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VIEWS & COMMENTS

Optimization and integration of polymer composites manufacturing powered by artificial intelligence

Zijie Wu (✉)[1,2], **Yufan Yang**[2], **Jie Hao**[2], **Constantinos Soutis** (✉)[1,3]

1 Yaoshan Laboratory, Pingdingshan 467000, China
2 Aerospace Institute of Advanced Materials Processing Technology, Beijing 100074, China
3 Aerospace Research Institute, The University of Manchester, Manchester, M13 9PL, UK

Abstract Polymer composite materials, known for their high specific strength and stiffness, are gradually attracting wider attention in the context of product weight reduction and environmental protection with embedded functionality (smart composites). This article provides practical examples and discusses future development trends of polymer composites fabrication, offering feasible ideas and methods for future economically viable engineering applications, where artificial intelligence can be used as an optimization tool.

Keywords polymer composites, artificial intelligence, process integration

1 Background

In today's era of rapid technological advancement, polymer composites are leading an industrial revolution with their outstanding performance and diverse application prospects. Particularly in the context of the booming automotive industry and burgeoning autonomous aerial vehicles economy, the demand for lightweight materials is becoming increasingly urgent [1,2]. Composite materials not only offer superior specific strength and stiffness compared to traditional metal materials but also meet the high standards of various project domains through their unique properties, such as corrosion resistance and tailoring mechanical characteristics [3]. In the aerospace sector, the use of composite materials in the Boeing 787 aircraft has exceeded 50%, resulting in significant reductions in fuel consumption [4] and enhanced durability [5]. In the automotive manufacturing field, polymer composites are also utilized in the production of body structural components [6] and interiors [7], demonstrating significant lightweight advantages. The potential of polymer composite materials in modern industrial applications is immense. Depending on the requirements, different resins, fibers, and molding methods can be selected for production, making composites a key factor in driving future lightweight technology and sustainable development, where automation can improve quality and reduce cost (Industry 4.0).

The molding processes are diverse, each with distinct characteristics, depending on applications and operating conditions. For instance, hot pressing is ideal for manufacturing products that require high mechanical performance and consistency. Resin transfer molding is suitable for producing composite products of moderate complexity [8]. Non-load-bearing components with complex geometries and high volume production are often manufactured using injection molding [9]. Filament winding is primarily used in the manufacturing of cylindrical components. As an emerging versatile material, composites are gradually evolving from single-function to multifunctional integration. This shift is driven not only by the ultimate pursuit of material performance but also by the comprehensive demands for lightweight, high reliability and intelligence, reduced cost, and environmental adaptability of components [10]. Multifunctional integration and collaborative optimization technologies have become key drivers in the advancement of composite materials. Critically, this integration and optimization are increasingly empowered by artificial intelligence (AI), which enables data-driven process-structure-property-performance optimization. AI algorithms facilitate intelligent process selection, real-time parameter control, and predictive quality analytics, significantly enhancing manufacturing efficiency, ensuring superior and consistent product quality, and enabling adaptive,

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E-mails: zijie.wu@outlook.com (Wu Z.),
constantinos.soutis@manchester.ac.uk (Soutis C.)

synergistic process integration to meet the demands of increasingly complex and variable product manufacturing requirements, as shown in Fig. 1.

The primary goal of optimizing composite material manufacturing is to develop an integrated system that selects and combines various suitable processes tailored to the specific requirements of products with complex geometries. AI plays a pivotal role in facilitating this transition toward a more intelligent, integrated manufacturing framework. Utilizing AI-driven digital twins and multi-objective optimization algorithms, the system can dynamically simulate, assess, and determine the best process combinations, drastically cutting down on the traditional dependence on trial-and-error approaches and reducing labor costs. Moreover, the incorporation of advanced manufacturing technologies from diverse disciplines enhances product development and performance. Currently, professionals in the composite materials sector are exploring preliminary integrated optimization solutions, which generally follow two main approaches: interdisciplinary integration (involving materials science, processing, chemistry, mechanics, and electronics) and the synergistic use of various molding processes. AI, as one of the most promising fields, is poised to become a crucial optimization tool supporting the future of interdisciplinary and integrated advancements in composite materials.

2 Automation in manufacturing

Composites manufacturing technology inherently involves multidisciplinary crossover and multi-technology integration [12]. The research content encompasses the design theory and simulation of composite material performance, as well as their forming, processing, assembly, inspection, monitoring, and the corresponding evaluation and repair [13]. Therefore, the interdisciplinary complementarity in composite material forming and manufacturing has already achieved significant research findings, with multiple cross-disciplinary approaches being applied in the design and manufacturing of composite materials. Aerospace companies like Boeing and Airbus have combined digital design methods with traditional manufacturing modules, optimizing and integrating stress analysis with manufacturing mechanical performance while reducing costs [11]. Regarding filament winding processes, leading companies such as Entec Instruments in the USA, BSD (BOLENZ & SCHAEFER) in Germany, and Harper International in the USA have produced multi-spindle and multi-axis linked winding forming equipment. These machines monitor forming parameters in real-time using sensors like electronic tension meters, employing closed-loop control during production to reduce fabrication-induced defects and enhance product stability. Currently, related companies have developed large-scale precision computerized numerical control winding equipment with 11 axes, integrating computer-aided design/manufacturing (CAD/CAM) and finite element analysis software, offering integrated design-manufacturing capabilities [14]. These successful cases of interdisciplinary integration in industry are primarily based on traditional, mature mathematical methods and mechanical equipment. Currently, the interdisciplinary integration of composite materials and the field of AI largely remains at the

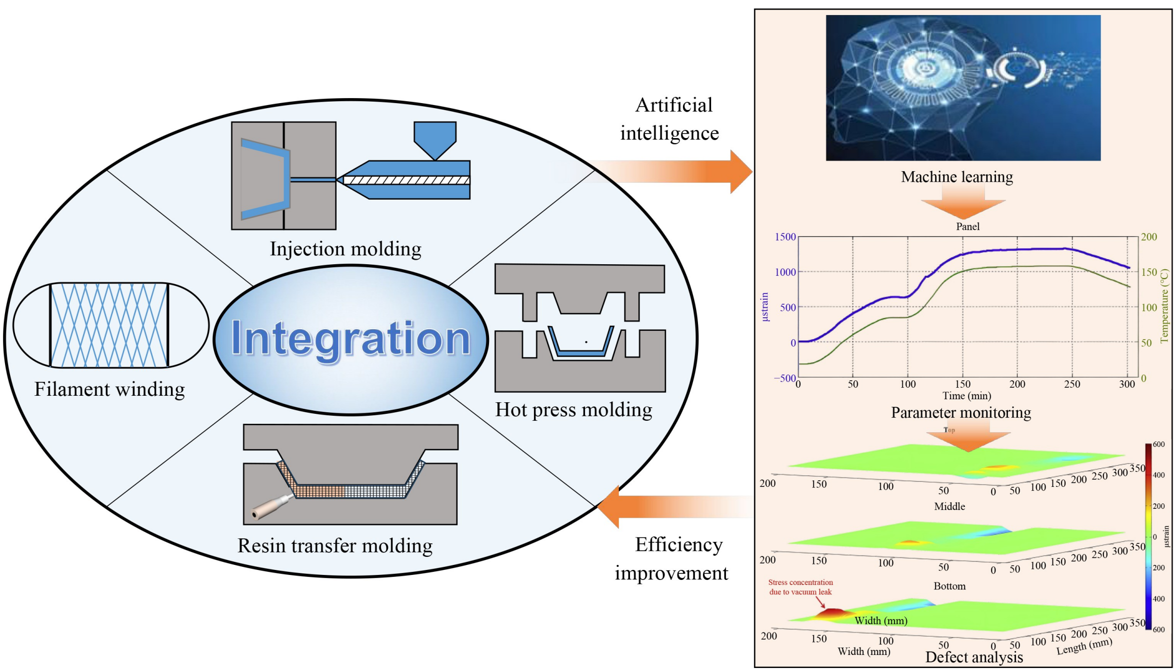

Fig. 1 AI-aided composite process optimization integration. Reprinted with permission from Ref. [11], copyright 2015, Elsevier.

experimental stage. However, with the continuous development of AI technology, a substantial amount of research has already been conducted. It is certain that the future of the composite materials manufacturing industry will trend toward AI-driven intelligence. Humfeld et al. [15] at Boeing addressed the challenges of monitoring the out-of-autoclave curing process of composite materials, characterized by long and cumbersome cycles for parameter and quality optimization. They proposed using an AI method known as Physics-Informed Neural Networks to model the curing process of composite materials. By inputting desired final curing degrees and cycle times, the trained model calculates the optimal temperature process parameters curve and predicts the final material's degree of cure (mechanical properties). Similarly, Fontes et al. [16] at the Concordia Composite Materials Center applied AI modeling to optimize predictions for the dynamic *in situ* automated fiber placement (AFP) manufacturing process, using experimentally measured temperatures to forecast thermal histories during AFP. At the University of Bristol, Feng and colleagues [17] developed a multiscale non-orthogonal viscoelastic material modeling approach to describe the constitutive behavior of carbon fiber reinforced polymer braids during the curing process, aimed at optimizing preforming and subsequent process parameter settings. Li et al. [18] proposed an innovative machine learning (ML) solution to address the industry challenge of accurately measuring the thickness of thin coatings (50–500 μm) on aircraft carbon fiber composites. The solution utilizes an open-ended microwave resonant cavity sensor that directly contacts the coating surface, capturing coating parameter information by monitoring changes in resonance frequency. Additionally, an innovative artificial neural network model is constructed for analysis and prediction. This method does not require prior knowledge of the coating or substrate material types, overcoming the traditional reliance on material-specific prior information. In our recent study, we have also explored interdisciplinary studies in the field of composite materials. For instance, we developed a numerical framework model for analyzing internal deformations and residual stress-strain in liquid composite molding processes. By employing ANSYS software, we linked flow simulations with transient structural models to achieve digital analysis and prediction of internal flow-induced material deformation, thus optimizing the manufacturing processes of material systems [19]. In the field of composite materials, particularly in forming processes and simulation predictions, the application of AI is still in its early stages. Although AI models hold the potential to enhance accuracy and stability, they have yet to reach industrial maturity. Once fully developed, AI could significantly boost productivity and reduce experimental costs, marking it as a key trend for future developments. However, our comprehensive review [20] of AI's role in designing composite materials reveals that, despite the significant promise of deep learning, its effectiveness is currently limited by the scarcity of high-quality material data and the complexity of processing principles. While there is a robust research foundation within the interdisciplinary field of composite materials, a considerable gap still exists before AI applications can be considered mature engineering solutions. This gap highlights the critical need for continued research and refinement to transform theoretical potential into practical applications. Although AI models promise to enhance accuracy and stability, they currently fall short of industrial maturity. The potential benefits of AI, once fully developed and integrated, include significant improvements in productivity and reductions in experimental costs.

Taking autoclave forming technology as an example, the manufacturing process is still predominantly manual or semi-mechanical, characterized by long cycles, low efficiency, and poor precision, which restricts the development of the industry. To achieve precision manufacturing of composite material components, it is necessary to develop digital forming control systems for complex composite components and to research and develop large-scale digital forming equipment integrated with CAD/CAM. The integration of AI technology is also essential, and scholars have already attempted to apply artificial neural networks (ANN) to model and optimize key parameters in the autoclave curing process, such as temperature, pressure, and time. Priyadharshini et al. [21] have proposed that by analyzing historical process data, ANNs can predict optimal curing curves, reducing defects (such as voids and deformations) and enhancing the performance of composite materials. Humfeld et al. [22] have developed an ML model trained to control the thermal history of autoclave-formed products in real-time. By importing data and training the model, it can actively control the autoclave to optimize the curing process in real-time, reducing scrap rates, and improving product quality, as shown in Fig. 2. In summary, the transition from traditional to AI-enhanced manufacturing processes in the composites industry represents a pivotal shift toward higher efficiency, precision, and quality. The successful integration of advanced AI technologies and digital tools promises not only to overcome the current limitations, but also to set new standards in the manufacturing of composite materials.

3 Integrated fabrication processes

The homogeneous structure of a single material can no longer meet the complex functional application needs, such as the integrated heat-protection and load-bearing in aircraft, or the explosion-resistance, stealth, and load-

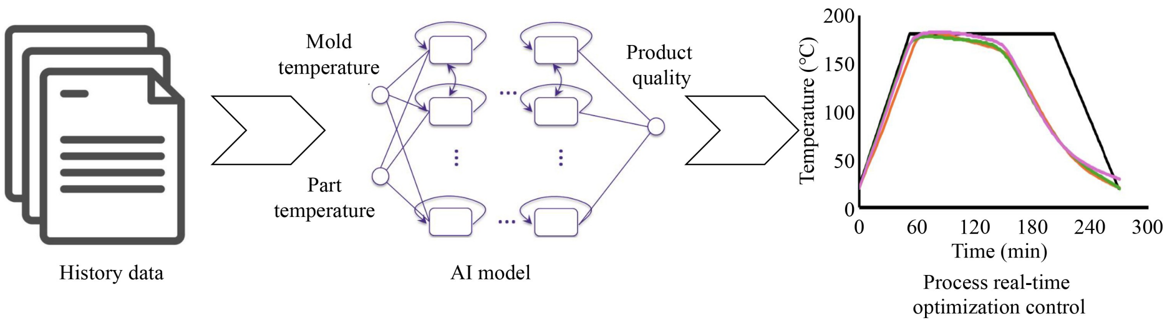

Fig. 2 AI optimizes the autoclave process and real-time regulation.

bearing integration in ships. To achieve the manufacturing of multifunctionally integrated composite material components, the integration of multiple processes is an inevitable trend. However, currently, most practitioners have not yet developed such a design awareness and approach. There are a few existing integrated solutions for composite material forming processes on the market, and their maturity is relatively low. For components with complex surface geometry and certain load-bearing performance requirements, Lafranche et al. [23] proposed an injection over-molding (IOM) process integration solution. This solution combines the processes of hot pressing and injection molding, as illustrated in Fig. 3. Hot pressing is used to produce a base product with continuous fiber reinforcement that exhibits good mechanical properties. This base is then inserted into an injection molding mold, where complex functional structures are molded onto its surface, with the connection between the two completed in one step through injection molding. The IOM process integration solution effectively meets the requirements for load-bearing performance and complex functional structures, representing an innovative and valuable attempt at the integration of composite material processes. Admittedly, the IOM process still faces significant challenges, such as ensuring the adhesion between the base and the injection molding materials, which currently requires adjustments in process parameters [24] or surface treatments [25] to enhance interfacial adhesion quality. Nonetheless, given the increasingly complex performance requirements of products, there is an urgent need for such research, design ideas, and case studies.

The integration of current manufacturing processes remains underdeveloped, requiring extensive experimental validation that is both time-consuming and labor-intensive. To address these challenges, AI can be leveraged to simulate and analyze the integration of composite material forming processes. This approach aims to develop practical, viable integrated processes that can be applied to specific products. Furthermore, AI can play a crucial role in monitoring the workflow and analyzing the quality of the formed products. The more complex the manufacturing processes become, the higher the need for AI involvement. Much more research effort

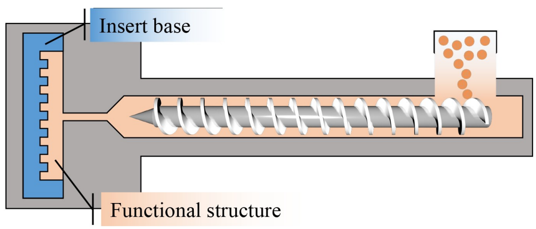

Fig. 3 IOM process, where hot pressing and injection molding are combined.

is required to fully develop AI's capabilities, bridging the gap between theoretical potential and practical application in the field of composite materials.

In the integration of composite material forming processes today, the scientific and rational design of production routes is crucial. To enhance production flexibility and promote collaborative cooperation among manufacturers from different technical backgrounds, adopting a modular design has become a necessary strategy. This approach not only breaks down barriers between technological collaborations but also supports the effective integration of various technological strengths. At the same time, it encourages the formation of interdisciplinary and cross-background design teams to tackle complex technical challenges through collaborative innovation. This not only reduces costs but also enhances product quality through advanced design concepts and technological iterations. Moreover, the incorporation of AI into composite material manufacturing addresses significant challenges, such as the difficulty in characterizing the forming process *in situ* and the implementation of multiple process parameters. As one of the hottest research fields today, AI can analyze complex data to optimize process parameters dynamically, predict material behavior, and enhance the scalability and automation of production processes. This is a key direction for future development in the interdisciplinary integration and process optimization of composite materials. Additionally, process technicians need to continually strengthen their learning and broaden their perspectives, establishing a comprehensive knowledge system that spans from structural design and theoretical calculations to simulation and process forming. The application of simulation technology, developed in conjunction with design units and enhanced by AI, can propose cost-effective, highly automated, and scalable industrial solutions. Such a cooperative model will promote deep collaboration between design and production units, creating a new work pattern driven by engineering implementation. This will effectively enhance the technological level and market competitiveness of the entire industry, making polymer composites more attractive in terms of cost and performance.

4 Conclusions

The integration and intelligentization of composite material manufacturing processes are key directions for future development. To achieve efficient and high-quality manufacturing of composite materials, it is essential to deeply explore the integration potential and implementation paths of various process technologies. This involves not only theoretical innovation but also the improvement of research methods and evaluation systems. By establishing a scientifically effective process integration platform that consolidates different manufacturing technologies and optimizes production workflows, it is possible to enhance efficiency and product quality while reducing overall costs. AI plays a central role in this process, especially in dynamically optimizing process parameters, predicting defects, real-time control, and multi-process collaborative simulation, demonstrating great potential. Although the application of AI in composite material manufacturing is still transitioning from experimental to industrial stages, its advantages in enhancing manufacturing precision, automation levels, and scalability have been preliminarily validated. In the future, as AI technologies deeply integrate with composite material design and manufacturing, combined with modular design, interdisciplinary team collaboration, and digital tools, it will drive the industry from traditional empirical-driven to data-intelligence-driven transformations, further enhancing the technological level and market competitiveness of the sector.

Competing interests The authors declare that they have no competing interests.

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