6-2023

COMPOSITES 4.0: ENABLING THE MODERNIZATION OF LEGACY MANUFACTURING ASSETS IN SOUTH CAROLINA

Amit Makarand Deshpande
Clemson University

Gayatri Keskar
Clemson University, gkeskar@clemson.edu

Sai Aditya Pradeep
Clemson University, spradee@clemson.edu

Saeed Farahani
Cleveland State University

Srikanth Pilla
Clemson University, spilla@clemson.edu

Manufacturing Science and Engineering Conference
MSEC2023
June 12-16, 2023, New Brunswick, New Jersey

MSEC2023-104904

COMPOSITES 4.0: ENABLING THE MODERNIZATION OF LEGACY MANUFACTURING ASSETS IN SOUTH CAROLINA

Amit Makarand Deshpande
Department of Automotive Engineering, Clemson University, Greenville, SC, 29607, USA
Clemson Composites Center, Clemson University, Greenville, SC, 29607, USA

Gautami Girish Keskar
Department of Automotive Engineering, Clemson University, Greenville, SC, 29607, USA
Clemson Composites Center, Clemson University, Greenville, SC, 29607, USA

Sai Aditya Pradeep
Clemson Composites Center, Clemson University, Greenville, SC, 29607, USA

Saeed Farahani
Department of Mechanical Engineering, Cleveland State University, Cleveland, OH, 44115, USA

Srikanth Pilla*
Department of Automotive Engineering, Clemson University, Greenville, SC, 29607, USA

**Corresponding author:* spilla@clemson.edu

ABSTRACT

Composites 4.0 is the implementation of Industry 4.0 concepts to plastics and composites manufacturing with the goal to overcome the complexities associated with these materials. Due to very complex process-structure-property relationships associated with plastics and composites, a wide range of process parameters need to be tracked and monitored. Furthermore, these parameters are often affected by the tool and machinery, human intervention and variability and should thus, be monitored by integrating intelligence and connectivity in manufacturing systems. Retrofitting legacy manufacturing systems with modern sensing and control systems is emerging as one of the more cost-effective approaches as it circumvents the substantial investments needed to replace legacy equipment with modern systems to enhance productivity.

The goal of the following study is to contribute to these retrofitting efforts by identifying the current state-of-the-art and implementation level of Composites 4.0 capabilities in the plastics and composites manufacturing industry. The study was conducted in two phases, first, a detailed review of the current state-of-the-art for Industry 4.0 in the manufacturing domain was conducted to understand the level of integration possible. It also helped gain insights into formulating the right questions for the composites manufacturing industry in South Carolina. Second, a survey of the plastics and composites manufacturing industries was performed based on these questions, which helps identify the needs of the industry and the gap in the implementation of Composites 4.0. The study focuses on the three leading composite manufacturing industries: injection molding, extrusion, and 3D printing of thermoset and thermoplastic materials.

Through the survey, it was possible to identify focus areas and desired functionalities being targeted by the industries surveyed and concentrate research efforts to develop targeted solutions. After analyzing the survey responses, it was found that updating old protocols using manufacturer support and customized integration of cost-effective solutions like retrofit kits, edge gateways, and smart sensors were identified as best-suited solutions to modernize the equipment. Composites 4.0 is already being implemented for Preventive Maintenance (PM), Manufacturing Execution System (MES), and Enterprise Resource Planning (ERP) to some extent, and the focus is on process optimization and equipment downtime reduction. The inferences drawn from this study are being used to develop highly targeted, supplier-agnostic solutions to modernize legacy manufacturing assets.

Keywords: Composites 4.0, Industry 4.0, Injection Molding, Extrusion, 3D printing, Smart Manufacturing

1. INTRODUCTION

1.1. Motivation for Industry 4.0 for Composites Manufacturing

The last two centuries have seen unprecedented growth in industrialization and mass manufacturing, characterized by four industrial revolutions, the most recent being Industry 4.0, initially introduced in 2011, and officially recognized in 2013 as the cornerstone for the next revolution in manufacturing focused on real-time process and quality control to enable flexible, efficient, and sustainable production systems [1]. The transition to Industry 4.0 focuses on the collaboration of conventional production processes with information technology, data analysis, and artificial intelligence. Key drivers for Industry 4.0 are cyber-physical systems (CPS), Internet of Things (IoT), Cloud Computing, and Big Data [2]. These components also enable risk reduction with applications like alarming, in-line monitoring, quality control, and real-time parameter adjustment.

Fiber reinforced plastic (FRP) composites are extremely lucrative due to their high specific stiffness and strength, lower processing temperatures, resistance to corrosion and ability to conform to complex part geometries [3]. However, despite these potential benefits, their adoption has been slow, and manufacturers take an extremely conservative approach when deploying new designs. This can be attributed, in large part, to significant efforts involved in realizing commercially reproducible, defect free and consistent components when there is significant variability in the end component microstructure, which in turn affect the macroscopic properties, due to the processing parameters [4], [5]. This, also limits the ability to model the process-structure-property relations [6] by incorporating multi-physics interactions occurring during manufacturing which, when deployed, can help control the end component properties within permissible control limits. Furthermore, wide range of anomalies are possible during the material development and manufacturing of composites, due to complexities in processing, dealing with shear and layer lines when laying up material, investigating the anisotropic nature of composite materials, obtaining void-free parts, building parts with complex geometries, programming the equipment automation, etc. [7].

1.2. Composites 4.0

As summarized in the previous section, overcoming these complexities arising due to highly interlinked process-structure-property relations is a necessity to enhance the productivity of composites and plastics manufacturing methods. Industry 4.0 concepts such as digital twin, cyber-physical systems and big data analysis can help develop fast and accurate models that address this gap in understanding of the multi-physics interactions at various material scales and capture these process-structure-property relations. Furthermore, since these models are data-driven, the ability to enable in-situ monitoring can be easily incorporated in production and real-time property prediction becomes possible. This in turn, has the potential to enhance the quality and ultimately, the productivity of existing and incumbent plastics and composites manufacturing processes. This drastic change in the approach to plastics and composites manufacturing is revolutionary and since, it is driven by incorporation of Industry 4.0 concepts, aptly named Composites 4.0.

Composites 4.0 aims to address the above challenges of plastics and composites manufacturing using the data-driven approach characteristic of Industry 4.0. In the long run, it will enable digitalization of design, production, delivery, operations, and maintenance [8] making the products quality-reliable, and the associated manufacturing processes cost-effective, intelligent, and adaptive.

Due to the complex multi-scale micro-macro property translation and the ability to have multiple constituent materials within the composition of a plastic or composite component, there can theoretically be more optimal solutions in terms of the material design that may go unexplored when the design development process follows the traditional simulation-experimentation approach. However, there have been recent efforts to develop open-source libraries [9] with various kinds of data to serve as input for new data-drive material synthesis and property prediction techniques [10] that significantly reduce the concept-to-market deployment time and cost [11].

Vison based machine learning (ML) approaches using convolutional neural networks (CNNs) have been demonstrated to be effective for inspecting composite components using laser profilometers and identifying the type of defects occurring in the component and propose a change in the manufacturing process parameters of the automated fiber placement (AFP) process [12]. This automated inspection methodology can help reduce the inspection time by up to 50% [13]. Significant work has also been done to utilize pre-existing data to develop data-driven models to make process adjustments in close loop manufacturing for processes such as resin infusion [14],[15].

For composites processing, where novel material systems or processes are involved, the available data is limited and thus, transfer learning (TL) techniques that can handle uncertainties and production data shifts on the factory floor with change in process settings have proved to be quite effective [16]. Reinforcement learning based AI schedulers, utilizing reward functions have enabled data-driven dynamic scheduling of manufacturing jobs under uncertainty by utilizing internet-enabled sensor networks to track activities and gather data to improve multi-objective production scheduling in real-time [17].

However, a majority of these ML and AI based methods are driven by carefully gathered, curated, and labelled data, that can vary based on the manufacturing equipment. This adds significant time and computational costs when such methods are to be deployed to the industry. Hence, identifying the specific requirements for each plastic and composites manufacturing process is necessary. The subsequent survey of specific industries, their goals in terms of productivity and their level of adoption of Industry 4.0 concepts addresses this gap preventing the deployment and adoption of these above methods in the traditionally conservative composites manufacturing industry.

2. TARGET INDUSTRIES

As of Q4 of 2021, manufacturing accounted for over $2.3 trillion out of the almost $21 trillion of the U.S. gross domestic product (GDP). It is the second largest sector by contribution to the total GDP of the country behind Services (~$13.7 trillion)[1]. South Carolina directly accounts for a significant chunk of both these sectors due to the presence of large automotive OEMs, aerospace companies and their suppliers. Prominent among them are BMW, Daimler, Volvo, Michelin, ZF transmissions, Bosch, Boeing[2] and other advanced manufacturing facilities, accounting for almost $80 billion[3] of the state's total GDP of approximately $215 billion[3]. Consequently, it follows that these industries, namely advanced manufacturing, automotive and food processing, be the focus of the subsequent study and documentation.

In this paper, the leading plastics and composites manufacturing industries in South Carolina, were to be targeted for a detailed study of methods to modernize or retrofit legacy equipment. Several Tier-1, and -2 automotive suppliers in the injection molding industry and other small-and-medium sized injection molders are well established in South Carolina, like Yanfeng, Plastic Omnium, and many more [18]. Also, extrusion industry is an integral part of the South Carolina industry as it employs up to 0.7 million people and accounts for around $30 billion in payroll [19]. Additionally, owing to heavy investments by plastic manufacturers, the 3D printing industry is gaining a boost. Hence, the industries of injection molding, extrusion and additive manufacturing have been chosen as the target industries for further study.

3. LITERATURE REVIEW OF THE TARGET INDUSTRIES

To understand the state-of-the-art for the selected manufacturing processes, several cases of integration of Composites 4.0 in manufacturing have been reviewed. At the level of manufacturing systems, the application domains included alarming, in-line monitoring, quality control, and real-time parameter adjustment. At the level of manufacturing support systems, the domains of documentation, product design, maintenance management, production planning, and preventive maintenance were explored.

3.1. Injection Molding

With the ever-increasing use of plastics and composites in the automotive domain, the plastic injection molding process has an even wider scope for improvement. Also, in assets of injection molding like the mold tool, feeding unit, injection unit, and the clamping unit, the feasibility of implementation of Industry 4.0 or Composites 4.0 is already being studied. Ageyeva et al. [20] proposed an increase in the use of infrared measurement devices for measuring the in-mold temperature along with the use of piezoelectric crystal-based sensors. This will enable direct and quick measurement of temperature and other parameters like viscosity, warpage, shrinkage, and others. In the domain of real-time parameter adjustment, Loftis et al. [21] used real-time data from the machine to monitor the quality of the molded parts with the help of built-in sensors and a dimensional reduction method. The above study also proposes user selections for training AI as the next alternative method for data extraction. Farahani et al. [22] obtained data from an injection molding machine using in-mold sensors and data sources. This data was used to determine the quality indices of the final molded parts with respect to the shot size, material disturbances, and shutdown of the mold cooling system. The most efficient machine learning algorithm and data source were noted from the results of the Partial Least Square (PLS) regression analysis.

Predictive maintenance is one of the most critical fields to analyze for optimizing the composite manufacturing process. Farahani et al. [23], [24] worked on implementing an Industry 4.0 framework using edge and cloud computing to detect any signs of maintenance issues. They used Principal Component Analysis (PCA) for a cloud-based system and achieved an error of as low as 3.29%.

3.2 Extrusion Industry

Extrusion is one of the most well-established processes in the plastics industry. With machine-to-machine communication receiving a boost and AI techniques being developed to utilize the data being received, investigations are now underway to explore the implementation of Industry 4.0 to extrusion.

Abeykoon et al. [25] demonstrated an approach towards real-time closed-loop control of melt temperature and reliable results were achieved in maintaining desired temperatures. In this way, the melt viscosity and the melt quality can be indirectly controlled. Efforts have also been made by Zairi et al. [26] to model the plastic flow considering viscoelastic properties, to ultimately predict the microstructure of the extruded product. The effect of the die geometry on the final product and the loading conditions were also factored into the study.Sajko et al. [27] worked on predicting the manufacturing lead time of the extrusion process by using Artificial Neural Networks (ANNs). The number of cavities, tool type, tool category, order type, the number of orders and tool diameter were some of the parameters studied to accurately predict the number of working days to manufacture the tool.

3.3 3D Printing Industry

The 3D printing market is growing at about 25% per year, highlighting the need to develop strategies to achieve sustainability, reduced cycle times and costs, and better predict the end product's properties.

ANNs is one such strategy that considers the entire manufacturing process and optimizes it, an approach that has been investigated by Rojek et al. [28] where the decision-making process for energy consumption of the 3D printer was developed using ANNs. Although these Computer Intelligence (CI) based solutions are complex for implementation, they are significantly efficient in the aspects on accuracy, processing time and computational cost.

A key challenge in 3D printing of composite materials is the labor-intensive post-processing. This issue is addressed by Fox et al. [29] using automation and digitalization and more specifically using machine-to-machine communication techniques. Mass customization is a primary advantage of this implementation. Another case study by Goh et al. [30] demonstrates the use of ANNs and Convolutional Neural Networks (CNNS) to validate the FEA simulation for 3D printing. CNNs were found to be more efficient than ANNs as they better capture the 2D and 3D spatial features on the parts. Due to this reason, CNNs are also widely used for anomaly detection in in-situ monitoring.

This systematic literature review gives us an insight into the current state-of-the-art of Composites 4.0 in the industry today. Composites 4.0 efforts are directed not only towards the optimization of processes and products, but it also improved energy efficiency, less human-machine interference resulting in reduced part-to-part variation, and reduction in processing costs. Furthermore, the sensors used to gather the data used in the above studies have also been reviewed. It is possible to gain the same sensing capabilities through retrofitting legacy equipment for the above manufacturing processes, making it a cost-effective solution.

4. INDUSTRIAL SURVEY FORMULATION

The literature review provides an overview of the dynamics of Composites 4.0 in the target industries. To gain insights into the industrial needs, their priorities, and the value they see in Composites 4.0, industrial surveys were sent out to leading industries majorly based in South Carolina, in the respective domains of injection molding, extrusion, and 3D printing.

The survey questionnaire consisted of two sections. The first section delved into the knowledge of the respondents with respect to Industry 4.0, and their take on the transition to digitalization. The questions in this section were also based on Industry 4.0 concepts and technologies currently operating in the organizations, and principal focus areas being targeted by the organization.

The second section investigated the equipment-related concerns that would ideally be addressed through the adoption of Industry 4.0. The section enquires the respondents about the maintenance tools implemented, mean time between failures, mean time to repair, mean time between failures, usual nature of failures, causes of most press failures, and many more. Furthermore, quality-related questions such as the parameters to be optimized in the final part, average defect rate, frequently occurring quality issues, and the parameters to be controlled during the processes have been addressed in this section.

A total of 12 responses for injection molding, 3 for extrusion, and 4 for thermoplastic 3D printing were received, which are discussed in the next section of the paper.

5. RESULTS AND DISCUSSION

A total of 19 responses, each representing an entire manufacturing facility, were assessed to draw inferences based on statistical analysis. The fact that a majority of the responses received are from managerial staff responsible for entire facilities and floor engineers with access to data from multiple manufacturing units, gives sufficient confidence for inferences to be drawn since the sample size represents multiple manufacturing units for each of the manufacturing processes as illustrated in FIGURE 1. Injection molding received 12 responses, thermoplastic 3D printing received responses from 4 facilities, while 3 responses were received from extrusion facilities.

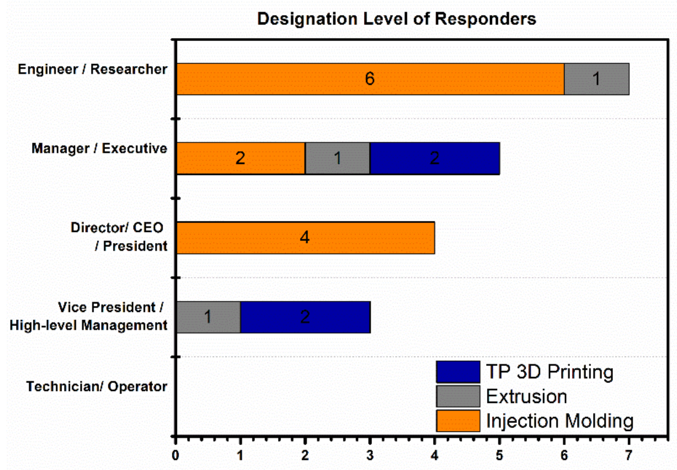

FIGURE 1: DESIGNATION LEVEL OF RESPONSES

5.1. Industry 4.0 Awareness and Focus

The responses represent all technical domains of expertise in an organization, as illustrated in **Error! Reference source not found.**, ensuring that the data represents various viewpoints of Industry 4.0 elements within an organization without significant bias.

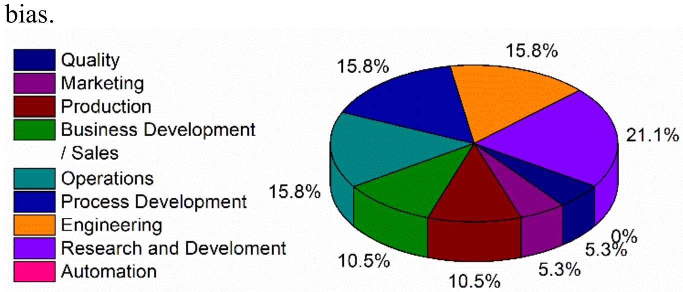

FIGURE 2: DOMAIN EXPERTISE OF RESPONDERS

To gauge the responders' familiarity with Industry 4.0 elements and its value to their composites manufacturing operations, they were required to state whether they were aware of Industry 4.0 elements. This allowed the authors to also gauge the awareness of Industry 4.0 and the possible benefits it can bring in composites manufacturing operations at different levels of organization, as illustrated in TABLE 1 .

TABLE 1: FAMILIARITY OF INDUSTRY 4.0 ELEMENTS AT VARIOUS LELVELS OF THE ORGANIZATION

Familiarity of Industry 4.0 elements at various organization levels	Yes	No
Vice President / High-level Management	5%	5%
Director/ CEO / President	21%	0%
Manager / Executive	21%	5%

Engineer / Researcher	32%	11%

Assessment was done to identify and compare current and planned implementation of Industry 4.0 concepts in these organizations, as illustrated in FIGURE 3. Most injection molding facilities have adopted some or most aspects of industry 4.0 and are targeting a higher level of integration. This can be attributed to the fact that injection molding has been prevalent for a few decades and increasing adoption of plastics in automotive and other applications that require higher quality components, is driving the need to make this transition. For the extrusion industry, 66% of responders represent facilities with some adoption of Industry 4.0 concepts and major integration in the future is desired. The remaining 33% do not have any implementation nor is any planned for the future, indicating that their organization may not see value in Industry 4.0 transition. For thermoplastic 3D printing, there is some level of implementation observed and further plans are in place for the future. This conservative approach and outlook may be attributed to the fact that 3D printing is a new processing method with a smaller footprint in the current market.

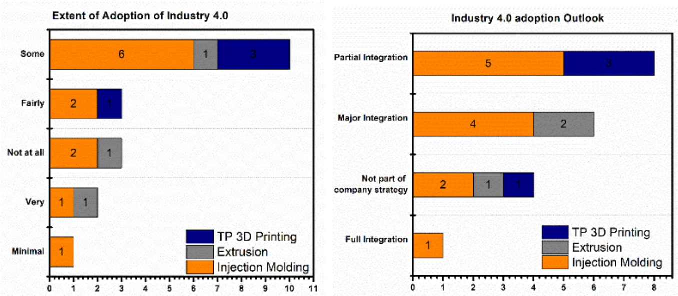

FIGURE 3: INDUSTRY 4.0 STATE OF ADOPTION (LEFT); FUTURE FOCUS FOR INDUSTRY 4.0 ADOPTION (RIGHT)

58% of facilities have some level of adoption of Industry 4.0 in their manufacturing setup, with 42% believing some additional integration is desired, followed by 31% believing a greater extent of adoption is required, as illustrated in TABLE 2. This constitutes 73% of the facilities surveyed, who want to incrementally elevate their adoption level of Industry 4.0. This further underscores the authors' opinion about retrofitting being a suitable approach to accelerate adoption of Industry 4.0 in the target industries.

TABLE 2: CURRENT V/S PLANNED INDUSTRY 4.0 ADOPTION

Industry 4.0 Adoption		Outlook: None Planned	Partial Integration	Major Integration	Full integration
Current Extent of Adoption	Very			5%	5%
	Fairly		5%	5%	
	Some	5%	37%	16%	
	Minimal			5%	
	Not at all	16%			

The literature review enabled identification of Industry 4.0 implementation domains for the manufacturing processes associated with the target industries. Based on the responses, the main elements of Industry 4.0 cited by the responders can be identified, as illustrated in FIGURE 4.

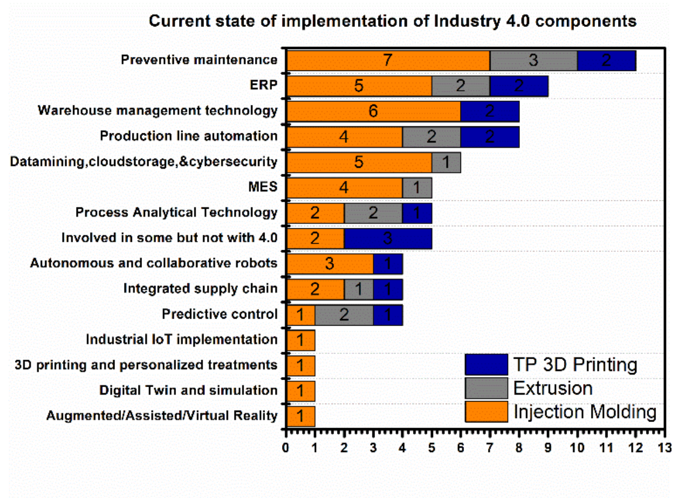

FIGURE 4: CURRENT FOCUS AREAS FOR INDUSTRY 4.0 ADOPTION IN THE TARGET INDUSTRIES

Preventive maintenance is the focus area for all target industries. This is followed by resource planning and warehouse management i.e., inventory management. This is indicative of Industry 4.0 elements being adopted to further enhance gains associated with Lean manufacturing introduced during the third industrial revolution. However, scrutiny of survey responses associated with preventive maintenance indicate that the current elements of Industry 4.0 in place leave significant room for improvement as summarized in TABLE 3.

TABLE 3: ANALYSIS OF EFFECTIVENESS OF IMPLEMENTED ELEMENTS OF INDUSTRY 4.0 ON ENHANCING PREVENTIVE MAINTENANCE

		Predictive Maintenance tools implemented? Yes	No
Is unexpected failure still prevalent?	Yes	63%	11%
	No	16%	11%

Although the main domain for Industry 4.0 implementation was preventive maintenance, unexpected failure is still prevalent. This is one of the drivers for further enhancing the level of Industry 4.0 elements.

Thus, the survey also focused on the future focus areas for the plastics and composites manufacturing target industries, as illustrated in FIGURE 5. Overall, process optimization (73.68%) and general operations (57.89%) are cited to be the dominant focus areas in the future. However, a slight disagreement exists in the focus areas of each of the target industries, with injection molding and extrusion in alignment with the consensus, while 3D printing is focused on process optimization and capacity expansion. This observation supports the previously stated remarks on the maturity and footprint of this process.

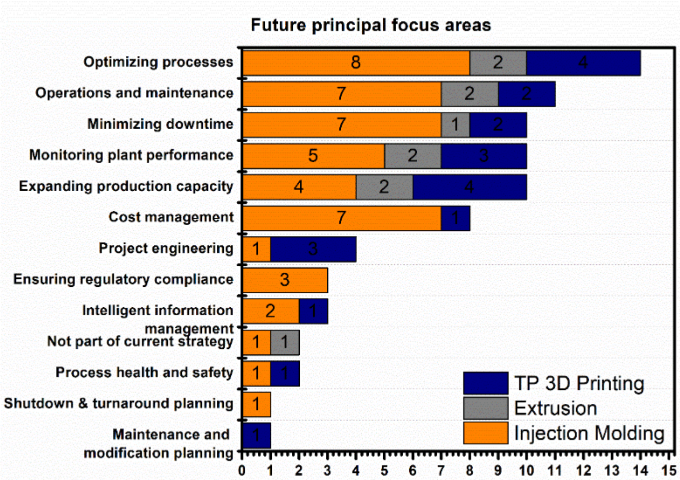

FIGURE 5: FUTURE INDUSTRY 4.0 FOCUS AREAS IDENTIFIED BY THE SURVEY

5.2. Injection Molding Process Survey Results

Based on the focus areas identified for injection molding, a further detailed survey was conducted to identify the tools in place (FIGURE 6), the key part manufacturing parameters being monitored (FIGURE 7), key defects observed (FIGURE 8), and the process parameters identified for control and monitoring through implementation of Industry 4.0 elements.

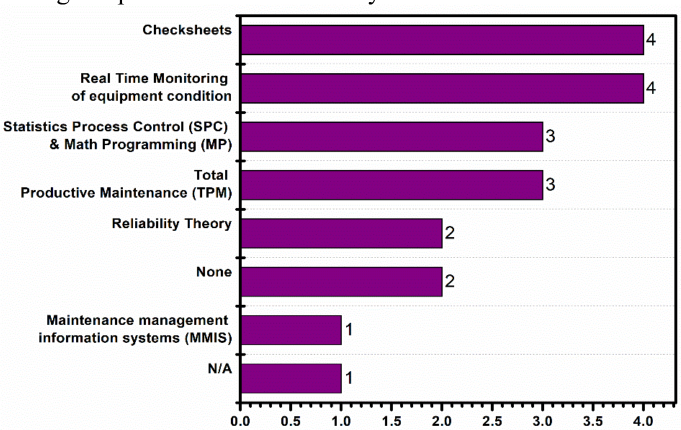

FIGURE 6: PREDICTIVE MAINTENANCE TOOLS USED

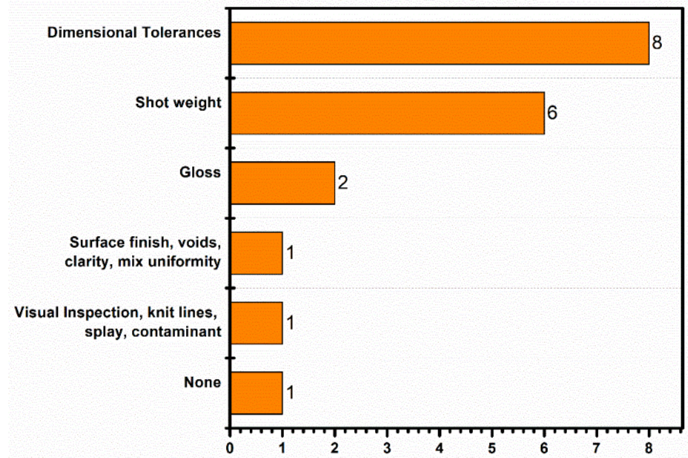

FIGURE 7: PARAMETERS THAT ARE BEING CHECKED/OPTIMIZED

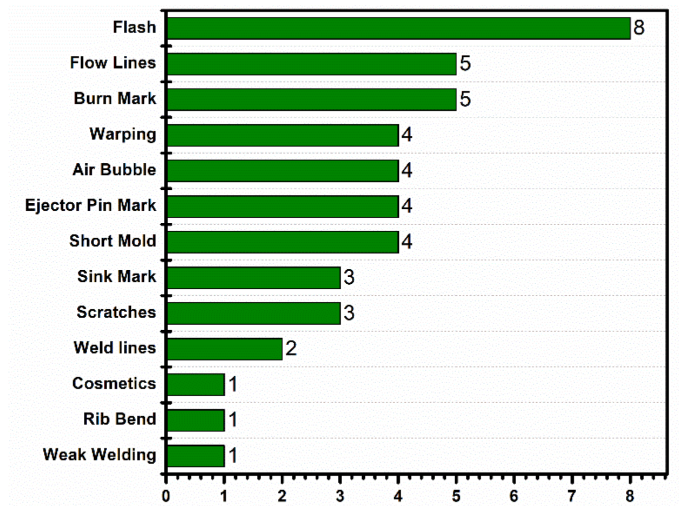

FIGURE 8: MOST FREQUENTLY OCCURRING QUALITY ISSUES IN THE PARTS

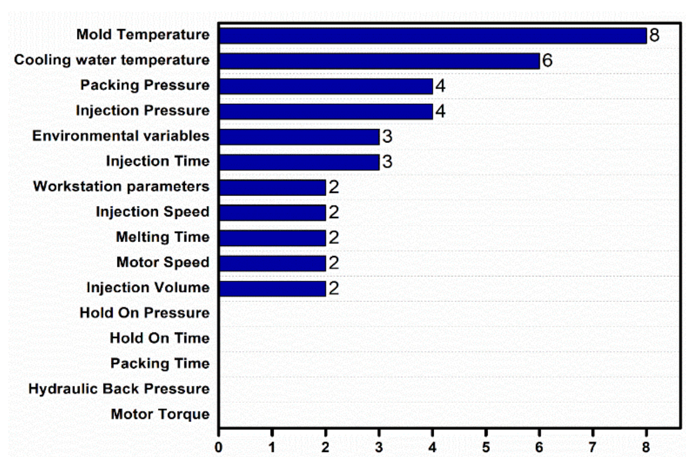

FIGURE 9: PARAMETERS TO CONTROL AND REDUCE QUALITY ISSUES

These results of the injection molding survey not only give an idea about the key performance metrics that the industry is focused on when deploying Industry 4.0 concepts, but also gives a comprehensive idea about the assets to focus on while retrofitting the lab equipment.

The main enablers to predictive maintenance were identified to be Statistical Process Control (SPC), Check sheets, and real-time monitoring of equipment as illustrated in FIGURE 6. In addition to the manufacturing equipment, another factor that is a driver for implementation of Industry 4.0 is the enhancement possible in terms of part quality. The key product quality attributes that form the basis for this Industry 4.0 transition were identified, as illustrated in FIGURE 7. It can be inferred that dimensional tolerances and the final part weight are the two most critical parameters that the organizations work on monitoring with focus on preventing flash, burn mark, or flow lines, as illustrated in FIGURE 8. This, according to the survey, can be achieved by iterating majorly the process parameters of cooling temperature, mold temperature, injection pressure, and packing pressure as illustrated in FIGURE 9.

5.3. Extrusion Process Survey Results

The extrusion survey was also sent out to a few industries, and responses were received from employees in the Research and Development and Process Development sectors of the industry, who have had more than 15 years of experience in this domain. Since the number of responses in this target industry are limited, limited inferences may be drawn from the data available.

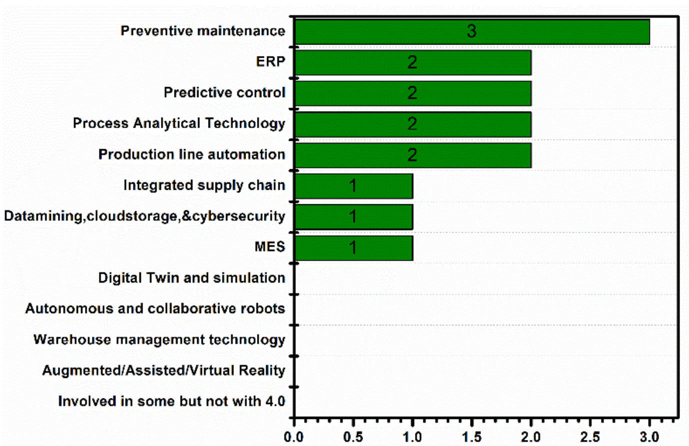

FIGURE 10: MAJOR ELEMENTS CURRENTLY OPERATING IN THE ORGANIZATIONS

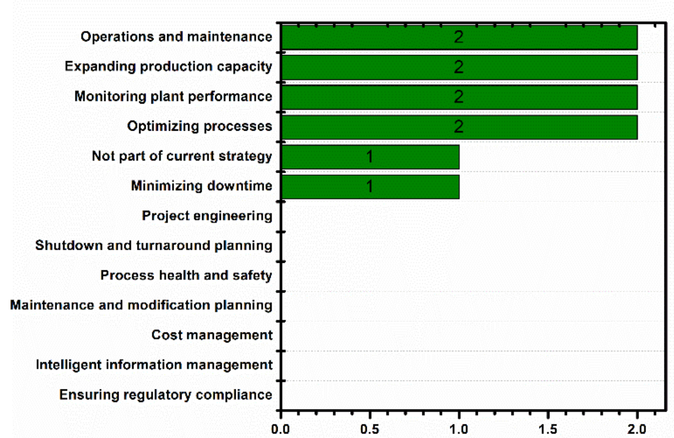

FIGURE 11: MAJOR AREAS WHICH THE ORGANIZATION WOULD FOCUS ON FOR INDUSTRY 4.0 ADOPTION

Extrusion manufacturing facilities are focused on working in the areas of preventive maintenance, enterprise resource planning (inventory management) and process analysis and control, as illustrated in FIGURE 10. The motive, however, is inconclusive currently, due to the lack of statistically sufficient sample size of responses. FIGURE 11 illustrated the key focus areas driving further implementation of Industry 4.0 elements in the extrusion industry.

5.4. Thermoplastic 3D Printing Process Survey Results

As alluded to earlier, the driving motivation for thermoplastic 3D printing varies from that of injection molding and extrusion, despite 3D printing sharing a lot of the process physics with extrusion. As illustrated in FIGURE 12, the focus right now is ERP, inventory management and predictive maintenance.

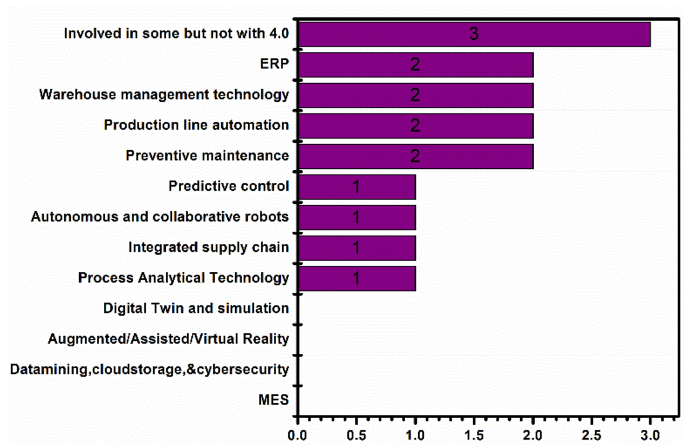

FIGURE 12: MAJOR FOCUS AREAS FOR THERMOPLASTIC 3D PRINTING

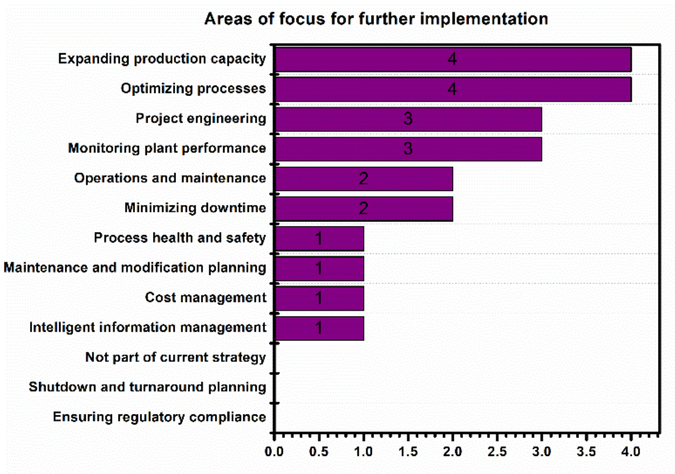

FIGURE 13: FUTURE FOCUS AREAS FOR INDUSTRY 4.0 ADOPTION FOR THERMOPLASTIC 3D PRINTING

As previously discussed in section 5.1 and illustrated above in FIGURE 13, the focus areas for 3D printing are focused more on increasing production capacity, process speed and efficiency as opposed to predictive maintenance and down-time reduction identified for injection molding and extrusion.

6. FUTURE SCOPE OF WORK

To ensure that significant bias is not present in the collected data due to the departmental affiliations of the responders, analysis of response bias categorized by departmental affiliations is proposed. Furthermore, additional enquiries need to be made on the readiness of the target industries to invest in the transition to Industry 4.0. Furthermore, a quantitative inquiry into expected expenditure and expected return on investment needs to be performed by these target industry enterprises.

The scope of this project covered a systematic literature review of the existing Composites 4.0 retrofitting approaches specific to the target industries. Also, the industrial surveys facilitated the team to get an insight into the varied approaches towards Composites 4.0. Current inferences give sufficient direction to research entities to perform research and demonstrate capabilities associated with these plastic and composites manufacturing processes, particularly, injection molding. Further inquiry and outreach are planned for extrusion and thermoplastic 3D printing. A similar survey is also planned for thermoset 3D printing- primarily focused on medical applications. Analysis of the process specific survey answers for injection molding have helped in the selection and installation of retrofit kits and smart sensors for the equipment to be modernized. These efforts are currently underway.

The next step will include a non-biased evaluation of multiple retrofitting options with the help of manufacturer support as well as with customized integration, which will be a benchmark for several Small and Medium-sized Enterprises that would look forward to retrofitting their manufacturing systems as part of incremental progress towards implementation of Industry 4.0. These retrofitting setups are expected to result in less machine downtime and consequently increased productivity of the industries, without procuring high-cost equipment for the same.

7. CONCLUSION

The specific challenges in plastic and composite materials development and manufacturing are described in this paper. The concept of Composites 4.0 was introduced as a special implementation of Industry 4.0 technologies aiming to overcome these challenges and create capabilities that have not previously been possible. The state-of-the-art on Composites 4.0 implementations in the three targeted industries, namely injection molding, extrusion, and 3D printing, were reviewed. A customized survey was designed and conducted for each industry. The results of these surveys were presented and analyzed to extract the specific needs of each industry and serve as important focus areas for projects that are looking to develop a framework for Industry 4.0 that address these gaps. Finally, the outlook of composites 4.0 was discussed and future research directions were proposed.

ACKNOWLEDGEMENTS

This is a South Carolina Research Authority (SCRA) funded project. The authors wish to express sincere gratitude to the SCRA team for their generous donation and constant support.

REFERENCES

[1] "Plattform Industrie 4.0 - What is Industrie 4.0?" https://www.plattform-i40.de/IP/Navigation/EN/Industrie40/WhatIsIndustrie40/what-is-industrie40.html (accessed Nov. 19, 2022).

[2] M. Mohamed, "Challenges and Benefits of Industry 4.0: An overview," *International Journal of Supply and Operations Management*, vol. 5, no. 3, pp. 256–265, 2018, [Online]. Available: www.ijsom.com

[3] Autar K Kaw, "Mechanics of Composite Materials."

[4] T. S. Mesogitis, A. A. Skordos, and A. C. Long, "Uncertainty in the manufacturing of fibrous thermosetting composites: A review," *Compos Part A Appl Sci Manuf*, vol. 57, pp. 67–75, Feb. 2014, doi: 10.1016/J.COMPOSITESA.2013.11.004.

[5] K. D. Potter, "UNDERSTANDING THE ORIGINS OF DEFECTS AND VARIABILITY IN COMPOSITES MANUFACTURE."

[6] S. Mazumdar, "Composites Manufacturing : Materials, Product, and Process Engineering," *Composites Manufacturing*, Dec. 2001, doi: 10.1201/9781420041989.

[7] C. Binetruy, "COMPOSITES MANUFACTURING OVERVIEW OF CURRENT ADVANCES AND CHALLENGES FOR THE FUTURE," 2014.

[8] G. D. Goh, S. L. Sing, and W. Y. Yeong, "A review on machine learning in 3D printing: applications, potential, and challenges," *Artif Intell Rev*, vol. 54, no. 1, pp. 63–94, Jan. 2021, doi: 10.1007/s10462-020-09876-9.

[9] N. Sajko, S. Kovacic, M. Ficko, I. Palcic, and S. Klancnik, "Manufacturing lead time prediction for extrusion tools

with the use of neural networks," *Management and Production Engineering Review*, vol. 11, no. 3, pp. 48–55, 2020, doi: 10.24425/mper.2020.134931.

[10] N. X. Ho, T. T. Le, and M. V. Le, "Development of artificial intelligence-based model for the prediction of Young's modulus of polymer/carbon-nanotubes composites," *https://doi.org/10.1080/15376494.2021.1969709*, 2021, doi: 10.1080/15376494.2021.1969709.

[11] C. Qiu and J. Yang, "Machine Learning Applications in Composites: Manufacturing, Design, and Characterization," *ACS Symposium Series*, vol. 1416, pp. 65–85, Jun. 2022, doi: 10.1021/BK-2022-1416.CH004/ASSET/IMAGES/LARGE/BK-2021-00661M_G006.JPEG.

[12] C. Sacco, A. Baz Radwan, A. Anderson, R. Harik, and E. Gregory, "Machine learning in composites manufacturing: A case study of Automated Fiber Placement inspection," *Compos Struct*, vol. 250, p. 112514, Oct. 2020, doi: 10.1016/J.COMPSTRUCT.2020.112514.

[13] S. Meister, M. Wermes, J. Stüve, and R. M. Groves, "Investigations on Explainable Artificial Intelligence methods for the deep learning classification of fibre layup defect in the automated composite manufacturing," *Compos B Eng*, vol. 224, p. 109160, Nov. 2021, doi: 10.1016/J.COMPOSITESB.2021.109160.

[14] A. T. Seyhan, G. Tayfur, M. Karakurt, and M. Tanoğlu, "Artificial neural network (ANN) prediction of compressive strength of VARTM processed polymer composites," *Comput Mater Sci*, vol. 34, no. 1, pp. 99–105, Aug. 2005, doi: 10.1016/J.COMMATSCI.2004.11.001.

[15] J. Luo, Z. Liang, C. Zhang, and B. Wang, "Optimum tooling design for resin transfer molding with virtual manufacturing and artificial intelligence," *Compos Part A Appl Sci Manuf*, vol. 32, no. 6, pp. 877–888, Jun. 2001, doi: 10.1016/S1359-835X(00)00147-0.

[16] M. Ramezankhani, B. Crawford, A. Narayan, H. Voggenreiter, R. Seethaler, and A. S. Milani, "Making costly manufacturing smart with transfer learning under limited data: A case study on composites autoclave processing," *J Manuf Syst*, vol. 59, pp. 345–354, Apr. 2021, doi: 10.1016/J.JMSY.2021.02.015.

[17] T. Zhou, D. Tang, H. Zhu, and L. Wang, "Reinforcement Learning with Composite Rewards for Production Scheduling in a Smart Factory," *IEEE Access*, vol. 9, pp. 752–766, 2021, doi: 10.1109/ACCESS.2020.3046784.

[18] "South Carolina | Injection Molded Plastics." https://www.injection-molded-plastics.net/category/south-carolina/ (accessed Nov. 18, 2022).

[19] "South Carolina | Plastics Industry Association." https://www.plasticsindustry.org/factsheet/south-carolina (accessed Nov. 18, 2022).

[20] T. Ageyeva, S. Horváth, and J. G. Kovács, "In-mold sensors for injection molding: On theway to industry 4.0," *Sensors (Switzerland)*, vol. 19, no. 16. MDPI AG, Aug. 02, 2019. doi: 10.3390/s19163551.

[21] J. Loftis, S. Farahani, and S. Pilla, "ONLINE QUALITY MONITORING OF PLASTIC PARTS USING REAL-TIME DATA FROM AN INJECTION MOLDING MACHINE," 2020. [Online]. Available: http://asmedigitalcollection.asme.org/MSEC/proceedings-pdf/MSEC2020/84256/V001T02A001/6619047/v001t02a001-msec2020-8469.pdf

[22] S. Farahani *et al.*, "Evaluation of in-mold sensors and machine data towards enhancing product quality and process monitoring via Industry 4.0," *International Journal of Advanced Manufacturing Technology*, vol. 105, no. 1–4, pp. 1371–1389, Nov. 2019, doi: 10.1007/s00170-019-04323-8.

[23] S. Farahani, B. Xu, Z. Filipi, and S. Pilla, "A machine learning approach to quality monitoring of injection molding process using regression models," *Int J Comput Integr Manuf*, vol. 34, no. 11, pp. 1223–1236, 2021, doi: 10.1080/0951192X.2021.1963485.

[24] S. Farahani, V. Khade, S. Basu, and S. Pilla, "A data-driven predictive maintenance framework for injection molding process," *J Manuf Process*, vol. 80, pp. 887–897, Aug. 2022, doi: 10.1016/j.jmapro.2022.06.013.

[25] C. Abeykoon, A. McMillan, and B. K. Nguyen, "Energy efficiency in extrusion-related polymer processing: A review of state of the art and potential efficiency improvements," *Renewable and Sustainable Energy Reviews*, vol. 147. Elsevier Ltd, Sep. 01, 2021. doi: 10.1016/j.rser.2021.111219.

[26] F. Zaïri, B. Aour, J. M. Gloaguen, M. Naït-Abdelaziz, and J. M. Lefebvre, "Numerical modelling of elastic-viscoplastic equal channel angular extrusion process of a polymer," *Comput Mater Sci*, vol. 38, no. 1, pp. 202–216, 2006, doi: 10.1016/j.commatsci.2006.02.008.

[27] N. Sajko, S. Kovacic, M. Ficko, I. Palcic, and S. Klancnik, "Manufacturing lead time prediction for extrusion tools with the use of neural networks," *Management and Production Engineering Review*, vol. 11, no. 3, pp. 48–55, 2020, doi: 10.24425/mper.2020.134931.

[28] I. Rojek, D. Mikołajewski, M. Macko, Z. Szczepanski, and E. Dostatni, "Optimization of extrusion-based 3d printing process using neural networks for sustainable development," *Materials*, vol. 14, no. 11, May 2021, doi: 10.3390/ma14112737.

[29] B. Fox and A. Subic, "An Industry 4.0 Approach to the 3D Printing of Composite Materials," *Engineering*, vol. 5, no. 4, pp. 621–623, Aug. 2019, doi: 10.1016/j.eng.2019.06.003.

[30] G. D. Goh, S. L. Sing, and W. Y. Yeong, "A review on machine learning in 3D printing: applications, potential, and challenges," *Artif Intell Rev*, vol. 54, no. 1, pp. 63–94, Jan. 2021, doi: 10.1007/s10462-020-09876-9.