Dynamic Offloading Policy for Multi-user MEC System using Deep Reinforcement Learning

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***Abstract*— In this work, a deep reinforcement learning decentralized computation offloading procedure is examined for a stable Mobile Edge Computing (MEC) framework. MEC is a promising answer to solving the challenge of resource limitation of mobile devices from computation concentrated tasks which makes the device empower to offload workloads to the nearest edge server. For Multiple mobile user in MEC, the plan of computation offloading strategy is trying to limit the computation and delay constraint. In some of the studies they used Markov decision process (MDP), Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) to address those issues. Because of having some Limitations this paper proposed to use Deep Deterministic Policy Gradient (DDPG) where no global information is required for computation offloading policies.This proposed DDPG decentralized method can outperform the other deep networks in terms of computational cost with power consumption and buffering delay.**

***Keywords*— Edge computing, Offloading, Reinforcement learning, DDPG.**

I. INTRODUCTION

Internet Things (IoT) is extending step by step and making our lives simpler by offering numerous applications like smart urban areas, home computerization, security surveillance, and smart health sectors regardless of the time and place. These IoT applications and services are producing enormous amount of information, which can be extremely valuable whenever investigated appropriately well on schedule. Big data handling process use cloud computing assets in order to process huge tasks. While it demands for high bandwidth, cloud computing is not appropriate for real-time service networks. To handle and overcome these issues, Mobile Edge Computing (MEC) was proposed which can facilitate in the IoT scenario where real time cases are more important with low latency and high bandwidth [1] where data can be processed closer to the users and end points. This can empower mobile devices to offload their computation intensive tasks to the base station (BS) which is associated with MEC server. Thus the QoE improves in terms of reduced latency and required power.

To adapt stochastic task appearances and time-fluctuating remote wireless channels, dynamic control of radio with computation assets in MEC frameworks become very challenging. Authors in [2] proposed a threshold-based unique calculation offloading strategy to limit the power utilization for stochastic remote channels considering DRL. In [3], the authors described a reinforcement learning (RL) based algorithm for optimal computation offloading policy for MEC system, which works without having the earlier information on the framework. Typical RL algorithms can't scale with high quantity of agents increments, since the blast of state space will make customary plain techniques absurd. Regardless, by applying deep neural network (DNNs) for function estimate, deep reinforcement learning (DRL) has been shown to productively surmised Q-estimations of RL [4]. Many research papers have tried to employ DRL for resource allocation and task scheduling in MEC system. In [4], total sum cost in terms of buffering delay with power utilization of a MEC framework is thought of. With no earlier information on network insights of the MEC framework, a unique computation offloading strategy will be found out freely at every portable client dependent on neighborhood perceptions of the MEC framework. In addition, not exactly equivalent to other DRL based methodologies while other works make choice based on discrete action spaces, this paper adopted a continuous action space based calculation called DDPG which guarantees power tradeoff during neighborhood execution and assignment offloading.

II. SYSTEM MODEL

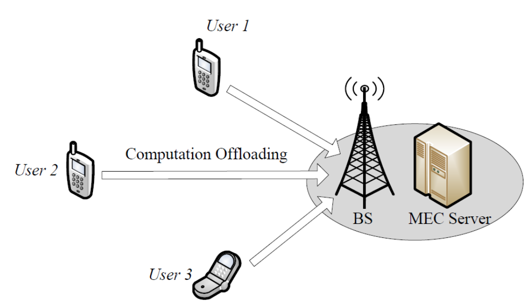

Fig. 1. Multi user MEC system with BS

Here as shown in Fig. 1, a MEC framework comprising of single base station (BS) with an appended MEC framework and numerous mobile clients considering stochastic task with time-varying channels. With no earlier information on network information of the MEC framework, a special offloading procedure will be found out uninhibitedly at each mobile client reliant on local view of the MEC structure. Also, not the same as other strategies like DRL in existing works choosing decisions in discrete action spaces, we get a consistent action space based calculation named DDPG to induce better energy control of neighborhood execution and undertaking offloading. A MEC framework is thought of with multi-user MIMO system, where every portable client considering stochastic task appearances while channels are time-varying to autonomously learn in dynamic offloading strategies without any preparation to limit long haul normal computational cost regarding power utilization and buffering delay.

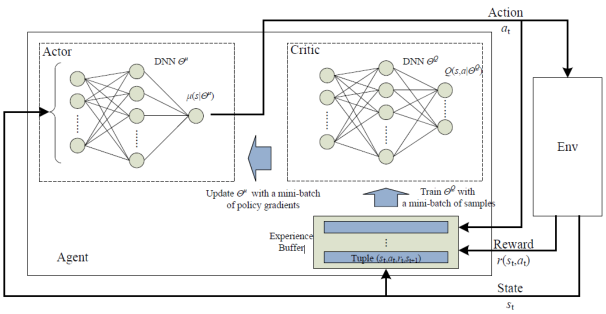

Fig. 2. DDPG diagram

DDPG (see Fig. 2) is the recent extension of DRL which we are trying to use or propose to use in MEC system for decentralized dynamic offloading scenario. By applying DDPG, a DRL structure for decentralized computational offloading has been planned, which empowers every mobile client to use just nearby perceptions of the MEC framework to progressively learn productive policies for dynamic energy allotment of both neighborhood execution with computation offloading in a continuous space.

Here, how every versatile user $m \in M$ exploits nearby execution or computation offloading to fulfill its applications is our major concern. A few bits among all requested bits of the processing tasks will be handled on the cell phone, and MEC structure will help to offload some other bits and will be executed there. Measurement of data bits which is processed locally for the distributed local power utilization is discussed here. For edge computing leveraging, it is important to deal with adequate resources for computation such as a high-recurrence multi-core CPU. Thus, it will in general be normal that different applications can be dealt with in comparing with an immaterial execution latency, while the incoming delay is overlooked because of the little estimated computation output. Among these lines, every data bits will be offloaded to MEC by means of the BS will be dealt with.

III. COMPARATIVE RESULT

We likewise explore the results by assuming different estimations of tradeoff factor (set as 0.3 to 0.8) for the average delay tradeoff. In Fig. 3, it be observed from the graph that, between normal power utilization and buffering delay there exists tradeoff. In particular, the higher the tradeoff, the power utilization will be diminished by yielding the execution delay. It is moreover significant that for every estimation of tradeoff factor, the policy gained from DDPG consistently has better execution to the extent both usage of power and buffering delay, that shows the prevalence of the DDPG based strategy for having control in power utilization. For the multi-client MEC system we considered 3 mobile user. Considering the multi-client circumstance, power use can be constrained with a satisfied normal buffering delay, by picking an authentic estimation of tradeoff factor.

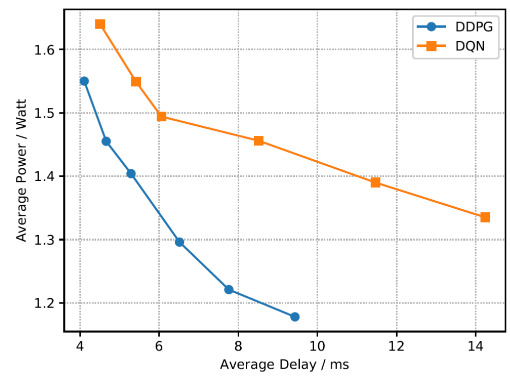

Fig. 3. Single user agent power delay trade-off

IV. CONCLUSIONS

This paper argues that every task offloaded to the MEC server by means of the BS will be handled using the proposed DDPG. The proposed approach allows is used to limit the long term calculation cost regarding power utilization and buffering delay. In achieving this, purpose of DRL based decentralized dynamic offloading calculations has been researched. In particular, by embracing the constant action space based DRL based approach called DDPG, a productive calculation offloading strategy has been effectively learned at every mobile user, which can apportion power of local execution and task offloading adaptive from its local perception of the MEC framework.

ACKNOWLEDGMENT

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