Smart Manufacturing with Artificial Intelligence and Digital Twin: A Brief Review

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Abstract— **Digital twin and artificial intelligence technologies have proliferated as crucial enablers for Industry 4.0. With a digital twin, companies can digitally test and validate a product before it exists in the real world. By digitally recreating the planned production process for real-world use, engineers can identify any potential process changes before they happen. This brief survey summarizes their general developments and the current state of AI integration in smart manufacturing and advanced robotics. This survey also covers industrial automation and emerging techniques, such as 3D printing.**

Keywords— Industry 4.0, artificial intelligence, machine learning, neural nets, digital twin, smart manufacturing, robotics sustainability

I. Introduction

Environmental issues such as carbon emission and pollution have required industries to shift from conventional economic growth to sustainable development. Achieving holistic sustainability will ordinarily require balancing financial, environmental, social & governance factors [3]. Balancing these factors will increase manufacturing costs and simultaneously raise severe challenges for their organizations & processes.
Smart manufacturing and Industry 4.0 aim to construct a universal networked architecture that addresses the interoperability and compatibility issues within and across all automation systems and factories, thus improving the flexibility and agility of conventional manufacturing [1]. With the profound research and development of Industry 4.0, artificial intelligence (AI) and digital twin have drawn growing research attention [2].

Digital twin technology facilitates us to build a virtual design of any object or system and enables us to view the insights of the real-world behavior of that object or system under any circumstances. Combining AI that uses the data gathered from sensors or measurements and digital twin will alter and enhance the behavior of the digital twin. AI-powered digital twin technology is expected to adopt the traditional model-based approaches to the evolving boundary conditions. Further, this technology efficiently provides a demand-oriented, real-time evaluation basis to support decision-making in multi-objective problems [4].

So far, much research has discussed and characterized the digital twin from the viewpoint of general concepts. However, there is a need for more specific studies that focus on AI to provide an accurate account between it and other technologies like modeling or simulation methods that can be used across various fields. This would also allow us to understand how these two factors come together when applied using product design approaches such as fault diagnostics and prognosis technologies [5].

II. Manufacturing

In recent years, research in the field of Industry 4.0 has been ongoing for some time now, with an increased focus put on cyber-physical production systems and integrative techniques [6]. This involves using simulation models to provide the basis for creating digital twins throughout the product lifecycle. This is regarded as an essential enabler for the future of manufacturing industries.

In this age of big data, data analysis can provide digital twinning throughout all stages of a product's life cycle. This enables efficiency in manufacturing industries throughout all stages of the product's life cycle. From the completed product to its end life, thus ensuring resources can be reused [7].

Fig 1. A holistic assessment of sustainable productivity, adapted from [7].

Financial, environmental, social, and governance factors are important indicators that can be used in understanding productivity in manufacturing [7], Figure 1. These indicators can provide a way of assessing how many products are being made and their environmental impact. This includes factors such as water use and waste generation in production processes, along with company policies that affect employees' quality of life. The research shows that embracing the trilemma of productivity, availability, and quality (proclaimed as financial) toward sustainable, resilient manufacturing companies can improve their environmental footprint.

III. General Developments

Individual customer demand for products at a premium poses a new challenge to production systems in the current market environment. This includes volatile markets demanding more flexibility in using resources like capital expenditure or labor hours. Manufacturers may have to consider automation as an option [8]. This could be done through mixed reality assistance, allowing industrial enterprises to see what they need before making any decisions. This would also provide them opportunities within automated systems, such as 3D printing toolsets. Where necessary, data files will automatically download onto designated devices during processing time, so there is no human involvement [9]. With the help of AI and sensors enhanced by cloud computing and edge computing [10], the initiative of the digital twin becomes a distributed control system capable of handling increasingly complex operational problems. Such as production planning or scheduling, detailed environments can be generated in 3D point clouds [11]. Given these technologies, the digital twin has shown that it can deal with complex production and operational problems [12]. The era of Industry 4.0 has led to a paradigm shift in the manufacturing process, which is creating new challenges for industrial enterprises. This would include production systems and management, automated productions methods (such as robots), and cloud and edge computing.

IV. Integrating AI

The availability of data from industrial production processes in a networked system landscape acts as a technical enabler for increasing the relevance and potential application areas such as AI-driven approaches. Utilizing AI at this level improves the adaptability of digital twins, which can dynamically change the boundary conditions at the factory floor level. This further opens up new possibilities to optimize manufacturing systems. Table 1 lists the different AI algorithms that have been used in digital twins. An example of this is the line-less mobile assembly which allows agile building and maintenance of large-scale components. This can be enabled by modeling and scheduling software with access to dynamic conditions that change quickly at small scales within individual facilities [13].

Table 1. AI algorithms used in digital twins

Algorithm Type	**Algorithm**	**Use Case**
Supervised Learning	AdaBoost, XGBoost, Decision Tree	Optimum yield of the light oil [21]
	Support Vector Machine, Decision tree	Anomaly detection of surface deviations [27]
	Artificial Neural Network	Welding quality prediction of deformation [27]
	Convolutional Neural Network	Feature recognition of parts [44]
	Monte Carlo method	Simulating the workspace of the mechanisms [45]
	Recurrent Neural Network	Prediction of dynamic states in metal cutting [39]
Unsupervised Learning	Principle component analysis	Object recognition of a smart gripper [41]
	K-means clustering	Anomaly detection of surface deviations of a truck component [38]
	Autoencoder	Fringe projection profilometry for 3D [46]
	Generative Adversarial Network	Prediction of machining vibration signals [47]
Reinforcement Learning	Deep Q-Network	Optimization of conveyor systems [20]

The parallel computing power of GPUs is a considerable advantage when it comes to simulating manufacturing processes. To make use of this, engineers often compensate for offline simulations with more detailed preprocessed models that can be trained using machine learning and deep-learning methods. This not only updates time-consuming numerical calculations. But also capture critical insights about how materials interact within their system without needing high precision at all levels.

Inline sensors that use machine learning and deep-learning methods to monitor production will provide companies with more information about their processes. This means they can optimize the space-time yield, accelerating innovation in areas such as new products or services for customers. A lightweight model equipped with these types of software could be used during rapid scaling up periods. This way, fast insights can be gained without sacrificing accuracy.

There are many approaches to condition monitoring and predictive maintenance. The most common one is using process indicators that can be recorded from sensors directly or determined indirectly by them. Nevertheless, this increases the installation cost because there must be an external source for each type of sensor attached on top of the machinery.

Most supervised learning algorithms require large amounts of labeled training data to obtain models with high accuracy in predicting future behaviors or trends from historical records. Labeling data is often an expensive and time-consuming task. The complexity and the size of the data set determine how much work goes into labeling. The accuracy of the labeling and the feature selection affect the outcome of the learning algorithm. The algorithms that are generally found in digital twins include support vector machines [37], decision trees [18], k-nearest neighbors [38], convolutional neural networks and recurrent neural networks [39].

Unsupervised learning is a method that does not require any labeling of data. The model infers patterns from the unlabeled input clustering algorithms such as principal component analysis [41] and k-means clustering [40]. These two methods have different goals. Principal component analysis helps to reduce the number of features while preserving variation, whereas clustering reduces data points by summarizing several points into their expected or mean values (in the case of k-means). Additionally, generative adversarial networks [44] variational autoencoders [44] also use unlabeled data.

A significant challenge in applying clustering algorithms is that the number of clusters is unknown and must be determined a priori. The similarity between two items is determined by the Gaussian, Euclidean, or cosine distance for clustering algorithms. These can be acceptable for specific tasks, but none defines what should happen if there is no exact match between them. Nevertheless, something needs to occur with these situations where intelligent agents have goals and behaviors defined against environments that may contain unknown obstacles.

Reinforcement learning algorithms do not merely look at one agent interacting within its world; instead, they consider all possible interactions between multiple bots. Then use a reward function to maximize cumulative rewards while accounting for both successfully executed actions. Researchers have used reinforcement learning algorithms to optimize decision-making processes in inbox sorting, conveyor systems, and other digital twin scenarios. These include deep deterministic policy gradient, Q learning [23], and deep reinforcement learning [24] models. Reinforcement learning algorithms are dependent on reward structures that need accurate data, or they will break down during training due to sometimes incorrectly logged references.

V. Production Planning and Control

Production planners need to use artificial intelligence and digital twin to produce more efficiently. Figure 2 shows the connection between multiphsics modeling and digital twin and how they are connected using a data-driven approach. The maturity model of this approach [14] would allow for digitally connected intelligent systems that are adaptive in nature. They can adjust on-the-fly when faced with different circumstances or conditions during planning stages before implementing any optimizations at the green design and production planning phase. Ordinarily, decision trees [15] can be used in the digital twin to create rules that are enabled in intelligent systems. This will enable them to optimize key performance indicators better than before. Additionally, genetic algorithms [16] have been used to solve scheduling problems in production lines. Others [18] have used a deep Q-network with graph convolution networks to solve the dynamic scheduling problems.

The digital twins at the production control stage can be equipped with decision trees [19] and tree-based ensemble models such as AdaBoost [20] or XGBoost [21] and Deep Neural Networks [22]. These methods optimize resource allocation for manufacturing performance indicators on time. However, multi-objective problems are usually interpreted as non-deterministic polynomial-time hard. Because this is due to the complexity and dynamics within factory production environments and can be ameliorated using reinforcement learning algorithms, have been used [23]. In particular, deep Q network and deep reinforcement learning for heuristic optimization or supervised approaches have successfully achieved global optimal economic and logistic KPIs [24].

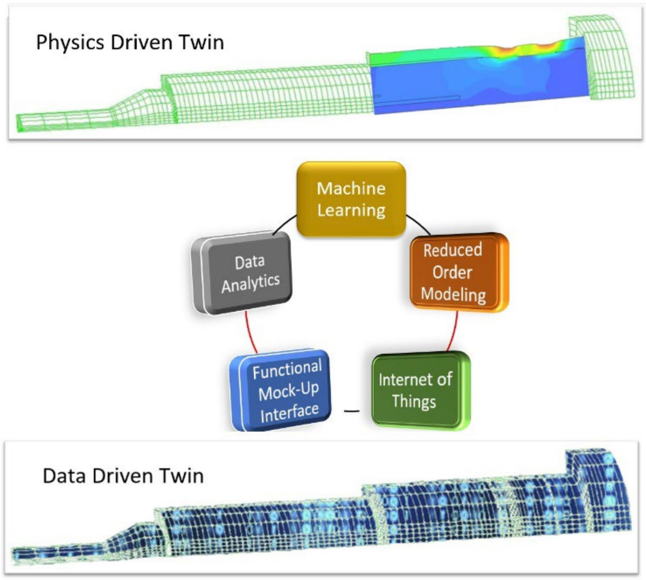

Fig. 2. Diagram showing the connection between a multiphysics model and a digital twin.

Humans in the manufacturing equation are unpredictable and vary significantly from one another in terms of moods. Researchers [25] have sought to incorporate humans as a component of smart manufacturing. The solution they came up with is called situational selection. This allows decisions based on how an agent will behave when given specific incentives (rewards). This concept uses machine learning algorithms (reinforcement learning) trained using data gathered from human behavior patterns monitored over time. These models allow forecasting what someone might do based solely on their current state/mood without any input about personal preferences.

VI. Quality Control

Machine learning has helped identify potential quality issues that would otherwise go unnoticed by less sophisticated methods. Various computer vision models have been used [26] to address quality issues and efficiency in the assembly of products. Decision trees, support vector machines, or artificial neural networks have been used to predict or detect deformations in production [27]. These algorithms [28] have also been used to support decision-making in the production planning stage using historical production data. Digital twins of production systems, in combination with model-based system engineering, can be modeled and adapted modularly as a virtual testbed, which provides optimization opportunities for the runtime environment [29].

VII. Robotics

Robotic systems are becoming popular in industry due to their ability for multi-robot coordination or collaboration [30]. With a digital twin of these robots, human safety is often considered when interacting with them, which creates an environment that is sustainable working alongside robotics technology without risks associated with traditional work. Many different methods can be used to implement robots in the real world. Examples include kinematics and communication control planning energy modeling for industrial robot tasks like welding or cleaning products [31].

Recently, new concepts and use cases utilizing artificial intelligence for semi and fully autonomous robotic systems have been reported [32]. These include transfer learning and imitation learning, also known as apprenticeship learning or learning from demonstration. Imitation Learning, featured in digital twins, generates high accuracy output. Many times, it is not possible to build high-fidelity dynamic models. This can lead engineers in the field to have difficulty making decisions about how an object would behave if made with certain materials used during its construction process. With digital data-driven twins that are AI-ready, complex robotic systems can be built [33].

VIII. CONCLUSION

The industrial and systems engineering field has been using artificial intelligence to enhance productivity. This technology increases efficiency and provides a holistic view of sustainability. That can be used by businesses everywhere to make better decisions on where they invest money, what programs need to be implemented next. From such a perspective, digital twins are AI-enabled and are considered service agents [34]. Digital twins provide innovative, intelligent services via a network of machines that can be accessed as needed. This allows for the delivery and sustainability of manufacturing solutions, helping manufacturers accomplish a vital shift to ongoing service offerings [35].

The mainstay of the manufacturing industry has long been a focus of research. Nevertheless, complex, and varying working conditions make it challenging to transfer findings from these studies into real-world settings that often require more elaborate analytical models or empirical measurements on an individual level than what can be found in practice with just sparse datasets alone. The data-driven approach to manufacturing can provide an additional unique opportunity for improvement by using each system as a "tuning fork". This would further enhance the database, which houses all measured information about production indicators and labeled training samples used during model development.

The availability of datasets is improving, which extends the boundaries for machine learning and deep-learning systems in fault diagnosis. This allows manufacturers to use these technologies with greater success. It also opens new prospects when using AI-driven digital twins like prognostics or system health management.

AI-driven digital process twins are envisioned to learn and interpret the implicit correlation between manufacturing processes. Material and process parameters from an aggregate of (heterogeneous) data used in machine learning can ramp up production and quality assurance.

The development and deployment of algorithms in practice can be improved by considering new sensor technologies [36]. Despite being significant to the engineering process, sensor technologies are often overlooked when constructing models, which are essential in deploying them successfully on real-world problems.

The development of new manufacturing techniques, such as 3D printing and lightweight production for metals or composites, lead to innovative concepts. Such techniques will also save resources during the design and manufacturing phases. These new manufacturing techniques also provide an essential basis for future products to operate without consuming too much energy sustainably. These advancements are, therefore, all-encompassing in their sustainability upgrades.

Digital twins are a new way to bring digital data and physical reality together. These artificial intelligence techniques involve several methods, including supervised learning, unsupervised learning, reinforcement algorithms, or other intelligent computational models that can be used for machine-type thinking.

The potential for digital twins to contribute toward industrial economic growth and continuously upgrade sustainable aspects is remarkable. AI techniques allow these virtual creations to arm themselves with tools that help them make models based on observed behavior and historical data. This improves efficiency when analyzing large amounts of less compatible information sets. This increased prediction accuracy can be valuable across many fields, including resource management.

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