Transdisciplinarity and the Future of Engineering
B.R. Moser et al. (Eds.)

doi:10.3233/ATDE220675

Multi-Objective Optimization of Composite Structure Using Rule-Based Parametrization

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Abstract. Ultra-light unmanned aerial vehicles (UAV) benefit from use of composite materials due to weight savings and ease of manufacturing for piece production. However, complex shape and internal structure of wings limits the use of hand calculations that can be employed to optimize the structure. Therefore, design process can greatly benefit from the FEM (Finite Element Method) calculations coupled with CFD (Computational Fluid Dynamics), composite mechanics and composite failure theories. This multi-physics approach allows to accurately describe behavior of a wing during flight. Due to nonlinear response of a system after changes in wing design and flight characteristics, we present a method of optimization using artificial neural networks. This allows to accurately describe influence of given parameters on the stress and strain distribution as well as reduce number of design points. Material data has been gathered from experimental tests of simple specimens. Based on this data more complex elements were designed using FEM and tested experimentally in order to validate numerical calculations in a transdisciplinary rapid prototyping exercise. Advanced failure criteria not only predicted failure but also failure mechanism, thus catastrophic failure can be prevented. In the future this multi-physics approach can incorporate numerical analysis of manufacturing and curing process therefore reducing need for experimental validations. Further development of neural networks will lead to them being directly implemented into FEM codes.

Keywords. composite modeling, parametric optimization, Finite Element Method, Computational Fluid Dynamics, neural networks, model validation

Introduction

The design process of modern ultra-light unmanned aerial vehicles (UAV) in smaller companies, that develop and manufacture single series aircrafts, begins by hand calculations. Calculations are backed by standards and recommendations, but in many cases aircrafts that are being designed do not fit in those design brackets. Combined with the fact that aerodynamic forces acting upon wings are hard to predict and that UAV are made out of sandwich-structured composites which deform nonlinearly makes design process an ideal place to introduce Finite Element Method coupled with a optimization scheme.

This is particularly important for ultra-light structures, such as the High Altitude Long Endurance Unmanned Aerial Vehicle Twin Stratos (HALE UAV TS) family (Fig.

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1), which includes the TS12 and TS17, being built by the scientific and technical consortium [1]. TS is a UAV in a double-hull with A-type tail. The drive is made of electric motors and the hybrid power source is photovoltaic cells connected to a buffer lithium-ion battery. The distinguishing features are: very large size and low weight, which forces the use of a special design methodology including energy optimization through the use of Model -Based Design, the use of ultra-light construction. The design methodologies used in this case were tested by consortium members in aviation [2, 3] as well as automotive [4] and robotic [5] applications. Design methods for thin-walled structures, on the other hand, were implemented through the use of generative design [6]. The structural optimization of the structure is a particular challenge.

In this article we present a way of overcoming difficulties associated with FEM calculations, mainly focusing on reducing calculation time and number of calculations needed to land on optimal design. Previous works [7-10] show multiobjective optimization where ply-order, ply-number and slight changes to geometry were analyzed. This work extends complexity of composite structure analysis by including more failure criterions, better suited for this specific case according to [11], as well as combining multiple load cases in one optimization scheme. Another improvement is the use of nonlinear material behavior based on experimental data. Composite structure has been recreated in ANSYS ACP software as it supports number of most used failure criterions and advanced fiber orientation tools [12]. Being part of ANSYS product family it also benefits from seamless integration with FEM solvers such as ANSYS Mechanical and LS-DYNA. For optimization process LS-OPT software was used [13]. Coupling between FEM and optimization calculations was achieved using Excel spreadsheet, thus minimizing the need for self-developed scripts to a minimum. Neural networks were used in this work due to inability to fit response surfaces based on polynomial functions to design points [14]. The overarching goal of this paper is to increase strength of wing structure without drastically increasing its mass as to allow unlimited flight duration at the altitude of 20 km resulting from the positive energy balance of the power supply system.

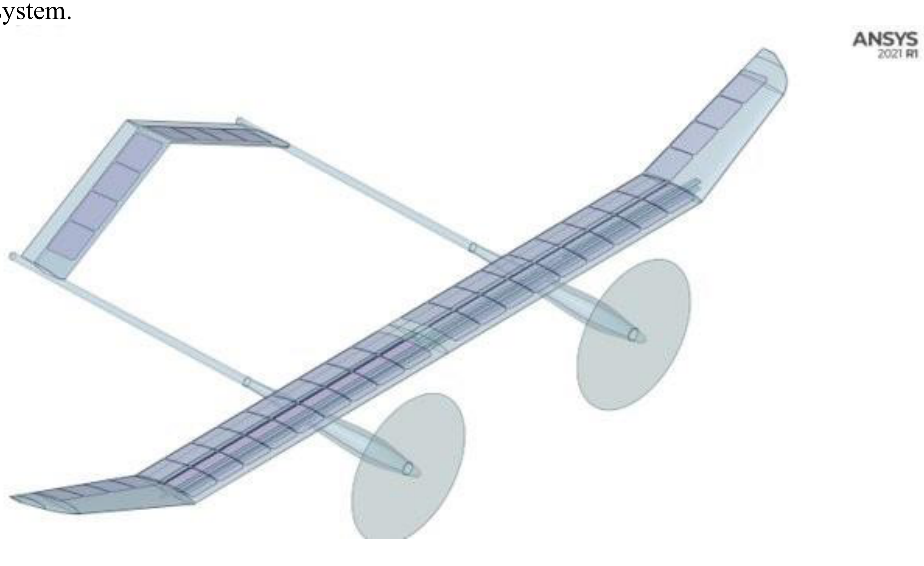

Figure 1. Geometry prepared for optimalization in ANSYS SpaceClaim.

1. Methodology of numerical calculations

Hand calculations can only roughly predict magnitude of stresses in a wing structural members, thus requiring large factors of safety when choosing their size and location. However modern lithium-ion batteries do not possess enough energy density to justify implementation of such high factors of safety. One of more economical solutions for acquiring accurate stress distribution is to use numerical calculations based on Finite Element Method. Those numerical calculations are grounded on set of assumptions and simplifications. Their goal is to approximate real life model behavior using least computing power together with minimizing time needed to prepare calculations. This however requires adequate experience and know-how frequently coupled with debugging process. The reason is that advanced numerical simulation preparation process has not been streamlined and there are large differences between each process. Wing design simulation is especially prone to errors resulting from bad numerical modeling as it requires combination of multi-physics calculations (one way coupling between fluid and wing structure) with advanced material models that need to be calibrated by experiments.

1.1. Starting geometry

Starting geometry was received from researchers tasked with developing preliminary structural design. Weight and location of electric equipment was received from another group of engineers specializing in electric propulsion. First step in reduction of amount calculations needed is clever geometry preparation. Due to existence of symmetry plane geometry can be reduced in half. Wing structure is made out of multiple material layers that do not have uniform thickness across whole wing. Instead of modeling the thickness as a geometric feature it can be included in material definition of each composite layer. Therefore, wing structure is modeled as a thin shell. This approach is only valid for structures where thickness is much smaller than width and length as well as radius of curvature being reasonably large. Any instrumentation located inside the UAV was reduced to point mass and connected to wing structure in a way that does not arbitrarily increase stresses around a connection.

1.2. Aerodynamic data

In order to fully understand the response of a wing during a flight data from most critical flight phases has to be gathered. This data can take a form of static pressure distribution over a wing and hull computed using CFD (Computational Fluid Dynamics). Three different flight phases have been calculated by aerospace engineer, where values of wing angle of attack and UAV horizontal speed were taken from standards. Table 1 shows those values.

Table 1. Flight parameters for different phases.

Name of phase	Speed [m/s]	Angle of attack [deg]
Max speed	37,95	0
Max angle of attack	10,97	14,9
Upside down	24,81	7,45

Calculations have been carried out in ANSYS Fluent which is leading software when it comes to CFD. Because the analyzed fluid was air at normal conditions the flow is turbulent and adequate turbulence model had to be chosen. Most commonly k-ω SST turbulence model [9] is used, that uses blending function to apply k-ε model at domain inlets, k-ω in a vicinity of walls and blends those models in space between those boundary conditions. Meshed domain included enough space in front and after the UAV to allow stream stabilization and eddy formation. Additionally polyhedral mesh was generated to reduce number of cells. In order to properly capture boundary layer, that is responsible for pressure and viscous forces acting upon the wing, inflation layers were used. Results of static pressure distribution for max angle of attack flight are presented on figure 2.

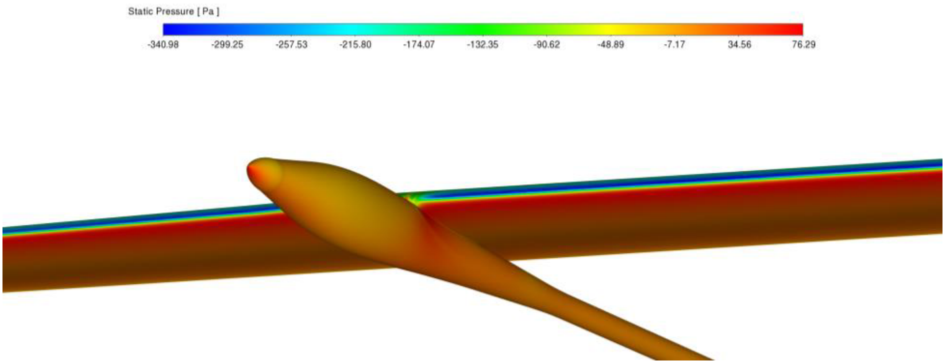

Figure 2. Static pressure distribution over UAV for max angle of attack flight.

1.3. Parameter identification

The need for experimental material parameters for composite materials is higher than for metals due to significant influence of manufacturing process on resultant material properties. In this paper we present semi-automatic method of acquiring material data form tensile testing by curve fitting using LS-OPT functionality coupled with calculations in LS-DYNA. Multiple tensile tests of simple rectangular specimens with different fiber directions were performed by group of researches specializing in composite manufacturing and testing. Each test produced a

Figure 3. Experimental specimens and corresponding numerical model.

unique stress-strain plot. Those plots were then imported into LS-OPT and numerical models imitating real samples were prepared. By optimizing numerous parameters using different fiber direction simultaneously it was possible to acquire one set of material input parameters. Figure 4 shows LS-OPT flowchart that uses two different fiber orientation analyses and iterative optimization scheme.

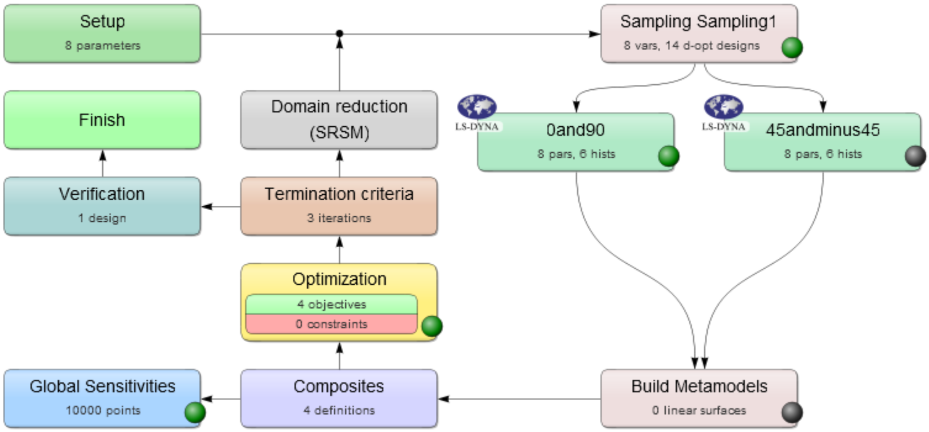

Figure 4. Flowchart for composite parameter identification.

1.4. Failure theories

Failure analysis of composites is significantly more complex than for isotropic materials due to multiple failure modes and orthotropic material behavior. This fact leads to large number of available failure criteria. It is the engineer's duty to correctly select adequate criterion or to apply multiple criterions simultaneously. Structure of a wing presented in this paper consist of Carbon/Epoxy woven a unidirectional composites and sandwich structure composites with honeycomb core and Carbon/Epoxy face skin. One of the objectives of optimization is making sure that most likely failure mode will not lead to catastrophic failure. Therefore Tsai-Hill and Tsai-Wu were excluded as they do not differentiate between different failure modes. Because of moderate curvature on most critical parts of wing the Puck 2-D failure criterion was chosen. To evaluate sandwich composite behavior additional face skin wrinkling and core failure criterions were added. As a result, it was possible to predict 7 different failure modes. The preferable failure mode in tension was fiber failure and in compression it was face wrinkling.

1.5. Mesh generation and calculations

Shell mesh with quadratic shape functions was generated once and used for every calculation. As a result, big chunk of computational time was saved. Due to complex shape of some bodies small percentage of mesh used triangular elements although quadrilateral elements are strongly recommended. Mesh sensivity study was performed to generate coarsest mesh that did not differ in results from very fine mesh more than 5%. As a result, number of elements was decreased from around 2 million to only 130 thousand. This approach was combined with densification of mesh in areas with high gradients of stresses. Nonlinearities in the model exist in form of geometric and material nonlinearities, thus Newton-Raphson method was used to iteratively solve each case. This significantly increases calculation time but getting good quality results without including nonlinearities is impossible. Each case took approximately 90 minutes to solve on machine using 4 core Intel Core i7-6700HQ 2.60GHz CPU and 16 GB of RAM.

2. Optimization

2.1. Rule-based parametrization

ANSYS ACP allows many different ways to change layer stackup, composite layer thickness, fiber orientation and layer connections. In order to minimalize number of variables rule-based parametrization was used. This approach is based on generating virtual 3D entities or importing geometries from external sources, that combined with Boolean operations can select arbitrary set of elements. Figure 5 shows combined planar and tube rule-based element selection which was parametrized to change width or length of green stripe. This stripe was then used to lay additional unidirectional carbon composite layer. By combining rule-based parametrization with shell elements it was possible to completely skip mesh generation step. In order to control fiber direction in each optimized layer Excel spreadsheet was used with added functionality of logical operators.

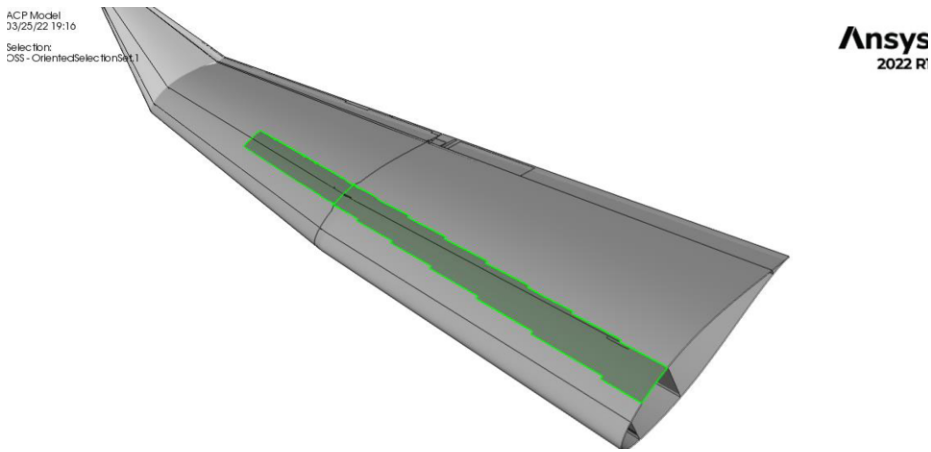

Figure 5. Rule-based element selection example.

2.2. Design parameters

Crucial point of every optimization calculation is identification of input and output parameters that are important in terms of their influence on analyzed model and set of goals that have been established. As a results of material types and parameters being imposed in advance as well as approach that does not allow changes in location of ribs, spars and modifications to airfoil profile this task was somewhat facilitated. Nevertheless, almost infinite number of layer stackups, fiber orientations and rule-based selections was possible. It was necessary to make some input parameters dependent on one another and make sure that physically impossible combinations were eliminated (for example a stackup layer where two plies are separated by void). Also rule-based selection shapes were reduced to simple rectangular areas as to further cut down on parameter number. Output parameters included most likely to occur failure mode, area of carbon/epoxy composite, number of elements that fulfill one of failure criterion in more than 90% and maximum vertical displacement of hull and wing tip. Figure 6 shows integration of each used module inside ANSYS Workbench together with imports of external pressure data generated from CFD calculations and integration of Excel spreadsheet that is used to exchange data with LS-OPT.

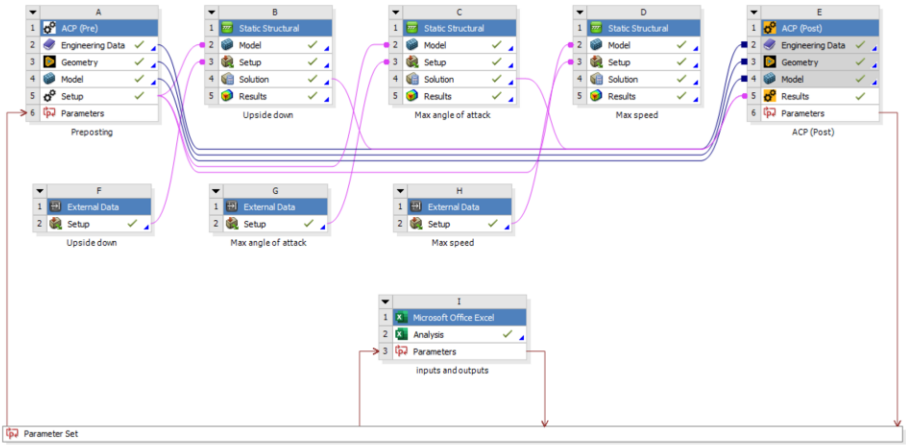

Figure 6. Graphical workflow representation in ANSYS Workbench.

2.3. Neural networks

In general, neural networks can be thought of as computing devices consisting of numerical units called neurons that are connected to each other in very specific way [16]. Each neuron can be located on so called layer shared with other neurons and connected to neurons in layer above and below. Those connections have specified weights and biases that change during "learning" based on information from training algorithm. In this case training algorithm steered network parameters towards minimizing mean squared error between generated response surfaces and design points. Quality of training data greatly affect accuracy of generated response surfaces thus all previously mentioned steps were taken to minimalize numerical error that can occur due to badly prepared model. The minimal number of data points required for network training is related to the unknown complexity of the underlying response surface [16]. A large number of designs can lead to so-called "curse of dimensionality". In case of this optimalization task we observer a large number of input parameters that do not significantly influence output parameters, as a result neural network-based approach performed better than one based on polynomial approximation due to ability to set outgoing weights from a particular input to zero, thus effectively ignoring this input parameter. Goodness of fit plots for neural network method and polynomial approximation method are given in figure 7.

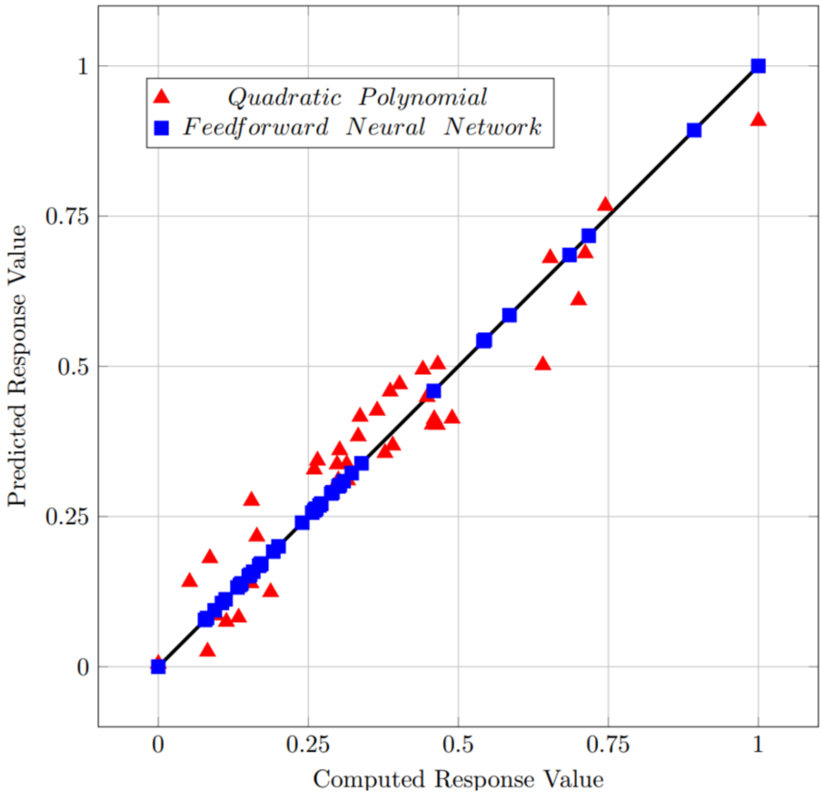

Figure 7. Goodness of fit plot.

2.4. Results

Numerical calculations have shown that case regarding flight with maximum speed and zero angle of attack generates highest stresses and wing tip deformation. Optimization has produced three design point candidates in which most likely failure mode is face wrinkling on bottom part of the wing, and maximum value of failure criterion is around 90%. Carbon/Epoxy composite layers on spars have been drastically rearranged but total area increased only slightly. Maximum wing tip deformation for max speed case has been reduced from 226 mm to 77 mm. Figure 8 shows comparison between starting design and one of design point candidates. Note that displacements were scaled 5 times for ease of comparison.

3. Conclusion

The presented method enables relatively easy optimization of complex composite structures without the use of high computational power. It takes into account structural, material, aerodynamic and flight mechanics aspects. In addition, the results are easily interpreted, which significantly increases the sense of understanding the phenomena occurring during the operation of the UAV ANSYS ACP and LS-OPT are both very powerful tools that enable even unexperienced users to prepare complex numerical models and advanced optimization analysis. Performed numerical optimalization proves that it is possible to significantly improve UAV wing design without large geometric changes. It also shows that wing design parameters do not exhibit linear dependence, and their influence is hard to predict. The use of neural network approach for surface response generation is justified due to inability of standard polynomial approximation to generate satisfactory results. This work can be further expanded by including geometry transformations coupled with mesh morphing. Also honeycomb internal structure can incorporated into input parameters. Final and most difficult to achieve extension of this approach would be incorporation of CFD calculations for airfoil shape and dimensions optimization. Optimization of wing structure is only part of a larger project aimed to develop High Altitude Long Endurance Unmanned Aerial Vehicle called Twin Stratos [1]. This project is highly transdisciplinary and involves many stakeholders who specialize in fields such as aerodynamics, aviation, electric propulsion, electronics, structural design, material engineering and more. Optimized layer locations and orientations, as well as locations of high stress within structure will be passed back to researchers mentioned in subsection 1.1 for further processing and will lead to changes in structural design. Twin Stratos UAV is expected to serve as a platform for various types of sensors enabling the measurement of atmospheric pollutants both during the day and at night. As fossil fuel suppliers in Europe are being promptly replaced, it will be beneficial to observe how different grades of fuels from individual suppliers influence air quality over Europe.

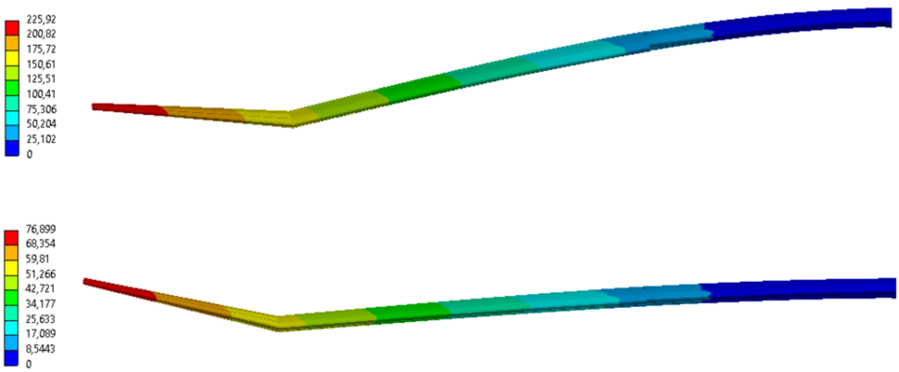

Figure 8. Displacement map for initial (top) and optimized (bottom) model.

Acknowledgement

This research was partially founded from EEA and Norway Grants 2014-2021 and was partially carried out in the framework of the project No. NOR/POLNOR/LEPolUAV/0066/2019: *Long-endurance UAV for collecting air quality data with high spatial and temporal resolutions*" and the program: *Student Scientific Associations Create Innovations* founded by the Ministry of Education and Science and carried out partially under the project No. SKN/SP/496278/2021: *Optionally Piloted aErial Research plAtform (OPERA)* and Individual Study Programs implemented in the form of Project Based Learning under the project: *Silesian University of Technology as a Center of Modern Education based on research and innovation* under the project*: Optimization of ultralight aerospace structures*

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