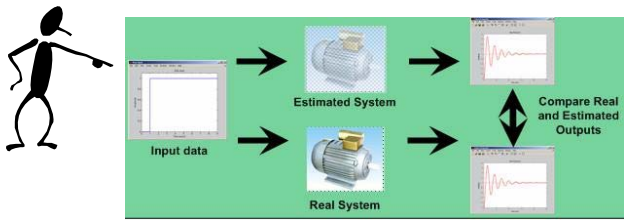
EMPIRICAL MODEL IDENTIFICATION



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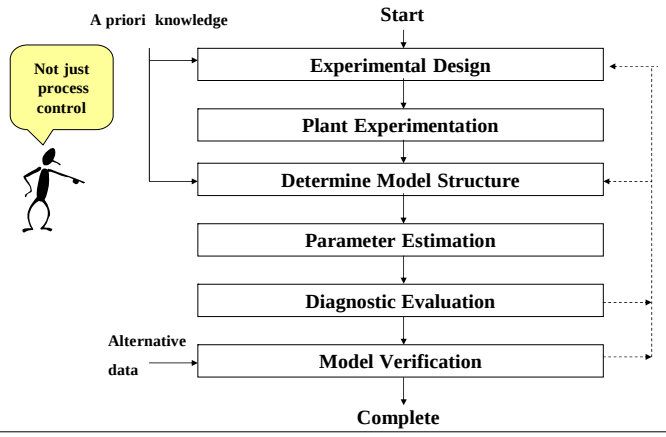
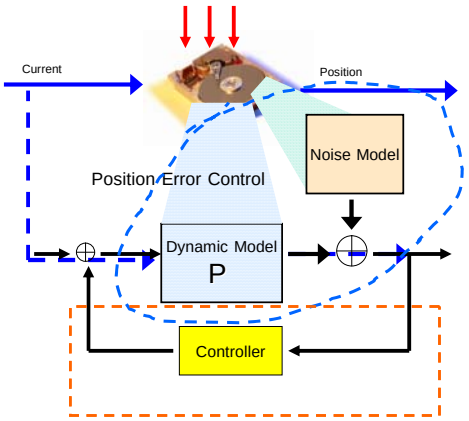
EMPIRICAL MODEL BUILDING PROCEDURE

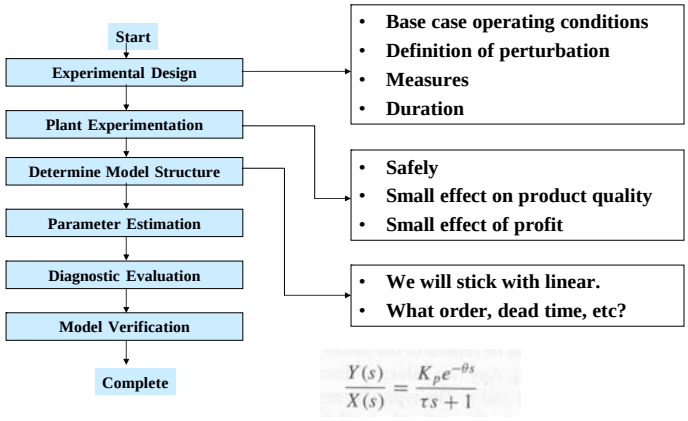


Using Models for Control System Design



- Estimate plant with parameter uncertainties
- Estimate noise model

EMPIRICAL MODEL BUILDING PROCEDURE



$$\frac{Y(s)}{X(s)} = \frac{K_p e^{-\theta s}}{\tau s + 1}$$

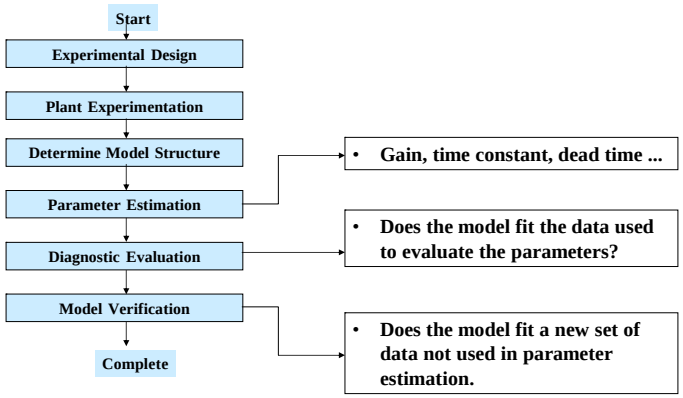
EMPIRICAL MODELLING

We have invested a lot of effort to learn fundamental modelling. Why are we now learning about an empirical approach?

TRUE/FALSE QUESTIONS

- We have all data needed to develop a fundamental model of a complex process
- We have the time to develop a fundamental model of a complex process
- Experiments are easy to perform in a chemical process
- We need very accurate models for control engineering

EMPIRICAL MODEL BUILDING PROCEDURE

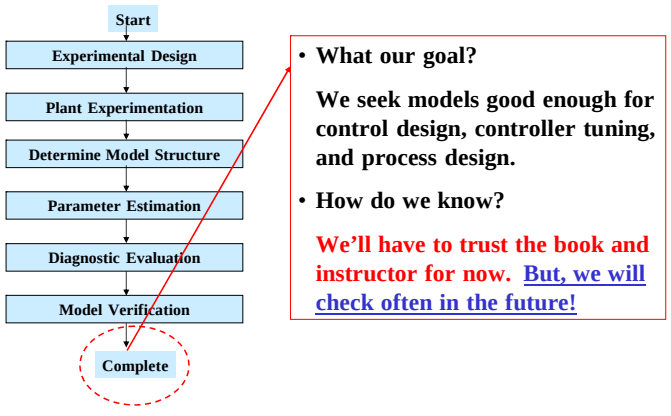


EMPIRICAL MODELLING

Fundamental Model vs. Empirical Model

	Fundamental Model	Empirical Model
Method	Fundamental Principles	Experiments
Advantages	Excellent relationships between parameters in physical systems and the transient behavior of the systems	Good for process design since it is easy to use Easy, less effort
Disadvantages	Complex. ex. distillation column, 10 compounds, 50 trays 500 diff. Eqs Large engineering effort	Less accuracy; do not provide enough information to satisfy all process design and analysis requirement

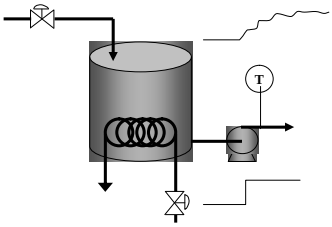
EMPIRICAL MODEL BUILDING PROCEDURE



EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve - **The simplest and most often used method. Gives nice visual interpretation as well.**

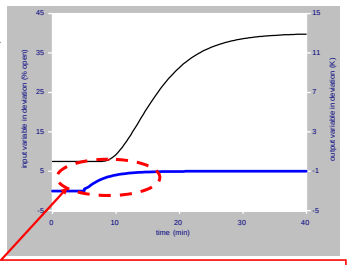
1. **Start at steady state**
2. **Single step to input**
3. **Collect data until steady state**
4. **Perform calculations**



EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve

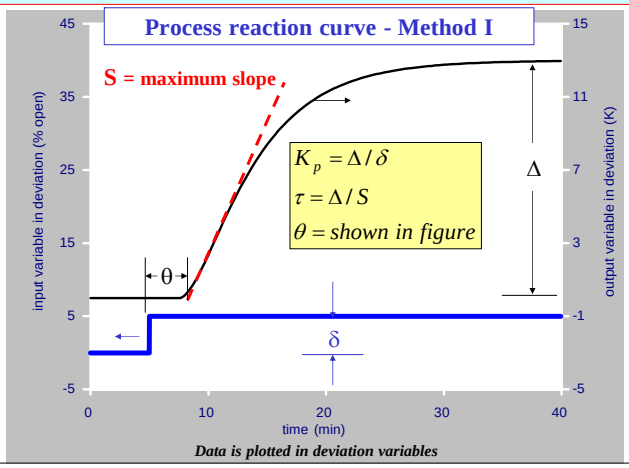
Start
Experimental Design
Plant Experimentation
Determine Model Structure
Parameter Estimation
Diagnostic Evaluation
Model Verification
Complete



Input should be close to a perfect step; this was basis of equations. If not, cannot use data for process reaction curve.

EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve - Method I



Data is plotted in deviation variables

EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve

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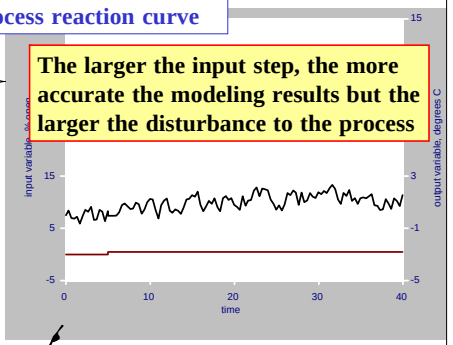
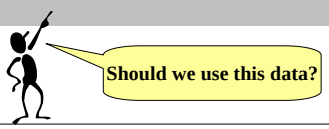
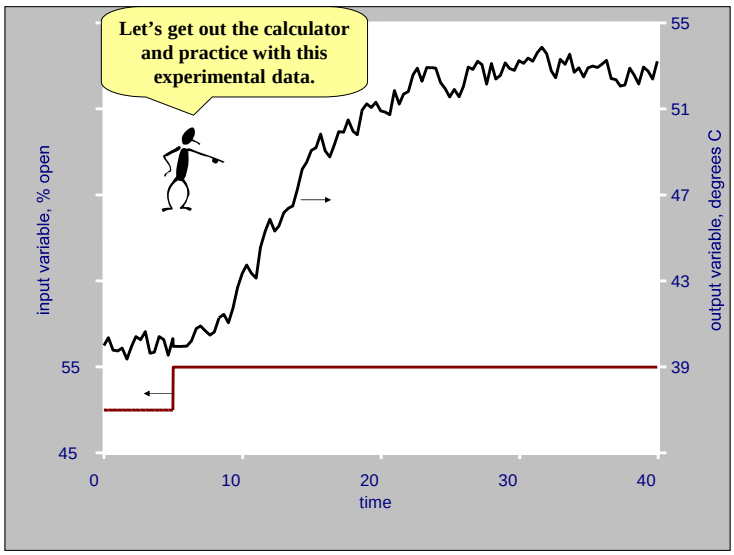
The larger the input step, the more accurate the modeling results but the larger the disturbance to the process







EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve

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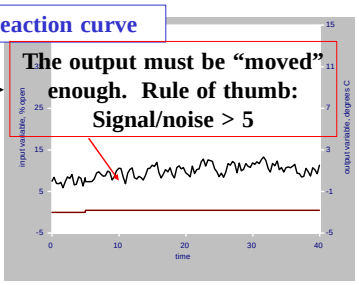
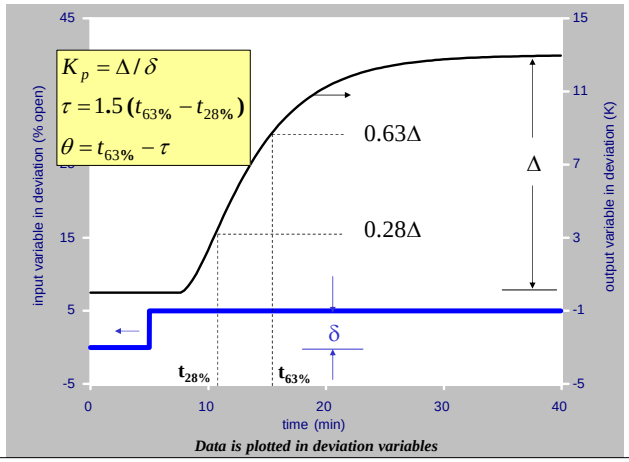
The output must be "moved" enough. Rule of thumb: Signal/noise > 5



Ex. If an output temperature varies 1℃ due to noise, the input magnitude should be larger enough to course an output change of at least 5℃

EMPIRICAL MODEL BUILDING PROCEDURE



Data is plotted in deviation variables

EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve

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The experiment would be expected to last at least a time equal to the dead time plus four time constants, $\theta + 5\tau$

EMPIRICAL MODEL BUILDING PROCEDURE

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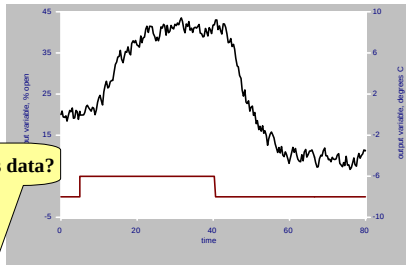

Should we use this data?

Since model errors can be large if another, perhaps unmeasured, input variables changes, experiments should be designed to identify whether disturbances have occurred.

EMPIRICAL MODEL BUILDING PROCEDURE

Statistical method

Provides much more general approach that is not restricted to

- step input
- first order with dead time model
- single experiment
- "large" perturbation
- attaining steady-state at end of experiment

Requires

- more complex calculations

EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve

Start
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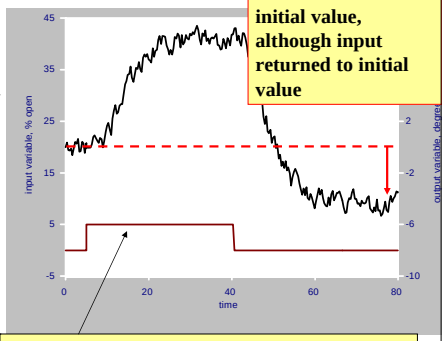
Complete

Output did not return close to the initial value, although input returned to initial value



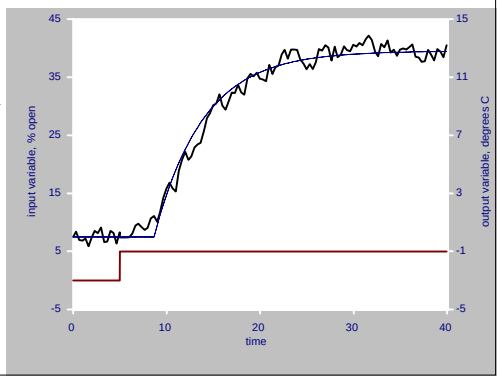
This is a good experimental design; it checks for disturbances

EMPIRICAL MODEL BUILDING PROCEDURE

$$\min \sum_i \left[\left(Y_i'\right)_{predicted} - \left(Y_i'\right)_{measured} \right]^2$$

Now, we can solve a standard regression problem to minimize the sum of squares of deviation between prediction and measurements.

Details are in the book.



EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve

Start
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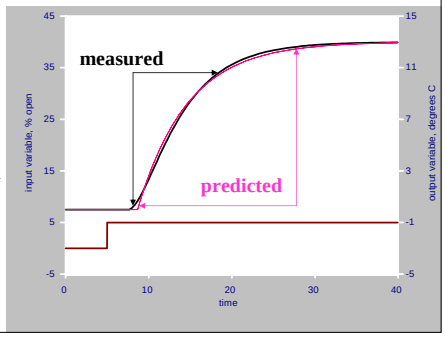
Complete

Plot measured vs predicted



EMPIRICAL MODEL BUILDING PROCEDURE

Statistical method

Start
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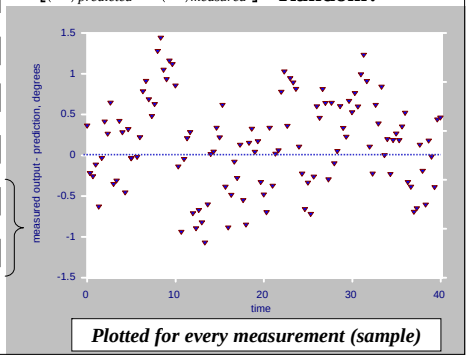
Complete

$\left[\left(Y_i'\right)_{predicted} - \left(Y_i'\right)_{measured} \right]$ **Random?**



Plotted for every measurement (sample)

EMPIRICAL MODEL BUILDING PROCEDURE

Process reaction curve

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Complete

If additional data is collected that is not used to calculate the model parameters, it can be compared with the model using the same techniques in diagnostic step

EMPIRICAL MODEL BUILDING

How accurate are empirical models?

- Linear approximations of non-linear processes
- Noise and unmeasured disturbances influence data
- Lack of consistency in graphical method
- Lack of perfect implementation of valve change
- Sensor errors

Let's say that each parameter has an error ± 20%. Is that good enough for future applications?