DRL Based Service Migration and Resource Allocation in Vehicular Edge Networks

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Motivation

Modern Smart Vehicles generate large amount of data and provide various services to the users such as In Vehicle Infotainment (IVI), Advanced Driver Assistance and Vehicle safety which needs significant computing power. Due to limited amount of computing resources on vehicle, This data is offloaded to Mobile Edge Computing Server (MEC Server) for faster computing. However these applications run latency sensitive, data and compute intensive tasks. It becomes a challenge to maintain Quality of Service Consistently and maintain service delay close to minimum for a service provider in mobile, dynamic environment.

Existing Work

Task offloading in dynamic environments has been an active research topic. **Service Migration (SM)** is a popular method to keep applications hosted as service on the edge network close to the user. Using service migration, the services hosted on an edge server can be migrated to another through which communication distance between the subscriber and service is minimum. We broadly classify service migration into two types:

- **Vehicle Initiated Migration [1]:** used this method where in vehicles decided upon service migration and task offloading based on their location in the environment. However, bandwidth channels and computing resources were allocated equally to these vehicles and the migration was jointly optimized with the routing which implied a non adaptive route planning.
- **Network Initiated Migration [2]:** In this scenario, the network (MEC servers) made the decision of service migration by grouping the vehicles and initiating the migration for the entire group. This approach however, computing and bandwidth resources were allocated equally and the simulation was conducted in a closed environment.

These methods further carried out the simulation by Formulating a **Markov Decision Process (MDP)** through which merit of each action was determined for a given system state. This MDP was learned and solved by using *Deep Reinforcement Learning (DRL)*.

Our Approach

We intend to carry out a network initiated migration based environment with the ability to provide **Bandwidth Resource Blocks (BRBs)** and **Compute Resource Blocks (CRBs)** adaptively. A single agent based MDP problem is formulated by grouping the users based on time slots remaining, application hosted under each 5G Base Station called **Road Side Unit (RSU)**. State Vector is formulated by accumulating the states seen by the RSU and appending additional state information of the MEC server. Action vector consists of CRBs and BRBs allocated to each group and migration decisions made by the MEC Server. The resources alloted to each group is further divided equally among the users active in the group. We then use **Deep Deterministic Policy Gradient (DDPG)** to solve the MDP and train the agent to take decisions accurately.

References

[1] Q. Yuan, J. Li, H. Zhou, T. Lin, G. Luo, and X. Shen, "A joint service migration and mobility optimization approach for vehicular edge computing," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 8, pp. 9041–9052, 2020.

[2] W. Chen, M. Liu, F. Wu, H. Wu, Y. Miao, F. Lyu, and X. Shen, "Msm: Mobility-aware service migration for seamless provision: A data-driven approach," *IEEE Internet of Things Journal*, vol. 10, no. 17, pp. 15 690–15 704, 2023.

System Model

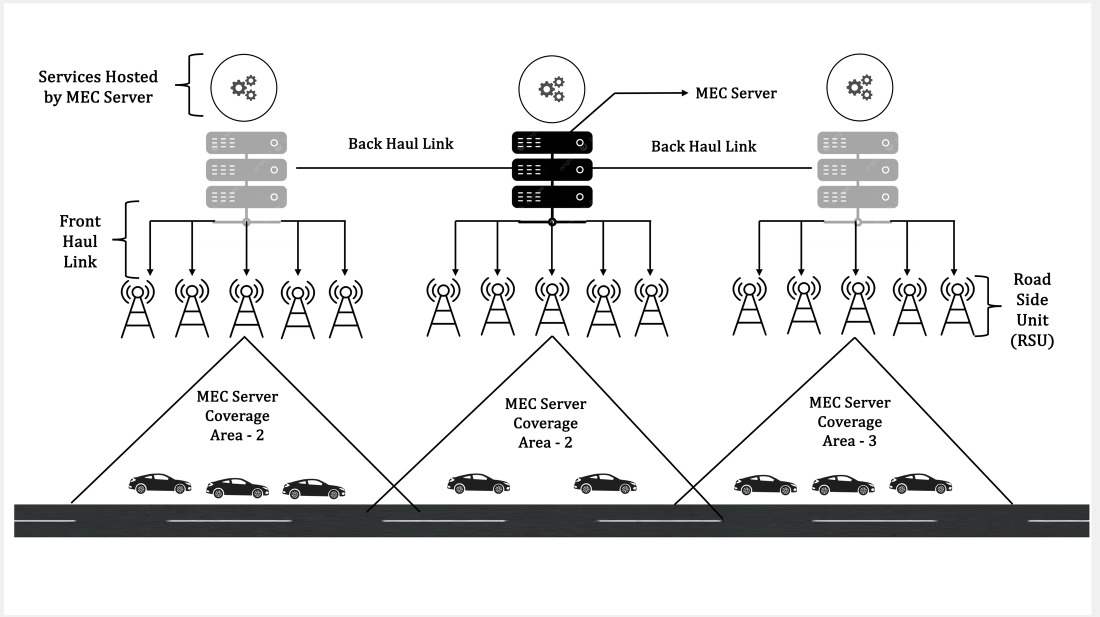

Figure 1. Overview of the System Model

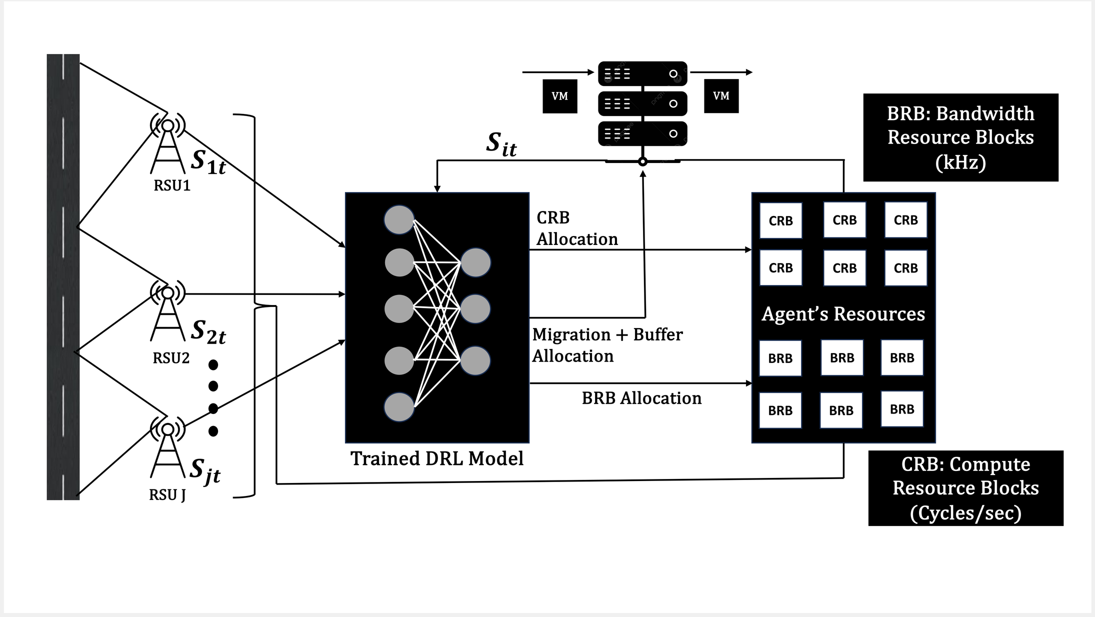

Figure 2. System Model: System Integrated with DRL model.

Formulation

State Vector: $S_t = [\{V_{j,k,t} : \forall j, \forall k\}, W_t, X_{i-1,t}, Y_{i+1,t}]$

where:

$V_{j,k,t}$ = vehicle hosting Application k under RSU j under time slot t.

W_t = number of vehicles with $\mathcal{T}$ time slots remaining under the MEC server (Agent).

$X_{i-1,t}$ = number of vehicles migrated by MEC server i-1 to i.

$Y_{i+1,t}$ = number of reservations (CRBs) made by MEC server i+1 for i.

Action Vector:

$A_t = [\{b_{j,k,t} : \forall j, \forall k\}, \{c_{k,t} : \forall k\}, y_{i,t}, x_{i,t}]$

Where:

$b_{j,k,t}$ = Bandwidth Resource block allocated for vehicle group under RSU j hosting application k at time slot t.

$c_{k,t}$ = Compute Resource Block for application k at time slot t.

$y_{i,t}$ = allocations made by MEC server i for i-1 at time slot t.

$x_{i,t}$ = allocation prediction made by MEC server i for i+1.

Reward:

A utility function with sum of computation and communication delay as input.

Note: The parameters which define the MDP are subject to constraints.

Results

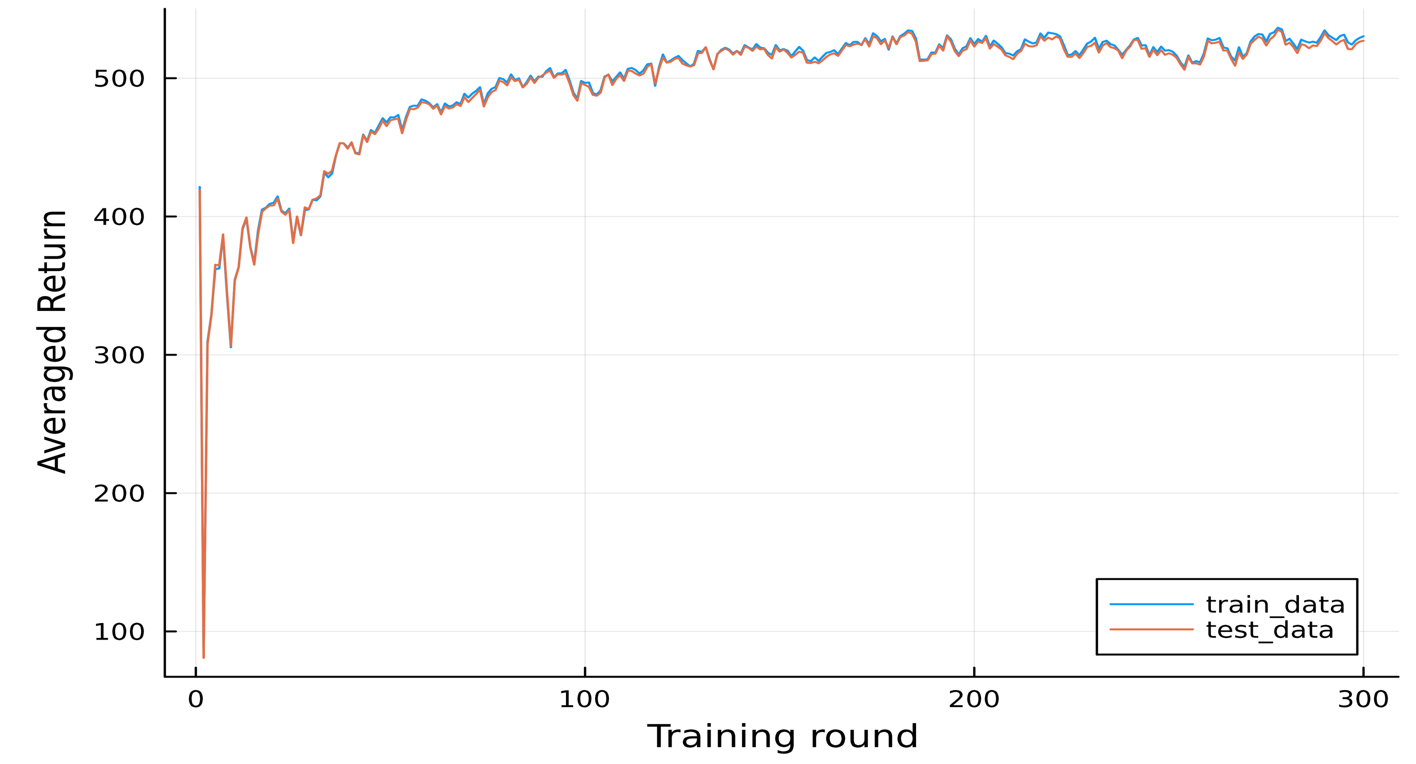

Figure 3. Expected Return v/s Training Round

from Fig. 3 we infer that the DRL model trained through DDPG algorithm is able to allocate resources and migrate services accurately with significant expected returns.

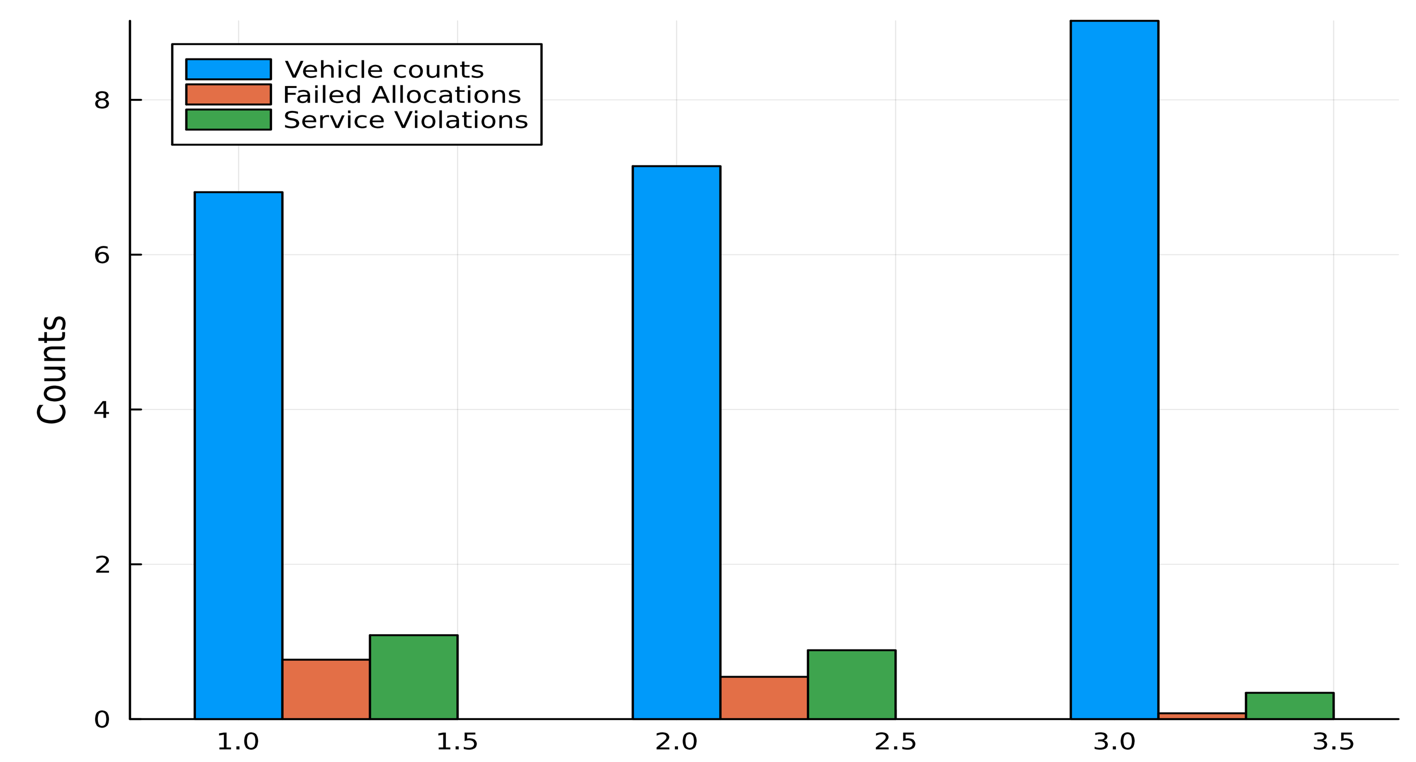

Figure 4. Quality of Service achieved by the model

From Fig. 4 we extract the information of quality of service being maintained by this scheme. From this figure, we can show that the model is facing low failed allocation counts and service violations post training through DDPG.

Conclusion and Future Work

We considered the task offloading in mobile environment problem. We found that bandwidth and computing resource allotment was not performed in the literature. We introduced a joint bandwidth and compute resource allocation scheme in service migration based vehicular environment. The formulated MDP was learnt by the DDPG trained DRL model. We achieved a significant QoS and service delay improvement.

We are trying to extend this problem to a multi-agent, multi grid based environment where each MEC server collaborate with multiple MEC servers to jointly optimize service delay.