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Fast Generation of High-Performance Driveshafts: A Digital Approach to Automated Linked Topology and Design Optimization

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Abstract—In this article, we investigate an approach that digitally links individual development process steps by using the drive shaft of an aircraft engine as representative example of a fiber polymer composite. Such high-performance lightweight composite structures have many adjustable parameters that influence the mechanical properties. Only a combination of optimal parameter values can lead to energy efficient lightweight structures. The development tools required for the Engineering Design Process (EDP) are often isolated solutions and their compatibility with each other is limited. A digital framework is presented in this study, which allows individual specialised tools to be linked via the generated data in such a way that automated optimization across programs becomes possible. This is demonstrated using the example of linking geometry generation with numerical structural analysis. The proposed digital framework for automated design optimization demonstrates the feasibility of developing a complete digital approach to design optimization. The methodology shows promising potential for achieving optimal solutions in terms of mass, material utilization, eigenfrequency and deformation under lateral load with less development effort. The development of such a framework is an important step towards promoting a more efficient design approach that can lead to stable and balanced results.

Keywords—Digital Linked Process, composite, CFRP, multi-objective, EDP, NSGA-2, NSGA-3, TPE.

I. Introduction

Mitigating climate change by reducing energy consumption has become a major global priority. Efficient Engineering Design Processes (EDP) enable the development of sustainable lightweight systems fulfilling increasing technical, economic, and ecological requirements. During flight manoeuvres of a geared engine as shown in Fig. 1, changes in the position of the rotating engine create gyroscopic forces that counteract the change in position. This results in constraining forces in the power transmission, leading to increased stresses in the gear teeth and potentially reducing their service life. Fiber reinforced polymers (FRPs), with their directional and adjustable properties, make it possible to design drive components that remain flexible with high torsional strength (cf. Fig. 1). This combination of properties can significantly reduce the loads in the engine and extend the life of the gearbox.

FRP materials, with their outstanding and directional depending material properties lead to a wide range of adjustable component properties. The combination with adjusted structural parameters leads to additional complexity of the EDP. Each single solution, as a combination of material and structural parameter sets, provides different stress orientations and levels in different areas of the component, depending on the material allocation and orientation [1]. In order to fulfil the required functions, different levels of functionality need to be checked and compared. Conventional EDP approaches reach their limits when it comes to finding the optimal solution with a reasonable amount of development resources.

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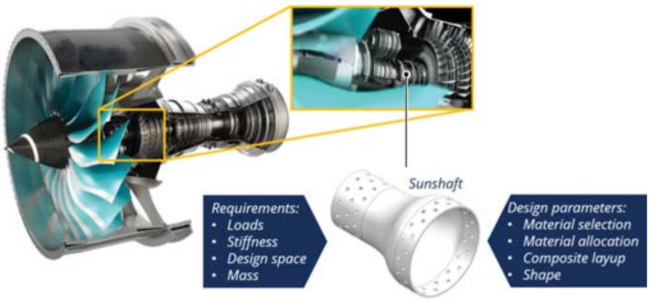

Fig. 1 Sectional view of the Rolls-Royce UltraFan® engine utilizing a Power Gearbox, focusing on the torsionally stiff and flexible FRP structure of the sun shaft, requirements and adjustable structure and material parameters

The aim of this study is based on [2] and it investigates the feasibility of a comprehensive digital framework for the EDP that can archive optimal solutions while minimizing the development effort using the example of a drive shaft for a Rolls-Royce jet engine. The developed composite driveshaft can replace the current metallic drive shaft. This example unifies a rather simple and comprehensible structure that is subject to several requirements on the one hand, and the design parameters to achieve them on the other (cf. Fig. 1).

A. Digital Driveshaft Optimization

Optimizing driveshafts for various applications has garnered extensive attention within the field of engineering [3]–[8]. Researchers have primarily focused on investigating material optimization, with focus on FRPs in particular [3], [4], [7].

While mass reduction, strength enhancement, and eigenfrequency manipulation have been frequently employed as optimization objectives [5], [6], the enhancement of bending deformation has received comparatively little attention. Bending deformation plays a critical role in the overall flexibility and performance of a driveshaft, especially in applications where the shaft acts as a decoupler for unwanted bending loads as well as lateral loads. Apparently, a lower bending stiffness directly interferes with the eigenfrequency, reducing the achievable revolutions per minute (RPM). The ability to optimize a driveshaft for both increased bending deformation and other vital parameters presents a significant unaddressed research gap.

Further, driveshaft optimization studies often use single parameter variation [5], [7]. In that approach, a single parameter is changed while other parameters are held constant. While informative, that methodology overlooks the intricate interplay between different performance metrics and the complex parameter dependencies. In contrast, multi-objective optimization allows multiple objectives to be considered simultaneously, providing a more comprehensive assessment of the design space [9]. Despite its potential benefits, a few studies have explored multi-objective optimization in driveshaft design e.g. [6]. This was often done by using conventional optimization algorithms that are prone to problems such as localized solutions and suboptimal performance [10], [11]. Nevertheless, the field of optimization research has made significant progress, ushering in cutting-edge algorithms designed to effectively address these limitations. Noteworthy among these advancements is the work by Deb and Jain [12], which introduces state-of-the-art algorithms that not only confront these constraints head-on but also provide enhanced and robust optimization solutions. This raises the pertinent research inquiry to what extent these novel methodologies have contributed to improved outcomes.

B. Multi-Objective Optimization

Multi-objective optimization, as opposed to single-objective optimization, involves optimizing multiple objective functions simultaneously with the aim of uncovering the Pareto front, which represents the intricate balance between these objectives [13], [14]. Traditionally, multi-objective optimization focused on two or three dimensions for intuitive visualization [15], but the growing demand for optimizing numerous objectives has highlighted the challenges of dealing with high-dimensional objective outputs. This has led to increased research attention on multi-objective optimization problems, especially recently. To address the complexities of multi-objective optimization, algorithms like the Non-dominated Sorting Genetic Algorithm II (NSGA-II) have been developed and refined [12].

In the area of multi-objective optimization, several significant challenges have been identified [12]:

1) *Ranking Individuals*: With a large number of individuals converging to the Pareto front in each generation, the task of determining their relative superiority or inferiority within the same rank becomes pivotal.
2) *Convergence and Diversity*: Maintaining a good balance between converging to optimal solutions and preserving diverse solutions in many-objective optimization is crucial to avoid premature convergence [16].
3) *Metrics and Computation*: Developing metrics that encompass both performance and diversity turns into a formidable undertaking. Additionally, the computational costs associated with these metrics can become prohibitive.
4) *Visualization and Representation*: The visualization and representation of the complex Pareto front becomes increasingly difficult as the dimensionality of the objective space escalates.

These challenges become more prominent as the objective space dimensions increase, driving the development of innovative algorithms tailored to address these issues within the research community.

A recent and promising multi-objective algorithm is NSGA-III, proposed by Deb and Jain [12], [17], which is a modified version of NSGA-II. NSGA-III addresses the issue of ranking individuals by selecting surviving individuals in each generation through a ranking process based on the dominance of their objective values. It also ensures diversity among the selected individuals by allocating them to predefined reference points as evenly as possible. This modified selection procedure results in a more evenly distributed search across each dimension, making NSGA-III a stable and reliable tool suitable for a wide range of applications, including large-scale agriculture, task allocation, and design exploration [18]–[20].

A significant challenge frequently encountered in real-world scenarios is the inherent demand for computationally expensive simulations to address the given problem. In the pursuit of overcoming this challenge, Ozaki et al. formulated a surrogate-based multiobjective optimization algorithm, circumventing the necessity for an extensive evaluation budget. This algorithm, called the ”Multiobjective Tree-structured Parzen Estimator” (TPE), aims to solve this issue. Further, empirical assessments conducted on various benchmark problems underscore that TPE better aproximate the Pareto fronts than existing methods with a limited budget [21].

C. Research Objective

Given these gaps in the current literature, the research objectives of this study are as follows:

1) Developing a framework in which fast design iterations and optimizations of driveshafts are made accessible to improve the further development of resource-efficient and cost-effective lightweight designs.
2) Investigate the potential for optimizing FRP driveshaft structures to simultaneously enhance mass reduction, strength, eigenfrequency, and bending deformation.
3) Utilize state-of-the-art optimization algorithms to overcome known issues associated with localized solutions and suboptimal performance.

II. Method

This section outlines the methodology adopted to address the intricate challenge of determining an optimal configuration for the driveshaft system. The process involves a series of systematic steps (cf. Fig. 2) aimed at achieving a refined solution while considering various engineering aspects.

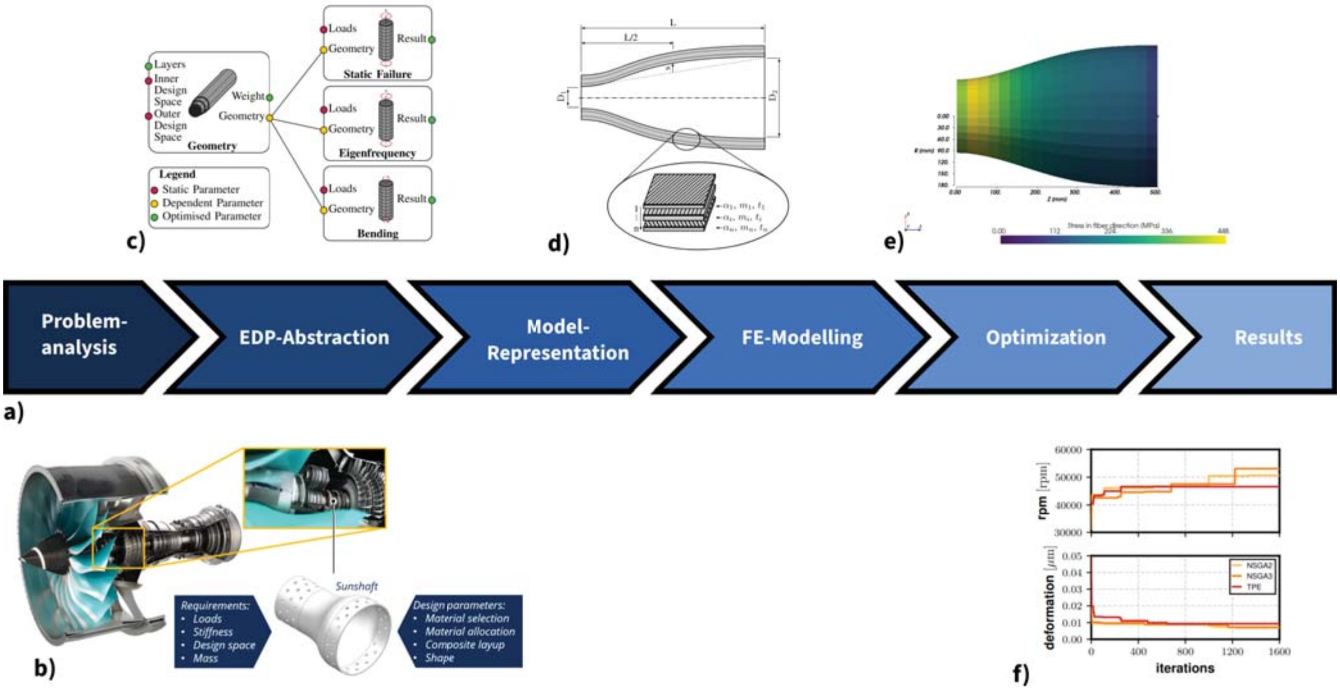

Fig. 2 Method from problem analysis to results (a) with visualisation of exemplary results (b-f)

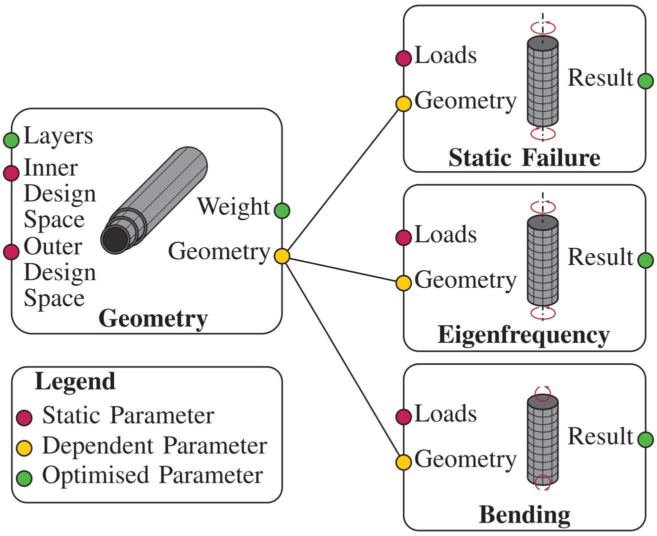

Fig. 3 Abstraction of the EDP with shared topology representation and multiple modular evaluation systems as the basis for the development of a digital framework

A. EDP-Abstraction

In the process of optimizing various driveshaft designs, it is imperative to automatically evaluate each iteration. These evaluations take place after the initial design is created and are conducted separately. Therefore, the entire system can be described as a composition of multiple components [2]: the design module and several evaluation modules. Each module is equipped with specific inputs and outputs. For instance, the geometry module encompasses multiple inputs relating to the different design parameters and generates the driveshaft's mass and geometry as an output. The various evaluation modules share a common structure: they take geometry and load cases as inputs and produce evaluative objectives as outputs. Interconnections among these modules are established through dependencies, with a prime example being the utilization of a shared geometry representation, see Fig. 3.

To facilitate the interchangeability of evaluations across different objectives, the development of a unified representation of the evolving geometry is essential.

B. Model Representation

A fundamental requirement for this unifying representation is the ability to accommodate varying shapes of the driveshaft geometry, provided that the shape is rotationally symmetric. This representation can be realized by conceptualizing the driveshaft as a rotational function along the z-axis (see Fig. 4). This abstraction offers a versatile framework for capturing the essence of different driveshaft configurations, enabling a consistent evaluation methodology across optimization objectives.

Beyond the geometric considerations, it becomes advantageous to introduce the concept of a ply stacking. Such a stackup is characterized by a layup of different materials, and its definition can be parameterized by z (vertical position) and phi (angular position). This parametric definition allows for the representation of materials that vary along the length of the driveshaft.

Furthermore, the introduction of fiber angles for each layer within the ply stackup proves to be particularly valuable, especially in the context of working with FRPs. These additional angles provide a means to precisely define the orientation of individual layers within the stackup. This level of granularity is crucial when dealing with

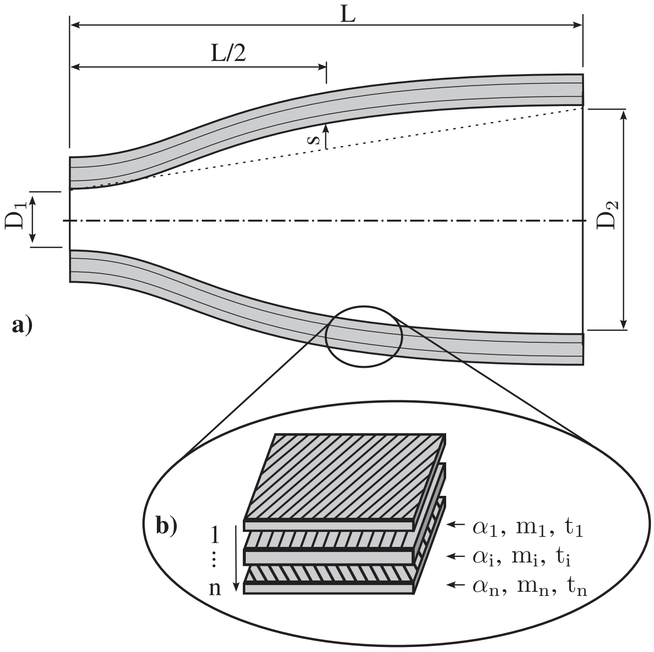

Fig. 4 Schematic drawing of the driveshaft showing all geometry based parameters of the structure (a) and the laminate (b)

directional-dependent materials such as FRPs, where the mechanical properties are highly dependent on the orientation of the reinforcing fibers.

The resulting representation strikes a balance between simplicity and comprehensiveness, making it suitable for integration into various finite element analysis codes, such as PyMAPDL [22].

C. FE-Modelling

For a good performing optimization study, fast and accurate evaluations for each iteration are important. To achieve this, multiple, modular evaluation tools have been developed using the finite element method (FEM) framework and implemented using the simulation capabilities offered by the PyMAPDL software [22].

1) Mass Evaluation: The mass of the driveshaft was estimated by numerical integration of the density over the occupied volume of the respective material.

2) Material Utilization: Evaluating the material utilization of the driveshaft was achieved by taking the maximum from two distinct loading cases: axial static pressure and axial torque. By computing the maximum utilization for each element with respect to the material specific failure criteria (see Appendix A) the critical weakest point of failure was identified.

3) Eigenfrequency Analysis: Finding a design with the most suitable eigenfrequency behavior was done by computing the first ten natural frequencies using standard numerical techniques. Then, the closest frequency to the loading condition was identified and the absolute difference from the baseline case was calculated. This analysis facilitated a deeper understanding of the dynamic behavior of the driveshaft under various loading scenarios.

4) Deformation under lateral force: The performance of the driveshaft under lateral force was evaluated by fixing the driveshaft at one end and applying a force of 1N at the other end. These simulations were used to quantify the resulting displacement to ensure a sufficient decoupling of forced displacements from the load applied by the flexible driveshaft.

D. Optimization

The core of the proposed methodology revolves around the integration of the driveshaft design and evaluation system within an optimization framework. This approach facilitates the simultaneous consideration of various performance metrics during the design process. By encapsulating the driveshaft design and evaluation tools within the optimization routine, a holistic perspective is adopted, allowing the exploration of design spaces that lead to improved performance across multiple criteria.

TABLE I
DRIVESHAFT CONSTANTS

Constants	Unit	Value
L	[mm]	500
D_1	[mm]	170
D_2	[mm]	340
T_{max}	[Nm]	160×10^6
N_{max}	[N]	-2000
rpm_{min}	[rpm]	6000
n	[/]	4

TABLE II
DRIVESHAFT PARAMETERS

Parameter	Unit	Range
s	[/]	0.0–1.0
t	[mm]	10–18
α_i	[°]	−90.0–90.0
m_i	[/]	["CF_{230}", "CF_{395}", "CF_{40}"]

1) Parameter Variation: This study aims to identify the optimal values for key parameters that significantly influence the behavior of the driveshaft, see Fig. 4. While the diameters, length, mechanical load and numbers of layers were kept constant, see Table I, the other key parameter were marked to be changed in a certain domain, see Table II.

The optimization process involved a systematic variation of the shape parameter (s), which defines the cross-sectional geometry of the drive shaft. Different values of (s) were considered to assess their impact on factors such as torsional stiffness and mass. The number of material layers (n) was also varied to investigate its effect on overall strength and durability.

For each material layer (i), the orientation (α_i) of the fibers or materials (m_i) was adjusted to explore its influence on load distribution and stress propagation. The materials were selected from three different carbon FRP materials, with "CF_{230}" having a higher strength, "CF_{395}" having a higher modulus and "CF_{40}" having the highest compressive strength, see Appendix A. Additionally, the thickness (t) at the smaller diameter was defined and adapted over the length of the driveshaft so that the the cross area stayed the same. The thickness of each layer (t_i) was calculated by dividing the $t(z)$ with n.

2) Multi-objective Criteria: By using the multi-objective optimization approach the driveshaft was optimized to:

1) reduce mass,
2) minimize mechanical utilization,
3) maximize the difference between eigenfrequency and frequency in the use case,
4) and maximizing the bending deformation.

In this study, the optimization process was carried out using the different optimization algorithm within the Optuna framework [23]. In order to ensure a balanced exploration of the parameter space without overwhelming computational resources, a limit of 1600 distinct trials was imposed on the search process. This number represents a pragmatic compromise between obtaining comprehensive results and avoiding computational overload. It also accounts for the trade-off between exploring a broad range of solutions and ensuring a meaningful analysis of the resultant data.

3) Optimization Algorithm: From the spectrum of available optimization algorithms NSGA-II, NSGA-III and TPE are widely used for multi-objective optimization tasks. NSGA-III excels in handling the inherent trade-offs between conflicting objectives by generating a Pareto-optimal front, which represents solutions that cannot be improved in one criterion without worsening another. Conversely, the TPE algorithm caters to computationally expensive problems through the integration of priors to model the belief regarding optimal parameters. Nonetheless, determining the most suitable algorithm for the given problem remains an open question. Consequently, these three algorithms were employed individually to construct a benchmark test. The outcomes of this optimization endeavor are elaborated upon in detail in Section III-B.

III. Results and Discussion

A. Framework

The proposed digital framework for automated design optimization was developed in Python and published at Github under the BSD-3-License [24]. Further, the developed system shows advantages in the field of structural optimization. These advantages encompass several key aspects, including modularity and expandability, rapid adaptability, enhanced speed, and the consideration of complex optimization boundary conditions.

1) Modularity and Expandability: One of the major strengths of the digital framework lies in its modular nature, allowing for the incorporation of new functionalities and features. Specifically, the framework enables mass determination, eigenfrequency analysis, and assessment of stress and torsional loads. These capabilities empower engineers and researchers to efficiently explore and optimize the performance of various structures under diverse load conditions, enhancing the overall design process.

2) Rapid Adaptability: The digital framework is characterized by its ability to quickly adapt to changes in geometry and design conditions. The incorporation of new geometries and adjustment of relevant parameters can be accomplished within a timeframe of approximately two days. This feature not only saves valuable time during the optimization process but also encourages iterative design improvements, ultimately leading to better-performing structures.

3) Speed: This is a critical aspect of any modern development process. The framework achieves fast design iterations by utilizing optimized simulations to run as fast and precise as possible resulting in optimization runs with 5000 different simulations in under 7 hours. Therefore, enabling engineers to efficiently evaluate multiple design scenarios and presenting a versatile approach to structural analysis and design.

4) Consideration of Complex Optimization Boundary Conditions: The digital framework uses state-of-the-art optimization algorithms to account for complex optimization constraints. For example, the framework enables the optimization of fiber angles considering maximum and minimum fiber angles due to manufacturing restrictions. By accounting for such complex constraints, the digital framework ensures that the final design exhibits improved performance and reliability under real-world conditions.

B. Optimization Results

Of all the optimization trials for each optimization algorithm, only a few had a maximum utilization value less than 1. NSGA-II found 9, NSGA-III found 9 and TPE found 13 of these configurations. These trials stand out as the most promising candidates for practical applications due to their adherence to the utilization constraint. Further analysis was performed on these trials to identify the best performing solutions in each objective category.

The outcomes of the optimization process were visually summarized in Fig. 5. This figure illustrates the distribution of the useful trials and highlights the candidates that excel in specific objectives. The candidates achieving the best outcomes were then identified for mass reduction, maximizing utilization within the constraint, maximum difference between eigenfrequency and engine frequency, and higher bending deformation.

To provide a concise overview of the findings, Table III was constructed. This table presents a summary of the best candidates in each objective category, showcasing their key performance metrics. The metrics include mass, utilization values, differences between eigenfrequency and engine frequency, and bending deformation properties.

A notable observation that emerged from the analysis is that the candidate with a $[-45°/45°/-45°/45°]$ stackup has the lowest mass and the greatest lateral deformation. This finding underlines the understanding of optimal fiber angles in driveshaft designs, since this configuration is known to be perfect for torque loads and suboptimal under lateral forces.

Interestingly, all three optimization algorithms identified this configuration as one with the lowest mass and greatest lateral

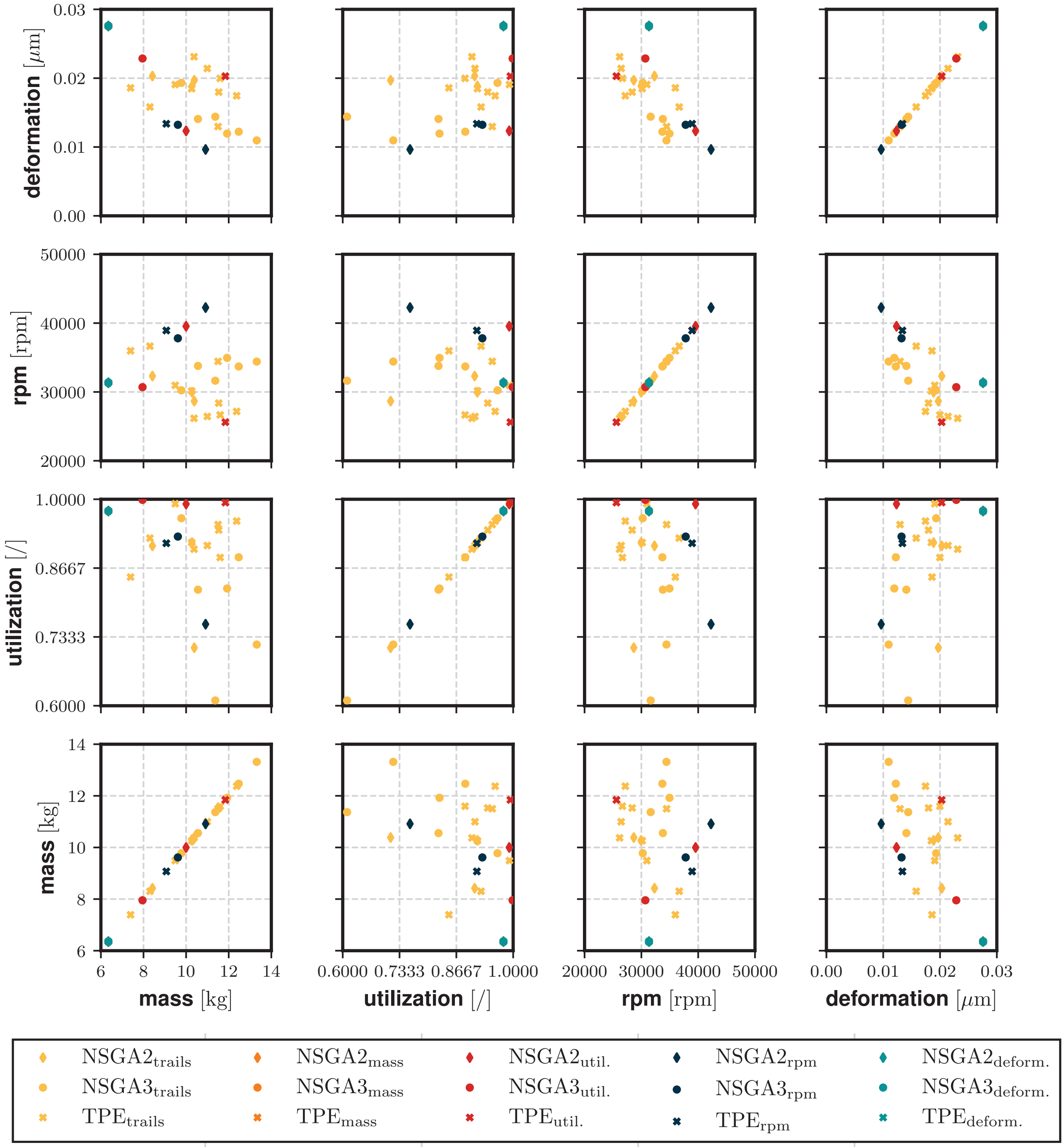

Fig. 5 The tested configurations of different driveshafts. Designs that would not withstand the loading were filtered out; the results were produced with three different optimization algorithm: NSGA-II, NSGA-III and TPE are projected onto two objective axes across four categories: mass, material utilization, RPM difference, and bending deformation

TABLE III
BEST CANDIDATES FROM DIFFERENT OPTIMIZERS IN DIFFERENT CATEGORIES

Category	**Trail**	α [°]	**m** [/]	**s** [/]	**t** [mm]	**mass** [kg]	**util.** [/]	**rpm** [rpm]	**deform.** [μm]
$\text{NSGA2}_{\text{mass}}$	1500	[-45, 45, -45, 45]	[CF_{40}, CF_{40}, CF_{40}, CF_{40}]	0.2	10.8	6.4	0.98	31337	0.03
$\text{NSGA3}_{\text{mass}}$	1531	[-45, 45, -45, 45]	[CF_{40}, CF_{40}, CF_{40}, CF_{40}]	0.2	10.8	6.4	0.98	31337	0.03
TPE_{mass}	1233	[-45, 45, -45, 45]	[CF_{40}, CF_{40}, CF_{40}, CF_{40}]	0.2	10.8	6.4	0.98	31337	0.03
$\text{NSGA2}_{\text{util.}}$	1157	[-36, -39, 35, 23]	[CF_{395}, CF_{395}, CF_{395}, CF_{40}]	0.1	17.2	10.0	0.99	39543	0.01
$\text{NSGA3}_{\text{util.}}$	1287	[-60, -46, 44, 48]	[CF_{40}, CF_{395}, CF_{395}, CF_{395}]	0.4	12.8	8.0	1.0	30696	0.02
$\text{TPE}_{\text{util.}}$	858	[-58, 59, -59, 59]	[CF_{40}, CF_{40}, CF_{40}, CF_{40}]	0.9	16.0	11.8	0.99	25607	0.02
$\text{NSGA2}_{\text{rpm}}$	1211	[41, -57, -38, 46]	[CF_{395}, CF_{40}, CF_{395}, CF_{395}]	0.4	17.2	10.9	0.76	42259	0.01
$\text{NSGA3}_{\text{rpm}}$	1057	[56, -37, 55, -42]	[CF_{40}, CF_{395}, CF_{395}, CF_{395}]	0.4	15.2	9.6	0.93	37797	0.01
TPE_{rpm}	620	[-44, 48, -52, 48]	[CF_{40}, CF_{395}, CF_{395}, CF_{395}]	0.3	14.8	9.1	0.91	38930	0.01
$\text{NSGA2}_{\text{deform.}}$	1500	[-45, 45, -45, 45]	[CF_{40}, CF_{40}, CF_{40}, CF_{40}]	0.2	10.8	6.4	0.98	31337	0.03
$\text{NSGA3}_{\text{deform.}}$	1531	[-45, 45, -45, 45]	[CF_{40}, CF_{40}, CF_{40}, CF_{40}]	0.2	10.8	6.4	0.98	31337	0.03
$\text{TPE}_{\text{deform.}}$	1233	[-45, 45, -45, 45]	[CF_{40}, CF_{40}, CF_{40}, CF_{40}]	0.2	10.8	6.4	0.98	31337	0.03

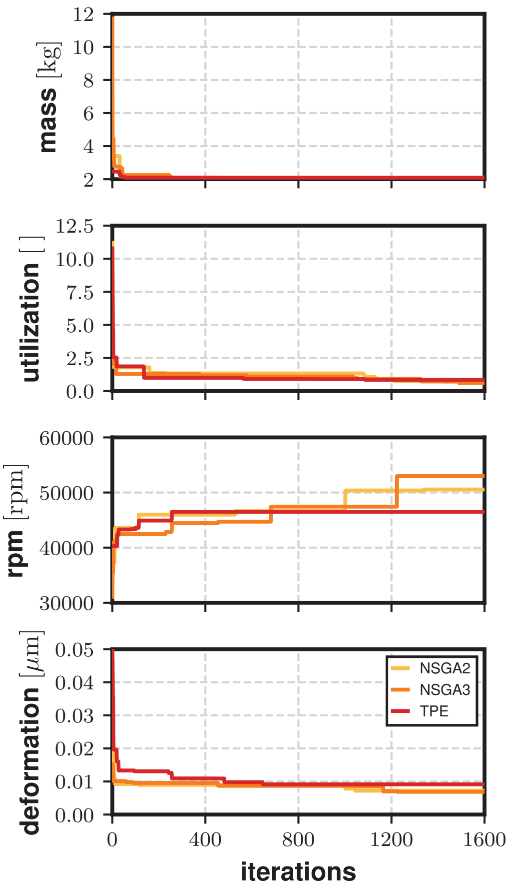

Fig. 6 Best configuration value in one of the categories mass, utilization, rpm and deformation over the optimization iterations

deformation. But TPE found this configuration nearly 300 trails before the other.

As depicted in Fig. 6, the TPE algorithm demonstrates a remarkable ability to identify superior solutions, particularly concerning the earlier convergence of values in various categories. TPE's adeptness at quickly identifying optimal solutions in these categories sets it apart from both NSGA-II and NSGA-III.

Interestingly, the comparative performance of NSGA-II and NSGA-3 raises pertinent questions. NSGA-III seems to perform slightly worse than NSGA-II in the simulations. This discrepancy might be attributed to the design philosophy of NSGA-III, which intentionally places less emphasis on the axes in an attempt to achieve a more balanced exploration of the solution space. Consequently, the perceived underperformance of NSGA-III could stem from its inherent design trade-offs.

To gain a better understanding of the factors influencing the optimization outcomes, a normalized importance plot was generated (Fig. 7). This plot reveals the relative importance of various design parameters with respect to each objective.

The findings from the analysis underscore the paramount significance of layer thickness in the pursuit of mass reduction. The overall thickness also plays a crucial role in generating driveshaft configurations with better material utilization and higher lateral deformation. In addition, the analysis reveals the critical role of fiber angles in manipulating the driveshaft's dynamic behavior. A nuanced interplay between fiber orientations significantly affects the driveshaft's response to changes in frequency and deformation.

A notable revelation from the analysis is the profound impact of a combined approach involving thickness, geometry shape, and fiber angles, when optimizing for lower material utilization. The complex interdependence of these factors requires a holistic optimization strategy, wherein their combined effects are carefully calibrated.

Curiously, the research findings indicate that neither of the optimization algorithm places substantial importance on material selection. This observation can be attributed to the comparable material properties of the candidate materials under consideration. The marginal differences in material behavior render their impact less pronounced in the optimization process. However, this does not negate the importance of material selection in other design contexts where material properties differ significantly.

The optimization results give strong indications, that an application of the methodology to the development of FRP structures, using the example of a high-performance

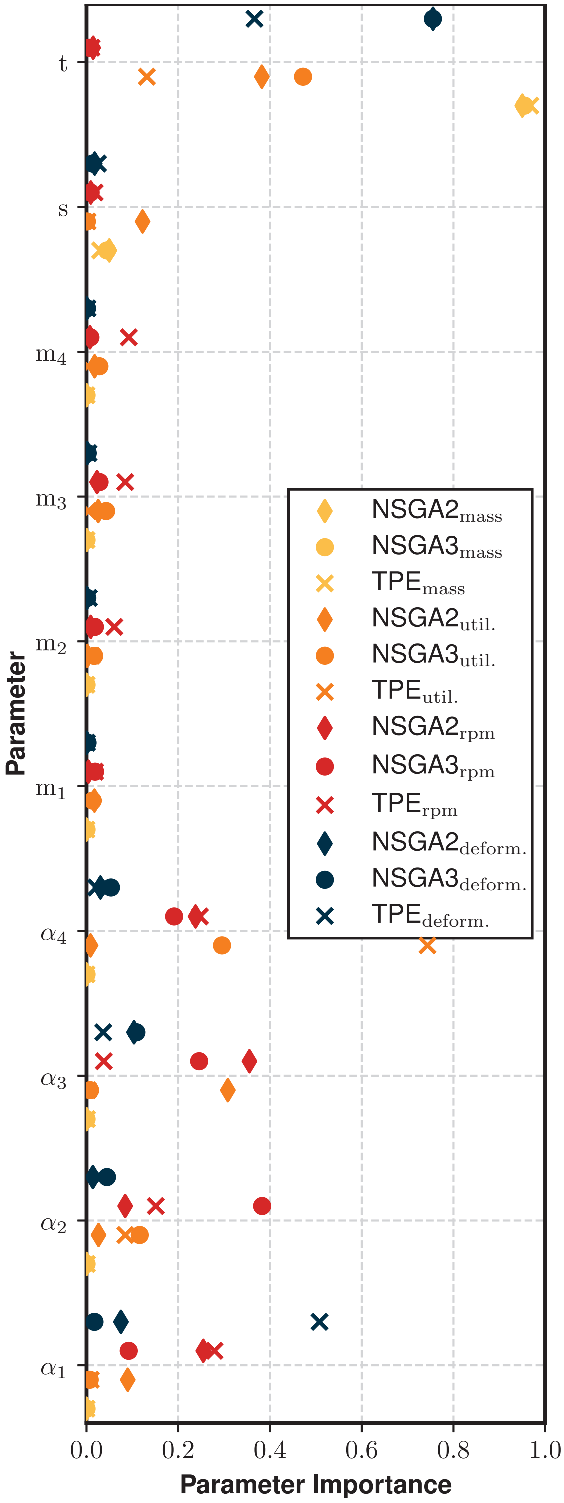

Fig. 7 The normalized parameter importance, when finding the best results

lightweight driveshaft for a Rolls-Royce jet engine of future generation in the lower technology readiness levels, is not only feasible in an digital environment, but also provides valuable performance improvements and insights.

IV. Conclusion

In conclusion, the research presented in this article signifies an important step towards a more efficient design approach for high-performance lightweight composite structures. This was illustrated with the driveshaft of an aircraft engine as suitable representation of a fiber-polymer composite. The investigation focused on digitally linking individual development process steps, like geometry generation, meshing and FEM analysis, with the aim to optimize various adjustable parameters that influence mechanical properties.

The study presented a digital framework for automated design optimization, which not only streamlines the Engineering Design Process but also enhances compatibility between isolated development tools. This framework, demonstrated by linking geometry changes with multiple numerical structural analysis, showcases the potential for achieving optimal solutions with significantly reduced development effort.

In the culmination of this study, numerous optimization investigations have been undertaken, employing a variety of optimization algorithms, including NSGA-II, NSGA-III, and TPE. These algorithms were employed in the pursuit of identifying an optimal synthesis of geometry and material configurations. The overarching objective was to achieve designs characterized by minimal mass and material utilization, while concurrently demonstrating substantial differentials in eigenfrequency and bending deformation performance.

Across all the diverse algorithms employed, a consistent trend in results emerged, underpinning the robustness of the findings. Particularly noteworthy is the performance of the TPE algorithm, which not only yielded outcomes consistent with the other methods but also found the best configurations significantly earlier. The harmonization of outcomes underscores the validity and reliability of the identified optimal solutions, reinforcing the significance of this research in advancing the understanding and application of optimization techniques in engineering design.

Since all optimization approaches identified a $\pm 45°$, which is a known optimal solution for driveshafts under torque loading by lightweight specialists, it raises the possibility that an expedited manual process might yield comparable results in a similar timeframe. However, the fast process that allows to test thousands of different configurations and the growing database of evaluated designs could prove invaluable in scenarios involving unforeseen alterations to the specifics of the use case. Although not within the scope of this paper, this aspect holds potential interest for future research endeavors.

In summary, the findings underscore the potential of an interconnected digital infrastructure to revolutionize design and development processes across various industries, offering a promising path towards resource-efficient, cost-effective, and high-performance lightweight designs.

APPENDIX A
MATERIAL PROPERTIES

TABLE IV
MATERIAL PROPERTIES: CF_{230} (UD PREPREG 230 GPA)

Property	Unit	Value
$E_{\|\|}$	[MPa]	121000
$E_{\perp}$	[MPa]	8600
$\nu_{\|\|\perp}$	[ ]	0.27
$\nu_{\perp\perp}$	[ ]	0.4
$G_{\|\|\perp}$	[MPa]	2634.2
ρ	$\left[\mathrm{kg/mm^3}\right]$	1.49
$R^{+}_{\|\|}$	[MPa]	2231
$R^{-}_{\|\|}$	[MPa]	-1082
$R^{+}_{\perp}$	[MPa]	29
$R^{-}_{\perp}$	[MPa]	-100
$R_{\|\|\perp}$	[MPa]	60
failure	[ ]	Cuntze

TABLE V
MATERIAL PROPERTIES: CF_{395} (UD PREPREG 395 GPA)

Property	Unit	Value
$E_{\|\|}$	[MPa]	209000
$E_{\perp}$	[MPa]	9450
$\nu_{\|\|\perp}$	[ ]	0.27
$\nu_{\perp\perp}$	[ ]	0.4
$G_{\|\|\perp}$	[MPa]	5500
ρ	$\left[\mathrm{kg/mm^3}\right]$	1.54
$R^{+}_{\|\|}$	[MPa]	1979
$R^{-}_{\|\|}$	[MPa]	-893
$R^{+}_{\perp}$	[MPa]	26
$R^{-}_{\perp}$	[MPa]	-139
$R_{\|\|\perp}$	[MPa]	100
failure	[ ]	Cuntze

TABLE VI
MATERIAL PROPERTIES: CF_{40} (HTS40 UD EPOXY 0.55)

Property	Unit	Value
$E_{\|\|}$	[MPa]	133400
$E_{\perp}$	[MPa]	5750
$\nu_{\|\|\perp}$	[ ]	0.2875
$\nu_{\perp\perp}$	[ ]	0.37
$G_{\|\|\perp}$	[MPa]	2358
ρ	$\left[\mathrm{kg/mm^3}\right]$	1.558
$R^{+}_{\|\|}$	[MPa]	852
$R^{-}_{\|\|}$	[MPa]	-631
$R^{+}_{\perp}$	[MPa]	57
$R^{-}_{\perp}$	[MPa]	-200
$R_{\|\|\perp}$	[MPa]	132
failure	[ ]	Cuntze

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