

A 2-Stage Design Procedure for Computer Experiments

Comparative Study between Optimal Design and Space-Filling Design

N. Youssef
Supervisor: H. Wynn

Workpackage 3.1 Experimental Design

8 July 2009



Outline

- 1 Design for Computer Experiments
 - Space Filling Designs
 - Model Based Optimal Design (Maximum Entropy Design)
 - Proposed 2-Stage Design
- 2 Kriging and Prediction
 - Prediction Method
 - Measuring Accuracy of Prediction
- 3 Applications
 - Saltelli Simulator Example
 - Application on Rolls Royce Simulator
- 4 Conclusions
- 5 Main References

Design of Computer Experiments

- Designs generated by elementary methods for selecting samples (Simple random sampling, stratified random sampling, etc...)
 - ▶ The design may be evenly spread over the full experimental region but not onto all the factors
- Space filling designs,
 - ▶ latin hypercube design
 - ▶ designs based on measures of distance, e.g. maximin, minimax designs
 - ▶ Uniform designs or low discrepancy sequences borrowed from the Quasi-Monte Carlo Literature, e.g. Sobol's sequence, Halton sequence,...
 - ▶ Halton sequence construction is simple depending on the choice of a prime number
 - ▶ Sobol's sequence is well known space filling design, very useful for performing sequential designs

- Model-Based optimal design
 - ▶ Selecting the design is based on a statistical criterion
 - ▶ The design is selected according to the model chosen for $Y(x)$
 - ▶ D -optimality is one example
 - ▶ Integrated mean squared error and Maximum Entropy Sampling criteria are common in computer experiments

Maximum Entropy Sampling Design (Shewry and Wynn (1987))

- Entropy is negative of information

$$\text{Ent}(Y_S) = E_{Y_S}[-\log p(Y_S)]$$

- ▶ Y_S vector of observations
- ▶ $p(\cdot)$ density function of Y
- ▶ $D_S = \{x_1, \dots, x_n\}$
- Partition $Y_N = (Y_S, Y_{N \setminus S})$
- $\text{Ent}(Y_N) = \text{Ent}(Y_S) + E_{Y_S} \text{Ent}(Y_{N \setminus S} | Y_S)$
- $\text{Ent}(Y_N)$ is fixed
- $\text{Min Ent}(Y_{N \setminus S} | Y_S) \equiv \text{Max Ent}(Y_S)$
- In the Gaussian case,

$$\text{Ent}(Y_S) = \frac{n}{2} [1 + \log 2\pi] + \frac{\log |\Sigma_S|}{2}$$

- The problem is finding the design that maximizes $\log |\Sigma_S|$

The Proposed Method for 2-stage Design

- 1 Initial data set (outputs and inputs)
- 2 MLE's are obtained for all model parameters
- 3 Given the initial data set another design is chosen
- 4 The output corresponding to the design points is obtained from the simulator
- 5 The new design points with their outputs are added to the initial data set
- 6 Another training data set is obtained used for validating our results
- 7 A comparison is made based on the accuracy of prediction

Kriging for Computer Experiments



$$Y(x) = f^T(x)\beta + Z(x)$$

- $Y(x)$ is a Gaussian process with mean

$$E(Y(x)) = X^T \beta$$

where X is the design matrix and var-cov matrix

$$\text{cov}(Y(x), Y(x')) = \sigma^2 R(x - x')$$

R is the correlation matrix of process $Z(x)$, σ^2 constant.

- $R(x - x')$ has several forms, e.g. the exponential structure

$$\text{corr}(Z(x), Z(x')) = \prod_{i=1}^d \exp(-\theta(x - x')^p)$$

Prediction with Kriging

- MLE's for β and σ^2 are given by

$$\hat{\beta} = (X^T R^{-1} X)^{-1} X^T R^{-1} y_D$$
$$\hat{\sigma}^2 = \frac{1}{N} (y_D - X \hat{\beta})^T R^{-1} (y_D - X \hat{\beta})$$

- MLE's for covariance parameters are obtained using a software created by Ron Bates(LSE)
- The **BLUP** of the response $Y(x_*)$ is

$$\hat{y}(x_*) = f^T(x_*) \hat{\beta} + r^T R^{-1} (y_D - X \hat{\beta})$$

where

$$r = [R(x_1, x_*), \dots, R(x_n, x_*)]$$

Measuring Accuracy of Prediction

- Cross validation EMPIRICAL ROOT MEAN SQUARED ERROR , (Welch et al, (1992))

$$\text{ERMSE}_{-1} = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_{D_{-1}}(x_i) - y_D(x_i))^2}$$

- ▶ \hat{y}_{-1} data set without observation i , no validation data
- ▶ Parameters are re-estimated except the covariance parameters
- EMPIRICAL ROOT MEAN SQUARED,

$$\text{ERMSE} = \sqrt{\frac{1}{N_v} \sum_{i=1}^{N_v} (\hat{y}_v(x_i) - y_v(x_i))^2}$$

- ROOT MEAN SQUARED ERROR

$$\text{RMSE} = \sqrt{\frac{1}{N_v} \sum_{i=1}^{N_v} \text{MSE}(\hat{y}_v(x_i))}$$

Other Measures of Prediction Accuracy

- Mahalanobis Distance,

$$MD(y_*) = (y(x_*) - \hat{y}(x_*))^T \text{Var}(\hat{y}(x_*))^{-1} (y(x_*) - \hat{y}(x_*))$$

borrowed from the literature of the regression diagnostics to detect leverages

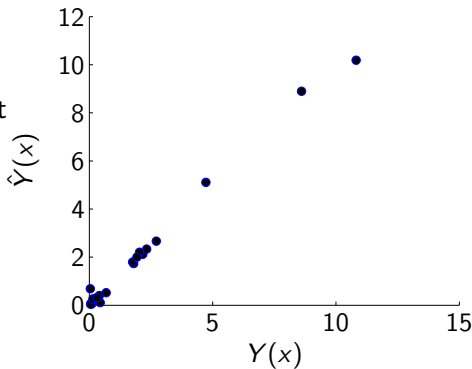
- Extremely large or small values indicates problems with the predictor (Emulator)

Saltelli Simulator (2000)

$$Y(x) = \frac{(x_2 + \frac{1}{2})^4}{(x_1 + \frac{1}{2})^2}$$

- Initial design of 20 points by simple random sampling
- $Y(x) = \mu + Z(x)$
- More complicated model did not show any improvement in prediction (Welch et al, 1989)
- MLEs for model parameters are obtained including the covariance parameters
- Validating the model using the initial design

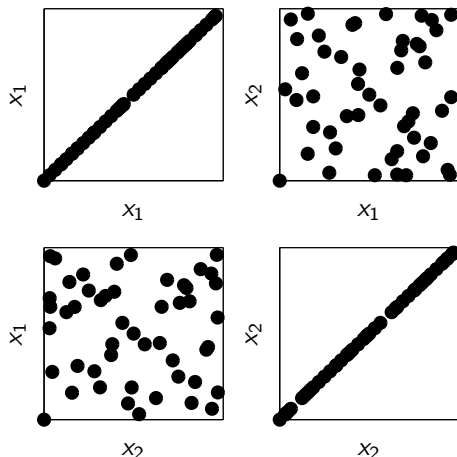
Figure: Cross-Validation: Predicted vs. Observed



Space filling design results for Saltelli's simulator(2000)

- Sobol's sequence is chosen as design
- We observe the $Y(x)$ at those set of points
- The results were augmented to the initial design
- No loss for the runs

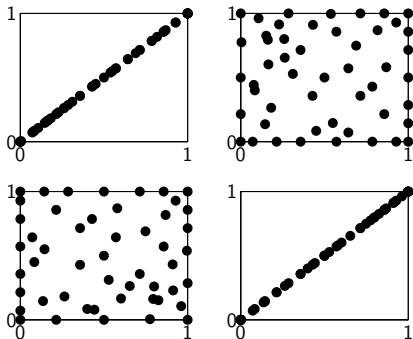
Figure: Sobol's sequence of 30 points



Entropy design for Saltelli simulator (2000)

- A design of size 30 obtained in addition to the initial design
- Based on the MLEs obtained from the initial design
- Exchange algorithm has been used

Figure: Entropy design with Initial design



Saltelli Simulator Results

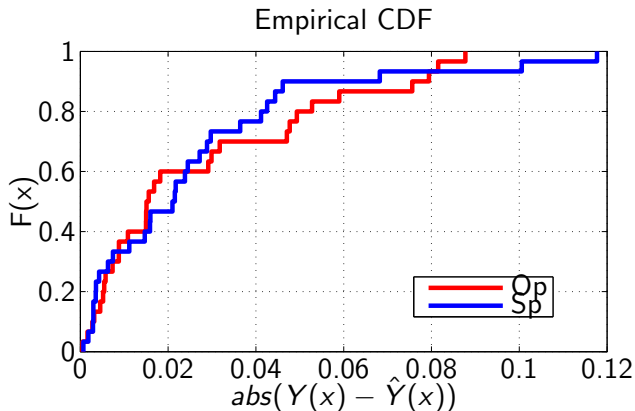


Figure: CDF for the absolute prediction error for Space filling and Optimal design

Saltelli Simulator Results

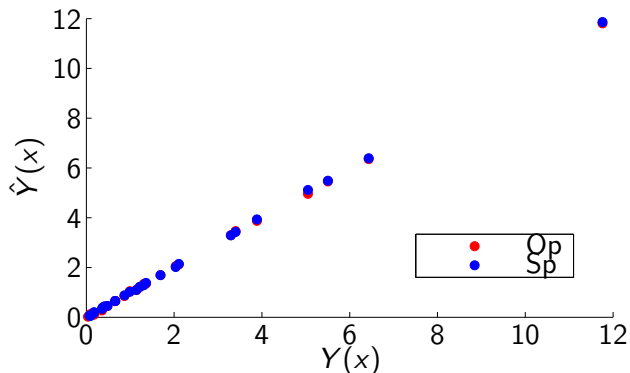


Figure: Predicted vs. Observed output for Space filling and Optimal design

Numerical Results for Saltelli Simulator

Parameter	Ini. des. est.	Sp. fill. est.	Opt. des. est.
$\hat{\mu}$	5.1276	11.2654	19.6862
$\hat{\sigma}^2$	28.1399	80.9928	357.4433
$\hat{\theta}_1$	2.7072	2.9366	2.3792
$\hat{\theta}_2$	0.88804	1.172	0.8761
\hat{p}_1	1.999	1.999	1.999
\hat{p}_2	1.999	1.999	1.999

Table: MLEs for the model parameters

- The estimates of the mean parameter are different
- Very close covariance estimates

Accuracy Measure Results for Saltelli Simulator

Measure	Ini. des. est.	Sp. fill. est.	Opt. des. est.
ERMSE ₋₁	0.2635	0.024743	0.2232
ERMSE	0.29005	0.038109	0.038426
RMSE	0.14023	0.047151	0.05117
Mah Dist	124.7476	32.8165	14.5268
Max abs. dev.	1.0727	0.11771	0.087713

Table: Accuracy measures of prediction

- Improvement in prediction than the initial design
- The optimal design is very similar to space filling one in terms of ERMSE

Application:Rolls Royce four Blade Fan Assembly Simulator

- The outputs are maximum amplitude for each blade a_1, \dots, a_4 and frequency f_1, \dots, f_4 at which that maximum resonant frequency occurs
- Because of symmetry, the analysis is for one output, the amplitude of the first blade
- The design variables x_1, \dots, x_4 are the small amounts of 'mass' added to the blades.
- The amount of mass can take positive or negative values ($\pm 3 \times 10^{-6}$).
- To simulate we run ANSYS software, to perform modal and harmonic analysis
- The design points are transformed to be in $[0, 1]$ in the selecting process

Rolls Royce Results

Initial design is obtained by a combination of two fractional factorial design of ± 1 and ± 0.5 .

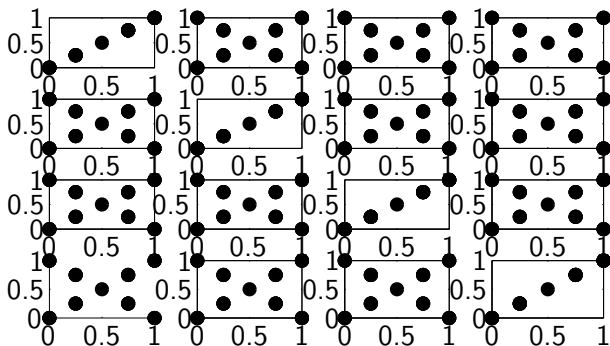


Figure: Initial Design of 33 Points

Rolls Royce Initial Results

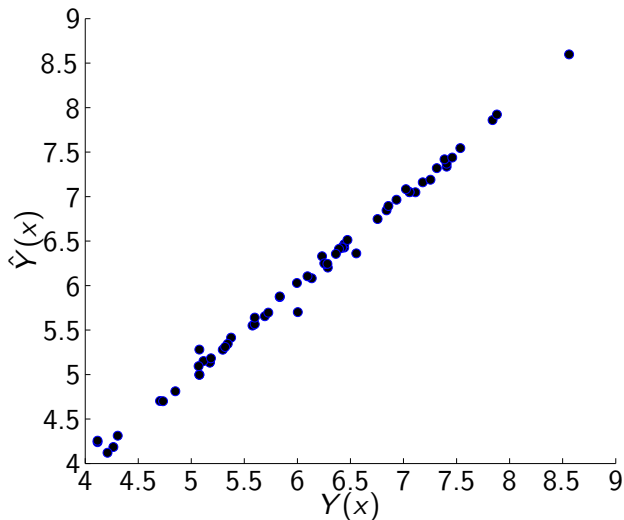
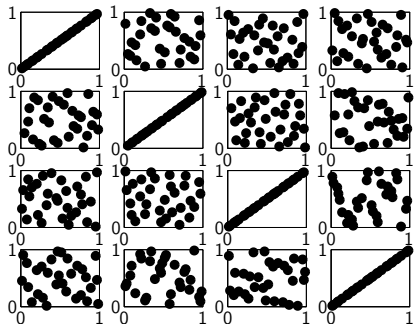


Figure: Cross Validation prediction for initial design

Space Filling Design for Rolls Royce Simulator

- Sobol's sequence of 30 points is obtained
- The 30 points are added to the initial 33 points
- The MLE's are obtained for all model parameters including the covariance parameters

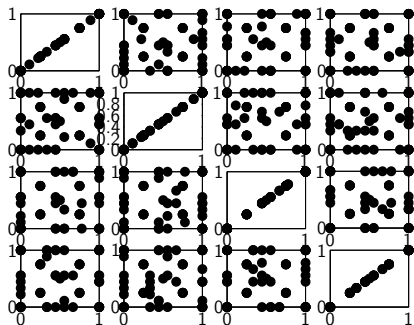
Figure: Sobol's sequence of 30 points



Maximum Entropy Sampling Design for Rolls Royce Simulator

- Maximum Entropy Sampling is obtained using the initial design points
- The design points are chosen over a grid, (10×10).
- Exchange algorithm is used to find the optimal design put of 10^4 points
- The MLE's are obtained for all model parameters

Figure: Entropy Design Including the Initial Design (63 points)



Rolls Royce Simulator Graphical Results

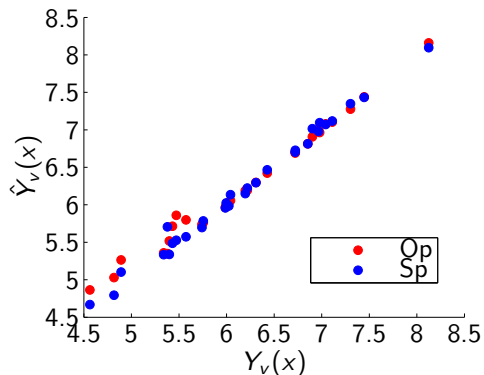


Figure: Prediction for Space filling and Optimal design

Rolls Royce Results

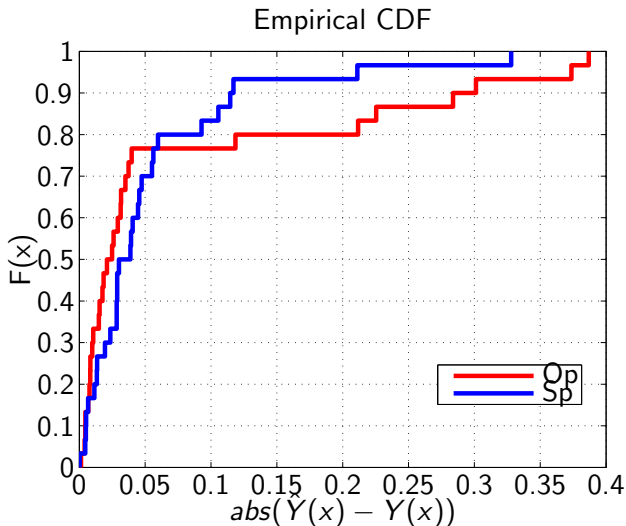


Figure: CDF for the absolute prediction error for Space filling and Optimal design

Numerical Results for Rolls Royce Simulator

Parameter	Ini. des. est.	Sp. fill. est.	Opt. des. est.
$\hat{\mu}$	5.5223	5.0722	4.8029
$\hat{\sigma}^2$	1.472	1.6301	1.6003
$\hat{\theta}_1$	0.52291	0.5004	0.45445
$\hat{\theta}_2$	0.17127	0.29412	0.26167
$\hat{\theta}_3$	0.4247	0.31322	0.2212
$\hat{\theta}_4$	0.35561	0.21175	0.21745
$\hat{\rho}_1$	1.9621	1.9796	1.4326
$\hat{\rho}_2$	1.7793	1.972	1.999
$\hat{\rho}_3$	1.999	1.991	1.999
$\hat{\rho}_4$	1.999	1.6136	1.999

Table: MLEs for the model parameters

- The estimates of the parameters are quite similar
- Some differences in the values of covariance parameters estimates

Accuracy Measure Results for Rolls Royce Simulator

Measure	Ini. des. est.	Sp. fill. est.	Opt. des. est.
ERMSE ₋₁	0.093422	0.086923	0.069252
ERMSE	0.066662	0.086636	0.13913
RMSE	0.10691	0.051009	0.088515
Mah Dist	4.4448	181.682	45.1828
Median abs.dev.	0.0395	0.0344	0.0229
Max abs. dev.	0.17144	0.32793	0.38686

Table: Accuracy measures of prediction

- Improvement in prediction
- The optimal design has a greater percentage of small absolute deviations than space filling
- Mahalanobis distance for optimal design is smaller than space filling design (cross correlation)

Some Interesting Results

Measure	Sp. fill. est.	Opt. des. est.
Entropy	-42.5889	-37.3700
RMSE1	0.0612	0.0707
RMSE2	0.0614	0.0529

Table: Entropy values and Sum of Mean Squared Error at the un-sampled points

- Using the same estimates for the covariance parameters, the RMSE1 favours the optimal design
- It is trivial because the Entropy design aims at minimizing the predictive variance
- Using the updated estimates of the covariance parameters, RMSE2 is in Space filling design side

Conclusions

- We cannot say which design is better
- They are very similar in the prediction accuracy results
- Space-filling shows the ability to learn about the covariance parameters
- We have to decide what we are aiming at from our experiment, then we decide which method we can choose

Main References

- Bastos and O'Hagan, Technometrics,(2009).
- Sacks J. et al, Technometrics,(1989).
- Saltelli A. et al, Statistical science, (2000).
- Shewry and Wynn , J. of Apply Statistics,(1977).