Resource allocation optimization using artificial intelligence methods in various computing paradigms: A Review

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Abstract
With the advent of smart devices, the demand for various computational paradigms such as the Internet of Things, fog, and cloud computing has increased. However, effective resource allocation remains challenging in these paradigms. This paper presents a comprehensive literature review on the application of artificial intelligence (AI) methods such as deep learning (DL) and machine learning (ML) for resource allocation optimization in computational paradigms. To the best of our knowledge, there are no existing reviews on AI-based resource allocation approaches in different computational paradigms. The reviewed ML-based approaches are categorized as supervised and reinforcement learning (RL). Moreover, DL-based approaches and their combination with RL are surveyed. The review ends with a discussion on open research directions and a conclusion.

Keywords: Resource allocation, Deep learning, Reinforcement learning, Cloud computing, Edge computing, Internet of Things

1 Introduction
The Internet of Things (IoT) incorporates heterogeneous interrelated devices, objects, human users, etc., with common data transfer among diverse platforms and infrastructures, enabling integration and synchronization of systems in a distributed manner. Cyber-physical systems are IoT technology that supports the interaction between human users and objects on the Internet. They are increasingly being used in various industries, including healthcare, transportation, and smart homes [1-5]. Both hardware and software applications—displayed as objects in the IoT environment [6] provide end-user services of a stipulated quality to meet user expectations. However, despite the ubiquitous and rapid proliferation of smart devices, there is no integrated mechanism for comprehensive and fully compatible resource allocation. A work-around solution
for allocating resources to different users in the IoT environment is through the use of smart agents and tools. Their performance can be quantified in various factors, such as power consumption, response time, security level, and cost.

Cloud computing technology, the most popular computing environment on the Internet, can be divided into three categories: the public is the traditional model, e.g., Google App Engine; private comprises infrastructures developed for internal organizational use, e.g., Amazon virtual cloud; and hybrid, which combines public and private clouds (Figure 1) [7-10]. User applications are stored in databases on cloud servers, and cloud systems administrators are the ones who decide what type of cloud to be allocated to users. According to the selected cloud type, a series of applications can be transferred from smart mobile devices to cloud servers. According to user needs, resource providers manage this data exchange using resource virtualization of memory, communication bandwidth, disk, CPU, and software platforms. Cloud computing can provide three types of services: infrastructure as a service (IaaS), e.g., Linode, Rackspace, Cisco Metapod; platform as a service (PaaS), e.g., Windows Azure, Heroku, Google App Engine; and software as a service (SaaS), e.g., Google Apps, Salesforce, Cisco WebEx. Resources in cloud data centers are allocated as on-demand virtual machines. These must possess effective compatibility to empower the cloud computing pattern. It is thus necessary to strategize resource allocation and virtual machine management [11, 12]. This high-level decision-making may potentially be enhanced or replaced by artificial intelligence (AI)-enabled automated algorithms.

![Cloud Computing Diagram](image)

**Figure 1.** Conventional cloud computing model.

Conventional cloud computing is limited by time delay, particularly with long-distance data transfer, which may degrade the quality of service. A new method, fog computing, has recently emerged that by mediating between the IoT and cloud levels, can facilitate data preprocessing and resource management, as well as shorten data transfer delay and reduce network traffic overhead. The computing environment can be conceived as a three-layered framework comprising IoT, fog calculations, and cloud computing [13-16] (Figure 2), in which fog computing extends cloud services to the edge of the network nearer to the end-user to effect the reduction of data processing time and network traffic overhead. This can enhance service provision, especially for devices and applications requiring real-time interactions [17]. The basic entity in fog computing is the fog node, which executes the IoT application [18]. Any device with a network connection, computing, and storage can become a node, e.g., switches, routers, hubs, industrial controllers, surveillance
cameras, etc. With the capacity for a large number of server nodes, fog computing offers one-step customer-server communication and real-time interactions with definable security, low jitter, and reduced time delay. Whereas fog calculations process information starting from where they have been generated to where they are stored, edge computing, a subset of fog computing, is concerned only with processing information close to where it has been created. IoT applications include many services requested by users of a system that must be responded to in real-time by the fog and cloud layers. Resource allocation on local area networks, as in edge computing, confers the advantages of short distances and shorter time delays for users close to the network edge [19].

Figure 2. Multilayer framework for smart computing environments.

AI methods such as supervised and reinforcement learning (RL), especially deep reinforcement learning methods (DRL), can be exploited to optimize resource allocation using various computing paradigms [20-22]. Machine learning (ML) and deep learning (DL) are increasingly exploited in cloud-based systems for resource management and virtualization. They do not require initial state transition and workload modeling. In particular, RL agents can learn to assign resources autonomously to run a cloud system [11]. We were motivated to perform an updated and comprehensive review on AI-enabled resource allocation in various smart computing environments. Many of the published reviews in the literature, which have been summarized in Table 1, do not focus on AI and are limited to specific computing paradigms.

In contrast, a wide variety of computing paradigms have been considered in this paper, including cloud computing, vehicular fog computing, wireless network, IoT systems, vehicular network, 5G networks, machine-to-machine communication, train-to-train communication network, peer-to-peer network, mobile cloud computing, cellular, and wireless IoT networks. From Table 1, it is apparent that there are gaps in investigative research into problem issues such as high latency, high jitter, lack of location awareness, limited mobility support, and lack of support for real-time interactions. Of note, there is a secular trend for researchers to study resource allocation in nascent edge computing, fog computing, 5G mobile network, and wireless network environments. On account of their good performance, the adoption of ML and DL methods for automated decision-making with different computing paradigms has burgeoned. This study dissected many of these new computing paradigms to provide a comprehensive update on resource allocation issues in the contemporary computing landscape.
Table 1. Summary of articles related to resource allocation.

| Paper                      | DL/ML | Short description                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | Paradigm                  |
|----------------------------|-------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------|
| Yousefzai [23]             | N/A   | Examined the schemes based on cloud computing resources by using effective features, e.g., optimization goals, optimization methods, design approaches, and useful functions                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | Cloud computing           |
| Atman [24]                 | ML    | Categorized reinforcement learning and heuristic learning methods for public safety communications on 5G networks                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | Edge computing            |
| Ghabai-Arani [25]          | N/A   | Examined categories of resource management: application placement, resource scheduling, task loading, load balancing, resource allocation, and resource provisioning for the computing environment; and approaches for resource allocation: auction, and optimization                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | Fog computing             |
| Hameed [26]                | N/A   | Energy efficiency for resource allocation problem                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | Cloud computing           |
| Beloglazov [27]            | N/A   | Discussion on advancements achieved in energy-efficient computing                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  | Cloud computing           |
| Shuja [28]                 | N/A   | Analyzed mechanisms to control and coordinate data center resources for energy-efficient operations                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | Cloud computing           |
| Aceto [29]                 | N/A   | Focused on resource monitoring in the cloud computing environment                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | Cloud computing           |
| Jennings [30]              | N/A   | Developed conceptual framework for cloud resource management; recognized challenges of cloud: provision of predictable performance for cloud-hosted applications, achieving global manageability, scalable resource management, understanding economic behavior, and pricing                                                                                                                                                                                                                                                                                                                                                                                                                                                                       | Cloud computing           |
| Goyal [31]                 | N/A   | Discussed implementation details of parallel processing frameworks, e.g., Google MapReduce and Microsoft’s Dryad; focused on security issues in cloud systems                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    | Cloud computing           |
| Hussain [32]               | N/A   | Presented working process for commercial cloud computing service providers and open-source deployment solutions                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | Cloud computing           |
| Huang [33]                 | N/A   | Examined dynamic resource allocation problem task scheduling strategies; examined operation mechanism of system with a SaaS-based cloud computing service under existing infrastructure                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Cloud computing           |
| Ahmed [34]                 | N/A   | Studied virtual machine migration optimization features underlying cloud data center service operators                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | Cloud computing           |
| Ahmed [35]                 | N/A   | Studied virtual machine migration optimization features underlying cloud data center service operators                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | Cloud computing           |
| Vinothina [36]             | N/A   | Analyzed the classification of strategy types and challenges related to resource allocation and their effects on cloud computing; focused specifically on CPU and memory resources                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     | Cloud computing           |
| Anuradha [37]              | N/A   | Examined resource allocation techniques in cloud computing; made a comparison between merits and demerits techniques, and their examined strategy consisted of prediction algorithms for resource requirements and resource allocation; identified efficient resource allocation strategies with effective use of limited resources                                                                                                                                                                                                                                                                                                                                                                      | Cloud computing           |
| Mohamaddiah [38]           | N/A   | Examined resource management, i.e., resource allocation and monitoring strategies; examined problem-solving approaches of resource allocation in the cloud environment                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | Cloud computing           |
| RamMohan [39]              | N/A   | Provided strategies for resource allocation and their applications in the cloud; explained resource allocation in a cloud environment based on dynamic proportions                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | Cloud computing           |
| Casta`neda [40]            | N/A   | Provided a comprehensive overview of various methodologies to achieve common optimization tasks in the downlink of multi-user multiple-input communication systems                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     | Wireless networks         |
| Manvi [41]                 | N/A   | Examined resource management methods, e.g., resource provisioning, resource allocation, resource matching, and resource mapping; provided an overall overview of methods for IaaS in cloud computing                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | Cloud computing           |
| Su [42]                    | N/A   | Examined techniques and models of resource allocation algorithms in 5G network slicing; expressed ideas on software-defined networking and network function virtualization and their tasks in network slicing; presented the management and orchestration architecture of network slice                                                                                                                                                                                                                                                                                                                                                                                                  | 5G wireless networks     |
| Current paper              | ML and DL | Reviewing machine learning and deep learning methods for resource allocation in different computing paradigms                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       | Wireless, 5G, IoT, edge, fog, cloud, and vehicular fog computing |
2 Search strategy

We performed a literature search for publications up to 20th January 2022 in Google Scholar using combinations of the following terms: "resource allocation", "efficient power consumption", "machine learning", "deep learning", "cloud computing", "edge computing", "fog computing", "Internet of Things", "wireless network", and "mobile edge computing". The logic that we adopted to combine these search terms using AND and OR operations is depicted in Figure 3.

![Figure 3. A literature search using combinations of categories of search terms.](image)

The initial search yielded 460 papers, further reduced to 58 papers after excluding unsuitable papers. The exclusion criteria were non-English papers with low citation counts outside this review's scope. Five of the authors of this paper reviewed all the publications based on the aforementioned eligibility criteria, and only papers with at least three positive votes from authors were considered in this review. Additional publications were obtained by manual scrutiny of the references of the 58 selected papers. A final collection of 46 IEEE, 24 Springer, 16 Elsevier, and 23 miscellaneous (from other publishers) publications were included in the review. The taxonomy of the reviewed papers [43] is illustrated in Figure 4.
3 Comprehensive literature study for resource allocation problem
This section presents articles and the taxonomies related to ML and DL.

3.1 Taxonomy related to machine learning methods
ML methods for resource allocation can be divided into RL, supervised learning, and unsupervised learning. The taxonomy related to ML methods for resource allocation problems in different computational environments is shown in Figure 5.

Figure 4. Taxonomy of the reviewed papers in this survey.
Figure 5. Taxonomy related to machine learning methods for resource allocation problems in different computing environments. CC, cloud computing; P2PN, peer-to-peer network; QL-KMM2Mn, Q-learning, K-means machine-to-machine network; QL-VCC, Q-learning vehicular cloud computing; RL-5GN, reinforcement learning 5G network; RL-IOT, reinforcement learning Internet of Things; RL-VCC reinforcement learning 5G network vehicular cloud computing.

3.1.1 Supervised learning methods for resource allocation
Shi et al. [44] applied the Markov decision process (MDP) and Bayesian learning to the study of optimal dynamic resource allocation in the cloud computing environment [45]. They found the former helpful for the allocation of cloud resources for components of network function virtualization, while the latter was predictive of future resource utilization based on historical usage patterns. Their proposed method outperformed greedy techniques, such as dynamic scaling, cost modeling, and virtual machine placement, regarding the total cost of cloud resource allocation. Rohmer et al. [21] proposed a learning-based resource allocation framework for P2P video-on-demand streaming. Using real data [46], they proposed a Bayesian method for predictive analysis of popularity, which enabled dynamic switching between resource allocation strategies in P2P systems. This outperformed fixed strategies like lowest popularity score, lowest critical score, highest uplink first, and greedy in terms of mean rejection rate, maximum rejection rate, etc.

3.1.2 Reinforcement learning methods for resource allocation
RL, a popular AI field, has been applied to diverse domains with good results. In a typical RL workflow (Figure 6), at every time step $t$, the agent observes the environmental state $S_t$ from state space $S$. Depending on $S_t$, the agent chooses action $A_t$ from the set of possible actions $A$. After the action execution, the environment provides the agent with a reward $R_{t+1}$ as well as the next state $S_{t+1}$. The probability of observing $S_{t+1}$ given that action $A_t$ is executed at the state $S_t$ is represented by $p(S_{t+1}, R_{t+1}|S_t, A_t)$. Action selection is made using a policy function $\pi(A_t|S_t)$ which outputs the probability of choosing action $A_t$ given that the observed state is $S_t$. The objective is to learn an optimal policy $\pi^*$ such that the expected sum of discounted rewards is maximized.
Atman and Nayan [24] applied RL and heuristic learning to adaptive resource allocation for 5G mobile networks for public safety communications. In [47], an evolutionary genetic algorithm-based RL model enabled fast convergence to the global optimum through iterative genetic optimization, yielding superior results for long-term network use that exceeded the naïve strategy by over 90%. In the RL model in [48], an adaptive Q-learning algorithm was used for approximate dynamic programming, which achieved fast convergence toward maximum revenue generation for the network owner. Gai and Qiu [4] used the quality of experience level metric combined with RL to devise the RL mapping table method for updating/maintaining the cost table and RL-based resource algorithm for achieving quality of experience level to realize the Smart Content-Centric for Internet-of-Things in a cyber-physical system. While the number of computational nodes significantly impacted training time, training time could be shortened by grouping computational nodes with similar capabilities together. AlQerm and Shihada [20] developed a participatory online learning algorithm with power and modulation adaptation capability in 5G systems that solved cross-tier and co-tier interference problems for optimal allocation, yielding significant improvements in throughput and spectral efficiency, fairness, and outage ratio for different underlay edge transitions. It outperformed downlink spectrum allocation [49], joint resource allocation and link adaptation algorithm [50], and matching resource management schemes [51]. Hussain et al. [52] used the Q-learning algorithm for slot assignment in the machine-to-machine communication network and the k-means clustering algorithm [53] to overcome congestion. The experiments showed that Q-learning increased the probability of slot assignment by more than five times compared to Ethernet slot assignment protocols such as ALOHA and slotted ALOHA.

Hamidreza Arkian et al. [54] proposed the cluster-based vehicular cloud architecture with learning-based resource management (COHORT) architecture, demonstrating increased efficiency, stability, and reliability. An improved COHORT clustering plan, in which fuzzy logic was used for the eclipse selection [55], was compared with two plans based on user-oriented fuzzy logic [56] and lowest-ID clustering schemes [57]. The experiments showed that by increasing the maximum speed from 60 to 120 km/h, the cluster head duration for the COHORT scheme decreased by 15% versus much lower decrements for both the lowest-ID and user-oriented fuzzy logic schemes. Compared with the disCoveRing and cOnsuming services WithiN vehicular clouds (CROWN) architecture [58], COHORT exhibited fewer service discovery and consumption delays as the number of vehicles increased. Salahuddin et al. [19] compared MDP and greedy heuristics [59] for minimizing overhead in the vehicular cloud environment. MDP resulted in better long-term benefits and lower overhead for resource provision.

![Figure 6. The agent-environment interaction in reinforcement learning.](image-url)
Moreover, between the MDP and myopic heuristic methods, the MDP method has a lower overhead for the same configuration selection. The MDP and greed heuristic methods might lead to the same configuration choice. Hence, MDP should perform the myopic heuristic method even in the worst-case scenario.

3.1.3 Takeaway notes on machine learning applications in resource allocation

Table 2 summarizes ML-based (supervised learning and RL) studies on resource allocation in various computing paradigms, many of which involved cloud computing [60]. For example, Shi et al. proposed a 1-step MDP for the dynamic allocation of cloud resources. As a result, their model had a slower response time (time taken to find resource allocation solution) than the genetic algorithm. But when resources must be allocated at specific deadlines, the 1-step optimization failed to foresee the future, which resulted in MDP incurring higher costs versus genetic algorithm.

| Study          | Method                                   | Computing paradigm          | Language/Library | Results/notable features                                                                 |
|----------------|------------------------------------------|----------------------------|------------------|-----------------------------------------------------------------------------------------|
| Shi [44]       | MDP-Bayesian learning                    | Cloud computing            | WorkflowSim      | Time ratio: genetic algorithm/1-step MDP 708/20=35.4; Cost ratio: 1-step MDP/genetic algorithm 6000/1200=5 |
| Rohmer [21]    | Learning-based resource allocation        | P2P streaming system       | Python           | Mean rejection rate=9.2%; max rejection rate=55.2%; mean entropy value=6.20; entropy standard deviation=0.87 |
| Gai [4]        | RL mapping table, RL resource algorithm   | IoT                        | Java             | Average training time: Time/number of input tasks=incremental                           |
| AIQerm [20]    | Online learning                          | 5G systems                 | N/A              | Increased system throughput, spectral efficiency, and Jain’s fairness index; decreased mean signal to interference and noise ratio, and average outage ratio |
| Arkian [54]    | Q-learning with fuzzy logic clustering    | Vehicular cloud computing  | OMNet++ and SUMO | Proposed approach: COHORT facilitates cooperation as a service by sharing resources among moving vehicles |
| Hussin [52]    | Q-learning with K-means clustering        | Machine-to-machine         | N/A              | With increasing the learning rate; the convergence time: decrease, the convergence rate: increase |
| Salahuddin [19]| RL-based MDP                              | Vehicular cloud computing  | MATLAB           | Minimized cumulative virtual machine migration overhead                                  |
| Xiang [61]     | MDP                                      | Adaptive intelligent dynamic water resource planning | N/A              | MDP has been used to optimize several policies for efficient environmental planning    |
| Jorge-Martinez [62]| Kubernetes container scheduling technique    | Mixed cloud computing environment | Kubernetes     | Improved scheduling efficiency of Kubernetes container; takes into account user’s desire for decreased time to launch and cloud provider’s desire for reduced energy usage |
| Zhou [63]      | State-action-reward-state-action (based actor-critic reinforcement learning) | Internet of Remote Things | Python           | Optimal resource allocation and Internet of Remote Things data scheduling using casual information at Low-earth orbit satellites |
| Abedi [64]     | AI-based task distribution algorithm      | Fog cloud computing-IoT    | N/A              | Noticeable reduction in response time and internet traffic compared to cloud-based and fog-based approaches |
| Alemzadeh [65]| Artificial neural networks               | Resource allocation for infrastructure resilience | N/A              | Efficient resource allocation before and after contingencies using multiple trained models; approach evaluated by the real-world interdependent infrastructure of Shelby County, Tennessee |
| Pham [66]      | Whale optimization algorithm             | Wireless networks          | N/A              | Tackled resource allocation in wireless networks using whale optimization algorithm; applied WOA to power allocation for secure throughput maximization, mobile edge computing offloading, resource allocation in 5G wireless networks, etc. |
| Wang [67]      | Modified Q-learning                      | Wireless networks based on mobile edge computing | N/A              | Minimization of the maximal computational and transmission delay for users requesting computational tasks; used RL to learn resource allocation policy based on users’ computational tasks; reduced the maximal delay up to 18% among all users and up to 11.1% compared to the standard Q-learning algorithm |
| Deng [68]      | Improved quantum evolutionary algorithm based on niche co-evolution strategy and enhanced particle swarm optimization | Airport flight management data | N/A              | Suitable gate allocation to airport flights within different time intervals; method evaluated on the actual data from Baiyun Airport; reduced airport management costs |
| Authors   | Method                                                                 | Field                                      | Platform          | Tool  | Summary                                                                                                                                                                                                 |
|----------|------------------------------------------------------------------------|--------------------------------------------|-------------------|-------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Lin [69] | Alternating direction method of multipliers                           | Mobile edge computing                      | N/A               | N/A   | Eliminated the need to search in a high-dimensional space for service placement decisions; computational complexity linear growth in the number of users; scalable to large networks; achieved near-optimal performance in simulation |
| Geetha [70]| Integrated artificial neural network-genetic algorithm               | Cloud computing                            | N/A               | N/A   | Handled unlimited incoming requests in a parallel and distributed manner while ensuring the quality of service; achieved lower (0.5 ms) average turnaround compared to ant colony optimization                                          |
| Merluzzi [71]| Stochastic Lyapunov optimization                                     | Edge machine learning                      | N/A               | N/A   | Offered wireless edge service for training/inference of machine learning tasks while considering limitations of edge servers; aims were energy consumption minimization while considering end-to-end service delay and accuracy, learning accuracy optimization, and ensuring end-to-end delay and bounded average energy consumption |
| Mansor   | Blockchain-assisted data offloading for availability maximization, naïve Bayes | Mobile edge computing                      | MATLAB            |       | Reduced data drops and service delays to maximize data delivery                                                                                                                                          |
| Liang [73]| Hierarchical RL, semi-MDP                                            | Industrial IoT                             | N/A               | N/A   | Improved resource utilization and user quality of experience level with system quality of service guarantee; outperformed traditional greedy algorithm                                                                 |
| Ruan [74]| Evolutionary optimization algorithm                                    | Open radio access network                  | MATLAB            |       | Proactive, dynamic resource allocation scheme; resource deployment for upcoming traffic data processing; evaluated on real-world/artificial datasets; outperformed greedy algorithm                                                                 |
| He [75]  | Meta-hierarchical reinforcement learning                               | Dynamic vehicular networks                 | N/A               |       | Combined hierarchical RL with meta-learning; significant resource management improvement in dynamic vehicular networks by adapting to different scenarios quickly                                                                 |
| Zong [76]| Multi-agent recurrent attention actor-critic, a DRL method            | COVID-19 resource allocation               | N/A               |       | Determined optimal lockdown resource allocation strategies for Arizona, California, Nevada, and Utah in the United States; more flexible resource allocation strategies helpful for wise allocation of limited resources to prevent infection |

| MDP, Markov decision process; RL, reinforcement learning |

### 3.2 Taxonomy related to deep learning methods

Some of the applications of DL methods in resource allocation are illustrated in Figure 7.

![Figure 7. Taxonomy related to DL methods for the resource allocation problem in various computational paradigms.](image-url)

- **DRL-CC**, deep reinforcement learning-cloud computing
- **DRL-MEC**, deep reinforcement learning-mobile edge computing
- **DRL-T2TN**, deep reinforcement learning-train-to-train network
- **DRL-VFC**, deep reinforcement learning-vehicular fog computing
- **DRL-VN**, deep reinforcement learning-vehicular network
- **DRL-WN**, deep reinforcement learning-wireless network
3.2.1 Deep reinforcement learning methods for resource allocation
Karthishbab and Raj [10] used a DRL algorithm based on Q-learning for fair resource allocation in cloud computing environments. The proposed approach outperformed first-in, first-out, and greedy methods in terms of the average response time and average waiting time, even with increasing requests while guaranteeing the quality of service. Excessive power consumption in cloud computing systems reduces system reliability and increases cooling costs. Therefore, balancing power consumption and performance is an important design factor in cloud computing platforms. Liu et al. [11] proposed a joint virtual machine resource allocation and power management framework consisting of a global tier that used deep Q learning to allocate virtual machine resources to servers and a local tier for distributed power management in local servers. A self-cryptographic neural network and weight-sharing scheme were employed to accelerate convergence speed and control the high-dimension mode space. Experiments were implemented using the methods mentioned in actual Google cluster-usage traces [77]. The proposed hierarchical framework was observed to optimize power/energy consumption significantly better than the base round-robin method without significant difference in terms of delay. Wang et al. [78] used deep Q learning to propose in their DRL resource allocation method for smart resource allocation in mobile computing. The method was designed to minimize the expected service time of requests made by mobile devices distributed in different districts. Additionally, the computing load on each mobile edge computing server and network load on data links were balanced in order to achieve a better quality of service. The proposed method improved the average service time as the request aggregation district numbers increased compared to the open shortest path first method [79].

Chen et al. [80] proposed a novel fog resource scheduling scheme based on the minimization of perception-reaction time. Perception-reaction time represents the time consumption of safety-related applications and is closely related to road security and efficiency. Due to the intractability of the formulated optimization problem, DQN was used in [81] to reduce overall delay in the fog computing environment for vehicular applications in the information-centric network Internet of Vehicles. DQN conferred better performance than Q learning, location greedy, and resource greedy algorithms. Vehicular fog computing combined with perception-reaction time criterion is more stabler than architectures such as no fog and no information-centric network. Ye et al. [82] focused on decentralized resource allocation in vehicle-to-vehicle communications for unicast and multicast vehicle communications. Their experiments revealed the superior performance of DQN for resource allocation in vehicle-to-vehicle communications and higher capacity in vehicle-to-infrastructure compared to the random method and dynamic proximity aware resource allocation [83].

DRL can be used for resource allocation in vehicular networks, including methods that encompass observer, objective-oriented unsupervised learning paradigm, and learning accelerated optimization paradigm were examined (Figure 8). Each V2V agent observes the environment and then utilizes its local copy of the trained DRL agent to monitor the resource block selection and power control in a distributed way. Liang et al. [22] used DRL to solve wireless resource allocation problems in the vehicular wireless network environment. Deep deterministic policy gradient yielded the best results among the evaluated RL methods. They reported that their method outperformed weighted minimum mean-squared error [84], significantly reducing computational complexity for the non-deterministic polynomial hard power resource allocation problem [85]. The feed-forward network and convolutional neural network [86] methods in the linear sum assignment programming problem could be used as a real-time solution. The performance of the
two unsupervised methods in [87] using DNN was better than the heuristic weighted minimum mean-squared error. Zhao et al. [88] used distributed DRL for computing resource management, resource allocation, and system complexity reduction in vehicular fog computing environments. They proposed a contract-based incentive mechanism for resource allocation in the vehicular fog network. As the number of vehicles increased, the proposed mechanism incentivized more vehicle participation, improving quality, efficiency, and maintenance. This contrasts with the conventional offloading mechanism in which the computational load of non-cooperative vehicles is returned to the roadside unit, leading to an increase in pressure.

**Figure 8.** Deep reinforcement learning training model for resource allocation in vehicular networks.

Zhao et al. [89] used multi-agent DRL to reduce co-channel interference, prevent collisions, and increase system power in their proposed smart resource allocation method in train-to-train communications. The multi-agent deep Q-network method addressed the train-to-train resource allocation problem, which yielded successful data transfer and improvements in train-to-train connection throughput and overall system throughput. The proposed design was compared with the train-to-train communication resource allocation [90] and the random allocation scheme. In [90], Stackelberg's game theory for power control and weight factors based on proportional fairness standard was proposed for channel selection to address resource allocation in train-to-train communications.

### 3.2.2 Takeaway notes on DL applications in resource allocation

The ability to deal with continuous (as well as discrete) data and high dimensional problems has made DL the de facto standard in many learning problems [91]. DL methods are usually trained in a supervised manner using labeled training data [92], which in practice, are usually available. It is advantageous to combine DL and RL, i.e., DRL, for resource allocation problems to exploit their strengths and attenuate their weaknesses [93]. Table 3 summarizes the results of the reviewed DL-based methods, which have been applied to various computing paradigms like cloud computing, vehicular fog computing, vehicle-to-vehicle communications, mobile edge computing, etc. DRL methods are commonly used, and DRL-based resource allocation yields good performance in co-channel interference, system and energy efficiency, latency, response time, and complexity.

**Table 3.** Using deep learning methods for resource allocation in different computing paradigms.
| Study   | Technique | Computing Paradigm | Language / library | Result |
|---------|-----------|--------------------|--------------------|--------|
| Karthiban [10] | DRL | Cloud computing | CloudSim | Improved average response and waiting time; efficiency 94% |
| Chen [80] | DRL | Vehicular fog computing | N/A | Reduced perception-reaction time; lower average delay for non-safety |
| Ye [82] | DRL | Vehicle-to-vehicle communications | N/A | Increased vehicle-to-infrastructure capacity; optimal vehicle-to-vehicle latency |
| Liu [11] | DRL-LSTM | Cloud computing | N/A | Low energy usage, power/energy savings up by 16.12%; reduced latency by 16.67% |
| Liang [22] | DRL | Vehicular networks | N/A | Accuracy: Hungarian algorithm (100%), CNN (92.76%); classifier accuracy: graph embedding for 1500 training samples (83.88%) |
| Zhao [88] | Distributed DRL + Adam optimizer | Vehicle fog computing | Python | Reduced system complexity; improved computing power and entire system performance |
| Zhao [89] | Multi-agent DRL | Train-to-train | N/A | Improved throughput of the train-to-train link; reduced co-channel interference in the system effectively |
| Wang [78] | DRL resource allocation | Mobile edge computing | Python | Increased minibatch size leading to faster convergence of DRL resource allocation algorithm |
| Guan [94] | DQN | 6G wireless networks | Python + Tensorflow | Hierarchical resource management framework for network slicing to offer diversified services; outperformed greedy resource management |
| Goswami [95] | CNN | Secure industrial IoT network | N/A | CNN-based power allocation in industrial IoT applications; less network residual energy vs. IEEE 802.11; even distribution of power resources |
| Bal [96] | Resource allocation with task scheduling using hybrid machine learning | Cloud computing | N/A | Comprised an improved cat swarm optimization algorithm-based short scheduler for task scheduling that minimized make-span time minimization and maximized throughput maximization; a group optimization-based DNN for efficient resource allocation given bandwidth and resource load constraints; and a lightweight authentication scheme named NSUPREME; outperformed first come, first served and round-robin approaches in resource utilization, energy consumption, and response time |
| Chen [97] | AI-aided joint bit rate selection and radio resource allocation | Fog computing-based radio access | Python | Handled complex optimization in fog computing-based radio access; predicted channel quality change using LSTM; achieved higher guaranteed quality of experience in terms of high average bit rate, low rebuffering ratio, and average bit rate variance |
| Eramo [98] | LSTM | Cloud resource allocation | N/A | LSTM-based traffic forecasting algorithm for resource allocation in network function virtualization; applied different weightings for over-provisioning and under-provisioning; reduced cost by 40% compared to methods based on symmetric cost minimization of prediction error |
| Lee [99] | DNN | Wireless communications systems | Python | Variant of multiobjective evolutionary algorithm based on decomposition (MOEA/D-DU) was combined with ensemble fitness ranking with ranking restriction scheme to achieve better balance between the convergence and diversity in multiobjective optimization; outperformed state-of-the-art methods on test suite problems |
| Lim [100] | DL | Edge computing | N/A | Two-level resource allocation and incentive mechanism design that relied on evolutionary game theory to model cluster selection process dynamics at a lower level; DL-based auction mechanism for evaluation of clusters heads’ services; achieved unique and stable evolutionary game as well as revenue maximization for cluster services |
| Wang [101] | DNN | Integrated mobile edge computing and vehicular edge computing | Python | Dynamically allocated DNN inference computation to multiple vehicles using edge server; allocation optimized using chemical reaction optimization; achieved lower overall latency and failure rate compared to competing schemes; edge, local, and neurosurgeon |
| Ali [102] | DL: power migration expand + EESA | Mobile edge computing | N/A | Novel power migration expand resource allocation and allocation requests to servers with EESA; 26% less energy consumption of mobile edge server, improved service rate by 23%, compared with other algorithms; 70% EESA accuracy for allocating the resources of multiple servers to multiple users |
| He [104] | Blockchain + A3C [103], a DRL method | Edge computing resource allocation in IoT | Pytorch 1.3.1 with Python 3.7 | Enforced security and privacy between IoT devices and edge computing nodes by combining blockchain and DRL, i.e., A3C; used A3C to allocate resources; evaluated method on simulation with three data service subscribers and three edge computing nodes |
| Fang [108] | DQN | Layered fog radio access network | N/A | Used cooperative caching with DQN [105], a DRL-based resource allocation approach, to transmit contents with low latency; evaluated method in a layered fog radio access network; less average network delay compared with cooperative caching with popularity [106], distributed caching with least recently used [107], and no-cache |
| Eramo [109] | Convolutional LSTM | Network function virtualization | Python | Used LSTM in an integrated resource prediction/allocation approach comprising monitoring agent, prediction/allocation agent, and reconfiguration and placement agent; was superior to methods that performed resource prediction and allocation processes separately |
4 Open research challenges and future work

Resource allocation is usually formulated as an optimization problem. Accordingly, it is susceptible to intractable optimization problems [110], in which problem constraints would have to be relaxed at the cost of risking sub-optimal solutions. ML/DL methods have the potential to come up with acceptable near-optimal solutions in reasonable amounts of time for challenging optimization problems. To this end, researchers’ interest in interdisciplinary approaches has increased, and various AI methods (ML/DL-based) are under investigation for resource allocation [111]. In this work, we have comprehensively reviewed the findings of studies of AI approaches to the resource allocation problems in diverse computing paradigms and have discussed the successes and shortcomings. Future work is still needed to develop new methods capable of handling resource allocation with reasonable computational complexity and performance. This comprehensive review will constitute a valuable reference for researchers in the field.

The performance of AI methods is dependent on the availability and quality of training data. There is a huge problem of noisy and unlabeled data in heterogeneous platforms such as IoT, mobile edge computing, etc. Many AI methods rely on supervised training, which requires labeled training data with good quality. Preparing such data may be difficult and time-consuming, which poses a limitation to applying AI methods. For example, one fast-growing use case is the Internet of Medical Things, which concerns remote healthcare services. Researchers' ultimate goal is to develop AI-based healthcare systems that dispense with the need for human intervention. However, there is extremely low tolerance for erroneous decisions in safety-critical domains such as healthcare. Therefore, high-quality labeled training samples are mandatory for training AI models. Such data are challenging to obtain since the labeling process is typically carried out fully manually by medical experts.

Another factor affecting the performance of complex AI models is hyperparameter tuning. For a DL model to be trained for a specific task, apart from model parameters that will have to be adjusted during the training process, model hyperparameters such as the number of hidden layers, learning rate, regularization coefficient, etc. are critical to successful training. Hyperparameter tuning requires searching a complex multidimensional space, which is onerous and can be confusing. Hyperparameter optimization tools like Wandb [112], Comet [113], etc., may facilitate the process by keeping track of the conducted optimization experiments. As an illustration, Figure 9 depicts the sample outputs of tuning hyperparameters like learning rate, weight decay, b1 and b2 (for Adam optimizer), etc., using Comet during training of a typical DNN. The effect of each hyperparameter can be easily visualized, leading to easier and more effective hyperparameter tuning.
Figure 9. Sample output of hyperparameter optimization using Comet tool. Each sinusoid curve corresponds to one training experiment. The color scale on the right side represents the validation F1-score, with warmer and cooler colors corresponding to higher and lower scores, respectively.

Another important challenge regarding applying AI methods in different computing paradigms is the ability to make the models contextual. Existing literature on AI methods and DL is mostly about designing and training a model specialized at doing a single task [111]. However, in computing paradigms such as IoT, the tasks may dynamically change, and training DL models to adapt to new changes will impose high computation costs, which is impractical. Existing works have utilized conditional generative adversarial networks to interpolate between different 3D objects [114] or between different ages of a human face [115, 116]. Following the footsteps of these studies, it might be possible to train generative adversarial networks to output appropriate parameters set for another DNN based on a set of input conditions. This way, the training effort is devoted to the generative adversarial network, and no further training will be required when running the application.

Effective resource allocation approaches must be able to withstand unforeseen resource shortcomings. For instance, should a cloud computing server temporarily loses some of its computation resources due to a cyber-attack, it will be necessary to change the resource allocation priorities. Tasks with higher priorities will be granted access to the available resources. Dynamically changing the resource allocation strategy is indirectly related to the contextual models mentioned in the previous paragraph.

5 Conclusion

Communication between different systems, including smart devices, storage, servers, communication networks, is an undeniable part of daily life. Optimizing and increasing the efficiency of this communication is an important consideration, and resource allocation is a critical bottleneck. Researchers are using innovative AI methods to optimize resource allocation according to the data flow during network operation to solve the challenge of resource allocation. These measures have moved the industry towards automated resource management on a large and complex scale. This article has reviewed various AI methods used to solve the resource allocation problem in different computing environments and summarized the performance in terms of response time, energy efficiency, throughput, cost, service consuming delay, convergence time,
latency, etc. New resource allocation methods are continually being developed, and the computing environments have shifted from cloud to fog and edge. While resource allocation in the cloud environment has been the subject of much research in the last decade, recent attention has focused on resource allocation at the level of smart devices.

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