Delay-Aware Task Offloading for Mobile Fog Nodes in Smart Cities: A Fuzzy and Q-Learning Approach

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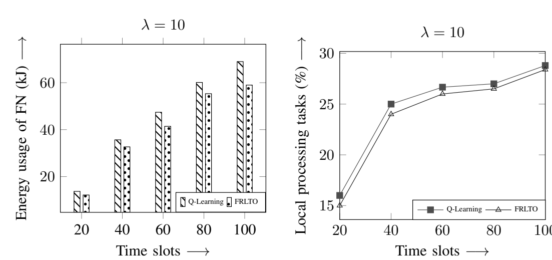
I. Introduction

Vehicular services, such as remote intelligent control, vehicular video streaming and virtual reality-based driving assistance, are delay-sensitive tasks [1]. These tasks request more computational powers and consume more energy for processing. Thus, these tasks are offloaded to the fog node (FN) in the fog computing (FC) infrastructure. Therefore, integrating vehicular networks and FC leads to fog computing-based vehicular ad-hoc networks (FCVANETs) [2]. In FCVANETs, vehicular services are disrupted when the FN's battery is depleted, particularly in remote areas lacking consistent power, such as forests and mountainous terrain. Reviving the FNs necessitates either solar energy or human intervention, and providing continuous services until the next recharge cycle without exhausting energy is challenging. As a result, we consider that FNs are equipped with powerful batteries that are periodically recharged but lack a permanent power source. Further, we consider the FNs coverage regions overlapping with neighbouring FNs and delivering services to the requested vehicles in the overlapping regions. However, vehicles without service requests and ample computational capabilities are designated as mobile fog nodes (MFNs). We introduce a task-offloading approach called fuzzy and reinforcement learning task offloading (FRLTO) to increase the lifetime of FCVANETs. The existing work [2] addresses FN factors, such as energy consumption, latency, delay constraints, and reliability, but overlooks the challenges that arise in FCVANETs when the coverage areas of FNs intersect with neighbouring FNs. Conversely, the task offloading approach presented in this work considers factors such as task data size, delay constraints, and MFNs' sojourn time within the overlapping region.

II. Design and Evaluation

FRLTO is designed to enhance the energy efficiency of FNs by offloading tasks among the MFNs. It uses fuzzy and Q-learning based reinforcement learning (RL) to offload tasks based on task data size, delay constraints and the sojourn time of MFNs. The RL agent is trained to select a suitable MFN (i.e., maximum weighted MFN) in each time slot t to meet the delay constraint of tasks. However, the selection of MFN depends on the availability of MFN's computational resources and sojourn time. Thus, the agent assigns weights to MFNs using fuzzy logic (i.e., triangular membership function) based on task data size, MFN's sojourn time, and task deadline. Consequently, fuzzy inference rules are derived to assign weights to MFNs. The selection of maximum weighted MFN is considered the current RL agent policy. We simulate the FRLTO approach with a mean arrival rate of 10 vehicles/s in the overlapping region for 100 seconds. Subsequently, the average FN energy usage is determined as the number of vehicles entering the network increases. FRLTO is evaluated with vehicles in the overlapping region of 900 meters, maintaining steady speeds ranging between 15 m/s and 25 m/s. The offloaded tasks in the FNs have the data size, CPU needs and deadlines ranging from 10 to 40 MB, 1000 to 2500 Megacycles and 1 to 10 s, respectively. Further, the FN and MFN bandwidths are 20 MHz and 10 MHz, respectively. The RL agent's discounting factor, epsilon and learning rate are 0.9, 0.2 and $\frac{1}{S_t}$, respectively, where S_t is the system state at time slot t. Fig. 1a and Fig. 1b show that the FRLTO outperforms the Q-learning regarding average FN energy usage and percentage of tasks processed in FNs with an improvement of 10.95% and 3.19% on average, respectively.



(a) Average FN energy usage (b) Local processing of tasks

Fig. 1: Average energy usage of FN and local processing of tasks in FNs using Q-learning and FRLTO algorithms.

III. Conclusion

FRLTO enhances the efficiency of FNs during discharge time in terms of the average energy usage of FN and the percentage of tasks processed in FNs compared to Q-learning.

References

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