DESIGN OPTIMIZATION OF BRAKE DISC GEOMETRY USING DOE in ANSYS

Abstract:

In this study, Optimization of brake disc geometry in a four-wheeler vehicle using Design of Experiments (DOE) in ANSYS. The analysis is conducted on multiple objectives like minimize the maximum stress in the brake disc, design a brake disc for emergency braking conditions with minimal volume, minimize the maximum temperature in the brake disc and maximize the first natural frequency of the brake disc. Before performing the optimization, Static structural, Modal and Transient Thermal analysis is performed to analyze various parameters like stress, deformation, and heat flux. The same parameters are considered, and Optimization of the geometry is performed. Response surface is used as Design Exploration method and Latin Hypercube Sampling (LHS) is considered for DOE method. Multi-objective Genetic Algorithm (MOGA), Mixed-Integer Sequential Quadratic Programming (MISQP) is used as Optimization algorithm. The results show that both optimization methods converge.

Keywords: Design Optimization, Ansys, Design of Experiments (DOE), Mixed-Integer Sequential Quadratic Programming (MISQP), Multi-objective Genetic Algorithm (MOGA)

Contents:

1. Introduction

Design exploration:

Describes the relationship between the design variables and the performance of the product using Design of Experiments (DOEs) and Response surfaces. DOEs and response surfaces provide all the information required to achieve simulation-driven product development. Once the variation of product performance with respect to design variables is known, it becomes easy to understand and identify the changes required to meet requirements for the product. After response surfaces are created, we can analyze and share results using curves, surfaces, and sensitivities that are easily understood. The results obtained can be used at any time during the development of the product without requiring additional simulations to test a new configuration.

Latin Hypercube Sampling (LHS) DOE method:

This DOE method avoids clustering samples, and the points are randomly generated in a square grid across the design space, but no two points share the same value. That is, no point shares a row or a column of the grid with any other point. In this study, Full Quadratic Samples property is used to generate the samples, so that a full quadratic model is formed.

Response Surfaces:

Response surfaces are functions of varying natures in which the output parameters are described in terms of the input parameters. Built from the DOE, they quickly provide the approximated values of the output parameters throughout the design space without having to perform a complete solution.

The accuracy of a response surface depends on:

- Complexity of the variations of the solution
- Number of points in the original DOE
- Response surface type

Response Surface Types Used in this project are:

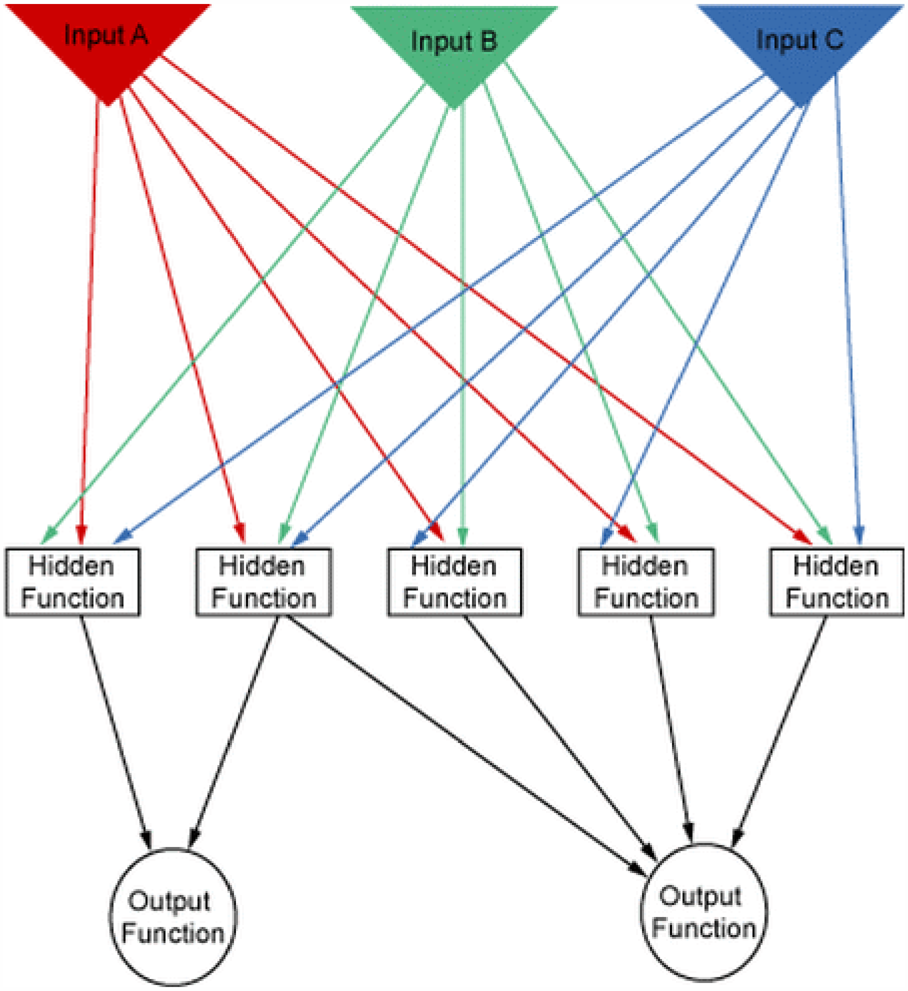
- Genetic Aggregation:

Genetic Aggregation is the default algorithm for generating response surfaces. It automates the process of selecting, configuring, and generating the type of response surface best suited to each output parameter in the problem.

From the different types of response surface available (Full 2nd-Order Polynomials, Non-Parametric Regression, Kriging, and Moving Least Squares), Genetic Aggregation automatically builds the response surface type that is the most appropriate approach for each output.

Genetic Aggregation takes more time than classical response surfaces such as Full 2nd order Polynomial, Non-Parametric Regression, or Kriging because of multiple solves of response surfaces and the cross-validation process. In general, Genetic Aggregation is more reliable than the classical response surface models.

- Neural Network:



The output solution is:

$$f_k(x_i)=K(\sum w_{jk} g_j(x_i))$$

Where K is a predefined function, such as the hyperbolic tangent or an exponential based function, to obtain something like the binary behavior of the electrical brain signal (like a step function). The function is continuous and differentiable.

The weight functions (W_{jk}) are issued from an algorithm that minimizes (as the least squares method) the distance between the interpolation and the known values (design points). This is called learning. The error is checked at each iteration with the design points that are not used for learning. Learning design points need to be separated from error-checking design points.

The error decreases and then increases when the interpolation order is too high. The minimization algorithm is stopped when the error is the lowest.

This method uses a limited number of design points to build the approximation. It works better when the number of design points and the number of intermediate cells are high. It can give interesting results with several parameters.

Goal-Driven Optimizations:

Response Surface Optimization: This system draws its information from its own Response Surface cell and so is dependent on the quality of the response surface. The available optimization methods are Screening, MOGA, NLPQL, and MISQP, which all use response surface evaluations rather than real solve.

In this project, only response surface optimization is performed and MOGA, MISQP optimization methods are used.

Direct Optimization: This system has only one cell, which utilizes real solves rather than response surface evaluations. The available optimization methods are Screening, NLPQL, MISQP, Adaptive Single-Objective, and Adaptive Multiple-Objective.

This system takes lot more time when compared to that of Response system as it solves everything without using any previous evaluations.

Optimization Methods:

Two optimization methods are used in project in-order to compare both the optimization results. Multiple objectives can be given in MOGA and one objective with different constraints is given in MISQP.

Multi-Objective Genetic Algorithm (MOGA):

MOGA used in GDO is a hybrid variant of the popular NSGA-II (Non-dominated Sorted Genetic Algorithm-II) based on controlled elitism concepts. It supports all types of input parameters.

The Pareto ranking scheme is done by a fast, non-dominated sorting method that is an order of magnitude faster than traditional Pareto ranking methods. The constraint handling uses the same non-dominance principle as the objectives. Therefore, penalty functions and Lagrange multipliers are not needed. This also ensures that the *feasible solutions are always ranked higher than the infeasible solutions.*

The first Pareto front solutions are archived in a separate sample set internally and are distinct from the evolving sample set. This ensures minimal disruption of Pareto front patterns already available from earlier iterations. You can control the selection pressure (and, consequently, the elitism of the process) to avoid premature convergence by altering the Maximum Allowable Pareto Percentage property.

Mixed-Integer Sequential Quadratic Programming (MISQP):

MISQP (Mixed-Integer Sequential Quadratic Programming) is a mathematical optimization algorithm as developed by Oliver Exler, Thomas Lehmann and Klaus Schittkowski (NLPQL). This method solves Mixed-Integer Non-Linear Programming (MINLP) of the form:

Minimize: $f(x,y)$

Subject to: $g_j(x,y)=0,\ \ j=1,\ldots,m_e,$

$$g_j(x,y)\geq 0,\ \ j=m_e+1,\ldots,m$$

Problem functions are evaluated only at integer points and never at any fractional values in between.

MISQP solves MINLP by a modified sequential quadratic programming (SQP) method. After linearizing constraints and constructing a quadratic approximation of the Lagrangian function, mixed-integer quadratic programs are successively generated and solved by an efficient branch-and-cut method. The algorithm is stabilized by a trust region method as originally proposed by Yuan for continuous programs. Second order corrections are retained. The Hessian of the Lagrangian function is approximated by BFGS updates subject to the continuous and integer variables. MISQP is able to solve also non-convex nonlinear mixed-integer programs.

2. Design Problem Statement

Objectives and Constraints for performing MOGA:

- Minimize the brake disc volume for emergency braking conditions
- Minimize the maximum stress in the brake disc
- Maximize the first natural frequency of the brake disc
- Minimize the maximum temperature in the brake disc
- No Constraints

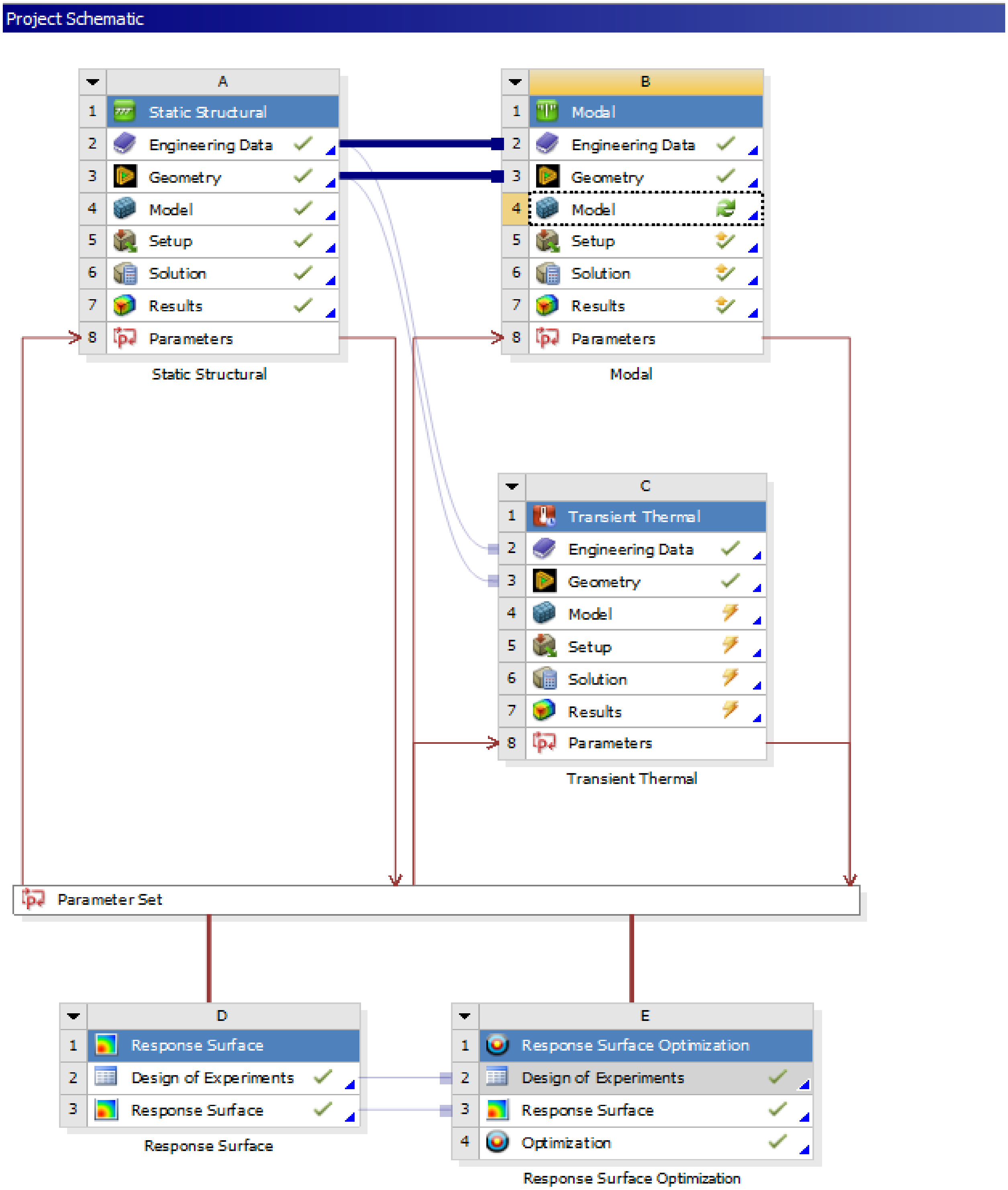
Objectives and Constraints for performing MISQP:

- Minimize the maximum stress in the brake disc

Constraints:

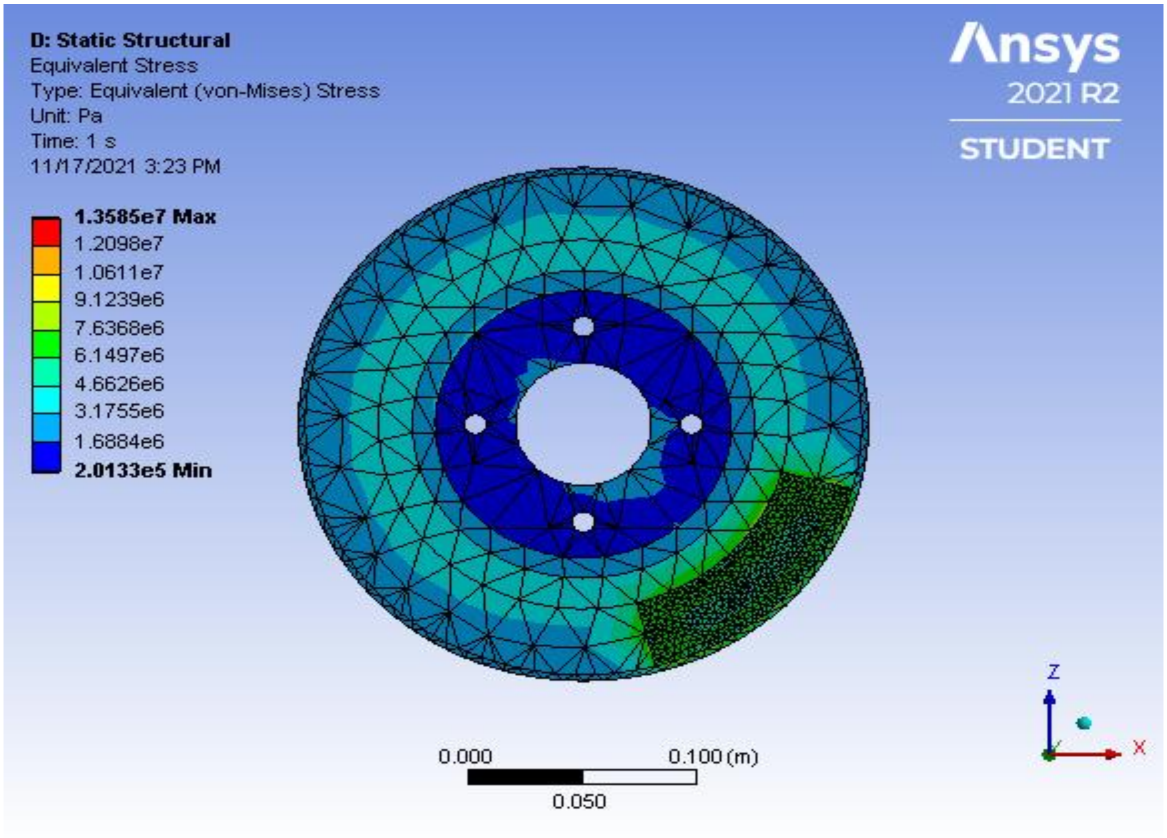
- Natural frequency of the brake disc
- The maximum temperature in the brake disc.
- The brake disc volume for emergency braking conditions

Project Schematic:



3. Static Structural Analysis System

3.1. Equivalent Stress Analysis (Von-Mises)



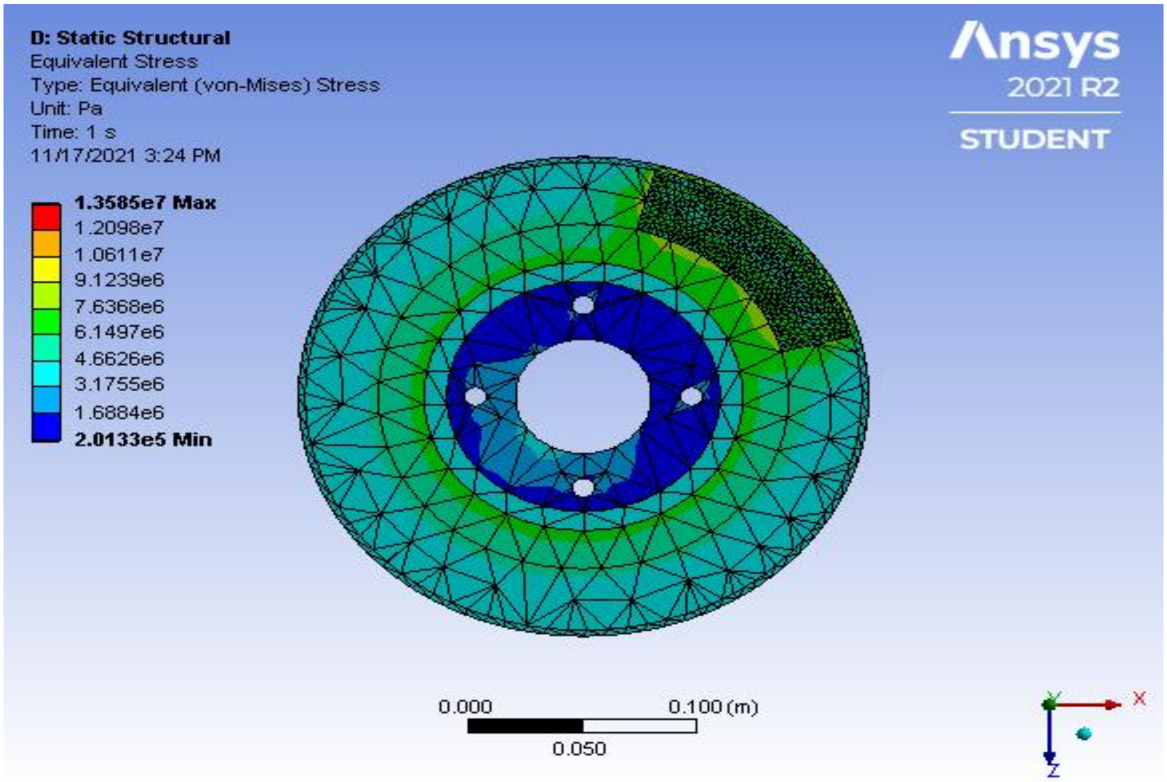
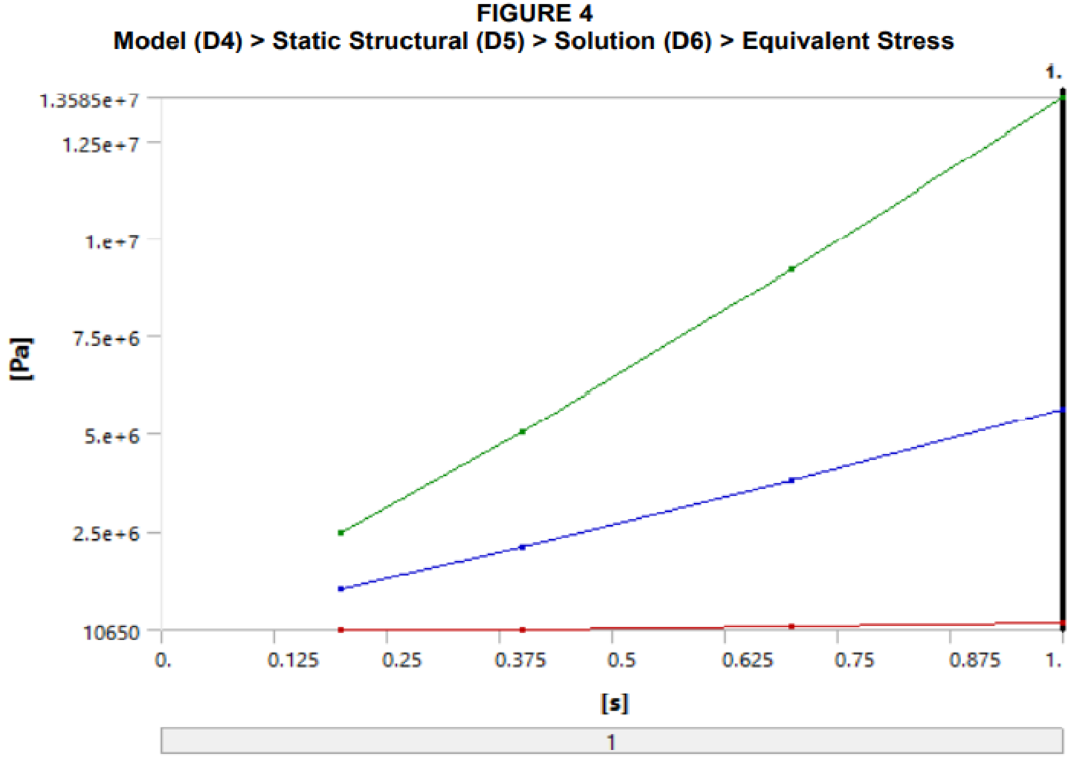
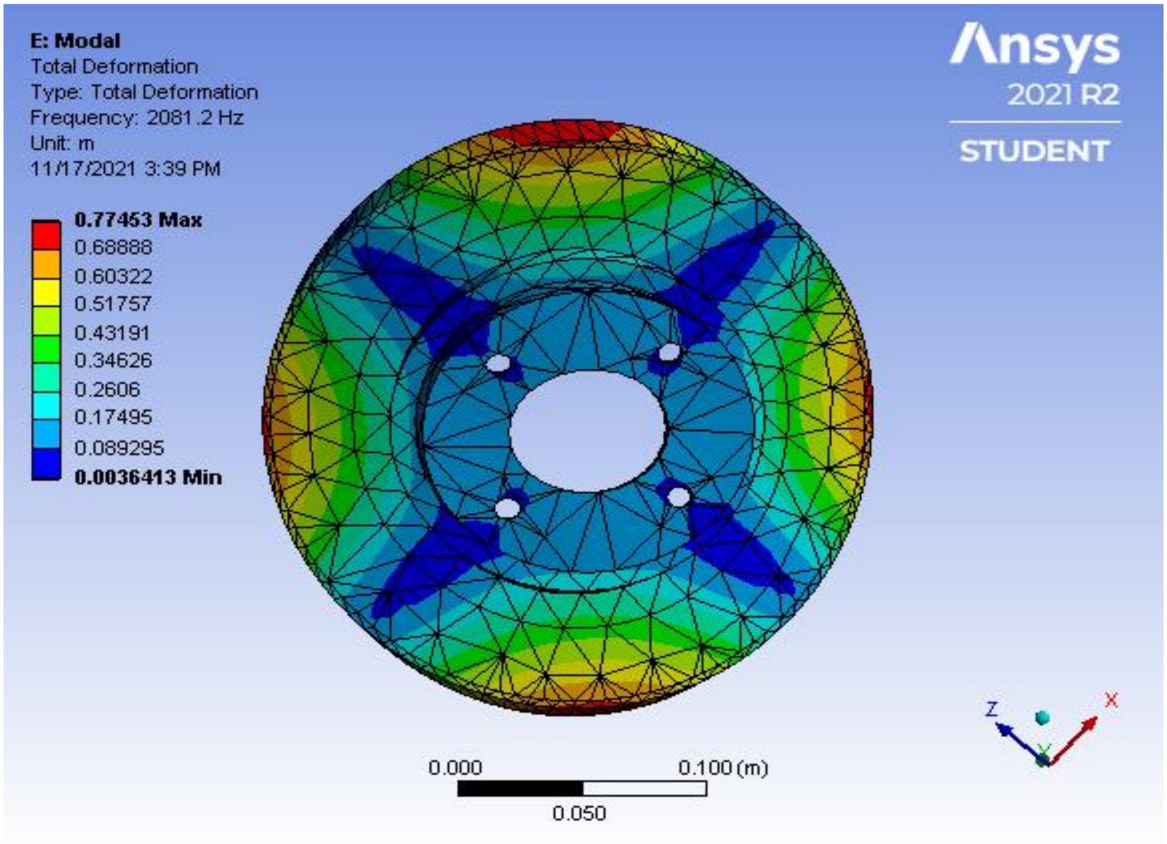

D: Static Structural
Equivalent Stress
Type: Equivalent (von-Mises) Stress
Unit: Pa
Time: 1 s
11/17/2021 3:24 PM
1.3585e7 Max
1.2098e7
1.0611e7
9.1239e6
7.6368e6
6.1497e6
4.6626e6
3.1755e6
1.6884e6
2.0133e5 Min
Ansys
2021 R2
STUDENT
0.000
0.100 (m)
0.050
X
Z

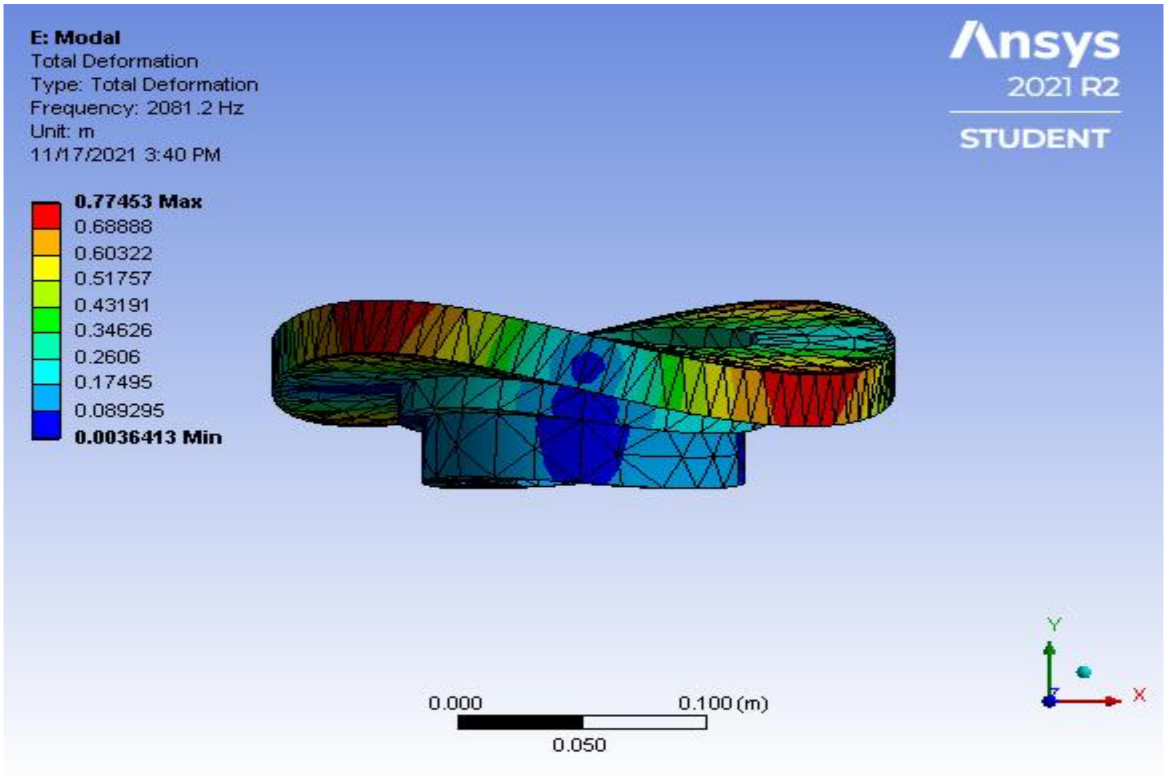
FIGURE 4


Model (D4) > Static Structural (D5) > Solution (D6) > Equivalent Stress
[Pa]
1.3585e+7
1.25e+7
1.e+7
7.5e+6
5.e+6
2.5e+6
10650
0.
0.125
0.25
0.375
0.5
0.625
0.75
0.875
1.
[s]
1

4. Modal Analysis System

4.1. Total Deformation Analysis




E: Modal
Total Deformation
Type: Total Deformation
Frequency: 2081.2 Hz
Unit: m
11/17/2021 3:40 PM
0.77453 Max
0.68888
0.60322
0.51757
0.43191
0.34626
0.2606
0.17495
0.089295
0.0036413 Min
Ansys
2021 R2
STUDENT
0.000
0.050
0.100 (m)
Y
X

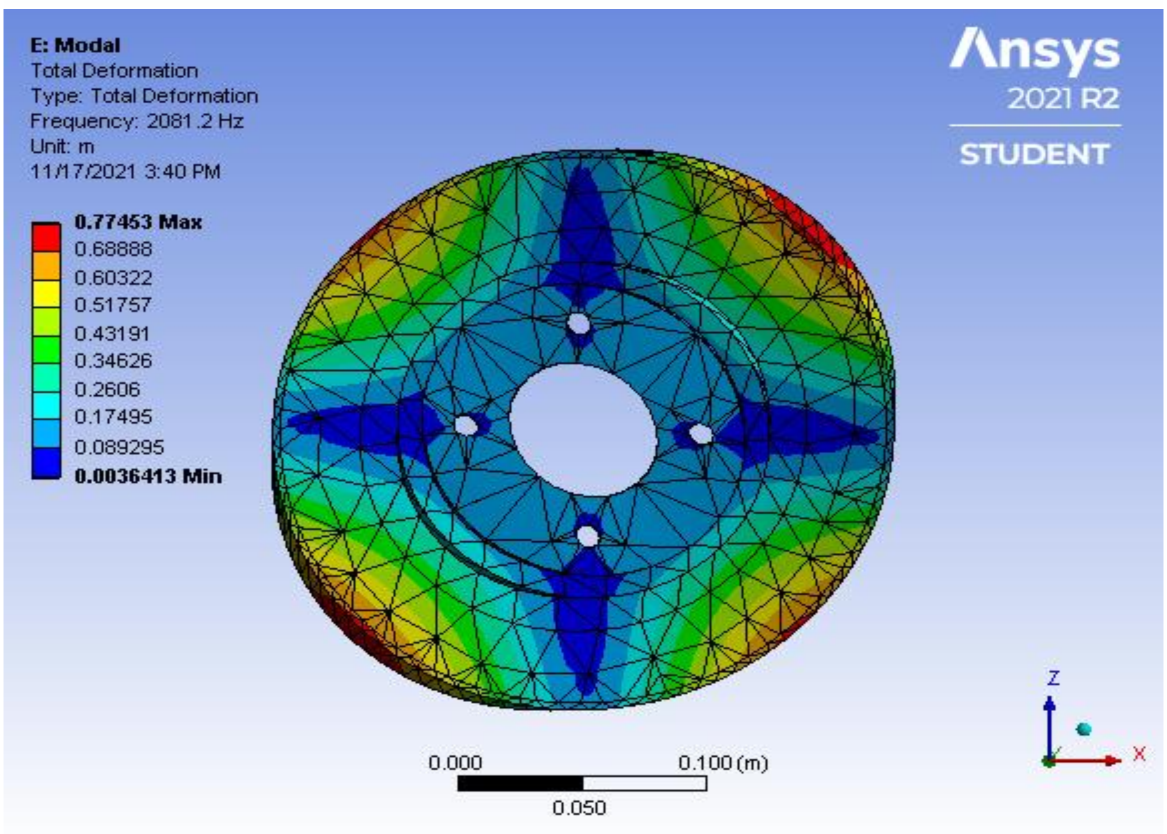

E: Modal
Total Deformation
Type: Total Deformation
Frequency: 2081.2 Hz
Unit: m
11/17/2021 3:40 PM
0.77453 Max
0.68888
0.60322
0.51757
0.43191
0.34626
0.2606
0.17495
0.089295
0.0036413 Min
Ansys
2021 R2
STUDENT
0.000
0.050
0.100 (m)
Z
X

TABLE 18
Model (E4) > Modal (E5) > Solution (E6) > Results

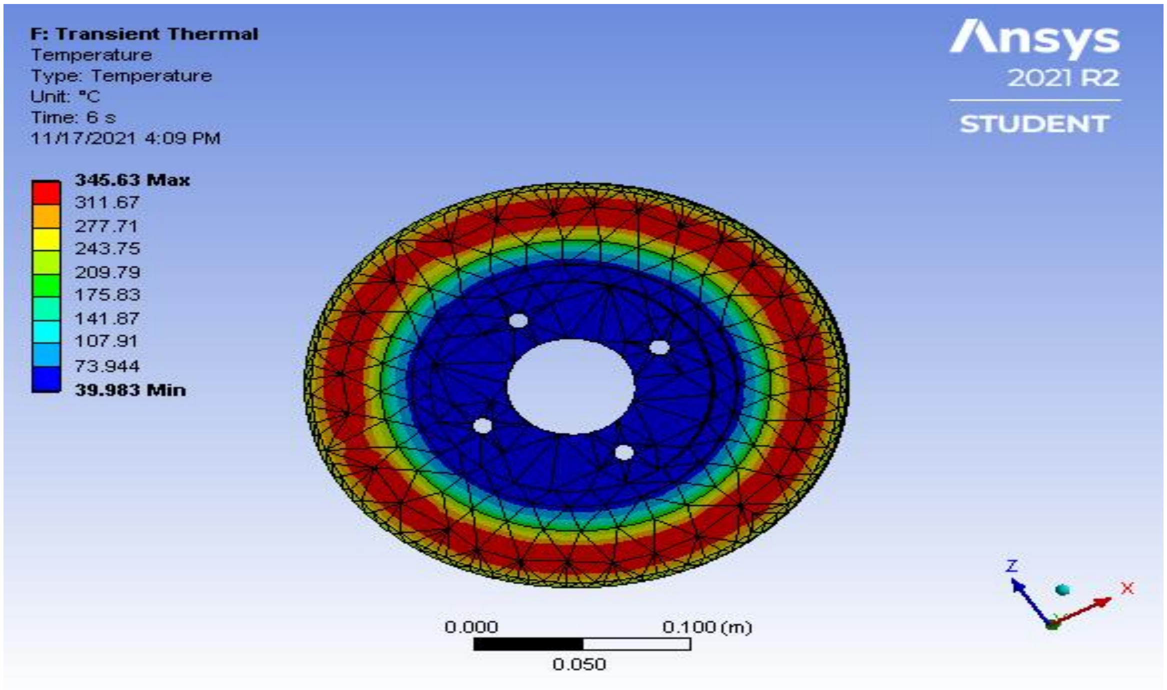
Object Name	*Total Deformation*
State	Solved
Scope	
Scoping Method	Geometry Selection
Geometry	All Bodies
Definition	
Type	Total Deformation
Mode	7.
Identifier	
Suppressed	No
Results	
Minimum	3.6413e-003 m
Maximum	0.77453 m
Average	0.32819 m
Minimum Occurs On	Solid
Maximum Occurs On	Solid
Information	
Frequency	2081.2 Hz

TABLE 19
Model (E4) > Modal (E5) > Solution (E6) > Total Deformation

Mode	Frequency [Hz]
1.	0.
2.	
3.	
4.	2.0187e-003
5.	3.9598e-003
6.	5.8548e-003
7.	2081.2
8.	2087.2
9.	3628.9
10.	3649.5

5. Transient Thermal Analysis System

5.1. Temperature (Maximum)



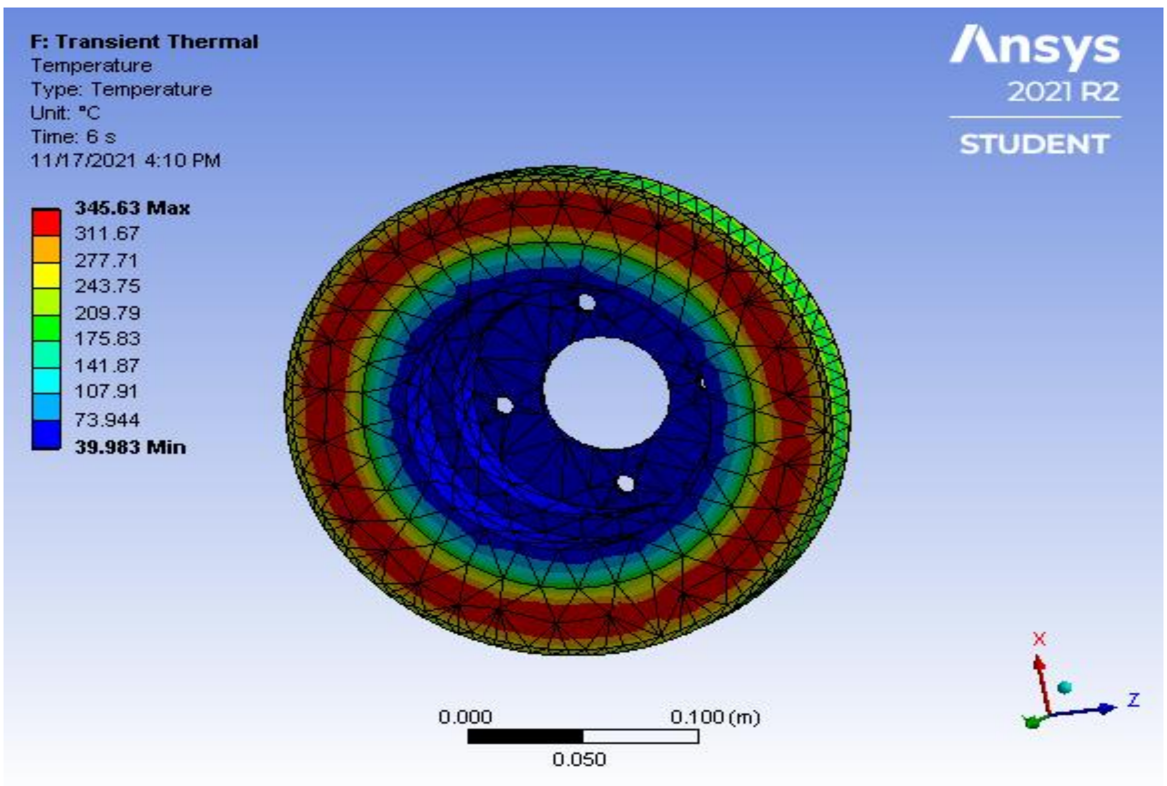


FIGURE 4

Model (F4) > Transient Thermal (F5) > Solution (F6) > Solution Information > Temperature - Global Maximum

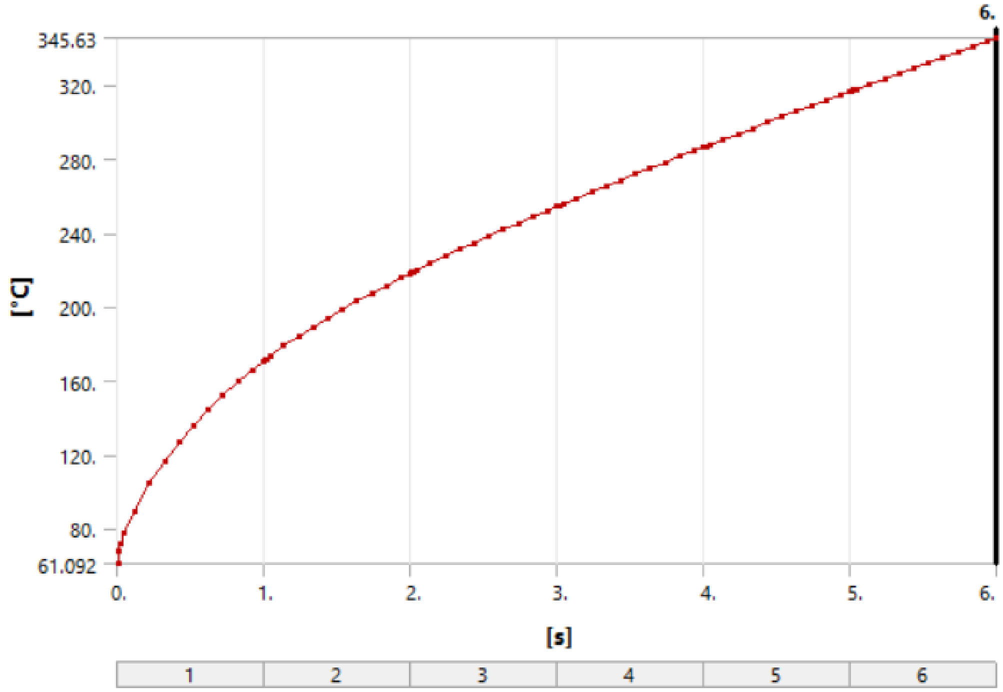


FIGURE 5

Model (F4) > Transient Thermal (F5) > Solution (F6) > Solution Information > Temperature - Global Minimum

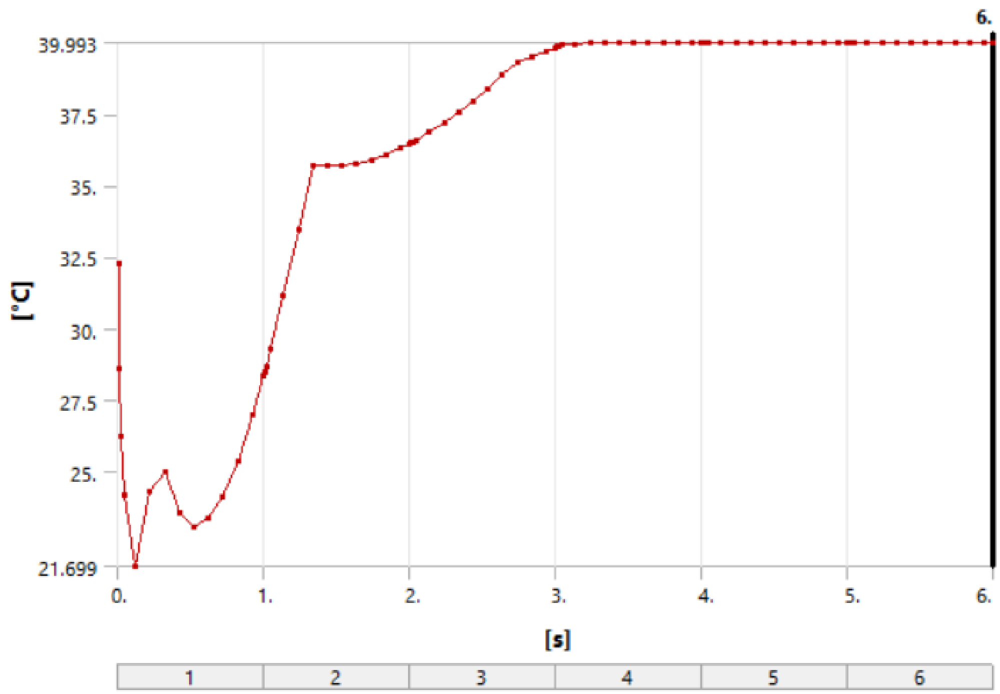
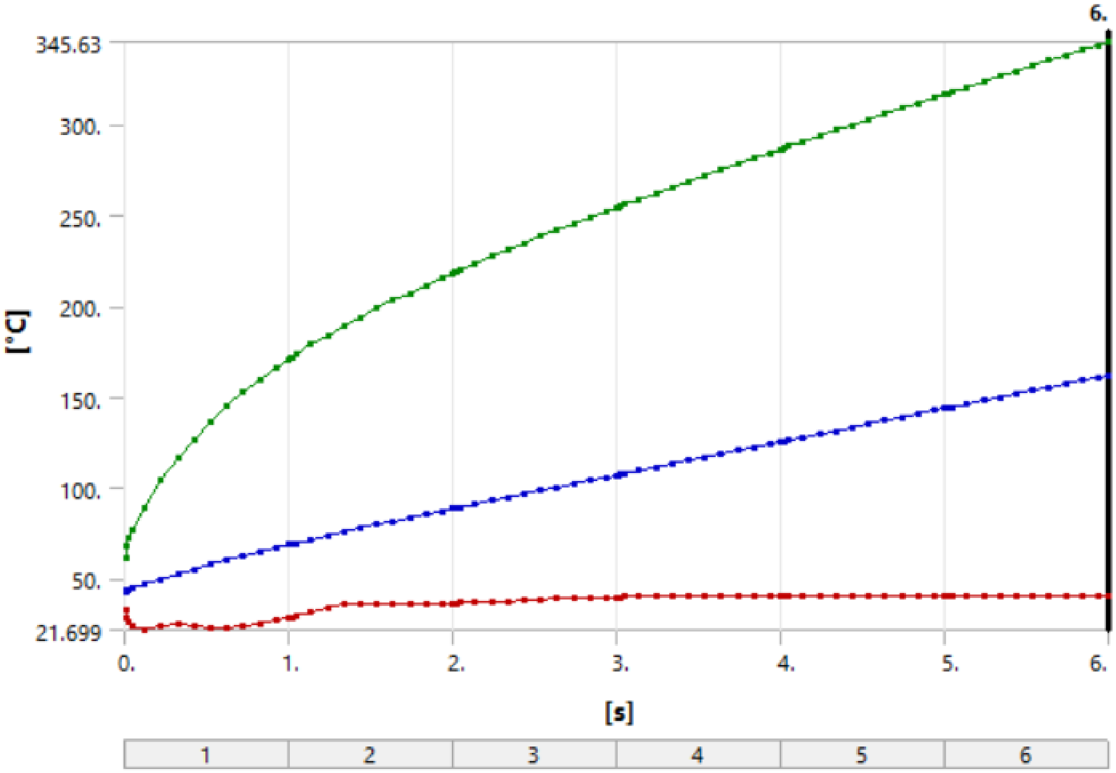


FIGURE 6

Model (F4) > Transient Thermal (F5) > Solution (F6) > Temperature



6. Design Exploration

6.1. Response Surface

6.1.1. Design of Experiments

# Design Points of Design of Experiments							
# Latin Hypercube Sampling Design : Full Quadratic Model Samples : Random Generator Seed = 0							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
1	130.65	76.25	24.25	347.335	12168527	1929.873	0.001108611
2	135.75	66.25	27.25	333.9154	14109384	1917.722	0.001419614
3	123.85	86.25	26.75	343.1153	12709887	1797.193	0.000951535
4	134.05	81.25	23.75	348.9974	12636418	1769.64	0.001117192
5	125.55	78.75	24.75	343.3849	12326001	1970.954	0.001003402
6	139.15	83.75	25.25	340.9189	13252820	1665.707	0.001257794
7	132.35	88.75	26.25	342.8882	15267361	1648.022	0.001092256
8	137.45	73.75	25.75	340.044	12754570	1842.297	0.001330828
9	128.95	71.25	27.75	334.6909	13365303	2111.68	0.001241109
10	127.25	68.75	23.25	350.7992	11817308	2059.065	0.001063308

# Design Points of Design of Experiments							
# Latin Hypercube Sampling Design : User-Defined Samples : Number of Samples = 10							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
1	130.65	76.25	27.5	337.1126	13637134	1991.4	0.001223531
2	135.75	66.25	33.5	323.6892	15593570	2122.609	0.001695269
3	123.85	86.25	32.5	329.6615	14876209	1929.376	0.001094238
4	134.05	81.25	26.5	340.7363	13834428	1815.742	0.001215403
5	125.55	78.75	28.5	332.3253	13388076	2041.919	0.001116042
6	139.15	83.75	29.5	330.1255	15123260	1743.84	0.00142267
7	132.35	88.75	31.5	330.4062	16444647	1762.376	0.001251251
8	137.45	73.75	30.5	329.9389	14652239	1953.075	0.001531587
9	128.95	71.25	34.5	326.2853	15997386	2291.631	0.001486068
10	127.25	68.75	25.5	341.5448	12202313	2121.502	0.001144356

Charts:

Parameters Parallel:

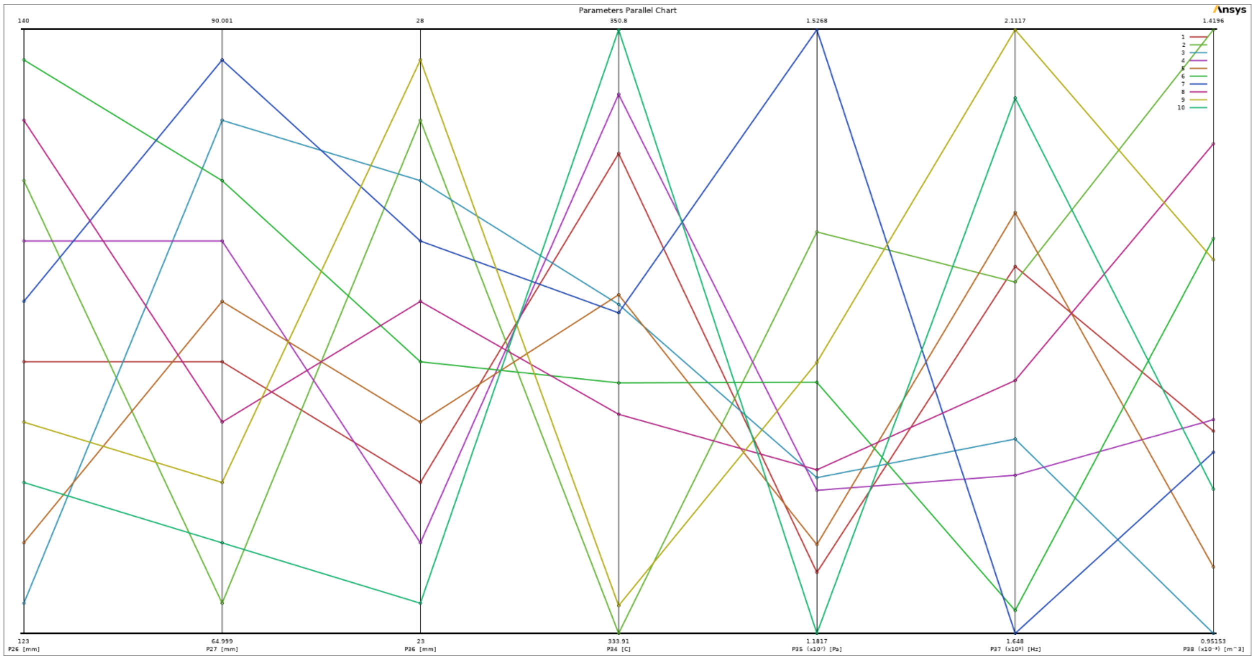


Figure 1: LHS-Full Quadratic Model Samples

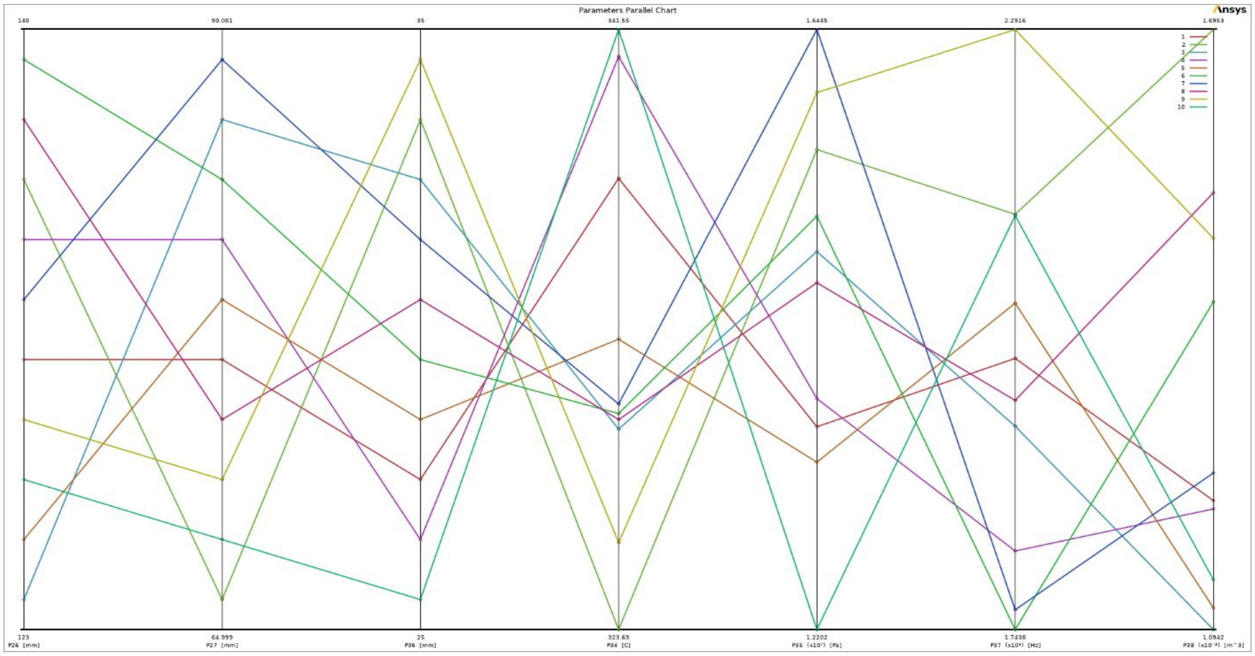


Figure 2: LHS-User-defined samples

Design Points Vs Parameters

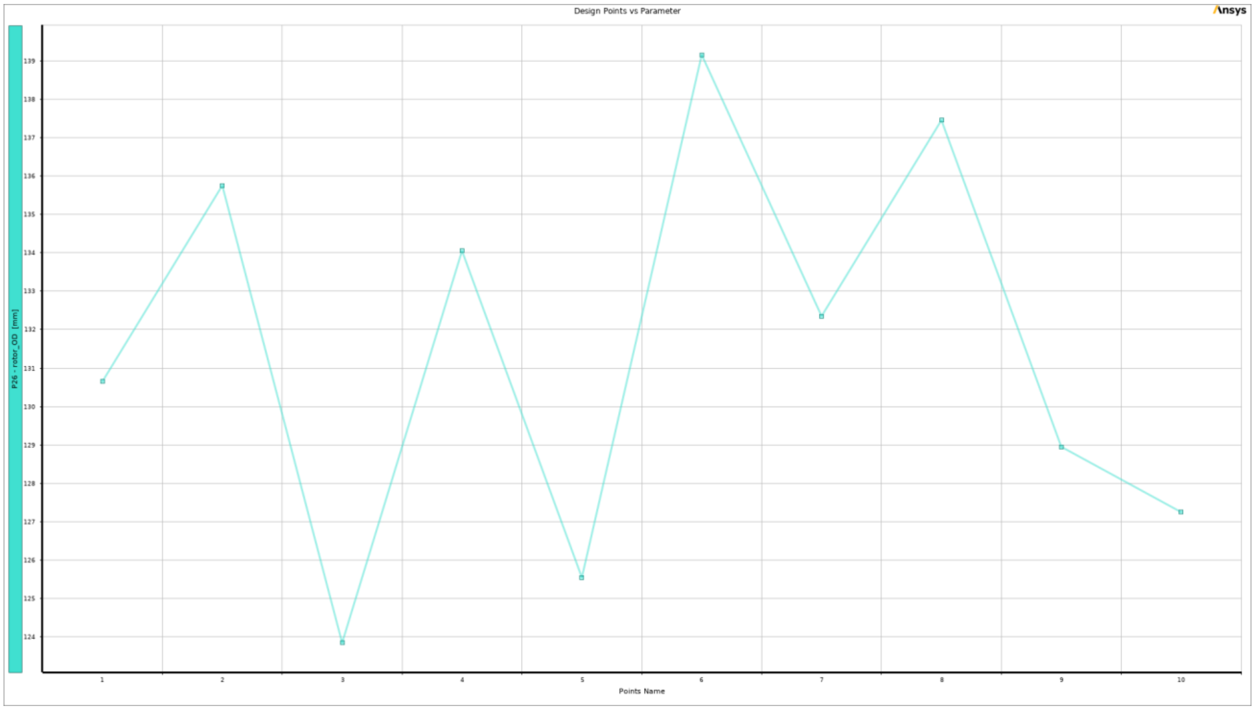


Figure 3: LHS-User defined samples

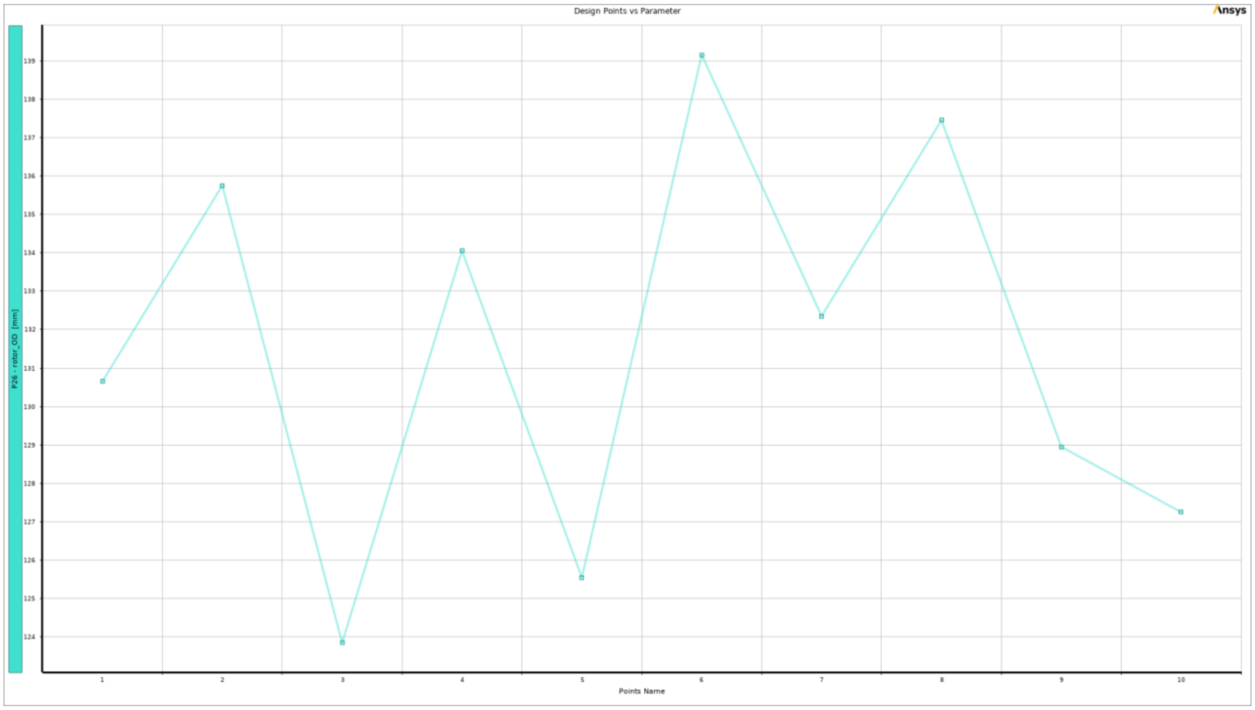


Figure 4: LHS - Full Quadratic Model Samples

6.1.2. Response Surface

# Response Points – Full Quadratic Model samples							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
Response Point	131.5	77.5	25.5	343.2609	13084108	1842.302	0.001153

# Response Points - LHS User define samples							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
Response Point	131.5	77.5	30	331.6884	14683651	2000.125	0.001321

Table of Schematic D3: Response Surface

	A	B	C	D	E
1		P34 - Temperature Maximum	P35 - Equivalent Stress Maximum	P37 - Total Deformation Reported Frequency	P38 - Geometry Volume
2	Coefficient of Determination (Best Value = 1)				
3	Learning Points	0.9994	1	1	1
4	Cross-Validation on Learning Points	0.93183	1	1	0.99993
5	Root Mean Square Error (Best Value = 0)				
6	Learning Points	0.13634	0.35899	0.00010309	1.4054E-09
7	Verification Points	5.4426	1.3243E+07	90.076	2.0852E-05
8	Cross-Validation on Learning Points	1.4557	1.5268	0.00058311	1.5781E-06
9	Relative Maximum Absolute Error (Best Value = 0%)				
10	Learning Points	4.3746	0	0	0
11	Verification Points	154.08	279.93	58.91	14.868
12	Cross-Validation on Learning Points	51.304	0.00028905	0.00066378	1.6933
13	Relative Average Absolute Error (Best Value = 0%)				
14	Learning Points	1.9848	0	0	0
15	Verification Points	50.672	129.91	36.37	7.717
16	Cross-Validation on Learning Points	20.474	8.42E-05	0.00025522	0.59985

Figure 5: Response and Samples for Full Quadratic Model

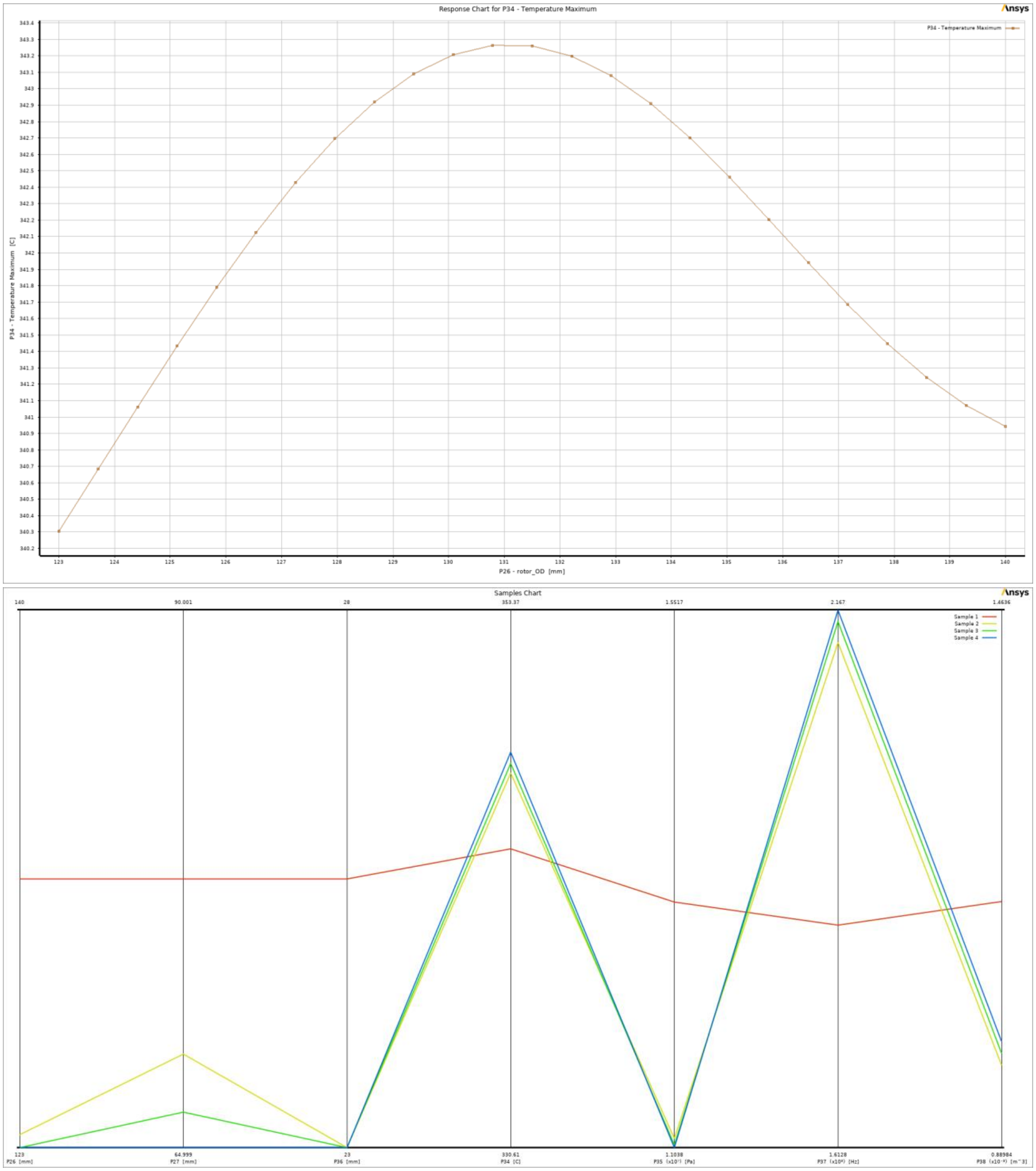
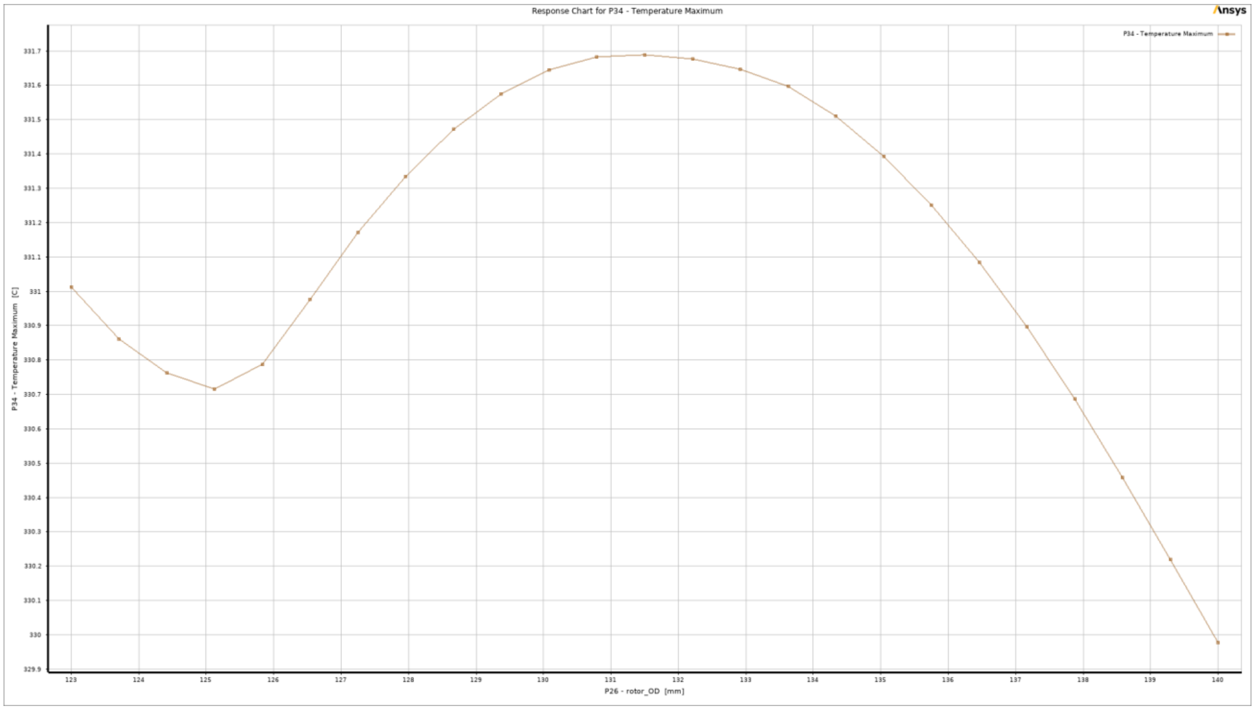
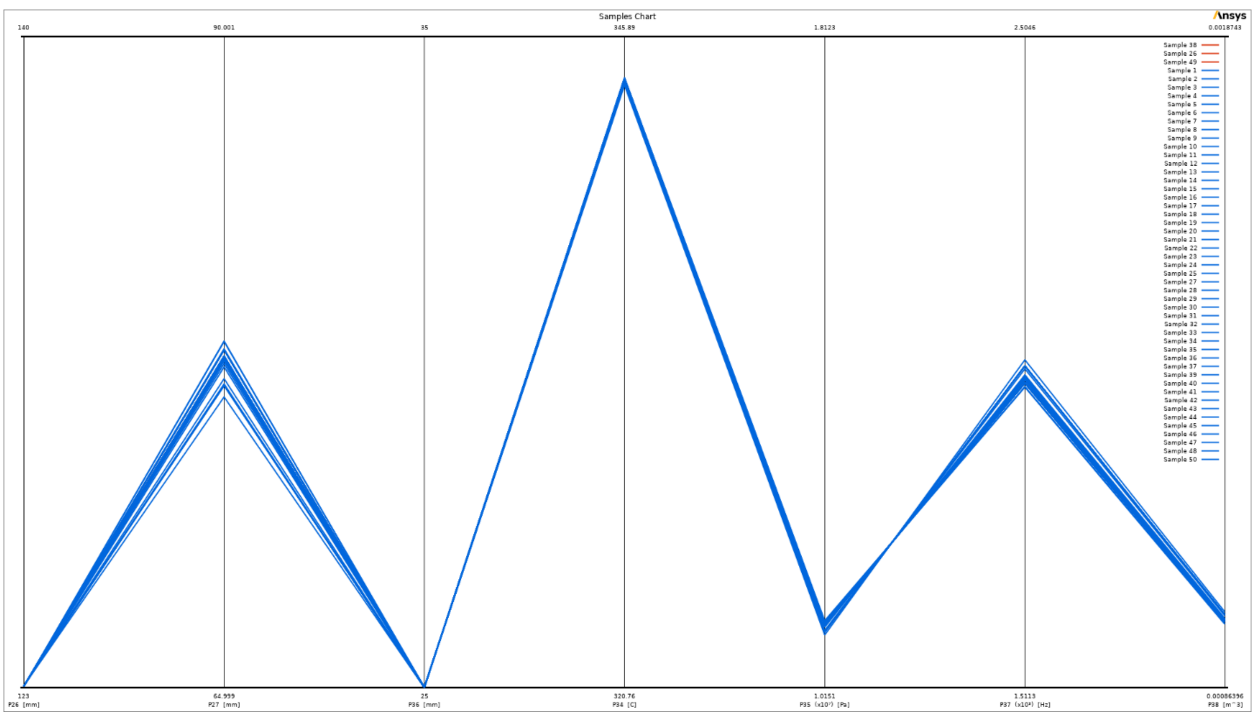


Figure 6:Response and Samples for User-defined LHS





6.2. Response Surface Optimization

MISQP & MOGA

Table of Schematic E4: Optimization

	A	B	C	D	E
1	⊟ Optimization Study				
2	Minimize P35	Goal, Minimize P35 (Default importance)			
3	P34 <= 350.8 C	Strict Constraint, P34 values less than or equals to 350.8 C (Default importance)			
4	P37 >= 1648 Hz	Strict Constraint, P37 values greater than or equals to 1648 Hz (Default importance)			
5	P38 <= 0.0014196 m^3	Strict Constraint, P38 values less than or equals to 0.0014196 m^3 (Default importance)			
6	⊟ Optimization Method				
7	MISQP	The MISQP method (Mixed-Integer Sequential Quadratic Programming) solves mixed-integer nonlinear programming problems by a modified sequential quadratic programming (SQP) method. Under the assumption that integer variables have a smooth influence on the model functions, i.e., that function values do not change drastically when in- or decrementing an integer variable, successive quadratic approximations are applied. It supports a single objective and multiple constraints. The starting point must be specified to determine the region of the design space to explore.			
8	Configuration	Approximate derivatives by Central difference and find 3 candidates in a maximum of 20 iterations.			
9	Status	Converged after 22 evaluations.			
10	⊟ Candidate Points				
11		Starting Point	Candidate Point 1	Candidate Point 2	Candidate Point 3
12	P26 - rotor_OD (mm)	131.5	123	123	123.41
13	P27 - rotor_ID (mm)	77.5	65	66.665	69.346
14	P36 - rotor_thickness (mm)	25.5	23	23	23
15	P34 - Temperature Maximum (C)	343.26	347.35	346.88	346.48
16	P35 - Equivalent Stress Maximum (Pa)	1.3084E+07	1.1038E+07	1.1063E+07	1.1117E+07
17	P37 - Total Deformation Reported Frequency (Hz)	1842.3	2167	2155.2	2133.2
18	P38 - Geometry Volume (m^3)	0.0011529	0.0010029	0.00099035	0.0009779

Table of Schematic E4: Optimization

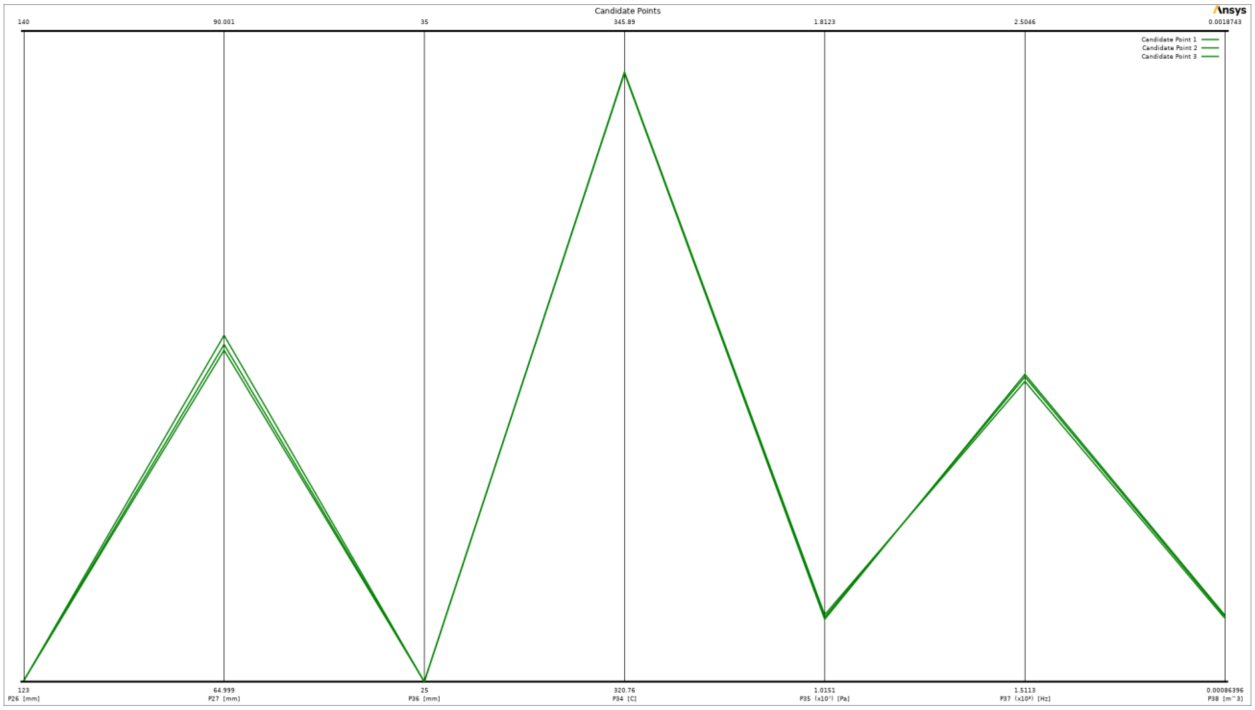
	A	B	C	D	E	F	G	H	I
1	Name	Parameter	Objective			Constraint			
2			Type	Target	Tolerance	Type	Lower Bound	Upper Bound	Tolerance
3	Minimize P35	P35 - Equivalent Stress Maximum	Minimize	0		No Constraint			
4	Minimize P34	P34 - Temperature Maximum	Minimize	0		No Constraint			
5	Maximize P37	P37 - Total Deformation Reported Frequency	Maximize	0		No Constraint			
6	Minimize P38	P38 - Geometry Volume	Minimize	0		No Constraint			
*		Select a Parameter							

Table of Schematic E4: Optimization

	A	B	C	D
1	⊟ Optimization Study			
2	Minimize P34	Goal, Minimize P34 (Default importance)		
3	Minimize P35	Goal, Minimize P35 (Default importance)		
4	Maximize P37	Goal, Maximize P37 (Default importance)		
5	Minimize P38	Goal, Minimize P38 (Default importance)		
6	⊟ Optimization Method			
7	MOGA	The MOGA method (Multi-Objective Genetic Algorithm) is a variant of the popular NSGA-II (Non-dominated Sorted Genetic Algorithm-II) based on controlled elitism concepts. It supports multiple objectives and constraints and aims at finding the global optimum.		
8	Configuration	Generate 100 samples initially, 50 samples per iteration and find 3 candidates in a maximum of 20 iterations.		
9	Status	Converged after 571 evaluations.		
10	⊟ Candidate Points			
11		Candidate Point 1	Candidate Point 2	Candidate Point 3
12	P26 - rotor_OD (mm)	123.04	123.05	123.05
13	P27 - rotor_ID (mm)	77.76	77.974	78.324
14	P36 - rotor_thickness (mm)	25.003	25.004	25.005
15	P34 - Temperature Maximum (C)	344.26	344.29	344.33
16	P35 - Equivalent Stress Maximum (Pa)	1.0921E+07	1.0942E+07	1.0974E+07
17	P37 - Total Deformation Reported Frequency (Hz)	1981	1976.8	1970.1
18	P38 - Geometry Volume (m^3)	0.00096738	0.00096565	0.00096275

6.2.1. Candidate Points

MOGA



MISQP

# Candidate Points - MISQP							
# Name	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
Starting Point	131.5	77.5	25.5	343.2609	13084108	1842.302	0.001153
Candidate Point 1	123	65	23	347.3505	11038024	2166.973	0.001003
Candidate Point 2	123	66.66481	23	346.8797	11062866	2155.183	0.00099
Candidate Point 3	123.407	69.34568	23	346.478	11117098	2133.243	0.000978

6.2.2 Min-Max

MISQP

# Output Parameter Minimums							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
P34 - Temperature Maximum	133.0495	65	28	330.6136	14006981	1975.712	0.001371
P35 - Equivalent Stress Maximum	123	65	23	347.3505	11038024	2166.973	0.001003
P37 - Total Deformation Reported Frequency	140	90	24.78804	341.1345	14048559	1612.776	0.001202
P38 - Geometry Volume	123	90	23	346.586	11602984	1861.154	0.00089
# Output Parameter Maximums							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
P34 - Temperature Maximum	135.0405	73.64003	23	353.3691	12064930	1926.748	0.001186
P35 - Equivalent Stress Maximum	140	90	28	334.7573	15517270	1617.72	0.001295
P37 - Total Deformation Reported Frequency	123	65	23	347.3505	11038024	2166.973	0.001003

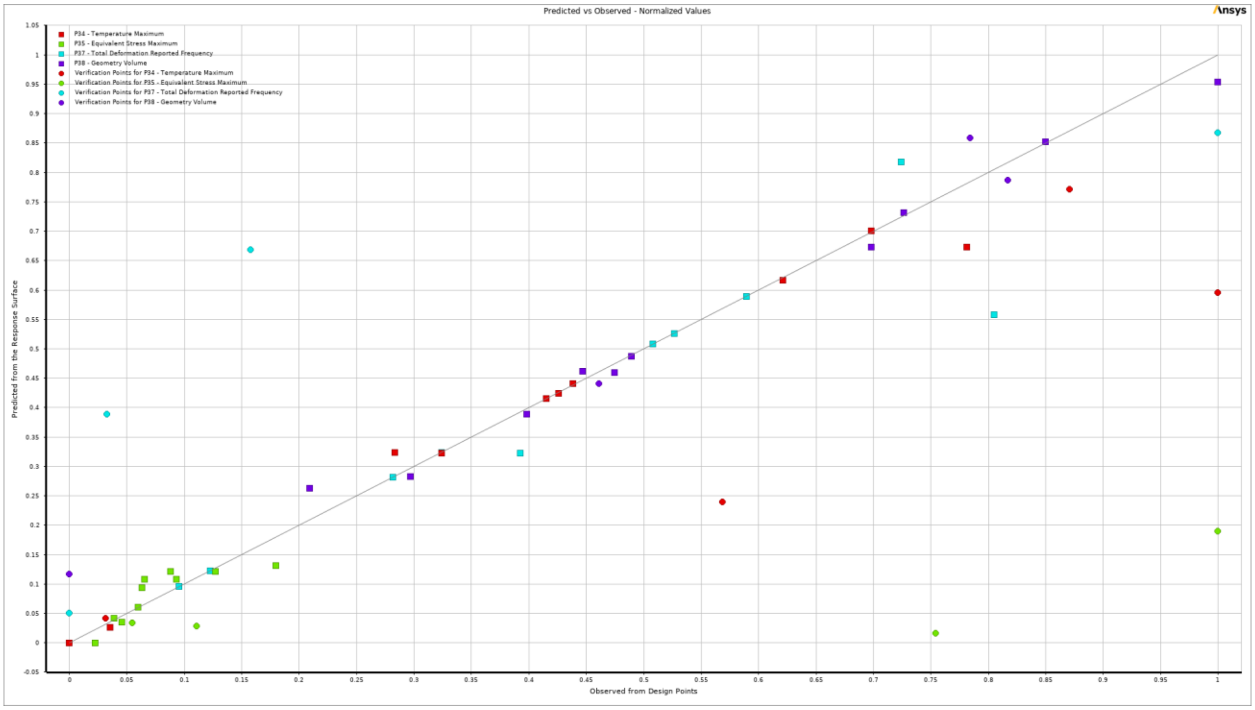
P38 - Geometry Volume	140	65	28	333.7561	14737792	1845.009	0.001464

MOGA

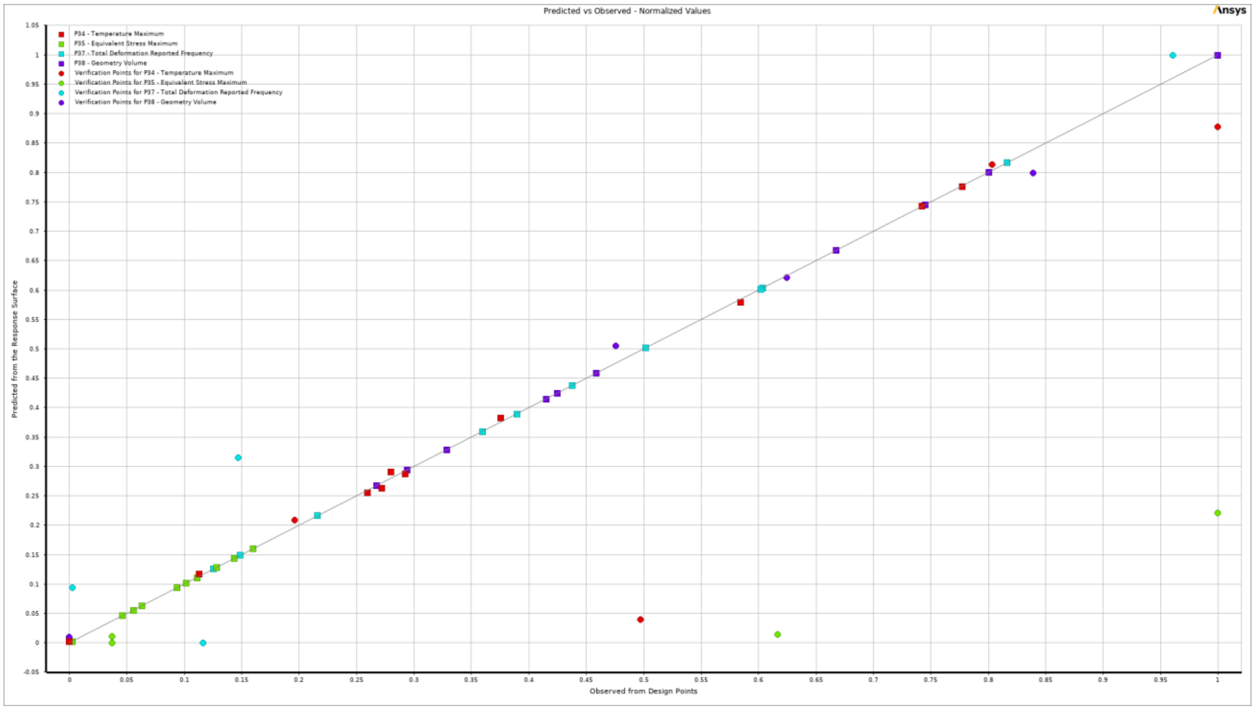
# Output Parameter Minimums							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
P34 - Temperature Maximum	123.5008	65	34.06686	320.7636	13734336	2486.974	0.001418
P35 - Equivalent Stress Maximum	123	65	25	340.1318	10151193	2200.309	0.001076
P37 - Total Deformation Reported Frequency	140	90	25	342.4128	14176301	1511.299	0.00122
P38 - Geometry Volume	123	90	25	344.2667	11862057	1720.996	0.000864

6.2.3. Goodness of Fit

MISQP

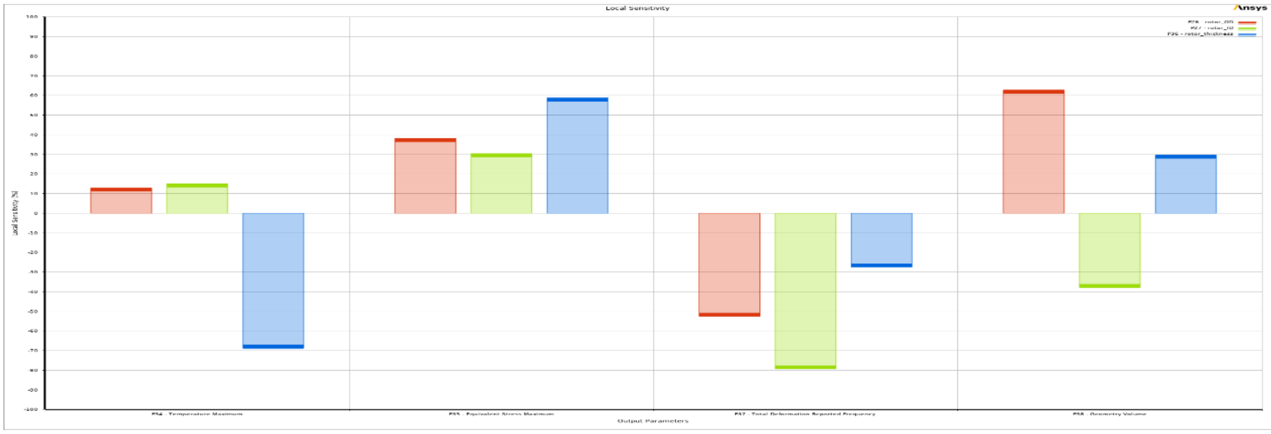


MOGA



6.2.4. Local Sensitivity

MISQP



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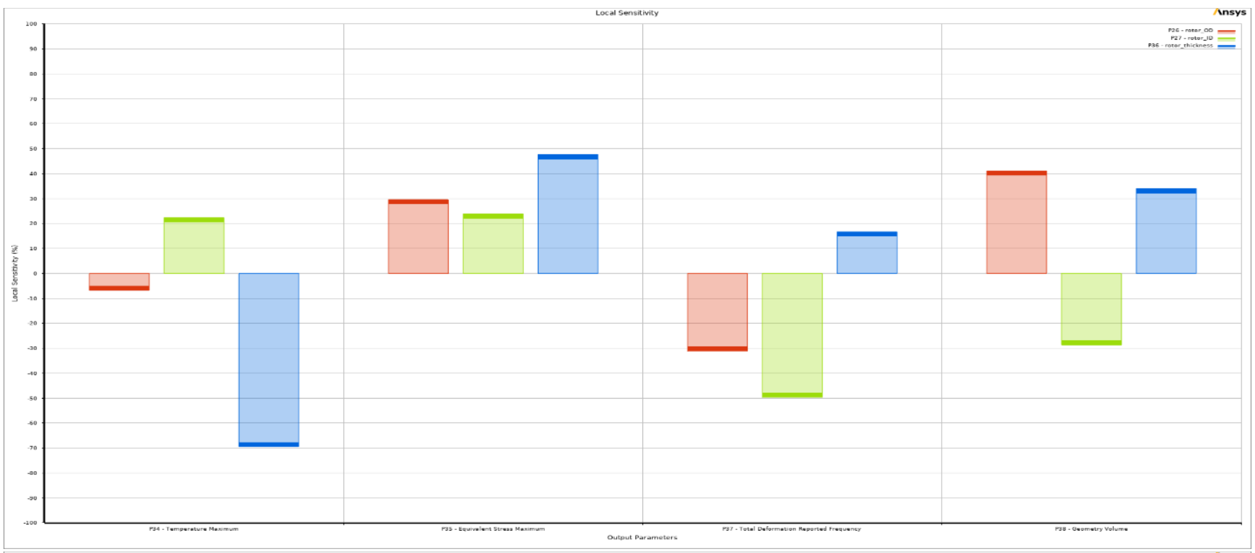
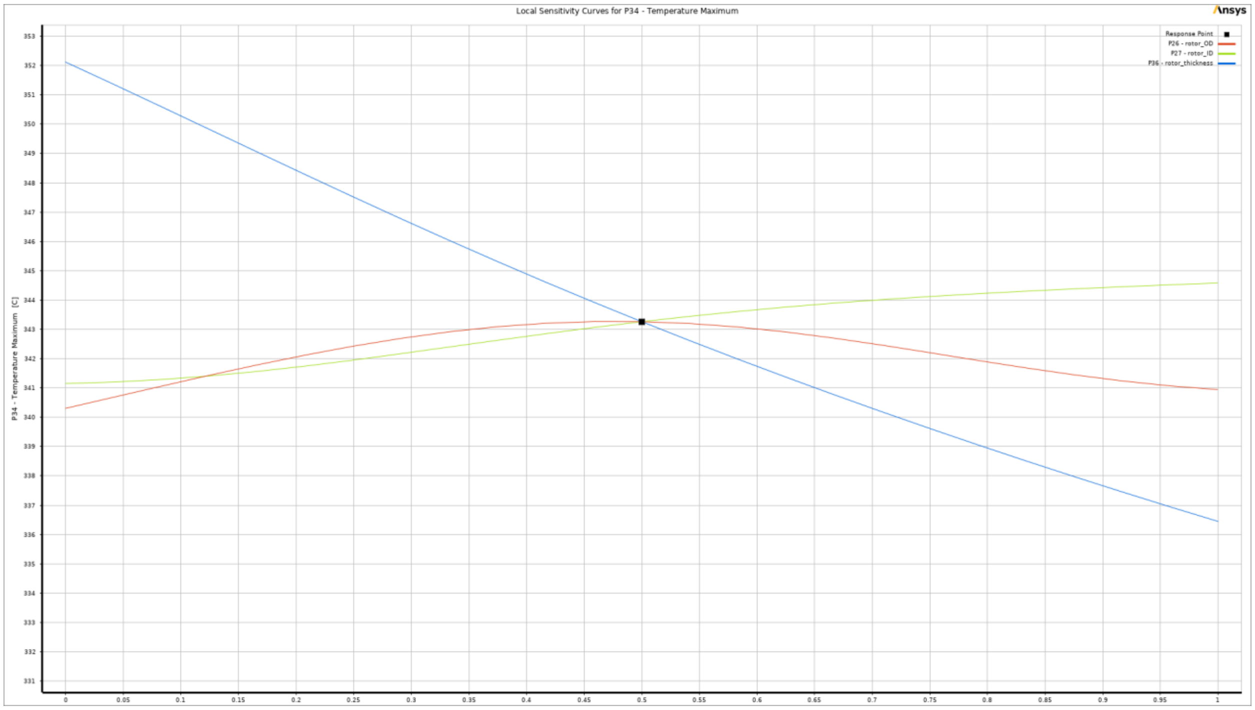


6.2.5. Local Sensitivity Curve:

MISQP



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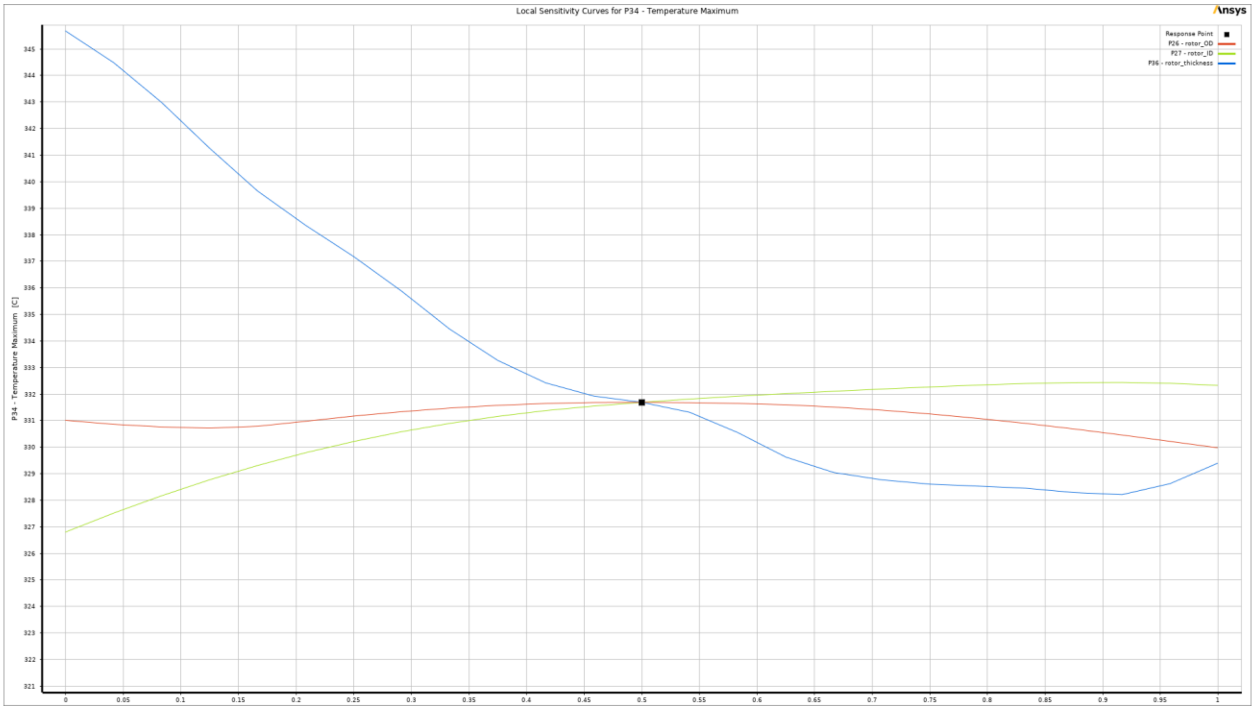
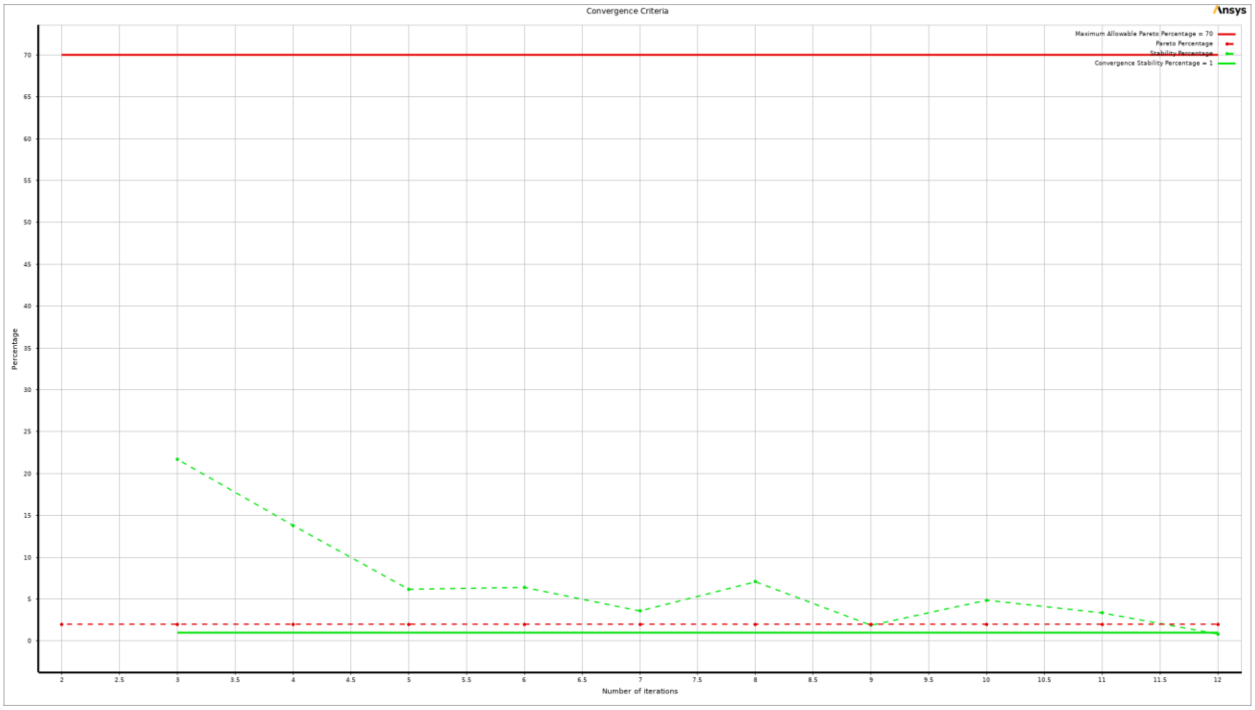
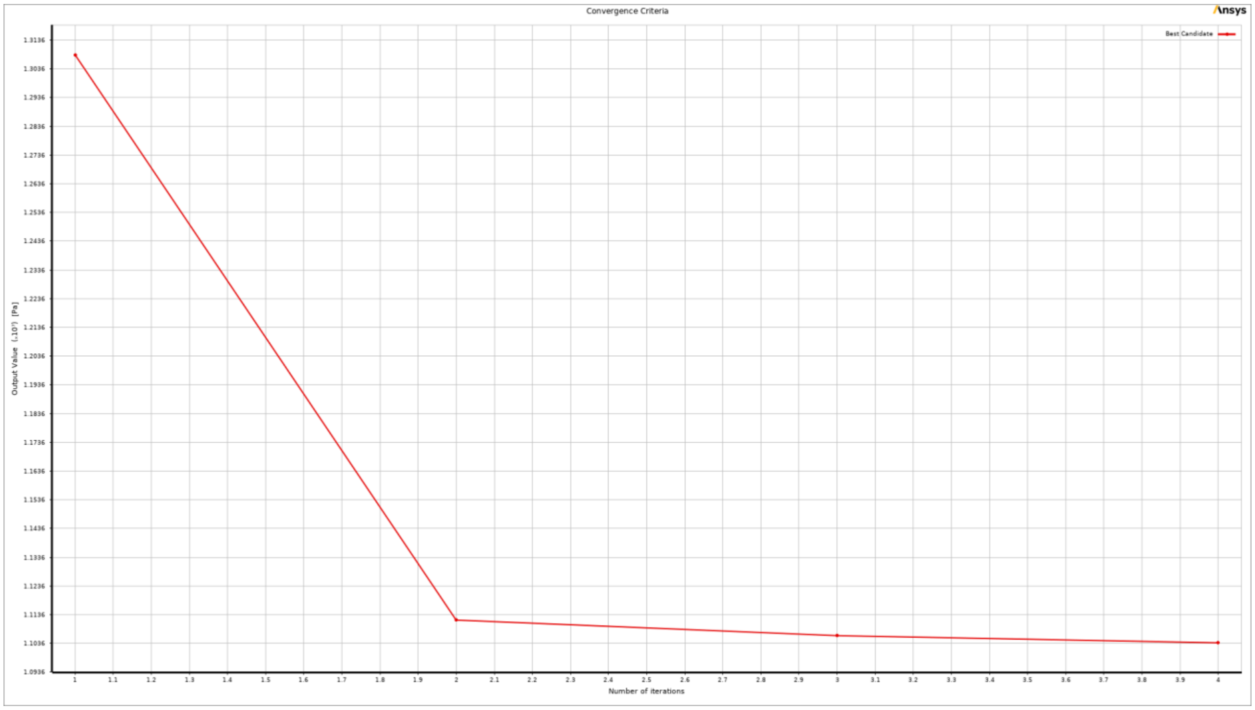


6.2.6. Convergence

MOGA

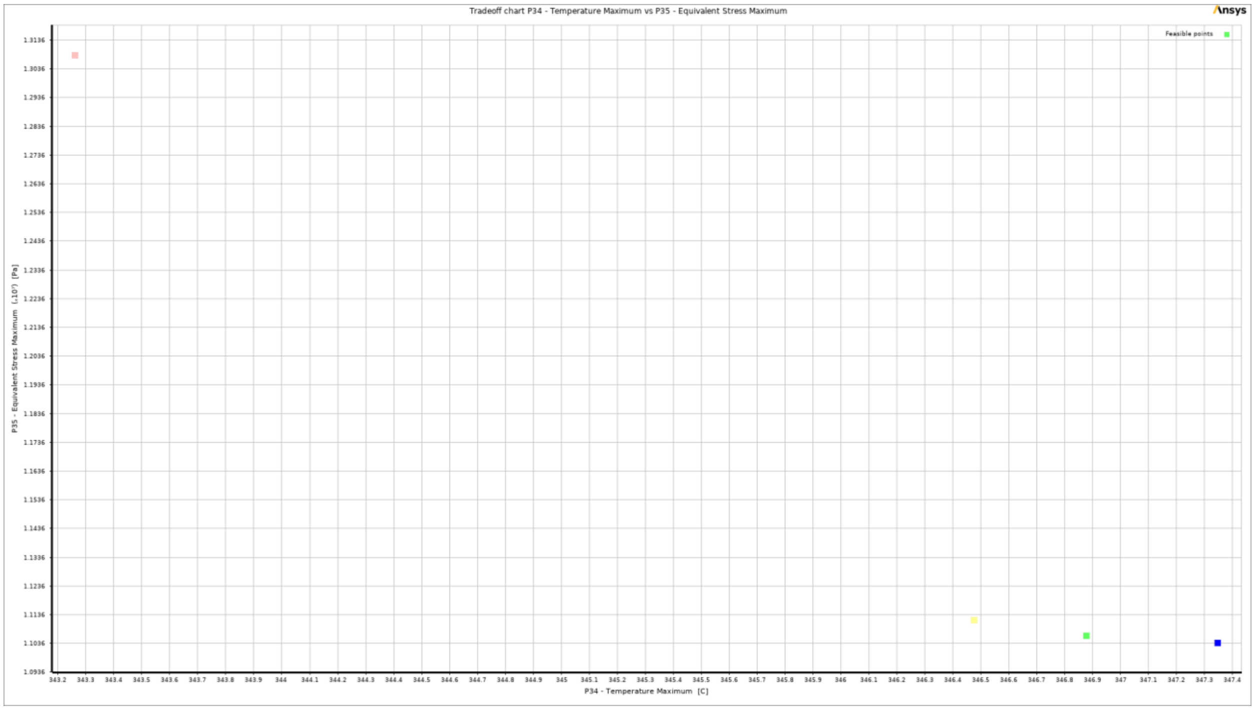


MISQP

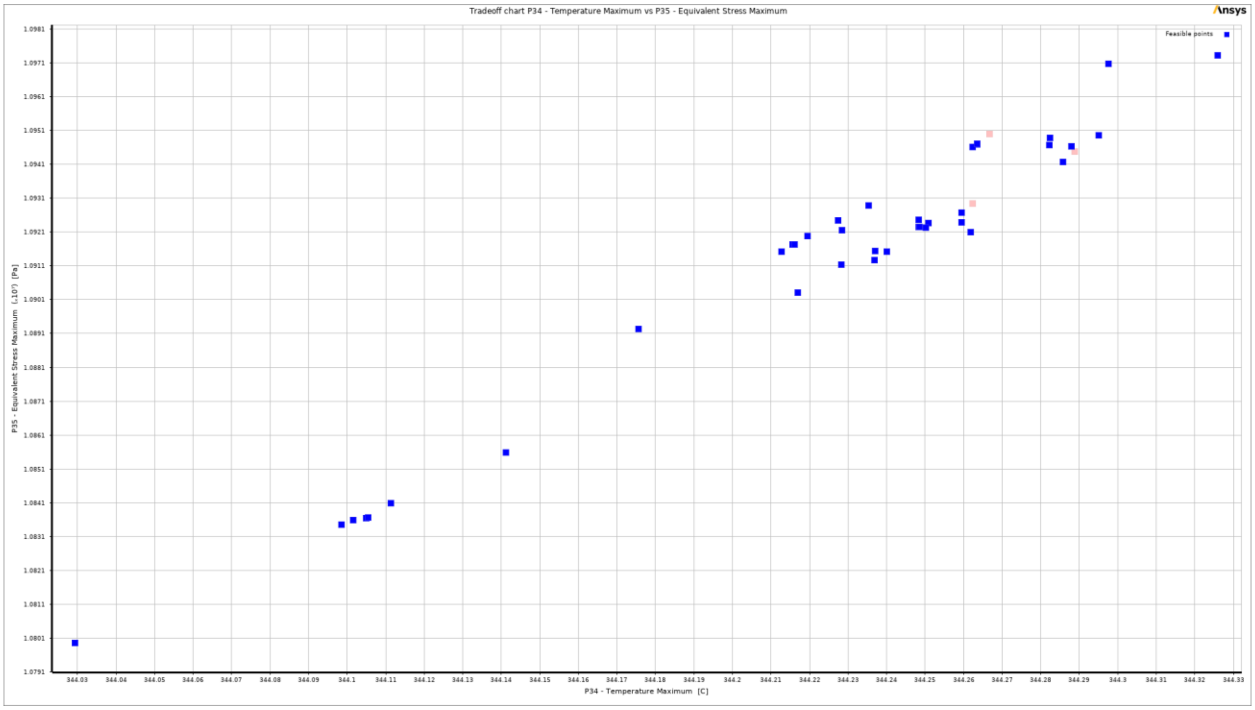


6.2.7. Trade-off

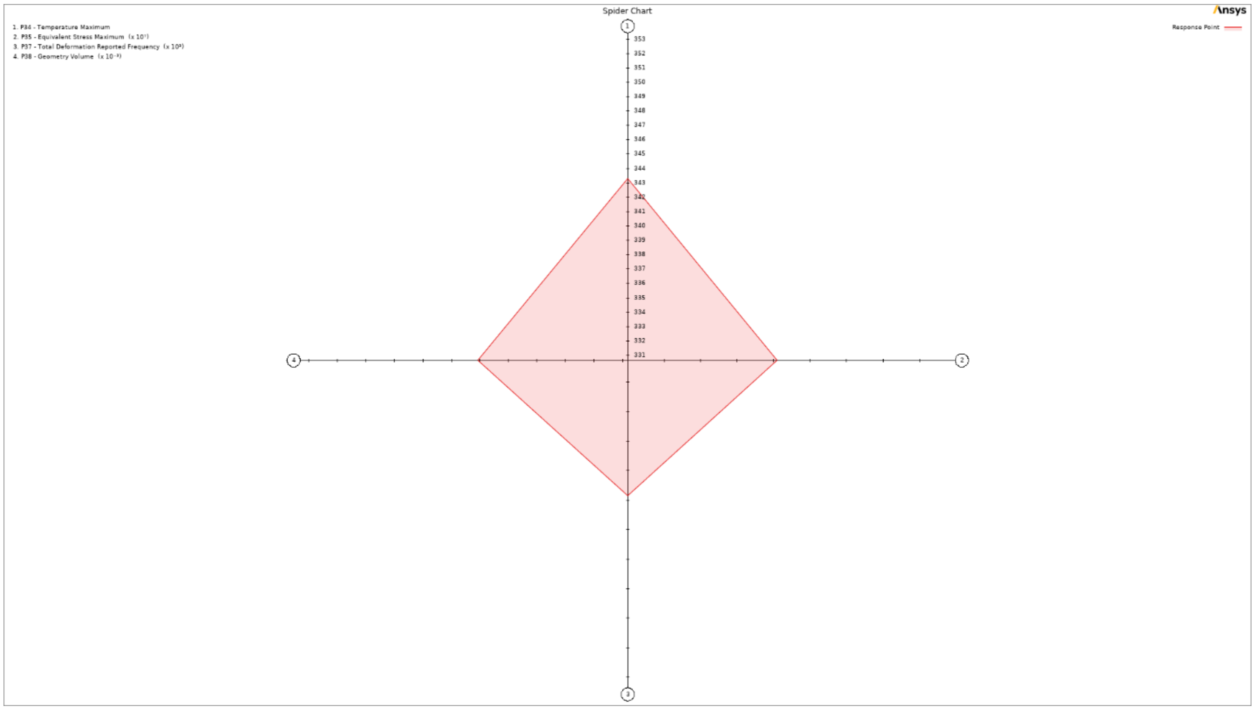
MISQP



MOGA



6.2.8. Spider Chart – MISQP



6.2.9. Tolerances - MOGA

Table of Schematic D3: Response Surface: Tolerances

	A	B	C	D	E	F
1	Name	Calculated Minimum	Calculated Maximum	Maximum Predicted Error	Refinement	Tolerance
2	P34 - Temperature Maximum (C)	320.76	345.89	3.8239		
3	P35 - Equivalent Stress Maximum (Pa)	1.0151E+07	1.8122E+07	1.5288		
4	P37 - Total Deformation Reported Frequency (Hz)	1511.3	2504.6	0.0008198		
5	P38 - Geometry Volume (m^3)	0.00086397	0.0018743	1.532E-05		

6.2.10. Verification Points

MISQP

# Verification Points							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38

1	138.3228	65.13904	23.03976	352.7247	12520745	1688.421	0.001292
2	123.874	89.97451	23.07008	355.5125	27869193	1606.918	0.000827
3	123.2752	65.24269	25.78306	346.202	13751906	2239.157	0.001101
4	139.8732	89.86611	27.97669	334.5982	33259196	1585.291	0.001311

MOGA

# Verification Points							
#	P26 - rotor_OD (mm)	P27 - rotor_ID (mm)	P36 - rotor_thickness (mm)	P34 - Temperature Maximum (C)	P35 - Equivalent Stress Maximum (Pa)	P37 - Total Deformation Reported Frequency (Hz)	P38 - Geometry Volume (m^3)
Name	P26	P27	P36	P34	P35	P37	P38
1	138.3228	65.13904	25.07951	342.1501	13133005	1760.59	0.001387
2	123.874	89.97451	25.14016	346.6562	28719685	1646.308	0.000875
3	123.2752	65.24269	30.56612	335.1151	13134421	2406.026	0.001265
4	139.8732	89.86611	34.95338	328.2054	39014828	1736.539	0.001563

7. Conclusion

In this study, Optimization of brake disc is performed using two different Optimization algorithms and DOE methods, and the results are documented.

The 2 different optimization techniques are as follows:

MISQP →LHS – Full Quadratic Model Samples – Neural Network – Single objective

MOGA→ LHS – User-defined Samples - Genetic Aggregation – Multiple Objectives

The results of convergence, sensitivity analysis of both the optimized solutions show little variation in the optimized functions.

8. References

DesignOptimization2021Fall/Project 2 ansys design optimization.md at main · DesignInformaticsLab/DesignOptimization2021Fall (github.com)

Ansys DesignXplorer Overview