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Impact of AI-Driven Digital Twins in Industry 4.0: An Exploratory Analysis

Dr. Prakash Upadhyay[1], Tushar Sharma[2], Ahmadi Fatima[3]
[1]Assistant Professor- Computer Science, St. Xavier's College of Management & Technology, Patna Bihar, India.
[2,3]UG – Computer Science, St. Xavier's College of Management & Technology, Patna Bihar, India.
Email Id: *Prakashupadhyay@sxcpatna.edu.in[1], tusharsharma8789l@gmail.com[2], ahmadifatima2002@gmail.com[3]*

Abstract
Human society is witnessing a revolutionary growth of digital twin (DT) and artificial intelligence (AI) technologies, which has greater impact on Industry 4.0 revolution specially in academia and industry. DT is a digital representation of a physical entity, with data and infrastructure serving as its foundation, algorithms, and models as its core, and software and services as its application. The methodical and thorough integration of domain-specific expertise is even more essential to the foundations of DT and AI in industrial sectors. This paper provides a thorough analysis of more than 30 articles on AI-driven DT technologies employed in Industry 4.0 over the previous five years. It also describes the general advances of these technologies and the current status of AI integration in the domains of advanced robotics and smart manufacturing which are affecting human society. These include established methods like industrial automation as well as complex mechanism like 3D printing and human-robot collaboration. Additionally, the benefits of AI-powered DTs are explained in relation to sustainable development. The development potential and practical difficulties of AI-driven DTs are examined, with varying emphasis on various levels.
Keywords: *Artificial Intelligence; Digital Twin; Digital Shadow; Industry 4.0; Machine Learning; Sustainability;*

1. Introduction

Smart manufacturing and Industry 4.0 are essential components of modern society and the national economy. By building an open, networked architecture, Industry 4.0 promises to improve the flexibility and agility of traditional production by addressing compatibility and interoperability problems both within and across automation systems and industries at all levels. Advanced robotics is also essential to smart manufacturing since it acts as an intelligent agent that is present across production lines. Digital twins (DT) are gaining more and more interest in research because of the extensive study and development of Industry 4.0 and artificial intelligence (AI)[1]. Finding equilibrium among the FESG (financial, environmental, social, and governance) aspects is often necessary to achieve holistic sustainability. This drives up expenditures for production companies while also posing serious problems for their processes and organizational structure. In these circumstances, it is anticipated that AI-powered DT technology would modify conventional model-based methods to fit changing boundary conditions and offer a demand-oriented, real-time evaluation foundation that effectively supports decision making in multi-objective challenges. Numerous studies have already been conducted on DT, discussing and characterizing it from the perspectives of broad concepts, specific fields, and technologies—all without specifically focusing on artificial intelligence (AI), this unique enabler—that is, product design, modeling and simulation, and fault diagnostics. The methodical and thorough integration of domain-specific knowledge is much more essential to the foundation of DT and AI. Currently, a thorough industry-focused analysis of "AI + DT" technologies in relation to sustainability and the circular economy is still lacking. The

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following research questions (RQ) are put forward to further aid in the development and landing of these generalized technologies (GT) in advanced robotics and smart manufacturing:

RQ1: What are the most recent studies on DTs and realistic case solutions?

RQ2: What is the progress in the integration of the two categories mentioned above?

RQ3: With respect to sustainability what are the benefits of AI- enabled DTs.?

RQ4: Practical problems in using AI-enabled DTs in the real world and in the future?

By reviewing recent advancements in DTs from a domain-specific standpoint, investigating applied AI techniques in each subarea, classifying their role in sustainable development, and summarizing real-world issues in a range of application domains, this paper aims to close this research gap [5]. The present study makes the following contributions:

- The AI-driven DTs of Industry 4.0 have completed their general development and application scenarios using standard AI techniques.
- The benefits of AI-driven decision trees (DTs) for sustainable development are explained in detail with reference to the FESG criteria, which allow for a quantitative evaluation of sustainability.
- With a focus on various levels, the difficulties and future potential of AI-driven DTs in advanced robotics and smart manufacturing are examined.

1.1. Exploring the Definition of Some Major Technical Terms

1.1.1. Digital Twins

The National Aeronautics and Space Administration (NASA) defined DT as a Multiphysics, multiscale, probabilistic simulation that mimics the life of its twin through the use of physical models, sensor updates, fleet history, and other resources [2]. Grieves and Vickers subsequently described DT as a dynamic model that is based on enormous amounts of data and processing power that vary throughout the lifecycle, including creation, production, operations, and disposal [4]. Tao et al. suggested an extended five-dimension DT model [3], which includes a physical entity, a virtual entity, service, data, and connection, based on the architecture in [6].

1.1.2. Digital Shadow

The U.S. Air Force initially introduced the idea of "digital thread" as a framework for combining conceptual and top-level architectural models from model-based systems engineering (MBSE) with specific design models [7]. The National Institute of Standards and Technology (NIST) advanced this concept further with the aim of sharing data about equipment performance and health as well as product design and quality throughout the product lifecycle [8]. With the model-based ensemble of data in design, production, and inspection, a single digital thread is thus established, enabling full process tracking in a smooth, real-time, collaborative process of development across the project stakeholders [9].

1.2. Limitation of Exploratory Analysis

This survey offers a basic understanding of the state-of-play for AI-driven DT technologies in Industry 4.0, including the three previously mentioned topics (Digital Twin, Digital Thread, AI). Although the meanings and applications of the Digital Transformation (DT) are interpreted differently, they all adhere to the same philosophy: using digital replicas with near real-time capabilities to improve traditional organizations and processes throughout the product lifecycle in an efficient manner will increase industry competitiveness and optimize resource allocation. Thus, the focus here is not on standalone machine learning (ML) technologies, 5G communication, or Internet of Things (IoT) technologies without digital duplicates. Based on this, more than 30 manuscripts are covered, who deals with manufacturing, smart city and robotics in industries.

1.3. Paper Organization

The paper is organized as follows. Section 2 examines digital production twins at three distinct levels in the context of sustainable, resilient manufacturing; Section 3 covers the applications of DT in robotics and human–robot

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interaction/collaboration, Section 4 compares AI techniques horizontally; Section 5 wraps up the paper's contributions and discusses future research.

2. Flexible and Environmentally Friendly Manufacturing

To address the volatile, uncertain, complex, ambiguous market environment, extensive research has been performed recently in the fields of Industry 4.0, cyber–physical production systems and integrative production approaches. A strong foundation for creating digital production twins throughout the product lifecycle is provided by the pervasive use of simulation models and ubiquitous networking, which is seen as a crucial enabler for upcoming manufacturing transformation and upgrading in the big data era [18-19]. A future vision of a more ecologically conscious society, known as "sustainable productivity," is replacing the conventional resource-intensive productivity thinking in the context of the circular economy and sustainability promises (such as the European Green Deal). With the integration of FESG factors as a novel indicator for quantitatively evaluating sustainable production, this understanding of productivity pushes manufacturing companies to adopt the necessary sustainability transformation by measuring their performance with respect to tangible and intangible services, business models, and value creation systems made up of resources, processes, and organizational structures. There are three levels of discussion for various research on digital technologies (DTs), including general advancements and AI-integrated cases, in terms of improving the financial trilemma of productivity, availability, and quality toward environmentally, socially, and governance-sustainable resilient manufacturing: For smart manufacturing we cover the factory and shop floor, as well as machinery and equipment, process and material.

2.1. Production House and Production Environment

2.1.1. General Developments

Due to dynamic market environment and individual customer demand, Production systems and management in industrial firms face new problems. These challenges can have a substantial impact on manufacturing productivity and profitability. Automated production systems, including mixed reality assistance systems [11], could be quickly modularized [12] and reconfigured [13], improved with artificial intelligence [14] and sensors, and combined with cloud and edge computing [17] to become distributed control systems. Detailed production environments could also be created and updated in the form of 3D point clouds [18]. All of these possibilities are possible within the various concepts and frameworks that have been presented thus far.

2.1.2. AI-Integration in Production House and Environment

In this context, the accessibility of industrial production data within a networked system landscape serves as a technological enabler to raise the relevance of subjects like artificial intelligence and data-driven methodologies. This creates even more opportunities for the optimization of (novel) production systems, such as the line-less mobile assembly systems that allow big components to be assembled quickly by utilizing scheduling and modeling tools [20]. Enhancing DTs' ability to adapt to constantly changing boundary conditions at the factory and shop floor level is the main goal of using AI at this level. Production planning, production control and quality control are typical application subfields with AI-integrated DTs. While studying the papers, we found following AI Enabled Technologies that are being used in Production House and its Environment.

Production Planning: Production planners can use artificial intelligence (AI) to help them identify plans with improved key performance indicators (KPI), derive optimization measures, and autonomously implement the strategies to achieve better sequencing and reallocation of resources (E-factor). This satisfies the maturity model of production planning and control (PPC) proposed by Busch et al. toward digitally connected, intelligent, and adaptive PPC systems. Decision trees might be utilized in DT to develop traditional rules for smart systems during the green design and production

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planning stages, which would help with multidimensional process decision-making and strategic planning [21]. Hu and colleagues presented a Petri-net-based method for dynamic scheduling that utilizes a deep Q-network (DQN) in conjunction with a graph convolution network (GCN) to address dynamic scheduling issues related to shared resources and route flexibility. Similarly, metaheuristic techniques like the genetic algorithm (GA) and other optimization techniques [23] were frequently used to address scheduling issues in production lines in Table 1.

Table 1 AI-Integration in Production House and Environment

Sub System	AI-Category	Key Methods	Application-Case
Production Planning	Supervised Learning	Decision tree	Material Selection; Tool Holder Selection;
	Reinforcement Learning	DQN	Dynamic Scheduling Of Flexible Manufacturing Systems
	Computational Intelligence	DES, multi-objective optimization	Production Scheduling Optimization, Automatic Flow-Shop Manufacturing System
Production Control	Supervised Learning	PGN, DNN	Resource allocation for sequential manufacturing Operations, Process Optimization
	Reinforcement Learning	DQN, TRPO	Optimization of conveyor systems and Order Dispatching, Human Behavior Forecasting
Quality Control	Supervised Learning	CNN	Feature recognition of parts
		Rest Net	Use of CAD in surface detection of Production
Logistics	Computational Intelligence	Self-learning generic positioning	Defect detection and location information preservation

Production Control: To enhance resource allocation and manufacturing metrics for performance in a timely way DNN, decision trees [23], and tree-based ensemble models were incorporated in various digital production twins during the production control stage. However, because of the complexity and dynamics of production environments, multi-objective problems at the factory level are typically understood as non-deterministic, polynomial-time hard. With the aim of autonomously achieving the global optimal economic and logistic KPIs in the logistic simulation environment factor, the major task is typically mathematically formalized as a Markov decision process (MDP). Reinforcement learning (RL), such as DQN and deep RL, were used as a substitute for heuristic optimization and supervised approaches in various investigations to address this challenge. May et al. proposed a paradigm for the contextual decision-making process for production control agents by anticipating human behavior modeled by a reinforcement learner in order to include humans as a crucial component of smart manufacturing.

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Quality Control: Conventional supervised machine learning models, like artificial neural networks (ANN), decision trees, and support vector machines (SVM), were supposed to identify or forecast possible surface irregularities and deformations during the quality control phase. The use of deep learning (DL) computer vision models, such as residual and convolutional neural networks, was implemented to identify potential quality problems during the automated production and machining of parts. These models could then be applied to improve the efficiency and quality of assembly processes (E-factor), or they could be traced back to the production planning stage to support decision-making as a "smart expert" in a cooperative setting. DTs of production systems in conjunction with MBSE can be modeled and modified modularly as a virtual testbed, which in turn might provide a runtime environment for simulation-based optimization. This approach is in line with the broader idea of incorporating ML approaches into the digital production twins. Hence, maintaining a profitable business is still necessary for long-term operations. At this level, DTs improve manufacturing processes' resilience, productivity, and transparency. This allows end-to-end data availability throughout the value chain and, consequently, a comprehensive sustainability assessment. AI-enabled DT can also be viewed as a service agent from the standpoint of business development [24], offering cutting-edge smart services through DT network platforms [25] and subscription business models. This helps manufacturers achieve a paradigm shift from the one-time provision of production hardware to the continuous delivery of manufacturing solutions (SG-factor) while also making a sustainable contribution to long-term innovation.

3. Advanced Robotics

3.1. Overview

A digital twin of a robot is becoming increasingly important in real-world scenarios, such as multi-robot coordination and collaboration, safe human-robot interaction (HRI), and complex human-robot collaboration (HRC).

Table 2 AI-Equipped DTS and Groups

Subsystem of Robotics	AI Technology Used	Key Methods	Application-cases
Control	Computational Intelligence	Vision-based Markovian chain, QP	Automate fan-blade reconditioning, maintenance, repair and overhaul
	Supervised Learning	GD	Recognizing integrated models' enhanced value for through-life engineering services
	Reinforcement Learning	Trial-and-error search	Weightlifting robot control
Planning	Computation Intelligence	Proximal policy optimization	Pick-and-place tasks for an industrial robotic Arm
	Reinforcement Learning	DQN	Automate smart manufacturing systems
HRI/HRC	Supervised Learning	CNN, DN, ANN	Standing-posture recognition in HRC, enabling industrial robots to bypass obstacles
	Reinforcement Learning	DDPG	improve efficiency in assembling medical equipment, e.g. COVID Case
Predictive Maintenance	Supervised Learning	DNN	Maximizing the overall plant availability of modern manufacturing systems
Workspace Modeling	Supervised Learning	MonteCarlo method	Simulating the workspace of the mechanisms

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Additional instances can be discovered in industrial robot energy modeling, kinematics, communication, control, planning, and manufacturing use cases like welding, cleaning, pick-and-place, assembly, manufacturing, warehouse, maintenance, and construction. A few popular robotics simulation programs are CoppeliaSim (also known as V-REP) [23], MuJoCo [28], and Gazebo [29]. New ideas and examples of applying artificial intelligence to partially and completely autonomous robotic systems have recently been published. Examples include imitation learning, often referred to as apprenticeship learning or learning from demonstration, and transfer learning [30]. While data-driven and AI-equipped DTs assist with complicated robotic systems for which it is not practical to generate high-fidelity dynamics models, classic DTs have been developed for systems that we have a firm grasp of (i.e., model-based) (model-free). The latter is increasingly being used, even in the construction of biomimetic robotic systems (robotic fish). Table 2 lists AI-equipped DTs and groups them according to the subfields—such as control, planning, and HRI/HRC—and learning algorithms that are employed. These scenarios prioritize human safety and contribute to the creation of a sustainable working environment (SG-factor). This development is accompanied by the widespread deployment of robotic systems in industry and daily life. Many have attempted to build robot DT using typical simulation/cloud frameworks.

3.2. Control Segments of Robotics

Modern robotic control relies heavily on feedback, which provides commands for the subsequent execution loop based on precise data gathered from external sensors and physical sensors mounted on robots. On these robotic systems, there are situations when safety controllers must be enabled in real time. In this subfield, numerous attempts have been made to use AI + DT. When paired with data, artificial intelligence (AI)-driven deep learning models (DTs) can achieve nontrivial sensing and manipulation tasks and become more adaptable and generalizable in a changing environment. A smart soft-robotic gripper system based on triboelectric nanogenerator sensors was described by Jin et al. at the sensing stage in order to record continuous motion and tactile data for soft gripper control. To improve task performance and system understanding, data- or AI-driven methods are also included in various touch, haptic, and force sensing [28]. A humanoid robot was able to lift a weight of unknown mass through autonomous trial-and-error search thanks to Verner et al.'s implementation of online reinforcement learning via a fake digital twin at the controller stage, one level higher [27]. Grinshpun et al. also reported on the creation and application of control algorithms for soft robotics in, specifically mentioning industrial peg-in-hole insertion jobs. As an example of an application, Oyekan et al. used a robotic arm and vision-based Markovian chain to automate fan-blade reconditioning for aerospace maintenance, repair, and overhaul (E-factor). Another instance is the development of a DT by Klamt et al. for the well-known CENTAURO robotic system, which aids rescuers during disaster response operations.

3.3. Planning

High-level robotic planning is another essential component in the realization of autonomous robotic systems, and it comes into play once the low-level robotic control is functioning well. In contrast to the low-level control subfield, which places greater emphasis on the robustness and reaction of the system, high level planning is more concerned with strategically identifying a nearly optimal solution among all viable possibilities, given particular limitations. Reinforcement learning has shown enormous promise in adding intelligence to complex systems planning, such as a humanoid robot with many degrees of freedom (DOFs), when compared to conventional search-based motion planning algorithms [26]. However, because it takes money and time to get the data from the actual physical system, training reinforcement learning is typically challenging. Additionally, the system may not be able to learn anything beneficial due to the constraint of dimensionality [27]. In [28], Matulis et al. integrated digital twin and reinforcement

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learning for a robotic manipulator to plan pick-and-place motions; in [25], Liu et al. proposed a multitasking oriented robot arm motion planning scheme based on deep reinforcement learning and twin synchro-control. These examples suggest that the combination of "DT + RL" is a promising approach (SG-factor) when a robotic system's digital twin matures and provides reliable data.

3.4. HRI and HRC

One of the most significant advantages that DT could have for robot-involved scenarios in the context of Industry 4.0 is safer human-robot interaction and collaboration [28] (SG-factor). It seems sense that HRI and HRC situations would be more complicated and difficult than robot-only applications because of the variety and randomness of human behavior in addition to the uncertainties in the environment and sensors. AI-enabled DTs have an advantage over traditional ones in that they can adapt more effectively to these (sometimes implicit, like [29]) variables, which are difficult to fully characterize and analyze. Wang et al., for instance, suggested a real-time process-level digital twin in for cooperative human-robot construction work. To enable both planning and improvisation, the suggested DT coupled the as-designed BIM model with the changing as-built workspace geometry collected from on-site sensors. It did this by utilizing immersive virtual reality (VR). Li et al. presented DL-based human standing-posture recognition in HRC in [27].

3.5. Maintenance Through ROBOT and Other Applications

Robotic machinery require maintenance and have downtime much like any other equipment that has a physical component (E-factor). In [29] Khalastchi et al. and Vallachira et al. reported examples of using data-driven approaches in robot anomaly/failure detection without specifically discussing the notion of DT. In [15], Anton et al. employed DT equipped with deep learning for predictive, personalized maintenance in addition to monitoring the overall health of the system. Similar to this, Aivaliotis et al. integrated deterioration curves in the industrial robot predictive maintenance [26]. Table 4 has some more applications, such as estimating the length of lawn grass for a robotic lawn mower using a random forest approach and computing the workspace of a serial robot manipulator using the Monte Carlo learning method [30].

3.6. Challenges and Future work

In the field of robotics, creating and deploying digital twins presents a number of significant obstacles. First, because of the intricate interaction characteristics at the interfaces between robots and their environments, humans, and other robots, multibody physical simulation is inherently challenging. Furthermore, because robot movement can frequently occur at a very high speed (such as on an assembly line), real-time sensor feedback is essential to the digital twin's ability to make quick judgments. Many academic researchers opt to employ simulation environments, like Gazebo (e.g., [29]), to create robots. However, despite years of development, these robotic simulators still have many unresolved limits and may need high-performance computing (HPC) systems. Second, human user inputs and disruptions introduce an additional degree of unpredictability and uncertainty to the entire collaborative system/workspace, jeopardizing HRI/HRC safety. A further way to make the human-robot interaction intuitive is to incorporate virtual reality or augmented reality (AR) technology alongside standard-compliant (e.g., ISO 13482) safety procedures that must be enabled on both the physical and digital fronts [30]. Additionally, Rückert et al. proposed combining product life cycle data into activities involving human-robot collaboration during assembly.

4. Use of AI Driven Digital Twins in Industry 4.0

While continuously improving sustainable aspects, such as the E-factor (e.g., reduced carbon emission and resource consumption through CM, PdM, 3D printing and lightweight production of metals and polymers) and SG-factor (e.g., enhanced working conditions, collaboration and innovation through HRI/HRC), DTs have demonstrated remarkable potentials to contribute to industrial economic growth, or the F-factor (i.e., the productivity,

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availability, and quality of manufacturing). With the use of artificial intelligence (AI) techniques, digital twins can build models based on observed behavior and historical data, increasing prediction accuracy and streamlining data analysis from a variety of inconsistent and diverse sources. Four general categories can be used to group the AI approaches used in digital twins: reinforcement learning, supervised learning, unsupervised learning, and other intelligent computational techniques. Algorithms for supervised learning are machine learning techniques where models are trained with labels. SVM, decision trees [21], k-nearest neighbors, convolutional neural networks (CNN), and recurrent neural networks (RNN) [22] are examples of common supervised learning techniques used in digital twins. In actuality, data labeling can be a costly undertaking. To produce a model with a high prediction accuracy at the training stage, the majority of supervised learning algorithms need a substantial amount of labeled data. Generally speaking, more data are required to get workable findings the more sophisticated the design. Unsupervised learning techniques don't need data labeling; instead, the model is meant to identify patterns in the unlabeled input data. Unsupervised learning refers to clustering algorithms that use unlabeled data during the training phase, such as principal component analysis (PCA) [26] and k-means methods [20], as well as generative models that use generative adversarial networks (GAN) and variational autoencoders (VAE). Applying unsupervised learning techniques is a hurdle since it is typically unknown how many clusters there will be beforehand. Algorithms for reinforcement learning are focused on how intelligent agents should behave in a given environment to maximize the concept of cumulative reward. Q-learning [16], deep reinforcement learning, and deep deterministic policy gradient are a few examples of reinforcement learning algorithms that researchers have used to maximize decision-making in DT settings such as box sorting and conveyor systems. A reinforcement learning system's effectiveness is typically highly dependent on the accuracy of the data logging and the selection of incentive structures. During training, logging to the wrong references could contaminate the data and cause the system to crash.

Conclusion

We have observed that the current infrastructure still places constraints on the development and use of AI-enabled models and algorithms, the DT's core, and that building it will require interdisciplinary cooperation and the integration of domain-specific expertise (basic level). In the near future, new developments in innovative sensors as well as advantages from 5G communications are anticipated. From an application perspective, manufacturers can transform their paradigm through smart services and new business models, but first they must be prepared to share a reasonable amount of their data and knowledge with partners. This needs to be built on standardized notions of data ownership and security. Future work will encompass a deeper survey on AI-driven DT technologies in the application sectors of mobility and smart cities, renewable energy, and healthcare. We think that by rearranging and combining a number of extremely pertinent topics in both horizontal and vertical directions, a synergistic effect will occur that will enable the work in this study to contribute to additional AI-driven, DT-related research and assist different branches in creating new innovations in their corresponding smart and sustainable fields.

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