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Tagung des AMA Wissenschaftsrats/Scientific Advisory Board
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Condition Monitoring auf Basis statistischer, semantischer und hybrider Signalverarbeitung – Projekt ICM-Hydraulik

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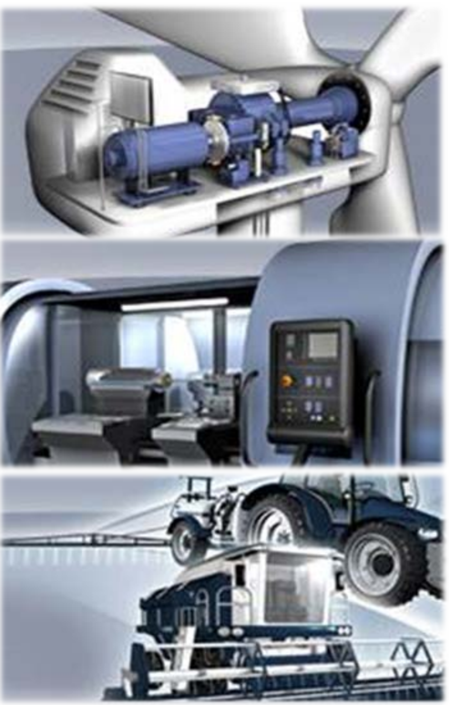
Introduction

Project Objectives

ICM-Hydraulic System Innovations

Intelligent Condition Monitoring

- Condition-based maintenance requires human experts to interpret complex interdependencies between measured sensor data and system conditions



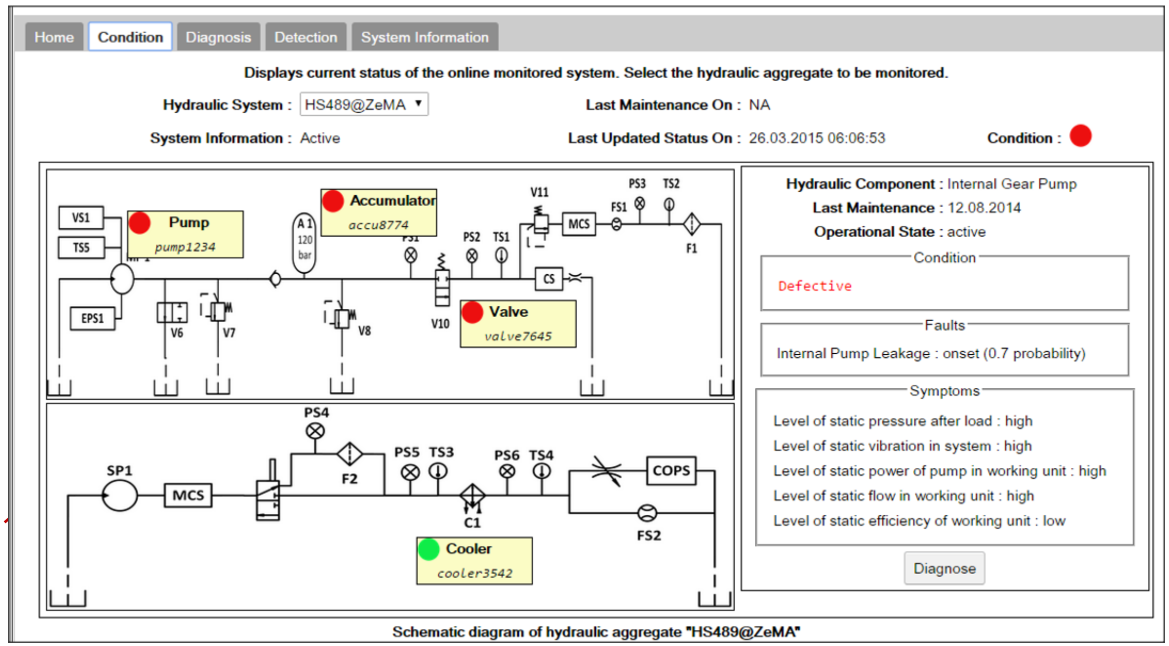
CM Automation
Challenges

- Knowledge-based **explanation** of detected faults to experts and non-experts
- Fast **quantitative and qualitative reasoning** on sensor data for fault detection and diagnosis
- **Adaptation** to different hydraulic systems

iCM-Hydraulic

- Combines statistic and semantic technologies to detect and diagnose probable faults with user understandable explanation

Mobile client for monitoring hydraulic test benches



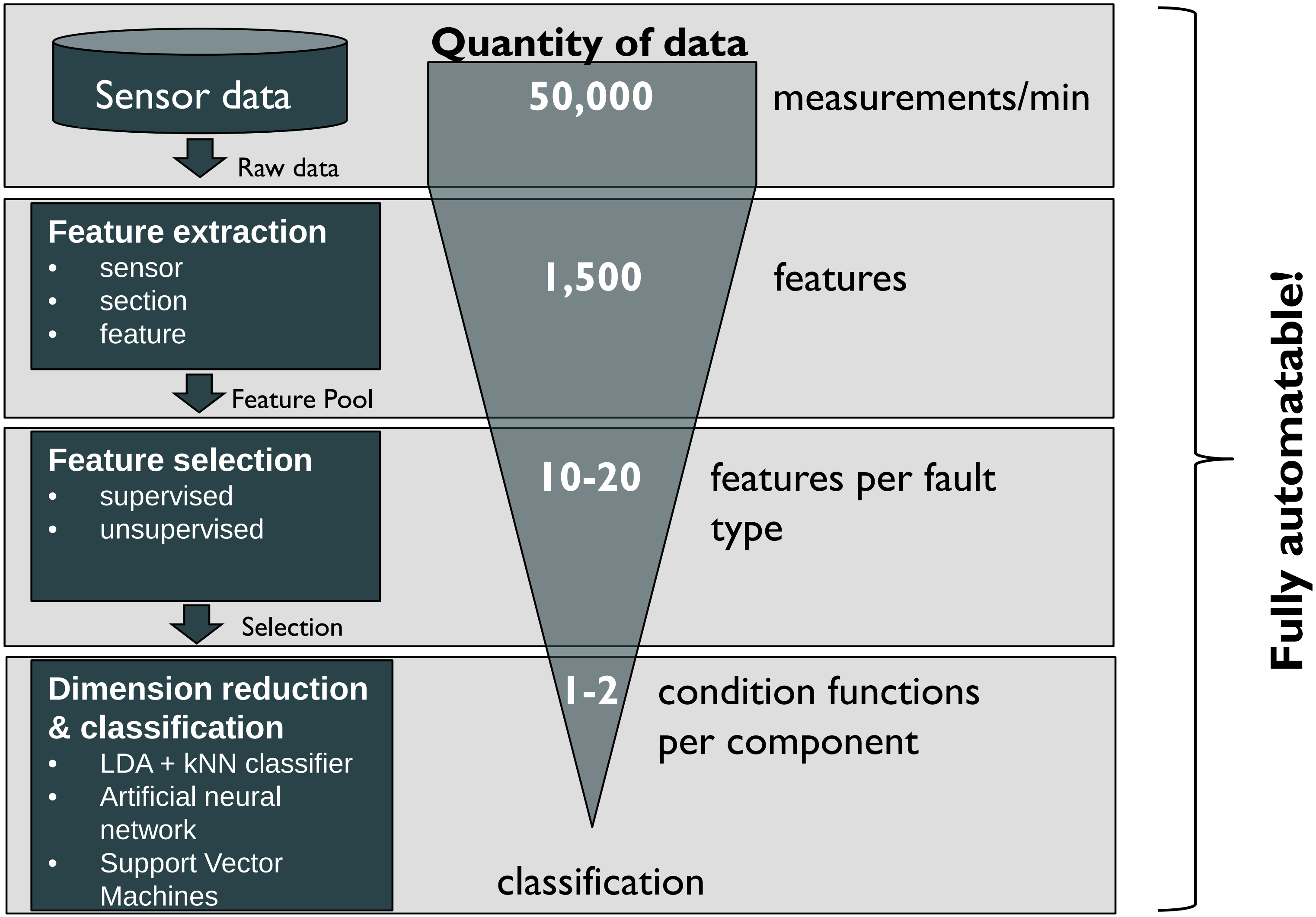
Information on probability and symptom states for Pump's 'Poor' condition. "Diagnose" details possible causes of fault and condition.

- Configuration: 2 hydraulic test benches, 17 sensors, 1 min working cycle
- Performance: 50k obs/min per bench (throughput)
- Fast offline and online analysis

Statistical Fault Classification

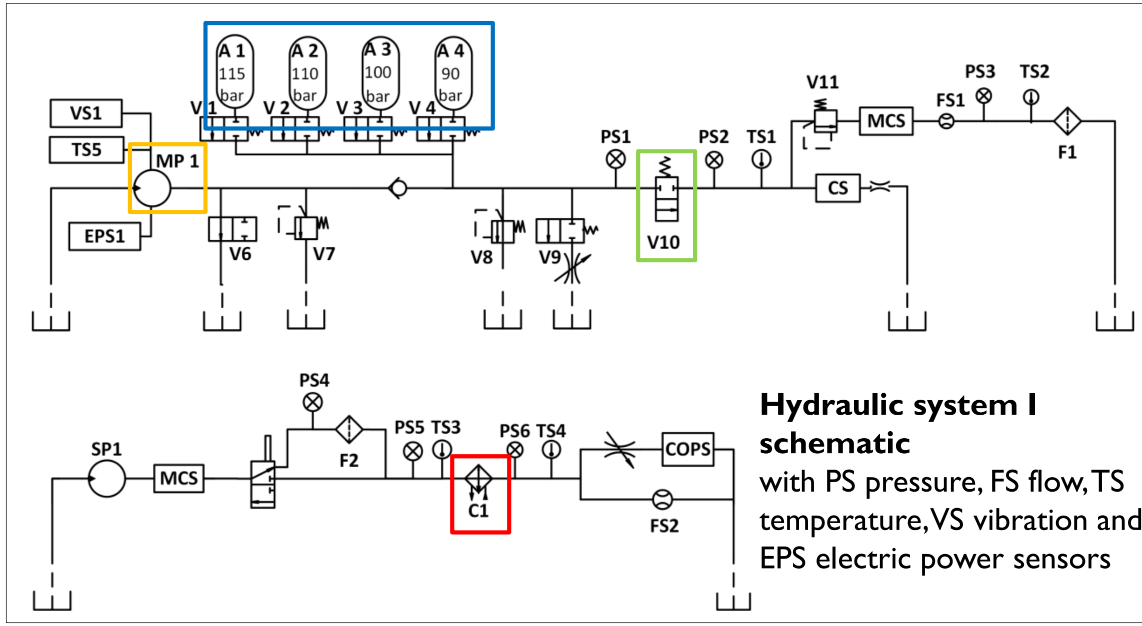
Concept of automated statistical analysis
Component fault detection
(Sensor fault detection and compensation)

Statistical Analysis Overview



Experimental Setup and Faults

- Hydraulic test bench
  - Consists of working and cooling-filtration unit
  - Experimental fault simulation of components
  - Two test benches
    1. for characterization of component faults
    2. for long-term and transferability analysis



Hydraulic system I schematic
with PS pressure, FS flow, TS temperature, VS vibration and EPS electric power sensors

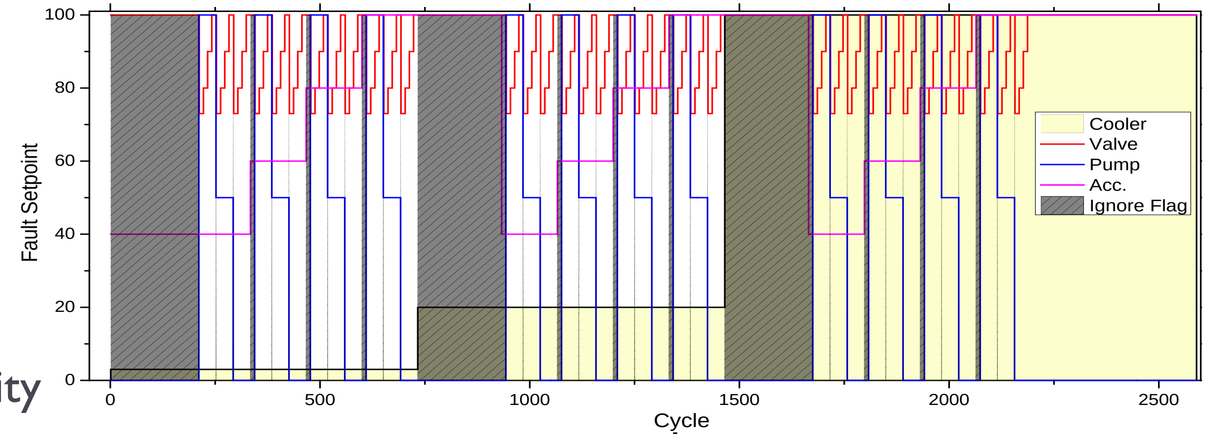
Comp.	Condition	Control parameter	Possible Range
Cooler C1	Cooling power decrease	Fan duty cycle of C1	0…100 % (0.6…2.2 kW)
Valve V10	Switching charact. degradation	Control current of V10	0…100 % of nom. current.
Pump MP1	Internal leakage	Switchable bypass orifices (V9)	3 x 0.2 mm, 3 x 0.25 mm
Acc. (A1-A4)	Gas leakage	Accumulators A1-A4 with different pre-charge pressures	90, 100, 110, 115 bar

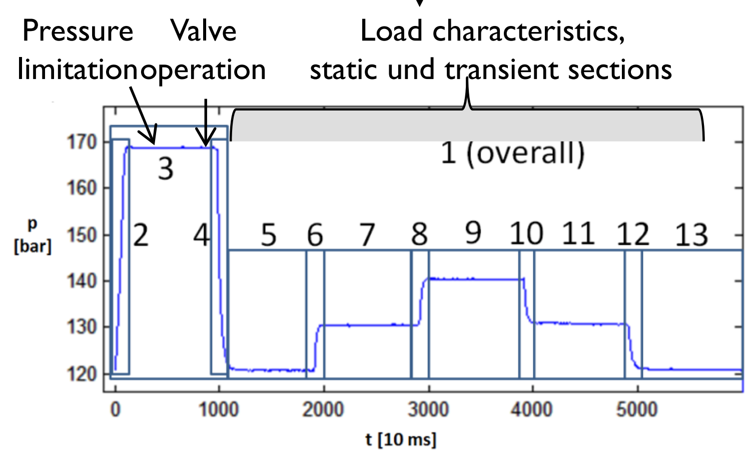
Experimental fault simulation of components

Fault Characterization Measurement

- Configuration of complex nested fault measurements
  - Combination of all fault types and severity grades to involve interferences
  - During measurement: test bench performs constant working cycle

Automated fault characterization measurement with duration of 36 hours

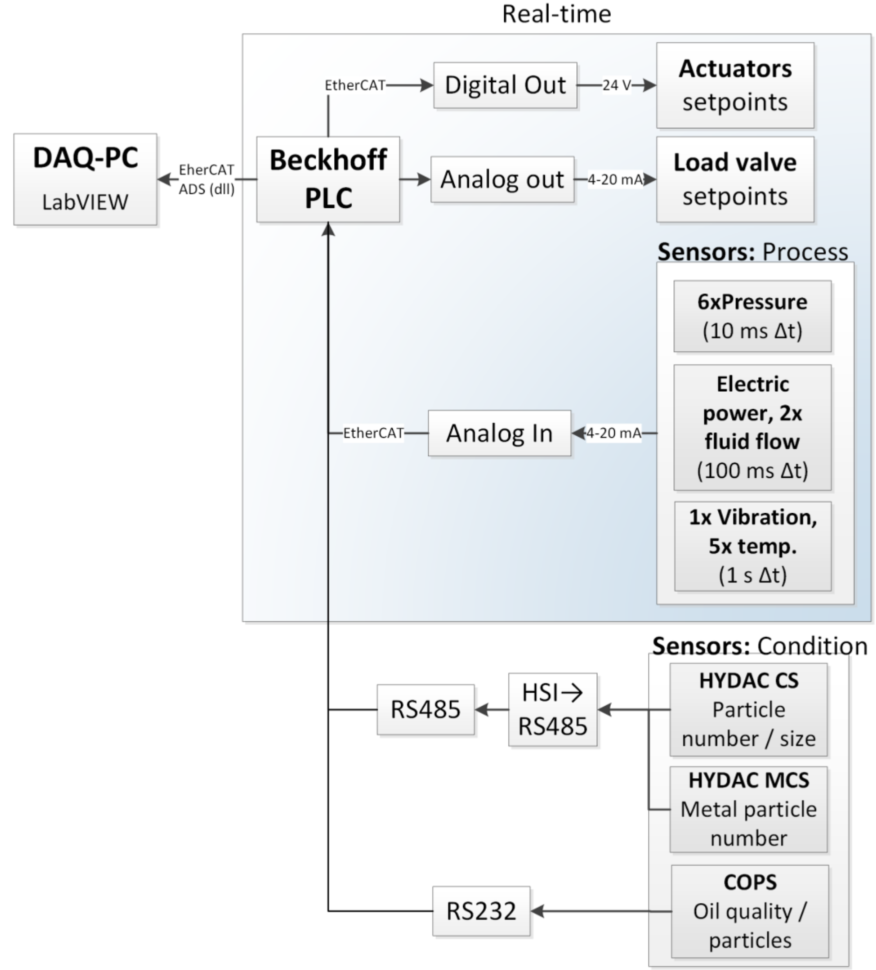




Constant working cycle, duration 60 sec, measured by PS1

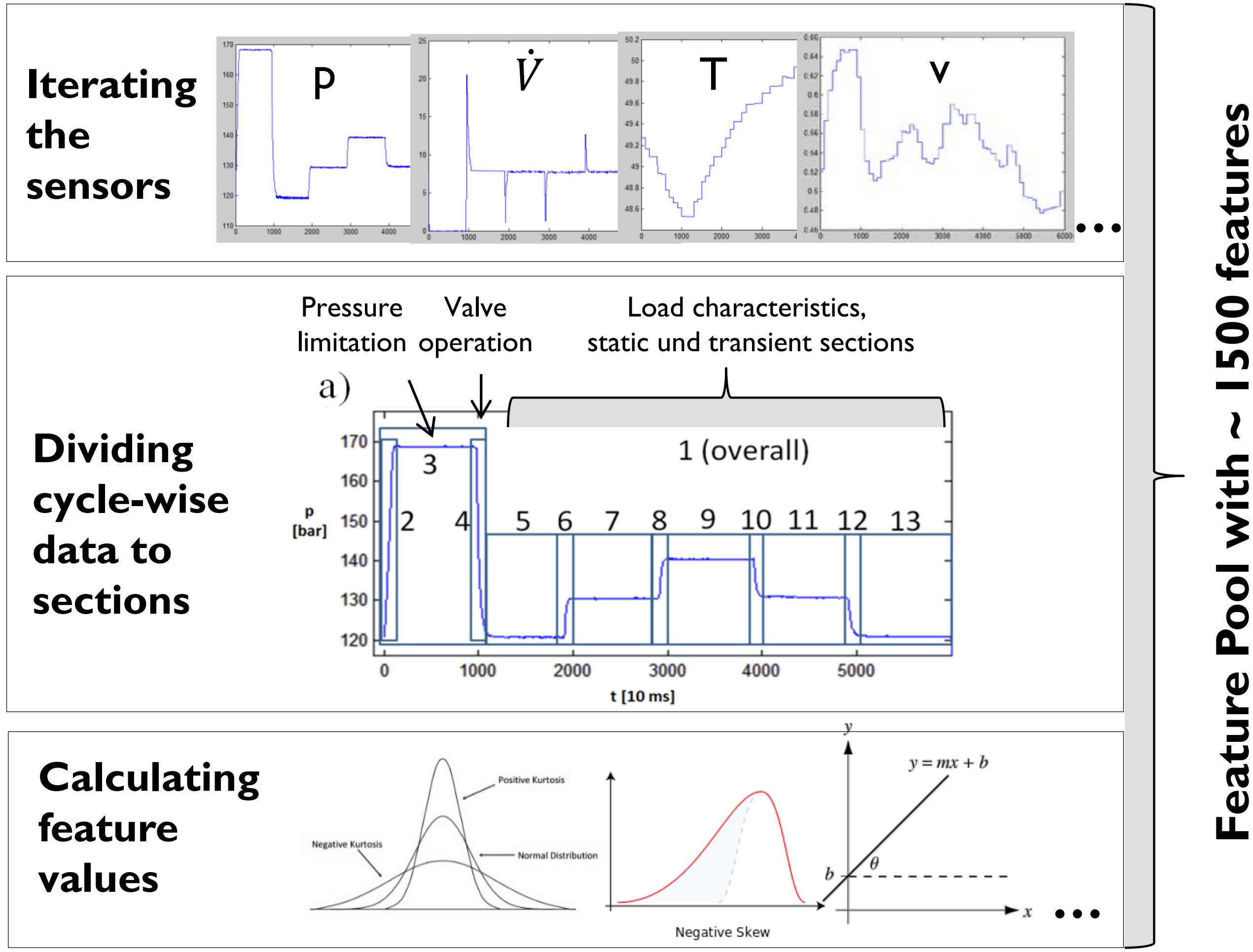
Sensors and Data Acquisition

- Working cycle and data acquisition controlled by PLC
  - Sensor data synchronized with process
  - Sampling rate of each sensor type dependent on underlying physical quantity
  - Measurements of 17 process sensors (14 physical and 3 virtual sensors) and fault set points stored by DAQ-PC in CSV format



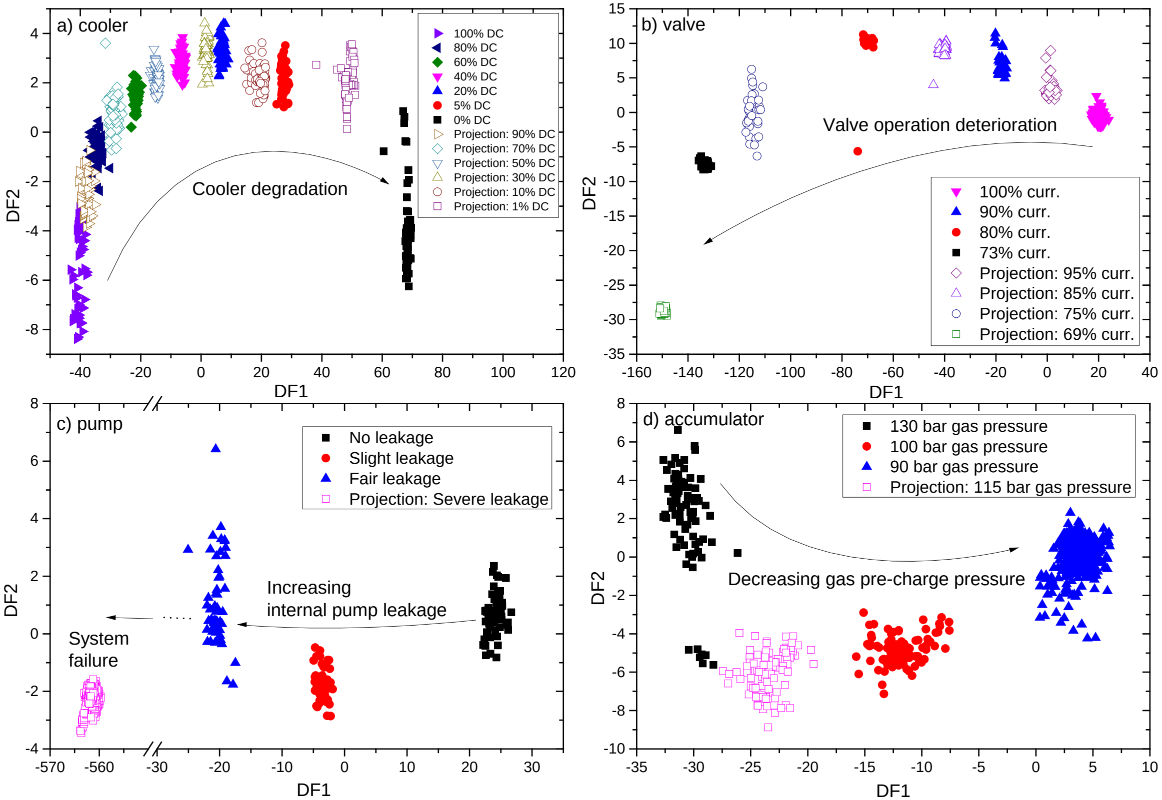
Feature Extraction Time Domain

- Computing feature values of each sensor and cycle interval
- Features used
  - Signal shape (slope, min, max, position of max,…)
  - Statistical (median, variance, skewness,…)



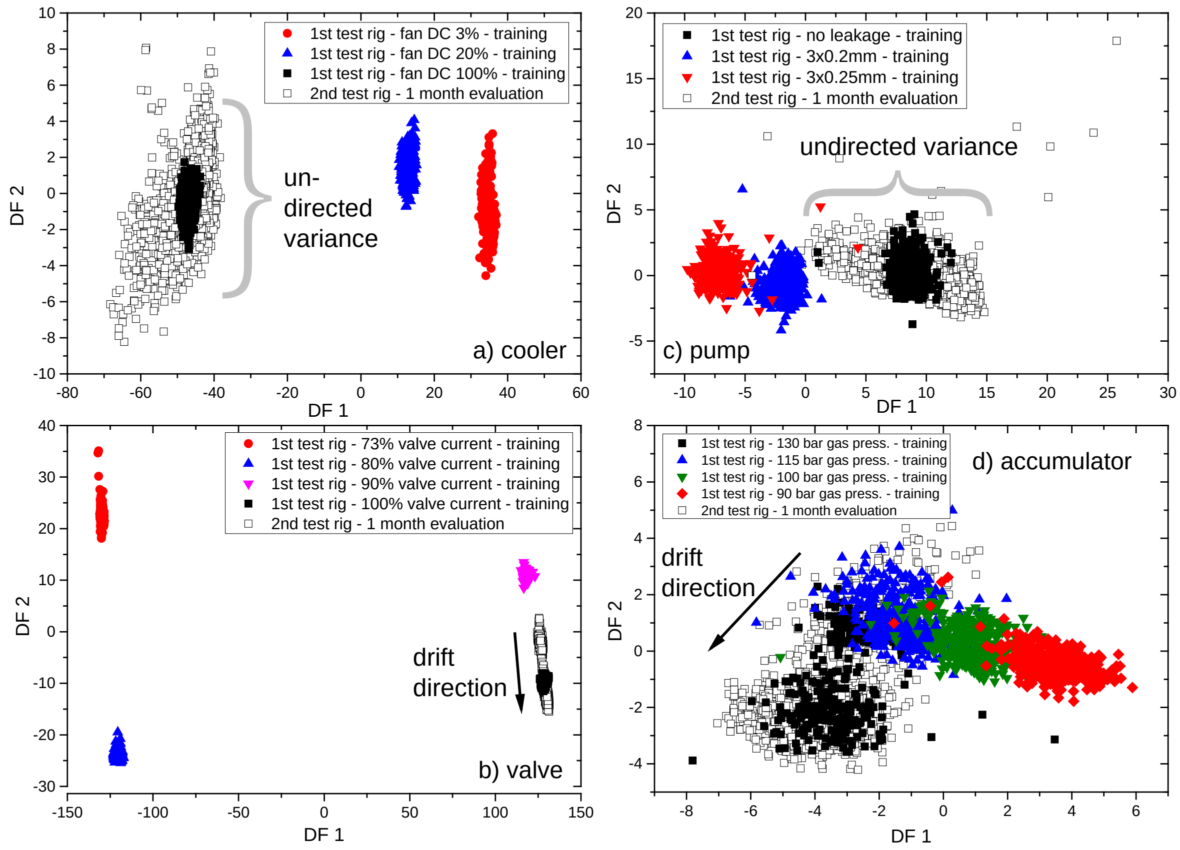
Representation of Faults in LDA Space

- 2-D LDA space shows the fault progression of components
- DF1 allows the quantification of fault severity grade
- Successful evaluation of statistical model by projection of fault grades not contained in training (→ interpolation)



Transferability of Statistical Model

- Training data with fault information collected with system I (~ 1 day)
- Subsequent feature extraction, selection and training of LDA
- Projection of long-term data (1 month) of system II with offset calibration



→ Learned statistical model transferable between systems with small adjustments
→ Long-term stability

Statistical Classification: Properties

- Classification rates of or near 100 % for studied fault scenarios
- Transfer of statistical model successful
- Detection of typical sensor faults possible
- Compensation of up to 5 defect sensors
- Computing time for training of ~120 Mio. raw data points

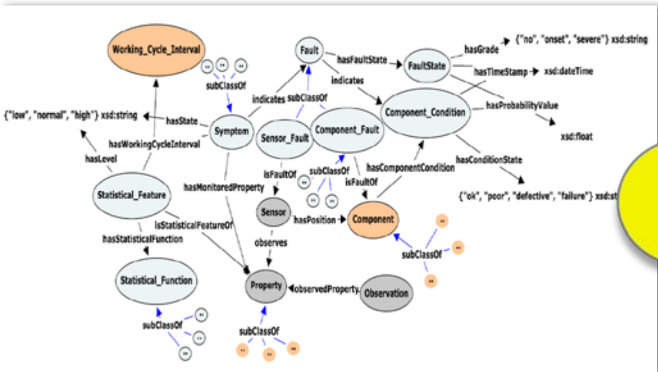
  (17 sensors, 6000 values per cycle, 1250 cycles) @ Intel Core i5 CPU, 8 GB RAM
  - Feature extraction: ~ 5 mins
  - Feature selection: 0.2 sec per fault
  - LDA: 0.1 sec per fault
  - Classification of new cycle: < 0.1 sec per fault

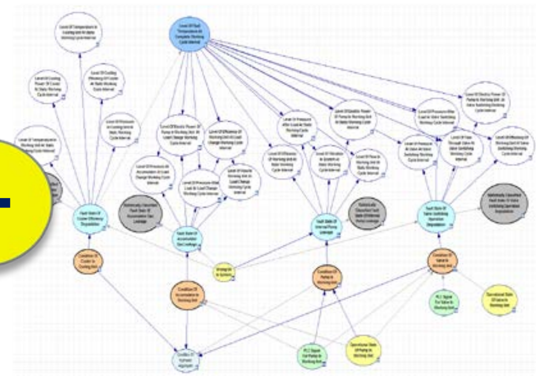
  → technically feasible

Semantics-Empowered Fault Detection and Diagnosis

Semantic Domain Model
Hybrid Fault Detection Online
Semantic Diagnosis
Performance

Semantic Domain Model





Domain ontology in OWL2:

- *Domain knowledge* on concepts and relations
  - Machine components, sensors
  - Faults, symptoms, conditions
- *Instances and sensor data (facts)*

Based on HYDAC expert knowledge,
ISO 2041, 13372, 17359:2011,
W3C Semantic Sensor Ontology

Belief Network:

- *Probabilistic knowledge* on causal relations

Symptoms S with P(S|F)
E.g. Pressure Level After Load

Fault State Of Internal...	No	Onset	Severe
high	0.0376078...	0.0106769...	0.13879991
low	0.92478422	0.95024557	0.82212257
normal	0.0376078...	0.0390775...	0.0390775...

Faults F with P(F|C)
E.g. Pump Leakage

Condition Of Pump...	OK	Poor	Defective	Failure
No	0.9	0.3	0.1	1
Onset	0.05	0.6	0.3	0
Severe	0.05	0.1	0.6	0

Conditions C with P(C|EF)
E.g. Pump Condition

PLC Signal For Pump In W...	Active		Inactive	
Operational State Of Pump...	Active	Inactive	Active	Inactive
OK	0.32462263	0	0	1
Poor	0.32462263	0	0	0
Defective	0.34085376	0	0	0
Failure	0.0099009...	1	1	0

External Factors with P(EF)
E.g. PLC Signal, Operational Pump State

→ Automated logic-based and probabilistic reasoning for fault detection and diagnosis

Hybrid Fault Detection Online (1)

Multi-variate **sensor data stream** [326 KB] Per working cycle (1 min)

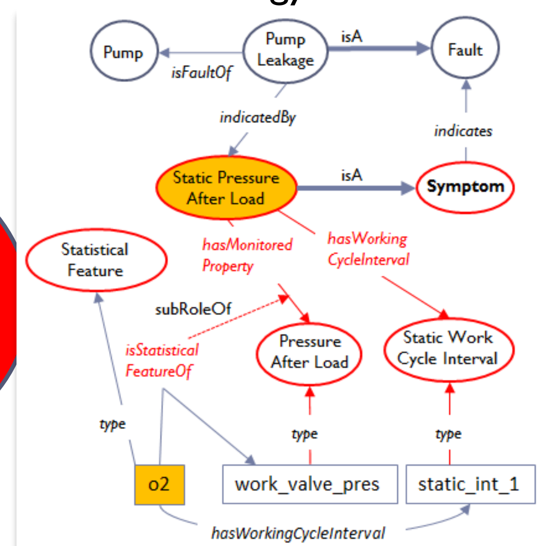
Feature data stream bucket

[TS = "22.10.2014T22:10:23"; ct = (Kurtosis, 19.7, 29-30); ***vp = (Median,9.3,10-19);*** v = (Median, 4.0, 9-10); …]

- **Semantic feature data annotation**

(o2 type StatisticalFeature)
(o2 **isStatisticalFeatureOf** ***work_valve_pres***)
(o2 **hasFunction** median)
(o2 **hasValue** "9.3"^^xsd:float)
(o2 **hasWorkingCycleInterval** static_working_cycle_1)
(o2 **hasLevel** "Low")
(o2 **hasTimeStamp** "22.10.2014T22:10:23"^^xsd:dateTime)

Part of Ontology:



- **Logical inference of all implicit facts**

(o2 type Symptom), (o2 type Static_Pressure_After_Load), (o2 hasState "low"), …

Symptom queries:

```
REGISTER Query PALSWCI
SELECT  ?f  ?l
FROM    STREAM <http://.../stream>
RANGE   1min STEP 1min
WHERE { ?f type Static_Pressure_After_Load.
        ?f hasState ?l. }
```

Retrieval of infered actual symptoms
e.g. Static pressure (of valve) after load is low

Hybrid Fault Detection Online (2)

- **Probabilistic inference of most likely fault states and conditions**

Symptoms: (**Static_Pressure_After_Load** hasState "**low**")
Ext. Factors: (**Operational_Pump_State** hasState "**active**")

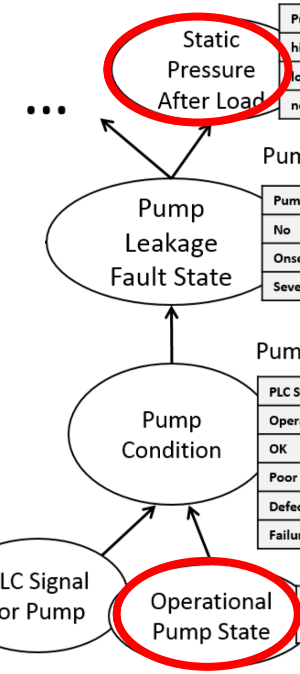
Statistical fault classification:

Pump_Leakage = Onset,
Valve_Op_Degradation = No,
Cooling_Op_Degradation = No,
Accumulator_Gas_Leakage = No

Evidence

F.e. fault F:

P(Pump_Leakage = Onset | SPAL = low, OPS = active) = 0.7
P(Pump_Leakage = Severe | SPAL = low, OPS = active) = 0.2
...



Pump Leakage **Symptoms** S   P(S|F)

Pump Leakage Fault State:	No	Onset	Severe
high	0.0376	0.0106	0.1387
low	0.9247	0.9502	0.8221
normal	0.0376	0.0390	0.0390

Pump Leakage **Fault** F   P(F|C)

Pump Condition:	OK	Poor	Defective	Failure
No	0.9	0.3	0.1	1
Onset	0.05	0.6	0.3	0
Severe	0.05	0.1	0.6	0

Pump **Condition** C   P(C|EF)

PLC Signal for Pump	Active		Inactive	
Operational Pump State	Active	Inactive	Active	Inactive
OK	0.3246	0	0	1
Poor	0.3246	0	0	0
Defective	0.3408	0	0	0
Failure	0.0099	1	1	0

External Factors P(EF):

PLC Signal for Pump:

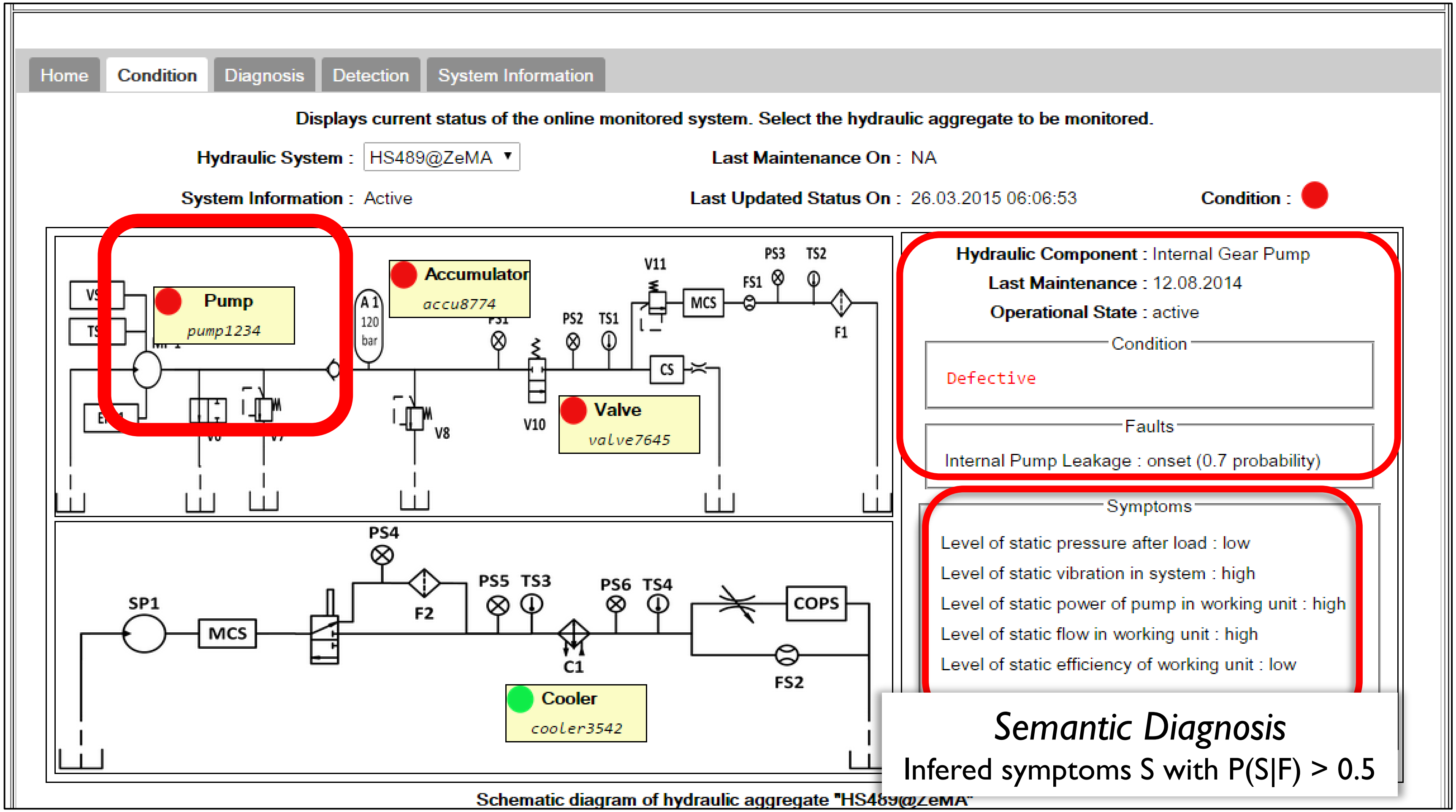
Active	0.95
Inactive	0.05

Operational Pump State:

Active	0.95
Inactive	0.05

→ *Semantic validation and explanation of statistical fault classification*

GUI: Detection and Diagnosis Online



Semantic Diagnosis

Infered symptoms S with P(S|F) > 0.5

Semantic Diagnosis: Overview

HYDAC

iCM-Hydraulic system

- **Answers** given **diagnosis queries**

  with **query-specific combination of semantic reasoning tools**

  Online: (in parallel, over stream data)

  1. *Most likely explanation of detected component condition ?* [C-SPARQL, GeNIe]
  2. *Which other components are affected by detected fault(s) ?* [STAR]
  3. *Semantic relations between these faults in the hydraulic circuit ?* [C-SPARQL, STAR, Hermit, GeNIe]

  Offline: (batch, over central store with historic data)

  4.- 6. Answer 1. – 3. over historic data [SPARQL, STAR, Hermit, GeNIe]

  7. *Progression of component's conditions and faults with probabilities ?* [SPARQL]
  8. *Frequency of pump's fault occurrence w.r.t. high fluid temperature level ?* [SPARQL]

- **Generates human-understandable diagnosis results**

  with **query-specific semantic explanation templates**

Example: Semantic Diagnosis Online

Situation 1:
Faults of **pump**,
gas accumulator,
pressure control valve.

Semantic relations with other component faults detected at same time?

* *Pump pump 1234* with **internal pump leakage ipl123** is located ***before*** faulty component *accumulator accu8774* with **gas leakage** agl456, detected at time *12.03.2015 23:00:09*. Therefore, detected **internal pump leakage** might have caused detection of *accumulator gas leakage*.

* *Pump pump 1234* with **internal pump leakage ipl123** is located ***before*** faulty component *relief valve valve7645* with **switching operation degradation** sod789, detected at time *12.03.2015 23:00:09*. Therefore, detected **internal pump leakage** might have caused detection of *valve switching operation degradation*.

Situation 2:
Faults of **pump**,
gas accumulator.

Other components affected by detected component fault?

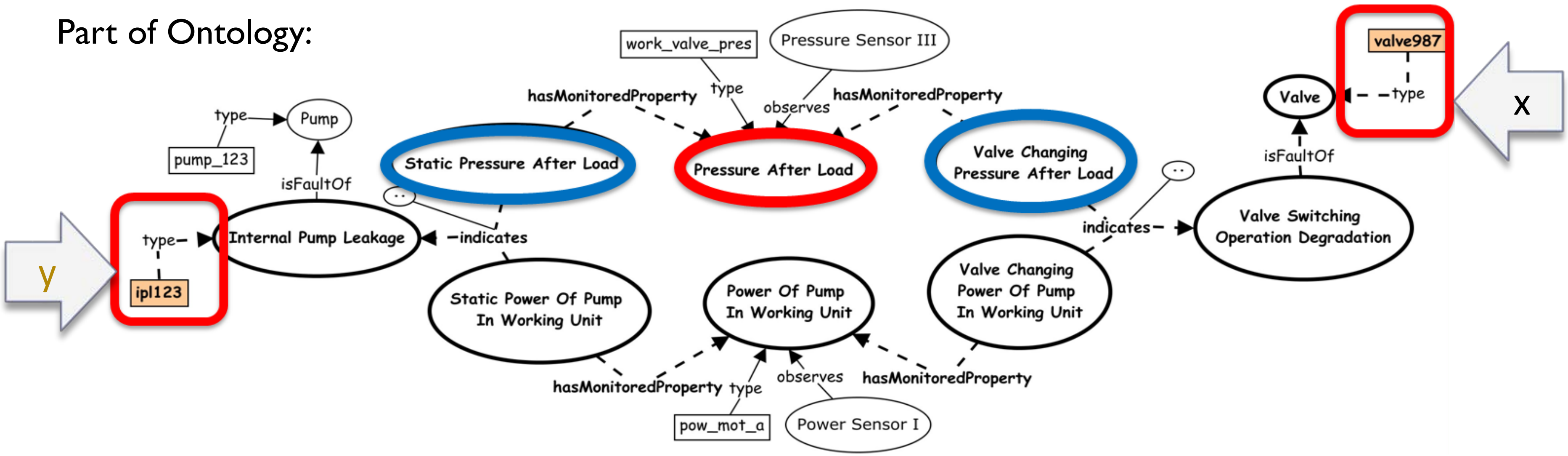
Displays other components monitored by sensors monitoring faulty component alongwith probable condition of components given the fault..

Sensor	Monitored Component	Component Condition
PressureSensor3	valve7645	OK(0.7)
	accu8774	Poor(0.9)
PowerSensor1	valve7645	OK(0.7)
	accu8774	Poor(0.9)
FlowSensor1	valve7645	OK(0.7)
	accu8774	Poor(0.9)

Example: Semantic Reasoning

- *What is the* ***most likely condition*** *of* ***other components that are affected*** *by the detected pump leakage, and* ***which sensors*** *are involved?*

Part of Ontology:

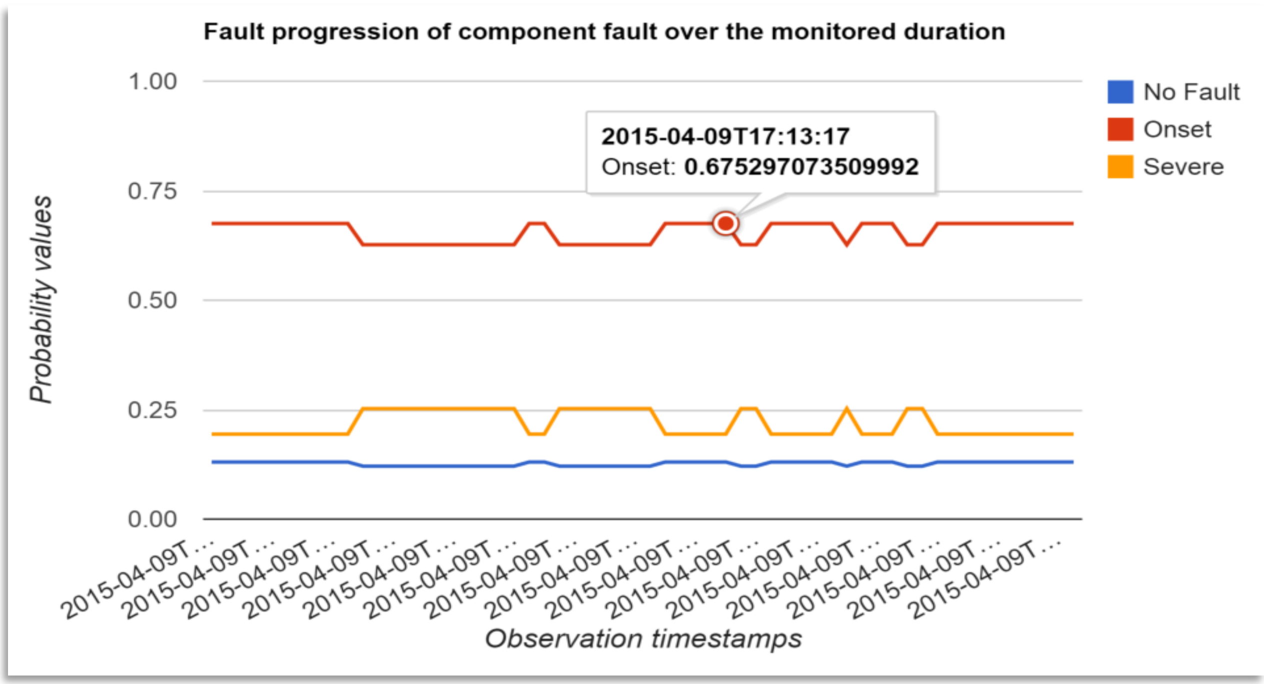


- *For each* **shortest path** between machine components x and pump leakage instance y find symptoms s1 of y, s2 of x with *same* monitored property p
- Retrieve **sensor instances** of $Sensor \sqcap \exists observes.(P \sqcap \exists monitorsSymptoms(S1 \sqcap S2))$.
- Compute **most likely condition c of x**: $max_{x=c}\Pr(x = c|Y = s)$

ZeMA DFKI

Example: Semantic Diagnosis Offline

- *Progression of detected component's fault states with probabilities ?*



- *Frequency of pump leakage occurrence w.r.t. high fluid temperature level in the hydraulic aggregate ?*
- *F.e. fault type occurrence in the past (interval) return average contamination values with change of fault grades*

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Performance of Semantic Diagnosis

- Setting
  - Hardware: i7@3.40 GHz; 16GB RAM, JDK 1.7; 14 GB MaxJVM-HeapSpace
  - Historic data:
  - Stream: 660 RDF triples/min

Recording Days	RDF-encoding	Materialization
1 [1440 working cycles]	1,067,453 triples	7,685,661 triples
2 [2880 working cycles]	2,134,906 triples	15,157,832 triples

- **Fast average query response time**
  - *Online:* *< 1 min*
  - *Offline:* *~ 1 min*
- Semantic annotation: 0.3 sec
- Semantic explanation: 1 sec
- Historic data loading: 15/35 min

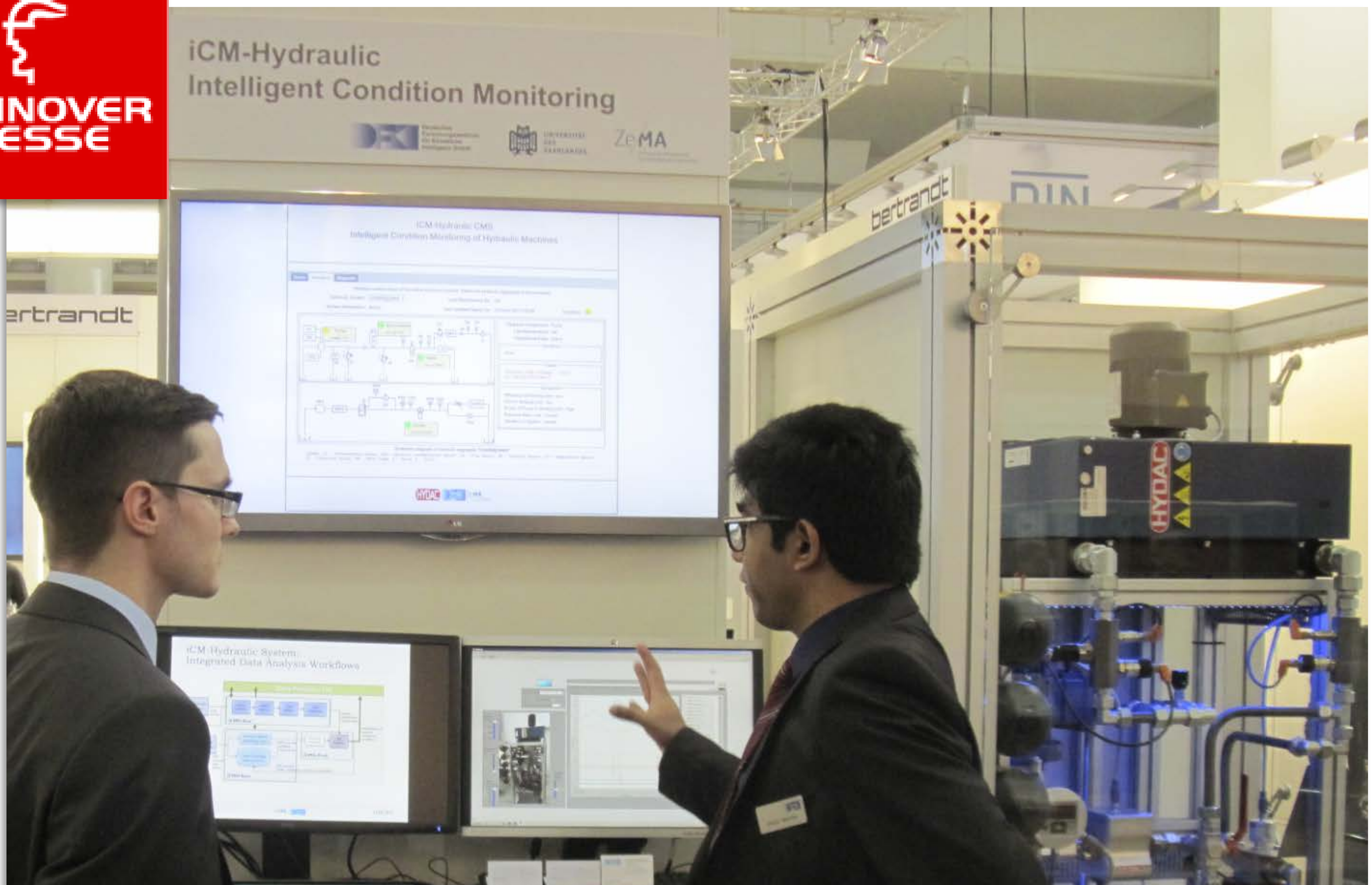
	AQRT	StatC	C-SPARQL	STAR	DL	BN
Q1	25.5s	0.5s	23s	-	-	1s
Q2	1.6s	-	-	0.6s	-	-
Q3	41s	-	1s	13s	26s	1s

		StatC	SPARQL	STAR	DL	BN
Q4	1-day	0.43s	23s	-	-	1s
	2-days	0.43s	25s	-	-	1s
Q5	1-day	-	0.32s	0.81s	-	-
	2-days	-	0.36s	0.83s	-	-
Q6	1-day	-	0.12s	12s	26s	1s
	2-days	-	0.13s	12s	27s	1s
Q7	1-day	-	0.30s	-	-	-
	2-days	-	0.35s	-	-	-
Q8	1-day	-	0.21s	-	-	-
	2-days	-	0.29s	-	-	-

- **High precision:** MAP = 1, Customer eval

[8 test queries, rnd samples of test data for 1,250 working cycles with simulated grades of 4 component faults]

iCM-Hydraulic @ Hannover Industry Fair 2015



Publications

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- M. Klusch, A. Meshram, A. Schuetze, N. Helwig: ICM-Hydraulic: Semantics-Empowered Condition Monitoring of Hydraulic Machines; Proceedings of the 11th ACM International Conference on Semantic Systems, Vienna, Austria, ACM, 2015
- N. Helwig, S. Klein, A. Schütze: Identification and Quantification of Hydraulic System Faults based on Multivariate Statistics using Spectral Vibration Features; EUROSENSORS 2015, Freiburg, Germany, September 6 to 9, 2015; Procedia Engineering, doi: 10.1016/j.proeng.2015.08.835
- N. Helwig, A. Schütze: Detecting and compensating sensor faults in a hydraulic condition monitoring system; Proc. SENSOR 2015 - 17th International Conference on Sensors and Measurement Technology, Nuremberg, Germany, May 19-21, 2015; doi: 10.5162/sensor2015/D8.1
- N. Helwig, E. Pignanelli, A. Schütze: Condition Monitoring of a Complex Hydraulic System Using Multivariate Statistics; Proc. I2MTC-2015 - 2015 IEEE International Instrumentation and Measurement Technology Conference, paper PPS1-39, Pisa, Italy, May 11-14, 2015
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- M. Klusch, A. Meshram, P. Kapahnke, A. Schuetze: ICM-Wind: Semantics-Empowered Fluid Condition Monitoring of Wind Turbines; Proc. 29th ACM Symposium on Applied Computing (SAC); Korea; ACM Press. available online

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