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REVIEW ARTICLE

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Introduction to data-driven systems for plastics and composites manufacturing

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Abstract
Applications of high-performance plastics and composites have widely been expanded to various industries due to their superior properties, such as high strength-to-weight ratio, chemical resistance, and thermal/electrical insulation. However, the numerous possible combinations of polymers and reinforcements/fillers, the variability of these materials, and their complex manufacturing processes pose challenges in terms of efficiently developing new plastics and composites, accurately modeling their properties, and effectively monitoring and controlling their manufacturing processes. Integrating data-driven techniques, such as machine learning, artificial intelligence, and big data analytics, is a promising pathway to overcome these challenges as it is demonstrated by the state-of-the-art research works presented in this special issue. This article provides background to the readers and introduces the range of topics covered by the articles in this special issue.

KEYWORDS
data-driven material development and modeling, data-driven process control and monitoring, data-driven sustainability, plastics and composites manufacturing

1 | BACKGROUND

The advances in the areas of digitalization and data analytics such as the internet of things (IoT), cloud and edge computing, big data, and artificial intelligence (AI) along with the technological advancements in automation and additive manufacturing can significantly impact manufacturing industries. In this context, the plastics and composites manufacturing industry is taking a slightly longer time to visibly adopt these technologies. The main reason is that plastics and composites manufacturing is more challenging than other industries in terms of data collection and analysis due to their inherent complexity. The extensive possible combinations of polymers, fillers, and reinforcements; the multi-physics nature of their manufacturing processes; complex tooling systems; and the requirement of human expertise in some sections complicate every aspect of their design and manufacture. This means that the plastics and composites industries have more to gain from these new technologies by implementing data-driven systems for accelerating material development, optimizing product design, and enhancing their manufacturing. In this regard, the following topics are discussed in this special issue.

2 | DATA-DRIVEN MATERIAL DEVELOPMENT AND MODELING

The main opportunities and issues in the manufacturing processes involving polymeric systems are related to the high reactivity of the resins at relatively low temperatures. This means that precise planning of each step (from the storage of the raw materials to the final product delivery) must be carefully planned and carried out. Nevertheless, on the other hand, it means that the physical and mechanical properties of the resin system can be precisely calibrated to improve the manufacturability and behavior of the final product.

Currently, data-driven approaches are providing researchers with paramount support in the definition of optimal manufacturing setups to avoid the presence of process-related weaknesses as shown by Gao, et al. in their work related to predicting the strength of injection molded fiber-reinforced composites.[1] Due to their wide applications, the requirements to be fulfilled can be highly different, ranging from the optimization of the static or dynamic properties to the improvement of the contact properties and wear resistance. In different cases, the optimal material definition can be achieved by the inclusion of ingredients or by choosing a better topology. Topology optimization is particularly relevant in 3D printing processes due to its versatility and the possibility to realize complex internal fillings and shapes. Of course, the drawback of the high flexibility is the complexity in the definition of the optimal topology, and data-driven methods are the only reasonable way to define the deposition strategy. In this regard, Agarwal et al. utilized several machine learning models for predicting the compressive strength of additively manufactured orthopedic cortical screws[2] and Cai et al. employed machine learning methods to link the dynamic strength of 3D-printed continuous fiber reinforced biocomposites with different printing parameters.[3] The model-based choice and dosage of additives included in the polymeric systems play a key role in the mechanical and tribological properties conferred on the products as investigated by Singh et al. by developing a neural network model to predict such properties of FDM printed polylactic acid parts and accordingly optimize the printing process parameters.[4]

Based on the phenomenological modeling of constitutive law, reaction kinetics, and heat transfer, the optimization of the process parameters can be performed by using advanced computation techniques for data-driven and/or physics-based modeling. This possibility is particularly intriguing in the case of multi-material/multi-layer applications, largely widespread in the aeronautics and automotive industry. In these cases, the presence of different polymers gives place to the necessity to find optimal conditions to co-cure all the phases and achieve high-quality sandwiches in terms of porosity and overall quality. This opportunity was demonstrated by Lavaggi et al. in their study on the development of several theory-guided machine learning (TGML) models for finding the optimal autoclave co-curing of sandwich composite structures.[5]

Often the realization of composite or polymeric parts is not the last productive step in the manufacturing process, and the product can be furthermore treated, drilled/milled, and assembled. The material removals are particularly critical in fiber-reinforced polymers, where the cutting processes determine discontinuity and local misorientation of the continuous reinforcement. Clearly, the development of data-driven strategies based on numerical and experimental outcomes can support the selection of optimal parameters or additives to improve and control the quality of the product, which is described by two articles in this special issue related to the drilling of fiber-metal laminated structures[6] and water jet drilling of glass fiber-reinforced composites.[7]

3 | DATA-DRIVEN PROCESS MONITORING AND OPTIMIZATION

There are often too many initial parameters involved in plastics and composites manufacturing processes including different material properties and compositions, process settings, and geometrical specifications. Finding the correlation between these initial parameters and the quality of the final product is a challenging process, especially considering the interactions of these parameters. Hence, machine learning and other data analytics methods can be used to better understand such correlations and develop data-driven models to monitor process conditions and/or predict product quality based on a set of training data. Although physics-based simulations can also be used to obtain insight into the manufacturing processes and predict the quality of the final part, they usually require high computational effort which limits their applications in a real-time process monitor or parameter adjustment. On the other hand, experimentally generating the training data set needed for developing the data-driven predictor models is a tedious and costly process. Hence, an efficient approach is oftentimes to validate a physics-based simulation using limited experimental results and then use the validated simulation to generate the needed data set for training the predictor models. In this regard, Hoa et al. used a unique combination of finite element and machine learning methods to predict several process variables, such as the degree of cure and temperature distribution, during the curing of thermoset prepreg in compression molding.[8] The developed predictor models provided a more efficient way of searching the process window (compared to the physics-based simulations) hence enabling more accurate process optimization.

The use of data-driven techniques is not only suitable for automated processes and can be used to improve manual processes, such as vacuum infusion molding, by reducing trial-and-error experiments and/or scrap rates. To enable real-time process monitoring and perhaps real-time parameter adjustment in such manual processes, vision systems are effective tools for the real-time collection of transient process variables as investigated by Lazaro et al. in their study on monitoring and controlling resin flow during infusion process.[9] This will provide further opportunities to analyze the collected graphical data using image processing tools and train deep learning models to predict the quality or performance of the final part during the manufacturing processes. Such vision-based systems coupled with data-driven techniques can be used to develop in-line systems to monitor the size and dispersion of the reinforcements in different composite manufacturing processes. This opportunity was explored by Zhu et al. in their work on the development of in-line property monitoring and characterization of the extruded glass bead-filled polypropylene.[10]

Not always it is possible to monitor composites manufacturing processes using vision-based systems, especially in closed-tool processes in which the tooling needs to be modified to accommodate the installation of the camera and lighting devices. Moreover, vision systems only capture information from the surface layer of the composite structures, which is insufficient for monitoring all the process variables and understanding the process status, especially in thick or sandwich structures. Placing a network of compatible sensors at different locations and layers of a composite structure and monitoring their resistance variation during the composites processing is a potential approach to overcome the limitation of vision systems as presented by Zhang et al. in this special issue.[11] They developed a flexible MXene/CNT film with high conductivity and good compatibility with resin and demonstrated its application for online monitoring of large and complex liquid composite molding. Using such networks of embedded sensors, the collected data from the process is not limited to the flow of the resin, and other critical process variables, such as reinforcement compaction response, infiltration, race tracking, and resin cure can also be monitored as explored by Khan et al. for both thermosets and thermoplastics.[12] Besides the technical requirement of developing sensors, which need to be accurate, compatible with the resin, and yet inexpensive, analyzing the data collected by these sensors (usually resistance variation) is also a highly challenging task. Hence, data-driven techniques can be used to analyze the collected data from the embedded sensors and correlate them not only to the process variables (e.g. flow position, flow rate, and infiltration status) but also to the quality and performance of the final products.

The use of recent advancements in monitoring techniques and instrumentation is not only limited to the composites manufacturing processes and has been expanded to their post-processing steps as well. As the majority of defects created during machining, drilling, or cutting of composites, such as matrix burnout, fiber pull-out, and delamination, are directly or indirectly related to the heat generated during these processes, monitoring the tool/workpiece temperature is critical in optimizing their parameters and/or providing real-time control. This opportunity was explored by Parodo et al. in their study on monitoring the drilling process of fiber metal laminated using the data captured from the thermocouples embedded in their drill bits.[6]

4 | DATA-DRIVEN SUSTAINABILITY

With the widespread application of petrochemical plastics, our planet is being polluted by plastic wastes, from land to ocean, and recently microplastic particles were even found in our and animal bodies. This becomes a serious sustainable development problem for humans, which requires great efforts to effectively recall or recycle non-degradable petrochemical plastics to avoid their environmental pollution. Besides improving recycling and upcycling measures, the use of degradable and natural polymers such as polylactic acid, polybutylene terephthalate, ramie, cellulose, and their composites should be expanded to reduce the dependency on petrochemical plastics. Whether the former or the latter, data-driven approaches can play an important role in the sustainability of plastics and composites manufacturing. In this regard, Verma et al. provided a comprehensive discussion on recycling plastics and plastic waste using artificial intelligence (AI) and blockchain technology.[13] They also detailed the recently developed plastic regulation policies, AI utilization, and AI-enabled multi-sensor to alleviate manual segregation in the collection of plastics from waste and the follow-on recycling. Their demonstration of using blockchain technology in the plastics circular economy and effective utilization of plastic waste management is another interesting contribution of this paper.

Data-driven systems can also be used to expand the application and improve the properties of biodegradable materials as a promising approach to maintaining sustainability in plastics and composites manufacturing. In this special issue, this opportunity was demonstrated by three studies related to the additive manufacturing of natural or degradable polymers. In the first one, Singh et al. introduced a feedforward backpropagation artificial neural network model for the prediction of tensile strength, material consumption, build time, and surface quality considering multiple printing process parameters in additive manufacturing of PLA parts.[14] In the second study conducted by Cai et al., a machine learning method was employed to link the dynamic strength of 3D-printed continuous ramie fiber reinforced biocomposites (CRFRC) with different printing parameters, and build their nonlinear and interactive relationships.[3] The trained models from experimental data were utilized to predict the dynamic strength of CRFRC printed using different conditions. In the last study, Agarwal et al. studied the application of several machine learning models including k-nearest neighbors, support vector regression, decision trees, and random forest for predicting the compressive strength of additively manufactured polylactic acid-based cortical screws.[2]

5 | CONCLUDING REMARKS AND OUTLOOK

The range of studies presented in this special issue shows the potential of using data-driven techniques to improve the plastics and composites industries by solving the inherent complexity of the material and manufacturing systems used in these industries. The amount of data available in the manufacturing industry is growing rapidly, driven by advances in sensor technology, the increasing prevalence of connected devices, and the rise of the Industrial Internet of Things (IIoT). These advancements enable collecting vast quantities of data from every aspect of the plastics and composites manufacturing process, from raw material inputs to finished product outputs. Additionally, the technology to process this data is becoming more advanced, with new tools and algorithms being developed specifically for the manufacturing industry.

As the amount of data available continues to grow and the technology to process it becomes more advanced, the potential for data-driven systems in plastics and composites manufacturing is immense. The integration of Industry 4.0 principles, such as digital twins and networked systems, will enable real-time monitoring and predictive modeling of material behavior and manufacturing processes, leading to a significant reduction in material waste, energy consumption, and production cycle times. Furthermore, the implementation of these systems will facilitate the development of novel plastics and composite formulations by harnessing the potential of high-dimensional data generated from multiscale experiments and simulations. This shift towards a more data-centric approach will foster the creation of next-generation materials with superior mechanical, thermal, and chemical properties, ultimately driving innovations in various sectors, including aerospace, automotive, and renewable energy. As a result, the development and utilization of data-driven systems will not only propel the plastics and composites industry to new heights but also contribute to sustainable development goals by reducing the overall environmental footprint of these materials.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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