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Revolutionizing Industry 4.0: AI and Emerging Technologies in Smart Manufacturing

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Abstract: ***Smart manufacturing refers to the amalgamation of multiple advanced technologies, most notably Artificial Intelligence to enhance production to improve operational parameters across 4 dimensions of YETQ- Yield, Energy, Throughput and Quality. Leading manufacturers have realized significant value from data and analytics, AI, and machine learning (ML). This paper summarizes the key applications of AI in manufacturing, ranging from quality and maintenance, AI enabled automation, and automated process control. We also discuss real world examples to showcase the transformative impact of AI on the industry. We also briefly touch upon the most recent advancements in AI, notably GenerativeAI which will further unlock operational efficiencies.***

Keywords: Artificial Intelligence, Operations, Industry 4.0, Manufacturing, GenerativeAI

1. Introduction

The last decade has seen companies operating under increasing levels of disruption. Quickly changing customer preferences, as well as demand uncertainty and disruptions, are challenging planning systems to unprecedented degrees. National security interests, trade barriers, and logistics disruptions are pushing businesses to find alternatives to globalized supply chains. Major swings in demand are calling for drastic operational and capital cost reduction in some areas and rapid growth in others. Physical distancing and remote work are forcing manufacturers to reconfigure manufacturing flows and management. Meanwhile, increased global concern for the environmental impact of human activities has forced companies to rethink manufacturing strategies.

To address these disruptions, successful manufacturers are leveraging Industry 4.0 to achieve faster, more sustainable change. At the core of Industry 4.0 is the integration of digital and Artificial Intelligence (AI) into manufacturing processes. The use of AI is aimed to create more efficient, agile and reliable manufacturing systems.

Our next generation of industry—Industry 4.0—holds the promise of increased flexibility in manufacturing, along with mass customization, better quality, and improved productivity. It thus enables companies to cope with the challenges of producing increasingly individualized products with a short lead-time to market and higher quality. Intelligent manufacturing plays an important role in Industry 4.0. Typical resources are converted into intelligent objects so that they are able to sense, act, and behave within a smart environment.

2. Key AI Applications in Smart Manufacturing

2.1. Advanced Process Control leveraging AI Models

More recently AI has been used heavily to improve manufacturing processes. In Japanese chemical companies, KAIZEN activities aimed at safe and stable operation are actively continuing. One important activity is improvement in the control performance of PID control systems. The aims of this improvement activity, in which controllers are retuned appropriately, are (1) to realize stable operation by reducing the influence of disturbances, (2) to realize automatic rapid transition of operating conditions such as production rate, (3) Not just achieve nameplate capacity of equipment, but oftentimes surpass it.

AI models are trained on millions of data points coming from sensors to create predictive models, which are then fed to an optimization engine to identify the right process parameters in near real time. These could be coming out as recommendations for humans to evaluate and make real time process changes, or directly fed into PID control systems, based on the criticality of the operation.

A few examples:

- **Steel Industry:** Tata Steel employs AI to optimize blast furnace operations, building a superheating-optimization model, which would examine real-time operational data and recommend process set points conducive to a higher strike rate.
- **Chemical Manufacturing:** AI-driven process control models help fine-tune reaction conditions in real-time, minimizing waste and energy usage. As quoted by Kano et al (2020), Daicel Chemical Industries has tripled the productivity per plant employee since “Intellectual and Integrated Production System” was established in the Aboshi plant in 2000. This notable activity was motivated by the effort in Mitsubishi Chemical Corporation (MCC) in the 1990s. MCC has developed Super-stable Operation Technologies (SSOTs) and Super-stable Maintenance Technologies (SSMTs) to maintain production stability and prevent facility accidents. SSOTs aim to keep plant operation stable by prevention and prediction of various troubles such as fouling, plugging, corrosion, and so on, and SSMTs are facility management technologies to ensure high standards of stability.

2.2. Quality Control

AI enhances quality control by identifying defects pre-emptively, even in the absence of actual sensors, such that product quality can stay to expected standards. There are two key ways this is done:

1) **Machine vision systems**: powered by AI, can detect anomalies in products during the manufacturing process.
2) **Soft sensors**: A soft-sensor, or a virtual sensor, is a key technology for estimating product quality or other important variables when on-line analyzers are not available. The task is to integrate quality problems and process control problems; in order to do so, a model is required that can translate information on product quality requirements into specifications for physical state variables in the process.

One example of AI being used for quality control is with Pepsi, who employ AI to improve product quality by automating texture analysis in Cheetos chip manufacturing. They use analysis of sound and laser data to assess texture of chips in real time, allowing for higher consistency and quality.

2.3. Predictive Maintenance

The production environment relies on equipment to work properly. A fault in a component or sub-system may cause a stop in the entire production line. The production stops are associated with huge costs in many folds including but not limited to the loss of production and time in downtime, losses of efforts in identification of the cause of the failure and repair, wastes of products produced right after bringing back the system until normal operations due to low quality, costs of repairs and deterioration of equipment (Froger et al, 2016)

Predictive maintenance (PdM) has become a common objective in the industry to reduce maintenance costs and ensure sustainable operational management (Stock & Seliger, 2016). The essence of the PdM is to predict the next error in a manner that preventive maintenance can be performed before the failure takes place. PdM also has the potential to promote sustainable practices in production by maximizing the useful lives of production (Lee et al, 2014).

As an industry example LG uses predictive maintenance to predict malfunctions in the production line in advance, thereby contributing to productivity improvement.

2.4. Intelligent Automation

Along with the widespread deployment of robotic systems in industry (Huang et al, 2021) and daily life having a digital twin of robots becomes more and more critical in practical scenarios, such as multi-robot coordination/collaboration as well as those that require safe human–robot interaction (HRI) and/or complex human–robot collaboration (HRC) which place human safety as a high priority, thus helping to create a sustainable working environment. Examples could be found in kinematics, communication, control, planning, and industrial robot energy modeling, in use cases like welding, cleaning, pick-and-place, assembly, manufacturing, warehouse and maintenance. Recently, new concepts and cases utilizing artificial intelligence towards semi- and fully autonomous robotic systems have been reported, e.g., transfer learning and imitation learning (also known as apprenticeship learning or learning from demonstration). While traditional DTs have been developed for systems that we have a solid grasp of (in other words, model-based), data-driven and AI-equipped DTs help with complex robotic systems for which building high-fidelity dynamics models is not feasible (model-free). The latter has been applied in more and more cases, even for biomimetic robotic system development (e.g., robotic fish)

2.5. Other use cases

Above was a select use of use cases, a few noteworthy ones which are very relevant to manufacturing companies:

1) Supply chain optimization: By analyzing historical data and market data, AI systems can forecast demand more accurately, allow us to keep limited inventory to reduce working capital, as well as lower costs by timely and cheaper procurement.
2) Augmented Reality (AR) and Virtual Reality (VR): technologies are revolutionizing training and maintenance in manufacturing. Enhanced manufacturing training provides immersive, hands-on simulations for complex equipment and processes. Advanced troubleshooting is possible with real time guidance, overlaying diagnostic information on equipment.

3. Challenges and considerations with using AI in manufacturing

While AI can provide unprecedented benefits when implemented right and at scale, implementation typically comes with lots of challenges. This is especially because manufacturing is only now catching up to the investments which financial services and marketing and sales functions have benefitted from:

1) IT/OT setup and integration: Not all manufacturing plants are well equipped with sensors and have enough data being stored for use of these AI models. Apart from having the data available, proprietary data formats, and data integration challenges from OEMs pose a significant challenge to being able to use these effectively.
2) Cost of Implementation: High initial costs of AI technology and infrastructure can be prohibitive for small- and medium-sized enterprises (SMEs). As the cost of these services comes down based on higher adoption, this could open up adoption for a much larger number of manufacturing locations.
3) Regulatory and Ethical Concerns: With the rapidly changing AI landscape and regulations just catching up, data privacy and bias mitigation remain a concern.
4) Cybersecurity Risks: Increased connectivity exposes manufacturing systems to cyberattacks, necessitating advanced cybersecurity measures. There have been multiple instances of such attacks halting production systems altogether.
5) Workforce: Last but not the least, all these AI models need a bench of experts to develop and maintain these systems. AI talent is scarce, especially so in the remote locations where these facilities typically are. Manufacturers are left with limited choices and have to rely on upskilling their process engineer to understand AI.
6) Addressing these challenges requires a comprehensive strategy encompassing people, technology and processes.

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4. Generative AI in Smart Manufacturing

Generative AI is emerging as a transformative tool in manufacturing, just like all other industries leveraging AI. A few common use cases:

1) Automate Documentation and expert support: Generative AI, with expert chatbots enabled by multimodal RAG systems has made access to complex technical manuals much easier and more efficient.
2) Advanced predictive maintenance: Applications of GenAI in PdM span synthetic data preparation, anomaly detection via VAEs as well as time series forecasting with transformer models. These are especially important given some of the challenges we highlighted earlier with respect to data availability in manufacturing setups.
3) Enhance Product Design: Generative design tools explore a vast array of design options based on provided business and technical constraints, leading to innovative and optimized product designs.

5. Conclusion

AI is revolutionizing the manufacturing industry by enabling smarter, more efficient, and flexible production systems. Through predictive maintenance, quality control, supply chain optimization, intelligent automation, process control using AI models, generative AI, and AR/VR technologies, AI enhances productivity and product quality. Real-world implementations by companies like LG, Pepsi and Tata Steel show this is possible at scale. There are challenges with data, costs, risks and talent to implement these, but with the right strategy and implementation, these can be overcome.

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Anurag Bhagat received his Bachelors in Computer Science and Engineering from Indian Institute of Technology, Kanpur in 2011. He is a seasoned AI leader with 13 years of experience in consulting, solving business problems across geographies leveraging data & AI. He has have served multiple industries as well as functions such as operations, procurement, marketing and sales, pricing with a special focus on improving operations of big organizations at scale using AI. He currently advises clients on GenAI strategy. He currently works at Amazon as a Senior Strategist.