

MATLAB EXPO

다양한 엔지니어링 최적화 문제를
해결하는 효과적인 방법

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Agenda

Solving engineering optimization problems

- Parameter estimation with experiment data
 - Sensitivity Analyzer / Global Optimization Toolbox
- Optimal calibration with experiment data
 - Model-Based Calibration Toolbox
- Conclusions

Parameter estimation with experiment data

Problem statement

- **Goal:**

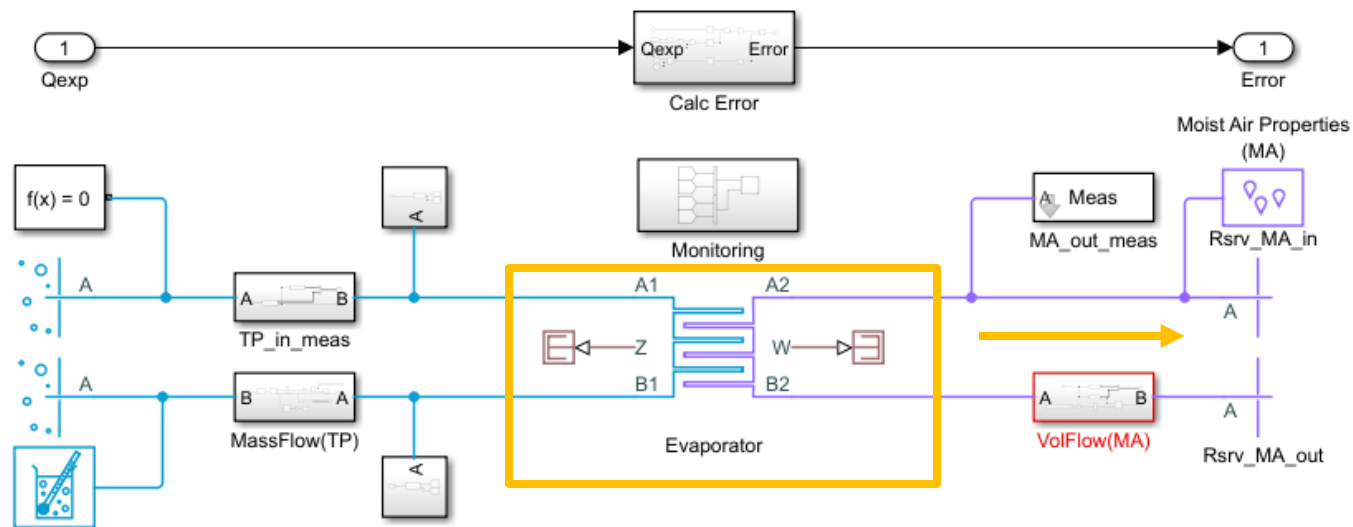
To introduce an optimization workflow using “**Global Optimization Toolbox**” in physical modeling

- An evaporator modeling example based on experiment data including
- How to use “**Sensitivity Analyzer**” for more efficient parameter estimation
- How to use “**ga**” solver of Global Optimization Toolbox

Parameter estimation with experiment data

Plant model review

- And evaporator model



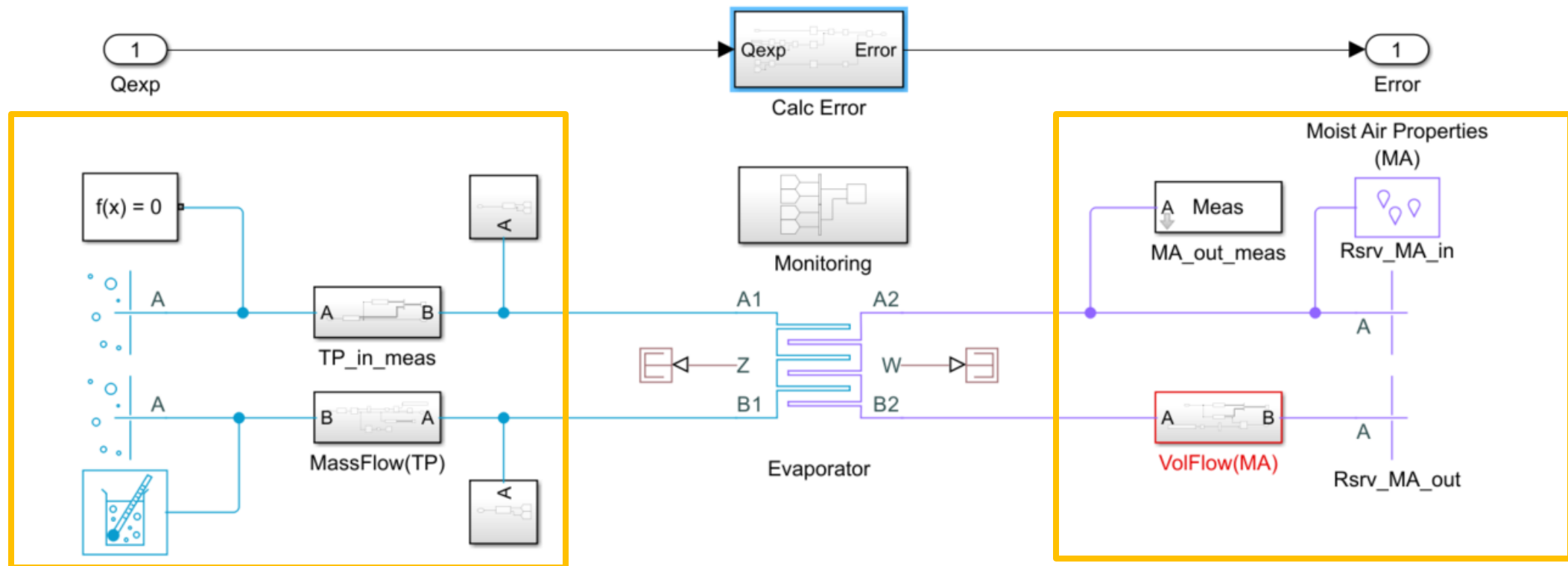
- 12 heat transfer equation coefficients
- 5 pressure loss params

How to find out parameter values?

Parameter	Value	
Flow arrangement	Cross flow	
Cross flow arrangement	Both fluids unmixed	
Thermal resistance through heat transfer ...	Evaporator.NonGeom.Cfg.ThrmResistHeatTSurf.Value	K/W
Cross-sectional area at port A1	Evaporator.Geom.Cfg.CrsSecAreaPortA1.Value	m ²
Cross-sectional area at port B1	Evaporator.Geom.Cfg.CrsSecAreaPortB1.Value	m ²
Cross-sectional area at port A2	Evaporator.Geom.Cfg.CrsSecAreaPortA2.Value	m ²
Cross-sectional area at port B2	Evaporator.Geom.Cfg.CrsSecAreaPortB2.Value	m ²
Number of tubes	Evaporator.Geom.TP.NumTubes.Value	
Total length of each tube	Evaporator.Geom.TP.TotalLengthEachTube.Value	m
Tube cross section	Generic	
Cross-sectional area per tube	Evaporator.Geom.TP.CrsSecAreaPerTube.Value	m ²
Wetted perimeter of tube cross section fo...	Evaporator.Geom.TP.WetPerTubeCrsSec4PerLoss.Value	m
Perimeter of tube cross section for heat tr...	Evaporator.Geom.TP.PerTubeCrsSecHeatFlt.Value	m
Pressure loss model	Correlation for flow inside tubes	
Aggregation of coefficients	Evaporator.NonGeom.TP.ApproxCoeffs.Value	
Internal face	Evaporator.NonGeom.TP.InternalFace.Value	
Laminar flow upper Reynolds number limit	Evaporator.NonGeom.TP.LamFlowUpReLim.Value	
Turbulent flow lower Reynolds number limit	Evaporator.NonGeom.TP.TurFlowLoReLim.Value	
Laminar flow upper Reynolds number limit	Evaporator.NonGeom.TP.LamFlowUpReLim.Value	
Heat transfer	Evaporator.NonGeom.TP.HeatTransfer.Value	
Coefficients [a, b, c] for a*Re^b*R^c in m...	Evaporator.NonGeom.TP.Liq.CoeffA, Evaporator.NonGeom.TP.Liq.CoeffB, Evaporator.NonGeom.TP.Liq.C...	
Coefficients [a, b, c] for a*Re^b*R^c in m...	Evaporator.NonGeom.TP.Mix.CoeffA, Evaporator.NonGeom.TP.Mix.CoeffB, Evaporator.NonGeom.TP.Mix...	
Coefficients [a, b, c] for a*Re^b*R^c in m...	Evaporator.NonGeom.TP.Vap.CoeffA, Evaporator.NonGeom.TP.Vap.CoeffB, Evaporator.NonGeom.TP.Vap...	
Fouling	Evaporator.NonGeom.TP.FoulingFct.Value	K^-1m^2/W
Total fin surface area	Evaporator.NonGeom.TP.TotalFinArea.Value	m ²
Fin efficiency	Evaporator.NonGeom.TP.FinEff.Value	
Inlet fluid energy specification	Vapor quality	

Parameter estimation with experiment data

Plant model review

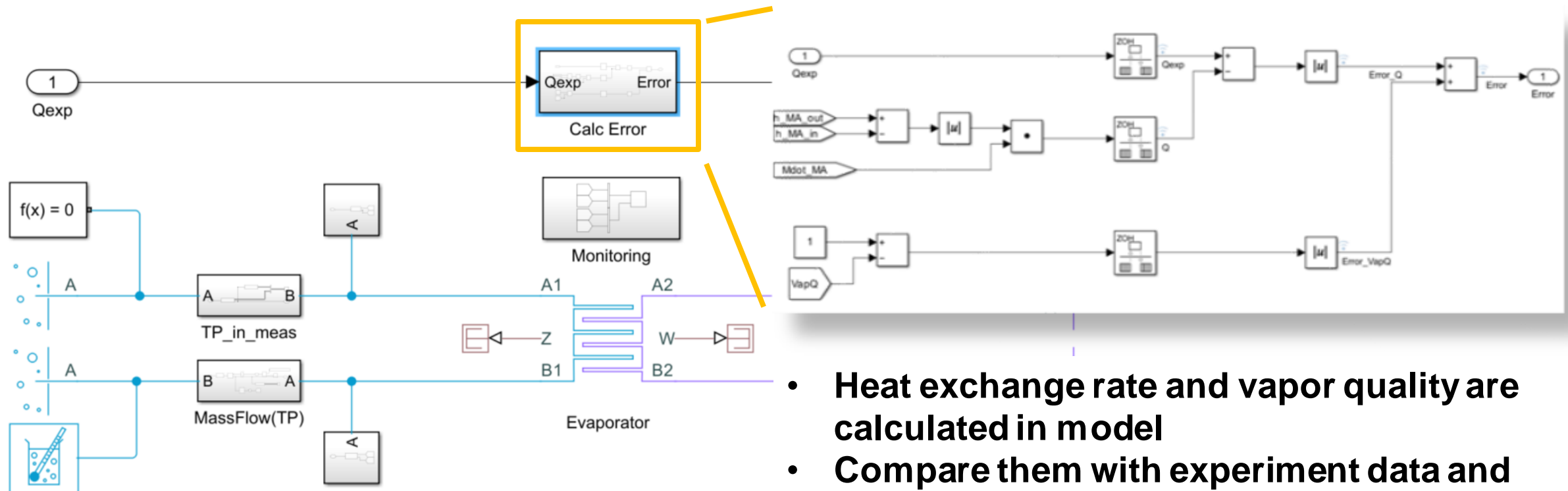


- I/O conditions are set according to the experiment data

Parameter estimation with experiment data

Plant model review

- Calculation error is designed for optimization objective function

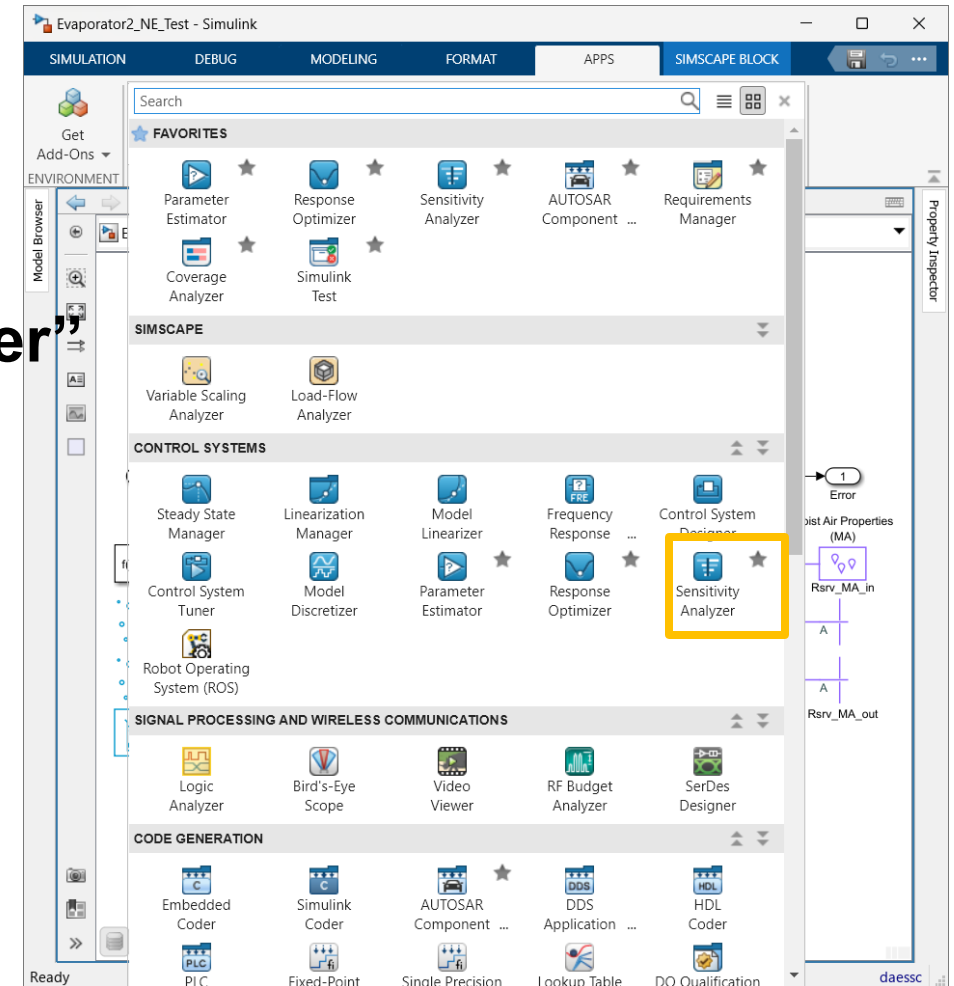


- Heat exchange rate and vapor quality are calculated in model
- Compare them with experiment data and errors can be used directly in objective function

Parameter estimation with experiment data

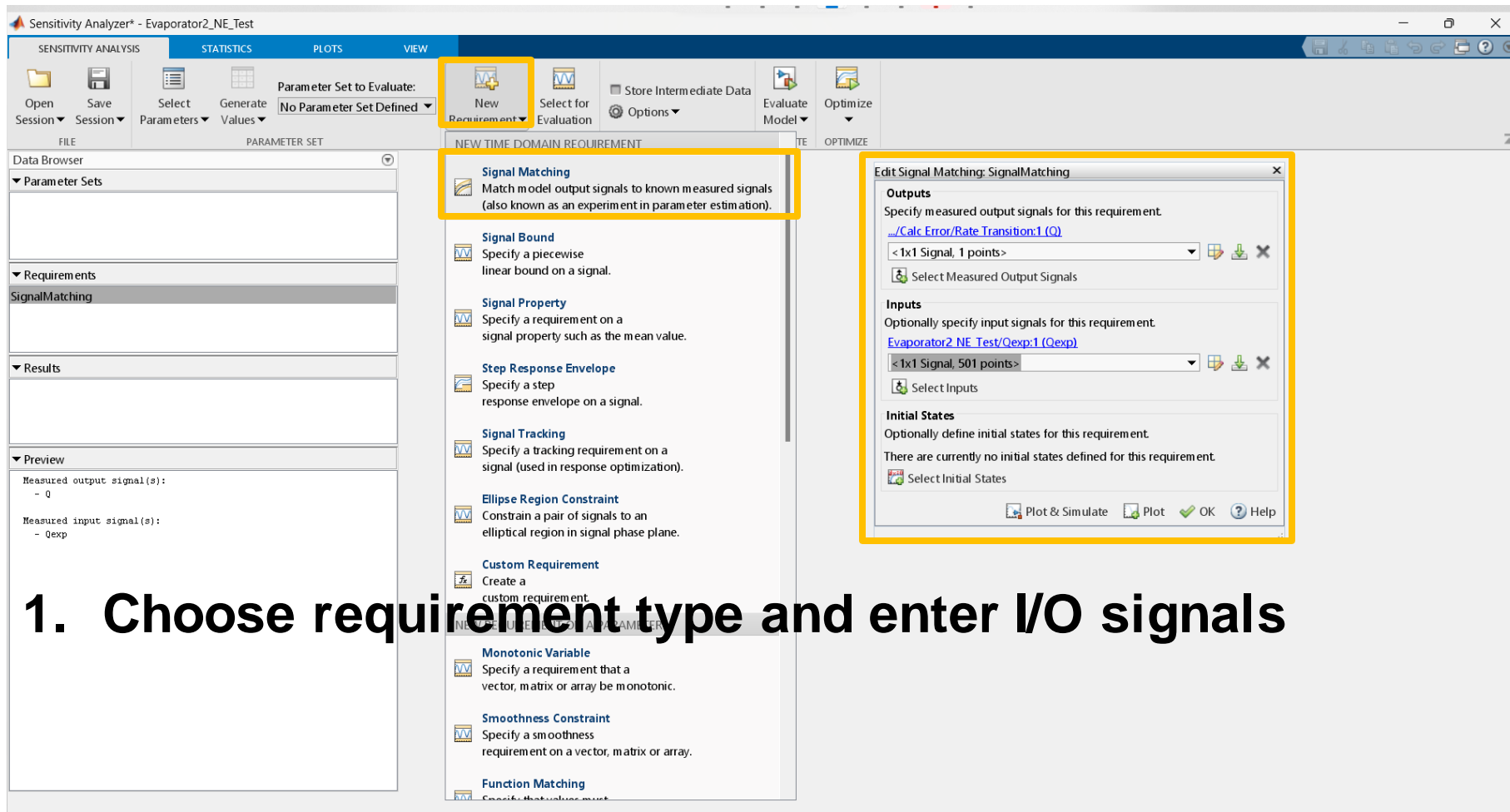
Sensitivity Analyzer

- Q: What parameters are to be tuned?
- A: The most impactful ones
- Q: What are the most impactful ones?
- A: If you don't know, try **“Sensitivity Analyzer”** from Simulink Apps
- **“Sensitivity Analyzer”**
 - Explore design space and [determine most influential model parameters](#)



Parameter estimation with experiment data

Sensitivity Analyzer



1. Choose requirement type and enter I/O signals

Parameter estimation with experiment data

Sensitivity Analyzer

The screenshot shows the MATLAB Sensitivity Analyzer interface. The 'Select Parameters' dialog box is open, displaying a table of variables. The table has columns for 'Variable', 'Current Value', and 'Used By'. The 'Used By' column contains links to the variables used in the model. A yellow arrow points to the 'Select Parameters' button in the top toolbar. Another yellow arrow points to the input field at the bottom of the dialog box, where the parameter name 'Evaporator.NonGeom.TP.LamFricConst4DarcyFricFctValue' is being entered.

Variable	Current Value	Used By
Evaporator.NonGeom.MA.PresLossCoeff.Va...	10	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.LamFricConst4Da...	64	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.TurFlowLoRelm t...	4000	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.LamFlowUpRelm...	2000	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.AggEqvLgthLocR...	0.1	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.MA.Coeff.c	0.33	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.MA.Coeff.b	0.8	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.MA.Coeff.a	0.023	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Vap.Coeff.c	0.33	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Vap.Coeff.b	0.8	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Vap.Coeff.a	0.023	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Mix.Coeff.c	0.33	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Mix.Coeff.b	0.8	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Mix.Coeff.a	0.05	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Liq.Coeff.c	0.33	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Liq.Coeff.b	0.8	Evaporator2_NE_Test/Evaporator
Evaporator.NonGeom.TP.Liq.Coeff.a	0.023	Evaporator2_NE_Test/Evaporator
AirFlowRate	< 1x1 timeseries >	Evaporator2_NE_Test/VolFlow(MA)/Constant2
Evaporator	< 1x1 struct >	Evaporator2_NE_Test/Evaporator

Evaporator.NonGeom.TP.LamFricConst4DarcyFricFctValue

OK Cancel Help

2. Choose parameters or enter parameter names

Parameter estimation with experiment data

Sensitivity Analyzer

The screenshot shows the MATLAB Sensitivity Analyzer interface. The 'Generate Random Parameter Values' dialog box is open, displaying the following settings:

- Number of Samples: 50
- Overwrite previous values in parameter set when generating new values
- Append to previous values in parameter set when generating new values
- Sampling Method: Random

The dialog also displays a table of parameters and their distributions:

Parameter	Distribution	Lower	Upper	Cross-Correlated
Evaporator.NonG...	Uniform	6.525	7.975	<input type="checkbox"/>
Evaporator.NonG...	Uniform	24.5161184...	29.9641447...	<input type="checkbox"/>
Evaporator.NonG...	Uniform	1.61895789...	1.97872631...	<input type="checkbox"/>
Evaporator.NonG...	Uniform	1.7325	2.1175	<input type="checkbox"/>

Below the table, a distribution plot is shown for the parameter 'Evaporator.NonGeom.MA.PresLossCoeff.Value'. The plot displays a uniform distribution with a mean of 7.25 and a standard deviation of 0.418579.

3. Generate parameter values to be used in exploration

Parameter estimation with experiment data

Sensitivity Analyzer

The screenshot displays the Sensitivity Analyzer interface for a parameter set named 'ParamSet'. The 'Evaluation Options' dialog box is open, showing the 'Parallel' tab. The checkbox 'Use the parallel pool during optimization' is checked and highlighted with a yellow box. The background shows a table of parameter values and a list of parameters.

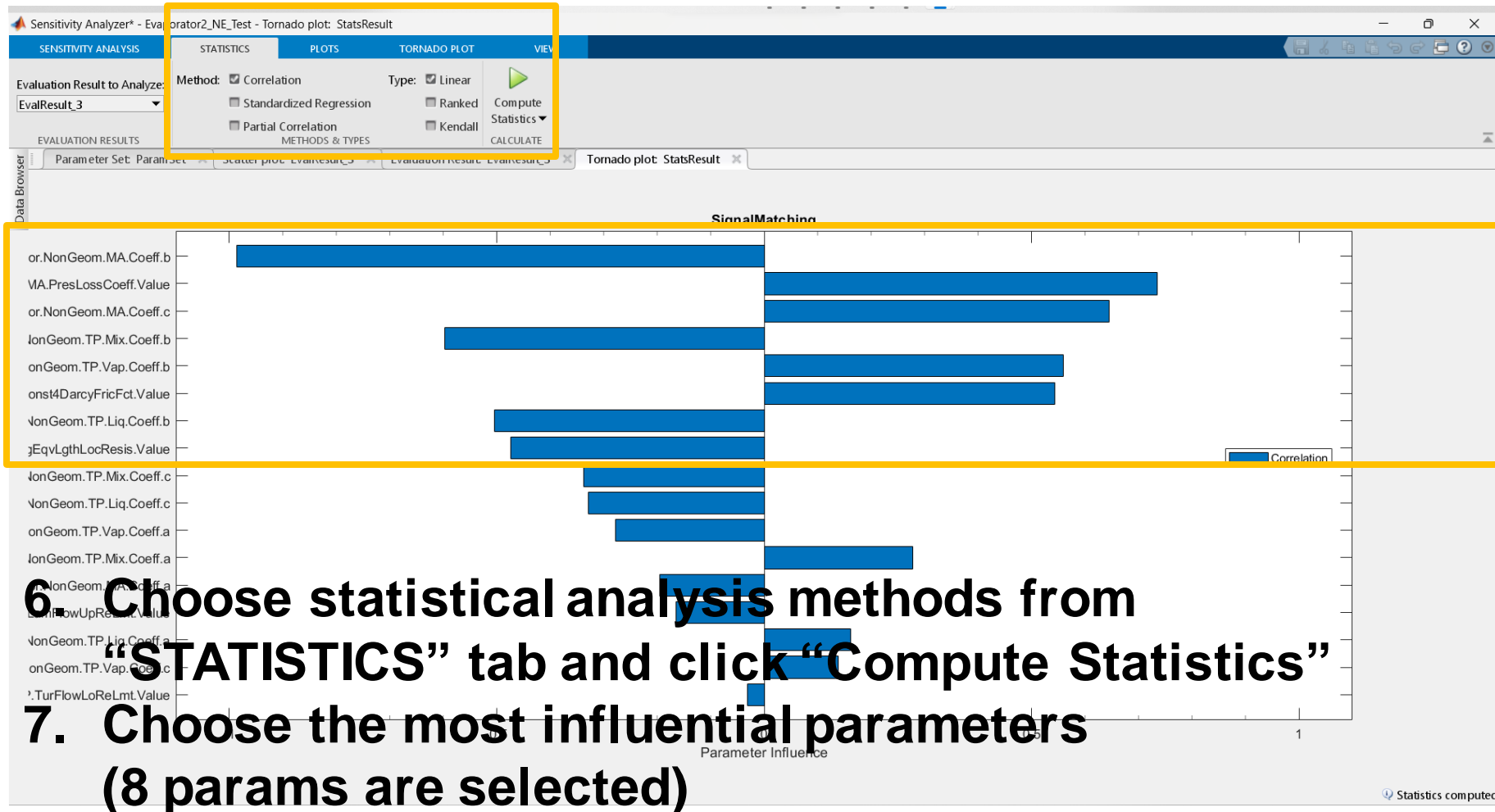
4. Choose options; "Use the parallel pool during optimization" is very helpful for speed up

5. Evaluate

Evaporator.N...	Evaporator.N...	Evaporator.N...	Evaporator.N...	Evaporator.N...	Evaporator.N...	Evaporator.N...	Evaporator.N...	Evaporator.N...	Evaporator.N...		
0.3075	0.0251	2.6682	0.7447	0.2200							
0.3054	0.0237	2.8459	0.8779	0.1855							
0.3231	0.0249	2.5941	0.8066	0.1948							
0.3011	0.0213	2.8170	0.7228	0.1878							
0.3207	0.0221	2.6915	0.8513	0.1969							
0.3247	0.0241	2.5868	0.7283	0.2188							
0.3099	0.0248	2.8862	0.8441	0.2174							
0.3167	0.0235	2.6316	0.7706	0.2035							
0.3416	0.0215	2.9018	0.8284	0.2019							
0.3404	0.0225	2.7212	0.7329	0.1955							
0.3454	0.0247	2.6744	0.8021	0.1922							
0.3351	0.0246	2.6312	0.8181	0.2068							
0.3354	0.0237	2.7118	0.7973	0.1923							
0.3377	0.0228	2.7591	0.8387	0.1912							
0.3147	0.0210	2.9406	0.8325	0.2040							
0.3385	0.0237	2.5224	0.7497	0.2025							
0.3401	0.0233	2.9689	0.7992	0.1978							
0.3531	0.0214	2.9280	0.7308	0.2062							
0.2975	0.0251	2.6009	0.7634	0.1857							
0.3407	0.0240	2.7338	0.8794	0.1975							
0.3608	0.0222	3.0158	0.8747	0.1870							
0.3271	6.2254	0.1833	0.3358	0.7545	0.0465	0.3060	6.5411	0.0213	2.8826	0.7232	0.2111
0.3134	6.7789	0.2015	0.3328	0.7480	0.0482	0.3537	6.3947	0.0223	2.5241	0.8087	0.1884
0.3060	6.745	0.206	0.2991	0.7536	0.0439	0.3511	6.095	0.022	2.5438	0.8696	0.1918
0.3289	7.2267	0.1964	0.2988	0.6671	0.0494	0.3025	5.9016	0.021	2.8079	0.8242	0.1908
0.3182	6.7929	0.2094	0.3478	0.7281	0.0501	0.3295	6.2776	0.0214	2.8498	0.8426	0.2022
0.3541	6.3725	0.1877	0.3445	0.6895	0.0474	0.2511	6.0330	0.0220	2.7276	0.7336	0.2084
0.3443	6.188	0.191	0.3345	0.741	0.0426	0.3094	6.14	0.0226	2.7659	0.8481	0.2167
0.3081	6.7042	0.1922	0.2142	0.7556	0.0544	0.2534	6.521	0.0240	2.7602	0.7811	0.1870

Parameter estimation with experiment data

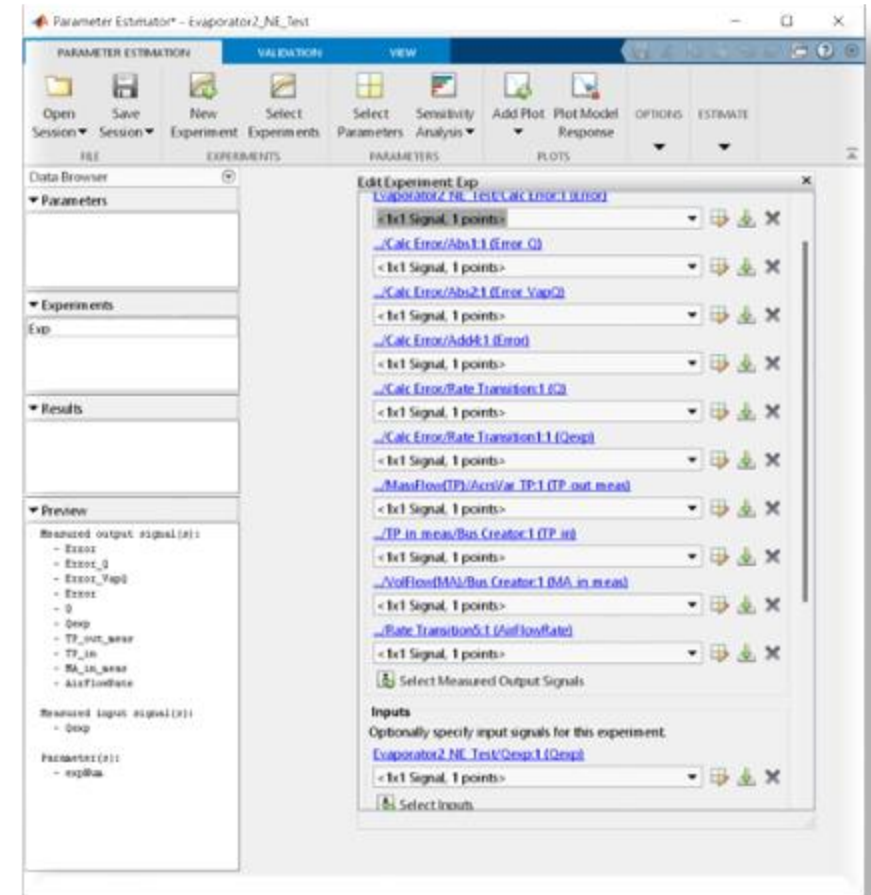
Sensitivity Analyzer



Parameter estimation with experiment data

Parameter Estimator

- Easy to use
 - MATLAB App based convenient GUI
 - Auto-code generation
- Limitations
 - Local minimum problem
Most solvers of SDO are not global optimization algorithm (except “patternsearch”)
 - Linear / nonlinear constraints are not applicable



Parameter Estimation App

Parameter estimation with experiment data

Global Optimization Toolbox

- Derivative-free algorithms
 - To break away local minima, they use heuristic / random / stochastic algorithms
 - “GlobalSearch”, “MultiStart” and “surrogateopt” use derivatives,
 - But they have their own mechanism to overcome local minima problem

- Global Optimization Toolbox

ga / particleswarm	GlobalSearch / MultiStart	patternsearch / simulannealbnd	surrogateopt	gamultiobj / paretosearch
Population-based (genes, particles) heuristic algorithm	Multiple-starting points with derivative algorithm	Single-starting points with random / stochastic exploration algorithm	Uses approximation function(surrogate)	Applicable for multi- objective optimization problems

Parameter estimation with experiment data

Global Optimization Toolbox – GA

- Genetic Algorithm (GA)
 - It is a general tool that can be used extensively in various optimization problems
 - The function “ga” of Global Optimization Toolbox has the most options that can reflect various kinds of constrains such as “Liner”, “Non-linear”, “Integer constraint”
- Terms & Concepts
 - To use the “ga” function, users should know terms basic concepts of genetic algorithm
 - The terms were taken from the principles of genetics and natural selection

Parameter estimation with experiment data

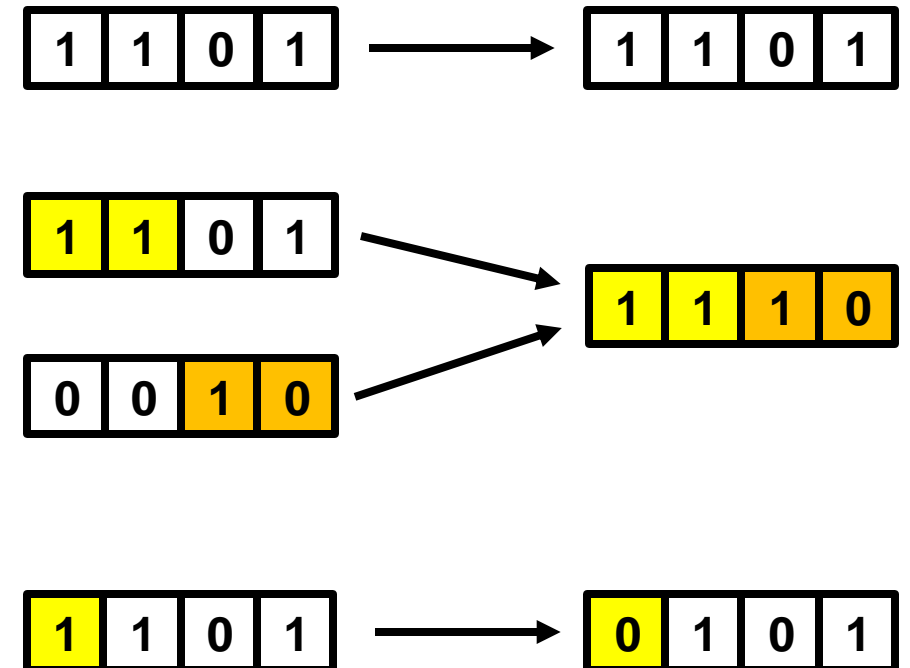
Global Optimization Toolbox – GA

- Fitness function
 - Equivalent to objective function of optimization problems
- Individual
 - An object with a gene that has a value of a variable to be optimized
- Population
 - A set of individuals that are evolved together
- Generation
 - A stage of GA, individuals in a generation are evaluated using fitness function and best individuals are selected for reproduction

Parameter estimation with experiment data

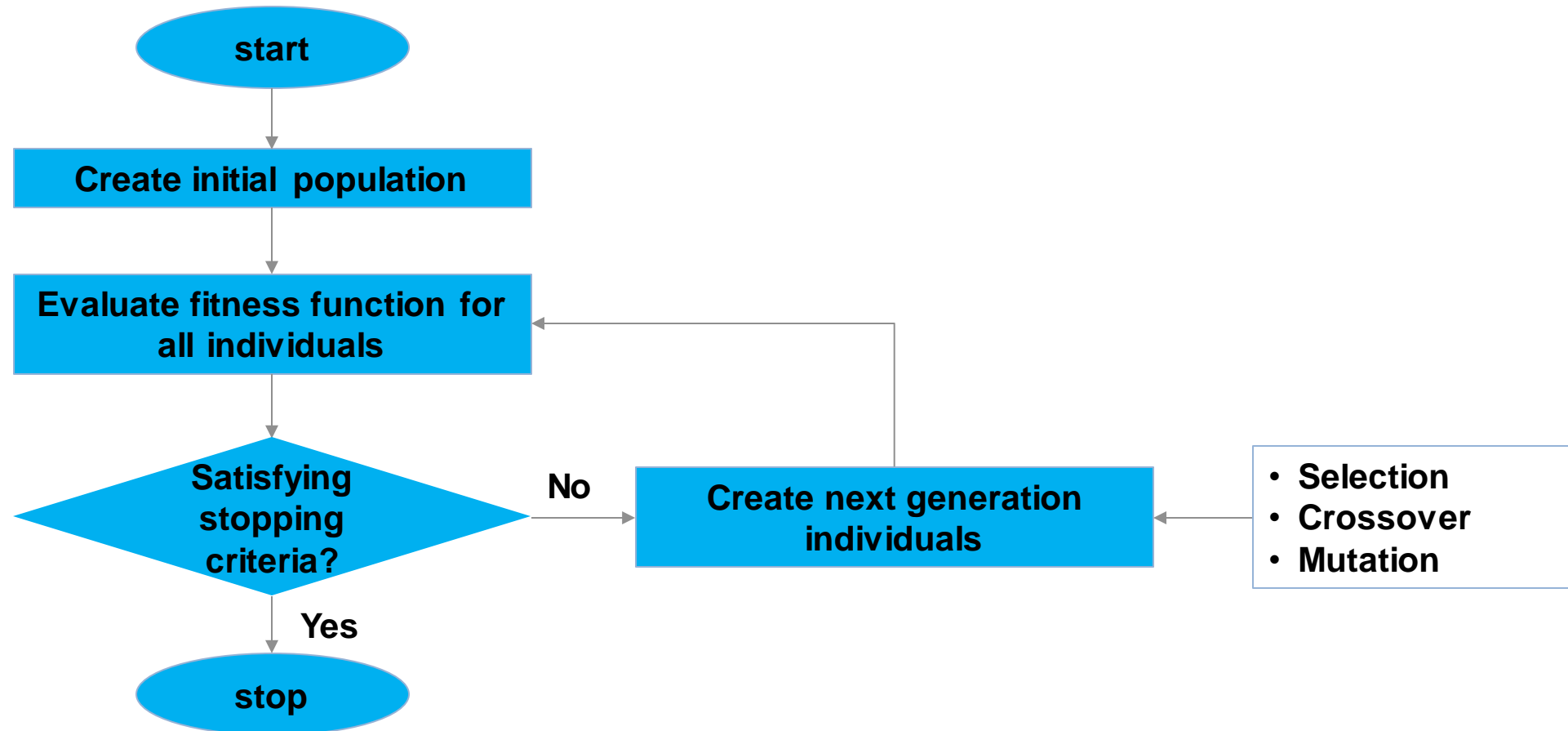
Global Optimization Toolbox – GA

- Selection
 - Elite individuals are selected and survive in the next generation
- Crossover
 - Genes of individuals are combined with genes of other individuals for the next generation
- Mutation
 - An unexpected change in gene



Parameter estimation with experiment data

Global Optimization Toolbox – GA



Parameter estimation with experiment data

Evaporator modeling

- Experiment data

Vdot_air (CMS)	T _{air_in} (°C)	Hd_in_abs (kg/kg)	T _{air_out} (°C)	Q_air (kW)	Mdot_ref (kg/s)	T _{ref_in} (°C)	T _{ref_out} (°C)	P _{ref_in} (bar)	P _{ref_out} (bar)	x_ref
0.0500	27	0.0200	5.0	3.00	0.03000	3.00	5.00	2.50	2.25	0.300

- Refrigerant absorbs heat from moisture air as much as experiment data
 - Refrigerant phase should be converted from mixture to vapor
- Parameters to be tuned
 - 12 Colburn equation coefficients
 - 5 pressure loss parameters

Parameter estimation with experiment data

Evaporator modeling

- Objective function

Create simulation input data object

Update with optimization vars

Set vars with updated vars for simulation

```
%% Create Simulink simulation input data type "in"
```

```
in = Simulink.SimulationInput mdl;
```

```
%% Loop for selected experiments
```

```
for expNum = expSet
```

```
    % Reference experiment result update
```

```
    [Qexp] = createQexp(expNum, tini, ts, tfin, Q_air);
```

```
    % For initial condition setting
```

```
    [Evaporator] = initEvaporator2(expNum, Evaporator);
```

```
    % I/O condition setting
```

```
    [Rsrv_TP_in, Rsrv_TP_out, Rsrv_MA_in, Rsrv_MA_out] = ...  
        createReservoirs_Evaporator2_NE(expNum, Evaporator);
```

```
% Insert update workspace variables with updated data information
```

```
in = in.setVariable("expNum", expNum);
```

```
in = in.setVariable("Qexp", Qexp);
```

```
in = in.setVariable("Evaporator", Evaporator);
```

```
in = in.setVariable("Rsrv_TP_in", Rsrv_TP_in);
```

```
in = in.setVariable("Rsrv_TP_out", Rsrv_TP_out);
```

```
in = in.setVariable("Rsrv_MA_in", Rsrv_MA_in);
```

```
in = in.setVariable("Rsrv_MA_out", Rsrv_MA_out);
```

Parameter estimation with experiment data

Evaporator modeling

- Objective function

Simulate with
simulation input
object

```
% Simulation
ErrorMessage = [];
try
    % Simulink "run" with "in"
    out = sim(in);
catch
    % For the case of simulation error
    ErrorMessage = "Invalid parameters!"
end
```

Evaluate object
function with
Simulink
simulation results

```
% Evaluate objective function
if isempty(ErrorMessage) && isempty(out.ErrorMessage)
    % Account only steady-state error with scale factor like "0.9"
    idx = find(out.logout.get('Error').Values.Time > tfin*0.9);
    data = out.logout.get('Error').Values.Data(idx(1):end);

    % Accumulate average error
    Ftmp = Ftmp + mean(data);
else
    % Penalty for simulaton error case
    Ftmp = 100;
end
```

Parameter estimation with experiment data

Evaporator modeling

- Option setting for optimization

- Set population size
- Set elite size



```
%%  
optset.nvars = length(optset.x0);  
% ga, gamultiobj, GlobalSearch, particleswarm, MultiStart, surrogateopt  
optset.PopulationSize = 4*optset.nvars;  
if optset.PopulationSize > 40  
    optset.PopulationSize = 20;  
end  
optset.EliteCount = ceil(0.10*optset.PopulationSize); % ga  
  
% Check conditions  
assert(optset.PopulationSize > 1);
```

Parameter estimation with experiment data

Evaporator modeling

- Option setting for optimization

- There are various stopping criterion for optimization solvers
- For “ga” solver
 - Max generation
 - Max stall generation
 - Max time
 - Fitness limit
 are the main stopping criterion

```

%% Stopping Criterion
% 1. Tolerances
% FunctionTolerance is a lower bound on the change in the value of the objective function
optset.FunctionTolerance = 1e-3;
% ConstraintTolerance is an upper bound on the magnitude of any constraint violation
optset.ConstraintTolerance = 1e-3;
% OptimalityTolerance is a tolerance for the first-order optimality measure
% First-order optimality is a measure of how close a point x is to optimal
optset.OptimalityTolerance = 1e-3;           % GlobalSearch, MultiStart
% Tolerance on function values for considering solutions equal, specified as a scalar
% Solvers consider two solutions identical if they are within XTolerance relative difference
optset.XTolerance = 1e-3;                   % GlobalSearch, MultiStart
% When the current mesh size is less than the value of MeshTolerance, the algorithm stops
optset.MeshTolerance = 1e-3;               % patternsearch, paretosearch
optset.StepTolerance = 1e-3;               % patternsearch

% 2. Iterations and Function Counts
optset.MaxIterations = 100;
optset.MaxFunctionEvaluations = optset.MaxIterations*(optset.nvars + 1);

% 3. Others
optset.MaxTime = 1*60*60;                   % [sec]
optset.MaxGenerations = 20;                 % ga, gamultiobj
% The algorithm stops when the average relative change in the fitness function
% over MaxStallGenerations is less than Function tolerance.
optset.MaxStallGenerations = optset.MaxGenerations*0.8; % ga, gamultiobj
optset.FitnessLimit = 0.15;                 % ga, (Lower limit of objective function value)
optset.ObjectiveLimit = optset.FitnessLimit; % surrogate

```

Parameter estimation with experiment data

Evaporator modeling

- Constraints
 - Linear inequality / equality
 - Nonlinear
 - Integer
- Example (Linear inequality)
 - $-x(1) + x(2) \leq -1$
 - $-x(1) + x(2) \leq 5$
 - $A_{ineq} = \begin{bmatrix} -1 & -1 \\ -1 & 1 \end{bmatrix}$
 - $b_{ineq} = \begin{bmatrix} -1 \\ 5 \end{bmatrix}$

%% Constraints

```
optset.Aineq = [];  
optset.bineq = [];  
optset.Aeq = [];  
optset.beq = [];  
optset.nonlcon = [];  
optset.intcon = [];
```


Parameter estimation with experiment data

Evaporator modeling

- There are “ga” solver its own options such as
 - Initial population creation
 - Plot function during optimization
 - Hybrid function that runs after “ga” optimization to find more delicate solution

```
%% ga
optset.CreationFcn = 'gacreationuniform';
% PlotFcn options
% 'gaplotbestf' plots the best score value and mean score versus generation
% 'gaplotbestindiv' plots the vector entries of the individual with the bes
% 'gaplotexpectation' plots the expected number of children versus the raw
% 'gaplotrange' plots the minimum, maximum, and mean score values in each g
optset.ga.PlotFcn = {@gaplotbestf,@gaplotbestindiv};
optset.ga.OutputFcn = {@outputfcn_ga};
optset.ga.hybridsolver = 'fmincon';
optset.ga.hybridopts = optimoptions(...
    optset.ga.hybridsolver,...
    'Algorithm','sqp',...
    'ConstraintTolerance',optset.ConstraintTolerance,...
    'Display','iter',...
    'MaxFunctionEvaluations',ceil(min(100,optset.MaxFunctionEvaluations/10))
    'MaxIterations',ceil(min(3,optset.MaxIterations/10)),...
    'OptimalityTolerance',optset.OptimalityTolerance,...
    'PlotFcn','optimplotfval' ...
);
```

Parameter estimation with experiment data

Evaporator modeling

- Run “ga”
 - **$x = \text{ga}(\text{fun}, \text{nvars}, \text{A}, \text{b}, \text{Aeq}, \text{beq}, \text{lb}, \text{ub}, \text{nonlcon}, \text{intcon}, \text{options})$**
 - fun: objective function handle
 - nvars: number of variables
 - A, b: linear inequality constraint matrix and vector
 - Aeq, beq: linear equality constraint matrix and vector
 - lb, ub: lower and upper bounds
 - nonlcon: non-linear constraint
 - intcon: integer constraint
 - options: other options such as max time, max iteration, max generation, etc.

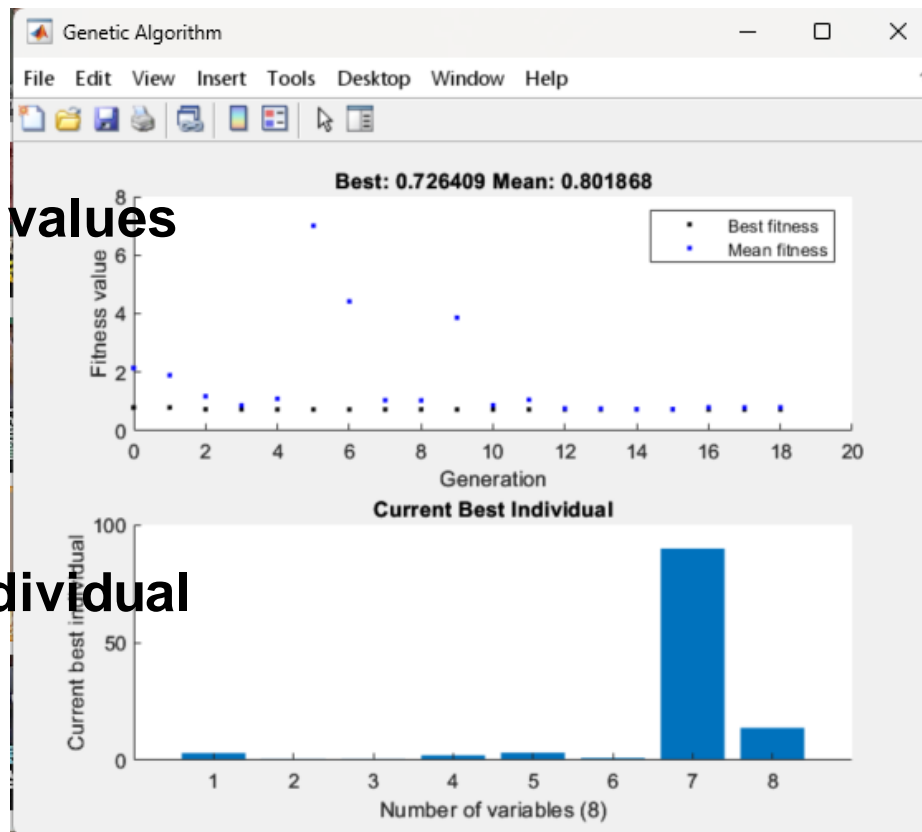
[Find minimum of function using genetic algorithm - MATLAB ga \(mathworks.com\)](https://www.mathworks.com/help/ga/)

Parameter estimation with experiment data

Evaporator modeling

- “ga” optimization

Fitness values



Best individual

**Other params except the estimated
8 params are remain at default values**

```

Command Window
Solver stopped prematurely.
fmincon stopped because it exceeded the iteration limit,
options.MaxIterations = 3.000000e+00.

FMINCON terminated.

info =

struct with fields:

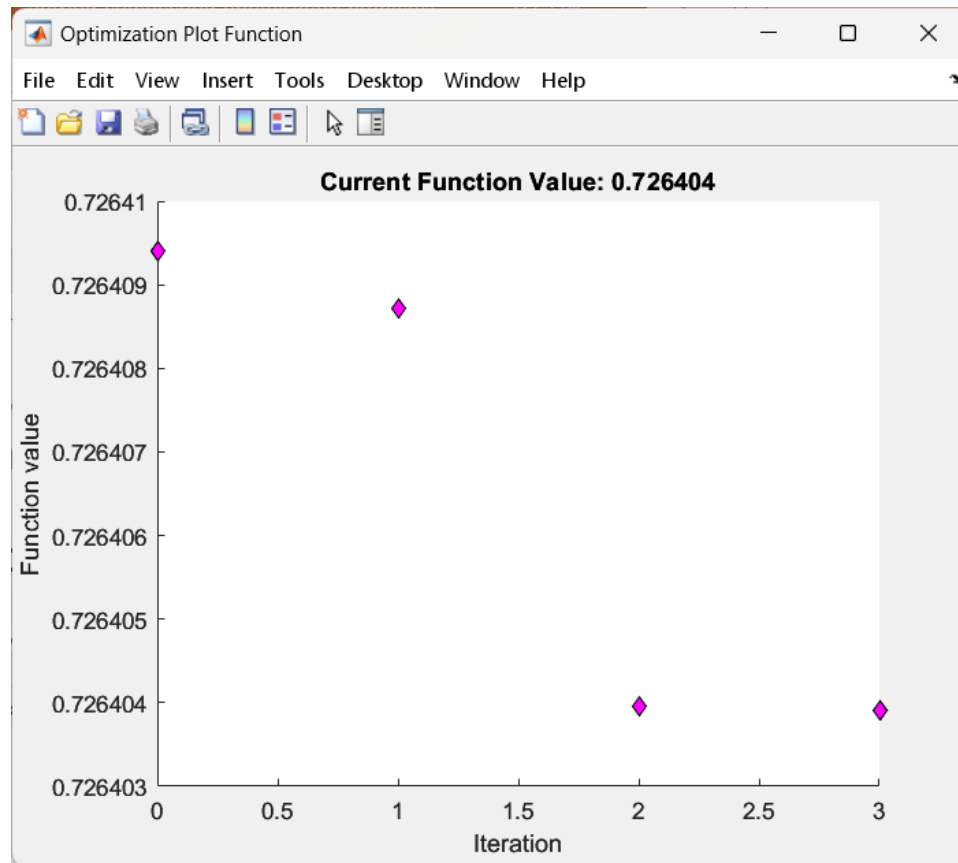
    StartTime: 14-May-2023 17:15:47
    StartDate: 14-May-2023
    model: 'Evaporator2_NE_Test'
    solver: "ga"
    problem: [1x1 struct]
    options: [1x1 optim.options.GaOptions]
    optset: [1x1 struct]
    fval: 726.4039e-003
    exitflag: 1.0000e+000
    output: [1x1 struct]
    population: [32x8 double]
    scores: [32x1 double]
    exitmessage: "Without nonlinear constraints — Average cumu
    xopt: [3.1019e+000 601.9430e-003 601.8701e-003 2.1019e
    StopTime: 14-May-2023 17:52:11
    TimeCost: 00:36:24
  
```

fx >>

Parameter estimation with experiment data

Evaporator modeling

- Hybrid function optimization



Command Window

“fmincon” is used after “ga” optimization

Even after hybrid function execution, the error is not small enough

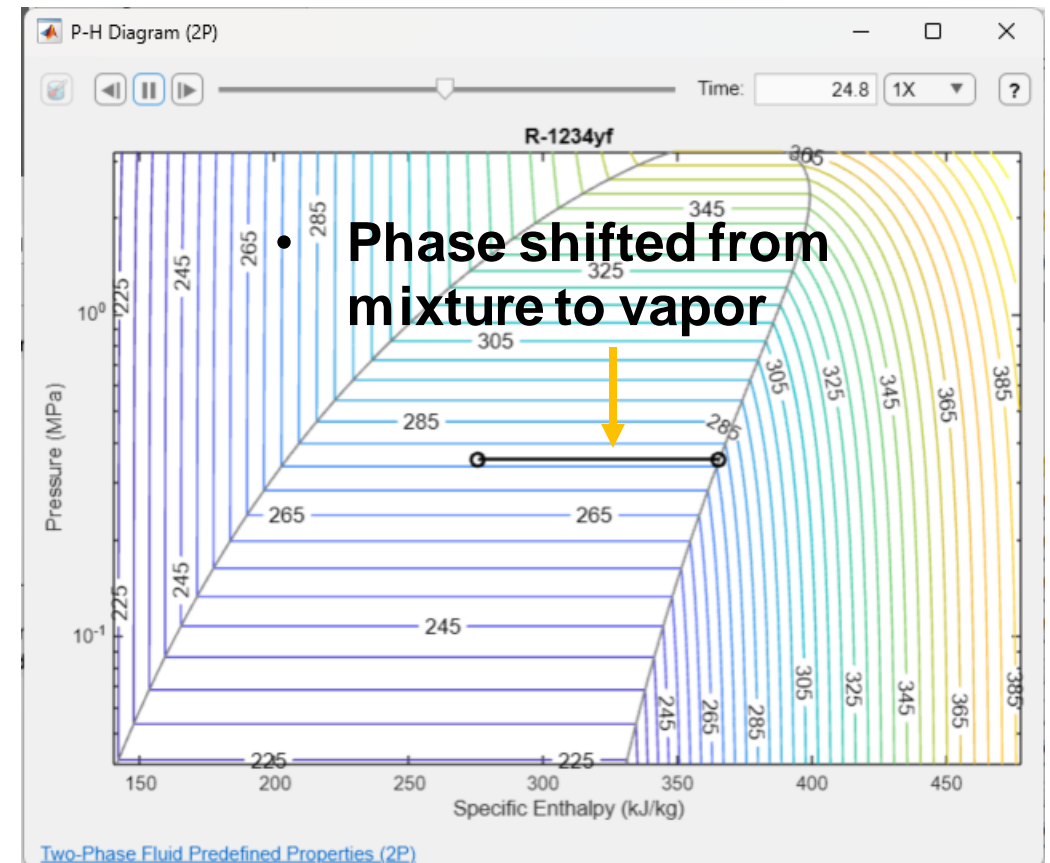
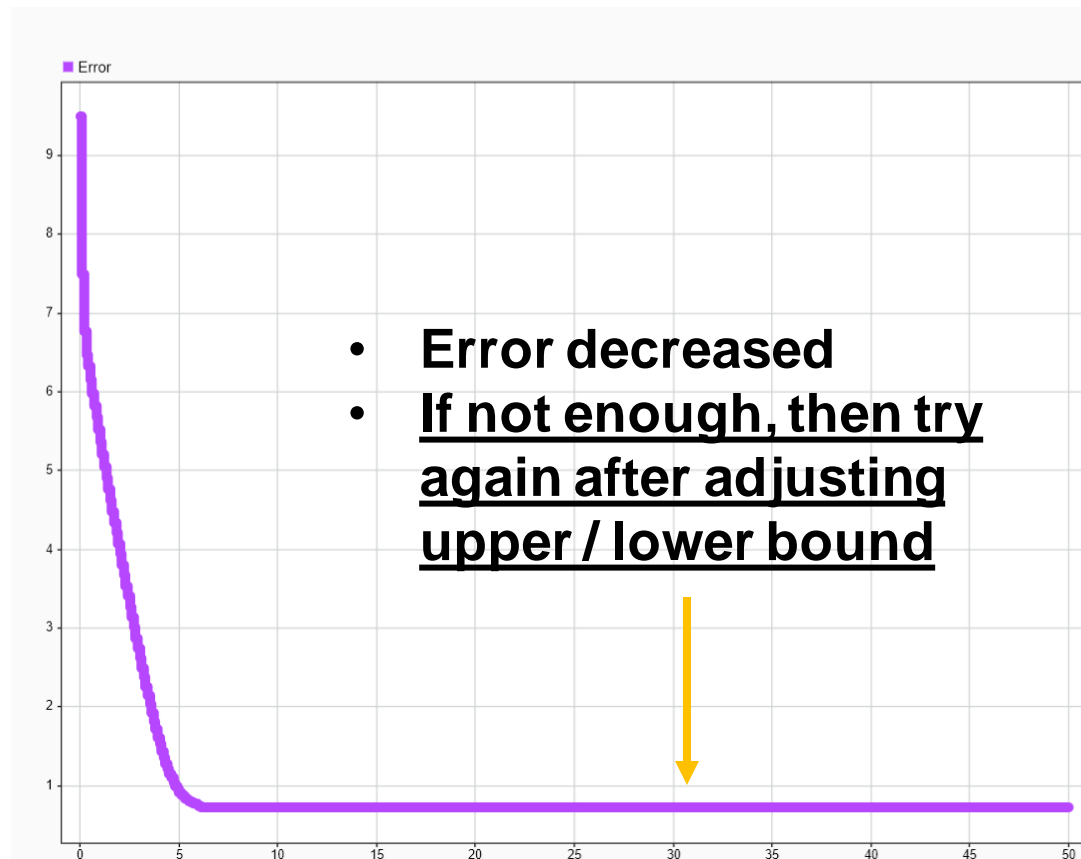
```

726.4039e-003
726.4039e-003
F =
726.4039e-003
F =
726.4039e-003
F =
726.4039e-003
3      78      7.264039e-01      0.000e+00      4.035e-02
Solver stopped prematurely.
fmincon stopped because it exceeded the iteration limit,
options.MaxIterations = 3.000000e+00.
fx
  
```

Parameter estimation with experiment data

Evaporator modeling

Results



Optimal calibration with experiment data

Problem statement

- **Goal:**
To introduce an optimization workflow using “**Model-Based Calibration Toolbox**” in look-up table modeling
 - Look-up table calibration example for motor current control
 - How to model statistical modeling with experiment data
 - How to calibrated look-up table for optimized performance with the fitted model

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Calibration Table Generation Workflow Steps

Workflow Steps	Description
Collect and Post Process Motor Data	Required data: <ul style="list-style-type: none"> D/Q-axis current: I_d, I_q Motor torque and speed D/Q-axis flux: λ_d, λ_q Allowed flux: λ_{max}
Model Motor Data (MBC Model Fitting)	Use a point-by-point model to fit data: <ul style="list-style-type: none"> Import data Filter and group data Fit model
Generate Calibration (MBC Optimization)	Calibrate and optimize the data using objectives and constraints: <ul style="list-style-type: none"> Create functions (Objective, Constraint) Create LUT (Lookup Tables) from model Optimization Fill and export LUT

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Test motor and process data
 - PMSM equations

- $V_d = R_s i_d + \frac{d\lambda_d}{dt} - p\omega_m \lambda_d$

- $V_q = R_s i_q + \frac{d\lambda_q}{dt} + p\omega_m \lambda_q$

for steady-state, the 1st and 2nd equations become

- $\lambda_d = \frac{(R_s i_d - V_d)}{p\omega_m}, \lambda_q = \frac{(V_d - R_s i_q)}{p\omega_m}$: d/q flux linkage

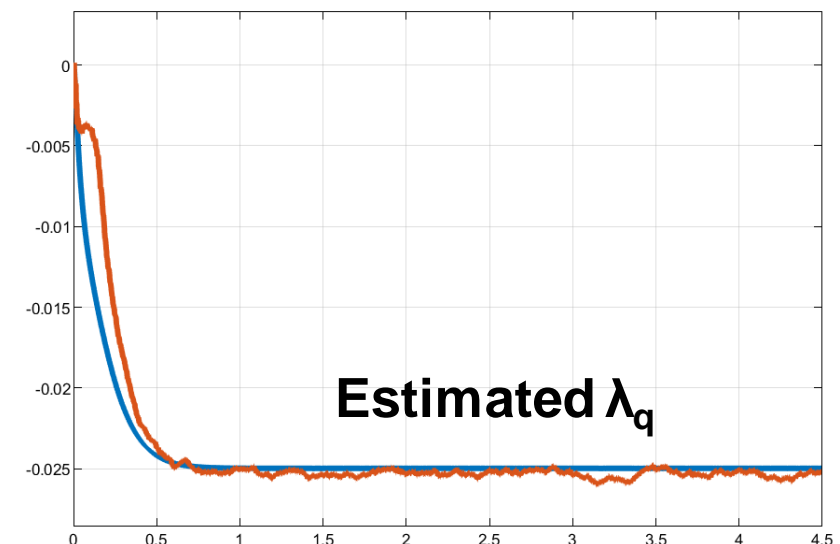
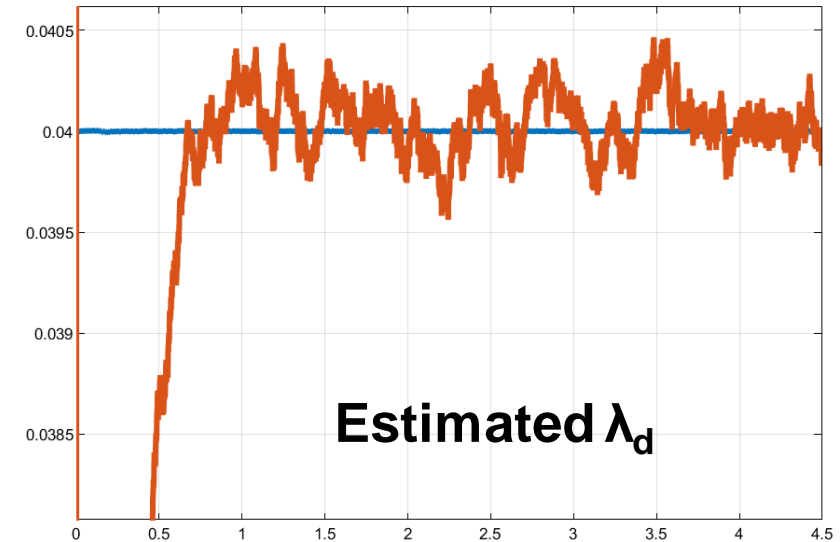
- $\lambda_{total} = \sqrt{\lambda_d^2 + \lambda_q^2}$

- $\lambda_{max} = \frac{V_{dc}}{\sqrt{3}p\omega_m}$: **allowed flux @given speed**

or calculation with L_d and L_q

- $\lambda_d = L_d i_d + \lambda_m$

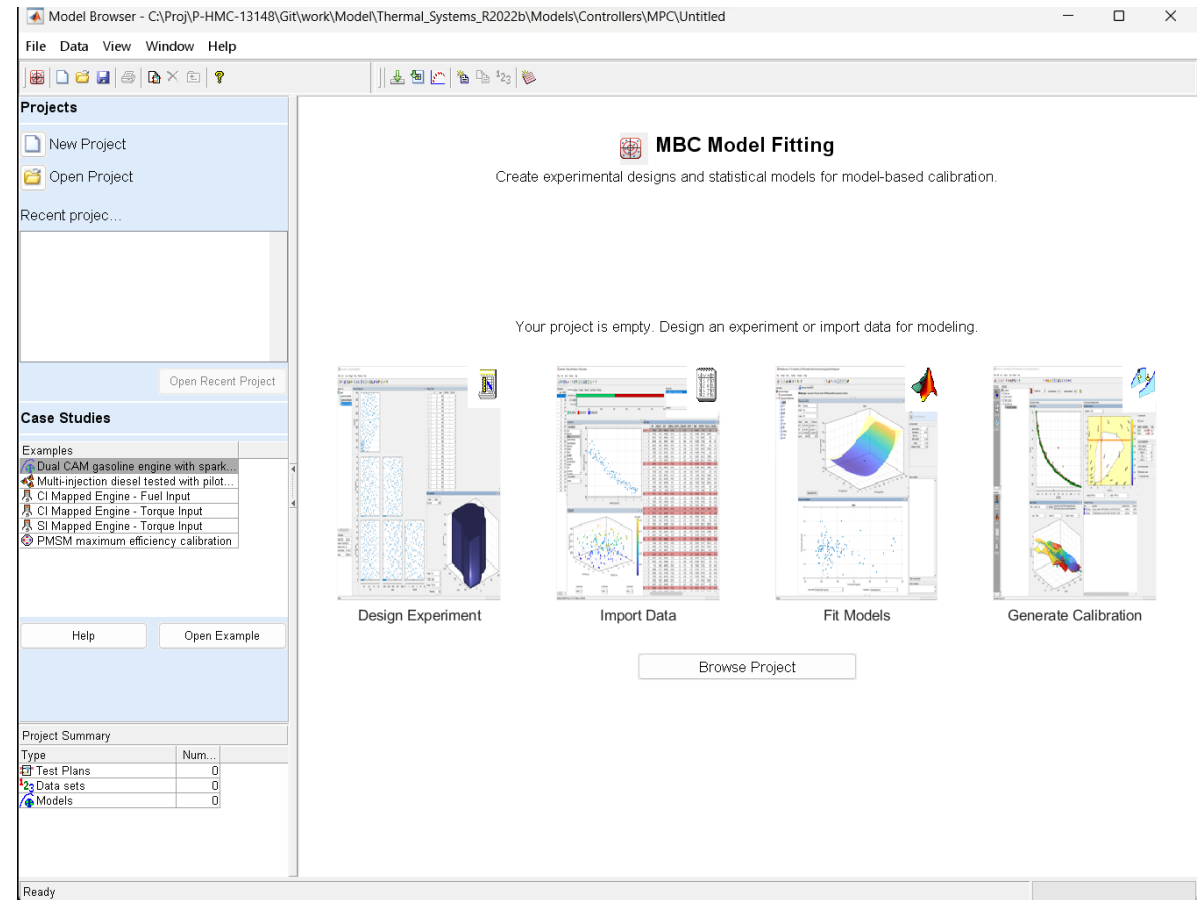
- $\lambda_q = L_q i_q$



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- **Model-Based Calibration Toolbox**
 - Is specialized for design of experiments, fitting statistical models, and generating calibrations and lookup tables of complex nonlinear systems
 - Users can automate the model fitting and calibration process by using the toolbox apps or MATLAB functions



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Import data
 - Flux total
 - Flux allowed
 - Flux d-axis
 - Flux q-axis
 - Current d-axis
 - Current q-axis
 - Torque
 - Speed

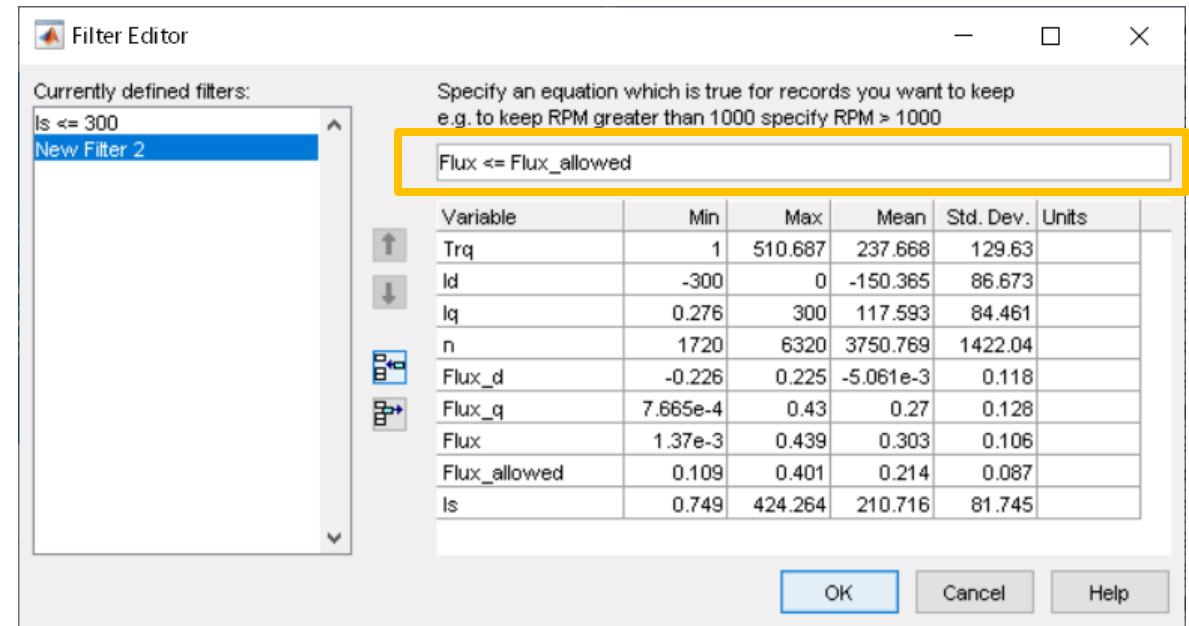
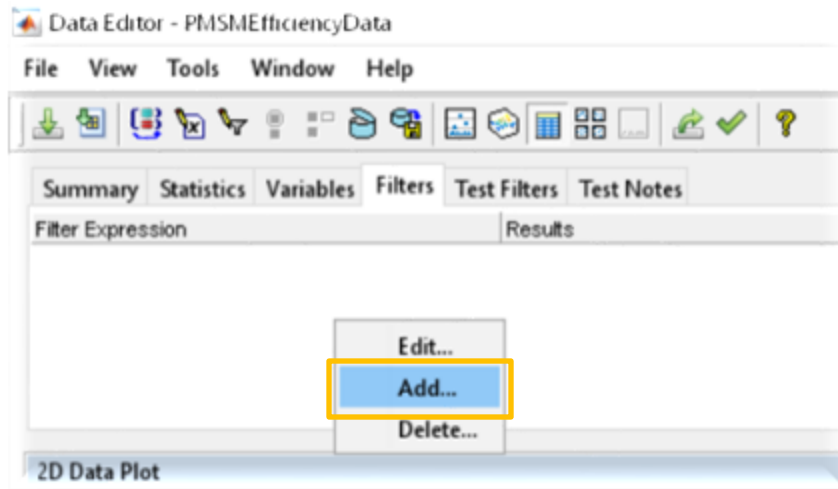
The screenshot displays the MATLAB Data Editor interface for a project named 'PMSMEfficiencyData'. It features a 'Summary' section with a progress bar indicating 30472 records and 9 variables. Below this is a '2D Data Plot' showing 'Flux' on the y-axis (ranging from 0 to 0.45) and 'Speed' on the x-axis (ranging from 0 to 3.5 x 10^4). The plot contains a dense blue shaded area representing the data distribution. To the right of the plot is a 'Data Table' with the following columns: Flux, Flux_allo..., Flux_d, Flux_q, Id, Iq, Is, Trq, and n. The table contains 36 rows of numerical data.

	Flux	Flux_allo...	Flux_d	Flux_q	Id	Iq	Is	Trq	n
4	0.206	0.401	-0.206	7.939e-4	-281.633	0.277	281.633	1	1720
5	0.199	0.401	-0.199	8.041e-4	-275.51	0.276	275.51	1	1720
6	0.192	0.401	-0.192	8.148e-4	-269.388	0.276	269.388	1	1720
7	0.184	0.401	-0.184	8.261e-4	-263.265	0.276	263.265	1	1720
8	0.177	0.401	-0.177	8.38e-4	-257.143	0.276	257.143	1	1720
9	0.169	0.401	-0.169	8.504e-4	-251.02	0.277	251.021	1	1720
10	0.161	0.401	-0.161	8.634e-4	-244.898	0.278	244.898	1	1720
11	0.154	0.401	-0.154	8.769e-4	-238.776	0.278	238.776	1	1720
12	0.146	0.401	-0.146	8.911e-4	-232.653	0.279	232.653	1	1720
13	0.138	0.401	-0.138	9.059e-4	-226.531	0.279	226.531	1	1720
14	0.13	0.401	-0.13	9.214e-4	-220.408	0.28	220.408	1	1720
15	0.122	0.401	-0.122	9.378e-4	-214.286	0.281	214.286	1	1720
16	0.114	0.401	-0.114	9.549e-4	-208.163	0.282	208.163	1	1720
17	0.106	0.401	-0.106	9.73e-4	-202.041	0.282	202.041	1	1720
18	0.098	0.401	-0.098	9.921e-4	-195.918	0.283	195.919	1	1720
19	0.09	0.401	-0.09	1.012e-3	-189.796	0.284	189.796	1	1720
20	0.081	0.401	-0.081	1.034e-3	-183.673	0.285	183.674	1	1720
21	0.073	0.401	-0.073	1.056e-3	-177.551	0.287	177.551	1	1720
22	0.064	0.401	-0.064	1.08e-3	-171.429	0.289	171.429	1	1720
23	0.056	0.401	-0.056	1.106e-3	-165.306	0.29	165.306	1	1720
24	0.047	0.401	-0.047	1.133e-3	-159.184	0.293	159.184	1	1720
25	0.038	0.401	-0.038	1.162e-3	-153.061	0.295	153.062	1	1720
26	0.029	0.401	-0.029	1.192e-3	-146.939	0.298	146.939	1	1720
27	0.02	0.401	-0.02	1.225e-3	-140.816	0.301	140.817	1	1720
28	0.01	0.401	-0.01	1.26e-3	-134.694	0.305	134.694	1	1720
29	1.37e-3	0.401	-4.413e-4	1.297e-3	-128.571	0.309	128.572	1	1720
30	9.414e-3	0.401	9.319e-3	1.337e-3	-122.449	0.313	122.449	1	1720
31	0.019	0.401	0.019	1.38e-3	-116.327	0.318	116.327	1	1720
32	0.029	0.401	0.029	1.426e-3	-110.204	0.324	110.205	1	1720
33	0.039	0.401	0.039	1.476e-3	-104.082	0.33	104.082	1	1720
34	0.05	0.401	0.05	1.53e-3	-97.959	0.337	97.96	1	1720
35	0.06	0.401	0.06	1.59e-3	-91.837	0.344	91.837	1	1720
36	0.07	0.401	0.07	1.655e-3	-85.714	0.352	85.715	1	1720

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Filter and group data
 - Add filtering conditions

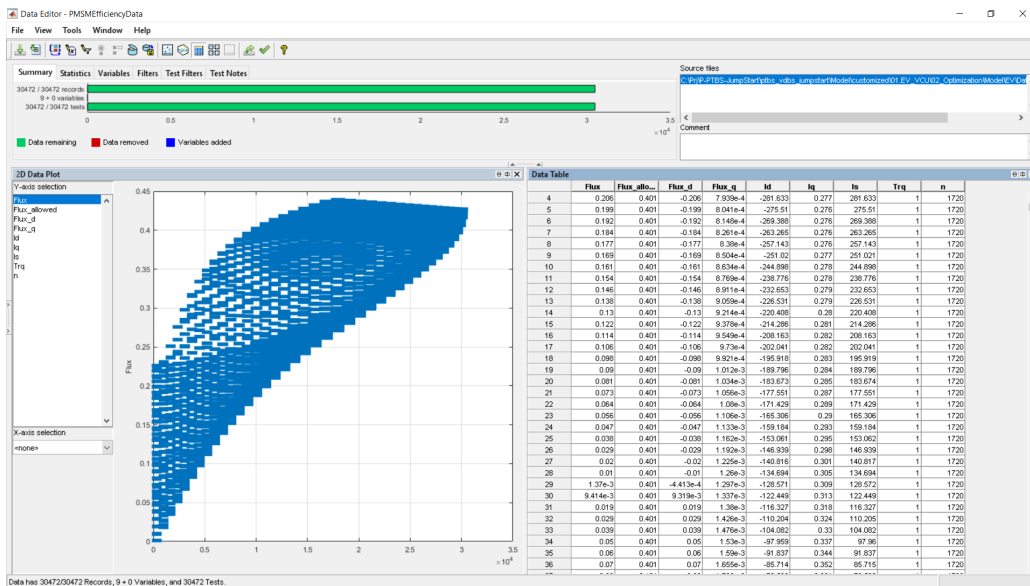


Optimal calibration with experiment data

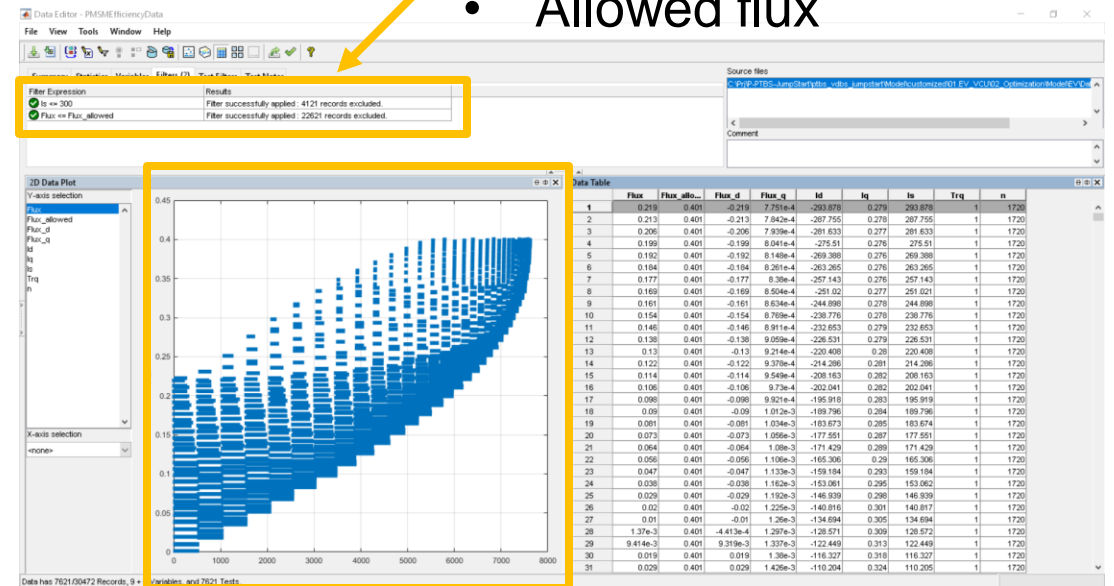
Look-up tables for flux-based motor controller

- Filter and group data

- Max current
- Allowed flux



Before

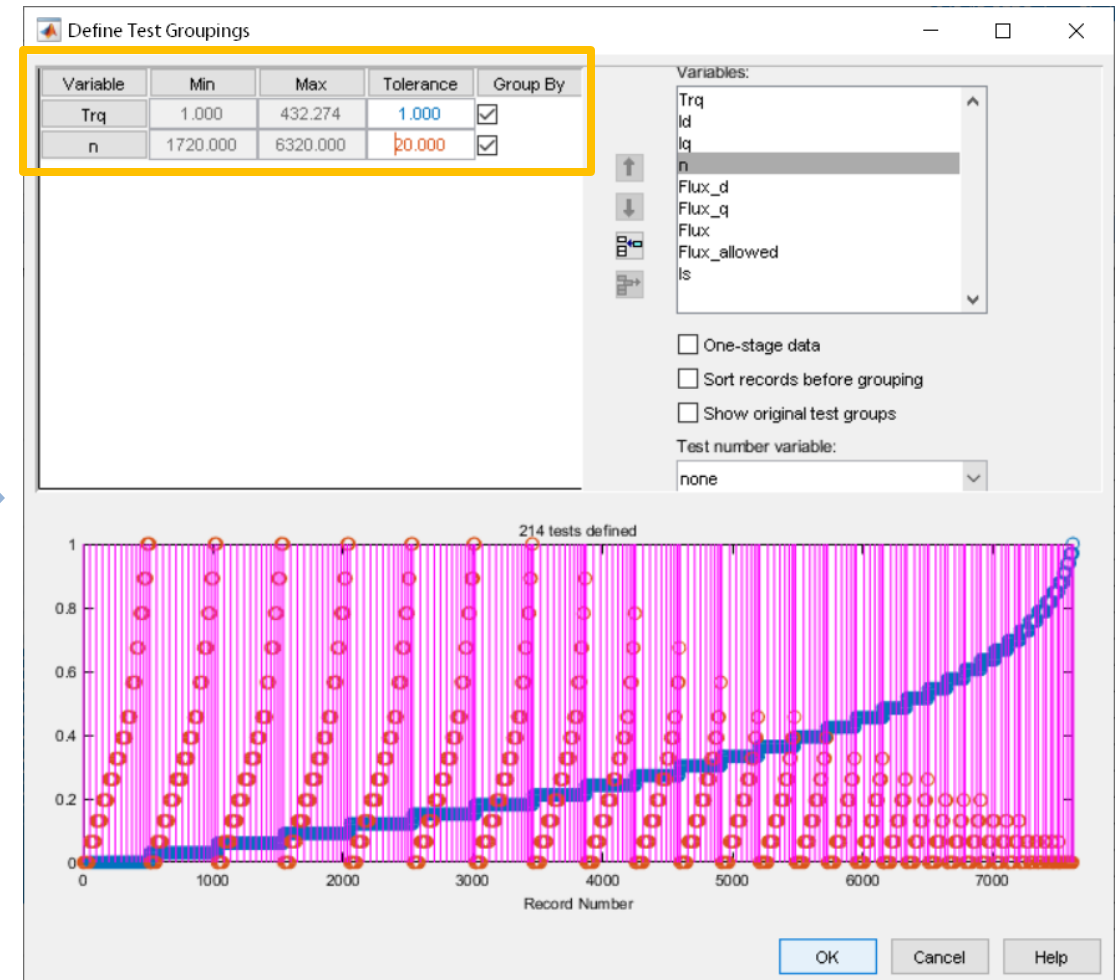
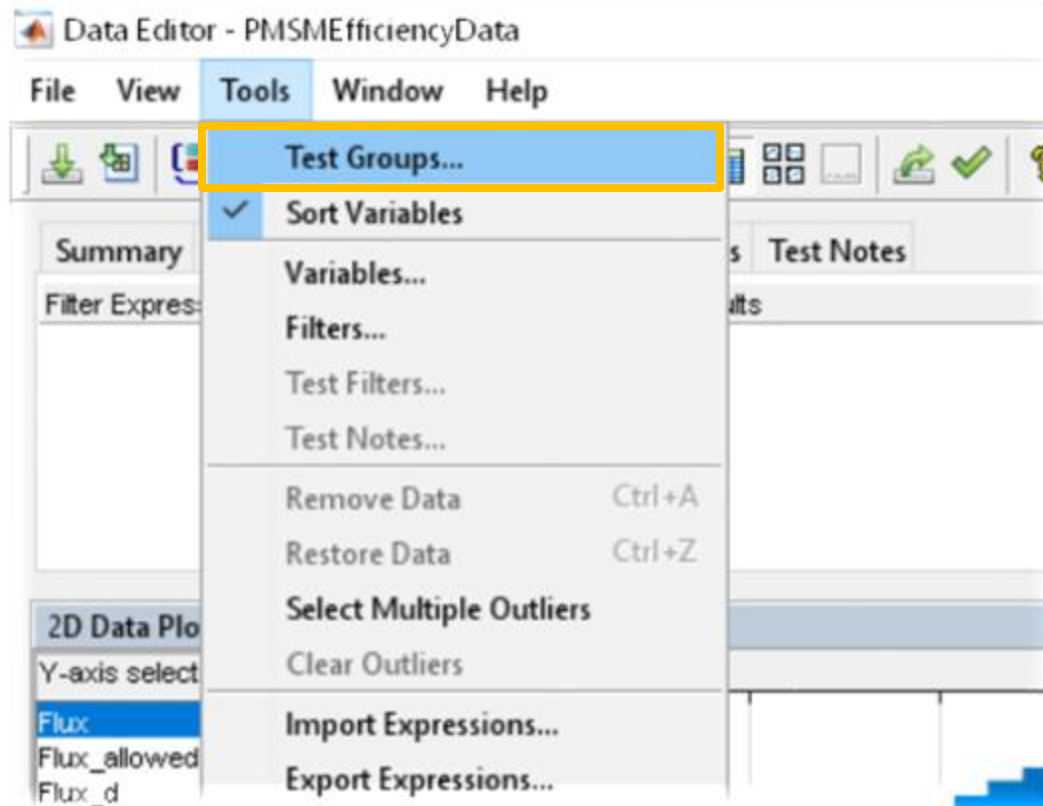


After

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Filter and group data
 - By torque & speed



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Fit model

Data Editor - PMSMEfficiencyData

Test	Trq	n
1	1	1720
2	1	2020
3	1	2320
4	1	2620
5	1	2920
6	1	3220
7	1	3520
8	1	3820
9	1	4320
10	1	4820
11	1	5320
12	1	5820
13	1	6320
14	14.069	1720
15	14.069	2020
16	14.069	2320
17	14.069	2620
18	14.069	2920
19	14.069	3220
20	14.069	3520
21	14.069	3820
22	14.069	4320
23	14.069	4820
24	14.069	5320
25	14.069	5820
26	14.069	6320
27	27.138	1720
28	27.138	2020
29	27.138	2320
30	27.138	2620
31	27.138	2920
32	27.138	3220
33	27.138	3520
34	27.138	3820
35	27.138	4320
36	27.138	4820
37	27.138	5320
38	27.138	5820
39	27.138	6320
40	40.207	1720

MBC Model Fitting
Create experimental designs and statistical models for model-based calibration.

Your project contains data. Now fit models to data.

Fit Models

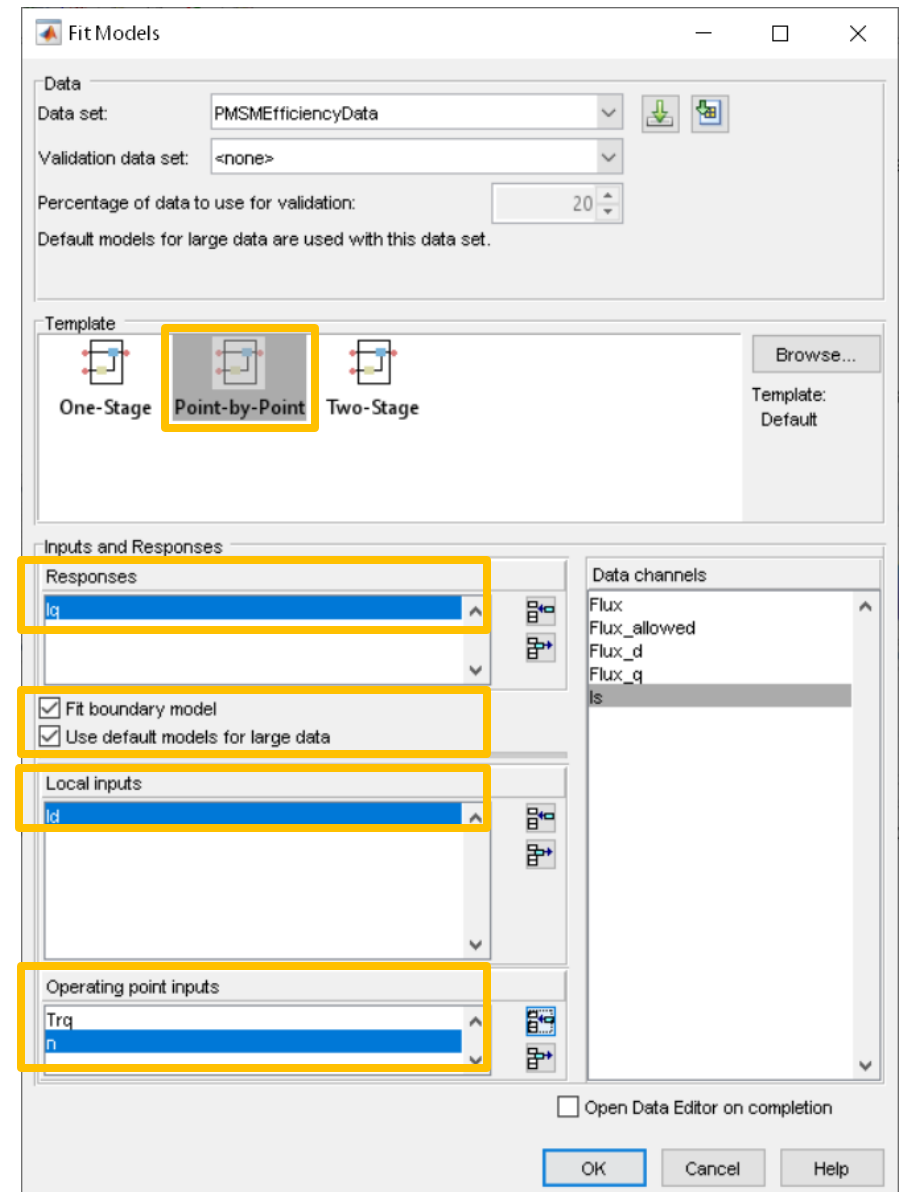
Type	Number
Test Plans	0
Data sets	1
Models	0

0.02	0.401	-0.02	1.229e-3	-140.81b	0.301	140.817	1	1720
0.01	0.401	-0.01	1.26e-3	-134.694	0.305	134.694	1	1720
1.37e-3	0.401	-4.413e-4	1.297e-3	-128.571	0.309	128.572	1	1720
9.414e-3	0.401	9.319e-3	1.337e-3	-122.449	0.313	122.449	1	1720
0.019	0.401	0.019	1.38e-3	-116.327	0.318	116.327	1	1720
0.029	0.401	0.029	1.426e-3	-110.204	0.324	110.205	1	1720

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Fit model
 - Point-by-Point:
 - Allows to build a model at each operating point
 - Responses / Local inputs
 - Set I_q as the response of the model
 - Set I_d as the local inputs
 - Select modeling options
 - Fit boundary model:
 - Describes the limits of the operating envelope
 - Use default models for large data:
 - Default model is GPM (Gaussian Process Model)
 - Operating point inputs
 - Torque
 - Motor rotating speed

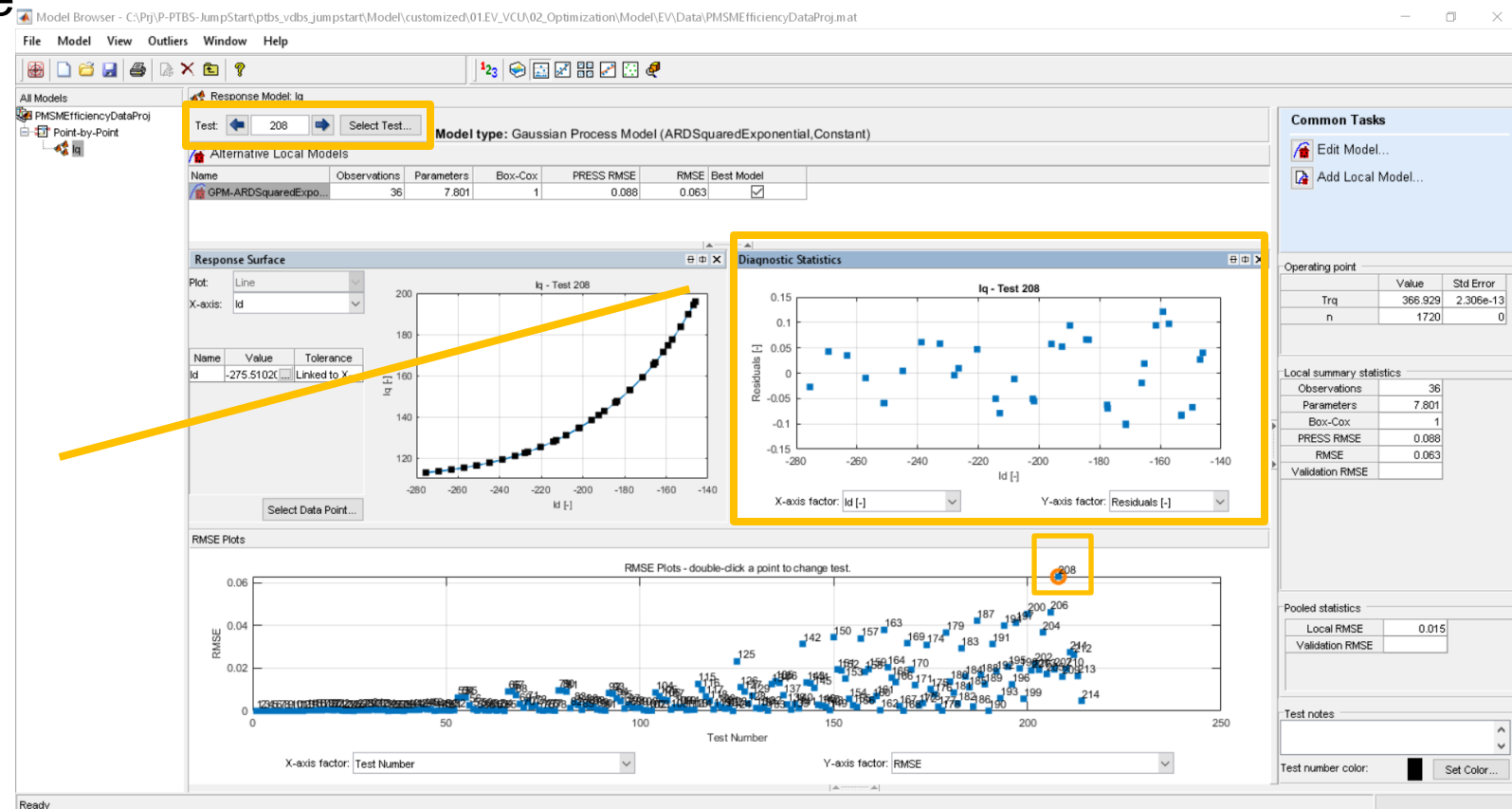


Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Fit model
 - Test 208 shows a little large RMSE
 - You can move to test 208 by using “Select Test”

- Shows a little large distribution
- If there are some outliers, they can be removed by “Outliers”

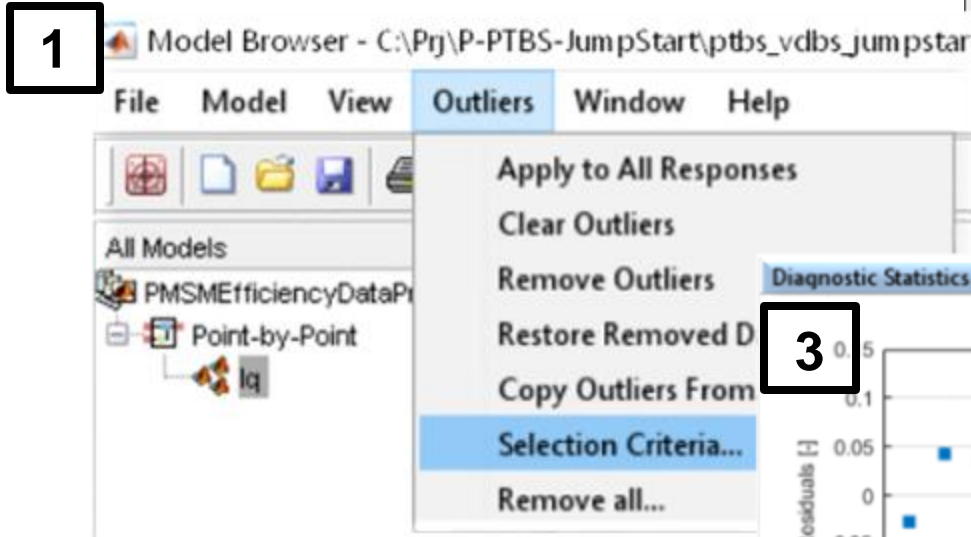


Optimal calibration with experiment data

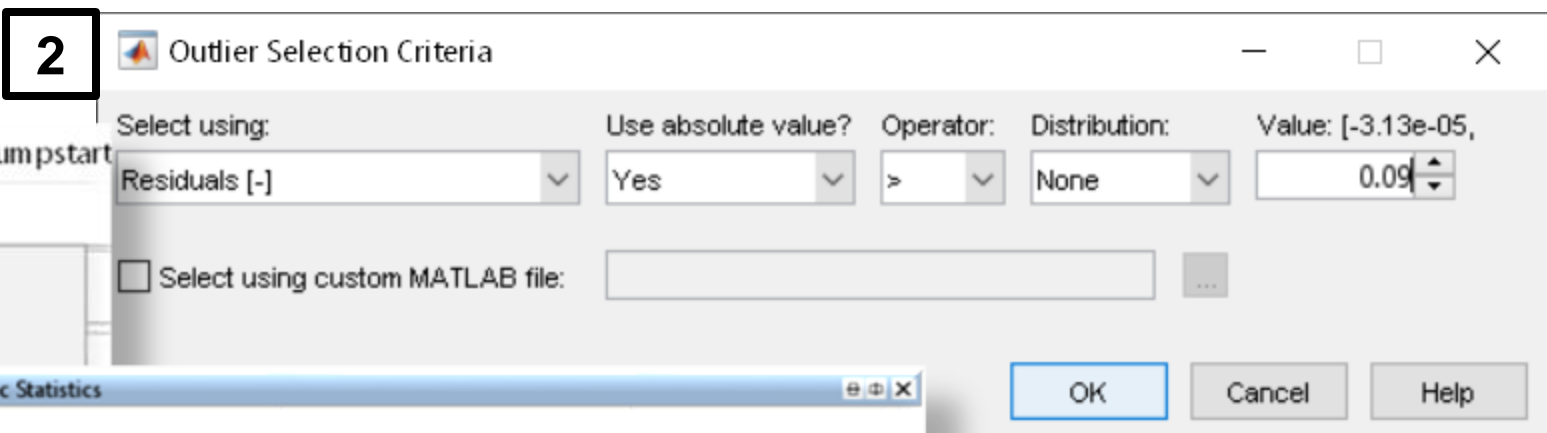
Look-up tables for flux-based motor controller

- Fit model
 - Remove outliers

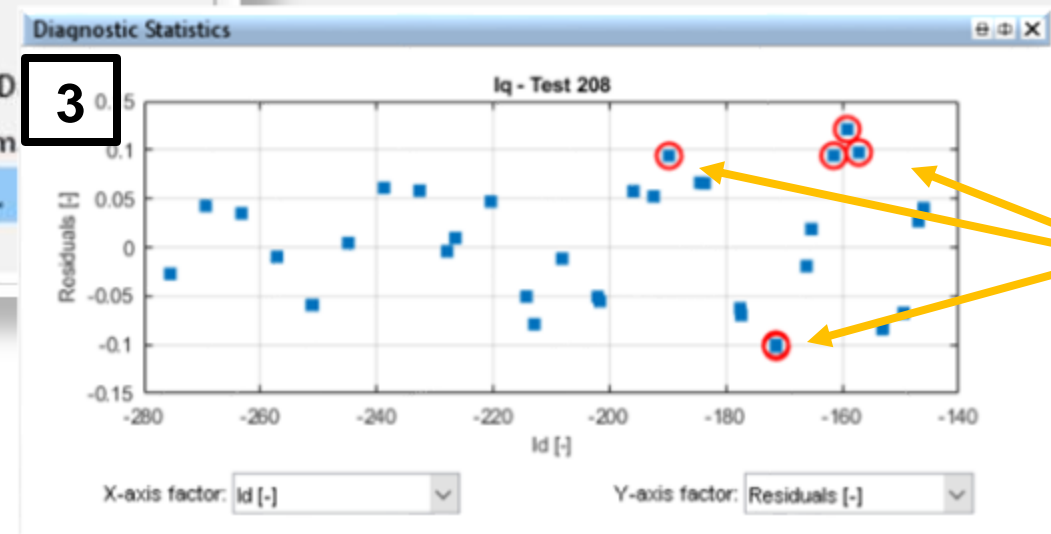
1



2



3

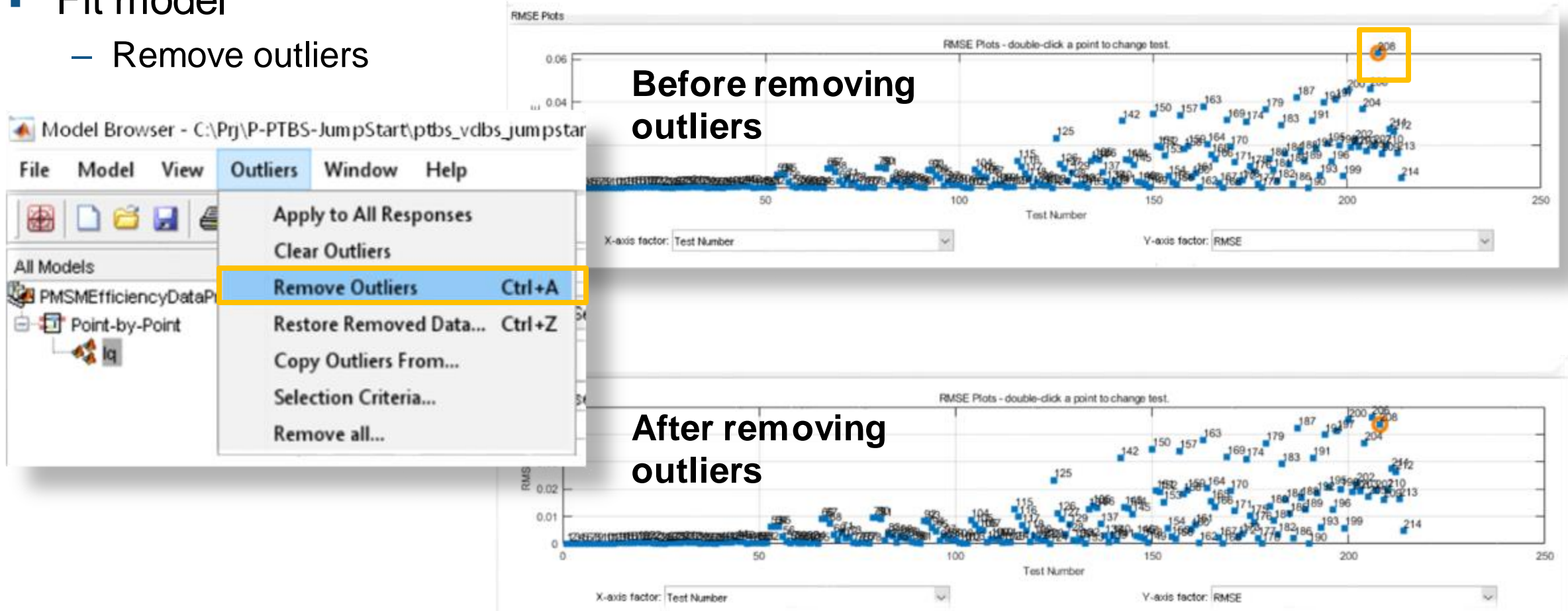


Selected outliers in the small circles

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Fit model
 - Remove outliers



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Create functions

MBC Model Optimization


Generate optimal look-up tables for model-based calibration.

Create an optimization for a model and use results to fill lookup tables

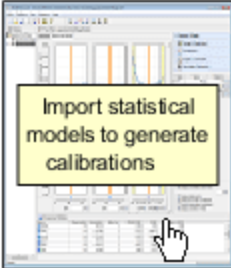
Import Models to CAGE

These models will be imported to CAGE when you click OK.

If a model is replaceable in CAGE you can select Replace or Create new in the Action column. Double-click CAGE Model Name cells to edit names.

Original Name	Action	CAGE Model Name
 iq	Create new	iq

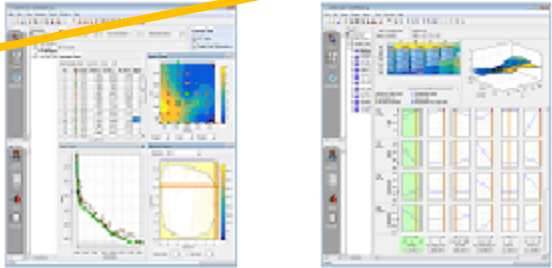
Import



Import statistical models to generate calibrations

Models

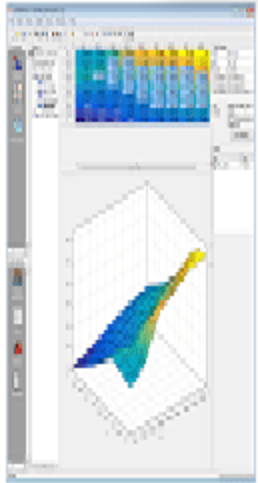
Use models to generate calibration



Optimization


Lookup Tables and Tradeoff

Export

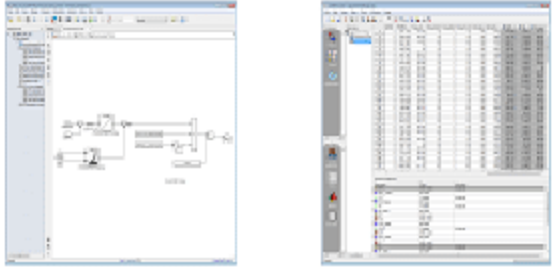


Lookup Tables

Import model



Simulink Lookup Tables



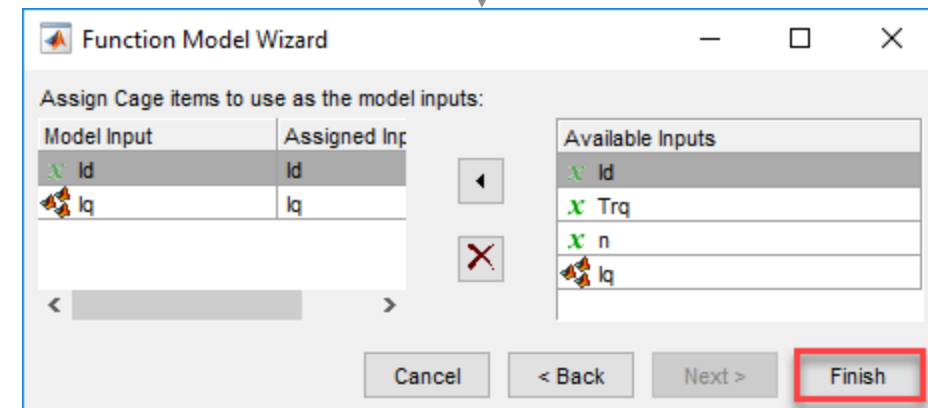
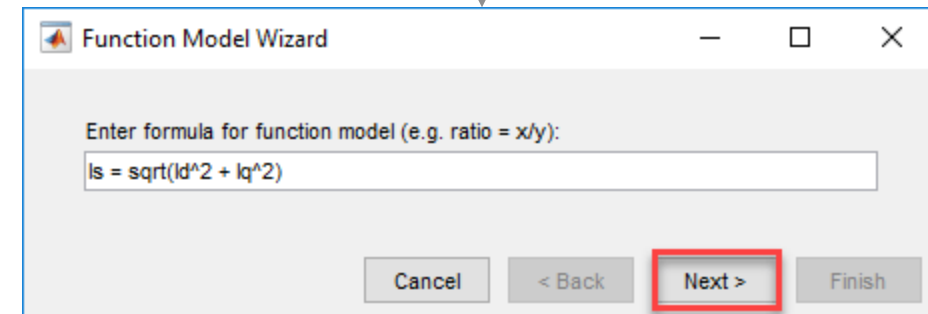
Feature Filling

Data Set

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

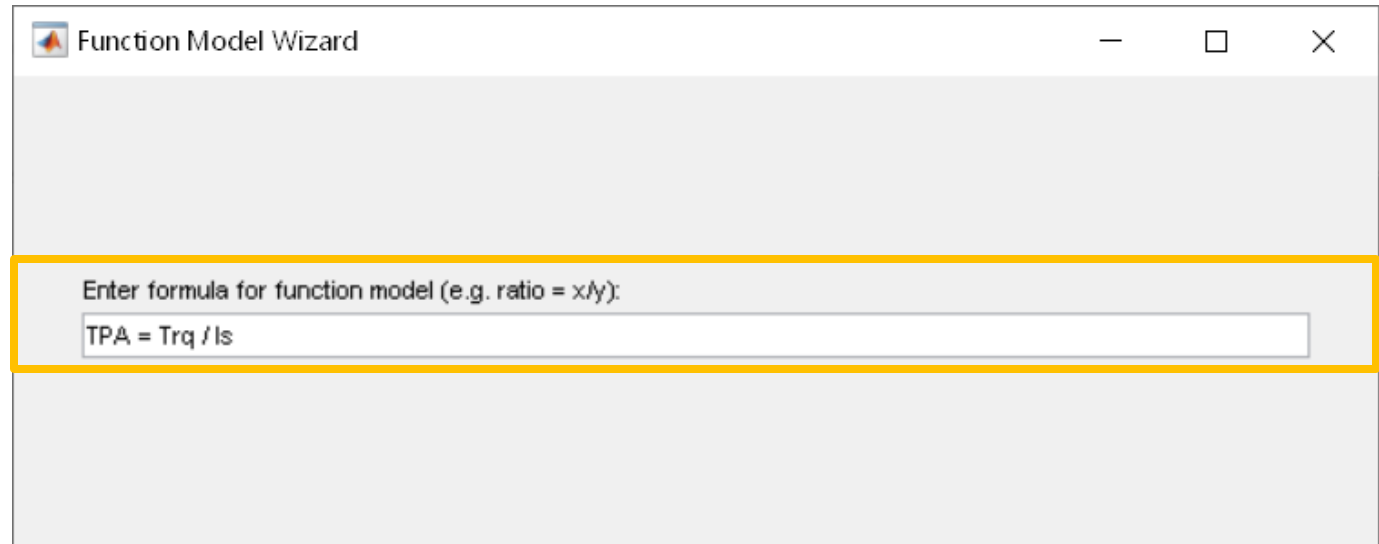
- Create functions
 - Current magnitude, I_s
 - $I_s \leq 300$ A, the constraint



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Create functions
 - $TPA = Trq / Is$
 - TPA(Torque Per Ampere) is the objective function to be maximized by optimization



Models					
Name	Type	Inputs	Lower Output Limit	Upper Output Limit	Description
iq	Point-by-point ...	Id, Trq, n	-Inf	Inf	Created by tchoi on 30-Mar-2022.
Is	Function model	Id, Iq	-Inf	Inf	$\sqrt{Id^2 + Iq^2}$
TPA	Function model	Is, Trq	-Inf	Inf	Trq / Is

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Create LUT from model

Set LUT format such as table rows, columns

Select LUT outputs

Create LUT with lq point-by-point model

Model
Select a model to base the new lookup tables on.

Model	Type	Variable Inputs
lq	Point-by-point mo...	Id, Trq, n
Is	Function model	Id, Trq, n
TPA	Function model	Id, Trq, n

Lookup Table Inputs
Select the lookup table inputs and set up the normalizers to use for all the new lookup tables.

Use model operating points

Rows (Y) input: Trq
Columns (X) input: n
Normalizer: <New>
Table rows: 31
Table columns: 29

Trq normalizer:
n normalizer:

Input	Table Output
1	0
15.376	1
29.752	2
44.127	3
58.503	4
72.879	5
87.255	6
101.631	7
116.006	8

Input	Table Output
1720	
2103.333	
2486.667	
2870	
3253.333	
3636.667	
4020	
4403.333	
4786.667	

Lookup Tables
Select the items to create lookup tables for. Select the lookup table fill process.

Normalizers: Trq_norm_2, n_norm_2

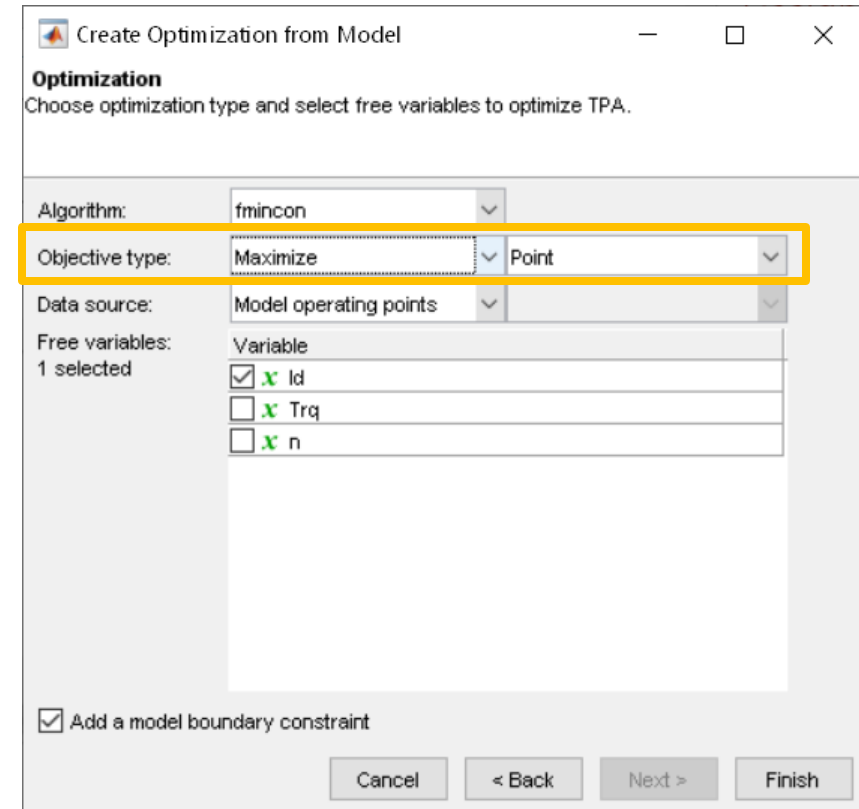
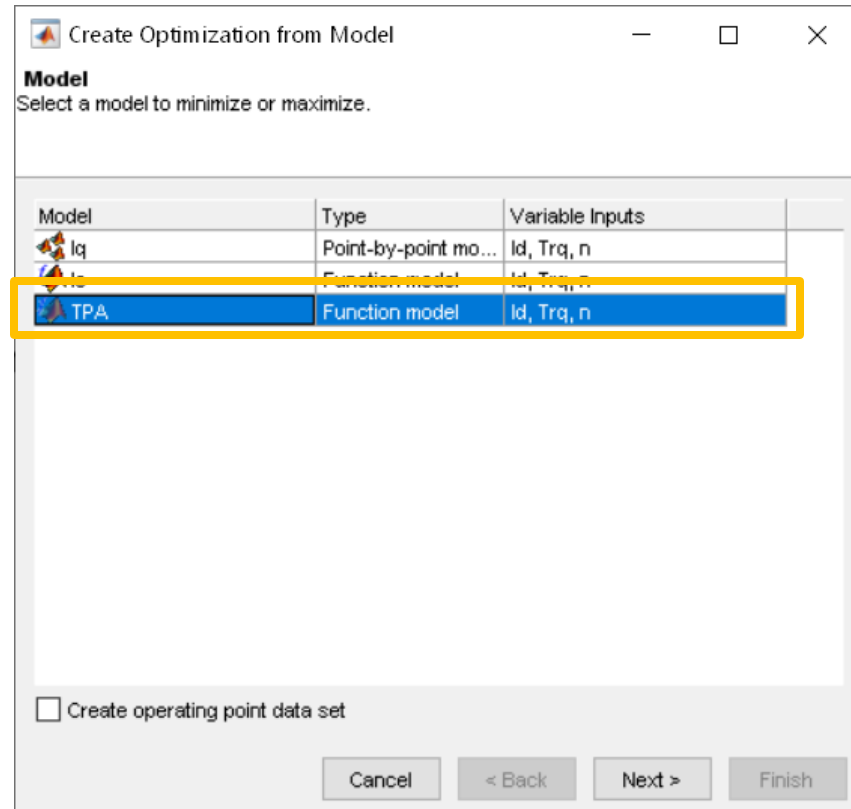
Item	Lookup Table Name	Table Bounds
<input checked="" type="checkbox"/> Id	Id_Table	[-293.878, 0]
<input checked="" type="checkbox"/> lq	lq_Table	[-Inf, Inf]

Lookup table fill process
 Optimization/Tradeoff
 Models
 None

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

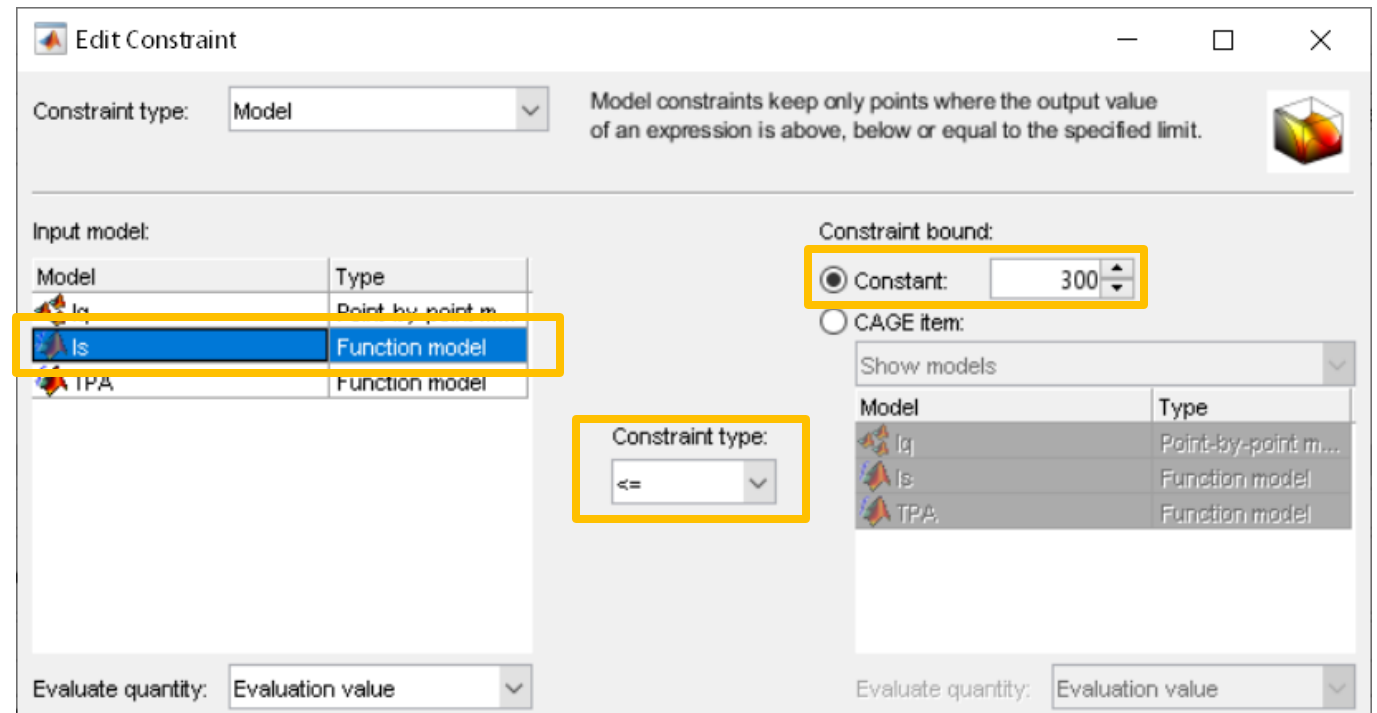
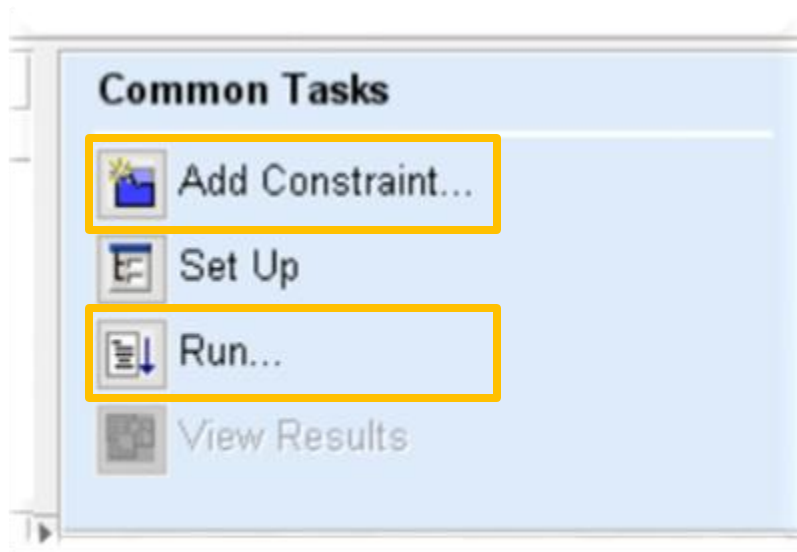
- Optimization
 - Objective function: TPA, maximized



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Optimization
 - Add Constraints & Run



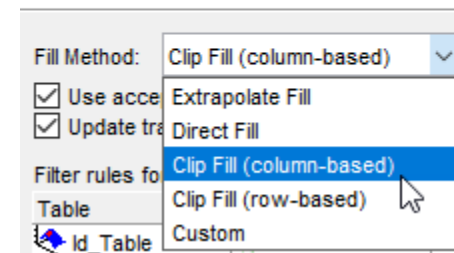
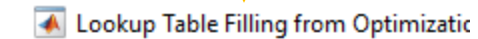
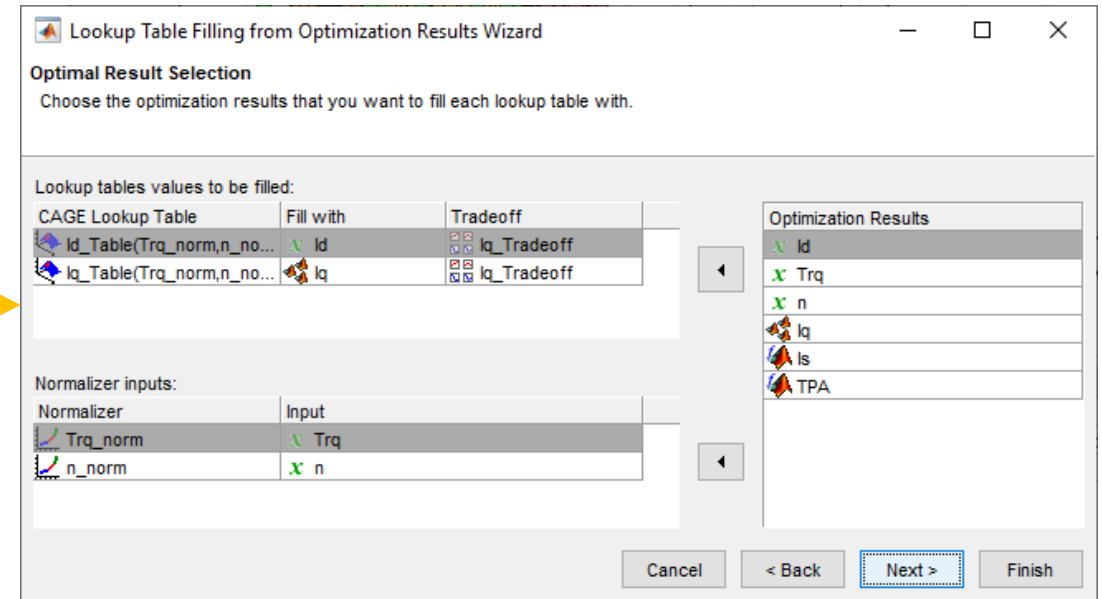
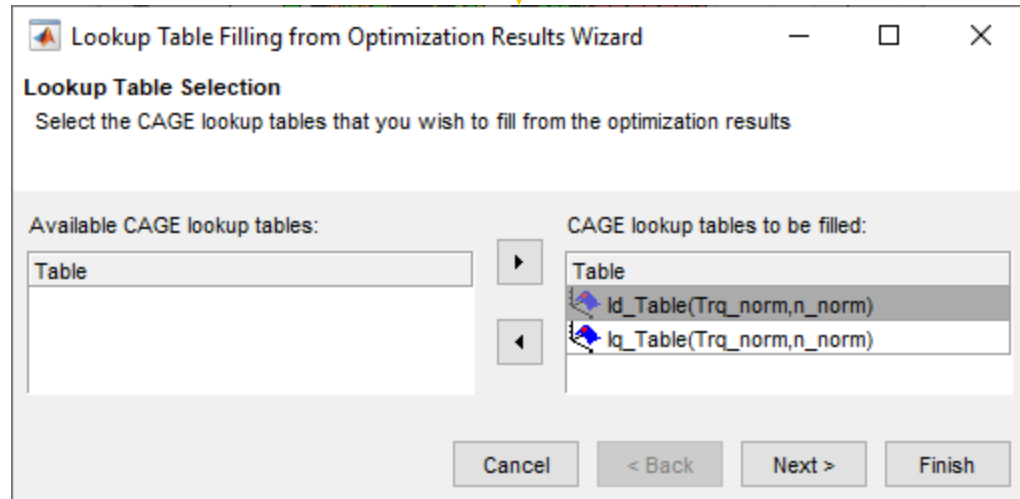
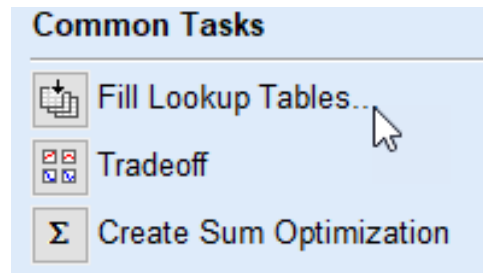
Constraints			
Name	Description	Type	Soft Constraint
TPA Boundary	Boundary constraint of TPA(ld, Trq, n)	Model	<input type="checkbox"/>
Is	Is(ld, Trq, n) <= 300	Model	<input type="checkbox"/>

Cancel Help

Optimal calibration with experiment data

Look-up tables for flux-based motor controller

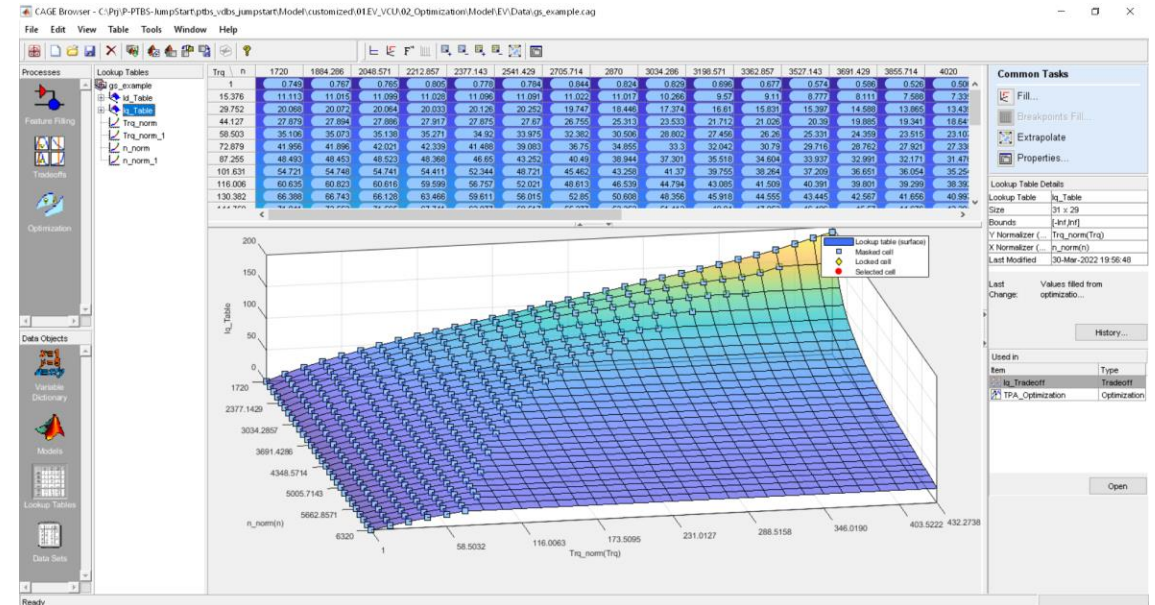
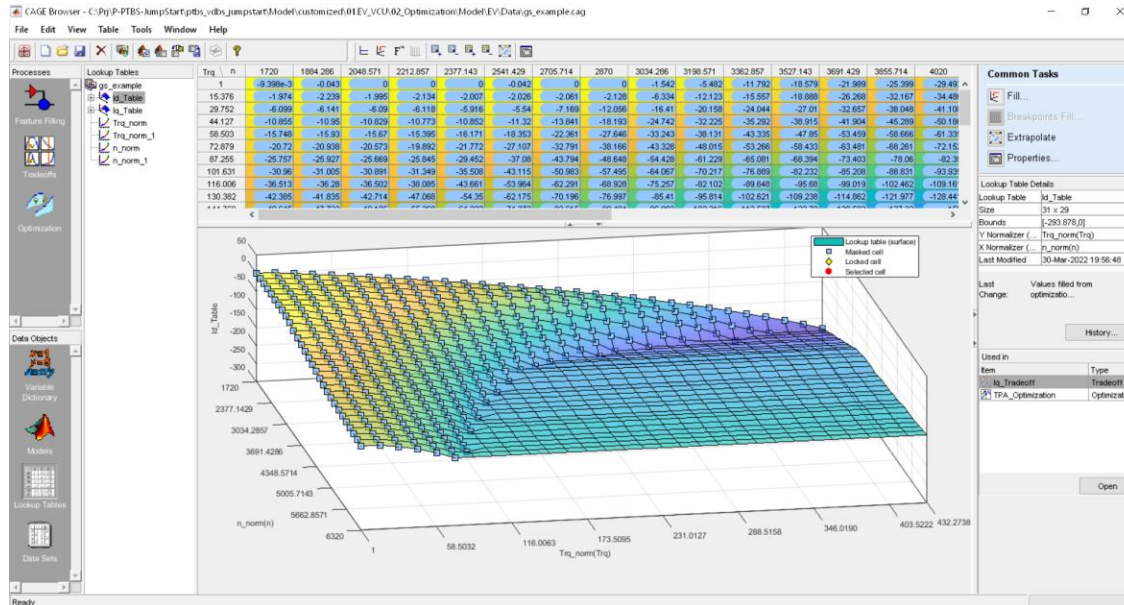
- Fill and export LUT



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

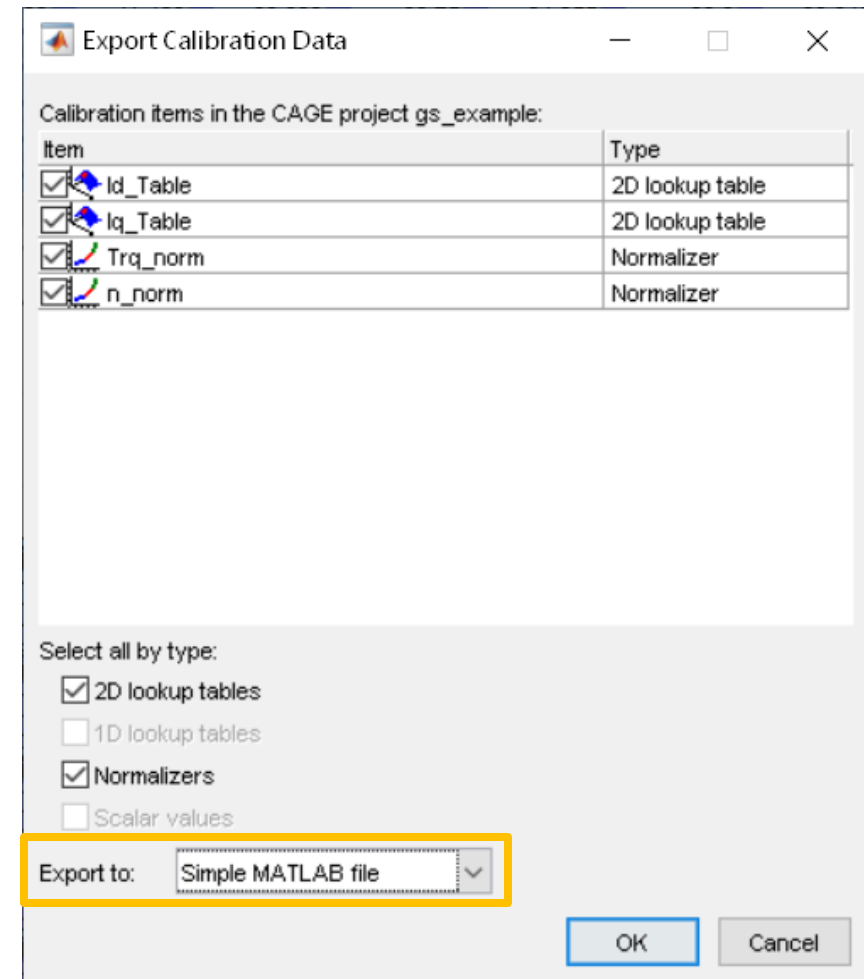
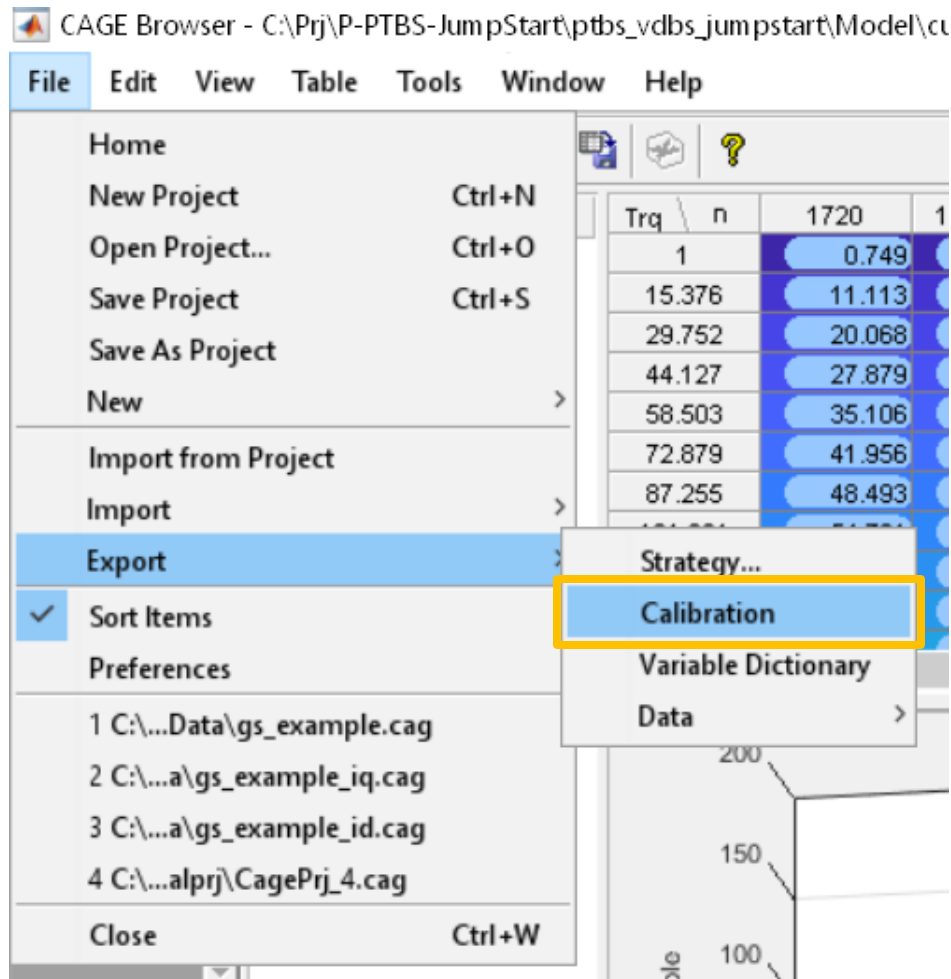
- Fill and export LUT
 - Examine LUT



Optimal calibration with experiment data

Look-up tables for flux-based motor controller

- Fill and export LUT



Conclusions

- Has shown **how to apply “Global Optimization Toolbox” to parameter estimation** for physical modeling
 - **The optimization workflow “Sensitivity Analyzer” and “Global Optimization Toolbox” combined has shown how to make parameter estimation problem much more efficient**
- Has shown **how to create optimized lookup table with “Model-Based Toolbox”**
 - From experiment data import / preprocessing / fitting model / table optimization
- **These workflows can be modified easily to be applicable to other kinds of optimization problems** beyond the example shown above

MATLAB EXPO

Thank you



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