Deadline-Aware Adaptive Fuzzification for Task Offloading in Vehicle-to-Vehicle Networks

Vishesh Kothari, Supriya Dilip Tambe, and Antony Franklin A.
Indian Institute of Technology, Hyderabad, India
vish.kothari96@gmail.com, cs18resch11002@iith.ac.in, and antony.franklin@iith.ac.in

***Abstract*—Task offloading in Vehicle-to-Vehicle (V2V) networks distributes computational workloads to nearby vehicles, thereby enhancing resource utilization and minimizing latency. This process is complex due to uncertainties, such as variable network conditions and mobility, where applying fuzzy logic (fuzzification) offers a robust solution to manage such unpredictability. However, existing methods often overlook strict deadlines for tasks and dynamic vehicular contexts, leading to suboptimal performance. This paper proposes the Deadline-Aware Adaptive Fuzzification (DAAF) approach to address these challenges in V2V communications within Vehicle-to-Everything (V2X) systems. Motivated by the need to select adaptive fuzzy rules and deadline-sensitive offloading in highly dynamic environments, DAAF integrates the Computational Power Factor (CPF), Mobility Factor (MF), Link Quality Factor (LQF), and task deadlines into its fuzzy logic framework, ensuring timely and efficient task execution. Simulations using Omnet++, SUMO, and Veins show that the DAAF approach reduces the Average Completion Time (ACT) by 12% at 250 vehicles, achieves a peak Task Completion Ratio (TCR) of 90% at 150 vehicles with a 15% improvement over static fuzzy logic, and enhances the Average Execution Time (AET) by 7.7%, outperforming baseline methods in dense urban scenarios.**

***Index Terms*—Adaptive systems, Deadline-aware, Fuzzy logic, Task offloading, V2V communication.**

I. Introduction

Connected and autonomous vehicles rely heavily on Vehicle-to-Vehicle (V2V) communication. V2V supports critical applications/tasks, such as collision avoidance, traffic management, and navigation, but these applications generate computational demands that often exceed the onboard vehicle's capabilities [1]. Task offloading, delegating computation to nearby vehicles, helps reduce latency and improve system efficiency. Effective V2V offloading remains challenging due to high mobility, fluctuating link quality, varying traffic density, and limited bandwidth [2]. Many vehicular tasks are deadline-sensitive, complicating offloading decisions [3]. Although fuzzy logic is well-suited for handling such uncertainty, existing fuzzy-based schemes typically rely on static rule bases that limit adaptability in dynamic V2V environments [4].

Task offloading in vehicular networks has been widely studied from two primary directions: deadline-aware decision making and fuzzy logic-based offloading. Deadline-aware approaches aim to satisfy the stringent timing requirements of vehicular applications. Fog–cloud coordination methods, such as [5], ensure timeliness and resource guarantees but rely on static formulations that struggle under highly dynamic V2V conditions. Traffic-light-assisted scheduling [3] and learning-based offloading using Deep Reinforcement Learning (DRL) [6] improve delay performance, but typically assume stable mobility patterns or require substantial training overhead.

Fuzzy logic has also been extensively applied in offloading due to its robustness against uncertain wireless and mobility conditions. Prior work includes fuzzy rule-based computation offloading in V2V systems [2], latency-sensitive IoV edge offloading [7], a fuzzy logic-driven method for selecting optimal edge server offloading [8], multi-tier edge decision frameworks [9], and fuzzy RL for energy-efficient vehicular fog computing [4]. While these methods effectively handle uncertainty, they rely on choosing *static* rule bases and generally assume moderate link stability, making them insufficient for highly dynamic V2V environments. Moreover, fulfillment of task deadlines is rarely considered a primary determinant of offloading.

Motivation: Existing work either satisfies deadlines without accounting for fast-changing V2V connectivity or uses fuzzy logic without deadline awareness or adaptability. This motivates the development of a framework that jointly incorporates deadline sensitivity, mobility, link quality, and real-time environmental changes. To address these challenges, this paper proposes a Deadline-Aware Adaptive Fuzzification (DAAF) approach for V2V task offloading. DAAF dynamically adapts fuzzy rules based on real-time conditions, including computational power, mobility, link quality, traffic type, and task deadlines, thus enabling more reliable and timely task completion. It considers adaptive, traffic-aware fuzzy rule switching for deadline-aware Urban and Highway scenarios.

The main contributions are as follows:

- A novel decentralized DAAF framework that integrates deadline awareness with adaptive fuzzy logic for V2V task offloading.
- An adaptive mechanism that updates fuzzy rules using historical execution outcomes, improving performance across diverse and dynamic traffic scenarios.
- A comprehensive simulation-based evaluation demonstrating improved completion time and task completion ratio over existing baseline and state-of-the-art approaches.

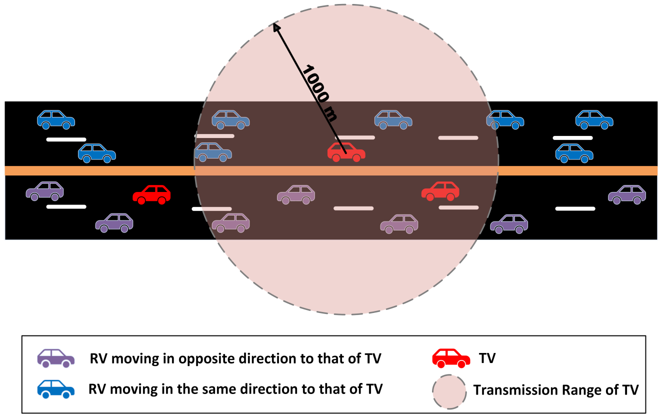

Fig. 1: System Model for task offloading in V2V communication networks

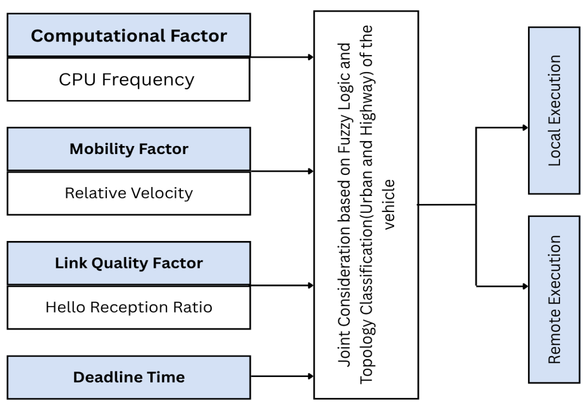

Fig. 2: Proposed Fuzzy Logic Scheme.

II. System Model and Adaptive Fuzzy Framework

This section describes the system model and the proposed Deadline-Aware Adaptive Fuzzification (DAAF) mechanism, as illustrated in Fig. 1, which is used for V2V task offloading. The goal is to make offloading decisions that account for computational capability, mobility, link quality, and task deadlines while adapting to dynamic vehicular conditions.

A. System Overview

We consider a V2V environment where Task Vehicles (TVs) generate delay-sensitive tasks and Resource Vehicles (RVs) provide computation. The system assumes binary (all-or-nothing) offloading, strict task deadlines, heterogeneous vehicle capabilities, cooperative resource sharing, and dynamically changing mobility and link conditions. IEEE 802.11p is used for reliable V2V communication. A TV offloads a task only when a neighbouring RV offers better processing and communication conditions; otherwise, it executes the task locally without offloading.

B. Fuzzy Decision Inputs

DAAF evaluates four factors using fuzzy logic:

*1) **CPF**:* We need to choose the vehicle that can process the offloaded task the fastest. CPF is the ratio of the vehicle's CPU frequency to the maximum CPU frequency among all the neighbours of the vehicle. It is calculated as:

$$CPF(x) = \frac{f(x)}{\max_{y \in N_x} f(y)}, \tag{1}$$

Where $f(x)$ is the computational resource (e.g., CPU speed) of vehicle x, and N_x is the neighbour set constructed from the beacon frames received. A higher value of CPF indicates that the vehicle x is a better candidate for task offloading.

*2) **MF**:* To account for dynamic topology changes in V2V networks, the Mobility Factor (MF) reflects how similar a vehicle's speed is to that of its neighbours. It is defined as the normalized difference between the vehicle's speed and the neighbour's average speed. It is calculated as:

$$MF(x) = 1 - \frac{\|v(x) - \text{avg}_{y \in N_x} v(y)\|}{\| \max_{y \in N_x} v(y) - \min_{y \in N_x} v(y)\|}, \tag{2}$$

where $MF(x)$ indicates the mobility factor of vehicle x and $v(\cdot)$ denotes vehicle velocity. MF is updated periodically by a weighted exponential moving average approach as follows:

$$MF(x) = (1-\alpha) \cdot MF_{i-1}(x) + \alpha \cdot MF_i(x)$$

With $\alpha = 0.7$, giving more weight to recent velocity changes.

*3) **LQF**:* In V2V networks, wireless link reliability is estimated using beacon frame reception counts over a 10 seconds sampling window, mitigating the effects of packet loss and congestion. The beacon reception ratio(R) is considered as follows:

$$R_i(c,x) = \begin{cases} \frac{N_r(c,x)}{N_s(x)}, & \text{if } N_s(x) \geq 10 \\ \frac{N_r(c,x)}{N_s(x)} \cdot [\epsilon(N_s(x))], & \text{otherwise,} \end{cases} \tag{4}$$

where $N_r(c,x)$ is the number of hello messages received at c from x and $N_s(x)$ is the number of hello messages sent by x in the beacon frames. As shown in Equation (4), $\epsilon(\cdot)$ is a discount function to avoid overestimation when there are few (less than 10) hello messages sent by x. Here, $\epsilon(x) = 1 - \left(\frac{1}{2}\right)^{N_s(x)}$ is the discount function. LQF is calculated as:

$$LQF(c,x) \leftarrow (1-\alpha) \cdot LQF_{i-1}(c,x) + \alpha \cdot R_i(c,x), \tag{5}$$

where $LQF_{i-1}(c,x)$ is initialized to 0. LQF is the periodically updated value of the hello message reception ratio, which reflects the wireless channel condition among neighbouring vehicles. A higher $LQF(c,x)$ value indicates better link quality between the vehicle c and x.

*4) **Task Deadline**:* In V2V communication, this is the strict time limit for task completion, which is crucial for collision avoidance and navigation tasks. Delays can compromise safety or efficiency, as noted in [3], [6]. DAAF integrates deadline time into fuzzy logic, dynamically adjusting offloading decisions based on real-time conditions. This ensures task deadline constraints, addressing dynamic vehicular challenges.

C. Adaptive Traffic-Aware Rule Switching

Vehicles estimate local traffic density by counting the number of unique neighbors detected through periodic beacon exchanges. When more than 25 neighbours are observed, the environment is classified as **Urban**; otherwise, it is treated as **Highway**. Since these scenarios differ significantly in connectivity and mobility patterns, DAAF dynamically switches between the corresponding fuzzy rule bases. This enables the decision logic to adapt to varying network conditions and maintain reliable offloading performance in both dense and sparse settings, eliminating the need for manual parameter tuning.

D. Fuzzy Rule Base

The fuzzy inference system generates an offloading suitability score using four inputs: CPF, MF, LQF, and Deadline. Each input has three linguistic levels(Low, Medium, and High), resulting in a total of 81 rules in each scenario-specific rule base. Urban and Highway rule bases follow the same structural combinations; however, they differ in output rankings to better reflect the characteristics of each environment. In urban scenarios, where link opportunities are more abundant, rules assign higher suitability to strong links and stable mobility patterns. In Highway scenarios, the rules are more conservative to account for sparser connectivity and higher variations in mobility.

For instance, consider a TV that must offload a task with a strict 0.8-second deadline and identifies two candidate RVs: the first offers high CPF (1.0), strong LQF (0.90), and good MF (0.95); the second provides slightly lower CPF (0.85) but superior highway mobility alignment (MF = 0.97). In a dense urban environment, the TV detects high neighbor density and activates the urban rule set, where LQF is emphasized due to interference and signal variability, resulting in the selection of the first RV. As the vehicle enters a highway and neighbor density decreases, the system switches to the highway rule set, which prioritizes MF and CPF to ensure link continuity at higher speeds, making the second RV the preferred choice. This context-driven, deadline-aware adaptation in DAAF ensures that the selected RV maximizes the likelihood of meeting the deadline under current conditions, instead of relying on a static decision model.

E. Adaptive Fuzzy Offloading Mechanism

The offloading decision at each TV follows the steps below:

1) **Neighbour Data Collection:** Each vehicle maintains a neighbour table using periodic beacon frames that carry position, velocity, CPU frequency, and link information.
2) **Traffic Classification:** The vehicle estimates traffic density from the number of neighbours and classifies the scenario as *Urban* or *Highway*.
3) **Factor Computation:** For each neighbour, the CPF, MF, LQF, and the task deadline are computed or updated.
4) **Fuzzy Evaluation:** The appropriate fuzzy rule base (Urban or Highway) is applied to generate a fuzzy score for each neighbour.
5) **Decision:**
   - If the TV's CPF is greater than or equal to all neighbours, the task is executed locally at the TV; offloading is not performed.
   - Otherwise, the task is offloaded to the neighbour with the maximum fuzzy score.

Time Complexity: The DAAF algorithm runs on every TV. The time complexity of the DAAF algorithm is $O(N)$ per task, at the TV, where N is the number of neighbouring vehicles. Since the fuzzy rule base size is constant(81 rules), fuzzy inference contributes a constant overhead. For T tasks at each vehicle, the total complexity becomes $O(TN)$.

III. Experimental Analysis

A. Experimental Setup

We evaluate DAAF using the integrated OMNeT++ [10], INET framework [11], SUMO [12], Veins [13] co-simulation framework, where OMNeT++ manages network events, SUMO provides microscopic vehicular mobility, and Veins synchronizes both simulators for realistic V2V interactions. For communication, we use IEEE 802.11p, the most stable and fully supported V2V protocol in these tools. The integration of IEEE 802.11bd will be incorporated in future work once mature implementations are supported by these tools. The road network is a 2 km × 2 km OpenStreetMap segment simulated in SUMO. One vehicle is randomly selected as the TV, and all others act as RVs. Mobility and beacon exchanges from SUMO are synchronized with OMNeT++ to update neighbour information and link quality. Each scenario is executed 75 times for different traffic densities, and the results are averaged. The complete simulation parameters are provided in Table II. The simulation setup is available at [14].

B. Performance Metrics

The key performance indicators used to measure the performance of the proposed algorithm, as well as the baseline schemes, are below:

- **Average Completion Time (ACT):** The total round-trip time for an offloaded task. A lower ACT indicates better overall efficiency.
- **Task Completion Ratio (TCR):** The ratio of tasks completed within their deadlines to the total number of tasks generated. A higher TCR signifies greater reliability and adherence to time constraints.
- **Average Execution Time (AET):** The time an RV takes to process an offloaded task, reflecting the computational efficiency of the selected vehicle. A lower AET is better.
- **Average Communication Time (ACOT):** The propagation time for a task packet to travel from the TV to the RV indicates the communication link's efficiency. A lower ACOT suggests reduced network latency.

C. Considered Approaches for Comparison

To evaluate the performance of the proposed approach, it is compared with state-of-the-art and baseline approaches as follows:

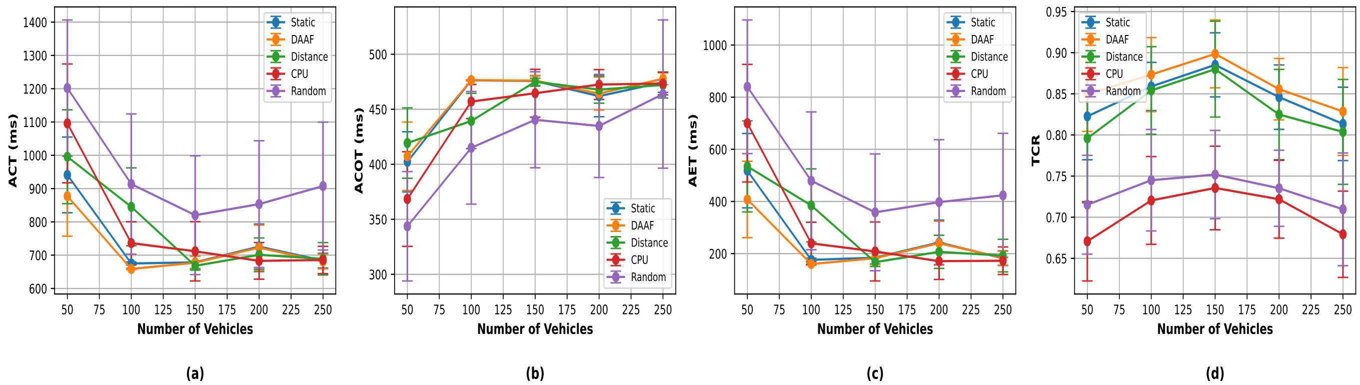

Fig. 3: Performance comparison results by varying the number of vehicles:(a) ACT of the offloading algorithms, (b) AOCT of the offloading algorithms, (c) AET of the offloading algorithms, and (d) TCR of the offloading algorithms

- **Static Fuzzy Logic Offloading (Static) [2]:** It employs a fixed fuzzy rule base that does not adapt to dynamic traffic conditions or vehicle density, limiting its flexibility in varying scenarios.
- **Greedy Distance Offloading (Distance):** It selects the nearest RV from the TV's one-hop neighbour table, prioritizing proximity over other factors like computational power or link quality.
- **Greedy CPU Offloading (CPU):** This algorithm offloads the task to the RV having the highest CPU frequency(from the one-hop neighbour table built by TV).
- **Random Offloading (Random):** This randomly selects an RV from the available neighbours, serving as a baseline to evaluate the benefits of informed decision-making.

D. *Result Analysis*

We evaluate DAAF under vehicle densities ranging from 50 to 250 and compare it with state-of-the-art and baseline schemes. The results are summarized in Table I, trends illustrated in Fig. 3, and briefly discussed below.

- **ACT:** DAAF achieves the lowest completion time across all densities, reaching 654 ms, which is a 12% improvement over Static Fuzzy Logic. Performance improves with density, as there are more RVs/candidates that the DAAF can choose from, to provide computational support to the TV.
- **TCR:** DAAF attains a peak TCR of 90% at 150 vehicles and maintains above 85% at higher densities, outperforming other schemes by up to 15%. Its deadline-aware scoring and dynamic rule adaptation ensure more tasks are completed within their time limits.
- **AET:** Due to better partner selection, DAAF reduces execution time to 131 ms, a 7.7% gain over Static. Higher densities enable DAAF to select RVs with stronger computational capabilities consistently.
- **ACOT:** DAAF maintains stable communication delays (around 475 ms), benefiting from its consideration of link quality and mobility. This results in lower contention and fewer retransmissions compared to the baselines.

TABLE I: Performance Comparison at 250 Vehicles

Scheme	ACT (ms)	AET (ms)	TCR (%)	ACOT (ms)
DAAF	**654**	**131**	**90**	**475**
Static [2]	740	142	75	500
Greedy CPU	825	167	70	482
Greedy Distance	1012	228	62	488
Random	1194	310	58	485

TABLE II: Simulation Scenario Parameters

Parameter	Value
Simulation Time	500 seconds
Number of Vehicles	50, 100, 150, 200, 250
Transmission Range	1000 meters
Bit Rate	3 Mbps
Mobility Model	Vehicular Mobility
Radio Path Loss	Nakagami Fading
Task Packet Size	512 KB
Beacon Packet Size	150 B
Deadline Time	500 msec
No of Tasks	10

IV. Conclusion and Future Work

DAAF enhances V2V task offloading by integrating deadline awareness with adaptive fuzzy logic, resulting in lower ACT and ACOT, faster execution times, and higher TCR compared to Static Fuzzy Logic. These gains, validated across varying densities (250 vehicles) with 95% confidence, demonstrate DAAF's effectiveness in dynamic and dense urban environments. Overall, DAAF enhances reliability for time-critical vehicular applications and contributes to the development of an efficient intelligent transportation system. Future work includes validating the approach on real-world testbeds to capture environmental and mobility uncertainties.

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