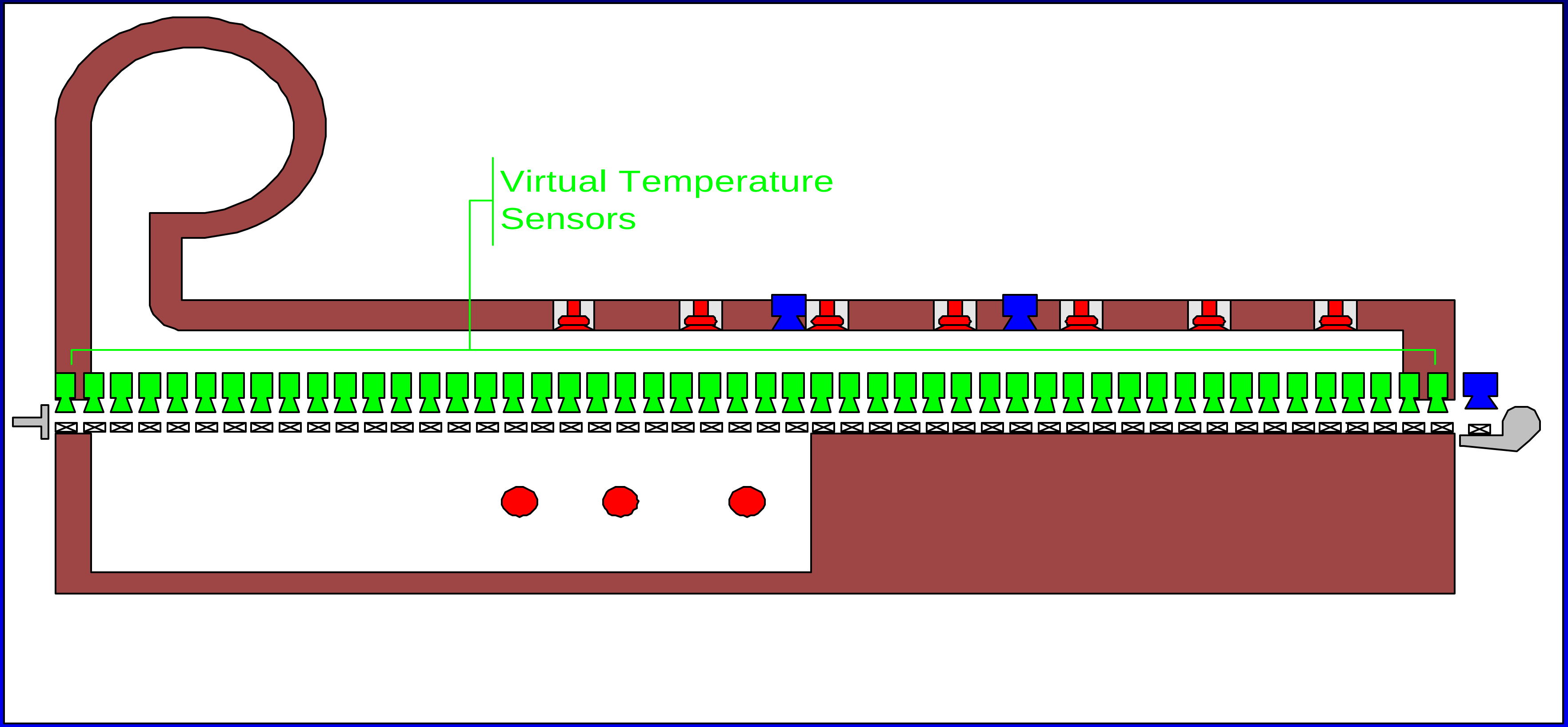
Virtual Sensor Technology for Process Optimization

Edward Wilson
Neural Applications Corporation
ewilson@neural.com

Virtual Sensor (VS)

- Also known as “soft sensor,” “smart sensor,” “estimator,” *etc.*
- Used in place of real sensor (RS)
- Takes readings from RSs and control variables, calculates values of (unsensed) process variables.

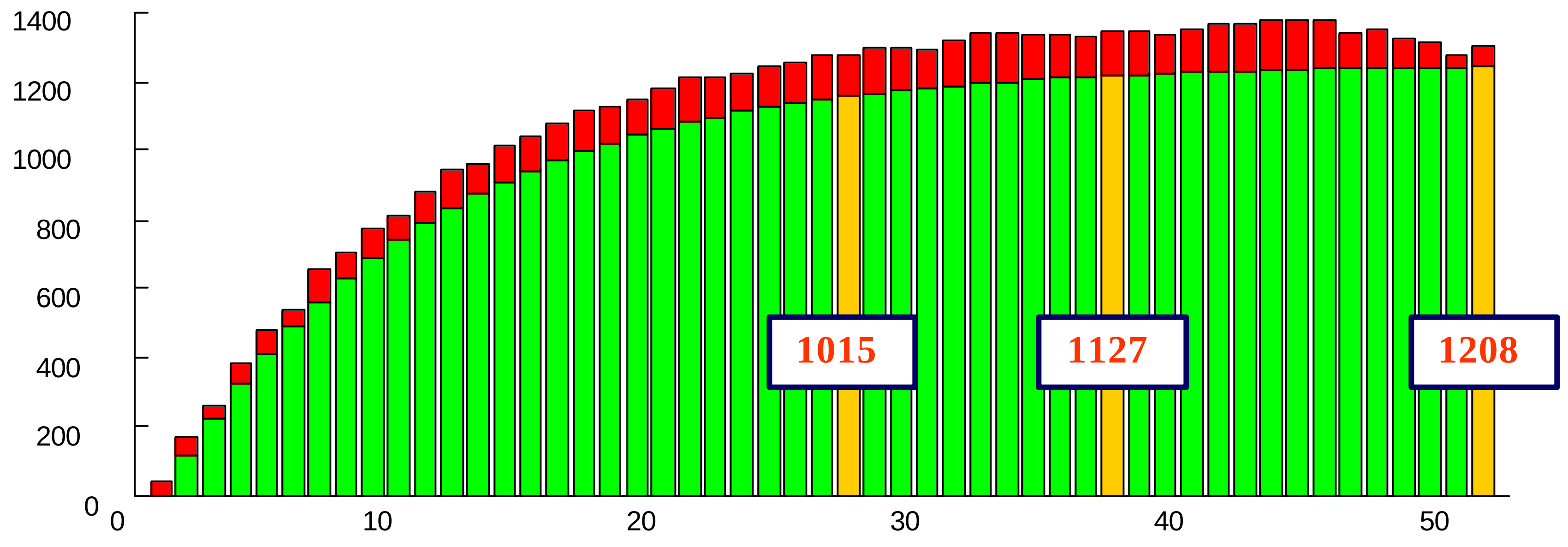
Reheat Furnace Virtual Sensor



- Real Sensor -> process model -> VS outputs

Virtual Sensor - Example Output

- Reheat furnace example



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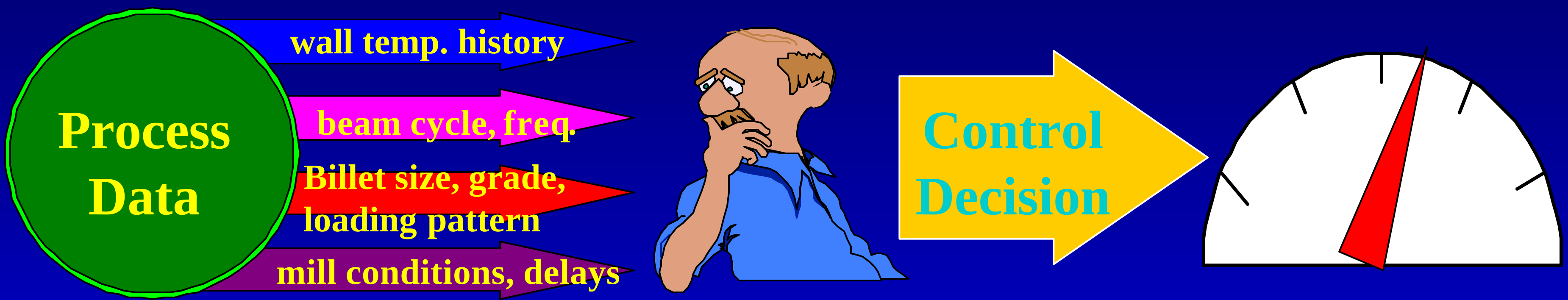
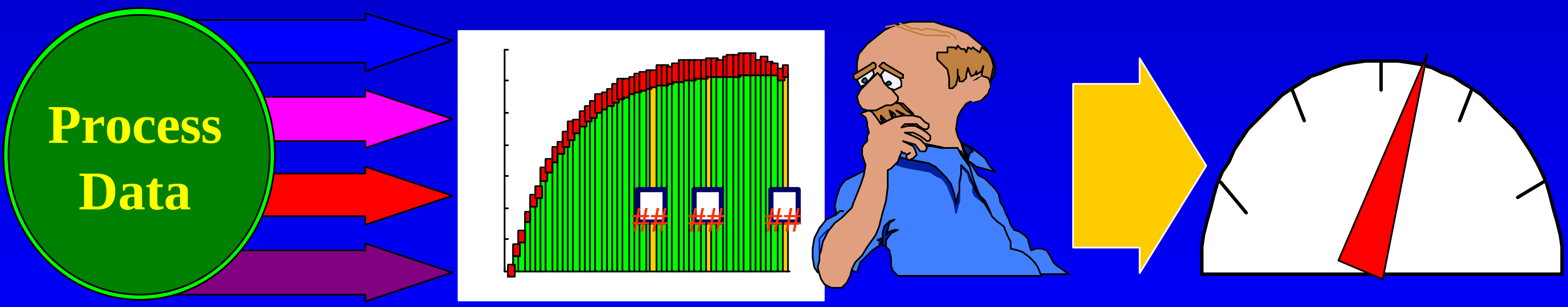
Virtual Sensor Utilization





Goals of Talk (Outline)

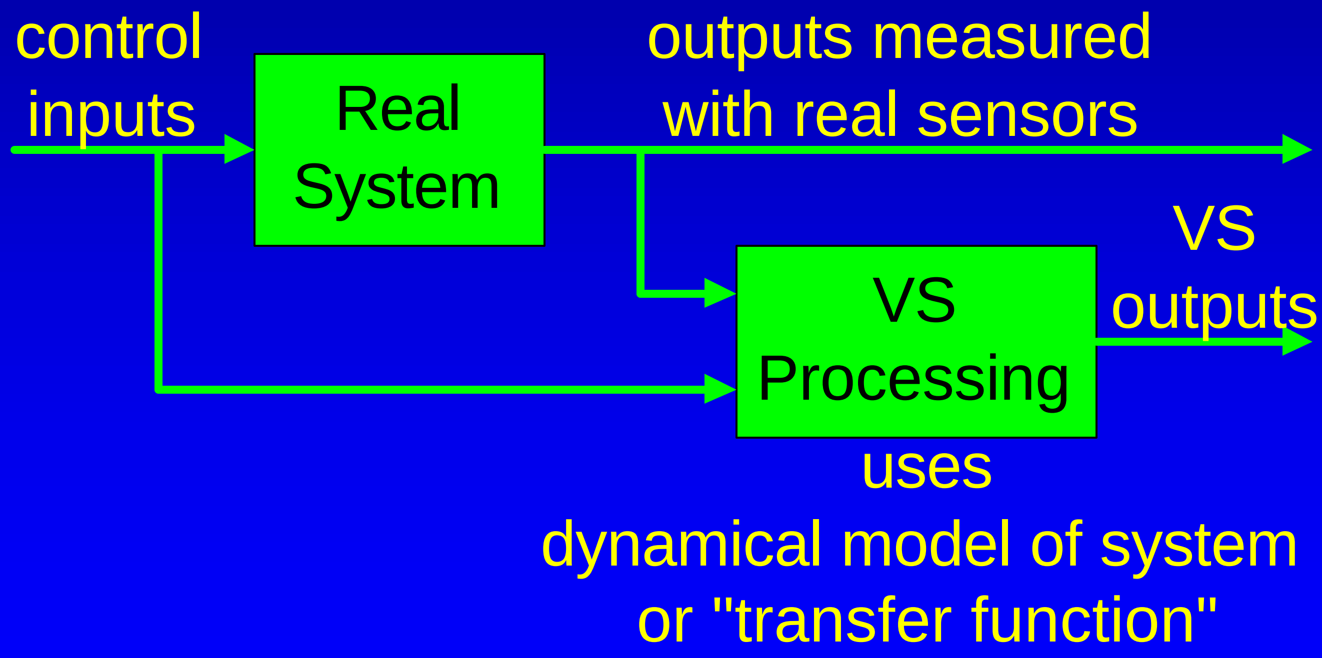
- Introduce technology (background information for following talk)
  - Virtual sensor
  - Neural network
- Example applications
- Discuss how to identify potential applications of this technology

Types of VS Applications

- Replace a temporarily installed sensor
- Provide continuous output based on periodic RS measurements (e.g., lab analyzers)
- Predict ahead for systems with built-in delay - allows predictive control
- Provide robustness - substitute VS when RS fails or is down for maintenance
- In all cases, model is needed

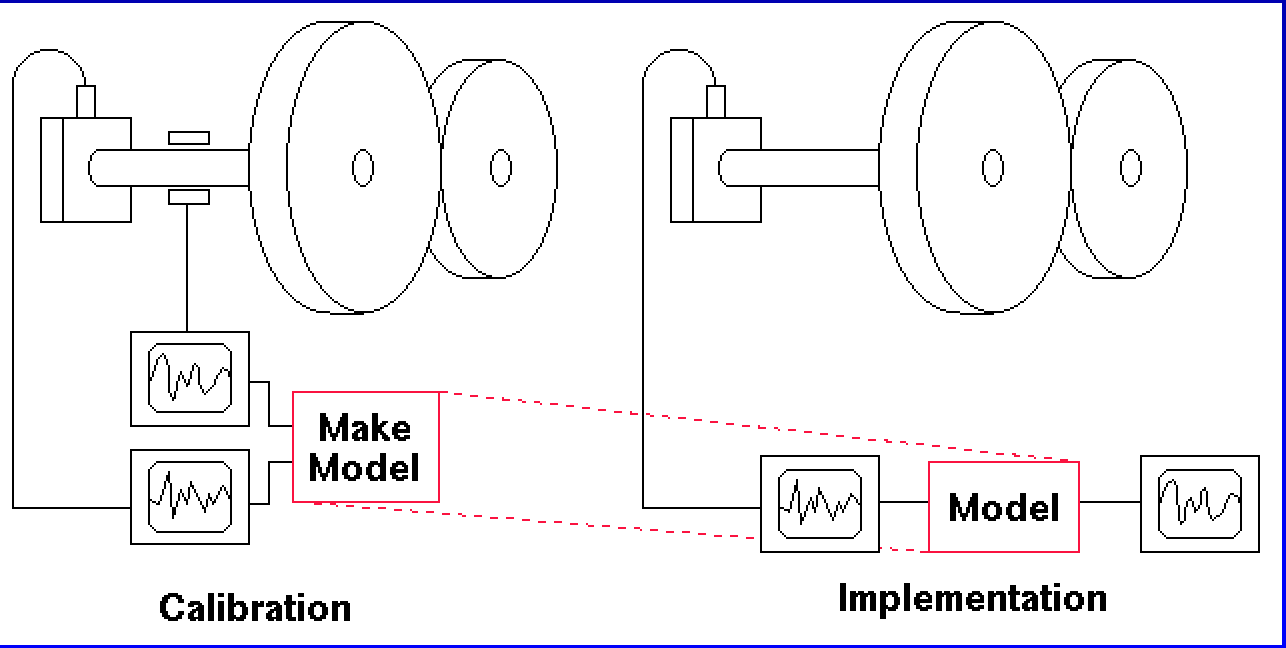
Basic Virtual Sensor Technology

- VS - gives measurement in place of a RS
- Requires system model to process data from RSs

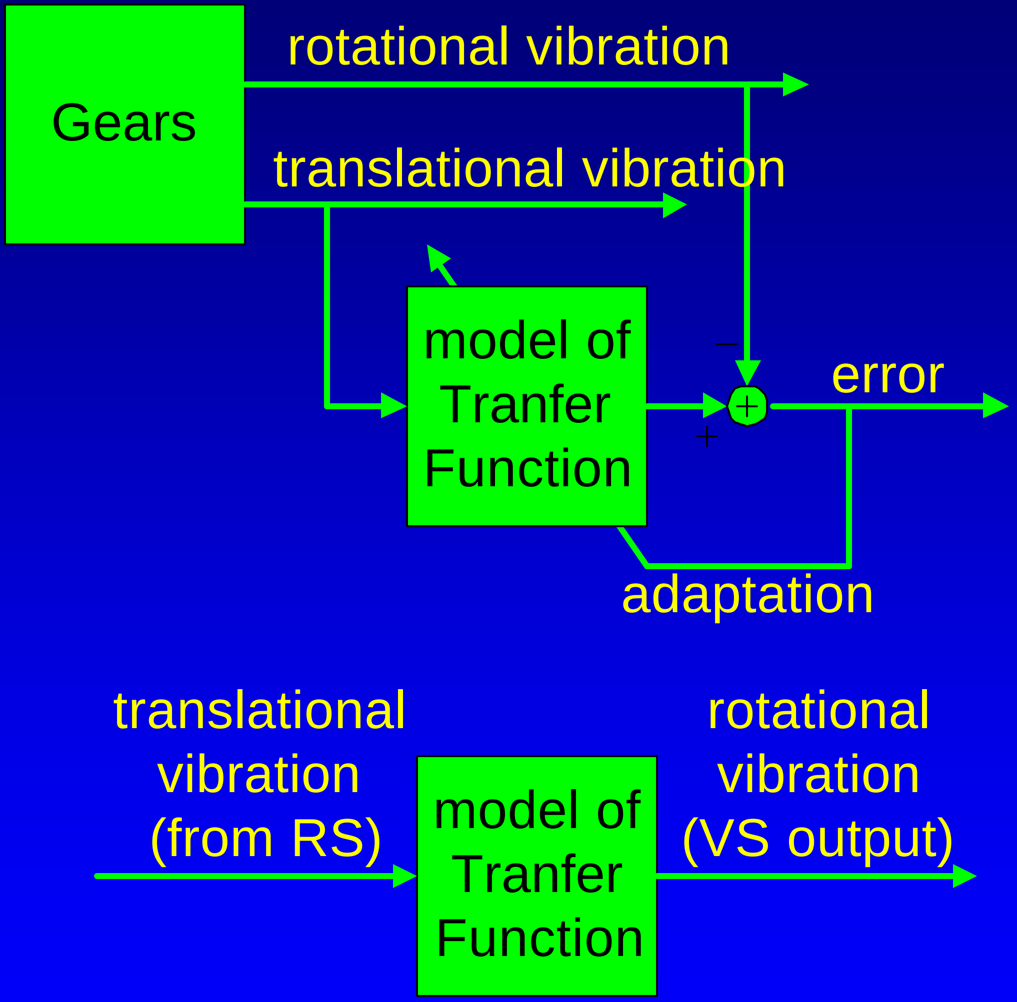


Gear Vibration VS

- Gear research by Joel Limmer at Mechanical Diagnostics Laboratory at RPI
- Uses temporarily installed rot. vib. sensor

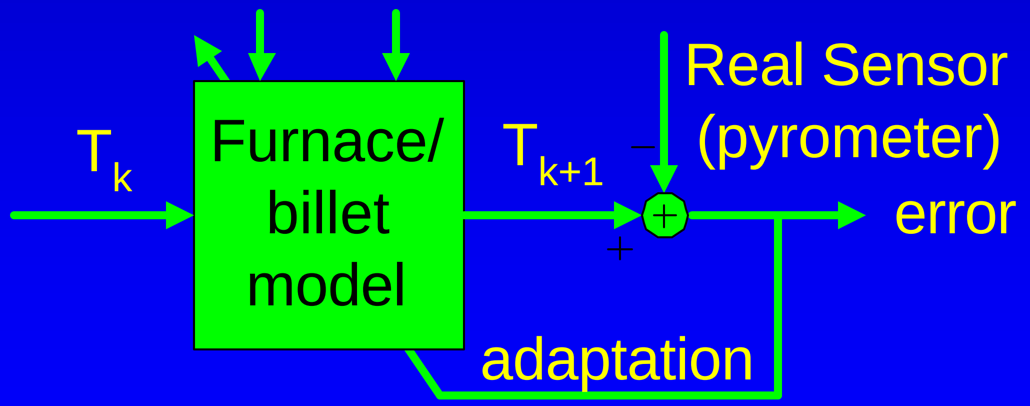


Transfer Function Example



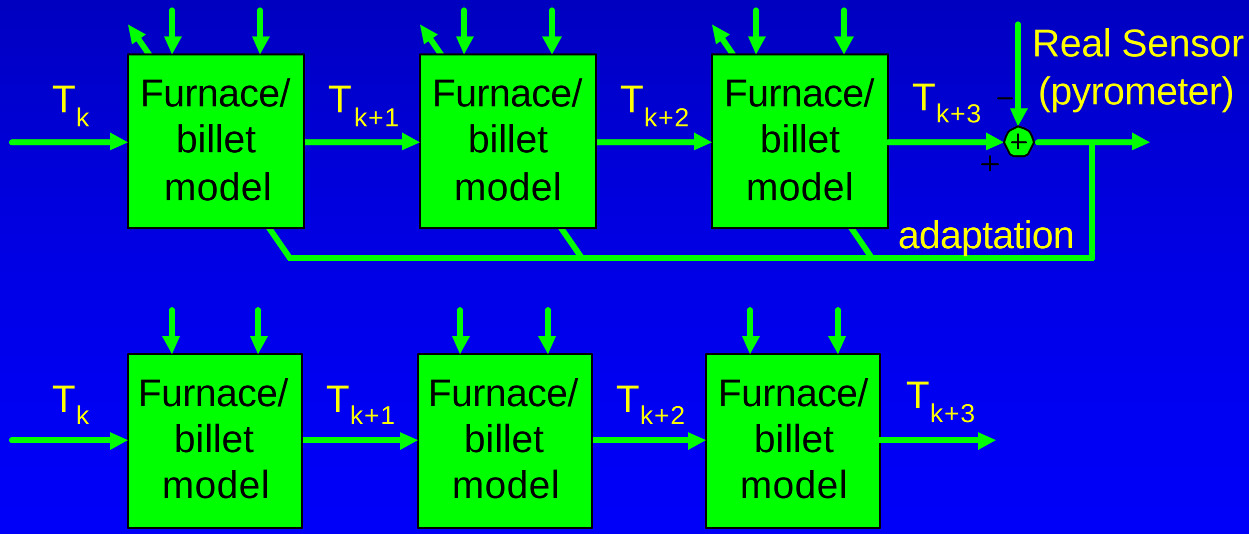
Dynamical Model Example

- Example from Reheat Furnace
- Develop dynamical model that can be run forward in time to predict future outputs
- RS used to develop model (adapt parameters)



Dynamical Modeling

- Can be modeled, even with intermittent RS data
- ***<u>If accurate model</u>***, can predict ahead, optimize control inputs



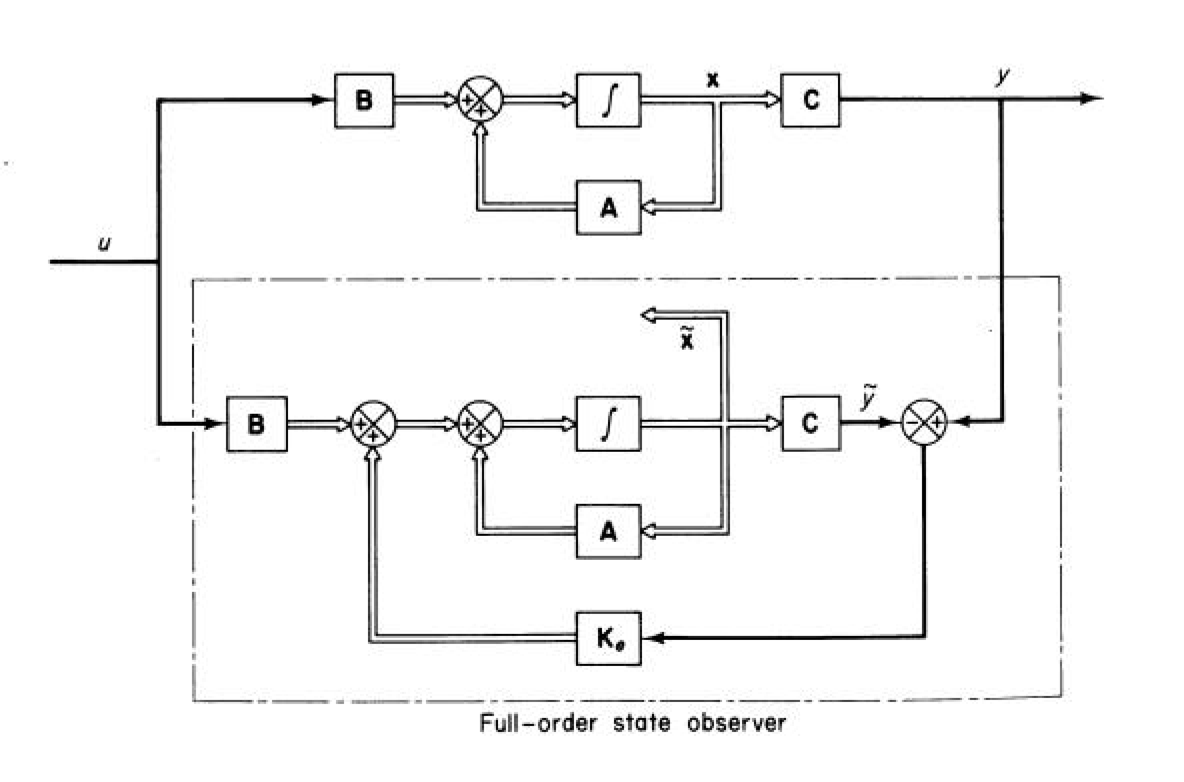
Model Accuracy is Critical

- VS output depends on model accuracy
- RS accuracy important
  - used to build model
  - used as inputs to VS processing (GIGO)
- VS measurement must be "observable" from RS data

- **Often, this is where the real challenge is**

Modern Control - Estimator

- Primarily for Linear Systems. Also Kalman Filter, EKF.
- State-feedback control
- If model unknown, must be “identified.”



Virtual Sensor Modeling

- Industrial control systems generally don’t use state feedback control -> not full estimator, just certain VSs for (e.g., PID) control loops.
- Often nonlinear / poorly understood / time-varying processes
- Use **Neural Networks** (NN) for modeling. (e.g., hybrid NN with linear model)

Outline

- Introduce Technology
  - – Virtual sensor
  - – **Neural network**
- Example applications
- Discuss how to identify potential applications of this technology

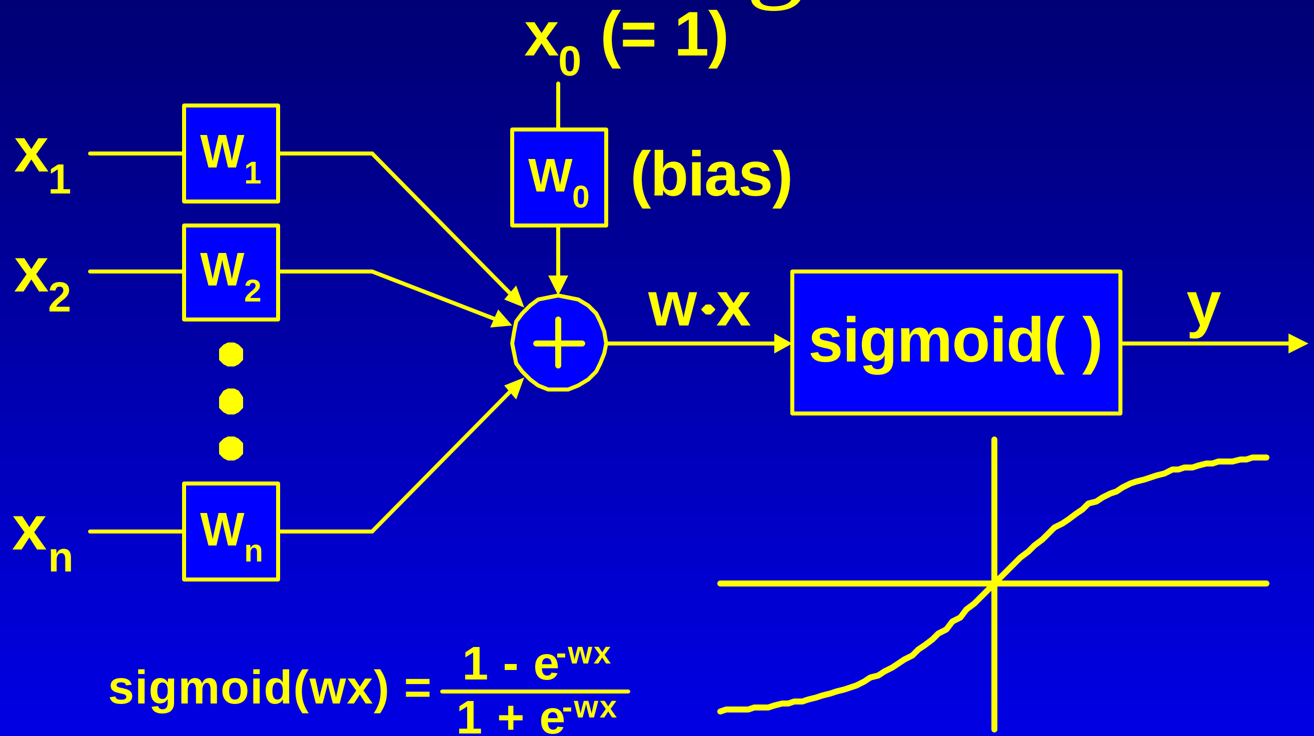
Properties of Neural Networks

- Neural Networks (NNs) are known to have valuable capabilities such as:
  - Nonlinear ==> deal with real-world
  - Adaptive ==> “trained” with data to solve problems, adapt to changing systems
  - Parallel architecture ==> fast in hardware
  - Generic functional element ==> can model anything
- However …
  - costs must be weighed vs. these benefits

Biological Motivation, Engineering Application

- Human brain:
  - Massively parallel network of simple processors with great capabilities 15 billion neurons
  - 10,000 inputs per neuron
  - 1-2 ms neuron response time
- ANNs studied in a variety of fields
  - Engineering
  - Psychology

Model of Single Neuron

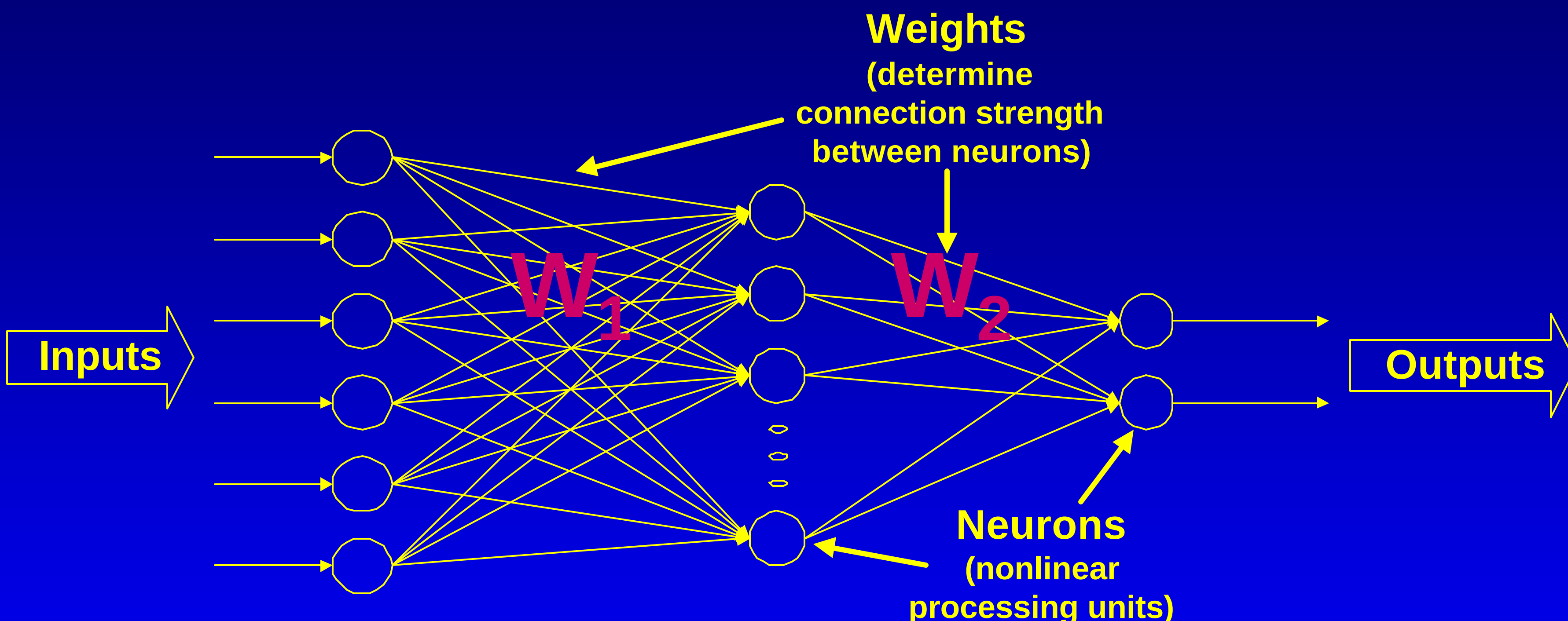


$$\text{sigmoid}(wx) = \frac{1 - e^{-wx}}{1 + e^{-wx}}$$

$$y = \text{sigmoid}(w_1x + w_2x + \ldots + w_nx + \text{bias})$$

- Implement in software or hardware
- Loosely modeled from biology, but chosen for processing and training
- This type most common for engineering applications

Model of Neural Network



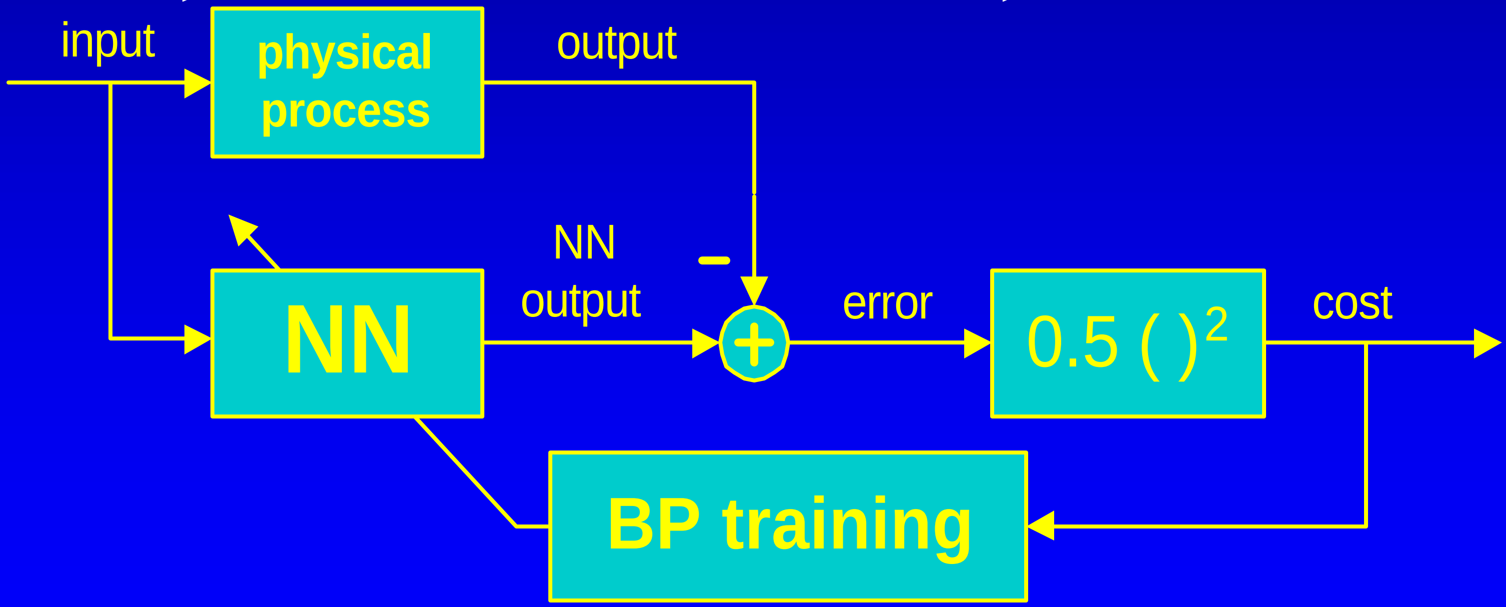
- output = W_2*sigmoid(W_1*inputs)
- proven to be a generic nonlinear functional element
- Functionality defined by architecture, weights, (training)

NN Background - Summary

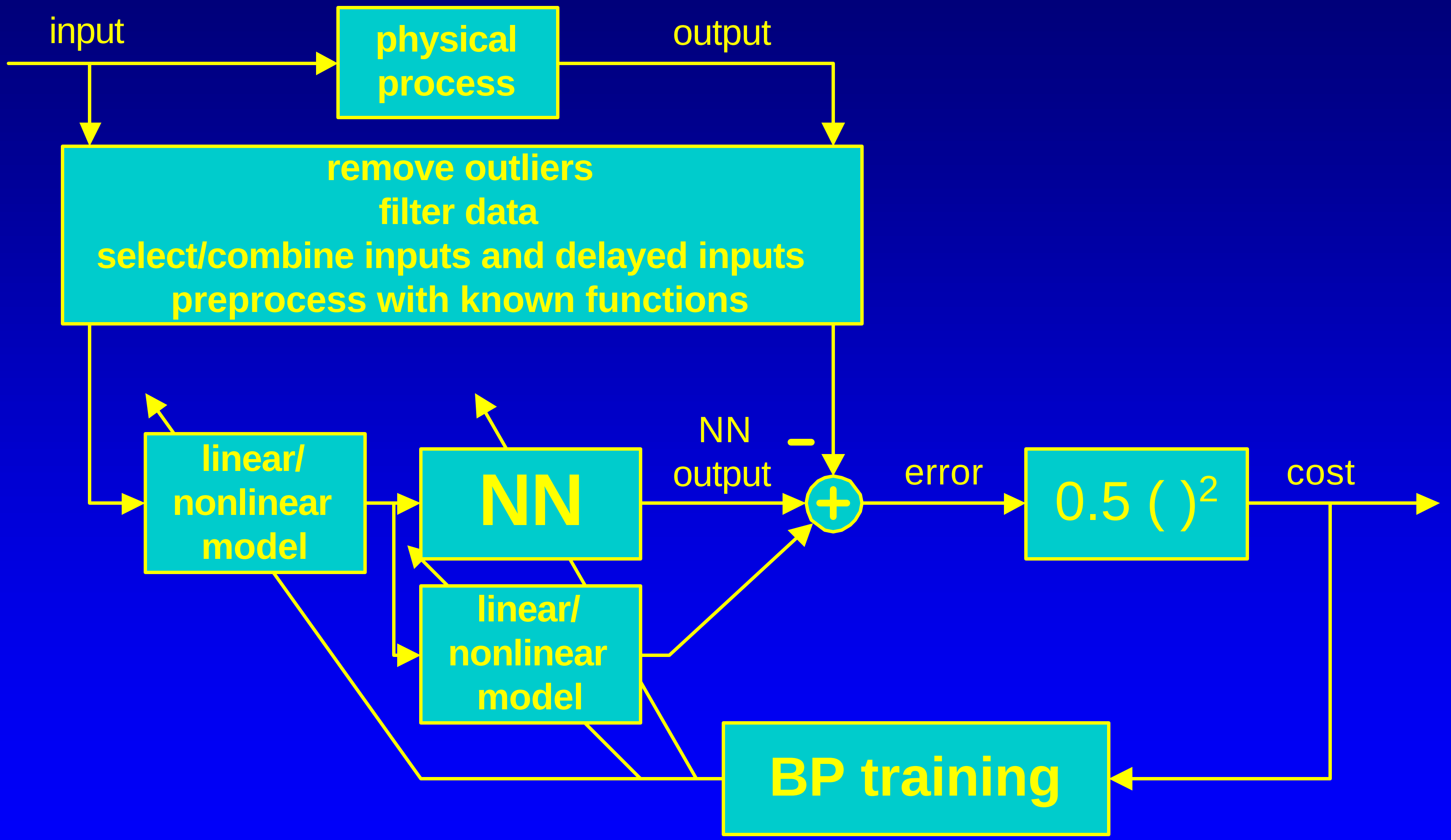
- Generic nonlinear functional element - can implement any MIMO mapping function to arbitrary accuracy (universal approximator)
- “Trained” with data
- Solid mathematical foundation - BP gets derivatives, then standard gradient-based optimization problem
- Parallel architecture, but usually implemented in software on serial computer
- Black box - difficult to understand inner workings

Training NN Model

- NN trained to emulate a physical process
- Parameter ID issues :sample rate, sufficient data, sufficient dof in model, etc.



Data Pre-processing, Structure



Technology Summary

- Virtual sensors
  - make virtual measurements by processing control inputs and measurements from real sensors
  - depend on accurate system model
  - for nonlinear, complex systems, NN model used
- Neural networks
  - generic nonlinear processing element
  - functionality set by “training” with data
  - can be used in “hybrid” modeling structures

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- **Example applications**
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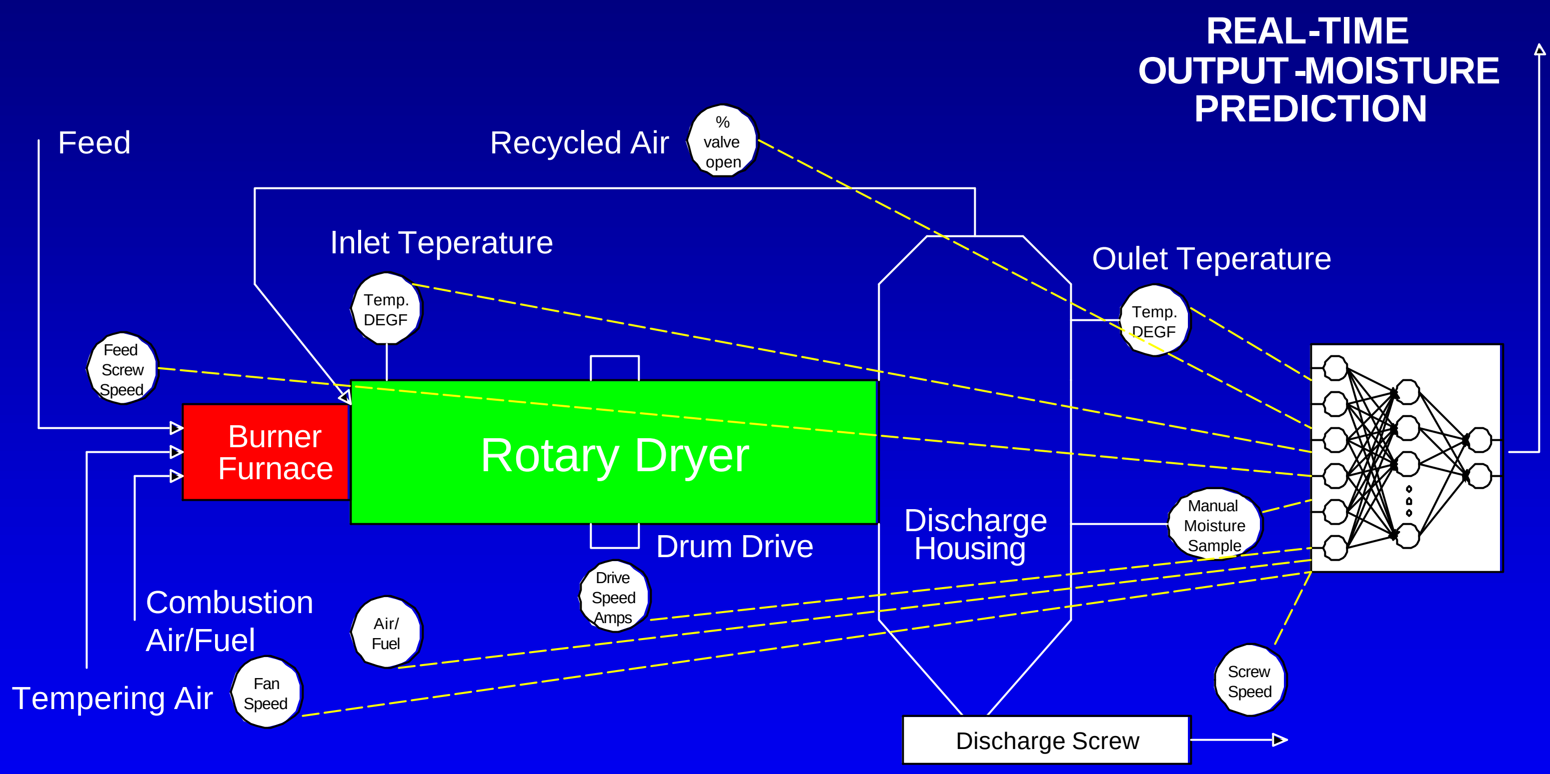
Neural-Network Dryer Example

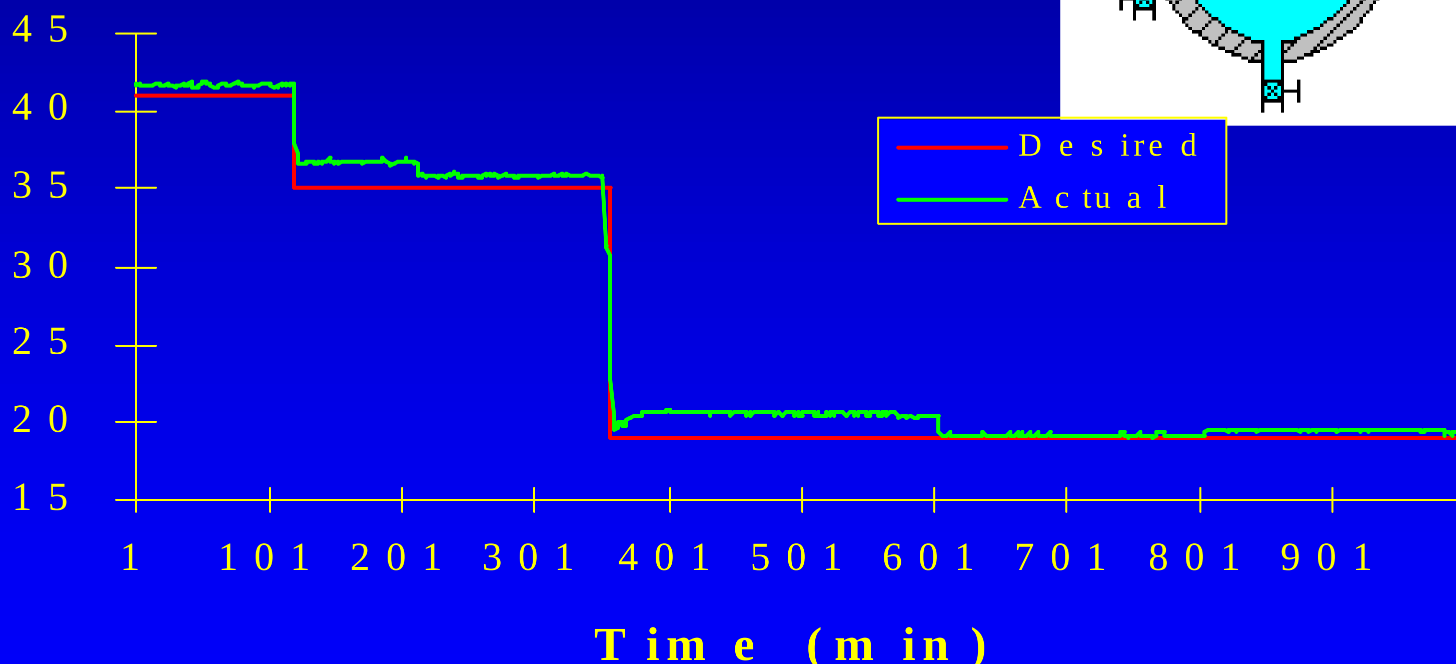


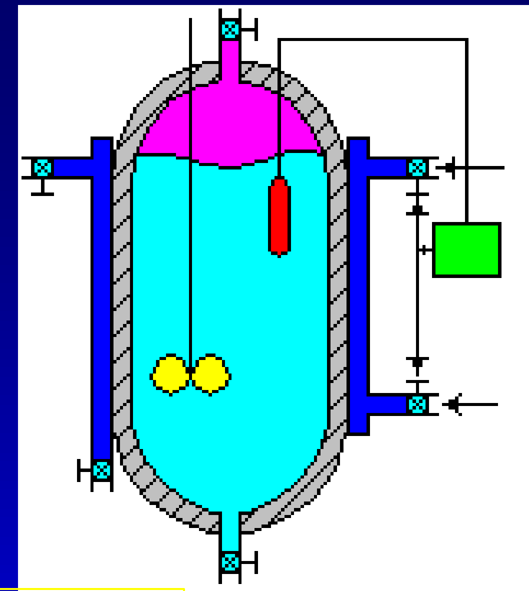
- Delayed sensing of product water content

Chemical Reaction Tank

Reduce Process Variation

Standard Deviation BEFORE = 1.38

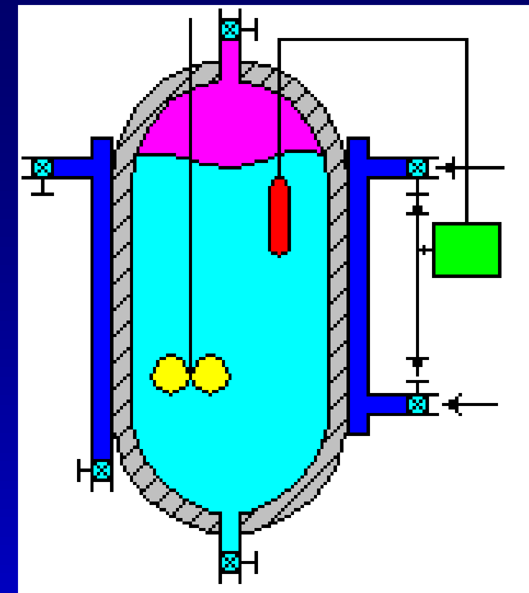


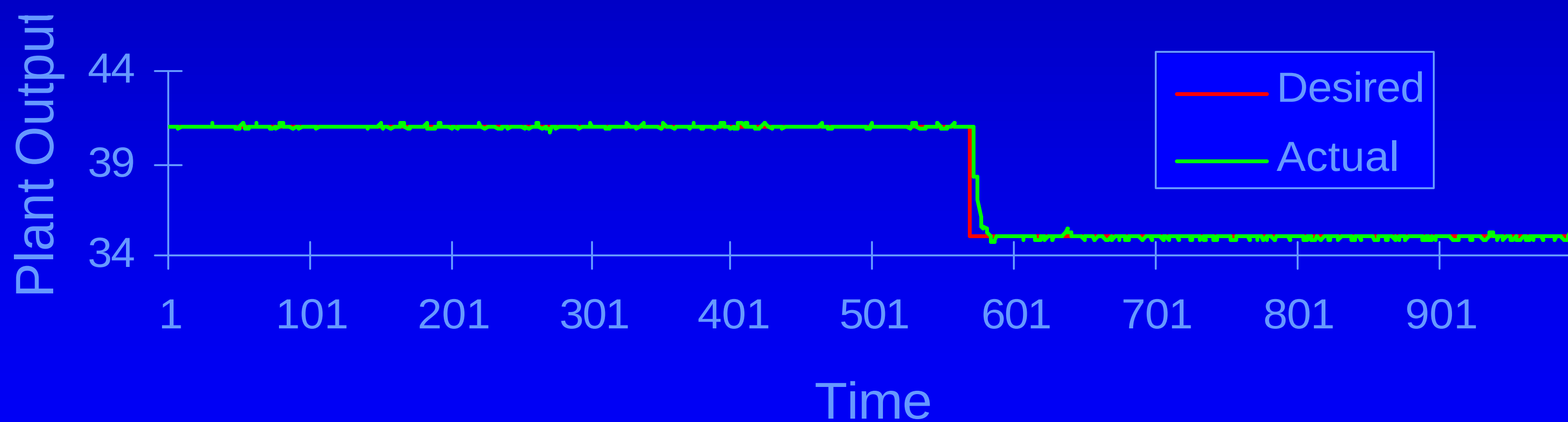


Chemical Reaction Tank

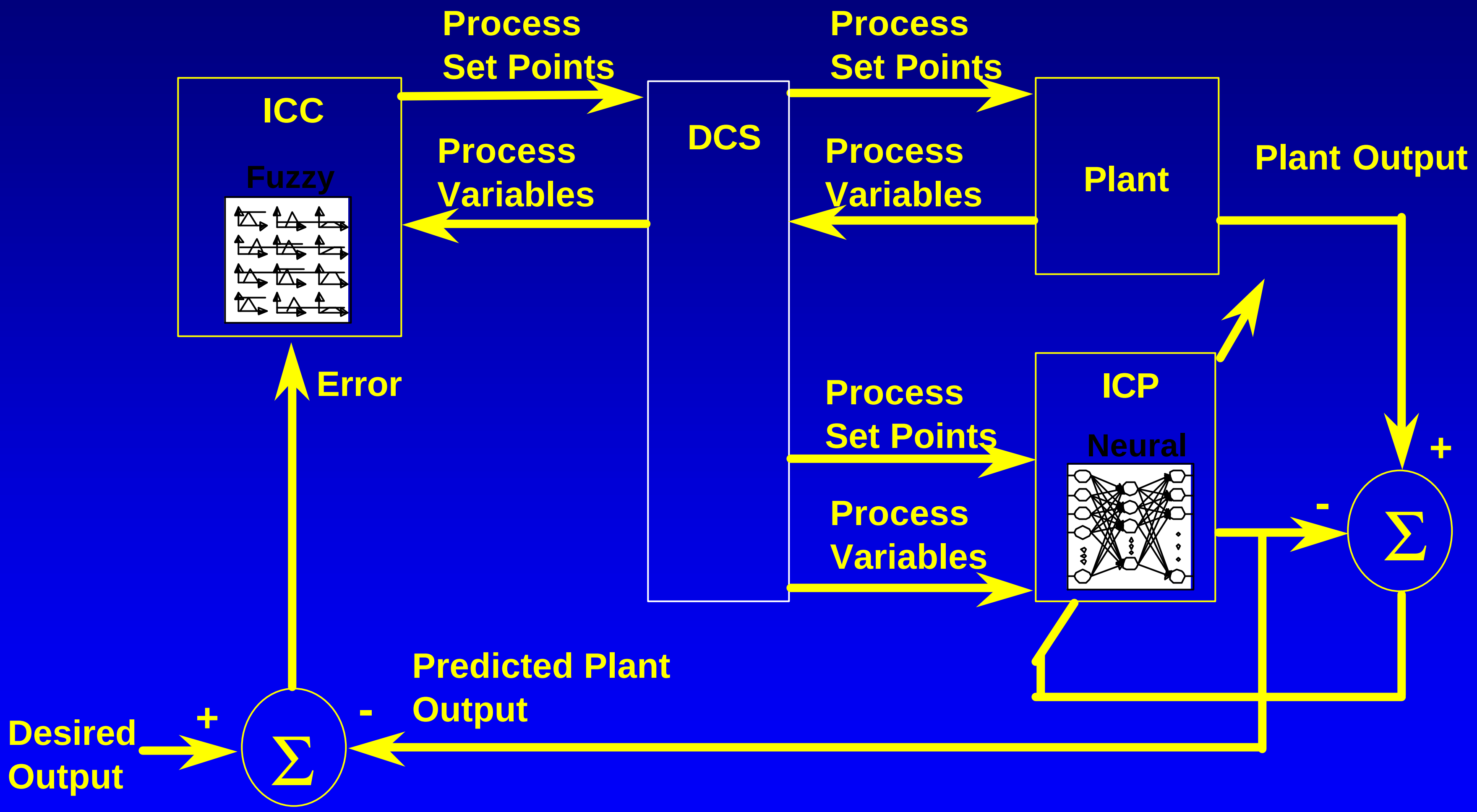
Reduce Process Variation

Standard Deviation AFTER = 0.85

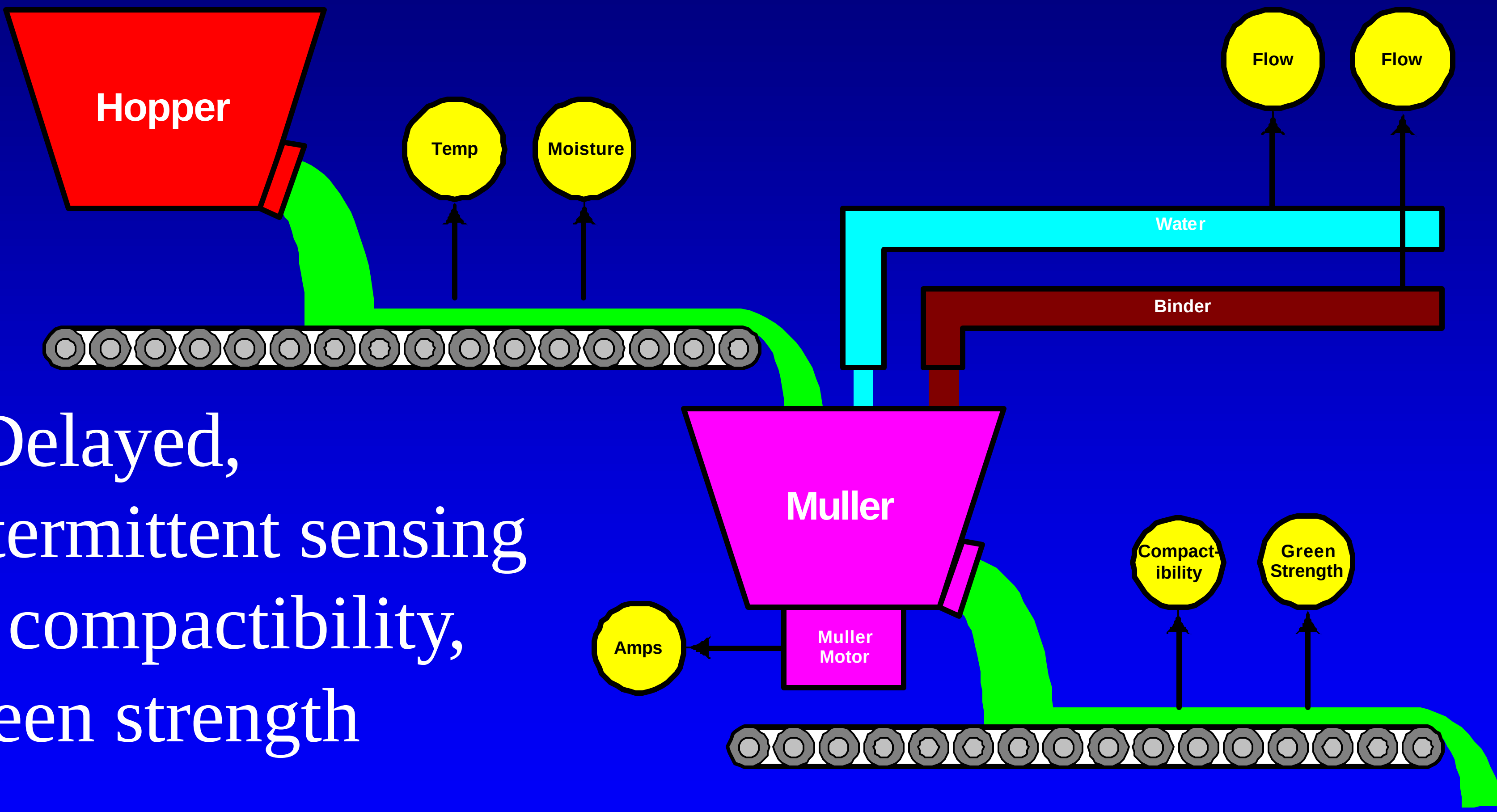




ICCP Block Diagram

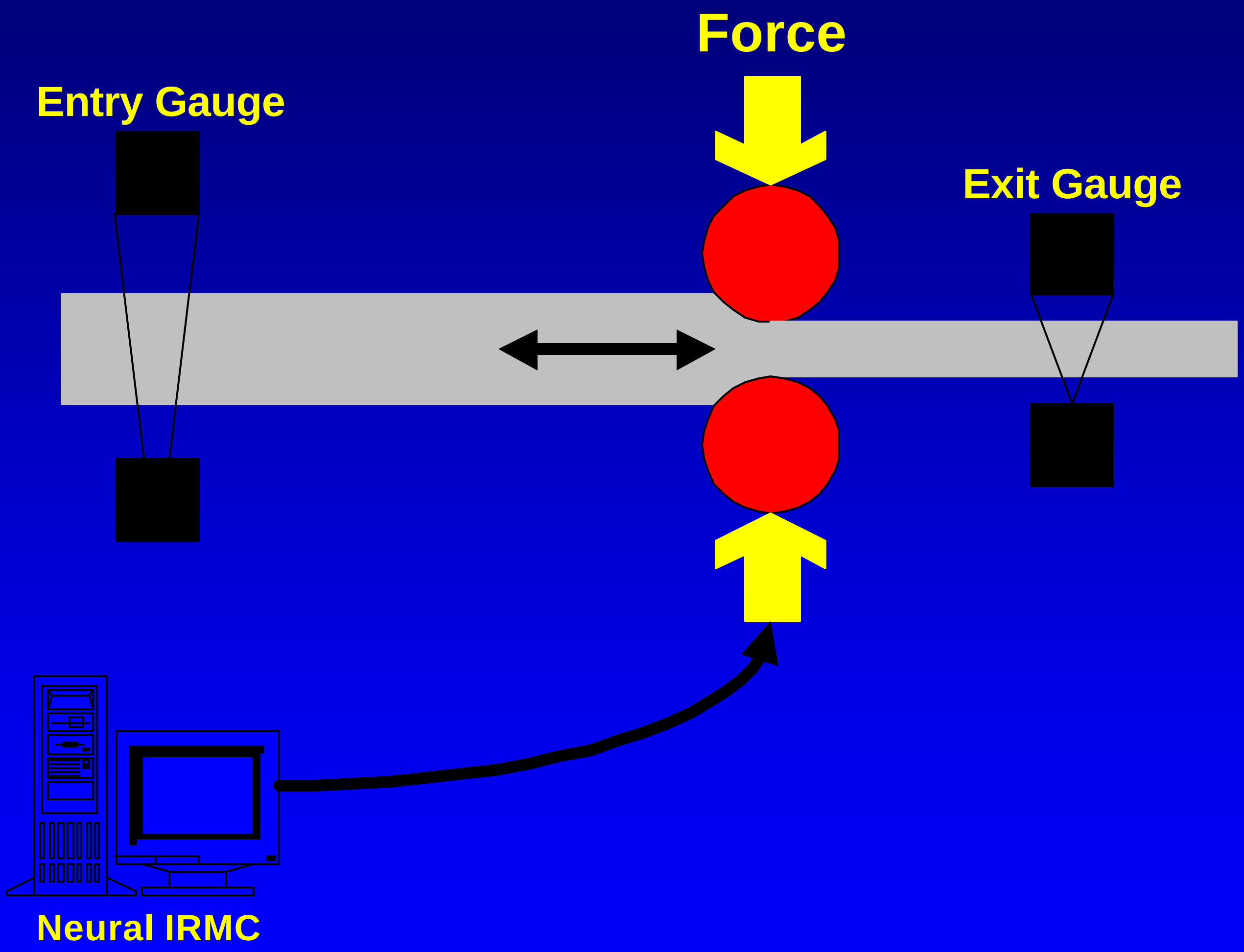


Green Sand Process Example

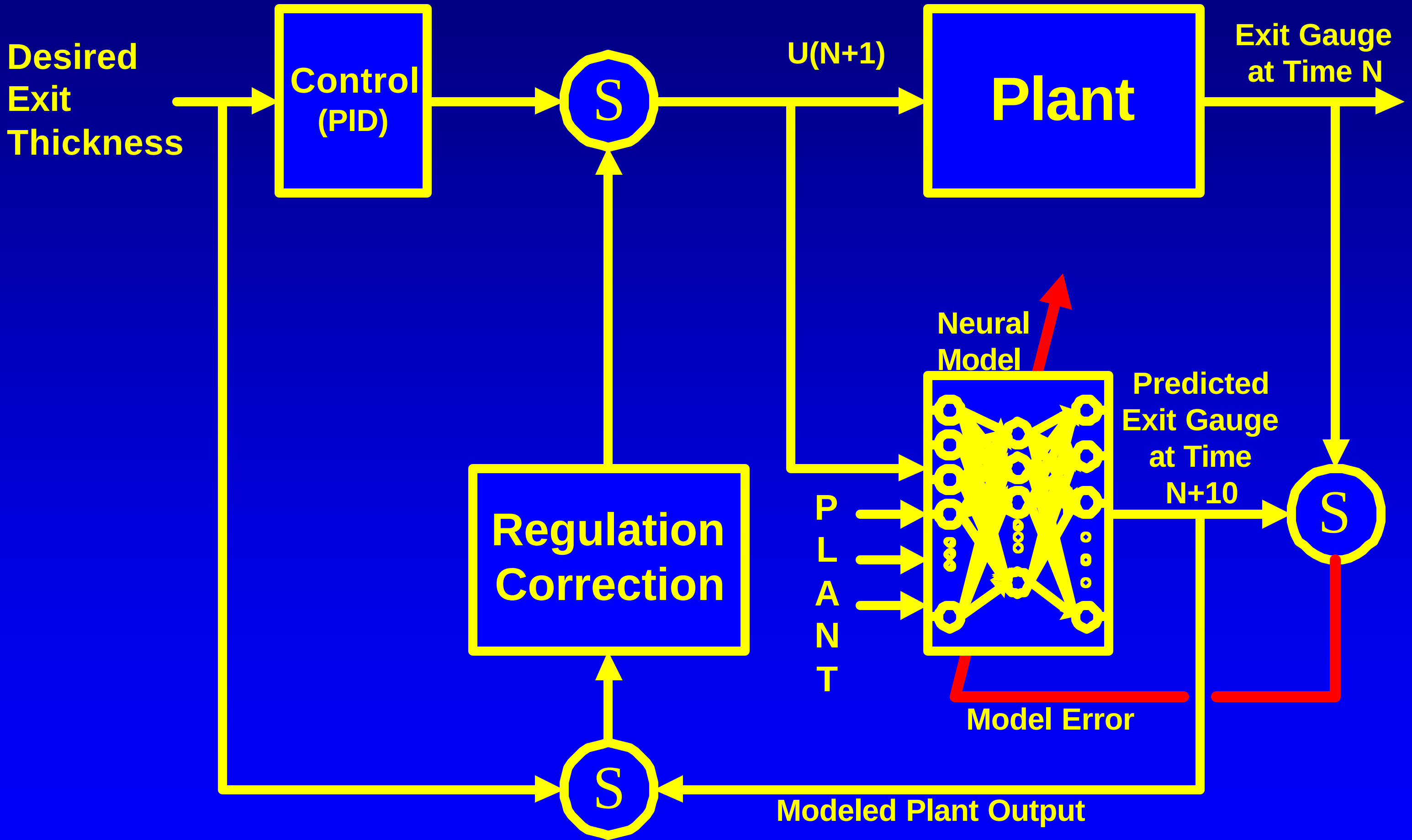


- Delayed, intermittent sensing of compactibility, green strength

Rolling Mill Application



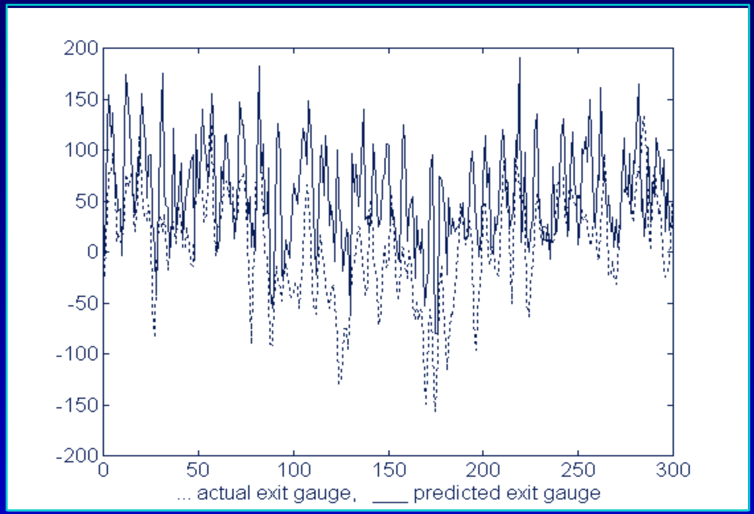
Rolling Mill Gauge Predictor/Controller

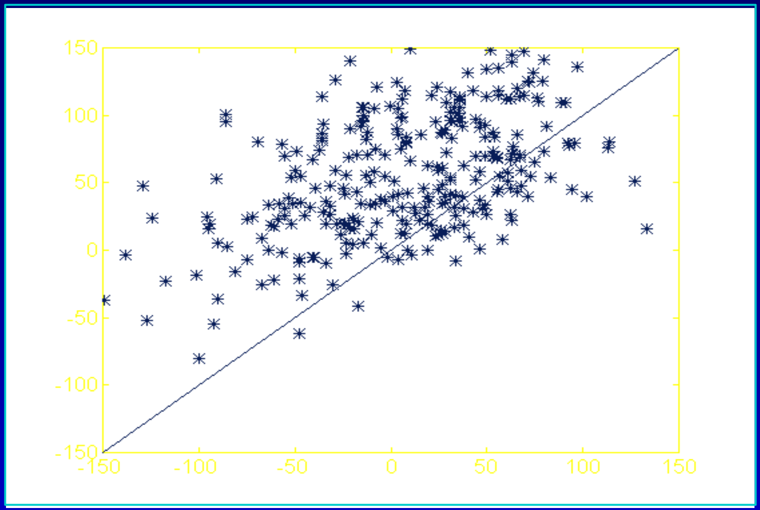


Gauge Predicted vs. Actual Exit Gauge

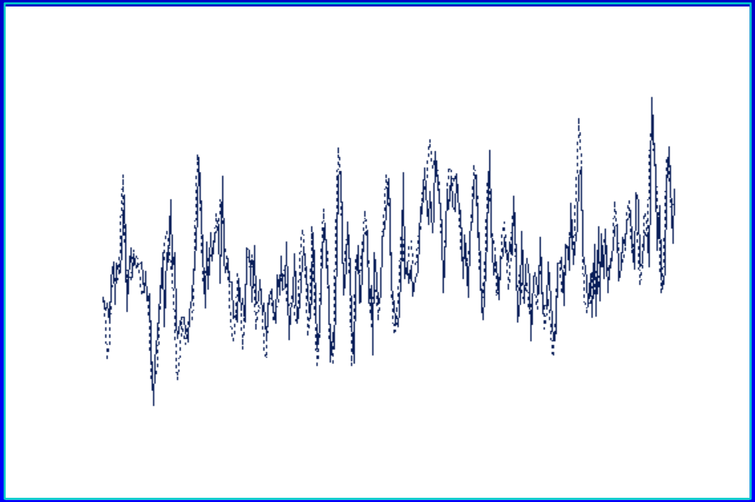
Plotted vs. Time | **Scatter Plot**

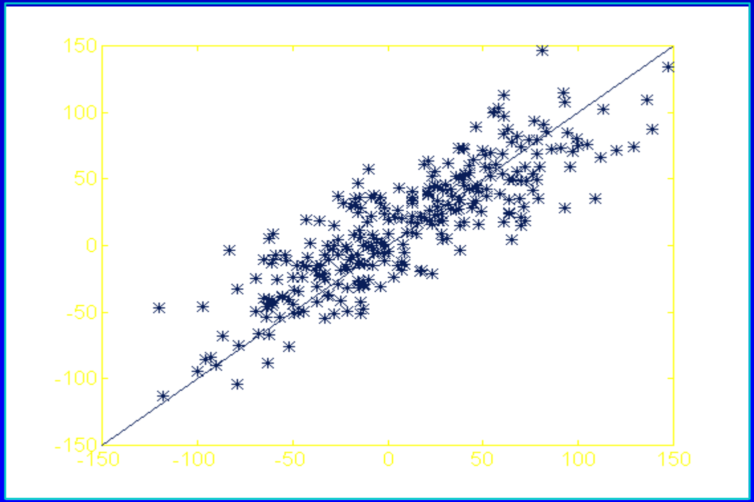
Trained on coil #1, Tested on coil #2





Trained on many coils, Tested on coil #2

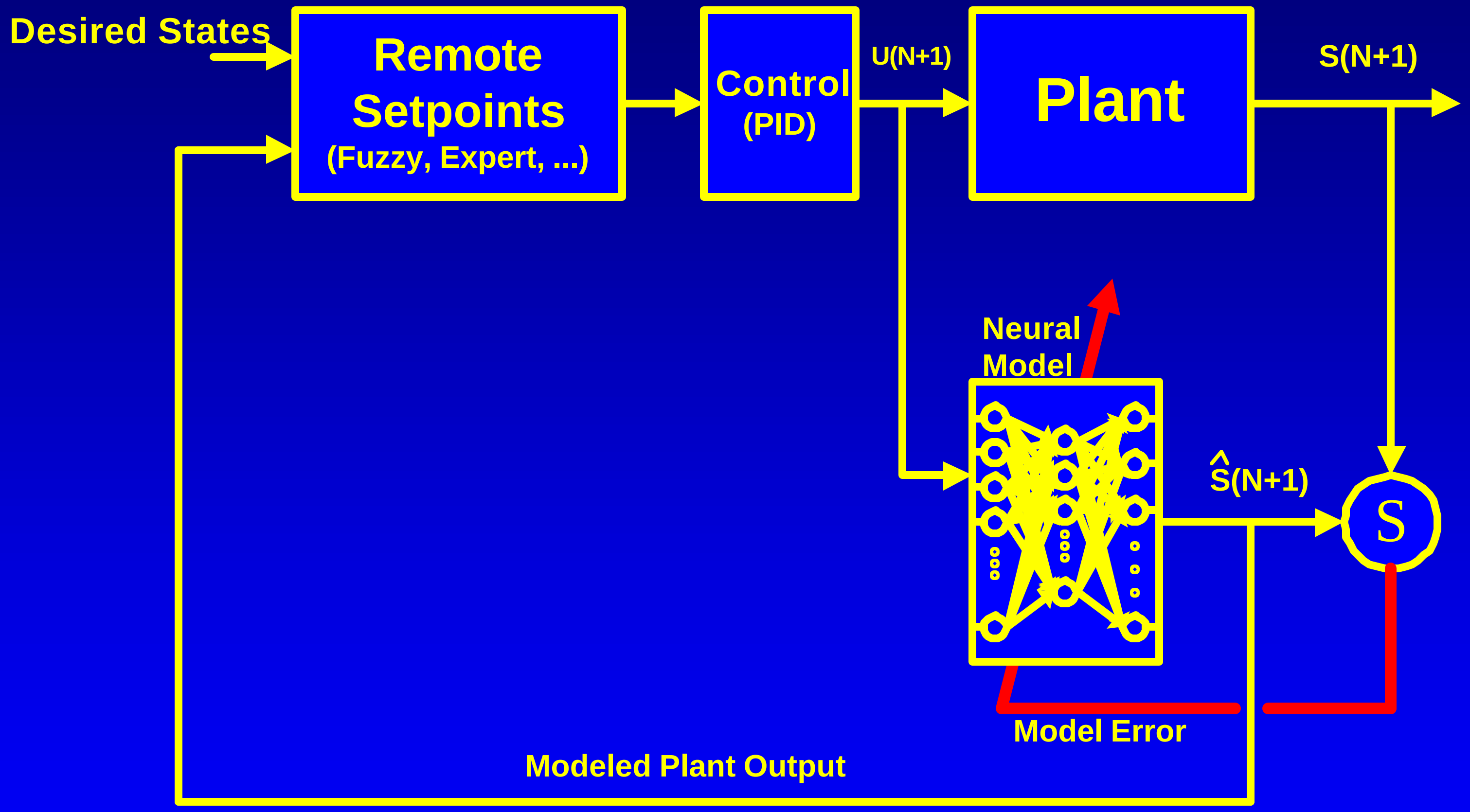




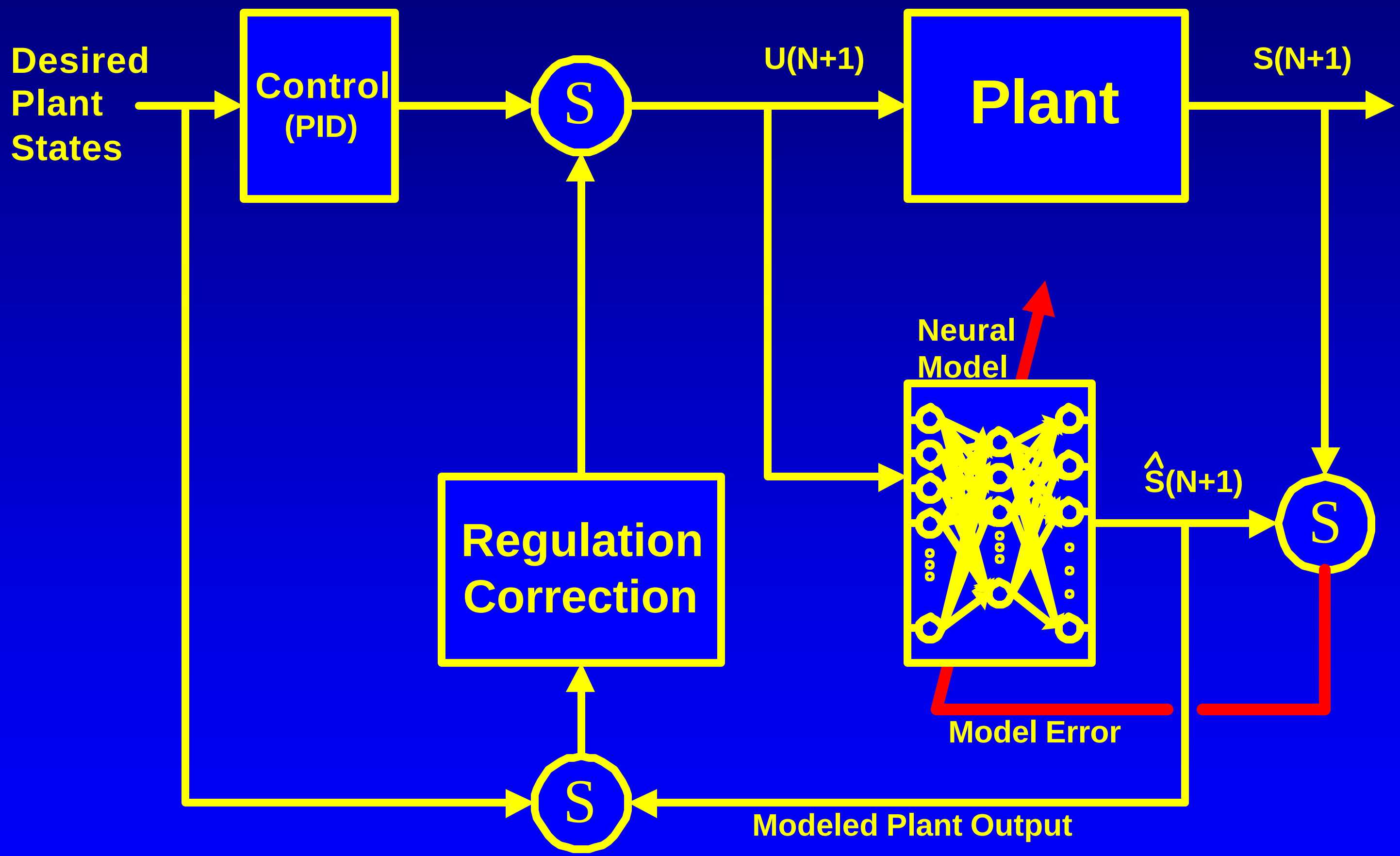
Hybrid Sensing/Control Solution

- No Universal Solution to Control Problems
- VS with PID vs. Intelligent *controller*
- Best solution may draw upon various technologies
  - Neural Networks
  - Fuzzy Logic
  - Statistics
  - Classical Methods
- Always requires some level of process knowledge

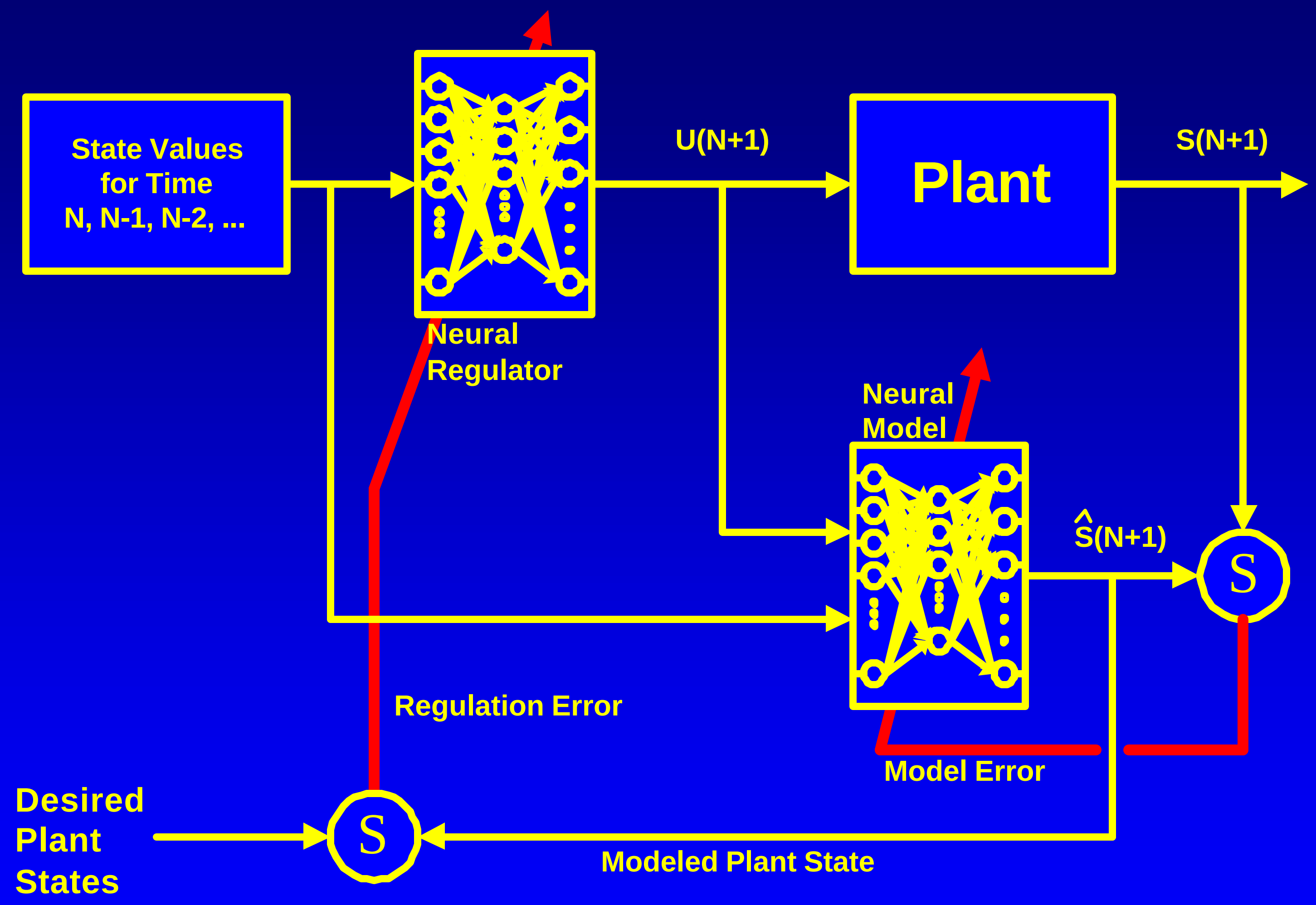
Neural/Fuzzy Remote Set-point Generator



Neural Network Predictive/Corrective Controller



Neural Network Based Predictive Controller



Application Summary

- NN may serve key role, but is part of system
- NN modeling is parameter optimization
  - choose structure of function to be adapted with minimal but sufficient dof
  - need sufficient data
  - use known structure to extent possible
    - » e.g., linear + polynomial + NN
    - » allows input of pre-calculated solutions
    - » gradient-based optimization
- Preprocessing important

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Where to use VS / NN

"This is a very hard problem and I don't know to solve it, so I'll see how a NN does at it."

- Important decision
- Benefits *vs.* costs
- Evaluate other solution methods
  - cost of nonlinear optimization
- Significant effort analyzing physical system and developing data pre-processing, system architecture, NN architecture, etc.
- System-level analysis

Where to Use NNs

one liner: "Use NN when data availability outweighs process understanding"

- Benefits - Nonlinear, Adaptive, Generic, Scalable processing, Parallel hardware
- Costs - Nonlinear optimization, Requires data, Black box
- Evaluation of "conventional" methods
- Use NN where these fall short
- Structure total solution to use NN in conjunction with these

Summary

- Virtual sensing technology can provide:
  - improved control by providing virtual measurements
  - predictive capability
  - continuous output from periodic real measurements
  - robustness to RS failure
- VS output limited by accuracy of model and RSs
- Model structure important - process understanding needed
- Neural-network technology useful for modeling data-rich/theory-poor processes