Heuristic procedure for optimal structural design of a subsonic aircraft wingbox

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Abstract: The wingbox optimal design is characterized by the intrinsic non-linearity and large scale of the optimization procedures, as well as the inevitable presence of multiple imposed constraints, which limit the capabilities of the gradient optimization methods. Using a parametric finite element model this paper proposes a heuristic structural-optimization algorithm suitable for the stage of detailed design of a wingbox. The approach is demonstrated by solving an optimization problem for the minimum mass of a subsonic jet tapered wing's load-bearing structure while adhering to the constraints of not exceeding the maximum von Mises stress and providing a margin of structural stability. The final evaluation and assessment of the optimization process, as well as the obtained results, revealed that the proposed procedure effectively converges to global minima while taking all of the imposed constraints into account.

Keywords: *wingbox, structural optimization, PSO, FEM, adaptive penalization, subsonic jet*.

1. Introduction

The wingbox design process must balance the opposing requirements of low mass and high structural stiffness. Traditionally, beam finite element models are used to idealize the load-bearing structure of large aspect ratio wings during the early phases of design [21]. The process of determining the needed number of spars, stringers, and ribs, as well as their dimensions, cross sections, structural materials, and relative placements, is defined as initialization of the basic wingbox. At this stage of the design process, relevant statistics or internal layout considerations are frequently used to drive decisions. The acquired results enable for the creation of a more complete finite element model in the future [22, 23].

The required cross-sectional areas and thicknesses of the load-bearing structural components are estimated applying appropriate sizing optimization methods with the objective of minimizing structural mass while not exceeding the material's maximum von Mises stress and maintaining structural stability.

The majority of structural optimization problems are nonlinear, constrained and large in scale, which limits the application of gradient optimization methods [4]. As a result, many heuristic and metaheuristic optimization strategies, as well as optimality criteria approaches, are frequently used. The sizing structural optimization procedure is often referred to as a process for estimating of the optimal values for a large number of structural design variables under a variety of functional and box constraints.

Heuristic optimization methods are best suited for problems with high dimensionality, multimodality or lack of gradient information, mainly because in these kind of methods the extremum is searched stochastically. The ability of these optimization methods to mimic processes and phenomena observed in nature is one of their distinguishing characteristics. Typical heuristic methods for optimization are the genetic algorithms [7, 11], the optimization with simulated annealing model [14], etc. Common drawback of the genetic optimization methods is their requirement for design variables and objective encoding/decoding, as well as the challenges associated with the handling of the constraints. Another type of heuristic optimization procedures replicate the social interaction between individuals with common interests inside a distinct group. Typical examples in nature are the fish schooling, the flock of birds or the bee swarm (Fig. 1). These optimization approaches allow for parametric manipulation of the group's individual and collective intelligence. The most well-known examples of this family of algorithms include optimization methods based on an ant colony model [5] or on a swarm of intelligent particles, known as Particle Swarm Optimization or PSO [13].

Fig. 1 Some heuristic algorithms replicate the social interaction between individuals in a group

The primary benefit of the heuristic approach to structural optimization lies in its ability to perform direct global optimization. The main challenge in heuristic optimization methods is taking into consideration all of the imposed functional and box constraints. Several strategies for eliminating this issue have been proposed as a result of numerous studies in this field. Among the most commonly used are the penalty method, the constraint aggregation method, the method of the combined KS-function [15, 16], etc. The efficient handling of the imposed constraints generally depends on the level of control over the optimization process. As a result, the current paper investigates the concept of heuristic sizing optimization of load-bearing structural components for the wingbox of a tapered wing by structural optimization approach based on a swarm of intelligent particles (PSO).

2. Methodology

The method of optimization by a swarm of intelligent particles is based on the notion that social exchange of information among individuals in a specific group provides an evolutionary advantage [13]. The approach has been used at different stages of design in electronics, automation, energy, and mechanical engineering. Particle swarm optimization is one of the most popural and state-of-the-art research methods in the field of aircraft structural optimization [2,3,6,8,12,19,20].

The optimization process is stochastic in nature and is carried out by updating the positions of each particle by a velocity vector, the magnitude and direction of which are determined according to the individual and collective achievements of the particles in the swarm (Fig. 2). Convergence to the extremal value is achieved by moving particles within the boundaries of the feasible search space via mutual sharing of information based on individual and collective memory. As a result, the position of each particle is updated depending on the social behavior of the entire swarm, which adjusts itself to the search space, concentrating on the areas with the best values of the objective function.

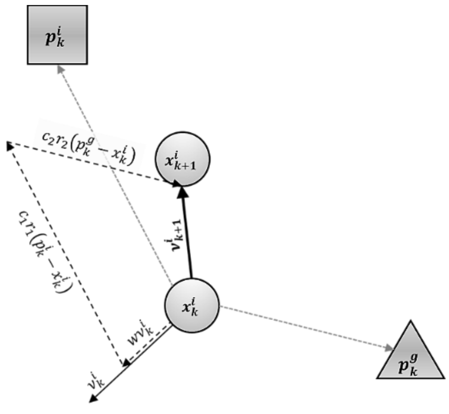


Fig. 2 Basic principle of updating the position and velocity of each of the particles in the swarm

In the *N*-dimensional search space, the position of each particle is represented by an *N*-dimensional vector $\boldsymbol{x} = \{x_1, x_2, \dots, x_i, \dots, x_N)^T$ and its velocity by another *N*-dimensional vector $\boldsymbol{v} = \{v_1, v_2, \dots, v_i, \dots, v_N)^T$.

Mathematically, the position x of the particle i in the iteration $k + 1$ is determined as follows:

(1) $$x_{k+1}^i = x_k^i + v_{k+1}^i \Delta t \, ,$$

where v_{k+1}^i is the updated velocity vector of the particle, Δt is the time step of the process, which is assumed to be equal to one.

The velocity vector of the particle is updated according to the following expression:

$$v_{k+1}^i = wv_k^i + c_1 r_1 \frac{p_k^i - x_k^i}{\Delta t} + c_2 r_2 \frac{p_k^g - x_k^i}{\Delta t}, \tag{2}$$

where v_k^i is the velocity vector at iteration k; p_k^i and p_k^g represent, respectively, the best position of the particle i and the best position achieved by the whole swarm in the boundaries of the search space up to the current iteration; r_1 and r_2 are uniformly distributed random numbers from 0 to 1; c_1 is the so-called cognitive parameter which indicates the degree of confidence in the individual achievements of the particles; c_2 is the so-called social parameter that indicates the degree of trust in the collective achievement of the swarm; w represents the so-called inertia coefficient, which scales the velocity vector throughout the optimization procedure.

In order to maintain the dynamic stability of the swarm, the sum of the coefficients c_1 and c_2 must not exceed 4 [13, 17].

In order to account for the imposed functional constraints, an adaptive parameterless penalty function approach has been applied [17]. The penalty coefficient p_j is based on the arithmetic mean of the objective function and the degree of violation of each of the constraints in the current iteration:

$$f'(x_k) = \begin{cases} f(x_k), if\ x_k\ is\ feasible \\ f(x_k) + \sum_{j=1}^{m} p_j \hat{g}_j(x_k)\ \ , if\ x_k\ is\ not\ feasible \end{cases} \tag{3}$$

$$p_j = \left|\bar{f}(x_k)\right| \frac{\bar{g}_j(x_k)}{\sum_{l=1}^{m}[\bar{g}_l(x_k)]^2} \tag{4}$$

$$\bar{g}_j(x_k) = \frac{1}{n}\sum_{k=1}^{n} \max\left[0, \hat{g}_j(x_k)\right] \tag{5}$$

where $\bar{f}(x_k)$ is the arithmetic mean of the objective function in the swarm at iteration k, $\bar{g}_j(x_k)$ is the arithmetic mean of the j-th functional constraint in the swarm at iteration k. Thus the penalty coefficients are distributed in the swarm in such a way that those particles that have violated the imposed constraints the most will be sanctioned more than others.

Flowchart of the algorithm for heuristic sizing structural optimization of the wingbox of a tapered wing by a swarm of intelligent particles is presented in Fig. 3.

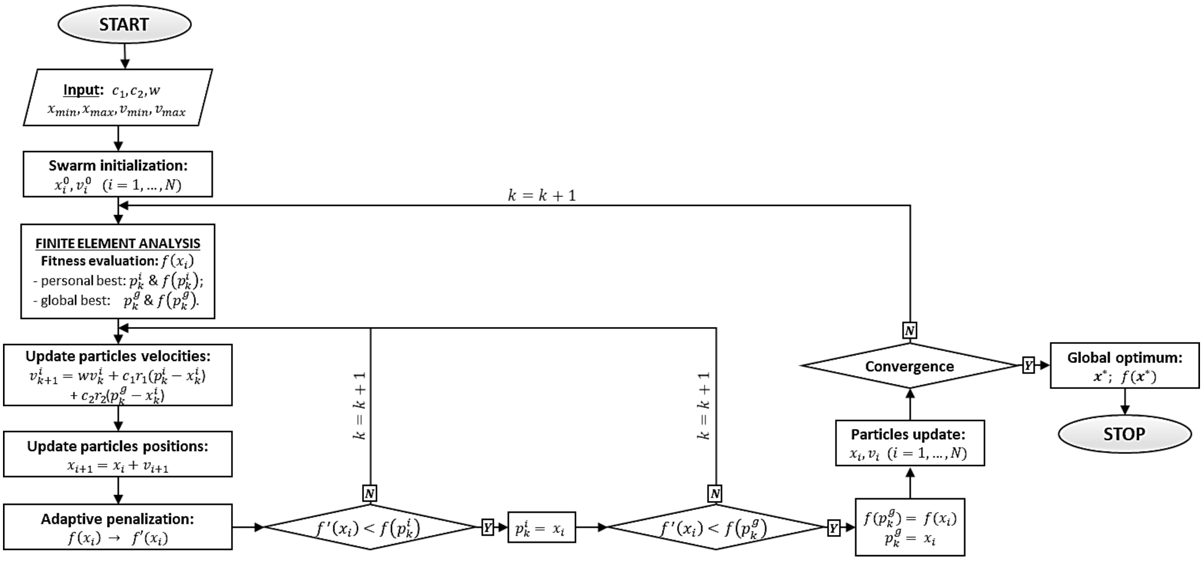


Fig. 3 Flowchart of the heuristic sizing structural optimization procedure for wingbox detail design

3. Numerical experiment

The proposed structural optimization procedure is demonstrated by applying it at the stage of detailed design of a wingbox for the tapered wing of a subsonic jet aircraft with specific wing load 585 kg/m^2. The aerodynamic load is distributed approximately according to an elliptical law and corresponds to the conditions at steady level flight with cruising speed $V = 750\ km/h$ (Fig.10). Fig. 4 shows the values of the basic geometric parameters of the wing.

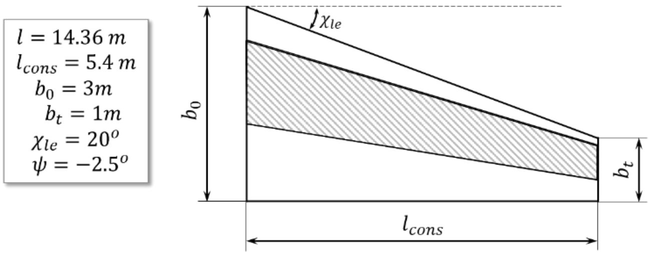


Fig. 4 Wing planform basic parameters

The stress and strain evaluation of the wingbox structure is performed by the finite element method. A parametric finite element model was synthesized using the APDL programming language. The model is numerically validated in accordance with [1]. Table 1 shows the structural materials, the selected types of finite elements and the variable parameters in model of the wingbox and its load-bearing components.

Table 1: Basic parameters of the load-bearing components

Load-bearing component	Structural material	Finite element	Variable parameter
Front spar flange	2618	3-D 2-node BEAM	$0.01 \leq R_{fl.fr} \leq 0.08$
Front spar web	2618	3-D 4-node SHELL	$0.001 \leq \delta_{web.fr} \leq 0.01$
Rear spar flange	2618	3-D 2-node BEAM	$0.01 \leq R_{fl.r} \leq 0.08$
Rear spar web	2618	3-D 4-node SHELL	$0.001 \leq \delta_{web.r} \leq 0.01$
Upper skin panels	7075-T6	3-D 4-node SHELL	$0.001 \leq \delta_{skin.up} \leq 0.005$
Upper skin stringers	7075-T6	3-D 2-node BEAM	$0.005 \leq R_{str.up} \leq 0.01$
Bottom skin panels	2024-T3	3-D 4-node SHELL	$0.001 \leq \delta_{skin.bot} \leq 0.005$
Bottom skin stringers	2024-T3	3-D 2-node BEAM	$0.005 \leq R_{str.bot} \leq 0.01$
Ribs	2024-T3	3-D 4-node SHELL	$\delta_{\text{реб}} = 0.003$

A structural optimization problem is defined with the objective of minimizing the wingbox mass while satisfying the compatibility condition between the nodal loads and their deflections, as well as the imposed functional constraints on equivalent stresses and the buckling load factor and also the box constraints on design variables:

$$\begin{gathered} \min m_{wingbox} \\ KU = F \\ \sigma_{v\,max} - \sigma_{allowed} \leq 0 \\ \lambda_I \geq 2.5 \\ 0.001 \leq \delta_{skin.bot} \leq 0.005 \\ 0.001 \leq \delta_{skin.top} \leq 0.005 \\ 0.001 \leq \delta_{web.fr} \leq 0.01 \\ 0.001 \leq \delta_{web.r} \leq 0.01 \\ 0.005 \leq R_{str.bot} \leq 0.01 \\ 0.005 \leq R_{str.up} \leq 0.01 \\ 0.01 \leq R_{fl.fr} \leq 0.08 \\ 0.01 \leq R_{fl.r} \leq 0.08 \\ \sigma_{allowed} = 400\ MPa \end{gathered} \tag{6}$$

A swarm of 20 particles with a cognitive coefficient $c_1 = 1.5$ and a social coefficient $c_2 = 0.5$ was initialized. The inertia coefficient w changes dynamically from 0.9 to 0.4 during iterations. The convergence criteria for of the optimization procedure is the variation σ^2 of the objective function in the swarm. The optimization procedure converges to a global extremum at a point in the search space, characterized by the following values for the vector of design variables:

Optimal design variables

- $R_{fl.fr} = 38.86\ mm$
- $\delta_{web.fr} = 10\ mm$
- $R_{fl.r} = 10.2\ mm$
- $\delta_{wall.r} = 14.9\ mm$
- $\delta_{skin.up} = 3\ mm$
- $R_{str.up} = 15\ mm$
- $\delta_{skin.bot} = 8\ mm$
- $R_{str.bot} = 2.84\ mm$

Optimal wingbox parameters

- $m_{wingbox\ min} = 529.3\ kg$
- $\sigma_{z\ max} = 202.6\ MPa$
- $\sigma_{z\ min} = -275.6\ MPa$
- $\sigma_{v\ max} = 382.3\ MPa$
- $u_{y\ max} = 0.1916\ m$
- $\lambda_I = 2.795$

Fig. 5, 6, 7 and 8 present the plots for the change of the objective function and its variation in the swarm, as well as the values of the functional constraints for each particle of the swarm during the optimization procedure. The final assessment of the optimization process, as well as the obtained results, reveal that the proposed procedure converges to global minima while satisfying all of the imposed constraints.

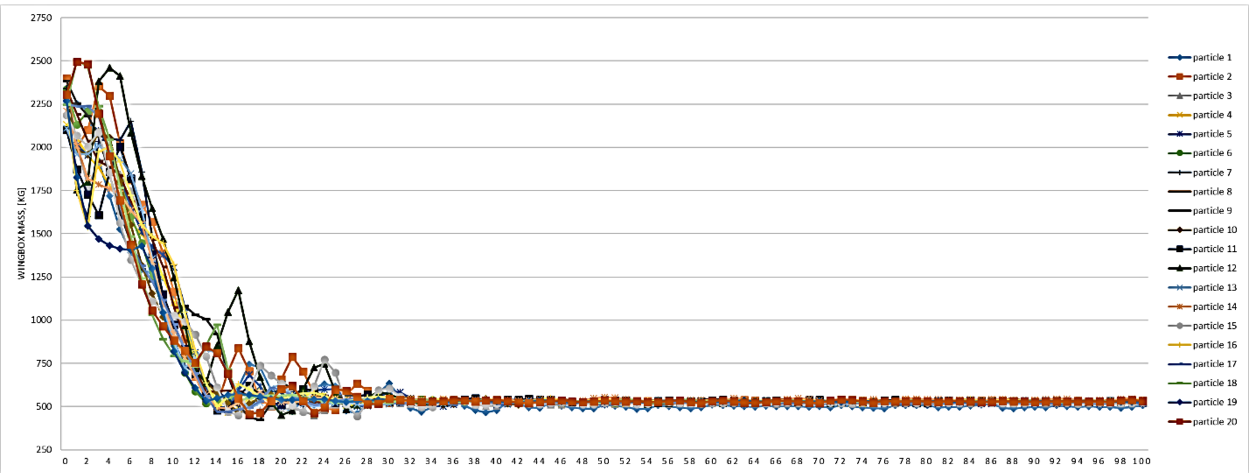


Fig. 5 Convergence of the objective function: wingbox minimal mass, [kg]

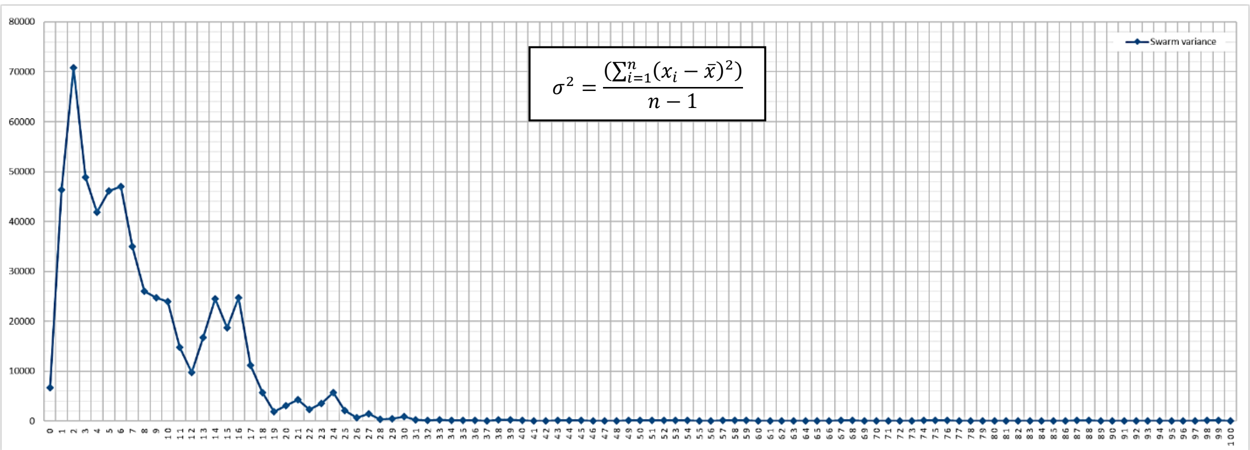


Fig. 6 Change in the variation σ^2 of the objective function in the swarm

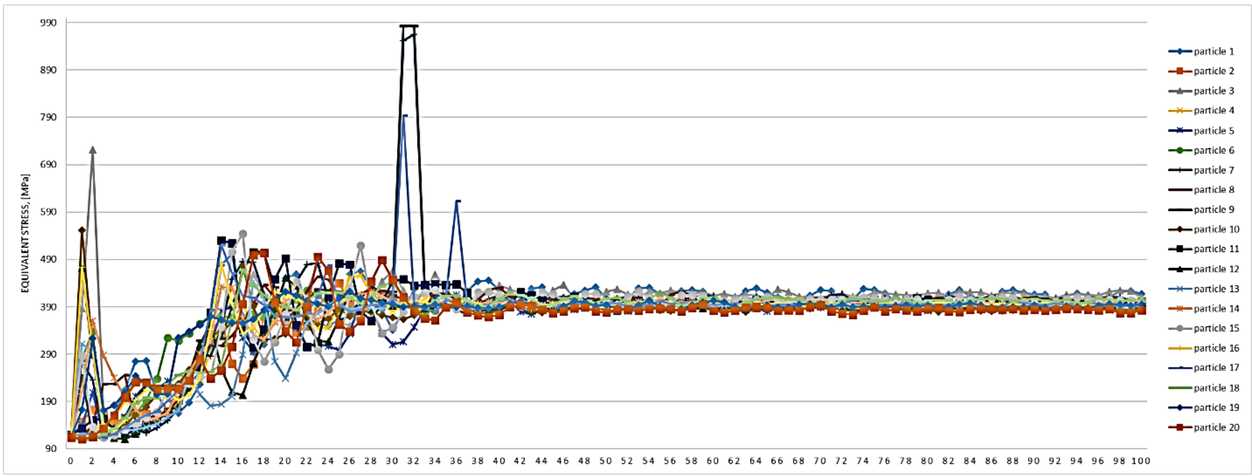


Fig. 7 Convergence of the maximum von Mises stress $\sigma_{v\,max}$ towards the imposed constraint

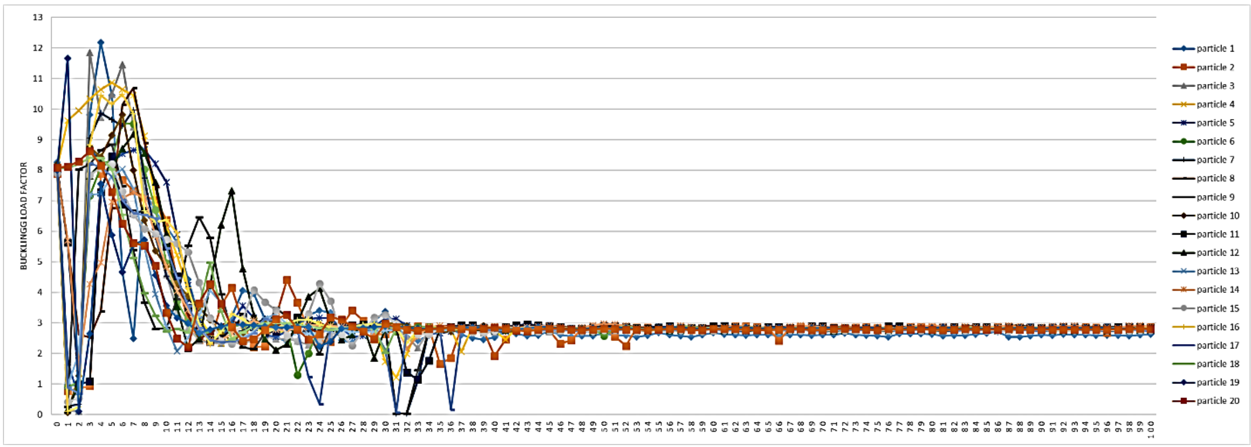


Fig. 8 Convergence of the buckling load factor λ_{min} towards the imposed constraint

Fig. 9 shows the obtained optimal wingbox. The boundary conditions for the finite element analysis are visualized in Fig. 10. The vertical displacements, normal and equivalent stresses as well as the distribution of the buckling load factor in the optimal wingbox as a result of the applied boundary conditions are presented in Fig. 11.

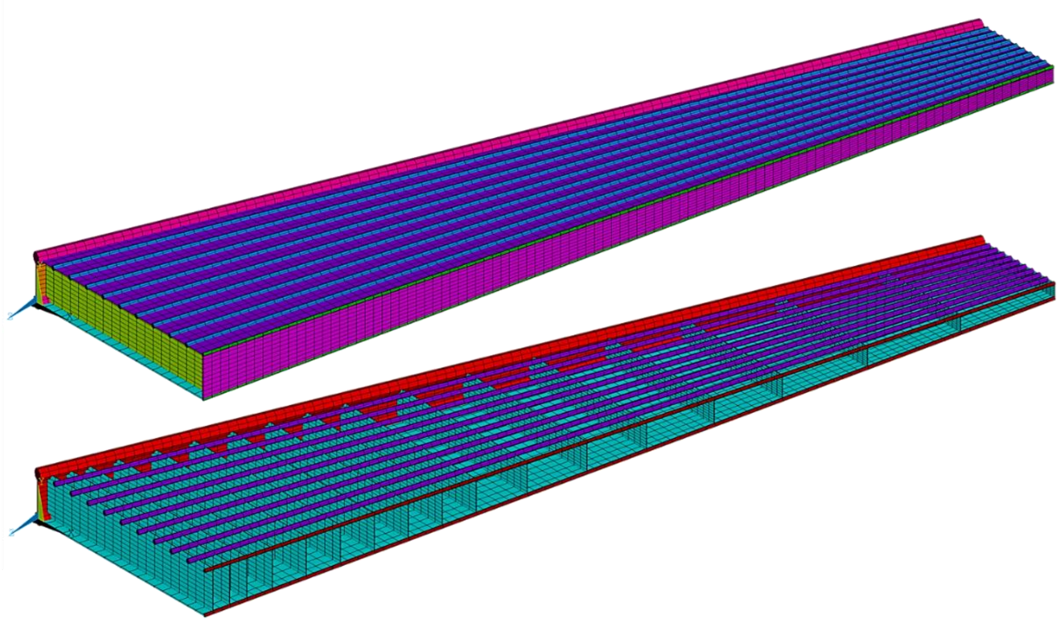
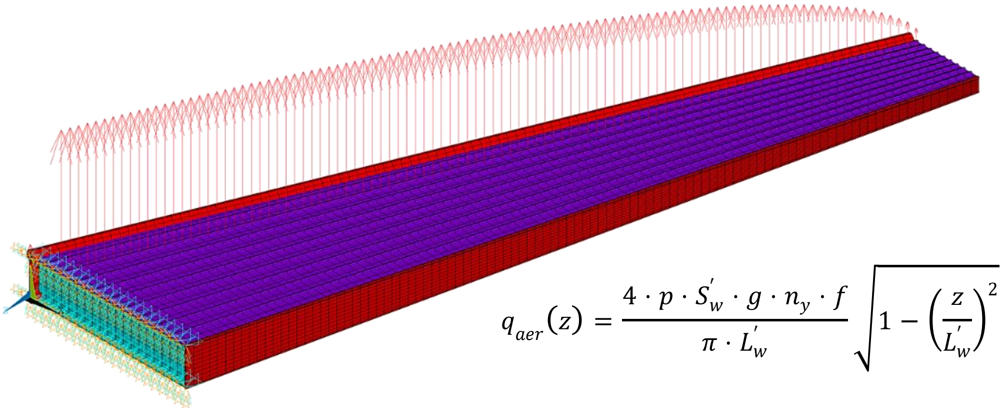
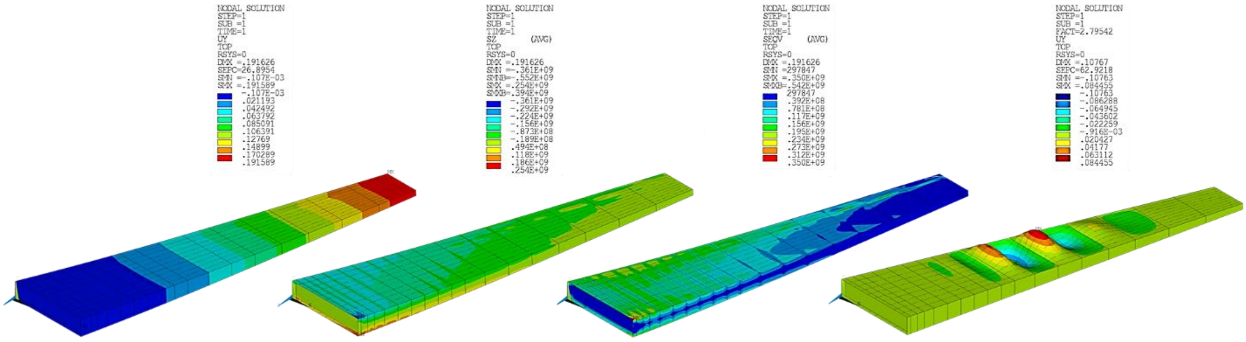


Fig. 9 Optimal wingbox load-bearing structure



$$q_{aer}(z) = \frac{4 \cdot p \cdot S_w' \cdot g \cdot n_y \cdot f}{\pi \cdot L_w'} \sqrt{1 - \left(\frac{z}{L_w'}\right)^2}$$

Fig. 10 Boundary conditions for the finite element analysis



$u_{y\,max} \approx 0.19\ m$ $\quad$ $\sigma_{z\,min} \approx -361\ MPa$, $\sigma_{z\,max} \approx 254\ MPa$ $\quad$ $\sigma_{екв\,max} = 350\ MPa$ $\quad$ $\lambda_I = 2.795$

Fig. 11 Vertical displacements, normal and equivalent stresses, distribution of the buckling load factor in the optimal wingbox

4. Conclusion

A heuristic technique based on a swarm of intelligent particles is suggested for structural optimization of a wingbox. Based on a parametric finite element model, an optimization procedure for the minimum mass of the load-bearing structure is implemented under the condition of not exceeding the maximum allowable equivalent stress and providing a margin of stability for the structure by varying the values of eight design variables. The key issue for the heuristic structural optimization approach was to account for all of the constraints. For this reason, the algorithm modifies the objective values of the individual particles using a parameterless adaptive penalization technique. The optimization process and the results demonstrate that the proposed method takes into consideration all of the specified constraints and successfully converges to a global minimum.

The proposed heuristic structural-optimization procedure can be further developed in the future through research on the following topics:

- investigation of the influence of cognitive and social coefficients on the efficiency of the optimization procedure;
- investigation of the possibility for estimation of the required number of spars, ribs, and stringers as a result of heuristic layout optimization considering different internal layout requirements;
- investigation of the possibility for simultaneous handling of boundary conditions for more than one load case;
- integration of topology optimization procedure for optimal distribution of structural material in the load-bearing components.

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