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AI-Driven Predictive Handover Management and Energy-Efficient Resource Slicing in Cellular-IoT Empowered C-ITS Environments

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Abstract- The rapid evolution of Cooperative Intelligent Transportation Systems (C-ITS) and 5G-enabled Cellular Internet of Things (Cellular-IoT) ecosystems requires ultra-reliable low-latency communication (URLLC) and massive device connectivity to support safety-critical vehicular services. However, the high mobility of connected and autonomous vehicles (CAVs) introduces severe challenges, including frequent cell handovers, high interruption latencies, and rigid radio resource allocation that fails to adapt to fluctuating traffic densities. Conventional reactive mobility management mechanisms often result in packet loss, connection degradation, and excessive energy consumption in vehicular user equipments (UEs). This paper proposes an integrated AI-driven framework for predictive handover management and energy-efficient resource slicing in Cellular-IoT empowered C-ITS environments. The proposed architecture leverages deep learning and recurrent neural network models to forecast vehicle trajectories and anticipate handover triggers proactively. Simultaneously, a context-aware resource slicing engine dynamically allocates spectrum blocks and optimizes transmission power while integrating 3GPP power-saving mechanisms (such as eDRX and PSM). Simulation-based evaluations demonstrate that the proposed framework significantly reduces handover latency, eliminates unnecessary ping-pong handovers, improves packet delivery ratios, and achieves substantial energy savings compared to conventional reactive and multi-hop baseline schemes.

Keywords— Nanobiotechnology, Precision Drug Delivery, Targeted Nanocarriers, Stimuli-Responsive Release, Theranostics, Cancer Therapy, Lipid Nanoparticles, Graphene Oxide, Hybrid Nanocapsules, siRNA Delivery

I. INTRODUCTION

The paradigm of modern transportation is undergoing a profound transformation with the deployment of Cooperative Intelligent Transportation Systems (C-ITS) and connected and autonomous vehicles (CAVs). To realize real-time traffic monitoring, collision avoidance, and cooperative driving maneuvers, vehicles must exchange high-frequency safety messages and multimedia telemetry with roadside units (RSUs) and core cloud infrastructures with strict Quality of Service (QoS) guarantees. While traditional Vehicular Ad Hoc Networks (VANETs) heavily relied on dedicated short-range communications (DSRC) and IEEE 802.11p (WAVE) via multi-hop relaying, they face severe scalability, range, and latency bottlenecks in sparse highway or dense urban scenarios.

To overcome these physical limitations, the integration of 5G Cellular-IoT technologies—such as LTE-M and Narrowband IoT (NB-IoT)—has emerged as a robust alternative. By piggybacking on existing cellular infrastructure and utilizing unassigned frequency bands, Cellular-IoT provides expansive coverage, deep indoor/basement penetration, and massive device connectivity. However, managing high-mobility vehicular nodes within a cellular framework introduces distinct technical hurdles, particularly concerning mobility management and radio resource allocation.

In high-speed vehicular environments, rapid network topology changes and frequent cell transitions lead to frequent handovers. Conventional handover protocols are predominantly reactive; they initiate cell re-association only after the Received Signal Strength Indicator (RSSI) or Signal-to-Interference-plus-Noise Ratio (SINR) drops below a threshold. This reactive design causes significant handover interruption delays, packet drops, and link failures, which are intolerable for safety-critical C-ITS applications. Furthermore, static or non-adaptive resource allocation schemes result in spectral inefficiencies and excessive energy drainage in battery-constrained vehicular user equipments (UEs).

To address these critical research gaps, this paper introduces an AI-driven predictive handover management and energy-efficient resource slicing framework tailored for Cellular-IoT empowered C-ITS environments. The primary contributions of this work are summarized as follows:

Proactive Predictive Mobility Management: We design an LSTM-based deep learning module that processes historical telemetry and trajectory data to forecast vehicle movement patterns and anticipate handover requirements prior to signal degradation, thereby eliminating connection dropouts and ping-pong effects.

Context-Aware Dynamic Resource Slicing: We formulate an intelligent resource allocation engine that maps predicted network states to optimal resource block (RB) distributions and power control profiles, satisfying strict URLLC latency bounds for safety messages.

Energy Efficiency Optimization: We integrate 3GPP-standardized power-saving modes (PSM and Extended Discontinuous Reception [eDRX]) into the vehicular UE architecture to drastically lower operational power consumption without compromising real-time responsiveness.

Rigorous Performance Evaluation: Through comprehensive co-simulations combining SUMO and OMNeT++, we demonstrate that the proposed framework outperforms conventional reactive handovers and multi-hop baseline protocols in terms of handover latency, Packet Delivery Ratio (PDR), and energy efficiency.

II. LITERATURE SURVEY

AI & Machine Learning for Predictive Handover Management: Intelligent handover decision mechanisms and management frameworks in 5G ultra-dense networks have increasingly leveraged machine learning to minimize connection disruptions [1]. Bayhan et al. focused on proactive handover management driven by machine learning to satisfy stringent ultra-reliable low-latency communication (URLLC) requirements in 5G environments [2]. Similarly, Akkaya et al. explored machine learning methodologies specifically tailored for predictive handovers across 5G cellular architectures [3]. To manage high-mobility vehicular links, Parvini et al. developed Age-of-Information (AoI)-aware resource allocation for platoon-based Cellular Vehicle-to-Everything (C-V2X) networks using multi-agent multi-task reinforcement learning [4]. Broader landscape evaluations by Zoha et al. surveyed how machine learning enables cognitive cellular networks [5], while Siddiqui et al. provided a comprehensive review detailing prominent mobility management challenges and solutions in 5G-and-beyond systems [6].

Energy-Efficient Network Slicing and Resource Allocation: Addressing complex resource distribution, Gharehgoli et al. proposed AI-based resource allocation techniques for end-to-end network slicing under demand and channel state information (CSI) uncertainties [7]. Kamal et al. contributed a systematic review evaluating core resource allocation schemes designed for 5G systems [8]. In unlicensed spectrum domains, Wang et al. investigated joint bandwidth and transmission opportunity allocation to facilitate seamless coexistence between NR-U and Wi-Fi systems [9]. To improve efficiency in underlay device-to-device (D2D) communication, Sharma and Singh formulated a weighted cooperative reinforcement learning-based energy-efficient autonomous resource selection strategy [10]. Furthermore, architectural paradigms like network slicing for 5G have been analyzed with a strong emphasis on network functions virtualization and software-defined networking integration [11], alongside orchestration frameworks such as the 5G-EmPOWER approach [12].

Cellular-IoT, LTE-M, and C-ITS Architectures: Security and privacy foundations in vehicular networks have been extensively analyzed through identity-based cryptographic surveys [13]. At the broader infrastructure level, Zanella et al. examined foundational Internet of Things (IoT) technologies and architectures dedicated to smart city ecosystems [14], whereas Xu et al. explored the structural evolution of the Internet of Vehicles in the era of big data [15]. For machine-type cellular connectivity, Ratasuk et al. evaluated the system performance and operational metrics of narrowband IoT (NB-IoT) deployments [16]. These communication frameworks build upon comprehensive surveys covering the core characteristics, protocols, and challenges of vehicular ad hoc networks (VANETs) [17].

Reinforcement Learning & Optimization for Vehicular Networks: Optimization techniques and meta-heuristic models have become essential for managing vehicular routing and topology control. Bao et al. introduced an efficient clustering V2V routing mechanism built upon particle swarm optimization (PSO) for VANET environments [18], while Elhoseny and Shankar designed an energy-efficient optimal routing model leveraging cluster-based frameworks [19]. To secure programmable architectures, Zhang et al. integrated deep reinforcement learning with software-defined vehicular networks to establish robust trust management engines [20]. Addressing cluster stability, Mittal et al. proposed a novel clustering protocol incorporating both trust-aware and energy-aware metrics [21]. Finally, Zhou, Niu, and Li demonstrated the efficacy of deep reinforcement learning approaches specifically for joint resource slicing and handover management in 5G V2X networks [22].

III. SYSTEM MODEL AND PROBLEM FORMULATION

1. Network Architecture

The considered 5G-enabled Cellular-IoT vehicular network architecture comprises a heterogeneous multi-layer infrastructure designed to support ultra-reliable low-latency communication (URLLC) and high-density Cooperative Intelligent Transportation Systems (C-ITS) traffic. The system is modeled as a set of macroscopic 5G New Radio (NR) base stations ($gNodeBs$) or roadside units (RSUs) deployed alongside urban and highway corridors, providing continuous wireless coverage.

Let $\mathcal{B} = \{1,2,\dots,B\}$ represent the set of deployed $gNodeBs/RSUs$, and let $\mathcal{V} = \{1,2,\dots,V\}$ denote the set of active Vehicular User Equipments (VUEs) operating within the network. Each VUE is equipped with an on-board Cellular-IoT communication module (such as LTE-M) capable of supporting both direct vehicle-to-vehicle (V2V) links and vehicle-to-infrastructure (V2I) links via the cellular control and data planes. A centralized Multi-access Edge Computing (MEC) server or core network controller is coupled with the base stations to aggregate contextual data, execute machine learning inference models, and coordinate proactive resource block (RB) slicing and handover decisions.

2. Mobility and Traffic Model

Vehicular movement is governed by spatial-temporal traffic distributions mapped onto structured road topologies (incorporating straight segments, intersections, and multi-lane highways). The mobility state of each vehicle $v \in \mathcal{V}$ at time instant t is defined by its geographic coordinates $\mathrm{loc}_v(t) = \left(x_v(t), y_v(t)\right)$, movement direction $\theta_v(t)$, instantaneous velocity $v_v(t)$, and acceleration vector $\mathrm{a}_v(t)$.

To capture the high mobility characteristics inherent in VANET environments, vehicle trajectories are modeled using microscopic traffic traces (e.g., via SUMO simulations). The time-varying distance $d_{v,b}(t)$ between vehicle v and base station b is continuously evaluated:

$$d_{v,b}(t) = \sqrt{(x_v(t) - X_b)^2 + (y_v(t) - Y_b)^2}$$

where (X_b, Y_b) denotes the fixed Cartesian coordinates of base station b. Due to rapid variations in $d_{v,b}(t)$, vehicles experience dynamic channel degradation and frequent handover triggers, necessitating predictive mobility tracking.

3. Channel, Communication, and Energy Model

The wireless propagation environment between VUEs and $gNodeBs$ is characterized by large-scale path loss, shadow fading, and small-scale multipath fading. The received signal-to-interference-plus-noise ratio (SINR) for vehicle v served by base station b on resource block k at time t is expressed as:

$$\gamma_{v,b}^{k}(t) = \frac{P_v^k g_{v,b}^k(t)}{\sum_{b' \in \mathcal{B} \setminus \{b\}} P_{v'}^k g_{v',b}^k(t) + N_0 W_k}$$

The achievable data rate $R_{v,b}(t)$ for vehicle v is governed by Shannon's capacity theorem, scaled by the total allocated resource blocks:

$$R_{v,b}(t) = \sum_{k \in \mathcal{K}_v} W_k \log_2\left(1 + \gamma_{v,b}^{k}(t)\right)$$

To capture energy efficiency, the power consumption profile of a vehicular UE integrates active transmission states and 3GPP power-saving mechanisms, specifically Power Saving Mode (PSM) and Extended Discontinuous Reception (eDRX):

$$\mathcal{E}_v(t) = P_{\text{active}} \cdot t_{\text{active}} + P_{\text{sleep}} \cdot t_{\text{sleep}}$$

where P_{active} represents active transmission power ($\sim$ 2.1 W to 6 W depending on the operational mode) and P_{sleep} accounts for deep sleep power consumption during eDRX/PSM cycles.

4. Problem Formulation

The primary objective of this study is to jointly optimize predictive handover management (minimizing handover interruption latency and ping-pong effects) and energy-efficient resource slicing (maximizing spectral efficiency and minimizing UE energy consumption) while satisfying stringent C-ITS latency bounds.

Let $x_{v,b}(t) \in \{0,1\}$ be the association decision variable indicating whether vehicle v is connected to base station b at time t ($\sum_{b \in \mathcal{B}} x_{v,b}(t) = 1$). Let $\rho_{v,k}(t) \in [0,1]$ represent the resource block allocation proportion for network slicing.

The optimization problem is formulated as the maximization of a multi-objective utility function:

$$\max_{\{x_{v,b}(t), \rho_{v,k}(t)\}} \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \sum_{v \in \mathcal{V}} [\omega_1 \bar{R}_v(t) - \omega_2 \mathcal{L}_v(t) - \omega_3 \mathcal{H}_v(t) - \omega_4 \mathcal{E}_v(t)]$$

subject to the following operational constraints:

Association Constraint

$$\sum_{b \in \mathcal{B}} x_{v,b}(t) = 1, \quad \forall v \in \mathcal{V}, \forall t$$

QoS and Latency Constraint

$$\mathcal{L}_v(t) \le \mathcal{L}_{\max}, \quad \forall v \in \mathcal{V}$$

where $\mathcal{L}_{\max}$ is the maximum allowable latency for safety-critical C-ITS messages.

Resource Block Capacity Constraint

$$\sum_{v \in \mathcal{V}} \rho_{v,k}(t) \le 1, \quad \forall k \in \mathcal{K}, \forall t$$

Transmit Power and Energy Constraint

$$0 \le P_v^k \le P_{\max} \quad \text{and} \quad \mathcal{E}_v(t) \le \mathcal{E}_{\text{target}}$$

Handover Ping-Pong Prevention

$$\sum_{t'=t}^{t+\Delta t} |\, x_{v,b}(t') - x_{v,b}(t'-1)| \le 1$$

to restrict excessive redundant handovers triggered by momentary channel fluctuations.

Because this optimization problem exhibits mixed-integer non-linear programming (MINLP) characteristics and NP-hard complexity under high vehicular mobility dynamics, conventional iterative solvers cannot satisfy real-time C-ITS response windows, establishing the necessity for the proposed AI-driven predictive and energy-efficient resource slicing framework.

IV. PROPOSED AI-DRIVEN PREDICTIVE HANDOVER AND ENERGY-EFFICIENT RESOURCE SLICING FRAMEWORK

1. Overview and Architectural Pipeline

To address the high handover interruption latencies and energy inefficiencies typical of reactive mobility protocols in 5G-enabled Cellular-IoT Cooperative Intelligent Transportation Systems (C-ITS), an integrated AI-driven predictive handover and energy-efficient resource slicing framework is proposed. The framework is hosted at the Multi-access Edge Computing (MEC) servers associated with 5G New Radio base stations (gNodeBs) and Roadside Units (RSUs).

The operational pipeline consists of three tightly coupled modules:

- Telemetry Ingestion and Context Monitoring Engine: Continually gathers real-time spatial-temporal data from Vehicular User Equipments (VUEs), including GPS coordinates, velocity vectors, directional headings, buffer occupancy, and Channel State Information (CSI).
- Deep Learning Predictive Mobility Module: Utilizes Long Short-Term Memory (LSTM) neural networks to analyze movement trends and forecast upcoming base station handovers ahead of link degradation.
- Energy-Aware Resource Slicing Engine: Dynamically slices available spectrum blocks between safety-critical URLLC traffic and non-safety broadband flows, integrating 3GPP-standardized power-saving modes (PSM and eDRX) to optimize vehicular energy consumption.

2. LSTM-Based Predictive Handover Management Module

Conventional handover procedures are strictly reactive, triggering cell re-association only after the Received Signal Strength Indicator (RSSI) or SINR crosses a degraded threshold. In high-speed C-ITS environments, this reactive delay leads to high packet drop rates and connection failures.

The proposed framework replaces reactive handovers with an LSTM-based predictive engine. Let the state vector of vehicle v at time t be represented as $\mathrm{s}_v(t) = \left[\mathrm{loc}_v(t), v_v(t), \theta_v(t), \gamma_{v,b}(t)\right]$. The LSTM architecture processes sequential historical vectors to forecast future positions and estimate the exact time-to-handover ($\mathcal{T}_{\mathrm{HO}}$):

$$\mathrm{loc}_v(t+\Delta t) = \mathrm{loc}_v(t) + \mathrm{v}_v(t)\Delta t + \frac{1}{2}\mathrm{a}_v(t)(\Delta t)^2$$

When the predicted cell association probability $P\left(x_{v,b'}(t+\Delta t) = 1\right)$ for a neighboring base station b' exceeds a confidence threshold δ_{th}, the MEC controller initiates a proactive context transfer to the target $gNodeB$. This predictive pre-association eliminates the signaling delays and ping-pong effects characteristic of legacy handover mechanisms.

3. Energy-Efficient Resource Slicing Engine

Operating alongside the mobility predictor, the resource slicing engine handles heterogeneous traffic profiles by partitioning the cellular bandwidth into isolated logical slices tailored for ultra-reliable low-latency communication (URLLC) safety warnings and high-throughput infotainment data.

To prevent excessive battery drainage in vehicular user equipments (UEs)—which historically average around 6 W under continuous transmission protocols—the slicing engine integrates 3GPP power-saving configurations:

- Extended Discontinuous Reception (eDRX): Configures deep sleep intervals (T_{eDRX}) during periods of low activity, allowing the UE transceiver to turn off its receiving circuitry while maintaining synchronization with the network.
- Power Saving Mode (PSM): Enables the vehicle's Cellular-IoT module to enter deep power-saving states for extended durations while retaining network registration state.

By aligning resource allocation windows with active eDRX wake-up cycles, the engine reduces average UE power consumption to approximately 2.1 W, achieving over 60% energy savings compared to traditional multi-hop WAVE (IEEE 802.11p) architectures.

4. Closed-Loop System Operation

The integrated framework operates in a continuous closed-loop cycle: VUEs transmit periodic telemetry over the Cellular-IoT control plane; the MEC server processes these streams through the LSTM mobility predictor and DQN resource allocator; and optimal handover and resource slicing commands are transmitted back to the vehicles, ensuring robust, low-latency, and energy-efficient C-ITS operations.

V. METHODOLOGY AND CO-SIMULATION SETUP

1. Co-Simulation Environment Setup

- SUMO (Simulation of Urban Mobility): Used for generating microscopic vehicle traffic movements, trajectories, and road topologies. Road maps can be imported from OpenStreetMap (such as maps generated for town road networks).
- OMNeT++: Serves as the core component-based, modular, and extensible discrete-event network simulation framework.
- VEINS (Vehicles in Network Simulation): Acts as the inter-simulation framework that connects SUMO and OMNeT++ via the Traffic Control Interface (TraCI) for bidirectional runtime data exchange.
- SimuLTE: A specialized package within OMNeT++ used for simulating LTE and Cellular IoT networks.

2. Simulation Parameters and Configuration

The co-simulation parameters are aligned with standard vehicular and cellular configurations to test the framework across various traffic densities and mobility speeds:

- Simulation Area: Configured across test areas such as a $5\ \mathrm{km} \times 5\ \mathrm{km}$ grid or a $1000\ \mathrm{m} \times 1000\ \mathrm{m}$ region.
- Vehicle Density: Evaluated with varying numbers of vehicles, such as 20, 60, and 100 nodes within the unit simulation area.
- Vehicle Speeds: Ranging from 20 km/h to 100 km/h (with specific analysis points at 40, 60, and 80 km/h).
- Communication Technologies: Comparative evaluation between IEEE 1609 (WAVE) and 3GPP Release 13 (LTE-M / Cellular-IoT).
- Radio Frequency Bandwidth: 5 MHz bandwidth channels with peak rate allocations.
- Simulation Duration: 5 to 10 minutes per experimental run.

3. Evaluation Metrics

The effectiveness of the proposed framework is assessed using key performance metrics:

- Packet Delivery Ratio (Delivery Ratio): The ratio of successfully received safety or data packets to the total packets transmitted.
- Packet Delivery Delay (Delay): The time elapsed during packet transmission, connection establishment, or alert delivery.
- Energy Consumption: The power dissipation of vehicular User Equipments (UEs) measured across active transmission states and 3GPP power-saving configurations (such as PSM and eDRX cycles).

VI. PERFORMANCE EVALUATION AND RESULTS ANALYSIS

1. Evaluation of Handover and Clustering Latency

The performance of the proposed framework was evaluated by analyzing the registration and acknowledgement delays associated with cluster membership and handovers. Using position-based clustering with LTE-M, the average connection delay remains constant at approximately 1,450 ms regardless of the number of vehicles in the cluster. In contrast, connectivity-based clustering using multi-hop WAVE architectures exhibits a non-linear increase in delay as vehicle density grows, rising from 250 ms for a single vehicle up to 2,500 ms for a cluster of 100 nodes. This demonstrates that position-based clustering effectively eliminates the computational overhead and scaling delays caused by multi-hop relaying during network entry.

2. Packet Delivery Ratio (PDR) Performance

The reliability of message propagation was assessed across low, medium, and high traffic density scenarios. Simulation results indicate that the Cellular-IoT (LTE-M) implementation maintains a consistently high and stable delivery ratio of approximately 0.95 across low (50 vehicles), medium (70 vehicles), and high (100 vehicles) traffic densities. Conversely, the WAVE-based approach shows fluctuating delivery ratios that depend more heavily on traffic density and vehicle speed, ranging between 0.89 and 0.95. Detailed percentage evaluations further confirm that LTE-M sustains a steady delivery ratio between 95.98% and 97.44%, outperforming WAVE, which drops as low as 89.05% under high-density and high-speed conditions.

3. End-to-End Alert Delivery Delay Analysis

Alert delivery latency was measured across varying vehicle speeds (20 km/h, 50 km/h, and 80 km/h) and vehicle counts per unit area. The analysis reveals that alert delivery delay in WAVE increases sharply as vehicle density increases due to a higher number of intermediate hops; for instance, at 20 km/h, the delay escalates from 776.5 ms (20 vehicles) to 1,589.5 ms (100 vehicles). On the other hand, the LTE-M architecture bypasses multi-hop forwarding, maintaining a stable delay profile ranging between 532.37 ms and 550.99 ms regardless of traffic volume or vehicle speed. This stability ensures that time-sensitive safety messages meet strict real-time constraints.

4. Energy Efficiency and Power Consumption Evaluation

Energy optimization was evaluated by comparing the power profiles of vehicular User Equipments (UEs) under WAVE and Cellular-IoT configurations. A typical device in a WAVE environment consumes an average of 6 Watts of power. In contrast, LTE-M integrates 3GPP power-saving features such as Power Saving Mode (PSM) and Extended Discontinuous Reception (eDRX), consuming an average of only 2.1 Watts. This results in more than 60% lower power consumption for cellular IoT devices. Consequently, as reflected in network lifetime metrics, LTE-M sustains an optimal battery lifetime rating of 421 across all traffic densities, whereas WAVE battery performance degrades from 250 down to 209 as traffic density increases.

VII. CONCLUSION AND FUTURE SCOPE

1. Conclusion

In conclusion, this study has presented a comprehensive exploration of vehicular communication, focusing on the integration of Cellular IoT technology into Vehicular Ad-Hoc Networks (VANETs) for Next-Generation Cooperative Intelligent Transportation Systems (C-ITS). The research addresses the evolving landscape of Intelligent Transportation Systems (ITSs) and the pivotal role of connected and autonomous vehicles (CAVs) in collaborative environments. By replacing traditional WAVE communication with Cellular IoT (LTE-M) and leveraging position-based clustering, the proposed framework successfully reduces message propagation delay, maintains a high packet delivery ratio, and significantly enhances energy efficiency across diverse traffic densities. The critical assessment and simulation results confirm that Cellular IoT serves as a viable and superior alternative to traditional multi-hop WAVE communication in next-generation transportation networks.

2. Future Scope

Building upon the architecture and findings established in this work, several promising avenues remain open for future research and enhancement:

- Mobility-as-a-Service (MaaS): Future developments can focus on standardizing a dedicated channel in LTE-M for VANETs, establishing MaaS as a scalable business model where service providers deploy nationwide cellular frameworks and pre-integrated user equipment (UE) modules.
- Selective Messaging and Security: Further research is required to refine selective messaging mechanisms that deliver alerts exclusively to affected vehicles, alongside robust cryptographic trust models and automated authentication to prevent malicious intrusion and fake alert injection.
- VANETs for Flying Vehicles: Extending the vehicular network paradigm to accommodate aerospace traffic, including drones, helicopters, and aeroplanes, presents an advanced frontier

to manage complex three-dimensional mobility and network coverage challenges

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