DOI: 10.13009/EUCASS2023-931
Aerospace Europe Conference 2023 – 10TH EUCASS – 9TH CEAS

Thermoplastic Induction Welding for Sustainable Aircraft: an Industrial Perspective

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Abstract
Thermoplastic components are key elements for more sustainable structures in the aerospace industry due to their light-weight and weldability that improve manufacturing and offers better opportunities for recyclability. In this paper, we discuss the main research challenges associated with induction welding of thermoplastic composites at scale and their impact on sustainable aviation. A framework of methods to address these challenges, formulated as multidisciplinary design optimization problems, is discussed together with ongoing projects and partnerships.

1. Introduction

Thermoplastic components are of interest for the next generation of structures in the aerospace industry. One key property is their weldability that allows a reduction of manufacturing times and costs while also enabling broader opportunities for recyclability. In particular, thermoplastic induction welding [6] is an efficient way to join components together without the use of additional fasteners which would lead to lighter weight structures. All these elements can be pivotal to the development of more sustainable aircraft, which motivates the interest in scaling the adoption of thermoplastic induction welding to help make the step from manufacturing single parts to a broader family of assembled structural components.

During the induction process eddy-currents are generated in composites to provide heating in specific areas and weld components together. To enable tailoring and scaling, different design variables characterizing inductor (coil) and welding process need to be considered: the coil shape, the amperage supplied to the coil, the speed of the coil, and the distance of the coil from the component. These variables can be adjusted to achieve high precision welding [5, 12]. Optimizing these variables has a direct impact on the quality of welding: minimizing time and energy, in turn making thermoplastics more affordable. The material composition and associated properties need also to be considered as those impact the welding process. Manual tailoring is an important part of the thermoplastic induction welding recipe process and automating these tailoring steps would lead to more efficient experimental campaigns while improving the overall welding process.

The coupled multi-physics nature and the multi-variables dependency of the welding process motivate the interest in multidisciplinary design optimization (MDO) methodologies to broaden and scale the use of induction welding techniques [23, 26]. The small amount of data available drives the use of physics-based learning [35] combined with efficient experimental testing campaign on use-cases of interest. Multi-physics modelling permits to capture complex and coupled physics phenomena [7, 25], and is used to complement testing and support optimization by evaluation. This work provides an overview of the main research challenges associated with the use of induction welding of thermoplastic composites at scale. A framework of methods and approaches to address these challenges will be discussed together with ongoing projects and international partnerships. The goal is to automate and accelerate tailoring of welding recipes and inductors scaling over different families of aerospace structures.

The rest of the paper is organized as follows. Section 2 discuss the impact of thermoplastic induction welding for sustainable aviation and identifies open challenges and their priorities. Section 3 gives an overview of the current state-of-the-art of thermoplastic induction welding and necessary background knowledge. Section 4 details the welding process, from the experimental setup to the physics behind welding. Section 5 focuses on computational methods of

DOI: 10.13009/EUCASS2023-931

interest for the welding process and give insights into research areas to develop. Section 6 offers an overview of past and ongoing thermoplastic induction welding projects at Collins Aerospace and international partnerships in this area. Section 7 concludes this paper and discusses perspectives.

2. Thermoplastic welding and sustainable aviation

Thermoplastic composites (TPCs) are recognized as key enablers towards environmentally responsible aerospace [13]. Their structural properties combine remarkable durability, the ability to withstand high temperatures and very low density, which together motivate the great interest in TPCs for light-wight aerospace components to achieve major reduction of fuel demand. In addition, TPCs are weldable which could allow to cut the use of mechanical joints with further weight savings and decrease manufacturing times and energy, while also opening broader opportunities for recyclability. In particular, the possibility to be re-used and re-shaped at reduced energy demand make TPCs particularly attractive to replace families of thermosets composites and metallic components. Overall, the relevance of thermoplastics composites to sustainable aviation can be leveraged and measured at different stages of the whole aircraft lifecycle: from designing for low emissions, to development, manufacturing, and deployment; from operations and maintenance, to decommissioning and after-life.

The design of aerospace vehicles for low (ideally net zero) emissions majorly relies on the reduction of the overall empty weight, as it directly determines a lower demand of propulsive energy, whichever the power architecture is or will be in the future [1, 2, 8, 15]. Therefore, reducing the structural weight of aircraft is of primary interest because it permits to obtain superior performance in terms of fuel efficiency and to contain the carbon footprints associated with the overall operations of commercial flights. To achieve these goals, TPCs offer the ideal combination of strength, durability, fatigue properties and light-weight characteristics for their low density and weldability. This motivates the growing attention dedicated to the design and integration of thermoplastics composites for both critical load-bearing primary structures (e.g., nacelles, structural elements) and load-bearing secondary components (e.g., fan cowl doors of the nacelles, seats bones, or other interior elements).

The manufacturing and joining of thermoplastics components are envisioned to have transformational positive impact on the sustainability journey, in particular if compared to the processes demanded by thermosets. Differently from thermosets, TPCs do not require energy intensive and time demanding curing in autoclaves, but can be rapidly casted via heat-moulding. This allows to reduce manufacturing times from hours to minutes for a given component, not to mention the tremendous savings in energy demand. Further, TPC components can be assembled and integrated into more complex structures through welding-based joining. This process permits to join together components without the use of mechanical fasteners and/or adhesives therefore reducing the processing time and the weight of the final assembly. Different welding techniques can be adopted, depending on the particular TPC and geometry and desired structural properties of the components to join; Section 3 provides an overview of the state-of-the-art with particular emphasis on the induction welding of thermoplastics, being the focus of this work. Upon decommissioning, the use of welded thermoplastics composites permits to completely recycle the structural components. In fact, TPCs forming relies on re-melting and, after-life, the material can be retrieved and reshaped into new components actualizing the ideal circular economy paradigm.

3. State-of-the-Art: Thermoplastic Induction Welding

The possibility of assembling components through welding is one of the major features of thermoplastic composites (TPC) and positively contributes to their cost-effectiveness in manufacturing. Welding techniques can be classified based on how heat is generated and transferred to weld the components [27]. Some of the welding techniques used or studied for assembly of TPC structures are: resistance, induction, conduction, slip, and ultrasonic welding [9, 39]. In addition, assembly by full co-consolidation or partial co-consolidation (fusion forming and co-fusion) of parts can be seen as forms of welding. In general, application specific variants of each of these welding methods are developed in the industry. Depending on the accessibility of the weld zones of the parts, the size of the parts and the materials applied, welding can be continuous, discrete and/or blind; the weld force can be applied by match metal tooling (co-consolidation), bladders, rollers, actuators or any other method that fits a welding method and its specific application. An overview [1] of some of the welding technologies classified according to the size of the weld pool, i.e., the part of the components that is melted during the welding process, is given in Figure 1.

So far the application of welded thermoplastic primary aerostructures is limited to induction welded control surfaces and stabilizers. Resistance welding has been commercially applied only in secondary wing structures [31, 32, 33].

[1] Based on Michel van Tooren presentation at ACMA Thermoplastic Composites Conference 2022, San Diego, CA, USA.

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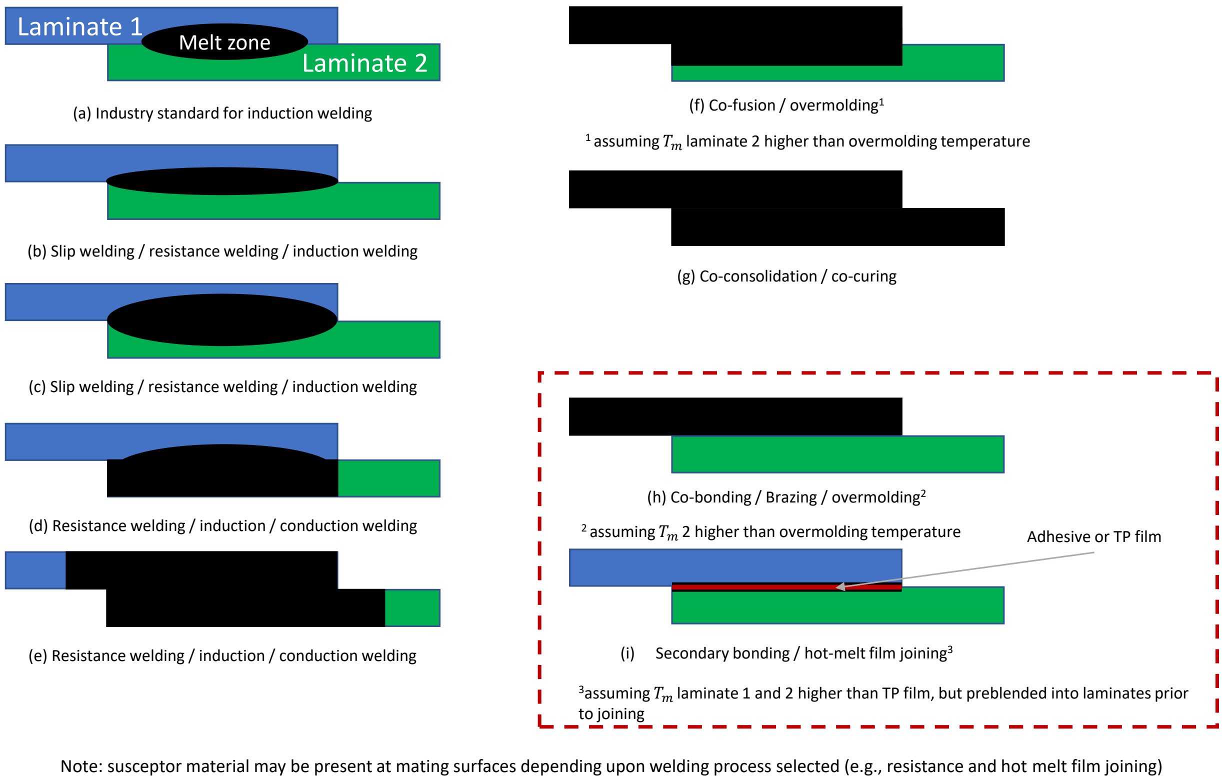

Figure 1: Overview of welding technologies (classified by the size of the weld pool)

All those applications are based on fabric reinforced polymer matrix composites with a relative low melting point. Another survey [4] gives an overview of the induction welding process and its nature over thermoplastic composites. In particular, it addresses the heat generation mechanism during the induction process and the parameters used to setup the welding procedure. Based on these considerations, induction welding is shown to be a proven and effective technology for welding thermoplastics. Heating mechanism assumed responsible for induction welding of thermoplastic composites are Joule heating of fibres, Joule and/or dielectric heating of polymer and fibre-to-fibre contact resistance heating [25]. Here, finite element simulation is applied to identify which heating mechanisms are induced. Results show that Joule heating of fibres and Joule heating of polymer are the most dominant heating mechanisms in induction welding of thermoplastic composites. Microscopic level modelling of induction welding heating mechanisms in thermoplastic composites was addressed in [7] where the authors studied the behaviour of carbon fibres with and without surrounding polymer in an alternating electromagnetic field at a microscopic level in ANSYS Maxwell using the solid loss to quantify heat generation in the composite material. The results obtained from the simulations indicate that fibre orientations in adjacent layers is a dominant parameter that affect the solid losses generated during induction welding. In [5], the authors showed 1) the effect of the induction welding coil shape adjustment on the volumetric heat generation by modifying the electrical field that is inducing the currents and thus volumetric heat generation and 2) the importance of composite laminate stacking sequence for the magnitude and direction of the eddy current responsible for volumetric heat generation. Details of the induction welding process are discussed in the following section.

4. Thermoplastics induction welding

An efficient welding process is essential to achieve a proper joining between two composite material panels. Taking into account behaviours based on the underlying physics mechanisms and the material composition and properties, the welding recipe can be finely tuned to improve the welding and achieve high-quality joining between components while reducing the associated costs. This section gives an overview of the induction welding process, the underlying physics mechanism and the drawbacks of the current methodologies.

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4.1 Thermoplastic Composites: Material Composition & Properties

Thermoplastic composites (TPC) are increasingly being used in the aerospace industry to replace metallic parts because of their outstanding performance and lightweight. Thermoplastic composite materials come in both amorphous and semi-crystalline forms and can be classified into different grades according to the performance suited for specific industrial applications. The most common types of TPC materials in the aerospace industry include polyphenylene sulfide (PPS), polyaryletherketone (PAEK), polyetheretherketone (PEEK) and polyetherketoneketone (PEKK) because of their high stiffness and retention of structural and thermal properties above glass transition temperature.

One of the carbon fibre reinforced polymer (CFRP) used at Collins Aerospace is the Toray Cetex® TC1225 low-melt polyaryletherketone (LMPAEK) resin with Toray T800 intermediate modulus carbon fibre because of its high tensile strength, processability, and weight saving properties. PAEK has a lower melting temperature T_m than other thermoplastic materials such as polyetherketoneketone (PEKK) and polyetheretherketone (PEEK) which enables faster processing in induction welding. Other material used at Collins Aerospace include low-melt polyaryletherketone (LMPAEK), PEEK, and PPS. An example of simple weld set-up is shown in Figure 2 with two laminate panels with small overlap, called the weld zone. This setup allows an application of pressure on the overlap section to facilitate the joining of the two panels [25].

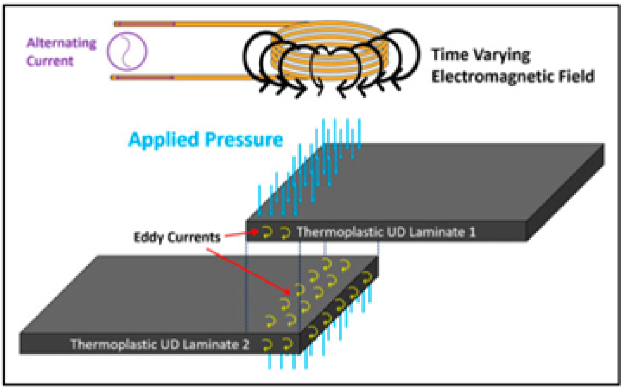

Figure 2: Experiment setup of CFRP composite flat panels for induction welding trials

4.2 Induction welding underlying physics

Composite materials contain an electrically conductive carbon fibre reinforced polymer (CFRP) that is essential for the induction welding process. Consider two superposed CFRP laminates to be joined together, with an induction coil placed above them, at a given distance. Alternating current (AC) flows through the coil and, in turn generates an electromagnetic field $\vec{B}$ around the coil as well as inside the laminates. According to Faraday's Law and Maxwell's equations [6], an electric field $\vec{E}$ is generated,

$$\vec{\nabla} \times \vec{E} = -\frac{\partial \vec{B}}{\partial t}. \tag{1}$$

Following Ohm's law [25], an electric current is then induced, where $\vec{j}$ denotes the electric current density and σ is the electrical conductivity tensor,

$$\vec{j} = \sigma \vec{E}. \tag{2}$$

The volumetric heat generated $\dot{Q}'''$ is then calculated by using Joule's law,

$$\begin{aligned} \dot{Q}''' &= \frac{\partial^2 Q}{\partial V \partial t} \\ &= \vec{j} \cdot \vec{E} \\ &= \vec{j} \cdot \sigma^{-1} \vec{j} \\ &= \vec{j}^T \sigma^{-1} \vec{j}. \end{aligned} \tag{3}$$

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The resulting volumetric heat generated is the sum of volumetric heat generated in 3D directions, and can vary from direction to direction within each ply of the thermoplastic composite laminate depending on the orientation and stacking sequence. These coupled thermo-electro-magnetic phenomena permit more than one laminate to be heated together and thus further enables the process of induction welding.

4.3 Induction welding recipe

The Joule heating phenomena in the overlap area, as described by Equations 1, 2, and 3, increases the temperature of the panels to at least reach the melting temperature of TPC material. Holding the heating above the melting temperature for a certain period of time allows for thorough melting across the welding zone before the panels are reconsolidated. This results in a welded single shear lap joint. In some cases, when the induction coil length spans across the length of the panels, stationary heating is doable by fixing the position of the coil at a small distance from the panels. In general, due to the size and the geometry of the induction coil, stationary heating does not generate enough heat across the weld zone as the length of the coil is significantly shorter than that of the panels. To avoid that, the induction coil has to move across the panels to generate a uniform Joule heating over the weld zone. Movement is achieved by mounting the induction heater on a robotic arm programmed to perform linear motion. During development stages thermocouples are placed between panels, along the weld zone, to monitor temperature response and help develop weld recipes that achieve specified time and temperature response. Note that for lot of parts that are being considered for thermoplastic components, closed-loop control based on measurements cannot be used. For those cases, welding recipes broad enough to take into account material and manufacturing variability need to be developed.

Devising a suitable welding recipe consists in choosing values for the parameters (the coil shape, the amperage supplied to the coil, the speed of the coil, and the distance of the coil from the component) such that the weld zone is heated above the melting temperature for a given processing time. Finding these values is difficult, as parameters vary when the coil is moving across the welding path to ensure proper welding. Parameters that vary along weld length can include: variable laminate thickness and lay-up, width of the weld, depth of the weld, etc. So far, induction welding recipes are developed manually, as described in the following section, which can become expensive for more complex parts, motivating the interest for computational approaches for recipe tailoring.

4.4 Manual tailoring

A highly efficient induction welding process is achieved by minimizing both the processing time and the energy consumption. This can be formulated as a multi-objective optimization problem. Manual tailoring of the welding recipe is the standard process to find a suitable recipe. Such a process is done by conducting numerous trials until the temperature response is uniform within the weld zone, with respect to a specified tolerance on thermocouple readings. Usually, two methods are employed to find suitable values for the parameters: 1) a piecewise variation, by segment, is applied on parameters across the welding path; 2) variation is computed as a function of the coil position along the length of the weld zone.

The first option is preferred for manual tailoring, as the induction welding operator can easily adjust the parameter using the temperature readings from the previous trial. The second approach also provides a better customization of the recipe without requiring rigorous calculation. Even with these methods, finding a suitable recipe often results in numerous heating trials, thus costing a significant amount of time, labour, energy, and materials. Such drawbacks make the manual tailoring of recipe less attractive, but still needed. These limitations bring interest in multidisciplinary design optimization, multi-physics modelling, or even physics-based learning to develop methods to address this multi-objective problem and reduce the costs of manual tailoring.

5. Methods

Finding a suitable thermoplastic welding recipe remains mostly a manual process with all the drawbacks associated with its costs and time demand. More automated tailoring procedures would have a transformative impact but require the development of advanced computational methods that ideally bring together physics-based numerical modelling, data-driven learning, and optimization. In fact, welding recipe tailoring is an optimization problem whose automation relies on a computationally guided search of the most suitable recipe for a given set of components to weld. The search can be generally informed by the evaluation of numerical simulations and/or experimental observations (Section 5.3).

Numerical models of the structural components (TPC) and of the thermo-electro-magnetic phenomena are essential to simulate and understand the coupled physical dynamics at the basis of the welding process (Section 5.2). Those allow to conduct more experiments in virtual settings with a reduction of time, costs, and energy consumption

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with respect to a similar campaign conducted in the physical laboratory. Nevertheless, physical experiments remain essential to observe and measure the effects of more complex multi-physics interactions that numerical models might fail to capture but whose impact on the welding quality is critical. In addition, the cost and energy expense associated with the collection of experimental measurements limit the overall amount of observations collected in physical campaigns and locate the recipe tailoring problem is the world of small data. The need to efficiently integrate the few experimental observation with the numerical simulations motivates the interest in advanced data-driven methods to efficiently learn from small data by embedding physical constraints (Section 5.4).

The multi-physics nature of the problem makes the optimization task computationally intractable if exclusively driven by full order, fully coupled simulations. On the other hand, the physical couplings are responsible for the quality of the welding joining and must be formally captured. We recognize that these characteristics advocate for the consideration of a body of methodologies to formulate and capture the essential domains couplings while decomposing the optimization problem for a more efficient computational task. Those are referred to as multidisciplinary design optimization (MDO): whilst theses methodologies are commonly developed to address design problems, this work adopts MDO to address the tailoring of multi-physics manufacturing processes and proposes MDO formulations for the optimization of the induction welding of thermoplastic composites (Section 5.1).

5.1 Multidisciplinary Design Optimization (MDO)

Multidisciplinary Design Optimization [29] (MDO) is a field of engineering that employs optimization to solve engineering design problems involving multiple disciplines. The motivation behind MDO is that the performance of a system is not only driven by individual disciplines but also by their interactions. Solving such systems requires a sound mathematical formulation of the problem, and especially of the interactions between disciplines. MDO can be applied on three aspects of the optimization problem: parametrization, formulation, and methodology. An MDO formulation, or architecture, allows to compute a correct and efficient decomposition of the complex multi-physics problem into amenable computable architectures. Different methodologies are involved in an MDO architecture such as Model-Based System Engineering [37] (MBSE) capabilities to enable a seamless integration of models, surrogate-based modelling to capture the physical behaviour of the system for optimization or uncertainty quantification methodologies to model perturbation on the parameters. In the following, MDO architectures are formulated by using the eXtended Design Structure Matrix [28] (XDSM).

The overall thermoplastic induction welding process can be improved at two different stages: the design of the coil shape and the tailoring of the welding recipe. An efficient coil shape, i.e., one generating a magnetic field adapted to the component and inducing an appropriate temperature to weld, directly improve the induction welding of components. Finding such a coil shape for the induction welding of thermoplastic components is a difficult task. State-of-the-art approaches [26] often start from an initial geometry for the coil shape, which is then updated throughout the different physics-based evaluation of the shape. Such an approach does not scale to more complex shapes. Indeed, updating the shape during the performance evaluation can lead to infeasible candidate coil shapes where some constraints are not satisfied (e.g., non-intersection of coil material). To address this, the coil shape problem can be formulated by the MDO architecture shown in Figure 3. A coil shape exploration should only provide feasible coil topologies to the physics evaluation. Ensuring that all feasibility constraints are met at an early stage avoid to lose time evaluating coils not usable for welding. Here the different physics-based models rely on different disciplines, namely magnetism, heat generation, and thermo-structural to evaluate the performance of a coil on a given component. The novelty of this MDO architecture lies in the first block, coil shape exploration, and the feedback from the physics evaluation, in the form of the induced temperature T.

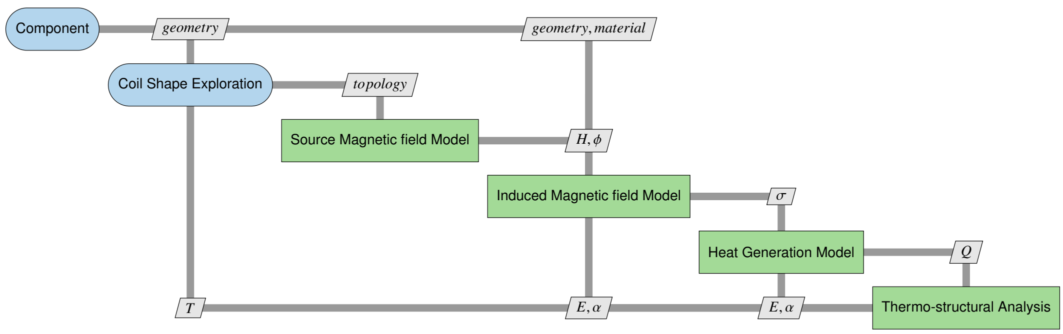

Figure 3: Coil shape exploration problem – MDO formulation

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Finding a suitable welding recipe in an automated way brings opportunities to reduce the need for manual inputs. As this process remains mainly manual, automation enable a faster and less costly approach to find a solution. The recipe optimization process is formulated by an MDO architecture depicted in Figure 4. Here, the physics evaluation of a candidate recipe is similar to the one used for the coil shape (see Figure 3). Recipe optimization consists in finding suitable parameters, namely the amperage supplied to the coil A, the distance from the components d, the speed of the coil s, and the welding trajectory t, such that the components are fully joined together after welding. As in Figure 3, the feedback from the physics evaluation, in the form of the temperature T induced in the components, is essential to fine-tune the recipe and optimize parameters. The physics evaluation step, captured by the green blocks, can be addressed with different approaches: multi-physics modelling, experimental trials, or physics-based learning.

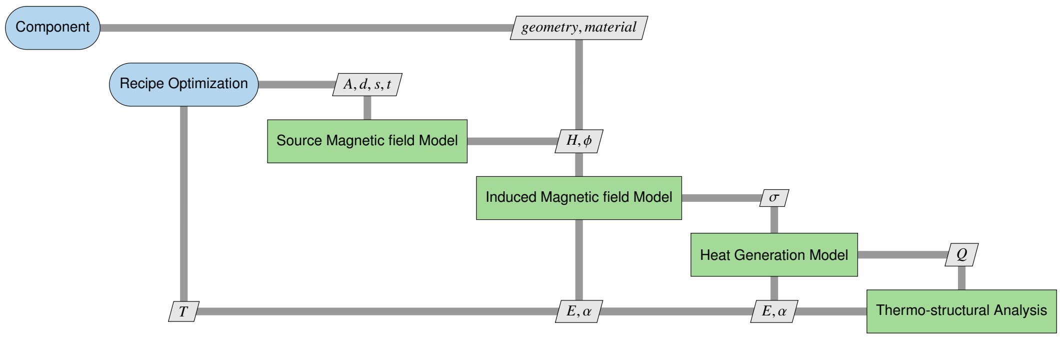

Figure 4: Recipe optimization problem – MDO formulation

Both the coil shape exploration and the recipe optimization problems have been formulated separately in Figure 3 and Figure 4, even though these problems are strongly coupled. Solving each problem separately is often easier and less computationally expensive, whereas solving them together can be more costly, it also offers great opportunity to capture the relations between them and tailor the solving to find more suitable solutions. This coupled problem can be addressed in different ways, each with a dedicated formulation by an MDO architectures. Two different architectures for the formulation of the overall welding problem are presented and analysed thereafter. One having a coupled solving of the sub-problems whereas the other one computes them in a more sequential order.

Figure 5 formulates a coupled solving of the coil shape and recipe problems. In this setting, the physics evaluation of the system happens only when a candidate coil shape and a candidate welding recipe are computed. A drawback from this architecture is that a combination of coil shape and recipe are always evaluated together. It is not possible to assess the performance of a coil shape for a given component before making decisions at the recipe tuning phase. Solving such a problem is difficult in practice as both sub-problems are solved without much knowledge of the other computation. But, one main feature of this architecture is the ability to solve in parallel the coil shape exploration and the recipe optimization while running only once the physics evaluation for the candidate solutions. This is a strong advantage of this architecture, as it is the most time-consuming computation of the overall problem.

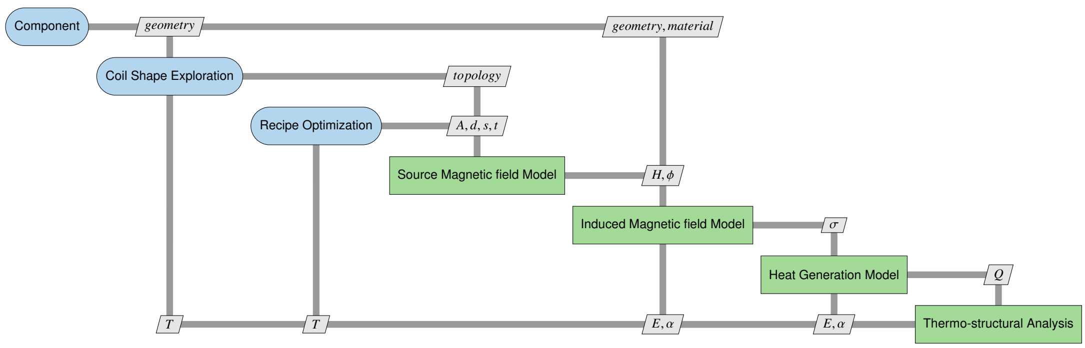

Figure 5: Coil shape exploration and recipe optimization problem – MDO formulation (coupled solving)

Figure 6 proposes a sequential solving of the coil shape and recipe problems. In fact, this architecture corresponds to the concatenation of Figure 3 and Figure 4 with knowledge about the coil shape impact on the temperature behaviour fed to the recipe optimization. Solving such a problem is much more amenable in practice, the coil shape exploration is solved first and does not expect feedback from the recipe optimization sub-problem. One important drawback of

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this architecture is to run at least once per sub-problem a similar physics-based simulation of the performance of the induced heating.

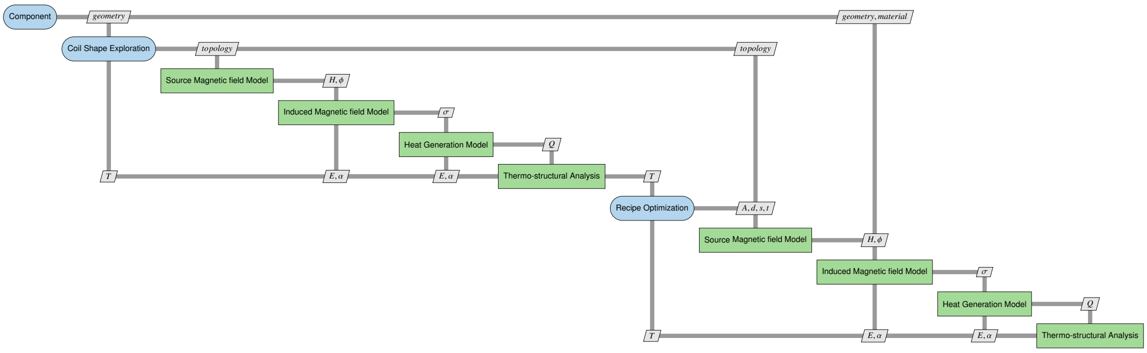

Figure 6: Coil shape exploration and recipe optimization problem – MDO formulation (sequential solving)

The coil shape exploration problem and the recipe optimization problem are both naturally written as multidisciplinary design optimization problems. Each problem involve physics from different disciplines, such as magnetism, heat generation, or thermo-structural properties. Solving these problems is a difficult task and requires the applications of methods and algorithm from different fields. Multi-physics modelling is essential to perform the physics evaluation of candidate solution, but is not always the right solution as it is time-consuming. Physics-based learning provides surrogate of physical phenomena and are usually easier to compute compared to traditional physics modelling. Optimization is making use of feedbacks from the physical systems to guide the search and find suitable parameters to improve the overall welding process. These different methods are addressed in the following sections.

5.2 Multi-physics modelling

Multi-physics modelling [40], also called multi-physics simulation, is dedicated to the simultaneous simulation of different domains of a physical system and their interaction among them. Multi-physics modelling is essential for thermoplastic induction welding, paired with the experimental effort, it helps to understand the coupled physical phenomena of the welding process. Modelling of induction welding based on combined Electro-Magnetic (EM) and Heat Transfer (HT) simulations have received more attention in recent years [14, 16, 17, 18, 22, 24, 25]. Also, methods to experimentally determine anisotropic electrical conductivity of thermoplastic materials that are essential for EM analyses are being developed [36, 41].

In induction welding the EM field is created with a copper coil that is moved over the parts to locally heat the material in the zone to be welded. Current and frequency of the excitation are specified for the copper coil. Electromagnetically induced eddy currents in carbon fibre reinforced thermoplastic polymer are calculated and transferred to thermal solver to calculate heat generated in composite material. That is, Joule heating, or volumetric heat generation, is calculated in every composite layer and it is used as a heat source in static or transient thermal analyses for temperature calculations. Several commercially available software packages are available that can perform coupled EM/HT simulations (e.g., ANSYS Maxwell, LS-Dyna, Abaqus, Comsol). Also, new methods are being developed to model the fundamental mechanisms of the induction heating/welding process (WelDone software) [25]. These modelling approaches utilize either Finite Element Models (FEM) [19], or a combination of FEM with Boundary Element Methods (BEM) [3]. While most software packages can model induction welding at single static coil position some can provide welding analysis of the moving coil (see Figure 7). Since very detailed 3D models are needed to obtain accurate simulation results, new approaches for modelling of large structures need to be investigated to achieve reasonable computational efficiency.

The quality of induction welding depends on several parameters including coil shape, coil speed, coil current and frequency, composite lay-up and size, thermoplastic material and it's electrical and thermal properties, material form (tape or fabric), and overall thermal management. These parameters affect maximum temperature, the size of locally heated area, and the temperature uniformity across the weld. Effect of all these parameters can be investigated using multi-physics simulations. Most of the new coil designs, thermal management systems, and initial welding recipes at Collins Aerospace are based on results of initial EM/HT simulations. However, due to large computational requirements, there is a need for optimization and automation of physics-based modelling for detailed welding recipe development.

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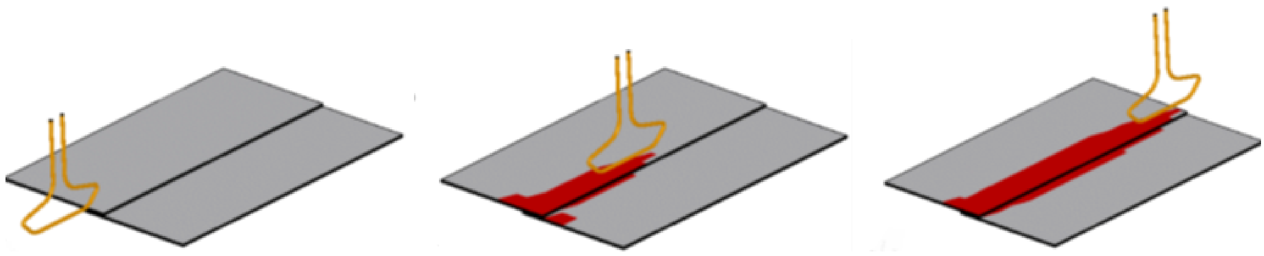

Figure 7: Simulation of induction welding of two composite layers (lap joint) showing increase in temperature along the weld length at different time steps as a function of moving coil position

5.3 Optimization by evaluation

Optimization [34] is broadly used in engineering. Common problems range from design of systems and structures to processing planning. Solving these problems often involves the evaluation of disciplinary models and the optimization of objective functions. Usually, an optimization process consists of evaluating the objective function and comparing it to its previous evaluations. Termination is often guaranteed by using a reachable stopping criteria. Often, the use of traditional evaluation, as in multi-physics modelling, is too expensive to compute during the optimization phase. Multi-physics modelling needs to solve numerically the model and involves different physics disciplines, each computed by a dedicated numerical method. That is why a surrogate of the multi-physics system or even results from experimental trials are preferred to evaluate objective functions. These sound approximations of the system behaviours are easier to compute and provide knowledge about future states to guide the optimizer decisions and find an optimal parametrization of the system. In the case of thermoplastic induction welding, optimization by evaluation is a key method to optimize the overall process. It supports the decision making process in different areas of the problem, such as coil topology, manufacturing process calibration, and material and component shape. Open questions and limitations of current approaches for each areas are addressed in the following.

The shape of a coil is of major importance in the welding process [5]. It directly impacts the electromagnetic field generated, and in turn the heat profile and welding efficiency. As such, computing a suitable coil shape for a given component to weld will increase production rate. State-of-the-art approaches [26] use Level-Set Topology Optimization (LSTO) and Finite-Element Analysis (FEM) to parametrize the coil geometry and to compute valid coil shapes and topologies. While it is efficient for 2D coils it does not scale to more advanced 3D coils as major physical and feasibility constraints cannot be captured and satisfied (e.g., non-intersection of coil material). This approach starts from an initial parametrized coil geometry, and computes in turn the magnetic field, the induced current, and the temperature field in the components. A downside of this computation flow is that the coil geometry is updated throughout different steps. Meaning that when checking the convergence criteria at the end, the coil shape can be invalid. This is identified as a major flaw of the process, preventing scaling this method to more complex applications. Enforcing geometry constraints first is an avenue to explore for the use of optimization by evaluation for computing efficient coil topologies.

The manufacturing process calibration is done manually: it is a time and energy consuming task, as the experimental bench needs to be setup for each test and cooling time is needed in between runs to achieve room temperature before starting a new test. In-between experimental trials, the process parameters are tuned according to the feedback from the component, i.e., temperature reading in time at strategic positions on the component to weld. The addition of this feedback makes the formulation of the optimization problem unconventional, but also a great opportunity to capture. Straightforward approaches could use traditional machine learning [21] to learn a surrogate of the temperature behaviour and predict its evolution in time. Drawbacks for this are the need for a large number of experimental observations to train and validate the model, and the need to compute again the whole model when updating a subset of constraints. In turn, more time is needed during the data acquisition phase to setup the bench and allow for cooling.

Another important aspect of welding is concerned with the choice of material and component shape optimization. The material used for the composition of the component to weld has a direct impact on the efficiency of melting and joining after the passing of the coil over the weld zone. Choosing an appropriate material is an optimization problem, where depending on the different properties and known behaviour under heat, time to reach welding point is minimized while the quality of the weld should be maximized. Usually, when computing a suitable recipe, the shape of the component is considered as given. Though, component shape optimization remains important during the design process of new components.

The coupling of traditional optimization approaches with physics-based models is a difficult task. Often, one of the main drawbacks is the heavy numerical computations needed to simulate the physical system. One way to

DOI: 10.13009/EUCASS2023-931

avoid such a limitation is to rely on surrogate computed from physics-based learning. These surrogate are built from experimental data and are usually fast to compute.

5.4 Physics-based learning

Experimental datasets from thermoplastic induction welding trials are often few and not varied enough to cover the parameter space. This limitation makes it difficult to use traditional Machine Learning (ML) approaches for learning and predicting future states of the multi-physics system. Physics-constrained learning [35] combines the predictive capabilities of traditional ML with embedded knowledge about the physics of the system. Other approaches focus on multisource/multifidelity modelling and optimization [23] or model-order reduction [10, 11] to compute fast and sound predictions of the system. These approaches infer the behaviour of the system from fewer traces of executions while keeping information about the physics nature of the system, thus offering a natural explanation of the prediction computed. Such predictive capabilities are deeply needed in the optimization process. Learning about the system behaviour addresses the high computational costs of individual physics-based simulations and experimental campaigns, thus making the optimization by evaluation tractable and suitable to time and costs constraints.

6. Thermoplastics induction welding at Collins Aerospace

Collins Aerospace considers research and development in sustainable advanced structures pivotal for next generation aircraft. As such, research advances in this area are framed under the Advanced Structure Strategic Initiative which is synergistically pursued by Collins Aerospace at large. Accordingly, Collins Aerospace is participating in and committed to a variety of government funded and public disclosed projects on the topic of thermoplastic induction welding and next generation composite structures. Among those, Hi-Rate Composite Aircraft Manufacturing [38] (HiCAM), is a project concerned with a more rapid production of composite aircraft to meet the goal of increasing global demand for lightweight transport aircraft. HiCAM is part of the Sustainable Flight National Partnership and aims to increase the rate of composite aircraft manufacturing, reduce costs, and improve performance. This project is executed by the Advanced Composites Consortium, of which Collins Aerospace is a member. Collins Aerospace is also a member of the Industrial Advisory Board of the NASA University Leadership Initiative (ULI), and is part of a ULI project led by the University of South Carolina [30]. This initiative seeks to develop capabilities for thermoplastic, UD-tape based, fastener-free assemblies for next-generation aerospace systems. In addition, Collins Aerospace partnership with Raytheon Technologies Research Center (RTRC) on Multi-source Machine Learning and Thermoplastic Enhanced Aerostructure Manufacturing [20] (mTEAM), seeks to develop a novel welding process for manufacturing applications in the aerospace industry. The process aims to integrate machine learning and real-time computer modelling of components to reduce production lead time. This project, led by RTRC, is funded under the Department of Energy (DEO) Advanced Manufacturing Office (AMO). Collins Aerospace was also selected by the Air Force Research Laboratory (AFRL) to build an advanced high-impact resistant, F-16 ventral fin using Collins' thermoplastic welding technology, which will significantly reduce weight and cost of the current design. The project work includes application of a specialized welding process, component design and prototype fabrication for the F-16 ventral fin.

7. Conclusion

The broader use of thermoplastic components for next generation aircraft is expected to lead to major reduction of structural weight, in turn reducing the associated energy consumption during flight, regardless of the specific power architecture adopted. In addition, heat-mouldability and weldability of thermoplastic composites opens new possibilities to recycle and to reuse aerospace structural components upon decommissioning, thus supporting the effective implementation of a circular economy paradigm. To broaden the use of thermoplastic components, challenges associated to the tailoring and the scaling of the welding process demand dedicated methodologies to be developed. Indeed, expensive manual tailoring remains an important part of both the design of the inductor/coil shape and the development of the recipe. Thus, the need for automation and more efficient computation is present at all stages of the manufacturing process.

This work stems from the recognition of the multi-physics nature of thermoplastics induction welding and provides a high-level overview of methods and research areas to address the challenges. In particular, we discussed several formulations of coil shape exploration and recipe optimization as MDO problems. Such formulations enable a better understanding of the physics phenomena governing the manufacturing process and provide ways to handle the parametrization and decomposition of the optimization problems to make them tractable. In addition, the architectural representations of the optimization problems are leveraged to identify the pain points felt by the industry and map the

DOI: 10.13009/EUCASS2023-931

active research areas – multi-physics modelling, optimization by evaluation and physics-based learning – that offer approaches to address them. The relevance of these research fields to the sustainability roadmap pursued by the aerospace industry is demonstrated by the number of programs we actively joined to advance thermoplastics induction welding for next generation aerospace structures.

References

[1] Aerospace Technology Institute. SUSTAINABLE AVIATION: ATI Framework, 2021. https://www.ati.org.uk/wp-content/uploads/2021/08/insight_16-sustainability.pdf.

[2] Aerospace Technology Institute. AVIATION EMISSIONS: Modelling the road to Net Zero 2050, 2022. https://www.ati.org.uk/wp-content/uploads/2022/07/insight-aviation-emissions-modelling.pdf.

[3] Ferri MH Aliabadi. Boundary element methods. In *Encyclopedia of continuum mechanics*, pages 182–193. Springer, 2020.

[4] Nabanita Banik. A review on the use of thermoplastic composites and their effects in induction welding method. *Materials Today: Proceedings*, 5, 2018.

[5] Darun Barazanchy, Jaspreet Pandher, and Michael J Van Tooren. The effect of induction welding coil shape on heat generation. In *AIAA SCITECH 2022 Forum*, page 0406, 2022.

[6] Darun Barazanchy and Michel van Tooren. Heating mechanisms in induction welding of thermoplastic composites. *Journal of Thermoplastic Composite Materials*, 36(2):473–492, 2023.

[7] Darun Barazanchy, Michel JL van Tooren, and Mohammod Ali. Microscopic level modeling of induction welding heating mechanisms in thermoplastic composites. *Journal of Thermoplastic Composite Materials*, 36:1017 – 1033, 2021.

[8] Valentin Batteiger, Roeland DeBreuker, Irene Dedoussi, Jan Delfs, Friedrich Dinkelacker, Ali Elham, Santiago J. Garcia, Jens Friedrichs, Stefan Goertz, Volker Grewe, Wim Haije, Christoph Herrmann, Frederic Lachaud, Axel Mertens, Joseph Morlier, Ulrike Krewer, Rolf Radespiel, Arvind Gangoli Rao, Peter Schmollgruber, Uwe Schröder, Jörg Seume, Mirjam Snellen, Andreas Strohmayer, Leo Veldhuis, Irene Fernandez Villegas, Roelof Vos, Henri Werij, and Feijia Yin. Accelerating the path towards carbon-free aviation. CoE, Sustainable and Energy Efficient Aviation (SE^{2}A) and Aeronautics Research Centre Niedersachsen (NFL), 2023. https://doi.org/10.24355/dbbs.084-202207041441-0.

[9] A Benatar and T G Gutowski. Method for fusion bonding thermoplastic composites. *SAMPE Q.; (United States)*, 18:1, 1986.

[10] Peter Benner and et al. *Model Order Reduction Volume 1: System- and Data-Driven Methods and Algorithms*. De Gruyter, Berlin, Boston, 2021.

[11] Peter Benner and et al. *Model Order Reduction Volume 2: Snapshot-Based Methods and Algorithms*. De Gruyter, Berlin, Boston, 2021.

[12] Anindita Chakraborty, B. Blakeslee, John Mendoza, John J. Gangloff, Justin B. Alms, L. Q. Xing, Michael A. Klecka, Z P Wang, and W. R. Zhao. Automated induction welding of large thermoplastic composite structure. *SAMPE 2022, Charlotte, NC, USA*, 2022.

[13] Collins Aerospace. Thermoplastic composites: Lightweight structures at lower manufacturing costs, 2023. https://www.collinsaerospace.com/what-we-do/industries/commercial-aviation/aerostructures/advanced-structural-materials/thermoplastic-composites.

[14] Pierre Couarraze and Guillaume Vincent. Process development for continuous induction welding of aeronautical fuselage parts – the sideffect project. *SAMPE Europe Conference 2020 Amsterdam-Netherlands*, 2022.

[15] Lynnette Dray, Andreas W Schäfer, Carla Grobler, Christoph Falter, Florian Allroggen, Marc EJ Stettler, and Steven RH Barrett. Cost and emissions pathways towards net-zero climate impacts in aviation. *Nature Climate Change*, 12(10):956–962, 2022.

[16] M Duhovic, L Moser, P Mitschang, M Maier, I Caldichoury, and P L'Eplattenier. Simulating the joining of composite materials by electromagnetic induction. In *12th international LS-DYNA user conference*, 2012.

DOI: 10.13009/EUCASS2023-931

[17] Miro Duhovic, I Caldichoury, P L'Eplattenier, P Mitschang, and M Maier. Advanced 3d finite element simulation of thermoplastic carbon fiber composite induction welding. In *ECCM 16–European conference on composite materials*, 2014.

[18] Miro Duhovic, Joachim Hausmann, Pierre L'Eplattenier, and Inaki Caldichoury. A finite element investigation into the continuous induction welding of dissimilar material joints. In *Proceedings of the 10th European LS-DYNA Conference*, volume 15, 2015.

[19] Jacob Fish and Ted Belytschko. *A First Course in Finite Elements*. John Wiley & Sons, Inc., Hoboken, NJ, USA, 2007.

[20] John Gangloff, Wenping Zhao, Soumalya Sarkar, Sudeepta Mondal, Lei Xing, Abhijit Chakraborty, Amit Surana, Benjamin Bedard, and Justin Alms. Multi-source machine learning and thermoplastic enhanced aerostructure manufacturing. *SAMPE 2023, Seattle, WA, USA*, 2023.

[21] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.

[22] Patrice Gouin O'Shaughnessey, Martine Dubé, and Irene Fernandez Villegas. Modeling and experimental investigation of induction welding of thermoplastic composites and comparison with other welding processes. *Journal of Composite Materials*, 50(21):2895–2910, 2016.

[23] Francesco Grassi, Giorgio Manganini, Michele Garraffa, and Laura Mainini. RAAL: Resource Aware Active Learning for Multifidelity Efficient Optimization. *AIAA Journal*, 61(6):2744–2753, 2023.

[24] Wouter JB Grouve, Francisco Sacchetti, Evan J Vruggink, and Remko Akkerman. Simulating the induction heating of cross-ply c/pekk laminates–sensitivity and effect of material variability. *Advanced composite materials*, 30(5):409–430, 2021.

[25] Maxi Holland, Michel JL van Tooren, Darun Barazanchy, and Jaspreet Pandher. Modeling of induction heating of thermoplastic composites. *Journal of Thermoplastic Composite Materials*, 35:1772 – 1789, 2020.

[26] Jaeyub Hyun, Darun Barazanchy, Jaspreet Pandher, Michael van Tooren, Milan Mitrovic, and Alicia Kim1. Development of optimization tool for induction heating coils for thermoplastic composites. *SAMPE 2021, Baden / Zürich, Switzerland*, 2021.

[27] Villegas IF, Moser L, Yousefpour A, Mitschang P, and Bersee HE. Process and performance evaluation of ultrasonic, induction and resistance welding of advanced thermoplastic composites. *Journal of Thermoplastic Composite Materials*, 26:1007 – 1024, 2013.

[28] Andrew B. Lambe and Joaquim R. R. A. Martins. Extensions to the design structure matrix for the description of multidisciplinary design, analysis, and optimization processes. *Structural and Multidisciplinary Optimization*, 46:273–284, 2012.

[29] Joaquim RRA Martins and Andrew Ning. *Engineering design optimization*. Cambridge University Press, 2021.

[30] NASA. NASA Looks to University Teams to Advance Aviation Technology, 2023. https://www.nasa.gov/press-release/nasa-looks-to-university-teams-to-advance-aviation-technology.

[31] Arnt Offringa. Design and application of a pultrusion for multiple use in the fokker 100. *Composite Structures*, 10(3):199–209, 1988.

[32] Arnt R. Offringa. Thermoplastics-moving into series production. In *37th International SAMPE Symposium and Exhibition*, pages 1028–1039, January 1992.

[33] Arnt R. Offringa. Thermoplastic composites—rapid processing applications. *Composites Part A: Applied Science and Manufacturing*, 27(4):329–336, 1996. 4th International Conference on Automated Composites.

[34] Singiresu S Rao. *Engineering optimization: theory and practice*. John Wiley & Sons, 2019.

[35] Renee C. Swischuk, L. Mainini, Benjamin Peherstorfer, and Karen E. Willcox. Projection-based model reduction: Formulations for physics-based machine learning. *Computers & Fluids*, 2019.

[36] Sebastiaan Van den Berg, Martin Luckabauer, Sebastiaan Wijskamp, and Remko Akkerman. Determination of the anisotropic electrical conductivity of carbon fabric reinforced composites by the six-probe method. *Journal of Thermoplastic Composite Materials*, page 08927057231154546, 2023.

DOI: 10.13009/EUCASS2023-931

[37] A Wayne Wymore. *Model-based systems engineering*, volume 3. CRC press, 2018.

[38] Richard D. Young. Hi-Rate Composite Aircraft Manufacturing (HiCAM) Project Overview - NASA Technical Reports Server (NTRS), June 2022. https://ntrs.nasa.gov/citations/20220010030.

[39] Ali Yousefpour, Mehdi Hojjati, and Jean-Pierre Immarigeon. Fusion bonding/welding of thermoplastic composites. *Journal of Thermoplastic Composite Materials - J THERMOPLAST COMPOS MATER*, 17:303–341, 07 2004.

[40] Q. Zhang and S. Cen. *Multiphysics Modeling: Numerical Methods and Engineering Applications: Tsinghua University Press Computational Mechanics Series*. Elsevier Science, 2015.

[41] Qian Zhao, Kai Zhang, Shuang Zhu, Hanyang Xu, Dianguo Cao, Lina Zhao, Ronghua Zhang, and Wuliang Yin. Review on the electrical resistance/conductivity of carbon fiber reinforced polymer. *Applied Sciences*, 9(11):2390, 2019.