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# Collective Intelligence Using 5G: Concepts, Applications, and Challenges in Sociotechnical Environments

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**ABSTRACT** Distributed intelligence is a well-known approach for optimizing interactions among numerous smart devices that interconnect and operate together as Internet of Things (IoT) systems. A modern form of human-machine *collective intelligence* emerges when humans interact with IoT systems in sociotechnical environments such as smart homes. Fifth-generation (5G) communication networks are designed for high-speed reliable wireless connectivity and expected to boost IoT and (distributed) collective intelligence by revolutionizing human–device–human interactions. In this paper, we contribute a comprehensive review of state-of-the-art sociotechnical environments that exhibit collective intelligence, supported by 5G-enabled IoT. We discuss the latest developments in 5G and their implications for collective intelligence. Further, we explain the key challenges for using 5G to support collective intelligence, e.g., data processing, security, and radio resource management. Finally, we describe four practical applications of collective intelligence to sociotechnical environments—road traffic control, unmanned aerial vehicles, electrical load demand response, and augmented democracy.

**INDEX TERMS** Collective intelligence, fifth generation (5G) communication, sociotechnical environments, wireless networks, Internet of Things (IoT).

## I. INTRODUCTION

Throughout human history, humans have gathered as a group and collectively made decisions that benefited the group and its members. Collective decision-making has been discussed and advocated by social scientists, economists, and philosophers on the basis that a diverse collection of independent decision-making individuals is often more likely to make better decisions than individuals or even experts [1].

Until the 20<sup>th</sup> century, studies on collective decision-making were usually confined to small groups

of humans (e.g., Condorcet's jury theorem (1785) [2]). However, two recent technological revolutions have transformed the collective decision-making landscape. First, the *computing revolution*—characterized by a tremendous boost in computational power and storage capabilities—has led to the development of devices that can observe the environment, perform computations, make independent decisions, and act autonomously. Second, the *Internet revolution*—characterized by a system of interconnected distributed computers—has enabled these devices to communicate with each other nearly synchronously with high accuracy. As a result, the modern world consists of local and global systems of networked architectures where numerous distributed

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devices—often called *agents*—exchange information and take actions with a high level of autonomy. These distributed agents are normally characterized by some amount of *intelligence*, i.e., the ability to independently observe the environment, make decisions, and perform actions to achieve goals. Moreover, since these “agents” also typically interact with other nearby agents through a communication network, they are capable of active coordination to collectively make decisions using, for example, mathematical tools such as game theory. Furthermore, human and virtual (software) agents often operate in the same environment today.

Thus, in modern collective decision-making, human and virtual intelligent agents, who are distributed throughout the action domain, interact to exchange information and collectively make decisions to achieve goals, with or without active discussions. This leads to a form of “shared” or “group” intelligence that is generally referred to as **collective intelligence**. Thus, while earlier adopters of the collective-intelligence concept referred to a form of decision-making where humans alone collectively make decisions to achieve a desirable outcome, a more updated modern definition is as follows [3]:

*Collective intelligence is a form of decision-making where intelligent, distributed human and software agents, situated in a networked communication system, receive information and feedback from their immediate environment and other agents and make decisions collectively to perform tasks that, together, achieve a common desirable outcome.*

Collective intelligence in this modern sense is characterized by four main features:

- 1) **Collaboration:** Human and intelligent software agents make *coordinated* decisions.
- 2) **Information exchange:** Human and intelligent software agents *exchange* information that is required to achieve a common desirable outcome.
- 3) **Distribution:** Human and intelligent software agents are *dispersed* in the network.
- 4) **Self-management and adaption:** Human and intelligent software agents are capable of *autonomously* adapting behaviors to manage themselves.

Here, it is important to note that collective intelligence can include interactions between human–human agents, human–machine agents or machine–machine agents, and this paper focuses on human–machine agents wherever possible. The key idea in collective intelligence is that *collaboration or cooperation among various individuals enables them to accomplish tasks that are beyond the aggregation of their individual capabilities*. Note that in this sense, collective intelligence expands on the concept of *collective learning* that refers to a dynamic and cumulative process in which knowledge is produced as an emergent result of dynamic and evolutionary interactions where information is shared between humans and software agents [4], [5]. Collective learning and collective intelligence are complex and highly inter-disciplinary concepts. Just as knowledge and learning are important essential ingredients for the formation of

human intelligence, the collective learning process is important for the development of collective intelligence. In other words, collective intelligence is the *outcome* of collective learning, where collective learning is a fully decentralized approach for coordinated multi-objective decision-making in multi-agent distributed systems.

Collective intelligence (Fig. 1) concepts are most often applied to decentralized sociotechnical environments, i.e., to system environments wherein people and technology interact regularly using a decentralized approach for managing the interactions. Many modern and futuristic technological applications, e.g., traffic systems and smart homes, are decentralized sociotechnical environments. Furthermore, in such sociotechnical environments, the underlying communications network is crucial for enabling the interactions among the distributed agents. The fifth-generation communications technology—popularly called 5G—is the latest communications technology standard that has emerged from a tremendous collective effort to standardize, specify, design, and manufacture the next generation of mobile communications [6]. 5G is an ambitious advancement that is expected to go beyond the fourth generation of mobile networks (4G) and its important innovation, mobile broadband communications. In particular, 5G is expected to provide greater bandwidth and higher download speeds and to revolutionize the way humans interact with each other and with smart devices. Hence, 5G is a key enabler of the Internet of Things (IoT) paradigm and machine-to-machine communications, and consequently collective intelligence [7], [8].

Therefore, in this paper, we discuss collective intelligence enabled by 5G communications technology and applied to decentralized sociotechnical environments characterized by distributed agents and distributed intelligence. We present the latest developments in 5G along with a discussion of a recently developed related computing concept—pervasive edge computing—and describe its theoretical foundations. Both 5G and pervasive edge computing are expected to revolutionize human–device–human interconnections and support collective intelligence, but many challenges remain to realize fully developed practical solutions. We have identified the key challenges—e.g., data processing, security, privacy, and radio resource management—and described them in detail, focusing on the current research status and future research potential.

Since many modern and future technologies comprise strong interactions between people and technology, especially via the increasingly ubiquitous Internet, collective intelligence is applicable to many fields, for example, medical technology, energy sector, and public transportation. In particular, Internet-enabled applications are proliferating today, leading to the creation of several sociotechnical environments with strong human–machine interactions, and collective intelligence (and learning) is a valuable paradigm to model and optimize these interactions. In this paper, we have chosen four modern practical sociotechnical environments where some form of collective intelligence can be applied: road

traffic control, unmanned aerial vehicles (UAVs), electrical load demand response, and augmented democracy. We have chosen these examples carefully to illustrate the application of collective intelligence to different fields—transportation, robotics, electricity grid, and sociology, respectively—that have a huge impact on society and societal progress, often directly affecting the environment, social interactions, economic progress, politics, etc. The transportation sector, for example, has one of the largest carbon footprint in several countries, whereas electrification influences numerous socio-economic factors, ranging from health to education [9], [10]. Therefore, in this paper, we demonstrate the wide applicability of collective intelligence in modern society and to impactful fields by surveying important previous and current academic research, developments, and trends.

In contrast to this work, most survey papers and books on collective intelligence have focused on general frameworks and discussions without explicitly discussing the impact of 5G communication technologies and 5G-enabled IoT, and the consequent challenges and opportunities [11]–[13]. In this paper, we provide a holistic perspective on a missing link in the current state-of-the-art on collective intelligence, *viz.*, the relationship of 5G communication with collective intelligence and its impacts. First, based on the discussions in prior literature and modern trends, we provide a timely definition for collective intelligence. Then, the paper explicitly and extensively surveys and discusses state-of-the-art research on collective (distributed) intelligence in the 5G context. Moreover, this paper also highlights cross-layer aspects of 5G and collective intelligence; that is, the paper not only considers the application layer and the challenges in their implementations, but also discusses the requirements from the lower communication and infrastructural layers for enabling efficient collective intelligence. Thus, this paper presents state-of-the-art research in collective intelligence and 5G-enabled collective intelligence that will enable researchers to clearly the key ideas and principles, the challenges that hinder successful implementations, and the potential future developments.

The rest of this paper is organized as follows. Section II explains the key concepts underlying the implementation of collective intelligence in decentralized sociotechnical environments. Section III deals with the challenges that still remain before the promise of 5G-based collective intelligence is realized. Section IV describes some practical applications of collective intelligence to decentralized sociotechnical environments, and Section V summarizes and concludes the paper.

## II. KEY CONCEPTS IN COLLECTIVE INTELLIGENCE

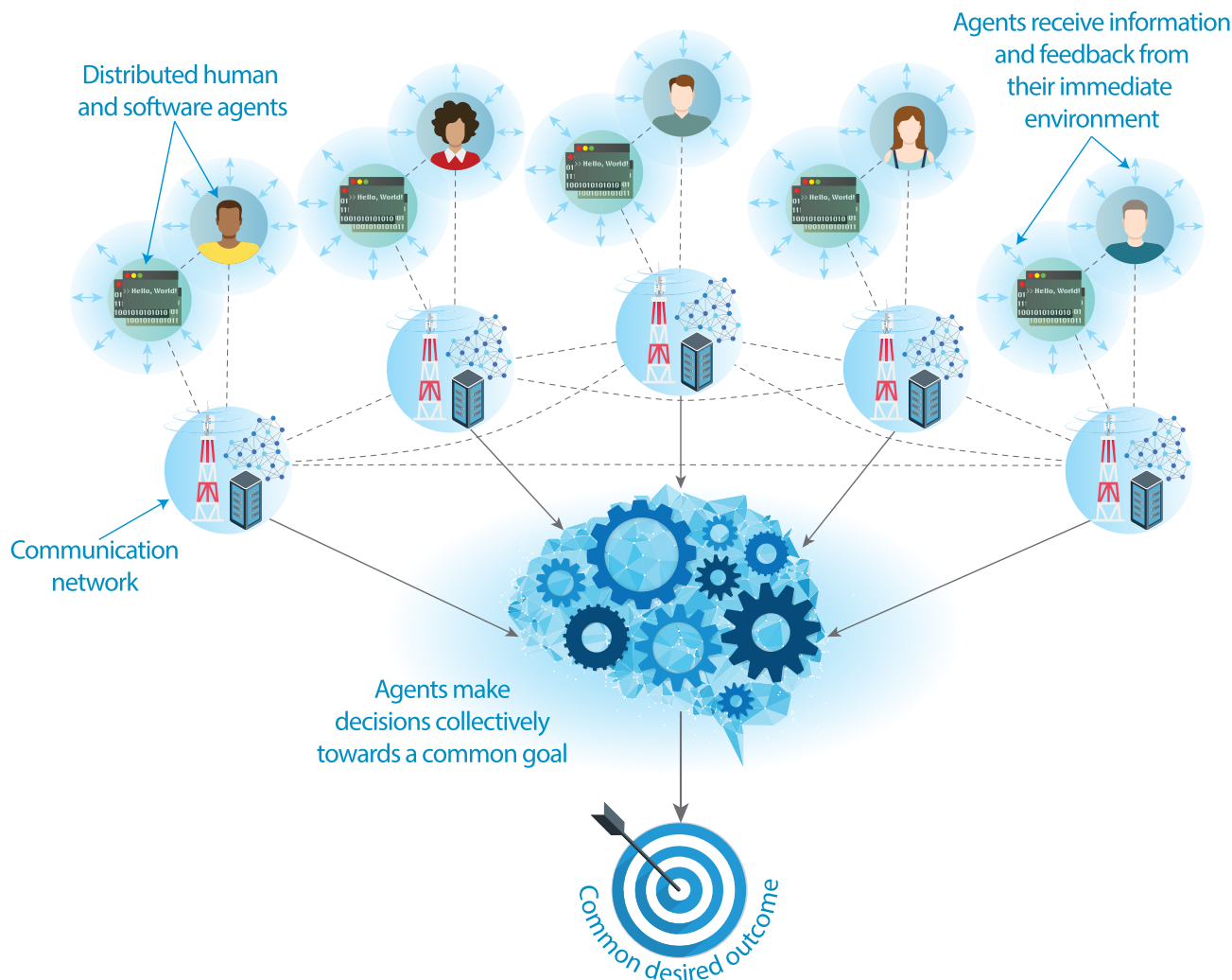
In this section, we explain the key concepts underlying the implementation of collective intelligence—the decentralized sociotechnical environments and IoT systems where it is most naturally applied, 5G communications network that supports its deployment, and the pervasive edge computing architecture that enhances its capabilities and performance.

### A. DECENTRALIZED SOCIOTECHNICAL ENVIRONMENTS

Collective intelligence is particularly suitable for decentralized sociotechnical environments because they promote all four characteristics, collaboration, distribution, information exchange, and self-management. In this section, we first explain the idea of the near-ubiquitous decentralized sociotechnical environments and explain the impact of the IoT paradigm on its proliferation.

Sociotechnical environments refer to system environments defined by regular interactions between people and technology such as human–machine interactions and tactile internet [14]–[16]. They are enabled by sociotechnical systems in which designers attempt to jointly optimize both the social and technical elements so that social criteria such as human well-being and productivity have the same weight as technical criteria such as device lifetimes or efficiencies. In decentralized sociotechnical environments (Fig. 2), the primary actors—people and technology—are not only distributed in the network, but can also make independent decisions. Decentralization is an important approach for designing complex social environments with distributed actors, giving several benefits such as privacy preservation, self-adaption, independence, and social welfare [17]. The concept of sociotechnical systems and environments has evolved from simple one-to-one interactions between humans and machines to today’s idea that sociotechnical environments comprise a collection of massive number of IoT devices, where IoT refers to a network of “intelligent” physical objects—*i.e.*, objects embedded with sensors, software, and technologies—that connect and exchange data with other devices and systems over the Internet [14]–[16].

IoT for decentralized sociotechnical environments has been an active research area since early 2010s. In 2011, Vermesan *et al.* [18] suggested a roadmap to practically realize the IoT concept and design a complex social environment that enables pervasive IoT objects to dynamically and sustainably coordinate with each other. Further, the benefits of decentralized sociotechnical systems in the context of self-adaption of IoT applications for decentralized services have been explored extensively. For instance, Chernyshev *et al.* in [19] reported recent technological trends of IoT devices and key challenges facing their implementation from the viewpoints of network connectivity, data communication, and smart services. They contended that the key feature of IoT would be self-\* capabilities, which means that the IoT devices will need to be designed such that they learn, configure, act and react in runtime. In another work [20], Christian and his group extensively discussed the design patterns for self-adaptive systems and IoT. They defined self-adaptive systems based on [21] and [22] along with a taxonomy of centralized and decentralized self-adaptive systems. Four key steps—monitor, analyze, plan, and execute (MAPE)—were considered to be key for the basic implementation mechanism of self-adaptive systems and dynamic IoT services. Some real-world examples of MAPE include SmartSantander [23],



**FIGURE 1.** Collective intelligence: a form of “group” intelligence that emerges when intelligent, distributed humans and software agents in a networked communication system interact to take collective decisions or perform collaborative actions to achieve a common desirable outcome.

Feed me [24], DeltaIoT [25], Platform as a service, and Xively [19].

Agent-based and multi-agent-based methods can also be used to design complex decentralized self-adaptive systems with key features such as autonomous control and cooperative decisions [26]. In [27], interaction patterns were designed to improve human interactions with ubiquitous IoT applications considering social and behavioral relationships. Similarly, the authors in [28] addressed the heterogeneity problem of IoT devices using agent-based modeling with a three-pattern strategy (strategy, dependency injection, and reflection), while the authors in [29] designed the following eight patterns for enabling the dynamic communication of IoT devices: device gateway; device shadow; rules engine; device wakeup trigger; remote lock and wipe; delta update; remote device management; and visible light communication. And in [30], the authors proposed security patterns for IoT for mobile applications. Further, in [31], the authors investigated the concepts of self-integration of various devices at run time and proposed a decentralized framework that encourages

the re-usability of (i) application-independent decentralized services and (ii) various IoT applications by the same decentralized service.

These researches into IoT-enabled decentralization implement some form of collective intelligence, and Table 1 lists the key collective intelligence principle explored by the researchers. However, none of these researches implement a complete collective intelligence solution, because of two reasons. First, managing numerous decentralized devices and their tradeoffs is a complex task. Secondly, an important enabling technology—a fast, reliable, and secure communication network for numerous small interconnected devices—is still not fully mature. In the next section, we will discuss recent and current technological developments in the search for building such a communication network.

### B. FIFTH GENERATION (5G) COMMUNICATION NETWORKS AND BEYOND

To realize its full potential, IoT-enabled decentralized sociotechnical environments require a flexible

**TABLE 1. Collective-intelligence principles and characteristics in researches into IoT-enabled decentralized sociotechnical environments.**

Research work(s)	Work area(s)	Collective intelligence principle
Vermesan <i>et al.</i> [18] (2011)	Roadmap to practically design a complex social environment for pervasive IoT objects to dynamically and sustainably coordinate with each other	<b>Distribution; Coordination</b>
Jung <i>et al.</i> [28] (2014)	Agent modeling to hide the heterogeneity of IoT devices using design patterns such as strategy, dependency injection, and reflection	<b>Coordination</b>
Chernyshev <i>et al.</i> [19] (2017)	Survey of technological trends of IoT devices and key challenges facing their implementation from the viewpoints of network connectivity, data communication, and smart services	<b>Coordination</b>
Reinfurt <i>et al.</i> [30] (2017)	Survey and extraction of core IoT principles of security patterns (frequently re-occurring problems and their proven solutions) for IoT devices and networks	<b>(Security of) Coordination</b>
Reinfurt <i>et al.</i> [29] (2019)	Survey and extraction of core IoT principles as patterns: device gateway; device shadow; rules engine; device wakeup trigger; remote lock and wipe; delta update; remote device management; and visible light communication	<b>Coordination</b>
Vega-Barbas <i>et al.</i> [27] (2017)	Design of a set of interaction patterns to improve human interactions with ubiquitous IoT applications considering social and behavioral relationships	<b>(Machine–human) Coordination; (Machine–human) Information exchange</b>
Krupitzer <i>et al.</i> [21] (2015)	Taxonomy of self-adaptation and a survey on engineering self-adaptive systems.	<b>Self-adaptation</b>
Weyns <i>et al.</i> [22] (2018)	Survey and discussion of the evolution of the field of self-adaptation in terms of six waves of research efforts—automating tasks, architecture-based adaptation, runtime models, goal driven adaptation, guarantees under uncertainties, and control-based approaches.	<b>Self-adaptation; Autonomy</b>
Krupitzer <i>et al.</i> [20] (2020)	Proposal of a taxonomy on design patterns for self-adaptive systems; a definition of self-adaptive systems based on [21] and [22]; and proposal of four key steps—monitor, analyze, plan, and execute (MAPE)—as the key for implementing self-adaptive systems and dynamic IoT services in sociotechnical environments.	<b>Self-adaptation</b>
Savaglio <i>et al.</i> [26] (2020)	Survey of agent-based computing paradigms and solutions for current and future IoT development in decentralized sociotechnical environments	<b>Distribution; Collaboration; Information exchange</b>
Fanitabasi <i>et al.</i> [31] (2020)	Introduction of a novel testbed architecture for decentralized sociotechnical systems running on IoT.	<b>Self-adaptation; Self-management</b>

communication network that can support different requirements, from ultra-reliable low-latency communications to massive connectivity [32]. Recent advances in 5G hold great promise since they offer greater bandwidth, faster data transmission, and improved spectral efficiency supported by localized private networks and micro-operators [33]–[35]. In this section, we introduce the 5G communications network and discuss its present status and future potential as a key enabling technology of collective intelligence, having been developed with the explicit intention to enable communication between pervasive devices.

The International Telecommunication Union (ITU) established the requirements for 5G through International Mobile

Telecommunications-2020 (IMT-2020) and its specifications are still currently being deployed worldwide along with the values and trends from the current International Communications Union - Radio-communication Sector (ITU-R) recommendations for 5G such as usage scenarios, traffic estimates for 2020 and beyond, etc [35]. In these recommendations, there is no explicit indication of the expectation of traffic generated by collective intelligence (or collective intelligence-like paradigms) or a proper traffic model for collective intelligence. Further, 5G standards development organisations, such as ITU, Third Generation Partnership Project (3GPP), Institute of Electrical and Electronics Engineering (IEEE), and 5G Infrastructure Public Private



**FIGURE 2.** Decentralized sociotechnical environments, where people and technology are distributed in the network, but interact regularly and make independent or collective decisions.

Partnership (5G PPP), have established the full buffer packet arrival and Poisson packet arrival as the main traffic models [7], [36]. In the full buffer traffic model, an infinite amount of data waits for transmission in the output buffer associated with each data source. Since collective intelligence operates with relatively numerous mobile terminals, it is plausible to assume that the devices’ processing capacities and the amount of information useful for training data generated by each user are heterogeneous. Therefore, it yields random time intervals (statistically different for two distinct mobile terminals) between the sending packets. Thus, regardless of the collective-intelligence technique adopted, the full buffer model is a somewhat unrealistic approach to collective intelligence. On the other hand, the Poisson packet arrival model, in which the Poisson process is used to represent the

message arrivals in a packet-data network, characterizes this scenario better.

5G is being specified to support a broad range of applications with diverse requirements such as gigabyte rates, smart homes, smart cities, self-driving cars, industrial automation, augmented reality, 3D videos, and Ultra-High Definition (UHD) screens. These applications can be classified into three major classes—enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (URLLC) [32]. eMBB comprises applications with ultra-high data rate requirements that can exceed 1 Gbits per second, e.g., interactive control of IoT devices via augmented reality or communication among industrial wireless routers or IoT gateways. The mMTC class is focused on enabling energy-efficient communication to

massive numbers of low-powered devices with low data rate requirements, possibly reaching up to one million connections/km<sup>2</sup>; this can support, for example, the massive number of sensors in futuristic smart factories and smart grids. URLLC incorporates a set of features that aim to provide low latency (as low as one millisecond) and ultra-high reliability for time- and mission-critical applications such as smart grids, remote surgery, industrial internet, and intelligent transportation systems. The most important stringent requirements, or the key performance indicators, are latency, reliability and, availability [37]. Table 2 lists some of the key requirements of 5G technology as specified in IMT-2020 along with its relevance to collective intelligence principles and applications [35], [38]–[40]. In this table, *peak data rate* refers to the maximum attainable data rate under error-free conditions; *peak spectral efficiency* to the maximum theoretical data rate under standardized conditions divided by channel bandwidth; *user experienced data rate* to the fifth percentage point of the cumulative distribution function (CDF) of the number of correctly received bits for a certain time; *5<sup>th</sup> percentile user spectral efficiency* to the fifth percentage point of the normalized throughput of any user, i.e., the number of bits that are accurately received; *latency* to the time interval for a response to be received by the sender with respect to the transmitted data; *connection density* to the overall number of devices satisfying a targeted quality of service (QoS) in a given area; *reliability* to the success probability of a given amount of traffic transmission within a determined duration of time, that is, the success probability of transmission of the packets (layer 2 and layer 3) within a mandatory time limit; and *mobility* to the maximum speed of user equipment (UE) at which a predetermined QoS set is achievable [35], [38]–[40].

To make these stringent applications possible, new technologies and strategies have been incorporated into 5G. Massive multiple-input multiple-output (MIMO) is one such technology [41]. By using a large number of antennas, massive MIMO can realize spatial multiplexing through beamforming and thereby support massive parallel access, which is crucial for enabling low-latency communication [42]–[44]. Important advanced technologies have been implemented in the core network of 5G, including novel resource allocation protocols, network slicing, which is enabled by software-defined networking (SDN), and network function virtualization.

Furthermore, 5G expands the bandwidth of previous generations of communication systems by leveraging new radio frequencies, spanning from low and mid bands (sub-1 GHz to 6 GHz) for long-range communication (important to mMTC), to high bands above 26 GHz, known as millimetric wave (mm-wave) spectrum, for ultra-high data rates (important to eMBB) [45]. High-range bands have the capacity to provide huge amounts of capacity across a limited geographical area. Thus, mm-wave is key for 5G implementations in areas where there are many devices and a need for high capacity, such as dense cities [46]–[48].

However, a drawback of adopting the mm-wave spectrum is that the transmitted signals are susceptible to stronger attenuation and absorption, which limits the communication range. To address this, the pervasive deployment of small cells, also known as network densification [6], has become a key feature of 5G networks. The employment of super-large antenna arrays (with several hundreds of antenna elements) in massive MIMO has also become indispensable to overcome deep fading in mm-wave systems. Further, to overcome propagation losses in mm-wave systems, a hybrid analog and digital beamforming technique is employed resulting in sufficient beamforming gains, along with reasonable energy, cost and complexity [49].

The decentralized infrastructure of 5G makes it very suitable for supporting collective intelligence in sociotechnical environments. It is possible, for instance, to implement collective self-adaptive systems (CSAS) [3] by exploiting the edge servers of small cells and efficiently computing even the most complex tasks in a distributed and intelligent manner. Diverse collective learning strategies, relying on local or aggregate information of the network agents, can be employed in such 5G-supported collective self-adaptive systems; the agents' information can be exchanged both directly, between neighboring small cells (ideal for reducing latency), and indirectly, by exploiting the core network with "cloud computing" (ideal for ultra-complex tasks). Further, grant-free random access techniques support dynamic and asynchronous communication (required in many IoT applications), and its integration into 5G is being investigated [50]–[52].

Today, 5G is in the deployment phase around the world, heralding a new era of ubiquitous connectivity, where decentralized sociotechnical environments will become a reality. However, although 5G generally provides a better user experience to end users, there are a few drawbacks. As commented previously, a typical issue of operating in the mm-wave spectrum is the attenuation and absorption by trees, towers, walls, and buildings [53]. Another drawback is the costs related to the development and maintenance of 5G infrastructure, including the adaptation cost of existing cellular infrastructure and the need for using massive antenna arrays [54], [55]. The battery drain on 5G devices is inefficient because of the complexity of signal processing algorithms deployed in the end device. Moreover, current commercial deployments of 5G are limited to urban areas, which reduces the possibilities of ubiquitous rural access. In general, most of the drawbacks can be summarized as inefficient usage of the energy utilized during transmission. This issue is one of the fundamental motivations for the current research on sixth generation (6G) communication networks [56]–[58].

Even as 5G is evolving and maturing, engineers and researchers have already initiated the development of 6G connectivity. Advanced multiple access techniques such as non-orthogonal multiple access (NOMA) and rate-splitting multiple access (RSMA) are being considered for boosting

the connectivity capacity of 6G networks and supporting super-overloaded scenarios [59], [60]. In some cases, solutions based on some form of collective intelligence, such as swarm intelligence, have been proposed [61], for example, for joint task offloading and resource management in mobile edge computing (MEC) systems that use NOMA [62]. Swarm intelligence and especially machine learning (ML)-assisted swarm intelligence is still a nascent topic and a prospective technique that has significant potential to address the problems with existing multiple access technologies, such as connectivity capacity, speed, and fair usage. UAVs are another alternative since their flexibility and coverage make them attractive for extending the communication range [63]. Furthermore, some sociotechnical applications envisaged in 6G, such as 3D holograms, may demand data rates of the order of terabits per second, and achieving terahertz communication, i.e., terahertz-spectrum bandwidths, is an active topic of 6G research [45].

Intelligent reflecting surfaces (IRSs) are expected to be another key technological component of 6G communication systems. These disruptive devices can deliver higher spectral and energy efficiencies by making the wireless environment controllable and smart. More specifically, an IRS consists of a set of software-configurable elements that, with adequate phase and amplitudes of reflection, can collectively forward impinging electromagnetic signals with an optimized radiation pattern [64]. This attractive capability enables IRSs to fine-tune the properties of the propagation environment and implement functions such as beam steering, signal absorption, and polarization control (potentially imposing ultra-low power consumption) [64], [65].

## C. PERSVASIVE EDGE COMPUTING WITH 5G AND BEYOND

### 1) INTRODUCTION

Although recent advances in 5G hold great promise, new developments in both radio access technologies and core network solutions are needed to fully realize its potential. Currently, the predominant network design comprises cellular systems based on human-generated data communication, such as web browsing, video streams, or telephone calls, that typically involves long data streams with dominance of downlink, and cloud computing that involves centralized data processing units working as X-as-a-Service [66]). In this paradigm, the computations for data processing often require tremendous processing capacity along with a high amount of energy during the process of training and operation. Current research aims to replace this traditional paradigm by a new network design that is based on machine-type communications comprising automated data communication among devices and data transport infrastructures (without involving humans) and edge computing [32], [67].

The *edge computing* paradigm aims to exploit the storage and computing capabilities of different devices at (or near) the network edge, where edge can be considered to be any computing and networking resource, such as a smart

phone or a 5G base station, that lies between the data source and the core network, also called the “cloud.” The term *pervasive edge computing* then refers to a distributed architecture with widespread deployment of these (potential) edge computing elements in a network.<sup>1</sup> The main aim of pervasive edge computing is to move data processes away from centralized servers so that at least some IoT applications do not need to send their data through the core network, thereby avoiding congestion and potentially high delays [68]. This can also reduce the processing capacity needed for deep learning computations. Moreover, because pervasive edge computing can pre-process data by filtering during the acquisition phase, it improves the speed of data analysis and decision-making processes [69]. Sensitive data can be processed on a local edge device to ensure data security and privacy [70]. Pervasive edge computing has numerous applications, including virtual reality and augmented reality, network optimization, and vehicular computing [70].

### 2) COMPUTATION OFFLOADING

The key idea behind pervasive edge computing in 5G (and other communication) networks as well as its main challenge is effective computation offloading [71]. Computation offloading refers to the ability of end devices to offload computation tasks to edge servers as well as receive the results from servers after they have executed the tasks. Computation offloading could have many objectives, such as network latency minimization, energy consumption minimization, task dropping minimization, computation rate maximization, computation efficiency (or energy efficiency) maximization, and payment minimization [71]. In the 5G case, the offloading problem can be formulated as an optimization problem with, for example, latency minimization as an objective as follows:

$$\min_{f_l, P_t, \lambda} L(f_l, P_t, \lambda)$$

Here  $f_l$  represents the number of computing resources that should be allocated;  $P_t$ , the transmission power setting; and  $\lambda$ , the ratio of locally executed tasks.

As a more concrete example, consider the work by Chen and Hao [72] who achieve binary offloading using mixed integer linear optimization. In binary offloading, the task dataset is fully processed either locally or remotely on an edge server. This contrasts with partial offloading where the task dataset can be subdivided further into several sub-tasks so that a part of the task is processed locally and the remaining is processed at the server [73]. Chen and Hao [72] use multiple edge computing servers with the objective of minimizing the overall latency. Their objective function is as follows:

$$\sum_{\text{task } i} [x_i t_i^L + (1 - x_i) t_i^E]$$

<sup>1</sup>It also incorporates the more restrictive (or fuzzy) concepts of mobile edge computing, edge servers, edge nodes, and fog network.



**TABLE 2. Technical requirements envisaged in 5G in terms of the minimum values for the applicable usage scenarios, and their relevance to collective intelligence (CI) principles and applications. Here, eMBB: enhanced mobile broadband; mMTC: massive machine-type communications; and URLLC: ultra-reliable low-latency communications (URLLC).**

Technical requirement	Minimum requirement	Applicable usage scenario	CI principle	Example real-world CI application
Peak data rate	Downlink: 20 Gbit/s; Uplink: 10 Gbit/s	eMBB	Self-management and adaption, Information exchange, Collaboration	Internet and Internet-based applications, Video calling
Peak spectral efficiency	Downlink: 30 bit/s/Hz; Uplink: 15 bit/s/Hz	eMBB	Self-management and adaption, Information exchange	Internet and Internet-based applications, Video calling
User experienced data rate	Downlink: 100 bit/s; Uplink: 50 bit/s	eMBB	Self-management and adaption	Mobile applications, Internet, Virtual reality networks
5 <sup>th</sup> percentile User spectral efficiency	(in dense urban areas) Downlink: 0.225 bit/s/Hz; Uplink: 0.15 bit/s/Hz	eMBB	Self-management and adaption	Mobile applications, Internet, Virtual reality networks
Latency	Downlink: 4 s for eMBB and 1 s for URLLC	eMBB, URLLC	Collaboration, Information exchange	Unmanned aerial vehicles, Mission-critical applications, Time-critical applications
Connection density	Downlink: 1,000,000 devices/km <sub>2</sub>	mMTC	Distribution	IoT devices, Internet, Smart homes
Reliability	1-10 <sup>-5</sup> success probability of transmission of packets	URLLC	Information exchange	Smart energy metering, Banking systems, Mission-critical applications, Augmented democracy
Mobility	1.12 bit/s/hz (normalized traffic channel link data rate) and 30 km/h in dense urban areas	eMBB	Information exchange, Collaboration	Traffic control, Unmanned aerial vehicles

This represents the sum of the latency of the local processing task,  $t_i^L$ , which is fixed, and the latency of the offloading task,  $t_i^E$ , which is variable.

Computation offloading and the resulting resource allocation challenges play a crucial role in determining the overall edge computing performance, and more complicated techniques and their mathematical basis have been explored, for example, energy efficient algorithms [74], game theory-based solutions [75], non-convex mixed-integer programming [76], and deep learning [77].

However, computation offloading has a few drawbacks, the most important of which are delays, energy consumption, and problems dealing with time-varying task arrivals and stochastic channel conditions [78]. To resolve this and improve the performance of edge computing systems, task caching or cache-assisted edge computing has been proposed as a promising technique. The idea here is to cache some tasks, such as popular or repetitive or common tasks, and their related data at the network edge, and to execute or offload only uncached tasks to the server [79]. Caching popular

IoT data items at the network edge reduces duplicate content transmissions, latency, and energy consumption [80]. It should be noted here that the tasks can be quite diverse in terms of computational complexity, content popularity, and input data size, and it is important to manage cache-assisted edge computing smartly, for example, using novel architectures for green and secure computations [80] or taking advantage of artificial intelligence (AI)-based technologies [78]. Today, the design of energy-efficient cache-assisted edge computing systems that jointly optimize communication, caching, and computation resources continues to be an active and interesting research area in modern wireless communication systems.

### 3) FEDERATED LEARNING

A key new technique that enables pervasive edge computing for ML- and AI-based techniques was introduced by Google in 2016—federated learning [81], [82]. Since federated learning enables AI-based edge computations, it is poised to become a crucial technology for building 5G-enabled

collective intelligence [83]. In federated learning, an ML algorithm is trained across multiple decentralized edge devices having multiple local data samples, without explicitly exchanging any data. It is important to note the differences between federated learning and traditional distributed learning. Distributed learning aims to process datasets by parallelizing computing power under the assumption that the local datasets are independent and identically distributed and roughly have the same size. Federated learning, on the other hand, aims to train heterogeneous datasets of different sizes. Moreover, distributed learning nodes typically comprise datacenters with powerful computational capabilities and fast network connections, whereas federated learning aims to deal with small clients, such as smartphones and IoT devices, on unreliable networks such as Wi-fi.

Thus, federated learning deals with data that is not independent and identically distributed and has unbalanced usage, massive distribution, and limited communication. As described in the original paper that proposed federated learning [81], consider a (fixed) set of  $K$  clients and that each client has a fixed local dataset. Further, for efficiency, consider that a random fraction  $C$  of the  $K$  clients is selected. The central server sends the current global algorithm state (e.g., the current model parameters) to each client. Now, consider the following general finite-sum objective:

$$\min_{w \in \mathbb{R}^d} f(w)$$

where

$$f(w) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n f_i(w)$$

In ML,  $f_i(w) = l(x_i, y_i; w)$ , i.e., a function yielding the prediction loss on a data pair  $(x_i, y_i)$  with model parameters  $w$ . The federated learning objective can then be written as follows:

$$f(w) = \sum_{k=1}^K \frac{n_k}{n} F_k(w)$$

where

$$F_k(w) = \frac{1}{n_k} \sum_{i \in P_k} f_i(w)$$

Here, the assumption is that the data is partitioned over  $K$  clients, with  $P_k$  being the set of indexes of data points on client  $k$  and  $n_k = |P_k|$ . Then, their paper proposed a ‘‘FederatedAveraging’’ optimization algorithm to solve the above objective assuming a non-IID setting (that is, non-independent and identically distributed data and  $F_k$  as an arbitrarily bad approximation to  $f$ ) [81]. Interestingly, they also used additional computations as an explicit goal to decrease the number of communication rounds required to train a model.

#### 4) CHALLENGES

Although pervasive edge computing provides significant benefits to IoT systems, cloud computing cannot be eliminated completely because having a centralized location for the data storage and analysis still has many benefits in different applications. Pervasive edge computing is important for offloading some tasks from the core network and to fulfill strict latency requirements, but the remaining data may still have to be sent to the cloud for processing because of its better processing capabilities. Moreover, the limited processing power and storage capabilities of the edge device could lead to a loss of generalisation of the training process with increasing susceptibility to unseen data [84]. Further, the danger with datasets having locally obtained samples is that we may obtain non-IID data, and migrating to a training process with non-IID datasets is not trivial [85]–[87]. It is also important to note that the benefits of pervasive edge computing, such as lower end-to-end latency, is not always attained in all scenarios. For example, latency depends not only on the distance between the user and the processing server, but also on other factors such as the edge traffic, processing power of edge servers, and computational complexity of tasks. Similar tradeoffs are present between pervasive edge computing and cloud computing in the case of backhaul bandwidth, robustness of failure, monetary cost, etc. [70]. Therefore, cooperation among local, edge, and cloud computing is often essential to meet the diverse network requirements of collective intelligence. Fig. 3 illustrates the decentralized process of edge computing and contrasts it with the centralized process of cloud computing.

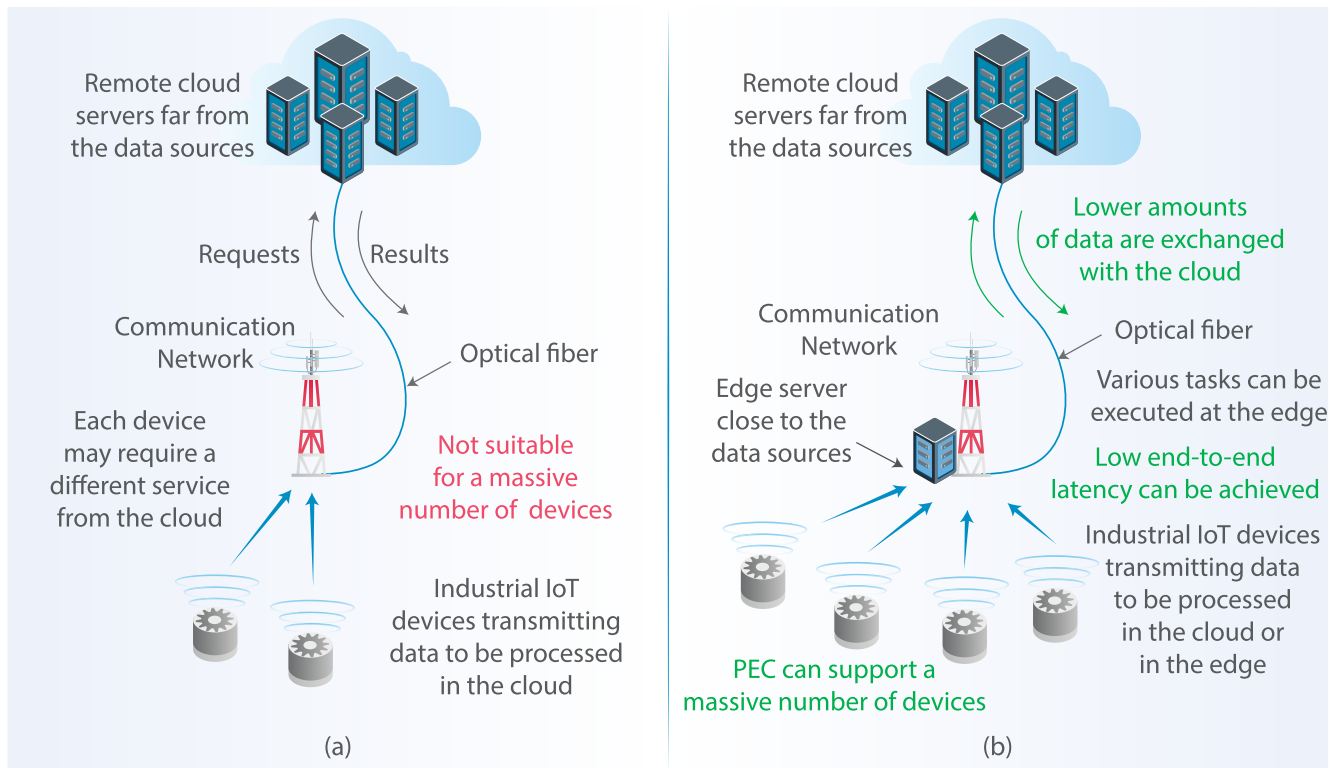
Thus, implementing collective intelligence requires data processing to be driven to the edge of the network, and this implies three main processes with its own challenges—data acquisition, data processing, and communication of the results [88], [89]. In effect, there exists a symbiotic relationship between IoT, pervasive edge computing, 5G on the one hand and collective intelligence on the other: IoT, pervasive edge computing, and 5G enable collective intelligence, while at the same time, require collective intelligence to function efficiently.

### III. CHALLENGES WITH 5G COMMUNICATION IN COLLECTIVE INTELLIGENCE

In this section, we describe the key challenges faced by 5G and 5G-enabled collective intelligence to enable a complete collective-intelligence solution for decentralized sociotechnical environments with distributed intelligent agents.

#### A. SECURITY AND PRIVACY CHALLENGES

Collective intelligence is based on human–device connectivity and networks, and the scale of interactions and continuous connectivity lead to numerous concerns about security, safety, and privacy. The security of distributed multi-agent systems can be defined as its ability to deal with threats to its goals



**FIGURE 3.** Cloud versus edge computing. (a) Typical cloud computing architecture: mainly centralized with computational tasks being performed in the servers at the core network and the Internet. (b) Typical edge computing architecture: decentralized with computational tasks distributed among nodes that are located at the edge of the core network; the cloud acts as a complementary processing and storage unit (adapted from [70]).

that are intentionally caused by other intelligent agents [90]. The security of distributed multi-agent systems is threatened when its agents fail, usually by not always consistently follow pre-specified rules or protocols. The resulting failure leads to the so-called *Byzantine fault* in networked systems, where it is clear that there is a failure but it is not easy to identify the agent causing the failure, since their behavior may be different to different observers [91]–[93]. Byzantine fault tolerance is an important research area in communication networks and their applications [94]–[96]. Inappropriate or incorrect agent behaviour can have many undesired effects, including enhanced security and privacy threats, loss of data, financial costs, and injuries to humans or systems.

Significant research work has explored methods to solve security issues with communication networks (5G or otherwise) deployed in multi-agent systems embedded with some form of collective intelligence [97], [98]. A popular method is to use blockchain; for example, a blockchain consortium was proposed in [99] to guarantee secure data sharing and storage on a vehicular ad-hoc network; a digital signature technique based on the nature of bilinear pairing for elliptic curves was used to ensure reliability and integrity when transmitting data to a node. Giechaskiel *et al.* presented an analysis of scenarios in which cryptographic building blocks can break; they discussed the subsequent effects depending on the type of breakage, ranging from minor privacy violations to a

complete breakdown of the currency [100]. In [101], the authors proposed a cooperative jamming approach where UAV jammers help the UAV transmitter to defend against ground eavesdroppers using a fake beamforming noise. The UAV jammers cooperatively jam a ground-based eavesdropper using a multi-agent deep reinforcement learning method. A distributed tracking problem for a complex dynamical network of cyber-physical systems was investigated in [102]. The authors considered that the communication channel for controllers and observers was subject to frequent malicious attacks and proposed an algorithm to properly select the feedback gain matrices based on the Lyapunov stability theory. To reduce security vulnerabilities in IoT communication layers, a model was proposed in [103] based on a combined multi-agent and multi-layered game formulation with the aim to detect/prevent intrusion systems that can effectively identify the malicious nodes and restrict it from further communications. Finally, in order to increase security in decentralized intelligent systems that employ distributed ledger technologies, the authors in [104] proposed a decentralized application model following the principles of Ethereum blockchain network, including a Casper-like consensus mechanism and a graph model for the functionality of the blockchain components.

In many cases, the goal is to enable *privacy preservation*. Privacy preservation is considered to be achieved in

multi-agent systems when every agent's local information is known only to itself. An agent's local data, e.g., personal data, is used for local processing and only selected results of the processing is transmitted into the larger network [5], [105]. Thus, the agents preserve the privacy of their local training datasets while also benefiting from the results of other participants [106]. For instance, in [107], privacy preservation was addressed for a decentralized optimization scenario in which adversaries try to steal information from other participating agents. An important method of enabling privacy and security in wireless communication networks that constitute the collective-intelligence support framework is distributed ledger technology. Distributed ledger technology makes it possible to securely and safely transmit data processed at edge servers to other edges or to the cloud. In this context, a privacy-by-design approach has been proposed with which several critical operations of decentralized and distributed systems can be performed, such as decentralized data analytics [108], [109], social interactions analysis [110], [111], and decentralized planning and resource allocation [105]. These operations integrate several state-of-the-art techniques such as informational self-determination, homomorphic encryption, differential privacy, obfuscation, and anonymity. Privacy preservation may sometimes limit the quality of service since the accuracy and quality of data are deteriorated to hide information content. To combat this problem, privacy-preserving semi-supervised learning over graphs has been considered in [112]. However, the precise tradeoff between (lowering of) privacy protection and learning accuracy is still unknown. Pareto optimal tradeoffs can be configured and regulated by tuning the parameters of the privacy techniques, as shown in [113]. Incentives, such as monetary incentives or incentives related to well-being and comfort, can be used to coordinate data sharing choices in a crowd.

Edge computing enables content perception, real-time computing, massive data processing, parallel communication, and distributed architectures. However, it has also introduced several new challenges in the field of data security and privacy preservation, such as denial of service attacks, man-in-the-middle attacks, and information injection [114]. Since processing is now performed away from a central server at network edges, it is often more difficult to effectively control information and data flow. At the same time, distribution of information means that an attacker has to carry out multiple attacks to fully compromise a system.

In particular, cache-assisted edge computing (discussed earlier in Section II-C3) enhances security and privacy because fewer information needs to be exchanged. At the same time, edge caching has more frequently changing wireless channels and mobile traffic, making it vulnerable to cyberattacks and privacy invasions. In addition to generic cyberattacks such as wireless jamming, malware attacks, etc., edge caching faces caching-specific threats such as cache poisoning attacks, cache pollution attacks, cache side-channel attacks, and cache deception attacks [115]. Federated

learning is another promising enabler of enhanced data security and privacy in edge computing [116], [117]. Since a user only needs to transfer limited data for improving a particular machine learning model, sensitive metadata cannot be transmitted, mixed with other data, perturbed, or anonymized, thereby ensuring that personal information is not unintentionally disclosed, i.e., privacy). Nevertheless, any transmission of information automatically implies the possibilities of privacy and security breaches. Hence, considerable research is ongoing to ensure data security and privacy in federated learning, with many different techniques being proposed, such as homomorphic encryption and differential privacy [118], [119].

## B. RADIO RESOURCE MANAGEMENT CHALLENGES

5G needs to provide different quality of service for delay, reliability, data rate, and massive connectivity, depending on the sociotechnical system. This leads to several key radio resource allocation challenges. Most of these challenges are important topics of ongoing and future research, and some of them are described below:

- 1) **Joint collective intelligence and time-critical communication services design:** Some sociotechnical systems such as autonomous driving require time-critical<sup>2</sup> communication services, but this is difficult due to possible resource limitations and rapidly changing dynamics of wireless communications. In designing resource allocation algorithms for such use cases, service performance metrics such as latency and reliability should be considered. Moreover, many systems requiring time-critical communication nowadays have significant ML components, and as a result, performance metrics such as loss, accuracy, and convergence time should also be considered. This requires joint design of collective intelligence and time-critical communication, which is not easy to solve.
- 2) **Joint collective-intelligence design and resources allocation for pervasive edge computing:** The joint allocation of radio and processing resources along with offloading decisions by users is a challenging task. In pervasive edge computing, processing power and storage are distributed on the edge of the radio access network (RAN), as discussed previously; battery-powered and resource-limited users can then use the available processing power to perform computationally-extensive tasks. Since processing resources for pervasive edge computing are limited and shared by users, the allocation of processing resources and limited RAN resources to users becomes problematic and requires some kind of tradeoff. Therefore, the joint allocation of RAN resources and processing resources for pervasive edge computing is a

<sup>2</sup>Ultra-reliable low-latency communications is referred to as time-critical communication here to emphasize that it is designed for applications that are sensitive to time, but with very precise reliability and availability requirements.

necessity. Finally, the heterogeneity of multiple servers in terms of processing power and server allocation to each user ensures users' quality of service. In general, given the tolerable latency and processing resources required by each user, whether the task should be performed locally, offloaded to the pervasive edge computing server, or offloaded to the cloud is a challenging decision.

- 3) **Resource allocation for joint device-to-device communication, uplink and downlink:** Since information exchange among human and software agents is observed in systems exhibiting collective intelligence, it is important to jointly allocate resources for uplink and downlink device-to-device communication. The resource allocation for joint uplink, downlink, and device-to-device communication outperforms disjoint allocation, because the joint optimization results in more degrees of freedom than the disjoint case. This is especially important for delay-sensitive sociotechnical systems. A recent interesting research area in this context is the dynamic resource allocation for sidelink communication, which has been introduced in standard 3GPP Release 16 and 17 [120]–[123].
- 4) **Joint radio access and core resources allocation for network slicing:** Collective intelligence in sociotechnical systems requires different services with diverse requirements that can be provided by network slicing, enabled by softwarization and network function visualization. Network slicing must be performed in an end-to-end manner from the radio access network to the transport networks, with joint resource allocation for access, core, and transport networks. Moreover, since service demands and network conditions vary dynamically, slices need to be dynamically created, modified, and deleted; this requires resources to be flexibly and dynamically allocated to logical networks based on their service requirements and desired collective-intelligence performance.

Since 5G and beyond networks should be able to provide critical and real-time services, traditional resource management methods (based on optimization, heuristics, and exhaustive searches) are not suitable for addressing the challenges mentioned above, due to their high computational complexity and possibility of being far from the optimal solution [124]. A few ML techniques have been demonstrated to work well with resource allocation challenges in 5G [125]. For example, deep reinforcement learning was used by the authors in [126] for network slicing using radio resource allocation, whereas Huang *et al.* [127] used convolutional neural networks to optimize channel state information through cooperative resource allocation.

However, these researches are still limited in terms of supporting a collective intelligence framework and meeting the abovementioned challenges. Resource management algorithms enabled by ML should be devised for 5G to realize an autonomous network in which dynamic, efficient and

agile resource allocation is performed in radio access, edge, core, and transport networks to address the aforementioned challenges. To accomplish this, a combination of multiple classification and regression methods, unsupervised learning, and reinforcement learning techniques, under the umbrella of collective intelligence, can be employed so that the higher degree of freedom provided by the key enabling technologies of 5G can be efficiently utilized and the corresponding resource allocation challenges can be adequately addressed. It is worth noting that convex optimization may nevertheless still be required not only for benchmarking, but also for provisioning of the training data for supervised learning techniques.

### C. SUPPORTING KEY CHARACTERISTICS OF COLLECTIVE INTELLIGENCE WITH 5G

Collective intelligence has several general key characteristics, listed as follows, and it is an ongoing important research challenge to apply 5G to enhance their implementations [3].

- 1) **Neighbor connectivity:** To achieve collective intelligence, it is important to ensure that the neighboring nodes (i.e., the agents) of a network are connected either *statically* or *dynamically*. In static connections, the interactions and the network remain constant, i.e., the same nodes interconnect throughout the time frame, whereas in dynamic connections, different nodes interconnect at different time steps. In dynamic connections, a network can also be only partially connected, i.e., not all nodes are interconnected at every time step. For example, consider an electricity distribution grid where  $n$  prosumers (customers who also generate electricity) connect to a substation through power lines, exchanging electricity; this represents static connectivity since the neighboring nodes are always interconnected identically. However, if the prosumers also exchange electricity with each other, selling or buying excess production, then the network is dynamically connected; different customers may sell (buy) electricity to (from) different customers in the network at every time step. Using 5G communications to enable dynamic neighbor connectivity is an ongoing research topic. One approach is to implement network function visualization that can provide agile provisioning of mobile functions on demand by allowing customized network slicing and creating programmable networks for 5G-enabled IoT applications so that devices can be reconfigured to create multiple networks [128]–[130].
- 2) **Interaction protocols:** An important characteristic of collective intelligence is the nature of interactions in the network and the protocols that structure the interactions. Interactions could be topology-based (e.g., tree or ring structure), random graphs (e.g., with gossip algorithms), random walks or agent migrations, or bioinspired models (ant/pheromones, etc.) [131]. 5G communication technologies have the potential to enhance these interactions in multiple ways, for

example, multi-tenancy [132], bioinspired resource allocation [133], cognitive radio networks [134], and dense multiple-radio access technology [134].

- 3) **Knowledge exchange:** A key factor that characterizes a collective-intelligence-based network is the quantity of *information* in the network and how it is handled. As explained earlier, the pervasive edge computing concept allows local data to be processed locally, and only essential information is sent to a central cloud for further processing, with the nature and type of knowledge exchange depending on the application/service [70]. Thus, none of the individual nodes have full information. However, interactions could be organized separately as well, with all the nodes having full information and the aggregation and processing being done centrally. The role of 5G in both cases was explained earlier in Section II-C.
- 4) **Exploration–exploitation tradeoff:** Optimizing the efficiency of collective intelligence involves making a tradeoff between “exploitation,” which implies using known solutions, and “exploration,” which implies looking for new solutions [135], a choice that often leads to a tradeoff between cost and effectiveness. While current 5G research has not explicitly focused on this issue, the key features of 5G communication, such as speed, latency, and reliability, will play key roles in designing future collective-intelligence networks.

#### IV. COLLECTIVE INTELLIGENCE IN PRACTICE

In this section, we describe four modern real-world applications of collective intelligence in distributed-intelligence scenarios—road traffic control, UAVs, electrical load demand response in smart grids, and augmented democracy (Fig. 4).

##### A. ROAD TRAFFIC CONTROL

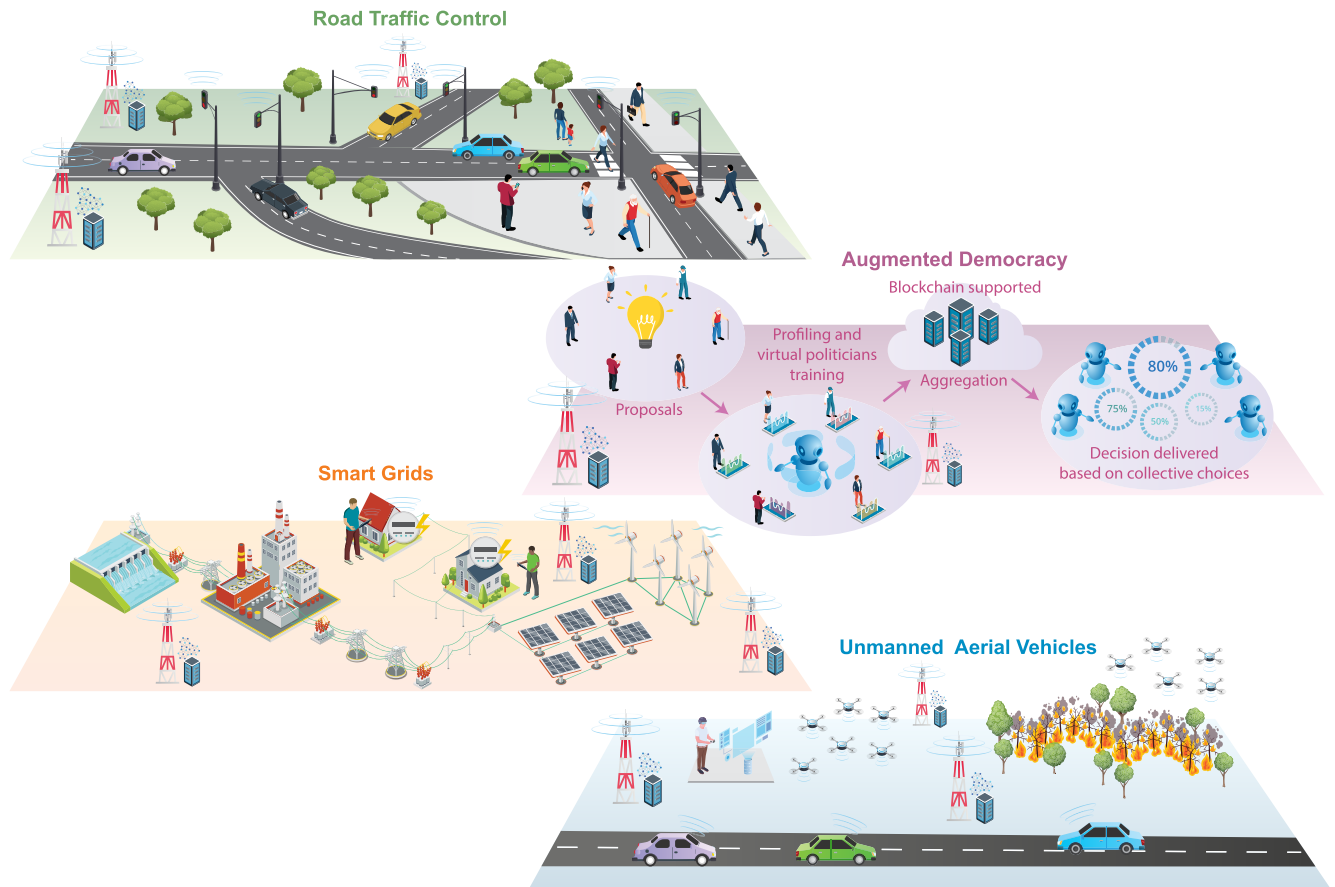
In road traffic control, distributed intelligent decision makers—humans, vehicles, vehicular devices, and signalling systems—constantly interact to achieve a common goal (e.g., minimum travel time for all participants) under some constraints (e.g., safety and comfort). Optimizing road traffic flow is challenging when there are numerous vehicles using the road, for example, in cities. Safety requirements must be balanced with delays while ensuring fair treatment to all users of the road infrastructures, including pedestrians. Early traffic control systems relied on traffic policing personnel or traffic lights. Modern systems typically use automated variants of traffic lights, but often incorporating some form of central planning and control to deal with peak traffic situations in crowded cities with a high population. Although it is extremely complex to plan ahead for all possible situations and the signal control process requires huge amounts of traffic data and excellent communication, rapid advances in the communication abilities of IoT-enabled devices, e.g., 5G, promise new and effective solutions for road traffic control.

Initially, Adaptive Signal Traffic Control (ASTC) was developed and widely discussed to succeed traditional

traffic control mechanisms. ASTC is usually deployed at intersections to adapt the traffic signal timing based on actual traffic demand [136]. Since monitoring and control processes are repeated regularly, ASTC requires detectors such as loop detectors and a communication network to exchange information with local traffic controllers and/or a server. ASTC is well known to reduce congestion and delays, and many recent researches have focused on its safety aspects [136]–[138]. Its main benefits are that it equally distributes green-light time for all traffic movements, progressively moves vehicles through green lights, and reduces unnecessary delays by decreasing congestion and creating smoother flow.

More recently, tremendous advances in data acquisition and manipulation methods and computing power are driving the development of data-driven approaches to solve the road traffic control problem. Intelligent Traffic Control Systems (ITCS) is based on intelligent and data-driven monitoring, feedback, and evaluation systems. Various distributed sensors monitor traffic flow and collect relevant data using detection and image processing algorithms. The data is communicated to a central server that analyzes the data and gives real-time traffic feedback to vehicles, for example, by broadcasting traffic statuses to electronic signboards or directly to vehicles. The main objective of ITCS is to streamline the operation of vehicles, assist drivers with traffic information, and ensure safety and ease of travel of passengers. ITCS implementations often use multi-agent methodologies (e.g., [139]), or AI methods such as reinforcement learning [140], long short-term memory (LSTM) [141], and deep learning [142].

Two new IoT-enabled communications paradigms—vehicle to vehicle (V2V) and vehicle-to-everything (V2X)—are key drivers for data-driven approaches [143]. In V2V, autonomous vehicles communicate with each other, for example, by signalling approaching challenges such as faster routes, weather conditions, traffic jams, pedestrians, and crises [144]. In V2X (sometimes called vehicle-to-infrastructure (V2I)), the vehicles connect to *everything* so that not only vehicles but also pedestrians and associated road infrastructure (e.g., traffic lights, lane markers, street lights, signage, and parking meters) are connected in one reliable network, exchanging data wirelessly. As a result, continuous information about the weather, road conditions, traffic jams, etc. can be used to improve travel efficiency and safety. V2X is especially useful under bad weather conditions, where traditional systems may fail. Dedicated short-range communication has been proposed to enable V2X, since it provides low latency, fast network connectivity, high-speed communication, and secure networks [145], [146]. However, dedicated short-range communication infrastructure can be expensive and alternatives are also being explored, including long range (LoRA) communications [147]. The long term evolution (LTE) V2X standard (from 3GPP Release 14) and the new radio (NR) V2X standard (from 3GPP Release 16) are significant enablers for V2X



**FIGURE 4.** Four real-world applications of collective intelligence—road traffic control, unmanned aerial vehicles, electrical load demand response in smart grids, and augmented democracy.

communications [148], [149]. Today, V2X technology is being studied intensively (e.g., [150]–[155]).

Research and development of traffic control systems has been significantly aided by simulation software [156]. Traffic simulation tools can be divided into four types: (1) Macroscopic, where average vehicle dynamics (e.g., traffic density) are simulated; (2) Microscopic, where vehicles and their dynamics are modeled individually; (3) Mesoscopic, a combination of macroscopic and microscopic models; and (4) Submicroscopic, where not only vehicles but also their functions (e.g., gear shifts) are explicitly simulated [157]. Some prominent examples of traffic flow simulators are Simulation of Urban MObility (SUMO) [158], Green Light District Simulator (GLD) [159], Approximately Orchestrated Routing and Transportation Analyzer (AORTA) [160], and CityFlow [161].

The discussion so far primarily clarifies the historical development and current status of practical intelligent traffic management. These approaches show some features of collective intelligence, e.g., interconnection and distribution, but the use of modern collective-intelligence methodologies, such as swarm intelligence, is still at a nascent stage and primarily theoretical, because supporting technologies are continually evolving. Hence, other collective-intelligence

features such as collaboration and self-management are yet to be fully realized. The dominant collective-intelligence methodology that has been explored so far in the literature is swarm intelligence, and algorithms such as ant colony optimization (ACO) and particle swarm optimization (PSO) have proven to be reasonably effective in traffic routing optimization when the vehicles are connected [162]–[165]. The authors in [162] and [164] have extensively surveyed swarm optimization techniques applied to intelligent traffic management. Today, theoretical ideas based on collective intelligence are continuously advancing, and there is significant possibility to implement them practically due to the rapid progress in fast and reliable communication networks. This has, for example, already led to the proposal and development of exciting paradigms such as V2V and V2X. Hence, traffic management can be expected to soon become a prominent modern example of collective intelligence in practice.

### B. UNMANNED AERIAL VEHICLES (UAVs)

Unmanned aerial vehicles (UAVs), popularly called drones, and UAV swarms are an important modern example of collective intelligence. In UAV swarms, humans interact with and control a swarm of UAVs equipped with intelligence characterized by an ability to sense and respond to their

environment. UAV technology has progressed rapidly, both in terms of its capabilities—e.g., explorations of remote areas or dangerous environments—and the type of problems it can help solve. Equipped with advanced cameras, sensors, and communication abilities, UAVs have numerous applications today, including aerial surveys and monitoring, delivery of goods, search-and-rescue operations, agriculture, and aerial photography.

Based on the idea that collaboration can lead to the emergence of a form of collective intelligence that enables UAVs to perform tasks that are otherwise beyond the aggregation of their individual capabilities, many researchers have applied the principles of collective intelligence to solve various problems related to UAVs. In the most popular approach, swarm intelligence—that deals with the collective behaviour arising from decentralised self-organising systems, where individuals only interact locally with one another and with the environment—is applied to the self-coordination of numerous simple robots or multi-agent systems such as UAVs. This approach, called swarm robotics, emphasises the physical embodiment of individuals and scalability [166], [167]. From a broader perspective of multi-agent robot systems and their diverse applications, Osaba *et al.* gave a comprehensive review of the contributions of multiple researchers to several problems, including the path planning problem, target localization problem, and swarm segregation problem that are solved using techniques such as particle swarm optimization, ant colony optimization, and evolutionary algorithms [168]. Swarm intelligence and swarm robotics have also been applied specifically for UAVs. For example, in [169], the authors employed swarm intelligence and swarm robotics to use UAVs for fighting wildfires autonomously. The key problem solved by the authors is to enhance fire suppression capabilities by enabling robot swarms to be coordinated and controlled simultaneously, while also maintaining centralised communication with ground control during wildfire events. In another study, Vászárhelyi *et al.* focused on ensuring that large swarms of autonomous UAVs are able to seamlessly and easily navigate in confined spaces, with the basic premise that their solution promotes stable swarm behavior, resembling those of natural systems with collective intelligence [170]. Taking advantage of collective-intelligence principles, Alfeo *et al.* presented a swarm intelligence-based algorithm to enable a swarm of autonomous drones to discover static targets in unstructured environments in minimum time [171].

Some other collective-intelligence type approaches have also been applied to UAVs. For example, Howden and Hendtlass proposed a collective-intelligence algorithm to control many UAVs that survey complex areas for bushfires [172]. In their paper, the UAVs are in regular contact with a base station to report any bushfires but they autonomously determine their path over the area to be surveyed. Further, they periodically share information to avoid duplication. Howden also employed distributed pheromone maps to track a moving fire front using a UAV swarm that is controlled in a

fully decentralized and self-contained manner [173]. In [174], Varela *et al.* proposed a collective-intelligence model to achieve real-time co-ordination of a UAV swarm performing search operations. They employed exploitation algorithms to solve this problem on the basis that evolutionary algorithms are good for coordination and cooperation strategies in systems comprising multiple units and at regulating the exploration-versus-exploitation tradeoff, both of which are intrinsic in collective intelligence. They compared their results to the more common swarm intelligence approach and found that their proposed evolutionary algorithm outperforms swarm intelligence-based approaches when the number of targets increase. In [175], the authors proposed a heuristics-based solution for increasing the intelligence of a group of UAVs by using a distributed intelligence approach for cooperatively searching for a target. They found out that distributed decision-making methods were more effective than an autonomous intelligence approach where the drones do not cooperate or act collectively. UAVs often have to operate in quickly evolving “emergency” situations where they have to be capable of flying nearly autonomously and cooperatively without central control. Flexible plans must be quickly created with mutual collaboration. To address this problem, the authors in [176] discussed the applicability of a collective-intelligence model architecture that uses cloud computing, semantic agents, and some form of evolutionary computing algorithms for the co-ordination and co-operation. Collective-intelligence-based models and solutions have also been used for computation offloading in aerial edge networks using UAVs [177].

### C. DEMAND RESPONSE IN SMART GRIDS

Demand response (DR) programs are an important and highly researched component of modern smart grids, and many studies have explored communication-related aspects of their implementations, including 5G-enabled IoT-based smart grids [178]. In DR programs, end users actively participate in the electricity distribution business by trading their controllable loads; this, in turn, benefits the distribution system by reducing peak load demand and flattening the system load profile. End users determine their preferences for operating their home appliances based on their comfort levels and exchange this information with the electricity grid operator. Thus, end users interact with smart devices to balance their comfort levels and profits, and this leads to a better electricity grid. DR programs comprise two main types—incentive-based programs and price-based programs. Incentive-based programs regulate load by providing various incentives to customers, such as bonuses or credits, whereas price-based programs influence customer behaviors explicitly through different time-of-use (TOU) price policies [179].

DR programs require a robust communication system that can enable the exchange of data such as price signals, incentives, and load-usage preferences. Data from the customer end is transmitted by an advanced metering infrastructure (AMI) system (smart meters). Collective-intelligence



concepts have a key role to play in the design of DR programs, since many benefits can be obtained by the collective efforts of many individuals [180]. For example, consider end users who have agreed to cooperate in a DR program. A single end user calculates several possible schedules based on the degree of flexibility and (dis)comfort levels, with each schedule having a different cost. These plans are sorted from fully non-cooperative (no flexibility, maximum comfort, and highest cost) to fully cooperative (complete flexibility, minimum comfort, and lowest cost). All end users submit their individual plans to a server that calculates and proposes a schedule based on the system-level optimization objectives such as peak-load-demand minimization. Cooperating users can be further rewarded based on their plans. Using such an idea, the authors in [181] used collective intelligence to develop an appliance-level flexible scheduling framework based on consumers' self-determined flexibility and comfort requirements. In their study, the cooperative approach had higher peak-shaving than non-cooperative schemes that focused on the efficiency of individual appliances.

In [105], the authors developed an algorithm based on collective intelligence and learning—the Iterative Economic Planning and Optimized Selections (I-EPOS) algorithm—and used it to solve the DR problem. I-EPOS is a combinatorial optimization tool with a multi-agent, fully decentralized structure. Every I-EPOS agent—representing a user—has a set of discrete energy consumption plans provided by a scheduling entity. The task of I-EPOS is to coordinate and choose a subset of the users' plans such that the variance of the total energy demand is minimized over the day, with the objective to flatten the system load. I-EPOS has also been used to present a new flexible scheduling model for a community microgrid; here, the authors proposed a coordinated net load scheduling of the households by utilizing a decentralized and cooperative strategy based on the technical, social, and economic viewpoints of prosumers [182]. Another collective-intelligence-based platform is EnergyUse, an online platform to visualize energy consumption and share experiences regarding the energy savings in an energy community [183].

#### D. AUGMENTED DEMOCRACY

Democracy refers to self-governance, i.e., to the right of people living in a community to govern themselves [184]. Democratic decision-making refers to decisions that are made collectively by a group of people, through discussions and deliberations. Decisions made by deliberations usually result in fair and legitimate actions since they are representative decisions that result from reasoning rather than corruptible individual choices [185]. Augmented Democracy is a relatively new concept that originated as a result of the rapid recent advances in communications technology and AI. In augmented democracy, software agents called *avatars* or *digital twins* expand the ability of people to participate directly in democratic decisions. An avatar is a personalized virtual representation of a human, which augments or enhances the human's ability to make decisions

by either providing additional information or making decisions themselves. Internet users regularly interact with simple versions of digital twins, e.g., on music or movie streaming websites, such as Spotify, where virtual representations of users can automatically choose the next item on a playlist. Similarly, social networking sites and digital advertisements often function as digital twins making recommendations and assisting decision-making.

In augmented democracy, citizens are empowered to create avatars to augment their ability to participate directly to make democratic decisions, including voting in elections or on newly proposed bills [186]. In practice, the augmented democracy process can begin when a proposal is tabled by community representatives or lawmakers, and the community members are either required to vote on it or provide feedback. In a profiling process, all the participants from the community are identified through their registered electronic devices (cellphones, tablets, computer, etc.), or through fixed electronic points. During this profiling, an avatar with a participant's personal information, desires, political views, etc., is created as the participant's virtual representative. This avatar is further developed and refined by collecting data from the participant; the data can include active data such as surveys, questionnaires, and other feedback, and passive data such as reading habits and social media behavior.

Subsequently, the avatar collects information regarding the bills and predicts how the user will vote on such a bill. The avatar can then make a choice regarding the proposal, which can be ratified by the user. The avatar's decision is available only to the user and may or may not be enforceable. Thus, the avatar only provides the user the crucial ability to make informed choices. The user's final decision is communicated to a cloud device that performs data aggregation to make a final decision on the proposal. Or, lawmakers can capture the level and geographic distribution of the predicted support for a bill. Thus, in augmented democracy, avatars expand the ability of people to participate directly in a large number of democratic decisions. Note that in this system, all the virtual processes are enhanced by the latest 5G communication technologies and federated learning techniques with the edge–cloud paradigm. Moreover, encryption techniques and distributed ledgers such as blockchain can be used to increase the security of the process.

Augmented democracy has been proposed as a method to rectify a flaw that has been observed in conventional democratic political systems. Conventionally, a proposal is debated among a few selected individuals who were elected previously. These community representatives are often chosen based on their broad beliefs and goals and not their opinions on some specific policies or proposals. As a result, when decisions have to be taken on specific bills, there is no direct link between community members and community representatives, leading to a lack of trust in the system to take fair and legitimate decisions [187]. In augmented democracy, participants would be more willing to accept the final decision since all community members

can participate, via their avatars, in making decisions on proposals that affect their community. Thus, augmented democracy enhances citizen participation and engagement in decision making and public policy such that the outcomes are meaningful to citizens.

Augmented democracy has been discussed most prominently in political and social sciences centering on systems and processes that involve digital and/or participatory elements that could be used in decision-making processes [186]–[191]. Interestingly, in [190], the augmented democracy paradigm has been applied to urban transport in smart cities. Their idea is that vehicle users can act as witnesses with the capacity to intervene and testify about the physical world. Consider citizens navigating over several urban points of interest. They cannot only make informed and trustworthy choices by proving witnessed presence in one of these points but they can also access live updates about the collective choices made by other citizens in relevant points of interests. The authors showed that this scenario, while challenging, is technically feasible using secure, privacy-preserving, decentralized information systems such as blockchain consensus.

## V. CONCLUSION

In this paper, we have surveyed and reviewed an important approach to distributed intelligence called collective intelligence that emerges when humans interact with IoT systems in sociotechnical environments. Collective intelligence is characterized by four main features—collective decision-making, information exchange, distributed (dispersed) decision makers, and self-management and adaption. Further, human-device-human interactions are also being transformed by the latest communications technology standard—5G. Hence, we discuss 5G technologies and 5G-enabled IoT and their implications for collective intelligence.

We also focus on key challenges facing 5G implementation for supporting collective intelligence. In particular, the current version of 5G is designed for large-scale IoT deployments that focus on telemetry, and hence, it is uplink dominated, based on short messages. On the other hand, collective intelligence will require both uplink and downlink resources, especially if enabled by pervasive edge computing, and 5G may not necessarily be the optimal technology for collective intelligence. At the same time, tradeoffs exist in any IoT systems that are designed for telemetry.

Today, collective intelligence is built “inter-cooperatively” in large-scale Internet-based networked systems [192]. As a result, network-level advancements, in addition to communication technologies, are crucial for the successful practical deployment of collective intelligence [192]. Network-level technologies are being intensively researched today with several promising prospective technologies being introduced. This includes node-network interfacing technologies such as pervasive edge computing with federated learning (mentioned earlier in Section II-C) where, for example, Casadei et al. [88] recently proposed an interesting aggregate

computing framework to apply collective intelligence at the edge. In addition, research is ongoing for establishing ideal network structures [193], network technology standardization, low-power high-speed networks [194], big data sharing over networks [195], network software technologies [196], and network technologies in IoT-based sociotechnical environments [197].

In this paper, we also show that despite these challenges, in practice, some form of collective intelligence has already been applied to some sociotechnical environments, e.g., road traffic control and unmanned aerial vehicles. In the future, we will study and compare various communication technologies and their implications for IoT systems and collective intelligence. We will also develop collective-intelligence-based algorithms for IoT networks supported by robust 5G communication systems, overcoming the various technical challenges mentioned in this paper.

## REFERENCES

- [1] J. Surowiecki, *The Wisdom of Crowds*, 1st ed. New York, NY, USA: Anchor, Aug. 2005.
- [2] H. P. Young, “Condorcet’s theory of voting,” *Amer. Political Sci. Rev.*, vol. 82, no. 4, pp. 1231–1244, 1988.
- [3] M. D’Angelo, S. Gerasimou, S. Ghahremani, J. Grohmann, I. Nunes, E. Pourmaras, and S. Tomforde, “On learning in collective self-adaptive systems: State of practice and a 3D framework,” in *Proc. IEEE/ACM 14th Int. Symp. Softw. Eng. Adapt. Self-Managing Syst. (SEAMS)*, May 2019, pp. 13–24.
- [4] T. N. Garavan and R. Carbery, “Collective learning,” in *Encyclopedia of the Sciences of Learning*, N. M. Seel, Ed. Boston, MA, USA: Springer, 2012, pp. 646–649.
- [5] E. Pourmaras, “Collective learning: A 10-year Odyssey to human-centered distributed intelligence,” in *Proc. IEEE Int. Conf. Autonomic Comput. Self-Organizing Syst. (ACSOS)*, Aug. 2020, p. 10.
- [6] M. Zhong, Y. Yang, H. Yao, X. Fu, O. A. Dobre, and O. Postolache, “5G and IoT: Towards a new era of communications and measurements,” *IEEE Instrum. Meas. Mag.*, vol. 22, no. 6, pp. 18–26, Dec. 2019.
- [7] J. Navarro-Ortiz, P. Romero-Diaz, S. Sendra, P. Ameigeiras, J. J. Ramos-Munoz, and J. M. Lopez-Soler, “A survey on 5G usage scenarios and traffic models,” *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 905–929, 2nd Quart., 2020.
- [8] S. Li, L. Da Xu, and S. Zhao, “5G Internet of Things: A survey,” *J. Ind. Inf. Integr.*, vol. 10, pp. 1–9, Jun. 2018.
- [9] D. M. Herold and K.-H. Lee, “Carbon management in the logistics and transportation sector: An overview and new research directions,” *Carbon Manage.*, vol. 8, no. 1, pp. 79–97, Jan. 2017.
- [10] *State of Electricity Access Report 2017*, World Bank, Washington, DC, USA, 2017.
- [11] J. M. Leimeister, “Collective intelligence,” *Bus. Inf. Syst. Eng.*, vol. 2, no. 4, pp. 245–248, 2010.
- [12] S. Suran, V. Pattanaik, and D. Draheim, “Frameworks for collective intelligence: A systematic literature review,” *ACM Comput. Surv.*, vol. 53, no. 1, pp. 1–36, 2020.
- [13] M. M. Peeters, J. van Diggelen, K. Van Den Bosch, A. Bronkhorst, M. A. Neerinx, J. M. Schraagen, and S. Raaijmakers, “Hybrid collective intelligence in a human-AI society,” *AI Soc.*, vol. 36, no. 1, pp. 217–238, 2021.
- [14] E. Mumford, “The story of socio-technical design: Reflections on its successes, failures and potential,” *Inf. Syst. J.*, vol. 16, no. 4, pp. 317–342, 2006.
- [15] D. Shin, “A socio-technical framework for Internet-of-Things design: A human-centered design for the Internet of Things,” *Telematics Informat.*, vol. 31, no. 4, pp. 519–531, Nov. 2014.
- [16] A. Asatiani, P. Malo, P. R. Nagbøl, E. Penttinen, T. Rinta-Kahila, and A. Salovaara, “Sociotechnical envelopment of artificial intelligence: An approach to organizational deployment of inscrutable artificial intelligence systems,” *J. Assoc. Inf. Syst.*, vol. 22, no. 2, pp. 325–352, 2021.

- [17] C. Bettini and D. Riboni, "Privacy protection in pervasive systems: State of the art and technical challenges," *Pervasive Mobile Comput.*, vol. 17, pp. 159–174, Feb. 2015.
- [18] O. Vermesan, P. Friess, and P. Guillemin, "Internet of Things strategic research roadmap," in *Internet of Things-Global Technological and Societal Trends*, vol. 1. Aalborg, Denmark: River Publishers, 2011, pp. 9–52.
- [19] M. Chernyshev, Z. Baig, O. Bello, and S. Zeadally, "Internet of Things (IoT): Research, simulators, and testbeds," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1637–1647, Jun. 2018.
- [20] C. Krupitzer, T. Temizer, T. Prantl, and C. Raibulet, "An overview of design patterns for self-adaptive systems in the context of the Internet of Things," *IEEE Access*, vol. 8, pp. 187384–187399, 2020.
- [21] C. Krupitzer, F. M. Roth, S. VanSyckel, G. Schiele, and C. Becker, "A survey on engineering approaches for self-adaptive systems," *Pervas. Mobile Comput.*, vol. 17, pp. 184–206, Feb. 2015.
- [22] D. Weyns, "Engineering self-adaptive software systems—An organized tour," in *Proc. IEEE 3rd Int. Workshops Found. Appl. Self\* Syst. (FAS\*W)*, Sep. 2018, pp. 1–2.
- [23] L. Sanchez, L. Muñoz, J. A. Galache, and P. Sotres, "SmartSantander: IoT experimentation over a smart city testbed," *Comput. Netw.*, vol. 61, pp. 217–238, Mar. 2014.
- [24] A. Bennaceur, C. McCormick, J. García-Galán, C. Perera, A. Smith, A. Zisman, and B. Nuseibeh, "Feed me, feed me: An exemplar for engineering adaptive software," in *Proc. IEEE/ACM 11th Int. Symp. Softw. Eng. Adapt. Self-Manag. Syst. (SEAMS)*, May 2016, pp. 89–95.
- [25] M. U. Iftikhar, G. S. Ramachandran, P. Bollansée, D. Weyns, and D. Hughes, "DeltaIoT: A real world exemplar for self-adaptive Internet of Things (artifact)," in *DARTS-Dagstuhl Artifacts*, vol. 3. Wadern, Germany: Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2017.
- [26] C. Savaglio, M. Ganzha, M. Paprzycki, C. Badica, M. Ivanovic, and G. Fortino, "Agent-based Internet of Things: State-of-the-art and research challenges," *Future Gener. Comput. Syst.*, vol. 102, pp. 1038–1053, Jan. 2020.
- [27] M. Vega-Barbas, I. Pau, J. C. Augusto, and F. Seoane, "Interaction patterns for smart spaces: A confident interaction design solution for pervasive sensitive IoT services," *IEEE Access*, vol. 6, pp. 1126–1136, 2018.
- [28] E. Jung, I. Cho, and S. M. Kang, "An agent modeling for overcoming the heterogeneity in the IoT with design patterns," in *Mobile, Ubiquitous, and Intelligent Computing*. New York, NY, USA: Springer, 2014, pp. 69–74.
- [29] L. Reinfurt, U. Breitenbücher, M. Falkenthal, F. Leymann, and A. Riegg, "Internet of Things patterns for communication and management," in *Transactions on Pattern Languages of Programming IV*. Springer, 2019, pp. 139–182.
- [30] L. Reinfurt, U. Breitenbücher, M. Falkenthal, P. Fremantle, and F. Leymann, "Internet of Things security patterns," in *Proc. PLoP*, vol. 2017, p. 20.
- [31] F. Fanitabasi, E. Gaere, and E. Pournaras, "A self-integration testbed for decentralized socio-technical systems," *Future Gener. Comput. Syst.*, vol. 113, pp. 541–555, Dec. 2020.
- [32] P. Popovski, K. F. Trillingsgaard, O. Simeone, and G. Durisi, "5G wireless network slicing for eMBB, URLLC, and mMTC: A communication-theoretic view," *IEEE Access*, vol. 6, pp. 55765–55779, 2018.
- [33] S. Mumtaz, A. Bo, A. Al-Dulaimi, and K. Tsang, "Guest editorial 5G and beyond mobile technologies and applications for industrial IoT (IIoT)," *IEEE Trans. Ind. Informat.*, vol. 14, no. 6, pp. 2588–2591, Jun. 2018.
- [34] Y. Siriwardhana, P. Poramage, M. Liyanage, J. S. Walia, M. Matinmikko-Blue, and M. Ylianttila, "Micro-operator driven local 5G network architecture for industrial internet," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2019, pp. 1–8.
- [35] O. O. Erunkulu, A. M. Zungeru, C. K. Lebekwe, M. Mosalaosi, and J. M. Chuma, "5G mobile communication applications: A survey and comparison of use cases," *IEEE Access*, vol. 9, pp. 97251–97295, 2021.
- [36] 3GPP. *3rd Generation Partnership Project; Technical Specification Group Radio Access Network; Study on RAN Improvements for Machine-Type Communications (Release 11), v11.0.0*. Accessed: Oct. 29, 2020. [Online]. Available: <https://portal.3gpp.org/desktopmodules/Specifications/SpecificationDetails.aspx?specificationId=2630>
- [37] Z. Li, M. A. Uusitalo, H. Shariatmadari, and B. Singh, "5G URLLC: Design challenges and system concepts," in *Proc. 15th Int. Symp. Wireless Commun. Syst. (ISWCS)*, Aug. 2018, pp. 1–6.
- [38] W. Xiang, K. Zheng, and X. S. Shen, *5G Mobile Communications*. Cham, Switzerland: Springer, 2016.
- [39] D. Jiang and G. Liu, "An overview of 5G requirements," in *5G Mobile Communications*. Cham, Switzerland, 2017, pp. 3–26.
- [40] G.-R. Barb and M. Oteşteanu, "5G: An overview on challenges and key solutions," in *Proc. Int. Symp. Electron. Telecommun. (ISETC)*, Nov. 2018, pp. 1–4.
- [41] A. S. de Sena, D. B. da Costa, Z. Ding, and P. H. J. Nardelli, "Massive MIMO–NOMA networks with multi-polarized antennas," *IEEE Trans. Wireless Commun.*, vol. 18, no. 12, pp. 5630–5642, Dec. 2019.
- [42] J. Zeng, T. Lv, R. P. Liu, X. Su, Y. J. Guo, and N. C. Beaulieu, "Enabling ultrareliable and low-latency communications under shadow fading by massive MU-MIMO," *IEEE Internet Things J.*, vol. 7, no. 1, pp. 234–246, Jan. 2020.
- [43] R. Chataut and R. Akl, "Massive MIMO systems for 5G and beyond networks—Overview, recent trends, challenges, and future research direction," *Sensors*, vol. 20, no. 10, p. 2753, 2020.
- [44] H. Jiang, D. Qu, J. Ding, Z. Wang, H. He, and H. Chen, "Enabling LPWAN massive access: Grant-free random access with massive MIMO," *IEEE Wireless Commun.*, early access, May 9, 2022, doi: 10.1109/MWC.102.2100276.
- [45] L. Zhang, Y.-C. Liang, and D. Niyato, "6G visions: Mobile ultra-broadband, super Internet-of-Things, and artificial intelligence," *China Commun.*, vol. 16, no. 8, pp. 1–14, Aug. 2019.
- [46] L. Li, X. Niu, Y. Chai, L. Chen, T. Zhang, and D. Cheng, "The path to 5G: mmWave aspects," *J. Commun. Inf. Netw.*, vol. 1, no. 2, pp. 1–18, Aug. 2016.
- [47] F. Al-Ogaili and R. M. Shubair, "Millimeter-wave mobile communications for 5G: Challenges and opportunities," in *Proc. IEEE Int. Symp. Antennas Propag. (APSURSI)*, Jun. 2016, pp. 1003–1004.
- [48] J. Lee, E. Tejedor, K. Ranta-Aho, H. Wang, K.-T. Lee, E. Semaan, E. Mohyeldin, J. Song, C. Bergljung, and S. Jung, "Spectrum for 5G: Global status, challenges, and enabling technologies," *IEEE Commun. Mag.*, vol. 56, no. 3, pp. 12–18, Mar. 2018.
- [49] X. Gao, L. Dai, and A. M. Sayeed, "Low RF-complexity technologies to enable millimeter-wave MIMO with large antenna array for 5G wireless communications," *IEEE Commun. Mag.*, vol. 56, no. 4, pp. 211–217, Apr. 2018.
- [50] J. Ding and J. Choi, "Comparison of preamble structures for grant-free random access in massive MIMO systems," *IEEE Wireless Commun. Lett.*, vol. 9, no. 2, pp. 166–170, Feb. 2020.
- [51] R. Abbas, M. Shirvanimoghaddam, Y. Li, and B. Vucetic, "A novel analytical framework for massive grant-free NOMA," *IEEE Trans. Commun.*, vol. 67, no. 3, pp. 2436–2449, Mar. 2019.
- [52] D. C. Melgarejo, C. Kalalas, A. S. de Sena, P. H. J. Nardelli, and G. Fraidenraich, "Reconfigurable intelligent surface-aided grant-free access for uplink URLLC," in *Proc. 2nd 6G Wireless Summit (6G SUMMIT)*, Mar. 2020, pp. 1–5.
- [53] R. Borralho, A. Mohamed, A. U. Quddus, P. Vieira, and R. Tafazolli, "A survey on coverage enhancement in cellular networks: Challenges and solutions for future deployments," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 2, pp. 1302–1341, 2nd Quart., 2021.
- [54] M. A. Adedoyin and O. E. Falowo, "Combination of ultra-dense networks and other 5G enabling technologies: A survey," *IEEE Access*, vol. 8, pp. 22893–22932, 2020.
- [55] M. N. Patwary, S. J. Nawaz, M. A. Rahman, S. K. Sharma, M. M. Rashid, and S. J. Barnes, "The potential short-and long-term disruptions and transformative impacts of 5G and beyond wireless networks: Lessons learnt from the development of a 5G testbed environment," *IEEE Access*, vol. 8, pp. 11352–11379, 2020.
- [56] M. H. Alsharif, A. H. Kelechi, M. A. Albreem, S. A. Chaudhry, M. S. Zia, and S. Kim, "Sixth generation (6G) wireless networks: Vision, research activities, challenges and potential solutions," *Symmetry*, vol. 12, no. 4, p. 676, Apr. 2020.
- [57] P. Yang, Y. Xiao, M. Xiao, and S. Li, "6G wireless communications: Vision and potential techniques," *IEEE Netw.*, vol. 33, no. 4, pp. 70–75, Jul./Aug. 2019.
- [58] I. F. Akyildiz, A. Kak, and S. Nie, "6G and beyond: The future of wireless communications systems," *IEEE Access*, vol. 8, pp. 133995–134030, 2020.
- [59] B. Clerckx, Y. Mao, R. Schober, and H. V. Poor, "Rate-splitting unifying SDMA, OMA, NOMA, and multicasting in MISO broadcast channel: A simple two-user rate analysis," *IEEE Wireless Commun. Lett.*, vol. 9, no. 3, pp. 349–353, Mar. 2020.

- [60] A. S. de Sena, "Massive MIMO-NOMA networks with imperfect SIC: Design and fairness enhancement," *IEEE Trans. Wireless Commun.*, vol. 19, no. 9, pp. 6100–6115, Jun. 2020.
- [61] A. Akbar, S. Jangsher, and F. A. Bhatti, "NOMA and 5G emerging technologies: A survey on issues and solution techniques," *Comput. Netw.*, vol. 190, May 2021, Art. no. 107950.
- [62] H.-G.-T. Pham, Q.-V. Pham, A. T. Pham, and C. T. Nguyen, "Joint task offloading and resource management in NOMA-based MEC systems: A swarm intelligence approach," *IEEE Access*, vol. 8, pp. 190463–190474, 2020.
- [63] Z. Xiao, L. Zhu, and X.-G. Xia, "UAV communications with millimeter-wave beamforming: Potentials, scenarios, and challenges," *China Commun.*, vol. 17, no. 9, pp. 147–166, Sep. 2020.
- [64] A. S. de Sena, P. H. J. Nardelli, D. B. da Costa, F. R. M. Lima, L. Yang, P. Popovski, Z. Ding, and C. B. Papadias, "IRS-assisted massive MIMO-NOMA networks: Exploiting wave polarization," *IEEE Trans. Wireless Commun.*, vol. 20, no. 11, pp. 7166–7183, Nov. 2021.
- [65] A. S. de Sena, D. Carrillo, F. Fang, P. H. J. Nardelli, D. B. D. Costa, U. S. Dias, Z. Ding, C. B. Papadias, and W. Saad, "What role do intelligent reflecting surfaces play in multi-antenna non-orthogonal multiple access?" *IEEE Wireless Commun.*, vol. 27, no. 5, pp. 24–31, Oct. 2020.
- [66] N. Fernando, S. W. Loke, and W. Rahayu, "Mobile cloud computing: A survey," *Future Generat. Comput. Syst.*, vol. 29, no. 1, pp. 84–106, 2013, doi: [10.1016/j.future.2012.05.023](https://doi.org/10.1016/j.future.2012.05.023).
- [67] H. Shariatmadari, R. Ratasuk, and S. Iraji, "Machine-type communications: Current status and future perspectives toward 5G systems," *IEEE Commun. Mag.*, vol. 53, no. 9, pp. 10–17, Sep. 2015.
- [68] Y. Miao, G. Wu, M. Li, A. Ghoneim, M. Al-Rakhami, and M. S. Hossain, "Intelligent task prediction and computation offloading based on mobile-edge cloud computing," *Future Gener. Comput. Syst.*, vol. 102, pp. 925–931, Jan. 2020, doi: [10.1016/j.future.2019.09.035](https://doi.org/10.1016/j.future.2019.09.035).
- [69] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE Internet Things J.*, vol. 3, pp. 637–646, 2016.
- [70] A. Narayanan, A. S. D. Sena, D. Gutierrez-Rojas, D. C. Melgarejo, H. M. Hussain, M. Ullah, S. Bayhan, and P. H. J. Nardelli, "Key advances in pervasive edge computing for industrial Internet of Things in 5G and beyond," *IEEE Access*, vol. 8, pp. 206734–206754, 2020.
- [71] H. Lin, S. Zeadally, Z. Chen, H. Labiod, and L. Wang, "A survey on computation offloading modeling for edge computing," *J. Netw. Comput. Appl.*, vol. 169, Nov. 2020, Art. no. 102781.
- [72] M. Chen and Y. Hao, "Task offloading for mobile edge computing in software defined ultra-dense network," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 3, pp. 587–597, Mar. 2018.
- [73] S. Bi and Y. Zhang, "Computation rate maximization for wireless powered mobile-edge computing with binary computation offloading," *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 4177–4190, Jun. 2018.
- [74] L. Ji and S. Guo, "Energy-efficient cooperative resource allocation in wireless powered mobile edge computing," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4744–4754, Jun. 2019.
- [75] R. Roostaei, Z. Dabiri, and Z. Movahedi, "A game-theoretic joint optimal pricing and resource allocation for mobile edge computing in NOMA-based 5G networks and beyond," *Comput. Netw.*, vol. 198, Oct. 2021, Art. no. 108352.
- [76] Z. Kuang, Z. Ma, Z. Li, and X. Deng, "Cooperative computation offloading and resource allocation for delay minimization in mobile edge computing," *J. Syst. Archit.*, vol. 118, Sep. 2021, Art. no. 102167.
- [77] T. Liu, S. Ni, X. Li, Y. Zhu, L. Kong, and Y. Yang, "Deep reinforcement learning based approach for online service placement and computation resource allocation in edge computing," *IEEE Trans. Mobile Comput.*, early access, Feb. 4, 2022, doi: [10.1109/TMC.2022.3148254](https://doi.org/10.1109/TMC.2022.3148254).
- [78] S. Nath and J. Wu, "Deep reinforcement learning for dynamic computation offloading and resource allocation in cache-assisted mobile edge computing systems," *Intell. Converged Netw.*, vol. 1, no. 2, pp. 181–198, Sep. 2020.
- [79] Y. Cui, W. He, C. Ni, C. Guo, and Z. Liu, "Energy-efficient resource allocation for cache-assisted mobile edge computing," in *Proc. IEEE 42nd Conf. Local Comput. Netw. (LCN)*, Oct. 2017, pp. 640–648.
- [80] M. I. A. Zahed, I. Ahmad, D. Habibi, and Q. V. Phung, "Green and secure computation offloading for cache-enabled IoT networks," *IEEE Access*, vol. 8, pp. 63840–63855, 2020.
- [81] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. Y. Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Proc. 20th Int. Conf. Artif. Intell. Statist.*, 2017, pp. 1273–1282.
- [82] P. Kairouz, H. B. McMahan, and B. Avent, "Advances and open problems in federated learning," *Found. Trends Mach. Learn.*, vol. 14, nos. 1–2, pp. 1–210, Jun. 2021.
- [83] S. Niknam, H. S. Dhillon, and J. H. Reed, "Federated learning for wireless communications: Motivation, opportunities, and challenges," *IEEE Commun. Mag.*, vol. 58, no. 6, pp. 46–51, Jun. 2020.
- [84] M. Mohri, A. Rostamizadeh, and A. Talwalkar, *Foundations of Machine Learning*. Cambridge, MA, USA: MIT Press, 2012.
- [85] M. Frid-Adar, I. Diamant, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan, "GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification," *Neurocomputing*, vol. 321, pp. 321–331, Dec. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0925231218310749>
- [86] W.-N. Hsu, Y. Zhang, and J. Glass, "Unsupervised domain adaptation for robust speech recognition via variational autoencoder-based data augmentation," in *Proc. IEEE Autom. Speech Recognit. Understand. Workshop (ASRU)*, Dec. 2017, pp. 16–23.
- [87] E. B. P. Kairouz and H. B. McMahan, "Advances and open problems in federated learning," *Found. Trends Mach. Learn.*, vol. 14, no. 1, 2021, doi: [10.1561/22000000083](https://doi.org/10.1561/22000000083).
- [88] R. Casadei, M. Viroli, G. Audrito, D. Pianini, and F. Damiani, "Engineering collective intelligence at the edge with aggregate processes," *Eng. Appl. Artif. Intell.*, vol. 97, Jan. 2021, Art. no. 104081.
- [89] H. Nishizaki, "Data augmentation and feature extraction using variational autoencoder for acoustic modeling," in *Proc. Asia-Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA ASC)*, Dec. 2017, pp. 1222–1227.
- [90] D. Spears, W. Kerr, and W. Spears, "Safety and security multi-agent systems," in *Safety and Security in Multiagent Systems*, M. Barley, H. Mouratidis, A. Unruh, D. Spears, P. Scerri, and F. Massacci, Eds. Berlin, Germany: Springer, 2009, pp. 175–190.
- [91] L. Su and N. H. Vaidya, "Fault-tolerant multi-agent optimization: Optimal iterative distributed algorithms," in *Proc. ACM Symp. Princ. Distrib. Comput.*, 2016, pp. 425–434.
- [92] F. Fanitabasi, "A review of adversarial behaviour in distributed multi-agent optimisation," in *Proc. IEEE/ACM Int. Conf. Utility Cloud Comput. Companion (UCC Companion)*, Dec. 2018, pp. 53–58.
- [93] L. Lamport, R. Shostak, and M. Pease, "The Byzantine generals problem," in *Proc. Concurrency: Works Leslie Lamport*, 2019, pp. 203–226.
- [94] J. Almeida, J. Rufino, M. Alam, and J. Ferreira, "A survey on fault tolerance techniques for wireless vehicular networks," *Electronics*, vol. 8, no. 11, p. 1358, Nov. 2019.
- [95] V. Mohammadian, N. J. Navimipour, M. Hosseinzadeh, and A. Darwesh, "Comprehensive and systematic study on the fault tolerance architectures in cloud computing," *J. Circuits, Syst. Comput.*, vol. 29, no. 15, Dec. 2020, Art. no. 2050240.
- [96] A. Ghosh, R. K. Maity, S. Kadhe, A. Mazumdar, and K. Ramachandran, "Communication efficient and byzantine tolerant distributed learning," in *Proc. IEEE Int. Symp. Inf. Theory (ISIT)*, Jun. 2020, pp. 2545–2550.
- [97] Y. Wu, A. Khisti, C. Xiao, G. Caire, K.-K. Wong, and X. Gao, "A survey of physical layer security techniques for 5G wireless networks and challenges ahead," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 4, pp. 679–695, Apr. 2018.
- [98] R. Khan, P. Kumar, D. N. K. Jayakody, and M. Liyanage, "A survey on security and privacy of 5G technologies: Potential solutions, recent advancements, and future directions," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 1, pp. 196–248, 1st Quart., 2020.
- [99] X. Zhang and X. Chen, "Data security sharing and storage based on a consortium blockchain in a vehicular ad-hoc network," *IEEE Access*, vol. 7, pp. 58241–58254, 2019.
- [100] I. Giechaskiel, C. Cremers, and K. B. Rasmussen, "When the crypto in cryptocurrencies breaks: Bitcoin security under broken primitives," *IEEE Security Privacy*, vol. 16, no. 4, pp. 46–56, Jul. 2018.
- [101] Y. Zhang, Z. Mou, F. Gao, J. Jiang, R. Ding, and Z. Han, "UAV-enabled secure communications by multi-agent deep reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 69, no. 10, pp. 11599–11611, Oct. 2020.
- [102] Y. Wan, J. Cao, G. Chen, and W. Huang, "Distributed observer-based cyber-security control of complex dynamical networks," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 64, no. 11, pp. 2966–2975, Nov. 2017.
- [103] B. U. I. Khan, F. Anwar, R. F. Olanrewaju, B. R. Pampori, and R. N. Mir, "A novel multi-agent and multilayered game formulation for intrusion detection in Internet of Things (IoT)," *IEEE Access*, vol. 8, pp. 98481–98490, 2020.

- [104] K. Tsoulis, G. Palaiokrassas, G. Fragkos, A. Litke, and T. A. Varvarigou, "A graph model based blockchain implementation for increasing performance and security in decentralized ledger systems," *IEEE Access*, vol. 8, pp. 130952–130965, 2020.
- [105] E. Pournaras, P. Pilgerstorfer, and T. Asikis, "Decentralized collective learning for self-managed sharing economies," *ACM Trans. Auto. Adapt. Syst.*, vol. 13, no. 2, pp. 1–33, Nov. 2018.
- [106] E. Antwi-Boasiako, S. Zhou, Y. Liao, Q. Liu, Y. Wang, and K. Owusu-Agyemang, "Privacy preservation in distributed deep learning: A survey on distributed deep learning, privacy preservation techniques used and interesting research directions," *J. Inf. Secur. Appl.*, vol. 61, Sep. 2021, Art. no. 102949.
- [107] C. Zhang, M. Ahmad, and Y. Wang, "ADMM based privacy-preserving decentralized optimization," *IEEE Trans. Inf. Forensics Security*, vol. 14, no. 3, pp. 565–580, Mar. 2019.
- [108] K. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, and K. Seth, "Practical secure aggregation for privacy-preserving machine learning," in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur.*, Oct. 2017, pp. 1175–1191.
- [109] E. Pournaras, J. Nikolic, A. Omerzel, and D. Helbing, "Engineering democratization in Internet of Things data analytics," in *Proc. IEEE 31st Int. Conf. Adv. Inf. New. Appl. (AINA)*, Mar. 2017, pp. 994–1003.
- [110] F. Musciotto, S. Delpriori, P. Castagno, and E. Pournaras, "Mining social interactions in privacy-preserving temporal networks," in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining (ASONAM)*, Aug. 2016, pp. 1103–1110.
- [111] L. Bahri, B. Carminati, and E. Ferrari, "Decentralized privacy preserving services for online social networks," *Online Social Netw. Media*, vol. 6, pp. 18–25, Jun. 2018.
- [112] H. Arai and J. Sakuma, "Privacy preserving semi-supervised learning for labeled graphs," in *Proc. ECML PKDD (Lecture Notes in Computer Science)*, vol. 6911. Berlin, Germany: Springer, 2011, pp. 124–139.
- [113] T. Asikis and E. Pournaras, "Optimization of privacy-utility trade-offs under informational self-determination," *Future Gener. Comput. Syst.*, vol. 109, pp. 488–499, Aug. 2020.
- [114] J. Zhang, B. Chen, Y. Zhao, X. Cheng, and F. Hu, "Data security and privacy-preserving in edge computing paradigm: Survey and open issues," *IEEE Access*, vol. 6, pp. 18209–18237, 2018.
- [115] J. Ni, K. Zhang, and A. V. Vasilakos, "Security and privacy for mobile edge caching: Challenges and solutions," *IEEE Wireless Commun.*, vol. 28, no. 3, pp. 77–83, Jun. 2021.
- [116] V. Mothukuri, R. M. Parizi, S. Pouriyeh, Y. Huang, A. Dehghantaha, and G. Srivastava, "A survey on security and privacy of federated learning," *Future Gener. Comput. Syst.*, vol. 115, pp. 619–640, 2021.
- [117] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Trans. Intell. Syst. Technol. (TIST)*, vol. 10, no. 2, pp. 1–19, 2019.
- [118] X. Liu, H. Li, G. Xu, R. Lu, and M. He, "Adaptive privacy-preserving federated learning," *Peer-Peer Netw. Appl.*, vol. 13, no. 6, pp. 2356–2366, Nov. 2020.
- [119] R. S. Antunes, C. André da Costa, A. Küderle, I. A. Yari, and B. Eskofier, "Federated learning for healthcare: Systematic review and architecture proposal," *ACM Trans. Intell. Syst. Technol.*, vol. 13, no. 4, pp. 1–23, Aug. 2022.
- [120] X. Gu, J. Zhang, K. Shi, and Q. Wang, "Dynamic resource allocation for 3-D sidelink communication in unlicensed spectrum," *IEEE Commun. Lett.*, vol. 25, no. 1, pp. 303–307, Jan. 2021.
- [121] W. Xing, H. He, Y. Lu, J. Yang, Y. Hu, and L. Chen, "A novel method on resource allocation for V2X," in *Proc. Int. Wireless Commun. Mobile Comput. (IWCMC)*, Jun. 2020, pp. 18–23.
- [122] T. T. Thanh Le and S. Moh, "Comprehensive survey of radio resource allocation schemes for 5G V2X communications," *IEEE Access*, vol. 9, pp. 123117–123133, 2021.
- [123] A. Bazzi, A. O. Berthet, C. Campolo, B. M. Masini, A. Molinaro, and A. Zanella, "On the design of sidelink for cellular V2X: A literature review and outlook for future," *IEEE Access*, vol. 9, pp. 97953–97980, 2021.
- [124] M. Rasti, S. K. Taskou, H. Tabassum, and E. Hossain, "Evolution toward 6G wireless networks: A resource management perspective," *IEEE Wireless Commun. Mag.*, vol. 3, no. 1, p. 4, 2017.
- [125] A. Ly and Y.-D. Yao, "A review of deep learning in 5G research: Channel coding, massive MIMO, multiple access, resource allocation, and network security," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 396–408, 2021.
- [126] Y. Abiko, T. Saito, D. Ikeda, K. Ohta, T. Mizuno, and H. Mineno, "Radio resource allocation method for network slicing using deep reinforcement learning," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2020, pp. 420–425.
- [127] D. Huang, Y. Gao, Y. Li, M. Hou, W. Tang, S. Cheng, X. Li, and Y. Sun, "Deep learning based cooperative resource allocation in 5G wireless networks," *Mobile Netw. Appl.*, vol. 5, pp. 1–8, Dec. 2018.
- [128] A. N. Al-Quzweeni, A. Q. Lawey, T. E. H. Elgorashi, and J. M. H. Elmirghani, "Optimized energy aware 5G network function virtualization," *IEEE Access*, vol. 7, pp. 44939–44958, 2019.
- [129] R. Ahmed, A. K. Malviya, M. J. Kaur, and V. P. Mishra, "Comprehensive survey of key technologies enabling 5G-IoT," in *Proc. 2nd Int. Conf. Adv. Comput. Softw. Eng. (ICACSE)*, 2019. [Online]. Available: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3351007](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3351007)
- [130] X. Cheng, Y. Wu, G. Min, and A. Y. Zomaya, "Network function virtualization in dynamic networks: A stochastic perspective," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 10, pp. 2218–2232, Oct. 2018.
- [131] A. Madhja, S. Nikolettseas, and A. A. Voudouris, "Energy-aware tree network formation among computationally weak nodes," *Comput. Netw.*, vol. 168, Feb. 2020, Art. no. 107068.
- [132] I. Sanchez-Navarro, A. Serrano Mamolar, Q. Wang, and J. M. Alcaraz Calero, "5GTopoNet: Real-time topology discovery and management on 5G multi-tenant networks," *Future Gener. Comput. Syst.*, vol. 114, pp. 435–447, Jan. 2021.
- [133] D. Wu, Z. Zhang, S. Wu, J. Yang, and R. Wang, "Biologically inspired resource allocation for network slices in 5G-enabled Internet of Things," *IEEE Internet Things J.*, vol. 6, no. 6, pp. 9266–9279, Dec. 2019.
- [134] H. Fourati, R. Maaloul, and L. Chaari, "A survey of 5G network systems: Challenges and machine learning approaches," *Int. J. Mach. Learn. Cybern.*, vol. 12, no. 2, pp. 385–431, Feb. 2021.
- [135] M. Turalaska, G. R. De Mel, R. Lickorish, L. Turner, R. Whitaker, and D. Braines, "Optimizing the efficiency of collective decision making in groups," *Proc. SPIE*, vol. 11746, Apr. 2021, Art. no. 117460L.
- [136] W. Jin, M. Chowdhury, S. Mahmud Khan, and P. Gerard, "Investigating the impacts of crash prediction models on quantifying safety effectiveness of adaptive signal control systems," *J. Saf. Res.*, vol. 76, pp. 301–313, Feb. 2021.
- [137] Z. H. Khattak, M. D. Fontaine, and R. A. Boateng, "Evaluating the impact of adaptive signal control technology on driver stress and behavior using real-world experimental data," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 58, pp. 133–144, Oct. 2018.
- [138] M. S. Salek, W. Jin, S. M. Khan, M. Chowdhury, P. Gerard, S. B. Basnet, M. Torjkazi, and N. Huynh, "Assessing the likelihood of secondary crashes on freeways with adaptive signal control system deployed on alternate routes," *J. Saf. Res.*, vol. 76, pp. 314–326, Feb. 2021.
- [139] K. Dresner and P. Stone, "A multiagent approach to autonomous intersection management," *J. Artif. Intell. Res.*, vol. 31, pp. 591–656, Mar. 2008.
- [140] H. Wei, G. Zheng, V. Gayah, and Z. Li, "Recent advances in reinforcement learning for traffic signal control: A survey of models and evaluation," *ACM SIGKDD Explor. Newslett.*, vol. 22, no. 2, pp. 12–18, 2021.
- [141] F. Kong, J. Li, and Z. Lv, "Construction of intelligent traffic information recommendation system based on long short-term memory," *J. Comput. Sci.*, vol. 26, pp. 78–86, May 2018.
- [142] Z. M. Fadlullah, F. Tang, B. Mao, N. Kato, O. Akashi, T. Inoue, and K. Mizutani, "State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2432–2455, 1st Quart., 2017.
- [143] K. Dar, M. Bakhouya, J. Gaber, M. Wack, and P. Lorenz, "Wireless communication technologies for its applications [topics in automotive networking]," *IEEE Commun. Mag.*, vol. 48, no. 5, pp. 156–162, May 2010.
- [144] M. N. Ahangar, Q. Z. Ahmed, F. A. Khan, and M. Hafeez, "A survey of autonomous vehicles: Enabling communication technologies and challenges," *Sensors*, vol. 21, no. 3, p. 706, Jan. 2021.
- [145] K. C. Dey, A. Rayamajhi, M. Chowdhury, P. Bhavsar, and J. Martin, "Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication in a heterogeneous wireless network—performance evaluation," *Transp. Res. C, Emerg. Technol.*, vol. 68, pp. 168–184, Jul. 2016.
- [146] K. Abboud, H. A. Omar, and W. Zhuang, "Interworking of DSRC and cellular network technologies for V2X communications: A survey," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9457–9470, Dec. 2016.

- [147] A. P. A. Torres, C. B. D. Silva, and H. T. Filho, "An experimental study on the use of Lora technology in vehicle communication," *IEEE Access*, vol. 9, pp. 26633–26640, 2021.
- [148] S. A. AbdelHakeem, A. A. Hady, and H. Kim, "Optimizing 5G in V2X communications: Technologies, requirements, challenges, and standards," in *Research Anthology on Developing and Optimizing 5G Networks and the Impact on Society*. Hershey, PA, USA: IGI Global, 2021, pp. 972–1011.
- [149] M. Allouch, S. Kallel, A. Soua, O. Shagdar, and S. Tohme, "Survey on radio resource allocation in long-term evolution-vehicle," *Concurrency Comput., Pract. Exper.*, vol. 34, no. 7, p. e6228, 2021.
- [150] A. Martínez, E. Cañibano, and J. Romo, "Analysis of low cost communication technologies for V2I applications," *Appl. Sci.*, vol. 10, no. 4, p. 1249, Feb. 2020. [Online]. Available: <https://www.mdpi.com/2076-3417/10/4/1249>
- [151] P. K. Singh, R. Singh, S. K. Nandi, K. Z. Ghafoor, and S. Nandi, "Seamless V2I communication in HetNet: State-of-the-art and future research directions," in *Connected Vehicles Internet Things: Concepts, Technologies and Frameworks for the IoV*, Z. Mahmood, Ed. Cham, Switzerland: Springer, 2020, pp. 37–83.
- [152] A. K. Biswal, D. Singh, and B. K. Pattanayak, "IoT-based voice-controlled energy-efficient intelligent traffic and street light monitoring system," in *Green Technology for Smart City and Society*, R. Sharma, M. Mishra, J. Nayak, B. Naik, and D. Pelusi, Eds. Singapore: Springer, 2021, pp. 43–54.
- [153] A. Guillen-Perez and M. Cano, "Intelligent IoT systems for traffic management: A practical application," *IET Intell. Transp. Syst.*, vol. 15, no. 2, pp. 273–285, Feb. 2021.
- [154] U. Maheria, C. Fancy, and M. Anand, "IoT-based traffic congestion and safety management with street light control system," in *Artificial Intelligence Techniques for Advanced Computing Applications*, D. J. Hemanth, G. Vadivu, M. Sangeetha, and V. E. Balas, Eds. Singapore: Springer, 2021, pp. 495–501.
- [155] M. A. Mondal and Z. Rehena, "An IoT-based congestion control framework for intelligent traffic management system," in *Advances in Artificial Intelligence and Data Engineering*, N. N. Chiplunkar and T. Fukao, Eds. Singapore: Springer, 2021, pp. 1287–1297.
- [156] P. Gora, C. Katrakazas, A. Drabicki, F. Islam, and P. Ostaszewski, "Microscopic traffic simulation models for connected and automated vehicles (CAVs)—state-of-the-art," *Proc. Comput. Sci.*, vol. 170, pp. 474–481, Jan. 2020.
- [157] P. A. Lopez, E. Wiessner, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flotterod, R. Hilbrich, L. Lucken, J. Rummel, and P. Wagner, "Microscopic traffic simulation using SUMO," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 2575–2582.
- [158] D. Krajzewicz, "Traffic simulation with SUMO—simulation of urban mobility," in *Fundamentals of Traffic Simulation*. New York, NY, USA: Springer, 2010, pp. 269–293.
- [159] M. Wiering, J. Vreeken, J. van Veenen, and A. Koopman, "Simulation and optimization of traffic in a city," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2004, pp. 453–458.
- [160] D. Carlino, M. Depinet, P. Khandelwal, and P. Stone, "Approximately orchestrated routing and transportation analyzer: Large-scale traffic simulation for autonomous vehicles," in *Proc. 15th Int. IEEE Conf. Intell. Transp. Syst.*, Sep. 2012, pp. 334–339.
- [161] H. Zhang, S. Feng, C. Liu, Y. Ding, Y. Zhu, Z. Zhou, W. Zhang, Y. Yu, H. Jin, and Z. Li, "CityFlow: A multi-agent reinforcement learning environment for large scale city traffic scenario," in *Proc. World Wide Web Conf.*, San Francisco, CA, USA, May 2019, pp. 3620–3624.
- [162] P. W. Shaikh, M. El-Abd, M. Khanafer, and K. Gao, "A review on swarm intelligence and evolutionary algorithms for solving the traffic signal control problem," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 1, pp. 48–63, Jan. 2022.
- [163] U. K. Lilhore, S. Simaiya, P. Ghosh, A. Garg, N. K. Trivedi, and A. Anand, "Role of swarm intelligence and artificial neural network methods in intelligent traffic management," in *Machine Learning and Autonomous Systems*. Cambridge, MA, USA: Springer, 2022, pp. 209–222.
- [164] E. Mathew, "Swarm intelligence for intelligent transport systems: Opportunities and challenges," in *Swarm Intelligence for Resource Management in Internet of Things*. Cambridge, MA, USA: Academic, 2020, pp. 131–145.
- [165] T.-H. Nguyen and J. J. Jung, "Swarm intelligence-based green optimization framework for sustainable transportation," *Sustain. Cities Soc.*, vol. 71, Aug. 2021, Art. no. 102947.
- [166] E. Şahin, S. Girgin, L. Bayindir, and A. E. Turgut, "Swarm robotics," in *Swarm Intelligence: Introduction and Applications* (Natural Computing Series), C. Blum and D. Merkle, Eds. Berlin, Germany: Springer, 2008, pp. 87–100.
- [167] L. Bayindir and E. Şahin, "A review of studies in swarm robotics," *Turkish J. Elect. Eng. Comput. Sci.*, vol. 15, no. 2, pp. 115–147, 2007.
- [168] E. Osaba, J. Del Ser, A. Iglesias, and X.-S. Yang, "Soft computing for swarm robotics: New trends and applications," *J. Comput. Sci.*, vol. 39, Jan. 2020, Art. no. 101049.
- [169] M. S. Innocente and P. Grasso, "Self-organising swarms of firefighting drones: Harnessing the power of collective intelligence in decentralised multi-robot systems," *J. Comput. Sci.*, vol. 34, pp. 80–101, May 2019.
- [170] G. Vicsárhelyi, C. Virágh, G. Somorjai, T. Nepusz, A. E. Eiben, and T. Vécsek, "Optimized flocking of autonomous drones in confined environments," *Sci. Robot.*, vol. 3, no. 20, Jul. 2018.
- [171] L. Antonio, A. Mario, G. C. A. Cimino, and D. Nicoletta, "Design and simulation of the emergent behavior of small drones swarming for distributed target localization," *J. Comput. Sci.*, vol. 29, pp. 19–33, Nov. 2018.
- [172] D. Howden and T. Hendtlass, "Collective intelligence and bush fire spotting," in *Proc. 10th Annu. Conf. Genetic Evol. Comput. (GECCO)*, 2008, pp. 41–48.
- [173] D. J. Howden, "Fire tracking with collective intelligence using dynamic priority maps," in *Proc. IEEE Congr. Evol. Comput.*, Jun. 2013, pp. 2610–2617.
- [174] G. Varela, P. Caamaño, F. Orjales, Á. Deibe, F. López-Peña, and R. J. Duro, "Autonomous UAV based search operations using constrained sampling evolutionary algorithms," *Neurocomputing*, vol. 132, pp. 54–67, May 2014.
- [175] L. Giacomossi, F. Souza, R. G. Cortes, H. Mirko Montecinos Cortez, C. Ferreira, C. A. C. Marcondes, D. S. Loubach, E. F. Sbruzzi, F. A. N. Verri, J. C. Marques, L. A. Pereira, M. R. O. A. Maximo, and V. V. Curtis, "Autonomous and collective intelligence for UAV swarm in target search scenario," in *Proc. Latin Amer. Robot. Symp. (LARS), Brazilian Symp. Robot. (SBR), Workshop Robot. Educ. (WRE)*, Oct. 2021, pp. 72–77.
- [176] M. Cochez, J. Periaux, V. Terzian, and T. Tuovinen, "Agile deep learning UAVs operating in smart spaces: Collective intelligence versus 'mission-impossible,'" in *Proc. Eur. Congr. Comput. Methods Appl. Sci. Eng. Cham, Switzerland: Springer*, 2015, pp. 31–53.
- [177] J. Su, S. Yu, B. Li, and Y. Ye, "Distributed and collective intelligence for computation offloading in aerial edge networks," *IEEE Trans. Intell. Transp. Syst.*, early access, Mar. 30, 2022, doi: [10.1109/TITS.2022.3160594](https://doi.org/10.1109/TITS.2022.3160594).
- [178] S. Ahmadzadeh, G. Parr, and W. Zhao, "A review on communication aspects of demand response management for future 5G IoT-based smart grids," *IEEE Access*, vol. 9, pp. 77555–77571, 2021.
- [179] Y. Chai, Y. Xiang, J. Liu, C. Gu, W. Zhang, and W. Xu, "Incentive-based demand response model for maximizing benefits of electricity retailers," *J. Mod. Power Syst. Clean Energy*, vol. 7, no. 6, pp. 1644–1650, Nov. 2019.
- [180] V. M. Nik and A. Moazami, "Using collective intelligence to enhance demand flexibility and climate resilience in urban areas," *Appl. Energy*, vol. 281, Jan. 2021, Art. no. 116106.
- [181] F. Fanitabasi and E. Pournaras, "Appliance-level flexible scheduling for socio-technical smart grid optimization," *IEEE Access*, vol. 8, pp. 119880–119898, 2020.
- [182] A. Mashlakov, E. Pournaras, P. H. J. Nardelli, and S. Honkapuro, "Decentralized cooperative scheduling of prosumer flexibility under forecast uncertainties," *Appl. Energy*, vol. 290, May 2021, Art. no. 116706.
- [183] L. S. G. Piccolo, A. De Liddo, G. Burel, M. Fernandez, and H. Alani, "Collective intelligence for promoting changes in behaviour: A case study on energy conservation," *AI Soc.*, vol. 33, no. 1, pp. 15–25, Feb. 2018.
- [184] D. Held, *Models of Democracy*. Redwood City, CA, USA: Stanford Univ. Press, 2006.
- [185] C. F. Karpowitz, C. Raphael, and A. S. Hammond, "Deliberative democracy and inequality: Two cheers for enclave deliberation among the disempowered," *Politics Soc.*, vol. 37, no. 4, pp. 576–615, Nov. 2009, doi: [10.1177/0032329209349226](https://doi.org/10.1177/0032329209349226).
- [186] O. Perez, "Collaborative e-rulemaking, democratic bots, and the future of digital democracy," *Digit. Government: Res. Pract.*, vol. 1, no. 1, pp. 1–13, Feb. 2020.

- [187] A. Fung, "Putting the public back into governance: The challenges of citizen participation and its future," *Public Admin. Rev.*, vol. 75, no. 4, pp. 513–522, Feb. 2015, doi: [10.1111/puar.12361](https://doi.org/10.1111/puar.12361).
- [188] K. Ross and T. Bürger, "Face to face(book)," *Political Sci.*, vol. 66, no. 1, pp. 46–62, Jun. 2014.
- [189] P. Burgess, "Algorithmic augmentation of democracy: Considering whether technology can enhance the concepts of democracy and the rule of law through four hypotheticals," *AI Soc.*, vol. 37, no. 1, pp. 97–112, Mar. 2021.
- [190] E. Pournaras, "Proof of witness presence: Blockchain consensus for augmented democracy in smart cities," 2019, *arXiv:1907.00498*.
- [191] R. Hänggli, E. Pournaras, and D. Helbing, "Human-centered democratic innovations with digital and participatory elements," in *Proc. DG.O.: 22nd Annu. Int. Conf. Digit. Government Res.*, Jun. 2021, pp. 227–233.
- [192] F. Xhafa and N. Bessis, *Inter-Cooperative Collective Intelligence: Techniques and Applications*. Springer, 2014.
- [193] E. S. Bernstein, J. C. Shore, and A. J. Jang, "Network centralization and collective adaptability to a shifting environment," *Org. Sci.*, 2022. [Online]. Available: <https://pubsonline.informs.org/doi/full/10.1287/orsc.2022.1584>
- [194] N. Barkovskis, K. Ozols, and A. Elsts, "Survey of low-power wireless network technologies for the Internet of Things," *Autom. Control Comput. Sci.*, vol. 55, no. 2, pp. 177–194, Mar. 2021.
- [195] A. Jung, "Networked exponential families for big data over networks," *IEEE Access*, vol. 8, pp. 202897–202909, 2020.
- [196] V. Dasu and S. Raghunath, "Network technologies and microcontrollers in Internet of Things (IoT)—A review," *i-Manager's J. Commun. Eng. Syst.*, vol. 10, no. 1, p. 1, 2021.
- [197] S. M. Mousavi, A. Khademzadeh, and A. M. Rahmani, "The role of low-power wide-area network technologies in Internet of Things: A systematic and comprehensive review," *Int. J. Commun. Syst.*, vol. 35, no. 3, p. e5036, 2022.



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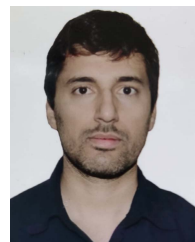
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