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A review on dynamic resource allocation in Industrial Internet of Things using Machine Learning

Pankaj Singh Sisodiya,* Vijay Bhandari

Department of Computer Science & Engineering, Madhyanchal Professional University, Bhopal, India.

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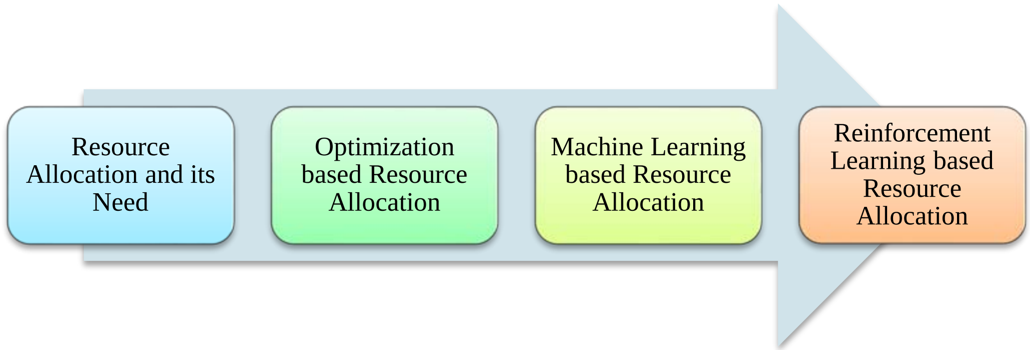
ABSTRACT



Internet of Things (IoT) application solutions are getting more common and their usage areas are expanding. As a result, there is continuous advances in development of new IoT technologies. The new technology development has huge advantages however, it also has limitations. Resource management and allocation is one of the biggest problems faced by IoT systems. Industrial IoT operations for computing and storing data use fog, edge computing, or cloud techniques. These computing nodes receive data from devices with limited resources. For computing and storage, resource management decisions must be made in fog, the cloud or edge nodes. For the system to function properly, resource management and allocation must be accurate and complete. There are many approaches suggested for this including one based on Machine Learning. This paper examined the Internet of Things resource allocation and management based on machine learning. In addition, various literature on resource allocation using reinforcement learning, optimization, and machine learning is compared in terms of several performance characteristics. Future research can concentrate on the suggested work's scalability and also expand and apply it in a larger and more sophisticated model.

Keywords: Resource Allocation, Dynamic, Internet of Things, Industrial IoT, Machine Learning

INTRODUCTION

Resource allocation has been significantly impacted by the revolutionary ways in which we interact with technology and data brought about by digitization. Nowadays, digitization has made it possible for businesses to gather vast amounts of data from numerous sources, including devices, machines, and sensors.[1,2] The performance of processes and systems can be understood through analysis of this data, which can subsequently be applied to improve resource allocation. with the development of Industry 1.0 into the Internet of Things (IoT). During the 18th century, the first generation (1.0) of industries used steam power to produce the necessary materials for their operations. Industry 4.0 has recently advanced.[3,4] By using new infrastructure to connect industrial processes with the internet, Industry 4.0 enables engineers to remotely control machines and have fast access to information via cloud storage.[5,6] Figure 1 shows the entire period of industrial change as well as the different important IIoT applications. The progression from Industry-1.0 to Industry-4.0 has resulted in a major rise in data generation. It's crucial to maximize energy efficiency and minimize power loss in the Industrial Internet of Things (IIoT).

This can be accomplished through the appropriate allocation of resources, which entails figuring out how to use the resources in the most effective and efficient way possible.[7,8] Advanced technologies like cloud computing, machine learning and edge computing have emerged as a result of digitization and can be used for dynamic resource allocation. In the Industrial Internet of Things (IIoT), dynamic resource allocation refers to the real-time distribution of

*Corresponding Author: Pankaj Singh Sisodiya, Dr. Vijay Bhandari
Email: sisodiya.pankaj90@gmail.com (PSS), bhandarivijay314@gmail.com (VB)

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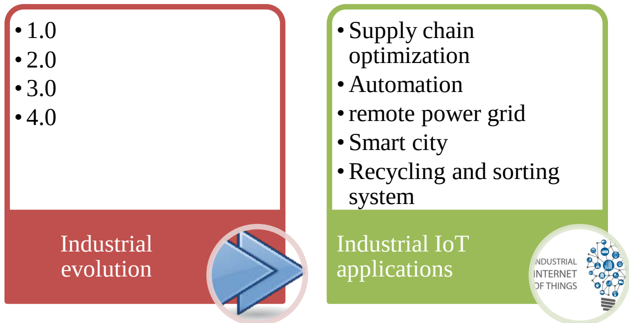

Figure 1. Evolution and Application of Industrial IoT

computer resources including storage, network bandwidth, CPU, and memory among various processes, services, and applications according to their demand and priority.[9,10] These gadgets produce a lot of data, which must be analyzed, processed, and used in real time.[11] Dynamic resource allocation can aid in making sure that this data is processed reliably, efficiently, and in a scalable manner. Edge computing enables data processing to take place nearer to the data's source, reducing latency and enhancing data security. This method makes optimal use of computational resources since it only processes the data that is essential, eliminating the need for further data transfer and storage.[12] Through online access to a pool of computing resources, cloud computing enables businesses to scale their computing resources in response to demand. By swiftly provisioning and de-provisioning computing resources as needed, it enables efficient distribution of computing resources without the requirement for actual hardware. Depending on the unique requirements of the industrial context, resource allocation in the IIoT can be adjusted utilizing a variety of techniques such as optimization techniques, machine learning-based, and reinforcement learning methods. Resource allocation in IIoT (Industrial Internet of Things) refers to the efficient and effective distribution of resources across multiple devices and systems in an industrial setting, including bandwidth, storage, energy, and processing power.

Resource Allocation, Its Need, Techniques and Its Components

Utilizing edge computing, which enables data processing to take place closer to the source of the data, minimizes the amount of data that needs to be transmitted and reduces energy consumption, is a traditional approach to reducing power loss. This method also allows for real-time processing, which can aid companies in swiftly recognizing and resolving power loss problems, but it has a number of drawbacks.[13,14] Most of the methods used today include decision-makers who choose how and where to allocate resources. This decision-maker in a typical cloud system is a central server. The decision-maker in an edge system is an edge host. Both strategies have shortcomings. The best resource allocation plan may not always be possible on edge hosts due to a lack of global information. However, the cost to privacy is on central servers. We require a solution that can accomplish both. Some of its needs are presented below in figure 2.

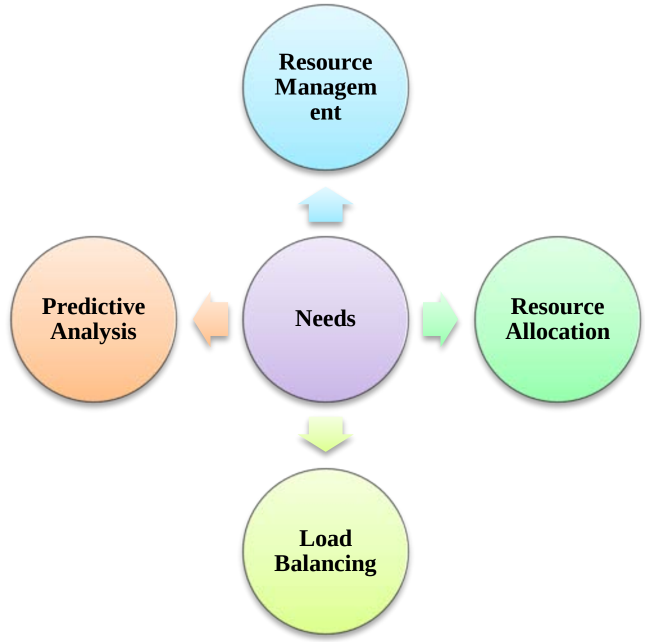

Figure 2. Need of Resource Allocation for Industrial IoT

Using ML algorithms to analyze data and discover resource usage trends is another strategy for improving energy efficiency. The best possible resource allocation can then be made using this information, ensuring that energy is used effectively and reducing power loss. Algorithms for machine learning can be trained to evaluate data and discover patterns and connections between factors like system load, application performance, and resource usage.[15] Real-time resource allocation can be optimized using this data to forecast upcoming resource needs. For instance, firms can modify their resource allocation by using machine learning algorithms to forecast patterns of energy usage in various conditions. In the IIoT, lowering power loss and improving energy efficiency are urgent tasks. Organizations may significantly enhance energy efficiency, lower power loss, and lower expenses by using edge computing and machine learning techniques to optimize resource allocation. Millions of smart things make up the IoT ecosystem, and resource allocation is necessary for these smart objects to successfully communicate and function. Resource allocation is necessary for several reasons. First, it ensures Quality of Service (QoS) is maintained. Second, it helps manage system irregularities without compromising reliability. Third, it minimizes idle time for devices waiting for resource allocation. Fourth, it enables dynamic resource scheduling and optimal utilization of available resources. Lastly, resource allocation can help reduce power consumption. Dynamic resource allocation in IIoT systems involves several components, including:

1. Resource Management: Monitoring the availability and use of the system's computer resources is the responsibility of resource management. It recognizes system changes and decides how to allocate resources to fulfill system demands.

2. Resource Allocation: Resource allocation is the process of allocating computing resources to particular tasks or applications in accordance with their demands and priorities at the time. The allocation can be changed by the system in real-time in response to demand from various machines, sensors, and devices in real-time.
3. Load Balancing: To maximize the use of computing resources, load balancing requires dividing the workload across them. In order to divide the workload among resources more equitably, the system can direct requests to the resource that is least under load or employ other techniques.
4. Predictive Analytics: Based on past data, system patterns, and other variables, predictive analytics is used to forecast future resource requirements. This aids the system's proactive resource allocation and preparation for incoming requests.

Optimization Based Resource Allocation in Industrial IoT

Using mathematical algorithms, optimization strategies look for the optimal answer to a problem. Utilizing optimization techniques in IIoT allows for the most successful and effective resource allocation. The formulation of a linear objective function and a set of linear constraints to improve resource allocation is a common optimization approach known as linear programming. Other popular optimization techniques in IIoT include mixed-integer programming, non-linear programming, and integer programming. Some of the recent most promising technologies of resource allocation using optimization are presented in figure 3.

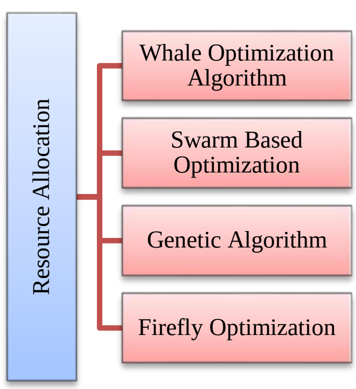

Figure 3. Optimization based Resource Allocation Techniques

Fan et al.[16] aimed to optimize job offloading, ML model accuracy, and resource allocation to minimize long-term average system cost. They used Lyapunov optimization and proposed a Benders decomposition method and a heuristic approach. The effectiveness of their plan was confirmed through theoretical analysis and simulations. Their methods outperformed previous techniques, reducing overall cost by up to 18%. The simulations also showed that a significant portion of workloads could be offloaded to edge servers based on different levels of ML model accuracy. In order to achieve optimal RA and lower the overall communication cost between resources and gateways, the IoT RA problem is solved by Sangaiah et al.[17] using the whale optimization algorithm (WOA). The suggested algorithm has been contrasted with other ones that are already in use. Results show that the suggested algorithm performs as expected. The suggested solution is superior than others in terms of "total communication cost" based on a number of benchmarks.

Sing et al.[18] proposed a two-module approach, including the Task Classification and Buffering (TCB) module, for task handling. Their algorithm, Whale Optimized Resource Allocation (WORA), was compared to FLRTS, MOMIS, and SJF. Simulation results showed significant improvements with WORA. It achieved cost savings of 10.3% compared to MOMIS and 21.9% compared to FLRTS when executing 100 to 700 jobs across 15 fog nodes. WORA also consumed 18.5% less energy than MOMIS and 30.8% less energy than FLRTS. Additionally, WORA outperformed MOMIS and FLRTS in terms of task completion success and achieved better makespan. Ahmed et al.[19] addressed resource allocation in wireless sensor IoT networks by leveraging deep learning architectures. The goal is to develop an energy-efficient and data-optimized approach. The study focuses on two conflicting optimization goals: spectral efficiency (SE) and energy efficiency (EE). The researchers improve the energy efficiency of a deep neural network using whale optimization and optimize data using a heuristic-based multi-objective firefly technique. The proposed method achieves optimal power distribution and relay selection in a cooperative multi-hop network topology. The resource allocation and relay selection process aim to reduce total transmit power while meeting Quality of Service (QoS) requirements. Simulation results show that the proposed model performs competitively, achieving QoS of 75%, spectrum efficiency of 85%, network lifespan of 91%, throughput of 96%, and energy efficiency of 95% compared to previous methods. Pilloni et al.[20] enhanced virtualization technologies using Virtual items (VOs) to distribute tasks among objects. They improved the information model by including quality of information (QoI) and presented architectural options. They also proposed a distributed method where VOs negotiate for resource distribution, improving system performance by an average of 27% compared to static frequency allocation and meeting QoI standards. Karthick et al.[21] introduced GSIWOA-RM, a resource management method for IoT using Galactic Swarm-Improved Whale Optimization Algorithm. GSIWOA-RM combines GSOA for global control and WOA for balancing exploration and exploitation. Simulation results show improved throughput (28.32%), reduced latency (21.82%), and minimized energy consumption (19.24%) compared to baseline methods.

Machine Learning Based Resource Allocation in Industrial IoT

Using historical data, machine learning-based techniques train models that can make predictions and judgments based on the data. In the IIoT, resource allocation can be predicted based on resource usage patterns using machine learning-based methods. For instance, resource allocation may be optimized for energy usage by training machine learning models to anticipate the energy consumption of a particular system based on past data. Below Figure 4 presents the machine learning based resource allocation techniques.

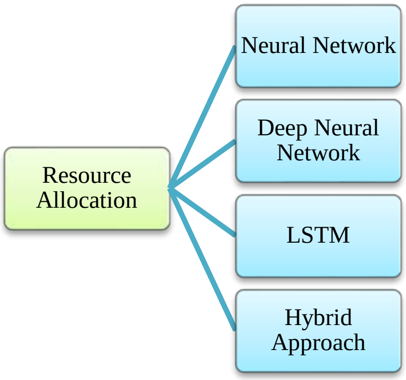

Figure 4. Machine Learning based Resource Allocation Techniques

Sun et al.[22] introduced AttCVNN, a complex-valued power allocation network with in-channel and cross-channel attention mechanisms. It surpasses alternative methods like equal power allocation, FNN, CVFNN, and AttCNN in performance. AttCVNN consistently achieves superior results, with a notable gain of 0.571 bps/Hz at INR=0 dB compared to equal power allocation. The model's time complexity is 17.92 million FLOPs. Hasan et al.[23] proposed a hybrid intelligent deep learning technique to protect IIoT infrastructure from complex botnet attacks. The method is thoroughly examined using recent datasets and benchmark deep learning algorithms, with performance evaluation measures and cross-validation. The suggested approaches demonstrate excellent recognition of multi-variant bot assaults and promising speed efficiency. The hybrid models CNN2D-LSTM and DNN-DNN achieve 99.93% detection accuracy, while CNN2D-CNN3D hybrid model achieves 99.92% accuracy. The time complexity of the proposed algorithms is shown in Figure 11, with the hybrid DNN-LSTM model taking 0.066 milliseconds for testing, and the hybrid CNN2D-LSTM, DNN-DNN, and CNN2D-CNN3D models taking 0.061, 0.068, and 0.067 milliseconds, respectively. Rashid et al.[24] provided a Federated Learning (FL) approach in this research for identifying undesirable intrusions. By using local IoT device data for federated training, this solution provides privacy and security. With a central global server, which aggregates them and disseminates a better detection algorithm, local IoT clients merely exchange parameter changes. Each IoT client receives an updated model from the global server following a round of FL training, and then trains on its own local dataset so that IoT devices may maintain their own privacy while the overall model is optimized. We performed extensive tests using a brand-new dataset called Edge-IIoTset to gauge the effectiveness of the suggested approach. The accuracy (92.49%) achieved by the suggested intrusion detection model in the performance assessment is comparable to the accuracy (93.92%) provided by the traditional centralized ML models when employing the FL approach. This proves the validity and efficacy of the proposed intrusion detection model. Khowaja et al.[25] suggested the use of sparse autoencoder, LSTM with the action-value function, and phase space embedding to categorize malware applications. In order to request or anticipate a label, the network depends on its uncertainty. The experimental findings indicate that the suggested technique can improve accuracy while utilizing fewer labeled requests than the supervised learning strategy. The outcomes also demonstrate the trained network's resistance to adversarial assaults, demonstrating the robustness of the suggested approach. The choice of incentives and the use of decision-level fusion procedures to improve classification performance are also explored in this work, as well as the tradeoff between the quantity of label requests and classification accuracy. We also offer a hypothetical framework as a consequence of the suggested strategy. Changchun et al.[26] proposed a two-model prediction strategy for production progress in make-to-order manufacturing workshops. They utilized transfer learning, IIoT, and big data to address the challenges of limited historical order data and poor generalization. Their approach involved using a CNN model with transfer learning for extracting information from past and present orders, and an LSTM model with transfer learning to handle nonlinear feature relationships. Comparative experiments validated the effectiveness of their approach in an IIoT-enabled manufacturing workshop.

Reinforcement Learning based Resource Allocation in Industrial IoT

A machine learning technique called reinforcement learning includes teaching an agent to respond in a way that will maximize a reward signal. By teaching the agent to distribute resources based on feedback from the environment, reinforcement learning can be utilized in the IIoT to optimize resource allocation. According to workload, energy usage, and performance data, the agent can learn how to allocate resources. For instance, to ensure peak performance, an agent can learn to provide a system extra resource when it is under heavy load. Below Figure 5 presents the reinforcement learning based resource allocation techniques. Mishra and Chaturvedi[27] proposed a novel method for improving the energy efficiency (EE) of an Internet of Things (IoT) network that supports simultaneous wireless information and power transfer (SWIPT) and utilizes energy harvesting (EH). The study addresses the optimization problem of EE, considering minimum data rate requirements, time allocation for device-to-device (D2D) links, D2D and IoT user needs, and joint spectrum sharing. The feasibility of transmit power for D2D and IoT users is also taken into account. The first subproblem is tackled using a Q-learning technique based on reinforcement learning (RL), while the second subproblem is solved using a convex optimization method based on the Dinkelbach and majorization-minimization (MM) approaches.

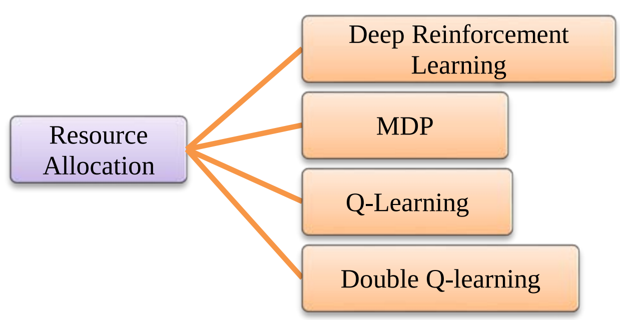

Figure 5. Reinforcement Learning based Resource Allocation Techniques

The proposed algorithm demonstrates an EE improvement of 5.26%, 110.52%, and 143.90% compared to the method in reported by Ahmed etl.al.[19], random allocation, and constrained allocation, respectively. Simulation results not only validate the superiority of the proposed algorithm over existing methods but also show significant EE gains through energy harvested from D2D and IoT users and spectrum sharing. Deng et al.[28] focused on the significance of edge computing (EC) in managing the growing number of IoT devices connected to the network's edge. They highlight the challenges associated with maintaining credibility and service-level agreements (SLAs) for IoT services operating in uncertain environments. The authors propose a solution that encodes the state of service provisioning systems and resource allocation and models it as a Markov decision process (MDP). They use reinforcement learning (RL) to train a resource allocation policy that maximizes the credibility of services by dynamically adjusting resource allocation based on system states. Through experiments conducted on the YouTube request dataset, the authors demonstrate that their approach improves the performance of the edge service provisioning system by at least 21.72% compared to baseline methods. Tianqing et al.[29] proposed a concurrent federated reinforcement learning method for resource allocation. This approach combines shared decision-making, privacy protection from federated learning, and problem-solving capabilities of reinforcement learning. The method achieves cutting-edge performance in terms of task completion speed, resource utilization, and system-wide utility, as demonstrated through trials. Fang et al.[30] addressed the challenge of low-latency content transmission and efficient resource allocation in next-generation wireless networks. They present a deep reinforcement learning (DRL)-based resource allocation strategy for a layered fog radio access network (FRAN). The strategy optimizes resource utilization and content delivery by considering communication, caching, routing, and computing allocation. Simulation results show that the proposed approach outperforms current cloud-edge cooperation strategies in the FRAN significantly. Li et al.[31] highlighted the potential of mobile-edge computing (MEC) to address energy overhead and service latency challenges in IoT applications. However, they identify unresolved issues such as network capacity, resource management, and security. In this article, they propose leveraging 6G and blockchain technology to enhance MEC-enabled IoT networks. They introduce a unique intelligent optimization technique called collective reinforcement learning (CRL) for intelligent resource allocation, distributed training result sharing, and preventing excessive resource consumption. By optimizing offloading options, block intervals, and transmission power, the proposed system aims to reduce energy and delay consumption. Evaluation results demonstrate the superiority of the recommended strategy compared to existing systems. Rosenberger et al.[32] focused on using deep reinforcement learning (DRL) for resource allocation in industrial edge devices. They utilize multi-agent systems (MASs) for decentralized decision-making due to the structure and security considerations of IIoT systems. Their approach involves a network composed of real and simulated IIoT hardware, which can handle dynamic changes in the target system. The performance evaluation considers MAS overhead, improved resource usage, and latency/error rates. The study shows that agents effectively utilize resources with minimal impact on traffic, computational power, and time. The agents also acquire new behaviors and can apply them to real systems beyond training goals. The execution time for the proposed approach is 0.74 seconds. Ali et al.[33] presented a Dynamic Reinforcement Learning Resource Allocation (DRLRA) technique to effectively allocate resources such as Transmit Power (Tp), channels, and Spreading Factors (SF) to enhance consumption and reliability for end devices (EDs). The proposed model is compared with adaptive priority-aware resource allocation (APRA) and adaptive data rate (ADR) algorithms using various evaluation metrics. The results demonstrate that DRLRA improves energy consumption and network capacity, outperforming ADR and APRA in terms of Packet Error Rate (PER) and Packet Success Rate (PSR). Despite a slightly higher PER, DRLRA achieves a reduced PER and higher PSR compared to the other methods, with PSR outperforming ADR and APRA by 1.6% and 0.5%, respectively. Zhou et al.[34] proposed a deep reinforcement learning-enhanced two-stage scheduling (DRL-TSS) model to address the operational complexity problem in end-edge-cloud IoT systems. DRL-TSS optimally assigns computing resources within an edge-enabled infrastructure, utilizing a presorting scheme and a DRL mechanism based on instant rewards. Experimental results show that the proposed algorithm achieves a 1.1 approximation ratio and better learning efficiency for optimal IoE applications. Compared to three other scheduling techniques, DRL-TSS maintains stable performance as the number of executed tasks increases and achieves the lowest approximation ratio (approximately 1.0) in tests with 500 and 1000 tasks.

Current Challenges and Future Scope

Following challenges are derived from the above meta-analysis presented in the paper:

- One challenge in optimization algorithms for IIoT is the complexity of the optimization problems, especially when dealing with large-scale systems and heterogeneous resources. Developing efficient algorithms that can handle such complexity is a challenge.[35-40]
- A challenge in machine learning-based resource allocation methods is the availability and quality of historical data. The performance of these methods heavily relies on the availability of relevant and representative training data.
- Reinforcement learning-based resource allocation faces challenges in defining appropriate reward signals and designing efficient training processes. Finding the right balance between exploration and exploitation and addressing the curse of dimensionality are also challenges in reinforcement learning.

These challenges motivate researchers in following future directions:

- Developing more advanced optimization algorithms that can handle the increasing complexity and scale of IIoT systems. This includes exploring techniques such as metaheuristic algorithms, hybrid optimization methods, and parallel/distributed optimization approaches.

- Advancing machine learning techniques for resource allocation by incorporating more sophisticated models, such as deep learning architectures, and exploring transfer learning and federated learning approaches. Developing methods that can handle dynamic and real-time resource allocation is also important.
- Enhancing reinforcement learning-based resource allocation by addressing challenges such as sample efficiency and scalability. Advancements in deep reinforcement learning, multi-agent systems, and hierarchical reinforcement learning can lead to more efficient and adaptable resource allocation strategies in the IIoT context.

CONCLUSION

The application scenarios of Internet of Things (IoT) technology are currently becoming more commonplace, driven by the quick development of smart mobile devices, industrial 4.0, improvements in various industries, and 5G network technologies. The industrial IoT (IIoT) is created by the fusion of IoT and industrial manufacturing systems. Prior to adopting data-driven, ML-based techniques, resource management was handled by static policies, but these have substantial limitations in a number of dynamic circumstances. Task scheduling, VM consolidation, resource optimization, energy optimization, and Workload estimation are just a few of the resource management activities that are handled by machine learning. In this essay, we look into the issue of joint power control and computing resource allocation in dynamic resource management. We looked at various machine learning, reinforcement learning, and optimization-based algorithms to address various problems. Future research can concentrate on the suggested work's scalability and also expand and apply it in a larger and more sophisticated model.

CONFLICT OF INTEREST STATEMENT

Authors declare no CoI for publication of this article.

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