# Design of experiments for smoke depollution of diesel engine outputs

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#### ENBIS-EMSE 2009 Conference 1<sup>st</sup> July 2009





# Talk Overview

#### 1. deNOx model: study case

- 1. NOx trap: the way it works
- 2. NOx trap: the mathematical formulation
- 3. NOx trap: experimental and simulated results
- 2. Kriging with non linear trend (KNL)
  - 1. **Presentation**
  - 2. Kriging predictor
  - 3. Application on deNOx model and results
- 3. Conditioning by derivatives: improvement for KNL?
  - 1. **Presentation**
  - 2. Test model: presentation
  - 3. Application on test model and results
  - 4. First results on deNOx model

#### Conclusions

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### ➡ 1. NOx trap: the way it works

### Smoke post-treatment at the diesel engine output: NOx trap





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# Reduce pollutants emissions at the diesel engine output



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Smoke post-treatment at the diesel engine output: NOx trap





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### ➡ 1. NOx trap: the way it works

The NOx trap operates in two phases

- 1. NOx capture phase until saturation of active sites
- 2. NOx release phase after reducing the oxydated species





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#### Simplification of the problem

- Complex system: to reduce the complexity of the problem, at first, only capture phase is considered
- During this phase, the kinetic model have four dominant reactions: oxydation of CO, HC, NO et H<sub>2</sub>







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#### Kinetic model



Strain Two kinetic parameters for each reaction



### → 2. NOx trap: the mathematical formulation

- Mathematical model

The mathematical model of the NOx trap has the form,

$$Y=f(x,\beta)$$

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#### System inputs, denoted by x

On the experimental system, inputs are selected and controlled by the experimenter:

• Mass composition of five species present in the exhaust gas

 $c_1, c_2, c_3, c_4, c_5$ 

- ullet Mass flow of gas entering in the NOx trap, Q
- Entering gas temperature increase linearly with the time

$$x = (c_1, c_2, c_3, c_4, c_5, Q, T)^t$$



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System outputs, denoted by *Y* 

Mass composition of the three pollutants:

 $y_{HC}, y_{NOx}, y_{CO}$ 



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### → 3. NOx trap: experimental and simulated results



#### Inadequacy of the computer model

Kinetic parameter estimation from a learning set of 20 experiments

⇒ Important differences between computer model and experiments



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### 1. Presentation

#### Why kriging?

- 1. To resolve the inadequacy of the mathematical model
- 2. To determine the new experimental points, through variance prediction







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Kriging with non linear trend

Differences between computer model and experiments = Gaussian process

 $y(x)=f(x,\beta)+z_{\sigma^2,\theta}(x)$ 

where  $z_{\sigma^2,\theta}(x)$  is a Gaussian process such as E(z(x))=0 et  $cov(z(x),z(x+h))=\sigma^2 R_{\theta}(h)$ 







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Estimation of  $\beta$ ,  $\sigma^2$ ,  $\theta$ 

- Estimation by maximum likelihood
  - The analytical formula for  $\boldsymbol{\beta}$  is replaced by a minimization procedure







### 2. Kriging predictor

- Kriging predictor

$$\hat{y}(x_0) = rR^{-1}Y - (F^T R^{-1}r - f)^T (F^T R^{-1}F)^{-1} F^T R^{-1}Y$$

#### Notation

- Let *m* be the number of design points
- $Y = (Y_1, ..., Y_m)^T$  output observed at location  $S = (S_1, ..., S_m)^T$
- $x_{\theta}$  : point to be predicted
- R : correlation matrix between observations
- ullet r : correlation vector between observations and the point to be predicted
- $F=f(S,\beta)$ : value of computer model at design points
- $f=f(x_0,\beta)$  : value of computer model at the prediction point







### → 2. Kriging predictor

- Kriging predictor

$$\hat{y}(x_0) = rR^{-1}Y - (F^T R^{-1}r - f)^T (F^T R^{-1}F)^{-1} F^T R^{-1}Y$$

Prediction variance

$$\varphi(x_0) = \sigma^2 \left( 1 + \left\| F^T R^{-1} r - f \right\|_{(F^T R^{-1} F)} + \left\| r \right\|_R \right)$$

where  $\left\| u \right\|_A = u^T A^{-1} u$ 







### ➡ 2. Kriging predictor

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$$\left\|u\right\|_{A} = u^{T} A^{-1} u$$

#### **Parameters estimation**

Parameters are obtained by solving recursively the simultaneous equations:

$$\begin{vmatrix} \hat{\beta} = \min_{\beta} (Y - F)^T R^{-1} (Y - F) \\ \hat{\sigma}^2 = (Y - F)^T R^{-1} (Y - F) / m \\ \hat{\theta} = \arg\min\left[\hat{\sigma}^2 |R^{-1}|^{1/m}\right] \end{vmatrix}$$



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### → 3. Application on deNOx model and results

- Application

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•12 experimental points are taken uniformly along the temperature for each of the 19 first experiments

•CO and HC prediction for the 20th experiment, outputs are treated independently



### → 3. Application on the deNOx model and results

Influence of the number of design point

• HC concentration evolution prediction of the 20th experiment

• The approach is the same but 15 points are taken uniformly along the temperature instead of 12



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### Solution → 3. Application on the deNOx model and results

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### → 1. Presentation

#### Notation

- Let  $(s_1, \ldots, s_{m_1})$  the design points where function value is known
- Let  $(v_1, \ldots, v_{m_2})$  the design points where partial derivative according to the first direction is known
- Exponent (1) denotes the output derivative along the first direction
- Let,

 $Y = (Y_1, \dots, Y_{m_1}, Y_1^{(1)}, \dots, Y_{m_2}^{(1)})^T \text{ and } F = (f(s_1, \beta), \dots, f(s_{m_1}, \beta), f^{(1)}(v_1, \beta), \dots, f^{(1)}(v_{m_2}, \beta))^T$ 







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#### **Covariance structure**

Gaussian spatial correlation is used, defined by,

$$R(h) = \exp\left\{-\sum_{l=1}^{k} \theta_{l} h_{l}^{2}\right\}$$

The pairwise joint covariance of Y(.) and  $Y^{(1)}(.)$ , is given by, (Santner, Williams and Notz, 2003)

$$Cov(Y(s_i), Y^{(1)}(v_j)) = \sigma^2 2\theta_1(s_i^1 - v_j^1)R(s_i - v_j)$$
$$Cov(Y^{(1)}(v_i), Y^{(1)}(v_j)) = \sigma^2 (2\theta_1 - 4\theta_1^2(v_i^1 - v_j^1)^2)R(v_i)$$

 $-v_i$ )

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### ➡ 1. Presentation

Covariance matrix C

Covariance matrix is defined by,

$$C = \begin{pmatrix} C_{00} & C_{01} \\ C_{01}^{T} & C_{11} \end{pmatrix}$$

where:

•  $C_{00}$  is the  $m_1 \times m_1$  matrix of correlations between the elements of  $Y_i, 1 \le i \le m_1$ 

- $C_{01}$  is the  $m_1 \times m_2$  matrix of correlations between  $Y_i$  and  $Y_j^{(1)}$ ,  $1 \le j \le m_2$
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#### Kriging equations

Kriging equations are the same as for kriging with non linear trend







### ➡ 2. Test model: presentation

Application on two model

Kriging with non linear trend conditioning by derivatives (KNLD) is applied on:

- the test model: similar to study case but simpler and totally mastered
- the deNOx model







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#### Application on two model

Kriging with non linear trend conditioning by derivatives (KNLD) is applied on:

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- the deNOx model

**Equations system: represents the experimental system** 

Langmuir-Hinshelwood formalization:

$$\begin{cases} \frac{d[A]}{dt} = -\frac{k_0 \exp\{-\frac{E}{RT}\}[A]}{1 + b_0 \exp\{-\frac{\Delta H}{RT}\}[A]}\\ [A]_0 = -A_0 \end{cases}$$

Let g(x) be the model governed by this system



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#### **Kinetic parameters choice**

• g(x) depends on a hidden kinetic parameter vector,  $\xi = \{k_o, E, b_o, \Delta H\}$ ,

•  $\boldsymbol{\xi}$  has been chosen to conduct to very different concentration evolutions of A depending on the temperature

### 2. Test model: presentation

Second system: represents the mathematical model

Consider the following simple kinetic system:

$$\begin{cases} \frac{d[A]}{dt} = -k'_0 \exp\{-\frac{E'}{RT}\}[A] \\ [A]_0 = A_0 \end{cases}$$

Let  $f(x,\beta)$  be the model governed by this system, where  $\beta = \{ko',E'\}$ 







### ➡ 2. Test model: presentation

**Second system: represents the mathematical model** 

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Let  $f(x,\beta)$  be the model governed by this system, where  $\beta = \{ko',E'\}$ 

#### **Objective**

Determine parameters  $\beta$ ,  $\sigma^2$ ,  $\theta$  such as:

 $g(x)=f(x,\beta)+z_{\sigma^2,\theta}$ 







### ➡ 2. Test model: presentation

Simulations

Simulations for three different A<sub>0</sub> at a fixed time (80 seconds)

Solid line: 'experimental results' (function g), Dotted line: 'estimated model' (f)







### ➡ 3. Application on test model and results

#### Application

Test model prediction by KNL (red dotted line) and kriging with non linear trend conditioning by derivatives (red solid line) compared to experimental results (blue line)

> 3 initial concentration, 8 fixed time and 10 temperatures on each simulation









### ➡ 4. First results on deNOx model

#### Application

- HC concentration evolution prediction of the 20<sup>th</sup> experiment by KNL and kriging with non linear trend conditioning by derivatives (KNLD)
- 15 experimental points taken uniformly along the temperature on the 19 first experiments
- On each experimental point function and derivative values are supposed to be known



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#### **Points presented**

- 1. Kriging with non linear trend (KNL)
- 2. Kriging with non linear trend conditioning by derivatives (KNLD)







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- 2. Kriging with non linear trend conditioning by derivatives (KNLD)

#### 1. KNL: problems

- Numerical problems when number of design sites increases
  - Oscillations problems where response is less variable





#### **Points presented**

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- 2. Kriging with non linear trend conditioning by derivatives (KNLD)

#### 1. KNL: problems

- Numerical problems when number of design sites increases
  - Oscillations problems where response is less variable
- 2. KNLD: improvement for KNL
- Prediction is better, i.e. oscillations are less strong
- Model is too constrained





#### **Points presented**

- 1. Kriging with non linear trend (KNL)
- 2. Kriging with non linear trend conditioning by derivatives (KNLD)

#### 1. KNL: problems

- Numerical problems when number of design sites increases
  - Oscillations problems where response is less variable

#### **2. KNLD: improvement for KNL**

- Prediction is better, i.e. oscillations are less strong
- Model is too constrained

#### Perspectives

- 1. Take into account derivative information only on both, initial and final stages for KNLD
- 2. Determine an experimental design through variance prediction
- 3. Compare this experimental design to classical ones

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# Thank you for your attention!









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