Intelligent Task Offloading with Cognitive DRL Models for Vehicular Digital Twins

Sarah Al-Shareeda, Nasir Saeed, Keith Redmill, Bander A. Jabr, Yasser Bin Salamah, Fusun Ozguner, Ahmed Al-Dubai, and Berk Canberk

Appendix A
Notations Dictionary

Table I summarizes the used notations in this work.

TABLE I
NOTATIONS

Symbol	Description
n	Number of vehicles
m	Number of RSUs
RSU_j	RSU indexed by j
R	Coverage range of each RSU (Km)
F_{RSU_j}	Computing resource of RSU_j (GHz)
L_{RSU_j}	Fixed location of RSU_j
V_i	Vehicle indexed by i
T_{ij}	Data rate from V_i to RSU_j (Mbps)
T_{iC}	Data rate from V_i to the cloud (Gbps)
F_C	Cloud's computation resource full capacity (GHz)
f_{V_i}	Computation resources of vehicle V_i (GHz)
$v_{V_i}^t$	Speed of V_i at time t (Km/h)
$l_{V_i}^t$	Location of V_i at time t
S_{V_i}	Safety application/task run by V_i
d_{V_i}	Size of the task S_{V_i} (Byte)
c_{V_i}	Computation resource requirement of S_{V_i} (Hz/Byte)
τ_{V_i}	Deadline for completing S_{V_i} (seconds)
$\bar{d}_{V_i}$	Result size of task S_{V_i} (Byte)
T_{V_i}	Computation time for task S_{V_i} on vehicle V_i
T_{V_iC}	Time to offload and compute task S_{V_i} in the cloud
$F_C^{V_i}$	Cloud computation resources for vehicle V_i's task
D_C	Distance to the cloud server
s	speed of light
T_{ij}^{upload}	Data rate for uploading from vehicle V_i to RSU_j
T_{iC}^{upload}	Data rate for uploading from vehicle V_i to the cloud
$T_{iC}^{download}$	Data rate for downloading from the cloud to vehicle V_i
$T_{ij}^{download}$	Data rate for downloading from RSU_j to vehicle V_i
$T_{V_iRSU_j}$	Time to offload and compute task S_{V_i} at RSU_j
$T_{V_iRSU_{j,k}}$	Time for S_{V_i} with handover from RSU_j to RSU_k
$f_{RSU_j}^{V_i}$	Computation resources at RSU_j for vehicle V_i's task
D_E	Distance to the edge server (RSU)
T_b	Data rate of the wired backhaul link between RSUs
$T_{V_i}^{total}$	Time to complete S_{V_i}, with local or remote processing
x_{V_i}	Decision variable for offloading task S_{V_i}
y_{V_i}	Handover factor for S_{V_i} in edge computing scenario
$State_{Cloud}$	State vector for CT
$State_{Edge}$	State vector for ET
$State_{Hybrid}$	Combined state vector of CT and ET
$Action_{cloud}$	Offloading and resource allocation for CT
$Action_{edge}$	Offloading and resource allocation for ET at RSU
$Action_{Hybrid}$	Combined CT and ET actions
$Reward_{deployment}$	Reward based on task execution time
π_θ	DRL policy parameterized by θ
$log(p(\pi_\theta))$	Log probability of policy π_θ
$H(\pi_\theta)$	Entropy of policy's action distribution
$L^{Clip}(\pi_\theta)$	Clipped loss function of PPO
$\hat{r}(\pi_\theta)$	Ratio of new and old policy probabilities
$\hat{\epsilon}$	PPO clipping threshold
$\hat{A}$	Advantage function for actions
T_{total}	Total execution time for all tasks
γ	Discount factor in DRL
lr	Learning rate
AER	Average Episode Reward

Appendix B
Related Work: Deployments and Challenges

This section examines various deployment types for DTs-assisted vehicular networks. We also provide their advantages, disadvantages, and relevant use cases from the literature. Key challenges facing these DTs are defined, and the performance of different deployment models under these conditions is evaluated. The section also reviews literature for countermeasures and enhancement strategies, summarized in III.

A. Vehicular Cognitive DT Deployments

This subsection categorizes DT deployment types into cloud, edge, and hybrid models [1], [2]. We cover their effectiveness, strengths, constraints, and relevant use cases from the literature.

1) CT Deployment: CT deployment is highly effective for vehicular DTs, requiring substantial computing power and extensive storage. This method involves transmitting data from vehicles and infrastructure to a remote cloud server for comprehensive processing and analysis; see Fig. 1(a). The cloud excels in large-scale data processing tasks due to its robust computational resources and substantial storage capacity, facilitating processing and analysis. CT deployment supports complex algorithms and sophisticated ML/DL models, enhancing vehicular network performance [2]. Ge *et al.* [3] use this model for efficient data gathering and processing within Cellular-V2X and 4G/5G networks. Wang *et al.* [4] demonstrate the cloud's capabilities in real-time vehicle monitoring within Advanced Driver Assistance Systems (ADAS). Barbie *et al.* [5] and Shoukat *et al.* [6] highlight the cloud's proficiency in managing complex vehicular maneuvers and safety decisions in mixed-traffic environments. Wang *et al.* [7] and Al-Shareeda *et al.* [8] showcase the versatility of cloud-based DTs in co-simulating connected vehicles and pedestrians, addressing network performance requirements. Despite its strengths, CT deployment has potential latency issues due to real-time communication between vehicles and the cloud, causing delays in round-trip communication. Privacy concerns are significant, as sensitive vehicle data is transmitted/stored on remote servers. Overall, while CT deployment substantially benefits computational power and storage for vehicular DTs, addressing latency and privacy issues is crucial for optimal implementation.

2) ET Deployment: ET deployment, shown in Fig. 1(b), is essential for low-latency applications. By positioning virtual twins close to vehicles, ET enables real-time data processing and analysis, avoiding the need to send data to distant cloud servers. This enhances real-time data collection and decision-making capabilities.

ET deployment allows real-time decision-making by processing data near vehicles, significantly reducing latency. Enhanced privacy is achieved by retaining sensitive data within the car or on proximate edge devices. Maheswaran *et al.* [9] and Han *et al.* [10] use ET to update autonomous vehicle locations and enhance driving tests. Fan *et al.* [11] demonstrate an ET-based architecture aiding lane-changing decisions for Connected Autonomous Vehicles (CAVs). Hui *et al.* [12] and Kumar *et al.* [13] highlight ET's role in reducing latency and enhancing data privacy in distributed autonomous driving and traffic congestion avoidance. ET deployment has limitations. Edge devices have limited computational resources compared to cloud servers, constraining algorithm complexity. Managing and coordinating distributed edge devices across extensive vehicle fleets presents logistical challenges, including synchronization and additional infrastructure and maintenance costs. In summary, ET deployment offers significant benefits for real-time processing and enhanced privacy in vehicular networks, but addressing its computational and management challenges is crucial for optimal implementation.

3) HT Deployment: HT deployment integrates features of both cloud-based and edge-based implementations, as illustrated in Fig. 1(c). This strategy uses edge-based twin objects for processing tasks near the physical twins, leveraging the edge's immediate processing capabilities. When the edge's computing power is exhausted, the system shifts to cloud-based twin objects, utilizing the cloud's extensive scalability and storage. HT deployment is particularly beneficial for applications requiring low latency and high computational power, ensuring system responsiveness and efficiency by dynamically shifting the processing to the cloud when necessary [1], [14].

HT deployment offers real-time processing at the edge for latency-sensitive applications while leveraging the cloud's vast resources for complex and data-intensive tasks. This dual resource allocation reduces dependency on constant cloud connectivity and enables efficient task execution at the edge. For instance, hybrid deployments develop task offloading schemes in vehicular fog networks, prioritizing tasks based on urgency [15]. Dai *et al.* [16] introduce a task-offloading strategy with resource allocation to maximize system utility through optimization. The literature frequently adopts Markov Decision Processes (MDPs) to devise offloading strategies, optimizing trade-offs to fulfill specific objectives [17], [18]. Jang *et al.* [19] propose a Lyapunov optimization-based algorithm to enhance system stability while reducing task processing delays. Liu *et al.* [20] employ an asynchronous DRL algorithm for a hybrid-based task offloading approach, addressing distributed task offloading and multi-resource management challenges. Managing tasks and data distribution between the edge and the cloud requires efficient communication and

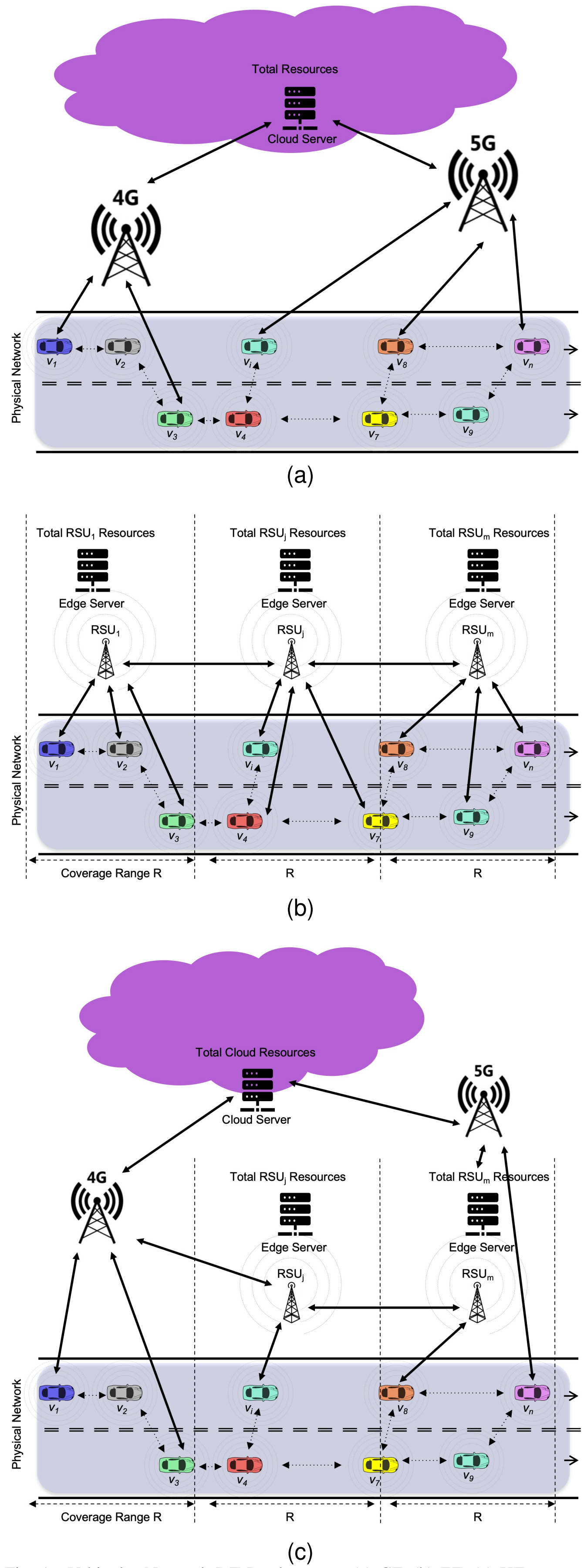

Fig. 1. Vehicular Network DT Deployments (a) CT. (b) ET. (c) HT.

synchronization mechanisms across the network, including vehicles, edge devices, and cloud infrastructure. Ensuring effective coordination and seamless data transfer between these components is crucial for maintaining the network's integrity and performance. These management requirements introduce additional layers of complexity, necessitating sophisticated strategies to realize the full benefits of HT deployment. Hence, HT deployment offers significant advantages for vehicular networks by combining real-time edge processing and extensive cloud resources, though managing its complexities is essential.

B. Challenges in Vehicular Cognitive DTs

Successfully deploying cognitive DTs in vehicular networks requires overcoming key challenges to ensure effective interaction with dynamic physical systems. This subsection identifies these challenges and assesses the performance of the three deployment models in addressing them. It also highlights literature-sourced countermeasures, offering an overview of strategies for addressing these challenges [1], [14].

1) Latency Sensitivity: Latency sensitivity refers to the critical need to minimize data transmission and processing delays, essential for real-time decision-making in vehicular environments. High latency can adversely affect the responsiveness and effectiveness of network operations.

Best Deployment: Edge deployment is claimed to be the most effective approach to address latency sensitivity. By situating cognitive twins on edge servers near vehicles, ET significantly reduces transmission distances, minimizing latency and enhancing data processing speed and efficiency.

Enhancements: Implementing data caching mechanisms at the edge reduces the need for frequent data retrieval from distant servers. Advanced edge computing techniques, including edge AI models and analytics, facilitate immediate data processing and decision-making. Optimization methods like data compression and aggregation reduce data transmission volume, lowering latency. Studies in [21] and [22] optimize communication between connected vehicles and the cloud for delay-sensitive ITS features. Fu *et al.* [23] leverage ETs for time delay data gathering and predictive analysis using Radial Basis Function (RBF) and Elman Neural Network (ENN), highlighting the effectiveness of these countermeasures in reducing latency. Similarly, Zheng *et al.* [24] utilize a learning-based game theoretic approach to address the synchronization issue in ET of vehicular networks.

2) Scalability and Data Volume: Scalability and data volume challenges arise from handling numerous vehicles and vast amounts of data. This includes scaling computational and storage resources and managing diverse data effectively.

Best Deployment: Cloud deployment is assumed to be the most suitable for addressing scalability and data volume challenges due to its unlimited resources and dynamic scaling capabilities. The cloud efficiently manages the increasing computational and storage demands of vehicular networks.

Enhancements: Enhancements related to scalability issues focus on task offloading and resource allocation. For instance, the authors in [25] use multi-agent DRL for task offloading and edge resource allocation. Li *et al.* [26] introduce a two-tier allocation scheme for computing resources at edge servers, balancing network dynamics and service demands. Zheng *et al.* [27] present a cloud deployment model optimizing computing resource allocation and minimizing task latency and energy consumption. Dai *et al.* [16] offer a hybrid offloading and resource allocation DT in vehicular edge computing and networks. Similarly, hybrid DTs are used in [15] for task offloading in vehicular fog and cloud computing systems. The authors in [28] model computation offloading and service caching with Mixed-Integer non-linear programming (MINLP). Yang *et al.* [29] optimize intra-twin downlink data synchronization using Lyapunov optimization. Dai and Zhang [30] use DRL-based ET technology to minimize task offloading latency. Pillai and Babbar [31] explore efficient task offloading and resource allocation among RSUs using ET mirrors. Zhang *et al.* [32] present a social-aware edge caching mechanism using ET and DL for dynamic RSU and smart vehicle management.

3) Connectivity and Reliability: Connectivity and reliability ensure the smooth functioning of vehicular networks by maintaining consistent and robust communication links between vehicles, DTs, and network infrastructure [33].

Best Deployment: Hybrid deployment effectively addresses connectivity and reliability challenges by combining the strengths of cloud and edge deployments. Edge servers or fog devices ensure direct and reliable connectivity between vehicles, using cellular or WiFi technologies to establish resilient network connections.

Enhancements: Hybrid deployments use redundant connectivity options, backup channels, and network optimization techniques like network coding and multipath routing to enhance reliability. Proactive network monitoring, fault tolerance mechanisms, and dynamic rerouting maintain resilience against failures. Zheng *et al.* [34], [35] enhance network connectivity performance using CTs and Transfer Learning (TL). Ding and Ho [36] integrate a city-model-aware approach for efficient DL-based channel estimation. They enable precise radio ray reflection and attenuation modeling, critical in highly dynamic vehicular channels. Their DT allows for realistic channel estimation, significantly improving the bit error rate performance of DL algorithms used for this purpose by 32% compared to generic methods. In [37], the authors use aerial vehicles as ETs to support IoT network communication. They ensure Ultra-Reliable, Low-Latency Communication (URLLC). Zelenbaba *et al.* [38] propose methods for constructing cloud twins to assess link reliability and latency. Yuan *et al.* [39] use Double Deep Q-learning Networks (DDQN) and Deep Deterministic Policy Gradient (DDPG) to optimize downlink task offloading and wireless channel quality.

4) Security and Privacy: Security and privacy are crucial for protecting sensitive vehicular data against unauthorized access and breaches, ensuring the operational integrity of vehicular networks. Essential countermeasures include robust data encryption, stringent access controls, compliance with privacy regulations, and dynamic monitoring systems [40]–[42]. Our study's main focus is not this challenge. Hence, we will not delve into the various aspects covered in the literature to deal with it. Nevertheless, hybrid deployment is the most robust solution for addressing security and privacy concerns. It combines the strengths of edge and cloud computing to ensure a secure and private network environment. We refer the readers to these comprehensive surveys on the topic [43], [44].

C. Claims Summary: Deployment Strategies vs. Challenges

Table II compares how the three cognitive DT deployment models address key challenges in vehicular networks. It underscores the superiority of edge-based deployments in minimizing latency and highlights the robust connectivity, reliability, and stringent security and privacy measures offered by hybrid models. Additionally, the table emphasizes cloud-based twins' scalability and high data handling capabilities. We will visit this summary of claims in Section VI.

TABLE II
VEHICULAR NETWORKS' COGNITIVE DT DEPLOYMENTS VS. OPEN CHALLENGES

Challenge	Cloud	Edge	Hybrid
Latency Sensitivity	Good	Best	Good
Scalability and Data Volume	Best	Good	Good
Connectivity and Reliability	Good	Good	Best
Security and Privacy	Good	Good	Best

TABLE III
SUMMARY OF RELATED WORKS AND THEIR AIM CATEGORIZED BY ADOPTED DT DEPLOYMENT

Literature	Aim
	Surveys
[45]	Survey on AI-based traffic analysis in DTs for 6G
[46]	Survey on cognitive DTs in vehicular networks
[1], [14]	Survey on DTs in wireless networks
[2]	Defining DT deployments in networks
[33]	Survey on AI-enhanced connectivity in 6G DTs
	CT
[47]	Creating dynamic vehicular twins
[48]	Analyzing DT synchronization performance
[3]	Efficient data gathering and processing
[4]	Real-time vehicle monitoring within ADAS
[5], [6]	Managing vehicular maneuvers and safety decisions
[7]	Co-simulating vehicles and pedestrians
[8]	Addressing network performance requirements
[34], [35]	Enhancing network performance with DTs and TL
[27]	Task offloading in cloud-based twin deployment
[36]	Efficient DL-based channel estimation
[38]	Assessing link reliability and latency
	ET
[9], [10]	Updating vehicle locations and driving tests
[11]	Lane-changing decisions for CAVs
[12], [13]	Distributed autonomous driving and congestion avoidance
[21]	Optimizing communication with the cloud
[22]	Delay-sensitive ITS features and minimizing data usage
[23]	Time delay data gathering and predictive analysis
[24]	Learning-based game theory for ET synchronization
[25]	Multi-agent DRL for task offloading and resource allocation
[26]	Two-tier edge resource allocation scheme
[28]	Computation offloading and service caching
[29]	Optimizing data synchronization using Lyapunov optimization
[30]	ET technology and DRL-based task offloading
[31]	Task offloading and resource allocation using ET mirrors
[32]	Social-aware vehicular edge caching
[37]	Using aerial vehicles as ETs for IoT communication
[39]	Optimal offloading and channel quality with DDQN and DDPG.
	HT
[15]	Task offloading in fog and cloud systems
[16]	Hybrid offloading and resource allocation in edge networks
[17], [18]	Task offloading policy using Markov decision process
[19]	Offloading algorithm based on Lyapunov optimization
[20]	Asynchronous DRL for collaborative task offloading

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