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Review

Electronic Artificial Intelligence and Digital Twins in Industry 5.0: A Systematic Review and Perspectives

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Abstract

This review analyzes the Electronic Digital Twin (EDT) tools characterizing the industrial transformation phase from Industry 4.0 to Industry 5.0. The goal is to provide innovative research EDT solutions to integrate in manufacturing production processes. Specifically, this research is focused on the possibility of combining the advanced technologies and electronics and mechatronics of industrial machines with Artificial Intelligence (AI) algorithms. Furthermore, this review provides important elements about possible future implementations of AI-EDTs and some circuital examples to support the understanding of the concept of circuit simulation in EDT models. EDTs are useful to comprehend the modeling concepts functional to the AI application using the output of the circuit simulations. The output of the circuit is used to train the AI model, thus strengthening the capability to classify and predict the real behavior of production machines with a good accuracy. This review discusses perspectives, limits, and advantages of EDTs and is useful to define new research patterns integrating structured EDTs in advanced industrial environments. The focus of this paper is the definition of possible perspectives of EDT implementations, including AI, in data-driven processes in specific strategic areas of industrial research by classifying the scientific topics in six main pillars. This paper is also suitable for the researcher to develop innovative topics for projects scaled into different work packages based on EDT facilities.

Keywords: Electronic Digital Twins; AI-based modeling; Industry 5.0; advanced manufacturing modeling

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1. Introduction

1.1. Research Methodology and DT Research Topics

This review analyzes innovative and recent research topics about Electronic Digital Twin (EDT) models in advanced Industry 5.0 scenarios. The research methodology is indicated in Figure 1, separating two main phases: a first one finding keywords grouped into six main research 'pillars' about EDTs in European research projects [1] of the last three years and a second one focusing the attention on the sub-topics correlated with this project's keywords. These sub-keywords are matched successively with research papers of the last five years. Search engines have been filtered for the last five years. This search yielded several papers. Papers from 2021 and 2022 were partially replaced due to their repetitive nature with more recent articles or because they were updated with new papers offering added values. This review describes the recent research advances in Digital Twins (DTs), explaining the possible EDT implementations and possible perspectives, starting with the analysis of the projects, which suggest different research pillars to be analyzed more accurately. DTs refer to digital physical–cyber models in general, including digital

technology, while EDTs refer to electronic circuit models. Industry 5.0 facilities integrate both DT and EDT models.

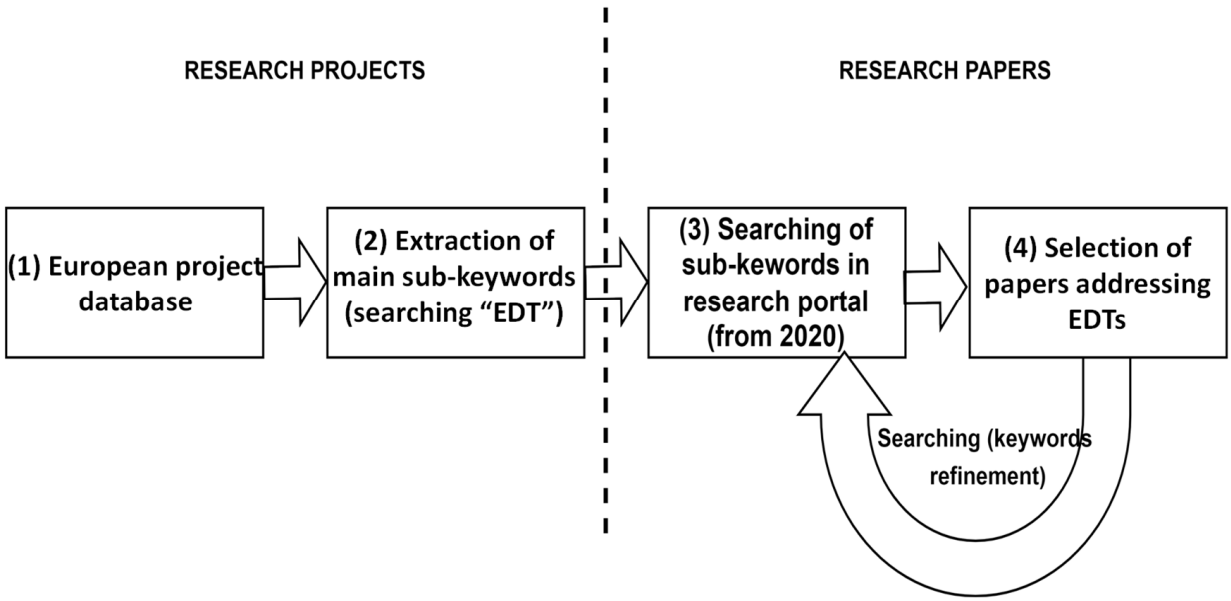


Figure 1. Block scheme of the applied methodology selecting research papers about EDT.

In Table 1 the topics and the keywords of the first phase are listed. More details of the second phase are discussed in Sections 2–7, matching the recent research with AI-EDT perspectives.

The choice of European projects as a reference for this research is due to the fact that within the 'Next Generation EU', the program promoted by the European Union to promote the recovery of Member States after the COVID-19 pandemic, research topics have been planned and defined to use resources until 2026. This programming is based on a pre-evaluation of research, so the funded projects constitute good feedback on the validation of research activities. This criterion can also be applied for other international programs about research. Limitations are mainly due to an analysis of projects performed for only the European area. Instead, the search for works is global. This could also be an element of the methodological exploration to see how a European project is related to scientific research in general. According to the summary in Table 1, it is evident that the projects consider the technology evolution from Industry 4.0 to Industry 5.0 facilities in manufacturing, including the healthcare sector for specific applications about social–health aspects (food, infection, territorial health). Particular attention in the industrial research is focused on alternative energy smart systems, DT virtual manufacturing, and robotics integrating Artificial Intelligence (AI) algorithms. Finally, research in advanced industrial networks is focused on inspection systems of production and defects and on cybersecurity including data security and control systems.

Figure 2 schematically illustrates the goal of this paper by proposing possible EDT perspectives matched with the research pillars. The sequence from one to six (pillars mentioned in Table 1) follows the logic of searching and matching project keywords with search terms: many projects start with Industry 4.0 objectives (pillar 1), upgrade to Industry 5.0 (pillar 2), and then move on to expanding sectors (healthcare related to pillar 3 and energy related to pillar 4) and specific applications such as inspection systems (pillar 5) and cybersecurity (pillar 6). The sequential order is also partly proportional to the number of similar projects found for that specific topic.

Table 1. EDT and topics (six main pillars) found in European project portal (Koeshio portal [1]) for the last five years.

Keyword Matching (Research Pillar)	Main Description	Further Keywords Found in Projects and to Analyze in Literature
(1) Agile manufacturing and Industry 4.0	Digital technologies for manufacturing 4.0 and advanced robotization	Wind tower manufacturing; plastic extrusions for the automotive industry; gas turbine compressors (energy sector); innovative range of encoders for the control of machinery for food production environments; electric vehicles; Automated Guided Vehicle (AGV) production; drone technologies; additive manufacturing; advanced automation technologies for the manufacture of transmission components (automotive sector); microelectronics one-chip sensor systems; robotization of aeronautical painting processes; Virtual Reality (VR) and robot simulation for collaborative robot's production activities; physical product manufacturing with digital and virtual manufacturing Cyber–Physical System (CPS); prototypes in precision production.
(2) Industry 5.0	Active production control by mechatronics matching Artificial Intelligence	Opto- and mechatronic systems necessary to control technological processes; materials engineering; new materials and technologies; Internet of Things (IoT) and intelligent devices; design and synthesis of Radio Frequency (RF) and microwave components; design and development of System on Chip (SoC)-integrated circuits; AI robotics.
(3) Advanced healthcare	Digital healthcare services and studies	Healthy food; 3D/4D ultrasound imaging; Digital Twins for personalized healthcare by means AI; clinical decision aid system for surveillance of infections; construction of DT modeling the state of health of a territory regarding pollen and mold allergens; data processing and health sensor advanced technology.
(4) Smart energy	Modern energy systems	Energy performance of a building; building and testing prototypes of charging stations compatible with commercially available electro-mobile devices; AI for collaborative robotic production systems improving energy consumption; real-time integration of electric consumption in automatic learning systems using smart meters; smart water heating boiler management using AI; smart city; smart factory.
(5) Inspection and monitoring	Production and defect inspection	Industrial Internet of Things (IIoT)-based system development for monitoring and controlling production progress; inspection of correct connection of electric connectors on motors using collaborative robotics and artificial vision techniques; development of specific sensors towards zero defects; inspection and monitoring of complex industrial systems.
(6) Cybersecurity	Industrial network security	Industry 4.0 cyber security; intelligent gateway architectures improving cybersecurity; IoT data security; non-intrusive monitoring of performance in electrical systems.

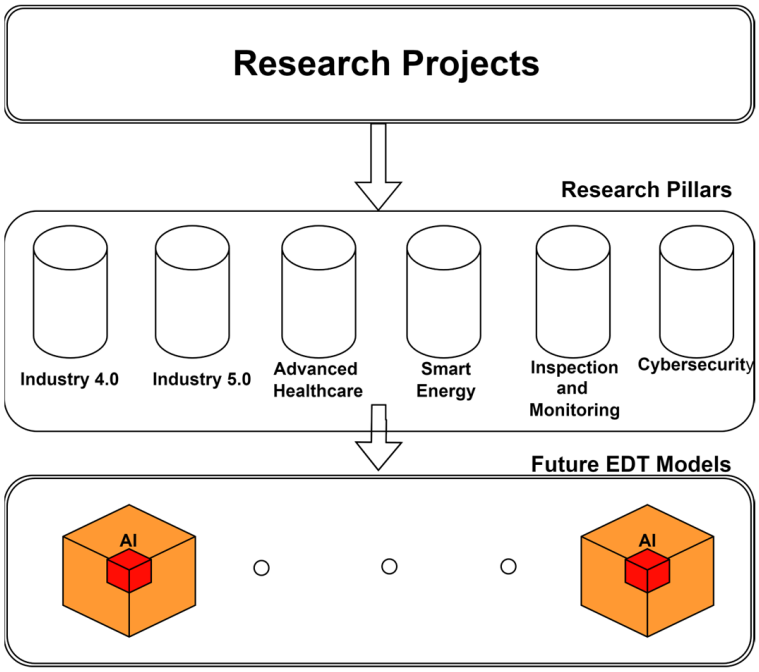


Figure 2. Schematic goal of the review.

The possible implementations of EDTs are sketched in Figure 3a, where the production pipeline is loaded by raw materials to process and is coupled with physical components (sensor and actuators, machines, and hardware components) and with AI-EDTs improving the production and processes (output of the pipeline). Both the AI-EDT and the physical facilities are synchronized to obtain a full interconnected network, ensuring continuous and efficient production. Each AI-EDT could model and simulate a specific part of a production plant. All the AI-EDT models could be structured as a hierarchical model (see Figure 3b) where the root controls and synchronizes all the intermediate and leaf (basic circuits or basic electro-mechanical systems) AI-EDTs.

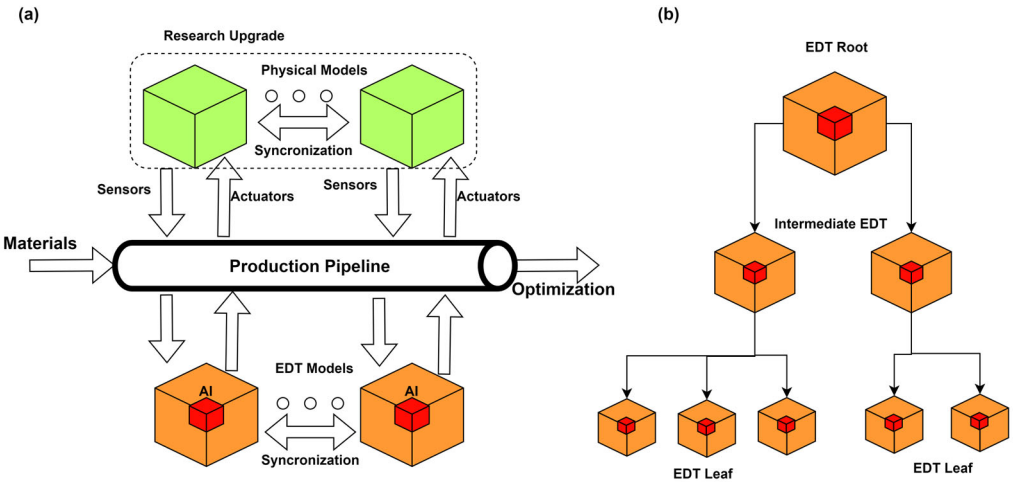


Figure 3. (**a**) Production pipeline matching AI-EDT with physical models. (**b**) Hierarchical model of AI-EDT.

The next sections discuss the research sub-topics correlated to the project's keywords and is useful to articulate new research projects. Journals and, subsequently, conference proceedings are considered a priority for the paper selection, especially the papers integrating AI. The gap in the literature regarding the identified research topics is mainly about perspectives and possible electronic upgrades of the research, thus suggesting the

addition of this information in each discussed research pillar in Sections 2–7 (last columns of the tables of each section). Furthermore, this review provides some circuital examples supporting the reader in understanding the EDT concept based on the circuit simulation. The circuit simulation and the AI data processing of the output signals of the circuits are performed by using open-source tools based on graphical user interfaces. In this review, the circuit models are implemented by means of the LTSpice tool, besides the example of the AI prediction is performed by the Konstanz Information Miner (KNIME) tool. More details about the implementation of AI processing circuit data are discussed in Section 8.

Below is a summary of what will be discussed in this review, including the output of the methodology in Figure 1.

The sub-topics found in the literature are representative of DT models for industrial scenarios. Referring to production systems, DT models are addressed based on reliability analyses, the design, the monitoring, the maintenance of electrical and electronic components for renewable energy systems [1–8], the Industry 4.0 facilities [9–37], and, in general, on the sensing and actuation [38–49]. Ever-increasing research is being produced on optoelectronic solutions, as they are very fast and safe from the point of view of signal interference: optoelectronics is suggested in communication networks and in machinery [50–58] to increase production efficiency in advanced production scenarios. The production efficiency and the increase in quality are achieved by advanced image vision [59–64] and virtual models matching with mechatronic systems [65–86]. DTs are fundamental for the healthcare sector in continuous industrial evolution regarding medical products and services [87–91], wearable technologies [92–95], IoT systems [96–98], image processing, and mechatronics useful for rehabilitation [99–104]. Essential to all DT applications are the energy-harvesting modeling sources [105–126]. Energetic aspects are studied mainly in smart systems, such as smart buildings [127–130]. A particular focus of the research on DT implementation is on machinery inspection and monitoring [131–148], material manufacturing [149–165], and cybersecurity [166–194]. All the sub-topics grouped into six research pillars are deeply discussed in the next sections.

With the analysis of the actual literature, the added value of this review is the preposition of perspectives and possible upgrades of the DT, focusing our attention on EDTs and on the role of AI.

1.2. Research Questions

The research questions are related to the identification of DT models matching with industrial projects and with recent academic studies focusing the attention of new technologies. The main goal is to find, starting with the discussed technologies grouped into 'research pillars', possible AI solutions based on circuit models and constituting the specific class of EDTs. Circuit simulations providing data for AI data processing could be an important requirement in advanced DT industrial applications. In this direction, the work describes some examples suggesting the methodology to apply and facilitating the comprehension of mechanisms matching circuit models with AI data processing and highlighting advantages, disadvantages, procedures for the integration of the EDT technologies in industrial processes, perspectives, and limitations.

2. First Research Pillar: Agile Manufacturing and Industry 4.0

The first pillar focuses on identifying the phases of the hardware component life cycle (monitoring, maintenance, fault detection) not only in production but also in the operational phase. The literature discusses specific components matching industrial projects in DT and EDT manufacturing and concerning agile approaches.

Specifically, this pillar is related to the upgrade of the actual Industry 4.0 scenario, adopting DTs and EDTs for turbine technology (the topic is correlated with energy systems and suggests new frontiers for industries working on wind energy), for flexible advanced manufacturing facilities, and for sensor systems. DTs modeling wind turbines are useful for the reliability analysis, design, monitoring, and maintenance [1–8]. Precisely, EDTs could be applied for the improvement of the whole life cycle of wind turbines and for a continuous re-design of the mechanical, electrical, and electronic components. Advanced Industry 4.0 environments are characterized by advanced DT technologies [9–37], ensuring flexible production management and efficient predictive maintenance. In this direction, AI-based EDTs could provide a 'zero-defect' condition, optimizing sustainable production and machines, generating a production capable of quickly switching the typology of products in relation to needs and market demands (change in the short-term products and services). Production is always optimized by sensor systems. The production of new sensors, actuators, and electronic components [38–49] is very important for the industrial upgrade, where AI-EDTs could play an important role in system integration, including heterogeneous technologies, and at the same time efficiently synchronizing the interconnected machines of the whole supply chain. Furthermore, the introduction of AI-EDTs requires a change in the organizational model to decrease the human resource cost expressed by the worker-hour indicator. In this direction, the AI algorithms could support the re-planning of the new organizational models and the change in management control. Table 2 lists more details about the first research pillar of the EDT in Industry 4.0 and AI implications.

Table 2. First research pillar: EDT for agile manufacturing implemented in Industry 4.0 environment.

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in this Review)
Wind turbine (renewable energy systems)	DT-based monitoring framework for wind turbines for reliability analysis	DT framework enabling real-time monitoring, fault diagnosis, and operation optimization of the wind turbines [2]; prevention of turbine failure and timely maintenance [3]; reliability assessment of wind turbine power modules (regarding wind turbulence on the electro-thermal behavior) [4]; mobile robot assistance wind turbine [5]; online real-time monitoring of Power Electronic Converters (PECs) [6]; methodology and guidelines for the wind turbine design [7]; blade design and optimization (virtual model) [8].	The AI-EDT could be implemented for the whole life cycle of wind turbines starting with the design of optimized electrical and electronic components (mainly power components) and following the monitoring of the implemented systems for the optimization of the re-design and of the maintenance services (by means the simulation of real scenarios).

Table 2. *Cont.*

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in this Review)
Advanced machinery and processes for manufacturing production	Advanced and flexible manufacturing systems	Intelligent design–manufacturing–maintenance of mechanical equipment [9]; efficient testing and optimization of production processes improving quality control and predictive maintenance [10]; wireless and wired DT embedded in ethernet industrial networks [11]; electronic cam servo motion control driven by DT [12]; product twin for flexible and collaborative manufacturing environment [13]; Green Performance Evaluation of Smart Manufacturing (GPEoSM) [14]; models of sustainable intelligent manufacturing [15]; detection of a system's actions in pneumatics (backflow) [16]; AI algorithms finding causes of the problem of metal residues between electronic circuits [17]; DT following the whole product life cycle [18]; DT driven by data of Internet of Things (IoT) sensors detecting defects [19]; random phase noise in WiFi Channel State Information (CSI) [20]; machine control, monitoring and synchronization between the physical and virtual models [21]; DT for Automated Guided Vehicles (AGVs) [22]; design, development, deployment, commissioning, and maintenance of robotics systems [23]; holistic overview of robotics [24]; rapid production line variant design [25]; improvement of the powertrain system of electric vehicles (EVs) [26]; approach based on pipe machining production line [27]; automotive production lines [28–30]; electrical cable intelligent production lines [31]; multisystem fault diagnosis [32]; DT improvement by heuristics and Reinforcement Learning (RL) [33]; reconfiguration of human–robot collaborative assembly lines [34]; 3D visualized human–machine interaction [35]; railway axle production line [36]; DT enabling apparel manufacturing plants [37].	EDT could integrate different AI algorithms suitable to ensure good flexibility of manufacturing production. The AI-EDT could constitute the integration of different cyber–physical models of the whole production line supporting quality processes, predictive maintenance of machines, and production management, including the optimization of the organizational models. The goal is to achieve 'zero-defects' conditions, production optimization, and cost decrease (energy costs, raw materials costs, human resource costs as worker-hour indicator, time delays, etc.), thus ensuring the production switching also in the short period according to the market demand. The AI-EDTs are suitable for the matching of the skills of workers, thus improving the organizational models.
Sensor systems and electronics	Manufacturing of electronic components	Printed Circuit Board (PCB) manufacturing for full Surface Mount Technology (SMT) process lines [38]; electronic product behavior analysis [39]; power electronics-based energy conversion systems (PEECSs) [40]; IoT electric power systems [41]; encoder [42–45]; Programmable Logic Controller (PLC) systems and components [46,47]; DT for automotive MEMS pressure sensors [48]; optoelectronics in production lines [49].	Different advanced electronic components (sensor, actuators, PLC) could provide digital information for the whole synchronization of all the production machines, taking into account the heterogeneous technologies and the different computational costs. The AI-EDTs are useful for optimizing the production synchronization.

3. Second Research Pillar: Industry 5.0

The second pillar focuses on identifying hardware components and support tools for an upgrade of the manufacturing industry, in line with what is developed in projects aimed at mechatronics and DT implementations. Specifically, this pillar is associated with the innovative technologies indicating the digital transformation of the industry from the Industry 4.0 to Industry 5.0 framework.

New advances are found in the literature relating to optoelectronics, mechatronics, and image vision techniques. All the technologies are assisted in the Industry 5.0 environment by AI algorithms, representing the main difference if compared with the traditional Industry 4.0 framework. AI integrated in Industry 4.0 systems constitutes the upgrade of the industry for an Industry 5.0 framework, where machine learning algorithms are able to improve image processing, to execute AI-driven processes, and to improve the quality of production. More details about AI integration protocols are discussed in Section 8.3.

Optoelectronics is implemented in communication networks and for machinery components [50–58]. Image vision techniques are applied to control production and defects [59–64], implementing 3D and 4D image analysis techniques, and a DT is widely applied for the matching of mechatronics and virtual models of the manufacturing production processes [65–86]. Possible evolutions of the EDT in Industry 5.0 are related the design of new materials for high-sensitivity sensors (as for nanotechnology-based sensors), the real-time solving of bottlenecks of production processes, and the continuous setting and adjustment of machine control parameters to achieve 'zero-defect' production by ensuring quick production and minimizing the risk of machine failure. Due to the increase of the industrial Knowledge Base (KB), powerful communication networks could be adopted integrating big data, edge computing, Graphical Processing Unit (GPU) boards, and quantum computers, which would strengthen the AI-EDT models and, in particular, the training models.

Table 3 summarizes the main topics of the second pillar found in the scientific literature.

Table 3. Second pillar: EDT in Industry 5.0 scenarios.

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in this Review)
Optical components and networks	Optical sensing, actuation, and communication network based on AI	Artificial Neural Network (ANN) DT optimizing Whispering Gallery Mode (WGM) optical sensors [50]; optoelectronic sensors [51] and actuators using optical fiber [52]; AI-driven DT for optical network [53,54]; optical fiber communication systems [55]; forecasting of optical networks [56]; optical communication fault management [57]; re-configurable optical add and drop multiplexers (ROADMs) [58].	AI supporting design and modeling of industrial optoelectronic sensor components finding new solution in nanotechnology materials (improving high sensitivity); AI-DT optimizing the traffic and robustness of calculator networks to avoid possible bottlenecks imitating communications.
Image vision-integrated tools and facilities	Imaging, laser, and ultrasound techniques	3D and 4D volumetric Ultrasound Tomography (UST) [59]; integration of 4D imaging with 4D printing [60]; laser-induced ultrasound scanning PCB defects [61]; Laser Ultrasonic Testing (LUT) detecting inclusions and subsurface cracks [62]; ultrasound imaging using multi-parameter genetic algorithm for micro-defect detection [63]; vision inspection process [64].	AI-supervised algorithms accelerating automatisms detecting real-time product defects for 'zero-defect' production and improving the in-line production (integration of AI for auto-corrective actions and for machine parameter setting).

Table 3. *Cont.*

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in this Review)
Mechatronics and manufacturing processes	New Industry 5.0 environments and applications	Hybrid DT framework integrating AI and physics-based models [65]; Cyber Twins (CTs) integrating machine simulators [66]; deep learning-based DT for human–robot collaborative manufacturing systems [67]; mixed-reality and holographic industrial environments [68]; DT mechanism model of Computer Numerical Control Machine Tools (CNCMTs) [69]; fault diagnosis and predictive maintenance [70]; virtual twinning in mechatronic product development [71]; kinematic and dynamic models for mechanical systems [72]; trajectory controllers for electro-mechanical systems [73]; importing of the native PLC code via XML [74]; engineering approach of OPC-UA PLC systems [75]; DT-driven virtual commissioning method to simulate CNCMT [76]; Ultra Precision Machining (UPM) for high-end cutting-edge products [77]; integration of Industrial Internet of Things (IIoT) and smart manufacturing facilities [78]; Extended Kalman Filter (EKF) DT for motor drive [79]; automobile connecting rod production line model [80]; DT framework incorporating robots [81]; Self-Optimizing Control (SOC) framework controlling mechatronic systems [82]; AI predicting noises and anomalies in machine filters [83], operational amplifiers [84], and Proportional Integral Derivative (PID) controllers [85]; AI adjusting control machine parameters (process mining) [86].	AI-DT selecting the best procedure and algorithms to improve the mechatronic commands and control systems according to the selected technology (PLC, robot, CNC machines, etc.). Furthermore, the EDT based on the integration of circuit models could classify and predict all the possible noises and interferences, solving machine problems and failures in real time.

4. Third Research Pillar: Advanced Healthcare and Industry

The third pillar aims to define healthcare research topics related to DTs and EDTs in line with contemporary industry products and services and with project advances. This pillar is correlated with innovative medical products and services [87–91] and the EDT models related to wearable sensor technology [92–95], the IoT [96–98], image processing [195–201], and mechatronics for rehabilitation [99–104]. Possible perspectives for EDTs are related to the introduction of new health products and telemedicine care services and the construction of advanced patient 'avatar' models or 3D organoids optimizing the care patterns, the exams to execute, and the rehabilitation processes. Actually, AI is adopted for the construction of patient models, and future perspectives are addressed to improve the AI-based avatar model by means of real-time data fusion, merging different information about patients characterized by similar features. For organoid and avatar models, advanced technologies, such as edge calculus engines, GPUs, big data systems, and quantum computers, could be used.

Table 4 lists different research topics related to advanced healthcare systems.

Table 4. Third research pillar: EDT in healthcare industry and in research.

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in This Review)
Healthcare market	Innovative products and services	Machine learning (ML) for predictive controller of medical microrobot [87]; DT improving healthcare services (personalized healthcare, intelligent rehabilitation, telemedicine, smart diet management, etc.) [88]; production of medicine, vaccine, antibacterial, on-demand molecule production, and on-demand tissues and organs [89]; 3D modeling and simulations of microwave sensors [90]; hardware matching with AI-based software correcting the noisy EEG electrode signals in real time [91].	AI accelerating healthcare services (diagnostic and therapeutic assistance pathways) and optimizing precision medicine (dose of medicines) by means of electronics with therapeutic compliance. Innovative products in healthcare industries could be the 3D organoids reflecting the real behavior of the human body tissues (aspect useful for the surgical training of doctors or to understand the tissue degeneracy of cancer).
Wearable sensors	New solution of clothing sensors	DT created by biometric data from the patient gathered from wearables [92]; smartwatches, biosensors, and fitness trackers for chronic disease management [93]; biomechanical human body models and wearable inertial sensor models to analyze gait events dynamically [94]; multifunctional smart clothing system constructed with several sensors [95].	EDT could potentially represent the 'avatar' of the patient monitored by smart and miniaturized wearable sensors. AI could improve the avatar real-time creation fusing and analyzing patient's physiological data (temperature, heart rate, blood oxygen level, etc.) and including data processing of the patient's health historical data of patients characterized by similar features (optimization of the training model). 'Avatars' could be processed by advanced technologies, such as GPU, big data, and edge and quantum computing.
Medical IOT	IoT connectivity of human body sensors	Multi-sensor data fusion combined with Support Vector Machine (SVM) algorithm [96]; IoT- and ML-based electrocardiogram (ECG) classifier model for cardiac diagnostics [97,98].	AI-EDT addresses edge computing using IoT technologies. IoT is a fundamental technology for future telemedicine.
Medical imaging	Medical imaging tools integrated in AI-DT models	DT integrating MRI, CT, PET, and ultrasound imaging data [195]; 3D-Printed Phantom Twin for ultrasonography of the lower limb [196]; 3D physical and virtual models from ultrasound and magnetic resonance imaging [197]; AI ultrasound imaging in Obstetrics and Gynecology [198]; super phantoms replicating complex anatomic and functional imaging properties of tissues and organs [199]; AI and biophysical models for cardiovascular imaging [200]; human cell and tissue bio-manufacturing using image analysis [201].	The deep learning EDT models could provide more accurate diagnostic and prognostic responses. In order to accelerate the AI image processing calculus, this could be applied innovative technologies such as quantum computers supporting the correct parametrization of the AI training models.
Rehabilitation systems	Electronic solutions	Adaptive DT models with Multi-Level Inverter (MLI) improving energy efficiency in rehabilitation systems [99]; electronic and mechanical DT for stroke rehabilitation [100]; robot-assisted telerehabilitation system [101]; AI predicting movements from EEG patterns [102]; virtual–real interaction system for an ankle rehabilitation robot (VRIS-ARR) [103]; wearable sensors monitoring rehabilitation [104].	Fully connected AI-EDT integrating mechanical response analyses and remote control of rehabilitation (telerehabilitation services and production of new robotic systems). AI algorithms could automatize telerehabilitation planning in real time and the exercise to perform according to the AI classification and recognizing the correct and the wrong exercises (classification of exercise performed by the patients).

5. Fourth Research Pillar: Smart Energy

The fourth research pillar combines the topics on energy system designs with the research themes associated with the related DTs and EDTs. Specifically, the smart energy systems are the fourth research pillar discussed in the literature. Some important topics are the EDT energy harvesting of thermoelectric, piezoelectric, triboelectric, and electromagnetic generators [105–117], AI-EDT and hardware components of renewable energy sources [118–126], and EDTs applied to smart buildings [127–130]. Possible advances of EDTs are related to fully integrated and interconnected energy self-powered systems of complex smart grids and the modeling of energy efficiency and secure buildings. Concerning energy-harvesting devices, AI algorithms could provide more information about energy conversion efficiency, including electronic optimization matching with the behavior of the energy sources (optimizing signal variations, signal discontinuities, etc.). The AI control and optimization mainly concern the increase in the energy conversion rate due to the optimization of the collected energy and the correct filtering of the high-energy signal components.

In regard to real-time decision-making in smart grids, AI could support energy balancing by means of failure classifications and power load predictions.

Another implementation of AI decision-making is in smart building systems, where AI is able to predict the power load and, consecutively, to optimize energy routing through the electrical panel.

Table 5 records different research topics related to the pillar of smart energy.

Table 5. Fourth research pillar: EDT and smart energy systems.

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in This Review)
Energy harvesting	Low-power energy-harvesting components	Thermoelectric human body systems and Seebeck circuit modeling [105–107]; piezoelectric energy harvesting (generation of electrical power by vibration) [108,109] and using LTSpice circuit modeling [110]; electromagnetic energy harvesting [111]; AI-assisted wearable hip joint energy harvester (HJEH) using an electromagnetic generator (EMG) integrated with a freestanding triboelectric nanogenerator (FS-TENG) [112]; triboelectric nanogenerators in Civil Engineering Infrastructure 4.0 [113]; triboelectric nanosensors [114]; solar photovoltaic DT [115]; real-time control of hybrid energy system using DT and IoT [116]; IoT driving energy systems [117].	Implementations of fully integrated EDT for totally energy independent production lines, including low-power supplies and communication networks based on IoT wireless systems autoconfigured by AI algorithms. AI-EDTs are suitable for the optimization of electronic components following signal variations and signal discontinuities.
Components of renewable energy systems	Modeling and optimization of technologies enhancing the efficiency of renewable energy	DT for self-security of smart inverters [118]; fault localization in Low-Voltage (LV) Distribution Networks (DNs) [119]; AC/DC hybrid electric equipment [120]; fault data generation of lithium-ion batteries [121]; DT of energy components [122]; ML applied in smart grids, renewable energy, and for electric vehicle optimization [123]; modeling by graphs with nodes and edges of complex energy systems [124]; smart metering systems [125,126].	AI-EDT could be interfaced to a capillary network and set of components to provide the energy balancing of complex smart grids by means of grid failure classifications and power predictions of different interconnected nodes.
Smart energy building	Technologies optimizing building energy	Smart building controlling energy and wellness [127–130].	EDT using AI for energy efficiency and building security. Improvement of the energy routing through the electrical panel.

6. Fifth Research Pillar: Inspection and Monitoring

The fifth research pillar focuses on the design theme of industrial inspection processes by identifying some DT and EDT solutions to assist in production efficiency. Specifically, this pillar is related the EDT and the DT mainly for the inspection of production machines [131–148] and simulating the processing of materials to be used in manufacturing processes [149–165]. The goal for future AI-based EDTs is to apply the model to the whole supply chain, selecting operative procedures according to a risk map defining the priorities of the interventions to execute. Other new frontiers of EDTs are the applications for intelligent materials capable of self-healing and self-repair actions and constituting stable materials to be applied as robust products due to the possibility to control and correct the material defects in each production phase and to avoid production interruptions. Examples of AI-EDTs improving the self-healing of innovative materials are mainly in the control (by changing the input electromagnetic source power intensity or the signal profile) and the localization (source orientation and source collimation) of external stimuli, enabling self-reconfiguration or self-repairing processes [150]. The exponential advancement of hardware and software technology with the advent of AI will increasingly push researchers to find new solutions in basic sciences, such as physics, chemistry, and mathematics. In this direction, the research of smart or self-healing materials could represent a new frontier for the search for new solutions capable of monitoring the state of innovative materials and restoring them with specific control signals. Smart materials could therefore replace current materials used in manufacturing by exploiting their capabilities and properties.

Table 6 indicates the main research topics of the fifth pillar, which are mainly classified in IIOT inspection systems and in the inspection of materials and of related processes.

Table 6. Fifth research pillar: EDT concerning inspection and monitoring.

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in this Review)
IIOT inspections	IIOT focused on the inspection of machines	Distributed IIOT sensors for predictive maintenance [131,132]; monitoring of electric induction motors combining IIOT and Finite Element Method (FEM) simulations [133]; augmented reality interconnected to industrial cyber–physical environments [134]; control of cutting machines [135]; IIOT for monitoring fault detections [136] and for logistics [137,138]; quality product inspection by Software-Defined Edge Intelligent Controller (SD-EIC) [139]; control of robotic pick-and-place operation [140]; AI powering control systems (RNN, LSTM, and GRU models) [141]; robotic system for remote diesel defect inspection [142]; deep learning for inspection of electro-hydrostatic actuators [143]; AI and 6G network monitoring industrial scenarios [144,145]; Motor Monitoring and Analysis System (SMAM) implementing ESP32 microcontrollers and temperature, voltage, and current sensors [146]; Mixed Reality (MR) and AI supporting object recognition [147]; 5G network for multitask industrial applications [148].	AI-EDT assigned to each machine of the whole supply chain predicting failures in real time and assigning a risk level to execute possible timely corrective actions.
Inspection of materials and of related processes	Material manufacturing and quality processes	AI supporting semiconductor [149] and intelligent materials manufacturing [150]; quality of extruded materials [151]; modeling of complex material flow [152]; material consumption in thermoforming process [153]; micro-injection in molding processes [154]; Zero-Defect Manufacturing (ZDM) and cost reduction [155]; failure of fused deposition process [156]; 3D additive manufacturing [157]; defects in Laser-Directed Energy Deposition (L-DED) [158]; crack initiation and propagation [159–163] and equivalent resistive circuits modeling the physical effects [164,165].	AI-EDT optimizing the choice of the raw materials predicting defects and cracks (by means of equivalent circuits) also during the fabrication processes. Other possible EDT perspectives are also in the use of self-healing and self-repair materials, reducing the cost of waste for a sustainable production and the related delays.

7. Sixth Research Pillar: Cybersecurity

The sixth pillar focuses on DT and EDT solutions to improve industrial network security. Specifically, this pillar is related to cybersecurity, data security [166–188], and hardware attacks [189–194]. Possible innovative solutions in cybersecurity are the application of AI algorithms for attack classification and the use of blockchain technologies for improving the data security level. The future AI-EDT models will take into account the real-time physical and virtual network segmentations, new techniques of sensor data encryption for blockchains, and the real-time controlling and correcting of the cyber attacks in each level of the industrial network. Table 7 summarizes the main topics of the sixth research pillar classified as network security, blockchain solutions, and hardware security.

Table 7. Sixth research pillar: EDT improving cybersecurity.

Sub-Topics	Main Description	DT/EDT Function	Perspectives and Possible Upgrades of the Research (Proposed in This Review)
Secure industrial network	Cybersecurity of Industrial Control System (ICS) Network	AI-based framework detecting attacks and mitigating their impact for edge cloud systems applied to gas pipelines [166]; threat classification and guidelines to use DT [167]; DT and Hardware in the Loop (HITL) approach using neural networks to classify attacks [168]; priorities of security aspects in DT [169]; Binary Arithmetic Optimization Algorithm with Variational Recurrent Autoencoder-Based Intrusion Detection (BAOA-VRAID) approach detecting intrusions [170]; framework of cyber–physical manufacturing systems (CPMS) for cyber attack detection in closed-loop controllers [171]; Virtual Private Network (VPN) and AI–big data systems for secure multimedia networks [172]; cybersecurity threat modeling in ICS [173–177]; detection of anomalies in PLC systems [178,179]; secure industrial multi-level architectures [180]; VPN for secure industrial networks with robots [181].	EDT automating the scanning port test by means of the AI classification of threats and attacks and virtually segmenting the ICs network based on the detected risk. Furthermore, the AI-EDT could provide different solution for a reconfiguration of the Information Technology (IT) and the Operational Technology (OT) network, ensuring continuous network security (configuration of each component of the Local Area Network (LAN), including firewall, router, bridge, servers, and switch). The AI-EDTs are also useful to design hybrid virtual networks combing Virtual LAN (VLAN) and VPN channels ensuring data encryption. Furthermore, AI-EDTs are suitable for a continuous update of the classification of threats.
Blockchain	Blockchain integrated in industrial information systems	Blockchain-based Non-Fungible Tokens (NFTs) preventing attacks by ensuring traceability and accountability among distributed nodes [182]; Ethereum blockchain DT modeling [183]; improvement of security by blockchain [184–188] and Web3 technologies [184].	EDT encrypting sensor data to be included in blockchain information structures, certifying the production data and the firm knowledge.
Hardware attacks	Hardware Trojan (HT) attacks in ICS	HT modeling [189–192] and AI predicting hardware attacks [193,194].	AI-EDT predicting and applying real-time corrective actions due to attacks (denoising, elimination of interferences or disturbs, parameter regulation of PID control system, etc.) for the circuits of a production line.

8. Discussion

8.1. Circuit Modeling and AI Data Processing Integration

As a complete example of circuit application and data analysis with AI, a basic example 'transversal' for all the pillars mentioned is proposed. This example concerns the modeling of the most common noise, namely white noise. The example discussed can therefore be integrated with more complex models related to the topics discussed in this paper.

The circuit modeling and simulations represent the first data processing stage of the EDT matching the real industrial environment with machine technologies. The second stage of the EDT data processing considers AI data processing, where the digital output of the circuit (electrical variables such as currents, voltages, and powers estimated by Kirchhoff's circuit laws) is the input of the AI engine. A typical basic EDT example in industrial electronics is the integration of source generators modeling noises [47,49,91] and, consecutively, the simulation of the real behavior of electronic components characterized

by the signal over the noise (S/N) signals. The example illustrated in this section considers a complete application the AI-EDT, taking into account a basic element of the circuit model and the white noise typically characterizing the interferences in machine environments: Figure 4 represents the modeling of a white noise generator (B1) connected to a resistor R1 with the function of modulating the signal noise amplitude at the output of the generator. The circuit of Figure 4 can be implemented in different LTSpice EDT circuits influenced by white noise, by coupling the generators in the precise sections where the disturbances are located. The parametric analysis performs different simulations of the voltage output signal, varying the ripple frequency of the noise. Figure 5 illustrates the parametric analysis of the circuit of Figure 4, varying the frequency parameter k (k = 1, 5, and 10): as expected a higher frequency is observed for k=10, preserving the random behavior of the Vout signal (more ripples are observed).

The parametric analysis can be analyzed in the time domain and in the frequency domain by means of the Fast Fourier Transform (FFT). Figure 6 shows the frequency parametric analysis applying the FFT to the signals of Figure 5. Also, for the frequency behavior more ripples are observed for the case of k = 10.

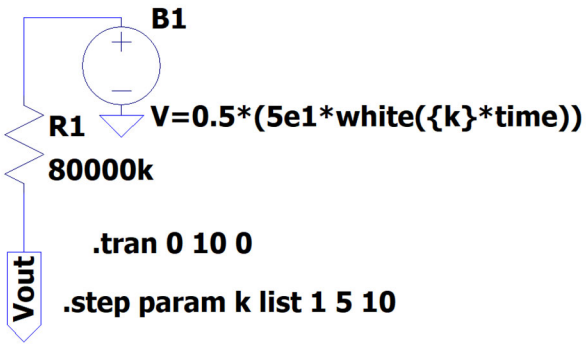


Figure 4. Example of circuit model of white noise source generator. The parameter k varies the ripple frequency of the noise signal generated by voltage generator source B1. The R1 resistance of 80 MΩ is properly selected to visualize the output signal in a range between −12 Volts and 12 Volts.

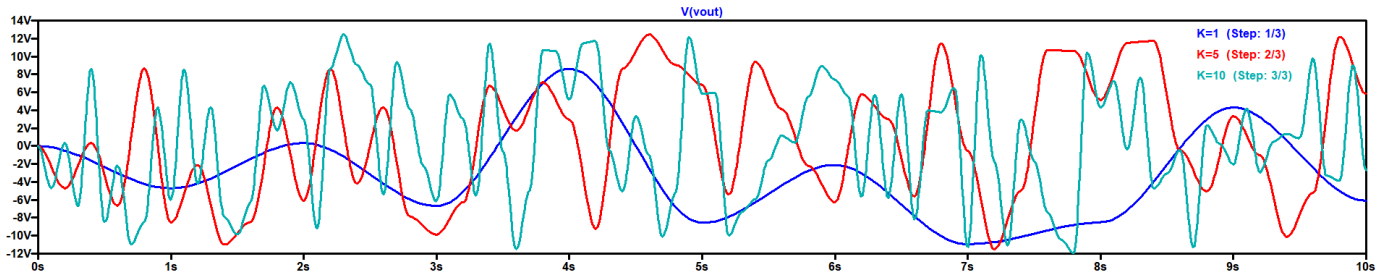


Figure 5. LTSpice parametric analysis: time domain results of the voltage output signal Vout, varying the k parameter of the circuit of Figure 7. More ripples are observed for k = 10.

In order to show how the AI algorithm can be applied for executing the digital data of the circuit (Vout voltage signals), a further signal is added to the signals of Figure 5 to predict the target voltage. The target signal indicates the 'labelled' signal to predict. For the proposed case the target signal is obtained, fixing the parameter value of k = 3 and providing the time domain trend of Figure 7. The AI prediction can be performed by implementing a workflow capable of processing the output data of the circuit of Figure 4. As an example of the AI implementation, the KNIME workflow of Figure 8 implements the supervised Random Forest (RF) algorithm applied to the output results of the circuit of Figure 4. Figure 9 estimates the predicted voltage (prediction of the target signal) as having a trend similar to the target signal, thus proving the good performance of the RF

algorithm. This similarity is due to the self-learning of the algorithm. The RF performance of the proposed example is estimated by the following metrics, referring to a normalized dataset: Mean Absolute Error (MAE) = 0.135, Mean Squared Error (MSE) = 0.03, Root Mean Squared Error (RMSE) = 0.174, and Mean Signed Difference = 0.013.

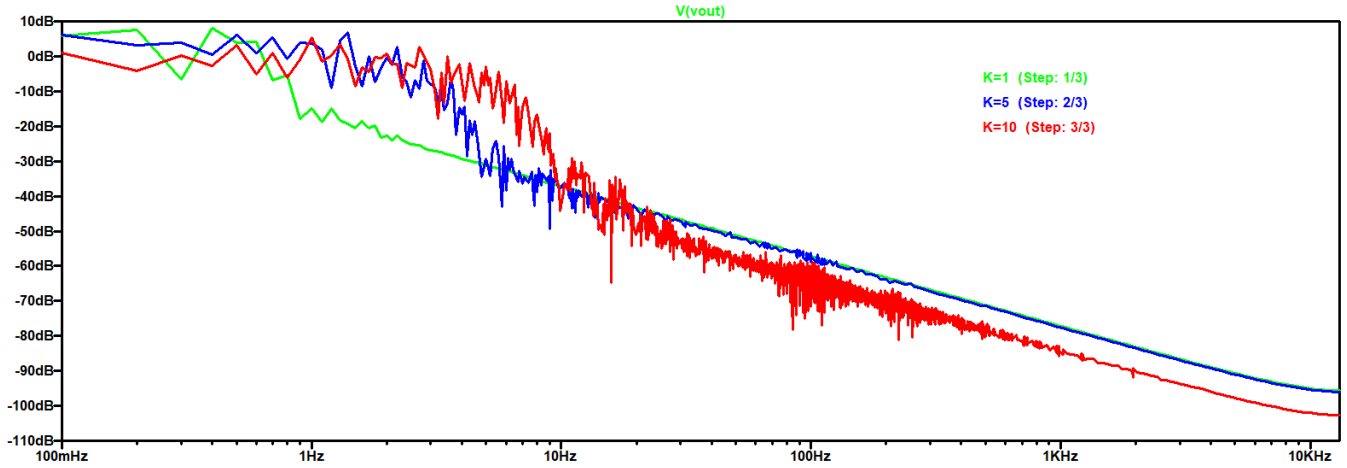


Figure 6. LTSpice parametric simulation FFT: frequency behavior of the circuit of Figure 4. More ripples are also observed in the frequency band for the case of k = 10.

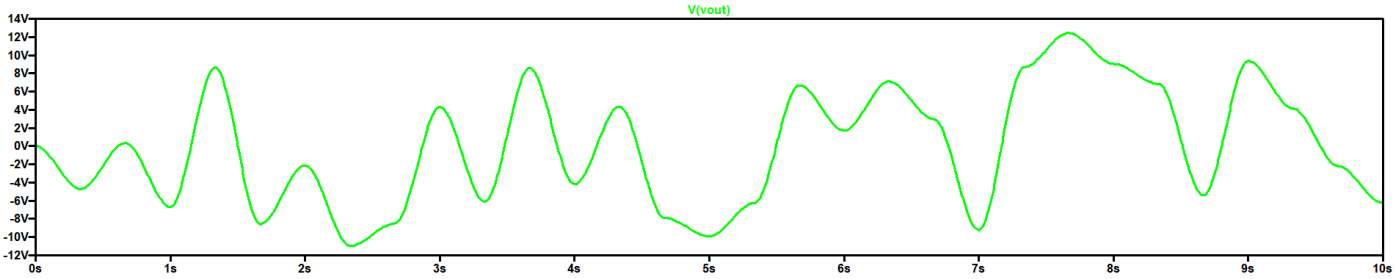


Figure 7. LTSpice output of Figure 4: target signal obtained with k = 3.

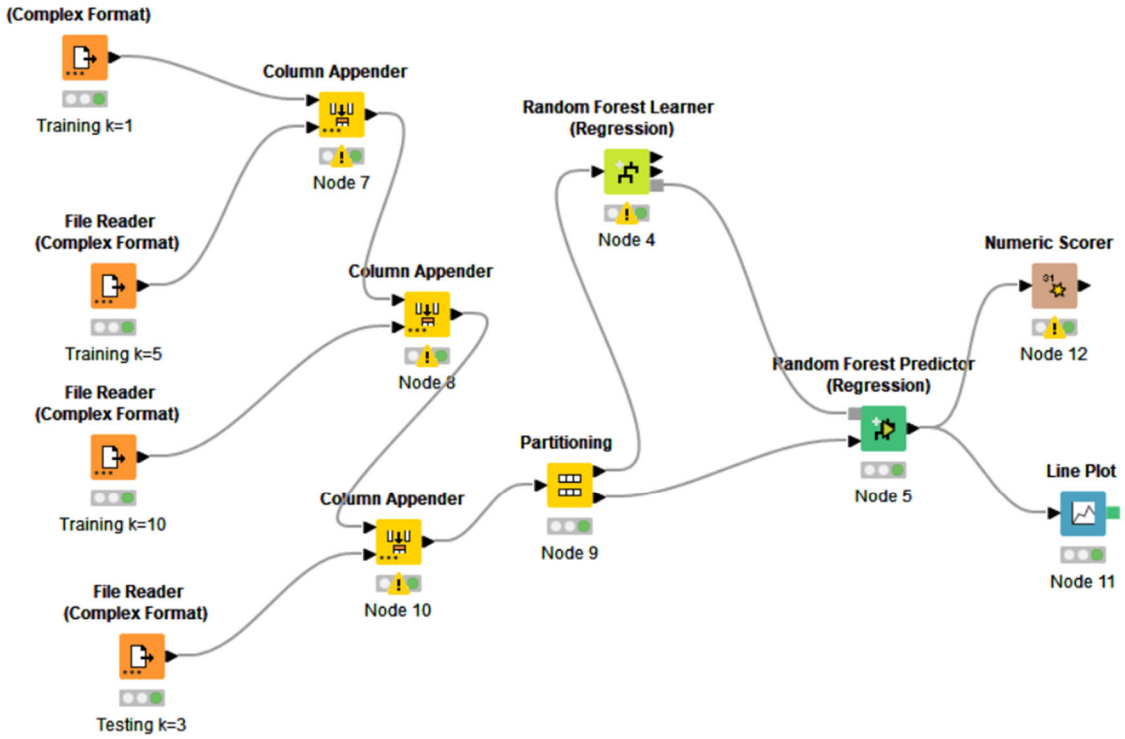


Figure 8. KNIME workflow providing the results of Figure 9.

Other examples of circuit simulations are discussed in Appendix A.

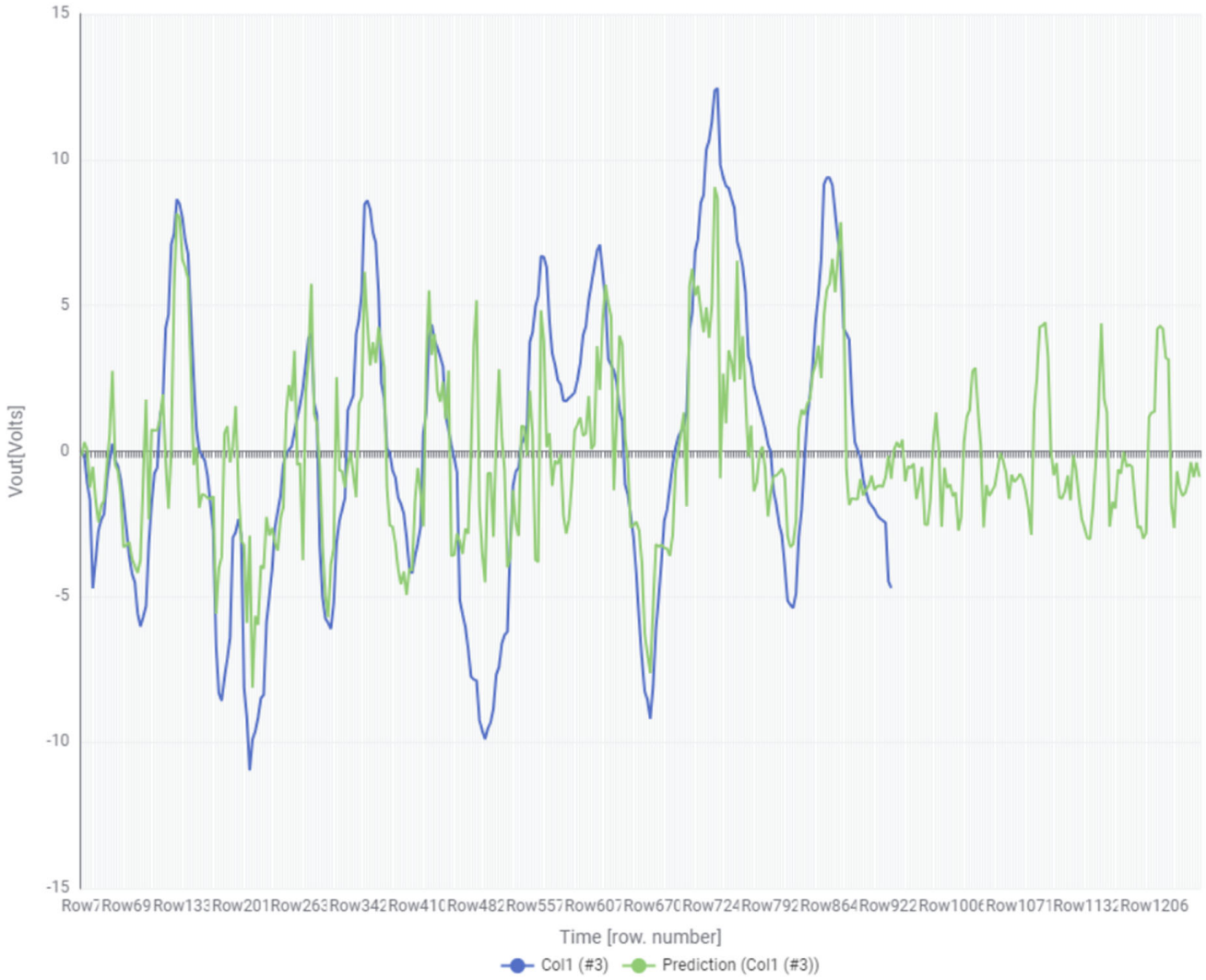


Figure 9. RF output results: comparison between the target signal (Col1(#3)) and the predicted one (Prediction (Col1(#3))). The analyzed dataset is composed of 15,520 samples; the training and the testing dataset are 70% and 30% of the analyzed dataset, respectively; and the hyper-parameters are tree depth = 10, minimum node size = 5, and number of models = 100.

8.2. EDT Framework: Advantages and Disadvantages

The EDT is a sub-class of DTs: specifically, the DT includes the whole digital environment, including the software, while the EDT is the reproduction of circuits and hardware components. Figure 10 illustrates an example of a DT/EDT framework for manufacturing industries, deducted from the literature: AI is executed locally or by cloud computing, for both the DT and EDT, by processing the local data (machine data, ERP data, sensor data, etc.).

Table 8 discusses the main advantages and related disadvantages of the main functionalities of the EDT tools.

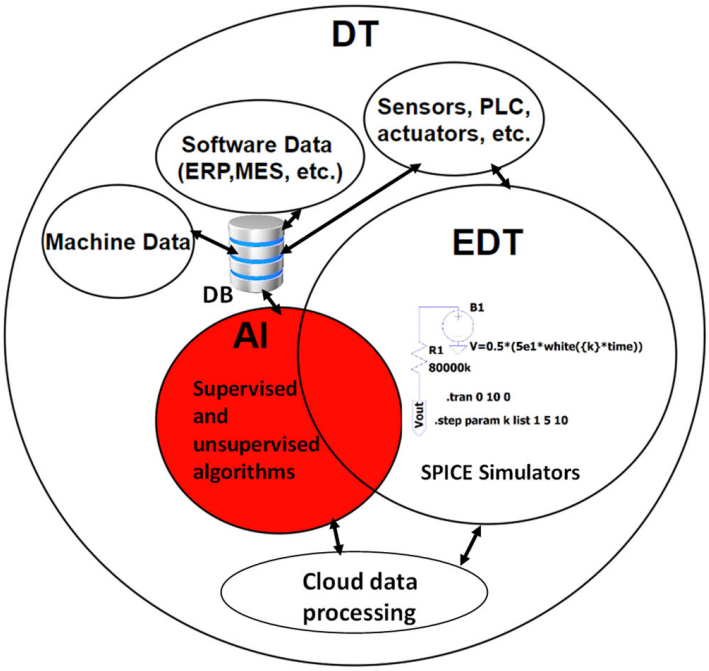


Figure 10. DT and EDT framework for manufacturing industries. AI data processing is performed locally or by cloud computing.

Table 8. Main advantages and disadvantages of the EDT tools.

EDT Tool	Advantages	Disadvantages
Platform integrating different hardware and software models simulating the whole industrial environment	The possibility to integrate many tools into a unique platform allows us to simulate the whole production line [202,203] and extended the simulation case on the whole supply chain (simulations of the behavior of the whole supply chain modeling all the production lines). The platform could operate in the whole process management of industrial production (data layer, model layer, application layer) [204].	High cost for a full integrated EDT: the costs include the human resource costs (working time), computational cost, and economic cost (investment in new technologies). A high computational cost requires new calculus solutions, such as edge computing or quantum computing. Furthermore, the EDT solutions could be characterized by a high impact, integrating the EDT in the operational procedures. This could require a transient to test the adoption of the EDT model.
EDT hierarchical modeling	Possibility to structure a hierarchical [205–208] EDT starting with the material and finishing with logistics, thus defining different operation levels and production priorities based on a risk assessment.	Possible reduced flexibility and ability to adapt to production change. Limited communication between lower and higher levels of the organization.
Big data analytics	Possibility to integrate the EDT big data analytics approaches (for health wearable sensors [209], logistics processes [210], and for the production of electrical vehicles [211]), optimizing quality processes and the machine predictive maintenance.	Big data analytics requires the availability of massive amounts of data of the company's digital knowledge base.
AI training	Possibility to use the output of the electrical variables of the circuit simulation for the construction of the training models of the AI-supervised algorithms [85,91].	The circuital data could be insufficient. This could require the construction of augmented data [212,213] to strengthen the AI training process.

8.3. Limitations, Practical Use Cases, and Workflow Protocol for EDTs Integrating AI

The EDTs discussed in the research pillars are characterized by some important limitations. Table 9 lists the main limitations and the corresponding mitigation procedures.

Table 9. Limitations and related mitigations of EDT with Industry 5.0 facilities.

EDT Limit	Limit Description	Limit Mitigation
EDT real-time analysis	The common technologies are characterized by a time delay of the simulation (computational cost of data processing).	Use of edge computing, GPU boards, or quantum computing to ensure real-time data processing also considering very large datasets to process.
Knowledge base (KB)	The company should have a knowledge base of certified digital data. This requires a careful selection of the data that will be considered useful for data processing purposes.	Implementation of well-defined procedures regarding the extraction of data from company systems (hardware and software) and regarding the fusion of the same to make them usable by AI engines.
Organizational model	The use of advanced EDT requires an upskill or reskill of the human resources involved in the EDT production process.	The company should actuate a continuous training plan for human resources, defining new roles in the organizational model and efficiently allocating the working teams.
Real industrial environment modeling	The model cannot predict all real-world situations, especially for unforeseen events that occur with low probability but can be extremely risky.	For accurate modeling, continuous optimization of the EDT becomes necessary. The AI algorithms could support this optimization.
Ethical aspects	Ethical aspects related to confidentiality and privacy of data.	Composition of an internal scientific ethics committee within the company.
Sustainability	EDT typically does not include all the sustainability aspects [214–218].	Design of EDT based on sustainability aspects.

EDTs integrating AI is the future challenge of Industry 5.0. This integration is to be considered in processes embedded in regular production processes.

Table 10 summarizes all the steps involved in the integration of the EDT in industrial processes according to the Business Process Modeling and Notation (BPMN) scheme of Figure 11. The BPMN is a standard notation useful to verticalize processes associated with the logic of circuits [219].

Table 10. Use criteria of EDT deduced from the analysis.

Function of the Model (Sequential Steps)	Use Criteria	Possible Setting of the EDT
(1) Circuit model	Design of the circuit layout and modeling of the technological elements to simulate the circuit, network, signal, etc., including a.	Primary testing of different parts of the circuit to check each part of the model.
(2a) Circuit simulation	Simulation execution providing digital data (voltage, current, power).	Setting the numerical parameters of the equations, solving the circuital layout (calculus error, precision, etc.).
(2b) Real data monitoring	Sensor data reading the machine and the process parameters.	Adjusting sampling time or other calibration parameters to achieve accurate data.
(3a) AI training	Creation of the ANN training model by considering different voltage outputs and fusing sensor data (2b) with circuital data (2a).	Cleaning of the dataset (filtering of wrong data or missing values) and possible introduction of augmented data (artificial data) to increase the efficiency of the training model.
(3b) AI testing	Selection of the testing dataset of the real physical model.	Change in the testing dataset dimension to increase the AI performance.
(4) Optimization process	Optimization process for the design or the re-design, the machine setting and maintenance, security, and quality.	Processes are re-mapped according to the results of the EDT and setting of the new EDT specifications.
(5) Iteration of circuit modeling and simulation	According to the results of task 4, decide if we need to re-engineer the model or simply re-execute the circuit simulation varying some parameters.	Definition of the time to update the circuital data optimizing the total computational time.
(6) Ending of the EDT use	The process is stopped when the EDT no longer represents the real scenario (machine change, production line, processes, etc.).	The resource and the tools are assigned to other EDT models or facilities.

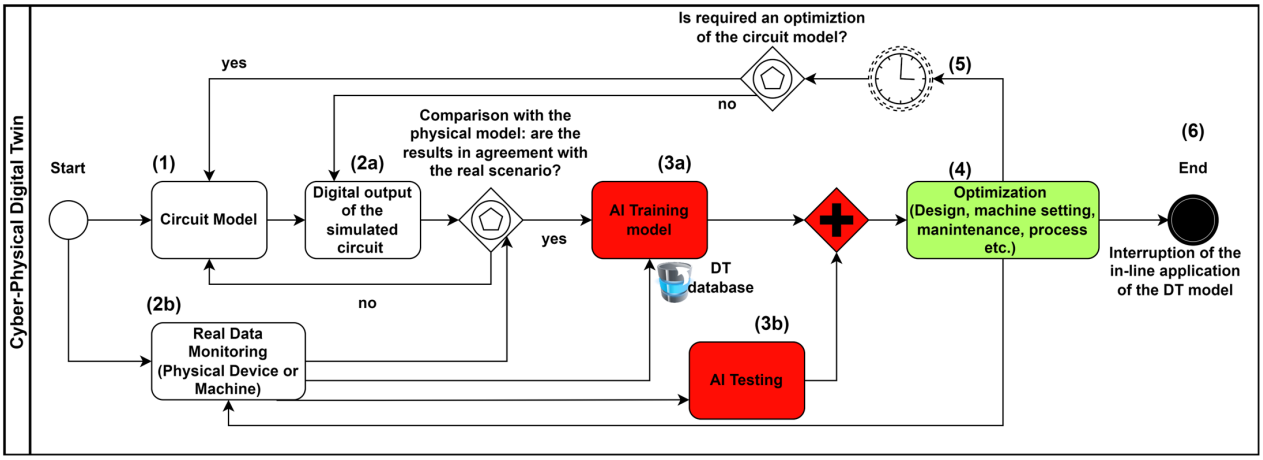


Figure 11. AI-based DT: BPMN explaining the integration of the AI in the circuital model optimizing the manufacturing process.

8.4. Workflow Methodology, Correlation, and Technology Readiness of Research Pillars

The flux diagram in Figure 12 represents the workflow, summarizing the review objectives and describing the adopted methodology. Specifically, the flux indicates the following steps:

- Keyword matching and the use of academic search engines to find papers;
- The verification of the presence of important research features, such as a DT framework architecture, project specifications, AI applications, a circuital approach, and AI-based process integration;
- The definition of perspectives and possible electronic upgrades of the research pillars (last column of Tables 2–7);
- The analysis of relationships between research pillars and the estimation of the related association strengths.

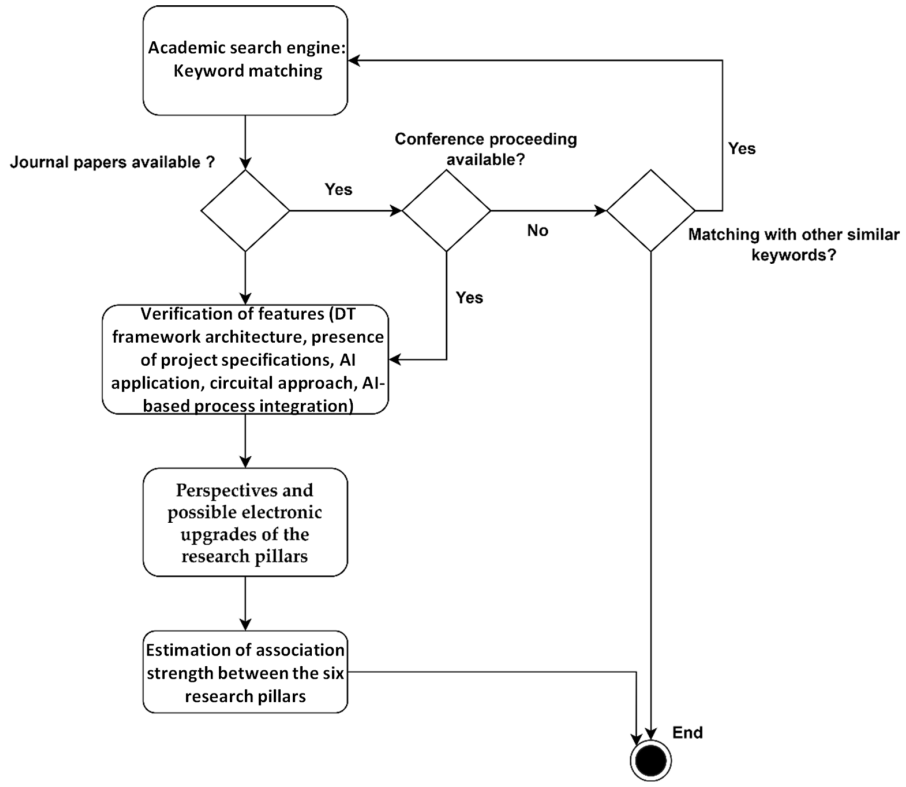


Figure 12. Theoretical workflow representing the review objectives.

An approach to visually map the relationships between research pillars is the Visualization of Similarities (VOS) [220,221]. An open-source tool suitable for this visualization is the VOSviewer. By applying this tool (Version 1.6.20), Figure 13 illustrates the clustering analysis (three clusters grouping pillars 1 and 4 and grouping pillars 3, 5, and 6) and the association strength output, normalizing the strength of the links between pillars (thicker arcs represent higher dependency weights).

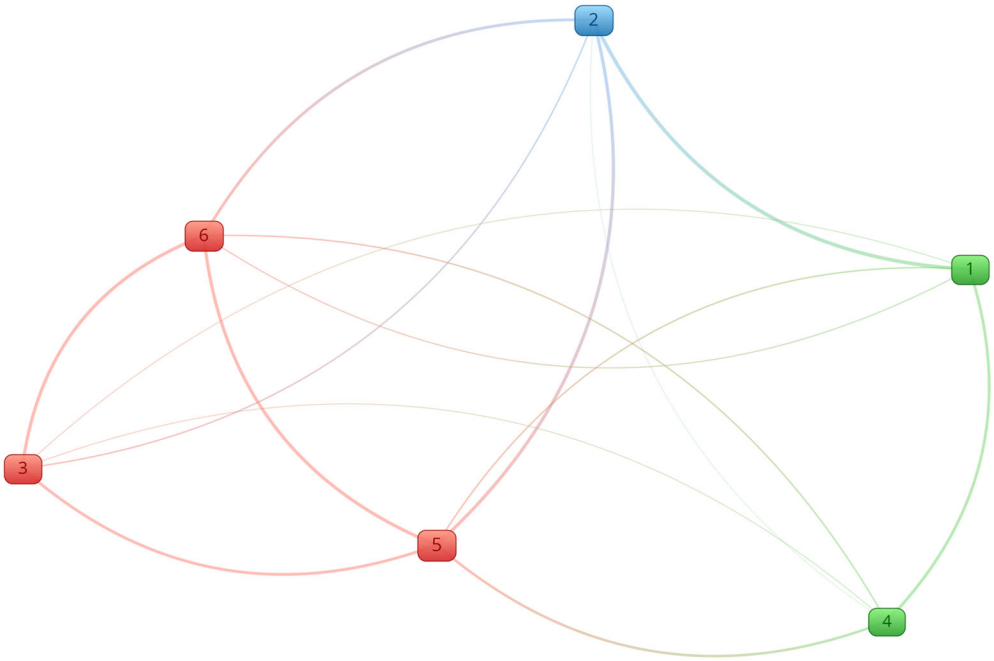


Figure 13. VOSviewer: colored clustering and application of the association strength between the six research pillars (numbered as 1, 2, 3, 4, 5, and 6). The graph provides a meta-level view of how the six pillars interrelate, strengthening this survey's utility for future research planning.

Other information about research maturity of pillars is indicated by the heat map in Figure 14, where a score is assigned for each pillar regarding the scientific impact (deduced from the articles found) and the reachable Technology Readiness Level (TRL).

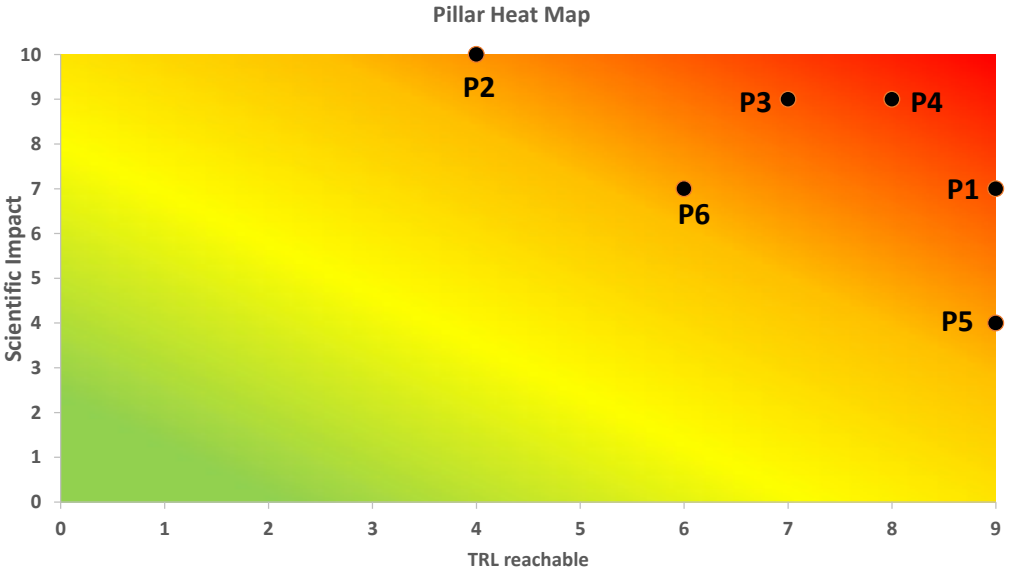


Figure 14. Pillar heat map matching scientific impact and reachable TRL of pillars (P1, P2, P3, P4, P5, and P6).

8.5. AI Importance and Research Gap

Much of the work on AI is focused on creating training dataset models with a good accuracy. Inference acceleration enables AI to solve ever-larger problems on ever-smaller devices, such as for high computing for DNN-based inference [222] and for edge computing approaches [223]. In order to improve the AI computational cost, GPU boards [224] and edge [225] and quantum computing technologies can be adopted [226,227].

Another important aspect about the AI-EDT is the link between the manufacturing processes and the developed models supporting the different production phases, including monitoring, modeling, optimization, design and preparation, control, and operation [228–231]. Important advances for AI-based EDTs are the application of Convolutional Neural Network (CNN) matching the requirements for ultra-high voltage direct current (UHVDC) projects [232], Long Short-Term Memory (LSTM) predicting the health condition of parts of Computer Numerical Control (CNC) machine tools [233], or hybrid CNN-LSTM networks improving AI algorithm performances [234].

Circuit simulators and the related output data in EDT models represent the AI datasets, predicting the real behavior of the production machine with a good accuracy. In particular, for the optocoupler switch of a PLC, circuit simulations process different white noises and interferences (pulsed signals) of the 3D environment modeled by input ports: the AI-RF algorithm provides good matching between the simulated and the predicted trend of the optocoupler output voltage with an MAE of 0.8% [47]. Concerning amplification circuits, the real machine environment is modeled by the interference of sinusoidal pulse signals with different carriers (each carrier frequency represents an interference, and two interferences are simultaneously coupled into the amplification system): the AI-ANN-MLP algorithm provides the prediction of the amplified signal with an MAE of 2% [84]. Passive RC filters are modeled to integrate electronic noises (Johnson noise or Schottky noise) and switching circuits, selecting the best filtering network according to the ANN classification with an MAE of 6% [83]. The simulations of PID control circuits are used to train ANNs for predicting anomalies by observing when the predicted values exceed the envelope of the input signal and constructing precise risk maps (k-means algorithm) [85].

In order to highlight the completeness of the methodology followed in this review, Table 11 lists the research gaps in the prior selected research reviews according to the main features, such as the framework, project matching, AI prediction or classification, circuital approach, and DT-AI process integration.

Table 11. Research gap in the prior selected research reviews.

Reference	DT Framework Based on an Architecture	Topics Matching with Projects	AI Prediction/Classification	Circuital Approach	Procedure Integrating DT and AI in Production Processes
[13]	√	√			
[15]	√				
[18]	√				
[77]	√		√		√
[113]	√	√		√	
[123]	√		√		
[124]	√	√	√		
[185]	√		√		
[203]	√	√			
Proposed work	√	√	√	√	√

9. Conclusions

This review discusses the recent topics on DTs and EDTs, with a particular focus on the development of the use of models in industrial scenarios, by selecting six main research pillars suggested by projects. Specifically, the pillars are related to Industry 4.0

manufacturing, Industry 5.0 facilities, advanced healthcare, smart energy, inspection and monitoring systems, and cybersecurity. Each research pillar is classified by grouping different research sub-topics according to the output provided by the research engine portals of scientific publications. This review proposes some examples of EDT models to facilitate the comprehension of the modeling approach and possible implementations of AI related to the discussed pillars. This review focuses on the following consequential items:

- Finding research topics on DT matching in recent industrial research projects using a defined methodological approach (see Figures 1 and 12) and defining the relationships and impacts of the identified research pillars (see Figures 13 and 14);
- Finding useful elements to define possible upgrades of DTs and EDTs, including AI (see last columns of Tables 2–7);
- Suggesting a methodological approach for implementing EDTs based on the use of circuit models (see Section 8.1 and the Appendix A);
- Proposing the integration of EDT models into manufacturing processes (see Figure 11).

Finally, this review highlights perspectives, advantages, disadvantages, and limitations for the future development of the EDT models in industrial processes. This study is also suitable for researchers to define possible new projects, including parts of the developed discussion, and finding possible correlations and relationships between the discussed topics.

Review's Limitations and Future Research Directions

This review is focused on identifying some topics that can be associated with DTs, using a well-defined research methodology. Specifically, the European research context has been considered as a 'starting point'. This certainly limits the selection of other sub-topics that could be particularly important in the international design scenario. In this direction, future works will be oriented to find possible correlations between different project portals of multiple continental areas.

Furthermore, many weaknesses of the cited publications are to be identified in the discussion of the full integration of circuit models with AI. For this reason, in addition to an effort to understand how AI can be implemented in the perspective of use, a further step has been taken in defining, in Figure 11, the integration procedure between AI and EDTs specifically for manufacturing processes.

This review suggests different advanced industrial frameworks, including AI, for the improvement of product quality, simulating the behavior in real scenarios by means of the EDT. The EDT models are useful for simulating the whole product life cycle and processes of production monitoring, product implementation, and deployment. A new research direction is the AI data-driven processes supported by EDTs capable of dynamically adjusting the production or the implementation process, thus increasing the quality and the efficiency.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Design and production in Industry 4.0 environments are supported by circuit modeling and simulation. This Appendix demonstrates some EDT examples. Since three-phase motors are commonly used in industrial environments, it is useful to model the related circuit systems. As a circuit example, the model in Figure A1a shows a typical layout of the

power supply circuit of a star-connected network, where the input voltage signals modeled by voltage generators V1, V2, and V3 are mismatched by a phase of 120° (see in Figure A1b the time domain voltage signals corresponding to the labels V1out, V2out, and V3out). The circuit model is useful for understanding how the electrical signals are applied to specific load networks to ensure a balanced power supply and to know the distribution of the electrical power on the different loads.

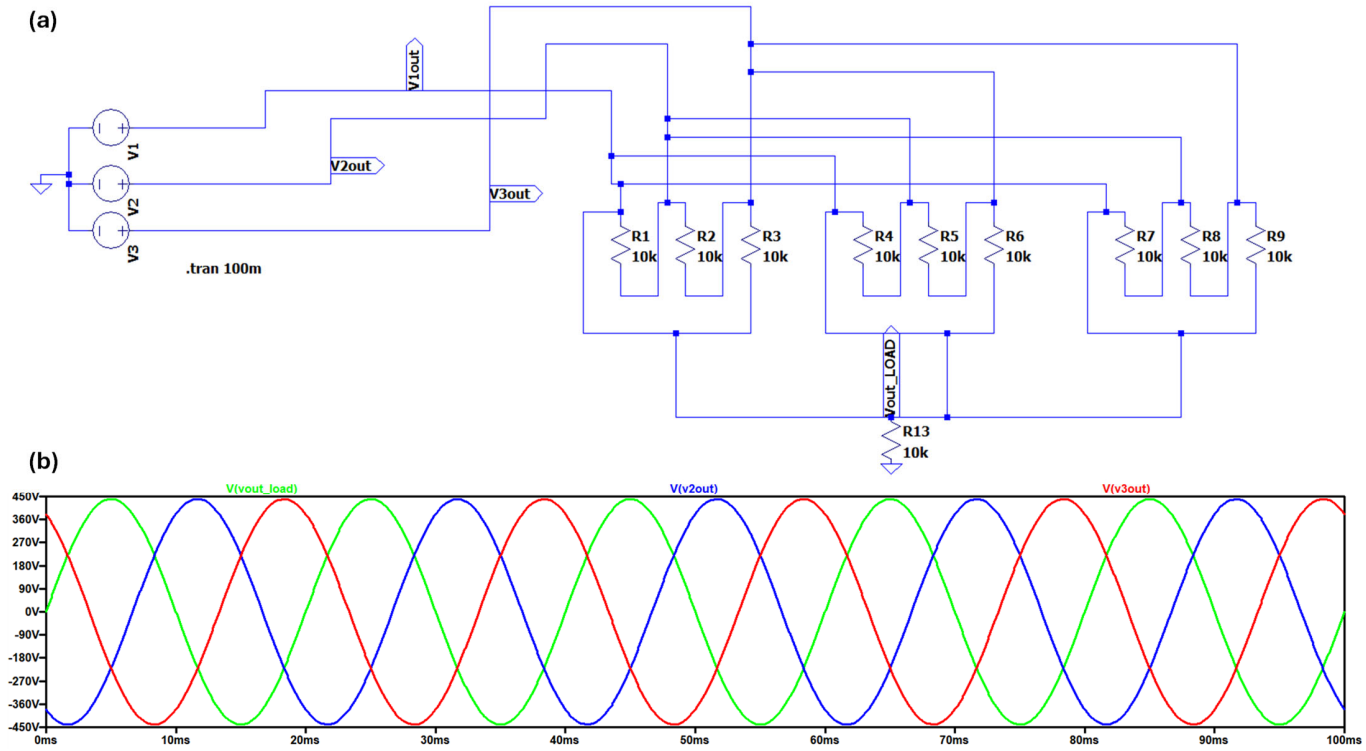


Figure A1. LTSpice simulation: (**a**) circuital EDT modeling a three-phase network powering a star-connected balanced three-phase load. (**b**) Time domain transient analysis calculating the input voltage signals of the electrical three-phase network (phase mismatch of 120° between the voltage signals). The resistances of 10 kΩ are able to provide an output voltage of 450 Volts.

The second example in Figure A2 simulates the transmission of a pulsed signal traveling on a transmission line, which can be a coaxial cable typically implemented in standard Ethernet industrial networks. The simulation allows for the comprehension of the effect of the time delay during the data protocol transmission, thus simulating the real network behavior and taking into account the delay occurring at the physical level (first level of the ISO/OSI scale related the transmission medium). The example proves that it is possible to simulate both the electrical signal and the information signal that travels in an industrial network.

The third example considers an EDT model detecting Electroencephalogram (EEG) signals in medical devices. The design of new healthcare hardware sensors is typically performed by the circuit modeling and simulations. The difficulty of the EDT implementation is mainly the circuit modeling of physical interactions between sensors and human body parts. In this direction, in order to test the efficiency of a real medical device, a good approach is to simulate the circuit by considering a real physiological signal as the input signal. Figure A3 illustrates the example of an EEG electrode, where the brain signal is 'imported' in the circuit by the V2 generator reading a text file (brain signal exported by a real electrode). The model simulates the signal coupling in the skin region and at the skin/electrode interface (gel materials), using different resistances and capacitances. A possible noisy output can be analyzed by AI algorithms extracting the correct trend of the

brain signal and correctly processing the output of the EEG amplification system [91]. Other medical devices detecting physiological parameters can be modeled by similar electrical components, reproducing the interaction of the electronic components with the human body tissues characterized by other specific resistances, capacitances, and inductance parameters modeling the physiological domain.

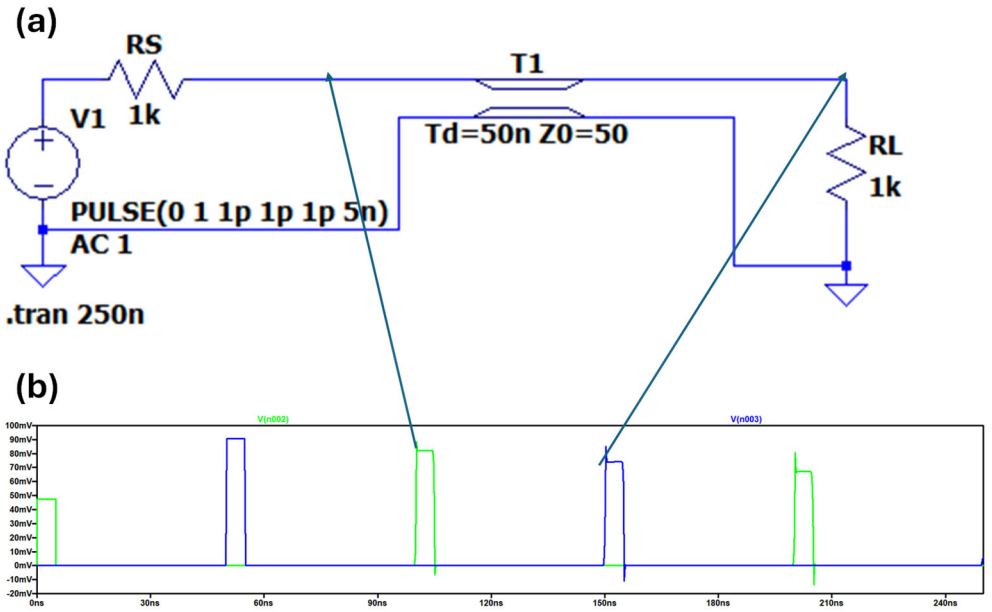


Figure A2. LTSpice simulation: (**a**) circuital EDT modeling a transmission line of an industrial network with a characteristic impedance of 50 Ω. (**b**) Simulation illustrating the delay between the input pulse signal and the output one due to the crossing of the transmission line. The input resistance of RS = 1 kΩ and load resistance of RL = 1 kΩ are able to provide a voltage signal between 50 mV and 80 mV in the observed time window.

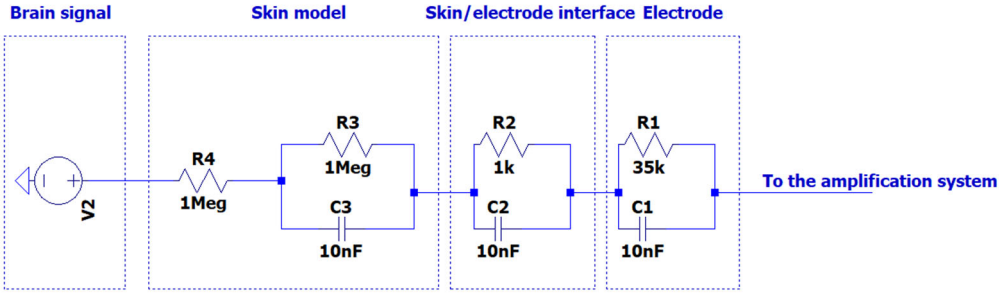


Figure A3. Example of circuit LTSpice model of an EEG electrode connecting all the regions and the human body interfaces characterizing the EEG signal transmission. The resistances R1, R2, R3, and R4 and the capacitances C1, C2, and C3 are related to a physical model simulating the skin/electrode interface [91].

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