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SURVEY

Deep Learning for Resource Management in Internet of Things Networks: A Bibliometric Analysis and Comprehensive Review

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ABSTRACT In this study, we conducted a bibliometric analysis and comprehensive review of the studies published between the period of 2012 and 2022 on resource management in internet of things (IoT) networks using the Scopus database to determine the current state of research and gain insight into the research challenges and opportunities in the field. The bibliometric analysis technique was employed to bibliometrically analyze the published studies that were collected from the Scopus database and this helped to discover the majority of research subjects in the field of resource management in IoT networks. Following this, we conducted a comprehensive review of the relevant studies to provide an insight into the recent progress and the research gaps in the field. According to the results of our bibliometric analysis and the comprehensive review, we discovered that resource management problems in IoT networks is still a growing challenge as a result of the limited available resources for operating IoT networks. Resource management problem is a critical research area due to the advantages of IoT in terms of collecting vital data that could be used in analyzing and predicting human behavior as well as environmental conditions. Also, the results of our bibliometric analysis and comprehensive review further revealed that research on the use of conventional artificial intelligence techniques, such as optimization approaches and game theory approaches, for resource management are common, while research on the use of the modern artificial intelligence technique, like deep learning approaches, is less common. Therefore, this study aims to fill the research gap in the area of resource management in IoT networks by introducing the use of deep learning approaches. Deep learning is a powerful artificial intelligence method that is advantageous for obtaining low-complexity resource allocation solutions in a near real-time. Also, various open research issues that are associated with the use of deep learning approaches are highlighted as future research directions to enable the development of novel deep learning models for IoT networks.

INDEX TERMS Internet of Things, resource management, resource allocation, artificial intelligence, game theory, optimization theory, machine learning, deep learning, bibliometric analysis.

I. INTRODUCTION

Internet of Things (IoT) networks are useful for collecting vital data that could be used to analyze and predict human behavior, agricultural phenomena (e.g., plant disease detection, plant recognition, crop yield estimation), and environmental conditions (e.g., weather). Consequently, they have been widely deployed in various daily activities to achieve a smart world in several critical applications such as smart environment, smart health, smart agriculture, smart city, and smart industries [1], [2]. These applications are bandwidth intensive, power consumers, and sensitive to data transmission delay because of the big data they generate and the need for real-time data transmission requirement.

The IoT networks use devices (e.g., smart phones, drones, smart sensors, and smart cars) that are characterized by high

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throughput, low data transmission delay, and long battery lifetime to satisfy different critical application requirements. Unfortunately, the IoT networks are resource-constrained technologies with limited battery power resources, limited computational resources (e.g., power, time, and memory), and limited storage resources at the device level. Also, at the radio / network level, they have limited bandwidth, channel, spectrum, and transmit power resources [1], [3]. The limited device resources are typically costly to acquire, for example the cost of acquiring new in-built batteries for a large number of devices after deployment is significantly high while battery replacement is impractical and inefficient in some use-cases (e.g., implanted biomedical devices). Similarly, their radio resources are also costly to acquire, for example the cost of procuring new radio resources (e.g., spectrum) is significantly high [1]. Consequently, because of these limitations, the prolong battery lifetime, low data transmission delay, and high throughput requirements of the various critical IoT applications may not be easy to achieve. Therefore, the scarce resources of IoT networks need to be strictly managed to satisfy the stringent requirements of the IoT applications to increase throughput, reduce data transmission delay, and increase their battery lifetime.

For the reasons highlighted above and towards a successful implementation of the IoT technologies in different critical applications, researchers in this field have considered the use of different artificial intelligence techniques such as optimization approaches and game theory approaches in many IoT applications to develop resource management schemes to manage power, bandwidth, and computational resources in order to optimize the power requirements of devices, increase throughput, and reduce data transmission delay. However, the resource management solutions that are based on optimization and game theory approaches typically have high computations. Other researchers have combined computing technologies (e.g., cloud computing and fog computing) with IoT to improve on the limited power and bandwidth resources concerns by offloading the computation task of the IoT devices to the cloud systems or fog systems. But then, this has resulted to an increased computational complexity and cost because of the problem of how to optimally allocate the computational resources of the cloud and fog computing to the IoT devices [4]. Also, both cloud and fog computing are still developing technologies with several resource allocation issues [4].

Due to the scarce resources necessary to drive the IoT networks in different time-critical applications [4], there is a need to improve the performance of the IoT networks. In addition, there is a need to improve on the shortcomings of most of the solutions obtained to the resource management problem formulations for IoT networks, which calls for more intensified research efforts. Therefore, this paper presents the major resource management challenges of IoT networks, review different artificial intelligence methods like optimization theory approaches, deep learning approaches, game theory approaches, as well as their benefits and disadvantages, to assist researchers who are interested in this research area. Also, this paper motivates the use of deep learning approaches for solving major resource allocation problems in the IoT networks to improve on the computational complexity problems of the optimization theory and game theory approaches. Deep learning is a powerful modern artificial intelligence method that is advantageous for obtaining low-complexity resource allocation solutions compared to other artificial intelligence methods such as optimization, machine learning (ML), and game theory. Moreover, this paper is closed with the presentation of some research challenges and future research directions to develop new sophisticated resource management algorithms for IoT networks using deep learning. Following these efforts, the major contributions of this paper are presented as follows:

1) We provide a bibliometric analysis of the studies published on resource management in IoT networks between the period of 2012 and 2022.
2) We provide a comprehensive review of optimization, deep learning, and game theory approaches in wireless IoT networks, along with their benefits and disadvantages. We also provide a comprehensive review and analysis of the resource allocation solutions that are based on game theory, optimization, and deep learning approaches for IoT networks.
3) The performance comparison of resource allocation solutions using deep learning theory, game theory, and optimization theory approaches in IoT networks was presented.
4) The provision of future research directions for developing novel resource allocation approaches for IoT networks based on the promises inherent in deep learning.

The details about the structuring of this work are provided as follows. Section II presents the research design and methodology of this study. Section III presents a discussion on the benefits of IoT networks and resource management challenges associated with IoT networks. Section IV presents a review of key optimization approaches that could be used to seek solutions to resource management challenges in IoT networks. Section V presents a review on the basics and use of deep learning to improve the resource management challenges in IoT networks. Section VI presents a review on the examples of the game theory approaches used for solving resource management challenges in IoT networks. In Section VII, the comparison of game theory, deep learning, and optimization theory approaches is presented. Section VIII presents the major challenges associated with the use of deep learning approaches for solving resource management problems in IoT networks and the key future research directions. Section IX concludes this study.

II. RESEARCH DESIGN AND METHODOLOGY

The review technique employed in this study entails three phases. They are (1) the data collection phase, (2) the bibliometric analysis phase, and (3) the comprehensive review and analysis phase.

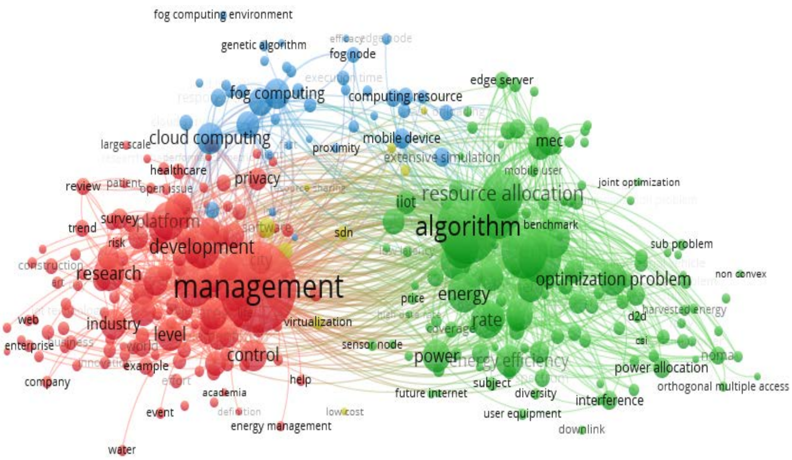

FIGURE 1. Cluster analysis of the studies published on resource management in IoT networks.

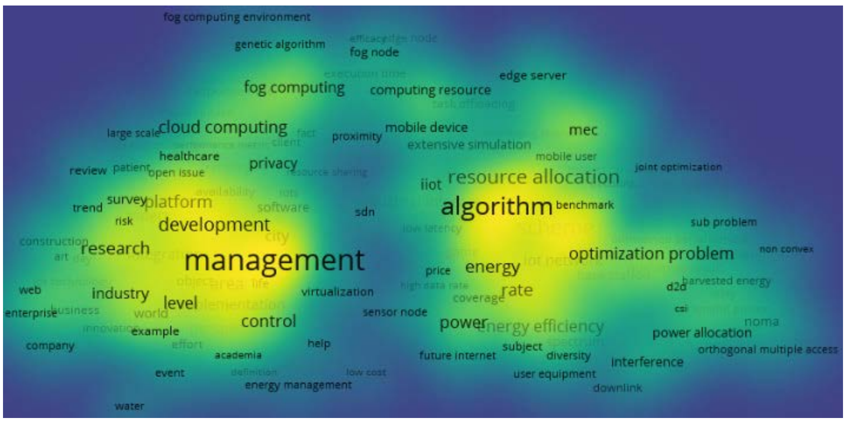

FIGURE 2. Density analysis of the studies published on resource management in IoT networks.

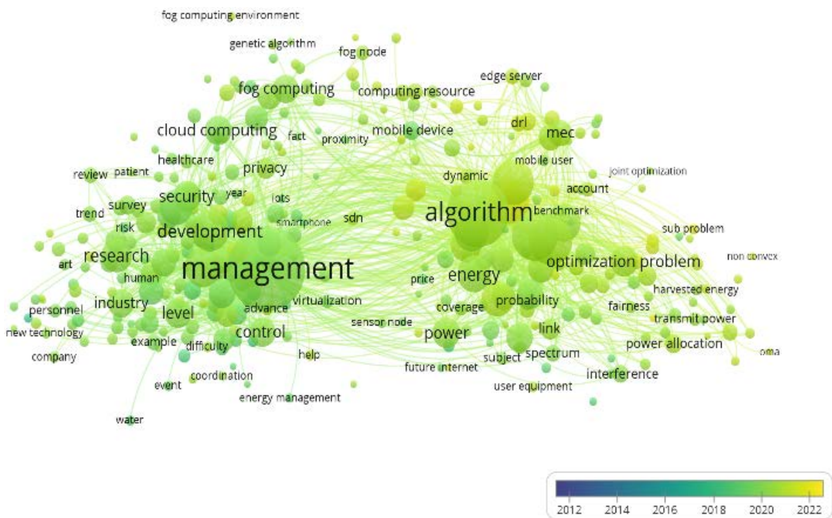

FIGURE 3. Timeline analysis of the studies published on resource management in IoT networks.

A. DATA COLLECTION OF RELEVANT STUDIES

This phase involves the collection of studies that are relevant to resource management in IoT networks. To achieve this, the guideline proposed in [5] was followed. Consequently, the published studies related to resource management in IoT networks were collected from the standard Scopus database.

The Scopus database was used in this study because it contains the journal articles published in important scientific databases such as IEEE Xplore and ScienceDirect [5]. In the Scopus search engine, we input the search string such as ''resource management'' AND ''Internet of Things'' to retrieve the studies published between 2012 and 2022. Also, various inclusion and exclusion criteria, such as Literature Type (Articles and Review) and Language (English), were applied to reduce unrelated studies. The essence of this phase was to thoroughly screen and select the important relevant articles for a comprehensive review. Based on this effort, 14 articles relevant for the scope of this study were selected. These articles are comprehensively reviewed and analyzed during the third phase.

B. BIBLIOMETRIC ANALYSIS OF RELATED RESEARCH

This phase was used to bibliometrically analyze the collected raw data of published studies from the Scopus database using the keywords cluster, density, and timeline analysis as conducted in [6]. For this to be achieved, the VOSviewer [7] software was employed to analyze the knowledge domain of the collected articles using the search terms (keywords, titles, and abstracts), type of analysis (co-occurrence), and counting method (full counting). The results of the bibliometric analyses allow researchers to understand the relationships among the frequency of the co-occurring keywords in the collected articles, and also to understand the core future research directions of the topics in a field.

The keywords cluster analysis of the collected published studies on resource management in IoT networks is presented in Figure 1. The figure reveals how a collection of keywords is grouped into various clusters that include nodes, links, and colors. The size of the nodes indicates the frequency of co-occurrence, the links indicate the co-reference, and the different colors identify individual clusters.

In Figure 1, there are three major clusters, which are presented as green, red, and blue. The clusters indicate how strong is the connection between the keywords in the published studies. The red cluster denotes ''management'' and has been a major research focus in the area of resource management and IoT networks. This cluster revealed a strong connection with ''research'', ''development'', ''control'', ''industry'', ''review'', ''survey'', ''healthcare'', ''water'', and ''energy management''. This implies that ''management'' subject has been an important focus of the studies published on resource management and IoT networks between 2012 and 2022. The green cluster represents ''algorithm''. This cluster is strongly linked with different subjects such as ''resource allocation'', ''optimization problem'', ''iiot'', ''energy'', ''price'', ''rate'', ''power'', ''energy efficiency'', ''power allocation'', ''sensor node'', ''non convex'', and ''joint optimization''. The ''algorithm'' cluster revealed that research on seeking solutions to resource allocation issues in IoT using optimization approaches and game theory approaches are common. However, research on the use of deep learning approaches is less common. This research gap provides a scope for more research efforts on the use of deep learning approaches to improve resource management in IoT networks. The blue cluster denotes ''cloud computing''. The blue cluster is strongly linked with ''fog computing'', ''computing resource'', ''fog node'', ''mobile device'', ''genetic algorithm'', and ''fog computing environment''. The cluster revealed that research interests in the use of computing technologies for resource management in IoT are less popular due to the complexity of allocating the computing resources of such technologies to the IoT devices. The blue cluster further revealed the use of optimization approaches, like genetic algorithm, to compute the allocation of the computing resources of fog computing. It is also important to point out that the clusters are strongly linked with ''management''. This is an indication that ''management'' is a popular and leading research in the published studies over the last decade. Additionally, this reveals that ''management'' is a major research area in IoT towards addressing the resource management challenges associated with IoT.

The keywords density analysis of the collected published studies on resource management in IoT networks is presented in Figure 2. The figure reveals the number of times that the keywords in the search string manifested in the published studies over the period of 2012 and 2022. The results of the keywords density analysis also confirm the outcomes of the cluster analysis.

The timeline analysis of the published studies between the period of 2012 and 2022 on resource management in IoT networks is shown in Figure 3. The figure shows the visualization of the mapping of keywords unto the color-coded timespan of the studies that were conducted between the period of 2012 and 2022.

Figure 3 further reveals the changes in the direction of research focus between the period of 2012 and 2022. This indicates that within the timeline, more studies focus on the use of optimization approaches for resource management in IoT networks while some studies also focus on the use of game theory approaches for resource management in IoT networks.

Therefore, according to the results of our bibliometric analysis of the studies published between the period of 2012 and 2022, resource management in IoT networks is still a growing challenge as a result of the limited available resources for operating IoT networks. Consequently, the resource management problem is a critical research area due to the advantages of IoT in the context of collecting vital data that are useful for analyzing and predicting human behavior as well as environmental conditions related to air quality, water quality, and weather. Also, the results of our bibliometric analysis revealed that research on the use of artificial techniques, such as optimization approaches and game theory approaches, for resource management are common while research on the use of artificial intelligence, like deep learning approaches, is less common. Based on the results of the bibliometric analysis, we were able to

TABLE 1. Comparison with the existing related studies.

Reference	Contribution of the existing related research	Contribution of this study
[1]	Shaarma and Wang presented a comprehensive review on machine type communications in cellular IoT networks. The work reviewed the challenges of quality of service provisioning, congestion, and transmission scheduling that are associated with the cellular IoT networks. Also, the work briefly discussed some conventional ML approaches that can be employed to address some of these challenges. However, details on how data can be collected and prepared for solving quality of service provisioning, congestion, and transmission scheduling problems in cellular IoT networks is not provided. Also, there is no clear information on how ML algorithms can be trained to address the challenges identified in the work.	Unlike [1], this study presents a review on the major resource management challenges in IoT networks and the use of deep reinforcement learning, optimization, and game theory approaches for seeking solutions to the challenges. This study discussed how data for training and testing can be collected. Also, we study presented a review on how ML algorithms can be trained.
[2]	Olatinwo and Joubert presented a comprehensive review on different optimization approaches that can be used employed to address different resource management challenges in IoT networks. The work also discussed different resource allocation solutions that are based on optimization approaches for IoT. However, the work did not consider other artificial intelligence technique like game theory and deep learning.	Contrary to [2], in this study, we present a review on how the supervised deep learning, unsupervised deep learning, deep reinforcement learning, and game theory approaches could be applied in IoT networks to develop computational models for the major resource management problems associated with the IoT networks.
[8]	Li and Xu presented a review of the major resource management problems in the IoT networks. The work considered and reviewed resource management problems related to energy, spectrum, bandwidth, channel access, and computation resources. The work also reviewed some of the solutions in literature regarding the management of the use of the scarce resources. In the work, different types of technologies for improving the services of IoT were also considered. Such technologies including fog computing (which is currently at an infant stage), machine-to-machine communication, device-to-device (D2D) communication.	In contrast to [8], we reviewed how different artificial intelligence approaches, such as supervised deep learning, unsupervised deep learning, deep reinforcement learning, optimization, and game theory, could be employed in IoT networks to develop solutions for the major resource management challenges associated with the IoT networks.
[9]	Chen *et al.* presented a comprehensive review is presented on different types of traditional ML algorithms that are based on the artificial neural networks that can be employed for addressing different challenges in IoT, for example wireless communication problems like transmission time scheduling and channel resource allocation in wireless networks. However, the work did not consider how the identified ML algorithms can be used to solve resource allocation problems in IoT networks.	In contrary to [9], we considered the review of different modern and conventional artificial intelligence approaches other than the ones presented in [9] to seek solutions to the resource management challenges in IoT networks. The approaches are deep reinforcement learning, optimization, and game theory.
[10]	Gai and Qiu presented a study on the use of reinforcement learning for solving resource allocation problem in IoT environment. The work further presented a discussion on how reinforcement learning works and it was employed in the study to compute resources for IoT devices.	In contrast to [10], this study presents a review on different artificial intelligence approaches to tackle the major resource major resource management challenges in IoT networks. Examples of the different approaches considered in this study are supervised deep learning, unsupervised deep learning, optimization, and game theory.
[11]	Chen *et al.* conducted a comprehensive review on the IoT resources at the device level and also at the network / radio level. These resources include computational resources, storage resources, bandwidth resources, spectrum resources, and energy resources. To address these resource management challenges, the authors conducted a review on the use different scheduling methods to manage the IoT device resources. The authors classified the scheduling methods into three classes, namely the quality of service scheduling method, the architecture based scheduling method, and network infrastructure based scheduling method. The authors reported the use of quality of service based methods like the mathematical programming method, probabilistic method, and the virtualization method for IoT resource management. The use of architecture based scheduling methods like centralized architecture, distributed architecture, and service oriented architecture were discussed. Also, the use of network infrastructure based scheduling method was discussed to manage the physical network resources in order improve the use of the scarce power, spectrum, bandwidth, and computational resource. The work also reviewed some of the important simulators that are used for IoT resource scheduling.	Different from [11], we focus on the use of unsupervised deep learning, supervised deep learning, game theory, and optimization approaches to find solutions to the major resource management challenges in IoT networks.
[12]	A review is presented on the use of game theory approaches for seeking solutions to various resource management challenges, such as channel management and power management, in D2D communication in IoT networks. The work discussed some examples of game theory approaches that could be employed for computing resource allocation solutions.	Contrary to [12], we present a review on different artificial intelligence approaches other than the approaches presented in [12] to compute resource allocation solutions for the major resource management problems in IoT networks. These approaches include deep reinforcement learning, optimization, unsupervised deep learning, and supervised deep learning.

TABLE 1. *(Continued.)* **Comparison with the existing related studies.**

[13]	Shamshirband *et al.* conducted a comprehensive survey on how evolutionary optimization and game theory can be used to address the resource allocation problems in computing environments like edge computing, fog computing, cloud computing, and IoT. In the work, different resolution allocation that are based on the evolutionary optimization and game theory approaches for various computing environments were reviewed to understand their benefits and shortcomings.	Different from [13], we reviewed different artificial intelligence approaches on supervised learning, deep reinforcement learning, and unsupervised learning and how these approaches could be applied in IoT networks to address resource management challenges.
[14]	Frikha *et al.* presented a comprehensive review on the use of deep reinforcement learning and the traditional reinforcement ML approach to address some resource management related to energy, spectrum access, resource allocation, and time slot scheduling in the wireless IoT networks. Based on the review, authors discussed the proposed approaches for addressing the resource management challenges identified in the work. Also, the work discussed the limitations of the proposed approaches.	Contrary to [14], we reviewed optimization, unsupervised deep learning, supervised deep learning, and game theory approaches for solving different resource management issues in IoT networks.
[15]	Khan *et al.* conducted a comprehensive on the major challenges on several major IoT applications like the internet of smart grids, the industrial IoT, the internet of medical things, and the internet of vehicles. The challenges identified in the work include resource management like time-slot management, transmit power management, computational resource management, cache storage management, and spectrum management. The identified IoT applications are time-sensitive systems that require real-time data communication. However, their performance is currently limited due to their inherently associated resource management issues. The study discussed some of the proposed solutions to the resource management problems using graph-based, optimization, and ML approaches.	In contrast to [15], we conducted a review on using different approaches, like deep reinforcement learning, unsupervised deep learning, supervised deep learning, and game theory to solve resource management issues in IoT applications.
[16]	Chakraborty and Rodrigues presented a comprehensive review on the use of deep reinforcement learning for solving some resource management problems related to communication and computation in IoT. The work presented four major problems in IoT that are associated with resource management. The problems include IoT scheduling, resource allocation, real-time data collection as well as the connectivity and networking of large scale IoT. In the work, the authors discussed the advancement and the problems of deep reinforcement learning method. The work presented a review on the basics of deep reinforcement learning and how the approach can be used for addressing energy management and resource optimization in different IoT networks.	Different from [16], we reviewed supervised deep learning, unsupervised deep learning, game theory, and optimization approaches for resource management problems in IoT networks.
[17]	Chowdhury and Raut presented a comprehensive review on the resource management challenges of the D2D communication technology in IoT. The major resource management problems considered by the work are power consumption and resource allocation. The authors also discussed the use of D2D communication in healthcare systems. In the work, the authors reviewed some of the methods that have been exploited to provide solutions to the power consumption and resource allocation challenges in the D2D networks. Such methods include the use game theory, particle swarm optimization, and water-filling algorithm. The advantages and the disadvantages of these methods were also considered for addressing resource management challenges.	Unlike [17], we conducted a review on different artificial intelligence approaches, including deep reinforcement learning, unsupervised deep learning, and supervised deep learning, to seek solutions to the resource management problems associated with IoT networks.
[18]	Naren *et al.* conducted a comprehensive review on the computation resource allocation approaches in the IoT based vehicular edge computing to manage the limited computation and power resources. The approaches reviewed include optimization, game theory, reinforcement learning, and software defined network.	Different from [18], we reviewed different artificial intelligence approaches used to develop resource allocation models other than the approaches reviewed in [18]. The approaches include supervised learning, deep reinforcement learning, and unsupervised learning. We also presented a review on how these approaches could be applied in IoT networks to address different resource management challenges.
[19]	Zahoor and Mir presented a review on different resource management issues in IoT and also on different approaches that have been explored and exploited for resource management. The approaches are data aggregation protocols, routing, and resource virtualization.	Contrary to [19], we conducted a review on the use of artificial intelligence approaches, such as deep reinforcement learning, unsupervised deep learning, and supervised deep learning, to improve on the resource management issues in IoT networks.

determine the best relevant studies and present a comprehensive review and analysis of the studies in the following section.

C. COMPREHENSIVE REVIEW OF RELATED RESEARCH

In this phase, we provide in Table 1 a comprehensive review and analysis of the collected relevant papers on resource management challenges and artificial intelligence approaches in the IoT networks. Examples include [1], [2], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19]. Also, in Table 1, we provide a comparative analysis of this study and the existing related studies.

To complement the existing studies, we focus this study on the major resource management challenges in IoT networks. Also, different from the existing surveys that have considered the use of either game theory, deep learning theory, or optimization theory to seek solutions to either the power resource management, channel resource management, bandwidth resource management, spectrum resource management or computational resource management problems in IoT networks, our work covers a comprehensive review of the use of optimization approaches, game theory approaches, and deep learning approaches for seeking solutions to the major resource management challenges in IoT, including bandwidth resource management, power resource management, channel resource management, spectrum resource management, and computational resource management. Also, their advantages, disadvantages, and their proposed resource allocation solutions for IoT networks, are discussed. Table 1 present the comparison of this work and the existing related studies.

III. IoT NETWORKS: BENEFITS AND RESOURCE MANAGEMENT CHALLENGES

In this section, we discuss the benefits of IoT in various applications. We also discuss the inherent resource management issues in the IoT networks. To address different resource management issues in IoT networks, we study different recent approaches for solving resource allocation problems, their advantages and disadvantages. We also compare the approaches and provide different future research directions for the use of deep learning approaches for resource management in IoT.

A. BENEFITS OF IoT IN REAL-LIFE APPLICATIONS

IoT is an appealing technology for addressing different application challenges. It enables real-life applications to be smart by connecting several smart devices (e.g., sensors and actuators) together through the internet to make the devices and their data accessible ubiquitously [20] and [21]. Also, it leverages the devices to collect, compute, and transmit data for decision-making purposes.

To transmit data to remote locations at the application layer, the IoT employs different types of communication protocols to enable the exchange of data between a specific application and the end-users [22], [23]. The application layer communication protocols used in IoT are based on the exclusive-pair, publish-subscribe, request-response, and the push-pull communication model [24]. The exclusive-pair communication model provides a continuous bidirectional full-duplex communication setup between a client and a server. An example of an exclusive-pair protocol is the WebSocket protocol. The publish-subscribe communication model entails a data publisher, a data consumer, and a data broker. The data publisher represents the data source, the data broker performs the role of receiving data for a topic published by the publisher while the data consumer performs the role of subscribing to the topics managed from the broker. Some examples of the publish-subscribe protocols include AMQP and MQTT. The request-response model provides a stateless bidirectional communication setup between a client and a server where the client sends a request to the server and the server provides a response to the request. Some examples of the request-response communication protocols include XMPP and RESTful HTTP. The push-pull communication model entails a data publisher that pushes its data into a data queue and a data consumer that pulls the published data from the data queue. An example includes a queue-based protocol.

The use of IoT technology is vital to everyday human activities. Such activities can be classified into several areas, including smart industries, smart environment, smart city, and smart health [1], [21].

Examples of the IoT applications under the class of smart industries are water industry [25], automatic interactions among machines [26], quality control, inventory tracking, logistics and supply chain, packaging optimization, and production on demand [27], [28]. Examples of the IoT applications under the category of smart environment are smart water quality sensing [29], [30], [31], [32], [33], [34], [35], smart agriculture [36], [37], [38], [39], smart industrial plants, smart lighting [40], [41], [42], smart homes [43], [44], [45], [46], and smart water supply [47], [48], [49], [50], [51]. Examples of the IoT applications under the category of smart health [52], [53], [54], [55] include the monitoring of the organs or health conditions of a patient, remote surgery, diagnosing a patient's health condition(s), authentication of patients, and making real-time information about a patient's health condition available to the appropriate remote healthcare centers [56], [57]. Examples of the IoT applications under the class of smart city include intelligent transportation [58], [59], [60], [61], [62], assisted driving [63] and [64], passenger services, logistic services [65] and [66], car parking and counting [67], [68], [69], [70], fleet management [71], [72], [73], emergency reporting services [74], [75], [76], and intelligent traffic control [77], [78], [79].

For instance, in smart water quality sensing and water supply applications, IoT technology could assist to efficiently monitor changes in water quality, control the distribution of clean water for various consumption uses, guarantee the safety of the public health since it helps to increase access to clean water, and prevents the distribution of unclean water to the public.

In smart industries, under the concept of Industry 4.0, IoT technology could be leveraged to monitor and manage several industrial applications and processes by connecting machines that combine different sensor devices to a central system to allow visualization and decision activities.

An important implementation goal for devices in IoT application networks is small size. The devices consist of sensors, processors, communication radios, and batteries that are used for sensing, processing, transmission, and power supply operations, respectively. Because of the small size of the devices, they only have space to accommodate tiny batteries with limited battery power. They use standard radios with a limited bandwidth for wireless communication channels, and processors with a limited processing speed and storage constraints. These limitations have made the study of resource management an essential research focus for IoT networks to efficiently manage the scarce resources–typically, power, bandwidth, and time–and to improve the network performance of critical real-life applications.

B. RESOURCE MANAGEMENT CHALLENGES IN IoT NETWORKS

This section discusses the major resource management challenges that currently confronts the performance of the IoT networks. Figure 4 describes the major challenges in IoT networks. The resource management challenges described in Figure 4 are discussed as follows.

1) POWER RESOURCE MANAGEMENT

One of the major issues to address while implementing IoT networks for different critical applications is the problem of power management due to the limited power resources of IoT devices. The IoT devices deployed in various applications run on battery. Most times, it may be impractical, inefficient, and costly to replace the in-built batteries of the devices after deployment. Unfortunately, once the battery power of these devices is drained, it becomes impossible for the network to sense and communicate their measurements to remote locations. Also, many of the sensing field areas are off a conventional power grid [80]. Consequently, it may be impossible to supply the necessary power required to satisfy the communications bandwidth and latency (or transmission delay) requirements of different applications since data sampling rate is application-dependent [81]. The objective of power resource management is to achieve a minimum energy consumption and a maximum energy efficiency to improve the performance of IoT networks. Hence, sophisticated power management algorithms are needed to optimize the power requirements of IoT devices to reduce energy consumption, extend device lifetime, and improve the energy efficiency of the network on the basis of the limited power resources.

2) COMPUTATIONAL RESOURCE MANAGEMENT

Typically, various critical applications such as the industrial IoT (IIoT) and the internet of medical things require real-time data processing and minimal data transmission delay. To achieve this, the objective of the computational resource management is to efficiently minimize computations such as the computational time (i.e., delay) and the computational power. Hence, the computational resource management is essential to minimize the amount of time used by devices while sending their critical data. This is due to the nature of the data of critical applications and the need to ensure the safety of lives. As a result, critical application data needs to be communicated timeously to the appropriate quarters to aid quick decisions. To support the data latency requirements of different devices with low computational power, efficient computational resource management algorithms must be developed to improve the latency performance in critical IoT applications.

3) BANDWIDTH RESOURCE MANAGEMENT

The devices deployed in various critical IoT applications are mostly heterogeneous in nature due to the increasing use of different detected parameters in sensor fusion applications. This results in heterogeneous traffic with different throughput requirements. Bandwidth is a scarce resource in IoT applications due to limited available electromagnetic spectrum, but further depends on the transmit power as another scarce resource. The objective of bandwidth resource management is to increase the achievable throughput of the IoT devices in the IoT networks to improve their data transmission performance. Since bandwidth determines the data transmission capacity (i.e., throughput) of a wireless channel according to Shannon's equation [82], [83], efficient bandwidth resource management algorithms will contribute to supporting the throughput requirements of different devices.

4) CHANNEL RESOURCE MANAGEMENT

The channel is a communication medium that is used by the devices in an IoT network to exchange control messages and packets in the downlink channel and uplink channel, respectively. The control message from a base station device is used to schedule the IoT sensor devices to transmit their packets to the base station over the uplink channel [84]. Due to the limited channel resource and the quantum number of IoT devices that want to use the channel, the objective of channel resource management is to prioritize control messages as well as manage (control) the channel. Channel resource management can be achieved by formulating the channel resources as a resource allocation problem and solve using different artificial intelligence techniques. Furthermore, the IoT networks may integrate various devices that wants to sense and communicate critical data to the base station. As a consequence, for proper utilization of the channel it is very important to design different access management schemes to manage the devices channel utilization process to prevent problems like access collision, energy wastage, energy consumption, and delay. For example, it is well established that significant energy is mostly expended by IoT devices during data communication due to several factors, including the wireless channel conditions causing congestions and collisions. Hence, another objective of the channel resource management is to manage how the IoT devices can efficiently access the channel.

5) SPECTRUM RESOURCE MANAGEMENT

Spectrum is a scarce wireless communication resource that is mostly shared by the unlicensed the IoT devices, which

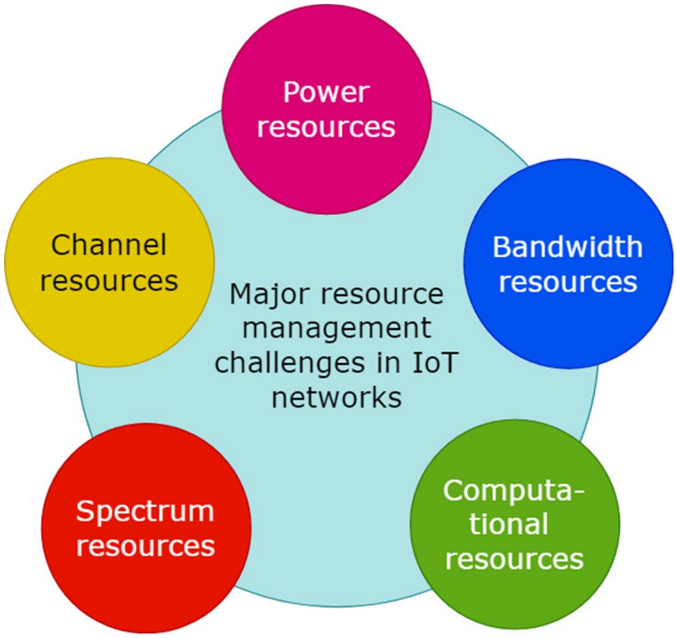

FIGURE 4. Resource management challenges in IoT networks.

does not have an exclusive right to licensed band of the spectrum, with the licensed devices. Because of the limited available spectrum, spectrum resource management has been a growing problem because of the growing increase in the number of spectrum uses.

Also, because of the increasing demands and competition for the limited spectrum resources by the IoT devices, the objective of spectrum resource management is to manage and improve the use of the limited spectrum resource to avoid a collision problem. This helps to improve the spectrum efficiency performance of an IoT network.

IV. A REVIEW OF OPTIMIZATION THEORY APPROACHES FOR RESOURCE MANAGEMENT CHALLENGES IN IoT NETWORKS

Optimization approaches are powerful operation research tools that have been exploited by researchers to develop resource management techniques for IoT networks. The examples of such approaches are based on convex programming, heuristic programming, and meta-heuristic programming. These approaches, their applications, advantages, disadvantages, and their resource allocation solutions for IoT networks are briefly reviewed in this section.

A. CONVEX OPTIMIZATION APPROACHES

Convex optimization approaches involve the use of linear programming methods (e.g., simplex method and interior method) to solve resource management problem formulations that could be proven to be convex in nature using techniques like partial derivatives and Lagrangian [2]. The implication of this is that convex optimization approaches can only be applied to IoT network resource management problems if the convexity of formulated problems as an optimization problem could be established. When convex optimization approaches are employed to solve IoT networks resource management problems, optimal solutions are typically obtained to such problems.

In literature, convex optimization approaches have been developed for solving resource management problems related to wireless IoT networks. A good example is presented in [85] where an interior method-based resource allocation algorithm was proposed to jointly solve power and transmission time allocation problems in IIoT to compute optimal power and transmission time solutions for improving user fairness and throughput.

Advantages: Convex optimization approaches are suitable for obtaining an optimal resource allocation solution for IoT applications resource management problems.

Disadvantages: Most convex optimization approaches have a high computational complexity (e.g., computational time and computational power) and may not be suitable for obtaining resource allocation solutions in real-time operations for time-critical IoT applications [2] and [86].

B. HEURISTIC OPTIMIZATION APPROACHES

Heuristics are problem-specific techniques that have been widely employed in wireless IoT networks, either separately or jointly with other optimization techniques, to solve complex resource management problems when other optimization techniques do not fit.

Heuristic optimization approaches in wireless IoT networks may be developed using the optimization framework of problem-independent metaheuristic algorithms or logical ideas depending on the resource management problem that is formulated in the context of complexity.

As an example, [87] employed the framework of a whale optimization algorithm to develop a heuristic algorithm for solving an IoT resource management problem that involved the improvement of the overall communication cost of the network gateways in an IoT network. In [88], the authors proposed a heuristic algorithm based on the rules of logic for a channel allocation resource management problem. The authors in [89] employed strategies from genetic algorithms (GAs) to develop a heuristic that seeks a solution for reducing the overall power consumption of the network by considering the transmit power allocation and the distribution of resource blocks among IoT devices in a fog computing enabled IoT network.

Advantages: Typically, heuristic algorithms are advantageous in terms of reducing the computational complexity of resource management solutions. Heuristic algorithms are suitable for solving hard optimization problems.

Disadvantages: Most of the solutions obtained to resource management problems using heuristic algorithms are sub-optimal. This implies that the quality of such solutions may diminish when the problem dimensionality is increased. Most times, the sub-optimal solutions obtained to IoT networks resource management problems may not be close to optimal solutions. Using heuristic approaches, the computation of resource allocation decisions for obtaining solutions to resource management problems require online computations that often waste the limited power resources. Also, most resource allocation algorithms based on heuristics in IoT applications are still confronted by the difficulty of obtaining resource allocation solutions in real-time operations. Heuristic algorithms are problem-specific and may not be reused for other resource allocation problems.

Because of the dynamic and heterogeneous nature of IoT networks in time-critical applications, heuristic algorithms may not efficiently handle the dynamically changing and heterogeneous characteristics of IoT networks. Hence, more adaptive and strategic approaches are required to address this.

C. META-HEURISTIC OPTIMIZATION APPROACHES

Most times, resource management problems in wireless IoT networks are non-linear, and consequently convex programming approaches cannot be applied. Meta-heuristic optimization approaches, which are suitable for most optimization problems in practice, are sought to solve non-linear IoT resource management problems, and near-optimal solutions are often obtained.

Meta-heuristic optimization approaches are formed from the concepts of swarm intelligence and evolutionary theory. In the realm of wireless IoT networks, they may be applied to various types of optimization problems which involves adapting the standard meta-heuristic or non-linear optimization approaches such as particle-swarm optimization (PSO), ant colony optimization (ACO), forest optimization, and GAs to several resource management problems in wireless IoT networks. Researchers have exploited these approaches to make the reward function converge quickly to a near optimal solution for an objective function.

For example, in [90] the authors formulated a non-convex energy efficiency optimization problem owing to the lack of convexity of the problem structure. To address the power and time management issues of the formulated optimization problem, a PSO algorithm was adapted. In [91], we describe an adapted PSO algorithm to solve both time and power resource management problems of an IoT network to improve energy efficiency. In [92], a PSO algorithm was applied to a cognitive wireless sensor network to address the spectrum sensing problem and determine which of the devices that may use the channel in order to improve the network energy efficiency and throughput. In [93], the authors considered the application of ACO to the problem of computational overhead in IIoT to compute near-optimal solutions that can reduce the computation overhead and latency to increase the efficiency of the system. The authors of [94] developed a forest optimization resource allocation algorithm for the proposed IoT system to reduce the energy consumption and delay associated with the process of computing and allocating resources. The work in [94] also considered other conventional optimization approaches that are based on GA and PSO. The proposed forest algorithm was compared with both GA and PSO, and the forest optimization resource allocation algorithm outperformed the other algorithms in terms of computational complexity and network performance.

Advantages: Meta-heuristic approaches work well for the IoT network resource management problems they are applied to and may be adapted to most IoT resource management optimization problems in practice.

Disadvantages: The computation of resource allocation decisions for obtaining solutions to resource management problems using meta-heuristic algorithms require intensive online computations that expends the scarce power resources.

Also, in practice, resource allocation meta-heuristic algorithms are computationally complex and costly because they incur high timing overhead during operation, especially when many IoT devices are considered. Unfortunately, the IoT networks in time-critical applications may not tolerate the delay due to the timing overhead and computational complexities as such applications require a real-time processing and are sensitive to delay due to their critical data to human lives, public safety, health, and well-being. Solutions obtained to most IoT network resource management problems in literature using meta-heuristic algorithms are only near optimal, which may obviously impact the QoS performance of the network. This limitation is typically due to the settings of parameters and operators for the designed objective functions to be solved.

D. SUMMARY

A summary of the reviewed optimization method is presented in Table 2 to compare different optimization methods based on the addressed resource allocation problem, cost function, benefits, and disadvantages of the proposed optimization solutions

V. DEEP LEARNING FOR RESOURCE MANAGEMENT CHALLENGES IN IoT NETWORKS

Deep learning (DL) is a subset of ML and artificial intelligence that was introduced in 2006 by Hinton *et al.* [95]. DL originates from neural network and has a good learning capability from data compared to ML [96]. DL has a better efficiency compared to ML for a large data. Also, DL uses multiple layers for data abstraction representation and building computational models. These advantages have significantly increased the popularity of DL and enabled DL to be successfully applied in several fields like natural language processing, computer vision, and healthcare to develop computational models.

Because of the capabilities of DL, it is emerging as a promising learning theory approach for solving resource management problems in wireless IoT networks. DL is a data-driven approach that leverages data to solve resource management problems in practical IoT networks. As described in Figure 5, DL also uses a processing pipeline that is similar to ML, but then, DL uses a generic feature extractor to obtain non-hand-crafted features from the input data unlike ML. With this, DL is able to learn a deeper insight from a large volume of input data and is able to provide a reliable model. The major steps in a DL processing pipeline can be classified into five phases, namely (1) data collection, (2) data understanding and preparation, (3) DL model building and training, (4) model validation, and (5) model deployment. The data collection phase is used to collect the training and test data for developing a resource management model. The data understanding and preparation phase is used to perform an exploratory data analysis and prepare the dataset to be in the right format that can be fed into a DL algorithm. The data preparation entails the data representation of the input data in a matrix representation containing a bunch of vectors. A better data representation is important to remove noise and complexity from the dataset. This helps to obtain a data representation with a reduced size [97].

A better data representation makes the input data to use less memory resources and helps to speed-up the training and running of DL models for resource management. A better data representation also helps DL to efficiently learn the important information from the input data without memorizing noise, thus, speeding up the training and running of DL model. Also, a better data representation helps to build a reliable model [97].

The DL model building and training phase is used to train a DL algorithm on the training dataset while the model validation phase is used to validate the trained model using the test dataset. Lastly, the model deployment phase is used for deploying a trained DL model on IoT devices. To provide insight into different DL algorithms that can be used to build DL models for resource management in IoT networks, different DL algorithms are discussed in the subsequent sections under DL approaches.

Also, this section presents different DL approaches, their advantages, disadvantages, and different resource allocation solutions that are based on DL.

A. DEEP LEARNING APPROACHES

DL approaches have recently been employed to seek solutions to a variety of IoT network resource management challenges, such as power resource management, bandwidth resource management, and spectrum resource management, by developing a deep learning model.

A DL model is a multi-layer neural network that performs the feature extraction and transformation of the input data into a vector representation (or feature vectors) [98]. Hence, a DL model could also be simply referred to as a deep neural network (DNN) model. A DL/DNN model consists of essential components like neurons, weighted connections, input, multiple hidden, and output layers, activation functions [98].

The input, hidden, and output layers are densely connected layers of a deep learning model, and each layer may consist of multiple neurons. The input layer is used to only accept and pass the input data x (e.g., network data such as channel realizations) to the hidden layers positioned at the centre of a deep learning network. No computation is performed by the neurons in the input layer.

The hidden layer is used to perform computations like feature extraction, transformation, weighted sum, and non-linearity of the weighted sum on the input data through its neurons. For example, each neuron of the hidden layer does a non-linear operation on the input data. Each neuron computes the weighted sum (Σ) or net input h of all its input data by multiplying each signal with its corresponding weight and adding up the computed dot products, and sending the weighted sum to its activation function as described in Figure 6 and Eqn. (1) [99].

$$h = \sum_{k=1}^{K} x_k w_k = x_1 w_1 + x_2 w_2 + \ldots + x_K w_K \tag{1}$$

where x is the input data and w is the weight of the connection link between the neurons in the input layer and the neurons in the hidden layer.

An activation function is a mathematical function that enables the neurons in a DNN to communicate with each other over their weighted connections. It converts the weighted sum to a linear function as an output y. This output is then passed to the next layer through another associated weighted connection. The examples of some available activation functions in DL/DNN are sigmoid function, rectified linear unit (ReLU) function, and tanh function. The sigmoid function takes real number values as an input and convert it to an output that is restricted to a value between 0 and 1. The sigmoid function produces an s-shaped curve. The ReLU function converts the input of whole number values to an output of positive numbers, and produces a rectified curve. While the tanh function also takes real number values and convert it to an output that is restricted to a value between −1 and 1 [99]. Similar to the sigmoid function, the tanh function also produces an s-shaped curve. Table 3 presents the mathematical representation of these commonly used activation functions.

Using the sigmoid activation function in Table 3, for example, the computation of the output value y of the neuron given in Figure 6 is described in (2) and (3) [99] as:

$$y = f(h) = f(x_1w_1 + x_2w_2 + \ldots + x_kw_k) \tag{2}$$

$$y_{sigmoid} = \frac{1}{1 + e^{-(x_1w_1+x_2w_2+\ldots+x_kw_k)}} \tag{3}$$

The ReLU function is advantageous for performing computations in the hidden layer to reduce the problem of vanishing gradients during training while the tanh and sigmoid functions are advantageous for computing the output of the output layer neuron(s). However, the derivative of the ReLU function is faster to compute compared to the sigmoid function, and this makes the ReLU function to be advantageous over the sigmoid function for DNN training.

Afterward, the hidden layer transfers the computation results to the output layer. The output layer then produces the information learned by the network as the output. Note, the flow of data (i.e., data propagation) from the input layer to the output layer is known as a forward propagation. That is, forward propagation explains how the information flow from the input layer to the output layer of a DNN.

The neurons are an essential component in a DL model. The neurons are modeled based on how the neurons in the human brain work together as groups of neurons to perform a functionality. The neurons in a deep learning model are nodes that enable the flow of data and computations within the model.

The weighted connections or synapses are employed to connect the neurons in the input layer to the next neurons in the hidden layer, and to the neuron(s) in the output layer. Each weighted connection has an associated weight that is relative to the importance of the neurons in a DL model.

To develop a reliable model, the weights of the neurons are fine-tuned iteratively during the training of a DL model based on the loss function at the output layer. To measure the performance of a DL model, in each epoch, the loss function of the model is computed on the test set using a mean square error (MSE) [99] or a cross-entropy [99] as described in (4) and (5).

$$MSE\ loss = \frac{1}{m}\sum_{i}(y_i^p - y_i)_i^2 \tag{4}$$

where y_i^p is the prediction of the model and y_i is the expected output for a given training sample x.

$$Cross\ entropy\ loss = -\frac{1}{K}\sum_{k=1}^{K}\left(\left(y_e^{(k)} log\left(y_p^{(k)}\right)\right) + \left(1 + y_e^{(k)}\right) log\left(1 - y_p^{(k)}\right)\right) \tag{5}$$

where $y_e^{(k)}$ is the expected output and $y_p^{(k)}$ is the predicted output of the kth training sample for a given input sample $x^{(k)}$.

From (5), the cross entropy loss uses negative log probabilities to find the difference between the predicted output and the expected output.

The loss function represents the cross-entropy loss between the expected output and the predicted output or the measure of the prediction error of a model. The loss function is used to determine if the prediction accuracy of the trained DL model is good. For example, the lower the loss function, the higher the prediction accuracy of the trained model.

During training, the backpropagation algorithm is used to back propagate the computed loss function, which is the difference between the predicted result and the expected result, for each training epoch from the output layer to the hidden layer [100], [101] as shown in Figure 7 to fine-tune the weights of each neuron in the hidden layer by calculating the gradient (i.e., partial derivative) of the loss function with respect to the weights of each neuron in the hidden layer using a gradient-based optimization algorithm (i.e., an optimizer) [102], [103]. The optimizer is employed to calculate and adjust the weights of the hidden layer to minimize the loss function. Examples of the gradient-based optimization algorithms are Adam algorithm [102] and stochastic gradient descent algorithm [103]. The differentiation process follows the chain rule. The process continues until the loss function reduces to a threshold [104], [105], [106]. Figure 7 provides a typical illustration of the training of a DL model.

The use of DL to solve resource management problems in IoT applications relies on training and building a DL/DNN model to which network data in the form of channel representation or matrix representation is provided as training sample inputs. This requires following the DL model building pipeline described in Figure 5 to train and test a DL-based resource management model in any of Tensorflow [107], MXNet [108] or PyTorch environment [109]. The model is then evaluated to investigate its prediction accuracy by testing it on unseen channel data samples that it has not been exposed to before. The result visualization of the model is also carry out to visualize the results of the model using the Matplotlib tool [110]. The model deployment phase is used to deploy the DL-based resource management model that have been trained and tested in a Keras, Tensorflow, MXnet, or PyTorch environment where it can be compiled into an executable form for deployment and exported to different IoT devices hardware/processor platforms like the Texas Instruments [111], Intel [112], ARM [113], and Raspberry Pi [114]. Figure 8 gives an insight into the process of DL model compilation and deployment on IoT devices.

The trained model may then be used to compute and provide a resource allocation solution to a resource management problem. However, the computation of the resource allocation solutions may be intensive as each layer of the model carries out the task of matrix-vector multiplications [115]. But then, it may be advantageous over the conventional optimization approaches depending on the design.

TABLE 2. Summary of proposed optimization methods for resource management in IoT networks.

Ref.	Optimization method	Resource allocation	Objective	Advantages	Disadvantages	Year
[87]	Whale-based heuristic algorithm	Spectrum (e.g., channel scheduling)	Minimize communication cost	Low computational complexity, Provides a suboptimal solution, Suitable for a large sized network.	Solutions are problem specific, Maybe difficult to numerically analyze.	2020
[88]	Heuristic algorithm	Harvested energy, Spectrum (e.g., channel scheduling)	Maximize throughput			2019
[89]	Custom GA	Transmit power, Resource block	Minimize energy consumption			2019
[90]	PSO	Energy harvesting time, Information transmission time	Maximize energy efficiency	Provides a near optimal solution, Easy to implement, Suitable for a large sized network.	High computational complexity	2018
[91]	PSO	Harvested energy, Energy harvesting time, Information transmission time	Maximize energy efficiency, Maximize throughput			2020
[92]	PSO	Spectrum	Maximize energy efficiency			2020
[93]	ACO	Time	Minimize latency, Minimize computational time	Suitable for a large sized network, Provides a near optimal solution, Provides a reduced computational time	Maybe difficult to numerically analyze.	2021
[94]	Forest optimization algorithm	Power	Maximize energy efficiency	Provides a reduced computational time, Provides a near optimal solution,	Maybe difficult to numerically analyze.	2021

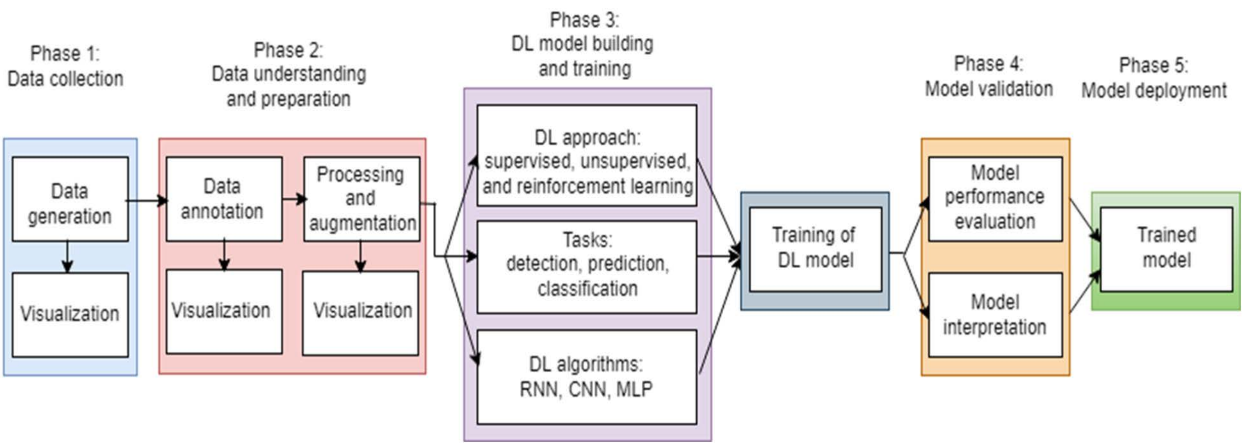

FIGURE 5. DL pipeline.

To make the reading of this paper to be interesting, a list of the abbreviations of some important terms used in this section is presented in Table 4.

The development of DL models involves the use different DL architectures in Keras and Tensorflow such as convolutional neural networks (CNNs), recursive neural networks, and recurrent neural networks (RNNs) along with fundamental ML techniques like supervised, reinforcement, and unsupervised learning to develop different DL models for solving IoT applications optimization problems. The DNN architectures used to develop DL models for resource management problems have varying benefits and shortcomings. This must be considered when selecting a DL algorithm for designing a DL-based resource allocation algorithm for IoT networks. An example of a DL model for solving resource management problems (e.g., time resource allocation and power resource allocation) in IoT applications is given in Figure 9. In Figure 9, we show how the input data in the form of a channel representation or matrix representation is fed into a DL/DNN architecture through the input layer to predict power resource allocation for the IoT devices in the IoT applications.

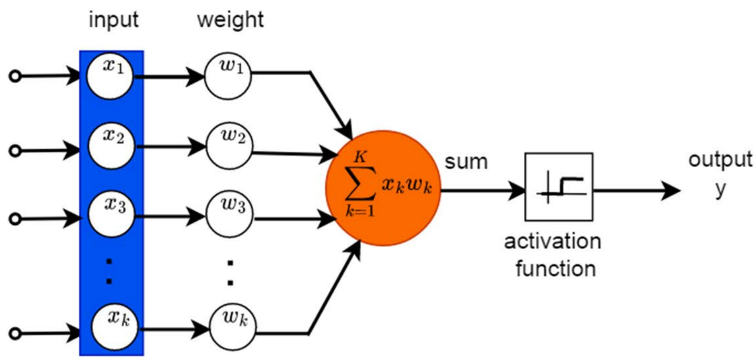

FIGURE 6. Illustration of an artificial neuron with a weighted sum plugged into an activation function.

TABLE 3. Examples of activation functions.

Activation function	Mathematical representation
Sigmoid	$f(x)_{sigmoid} = \frac{1}{1+ e^{-x}}$
ReLU	$f(x)_{relu} = max(0, x)$
Tanh	$f(x)_{tanh} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$

Examples of DL approaches for resource management include the supervised DL approaches, the unsupervised DL approaches for resource management, and the deep reinforcement learning approaches.

1) SUPERVISED DEEP LEARNING APPROACH

The supervised deep learning approach is formed by combining DNNs with supervised learning [105]. This approach uses labeled data. Hence, a supervised DL approach for resource management is a data-driven supervised learning method that combines a DL technique with a conventional optimization method to enable a DL architecture to learn from the resource allocation solutions of the conventional optimization method, which serves as labeled data. Examples of the DL architectures used in supervised DL approaches are MLP, CNN, and RNN [1]. Examples of the RNN architectures are GRU, Bi-GRU, Bi-LSTM, and LSTM. Also, examples of the CNN architectures are ResNet, Xception, AlexNet, and VGG.

In this approach, IoT resource management problem formulations and a conventional optimization approach (e.g., GAs, PSO) may be treated as a black-box and applying a DL technique to the black-box to learn the input parameters and output solution (i.e., resource allocation solutions) of the conventional optimization algorithm. In this approach, the conventional optimization technique is leveraged as a supervisor and its output solution is employed to train and develop a supervised DL-based approach as a resource management algorithm.

Supervised DL approaches can be easily implemented for resource management by using important open-source frameworks like Tensonflow, Keras, and Torch, which contain several DL algorithms. To evaluate the performance of this approach, it may be tested for resource allocation solution prediction accuracy. Examples of the proposed supervised DL approaches for resource management include [106], [117], [118], and [119].

In [117], a supervised DL based approach was presented to predict an optimal transmit power for different channel coefficients in a wireless powered communication network (WPCN). The authors employed a multilayer perceptron (MLP) architecture to learn the resource allocation solutions (i.e., output labels) of an iterative optimization algorithm used to solve the formulated transmit power minimization problem and the channel vectors (i.e., input labels) that correspond to the resource allocation solutions as the training data. The proposed model achieved an approximate resource allocation accuracy compared to the iterative optimization algorithm using the standard MSE for performance evaluation. The authors did not report the percentage of the prediction accuracy for the proposed model. Also, the proposed model achieved an improved computational complexity against the baseline iterative optimization algorithm.

Advantages: The proposed MLP model for computing an optimal transmit power and time allocation for the formulated problem achieved a low MSE, indicating a high prediction accuracy in transmit power and time, due to the use of normalization in the model.

Disadvantages: The computation time of the proposed MLP model is low.

In [118], a supervised DL based approach was presented to predict the optimal transmit power and PS ratios resource allocation that can minimize the sum-transmit-power of a SWIPT-based IoT system. They used a conventional optimization algorithm to solve the optimization problem of the paper. The power and PS ratios resource allocation solutions (i.e., output labels) computed by the optimization algorithm with their correspondence channel vectors (i.e., input labels) were learned by using four DL architectures like FFNN and RNN architectures like LSTM, Nonlinear AutoRegressive network with eXogeneous inputs (NARX) [118], and layer recurrent network (LRN). The performance of the models was evaluated in terms of prediction accuracy using MSE. The authors reported resource allocation prediction accuracies of 6.1%, 5%, 0.35%, and 5.6% on the LRN, NARX, LSTM, and FFNN models in comparison with the baseline optimization algorithm. Also, the models achieved a better computational time compared to the baseline optimization algorithm. The developed models were deployed on the system devices by testing it in a deployable environment.

Advantages: The proposed FFNN and the RNN models (i.e., NARX and LRN) are beneficial for obtaining resource allocation solutions with a low computational time. The RNN models (i.e., LSTM and NARX) are advantageous in terms of a low MSE loss for resource allocation prediction (i.e., a high prediction accuracy in resource allocation). Also, the proposed RNN models have a low computational power with respect to the number of the devices in the system. Disadvantages: The proposed LSTM model is not efficient for obtaining resource allocation solutions in terms of the computational time. The proposed FFNN model has a high MSE loss for resource allocation prediction compared to the RNN models. The RNN methods are susceptible to the exploding gradient issue.

In [106], a supervised DL model was presented to compute power and sub-band allocation solutions for a wireless network with an objective to improve the overall network throughput. The authors employed a GA algorithm to solve and obtain solutions to a power and sub-band allocation problem based on the channel quality information (CQI) value and the location indicator (LI) of the network devices. Furthermore, they employed an SAE architecture that consists of a block AEs was used to pre-train and develop the DNN model for predicting power and sub-band allocation solutions in their work. The prediction accuracy of the model was evaluated using the MSE. The authors reported prediction accuracies of 86.14% and 86.31% for their model with three and four hidden layers compared to the baseline GA algorithm. The developed model was deployed on the system devices by testing it in a deployable environment.

Advantages: The proposed AEs model has a high training accuracy on small training samples as well as a high test accuracy on large training samples.

Disadvantages: The proposed AEs model requires a large hyperparameter tuning and processing time during training, indicating a high computational time and a high computational power in computing resource allocation for the system devices. Hence, the proposed AEs model may not be efficient to provide resource allocation solutions in a real-time manner. The AEs model also needs sufficient data to be able to build a reliable model that can generalize well.

In [119], a supervised DL based approach was presented to compute the transmit power for the devices in a wireless network by extracting and learning the spatial features in

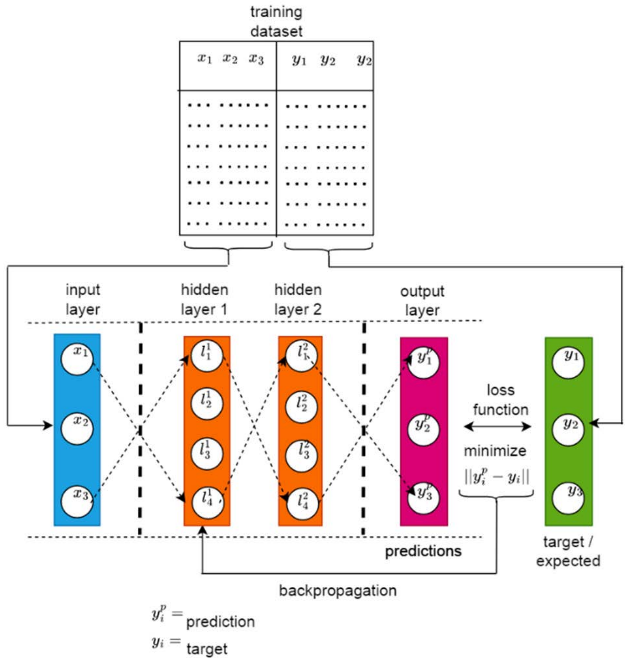

FIGURE 7. An illustration of a DL model training.

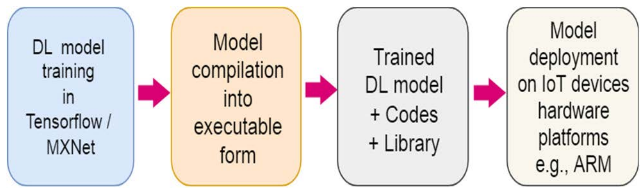

FIGURE 8. DL model compilation and deployment process.

the channel gain in order to maximize the energy efficiency or the spectral efficiency of the network. In the paper, the channel samples (in dB) of a pre-trained CNN was used to reproduce an existing power control scheme of transmit power results for the given channel data samples. Also, the authors used a CNN architecture with a 3 X 3 convolution to perform a 2D spatial convolution on the input data. The channel samples (i.e., the training data) are fed into the CNN model to find a transit power for each channel sample and to train a CNN model. Then, the model was used to predict an optimal transmit power allocation based on current channel state information to improve the energy efficiency or the spectral efficiency of the network. The performance of the proposed model outperformed a baseline CNN model in terms of computational time. The authors did not report the percentage of prediction accuracy. The developed model was deployed on the system devices by testing it in a deployable environment.

Advantages: The proposed CNN model achieved a high prediction accuracy in transmit power resource allocation.

Disadvantages: The proposed CNN model has a high computational time with respect to the number of devices in the system. It also requires a high computational power.

TABLE 4. List of abbreviations.

Term	Abbreviation	Term	Abbreviation
Auto-encoders	AEs	Multilayer perceptron	MLP
Deep neural network	DNN	Recurrent neural network	RNN
Convolutional neural network	CNN	Long short-term memory	LSTM
Deep belief network	DBN	Local response normalization	LRN
Gated recurrent unit	GRU	Bidirectional LSTM	Bi-LSTM
Generative adversarial network	GAN	Visual geometry group	VGG
Restricted Boltzmann machine	RBM	Sparse encoder	SAE
Variational encoder	VAE	Denoising encoder	DAE
Deep Boltzmann machine	DBM	Feedforward neural network	FFNN

2) UNSUPERVISED DEEP LEARNING APPROACH

The unsupervised deep learning approach is formed by combining DNNs with unsupervised learning. This approach uses unlabeled data. Consequently, an unsupervised DL approach for resource management is an unsupervised method that does not learn from any conventional optimization algorithm solutions, but learn directly from the formulated optimization objective function of an IoT application resource management problem. Examples of the DL architectures used in unsupervised DL approaches are RBM, DBN, GAN, and DBM. Examples of the variants of the auto-encoder (AE) are SAE, VAE, and DAE [1]. In this approach, the objective function could be set as a loss function to train a DL model. Then, the DL model can be fine-tuned to optimize the loss function using an optimizer like a stochastic gradient descent [120].

Unsupervised DL approaches can be easily implemented for resource management by using important open-source frameworks like Keras, Tensorflow, and PyTorch, which contain several DL algorithms. Examples of the proposed unsupervised DL approaches for resource management are [116] and [120].

In [120], a supervised and an unsupervised DL based approaches were presented to compute the transmit power allocation and the power splitting ratio that can minimize the power consumption of a SWIPT system. The authors used a GA algorithm to obtain a resource allocation solution to the formulated power minimization problem in the paper based on the channel gains between the devices and the BS. The channel gains and the generated resource allocation solutions are used as a training sample (x, y). The authors constructed a DBN model to extract and learn the features of the training dataset. The model was evaluated using cross-entropy and the model achieved an approximate transmit power allocation and a power splitting ratio prediction accuracy. Also, the model achieved an improved computation time in resource allocation prediction. However, the authors did not discuss the percentage of the prediction accuracy of the proposed model. The developed model was deployed on the system devices by testing it in a deployable environment.

Advantages: The proposed DBN model for resource allocation was able to achieve a near real-time computational time for resource allocation to the devices in the system.

Disadvantages: The computation power of the proposed DBN is linearly proportional to the number of devices in the system. Hence, the computational requirement is increased as the system devices increase. Also, the proposed model has a low prediction accuracy in resource allocation.

The authors of [116] have presented an unsupervised DL approach to compute an optimal transmit power for interference management and sum-throughput maximization of an IoT system. The authors used a PCNet architecture to learn the features of training dataset and develop a DNN model for computing an approximate transmit power for a given channel realization. The authors reported an accuracy of 6.12% and 5.92% for their model compared to the conventional optimization algorithms. The model was deployed on the system devices by testing it in a deployable environment.

Advantages: The proposed PCNet model achieved a low computational time and also requires a low computational power for resource allocation.

Disadvantages: The proposed PCNet model has a low prediction accuracy for resource allocation with a small dataset.

3) DEEP REINFORCEMENT LEARNING APPROACH

The deep reinforcement learning approach is formed by combining DNNs with reinforcement learning [121]. In a deep reinforcement learning (DRL) approach for resource management, an IoT application resource management problem may be mathematically modeled using the Markov decision process (MDP) framework. The MDP framework is employed to model the state space, the action space, and the reward of an agent. In this approach, a neural network is employed as an agent. The state space consists of the environment states, wheras the action space consists of a set of actions available to the agent in each environment state. At each discrete time with a step t, the agent interacts with the environment and observes the environment state from the state space and learns from its interaction with the environment. Then, the agent makes an action from the action set. Based on the action chosen, the agent receives either a reward or a penalty for making a good or a bad decision, respectively. Following this, the environment moves to a new state with a transition probability. The reason why the agent learns from its interactions with the environment is to compute an optimal policy that optimizes the overall accumulative rewards of different actions from the environment states. Examples of deep reinforcement learning approaches are deep Q-networks (DQNs), dueling DQNs, and deep Q-learning (DQL) [1].

Examples of the proposed deep reinforcement learning approaches for resource management are [122] and [123]. In [122], a dueling DQN model was presented to compute a transmit power solution for the secondary users (SUs) to enable them to accurately sense the spectrum usage in almost

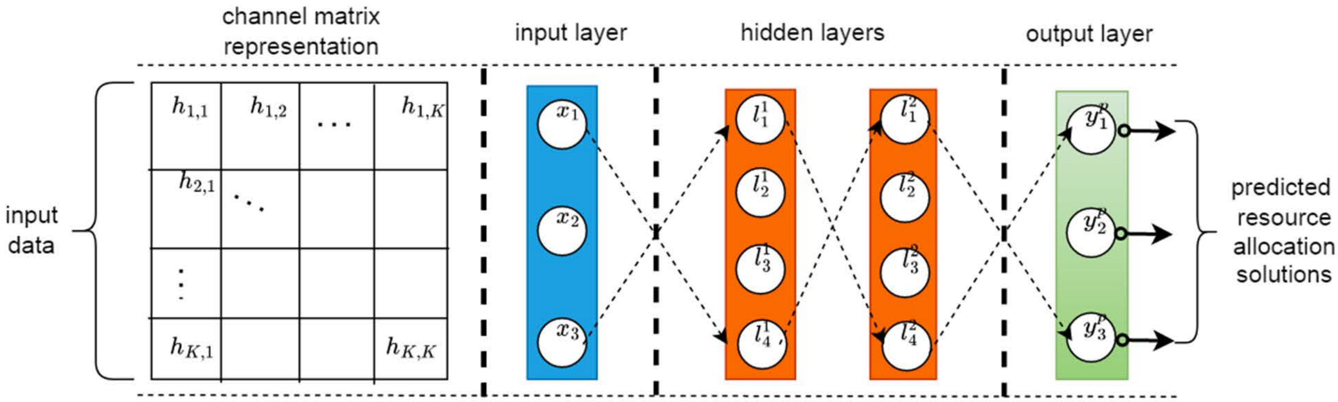

FIGURE 9. A DL/DNN architecture with input data in the form of a channel representation, two hidden layers for resource allocation computation and prediction in IoT applications.

real time. The authors used a social network consisting of third-party sensing devices to collect the power information of the primary users (PUs) for the SUs. Also, they employed a dueling DQN algorithm that combined neural networks to train on the collected PU power information to enable the model to predict an optimal transmit power to realize a dynamic spectrum sharing among the PUs and the SUs. The model achieved an improved prediction accuracy in resource allocation. The model was deployed on the system devices by testing it in a deployable environment.

Advantages: The proposed dueling DQN model has a high prediction accuracy for RA with a large number of PUs power information dataset.

Disadvantages: The proposed dueling DQN model has a high computational power and a high computational time for RA.

In [123], a DRL approach was presented to compute an optimal transmit power for the SUs in a cognitive radio sensor network (CRSN) to allow them to share a spectrum resource with the PUs without causing interference, and to improve the channel usage success rate of the SUs. The network is composed of a set of SUs, PUs, and sensor devices. The sensor devices that were deployed spatially in the CRSN environment were used to collect the power information of the PUs using a channel model and the locations of the devices in the environment. The generated power information serves as the training data. The authors developed a DQN model that was trained using the input data and the model was used to predict an optimal transmit power for the SUs to allow spectrum sharing among the PUs and the SUs. Thereafter, the predicted transmit power is used by the SUs to update or adjust their transmit power and allow them to send their own data successfully. The performance of the DQN model was evaluated using the loss function in the transmit power prediction for the SUs. The model achieved an improved computational time. The developed model was deployed on the system devices by testing it in a deployable environment.

Advantages: The proposed DQN model achieved a low computational time due to the small PU datasets and the number of sensors available in the model.

Disadvantages: The proposed DQN model has a high loss function, indicating a low prediction accuracy for resource allocation, due to the small number of the used PU datasets.

B. SUMMARY

A summary of the studied DNN models is presented in Table 5. Using DL approaches, the resource allocation decisions for obtaining solutions to resource management problems can be taken offline or their intensive online computation could be minimized to reduce the use of power resources related to online computations as in the case of the optimization theory approaches. With DL approaches, optimal resource allocation solutions may be computed for IoT networks resource management problems with a low computational complexity.

DL approaches are suitable for solving both convex and non-convex resource allocation problems in IoT networks and can provide resource allocation solutions in an almost real-time manner.

The prediction accuracy of the DL-based resource allocation approaches for IoT networks is still low and the level of prediction accuracy also depends on the quality of the available input data. Most DL-based resource allocation algorithms for IoT networks have a large size and may not work well on most of the devices in IoT networks in practical applications due to their limited storage space.

The supervised DL approach may be disadvantageous to obtain an optimal solution to some IoT applications resource management problems since its performance is technically bound by the resource allocation solution of the adapted conventional optimization algorithm.

The unsupervised DL approach may be limited in performance in terms of training and obtaining an optimal resource allocation solution, when applied to IoT applications resource management problems. The conventional loss functions used to train DL with a guaranteed performance are typically designed for classification and regression problems.

The deep reinforcement learning approach does not use the obtained optimal or near-optimal resource allocation solutions but leverages a trial-and-error means to seek optimal resource allocation solutions to IoT application resource management problems. Hence, it may be limited in performance.

C. IoT NETWORK DATASET FOR RESOURCE MANAGEMENT RESEARCH

The dataset plays a huge role in the training and building DL models to solve resource management problems in IoT applications. The examples of the network dataset types that could be employed to train a DL model for resource management are simulated dataset, real IoT device dataset, and synthetic dataset. The simulated datasets are generated by simulating a wireless channel model and other system conditions, including the locations of the devices in the systems. The real IoT device datasets are generated from the devices through measurements. The synthetic network dataset may be generated from the real IoT network dataset through the process of augmentation to increase the network dataset samples available to train a DL model. Currently, different from other application domains where there is a quantum number of datasets, in the area of resource management in IoT networks there exists only a few datasets for doing resource management research. The available datasets do not represent all channel environments of IoT networks. This is because it is presently not practical to produce a dataset that can capture different resource management problems in various channel environments of IoT applications.

Hence, a particular dataset for a specific network problem may not be technically useful to train and test different models. This can be attributed to the stochastic and dynamic nature of wireless channels with several channel realizations at different times. Owing to this fact, it is impractical for the training dataset generated based on a particular IoT network scenario to be re-used for other scenarios.

Because of the stochastic nature of wireless channels and the need to obtain an appropriate dataset for a particular network scenario, there is currently no benchmark datasets for doing resource management research. As a result of this, researchers working on resource management problems in IoT networks must create their own datasets. To achieve this, researchers often use a simulation approach to create datasets that capture the channel environments in their formulated scenarios and resource management problems. The process involved in creating their own datasets is time consuming and resource-intensive.

VI. A REVIEW OF GAME THEORY APPROACHES APPLIED TO RESOURCE MANAGEMENT CHALLENGES IN IoT NETWORKS

Game theory has been exploited in literature as an optimization approach to compute resource allocation solutions for IoT networks. This section presents a review of different game theory approaches, their advantages, disadvantages, and different resource allocation solutions that are based on game theory.

A. GAME THEORY APPROACHES

Game theory is one of the alternative approaches leveraged to solve resource management problems in IoT networks. Game theory is a strategic approach employed to model the behavior of devices as rational agents to optimize their gains. It can also be used to achieve a distributed resource allocation among a set of resource competitors, making it a powerful tool for solving resource management challenges in wireless IoT networks.

Game theory approaches are applied mathematics that use computational approaches and optimization concepts to deal with decision making problems for the optimal control of resources by dynamically optimizing and adjusting a measure of performance [124]. It provides mathematical optimization frameworks that could be leveraged to manage scarce and critical resources in IoT networks, *i.e.* transmission time, bandwidth, and power resources.

Generally, games are classified into two categories, namely cooperative games and non-cooperative games [125]. In a cooperative game, there exists a set of IoT devices that have agreed to work collectively with the aim of maximizing their overall objective function values. This type of game involves enforcing an agreement. To do this, a cooperative policy is used to introduce a binding agreement or a coalition among the devices, and this enables them to always cooperate to make decisions together and negotiating how to allocate resources, while no agreement exists between the devices in a non-cooperative game and they may consequently defect. Examples of game theory that falls under the cooperative games are the coalition games, repeated games, and bargaining games [126], while examples of game models in the category of the non-cooperative game are the bid auction game theory, Stackelberg game theory, potential game theory, and the stochastic game [127].

Both cooperative and non-cooperative game theory may be used for modeling as well as analyzing the resource allocation strategies developed for different heterogeneous IoT devices in a resource management problem. To compute optimal or near-optimal resource allocation solutions for resource allocation game problems, equilibrium solution concepts like Nash equilibrium (NE) and Stackelberg equilibrium (SE) are used for non-cooperative games, while the Nash bargaining solution (NBS) is used for cooperative games [127].

1) EXAMPLES OF COOPERATIVE GAMES SOLUTIONS

In [128], a cooperative coalition game theory was employed to formulate a power control problem in D2D communication. In the study, the D2D users were modeled as players and a coalition game framework was developed to model the coalition of D2D pairs to form a group of D2D users and to encourage them to increase their objective function, which is sum rate. The D2D pair coalition is a mutual agreement between D2D users to share resource blocks (i.e., channels). Each D2D pair coalition decision space strategy includes the transmit power resource vector for transmission and a resource block for reuse/sharing. To cater for heterogeneity among the D2D users, different power was assigned to the resource block based on the interference a user encountered when reusing the resource block. So, the transmit power allocated to each D2D user depends on the coalition it belongs to and the interference of the reused resource block.

In [129], the authors formulated a cooperative power control bargaining game framework where radars are modeled as players. The NBS equilibrium concept was employed to encourage the players to bargain and play the NBS strategy to control the allocation of transmit power. The decisions available to the players included a set of transmit power. The objective function values of the radars are based on the NBS strategy, where the existence of the game is established computationally to analyze the fairness in transmit power allocation.

2) EXAMPLES OF NON-COOPERATIVE GAMES SOLUTIONS

The development of a non-cooperative auction theory algorithm was presented in [130] to allocate the network bandwidth/time-slot resources among the devices in a wireless sensor network system. In the study, bandwidth represents the commodity that the sensor devices in the network are bidding for, and the BS allocated bandwidth to the highest bidders among the devices. The formulated auction game contributed to optimizing the network performance in terms of throughput and delay.

In [131], a non-cooperative repeated game theory was employed to formulate a power control problem for the wireless communication channels of an IoT network. In the study, wireless channels were modeled as players and a repeated game framework was developed to model the repeated interactions among different wireless channels. Each channel's decision space strategy includes the power cost for transmission and the signal-to-interference noise ratio (SINR) cost for channel service quality. The decisions available to each player is based on NE and the no-regret solution strategy concepts. For equilibrium analysis, the strategy concepts were analyzed to establish or prove the existence and uniqueness of the proposed power control repeated game model.

In [132], the authors considered a power allocation and interference management problem in a small-cell network to reduce power consumption and the interference of macrocell user equipment (MUE) and small-cell user equipment (SUE). This study formulated a Stackelberg game framework to model the SUE as the follower and the MUE as the leader. The Stackelberg equilibrium concept was employed to compute the strategies to be played by the followers. By leveraging this strategy, the followers chose a transmit power from the power allocation vector available in the decision space. This helped to avoid interference among the users during transmission. For equilibrium analysis, the existence of the SE was established to prove the optimality of the developed Stackelberg game.

Advantages: Resource allocation algorithms based on game theory are suitable for computing an optimal or a near-optimal resource allocation solution for IoT applications.

Disadvantages: Most resource allocation algorithms based on game theory have a high computational complexity, which may increase the computational power cost and cause long delays in real-time operations. These disadvantages may significantly impact the performance of time-critical IoT applications.

B. SUMMARY

A summary of the reviewed game theory method is presented in Table 6 to compare different game theory methods based on the addressed resource allocation problem, cost function, benefits, and disadvantages of the proposed optimization solutions.

VII. COMPARISON OF GAME, DEEP LEARNING, AND OPTIMIZATION THEORY APPROACHES FOR RESOURCE MANAGEMENT IN IoT NETWORKS

The optimization theory provides several mathematical programming algorithms that could be employed to solve different categories of IoT networks resource management problems, for example convex and non-convex problems. But then, most of the resource allocation algorithms designed for resource management problems related to IoT networks using optimization theory are often faced with a high computational complexity related to computation power, computational time as well as storage space. This concern may increase the power consumption and the data transmission delay of the devices in IoT networks. This may eventually conflict with achieving the goals of time-critical IoT applications.

The game theory provides mathematical optimization frameworks that could be leveraged to solve resource management challenges related to IoT networks to address the issues of transmission time, bandwidth, and power resources management. Also, it provides different equilibrium solution concepts to compute optimal or near-optimal resource allocation solutions for the resource management challenges in IoT networks. However, most of the resource allocation algorithms developed for IoT networks resource management problems using game theory have a high computational complexity with a high computational power cost and long delays in real-time operations. Also, this concern may affect the performance of critical IoT applications in terms of data transmission delay, power efficiency, and throughput.

The deep learning theory approach provides powerful mathematical tools that can be leveraged to obtain an optimal or near-optimal resource allocation solution that are less costly. But then, most of the existing resource allocation algorithms based on DL approaches in literature are less efficient in terms of prediction accuracy. Some suffer from an increase in training complexity with a large number of

TABLE 5. Summary of proposed DL models for resource management in IoT networks.

Refs	DL approach	DL method	Dataset type	Input data	Resource allocation	Objective	Results	Advantages	Disadvantages	Year
[117]	Supervised DL	MLP	Simulated	Channel	Transmit power, DL time for EH, UL time for EH	Maximize sum-throughput	Not provided	It achieves a high prediction accuracy in transmit power and time allocation	It has high computational time.	2020
[118]	Supervised DL	FFNN, LSTM, NARX, LRN	Simulated	Harvested energy, SINR, and channel realizations	Transmit power, Power-splitting ratios	Minimize sum-transmit-power	5.6%, 0.35%, 5%, 6.1%	FFNN, NARX and LRN methods have a low computational time. LSTM and NARX methods have a low MSE loss for resource allocation prediction. RNN methods have a low computational power with respect to the number of devices.	LSTM method is not efficient for resource allocation prediction in terms of computational time. FFNN method has a high MSE loss for resource allocation. RNN methods are susceptible to exploding gradient issue.	2020
[106]	Supervised/ unsupervised DL	SAE	Simulated	Channel quality information, location indicator	Power, Sub-band	Maximize throughput	86.14% and 86.13% for three and four hidden layers	High training accuracy on small training samples. High test accuracy on large training samples.	Low test accuracy on small training samples. Requires a large dataset. High computational time. Requires large hyperparameter tuning.	2019
[119]	Supervised DL	CNN	Simulated	Channel	Transmit power	Maximize energy efficiency, Maximize spectral efficiency	Not provided	High prediction accuracy in transmit power resource allocation	High computational time with respect to the number of devices. High computational power.	2018
[120]	Supervised/ Unsupervised DL	DBN	Simulated	Channel gains	Transmit power, Power splitting ratio	Minimize network transmit power consumption	Not provided	It has a near real-time computational time	It has a low prediction accuracy in resource allocation	2019
[116]	Unsupervised DL	PCNet	Simulated	Channel realizations	Transmit power control	Maximize sum-throughput	6.12%	Low computational time. Low computational power.	Low prediction accuracy for resource allocation with small dataset.	2020
[122]	RDL	Dueling DQN	Simulated	PU power information	Spectrum	Maximize spectrum sharing success rate	Not provided	High prediction accuracy for resource allocation with a large PUs dataset	High computational power. High computational time.	2021
[123]	RDL	DQN	Simulated	PU power Information	Spectrum	Maximize spectrum sharing success rate	Not provided	Low computational time with a small PUs dataset	High loss function due to small PUs dataset.	2018

devices, while some are not efficient for deployment on the devices in IoT networks due to the size and computational resource requirements caused by storage space and power limitations.

Based on these quantitative and/or performance comparisons and the need to develop new sophisticated power-, bandwidth-, channel-, computation and delay-aware resource allocation algorithms for critical IoT applications, the use of DL approaches is promising. However, the use of the DL methods is associated with a number of major challenges that need to be further investigated and addressed to improve the performance of DL approaches for resource allocation in IoT networks. Such challenges include small training dataset size problem, hyperparameter optimization problem (e.g., number of neurons in individual hidden layer, number of hidden layers, activation function, number of batch size and epochs during processing, optimizers), and computational complexity problems (e.g., power, time, and storage) for large-scale deep learning model.

VIII. CHALLENGES OF DEEP LEARNING APPROACHES AND FUTURE RESEARCH DIRECTIONS

Currently, the DL methods have a number major challenges that affect the deployment of DL methods on IoT devices while other challenges affect the performance of resource allocation in IoT networks. Such challenges include the model size, scarcity of well-prepared datasets [133], [134], lack of optimal hyperparameters, low resource allocation prediction accuracy, and the need for an improvement in the computational time of resource allocation. Consequently, to develop efficient resource management solutions for critical IoT applications using the deep learning methods, these major challenges still require further research efforts. Hence, important future research directions are provided as follows.

1) ADDRESSING THE DATASET SIZE PROBLEM ASSOCIATED WITH THE DEVELOPMENT OF DL-BASED RESOURCE MANAGEMENT MODELS FOR IoT NETWORKS

Datasets are useful for improving the prediction accuracy and the overall performance of the DL-based resource management models for IoT networks. It is well established that DL requires a large training dataset to be able to build a model that can achieve a good prediction accuracy and generalize well in practice. Hence, researchers working in the area of resource management in IoT networks need to generate a sufficiently large dataset to build resource management models with a good prediction accuracy and capability to generalize well by being able to compute an optimal resource allocation for any channel value. The use of data augmentation methods is promising for increasing the training set. Data generation of simulated data is another useful method. Also, the use of transfer learning method is promising in cases of low-resource dataset. Transfer learning method enable the reuse of the learned representations of a pre-trained DL model for resource management provided the problem domain of two resource management tasks is related. Hence, the transfer learning method is only useful if provided the problem domain of two resource management tasks is related.

2) IMPROVING THE COMPUTATIONAL SPEED OF DL-BASED RESOURCE MANAGEMENT ALGORITHMS FOR IoT NETWORKS

In practical applications, DL-based resource allocation algorithms compute solutions with almost real-time operations. To improve the computational speed of the DL-based resource allocation algorithms for IoT networks, future research is required to explore and develop new acceleration methods for hyperparameter optimization. Future research can also explore the use of techniques like parallel computing and distributed computing [135], [136]. This line of research is believed to reduce the computational speed of DL-based resource allocation algorithms for IoT networks and to also contribute to reducing the power requirements of the devices that implement the DL-based resource allocation algorithms. Also, future studies are required to explore the use of hybrid models to improve on the computational time.

3) ADDRESSING THE COMPUTATIONAL COMPLEXITY ISSUES OF DL-BASED RESOURCE MANAGEMENT ALGORITHMS FOR IoT NETWORKS

The DL technique is promising to solve the resource management challenges arising in time-critical IoT applications, unfortunately, most of these solutions are inefficient due to computational complexity issues in terms of their computational storage space and computational power requirements when deployed on the constrained IoT devices. To enable DL resource management algorithms to be more efficient, future research is necessary to develop new methods for improving the computational complexity of DL resource management models. This line of research can benefit from the use of techniques that are suitable for improving the efficiency of DL models. Examples are knowledge distillation and pruning techniques [137]. This line of research is believed to significantly contribute to enabling DL-based resource allocation algorithms for the devices in IoT networks.

4) REDUCING THE COMPUTATION POWER OF DL-BASED RESOURCE MANAGEMENT ALGORITHMS FOR IoT NETWORKS

In practice, the DL model computes resource allocation solutions through the matrix-vector multiplication operations of the layers. This computation process is sometimes intensive and requires the model to draw the scarce power resource of the IoT devices. Consequently, it is of high importance to see future studies explore and develop techniques for the DL models used for resource allocation computation in IoT networks to reduce their computational power. To achieve this, the use of model distillation and pruning techniques is promising to reduce the computational complexity of the model by reducing the size of the model and by removing the redundant parts of the model [138].

5) IMPROVING THE PREDICTION ACCURACY OF DL-BASED RESOURCE MANAGEMENT ALGORITHMS FOR IoT NETWORKS

Despite the promising benefits of the DL-based resource management algorithms for solving resource allocation problems in IoT applications in almost real-time operations, their accuracy is still limited in terms of the predicted resource allocation solutions. This limitation may not guarantee the efficient usage of scarce bandwidth, power, and computation resources. As a result, further research efforts are essential to design new methods for the DL-based resource allocation algorithms in IoT networks to improve their prediction accuracy performance.

6) DEVELOPING EFFICIENT DL-BASED RESOURCE ALLOCATION ALGORITHMS FOR IoT NETWORKS

In practice, there is no single DL architecture that is all-round superlative to obtain the best resource allocation solutions for different resource management challenges arising in IoT networks due to the varying benefits and shortcomings of different DL architectures. Consequently, when designing DL-based resource allocation approaches for IoT networks, it will be interesting to explore and exploit different types of DL architectures for different resource allocation problems associated with IoT networks to be able to develop efficient DL-based resource allocation algorithms. This research would help to obtain optimal resource allocation solutions for improving throughput, power, and data transmission delay for various critical IoT applications.

7) ADDRESSING THE PERFORMANCE ISSUE RELATED TO UNSUPERVISED DL APPROACHES FOR IoT APPLICATIONS RESOURCE MANAGEMENT PROBLEMS

Due to current lack of standard loss functions for resource management problems related to IoT applications leveraging unsupervised DL models, efficient structures must still be thoroughly investigated and developed to guarantee that the resource allocation solutions of the unsupervised DL approach converge to an optimal point. There is a large scope for improvement in the performance and resource allocation solutions of the unsupervised DL approaches designed for solving the resource management problems associated with the IoT networks.

8) IMPROVING THE PREDICTION PERFORMANCE OF DL-BASED RESOURCE MANAGEMENT MODELS FOR IoT NETWORKS

The DL-based resource management models mostly use gradient descent optimization algorithms (e.g., Adam and SGD) that requires a differentiation or continuous function to train a DL model. The use of algorithms based on gradient descent to optimize the weights and the biases in a DL model often results in a local optimal solution in prediction due to losses during training [116]. To improve the performance of DL-based resource management models, it is key to address the inherent limitations of gradient descent optimization algorithms. A promising method is to investigate the design of novel custom stochastic optimization algorithms that uses a random search strategy or a Bayesian optimization strategy to optimize for network parameters, to improve the training speed, and to obtain a global optimal solution in prediction.

9) ADDRESSING THE COMPLEXITY ISSUE OF DEEP REINFORCEMENT LEARNING APPROACHES DESIGNED FOR IoT NETWORKS

Even though the deep reinforcement learning approaches have promising potential to obtain optimal resource allocation solutions for IoT networks resource allocation problems, they are mostly confronted with a complexity issue during training. For example, as the number of IoT devices implementing a deep reinforcement learning approach is increased, the training complexity of this approach may escalate. This concern may increase the computational resources required of the learning algorithm implementation devices. Also, it may hinder the goal of obtaining resource allocation solutions in real-time operations as required by the time-critical IoT applications. To address the complexity issue associated with the deep reinforcement learning-based resource allocation approaches in IoT networks, future research is required to design and integrate efficient training techniques in such approaches to reduce the training complexity and computational resources. This line of research would contribute to efficiently managing the device power and speed.

10) ADDRESSING THE HYPERPARAMETER OPTIMIZATION ISSUE ASSOCIATED WITH THE DEVELOPMENT OF DL-BASED RESOURCE MANAGEMENT MODELS FOR IoT NETWORKS

The DL-based resource management models require the definition of hyperparameters like the number of hidden layers, the number of neurons in each hidden layer, the activation function(s), the optimizer, and the hidden layer parameters (e.g., weights and biases). The building of a good DL model for resource allocation prediction depends on the optimal tuning of the hyperparameters. To guarantee the realization of optimal hyperparameters to build a good model, future research need to consider the investigation and development of new optimization methods that can be used to determine optimal hyperparameters that enable the network to output a good solution. It will be interesting to also explore the use of different optimization techniques like Bayesian optimization and random search techniques.

11) OPTIMAL ACTIVATION FUNCTION SELECTION STRATEGIES FOR IMPROVING THE PREDICTION ACCURACY PERFORMANCE OF DL-BASED RESOURCE MANAGEMENT MODELS FOR IoT NETWORKS

The use of multiple activation functions may be advantageous to build a DL-based resource management model with a good prediction accuracy for IoT networks. But then, there is a need to be able to select an appropriate activation function based on the system channel conditions. This requires the investigation

TABLE 6. Summary of proposed game theory methods for resource management in IoT networks.

Ref.	Game theory method	Resource allocation	Objective	Advantages	Disadvantages	Year
[128]	Cooperative (coalition) game	Transmit power	Maximize sum rate	Produces optimal resource allocation solutions. Produces a low-complexity resource allocation.	Large number of variables. Complex solution models.	2020
[44]	Cooperative (coalition) game	Harvested power control	Maximize SINR			2018
[129]	Cooperative (bargaining) game	Transmit power	Minimize power consumption	Produces a low-complexity resource allocation. Produces optimal resource allocation solutions.	Complex solution models. Large number of variables.	2018
[131]	Non-cooperative (repeated) game	Power control	Maximize SINR	Produces near-optimal resource allocation solutions	High computations. Lacks stability for an optimal solution.	2016
[132]	Non-cooperative (Stackelberg) game	Transmit power	Minimize power consumption	Produces a low-complexity resource allocation. Produces near optimal resource allocation solutions .	Large number of variables. Complex solution models.	2019

and design of an optimal search strategy that can select the best activation function. A good idea could be to explore and exploit a tabu search method to design an efficient strategy.

12) REDUCING DL MODELS COMPUTATIONAL RESOURCES FOR RESOURCE ALLOCATION PREDICTIONS WITH THE SAGEMAKER NEO TOOL

In practice, the DL models require significant computational resources (e.g., computational size, computational power, and computational time) for resource allocation inference in IoT networks, as they sometimes contain several unnecessary codes and functionality which may not really contribute to the resource allocation prediction of DL models. Such redundant associated codes and functionality increases the computational resources of the DL models. These limitations currently make it hard to deploy DL models for resource allocation on the resource-constrained IoT devices. To make DL models deployable on the low-resource IoT devices, future research may consider the use of the SageMaker Neo tool [139]. This tool is envisaged as a promising tool that can be employed to compile and deploy a computationally efficient resource allocation DL model on IoT devices hardware/processor platforms like the Texas Instruments, Raspberry Pi, ARM, Intel, NVIDIA, and Xilinx [111], [113], [114]. The use of the SageMaker Neo tool has to do with using the tool to optimize an already built DL model in Keras, Tensorflow, PyTorch or MXNet by training and tuning the model, choosing a target hardware platform, and deploying the optimized trained model on the IoT devices. Also, according to the results of the performance test reported on the Resnet-50 model with the MXNet tool and the SageMaker Neo tool in [140], it was reported that the SageMaker Neo tool achieved a computational time of about 5 times faster and a computational size of about 15% more efficiency in RAM usage over the MXNet in making predictions with the ResNet-50 model.

IX. CONCLUSION

This study has presented a comprehensive review of the use of deep learning approaches towards addressing the resource management challenges in IoT networks to improve the performance of IoT networks for various time-critical applications (e.g., industrial IoT, IoT-enabled water quality sensing networks, remote surgery). First, we collected the related published studies between 2012 and 2022 from the Scopus database. Subsequently, we conducted a bibliometric analysis of the collected studies to determine the current research focus in the field. Following this, we conducted a comprehensive review of the relevant studies to determine the existing research gaps. The bibliometric analysis and the comprehensive review revealed that research on the use deep learning approaches for solving resource management challenges in IoT networks is less common. Because of the usefulness of IoT networks in various applications and the resource limitations associated with the IoT networks as well as the need to efficiently use the limited available resource, the IoT networks require advanced and sophisticated resource management solutions to be investigated and developed to improve their data communication performance and operation lifetime. To fill this research gap, in this study, we introduced the use of deep learning on account of its advantages over other artificial intelligence techniques (e.g., optimization approaches and game theory approaches) in the context of computational complexity. Also, because of the lack of optimal solutions for most IoT networks resource management formulations when using the conventional optimization approaches, as such problems are mostly non-convex, we motivate for the use of deep learning, the approaches in this paper to compute resource allocation for the IoT devices in the IoT networks. Moreover, we discussed the fundamentals of deep learning approaches along with their uses, benefits, and challenges. Additionally, we point out important potential research directions and discusses the challenges to address when developing deep learning models to seek resource management solutions in IoT networks. Moreover, an important future work is to extend this work to other areas of IoT, for example IoT network security. This line of future work will help to manage the resource utilization of the resource-intensive security schemes in IoT networks.

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