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Topic Insights

Recent Advances in Smart Process Manufacturing

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Smart process manufacturing is an integral and growing part of modern industrial engineering; it may be most readily characterized as a domain at the intersection of traditional manufacturing and modern, technologically intensive capabilities that address a dynamic and global market. It has long been a goal to reduce the operating cost of the manufacturing process, in addition to improving quality [1] and ensuring timely delivery (traditionally referred to as "quality, cost, delivery" (QCD) [2]). Although QCD has been an outstanding initiative and an evolving management approach for manufacturing industries, new, technologically intensive enablers such as the Internet of Things (IOT), big data analytics, the integration of cyber–physical systems (e.g., digital twins), the use of virtual, augmented, and mixed reality, and the potential for the utilization of artificial intelligence (AI) [3] come together to make these goals achievable on shorter timescales, with greater reliability and flexibility. Product development innovation cycles are increasingly shorter as a result, allowing products to enter the marketplace faster and providing a competitive edge for early-adapting industries. What these technologies actually enable is the ability to efficiently analyze the manufacturing environment, optimize processes faster, and facilitate decision-making based on the accumulated information [4], hence reducing operating risks. This information may then be utilized through a robust enterprise resource planning (ERP) system to close the loop and progressively automate self-optimization of the manufacturing environment.

The supply chain is a key component of smart process manufacturing and—as may be surmised—does not occur without true systems integration of the manufacturing enterprise. Here, the concept of "inherent interconnectedness" means that deficiency or surplus in the supply chain, or even in the labor market, may be predicted in advance based on simple models or principles. This is because systems that can communicate across the materials, process, and labor requirements can ensure that deficiencies do not impact production and that surplus does not cause unnecessary cost or waste. Through correct utilization and integration of ERP systems, including human resources and employee training, the entire supply chain may be established in advance of capital investment, and may therein be optimized on the basis of cost, delivery lead time, and quality—or indeed, any weighting given to each of these parameters. The supply chain model can then be viewed holistically, and the future utilization of technology such as blockchain to manage logistics and build efficient supply networks therefore holds notable opportunities [5].

There are critical categories to consider for the strategic analysis of manufacturing. Standards and adherence to tight manufacturing parameters are key drivers of smart manufacturing and, in many ways, integration of the standards themselves into the manufacturing plant is key to the next generation of automation. Important manufacturing standards such as ISO 9001:2015 and AS9100D:2016, for example, included in their most recent revisions a significant shift in the way in which risk is assessed and managed. Manufacturing standards related to specific sectors focus on the process or on the outcomes, so it is easy to understand that the future of inherently interconnected manufacturing must incorporate both. AI-assisted decision-making is then clearly key to reducing risk and improving outcomes. This interconnectedness must also, as a consequence, produce data that can be evaluated continuously. Product performance is a measurable attribute and a key metric of the smart process manufacturing domain. Initiating a zero-defect plan (ZDP) [6,7] through technologically intensive initiatives, for example, means that both product reliability and promptness of delivery are improved simultaneously. The so-called "cost of quality" is actually the cost of poor quality [8], since nonconforming products increase total product cost and lengthen (delivery) lead time. Big data analytics utilizing increasingly advanced statistical techniques may be the correct means to validate or initiate improvements, but what they are also able to achieve is to differentiate or identify inconsistency and thereby impact variances that may otherwise not have been detectable.

The features of a product are typically defined by the flexibility of the manufacturing process. Although minimizing the features of a product line is undoubtedly cost effective, smart manufacturing requires those attributes supplementing the basic function of a product to be rapidly modifiable in order to meet individual customers' needs without impacting cost. Additive manufacturing is an obvious example of this mass customization in manufacturing, and decentralized production is one of the clear outcomes. Today, it is becoming possible, for example, to use the additive manufacturing of spare parts for some engineered products [9].

Reliability of a product or process is a measure of the probability that it will cease to operate as originally intended within a given timeframe. As a product ages, its reliability proportionately

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decreases. If the product durability is high for the intended operation, the reliability is similarly extended. Although product reliability, durability, and quality are integrally linked, what reliability can mean in the context of smart process manufacturing is actually the ability to minimize downtime and conduct predictive or preventative maintenance of the manufacturing facility itself, in a more strategic and optimized manner. Such predictive analytics require smart sensors as an increasingly important part of this reliability, since in manufacturing operations, it is especially important to extend the useable lifetime of both plant and equipment. Smart sensors utilized in this manner allow the plant and equipment themselves to become capable of notifying responsible teams in advance of major breakdowns or incidents, so that scheduled maintenance can be conducted and planned without impacting production. In addition, the concept of smart predictive systems has significant cost advantages that drive down overheads; in certain environments, rapid response for decision-making becomes acute when certain thresholds are reached that may be safety critical. In this regard, the increasing opportunity to use AI-augmented decision-making and augmented reality means that specialists can advise on a course of remedial action within the shortest timeframe from a remote location, for example [10].

In this special issue of *Engineering*, Shang and You provide a review of the use of data analytics and machine learning in manufacturing, and consider both passive applications (e.g., soft sensing or monitoring), in which interpretability of the data is critical, and active applications (e.g., process control and decision-making), where system functionality is paramount. Litster and Bogle consider the opportunity for smart process manufacturing in formulated products such as food, pharmaceuticals, agricultural products, and chemical products, where digitalization, big data, and predictive models may be used to develop solutions within the supply chain, which can impact timely delivery and product quality. Zhong et al. introduce a knowledge-based system for the operational optimization of a polyethylene production process, and demonstrate how the method can improve and regulate the process simultaneously.

Yue et al. consider the problem of optimizing the additions of aluminum fluoride (AlF_3) into aluminum reduction cell electrolyte, in order to accelerate decision-making using augmented fuzzy cognitive maps. It is proposed that the developed model has potential for automatic decision-making for AlF_3 additions. Mao et al. demonstrate the utility of using AI methods to consider knowledge acquisition and knowledge-based reasoning, so as to provide an effective strategy for dynamic risk assessment and AI-augmented decision-making. The opportunities for incident early warning, especially in chemical production industries, are a notable focus. Plehiers et al. examine a framework of four deep learning artificial neural networks in order to provide predictive accuracy on (naphtha) steam cracker effluent compositions, with the opportunity for implementation being both financially and environmentally beneficial.

Pankajakshan et al. propose an online multi-objective experimental design methodology for the identification of a kinetic model for the esterification of benzoic acid and ethanol, which provides optimal tradeoffs for experiment design in the presence of multiple constraints. The strategy involves a decision-making step that works to problem solve while minimizing the cost of the materials consumed in the process. Zhou et al. review the opportunities for the use of big data in materials research to reduce discovery timelines, and draw attention to the use of machine learning in accelerating experimental result delivery, where thousands of opportunities for new materials can be evaluated before experimental work is required to verify the outcome. Finally, Liu and Papageorgiou provide the outcomes of an experimental program for the multiscale optimization of antibody manufacturing processes wherein multilevel models are developed and evaluated, such that the cost of the process may be reduced.

In summary, this issue of *Engineering* presents nine key papers that comprise a diverse set of topics and provide examples of how smart process manufacturing is being utilized to produce improved products, accelerate industrial research, reduce risk and cost, solve increasingly complex engineering problems, and aid in decision-making for key manufacturing sectors.

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