1. Empirical model building idea

In some situations it is not feasible to develop a theoretical (physically-based model) due to:

1. Lack of information
2. Model complexity
3. Engineering effort required.

An attractive alternative: Develop an empirical dynamic model from input-output data.

- **Advantage:** less effort is required
- **Disadvantage:** the model is only valid (at best) for the range of data used in its development i.e., empirical models usually don’t extrapolate very well.

Alternatively, \( \tau \) can be found from the time that the normalized response is 63.2% complete; this method is also labelled the tangent and point method.
This method is also labelled a two point method.

Method I
- Developed first
- Prone to errors because of evaluation of maximum slope

Method II
- Developed in 1960’s
- Simple calculations

Recommended

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**

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

Should we use this data?

The output must be “moved” enough. Rule of thumb:

Signal/noise > 5

EMPIRICAL MODEL BUILDING PROCEDURE

**Process reaction curve**

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.
Example

Consider the two storage tanks example, in which the model to be identified relates the valve position in the heating oil inlet to the outlet temperature of the second tank.

Determine a model for the process, using the target and plant method 2 and the two-point method, based on the following input-output data recorded:

Solution: The gain, $K_u$, is obtained the same way in both methods as $K_u = \frac{\text{change in output}}{\text{change in input}}$. 

Change in output = $12.7^\circ C - 6^\circ C$.

$K_u = \frac{12.7^\circ C}{5\%} = 25^\circ C / 5\%$. 

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**EMPIRICAL MODEL BUILDING PROCEDURE**

**Process reaction curve**

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

**Plot measured vs predicted**

- Measured
- Predicted
2. Laboratory

Background and objectives: Empirical model identification is a procedure in which a model of the relationship between input and output variables is determined. The model is determined by introducing small variations in the input variable and the resulting dynamic response is used to determine the model. The procedure follows the flow chart below.

We are going to concentrate on the Parameter Estimation, Diagnostic Evaluation and Model Verification stages in this laboratory. The process whose model is to be obtained is the laboratory Process Simulator (PCS312) from Feedback Instruments Ltd. This process will be set up as three lags in series, each of time constant 10 ms, in series with a distance-velocity lag (approximate time delay) of 10 ms. The nominal transfer function for this process is thus

\[ G_n(s) = \frac{e^{-10s}}{(1+0.01s)^5} \]

However, the 10 ms distance-velocity lag is not a real time delay; it is implemented using resistors and capacitors and its actual transfer function is

\[ G_a(s) = \frac{1.022 + 0.0355s + 33.21.10^{-4}s^2}{(1+0.00324s)(1+0.0103s)^3} \]

Thus, the actual process transfer function is

\[ G_a(s) = \frac{1}{(1+0.01s)^5} \frac{1.022 + 0.0355s + 33.21.10^{-4}s^2}{(1+0.00324s)(1+0.0103s)^3} \]

Picture of the process simulator
Plant experiment and parameter estimation: In this laboratory, we will take the step input signal to the process from MATLAB/SIMULINK through the DT2811 data acquisition board, with the aid of the HUMUOSFT data acquisition package. The output of the process (step response) will be imported into the PC. The process model structure to be identified is a first order lag plus time delay (FOLPD) process model of the form

\[
G_m(s) = \frac{K_m e^{-\tau_m s}}{1 + \tau_m s}
\]

where \( K_m \) = model gain, \( \tau_m \) = model time constant and \( \tau_m \) = model time delay. A number of parameter estimation methods will be investigated, namely

1. Alternative tangent and point method
2. 2-point method

The tangent and point method, and the two point method, are detailed earlier.

A diagnostic evaluation will be done by comparing the process model step response outputs (obtained in simulation using SIMULINK) with the actual process step response output.

Model verification will be done by comparing the process model step response outputs with the process response output under two separate operational conditions:

1. The input signal to the process (from MATLAB/SIMULINK/HUMUOSFT) is a positive step, of 0 to 0.8 (corresponding to a voltage step input of 0 V to 4 V).
2. The input signal to the process is a negative step, from 0.8 to 0 (corresponding to a voltage step of 4 V to 0 V).

Apparatus: Process Simulator, Oscilloscope, PC, DT2811 data acquisition board.

Method:

1. Plant experiment and parameter estimation: Set up the process as three lags in series with a distance-velocity lag, on 'FAST'. The procedure for interfacing the process with MATLAB/SIMULINK/HUMUOSFT is given in Appendix A. Use the following command in the MATLAB command window to record both input and output:

\[
>> \text{plot}(t,y,'k',t,u,'r-');
\]

Print out a plot of the process input and output, and determine process models using the tangent and point method and the 2-point method.

2. Diagnostic evaluation: This involves comparing the outputs of the models developed with that of the process. The model step responses can be obtained using SIMULINK. Use the plot facility in the MATLAB command window to plot the step response comparisons.

3. Model verification: Compare the model outputs with the process output under two separate process operation conditions:

   a) The input signal to the process (from MATLAB/SIMULINK/HUMUOSFT) is a positive step, of 0 to 0.8 (corresponding to a voltage step input of 0 V to 4 V).
   b) The input signal to the process is a negative step, from 0.8 to 0 (corresponding to a voltage step of 4 V to 0 V).

Appendix A: Interfacing the process with MATLAB/SIMULINK/HUMUOSFT

- Check that the data acquisition card is plugged in to the back of the PC.
- Open MATLAB and open a new SIMULINK model file. The version of MATLAB used must contain the 'Real-time Toolbox'. This can be checked by looking in the SIMULINK library browser in Figure 4 below.

![Figure 4](image)

*Note: Setting the real-time sample time, depends on processor speed and if other computer applications are running in the background, among other factors. It may be possible to set the real time sample time as low as 0.005 seconds, in some cases.*
3. Case study: Empirical model building for the flow and temperature process of the Instrutek VVS-400 Heating and Ventilation rig

- Now, the software should be ready to interface with the hardware, i.e. wires from the process input ("supply disturbance" socket on the process simulator) and output ("minus measured value" socket on the process simulator) can be connected to the data acquisition card and the rig can be turned on. Don’t forget to connect all ground terminals together.
- A typical SIMULINK model file set-up is shown in Figure 6. Note that the simulation parameters step size is set the same as the real-time sample time (set previously). The simulation will be run under the fixed step option. Set the step value to 0.4; a step of 0-0.4V in MATLAB/SIMULINK/HUMUSOFT corresponds to a step change of 0-2 V on the process. Apply the step at time 0.1 seconds. Run the simulation from start time 0 to stop time 0.4 seconds.

Flow control system block diagram - local controller used

A similar block diagram may be constructed for the temperature process.
**Flow “Process” - Computer control**

- The process is linked via a data acquisition package to MATLAB.
- The controller output is sent out through a data acquisition card, with a range of 0 to 5V.
- The output of the orifice plate is converted by the signal conditioning circuitry of the Instrutek rig to a voltage signal, which in turn is input to the PC using the data acquisition card.
- The concept is summarised in the block diagram.
- The block diagram represents the effective (dynamic) relationship between the manipulated variable (i.e., the controller output signal) and the controlled variable (i.e., the process output signal). The controller will, in general, be designed based on this relationship.

**Flow process**

- Open loop step tests, using small steps over the full range of fan speed were carried out, to obtain models for the flow process at different operating points (allows process linearity to be checked).
- The load vane was fully open.
- The alternative tangent and point method was used to approximate the process as a first order lag plus time delay (FOLPD) model.

**Interfacing Hardware with MATLAB/Humusoft**

- Similar issues arise for the temperature process.
- Models were obtained from three different starting flow settings: 30% of maximum fan speed, 50% of maximum fan speed and 70% of maximum fan speed.
- The step change in fan speed chosen was 20%.
- These settings meant that the number of experiments carried out was achievable.
- Increasing and decreasing step responses were obtained experimentally and imported into the Matlab/Simulink environment using HUMUSOFT. The figure shows the Simulink set-up.
- The temperature process was kept constant (i.e., at a heater setting equivalent to 24% of maximum, corresponding to a measured temperature of ≈24°C).
Flow process

The alternative tangent and point method was applied to each plot to determine the model parameters. Typical result:

Flow process - overall results

The results show that the flow process is non-linear; static tests have also shown other non-linear behaviours (see case study in Measurement Devices presentation).

A summary of the average results is as follows:

\[ G_m(s) = \frac{0.45e^{-0.98s}}{1 + 2.70s} \]  
Fan speed setting < 55% of maximum

\[ G_m(s) = \frac{1.08e^{-1.08s}}{1 + 1.93s} \]  
Fan speed setting = [55%,75%] of maximum

\[ G_m(s) = \frac{1.76e^{-0.93s}}{1 + 1.45s} \]  
Fan speed setting > 75% of maximum

In fact, model parameters vary at each fan setting taken, and vary too if fan speed is increased or decreased. Models were not determined at a range of heater settings (why?)

Temperature process

• Open loop step tests, using small steps over the full range of heater setting were carried out.
• In addition, these tests were carried out at three fan speed settings (30%, 50%, and 70% of maximum) – why?
• The load vane was fully open.
• The alternative tangent and point method was used to approximate the process as a first order lag plus time delay (FOLPD) model.
• Typical result:

Temperature process - overall results

The results show that the temperature process is non-linear; static tests have also shown other non-linear behaviours

A summary of the average results is as follows:
Clearly, the temperature process is nonlinear. In addition, model parameters vary at each heater setting taken, and vary too if heater setting is increased or decreased. Furthermore, the measurement problem is greater (i.e. signal/noise < 5).

4. Tutorial question 1

(a) Using a flowchart, summarise the procedure for determining the models of processes using the empirical identification approach. Discuss each stage of the procedure outlined in the flowchart.

(b) A number of experiments have been carried out on a laboratory heating and ventilation system, to obtain:

(i) the relationship between heater setting and measured temperature
(ii) the relationship between fan speed setting and measured flow.

The experimental results are provided below.

1. 50% to 70% step change, followed immediately by a 70 to 50% step change, in fan speed setting:

2. 15% to 25% step change, followed immediately by a 25% to 15% step change, in heater setting:

3. 55% to 65% change in heater setting:

4. 60% to 80% step change in fan speed setting:

Discussing briefly the results of each experiment, state whether the data may be used for estimation using process reaction curve identification methods, and, if so, which process reaction curve identification methods, with which you are familiar, would be appropriate.
Solution

a) The procedure for determining the models of processes using the empirical identification approach may be summarized in the following flowchart:

(i) Experimental Design: This stage involves the preparation of a test plan, which will include:
- Deciding on the process operating conditions around which the model will be accurate
- Defining the input signal to be used in the experiment (shape, duration, size)
- Defining the variables to be measured, and how frequency they are to be measured
- An estimate of the experiment time
- A-priori knowledge of the process is desirable.

(ii) Plant experiment: This follows the procedure laid down in the test plan. The plant must be monitored during the course of the experiment to make sure that disturbances during the course of the experiment do not invalidate the test results.

(b) In (1), the output returns to its initial value after a step in one direction, followed by a step in the opposite direction. This means that no DC disturbance occurred during the course of the experiment. Models could be estimated from this data; the noisy nature of the data suggests that area-based model parameter estimation methods are likely to give the best results. In (2), the data is too noisy (S/N ratio < 5) to allow any models to be determined. It would be best to repeat the experiment, allowing a greater percentage change in the latter setting. In (3), there is no assurance that a DC disturbance has not distorted the test results; in addition, the output does not seem to have come to a final steady-state value when the experiment was terminated. This data should not be used for model parameter estimation. In (4), as in (3), there is no assurance that a DC disturbance has not distorted the test results. However, unlike (3), the output does seem to have come to a final steady-state value when the experiment was terminated. If it could be ascertained that a DC disturbance has not distorted the test results, a model could be estimated, perhaps using the area method (due to the noisy nature of the data).

Tutorial question 2

(a) Process reaction curve methods may be used to estimate process model parameters, within the framework of an empirical model building procedure. Three such process reaction curve methods are the tangent and point method, the alternative tangent and point method, and the two point method.

Outline using diagrams if appropriate, how each of the above methods may be used to obtain a process model.

(b) The measured open loop response of an electrohydraulic actuator to a unit step input is as follows:

<table>
<thead>
<tr>
<th>t (min)</th>
<th>0</th>
<th>0.5</th>
<th>1.0</th>
<th>1.5</th>
<th>2.0</th>
<th>2.5</th>
<th>3.0</th>
<th>3.5</th>
<th>4.0</th>
<th>4.5</th>
<th>5.0</th>
<th>5.5</th>
<th>6.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output (A)</td>
<td>0.08</td>
<td>0.05</td>
<td>0.15</td>
<td>0.28</td>
<td>0.42</td>
<td>0.57</td>
<td>0.70</td>
<td>0.80</td>
<td>0.88</td>
<td>0.92</td>
<td>0.95</td>
<td>0.97</td>
<td></td>
</tr>
</tbody>
</table>

Determine models of the plant, using:

(i) The tangent and point method

(ii) The alternative tangent and point method

(iii) The two-point method
Consider the non-isothermal Continuous Stirred Tank Reactor (CSTR) shown.

Solution

Before we begin to perform the calculations, we must thoroughly evaluate the experiment and data to be sure that

1. the procedures were designed and performed correctly and
2. the data represents the process

Let’s begin with the experiment procedures for the process reaction curve method.

<table>
<thead>
<tr>
<th>Process reaction curve</th>
<th>True for this experiment?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is the input signal nearly a perfect step?</td>
<td>Yes</td>
</tr>
<tr>
<td>Are the assumptions of output behavior valid?</td>
<td>Yes</td>
</tr>
<tr>
<td>(i.e. smooth, S-shaped output response)</td>
<td>Yes</td>
</tr>
<tr>
<td>Did process begin at steady state?</td>
<td>Yes</td>
</tr>
<tr>
<td>Did the process achieve a new steady state?</td>
<td>Yes</td>
</tr>
<tr>
<td>Is the signal to noise ratio large enough?</td>
<td>Yes</td>
</tr>
<tr>
<td>Was the experiment repeated, process returned to initial operation</td>
<td>No</td>
</tr>
</tbody>
</table>

We see that the essential features have been satisfied. We can proceed with caution if the experiment has not been repeated.
Now, we employ our understanding of engineering principles to evaluate the data.

- During the experiment, cooling valve c was opened by 20%.
- This should cool the reactor.
- Because of the temperature dependence of the reaction rate, the rate should decrease.
- Because the rate decreased, the concentration of reactant should increase in the reactor.

However, the experimental data indicate that the concentration decreased. Therefore, a severe inconsistency exists in the data. **We should not use the data.** We should repeat the experiment.

Many possible explanations are possible; just a few are given in the following.

- The feed temperature changed during the experiment.
- The feed concentration changed during the experiment.
- We plotted the % closed for valve c, but labeled it % open.

Overall, we must have data that conforms to the experimental methods and is consistent with engineering principles, before we build empirical models for process control.

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**Tutorial question - continued**

Two additional experiments, \( \pm 20\% \) and \( \pm 20\% \) changes in \( \nu_C \), were performed. The other input variables were monitored to make sure there were no changes. The process reaction curves for the two different experiments are shown.

3. Discuss the good and poor aspects of these experiments for use with the process reaction curve modelling method.
4. Determine the parameters for the first order with dead time model using two different sets of experimental data.
5. Compare the parameter values in part 4 obtained from two different experiments, and explain any differences.
6. Discuss experimental designs that could help identify the problem encountered in 1.

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**Solution**

3. Discuss the good and poor aspects of these experiments for use with the process reaction curve modelling method.

<table>
<thead>
<tr>
<th>Process reaction curve</th>
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<tbody>
<tr>
<td>Is the input signal nearly a perfect step?</td>
<td>Yes</td>
</tr>
<tr>
<td>Are the assumptions of output behavior valid? (i.e. smooth, S-shaped output response)</td>
<td>Yes</td>
</tr>
<tr>
<td>Did process begin at steady state?</td>
<td>Yes</td>
</tr>
<tr>
<td>Did the process achieve a new steady state?</td>
<td>Yes</td>
</tr>
<tr>
<td>Is the signal to noise ratio large enough?</td>
<td>Yes</td>
</tr>
<tr>
<td>Two steps to test for linearity</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Agrees with engineering principles for chemical reactor**

Was the experiment repeated, process returned to initial operation | No |

Note that this data

- satisfies the essential experimental criteria, and
- is consistent with our qualitative understanding of the process dynamics.

We decide to use this data, given the careful monitoring of the process and two experiments, which allows checking of results.
Some formative feedback

Why do practicing engineers often use empirical models and not always develop fundamental models?

1. They didn't pay attention in their fundamental modelling course
2. To obtain a model that is accurate over a wide range of conditions
3. Fundamental models can require lots of time and data
4. Performing experiments in operating plants is so easy.

To apply the process reaction curve (graphical method), the process response must

1. Be exactly first order
2. Be exactly first order with dead time
3. Have a positive gain
4. Have an overdamped, monotonic step response.

What is the major deficiency in process reaction curve Method I?

- Evaluating $\Delta$
- Evaluating $\delta$
- Evaluating $\theta$
- Evaluating $S$.

What was the basis for selecting the times to be at 28% and 63% of the total change in Method II?

- Only those two times can be used
- One point is enough, extra point improves accuracy
- Two points (equations) are required to determine two parameters ($\theta + \tau$).
- These times improve the signal-to-noise ratio because they are far apart in time and the output variable is changing rapidly.
How can we determine how close to linear a process behaves? (noting that in a strictly linear system, the parameters do not change with operating conditions)

- Perform only one process reaction curve experiment
- Perform several process reaction curve experiments with the same \( \delta \) and compare values of \( K_p \), \( \theta \) and \( \tau \).
- Perform several process reaction curve experiments with different magnitudes and signs of \( \delta \) and compare values of \( K_p \), \( \theta \) and \( \tau \).

\[
\frac{CV(s)}{MV(s)} = \frac{K_p e^{\theta}}{\tau s + 1}
\]

\( = \) parameter variation

Other tutorial questions

Would any difficulties occur if the process were not at steady state when a process reaction curve experiment was initiated?

A. Yes, difficulties could occur if the process were not at steady state at the onset of a process reaction curve experiment. The process reaction curve method can determine a model between ONE input and an output. If the process is not initially at steady state, the output is being influenced by some other variable, in addition to the manipulated input, during the transient response. This combination of inputs would violate the requirement of the graphical method to have a SINGLE step input, and any subsequent calculations could lead to an wrong model.

What is the signal-to-noise ratio for the output data in the graph? Would this data be acceptable for estimating parameters using the process reaction curve method?

A. From the graph it is apparent that the magnitude of the noise varies slightly from roughly 0.2 to 0.4 °C. The initial and final temperatures are 36.6 °C and 39 °C, respectively; therefore, the total change in the signal is about 2.5 °C. If we were to assume an average noise value of 0.3, then the signal to noise ratio would be roughly 8.3. In this case, this would be acceptable because the magnitude of the noise is small enough (signal/noise > 5) to perform graphical analysis. In order to determine whether this data is acceptable for estimating model, we ask, in addition: Is the input signal nearly a perfect step? Yes; Are the assumptions of the model identification method which is to be used valid? (i.e. smooth, S-shaped output response) Yes; Did process begin at steady state? Yes; Did the process achieve a new steady state? Yes. The data satisfies all of the criteria above. One criterion which is not addressed is the diagnosis for a change (disturbance) in another input variable. A better experimental design would include returning to the input (heater power) to its original value in a step at time = 800 s, and performing another process reaction curve calculation to ensure that the two models are similar.

As a rough estimate, what accuracy do you expect from the empirical modelling method? Express your answer in percent error in parameters.

A. The empirical modelling methods are very useful when the fundamental models are extremely complicated. It must be noted that caution should be used when employing empirical models because of the limitations of the range over which they are valid. In general, the parameters should be determined within ± 20%. For some complex processes, greater model inaccuracy is typical because of extreme non-linearity, noise, and many unmeasured disturbances.
The experimental data have been obtained for the heater process shown in the figure. Evaluate the data to determine whether the data can be used for the process reaction curve calculations.

A. We must be sure that the data represents the effect of the (one) manipulated variable on the measured variable, with no other important input variables changing significantly. We note that the fuel flow increased, but the measured temperature decreased! This would lead us to question the data and perform another experiment, this time with a return step to check for disturbances.

Two process reaction curve experiments were performed, both from the same initial operating conditions for the continuous flow stirred tank in the figure. Suppose that the temperature responses were very different. Discuss reasons why this situation might occur and methods for determining the cause of the discrepancy.

A. One possible explanation to why different temperature responses could result from two identical tests could be a disturbance. Typical disturbances for the heat transfer experiment would be the inlet temperature, upstream pressure of the heating medium, and feed flow rate. These disturbances would cause a discrepancy in the results of the two experiments. In order to avoid unmeasured disturbances, the personnel performing the experiments ensure that all of the input process variables that could influence the output remain essentially unchanged during the experiment.

Another possible cause of discrepancies would be a sticky valve that did not move the amount expected. To avoid this error, we should monitor the actual valve position to ensure that the stem moves the amount desired.

5. Lifelong learning

Books: