

# Machine Learning Reliability Techniques for Composite Materials in Structural Applications.

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Noesis Solutions

# Optimus<sup>®</sup> by Noesis Solutions



Optimus<sup>®</sup> is a **Process Integration & Design Optimization (PIDO)** software

that automates  
simulation based design processes

and directs  
parametric simulation campaigns  
toward the best product design



# Agenda

1

Self-Organizing Map (SOM)

2

Self-Organizing Map Based Adaptive Sampling (SOMBAS)

3

Application to Reliability Analysis

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Self-Organizing Map (SOM)

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Self-Organizing Map Based Adaptive Sampling (SOMBAS)

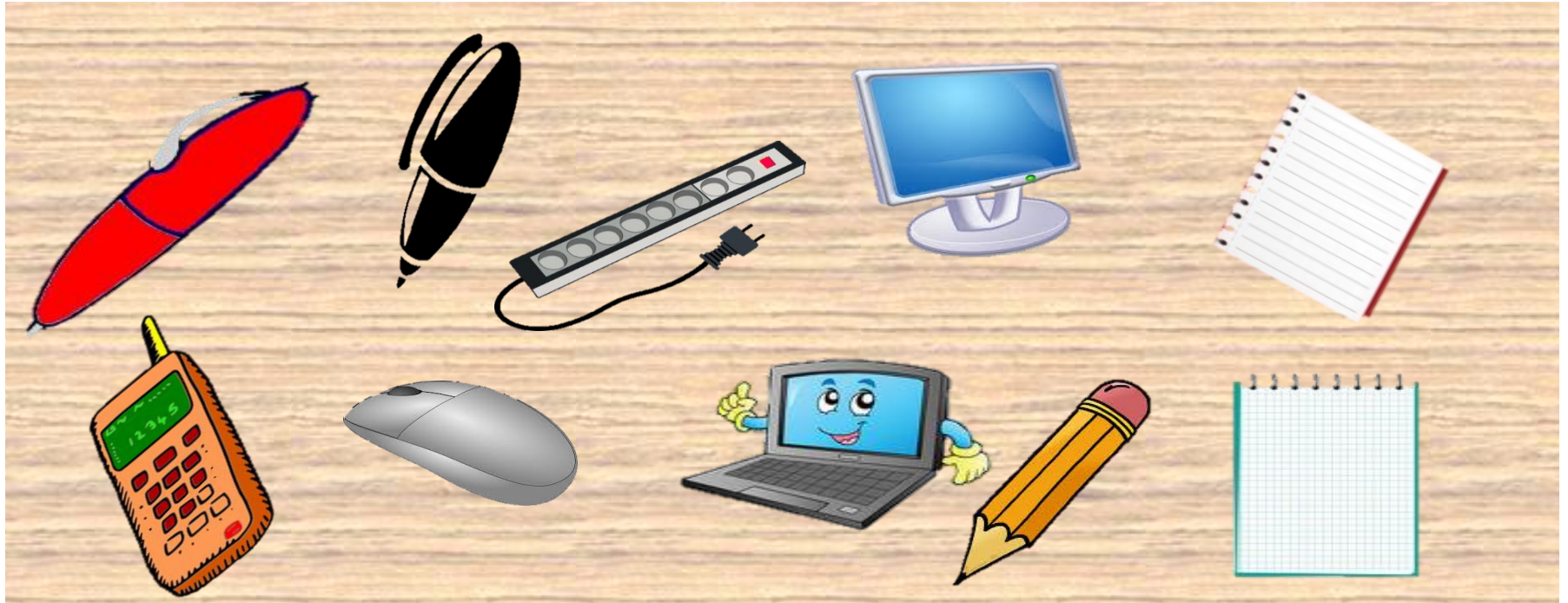
3

Application to Reliability Analysis

# Self-Organizing Map

- The Self-Organizing Map (SOM) is a powerful technique for organizing data into a specified number of bins.
- The data points are grouped into bins respecting their similarities.
- First described by Kohonen (1982), also known as Kohonen maps or Kohonen networks.
- All bins are organized in a lattice that can preserve the topological properties of the data and can then displays the final results graphically in a very simple manner.

# Ex: Organize your Desk



# Filling the boxes

- Suppose we have 6 bins and we want to fill in the boxes
- We put in the same bin only “similar” objects and in a closer bin something that is still alike for some characteristics





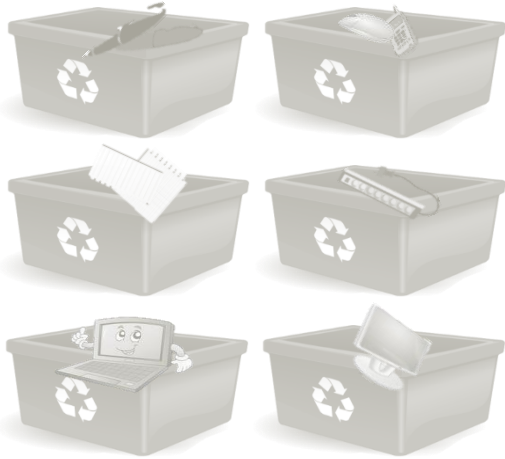
# Coloring the bins

- The grid can now be colored according to the characteristics (values) of the contained objects.
- We may color the bins according to:
  - Weight
  - Dimension
  - Cost

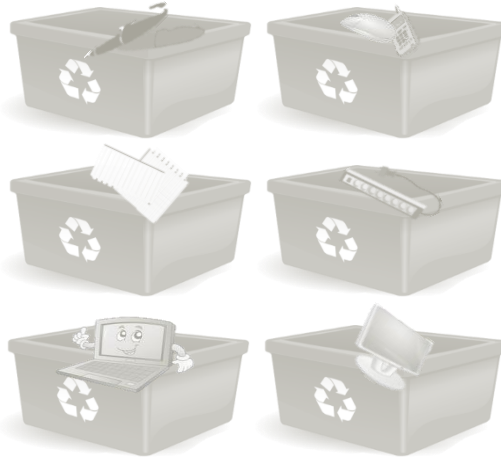


# Comparing the maps

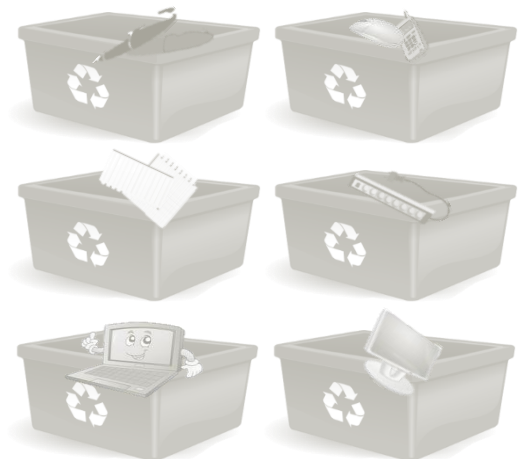
Weight



Dimension

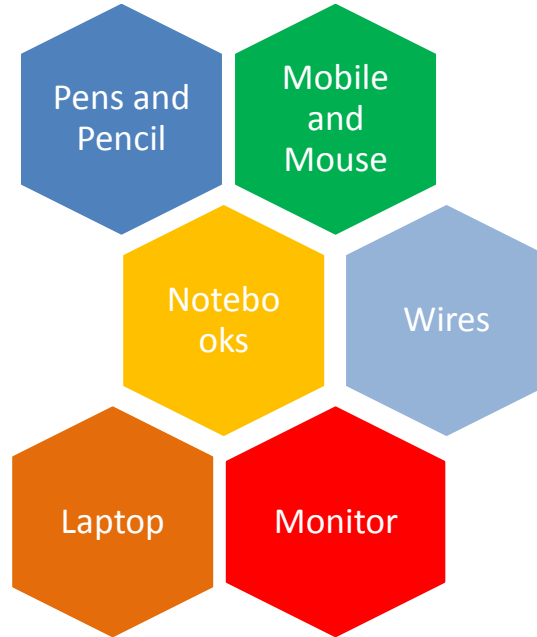


Cost



# Definitions

- A SOM consists of components that are named grid **nodes** (or neurons, or units)
- The usual arrangement of nodes is a 2-D **hexagonal** grid
- A weight vector is associated with each node.
- The weight vectors are more similar at the nearby

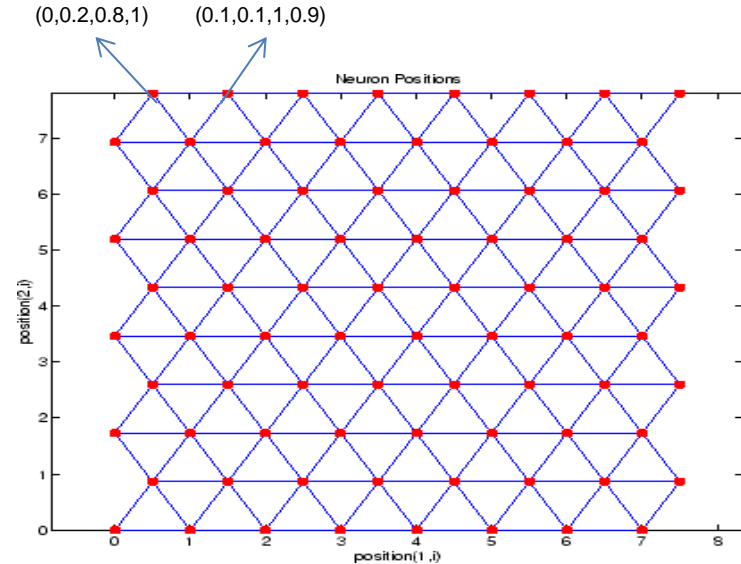


$w=[\text{weight, dimension, cost}]$



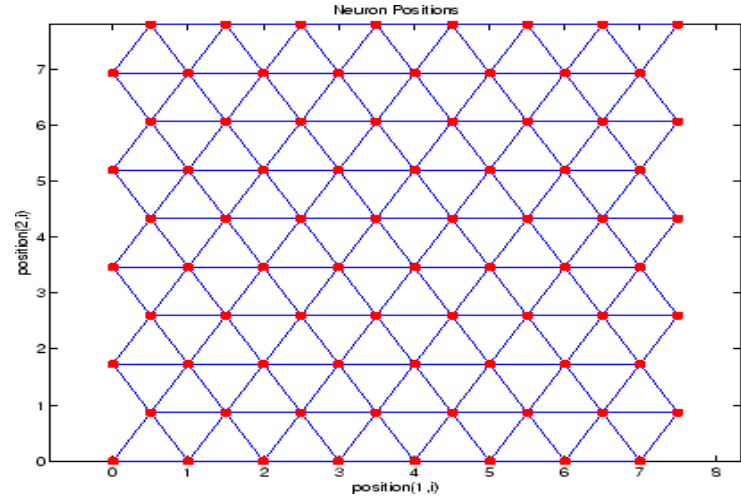
# How it works

- From a mathematical point of view, a self-organizing map (SOM) is a type of **artificial neural network** trained using unsupervised learning to produce a discretized representation of the training samples
- The self-organizing map consists of a number of hexagonal cells organized in a 2-dimensional grid with  $n_r$  rows and  $n_c$  columns.
- Each cell  $c$  is corresponding to a vector of weights, ranging between 0 and 1,  $w \in [0,1]^d$  where  $d$  is the dimension of the selected space.



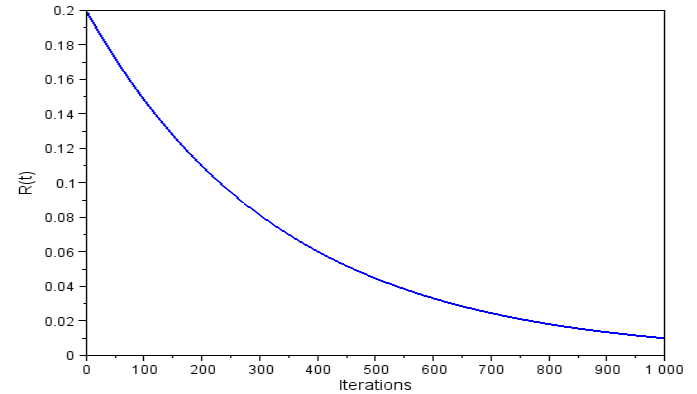
# Simplified Algorithm

- Generate random weights for each cell
- Loop for each iteration:
  - Put each experiment in the cell with the closest weight.
  - Re-compute the weight according to
    - Average weight of the experiments in each cell
    - Learning rate
    - Neighborhood function
  - Check stopping criteria's



# Learning Rate

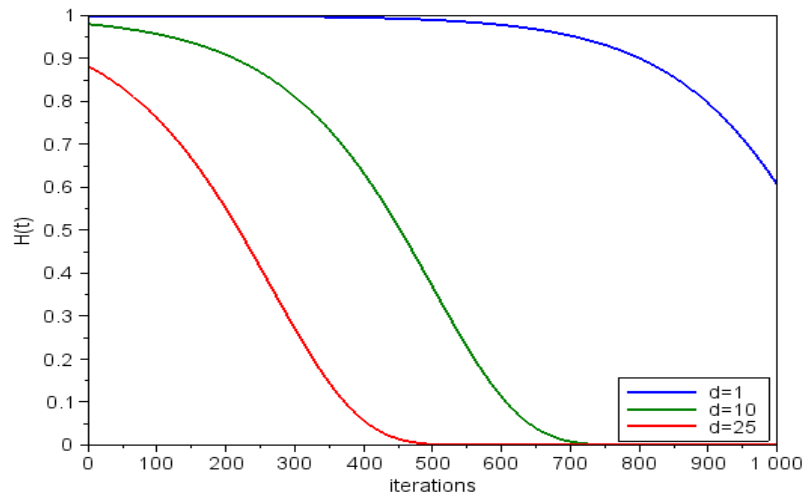
- Allow big changes in the weight of each cell at the beginning
- Slowly, freezes the ability of the algorithm to modify the weights of the cells



This plot is generated with  $R_0=0.2$   
and  $N=1000$

# Neighborhood function

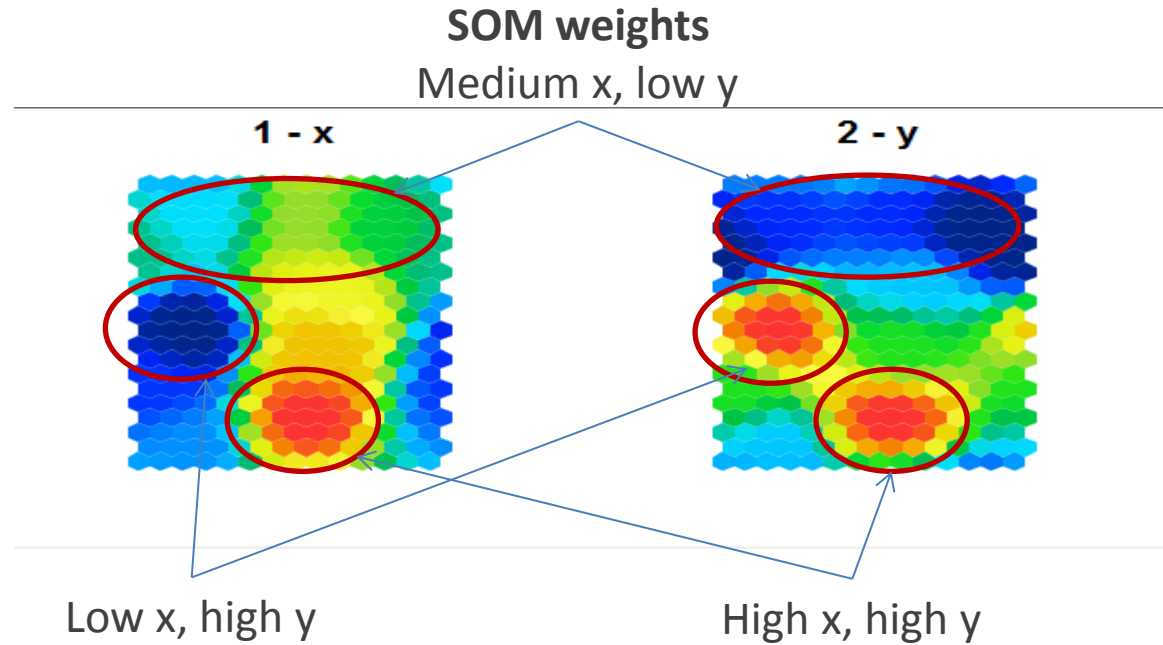
- $H(t)$  is representing the neighborhood function that preserves the topological properties of the points.
- The higher the value of this function, the bigger is the radius of influence of any modification on the map.
- As the learning rate function, the neighborhood function is decreasing over time



$H(t)$  for a cell that is distant 1, 10 or 25 respectively (SOM with radius 50, 1000 iter.)

# SOM's plots

- The SOM plot for a variable indicates regions where the variable has low or high values
- When minimizing a certain output, one can look for cells with a dark blue color (and see the ranges of the corresponding inputs)





# Post-processing with SOM

- On SOM, there is no coordinates showing the location on the map.
- If two SOMs show similar patterns, that means these parameters are correlated.
- If you see similar patterns but inverted in color between SOM plot of different parameters, that means that these parameters are anti-correlated.
- In Optimus, the SOM can be trained for each input parameter and output response.

# Post-processing with SOM

- You can also check whether a cell has any associated samples to it
- You can identify interesting design spaces, and trade-off relationships among parameters
- You can see clusters of similarities
- You can look for constraint satisfying regions
- You can sample further in the identified interesting design spaces.

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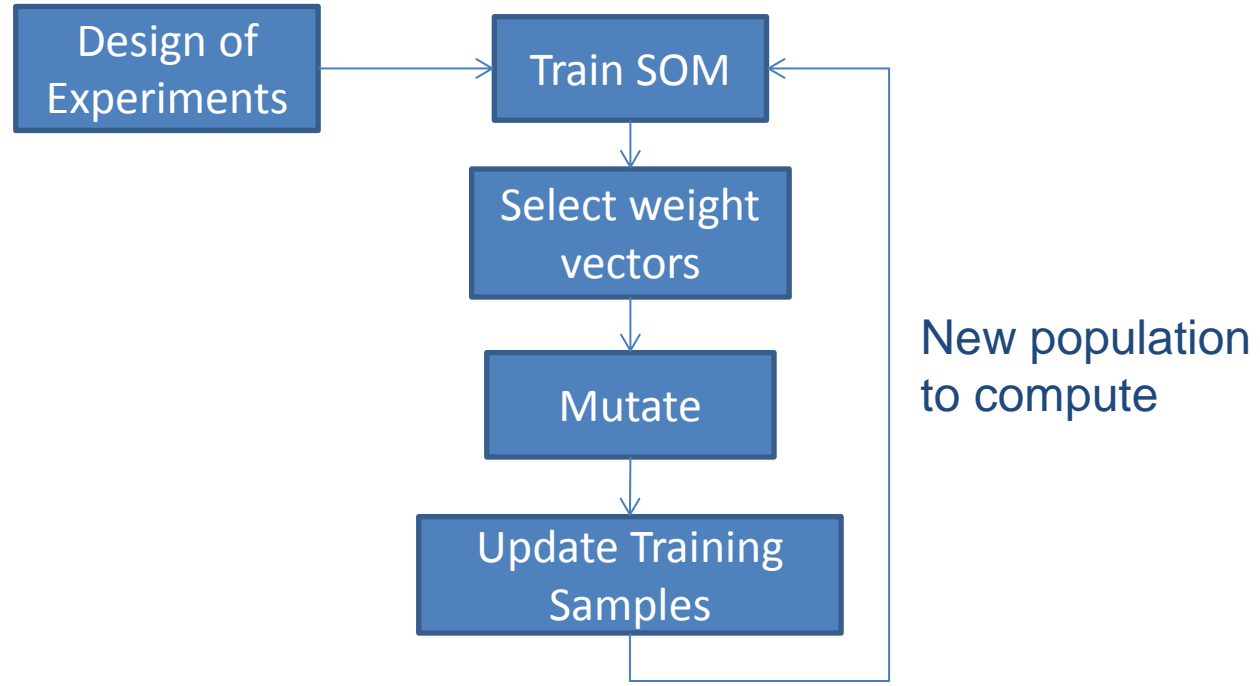
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Application to Reliability Analysis

# SOM vs Response Surface Model

- A Self Organizing Map can also predict values of a sample
- SOM can better handle discontinuous function
- Quantitative accuracy of performance is not always of primary importance but relative merit is
- Unlike RSM's, SOM do not need all the inputs for output evaluation

# SOM based Adaptive Sampling (SOMBAS)

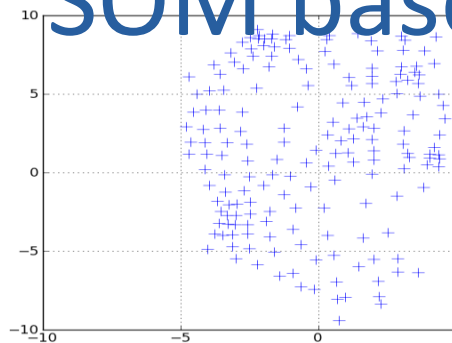


# Updating Training Samples

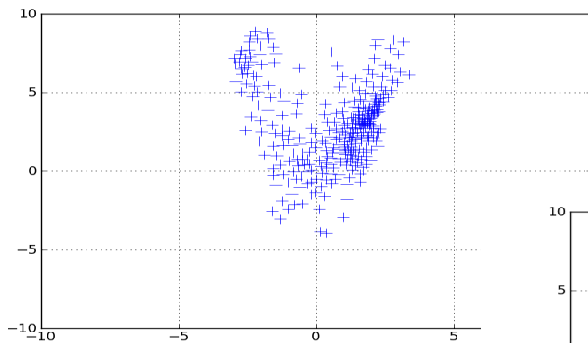
1. Randomly pick one sample from the training sample set
2. If the new mutated sample (weight vector) is better than the picked training sample replace the training sample with the new one.
3. Otherwise keep the old training sample

SOMBAS Merit Function: To be below a certain threshold

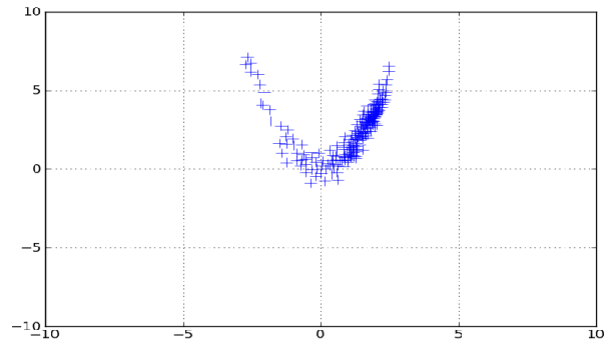
# Optimal Region Identification of SOM based Adaptive Sampling



Iteration 1

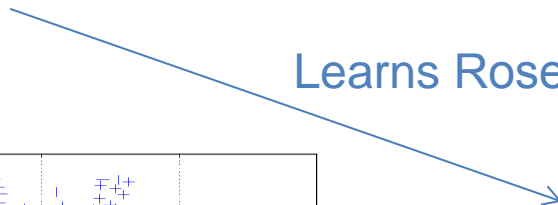


Iteration 5

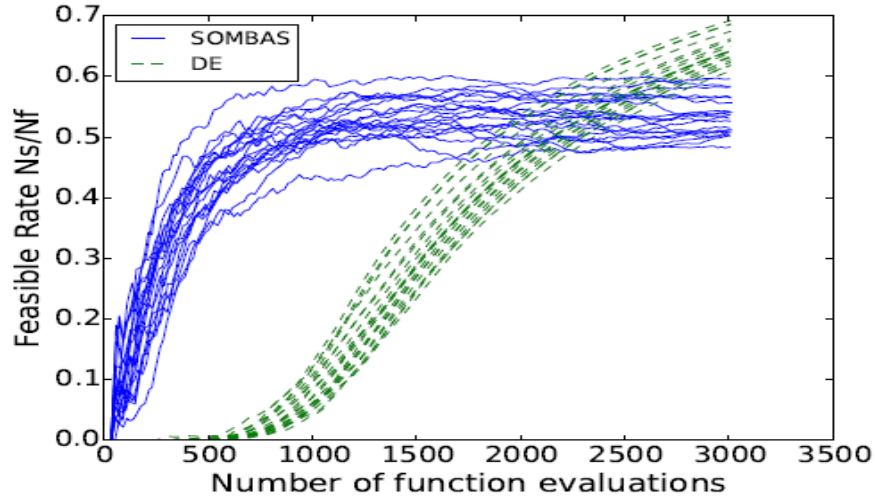


Iteration 9

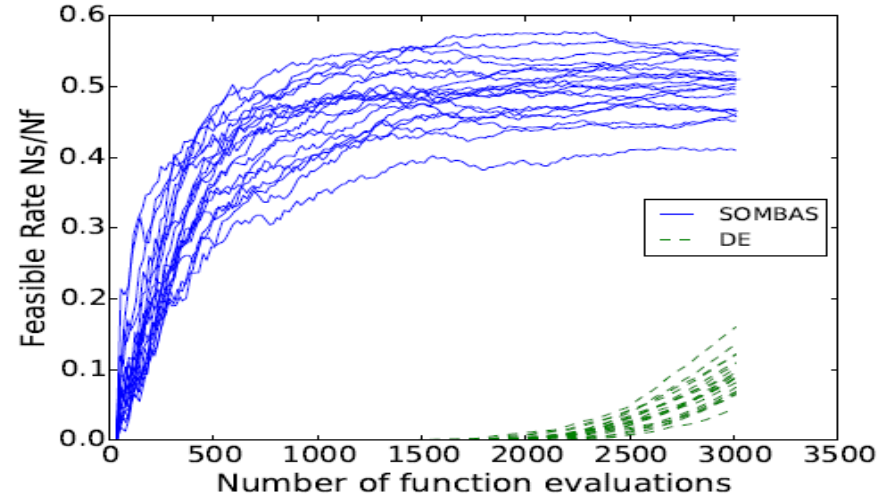
Learns Rosenbrock's valley!



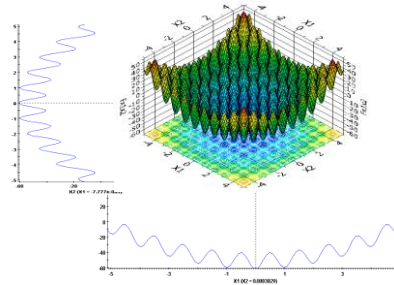
# SOMBAS: Feasible Region Identification



(a) Rastrigin 30 dimensions, feasible solution as  $f \leq 600$



(b) Rastrigin 100 dimensions, feasible solution as  $f \leq 2000$





# SOMBAS vs DE

Population/training sample size (30 ~ 45) adapted in favor of DE and number of function evaluation limited to about 2000. Tested functions are in 30 dimensions.

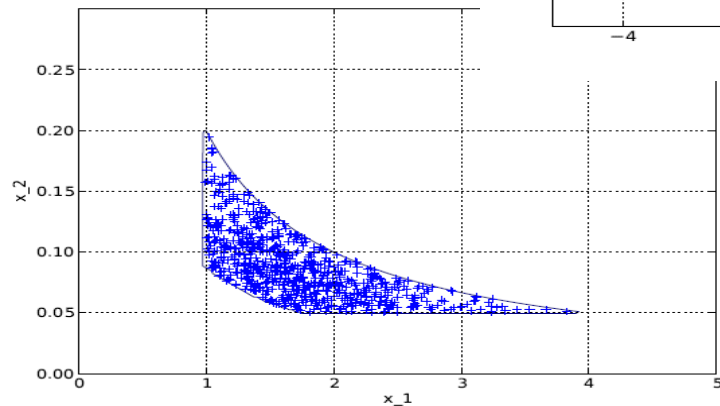
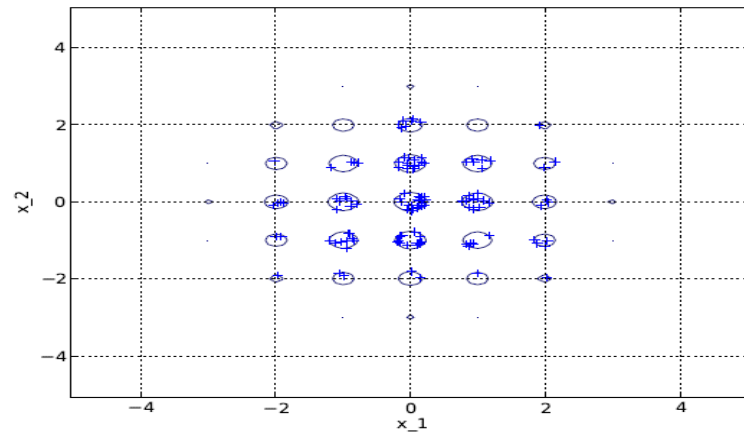
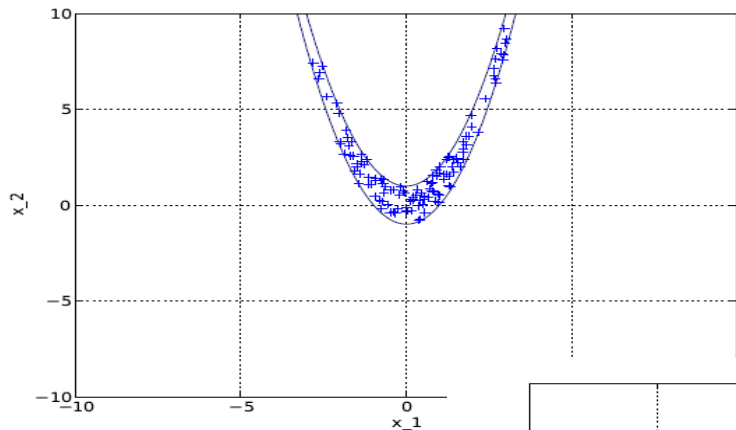
	<i>SOMBAS</i>		<i>DE</i>	
Function	$\tilde{N}_f$	$\tilde{f}$	$\tilde{N}_f$	$\tilde{f}$
Rosenbrock	2019	193	2025	$4.25e + 05$
Rastrigin	2013	189	2030	293
Rotated Ellipsoid	2003	63.5	2010	418
Ackley	2005	4.08	2020	6.12
Manevich	2014	0.0177	2010	0.101

# SOMBAS vs DE

Large population/training sample size (900) and number of function evaluation limited to about 2000. Tested functions are in 30 dimensions. Number of function evaluation  $N_f$  and minimum response  $f$  are average of 20 runs.

Function	<i>SOMBAS</i>		<i>DE</i>	
	$\tilde{N}_f$	$\tilde{f}$	$\tilde{N}_f$	$\tilde{f}$
Rosenbrock	2283	201	2700	$1.33e + 06$
Rastrigin	2083	219	2700	731
Rotated Ellipsoid	2379	11.9	2700	533
Ackley	2353	2.38	2700	12.5
Manevich	2196	0.0982	2700	3.41

# Non-Convex Space Filling of SOMBAS



# Summary

- The new method identifies interesting region (domain) in the input space and samples from it
- The method does not rely on parameterized distributions
- Fast initial decrease in objective functions (in the tested functions)
- Good diversity seeking of feasible solutions (yet qualitative)
- Needs more evidence

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# Application to Composite Materials

- Many layers of material:
  - Directions of the layers gives different characteristics of the final material.  
(Small modification of the direction can cause huge difference in the final result)
- The problem is
  - Highly Non Linear
  - High-Dimensional
  - Difficult to optimize

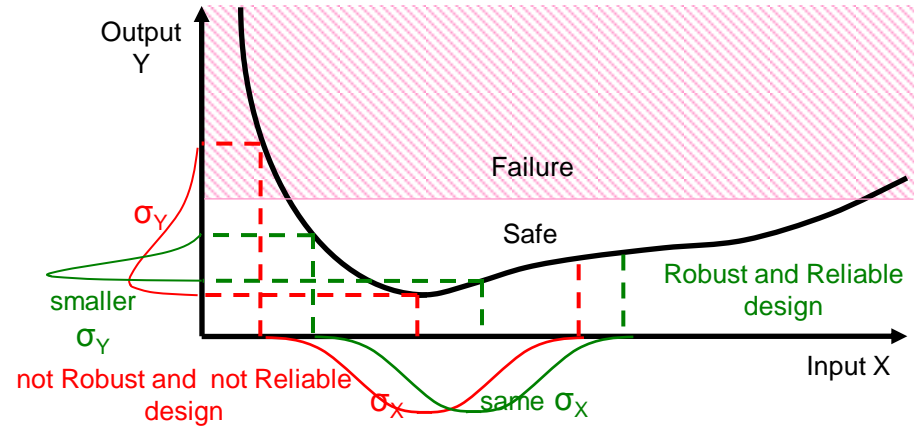
# Motivation

- **Uncertainty** is inevitable in engineering design optimization
- Uncertainty can degrade the global performance of an optimized design solution
- Uncertainty can change feasibility of the selected solution
- Uncertainty propagates when several disciplines are coupled and the propagation of uncertainty has to be accounted
- It is important to identify uncertainty and how to best allocate investments to reduce uncertainty under a limited budget.

Uncertainty

# Reliability

- Probability that a failure is attained as a result of input variability
- Failure probability and reliability index are used as measure of the reliability of outputs
- A reliable design has a low failure probability with respect to pre-defined failure constraints



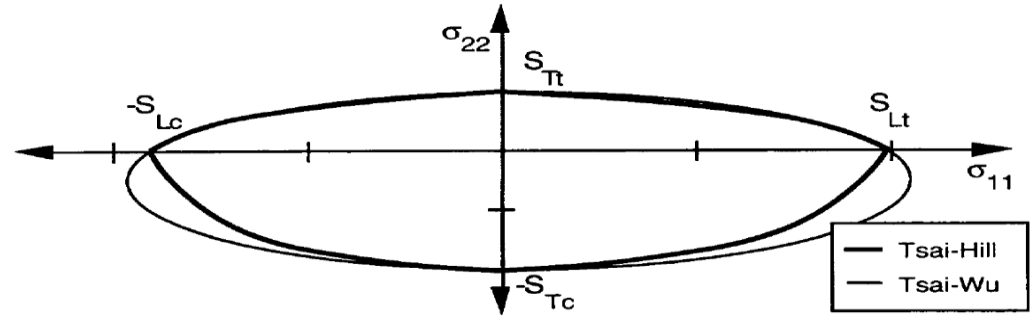


# Motivation

- Current reliability approaches have inherent limitations:
  - FORM/SORM: multiple failure criteria and/or closed LSF cannot be handled properly
  - Monte Carlo simulation/subset simulation: number of samples, even for low probabilities, can still be very prohibitive to compute
- Challenges: either too approximate, or too expensive
- A trade off exists, that can be tuned between the two extremes

# Motivation: composite materials

- Composites typically use energetic criteria for failure estimation



- Example: Tsai-Hill

$$G = 1 - \left[ \left( \frac{\sigma_1}{F_1} \right)^2 - \frac{\sigma_1 \sigma_2}{F_1^2} + \left( \frac{\sigma_2}{F_2} \right)^2 + \left( \frac{\sigma_{12}}{F_{12}} \right)^2 \right]$$

**$G > 0$  SAFE**

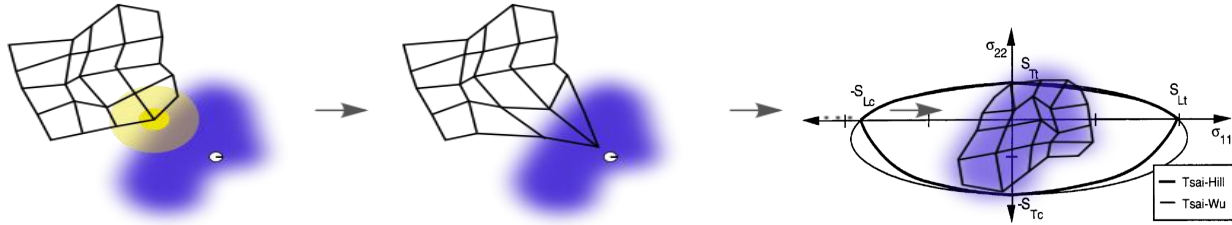
**$G \leq 0$  FAILURE**

# Motivation: composite materials

- Energetic criteria for composites have:
  - A closed limit state function
  - Progressive failure mechanisms
- None of the actual reliability techniques can handle this problem properly
  - FORM / SORM fail miserably
  - Monte Carlo / Subset simulation need too many samples to estimate Pf in the order of  $10^{-6}$

# Procedure outline

- Feasible region identification:
  - SOMBAS will learn the feasible region for composites, taking into account all possible failure modes and even multi-connected regions.



# Advantages

- Much faster integration capability
  - with respect to reference Monte Carlo or subset simulation approaches
- No constraint on the shape of the integration domain:
  - the domain can be closed, open or even multi-connected – SOMBAS is able to address all these kind of domains.
- Tunable accuracy:
  - Total number of samples vs accuracy can be assessed

# Conclusion

SOMBAS is a new, revolutionary approach

Preliminary results are impressive on high dimension problems

Self-Organizing Maps also gives the probability of failure

Thank You !

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