Model Validation Guide

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Chapter 1. Introduction

gPROMS employs a rigorous optimisation-based approach for Model Validation by offering *Parameter Estimation* capabilities (i.e. fitting model parameters to experimental data) together with *Experiment Design* capabilities (i.e. determining the best set of experiments to perform that will give the most precise parameter estimates).

Model Validation involves an iterative procedure as shown in the figure below. Once you perform the experiments that have been designed and collect the appropriate measurement data, these can be used to generate better estimates of the parameters. If necessary, the model with the updated parameters can then be used to design further experiment(s) and the cycle is repeated until you are satisfied that the model is validated.

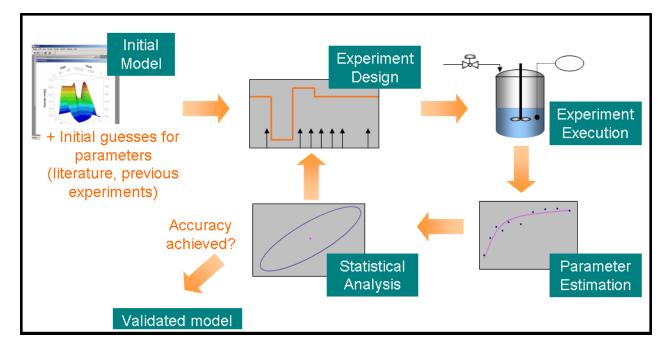


Figure 1.1. Iterative model development and validation procedure.

Experiments in gPROMS

Experiments are used to improve the understanding of processes and create accurate models. The quality of information generated by experiments depends strongly on the experimental conditions as well as what is measured and when it is measured. In gPROMS we can consider:

- 1. The processing of data from experiments to estimate the values of unknown model parameters this is *Parameter Estimation*
- 2. The use of models to design experiments for the purposes of estimating the values of the unknown model parameters this is *Experiment Design*

To use experiments and experimental data in gPROMS we need to be able to represent this information mathematically; there are two fundamentals aspects to this

- 1. A description of the experiment operating policy
- 2. A description of the experimental measurements

Experiment operating policy

In gPROMS an experimental recipe consists of the following information

- 1. The experiment duration
- 2. The initial conditions in the experimental equipment (such as the initial temperature and amount of material in the experimental equipment)
- 3. The time variation of the controlled inputs to the system (such the heat input to the system)
- 4. The values of time-invariant quantities (such as the diameter of the experimental equipment)

Given this information, a model of the experimental equipment can be used to predict the behaviour of the measured quantities. Note that for dynamic experiments all of the above information is required to define an experiment; whereas for steady-state experiments only the values of time-invariant quantities need to be provided. In Parameter Estimation the above information is known; whereas the purpose of Experiment Design is to determine this information.

In gPROMS in order to specify the time variation of controlled inputs we consider the time horizon of the experiment to be broken into a number of time intervals. A time-varying control is simply an ASSIGNed variable that is adjusted during an experiment. The user can specify the variation in a Variable value using one of the following mechanisms:

- Piecewise constant controls the quantity holds a different constant value during each time interval during the experiment.
- Piecewise linear controls the quantity varies linearly (from a start value to an end value) in a specified time interval during the experiment.

To simplify specification of the problem and the problem size the same control time intervals are used for all piecewise constant and piecewise linear controls within an experiment..

Measurements, Sensors and Variance models

Measurements of key quantities (corresponding to Model Variables) are taken throughout the duration of an experiment, each measurement consists of three pieces of information:

- The value of the measured quantity
- The time the measurement was taken
- The uncertainty to which the measurement is known this can be expressed as the statistical **standard deviation or variance** of the measurement.

Experimental measurements are taken using **sensors**: the uncertainty of the measurement is a property of the measurement technique associated with the sensor. Of course, it is often the case that the same sensor measures more than one variable. For example, a single composition sensor may measure the composition of multiple components in a given stream. Or, a given type of thermocouple may be used in a number of places on a plant to measure temperature.

When solving a Model Validation problem all measured Variables are associated with a sensor. The variance model of a given sensor comprises information associated with the variance of the error of the measurement produced by the sensor. The errors of the measurements are assumed to be statistically independent and normally distributed with zero mean. There are several types of sensor variance models. These can be considered to take the general form:

$$\sigma^2 = \sigma^2(z, B)$$

where z is the model prediction of the measured quantity and B is a set of parameters. The table below shows the variance models supported by gPROMS.

Table 1.1. Statistical variance models.

Variance model (gPROMS Keyword)	Mathematical Description
Constant variance (CONSTANT_VARIANCE)	$\sigma^2=\omega^2$

Variance model (gPROMS Keyword)	Mathematical Description
Constant relative variance (CONSTANT_RELATIVE_VARIANCE)	$\sigma^2 = \omega^2 \cdot \left(z^2 + arepsilon ight)$
Heteroscedastic variance (HETEROSCEDASTIC)	$\sigma^2 = \omega^2 \cdot \left(z^2 + arepsilon ight)^\gamma$
Linear variance (LINEAR_VARIANCE)	$\sigma^2 = (lpha z + eta)^2 + arepsilon$

The following points should be noted:

- The set of parameters, B, in the general statistical variance model comprises the parameters ω and γ , as appropriate.
- ε is a small but non-zero constant that ensures that the variance is still defined for predicted values that are equal to zero or very small.
- If $\gamma=0$ in the HETEROSCEDASTIC variance model, then this reduces to the CONSTANT_VARIANCE model.
- If $\gamma=1$ in the HETEROSCEDASTIC variance model, then this reduces to the CONSTANT_RELATIVE_VARIANCE model.

As the estimation of the parameters and the statistical analysis of the results depend strongly on the given or estimated standard deviations of the measurement errors, attention should be paid to the formulation of the variance model and the values of the respective variance model parameters. You are encouraged to specify the variance model and the values of the according parameters as precisely as possible. gPROMS will determine optimal estimates for the values of the variance model parameters within the bounds that you specify.

gPROMS Model requirements

Both Parameter Estimation and Experiment Design problems in gPROMS require a working gPROMS process model that runs robustly for steady-state and/or dynamic simulation.

Particular focus should be given to the following parts of the Process Entity:

- The **Assign** specifications mark certain system variables as fixed for the purposes of dynamic simulation. As far as Parameter Estimation and Experiment Design is concerned, some of these variables will belong to one of the following categories:
 - time-varying control variables;
 - · time-invariant control parameters; or
 - unknown parameters to be estimated.

It is very important to note that, for the purposes of model validation, unknown parameters are declared as Variables in gPROMS Model entities, and **not** as Parameters¹

• The **Initial** specifications in the Process will be used as the **default** initial conditions for the experiments. Some or all of the Initial specifications may then be overridden by specifying a value in an experiment.

In the Process Entity, Initial specifications can be given in the form of a general equation. However to specify Initial conditions in your experiments, corresponding Initial specifications must appear in the Process in the restricted form:

VariableName = ConstantExpression;

¹This is consistent with the general gPROMS rule that Parameters can *never* be the result of any gPROMS calculation. Of course, once the model validation problem has been solved successfully and their values have been found, they can either be declared as Parameters (Set to the estimated value) or be left as Variables (Assigned to the estimated value)

where *VariableName* is the name of a differential or algebraic variable, and *ConstantExpression* is either a numerical value or an expression consisting of only parameters and numerical values.

- The gPROMS solvers for Parameter Estimation and Experiment Design are configured in the SOLUTIONPARAMETERS section of a Process entity refer to Controlling the Execution of Parameter Estimation activities and Controlling the Execution of Experiment activities
- Any **Schedule** specification in the Process is ignored for the purposes of Parameter Estimation and Experiment Design. This also means that any Intrinsic Tasks² used by your Models will not be executed.

Experience indicates that most of the effort in defining Parameter Estimation and Experiment Design problems is, in fact, incurred in the construction of a robust model of your process. This will probably be exactly the same model as that used for dynamic simulations within gPROMS.

Therefore, it is worth investing some effort in ensuring that the model behaves properly over the *entire* range of possible parameter values. In particular, you should check that the differential and algebraic variables x and y remain within any specified bounds even for extreme values of the control variables and the parameters to be estimated.

²See the section "Defining Tasks" in the Model Developer Guidei

Chapter 2. Parameter Estimation in gPROMS

gPROMS can be used to perform *Parameter Estimation* for complex models using both dynamic and steady-state experimental data. This chapter covers the following issues:

- a description of what a Parameter Estimation problem is,
- the Performed Experiment and Parameter Estimation entities that are used to specify Parameter Estimation problems in gPROMS,
- running and controlling the execution of a Parameter Estimation activity, and
- how to analyse the results of a Parameter Estimation run.

Explanatory screen shots are taken from a batch reactor example included in the gPROMS distribution. Some basic familiarity with the gPROMS language and concepts is assumed in this guide.

What is Parameter Estimation?

A detailed gPROMS process model is constructed from equations describing the physical and chemical phenomena that take place in the system. These equations usually involve parameters that can be adjusted to make the model predictions match observed reality. Examples of model parameters include reaction kinetic constants, heat transfer coefficients, distillation stage efficiencies, constants within physical property correlations, and so on. The more accurate these parameters are, the closer the model response is to reality.

The process of fitting these parameters to laboratory or plant data is called Parameter Estimation. gPROMS contains powerful, state-of-the art Parameter Estimation capabilities that have been applied successfully to a wide range of problems. Key features are:

- Multiple parameters occurring in dynamic or steady-state models may be estimated simultaneously. Nonlinear models of arbitrary size and complexity including multi-unit flowsheets may be used.
- Data from both dynamic and steady-state experiments may be used.
- The results of the estimation are subjected to extensive statistical analysis.

Parameter Estimation in gPROMS is based on the Maximum Likelihood formulation which provides simultaneous estimation of parameters in both:

- the physical model of the process
- the variance model of the measuring instruments the **Sensor**, which can be:
 - constant variance (e.g. a thermocouple with an accuracy of +/- 1K)
 - constant relative variance (e.g. a composition analyser with an error of +/- 2%)
 - heteroscedastic variance, combining both of the above.

When solving a Maximum Likelihood Parameter Estimation problem, gPROMS attempts to determine values for the uncertain physical and variance model parameters, θ , that maximise the probability that the mathematical model will predict the measurement values obtained from the experiments. Assuming independent, normally distributed measurement errors, ϵ_{ijk} , with zero means and standard deviations, σ_{ijk} , this maximum likelihood goal can be captured through the following objective function:

$$\Phi = rac{N}{2}\,\ln{(2\pi)} + rac{1}{2}\,\min_{ heta}\left\{\sum_{i=1}^{NE}\sum_{j=1}^{NV_i}\sum_{k=1}^{NM_{ij}}\left[\ln{\left(\sigma_{ijk}^2
ight)} + rac{(ilde{z}_{ijk}-z_{ijk})^2}{\sigma_{ijk}^2}
ight]
ight\}$$
 ,

where the symbols have the following definitions:

Table 2.1. Objective function symbol definitions.

N	Total number of measurements taken during all the experiments.	
θ	Set of model parameters to be estimated. The acceptable values may be subject to given lower and upper bounds, i.e. $\theta^l \leq \theta \leq \theta^u$.	
NE	Number of experiments performed.	
NV_i	Number of variables measured in the i th experiment.	
NM_{ij}	Number of measurements of the <i>j</i> th variable in the <i>i</i> th experiment.	
σ_{ijk}^2	Variance of the <i>k</i> th measurement of variable <i>j</i> in experiment <i>i</i> . This is determined by the measured variable's variance model.	
$ ilde{z}_{ijk}$	kth measured value of variable j in experiment i .	
z_{ijk}	kth (model-)predicted value of variable j in experiment i .	

Performed Experiments

A Parameter Estimation problem makes use of data gathered from a set of experiments. Each experiment is characterised by a set of conditions under which it is performed, namely:

- the overall duration;
- the initial conditions, *v*;
- the variation of the control variables, u(t); and
- the values of the time-invariant parameters, p (these could be things like vessel volume and so on).

The Experiments Performed entity is used to specify the full details of an experiment. To create a new Performed Experiments entity, do the following:

- Pull-down the Entity menu from the top pane in gPROMS ModelBuilder.
- Click on New Entity. A dialog box will appear.
- Choose Performed Experiment for the Entity type and fill in the Name field.

An Experiments Performed entity editor window will open up in the right hand pane, as shown in the figure below.

PERFORMED EXPERIMENT C13T3 (ReactorE __U× Process Ŧ Saved variable set(s) Initial conditions Dynamic C Steady state Variable name Initial value R101.HOLDUP(1) 100.0 R 101 HOLDLIP(2) 100.0 R101.HOLDUP(3) 1.0 R101.HOLDUP(4) 1.0 293.0 General Controls Measured data gPROMS language Properties

Figure 2.1. Experiments Performed entity editor.

The Performed experiment entity editor has the following tabs for entering information:

- The General tab a form for defining the Process entity to use, the Saved variable sets to help with initialisation and the initial conditions for the experiment.
- The Controls tab a form for specifying the values of the time-invariant, piecewise constant and piecewise linear variables that are adjusted during the course of the experiment.
- The Measured data tab a form for entering the measured data and sensor used. There is also the option of
 specifying a measurement variance model if you wish to have a specific model or set of parameters for this
 particular experiment.
- The gPROMS language tab this provides a convenient means of reviewing all the information regarding the performed experiment in a text-based format. You are not advised to use this tab to enter data.
- Properties (a record of when the entity was created, last edited as well as the default tab to open on)

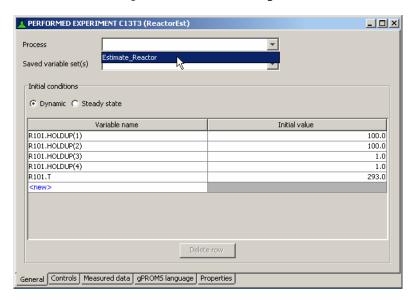
In addition, a Performed experiment can be automatically converted into a Process and simulated.

General information

In order to specify the Process entity to use for the Parameter Estimation, click on the General tab in the Experiments Performed entity editor and then choose the desired Process from the drop down menu at the top of the window (see figure below) - you can select a Process Entity from the same project as that containing this Experiment entity or any projects cross-referenced by the project. ¹

¹For backwards compatibility with v2.3, it is valid for the Process field to remain blank. In this case, the Parameter Estimation and/or Experiment Design activities will look for a Process with the same name as the activity being run. However, if you do not set the Process field, assisted pathname completion will not work within this editor.

Figure 2.2. Specifying the Process entity that will be used in conjunction with the experimental data.

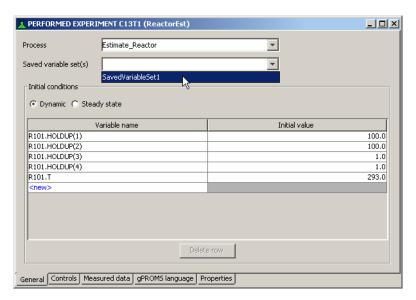


In some situations, initialisation is helped by specifying a Saved variable set. This can be done by choosing the desired Saved file from the drop down menu shown below, or it may be typed in manually.

Advanced notes:

- 1. A Saved variable set specified in the Performed Experiment will be applied **in addition** to specifications given in the PRESET section of the Process. Each entry of the Saved variable set file(s) specified in the Performed Experiment supersede any specification given in the Process.
- 2. gPROMS will also accept a path to a .gSTORE file located in the file system (as opposed to being embedded in the project).
- 3. Multiple files may be listed, separated using a comma.

Figure 2.3. Specifying the Saved Variable Sets that will be used to facilitate initialisation.



You have the option to provide different initial conditions to those contained in the Process. An experiment can have steady-state or dynamic initial conditions. If you to choose steady-state initial conditions, then simply check

the steady-state button in the Initial conditions section of the window. For dynamic initial conditions, check the dynamic button and enter information in the table underneath. Start by clicking the <new> cell in the table and type the full pathname of the gPROMS differential variable that you wish to specify an initial condition for. You MUST only provide initial conditions for variables that are given initial values directly in the Process.

When entering a variable name in the left hand column, *pathname completion* can be activated by pressing **Ctrl+Space**. Thereafter simply type in its value in the right hand column of the table as shown below.

T PERFORMED EXPERIMENT C13T1 (ReactorEst) _ UX Estimate_Reactor **T** -Saved variable set(s) Initial conditions Dynamic C Steady state Initial value Variable name R101.HOLDUP(1) R101.HOLDUP(3) R 101.HOLDUP(4) 1.0 R101.T 293.0 General Controls Measured data gPROMS language Properties

Figure 2.4. Specifying the initial conditions for the relevant differential variables in an experiment.

Controls

An experiment control is a variable that is adjusted during an experiment (such as a heating policy in a reactor). Experiment controls therefore form part of the "recipe" for running the experiment. The user can specify the variation in a Variable value using one of three different mechanisms:

- Time-invariant controls: provide a single variable value, this quantity will be the same for the duration of the experiment. Appropriate for steady-state and dynamic experiments.
- Piecewise constant controls: provide multiple variable values, the quantity holds a different constant value for specified time intervals during the experiment. Appropriate for dynamic experiments only.
- Piecewise linear controls: provide multiple variable values, the quantity varies linearly (from a start value to an end value) in a specified time interval during the experiment. Appropriate for dynamic experiments only.

Note that any Variables that are Assigned values in a Process but are not specified as controls in the experiment will retain their Assigned values, whether these are constants or functions of TIME.

The Control *interval durations* are synchronised for all piecewise constant and piecewise linear controls and adding or deleting control intervals therefore affects *all* piecewise control variables.

In order to define the controls, click on the Controls tab in the Experiments Performed entity editor and do the following:

• Click the <new> cell in the Control variables table at the top of the window and type the full pathname of the gPROMS control variable. This variable should have be ASSIGNED in the Process entity

Tip

Pathname completion can be activated by pressing Ctrl+Space.

- Choose from the drop down list in the right-hand column to specify whether the control variable is time-invariant, piecewise constant or piecewise linear.
- Repeat the above for each new control variable you wish to use.

Having chosen the format for the time-varying behavior of the control variable, select the relevant control by clicking on it in the top pane, and go to the lower part of the window to enter the details of its behavior during the experiment. Time-invariant controls simply need a value. Piece-wise constant controls need a duration for each interval², together with the corresponding value of the control. Piecewise linear controls need the interval duration, together with starting and final values for the control variable during each interval (as illustrated in the following figure).

To duplicate or delete an entire interval, select it and click on the Duplicate or Delete buttons at the bottom of the window.

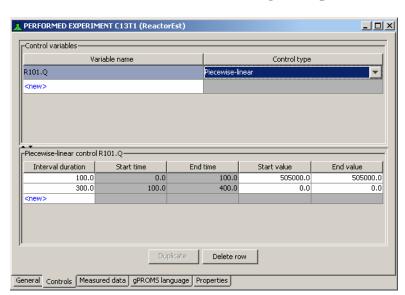


Figure 2.5. Specifying a piecewise linear profile for the behavior of a control variable during the experiment.

Measured Data

During an experiment, measurements of key variables are taken using sensors. The measured data for an experimental run should be entered in the table found on the Measured data tab of the Experiments Performed entity (shown below).

²When you enter the interval duration gPROMS automatically determines the start and end times of that interval, but the relevant cells are greyed out and you cannot edit them.

_ U × Time R101.T R101.C(1) R101.C(3) <unspecified> <unspecified> <unspecified> Variance model = <unspecified: 10.0 3746.911 898,5522 412.5493 2518.6 2358.859 504.1786 1504.12 3634.895 603.4858 30.0 40.0 883,7833 4407.922 715,2997 50.0 837.8405 548.0505 4849.769 60.0 348.6161 5080.333 964.3907 70.0 239.5115 5182.181 1092.912 80.0 175.4503 5281.883 1223.877 5272.164 1355.167 90.0 135.0508 5342.836 1487.682 100.0 100.9699 110.0 87.2978 5384.454 1485.921 Transpose General Controls Measured data GPROMS language Properties

Figure 2.6. Tabulation of the measured data for an experimental run.

The Measured data table accepts the following information: the gPROMS name of the measured variable, a name for the sensor used *(optional)*, a description of the measurement variance model for this sensor *(optional)* and the measured values at discrete points in time.

To add the experimental results for a particular variable, do the following:

• Click the <new> cell in the Variable name part of the table at the top of the window and type the full pathname of the gPROMS variable.

Tip

Pathname completion can be activated by pressing Ctrl+Space.

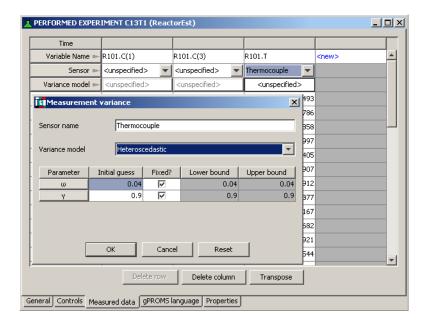
- If you wish to give a name to the sensor that was used for the measurement, then do so in the corresponding part of the table, and press **Enter**.
- If you wish to specify the variance model information for this particular sensor then click on the Variance model cell in the table. When you do so a dialog box will open. You need to then do the following:
 - Select the desired variance model from a drop down list and enter the initial guess and the lower and upper bounds for the relevant statistical parameters that will be used in the solution of the maximum likelihood parameter estimation problem [6].
 - If you wish to estimate the value of a given variance model parameter, then *uncheck* the Fixed value? box and enter appropriate lower and upper bounds.
 - Click OK to close the dialog box and apply the changes.
- To add the measurement data points, click on the <new time> cell in the table on the Measured data tab. Enter the time and the corresponding value for the measured variable. It is possible to copy and paste data into the table from an Microsoft ExcelTM spreadsheet. To do so, first make sure that your Excel data has the columns in the same order as in the gPROMS table. Then do the following:
 - select the numerical data in Excel and copy it (Ctrl+C). Do not select the column headings in Excel
 - go to the gPROMS table and click on the cell containing <new time>. Paste the numerical Excel data (Ctrl+V).

Tip

Measured variables do not need to have a value recorded at every time point. It is valid to leave cells in the table blank.

- To clear a single cell quickly, select the cell and press the **space** key.
- To delete an entire row or column, select a cell in the desired row or column, then click the Delete row or Delete column button below the table (as appropriate).
- It is possible to transpose the table using the transpose button below the table.

Figure 2.7. Defining the measurement variance model and its associated parameters.



When to assign a Sensor name

As mentioned previously, assigning a Sensor name to a measured variable is optional. If you are putting together your first experiments, you may wish to simply leave these <unspecified>. In this case, the measured variables will appear "by name" in the Parameter Estimation and/or Experiment Design editors (and reports).

Once you assign a sensor name to more than one variable in an experiment, those variables share the sensor. Changing the sensor's variance model will affect all variables with this sensor, but **only within the experiment**. Sensor names are local to an experiment, so a sensor specified in one experiment has no effect on any other experiment.

Once a sensor name has been given, that name will appear in the Parameter Estimation and Experiment Design editors, and in some places in the reports it will be used instead of the variable name.

Specifying a sensor name is useful:

- as a record that the variables were measured by the same physical measuring device, in the same batched measurement or taken under the same calibration of the measuring equipment,
- to help manage a large number of measured variables. When the Performed Experiment is added into a Parameter Estimation or Experiment Design entity, the variables are automatically grouped by their sensor name, reducing the number of items listed in the sensor group editor and helping to sort them.

When to set a Variance model

One approach is to leave the variance model <unspecified>, which allows all the variance model information to be given in a central location. It reduces the duplication of the variance model information. For example, you may intend to use the same variance specifications across a large number of experiments.

Even if a sensor name has been given, the variance model can be left <unspecified>. This effectively "links" the measured variables together, but omits the specification of the variance model (which must be given later in the a Parameter Estimation or Experiment Design entity).

The alternative approach is to record the variance model information within each experiment. This provides a more complete record of the conditions under which the experiment was performed. This is most useful if the variance information differs between experimental runs.

Note that a variance model specification given in the Parameter Estimation or Experiment Design editor will **override** a variance model specified in the Performed Experiments. This is an important ordering of precedence. This allows, for example, different Parameter Estimation activities to be defined, each having a different variance model specifications, but *without* requiring any changes to be made to the Performed Experiments themselves. This helps to maintain the integrity of the Performed Experiment entity as a record of experimental conditions.

Simulating a Performed Experiment

To help with debugging and diagnosis it is also possible to simulate the control strategy defined in a single experiment.

To do this:

- 1. Ensure a Process has been specified on the General tab of the Performed Experiment.
- 2. Select the Experiment entity in the Project Tree.
- 3. From the Activities menu, select Simulate selected experiment... (or click the short-cut button on the tool bar)

gPROMS will prompt you for the name of a new Process entity. This will be created within the same project as the original Process and, if there are no problems reported, will be automatically run as a Simulation activity.

Once the Simulation has completed, you can either delete the newly created Process or keep it.

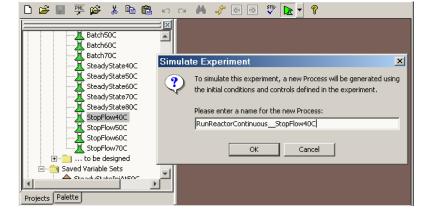


Figure 2.8. Simulating an experiment

The Process generated to Simulate a Performed Experiment

To simulate an experiment, gPROMS creates a copy of the existing Process and then automatically modifies the text to match the conditions specified in the Performed Experiment.

This approach has a number of advantages. Firstly, the structure of the Process remains intact, including any comments. Secondly, it provides a convenient way to view the modifications that gPROMS has made. To do so, simply select the two versions of the Process and press **F12** to activate the *text comparison* tool.

Specifically, the following modifications are made:

- Each Initial conditions is located in the Initial section of the Process, and modified with the value given in the
 Performed Experiment. Alternatively, if the Performed Experiment's initial condition is steady state, then this
 is set accordingly.
- Any Controls given in the Performed Experiment are located in the Assign section of the Process, and their values are modified.
- If any of the Performed Experiment's Controls are time-varying, a new Schedule section will be generated that mimics the control strategy.
- Any Saved Variable Set(s) specified in the Performed Experiment are added to the end of the Preset section of the Process (creating this section if necessary).

Limitations of automatic Process generation: The text modification approach employed to Simulate a Performed Experiment is not fool-proof. If a problem occurs during the generation of the Process, a message dialog will inform you of this fact. You will need to open the newly created Process and manually make some fixes, which are typically quite straightforward. Search for the text "Warning", and you will find the problems listed.

One problem, for example, occurs when elements of an array are specified using the square bracket notation [value, value, ...], and that array variable is referenced in the Performed Experiment. In this scenario gPROMS is unable to locate the correct location in the Process for automatic modification. See the figure below, which shows how this problem might look when viewed using the *text comparison* viewer.

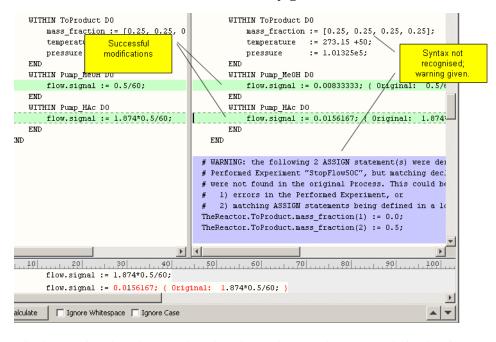


Figure 2.9. Text comparison of an original Process and an automatically generated Process.

After the required corrections have been made, select the newly created Process and Simulate it as you would any other Process (e.g. by pressing **F5**).

The Parameter Estimation entity

The complete specification of a Parameter Estimation problem requires some additional information which is not provided in the gPROMS Process or Experiments Performed entities. This includes information on the

unknown parameters to be estimated, the number of experiments that were performed, and sensor specifications (for example, if they have not already been defined in the Experiments Performed entity).

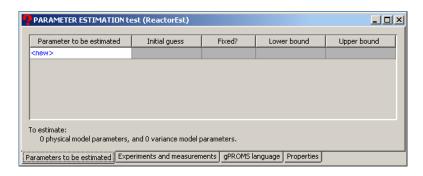
All of the above information has to be specified in a separate entity which appears under the Parameter Estimations entry in the gPROMS project tree.

To create a Parameter Estimation entity:

- From the Entity menu, select New Entity.
- Choose Parameter Estimation for the Entity type and fill in the Name field.

A Parameter Estimation entity editor window will open, as shown in the figure below.

Figure 2.10. Parameter Estimations Entity editor



The Parameter Estimations entity editor has the following tabs:

- The Parameters to be estimated tab (a form for defining the parameters that are to be estimated)
- The Experiments and measurements tab (a form for defining the set of experiments and measurement variance descriptions that will be used in the estimation)
- The gPROMS language tab this provides a convenient means of reviewing all the information regarding the performed experiment in a text-based format. You are not advised to use this tab to enter data³.
- Properties (a record of when the entity was created, last edited as well as the default tab to open on)

Parameters to be estimated

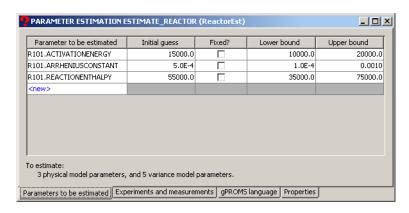
The Parameters to be estimated are a subset of the ASSIGNed variables in the Process entity, that will change the model predictions if they are adjusted. One could manually try and change them and run repeated simulations until the model predictions match the experiment data, or you can use the Parameter Estimation capabilities in gPROMS to do this in a rigorous and automated fashion.

In order to define these parameters you need to click on the Parameters to be estimated tab in the Parameter Estimations entity editor (as shown in the figure below).

³The Parameter Estimation editor is *destructively round-trip*: editing can be performed in the gPROMS language tab, and valid changes will be accepted when you perform a syntax check (**F4**) or change to a form-based view. However, any subsequent edits using the form-based editor will regenerate the language, and all comments and/or formatting will be lost.

⁴Note: even though we call it a *parameter* to be estimated, it should be defined in the gPROMS model as a **variable** and ASSIGNed in the Process entity.

Figure 2.11. Parameters to be estimated tab



Then simply click on the <new> cell in the table and type the full pathname to the variable.

Tip

Pathname completion can be activated by pressing Ctrl+Space.

Having entered the *parameter* you want to estimate, enter the initial guess and the lower and upper bounds in the column alongside. These will be used by the optimizer when solving the Parameter Estimation problem. If you wish to fix the *parameter* at the value defined by its initial guess, then check the cell in the Fixed? column of the table - this means the optimiser will not adjust this value when trying to minimise the deviation of the model from the experimental data.

Experiments and measurements

To define the experiments that will be used in the Parameter Estimation problem, click on the Experiments and measurements tab and then click the Add button at the top right of the window. gPROMS will then open a new window that includes a project tree with all the experiment entities that have been defined in this project or a cross-referenced project (as shown below).

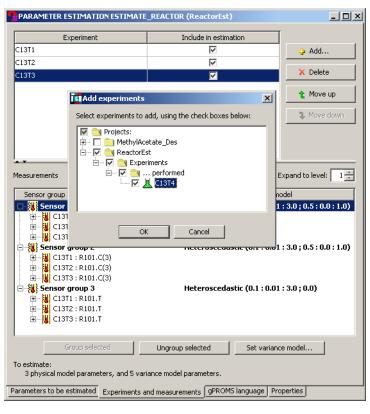


Figure 2.12. Specifying which experiments to include in a Parameter Estimation problem

In the Add experiments dialog, check the boxes of the experiments that you wish to include and select OK.

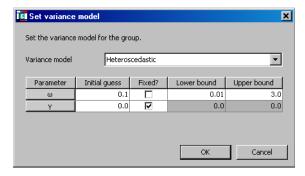
After all the experiments have been added you may want to consider the order of the experiments in the table which can be adjusted using the Move up and Move down buttons. The order of the experiments in the table corresponds to the order in which gPROMS solves them.

gPROMS will automatically create the table of all the sensors and the sensor groups in the lower half of the window. This is both a summary view and an editor. Here you may specify the statistical variance models for all the sensors and sensor groups. Any information provided here will **override** the sensor information provided in the individual experiments and if you have not provided a definition of a sensor for any of the measured variables in an experiment then it **must** be provided here. To change or add a Variance model for a sensor or sensor group, select the item in the tree and click the Set Variance model... button; this will open a window (as shown below) which allows you to set the Variance model. Enter the initial guess and the lower and upper bounds for the relevant statistical parameters that will be used in the solution of the maximum likelihood Parameter Estimation problem [6].

Note

Setting a variance model will always create a Sensor group, if one does not exist.

Figure 2.13. Setting a Variance model for a Sensor group



The information at the bottom of the window shows the total number of parameters to be estimated. If you have provided explicit values for all the sensors (or sensor groups) then 0 model variance model parameters will need to be estimated. On the other hand, if you have asked gPROMS to estimate the uncertainty of the measured variables then the number of the variance parameters will be displayed here.

Grouping sensors

When gPROMS solves a Parameter Estimation problem, the total number of parameters to be estimated is the sum of the unknown physical parameters together with the unknown variance model parameters. It is possible to reduce this number by grouping variance parameters together. For example, two different experiments may be performed where the concentration of a substance is measured using the same device. If it is expected that the measurement variance is the same for both experiments, then one would group them together and have a common variance model for both.

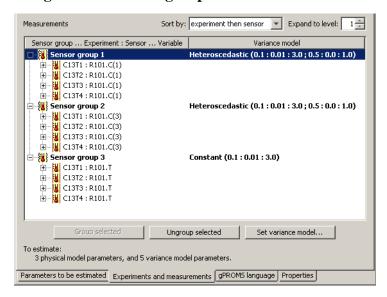


Figure 2.14. Sensor groups and Variance models

If you wish to **group measurements** and have a common variance model across all the experiments for those measurements, select the desired sensors and sensor groups⁵, then click the Group selected... button at the bottom of the window. There are now three possibilities:

- if you have not provided a Variance model for any of the sensors to be grouped then you will be asked to select a Variance model and give the appropriate variance parameter values for the new sensor group
- if one or more of the sensors to be grouped has a Variance model then this will be the variance model for the new sensor group assuming that there are no conflicts
- if two or more sensors to be grouped have conflicting Variance models then you will be asked to resolve the conflict and select a single variance model for the new sensor group

If you wish to **ungroup sensors**, select the appropriate sensor group, then click the Ungroup selected... button.

Note

When you ungroup a sensor, it will revert to using the variance model specification provided in the experiment entity, or to <urspecified> if it was not provided there.

Execution of a Parameter Estimation activity

For a fully defined Parameter Estimation problem the following entities are required:

⁵There are a number of ways to select multiple items: (1) click and drag, (2) click the first item in a range, then **Shift**+Click the last item, and (3) you can add or remove individual items from the selection using **Ctrl**+Click.

- one or more *Model* entities;
- · a Process entity;
- an Estimation entity
- one or more Performed Experiments entities

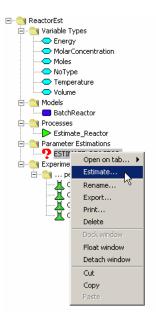
Note that the Experiment entities must all refer to the same Process.

Running the Parameter Estimation activity

You can execute a Parameter Estimation activity in a number of ways. First, select the Estimation entity from the project tree, and then either;

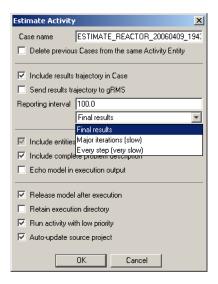
- 1. drop down the Activities menu and select Estimate..., or
- 2. click the red question mark in the tool bar, or
- 3. press **F5**.

Figure 2.15. Executing a Parameter Estimation activity from the Project Tree



If there are any syntactical or cross-referencing mistakes etc., these will be reported. Otherwise, the execution options dialog (below) will be displayed. Upon clicking OK, an execution Case is created and the activity begins.

Figure 2.16. The Parameter Estimation activity execution control dialog



Parameter Estimation reporting intervals: Most of the execution options for Parameter Estimation are identical to those for Simulation. The only extra option is in the reporting interval. In addition to the reporting interval period, you may also select at which stages of the optimisation the values are recorded into the results trajectory. The three options are:

- Final results no values are recorded until an optimal solution has been found.
- Major iterations values are recorded at every major iteration; that is, after a set of parameter values is accepted and a new search direction is being computed.
- Every step as above, and in addition, values are recorded during the line-search steps of the optimisation. This may include experiment evaluations that do not complete and so may be useful for diagnosing problems, such as problematic combinations of parameters.

Note

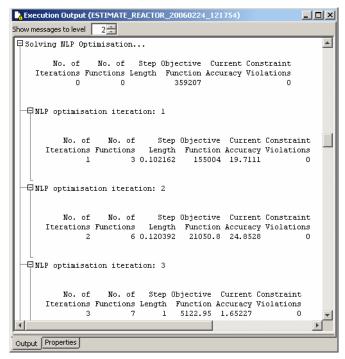
In addition to the reporting interval, the values of monitored variables are also recorded at each measurement time of the Performed Experiment. Therefore, if you wish to view the values of monitored variables at *just* the measurement times, simply enter a large reporting interval.

See also the Variable Trajectories section.

Monitoring the activity progress

You can monitor the progress that is being made during any Parameter Estimation activity from the Execution Output window. From the Execution Output window you can expand or collapse portions of the output by clicking on the + or - signs in the tree associated with the executing activity.

Figure 2.17. Monitoring the progress of a Parameter Estimation activity.



Adjusting the output level in the SOLUTIONPARAMETERS section of the Process will enable you to change the amount of information sent to the execution window during the execution of an Estimation activity.

Tuning the Parameter Estimation execution

It is possible to fine tune the numerical parameters associated with the underlying solvers used by gPROMS in the solution of a Parameter Estimation problem. This is done in the SOLUTIONPARAMETERS section of the Process entity. There is currently only one standard mathematical solver for Parameter Estimation in gPROMS, namely MAXLKHD.

The PESolver solution parameter may be used to configure the Parameter Estimation solver. The algorithmic parameters used by MAXLKHD along with their default values are shown below. Since the MINLP optimisation solver is integral to the Parameter Estimation activity, the default MINLP solver (SRQPD) is also shown, with selected relevant settings and their default values. Please see the Optimisation Guide for full details of the SRQPD solver.

```
SOLUTIONPARAMETERS
```

```
PESolver := "MAXLKHD" [
    "OutputLevel" := 0;
    "Statistics" := 0;
    "DASolver" := "DASOLV";
    "MINLPSolver" := "SRQPD" [
         "OutputLevel" := 0;
         "MaximumLineSearchSteps" := 20,
         "MinimumLineSearchStepLength" := 1e-005,
         "OptimisationTolerance" := 0.001,
         "Scaling" := 0
]
```

Solution Parameters for the MAXLKHD solver:

• OutputLevel: An integer in the range [-1, 2].

The amount of information generated by the solver. The following table indicates the lowest level at which different types of information are produced:

-1	(None)
0	Failed integrations and initialisations, optimisation failure, summary information from the SQP nonlinear programming code, final solution point and constraint values, best available point after failure
1	Name of each experiment being evaluated
2	Parsing of experiment-specific Saved Variable Sets.

• Statistics: An integer in the range [0, 2].

Controls the information produced by the solver in the machine-readable estimation statistics .stat-mr file at the end of the computation:

- 0: The parameter vector used for the calculation of the variance/covariance matrices includes both the model parameters and the variance model parameters.
- 1 : The parameter vector used for the calculation of the variance/covariance matrices includes only the model parameters.
- 2 : The variance/covariance matrices are not calculated.
- DASolver: A quoted string specifying a differential-algebraic equation solver.

The solver to be used for integrations of the model equations and their sensitivity equations at each iteration of the parameter estimation. This can be either the standard DASOLV solver or a third-party differential-algebraic equation solver (see the gPROMS System Programmer Guide). The default is DASOLV.

This parameter can be followed by further specifications aimed at configuring the particular solver by setting values to its own algorithmic parameters.

• MINLPSolver: A quoted string specifying a nonlinear programming optimisation solver.

Solution Parameters for the SRQPD sub-solver:

The following are only a subset of the parameters available in the default MINLP, SRQPD.

• OutputLevel: An integer in the range [-1, 4].

The amount of information generated by the solver. The following table indicates the lowest level at which different types of information are produced:

-1	(None)
0	Failed integrations and initialisations, optimisation failure, summary information from the SRQPD nonlinear programming code, final solution point and constraint values, best available point after failure
1	Values of optimisation decision variables, objective function and constraints in each major optimisation iteration
2	Start and end times of each interval of integration, optimisation decision variables and objective function at each line search trial
3	Derivatives of objective function and constraints

• MaximumLineSearchSteps: An integer in the range [1, 100].

The maximum number of line search steps in one optimisation iteration.

• MinimumLineSearchStepLength: A real number in the range $[10^{-10}, 1.0]$.

The minimum length of a line search step.

• OptimisationTolerance: A real number in the range [0.0, 1.0].

The solution tolerance for the parameter estimation. Convergence is deemed to occur when the following convergence criterion is satisfied:

$$rac{1}{\ket{\Phi^*}\ket{+1.0}}\left(\left|\sum_j rac{\partial \Phi^*}{\partial heta_j}\delta heta_j
ight| + \sum_j |\mu_j| \max(0, heta_j^L - heta_j^*, heta_j^* - heta_j^U)
ight)$$

$$\sum_{j} \max(0, heta_{j}^{L} - heta_{j}^{*}, heta_{j}^{*} - heta_{j}^{U}) \leq exttt{OptTol}$$

where:

- θ_j is the jth parameter to be estimated (including both model parameters and variance model parameters);
- θ_j^* is the final value of parameter θ_j ;
- θ_{j}^{L} is the lower bound imposed on parameter θ_{j} ;
- θ_j^U is the upper bound imposed on parameter θ_j ;
- Φ^* is the final value of the maximum likelihood objective function;
- $\delta\theta_j$ is the step taken in parameter θ_j at the last iteration of the parameter estimation calculation;
- μ_j is the Lagrange multiplier that corresponds to the bound constraints imposed on parameter θ_j ;
- Scaling: An integer in the range [0, 3].

The parameters to be determined in the context of a single parameter estimation problem may vary significantly in magnitude, which may adversely affect the performance of the optimisation algorithms. Consequently, appropriate scaling of these parameters is strongly recommended.⁶.

The scaling performed is of the general mathematical form:

$$ilde{ heta}_j = rac{ heta_j - c_j}{d_j}$$

where θ_j is the jth original parameter to be estimated and θ_j the corresponding scaled parameter. The constants c_i and d_i are determined automatically depending on the value of Scaling, as described below:

• Scaling = 0: No scaling (default).

$$d_j =$$
 1, (1a)

 $[\]frac{c_3}{^6}$ = 0. (1b) 6 A useful indication as to whether scaling is necessary is the condition number estimate that is printed out at each iteration of the optimisation calculation. It is recommended that scaling be undertaken for problems with condition numbers exceeding 10^{10} .

• Scaling = 1: Scaling according to the ranges of the parameters so that the scaled parameters vary between -1 and 1.

$$d_j = rac{1}{2} \left(heta_j^{ ext{max}} - heta_j^{ ext{min}}
ight),$$
 (2a)

$$c_j = rac{1}{2} \left(heta_j^{ ext{max}} + heta_j^{ ext{min}}
ight)$$
 (2b)

• Scaling = 2: Scaling according to the initial guesses of the parameters.

$$d_j = egin{cases} heta_j^0 & ext{if } | heta_j^0| > arepsilon, \ rac{1}{2} \left(heta_j^{ ext{max}} - heta_j^{ ext{min}}
ight) & ext{otherwise} \end{cases}$$
 (3a)

$$c_j = 0$$
 (3b)

where θ_j^0 is the initial guess for the jth parameter and ε is a small constant (currently set at 10⁻⁸).

• Scaling = 3: Scaling according to the value and the gradients of the objective function at the initial guess.

where θ^0 is the vector of initial guesses of the parameters and (ε is a small constant (currently set at 10^{-8} .

Analysing the Parameter Estimation results

You can analyse the results of a Parameter Estimation problem in a number of ways:

- 1. Variable values, stored in the Trajectories folder of the Case, allow you to view the model predictions of the measured variables and optionally other variables while the activity is running.
- 2. Information on the values of the estimation problems; the status of the optimisation problem and the statistical confidence of the estimated results is provided in three key results files accessed from the Results folder of the Case:
 - Comprehensive Parameter Estimation report file (in HTML format): PPP
 - Parameter Estimation report file (in plain text format): PPP.out
 - Statistical results for analysis in MS Excel: PPP.stat-mr

(where PPP is the name of the Parameter Estimation entity that has been executed to produce these results.)

Variable Trajectories

In the Execution Case results Trajectories are stored for all of the control and measured variables in each of the experiments. Note that from the execution dialog you have the option to choose whether to store only the results from the final solution or whether to record them for all of the major steps or even all of the steps during the solution of the Parameter Estimation problem.

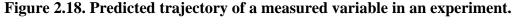
To view the results for a particular variable:-

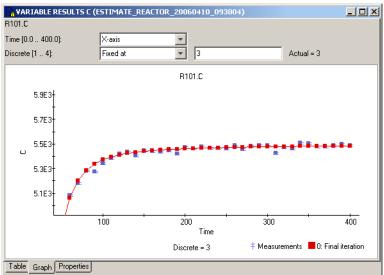
- · open the Trajectories folder in the Case
- select the desired Experiment and navigate to the desired Unit by expanding the results tree.
- double click on the desired variable. This will open up a results window for that variable. There are three tabs, corresponding to tabulated results, graphical results and a properties tab that summarises when the execution was carried out.

The figure below shows an example of a 2D plot of a measured variable. The model predictions for all variables are shown in red. In the 2D plots of a measured variable, the measured values (taken from data in the performed experiment) are also shown in blue, with error bars indicating the standard deviation of the measurements.

Note

The standard deviations here are indicative only, based on the *initial guess* of the variance model parameters. If the variance model parameters themselves are being estimated (and therefore may change during the parameter estimation activity), then see the comprehensive report for the calculated standard deviations.





Selecting variables to monitor. If no MONITOR section has been specified in the Process, then a default subset of the variables are recorded in the Trajectory. This subset consists of: the measured variables, the control variables, and the parameters being estimated.

To customise which variables are recorded, you can create a MONITOR section in the Process, as shown in the example below.

```
UNIT
TheReactor AS Reactor

MONITOR
TheReactor.Reactor.*;
TheReactor.Pump_*.mass_flowrate;
```

The MONITOR section will replace the default subset of variables being recorded.

Caution

Be aware that the amount of data being logged will increase if you monitor extra variables. The storage requirements for the variables will be multiplied by both the number of experiments and the number of

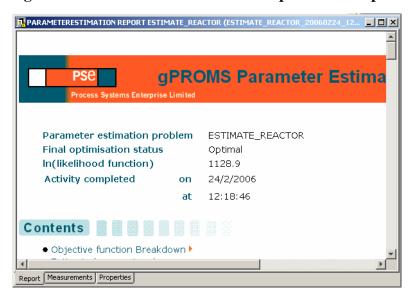
iterations reported, which it could result in a large amount of data being stored in the Case project, or sent to gRMS.

The Comprehensive report for Parameter Estimation

Found in the Results folder, the Parameter Estimation report file has the same name as the estimation activity that was executed. To view the report simply open it by double-clicking.

The figure below shows an example of a comprehensive report.

Figure 2.19. Parameter Estimation comprehensive report.



The report has three tabs:

- the Report tab
- the Measurements tab
- the Properties tab this provides details regarding the time of creation.

The Report tab includes the following information:

- a table of contents that allows quick access to the information listed below via "hyperlinks";
- general information such as the date and time of the execution of the activity, and its final status;
- a detailed breakdown of the value of the likelihood function in terms of the constant, variance and residual terms of each measured variable in each experiment;
- the initial guesses and final (optimal) values of all model parameters being estimated, together with the corresponding lower and upper bounds, the 90%, 95% and 99% confidence intervals, the 95% t-value and the standard deviation:
- the same information as above for any parameters describing the variance behaviour of the various sensors used for the measurements; these parameters will also have been estimated;
- a detailed analysis of each experiment, including the experimental controls and initial conditions, and the measured and estimated values of each measured point, as well as the corresponding difference ("residual");
- the variance/covariance matrix [31];
- the correlation matrix [31];
- a goodness-of-fit analysis based on the 95% χ^2 criterion.

From the Measurements tab you can compare the predicted and experimental values for the measured variables as well as seeing the statistical confidence in the results. You can select the variable to plot and the confidence interval from a drop down menus. You can also choose to view the data for the measured variable in tabular format..

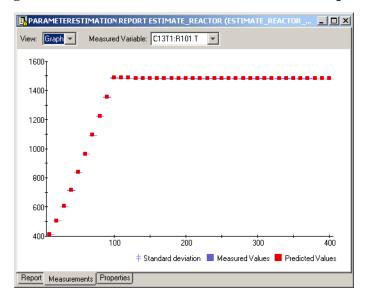


Figure 2.20. Parameter Estimation measurement plots

The summary report file

The text report (.out) file contains a summary report on the Parameter Estimation activity (giving the same information as the Comprehensive report), including:

- the outcome of the estimation run
- the final value of the objective function
- the final values of the estimated model parameters
- the final values of the sensor's variance model parameters

The file also contains computational statistics for the estimation calculation.

Example Parameter Estimation text output file

gPROMS Parameter Estimation

Estimation Name : ESTIMATE_REACTOR

Final Optimisation Status : Optimal Solution Found
Objective function : 1128.91

Constant term : 441.09

Variance term : 462.61 Least squares term : 225.207

Statistical Analysis:

Estimated Parameters:

Parameter	Final Value	Lower Bound	Upper Bound	95% Conf. Interval		I
R101.ACTIVATIONENERGY R101.ARRHENIUSCONSTANT	1.503E+004 0.0007556		2E+004 0.001	1.1E-005	2.7E+002 70	- : :
R101.REACTIONENTHALPY	5.502E+004	3.5E+004	7.5E+004	32	1.7E+003	
Variance Models:						
 Sensor Group 1: HETEROSCI	EDASTIC					
omega	0.1536	0.01	3	0.31	0.5	
gamma	0.6371	0	1	0.51	1.3	(
Sensor Group 2: HETEROSCI		0 01	2	0 001	4 0	
omega	0.1305 0.585	0.01	3 1	0.031	4.2 17	
gamma Sensor Group 3: HETEROSCI		0	T	0.034	17	
omega	0.4858	0.01	3	0.072	6.7	
gamma	0	0[*]	0[*]	0.0,2	. .	
2.3 5.87E-007 -0.717 0.03 -3.77 -9.69E-007 1.19 -0 -0.0101 -1.29E-009 0.0003 -0.00546 -9.55E-010 0.0003 -0.044 -4.24E-009 0.00069 Correlation matrix of est	.0403 0.0671 115 -7.02E-006 0612 -3.94E-00 94 3.09E-005 - timated parame	06 1.02E-006 05.54E-005 -4 0413 1	-0.000226 0.0		35	
2.3 5.87E-007 -0.717 0.03 -3.77 -9.69E-007 1.19 -0 -0.0101 -1.29E-009 0.0003 -0.00546 -9.55E-010 0.006 -0.044 -4.24E-009 0.00069 Correlation matrix of est	.0403 0.0671 115 -7.02E-006 0612 -3.94E-00 94 3.09E-005 - timated parame 	06 1.02E-006 05.54E-005 -4 0413 1 0413 1 0229 -0.833 1	-0.000226 0.0		35	
-107 -2.73E-005 266 2.3 5.87E-007 -0.717 0.03 -3.77 -9.69E-007 1.19 -0 -0.0101 -1.29E-009 0.0003 -0.00546 -9.55E-010 0.000 -0.044 -4.24E-009 0.00069 Correlation matrix of est	.0403 0.0671 115 -7.02E-006 0612 -3.94E-00 94 3.09E-005 - timated parame 	06 1.02E-006 05.54E-005 -4 0413 1 0413 1 0229 -0.833 1	-0.000226 0.0		35	
2.3 5.87E-007 -0.717 0.03 -3.77 -9.69E-007 1.19 -0 -0.0101 -1.29E-009 0.0003 -0.00546 -9.55E-010 0.006 -0.044 -4.24E-009 0.00069 Correlation matrix of est	.0403 0.0671 115 -7.02E-006 0612 -3.94E-00 94 3.09E-005 - timated parame 	06 1.02E-006 05.54E-005 -4 0413 1 0413 1 0229 -0.833 1	-0.000226 0.0		35	
2.3 5.87E-007 -0.717 0.03 -3.77 -9.69E-007 1.19 -0 -0.0101 -1.29E-009 0.0003 -0.00546 -9.55E-010 0.006 -0.044 -4.24E-009 0.00069 Correlation matrix of est	.0403 0.0671 115 -7.02E-006 0612 -3.94E-00 94 3.09E-005 - timated parame 	06 1.02E-006 05.54E-005 -4 0413 1 0413 1 0229 -0.833 1	-0.000226 0.0		35	

Intervals:

```
_____
```

Interval # 1 100
Interval # 2 300

Time-Varying Controls:

1. R101.Q
 (piecewise constant)

Interval Value 1 505000

2 0

Measurements:

Measured Variable R101.C(1) Sensor Group Sensor Group 1

Time	Meas.Value	Pred.Value	Deviation	%Deviation	StdDev	Dev/StdDev
10	3746.911	3720.9496	25.9614	0.692875	29.0673	0.893149
20	2518.6	2513.4938	5.10624	0.202741	22.5678	0.226263
30	1504.12	1509.8021	-5.6821	-0.377769	16.2498	-0.349672
40	883.7833	888.95174	-5.16844	-0.584809	11.58	-0.446325
50	548.0505	543.84439	4.20611	0.767467	8.54054	0.492487
60	348.6161	352.88585	-4.26975	-1.22477	6.40183	-0.666958
70	239.5115	242.7614	-3.2499	-1.35689	5.04007	-0.644812
80	175.4503	175.71184	-0.261537	-0.149066	4.13345	-0.0632732
90	135.0508	132.66329	2.38751	1.76786	3.49862	0.682415
100	100.9699	103.68624	-2.71634	-2.69024	2.90685	-0.934459
110	87.2978	84.205283	3.09252	3.54249	2.64949	1.16721
120	74.13863	70.888503	3.25013	4.38385	2.38755	1.36128
130	62.0976	61.209633	0.887967	1.42995	2.13261	0.416376
140	54.54854	53.85582	0.69272	1.26991	1.96357	0.352786
150	49.05154	48.079397	0.972143	1.98188	1.83508	0.529756
<	snip>					
350	14.34733	15.287814	-0.940484	-6.55511	0.838487	-1.12164
360	15.20852	14.783675	0.424845	2.79347	0.870214	0.488207
370	14.26656	14.311725	-0.045165	-0.31658	0.835477	-0.054059
380	14.57341	13.868976	0.704434	4.83369	0.846882	0.831797
390	11.8482	13.452799	-1.6046	-13.543	0.742229	-2.16186
400	14.05076	13.060872	0.989888	7.04509	0.827403	1.19638

<...and for all experiment measurement....>

Experiment	Variable	Contribution
C13T1	R101.C(1)	38.160398
C13T1	R101.C(3)	139.93596
C13T1	R101.T	-14.315856
C13T2	R101.C(1)	38.383615
C13T2	R101.C(3)	128.82448
C13T2	R101.T	-0.31047035

```
36.729493
     C13T3
            R101.C(1)
     C13T3
            R101.C(3)
                            129.8304
     C13T3
               R101.T
                           -4.881258
     С13Т4
            R101.C(1)
                           58.162784
            R101.C(3)
     C13T4
                           149.39776
     C13T4
               R101.T
                          -12.100016
         N/2*ln(2*PI)
                           441.0905
Sum of variance terms
                           462.61015
Sum of residual terms
                           225.20714
Computational Statistics
                                                     : 22.063
Total CPU Time
                                                                seconds
  ESTIMATE_REACTOR Optimiser Statistics
                                                     : 0.016
                                                                seconds (0.072520 % of to
    CPU Time
    Number of
              NLP Iterations
                                                     : 34
    Number of NLP Line Search Steps
                                                     : 38
  DASOLV Integrator Statistics
                                                     : 8.75902
                                                                seconds (39.700020 % of t
    CPU Time
    CPU Time Spent on Integration Only
                                                     : 3.01301
                                                                seconds (34.398934 %of DA
      40104 steps, 60972 residuals
                                                     : 0.781008 seconds
                                                     : 0.200001 seconds
      11848 Jacobians
    CPU Time Spent on Sensitivity Integration Only: 5.74601
                                                                seconds (65.601066 % of DA
      38060 steps, 95136 residuals
                                                      0.562005 seconds
                                                     : 0.372004 seconds
      49220 Jacobians
    Mean (Sensitivity+State)/(State) CPU Ratio
                                                     : 1.52437
```

Statistical analysis in Excel

gPROMS provides an advanced statistical analysis tool in Microsoft ExcelTM that allows the user to further analyse the results and create several statistical plots. The data that are necessary for the operation of this facility are stored in the .stat-mr file. It contains all the information that appears in the text based results file but in machine-readable format for import into Excel.

To use the Excel based tool on a Windows platform - double click the .*stat-mr* file; this will open Excel and will automatically import the statistics file⁷. If you running gPROMS on a non-Windows platform then you can export the .stat-mr data file for transfer to a MS Windows-based system.

The Excel tool makes it easy to

- 1. View and manipulate measurement and statistical data tables
- 2. Create overlay, residual and confidence ellipsoid plots

Data spreadsheets

A number of spreadsheets are created automatically when the statistics data file is loaded in Excel.

• Summary. This sheet summarises the contributions to the objective function of the constant, variance and residual terms, as well as the types of variance models used for each measured variable in each experiment and their respective contributions to the objective function. It also shows the estimated parameters. Parameters in red colour indicate either that the estimated value is at one of its bounds or that the confidence intervals are very large (see also the "Statistical significance" sheet). A sample summary sheet for the batch reactor example can be found in the next chapter.

⁷The security settings within Excel must allow the execution of macros.

- **Parameter estimates.** This sheet summarises the estimated values of the model parameters and the parameters of the different statistical variance models used, together with their initial guesses, and lower and upper bounds (see next chapter).
- Variance matrix. This sheet prints the variance-covariance matrix, V. This matrix contains the variances and covariances of the estimated process model and variance model parameters. The square root of each diagonal element, $\sqrt{v_{ii}}$, is the approximated standard deviation of the respective estimated parameter.

The following approximation to the variance-covariance matrix is used:

$$\mathbf{V} = H^{*^{-1}} \, \Gamma \, V_{\tilde{z}} \, \Gamma^T \, H^{*^{-1}}$$

where

$$H^* = \left[egin{array}{ccc} rac{\partial^2}{\partial heta^2} \, \Phi & rac{\partial^2}{\partial eta_{i,\,j} \, \partial heta} \, \Phi \ rac{\partial^2}{\partial eta_{i,\,j} \, \partial heta} \, \Phi & rac{\partial^2}{\partial eta_{i,\,j} \, \partial heta} \, \Phi \end{array}
ight], \quad \Gamma = \left[egin{array}{ccc} rac{\partial^2}{\partial ilde{z}_{i,\,j,\,k} \, \partial heta} \, \Phi \ rac{\partial^2}{\partial ilde{z}_{i,\,j,\,k} \, \partial eta_{i,\,j}} \, \Phi \end{array}
ight]$$

and $v_{\tilde{z}} = diag(\sigma_{ijk}^2)$ denotes the variance-covariance matrix of the measurement errors. The variance-covariance matrix of the estimated parameters, V, is of size $\dot{\boldsymbol{r}}^{n_p \times n_p}$, where N_p is the number of all estimated parameters (process model parameters θ and variance model parameters β) whose values do not lie at one of their respective lower or upper bounds.

• **Correlation matrix.** This sheet prints the correlation matrix, *R*, which is calculated from the variance-covariance matrix,

$$R_{ij} = rac{V_{ij}}{\sqrt{V_{ii}V_{jj}}}, \quad i
eq j, \ ext{where} \ R_{ij} = 1, \qquad i = j.$$

Values with absolute value close to one in the off-diagonals indicate a high correlation of the corresponding parameters i and j, and vice versa. The high correlation of these parameters can also be seen in the corresponding confidence ellipsoid plots (see below).

• **Information matrix**. This sheet prints the Fischer information matrix, *M*, which is equal to the inverse of the variance-covariance matrix *V*. It also prints the 90%, 95% and 99% F-values for this matrix (calculated using internal statistical functions).

An approximate $(1-\alpha)$ highest posterior density region for the parameters $p^t=(\theta^t,\beta^t)$ is given by

$$(p-\hat{p})^T\cdot \mathbf{M}\cdot (p-\hat{p}) \ \leq \ N_p\, s^2\, F(lpha,N_p,N-N_p)$$

with

$$s^2 = rac{1}{N-N_P} \, \sum_{i=1}^{NE} \sum_{j=1}^{NV_i} \sum_{k=1}^{NM_{ij}} rac{(ilde{z}_{ijk} - z_{ijk})^2}{\sigma_{ijk}^2}$$

which forms an ellipsoid in the N_p -dimensional parameter space. An α % confidence region means that if we repeat the experiments (which produces nearly the same measurements, but with slightly different observation values and therefore a different distribution of the measurement errors), and estimate the parameters out of the repeated experimental data, the values of the estimated parameters will lie in this confidence region with α % probability. Confidence ellipsoids for any chosen pair of parameters can be plotted by selecting the Plot option

⁸Again only those parameters whose values are not at one of their bounds are considered.

Note that the confidence ellipsoid is only a linear approximation of the non-linear confidence region and may not be very accurate for models which are highly non-linear in the parameters.

- Statistical significance. This sheet prints:
 - the estimated values of the process model and variance model parameters;
 - the 90%, 95% and 99% confidence intervals for the estimated model and variance model parameters. The confidence ellipsoid is bounded by the box

$$\otimes_{i=1}^{N_p}[\hat{p}_i-X_i(lpha);\hat{p}_i+X_i(lpha)]$$

The sides of the box, $[\hat{p}_i - X_i(\alpha); \hat{p}_i + X_i(\alpha)]$, are called the two-sided joint $\alpha\%$ confidence intervals.

These are calculated from
$$X_i(lpha)=t\left(rac{1+lpha}{2},N-N_p
ight)\cdot \sqrt{V_{ii}}$$

• 95% t-values for the estimated parameters. These are calculated from:

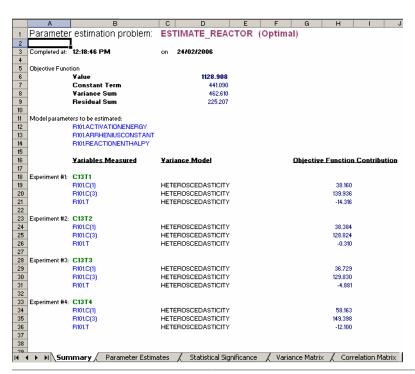
$$t_i = rac{\hat{p}_i}{X_i(0.95)}$$

The t-values show the percentage accuracy of the estimated parameters with respect to the 95% confidence intervals.

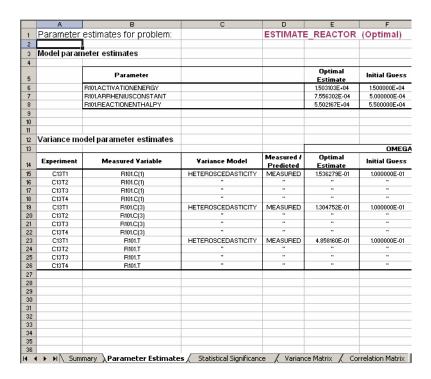
The associated t-values, t_i , are compared with the reference 95% t-value, $t(0.95,N-N_p)$, which is again calculated using internal statistical functions. A t-value larger than the reference t-value indicates that the corresponding parameter has been accurately estimated (the standard deviation and the confidence interval are small compared to the value of the estimated parameter); a smaller value indicates a poor estimate of the corresponding parameter.

- the standard deviations $\sqrt{v_{ii}}$ of the estimated parameters.
- Measured variable information. For each measured variable in each experiment, a sheet is produced with the measured and predicted values, the standard deviations and the absolute, relative and weighted deviations. One such sheet for the variable R101.C(1) in the batch reactor experiment C13T1 is shown in the next chapter.

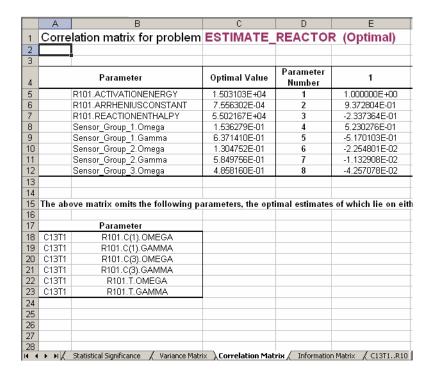
Sample summary sheet.



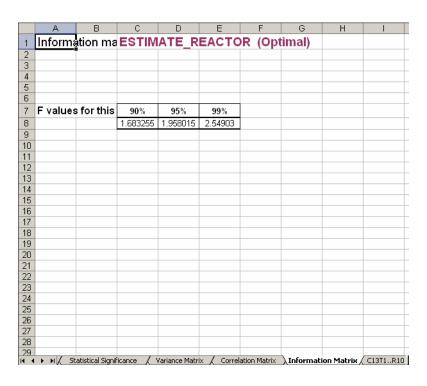
Sample parameter estimates sheet



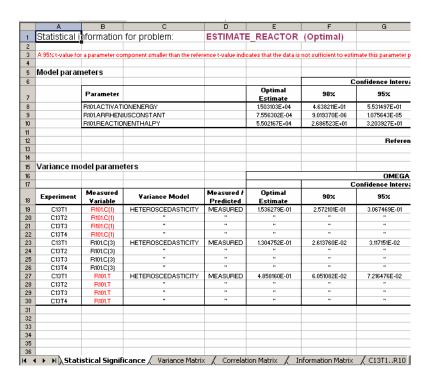
Sample correlation matrix sheet



Sample information matrix sheet



Sample statistical significance sheet



Sample measured variable sheet

	A	В	С	D	E	F	G
1	Parameter estimation problem:		ESTIMATE REACTOR (Optimal)				
2						,	
3	Mageuradyar	iable informatio	AD:			$\overline{}$	
	imeasureu vai	iabie iliiviiliau		040T4 D404 00	•		
4				C13T1R101.C(1)		
5							
6		Yariable Yalues Deviation					
				Standard			
	Measurement	Experimental	Model	Deviation of	Absolute	Percentage	Veighted
_	Time	Measurement	Prediction	Experimental			-
7				Measurement			
8	10	3.746911E+03	3.720950E+03	2.906726E+01	2.596140E+01	0.692874844	8.931492E-0
9	20	2.518600E+03	2.513494E+03	2.256775E+01	5.106240E+00	0.2027412	2.262627E-0
10	30	1.504120E+03	1.509802E+03	1.624977E+01	-5.682098E+00	-0.377768929	-3.496725E-0
11	40	8.837833E+02	8.889517E+02	1.157999E+01	-5.168441E+00	-0.584808606	-4.463253E-0
12	50	5.480505E+02	5.438444E+02	8.540537E+00	4.206106E+00	0.76746678	4.924872E-0
13	60	3.486161E+02	3.528859E+02	6.401829E+00	-4.269753E+00	-1.22477221	-6.669583E-0
14	70	2.395115E+02	2.427614E+02	5.040071E+00	-3.249896E+00	-1.356885245	-6.448116E-0
15	80	1.754503E+02	1.757118E+02	4.133452E+00	-2.615368E-01	-0.149066025	-6.327322E-0
16	90	1.350508E+02	1.326633E+02	3.498625E+00	2.387515E+00	1.767864162	6.824152E-0
17	100	1.009699E+02	1.036862E+02	2.906853E+00	-2.716335E+00	-2.690242781	-9.344591E-0
18	110	8.729780E+01	8.420528E+01	2.649495E+00	3.092517E+00	3.542491369	1.167210E+00
19	120	7.413863E+01	7.088850E+01	2.387549E+00	3.250127E+00	4.383850925	1.361282E+00
20	130	6.209760E+01	6.120963E+01	2.132612E+00	8.879673E-01	1.429954363	4.163756E-0
21	140	5.454854E+01	5.385582E+01	1.963568E+00	6.927200E-01	1.269914911	3.527863E-0
22	150	4.905154E+01	4.807940E+01	1.835077E+00	9.721427E-01	1.981880042	5.297557E-0
23	160	4.298377E+01	4.342218E+01	1.687002E+00	-4.384078E-01	-1.019938008	-2.598740E-0
24	170	3.961377E+01	3.958755E+01	1.601488E+00	2.621978E-02	0.066188557	1.637214E-02
25	180	3.571447E+01	3.637551E+01	1.499170E+00	-6.610380E-01	-1.850896872	-4.409359E-0
26	190	3.299957E+01	3.364579E+01	1.425523E+00	-6.462240E-01	-1.958280108	-4.533243E-0
27	200	3.212896E+01	3.129694E+01	1.401445E+00	8.320247E-01	2.589641027	5.936908E-0
28	210	2.969873E+01	2.925456E+01	1.332944E+00	4.441718E-01	1.495592011	3.332262E-0
29	220	2.643707E+01	2.746243E+01	1.237715E+00	-1.025360E+00	-3.878492916	-8.284297E-0
30	230	2.695787E+01	2.587719E+01	1.253195E+00	1.080677E+00	4.008760926	8.623370E-0
31	240	2.475480E+01	2.446500E+01	1.186937E+00	2.898039E-01	1.170697818	2.441611E-01
32	250	2.254412E+01	2.319896E+01	1.118261E+00	-6.548383E-01	-2.904696495	-5.855862E-0
33	260	2.262180E+01	2.205751E+01	1.120715E+00	5.642871E-01	2.494439578	5.035065E-0
34	270	2.140928E+01	2.102314E+01	1.082060E+00	3.861447E-01	1.803632479	3.568607E-0
35	280	2.096655E+01	2.008143E+01	1.067749E+00	8.851248E-01	4.221604417	8.289632E-0

Graphical analysis

In addition to the spreadsheets, the user can also create three types of statistical plots by choosing the Plot option from the Parameter Estimation menu on the MS Excel tool bar. Each of these is described below:

- Overlay chart. This overlays the measured and predicted values for whichever variable is chosen from a specified experiment. The user has the option of showing error bars by checking the Show standard deviations dialog box (see appropriate figure in the next chapter). These error bars correspond to $\tilde{z}_{ijk} \pm \sigma_{ijk}$. The user selects one or more variables (choose Flat list, if you want to select more than one variable). The charts can be plotted on the respective variable data worksheets, on a new sheet for each chart or all charts on one new sheet. A figure showing a plot of the batch reactor variable R101.C(1) in experiment C13T1 can be found in the following chapter. It can be seen that the agreement between the predicted values using the estimated parameters and the measured values is very close.
- **Residual chart**. This allows the user to plot the absolute deviation, relative deviation and/or weighted (scaled) residual for each measured variable in each experiment. As for the "Overlay chart", the user may select one or more variables and plot the charts on the respective data worksheets, on a new sheet for each chart or all the charts on one new sheet. Figures in the following chapter show the dialog window and weighted residual plot, respectively, for the batch reactor variable R101.C(1) in experiment C13T1.
- · Confidence ellipsoids.

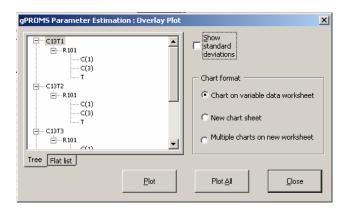
This option gives the confidence ellipsoids in two-dimensional space for any pair of parameters (p_i, p_j) according to the joint confidence region:

$$\left(egin{array}{c} p_i - \hat{p}_i \ p_j - \hat{p}_j \end{array}
ight)^T \left(egin{array}{c} V_{ii} & V_{ij} \ V_{ij} & V_{jj} \end{array}
ight)^{-1} \left(egin{array}{c} p_i - \hat{p}_i \ p_j - \hat{p}_j \end{array}
ight) \ \leq \ N_p \, s^2 \, F(lpha, N_p, N - N_p).$$

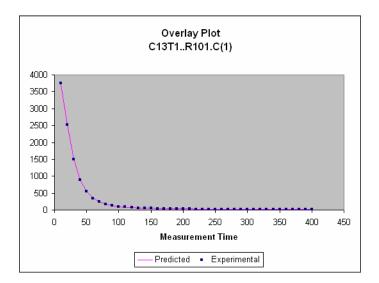
The parameters can be plotted against each other using different confidence levels (90%, 95% or 99%). The user may select any pair of parameters or plot the confidence ellipsoids for all pairs. An example of a confidence ellipsoid is shown in the next chapter.

Note: Although the variance model parameters have uncertainties, the user may wish to exclude these uncertainties from the calculations. In this case the vector p^t does not contain the parameters β^t and is defined as $p^t = \theta^t$.

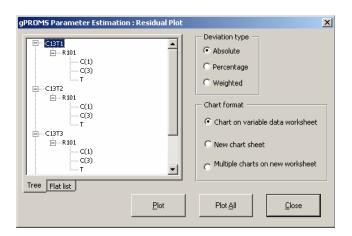
Overlay Plot Dialog Window



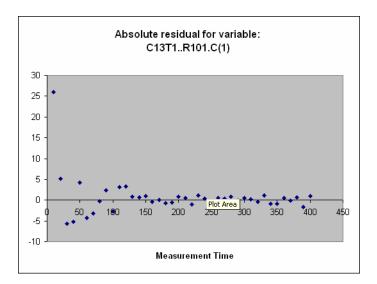
Sample Overlay Plot



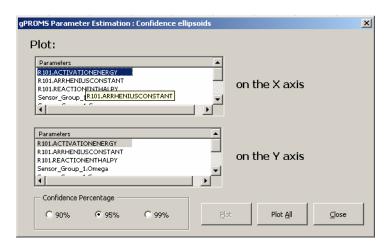
Residual Plot Dialog Window



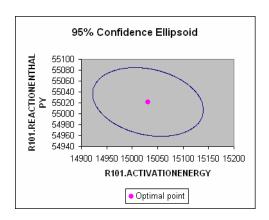
Sample Weighted Residual Plot



Confidence Ellipsoid Dialog Window



Sample Confidence Ellipsoid Plot.

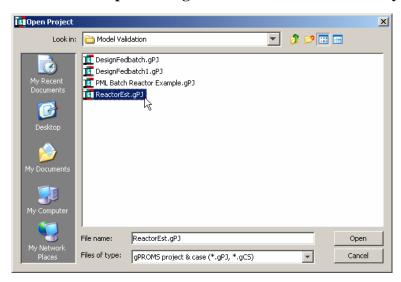


A Parameter Estimation example

The gPROMS installation includes a simple Parameter Estimation example - it is highly recommended that you take a look at this. You can access this by clicking on the browse examples button on the gPROMS Tool bar

and then navigating to General capabilities\Model Validation\ReactorEst.gPJ (as shown below). This section explains the features of the model.

Figure 2.21. Browsing for the Batch Reactor Parameter Estimation example in the gPROMS distribution directory.



The example considers the batch reactor shown in the figure below. The reactor is used to carry out the following liquid-phase endothermic reaction:

$$A + B \rightarrow C + D$$

An electrical heating element is used to provide the necessary heat to the reactor. The duty of this heating element is the control variable in the experiment.

Figure 2.22. Batch reactor.

Experimental and theoretical evidence indicates that the order of the reaction with respect to both A and B is one. We also know that the kinetic constant of the reaction follows an Arrhenius-type temperature dependence relationship. Based on this information, and assuming perfect mixing and ideal liquid mixture behaviour, we can construct the following mathematical model for the process:

Component mass balance

$$rac{dM_i}{dt} =
u_i r V \;\;,\;\; i = A,\; B,\; C,\; D.$$

Energy balance

$$rac{dH}{dt} = rV(-\Delta H_R) + Q$$

$$r=kC_AC_B$$

Arrhenius temperature dependence

$$k = k_0 e^{-E/RT}$$

Component concentrations

$$C_i = rac{M_i}{V}$$
 , $i = A$, B , C , D , $V = \sum_{i=A,B,C,D} rac{M_i}{
ho_i}$

Energy content

$$H = \sum_{i=A,B,C,D} M_i \hat{H}_i, \hat{H}_i = lpha_i (T-T_{ref}) + rac{eta_i}{2} (T^2-T_{ref}^2)$$
 , $i=A,\ B,\ C,\ D$

The tables below summarise the parameters and variables that appear in this model.

Table 2.2. Parameters in batch reactor Model.

Model Parameters	Description	
E	Reaction activation energy	
k_0	Arrhenius constant	
T_{ref}	Reference temperature	
$lpha_ieta_i$	Specific molar enthalpy coefficients of component <i>i</i>	
δh_r	Heat of reaction	
$ u_i $	Stoichiometric coefficient of component i	
$ ho_i$	Molar density of component i	

Table 2.3. Variables in batch reactor Model.

Model Variables	Description	
C_i	Molar concentration of component i	
Н	Total enthalpy content of the reactor	
\hat{H}_i	Specific molar enthalpy of component i	
k	Reaction constant	
M_i	Molar holdup of component i	
Q	Heating load	
r	Reaction rate	
T	Reactor temperature	

V Total volume of liquid in the reactor	
---	--

Before this model can be used to simulate or optimise the operation of the reactor, all parameters that appear in it must be given fixed values. Imagine, however, a situation where the kinetic characteristics of the reaction are unknown. That is, we do not know the values of k_0 , E and δh_r . In order to determine these, we can perform a number of experiments and measure the values of some or all process variables.

Four experiments have been performed, all under identical conditions. The duration of each experiment is 400s, the reactor is initially loaded with 100 mol of A, 100 mol of B, 1 mol of C and 1 mol of D, and the initial temperature is 293K. The heating element power supply is set to 505kW for the first 100s of operation and to zero thereafter. The experimental conditions are summarised below:

Table 2.4. Conditions for batch reactor experiments #1 to #4

Initial conditions	Heating policy
$M_A = 100 \text{ mol}$	$Q = 505 \text{ kW}, 0 \le t(s) \le 100$
$M_B = 100 \text{ mol}$	${ m Q} = 0,100 < t(s) \le 400$
$M_C = 1 \text{ mol}$	
$M_D = 1 \text{ mol}$	
T = 293 K	

The data from four typical experiments are shown in the table below. The reactor temperature and the concentrations of reactant A and product C are automatically measured every 10 seconds.

Table 2.5. Data from the batch reactor experiments

Experiment #	Time t (s)	Temperature T (K)	C _A (mol m ⁻³)	C _c (mol m ⁻³)
1	10	412.549	3746.911	898.552
	20	504.179	2518.600	2358.859
	30	603.486	1504.120	3634.895
	40	715.300	883.783	4407.922
	50	837.841	548.051 	4849.769
2	10	411.804	3700.752	898.216
	20	504.530	2520.929	2380.372
	30	604.027	1502.396	3626.625
	40	714.709	894.412	4388.874
	50	837.154	545.142	4828.031
3	10	412.823	3705.683	896.799
	20	503.740	2513.977	2386.384
	30	604.359	1516.819	3633.759
	40	715.539	895.847	4419.044

Experiment #	Time t (s)	Temperature T (K)	C _A (mol m ⁻³)	C _c (mol m ⁻³)
	50	836.518	551.290	4796.965
	•••	•••	•••	
4	10	411.235	3711.353	902.858
	20	503.830	2526.062	2409.363
	30	603.157	1527.653	3653.779
	40	716.325	895.004	4400.964
	50	837.703	543.662	4824.272
	•••	•••	•••	•••

We note that, for any given set of values of the unknown parameters, the model equations can be solved to predict the reactor behaviour at the experimental conditions. For instance, the plots below compares the predicted variation of $C_A(t)$ and T(t) for $k_0 = 6.5*10^{-4} \, m^3 mol^{-1} s$, $E = 20000 \, J/mol$ and $\Delta H_R = 55000 \, J/mol$, against the data obtained from the first experiment. It can be seen that the model predictions are rather poor.

Figure 2.23. Comparison of experimental composition data with model predictions based on nominal values of k_0 , E and δh_r

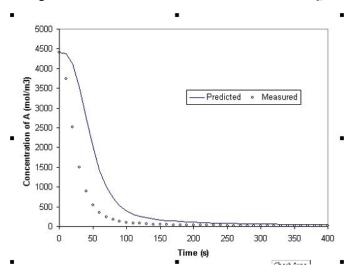
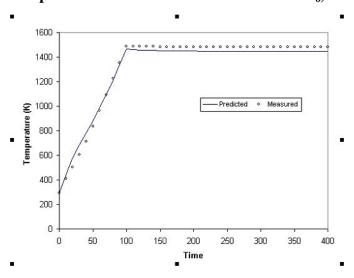


Figure 2.24. Comparison of experimental temperature data with model predictions based on nominal values of k_0 , E and δh_r



In practice, we obviously need to determine the values of the unknown parameters, k_0 , E and δh_r , in order to maximise the probability that the model will predict the values obtained from the experiments. This is the objective of the Parameter Estimation problem.

In our example we will assume that the following initial guess and bounds hold for the 3 different parameters of interest:

- The Arrhenius coefficient, k_0 (gPROMS pathname R101.ARRHENIUSCONSTANT), has an initial guess 5E-4 and the lower and upper bounds on its value are 1E-4 and 1E-3 respectively.
- The reaction activation energy, *E* (gPROMS pathname R101.ACTIVATIONENERGY), has an initial guess of 15000 and the lower and upper bounds on its value are 10000 and 20000 respectively.
- The heat of reaction, δh_r (gPROMS pathname R101.REACTIONENTHALPY), has an initial guess of 55000 and the lower and upper bounds on its value are 35000 and 75000 respectively.

Here the ???measured variable is assumed to be described by the same variance model for each of the experiments that were performed. Hence:

- The concentration of reactant A, C_A (gPROMS pathname R101.C(1)), and the concentration of product C, C_C (gPROMS pathname R101.C(3)), are both described by HETEROSCEDASTIC models on the PREDICTED_VALUES. The initial guess for ω is 0.1, with lower and upper bounds of 0.01 and 3 respectively, while the initial guess for γ is 0.5 with bounds of 0 and 1.
- The reactor temperature, T(gPROMS pathname R101.T), is also described by a HETEROSCEDASTIC model. The initial guess for ω is 0.1, with bounds of 0.01 and 3. However, γ is fixed at zero (the measurement error for the temperature is a constant value and does not depend on the size of T).

Chapter 3. Experiment Design in gPROMS

gPROMS can be used to perform *Experiment Design for parameter precision* for complex steady-state and dynamic models. This chapter covers the following issues:

- a description of what an Experiment Design problem is,
- the Experiments to be designed and Experiment Design entities that are used to specify Parameter Estimation problems in gPROMS,
- · how to analyse the results from an Experiment Design activity,
- how to control the execution of an Experiment Design activity.

Explanatory screen shots are taken from a fed batch fermentation problem included in the gPROMS distribution. Some basic familiarity with the gPROMS language and concepts is assumed.

What is Experiment Design?

Experiments are used to improve the understanding of processes and create accurate models. The quality of information generated by experiments depends strongly on the experimental conditions as well as what is measured and when it is measured. The aim is to design experiments in order to maximise the information content of the measurements in the context of their utilisation for estimating the model parameters. This is equivalent to minimising the variances of the parameters to be estimated. The variances are a measure for the uncertainty of the parameters, also represented by individual confidence interval approximations. Experiment Design therefore aims at minimising the variances (the uncertainty) of the parameters to be estimated.

Experiment Design in gPROMS supports the design of one or more new experiments. Designing more than one experiment simultaneously is of interest in cases where multiple sets of experimental apparatus are available, allowing several experiments to be carried out in parallel, or when the experiment duration is relatively short, in which case one may wish to design simultaneously all experiments to be performed within a single day or week. The Experiment Design calculations can take into account any experiments that have already been performed. This may, for example, result in different regions of the operating space being explored from the point of view of yielding maximum information.

Experiment Design for parameter precision aims at determining optimal experimental settings and measurement times in order to maximise the information content from the measured data generated by these experiments. This is equivalent to minimising the confidence ellipsoid of the parameters to be estimated.

Underlying mathematics of Experiment Design

In mathematical terms, we want to minimise some measure ψ of the variance-covariance matrix, v_{θ} , of the parameters to be estimated:

$$\min_{\mathcal{E}} \Psi(\mathbf{V}_{\theta})$$

The experiment decision variables ξ may be subject to equality or inequality constraints:

$$c(\xi) \ge 0$$

 $\xi^{\min} \le \xi \le \xi^{\max}$

The variance-covariance matrix is of the form:

$$\mathbf{V}_{ heta} = (H_{ heta}^{\star})^{-1}$$

The information matrix h_{θ}^{\star} is a $n_{\theta} \times n_{\theta}$ matrix, where n_{θ} is the number of parameters to be estimated, θ . It is given by

$$\left(H_{ heta}^{\star}
ight)_{\mu,
u} = \sum_{l=1}^{N_{exp}} \sum_{i \in \mathcal{MV}_l} \sum_{m=1}^{NM_{il}} \left(\; rac{\left(rac{\partial}{\partial heta_{\mu}} \, z_{il}(
ho_{iml})
ight) \left(rac{\partial}{\partial heta_{
u}} \, z_{il}(
ho_{iml})
ight)}{\sigma_{il}^2(z_{il}(
ho_{iml}),eta_{il})}
ight), \; \mu, \;
u=1,\ldots,N_{ heta}$$

The symbols in these equations have the following definitions:

Table 3.1. Symbol definitions.

\mathbf{v}_{θ}	The variance-covariance matrix of the parameters to be estimated.
$H_{ heta}^{\star}$	& The information matrix of the parameters to be estimated.
ξ	The set of experiment decision variables in all experiments.
n_{exp}	The number of experiments.
\mathcal{MV}_l	The set of measured variables in experiment l , i.e. $\mathcal{MV}_l \subseteq \{1,,N_{x_l}+N_{y_l}\}$
nm_{il}	The number of sampling points for measured variable i in experiment $l, i \in \mathcal{MW}_{l}$.
$ ho_{iml}$	The m -th measurement time for variable i in experiment l .
$z_{il}(ho_{iml})$	The model-predicted value of variable i at time point ρ_{iml} in experiment l .
$\sigma_{il}^2(z_{il}(ho_{iml}),eta_{il})$	The variance of the measurement error of variable i at time point ρ_{iml} in experiment l .

Equipment design and resource availability may impose certain operational and safety limits within which our control manipulations should be maintained. Experiment Design seeks to provide answers to the following questions

- What should be the initial conditions for the experiment?
- How long should we run the experiment for?
- How should we vary the controls (e.g. the time profiles of feed flowrates and external heating/cooling loads)?
- When should we take the measurement samples?

The overall aim is to generate the maximum amount of information for a subsequent estimation of the parameters $(\theta_1 \dots \theta_4)$ using gPROMS' Parameter Estimation facilities, while trying to maintain the process within the required operating envelop.

In order to compare the magnitude of different variance-covariance matrices, various real-valued functions have been suggested as a measure of "smallness". gPROMS supports three well-known criteria:

• **A-optimality:** minimise the trace of the variance-covariance matrix:

$$\Psi_{A}\left(\mathbf{V}_{ heta}
ight)=rac{1}{N_{ heta}}\,\sum_{\mu=1}^{N_{ heta}}\left(\mathbf{V}_{ heta}
ight)_{\mu,\mu}$$

This minimises the sum of the variances of the individual parameter estimates. It corresponds to minimising the dimensions of the smallest hyper rectangle within which the confidence ellipsoid can be inscribed.

• **D-optimality:** minimise the determinant of the variance-covariance matrix:

$$\Psi_{D}\left(\mathbf{V}_{ heta}
ight)=\det\left(\mathbf{V}_{ heta}
ight)^{rac{1}{N_{ heta}}}$$

This is also known as the minimum volume criterion since it minimises the volume of the confidence ellipsoid.

• **E-optimality:** minimise the largest eigenvalue of the variance-covariance matrix:

$$\Psi_E(\mathbf{V}_{\theta}) = \lambda_{\max}(\mathbf{V}_{\theta})$$

The eigenvalues of the variance-covariance matrix correspond to the lengths of the minor and major axes of the confidence ellipsoid. By minimising the largest eigenvalue, the design renders the confidence ellipsoid as spherical as possible.

The figure below shows a graphical interpretation of the different design criteria for a two-dimensional confidence ellipsoid.

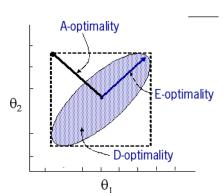


Figure 3.1. Interpretation of the different design criteria.

Experiments to be designed

The Experiments to be designed entity is used to specify the full details of the experiments to be designed.

Note experiments that have already been performed and which you want to take into account when designing an experiment are specified in exactly the same way as for Parameter Estimation.

In order to create a new Experiments Designed entity, do the following:

- Pull-down the Entity menu from the top pane in gPROMS ModelBuilder.
- Click on New Entity. A dialog box will appear.
- Choose Experiment to be designed for the Entity type and fill in the Name field.

When you do the above, an Experiments to be designed entity editor window will open up in the right hand pane, as shown in the figure below.

EXPERIMENT TO BE DESIGNED FEDBATCH_DES (DesignFedbatch) -Process Type of experiment Dynamic C Steady state Experiment duration Upper bound -Initial conditions Initial guess Lower bound Variable name Fixed? Upper bound Delete row General Controls | Constraints | Measurements and sensors | gPROMS language | Properties

Figure 3.2. Experiments to be designed entity editor

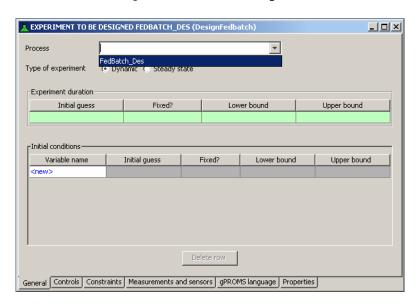
The Experiments to be designed entity editor has the following tabs:

- The General tab a form for defining the Process entity to use; the type of experiment to determine (steady-state or dynamic) and which initial conditions should be determined.
- The Controls tab a form for specifying the time-invariant, piecewise constant and piecewise linear variables that can be adjusted during the course of the experiment and that are to be optimally determined by the Experiment Design problem.
- The Constraints tab a form for defining any endpoint or interior-point constraints that need to be placed on the experiment that will be designed.
- The Measured data tab a for entering the quantities that can be measured and the sensor used to do this.
- The gPROMS language tab this provides a convenient means of reviewing all the information regarding the experiment to be designed in a text-based format. You are not advised to use this tab to enter data.
- Properties (a record of when the entity was created, last edited as well as the default tab to open on)

General information

In order to define the Process entity to use for a given experiment, click on the General tab in the Experiments to be designed entity editor and then choose the desired Process from the drop down menu at the top of the window as shown in the figure below.

Figure 3.3. Specifying the Process entity that will be used in conjunction with the experimental data.



gPROMS can be used to design both steady-state and dynamic experiments. If designing a dynamic experiment then you need to decide whether to optimally determine the duration of the experiment and the initial conditions for the experiment:

- · Determine experiment duration?
 - Fixed the experiment duration; give the value in the Initial guess field
 - Give the initial guess and lower and upper bounds for the duration of the experiment gPROMS will determine an experiment duration between these bounds
- What initial conditions?
 - Type the full pathname of the gPROMS differential variable that you wish to specify an initial condition for in the <new> cell in the initial conditions table.. You MUST only provide initial conditions for variables that are given initial values directly in the Process.
 - If you do not wish to type the pathname you can select the appropriate variable from a drop down list by holding the CTRL key down and hitting the SPACE button on your keyboard. The first time you do this, gPROMS will give you a list of relevant Units and Variables. Select the desired one and then repeat as necessary to drill down to the desired Variable.
 - Give the initial guess and lower and upper bounds for the initial condition gPROMS will determine the value of the initial condition between these bounds. If you want to fix the initial condition at a constant value then *check* the fixed box.

EXPERIMENT TO BE DESIGNED FEDBATCH_DES (DesignFedbatch) FedBatch_Des -Process Dynamic C Steady state Type of experiment Experiment duration Initial guess 10.0 5.0 10.0 Initial conditions Variable name ERMENT.y1 10.0

Figure 3.4. Specifying the initial conditions for the relevant differential variables in an experiment to be designed.

Controls

An experiment control is a variable that can be adjusted during an experiment (such as a heating policy in a reactor). Experiment controls therefore form part of the "recipe" for running the experiment. The user can specify the variation in a Variable value using one of three different mechanisms:

General Controls Constraints Measurements and sensors gPROMS language Properties

- *Time-invariant controls* provide a single variable value, this quantity will be the same for the duration of the experiment. Appropriate for steady-state and dynamic experiments.
- *Piecewise constant controls* provide multiple variable values, the quantity holds a different constant value for specified time intervals during the experiment. Appropriate for dynamic experiments only.
- *Piecewise linear controls* provide multiple variable values, the quantity varies linearly (from a start value to an end value) in a calculated time interval during the experiment. Appropriate for dynamic experiments only.

So when designing an experiment; gPROMS determines the optimal values and profiles for time-invariant, piecewise constant and piecewise linear control variables.

Note that any Variables that are Assigned values in a Process but are not specified as controls in the experiment will retain their Assigned values, whether these are constants or functions of TIME.

In order to define the experiment controls, click on the *Controls* tab in the *Experiments to be designed* entity editor and do the following:

- Click the <new> cell in the *Control variables* table at the top of the window and type the full pathname of the gPROMS control variable ¹If you do not wish to type the pathname you can select the appropriate variable from a drop down list by holding the CTRL key down and hitting the SPACE button on your keyboard. The first time you do this, gPROMS will give you a list of relevant Units and Variables. Select the desired one and then repeat as necessary to drill down to the desired Variable.
- Choose from the drop down list in the right-hand column whether the control variable is time-invariant, piecewise constant or piecewise linear. Note that if a steady-state experiment has been specified on the general tab then you only have the option to select time-invariant controls.
- Repeat the above for each new control variable you wish to use.

¹NOTE: This variable should be one of those you ASSIGNed in the associated Process entity.

Having chosen the format for the time-varying behavior of the control variable, select the relevant control by clicking on it, and then go to the lower part of the window to enter the details of its allowable behavior during the experiment. If one or more piece-wise constant or piece-wise linear controls have been selected then first define the time intervals.: the Control time intervals are synchronised for all piecewise constant and piecewise linear controls and adding or deleting control intervals therefore affects all control variables

- · Provide an initial guess and bounds on the allowable time duration for each interval
- To add another interval enter the value in the <new> row²
- 1. *Time-invariant controls* provide a value together with lower and upper bounds. gPROMS will determine a value between these bounds.
- 2. *Piece-wise constant controls* for each interval specify an initial guess for the control along with lower and upper bounds; gPROMS will determine a value between these bounds.
- 3. *Piece-wise linear controls* for each interval gPROMS will determine a starting value for the control and a final value for the control variable provide an initial guess for the starting and final value of the control along with lower and upper bounds; gPROMS will determine values between these bounds.

Should you wish to duplicate or delete an entire interval, simply select it and click on the Duplicate or Delete buttons at the bottom of the window.

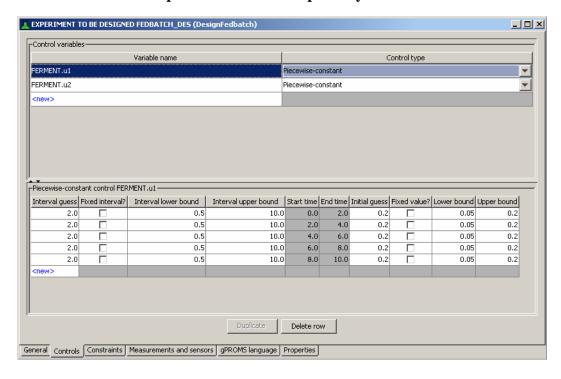


Figure 3.5. Specifying the bounds on a piecewise constant control profile that is to be optimally determined.

Constraints

The purpose of the Constraints tab is to allow the user to impose safety and operational limits on the designed experiment to ensure. This ensures that the result of the Experiment Design problem is an experiment that is allowable and feasible to run in practice. To capture these limits, gPROMS allows for the specification of *endpoint* and *interior-point* constraints on the predicted behavior of variables in the experiment that is to be designed. There are no interior point constraints for steady-state models.

²When you enter the interval duration gPROMS automatically determines the start and end times of that interval, but the relevant cells are greyed out and you cannot edit them.

In order to define an **endpoint constraint**, click on the Constraints tab in the Experiments to be designed entity editor and do the following:

- Click the <new> cell in the Variable name column of the Endpoint constraints table at the top of the window and type the full pathname of the gPROMS variable. Note that *pathname completion* can be activated by pressing **Ctrl+Space**.
- Specify the lower and upper bounds on the Variable. When gPROMS solves the Experiment Design problem it will ensure that the Variable indicated is restricted to within the specified bounds. Alternatively, check the Fixed? cell and specify the constraint value if you desire an endpoint equality constraint. Note: endpoint equality constraints are very challenging for numerical reasons and it is usually better to specify an endpoint inequality constraint with a tight lower and upper bound.
- Repeat the above for each new endpoint constraint you wish to add. If you wish to delete an endpoint constraint, click the *Delete* button at the bottom of the window.

Interior-point constraints are *inequality constraints* defined at the *start* of every time interval. Such constraints are slightly more complicated to specify because of the fact that it is possible to have the bounds varying from one interval to another.

In order to define an **interior-point constraint**, click on the Constraints tab in the Experiments to be designed entity editor and do the following:

- Click the <new> cell in the Variable name column of the Endpoint constraints table at the top of the window and type the full pathname of the gPROMS variable. If you do not wish to type the pathname you can select the appropriate variable from a drop down list by holding the CTRL key down and hitting the SPACE button on your keyboard. The first time you do this, gPROMS will give you a list of relevant Units and Variables. Select the desired one and then repeat as necessary to drill down to the desired Variable.
- Specify the lower and upper bounds on the Variable. When gPROMS solves the Experiment Design problem it will ensure that the Variable indicated is restricted to within the specified bounds at the start of each time interval. Alternatively, check the Varying? cell and then specify the lower and upper bounds on the interior point constraint for the start of each interval in the experiment to be designed.
- Repeat the above for each new interior-point constraint you wish to add. If you wish to delete an interior-point constraint, click the *Delete* button at the bottom of the window.

It should be noted that it is possible to supply constraints that make solution of the Experiment Design problem impossible - an *infeasible* problem (e.g. specification of too low a temperature may lead to an infeasible problem if there is only limited cooling available).

Figure 3.6. Experiment Design - imposing design constraints

Measurements and sensors

During an experiment, measurements of key variables are taken using sensors. The purpose of the Measurement and Sensors tab is to define the variables that will be measured and to specify how often or when the measurements can be taken.

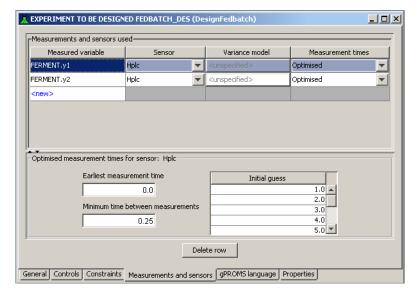


Figure 3.7. The measurements and sensors tab

Each measured variable must be associated with a sensor. In Experiment Design a sensor has a Variance model and a set of measurement times: the measurement times are either fixed or determined optimally.

To introduce a Variable that can be measured:

• Click the <new> cell in the Measured Variable part of the table at the top of the window and type the full pathname of the gPROMS variable. If you do not wish to type the pathname you can select the appropriate

variable from a drop down list by holding the CTRL key down and hitting the SPACE button on your keyboard. The first time you do this, gPROMS will give you a list of relevant Units and Variables. Select the desired one and then repeat as necessary to drill down to the desired Variable.

• You should provide a name for the sensor in the next column or if appropriate associate this Variable with an existing sensor.

For each sensor, you should provide the Variance model and information on when or how the measurement times are to determined.

- Click on the Variance model cell next to the sensor. When you do so a dialog box will open.
 - Select the desired variance model from a drop down list and
 - enter the appropriate values for the variance model you have selected, click OK to close the dialog box. Note that as gPROMS is not estimating parameters (as in Parameter Estimation) you must provide a fixed value for the uncertainty of the sensor's measurements.
- You must specify how frequently the sensor takes a measurement by selecting from the drop down menu in the adjacent cell.
 - for a fixed number of measurements, select *equidistant* in the bottom half of the window; enter the number of measurements to be taken and the earliest possible measurement time.
 - to take measurements at fixed times, select *fixed* in the bottom half of the window; enter the measurement times.
 - to let the optimiser choose the measurement times in the bottom half of the window; enter initial guesses for the measurement times along with the minimum allowable time between measurements and the earliest possible measurement time.
 - for a steady state experiment you should choose unspecified.

Should you wish to delete a measurement you can do so using the button at the bottom of the window.

The Experiment Design entity

This comprises information on the design criterion, the unknown parameters to be estimated and the measurements and sensors (together with their statistical variance models) used in one or more of the experiments.

In order to create a new Experiment Design entity, do the following:

- Pull-down the Entity menu from the top pane in gPROMS ModelBuilder.
- Click on New Entity. A dialog box will appear.
- Choose Experiment Design for the Entity type and fill in the Name field.

When you do the above, an Experiment Design entity editor window will open up in the right hand pane, as shown in the figure below.

Design criterion E-Optimal Minimise the largest eigenvalue of the variance-covariance matrix

Estimated parameters

Estimated parameter Value Scaling factor

<new>

Delete row

General Experiments and measurements gPROMS language Properties

Figure 3.8. Experiment Design entity editor.

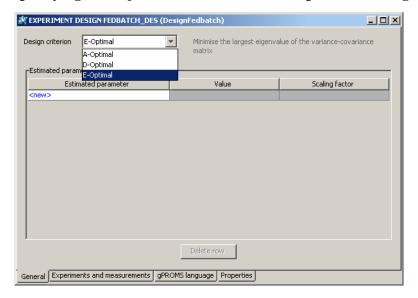
The Experiment Design entity editor has the following tabs:

- The General tab a form for defining the Experiment Design objective function as well as the parameters to be estimated by the experiment.
- The Experiments and measurements tab a form for defining the sets of experiments to be designed and those that have already been performed, together with the measurement variance descriptions that will be used in the estimation.
- The gPROMS language tab this provides a convenient means of reviewing all the information regarding the experiment to be designed in a text-based format. You are not advised to use this tab to enter data.
- Properties (a record of when the entity was created, last edited as well as the default tab to open on)

General information

In order to define the form of objective function for the Experiment Design problem, click on the General tab in the Experiment Design entity editor and then choose the desired objective from the drop down menu at the top of the window as shown in the figure below.

Figure 3.9. Specifying the objective function for the Experiment Design problem.



In addition to the objective, it is necessary to define the parameters that you are trying to get precise estimates for by designing optimal experiments: these should be added to the Estimated Parameters table along with the current estimate for the Parameter value.

3

• In order to define a new parameter to be estimated, simply click on the <new> cell in the table and type the full pathname to the variable. If you do not wish to type the pathname you can select the appropriate variable from a drop down list by holding the CTRL key down and hitting the SPACE button on your keyboard. The first time you do this, gPROMS will give you a list of relevant Units and Variables. Select the desired one and then repeat as necessary to drill down to the desired Variable.

For certain design criterions, scaling of the parameters can affect the solution obtained: so scaling of the parameter must be considered. If you are interested equally in all the values of parameters to be estimated then these numbers should be the same.

A- and E-optimal designs depend strongly on the actual value of the parameters to be estimated. If one parameter is much larger than the rest, the design will most likely try to reduce the variance of this specific parameter. As a side-effect, the variances of the other parameters may be reduced as well, but these are not taken into account directly by the optimisation. In order to make the confidence ellipsoid, given by the variance-covariance matrix V_{θ} , as spherical as possible, it is advisable to scale all parameters to the same value, e.g. unity. On the other hand, if the you want some parameters to be statistically more reliable than others, it is advisable to scale these parameters to a higher value than the rest.

In mathematical terms, we divide each parameter θ_{μ} by its scaling factor $scal_{\mu}$:

$$ilde{ heta}_{scal,\mu} = rac{ heta_{\mu}}{scal_{\mu}},\, \mu = 1,\ldots,N_{ heta}$$

This is the same as multiplying the variance-covariance matrix with the diagonal matrix $\operatorname{diag}(scal_1^2,\ldots,scal_{N_\theta}^2)$

i.e.

$$\mathbf{V}_{ heta_{scal}} = \mathbf{V}_{ heta} \cdot ext{diag}(scal_1^2, \dots, scal_{N_{ heta}}^2)$$

The D-optimal design is invariant to scaling of the parameters to be estimated.

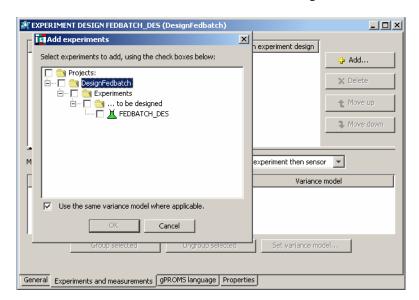
Experiments and measurements

On this tab you select the experiments (bothperformed and ...to be designed) to be included in the Experiment Design problem. In addition, you have the opportunity to check that the variance models for all the sensors have been fully defined.

To add experiments click on the *Experiments and measurements* tab and then click the *Add* button at the top right of the window. gPROMS will then open a new window that includes a project tree with all the experiment entities that have been defined in all open projects:

³Note: even though we call it a "parameter" to be estimated, it should be define in the gPROMS model as a variable and ASSIGNED in the Process entity.

Figure 3.10. Experiments Performed entities that can be included in the estimation problem.



Check the boxes of the experiments that you wish to include, and click OK.

For a description of Sensors and Sensor groups tables refer to the information given for Performed Experiments.

For the purposes of Experiment Design, gPROMS needs to have a value for the Variance of each sensor:

- Experiments... to be designed: when defining the measurement you had the option to specify the variance model and its parameters for each sensor. If you chose not do provide the variance model parameters then you must specify these here.
- Experiments... performed: when defining the measurement you had the option to specify the variance model and its parameters for each sensor. You could also choose to estimate the parameters for the sensors; for the purposes of Experiment Design the initial guess for the Variance parameter is used as a fixed value. If you chose not do provide the variance model parameters then you must specify these here.

If any sensors have unspecified variance parameters then you will be warned at the bottom of the *Experiments and measurements* tab. To make it easier to specify variance parameters then you can group sensors and measurements together - note the grouping sensors only links their variance models and NOT the measurement time information provided in the experiment.

Execution of Experiment Design activities

For a fully defined Experiment Design problem the following entities are required:

- one or more *Model* entities;
- · a Process entity;
- an Experiment Design entity
- one or more to be designed Experiment entities

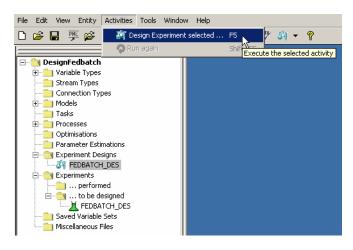
Note that the Experiment entites must all refer to the same Process.

To execute an Experiment Design problem, select the Experiment Design entity from the project tree and then either

- 1. from the Activities menu and select Design Experiment name..., or
- 2. click on the Design Experiment button at the top right of the tool bar, or
- 3. press F5.

If there are any syntactical, cross-referencing mistakes etc., these will be detected. Otherwise, an Execution Case is created.

Figure 3.11. Executing an Experiment Design activity.



You can analyse the results of an Experiment Design problem in a number of ways:

- 1. Variable values stored in the Trajectories folder of the Case
- 2. Information on the values of the design problem; the status of the optimisation problem and the statistical analysis of the results is provided in three key results files accessed from the Results folder of the Case:
 - Comprehensive Experiment Design report file (in HTML format): PPP
 - Experiment Design report and statistics files (in plain text format): PPP.out & PPP.stat
 - Experiment schedule files: EXPERIMENTNAME1. SCHEDULE, EXPERIMENTNAME2. SCHEDULE ...
- 3. Experiment templates stored in the Experiment Templates folder of the Case

where *PPP* is the name (in capitals) of the Experiment Design entity that has been executed to produce these results.

Variable Trajectories

In the Execution Case results Trajectories are stored for all of the control and measured variables in each of the experiments - these show the recommended behaviour for all the control variables and the anticipated behaviour (from the gPROMS model) of the measured variables. Note that from the execution dialog you have the option to choose whether to store only the results from the final solution or whether to record them for all of the major steps or even all of the steps during the solution of the Experiment Design problem.

To view the results for a particular variable:-

- open the Trajectories folder in the Case
- select the desired Experiment and navigate to the desired Unit by expanding the results tree.
- double click on the desired variable. This will open up a results window for that variable. There are three tabs, corresponding to tabulated results, graphical results and a properties tab that summarises when the execution was carried out. The figure below shows an example of graphical results for a measured variable.

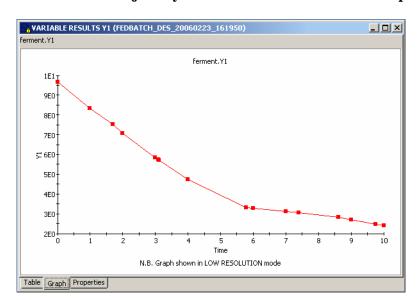


Figure 3.12. Predicted trajectory of a measured variable in an experiment.

The Comprehensive report for Experiment Design

Found in the Results folder, the Experiment Design report file has the same name as the Experiment design activity that was executed. To view the report simply open it by double-clicking.

The figure below shows an example of a comprehensive report.

EXPERIMENTDESIGN REPORT FEDBATCH_DES (FEDBATCH_DES_20060313_114616) gPROMS Experiment Design Experiment design FEDBATCH_DES Final optimisation status Optimal Design criterion E-optimal Value of design criterion 0.0889818 Activity completed on 13/3/2006 11:46:34 Contents • Model parameter • Sensors • Sensor Group 1 • Experiments FEDBATCH DESc • Initial conditions • ◆ FERMENT.y1 ▶ Control intervals • Interval # 1 • Interval # 3 ▶ Interval # 4 • Interval # 5 🕨 Time varying controls FERMENT.u1 FERMENT.u2 Variance-Covariance Matrix 🕨 Correlation Matrix > Report Measurements Properties

Figure 3.13. Comprehensive Experiment Design report.

The report has three tabs:

- the Report tab
- the Measurements tab
- the Properties tab this provides details regarding the time of creation.

The Report tab includes the following information:

- a table of contents that allows quick access to the information listed below via "hyperlinks";
- general information such as the date and time of the execution of the activity, its final status and the type and value of the design criterion;
- information on the various experiments and experimental decision variables (duration of the experiment, control interval durations, time-invariant and time-varying controls), including the values of:
 - the initial guess used,
 - the final value obtained,
 - the lower and upper bounds,
 - the Lagrange multipliers corresponding to the above bounds,

- information on the interior point and end-point constraints imposed (all active bounds are automatically highlighted).
- the variance/covariance matrix [31];
- the correlation matrix [31];

The *Measurements* tab allows you to view the predicted values for the measured variables from each designed experiment as well as seeing the statistical confidence that is anticipated for these results. You can select the variable to plot and the confidence interval from a drop down menus. You can also choose to view the data for the measured variable in tabular format.

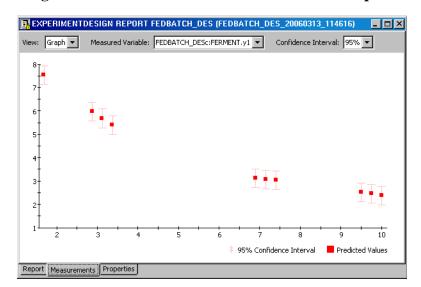


Figure 3.14. Parameter Estimation measurement plots

The Experiment Design text report and statistics files

The .out and .stat plain text files contain a summary report of the Experiment Design run in a simple text format; but of course the information is the same as that presented in the Comprehensive Report file.

The text report (.out) file provides the following information:

- the outcome of the Experiment Design run;
- the design criterion used and the final value of it;
- · for each experiment:
 - the final value of the experiment duration and the lengths of the time intervals;
 - the final values of the time-invariant control parameters, and the control-variable profiles; the latter are specified in terms of a single value per interval for piecewise-constant controls, and a pair of values for piecewise-linear controls (as usual, corresponding to the value of the control at the start and end of each interval);
 - the values of variables on which end-point and/or interior point constraints where specified, at the corresponding final and/or interior points;
 - the measured variables and the final values of sampling times and predicted values for the measured data and standard deviation of the measurement error at these points.
- Computational statistics on the performance of the numerical method.

The text statistics (.stat) file contains the results of the statistical analysis of the Experiment Design problem; in particular the following information is available

- the confidence intervals, individual t-values and standard deviations,
- the variance-covariance matrix,
- the correlation matrix of the parameters to be estimated.

Example Experiment Design text report file

gPROMS Experiment Design for Parameter Precision _____

gPROMS Process : FEDBATCH_DES1

Final Optimisation Status : Optimal Solution Found

Design Criterion : E-optimal Value of Design Criterion : 0.089641

Parameters to Be Estimated:	Nominal Values (fixed)	Scaling factor
	=======================================	=========
FERMENT.theta(1)	0.1	0.1
FERMENT.theta(2)	0.1	0.1
<pre>FERMENT.theta(3)</pre>	0.1	0.1
FERMENT.theta(4)	0.1	0.1
Sensors:		

CONSTANT_VARIANCE

(

0.2)

]

Experiment Decision Variables ([*] denotes an active bound)

Experiment 1: FEDBATCH DES

Hplc

Decision Variable ======== Duration	Value ===== 10	Lower Bound ======= 5	Upper Bound ====================================
Initial States:			
FERMENT.y1	9.5985	1	10
Control Intervals:			
Cantaral Tabanasal #1	1 7212	0 5	1.0
Control Interval #1	1.7312	0.5	10
Control Interval #2	1.444	0.5	10
Control Interval #3	2.6112	0.5	10
Control Interval #4	2.8723	0.5	10
Control Interval #5	1.3412	0.5	10

Time-Varying Controls: ______

1. FERMENT.u1

(piecewise constant)

C	or	ıtı	20	Τ
Γ'n	+ 4	277	72	٦

Interval	Value	Lower Bound	Upper Bound
======	====	========	========
# 1	0.05	0.05[*]	0.2
# 2	0.17201	0.05	0.2
# 3	0.2	0.05	0.2[*]
# 4	0.05	0.05[*]	0.2
# 5	0.097177	0.05	0.2

2. FERMENT.u2

(piecewise constant)

Control

Interval	Value	Lower Bound	Upper Bound
======	====	========	========
# 1	5.04	5	35
# 2	33.694	5	35
# 3	33.837	5	35
# 4	19.863	5	35
# 5	25.529	5	35

Measurements:

1. FERMENT.y1 , FERMENT.y2 (OPTIMISED)

1. FERMENT.YI , FERMENT.YZ (OPTIMISED)			
Sensor: Hplc			
Measured Variable	Time	Predicted Value	Standard Deviation
===========	====	=========	===========
FERMENT.y1	1.6971	7.4787	0.2
FERMENT.y2	1.6971	0.0034771	0.2
FERMENT.y1	3.0063	5.8171	0.2
FERMENT.y2	3.0063	0.73037	0.2
FERMENT.y1	3.2563	5.5444	0.2
FERMENT.y2	3.2563	0.95598	0.2
FERMENT.y1	3.5063	5.2634	0.2
FERMENT.y2	3.5063	1.3486	0.2
FERMENT.y1	7.0885	3.093	0.2
FERMENT.y2	7.0885	2.8612	0.2
FERMENT.y1	7.3385	3.0517	0.2
FERMENT.y2	7.3385	2.3375	0.2
FERMENT.y1	7.5885	3.0103	0.2
FERMENT.y2	7.5885	1.8368	0.2
FERMENT.y1	9.5	2.5404	0.2
FERMENT.y2	9.5	0.49742	0.2
FERMENT.y1	9.75	2.4697	0.2
FERMENT.y2	9.75	0.57685	0.2
FERMENT.y1	10	2.402	0.2
FERMENT.y2	10	0.65817	0.2

Computational Statistics

Total CPU Time FEDBATCH_DES1 Optimiser Statistics

CPU Time

Number of NLP Iterations

Number of NLP Line Search Steps

: 55.102 seco

: 0.02 seco

: 11

: 22

```
DASOLV Integrator Statistics
  CPU Time
                                                                       : 39.829
                                                                                  seco
  CPU Time Spent on (First Order) Sensitivity Integration Only
                                                                       : 6.65001 secon
    6013 steps, 9054 residuals
                                                                       : 0.410007 seco
    7728 Jacobians
                                                                       : 1.69301 secon
  CPU Time Spent on Second Order Sensitivity Integration Only
                                                                      : 33.179
    2689 steps, 3980 residuals
                                                                       : 0.230001 seco
    46507 Jacobians
                                                                       : 4.68701 secon
  Mean (1st+2nd Order Sensitivity)/(1st Order Sensitivity) CPU Ratio : 5.98931
```

Example Experiment Design text statistics file

Parameters to Be Estimated:				Scaling factor
FERMENT.theta(1)			0.1	0.1
FERMENT.theta(2)			0.1	0.1
FERMENT.theta(3)			0.1	0.1
FERMENT.theta(4)			0.1	0.1
Variance Models:				
Sensor Group 1 CONSTANT_VARIANCE		(0.2)	
Experiment 1: FEDBATCH_DESc				
Measurements:				
FERMENT.y1	Sensor	Group 1		
FERMENT.y2		Group 1		
(OPTIMISED)				
Measured Variable		Time	Predicted Value	Standard Deviation
===========		====	==========	==========
FERMENT.y1		1.6804	7.5428	0.2
FERMENT.y2		1.6804	0.0034492	0.2
FERMENT.y1		2.8671		0.2
FERMENT.y2		2.8671	0.72544	0.2
FERMENT.y1		3.1171	5.6937	0.2
FERMENT.y2		3.1171	0.9059	0.2
FERMENT.y1		3.3671	5.4046	0.2
FERMENT.y2		3.3671	1.2807	0.2
FERMENT.y1		6.8971	3.1218	0.2
FERMENT.y2		6.8971	3.3295	0.2
FERMENT.y1		7.1471	3.0805	0.2
FERMENT.y2		7.1471	2.7756	0.2
FERMENT.y1		7.3971	3.0393	0.2
FERMENT.y2		7.3971	2.2436	0.2
FERMENT.y1		9.5	2.5315	0.2
FERMENT.y2		9.5	0.46123	0.2
FERMENT.y1		9.75	2.4603	0.2
FERMENT.y2		9.75	0.52776	0.2
FERMENT.y1		10	2.3921	0.2
FERMENT.y2		10	0.59668	0.2
Variance-covariance matrix:				

```
0.0002385
-1.675E-005
             0.0008739
                         0.0002345
  0.0002338
             -6.32E-005
  0.0001552 -4.015E-005
                         0.0001496
                                     0.0001105
Correlation matrix:
         1
   -0.03669
                     1
     0.9886
               -0.1396
                                1
     0.9558
               -0.1292
                            0.9292
                                            1
Information matrix:
______
 1.985E+006
 -1.07E+005
                  6937
-1.503E+006 8.133E+004
                        1.169E+006
-7.926E+005 4.272E+004
                        5.576E+005
                                    3.827E+005
Parameters to Be Estimated:
                              Nominal Values (fixed)
                                                     Standard Deviation
                                                                        % Stan
______
                               =====
FERMENT.theta(1)
                                             0.1
                                                          0.015444
                                             0.1
                                                          0.029561
FERMENT.theta(2)
FERMENT.theta(3)
                                             0.1
                                                          0.015313
FERMENT.theta(4)
                                             0.1
                                                          0.010513
```

Experiment SCHEDULE files

For each experiment named *EXPERIMENTNAME*, a file *EXPERIMENTNAME*. SCHEDULE is created. This presents the *most recent* Experiment Design solution point in the form of a gPROMS Schedule

The Schedule file can be used to reproduce the detailed results of the Experiment Design optimisation for each experiment by carrying out a simulation activity within gPROMS. In order to do this:

- 1. Paste the Schedule into the Schedule section of the Process entity.
- 2. Paste the lines that appear inside the first Reset statement in the Schedule into the Assign section of the Process entity.
- 3. Paste the lines that appear inside the Initial statement in the Schedule into the Initial section of the Process entity.

Note that it is also possible to *Simulate* a designed Experiment using the Experiment templates.

Remember: the contents of the Schedule file do not necessarily represent an optimal or even a feasible solution to the problem: if the optimisation run is interrupted by the user, or ends without finding a satisfactory solution, the file will simply show the point last considered by gPROMS. Only if a comment at the top of the file states the following:

```
# Final Optimisation Status : Optimal Solution Found
```

should the results be relied upon as a (locally) optimal solution.

Example Experiment Schedule

```
# Schedule generated from Experiment Design for parameter precision
# for experiment FEDBATCH_DES
# Final Optimisation Status
                                   : Optimal Solution Found
# Design Criterion
                                   : E-optimal
                                   : 0.0896408
# Value of Design Criterion
 INITIAL
   FERMENT.Y1 = 9.59846;
   FERMENT.Y2 = 0;
SCHEDULE
   SEQUENCE
     RESET
         FERMENT.u1 := 0.05;
         FERMENT.u2 := 5.04004;
      END
     CONTINUE FOR 1.73124
      RESET
         FERMENT.u1 := 0.172015;
         FERMENT.u2 := 33.6937;
      END
      CONTINUE FOR 1.44401
      RESET
         FERMENT.u1 := 0.2;
         FERMENT.u2 := 33.837;
      END
      CONTINUE FOR 2.61125
      RESET
         FERMENT.u1 := 0.05;
         FERMENT.u2 := 19.8626;
      END
     CONTINUE FOR 2.87231
      RESET
         FERMENT.u1 := 0.0971769;
         FERMENT.u2 := 25.5291;
      END
      CONTINUE FOR 1.34119
   END
```

Designed Experiment templates

After a successful Experiment Design activity; for each designed experiment an Experiment template is generated. This presents the results of the Experiment Design in a Performed Experiment entity: the calculated values for the controlled variables and the initial conditions are entered on the appropriate tabs and the sensor information (variance models and measurement times) is also preserved. Note that the measured data is not available because, of course, the experiment has yet to be carried out.

To use the Experiment template you should copy them into your working project.

The experiment templates satisfy two purposes:

- To facilitate the iterative Model Validation cycle
- To enable easy simulation of the designed experiment using the Simulate Experiment capability

Controlling the execution of Experiment Design activities

It is possible to fine tune the numerical parameters associated with the underlying solvers used by gPROMS in the solution of an Experiment Design problem. This is done in the *SolutionParameters* section of the Process entity.

The specification for the default solver is shown below:

```
SOLUTIONPARAMETERS
EDSolver := "EXPDES" ;
```

Obviously, a specification in the simple form shown above is redundant since EXPDES is already the default solver. However, the solver has a number of parameters that can be used for configuring its precise behaviour for any particular problem being solved, as shown in the example below:

```
SOLUTIONPARAMETERS

EDSolver := "EXPDES" [ "OutputLevel" := 0;

"MINLPSolver" := "SRQPD";

"DASolver" := "DASOLV"];
```

• Outputlevel: An integer in the range [0, 3].

The amount of information generated by the solver. The following table indicates the lowest level at which different types of information are produced:

Tabl	e 3.2.	Outpu	ıtlevel
------	--------	-------	---------

0	Warning and error messages, best available point after failure;
2	Message "Evaluating contribution of experiment name";
3	Variance-covariance matrix of the parameters to be estimated (unscaled) in each optimisation step.

MINLPSolver: A quoted string specifying a nonlinear programming optimisation solver.

The optimisation solver to be used for solving the Experiment Design optimisation problem. This can be either the standard SRQPD solver or a third-party nonlinear programming solver. The default is SRQPD. This parameter can be followed by further specifications aimed at configuring the particular solver by setting values to

its own algorithmic parameters. Note that the solution parameter Scaling of the SRQPD solver defines different scaling methods of the Hessian of the SQP method (which can be seen as a scaling of the experiment decision variables ξ) whereas the SCALING_FACTOR of the parameters to be estimated in the Experiment Design entity defines the scaling of the parameters to be estimated.

• DASolver: A quoted string specifying a differential-algebraic equation solver.

The solver to be used for integrating the model equations and calculating their sensitivity equations at each iteration of the optimisation. This can be either the standard DASOLV solver (see Model Developer Guide) or a third-party differential-algebraic equation solver. The default is DASOLV. This parameter can be followed by further specifications aimed at configuring the particular solver by setting values to its own algorithmic parameters.

Experiment Design for parameter precision requires the calculation of first and second order sensitivities of the underlying differential-algebraic equation system. Second order sensitivities are calculated via so-called varied trajectories (or finite differences). This is similar to a finite difference calculation. The difference is that the algorithm uses the same discretisation for both the nominal solution and first and second order sensitivities, exploiting structure in the linear algebra calculations. Moreover, the accuracy for the first and second order sensitivities is retained at the same order of magnitude as the accuracy for the nominal solution.

The following algorithmic parameters used by DASOLV to control the calculation of second order sensitivities are shown below. This is followed by a detailed description of each parameter.

```
"DASOLV" [ "AbsolutePerturbationFactor" := 1e-07;

"RelativePerturbationFactor" := 1e-04;

"FiniteDifferences" := FALSE];
```

• AbsolutePerturbationFactor: A real number in the range $[10^{-20}, \, 10^{10}]$.

The absolute perturbation factor of the optimisation decision variables for calculating varied trajectories for second order sensitivity calculation.

• RelativePerturbationFactor: A real number in the range $[10^{-20}, 10^{10}]$.

The relative perturbation factor of the optimisation decision variables for calculating varied trajectories for second order sensitivity calculation.

• FiniteDifferences: A boolean value.

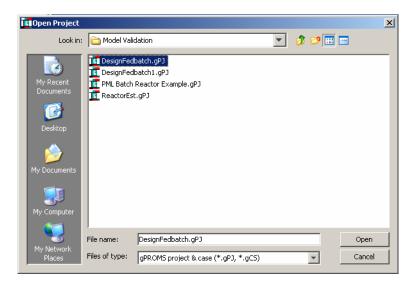
Second order sensitivities are by default calculated via so-called varied trajectories (see above). If this parameter is set to TRUE, second order sensitivities are calculated via ordinary finite differences on the first order sensitivities.

These solution parameters can be set in addition to those stated for the DASOLV solver (see Model Developer Guide).

An Experiment Design example

The gPROMS installation includes a simple Experiment Design example - it is highly recommended that you take a look at this. You can access this by clicking on the browse examples button on the gPROMS Tool bar and then navigating to General capabilities\Model Validation\DesignFedbatch.gPJ (as shown below). This section explains the features of the model.

Figure 3.15. Browsing for the Experiment Design example in the gPROMS distribution directory.



The example considers the fed-batch fermentation process shown in the figure below.

*u*₁, *u*₂ *y*₁, *y*₂

Figure 3.16. Fed-batch fermentation

The mathematical model for the process is as follows:

• Biomass concentration

$$rac{dy_1}{dt} = \left(r_m - u_1
ight)y_1 - heta_4\,y_1$$

• Substrate concentration

$$rac{dy_2}{dt} = -rac{r_m\,y_1}{ heta_3} + u_1\left(u_2-y_2
ight)$$

• Reaction rate

$$r_m=rac{ heta_1\,y_2}{ heta_2+y_2}$$

The table below summarises the parameters to be estimated and the design variables that appear in this model.

Table 3.3. Parameters and design variables in fed-batch fermentation model.

Model Variables	
$ heta_i,i=1\dots 4$	Parameters to be estimated
u_2	Dilution factor
u_2	Feed substrate concentration
y ₁	Biomass concentration
У2	Substrate concentration
$r_{ m m}$	Reaction rate

Before this model can be used to simulate or optimise the fermentation process, all parameters that appear in it must be given values. Imagine, however, a situation where the kinetic parameters are unknown. That is, we do not know the values of θ_i , $i=1\ldots 4$. To determine these, we can perform a number of experiments, measure the values of some or all process variables, and estimate the kinetic parameters that best fit the measured data (see Parameter Estimation in gPROMS for a more detailed description).

In the example, it is assumed that we design one new experiment, take up to 10 samples at different times and measure the biomass and substrate concentration, y_1 and y_2 , in each sample using a High Pressure Liquid Chromatograph (HPLC). The duration of the experiment should be between 5 and 10 hours. The dilution factor u_1 and the feed substrate concentration u_2 may be varied over time. We may also change the initial value of the biomass concentration $y_1(0)$ in the reactor.

Resource availability may impose an upper limit on the feed substrate concentration.

The Experiment Design problem seeks to provide answers to the following questions

- What initial biomass concentration $y_1(0)$ should we use?
- How long should we run the experiment for?
- How should we vary the feed flowrate for the dilution factor $u_1(t)$ and the feed substrate concentration $u_2(t)$ over the duration of the experiment?
- When should we take the measurement samples?

The unknown parameters to be estimated are θ_1 (gPROMS pathname FERMENT.theta(1)) to θ_4 (gPROMS pathname FERMENT. $\theta(4)$). We use the estimated value of each of the parameters as the SCALING_FACTOR so that the scaled values of all parameters are one.

An HPLC is used to measure both y_1 and y_2 . The variance model is described as CONSTANT_VARIANCE with ω equal to 0.5.

The table below contains the above information for the fed-batch fermentation experiment.

Table 3.4. Conditions for the fed-batch fermentation experiment

Type of Decision Variable	Variable	Initial Guess	Lower Bound	Upper Bound
Experiment Duration	t_{f}	10.0	5.0	10.0
Initial Condition	y ₁ (0)	7.0	1.0	10.0
Time-varying control (piecewise-constant)	u ₁ (t)	0.2	0.05	0.2
Time-varying control (piecewise-constant)	u ₂ (t)	15.0	5.0	35.0

Chapter 4. A Model Validation Example

In this example, the estimation of the kinetic parameters of a phenol hydro-deoxidation reaction is considered.

Note: You should load the Process Model Libraries and the PML Batch Reactor Example project file (from the examples/PML Flowsheets directory of your gPROMS installation)

The following figure shows the flowsheet developed using Process Model Library (PML) to represent a batch reactor. The reactor unit is an instance of the Reactor_drum_kinetic PML model. The influence of the vapour-liquid equilibrium is taken into account. The chemical reaction is assumed to happen in the liquid phase only.

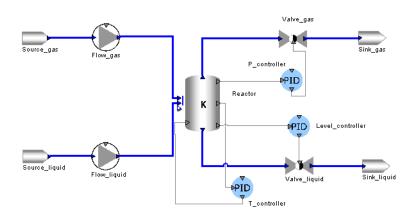


Figure 4.1. Batch Reactor Flowsheet

The table below shows the components used in the simulation and their corresponding array numbers in the gPROMS model:

 Array Number
 Component

 1
 hydrogen

 2
 phenol

 3
 benzene

 4
 cyclohexane

 5
 water

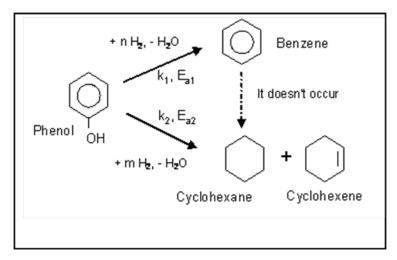
 6
 hexadecane

Table 4.1. Components of Phenol hydro-deoxidation

Reaction kinetics

Phenol hydro-deoxidation over a sulphided CoMo/Al2O3 catalyst follows the following reaction network:

Figure 4.2. Reaction Network



The kinetics of these reactions has been described as pseudo-first order in the liquid phase phenol concentration:

$$R_i = K_{0,i} \exp \{-E_{\alpha}/RT\} C_i^{liquid} i = 1,...,N_C$$

Experiment description

Reactor

A 50 ml stainless steel autoclave is used for the experiments. The autoclave is equipped with a spinning catalyst basket to avoid heat and mass transfer limitations between the catalyst particles and the liquid with the reactants.

Experiment procedure

Enough quantity of pre-sulphide catalyst is packed into the catalyst basket. The reactor is initially filled with 15 ml of hexadecane (770.676 kg/m³) and 1 g of phenol. The reactor is then sealed and, once the reaction temperature is reached, pure hydrogen is added until a pressure of 70.6 bar is reached. The degree of the reaction achieved during the temperature and pressure stabilisation is considered negligible with respect to the total degree of reaction at the end of the experiments. Five samples are withdrawn from the reactor liquid phase at minimum intervals of 6 min. The first sample can be taken after 3 min of the experiment start. The amount of liquid extracted during the sampling is negligible related to the total amount of liquid in the reactor. No hydrogen is added during the runs to compensate the pressure drop caused by the reaction and sampling.

The quantitative analysis of the liquid sample is performed by means of an on-line gas chromatography system. The concentration measurements have a relative error with a standard deviation of 0.02.

Experiments

Two experiments were performed with similar initial conditions (see table below):

Table 4.2. Initial conditions of experiments

Phenol initial mass	1 g
Hexadecane initial volume	15 ml (11.56 g)
Pressure	70.6 bar
Product initial masses	0

The experiments were performed at different temperatures, 523.15 and 533.15 K, respectively. The measurements of hydrogen, phenol, and benzene are specified in the tables below:

Table 4.3. Measurements for experiment 1 (T = 523.15 K)

Time (s)	C ₁ (mol/m ³)	C ₂ (mol/m ³)	C ₃ (mol/m ³)
360.0	570.6	2.4	1.7
1190.0	560.1	8.0	5.5
2410.0	561.6	15.9	11.6
3600.0	529.9	22.4	16.7
4790.0	534.6	30.9	22.3

Table 4.4. Measurements for experiments 2 (T = 533.15 K)

Time (s)	C ₁ (mol/m ³)	C ₂ (mol/m ³)	C ₃ (mol/m ³)
360.0	564.1	4.1	2.4
1190.0	553.1	13.1	7.8
2410.0	523.9	25.4	15.0
3600.0	501.6	36.8	22.7
4790.0	481.4	49.4	29.3

Parameter Estimation

In order to perform the Parameter Estimation, you need to do the following:

- 1. Load the Process Model Library and Batch reactor project.
- 2. Inspect the Batch Estimation entity; obseve where the estimated parameters and sensor groups are identified.
- 3. Inspect the EXP_1 and EXP_2 *Performed Experiment* entities; observe how the initial conditions, control variables and measure data are defined.
- 4. Select the Batch Estimation Entity and execute the Estimation activity
- 5. After the activity has executed: open the Comprehensive report this is found in the Results directory of the Execution Case. Have a look at the statistical analysis of the estimated parameters (e.g. confidence intervals, individual t-value, correlation matrix) and the lack-of-fit test.

Experiment Design

In order to increase the precision/certainty of the parameters to be estimated, another experiment is to be designed. To do so, do the following:

- 1. Inspect the Batch Experiment Design Entity. Note that:
 - The E-optimal design criterion is used to design the new experiment.
 - The values determined from the Parameter Estimation runs are used
 - The variance model for the Gas Chromatography sensor is specified.
 - All the information from the already performed experiments is taken into account.
- 2. Inspect the EXP_TBD *to be designed Experiment* entity; compare the specification of the initial conditions, control variables and measure data with the information provided for the *Peformed Experiments*.
- 3. Select the Batch Experiment Design entity and execute the Experiment Design activity

4.	After the activity has executed: open the Comprehensive report - this is found in the Results directory of the Execution Case. Have a look at the values of the experiment decision variables. Compare the statistical analysis with the one from the Parameter Estimation activity. Determine if the precision/certainty of the parameters to be estimated has increased.