A DRL based *4-r* Computation Model for Object Detection on RSU using LiDAR in IIoT

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***Abstract*—Internet of vehicle (IoV) network comprises Road Side Unit (RSU), which has become a computation and communication device for effective LiDAR data communication (ex: object detect information) between vehicle-to-infrastructure (V2I) and vehicle-to-vehicle. However, the LiDARs generate a massive volume of 3D data with a notable redundancy rate leads to inadequate object detection accuracy, and the high operational cost of RSU due to inadequate resource and time consumption. Estimating the computation capacity for RSU selection is an NP-hard problem. To address this issue, we propose a Deep Reinforcement Learning (DRL) influenced *4-r* computation model to measure RSU cost based on resource feasibility factor and object region detection rate based on novel region-of-interest (RoI) strategy. The resource feasibility factor appraises the residual capacity and cost of RSU based on a criterion of optimality. The RoI strategy eliminates irrelevant points, noise and ground points based on distance and shape measures of an object on RSU with feasible consumption of computation resources. The simulation results show that our mechanism achieves 83% average object detection accuracy rate, 81% average service rate and 17% service offloading rate than state-of-art approaches.**

I. Introduction

Internet of Vehicles (IoV) orchestration is an emerging paradigm in vehicular applications for the effective design of automated vehicles, in which RSU integrated LiDARs plays a vital role to accomplish the target. LiDAR sensors are frequently utilized in autonomous vehicles based on a detailed investigation of their deployment. The Light Detecting and Ranging (LiDAR) sensors are mainly three types. First, the Airborne sensor measures environmental and atmospheric conditions, which are mounted on satellites and aircraft. Second, spaceborne sensor measures docking distance of space station, space exploration by mounting on probe robots, and third, ground-based LiDARs to measure vehicle speed and distance, which become a prominent component for AVs, UAVs, and robots. Ground-based LiDAR sensor measures the objects with reliable depth information, which plays a vital role to localize the object with effective shape characteristics. The RSUs are enriched with limited computation resources and storage space to map the execution of latency constraint applications. The RSU-LiDAR is a static deployment. It detects the objects in abnormal environments such as rain, fog, and snow, but the LiDAR Point Clouds are sparse, irregular with high variable point density which causes occlusion and 3D space non-uniform sampling. For instance, complete traffic information is measured without noise and occlusions because of no vibrations, making the accurate computation for Autonomous Vehicles, autonomous harbours, and mining sectors. The background filter is not initiated for each object detection, but when the background changes, the performance might be diminished. In this regard, an Artificial Intelligent edge computing service is praised for IoV frameworks. Leveraging the RSU capability helps to apprehend the resource requirements to meet the QoS of connected vehicles [1], [2]. The RSUs interconnects to edge servers to provide the services to vehicles in their range of coverage with cloud service backbone. Suppose the computational service request violates the server computing capacity; the service request offloads to the cloud server for effective execution. In this scenario, 3-tired architecture is required to construct for effective vehicle orchestration. Recent computation offloading strategies pay attention to optimize the latency of applications [3], but achieving joint communication between servers is still a global challenge. The heterogeneity services (like object detection, object tracking) needs attention to balance the workload among the RSUs to enhance the service quality and system performance.

The RSU-vehicle communication enhances pedestrian and vehicle safety by sharing object detection, internet connective, road scene and traffic congestion information [4]. However, the RSU needs *novel sensor data manipulation strategies* to regulate data transmission service with limited resources in a scalable manner within the vehicle range. In [5], Bayes filter based object detection system has been designed with the LiDAR framework. In [6], robust curb tracking and localization system have been developed with the LiDAR framework. Various studies are attempted to minimize the cost of RSU but were not considered the object detection rate during cost analysis. Our main contributions are as follows:

1) Develop a Deep Reinforcement Learning (DRL) inspired *4-r* model to optimize the RSU cost and object region.
2) Develop a resource feasibility factor to assess the residual capacity and cost of RSU based on criterion of optimality for effective data transmission among vehicles and RSUs.
3) Develop a RoI strategy to remove noise, ground, and irrelevant objects to measure object region.
4) MATLAB Simulations for object detection and assessment of computation capacity to optimize the RSU lifetime.

The manuscript continues as Section II briefly explains research gaps and problem statements of extant approaches. Section III describes the proposed system and its mathematical model with novel algorithm in detail. Section IV, evaluates the investigation outcomes and Section V concludes the manuscript.

II. Related Work

This section describes object detection based on RoI and RSU deployment methods based on the deterministic instances to make an AV movement decision.

A. RSU-LiDAR Consolidation Methods

The majority of works mainly concentrated on formulating object detection difficulties of AV systems. In [7], an RSU LiDAR strategy has been designed for isolating the background by distinguishing the road lane. The point density helps for background dissemination, and the multiclassified density-based spatial clustering method (MCDBSCAN) is applied for lane assessment. In [8], a traffic control strategy is designed dependent on LiDAR and image through Gaussian-Bernoulli profound Boltzmann machine model (GB-DBM) with earlier information on intensity, road width, pole stature, environment structure and traffic-sign size. A voxel and random sample consensus (RANSAC) approach are designed based on statistical filtering with Gaussian distribution for ground-level assessment and snag identification [9]. A segment-based technique has been designed based on features like shape, size for adequate classification to recognize the vehicle orientation. The moving vehicles evaluated through the distance moved by the portions and movement direction are utilized in [10].

Data fusion with low noise from RSU LiDAR for effective object tracking and detection is challenging. Most approaches are being implemented based on onboard LiDAR and RSU LiDAR. Various calculations have been led for object detection utilizing the LiDAR data, and a large portion of simulations attempted based on airborne LiDAR, and onboard LiDAR [11]. In [12] an object detection and tracking strategy has been designed based on LiDAR information. Two equal mean-shift calculations were smeared towards object identification and tracking based on 2D/3D Kalman filter. Anyhow, this technique detects the proper shape of objects, but the detection range was restricted. In [13], a dynamic object localization mechanism has been designed utilizing 2D LiDAR and subsequently detect and removes the obstacles during object consolidation. This strategy is deficient in semantic translation during object detection and tracking. In [14], 3D LiDAR data is used to classify objects based on a spatial encoder-decoder strategy for autonomous vehicles. The Temporal-Channel Transformer (TCTR) has been designed with spatial data to detect the object. However, those methods need pre-trained and shaped data to detect the object, and the gate mechanism has been used to re-calibrate the features. In [15], a searching strategy has been designed to assess object angle, which does not suits L-shape box methods. In [16], a shape calculation method has been designed using a 2D bounding box. The shape has been measured by regulating the computation mechanism to diminish the least square errors.

B. Object Detection Methods

The RSU deployment affects latency, performance, and data transmission rate among vehicles within the region. Vehicle density-based RSU installation strategy has been designed with deployment cost and geography scheme; however, high vehicle density causes to violate the threshold value of cost [17], [18]. Dynamic linear dimensionality scheme has been used for RSU relocation to mitigate content conveyance during complex conditions [19]. In [20] *0-1 knapsack* approach has been used to minimize the cost of RSU installation in metropolitan regions. In [21], a novel analytical model considers connected and disconnected RSUs data to maximize the profit of RSU deployment. In [22], an adaptive algorithm has been designed to enhance the service execution rate by considering a novel offloading strategy to increase the data transmission rate among vehicles and RSU. In [23], a data transmission method has been designed based on RSU to extend the communication service in metropolitan regions. The author assumed parked vehicles as RSUs to offer service support to clients [24]. In [25], [26] parked vehicle has used to expand data transmission service in coverage of RSUs while cogitating content freshness, resource usage rate, and the vitality consumption. In [27], [28], the vehicular distributed computing framework enables pragmatic RSUs to gather information (Ex: LiDAR information) for sharing to related vehicles through multiple request replication strategies. A self-sorting method has been designed to choose several parked vehicles to expand the framework capacity.

In this regard, we design a DRL influenced *4-r* model to consolidate the RSU resource cost along with a moderate object detection accuracy rate in two steps. First, identifying the regions of the object using LiDAR data is accomplished by streamlining ground, noise and other objects through a RoI consolidation mechanism based on the KNN approach. Second, the resources of RSU has been optimized based on estimating data communication and computation delay factors to diminish service request execution (object detection through

RoI) cost that influence continuous monitoring and detection of the object.

III. Proposed Work

The vehicle requests are of two types. One is download request and computation request, which is processed based on the measured data from deployed sensors like LiDAR, and it can observe in Fig. 1. In our orchestration, LiDAR sensor data consider estimating the object region based on a novel RoI strategy. The service request is either executed at a vehicle or offloads to RSU to assess object orientation. Here, we have to notice the variations in resource consumption and latency's while executing the request at a vehicle and RSU. If the content request is generated from a vehicle, then RSU has to share the data or fetch it from a cloud server to execute the request. In this paper, the computation request is defined as identifying the object from the measured point clouds. The object detection process consists of three parts, pre-assessment, clustering based on RoI and depth measurement. The complete mechanism is divided into two main functions: RSU deployment with low cost, and, second, optimizing resource consumption while detecting the object. The Rate-Return-Range of RSU $(4-r)$ model is designed to assess the performance rate (execution of object detection request) and return cost (resource usage to execute the request), and coverage range (to accomplish the service reliability) factors while consolidating the RSU. Consequently, the RSU is interconnected with LAN, which helps to balance the execution mechanism.

A. 4-r Measurement based Intelligent RSU Computing using DRL

In our orchestration, $R = \{r = 1, 2, \ldots, R\}$ number of RSUs are connected with high-speed LAN and the RSUs are rich in computing & storage capacity to process the arrived service request. $V = \{v = 1, 2, \ldots, V\}$ number of vehicles which communicate with RSU through orthogonal frequency division multiplexing model. Let $S = \{1, 2, \ldots, s, \ldots, S\}$ number of service requests and $T = \{1, 2, \ldots, t, \ldots, T-1\}$ number of time slots concerning to update the measures and assessment strategies. The communication delay between RSU (r) and vehicle (v) at time t is measured as follows

$$\phi_{r,v}^{t} = \hbar \log_2 \left(\frac{1 + \phi_{po}^{v} g_{r,v}^{t}}{(np)^2} \right) \tag{1}$$

Where, $\hbar$ is RSU bandwidth capacity, ϕ_{po}^{v} is vehicle transmission energy and np, $g_{r,v}^{t}$ is energy noise and channel gain between vehicle and RSU. The RSU cost is formulated as

$$\mathbb{C}_r^t = \sum_{v_r \in V} \left(c_{vn} \cdot \phi_{r,v}^{t} + c_{df} \left(1 - q_v^t\right) s_{ed} \right) + c_{se} \cdot L_r \tag{2}$$

Where, v_r bunch of vehicles associated with RSU, c_{vn}, c_{df}, c_{sc} denotes virtual network cost, data sharing cost, service execution cost respectively and S_{ed} denotes anticipated service request size, $q_v^t \in \{0, 1\}$ is a data fetching decision, whereas $q_v^t = 0$ denotes the RSU fetch the data from server, L_r

Algorithm 1: RSU Computation Analysis

input : R number of RSUs, V number of vehicles, Let S number of service requests and T number of time slots
output: RSU computation decision

```
Let ρ_v = 0;
for each t = 1 to T do
    Estimate service count of each RSU;
    if φ^t_{r,v} ≤ φ̂^t_{r,v} then
        Estimate service queue cost of RSU as follows;
        κ_r/s_ed × κ_v^{s_ed};
        The service queue length is
        ρ^r_{v,t+1} = max{ρ^r_{v,t} + φ^t_{r,v} − φ^{t̂}_{r,v}, 0};
    end
    else
        Offload the request to the feasible RSU through
          LAN;
    end
end
```

Algorithm 2: RSU Computation Cost Analysis

input : $\kappa_r / s_{ed} \times \kappa_v^{s_{ed}}$, R number of RSUs, V number of vehicles, Let S number of service requests and T number of time slots
output: RSU cost minimization

```
Let κ_r/s_ed × κ_v^{s_ed} ≠ 0, φ^t_{r,v} ≠ 0, D ≠ 0, c_vn ≠ 0,
  c_df ≠ 0, c_se ≠ 0;
for each t = 1 to T do
    Estimate communication delay;
    φ^t_{r,v} = ħ log_2((1 + φ^v_{po} g^t_{r,v}) / (np)^2);
    Estimate computation delay with Eq. 6;
    if φ^t_{r,v} ≤ threshold && D ≤ threshold then
        Estimate the system cost ;
        C^t_r =
          Σ_{v_r ∈ V} (c_vn · φ^t_{r,v} + c_df (1 − q^t_v) s_ed) + c_se · L_r;
    end
    if C^t_r ≤ threshold then
        Continue the execution with RSU;
    end
    else
        Switch to other RSU or RSU updates the
          service through server;
    end
end
```

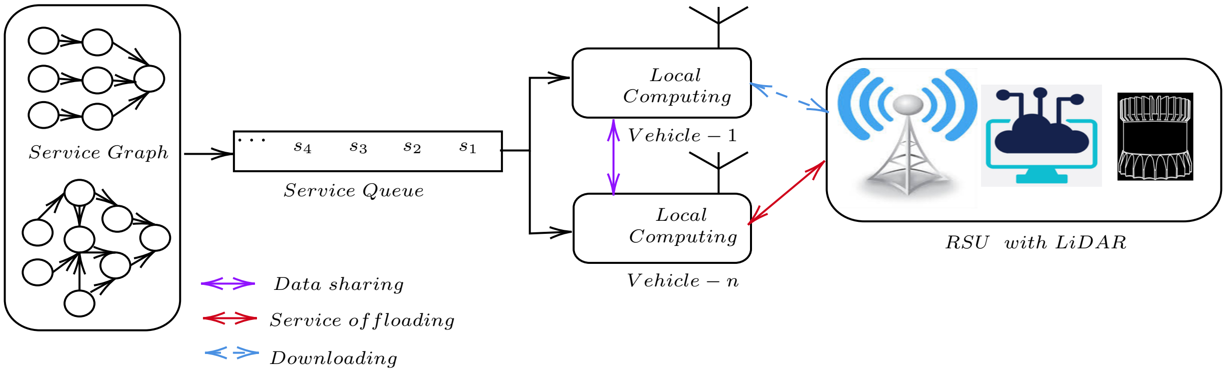


Fig. 1: System model

is load of RSU. The required data is not available, then data fetching may affect the computation performance, leads computation delay [29], [30]. Therefore, the data availability delay is estimated as follows

$$D_{fe,t} = \sum_{r=1}^{R} p_v^t q_v^t \left(\frac{s_{ed}}{\hbar_r \left(s_d^r \right)} \right) \tag{3}$$

Where, s_d^r refers service demand on RSU r and $p_v^t \in \{0, 1\}$ is a data offloading decision between vehicle and RSU, whereas $p_v^t = 0$ denotes the vehicle executes the request by itself other wise offload to nearby RSU. The communication delay is estimated as follows

$$D_{com,t} = \sum_{r=1}^{R} \left(1 - p_m^t\right) D_{cm,t}^m + \left(p_m^t + D_{tran,t}^m + \sum_{v=1}^{V} D_{cm,t}^v \right) \tag{4}$$

Where, vehicle computation delay is $D_{cm,t}^v = \sum_{v_r \in V} \frac{\Delta_v^t \times s_{ed} \times \kappa_v^{s_{ed}}}{\kappa_v}$. Here Δ_v^t is coverage capacity of vehicle, $\kappa_v^{s_{ed}}$ is anticipated MIPS for execution of bit-data, and κ_v MIPS count of vehicle. RSU transmission delay is $D_{tran,t}^m = \sum_{v_r \in V} \frac{\Delta_m^t \times s_{ed}}{\phi_{r,v}^t}$, here Δ_m^t is coverage capacity of RSU. The RSU computation delay is estimated as follows

$$D_{cm,t}^m = \frac{L_r}{\left(\kappa_r / s_{ed} \times \kappa_v^{s_{ed}}\right) - L_r} \tag{5}$$

Where, $\kappa_r / s_{ed} \times \kappa_v^{s_{ed}}$ denotes anticipated service rate. Now, the required data availability or fetching and concerning data transfer delay are augmented together to assess the network computation performance or computation delay as follows

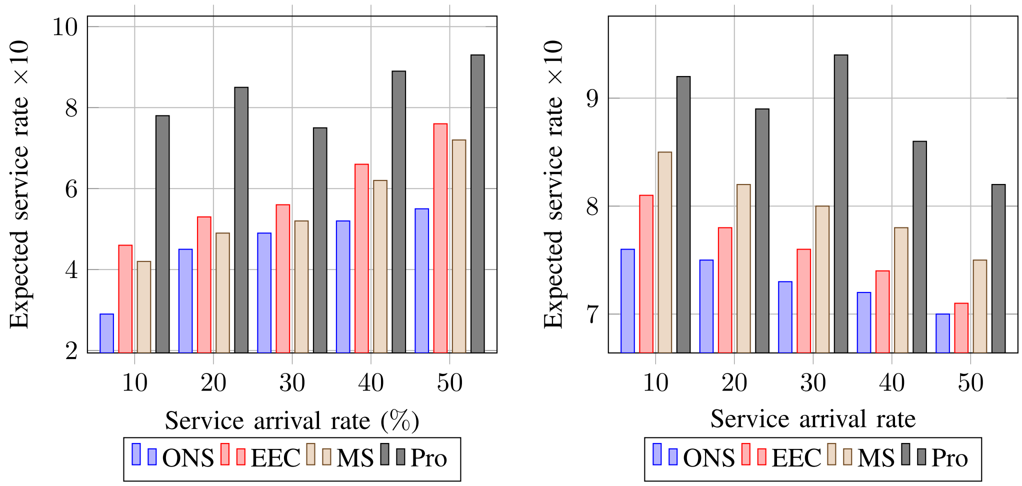
$$D = D_{fe,t} + D_{com,t} \tag{6}$$

Algorithm 1 illustrates the decision of service execution request. Line -2 defines the service queue initial value, which is $\rho = 0$. The estimation of RSU service queue cost concerning time is carried out with line-3, and line-4 measures the service list of RSU. Here, $\hat{\phi}_{r,v}^t$ is a threshold of service communication cost. If the service cost is less than the threshold value, measure the total queue cost and update it as a threshold value observed in Line 5-8. Otherwise, the service request is offloaded to RSU because the cost is too high, which causes to violate the threshold condition, as can be observed in line-10. Algorithm 2 illustrates the RSU computation cost estimation and analysis of the RSU orchestration cost optimization strategy. Line-2 defines the entail parameters. Line-5 estimate the communication delay between the vehicle and RSU and the computation delay of RSU estimate with Eq. 6. Before estimating the computation cost, the computation delay and communication delay are less than the threshold values. Line-9 estimates the system cost of RSU. As per the arrived service request, if the RSU cost is moderate, then continues the execution; otherwise, selects the optimal RSU or offload to the server.

B. Object Detection Request as a Computation Request

The point clouds ($\hat{P} = \{\hat{P}_j : j = 1, 2, \ldots, \hat{P}\}$) are filtered by which violates the distance threshold treated as noise points. The filtered point clouds are denoted as $P = \{p_j : j = 1, 2, \ldots, P\}$ of region $a = \{1, 2, \ldots, n\}$. Synthesis clustering is used to group or project the region of an object along with depth measurement. The downsampling is used to optimize point clouds based on a voxel filter, but random voxel size is not proficient; therefore, the k-nearest neighbour strategy is considered to optimize the grid size. Min-distance point clouds are selected to form the cluster, and the KNN mechanism is deployed to optimize the trade-off between too small and large distance point clouds. The RoI is estimates based on the minimum mean-variance of distance strategy. The RANSAC mechanism is considered to remove the ground points while training the model to divide the point clouds into small bins.

Algorithm 3 illustrates the assessment of object region to identify the object using point clouds. δ is a grid of point clouds filtered by the KNN approach based on distance. Line 4 & 5 assess the minimum distance point clouds to form a grid or cluster. The grid ground truth values were eliminated with the RANSAC mechanism and updated the grid with line-10. Measuring the region of the object is carried out based on estimating the distance from the identified centroid of the grid or cluster. Therefore, the minimum mean of distance parameters is considered to form the region, enabling the



(a) Service arrival rate (%) vs Expected service rate analysis at R=4 with 100Mbps

(b) Service arrival rate (%) vs Expected service rate analysis at R=9 with 100Mbps

Fig. 2: Service arrival rate (%) vs Expected service rate analysis at R=4 & 9 with 100Mbps

Algorithm 3: RoI based object detection

input : $\hat{P}$ point cloud, R number of RSUs, V number of vehicles

output: Region based Object detection

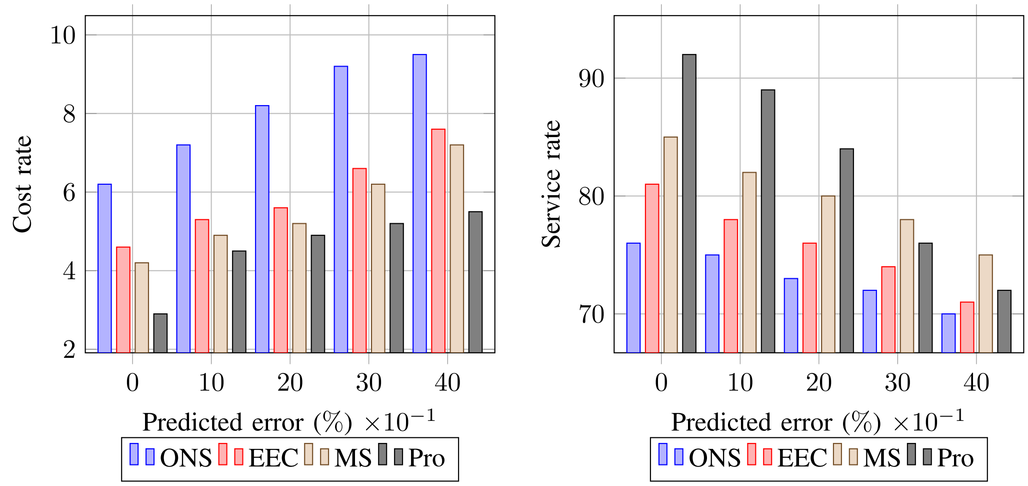
1 Let **for** $p = 1$ *to* $length(P)$ **do**
2 $\quad \delta \leftarrow knn(p[j])$;
3 $\quad \delta_{max} \leftarrow max\{\delta\}$;
4 $\quad \delta_{grid} \leftarrow min\{\delta_{max}\}$;
5 $\quad$ **for** $\delta = 1$ *to* δ_{grid} **do**
6 $\quad\quad$ Update the grid with *RANSAC* algorithm to remove the ground truth point clouds;
7 $\quad\quad \delta_{grid} \leftarrow RANSAC\{\delta_{grid}\}$;
8 $\quad\quad$ Estimate the Euclidean mean variance distance of grid point clouds to form the cluster;
9 $\quad\quad$ Update δ_{grid};
10 $\quad$ **end**
11 $\quad$ **for** $p =$ *1:numgrid* **do**
12 $\quad\quad$ Identify the centroid point of the grid based on distance as follows;
13 $\quad\quad \eta = \frac{1}{P} \sum_{p=1}^{P} \Big((x_p - x_{p+1})^2 + (y_p - y_{p+1})^2$
14 $\quad\quad + (z_p - z_{p+1})^2$;
15 $\quad\quad$ Update the $p[j] \leftarrow mean(\eta)$;
16 $\quad\quad p[j]$ enables bunch of object region points;
17 $\quad$ **end**
18 **end**

objects to observe from lines 12-18. The DRL influenced Rate-Return-Range of RSU $(4-r)$ model impacts performance *rate* by analysing point cloud data to complete the object detection request through algorithm 3 and *return* cost as per resource usage to execute the request and coverage *range* to accomplish high service reliability towards RSU consolidation using algorithm 1 and algorithm 2, respectively.

IV. Result Analysis

The PC runs 64-b Ubuntu 18.04.5 LTS on Intel Core i7-10700 CPU 3.80GHz × 16 and NVIDIA GeForce RTX3090 and 64 GB RAM with MATLAB-2021a for assessing the performance of our system. The S_{ed} anticipated data size of request is 25Mb, LAN capacity is $100Mps$, $\phi^{t}_{r,v}$ is 100mW, $\kappa_v^{s_v^{ed}}$ is 1 cycle/bit, vehicle transmission delay is $0.5s$ are fixed in simulation. The object detection accuracy is estimated based on the KITTI dataset.

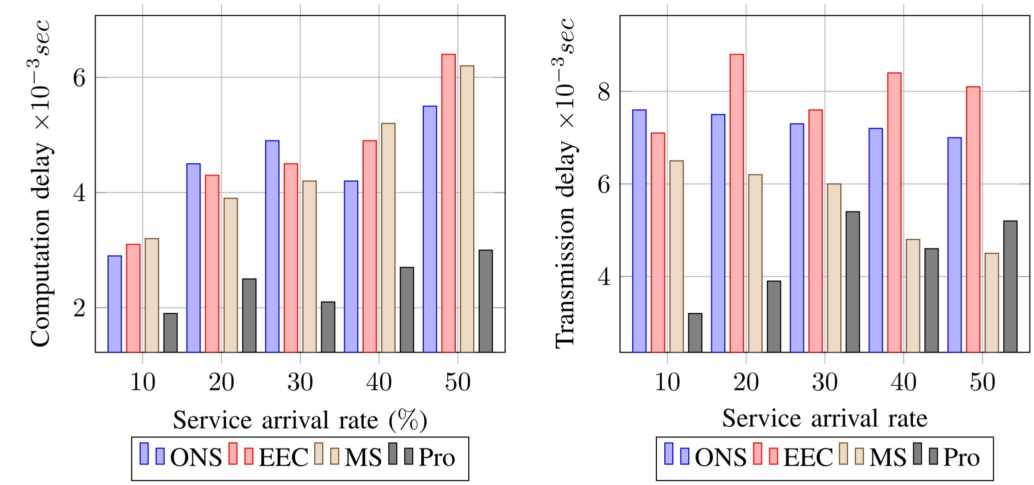
The proposed model performance is compared with three approaches. First, Online Scheduling (ONS) [31] scheme is designed for a data dissemination system for effective I2V and V2V communications to maximize the system performance through a greedy method by considering communication constraints and vehicle application requirements. Maximum Service (MS) [32] is designed for RSU based on bidirectional roadway strategy to enhance vehicle network performance through object-detection data dissemination scheduling policy. Energy Efficient Cost (EEC) [33] method is designed based on Energy-efficient dynamic offloading and resource scheduling (eDors) strategy to diminish RSU performance cost. Fig. 2 illustrates the service execution rate in two scenarios (*R=4 or 9* with 100Mbps LAN speed). The considered service arrival rate is *10-50*. The average service rate is 81% which has continued by increasing the service arrival rate till 50% with $R = 4$, 100 Mbps speed can observe in Fig.2(a). The EEC method has achieved a moderate service rate which is better than ONS and MS approaches. The prognosticated methods have an immense effect on achieving the average service rate of 81%. In the second scenario, the $R = 9$ with the same speed but increasing R influence the error rate and data congestion. The service rate is constantly increased along



(a) Predicted error (%) vs Cost rate

(b) Predicted error (%) vs Service rate

Fig. 3: Predicted error vs Service rate analysis



(a) Service arrival rate (%) vs Computation delay analysis at R=4 with 100Mbps and service size 20Mb

(b) Service arrival rate (%) vs Transmission delay analysis at R=9 with 100Mbps speed and 100Mb fetching capacity

Fig. 4: Service arrival rate (%) vs Computation and transmission delay analysis at R=4 & 9 with 100Mbps speed, 20Mb request size, and 100Mb fetching capacity

with the arrival rate, and the average service rate is 93.5% when the arrival rate is in between 10%-30% that can be observed in Fig.2(b).

Fig. 3 illustrates the comparative analysis of predicted error rate and service rate. While executing the service request, considering the error ratio and cost of service execution factors helps regulate the system performance. The predicted error rate range is [0,40], and service cost comparative analysis is shown in Fig. 3(a). The proposed system has achieved a low average cost than state-of-art approaches. The ONS method has achieved high costs because of continuous changes in resource requirements while executing the service. EEC and MS methods have achieved a moderate cost rate compare to the proposed system. Our system has accomplished the low cost due to leveraging the vehicle, RSU transmission and computation delay while selecting the RSU. Fig. 3(b) illustrates the service rate concerning prediction error rate. The service rate is relatively high when the predictor error rate is conditionally equant to zero. As the error rate increases, the service rate is proportionately decreased than state-of-art approaches. However, the MS method has achieved a constant service rate than ONS and EEC methods.

Fig. 4 illustrates the computation and transmission delay when *R=4 & 9* with 100Mbps speed, 20Mb request size, and 100Mb fetching capacity. Fig. 4(a) shows computation delay with first scenario. Subsequently, our approach has achieved a lower delay rate than other state-of-art approaches because of

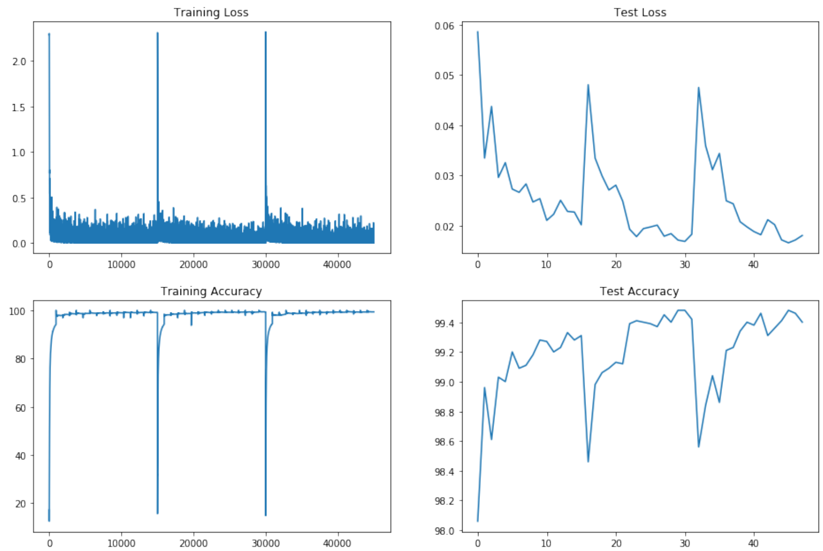


Fig. 5: Region based object detection train model accuracy

leveraging the computation delay of vehicle and RSU since the computation delay depends on required data availability to execute the service request. Therefore, transmission delay is additionally analyzed, represented in Fig. 4(b). If RSU is not feasible to execute the service request, then concerned data is to fetch from other RSU or offloaded to the server. Our approach has accomplished less delay in both cases, and the system performance has increased with an average error ratio and communication delay. The EEC has inadequate transmission delay because were considered the computation resource and energy factors of RSU with less transmission priority.

Fig. 5 illustrates object detection accuracy based on RoI consolidation. The loss rate is constant concerning time and epochs. The training and test accuracy are adequate when forming the object region to identify the object plane because the KNN approach eliminates the unwanted point clouds based on the distance factor. The ground point clouds are disseminated based on the RANSAC method while forming the cluster. The final grid is formulated to identify a region's centroid that helps form the cluster or grid by estimating the mean-distance of point clouds $p[j]$.

V. Conclusion

The RSU-LiDARs generate a massive amount of data that may include the noise and be redundant, leading to inadequate object detection accuracy and the high operational cost of RSU due to inadequate resource consumption. In this regard, the designed DRL influenced *4-r* computation model effectively optimizes the RSU resources along with a moderate object detection accuracy rate by accomplishing two objectives. First, identifying the regions of the object using LiDAR data is accomplished by streamlining ground, noise and other objects through a RoI consolidation mechanism based on the KNN approach. Subsequently, the RANSAC method efficiently forms the cluster based on region centroid. Second, the resources of RSU has been optimized based on data communication and computation delay factors by diminishing service request execution (object detection through RoI) cost that influence continuous monitoring and detection of the object. Our approach has achieved 83% average object accuracy than state-of-art approaches because of the RoI consolidation process, which effectively removes noise, redundancy, and ground data. Subsequently, 81% service rate has been achieved due to streamlining the RUS resource capacity through Deep Reinforcement Learning based criterion of optimality mechanism, which impacts on service offloading rate of RSU by 17% than state-of-art approaches.

Future work would concentrate on service (RSU data compression, computation and compunction) offloading consolidation and effective object tracking for V2I and V2V services based on data association measurements of extended objects.

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