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Recent Advances in Artificial Intelligence for Wireless Internet of Things and Cyber-Physical Systems: A Comprehensive Survey

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***Abstract*—Advances in Artificial Intelligence (AI) and wireless technology are driving forward the large deployment of interconnected smart technologies that constitute Cyber-Physical Systems (CPS) and Internet of Things (IoT) for many commercial and military applications. CPS is characterised by a communication, computing and control engineering based on large volume of data originating from various devices, plants, sensors, etc. Wireless technologies have enabled the ease of networking and communications for both CPS and IoT, by providing massive and critical connectivity and control mechanisms. However, they are prone to challenges such as low latency, throughput, and scheduling. Recent research trends focus on how to intelligently use data from CPS units to enhance wireless connectivity in CPS. Artificial Intelligence tools, particularly AI systems and machine learning (ML) algorithms, have been widely applied in literature to develop efficient schemes for wireless CPS/IoT. This paper presents a review on the role of Artificial Intelligence in wireless networking for CPS and IoT. In particular, we focus on machine learning paradigms such as Transfer Learning, Distributed Learning, and Federated Learning, that have evolved as building blocks for the utilization of large data for learning, adaptation, and predictions in CPS and IoT systems that leverage wireless networking. Furthermore, we also highlight challenges faced by current and future wireless networks pertaining to CPS/IoT, that are yet to be addressed.**

***Index Terms*—Artificial Intelligence (AI), Machine Learning (ML), Wireless Networks, Cyber-Physical Systems (CPS), Internet of Things (IoT),Distributed Learning, Federated Learning, Transfer Learning**

I. Introduction

The Internet of Things (IoT) and Cyber-Physical Systems (CPS) are widely used paradigm for describing the interconnection of physical devices that communicate information and can be controlled remotely [1], [2], [3], [4], [5]. Recent advances in wireless technology has enabled the use of wireless sensors, mobile devices, and other smart devices for a wide variety of commercial and military applications. The connections and communications for these interconnected wireless devices can be either in the homogeneous or heterogeneous domains. Most of the IoT and CPS devices are comprise of physical objects such as smart vehicles, drones, smart appliances, and other machines/machinery etc., that are embedded with sensors for either a single specific application or multiple applications. Another emerging CPS based paradigm is the fourth industrial revolution, also referred to as Industry 4.0, that describes the digitization of traditional manufacturing/production, products and other industrial ecosystems. [1], [2]

CPS has tight combination of communication, computing and control engineering that leverages data driven approaches with massive amount of data generated by massive number of inter-connected multitude of devices. This data, once collected, can assist in the digital transformation of industry and decision making. The plethora of connected devices require a wireless network architecture that is adaptive in real time, and robust to support the large data transfer. While also simultaneously, it is being able to improve Quality of Service (QoS) and Quality of Experience (QoE) for end users by making intelligent decisions. To expand in detail, future wireless networks are expected to handle critical missions at higher data rates, lower costs, and lower latency in communication, in addition to ensuring that the information services meet the CIA (Confidentially, Integrity and Availability) principles of information security [6], [5].

Furthermore, it is projected that the number of CPS and IoT connected devices will triple by 2023 compared to 2017 [7]. According to the Cisco annual report in 2020, there will be 3.6 per-capita, (approximately 29 billion) network devices, out of which 14.7 billion will be IoT connected devices by 2023 [8]. Future IoT will consist of massive amount of devices and sensors generating enormous data and will require uninterrupted communication between the IoT

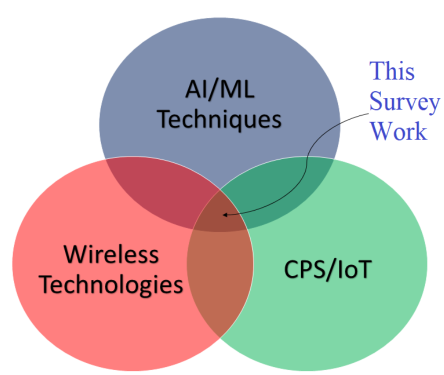

Fig. 1: Scope of this survey covering intersection of AI/ML and wireless networking for CPS/IoT applications.

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TABLE I: List of acronyms.

Acronym	Full meaning	Acronym	Full meaning
3GPP	3rd Generation Partnership Project	MIMO	Multiple-Input and Multiple-Output
AI	Artificial Intelligence	ML	Machine Learning
AMI	Advanced Metering Infrastructure	NB-IOT	Narrowband IoT
ANN	Artificial Neural Network	NOMA	Non-Orthogonal Multi Access
ASR	Automatic Speech Recognition	PCA	Principal Component Analysis
BLE	Bluetooth Low Energy	PF	Proportional Fair
C2M	Consumer-to-manufacturer	Q-Learning	Quality Learning
CIA	Confidentially, Integrity and Availability	QoE	Quality of Experience
CNN	Convolutional Neural Network	QoS	Quality of Service
CPS	Cyber-Physical Systems	RF	Radio Frequency
CSMA/CA	Carrier Sense Multiple Access/ Collision Avoidance		
CTF	Channel Transfer Function	RL	Reinforcement Learning
DBN	Deep Belief Networks	RNN	Recurrent Neural Network
DL	Deep Learning	RR	Round Robin
DRL	Deep Reinforcement Learning	RS	Random Scheduling
DQN	Deep Q-Network	RSS	Received Signal Strength
FDML	Feature Distribution Machine Learning	SAE	Stacked Auto Encoders
FL	Federated Learning	SG	Stochastic Gradient
FNN	Feedforward deep Neural Network	SNR	Signal to Noise Ratio
GAN	Generative Adversarial Networks	SON	Self Organized Network
IoT	Internet of Things	SSP	Stale Synchronous Parallel
KNN	K-Nearest Neighbor	SVM	Support Vector Machine
LoRa	Long Range	TL	Transfer Learning
LPWAN	Low Power Wide Area Network	UE	User Equipment
LTE	Long-Term Evolution	WiFi	Wireless Fidelity
M2M	Machine-to-machine	Wi-SUN	Wireless Smart Utility Network
MAC	Media Access Control	WLAN	Wireless Local Area Network
M-BUS	Meter-Bus	WM-Bus	Wireless Meter Bus
MDP	Markov Decision Process	WNAN	Wireless Neighborhood Area Network
		WPAN	Wireless Personal Area Network

devices, as well as the network technologies (physical and software). Based on these projections, millions of data packets will be transferred. Therefore, optimization of wireless links and networks to process such enormous data with minimum delay will play a critical role for data gathering and sending back the decision parameters for AI enabled systems. These challenges are complex and require advance hardware and software to be developed using data from network performance metrics and emerging CPS/IoT architectures, based on both traditional statistical and AI techniques. For example, self-driving cars communicate with roadside sensors, traffic signals, traffic signs, other vehicles, other road side units, pedestrians, etc. [9], [10], via sensors, embedded wireless modules, and software/algorithms. In order to have a fully autonomous vehicle, critical challenges such as the integration of multiple protocols in the presence of heterogeneous wireless technologies, robustness of connected vehicles upon failure of traffic and roadside sensors, and the dynamic actions of vehicles under uncertainties such as bad weather, and human failures, amongst others, need to be addressed. Another example is the smart healthcare system, where information technology has been widely used in a variety of applications such as remote patient monitoring, robotic surgery sensor, and glucose monitoring [11]. To adequately deliver these critical services for Healthcare-CPS, design challenges such as data collection, communication, diversified data analysis and data-driven decision making among others, must be addressed

A. Wireless Communications in CPS/IoT

There are several wireless technologies suitable for CPS and IoT applications. These technologies may be classified into short, medium, and long range, based on operational frequency and coverage range. Some of these technologies operate in either licensed spectrum (e.g Narrowband IoT (NB-IoT), Cellular) or unlicensed spectrum (e,g Sigfox, LoRa) [12]. We examine the different technologies in each coverage range.

1) Short Range: Short range wireless communication uses technologies whose signals have travel limits of about ≈ 150 meter [12]. Wireless technologies in short range that can be used to interconnect IoT devices includes Bluetooth, ZigBee, Z-Wave, M-Bus, Wi-Fi, X-Bee, etc., and are used in Wireless Personal Area Network (WPAN) and Wireless Local Area Network (WLAN). Bluetooth signals operate in the 2.4 GHz band and use frequency hopping to limit interference when multiple devices are connected. Since it's range is about 10 meters, it is only suitable for IoT devices in close proximity. Several research works [13], [14], [15], [16], [17] have suggested the use of Bluetooth due to its economic advantage and current utilization in most electronic devices. In [16], [17], the authors presented a Bluetooth BLE-backscatter approach for data uplink from a sensor tag to existing Bluetooth-enabled smartphones and tablets without any hardware or software modification. Zigbee is a low-power IEEE 802.15.4 wireless mesh network standard. Majority of Zigbee operates in 2.4 GHz. Due to its low power and high data rate, Zigbee is one of the main wireless technology protocols for WPAN. Researchers are currently extending its application to several IoT networks. [18], [19]. Wi-Fi is the most widely used network in homes, with a lot of research in literature focusing on Wifi for IoT [20], [21], [22]. The authors of [20], studied

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the use of non-conventional WiFi enabled IoT devices based on convention network access point for indoor localization problem pertaining to fingerprint maps.

2) Medium Range: Wireless Neighborhood Area Network (WNAN) such as Wireless Smart Utility Network (Wi-SUN) and Wireless Meter Bus (WM-Bus) offer medium range communications, where the range is about $\approx 5-10$ km [31], [12], [32]. Wi-SUN is used to enable seamless connectivity between smart-IoT devices, with a coverage of about 5 km [31]. WM-Bus is a star topology network developed for smart metering and Advanced Metering Infrastructure (AMI) applications, which governs communication links between data collection devices and water/gas/electric systems.

3) Long Range: Long range wireless technologies for IoT devices have a range of up to 100 km and are referred to as Low Power Wide Area Networks (LPWAN). Some LPWANs are licensed (Narrowband IoT and LTE-Machine), while others are unlicensed (e.g LoRa, Sigfox). Studies are currently ongoing to fully develop and apply these technologies [33], [34],[35].

The massive data collected by sensors in CPS and IoT can use wireless communications to exchange the data as well as the data can be used with AI/ML to address challenges associated communications in CPS/IoT, including communication related issues. AI has shown significant importance for future wireless communication and networking for CPS/IoT. The three-essential part of IoT/CPS are communication network, devices, and data. The core high-level requirements of IoT/CPS are communication, control, and computation, and together they form what is known as the 3C building block of CPS [36]. Table III shows some research efforts that applies AI/ML to IoT/CPS in order meet the IoT/CPS 3C requirements.

B. Summary of Related Surveys

AI for wireless networking in CPS, IoT and Industry 4.0 has been extensively investigated. Thus, related research articles & surveys are already present in literature, such as the works from Ahmadi et al., Lu et al., and Wu et al., [54], [55], [56]. The authors of [23] reported on Artificial Neural Network (ANN) based techniques for wireless networks, with detailed architecture of ANN and how it can be implemented in many wireless network application. They identified several wireless communication challenges that could be addressed via ANN techniques and analyzed several emerging applications and potential future works that would be significantly improved by the deployment of an ANN. The authors of [24] provided an overview of techniques, frameworks and applications of neural networks for wireless networking. Deep learning (DL) approaches to wireless networks have also been intensively investigated, and literature provides several reviews on the topic [25], [57], [26]. These surveys, while providing an overview of various applications of deep neural networks, are also focused on certain specific applications [58], [25]. The authors of [58] provide an in-depth theoretical description of deep learning for wireless network resource allocation. In [25], the authors provide an extensive review of deep learning schemes for wireless network performance enhancement. They analyzed promising future applications, such as the practical implementation on wireless platforms, DL for defining congestion threshold, and DL for link failure prediction in data transmission.

In [28], the authors reviewed DRL framework for diverse network problems including data rate control, network access and connectivity, and wireless caching. The authors in [29] provided a survey of machine learning algorithms including DL and RL for Self-Organized Networks (SON). The authors of [30] categorized and reviewed machine learning techniques and applied deep learning to mobile edge catching in a dynamic complex environment. Authors in [27] presented a DL architecture and discussed the importance of DL for future IoT data analytics challenges and its potential for future technologies. For more detailed surveys on wireless IoT/CPs, wireless technologies for IoT/CPs, readers are encouraged to read surveys by Li et al., Ahmadi et al., adn Lin et al,. [56], [59], [60]

Although the papers [23], [24] provided helpful insights, they do not address emerging distributed learning paradigms (e.g federated learning, collaborative learning, etc.) that are dominating how machine learning can be used in large networks of connected devices/sensors in CPS.

C. Contributions

This article provides a survey of AI/ML techniques applied to enable wireless networking for CPS and IoT systems. Our contribution to current state of the art via this survey consists of 3 major aspects:

- ML applications in wireless technologies: We provide a brief summary of the most widely used wireless technologies for CPS and IoT applications, then review the ML techniques that have been applied to solve some of the challenges of wireless networks for IoT and CPS.
- ML techniques and their literature review related to IoT and CPS: A description of each of the machine learning paradigm will be done and the recent research related to them will be discussed, especially those applications pertaining to wireless networks for IoT/CPS.
- Open Challenges: This section is dedicated to discussing open challenges in wireless networking for CPS and IoT systems that AI techniques can be used to fill the gap, and the future work needed to create robust AI systems for IoT/CPS.

D. Paper Organization

The rest of this paper is organized as follows: In Section II, we present different types of machine learning approaches, including newly evolved learning paradigms such as Transfer learning, Distributed learning, and Federated learning for wireless networking. Open challenges and future research directions in wireless networking for IoT and CPS will be

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discussed in Section III. Finally, Section IV summarizes and concludes this paper.

II. AI/ML for Wireless Networking for CPS/IoT

As mentioned previously, machine learning is a sub field of artificial intelligence that involves learning and inferencing using computational learning methods [61], [62]. ML uses experience (i.e available information that are typically in electronic data form) to make accurate decisions [62]. It can be categorized into three main techniques; supervised learning, unsupervised learning, and reinforcement learning.This section discusses these different types of ML techniques and frameworks that are used for wireless networking. A taxonomy for the different ML techniques is provided in Figure 2. In each section, a review of relevant papers relating to IoT and wireless networks follows the discussion.

1) Supervised Learning: Supervised machine learning is a class of learning algorithms that originated from learning by example. In supervised learning there is an input variable or feature X, and an output variable or target Y, that the learning process is trying to predict. An algorithm is used to learn the mapping function from the input to the output. During the training of a supervised learning algorithm, the training data-set consists of inputs paired with correct outputs. Learning stops when the algorithm achieves an acceptable level of performance. After the training process, a supervised learning algorithm determines the output (unseen) given new input.

In general form, the objective is to learn a function $h : X\ Y$ using a given training set $(x^(i), y^(i))$, such that the hypothesis function $h(x)$ is a predictor of the corresponding value of y [63]. Supervised learning's typical application problem includes regression and classification as shown in Figure 2. Commonly used supervised learning techniques include ANN, K-Nearest Neighbour(KNN), Support Vector Machine (SVM), [64], [65] .

In [48], SVM was used to predict the WiFi coverage and harvest radio frequency (RF) energy. Here the SVM is used as a supervised learning approach for regression because of its ability to penalize error during training with its loss function term, and maintaining adequate complexity with its regularization term [48]. The model harvests RF energy for efficient deployment in IoT scenarios. In [42], supervised learning algorithms, KNN and Random Forests were used to classify network traffic in an IoT mobile device analysis. A similar approach can be found in [43], where supervised ML was applied to measure data to classify indoor environments using different RF signatures. The authors compared different ML algorithm(SVM,KNN, Decision Tree, etc) (SVM, KNN, Decision Tree, etc)to evaluate the most effective model for three RF signature metrics, Channel Transfer Function (CTF), CTF auto-correlation and Received Signal Strength (RSS). The authors of [52], applied support vectors in a mission critical system where monitoring indoor air quality is important. The model takes sensor data as input for the SVM algorithm and used the output in the control of air quality to notify humans about the air quality condition.

2) Unsupervised Learning: Machine learning algorithms that learn patterns from unlabelled data are categorized as unsupervised. Unsupervised learning algorithms classify sample data into meaningful classes based on the correlation or similarities that exist between the samples [66]. The ability to infer from unlabelled data makes unsupervised learning a promising approach for real-world problems such as in CPS/IoT where data is generally unlabelled. Unsupervised learning is common in modern deep learning algorithms, and is widely considered as the dominant learning approach for the future. However, its application to real world wireless network problems are yet to be fully manifested [24]. The most commonly used unsupervised ML algorithms are K-mean clustering, Principal Component Analysis (PCA), and Neural networks.

Unsupervised ML algorithms have been used in the literature for different problems in wireless networking pertaining to IoT and CPS. In [67], the authors proposed a priority scheduling technique based on K-Means clustering algorithm to minimize transmission delay, reduce collision rate and maximize throughput of Long Range WAN (LoRaWAN) in IoT systems. The authors of [51] proposed a solution for delivering critical capabilities to the tactical edge. Important capabilities are enhanced by using K-means and Software-Defined Networking to increase the number of users that are connected to the wireless mesh networks via IoT devices in the battlefield. A digital twin of the environment is used to evaluate and validate whether the proposed K-Means clustering based topology management solution is capable of establishing and maintaining route through reduction of packet overhead in large wireless mesh networks. In [68], the authors leverage K-means clustering to develop a new optimization algorithm known as K-means Multi-group Quantum Particles Swamp Optimization, for deployment of actuator nodes in CPS. K-means clustering was used to generate an initial solution to improve the search efficiency of the Quantum Particles Swamp optimization algorithm. The paper [44], aimed to address latency minimization in CPS and implementation of network intelligence services in network virtualization based middle-

TABLE II: A summary of survey works on machine learning for CPS and IoT

Related works	Overview	Supervised	Unsupervised	Reinforcement	Deep Learning	Distributed	Federated	Transfer
[23]	Overview of ANNs for wireless networking.	✓	✓	✓	✓			
[24]	Survey of NNs for applications in wireless networks.	✓	✓	✓	✓			
[25]	Survey of the applications of DL algorithms for different network layers.	✓	✓	✓	✓			✓
[26]	Survey of the crossovers between DL & wireless/mobile networks.	✓	✓	✓	✓			✓
[27]	Survey of ML & DL techniques for analytics and learning in the IoT.	✓	✓	✓	✓			✓
[28]	Tutorial & survey for DRL approaches in communications and networking.	✓	✓	✓	✓	✓		
[29]	Survey on learning techniques of self-organizing networks (SON) solutions in cellular networks.	✓	✓	✓	✓			✓
[30]	Survey on DRL for mobile edge caching problems.		✓	✓	✓	✓		
This work	Survey on AI/ML techniques for wireless IoT/CPS	✓	✓	✓	✓	✓	✓	✓

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TABLE III: AI/ML Approaches to Wireless IoT/CPS.

AI/ML Research Endeavors to enhance deployment of IoT/CPS		
Automation & Control	Computation	Communication
• RL and DRL techniques application to automatic network reconfiguration are reported in [37], [38], [39]. • K-mean based AI solution was used to achieve minimum-latency communication in CPS Energy Internet ecosystem [44]. • Recursive PCA cluster framework was used in [49], [50] for data aggregation, control and fault diagnosis. • SVM was used by [52], where indoor air quality is being control.	• Distributed ML framework was proposed for fast convergence of Stochastic Gradient descent when used at the edge devices of IoT systems [40], [41] • FL was used for proper scalability between radio resource block and the numbers of clients involve in training process [45], [46], [47] • DNN and Deep TL were utilized to minimize latency for uplink in a MIMO cloud radio network.	• KNN and Random Forest were used to classify network traffic in an IoT mobile device analysis [42], [43] • SVM was used to predict WiFi Coverage and to harness RF energy [48]. • K-mean was used to reduced the numbers of users connected to a wireless network IoT systems in battlefield scenario [51]. • K-mean was used in data clustering for effective classification as reported in [53].

boxes. The authors proposed a k-means based AI solution to address these problems. In [53], the authors used a K-mean algorithm in a deep learning framework to cluster heterogeneous data. In [49], a recursive PCA cluster framework was proposed, where the method helps to overcome problems associated with detection of irregular sensor output, and data aggregation in IoT systems. The recursive PCA algorithm was used for sensor data aggregation after gathering the data into clusters. An automobile CPS online implementation problem was investigated in [50], a control and fault diagnosis framework based on recursive total principle component regression was proposed.

3) Reinforcement Learning: Reinforcement learning (RL) is a process in which the model or agent periodically takes a sequence of actions enabled by a feedback loop between the model algorithm and the environment [69], [70]. The actions of the agent follow a game-like situation based on the interaction with the environment. The algorithm employs a trial and error approach to converge at a solution. There is a reward or penalty for the actions that the agent performed. Typically a RL system or agent interacts with its environment, senses the state of the environment and its own current state, then selects an action to be taken. The main terminology for reinforcement learning is broadly divided into four terms: *Policies* defines how the agent states and actions at a given time; *Reward function* defines the rewards or penalties that the environment sent to an agent for each action taken; *Value function* represents the expected total reward for an agent starting from a particular state; *Environment model* represent the state and actions that can be taken by an agent. Reinforcement learning has been widely used in literature in the form of deep reinforcement learning, for many wireless networking application and CPS

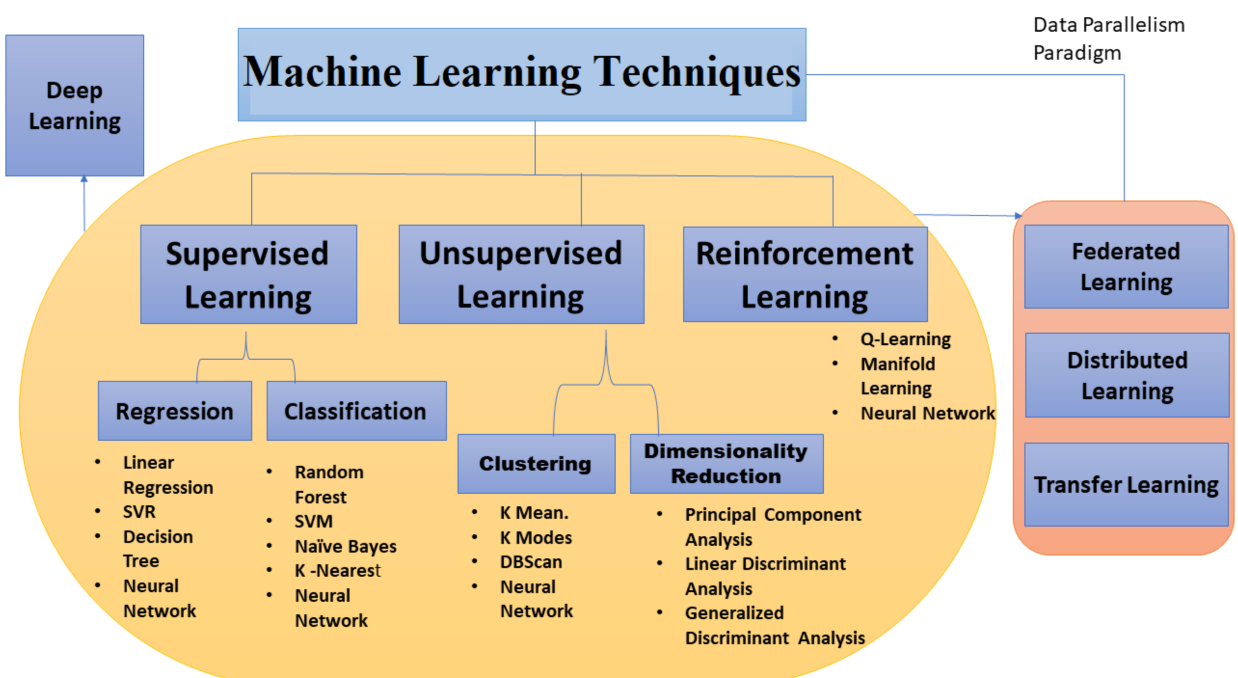

Fig. 2: A classification of machine learning into supervised, Un-supervised, and Reinforcement learning. classification also include data parallelism paradigm

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and IoT systems. Further details on reinforcement learning can be found in [69], [29].

In [37], the authors proposed a reinforcement learning based approach by designing policies to automatically reconfigure network systems and control systems dynamically in an industrial IoT system, the network systems include wireless cyber physical components. The authors of [38], developed a route planning algorithm based on deep RL to avoid service interruption and congestion in a smart grid CPS. In [39], an optimization problem was formulated for service placement, scheduling and resource allocation under uncertainty for an industrial CPS, this formulation included a deep Q-network to assist in scheduling decisions. Transfer reinforcement learning using Q-learning algorithm has also been studied in [71], [72], [73]. [71] studied a reinforcement learning approach for experience transfer in context awareness where a demonstrator agent has the privilege to access context aware policy. A Q-learning algorithm was proposed that converges to a true value function without any form of bias. [74] evaluated the potential of Q-learning as a strategy for minimizing network congestion by developing a Q-learning framework for channel bandwidth allocation for uncertain network communication in CPS applications.

A. Federated Machine Learning

Federated learning is an efficient distributed machine framework that supports learning at multiple user equipment or network edge using local training data. [75], [76], [77], [78] In federated learning, the training process is decentralized to ensure data security and privacy. The learning task is solved by each user equipment (UEs)/clients, which then updates the model parameters to a central (federated) server. The datasets of each UE are never updated to the global server. The global server maintains the current global model parameters and communicates (until the model converges or is interrupted) the global algorithm states or models to selected UEs for further training to improve current model. Figure 3 shows a federated learning model with each client performing an uplink upload $(\theta_1^{'}, \ldots, \theta_k^{'})$, while the federated server manages the downlink upload (θ^{+1}) and parameter aggregation.

Definition: Considering K numbers of clients. $D_k \triangleq \{x_j, y_j\}_1^K$ is the number of data samples available during training for client k. The sample data D_k may not be identical. Also, a given D_k may not have label y_j for training, hence, learning may be self-supervised or unsupervised. The clients jointly train the federated model, without sharing their respective local data during the process. x_k is a matrix of data set with its rows representing samples and columns representing features. The space of the features is denoted by X, the space of the label is Y, and I is the sample IDs space. X, Y, I constitute the complete training data set. The objective is to solve the global loss function $J(\theta) = \sum_{k=1}^{K} \frac{|D_k|}{D} J_k(\theta)$, after training local model of participating clients, using their respective loss function $J_k(\theta) = 1/|D_k| \sum_j^{|D_k|} f(x_j, y_j; \theta)$. Federated learning can be classified into three categories [78]; horizontal federated learning $X_i = X_j, Y_i = Y_j, I_i \neq I_j \forall i \neq j$, vertical federated learning$X_i \neq X_j, Y_i \neq Y_j, I_i = I_j \forall i \neq j$, and federated transfer learning, $X_i \neq X_j, Y_i \neq Y_j, I_i \neq I_j \forall i \neq j$.

Federated machine learning is a recently developed AI technique, that can aid wireless smart devices in analysis and intelligent decision making by training the clients using data observed or generated from their environment. AI/ML have been used extensively in literature to enable edge computing, with the aim of improving quality of experience (QoE) and reducing network traffic. Edge computing itself is a distribution computing paradigm aimed at bringing computation process close to user locations in order to improve services request response time and reduce bandwidth utilization. Therefore, FL makes a perfect framework for edge computing. [79] developed a criterion for evaluating the performance of the learning system, and provided closed form solutions for communication resource allocation in wireless federated learning system. [80] proposed a robust FL framework for wireless communication that is robust against malicious devices, and capable of reducing communication overhead.

In response to the need for a reliable wireless communication and an efficient data privacy scheme for better quality of experience for users, considerable research has been undertaken. [81] proposed a FL based algorithm for wireless network with a learning rate that is adjustable to environmental change. Their research evaluates the performance of FL (particularly convergence rate) using practical scheduling policies (random scheduling (RS), round robin (RR), and proportional fair (PF)). Since FL involves transmitting stochastic gradient and deep learning parameters across wireless channels, large latency in training can arise. Also, an enormous amount of energy is required to maintain communication between the devices and the FL server. The authors of [82] focused on improving performance associated with federated learning aggregation latency by utilizing non-orthogonal multi access (NOMA) in their evaluation. In addition, since federated learning algorithm requires frequent update of gradient parameters, the network may become overloaded. To alleviate this burden, compression of gradient parameter and reduction of frequency of upload during training are considered possible solutions.

Some research has been focused on designing new gradient descent methods to reduce the update rate [83], [84]. The schemes from [83], [84] assume an error-free update, and that radio resources at the client are dedicated [45]. However, enormous number of clients may be involved to achieve proper scalability. A possible solution for the scalability problem between the radio resources block and number of clients involved, has been presented in the study by [45], [46], [47], using analog transmission scheme that employs over-the-air computation that allows sharing of common blocks by the clients. The scheme proposed in [85], exploits simultaneous transmission with waveform superposition over a multi access channel. Essentially these methods require trade-offs between the number of connected clients, signal to noise ratio (SNR) and learning metric. Other studies have approached the potential overload in network problem by compressing stochastic gradients (SGs) either by quantization or by sparse [86], [87], [88].

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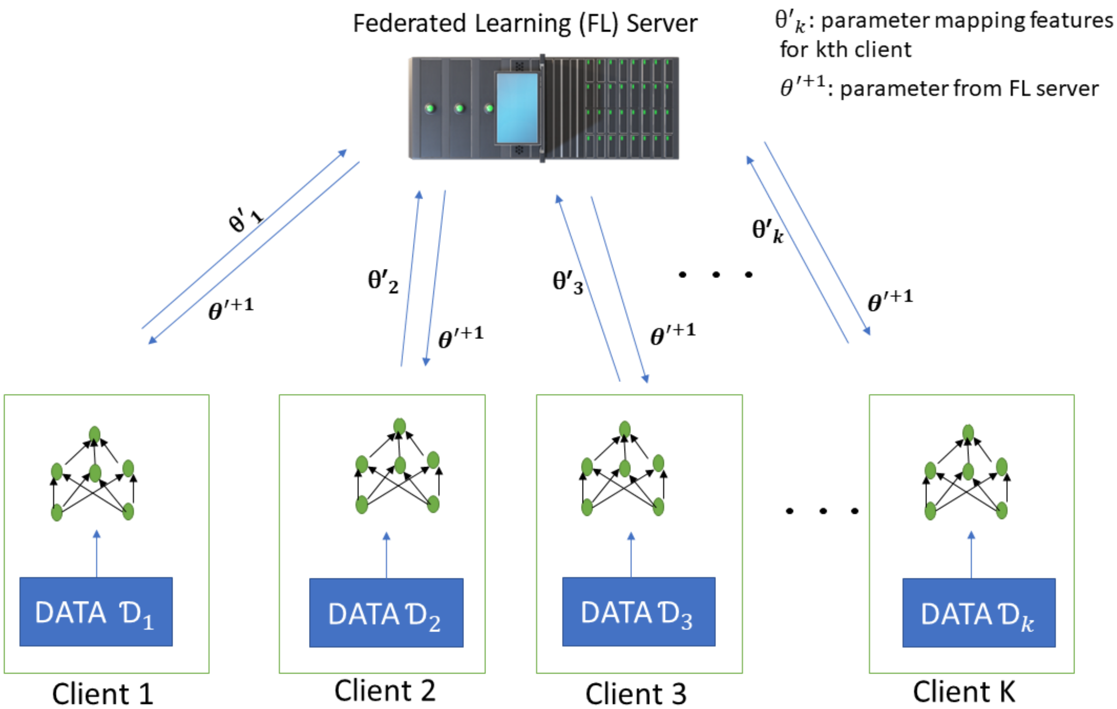

Fig. 3: An Illustration of Federated Learning Framework where clients report learning parameters to FL server and FL server broadcasts the global model after aggregating the parameters received from clients.

B. Distributed Machine Learning

Distributed machine learning refers to the process of splitting model training into multiple mini processors working in parallel to improve performance, accuracy and accelerate model training [89]. These multiple mini processors are known as worker nodes. Distributed machine learning also allows training data sets that are naturally distributed making it a promising approach for remote training in real world scenarios of IoT and CPS paradigms. The demand for distributed machine learning algorithm has grown significantly over the past decade due to the availability of massive data that are easily generated as a result of continuous development of newer technologies. Distributed machine learning algorithms are suitable for computationally intensive tasks, which makes it widely applicable to deep learning training of big data. In distributed machine learning, workload is divided into n segments to run simultaneously on n worker nodes. The two main types of distributed training are data parallelism and model parallelism.

1) Data Parallelism: In data parallelism, data is distributed across multiple nodes that train the subsets of data. Data parallelism is the most widely used ML distribution approach. It is applicable in any ML program by splitting data into multiple worker nodes. The worker nodes subsequently operate on their own data-set using the same algorithm. Data parallelism is applicable to ML algorithms with the assumption that data samples are independent and have an identical distribution [90].

2) Model parallelism: Model parallelism segments parallel paths of a model to run simultaneously on different nodes. Here, the parallel part of a model is segmented into different parts to run simultaneously on worker nodes using the same data. The worker nodes only synchronize their shared parameters. Since the nodes operate on subsection of the model, large models using deep learning can be executed.

Definition: Consider data x to be trained with model $A = A_{j1}, ...A_{jN}$ in model parallel algorithms, where the model parameters A_j are not, in general, independent of each other. The model A is partitioned and assigned to worker nodes $p = 1, ..., P$ working in parallel and updated by running update function Δ_L. The model is defined as $A(t) = F(A(t-1), \sum_{p=1}^{P} \Delta(A(t-1), x_p))$. Where $S_{p,(t-1)}$ is the scheduling function that restricts δ_L to the subset of A. The model parallel algorithms are effective only when each iteration of parallel updates is restricted to a subset of mutually independent parameters [91]. Further details on the definition can be found in [91].

Some distributed ML models focus on convergence speed to reduce the model training time in the presence of massive data and large model. Convergence solution have been proposed for both gradient descent and Stochastic gradient descent [40], [41]. In [40], the authors proposed a convergence solution for feature distributed machine learning (FDML) that analyzes asynchronous model parallel stochastic gradient descent in a version similar to widely used Stale Synchronous Parallel (SSP) algorithm. In this scheme, every participating worker node is responsible for updating its own local features and

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only upload its predicted model to a central model server. SVM learning algorithms have been used for sensor networks [92], [93]. These solutions take advantage of the fact that SVM is a quadratic optimization problem and allows the use of existing convex optimization methods. In [92], a gossip based incremental SVM algorithm was developed for a fully distributed communication between sensor nodes.

C. Deep Learning

The evolution of deep learning (DL) is the most promising one within the field of machine learning. It allows for learning using multiple levels of abstractions in multiple layers to discover intricate structures that are in large datasets. Deep learning uses back propagation algorithm to determine changes that need to be made to the internal parameters in each layer[94]. Although the current applications of deep learning are in image processing, speech recognition, video and natural language processing, it has the capability as a ML techniques for other fields. For example the amount of big data that future CPS and Iot systems can generate will require deep learning for intrinsic analysis.

Supervised deep learning includes fully connected Feed forward Deep Neural Networks (FNN), Recurrent Deep Neural Network (RNN), Convolutional Feed forward Deep Neural Networks (CNN), while unsupervised DL includes Deep Belief Networks (DBN) and Stacked Auto Encoders (SAE) [95], [96] and cyber-deception in wireless systems [97]. In [98], the authors aim to optimize the data collection in IoT networks with edge computing. A deep learning solution was proposed for dynamic network clustering in IoT networks with edge servers. A semi supervised DL framework for indoor localization based on Bluetooth in an IoT system was proposed in [27]. The framework deploys variational autoencoders as the main inference engine for the model's optimal policies. In IoT and CPS systems, the edge devices generate data samples that need to be properly labelled, and appropriate sample labels pose a challenge to the network. A semi-supervised deep Q-learning framework for human activity recognition in health based IoT was proposed in [99] by efficiently evaluating the improperly labelled sensor data, and using them to train the classifier to intelligently auto label. The authors of [100], formulated an offloading problem for IoT uplink MIMO Cloud Radio access network with latency as constraint, and utilized supervised deep neural network and deep transfer learning to learn from the proposed solution in order to enhance the performance of the algorithm.

D. Transfer Learning

Transfer learning (TL) aims to improve the ability to learn a new task on a target domain through the transfer of knowledge from a related task that has already been learned [101]. In contrast to other ML approaches that based learning on training separate isolated models for specific tasks and datasets without retaining any knowledge, TL leverages knowledge (e.g weight, features) from previous trained models to train a new model. Essentially, it involves the re-use of an already trained model for a different problem. TL learning can help reduce the dependency on many target domain data training [102]. Deep TL has been proposed in [103] for physical layer security in wireless communication systems by considering contested wireless environment such as wireless IoT in battlefield. Figure 4 is an illustration of the concept of transfer learning. For instance, in applications such as Automatic Speech Recognition (ASR), assuming that the task, say T_s, is to recognize a native English language speaker, given dataset $D1$, an ASR model is trained and tuned to classify the speaker from an unseen data from the same domain. We must be able (in ideal situation) to use the knowledge to detect a native speaker in New York (Target task, T_t) given dataset $D2$, if the trained model of T_s generalized well. However, this is not always the case due to performance degradation and possibility of source model not generalizing well. The potential of TL has made it popular in many promising applications in literature, hence, algorithms that facilitate use of TL are of interest in CPS and IoT development communities. Some early transfer learning approaches can be found in [104], [105], [106], for transfer of ML, in context of cognitive framework [106] and for planning task [105].

Recently, TL has been applied for many applications in wireless networking, CPS and IoT systems. In [107], [108], a deep transfer learning framework was developed for human activity recognition by exploiting channel state information of WiFi. The algorithm first extracts and classifies features using deep convolutional neural networks by transforming channel state information to images, then uses transfer learning to infer knowledge from the pre-trained model. [109] applied transfer learning between nodes in the same network of sensors. The authors used classifier ensemble random trees to create activity recognition model at a specific node and transfer the knowledge to another node within the same network. The scheme was tested for both relocation scenario (the training moved to an unknown location) and replacement scenario (a new node replaced the node at the training location). [100] used deep transfer learning in their scheme to adjust NN in dynamic IoT system. A deep transfer learning model has also been used in [110] to propose a tag signal detection in ambient back-scattering communications to reduce energy utilization in IoT systems.

Table IV shows some of the research work that utilize ML techniques to enhance IoT/CPS.

III. Research Challenges and Perspectives

CPS and IoT have massive number of devices connected and large scale sensor networks that monitor physical environment and communicate largely via wireless links/technologies based on the desired sensor application. Wireless networking for CPS is subjected to many communication problems that includes throughput, latency and bandwidth etc. For CPS to effectively map and characterize physical plants and communicate effectively, reliable data and information exchange is required. In this section, we present challenges that come with wireless IoT/CPS and current studies aiming to apply AI/ML to enhance network connectivity, reliable data exchange, and security in IoT systems.

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TABLE IV: AI/ML Research for Wireless IoT/CPS.

Approach	Objective	Merit (+) and Limitation (-)
K-mean clustering algorithm for Collision rate and transmission delay minimization of LoRaWAN based IoT system [67].	To enable the throughput maximization for users that are connected to the wireless mesh network via IoT devices.	+ Scalable to large data set. + Reduce interference in wireless Network. - Results depends on number of nodes.
Irregular sensor output detection using PCA cluster framework [49].	Data aggregation and outlier detection in IoT/CPS system.	+ Reduce computation burden on sensor nodes. - Centralized model/single point of failure.
Online implementation scheme for control and fault detection of vehicular CPS using recursive Principal Component Regression [50].	To enhance road safety and transportation system using high-level control and management scheme enabled by CPS.	+ Minimize irrelevant memory utilization. + Parallel-running batch processes monitoring. - Limited key performance indicator.
Route planning algorithm based on DRL [38].	To avoid service interruption and congestion in smart grid CPS.	+ Low risk impact. - Complexity.
Q-learning for bandwidth allocation in communication networks [74].	To reduce congestion in communication network for CPS application.	+ Applicable to complicated Nonlinear systems. - Computational Complexity.
A framework to analyse FL convergence in context of wireless networks [81].	To analyse the effectiveness of scheduling policies for FL used in wireless networking.	+ Eliminate single point of failure + enhance information security and privacy + Reduced complexity. - Cost: computation burden on UEs.
FL framework for resources allocation in wireless networks [79].	To allow decentralized DNN training for wireless system.	+ Eliminate single point of failure. + Enhance information security and privacy. + Reduced complexity. - Cost: computation burden on UEs.
Deep Q-learning for intelligent auto labelling [99].	Human activity recognition in healthcare based IoT.	+ Suitable for large data. + Applicable to weakly labeled data.
TL model was used to infer knowledge from a DL pre-trained model to extract channel state information of WiFi [107], [108].	Human activity recognition.	+ Use small data set due transfer of pretrained model. + Reduce computational complexity. - Require function transferred to be generic.
Supervised NN and Deep TL are used to solve the problem of offloading computational task to a MIMO cloud in IoT application [100].	To enhance radio access network performance.	+ Low complexity solution. + Fast computational time.
Deep TL model for tag signal detection [110].	To minimize energy utilization for tag network of IoT system.	+ Use small data set due transfer of pretrained model.

A. Connectivity

An objective of IoT/CPS is to allow exchange of data between connected devices irrespective of their geographical locations. AI/ML techniques are used in IoT systems to train data dependent models for informed decision and better QoS. This data exchange requires reliable communication network to achieve desire QoS objectives as well to collect reliable data for AI/ML training. However, due to ubiquitous nature of CPS and IoT systems, network connectivity is a challenge task that goes beyond traditional computer networking. Network connectivity in IoT described how an IoT equipment or device can be connected to a communication link beyond its local network, typically via wireless links, and establish or allow communication with another device in the IoT network. A solution is to develop scheduling schemes that can ensure connectivity in the IoT systems, by minimizing the network latency and maximizing the throughput. Power management and scalability are also important in network connectivity.

1) Scheduling in IoT/CPS: Time scheduling, i. e the order of executing task, is an important factor to be consider when deploying IoT systems, and when AI/ML models are to be used. Time scheduling can help manage application run time and increase throughput in the network. In IoT and CPS networks, throughput needs to be maximized to ensure reliable communication between elements of the network, including machine to machine communication (M2M). When scheduling task execution order, it is important to consider other factors that are directly related to scheduling and may also cause network throughput failure. Factors such as bandwidth capacity, limited power at edge devices, and availability of alternative network communication links all need to be considered in developing effective task scheduling system for better quality of service. For example, transferring DL models from an IoT device to another utilizes bandwidth due to large model size, and may cause low throughput or communication failure for other devices in the IoT network, therefore this task should be executed during the specific window with less bandwidth

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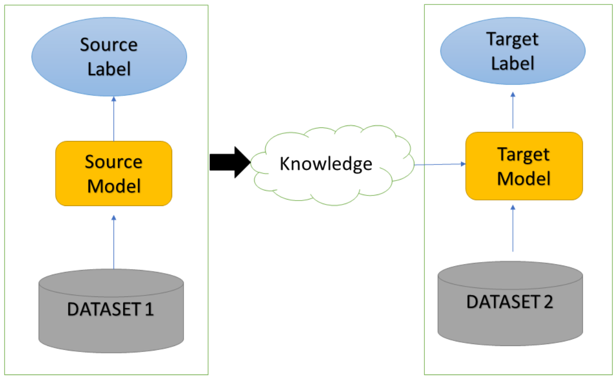

Fig. 4: An Illustration of Transfer Learning Framework

requirement. Resources allocation, i.e which machine the task is assigned to, is another perspective for scheduling resources to maximize throughput when AI/ML is deployed in CPS and IoT systems. Resources allocation is a challenging task due to the heterogeneous nature of device in IoT systems. Resource allocation is a challenge that impact in connectivity because of the difficulty in determining, at any instance, the memory capacity of edge device in large IoT networks. This is challenging because many edge device perform task and store data independently without the need to inform any other device in the network. Therefore, resource allocation schemes are important in scheduling task such as AI/ML modeling and training, to any device in CPS and IoT networks.

2) Power Management in CPS/IoT: Power management is another constraint that needs to be considered to ensure that connectivity remain established in IoT systems. Power management requirements increase with increase in number of devices. Some IoT and CPS devices such as actuators and machines are located where AC power is available, while others are in remote area, and they largely depend on battery power. Limitation of battery life pose a lasting challenge for AI/ML application in IoT networks despite improvements in storage technologies. It is important to develop solutions that can constantly monitor battery status of IoT devices to identify which one need to be recharged, which one may result in packet loss during routing, and which device has sufficient power to run AI algorithms.

3) Scalability: Massive deployment of CPS will require addition of new devices or applications to an existing CPS architecture or redesign of the current architecture for smooth integration. Expectations may include demands from different bandwidth, spectrum sharing, and automation. Effective route optimization and spectrum sharing will play a significant role in network architecture design, an example application to UAV is proposed using ML algorithm in [123]. In particular, transfer learning can be use to learn and store knowledge of a specific architecture, the knowledge can then be reused when network architecture changes or when a CPS domain is matched. Future work in AI/ML for IoT/CPS will need to address the challenges of developing network architecture standard that works across different connected device, while simultaneously maintain robustness in connectivity.

B. Latency in AI/ML deployment in CPS and IoT systems

Emergence of GPUs and other advanced technologies that makes it easier to process data at faster rate, contributes to the increased use of AI/ML in IoT systems. Most ML models require GPUs to timely and efficiently process large set of data that it needs to yield better results. These GPUs are largely available only in centralized or cloud infrastructures where storage and power are generally not limited. Therefore, one way of deploying AI in CPS and IoT, is to send data from sensors and edge devices to large units to be trained by ML models. In this approach, AI/ML deployment in IoT introduces additional latency in the system, and it generally not reliable in system with low latency requirement. Some devices may require low latency due to the rate at which they communicate their data, while others may communicate at very high rate. For example, Industrial IoT applications cannot afford system delays and latency needs to be minimized. Hence, deployment of AI/ML will only be effective if capacity is increase and latency minimization is developed. In contrast, an electric smart meter sends data at high intervals. In some cases these kinds of devices will have to coexist, communicate autonomously and use the same communication link. Also, due to the increasing numbers of connected devices in wireless networking of CPS, non-deterministic latency is one of the challenges of wireless networking for CPS [111], [112]. One of the recent 3GPP identified performance objective is to deliver a 20-byte application layer packet at a latency of about 10 seconds or less (from event triggering to packet ready to be transmitted), as the uplink is required for applications delivering critical service [113]. However, this latency depends on network and application requirements and how critical the application is to the overall network. In other to effectively apply AI/ML in IoT systems, It important to ensure latency is in the IoT systems, and latency imposed by the introduction of AI/ML in the system are minimized.

Recent trends in CPS and IoT focus on minimizing network latency. The authors of [114] used a federated decentralized learning paradigm to approach latency minimization problem in a multi-access edge computing IoT network. The task is formulated as a hospital-resident assignment task, acknowledging the facts that numbers of IoT devices can be large, an incomplete matching is performed. In [115], the authors consider a massive IoT system that has limited capacity and transmitting either periodic or critical information. A multi-state learning framework with finite memory was developed to allow heterogeneous IoT devices to allocate their limited resources in order to satisfy latency requirement. In their scheme, critical messages are prioritized by reallocating communication resources to information/messages that are delay intolerance. Furthermore, the scheme is capable of analyzing the expected network delay.

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The work in [116] studied downlink scheduling challenge for an industrial IoT system where the aim is to minimize the probability of transmission failure when the controller needs to send commands to multiple actuators. A generative adversarial network (GAN) framework is exploited to derive an arbitrary distribution framework using historical data samples for training.

C. Distributed Machine Learning for Wireless IoT/CPS

In distributed machine learning, a large process is split into multiple small processes working together to accelerate the model training process. Some nodes (e.g mobile phone, laptop etc.) of an IoT system can be designed to perform local computational processes if enabled with adequate computational resources (processors, RAM, RoM, etc). Decentralized computing has been currently extended to distributive learning methods, making it suitable for training models at the edge devices without the need to consider the entire network. This is possible because in many IoT/CPS networks, datasets originates from sensors and actuators at the edge devices. Distributive machine learning paradigms, such as, Federated learning and Distributive non-collaborative learning algorithms have been developed for this purpose. For instance federated learning has been applied to handle scalability between the radio resources block and number of devices in a network, network overload and power allocation [47], [87], [46]. This concept can be deployed for open challenges such as how ML techniques can be used to allocate critical missions to a device or deliver information during network resource allocation that is based not only on active device but also on how each device handles new assignment/mission. In some cases, where it is not possible to have all required data at a node/clients, training can be done by sharing the data-set. Furthermore, computational processes consume large amount of energy and it is not economically viable to make each device and plant module perform all the computational processes. Hence, its important to device a scheme to distribute computation processes and model training processes. In such cases, distributive collaborative learning will be the most promising learning paradigm. It is a topic of future research on how ML techniques can be used to enhance wireless network of IoT systems using datasets that maybe non-identically distributed with energy and bandwidth constraints.

D. Artificial Intelligence for IoT/CPS

Artificial Intelligence, Machine Learning and IoT/CPS are now synonymous with each other as both IoT and CPS rely heavily on AI/ML systems. AI for IoT/CPs holds tremendous growth and innovation potential. With advances in both IoT and CPS being dependent on the wireless technologies to maintain efficient operations, Artificial Intelligence will play a vital role in ensuring the availability and dependability of these systems. Since IoT/CPS both rely on the multitude of sensors and machines, AI systems can provide data-analysis and predictions with the accuracy and precision needed for a seamless and efficient operations. AI systems will play a critical role in IoT/CPS data fusion, analysis, prediction and security. With cost-effective, streamlined and distributed AI systems connected via the wireless networks, challenges such as data-fusion, security and privacy for the data still remain a large hurdle. While a plethora of new techniques and methodologies are available in literature for AI prediction and analysis in IoT/CPS such as blockchain, edge-learning and edge-computing [117], [118], [119]. Future work in AI for IoT/CPS will need to address the challenges of multi modal data-fusion and security of AI in IoT/CPS.

For data-fusion a plethora of challenges plague the advancements of AI in IoT. Challenges range from data modality to operational timing and fusion level. *Data modality* is at the heart of IoT/CPS where sensors collect data from a variety of modalities. Data from all different modalities must be handled and analyzed properly via appropriate fusion schemes and methods. *Data registration* is another major challenge for AI systems in IoT/CPS as incoming data from different modalities need to be calibrated properly and transformed into a common frame for accurate and efficient data fusion. *Data trivialness* can be a major challenge for data-fusion in applications such as IoT and Smart-cities. The data collected from the numerous sensors can be both trivial and non-trivial,which affects the data fusion process. One way to overcome this is via feature extraction prior to the fusion process. *Operational timing* is another vital factor for data-fusion, specially for dynamic, real-time applications where different sensors might be operating under different frequencies, rates and environments. Therefore, different time scales must be incorporated to address the differences within the data from varying sensors or modalities. [120], [121]

E. Security and Primacy in AI enabled Wireless IoT/CPS

AI security is also a vital challenge facing IoT/CPS. With millions of smart devices connected via wireless networks, the privacy and security of consumer data is at the fore-front of research topics for the field. With advances in adversarial attacks against AI/ML systems, IoT devices must be robust to protect against any potential threats. Due to the varying and large attack surface areas involved with CPS/IoT, AI/ML systems must be both proactive and reactive in their defense against adversarial attacks to protect consumer data security and privacy. AI/ML systems in IoT will have to be robust against a number of different adversarial attacks. Different attacks need to be detected and dealt with via appropriate counter measures. An in-depth review on the security of AI/ML systems and IoT/CPS is provided in [122], [123], [124], [70], [125]

IV. Summary

In this paper we have provided a comprehensive survey on the use of artificial intelligence and machine learning for wireless CPS/IoT systems. We enumerate the most widely used and most promising wireless technologies and their respective range of operation that can be potentially be used for AI/ML enabled CPS and IoT networks. Furthermore, we review main types of machine learning techniques and other machine learning paradigms that are commonly used in AI/ML enabled CPS and IoT networks, and identified current literature

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that focuses on machine learning for wireless networking for IoT/CPS. Finally, we provided open challenges for AI/ML enabled CPS and IoT networks and potential future research directions.

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