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(Review Article)

Digital Twins and Federated Learning for Industrial Internet of Things

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Abstract

The Internet of Things (IoT) is penetrating various facets of our daily life with the proliferation of intelligent services and applications empowered by artificial intelligence (AI). AI techniques require centralized data collection and processing that may not be feasible in realistic application scenarios due to the high scalability of modern IoT networks and growing data privacy concerns. Federated Learning (FL) has emerged as a distributed collaborative AI approach that can enable many intelligent IoT applications by allowing for AI training at distributed IoT devices without the need for data sharing. In this survey, we focus on DT and FL for IIoT. Initially, we analyzed the existing surveys. In this paper, we present the applications of DT and FL in IIoT.

Keywords: Digital Twins; Federated Learning; Industry 4.0; Cyber–Physical System; Industrial Internet of Things (IIoT)

1. Introduction

The Fourth Industrial Revolution brought big changes to the Internet of Things (IoT). This period is also known as the "connected age" [1]. The first industrial revolution began in 1780 with the invention of machines. The second revolution started in 1870, when electricity was used to power factories. In 1970, Industry 3.0, or the "automation age," introduced computers and automation to manufacturing. Recent years have witnessed the rapid development of the Internet of Things (IoT), which provides ubiquitous sensing and computing capabilities to connect a broad range of things to the Internet. To obtain insights into data generated from ubiquitous IoT devices, artificial intelligence techniques such as deep learning have been widely exploited to train data models for enabling intelligent IoT applications such as smart healthcare, smart transportation, and smart cities. Traditionally, AI functions are placed in a cloud server or a data center for data learning and modeling, which incur critical limitations given the IoT data explosion.

With the rise of IoT, we have entered Industry 4.0—the "connected age." This new phase focuses on smart technologies and strong connections between systems. Industry 4.0 is leading to rapid changes in technology, business, and society [2]. It includes advanced tools and systems like artificial intelligence (AI), cyber–physical systems [4], the industrial Internet of Things (IIoT) [5], cloud computing [6], and smart factories [7]. Figure 1 shows the evolution of the Industrial Revolution. Industry 4.0 uses technologies such as DT and FL. DT is the digital processing and evaluation of an industry, smart city, or network. Intelligent manufacturing is composed of six layers; the zero layer is called the manufactory area; the first layer is known as the manufactory building; the second layer is infrastructure; the third layer is operations, the fourth layer is the smart manufactory; and the fifth layer is DT [8]. All these layers are shown in Figure 2.

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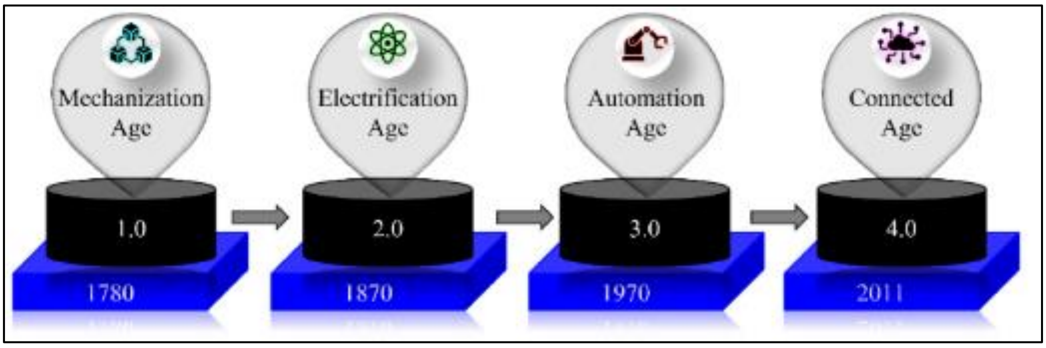

Figure 1 Industrial revolution from Industry 1.0 to Industry 4.0 (Adopted from [8])

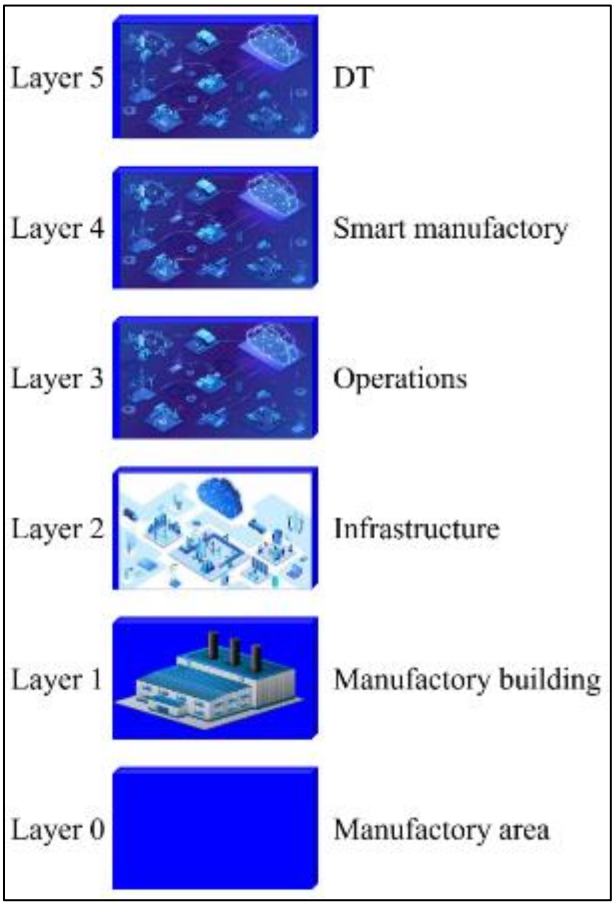

Figure 2 Different layers of intelligent manufacturing having DT. Simulations and DT are two different things (Adopted from [8])

2. Literature Review

DT and FL are used for several purposes. In the literature, there are a plethora of surveys discussing the application of DT and FL for healthcare, smart cities, next-generation networks, etc. In [9], the authors presented a comprehensive survey of DT's definition, use cases, applications, and challenges. This survey lacked information about FL. Another study [10] surveyed the applications, advantages, and challenges of using DT in networks. However, FL was not included in the scope of the survey.

Lim et al. reviewed the use of DT for the innovative purpose of businesses, the advancement of businesses using DT, and the challenges of using DT in businesses. However, the survey lacked a discussion about DT and FL for Industry 4.0 [11].

Minerva et al. reviewed the DT application in IoT. The survey presented detailed information on DT use cases, issues, and challenges in IoT. However, the survey lacked analysis of the use of DT and FL in IoV and IoD [12].

Gámez Díaz et al. explained the use of DT in the ecosystem. The survey analyzed the deployment of DT in sports. The survey only focused on the DT deployment in the ecosystem [13].

Löcklin et al. reviewed the DT in autonomous industrial systems (AISs). The authors explained the effectiveness of using DT for the verification and validation of AISs. The survey encompassed IIoT but did not discuss FL. Moreover, the article did not explicitly discuss IoV and IoD [14].

Liu et al. surveyed the implementation of DT in IoT. They presented a comprehensive analysis of the techniques for the deployment of DT and the challenges faced during the implementation of DT in IoT. The survey did not address DT and FL for IoV and IoD [15].

An overview of recent advancements in federated learning, machine learning, and Industry 4.0 technologies, particularly in IoT-based applications such as smart healthcare, intelligent transportation, and manufacturing systems, was described in [35]–[46]. They demonstrate how emerging AI-driven methods—including transfer learning, digital twins, and antenna design—are being applied across various domains to enhance performance, security, and sustainability in IoT-enabled environments.

3. Federated Learning

Since it was introduced in 2016 [35], Federated Learning (FL) has changed how smart Internet of Things (IoT) systems use artificial intelligence (AI). FL is a new kind of AI that works in a distributed way and protects user privacy. It brings a fresh approach to how AI can be used in IoT, especially with the growing use of mobile devices and rising concerns about personal data privacy.

With FL, AI tasks like training models can be done directly on IoT devices (like smartphones, sensors, or tablets) instead of sending data to a central server. This means the user's data stays on their device, but the device still helps train a shared AI model. This approach helps save network resources and better protects user privacy. Because of this, FL is seen as a strong alternative to traditional AI, which usually depends on collecting and processing all data in one place. It also makes it easier to roll out large-scale IoT services.

In IoT networks, FL involves two main parts:

- Data clients: IoT devices like smartphones, laptops, sensors
- Aggregation server: A central point (like a base station or access point) that collects model updates

Let’s say there are K participants (devices), labeled {1, 2, ..., K}. Each device trains an AI model using its own local data, which it never shares directly. After training, each device sends only the model updates (not the data) to the aggregation server.

For example, in vehicular IoT networks [36, 37], vehicles can use FL to sense traffic and work together to build better traffic maps that help reduce congestion.

In future IoT systems, FL will be very important. That’s because collecting all data from IoT devices in one place is not practical. Instead, FL lets users train a shared model while keeping data on their own devices.

In this setup:

- Each IoT user k uses their dataset to train a local model
- After local training, devices send their model updates to the server
- The server then combines (aggregates) all updates to create a global model

This way, the system benefits from training on distributed data without exposing private user information. Figure 3 shows how this FL system works in a network: how devices connect, train, and send their updates to the server.

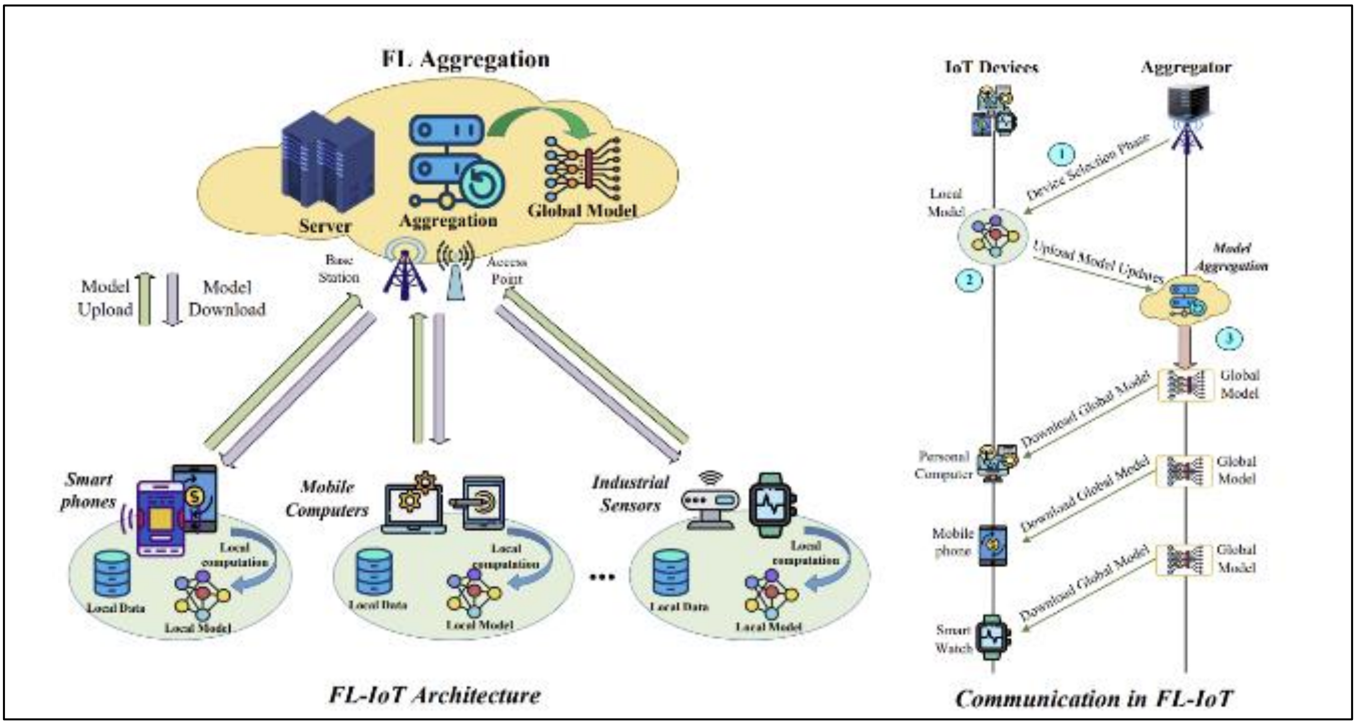

Figure 3 The network architecture and communication process for FL-IoT [34]

4. DT and FL in IIoT

DT is widely used in IIoT systems. Malakuti et al. [16] elaborated on the definition of DT and the role of DT in IIoT systems. The authors analyzed the decisions made by software architects regarding the architecture [16]. [17] focused on the interoperability of DT for IIoT systems. The results showed that DT simulation of the development of the 3GPP for ultra-reliable low latency (URLLC) reduces the delay and increases reliability [18].

In [19], the authors proposed a DT model for basalt fiber production. They illustrated the smart digitization of the fiber industry using IIoT. Thomas et al. developed an artificial intelligence (AI) and extended reality (XR)-based DT for the management of complex systems. They presented the advantages of using AI and XR for DT's improved training and performance [20].

FL is widely used for several purposes in IIoT networks. Zhang et al. demonstrated the data management by using a deep reinforcement learning (DRL)-based FL algorithm. The algorithm achieved 97% accuracy for the data management of the IIoT network [21]. Rahman et al. showed the importance of using FL to ensure the fairness and trustworthiness of the IIoT network [22].

Ferrag et al. [23] presented a realistic dataset for cybersecurity. The dataset can be used for training FL models [23]. Jia et al. presented a blockchain-enabled FL scheme for protecting the data using differential privacy and homomorphic encryption [24].

Lakhan et al. presented deadline, latency, and energy-efficient strategies and a BEFC scheme to ensure blockchain hashing and validation [25]. Makkar et al. [26] proposed Secure IIoT, an FL approach to avoid data breaches [26]. Similarly, the researchers demonstrated an FL and blockchain-enabled defensive transmission model and achieved 98% accuracy [27].

Vy et al. [29] demonstrated federated transfer learning (FTL) for low computing power IIoT gadgets and achieved an accuracy of more than 70% for the KDD99 dataset [29]. In [28,30], the authors highlighted the use of FL for intrusion detection in context-aware IIoT networks and software-defined network (SDN)-enabled IIoT, respectively.

[31] presented an FL-based cyber-threat hunting model for IIoT networks based on blockchain technology. Chen et al. proposed a communication-effective federated edge learning (FEL) algorithm for new radios in unlicensed spectrum (NRU)-based IIoT networks [32].

K et al. proposed a novel algorithm based on FTL for the authentication and privacy preservation of the IIoT network [33]. Table 1 shows a summary of the use of DT and FL in IIoT.

Table 1 Summary of the use of DT and FL in IIoT.

Ref.	Objective	FL	DT	Achievements
[16]	Architectural aspects	No	Yes	Elaborate on the role of DT in IIoT systems
[17]	Interoperability	No	Yes	A flexible solution for the interoperability of the DTs in IIoT
[18]	Wireless technology and protocols	No	Yes	Development of 3GPP for URLLC in minimizing delay and enhancing reliability
[19]	Fiber production	No	Yes	A DT for the digitization of the fiber industry using IIoT
[20]	Complex systems management	No	Yes	AI and XR-enabled DT development for the management of complex systems
[21]	Data management	Yes	No	FL algorithm with DRL for data management achieving 97% accuracy
[22]	TrustFed	Yes	No	Blockchain-enabled TrustFed framework to ensure fairness and trustworthiness
[23]	Cyber security dataset	Yes	No	Provides a realistic dataset for the cyber security of IoT and IIoT. The dataset can be used for the training of FL models
[24]	Data protection	Yes	No	Blockchain-enabled FL scheme for the protection of the data using differential privacy and homomorphic encryption
[25]	Multi-objective modeling and blockchain enabled system	Yes	No	Deadline, latency, energy-efficient strategies, and a BEFC scheme to ensure blockchain hashing and validation
[26]	Data breach protection	Yes	No	FL-based framework (SecureIIoT) to protect IIoT networks from data breaches
[27]	Defensive transmission model	Yes	No	FL and blockchain-enabled model for defensive transmission, and achieved 98% accuracy
[28]	FTL for low computing power IIoT devices	Yes	No	FTL for low computing power IIoT gadgets and achieved an accuracy of more than 70% for the KDD99 dataset
[29]	Intrusion detection	Yes	No	FL-based intrusion detection system for IIoT networks with improved efficiency
[30]	Intrusion detection	Yes	No	FL-based intrusion detection in SDN-enabled IIoT networks
[31]	Cyber threat hunting	Yes	No	FL-based cyber-threat hunting model for IIoT networks based on blockchain technology
[32]	Communication-effective FEL in NRU	Yes	No	Communication-effective FEL algorithm NRU-based IIoT networks
[33]	Authentication and privacy preservation	Yes	No	Novel algorithm based on FTL for the authentication and privacy preservation of the IIoT network

5. Conclusion

The use of DT and FL results in several open research issues, such as those relating to security, reliability, efficiency, privacy, and adaptability. Data security is very important in the present era, and IIoT produces massive amounts of data. These data are vulnerable to cyber threats, and the security of this data is very important. FL helps address this issue, but there is still a need to develop more robust techniques to resist cyber threats. Similarly, the reliability of DT and FL is also an open research issue that needs to be addressed. DT and FL are considered more reliable; however, there is a need for schemes to address the reliability of DT and FL in the IIoT. DT provides a virtual model of the networks, and the efficiency of the network can be analyzed using DT. However, the real-time deployment of the same DT model can face the problem of efficiency. This opens a new pathway for researchers to develop models that address the efficiency of DT-based networks and real-time networks.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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