

Task Offloading With Multi-Tier Computing Resources in Next Generation Wireless Networks

Kunlun Wang¹, Member, IEEE, Jiong Jin², Member, IEEE, Yang Yang, Fellow, IEEE,
Tao Zhang³, Fellow, IEEE, Arumugam Nallanathan⁴, Fellow, IEEE, Chintla Tellambura⁵, Fellow, IEEE,
and Bijan Jabbari⁶, Life Fellow, IEEE

Abstract—With the development of next-generation wireless networks, the Internet of Things (IoT) is evolving towards the intelligent IoT (iIoT), where intelligent applications usually have stringent delay and jitter requirements. In order to provide low-latency services to heterogeneous users in the emerging iIoT, multi-tier computing was proposed by effectively combining edge computing and fog computing. More specifically, multi-tier computing systems compensate for cloud computing through task offloading and dispersing computing tasks to multi-tier nodes along the continuum from the cloud to things. In this paper, we investigate key techniques and directions for wireless communications and resource allocation approaches to enable task offloading in multi-tier computing systems. A multi-tier computing model, with its main functionality and optimization methods, is presented in detail. We hope that this paper will serve as a valuable reference and guide to the theoretical, algorithmic, and systematic opportunities of multi-tier computing towards next-generation wireless networks.

Index Terms—Intelligent IoT, task offloading, multi-tier computing, resource allocation.

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Kunlun Wang is with the Shanghai Key Laboratory of Multidimensional Information Processing and the School of Communication and Electronic Engineering, East China Normal University, Shanghai 200241, China (e-mail: klwang@cee.ecnu.edu.cn).

Jiong Jin is with the School of Science, Computing and Engineering Technologies, Swinburne University of Technology, Melbourne, VIC 3122, Australia (e-mail: jiongjin@swin.edu.au).

Yang Yang is with the Terminus Group, Beijing 100027, China, also with the Peng Cheng Laboratory, Shenzhen 518055, China, and also with Shenzhen SmartCity Technology Development Group Company Ltd., Shenzhen 518046, China (e-mail: dr.yangyang@terminusgroup.com).

Tao Zhang is with the U.S. National Institute of Standards and Technology (NIST), Gaithersburg, MD 20878 USA (e-mail: taozhang1@yahoo.com).

Arumugam Nallanathan is with the School of Electronic Engineering and Computer Science, Queen Mary University of London, E1 4NS London, U.K. (e-mail: a.nallanathan@qmul.ac.uk).

Chintla Tellambura is with the Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB T6G 2R3, Canada (e-mail: ct4@ualberta.ca).

Bijan Jabbari is with the Department of Electrical and Computer Engineering, George Mason University, Fairfax, VA 22030 USA (e-mail: bjabbari@gmu.edu).

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I. INTRODUCTION

AS THE fifth generation wireless networks (5G) being commercially deployed, research efforts of the sixth generation wireless networks (6G) have begun to define 6G requirements and use cases. Four promising use cases have emerged. First, holographic telepresence allows realistic, full motion, three-dimensional (3D) images of people and objects to be projected as holograms into a meeting room to interact with each other in real time [1], [2]. Such remote holographic meeting, surgery, or distant learning will reduce the need for travel. The second key use case is digital twin, which creates a real-time, comprehensive, and detailed digital (virtual) copy of a physical object, or system [3]. Digital twins help push the boundaries of system reliability, used to support a wide range of capabilities such as diagnostics and fault prediction. The third one is connected industrial robots, such as Tactile Internet and intelligent cars. In this use case, the components of a control system (e.g., controllers, sensors, and actuators) are distributed across a wide geographic region [3], and therefore need to be connected via a wide area mobile infrastructure. In addition, these intelligent applications usually require stringent delay and jitter performance, with typical maximum tolerable network latency below 1 milliseconds. The fourth use case is automated network operation empowered by distributed artificial intelligence (AI), intelligent Internet of Things (iIoT), and big data technologies [4], [5], [6].

Many current and future applications require low latency, high reliability, and high data security protection [7]. These cannot be adequately met by the traditional cloud computing model, which requires to upload massive data and computing tasks to the cloud through fronthaul links and hence is difficult to meet the requirements of low latency and high energy efficiency. To provide low-latency services, a new computing paradigm called multi-tier computing was proposed by effectively combining edge computing and fog computing [8], [9]. With multi-tier computing, a large number of smart devices with varying computational resources, located around the end user, can communicate and cooperate with each other to execute computational tasks. A comparison between multi-tier computing and the current 5G-based edge computing is illustrated in Fig. 1. Multi-tier computing complements cloud computing and edge computing by offloading and dispersing computational (and communication and caching) tasks and resources along the continuum from the cloud to things.

Multi-tier computing makes the convergence of networking and computing possible by integrating with 5G and beyond systems [10], [11], supporting computational-intensive appli-

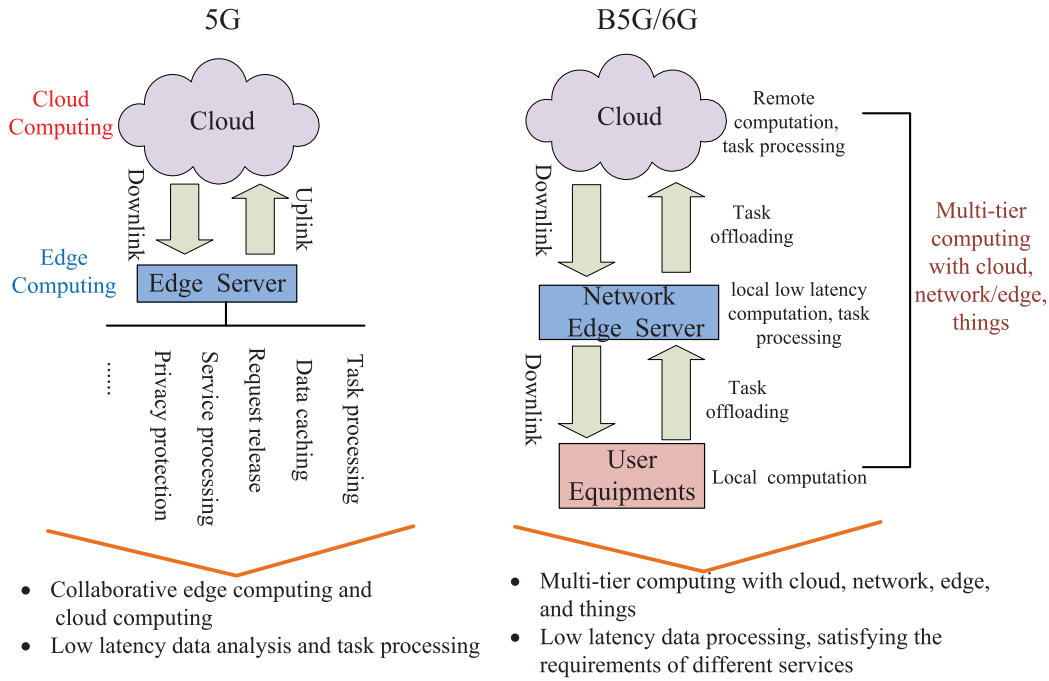


Fig. 1. Edge computing versus multi-tier computing.

cations that require low latency but high energy efficiency, high reliability and high security, including a wide range of new novel applications such as augmented reality (AR), dynamic network slicing [12], Tactile Internet [13], industrial robots and intelligent robotic cars, smart grids, and smart cities, etc. [14], [15]. The effectiveness of multi-tier computing depends largely on resource scheduling among edge and cloud nodes to reduce service latency and ease network congestion [9], [16], [17], [18]. Along the development of next-generation wireless networks, all kinds of user equipments (UEs) will be online all the time, promoting the advancement of IoT and bringing diversified applications. These novel intelligent applications typically require low latency and demand prompt computations for real-time task processing and high data rates. However, mobile devices often have limited computation, storage, and energy resources. To overcome these limitations, it is essential to offload computational tasks from the end users to nodes in the multi-tier computing systems. Such task offloading enables distributed smart devices to share their idle computation and storage resources, facilitating the efficient utilization of multi-dimensional resources for low latency task processing. In multi-tier computing, fog/edge conducts task computation for delay sensitive applications at the network edge and cloud supports time-tolerant tasks via local task offloading systems. As a result, it realizes both real-time processing and local computational system control, which is crucial for not only robust control systems, but also for the low latency applications. Moreover, multi-tier computing systems will empower new task offloading models with the advancement of B5G and future 6G wireless communication system, as well as the new generation of embedded AI. As computational power moves from the cloud to edge and UEs, the computing and networking will be deeply integrated along the development of wireless communication systems. Therefore, cloud-to-things computing capabilities should be better coordinated,

leading to a new stage of intelligent multi-tier computing systems.

A. Task Offloading in Multi-Tier Computing-Based Next-Generation Wireless Networks

Next-generation wireless communication systems present various novel technologies, including massive multiple-input multiple-output (MIMO), intelligent reflecting surface (IRS), non-orthogonal multiple access (NOMA), millimeter-wave (mmWave) communications, space-air-ground integrated networks (SAGIN) and edge AI, etc. A multi-tier computing model integrates these radio technologies and AI to reduce task execution latency, allows large-scale user access, and enables efficient task offloading to realize efficient collaborative computing and multi-dimensional communication, caching, computation resource coordination. An example of multi-tier computing-based next-generation networks is illustrated in Fig. 2. Basically, it consists of two types of nodes, i.e., task node (TN) and helper node (HN). In particular, multiple TNs are able to offload their tasks to multiple HNs. It remains a fundamental challenge to effectively map multiple tasks or TNs into multiple HNs to minimize the total cost, such as task offloading latency or energy consumption, in a distributed manner, known as the multi-task multi-helper (MTMH) problem [19], [20].

Massive MIMO can provide array gains, diversity gains, and multiplexing gains without increasing spectrum and power resources. It has been shown in [21] that massive MIMO schemes improve significantly the data rates at the cell edge and also increase exponentially the spectrum efficiency, resulting in an order of magnitude increase in system capacity. The integration of multi-tier computing and massive MIMO has been proven to enhance task offloading performance in terms of ultra reliability and low latency [17], [22], [23], [24]. In particular, Bursalioglu et al. [22] proposed an architecture

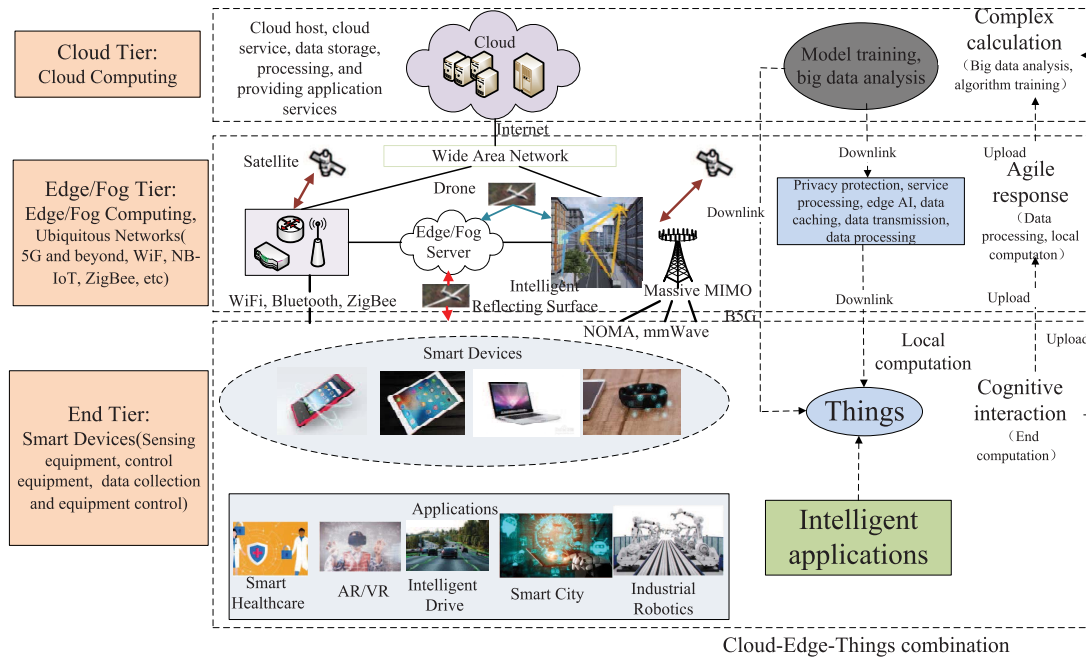


Fig. 2. Illustration of multi-tier computing network.

of fog massive MIMO, and the system performance is analyzed by densely deploying a large number of multi-antenna base stations (BSs), where the users are served by zero-forcing beamforming (ZFBF). Wang et al. [17] proposed an energy-efficient task offloading framework in a massive multiple-input multiple-output (MIMO)-aided fog computing system, where multiple task nodes offload their computational tasks via a massive MIMO-aided fog access node to multiple computing nodes for execution. In [23], Chen considered an edge computing framework based on distributed massive MIMO systems under fronthaul capacity constrain, aiming to minimize energy consumption on user devices. In [24], Mungara et al. proposed a new mechanism termed as dense fog massive MIMO, where the users are served by a large number of multiple antennas remote radio heads (RRHs), leading to high-throughput and low-latency transmission links. Although the above works demonstrate the advantages of massive MIMO-based multi-tier computing, the influence of imperfect channel condition on resource and task allocations is not studied, which is of paramount importance for time-varying multi-tier computing systems. On the other hand, to compensate for cloud computing, multi-tier computing systems provide computational capabilities both at the edge and center of the network. However, one of the major issues is how to manage task offloading and execution. More specifically, how to decide which tasks to perform at the end-user, fog/edge, or in the cloud. At a more granular level, the issue boils down to which node a particular task should be assigned to.

In B5G, the radio frequency may exceed 6 Gigahertz. Since higher-frequency signal is more sensitive to the blockage by obstacles, the coverage of each base station will be significantly reduced [25], [26]. Furthermore, devices at the cell edge or behind obstacles suffer from low task transmission rates, increasing both delay and energy consumption of task offloading in multi-tier computing systems [27]. IRS with

a large number of low-cost reflecting elements, regarded as an effective auxiliary wireless communication technology for achieving high spectrum and energy efficiency, has attracted increasing attention to circumvent these restrictions and is listed as one of the candidate key technologies in 6G by academia and industry [28], [29], [30], [31], [32], [33], [34]. Thanks to the combination of array aperture gain (achieved by combining a direct transmission signal with an IRS reflection signal) and the reflection-assisted beamforming gain (achieved by controlling the phase shifts of IRS elements), IRS is able to improve the successful task offloading rate and the efficiency of resource scheduling in multi-tier computing systems. Therefore, IRS will be a key technology for task offloading in next-generation wireless networks. In [18] and [35], the impact of IRS on computational performance is studied in a multi-tier computing system, demonstrating the benefits of the IRS to improve the task offloading, in comparison to the benchmark schemes.

Unlike orthogonal multiple access (OMA) techniques, non-orthogonal multiple access (NOMA) allows multiple nodes to concurrently communicate with a centre node over the same resource block, and hence enhancing the spectrum efficiency [36], [37]. Owing to the multiuser detection techniques such as successive interference cancellation (SIC) implemented at the receiver side [38], [39], NOMA can mitigate the co-channel interference, resulting in much better performance in terms of the network coverage and throughput compared to OMA techniques [40]. As expected, the integration of multi-tier computing and NOMA are able to boost the performance of multi-node task offloading [41], [42], [43]. Since higher-frequency signals like mmWave communications are highly correlated, making it conducive to the integration of NOMA, mmWave-NOMA is capable of supporting ultra-high bandwidth applications and massive access of users in multi-tier computing systems.

Meanwhile, by integrating satellite systems, aviation systems and ground communication systems, SAGIN is widely treated as a cornerstone of future 6G network. This new architecture supports seamless and near-instantaneous hyper-connectivity [44], aiming at global data acquisition with high temporal and spatial resolution, high-precision real-time navigation and positioning, and broadband wireless communications. Being an essential component of SAGIN, UAVs are deployed flexibly at the air-network layer, assisting terrestrial network in task offloading and communications/computing/caching resources management due to their flexibility and proximity [45]. However, even with efficient task offloading, it is still not trivial to meet the quality of experience (QoE) requirements of heterogeneous users in the SAGIN.

Because of increasingly complex wireless networks, a typical 5G node is expected to have 2000 or more configurable parameters. Therefore, a recent new trend is to optimize task offloading and wireless resource allocation through AI technologies [46], [47], i.e., applying AI at multiple protocol layers (e.g., physical layer resource allocation, data link layer resource allocation, and traffic control) [48]. Thanks to the rapid development of mobile chipsets, the computational capabilities of edge devices have been substantially improved. For example, smart devices nowadays have as much computational capability as computing servers a decade ago. In addition, edge servers could provide end users with low latency AI services that are not possible to achieve directly on the devices. Since the computational resources of edge servers are not as much as those of cloud centers, it is necessary to adopt joint design principles across edge servers and edge devices to reduce task execution latency and enforce privacy for task offloading [46]. As a result, advances in multi-tier computing systems offer an opportunity to move the frontiers of AI from the cloud center to the edge of the network, inspiring a new field of research called edge AI, including both AI model training and inference procedures.

In order to realize low-latency task processing and provision computing, storage and networking services, distributed AI and federated learning algorithms are performed on multi-tier computing servers at the access network [49]. Wireless networks with AI can support the on-demand intelligent low-latency services, commencing to emerge in complicated wireless network management and resource optimization [50], [51]. Since the data are processed at the edge server in the close proximity of smart device, there is no need to transfer a large amount of raw data to the back-end server. Thus, using edge AI on task offloading infrastructure not only saves network bandwidth on backhaul links, but also reduces greatly the task execution latency. Edge AI will be a significant step towards reducing task execution latency by intelligently enabling task offloading and local caching of popular file and content migration. In addition, intelligent task offloading for computational tasks will make it possible to further virtualize users' handsets and improve battery lifetime. In all, edge AI provides a new paradigm of optimization algorithms design for efficient task offloading and service-driven resource allocation in multi-tier computing systems [11]. By seamlessly integrating sensing, communications, computing and intelligence, edge AI will empower multi-tier computing systems to support

multiple intelligent applications, including industrial robots, intelligent robotic cars, and intelligent healthcare etc.

B. Main Contributions

Although the above discussions have demonstrated the benefits of task offloading in wireless communication systems, to the best of our knowledge, the task offloading with multi-tier computing resources in next-generation wireless networks has not been well studied. In this paper, a vision of multi-tier computing with intelligent task offloading is presented, focusing on its interactions with various wireless techniques and resource allocations. Future research directions and open problems are then discussed, embracing the era of multi-tier computing based next-generation wireless networks.

Against the above backdrop, our contributions could be further detailed as follows:

- The vision, challenges and solutions for task offloading in multi-tier computing systems towards next-generation wireless networks.
- The task offloading in multi-tier computing systems is presented, including the massive MIMO-aided task offloading, the task offloading with IRS, the task offloading with NOMA and mmWave, the task offloading in Space-Air-Ground Integrated Networks (SAGIN), and edge AI-empowered task offloading.
- The multi-tier computing resource allocation for task offloading is elaborated. Specifically, we introduce the main functionality and optimization methods as well as the algorithms for task offloading in multi-tier computing systems.
- We discuss the research directions and open problems of task offloading for multi-tier computing-based next-generation wireless networks.

C. Paper Organization

The rest of the paper is organized as follows. Section II introduces the enablement of multi-tier computing for next-generation wireless networks, while Section III presents the resource allocation for multi-tier computing systems. Section IV is focused on research directions and open problems for multi-tier computing. In Section V, we provide our conclusions.

II. ENABLEMENT OF TASK OFFLOADING FOR MULTI-TIER COMPUTING-BASED NEXT-GENERATION NETWORKS

In this section, we present the vision, challenges and solutions for task offloading in multi-tier computing systems, including the massive MIMO-aided task offloading, the task offloading with IRS, the task offloading with NOMA and mmWave, the task offloading in SAGIN, and edge AI-empowered task offloading.

A. Massive MIMO-Aided Task Offloading

With the advent of next-generation of wireless standards, new high-performance technologies are introduced. One of these key technologies is massive MIMO [52] that has been increasingly adopted in different networking and computing frameworks. However, the works of [9], [53], [54], and [55]

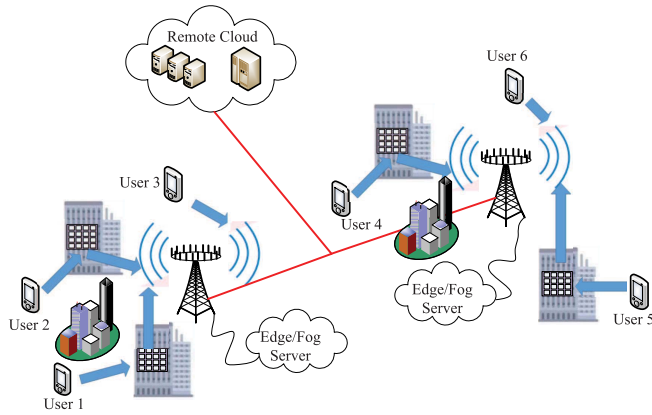


Fig. 3. Illustration of a massive MIMO and IRS-enabled multi-tier computing network.

mainly considered single-antenna computation offloading systems, by taking joint resources allocation and task offloading into account, but failed to exploit the MIMO advantages for task offloading efficiency. As we know that MIMO techniques have the potential of achieving high spectral efficiency (SE) [56], [57], [58], they have been introduced to boost the performance of edge users by increasing the task offloading data rate. In particular, equipping the base stations (BSs) with a large number of antennas, widely known as massive MIMO, has emerged as one of the most promising solutions [59], [60] to significantly improve system SE and energy efficiency trade-off. More specifically, as the number of antennas increases, channels become more deterministic, known as channel hardening. Data rates and communication resource allocations are hence largely determined by large-scale fading. This implies that resource allocation does not need to be updated frequently, leading to significant savings in signal transmission overhead. In summary, massive MIMO schemes improve spectrum and energy efficiency and support an increased number of users, both of which are critical for multi-tier computing systems.

As the core technology of wireless communication, relay technique has been integrated into various wireless communication standards to improve network coverage and throughput [61]. In particular, massive MIMO-enabled relay networks can enhance spectral efficiency and achieve more reliable data transmission for spatially distributed user nodes through intermediate massive antenna relay nodes [62], [63]. Thus, a massive MIMO-aided fog access node (FAN) serving as a relay is capable of significantly improving the data rate of offloaded tasks and the task execution efficiency. The new computing model that combines massive MIMO with multi-tier computing will facilitate efficient task offloading of computation-intensive tasks to achieve efficient collaborative computing and multi-dimensional communication, caching, computation resource scheduling.

B. Task Offloading With IRS

Next, we will introduce a concrete example of implementing IRS in multi-tier computing systems to reduce task offloading latency and energy consumption, as shown in Fig. 3. Each user could either offload its task to the multi-tier nodes such as edge/fog server for computation via the IRS or to the cloud via the IRS and massive MIMO node. In order to further improve uplink task offloading performance for resource-limited end

users, IRS technology has attracted extensive attention due to its advantages of low cost, easy deployment, fine-grained passive beamforming, and directional signal enhancement or interference nulling. By controlling surface reflective elements, IRS can be reconfigured to provide a more favorable wireless propagation environment for communications. Obviously, using IRS in multi-tier computing systems is an economical and environmentally friendly method to facilitate task offloading [18].

In [35], Chu et al. studied the impact of an IRS on computational performance in a mobile edge computing (MEC) system, targeting to optimize the sum computational bits and taking into account the CPU frequency, the offloading time allocation, transmit power of each device as well as the phase shifts of the IRS. In [18], Wang et al. investigated the task offloading problem in a hybrid IRS and massive MIMO relay assisted fog computing system, and formulated a joint task offloading, IRS phase shift optimization, and power allocation problem to minimize the total energy consumption. In [64], Zhou et al. studied an IRS-assisted MEC systems, in which IRS is deployed to assist task offloading from two users to the fog/edge access point connected to the edge cloud. Under the constraint of IRS discrete phase, the passive reflection phase of IRS and the user's computational task scheduling strategy is designed to minimize the total task processing latency. In [27], Bai et al. studied an innovative framework to employ IRS in wireless powered MEC systems, and the task offloading is based on orthogonal frequency-division multiplexing (OFDM) systems. The objective is to minimize the total task offloading energy consumption. On the basis of the above studies, it is evident that IRS can provide an additional link both for data transmission and for task offloading, so as to enhance computational capability.

C. Task Offloading With NOMA and mmWave

As we all know, NOMA performs significantly better in terms of the network coverage and spectrum efficiency than OMA [40]. Under this circumstance, the integration of multi-tier computing and NOMA is able to achieve far better performance for task offloading compared to multi-tier computing with OMA [41], [42], [43]. In particular, Wang et al. in [43] proposed a NOMA-based fog computing framework for industrial Internet of Things systems, where multiple task nodes offload their tasks via the NOMA strategy to multiple computing nodes for task computation. Accordingly, they formulated a joint task offloading and subcarrier allocation problem to minimize the total cost in terms of energy consumption and latency subject to the given communication and task computation constraints. In addition, Zhang et al. [41] proposed a network architecture of NOMA-based Fog Radio Access Networks (F-RANs), where the resource allocation with power and sub-channel allocation is studied to improve the network performance. Moreover, Wen et al. [42] and Wang et al. [65] formulated an energy efficiency maximization and a task completion time minimization problem in NOMA-enabled fog/edge computing networks, respectively. All the above works have manifested that the NOMA-based task offloading scheme can significantly reduce the energy consumption and latency cost compared to its OMA counterpart.

Regrading task offloading with mmWave, Zhao et al. have proposed single-user and multi-user mmWave task offloading framework respectively in [66] and [67], both of which aim to minimize the task offloading latency exploiting the benefits of the mmWave communications. As mentioned before, mmWave is conducive to the integration of NOMA. Yu et al. [68] analyzed the impact of NOMA and mmWave on task offloading, where the hybrid beamforming at the BS and the resource allocation at the end user are jointly optimized, and NOMA-mmWave is shown to improve the computation efficiency by the theoretical and simulation results.

D. Task Offloading in SAGIN

IoT seeks to connect billions of resource-constrained devices around us through heterogeneous networks. The SAGIN is viewed as a major candidate to support such IoT requirements, provisioning seamless and massive connectivity for smart services [44], [69]. In the past two years, 5G wireless networks have been commercialized and deployed around the world. Although 5G is still in its development, academia and industry have now shifted their attention to beyond 5G and 6G wireless networks, in order to meet the demands of ultra-low latency and high energy efficiency for IIoT [44]. Among the discussions about 6G, from the perspective of computing, communication, and caching, it is the trend to combine SAGIN with multi-tier computing technologies in the 6G networks.

Specifically, it is widely recognized that SAGIN will be the potential core architecture of the future 6G network to support seamless and near-instantaneous hyper-connectivity [44]. Thus, multi-tier computing with SAGIN promotes the task offloading performance. As a key part of this, in the integrated air-ground branch, unmanned aerial vehicles (UAVs) are flexibly deployed at the aerial network layer, assisting in communication, computing and caching of ground networks due to their flexibility and proximity [45]. However, in 6G networks, SAGIN still faces challenges such as the demands of temporal-spatial dynamic communication/computing/caching services, large-scale complex connection decisions and resource scheduling, and ubiquitous intelligence demands within the network. To sum up, it remains extremely challenging to realize these visions of 6G in SAGIN.

There have been heavy research efforts on the architecture of SAGIN and multi-tier computing in the existing literature. Cheng et al. [45] proposed a novel air-ground integrated mobile edge network, by investigating the potential benefits and applications of drone cells, and UAV-assisted edge computing and caching. To support diverse vehicular services, Zhang et al. [5] presented a software defined networking (SDN)-based space-air-ground integrated network architecture. Focusing on provisioning computing services by UAVs, Zhou et al. [70] proposed an air-ground integrated MEC framework to cater for the urgent computing service demand from the IoTs. Furthermore, Kato et al. [71] conducted a comprehensive study about how to deal with the challenges related to the space-air-ground integrated networks by AI techniques, including network control, spectrum management, energy management, routing and handover management, and security guarantee. In [72], Cheng et al. demonstrated a SAGIN edge/cloud computing architecture for offloading the

computation-intensive applications, considering remote energy and computation constraints, and developed a joint resource allocation and task scheduling approach to efficiently allocate the computing resources. In [73], Shang et al. studied MEC in air-ground integrated wireless networks to minimize the total energy consumption by jointly optimizing users association for computation offloading, uplink transmit power, allocated bandwidth, computation capacity, and UAV 3-D placement. However, how the air network layer allocate the communication/computing/caching resources intelligently for task offloading of the ground network layer in SAGIN has not been adequately addressed.

E. Edge Intelligence-Empowered Task Offloading

With the continuing increase in the quantity and quality of rich multimedia services, the traffic and computational tasks of mobile users and smart devices have significantly increased in recent years, bringing huge workload to the already congested backbone and access networks. Even with the help of multi-tier computing systems, it is challenging to satisfy the quality of experience (QoE) requirements of users. The main difficulty lies in the need of large amount of wireless data and task transmissions for task offloading, causing wireless channel congestion. Therefore, the optimization problem or decision making of the combined wireless communication resource allocation and multi-tier task offloading is the key. That is, how to share the communication resources and computing resources between edge nodes and the cloud. In response to the increasing complexity of wireless communication networks, AI technologies have been proposed as a new research trend to optimize resource allocations [46], [47], including but not limited to applying AI algorithms to physical layer resource allocation, data link layer resource allocation, medium access control, and traffic and congestion control [48]. Especially, reinforcement learning is often applied to jointly manage communication, computing, and caching resources. With learning based multi-tier computing systems, we can optimize task offloading, communication resource allocation, and content caching at edge nodes. Further, federated learning [74], as a distributed learning framework, always brings the following benefits for task offloading: 1) great reduction of the amount of data that must be uploaded through wireless uplink channel, 2) cognitive response to the changing wireless network environments and conditions, and 3) strong adaptability to the heterogeneous nodes in the wireless networks, 4) better protection of personal data privacy.

In learning-based multi-tier computing systems, task offloading decision and communication resource allocation vectors generally are binary variables, turning out challenging to find the optimal solution of resource allocations. Moreover, the feasible set and the objective function of the optimization problem are generally nonconvex, making the problem NP hard. In addition, in time-variant systems, channel conditions and computational cost are dynamic. Instead of solving the NP hard optimization problem by utilizing conventional optimization methods, the task offloading and communication resource allocation problem in multi-tier computing systems could be possibly solved using online learning algorithms. During the online learning process, the deep reinforcement

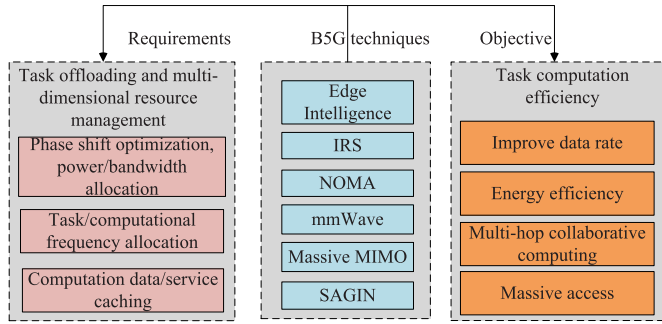


Fig. 4. Requirements and objective for designing multi-tier computing systems.

learning methods might be applied to jointly optimize the subcarrier allocation and task offloading in each time episode. Online federated learning framework is recently utilized to learn in a distributed way, in order to solve the task offloading and communication resource allocation problem. Based on the communication, computational resource allocation, the multi-tier task offloading decisions can then be optimized.

Furthermore, edge learning methods have been investigated in some edge/fog computing systems to simplify the optimization algorithm or fulfill online implementations [16], [43], [75], [76], [77], [78], [79], [80]. In [76], Huang et al. designed a deep learning-based task offloading strategy to minimize weighted energy consumption and latency. In [79], Wang et al. leveraged deep reinforcement learning method for smart resource allocation in a software defined network (SDN)-enabled edge computing architecture. In [78], Huang et al. proposed a deep learning-based task offloading strategy for offloading decisions and resource allocation of a wireless powered edge computing system. In [81], Yang et al. also used deep reinforcement learning method in IRS-aided edge computing systems to enhance system security and maximize the sum rate of the down-link task offloading. In [82], a convolutional neural network was constructed for channel estimation of a large IRS-aided massive MIMO communication system to estimate the direct and the cascaded channels, used for multi-tier task offloading.

III. MULTI-TIER COMPUTING RESOURCES ALLOCATION FOR TASK OFFLOADING

In this section, we first characterize the multi-tier computing resource allocation in next generation wireless networks, and then effective optimization methods are presented to achieve efficient task offloading with multi-tier resources.

A. Main Functionality

In this subsection, the computational and communication resources allocation, service placement, and security requirement are characterized for designing multi-tier computing systems, which is illustrated in Fig. 4.

1) *Computation*: Multi-tier computing architectures were envisioned to achieve rapid and affordable scalability by developing computation capabilities flexibly along the entire cloud-to-things continuum [83]. In essence, multi-tier computing systems distribute computing capability anywhere between the cloud and the things to take full advantage of the computational resource available along this continuum, thus extending

the traditional cloud computing architecture to the edge of the network. Thanks to multi-tier computing, some application components can be performed at the network's edge, like delay-sensitive components. While other components, such as time-tolerant and computation-intensive ones, are performed in the cloud. Satisfying diverse delay requirements will require both cloud computing with enormous resources to support time-tolerant tasks, and distributed fog/edge computing with limited resources and simple algorithms closer to the users to support time-sensitive tasks. With heterogeneous computing resources and collaborative service architecture, the proposed multi-tier computing systems are able to effectively support a full range of services in different environments. On this basis, multi-tier computing provides the advantage of low-latency task offloading since it allows task to be processed at the network edge, close to the end devices. Obviously, cloud computing alone is not adequate for supporting all IoT applications, while a multi-tier computing system can be complementary.

For smart devices with abundant computing resources, multi-tier computing seeks to achieve seamless integration of edge and cloud systems. This vision goes beyond treating the network edge and smart devices as separate computing platforms. Seamlessly integrating fleets and swarms of mobile IoT entities into a dense multi-tier enclave is a new distributed computing paradigm that improves the scalability, extensibility and assemblability of cloud services through edge of computing systems. Smart devices (cars, drones and robots) have spare computational resource, allowing the multi-tier computing platform to reduce energy consumption and task processing latency compared to the traditional edge computing scenarios relying on static and low-power edge servers.

2) *Communication*: Multi-tier computing systems distribute communication functions anywhere between the cloud and things to take full advantage of the communication resource available along this continuum. In massive MIMO-aided multi-tier computing systems, the achievable data rates are mostly determined by large-scale fading, and so is the communication resource allocation. This means that there is no need to frequently update communication resource allocations, hence reducing signaling overhead. IRS is capable of improving the success rate of the task offloading. Given the potential gains, if the line-of-sight (LoS) link between the task offloading nodes and computing nodes is blocked by obstacles, the task could be offloaded via the IRS reflected links. In this manner, we attempt to optimize the link selection and wireless communication resource allocation.

It is important to maintain the required data rates for task offloading. Take the task offloading from a car as an example. Given that a connected car produces tens of megabytes of data per second, an autonomous vehicle may generate up to a gigabyte per second [8]. Here, dense moving edge nodes can support accelerated data communication by largely utilizing directional high-rate communication in the massive MIMO, IRS or the SAGIN. Edge nodes at the same time provide novel strategies for smart devices to combine the benefits of centralized and ad-hoc topologies into a unified solution by using multi-hop, multi-connection mechanisms to communicate with adjacent network infrastructure when facing the intermittent connectivity.

3) *Storage*: Because the edge nodes often have limited storage resources, distributing the data among edge and cloud nodes is vital for optimizing task offloading latency or energy consumption at a given QoS level. On top of it, multi-tier computing also brings a large amount of cloud-like services closer to the end users. Caching computational data or services at edge nodes is hence crucial, which relieves the burden of backhaul transmission with transporting all the data to the clouds.

Accordingly, elastic storage capacity of edge nodes might be used to support applications running on resource constrained IoT devices. Due to the inherent flexibility of multi-tier computing systems, it is possible to integrate a large number of densely distributed devices. Caching capacity of edge servers is usually accessed by both smart devices and edge access points. For example, user nodes are possibly consolidated into special capacity areas. Then, multiple interconnected edge infrastructures that coexist in space and time could pool storage resources of adjacent edge networks together for sharing by smart devices and end users.

4) *Security*: In cloud computing systems, massive data need to be uploaded to the cloud data center through a front-haul link, where data security cannot be guaranteed. However, multi-tier computing systems present unique security challenges and opportunities. Dense edge nodes with established dynamic trust chains are acting as a trusted authority for other smart devices and systems. In particular, multi-tier computing systems with edge and cloud can handle responsibilities such as trusted computing platforms, and secure storage of short-term sensitive information. Multi-tier computing systems also utilize edge systems to facilitate local threat monitoring, detection, and protection for users and provide powerful proximity-based authentication services for better authentication through proxy smart devices.

However, the multi-tier computing systems meanwhile incur new security vulnerabilities, mainly from multiple heterogeneous nodes. For example, in a multi-node environment, when multiple potentially competing service providers and consumers share resources distributed across a set of hardware platforms, advanced authorization and authentication mechanisms should be created to effectively leverage this heterogeneous medium and devices between edge and cloud entities. Fortunately, a trusted execution environment supported by a public key infrastructure may be a suitable solution to the above problems. Nevertheless, the intelligent integration of hardware assistance and software security mechanisms in multi-tier computing systems remains an open research question.

Additionally, multi-tier computing systems have to cope with changing environments compared to existing edge computing systems that mainly operate under known conditions. In this case, the security mechanism for multi-tier computing systems is supposed to constantly adapt to the changing operating conditions. To address this challenge, multi-tier computing systems must dynamically adjust their overall security posture. It requires the design of new security protocols, which is able to respond to any security threat without causing service disruptions and to fulfill secured and uninterrupted operation of the task offloading.

B. Optimization Algorithms

With the exponential growth of real-time services, delay has emerged as a key figure of merits and become the design metric of multi-tier computing systems [84], and the total task offloading latency consists of the task computation latency at multi-tier computing nodes plus the round-trip task transmission latency. For local computing, the latency only includes the processing latency of local CPUs. For task offloading, if a task is to be processed by the edge/fog or cloud, the node needs to transmit the task through the shared wireless channel. Hence, the latency includes the task transmission latency and task computation latency in the edge/fog or cloud. In the meantime, IoT services urge for more and more computation and communication resources due to the rapid increasing number of connected devices. However, as these intelligent devices usually have limited computation and energy resources, it is a big challenge for the service providers to promote these novel applications. In this subsection, the effective optimization methods are presented to achieve low latency and energy efficient task offloading with multi-tier resources, and to decide which tasks to perform at the end-user, fog/edge, or in the cloud with dynamic resources. Therefore, the differences and difficulties in multi-tier computing systems need to solve a series of non-convex optimization problems with binary variables, as well as the stochastic variables.

1) *Nonconvex Optimization*: During task offloading process, most of the resource allocation problems in multi-tier computing systems need to solve a series of nonconvex optimization problems. For example, for IRS-aided multi-tier computing systems, there are four blocks of optimization variables, namely, task offloading ratio, power allocation at the relay node, and IRS phase shifts of two hops' task transmission. The optimization of task offloading ratio is related to the computing setting, while the optimization of power allocation and phase-shift matrices affects the communication design. However, the resource allocation problem in IRS-enabled multi-tier computing systems is difficult to solve due to two aspects. The first one is the coupling effect between the power allocation vector and the IRS phase-shift vector. The second one is that the objective function is non-convex with respect to the phase shifts. Obviously, it is an open challenge to obtain a globally optimal solution directly. In fact, alternating optimization technique is a widely applicable and efficient approach for solving optimization problems involving coupled optimization variables, which has been successfully applied to several communication resource allocation problems such as hybrid precoding [85], power allocation [86], and IRS phase shift optimization [28], [87]. In this case, a locally optimal solution is usually provided. To be specific, the resource allocation optimization problem can be transformed into a phase shift optimization problem, a power allocation problem, and a task allocation problem, respectively, by using the popular alternate optimization technique to decouple communication and computational design.

Remarkably, in contrast to the alternate optimization technique, distributed optimization algorithms for non-convex optimization have appeared in the literature [88]. In [89] and [90], Tatarenko et al. and Zeng et al. studied distributed gradient descent methods for unconstrained non-convex optimization

problems, respectively. Distributed optimization algorithms are generally divided into two categories: discrete time algorithms and continuous time algorithms. The existing work mainly focuses on discrete time algorithms, while continuous time problem has attracted extensive attention in recent years, mainly because of the wide application of continuous time setting in practical systems and the development of continuous time control technology. In addition, discrete time and continuous time algorithms are closely related to each other due to the time scale transformation. Specifically, when the time step size approaches zero, the optimization algorithm for discrete time system is similar to the continuous one. Note that coupled non-linear constraints are also an important constraint in distributed optimization problems. However, distributed algorithms dealing with coupled non-linear constraints are basically convex problems, i.e., both the objective function and the constraint are convex. In [84], Wang et al. developed distributed augmented Lagrangian based algorithms for non-convex optimization problems of multi-tier computing networks subject to local constraints and coupled non-linear equality constraints, and investigated the joint design of the task offloading, service caching and power allocation to minimize the total task scheduling delay.

2) *Mixed-Combinatorial Optimization*: Combinatorial optimization problems have been analyzed in many works (e.g., [91], [92], [93], [94]). Under the framework of combinatorial optimization, an important trend is analyzing combinatorial optimization problem within the framework of Euclidean combinatorial optimization, whose optimization is carried out in a Euclidean space. In [93] and [94], Barbolina et al. and Yemets et al. studied the Euclidean combinatorial optimization problems, and investigated the properties of its convex hull and methods of solving separate classes of Euclidean problems of combinatorial optimization. Additionally, the general permutation set problem is an important Euclidean combinatorial optimization problem.

As previously mentioned, the resource allocation problems in multi-tier computing systems involve optimizing computation, communication and caching. In general, task offloading, task data caching and communication resource allocations are binary variables. Specifically, in multi-tier computing for next-generation wireless networks, we need to jointly optimize the subcarrier and bandwidth allocation [95], [96], [97], transmit power and receive beamforming [17], [43], passive beamforming at IRS [18], device selection [9], [18], location updates task offloading [16], and computational frequency control [9], so as to reduce the latency and energy consumption in the task offloading procedure. Therefore, these resource allocation schemes can be formulated as a mixed combinatorial optimization problem that requires joint optimization of continuous value variables (e.g., beamforming, power control) and discrete value variables (e.g., task allocation, service placement, subcarrier allocation).

It should be noted that the existing optimization methods for mixed combinatorial optimization problems are mainly based on traditional iterative optimization approaches [18], [98], [99], [100], [101], or adopt a direct end-to-end online learning approaches [16], [79]. However, they may not achieve good trade-off between algorithm complexity and resource

allocation performance. Additionally, reinforcement learning (RL)-based approaches are often involved to solve combinatorial optimization problems that are unconstrained or have few constraints due to feasibility issues [43], [102]. Deep RL requires a Markov process to achieve satisfactory resource allocation performance [103]. However, Markov process may not exist in practical combinatorial optimization problems, as they have many non-convex constraints with memory. This results in difficult design of reward features for Markov optimization process, unfeasible solutions, and potential degradation of overall performance.

3) *Stochastic Optimization*: In multi-tier computing systems, stochastic optimization approach only relies on the probabilistic description about the uncertainty of computation capacity and radio channel condition, and is able to provide a trade-off between conservatism and probabilistic assurance for the achievable task offloading performance. Stochastic programming has been widely studied in the past decade due to its wide application in machine learning and resource allocation. In a stochastic optimization problem, the objective function or constraints are the expectation of some function of random variables (such as estimated computation capacity and channel condition in learning approach) [104]. The challenge of stochastic optimization is that the distribution of the random variables is often unknown. Most existing literature on stochastic programming assumes that the basic distribution of random variables is fixed and that independent samples are sequentially drawn from this common distribution. However, the basic distribution of random variables involved in stochastic optimization may change slowly over time in many practical applications.

Stochastic optimization in state-based systems with discrete or continuous time are often modeled as Markov chains. Their effective optimization method is an important research topic. The Markov model has a wide range of applications, especially in the area of task offloading in multi-tier computing systems. Specifically, some work modeled the task offloading problem as a stochastic programming problem, and jointly optimized the task allocation and the communication resources allocation [105]. However, in all these works, system parameters need to be acquired offline, which is impossible for a time-varying system [106]. It should be noted that there are multiple dynamic parameters in multi-tier computing systems. Therein, user mobility and channel condition are intrinsic features of wireless networks when nodes are usually in a mobility state. Then, due to changes in network topology, these parameters are time-varying, and the stochastic task offloading framework is considered as a method of online learning where users can learn time-varying system parameters.

In many multi-tier computing applications, optimization criteria are trade-offs between several competing goals, such as computational cost minimization and profit maximization. In this tradeoff model, it is important to establish an optimal strategy that may often not be intuitive. However, there are also optimization problems with no tradeoff characteristics, leading to counterintuitive optimal strategies. Therefore, the use of Markov decision process (MDP) to optimize stochastic systems should not be ignored. A reinforcement learning task that satisfies the Markov property is called an MDP, which is a

tool for modeling sequential decision-making problems. If the state and action spaces are finite, then it is called an finite MDP, which is crucial to the basis of reinforcement learning (RL). In MDP, future decisions are based on recent state. Thus, an optimal policy consists of actions based on the observed history to maximize the expected reward. RL has been widely adopted in the unknown environment, by continuously interacting with the environment to achieve the optimal results out of imperfect information. RL can further take advantage of high-dimensional characteristics of deep neural network (DNN), evolving into deep reinforcement learning (DRL). It is worthwhile noticing that DRL is capable of characterizing the infinite states caused by measurement error and environmental noise. There exists extensive literature in online learning task offloading for stochastic optimization, such as DRL [107], [108], [109], [110], which generally target at a broader set of learning problems in MDPs. As far as we are aware, high-dimensional action spaces are still an urgent and challenging problem in DRL. To make the problem tractable, the general optimization problem is reduced into an MDP that only considers a meaningful parameter. Furthermore, the Multi-Armed Bandit (MAB) problem is a special case of MDP problems for which regret learning frameworks are generally considered to be more efficient of computational complexity. Additionally, the use of the MAB model is appropriate and recognizable, taking advantage of the fact that the resources of edge node are limited. Based on the above analysis, MDP promises an online learning framework for learning computing resources and available communication, storage resources information for stochastic optimization, aiming to minimize task offloading cost.

IV. RESEARCH DIRECTIONS AND OPEN PROBLEMS

In this section, we present the research directions and open problems for task offloading in next-generation wireless networks, supported by the wireless network infrastructures in Section II.

A. Multi-Dimensional Resource Management

Compared to cloud computing, the edge nodes and end users in multi-tier computing systems may have limited resources. Therefore, communication, computing and caching resource allocation is a very important research issue in multi-tier computing systems. Specifically, next-generation wireless communication networks present various technologies, including massive MIMO, IRS, NOMA, SAGIN, and AI etc. These new communication technologies integrated with multi-tier computing will reduce task offloading delay, grant large-scale user access and promote rapid development of the intelligent services, as well as realize efficient collaborative computing and multi-dimensional communication, caching, computation resource sharing through efficient task offloading.

However, the computation power of multi-tier servers is typically limited. The wireless physical layer resource allocation and user access techniques are the key challenges that hinder the success of multi-tier computing for 5G and beyond in executing compute-intensive and latency-critical applications. The optimization of resource allocation may be multi-objective in different situations, e.g., diverse nature of

applications, heterogeneous server capabilities, user demands and characteristics, and channel connection qualities.

B. Multi-Tier Task Allocation

Since multi-tier computing systems provide extra computing capability at the network edge, one of the core problems is how to manage task allocation. More specifically, how to decide which tasks should be performed on end-user devices, at fog/edge systems, or in the cloud. At a more granular level, the challenge is to which computing nodes should a task be assigned. To achieve low latency and high energy efficiency of task offloading, computing tasks need to be scheduled to computing nodes with different capabilities according to different task computing models, communication bandwidths and channel qualities. Therefore, heterogeneity becomes an important factor in multi-tier computing architectural design. Dealing with different task computation and various communication protocols to manage task offloading becomes a major problem.

C. Heterogeneous QoS Management

With the development of various novel technologies, intelligent services are increasingly applied in many fields of human life, including business, manufacturing, health-care, entertainment, etc. On one hand, the number of smart services deployed around edge and cloud servers is growing rapidly. On the other hand, different service providers provision services with similar functions, and different edge servers may possess different service performance. Then, the smart devices will require services with different QoS requirements. In light of these descriptions, intelligent services are migrating to the network, i.e., to edge servers residing near end users.

Note that QoS requirements in multi-tier computing systems include task response time, throughput, reliability and availability, typically different for different users. However, user mobility and different server capabilities turn the applicability of traditional QoS management inapplicable. Therefore, how to monitor and manage QoS attributes, and schedule multi-dimensional resources timely and effectively to fulfill specific QoS requirement for each user becomes the main issue in multi-tier computing systems.

D. Data Privacy

In multi-tier computing systems, data and computation task need to be collected close to the physically distributed edge devices, and there exists a large number of devices in the systems. When analyzing sensitive information from distributed nodes, data privacy cannot be compromised. We should select computing nodes in a way that best protect the data privacy, considering the computing nodes in different parts of the network may have different privacy protection capabilities. The tasks collected, transmitted, and processed at the edge or in the cloud should be anonymized [111]. Then, multi-tier data analysis and processing is achieved securely in multi-tier computing systems. Note that distributed systems are in general more vulnerable to be attacked than centralized systems, and both the end devices and edge computing nodes in multi-tier computing systems are typically less powerful than the cloud. Therefore, these nodes may not have as adequate resources as the cloud to protect themselves. In addition, the devices and

edge computing nodes may not have enough intelligence and capability equipped to detect threats due to limited resources. In all, data privacy of multi-tier computing from things to the cloud will be the focus of future research in multi-tier computing systems.

V. CONCLUSION

In this paper, we investigated the key wireless communication techniques, effective resource allocation approaches and research directions to embrace the era of task offloading for multi-tier computing-based next-generation wireless networks. In particular, the multi-tier computing system model, multi-tier computing resources and optimization methods were presented for better facilitating the task offloading. We hope that this paper will serve as a valuable reference and guide to further promote the theoretical, algorithmic, and systematic development and advancement of task offloading with multi-tier computing resources in next-generation wireless networks.

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Kunlun Wang (Member, IEEE) received the Ph.D. degree in electronic engineering from Shanghai Jiao Tong University, Shanghai, China, in 2016. From 2016 to 2017, he was with Huawei Technologies Company Ltd., where he was involved in energy efficiency algorithm design. From 2017 to 2019, he was with the Key Laboratory of Wireless Sensor Network and Communication, SIMIT, Chinese Academy of Sciences, Shanghai. From 2019 to 2020, he was with the School of Information Science and Technology, ShanghaiTech University. Since 2021, he has been a Professor with the School of Communication and Electronic Engineering, East China Normal University. His current research interests include 5G wireless communications, fog/edge computing networks, resource allocation, and optimization algorithm. He is the Lead Guest Editor of IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS ON MULTI-TIER COMPUTING FOR NEXT GENERATION WIRELESS NETWORKS and the Review Editor of *Signal Processing for Communications*.



Jiong Jin (Member, IEEE) received the B.E. degree (Hons.) in computer engineering from Nanyang Technological University, Singapore, in 2006, and the Ph.D. degree in electrical and electronic engineering from the University of Melbourne, Australia, in 2011. From 2011 to 2013, he was a Research Fellow with the Department of Electrical and Electronic Engineering, University of Melbourne. He is currently an Associate Professor with the School of Science, Computing and Engineering Technologies, Swinburne University of Technology, Melbourne, Australia. His research interests include network design and optimization, edge computing and networking, robotics and automation, and cyber-physical systems and the internet of things as well as their applications in smart manufacturing, smart transportation and smart cities.



Yang Yang (Fellow, IEEE) received the B.S. and M.S. degrees in radio engineering from Southeast University, Nanjing, China, in 1996 and 1999, respectively, and the Ph.D. degree in information engineering from The Chinese University of Hong Kong in 2002.

He is currently the Chief Scientist of IoT at the Terminus Group, China. He is also an Adjunct Professor with the Department of Broadband Communication, Peng Cheng Laboratory, and a Senior Consultant with the Shenzhen Smart City Technology Development Group, China. Before joining Terminus, he has held a faculty member positions at The Chinese University of Hong Kong, Brunel University, U.K., University College London (UCL), U.K., CAS-SIMIT, and ShanghaiTech University, China. His research interests include multi-tier computing networks, 5G/6G systems, the AIoT technologies, intelligent services and applications, and advanced wireless testbeds. He has published more than 300 papers and filed more than 120 technical patents in these research areas. He has been the Chair of the Steering Committee of Asia-Pacific Conference on Communications (APCC) from 2019 to 2021. Currently, he is serving the IEEE Communications Society as the Chair for 5G Industry Community and the Chair for Asia Region at Fog/Edge Industry Community.



Tao Zhang (Fellow, IEEE) received the B.S. and M.S. degrees in electrical engineering from Northern Jiaotong University, Beijing, China, and the Ph.D. degree in electrical and computer engineering from the University of Massachusetts, Amherst, MA, USA.

He has been leading research, product development, and corporate strategies, which led to new technologies, products, and standards. He is currently managing the Transformational Networks and Services Research Group, U.S. National Institute of Standards and Technology (NIST). He was the CTO of Smart Connected Vehicles Business at Cisco Systems and the Chief Scientist and the Director of multiple research and development groups focused on wireless and vehicular networking at Telcordia Technologies (formerly Bell Communications Research). He co-founded the OpenFog Consortium and the Connected Vehicle Trade Association (CVTA) and served as the Founding Board Director for them. He holds over 100 patents awarded globally and coauthored two books *Vehicle Safety Communications: Protocols, Security, and Privacy* and *IP-Based Next Generation Wireless Networks* and over 100 peer-reviewed papers. He is a fellow of the Society for Information Reuse and Integration and a fellow of the Asia-Pacific Artificial Intelligence Academy. He served as the CIO and a Board Governor of the IEEE Communications Society and as a Distinguished Lecturer of the IEEE Vehicular Technology Society.



Arumugam Nallanathan (Fellow, IEEE) has been a Professor in wireless communications and the Head of the Communication Systems Research (CSR) Group, School of Electronic Engineering and Computer Science, Queen Mary University of London, since September 2017. He was with the Department of Informatics, Kings College London, from December 2007 to August 2017, where he was Professor in wireless communications from April 2013 to August 2017 and has been a Visiting Professor since September 2017. He was an Assistant

Professor with the Department of Electrical and Computer Engineering, National University of Singapore, from August 2000 to December 2007. His research interests include artificial intelligence for wireless systems, beyond 5G wireless networks, the Internet of Things (IoT), and molecular communications. He has published more than 500 technical papers in scientific journals and international conferences.

He was a co-recipient of the best paper awards presented at the IEEE International Conference on Communications 2016 (ICC'2016), IEEE Global Communications Conference 2017 (GLOBECOM'2017), and IEEE Vehicular Technology Conference 2018 (VTC'2018). He was also a co-recipient of IEEE Communications Society Leonard G. Abraham Prize in 2022. He is an IEEE Distinguished Lecturer. He has been selected as a Web of Science Highly Cited Researcher in 2016 and AI 2000 Internet of Things Most Influential Scholar in 2020. He is an Editor-at-Large for IEEE TRANSACTIONS ON COMMUNICATIONS and a Senior Editor for IEEE WIRELESS COMMUNICATIONS LETTERS. He was an Editor for IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS (2006–2011), IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY (2006–2017), and IEEE SIGNAL PROCESSING LETTERS. He served as the Chair for the Signal Processing and Communication Electronics Technical Committee of IEEE Communications Society and the technical program chair and a member of technical program committees in numerous IEEE conferences. He received the IEEE Communications Society SPCE Outstanding Service Award 2012 and IEEE Communications Society RCC Outstanding Service Award in 2014.



Chintha Tellambura (Fellow, IEEE) received the B.Sc. degree (Hons.) from the University of Moratuwa, Sri Lanka, the M.Sc. degree in electronics from the Kings College, University of London, U.K., and the Ph.D. degree in electrical engineering from the University of Victoria, Canada.

He was with Monash University, Australia, from 1997 to 2002. He is currently a Professor with the Department of Electrical and Computer Engineering, University of Alberta. His current research interests include the design, modeling, and analysis of current and future wireless networks.

Prof. Tellambura served as an Editor for IEEE TRANSACTIONS ON COMMUNICATIONS (1999–2011) and IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS (2001–2007) and for the latter, he was the Area Editor of *Wireless Communications Systems and Theory* (2007–2012). He has received best paper awards in the Communication Theory Symposium in 2012 IEEE International Conference on Communications (ICC) in Canada and 2017 ICC in France. He is the winner of the prestigious McCalla Professorship and the Killam Annual Professorship from the University of Alberta. In 2011, he was elected as a fellow of IEEE for his contributions to physical layer wireless communication theory. In 2017, he was elected as a fellow of Canadian Academy of Engineering. He has authored or coauthored over 600 journals and conference papers with an H-index of 80 (Google Scholar).



Bijan Jabbari (Life Fellow, IEEE) received the M.S. and Ph.D. degrees in electrical engineering from Stanford University, CA, USA. He is currently a Professor with the Department of Electrical and Computer Engineering, George Mason University, Fairfax, VA, USA. He is also an affiliated Faculty Member with Telecom Paris-Tech (ENST-Paris), France. His area of specialization and interests are wireless communication and networks with particular emphasis on multi-user access, resource allocation, mobility and performance optimization, and cognitive radio.

He was a recipient of the IET Fellow Grade, the IEEE Millennium Medal, and the Washington Metropolitan Area Engineer of the Year Award. He received the Outstanding Faculty Research Award from the School of Engineering, George Mason University. He was the Chairman of the IEEE Communications Society Technical Committee on Communications Switching and Routing. He was the General Chair of the IEEE GLOBECOM held in Washington, DC, USA, in 2016. He has served in various editorial capacities for a number of IEEE journals and IEEE TRANSACTIONS, including the IEEE TRANSACTIONS ON COMMUNICATIONS, as a Division Editor for IEEE WIRELESS COMMUNICATIONS of the *Journal of Communications and Networks* and in the Editorial Board of the PROCEEDINGS OF THE IEEE and in different editorship capacities for several other journals.