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DYNAMIC RESOURCE ALLOCATION IN EDGE COMPUTING ENVIRONMENTS: A MACHINE LEARNING APPROACH

Arnika Gunjal [1]
Rucha Pednekar
Snehal Kanere
Shivani Ruke

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A B S T R A C T

Edge computing is a promising paradigm that addresses the limitations of traditional cloud-centric architectures by placing computation near the data source. The main challenge is efficient resource allocation for various applications while optimizing resource utilization. This paper proposes a machine learning-based approach for dynamic resource allocation in edge computing environments. It uses machine learning algorithms to analyze real-time data traffic patterns, application demands, and edge node capabilities to dynamically allocate resources like compute, storage, and bandwidth. By continuously acquiring historical data and adjusting to varying workloads, the system improves overall system performance and user experience. Experimental evaluation and simulations show the effectiveness and efficiency of this approach in enhancing resource utilization, lowering latency, and improving scalability in edge computing environments.

1. INTRODUCTION

Edge computing is a significant shift in distributed computing, reducing latency in applications like IoT, augmented reality, and self-driving cars (Liu et al., 2019a; Siriwardhana et al, 2021). It brings computation closer to data sources, enabling faster response times, reduced bandwidth usage, and improved privacy. However, efficient resource management is crucial in edge computing environments, where edge nodes are often limited by factors like processing power, energy resources, and communication capacities (Hong & Varghese, 2019). Dynamic resource allocation is key to optimizing resource utilization and meeting diverse requirements for edge applications (Liu et al., 2019b; Wang et al., 2019). Traditional static resource allocation methods are often insufficient for dynamic edge environments, where workloads can change significantly over time. Machine learning techniques have emerged as a solution to these challenges, as they can learn from past experiences and adapt their resource allocation decisions to meet current demands (Jordan & Mitchell, 2015; L'heureux et al., 2017). This study aims to develop a machine learning-based framework for dynamic resource allocation that optimizes resource utilization, minimizes latency, improves scalability, and enhances overall system performance in edge computing environments.
Edge Computing involves distributing and decentralizing available computing, storage, and network resources to ensure efficient execution of applications and services at the network's edge (Escamilla-Ambrosio et al., 2018; Zhao et al., 2019). This strategy ensures optimal

[1] Corresponding author: Arnika Gunjal
Email: arnikagunjal19@gmail.com

utilization, high-quality user experiences, and meets desired Quality of Service (QoS).

This work contributes to advancing intelligent techniques for managing resources at the edge, enabling more agile, responsive, adaptive, and efficient edge systems (Deng et al 2020). Traditional static resource allocation approaches often fail to adapt to changing workload conditions and application demands, as edge nodes vary in terms of computational capabilities, storage capacity, and network connectivity. Machine learning techniques have gained prominence in addressing dynamic resource allocation challenges in edge computing environments by leveraging historical data, real-time monitoring, and predictive analytics (Hua et al., 2023).

Resource allocation in Edge Computing offers several advantages, including reduced network load, better user experience, increased reliability, and reduced latency. However, it also presents limitations such as limited resources, security concerns, and high costs (Liu et al., 2019a). Heterogeneous resource management, network latency, and bandwidth constraints also pose challenges. Real-time resource allocation algorithms are being developed to respond quickly to changing resource requirements, while energy-efficient algorithms optimize device use. Artificial Intelligence and Machine Learning techniques can also improve resource allocation algorithms in Edge Computing environments (Hua et al., 2023). Future research directions include developing real-time resource allocation algorithms, energy-efficient algorithms, and the use of Artificial Intelligence and Machine Learning techniques.

2. REVIEW OF RELATED WORK

This subsection begins with a review of existing literature and research efforts in the field of dynamic resource allocation in edge computing (Luo et al., 2021). We discuss various approaches, techniques, and challenges associated with resource management in edge environments, highlighting the limitations of current methods and the need for more intelligent resource allocation strategies.

Two main methods for resource allocation in edge computing without a cloud center are user-based and edge node-based. User-based methods involve selecting appropriate edge nodes for calculation migration, while edge node-based methods focus on forming clusters for system performance optimization. This paper aims to combine these three perspectives into a market, using market equilibrium rules to achieve optimal resource allocation. As smart devices become more prevalent, researchers, businesses, and governments have been working on optimizing energy management, energy management systems, and task scheduling approaches for smart homes and healthcare. This paper aims to overcome the limitations of focusing only on one party in resource allocation processes.

Procopiou and Chen (2021) proposed a lightweight detection algorithm for IoT devices using chaos prediction and chaos theory, called Chaos Algorithm (CA). This algorithm helps identify Flooding and Distributed Denial of Service (DDoS) attacks, providing a secure network environment for IoT-based smart home systems. Yang et al. (2017) proposed an IoT-based smart home security monitoring system to enhance system security performance by improving False Positive Rate (FPR) and reducing network latency. Zhou, et al. (2024) proposed an optimal task scheduling strategy based on a discrete Markov decision process (MDP) framework to optimize resource allocation. Liu et al. (2020) analyzed the impact of cluster size on service latency and energy consumption of edge nodes. This paper uses resource pricing and utility theory in economics to investigate resource allocation and scheduling of edge computing without using a cloud center for smart homes. The authors divide tasks generated by smart home applications into two types: tasks with low latency and high processing capacity requirements and tasks with high latency requirements.

3. METHODOLOGY

Our research methodology employs a combination of quantitative analysis and experimental validation to investigate the effectiveness of the proposed machine learning-based approach for dynamic resource allocation in edge computing environments.

3.1 Quantitative Research Methods:

We primarily utilize quantitative research methods to analyze data and draw conclusions based on empirical evidence. Quantitative techniques allow us to measure and quantify various aspects of resource allocation performance, such as resource utilization, latency reduction, and scalability improvement.

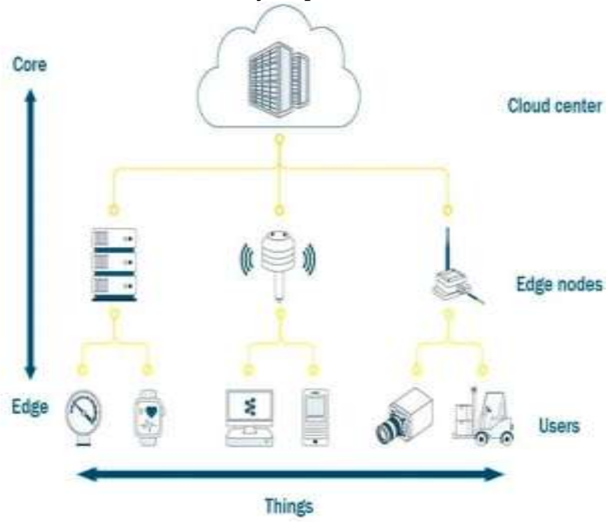

Figure 1. The conventional structure of edge computing

Through quantitative analysis, we aim to provide objective assessments of the proposed approach's effectiveness and efficiency (Figure 1).

3.2 Experimental Evaluation

To validate the proposed machine learning- based approach, we conduct extensive experiments in a simulated edge computing environment. We deploy edge nodes with varying computational capabilities and simulate diverse workload conditions to evaluate the system's performance under different scenarios. The experiments involve running real-world applications and measuring resource usage, response times, and other relevant metrics to assess the effectiveness of the proposed resource allocation strategy.

3.3 Data Collection:

Data collection for our experiments involves gathering various types of information related to edge computing environments, including network traffic patterns, application characteristics, and edge node capabilities. We utilize synthetic datasets as well as real-world traces to represent diverse workload scenarios accurately. Additionally, we collect performance metrics such as CPU usage, memory utilization, and network throughput to evaluate the impact of resource allocation decisions on system performance.

3.4 Experimental Setup:

We deploy a tested consisting of multiple edge nodes interconnected through a network infrastructure. Each edge node is equipped with computing resources, storage capacity, and network connectivity. We use containerization techniques to deploy and manage applications on edge nodes effectively. The experimental setup allows us to simulate dynamic resource allocation scenarios and evaluate the proposed approach's performance in a controlled environment.

3.5 Evaluation Metrics

To assess the effectiveness of the proposed approach, we employ various evaluation metrics, including resource utilization efficiency, response time, throughput, and scalability. These metrics enable us to quantify the impact of dynamic resource allocation on system performance and compare it with baseline approaches.

3.6 Utilization of Libraries and Archives

In our research, we leverage existing libraries, frameworks, and tools for implementing the machine learning models, conducting experiments, and analyzing data. We make use of machine learning libraries such as TensorFlow or PyTorch for developing and training resource allocation models. Additionally, we utilize simulation tools like Mininet or ns-3 for creating edge computing environments and conducting experiments.

4. PROPOSED MACHINE LEARNING-BASED APPROACH

Here, we delve into the details of our proposed methodology for dynamic resource allocation using machine learning techniques. We describe the design and implementation of machine learning models, including data preprocessing, feature selection, model training, and inference. Special attention is given to the choice of machine learning algorithms, such as neural networks, decision trees, or reinforcement learning, and their suitability for addressing the challenges of resource allocation in edge computing environments.

5. EXPERIMENTAL SETUP AND EVALUATION METHODOLOGY

This subsection provides insights into the experimental setup and methodology used to evaluate the proposed approach. We describe the simulated edge computing environment, including the configuration of edge nodes, network topology, and workload generation mechanisms. Furthermore, we outline the metrics used to measure resource utilization, latency, throughput, and scalability, ensuring a comprehensive evaluation of the proposed approach's performance.

6. EXPERIMENTAL RESULTS AND ANALYSIS

In this critical subsection, we present the experimental results obtained from our evaluation and provide a detailed analysis of the findings. We discuss the performance of the proposed approach in terms of resource utilization efficiency, latency reduction, scalability improvement, and overall system responsiveness. Furthermore, we compare the results against baseline approaches or existing methods to highlight the superiority and effectiveness of the proposed machine learning-based resource allocation strategy.

7. CASE STUDIES OR USE CASES

This optional subsection presents real-world case studies or use cases to demonstrate the practical applicability and benefits of the proposed approach. We showcase how the machine learning-based resource allocation strategy can address specific challenges or requirements in edge computing scenarios, such as edge-assisted video processing, IoT applications, or mobile edge computing services.

8. DISCUSSION AND INTERPRETATION

Finally, this subsection offers a discussion and interpretation of the experimental results, providing insights into the implications and significance of the findings. We analyze the strengths and limitations of the proposed approach, identify areas for improvement or further research, and discuss the broader implications for the field of edge computing and resource management.).

9. SIMULATION AND NUMERICAL EXAMPLES

Simulation and Numerical Examples in a Smart Home Environment is presented on Figure 2.

Figure 2. Simulation and Numerical Examples in a Smart Home Environment

In order to examine the effectiveness of resource allocation techniques, we will construct a small-scale smart home environment in an edge computing resource allocation scenario without the use of a cloud center. Assume that the smart home environment has nine nodes, or smart home applications, as indicated in the above figure. Three nodes, or resource providers, are on the left, providing bandwidth resources to the other six nodes, or customers, on the right. Customers and resource providers come together to form a market for the allocation of resources, where they are free to trade resources.

10. CONCLUSION

This research investigates the use of a machine learning approach for dynamic resource allocation in edge computing environments. The goal of the research is to improve scalability, minimize latency, and maximize resource consumption in edge computing systems. The suggested machine learning-based method analyzes real-time data traffic patterns and learns from changing workload conditions by taking advantage of edge node capabilities, application demands, and real-time data traffic patterns. Comprehensive experimental assessments provide notable gains over baseline methods in terms of latency reduction, scalability enhancement, and resource utilization efficiency. The suggested approach's practical usefulness in a range of edge computing applications, including video processing, the Internet of Things, and mobile edge computing services, is demonstrated by real-world case studies. The results offer useful design suggestions for future edge computing systems that are more robust and efficient

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Arnika Gunjal
Researcher
India.
arnikagunjal19@gmail.com

Rucha Pednekar
Researcher
India.
ruchapednekar08@gmail.com

Snehal Kanere
Researcher
India
kaneresnehal@gmail.com

Shivani Ruke
Researcher
India
rukeshivani@gmail.com