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Optimization of Rib distance in Wing box of the Aircraft for Maximization of Buckling Load

*Rahul ,**Mousam Sharma, ***Dr.Sanjay Chhalotre,

Asst. Prof ,* Professor, Department of Mechanical Engineering, Sagar Institute of Science & Technology/RGPV, Bhopal

*PG Students : Sagar Institute of Science & Technology/RGPV, Bhopal

ABSTRACT

In Aerospace/aircraft design, to keep the weight as low as possible optimization is paramount for better performance. Optimization of the aircraft component/assemblies fulfil all the design specifications. In aircraft wing design buckling is one of the most critical design parameters. Therefore, while designing it is desirable to achieve minimum weight of the structure with maximum buckling eigenvalue.

Buckling analysis plays a vital role in optimizing structural designs, ensuring structural integrity, and preventing catastrophic failures. It allows engineers to assess the stability of structural members under compressive loads, select appropriate materials and dimensions, and implement reinforcement strategies when necessary.

Buckling analysis is a critical aspect of structural engineering that focuses on predicting the failure mode known as buckling, which occurs when a slender structural member fails due to excessive compressive forces. Buckling can result in catastrophic failure, making it essential to understand and prevent it in various applications, including buildings, bridges, and aerospace structures.

In wing design optimization of buckling strength is possible by varying rib placement distance. In this study we will generate algorithm which will connect CAE tools with optimization technique using MATLAB software. While bending of wing top panel experiences compression and prone for buckling over the wing span therefore optimal placement of ribs to optimize the buckling strength is important. In this study an attempt will be made to generate an algorithm for the optimal placement of rib. The optimization algorithm will govern CAE software to get the optimal design.

The project aims to utilize power of optimization algorithm with CAE tools by to investigating how the positioning of ribs within the wing box structure influences buckling behaviour. By systematically studying different rib configurations, the project seeks to identify optimal rib placements that enhance the wing box's resistance to buckling, providing valuable insights for the design of robust and structurally sound aircraft wings.

The project intends to provide valuable insights into the role of rib distribution in improving the structural performance of wing boxes, leading to potential design recommendations and guidelines for optimizing wing box designs to mitigate the risk of buckling failures in aircraft wings.

Keywords: Wing Box, Buckling, Genetic Algorithm, Eigen Value, Rib Distance.

INTRODUCTION

Buckling is one of the most critical failure modes encountered in slender and lightweight aerospace structures, particularly aircraft wings that are subjected to significant compressive, bending, and torsional loads during flight. Accurate prediction of buckling behavior is essential to ensure structural safety, reliability, and weight efficiency. Buckling analysis enables engineers to identify the critical load levels at which structural instability occurs and to understand the associated deformation patterns, thereby preventing sudden and catastrophic failures.

In this context, eigenvalue-based buckling analysis plays a key role in evaluating the stability of structural components. By determining the critical eigenvalues and corresponding mode shapes, engineers can estimate the lowest buckling load and identify the most vulnerable regions of the structure. Such analyses are widely used during the preliminary and detailed design stages to optimize material usage, select appropriate structural dimensions, and implement effective reinforcement strategies.

This chapter focuses on the structural configuration of an aircraft wing box and its major components, including spars, ribs, and skin panels, which collectively carry aerodynamic and inertial loads while maintaining the wing's aerodynamic shape. The functional roles of these components in load transfer, stiffness enhancement, and buckling resistance are discussed. Furthermore, a three-dimensional finite element model of the wing structure is developed to simulate realistic loading and boundary conditions. The modeling methodology, element selection, geometric parameters, and material properties of the aluminium alloy used are presented in detail. This comprehensive description establishes the analytical framework required for assessing the buckling characteristics and structural performance of the wing under compressive loading conditions.

METHODOLOGY

Application of Evolutionary Algorithm for determination of optimum Eigen value

In this study non-traditional optimizers were used for arriving at Maximum Eigen Value to the equivalent FE model of wing. EA work on the Darwinian principle of natural selection and evolution. As the name suggests, utilizes biological concepts to get the engineering solution to the problem. GAs nowadays ais very popular for the solution of multi-dimensional engineering problems. GA optimization is a modern technique that was developed by Holland [15] in 1990s. It works without the application of calculus knowledge for reaching the optima. In mathematical terms, natural selection can be expressed as; only the fittest string will survive and reproduce through successive generations, where each generation is like an iteration. GA is like hill-climbing technique where the successive generations become better as compared to the previous generations. Unlike calculus, GAs is less prone to get stuck at local minima as they perform a global search during operation. GAs possesses flexibility, robustness, and efficiency along with self-repair and self-guidance of the strings. Further, for faster convergence and looking into high sensitivity of elemental thickness to mode shapes, we have combined Particle Swam Optimization technique with GA in this study.

Genetic algorithm

Genetic algorithm is a process of natural selection that belongs to a class of EA. Genetic algorithm is used to improve the quality of solution during optimization based on biological concepts such as reproduction, crossover, and mutations. In optimization using genetic algorithm, the population is operated by GA operators to improve the fitness. A representation of the GA process is given in Fig.-8

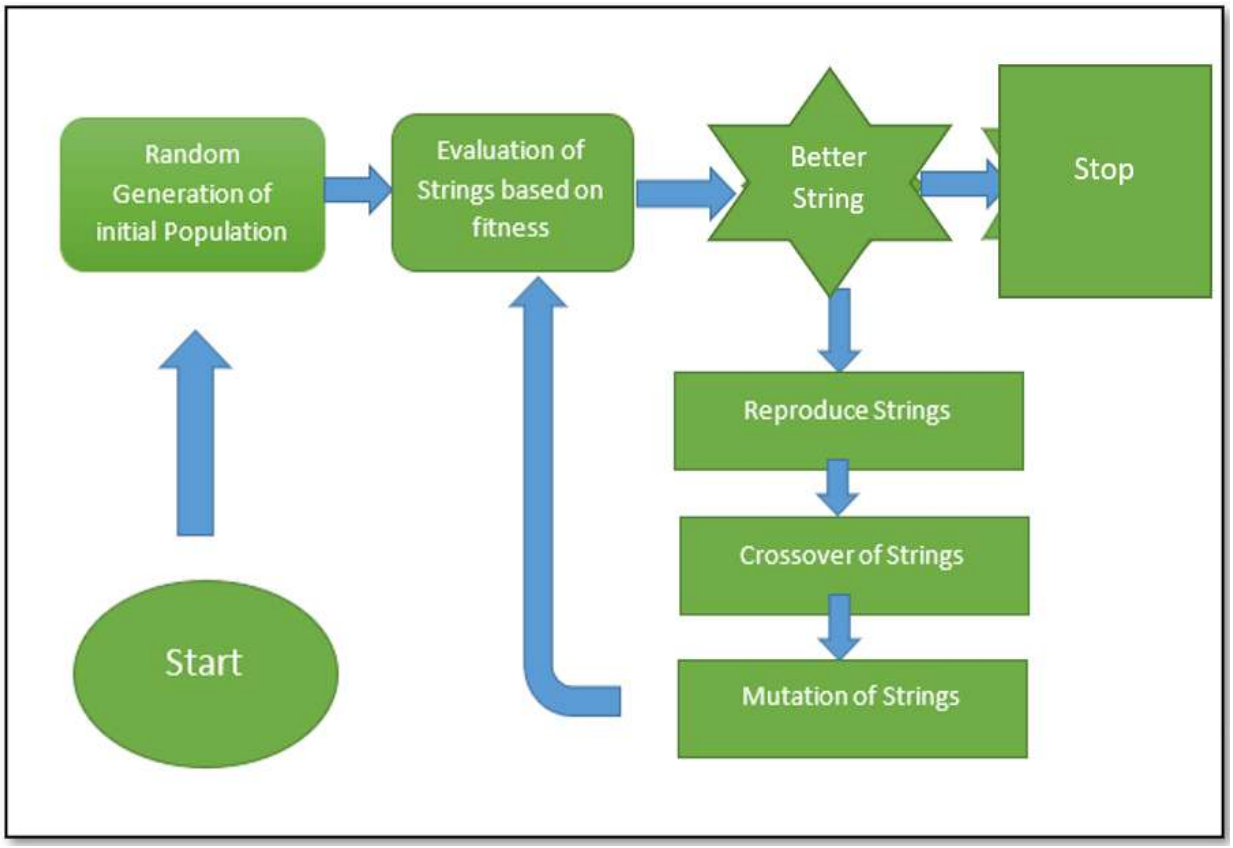

Figure 1: GA process for obtaining maximum Eigen value for Buckling equivalent FE model

GA solution sequence works on strings; strings are set of elemental thickness of 2D-FE model as shown in Fig. Solution sequence starts with randomly generated strings. Each string is evaluated by fitness function. Better fit strings are then selected and sent to the further generations. GAs is considered as intelligent algorithms as they have the power of self-exploration, self-guidance, self-correction, and natural-selection of the best solutions. During the process, strings experiences change by change in element thickness. The strings are evaluated by fitness function by performing Modal analysis using ABAQUS/CAE solver.

In the GA based search, fitness of strings is judged by their relative competition/fitness. It is important to note that application of GA procedure to a problem does not guarantee one particular optima as this approach is multi-modal. In this approach a new candidate, better than the previous one, can appear anytime, thus mimicking the nature's ideology. Fundamental ideas of GA are derived from natural genetics and artificially used in construction of the search algorithms. GAs is Artificially Intelligent and quite robust in itself. They self-correct the string population if any bad string is selected during the iterative process.

The classical optimization methods use point-by-point search approach where solution at each point is modified to a hopefully better solution. However, most real-life engineering problems are multi-modal in nature. The objective functions are multi-dimensional and orthogonal, i.e., if one response goes up, then the other goes down. For example, while optimizing an IC-engine one cannot have attainment of maximum power as the sole function, lowering emissions also has to be taken into consideration. Therefore, it is required to set a criterion, which can impose a penalty on them for deviating from their individual optima. In perspective of the present problem, close match of the mode shape and natural frequency is desirable. The development of the fitness function motivated designers/engineers to use GA for multi-objective optimization, where the task of optimization of multiple objectives is transformed to minimization of a single-objective function. The GA optimization in the present study starts with a pool of *n* strings as initial population, where each of the string specifies a Rib-to-Rib distance which can be graded based on the respective fitness value. The wing model comprises of 3 ribs with initial Rib to Rib distance is 250 each. After GA operations the parent population of n-strings is generated by random selection of Rib-to-Rib distance. Once the parent population is generated, it is graded/sorted based on the fitness value. Later half of the poor-quality strings are discarded and remaining half participate in reproduction to generate new strings. As per elitist strategy, the best string is left untouched by the GA operators and

automatically goes to the next generation. During successive operations better strings can appear which replace the elite string. As a part of the natural selection process, for every generation the good quality string with lower values (minimization problem) of Z are retained and poor-quality strings are rejected. At the end of optimization, the GA reaches near-global optimal solution, leaving possibilities for a better string to replace the existing strings.

ANALYSIS & SIMULATION WORK

Fitness Function

The fitness function considered for the string

Maximize (Z) = Bucking Eigen Value

Constraints,

200<a<300

225<b<275

225<c<275

Where, a, b, c, are rib to rib distance of the aircraft wing

In which distance between A and B is 250 similarly for B and C is also 250, the main objective is to create the maximum Eigen value by varying Rib to Rib distance. The fitness function maximizes Z, which comprises minimizing buckling in the upper panel of wing.

Buckling analysis of wing model

.Buckling analysis of the FE model has been carried out where Mass is an important factor to consider for structural studies and optimization. Thus, mass of the wing box for each rib configuration was also found out.

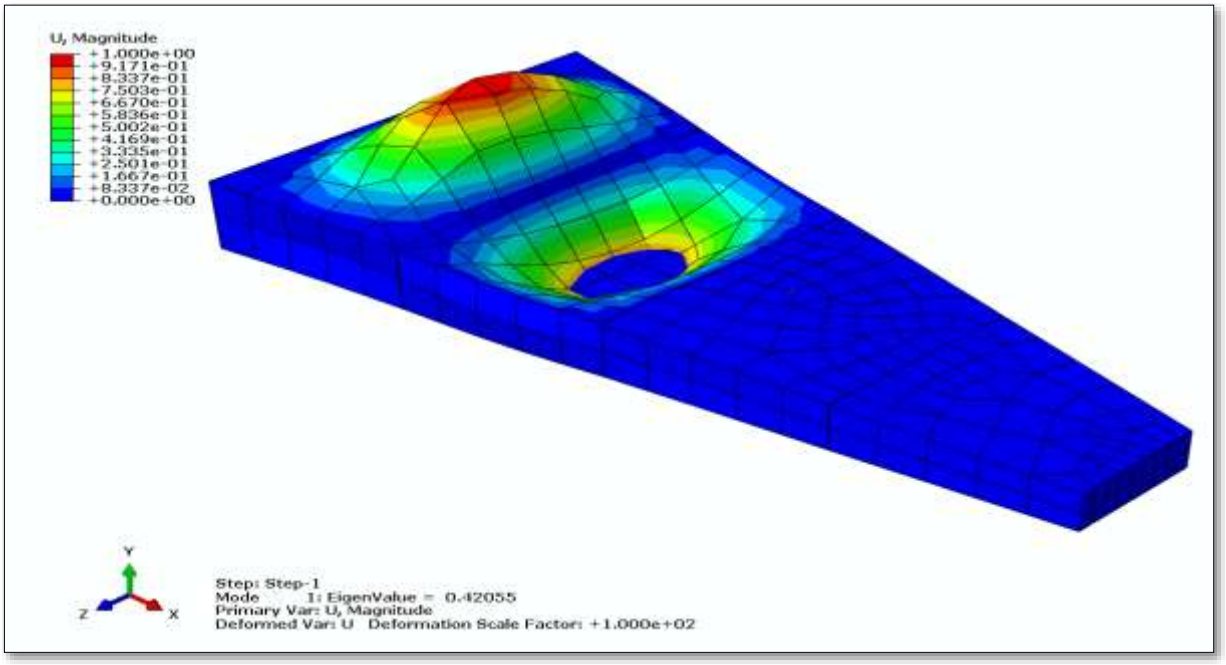

Figure 2: 3D FE Model of Wing under Buckling Load

3D Finite Element model of the Wing

The above 3D wing Model is constructed different single shell part i.e., 9 parts with different thickness value which are modelled and assembled in ABAQUS CAE, Also the meshing is done on same modelling software through which we got the buckling result.to get optimum Eigen value by the process of Genetic Algorithms.

The process of Genetic Algorithms is done by using MATRIX LABORATORY Coding in which ABAQUS CAE Macro recording python script used as base data for Rib to Rib distance Iteration.

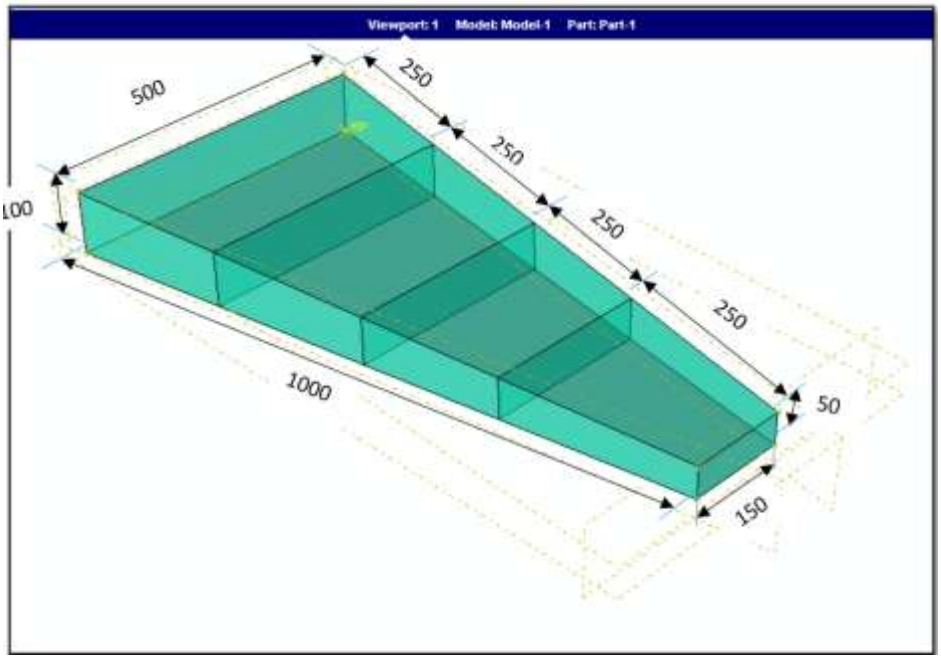

Figure 3: 3D FE Model of Wing and element

Problem Formulation

The stiffness and mass properties of 3D shell element mostly depend on thickness of element. Each element is assigned with suitable thickness in order to get desired modal parameter. GA based procedure has been implemented in the present study. GA optimizes the thickness value to a near optimal level in successive iterations by applying its operators like reproduction, mutation and crossover.

Flow sequence of Genetic algorithm process

The modelling and meshing are done in ABAQUS CAE environment, where element (Ribs) distance is defined. Different sectional properties are used to define different thickness for each element. A macro recording is running behind the ABAQUS CAE which gave us Optimum value of each iteration which is store as input file in text format. The application of ribs distance to each element is controlled outside of the CAE environment of ABAQUS by using python-scripting. A basic coding of procedure for modal parameters using a GA has been written in MATLAB. MATLAB gives input to python script, which submits the analysis job in ABAQUS solver. The steps involved in the GA process have been outlined as follows:

1. A set of initial Ribs distance is given while modelling wings in ABAQUS CAE then the optimized distance value is recorded in text format for each string and then it is submitted in the section assignment in ABAQUS via a python scripting.

2. The python script run the modal analysis in ABAQUS using optimized distance at each iteration.

3. A set of initial distance of Ribs will be generated using random number generator function in MATLAB where it gives various number of eigen values after varying Rib to Rib distance.

4. The best sixteen strings are taken out of initial population and parent generation is formed. Further, an ELITE member is preserved in this process.

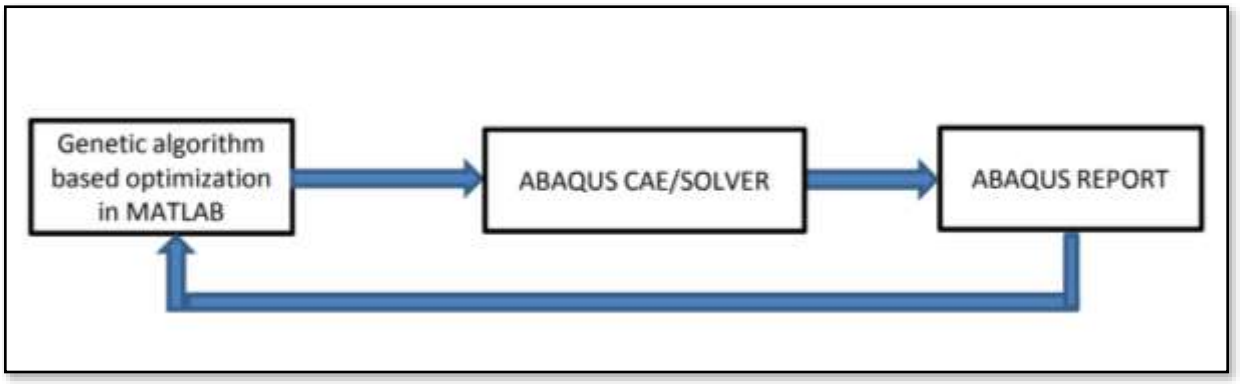

Figure 4: Data flow during target achievement

Solution sequence for optimal 3d model

A python script was generated on the basis of wing model design in ABAQUS CAE which help to optimized rib to rib distance for maximum buckling eigenvalue. Which in turn lead to max wing-load for panel buckling.

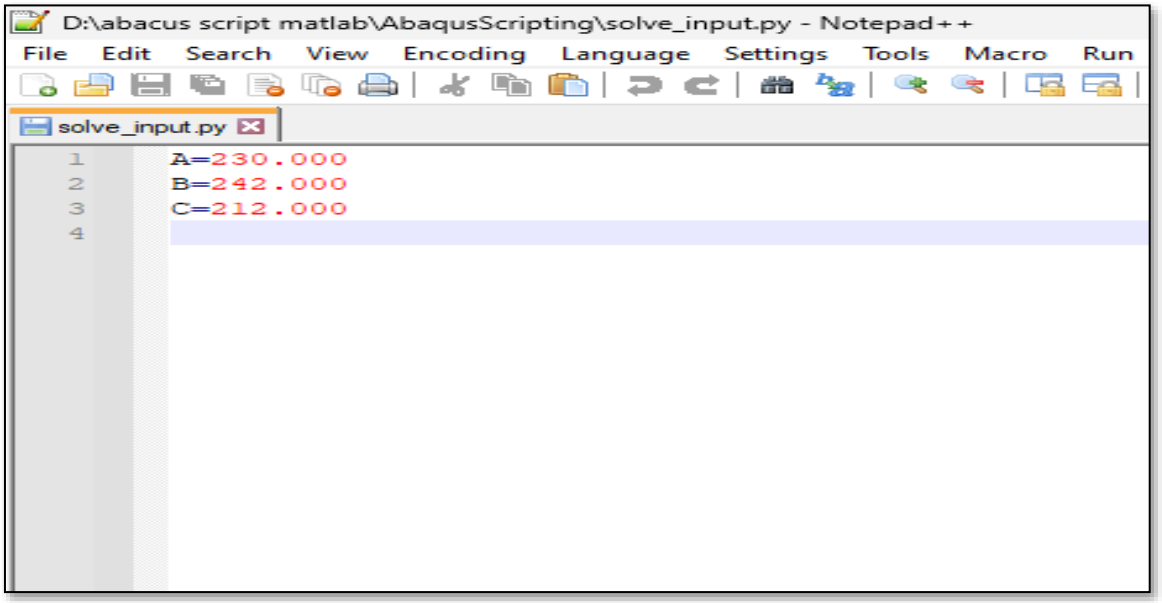

Figure 5: Variable input in ABAQUAS Script

The python script generated in ABAQUS CAE is integrated with MATLAB where the input.py file was read by MATLAB where once need to define the three variable of rib displacement in MATLAB coding, where it provides the iteration result according to Evolutionary Algorithm process.

MATLAB uses the GA process where it initially cleared the old variable, then pool is generated by using random number in between 200 to 300 for rib displacement. Where randomly generated number creates 3 size set pool. In this coding total 16 set pool was generated which is considered as initial population, from the 16 set pool top 8 was selected as best, from these top 8 the was mutation done to create best value.

Similarly, it was done for second and third set pool to get best value from these value crossovers was done from the previously obtained top 8 set value, again the most fit member is selected as best optimum Eigen value for maximum buckling. The result obtained in MATLAB is then again collaborated with ABAQUS CAE solver to get desired result.

In ABAQUS CAE python script the red box shown is the variable assigned to python code which is considered as Rib-to-Rib distance which is then assigned to ABAQUS CAE solver by writing job submit weight for completion at the end of coding. then this code is collaborated with MATLAB for further coding.

```
# -*- coding: mbcs -*-
# Do not delete the following import lines
from abaqus import *
from abaqusConstants import *
import __main__
import section
import regionToolset
import displayGroupMdbToolset as dgm
import part
import material
import assembly
import step
import interaction
import load
import mesh
import optimization
import job
import sketch
import visualization
import xyPlot
import displayGroupOdbToolset as dgo
import connectorBehavior
execfile('D:/AbaqusScripting/solve_input.py')
openMdb(pathName='D:/AbaqusScripting/wingssssl.cae')
session.viewports['Viewport: 1'].setValues(displayedObject=None)
p1 = mdb.models['Model-1'].parts['Part-1']
session.viewports['Viewport: 1'].setValues(displayedObject=p1)
p = mdb.models['Model-1'].parts['Part-1']
s = p.features['Shell extrude-1'].sketch
mdb.models['Model-1'].ConstrainedSketch(name='__edit__', objectToCopy=s)
s1 = mdb.models['Model-1'].sketches['__edit__']
g, v, d, c = s1.geometry, s1.vertices, s1.dimensions, s1.constraints
s1.setPrimaryObject(option=SUPERIMPOSE)
p.projectReferencesOntoSketch(sketch=s1,
    upToFeature=p.features['Shell extrude-1'], filter=COPLANAR_EDGES)
s1.delete(objectList=(d[8], d[7], d[9]))
s1.DistanceDimension(entity1=g[10], entity2=g[5], textPoint=(365.34534405885,
    80.48583984375), value=A)
s1.DistanceDimension(entity1=g[10], entity2=g[11], textPoint=(115.993225127548,
    -9.62750244140625), value=B)
s1.DistanceDimension(entity1=g[11], entity2=g[12], textPoint=(
    -163.373514723255, -18.0997009277344), value=C)
s1.unsetPrimaryObject()
p = mdb.models['Model-1'].parts['Part-1']
p.features['Shell extrude-1'].setValues(sketch=s1)
del mdb.models['Model-1'].sketches['__edit__']
p = mdb.models['Model-1'].parts['Part-1']
p.regenerate()
session.viewports['Viewport: 1'].partDisplay.setValues(mesh=ON)
session.viewports['Viewport: 1'].partDisplay.meshOptions.setValues(
    meshTechnique=ON)
session.viewports['Viewport: 1'].partDisplay.geometryOptions.setValues(
    referenceRepresentation=OFF)
```

Figure 6: Script for ABAQUS model analysis in MATLAB (Part I)

```
session.viewports['Viewport: 1'].view.setValues(nearPlane=313.134,
farPlane=1241.85, width=807.998, height=397.078, viewOffsetX=260.932,
viewOffsetY=48.5983)
p = mdb.models['Model-1'].parts['Part-1']
d, r = p.datums, p.referencePoints
p.WirePolyLine(points=((d[17], d[2]), (d[2], r[1]), (r[1], d[22]), (d[22],
d[17])), mergeType=IMPRINT, meshable=ON)
p = mdb.models['Model-1'].parts['Part-1']
e = p.edges
edges = e.getSequenceFromMask(mask=('[#f ]', ), )
p.Set(edges=edges, name='Wire-1-Set-1')
p = mdb.models['Model-1'].parts['Part-1']
dl, rl = p.datums, p.referencePoints
p.WirePolyLine(points=((dl[24], dl[23]), (dl[23], dl[26]), (dl[26], dl[25]), (
dl[25], dl[24])), mergeType=IMPRINT, meshable=ON)
p = mdb.models['Model-1'].parts['Part-1']
e = p.edges
edges = e.getSequenceFromMask(mask=('[#f0 ]', ), )
p.Set(edges=edges, name='Wire-2-Set-1')
p = mdb.models['Model-1'].parts['Part-1']
d, r = p.datums, p.referencePoints
p.DatumPlaneByThreePoints(point1=d[22], point2=d[17], point3=r[1])
p = mdb.models['Model-1'].parts['Part-1']
e, dl, rl = p.edges, p.datums, p.referencePoints
t = p.MakeSketchTransform(sketchPlane=dl[31], sketchUpEdge=e[1],
sketchPlaneSide=SIDE1, sketchOrientation=RIGHT, origin=(0.0, 50.0,
250.0))
s = mdb.models['Model-1'].ConstrainedSketch(name='__profile__',
sheetSize=2293.12, gridSpacing=57.32, transform=t)
g, v, d, c = s.geometry, s.vertices, s.dimensions, s.constraints
s.setPrimaryObject(option=SUPERIMPOSE)
p = mdb.models['Model-1'].parts['Part-1']
p.projectReferencesOntoSketch(sketch=s, filter=COPLANAR_EDGES)
s.Line(point1=(-50.0, 250.0), point2=(50.0, 250.0))
s.HorizontalConstraint(entity=g[6], addUndoState=False)
s.ParallelConstraint(entity1=g[4], entity2=g[6], addUndoState=False)
s.Line(point1=(50.0, 250.0), point2=(50.0, -250.0))
s.VerticalConstraint(entity=g[7], addUndoState=False)
s.PerpendicularConstraint(entity1=g[6], entity2=g[7], addUndoState=False)
s.Line(point1=(50.0, -250.0), point2=(-50.0, -250.0))
s.HorizontalConstraint(entity=g[8], addUndoState=False)
s.PerpendicularConstraint(entity1=g[7], entity2=g[8], addUndoState=False)
s.Line(point1=(-50.0, -250.0), point2=(-50.0, 250.0))
s.VerticalConstraint(entity=g[9], addUndoState=False)
s.PerpendicularConstraint(entity1=g[8], entity2=g[9], addUndoState=False)
p = mdb.models['Model-1'].parts['Part-1']
e1, d2, r = p.edges, p.datums, p.referencePoints
p.Shell(sketchPlane=d2[31], sketchUpEdge=e1[1], sketchPlaneSide=SIDE1,
sketchOrientation=RIGHT, sketch=s)
s.unsetPrimaryObject()
del mdb.models['Model-1'].sketches['__profile__']
session.viewports['Viewport: 1'].view.setValues(nearPlane=237.755,
farPlane=1386.52, width=613.494, height=301.491, cameraPosition=(
```

Figure 7: Script for ABAQUS model analysis in MATLAB (Part II)

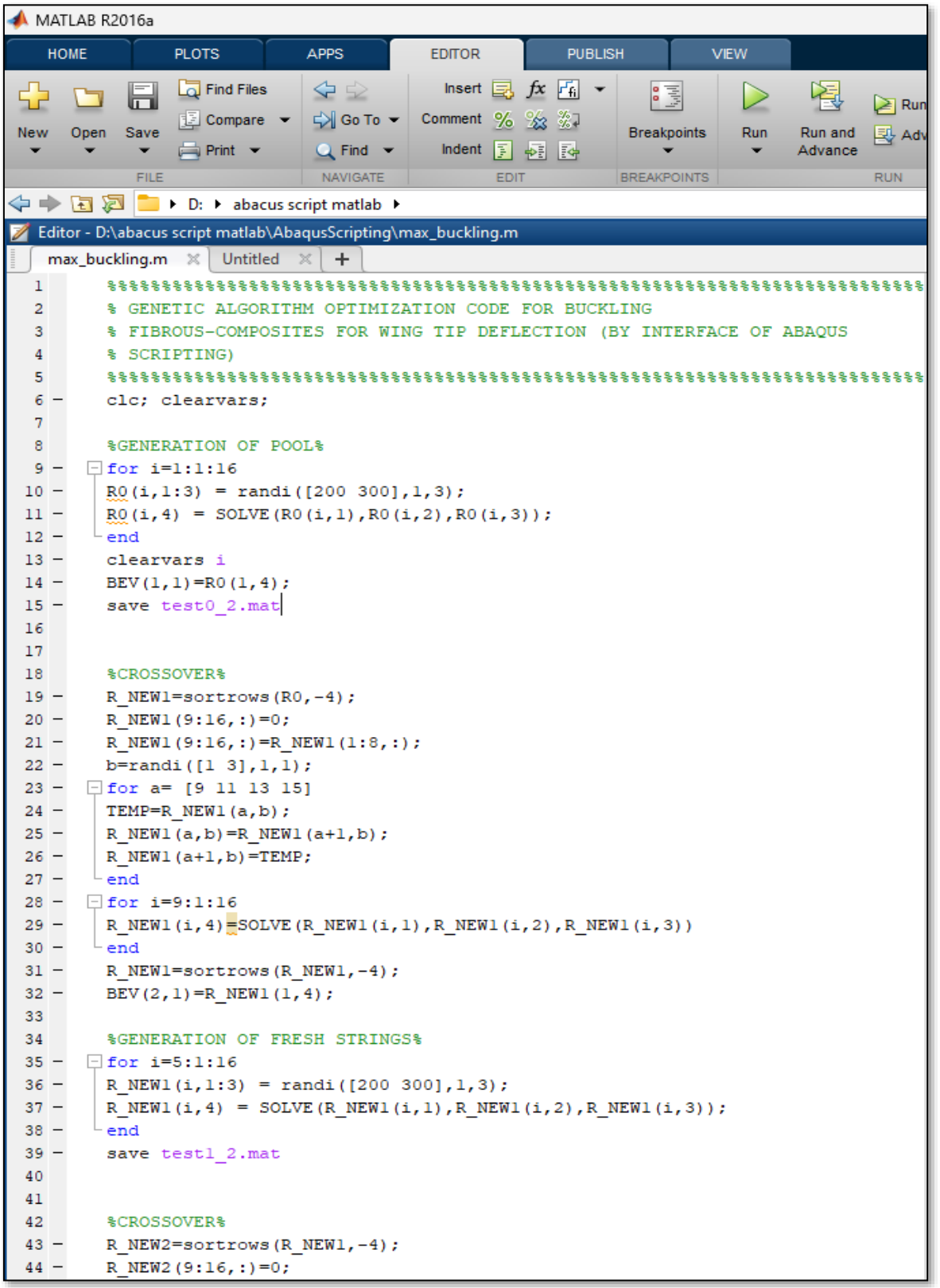

Figure 8: Genetic Algorithm Optimization code for Buckling (Part I)

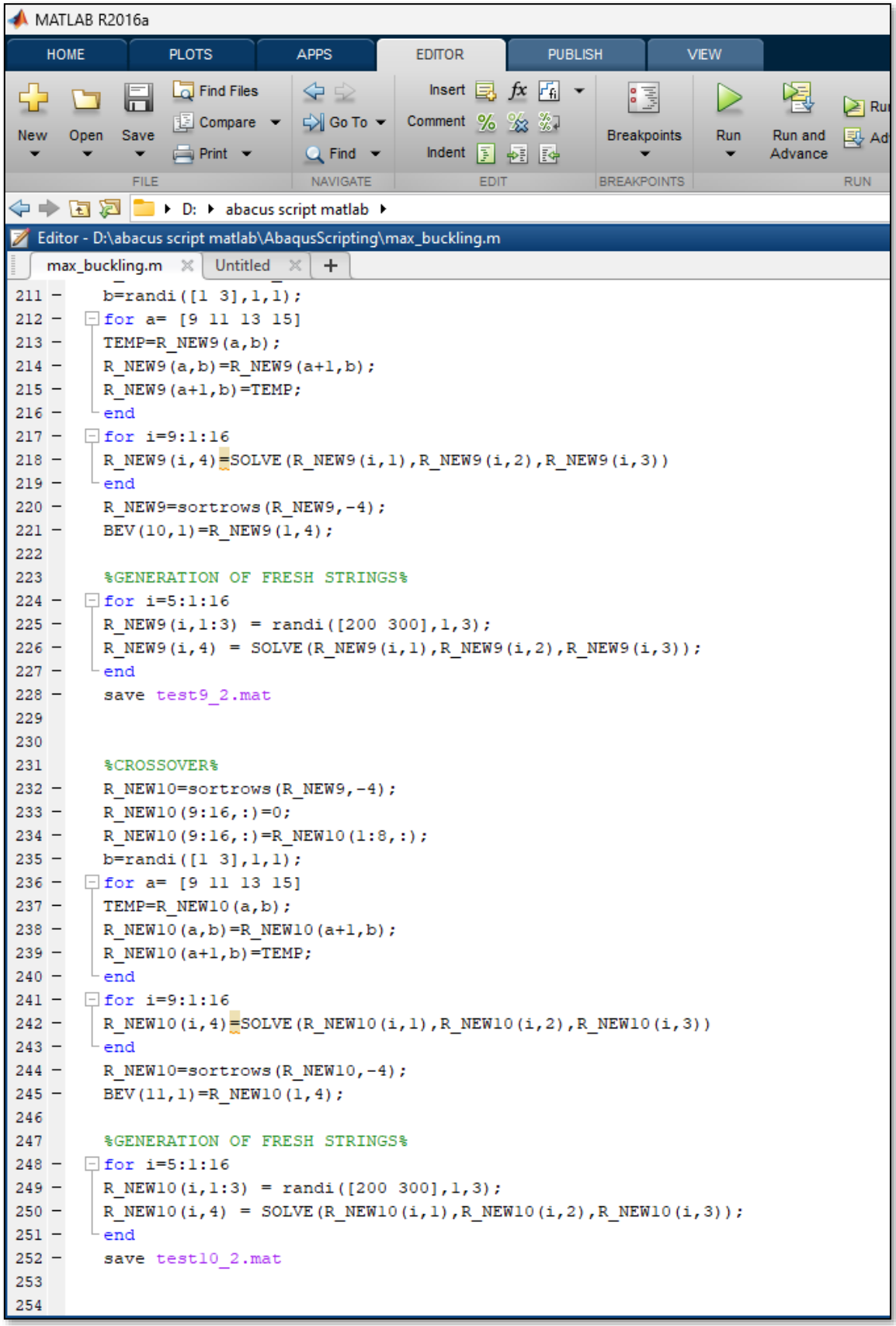

Figure 8: Genetic Algorithm Genetic

Figure 9: Genetic Algorithm Optimization code for Buckling (Part II)

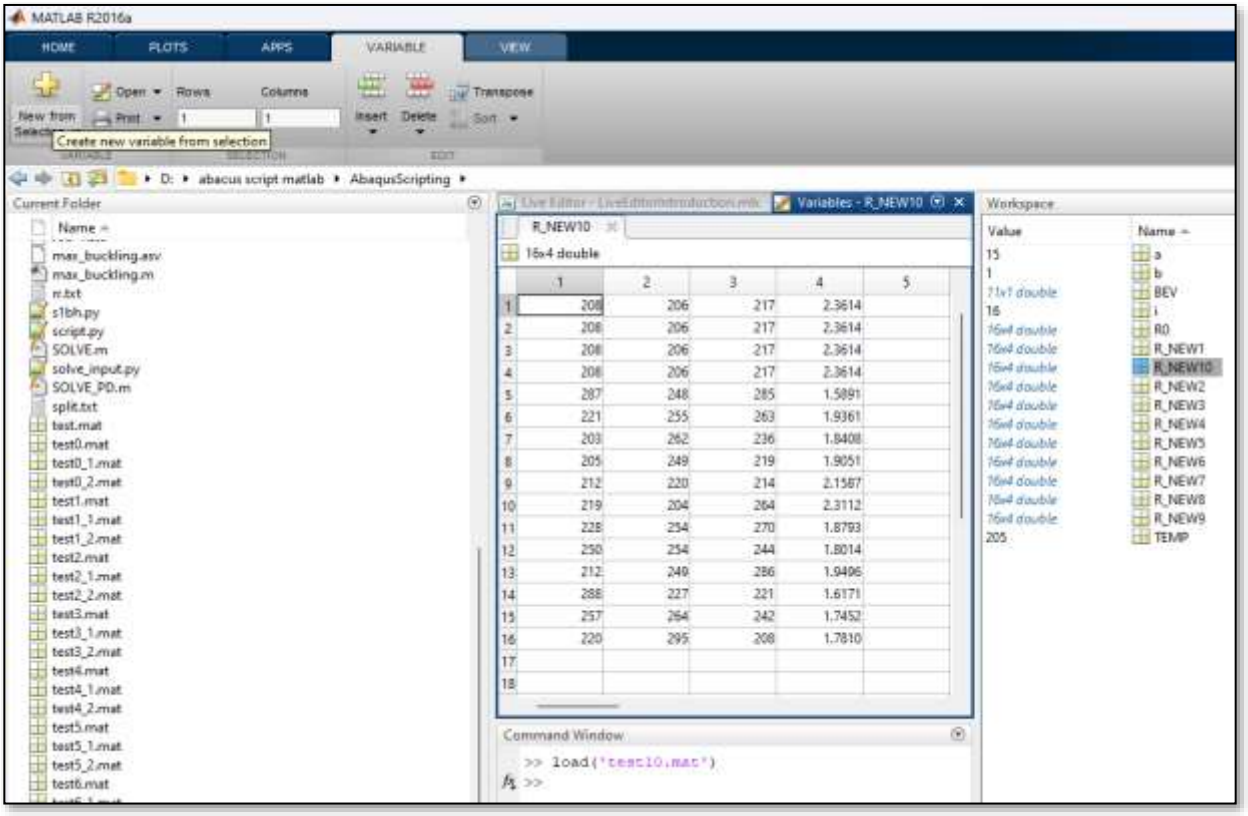

Figure 10: Buckling Eigen values generated in MATLAB software

In the above image MATLAB shows the result of Iteration performed for 16 pools set by the process of Evolutionary Algorithm, where top 8 out of 16 set pool is selected for further mutation and crossover process after certain Iteration top value is selected as optimum Eigen value for maximum buckling.

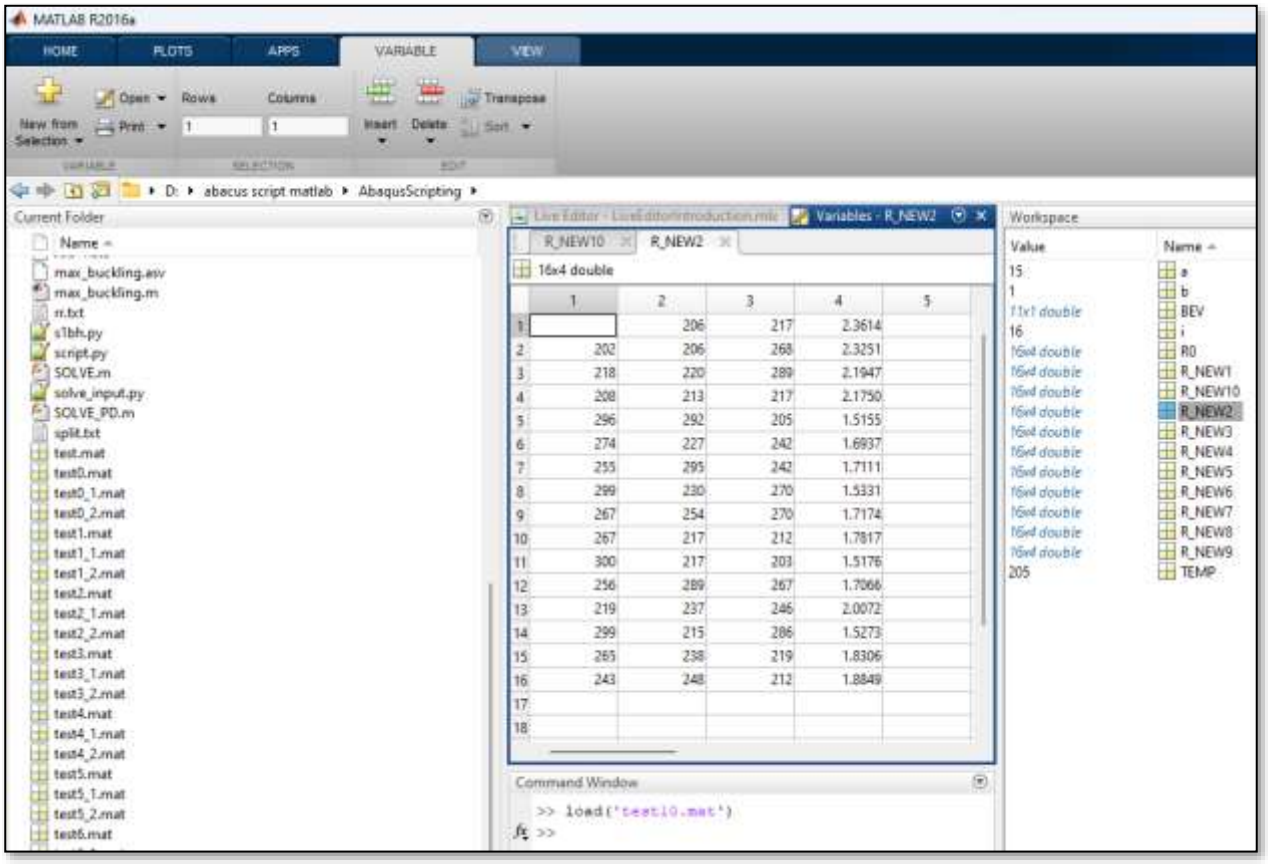

Figure 11: Buckling Eigen values generated in MATLAB software

In the above image MATLAB shows the result of Iteration performed for 16 pools set by the process of Evolutionary Algorithm, where top 8 out of 16 set pool is selected for further mutation and crossover process after certain Iteration top value is selected as optimum Eigen value for maximum buckling.

The above table shows the iteration performed in MATLAB software with varying Rib to Rib distance and the correspondence Eigen value, The required coding for these is generated using python script which was developed during modelling of wing box in ABAQUS CAE software.

There is total 16 Iteration of 3 set was performed in which top one selected at optimum Eigen value which is 2.3614 for which the Rib to Rib is following

A = 208,

B = 206,

C = 217,

From the above value it concluded the maximum buckling Eigen value is 2.3614.

RESULT & DISCUSSION

Table 1: Result Showing Iterations and its Eigen Values

No. of Iteration	Distance b/w Rib1 to Rib 2 (A)	Distance b/w Rib 2 to Rib 3 (B)	Distance b/w Rib 3 to Rib 4(C)	Eigen Value (λ)
1	208	206	217	2.3614
2	287	248	285	1.5891
3	221	255	263	1.9361
4	203	262	236	1.8408
5	205	249	219	1.9051
6	212	220	214	2.1587
7	219	204	264	2.3112
8	228	254	270	1.8793
9	250	254	244	18014
10	212	249	286	1.9496

There is total 16 Iteration of 3 set was performed in which top one selected at optimum Eigen value which is 2.3614 for which the Rib to Rib is following
A = 208,
B = 206,
C = 217,
From the above value it concluded the maximum buckling Eigen value is 2.3614.

The study intends to derive optimum Eigen value for Rib-to-Rib distance to minimize buckling in aircraft wing by using Genetic Algorithm process and mathematical problem-solving software like MATLAB (Matrix laboratory). Therefore, the buckling analysis of all possible combination can be done using the leads to larges saving in production resources.

Application of Evolutionary Algorithm

The modelled aircraft wing in ABAQUS CAE with varying Rib to Rib distance is the creation of random value.With this random value of rib-to-rib distance a population string is created. The further process like mutation and crossover of the generated population gives optimum Eigen value for maximizing the load capacity with minimum buckling. During the iteration for obtaining optimum Eigen value, the string is evaluated by the fitness function. The fitness function comprises of maximization ofbuckling value. Algorithms are coded in MATLAB and governs finite element analysis. The interface the process MATLAB code is interfaced with ABAQUS finite element solver using python scripting.
Following figure shows positive variation of Eigen value with respect to number of iterations. The plot shows continuous improvement in buckling eigen value as the number of iterations increases. This shows that with increase in number of iterations we are approaching towards the desired buckling eigen value. In fig 12 then eigen value remain constant after certain Iteration it show the optimum Eigen value which is 2.386, similar result is obtained in other solution figure i.e., 13 and 14

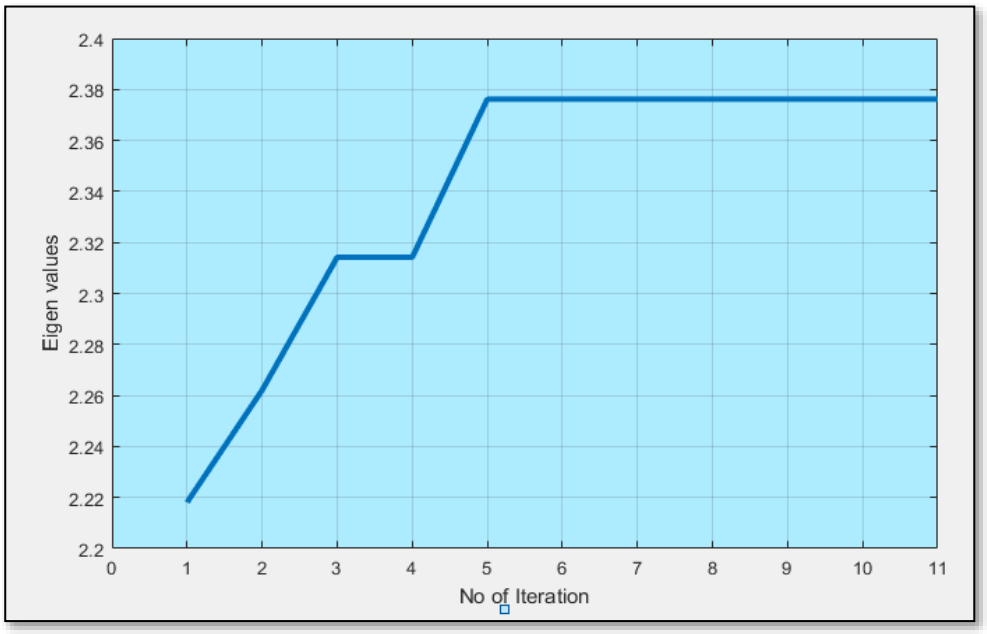

Figure 12: Difference value plot of Buckling Eigen value vs Number of Iteration (Solution -I)

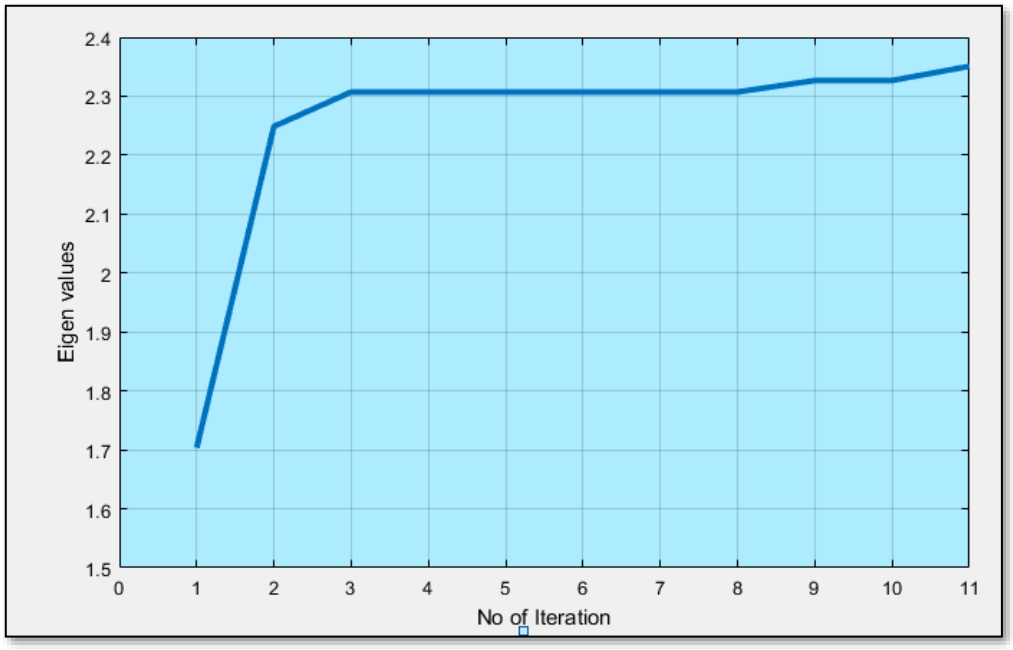

Figure 13: Difference value plot of Buckling Eigen value vs Number of Iteration (Solution -II)

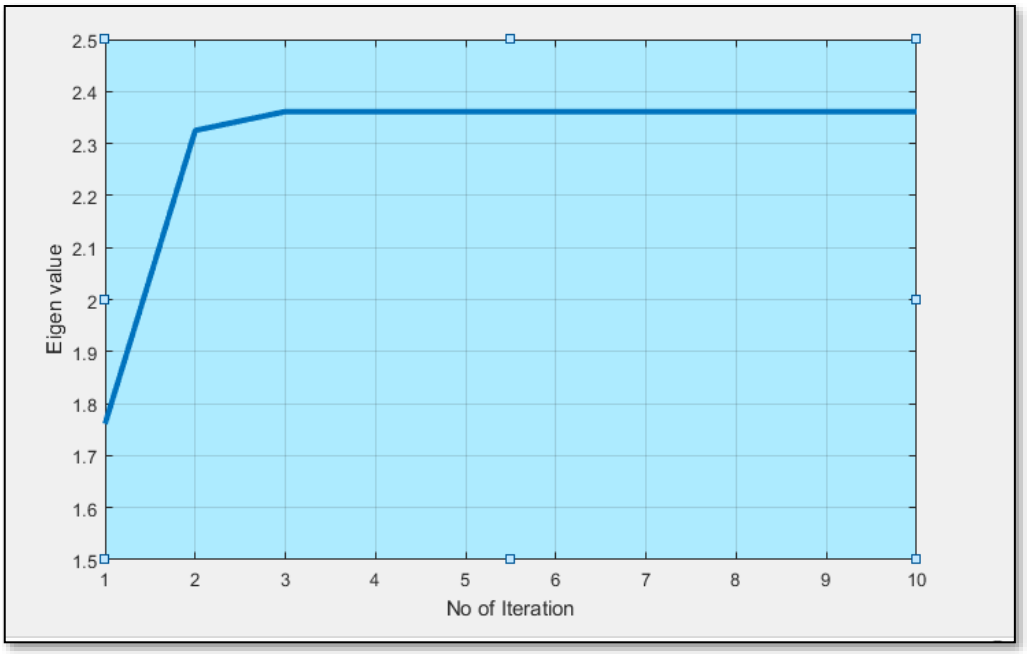

Figure 14: Difference value plot of Buckling Eigen value vs Number of Iteration (Solution -III)

The Figure 12, Figure 13 and Figure 14 shows plot of Buckling Eigen value with respect to number of iterations. It can be seen that eigen value of buckling is increasing with the expense of iterations. However, at the end of 6-7 iterations the increment attained a constant value.

A python script was generated on the basis of wing model design in ABAQUS CAE which helps to optimize rib to rib distance. To get the optimum Eigen value one need to do number of iterations in MATLAB with the help of MATLAB coding, for these the python script generated in ABAQUS CAE was used for MATLAB coding.

In MALAB 16 iterations are generated with varying rib to rib distance in which top one selected as the optimum eigen value. The above graphs were plotted between eigen values versus number of iterations with the help of data obtained from MATLAB.

CONCLUSION

The key points that can be concluded from this study can be enumerated as:

1. The fitness function very well guides the iterative procedure to get the buckling strength of equivalent FE model.
2. The fitness function constraints play important role in determination of buckling Eigen Value.
3. The Eigen value with respect to iteration plot indicates that solution is increasing in buckling eigen value and the procedure can be developed to get an optimum rib to rib distance.
4. Genetic Algorithm process play an important role in evaluating the optimum Eigen value for Rib-to-Rib distance.

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In current project, following literature information is inclined towards the above research area. The following journals are referred in preliminary literature review.

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