



UQ-PyL User Manual

(Version 1.1)

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1 Introduction

1.1 A Quick Start

UQ-PyL (**U**ncertainty **Q**uantification **P**ython **L**aboratory) is a software platform for performing various uncertainty quantification (UQ) activities such as Design of Experiments (DoE), Statistical Analysis, Sensitivity Analysis (SA), Surrogate Modeling and Parameter Optimization. This document describes how to set up problems and use these UQ methods to solve them through UQ-PyL. The mathematics of those UQ methods can be found in the separate theory manual.

We request that you cite the following paper when you report the results obtained by using the UQ-PyL software platform:

C. Wang, Q. Duan, Charles H. Tong, (2015), UQ-PyL – A GUI platform for uncertainty quantification of complex models. Under review for Environmental Modeling & Software.

1.2 Available UQ-PyL Capabilities

1.2.1 Design of Experiment

Full-Factorial design, Fractional-Factorial design, Plackett-Burman design, Box-Behnken design, Central-Composite design, Monte Carlo design, Latin Hypercube design (random, center, maxmin, center maxmin, correlate), Symmetric Latin Hypercube design, Improved Distributed Hypercube design, Sobol' sequence, Halton sequence, Faure sequence, Hammersley sequence, Good Lattice Point.

1.2.2 Statistical Analysis

Statistical moments, Confidence interval, Hypothesis test.

1.2.3 Sensitivity Analysis

Morris One at A Time (MOAT), Derivative-based Global Sensitivity Measure (DGSM), Sobol' Sensitivity Analysis, Fourier Amplitude Sensitivity Test (FAST), Metamodel-based Sobol', Correlation analysis, Delta Moment-Independent Measure (Delta), Multivariate Adaptive Regression Splines (MARS) based sensitivity analysis.

1.2.4 Surrogate Modeling

Generalized Linear Model (Ordinary Least Squares, Ridge Regression, Lasso, Least Angle Regression, LARS Lasso, Bayesian Regression, and Elastic Net), Regression

Tree, Random Forest, Nearest Neighbors, Support Vector Machine, Gaussian Process, MARS, Stochastic Gradient Descent.

1.2.5 Parameter Optimization

Shuffled Complex Evolution (SCE), Dynamically Dimensional Search (DDS), Adaptive Surrogate Modeling based Optimization (ASMO), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Monte Carlo Markov Chain (MCMC).

1.3 Overview about functionality of the UQ-PyL package

```
1  __init__.py
2 Doe/
3  __init__.py          # Ensure all needed files are loaded
4  __main__.py          # For GUI uses
5  box_behnken.py      # Box-behnken design
6  central_composite.py# Central-composite design
7  fast_sampler.py    # FAST sensitivity analysis design
8  faure.py           # Faure design
9  ff2n.py            # Factorial design
10 finite_diff.py     # DGSM sensitivity analysis design
11 frac_fact.py       # Factorial design
12 full_fact.py       # Full Factorial design
13 GLP.py             # Good Lattice Point design
14 halton.py          # Halton Quasi-Monte Carlo design
15 hammersley.py     # Hammersley Quasi-Monte Carlo design
16 lhs.py              # Latin Hypercube design
17 monte_carlo.py     # Monte Carlo design
18 morris_oat.py      # Morris One at A Time design
19 plackett_burman.py# Plackett Burman design
20 saltelli.py         # Sobol' sensitivity analysis design
21 sobol.py            # Sobol' Quasi-Monte Carlo design
22 symmetric_LH.py    # Symmetric Latin Hypercube design
23 analysis/
24  __init__.py          # Ensure all needed files are loaded
25  __main__.py          # For GUI uses
26  confidence.py       # Confidence Interval
27  correlations.py     # Correlation analysis
28  delta.py            # Delta sensitivity analysis
29  dgsm.py             # DGSM sensitivity analysis
30  extended_fast.py    # FAST sensitivity analysis
31  hypothesis.py       # Hypothesis Test
```

```

32     moments.py          # Statistics moments method
33     morris.py           # MOAT sensitivity analysis
34     sobol_analyze.py    # Sobol' sensitivity analysis
35     sobol_svm.py        # Metamodel based sobol' sensitivity
36     analysis
37     RSmodel/
38         __init__.py      # Ensure all needed files are loaded
39         __main__.py        # For GUI uses
40         BayesianRidge.py # GLP-Bayesian Ridge regression
41         DT.py             # Decision Tree regression
42         ElasticNet.py    # GLP-Elastic Net regression
43         gp.py             # Gaussian Process regression
44         kNN.py            # k-nearest neighbor regression
45         LAR.py            # GLP-LAR regression
46         Lars.py           # GLP-Lars regression
47         Lasso.py          # GLP-Lasso regression
48         MARS.py           # MARS regression
49         OrdinaryLeastSquares.py # GLP-Ordinary Least Squares
50         regression
51         RF.py             # Random Forest regression
52         Ridge.py          # GLP-Ridge regression
53         SGD.py            # Stochastic Gradient Descent regression
54         SVR.py             # Support Vector Machine regression
55     optimization/
56         __init__.py      # Ensure all needed files are loaded
57         __main__.py        # For GUI uses
58         ASMO.py           # ASMO optimization
59         DDS.py            # DDS optimization
60         MCMC.py           # Monte Carlo Markov Chain optimization
61         PSO.py             # Particle Swarm Optimization
62         SA.py              # Simulated Annealing optimization
63         SCE.py             # Shuffled Complex Evolution
64     optimization
65     util/
66         __init__.py      # Ensure all needed files are loaded
67         discrepancy.py    # Compute discrepancy of design
68         spyderlib/         # Spyder package
69         spyderplugins/     # Spyder package

```

2 Installation

2.1 Dependencies

UQ-PyL is an open-source package written in Python language. It runs on all major platforms (Windows, Linux, MacOS). It requires some pre-installed standard Python packages:

- ✧ Python version $\geq 2.7.6$
- ✧ Numpy $\geq 1.7.1$
- ✧ Scipy $\geq 0.16.0$
- ✧ Matplotlib $\geq 1.4.3$
- ✧ PyQt4 (If you use graphic user interface)
- ✧ Scikit-learn = 0.14.1

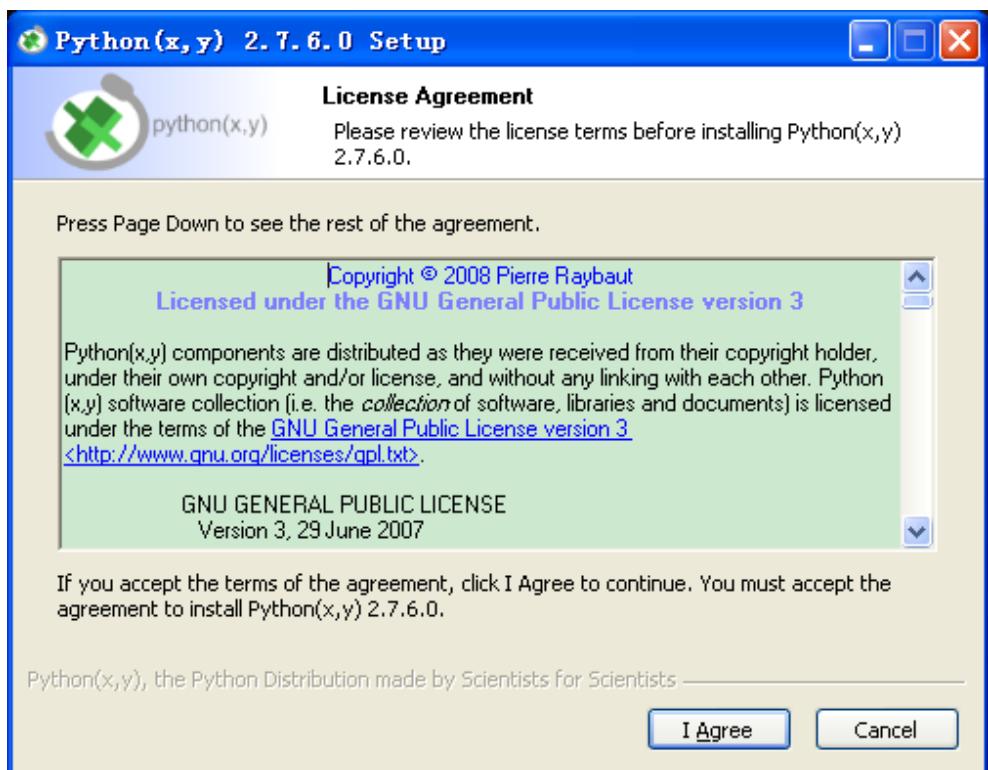
2.2 Detailed Installation

2.2.1 Windows platform

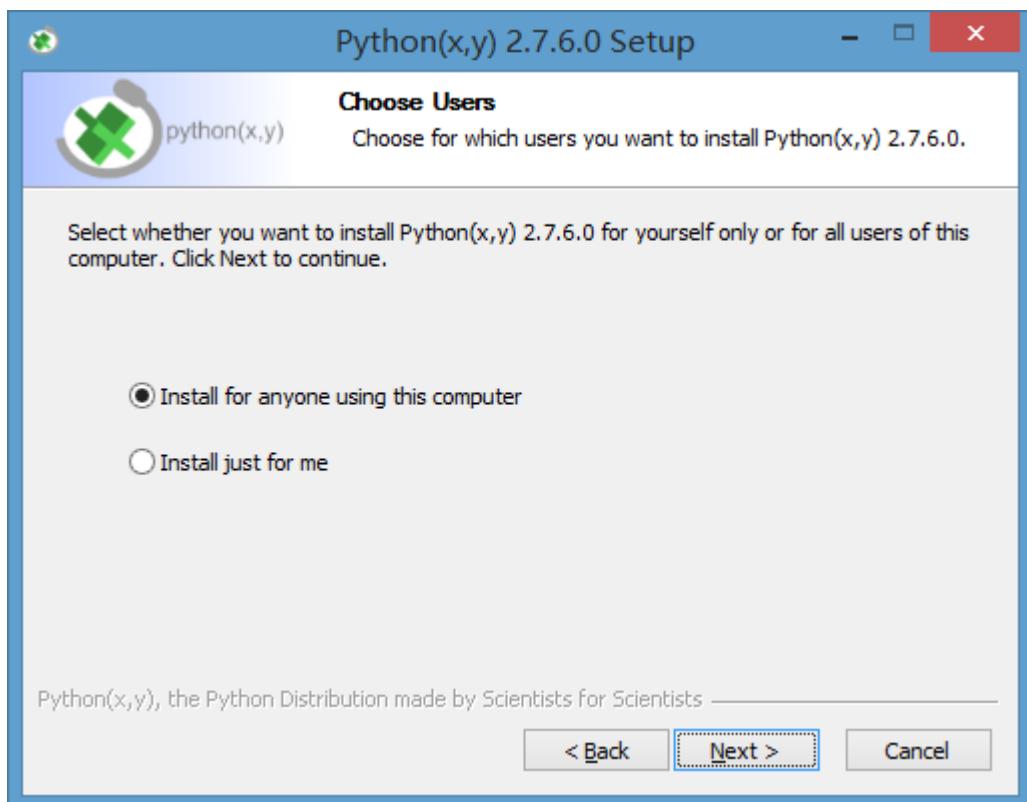
For Windows platform, there is a software integrate Python and some common packages called Python(xy). It contains all the packages UQ-PyL needed. You can just install Python(xy) and UQ-PyL to run UQ analysis.

Step 1. Install Python(xy) software.

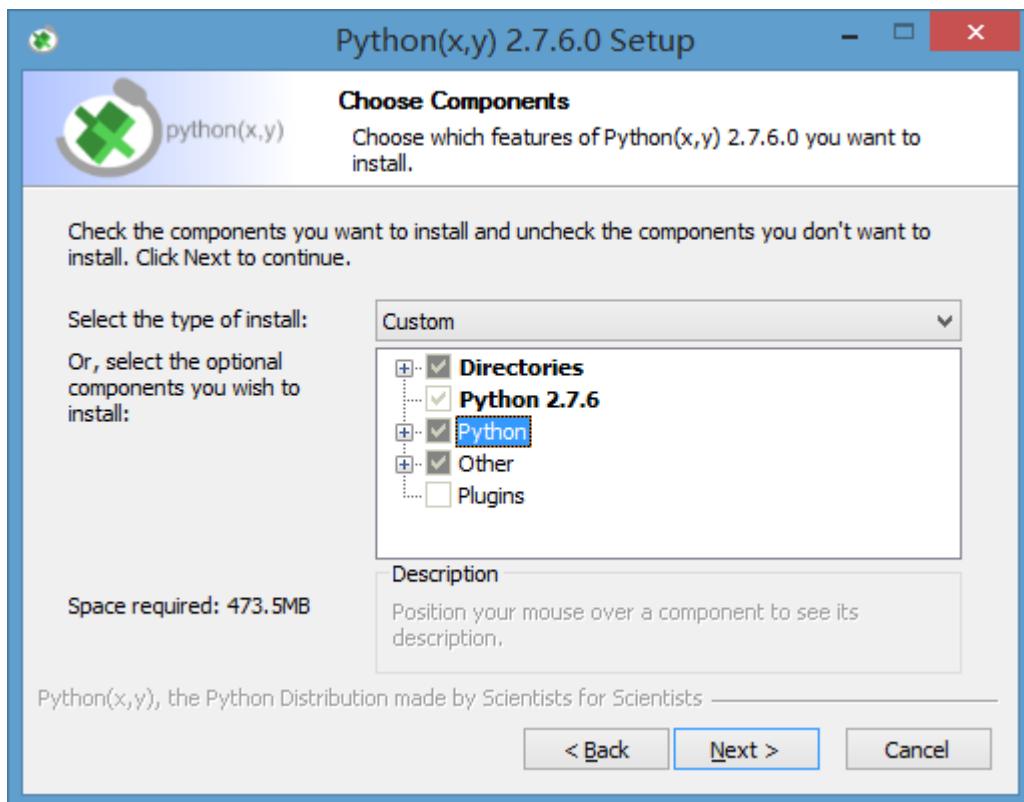
You can download “Python(xy)” from our website. Double click the Installation file to start installation.



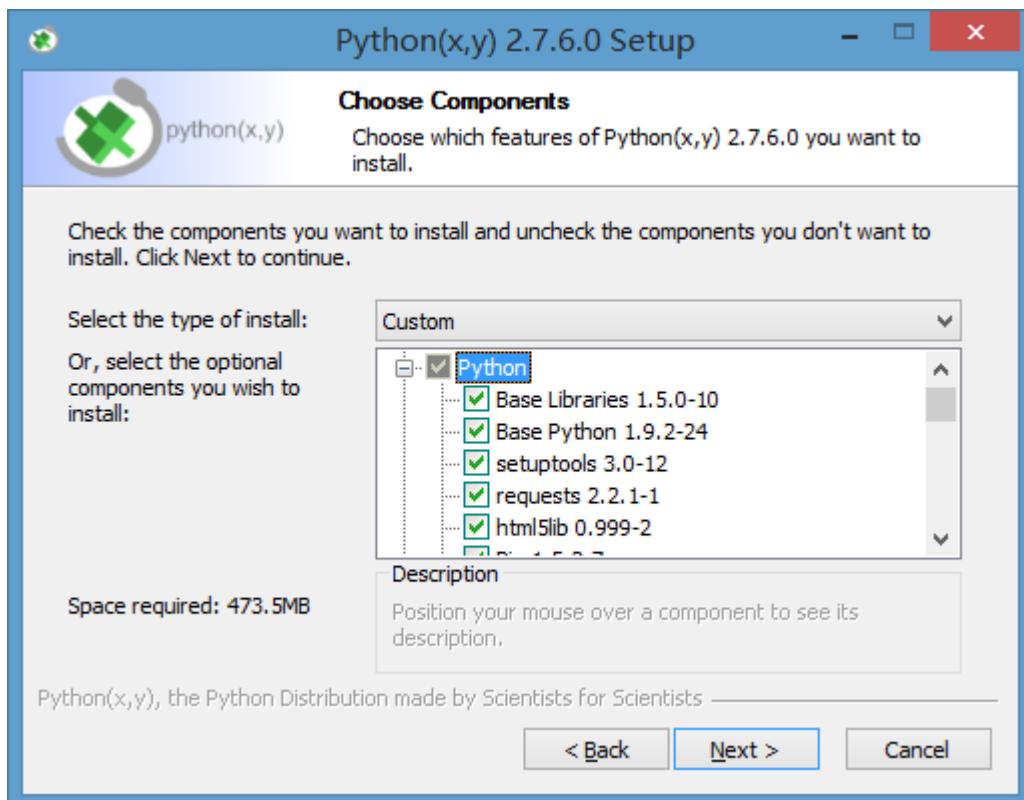
Click "I Agree" to continue.



Click "Next" to continue.



Choose “Custom” type to install.



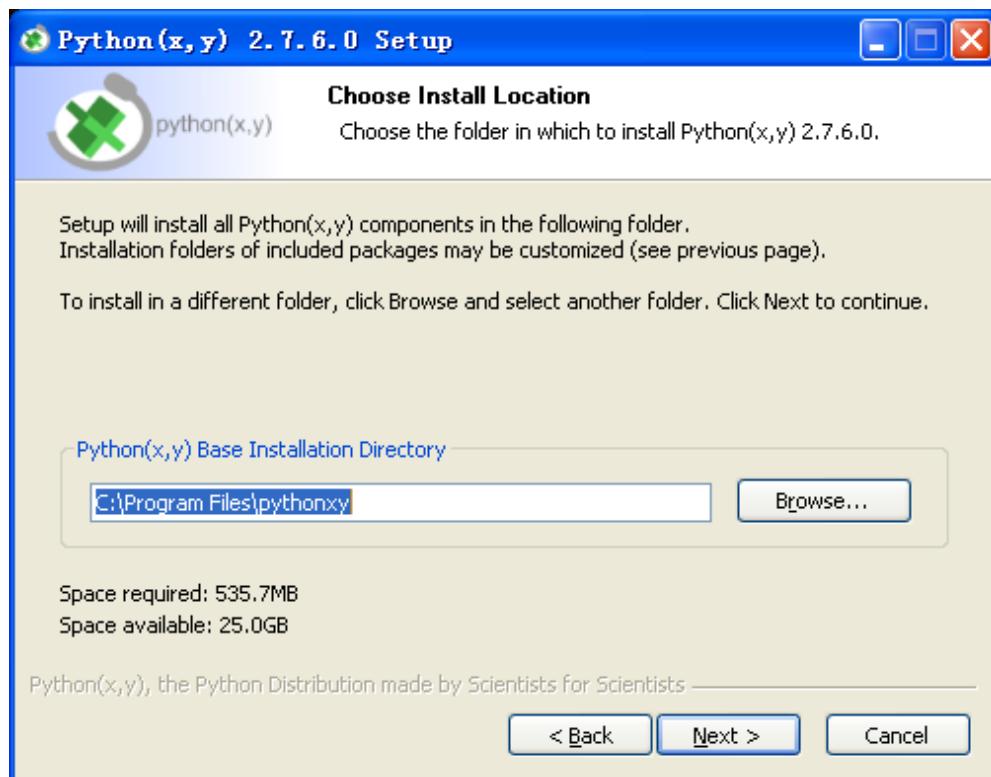
For “Python” option, you must check all the package UQ-PyL needed.

“

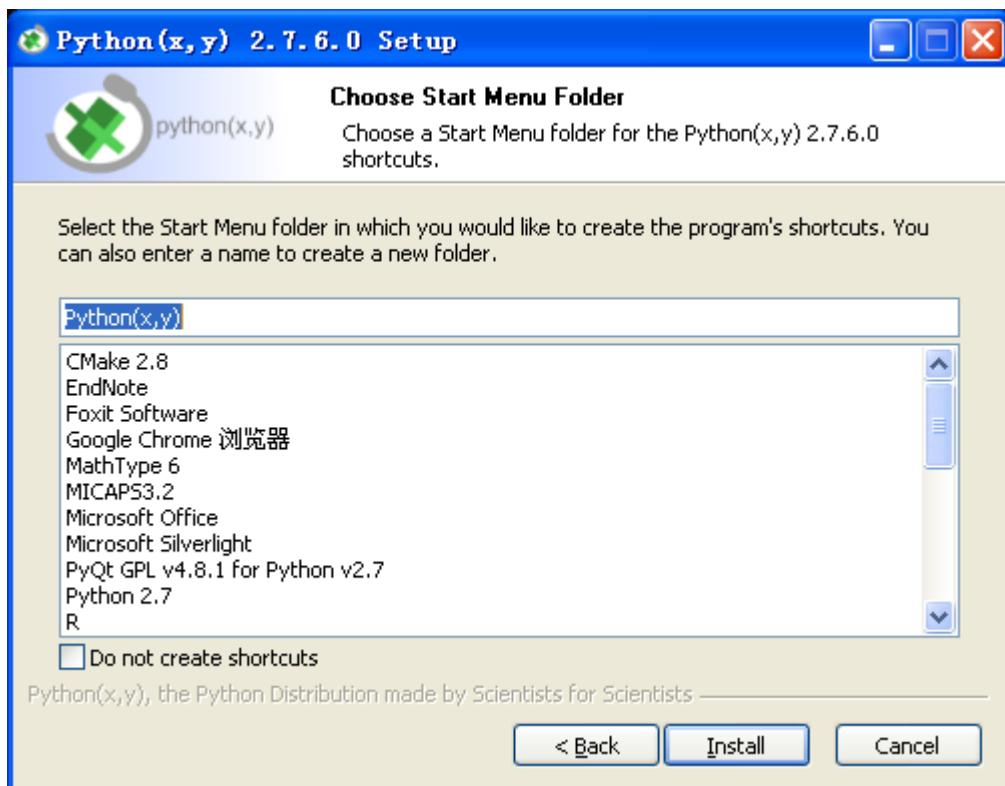
PyQt 4.9.6-4

NumPy 1.8.0-5
Scipy 0.13.3-6
Matplotlib 1.3.1-4
Scikit-learn 0.14.1-4 (**Please note: this one is not checked by default**)
"

Click "Next" to continue.



Click "Next" to continue.

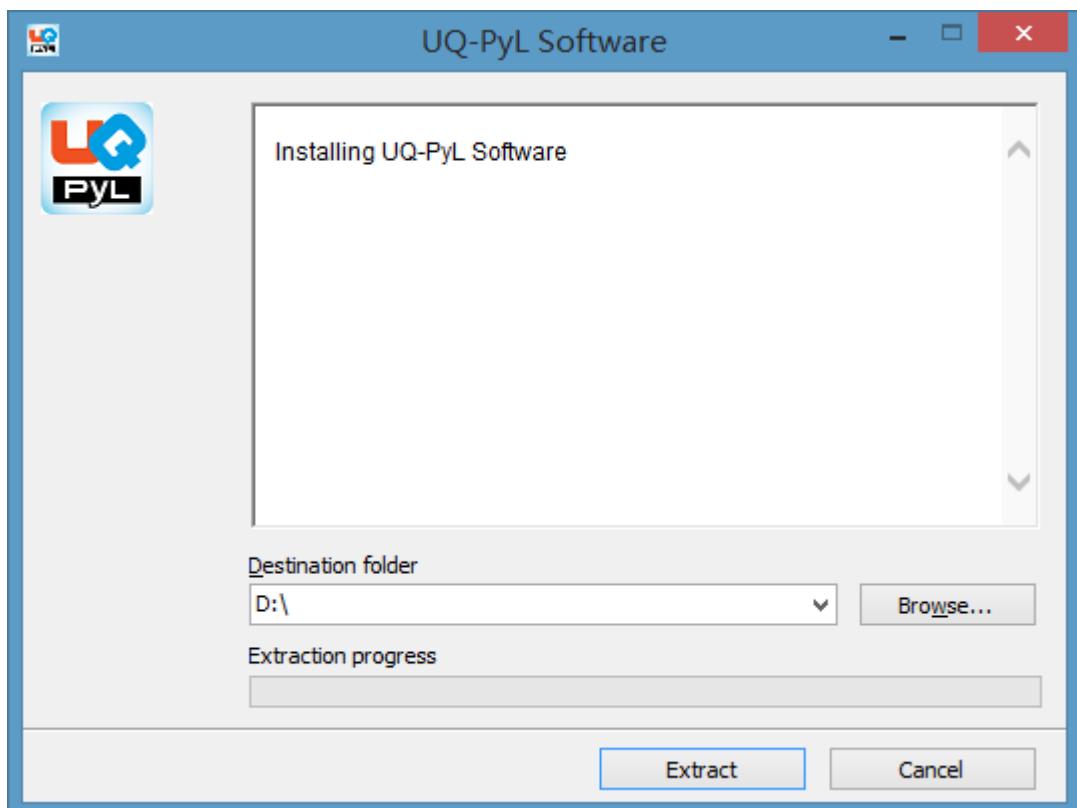


Click “Install”, then waiting for the installation process.

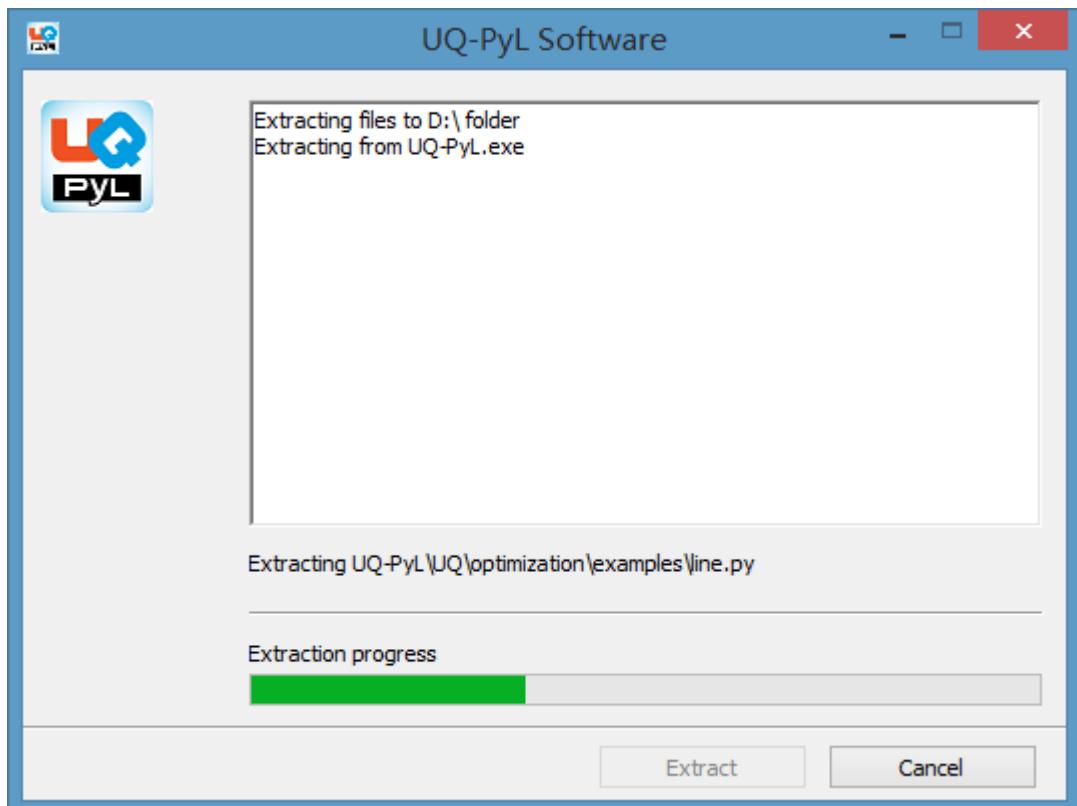
After installation, you executable python.exe file will be C:\Python27\python.exe. All the package will be in the C:\Python27\Lib\site-packages directory.

Step 2. Install UQ-PyL software

Please download UQ-PyL Windows version, double click to run the installation file.



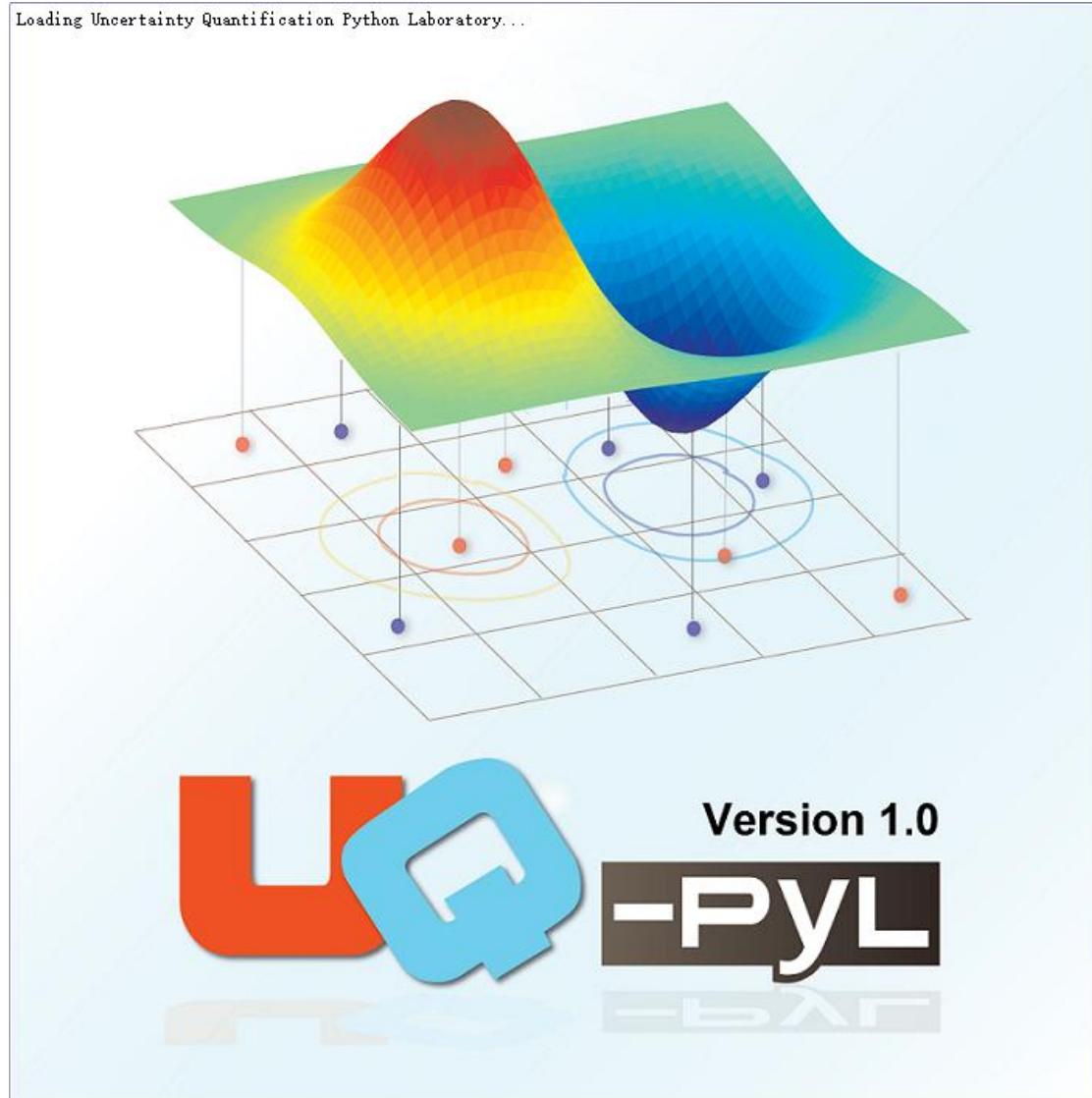
Choose the default directory D:\\ or your own path, then click “unzip” to continue.



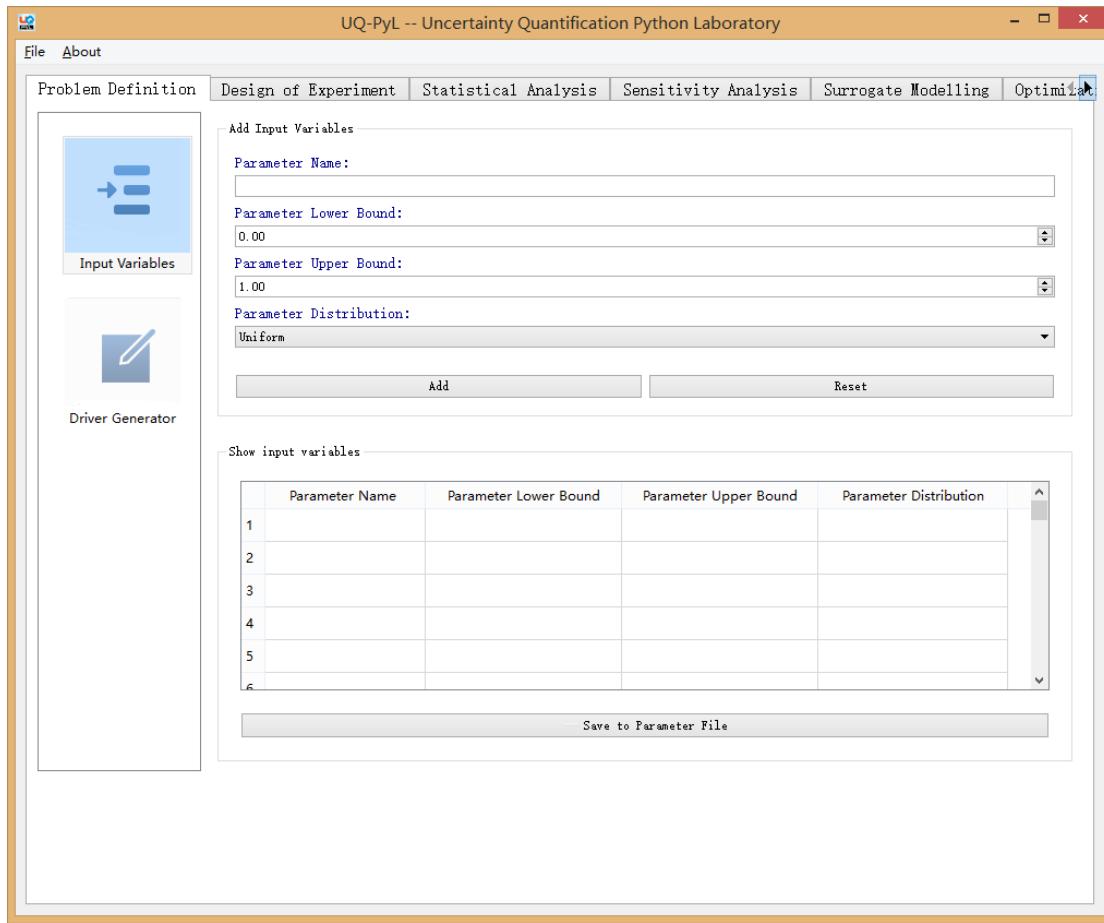
After unzip, there will be two shortcut on the desktop, one is refer to UQ-PyL software main page, the other is refer to interactive version of UQ-PyL software. Double click the shortcuts can start the UQ-PyL software. If the shortcut doesn't work,

please go to your install path, double click the “main.pyw” file or “main_interactive.pyw” file to start these.

In UQ-PyL main page, you can do uncertainty quantification analysis through pull-down menus. In interactive version of UQ-PyL software, you can write python script to run uncertainty quantification analysis and can see output results and internal variables’ values through the software’s interface.



UQ-PyL Splash Page



UQ-PyL Software Main Page

```

1 #!/usr/bin/env python
2 import sys
3 sys.dont_write_bytecode = True
4
5 from UQ_Dof import monte_carlo, normal, sobol, lhs, box_behnenken, central_composite, fast_sampler,
6 ffn, finite_diff, frac_fact, full_fact, morris_cat, plackett_burman, saltelli, symmetric_LH
7 from UQ_analyse import *
8 from UQ_optimization import GP, SWR, DTL, KNN, BayesianRidge,
9 OrdinaryLeastSquares, LAR, Lasso, Ridge, SGD, RF
10 from UQ_optimization import SCE, ABCD
11 from UQ_test_functions import Sobol_G, SMC
12 from UQ_optimization import scale_samples_general, read_param_file, discrepancy
13 import numpy as np
14 import random as rd
15
16 # Examples: Run Sobol, Morris, or FAST on a test function
17 # The parameters shown for each method are also the default values if omitted
18
19 # Set random seed (does not affect quasi-random Sobol sampling)
20 seed = 12345
21 np.random.seed(seed)
22 rd.seed(seed)
23
24 # Read the parameter sample file and generate samples
25 param_file = './UQ/test_functions/params/Sobol_G.txt'
26 pf = read_params_file(param_file)
27
28 # Generates samples (choose method here)
29 # param_values = monte_carlo.sample(500, pf['num_vars'])
30 # param_values = normal.sample(100, pf['num_vars'])
31 # param_values = sobol.sample(100, pf['num_vars'])
32 # param_values = halton.sample(100, pf['num_vars'])
33 # param_values = central_composite.sample(100, pf['num_vars'], calc_second_order = True)
34 param_values = morris_cat.sample(100, pf['num_vars'], num_levels = 4, grid_jump = 2)
35 # param_values = fast_sampler.sample(100, pf['num_vars'])
36 # param_values = symmetric_LH.sample(500, pf['num_vars'])
37 # param_values = lhs.sample(1000, pf['num_vars'])
38 # param_values = full_fact.sample((10,3,1))
39 # param_values = ffn.sample(8)
40 # param_values = frac_fact.sample("a ab")
41 # param_values = plackett_burman.sample(pf['num_vars'])
42 # param_values = saltelli.sample(1000, pf['num_vars'])
43 # param_values = box_behnenken.sample(1000)
44 # param_values = central_composite.sample(3)
45 # param_values = finite_diff.sample(1000, param_file, delta=0.001)
46 # rss = discrepancy.evaluate(param_values)
47 # print rss
48

```

Key Type Size Value
 V float_ (90) array([0.92016797, 0.93247791, 1.17311737, 0.65173187, 0.64312815, ...
 p_ str 1 ./UQ/test_functions/params/Sobol_G.txt
 p_ float_ (90,) array([0.66666667, 0. , 0.33333333, 0.66666667, 1. , ...
 pf dict 3 {'num_vars': 8, 'names': ['x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8'], 'bound ...
 s_ int 1 1

Spyder 2.2.5 internal shell on Python 2.7.6 32bits [Windows]
 >>> DiUQ-PyL/UQoptimization/SCE.py:79: SyntaxWarning: name 'functn' is assigned to before global declaration
 global functn
 DiUQ-PyL/UQoptimization/SCE.py:131: SyntaxWarning: name 'functn' is assigned to before global declaration
 global functn

Interactive UQ-PyL Software

2.2.2 Linux platform

Canopy is a globally recommended Python distribution. It contains Python and 100+ common built-it packages. It also contains all the package UQ-PyL used in one software. So you can install Canopy for all the dependences UQ-PyL needed. Please go to the official website (<https://www.enthought.com/products/canopy/>) for more information.

Step 1. Install Canopy software.

Canopy is a commercial software. However, it provide free use for academic usage. If you use Canopy for education or academic, you can download canopy-1.5.5-full-rh5-64.sh from our website or from Canopy official website. After downloading, you should install Canopy by steps below:

```
chmod 755 canopy-1.5.5-full-rh5-64.sh  
./canopy-1.5.5-full-rh5-64.sh
```

```
Welcome to the Canopy 1.5.5 installer!  
  
To continue the installation, you must review and approve the license term  
agreement.  
Press Enter to continue  
>>> [ ]
```

If you approve the license term, press Enter to continue

Canopy Product	License
Express	Canopy Express Software License Agreement
Basic & Professional	Canopy Subscription License Agreement
Academic	Canopy Software License for Academic Use

Please review your applicable license carefully.
By installing or using a Canopy product you
signify your assent to and acceptance of the
terms of the applicable license to Canopy. If
you do not accept the terms of the applicable
license, then you must not use the Canopy
products. Should you have any questions
regarding licensing, please contact us at
support@enthought.com.

ENTHOUGHT CANOPY EXPRESS

Software License Agreement

This Enthought Canopy Express Software License
Agreement (the "Agreement") is between Enthought,
Inc., a Delaware corporation ("Enthought"), and
the licensee subscriber who accepts the terms of
this Agreement (the "Customer"). The effective

Do you approve the license terms? [yes|no]
[no] >>> yes

Type "yes" then press Enter to continue.

```
Canopy will be installed to this location:  
/home/quanjp/Canopy  
  
* Press Enter to accept this location  
* Press CTRL-C to abort  
* or specify an alternate location. Please ensure that your location  
contains only ASCII letters, numbers, and the following punctuation  
chars: '.', '_', '-'  
  
[/home/quanjp/Canopy] >>> /home/quanjp/swgfs/software/Canopy
```

Type the path you want to install Canopy, then press Enter to continue.

```

Installing to /home/quanjp/swgfs/software/Canopy ... please wait
Must specify the vendor namespace for these files with --vendor
No directories in update-desktop-database search path could be processed and updated.
***
* Updating MIME database in /home/quanjp/.local/share/mime...
Wrote 2 strings at 20 - 44
Wrote aliases at 44 - 48
Wrote parents at 48 - 4c
Wrote literal globs at 4c - 50
Wrote suffix globs at 50 - 108
Wrote full globs at 108 - 10c
Wrote magic at 10c - 118
Wrote namespace list at 118 - 11c
***
done.

You can run the Canopy graphical environment by running the script:

/home/quanjp/swgfs/software/Canopy/canopy

or by selecting 'Canopy' in your Applications menu.

On your first run, your Canopy User Python environment will be initialized,
and you will have the opportunity to make Canopy be your default Python
at the command line. Details at support.enthought.com/forums

Thank you for installing Canopy!

```

Complete to install Canopy.

Step 2: Setting up Canopy environment

Enter into the Canopy directory, for me is “/home/quanjp/swgfs/software/Canopy”, you can see the file inside it.

```

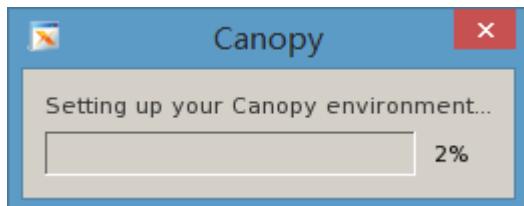
[quanjp@login02 Canopy]$ ll
total 336
drwxrwxr-x 3 quanjp quanjp 32768 Jul  4 07:23 appdata
drwxrwxr-x 2 quanjp quanjp 32768 Jul  4 07:23 bin
-rw-rw-r-- 1 quanjp quanjp 27157 Jul  4 06:41 __boot__.py
-rwxr-xr-x 1 quanjp quanjp    92 Jul  4 06:41 canopy
-rwxr-xr-x 1 quanjp quanjp    92 Jul  4 06:41 canopy_cli
-rwxrwxr-x 1 quanjp quanjp   401 Jul 31 14:06 canopy_desktop
-rw-rw-r-- 1 quanjp quanjp   394 Jul 31 14:06 canopy-mime.xml
-rw-rw-r-- 1 quanjp quanjp  9704 Jul  4 06:42 canopy.png
drwxrwxr-x 2 quanjp quanjp 32768 Jul  4 07:23 EXTRA-REPO
drwxrwxr-x 3 quanjp quanjp 32768 Jul  4 07:23 lib

```

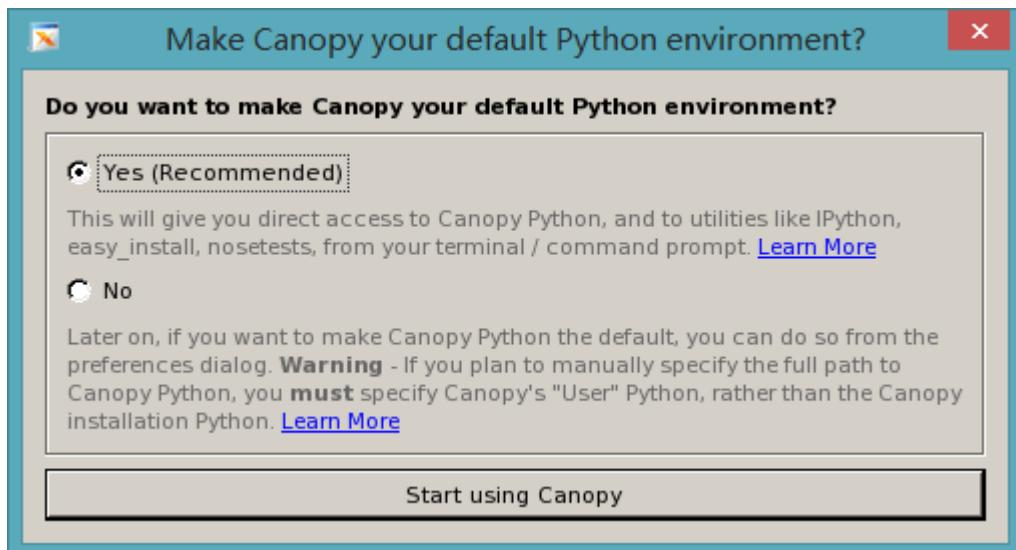
Run “./canopy” to setting up Canopy software



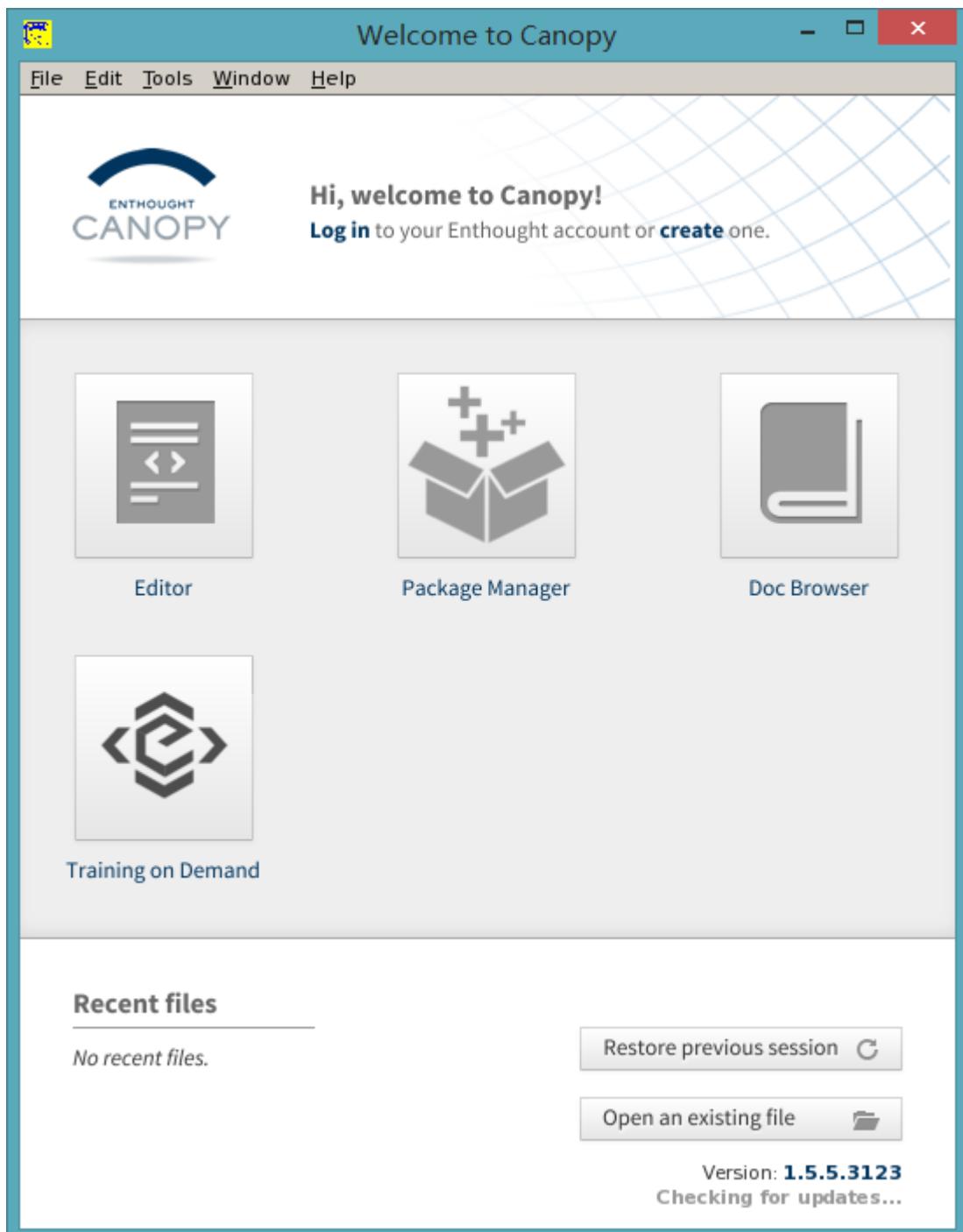
Enter the Canopy environment directory, for me is “/home/quanjp/swgfs/software/Python”, click “Continue” to continue. Your python installation will in this directory.



After that, a dialogue will display,



Choose “Yes”, then click “Start using Canopy”.



In “Package Manager” section, you can check what packages in your Python library now.

Actually, you can check your python installation in your python installation path. All files are in “YourPythonPath/User/” (for me is /home/quanjp/swgfs/software/Python/User/). The python executable file is in “YourPythonPath/User/bin/” and all the packages are installed in “YourPythonPath/User/lib/python2.7/site-packages/”.

Step 3: Test your Python installation

If you have multiple python environment, please specific one. Usually, modify

your .bashrc file can do it.

Add two sentence into your .bashrc file:

```
export PYTHON=/home/quanjp/swgfs/software/Python/User/bin  
export PATH=$PATH:$PYTHON:
```

Then enter command “source .bashrc” to make your .bashrc file renew.

Type “python” or “python2.7” command, if you can see “Enthought Canopy Python” that means you already accomplished the installation.

```
Enthought Canopy Python 2.7.9 | 64-bit | (default, Jun 30 2015, 22:40:22)  
[GCC 4.1.2 20080704 (Red Hat 4.1.2-55)] on linux2  
Type "help", "copyright", "credits" or "license" for more information.  
>>> [REDACTED]
```

You can check if all the packages UQ-PyL needed are already installed. Using “import” command, if no error messages that means you already have all the packages.

```
Enthought Canopy Python 2.7.9 | 64-bit | (default, Jun 30 2015, 22:40:22)  
[GCC 4.1.2 20080704 (Red Hat 4.1.2-55)] on linux2  
Type "help", "copyright", "credits" or "license" for more information.  
>>> import numpy  
>>> numpy.__version__  
'1.9.2'  
>>> import scipy  
>>> scipy.__version__  
'0.15.1'  
>>> import matplotlib  
>>> matplotlib.__version__  
'1.4.3'  
>>> import sklearn  
>>> sklearn.__version__  
'0.16.1'  
>>> import PyQt4  
>>> [REDACTED]
```

Step 4. Install UQ-PyL software

Download UQ-PyL Linux version, unzip the source code using command

```
tar -zxf UQ-PyL_Linux.tar.gz
```

Then enter into the UQ-PyL directory

```
cd UQ-PyL_Linux
```

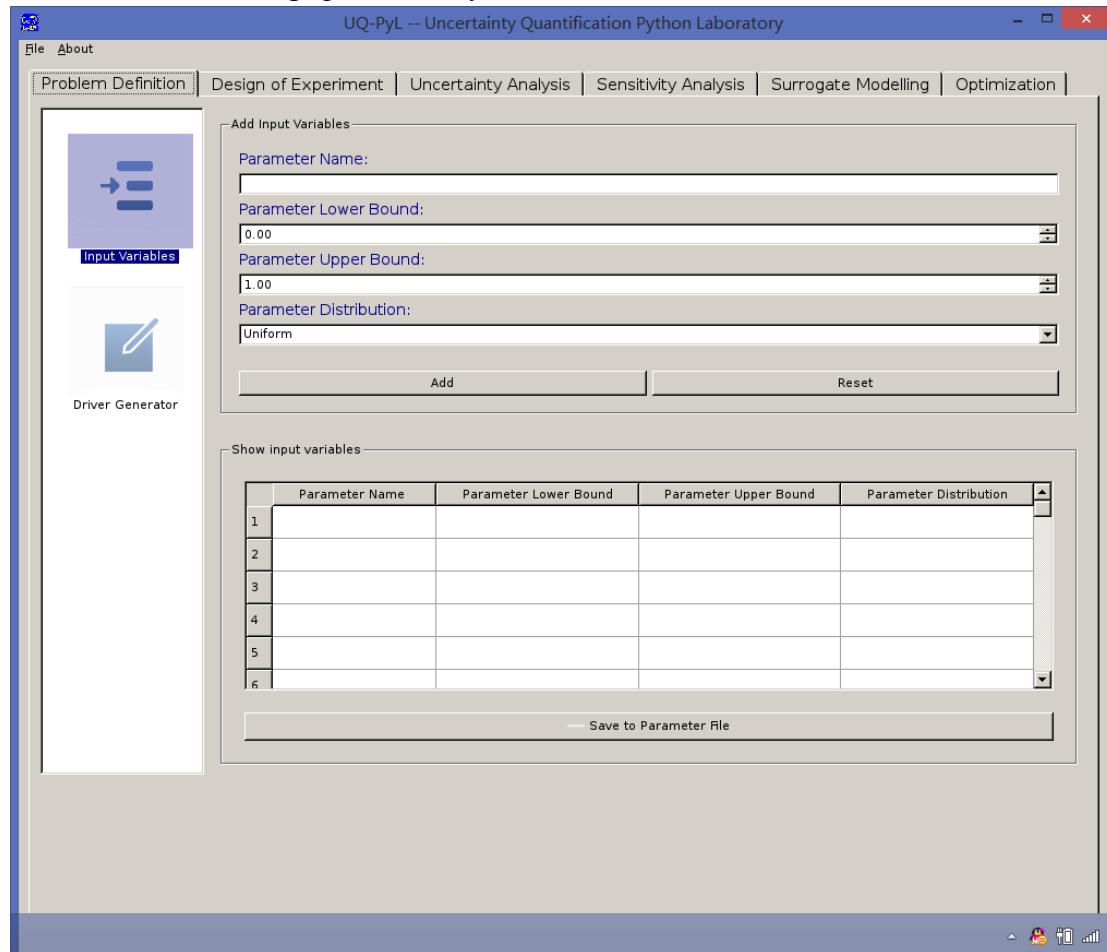
Enter command to run UQ-PyL main page

```
python main.pyw (or python2.7 main.pyw)
```

Or Interactive UQ-PyL Software

python main_interactive.pyw (or python2.7 main_interactive.pyw)

You can see the main page of UQ-PyL software.



2.2.3 MacOS platform

For MacOS platform, Canopy also has a MacOS version. You can download Canopy software and UQ-PyL MacOS version from our website. The installation process is very similar with Linux platform.

Step 1. Install Canopy software.

First, double click the .dmg file to start the installation.

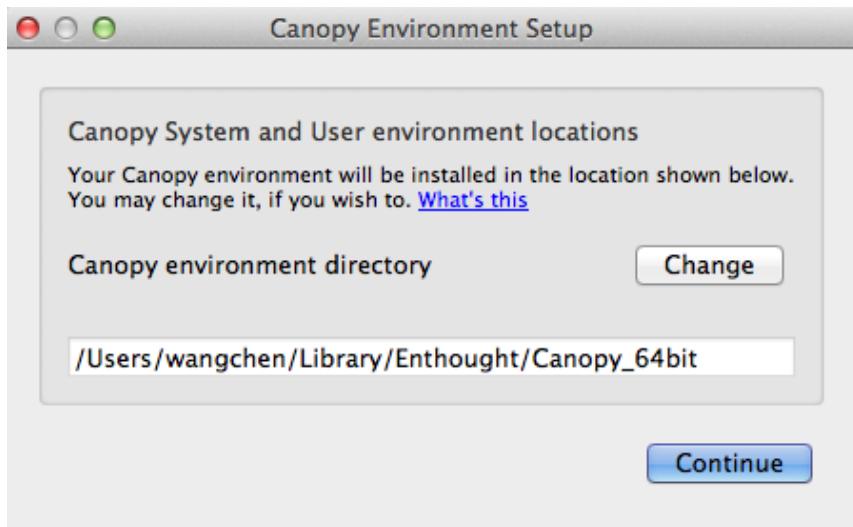


Pull Canopy icon to Application folder.

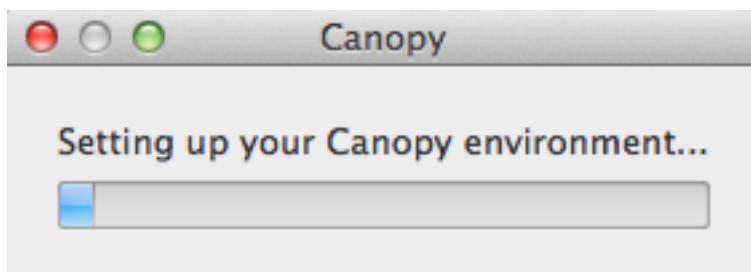


Step 2: Setting up Canopy environment

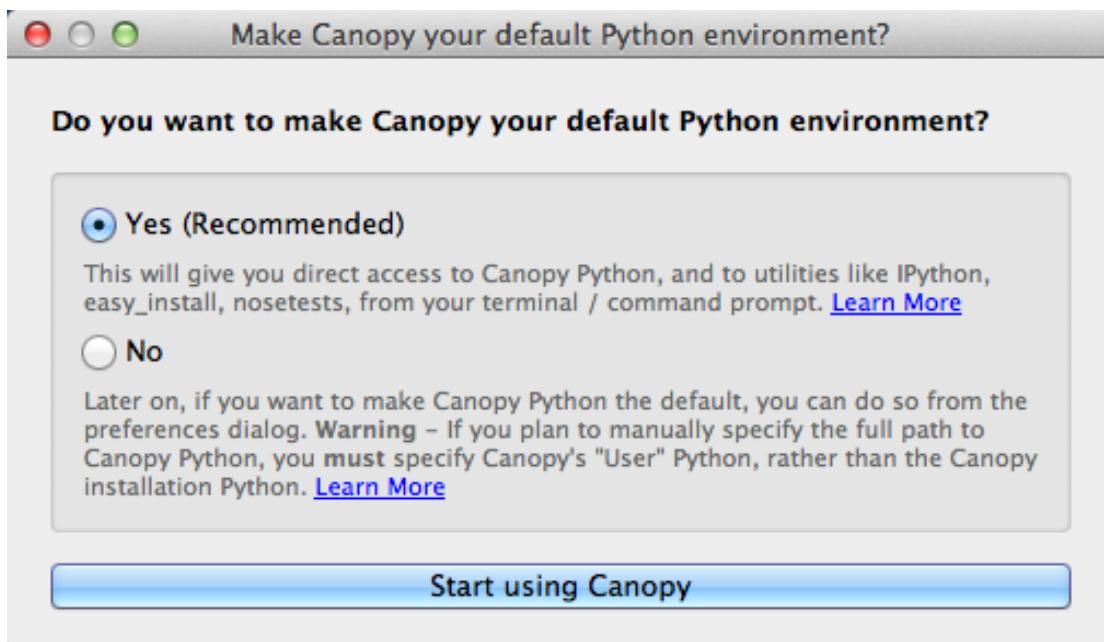
Double click “Canopy” icon to start setting Canopy environment.



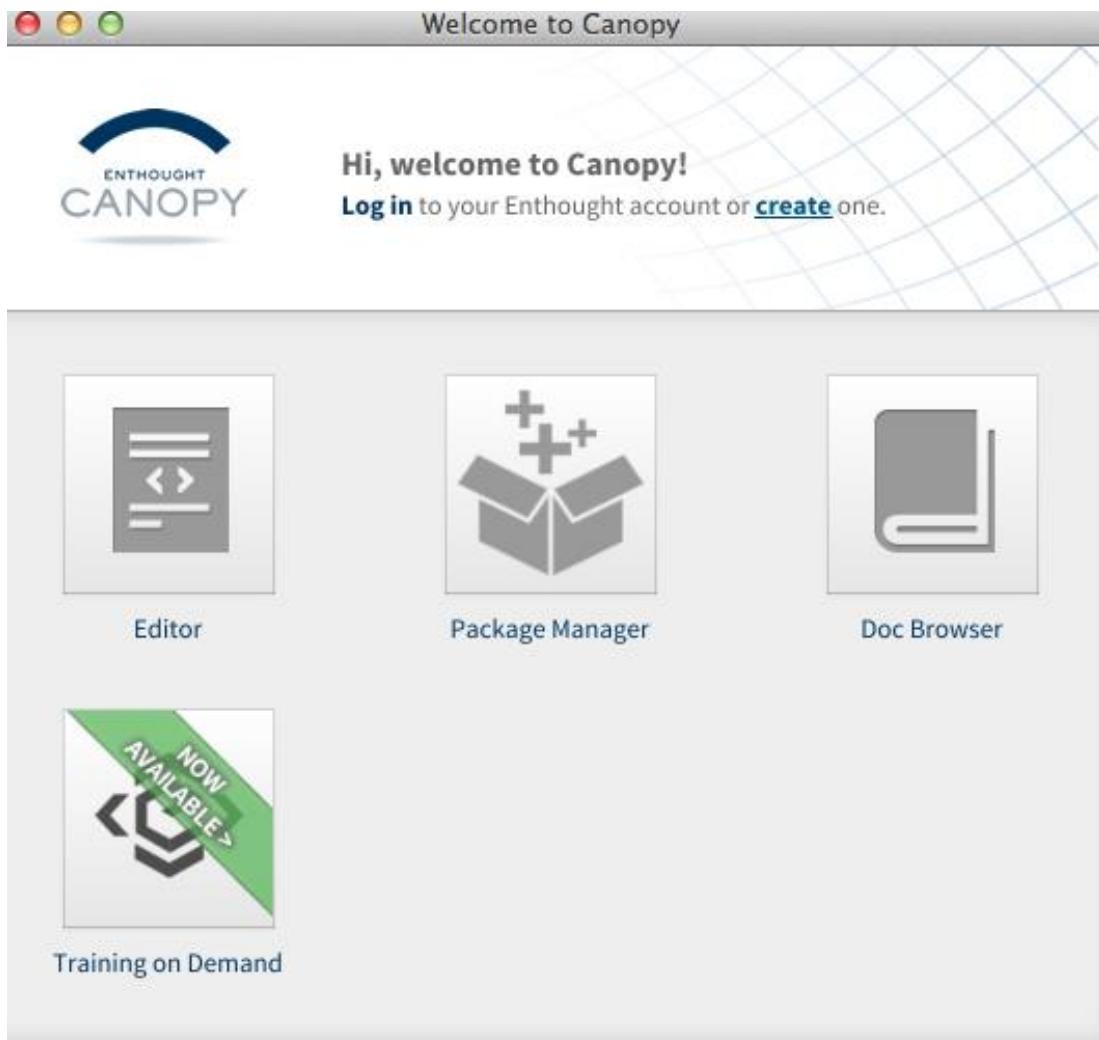
Write Canopy environment directory, click “Continue” to continue. Your python installation will be in this directory.



After that, a dialogue will display,



Choose “Yes”, then click “Start using Canopy”.



Recent files

No recent files.

Restore previous session

Open an existing file

Version: 1.5.5.3123

No updates found.

Also, you can check your python installation in your python installation path. All files are in “YourPythonPath/User/” (for me is /Users/wangchen/Library/Enthought/Canopy_64bit/User/). The python executable file is in “YourPythonPath/User/bin/”.

Step 3: Test your Python installation

If you have multiple python environment, please specific one. For MacOS you could add a line like this to the /etc/launchd.conf file

```
export PYTHONPATH=/Users/wangchen/Library/Enthought/Canopy_64bit/User/bin
```

Then enter command “source launchd.conf” to make your launchd.conf file renew.

Type “python” or “python2.7” command, if you can see “Enthought Canopy Python” that means you already accomplished the installation.

```
ouchenmatoMacBook-Pro:UQ-PyL_Linux wangchen$ python
Enthought Canopy Python 2.7.9 | 64-bit | (default, Jun 30 2015, 19:41:21)
[GCC 4.2.1 (Based on Apple Inc. build 5658) (LLVM build 2335.6)] on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>> █
```

Step 4. Install UQ-PyL software

Download UQ-PyL MacOS version, unzip the source code using command

```
tar -zxf UQ-PyL_Mac.tar.gz
```

Then enter into the UQ-PyL directory

```
cd UQ-PyL_Mac
```

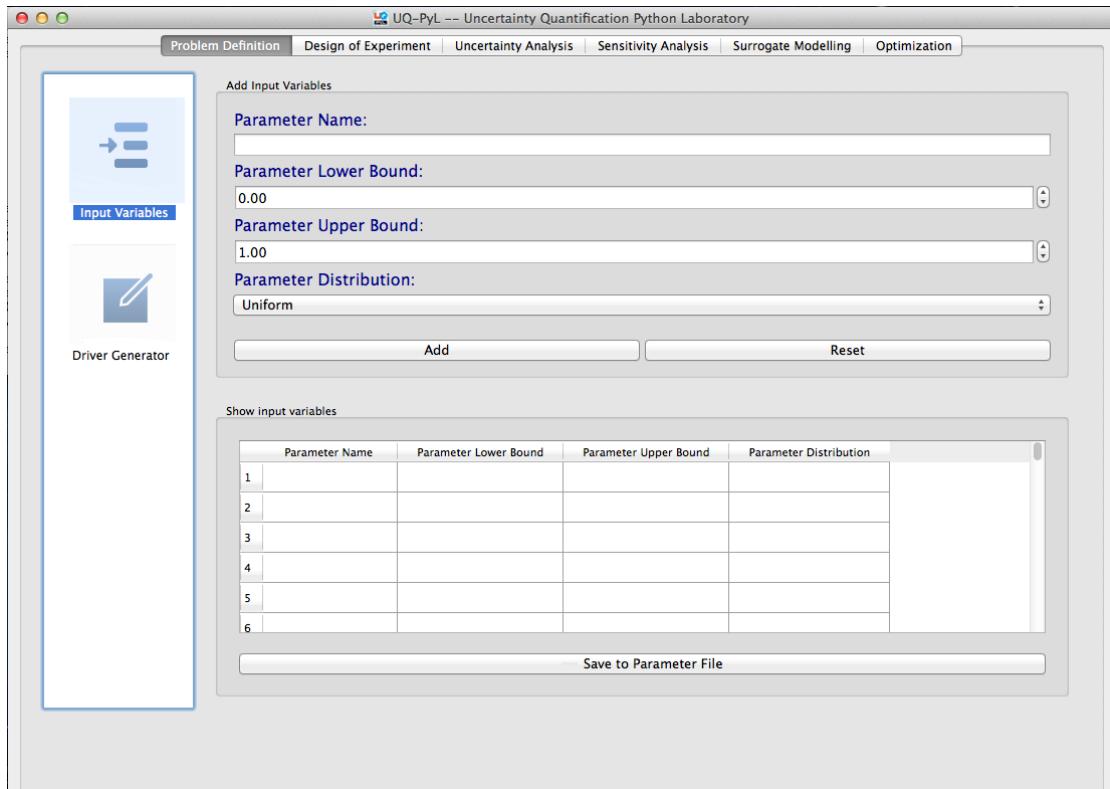
Enter command to run UQ-PyL main page

```
python main.pyw (or python2.7 main.pyw)
```

Or run Interactive UQ-PyL Software

```
python main_interactive.pyw (or python2.7 main_interactive.pyw)
```

You can see the main page of UQ-PyL software.



3 Using UQ-PyL

3.1 UQ-PyL Flowchart

Fig. 1 is the flowchart illustrating how UQ-PyL executes an UQ task. A typical task is carried out in three major steps: (1) model configuration preparation; (2) uncertainty propagation; and (3) UQ analysis. In the first step, the user specifies the model configuration information (i.e., parameter names, ranges and distributions), and the DoE information (i.e., the sampling techniques and sample sizes) to prepare for UQ exercise for a given problem. In the second step, the different sample parameter sets generated in the last step are fed into the simulation model (or mathematical function) to enable the execution of simulation model (function calculation). In the third step, a variety of UQ exercises are carried out, including statistical analysis, SA, surrogate modelling and parameter optimization.

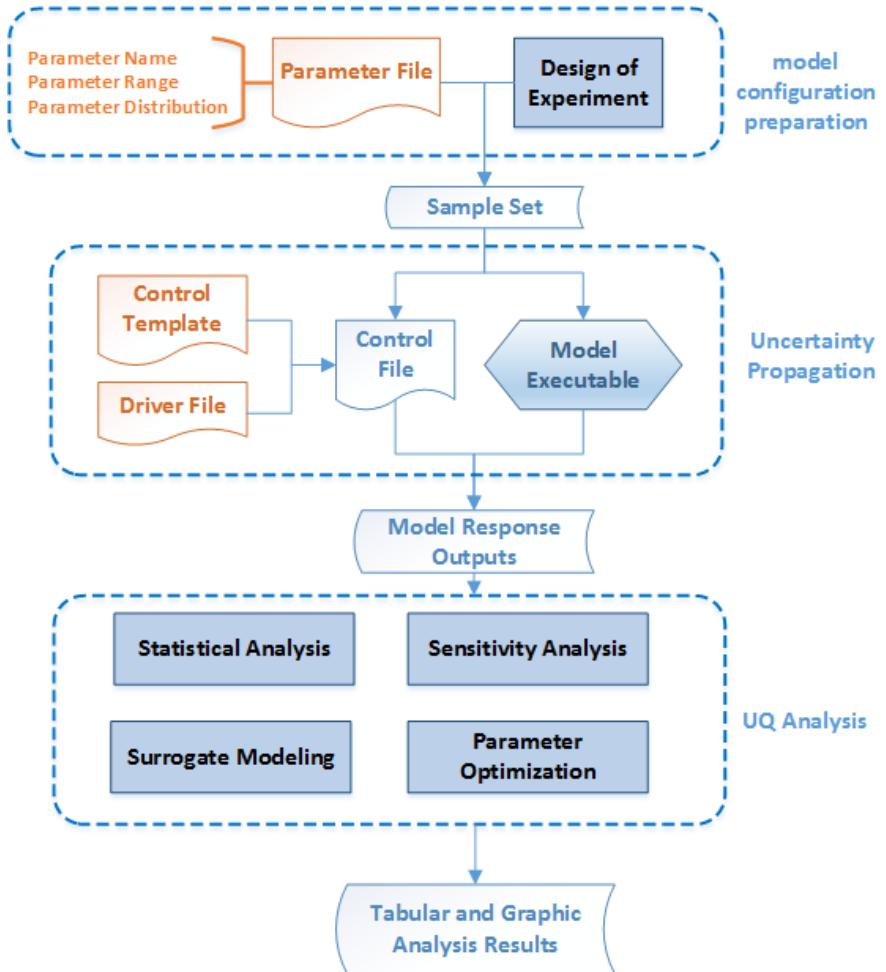


Fig 1. UQ-PyL flowchart

3.2 UQ-PyL Main Frame

UQ-PyL is equipped with a Graphic User Interface (GUI) to facilitate execution of various functions, but it can also run as a script program in a batch mode. Fig. 2 shows the main page of UQ-PyL. Different tab widgets allow user to execute different steps of UQ process, including problem definition, DoE, Statistical Analysis, SA, Surrogate Modeling and Parameter Optimization. One may click on the desired tab by mouse and/or enter the required information via keyboard to perform various tasks. After a task is completed, the software generates tabular results and/or graphical outputs. The graphical outputs can be saved in a variety of formats, including .png, .bmp, .tiff or .pdf formats, among others. Fig. 3 shows the interactive version of UQ-PyL software. In this page, you can write down python script to achieve UQ analysis and run the script to obtain the results. You can see the output results and internal variables' values through the page.

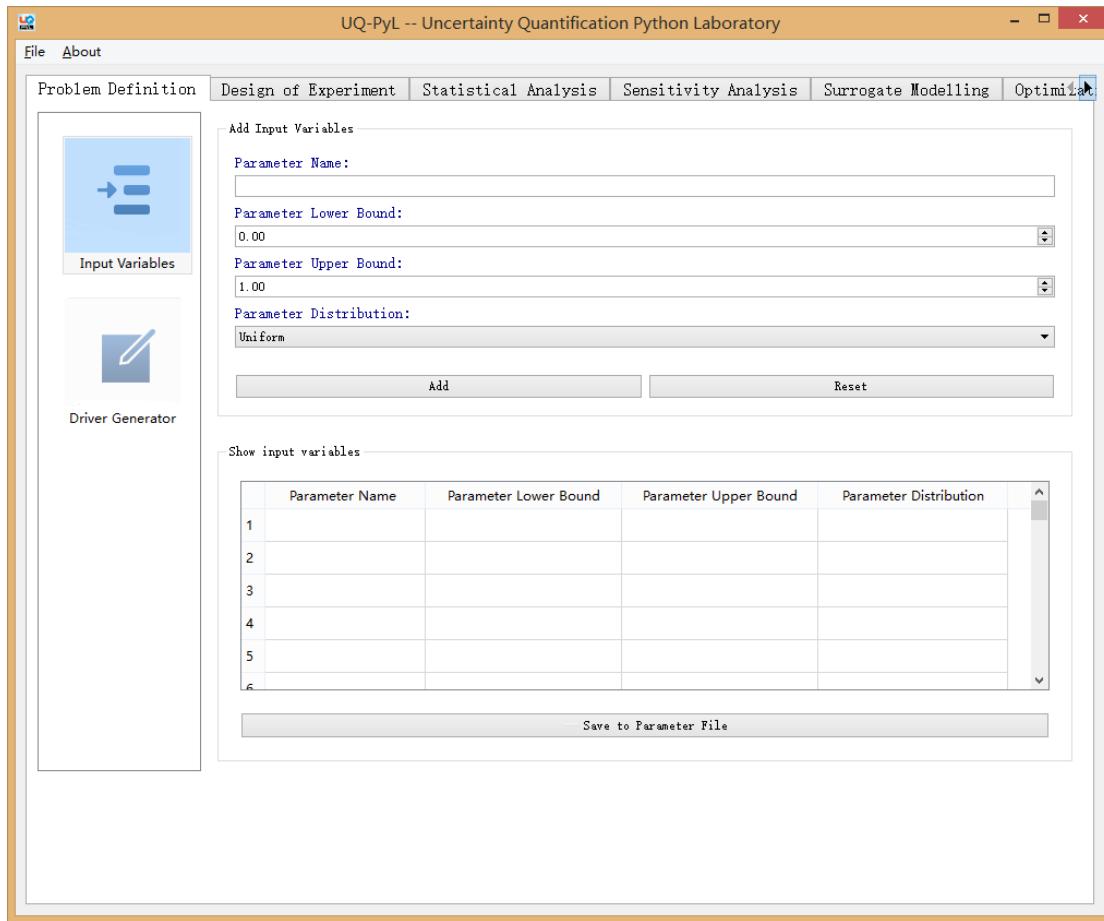


Fig 2. Graphic User Interface of UQ-PyL Main Page

```

# Optional: -E runs off bytecode (.pyc files)
2 import sys
3 sys.dont_write_bytecode = True
4
5 from UQDoF import monte_carlo, normal, sobol, lhs, box_behnenken, central_composite, fast_sampler,
6 ffn, finite_diff, frac_fact, full_fact, morris_cat, placette_burman, saltelli, symmetric_LH
7 from UQ_analyse import *
8 from UQ_optimization import gp, SWV, DTI, KNN, BayesianRidge,
9 OrdinaryLeastSquares, LAR, Lasso, Ridge, SGD, RF
10 from UQ_optimization import SCE, ASMC
11 from UQ-test_functions import Sobol_G, SAC
12 from UQ-test_functions import scale_samples_general, read_param_file, discrepancy
13 import numpy as np
14 import random
15
16 # Examples: Run Sobol, Morris, or FAST on a test function
17 # The parameters shown for each method are also the default values if omitted
18
19 # Set random seed (does not affect quasi-random Sobol sampling)
20 seed = 12345
21 np.random.seed(seed)
22 rd.seed(seed)
23
24 # Read the parameter sample file and generate samples
25 param_file = './UQ/test_functions/params/Sobol_G.txt'
26 pf = read_params_file(param_file)
27
28 # Generates samples (choose method here)
29 # param_values = monte_carlo.sample(500, pf['num_vars'])
30 # param_values = normal.sample(100, pf['num_vars'])
31 # param_values = sobol.sample(100, pf['num_vars'])
32 # param_values = halton.sample(100, pf['num_vars'])
33 # param_values = ffn.sample(100, pf['num_vars'], criterion='center')
34 param_values = ffn.sample(100, pf['num_vars'], calc_second_order = True)
35 param_values = morris_cat.sample(100, pf['num_vars'], num_levels = 4, grid_jump = 2)
36 # param_values = fast_sampler.sample(100, pf['num_vars'])
37 # param_values = symmetric_LH.sample(500, pf['num_vars'])
38 # param_values = lhs.sample(1000, pf['num_vars'])
39 # param_values = full_fact.sample((10,3,1))
40 # param_values = ffn.sample(8)
41 # param_values = frac_fact.sample("a ab")
42 # param_values = placette_burman.sample(pf['num_vars'])
43 # param_values = box_behnenken.sample(100)
44 # param_values = central_composite.sample(3)
45 # param_values = finite_diff.sample(1000, param_file, delta=0.001)
46 # rss = discrepancy.evaluate(param_values)
47 # print rss
48

```

Fig 3. Interactive Version of UQ-PyL Software

4 Examples

4.1 Sobol' g-function

4.1.1 Problem Definition

The expression of sobol' g-function is:

$$f(x) = \prod_{i=1}^n g_i(x_i)$$

where

$$g_i(x_i) = \frac{|4x_i - 2| + a_i}{1 + a_i}$$

The input parameter x_i is uniformly distributed within $(0, 1)$, $a_i = \{0, 1, 4.5, 9, 99, 99, 99, 99\}$.

The model is implemented using Python and the parameter file is shown below:

Model file (UQ-PyL/UQ/test_functions/Sobol_G.py)

```
from __future__ import division
import numpy as np

# Non-monotonic Sobol' G Function (8 parameters)
# First-order indices:
# x1: 0.7165  77.30%
# x2: 0.1791  19.32%
# x3: 0.0237  2.56%
# x4: 0.0072  0.78%
# x5-x8: 0.0001  0.01%

def predict(values):
    a = [0, 1, 4.5, 9, 99, 99, 99, 99]
    Y = np.empty([values.shape[0]])

    for i, row in enumerate(values):
        Y[i] = 1.0

        for j in range(8):
            x = row[j]
            Y[i] *= (abs(4*x - 2) + a[j]) / (1 + a[j])

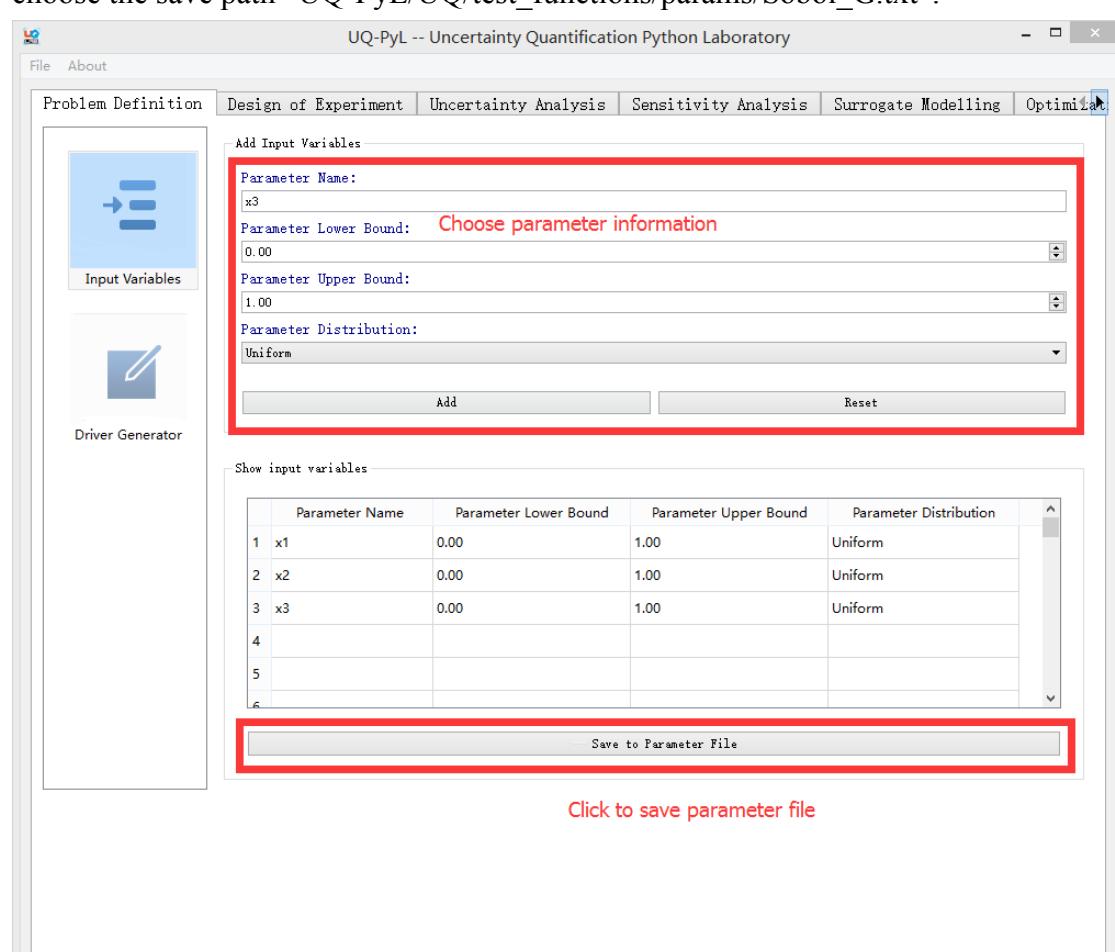
    return Y
```

Parameter file (UQ-PyL/UQ/test_functions/params/Sobol_G.txt)

```
x1 0.0 1.0  
x2 0.0 1.0  
x3 0.0 1.0  
x4 0.0 1.0  
x5 0.0 1.0  
x6 0.0 1.0  
x7 0.0 1.0  
x8 0.0 1.0
```

Parameter file can also be generated from GUI of UQ-PyL:

- Step 1: Enter “Parameter Name”, “Parameter Lower Bound” and “Parameter Upper Bound”, choose “Parameter Distribution”;
- Step 2: Click “Add” button to save this parameter information to table widget;
- Step 3: Enter every parameter’s information, click “Save to Parameter File” button, choose the save path “UQ-PyL/UQ/test_functions/params/Sobol_G.txt”.

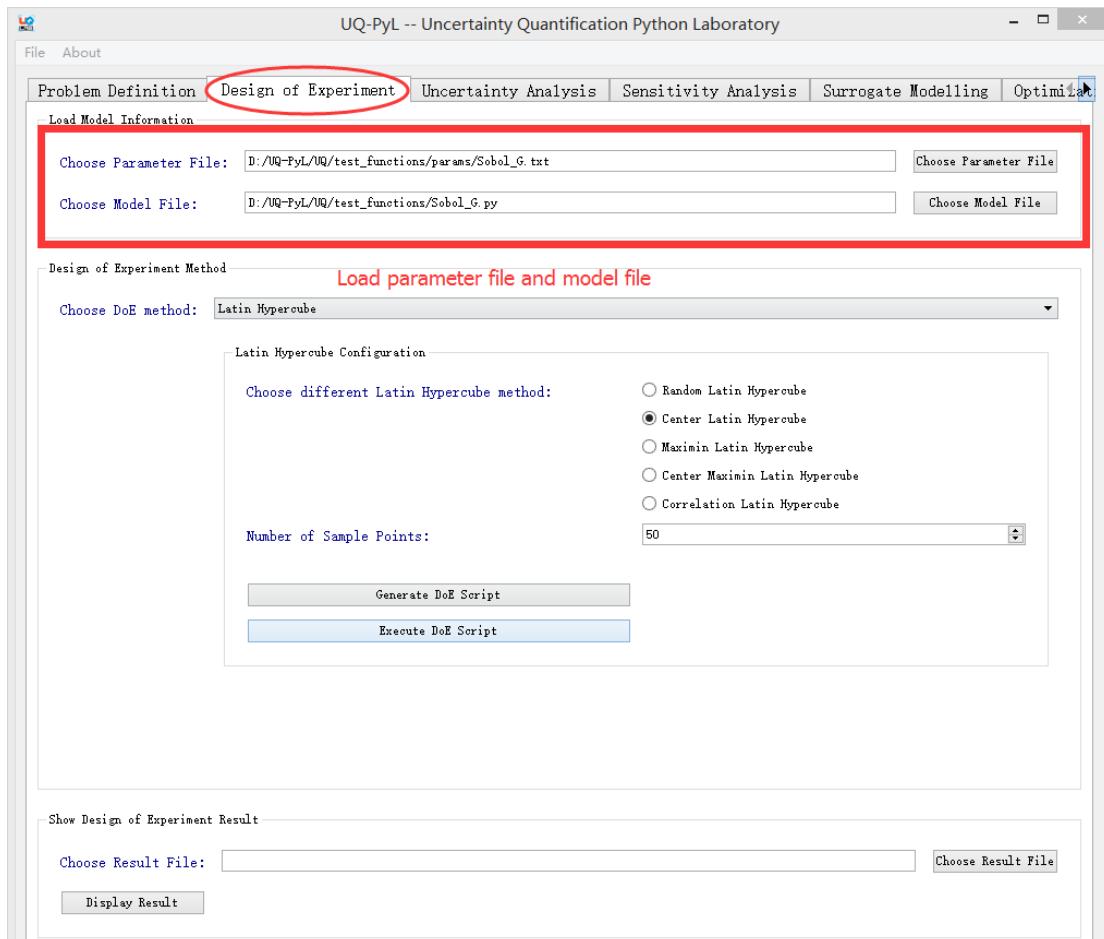


4.1.2 Design of Experiment

After problem definition, we do Design of Experiment, the experiment has three

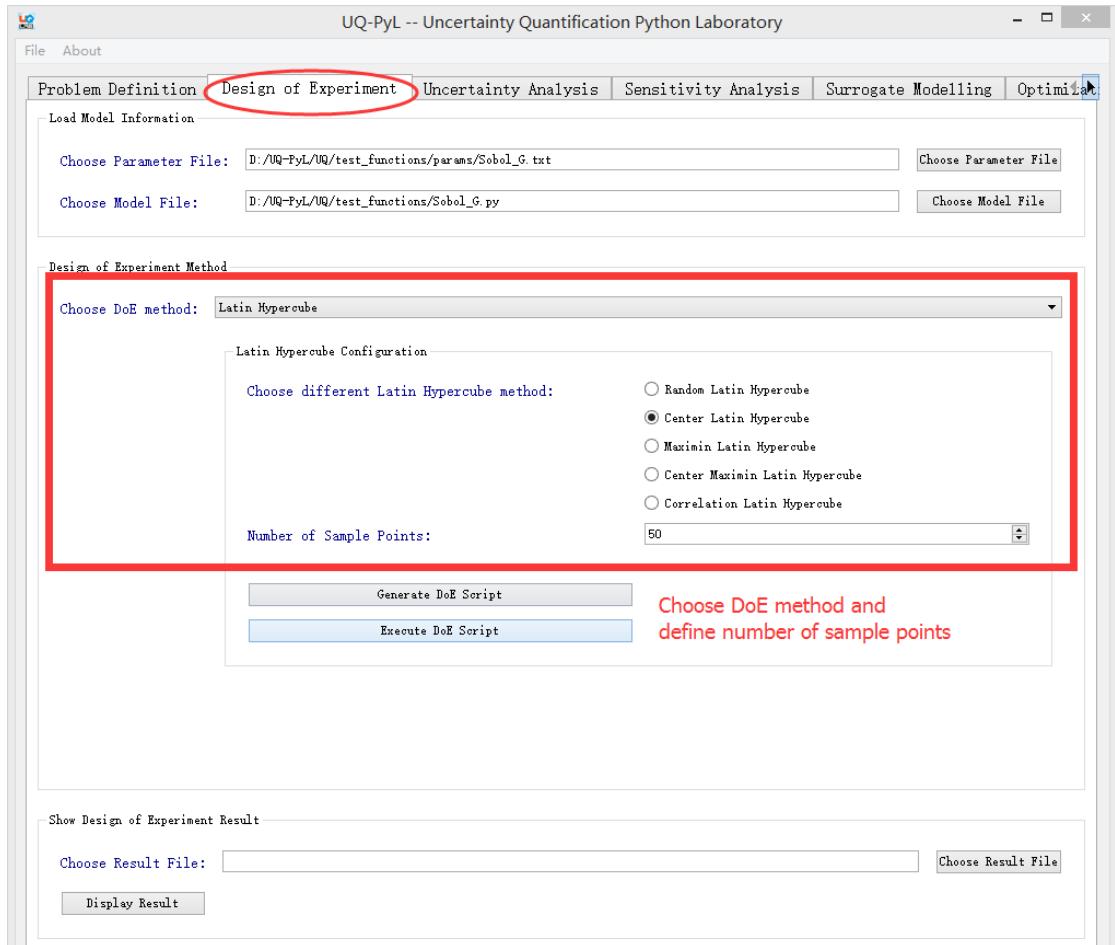
steps:

- 1) Define parameter and model information;
- 2) Choose Design of Experiment method;
- 3) Generate script and run the script.



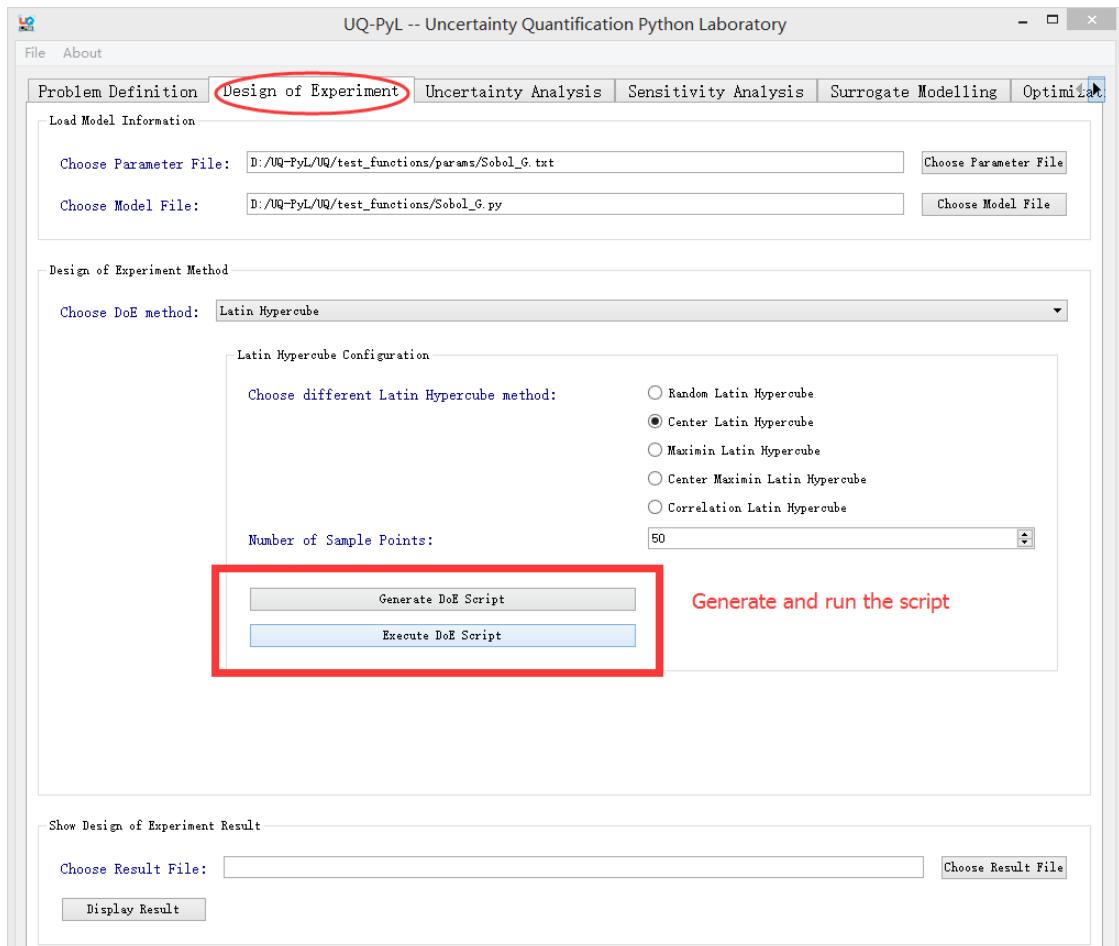
Step 1: Define parameter and model information

- ❖ Switch to “Design of Experiment” tab;
- ❖ Click “Choose Parameter File” button to choose “UQ-PyL/UQ/test_functions/params/Sobol_G.txt” file;
- ❖ Click “Choose Model File” button to choose “UQ-PyL/UQ/test_functions/Sobol_G.py” file.



Step 2: Choose DoE method

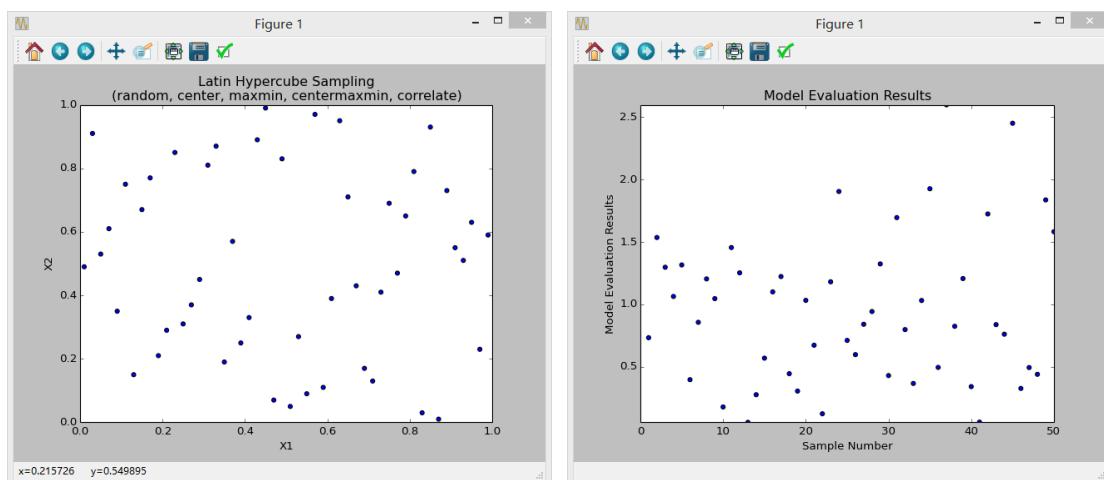
- ✧ Choose DoE method, like “Latin Hypercube”, choose one specific Latin Hypercube method, like “Center Latin Hypercube”;
- ✧ Set “Number of Sample Points”, like: 50.



Step 3: Run for DoE results

- ❖ Click “Generate DoE Script” button to generate DoE script which contains information you just choose;
- ❖ Click “Execute DoE Script” button to run DoE script.

Then, UQ-PyL gives the tabular and graphic results of DoE:



The result automatically save in text files, the name of files including DoE method used and current time.

 model_output_latin2_2015_05_18_22_12_46.txt	2015/5/18 22:12
 sample_output_latin2_2015_05_18_22_12_46.txt	2015/5/18 22:12

This step can also implemented using python script:

Python script file (Sobol_G_DoE.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True

from UQ.DoE import lhs
from UQ.test_functions import Sobol_G
from UQ.util import scale_samples_general, read_param_file, discrepancy
import numpy as np
import random as rd

# Set random seed (does not affect quasi-random Sobol sampling)
seed = 1
np.random.seed(seed)
rd.seed(seed)

# Read the parameter range file and generate samples
param_file = './UQ/test_functions/params/Sobol_G.txt'
pf = read_param_file(param_file)

# Generate samples (choose method here)
param_values = lhs.sample(50, pf['num_vars'], criterion='center')
res = discrepancy.evaluate(param_values)
print res

# Samples are given in range [0, 1] by default. Rescale them to your
# parameter bounds.
scale_samples_general(param_values, pf['bounds'])
np.savetxt('Input_Sobol\\.txt', param_values, delimiter=' ')

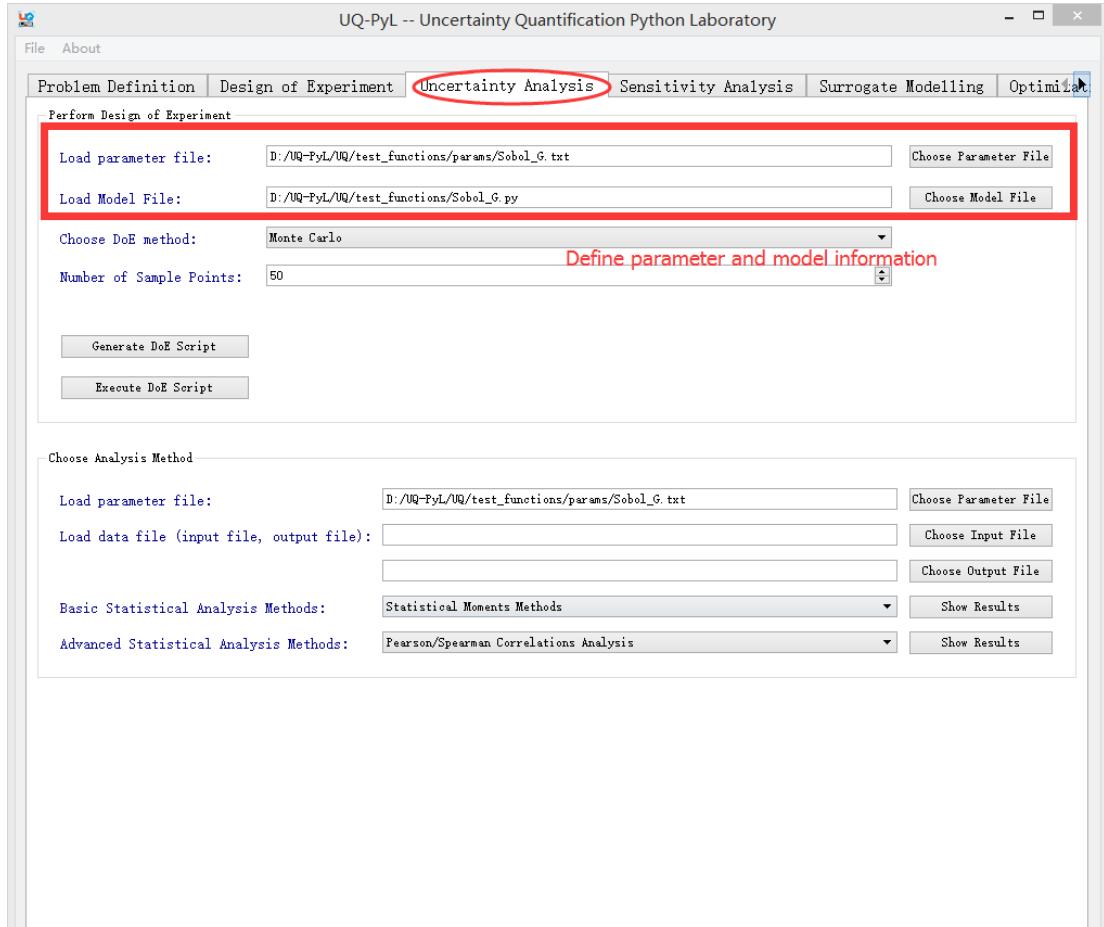
# Run the "model" and save the output in a text file
# This will happen offline for external models
Y = Sobol_G.predict(param_values)
np.savetxt("Output_Sobol\\.txt", Y, delimiter=' ')
```

4.1.3 Statistical Analysis

In this section, we do statistical analysis using UQ-PyL.

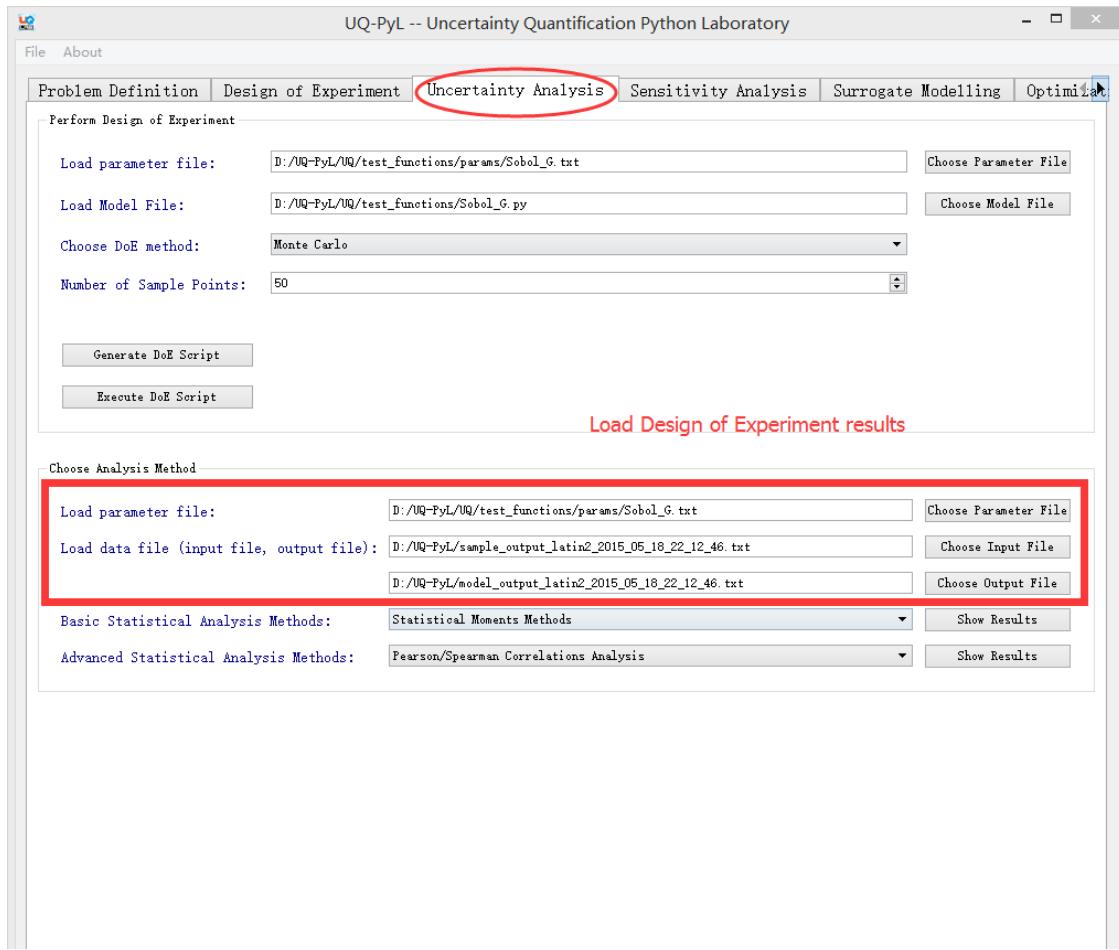
There are also three steps:

- 1) Define parameter and model information;
- 2) Do Design of Experiment or load Design of Experiment results;
- 3) Choose statistical analysis method and show the results.



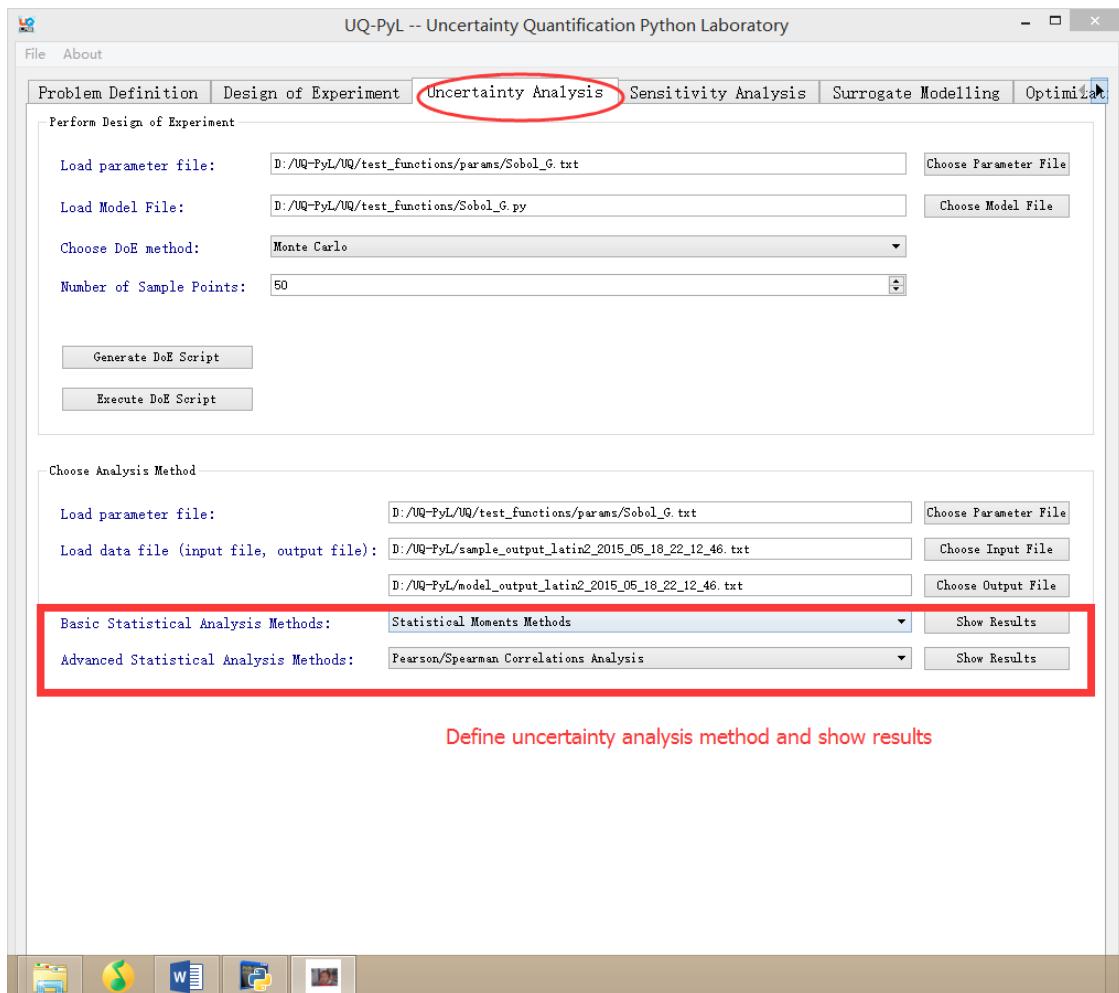
Step 1: Define parameter and model information

- ❖ Switch to “Statistical Analysis” tab;
- ❖ Click “Choose Parameter File” button to choose “UQ-PyL/UQ/test_functions/params/Sobol_G.txt” file;
- ❖ Click “Choose Model File” button to choose “UQ-PyL/UQ/test_functions/Sobol_G.py” file.



Step 2: Load DoE results

- ✧ Click “Choose Input File” button to choose sample file you just generated, for example: “sample_output_latin2_2015_05_18_22_12_46.txt”;
- ✧ Click “Choose Output File” button to choose model output file you just generated, for example: “model_output_latin2_2015_05_18_22_12_46.txt”.

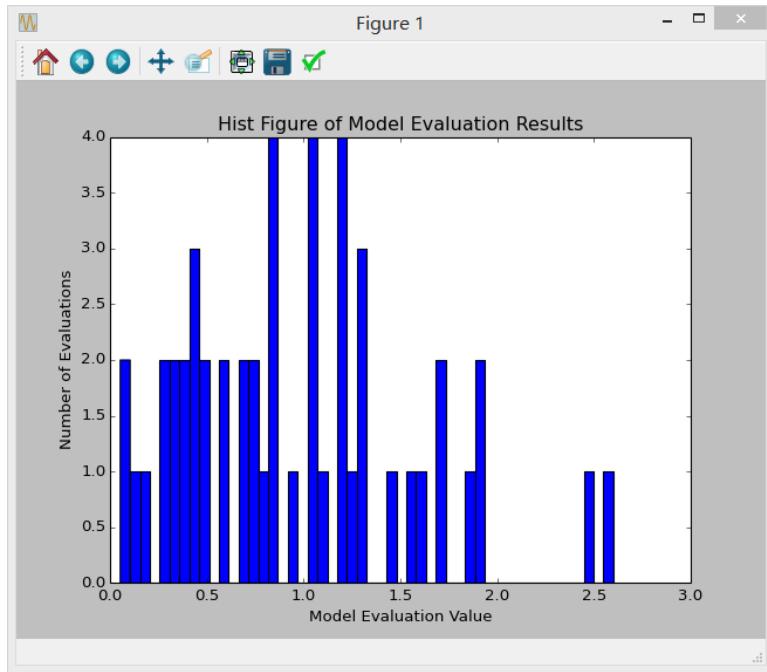


Step 3: Choose statistical analysis method and show results

- ❖ Choose statistical analysis method, like “Statistical Moments Methods”;
- ❖ Click “Show Results” button to show statistical analysis results.

UQ-PyL gives the tabular and graphic results:

```
C:\Windows\system32\cmd.exe
C:\>python -B -m UQ.analyze -m moments -p D:/UQ-PyL/UQ/test_functions/params/Sobol_G.txt -I D:/UQ-PyL/sample_output_latin2_2015_05_18_22_12_46.txt -V D:/UQ-PyL/model_output_latin2_2015_05_18_22_12_46.txt
The minimum value of output is: 0.0529446436
The maximum value of output is: 2.599489
The mean value (first moment) is: 0.9562312589
The variance value (second moment) is: 0.350640944697
The standard deviation is: 0.592149427676
The skewness value (third moment) is: 0.683569348056
The kurtosis value (fourth moment) is: 0.109158573535
```



This step can also be implemented using python script:

Python script file (Sobol_G_UA.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True

from UQ.DoE import lhs
from UQ.analyze import *
from UQ.test_functions import Sobol_G
from UQ.util import scale_samples_general, read_param_file, discrepancy
import numpy as np
import random as rd

# Set random seed (does not affect quasi-random Sobol sampling)
seed = 1
np.random.seed(seed)
rd.seed(seed)

# Read the parameter range file and generate samples
param_file = './UQ/test_functions/params/Sobol_G.txt'
pf = read_param_file(param_file)

# Generate samples (choose method here)
param_values = lhs.sample(50, pf['num_vars'], criterion='center')
res = discrepancy.evaluate(param_values)
print res
```

```

# Samples are given in range [0, 1] by default. Rescale them to your
# parameter bounds.
scale_samples_general(param_values, pf['bounds'])
np.savetxt('Input_Sobol\\.txt', param_values, delimiter=' ')

# Run the "model" and save the output in a text file
# This will happen offline for external models
Y = Sobol_G.predict(param_values)
np.savetxt("Output_Sobol\\.txt", Y, delimiter=' ')

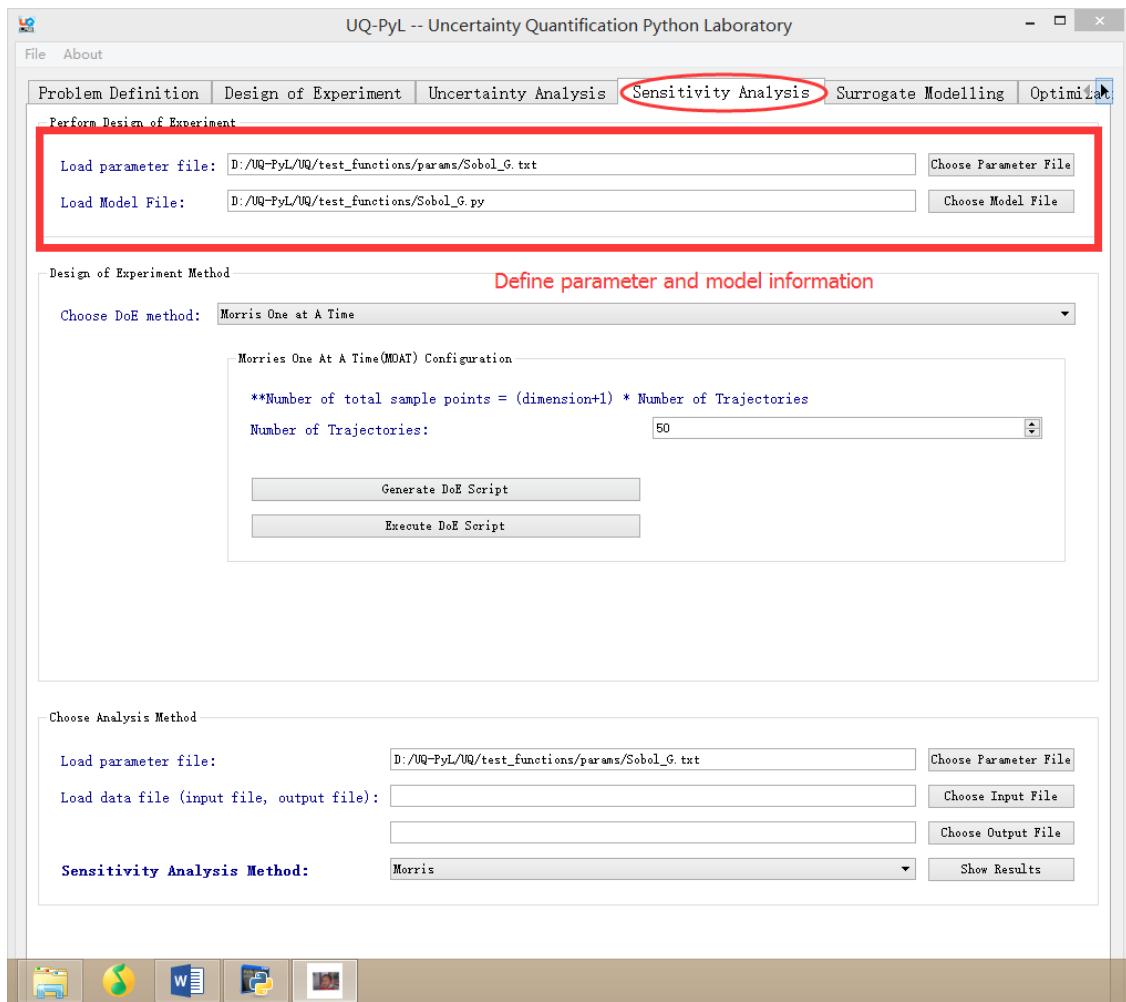
# Perform the sensitivity analysis/uncertainty analysis using the model
# output
# Specify which column of the output file to analyze (zero-indexed)
moments.analyze('Output_Sobol\\.txt', column=0)

```

4.1.4 Sensitivity Analysis

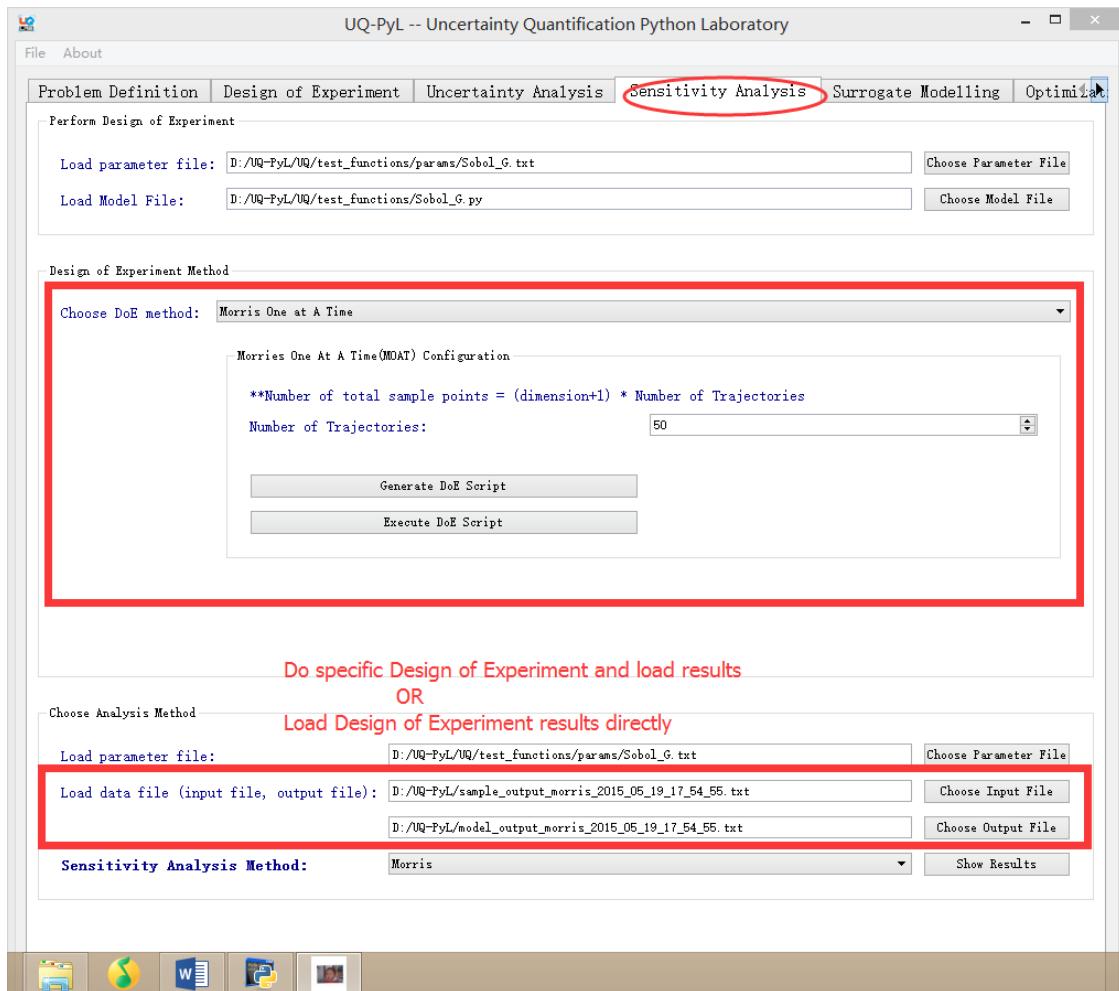
Next, we do sensitivity analysis using UQ-PyL. There are three steps:

- 1) Define parameter and model information;
- 2) Do specific Design of Experiment or load Design of Experiment results (Different sensitivity analysis method need different Design of Experiment method);
- 3) Choose sensitivity analysis method and show the results.



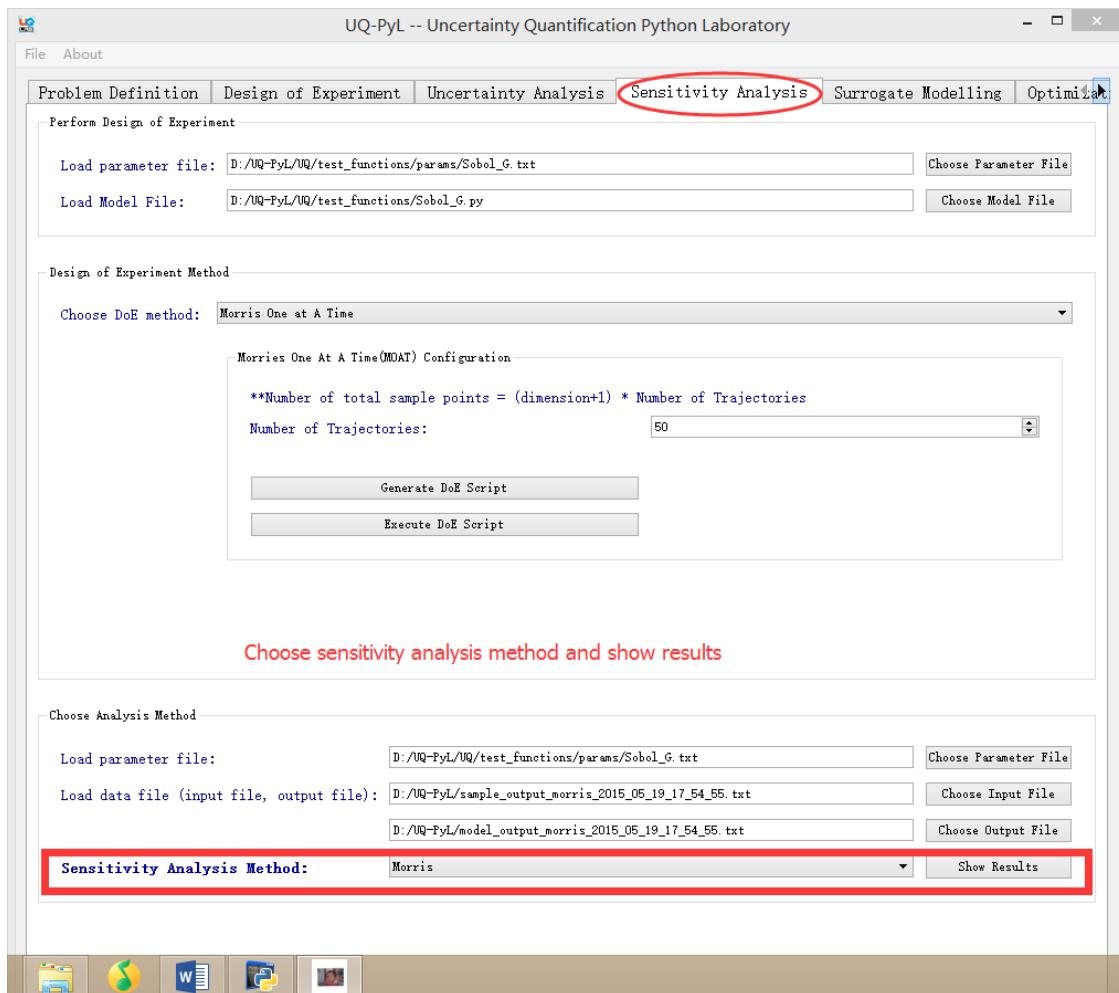
Step 1: Define parameter and model information

- ❖ Switch to “Sensitivity Analysis” tab;
- ❖ Click “Choose Parameter File” button to choose “UQ-PyL/UQ/test_functions/params/Sobol_G.txt” file;
- ❖ Click “Choose Model File” button to choose “UQ-PyL/UQ/test_functions/Sobol_G.py” file.



Step 2: Do specific DoE for specific sensitivity analysis method. For example, we do Morris analysis in this chapter. Then load DoE results.

- ❖ Choose DoE method, for this experiment is “Morris One at A Time”;
- ❖ Set “Number of Trajectories”, for example: 50;
- ❖ Click “Generate DoE Script” button to generate script;
- ❖ Click “Execute DoE Script” button to run script and acquire DoE result;
- ❖ Load input/output file you just generated: 1) Click “Choose Input File” button to load sample file, for example “UQ-PyL/sample_output_morris_2015_05_19_17_54_55.txt”; 2) Click “Choose Output File” button to load model output file, for example “UQ-PyL/model_output_morris_2015_05_19_17_54_55.txt”.



Step 3: Choose sensitivity analysis method and show results

- ❖ Choose sensitivity analysis method, like “Morris”;
- ❖ Click “Show Results” button to show sensitivity analysis results.

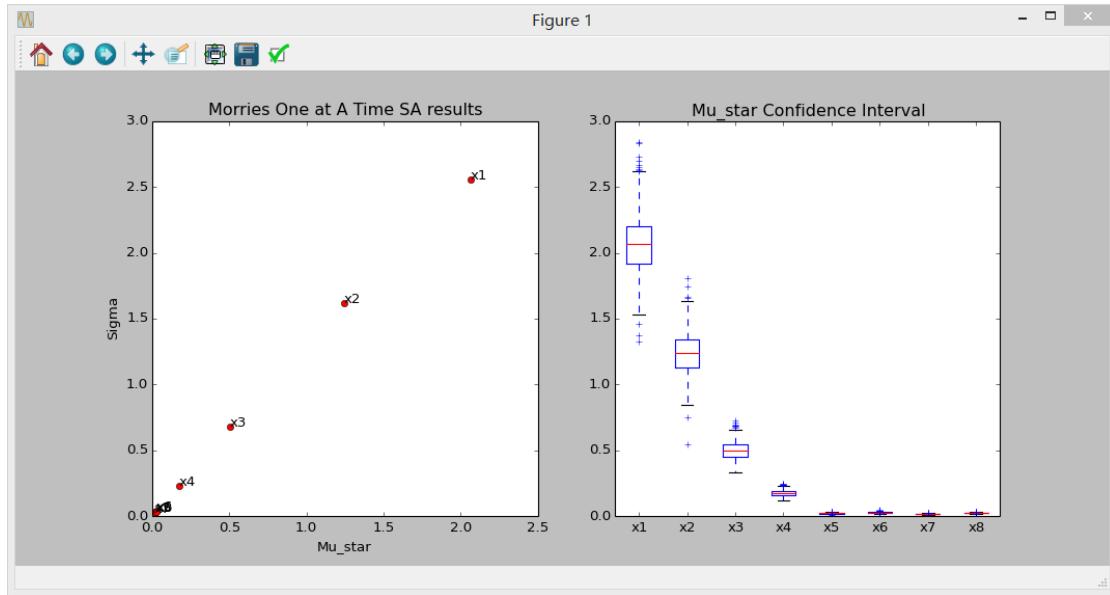
UQ-PyL gives the tabular and graphic results:

```

C:\Windows\system32\cmd.exe

D:\UQ-PyL>python -B -m UQ.analyze -m morris -p D:/UQ-PyL/UQ/test_functions/params/Sobol_G.txt -I D:/UQ-PyL/sample_output_morris_2015_05_19_17_54_55.txt -Y D:/UQ-PyL/model_output_morris_2015_05_19_17_54_55.txt
Parameter Mu Sigma Mu_Star Mu_Star_Conf
x1 -0.240158 2.559110 2.064960 0.422817
x2 0.290318 1.615201 1.246218 0.301561
x3 -0.049704 0.677892 0.503383 0.127671
x4 -0.031089 0.232696 0.174826 0.042758
x5 0.000593 0.031374 0.022963 0.005992
x6 0.005801 0.039410 0.029108 0.007550
x7 0.000105 0.024323 0.016801 0.004874
x8 0.006736 0.034242 0.025536 0.006663

```



This step can also be implemented using python script:

Python script file (Sobol_G_SA.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True

from UQ.DoE import morris_oat
from UQ.analyze import *
from UQ.test_functions import Sobol_G
from UQ.util import scale_samples_general, read_param_file
import numpy as np
import random as rd

# Set random seed (does not affect quasi-random Sobol sampling)
seed = 1
np.random.seed(seed)
rd.seed(seed)

# Read the parameter range file and generate samples
param_file = './UQ/test_functions/params/Sobol_G.txt'
pf = read_param_file(param_file)

# Generate samples (choose method here)
param_values = morris_oat.sample(50, pf['num_vars'], num_levels = 10,
grid_jump = 5)

# Samples are given in range [0, 1] by default. Rescale them to your
```

```

parameter bounds.

scale_samples_general(param_values, pf['bounds'])
np.savetxt('Input_Sobol\\.txt', param_values, delimiter=' ')

# Run the "model" and save the output in a text file
# This will happen offline for external models
Y = Sobol_G.predict(param_values)
np.savetxt("Output_Sobol\\.txt", Y, delimiter=' ')

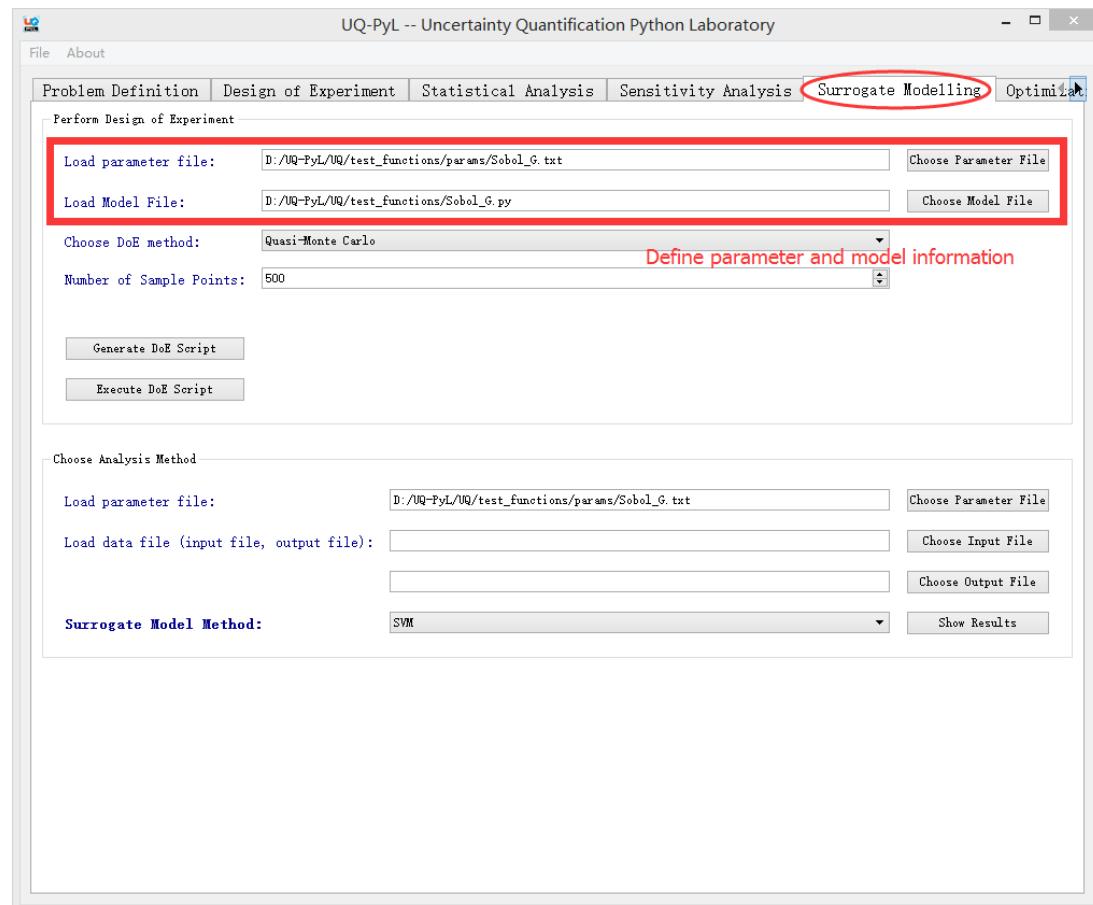
# Perform the sensitivity analysis/uncertainty analysis using the model
# output
# Specify which column of the output file to analyze (zero-indexed)
morris.analyze(param_file, 'Input_Sobol\\.txt', 'Output_Sobol\\.txt',
column = 0)

```

4.1.5 Surrogate Modeling

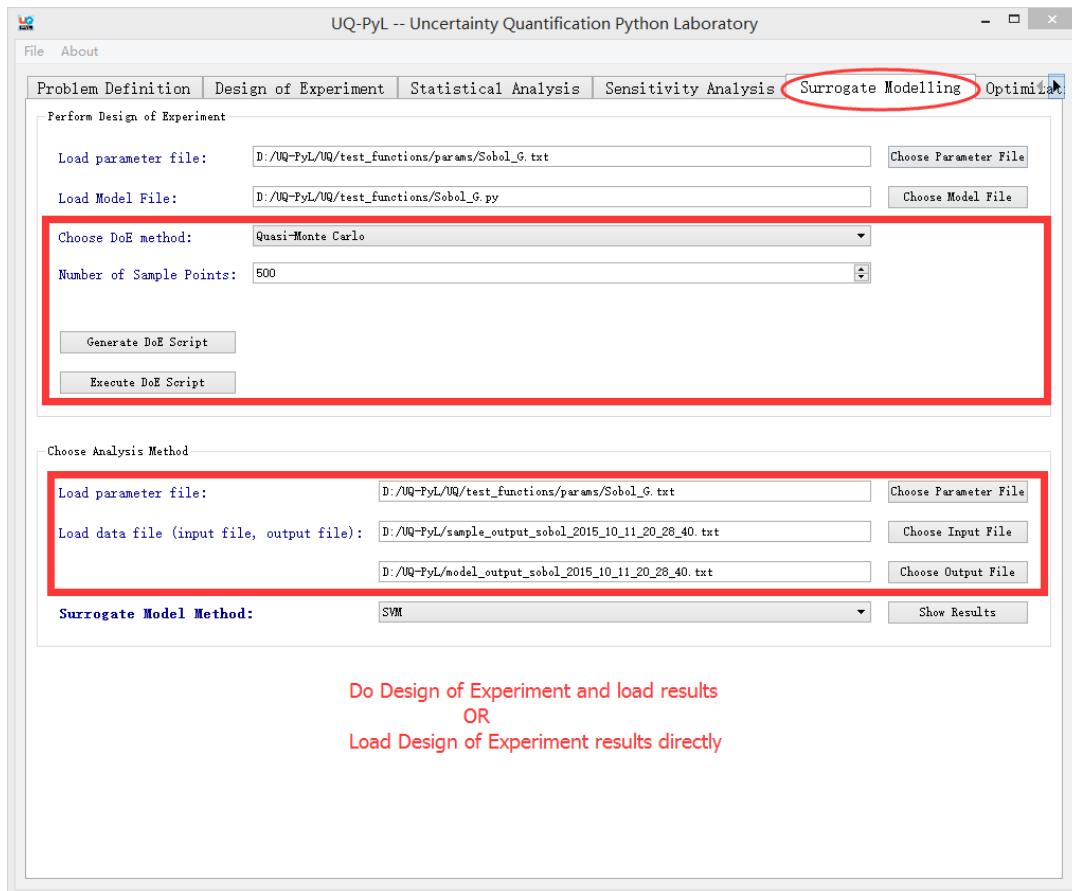
Next, we do surrogate modeling using UQ-PyL. There are three steps:

- 1) Define parameter and model information;
- 2) Do specific Design of Experiment or load Design of Experiment results;
- 3) Choose surrogate modeling method and show the results.



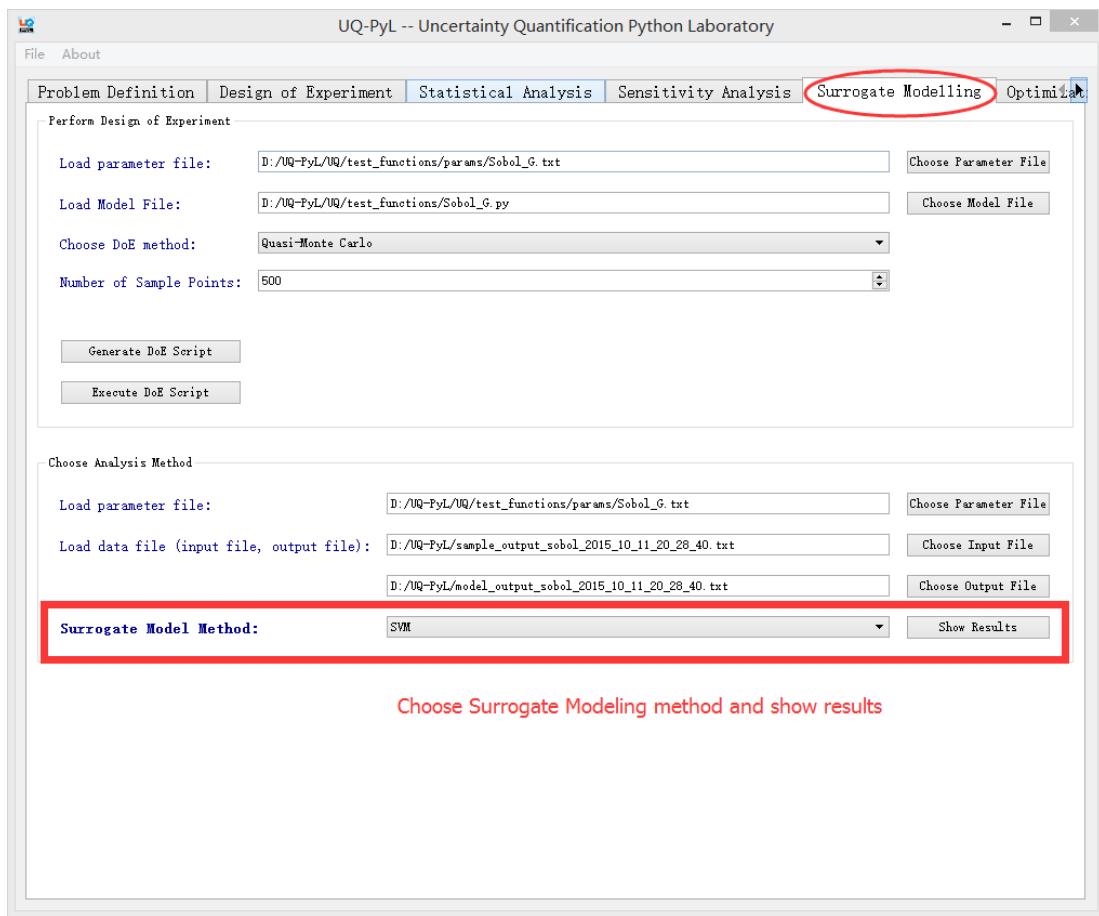
Step 1: Define parameter and model information

- ✧ Switch to “Surrogate Modeling” tab;
- ✧ Click “Choose Parameter File” button to choose “UQ-PyL/UQ/test_functions/params/Sobol_G.txt” file;
- ✧ Click “Choose Model File” button to choose “UQ-PyL/UQ/test_functions/Sobol_G.py” file.



Step 2: Do DoE for surrogate modeling method and load results.

- ✧ Choose DoE method, for example “Quasi Monte Carlo”;
- ✧ Set “Number of Trajectories”, for example: 500;
- ✧ Click “Generate DoE Script” button to generate script;
- ✧ Click “Execute DoE Script” button to run script and acquire DoE result;
- ✧ Load input/output file you just generated: 1) Click “Choose Input File” button to load sample file, for example “UQ-PyL/sample_output_sobol_2015_10_11_17_54_55.txt”; 2) Click “Choose Output File” button to load model output file, for example “UQ-PyL/model_output_sobol_2015_10_11_17_54_55.txt”.



Step 3: Choose surrogate modeling method and show results

- ✧ Choose surrogate modeling method, like “SVM”;
- ✧ Click “Show Results” button to show sensitivity analysis results.

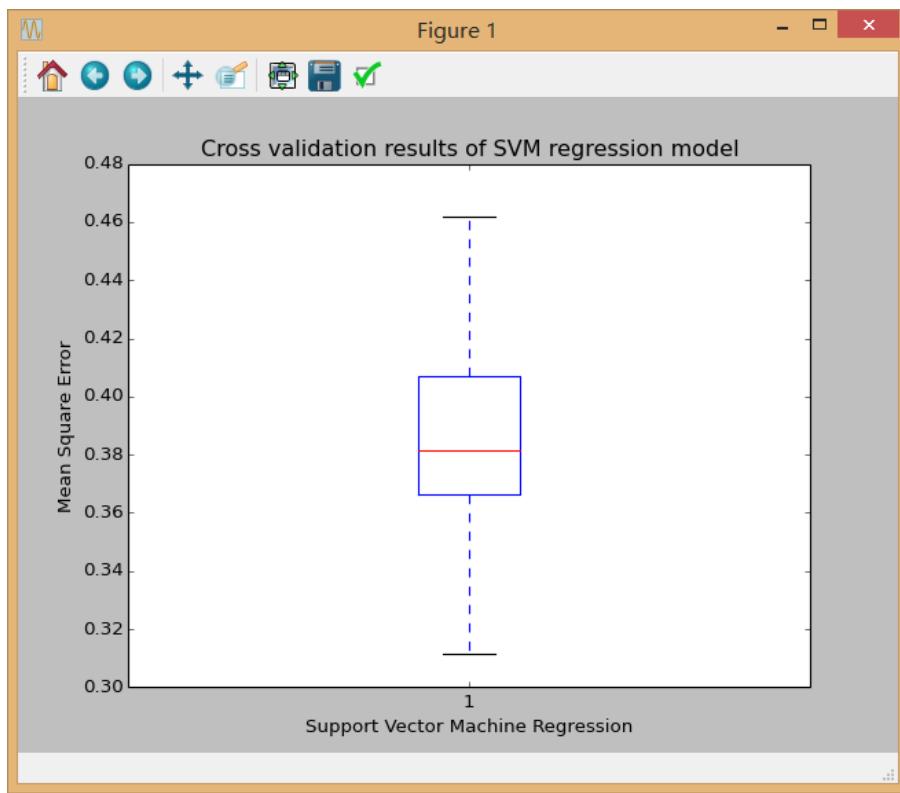
UQ-PyL gives the tabular and graphic results:

```

C:\Windows\system32\cmd.exe

D:\UQ-PyL>python -B -m UQ.RSmodel -m svm -I D:/UQ-PyL/sample_output_sobol_2015_10_11_20_28_40.txt -Y D:/UQ-PyL/model_output_sobol_2015_10_11_20_28_40.txt
C:\Python27\lib\site-packages\sklearn\cross_validation.py:1137: DeprecationWarning: Passing function as ``score_func`` is deprecated and will be removed in 0.15.
. Either use strings or score objects. The relevant new parameter is called ''scoring''.
scoring=scoring
The k-fold mean square error cross validation scores are:
[ 0.43070918  0.35159512  0.39358889  0.36591365  0.31136207  0.46200058
  0.36738373  0.36966313  0.40746706  0.40561528]
The mean value of the scores is: 0.386529869176
The standard deviation of the scores is: 0.0405546713962

```



In this new version of UQ-PyL, the software also save surrogate model as a *.pickle file automatically. For this example is “SVRmodel.pickle” file.

[SVRmodel.pickle](#) 2015/10/11 20:44 PICKLE 文件 98 KB

This file can be opened by a Text Editor, please see the context of this file below:

```

1 ccopy_reg
2 _reconstructor
3 p0
4 (caklearn.svm.classes
5 SVR
6 p1
7 c__builtin__
8 object
9 p2
10 Ntp3
11 Rp4
12 (dp5
13 S'_impl'
14 p6
15 S'epsilon_svr'
16 p7
17 sS'kernel'
18 p8
19 S'rbf'
20 p9
21 sS'vebose'
22 p10
23 I00
24 sS'probability'
25 p11
26 I00
27 sS'_label'
28 p12
29 cnumpy.core.multiarray
30 _reconstruct
31 p13
32 (cnumpy
33 ndarray
34 p14
35 (I0
36 tp15
37 S'b'
38 p16
39 tp17
40 Rp18

```

It saved the data structure of the surrogate model you built.

In section 4.3, we will introduce how to run simulations on surrogate models you built.

This step can also implemented using python script:

Python script file (Sobol_G_Surrogate.py)

```

# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True

from UQ.DoE import sobol
from UQ.RSmodel import SVR
from UQ.test_functions import Sobol_G
from UQ.util import scale_samples_general, read_param_file, discrepancy
import numpy as np
import random as rd

```

```

# Set random seed (does not affect quasi-random Sobol sampling)
seed = 1
np.random.seed(seed)
rd.seed(seed)

# Read the parameter range file and generate samples
param_file = './UQ/test_functions/params/Sobol_G.txt'
pf = read_param_file(param_file)

# Generate samples (choose method here)
param_values = sobol.sample(500, pf['num_vars'])

# Samples are given in range [0, 1] by default. Rescale them to your
# parameter bounds.
scale_samples_general(param_values, pf['bounds'])
np.savetxt('Input_Sobol\\.txt', param_values, delimiter=' ')

# Run the "model" and save the output in a text file
# This will happen offline for external models
Y = Sobol_G.predict(param_values)
np.savetxt("Output_Sobol\\.txt", Y, delimiter=' ')

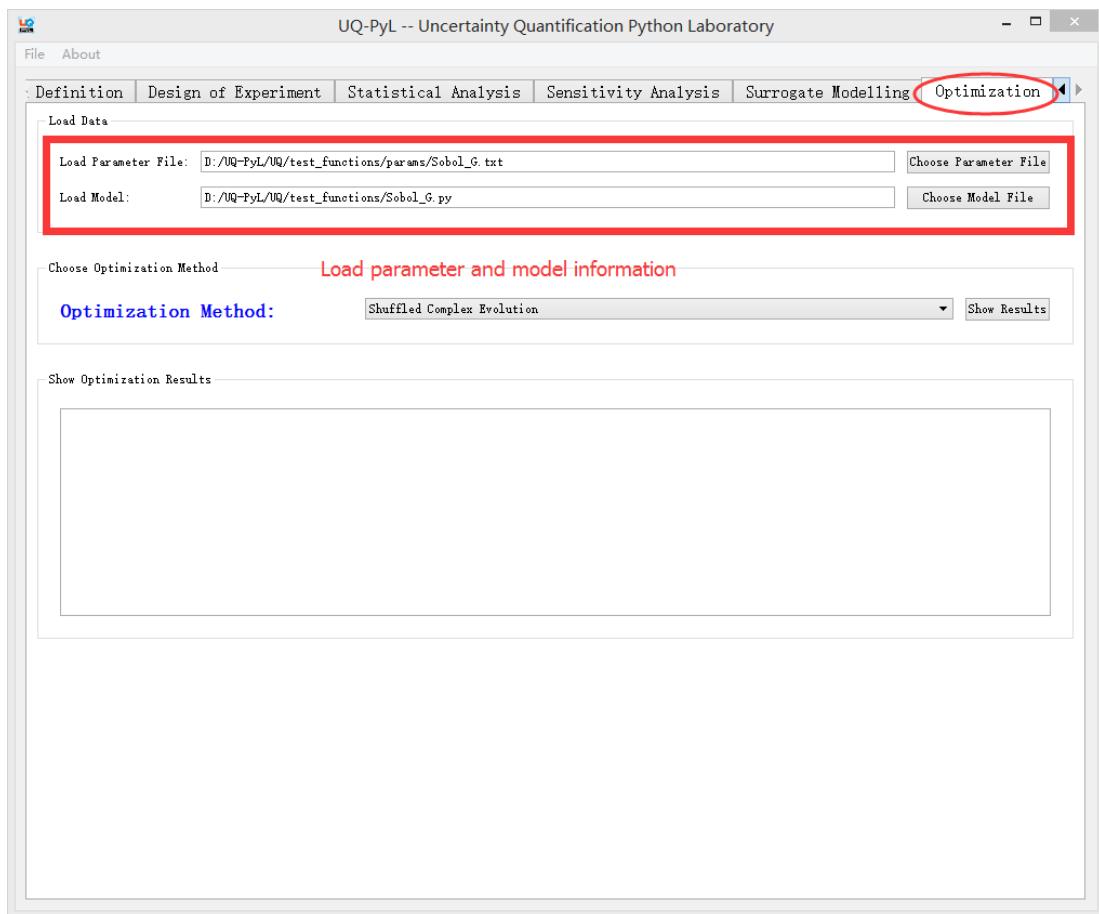
# Perform regression analysis using the model output
# Specify which column of the output file to analyze (zero-indexed)
model = SVR.regression('Input_Sobol\\.txt', 'Output_Sobol\\.txt',
column = 0, cv = True)

```

4.1.6 Parameter Optimization

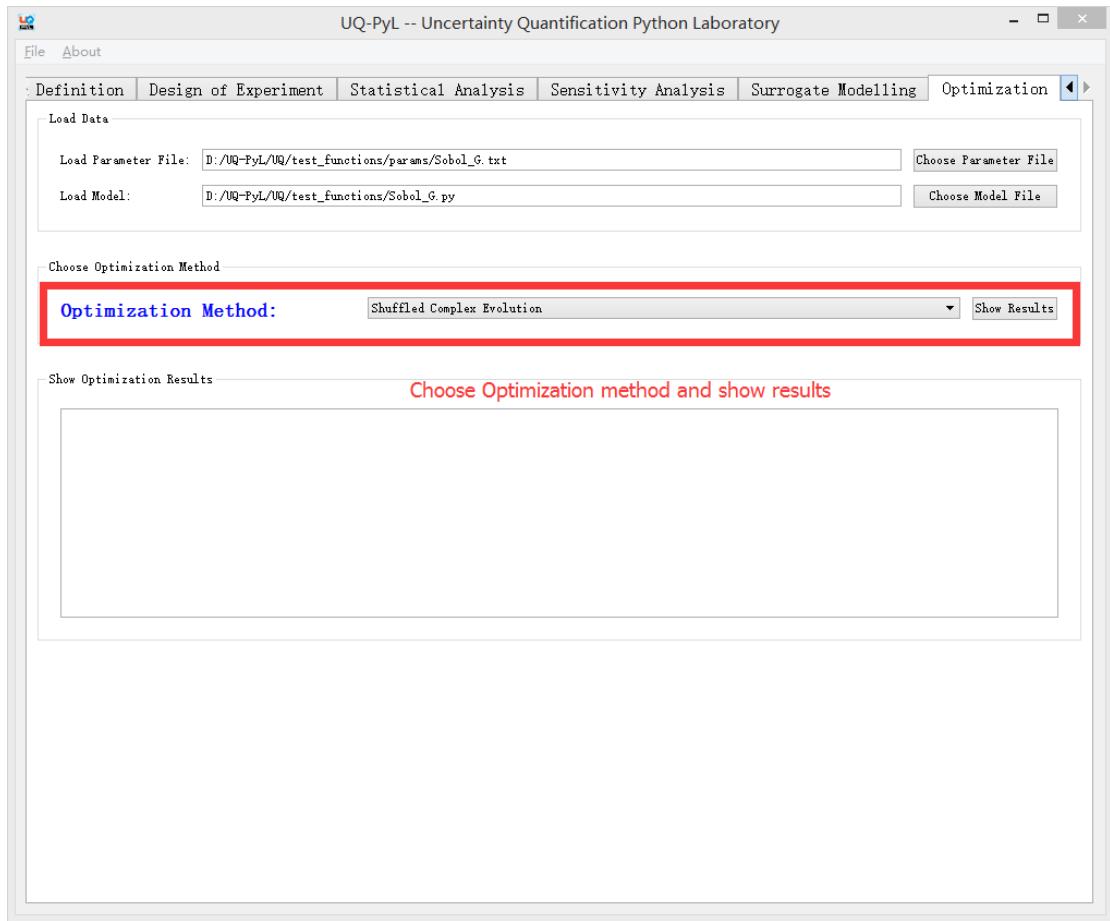
At last, we do parameter optimization using UQ-PyL. There are two steps:

- 1) Define parameter and model information;
- 2) Choose parameter optimization method and show the results.



Step 1: Define parameter and model information

- ✧ Switch to “Optimization” tab;
- ✧ Click “Choose Parameter File” button to choose “UQ-PyL/UQ/test_functions/params/Sobol_G.txt” file;
- ✧ Click “Choose Model File” button to choose “UQ-PyL/UQ/test_functions/Sobol_G.py” file.



Step 2: Choose parameter optimization method and show results

- ✧ Choose parameter optimization method, like “Shuffled Complex Evolution”;
- ✧ Click “Show Results” button to show parameter optimization results.

UQ-PyL gives the tabular and graphic results:

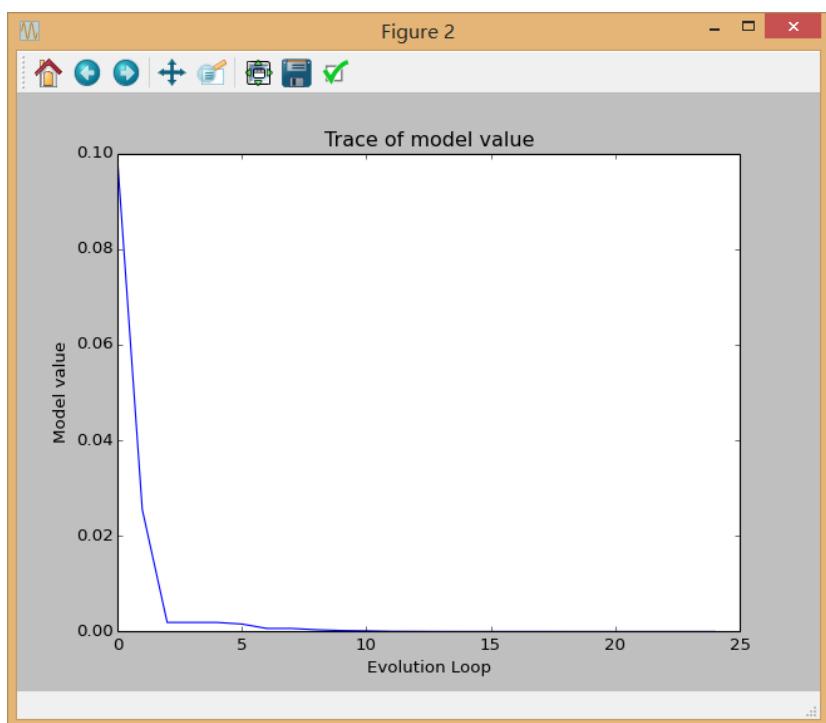
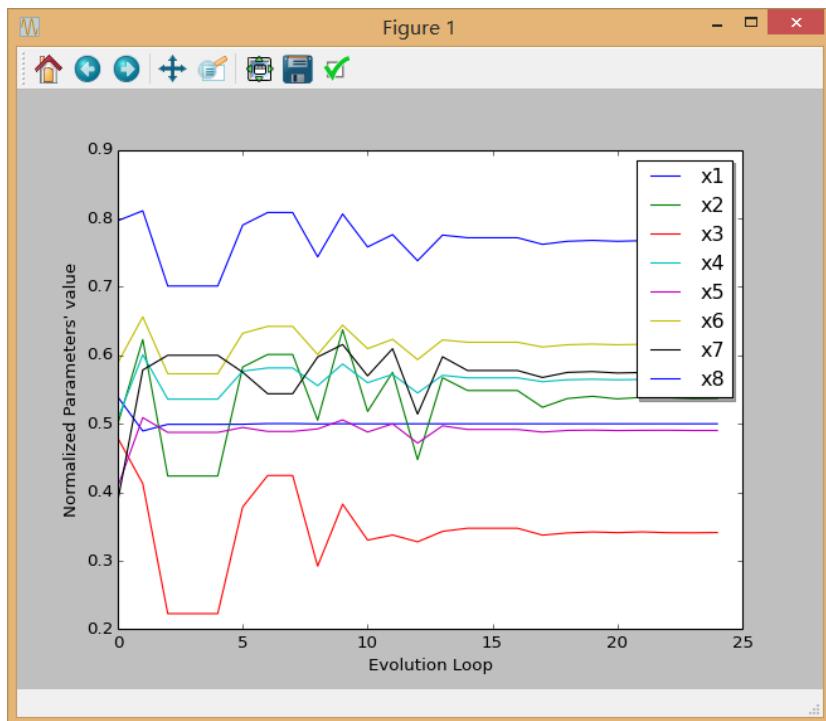
```

C:\Windows\system32\cmd.exe
BESTF: 0.000000
BESTX:
[ 0.4999998  0.53656488  0.34085105  0.56424082  0.49018645  0.61533234
 0.57451195  0.76638417]
WORSTF: 0.000014
WORSTX:
[ 0.50000747  0.53512092  0.34217853  0.5639931   0.48957986  0.61521099
 0.57198135  0.76636876]

Evolution Loop: 24 - Trial - 1288
BESTF: 0.000000
BESTX:
[ 0.4999999  0.53686945  0.34121577  0.56432256  0.49018741  0.61545587
 0.57439726  0.76657372]
WORSTF: 0.000004
WORSTX:
[ 0.50000185  0.53602233  0.34065989  0.5641151   0.49009352  0.61518117
 0.57425417  0.76617901]

THE POPULATION HAS CONVERGED TO A PRESPECIFIED SMALL PARAMETER SPACE
SEARCH WAS STOPPED AT TRIAL NUMBER: 1288
NORMALIZED GEOMETRIC RANGE = 0.000709
THE BEST POINT HAS IMPROVED IN LAST 10 LOOPS BY 251.225761

```



This step can also implemented using python script:

Python script file (Sobol_G_Optimization.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True
import shutil
```

```

from UQ.optimization import SCE, ASMO, DDS, PSO
from UQ.util import scale_samples_general, read_param_file
import numpy as np
import random as rd

# Read the parameter range file
param_file = './UQ/test_functions/params/Sobol_G.txt'

bl=np.empty(0)
bu=np.empty(0)
pf = read_param_file(param_file)
for i, b in enumerate(pf['bounds']):
    bl = np.append(bl, b[0])
    bu = np.append(bu, b[1])

dir = './UQ/test_functions/'
shutil.copy(dir+'Sobol_G.py', dir+'functn.py')

# Run SCE-UA optimization algorithm
SCE.sceua(bl, bu, pf, ngs=2)

```

4.2 SAC-SMA model

4.2.1 Problem Definition

The SAC-SMA is a rainfall-runoff model which has a highly non-linear, non-monotonic input parameter-model output relationship. There are sixteen parameters in the SAC-SMA model. Thirteen of them are considered tunable, and the other three parameters are fixed at pre-specified values according to Brazil (1988). Table 1 describes those parameters and their ranges.

No.	Parameter	Description	Range
1	UZTWM	Upper zone tension water maximum storage (mm)	[10.0, 300.0]
2	UZFWM	Upper zone free water maximum storage (mm)	[5.0, 150.0]
3	UZK	Upper zone free water lateral drainage rate (day^{-1})	[0.10, 0.75]
4	PCTIM	Impervious fraction of the watershed area (decimal fraction)	[0.0, 0.10]
5	ADIMP	Additional impervious area (decimal fraction)	[0.0, 0.20]
6	ZPERC	Maximum percolation rate (dimensionless)	[5.0, 350.0]
7	REXP	Exponent of the percolation equation (dimensionless)	[1.0, 5.0]
8	LZTWM	Lower zone tension water maximum storage (mm)	[10.0, 500.0]

9	LZFSM	Lower zone supplemental free water maximum storage (mm)	[5.0, 400.0]
10	LZFPM	Lower zone primary free water maximum storage (mm)	[10.0, 1000.0]
11	LZSK	Lower zone supplemental free water lateral drainage rate (day^{-1})	[0.01, 0.35]
12	LZPK	Lower zone primary free water lateral drainage rate (day^{-1})	[0.001, 0.05]
13	PFREE	Fraction of water percolating from upper zone directly to lower zone free water (decimal fraction)	[0.0, 0.9]
14	RIVA	Riverside vegetation area (decimal fraction)	0.30
15	SIDE	Ration of deep recharge to channel base flow (dimensionless)	0.0
16	RSERV	Fraction of lower zone free water not transferrable to lower zone tension water (decimal fraction)	0.0

Table 6. Parameters of SAC-SMA model

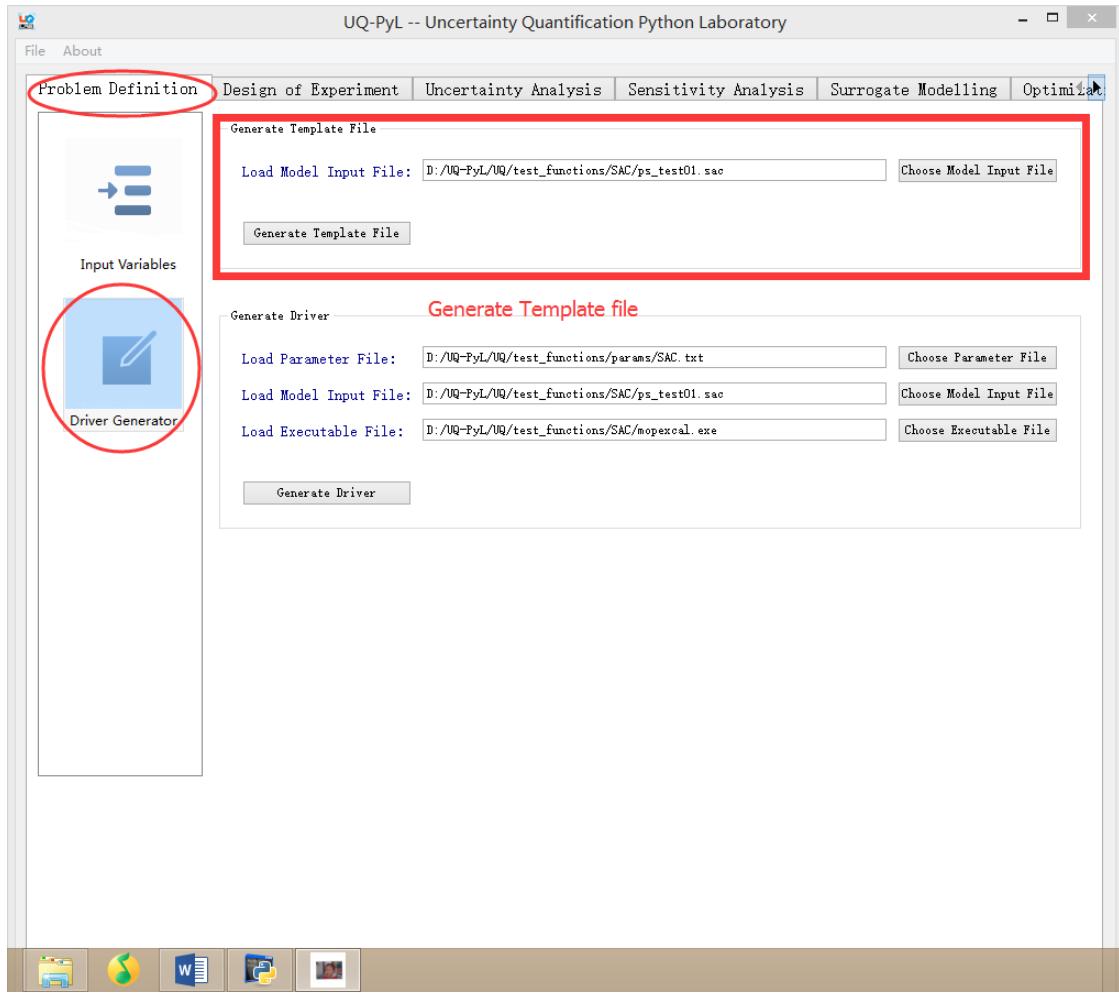
So we generate the parameter file (UQ-PyL/UQ/test_functions/params/SAC.txt) as:

```

UZTWM 10 300
UZFWM 5 150
UZK 0.1 0.75
PCTIM 0 0.1
ADIMP 0 0.2
ZPERC 5 350
REXP 1 5
LZTWM 10 500
LZFSM 5 400
LZFPM 10 1000
LZSK 0.01 0.35
LZPK 0.001 0.05
PFREE 0 0.8

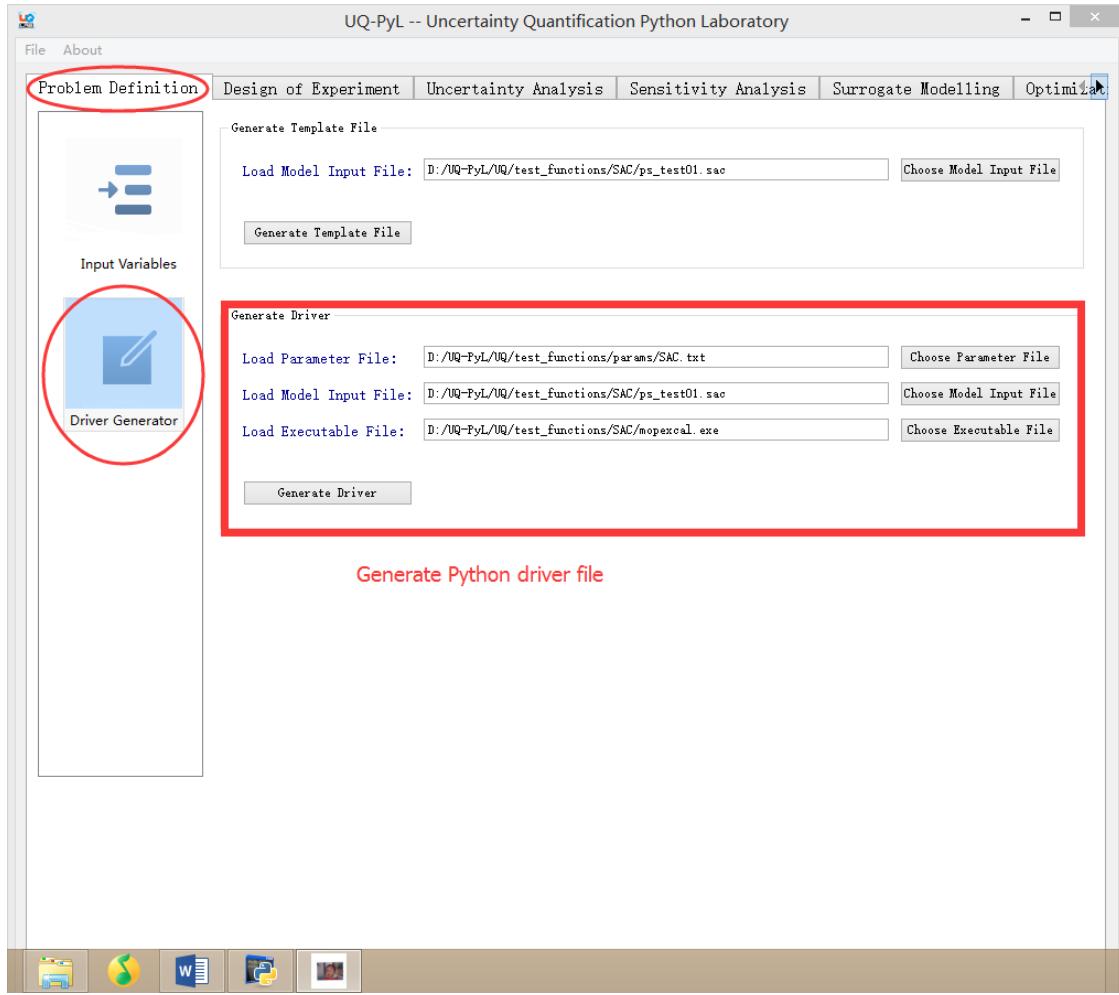
```

SAC-SMA model is an executable file on Windows or Linux or MacOS system. In order to using UQ-PyL, we need to generate a python driver to couple SAC-SMA model and UQ-PyL platform. The driver file can be generated automatically by UQ-PyL's GUI.



Step 1: Generate template file

- ❖ Choose “Problem Definition” tab, click on “Driver Generator” widget;
- ❖ Click “Choose Model Input File” to load model configuration file, for SAC model is “UQ-PyL/UQ/test_functions/SAC/ps_test01.sac”;
- ❖ Click “Generate Template File” to generate model configuration template file, this file will be used in model driver file.



Step 2: Generate driver file

- ❖ Click “Choose Parameter File” to load model parameter file, for SAC model is “UQ-PyL/UQ/test_functions/params/SAC.txt”;
- ❖ Click “Choose Model Input File” to load model configuration file, for SAC model is “UQ-PyL/UQ/test_functions/SAC/ps_test01.sac”;
- ❖ Click “Choose Executable File” to load model executable file, for SAC model is “UQ-PyL/UQ/test_functions/SAC/mopexcal.exe”;
- ❖ Click “Generate Driver” button to acquire model driver file.

The driver file (UQ-PyL/UQ/test_functions/SAC.py) shows below:

```

import os
import math
import string
import numpy as np
from ..util import read_param_file

#####
# USER SPECIFIC SECTION
#####
controlFileName = "D:/UQ-PyL/UQ/test_functions/params/SAC.txt"

```

```

appInputFiles = "ps_test01.sac"
appInputTmplts = appInputFiles + ".Tmplt"

#####
# FUNCTION: GENERATE MODEL INPUT FILE
#####
def genAppInputFile(inputData,appTmpltFile,appInputFile,nInputs,inputNames):
    infile = open(appTmpltFile, "r")
    outfile = open(appInputFile, "w")
    while 1:
        lineIn = infile.readline()
        if lineIn == "":
            break
        lineLen = len(lineIn)
        newLine = lineIn
        if nInputs > 0:
            for fInd in range(nInputs):
                strLen = len(inputNames[fInd])
                sInd = string.find(newLine, inputNames[fInd])
                if sInd >= 0:
                    sdata = '%7.3f' % inputData[fInd]
                    strdata = str(sdata)
                    next = sInd + strLen
                    lineTemp = newLine[0:sInd] + strdata + " " +
newLine[next:lineLen+1]
                    newLine = lineTemp
                    lineLen = len(newLine)
            outfile.write(newLine)
    infile.close()
    outfile.close()
    return

#####
# FUNCTION: RUN MODEL
#####
def runApplication():
    sysComm = "mopexcal.exe"
    os.system(sysComm)
    return

#####
# FUNCTION: CALCULATE DESIRE OUTPUT
#####

```

```

#=====
def getOutput():
    Qe = []
    Qo = []
    functn = 0.0
    ignore = 92
    I = 0
    outfile = open("ps_test01.sac.day", "r")
    for jj in range(ignore):
        lineIn = outfile.readline()

    while 1:
        lineIn = outfile.readline()
        if lineIn == "":
            break
        nCols = string.split(lineIn)
        Qe.append(eval(nCols[4]))
        Qo.append(eval(nCols[5]))
        functn = functn + (Qe[I] - Qo[I]) * (Qe[I] - Qo[I])
        I=I+1
    outfile.close()

    functn = functn/I
    functn = math.sqrt(functn)
    return functn

#####
# MAIN PROGRAM
#=====

def predict(values):
    pf = read_param_file(controlFileName)
    for n in range(pf['num_vars']):
        pf['names'][n] = 'UQ_' + pf['names'][n]

    Y = np.empty([values.shape[0]])
    os.chdir('D:/UQ-PyL/UQ/test_functions/SAC')

    for i, row in enumerate(values):
        inputData = values[i]

genAppInputFile(inputData,appInputTmplts,appInputFiles,pf['num_vars'],
,pf['names'])
    runApplication()
    Y[i] = getOutput()

```

```

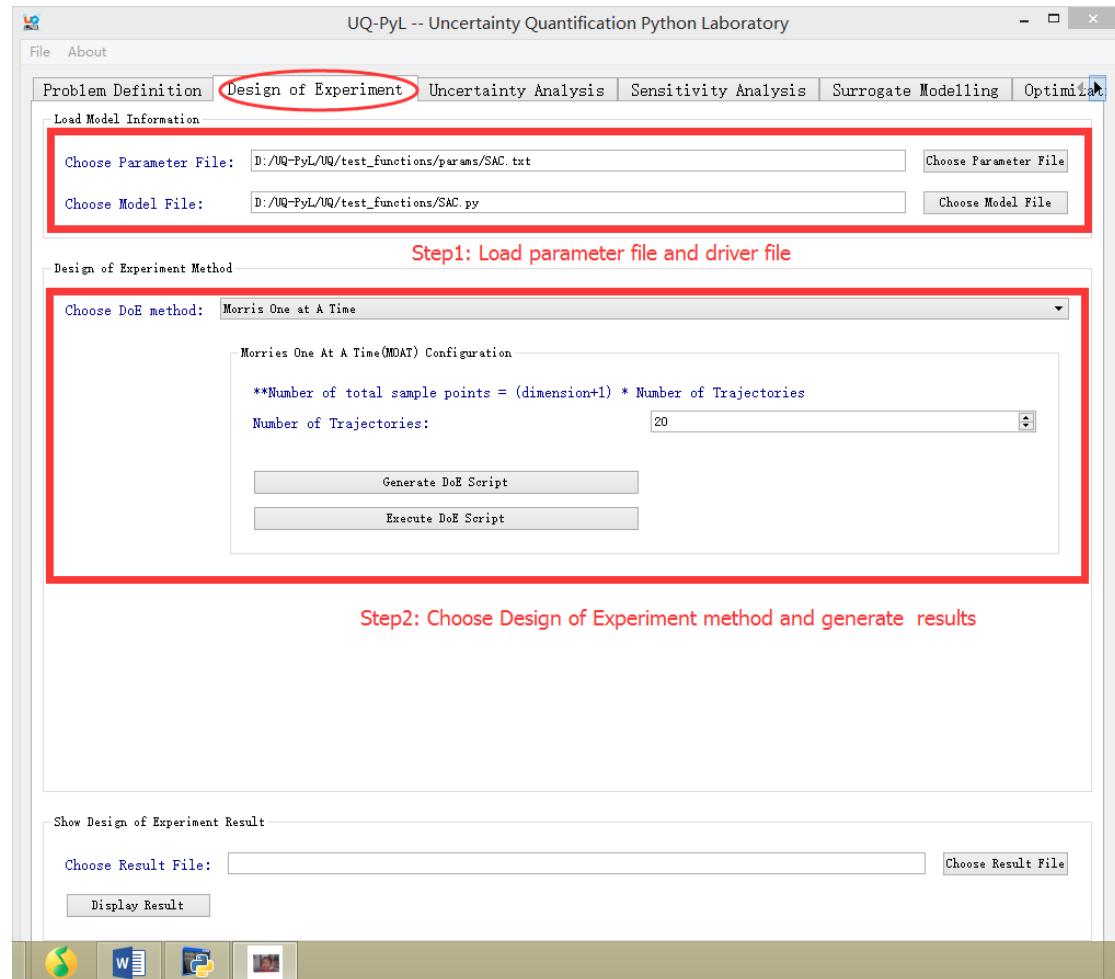
print "Job ID " + str(i+1)

return Y

```

4.2.2 Design of Experiment

We do Design of Experiment for SAC-SMA model:



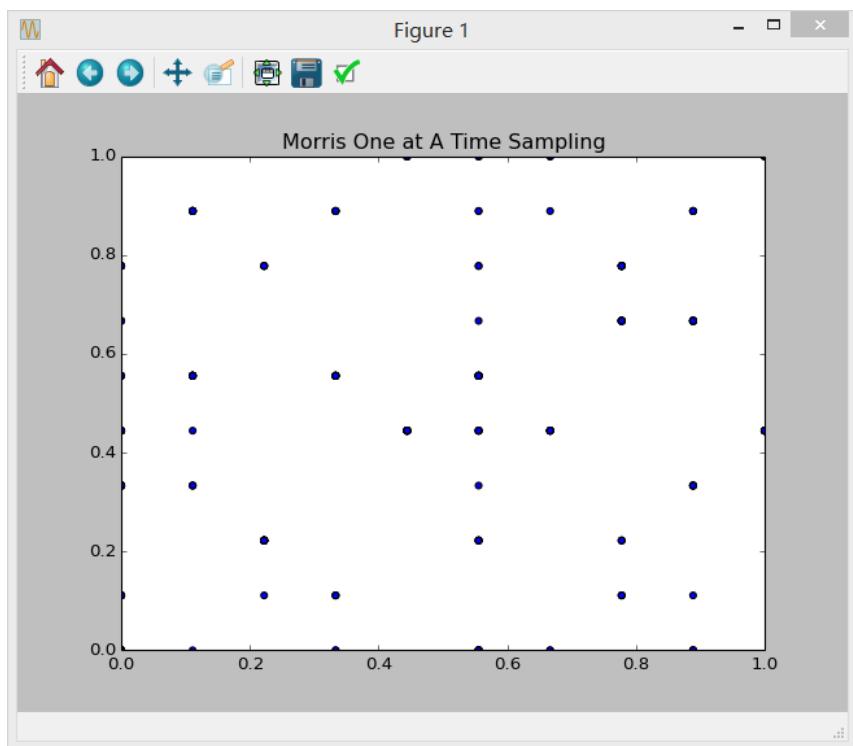
Step 1: Define parameter and model information

- ✧ Choose “Design of Experiment” tab;
- ✧ Load parameter file “UQ-PyL/UQ/test_functions/params/SAC.txt” and model file “UQ-PyL/UQ/test_functions/SAC.py” (for SAC model, it’s the model driver file generated before).

Step 2: Choose DoE method and run the results

- ✧ Choose DoE method “Morris One at A Time” and set “Number of Trajectories” = 20;
- ✧ Click “Generate DoE Script” button and “Execute DoE Script” button to acquire DoE results.

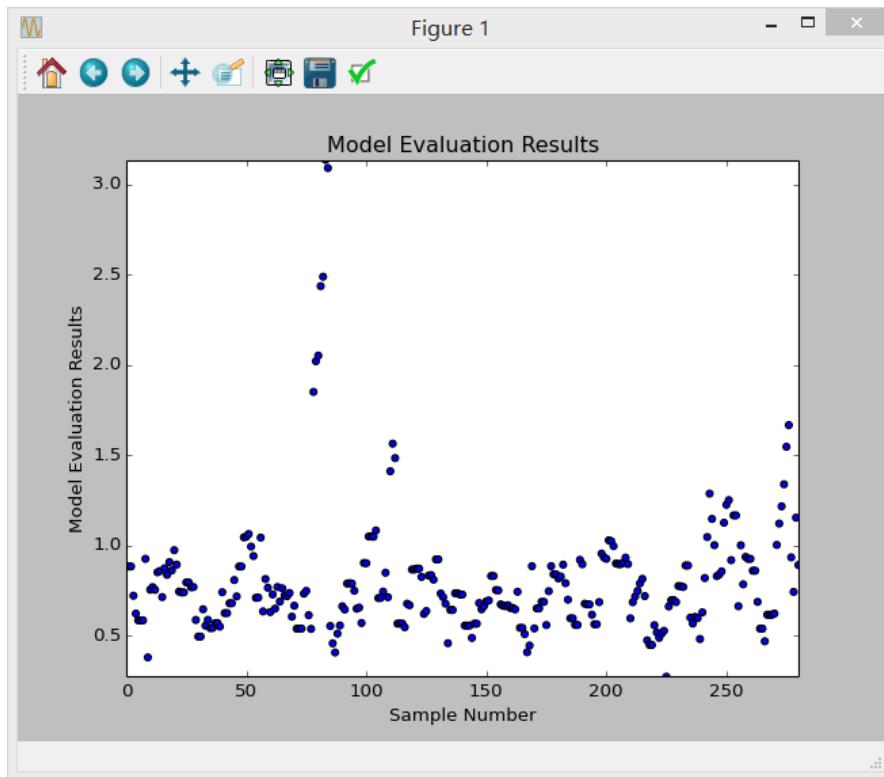
UQ-PyL gives the tabular and graphic results:



C:\Python27\python.exe

```
Job ID 6
Job ID 7
Job ID 8
Job ID 9
Job ID 10
Job ID 11
Job ID 12
Job ID 13
Job ID 14
Job ID 15
Job ID 16
Job ID 17
Job ID 18
Job ID 19
Job ID 20
Job ID 21
Job ID 22
Job ID 23
Job ID 24
Job ID 25
Job ID 26
Job ID 27
Job ID 28

微软拼音 半 :
```



This step can also implemented using python script:

Python script file (SAC_DoE.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True

from UQ.DoE import morris_oat
from UQ.test_functions import SAC
from UQ.util import scale_samples_general, read_param_file, discrepancy
import numpy as np
import random as rd

# Set random seed (does not affect quasi-random Sobol sampling)
seed = 1
np.random.seed(seed)
rd.seed(seed)

# Read the parameter range file and generate samples
param_file = './UQ/test_functions/params/SAC.txt'
pf = read_param_file(param_file)

# Generate samples (choose method here)
param_values = morris_oat.sample(20, pf['num_vars'], num_levels = 10,
```

```

grid_jump = 5)

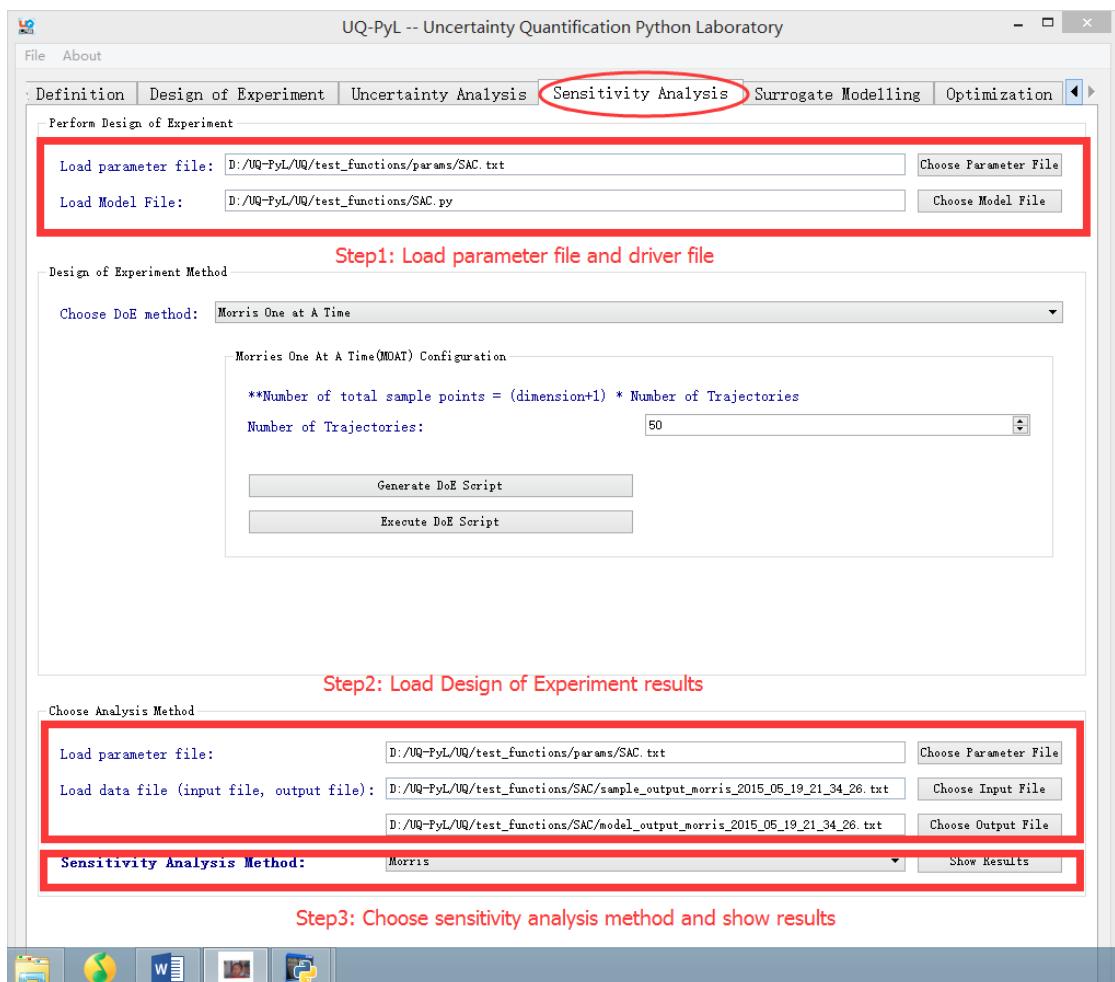
# Samples are given in range [0, 1] by default. Rescale them to your
# parameter bounds.
scale_samples_general(param_values, pf['bounds'])
np.savetxt('Input_Sobol\\.txt', param_values, delimiter=' ')

# Run the "model" and save the output in a text file
# This will happen offline for external models
Y = SAC.predict(param_values)
np.savetxt("Output_Sobol\\.txt", Y, delimiter=' ')

```

4.2.3 Sensitivity Analysis

Then, we do sensitivity analysis for 13 parameters of SAC-SMA model:



Step 1: Define parameter and model information

- ✧ Choose “Sensitivity Analysis” tab;
- ✧ Load parameter file “UQ-PyL/UQ/test_functions/params/SAC.txt” and model file (driver file) “UQ-PyL/UQ/test_functions/SAC.py”.

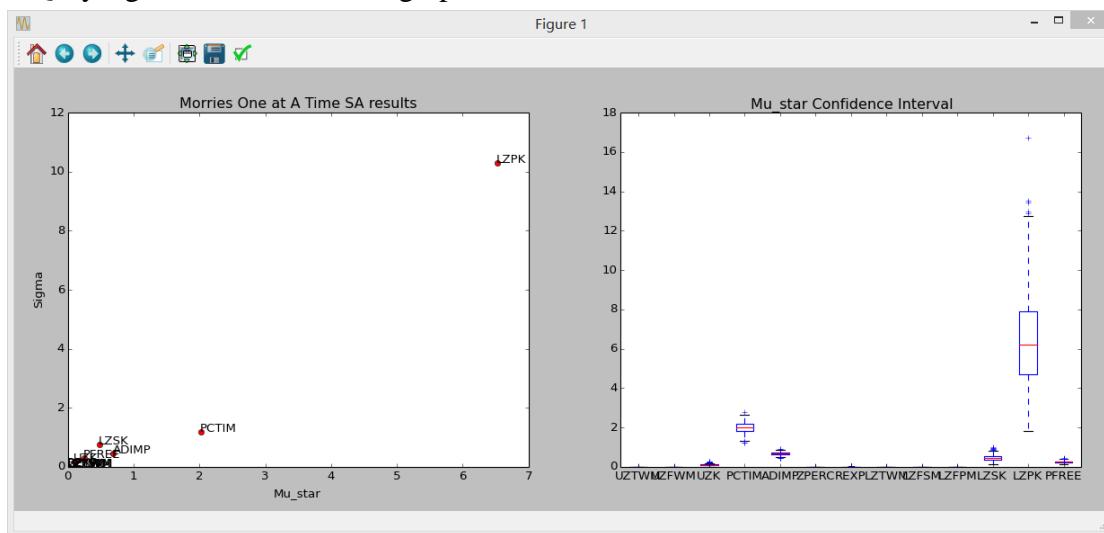
Step 2: Load DoE results

- ✧ Load DoE results, sample input file
“UQ-PyL/UQ/test_functions/SAC/sample_output_morris_2015_05_19_21_34_26.txt” and model output file
“UQ-PyL/UQ/test_functions/SAC/model_output_morris_2015_05_19_21_34_26.txt”.

Step 3: Choose sensitivity analysis method and show results

- ✧ Choose sensitivity analysis method “Morris” and click “Show Results” button to acquire sensitivity analysis results.

UQ-PyL gives the tabular and graphic results:



This step can also be implemented using python script:

Python script file (SAC_SA.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True

from UQ.DoE import morris_oat
from UQ.analyze import *
from UQ.test_functions import SAC
from UQ.util import scale_samples_general, read_param_file
import numpy as np
import random as rd

# Set random seed (does not affect quasi-random Sobol sampling)
seed = 1
np.random.seed(seed)
```

```

rd.seed(seed)

# Read the parameter range file and generate samples
param_file = './UQ/test_functions/params/SAC.txt'
pf = read_param_file(param_file)

# Generate samples (choose method here)
param_values = morris_oat.sample(20, pf['num_vars'], num_levels = 10,
grid_jump = 5)

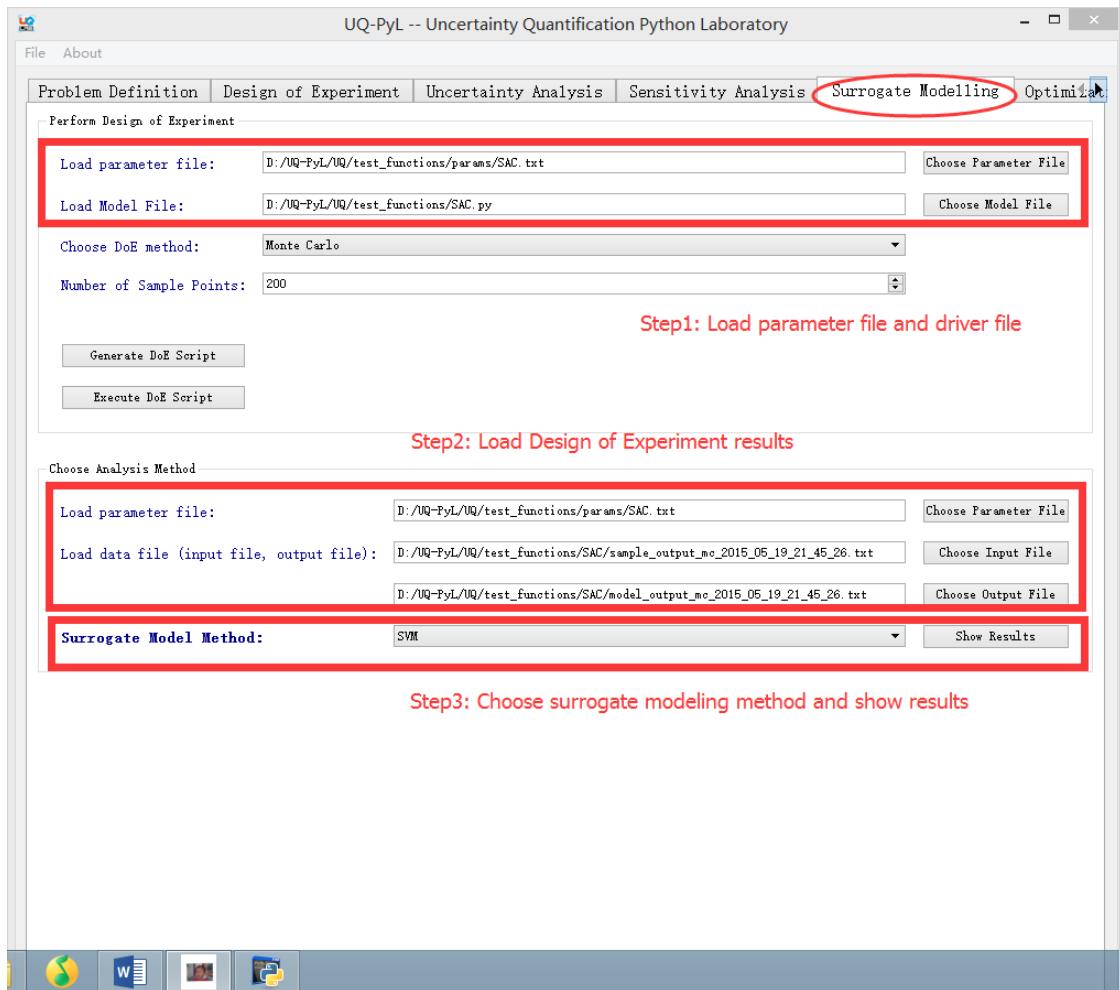
# Samples are given in range [0, 1] by default. Rescale them to your
parameter bounds.
scale_samples_general(param_values, pf['bounds'])
np.savetxt('Input_SAC.txt', param_values, delimiter=' ')

# Run the "model" and save the output in a text file
# This will happen offline for external models
Y = SAC.predict(param_values)
np.savetxt("Output_SAC.txt", Y, delimiter=' ')

# Perform the sensitivity analysis/uncertainty analysis using the model
output
# Specify which column of the output file to analyze (zero-indexed)
morris.analyze(param_file, 'Input_SAC.txt', 'Output_SAC.txt', column =
0)

```

4.2.4 Surrogate Modeling



Step 1: Define parameter and model information

- ✧ Choose “Surrogate Modeling” tab;
- ✧ Load parameter file “UQ-PyL/UQ/test_functions/params/SAC.txt” and model file (driver file) “UQ-PyL/UQ/test_functions/SAC.py”.

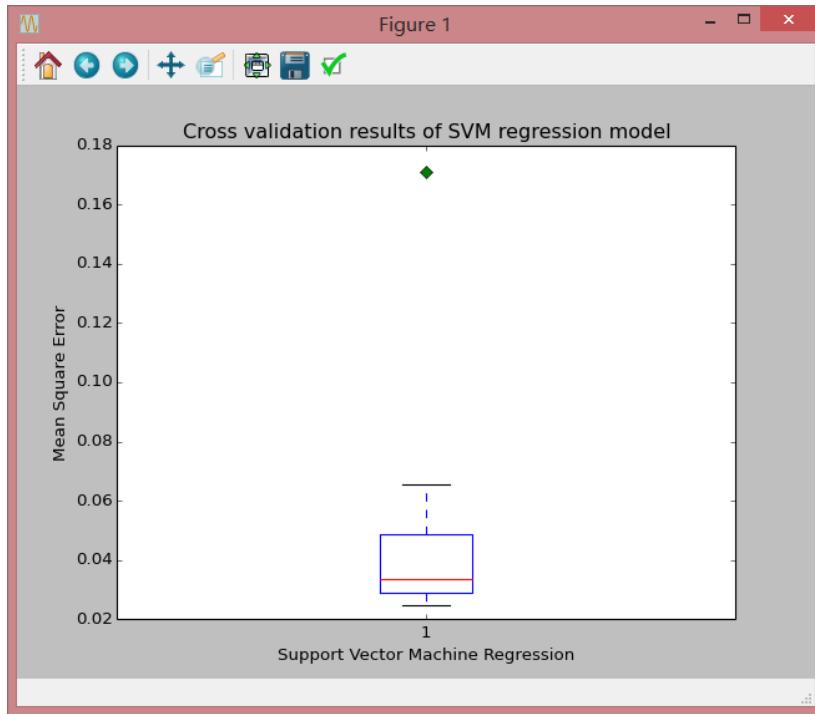
Step 2: Load DoE results for surrogate modeling

- ✧ Choose DoE results, sample input file “UQ-PyL/UQ/test_functions/SAC/sample_output_mc_2015_05_19_21_45_26.txt” and model output file “UQ-PyL/UQ/test_functions/SAC/model_output_mc_2015_05_19_21_45_26.txt”.

Step 3: Choose surrogate modeling method and show results

- ✧ Choose surrogate modeling method “SVM”;
- ✧ Click “Show Results” button to acquire surrogate modeling results.

UQ-PyL gives the tabular and graphic results:



This step can also implemented using python script:

Python script file (SAC_Surrogate.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True

from UQ.DoE import monte_carlo
from UQ.test_functions import SAC
from UQ.util import scale_samples_general, read_param_file, discrepancy
import numpy as np
import random as rd

# Set random seed (does not affect quasi-random Sobol sampling)
seed = 1
np.random.seed(seed)
rd.seed(seed)

# Read the parameter range file and generate samples
param_file = './UQ/test_functions/params/SAC.txt'
pf = read_param_file(param_file)

# Generate samples (choose method here)
param_values = monte_carlo.sample(500, pf['num_vars'])
```

```

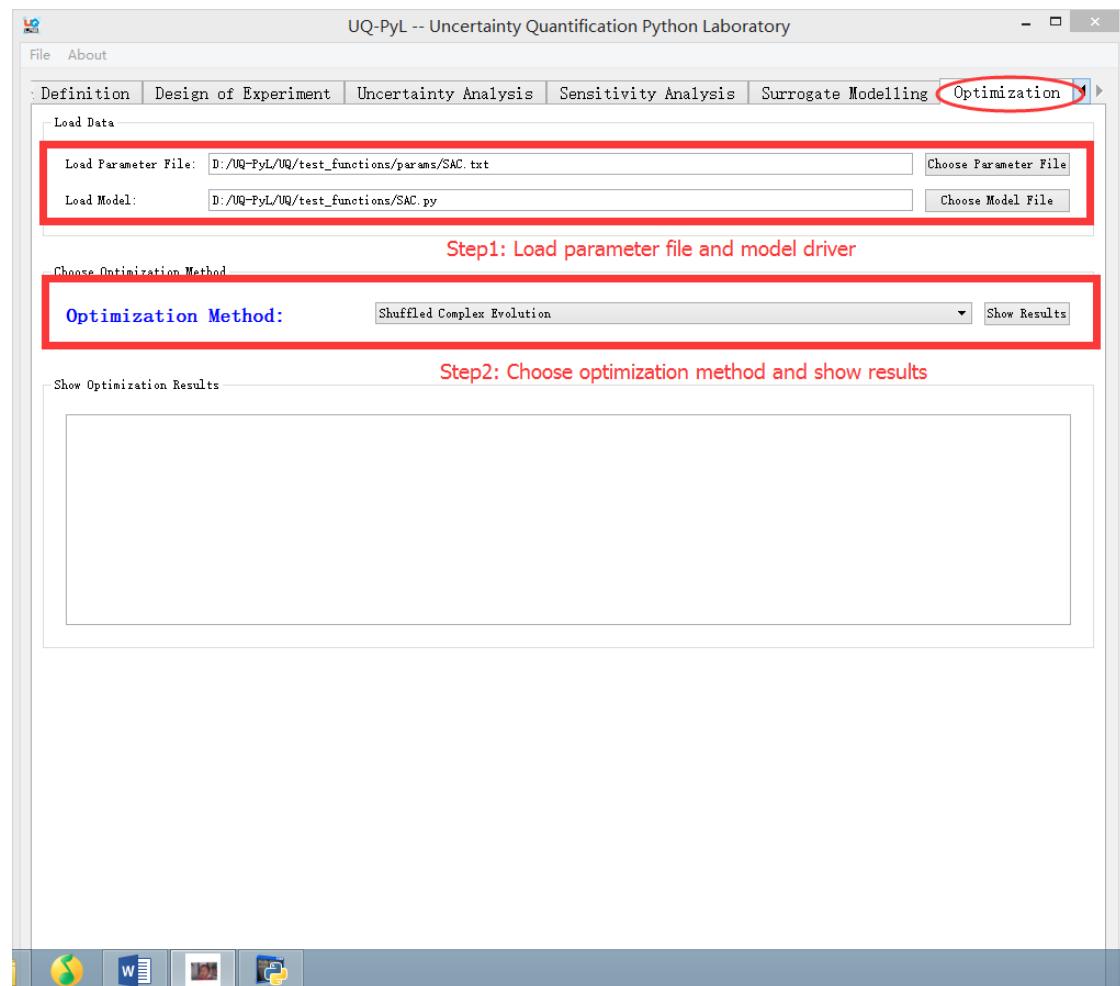
# Samples are given in range [0, 1] by default. Rescale them to your
# parameter bounds.
scale_samples_general(param_values, pf['bounds'])
np.savetxt('Input_SAC.txt', param_values, delimiter=' ')

# Run the "model" and save the output in a text file
# This will happen offline for external models
Y = SAC.predict(param_values)
np.savetxt("Output_SAC.txt", Y, delimiter=' ')

# Perform regression analysis using the model output
# Specify which column of the output file to analyze (zero-indexed)
model = SVR.regression('Input_SAC', 'Output_SAC', column = 0, cv = True)

```

4.2.5 Parameter Optimization



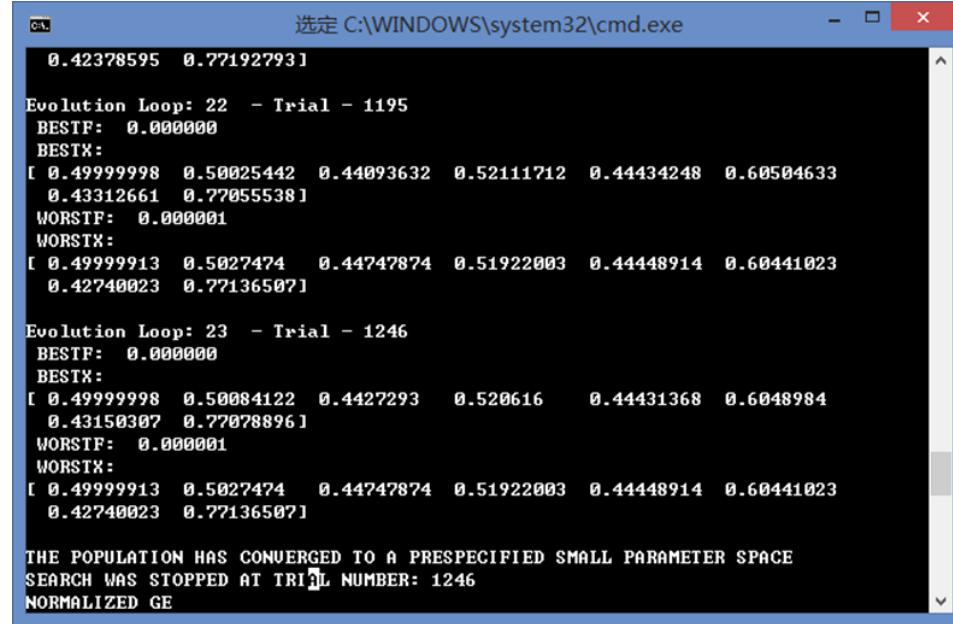
Step 1: Define parameter and model information

- ✧ Choose “Optimization” tab;
- ✧ Load parameter file “UQ-PyL/UQ/test_functions/params/SAC.txt” and model file (driver file) “UQ-PyL/UQ/test_functions/SAC.py”.

Step 2: Choose optimization method and show results

- ✧ Choose optimization method “Shuffled Complex Evolution” and click “Show Results” button to acquire optimization results.

UQ-PyL gives the tabular and graphic results:

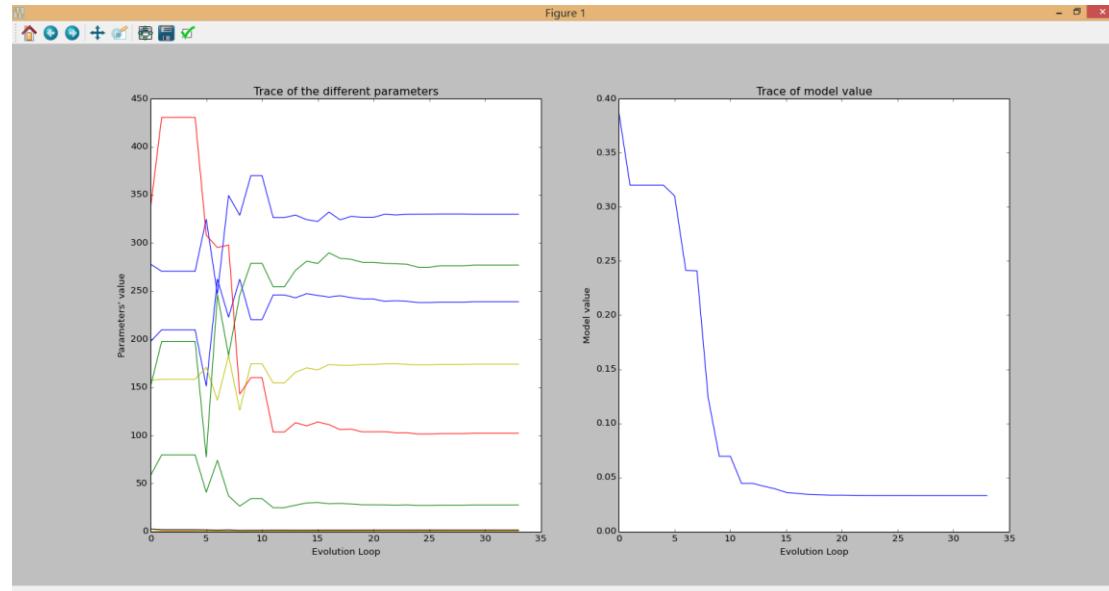


```
0.42378595 0.771927931

Evolution Loop: 22 - Trial - 1195
BESTF: 0.000000
BESTX:
[ 0.49999998  0.50025442  0.44093632  0.52111712  0.44434248  0.60504633
  0.43312661  0.77055538]
WORSTF: 0.000001
WORSTX:
[ 0.49999913  0.5027474  0.44747874  0.51922003  0.44448914  0.60441023
  0.42740023  0.77136507]

Evolution Loop: 23 - Trial - 1246
BESTF: 0.000000
BESTX:
[ 0.49999998  0.50084122  0.4427293  0.520616  0.44431368  0.6048984
  0.43150307  0.77078896]
WORSTF: 0.000001
WORSTX:
[ 0.49999913  0.5027474  0.44747874  0.51922003  0.44448914  0.60441023
  0.42740023  0.77136507]

THE POPULATION HAS CONVERGED TO A PRESPECIFIED SMALL PARAMETER SPACE
SEARCH WAS STOPPED AT TRIAL NUMBER: 1246
NORMALIZED GE
```



This step can also be implemented using python script:

Python script file (SAC_Optimization.py)

```
# Optional - turn off bytecode (.pyc files)
import sys
sys.dont_write_bytecode = True
import shutil
```

```

from UQ.optimization import SCE
from UQ.util import scale_samples_general, read_param_file, discrepancy
import numpy as np
import random as rd

# Read the parameter range file
param_file = './UQ/test_functions/params/SAC.txt'

bl=np.empty(0)
bu=np.empty(0)
pf = read_param_file(param_file)
for i, b in enumerate(pf['bounds']):
    bl = np.append(bl, b[0])
    bu = np.append(bu, b[1])

dir = './UQ/test_functions/'
shutil.copy(dir+'SAC.py', dir+'functn.py')

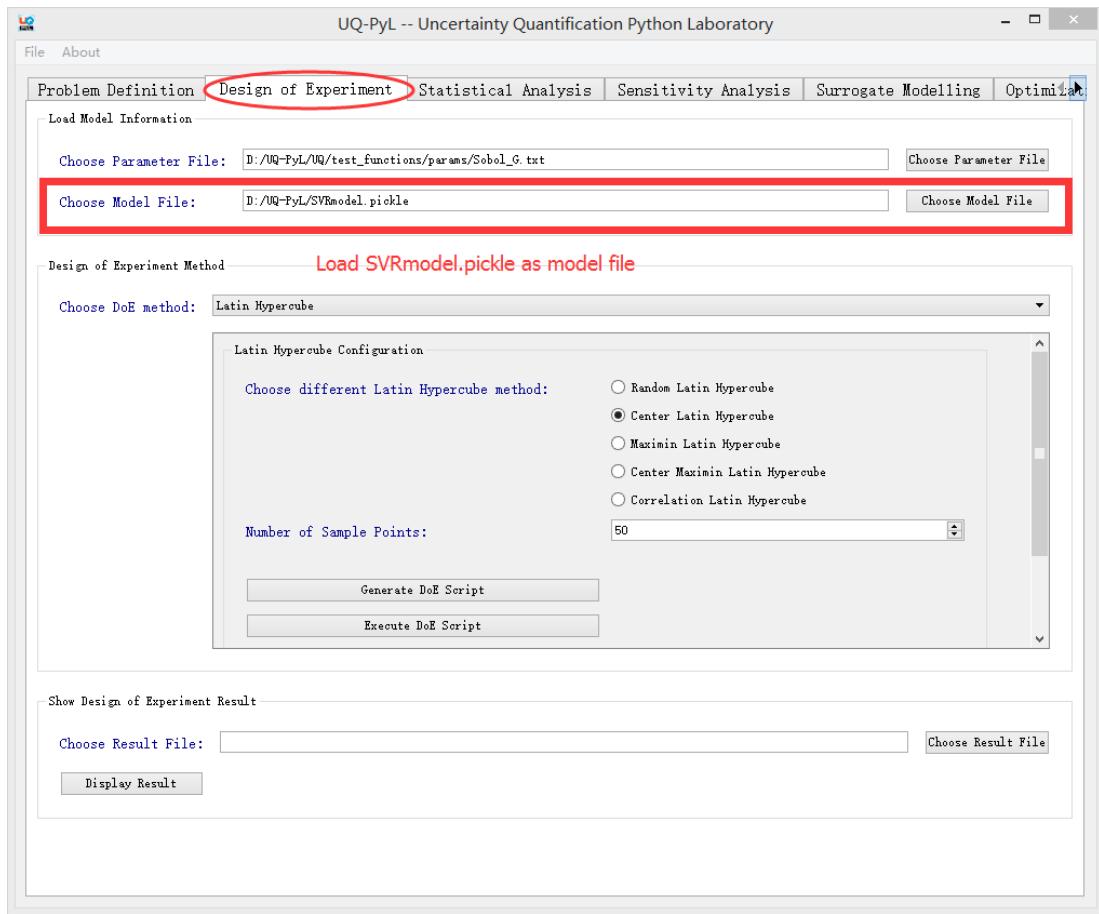
# Run SCE-UA optimization algorithm
SCE.sceua(bl, bu, ngs=2)

```

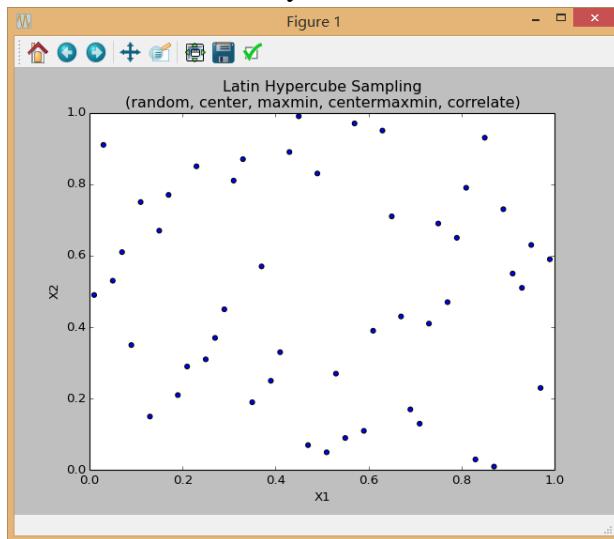
4.3 Run simulation on surrogate model

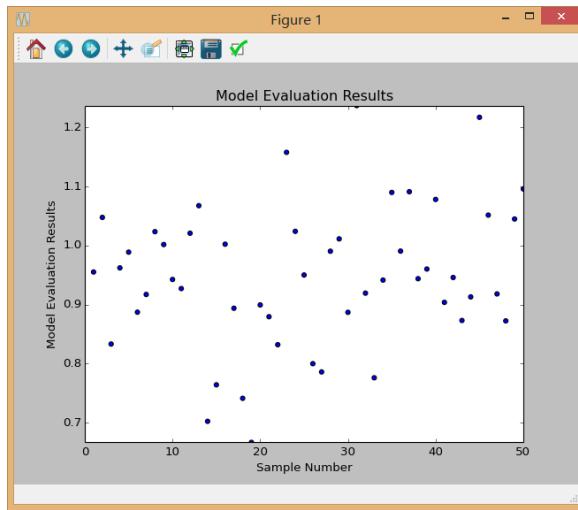
In Surrogate Modeling part, we generate a surrogate model from data sets of original model and save the surrogate model in a *.pickle file. Then we can run simulation on the surrogate model we saved.

For Design of Experiment part, we choose the model file as *.pickle file, then it can run DoE on the surrogate model you created. Let's take Sobol' G function as an example. In section 4.1.5 we have created a surrogate model and saved it as "SVRmodel.pickle" file. In Design of Experiment tab, we load "UQ-PyL/SVRmodel.pickle" file as model file, all the others as same as section 4.1.2:



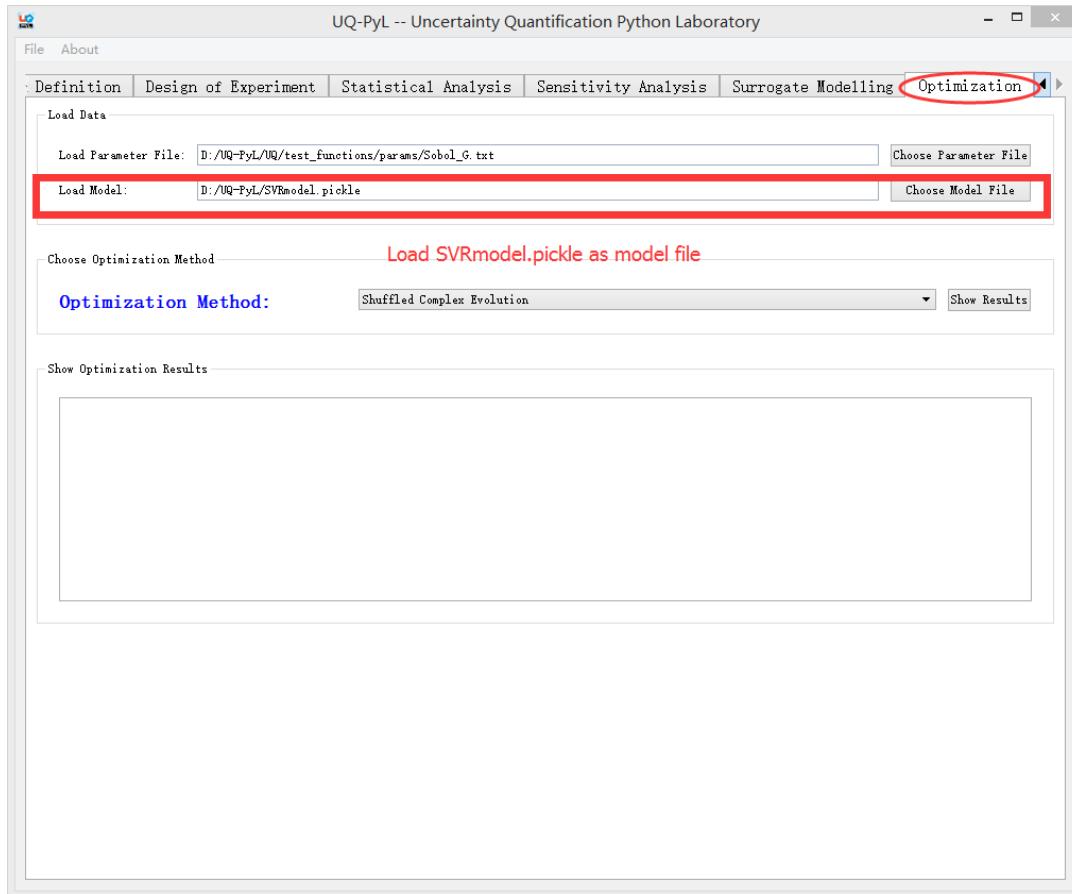
Then we do DoE analysis, it can obtain tabular and graphic results:





The result is different from run the same algorithm on the original Sobol' G function model.

For Parameter Optimization part, we also choose the model file as *.pickle file, then it can run global optimization algorithm on the surrogate model.

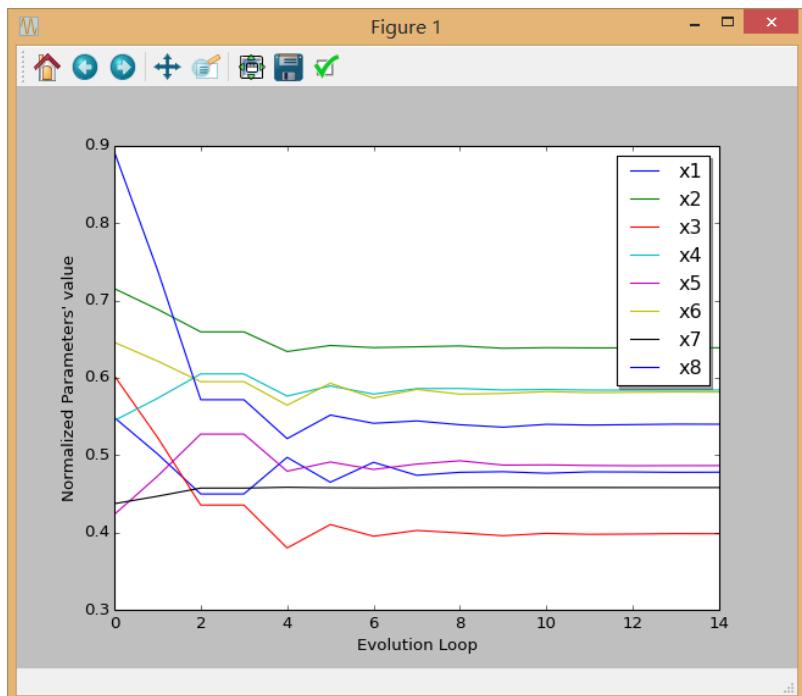


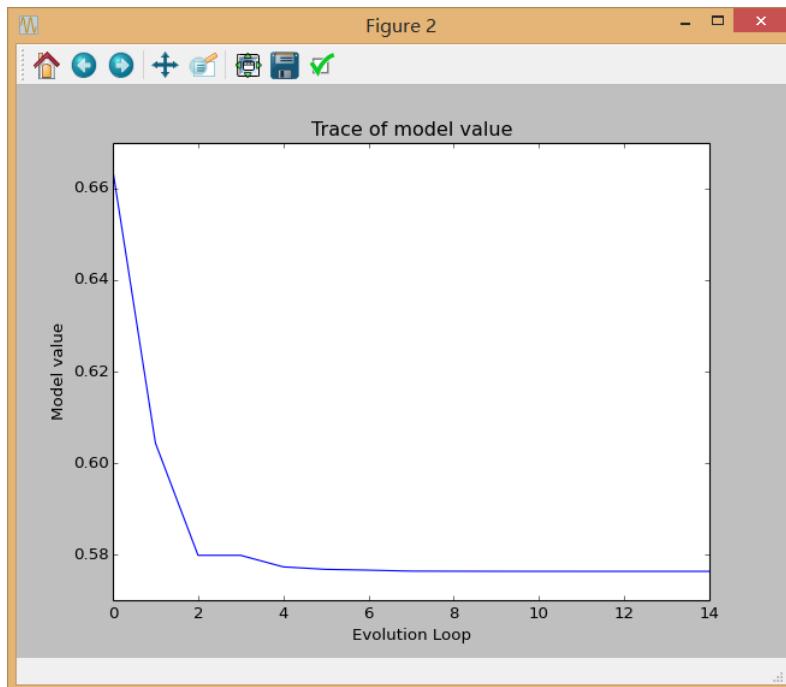
Then we do SCE parameter optimization algorithm, it can obtain tabular and graphic results:

```

C:\Windows\system32\cmd.exe
[ 0.47809971  0.63880959  0.3988901   0.58434864  0.48668063  0.58179596
  0.45837269  0.54025876 ]
WORSTF:  0.576408
WORSTX:
[ 0.47925921  0.64045023  0.40132286  0.58441515  0.48800051  0.58128183
  0.45816132  0.54382353 ]
Evolution Loop: 14 - Trial - 766
BESTF:  0.576394
BESTX:
[ 0.47827325  0.63882823  0.39877878  0.58431708  0.48674597  0.5815977
  0.45837516  0.5401269 ]
WORSTF:  0.576408
WORSTX:
[ 0.47700161  0.63716216  0.39605221  0.58439443  0.48579287  0.58188545
  0.45862374  0.53595416 ]
THE BEST POINT HAS IMPROVED IN LAST 10 LOOPS BY LESS THAN THE THRESHOLD 0.100000
CONVERGENCE HAS ACHIEVED BASED ON OBJECTIVE FUNCTION CRITERIA!!!
SEARCH WAS STOPPED AT TRIAL NUMBER: 766
NORMALIZED GEOMETRIC RANGE = 0.001337
THE BEST POINT HAS IMPROVED IN LAST 10 LOOPS BY 0.075609
微软拼音 半 :

```





Also, the result is different from run the same algorithm on the original Sobol' G function model.

4.4 Use Interactive UQ-PyL Software

4.4.1 How to run interactive UQ-PyL Software

In version 1.1, we have an interactive version of UQ-PyL software. Double click the



“UQ-PyL Interactive” icon you can enter the software. Also, you can run “.\UQ-PyL\main_interactive.pyw” file to enter into the interactive version of UQ-PyL software. Below is the main page of the software:

The screenshot shows the UQ-PyL Interactive Environment window. On the left is a code editor containing Python code for generating Sobol samples and calculating discrepancy. The right side has two panes: an upper pane showing variable values (Y, param_file, param_values, pf, seed) and a lower pane showing the Spyder internal shell output.

```

1 # Optional - turn off bytecode (.pyc files)
2 import sys
3 sys.dont_write_bytecode = True
4
5 from UQDoS import monte_carlo, normal, sobol, lhs, box_behnen, central_composite, fast_sampler,\n    ffn, finite_diff, frac_fact, full_fact, morris_cat, plackett_burnman, saltelli, symmetric_1D
6 from UQPy import *
7 from UQPy.Samples import *
8 from UQPy.Distributions import *
9 OrdinaryLeastSquares, LAR, Lasso, Ridge, SGD, RF
10 from UQPy.Optimization import SCE, AMG
11 from UQPy.TestFunctions import Sobol_G, SAC
12 from UQPy.Samples import scale_samples_general, read_param_file, discrepancy
13 import numpy as np
14 import random as rd
15
16 # Examples: Run Sobol, Morris, or FAST on a test function
17 # The parameters shown for each method are also the default values if omitted
18
19 # - no random seed (does not affect quasi-random Sobol sampling)
20 seed = 1
21 np.random.seed(seed)
22 rd.seed(seed)
23
24 # Read the parameter range file and generate samples
25 param_file = './UQ/test_functions/params/Sobol_G.txt'
26 pf = read_param_file(param_file)
27
28 # Generate samples (choose method here)
29 # param_values = monte_carlo.sample(500, pdf('num_vars'))
30 # param_values = normal.sample(100, pdf('num_vars'))
31 # param_values = sobol.sample(100, pdf('num_vars'))
32 # param_values = full_fact.sample(100, pdf('num_vars'))
33 # param_values = saltelli.sample(100, pdf('num_vars')), calc_second_order = True
34 param_values = morris_cat.sample(100, pdf('num_vars'), num_levels = 4, grid_Jump = 2)
35 # param_values = fast_sampler.sample(100, pdf('num_vars'))
36 # param_values = symmetric_1D.sample(500, pdf('num_vars'))
37 # param_values = central_composite.sample(500, pdf('num_vars'))
38 # param_values = lhs.sample(500, pdf('num_vars')), criterion='center'
39 # param_values = full_fact.sample(100, 3, 6)
40 # param_values = ffn.sample(5)
41 # param_values = frac_fact.sample("6 ab")
42 # param_values = box_burnman.sample(500, pdf('num_vars'))
43 # param_values = box_behnen.sample(3)
44 # param_values = central_composite.sample(3)
45 # param_values = finite_diff.sample(1000, param_file, delta=0.001)
46 # res = discrepancy.evaluate(param_values)
47 # print(res)
48

```

```

Key Type Size Value
Y float64 (90,) array([ 0.92016797,  0.93247791,  1.17311737,  0.65173187,  0.64312815, ...
param_file str 1 ./UQ/test_functions/params/Sobol_G.txt
param_values float64 (90, 8) array([[ 0.66666667,  0.          ,  0.33333333,  0.66666667,  1.          ,  ...
pf dict 3 {'num_vars': 8, 'names': ['x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8'], 'boun ...
seed int 1 1

Spyder 2.2.5 internal shell on Python 2.7.6 32bits [Windows]
>>> D:\UQ-PyL\UQ\optimization\SCE.py:79: SyntaxWarning: name 'functn' is assigned to before
global declaration
global functn
D:\UQ-PyL\UQ\optimization\SCE.py:131: SyntaxWarning: name 'functn' is assigned to before global
declaration
global functn
Parameter   Sigma Mu_Star Mu_Star Conf
x1 0.115184 2.616127 2.647760 0.445780
x2 0.127724 1.719138 1.542336 0.482545
x3 -0.039390 0.588605 0.542817 0.148633
x4 -0.118547 0.313918 0.298576 0.089000
x5 0.023367 0.093918 0.092459 0.011261
x6 0.023367 0.013464 0.014427 0.012365
x7 0.013475 0.027525 0.023902 0.011979
x8 -0.007195 0.034502 0.029983 0.011464

```

Interactive version of UQ-PyL software

The interface is very similar to MATLAB GUI, we use Spyder package (<http://pythonhosted.org/spyder/>) to achieve this function. The left part of the interface is a code editor, you can type your python code here. After run the python code, you can see internal variable values in the upper right of the interface and output results in the lower right part.

4.4.2 How to use interactive UQ-PyL Software

Method One: You can write your own python code in the editor part then click “Run”



button to run the python script. Variable values and output values will be display on the upper right part and lower right part of the interface.



Method Two: Also you can click “Open” button



to load a exist python script file, for example “.\UQ-PyL\python-example.py”, then click “Run” button to run the python script.

You can see the variable values below:

Key	Type	Size	Value
Y	float64	(90,)	array([0.92016797, 0.93247791, 1.17311737, 0.65173187, 0.64312815, ...
param_file	str	1	./UQ/test_functions/params/Sobol_G.txt
param_values	float64	(90, 8)	array([[0.66666667, 0. , 0.33333333, 0.66666667, 1. , ...
pf	dict	3	{'num_vars': 8, 'names': ['x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8'], 'boun ...
seed	int	1	1

And tabular and graphic outputs:

```

Parameter Mu Sigma Mu_Star Mu_Star_Conf
x1 -0.706156 2.641627 2.640762 0.445780
x2 0.127724 1.719118 1.542336 0.482545
x3 -0.039390 0.588605 0.542817 0.148633
x4 -0.118547 0.313918 0.295576 0.098900
x5 0.001200 0.025919 0.024397 0.005641
x6 -0.002367 0.039866 0.034427 0.012365
x7 0.013475 0.027525 0.023902 0.011979
x8 -0.007195 0.034502 0.029983 0.011464

```

