International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Analysis of Edge Computing Systems-An AI Based Perspective

Reddy Susmitha

B. Tech Student, Department of IT, GMR Institute of Technology, Rajam-532127, Andhra Pradesh, India
Email: 21341A12A7@gmrit.edu.in

ABSTRACT

In a wireless environment, the data is collected by a huge number of sensor devices and transferred to the cloud for storage and analysis. In this pattern the edge computing plays a crucial role that reduces data transmission time, reduces data size, minimizes the exposure of data to external networks, etc. Edge computing mainly focuses on the process of decision making and other related tasks, but there is a lack of knowledge in performing such tasks. For that, we need to adopt machine learning (ML) and deep learning (DL) models to enhance the intelligence and autonomy of edge devices. ML and DL are the recent advancements for giving out standard performance in terms of reducing time and improving efficiency. In this article, we have analysed various updated research articles with respect to advantages, challenges and open issues of edge computing by the help of AI-perspective.

Keywords: Wireless Environment, EDGE Computing, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL)

INTRODUCTION

In our digitally connected world, the convergence of AI and edge computing is leading to a profound transformation of our world. Imagine a scenario where data processing and intelligent decision-making occur closer to the source of information – this is the essence of edge computing. Edge computing, in essence, revolutionizes our data management methods by distribution of processing power, bringing it closer to devices and sensors, thereby enabling faster responses and reduced latency.

As edge computing spreads, AI is enhancing the capabilities of edge devices and making edge devices smarter. It helps these devices to do more than just collect data. They can study it, learn, and make quick, smart choices based on what they've learned. This mix of AI and edge computing pushes us into a world where machines can understand, figure out, and act on information superfast and super accurately.

In this paper, we dig deep into how AI and edge computing work together. We'll look at how AI programs fit into edge devices, how data gets handled right at the edge of the network, and how edge devices and the cloud team up. Also, we examine the security measures necessary to protect these systems from vulnerabilities, the adaptability of AI algorithms to changing environments.

By examining the connection between AI and edge computing, we want to see how powerful this combination is. This exploration shows how AI's intelligence is working with the distributed computing power of edge computing to change our digital world and make it possible to make decisions and process data in real time.

RESEARCH APPROACH

This research discussed the use of actor-critic reinforcement learning for resource management in mobile edge computing systems. It explained the challenges and issues faced in resource management in these systems. The proposed approach is to use actor-critic reinforcement learning for resource management in mobile edge computing systems. Actor-critic reinforcement learning is like having a smart system that learns how to manage resources in MEC.

This approach involves training an actor and a critic model to make resource allocation decisions based on the current system state and feedback from the environment. The actor model learns to select actions (resource allocation decisions) that maximize a reward signal, while the critic model evaluates the value of the chosen actions. By using this approach, the article aims to improve the efficiency and effectiveness of resource management in mobile edge computing systems.

These methods are designed to optimize resource allocation decisions considering dynamic user demands, varying network conditions, and limited computational resources available at the edge. The evaluation results show that the approach achieves better resource allocation efficiency and performance compared to traditional methods. The article suggests that this approach can be a promising solution for optimizing resource utilization in mobile edge computing systems.

METHODOLOGY:

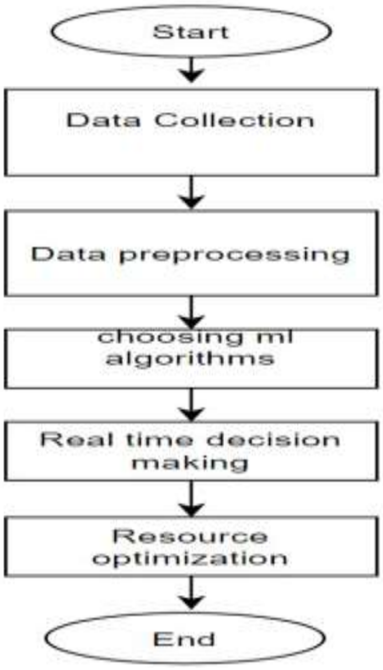

Fig 1 :Work flow of the proposed approach

The paper proposes an actor-critic (AC) with eligibility traces algorithm to address the offloading decision and resource allocation problem in mobile edge computing (MEC) systems based on reinforcement learning (RL) methods. The problem is modeled as a Markov decision process (MDP) considering the dynamic characteristics of the wireless environment. The actor part of the AC algorithm uses a parameterized normal distribution to generate probabilities for continuous stochastic actions, while the critic part employs a linear approximator to estimate the value of states. Actor is responsible for making decisions or take actions in an environment. It is a policy function that determines what action that an agent should take. Critic part evaluates the decisions made by the actor, it estimates the cumulative reward that an agent is likely to receive. The actor part updates policy parameters in the direction of performance improvement based on the estimated state values. An advantage function is designed to reduce the variance of the learning process.

Simulation results demonstrate that the proposed algorithm effectively maximizes the amount of tasks executed by the MEC server while reducing energy consumption and time-delays.

RESULTS

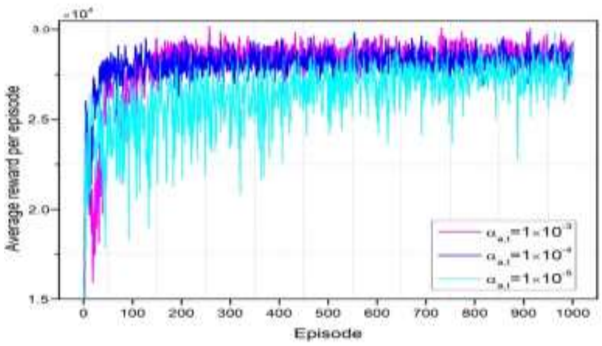

Fig 2: The average reward per episode with different learning rates of the actor

This section presents simulation outcomes of the proposed online and on-policy actor-critic algorithm, compared with various baseline learning algorithms. These simulations were conducted using a Python-based simulator. The evaluation seems to revolve around the stability, convergence, and variability of the learning processes, specifically related to rewards and the number of episodes required to reach certain states or behaviours in the algorithms being analysed.

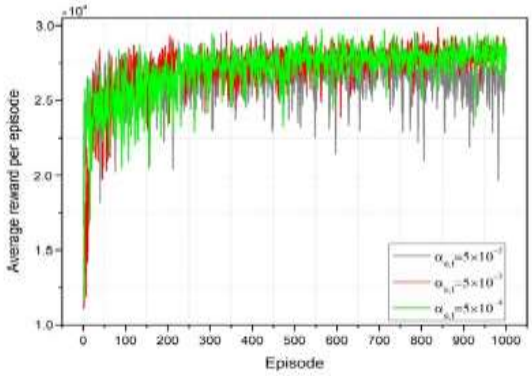

Fig 3: The average reward per episode with different learning rates of the critic

CONCLUSION

Edge computing has emerged as a transformative paradigm in the realm of distributed computing, bringing computation and data storage closer to the edge of the network. This decentralized approach offers a lot of benefits, including reduced latency, improved resource utilization, and enhanced privacy and security. The integration of artificial intelligence (AI) into edge computing systems has further revolutionized this technology, enabling intelligent decision-making and real-time data analysis at the edge. AI-powered edge computing systems can effectively handle complex tasks such as anomaly detection, predictive maintenance, and real-time optimization. In various industries, including manufacturing, healthcare, transportation, and smart cities, AI-powered edge computing is driving innovation and transforming operations. For instance, in manufacturing, edge computing can optimize production processes, reduce downtime, and improve quality control by analyzing sensor data in real-time. In healthcare, edge computing can enable real-time patient monitoring, remote diagnostics, and personalized treatment plans. The convergence of edge computing and AI has opened up a new era of intelligent and efficient computing, paving the way for a wide range of innovative applications across various industries. As these technologies continue to evolve, edge computing and AI are poised to play an increasingly critical role in shaping the future of computing and transforming industries worldwide.

References

1. Hua, H., Li, Y., Wang, T., Dong, N., Li, W., and Cao, J. (2023). Edge computing with artificial intelligence: A machine learning perspective. ACM Computing Surveys, 55(9), 1-35.
2. Singh, S., Sulthana, R., Shewale, T., Chamola, V., Benslimane, A., & Sikdar, B. (2021). Machine-learning-assisted security and privacy provisioning for edge computing: A survey. IEEE Internet of Things Journal, 9(1), 236-260.
3. Fu, F., Zhang, Z., Yu, F. R., & Yan, Q. (2020). An actor-critic reinforcement learning-based resource management in mobile edge computing systems. International Journal of Machine Learning and Cybernetics, 11, 1875-1889.
4. Akhtar, M. N., Shaikh, A. J., Khan, A., Awais, H., Bakar, E. A., & Othman, A. R. (2021). Smart sensing with edge computing in precision agriculture for soil assessment and heavy metal monitoring: A review. Agriculture, 11(6), 475.
5. Lv, Z., Chen, D., Lou, R., & Wang, Q. (2021). Intelligent edge computing based on machine learning for smart city. Future Generation Computer Systems, 115, 90-99.
6. Filho, C. P., Marques Jr, E., Chang, V., Dos Santos, L., Bernardini, F., Pires, P. F., ... & Delicato, F. C. (2022). A systematic literature review on distributed machine learning in edge computing. Sensors, 22(7), 2665.
7. Tian, K., Chai, H., Liu, Y., & Liu, B. (2022). Edge intelligence empowered dynamic offloading and resource management of MEC for smart city Internet of Things. Electronics, 11(6), 879.
8. Liu, X., Jin, J., & Dong, F. (2022). Edge-computing-based intelligent IoT: Architectures, algorithms and applications. Sensors, 22(12), 4464.
9. Singh, A., Satapathy, S. C., Roy, A., & Gutub, A. (2022). Ai-based mobile edge computing for iot: Applications, challenges, and future scope. Arabian Journal for Science and Engineering, 1-31.
10. Xia, X., Chen, F., He, Q., Cui, G., Grundy, J., Abdelrazek, M., ... & Jin, H. (2021). OL-MEDC: An online approach for cost-effective data caching in mobile edge computing systems. IEEE Transactions on Mobile Computing.
11. Wang, S., Chen, M., Liu, X., Yin, C., Cui, S., & Poor, H. V. (2020). A machine learning approach for task and resource allocation in mobile-edge computing-based networks. IEEE Internet of Things Journal, 8(3), 1358-1372.

12. Chen, Y., Chen, S., Li, K. C., Liang, W., & Li, Z. (2023). DRJOA: intelligent resource management optimization through deep reinforcement learning approach in edge computing. Cluster Computing, 26(5), 2897-2911.

13. Zhu, X., Luo, Y., Liu, A., Xiong, N. N., Dong, M., & Zhang, S. (2021). A deep reinforcement learning-based resource management game in vehicular edge computing. IEEE Transactions on Intelligent Transportation Systems, 23(3), 2422-2433.

14. Chen, Y., Liu, Z., Zhang, Y., Wu, Y., Chen, X., & Zhao, L. (2020). Deep reinforcement learning-based dynamic resource management for mobile edge computing in industrial internet of things. IEEE Transactions on Industrial Informatics, 17(7), 4925-4934.

15. Peng, H., & Shen, X. (2020). Deep reinforcement learning based resource management for multi-access edge computing in vehicular networks. IEEE Transactions on Network Science and Engineering, 7(4), 2416-2428.

16. Liu, X., Yu, J., Wang, J., & Gao, Y. (2020). Resource allocation with edge computing in IoT networks via machine learning. IEEE Internet of Things Journal, 7(4), 3415-3426.

17. Guo, Y., Zhao, R., Lai, S., Fan, L., Lei, X., & Karagiannidis, G. K. (2022). Distributed machine learning for multiuser mobile edge computing systems. IEEE Journal of Selected Topics in Signal Processing, 16(3), 460-473.

18. Ranaweera, P., De Alwis, C., Jurcut, A. D., & Liyanage, M. (2022). Realizing contact-less applications with multi-access edge computing. ICT Express, 8(4), 575-587.

19. Lapegna, M., Balzano, W., Meyer, N., & Romano, D. (2021). Clustering algorithms on low-power and high-performance devices for edge computing environments. Sensors, 21(16), 5395.

20. Tripathy, S. S., Imoize, A. L., Rath, M., Tripathy, N., Bebortta, S., Lee, C. C., ... & Pani, S. K. (2023). A novel edge-computing-based framework for an intelligent smart healthcare system in smart cities. Sustainability, 15(1), 735.