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Digital Twin Systems in Industry 4.0: A Review of Computing Techniques and Practical Applications

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Abstract*—The industry 4.0 has used digital twin systems which strongly integrate physical properties with their clients to monitor in real-time, do predictive analytics and optimize lifecycle at design, production, and service stages. It is a review of the computing techniques that underpin digital twins, including IoT sensing and edge/cloud computing to acquire data and scale and physics-based and data-driven modeling to provide the high-fidelity representation and AI/ML to support diagnostics, prognostics, and decision making, as well as computing capabilities maturity models and reference architectures to progress capabilities. Applications Practical implementations in the area of discrete and process manufacturing, smart logistics, energy and utilities, and urban systems have shown significant improvements in shrinking downtime, increasing quality, speeding up design cycles, and cost reduction through predictive maintenance and what-if simulation. Spite of the fast maturation rate, the adoption processes are challenged with a long-running equivocation: interoperable data management with non homogenous systems, the complexity and validation of models, security and privacy concerns with cyberspace, and the absence of standards and solid KPI to compare across domains. The review outlines the emerging directions which include AI-native twins, closed-loop autonomy, scalable cloud-edge orchestration, and blockchain and BIM to promote resilient, sustainable and self-optimizing industrial operations. The results overall meaning that digital twins are a key facilitator to data-centric and adaptive manufacturing ecosystems at the core of further development of Industry 4.0.

Keywords— Digital Twin, Cloud Computing, Data Governance, Edge Computing, Hybrid Modeling, Industry 4.0, Internet of Things, Interoperability, Predictive Maintenance, Physics-Based Modeling, Smart Manufacturing, Supply Chain Optimization

I. INTRODUCTION

Digital twins are high-fidelity virtual representations of physical assets, processes, or systems that mirror real-time The industry 4.0 has used digital twin systems which strongly integrate physical properties with their clients to monitor in real-time, do predictive analytics and optimize lifecycle at design, production, and service stages. It is a review of the computing techniques that underpin digital twins, including IoT sensing and edge/cloud computing to acquire data and scale and physics-based and data-driven modeling to provide the high-fidelity representation and AI/ML to support diagnostics, prognostics, and decision making, as well as computing capabilities maturity models and reference architectures to progress capabilities[1]. Applications Practical implementations in the area of discrete and process manufacturing, smart logistics, energy and utilities, and urban systems have shown significant improvements in shrinking downtime, increasing quality, speeding up design cycles, and cost reduction through predictive maintenance and what-if simulation[2]. Spite of the fast maturation rate, the adoption processes are challenged with a long-running equivocation: interoperable data management with non homogenous systems, the complexity and validation of models, security and privacy concerns with cyberspace, and the absence of standards and solid KPI to compare across domains. The review outlines the emerging directions which include AI-native twins, closed-loop autonomy, scalable cloud-edge orchestration, and blockchain and BIM to promote resilient, sustainable and self-optimizing industrial operations. The results overall meaning that digital twins are a key facilitator to data-centric and adaptive manufacturing ecosystems at the core of further development of Industry 4.0[3].

a) Industry 4.0 Context and Strategic Relevance

The Industrial 4.0 merges things like cyber-physical systems, the Internet of Things, artificial intelligence, and ubiquitous connections, forming intelligent factories that are able to make autonomous data-driven decisions and continuous optimization. Under this paradigm, the operationalization of Industry 4.0 through digital twins offers a translator system that transforms raw and heterogeneous data into practicable intelligence, used to optimize throughput, quality, and energy at product, asset, line, factory, and supply chains levels[4]. Twins are progressively being used by manufacturers that experience material shortage, talent shortage and unstable supply to increase visibility, recreate the production environment, and add schedule automation in real-time environment.Twins reduce the need to use physical models and create competitiveness that is more sustainable and also allow the business to react to the

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fluctuation in demand. They are not limited to their strategic relevance on operations that allow them to cross-functionally collaborate, forecast their demands more accurately, and be risk-aware that future planning can transform the vision into value-delivery today[5].

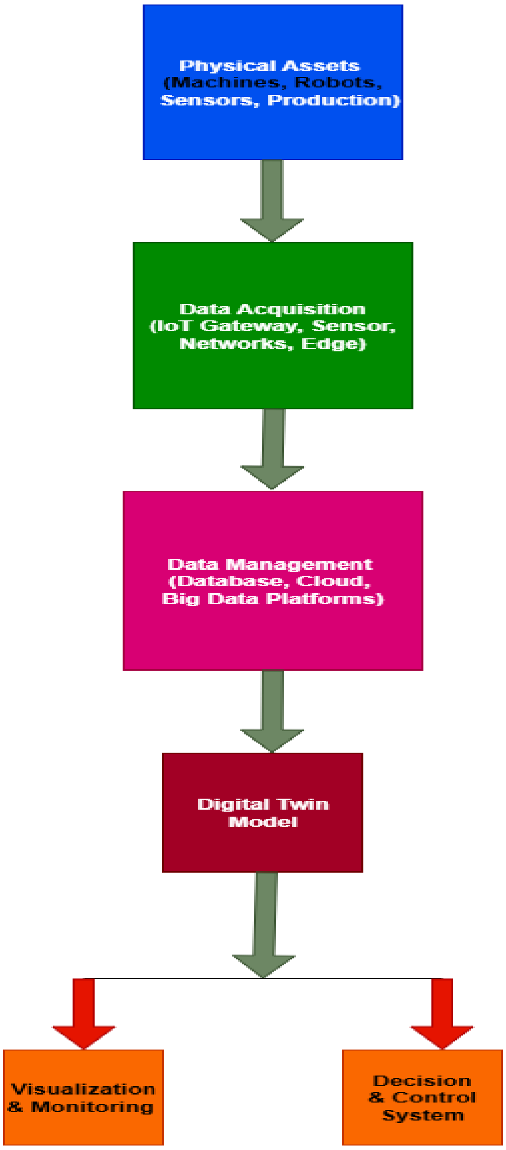

Fig 1 Digital Twin System Architecture for Industry 4.0

b) Reference Architectures and Core Components

The implementation of the reference model of a digital twin is usually structured into sensorized assets, connectivity, edge gateways, data pipes, model services, analytics/AI, and applications into a coherent, interoperable stack. On the edge, time-series signal (e.g. vibration, temperature) comprised gateways aggregate and preprocess lightweight ML to perform a simple screen of anomaly reduction before handing that need off to cloud platforms that can produce more pertinent analytics and lifecycle management. Inter-OT/IT interoperability MQTT and OPC UA are communication protocols that facilitate interoperability over OT /IT boundaries with a sense of reliability, security, and real-time streamline communication[6]. A physics-based simulator, a data-driven surrogate, and a hybrid design types along with their integration into the MES/ERP/HMI systems are considered core model services to contextualize the insights and take action. The human-in-the-loop interfaces provide what-if simulation, root-cause analysis, and decision support and the governance provides model versioning and synchronization of edge twin and cloud twins. This application framework allows higher-order deployments to a variety of industrial settings with consistent performance and stability[7].

c) Computing Substrate: Edge, Cloud, and Hybrid Orchestration The constraint of cloud to edge distribution in fulfilling real-time, realignment, as well as economic requirements forms the foundation of twin performance. Edge computing deploys inference and control as close as possible to assets to reduce latency and reliance on connectivity, making it possible to make instant decisions on anomalies, micro-optimizations, and independent operation during network outages. The cloud works in conjunction with elastic storage, model training, long-horizon analytics, and cross-site optimization, which result in the formation of a hybrid architecture in which tasks are divided according to the timeliness, data gravity, and regulatory requirements. New practices bring together "cloud-learned" twins to the edge device to enable real-time AI, and persistently backhaul contextual summaries to evolve the model and benchmark the fleet[8]. Enduring and efficient orchestration balances compute position, information integrity, and energy balances to assure twins are either receptive and scalable to asset collections and multi-plant corporations. This is the design paradigm of implementation of powerful, real-time operational intelligence in the Industry 4.0 environments[9].

d) Modeling Paradigms: Physics-Based, Data-Driven, and Hybrid

Digital twin fidelity is a product of the fusion of physics-based models (governing equations, KE, thermodynamics) with data-based surrogates (complex, nonlinear effects on sensor data) that are introduced in digital twin technology. Physics models provide interpretability, constraint obedience whereas machine learning will do well in pattern recognition, residual modeling, and quantification of uncertainty in noisy, multivariate predictive trends. Combining domain knowledge and GLM are known as hybrid algorithms that make the predictive more accurate, predictive, and sample efficient, frequently combining both the output of simulations with live signals to maintain continuual calibration. These paradigms can be applied in product, asset and factory twins to both prognostics, setting material/process parameter and schedule optimization during stochastic conditions. Model management -

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versioning, validation, and monitoring are used to ensure compliance with varying operating conditions, and surrogate modeling is used to provide acceleration in what-if analysis and the exploration of design space scaleably. Angular composite supports the industrial lifecycle with the provision of robust, explainable, and performant decision support[10].

*e) Data Infrastructure: IoT Sensing, Interoperability, and Governance*Digital twin fidelity is a product of the fusion of physics-based models (governing equations, KE, thermodynamics) with data-based surrogates (complex, nonlinear effects on sensor data) that are introduced in digital twin technology. Physics models provide interpretability, constraint obedience whereas machine learning will do well in pattern recognition, residual modeling, and quantification of uncertainty in noisy, multivariate predictive trends. Combining domain knowledge and GLM are known as hybrid algorithms that make the predictive more accurate, predictive, and sample efficient, frequently combining both the output of simulations with live signals to maintain continuual calibration[11]. These paradigms can be applied in product, asset and factory twins to both prognostics, setting material/process parameter and schedule optimization during stochastic conditions[12]. Model management -versioning, validation, and monitoring are used to ensure compliance with varying operating conditions, and surrogate modeling is used to provide acceleration in what-if analysis and the exploration of design space scaleably. Angular composite supports the industrial lifecycle with the provision of robust, explainable, and performant decision support. Digital twins create operational value in automotive, discrete and process manufacturing, energy, healthcare, cities, and logistics because they provide remote monitoring and predictive maintenance and optimization of resources. Twins are also used in factories to optimize production scheduling and uncover bottlenecks as well as to cut on overtime and costs using dynamic scenario testing between MES and IoT data streams. Automotive programs take advantage of twins design trial, simulation driving, and simulated training, reducing prototype times, and enhancing decision speed. Twins are used by utilities and energy operators to aid in reliability and maintenance planning, as well as in healthcare twins to aid in the optimization of the flow of the facilities and risk-aware clinical planning. Smart city twins inform the urban planning and sustainability processes through the capability of the fusion of multi-sources data and the what-if analysis of the changes in the infrastructures. These deployments highlight quantifiable uptime, quality, cost, and time-to-market advantages that prove twins to be a cross-domain facilitator of Industry 4.0 value creation..It is necessary to quantify value because pilots can be extended to enterprise-scale programs with pilots, KPIs that are associated with throughput, yield, OEE, downtime, schedule compliance, energy intensity, and cost-to-serve. The twins of the factory are able to squeeze the overtime by running the best sequencing and best batch sizing whereas predictive maintenance lowers unexpected halting and sustaining commercial finances by operating on off-putting examples[13]. Engagement In product development, there are fewer prototypes built physically and faster convergence durability on design that translates to shorter time-to-market and reduced engineering costs. End-to-end twins have enhanced planning accuracy, inventory turns, and service levels using demand and supply insights synchronized and resilient scenario planning. By making baselines, causal attribution instrumentation, and closed loop experimentation, one is sure that the gains observed are caused by twins interventions and not some exogenous effect. Open KPI systems foster stakeholder trust, guide scaling, and maintain investment, constructing technical in execution in association with concrete presupposed and financial and operational results.It is necessary to quantify value because pilots can be extended to enterprise-scale programs with pilots, KPIs that are associated with throughput, yield, OEE, downtime, schedule compliance, energy intensity, and cost-to-serve. The twins of the factory are able to squeeze the overtime by running the best sequencing and best batch sizing whereas predictive maintenance lowers unexpected halting and sustaining commercial finances by operating on off-putting examples. Engagement In product development, there are fewer prototypes built physically and faster convergence durability on design that translates to shorter time-to-market and reduced engineering costs[14]. 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Twins Edge-deployed twins perform low-latency corpus inference and control, with corresponding counterparts in the clouds consistently retraining models and communicating them back to the fleet, thereby performing self-adaptive processes. The interventions of hybrid modeling, reinforcement learning to plan and control, and modeling uncertainties are broadening the range of twins that includes the management of localized assets to the organization of factories and supply networks. Twin 2.0 Domain expansion smart city, healthcare, and immersive 3D/AR interfaces are

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rendering twins more collaborative and human-centered and enriching expert decision-making and training. Forbidden frontiers in research are standardization of semantics to be interchangeable, egged locality of computation under energy and distribution variations, and robust twining, with sparse data and distribution variations. These directions are the indication of a shift towards credible, scalable and sustainable twins at the core of the further development of Industry 4.0.

II. Literature Review

During Industry 4.0, digital twin (DT) technology has emerged as a revolution enabler in its physical and digital hybrid implementation to support real-time monitoring, predictive analytics, and the deployment of decisions. Systematic reviews have helped personalize conceptual models of the architectural framework and the application domain focusing on the two-way interaction as lifecycle optimization. Physics-based, data-driven, and hybrid modeling methods:Predictive maintenance (PdM) DTs can be used in predictive maintenance, health management, fault diagnosis, and remaining useful life estimation. Investigations show that DT-enabled PdM is better compared to traditional techniques because of high accuracy based on the continuity of processes of synchronization and simulations. Earlier frameworks outline architectural specifications, interoperability issues, data management, and model faithfulness and guarantee integration with enterprise systems. Another focus of the studies is data-driven implementations, which are successful to detect some anomaly despite the operation limitation and necessity of a strong model lifecycle management. Thematic hotstop in the industry indicate by means of the analysis of the scientific literature critical areas like the smart manufacturing and edge intelligence, as well as the lack of unified semantics and measures of evaluation. Also, DT maturity models offer organised inflows between monitoring and autonomous operations and technical capabilities to organisational value creation. Taken together, these works base DTs as an industrial predictive and adaptive strategy foundation. Aggression in architectural developments work on the research of edge-cloud orchestration, which exploits real-time inference at the edge and long-term learning in the cloud to finalize latency, bandwidth, and resilience. AI hybrid and distributed systems incorporated in DTs positively influence PdM with the involvement of dynamic anomaly identification, and adaptive control. Cloud-fog-edge networks also shorten the latency of control loops in production lines, at the same time being able to store historical data that are offline to analyze with analytics. The novel applications concern optimizing logistics based on AI-enhanced fleet management using AGV rather than optimizing their worth exclusively based on merit metrics instead of reacting to mutable conditions on the shop-floor. Another study also correlates the usage of DT with Industry 5.0 and facilitates human-centered, sustainable, and resilient production and suggests the use of cross-enterprise partnerships and interoperable models. The manufacturing studies applied positively report lower downtimes, increased energy efficiency and waste reduction using DT-based monitoring, quality control and planning.. Case-based implementations focus on predictive maintenance modular architecture, which allows the integration of models and execution in a closed loop. In the analysis, recurrent problems have been noted as cybersecurity, data interoperability, and availability of skills, alongside the suggestion in the views of gradual implementation, adoption of standards, and governance measures. On the whole, these papers tend to support the conclusion that scalable, adaptive, and secure DT ecosystems are the core values of their achievement to operational excellence, sustainability, and resilience in Industry 4.0 and beyond..

III. Preliminaries

1. State-Space Model (Discrete-Time) Equation:

$$x_k = F\,x_{k-1} + G\,u_k + w_k \qquad (1)$$

$$z_k = H\,x_k + v_k \qquad (2)$$

Nomenclature:
x_k: State vector,

z_k: Measurement vector,

F: State transition matrix,

G: Control matrix,

u_k: Input vector,

H: Observation matrix,

w_k: Process noise ($ \mathcal{N}(0,Q) $),

v_k: Measurement noise ($ \mathcal{N}(0,R) $),

Q: Process noise covariance,

R: Measurement noise covariance.

Relevance:
This model links the physical state of a system with its digital twin representation, enabling estimation and monitoring under uncertainty for various industrial applications such as process control, fleet tracking, and asset performance monitoring.

2. Kalman Filter – Time Update (Predict Step) Equation:

$$\hat{x}_{k|k-1} = F\hat{x}_{k-1|k-1} + G\,u_k \qquad (3)$$

$$P_{k|k-1} = FP_{k-1|k-1}F^T + Q \qquad (4)$$

Nomenclature:
$\hat{x}_{k|k-1}$: Predicted state,

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$P_{k|k-1}$: Predicted error covariance, others as above.

Relevance:
Used in digital twins for real-time state estimation, this step forecasts the system state based on known dynamics, crucial when sensor feedback is intermittent.

3. Kalman Filter – Measurement Update (Correct Step) Equation:

$$K_k = P_{k|k-1}H^T\,(H\,P_{k|k-1}H^T + R)^{-1} \quad (5)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(z_k - H\hat{x}_{k|k-1}\right) \quad (6)$$

$$P_{k|k} = (I - K_k H)P_{k|k-1} \quad (7)$$

Nomenclature:
K_k: Kalman gain,

I: Identity matrix, others as above.

Relevance:
This step refines predictions within a digital twin by integrating sensor data, improving decision-making for predictive maintenance and fault detection.

4. Extended Kalman Filter (Nonlinear Models):

$$x_k = f(x_{k-1}, u_k) + w_k \quad (8)$$

$$z_k = h(x_k) + v_k \quad (9)$$

$$F_k = \frac{\partial f}{\partial x}|_{\hat{x}}, H_k = \frac{\partial h}{\partial x}|_{\hat{x}} \quad (10)$$

Nomenclature:
$f(\cdot), h(\cdot)$: Nonlinear process & measurement models,

F_k, H_k: Jacobian matrices.

Relevance:
Handles nonlinear dynamics in Industry 4.0 systems such as robotic manipulators and autonomous vehicles.

5. Remaining Useful Life (RUL) Estimation Equation:

$$\mathrm{RUL} = \max\left(0, \frac{\theta_{\text{fail}} - \hat{\theta}_k}{\hat{r}}\right) \quad (11)$$

$$\hat{\theta}_{k+1} = \hat{\theta}_k + \hat{r}\,\Delta t + \epsilon_k \quad (12)$$

Nomenclature:
θ: Health indicator,

$\hat{r}$: Degradation rate,

θ_{fail}: Failure threshold,

Δt: Time step.

Relevance:
Widely applied in DT-driven predictive maintenance to schedule repairs before failure.

IV. Results and Discussion

Documented Outcomes from Digital Twin Deployments in Manufacturing

Company/Context	Outcome Metric	Reported Improvement	Notes
Agilent (Singapore)	Production cost	-25%	Digital twin–driven scheduling in pharma manufacturing[63]
Dr. Reddy's (India)	Production cost	-21%	Digital twin scheduling with OpEx program[63]
Sany Heavy Industry (China)	Production capacity	+44%	Factory throughput optimization via digital twin[63]
P&G (Japan)	R&D lead time	-72%	DT in product development process[63]
Unilever (Brazil)	Innovation lead time	-33%	DT for product development acceleration [63]
Buildings sector	Carbon emissions	-50%	DT potential emissions reduction (EY)[64][65]
Buildings sector	O&M efficiency	+35%	DT impact on operations &

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			maintenance (EY)[64]
Global manufacturing	DT adoption	29%	Firms with partial/complete DT adoption (IoT Analytics)[64]
Manufacturing leaders	Plan DT for ops	65%	Decision-makers planning DT to optimize ops (Forrester)[64]
Manufacturing leaders	DT for lifecycle sustainability	67%	Decision-makers prioritizing DT for sustainability (Forrester)[64]

Table 1 summarizes the examples of results in real-world rises in performance based on companies and industries finance digital twins (DT) solutions. It has the quantitative outcomes, including Agilent in Singapore laboring a decrease in the cost of pharmaceutical production of 25 percent by means of the planning using DT but has been applied to execution scheduling and Dr. Reddy Labs in India laboring arrived at a drop of 21 percent in costs of the identical. Sany Heavy Industry in China has quoted a percentage growth in production capacity of 44 per cent of production capacity on optimisation of throughput with the help of DT. Procter and Gamble cut R&D lead time by 72 percent in Japan with the help of DT enhanced product development processes, and Unilever in Brazil cut lead time innovation by 33 percent.

In addition to the cases of corporations, the impact on an industry level should also be noted: With EY calculations, carbon emissions in buildings could decrease by half with the use of DT; operations management and maintenance efficiency, in turn, could also rise by a third.

The adopted statistics of the market additional contextualize the numbers: 29 percent of all manufacturers worldwide have partially implemented DT, and 65 percent intend to apply DT in optimizing their businesses and 67 percent focus on the sustainability of lifecycle with DT.

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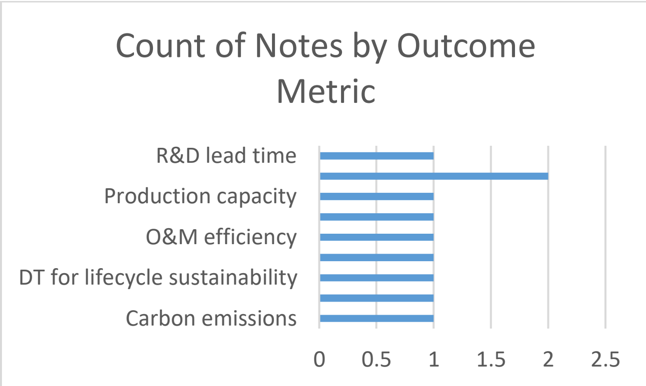

Fig 2. Documented Outcomes from Digital Twin Deployments in Manufacturing

Energy Savings Case Study from Machine Tool Digital Twin (E-KISS)

Parameter	Value
Annual operating hours (2-shift)	4,160h

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Baseline time split: Processing	27%
Baseline time split: Setup	28%
Baseline time split: Idle	45%
Electricity price	€0.2446/kWh
Energy savings (relative)	29.5%
Energy saved (absolute)	13,590kWh/year
Cost saved	€3,324/year per machine
Key actions	Shut down during idle, sensorization, DT with control parameter optimization

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Global Digital Twin Market Growth (All Sectors)

Year	Market Size (€B)	CAGR Note
2025	16.42	Fortune Business Insights
2032	240.11	39.8% CAGR (2025–2032)

Table 3 illustrates the future opportunities of deming the global market of digital twins to expand to EUR240.11B by the year 2032, threefold of the current EUR16.42B, which means that in 2025, the digital twin market will grow by 39.8%. Such a dramatic scale-up implies a mean of fast maturation and mainstreaming of manufacturing, energy, smart infrastructure, mobility, and healthcare. The convergence also indicates expansion with enabling stacks - IoT, cloud-edge orchestrations, AI/ML, as well as domain-modeling tools and reducing obstacles to adoption and expanding use-case libraries. To industrial strategists this sort of CAGR is an omen of a new competitive floor: having institutionalized twins as a product lifecycle, operations, and service, the firm is likely to have cost, responsiveness and sustainability advantages. The rate of adoption highlights, to policymakers and investors, the importance of standards, skills development, and cybersecurity systems to improve critical infrastructure protection as it is adopted across more sectors. The table has been kept purposefully small so that the CAGR could be seen and easily plotted in an area or even a simple line chart. It has the capability to project a market sizing story and may be joined with sectoral breakdowns in later illustrations. The figures in the research context justifies the focus on studies on scalability, governance, and cross-domain interoperability, as these are major factors that will ensure that value is captured in the mentioned scale. The market indicator is a validation that makes investments in platformization, reference architecture, and platform-based rollout initiatives, as a price to the implementation leaders to normalize macro growth into site outcomes..

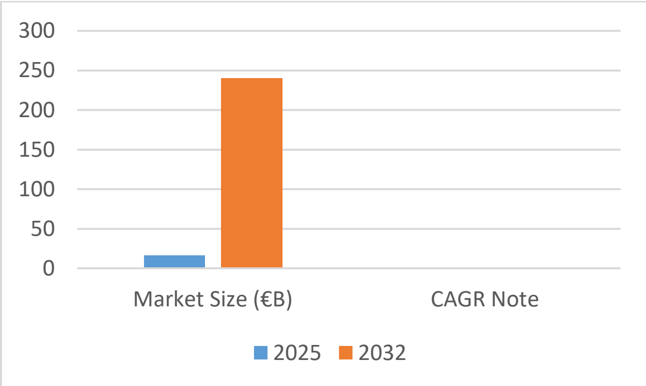

Fig 3. Global Digital Twin Market Growth (All Sectors)

Digital Twin Market in Buildings

Year	Market Size (€B)	CAGR Note
2023	1.49	Astute Analytica
2032	18.87	32.6% CAGR (2025–2032)

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Outcome Category	Studies Reporting	Notes
PHM (prognostics & health management)	23	From a 34-study PRISMA review
Remaining Useful Life (RUL) estimation	17	Subset of review studies
Fault diagnosis	Reported widely	Category within the 34-study set
Anomaly detection	Reported widely	Category within the 34-study set

Table 5 is a synthesis of emphasis on outcomes of 34 studies of a PRISMA review of digital twin based predictive maintenance (PdM). The resultant categories are dominated by four types, namely prognostics and health management (PHM) mentioned in 23 articles; remaining useful life (RUL) estimation described in 17 articles; and generalized reporting of fault diagnoses and fault detection. The numbers reveal that whereas PdM used to concentrate on detection and classification, the digital twin concept now offers the potential to functions focusing on anticipatory and lifecycle-aware--RUL and PHM- due to enabled physics/data models, and simulation in scenario. The fact that PHM and RUL are widespread points to their compatibility with maintenance planning periods, spare parts logistics and risk-based scheduling. The recommended bar or pie charts will be able to fast convey the research Oberate and remissiveness (e.g., fewer benchmark datasets across all dimensions were standardized, less quantification of uncertainty was reported). To the practitioners, the distribution provides an idea as to the most mature tooling and methodology, where pilots may be narrowed down to assets or processes with known algorithms. To researchers, its priorities include the problem of generalization across domains, managing drift, and combining multi-rate multi-moded sensor data at the same time. Another aspect that is strengthened in the table is the importance of hybrid modeling in which physics-rich constraints enhance the stability of RUL, and minimize false positive chances during anomaly detection. Finally, it introduces DT-enabled PdM as a continuum and further describes how twins can unlock the higher stages of continuum needed to achieve the value of maintenance necessity.

V. CONCLUSION

All literature reviewed proves that Digital Twin (DT) technology is a pivotal element of Industry 4.0 that allows the natural integration of physical and virtual systems to become more sensitive to greater monitoring and predictive maintenance and make independent decisions. In manufacturing, aerospace, construction, energy, logistics, and smart infrastructure, DTs are now contributing seen values in operational efficiency, cost, downtimes reduction, energy efficiency, and more sustainable results. The evolution of methodology includes physics-based models to data-driven and hybrid models enabled by an efficient edge-cloud orchestration and AI integration concepts in record time and real-time synchronization. Predictive maintenance is a more mature application of predictive control and is a dominant and more proven, that is of high value, application area since it shows its relevance in terms of better prognostics, fault diagnosis and also useful life estimation.All literature reviewed proves that Digital Twin (DT) technology is a pivotal element of Industry 4.0 that allows the natural integration of physical and virtual systems to become more sensitive to greater monitoring and predictive maintenance and make independent decisions. In manufacturing, aerospace, construction, energy, logistics, and smart infrastructure, DTs are now contributing seen values in operational efficiency, cost,

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