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Chapter 3: Enhancing efficiency in smart manufacturing processes through agentic artificial intelligence-driven autonomous systems

3.1. Introduction

The Fourth Industrial Revolution represents a major shift from the traditional concept of manufacturing mainly based on physical labor to the implementation of advanced digitized manufacturing processes. This in turn introduces a wide range of advanced production systems and models featuring an ultra-high level of interconnectivity and intelligence, able to respond in real-time to disturbances and cope with internal and external uncertainties. Despite generating huge quantities of data, research shows that the promised capabilities of those Cyber-Physical Systems have not yet reached their full potential. Autonomous Systems focus on improving the physical system level of autonomy without operator oversight, so the inter-agent and intra-agent tensions of these systems become even more challenging, particularly with regards to frictional and/or parasitic losses of the available productivity. These systems may already fuse natural and artificial intelligence, and the incoming and outgoing checks and balances of such technology using Agentic AI will help remove deadlocks from the operational model (Lee et al., 2015; Schuh et al., 2015; Qin et al., 2016).

Agentic AI applied to Smart Manufacturing has the ability to create and sustain a self-motivated operational model for each autonomous subsystem within an AS-based manufacturing environment, in relation to every other subsystem as well as to the whole system. Like in an ant colony or bee hive, these systems continually share information about their operational state, allowing the introduction of incentives that have the power to not only increase velocity and throughput but also maintain quality and resilience. The digital twin technology implemented in each node upon which Agentic AI is layered helps address the aforementioned issues with regards to these naturally chaotic autonomous business environments, enabling real-time checks and balances at next generation levels of Industrial AI (Wang et al., 2015; Wang et al., 2018).

3.1.1. Purpose and Scope of the Document

Whenever we look at any manufacturing or production system, the purpose is similar, i.e., to transform input resources into output products of specified attributes through efficient business processes. In this essence, the physical manufacturing system transforms its core Input-Process-Output but through the other components such as Information, Knowledge, and Control. Today's advancements in sensors and memory-based microprocessor technologies along with omni-present connectivity powered by cloud, mobile computing and intelligent algorithms have allowed the visionaries to augment the existing manufacturing systems into cyber-physical smart environments, or what we call Smart Manufacturing Systems. Now the manufacturing system elements are intelligent, semi-autonomous/decentralized, (up to) self-organizing with hierarchical but thin, cloud-based control structures.

But unfortunately, several industrial examples of large scale, end-to-end autonomous decision making are lacking. Behind the physical operations, the organizational bottlenecks are profoundly etched into enterprise-wide hierarchical decision making structures as the manufacturers are run as technologically illiterate factories. Classic Operational Research and Control Theory optimization have not moved from centralized decision making using combination of linear programming, Markov Chains and dynamic programming, Monte Carlo methods, etc. along with heuristics or metaheuristics. The decision-making models can use the information and knowledge extracted from available large amounts of semi-structured production data but does not have the necessary advanced agency properties to fill this gap.

3.2. Overview of Smart Manufacturing

Recent technological advancements, such as opened IoT opportunities; the availability of cloud computing services and data analytics; the promise of advanced robotics; the advancement of machine learning and artificial intelligence; additive manufacturing technology readiness; secure and efficient smart devices; cybersecurity; and global connectivity have pointed out a new era of manufacturing. An era of Smart Manufacturing (SM), which aims to create a very flexible, agile, and adaptable manufacturing capability; enable manufacturing operations driven by effective strategic goals in real time; guarantee efficient and closed-loop product lifecycle management, production planning and control, resource utilization, and product distribution throughout the entire supply chain; create self-optimizing production capacity and system resilience; and break through the current global complexity trend of the current supply chains of any industrial segment worldwide, pushing for bring back the manufacturing from developed economies to the place of consumption of products and services by using SM capabilities.

SM is very pragmatically defined as the modeling enabling interdisciplinary SM systems, which efficiently interconnect production resources throughout the entire value chain utilizing a data-driven and AI-powered approach to decision-making from product planning to production scheduling and control, and from product distribution to resource utilization, throughout the entire production lifecycle. Those products, services, and grow, which shall be sustainable, considering the environmental impact. The synthesis, planning, scheduling, and control of those multidisciplinary equipment, people, and knowledge intensive dynamic/complex/safe/request-based/realistic/demand-driven production systems, whose internal flows can use Big Data, Machine Learning, and Artificial Intelligence, are also Smart. Smart Manufacturing is also a form of Quality 4.0, which are able to very quickly technological learn and adapt to external uncertainties and risks affecting product demand, product quality, and product distribution due to its interdependence with internal and external flows of resources of space and time of those multispecialty production systems along the supply chain.

Fig 3 . 1 : Intelligent and Automated

3.2.1. Definition and Importance

The manufacturing industry is gradually shifting from mass production to smart manufacturing that leverages digitally-connected technologies to replace traditional technology-driven production. Smart manufacturing focuses on customer needs and aims to create value through economies of scope while maintaining competitive production costs. The emergence of Industry 4.0 technologies, such as Artificial Intelligence, Machine Learning, Internet of Things, Cloud Computing, Augmented Reality, and Advanced Robotics, offers a solution to this trend through innovations that enable cost-efficient, highly flexible, and fully automated manufacturing systems. Smart manufacturing thus advocates the use of the latest technological advancements to make industrial production more efficient in terms of cost, speed, and scale while enabling operations and supply chain flexibility to respond quickly and efficiently to shifting demand patterns in the market.

Smart manufacturing is increasingly gaining popularity in the digital era where all technologies and services are connected through the Internet. It represents a significantly refined and upgraded version of traditional manufacturing anchored in visions for the future roadmap of a competitive and profitable manufacturing sector. Smart manufacturing is the next revolution in manufacturing where smartness or intelligence, and flexibility are the new factors of competitive success for the manufacturing world. As more and more products are being combined with Information and Communication Technology, the ICT space has become an essential common platform for the automotive manufacturing sector. The high-tech market needs seamless smart factories based on ICT. Demand for product quality is rising while at the same time there is little adjustment of product prices, requiring large automobiles to be manufactured at lower cost and more profit. The advent of smart manufacturing will offer radical changes in the automobile manufacturing spaces and create new business opportunities.

3.2.2. Key Technologies and Trends

The Internet of Things (IoT), big data, cloud computing, and cybersecurity constitute the backbone of Industry 4.0 key technology. They provide basic physical functions for digital transformation, smart business models, and smart manufacturing systems and processes. With the fourth industrial revolution, the focus of manufacturing technology has shifted from the capability to mass-produce a large volume of the same standardized product in a rigid mass production system environment using non-flexible assembly lines to the efficiency of producing customized products with flexible manufacturing processes in maximum variety and minimum volume. This made the need for a federated ecosystem urgent. Therefore, digital technology is not only supporting smart manufacturing pre-systems but, more importantly, transforming smart manufacturing processes, i.e., how production is done. Digital transformation originates from the integration of several academic fields, namely, computer science, operations research, software engineering, econometrics, operations management, and industrial engineering.

Agent-based modeling, optimization, and simulation are the three original disciplines of the digital twin for a Smart Factory. Their decoupled combination has made digital twin serve Automation and Control: Agent-Based Control, Computer Vision, Machine Learning, Mechanism Design – Agent-Based Allocation, and Dual-Need Based Automated Markets; Cognitive Robotics; Cyber-Physical System. Smart Factory is agentified since it contains a multitude of autonomous systems, termed cyber agents or bit agents, capable of interacting with each other and with the physical environment in a goal-oriented manner. Agent-ified Smart Factory operates like an organism that has a high degree of synergy. Smart manufacturing brings efficiency in terms of cost and service time. It is about pursuing an economy of speed.

3.3. Understanding Agentic AI

1. Definition of Agentic AI

While the connotation of "autonomy" differs between human and artificial agents, thus, a few essential distinctions between them are required to justify the use of the term "autonomous systems" with AI. The concept of autonomy has traditionally been placed into two general categories: moral autonomy and functional autonomy. Moral autonomy encompasses the belief of a human standing that an action may originate from motives and principles according to which people must put forward their moral choices. Moral autonomy has traditionally been reserved for conscious beings, and does not apply to technology since, so far, no technological agent has ever been developed which is capable of according to moral principles autonomous moral choices. Functional autonomy, otherwise, refers to the capability of resources at some cost to some person at some time to make choices for pursuing some goal. Agents of this kind may be deliberative and interact with their environment through sensors and effectors. The use of the term "autonomous" in this sense does not imply moral agency nor qualifies them as being of a kind and for that reason there is no restriction against applying this qualification to machines. This is the view that other definitions of autonomy with respect to technical systems take, stating that these systems are indeed capable of selecting between alternatives, that this process is largely independent from human influence and that the consequences of this selection influence in turn their future behavior.

2. Characteristics of Agentic Systems

While it is unquestionable that the term "intelligent agent" has been widely used to describe a great variety of systems and scarcely has any theoretical significance, it is equally unquestionable according to its etymology that "intelligent agency" denotes a special class of very particular autonomous systems whose distinctive quality is some insight into their situation and intelligence. Other scholars highlight solely the functional aspects that characterize the terminology of agent-based systems, focusing in this respect on the degree of autonomy, decision-making ability and task performance capabilities of systems which differ in their functional aspects from classical ones like automated systems, expert systems or decision-support systems. It is not uncommon for scholars dealing with "agent" systems in AI to be more concerned with the functional characteristics of these systems, that are understood to be of a higher order than those of plain technical systems by virtue of their agentic nature, than with the semantic distinction between the two concepts of "intelligent agent" and "intelligent" agent.

3.3.1. Definition of Agentic AI

Agentic AI refers to a form of advanced artificial intelligence that possesses certain characteristics when describing these systems. The term "agentic" is derived from the term "agent," which has various meanings across different disciplines, including philosophy, mathematics, law, economics, and AI. Generally speaking, an agent may be described as a unit capable of performing actions in an environment to meet certain goals or preferences. What distinguishes agentic AI from other advanced AI systems, and even from other intelligent agents, is that its actions occur in the real world through an action cycle consisting of decision-action-outcome-feedback. In this context, agentic AI is considered a unit of highly capable advanced AI that interacts with the real world and takes actions without requiring human involvement, in order to achieve its own future goals. Its characteristic set of capabilities enables agentic systems to explore numerous physical and digital environments in pursuit of their goals.

Agentic AI is artificially intelligent in a sense that it uses a wide variety of solution methodologies to emulate its own intelligent behavior as well as that of naturally intelligent actors in the world. What distinguishes agentic AI from the vast majority of existing AI and advanced AI systems, both in academia and industry, is that these systems are monolithic and do not participate in open-ended action loops involving their own actions determining future states of the world. One of the most important comparisons of agentic AI to existing types of AI systems, however, is that unlike robotic and embodied AI systems, agentic AI does not have to be embodied in a physical body. This is an important distinction because the vast majority of autonomous systems deployed in the field today are embodied intelligent agents that require a physical body to operate. Agentic AI, on the other hand, may rely primarily on software to accomplish its goals through the use of intelligent actions in a diverse environment.

3.3.2. Characteristics of Agentic Systems

An agentic AI enacts actions as an autonomous artificial agent with the capability to perceive its environment, reason, adapt, and make independent decisions for taking action to accomplish specific tasks towards achieving goals. Simply possessing intelligence does not make an AI an agentic AI which can perform task(s) autonomously without or with minimal human input and which is responsible for its actions and the impact of its actions. Such an agentic AI should possess capabilities of environmentally situatedness, agency, and reliability. Situatedness denotes awareness of its objects of interest, how these objects evolve in space and time, and how its actions affect these objects over time. Agency reflects the high-level decision mechanism which enables the agentic AI to plan actions based on its current (and possibly predicted future) understanding of its environment and execute these actions using actuators on the objects of interest. However, the key distinguishing feature that makes agentic AIs different from all other autonomous AI systems is that the agentic AIs are responsible for their own actions and their consequences. Reliability refers to the ability of the agentic AI to act in a predictable manner.

The agentic intelligence combines cognitive functions like reasoning, learning, decision-making, etc. with perception, actuation, and other capabilities to perform actions fully or partially autonomously. Thus the following characteristics emerge: Autonomy. Responsible for its own actions. Agentic AI makes independent decisions and carries them out alone for all tasks or at least a significant portion of them. Reactive. Responds to their environment, especially to changes. Situative. Perceive and update the state of the environment. This includes to often monitor important features or a selected subset of features of the external environment to notice important changes. Agents can perceive internal information about the environment as they develop an understanding about it. Deliberative. Make plans and decide which course of actions to execute and when. Deciding involves reasoning modeled as decision- or action-selection process.

3.4. The Role of Autonomous Systems in Manufacturing

1. Types of Autonomous Systems

Manufacturing systems consist of many different kinds of processes that together comprise the productive competencies of the operations of a manufacturing company. These processes may occur in many different locations, using different technologies, and at different speeds. Autonomous systems may provide value at any one of these locations, contribute to different segments of the manufacturing process, and in collaboration, speed up the whole process. They may thus be exploited to enhance efficiency in important tasks such as product assembly, transportation of components or finished products, the machining of product components, and the assembly or installation of products.

A number of different types of autonomous systems are available, depending on both the level of sophistication and the set of tasks they are capable of performing. Popular examples of these are autonomous vehicles, both aerial and terrestrial, drones, automated guided vehicles, collaborative robots, and robotic systems with integrated autonomy. These systems feature different levels of mechanization and autonomy and may be used, as already mentioned, for several different tasks. The most popular and readily available are collaborative robots and automated guided vehicles. Automated guided vehicles and collaborative robots are used in loops to automate the assembly of electronic circuit boards. Until recently and up until today, collaborative robots have been used to assist manual employees, performing difficult and physically strenuous activities. More recently they have been exploited in a broader loop, enhancing performance in collaborative assembly.

2. Benefits of Autonomy in Manufacturing

The benefits of integrating autonomy into manufacturing are many, being related to both the micro, individual level, as well as the macro, system-wide level of companies. At the individual level – that of the employee – integrating autonomy into manufacturing can enhance employee safety and job satisfaction. Like in many other industries, in manufacturing today many of the employees experience high levels of physical and psychological strain, related not only to the repetitive character such as in assembly but also to the need for quick response to breaking incidents when urgency is prioritized over reliability. Integrating collaborative robots could, therefore, allow employees to concentrate on the fun parts of their job while enjoying the enhanced safety that collaborative robots can provide. At the company level, there are increased productivity and efficiency related to both the speed and reliability aspects of production.

3.4.1. Types of Autonomous Systems

There are various sorts of autonomous systems, including autonomous agents, team, swarm, and large language models (LLM)-based systems depending on their area of employment and interplay with professional people and domains. In recent history, AI-enhanced robots, automated guided vehicles, and collaborative robots or cobots have grown extremely recognizable. Robot-assisted surgery, unmanned underwater vehicles, unmanned aerial vehicles, space robots, and mobile robots are all instances of autonomous systems that operate in critical areas like healthcare, defense, security, disaster management, and exploration. The predominant motivation for creating such agents with autonomy in these areas is to reduce the risks involved in manual human operations that may involve harm to life. With bettering computer vision, spatial mapping, haptic simulation, and online planning and learning procedures combined with simpler vision systems and haptic devices, many researchers have been developing semi-autonomous and fully autonomous systems for such applications.

The increasing competitiveness of products, hastening of the introduction of new products, concern for security and safety, perilous nature of operations, and seeking for convenience in manufacturing operations are the major motivations for achieving a high final design. These compelling reasons have led researchers and engineers to develop technology-enhanced and more able autonomous systems for assistance and support of applied people in all areas of manufacturing. They embrace manufacturing, assembly, testing, packaging, inspection, handling, warehousing, and logistics. AI-enhanced mobile robots, automated guided vehicles, tele-scanners have been widely employed in manufacturing factories. Semiautonomous and fully autonomous manipulative robots are being developed and employed in process management, assembly, testing, handling, and packaging. Today there are capable robotic systems suitable for the growing demand for automation in specialized domains of manufacturing like micro-manufacturing, bio-manufacturing, and eco-manufacturing.

3.4.2. Benefits of Autonomy in Manufacturing

Agentic and autonomous systems, as advanced cybernetic mechanisms that act independently towards the realization of specific objectives following pre-defined action plans, are typically more capable than other systems of performing tasks related to cognitive and sensory-motor functions. These capabilities offer important use advantages, leading to a wide variety of applications of autonomy across many different sectors of the economy, entertaining both dual use and different cost-expertise trajectories across different categories of agents. Meanwhile, more cautious options articulated along different levels of autonomy can also be conceived of along a variety of investments along expertise and innovative capacities depicted by the increasing efficiency curve of autonomous systems. These advantages and options equally apply to the manufacturing of increasingly complex components and devices. From the traditional automation of manufacturing processes to the development and application of recently emerged autonomous manufacturing systems, efficiency steadily increases along with the reductions of required time and costs.

The most challenging limitation of traditional automation and even of existing cognitive robotic systems consists in the lack of autonomy. Human involvement is required for non-standard tasks related to the planning and supervision of the application of automation. Unlike interventionist task-sharing with machines with learning capabilities that still require guidance for interactive and non-routine tasks, autonomy allows the immediate deployment of agentic and autonomous machines that, provided that a certain level and definition of expertise of pre-learned decision-making and action task articulation has been achieved, can intervene without relying on human involvement. In this respect, autonomy can be applied also to assistive manufacturing agents developed across a variety of use levels along complementary tasks with human operators, advancing equally capable and enhance collective efficiency along bionic use models.

3.5. Efficiency Metrics in Manufacturing Processes

The pursuit of efficiency is what drives all alternate viewpoints toward improving the processes of smart manufacturing systems. To enhance a given aspect of the outcome, say through transcending a given limitation, the complementary aspects must not be sacrificed. To ensure holistic efficiency, meta-metrics of the outcome should collaboratively incorporate achievements, performance, quality and credibility, resource expenditures, relationships, organizational learning, and thoughtfulness, etc. The operationalization of the meta-metric framework requires appropriate definitions of lower-level explicit metrics along dimensions governed by relevant KPIs. Procedurally, it can be implemented in two-steps; outlining a taxonomy of lower level metric definitions per worker-identified KPI, and integrating them as composites along given dimensions toward assessing the relative success of competing initiatives or designs. From a process view, the typical dimension relates to the input, output, Learning time or productivity improvement time, information, utilities, adjustment and production, risk, and externalities. However, the explicit lower level KPI metric definitions need to be carefully tackled case-specifically.

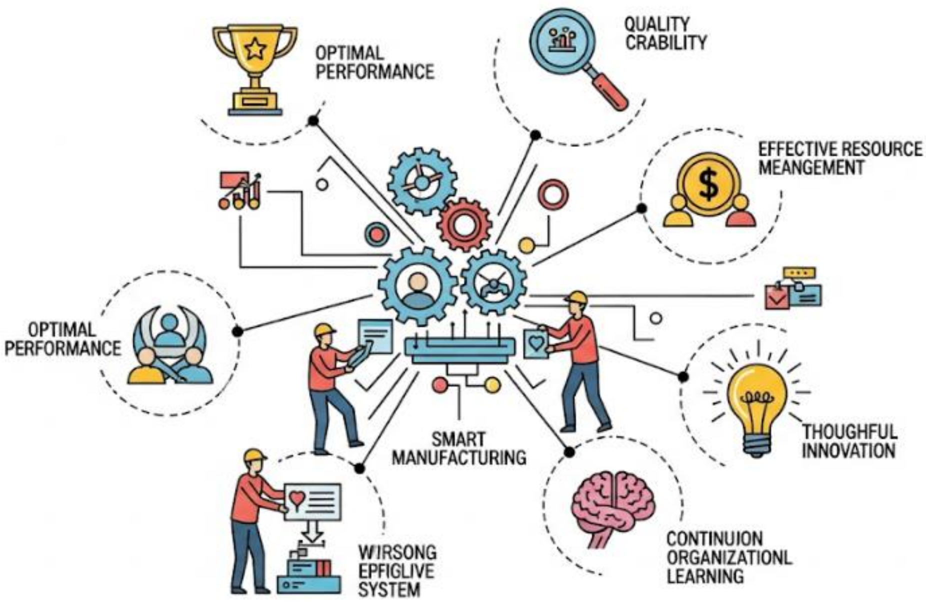

Fig 3 . 2 : Workers and Metrics Working Together

Many of the efficiency improvement processes in manufacturing are sufficiently visible and approximately measurable through workers. Efficiency for them is a collaborative approach with several ideas pinpointed toward self-sharing problems not arbitrary or limited to productivity. These need to be assessed explicit on a KPI basis through engagement questionnaire/survey forms with carefully specified scoring/weighting guidelines. Identifying popular or consensus ideas would imply their necessity and sureness through the sum of utilization and output improvement, cost reduction, and the number of reasons for not utilizing the idea or share of subjects whose opinions concur with negative or neutral scoring responses.

3.5.1. Key Performance Indicators (KPIs)

In smart manufacturing processes, enabling technology and the processes themselves need to become more sophisticated to foster more capable and robust practices in production systems. This includes the development of intelligent machines, production scheduling and load balancing functions, and manual component operations that incorporate real-time interactions between the operator and the production system. Key Performance Indicators (KPIs) need to be developed to reflect these efficiency improvements. More reliable equipment such as printers and tools should start running modified or novel products in environments where the human operator performs more cognitively directed or safety critical activities. Human to machine interaction in terms of programming, setup, quality assurance, and safety should be facilitated to minimize training and learning times. The above suggestions afford plentiful opportunities for improvement of both people and technology in directed or endogenous, that is, locally orchestrated and controlled changes.

Smart manufacturing processes can help improve the efficiency of translating an order for a product into the physical tangible and intangible characteristics in the product to ensure that the product satisfies the customer's needs. We propose to establish KPIs that will reflect a more efficient end use oriented decision process. The customer has resources that are financially limited and time constrained. Regrettably, many industry sectors are full of hidden inefficiencies resulting in wasteful consumption of the customer's resources. These inefficiencies represent potential opportunities for underserved demand and thus profitable additional service activities. When a customer-related KPI should be an important factor in balancing technology enabled efficiencies and operational costs, the customer KPI is usually missing in most smart manufacturing studies. Rather than having a commonly conducted survey probing customers about what factors would make everyday experience of using a product more enjoyable, valuable, and without friction.

3.5.2. Measuring Efficiency Improvements

The results of research are not valid until they are observed and measured. If a solution enhancing the efficiency of a manufacturing process is offered, then it must have an impact that needs to be monitored to maintain it over time. Effectiveness can be measured on its own through its ratio of the productive work achieved to the resources consumed. Resource utilization is however only an upper bound metric for performance evaluation. The total resources consumed should also increase or decrease along with the demand for production to be allocated efficiently, according to its scheduling. A disproportionate allocation of resources does not provide a clear insight on the effectiveness of the manufacturing process, since it derives both from a lower demand for product and variability that creates an execution time longer than expected. Variability can also happen throughout the execution time of the manufacturing cycle to each single component; bottlenecks could just create a partial or complete halt of production. Indeed, a bottleneck at work reduces the whole throughput of the manufacturing process. The expected cycle time for a product derived from its throughput rate should be divided through the work-in-progress inventory needed to decide production. Furthermore, if productivity is indeed considered a function of both cycle time and throughput rate, then it cannot be considered just a single value that needs to be observed at each iteration of the hardware-in-the-loop tooling layer implementation of a digital twin.

As anticipated, already available means of monitoring manufacturing operations provide a multitude of collected data. Most of them could be filtered and used for decision making and the generation of Key Performance Indicator graphs is indeed a common activity performed by Manufacturing Execution Systems. However, this activity is often done under the supervision of humans, using the data available to assist human decision makers in choosing the best possible solution when compared to pre-defined objectives. Little research has however provided an automated link between the acquisition of the data needed to generate the KPI graphs and a performant choice of parameters set able to improve the performance over a given factor.

3.6. Integration of Agentic AI in Manufacturing

1. Framework for Integration

Agentic AI can significantly improve decision-making and interactions within SMIs both on the supervisory level as well as the workcell level. For decision-making on the supervisory level, Agentic AI provides business process management systems and decision support systems with a higher level of automation. Thereby, reacting to situations in the ecosystem surrounding the production processes as well as to emergencies in the production processes can be supported. For implementation, Agentic AI can be integrated into the information-processing workflow of existing systems. When there are anomalies or detected facts presented in the information-processing workflow that require action, Agentic systems could provide ad-hoc assistance and propose or execute possible actions. At the workcell level, Agentic AI can be used in

Human-Agent Teams that provide a more efficient sharing of the shared decision space, can help to alleviate cognitive workload, and make robots in collaborative settings more capable. These aspects are especially relevant for the application of mobile manipulators and robots in the construction sector, where robots and workers exchange roles as task executor and task providing entity.

2. Challenges in Implementation

In our proposal presented above, we use workflow descriptions as the artifact that Agentic AI uses to perform agentic actions. This description is typically an artifact used by the underlying normative technology, such as a decision support tool for structured processes for business process characteristics or for semi-structured processes. These upstream systems provide only a basic integration of Agentic AI solutions. The challenge and research gap lie in how to trigger Agentic AI, i.e., which anomalies in the artifact descriptions trigger an agentic action, and how to provide the right information and the right form of information to both the human and the Agentic AI so that the human can work effectively with it.

To properly integrate Agentic AI for interactive decision-making, we propose a taxonomy of interactions types that outlines a structured representation of information requirements for all agents involved. Additionally, the right modeling of the artifacts is key for enabling the correct information flow and the right interaction type for the decision context of the decisions taken.

3.6.1. Framework for Integration

On its own, AI can’t guide high-level manufacturing decisions. Each manufacturing organization needs to have a system architecture that enables a seamless flow of data from the shop floor to business operations. An organization must expand its existing digital twin of product, process, and people to include the organization level digital twin and supporting multi-level dataflow to allow Agentic AI to operate effectively. This will provide visibility for the agentic AI into the business structure and multi-level goals across the organization layers. It will be a big-data-fueled and knowledge-enabled process architecture allowing both digital simulations for training and digital execution for decision and task automation. The Agentic AI will collaborate with organization members and Agentic AI embedded tools to optimize, learn, simulate alternative scenarios, plan and design the modified or alternative organizational structures, manufacturing processes, and supply chains, and deploy AI-enabled multi-intelligent systems.

Support for agentic AI has to be included in a multi-layer digital twin of the manufacturing organization architecture spanning from the Agentic AI embedded edge devices to central computing and data storage. It will be a semi-centralized AI with social and economic arrangements facilitating collaboration and competition between the digital twins of the organization members and departments. The large design space and task space of the organization and its manufacturing systems with many possible hypothetical organization and task structures demand a multi-agent AI organization architecture. With the rapid developments in the AI capabilities, the digitally-product-enabled design and manufacturing spaces of the smart market-driven manufacturing organization must evolve to include agents collaborating with humans in human-AI mixed work teams within the organization.

3.6.2. Challenges in Implementation

The increasing digitization of the physical world has enabled vast progress in new manufacturing capabilities based on the taming of complex technologies, new design paradigms, innovative and holistic approaches and a fundamental transformation of how factories are organized. These changes have opened the floodgates for new creative explorations and experimentation, newly generated wealth and quality employment generation. As we approach the metaverse, the work processes, tools, methods, organization and infrastructure of new age innovative digital-human partnerships have the potential to provide a path to achieve resiliency in growing the economy amidst significant challenges in sustaining the progress made to date. Agentic AI-driven autonomous systems can play a central role in this context here buoyed by a generation of young innovators with a deep sense of purpose, commitment and exploration who can envisage and enact new innovative systems realizations. However, challenges related to technology capabilities, investments in immature technologies, the pragmatic evolution of existing human institutional systems who are inexperienced in adopting and recognizing the value of Agentic AI-systems, existing competitive forces who would like to see established, blockages associated with incongruous government regulations, integration of emergent digital metaverse capabilities accelerating the transition to the next stage of human enabled exploration and transformation into new service arenas, resistance to change, unforeseen consequences, various legal issues associated with liability and ownership of such systems, worker safety, changes in employment roles and structures, human emotions, ethical or moral dilemmas in man-machine interaction, conflict resolution, overcoming the recalcitrant weaknesses associated with reluctance and hesitance to embrace innovation are impediments in the transformation process. These challenges and concerns are valid to varying degrees, and resonate with nearly all technology realms. They represent a state of reflecting our own selves.

3.7. Future Trends in Smart Manufacturing

In the recent years, many new technologies have impacted smart manufacturing: the Internet of Things, Artificial Intelligence, Advanced Robotics, Big Data and Analytics, Blockchain, Cloud Computing, Digital Twins, Flexible Electronics, Integrated Photonics, Machine Learning, Micro-Nano Devices, Additive Manufacturing, Cybersecurity, Cyber-Physical Systems, Fifth Generation Networks, interface Brain-Machine, Nano-Biomaterials, Near-Zero Energy manufacturing, Neuromorphic Manufacturing, Zero Defect Manufacturing. The IoT provides manufacturing engineers with complete visibility into shop floor operations. Thanks to real-time wireless data collection from factory floor sensors, production managers can track workers and machine performance, power consumption, inventory levels efforts needed to make process improvements. Big data analytics converts raw facts about production into actionable insights and recommendations. Smart manufacturing technology must help manufacturers optimize operations and maintain a competitive edge. The fourth industrial revolution is distinct from its predecessors in its use of cyber systems, most notably smart autonomous systems. Agentic AI´s new capabilities for flexibility and innovation efficiency will play a critical role in such surveillance-free manufacturing systems, for distributed cooperative production, not just task-sharing but task-innovation, originating, creating, developing new processes, product features and functions. New forms of industry organization, beyond the creative digital apps and solopreneur, custom-build startups and the gig economy will increasingly flourish.

AI will proliferate and by 2030 evolve into agentic AI, that will have capabilities for enhanced autonomy and adaptability, flexible and inventive general and specific efficiency in different domains of industry. The world economy´s move toward carbon neutrality and zero waste will demand the ability to create and apply radical innovations for adaptive progressivity in every nook and cranny of both maker and user economies. All of this will set off a revaluation of the concepts, the human dimensions of smart manufacturing, whether in its specific processes or general motivational and organizational environments.

3.7.1. Emerging Technologies

Significant disruptive technologies such as advanced robotics and autonomous systems, Artificial Intelligence (AI) in the form of agentic AI, Business Process Management (BPM), Cloud Computing, Cyber-Physical Systems (CPS), Digital Fabrication & 3D Printing, Digital Twin Technology, Edge Computing, Blockchain Technology, Internet of Things (IoT), and Augmented, Virtual, and Extended Reality (AR/VR/XR) are anticipated to revolutionize industrialization and automation. There are various known definitions for these technologies, some with more general separation into foundational technologies and peripheral or facilitating technologies. This section will review both types of these technologies relevant to the scope of this work. The foundational technologies: AI, Digital Twin Technology, IoT, and Autonomous Robotics and CPS will evolve and mature over the next decade and usher the next generation of smart manufacturing and service enabled with insight-to-action cycle. New research and development effort into deep autonomous agents; building human-like capability and functional equivalence into these agents will be also carried on extending the Ada and Ego computing paradigms to the next level of autonomous agentic computing. Insight-driven autonomous agents from these foundational technologies will act as partners in and external to the organization where more development effort, tools, and gems will be put into developing these agents and their collective efforts. The demand for more capable autonomous agents both as internal partners and external partners in the automation eco-system via agentic collaboration and co-creation will be driven by organizations requiring customized ability to deliver customized product and services on demand.

3.7.2. Predicted Developments in Agentic AI

Autonomous intelligence is expected to be a major driving force in creating a radical transformation of the way intelligent systems operate and our future interaction paradigms. Here, we look at the possible course of developments in the future intelligent coordinated behavior of multiple IDP agents. Up to now, systems research and development has focused primarily on making intelligent agents and their built-in learning capabilities work. Besides, at the present stage of agents' evolution, we expect the major part of their decision make-up to be still based on some expert knowledge in combination with learning capabilities. The preset shift from intelligent individual agents to collections of autonomous IDP agents leads one to expect that perhaps only some part of eventual intelligent evolution in agents will be dependent on agential education. Empirical data will eventually be compressed in algorithms and networks representing either limitations to the behavior of the agents or simple rules governing their interaction with others as well as with the environment.

Three trends might contribute to at least some level of intelligence exhibiting capability in future IDP agents. Firstly, the performance of single agents will constantly and by orders of magnitude increase, as they will benefit from the continuing exponential growth in performance of electronic devices. Higher level behavior in terms of higher levels of abstraction will rely on suitable knowledge representations capable of small size for low-level IDP agent educational programming. Secondly, increasingly available digital information about everything, even distant parts of the planet, combined with the increasing interactions of people and products and embedded services in cyberspace, will help design simple models for the running of the physical world and the collective behavior of its denizens. Education will thus involve enabling the IDP agents to process multi-sensorial information and learn classification paradigms based on statistical physical models about the physical world, as well as social models on the behavior of their diverse, albeit tiny human teammates, so that they will ultimately seamlessly fit into the surrounding agency.

3.8. Regulatory and Ethical Considerations

As agentic AI systems become increasingly prevalent in manufacturing, decision-makers must think through potential regulatory and ethical implications of these systems. This section will particularly highlight issues relevant to autonomous manufacturing system development and deployment, focusing on two special policy areas: standards compliance and ethical implications of agentic AI use in manufacturing processes.

It is certainly true that autonomous manufacturing systems must comply or adhere to industry-specific standards regulations that govern-designed aspects within manufacturing environments or target products. While many industry standards pertain to physical properties like safety and efficiency, a number of standards dictate what sort of systems are acceptable collaborators within production systems. No autonomous manufacturing system considered for deployment can ever have a guarantee that it is free from non-consideration bias or developer blind spots when it comes to workforce attitude, privacy, or even product quality. However, product quality assessments are among the many traditional criteria determined through inspection at the completion of a production cycle. While these policies can generally help policy-makers consider potential concerns about agentic AI use in automated manufacturing, the question of how they shape the design of agentic AI-assisted manufacturing remains understudied.

Social policy is particularly important to consider in the case of autonomous manufacturing systems. Since perfect or optimal security is unattainable, social policy plays a role in considering how the risks of malicious actor manipulation are going to be managed and what investments into mitigate those risks are going to be made. What societal communities around the world would you expect to integrate into or alongside smart autonomous manufacturing operations, and how are trust in the ethical principles behind agentic AIs embedded within the manufacturing chain with the entire global economy?

3.8.1. Compliance with Industry Standards

Autonomous intelligent systems have seen a great amount of growth in recent years. Based on AI techniques, these systems can replace humans in many repetitive decision making processes. Besides improving time efficiency and precision they can also eliminate human errors. However, these systems can also be used in morally challenging scenarios with far reaching implications. In this paper we are considering the implications of these systems in the context of the manufacturing domain. Manufacturing companies have to adhere to multiple standard protocols to maintain safety levels, environmental conditions, and quality control in their processes. Moreover, implementing these during the design stage can provide assistance for investigating the effects that AI implementations can cause at the level of processes and product quality, as well as do so at early development stages. The introduction of new technologies can alter the functioning of any particular company with respect to the compliance with regulations in the area of environment, safety, labor, and taxes. Politically, the shift from human-based intelligence to AI-based intelligence in the decision-making process could entail a change in regulations concerning taxes, labor, and safety. Major shifts may trigger the need for a significant update of existing standards, as a move from decision support to decision-making could take place. Industry could help by participating in committees that monitor and regulate compliance to consequential standards, thereby not overwhelming the last and least supported party in the business ecosystem. Depending on the trajectory taken by the industry, there may be opportunities to create asymmetries among competitive players, i.e. create advantages and disadvantages.

3.8.2. Ethical Implications of AI in Manufacturing

This chapter considers the ethical implications surrounding the use of AI in smart manufacturing applications. The topic of whether and how to apply ethical precepts to the development of systems incorporating human-like AI capabilities has provoked polar opposite opinions within the academic community: on one side these opinions hold that the question should be dismissed as non-applicable or answered in the negative, whereas on the other side the view is taken that precautions have to be taken to avert dire consequences for society, especially regarding the industrial use of AI. While there exists a broad literature discussing these matters, there is surprisingly little normative work specifically addressing the ethical implications of the most advanced AI technologies, particularly regarding generative AI. To our own ends we review also the expert consensus statements that have appeared as well as some existing solo accounts. We then comparatively assess several ethical principles and guidelines. In an attempt to shed some light into the problem we discuss the differences between industrial and general AI. Our take is that current capabilities of generative AI warrant at least a precautionary principle and radical transparency internal quota in industrial AI, along with a proportionate application of general AI ethics principles and guidelines, especially regarding its application in human-centric design and field testing. Finally, we highlight existing initiatives and organizations for the ethically responsible development of advanced AI technology.

The ethical implications surrounding the use of AI in smart manufacturing applications have provoked polar opposite opinions within the academic community: on one side these opinions hold that the question should be dismissed as non-applicable or answered in the negative, whereas on the other side the view is taken that precautions have to be taken to avert dire consequences for society. We aim to clarify the leading proposals regarding the ethical development and deployment of AI technology and study their implications for its application in the distributed autonomous systems employed in advanced manufacturing. To do so we review the expert consensus statements that have appeared and some existing solo accounts, while providing a comparative assessment of the principles involved.

3.9. Conclusion

Efforts to bridge the gap that exist between the conception and deployment of agentic AI systems, driven by autonomy can deliver on the promise of enhancing efficiency in smart manufacturing processes and the larger smart enterprise value chains. Not only will such disruptive technologies usher the new paradigm of the ever-evolving and enhancing AI-driven Industry 4.0 enterprise processes, but also pave the way for the same technologies and collaborative frameworks to assist strategy and decision making of the higher echelons of the smart enterprise. This treatise outlined a conceptual framework exploring the various dimensions comprising the thought processes, decision making, logic behind actions and execution of tactical actions that create and deliver on business value of agentic AI systems. Highlighted were the parallel existences of human agents and intelligent assistant agents. Explored as well were the dimensions of agentic AI systems that was needed to realize the promised efficiency enhancement potential anchored upon autonomy, proper heuristics and drive for optimization. In doing so, this treatise aligned the disparate threads around foundations, adjective agentic dimensions and the operating models needed to deliver on autonomous heuristic driven AI systems capable of humanlike operation. A framework of operation centered upon the collaborative symbiosis of agentic AI and human agents aided the unification. Several prototypes of different AI domains enhancing enterprise efficiency were drawn from diverse sources, giving insight and validation to the agentic dimensions. By way of implications, a clear need was established for further developing the enabling agentic dimensions and processes through which practical application of agentic AI systems would be delivered upon to transform enterprise processes.

The 5-D functional explanation augmented by the 3-AIR lens and the proposed AASP operating model capture the promise of industry automation along the journey through levels of agency, explain how it works, and how humans can collaboratively symbiotically engage with agentic AI systems to take responsibility and enable the transformation and optimization of industry and enterprise value chain processes and augment productivity like never before.

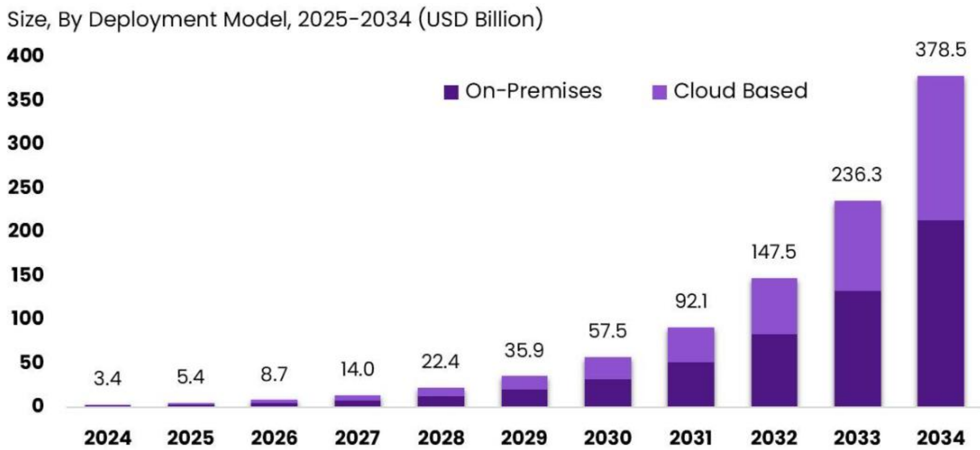

Fig 3 . 3 : Agentic AI in Digital Engineering Market Size

3.9.1. Summary and Key Takeaways

Summary and Key TakeawaysAs manufacturing processes globalize, they are dealing with heightened complexities and challenges, such as increasingly demanding customer requirements, fierce global competition, ever-increasing economic constraints, as well as a shrinking skilled labor pool. Digital Twins enable the foundation for data-driven manufacturing processes, however, struggle to depict realities in real-time, limiting their application as near real-time decision support tools. To enhance efficiency in smart manufacturing processes, whether planning, scheduling, pre-emptive maintenance, or resource allocation, this chapter proposed to fill the identified gaps of Digital Twins Technology through Agentic AI-driven Collaborative Autonomous Systems.

Traditionally, AI has been applied to specific components and processes in manufacturing processes but is just beginning to be embraced as the enabler of Agentic AI-driven Complex System Solutions for a variety of processes, such as manufacturing system decision-making, planning and scheduling, predictive and prescriptive analytics, and autonomy on the shop floor. Such composite systems enhance efficiency by moving decision-making and planning capabilities from humans to trusted Agentic AI, thereby realizing Key Performance Indicator improvement decision cycles on plan accuracy, cycle time, and agility to changing conditions at the sub-second frequency. Such solutions integrate agent definitions; deep learning for process state understanding; evaluation of KPIs using high speed, accurate simulation of all possible variations; and multi-agent collaboration for meeting KPI goals for the manufacturing process system. This chapter provided eight industry examples showing enhancements in efficiency and business outcomes through the proposed composite Agentic AI-driven autonomy solutions, and they span Manufacturing Process Design, Manufacturing Scheduling, Predictive Engineering and Scheduling, and Factory Floor Agentic AI Autonomy. Such composite Agentic AI solutions have the transformative potential to enhance efficiency by improving on the KPI improvement decision cycle on accuracy, cycle time, and agility at the millisecond time frequency.

References

Wang L., Törngren M., Onori M. (2015). Current Status and Advancement of Cyber-Physical Systems in Manufacturing. Journal of Manufacturing Systems, 37, 517–527. https://doi.org/10.1016/j.jmsy.2015.04.008

Schuh G., Gartzen T., Rodenhauser T., Marks A. (2015). Promoting Work-Based Learning Through Industry 4.0. Procedia CIRP, 32, 82–87. https://doi.org/10.1016/j.procir.2015.02.187

Lee J., Bagheri B., Kao H.A. (2015). A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems. Manufacturing Letters, 3, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

Qin J., Liu Y., Grosvenor R. (2016). A Categorical Framework of Smart Manufacturing Enabling Technologies. International Journal of Advanced Manufacturing Technology, 84(1–4), 315–334. https://doi.org/10.1007/s00170-015-7576-9

Wang Y., Kung L., Wang W.Y.C., Cegielski C.G. (2018). An Integrated Big Data Analytics-Enabled Transformation Model: Application to Health Care. Information & Management, 55(1), 64–79. https://doi.org/10.1016/j.im.2017.04.001