ロバスト性を考慮したトポロジー最適解群による航空機構造部材のトポロジー最適設計

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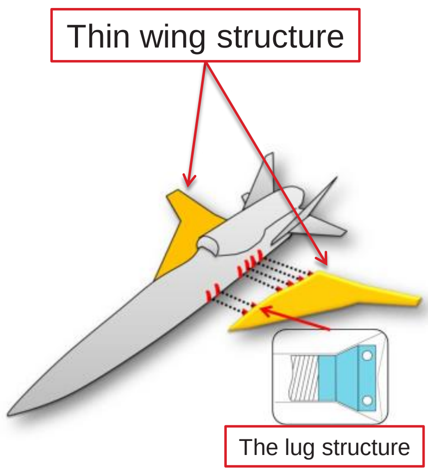
Background

Super Sonic Transportation

In the SST, it is required to
- High speed
- Economic viability
- Environmental compatibility

The lug structure

- small and restricted design domain
- several loadings that have uncertainties
- high stiffness
- weight reductions



Super Sonic Transportation

➡ Robust topology optimization is necessary to determine the optimal lug structure lay-out that is robust to loading perturbation.

Background

Robust topology optimization

- ➢Worst case approach, Average design approach(e.g. the expected and variance compliance model), etc.
- ➢It transform the probabilistic optimization problem into a **multiple load case** with some discretized approaches
- ➢It based on the compliance minimization problem of the multi-loadcase.

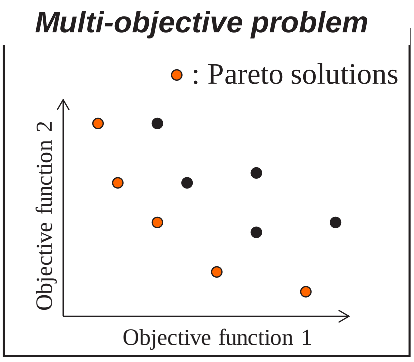
✓ A robust solution is the part of the Pareto-optimal solutions of the minimum compliance optimization problem with multi-loadcase.
✓ If there are two more independent loadings which have uncertainties, the number of objective functions that should be considered is increased

It is necessary to approach the robust topology optimization as Multi-Objective Optimization Problem(MOOP).

Background and objective

Multi-Objective Optimization Problem(MOOP)

- ➢It is important to find many optimal candidates such as **Pareto-optimal solutions**.
- ➢It is preferable for a designer to provide the Pareto-optimal solutions with **some useful information** in order to determine the final design from Pareto-optimal solutions.



Objective

To propose an efficient method for the robust topology optimization of the lug structure from the perspective of Multi-Objective Optimization Problem.
✓ finding Pareto-optimal solutions
✓ extracting some useful information
(e.g. trade-off relations, relations between topology and objective functions)

Proposed method

Minimization compliance problem of the multi-loadcase

- Robust topologies are explored from the Pareto-solutions obtained from the compliance minimization problem of the multi-loadcase.
  →Robust solution is the part of the Pareto-optimal solutions of the minimum compliance optimization problem of the multi-loadcase.
- **NSGA-IIa**(elitist non-dominated sorting genetic algorithms) was used to find Pareto-optimal solutions.

Advantage of Multi-Objective Genetic Algorithm

- It is possible to find a number of Pareto-optimal solutions in one single simulation run.
- Better global searching capability than sensitivity analysis methods
- It is possible to apply some problems which has non differentiable objective functions Fitness function based on objective is used for evolution of population.
  → Fitness function based on objective is used for evolution of population.

Proposed method

Design exploration by using Self-Organizing Map

- Self-Organizing Map (SOM) was used for the efficient exploration from the Pareto-optimal solutions obtained by NSGA-IIa.
- It is the one of the artificial neural network algorithms using unsupervised learning.
- A nonlinear projection algorithm from high- to low-dimensional space.
- For the projection, it classify the high dimensional data according to data similarity(distance).

✓Useful for visualizing the low dimensional views of high dimensional data.
✓It can be effectively utilized to visualize and explore properties of the data.

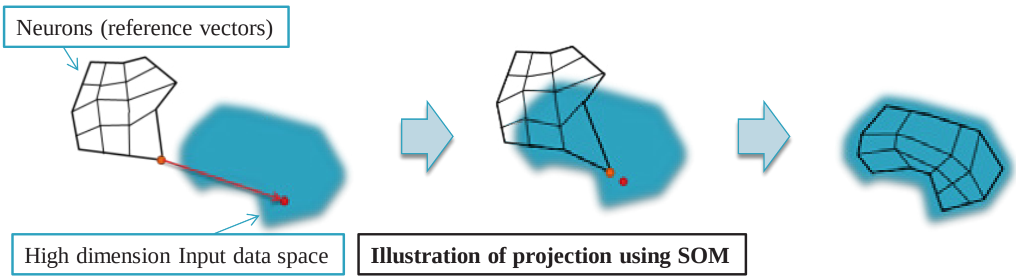


Illustration of projection using SOM

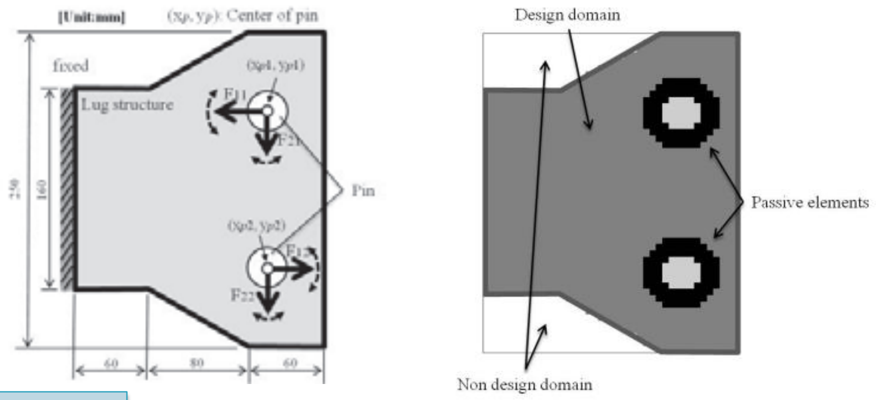
Proposed method

Procedure of the proposed method

1. **Define load cases** considering uncertainties of loads.
2. **Implement the NSGA-IIa** for minimize-compliance problem with the multi-load case.
3. **Classify the Pareto-optimal solutions** of the multi-load case problem **by using SOM** according to their topological characteristics .
4. **Calculate** the expected compliance and standard deviation of compliance for **robustness evaluation of Pareto-optimal solutions** .
   (Kriging surrogate model was used in order to reduce calculation cost.)
5. **Explore the robust topology** on the SOM.

The lug structure

The structural configuration of lug model and design domain



Loading uncertainty

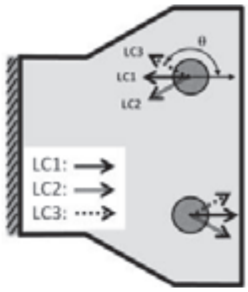
Normal distribution	Bending moment(F1)		Shear force(F2)	
	Mean	Std	Mean	Std
Magnitude	F_{11}(at y_{p1}=205mm)=80 F_{12}(at y_{p2}= 45mm)=80	5	10	10
Direction(θ) [°]	θ_{11}=180, θ_{12}=0	40	270	20

Loadcases

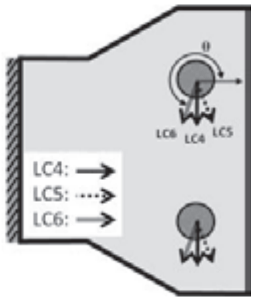
Load cases(3-levels)

➢To consider the uncertainty of the loading direction, three-levels direction loadcases were considered

For bending moment uncertainty



For shear force uncertainty



Magnitude and loading direction of each loadcases

No. Loadcase	Magnitude	loading direction(θ)
1	$1 \cdot 80/\lvert y_p-125 \rvert$	180°, 0°
2	$1 \cdot 80/\lvert y_p-125 \rvert$	220°, -40°
3	$1 \cdot 80/\lvert y_p-125 \rvert$	140°, 40°
4	1	270°
5	1	290°
6	1	250°

Topology optimization using MOGA

Multi-Objective Genetic Algorithm(MOGA)

➢Multi-objective optimization using NSGA-IIa

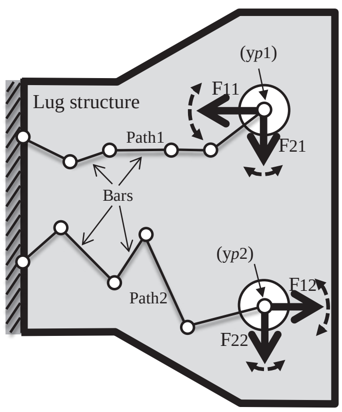
- Total generation=800, Population size=100, Total runs=5
- Crossover : 2point binary and PCX
- Mutation : Polynomial mutation

Minimization of each loadcase compliance with volume fraction *f*=0.4
→Total number of objective function is 6

Bar-representation method

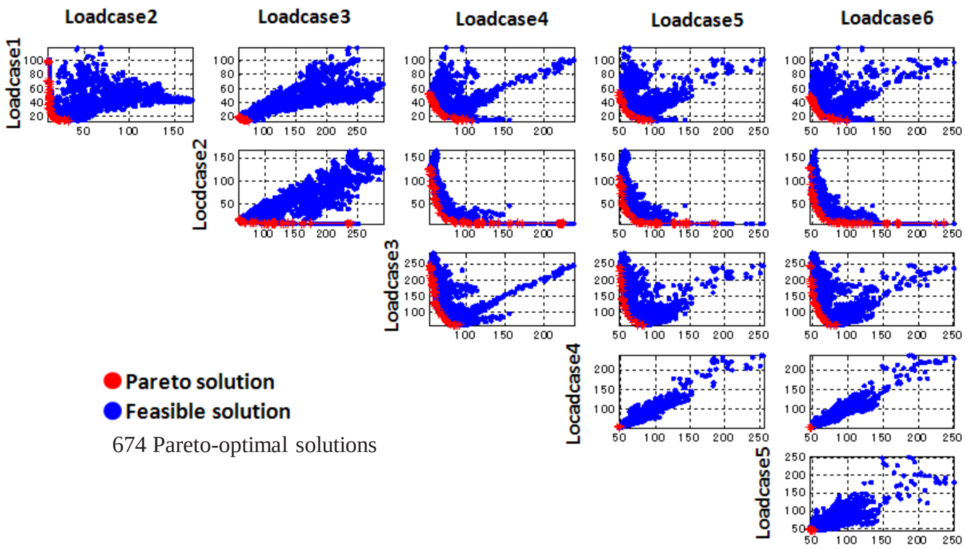
➢Design parameters are

- the position of each vertex and thickness of each bar. (5bars/path, 2path,)
- the position of *i*th pin about y-axis.



F1: Bending moment
F2: Shear moment
y_{pi} is the position of *i*th pin about y-axis.

Result of NSGA-IIa



Each loadcase compliance is represented in both axes

Calculation of robustness

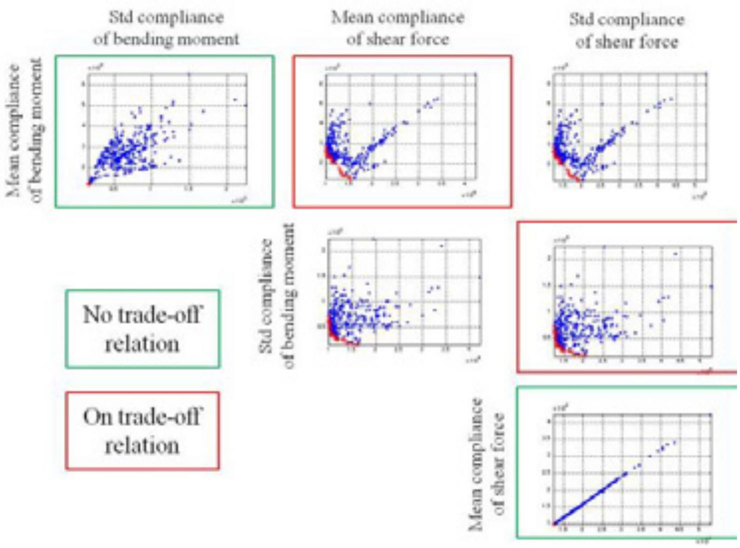
Monte Carlo simulation

✓Calculate **the expected compliance and standard deviation** of Pareto-optimal solutions
✓10,000 load samples

	Bending moment(F1)		Shear force(F2)	
	Mean	Std	Mean	Std
Magnitude	$F_{11}(y_{p1}$=205mm)=80 $F_{12}(y_{p2}$= 45mm)=80	5	10	10
Direction(θ) [°]	θ_{11}=180, θ_{12}=0	40	270	20

✓Kriging surrogate model
- Kriging model was used to approximate the compliance space of each topology
- Design variable of the Kriging model are magnitude and direction of loading
- 80 FEA results were used to construct the Kriging response surface

Result of Monte Carlo simulation



✓There are Pareto-optimal solutions in the robustness performance space.
✓There are some trade-off relations between objective functions.

➡ In order to find more information, SOM was used

Classification using SOM

Classification using SOM

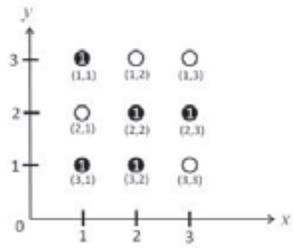
✓SOM was used in order to investigate efficiently about the relation between topology and robustness objectives
✓Some topology characteristics are defined for SOM classification

- All elements density value of the Finite Element Analysis model.
- The width and height, in element that density is 1, of the FEA model.
- The mean, variance and covariance of the density of FEA element about each axis.

Topology

1	0	0
0	1	1
1	1	0

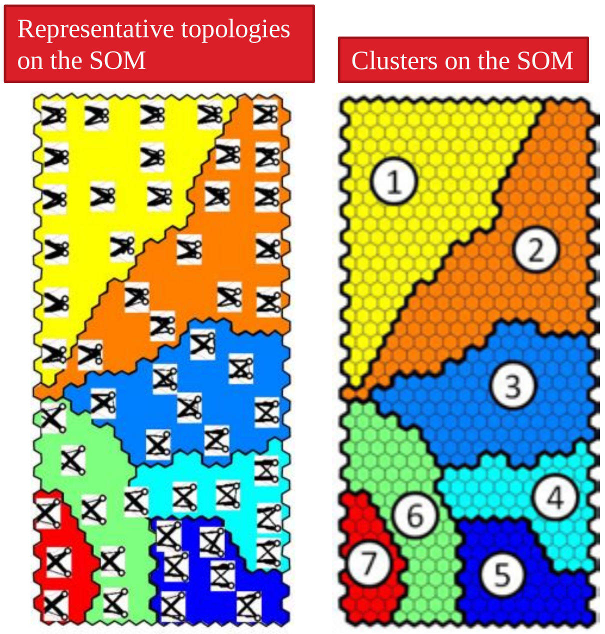
Density matrix of FEA



Density coordinate space

Result of topology classification

- ✓Result of classification of all Pareto-optimal solutions obtained by NSGA-IIa and clustering.
- ✓Topologies were classified according to topology characteristics
- ✓Adjacent individuals topology are similar to each other.
  →Adjacent topologies have similar characteristics and performances
- ✓There are 7 clusters on the SOM

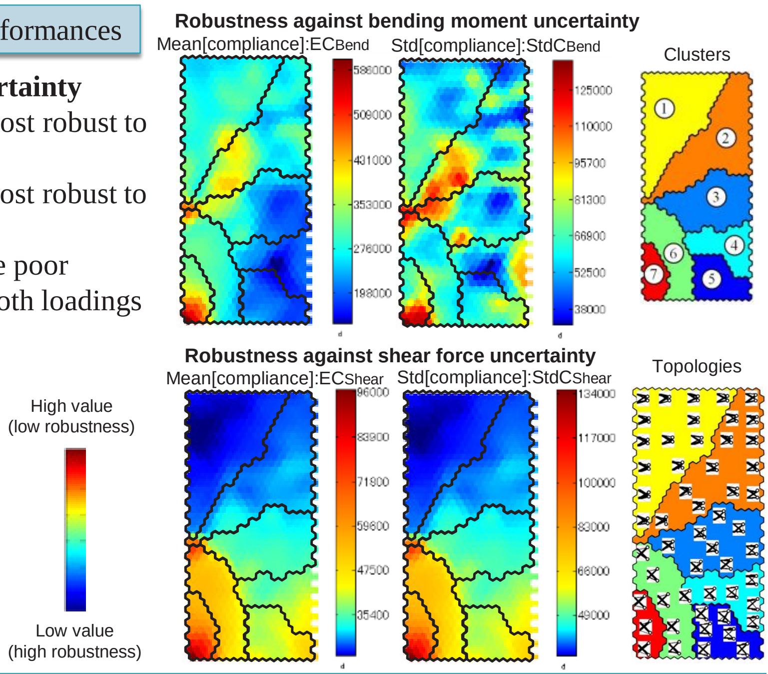


Information from the SOM(1)

SOM colored by robustness performances

Robustness to the loading uncertainty

- ✓Topologies in the cluster 4 is most robust to bending moment perturbation
- ✓Topologies in the cluster 1 is most robust to shear force perturbation
- ✓Topologies in the cluster 7 have poor performance of robustness to both loadings perturbation



Information from the SOM(2)

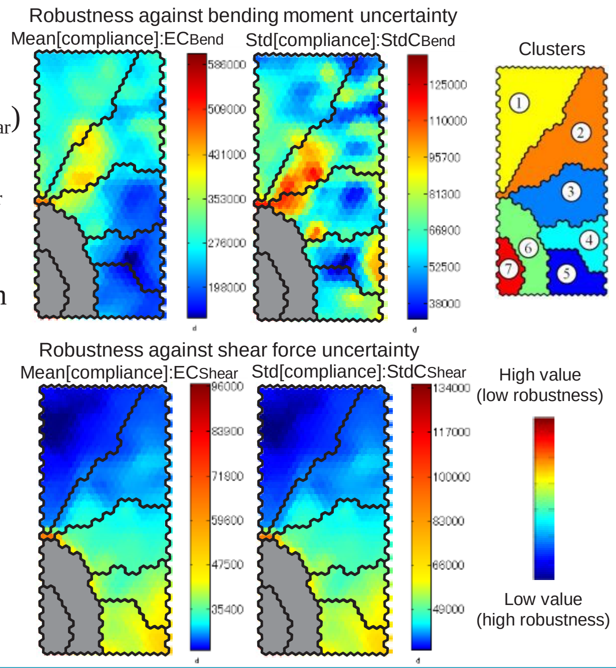
SOM colored by robustness performances

Trade-off relations

✓(EC_{Bend} and $StdC_{Bend}$), (EC_{Shear} and $StdC_{Shear}$) show similar SOM color pattern

→ EC_{Bend} and $StdC_{Bend}$, EC_{Shear} and $StdC_{Shear}$ are not in a trade-off relation

✓EC_{Bend} and EC_{Shear} are in a trade-off relation because its SOM patterns show almost opposite color patterns



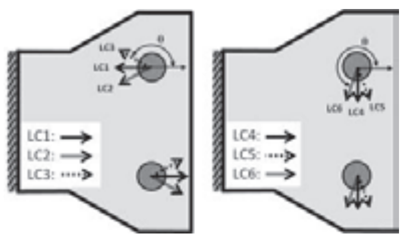
Information from the SOM(3)

Topology similarity

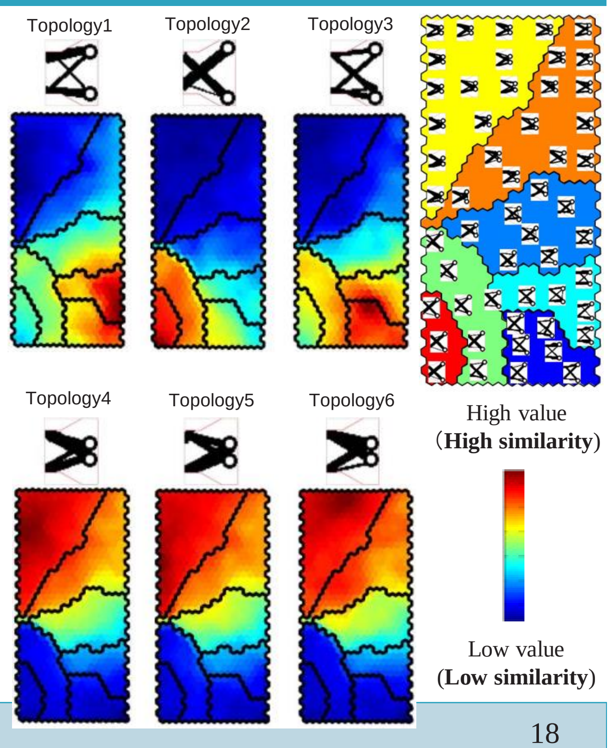
✓SOM colored by topology similarity to the each loadcase optimum topology shown above the each SOM

✓Topology on the red color unit has high similarity to the topology above each SOM

✓Topology on the blue color unit has low similarity to the topology above each SOM



6 loadcases



Information from the SOM(3)

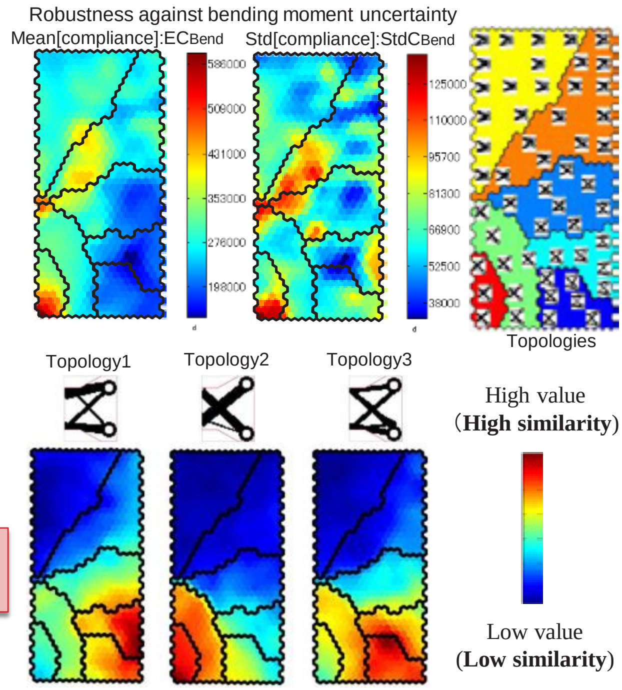
Topology similarity

✓Similar topologies to the topology3 (optimum topology of loadcase 3) have low EC_{Bend} and $StdC_{Bend}$ value.

✓Topology 3 is located between topology 1 and topology 2 on SOM.

→Topology 3 has both characteristics of topology 1 and 2.

It is the reason why topology 3 is robust to bending moment uncertainty.



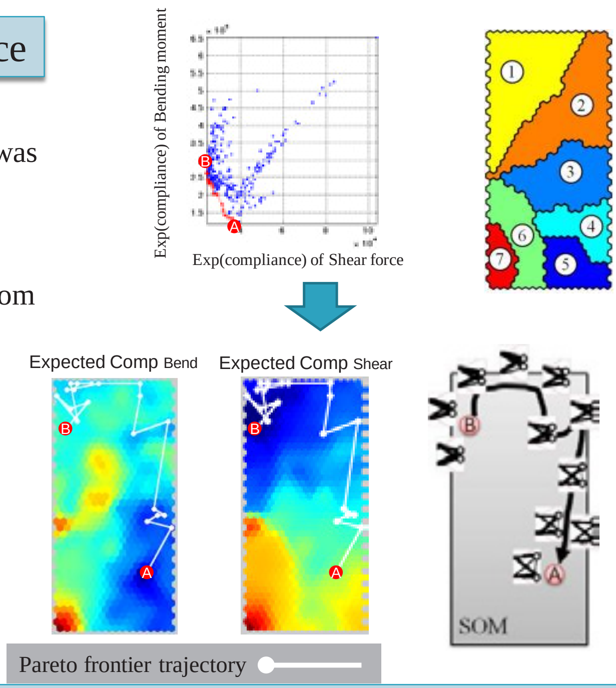
Robust topologies on the SOM

Mean compliance objective space

✓Trajectory of Pareto-optimal solutions between A and B in the objective space was plotted on the EC_{Bend} and EC_{Shear} SOM.

✓The Pareto-optimal solutions in the robustness objective space are located from the cluster 4 to 1 in order.

✓Topologies in the clusters 2, 3 have balanced robustness performance
→both characteristics of topology 3 and 4



Conclusion

- For the robust topology optimization of lug structure with loading uncertainty, Multi-Objective Genetic Algorithms was used with multi-loadcases problem.
- Exploration method of Pareto-optimal solutions by using SOM was proposed for the efficient exploration in the robust topology instead of using objective space plotting.
- Pareto optimum topologies of the lug structure are obtained.
- Proposed method shows effectively some trade-off relations between objective functions, and relations between topology and objective function.