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SURVEY

A Comprehensive Survey on Resource Management in 6G Network Based on Internet of Things

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ABSTRACT The transition to 6th Generation (6G) cellular networks offers significant improvements over 5th Generation (5G), enhancing data transfer, reducing latency, and improving network reliability. Advanced Multiple-Input Multiple-Output (MIMO) technology in 6G boosts network efficiency, particularly benefiting Ultra-Reliable Low-Latency Communications (URLLC). This paper reviews literature on resource management in the Internet of Things (IoT) within the 6G context. We categorize the study into four segments: network-aware resource management, dynamic resource allocation, predictive resource distribution based on traffic and architecture, and energy-centric resource allocation considering IoT device mobility and location. We provide a detailed perspective on current research and highlight future research avenues. Key contributions include a comparative study of IoT resource management techniques, an overview of resource management across LTE, 5G, and 6G networks, insights into applications like Intelligent Transportation Systems (ITS), Industrial IoT (IIoT), and Mobile CrowdSensing (MCS), and an emphasis on upcoming challenges. We emphasize the crucial role of efficient resource management in IoT, particularly in the 6G landscape.

INDEX TERMS 6G network, Internet of Things, resource management, survey, quality of service (QoS).

I. INTRODUCTION

The Internet of Things (IoT) integrates physical objects with the digital realm [1]. IoT infrastructure consists of intelligent devices with sensors and actuators, varying in computational and communication capabilities [2], [3]. These devices perform sensing, communication, computation, and actuation, essential for data collection and analysis within the IoT framework [4]. Sensors in the IoT network measure parameters like temperature, humidity, and pressure according to user requirements [5]. Devices collect local data and transfer it to a server or gateway for processing. Based on server responses, they issue instructions to actuators for precise adjustments [6]. This interaction between physical and digital realms underpins the expansive IoT network [7]. A diverse range of sensors ensures comprehensive and

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TABLE 1. List of abbreviations and acronyms.

Abbreviation	Definition	Abbreviation	Definition
5G	Fifth Generation	mMTC	Massive Machine-Type Communications
5G	Fifth Generation	mMTC	Massive Machine-Type Communications
6G	Sixth Generation	NA	Network Availability
6LoWPAN	IPv6 over Low-Power Wireless Personal Area Networks	NB-IoT	Narrow Band-Internet of Things
ABER	Average Bit Error Rate	NFT	Non-Fungible Token
ACDRA	AI-driven Collaborative Dynamic Resource Allocation	NFV	Network Function Virtualization
AI	Artificial Intelligence	NIB	Network-in-Box
AL	Alert Level	NoisyNet	Noisy Network
ANN	Artificial Neural Networks	NOMA	Non-Orthogonal Multiple Access
AP	Access Point	NR	Network Resilience
AR	Augmented Reality	NSM	Network Slice Mobility
AS-CRA	Attuned Slicing-Dependent	NTMA	Network Traffic Monitoring and Analysis
B5G	Beyond 5G	NTP	Network Traffic Prediction
BS	Base station	O-RAN	Open Radio Access Network
BPNN	Backpropagation Neural Network	OpEx	Operational Expenditure
BSs	Base Stations	OTA	Over-the-Air
CapEx	Capital Expenditure	P2M	Person-to-Machine
CAV	Connected and Autonomous Vehicle	PHR	Power Headroom Reporting
CNN	Convolutional Neural Network	PLR	Packet Loss Rate
CONF	Considering Confidentiality	PSM	Power Saving Mode
CSMA/CA	Carrier-Sense Multiple Access/Collision Avoidance	QoS	Quality of Service
CD	Connection Density	RAW	Restricted-Access Window
D2D	Device-to-Device	RFID	Radio-Frequency Identification
DAI	Distributed AI	RIS	Reconfigurable Intelligent Surfaces
DD-CCSR	Dynamic-Driven Congestion Control and Segment Rerouting	RL	Reinforcement Learning
DDaaS	Direction Decide-as-a-Service	RLF	Radio Link Failure
DEELB	Dynamic Energy-Efficient Load Balancing	RNN	Recurrent Neural Network
DNN	Deep Neural Network	RQ	Research Question
DQNs-RM	Deep Q Network	RRM	Radio Resource Management
DRL	Deep Reinforcement Learning	RRU	Remote Radio Units
EDM	Energy Demand Management	RSRP	Reference Signal Received Power
eDRX	Extended Discontinuous Reception	RSUs	Road Side Units
EE	Energy Efficiency	SA	Service Availability
EL	Expected Latency	SatComs	Satellite Communications
eNB	eNodeB (evolved NodeB)	SDN	Software-Defined Networking
EPA	Energy-efficient Power Allocation	SE	Spectral Efficiency
EPC	Electronic Product Code	SFC	Service Function Chaining
FDRL	Federated Deep Reinforcement Learning	SG	Smart Grid
FRL	Federated Reinforcement Learning	SIC	Successive Interference Cancellation
FSI	False State Injection	SL	Swarm Learning
GAN	Generative Adversarial Network	SLA	Service Level Agreement
HetNets	Heterogeneous Networks	SQP	Sequential Quadratic Programming
HO margin	Handover Margin	SST	Successful Service Time
HO	Handover	STIN	Satellite-Terrestrial Integrated Network
HQDL	Hybrid Quantum Deep Learning	SVFMF	Service Virtualization and Flow Management Framework
HSTNs	Hybrid Satellite-Terrestrial Networks	SVM	Support Vector Machine
IAB	Integrated Access and Backhaul	TerCom	Terrestrial Communication
IIoT	Industrial Internet of Things	THz	Terahertz
IoT	Internet of Things	TL	Transfer Learning
IPv6	Internet Protocol version 6	TTT	Time-To-Trigger
ITS	Intelligent Transportation Systems	UAV	Unmanned Aerial Vehicle
IWPS	Internet-Wide Port Scanning	Ucode	Universal Code
KKT	Karush-Kuhn-Tucker	UE	User Equipment
KPIs	Key Performance Indicator	UIoT	Ubiquitous IoT
LTE	Long-Term Evolution	URLLC	Ultra-Reliable Low-Latency Communications
LTE-M	Long Term Evolution for Machines	V2X	Vehicle-to-Everything
M2M	Machine-to-Machine	VLC	Visible Light Communication
M2P	Machine-to-Person	VNF	Virtual Network Function
MAS	Multi-agent System	VR	Virtual Reality
MCS	Mobile Crowdsensing	VSRNLMS	Variable Sampling Rate - Non-Linear Mean Squares
MEC	Mobile Edge Computing	WLAN	Wireless Local Area Network
MIMO	Multiple-Input Multiple-Output	WMSNs	Wireless Multimedia Sensor Networks
mIoT	Massive-IoT	XAI	Explainable Artificial Intelligence
MIPA	Minimum Interference Pilot Allocation		
MCAS	Maximum Channel gain AP Selection		

precise environmental data collection. Table 1 defines the abbreviations and acronyms used in this paper for better understanding.

From the initial generation to the fifth (5G) [8], technological innovations have been carefully designed to meet the needs of the end-users and network service providers [9].

The development of sensors and gateway devices, along with the evolution of Artificial Intelligence (AI) applications and users' demands, requires a large amount of data to be processed at a very high rate [10], [11]. Building on the groundwork established by 4G and 5G, the forthcoming sixth-generation (6G) [12] networks will go beyond personal communication, fully actualizing the IoT paradigm [13], [14]. This paradigm involves the connectivity of individuals, computational resources, vehicles, devices, wearable sensors, and autonomous robotic entities [15].

Developing an IoT framework poses numerous challenges related to Quality of Service (QoS) and resource management [16]. Establishing the set of QoS parameters for real-time heterogeneous IoT networks may include a large number of factors like delay [17], bandwidth utilization [18], power consumption [19], throughput [20], cross-layer coupling [21], multi-media in-network processing, fault tolerance [22], and resource constraints, being thus a highly complex task [23]. Within this complex milieu, routing protocols play a pivotal role. The linchpins affect many of these QoS factors, governing how data packets navigate through the network and directly influencing latency, throughput, and overall network reliability [24]. The choice of routing protocols is far from trivial; it requires careful consideration of the network's scale, the heterogeneity of devices, and their communication patterns [25]. Options for routing protocols vary from traditional ones, such as distance-vector and link-state protocols, to more advanced adaptive, context-aware protocols designed for the unique demands of IoT environments [26]. Research into IoT routing protocols focuses on optimizing trade-offs between efficiency and complexity [27]. Adaptive routing protocols respond dynamically to network changes, prioritizing routes with optimal QoS performance [28]. Leveraging cross-layer information, these protocols reduce overhead, increase fault tolerance, and enhance power efficiency, making them suitable for resource-constrained and dynamic IoT networks [29].

Multi-path routing methods are effective in environments with frequent link failures but have challenges with fault tolerance. They also demand significant processing power, storage, and energy, especially in IoT and 5G networks [30]. The Two-Tier fault-tolerant routing approach proposed by [16], effectively manages energy, network delay, and throughput in IoT systems by differentiating between devices with sufficient resources and those that are resource-constrained [31]. Designing a multi-path routing protocol for Wireless Multimedia Sensor Networks (WMSNs) under heavy traffic conditions increases the complexity of determining the optimal path from source to sink [16], [32]. To address multi-path QoS protocol issues, researchers [33] suggest using analytical models for load and traffic distribution. For real-time IoT applications, researchers propose heuristic algorithms combined with geographical routing to meet QoS requirements [34]. In fog-based IoT applications, cognitive caching can help achieve QoS parameters such as data freshness and request delay [35], [36]. This approach focuses on factors like data popularity, cache size, publisher load, and node connectivity [37].

A. MOTIVATION, SCOPE, AND AIM OF 6G NETWORK BASED ON IOT

The development of the 6G network, the latest cellular technology, represents a significant leap over 5G, offering major improvements in data transfer speed, latency, network capacity, and reliability [38]. A notable feature of the 6G network is the advanced implementation of massive Multiple-Input Multiple-Output (MIMO) [39] technology, which allows the use of a large number of antennas for data transmission and reception [13]. This significantly increases network efficiency and capacity, facilitating faster and more reliable data transfer. Enhanced massive MIMO technology, in particular, boosts the reliability and efficiency of Ultra-Reliable Low-Latency Communications (URLLC) [40], thereby expediting the data transfer process [41]. The primary purpose of this paper is to undertake a comprehensive review and evaluation of the existing literature on IoT applications, particularly concerning resource management in the context of the emerging 6G network. This review is organized into four distinct categories.

The first category focuses on network-aware resource management approaches, presenting the strategies and methods that prove important in the network context for efficient resource management.

The second category explores dynamic resource allocation based on network conditions, which involves the distribution or reallocation of resources in response to changing network conditions.

The third category examines predictive resource allocation methods based on traffic patterns and network topology, which employ predictive models offered by network traffic patterns and network structure for resource allocation.

Lastly, the fourth category evaluates energy-efficient resource-sharing methods based on the location and mobility of IoT devices, focusing on studies that seek to optimize energy use through geographic positioning of IoT devices during resource allocation.

In the manufacturing sector, the 6G-IoT [42] integration can enable predictive maintenance, ensuring efficient resource utilization by proactively identifying potential equipment failures [43]. In healthcare, wearable IoT devices interfaced via 6G could facilitate real-time patient monitoring, thereby reducing the necessity for redundant hospital resources and improving patient outcomes [44]. In addition, the logistics industry stands to gain from enhanced tracking and inventory management, ensuring optimal utilization of storage spaces and reducing the need for excess inventory [45]. A central motivation for integrating 6G and IoT is the potential to accommodate many devices, facilitating scalability in resource management strategies across diverse industries [46]. In addition, the ultra-low latency feature

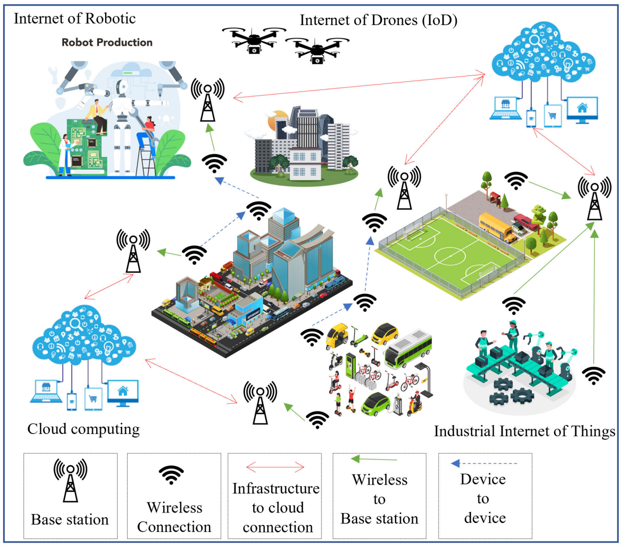

FIGURE 1. Use case of 6G network in IoT.

of 6G networks will enable real-time data collection and analysis, laying the foundation for proactive and predictive resource management [47].

The integration also ensures reliable and secure data transmission, a critical component of any resource management system [48]. Furthermore, 6G will support AI-driven systems, thereby enabling data-driven decisions in resource management based on information gathered from IoT devices [49]. Additionally, the focus will be on the energy-efficient operations of IoT devices necessary for reducing power consumption and increasing device longevity, thus promoting sustainable resource management [50]. Another driving factor is using 6G's high-frequency bands, which offers access to higher frequency bandwidth for IoT devices, thereby enhancing the speed and efficiency of resource management operations [51]. The convergence of 6G and IoT is also anticipated to improve device interoperability, thus creating a more cohesive and efficient resource management ecosystem [52]. Furthermore, given their ability to handle increased data traffic, 6G networks are considered suitable for managing extensive IoT systems, facilitating thus large-scale resource management [53]. The Figure 1 illustrates the interconnected ecosystem of robotic production within a smart city, showing how various elements such as manufacturing, smart grids, transportation, and public services communicate and operate via the IoT. The arrows represent the data flow and connectivity between these elements, highlighting the integrated and automated nature of modern urban environments.

B. CONTRIBUTIONS AND STRUCTURE

In the forthcoming years, resource management will emerge as a critical challenge within IoT and 5G networks [54]. This paper offers an exhaustive and methodical exploration of contemporary research on network-conscious resource management methodologies. It explores dynamic resource allocation guided by network conditions, predictive resource allocation informed by traffic patterns [55], network topology [56], and energy-efficient [57] resource allocation driven by the location and mobility of IoT devices. The paper also presents a variety of strategies to grapple with the resource management issue in a wide array of IoT applications. The main contributions of the paper are:

- It compares IoT resource management based on network-aware, dynamic resource allocation, predictive resource allocation based on traffic patterns and network topology, and energy-efficient resource allocation based on the location and mobility of IoT devices.
- It provides summaries and classifications of resource management in Long Term Evolution (LTE), 5G, and 6G networks.
- It covers a large number of resource management applications, including Intelligent Transportation Systems (ITS), Industrial IoT (IIoT), and Mobile Crowdsensing (MCS).
- It highlights the upcoming obstacles and suggests future research activities to propel resource management in IoT based on a 6G network.
- It demonstrates the importance of resource management in IoT systems.

Section II reviews related research, comparing it with our work. Section III details the IoT system architecture in 6G networks, discussing resource management evolution, challenges, and integration of edge and fog computing. Section IV explores resource management costs, efficiency, key performance indicators, and various allocation methods. Section V provides a discussion of the findings, while Section VI outlines future research directions. Finally, Section VII concludes the paper, summarizing key points and future prospects.

II. RELATED WORK

The arrival of 6G networks is expected to greatly improve the IoT by providing extremely fast speeds and better connectivity. For this to work well worldwide, there needs to be a unified standard. Research has mainly focused on reducing delays and making networks more reliable to fully utilize 6G's potential. Despite the progress, there are still significant hurdles, especially in creating standard protocols that ensure consistent performance for different IoT applications. Many current studies target specific areas like Vehicle-to-Everything (V2X) communication, which shows the necessity for a broader 6G IoT framework. Reviews of 6G research highlight important focuses and challenges that will shape future advancements in managing IoT resources. This section gives an in-depth overview of the major contributions to resource management in 6G IoT networks, covering both the successes achieved so far and the challenges that remain.

Alhashimi et al. [58] conducted an extensive examination of resource management strategies in 6G mobile communication systems, particularly focusing on heterogeneous networks (HetNets). The study synthesized existing knowledge and highlighted areas ripe for future research. A critical strength of this work is its thorough review of spectrum sharing and interference management techniques, which are essential for enhancing the quality of service.

Bhajantri [59] provided a detailed examination of resource management within the IoT ecosystem, emphasizing distributed systems such as fog, edge, and cloud computing. The paper's strength lies in its in-depth analysis of resource management phases, including modeling, discovery, estimation, and allocation.

Shen et al. [60] proposed an innovative wireless resource management approach for high-density IoT services in 6G networks. The authors developed a comprehensive simulation platform incorporating various wireless resource management technologies, promising efficient simulation of 6G network scenarios and diverse IoT services.

Guo et al. [50] explored the potential of 6G-enabled massive IoT, examining how technological advancements proposed for 6G can address the demands of increasingly data-intensive and latency-sensitive IoT applications. The paper introduced a four-tier network architecture enhanced by edge computing, effectively addressing the coverage requirements of IoT-enabled applications.

Manap et al. [61] examined Radio Resource Management (RRM) in upcoming 5G HetNets. The study provided an in-depth view of the expected issues in future 5G systems and highlighted the significance of combined optimization of radio resource allocation and other mechanisms.

Nguyen et al. [62] proposed a Federated Deep Reinforcement Learning (FDRL) based vehicular communication model for resource allocation, including computation power in cloud, fog, and edge servers, as well as spectrum at RoadSide Units (RSUs) and Base Stations (BSs).

Qamar et al. [63] conducted a comprehensive survey of 5G systems, fostering global research towards next-generation 6G wireless systems. The authors emphasized the need for a well-designed future radio network architecture that maximizes radio spectrum capacity and employs various emerging technologies.

Table 2 provides a comprehensive summary of key studies on resource management in 6G IoT networks, highlighting their focus, advantages, disadvantages, and future research directions.

A. COMPARISON WITH OUR WORK

This paper explores various aspects of resource management by examining current research. The goal was to cover all areas discussed in previous surveys. Many recent survey papers on resource management did not categorize the different techniques, leading to a fragmented understanding of the field. This lack of categorization obscures the relationships and distinctions between different techniques. In contrast, this study addresses this issue by identifying and categorizing specific techniques used in resource management for 6G networks.

For example, earlier surveys might mention network-aware resource management and dynamic resource allocation based on network conditions, but they didn't classify these methods into specific categories. This omission makes it difficult for readers to understand the relationships between techniques or their relevance to specific resource management challenges. A systematic approach groups relevant techniques into meaningful categories, aiding in understanding how different methods solve specific problems in resource management and identifying areas needing further research.

Meta-heuristic algorithms have proven to find suitable solutions [64]. These advanced optimization techniques solve complex resource management problems by finding near-optimal solutions through iterative, probabilistic methods [65]. Meta-heuristic algorithms are particularly useful in 6G network environments because they are flexible and robust, adapting to dynamic conditions and large solution spaces [66]. They mimic natural or social processes, such as evolution or flocking, to efficiently explore possible solutions [67]. This makes them very effective in handling the diverse and evolving challenges of resource allocation, ensuring optimized performance and efficiency in IoT-based 6G systems. By using these algorithms, system reliability and functionality can be improved to meet the complex demands of modern network management.

Another important aspect of this paper is a systematic review of publications focused on various components of resource management systems, including communication, security concerns, and application instances. The study highlights the technologies being developed that will form the backbone of future 6G networks. It ensures that crucial resource management strategies are properly overseen to avoid suboptimal resource utilization and diminished network capabilities, thereby supporting the potential advancements in 6G technology.

III. ARCHITECTURE OF IOT SYSTEM IN 6G NETWORK

The widespread use of IoT, made possible by the advanced features of 6G networks, has introduced new challenges in developing application services [68]. To support these smart applications, IoT integrates embedded computing into objects, using these resources to manage and control the workload of the applications [69]. These applications rely on device resources like storage, processing, energy, and communication [70]. With 6G networks, these resources become available more efficiently and effectively, resulting in higher data speeds, lower latency, increased capacity, and better resource management [71].

IoT devices in a 6G network are typically characterized by limitations such as limited memory, processing capacity, bandwidth, and energy [72]. These restrictions can pose challenges, especially for pervasive applications that require real-time responses and high data throughput [73]. To manage these scenarios, a framework that can efficiently control these resources is needed. As shown in Figure 2, the structure

TABLE 2. Summary of related work.

Author	Focus	Advantages	Disadvantages	Future Directions
Hayder Faeq Alhashimi et al. [58]	Resource management strategies in 6G mobile communication systems, focusing on HetNets	Extensive examination of spectrum sharing and interference management techniques	Lack of experimental or simulation-based validation of proposed solutions	Incorporate real-world tests to validate theoretical findings
Lokesh B. Bhajantri [59]	Resource management within the IoT ecosystem, emphasizing distributed systems (fog, edge, cloud computing)	In-depth analysis of resource management phases (modeling, discovery, estimation, allocation)	Absence of practical, experimentally tested solutions	Develop and experimentally validate resource allocation algorithms suited to distributed IoT architectures
Xiao Shen et al. [60]	Wireless resource management approach for high-density IoT services in 6G networks	Comprehensive simulation platform, efficient simulation of 6G network scenarios	Efficacy dependent on acquiring more detailed and realistic network information	Continuously compare with other efficient methods for 6G network utilization
Fengxian Guo et al. [50]	Potential of 6G-enabled massive IoT, introducing a four-tier network architecture enhanced by edge computing	Effectively addresses coverage requirements of IoT-enabled applications	Challenges warrant immediate attention from the wireless community	Delve into challenges and propose concrete solutions to overcome them
Sulastri Manap et al. [61]	Radio Resource Management (RRM) in upcoming 5G HetNets	Detailed survey of HetNets RRM schemes, insights into different approaches	Potential research areas for future RRM in 5G HetNets	Explore and enhance existing frameworks for RRM in 5G HetNets
Nguyen et al. [62]	Federated Deep Reinforcement Learning (FDRL) based vehicular communication model for resource allocation	Powerful tool to manage computational complexity and large data in heterogeneous vehicular networks	Current solutions may face challenges due to complexity	Simplify approaches to enhance practical applicability
Faizan Qamar et al. [63]	Survey of 5G systems, fostering global research towards next-generation 6G wireless systems	Valuable insights and fresh perspectives on challenges and potential solutions	Several spectrum management issues from simultaneous implementation of various techniques in 5G	Address spectrum management issues to ensure a smooth transition from 5G to 6G

for resource management in pervasive IoT applications in a 6G network consists of five layers: four horizontal ones—namely, the perception layer, transport (or communication) layer, processing layer, and application layer. These are enhanced by the capabilities of the 6G network. Additionally, there is a vertical layer—the resource management layer—which benefits from 6G's advanced resource allocation and management capabilities [74], [75].

Perception Layer: In the context of a 6G network, the perception layer employs an array of IoT devices and sensors interconnected via advanced 6G connectivity. Due to 6G's ultra-low latency characteristics, these sensors can transmit data in real-time, enhancing the granularity and precision necessary for real-world environmental perception. The foundational technologies in this layer, including Radio-Frequency Identification (RFID) [76], Universal Code (Ucode) [77], electronic product code (EPC) [78], Internet Protocol version 6 (IPv6) [79], and IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN) [80],

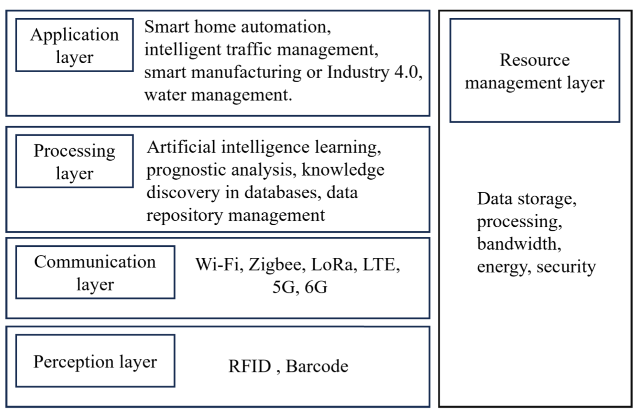

FIGURE 2. Resource Management Layers for IoT System.

identify and address physical devices. Ubiquitous IoT (UIoT) applications can accumulate substantial data through sensors, smartphones, and other embedded devices [81]. Despite the vastness of collected data, only a subset pertinent to the specific application context is required to deliver a particular service [82]. This selective approach ensures efficient data management and usage, minimizing redundancy and enhancing the service's efficacy. Every IoT device maintains a concise profile that includes data about its environment and resources. This profile, also known as a mini-profile, comprises an ID, sensed data, and resource parameters. The elements of this mini-profile distinguish each device, highlighting its similarities or differences from other devices within the IoT landscape. Such data is crucial for efficiently managing the distribution of information within its clusters or beyond, optimizing resource allocation, and minimizing data redundancy in the 6G IoT ecosystem.

Communication Layer: In a 6G network environment, the communication layer takes on an advanced role, facilitating high-speed, low-latency data transfer by utilizing advanced communication techniques like beamforming and MIMO technologies. With greater capacity, increased flexibility, and improved energy efficiency (EE) compared to previous generations, the 6G communication layer optimally transfers data across an extensive array of IoT devices. UIoT applications necessitate robust and diverse communication technologies to ensure smooth interactions among various heterogeneous devices. Such interactions encompass Machine-to-Machine (M2M) [83], Machine-to-Person (M2P) [84], and Person-to-Machine (P2M) [85] communications, with 6G networks promising enhanced functionality and connectivity across all these communication types. This layer also remains cognizant of resource-limited devices, ensuring efficient interaction among devices regardless of their individual resource capacities.

Processing Layer: The processing layer in a 6G network can leverage edge computing and AI capabilities. With 6G's URLLC, data processing can be done closer to the source, reducing latency and allowing for real-time analytics [86]. In addition, 6G's high bandwidth capability can handle the processing of large volumes of data produced by IoT devices. As most IoT applications are pervasive in nature, they generate an enormous quantity of data from IoT devices. The processing layer employs Machine Learning (ML), predictive analysis, data aggregation, or data mining algorithms on edge or cloud platforms to handle such massive data loads, particularly for resource-restricted IoT devices.

Application Layer: The application layer benefits from the enhanced capabilities of 6G networks. This layer can run sophisticated applications that require real-time responses, such as autonomous vehicles or real-time health monitoring systems. The increased speed, capacity, and lower latency of 6G enable more seamless, efficient, and effective applications.

Resource Management Layer: The resource management layer in a 6G network can use sophisticated resource allocation algorithms to efficiently manage resources like bandwidth, power, and computing capabilities. 6G is expected to support network slicing, which allows creating multiple virtual networks with different characteristics on a single physical network. This allows for more granular and effective resource management. EE is another critical area in resource management, and with 6G's improved EE, it is possible to manage and control the energy consumption of IoT devices more effectively.

A. EVOLUTION OF RESOURCE MANAGEMENT FROM 4G TO 6G

LTE enhances connectivity and speed for IoT applications but encounters resource management limitations [58]. Cat-M1 [87], Long Term Evolution for Machines (LTE-M) [88], and Narrow Band-Internet of Things (NB-IoT) [89], while ideal for large-scale IoT deployments, face challenges in handling a high volume of devices and limited spectrum efficiency, which can lead to congestion and slower data rates. Cat-M1 is a low-power wide-area network technology that offers moderate data rates of up to 1 Mbps, mobility, and voice support across a 1.4 MHz bandwidth, catering to IoT devices that need medium performance [90]. On the other hand, NB-IoT provides lower data rates of around 250 kbps [91] with robust penetration and power efficiency over a narrow 200 kHz bandwidth [92], suitable for stationary IoT applications that demand extended battery life [93]. Despite their suitability for expansive IoT systems, both technologies may struggle to manage the increasing number of devices efficiently, potentially compromising their operational effectiveness [94].

On the other hand, 5G brings significant improvements in IoT resource management. It can support many connected devices simultaneously, making it ideal for large-scale IoT deployments [11], [105]. The spectrum efficiency of 5G is enhanced by using millimeter waves, which reduces congestion and improves data rates [106]. Moreover, 5G offers ultra-low latency, as low as 1 ms, which is crucial for real-time IoT applications [107]. Additionally, 5G is designed to be more energy-efficient, making it suitable for low-power IoT devices. 6G is still under research and development but is expected to introduce even more significant advancements in IoT resource management. One key objective of 6G is to handle an even more substantial number of IoT devices seamlessly [72]. Furthermore, with the proliferation of connected devices in various industries, such as smart cities, industrial automation, and healthcare, 6G aims to provide efficient management and communication capabilities for these massive deployments [47]. To achieve this, 6G anticipates incorporating advanced technologies like AI for intelligent resource allocation. AI algorithms and ML techniques enable 6G networks to dynamically allocate network resources based on the specific requirements and context of IoT devices [73]. This intelligent resource management approach optimizes available spectrum, energy, and computational resources, improving system performance.

Furthermore, 6G is expected to explore higher-frequency bands, including terahertz waves, and to employ spatial

TABLE 3. Resource management capabilities for IoT in LTE, 5G, and 6G technologies.

Resource Management Aspect	LTE	5G	6G
Frequency Bands	Primarily sub-6 GHz bands	Sub-6 GHz and millimeter-wave (mmWave) bands [95]	Expected expansion into even higher frequency bands beyond mmWave [96] [97]
Network Slicing	Not natively supported	Native support for network slicing, enabling dedicated slices for IoT applications [96]	Enhanced support for network slicing, optimized for diverse IoT use cases [5]
QoS	Limited QoS capabilities	Advanced QoS mechanisms, including URLLC	Enhanced QoS support, low latency, and high reliability for IoT services
Massive Machine-Type Communications (mMTC)	Limited support for massive IoT deployments	Dedicated support for massive IoT deployments, with improvements in connection density, EE, and scalability [22]	Further enhancements in mMTC capabilities to handle even larger-scale IoT deployments
Low Power Consumption	Power-saving mechanisms, such as Power Saving Mode (PSM) and Extended Discontinuous Reception (eDRX) [98]	Enhanced power-saving features, including PSM, eDRX, and Power Headroom Reporting (PHR) [99]	Advanced power management techniques to minimize IoT device energy consumption
Security	Basic security features, such as Authentication and Encryption	Enhanced security protocols, such as mutual authentication, encryption, and integrity protection [100]	Strengthened security measures, including quantum-resistant encryption and improved device authentication
Device Density	Supports moderate device density per cell	Improved device density with higher connection densities per cell	Further optimizations for higher device densities, supporting massive IoT device deployments
Latency	Relatively higher latency compared to 5G	Lower latency through features like URLLC and edge computing [101]	Ultra-low latency achieved through advanced technologies and edge intelligence [102]
Over-the-Air (OTA) Updates	Supports OTA updates, but with limited capabilities	Enhanced OTA update mechanisms, enabling faster and more reliable firmware updates [103]	Advanced OTA update mechanisms, enabling seamless and secure updates for IoT devices [104]
Backward Compatibility	Supports backward compatibility with legacy technologies	Provides backward compatibility with LTE and previous generations	Expected to support backward compatibility with 5G and earlier technologies

multiplexing techniques, such as beamforming and massive MIMO [61], [108]. The advancements in spectrum utilization and efficiency will cater to the growing need for high-bandwidth IoT applications, such as augmented reality (AR), virtual reality (VR), and immersive multimedia. Another key element in IoT resource management is the reduction of latency, particularly for applications that are time-sensitive and mission-critical [109]. 6G is anticipated to offer ultra-low latency, with the potential to achieve levels below one millisecond. This advancement will facilitate real-time data transmission, making 6G highly suitable for applications such as autonomous vehicles, remote surgery, and industrial automation, where minimal delay is crucial for seamless and responsive operations [110], [111].

Moreover, 6G development strongly emphasizes sustainability [112] and EE. Recognizing the environmental impact of technology, 6G aims to design energy-efficient networks and devices. This involves optimizing power consumption in IoT devices, exploring energy harvesting techniques, and developing new energy-efficient communication protocols [113]. By minimizing energy consumption, 6G networks can support the widespread deployment of battery-powered IoT devices, reducing the need for frequent battery replacements or recharging and promoting long-term sustainability [73]. LTE, 5G, and the anticipated 6G generations present distinct capabilities and advancements in IoT resource management. While LTE exhibits limitations in device management, spectrum efficiency, latency, and energy consumption, 5G addresses these challenges and offers significant improvements. Looking ahead, 6G aims to handle a more substantial number of IoT devices seamlessly, leveraging AI for intelligent resource allocation, exploring higher-frequency bands, and emphasizing ultra-low latency and EE [51]. These advancements pave the way for transformative IoT applications across various industries, driving innovation and enhancing the overall efficiency and sustainability of IoT ecosystems [73], [110].

LTE technology, primarily operating in sub-6 GHz frequency bands, offers limited support for massive IoT deployments [105]. While LTE can handle a certain level of IoT connectivity, it may face limitations when dealing with a high density of IoT devices and the massive amount of data they generate. 5G, on the other hand, expands into both sub-6 GHz and mmWave frequency bands, providing dedicated support for massive IoT deployments [114]. It offers improvements in connection density, EE, and scalability. This means that 5G networks are designed to handle a significantly higher number of IoT devices per unit area, ensuring efficient and reliable connectivity [115]. The anticipated 6G technology is expected to further enhance the capabilities for mMTC. This means that 6G will be designed to handle even larger-scale IoT deployments, surpassing the capabilities of both LTE and 5G [116]. Regarding frequency bands, while LTE primarily operates in sub-6 GHz ranges, 5G extends into sub-6 GHz and mmWave bands [117]. This expansion into mmWave bands increases bandwidth and data transmission rates [118]. Anticipated 6G technology is expected to extend even further into higher frequency bands beyond mmWave, potentially unlocking new data capacity and communication capabilities [96]. Network slicing, a feature introduced in 5G, enables the creation of dedicated slices within the network infrastructure to cater to different IoT applications [119]. This ensures optimized resource allocation and tailored connectivity for diverse IoT use cases. 6G is anticipated to enhance support for network slicing further, refining it to better suit the requirements of various IoT applications. While LTE has limited QoS capabilities [120], 5G introduces advanced QoS mechanisms, including URLLC [121]. These mechanisms ensure high reliability, low latency, and optimized performance for critical IoT applications that require real-time responsiveness. In the future, 6G is expected to provide further improvements in QoS support, offering even lower latency and higher reliability for IoT services [110].

Table 3 provides a detailed comparison of resource management capabilities for IoT in LTE, 5G, and 6G technologies. LTE primarily operates in sub-6 GHz frequency bands, while 5G expands into both sub-6 GHz and mmWave bands, enhancing connection density, energy efficiency, and scalability. The anticipated 6G technology is expected to reach even higher frequency bands beyond mmWave, offering advanced support for network slicing and optimizing diverse IoT use cases. Enhanced QoS mechanisms, such as URLLC, are introduced in 5G and further improved in 6G to ensure low latency and high reliability for IoT services. Moreover, 6G aims to meet mMTC requirements by supporting larger-scale IoT deployments. Figure 3 illustrates the progressive improvements in QoS performance across these technologies, highlighting significant enhancements from LTE to 5G and further advancements anticipated with 6G.

B. OVERCOMING CHALLENGES IN RESOURCE MANAGEMENT FOR IOT SYSTEMS IN 6G

Managing resources efficiently is a critical task in distributed systems and has been a recurring subject of academic research [122]. In the context of 6G networks, effective resource management includes detecting and identifying all available resources, selecting the right resources, and then partitioning and distributing them to optimize the utility function [58], [111]. This optimization can encompass a large number of variables such as overall performance, cost-efficiency [123], energy conservation [124], data accuracy [125], coverage [126], and reliability [127], among others. Despite extensive research across diverse computing fields, resource management within 6G environments remains a challenging problem that requires innovative solutions. Several factors compound this challenge, including:

- the variety of 6G resources,
- the mutable nature of 6G ecosystems and their resources,
- the resource limitations of 6G nodes, and
- the potential performance decline due to failures in the diverse 6G ecosystems.

To mitigate these identified challenges, task scheduling becomes essential, whether the tasks are intricate user requests in the 6G environment or more internal operations within the 6G ecosystem [128]. Adherence to strict timelines is crucial in many real-time 6G applications. Therefore, the scheduler must manage the 6G resources to ensure that the scheduling process meets these deadlines. Figure 4 represents the complete range of 6G resource management activities.

The first step in managing resources in 6G networks is resource or service discovery, which involves finding and locating the specific device before identifying the service that needs to be activated. The next step is efficiently partitioning the resources to ensure higher utilization, which is crucial for optimal performance [58], [73]. This method is widely used in other distributed computing systems, such as cloud computing, through virtualization techniques and standard infrastructures. Below are various categories in resource management and the associated challenges with each.

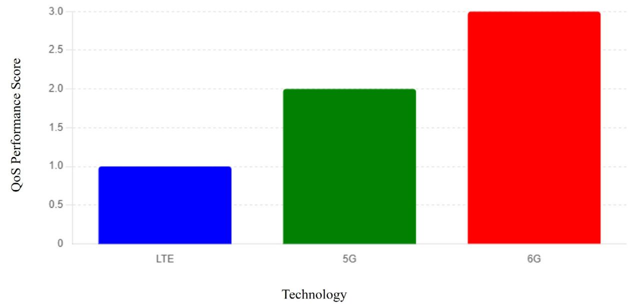

FIGURE 3. LTE, 5G, and 6G progressive improvements.

1) RESOURCE DISCOVERY

The integration of 6G technology in IoT systems profoundly transforms the process of service discovery, leveraging its advanced features for enhanced efficiency and responsiveness [129]. 6G offers higher bandwidth, making communication between IoT devices faster and more efficient, which helps quickly find and connect services [50]. Its very low delay is crucial for real-time applications, ensuring instant responses to service requests. Advanced network slicing

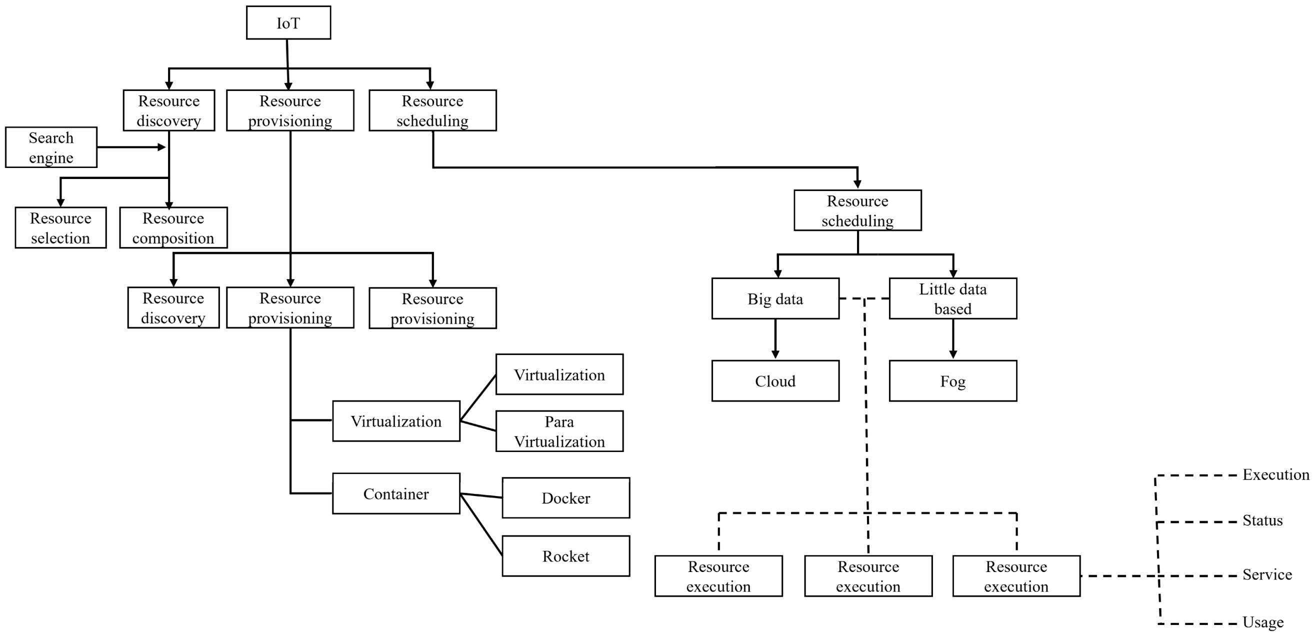

FIGURE 4. Resource Management Architecture for IoT Applications.

in 6G allows the creation of customized virtual networks, optimizing the service discovery process for specific IoT applications [130]. This technology can efficiently find services even as more devices are added to the network [131]. The advanced data handling of 6G is essential for managing small data and giving frequent, accurate updates about available services [132], providing frequent and accurate updates about available services. Integrating edge computing brings data processing closer to the source, speeding up service discovery and reducing network congestion. Together, these features of 6G improve IoT service discovery, making it more efficient, precise, and adaptable to changing needs.

2) RESOURCE PROVISIONING

In IoT resource provisioning, 6G plays a transformative role, introducing advanced capabilities crucial for managing diverse applications. 6G's promise of terahertz (THz) frequencies enables ultra-high data rates and minimal latency, critical for real-time IoT operations [129], [133]. This facilitates the efficient handling of numerous IoT devices with varying resource needs. 6G's higher spectral efficiency and network densification significantly improve capacity, essential in dense urban IoT environments. Moreover, 6G incorporates edge intelligence and AI-driven network orchestration, enabling dynamic and adaptive resource allocation tailored to the fluctuating demands of IoT devices. Network slicing, a hallmark of 6G, allows for the creation of multiple virtual networks, each optimized for specific IoT application requirements. This, combined with enhanced MIMO technologies and beamforming, ensures robust connectivity and efficient resource utilization in complex IoT networks.

3) RESOURCE SCHEDULING

Resource scheduling in the IoT context entails strategically allocating resources to tasks predicated on their priority and specific requirements. This process is crucial in optimizing resource utilization and promoting task efficiency, enhancing overall IoT performance and user experience. However, resource scheduling confronts a significant hurdle due to the voluminous data generated by IoT devices [129], [134]. The unpredictability of workloads and the necessity to prioritize tasks based on various factors, such as urgency and importance, compound the complexity of resource scheduling. Further, the dynamic nature of IoT systems necessitates that resource scheduling remains agile, adapting to real-time changes to preserve optimal performance. This real-time adaptation calls for robust scheduling algorithms that can react promptly and efficiently to changes in the IoT environment.

4) RESOURCE SELECTION

Resource selection is a pivotal process within the IoT framework that involves choosing the most suitable resource for a specific task. This decision-making process takes into account numerous factors, such as resource availability, capability, and the unique requirements of the task. However, the process of resource selection is not without its challenges [129], [135].

5) RESOURCE COMPOSITION

In the IoT domain, resource composition means combining different resources to create a more powerful and efficient resource that can handle complex tasks better [129], [136].

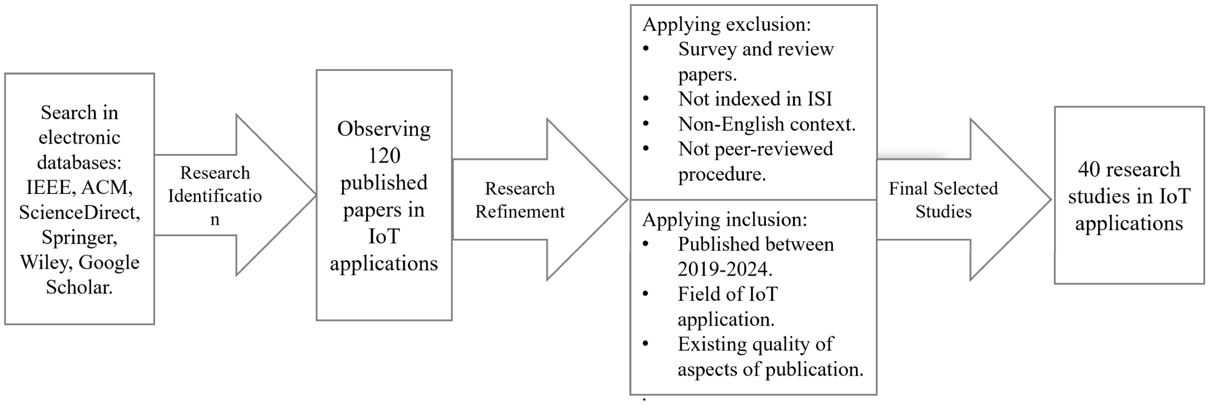

FIGURE 5. Our Research Journey - Exploring Sources and Methodology.

This process plays a crucial role in augmenting the functionality and versatility of the IoT network. However, resource composition presents a unique set of challenges. The main challenge is in effectively combining different resources to create a more valuable and efficient asset. The complexity of tasks, the diversity of devices, and other factors make this process difficult [137]. Therefore, successful resource composition needs advanced algorithms and management strategies to handle these complexities and achieve the best outcomes.

6) RESOURCE DETECTION AND PARTITIONING

Resource detection and resource partitioning hold critical significance in maintaining the operational efficiency of the IoT network [61]. Resource detection involves finding available resources, and resource partitioning helps organize these resources to improve performance and reduce redundancy. However, these tasks face many challenges. For example, new resources are always being added, making it hard to keep a complete list of available resources. Also, the constant changes in IoT devices, with devices frequently joining or leaving the network, make the detection process even more difficult [129], [136]. On the other hand, the primary challenge for resource partitioning lies in efficiently allocating resources among various tasks and applications while minimizing waste, particularly in terms of underutilized resources, idle resource time, inefficient allocation, and resource leakage, which are common in dynamic IoT environments [138].

7) VIRTUALIZATION

The incorporation of virtualization in IoT resource management has dramatically augmented its capabilities [139]. Full virtualization and para-virtualization techniques enable hardware emulation, allowing multiple operating systems to run concurrently on a single physical host. This significantly improves resource utilization efficiency and boosts the flexibility of the IoT network. However, deploying full virtualization and para-virtualization is challenging [3], [73], [136]. While these technologies improve resource utilization, they also add complexity and can affect performance. They require a lot of computational power, which can sometimes slow down the host system. Therefore, it's essential to find a balance between the benefits of these technologies and their computational demands to keep the IoT network efficient and effective.

8) DOCKER & ROCKET

Technologies like Docker and Rocket enable containerization, which packages and isolates applications with their entire runtime environment [140]. This simplifies the deployment and management of IoT applications, enhancing system flexibility and resilience to potential problems or failures [3], [141]. However, containerization also brings challenges, particularly related to security and isolation. Because containers share the host system's kernel, a security vulnerability in one container could potentially affect others.

9) SEARCH ENGINE

The main challenge in deploying a search engine for IoT resource management is dealing with the high volume and diversity of data. Furthermore, ensuring real-time search results and maintaining data privacy and security are other significant challenges.

10) RESOURCE MANAGEMENT

This involves overseeing and coordinating resources to ensure optimal utilization and meet the system's objectives. It includes planning, allocating, and managing resources throughout their lifecycle.

11) RESOURCE MONITORING

This is the continuous process of tracking resource performance, availability, and utilization. It helps identify issues, ensure compliance with service level agreements (SLAs), and make informed resource allocation decisions.

12) RESOURCE EXECUTION

This refers to the actual utilization of resources to perform tasks. It involves managing how resources are consumed by various applications and ensuring that they are used efficiently to meet the system's demands.

13) EXECUTION

This involves carrying out tasks using the allocated resources. It ensures that tasks are completed as planned and within the required timeframes, contributing to the system's overall efficiency.

14) STATUS

This pertains to the current state of resources, including their availability, performance, and health. Monitoring the status helps maintain the system's reliability and robustness by proactively addressing any issues that arise.

15) SERVICES

This refers to the functionalities provided by the system using the available resources. Effective service management ensures that resources are used to deliver services that meet user requirements and SLAs.

16) USAGE

This involves analyzing how resources are consumed over time. Usage analysis helps in understanding patterns, identifying areas for optimization, and making strategic decisions about resource scaling and provisioning.

C. METHODOLOGICAL APPROACHES FOR IDENTIFYING AND SYNTHESIZING PUBLISHED RESEARCH PAPERS

We conducted an exhaustive search of academic databases, including IEEE Xplore, ScienceDirect, and SpringerLink. The search terms used included "resource management," "6G networks," "IoT," "congestion control," "resource allocation," "energy efficiency," and "security."

- **Publication Date:** Only papers published between 2018 and 2024 were included to ensure the review covers the most recent advancements.
- **Relevance:** Only papers directly addressing resource management in 6G or IoT networks were included.
- **Journal Impact:** Preference was given to papers published in high-impact journals and conferences.
- **Exclusion:** Papers not meeting these criteria, such as those focused on unrelated technologies or those with insufficient methodological detail, were excluded.

The usage of Google Scholar and other digital resources like ScienceDirect, SpringerLink, Web of Science, and IEEE Xplore in the first phase is demonstrated in Figure 5. We utilized these databases using three keywords: "information shared in project teams" and "team groups." We began by performing an automated search on Google Scholar and the aforementioned digital databases to locate primary studies. Next, all citation data, abstracts, and keywords from the found publications were transferred to an Excel spreadsheet for additional evaluation. Our research led us to identify six prominent publishers, yielding 30 journal articles and 10 conference papers.

D. TRUST OF EXPLAINABLE AI (XAI) WITHIN THE SCOPE OF 6G AUTONOMY IN IOT

The IoT connects many devices, allowing them to share data effortlessly without human involvement. To gain users' trust, especially in critical areas like healthcare and infrastructure, XAI is crucial. XAI helps by making the decision-making processes of smart IoT devices clear and understandable to people. This transparency ensures that users feel confident in the technology's reliability and safety [142], [143]. XAI offers several key benefits:

- **Transparency:** Users must be able to understand why their IoT devices act in certain ways, especially when these devices have a significant impact [144].
- **Accuracy:** Explanations should accurately reflect the decision process of the device, not offer simplified justifications [145].
- **Consistency:** Similar devices in comparable situations should provide consistent explanations to build trust.
- **Understandability:** XAI needs to cater to users with varying technological backgrounds.
- **Feedback:** Two-way interaction between users and devices will enhance understanding and trust [146], [147].
- **Ethics and Fairness:** In IoT network, making fair decisions that benefit the user is very important.

For instance, if a smart thermostat changes the temperature, it should explain whether it did so to save energy, meet user preferences, or respond to weather forecasts. Consistency in these explanations is essential, just like in the 6G autonomy scenario. The system's explanations should be uniform across different devices and situations.

The ease of understanding the explanations provided by IoT devices is very important. However, this can be challenging due to the different levels of technical knowledge among users. User feedback and interaction are crucial because users need to understand how their inputs affect the device's decisions [146]. This helps them better understand their devices and build trust. Additionally, making ethical and fair decisions is very important for IoT devices [147]. The fairness of AI decisions is particularly significant due to their potential impact. Users need to trust that the IoT devices in their homes, cars, workplaces, and cities are making decisions in their best interest. Figure 6 shows how XAI is integrated within a 6G network, ensuring transparency and trust in the network slicing process for various applications and user groups.

E. INTEGRATION OF EDGE AND FOG COMPUTING IN 6G IOT

The integration of edge and fog computing, often called edge-fog computing, is designed to distribute the computational workload in IoT networks, which are expected to handle huge amounts of data [148]. This integration becomes even more powerful with the advent of 6G, promising unmatched network capabilities such as high-speed data transmission and extremely low latency [149]. Edge computing involves processing data at the network's edge, close to the data source, which reduces latency and conserves bandwidth [150]. In contrast, fog computing brings the cloud closer to the devices, allowing data to be processed locally or at nearby nodes. This provides a more distributed approach to data management, which further minimizes latency [151]. However, the vast potential of these related technologies has not been fully utilized yet, mainly due to concerns about resource management [152]. In a 6G IoT-centric edge-fog computing environment, resources must be efficiently allocated to ensure smooth operations. This involves managing hardware resources (such as computational power and storage) and network resources (like bandwidth and network interfaces). Resource management must also adapt to the dynamic nature of the IoT environment, including changes in network conditions and device capabilities. Effective resource allocation mechanisms that can adjust in real-time to these changes are crucial for optimal system performance [153].

Implementing intelligent decision-making algorithms based on technologies like ML and AI can effectively manage resources in 6G IoT systems. These algorithms can analyze network conditions, predict resource needs, and allocate resources optimally. The combination of edge and fog computing in 6G IoT offers significant opportunities to enhance IoT system capabilities [3], [134]. This promising area requires further research to realize its full potential. Efficient resource management strategies can transform IoT systems into more responsive, reliable, and efficient networks, driving the next wave of digital innovation [53]. Figure 7 illustrates the integration of edge and fog computing in 6G IoT. This integration improves latency, data rates, and EE, making it vital for future IoT applications. Using 6G technology in this context highlights its importance in meeting the growing demands and complexities of IoT networks.

Centralization and decentralization are fundamental concepts with substantial implications for designing and managing computing systems, including those based on edge, fog, and cloud computing architectures. Understanding these concepts is crucial to exploit the full potential of the 6G IoT environment [154], [155].

Centralized computing systems generally comprise a central server or a server cluster that executes all data processing tasks [156]. This central server is typically located in a data center, physically far from the end devices in the network. While centralized systems can manage large data volumes and offer formidable computing capabilities, they often have high latency due to the considerable distance between the data source and the data center. This can pose challenges for time-sensitive applications requiring real-time or near-real-time data processing.

Contrarily, decentralized systems distribute the data processing tasks across multiple nodes in the network. These nodes could be edge devices or intermediary nodes between the edge devices and the central server. Within the framework of edge-fog computing [135], decentralization is actualized by processing data at the network's edge or at intermediary nodes nearer to the edge devices.

Decentralized systems offer several advantages over their centralized counterparts. They reduce latency by processing data closer to the source, enhancing real-time applications' response time. They alleviate the load on network bandwidth, as not all data needs to be transmitted to a distant data center for processing [111].

F. RESOURCE MANAGEMENT THROUGH EFFICIENT HANDOVER IN 6G IOT NETWORKS

Handover is a critical procedure in cellular networks. It involves the seamless transfer of active calls or data sessions from one cell or channel to another [157]. This process becomes more complex in 6G networks due to the expected integration of terrestrial and non-terrestrial networks, like satellite networks and airborne BS [58], [158]. The variety of IoT devices in these networks, ranging from small sensors to large machines, adds to this complexity. These devices differ in mobility, power requirements, and data rate needs, creating unique handover challenges [159]. For example, a drone, being a high-speed IoT device, needs more frequent handovers than a stationary sensor. In a 6G network for the IoT, handover (HO) and error handling involve many parameters and procedures. Understanding these key terms and their roles is essential in 6G network resource management. Efficient resource use, maintaining quality of service, and addressing the diverse needs of IoT devices depend on this understanding [136].

The Handover Margin (HO margin) [160] is added to the signal strength of the serving cell to account for measurement inaccuracies and movement uncertainties. It helps optimize network resources by reducing unnecessary handovers, especially in high-speed scenarios, which is crucial for meeting the dynamic needs of IoT devices [131], [161]. Time-To-Trigger (TTT) refers to the time a neighboring cell's signal must exceed the serving cell's signal, including the HO margin, before a handover starts. Proper TTT calibration is key to preventing resource wastage from excessive handovers and maintaining service quality. Reference Signal Received Power (RSRP) [162] measures the average power of resource elements carrying cell-specific reference signals over the entire bandwidth. The User Equipment (UE) uses it to gauge a cell's signal strength, a critical factor for IoT devices with varied signal strength needs. The Handover Command instructs the UE to transition from the source eNodeB (eNB) or BS to the target eNB. It ensures the UE is always connected to the best available cell, which is vital for effective resource management [163]. Source eNB and Target eNB refer to the BS that the UE is currently connected

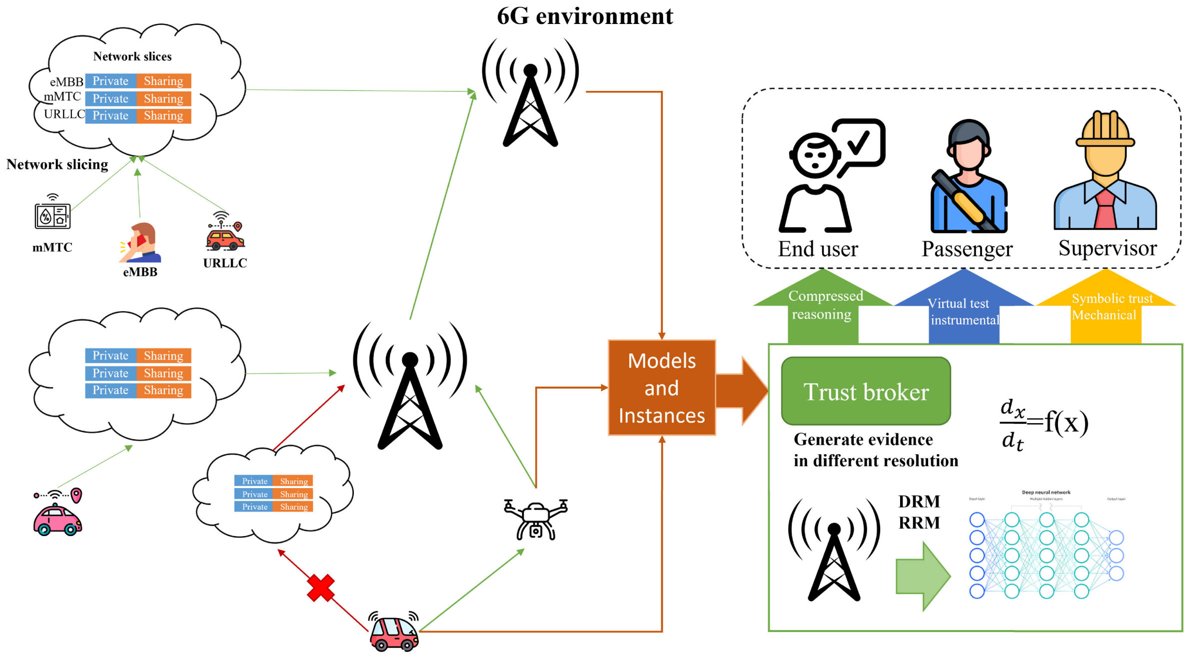

FIGURE 6. The 6G Network Partitioning and Trust Intermediary for Diverse Applications and End User Stakeholders.

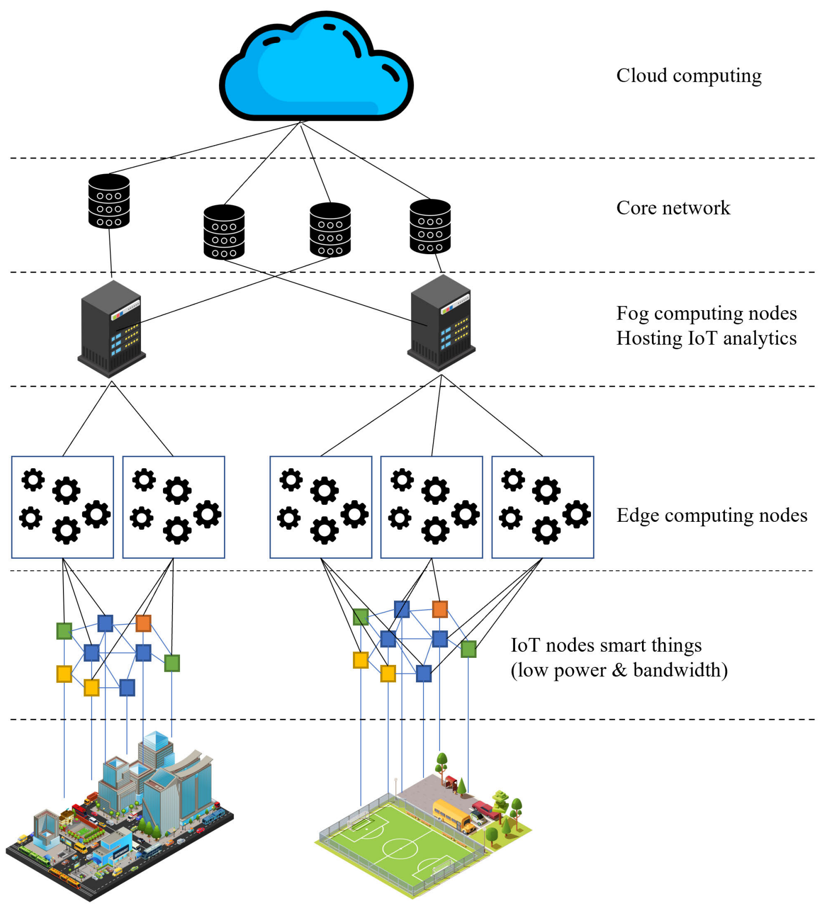

FIGURE 7. Integration of Edge and Fog Computing in 6G IoT.

to and will connect to after the handover, respectively. Comparing their signal strengths allows optimal network resource allocation. The Measurement Report, generated by the UE, includes measurements like the RSRP of the serving cell and neighboring cells. It helps the source eNB make informed handover decisions, optimizing network resource use [58], [72]. Time HO Failure is the period within which a handover fails. Minimizing this duration is essential to maintaining continuous connectivity, a critical demand in IoT applications where any disruption can have significant consequences [164]. X2 delay is the latency in the X2 interface that connects two eNBs. Regulating this delay is crucial for quick and effective handover decision-making and execution, ensuring IoT devices maintain connectivity with minimal interruption. Radio Link Failure (RLF) [165] occurs when the connection between the UE and the eNB fails [166]. Lowering the RLF threshold ensures robust connectivity, which is crucial for reliable IoT operations.

Figure 8 shows the details of the HO in IoT. It represents the process of a HO in a cellular network, illustrating the change in filtered RSRP from the source eNB to the target eNB over time. The graph shows the source eNB's signal strength decreasing and the target eNB's signal strength increasing, with key parameters such as HO margin, TTT, and X2 delay. The lower part of the figure highlights the sequence of events, starting with the measurement report from the UE to the source eNB, followed by the handover command from the source eNB back to the UE. The handover failure area indicates the potential risk of connection loss if the handover is not successfully completed before the source eNB's signal falls below the RLF threshold.

IV. RESOURCE MANAGEMENT IN 6G

The introduction of the 6G network revolutionizes the IoT landscape, increasing the demand for efficient resource management techniques. Consequently, various strategies are adopted to optimize network performance and ensure the best use of available resources. This paper identifies four critical categories for efficient IoT resource management in a 6G environment.

The first category, network-aware resource management, focuses on understanding the network's status to ensure optimal performance. This technique considers various parameters, including the QoS requirements of different IoT devices, network load, and the network's current capacity [11], [167]. By understanding the overall state of the network, resources are strategically allocated to maintain peak performance and minimize service disruptions.

Next is dynamic resource allocation based on network conditions. This method relies on adaptability and responsiveness to real-time network conditions [168]. For instance, during network congestion, resources are rerouted to less burdened sections or reshuffled to alleviate congestion. This technique is crucial due to the unpredictability of IoT devices, which can join or leave the network at will, causing fluctuations in traffic load and network volatility.

The third category is predictive resource allocation based on traffic patterns and network topology. This forward-looking approach leverages ML and AI [169]. It forecasts future traffic patterns by analyzing historical data, facilitating proactive resource allocation. Additionally, understanding network topology and the typical behavior of IoT devices allows anticipation of network load changes, enabling preemptive resource allocation to optimize performance and mitigate congestion risks.

Finally, energy-efficient resource allocation based on the location and mobility of IoT devices completes the quartet. This method targets energy conservation in IoT devices by considering their location and mobility [170]. For stationary devices, the network might allocate more resources since they are less likely to cause interference. Additionally, this technique includes strategies for energy harvesting, allowing IoT devices to source energy from their environment and minimize dependence on external power sources.

A. INDICATIVE COSTS ASSOCIATED WITH RESOURCE MANAGEMENT

Resource management in IoT and 6G networks involves various costs that can be broadly categorized into capital expenditure (CapEx) and operational expenditure (OpEx). These costs are influenced by the strategies employed for resource management, including predictive resource allocation, dynamic resource allocation, energy-efficient resource allocation, and network-aware resource management.

1) CAPEX

a: INFRASTRUCTURE COSTS

The deployment of 6G infrastructure involves significant investment in hardware such as BS, edge servers, and other networking equipment. Advanced ML algorithms and blockchain technology used for efficient resource management also contribute to higher infrastructure costs.

b: TECHNOLOGY UPGRADES

Implementing sophisticated resource management algorithms requires regular updates and upgrades to existing technology. This includes costs related to software development and the integration of new technologies like AI and edge computing.

2) OPEX

a: ENERGY CONSUMPTION

One of the major operational costs is energy consumption. Energy-efficient resource allocation strategies aim to minimize these costs by optimizing data transmission and processing, but there is often a trade-off between energy efficiency and network performance.

b: MAINTENANCE AND MANAGEMENT

Ongoing costs include maintaining the network infrastructure, monitoring system performance, and managing

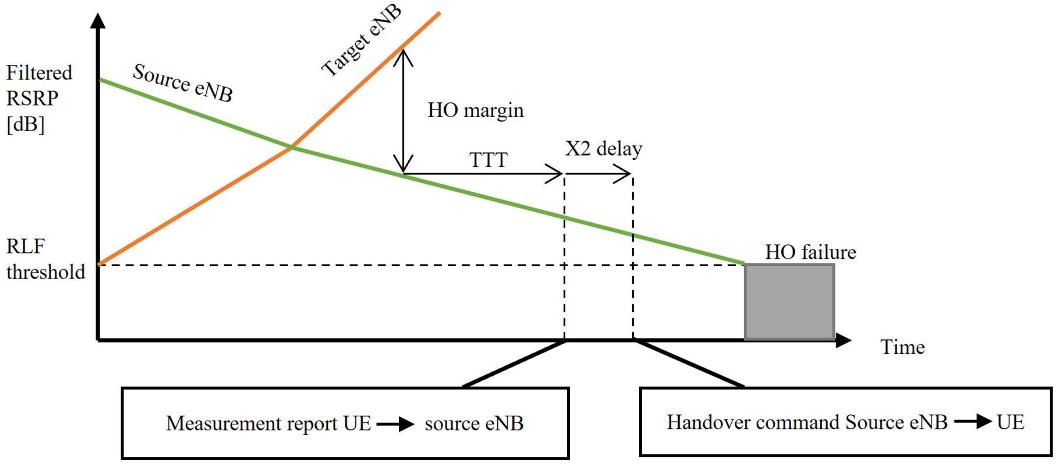

FIGURE 8. Handover in 6G IoT.

resources dynamically. These activities require sophisticated algorithms and tools, leading to increased computational costs and the need for high-performance computing resources.

c: SECURITY AND PRIVACY MANAGEMENT
Ensuring the security and privacy of data in 6G networks involves additional costs related to implementing advanced encryption technologies and secure protocols, as well as continuous monitoring to prevent cyber-attacks.

3) IMPLEMENTATION COMPLEXITY
a: TECHNICAL EXPERTISE
The complexity of implementing dynamic and predictive resource management strategies requires a skilled workforce. The costs associated with hiring and training personnel with the necessary expertise are significant.

b: ALGORITHM DEVELOPMENT
Developing and deploying advanced algorithms for resource management, such as those based on machine learning and AI, incurs substantial costs. These costs are associated with the research and development phase as well as the computational resources required for running these algorithms.

B. COST EFFICIENCY AND ECONOMIC VIABILITY
Evaluating the cost efficiency and economic viability of different resource management strategies is crucial. Each strategy offers unique benefits and challenges, and the economic implications vary based on the scale and scope of the network deployment:

1) PREDICTIVE RESOURCE ALLOCATION
This strategy requires investment in accurate predictive models, which can be costly to develop and maintain. However, it can lead to significant savings in the long run by optimizing resource usage based on anticipated demand.

2) DYNAMIC RESOURCE ALLOCATION
While offering high adaptability and responsiveness, this approach incurs costs related to real-time monitoring and decision-making processes. The implementation of dynamic resource allocation also involves higher computational costs due to the need for rapid data processing and analysis.

3) ENERGY-EFFICIENT RESOURCE ALLOCATION
The primary costs associated with this strategy involve the development and deployment of energy-efficient algorithms and the potential trade-offs with network performance. Despite these costs, the long-term savings in energy consumption can justify the initial investment.

4) NETWORK-AWARE RESOURCE MANAGEMENT
This approach demands comprehensive knowledge of the network and sophisticated algorithms to optimize resource allocation. The complexity and diversity of modern networks can lead to increased costs, but the potential improvements in network performance and user experience can offset these expenses.

C. KEY PERFORMANCE INDICATORS IN 6G: A DEEP DIVE
Given the rapidly evolving digital landscape, assessing these networks based on QoS is crucial. This is essential for effective network management and optimization. Our study highlights the importance of 9 key performance indicators (KPIs) [13], [58], [110], [136]. These KPIs are Latency, Jitter, Bandwidth, Packet Loss Rate, Bit Error Rate, Connection Density, Mobility, Network Availability, Energy Efficiency, and Security. Each indicator provides a unique perspective for evaluating and improving the performance of 6G networks in an IoT environment [3], [108], [171].

The following sections explain these KPIs in detail, including the formulas for their calculation. The aim is to provide researchers and practitioners with a comprehensive understanding of these metrics. This will help in the better design, implementation, and assessment of 6G networks in IoT systems.

1) LATENCY (L)

Latency in networks refers to the time it takes for a data packet to travel from a source to a destination. It's essentially a delay between the action and the response. In a 6G network context, lower latency is a key goal to enable real-time or near-real-time applications, such as autonomous driving or advanced augmented reality [49], [111], [172]. The formula provided measures the "Expected Latency" (EL). It represents a statistical expectation, an average value weighted by the likelihood of each outcome.

$$EL = \int_0^{\infty} l.f(l)dl \tag{1}$$

In the formula above, l is the latency variable, constrained from 0 to infinity to reflect the non-negativity and potential unboundedness of latency values. The selection of $f(l)$, the probability density function, is pivotal. While Gaussian distributions are commonly employed, network latency data, often skewed, might be more accurately modeled using distributions like exponential or log-normal.

2) JITTER (J)

Jitter refers to the variation in the delay of received packets. In the realm of IoT, this is frequently due to factors like network congestion, route changes, or other transient issues. Within 6G networks, it is critical to maintain low jitter levels to ensure seamless performance, especially for real-time applications such as video calls or gaming, where a consistent data packet stream is vital [172], [173].

The formula for jitter is expressed as:

$$J = \sqrt{\int (l - EL)^2 \cdot f(l)\, dl} \tag{2}$$

In this formula, l denotes the potential latency values, and EL represents the expected latency. The function $f(l)$ is the probability density function, which assigns probabilities to each latency value. Examples of such distributions could include normal, exponential, or uniform distributions, depending on the network characteristics. The integral $\int$ calculates a continuous summation across the entire range of latency values, typically from a to b, which define the domain of all possible latency values. The expression $(l - EL)^2$ computes the square of the difference between each latency value and the expected latency, and this value is then multiplied by the probability of that latency value $f(l)$ before being summed over all possible latency values. This approach effectively quantifies the variance of latency in the network, thereby measuring jitter.

3) BANDWIDTH (B)

In the context of network communications, bandwidth is the capacity of a wired or wireless network communications link to transmit the maximum amount of data from one point to another over a computer network or internet connection in a given amount of time usually one second [174].

The formula for calculating bandwidth in the context of a frequency spectrum is given as follows:

$$B_{total} = \int_{f_{lower}}^{f_{upper}} B(f)df \tag{3}$$

In this equation, f_{lower} and f_{upper} represent the lower and upper bounds of the frequency band, respectively. The bandwidth B is the difference between these two frequencies. This concept is crucial in understanding the range of frequencies a network can utilize for data transmission. In scenarios like 6G wireless systems, various frequencies may be allocated for different purposes, such as accommodating multiple users or managing interference.

4) PACKET LOSS RATE (PLR)

PLR is the percentage of packets the source sends but does not reach their intended destination. Packet loss can occur due to a number of reasons, such as network congestion, faulty hardware, or faulty software [45], [172], [173]. High packet loss rates can significantly degrade the quality of network services, particularly real-time services such as voice and video streaming.

The given formula represents packet loss as an expected value of a Bernoulli distribution:

$$PLR = E[X] = p \tag{4}$$

In this equation, $E[X]$ represents the expected value of the Bernoulli random variable X. X takes on the value of 1 with probability p (representing a packet loss) and 0 with probability $1 - p$ (representing successful transmission). Therefore, $E[X]$ or the expected value of X simply equals p, the probability of a packet loss. A lower PLR is generally better, as a higher percentage of packets successfully reach their destination. This is a critical metric for maintaining the quality of service in a 6G network environment, especially given the high data rates and real-time requirements of many 6G applications.

5) CONNECTION DENSITY (CD)

Connection density is an important network indicator representing the number of connected devices or nodes within a specific geographic area. In an IoT system, this can reflect the number of devices connected to a BS within its coverage area [172], [173]. A higher connection density can indicate a higher demand for network resources.

The formula given for connection density is:

$$CD = \lambda \cdot A \tag{5}$$

where the symbol λ stands for the average number of connections per unit area, and A is the total area considered.

The model used for this is the Poisson point process, a mathematical model often used in network analysis. It assumes that each point (or connection, in this case) in a certain area occurs independently of every other point, and the average density of points remains constant across the area.

6) NETWORK AVAILABILITY (NA)

Network availability is a critical performance indicator in any communication network, as it indicates the proportion of time during which the network is operational and available for use [49]. High network availability is essential to ensure reliable and seamless communication, which is particularly crucial in 6G networks where a wide range of services, many of them mission-critical, are expected to be deployed.

The formula given for network availability is:

$$NA = \frac{EU}{ET} \tag{6}$$

In this equation, NA stands for network availability. EU stands for expected uptime, which is the total time the network is expected to be operational and providing service. ET stands for expected total time, which is the total time period under consideration.

7) ENERGY EFFICIENCY (EE)

EE is a critical performance indicator in 6G wireless networks, reflecting the network's effectiveness in utilizing energy to perform its essential functions, such as data transmission [175]. This is particularly important in the context of modern communication systems that have substantial energy demands and require sustainable, green communication solutions [176], [177].

The formula given for EE is:

$$EE = \int_a^b \frac{D(t)}{P(t)} dt \tag{7}$$

Here, EE denotes the EE, measured over a specific time interval from $t = a$ to $t = b$. $D(t)$ represents the amount of data transmitted at time t, while $P(t)$ indicates the power consumed by the network at the same instant.

This formula essentially calculates the total amount of data transmitted per unit of energy consumed over a certain time period. The integral $\int$ sums up these efficiencies over the entire time period considered. A higher value of EE indicates that the network can transmit more data for a given amount of energy, making it more energy-efficient. In the context of 6G networks, EE will be a crucial factor, especially for IoT devices that may rely on batteries or energy harvesting. Therefore, improving EE will be a key target for 6G network design and optimization.

8) SERVICE AVAILABILITY (SA)

SA is a crucial performance indicator in 6G networks, especially for time-critical applications. It signifies the capability of a network to provide the necessary services, when needed, within the desired time frame [178], [179].

The formula given for service availability is:

$$SA = \frac{SST}{TRST} \tag{8}$$

In this formula, SA is defined as the ratio of Successful Service Time (SST) to Total Requested Service Time (TRST). SST denotes the duration during which the network successfully delivers the requested service. TRST represents the entire period during which the service was requested.

The ratio $SST/TRST$ indicates when the service is successfully delivered when requested. Hence, it gives a measure of the availability of the service. A higher value of SA indicates a higher degree of service availability, meaning that the network can provide the necessary services for a higher percentage of the time when requested. Service Availability becomes particularly important for applications that demand high reliability and continuous service, such as autonomous driving, remote surgery, and real-time industrial automation. Improving service availability will be a critical target for 6G networks to support these applications effectively.

9) NETWORK RESILIENCE (NR)

NR is a key performance indicator in 6G networks. It measures the ability of the network to maintain its service capabilities and connectivity in the face of failures or adverse conditions. A highly resilient network is capable of quickly recovering from failures and can adapt to changes effectively to ensure the continuity of the services provided [178], [179].

The formula given for network resilience is:

$$NR = P(\text{Network stays connected}|X \text{ failures}) \tag{9}$$

In this formula, NR represents network resilience, P denotes probability, and X stands for the number of failures. $P(\text{Network stays connected}|X \text{ failures})$ is the conditional probability that the network remains connected given X failures have occurred. The more resilient the network, the higher the probability NR will be, even when facing numerous failures (X). In other words, a highly resilient network can maintain connectivity even in the face of numerous network failures. Network resilience is particularly important when uninterrupted service is critical, such as emergency response, telemedicine, and autonomous driving. The development of 6G technologies aims to enhance network resilience significantly to ensure that critical services remain uninterrupted under various conditions.

D. NETWORK-AWARE RESOURCE MANAGEMENT APPROACH

Network-aware resource management approaches are essential for optimizing network operations. These approaches take into account factors like network topology, load, QoS requirements, and the dynamic nature of networks. By considering these factors, such strategies ensure efficient resource use and superior network performance in increasingly complex network environments. Traditional resource management often overlooks the state of the network infrastructure, leading to sub-optimal results. In contrast, network-aware systems consider the network's structure and allocate resources based on factors such as network topology, which significantly influences efficiency and utilization. Network load or congestion is another critical factor. These systems allocate resources to avoid bottlenecks and ensure smooth network operations. Additionally, considering QoS requirements is vital, as different applications have varying bandwidth, latency, and reliability demands. Figure 9 illustrates a network-aware resource management approach. It highlights the interconnected and hierarchical management of resources in a network, where smart services, IoT devices, and routers are optimized in real-time for efficient performance and reliability. Table 4 presents a detailed comparison of network-aware resource management approaches between IoT and 6G networks.

Verma et al. [180] proposed an optimized Internet-Wide Port Scanning (IWPS) method to enhance the security of IoT devices operating over IEEE 802.11ah Wireless Local Area Network (WLAN). This method involves setting an optimal scan rate for security administrators (sec-admins) to balance IoT device security with minimizing negative impacts on network performance and IPSec services. The optimal scan rate is determined using innovative mathematical models that evaluate IoT security based on port-scan network performance and IPsec services. These models include a novel queue model designed with a Markov chain for each IoT device and Access Point (AP). This model accounts for the heterogeneous traffic of IoT and scan-packet arrivals. It estimates the IoT and scan throughput based on the IEEE 802.11ah restricted-access window (RAW) mechanism, the carrier-sense multiple-access/collision avoidance (CSMA/CA) process, and monitored traffic. Additionally, a model to evaluate the risk to each IoT device is proposed, considering confidentiality (CONF), integrity, availability, and Alert Level (AL) at various scan rates. Using these models, comprehensive numerical analyses were performed to derive an optimal scan rate, reducing each device's risk while ensuring QoS. However, the proposed method has its limitations, first a sec-admin cannot control network parameters, and does not provide network operators with the ability to optimize the RAW parameters according to the scan traffic. The method also relies heavily on the precision and accuracy of the mathematical models, which might not fully capture the complexity and variability of real-world networks and IoT devices. Despite these drawbacks, the proposed method represents a significant step forward in maximizing IoT security, assuring QoS, and adapting to the heterogeneous nature of IoT traffic.

Tam et al. [179] introduced a new method called Deep Q-Networks with Resource Management (DQNs-RM). This method is a priority-aware resource management scheme for Software-Defined Networking (SDN), Network Function Virtualization (NFV), and Service Function Chaining (SFC) systems. It uses a Deep Reinforcement Learning (DRL) engine in the management layer to optimize configuration times and resource use in IoT networks. By looking at the state features of Virtual Network Functions (VNFs), this scheme effectively controls the creation and modification of VNFs. It also evaluates the average transmission delays for end-to-end IoT services. Additionally, the approach includes a scoring mechanism to evaluate the performance of existing chains. The simulation results show that the proposed method has several advantages. It adapts well to real-time IoT service requests and outperforms other approaches in terms of rewards, delays, delivery ratio, and throughput. However, the scheme relies heavily on accurate virtual resource mapping, VNF placement/creation, and an awareness of different real-time IoT service priorities. These requirements might present challenges in complex and rapidly changing network environments. Despite these potential drawbacks, DQNs-RM offers a promising solution for priority-aware resource management in IoT networks, providing optimized SFC and impressive performance metrics.

Kaur et al. [172] introduced a new method for placing microservices in 5G/6G networks. This method is optimized for a cloud-native model where services are broken down into microservices. The key feature of this method is a placement strategy that reduces end-to-end service latency. It takes into account the internal structure of services and the communication between microservices. The placement is treated as an optimization problem. It is solved using a hybrid algorithm that combines greedy and genetic methods. This technique focuses on two main aspects of latency. First, it allocates microservices close to end users to reduce communication costs. Second, it minimizes the communication delay between data centers to avoid long-distance communications. The strength of this approach is its ability to ensure reliable and timely service delivery over an ISP network. It also reduces communication costs by placing services near the end user. However, the study points out some limitations. The method does not yet handle online placement and migration of containerized applications or network functions while keeping the service active. Moreover, the approach assumes the accuracy and effectiveness of the combined greedy and genetic algorithms, which may not always provide the best solution in every situation. Despite these limitations, the proposed method offers a promising way to reduce latency in distributed 5G/6G networks.

Ali et al. [181] proposed a new method to improve wireless channel access for massive-IoT (mIoT) applications in beyond 6G wireless networks. They use a Reinforcement Learning (RL)-based framework applied to IEEE 802.11 standards Wi-Fi. This framework uses a practical approach by relying on measured channel collision probability data from the wireless environment. This helps in determining optimal resource allocation in mIoT. The main advantage of this approach is improved network performance in terms of throughput. It also increases the capacity to support many connected stations. Additionally, it allows for integrating machine learning-aware frameworks

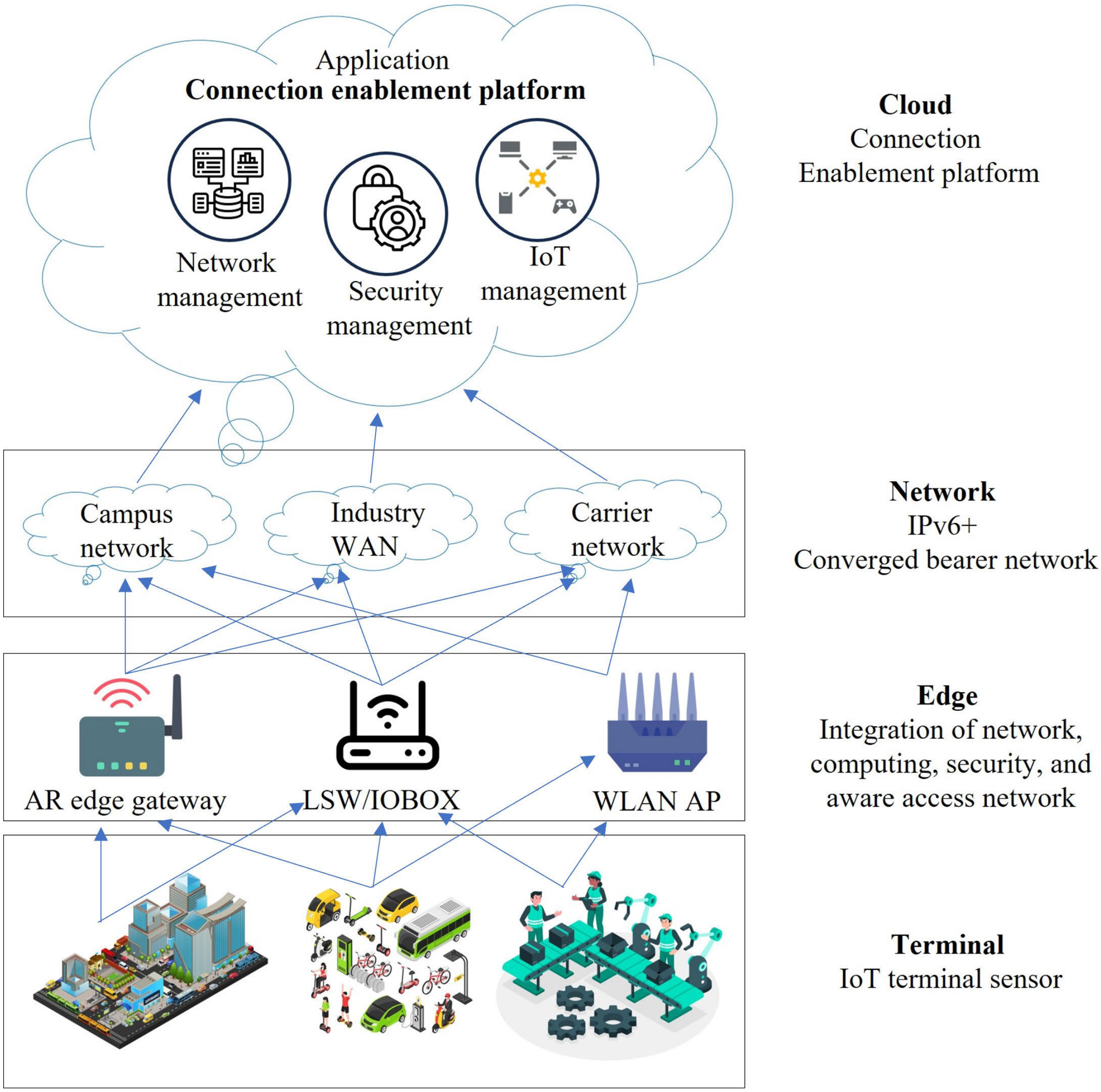

FIGURE 9. Optimizing Connectivity: A Schematic of Network-Aware Resource Management for Seamless Integration and Efficient Utilization of IoT Devices.

in wireless communication network standards, especially as they advance towards 6G.

Manogaran et al. [182] proposed a new resource allocation method called Attuned Slicing-Dependent Concurrent Resource Allocation (AS-CRA) for Network-in-Box (NIB) architectures in 6G communication technologies. This method uses learning-assisted slicing and concurrent resource allocation to improve service reliability for 6G users in the NIB architecture. AS-CRA uses the learning process outputs to classify resource allocation and user mapping, even with limited NIB infrastructure. It aims to balance virtualization and concurrency in resource allocation, considering user capacity and network blocking rate to optimize service responses. Simulations show that the model significantly improves power, latency, resource utilization rate, response ratio, and blocking rate. However, the method is complex because it is difficult to allocate resources and determine if there is enough capacity to complete the work on a project. Managing virtualization and concurrency in resource allocation to achieve optimal service responses is complex due to the high throughput and terahertz features of the 6G platform. The primary strength of the AS-CRA method is its ability to improve user capacity, resource utilization, and service response rate by controlling the blocking rate. This is achieved through deep learning-based classification [183], which differentiates blocking and non-blocking conditions, guiding the slicing process for virtualized or concurrent resource allocation. This resource allocation continues until all available users are allocated resources with minimum latency.

Shuaib et al. [184] proposed a new method called Dynamic Energy-Efficient Load Balancing (DEELB) to address common problems in IoT systems. These problems include load balancing, reducing operational costs, and using energy efficiently. DEELB focuses on dynamic resource allocation to ensure IoT devices use minimal energy, especially during high network traffic. DEELB also aims to find the least congested channel for load balancing to reduce network congestion. DEELB works with any type of computer node, including cloud- or fog-based nodes. This makes it suitable for different computing environments. The method integrates the processing power of cloud-based nodes with traditional client devices, making IoT applications run efficiently. DEELB has several advantages. It promotes energy efficiency, which is important since IoT devices often run on batteries and do not have direct power sources. DEELB handles high network traffic well by dynamically finding and interacting with the next hop to reduce network congestion. Its compatibility with any cloud- or fog-based node increases its applicability and scalability. Experiments show that DEELB performs better than other techniques, especially in terms of bandwidth usage. It also reduces packet loss and delays, improving overall network performance. However, DEELB has some disadvantages. Energy consumption may vary based on the specific IoT device and its characteristics. The complexity of the IoT network, including the number of devices, their distribution, and data traffic, can affect DEELB's performance. Additionally, DEELB may require complex algorithms to work efficiently, which can increase implementation difficulties and computational overhead.

Gupta et al. [185] proposed a new way to manage resources in a radio access network for IIoT devices. Their method uses DRL to handle network slicing efficiently, which is important for 5G and future technologies. They use a Generative Adversarial Network (GAN) NoisyNet model that learns the action-value distribution. This helps the network adapt to different service demands. A variation of their method, called Dueling GAN-NoisyNet, uses two generators. One estimates the action advantage function, and the other estimates the state-value distribution. This improves decision-making. The goal of their approach is to optimize IIoT rewards by increasing system throughput, Spectral Efficiency (SE), SLA, and transmission packet rate while reducing power consumption and transmission delay. The benefits of the GAN-NoisyNet method include smart resource allocation, the use of advanced technologies, performance optimization, and the dueling structure. However, there are some drawbacks. These include potential noise from GANs, reliance on learning quality, the need for improvements to handle complex restrictions and changing traffic, and high computational demands, especially in complex network environments.

Guo et al. [171] introduce a Device-to-Device (D2D) communication-aided digital twin-edge network. This network addresses the challenges of 6G communication technologies in IIoT environments. These challenges include managing many IoT devices, handling large amounts of data, accommodating device differences, and ensuring privacy. The proposed solution combines edge computing and digital twin technologies. Edge computing brings computation and storage resources closer to end devices. The digital twin creates a real-time virtual representation of physical devices, connecting the physical and virtual spaces. D2D communication helps resource-limited IoT devices maintain regular communication. Additionally, a digital twin-empowered Federated Reinforcement Learning (FRL) strategy is implemented. This strategy ensures privacy and trains decentralized resource allocation strategies on D2D communication links, improving network performance. The advantages of this method include efficient management of IoT devices, improved efficiency, reduced latency through edge computing, real-time virtual representation with digital twin technology, support for resource-limited IoT devices with D2D communication, and enhanced network performance with FRL. However, the model's effectiveness may be influenced by real-world factors. These factors include device movement, cross-cell interference, challenges in cooperation between the digital twin and its physical counterpart, potential scalability issues with increasing IoT devices and data volumes, and potential computational intensity requiring high-performance hardware for seamless operation.

Debbabi et al. [186] propose integrating AI with B5G network slicing to manage resources, using AI methods, training models, and architectures for real-time adaptability and system efficiency. They suggest shifting from non-cooperative to cooperative games in distributed learning to maximize social welfare and emphasize the need for better AI resource optimization in complex admission control scenarios, utilizing Artificial Neural Networks (ANN) with Reinforcement Learning. The paper also highlights EE and power optimization in future AI-based 6G networks, especially for power-demanding applications like haptic communication, holographic imaging, and mixed reality. Advantages of the proposed method include enhanced adaptability and efficiency through AI integration, improved decision-making and social welfare through cooperative games, better system understanding and optimization with AI resource optimization, and sustainable operation of power-demanding applications in the 6G network with EE and power optimization. However, disadvantages include the complexity of modeling behavior in AI-driven network slicing, challenges in shifting from non-cooperative to cooperative game frameworks, potential complications in AI integration due to power-hungry AI applications, and computational intensity in complex network environments when implementing the proposed method.

In [60], the authors proposed a new wireless resource management technique for high-density IoT services in 6G networks. The goal is to create a detailed simulation platform that uses various wireless resource management technologies. This platform would support different IoT

TABLE 4. Comparison of network-aware resource management approaches in IoT and 6G networks.

Author	Method	Advantages	Shortcomings
Shikhar Verma et al. [180]	IWPS	Balances security and network performance	Sec-admin perspective, math model dependent
Prohim Tam et al. [179]	PA-DQNs-RM	Real-time adaptability, superior performance	Needs accurate resource mapping, real-time priorities
Kiranpreet Kaur et al. [172]	Microservice placement	Reliable service, reduced costs	Needs online placement, algorithm dependent
Rashid Ali et al. [181]	RL-based framework	Improved performance, supports many stations	Data handling, coordination, RL robustness
Gunasekaran Manogaran et al. [182]	AS-CRA for NIB	Better reliability, user capacity, utilization	Project capacity, resource allocation
Mohammed Shuaib [184]	DEELB	Energy-efficient, reduces congestion, node compatible	Varies in consumption, complex networks
Rohit Kumar Gupta et al. [185]	GAN–NoisyNet model	Smart allocation, performance boost, cognitive decisions	GAN noise, learning quality, computational intensity
QiG et al. [171]	D2D communication-aided digital twin	Efficient management, improved performance, privacy	Cooperative efficiency, scalability, hardware needs
Fadoua Debbabi et al. [186]	AI with B5G slicing	Better adaptability, decision-making, energy-efficient	AI behavior modeling, integration complexity
Xiao Shen [60]	Novel wireless technique	Future relevance, versatile scenarios	High-density focus, implementation complexity

services and 6G scenarios, improving the overall design. The benefits of this method are important for the future of wireless resource management in 6G networks and high-density IoT services. Using multiple wireless resource management technologies makes it flexible for different situations. The proposed simulation platform helps in understanding and visualizing the 6G network better, leading to improved design and decision-making. Experimental results show it is more efficient than traditional platforms. However, there are some drawbacks. The focus on high-density IoT services and 6G networks might limit its use for other network types and services. The complexity of 6G networks can make it hard to simulate and manage resources accurately.

E. ENERGY-EFFICIENT RESOURCE ALLOCATION BASED ON THE LOCATION AND MOBILITY OF IOT DEVICES IN 6G NETWORK

In 6G networks, energy-efficient resource allocation is very important due to the growing number of IoT devices. The challenges like device density, mobility, and various QoS requirements become more significant in the 6G era because of its dynamic and diverse nature. Therefore, we need a more advanced approach to resource management that includes the location and movement of IoT devices in the allocation strategy. First, location-based resource allocation is crucial for achieving EE in 6G networks. The geographical location of a device affects signal attenuation and interference levels, influencing both energy consumption and communication quality. Thus, location-aware resource allocation can optimize radio resources, such as power, frequency, and spatial resources, based on the geographical distribution of devices. This optimization enhances both EE and network capacity. Besides location, the mobility of IoT devices adds another layer of complexity to resource allocation. As devices move, their location, signal quality, and network conditions change. This variability requires the use of mobility-aware resource allocation strategies. By predicting and adapting to device mobility patterns, these strategies can reduce handover failures, lower signaling overhead, and improve connection reliability, all of which contribute to EE. Using location and mobility information in resource allocation needs advanced techniques like ML and AI. ML algorithms can learn from historical data to predict the future locations and movements of IoT devices. This predictive ability allows the network to allocate resources proactively, reducing unnecessary energy use due to poor resource allocation or frequent handovers. Furthermore, AI can optimize the decision-making process by considering factors such as device location, mobility, energy status, and QoS requirements. AI-based algorithms can balance these factors to find the best allocation strategy that maximizes EE while meeting diverse service needs. Figure 10 shows the dynamic allocation of network resources in a 6G network, optimizing for EE by considering the varying locations and mobility patterns of IoT devices. Table 6 provides a comparative analysis of energy-efficient resource allocation in IoT and 6G networks.

Taneja et al. [176] present an energy-aware cell-free communication model designed for 6G-enabled networks, optimizing power consumption in high-density IoT environments. The method's core is the Minimum Interference Pilot Allocation-Maximum Channel gain AP Selection (MIPA-MCAS), which efficiently manages resources by minimizing

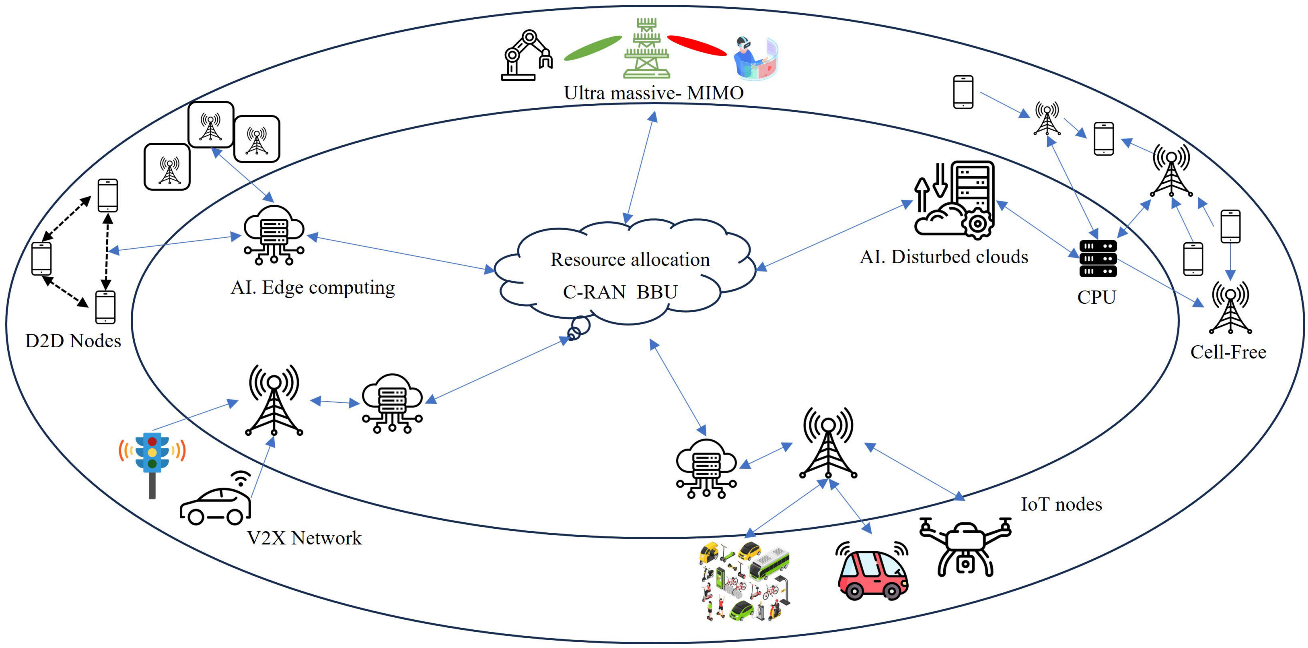

FIGURE 10. 6G Network Dynamics: Adapting resource allocation for mobile IoT devices.

interference power allocation and maximizing channel gain access point selection. The advantages of the proposed method include its emphasis on reducing power consumption, providing a practical solution for energy-aware resource management, improving spectral efficiency and network coverage, and outperforming other algorithms in terms of reducing mean square error and extending coverage. However, there are some disadvantages to consider, such as potential challenges in implementing the MIPA-MCAS algorithm in dynamic network environments, the dependency on specific power control methods, limitations in scenarios with high interference or resource constraints, the need for continuous adaptation to changing network conditions, and potential decreases in efficiency with larger network sizes or significant changes in device density. These considerations highlight the complexity and potential limitations of the proposed method in practical implementations.

Mukherjee et al. [187] focus on addressing the energy consumption problem in a dynamic network architecture or clustering for massive IoT systems. The method utilizes a Multi-agent System (MAS) with Distributed AI (DAI) to cluster sensor nodes, predict the main node's location, and optimize the model using a Backpropagation Neural Network (BPNN) and Convolutional Neural Network (CNN). The advantages of the proposed method include reducing resource waste, intelligent resource management, improved EE, and enhanced network performance. However, there are some disadvantages to consider, such as the complexity of implementing and maintaining the method due to its reliance on DAI and multi-agent systems. The dynamic nature of IoT systems and potential node movement may impact system performance. Using BPNN and CNN models may require significant computational resources and time. Integration and compatibility issues between different components may also affect system performance. Additionally, the proposed method may require consistent updates and adaptations to match changes in the industrial 6G environment and IoT applications.

Islam et al. [188] present a DRL-based resource allocation scheme for a 6G-enabled Smart Grid (SG) network to improve Energy Demand Management (EDM). This scheme uses smart meters in the dynamic edge network to handle resource-intensive computations and addresses security by examining False State Injection (FSI) attacks and introducing a lightweight detection mechanism using supervised classifiers. The proposed method benefits from DRL for automatic resource provisioning, increasing efficiency and speed in the smart grid, and reduces the computational load on the central server by utilizing smart meters. The lightweight FSI detection mechanism enhances security by identifying potential threats. Simulation results show success in dynamic resource allocation and FSI attack detection. However, there are drawbacks: DRL is complex and requires careful tuning and significant computational resources, which may be limiting in resource-constrained environments. The method relies on accurate state information from multiple edge servers, and inaccuracies can impact the DRL model's performance. Implementing the FSI detection mechanism can add computational overhead and complexity, and the DRL model may need many iterations to converge, slowing down the solution process. Additionally, the FSI detection mechanism might still produce false positives or negatives, posing security risks. These points highlight the complexity and potential limitations of the proposed method in practical implementation, necessitating careful calibration, accurate data, and ongoing security evaluations.

Khan et al. [189] focuses on enhancing the energy and spectral efficiency of Non-Orthogonal Multiple Access (NOMA)-enabled IoT devices through a power allocation technique. The method addresses the non-convex optimization problem using the Sequential Quadratic Programming (SQP) technique and considers transmit power, QoS, and Successive Interference Cancellation (SIC) constraints. Monte Carlo simulation compares the performance of the SQP-based approach with the conventional KKT-based optimization method. The advantages of the proposed method include its effective and reliable solution to the non-convex power allocation problem in NOMA-enabled IoT networks, improvement in energy and spectral efficiency while maintaining QoS requirements, and significant performance enhancements compared to the conventional KKT-based NOMA scheme. However, there are some limitations to consider. The non-convex nature of the power allocation optimization problem can make it challenging and complex to solve, potentially limiting the method's practicality. The method's performance heavily relies on specific constraints, such as transmit power, QoS, and SIC, which means it may not perform optimally under varying or unexpected conditions. Additionally, the proposed SQP-based scheme is computationally intensive, which can be a limitation in resource-constrained IoT environments. It is also important to investigate how the proposed method performs under conditions of device mobility, as this can significantly impact EE and spectral efficiency in IoT networks. These considerations underscore the complexity of the optimization problem and the need for careful implementation and evaluation of the proposed method in practical IoT scenarios.

Ashwin et al. [178] introduce a Hybrid Quantum Deep Learning (HQDL) model composed of a CNN and a Recurrent Neural Network (RNN) for resource management in 6G networks. The CNN component handles network reconfiguration, resource distribution, and slice collection, while the RNN component focuses on error proportion and load balancing. This hybrid model addresses critical challenges in 6G network systems, such as network slice failure and load balance, by redirecting demands and optimizing load distribution. The advantages of the proposed method include its potential to improve QoS in 6G networks through efficient resource management, the utilization of the strengths of both CNN and RNN techniques for improved performance, high overall accuracy in predicting suitable network slices for congestion situations, and the prevention of network slice failures while ensuring load balance and reliability. However, there are several disadvantages to consider. The hybrid deep learning approach may require significant computational resources, which could limit its practicality in certain environments. Extensive training and the collection of large datasets are necessary for the effective functioning of neural networks. The method's performance may be affected by varying or unexpected network conditions. Implementation and maintenance of the complex method may require expert knowledge. These considerations highlight the potential benefits and challenges of the proposed method, emphasizing the need for resource allocation and optimization techniques that balance performance and practicality in 6G network systems.

Ahmed et al. [190] introduce a resource allocation strategy for wireless sensor IoT networks using deep learning architectures, focusing on EE and data optimization. The proposed model combines a Deep Neural Network (DNN) based on whale optimization with a heuristic-based multi-objective firefly algorithm. The DNN improves EE, while the firefly algorithm optimizes data. The method achieves optimal power allocation and relay selection in a cooperative multi-hop network topology, reducing transmit power and meeting QoS standards. The study develops an energy-efficient protocol for IoT networks. The advantages of the proposed method include enhanced EE and data optimization, improved resource utilization and service delivery in IoT networks, and the integration of deep learning and heuristic algorithms for optimal power allocation and relay selection. The method demonstrates high performance in simulation results, achieving favorable metrics in throughput, EE, QoS, spectrum efficiency, and network lifetime. The approach offers a promising solution for addressing competing optimization objectives in IoT networks. However, there are some disadvantages to consider. The proposed method may be computationally expensive due to DL architectures and heuristic algorithms. Implementing the method may require expertise in both ML and IoT networking. The scalability and adaptability of the method to significant changes in the network environment could be limited. Balancing competing optimization goals in real-world IoT networks may be challenging due to the unpredictable nature of these environments. These considerations emphasize the potential benefits and challenges of the proposed method, highlighting the need for careful implementation and evaluation in practical IoT scenarios.

Raj et al. [177] propose an Energy-efficient Power Allocation (EPA) scheme for NOMA-based Visible Light Communication (VLC) systems in 6G networks, with a focus on meeting the connectivity demands of the IoT. The EPA scheme enhances capacity, EE, and fairness while reducing the Average Bit Error Rate (ABER). The trade-off between EE and ABER is evaluated through the energy utilization factor, particularly at high transmitted power values. The paper also analyzes the impact of power allocation on the user with the highest channel gain and the influence of increasing user numbers on system performance. The advantages of the proposed method include improved EE, capacity, fairness, and communication quality in the VLC-NOMA system. The EPA scheme demonstrates robust performance even with an increasing number of users. It offers a higher energy utilization factor, making it suitable for addressing the trade-off between EE and ABER. However, there are some limitations to consider. The trade-off between EE and ABER at high transmitted power values may present challenges in certain usage scenarios. The study does not address the effect of complex network topologies on the performance of the EPA scheme. These considerations highlight the potential benefits of the proposed EPA scheme but also indicate the need for further exploration in different network environments and topologies.

Aljubayrin [191] proposes a new optimization framework using an Unmanned Aerial Vehicle (UAV) as a flying Mobile Edge Computing (MEC) server. This UAV provides computational and communication resources to sensor nodes. The method has several advantages. It offers on-demand services when central cloud systems are not accessible. It also solves a joint optimization problem that balances computational energy efficiency. The main problem is divided into smaller sub-problems to handle computational complexity. However, the study does not mention any disadvantages. Managing the complex interactions between UAV flight trajectory, computation, and communication resources can be challenging. Ensuring the scalability and reliability of this solution in different real-world situations may also be difficult. While the proposed method shows potential in overcoming the limitations of central cloud systems and optimizing resource allocation, it is important to consider its possible limitations and practical challenges. More research and evaluation are needed to fully understand the performance and feasibility of the UAV-MEC solution in various scenarios.

Xiao et al. [192] explore the potential of using UAVs to improve EE in IoT applications. The idea is to dispatch the UAV to approach the IoT clusters geographically to enhance energy-efficient IoT transmissions. The study aims to maximize the system EE by optimizing the UAV trajectory and IoT communication resources. The authors have employed a large system analysis and the Dinkelbach method to turn the original fractional optimization problem into a subtraction form, which they then solved iteratively using a block coordinate descent framework. Advantages of the proposed method include taking into account both UAV propulsion energy and IoT communication energy, ensuring a comprehensive approach to EE. The iterative approach to optimize UAV trajectory and IoT communication resources could lead to solutions that are more efficient and adaptable to real-world conditions. The findings suggest that the more geographically isolated a cluster is, the higher its impact on the UAV trajectory, which provides an important insight for planning energy-efficient IoT deployments. Disadvantages of the proposed method include potential challenges in managing UAV trajectories and communication resources and the scalability of the proposed solution across diverse and larger IoT networks.

F. DYNAMIC RESOURCE ALLOCATION BASED ON NETWORK CONDITIONS

Dynamic resource allocation is vital in the emerging 6G network, especially for IoT. As the digital world expands, efficient resource management becomes more important. In a 6G network, IoT devices will produce large amounts of data from wearables, smart homes, industries, and cities. Dynamic resource allocation manages this data by adjusting network resources to the varying needs of IoT devices. The goal is to create a network that can sense, predict, and adjust to real-time demand changes. Dynamic resource allocation will prioritize resources based on network conditions, traffic type, and device needs. For example, if an autonomous vehicle needs data, the network will prioritize it over a less urgent device, like a smart meter, to ensure safety and efficiency. This adaptation is both reactive and predictive, thanks to advanced machine learning. The network can foresee changes in device behavior and adjust resources proactively. Dynamic resource allocation in 6G will use AI, edge computing, and cloud technologies to create an intelligent, connected network. Edge computing will process data closer to IoT devices, reducing latency and improving performance. Meanwhile, AI and cloud technologies will provide the computational power and storage needed for effective resource management. However, this approach also presents challenges. Figure 11 shows a cloud-edge computing architecture for dynamic resource allocation. A cloud server intelligently distributes tasks among edge servers, optimizing IoT data flow predictively and efficiently for the 6G network. Table 7 provides a comparative study of dynamic resource allocation based on network conditions in IoT and 6G networks.

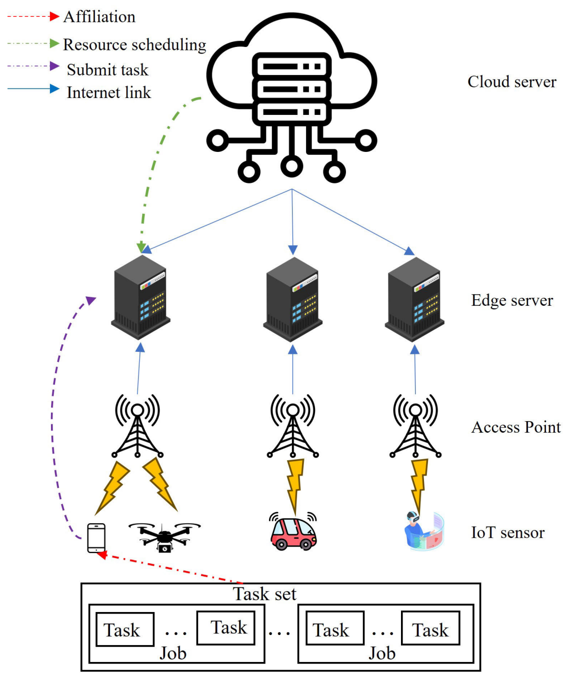

FIGURE 11. Dynamic Resource Allocation in 6G.

TABLE 5. Comparison of energy efficient resource allocation in IoT and 6G networks.

Author	Method	Advantages	Shortcomings
Ashu Taneja et al. [176]	MIPA-MCAS	Low power use, better spectral efficiency	Implementation challenges, power control dependency
Amrit Mukherjee et al. [187]	MAS with DAI	Reduced waste, smart management	High complexity, resource intensive
Shafkat Islam et al. [188]	DRL-based	Efficient, fast, secure	Model complexity, needs accurate data
Wali Ullah Khan et al. [189]	SQP for NOMA	Solves non-convex issues, better performance	Non-convex problem, high computational needs
M. Ashwin et al. [178]	HQDL model	Improved QoS, prevents failures	High resource use, extensive training
Quazi Warisha Ahmed et al. [190]	Deep learning	Better efficiency, optimized resources	High computational cost, scalability issues
Rishu Raj et al. [177]	EPA scheme	Better EE, capacity, fairness	EE-ABER trade-off, ignores complex topologies
Saad Aljubayrin [191]	UAV as MEC server	On-demand service, balanced EE	Managing UAV interactions, scalability
Xiao Tang et al. [192]	UAV deployment	Optimized trajectory, resource use	Managing trajectories, scalability issues

Fu et al. [193] propose a resource management framework for IoT that combines FL and blockchain technologies to enhance security. The advantages of the proposed method include improved security in IoT resource management through integrating FL and blockchain, the effectiveness of the Support Vector Machine (SVM) classifier in detecting malicious nodes, and the improved algorithm performance by excluding identified malicious nodes. However, the paper does not explicitly mention any disadvantages of the proposed method. Challenges may arise in implementing and managing an integrated blockchain and FL system in large-scale IoT networks due to the inherent complexity of such systems. Additionally, the effectiveness of the SVM classifier in accurately detecting all malicious nodes may have limitations. While the proposed method offers promising enhancements to IoT resource management security, further research and evaluation are necessary to understand its limitations and challenges fully. Addressing scalability, practical implementation issues, and the accuracy of malicious node detection would be important considerations in applying this approach.

Sheng et al. [194] present a two-part strategy to improve the wireless coverage of the new 6G Satellite-Terrestrial Integrated Network (STIN) with mega-constellations. This strategy focuses on examining the network structure for 6G service requirements, helping with the design of 6G STINs and intelligent resource scheduling to enhance coverage performance. The research also looks at how AI can help manage resources to meet changing service needs. The proposed method extends spatial and temporal coverage, improves wireless coverage for 6G STINs, creates a way to provide non-uniform coverage that matches uneven service demands, and examines how satellite constellation configurations affect coverage performance, identifying suitable network structures. However, the complex and new nature of 6G technology may make it difficult to implement, and managing intelligent resource scheduling efficiently could be challenging.

Ibrahim et al. [195] proposed a ground breaking solution for optimizing sixth-generation 6G-IoT networks based on willow catkin packet transmission scheduling with AI and Bayesian game-theoretic approach-based resource allocation. This solution, named fishnet-6G, integrates several advanced technologies to enhance network performance. Key components of fishnet-6G include a sierpinski triangle-based network architecture for improved connectivity, quantum density peak clustering for efficient device grouping, improved deep deterministic policy gradient for accurate traffic prediction, willow catkin optimization for dynamic packet scheduling, and a bayesian game-theoretic approach for optimal resource allocation. Fishnet-6G aims to reduce complexity, energy consumption, and latency while increasing throughput and reliability. The sierpinski triangle-based architecture provides scalable device connectivity. Quantum Density Peak Clustering boosts energy efficiency and communication by clustering devices effectively. The Improved deep deterministic policy gradient algorithm enhances packet scheduling by accurately predicting traffic. Willow catkin optimization dynamically adjusts scheduling based on quality of service metrics, reducing transmission delays and energy use. The bayesian game-theoretic approach optimizes resource allocation by balancing quality of service demands with efficiency. Evaluated using Network Simulator, this approach demonstrated superior performance compared to existing methods in terms of transmission rate, energy efficiency, throughput, latency, and packet loss rate. By integrating artificial intelligence and game-theoretic principles, it offers a comprehensive solution for 6G-IoT network challenges, highlighting its potential for future wireless communication systems.

Lin et al. [196] introduce an AI-driven Collaborative Dynamic Resource Allocation (ACDRA) algorithm envisioned for 6G-enabled massive IoT. The innovative approach considers the dynamic resource requirements of devices within the IoT architecture. The algorithm applies a dynamic nested neural network that can adapt its structure online to accommodate the training requisites for dynamic resource allocation. This nested neural network, complemented by Markov decision process training, constitutes the backbone of the ACDRA. The proposed method exhibits several advantages, such as improving the average resource hit rate by approximately 8% and demonstrating heightened resource-task allocation efficiency. In addition, the average decision delay time is curtailed by nearly 7% compared to three existing algorithms, signifying expedited decision-making in resource allocation. Moreover, the ACDRA algorithm supports the linear and orderly nesting of local neural networks on devices according to task requirements while offering dynamic structural adjustment flexibility via backtracking. Despite these benefits, some potential drawbacks may arise. Although the paper doesn't distinctly delineate any disadvantages, potential challenges might encompass the intricacies of real-time dynamic resource allocation and the system's performance when tasks undergo swift or significant transformations.

Ansere et al. [170] innovative, low-complexity joint resource allocation algorithm is designed to optimize the EE of the radio subsystem of IoT devices in 6G networks. This algorithm incorporates a mixed-integer nonlinear programming problem to jointly optimize power allocation, sub-channel allocation, user selection, and activating Remote Radio Units (RRUs) while considering channel conditions. The optimization problem is reformulated into a tractable and parametric form leveraging fractional programming properties. The reformulated problem is then optimally solved by applying the Lagrangian decomposition method and an enhanced Kuhn-Munkres algorithm. The proposed method presents multiple advantages, notably the significant improvement of EE in IoT systems compared to existing methodologies. Furthermore, it provides a practical and feasible solution to the computationally demanding mixed-integer programming problem. Additionally, by activating only a subset of RRUs, the algorithm optimizes EE in real-world IoT network implementations. Although the paper doesn't explicitly specify any disadvantages, potential limitations could encompass the complexity and computational cost of solving the original problem, necessitating sophisticated algorithms and significant computational resources.

Anjum et al. [197] proposed a ML-based resource allocation for 6G networks. This algorithm can dynamically adjust to real-time changes in network conditions, ensuring optimal resource utilization. This adaptability leads to improved network throughput and reduced latency, crucial for meeting the high demands of 6G networks. Additionally, the automation of resource allocation reduces the need for manual intervention, resulting in lower operational costs and increased scalability. The ability to learn from historical data and predict traffic patterns allows ML to preemptively address network congestion and enhance overall efficiency. However, the implementation of ML in 6G networks is not without its challenges. A significant disadvantage is the high computational complexity and resource requirement for training these algorithms. Collecting and processing the vast amounts of data needed for effective machine learning can be time-consuming and resource-intensive. Moreover, the deployment of these algorithms requires specialized expertise in both machine learning and network engineering, which might not be readily available in all organizations. There is also a concern regarding the latency introduced during the initial learning phases, which can temporarily impact network performance. Furthermore, security and privacy issues present notable disadvantages. The use of ML algorithms necessitates access to extensive user data, raising concerns about data privacy and the potential for misuse. Additionally, the reliance on these algorithms introduces vulnerabilities, as an error or malicious interference in the ML model can lead to significant disruptions in network operations. Ensuring the robustness and security of systems is therefore critical but can be complex and costly.

Sun et al. [198] propose a method that uses hybrid blockchain technology in a 6G cloud to help UIoT devices share spectrum dynamically. UIoT is a complex network with many elements, needing a system that supports openness and sharing among different operators. This method meets that need by using a hybrid blockchain for 6G spectrum sharing. UIoT devices' spectrum resources are divided into multiple parts, allowing secure and reliable random access to large amounts of data from these devices. The method also uses cloud computing and smart contracts to connect massive data and verify external data authenticity. The proposed method provides a secure and reliable way for random access to a lot of terminal data, enables dynamic spectrum sharing to optimize spectrum resources, improves overall network efficiency with cloud computing, and facilitates massive data interconnection. Smart contracts ensure data authenticity, increasing system trust, and the hybrid blockchain approach enhances network resilience and efficiency with a decentralized, secure mechanism. However, implementing this complex system can be challenging due to the integration of blockchain, cloud computing, and smart contracts. Blockchain operations can be computationally heavy and may increase network latency. Smart contracts might have vulnerabilities if their code is flawed. Seamless UIoT integration and operation across space, air, and ground networks could require significant resources and infrastructure. Protecting privacy and security in such a large, distributed network can also be very challenging.

Manogaran et al. [199] introduce the Service Virtualization and Flow Management Framework (SVFMF). This framework aims to optimize resource usage in a 6G-cloud environment. It offers high interoperability through terahertz data transfer and zero-latency service sharing. The SVFMF framework addresses the imbalance in service requests and responses. This imbalance is mainly caused by overloaded and idle virtual resources. The framework uses two main approaches: service virtualization and user allocation modules. Service virtualization uses linear decision-making to reduce computation and service discovery time. It identifies overloaded services and reallocates them. The user allocation module distributes service requests to idle service providers, reducing wait times for users. The framework uses deep machine learning to manage partial states and actions of service requests and virtual machines. Reward-based swapping of service requests among virtual machines minimizes service failures during allocation. Despite its advantages, the SVFMF framework has potential limitations. Its effectiveness depends on the quality of decision-making algorithms and ML models. Predicting and managing the volatile nature of user requests and virtual machine load is challenging. Implementing the framework may require significant computational resources and sophisticated software infrastructure. Overall, the SVFMF presents an innovative solution to resource management in a 6G-cloud environment. While it has some drawbacks, it is a promising research area that needs further exploration and testing in real-life settings.

Jia et al. [200] propose a novel approach to address the challenges of resource allocation in space air ground integrated networks. They tackle the problem posed by the stochastic nature of IoT data arrivals and the dynamic network topology due to the high mobility of non-geostationary orbit satellites. By employing Lyapunov optimization theory, the authors transform the long-term stochastic optimization problem into a series of deterministic problems that can be solved in each time slot. This transformation allows for the development of an online resource allocation algorithm that dynamically adjusts data admission, subchannel assignment, and power control based on the current network state and data backlog. The main benefit of the proposed method is its ability to adapt dynamically to real-time network conditions, ensuring efficient resource allocation and keeping the queue stable. The incorporation of queue stability constraints prevents data queues from growing indefinitely, thereby avoiding network congestion. Furthermore, the method aims to maximize long-term network utility by achieving a balance between throughput and fairness among IoT nodes. This balance is essential for equitable resource distribution in large-scale networks with numerous IoT nodes. The scalability of the method, facilitated by Lyapunov optimization and online algorithms, makes it particularly suitable for highly dynamic environments. However, the proposed method has some limitations. The complexity of the mathematical transformations and iterative algorithms may result in significant computational overhead, particularly in large-scale networks. Additionally, the algorithm's performance is heavily dependent on the accuracy of the network state and queue information at each time slot, which might be challenging to maintain in practical scenarios.

Singh et al. [201] proposed a hybrid multi-objective optimization method for 6G-enabled IoT networks that integrates multi-objective red fox optimization with differential evolution. This combination leverages the exploratory capabilities of the proposed method and the diverse solution space search of differential evolution, aiming to optimize critical network parameters such as data throughput, energy efficiency, packet loss ratio, packet delivery ratio, and latency.The algorithm starts with a variety of potential solutions and improves them step by step through small changes and combining them. This allows it to adapt to changing network conditions and maintain strong performance, even in complex situations where multiple goals need to be balanced. One of the key advantages of this hybrid method is its balanced approach to exploration and exploitation, allowing for comprehensive optimization across multiple conflicting objectives. The dynamic adaptation mechanisms ensure the algorithm remains flexible and responsive to evolving 6G network demands, making it suitable for a wide range of IoT applications. The ability to find Pareto-optimal solutions that represent the best trade-offs among various performance metrics enhances the network's overall efficiency, reliability, and responsiveness. However, the computational complexity and the need for careful parameter tuning can be challenging, potentially leading to increased processing requirements and slower convergence times. Despite these challenges, the proposed method's robustness and adaptability offer significant improvements over traditional optimization techniques. By addressing the multi-faceted optimization needs of 6G-enabled IoT networks, the hybrid algorithm can provide stable, high-quality solutions that meet the diverse demands of modern IoT applications.

G. PREDICTIVE RESOURCE ALLOCATION BASED ON TRAFFIC PATTERNS AND NETWORK TOPOLOGY IN 6G NETWORK

Predictive resource allocation uses traffic patterns and network topology. This strategy improves network performance by predicting future demands. Resources are allocated proactively, not reactively. AI and ML algorithms analyze traffic patterns and historical data to forecast future network loads. These tools identify trends, peak usage times, and potential bottlenecks in the network. This information helps allocate resources effectively, anticipating demand. Understanding network topology is also crucial. Knowing the physical and logical arrangement of the network helps to increase capacity or reroute traffic. This minimizes congestion and maintains service quality. Combining traffic pattern analysis

TABLE 6. Comparison of dynamic resource allocation based on network conditions in IoT and 6G networks.

Author	Method	Advantages	Shortcomings
Xiuhua Fu et al. [193]	FL and blockchain for IoT	Better security, effective SVM classifier	Complexity, SVM limitations
Min Sheng et al. [194]	Strategy for 6G STIN coverage	Extended coverage, AI for resource collaboration	Managing scheduling priorities
Ali.Ibrahim et al. [198]	Fishnet-6G	Reduces complexity, energy use, latency; increases throughput, reliability	High implementation complexity
Kai Lin et al. [196]	ACDRA algorithm for 6G IoT	Higher resource hit rate, efficient allocation	Dynamic allocation complexity, task changes
James Adu Ansere et al. [170]	Low-complexity joint allocation	Enhanced EE, solves complex problems	High computational cost, algorithm needs
Sana Anjum et al. [197]	ML-based resource allocation for 6G	Adapts in real-time, Optimizes resources , Lowers costs	High complexity, Resource-intensive , Requires expertise
Zhenqiang Sun et al. [198]	Blockchain for spectrum sharing	Secure access, dynamic sharing	Implementation complexity, latency, privacy
Gunasekaran Manogaran et al. [199]	SVFMF	Efficient utilization, reduces failures	Predicting user requests, computational needs
Jia, H. et al. [200]	Resource allocation in space-air-ground integrated networks	Adapts dynamically, Ensures queue stability, Avoids congestion	High computational overhead , Dependent on accurate network state and queue info
SP Singh et al. [201]	Hybrid multi-objective optimization combining red fox optimization and differential evolution	Adaptive, efficient, reliable, finds Pareto-optimal solutions	High complexity, needs parameter tuning, increased processing, slower convergence

and network topology enables dynamic and adaptive network management. This improves quality of service, reduces latency, and enhances user satisfaction. Predictive resource allocation helps networks move from reactive to proactive management. It creates a more resilient, efficient, and sustainable infrastructure. This infrastructure can handle the changing demands of the digital age. Figure 12 shows how machine learning-driven predictive analytics integrate within a 6G network. It highlights the dynamic allocation of resources by correlating real-time traffic patterns with historical data to optimize performance and service delivery.

Peng et al. [202] introduce a method for network traffic prediction to mitigate congestion in burgeoning mobile broadband networks and IoT applications by optimally allocating resources. The technique involves a Variable Sampling Rate - Non-Linear Mean Squares (VSR-NLMS) model, enabling adaptive sampling of network data. A Variable Sampling Rate - Long Short-Term Memory (VSR-LSTM) algorithm follows, designed to predict network traffic in real-time, adapting its sampling rate to traffic changes. This innovation involves using variable sampling rates, enhancing traffic prediction accuracy, and ensuring efficient network resource allocation. This method offers adaptability to network traffic changes, enhancing prediction accuracy over fixed-rate sampling. It optimizes network resource allocation, improving network efficiency and robustness against congestion. ML and LSTM integration also allow effective learning and retention of traffic data dependencies, augmenting prediction accuracy. However, the method's effectiveness relies heavily on the quality and diversity of training data. If this data doesn't represent potential network conditions comprehensively, prediction accuracy may be compromised. The method also demands significant computational resources, potentially limiting its use in resource-constrained environments. Finally, while variable sampling rates improve prediction accuracy, they also add complexity to the algorithm, potentially challenging implementation and maintenance compared to fixed-rate sampling methods.

Vološin et al. [203] introduces a cutting-edge vehicular route selection algorithm that considers radio and computing resource allocation for Connected and Autonomous Vehicles (CAVs) in MEC contexts. Unlike traditional methods, this approach incorporates vehicular routes to inform resource allocation decisions. The technique hinges on a graph search-based lexicographic A* algorithm to minimize the ratio of failed tasks along the vehicular route based on available radio and computing resources. Furthermore, to manage resources among CAVs, a blockchain-based framework utilizing Non-Fungible Tokens (NFTs) to represent exclusive rights to a given amount of resources for specific road segments and time intervals is introduced. This approach presents a comprehensive solution, integrating vehicular route selection and resource allocation in a decentralized manner using blockchain technology and NFTs for resource management and reservation. Advantages include a holistic approach considering both route selection and resource allocation, a decentralized, transparent blockchain-based framework, and using NFTs to provide exclusive rights to resources,

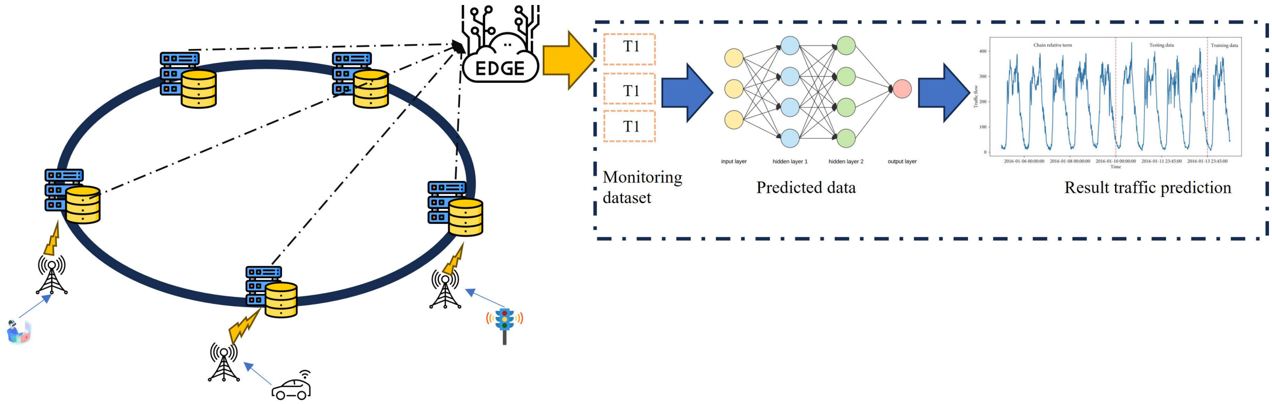

FIGURE 12. Predictive resource allocation in 6G networks: From data collection to traffic prediction.

reducing conflicts and enhancing resource utilization efficiency. However, challenges include potential computational demand and scalability issues due to blockchain reliance, fluctuating value and security vulnerabilities associated with NFTs, increased computational complexity due to the lexicographic A* algorithm, and reliance on accurate vehicular route and resource needs prediction for effective resource allocation.

Deebak et al. [204] introduce a Dynamic-Driven Congestion Control and Segment Rerouting (DD-CCSR) approach specifically tailored for the unique demands of 6G-enabled networks. The method aims to enhance network traffic management in the rapidly emerging IoT environments by addressing congestion and improving traffic monitoring and path adjustment. Utilizing the Deleroi superimposed principles and a forward-backwards interface, the DD-CCSR method achieves congestion mitigation and efficient traffic flow by dynamically rerouting segments based on network state, thereby minimizing transmission rate and signalling congestion. The technique has been implemented and evaluated on the IMS core platform, showcasing its positive impact on throughput rate and transmission delay. Advantages of this method include its dynamic nature, facilitating adaptability to network changes and ensuring optimal performance, and its comprehensive solution to network traffic management by combining congestion mitigation and improved network monitoring. In addition, incorporating Deleroi principles and a forward-backwards interface enhances the handling of low-rate data flow and overall performance. However, the method's effectiveness relies heavily on accurately determining network state information. Its dynamic nature may also increase system complexity, including computational requirements and system design. Implementing large-scale, real-world networks, especially those with diverse traffic patterns or varying architectural characteristics, could present challenges.

Fang et al. [205] introduce a systematic method to comprehend and optimize hybrid Satellite-Terrestrial Networks (HSTNs). This paradigm capitalizes on the merits of satellite and terrestrial communications for better coverage. This approach tackles substantial differences between Satellite Communications (SatComs) and Terrestrial Communications (TerComs), including disparities in channel fading, transmission delay, mobility, and coverage performance. Central to this method is the decomposition of an HSTN into three basic cooperative models: model X, model L, and model V. These models simplify and make the features of satellite-terrestrial integration more tractable compared to extensive heterogeneous HSTNs. The advantages of this method include a simplified approach to understanding and implementing HSTNs, making it more tractable than large-scale HetNets. In addition, the three cooperative models provide a structured framework to manage HSTNs' complexities, offering insights into their operation and design. Furthermore, this approach effectively harnesses the strengths of both satellite and terrestrial communications, overcoming traditional limitations. However, potential drawbacks include overlooking nuanced interactions within real-world HSTNs due to simplifying the three models. Furthermore, while these models offer a foundation for understanding HSTNs, they might only partially resolve issues, requiring additional investigation and development.

Liu et al. [206] present Direction Decide-as-a-Service (DDaaS), a groundbreaking solution to mitigate urban congestion in 6G-enabled ITS. DDaaS employs a three-layer service architecture powered by Swarm Learning (SL), ensuring organized traffic data transmission and control commands while preserving user privacy. The model layer gathers data, trains parameters, and predicts congestion values. The swarm network layer guarantees secure and reliable parameter transmission and fusion, while the decision-making layer makes optimal signal light switching decisions. Enhanced by an improved local model and aggregation method, DDaaS accurately predicts road resources at single intersections and uses a dynamic traffic control algorithm to respond swiftly to ITS changes. The effectiveness of DDaaS is proven through urban road simulation experiments using SUMO. Advantages include offering a holistic congestion solution, structured data handling and decision-making via a three-layer architecture, rapid adaptability through a dynamic traffic control algorithm, and ensuring privacy by only transmitting parameters. Conversely, potential drawbacks include dependency on accurate data collection and parameter training, resource-intensive implementation due to complexity, reliance on all three layers for optimal operation, and potential challenges in real-world deployment due to diverse traffic patterns, varied road infrastructure, and unpredictable user behavior.

Xu et al. [46] provides a fascinating exploration of the potential application of blockchain technology within 6G networks. This integration could enable more efficient resource management and sharing, particularly regarding spectrum scarcity. Integrating these two cutting-edge technologies presents opportunities and challenges warrant further study and consideration. Indeed, the unique properties of blockchain technology, such as transparency, decentralization, and immutability, could enhance resource allocation and management in various application scenarios, including IoT and D2D communications. Moreover, blockchain technology's improved security and privacy could mitigate some security concerns inherent in such a broad and interconnected network. However, the implementation of blockchain technology has its challenges. The computational power and energy required to run blockchain networks could present obstacles, particularly for lower-cost IoT devices. Moreover, the ever-growing size of the blockchain could pose scalability issues as more blocks are added. Furthermore, the latency associated with blockchain transactions could be problematic, particularly given the ambitious sub-1 ms latency targets of 6G networks. Lastly, while blockchain technology may enhance security, it could also introduce new privacy concerns, given the public visibility of transactions.

Lohrasbinasab et al. [207] examine existing Network Traffic Prediction (NTP) techniques within Network Traffic Monitoring and Analysis (NTMA). These techniques aim to predict future network load and behavior, which is critical in modern IoT, IoV, and 6G networks. The research categorizes NTP techniques into statistical-based and ML-based, critically reviewing and classifying recent studies while discussing NTP's challenges and future trajectories. Advantages include the comprehensive review of current NTP techniques, which benefits researchers in the field. By highlighting the challenges and future directions of NTP, the study offers valuable insights into potential areas for improvement and development. Furthermore, this research bridges the gap between practical implications and theoretical underpinnings of NTP techniques, elucidating the subtleties of network data processing in modern networking technologies. However, some limitations exist: the approach remains theoretical, not suggesting a specific practical solution to enhance NTP. While it assesses ML and statistical-based techniques, it doesn't compare them to real-world applications or offer methods to overcome identified challenges. Lastly, considering the dynamic nature of network traffic and rapidly evolving technologies, the study might only partially encompass all recent developments and advanced techniques in NTP.

Djenouri et al. [208] designed for urban traffic flow prediction in an edge IoT setting. The method combines graph preprocessing, forecasting, and an advanced optimization technique based on branch and bound in a streamlined pipeline. The preprocessing stage involves outlier detection to cleanse the initial urban traffic data of noise and irrelevant patterns. The refined data, presented as a linked graph, is subsequently employed to train an extended graph CNN for traffic flow prediction. Finally, the novel branch-and-bound optimization technique is used to fine-tune the framework's hyperparameters accurately. Critical advantages of the proposed method include its integrative pipeline approach, enhancing efficiency and cohesion in traffic flow forecasting. The application of graph preprocessing and outlier detection strategy facilitates the removal of noise and irrelevant patterns from traffic data, resulting in more precise predictions. Further, the branch-and-bound optimization technique provides exact hyperparameter tuning, enhancing predictive accuracy. Evaluation of multiple datasets and baseline methods illustrates that the proposed framework surpasses existing solutions, especially in large graph node scenarios. However, the framework has a few potential limitations. Given the model's complexity, it requires considerable computational resources and expertise for implementation and operation. The framework's performance also depends on the quality and characteristics of input data, and it could vary in urban environments with diverse traffic patterns and conditions.

Nagib et al. [155] investigate the utilization of RL algorithms for dynamic RRM in beyond 5G networks. However, these algorithms are not yet widely adopted in commercial cellular networks due to the slow convergence of RL agents in live networks and during significant contextual shifts. The emerging paradigm of Open Radio Access Network (O-RAN) offers increased control for MNOs, enabling more intelligent and RL-based network management. The paper addresses the challenge of adapting RL agents to changes made by MNOs in a RAN slicing scenario. Here, MNOs can modify the weights of the RL reward function, changing the priorities of fulfilling the SLAs of the slices. The authors propose an exhaustive experiment to examine the efficacy of Transfer Learning (TL) to hasten the convergence of RL-based RAN slicing in the discussed scenario. They then propose a predictive approach to enhance the TL-based acceleration by choosing the best-saved policy for reuse. As a result, RL agents can converge up to 14,000 learning steps faster than non-accelerated counterparts, with an ML-based predictive approach demonstrating up to 96.5% accuracy in selecting the best policy for reuse. This work addresses significant challenges in deploying RL-based RRM solutions in dynamic wireless network environments, marking a critical step towards robust intelligent resource management in O-RAN. The authors conclude that enhancing TL-based acceleration approaches is essential for RL's integration into commercial RRM solutions.

Yu et al. [209] propose an innovative network analytic approach to improve Network Slice Mobility (NSM) in the emerging 6G networks and Multi-access Edge Computing environments. Network slicing is a critical technology that allows networks to be divided into multiple virtual networks, each tailored to meet the requirements of specific applications or services. This will be crucial for supporting large data volumes for future 6G services, such as holographic-type communications, and time-sensitive services, like industrial control. The challenge addressed in the paper is efficient slice mobility due to the dynamic user resource demands within and between slices, leading to distinct mobility patterns, including scaling and migration. These demand changes necessitate network operation and management flexibility to ensure the QoS while minimizing mobility costs. To optimize NSM, the authors analytically propose a prediction-based intelligent network. This leverages user and network prediction data to make slice mobility decisions, aiming to maximize long-term profits while minimizing latency and mobility costs. The goal is to avoid resource competition from a long-term perspective by utilizing complementary user demand profiles or complementary network load in different MEC servers. This ensures that network slices with high priorities are always provisioned with enough resources to guarantee QoS-associated services. Performance evaluation results in a simulated environment demonstrate that the proposed prediction-based scheme achieves higher overall profits regarding mobility and network resources compared to the two benchmark solutions. This work represents a significant step toward improving the efficiency and profitability of network slicing and its mobility in 6G MEC environments.

V. DISCUSSION

Predictive resource allocation based on traffic patterns and network topology is important. These methods allow for proactive network management, forecasting future network traffic and adjusting resources as needed. This helps networks run smoothly, reduces latency, and improves QoS. However, these methods depend on accurate and comprehensive prediction models and must adapt to quickly changing network conditions. Predictive resource allocation is a forward-looking strategy for network management, enabling anticipatory adjustments to network resources based on expected future demands. As industries become more data-driven, maintaining consistent QoS and ensuring uninterrupted network operations have become essential. This strategy is especially useful in telecommunications and streaming services, where network traffic patterns are relatively predictable and can be modeled. The idea behind predictive resource allocation is to create models that accurately capture recurring patterns in network traffic. This could include hourly, daily, or weekly patterns based on user behavior or yearly patterns based on business cycles. Advanced machine learning and statistical models can create these predictive models, offering the ability to forecast network load with high precision. However, the effectiveness of predictive resource allocation depends on the accuracy of the predictive models used. These models are built based on historical data, and their accuracy decreases when faced with new scenarios or significant changes in network behavior. This can lead to under or over-allocation of resources, affecting overall network performance and efficiency. Moreover, predictive resource allocation needs to adapt quickly to changing network conditions. This adaptability depends on the network's architecture and the management system's ability to reconfigure resources based on predicted changes. This can be challenging in environments where network conditions change rapidly or unexpectedly. In such cases, the allocated resources may not match the actual demand.

Secondly, dynamic resource allocation methods based on network conditions aim to handle fluctuating network demand and varying network states. IoT and 6G networks are large and diverse, requiring flexible and adaptable resource management strategies. Dynamic allocation methods offer this flexibility, allowing networks to react to changes in real-time. These methods provide adaptability and responsiveness. However, their success depends on accurate network state information and the ability to process it quickly and efficiently. Dynamic resource allocation serves as a real-time solution to manage fluctuating network demands. Unlike predictive resource allocation, dynamic resource allocation is reactive, adapting to the network conditions as they evolve. This approach is critical in environments such as e-commerce platforms and cloud services, where network load can swing dramatically in minutes due to flash sales or sudden influxes of user traffic. The core concept of dynamic resource allocation is to continuously monitor the network conditions and adjust resources accordingly. Techniques such as load balancing, traffic shaping, and quality of service management play a pivotal role in this approach. Advanced ML algorithms can also analyze real-time network data and decide resource allocation. Despite these advantages, dynamic resource allocation presents its own set of challenges. First and foremost, it requires real-time or near-real-time monitoring of network conditions. The complexity and cost of implementing such a monitoring system can be prohibitive in certain contexts. Additionally, rapid decision-making capabilities are essential for real-time resource allocation, requiring advanced algorithms and high-performance computing resources. Furthermore, dynamic resource allocation strategies must also contend with the possibility of frequent changes in resource allocation, potentially leading to network instability or inconsistent performance. Therefore, designing an effective dynamic resource allocation strategy involves balancing the responsiveness to network changes with the need to maintain a stable and consistent network performance.

Network-aware resource management approaches consider the broader context of network operation, including network topology, node capabilities, and current network state. These methods prioritize resources based on network conditions and application requirements, leading to optimized network performance and improved user experience. Network-aware approaches promote robust and reliable network operation, but they require sophisticated algorithms and tools for successful implementation. In an increasingly connected world, the diversity of network conditions and application requirements has grown exponentially. Network-aware resource management approaches have been developed to handle this complexity. These strategies take into account the characteristics of the network infrastructure, the nature of the network traffic, and the requirements of the applications running on the network. Network-aware resource management approaches use techniques such as differentiated services, where network resources are allocated based on the priority of different types of traffic. They also consider the physical network topology, adapting resource allocation based on the location of nodes and the physical characteristics of network links. Despite their benefits, network-aware resource management approaches also present challenges. They require detailed knowledge of the network and sophisticated algorithms to make optimal resource allocation decisions. Additionally, they must deal with the inherent complexity and diversity of modern networks, which can lead to increased computational costs and complexity in implementation. Moreover, network-aware resource management approaches may be unnecessary in networks with relatively static or simple conditions. In such cases, the additional complexity and cost may not provide significant benefits over simpler resource allocation strategies.

Energy-efficient resource allocation addresses the critical issue of energy consumption in IoT and 6G networks. As the number of network nodes and data processing demands increases, energy efficiency becomes crucial in network management. Optimization of resource allocation can reduce the energy use of networks, extend device battery life, and ensure sustainable network operation. However, achieving energy efficiency presents several challenges. Energy consumption must be balanced with network performance, and energy-efficient algorithms must be implemented in dynamic and complex network environments. The goal is to reduce energy consumption while maintaining acceptable network performance, particularly in large-scale networks with numerous nodes and high data processing demands, such as IoT networks. Energy-efficient resource allocation strategies include mechanisms to switch off idle components, use low-power modes, and optimize data transmission to save energy. These strategies also consider the energy cost of data processing and transmission and aim to distribute the load in a way that minimizes total energy use. However, implementing these strategies is challenging due to the trade-off between energy efficiency and network performance, with higher energy consumption linked to higher data rates or lower latency. Therefore, it is necessary to balance energy savings with maintaining necessary network performance. Another challenge is the complexity of implementing energy-efficient algorithms in dynamic and complex network environments. These algorithms must handle numerous factors, including varying network conditions, different types of network traffic, and the specific energy characteristics of different network components.

In Figure 13, the specific values for the effectiveness scores of different network resource management strategies were derived from a comprehensive analysis of existing literature, empirical data, and expert evaluations. We evaluated each strategy across ten key metrics: adaptability, network performance, energy efficiency, implementation complexity, cost efficiency, scalability, accuracy of predictions, responsiveness, sustainability, and reliability. Scores for each metric were assigned based on a thorough review of recent journal articles, conference papers, technical reports, and case studies. This multi-source approach ensured a balanced and objective assessment, with each metric scored on a scale from 1 to 5, where 5 indicates the highest effectiveness. The aggregation of data from various studies and practical implementations provided a robust foundation for our comparative analysis. The criteria for evaluation were chosen to reflect the critical aspects of network resource management in IoT and 6G networks. For example, adaptability was assessed based on a strategy's flexibility and responsiveness to real-time network changes, while energy efficiency considered the trade-offs between energy consumption and network performance. Implementation complexity evaluated the technical challenges and computational requirements, and cost efficiency examined the economic viability of each strategy. Other metrics, such as scalability and accuracy of predictions, were measured through scalability tests and predictive model validations.

VI. FUTURE RESEARCH OVERVIEW

In the future development of 6G networks, managing the power requirements of billions of IoT devices will be crucial for long-term sustainability. Research in energy-efficient management could focus on designing power-efficient IoT devices, improving network protocols to reduce energy use, and creating smart algorithms to manage device operations. Battery technology will also be a key area, seeking to enhance capacity and efficiency. Given the dense deployment of IoT devices, smart spectrum allocation and management will be essential. The massive growth of IoT devices connected via 6G networks requires intelligent methods for using spectrum. Future studies may look into cognitive radio technologies or AI-driven dynamic spectrum access techniques to share spectrum and reduce interference effectively. As 6G is expected to rely heavily on edge computing to minimize latency, exploring strategies for managing resources like data storage, computational power, and network bandwidth at the edge will be important. Research could focus on balancing the load between central servers and edge devices and on effective data caching and computational offloading. Next, Network Slicing in 6G will cater to the unique needs of different applications, such as IoT, VR, or autonomous driving. Research into dynamically allocating and managing resources across network slices will be significant. Future studies could also explore policy and pricing models for network slicing. QoS management will be challenging due to the diverse nature of IoT devices and applications in 6G. Research could develop AI-based algorithms that adjust network parameters based on traffic type and network conditions. Traffic prediction models to allocate resources and maintain QoS preemptively could also be explored. 6G will enhance inter connectivity and data sharing, making robust security and privacy management necessary. Future research can focus on creating lightweight encryption techniques for IoT devices, developing advanced intrusion detection systems, and designing privacy-preserving mechanisms for data sharing in a 6G environment. Examining how 6G networks will be applied in various fields, such as healthcare, transportation, and manufacturing, is crucial. Each area will have unique requirements and challenges for resource allocation, providing fertile ground for research. The scale and complexity of 6G and IoT will introduce multiple points of failure, so developing risk-sensitive approaches to ensure robustness and resilience will be necessary. Reducing hardware costs will be important as 6G and IoT devices proliferate. Future research in hardware technology should focus on developing cost-effective, low-power, high-performance hardware. This includes designing compact, low-power chipsets and antennas for many IoT devices and exploring new materials and manufacturing techniques.

Table 7 provides a comprehensive overview of the challenges in 6G network development, such as technical complexity and spectrum management, along with potential solutions like fostering interdisciplinary collaboration and dynamic spectrum sharing.

A. ENERGY EFFICIENCY MANAGEMENT

Developing and deploying 6G wireless communication technology is expected to revolutionize data transmission and processing. This evolution, along with the growing IoT, offers many opportunities for global connectivity and resource management. However, it also presents a critical challenge: energy efficiency (EE) management.

1) CHALLENGE

Integrating IoT into 6G networks involves managing the massive increase in connected devices, data traffic, and network complexity. According to Cisco's Annual Internet Report, IoT devices are expected to reach 50 billion by 2030 [210]. The high-frequency mmWave bands used in 6G networks require much more power than previous generations, especially for densely deployed BS. If energy consumption in 6G networks, IoT devices, and BS is not effectively managed, it could lead to high operational costs and increased carbon emissions, which contradict sustainable development goals. This could also result in greater reliance on the power grid, raising the risk of grid instability and power shortages. The conventional network architecture needs scalability and adaptability to handle the growing energy demands of 6G and IoT integration. The current infrastructure must be adaptive to the dynamic needs of 6G, requiring energy efficiency across all layers, including the physical, network, and application layers. Additionally, the variability in IoT devices, from small sensors to complex industrial machinery, implies an uneven distribution of computational and communication capabilities. This disparity makes the energy management process complicated, as a one-size-fits-all solution would not be effective. Increased energy consumption means greater reliance on power grids and more carbon emissions, negating efforts towards building a sustainable future.

2) SOLUTION

Addressing the energy efficiency management issue in a 6G network powered by IoT requires a comprehensive approach. First, deploying energy-efficient hardware and technologies such as energy harvesting (EH) and advanced modulation schemes can significantly reduce energy consumption in 6G and IoT networks. EH uses renewable energy sources like solar, wind, and kinetic energy to power IoT devices, reducing grid reliance. Second, a shift in network architecture is needed. A decentralized, edge-based architecture, rather than a traditional centralized one, can manage energy more efficiently. Edge computing brings computation and data storage closer to where it is needed, reducing latency and network congestion, thus saving energy. AI and ML algorithms should be widely used to optimize energy consumption. These algorithms can learn from historical data to predict and adapt to network behavior, dynamically adjusting energy use. This leads to more efficient load balancing, spectrum usage, and power control, greatly improving energy management. Network slicing, a key feature of 6G, can also be used for energy efficiency. By allocating network resources based on the specific requirements of different IoT applications, energy waste can be minimized. For example, a low-latency slice for autonomous vehicles might have higher energy needs compared to a massive IoT slice for sensors. Finally, strict energy efficiency standards and regulations should be implemented to ensure that the development and deployment of 6G networks and IoT are environmentally friendly. This promotes the research and development of energy-efficient solutions and holds critical stakeholders accountable. In conclusion, while integrating IoT in 6G networks poses a significant energy efficiency management challenge, innovative technologies and strategic approaches can help overcome these hurdles. By investing in sustainable solutions and leveraging advanced technologies, we can enjoy the benefits of 6G and IoT without harming our environment.

B. SPECTRUM ALLOCATION AND MANAGEMENT

Managing and allocating the radio frequency spectrum is crucial in telecommunication systems, especially with new technologies like 6G and IoT.

FIGURE 13. **Effectiveness of resource management strategies in IoT and 6G networks by various performance metrics.**

1) CHALLENGE

Allocating and managing the spectrum in 6G networks and IoT presents significant challenges. The expected increase in connected devices will put immense pressure on the crowded spectrum. Each device needs to transmit and receive data, making congestion and interference a complex issue. Different device types have unique communication needs, adding to the complexity. Higher-frequency bands, like mmWave and THz, offer larger bandwidths but have limited range and are more affected by obstacles and environmental factors. This requires a denser deployment of BS, increasing costs and logistical challenges. Dynamic spectrum allocation, where resources are flexibly assigned based on real-time demand, is being explored. This needs sophisticated algorithms and significant computational resources to adapt to rapid changes in network conditions. Coordinating dynamic allocation to prevent interference is difficult, likely needing advancements in ML and AI. Regulatory challenges also exist. National and international bodies must harmonize spectrum use, balancing industry, service provider, and national security needs. Standards and regulations for new technologies like dynamic spectrum access, SDN, and network slicing are necessary for fair and efficient spectrum use. Thus, while 6G and IoT are promising, they bring substantial spectrum allocation and management challenges.

2) SOLUTION

Addressing these challenges in 6G networks for IoT requires advanced technologies and regulatory policies. A key strategy is dynamic spectrum access and cognitive radio systems, allowing flexible spectrum use based on real-time demand. Cognitive radio identifies and shifts to unoccupied communication channels, avoiding those in use. AI and ML can significantly improve network efficiency by developing predictive algorithms for network conditions and user demands, refining predictions over time. Network slicing divides a single physical network into several virtual networks, each meeting specific application needs. Massive MIMO and beamforming technologies enhance spectrum efficiency by focusing signals in specific directions, reducing interference and increasing capacity. Reconfigurable Intelligent Surfaces (RISs) can overcome propagation issues with higher frequency bands by shaping and steering wireless signals, improving signal strength and coverage. Robust regulatory measures are essential. International harmonization and regulation establish fair and transparent spectrum allocation rules and set standards for new technologies. Regulatory bodies should collaborate to ensure safe and efficient international spectrum use. Implementing these solutions, while challenging, could enable the full potential of 6G and IoT.

C. RISK-SENSITIVE APPROACHES IN 6G NETWORKS

As we approach the age of 6G technology, an array of complex challenges arises, emphasizing the necessity for a risk-sensitive approach in its implementation. This next-generation network will bring transformative changes, integrating AI, ML, advanced cloud computing, and the Internet of Senses, intensifying the cybersecurity landscape.

Amplifying potential vulnerabilities requires urgent attention to data privacy, AI security, spectrum management, and overall system resilience. The balance between unprecedented technological advancement and secure, efficient operation becomes a critical aspect, propelling us to develop comprehensive risk assessment and management strategies for the 6G era.

1) CHALLENGES

As we advance toward the 6G network, the industry faces multifaceted challenges that must be urgently addressed. A crucial aspect that is becoming increasingly evident is the need for risk-sensitive approaches. With the advent of 6G, networks will become much more pervasive, encompassing an unimaginable number of devices and creating massive amounts of data. The complex and dense network infrastructure also introduces a wide array of vulnerabilities. As 6G networks will rely heavily on AI and ML algorithms, the threats related to AI security need to be acknowledged. Furthermore, the sensitivity and diversity of data create substantial privacy and integrity risks, as data breaches or leakage could lead to enormous losses. Additionally, the incorporation of novel technologies such as advanced cloud computing, holographic interfaces, and the Internet of Senses will also contribute to the risk landscape. There's also the issue of spectrum sharing and allocation, where the risk of interference and poor network performance could exist if not managed properly. Lastly, the robustness and resilience of 6G systems in the face of natural disasters or system failures pose another substantial challenge. All these risks need to be assessed, managed, and mitigated in order to ensure the secure, seamless operation of 6G networks.

2) SOLUTION

Addressing the risks and challenges of 6G networks requires a proactive, multi-layered approach. First, a comprehensive risk assessment framework needs to be designed to assess and quantify risks from different sources. This framework should incorporate advanced AI and ML algorithms that can analyze, predict, and even prevent potential threats. Simultaneously, the industry needs to invest in developing robust, AI-based security systems that can detect and neutralize threats in real-time. Secondly, privacy-enhancing technologies like homomorphic encryption, differential privacy, and FL should be integrated to ensure the privacy and integrity of data. Regarding spectrum allocation, cognitive radio technologies, and AI-based dynamic spectrum management systems could be employed to mitigate the risk of interference and optimize network performance. Furthermore, robust disaster recovery plans and redundant systems should be implemented to ensure the resilience of 6G networks. Lastly, there should be a continuous effort to establish industry standards and regulatory guidelines for 6G networks, which can guide the industry in developing safe, secure, and efficient network systems. In essence, the journey toward 6G will require a balance between technological advancements and risk management strategies, with a consistent emphasis on privacy, security, and resilience.

D. HARDWARE TECHNOLOGY WITH LOW COST IN 6G NETWORKS AND IOT

With 6G and IoT, cost-effective, high-performance hardware is essential. Energy-efficient microchips offer better computing power and lower energy use, reducing operational costs, especially for IoT and edge computing. Massive MIMO technology in antenna systems increases network capacity and efficiency while reducing costs. Using new materials like graphene and advanced semiconductor technologies can create low-cost, high-performance hardware. Additionally, open-source hardware designs can significantly lower costs and encourage innovation. A comprehensive approach considering network architecture, deployment, and maintenance costs is necessary to achieve widespread connectivity and advanced services while keeping expenses low.

1) CHALLENGES

As we move towards a 6G network ecosystem, many challenges arise, particularly regarding cost-effective hardware for 6G networks and IoT. The main issue is the need for much higher processing power and lower latency to handle the large volume of data in the 6G IoT era. This requires advanced technology like AI and ML algorithms at the network edge, increasing the complexity and cost of devices. The demand for massive connectivity and high-frequency bands in 6G networks leads to more power consumption, causing battery life issues for IoT devices. Achieving high-speed, low-latency communication while maintaining power efficiency is a serious challenge. Moreover, security, privacy, and ethical concerns grow with the expanded attack surface, requiring sophisticated, expensive hardware solutions to protect data integrity and privacy. Lastly, standardizing various devices and network components is critical to reduce costs and promote interoperability in a diverse IoT ecosystem.

2) SOLUTIONS

To overcome these challenges, a multi-faceted approach is needed. New advances in nanotechnology and semiconductors can help create more power-efficient devices with better processing capabilities at lower costs. Deploying AI and ML for automated, intelligent network management can minimize power consumption and enhance the performance of 6G networks and IoT devices. Research and development of advanced battery technologies can significantly improve device power efficiency, and energy harvesting techniques can replenish energy for low-power IoT devices. For security, cost-effective, secure hardware solutions embedded with advanced encryption and blockchain technologies are necessary to ensure data integrity and privacy. Open-source hardware and software platforms can foster innovation and reduce costs for 6G IoT devices. Finally, international bodies like IEEE and ITU need to work on global standards for 6G and IoT to ensure interoperability and cost-effectiveness.

TABLE 7. Summary of challenges and solutions in 6G network development.

Subject	Challenges	Solutions	Implications
Energy Efficiency Management	- Massive increase in IoT devices and data traffic - High power requirement of mmWave bands - Sustainability concerns	- Deploy energy-efficient hardware - Shift to decentralized network architectures - Use AI and ML for energy optimization	- Reduces operational costs - Minimizes carbon emissions - Ensures sustainable development
Spectrum Allocation and Management	- Massive device connectivity causing spectrum congestion - High-frequency band limitations - Regulatory challenges	- Implement dynamic Spectrum Access and Cognitive Radio Systems - Use AI and ML for network management - International regulation and harmonization	- Optimizes spectrum usage - Minimizes interference - Promotes fair spectrum distribution
Risk-sensitive Approaches	- Increased vulnerabilities from AI, ML, and complex network infrastructures - Privacy and security concerns	- Develop comprehensive risk assessment frameworks - Integrate advanced AI-based security systems - Implement privacy-enhancing technologies	- Enhances network security - Protects user data - Prevents potential breaches
Hardware Technology with Low Cost	- High processing power and low latency requirements - Power consumption and battery life issues - Security and privacy concerns	- Innovate in nanotechnology and semiconductors - Develop advanced battery technologies - Create global standards for interoperability	- Lowers device costs - Improves device performance - Ensures widespread adoption
Scalability and Availability	- Rapid growth in IoT devices and services - High service demands from advanced applications - Sustainability and energy concerns	- Use network slicing for resource allocation - Apply decentralized networking models - Advance network infrastructure and green technologies	- Supports extensive network growth - Ensures reliable service - Promotes energy efficiency

The transition to 6G and a fully interconnected IoT world is challenging but achievable with technological innovation, international collaboration, and forward-thinking policy.

E. SCALABILITY AND AVAILABILITY IN 6G NETWORKS AND IOT

Scalability and availability in 6G networks, especially in IoT, are critical for resource management. As 6G is set to support many interconnected IoT devices with diverse requirements, networks must scale effectively to manage these increased demands without compromising performance or availability. Scalability involves the network's ability to accommodate a growing amount of work or its potential to be enlarged to accommodate growth. In the context of 6G and IoT, scalability must consider the increasing number of devices, the various types of data they produce, and the heterogeneous nature of their services. On the other hand, availability concerns the system's ability to operate and perform its required function at any given time. High availability is paramount with the increased reliance on IoT devices in critical applications, such as healthcare, smart cities, and autonomous vehicles. This ensures the network can provide reliable, uninterrupted service despite potential issues such as hardware failures, software bugs, or cyber-attacks.

1) CHALLENGES

The impending rollout of 6G networks and an extensive IoT framework presents vast challenges, especially when considering scalability and availability. As we embrace a fully digitalized and interconnected future, networks need to sustain an unprecedented level of scalability to accommodate the rapidly growing number of IoT devices and services. Each device would need constant, high-speed connectivity, causing network load to skyrocket, potentially overwhelming current infrastructures. In addition, 6G is expected to offer services like AI, holographic communications, and advanced reality applications requiring URLLC. Providing such services at scale is a significant hurdle. Availability is another concern; to benefit from 6G and IoT, consistent network accessibility, irrespective of location or time, is crucial. However, ensuring ubiquitous coverage, especially in remote, rural, and underdeveloped areas, is a logistical and infrastructural challenge. Although high-frequency bands provide greater capacity and speed, they have limited range and penetration capabilities, further exacerbating the issue. Finally, scalability and availability demands place immense pressure on energy consumption, raising sustainability issues that need to be addressed.

2) SOLUTION

Several solutions can be explored to navigate these challenges. Network slicing, a key feature expected in 6G, can ensure that diverse service requirements are met by allocating appropriate network resources dynamically, enabling scalability. Advancements in AI and ML can help optimize network resources and manage dynamic loads effectively, thus enhancing scalability and availability. Decentralized networking models, such as edge computing and fog computing, can bring processing capabilities closer to the end devices, reducing latency, enhancing scalability, and extending services to areas with limited connectivity. Also, advances in network infrastructure, like Integrated Access and Backhaul (IAB) and relay nodes, can increase network reach and improve service availability. The development of low-cost, high-performance small cells can also provide a cost-effective solution for enhancing both coverage and capacity. Green networking technologies and energy harvesting techniques should be employed to make networks more energy-efficient, addressing sustainability concerns. Lastly, collaborations between governments, network operators, and tech companies can help in building the necessary infrastructure and regulatory frameworks to ensure the scalability and availability of 6G networks and IoT on a global scale. These strategies, while challenging to implement, are fundamental steps towards the successful rollout of 6G networks and a robust IoT framework.

VII. CONCLUSION

This comprehensive review underscores the significance and complexity of network resource management in the intricate landscape of IoT and 6G networks. The paper delineated four crucial categories: Predictive resource allocation, dynamic resource allocation, Energy-efficient resource allocation, and network-aware resource management. Each of these categories, while presenting unique solutions, has its own set of challenges and prerequisites for effective implementation.

The Predictive approach, with its forward-looking strategy, emphasizes the importance of accurate forecasting models and adaptability. On the other hand, dynamic resource allocation provides real-time solutions to unpredictable network loads, although it demands rigorous real-time monitoring and quick decision-making capabilities.

The increasing focus on environmental sustainability accentuates the value of energy-efficient resource allocation. It strives for a balance between energy conservation and optimal network performance, highlighting the delicate tradeoffs involved in achieving both goals.

Lastly, network-aware resource management, while being the most holistic, requires a deep understanding of the network's nuances, demanding sophisticated algorithms to account for the vast diversity in modern network conditions.

In sum, the quest for efficient network resource management in the evolving world of IoT and 6G networks necessitates a blend of strategies. Each offers its strengths but also brings challenges that warrant further exploration and innovation. As the digital landscape becomes increasingly intertwined and complex, ensuring effective resource management remains paramount for seamless connectivity and optimal user experience. Future research endeavors in this domain will propel advancements, harmonizing the balance between performance, efficiency, and sustainability.

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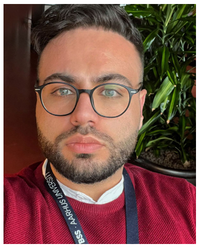

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