Complementing IIoT Services Through AI: Feasibility and Suitability

Fatemeh Banaie and Mahdi Hashemzadeh

1 Introduction

Internet of Things (IoT) has emerged as a new technology paradigm envisioned to enable the interoperable interactions of machines and devices over the internet. The structure of IoT entails the use of millions of smart devices which are able to efficiently share and process data among each other, thereby providing reliable monitoring and controlling systems [1]. IoT offers the ability to learn and interact with environmental indicators in realizing the automated real-time decision-making processes. This paves the way for enabling efficient productions and manufacturing processes in the industrial domain. Applying IoT to industrial applications has raised a new research area called Industrial IoT (IIoT) that enables the industry to analyze the acquired data from industrial assets and systems. This is a notable feature in the context of the fourth industrial revolution, known as industry 4.0 [2].

This infrastructure can lead to a significant improvement in performance, energy efficiency, and reduced response time of the devices [3]. However, IIoT-enabled multi-source manufacturing data generated by industrial devices are required to be analyzed in real-time to achieve the operation optimization and strategic decision-making [4]. The large quantity of data in resource-constrained devices and growing concerns of data privacy are preventing IIoT solutions to achieve the desired quality of services. Therefore, the realization of IIoT requirements in terms of the network reliability, real-time processing and transmission, and industrial information security can be met with the new technologies such as AI and edge computing techniques [5, 6].

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Edge computing refers to the edge-processing model that provides a flexible and efficient edge network for heterogeneous industrial devices. It leverages edge nodes with sufficient computing resources for implementing the local pre-processing of real-time industrial data, which is essential for accommodating the growing computational demands [7]. It can potentially reduce the communication bandwidth and overall delay of the system, thereby improve the overall performance of the system. More importantly, it also allows enterprises to build the effective solutions for protecting the security and privacy risks [7, 8]. In this context, edge computing incorporates AI technologies for data mining and analysis process [9].

The IIoT enables the successful cooperating of AI and big data techniques. AI-assisted data analysis framework requires proximate and prompt cloud resources for manufacturing data processing. Therefore, integrating AI into edge computing is a promising solution for deploying efficient distributed computing services [10, 11], known as Edge Intelligence (EI). The realization of edge intelligence in IIoT can be further reinforced by integrating ML methods. In particular, model training and model evaluation in data analysis and prediction processes can be carried out locally in edge devices called ML as a Service (MLaaS) [12]. EI provides some benefits in terms of *personalization*, *responsiveness*, and *privacy issues*. Notably, it enables not only accurate services through customizing AI models, but also provides fast and adaptive services for time-varying industrial process. Moreover, information processing at the network edge ensures the private services. The rest of this chapter discusses the opportunities and essential issues of the paradigm where ML models are executed locally in the industrial manufacturing network.

2 IIoT with Edge Intelligence

The IIoT provides an efficient computational platform that is able to monitor and control the manufacturing processes with the aid of information technologies. In this platform, the acquired data from industrial assets and devices can be efficiently processed and analyzed by incorporating the AI technologies. In smart manufacturing, data analysis is a critical feature in realizing the automation and intelligence of IIoT systems. Mainly, ML is a popular modeling technique that can be applied to data-driven applications. Learning techniques typically utilize a sufficient amount of data for training the model in different areas such as regression, classification, clustering, and forecasting. Thus, intelligent manufacturing requires cloud-assisted service for processing and analyzing the industrial big data. For this purpose, utilizing edge devices can be a promising development trend that provides computational power and service accuracy on the edge servers. The relationship between AI, EI, Edge Computing (EC), and IIoT is shown in Fig. 1. Given these concepts and the relationships between them, in this section, we investigate the preliminaries of an intelligent computing framework for IIoT.

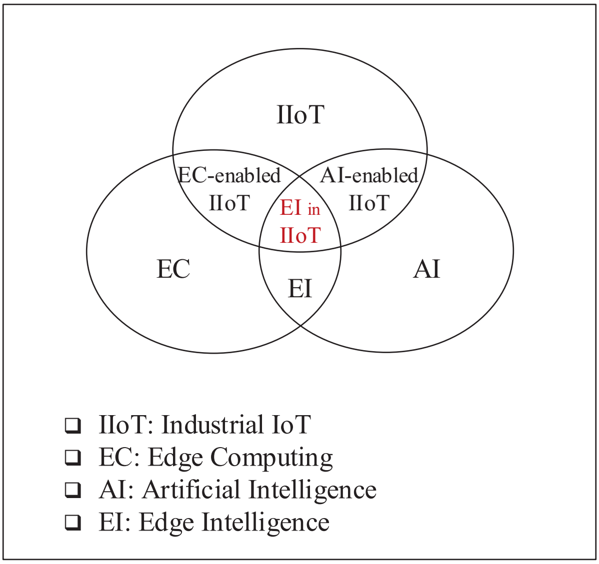

Fig. 1 AI, EC, EI, and IIoT in venn diagram

2.1 The Challenges of EC in IIoT

EC is an innovative paradigm for industrial devices that utilizes sensing, computational resources, and data processing techniques to provide an efficient manufacturing infrastructure. However, processing a large quantity of data in edge nodes may bring some new challenges in terms of the confidentiality of information and performance-related issues that should be addressed in design and implementation of a system. The following focuses on the detailed discussion of the design issues.

Data Processing and Analysis Big industrial data are mainly driven by millions of smart devices and business processes. To develop an efficient edge service in IIoT, it is critical to design the appropriate approaches for data capturing and storing the vast amount of heterogeneous data in distributed edge servers. Since the data quantity is huge and grows rapidly, the solution must not only be able to store the industrial data effectively, but also support scalability and flexibility. This is the requirement of applications envisaged in IIoT vision [13, 14]. In addition, data analysis schemes should be considered to meet the requirements of data processing and management. AI-enabled technologies are proved as an effective solution in providing a real-time data management platform in terms of accuracy, adaptability, and the security of data [15, 16].

Security and Privacy Integrating EC technologies with IIoT enhances the security and privacy of the produced data, as it decreases the data transmission in the network. However, traditional security solutions cannot guarantee the full requirements for edge services. Different kinds of malicious attacks can threat confidentiality due to the ubiquitous network environment [17, 18]. Moreover, existing cybersecurity frameworks are not applicable for industrial systems, as the unique characteristics of IIoT in providing the strict performance and reliability requirements for supporting the critical functionality [19]. AI technologies are the potent methods for investigating the normal/abnormal behavior of the manufacturing components and devices in the IIoT environment. In particular, these methods can assist in developing the security-based intelligent systems [20].

Energy Consumption In general, the total energy consumption consists of the amount of energy consumed by industrial devices for collecting and processing the industrial information, and the energy consumed for data transmission among these devices. Although edge-enabled computing enhances the energy expenditure of the sensory devices, big data processing, and association imposes the higher energy levels on the edge devices that need to be considered in design stages [21].

Resource Management and Task Scheduling An edge-enabled computing model provides flexible computations and storage services for intelligent industrial systems. However, the heterogeneity of this platform in terms of the higher real-time task requests, terminal assets and devices, and edge nodes necessitates the creation of an efficient task scheduling scheme. The problem lies in determining the rules about how to perform the data transmission and task scheduling among edge nodes to minimize the delay and energy consumption, whilst enhance the overall performance of the manufacturing systems. Moreover, the scheduling strategy should assign the tasks among edge nodes to guarantee the load-balancing and prolong the lifecycle of the system [7, 22].

2.2 Classifications of AI Techniques

Nowadays, AI has become an integral part of our daily lives. Motivated by the recent advancement in AI techniques and the impacts on a wide variety of domains, ranging from automatic face-focus to robotics, a set of intelligent applications have quickly ascended to the spotlight in the industrial field. In particular, AI is a generic term, which involves various techniques summarized in Fig. 2.

Among them, ML is an effective method that has received greater attention in recent years owing to the achieved accuracy [9]. As shown in Fig. 2, ML-based approaches are generally divided into supervised, unsupervised, and Reinforcement Learning (RL) methods. These methods can improve the performance of the system through training the machine using gathered data from the real world. Besides ML techniques that utilize neural networks for learning, the deep representation of data, achieve remarkable results in a broad spectrum of fields. In contrast to the ML approaches that require a feature extractor for transmitting raw data into proper representation, the Deep Learning (DL) method develops its own representations

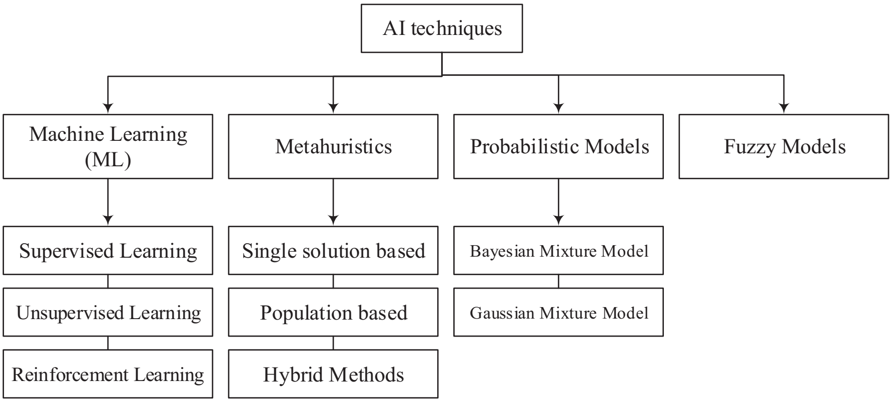

Fig. 2 Summary of AI technologies [23]

for pattern recognition. In this manner, systems can successfully learn more complex functions with unprecedented and undefined conditions.

2.3 Machine Learning Techniques in IIoT

ML is one of the popular AI-based techniques that provide the ability to learn with data and enhancing the performance of computer systems in decision-making processes, without having explicit programs [23, 24]. The aid of these techniques is to model the concepts from perceptions. According to these perceptions, learning techniques can be in three categories: *supervised learning,* in which labeled data are applied in classification or regression tasks, *unsupervised learning* with unlabeled data in clusters, and *reinforcement learning* approach that utilizes the concept of agents for maximizing the cumulative reward.

Nowadays, ML-based schemes have found their applications in upcoming decentralized and intelligent information and networking systems. They have significant potential in improving the deployment of communications and networking systems, as they are able to extract features from a large amount of data. The application of ML-based algorithms in networking is twofold. First, it can help in optimal decisions with learning network patterns, such as routing decisions in traffic patterns [25, 26]. Second, the performance and resource usage optimization in a network can be solved by the intelligent task allocation and scheduling schemes [27, 28].

The heterogeneous manufacturing data are analyzed through a ML-assisted approaches in IIoT. For example, the authors in [29] proposed an ML-aided information management system to enhance the user request service. They leveraged some indexing techniques for achieving the effective data management, then an ML algorithm is applied to improve the accuracy of the request processing. The authors in [10] investigated the tradeoff between the service delivery latency and energy expenditure in IIoT. Generally, cloud resources are used for data processing in these approaches. However, it imposes much cost in terms of network bandwidth and service latency, while transmitting data to the cloud servers; so, it is beneficial to apply the distributed computing services.

2.4 Machine Learning Techniques in Edge Computing

AI-aided edge computation services could efficiently empower the Manufacturing Devices (MD) with low latency computing capability. Typically, edge resources cannot afford the complex AI tasks. Thus, distributed AI services can be performed with multiple edge devices to provide an efficient service provisioning. For example, an AI-based privacy-preserving service division is presented in [30] that conducts the service composition on encrypted data using a homomorphic encryption algorithm. In [31], a federated deep reinforcement learning-based framework is proposed that improves latency by applying the edge caching technique. This framework utilizes the local training parameters of the base stations as the initial input for the global training in the next stage. In [32], a QoE-based computation offloading model is presented that improves the service latency, energy consumptions, and task success rate using a deep reinforcement learning algorithm. It could improve the QoE performance, besides achieving the better instability and faster convergence.

2.5 Edge Intelligent IIoT

The recent proliferation of the computation-intensive manufacturing applications generates a large volume of the industrial data at the network edge. This incurs an urgent need for AI techniques at the network edge to release the informative potential of big data. Big data has a crucial role in AI development that has recently moved from datacenters toward the growing widespread devices, e.g., IIoT devices. The emerging paradigm that moves computing tasks and services from core to the network edge has led to a promising area of EI. EI combines the edge advantages (e.g., reduced latency and network traffic) with AI strategies that result in further benefits in the following aspects [9].

1. *Big data analysis at the network edge*: the growing number of smart devices and assets leads to the large volume of industrial data in IIoT. In this context, decision-making processes can be accelerated through AI strategies in data analytic and information extraction. Among them, deep learning is a strong approach that can meet the requirements of big data analytic. Deep learning models have also achieved remarkable results in automatically identifying patterns and anomaly detection in data. Then, the extracted information is used for real-time predictive decision-making in industrial environments.

2. *Efficient data processing using edge resources*: it is already proved that data has a vital effect on the development of AI models. Traditionally, the acquired data from IoT devices and industrial assets are sent and stored in the cloud data centers. This incurs the higher latency and wastage of bandwidth resources. To address these challenges, computing tasks and services are moved to the network edge in recent years. In this way, the generated data can be processed locally to achieve low-latency responses in real-time manufacturing systems.
3. *Ubiquitous AI services*: AI has been recognized as an essential solution in a variety of application domains that influence our everyday lives [33–38]. The potential of AI in improving the smart products and services imposes the need for bringing AI closer for every person and device [39]. Clearly, edge computing can assist in achieving this goal by enabling ubiquitous AI at the network edge.

3 AI-Enhanced Cooperative Computing Architecture

This section introduces the architecture of smart manufacturing resources based on the cooperative edge computing in IIoT. It is consists of three operational layers named manufacturing assets, edge-devices, and remote cloud resources, as depicted in Fig. 3. Multi-source manufacturing data is collected and delivered to the base stations (BS) or edge devices. Real-time manufacturing services include self-monitoring, production and logistic status, fault detection, and service management [10, 40].

Edge layer provides a lightweight smart service by processing the real-time data and perception events, and transforming them into dynamic behaviors in manufacturing systems. Computing service of edge devices may be different, depending on the application and service accuracy. However, cooperative computing service through edge and cloud accommodates both prompt and comprehensive computing services. Owing to the additional cost of communications between edge and cloud servers, the deployment of computing services between them has a significant impact on performance. Additionally, a task scheduling strategy is required for assigning the computing tasks to the heterogeneous edge servers according to their specifications and quality of service (QoS) requirements.

4 Potential Advantages of Learning Techniques in Edge Intelligent IIoT

The applications of learning techniques in IIoT would enable the further extraction of the information, and the deployment of the innovative applications in the intelligent manufacturing domain. More specifically, applying information technologies in the industrial field can provide a flexible infrastructure for smart manufacturing

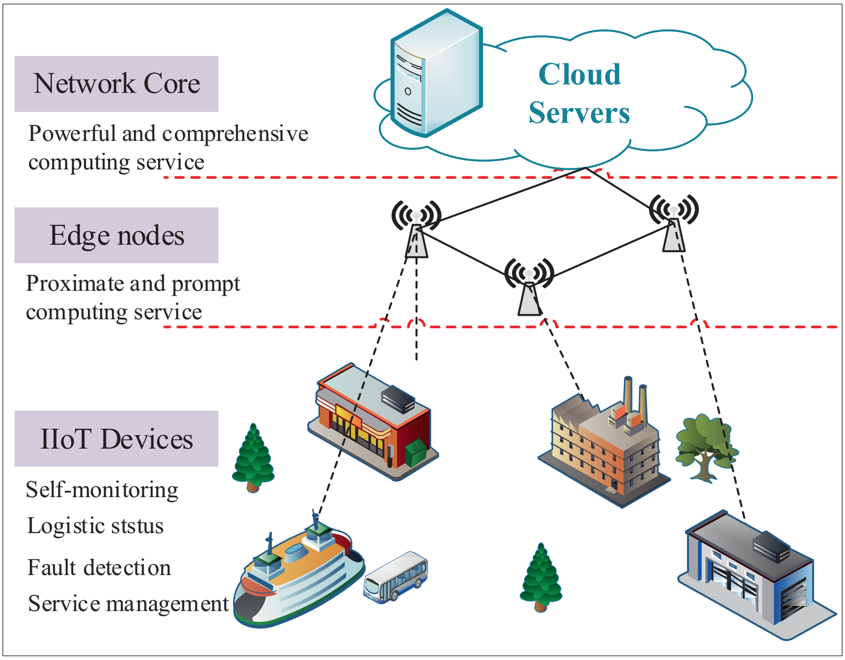

Fig. 3 Three-layered architecture for IIoT

services. This allows the industrial assets and devices to have a seamless autonomous communication in the service delivery process. For example, Prognostic and Health Management (PHM) is a novel paradigm that utilizes the collected operational information of the system for predicting and taking suitable decisions before system failure [41]. A large number of sensors are utilized to provide a real-time monitoring system, which is essential in IIoT [42]. This system has the ability to detect and predict the system failures by integrating the autonomous support system with the information system. The initial processing of data is performed at the network edge that enhances the latency of the emergency decisions.

In the context of big data, learning can be used for the efficient extracting and mining of the features in exact classifications or autonomous decision-making processes. Moreover, an intelligent edge-computing platform would be capable of learning the surrounding conditions, mapping out the events, monitoring and tracking manufacturing faults, effective action prediction, and providing a fast response to real-time changes.

5 Practical Limitation and Open Issues

Although there is a growing interest in EI, the study of EI is still in the early stage. This section discusses some challenges and open issues in EI-based IIoT, including software platforms and middleware, load balancing, EI model design, and security issues.

5.1 Software Platforms and Middleware

Recently, cloud-based AI service provisioning systems have received a lot of attentions in industrial field. In this regard, some companies, such as Amazon's Greengrass, Microsoft Azure, and Google Cloud IoT Edge try to deliver software platforms and middleware for the edge services. On the other hand, the growing number of AI-assisted computation-intensive applications leads to the development of the pervasive EI platform and middleware.

In order to realize the potential of EI services, several key challenges should be addressed in terms of the compatibility, portability, and programing issues. Owing to the diverse and heterogeneous EI services, a middleware should be developed for providing seamless and smooth services. This platform should support the portability between different AI programing frameworks, such as Tensor flow and Torch. Moreover, it should provide a lightweight virtualization and computing service [9].

5.2 Task Offloading and Load Balancing

Pervasive computing in EI is a distributed system paradigm that has variety of computing resources. Therefore, it is required to have an effective task offloading and load balancing scheme for task dissemination among the resources and servers. Particularly, data offloading schemes aid to balance the overall load of the system among the limited computing resources. This can help in improving the overall latency of the service delivery in system, which is necessary for manufacturing applications. In this context, machine learning models can be used to set up the efficient balancing schemes.

5.3 EI Model Design

AI models are usually resource-intensive and require powerful computing capability. To address this problem, model compression techniques can be applied to resize the AI models. To this end, model simplification is used for adapting the model to the edge resources, which includes weight pruning and data quantification. In weight pruning method, the removal of neurons with small contribution makes the model smaller. Data quantization utilizes a small data format with fewer bits in representing the input/output that improves the operational speed of the instructions [7].

5.4 Security Issues

Owing to the open nature of the pervasive computing, privacy and security problems is one of the key challenges of IIoT. Manufacturing assets and devices produce a large amount of data that may contain sensitive information about location, activity records, production process, and manufacturing information. Therefore, designing an appropriate distributed security mechanism is critical to guarantee the user privacy and data integrity for industrial applications. Distributed learning models are a feasible solution for the privacy-friendly local data training schemes.

6 Conclusion

Recent advances on ubiquitous computing play a crucial role in boosting AI techniques in a resource-constrained environment. Moving the AI frontier from the remote cloud to the network edge can pave the way for computation-intensive AI applications. This can help to tackle the limitations of the bandwidth and latency in computation-intensive decision-making processes.

This chapter reviewed the novel paradigm of edge intelligence, motivations for pushing artificial intelligence frontier to the network edge, and the reference architecture of edge intelligence in industrial IoT (IIoT). Specifically, we discussed the emerging learning models in the industrial field for training and perceiving manufacturing data and processes at the network edge. This review could be a good step for motivating researchers to make more attention to the industry development.

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