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Simultaneous partial topology and size optimization of a wing structure using ant colony and gradient based methods

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This article presents a methodology and process for a combined wing configuration partial topology and structure size optimization. It is aimed at achieving a minimum structural weight by optimizing the structure layout and structural component size simultaneously. This design optimization process contains two types of design variables and hence was divided into two sub-problems. One is structure layout topology to obtain an optimal number and location of spars with discrete integer design variables. Another is component size optimization with continuous design variables in the structure FE model. A multi city-layer ant colony optimization (MCLACO) method is proposed and applied to the topology sub-problem. A gradient based optimization method (GBOM) built in the MSC.NASTRAN SOL-200 module was employed in the component size optimization sub-problem. For each selected layout of the wing structure, a size optimization process is performed to obtain the optimum result and feedback to the layout topology process. The numerical example shows that the proposed MCLACO method and a combination with the GBOM are effective for solving such a wing structure optimization problem. The results also indicate that significant structural weight saving can be achieved.

Keywords: aircraft wing; structure layout topology; size optimization; ant colony optimization; gradient-based optimization method

1. Introduction

Structural weight saving is always an ultimate target in airframe design since it has a significant impact on aircraft performance (Heiko *et al*. 2003, Ji and Frederick 2004, Schuhmacher *et al*. 2004). As the demand for better performance and less environmental impact increases, the iterative process of aircraft design becomes more complicated for further structure improvement and weight saving. As an efficient approach, optimization methods and design tools are employed in aircraft industry (Xu *et al*. 2005). The design optimization process may be classified into two stages, a partial topology process for optimal structure configuration and component optimization according to the type of design variables. In general, topology design variables can be represented by discrete integers, while the component design variables such as the spar and stringer cross-section shape and skin thickness are represented by continuous values. Topology dictates the presence or absence of some primary structure parts. A typical wing structure consists of spars, ribs, stringers and skin. Most aircraft wings have at least two spars. Butler (1998) provided an overview on some of the existing optimization methods which may be applied in the wing structure design. The augmented Lagrangian method has been applied to the minimum weight design of an aircraft wing box. In the article by Singh and Yadav (1993), the thickness of skin and spar webs was selected as design variables and four approaches have been outlined for the solution of a constrained optimization problem. Ine-Wei and Chien-Chang (1989) developed a modular computer program called ARS4 (Automatic Resizing System 4) for the optimization of wing structures subject to size, stress, displacement and buckling constraints. Rothwell (1991) developed a multi-level optimization design program for stiffened shell structures, typically aircraft wings in preliminary design stage. The applicability of the proposed method to complicated structure design problems was tested on a composite wing box with multi constraints.

All the optimization techniques described above were focused on the detailed component optimization and have enabled structure weight saving. For aircraft wing structure however, if the configuration such as the number and location of wing spars are predetermined based on experience or previous design data base, the weight saving achieved by component optimization only may be limited. It is believed that much greater potential of weight saving may be achieved by optimizing the structure configuration in the same time. In practice, it would be very time consuming if the performance were made manually in an iterative manner compared with using the optimization techniques (Falco and Faria 2002).

In previous research, a commercial structure optimization code, Altair Optistruct, was employed to optimize a wing layout in conceptual design by Rao *et al.* (2008). In this particular study, a solid wing was taken initially as a design space and meshed by using hexahedral elements to derive the optimal location of spars and ribs for minimum compliance. Vladimir and Haftka (1995) presented an optimization approach for an efficient wing structure design of a civil transport. In that study, the wing structure was simplified as a truss model and a ground structure approach was used in the optimization. Hansen and Peter (2008) proposed a double level optimization approach for optimal primary structure layout and dimensions. In the top level of the optimization procedure, the topology parameters were determined by using an evolution strategy. In the second level the thickness and cross section of the structure modelled by using the MSC.Nastran Sol-200 module were optimized subject to design constraints.

Ant colony algorithm or optimization (ACO) is one of the latest and promising stochastic methods for optimization. This method was inspired by the behaviour of colonies of ants searching for food and was introduced in early 1990s by Dorigo (1997). Since then it has been successfully applied to dealing with several non-deterministic polynomial solvable (NP) hard combinatorial optimization problems, such as the travelling salesman problem (TSP) (Ugur and Aydin 2009). Some engineering problems such as the feeder bus network design problem (Kuan *et al.* 2006) and process engineering problems (Coelho and Mariani 2008) can be solved by using the ACO. Aymerich and Serra (2008) have shown that the average performance and the robustness of the ACO search strategy are competitive in general or even better in some cases than the widely used genetic algorithm (GA) or tabu search (TS). More recently, ACO was employed to solve the structure topology optimization problem. Chun-Yin *et al.* (2009) presented a modified ACO with specific definition of pheromone and cooperation mechanism between ants and successfully applied it to solving a topology optimization problem. Kaveh *et al.* (2008) employed the ACO in 2D and 3D structure topology in optimization problems.

In this current article, a partial topology for an optimal configuration combined with optimization for component details was performed simultaneously to minimize the weight of a wing structure in a specified aerodynamic load condition. The objective was to optimize the number and location of wing spars in conjunction with optimization of the spar flange and web sizes subject to stress and stiffness constraints. To solve the problem, a methodology and process was proposed to combine a modified ant colony optimization (ACO) method with a gradient-based optimization method (GBOM). In the partial topology stage, the process was set to determine the structural layout represented by design variables in the form of discrete integers. In the same time, the design variables for the structural component details in FE model were represented by continuous values and optimized.

2. Methodology for the wing structure optimization

The procedure was started from an initial wing structure configuration with a range of layout options. The optimum configuration was obtained by a process of removing or adding some structural components to the initial design. Since the layout option range was predetermined based on practical design consideration, the process was called a partial rather than a full topology optimization. This process has the advantage of easy implementation by changing the material properties of those structural components instead of recreating the FE model. The partial topology process for wing configuration can be solved by using the genetic algorithm, simulated annealing or ACO.

In the current example, the process was started from an initial wing configuration with sufficient number of spars for options. Based on the initial design, a FE model of the wing structure was created with the spar caps and webs modelled by using bar and shell elements of different materials. The material properties of individual structural component can be changed to model the components being added or removed. For example, when the Young's modulus of a cap was set to be nearly zero, the spar beam would virtually become a web as illustrated in Figure 1. When the Young's modulus associated with both the spar cap and web was set as nearly zero, the spar is virtually removed from the structure configuration.

In defining the status of the configuration, each component was coded by an integer in a design variable vector. For example, '1' and '2' represents the cap and web and '3' indicates the 'removal' of the spar in the partial topology process. The web and skin thickness and the cross section area of spar cap were selected as design variables in the structure optimization. The total structure weight was taken as the objection function. The maximum stress of the structure and the stiffness in terms of the displacement at a specified location was considered as constraints. The optimization problem is formulated below.

Find

$$\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_n]^T, \quad \mathbf{A_{cap}} = [A_{cap}^1, A_{cap}^2, \cdots, A_{cap}^n]^T$$
$$\mathbf{T_{web}} = [T_{web}^1, T_{web}^2, \cdots T_{web}^n], \quad \mathbf{T_{skin}} = [T_{skin}^1, T_{skin}^2, \cdots, T_{skin}^m] \tag{1}$$

Minimize

$$W = W_0 + \sum_{i=1}^{m} \rho S_{skin}^i T_{skin}^i + \sum_{i=1}^{n} \rho \beta_1^i T_{web}^i S_{web} + 2\sum_{i=1}^{n} \rho \beta_2^i A_{cap}^i L_{cap}^i$$

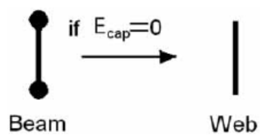

Figure 1. The spar beam and web.

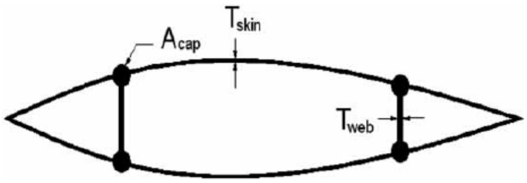

Figure 2. The cross section of wing structure.

Subject to

$$g_k(\boldsymbol{\alpha}, \mathbf{A_{cap}}, \mathbf{T_{web}}, \mathbf{T_{skin}}) \geq 0 \quad k = 1, 2, \cdots, K$$

$$\beta_1^i = \begin{cases} 1, & \alpha_i = 1 \\ 1, & \alpha_i = 2 \\ 0, & \alpha_i = 3 \end{cases} \quad \beta_2^i = \begin{cases} 1, & \alpha_i = 1 \\ 0, & \alpha_i = 2 \\ 0, & \alpha_i = 3 \end{cases}$$

where W represents the overall weight of the wing structure as the objective function, A_{cap} and L_{cap} are the cross section area and length of the spar cap, S_{web} and S_{skin} are the web and skin cross section area, T_{web} and T_{skin} are the web and skin thickness as illustrated in Figure 2. α is the design variable vector in the partial topology process. g_k is the constraint function with K number of constrain conditions. In this case, both stress and stiffness constraints are considered.

In the combination of wing configuration partial topology and component size optimization process, a mixture of discrete and continuous design variables was considered. For each optional structure layout, the component size optimization was performed. However, the optimized result from one of the iterations does not guarantee the global optimum design unless the design variables are considered simultaneously in a global optimization process.

To obtain the global optimum solution, an optimization strategy is proposed in this article. This is to conduct the wing configuration partial topology by using an evolutionary method and carry out the structure size optimization by using a gradient-based deterministic optimization method available in the MSC.Nastran SOL-200 module. A flow chart of the optimization procedure can be seen in Figure 3. In the beginning, a set of topology design variables representing some wing configuration options was randomly selected and optimized. In this process, the AC optimization (ACO) method was applied to deal with the integer design variables in a program as formulated in Equation (2). For each optimal layout, the components in the structure FE model were optimized by employing the MSC.Nastran SOL-200 optimization module with the continuous type of design variables as formulated in Equation (3). The optimization process was divided into two sub-problems. By coding the NASTRAN module in the loop of the ACO, the ACO method was used in an iterative manner based on the previous optimization solution to produce the next generation wing structure layout followed by size optimization. The iterative process was continued until the objective was achieved or the generation number reached a predetermined limit when a set of optimal configuration design variables and size design variables can be obtained.

Sub-problem 1: Find

$$\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_n]^T \tag{2}$$

Minimize

$$W = W_0 + \sum_{i=1}^{m} \rho S_{skin}^i T_{skin}^i + \sum_{i=1}^{n} \rho \beta_1^i T_{web}^i S_{web} + 2\sum_{i=1}^{n} \rho \beta_2^i A_{cap}^i L_{cap}^i$$

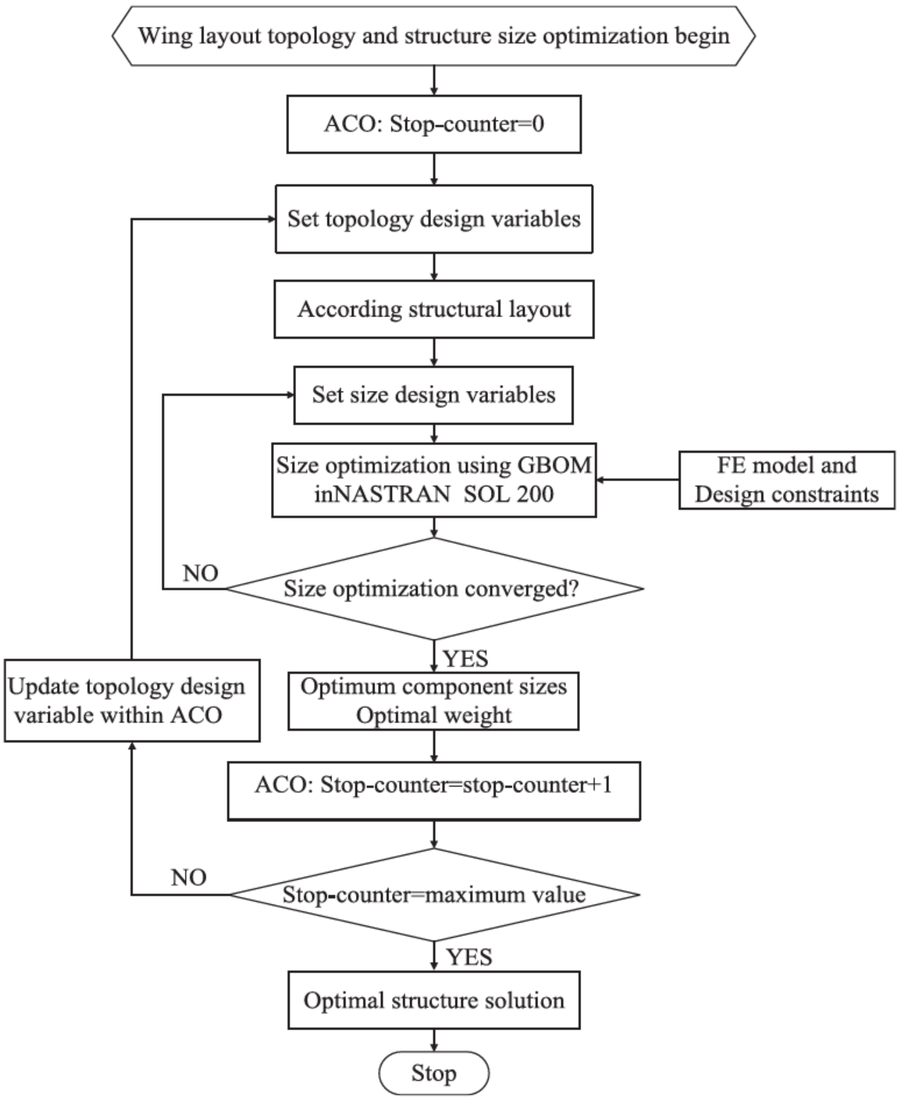

Figure 3. Flow chart of the wing structure optimization procedure.

Subject to

$$\beta_1^i = \begin{cases} 1, & \alpha_i = 1 \\ 1, & \alpha_i = 2 \\ 0, & \alpha_i = 3 \end{cases} \quad \beta_2^i = \begin{cases} 1, & \alpha_i = 1 \\ 0, & \alpha_i = 2 \\ 0, & \alpha_i = 3 \end{cases} \quad \alpha_i \in \{1, 2, 3\}$$

Sub problem 2: Find

$$\begin{aligned} &\mathbf{A_{cap}} = [A_{cap}^1, A_{cap}^2, \cdots, A_{cap}^n]^T, \quad \mathbf{T_{web}} = [T_{web}^1, T_{web}^2, \cdots T_{web}^n] \\ &\mathbf{T_{skin}} = [T_{skin}^1, T_{skin}^2, \cdots, T_{skin}^m] \end{aligned} \tag{3}$$

Minimize

$$W = W_0 + \sum_{i=1}^{m} \rho S_{skin}^i T_{skin}^i + \sum_{i=1}^{n} \rho \beta_1^i T_{web}^i S_{web} + 2 \sum_{i=1}^{n} \rho \beta_2^i A_{cap}^i L_{cap}^i$$

Subject to

$$g_k(\alpha, \mathbf{A}_{\mathbf{cap}}, \mathbf{T}_{\mathbf{web}}, \mathbf{T}_{\mathbf{skin}}) \geq 0 \quad k = 1, 2, \cdots, K$$

Within each iteration of the iterative configuration topology process for an optimized objective function, a number of size optimization processes associated with many FE analyses were performed. Therefore the efficiency of the overall optimization depends very much on the efficiency of the configuration topology process. Therefore, a modified ACO method was developed in this article to solve the partial topology optimization problem.

3. The ACO process for the wing configuration partial topology

In this section, details of the modified multi city-layer any colony optimization (MCLACO) method used to solve the configuration partial topology problem are described. Based on a wing configuration with a number of spars selected, each spar has three types of options: spar beams, webs or absence represented by integers '1', '2' and '3' respectively as the topology design variables. Figure 4 shows a city matrix of three rows and 12 columns, where the row is defined as city and column as city-layer. In this model, the three cities represent the '1', '2' and '3' spar types and the 12 city-layers represents a 12-spar wing configuration. A number of selected ants will travel through all the city-layers starting from the first one in order. If an ant is currently at one city in the ith city-layer, it can only select one city in the $(i + 1)$th city-layer as its next visit city. A complete route from a city in the first city-layer to the last one is formed after the ant has passed through every city-layer. The entire route taken by each ant is coded as a string composed of 12 bits, which agrees with the city-layer number. Figure 4 illustrates an example of the MCLACO process where an ant travels from the first city in the first city-layer. It represents the option of the first spar beam type for the first spar of the wing configuration. The ant then moves to the second city in the second city-layer, which represents the second beam type option for the second wing spar. Finally it opts for the first city in the 12th city-layer for the last wing spar where the process is completed. This example route can be coded in a string as [1 2 2 3 2 2 3 1 2 3 2 1]. Associated with the string, a structural layout can be produced as ['beam', 'web', 'web', 'absence', 'web', 'web', 'absence', 'beam', 'web', 'absence', 'web', 'beam'].

In the FE model, this wing structure layout can be realized by the modification of the NASTRAN FE #.bdf file. By using the NASTRAN SOL200 module, a size optimization was performed for the wing structure layout. After the size optimization, an optimum solution with a structure weight was obtained. The solution was coded as a route length [122322312321] as shown in Figure 4.

The details of the MCLACO method in searching for the optimum design variables are described below. At the first step of the process, m number of ants is selected and randomly distributed to the cities in the first city-layer to go through m different routes. The immediate task for all the

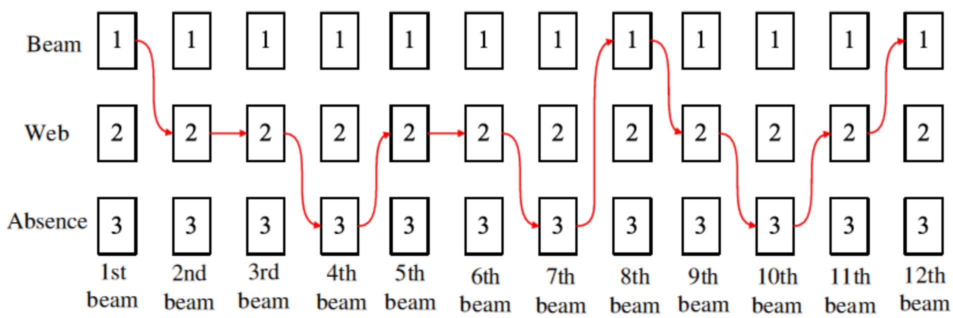

Figure 4. An example of 3-city in a 12 city-layer model of the MCLACO method.

ants is to find an objective city in the next city-layer. In the beginning of the MCLACO process, an intensity of trail information is used to simulate the pheromone of ants. The intensity of trail information between city i in the $(k+1)$th city-layer and city j in the kth city-layer is denoted as $\tau(i, j, k-1)$, where $i, j = 1, 2, \ldots, n$, and n is the number of cities in a city-layer corresponding to the options of a spar beam type. Without *a priori* available trail information, a fixed number τ_0 in the first generation of the search process was initiated as an intensity matrix of trail information. For an ant at city i in the $(k-1)$th city-layer, the probability to select city j in the kth city-layer to visit at the next step can be written in a formula:

$$j = \begin{cases} \arg \max\limits_{u \in allowed_k} \{[\tau(i, u, k)]^{\alpha}\} & \text{if } q < q_0 \\ S & \text{otherwise} \end{cases} \tag{4}$$

where α represents the degree of relative importance of the trail information; q is a parameter chosen randomly with uniform probability in [0, 1] and q_0 is a given parameter; S is a random variable selected according to the following probability distribution which have a higher level of pheromone trail:

$$P(i, j) = \frac{\tau^{\alpha}(i, j, k)}{\sum\limits_{u \in allowed_k} \tau^{\alpha}(i, j, k)} \tag{5}$$

The pheromone trail is updated in two levels: global and local updating. When each ant has completed its tour, if the edge is chosen by ant m, its amount of pheromone is changed by using the following local trail updating formula:

$$\tau(i, j, k) \longleftarrow (1-\xi) \cdot \tau(i, j, k) + \xi \cdot L(m) \tag{6}$$

where ξ is a parameter; $L(m)$ is the route length of ant m.

The local trail updating is motivated by trail evaporation of ants to avoid a high frequency selection of the same route by all the ants that could lead to a local convergence and premature solution. When all the ants complete their tours in one iterative process, the route selected by each ant represents an option of the wing structure configuration. The route length also produces an objective function in terms of structure weight as expressed in Equation (2). The best ant with the shortest route length deposits pheromone on the visited edges that belong to its tour while the other edges remain unchanged. The amount of pheromone $\Delta\tau$ deposited by the best ant is proportional to the tour length. The global trail updating is a process of a reinforcement learning scheme in which better solutions get a greater reinforcement expressed by a formula shown in Equation (7):

$$\begin{gathered} \tau(i, j, k) \longleftarrow (1-\rho) \cdot \tau(i, j, k) + \Delta\tau \\ \rho \in (0, 1) \\ \Delta\tau = \begin{cases} \rho / L_{gb} & if\,(i, j) \in \text{the longest path} \\ -\varepsilon \cdot \dfrac{L_{worst}}{L_{best}} & if\,(i, j) \in \text{the shortest path} \\ 0 & \text{others} \end{cases} \end{gathered} \tag{7}$$

The procedure of the MCLACO is summarized below and illustrated in Figure 5.

Step 1: Set parameters and initialize pheromone trails
Step 2: Allocate randomly each of the ants to a city in the first city-layer

Step 3: Every ant must travel to a city in the next city-layer depending on the probability distribution given in Equation (4)
Step 4: Perform a local update of pheromone according to Equation (6)
Step 5: Calculate the route length of all ants in size optimization to identify the best and worst ant, and perform a global update of pheromone using Equation (7)
Step 6: If the specified maximum iteration is completed, terminate the process; otherwise repeat Steps 2 to 5.

4. Example and optimization results

In order to demonstrate the methodology and optimization process proposed in this article, a wing of high aspect ratio as illustrated in Figure 6 for a multi-role aircraft is taken as an example. In the initial conceptual design configuration of the wing box, 12 spar beams were located with equal pitch chord-wise and numbered from the front to the rear spar. It is noted that this initial structure layout is a conservative design of mass 1005.5 kg. Span-wise, the wing structure is divided into 10 thin wall box sections by 11 ribs. The skin panels, spar webs and ribs were modelled by using 765 quadrilateral plate elements (CQUAD4) and the spar beams by 360 bar elements (CBAR). The whole wing FE model has 413 nodes and 1125 elements. The material properties include Young's Modulus 73.1 GPa, mass density 2700 $\mathrm{Kg/m^3}$ and Poisson ratio 0.33. The wing model was clamped at the inboard section and free at the tip. The aerodynamic loads were distributed

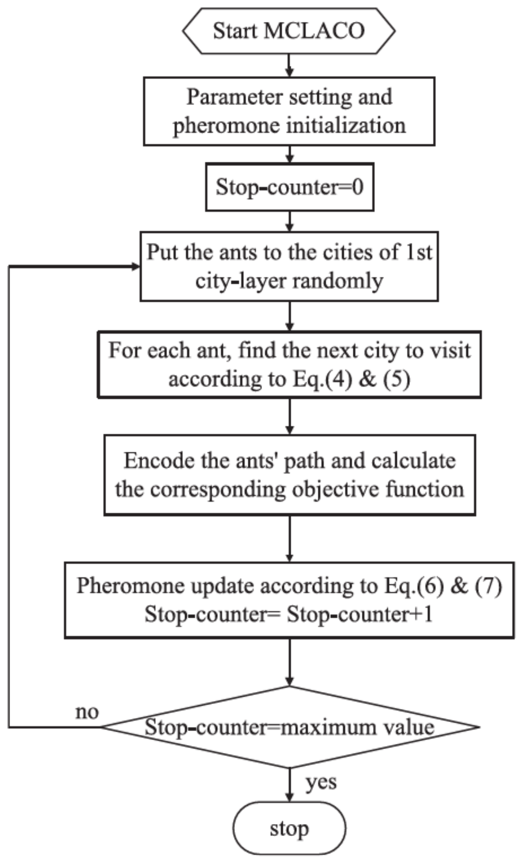

Figure 5. Flow chart of the MCLACO process.

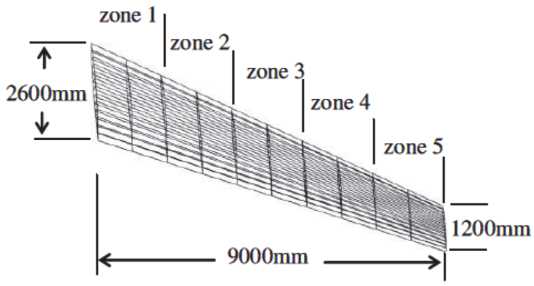

Figure 6. The geometrical and FE model of a wing.

along the span-wise sections from the second next to the root to tip with the value of 11.14 kN, 9.7 kN, 7.1 kN, 6.1 kN, 5.1 kN, 4.55 kN, 2 kN, 0.22 kN and 0.1 kN, which are transferred to nodal force of the wing FE model.

The wing structure was then optimized for a minimum structural weight with an optimum number of wing spar beams and component size subject to stress and stiffness design criteria. Each of the beams' status is defined by a set of topology design variables that varies within {123}. The thickness of the skin and web and the cross section area of the spar cap are included in the size optimization design variables. In order to reduce the design variables, the skin and beams were divided into five zones uniformly along the span and numbered as 1 to 5 from the wing root to tip as shown in Figure 6. The spar caps, web and skin design variables are independent in the five zones. There are total of 137 design variables, including 125 size and 12 topology ones, defined for the initial wing model. Note that the number of size design variables varies with the structure layout, which is determined in the configuration partial topology process.

The stress criterion applied to all the skin, web, beam elements of the FE model is required to be satisfied as a constraint and set in the GBOM when using the NASTRAN SOL-200 module. The stress criterion for the wing structure is expressed as

$$\max(\sigma^*) \leq \sigma^*_{allow} \tag{8}$$

where σ^*_{allow} is the allowed equivalent stress of 140 MPa for all the elements. The equivalent stress σ^* is based on Von Mises equivalent stress (Ugural and Fenster 1975, Govil *et al.* 1979) expressed as:

$$\sigma^* = (\sigma_{11}^2 + \sigma_{22}^2 - \sigma_{11}\sigma_{22} + 3\sigma_{12}^2)^{1/2} \tag{9}$$

where σ_{ij} is the stress component.

In this example, the partial topology process was performed by using MCLACO and the size optimization by employing GBOM in a NASTRAN module. The stiffness constraint was also set for the transverse displacement at the wing tip not to exceed 500 mm. According to the reference (Duan 2005), the parameters taken in this example for MCLACO are listed in Table 1.

To study the robustness of the ACO, the performance was carried out 20 times. In each of the performances, the initial structure layout was not necessarily the starting point since ACO produced its starting point randomly as described earlier. Table 2 shows the resulting optimal design configurations and objective function values in terms of structural weight. These objective

Table 1. Parameter values for the MCLACO process.

Parameter	α	q_0	ξ	ε	ρ	τ	N
Value	0.5	0.8	0.8	0.4	0.6	0.1	12

Table 2. The resulting optimum configurations and structural weight.

Run no.	Topology design solutions	Minimum structure weight (kg)
1	[3 3 1 2 1 1 1 3 2 1 1 2]	547.00
2	[2 2 1 1 1 1 1 3 1 1 3 3]	547.97
3	[1 3 1 1 1 1 1 2 3 1 1 2]	547.48
4	[3 1 2 3 1 1 1 2 2 1 1 3]	548.71
5	[1 3 1 1 1 1 1 1 2 1 2 2]	547.97
6	[2 2 1 1 1 1 1 2 2 1 1 3]	548.71
7	[2 1 1 1 1 1 1 3 2 1 2 3]	550.15
8	[1 1 1 1 1 1 1 1 3 1 1 1]	547.98
9	[1 3 1 1 1 1 1 1 2 1 2 2]	547.97
10	[2 2 1 1 1 1 1 1 3 1 3 2]	550.22
11	[1 2 1 1 1 1 1 3 2 1 3 3]	550.75
12	[2 2 1 1 1 1 1 2 2 1 1 3]	548.71
13	[2 2 1 1 1 1 1 2 3 1 2 1]	550.64
14	[1 2 1 1 1 1 1 1 2 1 3 3]	550.75
15	[2 1 1 1 1 1 1 3 2 1 2 3]	550.15
16	[3 3 1 2 1 1 1 3 2 1 1 2]	547.00
17	[1 2 1 1 1 1 1 3 2 1 3 3]	550.75
18	[2 1 2 1 1 1 1 1 1 1 1 1]	548.12
19	[2 2 1 1 1 1 1 3 1 1 3 3]	547.97
20	[2 2 1 1 1 1 1 2 2 1 1 3]	548.71

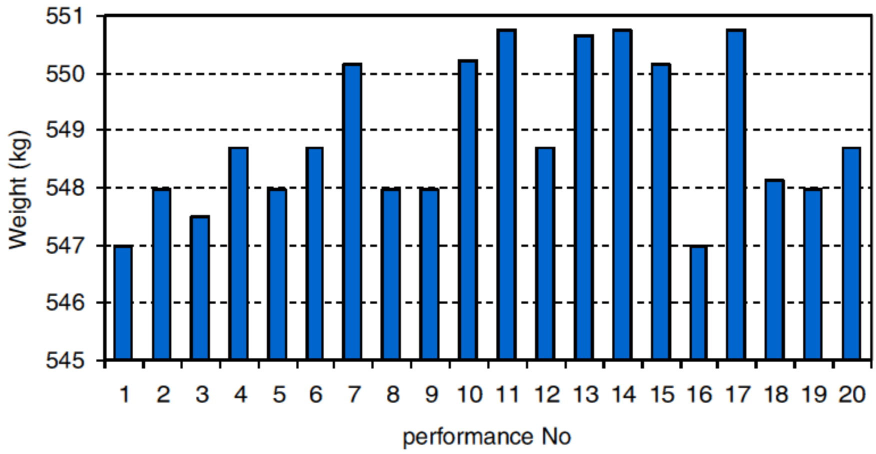

Figure 7. Objective function (weight) results of 20 performances.

function values of the 20 performances are also shown in Figure 7. It is noted that the maximum deviation of the objective function values between all the solutions is less than 0.7% and some of the solutions are identical.

Each of the solutions from the ACO stochastic process represents an optimum structure configuration and weight. In practice, if multi performances were carried out, an average of the results may be taken. For example, the average of the weight results in Table 2 is 548.9 kg. Alternatively a solution may be chosen depending upon not only the structural weight, but also the arrangement of the fuel tank, landing gear and equipment. If only one performance was carried out, the solution could be one of the 20 solutions. In this example, the first performance result from Table 2 is taken for detailed analysis. The optimal result of partial topology and size optimization during the iteration is shown in Figure 8 and Figure 9 respectively. In Figure 8, the minimum value shows the best of the 12 sample results in one generation. The average means the average objective function of the 12 results in one generation during the iterative process. The resulting design solution [3 3 1 2 1 1 1 3 2 1 1 2] represents an optimal structure layout of six beams and three webs.

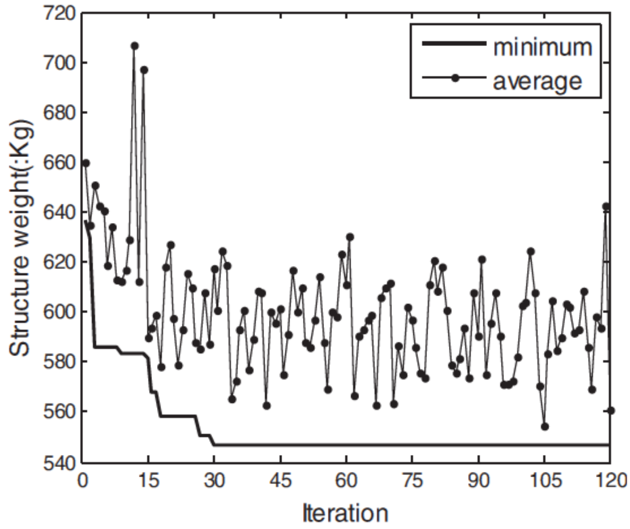

Figure 8. Convergence history of ACO.

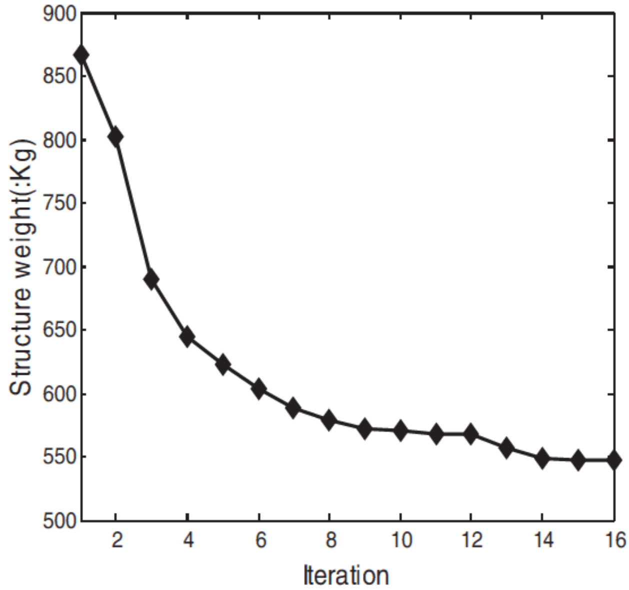

Figure 9. Convergence history of GBOM.

Figure 10 shows the optimal layout obtained by the MCLACO compared with the initial structure layout. Compared to the initial structure layout, three spar beams (Numbers 1, 2, 8) were removed due to small load in the region and three (Numbers 4, 9, 12) were reduced to webs. Table 3 shows the initial, lower and upper bound of the cross section area of the spar beam caps. Table 4 shows the optimized cross section areas of the beam caps. Table 5 shows the optimal skin thickness. It is noted that from zone 1 at the wing root to zone 5 at the tip, the cross section area of the caps and the skin thickness decreases according to the load distribution. For example, the cross section area of spar caps 5, 6 and 7 is much larger than the other beams. It reaches the upper bound in zone 1 and 2. This indicates that the materials in this region are very efficient in load carrying.

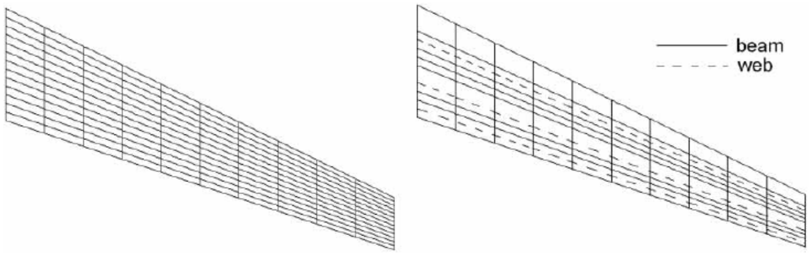

Figure 10. The initial and optimized wing structure layout.

Table 3. Initial cross section area of the beam caps.

	Cross section area of beam caps (mm^2)		
Zone	Low bound	Initial value	Upper bound
1	20.0	300.0	450.0
2	20.0	250.0	450.0
3	20.0	200.0	450.0
4	20.0	150.0	450.0
5	20.0	100.0	450.0

Table 4. The optimal cross section area of spar beam caps (mm^2).

	Zone				
Beam	1	2	3	4	5
3	387.2	385.1	331.1	230.60	20.0
5	450.0	450.0	450.0	383.60	36.1
6	450.0	450.0	448.4	382.20	32.9
7	450.0	449.1	448.3	33.91	20.0
10	234.4	207.5	130.3	20.00	20.0
11	221.6	178.2	72.4	20.00	20.0

Table 5. Optimized skin thickness.

Zone	Low bound (mm)	Initial value (mm)	Upper bound (mm)	Optimal results (mm)
1	2.0	8.0	10.0	7.2
2	2.0	7.0	10.0	5.8
3	2.0	6.0	10.0	3.4
4	2.0	5.0	10.0	2.0
5	2.0	4.0	10.0	2.0

Consequently, the objective function converges to a minimum value of 547 kg. The maximum transverse displacement at the wing tip (node 176) reaches the limit of 500 mm as shown in Figure 11. The stress plot of the wing FE model in Figure 12 shows that the maximum stress 86.6 MPa occurs at the wing root. The results indicate that the stiffness is more critical than the strength in this example.

In this particular example, a minimum weight is obtained by performing both the partial topology and size optimization simultaneously. As shown in Figure 8, the optimized weight is reduced from 636.7 kg in the first generation to 547 kg in the final generation. The partial topology resulted in a structure weight saving of 89.71 kg, a 19.56% reduction of the total weight. Compared to

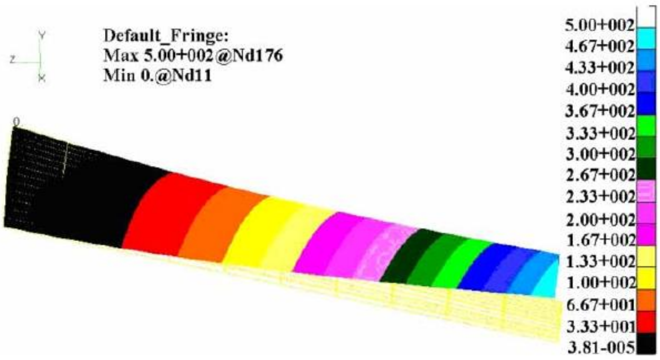

Figure 11. Deformation of the optimized wing structure.

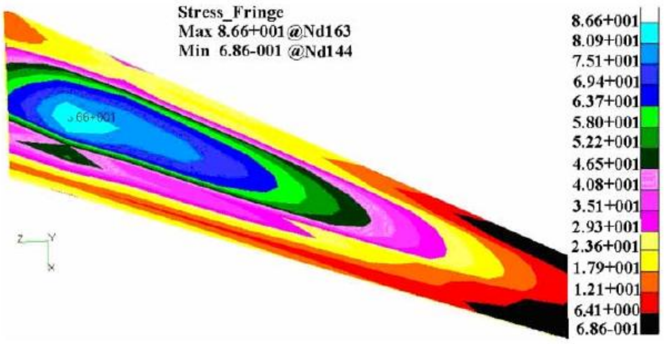

Figure 12. Stress distribution of the wing FE model.

1005.5 kg in the initial design, a total weight reduction of 45.6% has been achieved. This reveals that a more effective optimization can be achieved only if the structure layout is considered in the process. This is because the structure layout related to the load path has significant effect on the structure efficiency.

In practice, more constraints such as the arrangement of landing gear, integral fuel tank and systems will be considered in a wing structure design. More attention should be paid to the selection of a solution for optimum configuration when multi performance is carried out. Nonetheless, the effectiveness and applicability of the proposed approach has been demonstrated though this example. The proposed methodology is very useful for future investigations.

5. Conclusions

This article presents an optimization methodology and process for simultaneous partial topology of structural layout and size optimization of a wing structure. The process is very efficient because it simultaneously solves the layout topology problem by using the proposed MCLACO to deal with the discrete type of design variables and the size optimization problem by using the GBOM to deal with the continuous type of design variables. The example results of a wing structure show that the optimization process in the first few generations is much more effective and resulted in a significant weight reduction. It led to the final solution of total structure weight of 547 kg, which is a weight saving of 45.6% from the initial design. As part of the process, the wing layout topology resulted in a weight reduction by 19.56%, which shows the significance of the structure layout in the whole optimization process. It is noted, however, that the result might be too optimistic since it was based on the conservative initial structure layout in a conceptual design. Nevertheless, the program together with the methodology and process developed in this investigation provides a useful design tool for solving such a typical wing structure optimization problem.

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