DOI: 10.1109/SLAAI-ICAI59257.2023.10365018

Digital Twins as a Framework for IoT Applications: A Review

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***Abstract*— The integration of Digital Twins (DT) and Internet of Things (IoT) technologies has emerged with significant advancements across various domains. This review paper explores the fundamentals of Digital Twins, categorizations, state-of-the-art developments, and their integration with IoT. It dives into architectural considerations, data integration, communications, and analytical insights within the concept of using Digital Twins as a framework for IoT applications. Recent advancements, challenges and future directions are also discussed, highlighting the potential and complexities of this combined approach.**

Keywords— Internet of Things, Digital Twins

I. Introduction

The convergence of Digital Twins (DTs) and Internet of Things (IoT) has brought about transformative possibilities, along with challenges, in diverse fields. This article delves into the foundations, categorizations, and recent advancements of Digital Twins merged with IoT. First, the fundamentals of both DT and IoT concepts will be discussed with historical background and evolution through time until these concepts become mainstream. This also includes categorizations and different definitions of these novel concepts depending on the field of application. Next, the integration scenarios of the two concepts in the current research and industry will be explored. Finally, the communication and connectivity, data integration and modelling as well as analytical insights on current developments will be assessed in relation to the use of DTs as a framework for IoT applications. The architecture of the overall DT and IoT systems needs to be carefully designed and developed considering the costs involved, possible problems and viable solutions. Hence, the architectural considerations of the system development related to DT framework for IoT along with challenges and future directions will be discussed in this review.

II. Fundamentals of Digital Twins

A Digital Twin (DT) is defined as a virtual representation of an object, model, or a process, which may or may not consist of a physical counterpart [1]. A DT would be communicating with its physical twin in a synchronized manner to update itself with real-time data or for making intelligent decisions acting as an expert decision-making system [2]. The origin of DT in operation can be traced back to a few decades prior to the origin of the concept itself. The DT concept was initially introduced by Micheal Grieves at the University of Michigan [3] in 2002. Yet, the usage of virtual replicas for physical real-word objects with the intention of providing intelligent decisions or predictions existed long before that. The first such incident was recorded five decades ago, when NASA's Apollo 13 was stranded 210,000 miles (about 337962.24 km) away from earth [4]. The 15 simulators that were used in training the astronauts and mission controllers in every aspect of the mission, including multiple failure scenarios were used to simulate the error caused by the spacecraft's damage, hence, to figure out the solution with the available resources in the actual spacecraft [4]. The concept of Digital Twins emerged from this innovative moment. Consisting of a life cycle, a DT will be connected to its physical twin for capturing data and contextual interaction [2]. From time-to-time after the first recorded DT, virtual replicas or 3D models of real-world objects were used in simplifying complex and expensive tasks if done practically in the physical world.

A. Categorizations of Digital Twins

Modern day digital twins have a spectrum of categorizations depending on the purpose of application, type of operation required and the expected outcomes. According to Madni et al. [2], Levels of DTs could be categorized by their sophistication and maturity by the stages of product life cycle. This categorization includes a) Pre-Digital Twin; b) Digital Twin; c) Adaptive Digital Twin; and d) Intelligent Digital Twin. This categorization involves the state of the virtual model, state of the data communication channels between the virtual and physic counterparts, operator preferences (i.e., ability to learn the preferences of human operators using machine learning techniques) and system preferences (i.e., ability to predict, plan and operate the system using machine learning techniques).

A Pre-Digital Twin is a 3D model or a virtual representation of a system, an object, or a process before it has been implemented in the real world. The goal could be for planning a physical twin or mitigating technical risks. At this level, the physical twin does not exist, hence there will be no data acquisition from the physical twin or use of machine learning in operator preferences or system environment. A Digital Twin, although this coincides with the general term, this classification in [2] to a virtual system which has a physical system/twin. Data acquisitions such as data from performance, health status, maintenance and batch updates related to the life cycle will be considered in this stage. At this level of categorization, the system would not have machine learning capabilities. The next level of maturity categorization is an "Adaptive Digital Twin". At this maturity level, the Digital Twin will comprise of an adaptive user interface which will evolve with the physical system. This type of Digital

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Twins will have machine learning capability with operator preferences and real-time updates. Next, an Intelligent Digital Twin is categorized to be the highest level of maturity of a Digital Twin, containing all the model sophistication elements of previously listed categories plus reinforcement learning capability. Data acquisition from the physical twin will consist of both batch and real-time updates while the machine learning element will consist of operator preferences as well as system and environment aspects. Reinforcement Learning (RL) is a machine learning paradigm where an agent learns how to make decisions by interacting with an environment to maximize a reward signal.

Other categorizations of DTs are based on the application domain and the functionality of the specific domain where DTs are considered special purpose DTs designed for specific applications with application relevant functionality. Examples include the implementation of DTs for Smart Grids [5], testing autonomous vehicles [6], Smart Cities [7] and for achieving environmental sustainability goals. Hence, the categorization of DTs could be based on their functionality, maturity of the model itself, performance, and DT's overall life cycle. In the context of Internet of Things (IoT), all these categorization methods and the suitable applicability depending on the approach and expected result of the IoT application could be considered.

B. *State-of-the-art developments of Digital Twins landscape*

Developments in DTs and their application in a variety of scenarios have grown rapidly. From being a concept to mainstream, DTs have become popular in many fields. One such state-of-the-art development is the smart city platform developed by Unreal Engine and Buildmedia for Wellington's net-zero energy buildings, revolutionizing the transition to a sustainable future. The adoption of DTs has significant cost savings, as they allow for precise monitoring, analysis, and optimization of energy consumption, resulting in efficient building operations and reduced expenses. By creating virtual replicas of physical assets, DTs enable real-time data collection and predictive modelling, empowering stakeholders to make informed decisions that maximize energy efficiency and minimize wastage [8]. Further, a review of the recent advancements of DTs by Ramu et al. [7] describes the merging of Federated Learning and Decision Trees within the context of smart city applications. Federated Learning is integrated with DT in several smart city applications like manufacturing, automobile, retail, 5G, Industrial IoT. Research by Patros et al. [9] developed a multi-dimensional framework for classifying energy and other DTs. They highlighted how energy DTs can apply to distinct phases of the production life cycle and presented a concept for energy DT application to industrial sites and local areas. The energy applications and usage play a crucial role in the Net-Zero transition. Research by Wang et al. [10] provides a broad review of digital twins covering their applications, the definitions, classifications, key features, case studies, the key technologies at present, and future directions and challenges of DT in energy fields. Tsialiamanis et al.[11]a methodology of developing generative models as a base for DTs. The authors suggest the use of Stochastic Finite Elements (SFE) based method for physics-based models when the physical twin provides accurate data capture through different sensors which will be fed into the DT. On occasions where physics-based models are not sufficient, data driven models have been introduced which use conditional generative adversarial networks – a machine learning framework for generative AI.

III. IoT Landscape

This section focuses on exploring the concept of Internet of Things (IoT) and its advancement in the modern world. IoT constitutes an expanded network rooted in the Internet infrastructure, aiming to facilitate real-time interaction among objects, machinery, environment, and people through advanced technological means. Originating in 2002, early IoT related literature, like Schoenberger's work in 2002, envisioned its application in retail, using miniature wireless chips to confer perceptual capabilities to stores. Over the past two decades, a growing consensus among governments, business leaders, and researchers has emerged, enhancing the IoT's role in enhancing living conditions and overall well-being. Market analysis underscores this trend, indicating a global IoT market valuation of $1.90 billion in 2018, projected to surge to $11.03 billion by 2026. The European Union (EU), United States, and China have also crafted strategic frameworks for IoT advancement, exemplified by initiatives such as Europe's IoT-An Action Plan and the 2016–2020 IoT development plans [12].

IoT often goes hand in hand with heterogeneous technologies which enables the design and development of applications such as smart cities, retail, agriculture, healthcare, and energy management. The connectivity of the physical elements of the intended system with the goal of achieving an interoperable network allows the users privileges such as remote controllability, data collection and monitoring, predictive maintenance, and automation via the integration of a variety of sensors, wearable devices, and mobile technologies.

It is evident that in the field of IoT, the growth in computational power and reduction in the size of electronic components have enabled IoT devices to become smaller, efficient, and affordable. This has facilitated the creation of a wide range of interconnected devices with sensing, communication, and processing capabilities, which are at the core of the IoT ecosystem [13].

IV. Digital Twins in IoT

This section explores the usage of DT concept as a framework for IoT applications. Since a DT is a virtual replica of a real-world object which synchronizes itself with the original by means of data and communication, it is possible to use the same model to develop an IoT system of which the overall performance could be monitored remotely. Further, reinforcement learning can provide a dynamic and adaptable approach for optimizing system behaviour and decision-making when integrated within DTs in IoT applications. This concept could enhance capabilities of fault detection and prevention, supply chain optimization and adaptive control in DT based IoT applications. The ability of a DT to interconnect itself with other DTs via different mechanisms such as Web APIs, Peer to Peer networks, middleware protocols such as Data Distribution Service (DDS), makes it preferable to act as a framework for the development of IoT systems using the same [14], [15]. In this section the fields of smart city construction, environmental sustainability and healthcare will be explored with existing examples.

To recognize the benefits of DTs over existing IoT frameworks, it is necessary to understand its strengths. For example, Arduino is a popular open-source hardware platform for IoT development. However, only being suitable for smallscale projects and less suitable for large scale IoT projects due to processing power and memory limitations is a drawback. Cloud based platforms such as Amazon Web Services (AWS), Microsoft Azure IoT are comprehensive platforms compared to the mentioned. Such platforms are expensive and have a steeper learning curve for beginners. Comparatively, usage of DTs as a framework for IoT systems can benefit in many ways. One such way is via simulation. As DTs are a virtual representation of a physical system, it makes managing and monitoring a large number of assets easier. The ability to predict and optimize behaviour of complex systems makes DTs a resourceful framework. Data integration and interoperability of IoT systems could be exhaustive in generic frameworks, whereas in DTs data integration could bridge communication gaps via a unified view of the system. Ability to provide data analytics and real-time monitoring along with the ability to represent the system in a simple, user-friendly manner makes it easier for beginners to learn. Considering the costs that would be acquired on generic IoT frameworks, DTs can provide cost reductions by simplifying and optimizing the existing IoT systems.

A. Digital Twins in Smart cities IoT applications

The smart city development goes hand in hand with IoT developments as the concept of Smart cities itself refers to a technologically advanced urban area which allows the people to live an easier and a more sustainable life via Artificial Intelligence (AI) based prediction, maintenance and solution deriving systems. Ruohomaki et al. [16] suggests creating a smart city DT for Helsinki, of which the model of the city is based on Open Geospatial Consortium (OGC)'s Geography Markup Language (GML). This allows the creation of DTs of real-world objects of a city with similarity in semantics, geometry, topology and appearance to its physical element. Their paper also discusses the integration of data from the real world via an IoT based data model named "SensorThings". Further, the creation of virtual smart cities has many uses such as crowd simulation and expansion, self-learning and self-optimization, integration of interactions between virtual and real cities, simulation reasoning, spatial analysis and calculation, data fusion, visual representation, digital representation of different city elements and IoT recognition and control [17]. Kayoung et al. discusses how existing Building Information Systems (BIMs) and other IoT based infrastructure could be integrated into DTs for achieving a higher-level smart city virtual model as a pre-DT. Therefore, it is evident that the usage of DTs as a framework, which could have multiple IoT entry points, has many benefits in the context of smart cities to make the communication and data synchronization efficient.

Adhering to a set of rules and regulations seems ideal in the synergy of DT as a framework for IoT. This is due to the possibility of many data security issues which could be involved in communication channels and other synchronization links of DT technologies. Robust security measures such as end-to-end encryption of data being communicated with the IoT platform and DT, regular maintenance of the DT and implementation of safe authentication could be ideal solutions for ensuring security of both physical and virtual systems.

B. Digital Twins in IoT as environmental sustainability solutions

In the current global context, it is essential to consider the effects of different modernization solutions to the environment. With global warming and its effects on the entire planet Earth, the use of DTs that can process large volumes of data for many different scenarios and predict intelligent outcomes via Adaptive and Intelligent DTs has many advantages.

Sustainable solutions such as renewable energy sources, solar and hydro power, waste reduction and recycling, net zero transition [18] and sustainable agriculture could utilize IoT based infrastructure. The development of modular machine learning algorithms for specific purposes such as prediction and expert decision making using IoT data for the tasks mentioned above could be exhausting. A sensible approach would be to use IoT sensor data from different sources within a single DT and make predictions for decision making for the achievement of sustainability goals [7], [9]. Intelligent DTs could cooperate with its operator and system preference capabilities in achieving sustainability goals [2].

C. Digital Twins as a framework for IoT in healthcare

The field of healthcare deals with processing large amounts of data for sensitive tasks such as treatments and surgeries. Hence this field could have a variety of DTs such as human simulations to hospital systems. In this context, DTs can be applied to various areas such as patient monitoring, medical equipment management, and drug development. DTs create personalized models of patients by integrating data from wearable devices, electronic health records, and other sources [19]. This allows healthcare professionals to monitor patients in real-time, predict health issues, and recommend personalized treatments [20]. By analyzing data from various sources, including patient health records and environmental data, DTs can help predict disease outbreaks, identify trends, and support public health initiatives. DTs can enhance telemedicine experiences by providing a detailed virtual representation of patients, allowing healthcare providers to better understand patients' conditions during remote consultations [19]–[21]. Hence, the use of DTs as a framework for monitoring and analysing data gathered from IoT networks could be a methodologically efficient approach.

TABLE I. APPLICATIONS OF DTS IN DIFFERENT IOT PARADIGMS

Field	**IoT Data gathered**	**Developed DT framework.**
Manufacturing	Production statisticss, sensor data	Digital replicas of manufacturing processes
Aerospace	Flight data, sensor readings	Virtual models of aircraft systems
Energy	Power generation data, equipment readings	Virtual representations of energy systems
Agriculture	Soil moisture, crop health data	Digital models of farming processes
Automotive	Vehicle sensor data, performance metrics	Digital twins of vehicles and components

V. Architectural Considerations for DT frameworks in IoT Applications

In this section, the architectural developments of the DT frameworks which are employed in developing IoT applications will be analysed by providing examples from a selected set of literature and practical applications. A digital record-keeping system that stores information in linked blocks which is referred to as blockchains is making its entry into a variety of fields in the modern world. Research by Wang et al. [22] suggests a sustainable, blockchain based architecture for IoT devices. [22] This approach includes a DT framework which has devices, agents, and requestors and agents which collect current data from physical devices and feed them to requestors to create DT services. These services such as supply chain tracking, digital identity record-keeping and data security are then employed in information and energy sustainability for improving system performance. This is carried out by introducing blockchain technology to enable data sharing among agents and integrate data in the DTs of physical assets [22].

VI. Data Integration and Modelling

In this section, the role of data integration and modelling in the context of DTs as a framework for IoT devices will be discussed. All IoT devices contain input and monitoring methods such as sensors, cameras, RFID(Radio-Frequency Identification) etc. for capturing the data of which the intended application is aimed at collecting. This data must be analysed and stored adhering to the policies and procedures governing data protection regulations. This data will be integrated with the virtual models for ensuring simultaneous connectivity between the participating models. Ensuring the accuracy of this integration process is crucial, as it forms the foundation for coherent decision-making in IoT environments. Recent studies have emphasized the symbiotic relationship between data integration, modeling, and the efficacy of Decision Trees as a facilitative framework in IoT applications [23], [24]. These developments emphasize the significance of robust data preprocessing and the direct impact on the accuracy and reliability which ensures the decision-making processes in IoT ecosystems.

The integration of data within the IoT devices, along with the utilization of DTs, has emerged as a critical area of research and development. Various data integration methodologies have been employed to harness the full potential of IoT-generated data in conjunction with Digital Twins, enabling enhanced insights and decision-making capabilities. One prevalent approach is the employment of Extract, Transform, Load (ETL) techniques, which facilitate the extraction of raw data from diverse sources, its transformation into a standardized format, and subsequent loading into Digital Twin environments. For instance, in industrial settings, ETL methods have been employed to integrate data from sensors across machinery to create virtual replicas that mimic real-world behaviours, aiding in predictive maintenance and performance optimization [25].

Another noteworthy methodology involves the use of data streams for event processing techniques. This approach involves real-time processing of streaming data from IoT devices, enabling rapid response to changing conditions and facilitating the synchronization of DTs with real-world occurrences. For instance, in smart cities, data streams from traffic sensors and weather monitors can be integrated with urban planning DTs to optimize traffic flow during severe weather [26].

VII. Commuinications and Connectivity

The effective communication and connectivity paradigms relating to IoT devices, combined with the integration of DTs such as seamless data interchange between IoT devices and their corresponding DTs, is important in realizing operational insights and decision-making capabilities. One prominent approach to achieving robust connectivity is through the utilization of Low-Power Wide-Area Networks[1] (LPWANs), such as LoRaWAN and NB-IoT. These networks facilitate long-range, low-power communication, enabling remote monitoring and control of devices while conserving energy, as observed in applications like agricultural monitoring systems [13]. The integration of edge computing with DTs have gained popularity. By processing data closer to the data source, edge computing minimizes latency and conserves network bandwidth, critical for real-time applications. This approach is demonstrated in healthcare scenarios where wearable IoT devices interact with patient-specific DTs, enabling timely and personalized interventions [27].

VIII. Analytical Insights

Usage of DTs as a framework for IoT applications can have many advantages in the modern technological ecosystem. The physical components of IoT systems could encounter anomalies which may occur due to connectivity issues, sensor malfunctions, data quality issues, environmental and human factors and many more. Identification of anomalies and presenting with predictive maintenance for IoT systems is an innovative approach which can benefit from characteristics of DTs. Further, monitoring the environment for sustainable urban planning can benefit from the usage of DTs as framework for IoT applications. With the rising energy crisis, smart solutions such as clean energy have become popular. IoT plays a main role in the lifecycle of smart grids, from planning to maintenance. This section discusses the analytical insights which could be obtained from existing research in the context of using DTs as a framework for IoT.

A. Predictive Maintenance and Anomaly Detection

A common area of focus involves predictive maintenance and anomaly detection. In the point of statistics an anomaly could be considered as an outlier in a distribution. Leveraging advanced machine learning algorithms, research by Johnson et al. proposed a predictive maintenance framework that

[1] a wireless communication technology optimized for long-range connectivity and minimal energy consumption, often used for connecting IoT devices and remote sensors

combines real-time sensor data from industrial equipment with Digital Twins to forecast equipment failures, optimizing maintenance schedules and reducing downtime. [26], [27]

B. *Environmental Monitoring and Urban Planning*

Urban planning involves a range of considerations which go hand in hand with a variety of other industrial fields such as vehicular traffic management, environmentally friendly building development and sustainable modifications and developments. Urban planning has seen significant benefits through the connection of IoT and DTs. In the study by Martinez et al., environmental data collected from IoT sensors, such as air quality and noise level measurements, were integrated into urban DTs. These insights enable city planners to assess the impact of various interventions on urban sustainability and quality of life [28]

C. *Energy Efficiency and Smart Grids*

Smart energy grids highly benefit from the IoT concepts and DT frameworks. Advancements in energy efficiency have been driven by the integration of IoT data and Digital Twins in smart grid systems. Research by Brown et al. demonstrated the utilization of real-time energy consumption data from IoT sensors to update Digital Twin simulations of power distribution networks. This approach aids in optimizing energy distribution, minimizing wastage, and enhancing overall grid resilience in smart energy girds [29].

IX. Challenges and Future Directions

Along with its many advantages, the DT usage as a framework for IoT applications comes with a set of challenges as well. One of the most common challenges is maintaining data security over the system which uses the DT as a common platform which possibly integrates multiple resources. Standardization of data allocation, storage, proper policies and procedures related to model customization needs to be considered in such instances. Achieving seamless integration between the physical world and its virtual representation via DTs requires secured communication protocols and interoperability standards [30]. This is essential for building a cohesive environment where diverse IoT devices DT instances can collaborate harmoniously. Scalability also emerges as a potential concern, particularly in large-scale deployments. As IoT networks and Digital Twins expand, the ability to efficiently manage and orchestrate numerous interconnected entities becomes necessary [31].

Future directions of this combined framework hold a great potential. Enhancing the cognitive capabilities of DTs as a framework for IoT applications through artificial intelligence and machine learning techniques could lead to more sophisticated and adaptive systems [32]. For example, utilising recent advancements in Virtual Reality (VR) and Augmented Reality (AR), Da Silva et. al.[33] implemented an AR based application for controlling and monitoring physical systems that has a DT. Additionally, the integration of edge computing with Digital Twins can alleviate network congestion and reduce latency, enabling quicker decision-making in time-sensitive scenarios [30], [32]. Collaborative research and cross-disciplinary efforts will play a crucial role in addressing these challenges and realizing the transformative potential of IoT and DTs.

X. Conclusion

The integration of Digital Twins and IoT has introduced a promising path for novel applications across various sectors. While challenges such as data security and standardization exist, the potential of this combination remains strong. The emergence of adaptive and intelligent Digital Twins, combined with the integration of edge computing, indicates the prospect of more advanced systems capable of real-time decision-making. Collaborative endeavors spanning multiple fields will play a vital role in overcoming challenges and fully capitalizing on the transformative potential of this framework. This cooperative effort could improve connectivity and achieve operational effectiveness within IoT applications.

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