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A Review on Resource Allocation in IoT Network using Machine Learning

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Abstract
In the fields of data analytics and industrial automation, the Internet of Things (IoT) has become a game-changer. In IoT contexts, there is a growing demand for effective use of resources due to the interconnection of devices and systems. The constantly changing character of IoT systems, where resource availability and demand alter continually, presents one of the main obstacles in resource allocation management. The capacity of machine learning approaches to manage intricate and changing structures has garnered substantial interest in recent times. In the framework of the Industrial Internet of Things, this work gives a detailed comparison of various resource allocation in IoT network using machine learning algorithms.

Keywords: - Internet of Things, dynamic resource allocation, machine learning, variable resource distribution, Collaborative Learning

I. Introduction

Resource allocation in an Internet of Things (IoT) network is like managing a big party where you have limited snacks and drinks for many guests. You want to make sure everyone gets enough without running out too quickly or wasting anything. In an IoT network, this involves distributing things like data processing power, memory, and network bandwidth among different devices (the "guests" at the party). The goal is to use these resources efficiently so that all devices can function well without overloading the system or causing delays n. This strategy seeks to manage resources intelligently and in real-time by utilizing machine learning algorithms.

The Industrial Internet of Things, or IoT, has completely changed how industrial equipment and systems function by facilitating automated processes, data interaction, and seamless communication across a range of industries. A plethora of networked equipment, sensors, and devices work together in contexts of IoT to gather, process, and transfer data, improving profitability, effectiveness, and decision-making skills. But as IoT deployments get bigger and more elegant, allocating resources effectively has become a crucial concern.

The process of dynamically distributing and controlling resources in IoT systems, including as processors, storage, bandwidth, and energy, is known as dynamic resource allocation. Dynamic resource allocation adjusts to the requirements and circumstances of the system as a whole in real time, in contrast with standard static resource allocation techniques, typically distribute resources based on preset configurations. This flexibility is essential to IoT since workload fluctuations, network circumstances, and system demands can cause a fast variation in resource availability and demand.

The principal aim of variable resource distribution in the Internet of Things is to maximize resource consumption and improve the system's efficiency. Reactive resource allocation guarantees that resources are effectively utilized, reducing waste and enhancing overall system efficiency by intelligently distributing resources in accordance with real-time needs. Internet of Things systems become more reliable, adaptable, and can give fast response.

Furthermore, IoT's dynamic distribution of resources facilitates improved response to shifting conditions and workload trends. Because IoT systems frequently encounter variations in data volume, processing demands, and network circumstances, the capacity to dynamically assign resources enables the system to adjust resource levels in response to demand, guaranteeing peak performance and efficient use of resources at all times.

The difficulties of continually allocating resources in IoT can now be effectively addressed with the help of machine learning algorithms. IoT systems may anticipate demands on resources, identify trends in data, and allocate resources wisely by utilizing machine learning algorithms to evaluate both historical and current data. By taking into account variables like workload patterns, energy usage, and system performance measurements, machine learning models are able to adjust to changing circumstances and optimise the distribution of resources tactics.

This paper is organized as four parts in which first part introduce resource allocation in IoT networks as a critical aspect for efficient operation. The second part gives work done in IoT networks based on machine learning algorithms. The third part describe the challenges and requirements for effective resource allocation and discuss Machine Learning Techniques for Dynamic Resource Allocation. The fourth part Task Offloading Using Collaborative Learning and last part Summarize key findings from the review and Emphasize the importance of efficient resource allocation for IoT network performance.

II. Literature Review

Gong et al. [1] introduces machine learning-based approaches to optimize virtual machine migration and dynamically allocate resources in cloud computing. It highlights the limitations of static rules and manual settings in traditional cloud environments. Overall, it effectively emphasizes the significance of machine learning technology in addressing challenges related to resource allocation and virtual machine migration in cloud computing.

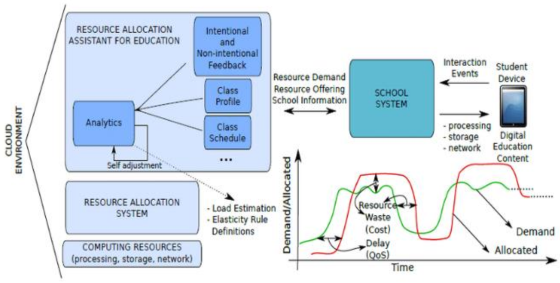

Figure 1. Architecture for Dynamic Resources Allocation Using Education [7]

Anoushee et al. [2] developed a new way to manage resources using a software-defined network (SDN) setup and improved reinforcement learning techniques. The goal was to efficiently use limited resources in Fog Nodes (FNs) while ensuring fast response times for IoT applications. Our simulations in various IoT environments with different latency needs showed that RL techniques consistently achieved the best performance, regardless of the specific IoT setup.

Liu et al. [3] introduced a new algorithm called PQ-RACO (Predictive deep Q-Network for SCMA Resource Allocation and Computation Offloading) for single-cell scenarios. This algorithm uses LSTM networks in IoT devices to predict the behaviors of other agents. However, PQ-RACO faces scalability challenges as the number of IoT devices increases Our simulations show that MQ-RACO outperforms several advanced MARL algorithms and other benchmark methods in terms of convergence speed and computation rate, demonstrating its effectiveness in resource allocation and computation offloading for SCMA in diverse scenarios.

Wang et al. [4] proposed a refined intelligent manufacturing enterprise as a case study to examine its human resource management challenges and how IoT can be used to develop an intelligent human resource management system. It concludes with specific strategies for implementation. This integration forms a network for information exchange and transmission between "things" (IoT devices) and "people," creatively implemented in the application layer software design.

Zhang et al. [5] proposed deep reinforcement learning (DRL) to securely allocate computing resources. Our approach starts by modeling a serverless multi-cloud edge computing network with diverse attribute characteristics across multiple computing resource nodes. We then devise a security mechanism to ensure data safety. Next, we formalize the network model and objectives, converting them into a Markov decision process for modeling. Finally, we introduce DRL with action constraints to develop an optimal resource allocation scheduling policy.

PLS Jayalaxmi et al. [6] presented DeBot, a deep learning model for bot detection in industrial network traffic. DeBot utilizes a Cascade Forward Back Propagation Neural Network (CFBPNN) model with a subset of features selected using the Correlation-based Feature Selection (CFS) technique. The model employs a time series-based Nonlinear Auto-regressive Network with eXogenous inputs (NARX) technique to analyze factors impacting the target variable and predict behavioral patterns. Their approach pioneers the use of optimal feature selection and cascading deep learning in bot detection for Industrial Internet of Things (IoTs). Experimental results on various bot datasets demonstrate the effectiveness of DeBot in achieving high accuracy and optimum F1-score.

Z Yang et al. [7] proposed a clustering-based sharded blockchain strategy for collaborative computing in the Internet of Things (IoT). They leverage the benefits of sharded blockchains, such as immutability and decentralization, to address trust issues in large-scale IoT systems. The sharding process involves K-means clustering-based user grouping and the assignment of consensus nodes, with the optimization of cluster numbers and consensus parameters jointly trained using deep reinforcement learning (DRL). The proposed scheme improves the scalability of sharded blockchains in IoT applications, even with high proportions of cross-shard transactions (CSTs).

Y Gong et al. [8] focused on the challenges posed by the exponential growth of edge-based Internet-of-Things (IoT) services and ecosystems, particularly in the context of Low Power Wide Area Networks (LPWANs) like LoRaWAN. They propose a Dynamic Reinforcement Learning Resource Allocation (DRLRA) approach to efficiently allocate resources such as channels, Spreading Factors (SF), and Transmit Power (Tp) to End Devices (EDs). The goal is to improve network performance in terms of consumption and reliability. The proposed model is extensively evaluated and compared with existing algorithms like Adaptive Data Rate (ADR) and Adaptive Priority-aware Resource Allocation (APRA), showing promising results using standard and advanced evaluation metrics.

Olatinwo et al. [9] conducted a bibliometric analysis and comprehensive review of studies published between 2012 and 2022 on resource management in Internet of Things (IoT) networks using the Scopus database. The aim was to understand the current state of research, identify challenges, and explore opportunities in the field. The bibliometric analysis helped identify key research subjects, while the comprehensive review provided insights into recent progress and research gaps. The study revealed that resource management in IoT networks remains a growing challenge due to limited available resources. It highlighted the importance of resource management, considering IoT's potential for collecting vital data and analyzing human behavior and environmental conditions. Notably, conventional artificial intelligence techniques, such as optimization and game theory approaches, were commonly used, but modern artificial intelligence techniques like deep learning approaches were less common.

To address this research gap, the study proposed the use of deep learning approaches, which offer advantages in obtaining low-complexity resource allocation solutions in near real-time. The paper also outlined open research issues as future directions to develop novel deep learning models for IoT networks.

The joint computational challenge of the transmit powers, CPU frequencies, and offloading decisions of IoT devices in a multi-mobile computing (MEC) the server and multi-IoT product cellular network was studied by Tian et al. [10]. In order to reduce the weighted total of task dropping costs, network energy usage, and processing strain on a single MEC server, they devised an optimization problem. The discrete integer variables and strongly coupled restrictions, which resulted in a mixed numerical nonlinear program (MINLP) issue, made the solution difficult. The scientists created an optimization technique based on advanced reinforcement learning (DRL) that took the changing environment into account in order to address this. The suggested algorithm's correctness and efficacy were shown by the simulation results.A dynamic spectrum access system for the conscious industrial web of things (CIoT) based on Q-learning was presented by Liu et al. [11]. The objective was to efficiently employ spectrum resources while guaranteeing that primary users' (PUs') regular communication is not interfered with. Underlay spectrum access, non-orthogonal multiple access (NOMA), and orthogonal multiple access (OMA) were the three access possibilities that were taken into consideration. To ensure transmission efficacy for the CIoT and PUs, the CIoT trained to access unoccupied channels in OMA, use busy channels while regulating output power for underlay, and erase interference in NOMA. In these settings, an algorithm for spectrum access based on Q-learning was developed to improve the transmission performance of the CIoT. The benefits of the Q-learning-based NOMA system were illustrated by simulation results, which included reduced interference and a throughput assurance for CIoT nodes.An energy-aware utilization approach for cordless virtual worlds (VR) in the web of things (IoTs) was proposed by Lin et al. [12]. They pose the issue of viewport displaying offloading, processing, and spectral resource allocation as a collaborative optimization issue in order to address the problems of extreme vista rendering requests and excess terminal energy consumption. The formulation takes into account the content connection among VR gear (VEs), fluctuating channel circumstances, and VR immersive experience. The problem is converted into a Markov decision-making method by the authors using dual approximation, and they then create an online learning algorithm based on reinforcement learning (RL) to determine the most effective course of action. They use RL with quantum parallelism to improve learning effectiveness. The outcomes of their simulation show how successful their suggested plan is.In order to investigate the compatibility between cyber-physical process surveillance systems (CPPSs) and the web of Things-centered real-time production logistics, Andronie et al. [13] carried out a quantitative literature survey. After analyzing studies released between 2017 and 2021, they find 164 pertinent sources. The results imply that the way these systems work together can have a big influence on how operations develop and how CPPSs set up their smart factories. For the successful design and deployment of CPPSs, the authors stress the significance of big data analytics powered by artificial intelligence and real-time sensor networks.Using a federated learning method, Guo et al. [14] established an effective and adaptable management solution for the industrial web of things (IoT) facilitated by mobile edge computing (MEC). During the optimization process, they use advanced reinforcement learning (DRL) to modify parameters such as transmit power, the allocation of bandwidth ratio, and job offloading ratio in order to reduce normalized system cost and lower communication costs. The outcomes of their simulations show that their suggested federated framework manages IoT networks in an effective and adaptable manner.

The handling of computational power in fog radio accessible networks (F-RANs) for mobile networks with 5G was covered by Khumalo et al. [15]. They suggest using the Q-learning algorithm, which is based on reinforcement learning (RL), to dynamically distribute resources in F-RAN designs. Their approach shows promise for Internet of Things applications as it decreases latency and performs better than reactive solutions.

In the context of the Internet of Things (IoT), Khalil et al. [16] investigated the major possibilities of deep learning (DL). They outline multiple DL use cases for IoT systems, such as smart manufacturing and agriculture, and examine numerous DL approaches and their applications in diverse industries. In order to spur additional developments in the field, the authors also address research problems, the efficient design as well as execution of DL-IoT, and future research prospects.Deep learning using reinforcement learning (DRL) was used by Wu et al. [17] to address the problem of interaction rescheduling and distribution of resources in industrial web of things (IoT) systems. They create a deeply intelligent scheduler (DISA) based on a double deep learning network (DDQN) framework and suggest a hierarchical timing model taking into account the heterogeneous architecture of central-edge computing. The results of their simulation demonstrate the advantage of their suggested method over alternative baseline solutions. In order to fulfill various quality of service (QoS) criteria, Zhou et al. [18] delves into the governance of wireless links in the Industry Internet of Things (IoT). They identify distinctive features in vast IoT situations and condense the QoS specifications for typical vast uncritical and severe IoT use cases. The authors offer a case study on enormous access utilizing neural network training and deep reinforcement approaches, as well as current algorithms for individual layer and cross-layer issues in large IoT.In the context of the Industrial Network of Things (IoT), Chen et al. [19] looked into the dynamic resource oversight challenge of concurrent control of electricity and computation allocating resources for mobile computing on the edge (MEC). They formulate the issue as a Markov decision-making procedure (MDP) and suggest a dynamic managing resources (DDRM) technique based on deep reinforcement learning to address it. Their deep deterministic policy gradient-based DDRM method effectively handles the large, action and state spaces, as shown by simulations that show a reduction in the long-term average latency of tasks.Spectrum resource management issues in the Industrial Network of Things (IoT) network were discussed by Shi et al. [20]. They suggest using an improved deep Q-learning networking (MDQN) to make it easier for various consumer devices (UE) in the IoT to share spectrum. The suggested method outperform other benchmark solutions in accomplishing agile spectrum allocation in the IoT network, where the base stations (BS) functions as just one device to centrally manage band resources.

III. Resource Allocation Challenges

The term "resource allocation challenges" describes the obstacles and intricacies associated with effectively allocating and overseeing finite resources across a range of fields, including finance, business, administration of projects, and logistics.A shortage of resources is one of the main issues with resource allocation. To guarantee that resources are distributed in a manner that is in line with their strategic goals and priorities, organizations frequently deal with restricted availability of vital resources including funds, personnel, time, tools, and supplies.

The fact the resource demand are changing presents another difficulty. The needs for resources may alter as business or projects advance as a result of unanticipated events, shifting demand, or shifting priorities. Conflicting demands for resources may provide a big obstacle. Within an organization, competing projects, divisions, or individuals may compete for the same resources. It might be difficult to fairly allocate resources, set priorities, and balance all of these competing demands.Allocating resources involves intrinsic issues related to uncertainty and risk. It's common for future consumer desires, market conditions, and outside influences to be uncertain. A comprehensive strategy that incorporates data-driven decision-making, strategic planning, and efficient communication is needed to address resource allocation issues. Aligning resource allocation with corporate goals and strategies is crucial for organizations, taking into account variables including project priority, manpower dependency issues, and mitigation of risks.

IV Machine Learning Techniques for Dynamic Resource Allocation

The many machine learning methods used for the dynamic allocation of resources in IoT contexts are examined in this section. An essential component of effectively handling computational resources is dynamic scheduling, particularly in situations where demands on resources fluctuate over time. Dynamic resource allocation can be made more efficient and automated with the help of algorithms that use machine learning. Figure 2 shows Reinforcement learning based on machine learning

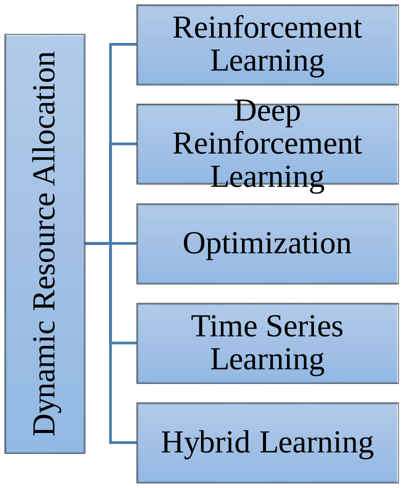

Figure 2. Reinforcement learning based on machine learning

Reinforcement Learning: When a system has to make consecutive judgments in order to maximize a goal, reinforcement learning, or RL, is a good fit for changing allocation of resources problems. With this method, the agent, or resource allocation system, engages with the surroundings and gains insight from input to enhance its decision-making. By optimizing for a variety of performance indicators and modifying allocation strategies in response to real-time input, reinforcement learning (RL) can be used to distribute resources dynamically.

Deep Reinforcement Learning: This approach combines reinforcement learning with deep learning capabilities. The best resource allocation strategy is approximated by means of deep neural networks. In difficult resource allocation settings, whereby the current state space is wide and continuous, deep reinforcement learning has demonstrated promising results. Resource allocation that is optimization-based sets the allocation of resources as an issue of optimization and determines the optimal resource allocation to fulfill limitations and optimize a certain goal. It entails choosing a suitable optimization technique, specifying the goals value and restrictions, and updating the allocation on a regular basis in response to shifting resource demands. It offers a methodical approach to effectively distribute resources in dynamic contexts, changing with the times to accommodate new requirements. Particle swarm optimization, genetic algorithms, Gray Wolf Optimization, and other algorithms are examples of optimization-based algorithms. Time Series Learning: By using historical consumption patterns as a basis, time series learning methods can be utilized to forecast future resource demands. The system can proactively assign resources to meet anticipated demands by anticipating the resource requirements, hence preventing inadequate use or overload. Hybrid Learning: To maximize resource allocation, hybridization teaching-based allocation of assets incorporates a number of machine learning techniques. It breaks the issue up into modules, combines learning with optimization, and adjusts to shifting circumstances. In varied and intricate contexts, this method improves throughput and offers smarter resource usage through versatility and adaptation.

V Task Offloading Using Collaborative Learning

The role of shifting from IoT nodes is the initial phase in the proposed model. In distributed systems, task offloading via collaboration Q-learning is a process that helps to improve job distribution amongst several computer nodes, especially in the context of cloud computing and edge computing in mobile devices (MEC). The main objective is to intelligently determine where to carry out various tasks depending on what's offered on various nodes in order to optimize system performance, decrease latency, and increase energy efficiency. Figure 3 presents a description of the working steps. Figure 3 describes the Functions of IoT Task Offloading Based on Machine Learning in which task arrival to each IoT sensor then tasks are assigned to multiple agents then process goes to the selection action states then if it performs well then process is assigned with the rewards then exchange of Information takes place among agents depend on the action we update the Q table then the model take decision to schedule and load the tasks.

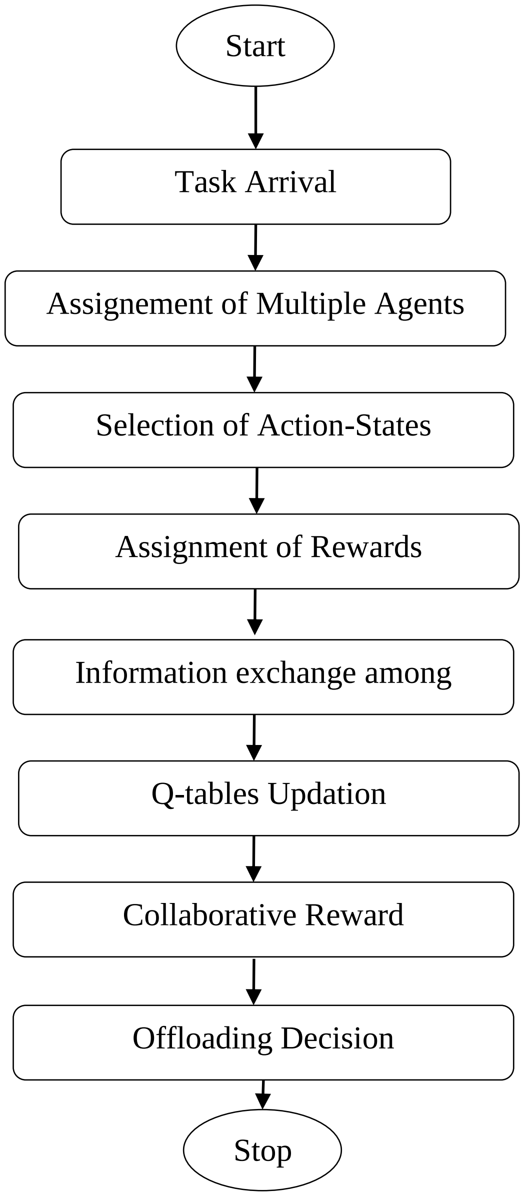

Figure 3. Functions of IoT Task Offloading Based on Machine Learning

VI Conclusion

IoT device integration in applications that use networks has grown in popularity in recent years. However, the sheer volume of data created, intricate protocols, and numerous sensors make keeping an eye on these networks difficult. Given the limited amount of environmental data currently available, researchers have looked into using algorithms based on machine learning to create dynamic choices mechanisms for Internet of Things devices in an effort to overcome these challenges.

The review shows how collaborative learning techniques like collective reinforcement learning is really good at smartly dividing tasks and adjusting to changes in the network. It also points out challenges like privacy worries and too much communication, stressing the importance of strong security and smooth communication methods. Looking ahead, researchers might try mixing collaborative learning with edge intelligence or solving compatibility problems to fit into different IoT setups better. Ultimately, using collaborative learning for task offloading could greatly boost edge computing's efficiency and open up new possibilities for creative uses in different fields.

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