



A Neural Network Approach for Diagnosis in a Continuous Pulp Digester

Pascal Dufour, Sharad Bhartiya,

Prasad S. Dhurjati, Francis J. Doyle III

Department of Chemical Engineering
University of Delaware

<http://fourier.che.udel.edu/~Agenda2020/>





Outline

- Motivation for diagnosis in the pulp digester
- Overview of fault methodologies
- Neural network approach and features
- Training set design discussion and results
- Features of the moving horizon estimation for a comparison study

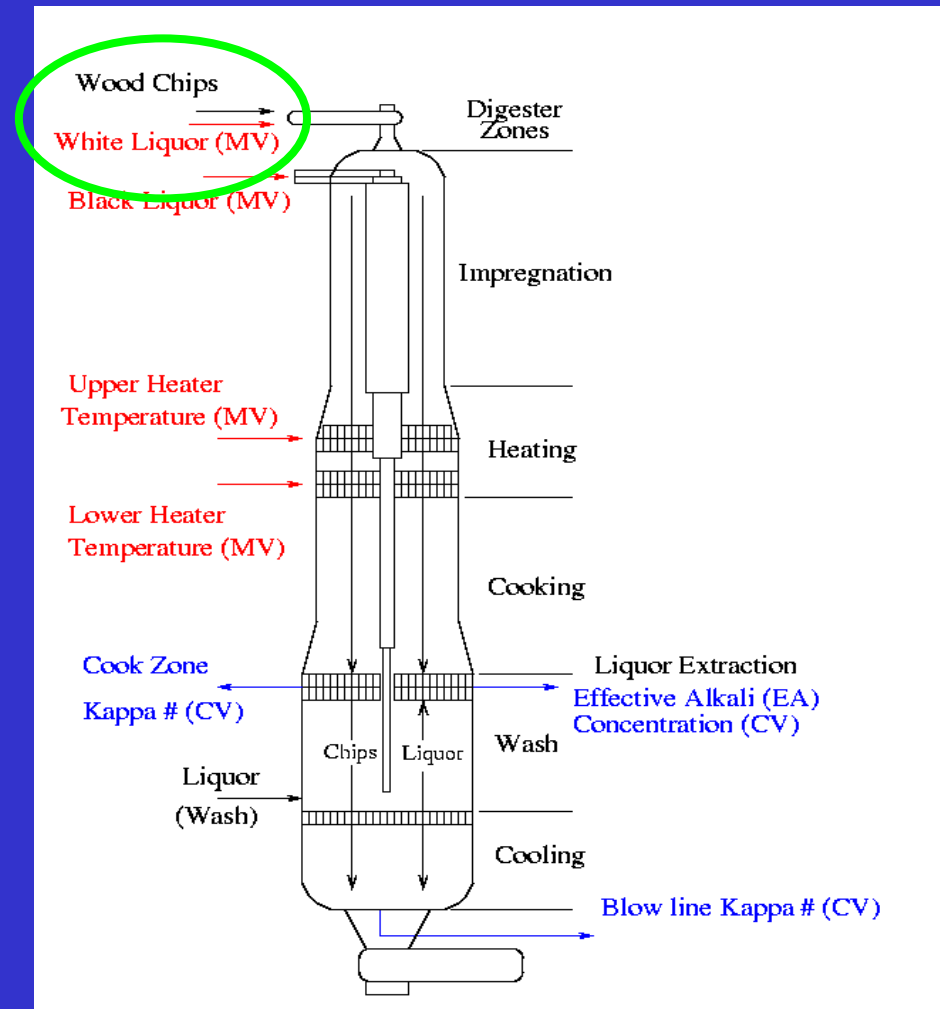


Feedstock Properties Variation: Motivation for Diagnosis

- Moisture content variations
($T_s=1$ day)
- + 5 unmeasured densities for the chips
- high reactivity lignin
 - low reactivity lignin
 - cellulose
 - galactoglucomannan
 - arabinoxylan
- + 2 unmeasured densities for the white liquor:
- EA
 - HS
- = disturbances in the control loops

06/28/01

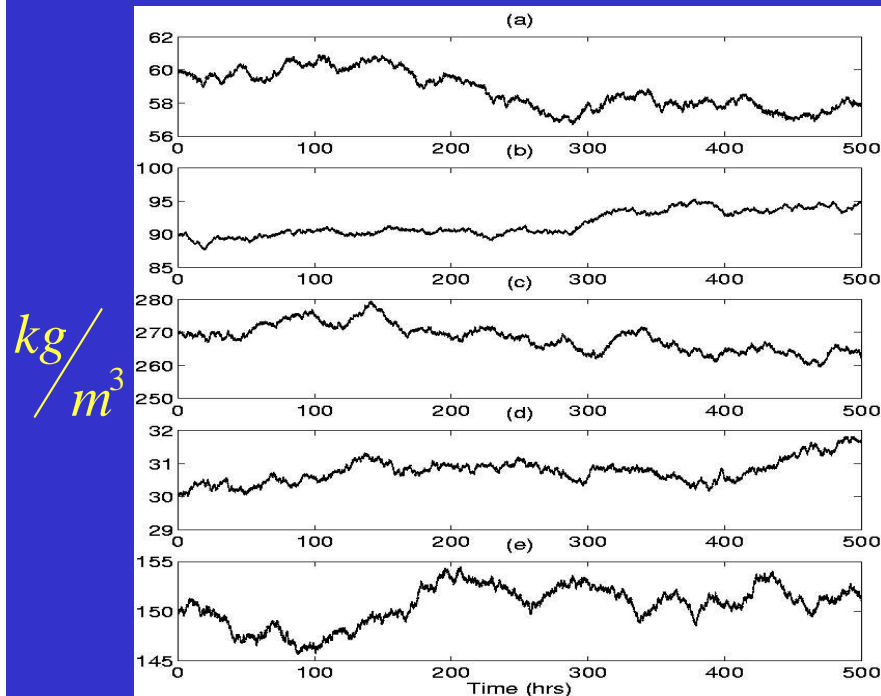
Doyle Research Group, University of Delaware



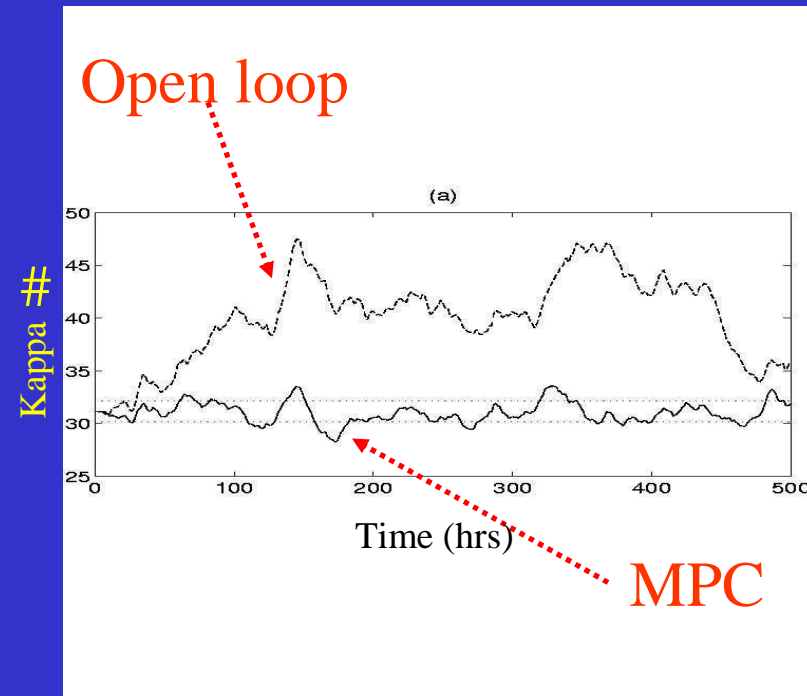


Feedstock Properties Variation: Motivation for Diagnosis

[Wisnewski and Doyle, JPC 98]



Chips Densities



Kappa Number

- No plant data are available: necessity of model based approach



Classification of Fault Methodologies

[over 140 references]

People Experiences

First Principles



Data Based

Model Based

Neural Network

Residual and statistic approach

Principal Component Analysis

Gross Error Detection

Qualitative Trend Analysis

Moving Horizon Estimation

Expert Rules

Extended Kalman Filter

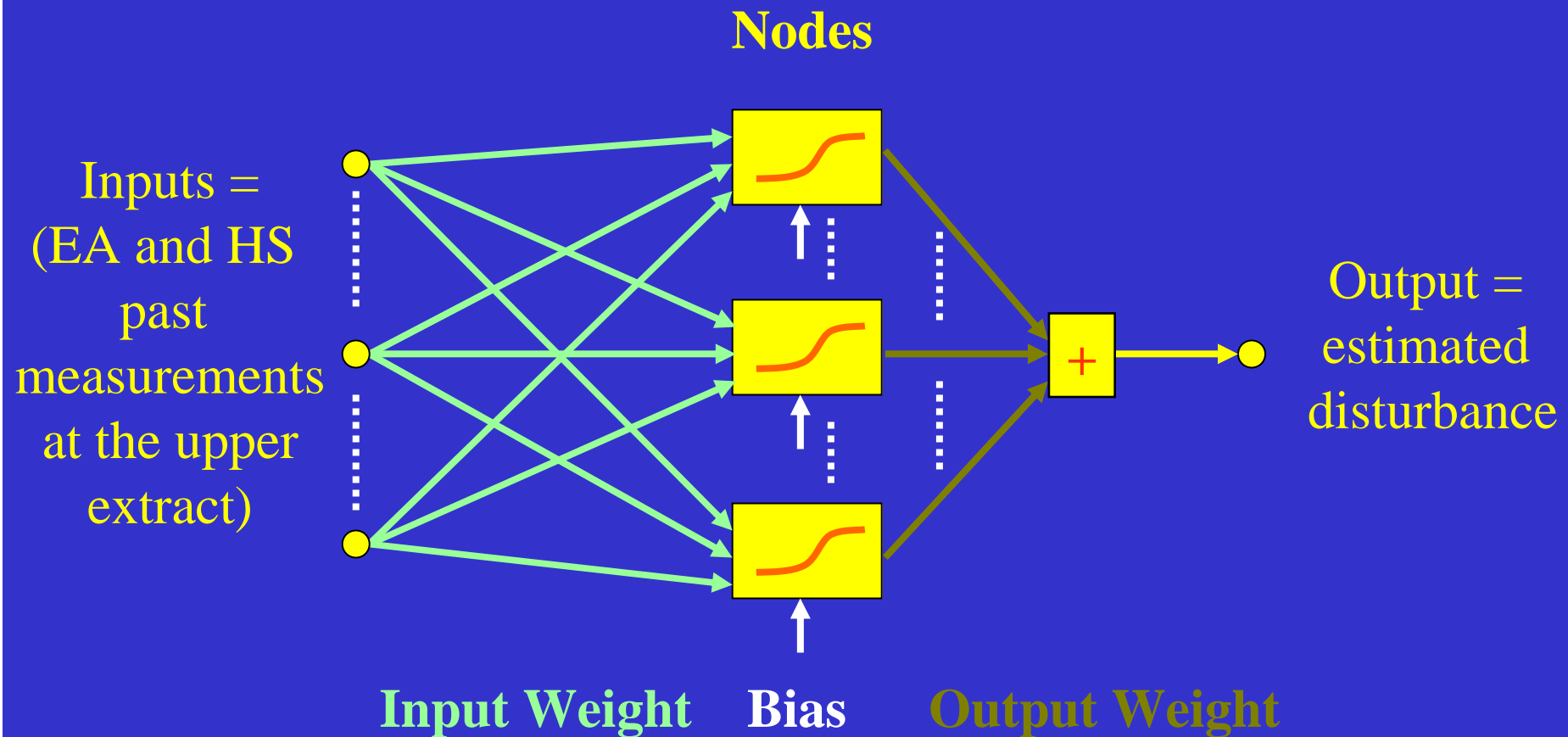
Fuzzy Rules

Observers

Decision Tree



Neural Network Approach





Neural Network Features

- Training (off-line): determination of the weight and the biases
 - Drawback: need rich data
 - Since no plant data are available for this training, an accurate model to simulate each fault scenario is needed: importance of modeling
 - Advantage: ease of modeling/retraining
- Use of the neural network:
 - Advantage: on-line algebraic determination of the neural network output
 - Drawback: poor extrapolation for untrained situations



Training Set Design: Case Study 1

Step 1: Variations Set Design

- Combination of step changes for:
 - Moisture content
 - 5 wet chips densities
 - 2 white liquor densities
- with 8 possible magnitudes from 92% to 108% around each nominal value with a step of 1%

Step 2: Data generation

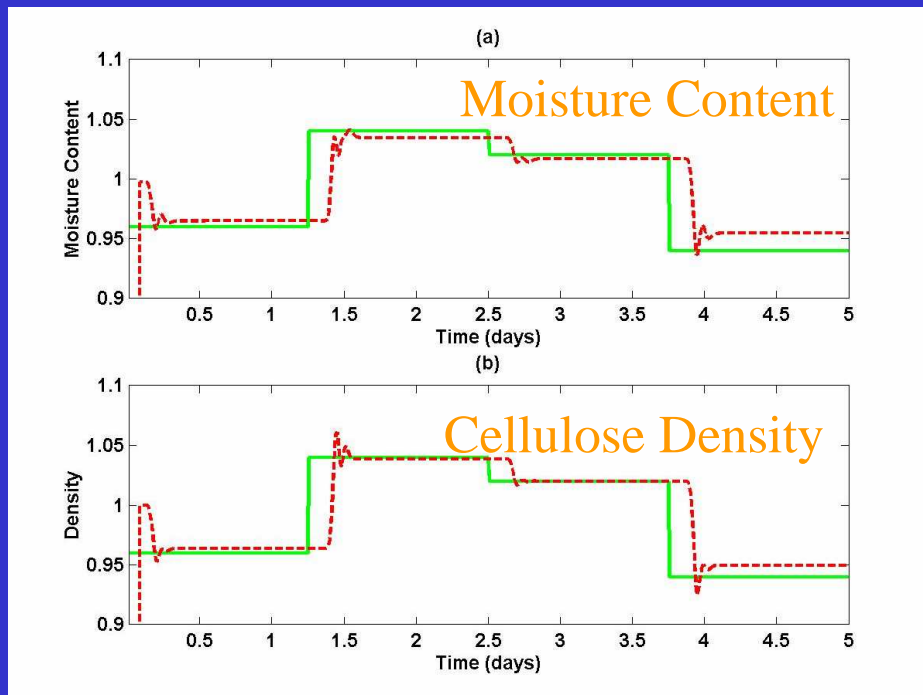
4096 simulations

Step 3: Get Training set

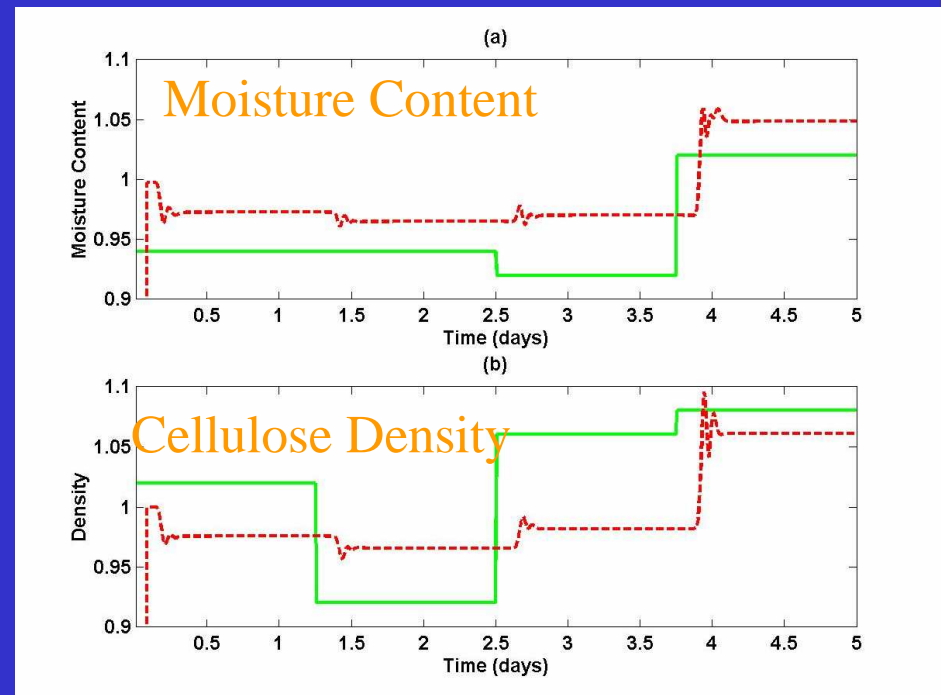
Measurements set includes variations set (fault cause) and EA and HS at the upper extraction in the digester (fault effect)



Use of Neural Networks: Case Study 1



Trained behaviors



Untrained behaviors

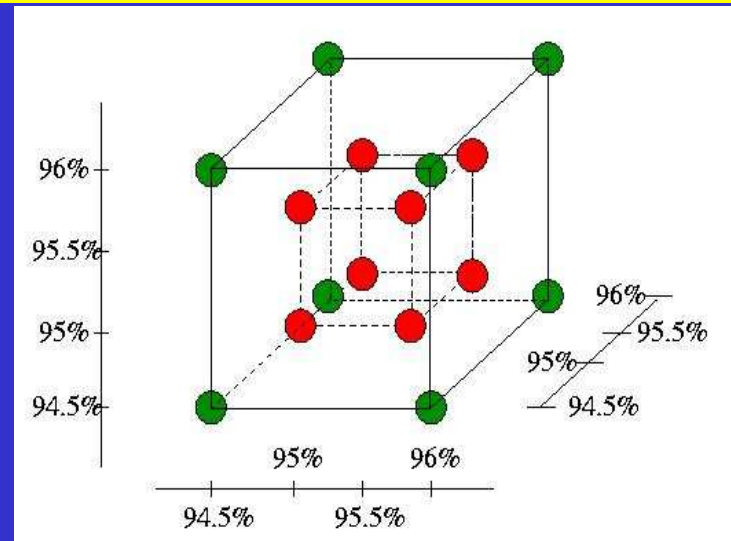


Case Study 1 Observations

- Result: moisture content, cellulose density and possibly araboxylan density and HS density can be inferred
- Extrapolation issue: how to choose the variations set of the 8 parameters to construct the training set?
 - Key: the training set has to be sufficiently representative such that interpolation can be done
 - Solutions:
 - use of co-centered polyhedrals (case study 2)
 - choose magnitudes randomly among all the discrete possibilities (case study 3)



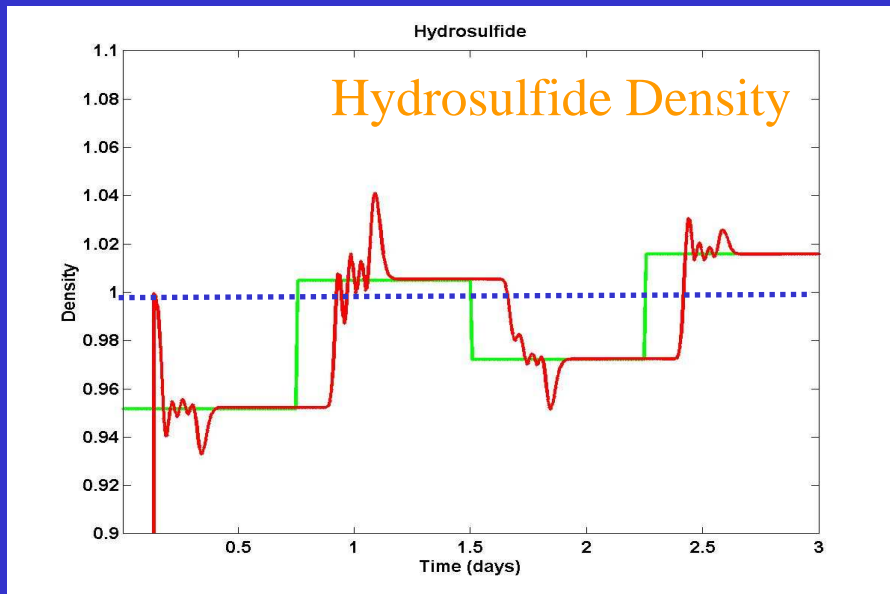
Training Set Design: Use of Co-centered Polyhedrals



- To reduce the size of the variations set, the 3 most sensitive signals that gave previously good results for the interpolation are chosen: moisture content, carbohydrate and HS densities
- Training set design: all 13 combinations from 94% to 106% around each nominal value with a step of 1%: $13^3 = 2197$ runs

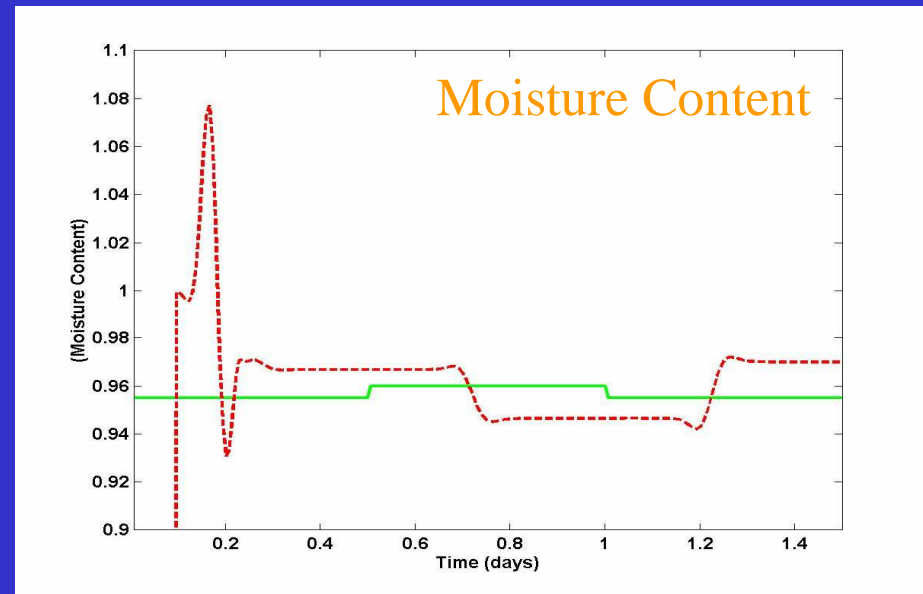


Case Study 2 Observations



Untrained behavior
(0.02% discretization step)

- Very good interpolation properties
- Poor extrapolation properties: include MVs in the training set design



Untrained behavior (with increase
of 3% in the upper extract flowrate)

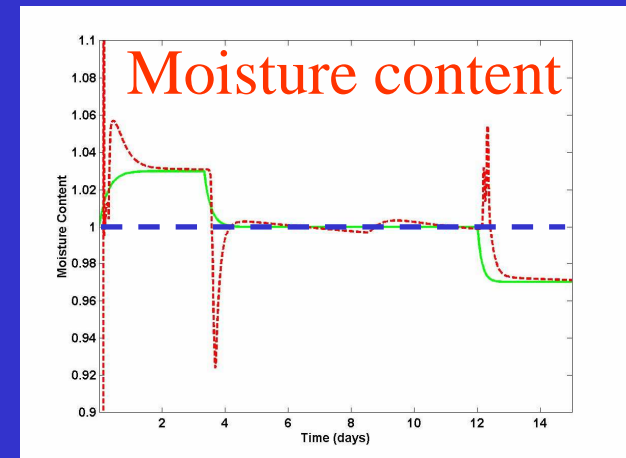
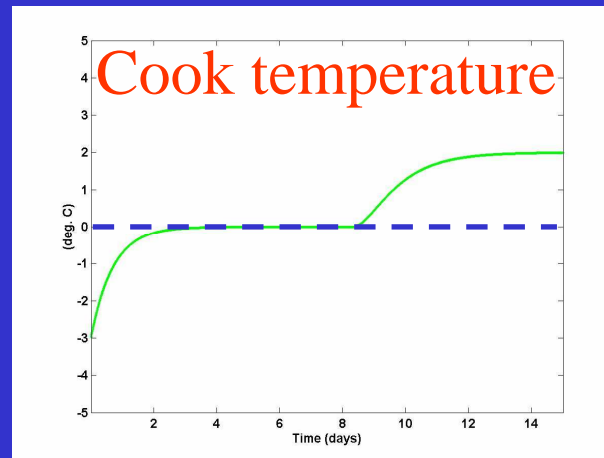
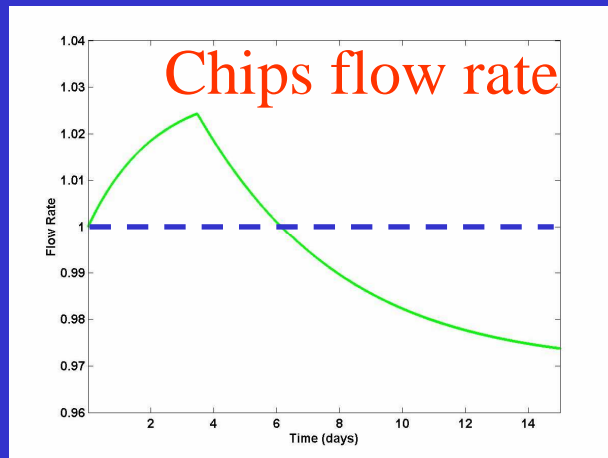


Training Set Design: Introduction of MVs

- Variations set design: 3 manipulated variables (2 flow rates and the cook temperature) that affect the measurements fed in the neural network and one of the signal that can be inferred
- Training set design: all 9 combinations from 92% to 108% around each nominal value with a step of 2%: $9^4 = 6561$ runs
- 2000 runs chosen randomly create the training set
- Only step variations are used
- Possible issue: neural network behavior vs. others variations in the property?



Case Study 3



Changes in MVs

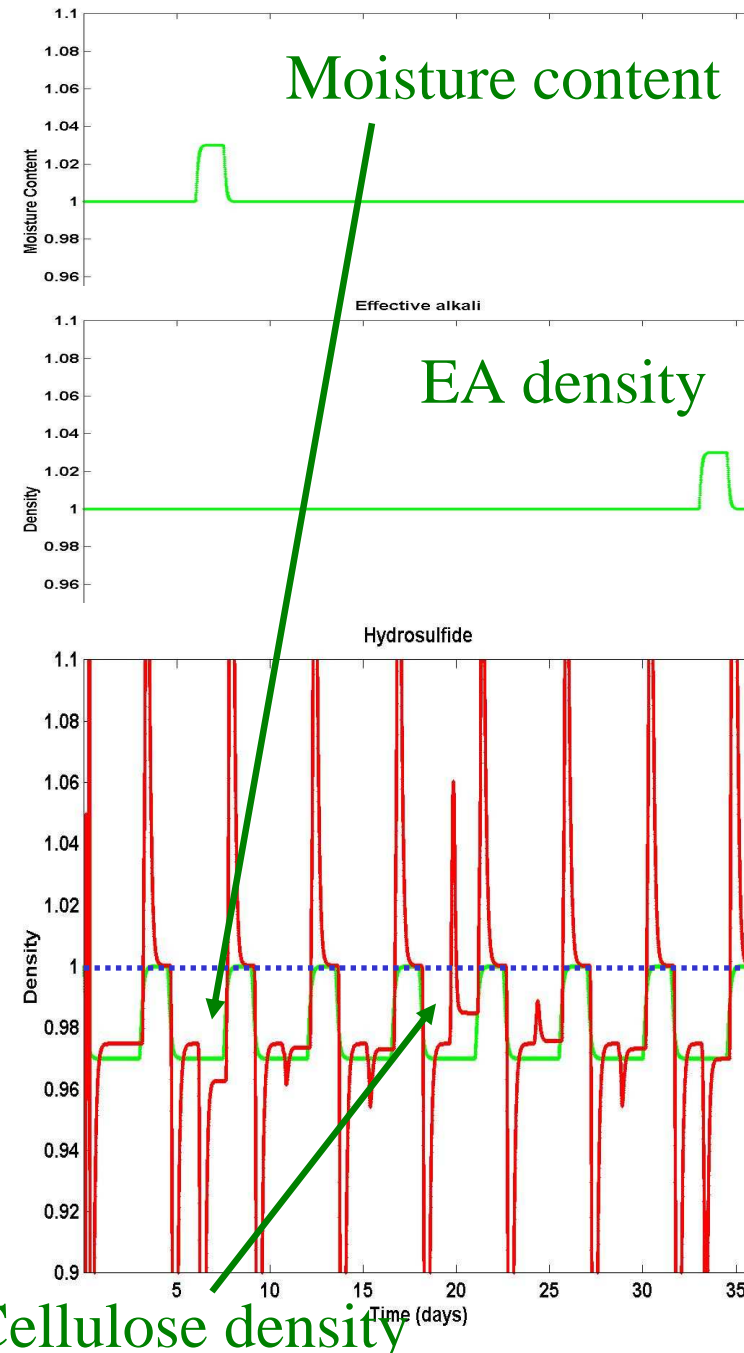
Neural Network

- Very good extrapolation properties to new signal shapes
- Insensitivity to MVs changes



Case Study 3: Robustness Analysis

- Disturb neural network with an impulse train from the first to the last components of properties
- Good extrapolation to signals and good robustness
- The NN outputs can be combined to correct the remaining errors

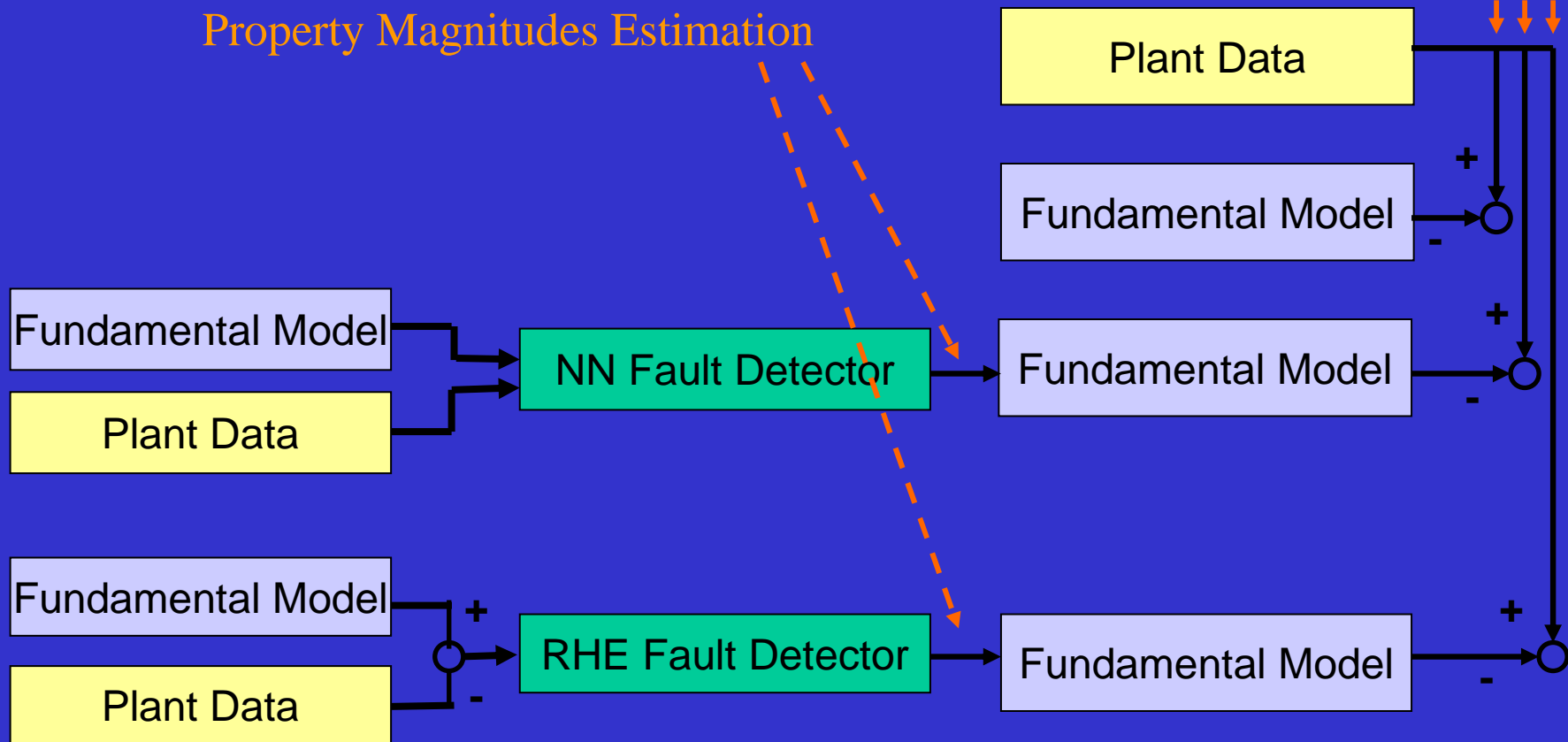




Neural Network vs. Residual Approach

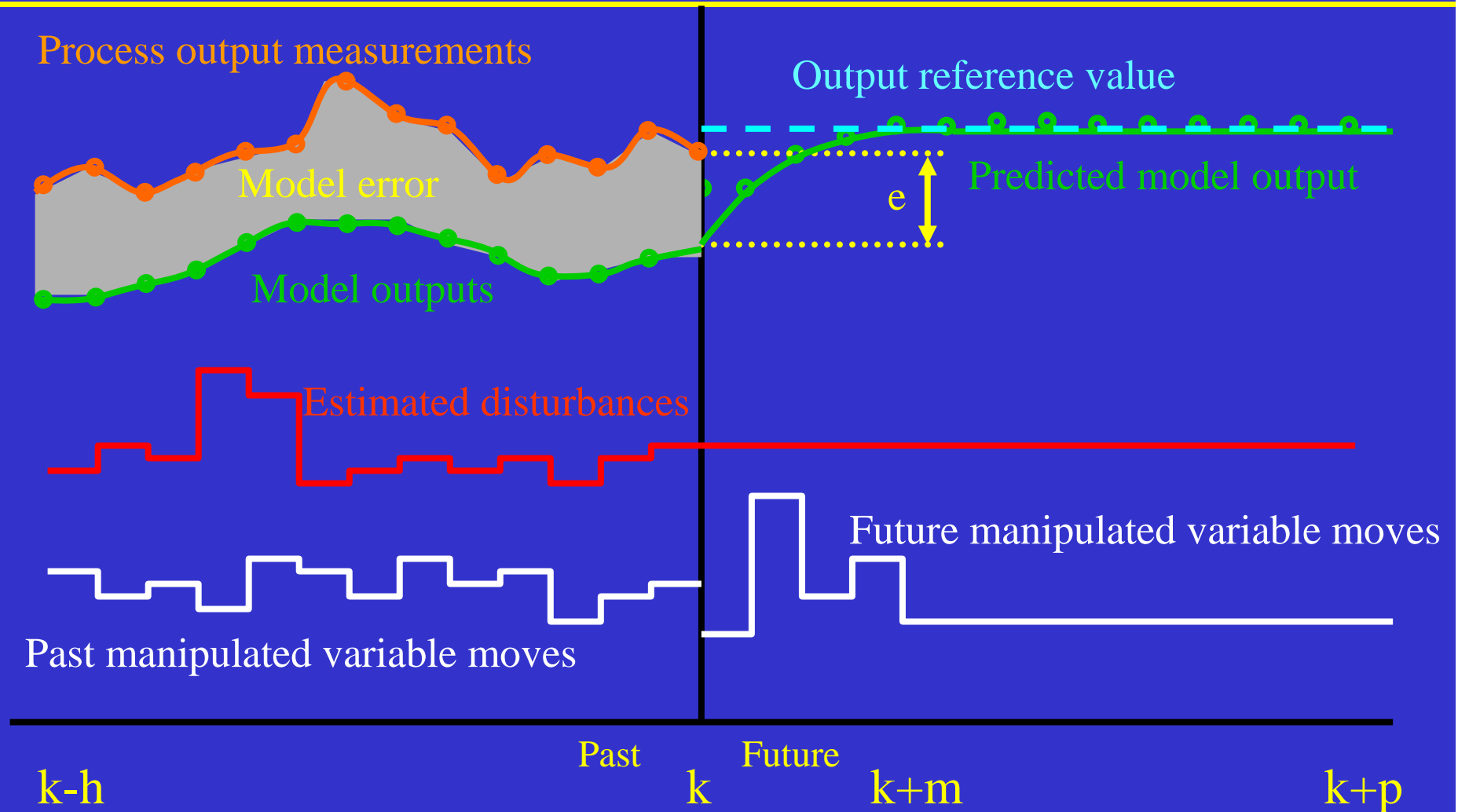
Final Methodologies Comparison

Property Magnitudes Estimation





Future Work: Horizon Based Control and Estimation





Future Work: Moving Horizon Estimation

[Gatzke & Doyle III, JPC 2000]

- Qualitative constraints:
 - Limit system to S simultaneous faults
 - Disturbances variation signifies a fault
- Multiple impulse response models used:
 - Models developed from step response
 - Multiple models used in parallel



Conclusions & Future Work

- 3 unmeasured disturbances + moisture content can be inferred
- Importance of the model since no plant data are available
- Importance of the training set design based
- Evaluation of the neural network approach in a closed loop control structure and in open loop at the plant
- Development of the MHE framework



Acknowledgments

• Funding:



• Collaboration:

Westvāco

