

# Factor screening of large models in presence of space constraints

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# **Abstract**

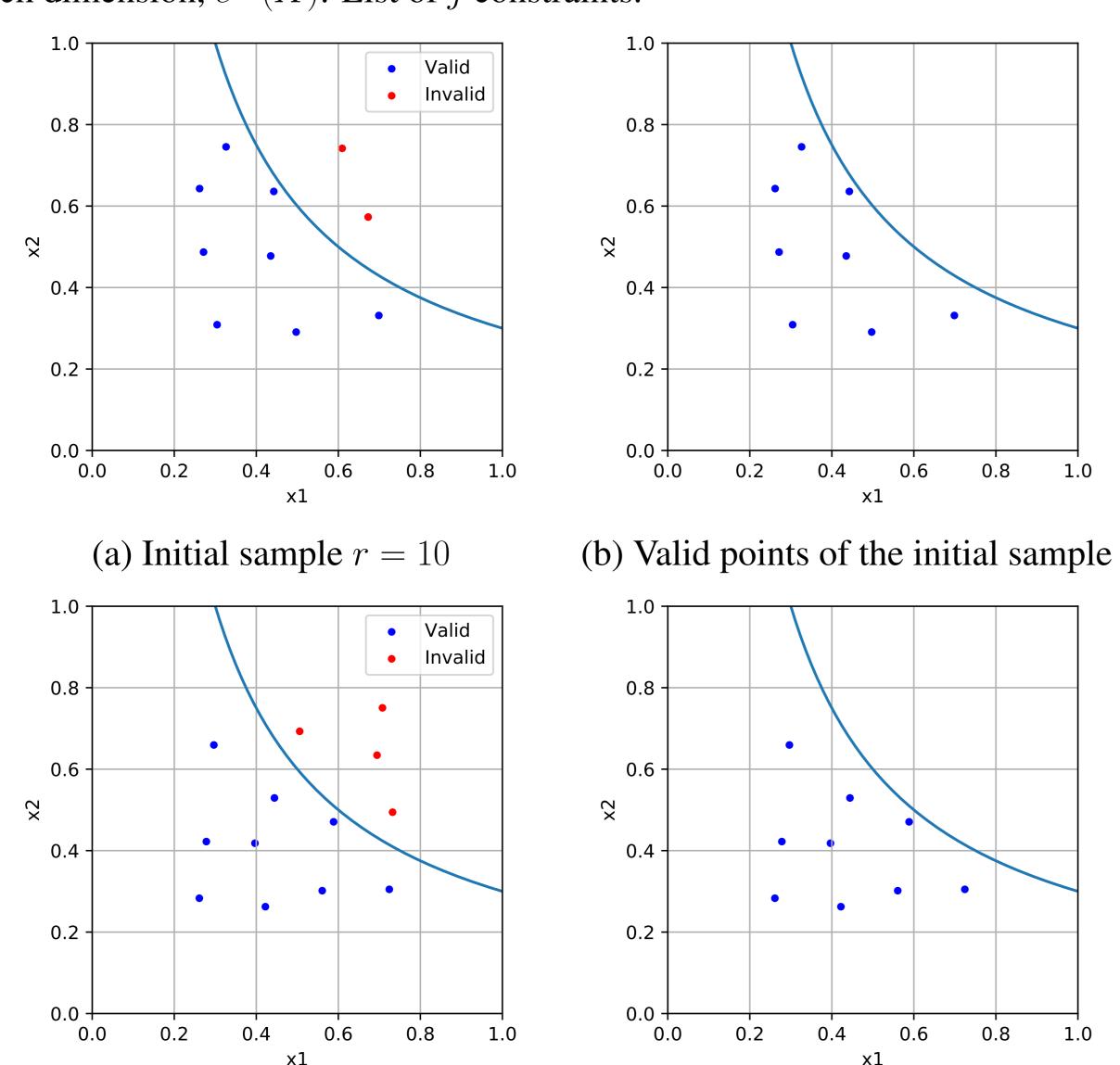
Real-time Hardware-in-the-Loop (HIL) simulation is a major step in design, development, and implementation of new power systems technologies. In many cases, the models of physical systems are elaborate with hundreds of input parameters and tens of output quantities. Knowing which inputs have the most (or the least) influence on the output quantities of interest (through factor screening) will help the analysts simplify these models and reduce the computational cost of the evaluation process. The assumption made by common factor screening methods is that the range of variation of each factor does not depend on the value of the other factors. In this work, we try to eliminate this assumption and consider the case where the normalized parameter space is not a perfect hypercube. The presented method is a variation of the Elementary effects (Morris' method 1991) that uses multiple degrees of freedom in the original method to take the space shape into account.

#### Introduction

The goals is to determine which inputs have the least influence over the outputs so that we can fix them somewhere in their range to simplify the model without losing its representation power.

# Method

A variation of Elementary effects [1] is presented considering the presence of space constraints. The inputs of the method are: r: Number of desired trajectories used to calculate elementary effects,  $p \in [0, 0.5]$ : The portion of change in each step of a trajectory,  $[L^{(i)}, U^{(i)}]$ : initial bounds of space in the form of lower and upper bounds of each dimension,  $c^{(j)}(X)$ : List of j constraints.



(c) Sample with adjusted size  $n_{new} = 15$ (d) Valid points after adjustment

Figure 1: Steps of selecting a valid initial sample for the factor screening in two dimensions. The space for the initial samples is slightly smaller than the overall design space by p% from both sides of all dimensions. In this example p = 20%.

# Method steps:

- 1. Normalize all the dimensions to [0, 1].
- 2. Shrink the space on all sides by p.
- 3. Take the initial sample using CVT method[2].
- 4. Reject the samples that violate any of the *j* constraints.
- 5. Retake the initial sample with adjusted size.
- 6. Construct parameter trajectories.
- 7. Simulate all trajectory points and calculate the elementary effects.
- 8. Calculate the screening measures: mean and standard deviation of the elementary effects.

$$\mu_i^* = \frac{1}{r} \sum_{j=1}^r |EE_i^j| \quad , \quad \sigma_i = \sqrt{\frac{1}{r} \sum_{j=1}^r (EE_i^j - \mu_i)^2}$$
 (1)

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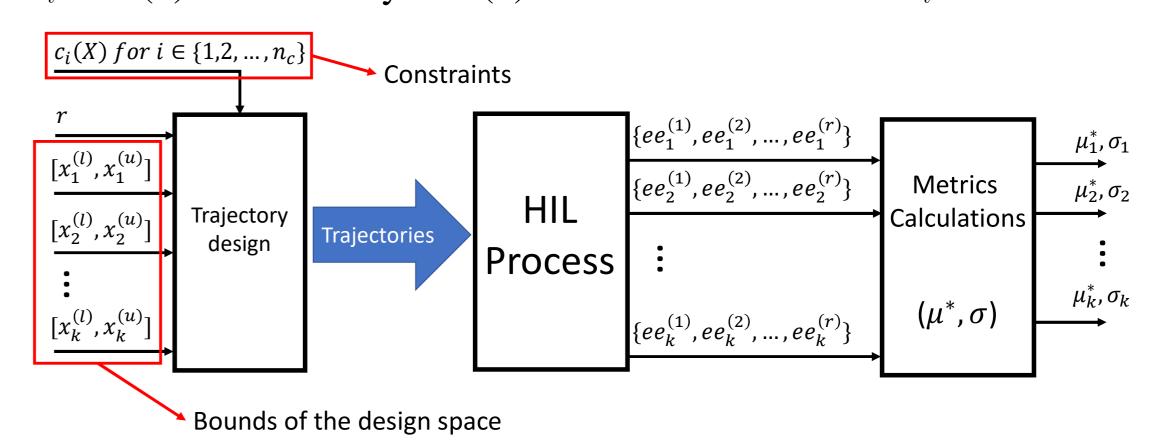
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where the elementary effects are defined as:

$$EE_i = \frac{[Y(X_1, X_2, ..., X_i + \Delta, ..., X_k) - Y(X_1, X_2, ..., X_i, ..., X_k)]}{\Lambda}$$
(2)

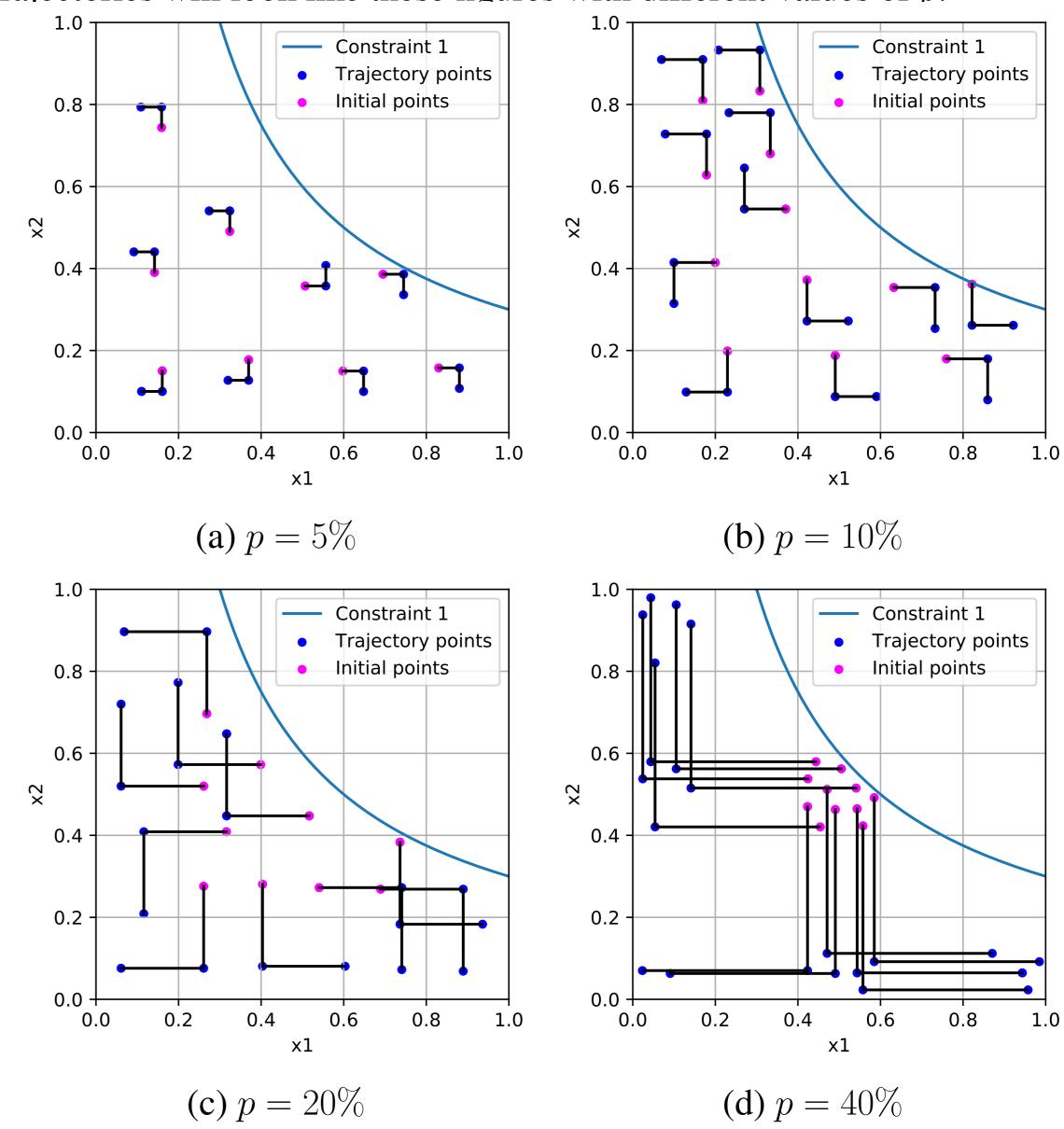
High  $\mu_i^* \longrightarrow$  Higher level of influence from  $X_i$  factor on Y(X). High  $\sigma_i \longrightarrow (1)$  non-linearity **OR** (2) factor interactions for  $X_i$ 



**Figure 2:** Overview of the process for factor screening of a real-time model

### **Trajectory construction**

The trajectories will look like these figures with different values of p:



**Figure 3:** The trajectory construction with different values for p

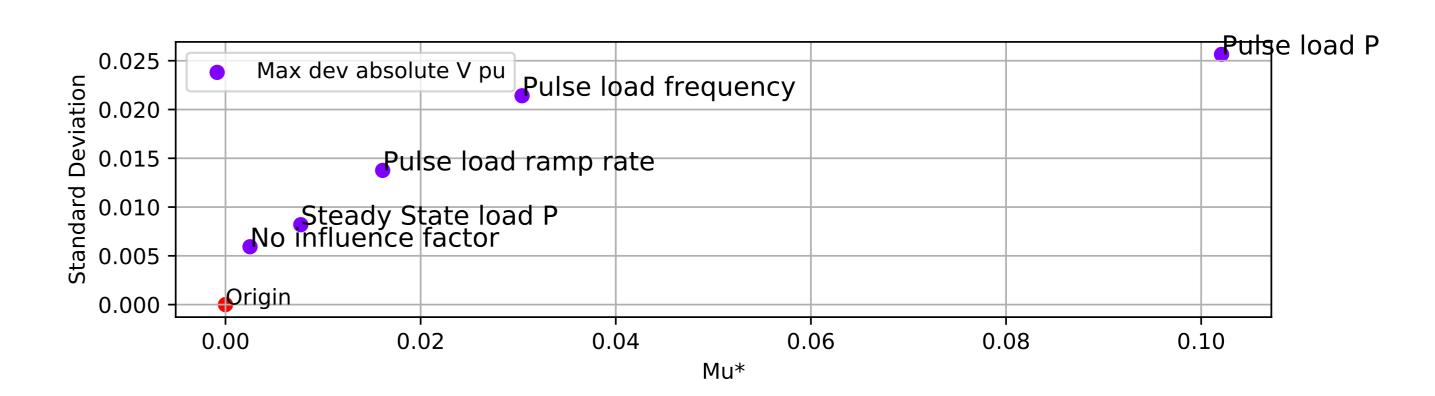


Figure 4: Results of the factor screening analysis for Maximum deviation of output voltage on an aC power generation module connected to a pulse load.

# **Conclusions**

We have shown a new method for constructing the Morris method trajectories in a constrained space.

• The value of parameter p provides a way for trading off the exploratory features of the trajectory set.

# References

[1] Max D Morris. Factorial sampling plans for preliminary computational experiments. Technometrics, 33(2):161–174, 1991.

ous other statistical sampling methods. *Reliability Engineering & System Safety*, 91(10-11):1266–1280, 2006.