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Machine Learning Methods for Environmental Monitoring and Flood Protection

UrbanFlood Workshop, 11th Nov 2010

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Outline

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Outline

1. Flood monitoring
2. Monitoring data processing
3. Development of AI component
4. Further plans
5. Conclusions

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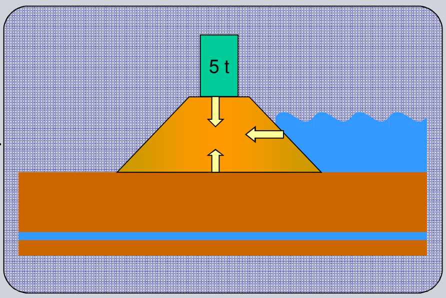
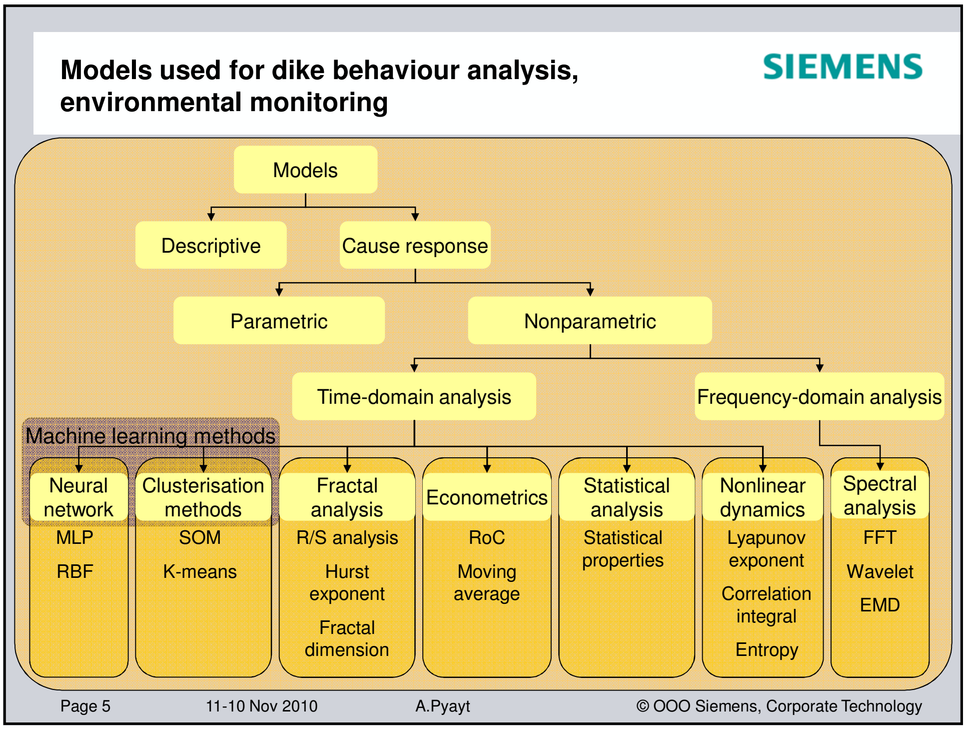
Flood monitoring

1. Flood can be caused by:
   1. environmental conditions
   2. dike failure

   Flood monitoring = structural health monitoring + environmental monitoring

   Dike abnormal behaviour detection
2. Dike failure can be caused by:
   1. environmental conditions
   2. hydrological factors
   3. human influence
3. Types of data:
   1. input (dike parameters, external parameters)
   2. output (flood probability, dike behaviour)





Models used for dike behaviour analysis, environmental monitoring
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Models
Descriptive
Cause response
Parametric
Nonparametric
Time-domain analysis
Frequency-domain analysis
Machine learning methods
Neural network
MLP
RBF
Clusterisation methods
SOM
K-means
Fractal analysis
R/S analysis
Hurst exponent
Fractal dimension
Econometrics
RoC
Moving average
Statistical analysis
Statistical properties
Nonlinear dynamics
Lyapunov exponent
Correlation integral
Entropy
Spectral analysis
FFT
Wavelet
EMD
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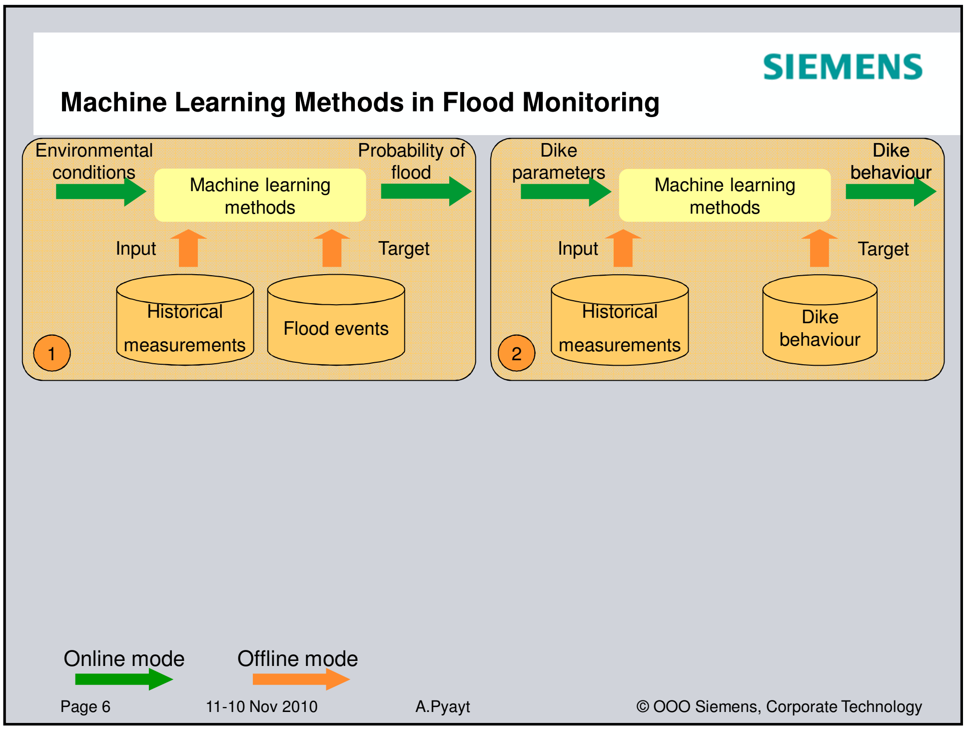

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Machine Learning Methods in Flood Monitoring
Environmental conditions
Machine learning methods
Probability of flood
Input
Target
Historical measurements
Flood events
1
Dike parameters
Machine learning methods
Dike behaviour
Input
Target
Historical measurements
Dike behaviour
2
Online mode
Offline mode
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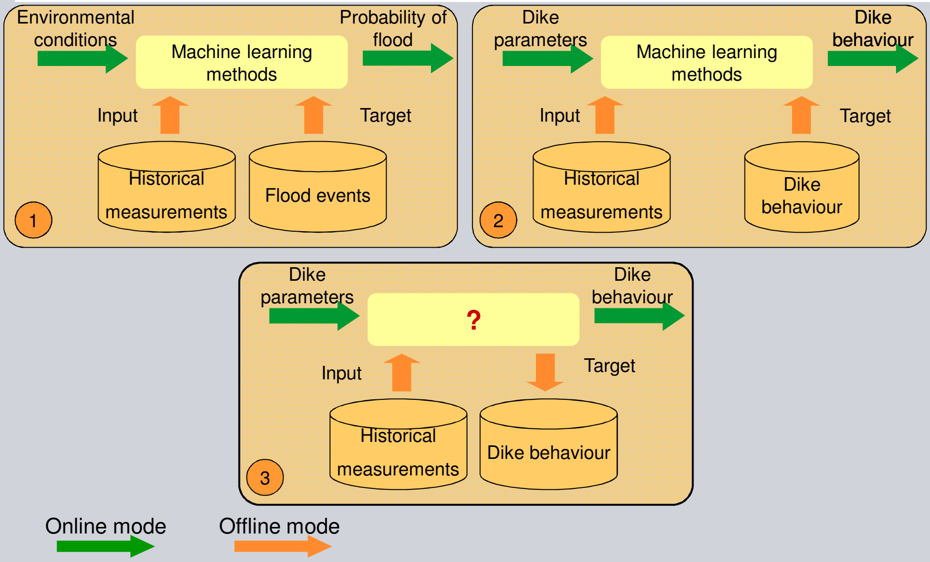
Flood monitoring using machine learning methods



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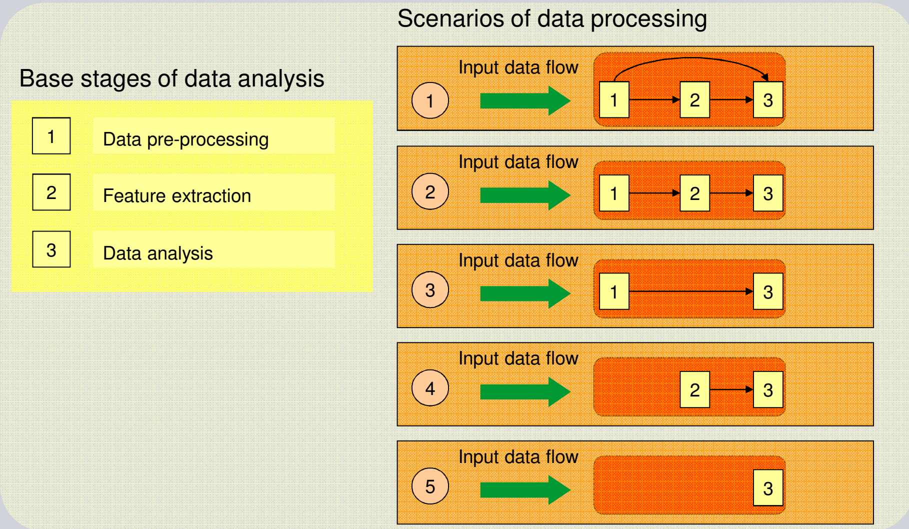
Schema of data processing



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1. Introduction
2. Monitoring data processing
    1. Pre-processing
    2. Feature extraction
    3. Analysis
    4. Abnormal behaviour detection approach
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Data pre-processing

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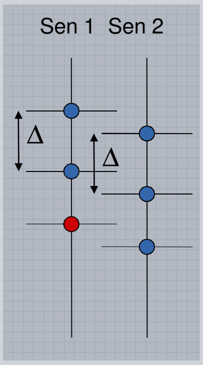

Raw data

- Measurement
- Gap

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Data pre-processing

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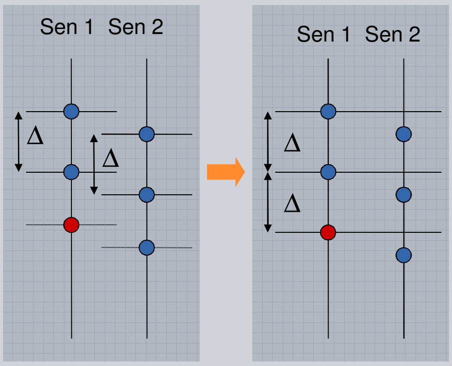

Raw data

Common time grid

- Measurement
- Gap

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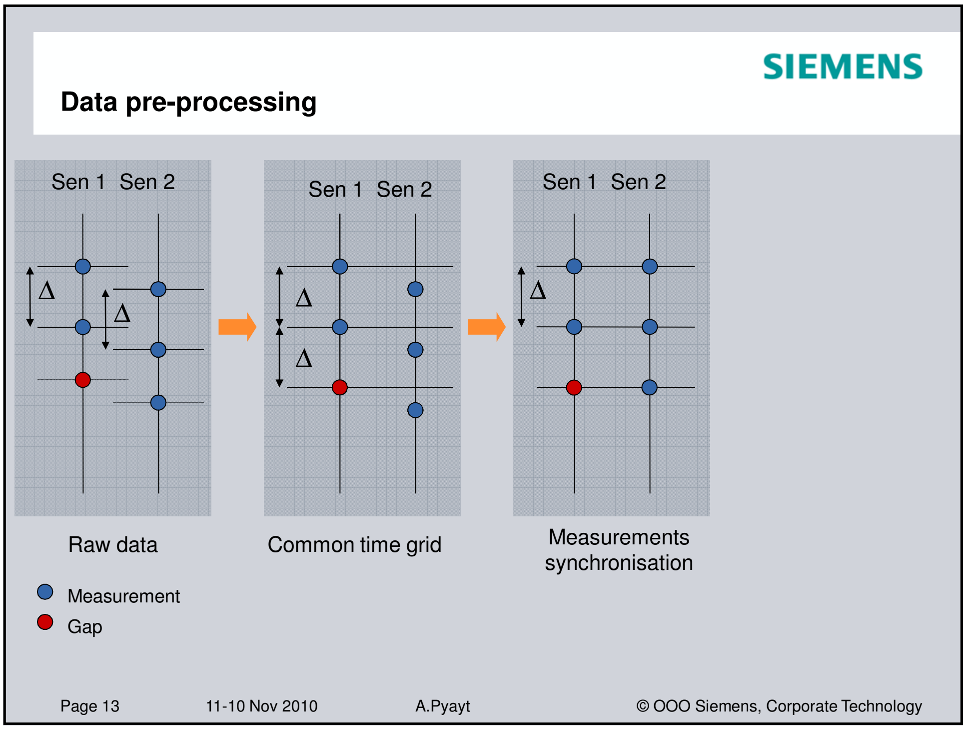
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Data pre-processing
Sen 1 Sen 2
Δ
Δ
Sen 1 Sen 2
Δ
Δ
Sen 1 Sen 2
Δ
Raw data
Common time grid
Measurements synchronisation
Measurement
Gap
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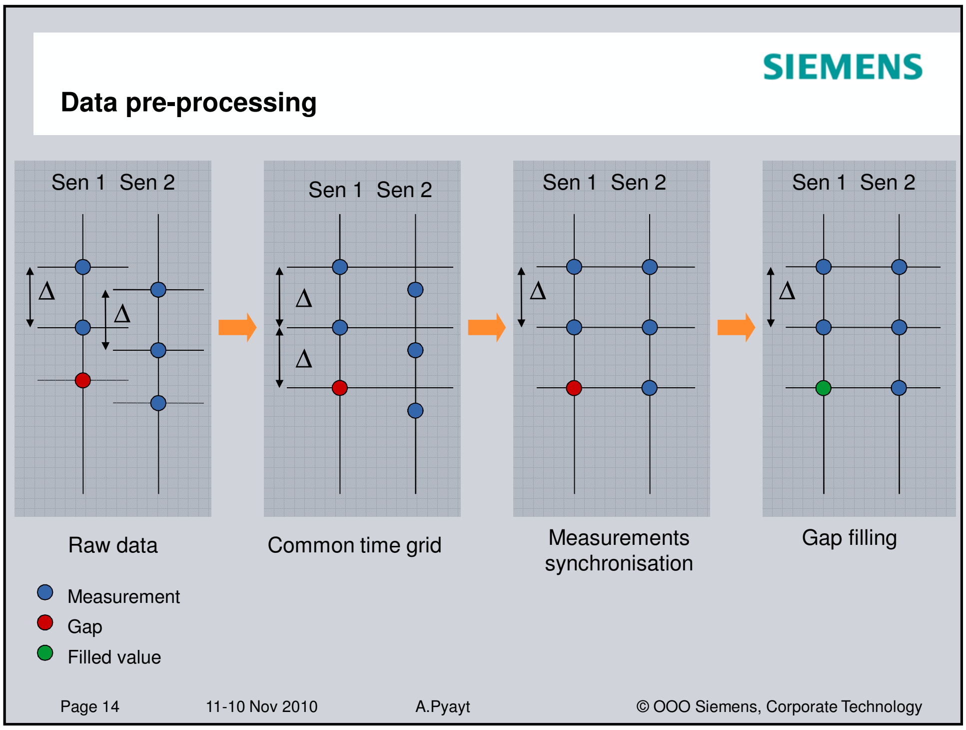
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Data pre-processing
Sen 1 Sen 2
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Δ
Sen 1 Sen 2
Δ
Δ
Sen 1 Sen 2
Δ
Sen 1 Sen 2
Δ
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Gap filling
Measurement
Gap
Filled value
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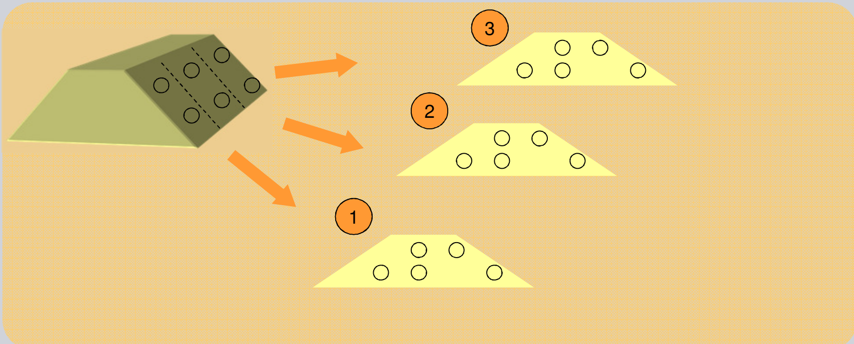
Feature extraction
Logical groups



Feature extraction
Logical groups. Physical redundancy

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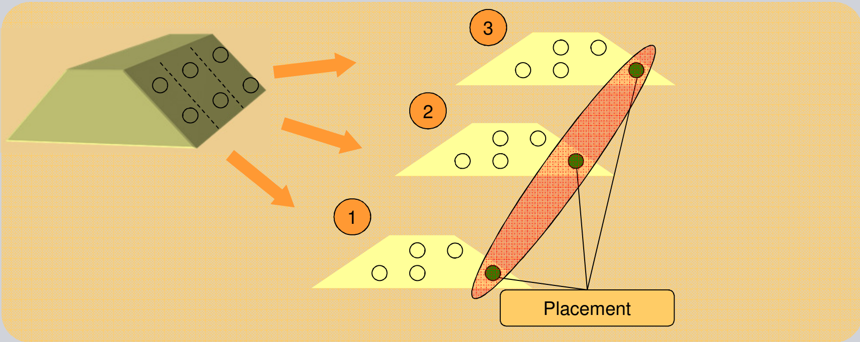

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Feature extraction
Logical groups. Physical redundancy

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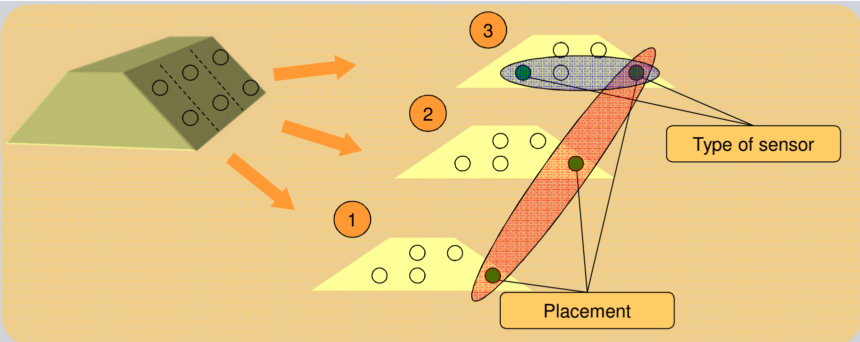

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Feature extraction
Logical groups. Analytical redundancy

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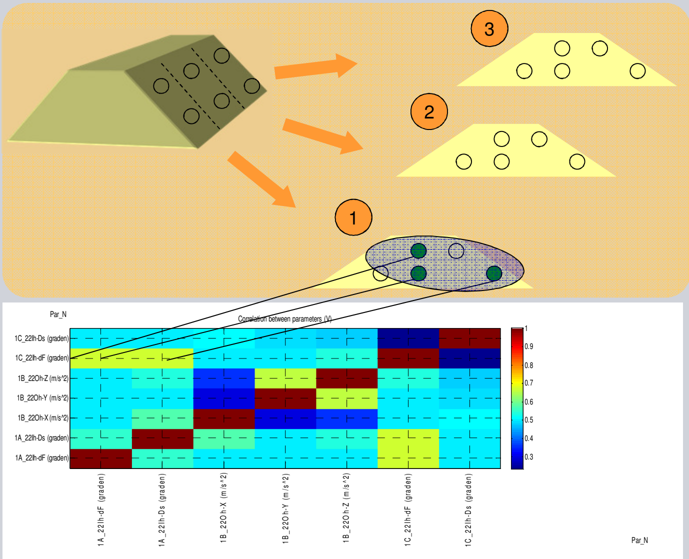

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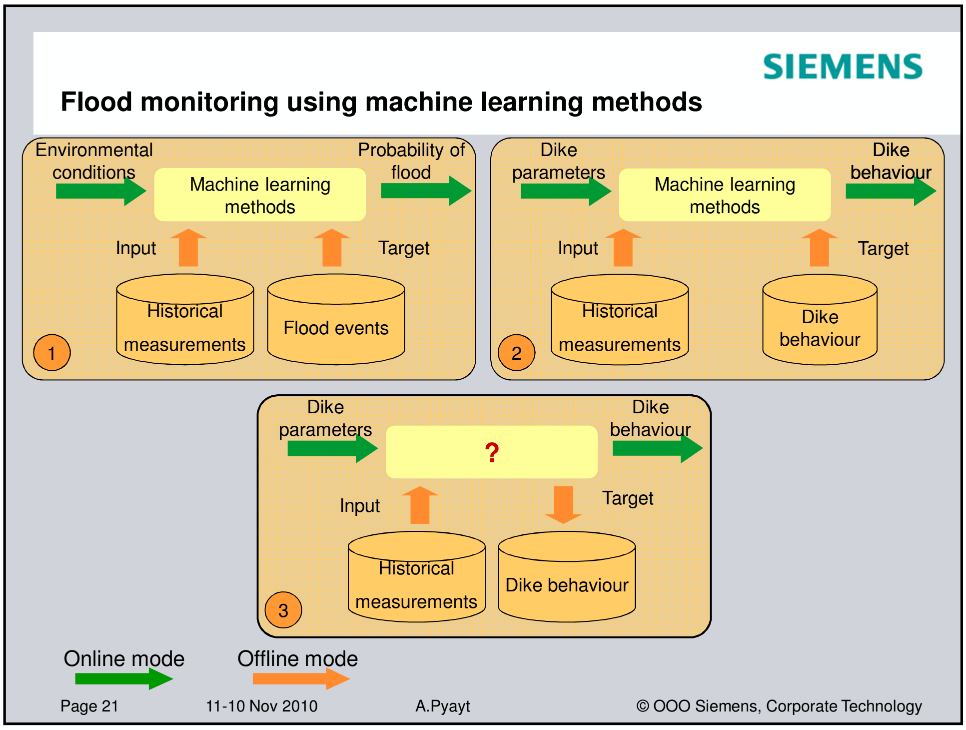
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Environmental conditions
Machine learning methods
Probability of flood
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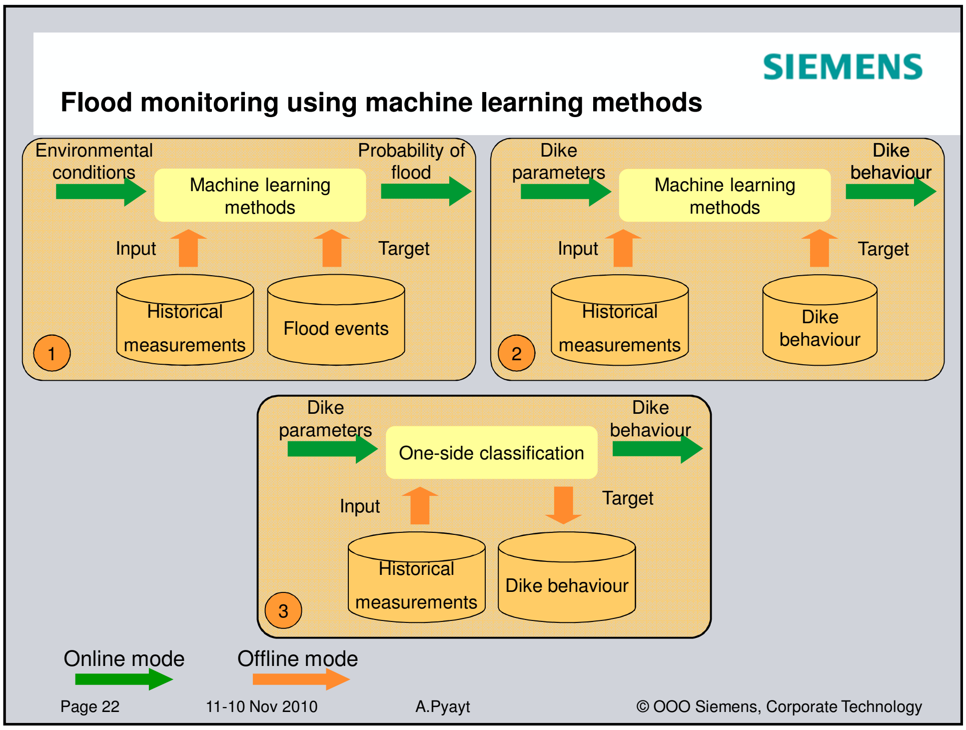
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One-side classification
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Data analysis
One-side classification

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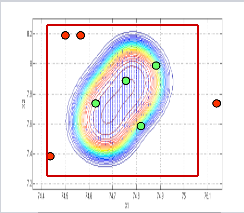
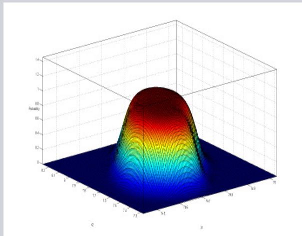
The advantages of the neural clouds concept in comparison with cube:

- *More sensitive to the changes in the system then box approach*
- *Allows to extract non linear dependencies between sensors*
- *Early detection of incompatibilities among sensors*

2 D data **Neural Cloud for raw data**



-- GOOD CONDITION
-- BAD CONDITION



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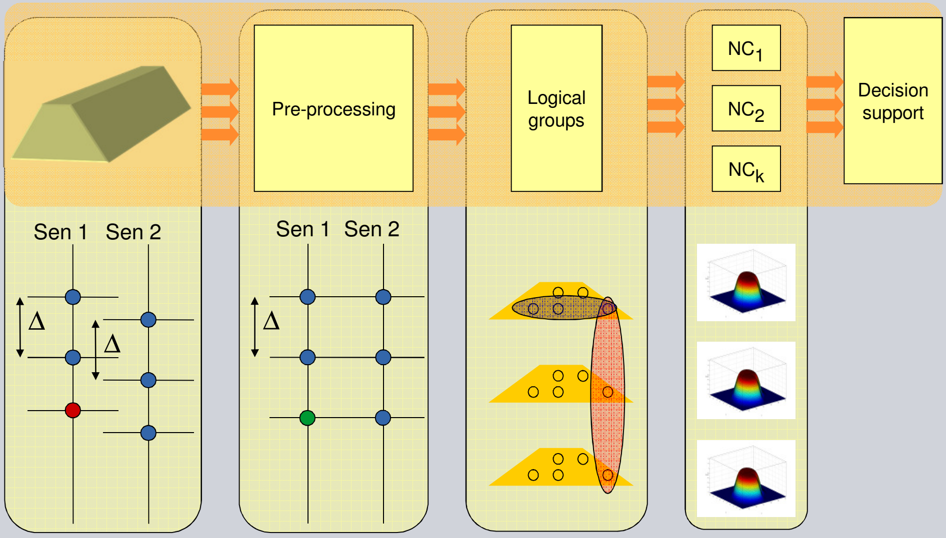
Schema of dike abnormal behaviour detection



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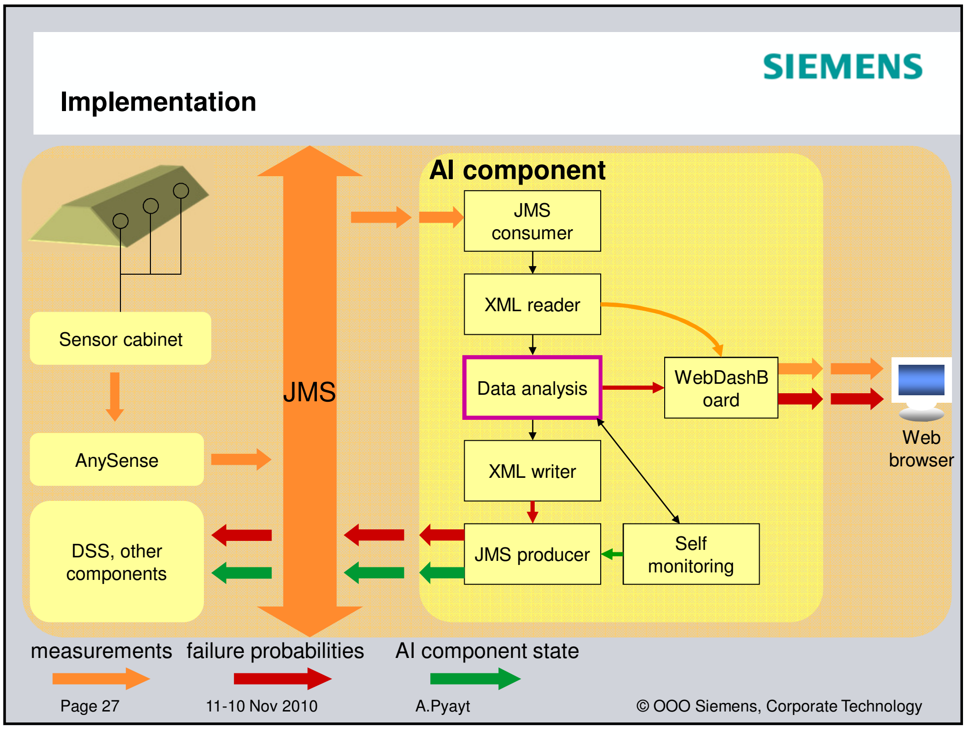
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Implementation
AI component
JMS consumer
XML reader
Data analysis
WebDashBoard
XML writer
JMS producer
Self monitoring
Sensor cabinet
AnySense
DSS, other components
JMS
Web browser
measurements
failure probabilities
AI component state
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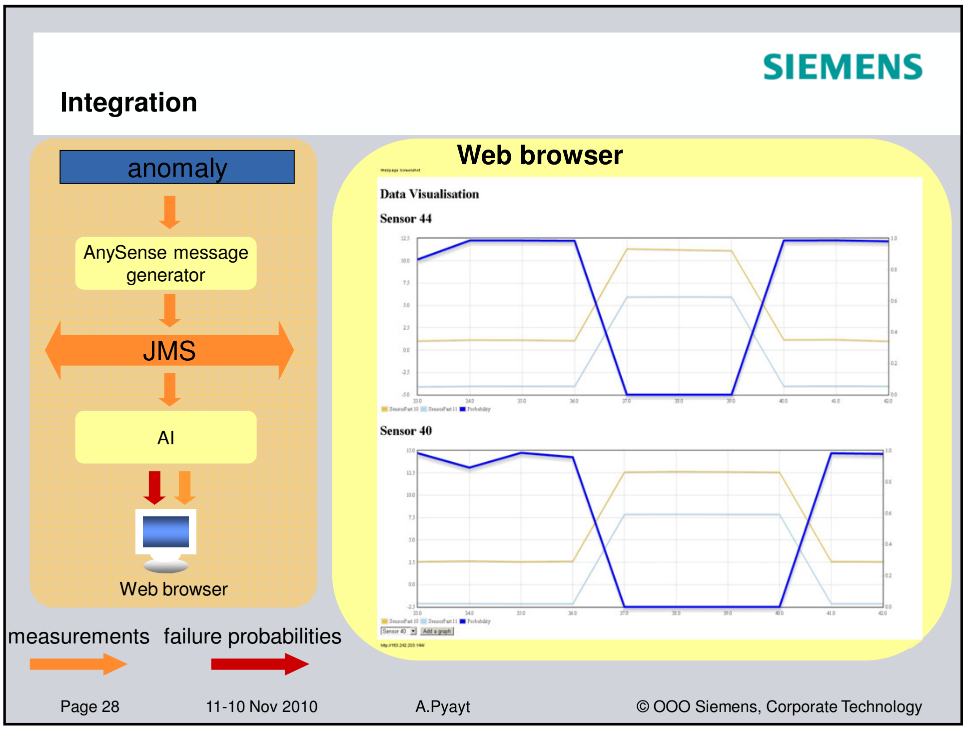
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Integration
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AnySense message generator
JMS
AI
Web browser
Web browser
Data Visualisation
Sensor 44
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measurements
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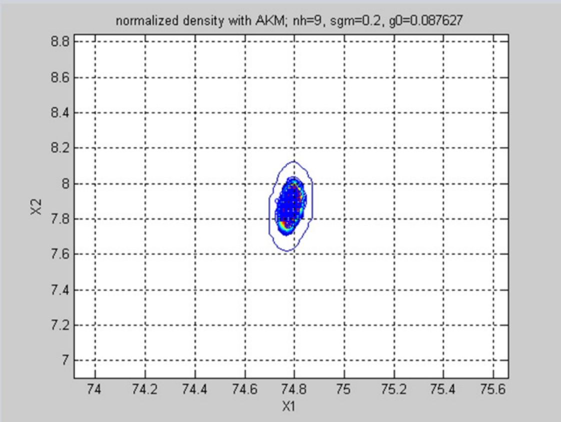
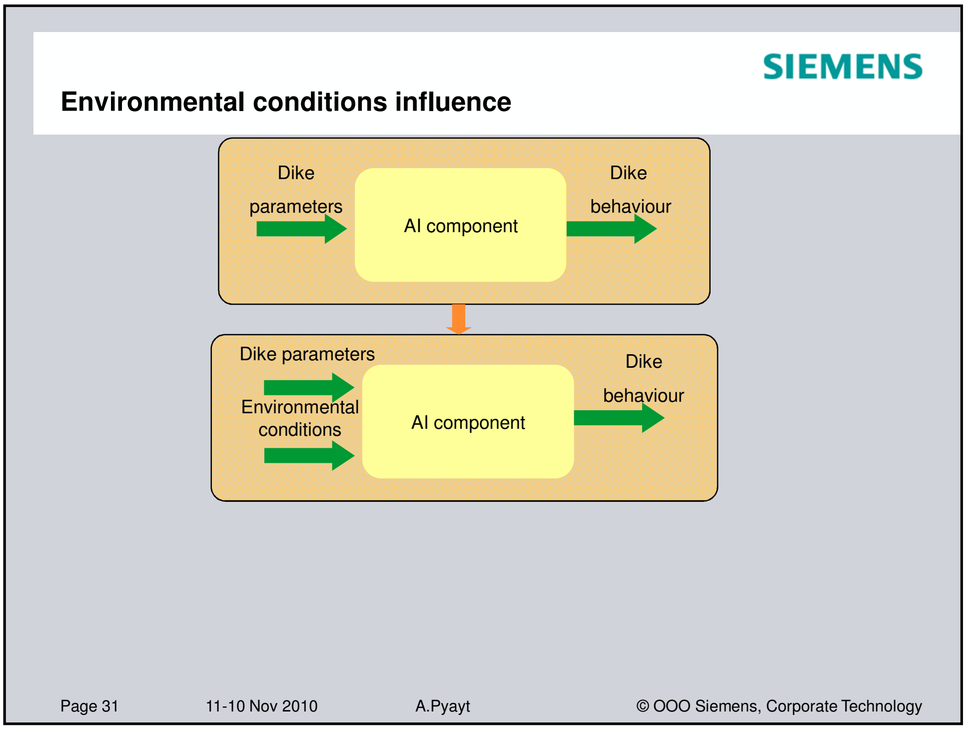
Example of cluster movement

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Environmental conditions influence
Dike
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AI component
Dike
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Dike parameters
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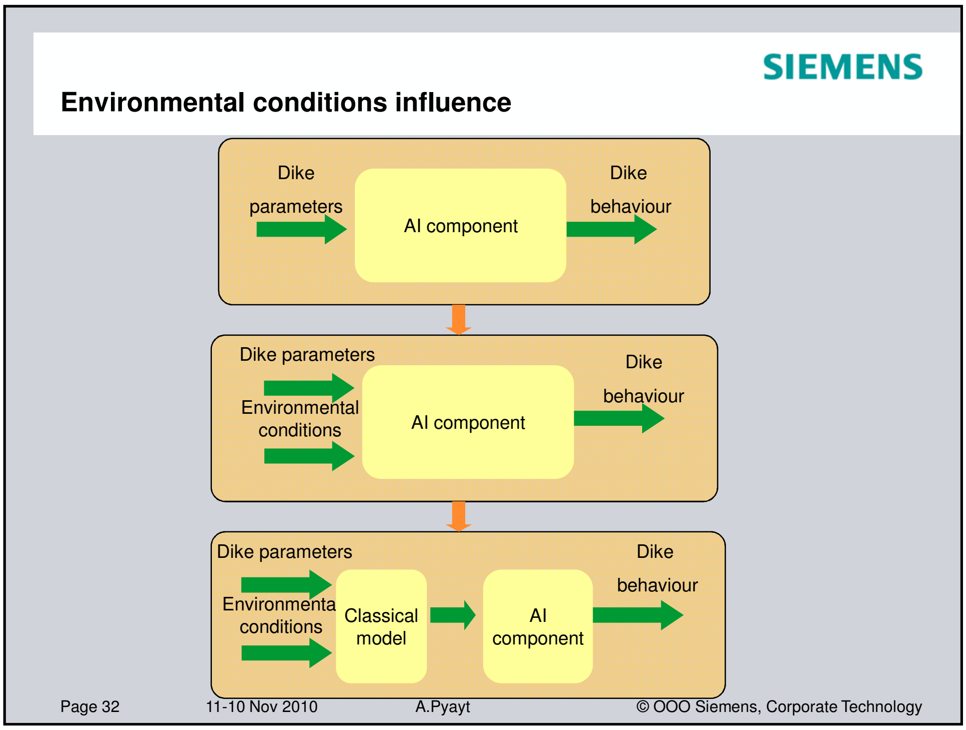
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AI component
Dike
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Conclusions

Summary

- Appropriate machine learning method for one-side classifiers selected
- Data processing cascade defined
- Possible combination of data processing stages reviewed
- AI component integrated into Early Warning System (EWS) prototype
- First tests completed on real-time, real-world data

Outlook

- Adaptation to environmental conditions and seasonal changes
- Development of hybrid system identification: physical models extended by machine learning methods
- Automated configuration of AI component for any dike

