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Surrogate Model Based Uncertainty Analysis and Key Process Parameter Determination for Product Reliability in Assembling Process

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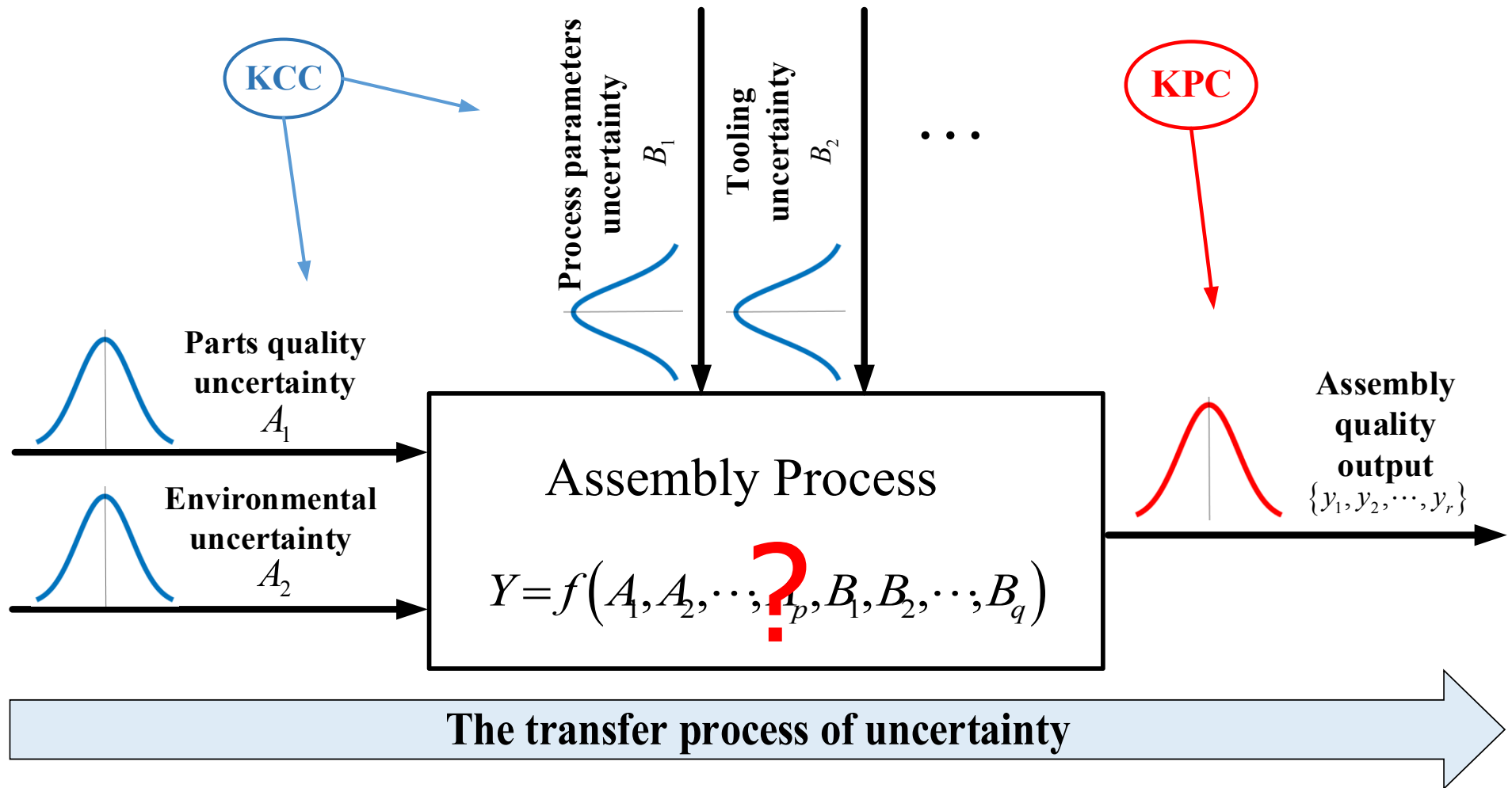
May 11, 2018

Problem

Some facts:

- Assembly is an **important stage** in product manufacturing process.
- The values of assembly quality characteristics are often **uncertain**.
- The variation of assembly quality characteristic value of high reliability products must be maintained in **a reasonable range**.

Problem

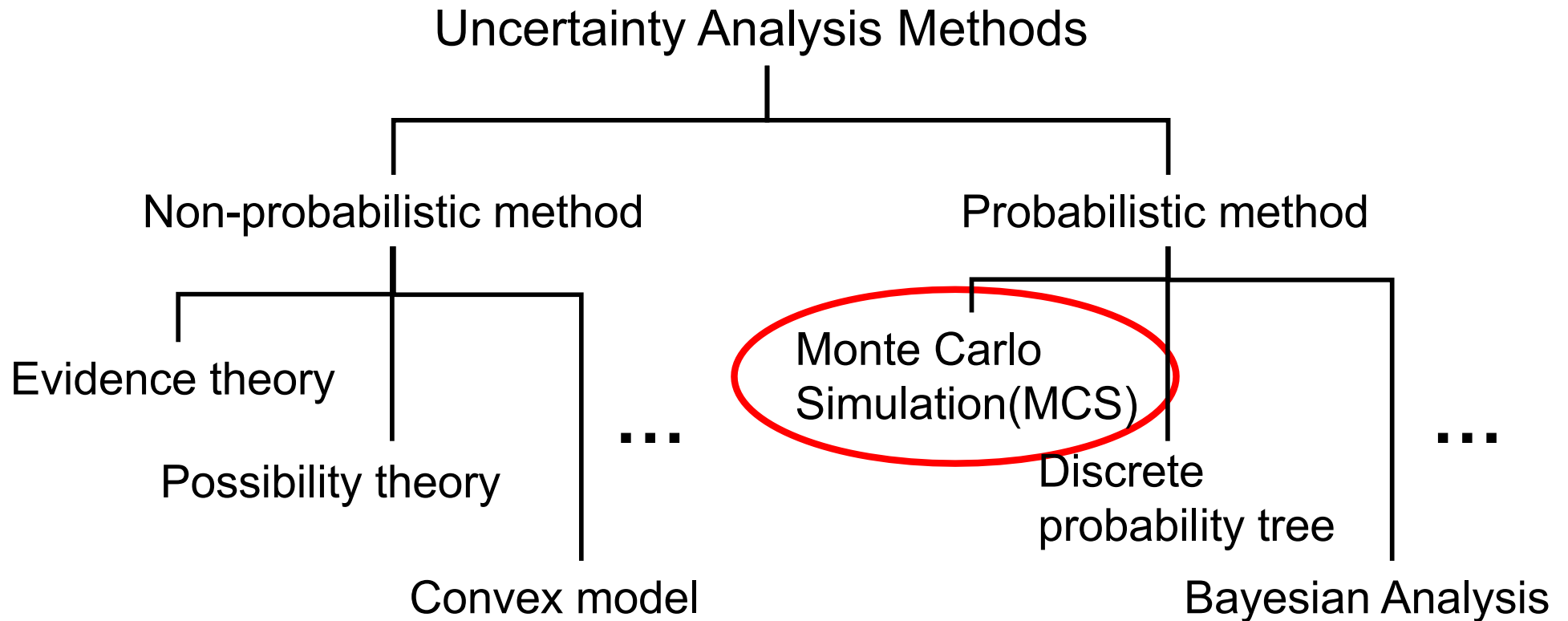


Problem

Research Questions:

- How to quantify the uncertainty in assembly process?
- How to reduce the fluctuation of assembly quality?

Methods

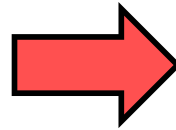


Methods

Advantages and disadvantages of MCS

Advantages

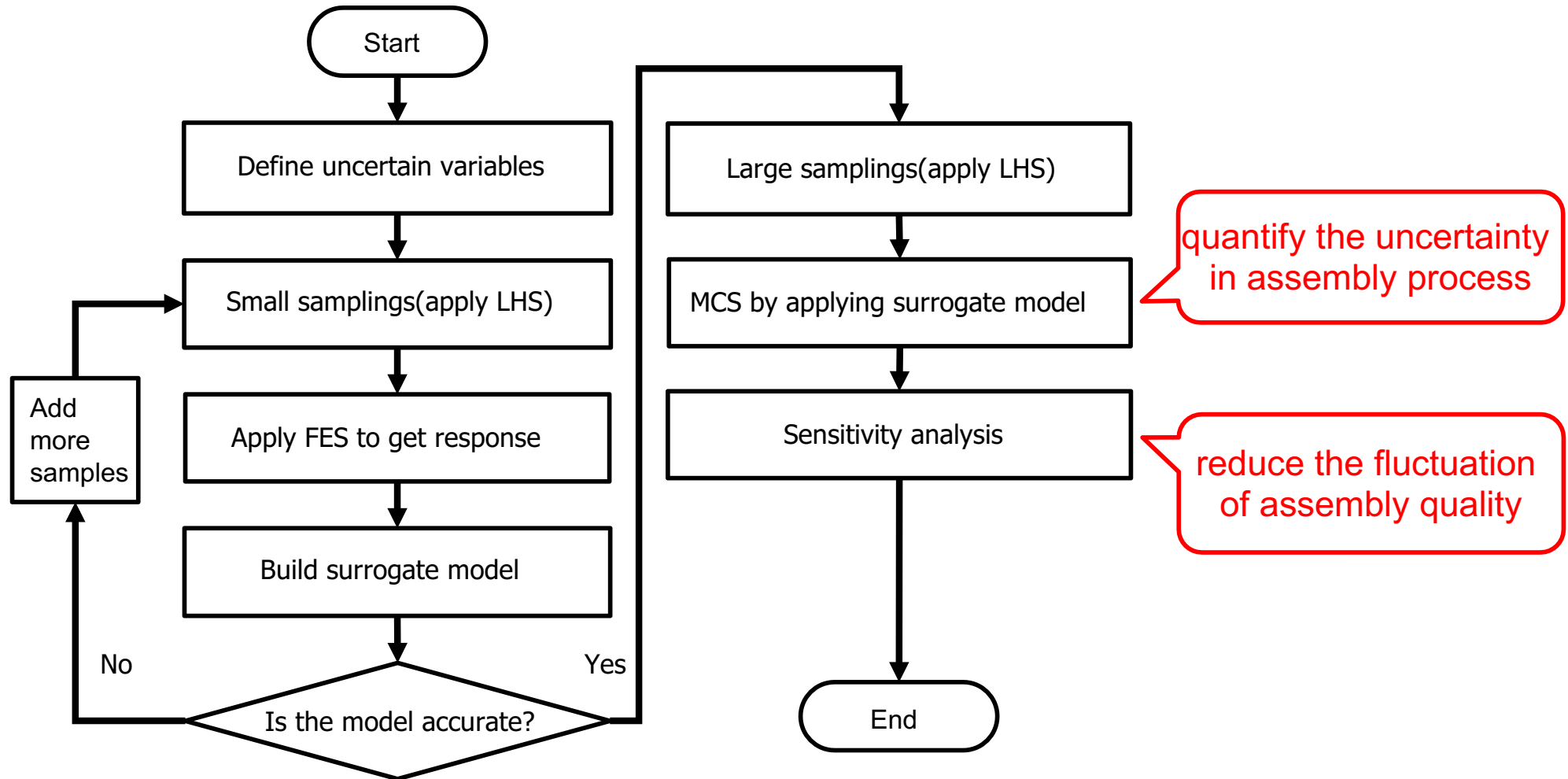
- Simple principle
- Large sample demand
- High accuracy
- Low computation speed
- Multiple unknown quantities can be calculated at the same time



MCS using Surrogate model

- Using small sample data to obtain the complex mapping relationship between KCC and KPC
- Increase the speed of calculation

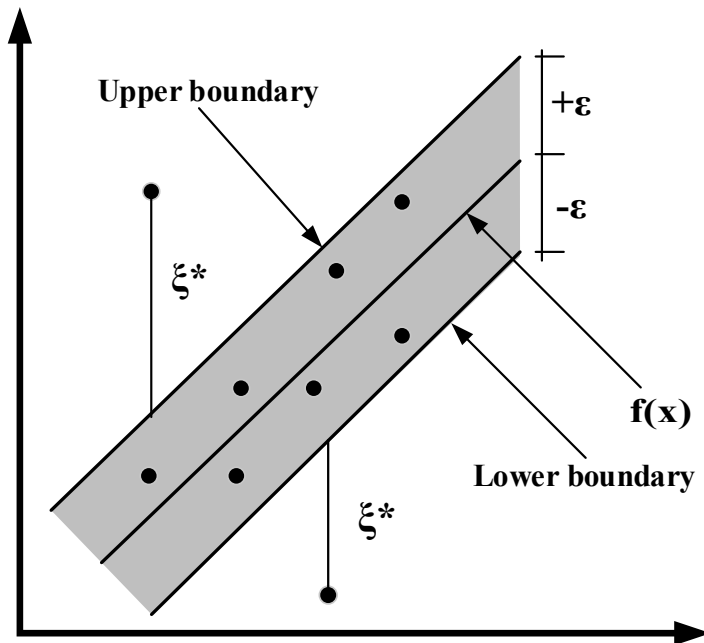
Flowchart of the surrogate model based uncertainty analysis



Construction of surrogate model

Support vector regression(SVR)

$$f(x) = \omega \cdot \varphi(x) + b \quad \omega, b?$$



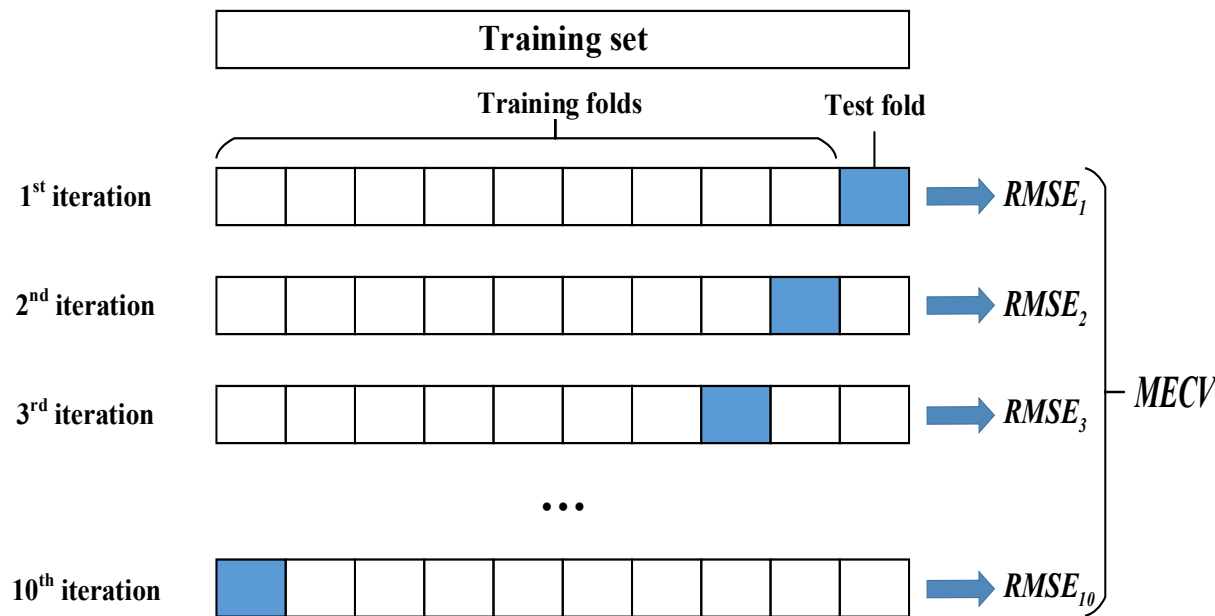
$$\begin{aligned} \min \quad & \frac{1}{2} \|\omega\|^2 + c \sum_{i=1}^n (\xi_i + \xi_i^*) \\ \text{s.t.} \quad & \begin{cases} y_i - \omega \cdot \varphi(x_i) - b \leq \varepsilon + \xi_i \\ \omega \cdot \varphi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{aligned}$$



Get w and b

Construction of surrogate model

Validation method of surrogate model accuracy



Steps:

1. Divide the experimental or simulation data into k equal parts;
2. Take one part for the validate of model accuracy, and the remaining parts are used as model training;
3. When each part has been used as model validation, stop training, take the model which has minimum residual error as the final model.

$$MECV = \frac{1}{k} \sum_{i=1}^k RMSE_k \quad RMSE = \sqrt{\frac{1}{m_t} \sum_{i=1}^{m_t} (y_i - \hat{y}_i)^2}$$

Sensitivity analysis based on MCS

Failure probability

$$P_f = P\{F\} = P\{y(x) < y_{down}^* \parallel y(x) > y_{up}^*\}$$

$$P_f = \int \cdots \int_F f_x(x_1, x_2, \cdots, x_n) dx_1 dx_2 \cdots dx_n$$

Dimensional sensitivity

$$\begin{aligned} S_{\theta_{x_i}^h} &= \frac{\partial P_f}{\partial \theta_{x_i}^h} \\ &= \int \cdots \int_F \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} d\mathbf{x} \\ &= \int \cdots \int_F \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} \frac{1}{f_X(\mathbf{x})} f_X(\mathbf{x}) d\mathbf{x} \\ &= E \left[\frac{I_F(\mathbf{x})}{f_X(\mathbf{x})} \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} \right] \end{aligned}$$

$$\mathfrak{S}_{\theta_{x_i}^h} = \frac{1}{m} \sum_{j=1}^m \frac{I_F(\mathbf{x}_j)}{f_X(\mathbf{x}_j)} \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} \Big|_{\mathbf{x}=\mathbf{x}_j}$$

Dimensionless sensitivity

$$\begin{aligned} S_{\theta_{x_i}^h} &= \frac{\partial P_f / P_f}{\partial \theta_{x_i}^h / \sigma_{x_i}} \\ &= \int \cdots \int_F \frac{\sigma_{x_i}}{P_f} \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} d\mathbf{x} \\ &= \int \cdots \int_F \frac{\sigma_{x_i}}{f_X(\mathbf{x})} \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} \frac{f_X(\mathbf{x})}{P_f} d\mathbf{x} \\ &= E \left[\frac{\sigma_{x_i}}{f_X(\mathbf{x})} \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} \right] \end{aligned}$$

$$\mathfrak{S}_{\theta_{x_i}^h} = \frac{1}{m} \sum_{j=1}^m \frac{\sigma_{x_i}}{f_X(\mathbf{x}_j)} \frac{\partial f_X(\mathbf{x})}{\partial \theta_{x_i}^h} \Big|_{\mathbf{x}=\mathbf{x}_j}$$

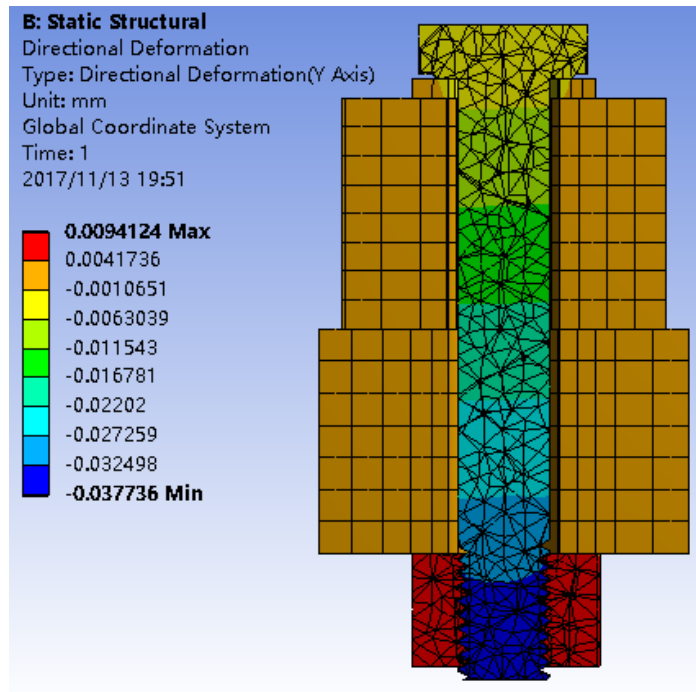
For normal variables

$$\mathfrak{S}_{\sigma_{x_i}} = \frac{\partial P_f / P_f}{\partial \sigma_{x_i} / \sigma_{x_i}} = \frac{1}{m} \sum_{j=1}^m (u_{ji}^2 - 1)$$

$$\mathfrak{S}_{\mu_{x_i}} = \frac{\partial P_f / P_f}{\partial \mu_{x_i} / \sigma_{x_i}} = \frac{1}{m} \sum_{j=1}^m u_{ji}$$

Case study

Finite element simulation of bolt assembly



Entity model parameters

major diameter: 10mm

pitch diameter: 9.026mm

minor diameter: 8.376mm

pitch: 1.5mm

half-thread angle: 30°

bolt effective length: 65mm

FES parameters

material of the bolt, nut and gasket: stainless steel

material of connecting parts: structural steel

grid size of bolt, nut and gasket: 1mm

grid size of connecting parts: 3mm

elastic modulus: 1.93×10^{13} pa

friction coefficients: 0.15, 0.2

Loading parameters

torque: 20N

loading time: 1s

Case study

Construction of surrogate model

Table 1 The probability parameters of uncertain variables

Variable	Mean value	Standard Deviation
T	20000($N \cdot mm$)	133
u_1	0.15	0.001
u_2	0.2	0.00133

Table 2 Samples and responses of bolt assembly with sample number of 50

Number	Inputs			Outputs	
	$T(N \cdot mm)$	u_1	u_2	$\Delta L(mm)$	$F_0(N)$
1	19896	0.1474	0.2038	0.0374	6121.364
2	20040	0.1509	0.1993	0.0378	6186.691
3	19624	0.1521	0.1967	0.0372	6090.653
4	19960	0.1505	0.2036	0.0372	6092.076
5	19656	0.1484	0.1974	0.0375	6139.046
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots

```

1 % 从Excel读取数据
2 data=xlread('shuju2.xlsx','B8:F84');
3 %数据预处理
4 input_train=data(1:30,1:3)';
5 output_train=data(1:30,5)';
6 input_test=data(31:50,1:3)';
7 output_test=data(31:50,5)';
8 %训练数据归一化
9 [input_train_one,inputps]=mapminmax(input_train);
10 [output_train_one,outputps]=mapminmax(output_train);
11 %训练数据转置
12 input_train_one_z=input_train_one';
13 output_train_one_z=output_train_one';
14 %LS-SVM网络初始化及训练
15 gam = 10;
16 sig2 = 0.4;
17 type = 'function_estimation';
18 [LSSVMnet,b]=trainlssvm(input_train_one_z,output_train_one_z,type,gam,sig2,'RBF_kernel');
19 %测试数据归一化及转置
20 input_test_one=mapminmax('apply',input_test,inputps);
21 input_test_one_z=input_test_one';
22 %测试数据仿真及转置
23 LSSVMoutput_test_one=evallssvm(input_train_one_z,output_train_one_z,type,gam,sig2,'RBF_kernel'),(LSSVMnet,b),input_test_one_z);
24 LSSVMoutput_test_one_z=LSSVMoutput_test_one';
25 %仿真结果反归一化
26 LSSVMoutput_test=mapminmax('reverse',LSSVMoutput_test_one_z,outputps);

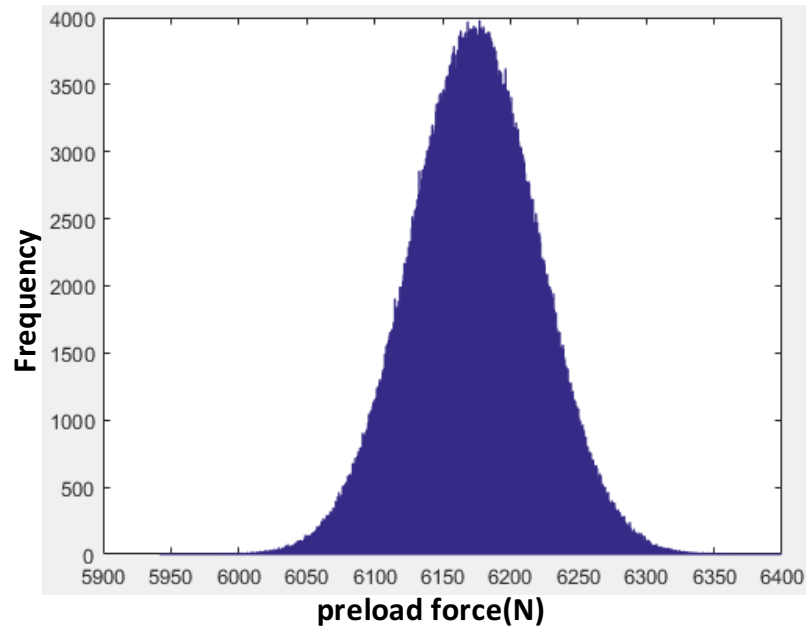
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MECV = 3.63

Meet the needs of MCS!

Case study

Surrogate model based MCS and sensitivity calculation



Calculation results

mean: 6173N

standard deviation: 2205N

qualified rate: 89% (between 6100N to 6250N)

calculation time: 30s

Table 3 Result of uncertain variables Sensitivity

	T	u_1	u_2
$S_\mu (\times 10^{-7})$	17.618	3.914	2.747
$S_\sigma (\times 10^{-7})$	-10.142	1.394	1.400

Torque **T** is the **key factor**

Closure

❖ This paper include

- *Theory* and *steps* of an uncertainty analysis method in product assembly process based on surrogate model and Monte Carlo Simulation.
- A *case study* of bolt assembly to verify the efficiency and correctness of the proposed method.

❖ Future work

- How to determinate the *influencing factors* of assembly quality exactly before the uncertainty analysis?
- How to analyze the sensitivity of parameters if they are *not random variables*?

Acknowledgements

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Thanks for your listening!

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