QoS-SLA-Aware Artificial Intelligence Adaptive Genetic Algorithm for Multi-Request Offloading in Integrated Edge-Cloud Computing System for the Internet of Vehicles

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Abstract—Internet of Vehicles (IoV) over Vehicular Ad-hoc Networks (VANETS) is an emerging technology enabling the development of smart cities applications for safer, efficient, and pleasant travel. These applications have stringent requirements expressed in Service Level Agreements (SLAs). Considering vehicles limited computational and storage capabilities, applications requests are offloaded into an integrated edge-cloud computing system. Existing offloading solutions focus on optimizing applications Quality of Service (QoS) while respecting a single SLA constraint. They do not consider the impact of overlapped requests processing. Very few contemplate the varying speed of a vehicle. This paper proposes a novel Artificial Intelligence (AI) QoS-SLA-aware genetic algorithm (GA) for multi-request offloading in a heterogeneous edge-cloud computing system, considering the impact of overlapping requests processing and dynamic vehicle speed. The objective of the optimization algorithm is to improve the applications’ Quality of Service (QoS) by minimizing the total execution time. The proposed algorithm integrates an adaptive penalty function to assimilate the SLAs constraints in terms of latency, processing time, deadline, CPU, and memory requirements. Numerical experiments and comparative analysis are achieved between our proposed QoS-SLA-aware GA, random, and GA baseline approaches. The results show that the proposed algorithm executes the requests 1.22 times faster on average compared to the random approach with 59.9% less SLA violations. While the GA baseline approach increases the performance of the requests by 1.14 times, it has 19.8% more SLA violations than our approach.

Index Terms—Artificial Intelligence (AI), Cloud Computing, Computation Offloading, Constrained Optimization, Edge Computing, Genetic Algorithm (GA), Intelligent Transportation System, Internet of Things (IoT), Internet of Vehicles (IoV), Quality of Service (QoS), Service Level Agreement (SLA), Vehicular Ad-hoc Network (VANET)

I. INTRODUCTION

Internet of Vehicles (IoV) over Vehicular Ad-hoc Networks (VANETS) are self-organizing networks of vehicles for data exchange between mobile vehicles and infrastructure [1]. Vehicles act as smart nodes having sensing, computing, storage, and networking capabilities [2], [3]. Data exchange is realized using vehicle-to-vehicle (V2V), vehicle-to-roadside (V2R), vehicle-to-infrastructure (V2I), vehicle-to-cloud (V2C), and vehicle-to-pedestrian (V2P) communication. Through ubiquitous data dissemination and processing, IoV provides mechanisms to develop applications for safe, and comfortable driving, pleasant travel, and efficient traffic management [4], such as accident prevention, multi-media, infotainment, image processing and pattern recognition in autonomous driving, and real-time navigation. However, the limited computation and storage capabilities of vehicles hinders the deployment of these compute-intensive and time-critical applications.

To respect applications Service Level Agreement (SLA) in terms of processing and resource requirements, vehicular cloud computing [5] has been introduced that enables execution of compute-intensive vehicles requests on remote cloud servers [6]. However, cloud may violate latency requirements for communication-bound applications due to long-distance data transmission between vehicles and the cloud. Consequently, Vehicular Edge Computing (VEC) [7] has emerged that pushes cloud services to the edge of the radio access network close to the mobile vehicles, reducing the communication delay. However, the VEC servers (deployed within Roadside Units (RSUs)) violate the stringent deadline constraints of compute-intensive applications due to limited computing capabilities compared to cloud servers. Consequently, it becomes crucial to introduce mechanisms to offload vehicles requests into an integrated edge-cloud computing system to respect SLA

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requirements in terms of latency for communication-bound applications (e.g., traffic alert and accident prevention), and processing for computation-bound applications (e.g., computer vision and multimedia), while optimizing applications’ Quality of Service (QoS) [8].

Several works in the literature proposed computation offloading algorithms for an integrated edge-cloud computing system in the Internet of Things (IoT)/IoV networks. Most of these works focus on either optimizing the applications’ QoS without considering SLA requirements [9]–[12], or respecting SLA without QoS optimization [13]–[18]. Few works proposed offloading solutions which are QoS-SLA-aware [19]–[25]. To the best of our knowledge, no work considers the impact of multi-request overlapping in heterogeneous edge-cloud computing system servers. In this paper, we propose a novel QoS-SLA-aware genetic algorithm (GA) for offloading vehicles requests. It aims to optimize the QoS by minimizing the total execution time of the vehicles’ requests while respecting SLAs in terms of latency, processing time, deadline, CPU, and memory requirements via an adaptive penalty function. The proposed offloading algorithm considers the impact of executing multiple requests in edge/cloud resources on application performance in IoV. The main contributions of this paper are as follows:

- We formulate an optimization algorithm for multi-request offloading in a heterogeneous integrated edge-cloud computing system for IoV that minimizes the total execution time of the vehicles’ requests while respecting the requests’ SLA requirements.
- We propose a novel Artificial Intelligence QoS-SLA-aware adaptive GA to obtain the solution of the formulated constrained optimization problem via an adaptive penalty function.
- Convergence analysis of the proposed GA is performed to obtain the optimal values of GA’s parameters.
- The performance of the proposed algorithm is compared with random and GA baseline approaches in terms of total execution time and SLA violations (SLAVs) with varying SLA requirements.

The rest of the paper is organized as follows. Section II discusses the related work. The system model of an integrated edge-cloud computing system for IoV is described in Section III. The offloading optimization problem is formulated in Section IV. Section V explains our proposed QoS-SLA-Aware adaptive genetic algorithm for offloading. Numerical experiments and performance results are provided in Section VI. Finally, the paper is concluded in Section VII along with future research directions.

II. RELATED WORK

Several works in the literature have proposed offloading solutions for an IoT-edge-cloud integrated computing system. We categorize these works into 1) QoS-aware that optimizes applications’ QoS without considering SLA requirements [9]–[12], 2) SLA-aware that respects applications’ SLA constraints without enhancing the QoS [13]–[18], and 3) QoS-SLA-aware that optimizes applications’ QoS while respecting SLA constraints [19]–[25].

In the context of QoS-aware offloading, Pham et al. [9] proposed a game-theoretic approach to execute mobile devices’ requests either locally on the device or an edge server. The algorithm optimizes the weighted sum of the request’s execution time and the device’s energy consumption. However, the communication time to deliver the request’s reply is not considered. Xu et al. [10] proposed an algorithm to offload vehicles’ requests on RSUs and macro base stations edge nodes such that the total execution time of the requests is minimized and the resource utilization of the edge nodes is maximized. The post request submission mobility of the vehicles is not considered in the algorithm. Khayyat et al. [11] proposed a deep learning-based approach to process vehicular requests either locally on the vehicle or on edge/cloud servers such that the weighted sum of the total execution time of the requests and the vehicle’s energy consumption is the minimum. Lastly, Xu et al. [12] proposed an offloading algorithm to process mobile devices’ requests either locally on the device or on edge/cloud servers such that the total execution time of the requests and the device’s energy consumption is the minimum. However, the algorithms in [9]–[12] do not consider the mobility of the mobile devices and the heterogeneity among the edge/cloud servers.

Regarding SLA-aware offloading, Sorkhoh et al. [13] proposed a Lagrangian relaxation-based algorithm that schedules the mobile devices’ requests on edge servers such that the weighted sum of requests acceptance is maximized with a constraint on the total execution time. The requests that cannot be processed by the edge servers, due to insufficient computing resources or higher execution time compared to the vehicle’s residence time, are rejected. Yuan and Zhou [14] proposed an offloading algorithm to execute mobile devices’ requests either on edge or cloud server such that profit of edge and cloud system is maximized while respecting the requests’ execution time. A deep reinforcement learning-based algorithm is proposed by Zhou et al. [15] to process the mobile devices’ requests either on the device locally or on the edge servers such that the total energy consumption of the mobile and edge layers is minimized while maintaining the execution time constraint of the requests. Wu et al. [16] proposed an offloading algorithm to process requests either locally on the IoT device or on the edge/cloud servers such that the total energy consumption of the IoT device is the minimum while maintaining the QoS violation, in terms of total execution time, under a threshold. Xu et al. [17] proposed an offloading algorithm to maximize the number of requests admission under the execution time constraint while minimizing the operational cost associated with the communication and processing of the admitted requests. A heuristic-based offloading algorithm is

1 Total communication time of a request is considered for latency.

2 Total execution time of a request, i.e., summation communication and computation times, is considered for the deadline.
proposed by Kovacevic et al. [18] to execute requests either on edge or cloud servers such that the overall network usage is minimized, i.e., the number of requests executed on the edge is maximized, considering the execution time requirement of the requests. However, the algorithms in [14]–[18] do not consider the mobility of the mobile devices and the heterogeneity among the edge/cloud servers. Moreover, the communication time to deliver the request’s reply is not considered in [15], [16].

In the context of QoS-aware offloading, Wang et al. [19] proposed an algorithm based on dynamic switching to execute IoT requests on either edge or cloud servers such that the total execution time of a request is the minimum. The algorithm is constrained by the maximum tolerable request’s execution time and the edge server’s maximum energy consumption. Wang et al. [20] proposed an algorithm that executes vehicles requests either locally on the vehicle or offloads them to the edge server such that the execution time of the requests and the cost for offloading the request is the minimum considering the constraint on the request’s execution time. Zhu et al. [21] proposed an algorithm to execute requests on mobile vehicles (referred to as fog nodes) such that the weighted sum of maximum execution time and total quality loss is the minimum considering the constraints on total execution time, and available CPU and memory of fog nodes. A partial offloading algorithm is proposed by Dai et al. [22] to execute vehicular requests locally on vehicle and edge servers such that the system utility in terms of total execution time is maximized and the load among the edge servers is balanced. The algorithm is constrained by the requests’ tolerable execution times. The maximum among the local and edge execution times is considered as the total execution time of a request. Peng et al. [23] proposed offloading algorithm to process a mobile device’s requests either locally or on an edge/cloud server such that summation of the total execution time of the requests and the device’s energy consumption is minimized while respecting the constraint on the request’s execution time. A fuzzy logic-based approach is proposed by Almutairi and Aldossary [24] that offloads IoT devices’ requests on either edge or cloud servers such that the total execution time of the requests is the minimum. Zhao et al. [25] proposed an offloading algorithm to process the vehicles’ requests either locally on the vehicles or to offload them to edge or cloud servers. The algorithm aims to optimize the weighted sum of the request’s execution time and the cost of computation resources while maintaining the maximum deadline constraints of the requests. However, the algorithms in [20], [21], [23], [24] do not consider the mobility of the IoT devices/vehicles, whereas [19], [21], [23], [25] do not consider communication time to deliver the reply of the request. The heterogeneity in the edge and cloud servers is not considered by [20], [25].

Table I presents the summary of the past works on computation offloading in an integrated IoT-edge-cloud computing system. It states the algorithms used, the components considered for processing the requests, the objective function used for optimization, the considered SLA requirements in offloading, consideration of heterogeneity among edge servers and cloud servers, communication time consideration to transmit the reply back to the IoT device/vehicle, and requests overlapping consideration. In addition, it also indicates the mobility consideration of IoT devices/vehicles and whether the speed during the mobility is dynamic or not. As shown in Table I, very few works in the literature have focused on QoS-SLA-aware offloading [19]–[25]. Moreover, only [22] considers the SLA constraint on memory requirement, and [25] considers the dynamic speed of the vehicle. To the best of our knowledge, no work considers the impact of requests overlapping on the offloading decision.

In this paper, we propose a QoS-SLA-aware adaptive GA for offloading in an integrated edge-cloud computing system for IoV that aims to improve the QoS by minimizing the total execution time of the applications’ requests while respecting the SLAs in terms of latency, processing time, deadline, CPU, and memory requirements. The proposed offloading algorithm considers the impact of executing multiple requests in edge/cloud resources on application performance in IoV.

III. SYSTEM MODEL

Fig. 1 shows our integrated edge-cloud computing system model for vehicular networks that consists of three layers: 1) vehicles, 2) VEC, and 3) cloud computing. The first layer consists of $H$ vehicles moving with dynamic speed on a bi-directional road. Each vehicle $v_h (h \in \mathcal{H})$ travels from a source to the destination location and has an application request $r_i (i \in \mathcal{I})$ that should be executed. A request is represented as a tuple $r_i = (\psi_{r_i}, \sigma_{r_i}, \theta_r, t_{r_i}, P_{r_i}^{\text{max}}, D_{r_i}^{\text{max}}, S_{v_h}(t), (x_{r_i}^{\text{src}}, y_{r_i}^{\text{src}}), (x_{r_i}^{\text{des}}, y_{r_i}^{\text{des}}))$. Requests in our system model are atomic and cannot be further divided into sub-requests. Consequently, each request can be executed on one at most one edge/cloud server. The requests vary in terms of computational requirement (i.e., length, CPU, and memory utilization values) and communication demand (i.e., data size).

The second layer (i.e., VEC) consists of $J$ RSUs placed alongside the road at equidistant. Each $RSU_j (j \in \mathcal{J})$ has a coverage range of $D_{RSU}$ and is equipped with an edge server $e_j$ through a wired connection. The edge servers are heterogeneous in terms of processing and storage capabilities. A vehicle $v_h$ can communicate to an edge server $e_j$ only if it is under the communication range of $RSU_j$. We define a binary variable $\alpha_{v_h}^{e_j}(t) \in \{0,1\}$ such that $\alpha_{v_h}^{e_j}(t) = 1$ denotes that $v_h$ is in the range of $RSU_j$ and can communicate to $e_j$ and $\alpha_{v_h}^{e_j}(t) = 0$ otherwise. The third layer (i.e., cloud computing) consists of $K$ heterogeneous cloud servers such that the processing and storage capabilities of a cloud server $c_k (k \in \mathcal{K})$ is higher compared to that of an edge server $e_j, \forall j \in \mathcal{J}$, i.e., $\mu_{e_j} \ll \mu_{c_k}$ and $\theta_{e_j} \ll \theta_{c_k}$. 
Table I: Summary of Past Works on QoS and/or SLA-aware Computation Offloading in an Integrated IoT-Edge-Cloud Computing System.

| Work                                                   | Algorithm                    | Considered component for requests processing | Optimization objective Function                                                                 | QoS-Aware                                                                 | SLA-Aware                                                                 | QoS-SLA-Aware                                                                 |
|--------------------------------------------------------|------------------------------|---------------------------------------------|--------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
|                                                        |                              | IoT/Vehicle | Edge | Cloud | Latency | Processing time | Deadline | CPU requirement | Memory requirement | Edge servers' heterogeneity consideration | Cloud servers' heterogeneity consideration | Request-reply delivery time consideration | Multi-request consideration | IoT/Vehicle mobility consideration | Dynamic vehicle speed consideration |
| [9] Game theory                                        |                              | ✓           | ✓    | ×      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [10] Decomposition-based evolutionary algorithm         |                              | ×           | ✓    | ×      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [11] Deep learning                                     |                              | ✓           | ✓    | ✓      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [12] NSGA III                                          |                              | ✓           | ✓    | ✓      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
|                                                        |                              | ×           | ✓    | ✓      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [13] Lagrangian relaxation                             |                              | ×           | ✓    | ×      | ×        | ×             | ✓         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [14] Simulated annealing                               |                              | ×           | ✓    | ✓      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [15] Deep reinforcement learning                       |                              | ✓           | ✓    | ×      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [16] Lyapunov optimization                             |                              | ✓           | ✓    | ✓      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [17] NR                                                |                              | ×           | ✓    | ×      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [18] Heuristic                                         |                              | ×           | ✓    | ✓      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
|                                                        |                              | ✓           | ✓    | ✓      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [19] Dynamic switching                                 |                              | ×           | ✓    | ✓      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [20] Game theory                                       |                              | ✓           | ✓    | ×      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [21] Linear programming and PSO                       |                              | ✓           | ×    | ×      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [22] Mixed integer non-linear programming              |                              | ✓           | ✓    | ×      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [23] NSGA II and SPEA                                  |                              | ✓           | ✓    | ✓      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [24] Fuzzy logic                                       |                              | ×           | ✓    | ✓      | ×        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |
| [25] Game theory and Lagrange multiplier               |                              | ✓           | ✓    | ✓      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |

This paper                                              |                              | ✓           | ✓    | ✓      | ✓        | ×             | ×         | ×             | ×             | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      | ×                                      |

NA – Not Applicable; NR – Not Reported; NSGA – Non-dominated Sorting Genetic Algorithm; PSO – Particle Swarm Optimization; SPEA – Strength Pareto Evolutionary Algorithm; ✓ Considered for cloud processing and not for edge processing; × Heterogeneous in terms of disk size, not processor
Fig. 1. Integrated edge-cloud computing system model for the Internet of Vehicles.

Each edge server in our model receives a set of requests from the communicating vehicles. The server makes the offloading decision for each request $r_i$, i.e., to execute the request locally on the edge $e_j$ or to offload it to a cloud server $c_k$ for execution. The offloading decision is made in a way that the total execution time of all the requests is the minimum while maintaining each request’s SLA in terms of latency, processing time, deadline, CPU, and memory requirements. A binary variable $\beta_{ri}$ is defined, such that $\beta_{ri} = 0$ if $r_i$ is executed locally on the edge server $e_j$ and $\beta_{ri} = 1$ otherwise. For each offloaded request, the edge server sends the request and information of the cloud server $c_k$ to the cloud manager. The cloud manager then schedules the request to $c_k$. Since both communication and computation are critical for making the offloading decision, we next introduce the communication and computation models in detail. Table II lists the notations used in this paper along with their definitions.

Table II: Notations and Definitions.

| Notation | Definition |
|----------|------------|
| $h, H, k, c_k$ | vehicle index, number of vehicles, set of vehicles, $h$th vehicle |
| $I, l, j, e_j, e_j, RSU_j$ | request index, number of requests, set of requests, $l$th request, the reply of $r_i$ |
| $j, j', j^*, e_j, RSU_j$ | edge server/RSU index, number of edge servers/RSUs, set of edge servers/RSUs, $j$th edge server, $j^*$th RSU |
| $k, K, c_k$ | cloud server index, number of cloud servers, set of cloud servers, $k$th cloud server |
| $z, Z, s_z$ | server (edge/cloud) index ($z = \{j, k\}$), set of edge and cloud servers ($Z = \{j\} \cup \{k\}$), $z$th server ($s_z = \{e_j, c_k\}$) |
| $\psi_{r_i}$ | length of $r_i$ in Million Instructions (MI) |
| $\alpha_{r_i}$ | size of $r_i$ in kilobytes (KB) |
| $\phi_{r_i}$ | CPU utilization of $r_i$ |
| $\gamma_{r_i}$ | maximum utilization of $r_i$ |
| $\tau_{max}$ | maximum tolerable deadline for $r_i$ |
| $D_{max}$ | processing time for $r_i$ |
| $P_{size}$ | population size, i.e., number of offloading solutions, in a generation |
| $P_{mem}$ | memory violation of $q$ |
| $P_{viol}$ | deadline violation of $q$ |
| $P_{c}$ | CPU violation of $q$ |
| $P_{aq}$ | normalized SLA violations of $q$ |
| $\gamma$ | the ratio of feasible and total offloading solutions in a generation |
| $Cummm(q)$ | cumulative fitness probability of $q$ |
| $Prob(q)$ | fitness probability of $q$ |
| $\lambda_{c}, \lambda_{m}$ | crossover rate, mutation rate |
| $\mu_{max}$ | number of requests for which the server allocation is mutated |

A. Communication Model

The communication time in our model consists of the time required to transmit the request data from $v_h$ to a scheduled server and the time required to transmit the reply back to $v_h$.
Depending on the offloading decision (i.e., edge or cloud execution) and the speed of $v_h$, there exist three scenarios as depicted in Fig. 2. Fig. 2 (a) shows scenario (1) where $r_i$ is executed locally on $e_j$ and $v_h$ is connected to $e_j$ when a reply on $r_i$ is sent to $v_h$. In this scenario, the communication time involves the request transfer time from $v_h$ to $e_j$ and the reply transfer time from $e_j$ to $v_h$. Fig. 2 (b) depicts scenario (2) where $r_i$ is executed on $e_j$ and $v_h$ is in the range of some edge server $e_{j+y}$ when a reply is sent to $v_h$. The communication time in this scenario includes the request transfer time from $v_h$ to $e_j$, the reply transfer time from $e_j$ to cloud server $c_k$, the reply transfer time from $c_k$ to $e_{j+y}$, and the reply transfer time from $e_{j+y}$ to $v_h$ [26]. The data transmission between $e_j$ and $e_{j+y}$ is achieved via the cloud instead of multi-hop RSU transmission. This is because multi-hop RSU transmission is performed at a low rate which increases the response time of the request [27]. Scenario (3) shown in Fig. 2 (c) indicates that $r_i$ is offloaded to the cloud and executed on a cloud server $c_k$. In this scenario, the communication time includes the request transfer time from $v_h$ to $e_j$, the request transfer time from $e_j$ to $c_k$, the reply transfer time from $c_k$ to $e_{j+y}$, and the reply transfer time from $e_{j+y}$ to $v_h$. In Fig. 2 (c), the vehicle moves out of $e_j$’s range before receiving a reply. Consequently, $c_k$ sends the reply to an edge server $e_{j+y}$. In case the vehicle is in the range of $e_j$, the reply will be transmitted from $c_k$ to $e_j$. Based on these scenarios, the total communication time for request $r_i$ when executed on a server $s_z \in \{e_j, c_k\}$ can be computed as stated in Equation 1.

\[
\begin{align*}
T_{r_i}(s_z) & = T_{r_i}^{\text{com}}(e_j, v_h) + T_{r_i}^{\text{rep}}(e_j, v_h) + T_{r_i}^{\text{rep}}(e_j, c_k) + T_{r_i}^{\text{rep}}(c_k, e_{j+y}) + T_{r_i}^{\text{rep}}(e_{j+y}, v_h) \\
& = T_{r_i}^{\text{com}}(v_h, e_j) + T_{r_i}^{\text{rep}}(e_j, c_k) + T_{r_i}^{\text{rep}}(c_k, e_{j+y}) + T_{r_i}^{\text{rep}}(e_{j+y}, v_h) + T_{r_i}^{\text{rep}}(c_k, v_h) + T_{r_i}^{\text{rep}}(e_j, v_h).
\end{align*}
\]

The communication times represented in Equation 1 can be computed using Equations 2 – 7.

\[
\begin{align*}
T_{r_i}^{\text{com}}(v_h, e_j) & = \frac{\alpha_r}{\omega_{v_h e_j}} \\
T_{r_i}^{\text{rep}}(e_j, v_h) & = \frac{\sigma_{r_i}}{\omega_{e_j, v_h}} \\
T_{r_i}^{\text{rep}}(e_j, c_k) & = \frac{\sigma_{r_i}}{\omega_{e_j, c_k}} \\
T_{r_i}^{\text{rep}}(c_k, e_{j+y}) & = \frac{\sigma_{r_i}}{\omega_{c_k e_{j+y}}} \\
T_{r_i}^{\text{rep}}(e_{j+y}, v_h) & = \frac{\sigma_{r_i}}{\omega_{e_{j+y}, v_h}} \\
T_{r_i}^{\text{rep}}(e_{j+y}, v_h) & = \frac{\sigma_{r_i}}{\omega_{e_{j+y}, v_h}} \\
T_{r_i}^{\text{rep}}(c_k, v_h) & = \frac{\sigma_{r_i}}{\omega_{c_k v_h}} \\
T_{r_i}^{\text{rep}}(e_j, c_k) & = \frac{\sigma_{r_i}}{\omega_{e_j c_k}}
\end{align*}
\]

In scenarios (2) and (3), the cloud manager should determine the RSU on the path between $v_h$’s source and destination under whose communication range $v_h$ will be when a reply is sent, i.e., $RSU_{j+y}$. The path between the source and destination can
be computed by the cloud offline using an extended A* algorithm [28]. The algorithm determines an optimal path between source and destination in a way that reduces fuel consumption and travel time. The selection of the A* algorithm is based on its performance compared to the shortest path algorithm. Each vehicle in our system model will transmit its speed to the communicating edge server. The edge server will further transmit the speed to the cloud manager. To determine $RSU_{i+y}$, the manager will compute $d_{vh}^{ri} - d_{vh}^{ri}(t)$, and $d_{vh}^{ri}(t)$ as stated in Equations 8 - 10 (Fig. 3). The $y^{th}$ RSU after $RSU_j$, i.e., $RSU_{j+y}$ can be then determined using Equation 11. The value of $v$ will be updated in real-time based on the speed of $v_h$.

\[ d_{vh}^{ri} = \left\{ \begin{array}{ll} x_{vh}^{r_i} - x_{vh}^{left} & ; x_{vh}^{r_i} < x_{vh}^{des} \\ x_{vh}^{right} - x_{vh}^{r_i} & ; x_{vh}^{r_i} > x_{vh}^{des} \end{array} \right. \]

\[ d_{vh}^{ri}(t) = s_{vh}(t) \times T_{r_i(s_2)} \]

\[ y(t) = \left\{ \begin{array}{ll} d_{vh}^{ri}(t) & ; \text{otherwise} \\ 0; \end{array} \right. \]

\[ y(t) = \left\lfloor \frac{d_{vh}^{ri}(t)}{T_{RSU}} \right\rfloor \]

\[ B. Computation Model \]

The computation time in our system model includes the processing time to execute the request on an edge/cloud server and the I/O time required for the request data transfer between memory and disk of an edge/cloud server. The processing time and I/O time are explained below in detail.

\[ B.1. Processing Model \]

The processing time of a request in our system model depends on whether the request is executed alone or with other requests on an edge/cloud server. Consequently, there exist three cases as shown in Fig. 4. The cases are as follows.

- Case (i): request $r_i$ is executed alone on an edge/cloud server $s_2$.
- Case (ii): execution of requests $r_i$ and $r_{i+1}$ overlap on server $s_2$ and $r_i$ completes execution before $r_{i+1}$. In this case, the processing speed of $s_2$ is divided among requests $r_i$ and $r_{i+1}$ [29].
- Case (iii): execution of requests $r_i$ and $r_{i+1}$ overlap on server $s_2$ and $r_i$ completes execution after $r_{i+1}$. In this case, the processing time of $r_i$ includes time $\tau_{r_i(s_2)}^m$ when execution of $r_i$ and $r_{i+1}$ overlaps and time $\tau_{r_i(s_2)}^a$ when $r_i$ executes alone after $r_{i+1}$ has finished execution.

The processing time for the three cases can be computed as stated in Equation 12.

\[ \tau_{r_i(s_2)}^{proc} = \left\{ \begin{array}{ll} \frac{\psi r_i}{\mu_{s_2}}; & \text{case (i)} \\ \frac{\psi r_i \times n_{r_i(s_2)}}{\mu_{s_2}}; & \text{case (ii)} \\ \tau_{r_i(s_2)}^m + \tau_{r_i(s_2)}^a; & \text{case (iii)} \end{array} \right. \]

where $\tau_{r_i(s_2)}^m, \tau_{r_i(s_2)}^a$, and $\bar{n}_{r_i(s_2)}$ can be calculated using Equations 13 – 15.

\[ \tau_{r_i(s_2)}^m = \min_{\forall r_{p(s_2)} \neq i} \left( \tau_{r_p(s_2)}^{proc} \right), \quad p \neq i \]

\[ \tau_{r_i(s_2)}^a = \left( \frac{\psi r_i - \left( \tau_{r_p(s_2)}^m / \mu_{z_2} \right)}{\mu_{s_2}} \right) \times (n_{r_i(s_2)} - \bar{n}_{r_i(s_2)}) \]

\[ \bar{n}_{r_i(s_2)} = \#_{r_{i,p} \in S_2} \left( r_{i,p(s_2)}^{proc} < T_{r_i(s_2)}, i \neq p \right) \]

\[ B.2. I/O Model \]

The I/O time for a request $r_i$ on server $s_2$ in our system model refers to the time it takes to transfer data between disk and memory in case the memory requirement of $r_i$ is more than the available memory of $s_2$. The I/O time of $r_i$ when executed on $s_2$ for the three cases discussed before can be computed using Equation 16.
\[ T_{r_i(s_2)}^{1/0} = \begin{cases} 
\left( x_{r_i(s_2)} \times \xi_{s_2} \right); & \text{cases (i) and (ii)} \\
\xi_{s_2} + \frac{\sigma_{r_i} \times \xi_{s_2} \times \bar{T}_{r_i(s_2)}}{\theta_{s_2}}; & \text{case (iii)} 
\end{cases} \quad (16) \]

where \( x_{r_i(s_2)} \) is calculated using Equations 17 and 18 as follows.

\[ x_{r_i(s_2)} = \begin{cases} 
\rho_{r_i(s_2)} - 1; & \rho_{r_i(s_2)} > 1 \\
0; & \rho_{r_i(s_2)} \leq 1 
\end{cases} \quad (17) \]

\[ \rho_{r_i(s_2)} = \begin{cases} 
\frac{\sigma_{r_i}}{\theta_{s_2}}; & \text{case (i)} \\
\frac{\sigma_{r_i} \times n_{r_i(s_2)}}{\theta_{s_2}}; & \text{cases (ii) and (iii)} 
\end{cases} \quad (18) \]

IV. PROBLEM FORMULATION

In this paper, we formulate a computation offloading optimization problem in an integrated edge-cloud computing system for IoV. The objective of the optimization problem is to minimize the total execution time of all the requests in the system under specified latency, processing time, deadline, CPU, and memory requirements constraints for each request. The total execution time of a request \( r_i \) is computed as the summation of the request’s communication, processing, and I/O times as stated in Equation 19. To this end, the corresponding optimization problem can be formulated as stated in Equation 20.

\[ T_{r_i(s_2)} = T_{r_i(s_2)}^{\text{com}} + T_{r_i(s_2)}^{\text{proc}} + T_{r_i(s_2)}^{1/0}, \forall i \in J, s_2 \in \{ e_j, c_k \} \quad (19) \]

Problem:

\[
\text{minimize} \sum_{\forall i \in J} T_{r_i(s_2)}, s_2 \in \{ e_j, c_k \} \quad (20)
\]

s.t.  

- **C1**: \( \forall i \in J, T_{r_i(s_2)}^{\text{com}} \leq T_{r_i(s_2)}^{\text{max}} \), \( s_2 \in \{ e_j, c_k \} \)
- **C2**: \( \forall i \in J, T_{r_i(s_2)}^{\text{proc}} \leq P_{r_i}^{\text{max}}, s_2 \in \{ e_j, c_k \} \)
- **C3**: \( \forall i \in J, T_{r_i(s_2)} \leq D_{r_i}^{\text{max}}, s_2 \in \{ e_j, c_k \} \)
- **C4**: \( \sum_{\forall r_i \in I} \varphi_{r_i(s_2)} \leq \varphi_{r_i}^{\text{max}}, s_2 \in \{ e_j, c_k \} \text{ and } \varphi_{r_i} \geq 1 \)
- **C5**: \( \sum_{\forall r_i \in I} \sigma_{r_i} \leq \theta_{s_2}, z \in \mathbb{Z} \)
- **C6**: \( \alpha_{e_i} (t) \in \{0, 1\}, \forall j \in J, \forall h \in \mathcal{H} \)
- **C7**: \( \sum_{j \in J} \alpha_{e_i} (t) = 1, \forall h \in \mathcal{H} \)
- **C8**: \( \sum_{\forall \xi \in \mathbb{Z}} \beta_{r_i}^\xi = 1, \forall i \in J \)

Here \( \sum_{\forall i \in J} T_{r_i(s_2)} \) is the total execution time of all the requests in the system. The constraints in the above optimization problem are as follows:

- **C1** ensures that the communication time of each request does not exceed the maximum tolerable latency requirement of that request.
- **C2** guarantees that the execution time of each request is less than the request’s permissible maximum processing time requirement.
- **C3** ensures that the total execution time of each request is below the maximum tolerable deadline for that request.
- **C4** ensures that the total CPU utilization of all the requests executing on a server should not exceed the server’s CPU utilization threshold. This is to ensure that the server is not overloaded as overloading may degrade the requests’ performances.
- **C5** is the constraint on the memory resource, i.e., the memory requirements of a request should be less than the server’s available memory. This is to reduce the amount of data transfer between disk and memory.
- **C6** and **C7** denote that each vehicle can only communicate to one edge server at a given time.
- **C8** ensures that each request is executed at most by only one edge/cloud server.

The optimization problem (Equation 20) for computation offloading is a Nondeterministic Polynomial-time (NP) hard where the search space and time to obtain the optimal solution increase exponentially with increasing requests and servers (edge and cloud). Consequently, in this paper, we propose an adaptive genetic algorithm to obtain the optimal solution in polynomial time.

V. PROPOSED QOS-SLA-AWARE GENETIC OFFLOADING ALGORITHM

The proposed offloading aims to minimize the total execution time of the vehicles’ requests while respecting each request’s SLA requirements. In this paper, we propose an adaptive Genetic Algorithm (GA) [30] to obtain the solution of the NP-hard offloading algorithm. GA is based on the theory of natural evolution where a subset of near-optimal offloading solutions from one generation is used to obtain the offspring solution for the next generation. At each generation, the algorithm converges towards the global optima. In the context of our optimization problem, global optima can be defined as an offloading solution that yields the minimum requests execution time while respecting each request’s SLA requirements. An offloading solution, referred to as chromosome in genetic algorithm terminology, consists of server allocation for each request. Each request-server allocation is known as a gene. The number of offloading solutions in each generation represents the population size \( P_{\text{size}} \) and remains constant throughout the generations. In the following, we explain the steps involved in our proposed algorithms.

A. Initialization of Offloading Solutions

In this step, a set \( Q \) of initial offloading solutions for the first generation is randomly developed to begin the exploration process in the search space. The number of solutions generated is equal to \( P_{\text{size}} \). The value of \( P_{\text{size}} \) should be carefully selected as it impacts the convergence of the algorithm. A small value
improves the computational performance of the algorithm, however, may restrict the search space leading to local optima instead of global. On the other hand, a large value allows the algorithm to explore a larger search space that might lead to global optima. However, this increases the computational time.

B. Evaluation of the Offloading Solutions

In this step, each offloading solution is evaluated, in terms of fitness, to determine how close it is to the optimal offloading solution. The closer a solution is to the optimal solution, the higher is its fitness. Consequently, based on our optimization objective function stated in Equation 20, an offloading solution having the least total execution time with no SLA violations will have the highest fitness value. To incorporate the SLA constraints in fitness computation, we implement an adaptive penalty function [31] that reduces the fitness value of an offloading solution that violates SLA requirements, referred to as an infeasible solution. To evaluate the fitness with an adaptive penalty, we first compute the non-penalized fitness value and the constraints violations for each solution as stated in Equations 21 – 26.

\[
\bar{F}_q = \sum_{t \in T_r(s_2), s_2 \in \{e_j, c_k\}} \forall q \in Q \quad (21)
\]

\[
p_{\text{lat}} = \sum_{t \in T_r(s_2), s_2 \in \{e_j, c_k\}} T_{r,s_2}^c - L_{r,s_2}^{\max} \quad (22)
\]

\[
p_{\text{proc}} = \sum_{t \in T_r(s_2), s_2 \in \{e_j, c_k\}} T_{r,s_2}^p - p_{r,s_2}^{\max} \quad (23)
\]

\[
p_{\text{deadline}} = \sum_{t \in T_r(s_2), s_2 \in \{e_j, c_k\}} T_{r,s_2}^c - D_{r,s_2}^{\max} \quad (24)
\]

\[
p_{\text{cpu}} = \sum_{t \in T_r(s_2), s_2 \in \{e_j, c_k\}} \left(\varphi_{t,s_2} - \varphi_{s_2, z}^{\max}\right), \forall z \in Z \quad (25)
\]

\[
p_{\text{mem}} = \sum_{t \in T_r(s_2), s_2 \in \{e_j, c_k\}} \left(\sigma_{t,s_2} - \theta_{s_2, z}\right), \forall z \in Z \quad (26)
\]

The non-penalized fitness and the constraints violations are normalized as using Equations 27 and 28 respectively. The adaptive penalized fitness is then calculated as stated in Equation 29.

\[
\bar{F}_q = \frac{\bar{F}_q - \min_{\forall q \in Q}(\bar{F}_q)}{\max_{\forall q \in Q}(\bar{F}_q) - \min_{\forall q \in Q}(\bar{F}_q)} \quad (27)
\]

\[
\bar{p}_q = \frac{1}{5} \left(\frac{p_{\text{lat}}}{\max_{\forall q \in Q}(p_{\text{lat}})} + \frac{p_{\text{proc}}}{\max_{\forall q \in Q}(p_{\text{proc}})} + \frac{p_{\text{deadline}}}{\max_{\forall q \in Q}(p_{\text{deadline}})} + \frac{p_{\text{cpu}}}{\max_{\forall q \in Q}(p_{\text{cpu}})} + \frac{p_{\text{mem}}}{\max_{\forall q \in Q}(p_{\text{mem}})}\right) \quad (28)
\]

\[
\bar{F}_q = \begin{cases} 
\bar{p}_q & \text{if } \bar{p}_q = 0 \\
\bar{F}_q - \bar{p}_q & \text{otherwise}
\end{cases} \quad (29)
\]

The final fitness score for each solution is then computed by taking the reciprocal of adaptive penalized fitness as stated in Equation 30. This is to assign the highest fitness value to the offloading solution having the least execution time and QoS violations.

\[
F_q = \frac{1}{\bar{F}_q + 1} \quad (30)
\]

C. Selection of Offloading Solutions to Reproduce Solutions for Next Generation

In this step, offloading solutions from the population are selected based on their fitness value to reproduce offspring offloading solutions for the next generation. In this paper, we use the fitness proportionate Roulette Wheel Selection (RWS) [32] method that constructs a roulette wheel based on the cumulative fitness probabilities of the offloading solutions. The fittest solution is, the larger the area occupied by that solution on the roulette wheel. The cumulative probability for each offloading solution can be computed using Equation 31. Offloading solutions are then selected based on the position of randomly generated numbers on the roulette wheel.

\[
\text{Cum}(q) = \sum_{I=1}^{Q} \text{Prob}(I) \quad (31)
\]

Where \( \text{Prob}(q) \) represents the fitness probability of offloading solution \( q \ (q \in Q) \) and can be computed using Equation 32.

\[
\text{Prob}(q) = \frac{F_q}{\sum_{q \in Q} F_q} \quad (32)
\]

D. Crossover to Develop Next Generation Offloading Solutions

In this step, the selected fit offloading solutions are used to produce offspring solutions by swapping the request-server allocations for two offloading solutions, known as parent solutions. Crossover operation produces fitter offspring offloading solutions from fit parent solutions leading to convergence of algorithm towards the optimal solution. The number of parent solutions selected for crossover depends on the crossover rate \( \lambda_c \). In this paper, we use a single point crossover where a cutoff point for crossover is generated randomly and all the server allocations for the requests after the cutoff point from the parents are swapped resulting in two offspring solutions. The parent solutions in the generation are then replaced by the two fittest solutions among the parent and offspring solutions.

E. Mutation to Diversify the Offloading Solutions in a Generation

In this step, the offloading decisions for some requests in the population are changed to diversify the offloading solutions and larger the search space. Without mutation, the algorithm may converge prematurely, i.e., on the local optima, as the search
space would be restricted around the non-optimal fit solutions in the population. The number of requests for which the offloading decisions are changed depends on the mutation rate parameter and can be calculated using Equation \ref{eq:mutation_rate}.

\begin{equation}
    n_{mut} = l \times p_{size} \times \lambda_m
\end{equation}

\textbf{F. Termination of the Algorithm}

In this step, the algorithm is terminated if the maximum number of user-defined generations is reached, or the optimal offloading solution is obtained. The evaluation, selection, crossover, and mutation operations are iterated until the termination condition is met.

\textbf{VI. PERFORMANCE EVALUATION}

The experimental environment, the set of experiments performed for the evaluation of the proposed offloading algorithm, and the analysis of the experimental results are described in this section. We analyze the impact of different genetic algorithm parameters on the convergence of the proposed algorithm. In addition, we compare the performance of the proposed algorithm with baseline approaches in terms of total execution time, and the number of requests violating SLA constraints.

\textbf{A. Experimental Environment}

We created a heterogeneous integrated edge-cloud computing system for IoV. 10 edge servers and 20 cloud servers were simulated using the different edge and cloud servers’ types stated in Table \ref{table:server_specifications}. Servers 1 and 2 are part of our Intelligent Distributed Computing and Systems (INDUCE) Research Laboratory, College of Information Technology, United Arab Emirates University. The specifications of the remaining servers, i.e., 3 – 6 are taken from the SPEC Power benchmark in a way that they belong to the same family of servers in our laboratory but with different capabilities. We implemented the network using MATLAB 2020a.

In our simulated network, we use the Vehicle-Crowd Interaction (VCI) – DUT dataset [37] to obtain the position of vehicles. In particular, we used the x_est and y_est columns of the dataset for the source and destination locations of vehicles in our experiments. Regarding the characteristics of the vehicles’ requests, we used three different ITS applications; facial recognition for autonomous driving, augmented reality, and infotainment [24], [38]. The network and application characteristics used in the experiments are stated in Table \ref{table:network_characteristics}. Table \ref{table:experiment_details} shows the values used for convergence analysis of the proposed adaptive genetic algorithm.

\textbf{Table III: Specifications of the Servers used in the Experiments.}

| Server | Location | Specification | Memory |
|--------|----------|---------------|--------|
| 1      | Edge     | AMD Opteron 252, 2.59 GHz, 2-Cores | 2GB    |
| 2      | Cloud    | Intel Xeon, 2.80 GHz, 2-Cores      | 4GB    |
| 3      | Edge     | AMD Opteron 6276, 2.30 GHz, 16-Cores [33] | 32GB   |
| 4      | Cloud    | Intel Xeon E3-1204L, v5, 2.10 GHz, 6-Cores [34] | 16GB   |
| 5      | Cloud    | Intel Xeon E-2176G, 3.7 GHz, 6-Cores [35] | 16GB   |

\textbf{Table IV: Network and Application Characteristics used in the Experiments.}

| Parameter | Value(s) |
|-----------|----------|
| Number of vehicles (H) | 20, 25, 30, 35, 40, 45, 50 |
| Vehicle – RSU bandwidth (Gbps) | \(\omega_{h,e,r}^v\) |
| RSU – cloud bandwidth (Gbps) | \(\omega_{e,c}^v\) |
| Time required for data swapping operation (seconds) | 0.05 |
| Server’s CPU utilization threshold \((\rho^\text{max}_s, \forall s \in \{e, c\})\) | 90 |
| Requests’ utilization (%) \((\rho^v, \forall v \in \mathcal{T})\) | N(20, 5) |
| Requests’ length (Million Instructions) \((\psi^v, \forall v \in \mathcal{T})\) | 9000 - 5000 [24], [38] |
| Requests’ size (KB) \((\sigma^v, \forall v \in \mathcal{T})\) | 1000 – 5000 [24] |
| Requests’ latency requirements (seconds) \((L^\text{max}_r, \forall v \in \mathcal{T})\) | 0.1, 0.3, 0.5, 0.7, 0.9, 1.1 |
| Requests’ processing time requirements (seconds) \((P^\text{max}_r, \forall v \in \mathcal{T})\) | 0.9, 1.1, 1.3, 1.5, 1.7, 1.9 |
| Requests’ deadline requirements (seconds) \((D^\text{max}_r, \forall v \in \mathcal{T})\) | 1.2, 1.4, 1.6, 1.8, 2 |

\textbf{Table V: Genetic Algorithm Parameters used for Convergence Analysis.}

| Parameter | Value(s) |
|-----------|----------|
| Crossover rate \((\lambda_c)\) | 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95 |
| Mutation rate \((\lambda_m)\) | 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1 |
| Population size \((P_{\text{size}})\) | 2 \times requests, 4 \times requests, 6 \times requests, 8 \times requests, 10 \times requests |
| Termination condition | 1000 iterations (generations) |

\textbf{B. Experiments}

In this section, we explain the experiments performed for convergence analysis of the proposed adaptive genetic algorithm and for comparison of the proposed algorithm with baseline approaches in terms of total execution time and the number of requests violating SLA constraints.

To analyze the convergence of the proposed algorithm we executed the algorithm with different values of \(\lambda_c\), \(\lambda_m\), and \(P_{\text{size}}\) (Table \ref{table:algorithm_parameters}). We first ran the algorithm with varying values of \(\lambda_c\) and keep the values of \(\lambda_m\) and \(P_{\text{size}}\) constant at 0.01 and 2 \times requests respectively. We then select the value of \(\lambda_m\) that has the fastest convergence as the optimal crossover rate. Next, we vary run the proposed algorithm with varying values of \(\lambda_m\) and the values of \(\lambda_c\) and \(P_{\text{size}}\) constant at optimal crossover rate and 2 \times requests respectively. We select the value of \(\lambda_m\) resulting in the fastest convergence as the optimal mutation rate. Lastly, we vary the values of \(P_{\text{size}}\) with \(\lambda_c\) and \(\lambda_m\) constant at their optimal values. We then select the value that has the least convergence time as the optimal value for \(P_{\text{size}}\).

We evaluate the offloading performance of the proposed algorithm with varying values of latency, processing time,
deadline requirements, and requests (Table IV). We vary each parameter while keeping the other three parameters constant at their corresponding minimum values. The value for deadline requirement is varied while varying the latency and processing time requirements. This is because the deadline is dependent on latency and processing time. For each run, we use the optimal values of $\lambda_c$, $\lambda_m$, and $P_{\text{size}}$. We measure the performance of the algorithm in terms of the total execution time of the requests and the number of requests violating SLA requirements. For latency, processing time, and deadline violations, we calculate the number of requests for which the value of communication time, processing time, and total execution time is greater than that tolerable by the request. To determine the number of requests violating CPU requirements, we consider the number of requests scheduled on a server where the total CPU utilization of all requests scheduled on that server is more than the server’s CPU utilization threshold.

To demonstrate the performance of our proposed algorithm, we compare it with the following baseline approaches:

1) **QoS-Aware Genetic Algorithm (GA-QoS):** An offloading scheme using a genetic algorithm whose objective is to minimize the total execution time of all the requests without considering the SLA constraints.

2) **Random Offloading:** An offloading scheme where each request is randomly scheduled either at the edge or cloud server without considering the QoS and SLA.

We repeat the experiments for GA-QoS and random offloading with varying latency, processing time, deadline requirements, and the number of requests.

### C. Experimental Results Analysis

In this section, we present the analysis of the results obtained from our experiments. In particular, we analyze the results on the convergence of our proposed algorithm and the comparison of the proposed algorithm with baseline approaches for QoS-SLA-aware offloading.

#### C.1. Convergence Analysis

Fig. 5 shows the convergence of our proposed algorithm in terms of penalized fitness score with varying values of $\lambda_c$. As shown in Fig. 5 (a) the value $\lambda_c = 0.95$ converges the algorithm in the least time. This is because a higher crossover rate diversifies the population by selecting more offloading solutions to perform the crossover operation. On the other hand, the offloading solutions are not much diverse when the crossover rate is low. The fastest convergence of the algorithm using $\lambda_c = 0.95$ is more evident from the fitness score distribution in Fig. 5 (b). As shown in the figure, all the distributions are left-skewed indicating that the majority of the fitness score for all values of $\lambda_c$ are near to 1. However, for $\lambda_c = 0.95$ most of the fitness score values are 1. Fig. 6 (a) and 6 (b) shows the convergence and distribution of total execution time of the requests with varying values of $\lambda_c$ respectively. As shown in the figure, $\lambda_c = 0.85$ results in the fastest convergence with the least total execution time. Although, $\lambda_c = 0.85$ optimizes the total execution time, it does converge the algorithm in terms of fitness (Fig. 5). This is because the fitness score in Fig. 5 considers both the optimization of total execution time and SLA violations, whereas Fig. 6 only considers the optimization of total execution time. Consequently, $\lambda_c = 0.85$ optimizes the time but violates SLA constraints. On the other hand, $\lambda_c = 0.95$ converges to an offloading solution with minimum execution time while respecting the SLA constraints. Consequently, we use $\lambda_c = 0.95$ in the remaining experiments.

Fig. 7 shows fitness convergence of the proposed algorithm with varying values of $\lambda_m$. As depicted in Fig. 7 (a) only $\lambda_m = 0.01$ converges the algorithm to an optimal fitness value of 1. This is also confirmed in the fitness distribution shown in Fig. 7 (b). This is because a higher mutation rate hinders the convergence as fitter offloading solutions are lost. Fig. 8 (a) and 8 (b) depict the convergence and distribution of total execution time with varying values of $\lambda_m$. As shown in the figures, $\lambda_m = 0.01$ converges the algorithm to the minimum execution time. No other values of $\lambda_m$ aids in the convergence of the algorithm. Consequently, we use $\lambda_m = 0.01$ in the offloading experiments.

![Fig. 5(a). Fitness score over iterations for the requests' offloading solution using the proposed algorithm versus crossover rate $\lambda_c$.](image)

![Fig. 5(b). Fitness score distribution over iterations for the requests' offloading solution using the proposed algorithm versus crossover rate $\lambda_c$.](image)
Fig. 6(a). Total execution time over iterations for the requests' offloading solution using the proposed algorithm versus crossover rate $\lambda_c$.

Fig. 6(b). Total execution time distribution over iterations for the requests' offloading solution using the proposed algorithm versus crossover rate $\lambda_c$.

Fig. 7(a). Fitness score over iterations for the requests' offloading solution using the proposed algorithm versus mutation rate $\lambda_m$.

Fig. 7(b): Fitness score distribution over iterations for the requests' offloading solution using the proposed algorithm versus mutation rate $\lambda_m$.

Fig. 8(a). Total execution time over iterations for the requests' offloading solution using the proposed algorithm versus mutation rate $\lambda_m$.

Fig. 8(b). Total execution time distribution over iterations for the requests' offloading solution using the proposed algorithm versus mutation rate $\lambda_m$. 
Fig. 9 shows the fitness convergence of the proposed algorithm with a varying value of \( P_{\text{size}} \). As shown in Fig. 9 (a) the algorithm converges to the optimal fitness score of 1 when the population size is set to 2 times the number of requests. This is also confirmed by the fitness distribution with varying values of \( P_{\text{size}} \) in Fig. 9 (b). As shown in Figs. 10 (a) and 10 (b), the total execution time of the requests converges to the minimum only when \( P_{\text{size}} = 2 \times \text{requests} \). Consequently, we use \( P_{\text{size}} = 2 \times \text{requests} \) in the experiments. Table VI shows the optimal values of genetic parameters used in the experiments to evaluate the offloading performance of the proposed and GA-QoS algorithms.

Table VI: Optimal Values of Genetic Algorithm Parameters.

| Parameter       | Value               |
|-----------------|---------------------|
| Crossover rate  | \( \lambda_c \) 0.95|
| Mutation rate   | \( \lambda_m \) 0.01|
| Population size | \( P_{\text{size}} \) 2 \times \text{requests} |

C.2. Comparative Performance Analysis

Figs. 11 and 12 show the total execution time and the number of requests violating SLA requirements respectively, for the proposed, GA-QoS, and random offloading algorithms with increasing latency requirements. As shown in Fig. 11 the random offloading algorithm has the highest execution time. While GA-QoS has better performance than the proposed algorithm (Fig. 11), it has SLA violations (Fig. 12) compared to the proposed algorithm with no violations. This is because GA-QoS focuses on minimizing the total execution time without considering the SLA constraints. However, the proposed algorithm minimizes the total execution time while considering the constraints. The GA-QoS has less violations than the random offloading algorithm thanks to its GA-based minimization strategy. In summary, the average total execution times with increasing latency requirements for the proposed, GA-QoS, and random algorithms are 13.98 seconds, 13.52 seconds, and 19.58 seconds respectively. The average number
of requests violating SLA constraints using the proposed, GA-QoS, and random algorithms are 0, 1, 10.33 respectively. The percentage of requests violating SLA constraints, on average, with increasing latency requirements are 0, 5, and 51.66 using the proposed, GA-QoS, and random approaches respectively.

Figs. 13 and 14 show the total execution time and the number of requests violating SLAs, respectively, for the proposed, GA-QoS, and random offloading algorithms with increasing processing time requirements. As shown in Fig. 13 the random offloading algorithm has the highest execution time with increasing processing time requirements. Compared to GA-QoS, the proposed algorithm results in a higher total execution time. This is because of the SLA constraints consideration in the proposed algorithm in addition to the objective of minimizing the total execution time. As shown in Fig. 14, the proposed algorithm has no requests with SLA violations. However, the memory requirement is violated using GA-QoS, and the processing time, deadline, and memory requirements are violated using the random algorithm. As shown in the figure, the number of requests violating processing time requirements for the random approach decreases with increasing processing requirements. This is because more requests are executed within the processing time constraint. As a result, the number of requests violating the deadline requirement also decreases as the deadline requirement also increases along with the processing time requirement. In summary, the average total execution times with increasing processing time requirements for the proposed, GA-QoS, and random algorithms are 16.33 seconds, 13.50 seconds, and 19.21 seconds respectively. The average number of requests violating SLA constraints using the proposed, GA-QoS, and random algorithms are 0, 1.33, 3.83 respectively. The percentage of requests violating SLA constraints, on average, with increasing processing requirements are 0, 6.66, and 19.16 using proposed, GA-QoS, and random approaches respectively.
particular, the average number of requests violating SLA requirements using the proposed, GA-QoS, and random algorithms are 23.71, 24, 28.60 respectively. The percentage of requests violating SLA constraints on average with increasing requests are 59.40, 59.22, and 77.35 using the proposed, GA-QoS, and random approaches respectively.

VII. CONCLUSION

Computation offloading is crucial in an integrated edge-cloud system for IoV to enhance the QoS and respect SLA requirements of both compute-intensive and time-critical applications. In this paper, we propose a QoS-SLA-aware adaptive genetic algorithm to offload vehicular applications’ requests on an edge/cloud server such that the total execution time of the requests is minimized. In addition, our proposed optimization algorithm is constrained by the requests’ SLA requirements in terms of latency, processing time, deadline, CPU, and memory. The proposed algorithm considers the overlapping of requests execution in the offloading decision. To the best of our knowledge, we are the first ones to propose a QoS-SLA-aware offloading algorithm in IoV that considers the overlapping of multi-request execution and dynamic speed of the vehicle for execution time minimization, while adhering to the performance and resource critical SLA constraints. Comparative analysis and numerical experiments carried out revealed that the proposed algorithm outperforms the random offloading approach in terms of total execution time. In the context of SLA constraints, the proposed algorithm outperforms both baseline genetic-based and random offloading approaches. As future research direction, we propose to investigate QoS-SLA-aware partial offloading where the request can be divided for simultaneous execution in an integrated vehicle-edge-cloud computing system.

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