Shape Optimization of FEA Models by Machine Learning-Based Surrogate Modeling

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AUGUST 26, 2023

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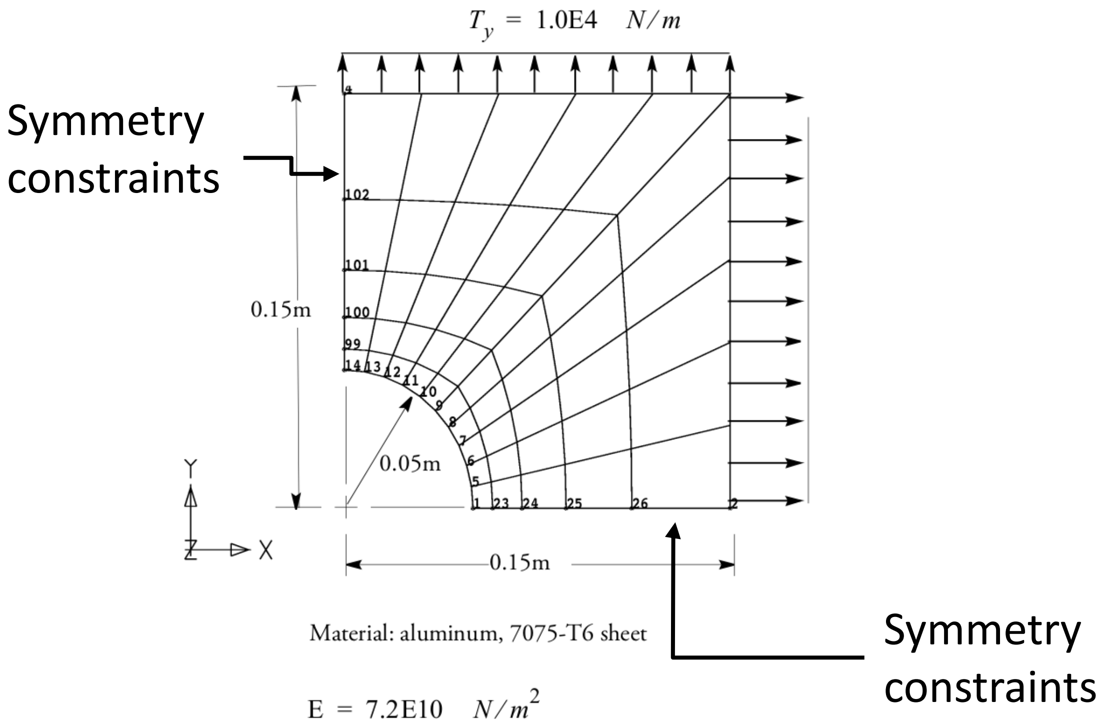
Goal: Use Gaussian process regression models for FEA shape optimization

Challenge: FEA solvers often include optimizers that support shape optimization. This shape optimization technology relies on moving the nodes of the mesh and in a majority of applications leads to mesh distortions. The prevalence of mesh distortions makes shape optimization impractical for many applications.

Solution: This work seeks an alternative by using Gaussian process regression (GPR) modeling to perform shape optimization.

Additional comments: This work uses a total of 16 MSC Nastran runs to find a near optimal design. 15 runs generated the training data to build the GPR models for mass and max. von Mises stress and 1 run was used to confirm a near optimal design. Most academic works demonstrate the GPR model works well with 1-5 parameters, often requiring 5-50 runs to generate enough training data for a reliable GPR Model. From experience, the GPR model also works well with up to 10 parameters, but may require up to 200 runs to generate enough training data. After 10 parameters, hundreds of runs may be needed to generate enough training data to build reliable GPR models. Neural network (NN) models were considered but ultimately not selected since NN models require 10x more samples/runs than GPR models to build reliable NN models. While GPR models are not susceptible to the mesh distortion issue, the main limitation of GPR models is the number of parameters, i.e. the curse of dimensionality, and the resources required to build each sample.

Details of the Structural Model



Material: aluminum, 7075-T6 sheet

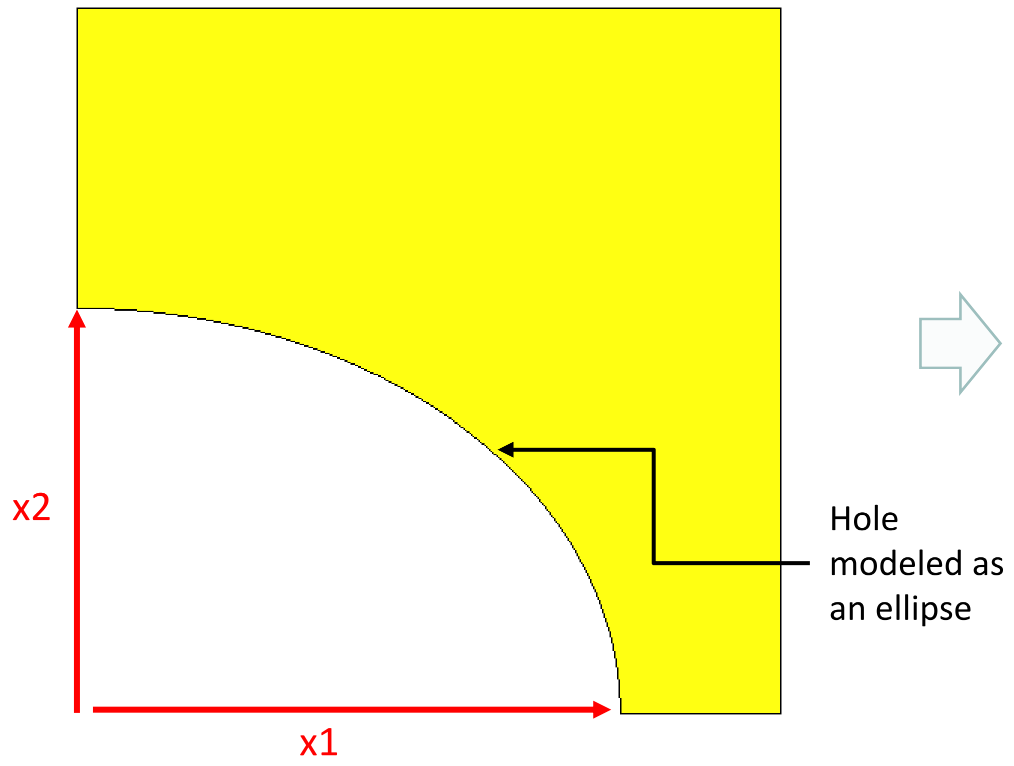
E = 7.2E10 N/m^2
μ = 0.33
ρ = 2.8E3 kg/m^3

Optimization Problem Statement

Inputs

x1: First parameter of ellipse
x2: Second parameter of ellipse

.01 m < x1, x2, < .14 m



Outputs

Design Objective
y0: Minimize mass

Design Constraints
y1: Max von Mises stress

r1 < 20 MPa

Samples for Training Data

Sample Number	x1 [m]	x2 [m]	y0 [kg]	y1 [Pa]
1	3.24E-02	6.46E-02	2.92E-01	2.01E+07
2	4.42E-02	4.40E-02	2.94E-01	1.08E+07
3	5.60E-02	9.81E-02	2.55E-01	3.13E+07
4	0.134459	2.90E-02	2.72E-01	4.40E+07
5	0.103962	1.67E-02	2.96E-01	2.26E+07
6	9.50E-02	5.19E-02	2.61E-01	7.67E+06
7	1.12E-02	0.122077	3.00E-01	6.51E+07
8	8.80E-02	0.131576	1.87E-01	7.59E+07
9	0.119557	7.97E-02	2.10E-01	1.67E+07
10	6.84E-02	0.103447	2.38E-01	3.29E+07
11	3.95E-02	7.73E-02	2.81E-01	2.36E+07
12	2.71E-02	0.03116	3.06E-01	1.03E+07
13	6.62E-02	0.122886	2.26E-01	5.57E+07
14	0.102139	3.70E-02	2.73E-01	1.36E+07
15	0.135655	0.105238	1.58E-01	6.39E+07

Latin hypercube sampling was used.

Inputs

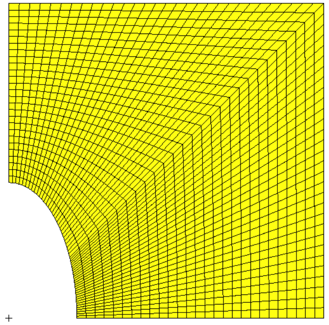
- x1: First parameter of ellipse
- x2: Second parameter of ellipse

Outputs

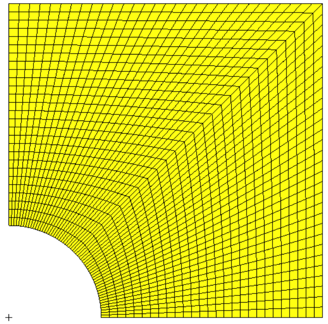
- y0: Mass
- y1: Maximum von Mises stress

Samples

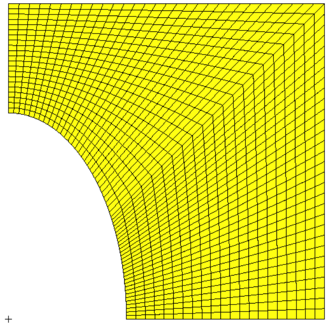
Sample 1



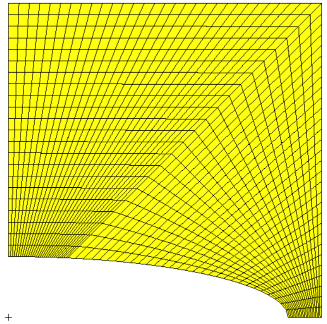
Sample 2



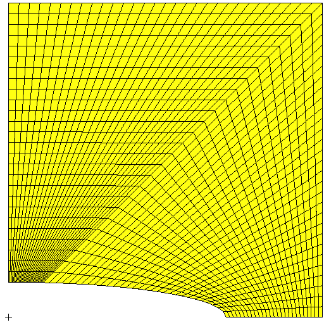
Sample 3

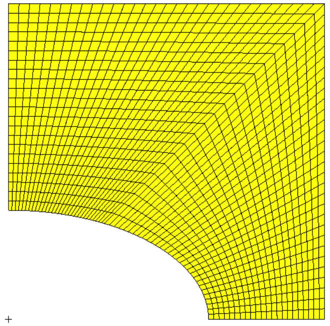


Sample 4



Sample 5





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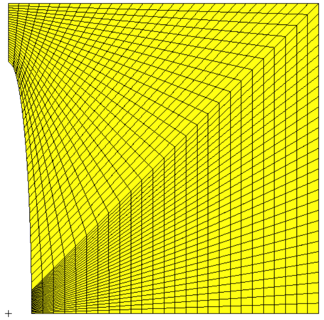
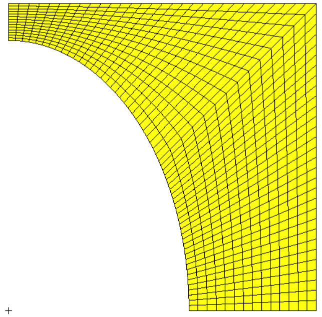
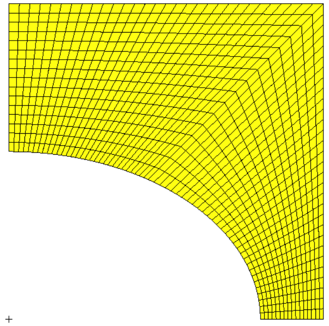


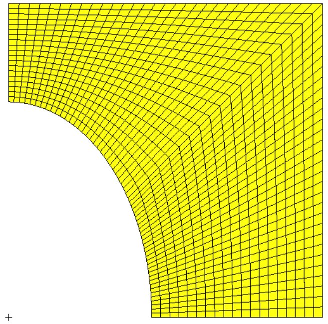
Sample 7



Sample 8



Sample 9



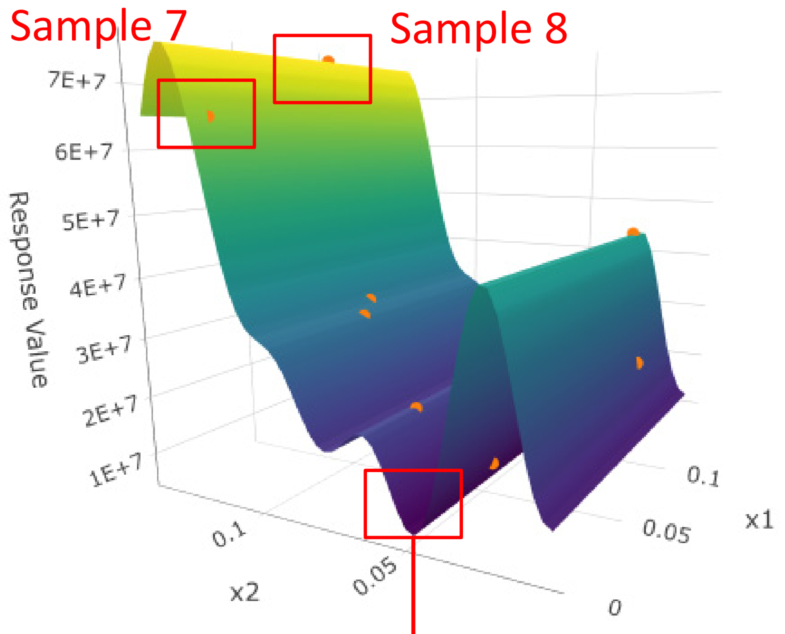
Sample 10

Initial Gaussian Process Regression

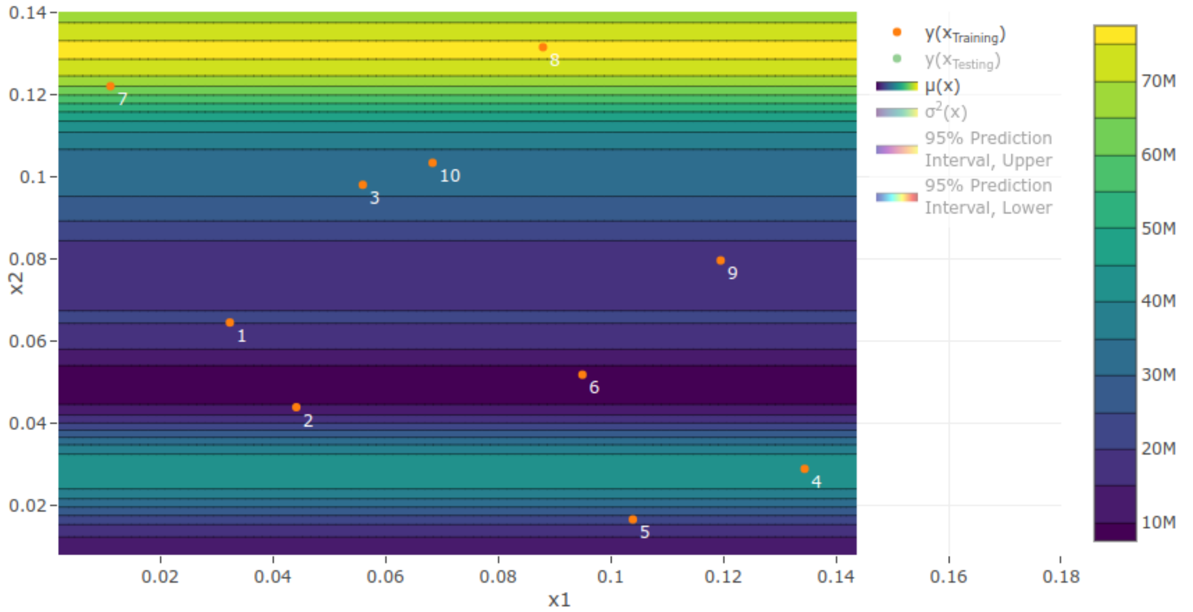
The first 10 samples were used to construct a GPR model for the von Mises stress.

In some regressions, samples with relatively large values tend to skew the GPR model. In this regression, samples 7 and 8 are skewing the GPR, which could lead to a highly unreliable GPR model. Inspecting the GPR model leads to this conclusion: For x2 approaching .15m, the von Mises stress drops. It is known that as the ellipse is increased, i.e. x1 and x2 is increased, the von Mises stress is always increasing, but is not reflected in the GPR model for von Misses stress.

Additional samples are necessary to build a more reliable GPR model.

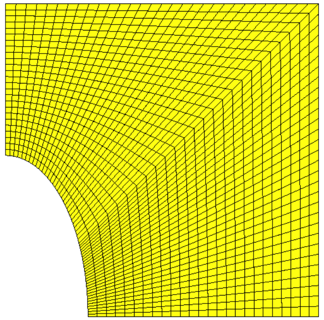


Max. von Mises stress is predicted to occasionally decrease as the ellipse gets larger (x2 parameter is increased)

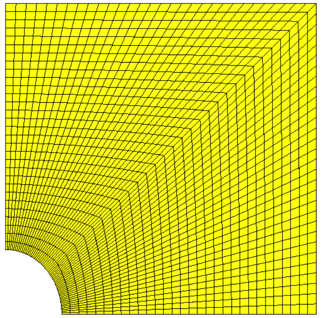


Samples

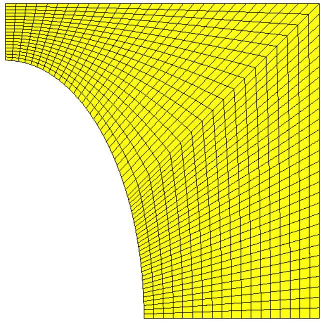
Sample 11



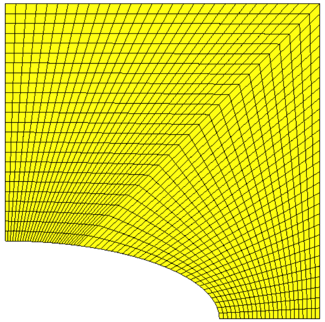
Sample 12



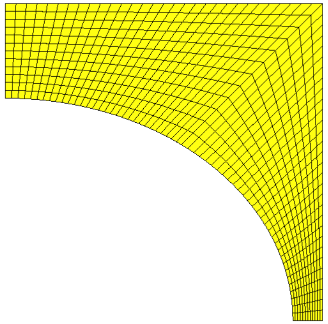
Sample 13



Sample 14

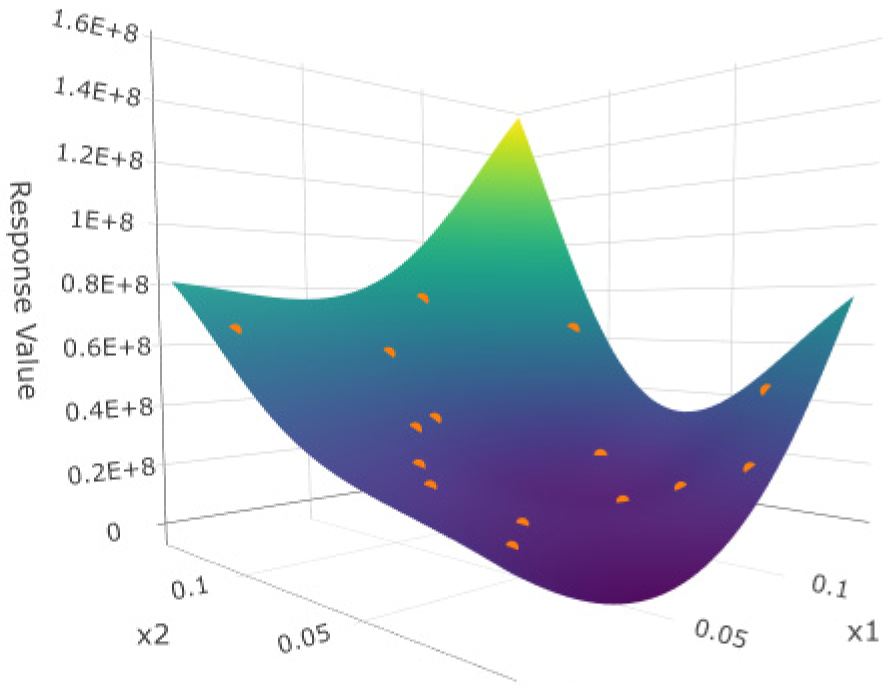


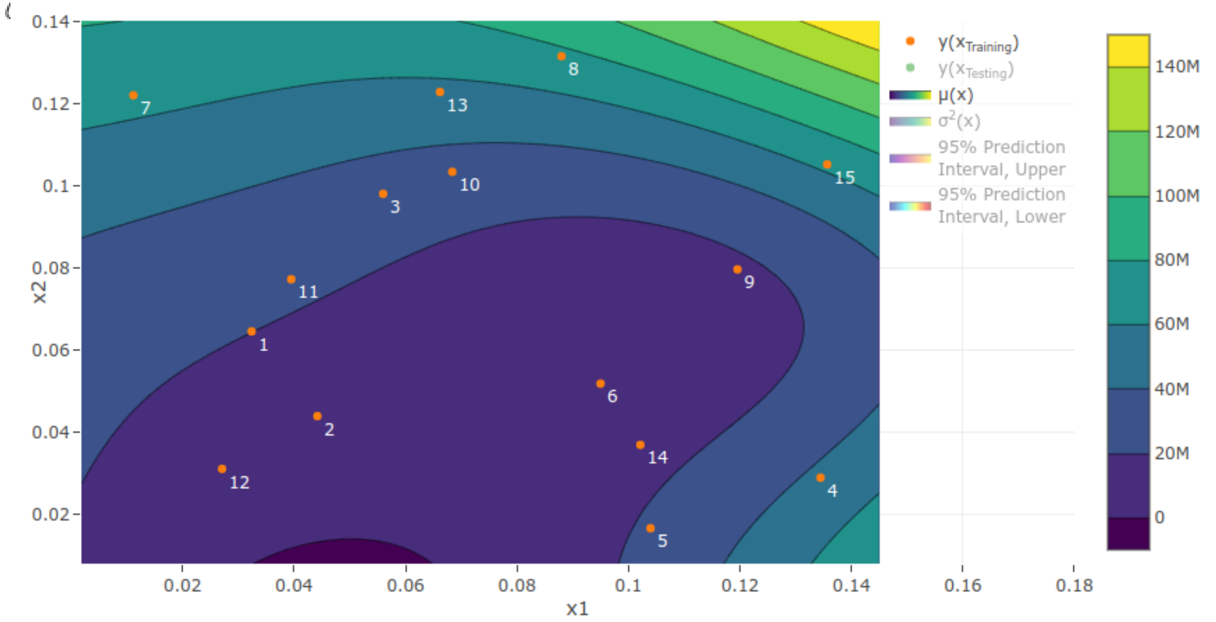
Sample 15



Second Gaussian Process Regression

Five additional samples 11-15 were included in the training data. The updated GPR model now aligns with this expectation: as the ellipse is increased, i.e. x1 and x2 is increased, the von Mises stress is increasing.

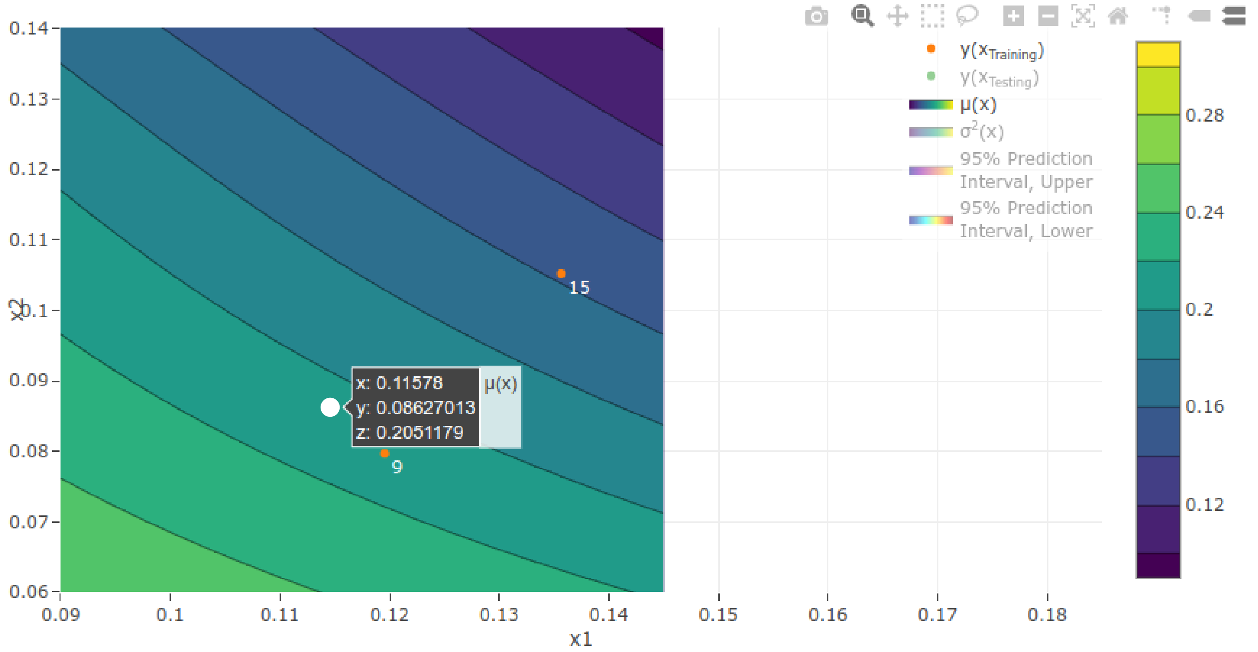




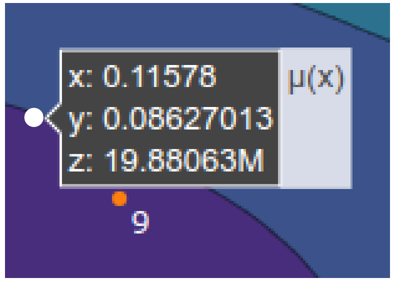
Determining an Optimal Design

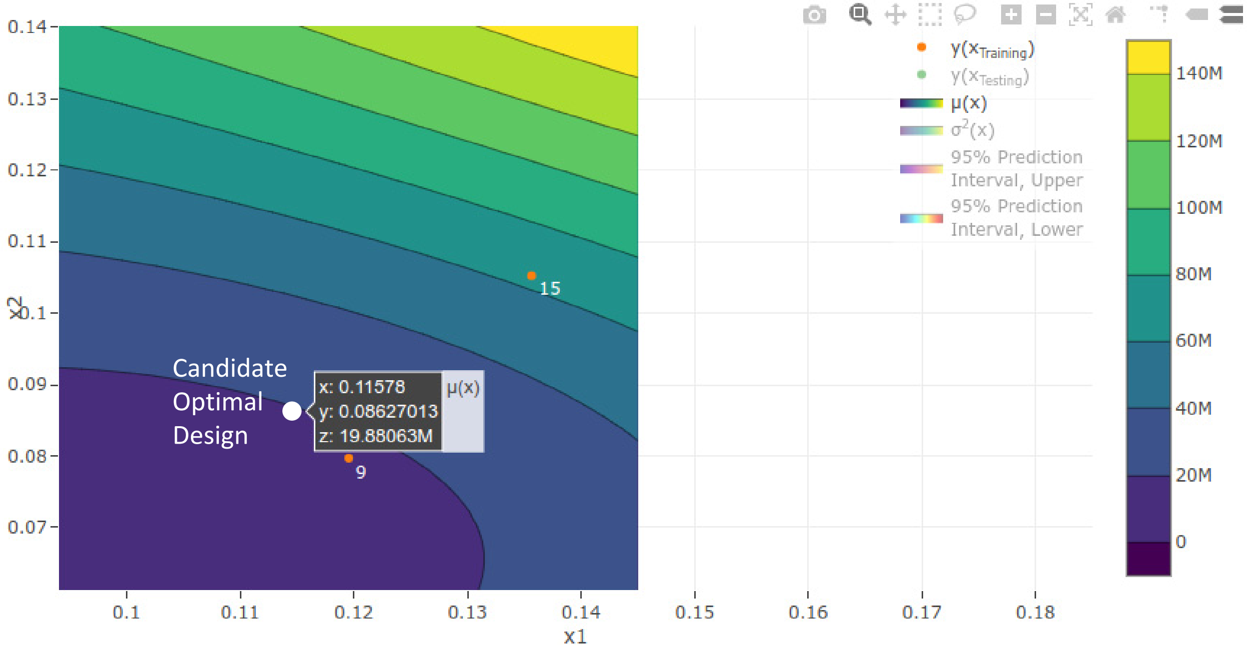
- A design is selected that according to the GPR models is both feasible and optimal. The following design is selected: x1=.11578 and x2=.08627013.

GPR Model for Mass



GPR Model for Max. von Mises Stress





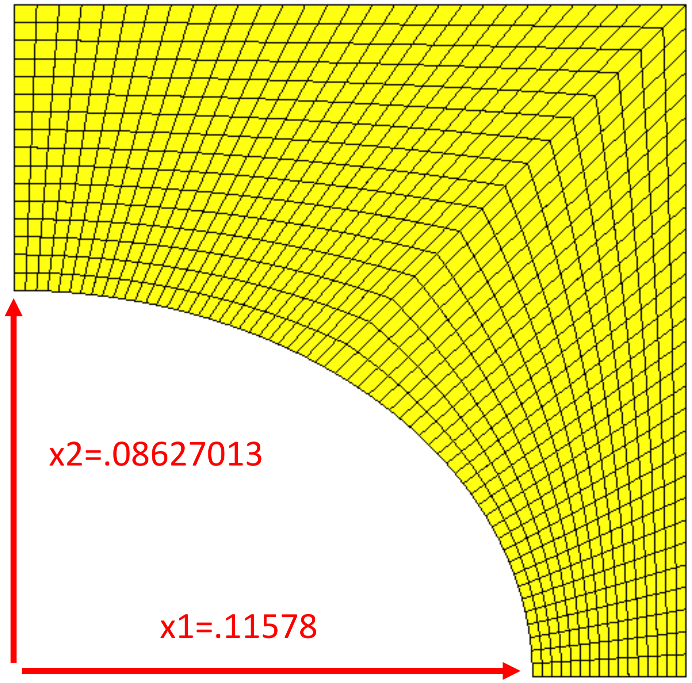
Evaluating the Optimal Design Candidate

A new FE model is created for the selected x1, x2.

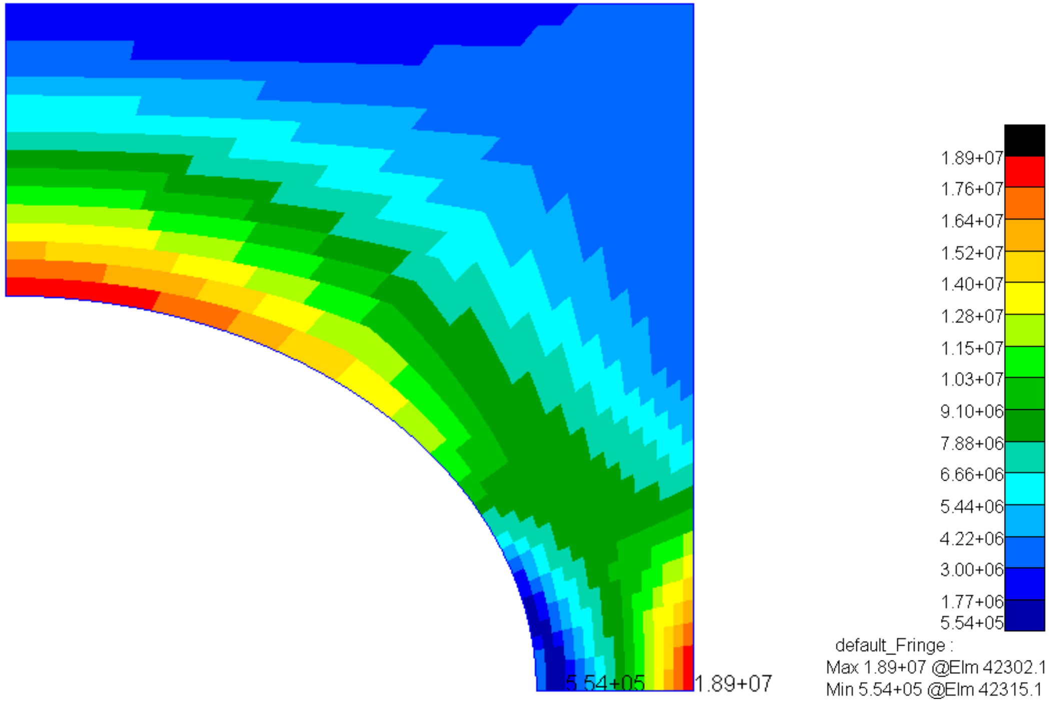
1. The actual max von Mises stress is found to be 18.9 MPa but the GPR for max von Mises predicted 19.88 MPa. GPR models will in a majority of cases have a degree of inaccuracy, but GPR models are effective in approximating the optimum.

2. This design is the best design so far and is near optimal because the 18.9MPa is close to its upper bound of 20MPa. A better design may be discovered.

3. The GPR models may be updated with this new design/sample, and a new design/sample may be selected.



MSC Nastran generated von Mises stress



Results

- With 16 FEA runs, Gaussian process regression was used to find a nearly optimal design.
- FEA based shape optimization relies on moving the nodes of the FE model and is highly susceptible to mesh distortions. GPR model based shape optimization is NOT susceptible to mesh distortions.
- The highest cost in GPR is the time and resources required to build each sample. If the expected cost of GPR is within budget, GPR should be considered. GPR models, and many other models such as Neural Network models, are not expected to support scenarios with hundreds of parameters but are practical for 1-10 parameter problems.

Number of Parameters	Number of Samples to train a reliable GPR Model
1-5	10 runs per parameter
6-10	20 runs per parameter
10-15	Possibly 50 runs per parameter
16 or greater	Possibly thousands of run required

Tools Used

FEM Construction: MSC Apex was used to create the geometry and mesh. Materials, element properties, supports and loads were also defined. Alternatively, the same FE models may be constructed in Patran.

Output Generator: MSC Nastran was used to output the von Mises stresses.

Gaussian Process Regression: The SOL 200 Web App was use to perform the regression. Alternatively, many open source Python libraries support Gaussian process regression.

Future Work

- Parameterization – As long as the optimization problem may be parameterized, GPR models may be constructed and optimization may be performed. Examples of other parameter includes location of holes and size of holes.
- Sample Generation - MSC Apex supports scripting, which could be leveraged to rapidly create multiple FE designs for given inputs xi. A future project may include a scenario where there are up to 10 xi parameters and 200 samples/designs are necessary to generate enough training data for a reliable GPR model.
- Bayesian Optimization – This work directly minimized the GPR model for the mass. The selected design candidate was suboptimal AND another global solution may exist. Bayesian optimization has been demonstrated to find designs closer to the optimum and performs a global search. A future project may employ Bayesian optimization for shape optimization of FEA models, but would be limited to 1-10 parameters.