Resource Allocation Optimization Using Artificial Intelligence Methods in Various Computing Paradigms: a Review

Javad Hassannataj Joloudari, Roohallah Alizadehsani, Issa Nodehi, Sanaz Mojrian, Fatemeh Fazl, Sahar Khanjani Shirkharkolaie, H M Dipu Kabir, Ru-San Tan and U Rajendra Acharya

March 28, 2022

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

Javad Hassannataj Joloudari[1,*], Roohallah Alizadehsani[2], Issa Nodehi[3], Sanaz Mojrian[4], Fatemeh Fazl[1], Sahar Khanjani Shirkharkolaie[4], H M Dipu Kabir[2], Ru-San Tan[5], U Rajendra Acharya[6,7,8]

[1]Department of Computer Engineering, Faculty of Engineering, University of Birjand, Birjand 9717434765, Iran
[2]Institute for Intelligent Systems Research and Innovation, Deakin University, Geelong, VIC 3216, Australia
[3]Department of Computer Engineering, Qom University of Technology, Qom, Iran
[4]Department of Information Technology, Mazandaran University of Science and Technology, Babol, Iran
[5]Department of Cardiology, National Heart Centre Singapore, Singapore
[6]School of Science and Technology, Singapore University of Social Sciences, Singapore
[7]Ngee Ann Polytechnic, Singapore, 599489, Singapore
[8]Dept. of Biomedical Informatics and Medical Engineering, Asia University, Taichung, Taiwan

[*]Corresponding author: javad.hassannataj@birjand.ac.ir

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.

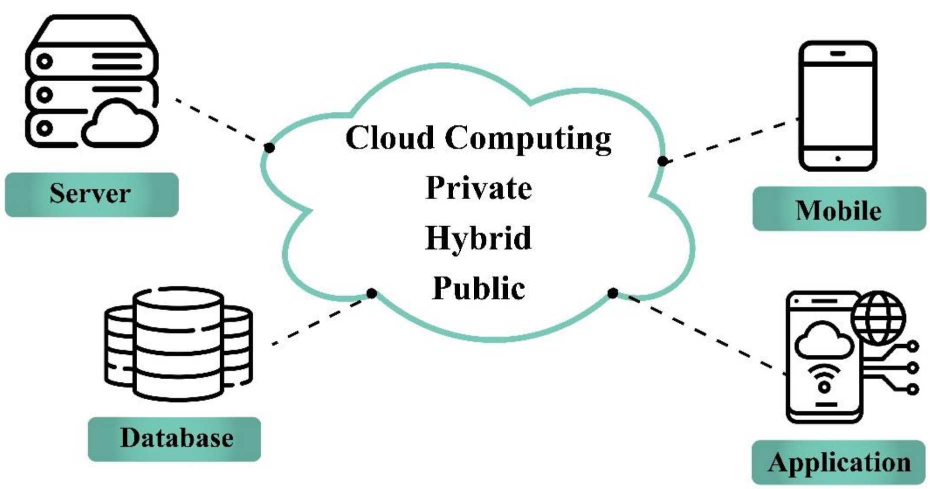

Figure 1. Conventional cloud computing model.

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].

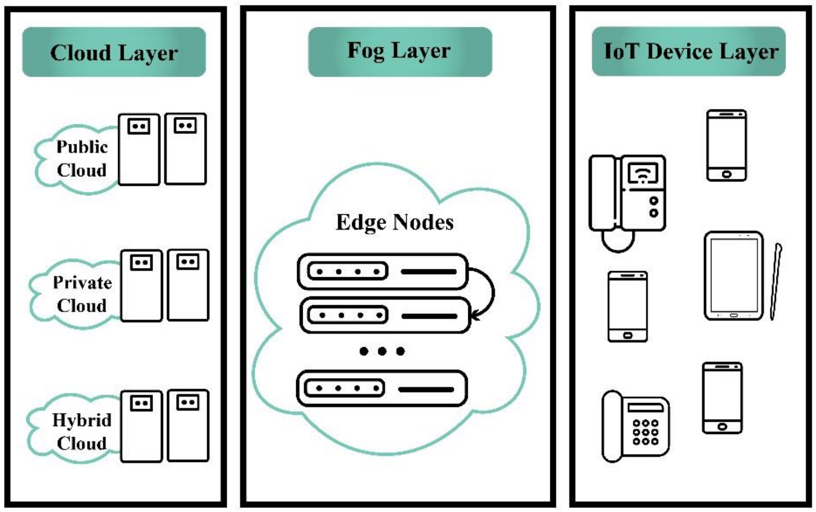

Figure 2. Multilayer framework for smart computing environments.

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
Ghobaei-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**

The contributions of this article are:

- Comprehensive literature review on ML- and DL-based methods for resource allocation problems in emerging computing environments.
- Comparison of AI methods used to solve resource allocation problems.
- Discussion of gaps and future research challenges in resource allocation in multilayer computing environments.

The rest of this article is organized as follows. In Section 2, the search strategy for the review is described. In Section 3, the findings of the literature review are presented. In Section 4, open research challenges and future works will be discussed. The conclusion is presented in Section 5.

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.

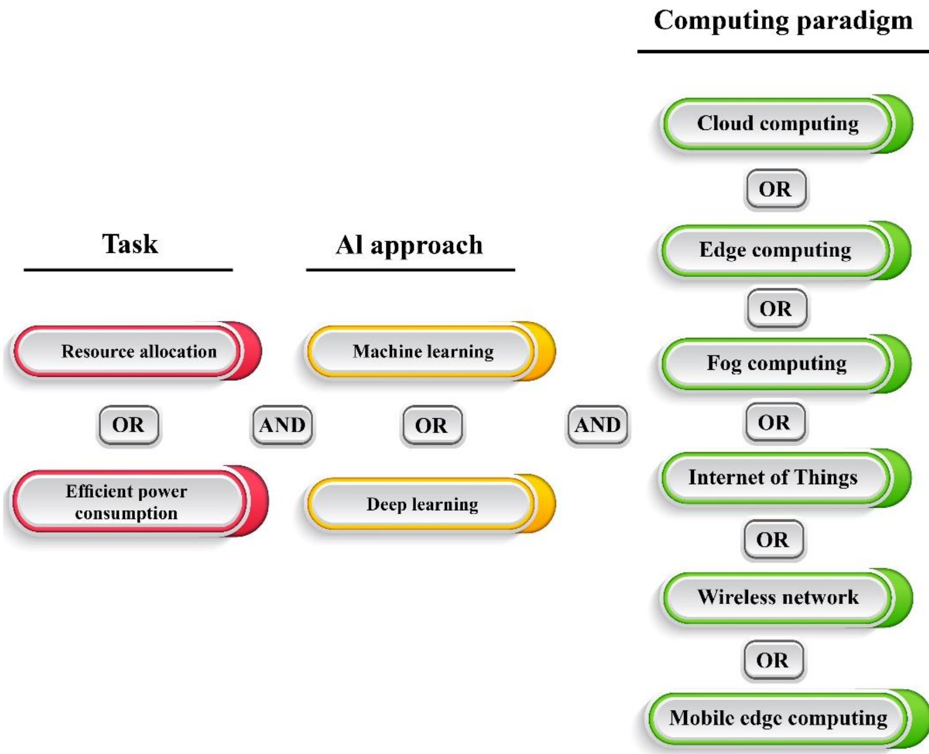

Figure 3. A literature search using combinations of categories of search terms.

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.

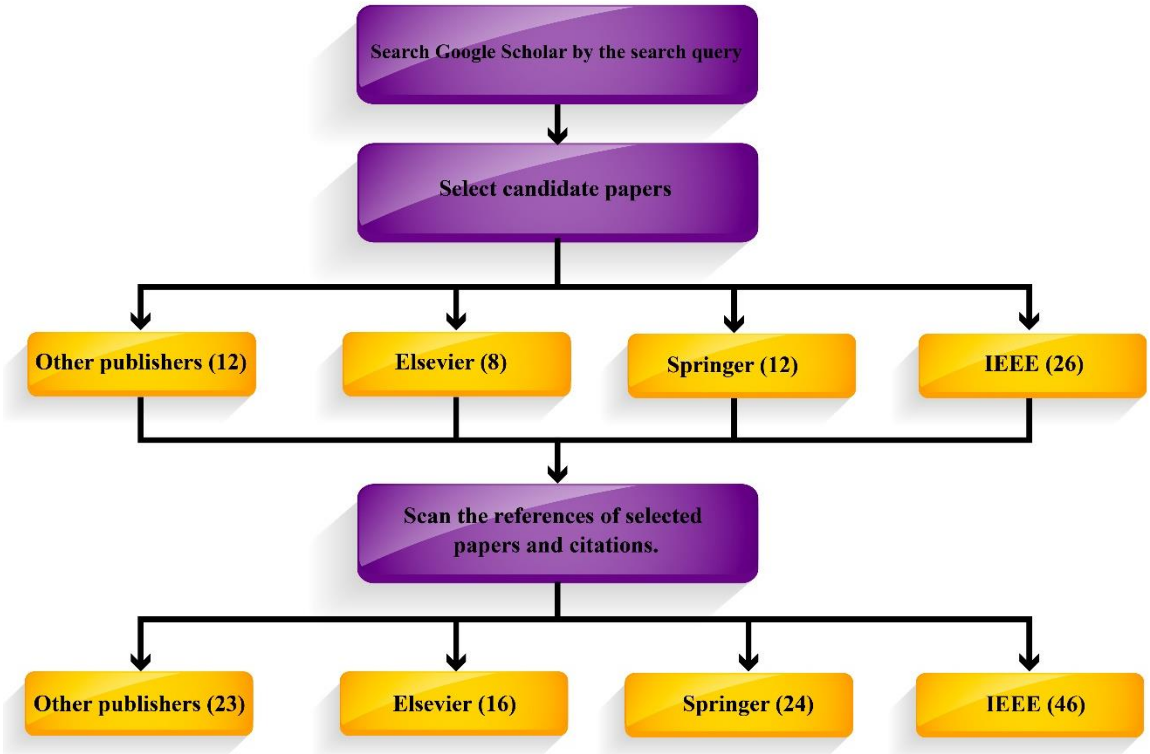

Figure 4. Taxonomy of the reviewed papers in this survey.

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.

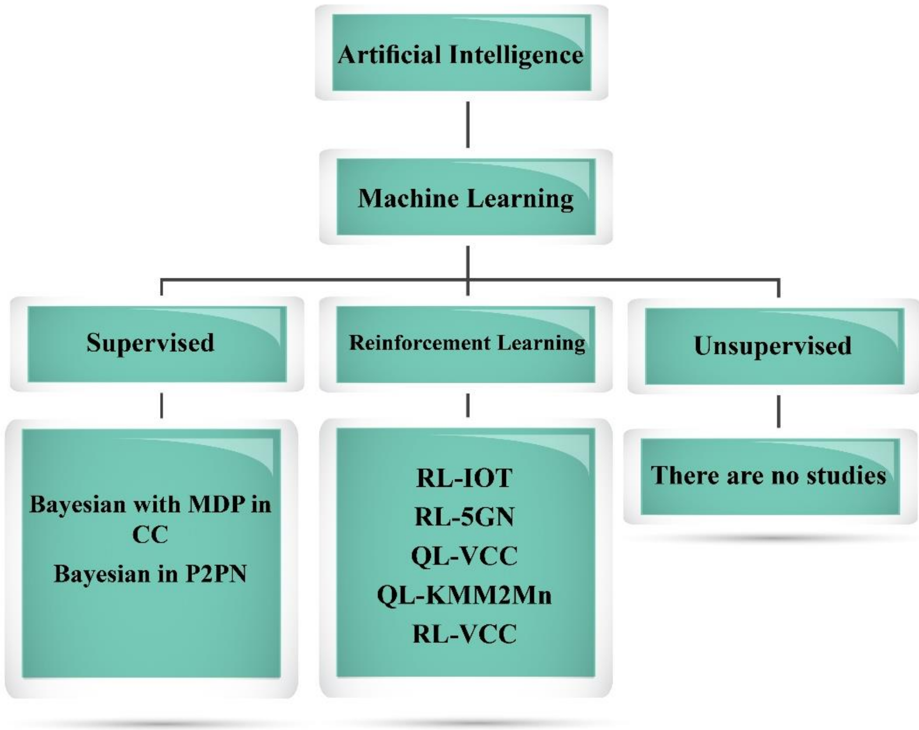

Figure 5. Taxonomy related to machine learning methods for resource allocation problems in different computing environments. CC, cloud computing; P2PN, peer-to-peer network; QL-KMM2Mn, Q-learning, K-means machine-to-machine network; QL-VCC, Q-learning vehicular cloud computing; RL-5GN, reinforcement 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 π^* such that the expected sum of discounted rewards is maximized.

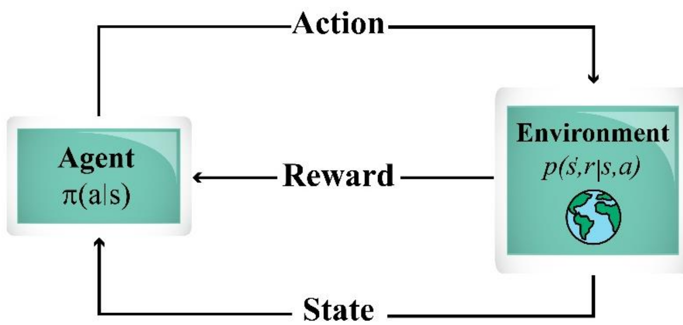

Figure 6. The agent-environment interaction in reinforcement learning.

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.

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.

Table 2. Using machine learning methods for resource allocation in different computing paradigms.

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
AlQerm [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 communication	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

Lin [69]	Alternating direction method of multipliers	Mobile edge computing	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	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	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
Manogaran [72]	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	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.

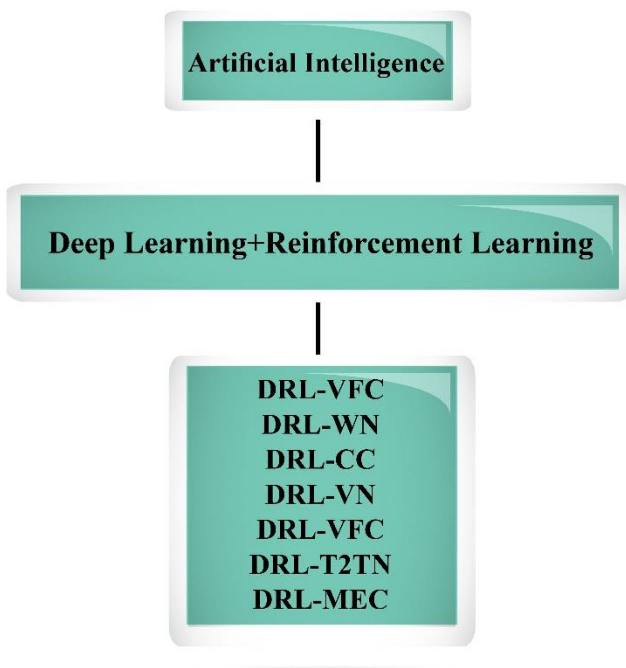

Figure 7. Taxonomy related to DL methods for the resource allocation problem in various computational paradigms.

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

Karthiban 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.

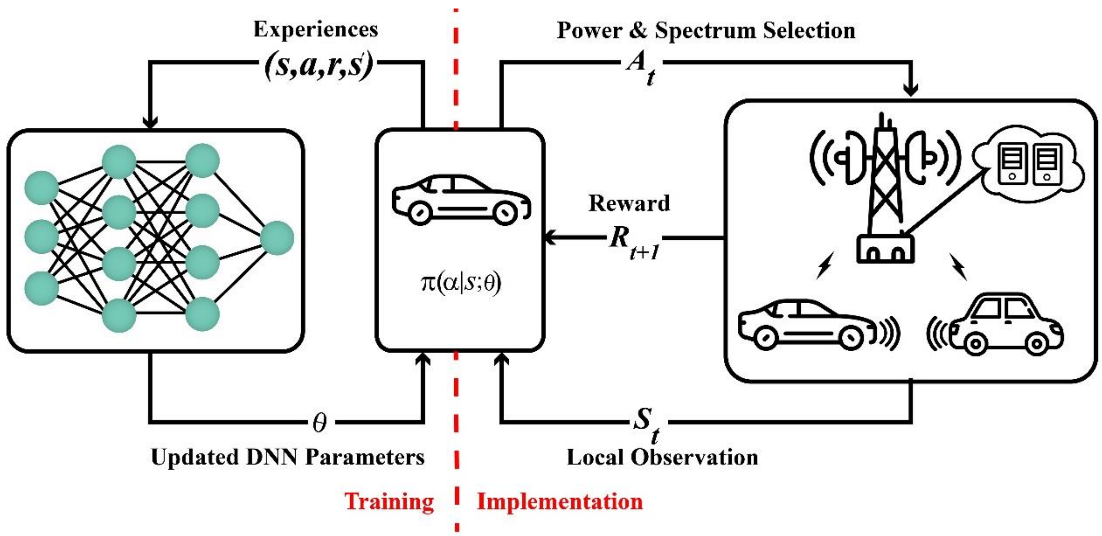

Figure 8. Deep reinforcement learning training model for resource allocation in vehicular networks.

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 by16.67%,
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

A3C, asynchronous advantage actor-critic; AI, artificial intelligence; CNN, convolutional neural network; DL, deep learning; DNN, deep neural network; DQN, deep Q learning; DRL, deep reinforcement learning; EESA, energy-efficient smart allocator; IoT, Internet of Things; LSTM, long short-term memory

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.

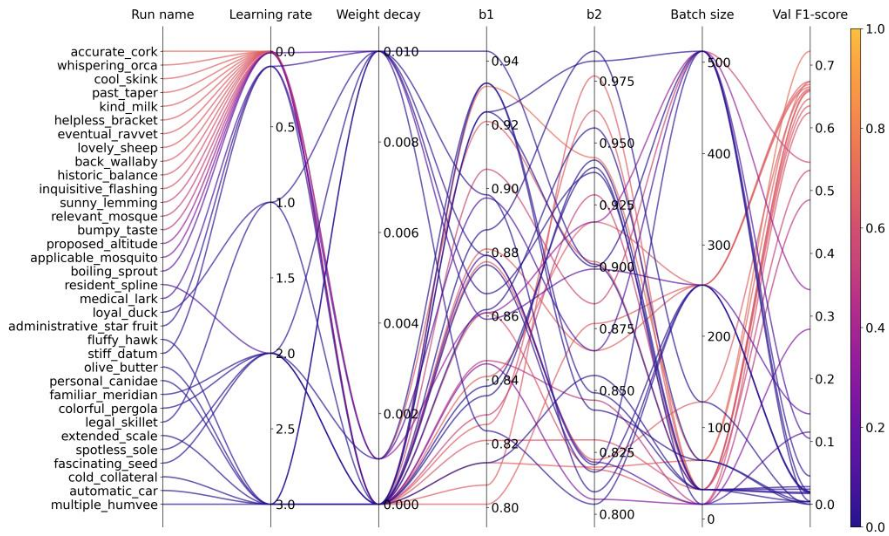

Figure 9. Sample output of hyperparameter optimization using Comet tool. Each sinusoid curve corresponds to one training experiment. The color scale on the right side represents the validation F1-score, with warmer and cooler colors corresponding to higher and lower scores, respectively.

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.

References

[1] Y. Ning, X. Chen, Z. Wang, and X. Li, "An uncertain multi-objective programming model for machine scheduling problem," *International Journal of Machine Learning and Cybernetics*, vol. 8, no. 5, pp. 1493-1500, 2017.

[2] K. Gai, M. Qiu, and X. Sun, "A survey on FinTech," *Journal of Network and Computer Applications*, vol. 103, pp. 262-273, 2018.

[3] R. Liu, C. Vellaithurai, S. S. Biswas, T. T. Gamage, and A. K. Srivastava, "Analyzing the cyber-physical impact of cyber events on the power grid," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2444-2453, 2015.

[4] K. Gai and M. Qiu, "Optimal resource allocation using reinforcement learning for IoT content-centric services," *Applied Soft Computing*, vol. 70, pp. 12-21, 2018.

[5] V. Hahanov, *Cyber physical computing for IoT-driven services*. Springer, 2018.

[6] H. Ma and J. Wang, "Application of artificial intelligence in intelligent decision-making of human resource allocation," in *International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy*, 2020: Springer, pp. 201-207.

[7] L. Tong, Y. Li, and W. Gao, "A hierarchical edge cloud architecture for mobile computing," in *IEEE INFOCOM 2016-The 35th Annual IEEE International Conference on Computer Communications*, 2016: IEEE, pp. 1-9.

[8] S. Bitam and A. Mellouk, "Its-cloud: Cloud computing for intelligent transportation system," in *2012 IEEE global communications conference (GLOBECOM)*, 2012: IEEE, pp. 2054-2059.

[9] S. Bitam, A. Mellouk, and S. Zeadally, "VANET-cloud: a generic cloud computing model for vehicular Ad Hoc networks," *IEEE Wireless Communications*, vol. 22, no. 1, pp. 96-102, 2015.

[10] K. Karthiban and J. S. Raj, "An efficient green computing fair resource allocation in cloud computing using modified deep reinforcement learning algorithm," *Soft Computing*, pp. 1-10, 2020.

[11] N. Liu *et al.*, "A hierarchical framework of cloud resource allocation and power management using deep reinforcement learning," in *2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS)*, 2017: IEEE, pp. 372-382.

[12] A. Patel, M. Taghavi, K. Bakhtiyari, and J. C. Júnior, "An intrusion detection and prevention system in cloud computing: A systematic review," *Journal of network and computer applications*, vol. 36, no. 1, pp. 25-41, 2013.

[13] X. Xu *et al.*, "Dynamic resource allocation for load balancing in fog environment," *Wireless Communications and Mobile Computing*, vol. 2018, 2018.

[14] S. Shamshirband *et al.*, "Game theory and evolutionary optimization approaches applied to resource allocation problems in computing environments: A survey," *Mathematical Biosciences and Engineering*, vol. 18, no. 6, pp. 9190-9232, 2021.

[15] I. Odun-Ayo, R. Goddy-Worlu, J. Yahaya, and V. Geteloma, "A systematic mapping study of cloud policy languages and programming models," *Journal of King Saud University-Computer and Information Sciences*, vol. 33, no. 7, pp. 761-768, 2021.

[16] H. A. Alobaidy, M. J. Singh, M. Behjati, R. Nordin, and N. F. Abdullah, "Wireless Transmissions, Propagation and Channel Modelling for IoT Technologies: Applications and Challenges," *IEEE Access*, vol. 10, pp. 24095-24131, 2022.

[17] I. Stojmenovic and S. Wen, "The fog computing paradigm: Scenarios and security issues," in *2014 federated conference on computer science and information systems*, 2014: IEEE, pp. 1-8.

[18] R. A. Sadek, "Hybrid energy aware clustered protocol for IoT heterogeneous network," *Future Computing and Informatics Journal*, vol. 3, no. 2, pp. 166-177, 2018.

[19] M. A. Salahuddin, A. Al-Fuqaha, and M. Guizani, "Reinforcement learning for resource provisioning in the vehicular cloud," *IEEE Wireless Communications*, vol. 23, no. 4, pp. 128-135, 2016.

[20] I. AlQerm and B. Shihada, "A cooperative online learning scheme for resource allocation in 5G systems," in *2016 IEEE International Conference on Communications (ICC)*, 2016: IEEE, pp. 1-7.

[21] T. Rohmer, A. Nakib, and A. Nafaa, "A learning-based resource allocation approach for P2P streaming systems," *IEEE Network*, vol. 29, no. 1, pp. 4-11, 2015.

[22] L. Liang, H. Ye, G. Yu, and G. Y. Li, "Deep-learning-based wireless resource allocation with application to vehicular networks," *Proceedings of the IEEE*, vol. 108, no. 2, pp. 341-356, 2019.
[23] A. Yousafzai *et al.*, "Cloud resource allocation schemes: review, taxonomy, and opportunities," *Knowledge and Information Systems*, vol. 50, no. 2, pp. 347-381, 2017.
[24] A. Othman and N. A. Nayan, "Efficient admission control and resource allocation mechanisms for public safety communications over 5G network slice," *Telecommunication Systems*, vol. 72, no. 4, pp. 595-607, 2019.
[25] M. Ghobaei-Arani, A. Souri, and A. A. Rahmanian, "Resource management approaches in fog computing: A comprehensive review," *Journal of Grid Computing*, pp. 1-42, 2019.
[26] A. Hameed *et al.*, "A survey and taxonomy on energy efficient resource allocation techniques for cloud computing systems," *Computing*, vol. 98, no. 7, pp. 751-774, 2016.
[27] A. Beloglazov, R. Buyya, Y. C. Lee, and A. Zomaya, "A taxonomy and survey of energy-efficient data centers and cloud computing systems," in *Advances in computers*, vol. 82: Elsevier, 2011, pp. 47-111.
[28] J. Shuja *et al.*, "Survey of techniques and architectures for designing energy-efficient data centers," *IEEE Systems Journal*, vol. 10, no. 2, pp. 507-519, 2014.
[29] G. Aceto, A. Botta, W. De Donato, and A. Pescapè, "Cloud monitoring: A survey," *Computer Networks*, vol. 57, no. 9, pp. 2093-2115, 2013.
[30] B. Jennings and R. Stadler, "Resource management in clouds: Survey and research challenges," *Journal of Network and Systems Management*, vol. 23, no. 3, pp. 567-619, 2015.
[31] A. Goyal and S. Dadizadeh, "A survey on cloud computing," *University of British Columbia Technical Report for CS*, vol. 508, pp. 55-58, 2009.
[32] H. Hussain *et al.*, "A survey on resource allocation in high performance distributed computing systems," *Parallel Computing*, vol. 39, no. 11, pp. 709-736, 2013.
[33] L. Huang, H.-s. Chen, and T.-t. Hu, "Survey on Resource Allocation Policy and Job Scheduling Algorithms of Cloud Computing1," *JSW*, vol. 8, no. 2, pp. 480-487, 2013.
[34] R. W. Ahmad, A. Gani, S. H. A. Hamid, M. Shiraz, F. Xia, and S. A. Madani, "Virtual machine migration in cloud data centers: a review, taxonomy, and open research issues," *The Journal of Supercomputing*, vol. 71, no. 7, pp. 2473-2515, 2015.
[35] R. W. Ahmad, A. Gani, S. H. A. Hamid, M. Shiraz, A. Yousafzai, and F. Xia, "A survey on virtual machine migration and server consolidation frameworks for cloud data centers," *Journal of network and computer applications*, vol. 52, pp. 11-25, 2015.
[36] V. Vinothina, R. Sridaran, and P. Ganapathi, "A survey on resource allocation strategies in cloud computing," *International Journal of Advanced Computer Science and Applications*, vol. 3, no. 6, pp. 97-104, 2012.
[37] V. Anuradha and D. Sumathi, "A survey on resource allocation strategies in cloud computing," in *International Conference on Information Communication and Embedded Systems (ICICES2014)*, 2014: IEEE, pp. 1-7.
[38] M. H. Mohamaddiah, A. Abdullah, S. Subramaniam, and M. Hussin, "A survey on resource allocation and monitoring in cloud computing," *International Journal of Machine Learning and Computing*, vol. 4, no. 1, pp. 31-38, 2014.
[39] N. R. Mohan and E. B. Raj, "Resource Allocation Techniques in Cloud Computing--Research Challenges for Applications," in *2012 fourth international conference on computational intelligence and communication networks*, 2012: IEEE, pp. 556-560.
[40] E. Castaneda, A. Silva, A. Gameiro, and M. Kountouris, "An overview on resource allocation techniques for multi-user MIMO systems," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 1, pp. 239-284, 2016.
[41] S. S. Manvi and G. K. Shyam, "Resource management for Infrastructure as a Service (IaaS) in cloud computing: A survey," *Journal of network and computer applications*, vol. 41, pp. 424-440, 2014.
[42] R. Su *et al.*, "Resource allocation for network slicing in 5G telecommunication networks: A survey of principles and models," *IEEE Network*, vol. 33, no. 6, pp. 172-179, 2019.
[43] H. W. Loh *et al.*, "Application of Photoplethysmography signals for Healthcare systems: An in-depth review," *Computer Methods and Programs in Biomedicine*, p. 106677, 2022.
[44] R. Shi *et al.*, "MDP and machine learning-based cost-optimization of dynamic resource allocation for network function virtualization," in *2015 IEEE International Conference on Services Computing*, 2015: IEEE, pp. 65-73.
[45] N. M. K. Chowdhury and R. Boutaba, "A survey of network virtualization," *Computer Networks*, vol. 54, no. 5, pp. 862-876, 2010.
[46] X. Cheng, C. Dale, and J. Liu, "Statistics and social network of youtube videos," in *2008 16th Interntional Workshop on Quality of Service*, 2008: IEEE, pp. 229-238.
[47] B. Han, J. Lianghai, and H. D. Schotten, "Slice as an evolutionary service: Genetic optimization for inter-slice resource management in 5G networks," *IEEE Access*, vol. 6, pp. 33137-33147, 2018.
[48] D. Bega, M. Gramaglia, A. Banchs, V. Sciancalepore, K. Samdanis, and X. Costa-Perez, "Optimising 5G infrastructure markets: The business of network slicing," in *IEEE INFOCOM 2017-IEEE Conference on Computer Communications*, 2017: IEEE, pp. 1-9.

[49] T. R. Omar, A. E. Kamal, and J. M. Chang, "Downlink spectrum allocation in 5g hetnets," in *2014 International Wireless Communications and Mobile Computing Conference (IWCMC)*, 2014: IEEE, pp. 12-17.
[50] S. Rostami, K. Arshad, and P. Rapajic, "A joint resource allocation and link adaptation algorithm with carrier aggregation for 5G LTE-Advanced network," in *2015 22nd International Conference on Telecommunications (ICT)*, 2015: IEEE, pp. 102-106.
[51] S. A. Kazmi *et al.*, "Resource management in dense heterogeneous networks," in *2015 17th Asia-Pacific Network Operations and Management Symposium (APNOMS)*, 2015: IEEE, pp. 440-443.
[52] F. Hussain, A. Anpalagan, A. S. Khwaja, and M. Naeem, "Resource allocation and congestion control in clustered M2M communication using Q-learning," *Transactions on Emerging Telecommunications Technologies,* vol. 28, no. 4, p. e3039, 2017.
[53] Y. Wang *et al.*, "Information Theoretic Weighted Fuzzy Clustering Ensemble," *CMC-COMPUTERS MATERIALS & CONTINUA,* vol. 67, no. 1, pp. 369-392, 2021.
[54] H. R. Arkian, R. E. Atani, A. Diyanat, and A. Pourkhalili, "A cluster-based vehicular cloud architecture with learning-based resource management," *The Journal of Supercomputing,* vol. 71, no. 4, pp. 1401-1426, 2015.
[55] H. R. Arkian, R. E. Atani, and S. Kamali, "FcVcA: A fuzzy clustering-based vehicular cloud architecture," in *2014 7th International Workshop on Communication Technologies for Vehicles (Nets4Cars-Fall)*, 2014: IEEE, pp. 24-28.
[56] I. Tal and G.-M. Muntean, "User-oriented fuzzy logic-based clustering scheme for vehicular ad-hoc networks," in *2013 IEEE 77th Vehicular Technology Conference (VTC Spring)*, 2013: IEEE, pp. 1-5.
[57] M. Gerla and J. T.-C. Tsai, "Multicluster, mobile, multimedia radio network," *Wireless networks,* vol. 1, no. 3, pp. 255-265, 1995.
[58] K. Mershad and H. Artail, "Finding a STAR in a Vehicular Cloud," *IEEE Intelligent transportation systems magazine,* vol. 5, no. 2, pp. 55-68, 2013.
[59] M. A. Salahuddin, A. Al-Fuqaha, and M. Guizani, "Software-defined networking for rsu clouds in support of the internet of vehicles," *IEEE Internet of Things journal,* vol. 2, no. 2, pp. 133-144, 2014.
[60] M. A. Wiering and M. Van Otterlo, "Reinforcement learning," *Adaptation, learning, and optimization,* vol. 12, no. 3, p. 729, 2012.
[61] X. Xiang, Q. Li, S. Khan, and O. I. Khalaf, "Urban water resource management for sustainable environment planning using artificial intelligence techniques," *Environmental Impact Assessment Review,* vol. 86, p. 106515, 2021/01/01/ 2021, doi: https://doi.org/10.1016/j.eiar.2020.106515.
[62] D. Jorge-Martinez *et al.*, "Artificial intelligence-based Kubernetes container for scheduling nodes of energy composition," *International Journal of System Assurance Engineering and Management,* pp. 1-9, 2021.
[63] D. Zhou, M. Sheng, Y. Wang, J. Li, and Z. Han, "Machine Learning-Based Resource Allocation in Satellite Networks Supporting Internet of Remote Things," *IEEE Transactions on Wireless Communications,* vol. 20, no. 10, pp. 6606-6621, 2021.
[64] M. Abedi and M. Pourkiani, "Resource allocation in combined fog-cloud scenarios by using artificial intelligence," in *2020 Fifth International Conference on Fog and Mobile Edge Computing (FMEC)*, 2020: IEEE, pp. 218-222.
[65] S. Alemzadeh, H. Talebiyan, S. Talebi, L. Duenas-Osorio, and M. Mesbahi, "Resource Allocation for Infrastructure Resilience using Artificial Neural Networks," in *2020 IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI)*, 2020: IEEE, pp. 617-624.
[66] Q.-V. Pham, S. Mirjalili, N. Kumar, M. Alazab, and W.-J. Hwang, "Whale optimization algorithm with applications to resource allocation in wireless networks," *IEEE Transactions on Vehicular Technology,* vol. 69, no. 4, pp. 4285-4297, 2020.
[67] S. Wang, M. Chen, X. Liu, C. Yin, S. Cui, and H. V. Poor, "A machine learning approach for task and resource allocation in mobile-edge computing-based networks," *IEEE Internet of Things Journal,* vol. 8, no. 3, pp. 1358-1372, 2020.
[68] W. Deng, J. Xu, H. Zhao, and Y. Song, "A Novel Gate Resource Allocation Method Using Improved PSO-Based QEA," *IEEE Transactions on Intelligent Transportation Systems,* pp. 1-9, 2020, doi: 10.1109/TITS.2020.3025796.
[69] Z. Lin, S. Bi, and Y.-J. A. Zhang, "Optimizing AI service placement and resource allocation in mobile edge intelligence systems," *IEEE Transactions on Wireless Communications,* vol. 20, no. 11, pp. 7257-7271, 2021.
[70] R. Geetha and V. Parthasarathy, "An advanced artificial intelligence technique for resource allocation by investigating and scheduling parallel-distributed request/response handling," *Journal of Ambient Intelligence and Humanized Computing,* vol. 12, no. 7, pp. 6899-6909, 2021.
[71] M. Merluzzi, P. Di Lorenzo, and S. Barbarossa, "Wireless edge machine learning: Resource allocation and trade-offs," *IEEE Access,* vol. 9, pp. 45377-45398, 2021.

[72] G. Manogaran, S. Mumtaz, C. X. Mavromoustakis, E. Pallis, and G. Mastorakis, "Artificial intelligence and blockchain-assisted offloading approach for data availability maximization in edge nodes," *IEEE Transactions on Vehicular Technology,* vol. 70, no. 3, pp. 2404-2412, 2021.
[73] H. Liang *et al.*, "Reinforcement learning enabled dynamic resource allocation in the Internet of vehicles," *IEEE Transactions on Industrial Informatics,* vol. 17, no. 7, pp. 4957-4967, 2020.
[74] G. Ruan, L. L. Minku, Z. Xu, and X. Yao, "Evolutionary Optimization for Proactive and Dynamic Computing Resource Allocation in Open Radio Access Network," *arXiv preprint arXiv:2201.04361*, 2022.
[75] Y. He, Y. Wang, Q. Lin, and J. Li, "Meta-Hierarchical Reinforcement Learning (MHRL)-based Dynamic Resource Allocation for Dynamic Vehicular Networks," *IEEE Transactions on Vehicular Technology,* pp. 1-1, 2022, doi: 10.1109/TVT.2022.3146439.
[76] K. Zong and C. Luo, "Reinforcement learning based framework for COVID-19 resource allocation," *Computers & Industrial Engineering,* vol. 167, p. 107960, 2022.
[77] C. Reiss, J. Wilkes, and J. L. Hellerstein, "Google cluster-usage traces: format+ schema," *Google Inc., White Paper,* pp. 1-14, 2011.
[78] J. Wang, L. Zhao, J. Liu, and N. Kato, "Smart resource allocation for mobile edge computing: A deep reinforcement learning approach," *IEEE Transactions on emerging topics in computing,* 2019.
[79] M. Caria, T. Das, A. Jukan, and M. Hoffmann, "Divide and conquer: Partitioning OSPF networks with SDN," in *2015 IFIP/IEEE International Symposium on Integrated Network Management (IM)*, 2015: IEEE, pp. 467-474.
[80] X. Chen, S. Leng, K. Zhang, and K. Xiong, "A machine-learning based time constrained resource allocation scheme for vehicular fog computing," *China Communications,* vol. 16, no. 11, pp. 29-41, 2019.
[81] V. Mnih *et al.*, "Playing atari with deep reinforcement learning," *arXiv preprint arXiv:1312.5602,* 2013.
[82] H. Ye, G. Y. Li, and B.-H. F. Juang, "Deep reinforcement learning based resource allocation for V2V communications," *IEEE Transactions on Vehicular Technology,* vol. 68, no. 4, pp. 3163-3173, 2019.
[83] M. I. Ashraf, M. Bennis, C. Perfecto, and W. Saad, "Dynamic proximity-aware resource allocation in vehicle-to-vehicle (V2V) communications," in *2016 IEEE Globecom Workshops (GC Wkshps)*, 2016: IEEE, pp. 1-6.
[84] Y. S. Nasir and D. Guo, "Multi-agent deep reinforcement learning for dynamic power allocation in wireless networks," *IEEE Journal on Selected Areas in Communications,* vol. 37, no. 10, pp. 2239-2250, 2019.
[85] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for interference management," *IEEE Transactions on Signal Processing,* vol. 66, no. 20, pp. 5438-5453, 2018.
[86] W. Lee, M. Kim, and D.-H. Cho, "Deep power control: Transmit power control scheme based on convolutional neural network," *IEEE Communications Letters,* vol. 22, no. 6, pp. 1276-1279, 2018.
[87] Q. Shi, M. Razaviyayn, Z.-Q. Luo, and C. He, "An iteratively weighted MMSE approach to distributed sum-utility maximization for a MIMO interfering broadcast channel," *IEEE Transactions on Signal Processing,* vol. 59, no. 9, pp. 4331-4340, 2011.
[88] J. Zhao, M. Kong, Q. Li, and X. Sun, "Contract-Based Computing Resource Management via Deep Reinforcement Learning in Vehicular Fog Computing," *IEEE Access,* vol. 8, pp. 3319-3329, 2019.
[89] J. Zhao, Y. Zhang, Y. Nie, and J. Liu, "Intelligent Resource Allocation for Train-to-Train Communication: A Multi-Agent Deep Reinforcement Learning Approach," *IEEE Access,* vol. 8, pp. 8032-8040, 2020.
[90] Q. Zhou, X. Hu, J. Lin, and Z. Wu, "Train-to-train communication resource allocation scheme for train control system," in *2018 10th International Conference on Communication Software and Networks (ICCSN)*, 2018: IEEE, pp. 210-214.
[91] R. Alizadehsani *et al.*, "Uncertainty-Aware Semi-Supervised Method Using Large Unlabeled and Limited Labeled COVID-19 Data," *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM),* vol. 17, no. 3s, pp. 1-24, 2021.
[92] F. Khozeimeh *et al.*, "Combining a convolutional neural network with autoencoders to predict the survival chance of COVID-19 patients," *Scientific Reports,* vol. 11, no. 1, pp. 1-18, 2021.
[93] D. Sharifrazi *et al.*, "Fusion of convolution neural network, support vector machine and Sobel filter for accurate detection of COVID-19 patients using X-ray images," *Biomedical Signal Processing and Control,* vol. 68, p. 102622, 2021.
[94] W. Guan, H. Zhang, and V. C. Leung, "Customized slicing for 6G: Enforcing artificial intelligence on resource management," *IEEE Network,* vol. 35, no. 5, pp. 264-271, 2021.
[95] P. Goswami, A. Mukherjee, M. Maiti, S. K. S. Tyagi, and L. Yang, "A Neural-Network-Based Optimal Resource Allocation Method for Secure IIoT Network," *IEEE Internet of Things Journal,* vol. 9, no. 4, pp. 2538-2544, 2022, doi: 10.1109/JIOT.2021.3084636.
[96] P. K. Bal, S. K. Mohapatra, T. K. Das, K. Srinivasan, and Y.-C. Hu, "A Joint Resource Allocation, Security with Efficient Task Scheduling in Cloud Computing Using Hybrid Machine Learning Techniques," *Sensors,* vol. 22, no. 3, p. 1242, 2022.

[97] J. Chen, Z. Wei, S. Li, and B. Cao, "Artificial intelligence aided joint bit rate selection and radio resource allocation for adaptive video streaming over F-RANs," *IEEE Wireless Communications,* vol. 27, no. 2, pp. 36-43, 2020.
[98] V. Eramo, F. G. Lavacca, T. Catena, and P. J. Perez Salazar, "Proposal and Investigation of an Artificial Intelligence (AI)-Based Cloud Resource Allocation Algorithm in Network Function Virtualization Architectures," *Future Internet,* vol. 12, no. 11, p. 196, 2020. [Online]. Available: https://www.mdpi.com/1999-5903/12/11/196.
[99] W. Lee, O. Jo, and M. Kim, "Intelligent resource allocation in wireless communications systems," *IEEE Communications Magazine,* vol. 58, no. 1, pp. 100-105, 2020.
[100] W. Y. B. Lim *et al.*, "Decentralized edge intelligence: A dynamic resource allocation framework for hierarchical federated learning," *IEEE Transactions on Parallel and Distributed Systems,* vol. 33, no. 3, pp. 536-550, 2021.
[101] Q. Wang, Z. Li, K. Nai, Y. Chen, and M. Wen, "Dynamic resource allocation for jointing vehicle-edge deep neural network inference," *Journal of Systems Architecture,* vol. 117, p. 102133, 2021/08/01/ 2021, doi: https://doi.org/10.1016/j.sysarc.2021.102133.
[102] Z. Ali, S. Khaf, Z. H. Abbas, G. Abbas, F. Muhammad, and S. Kim, "A deep learning approach for mobility-aware and energy-efficient resource allocation in MEC," *IEEE Access,* vol. 8, pp. 179530-179546, 2020.
[103] V. Mnih *et al.*, "Asynchronous methods for deep reinforcement learning," in *International conference on machine learning*, 2016: PMLR, pp. 1928-1937.
[104] Y. He, Y. Wang, C. Qiu, Q. Lin, J. Li, and Z. Ming, "Blockchain-based edge computing resource allocation in IoT: a deep reinforcement learning approach," *IEEE Internet of Things Journal,* vol. 8, no. 4, pp. 2226-2237, 2020.
[105] F. Jiang, J. Wang, and C. Sun, "Deep Q-Learning-Based Cooperative Caching Strategy for Fog Radio Access Networks," in *2021 IEEE/CIC International Conference on Communications in China (ICCC)*, 2021: IEEE, pp. 922-927.
[106] X. Wang, M. Chen, T. Taleb, A. Ksentini, and V. C. Leung, "Cache in the air: Exploiting content caching and delivery techniques for 5G systems," *IEEE Communications Magazine,* vol. 52, no. 2, pp. 131-139, 2014.
[107] Y. Kim and I. Yeom, "Performance analysis of in-network caching for content-centric networking," *Computer networks,* vol. 57, no. 13, pp. 2465-2482, 2013.
[108] C. Fang *et al.*, "Deep Reinforcement Learning Based Resource Allocation for Content Distribution in Fog Radio Access Networks," *IEEE Internet of Things Journal,* 2022.
[109] V. Eramo and T. Catena, "Application of an Innovative Convolutional/LSTM Neural Network for Computing Resource Allocation in NFV Network Architectures," *IEEE Transactions on Network and Service Management,* 2022.
[110] W. C. Chien, C. F. Lai, and H. C. Chao, "Dynamic Resource Prediction and Allocation in C-RAN With Edge Artificial Intelligence," *IEEE Transactions on Industrial Informatics,* vol. 15, no. 7, pp. 4306-4314, 2019, doi: 10.1109/TII.2019.2913169.
[111] F. Hussain, S. A. Hassan, R. Hussain, and E. Hossain, "Machine learning for resource management in cellular and IoT networks: Potentials, current solutions, and open challenges," *IEEE Communications Surveys & Tutorials,* vol. 22, no. 2, pp. 1251-1275, 2020.
[112] "https://wandb.ai/site," 2022.
[113] "https://www.comet.ml/site/," 2022.
[114] J. Wu, C. Zhang, T. Xue, B. Freeman, and J. Tenenbaum, "Learning a probabilistic latent space of object shapes via 3d generative-adversarial modeling," *Advances in neural information processing systems,* vol. 29, 2016.
[115] Z. Wang, X. Tang, W. Luo, and S. Gao, "Face aging with identity-preserved conditional generative adversarial networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 7939-7947.
[116] S. Liu *et al.*, "Face aging with contextual generative adversarial nets," in *Proceedings of the 25th ACM international conference on Multimedia*, 2017, pp. 82-90.