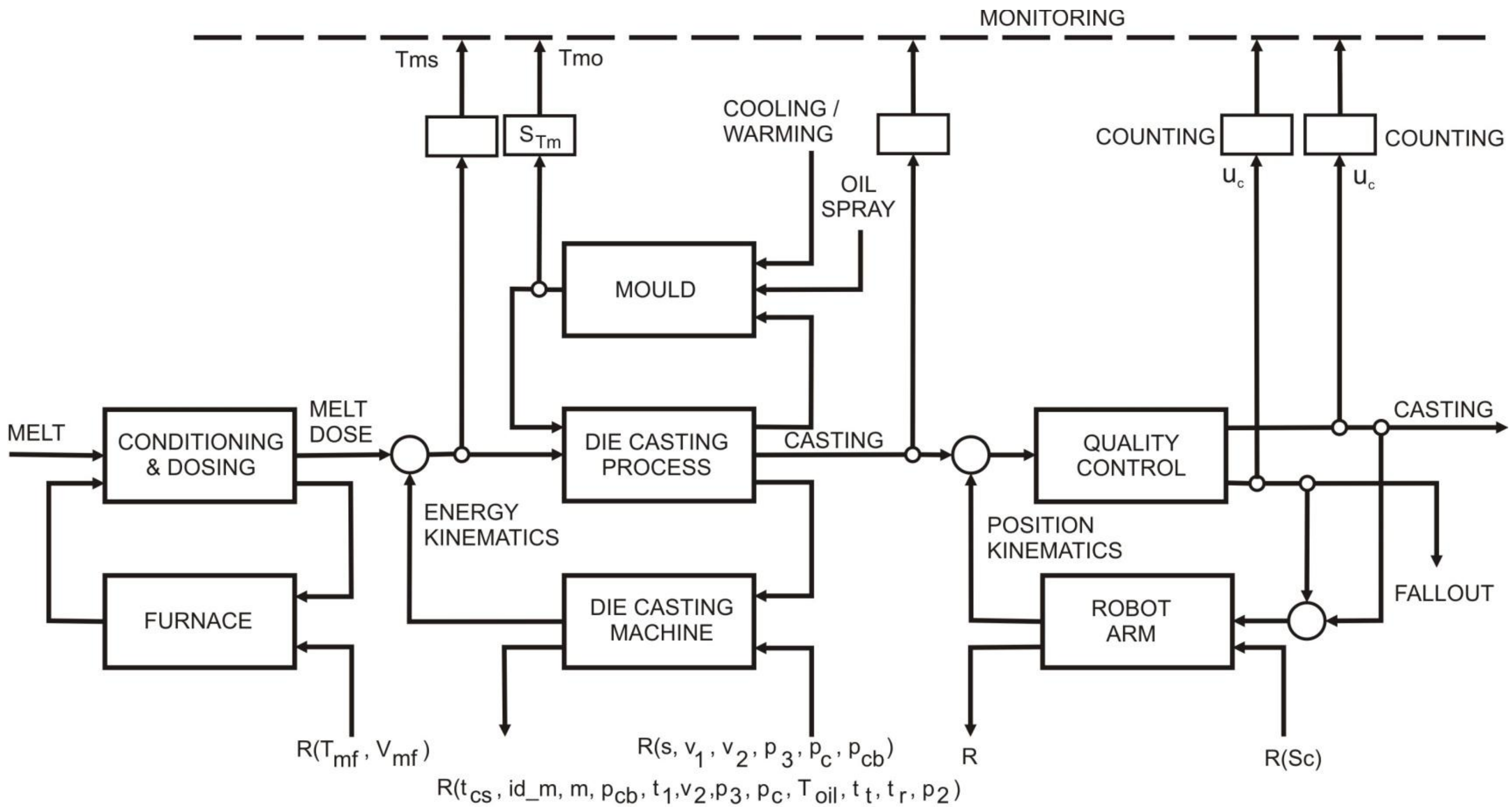
Architecture of the CoCAST system for web based monitoring of a die-casting cell

COCAST (CONT.)

High pressure die casting foundry with several die casting cells



Measuring points of the input and output process parameters in a die casting cell



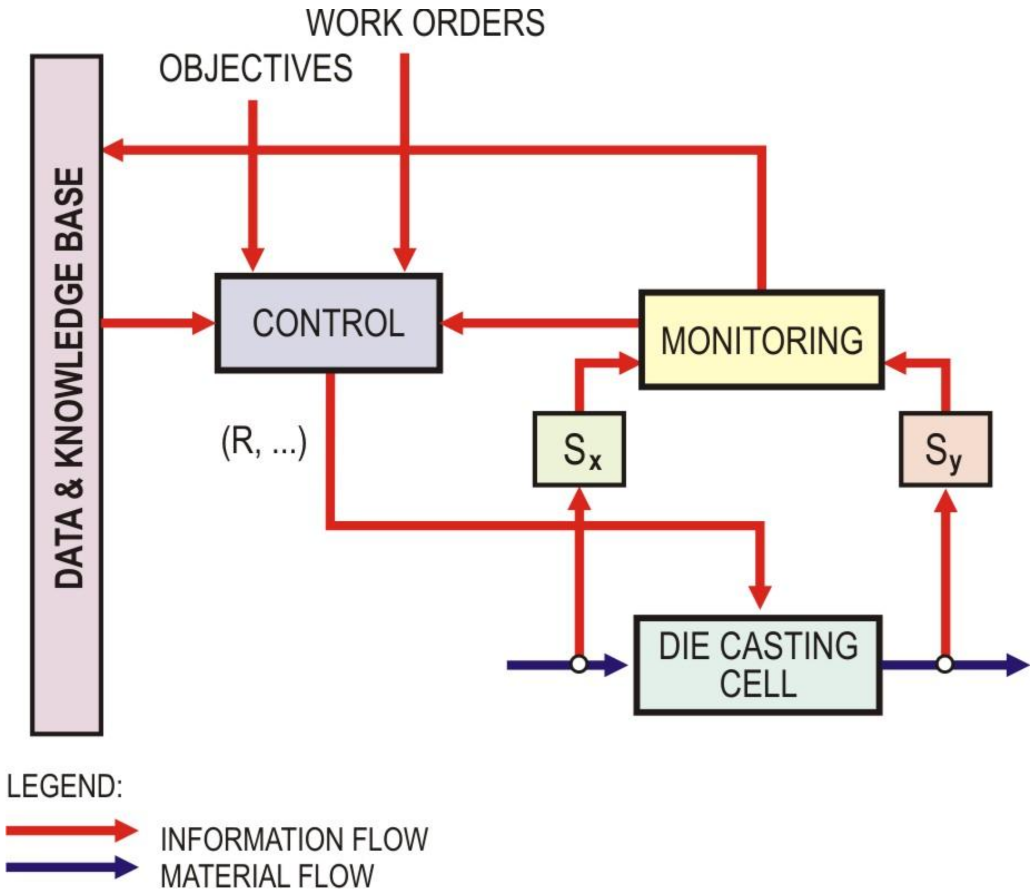
LEGEND:

T_{mf} - Melt temperature in furnace
V_{mf} - Melt volume in furnace
T_{ms} - Melt temperature in sleeve
T_{mo} - Mould temperature
t_{cs} - Cycle start times
id_m - ID machine
m - Mould
p_{cb} - Maximal pressure of coming back (mould opening)
t_1 - 1st phase time
v_2 - 2nd phase piston speed

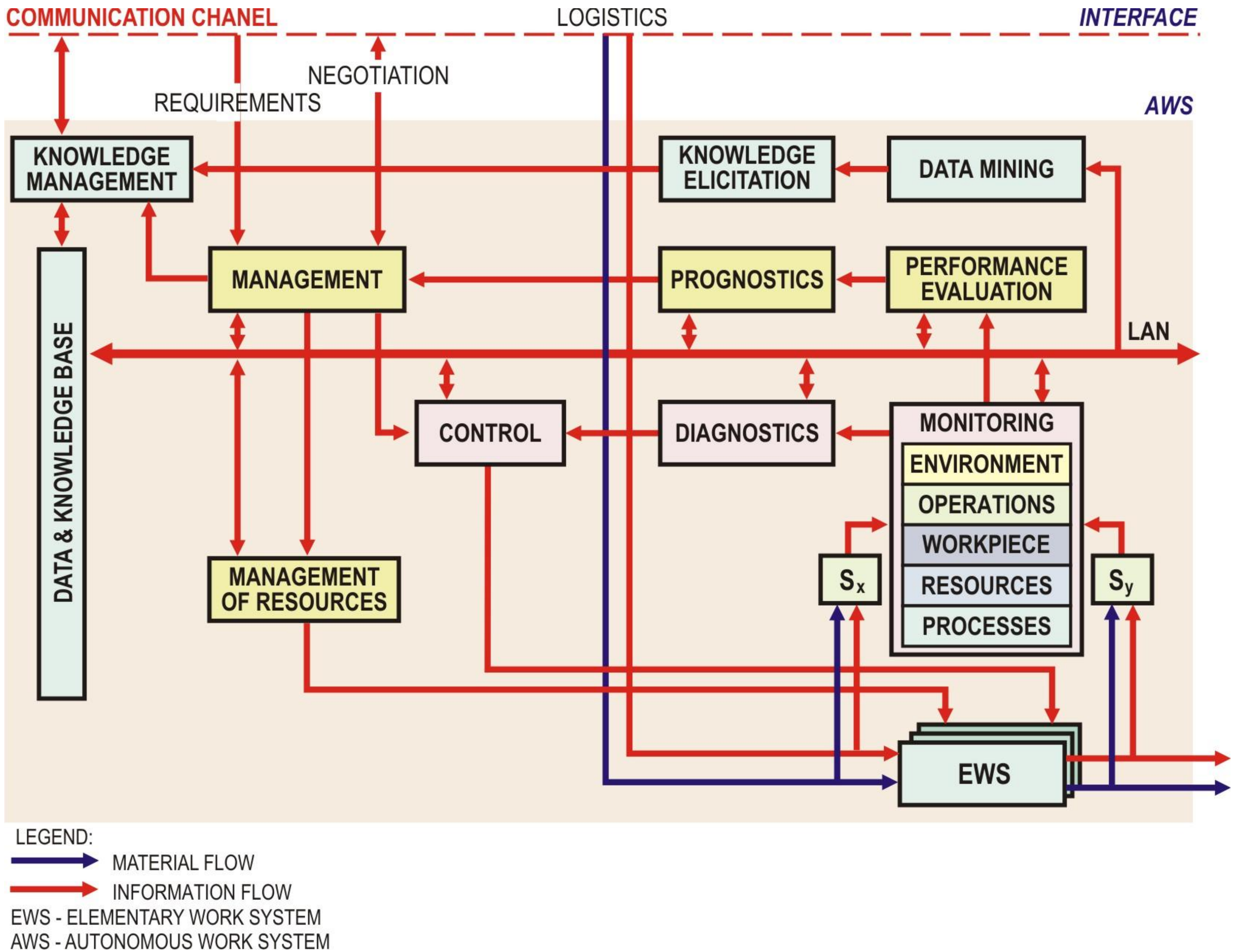
p_3 - 3th phase maximum pressure
p_c - Closing maximum pressure
T_{oil} - Oil temperature
t_t - Thickness of the tablets
t_r - Reaction time of the 3rd phase
p_2 - 2nd phase pressure
s - Stroke
v_1 - 1st phase piston speed
Sc - Cycle start

Process block diagram of the die-casting cell

MONITORING



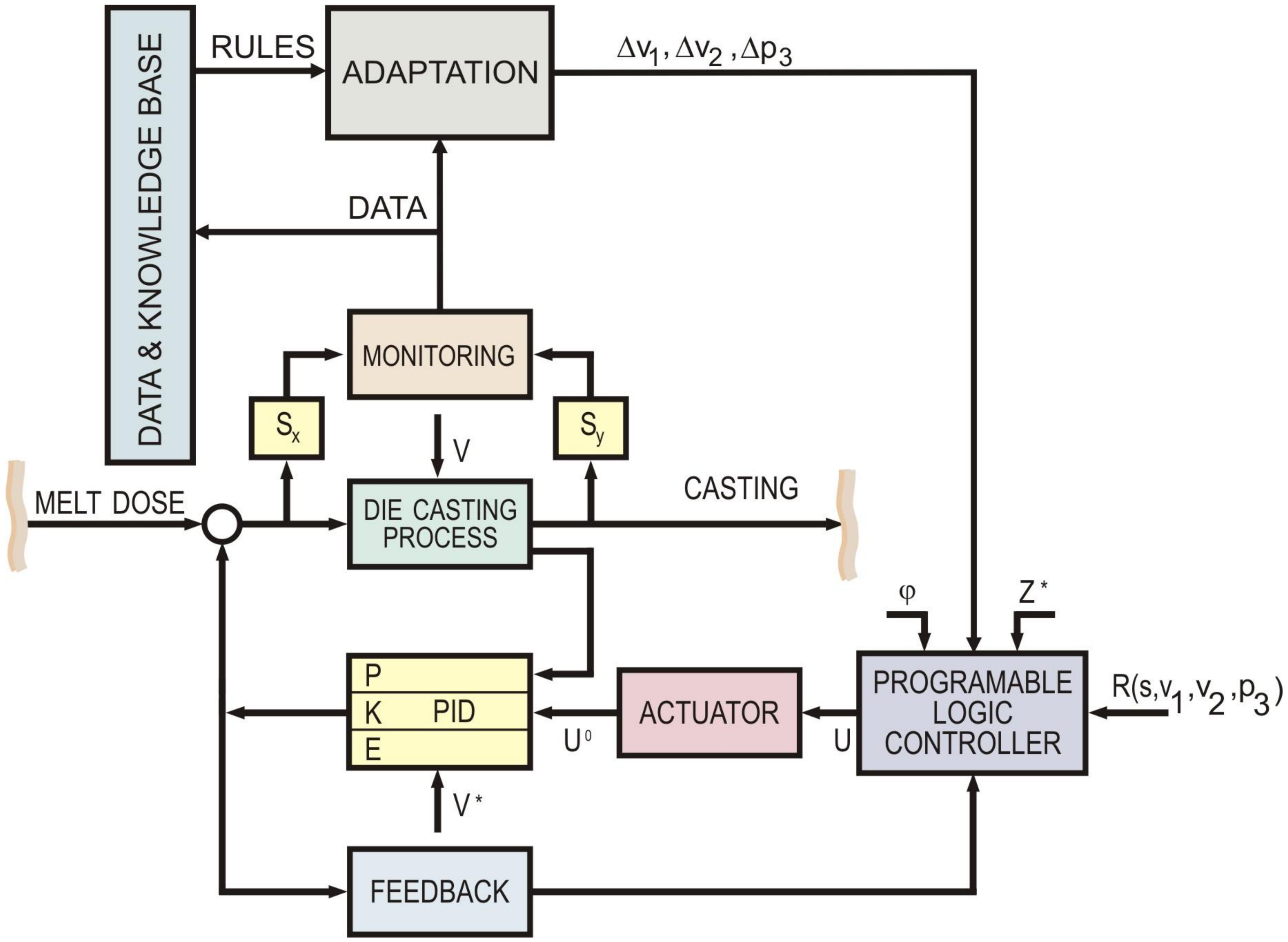
Real time control and monitoring of a die casting cell, and data acquisition



Model of a Self-learning autonomous work system - SL.AWS

LEARNING LOOP IN SL.AWS

- The learning loop is founded on the database where the data, which are collected in the real-time loop, are stored.
- The database contains data on processes, resources, workpieces, operations and environment, which represent input for data mining.
- The results of data mining are used for knowledge elicitation.
- Newly discovered knowledge is then stored in the D&K base and managed for further use.
- The new knowledge is used for adaptive process control as well as for interactive decision support during set up procedures, etc. It can also be used for forecasting of malfunctions, maintenance, etc.
- The knowledge can also be opened by the knowledge management to other systems in the network.
- The learning loop enables that the autonomous work system continuously learns on experiences from operations that are performed in the system and, on this basis, continuously improves and evolves.



Adaptive control of the die casting process based on discovered knowledge

DATA STRUCTURE

- During operations, each die casting process cycle is recorded. Each cycle record consists of values related to the attributes:

  1. Cell Id
  2. Tool Id
  3. Cycle Consequent Number
  4. Date & Time
  5. Pressure at Return
  6. Time of Phase 1
  7. Velocity of Phase 2
  8. Pressure at Phase 3
  9. Pressure at Closing
  10. Temperature of Oil
  11. Thickness of Tablet

IMPLEMENTATION OF DATA MINING METHODS

- Weka, open source software from The University of Waikato, is selected for performing data mining
- Weka is a collection of machine learning algorithms.
- The CoCAST database was examined with several Weka algorithms.
- The objective was to obtain a knowledge model, which would well correspond to the nature of die casting process data and would enable prediction and adaptive control of the process.
- For knowledge discovery two methods were used :
    1. Clustering, a descriptive data mining method, and
    2. Classification with rule algorithms, a predictive data mining method.

KNOWLEDGE MODEL

- For learning and building of a knowledge model the weka.classifiers.rules.M5Rules algorithm is applied.
- The algorithm provides a set of IF ... THAN ... rules, which forms the knowledge model.
- In case of the die casting process rules correlating input process parameters with output process parameters have to be extracted.
- The generic form of the rules for calculation of the three input parameters, i.e. Time of Phase 1, Velocity of Phase 2, and Pressure at Phase 3 are given in Eq. 1-3.
- This set of rules forms a knowledge meta-model and is universal for all die casting cells.

KNOWLEDGE META-MODEL FOR DIE CASTING

$$\begin{aligned}\text{Time\_of\_Phase\_1} = {} & w_{11}\text{Pressure\_at\_Return} + \\ & + w_{12}\text{Velocity\_of\_Phase\_2} + w_{13}\text{Pressure\_at\_Phase\_3} + \\ & + w_{14}\text{Pressure\_at\_Closing} + w_{15}\text{Temperature\_of\_Oil} + \\ & + w_{16}\text{Thickness\_of\_Tablet} + w_{10}\end{aligned} \qquad \textbf{Eq. 1}$$

$$\begin{aligned}\text{Velocity\_of\_Phase\_2} = {} & w_{21}\text{Pressure\_at\_Return} + \\ & + w_{22}\text{Time\_of\_Phase\_1} + w_{23}\text{Pressure\_at\_Phase\_3} + \\ & + w_{24}\text{Pressure\_at\_Closing} + w_{25}\text{Temperature\_of\_Oil} + \\ & + w_{26}\text{Tickness\_of\_Tablet} + w_{20}\end{aligned} \qquad \textbf{Eq. 2}$$

$$\begin{aligned}\text{Pressure\_at\_Phase\_3} = {} & w_{31}\text{Pressure\_at\_Return} + \\ & + w_{32}\text{Time\_of\_Phase\_1} + w_{33}\text{Velocity\_of\_Phase\_2} + \\ & + w_{34}\text{Pressure\_at\_Closing} + w_{35}\text{Temperature\_of\_Oil} + \\ & + w_{36}\text{Thickness\_of\_Tablet} + w_{30}\end{aligned} \qquad \textbf{Eq. 3}$$

CASE STUDY

- For the illustration of the concept a portion of data was extracted from the CoCAST database.
- The selected data match to die casting operations related to a particular batch. The batch corresponds to production of a certain casting with a particular tool on a particular die casting cell.
- Such dataset represents a basic learning unit.
- The batch was produced over a period of two years and a half in several lots with several shorter or longer interruptions among them.
- The investigated dataset is composed of 56.225 instances (records).

CASE STUDY (CONT.)

- It is to be pointed out that the instances were recorded only if the whole die casting cycle was successfully performed and resulted in a casting. In other cases appropriate alarm messages were recorded.
- The selected dataset was processed within the Weka environment according to the knowledge discovery steps.
- After the data cleaning the remaining dataset includes 56.047 instances and 7 attributes out of 11.

CASE STUDY (CONT.)

Selected attributes					Statistic values			
Name	Type	Missing	Distinct	Unique	Minimum	Maximum	Mean	StdDev
Time of Phase 1	Numeric	0 (0%)	904	98 (0%)	1337	3211	1828,02	160,70
Velocity of Phase 2	Numeric	0 (0%)	13196	5.258 (9%)	1,40	3,00	2,57	0,46
Pressure at Phase 3	Numeric	0 (0%)	13	1 (0%)	354,60	370,37	359,11	6,69
Pressure at Return	Numeric	0 (0%)	3373	407 (1%)	19,82	121,99	38,10	21,24
Pressure at Closing	Numeric	0 (0%)	40735	29.868 (53%)	85,06	100,00	94,86	3,07
Temperature of Oil	Numeric	0 (0%)	1396	109 (0%)	24,68	48,06	38,09	3,62
Thickness of Tablet	Numeric	0 (0%)	221	25 (0%)	0	33,90	15,35	9,65

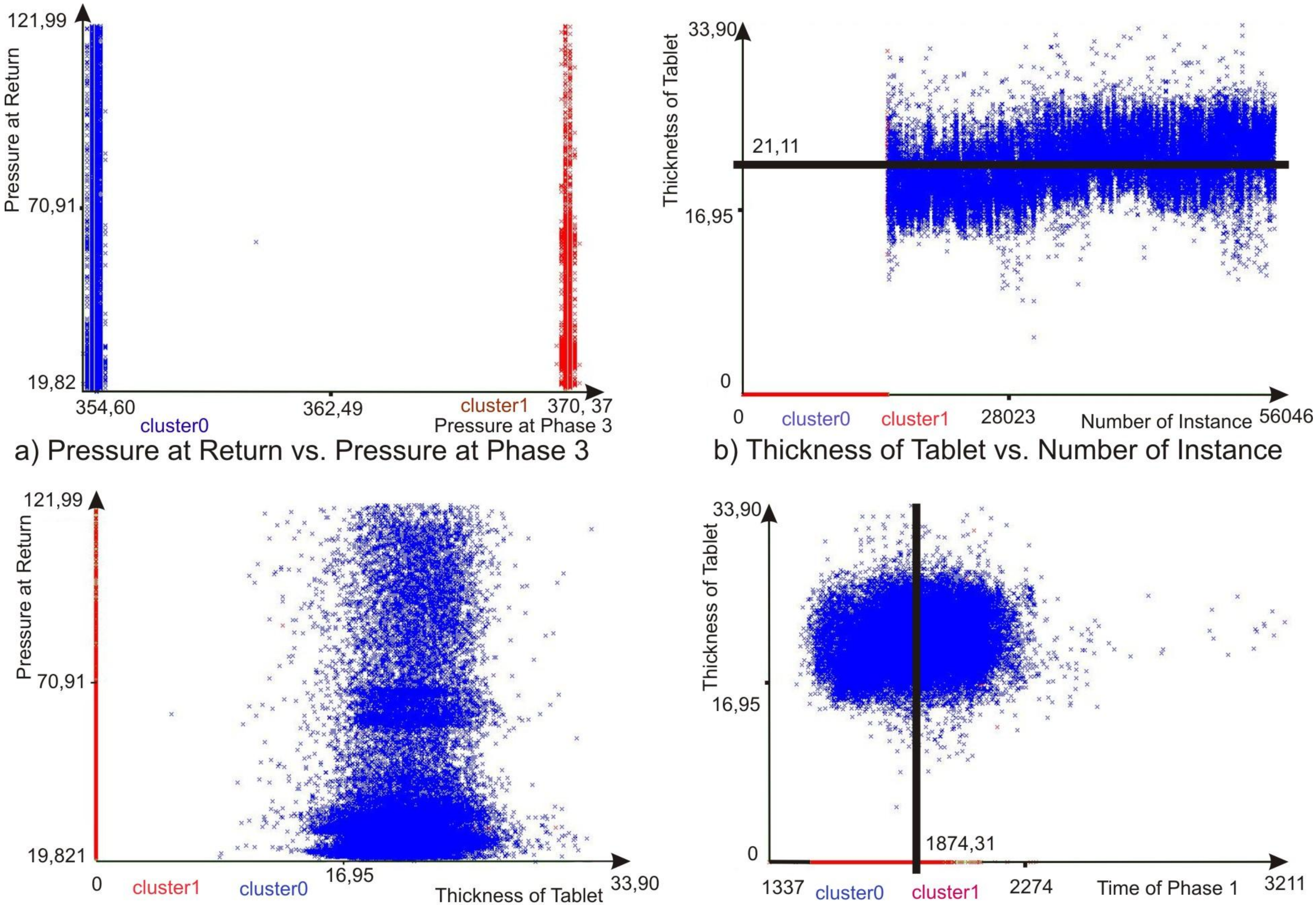
Statistic values of the selected atributes

CASE STUDY (CONT.)

- In order to get an impression and overview over the data, the clustering algorithm clusterers.Simple.KMeans was applied at first.
- The centroids thus indicate the central value of a cluster around which the instances belonging to the cluster are being distributed.

Attribute	Full Data 56047 (100%)	Cluster 0 40719 (73%)	Cluster 1 15328 (27%)
Time of Phase 1	1828,02	1874,31	1705,04
Velocity of Phase 2	2,57	2,84	1,86
Pressure at Phase 3	359,11	355,00	370,00
Pressure at Return	38,10	38,27	37,64
Pressure at Closing	94,85	94,73	95,18
Temperature of Oil	38,09	37,21	40,43
Thickness of Tablet	15,35	21,11	0,07

Cluster centroids



a) Pressure at Return vs. Pressure at Phase 3

b) Thickness of Tablet vs. Number of Instance

c) Pressure at Return vs. Thickness of Tablet

d) Thickness of Tablet vs. Time of Phase 1

Visualization of parameters and data clusters

CASE STUDY (CONT.)

- As we can see, the use of data mining and knowledge discovery software provides a new insight into the die casting process and its characteristics.
- For adaptive control another type of knowledge is needed.
- It has to be structured in a set of rules.
- For the die casting case the weka.classifiers.rules.M5Rules algorithm turned to be the most suitable one.

CASE STUDY (CONT.)

	Time of Phase 1	Velocity of Phase 2	Pressure at Phase 3
Number of Rules	136	182	9
Time to build the model	3237,28 sec	5700,42 sec	8,05 sec
Correlation coefficient	0,79	0,99	1,00
Mean absolute error	67,56	0,04	0,07
Root mean squared error	98,86	0,07	0,17
Relative absolute error	50,70%	9,51%	1,26%
Root relative squared error	61,52%	15,91%	2,60%
Total Number of Instances	56047	56047	56047

Cross-validation of models

CASE STUDY (CONT.)

- Consider that the objective of adaptive control would be more narrow distribution function dispersed around the centroid value. For the centroid values one can take the values calculated as the centroids of Cluster 0, which is the most significant cluster.
- Base on this assumption, the goal values for the process parameters would be:
  - Pressure_at_Return = 38,27 bar
  - Time_of_Phase_1 = 1874,31 ms
  - Velocity_of_Phase_2 = 2,84 m/s
  - Pressure_at_Phase_3 = 355 bar
  - Pressure_at_Closing = 94,73 bar
  - Temperature_of_Oil = 37,21 oC
  - Thickness_of_Tablet = 21,11 mm

CASE STUDY (CONT.)

- The rule set and the goal values form the knowledge model for the particular case.
- Let us now consider how the knowledge model can be applied for adaptive process control. In order to calculate the new reference values for the input process parameters for the next process cycle the values of the parameters of the last process cycle have to be known.
- These dictate selection of the appropriate rules, which are then used for the calculation of the new reference values for
  - Time_of_Phase_1
  - Velocity_of_Phase_2
  - Pressure_at_Phase_3

CASE STUDY (CONT.)

- Let us assume, that the measured values of the last process cycle are:
    - Pressure_at_Return = 90,10 bar
    - Time_of_Phase_1 = 1905 ms
    - Velocity_of_Phase_2 = 2,88 m/s
    - Pressure_at_Phase_3 = 355,04 bar
    - Pressure_at_Closing = 96,67 bar
    - Temperature_of_Oil = 37,93 oC
    - Thickness_of_Tablet = 20,60 mm
- Now, one can start to select the appropriate rules from the rule set.
- Selection of an appropriate rule is performed by verification of the conditional part of a rule.

CASE STUDY (CONT.)

- For example, the conditional part of Rule 1 for Time_of_Phase_1 states:

  IF

  Thickness_of_Tablet > 6,85
  Pressure_at_Return <= 32,19
  Pressure_at_Closing <= 92,21
  Temperature_of_Oil > 39,85
  Velocity_of_Phase_2 <= 2,92
- One can see at once that the conditional part of the rule is not satisfied because the following conditions are not satisfied:
  - Pressure_at_Return should be smaller of equal to 32,19, but in our case it is greater (90,10);
  - Pressure_at_Closing should be smaller of equal to 92,21, but in our case it is greater (96,67);
  - Temperature_of_Oil should be greater to 39,85, but in our case it is smaller (37,93).

CASE STUDY (CONT.)

- The first rule in the rule set, which conditional part is completely satisfied, is Rule 25. The action part of the rule gives the formula for calculation of the Time_of_Phase_1:

Time_of_Phase_1 =

0,5689 * Pressure_at_Return + 1036,8366 * Velocity_of_Phase_2 +
+ 67,4787 * Pressure_at_Phase_3 – 0,0899 * Pressure_at_Closing -
- 15,4466 * Temperature_of_Oil + 20,4164 * Thickness_of_Tablet -
- 24902,1816 **Eq. 4**

- Now we can substitute the variables with the goal values and we obtain the final result for the process parameter

Time_of_Phase_1 = 1.825,35 ms,

which can be considered for adaptive control.

CASE STUDY (CONT.)

- Analogously, for calculation of Velocity_of_Phase_2, the first rule, which conditional part correspond to the actual values of process parameters, is Rule 7:

  IF

  Pressure_of_Phase_3 <= 362,49
  Temperature_of_Oil <= 38,56
  Time_of_Phase_1 > 1763,50
  Time_of_Phase_1 <= 1922,50
  Temperature_of_Oil > 36,06
  Pressure_of_Closing > 94,10
  Pressure_of_Closing <= 97,22
  Thickness_of_Tablet <= 22,25
  Pressure_of_Closing > 94,98

CASE STUDY (CONT.)

THEN

Velocity_of_Phase_2 =

= 0 * Pressure_at_Return - 0 * Time_of_Phase_1+
+ 0,0001 * Pressure_at_Phase_3 +
+ 0,0002 * Pressure_of_Closing +
+ 0,0003 * Temperature_of_Oil – 0,0004 *
* Thickness_of_Tablet +
+ 2,9162 = 2,97 **Eq.5**

- Hence, the calculated reference value for the next cycle for
  Velocity_of_Phase_2 = 2,97 m/s,
  which is very close to the goal value (2,84 m/s).

CASE STUDY (CONT.)

- The last calculation is done for Pressure_at_Phase_3. Here several rules in the rule set fit the actual values. So the first one that fits the condition is selected, which is Rule 1:

IF

Thickness_of_Tablet > 2,60

Time_of_Phase 1 <= 2021,50

THEN

Pressure_at_Phase_3 =

= 0 * Pressure_at_Return+ 0 * Time_of_Phase_1 -

- 0,0029 * Velocity_of_Phase 2 - 0,0002 * Thickness_of_Tablet +

+ 355,02 = 355,09 Eq. 6

- So the calculated reference value for

Pressure_at_Phase_3 = 355,09 bar,

which again is very close to the goal value of 355,00 bar.

CONCLUSIONS

- The concept of a self-learning autonomous work system is introduced. It is based the concept of autonomous work systems.
- The self-learning AWS represents a potential building block of future intelligent adaptable manufacturing networks.
- Learning in AWS is introduced through a learning loop, which sets on the data & knowledge base and includes data mining, knowledge discovery and knowledge management.
- New discovered knowledge is stored in the data & knowledge base where it can be used for supporting decision making and adaptive process control.

CONCLUSIONS (CONT.)

- Hence, the learning feedback is established, which enables the work system to learn continuously on experiences form own operations.
- The concept of adaptive process control in die casting is presented as well. It is shown how new knowledge in form of rules can be applied for decrease of process variance and thus increase of product quality and productivity of operations.
- The presented approach is demonstrated in an industrial case study on a large set of production data. This illustration clearly indicates the feasibility of the approach.
- Further research will be oriented in the implementation of the adaptive control, as well as on issues of knowledge management in a manufacturing network.

PART 4: DEMONSTRATIONS

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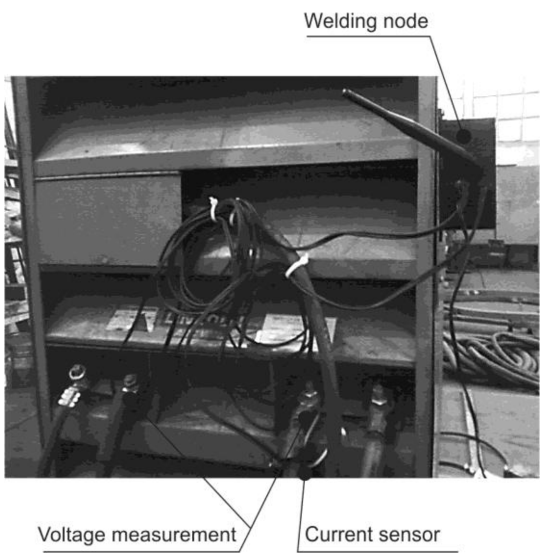
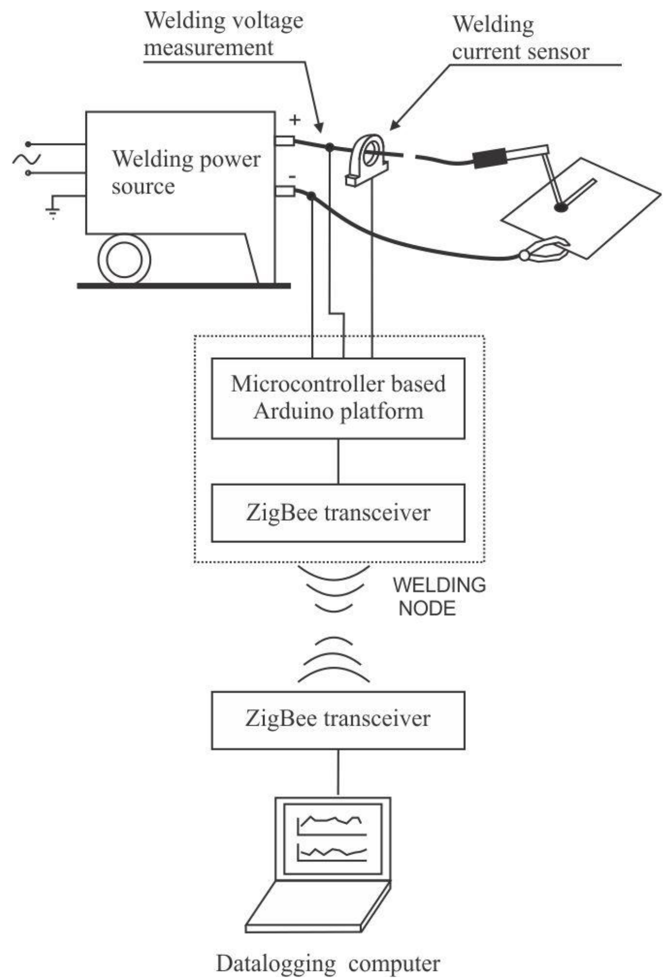
ONLINE MONITORING OF WELDING PARAMETERS

Courtesy of LitostrojPower d.o.o.

ONLINE MONITORING OF WELDING PARAMETERS (CONT.)



voltage	current	startDateTime	endDateTime
31.42	232.28	2011-07-12 09:07:43.000	2011-07-12 09:59:51.000
31.33	233.16	2011-07-12 11:02:47.000	2011-07-12 12:00:39.000
32.31	229.63	2011-07-12 12:11:14.000	2011-07-12 13:44:23.000
32.49	229.63	2011-07-12 13:50:48.000	2011-07-12 14:27:47.000
31.42	230.52	2011-07-13 07:48:40.000	2011-07-13 07:52:10.000
32.04	228.75	2011-07-13 07:58:28.000	2011-07-13 08:28:00.000
32.13	229.63	2011-07-13 08:38:01.000	2011-07-13 09:40:27.000
24.28	346.19	2011-07-13 10:50:32.000	2011-07-13 10:50:33.000
30.53	235.81	2011-07-13 10:50:33.000	2011-07-13 11:13:27.000
30.88	234.93	2011-07-13 11:15:24.000	2011-07-13 11:54:00.000



Schematic presentation of welding monitoring concept.

HYDROPOWER PLANT MONITORING AND CONTROL

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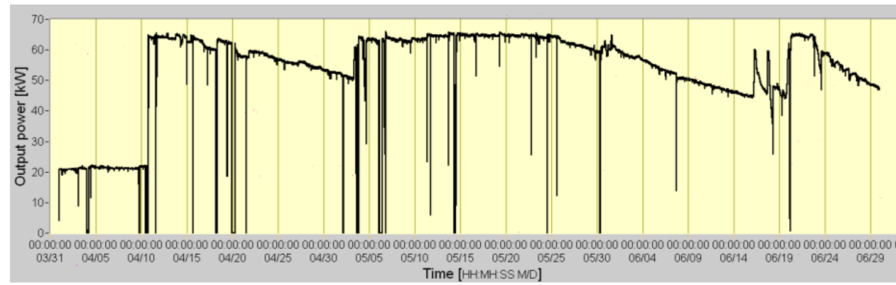

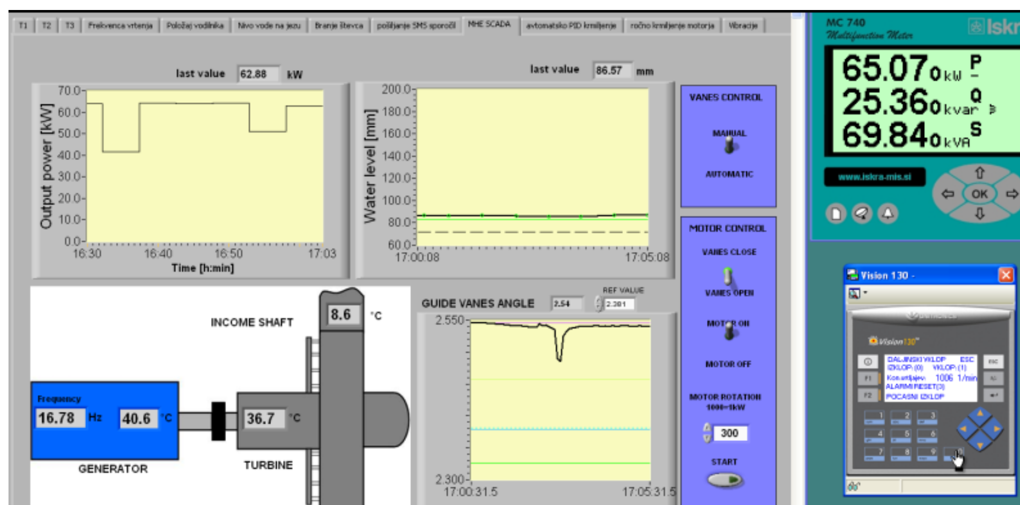

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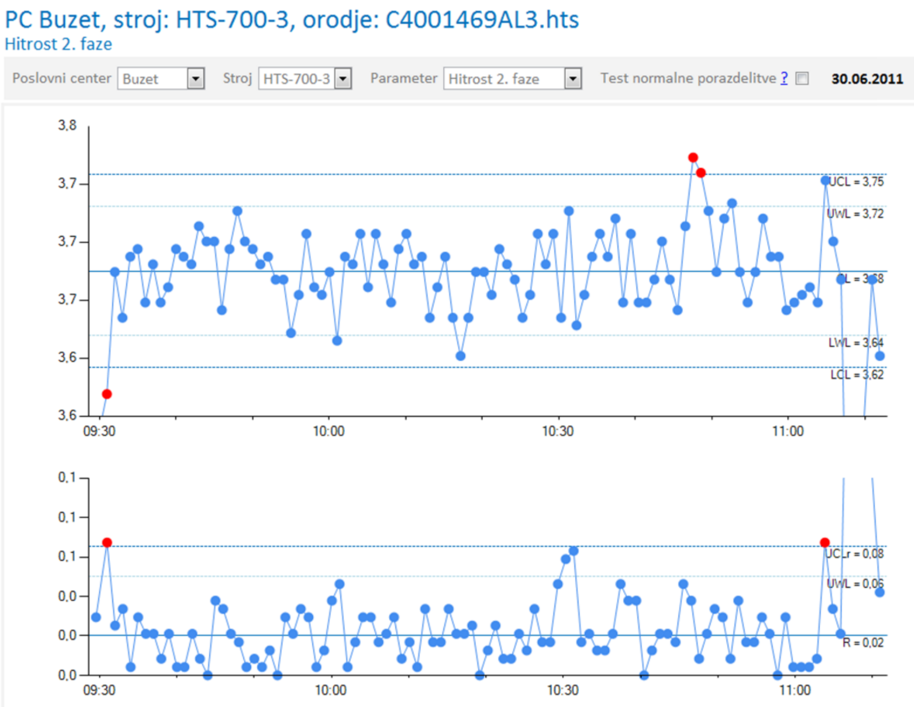
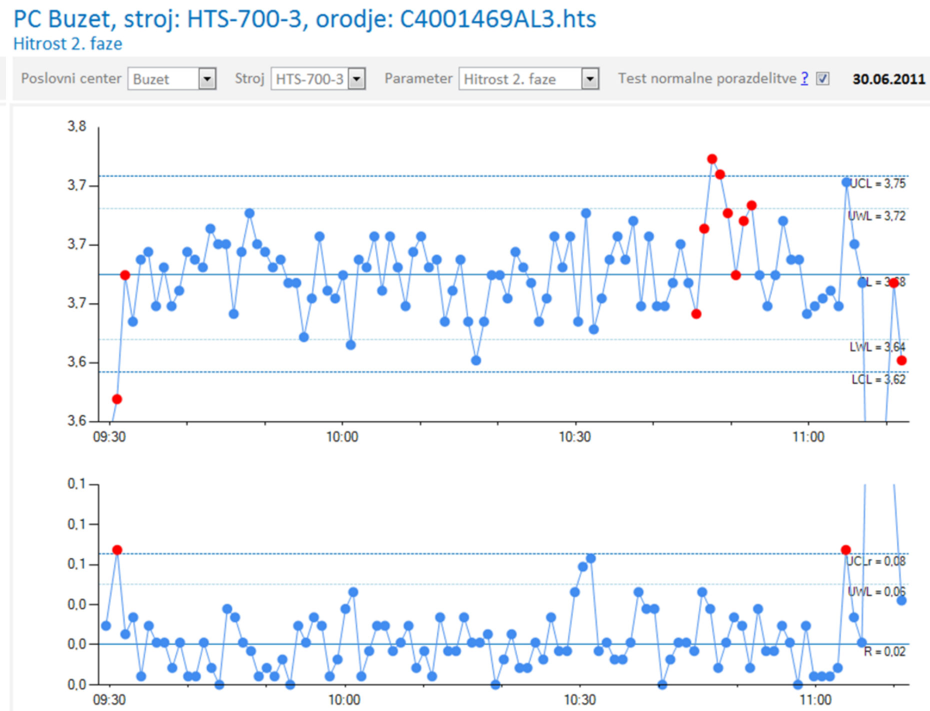
STATISTICAL PROCESS CONTROL



Control chart for a die-casting process parameter (without normality test)



Control chart for a die-casting process parameter (with normality test)

THANK YOU FOR YOUR ATTENTION!

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