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Resource Allocation in Edge Computing Environment Using Deterministic Policy Gradient Algorithm

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***Abstract*—In recent years, the edge computing paradigm enables the movement of processing units and storage nearer to the data available locations. The mechanism completes the computation in a short span of time in minimum bandwidth. Edge ecosystem is a type of distributed computing that is sensitive to topology and geography; the Internet of Things is a prime instance of this. Rather than referring to a single technology, Edge computing refers to an architecture. This paper proposes a resource allocation methodology that will enliven the situation between users and edge servers. By creating continuous control at the edge servers to determine resource allocation, edge computing improves reaction time, provides high security with decreased risk, scalability, lowers transmission costs, and versatility (offload targets, migration bandwidth and computing resources). The Deterministic Policy Gradient, Deep learning and Quality Network concepts are combined in the proposed system. The continuous action space is achieved by a deterministic policy gradient. The experience relay includes a quality network. In the proposed system, the actor-critic network produces a single continuous action instead of resulting probability based actions. The critic-part uses Q-value from a quality network based on current status and activity. The goal of the proposed system is to develop a Deep Deterministic Policy Gradient methodology to allocate servers for mobile users with the help of the Edge computing while taking computation resources, offloading goals and migration bandwidth into consideration. The simulation result indicates that deterministic policy gradients integrated deep learning models improve the system performance compared with Game theory.**

Keywords— Edge Computing; Resource Allocation; Deep Learning; Computational Intelligence; Deterministic Policy Gradient.

I. INTRODUCTION

Without the requirement of active user management, cloud computing involves the instantaneous accessibility of computer system assets, such as computational power and data storage (cloud storage). Large clouds frequently split functions among several sites and these sites serve as a data center. By providing a platform for distributed computing, Business apps can now be used in closer proximity to data sources including Industry 4.0 devices or local edge servers thanks to edge computing [19].

To fit the needs of devices that require external computational resources, a sophisticated mechanism for assigning edge and mobile computers is being created. This should increase response times while also saving bandwidth. When it comes to Internet-connected devices, the point of interaction between the device and the local network that hosts it is known as the network edge. Fig 1 describes the fundamental edge model.

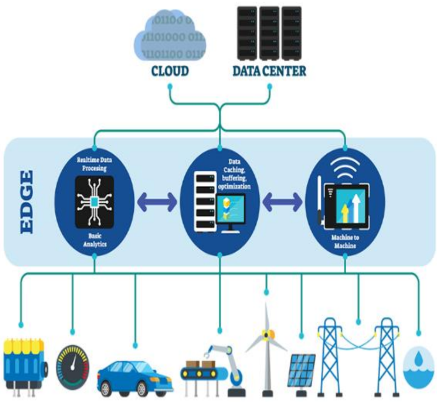

Fig.1 Edge Computing Model

One kind of machine learning called reinforcement learning maximizes reward by determining the best course of action in a given situation [20]. Numerous computer programmes and applications use it to decide what to do or how to proceed in a given circumstance.

Reinforcement learning is not the same as supervised learning because it depends on the reinforcement agent to decide how to finish the task, whereas A set of answers for supervised learning makes it possible to train the model with the right answers. It is compelled to learn from its errors in the absence of a training dataset.

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The goal of reinforcement learning is decision-making in a sequential manner. In short, the input's current state dictates its output, and the previous input's output dictates the input that follows it. We give dependent decision sequences labels since Reinforcement Learning decision-making is conditional. The objectives of the proposed system as follows

- Reducing the distance that data must travel by processing it closer to the information source.
- To provide maximum security.
- To reduce latency and the cost of transmission.

This technology maximizes bandwidth efficiency by evaluating data at the edge, not in the cloud, which requires data transfer from the Internet of Things, which requires high bandwidth, making it perfect for low-cost use in remote locations. It enables smart applications and gadgets to respond extremely immediately to data, which is critical in business and self-driving automobiles.

It may process data without storing it on the cloud, ensuring perfect security. Data may become corrupt while traveling over a long distance, reducing the data's dependability for businesses. The use of cloud computing is constrained by data processing at the edge.

In recent years, cloud computing-based smartphone applications have gained popularity, including augmented reality (AR), face recognition, and object identification. However, due to remote execution, cloud computing may result in excessive latency and increased backhaul bandwidth use. By bringing storage and processing elements nearer to mobile consumers, edge computing can solve these issues by enhancing response times and reducing the strain on backhaul networks.

II. LITERATURE SURVEY

One of the most commonly acknowledged disadvantages of cloud technology is downtime. Cloud computing platforms can be accessed through the internet by service providers. Sensitive data stored on external service providers still carries risk, even with cloud service providers who adhere to the strictest security guidelines and possess the highest industry certifications. Since every part of cloud computing is online, any vulnerabilities can be seen.

Severe attacks and security lapses happen sometimes, even to the best teams. Improved security protocols, cheaper connection costs, superior information management, and stable and consistent connections are edge computing's primary advantages over cloud computing. Because edge computers solely use connections to local networks and internet connection for data transfer, edge computing is far more secure instead of cloud computing.

Zhao et al., [1] uses the Radio access control mechanism, which will result in the maximum packet delay. In order to reduce packet latency, we leverage the mobile user's current position. The federated learning technique is inapplicable to the current proposed scheme, which solely takes into account the local optimal wireless access control. Yang et al., [2] discusses the strategies for allocating computational resources in mobile edge computing networks that provide low latency communications by using finite block length codes. Lillicrap et al., [3] deals with the principles of Deep Q-Learning to the domain of continuous action and resolves approximately five simulated physical tasks. Tiong et al., [4] Twin Average Delayed DDPG, or TAD3, arrives as a distinctive modification to TD3 and has been shown to outperform TD3 in a demanding continuous control situation. Cao et al., [6] introduces edge computing and contrasts it with cloud computing before going into detail about its architecture, keyword technology, security, and privacy protection.

He et al. [6] describes an approach for computational offloading and allocation of resources in mobile-edge networks. The Deep Deterministic Policy Gradient (DDPG) algorithm is used to achieve optimization. The energy consumption is significantly reduced. The DDPG method outperforms existing baseline algorithms. The approach reduces total system energy usage to 15.6 J.

Zhang et al. [7] design a lightweight trust evaluation mechanism to resolve trust models. The trust is established among the user devices and edge nodes. The resource allocation methodology depends on trust and agents. The goal of reducing system energy consumption. The research focuses on the efficiency of resource management. The edge network security enhanced using trust model.The proposed method protects malicious attacks and minimizes energy utilization. Furthermore, intelligent task migration improves user experience. The resource allocation system uses the Markov game model.

Behera et al. [8] propose a DSPS (Deadline-Sensitive Policy for Scheduling) technique for task scheduling. The HWVMR and VARVMR algorithms are used to anticipate Virtual Machine components. The study investigates the feasibility of offloading various tasks to edge nodes in the Mobile Edge network. When compared to existing methodologies, the proposed algorithms demonstrate considerable gains in efficiency and energy utilization. It focuses on task offloading, resource prediction, and task allocation in 5G/6G-enabled systems.

Qadeer et al. [9] describe a new agent that delivers improvements, reduces operational costs and rejection rates up to 28% and 72%. The agent causes a 32% increase in experience quality on average. The article presents a DDPG based methodology for resource management in the edge ecosystem. This approach compared to existing reinforcement learning agents, reduces operational expenses and rejection rates. Additionally, increases experience quality. The method integrates a Feature Learning and Experience Replay.

Shan et al. [10] recommended the DDPG approach to reduce system overhead.The approach reduces the service time. In addition to that energy utilization and resource management are focused in edge scenarios. The DDPG algorithm produces an improved result. It contains abstractions such as cache queues and allocation vectors.

Chi et al. [11] present a DRL-based strategy for improving long-term income and user request (UR) success rate. The algorithm provided lower latency, more income, and greater UR success rates. The approach