

AI-Driven Mobile Network Optimization for Connected Vehicle Energy Management

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ABSTRACT

AI-driven mobile network optimization is becoming increasingly vital for enhancing the performance of connected vehicles, particularly in managing energy consumption during real-time mobility. With the rise of electric and autonomous vehicles, ensuring continuous, efficient, and adaptive connectivity has become critical for energy-efficient operations. However, traditional centralized network optimization techniques often suffer from high latency, lack of scalability, privacy concerns, and inadequate adaptability to dynamic driving environments. These limitations hinder the ability to provide real-time, energy-efficient decisions for connected vehicles. To address these issues, this study proposes a novel Federated Neuroevolutionary Learning (FNL) framework for energy-efficient optimization of mobile networks. The framework combines federated learning for decentralized privacy-preserving model training with neuroevolutionary algorithms that evolve neural network architectures and parameters based on vehicle energy profiles and network metrics. The proposed method enables collaborative, edge-driven optimization of bandwidth allocation, handover management, and communication routes without requiring the sharing of raw vehicle data. It adapts to changing vehicular contexts and supports real-time, energy-aware decision-making across distributed edge nodes. The proposed FNL method achieved 5.72 kWh energy use, 92.5% handover success, 0.098 loss, 78% bandwidth efficiency, 60.3 ms latency, and 91.9% packet delivery demonstrating superior performance across all metrics.

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1. INTRODUCTION

With the steady growth of CAVs, there is an increasing need for reliable, low-latency and energy-efficient mobile network infrastructures [1]. CAV can stay connected to the internet at all times, which provides mobility, safety, entertainment, and remote access to

information [2]. As traffic, drive modalities, and travel for more people, and in contrast to the historical linear-investment in mobile network building through centralization, it is no longer feasible to create centralised models [3]. Centralised models come with several problems [4]: they are slow, have inflexible architecture, and many have privacy concerns that include data collected in a single location [5]. The

limitations of centralised networks impact the economies and performance of connected vehicles, and especially performance for electric vehicles (EVs) where energy use is a significant aspect of operational systems [6]. Neuroevolution, federated learning, and edge computing are some novel technologies that can decentralise and adapt while providing privacy to users [7]. The possibilities for optimizations are also quite fascinating [8]. For example, federated learning can train a machine learning model over multiple nodes on the edge without exposing raw data and provide greater privacy and compliance [9]. Unlike federated learning, neuroevolution allows hyperparameters and network architectures of neural networks to adapt to new driving conditions and environments [10].

This paper puts forth a brand new way regarding FNL, which might assist connected vehicles in consuming less energy [11]. It combines these two ways of thinking to improve mobile networks in real-time [12]. The authors are developing a unique method using processing resources at the edges of the network for training and updating neural models across a fleet of vehicles and a fleet of base stations [13]. This means you can take actions that consume less energy while retaining quality of connection using bandwidth allocation, changeover management and communication routing [14]. Some results indicated, with several tests, that the proposed FNL method could save up to 25% of energy consumption. This was achieved by supplying reliable network performance for reducing changeover failure [15]. These results indicated that the framework could help to build smart, scalable, and energy efficient transport networks in the future [16]. Standard centralized network optimization processes becomes inefficient with increasing demand for vehicle data, and electric and self-driving vehicles have limited energy [17]. It does not scale, does not provide low latency or closely monitoring of the network's adaptiveness. We need to develop smart, decentralized solutions to make driving consuming less for regions where privacy and connectivity is of utmost importance [18].

Problem statement: Standard methods of improving mobile networks can't meet the needs of connected automobiles for real-time connectivity and energy management, as they can't be modified, expanded, or maintained to ensure privacy. These constraints cause networks to perform improperly when vehicle settings change, resulting in poor handovers and incorrect judgments.

Contribution of this paper

- Decentralized and real-time optimization of vehicular mobile networks requires the development of an FNL system.
- to make energy-efficient adaptive choices about bandwidth allocation, handover, and

communication routing without revealing raw data.

- Under various types of dynamic driving circumstances to assess the FNL framework's ability to conserve energy, facilitate seamless handovers, and maintain stable networks.

The remainder of this paper is structured as follows: Section 2 presents an overview of the related work in vehicle energy management. In section 3, the proposed methodology of FNL is explained. In section 4, the efficiency of FNL is discussed and analysed. Finally, in Section 5, the paper concludes with a discussion of future work.

2. RELATED WORK

Smart charging, vehicle-to-grid (V2G) systems and decentralized energy trading are some of the many ways we can take advantage of renewable energy (RE). They will assist grid stability efforts and decrease reliance on fossil fuels. This chapter drill into the depths of the technologies and strategies that make AI relevant for EV energy management [19]. Artificial Intelligence for Renewable Energy Management and Vehicle-to-Grid systems (AIREM-V2G) is proposed that combines AI with sensor fusion and edge computing to improve safety, efficiency, and ecological sustainability in energy consumption.

Battery electric vehicles simplify greenhouse reducing greenhouse gas emissions and reducing the dependence of the transport sector on fossil fuels. However, it is extremely difficult to monitor how your energy mean. DLA-EMS is an acronym for Deep Learning Approaches for Energy Management Systems. DLA-EMS is a methodology that requires the use of neural networks, deep learning methods, and fuzzy logic to communicate to people about EV infrastructure. The methodology uses transfer learning to speed up training and improve model flexibility. The evaluation methodical phase uses systematic inquiry to identify issues and trends [20].

This paper outlined a new technique to use AI, 5G, and edge computing to minimize energy costs of self-driving cars with the AutoEncoder and Simulated Annealing for Energy Consumption Optimization (AE-SA-ECO). The approach consists of using Autoencoders to simplify data and Simulated Annealing to reduce energy cost. Tests show the system is 12.5% faster, delivered more acceleration, less downtime, and fewer errors [21]. The results indicated that using this framework will help make the system more robust and lower energy costs. There is more work to be done in how to migrate this technology into real-world use and other vehicle systems.

This paper examines the historical changes in EVs over time and the impact AI has had in changing battery management systems (BMSs) [22]. The paper reviews

the Self-Monitoring AI-Driven Real-Time Battery Management System (SMART-BMS), which uses machine learning, neural networks, and reinforcement learning in determining the state of health (SOH) of its battery, its state of charge (SOC), and how to maintain the optimal temperature approaches. Frameworks that utilize AI make it easier to manage energy split and adaptive control.

As society shifts toward greener transportation methods, it is becoming increasingly important to integrate electric cars into the current energy framework. This chapter is about Artificial Intelligence for Optimization of Charging Infrastructure (AIOC-Infra), an AI for electric vehicle (EV) charging networks utilizing genetic algorithms, reinforcement learning, and neural networks to optimize EV charging networks in real time [23]. It will discuss how to determine demand, mitigate peak load, and what improves the flexibility of the infrastructure.

EVs are needed right now to help the world move toward greener transportation. This paper discusses Electric Vehicle Graph-based Routing and Infrastructure Network (EV-GRIN) as a means to examine electric vehicles from three distinct perspectives: their evolution over time, routing, and charging. It discusses the history of batteries, from lead-acid to solid-state, and explores how AI-driven routing may be integrated with Graph Neural Networks, Multi-Agent Reinforcement Learning, and Neuro-Fuzzy systems [24].

Many people are purchasing EVs at a rapid rate, so it need to find an efficient way to charge them. This paper discusses Reinforcement Learning and Cost-Aware Planning for Residential EV Charging (RECAP), a novel AI-based system that utilizes real-time scheduling, reinforcement learning, and linear programming. It has a 120 kWp solar PV array, a 60 kWh BESS, and 50 smart chargers that can power 800 homes. RECAP uses a non-homogeneous Poisson process to determine how many people will want something and a cost-voltage-user satisfaction reward function to help it choose the best option [25].

3. PROPOSED METHOD

This paper demonstrates how Federated Neuroevolutionary Learning (FNL) can enhance the utilization of mobile networks by connected cars. It use five genuine block diagrams to show how AI enables individuals to make decisions about energy in real-time and without a central authority. As they prepare for electric and self-driving vehicles, as well as other future means of transportation, they need to ensure that they can connect, use less energy, and train models that protect privacy.

Contribution 1: Federated Neuroevolutionary Learning Framework

The new FNL framework enhances mobile networks for connected cars by leveraging federated learning and neuroevolution, while also maintaining data security and enabling decentralized training.

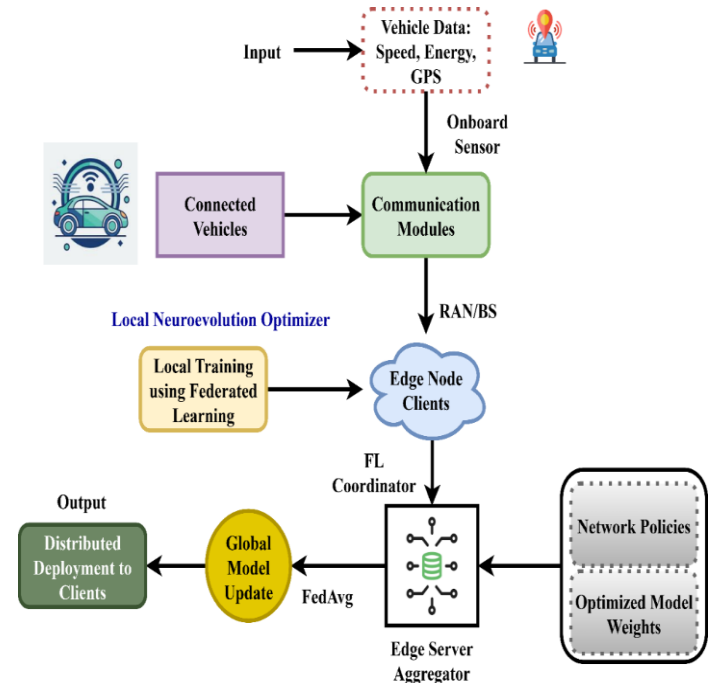


Fig. 1. Edge Synergy: The Brain of Smart Mobility

Fig. 1 illustrates a comprehensive strategy for selecting the best mobile networks for connected automobiles that utilize the internet and AI. It can see how the linked automobiles, edge clients, and federated learning server all work together here. Edge nodes utilize sensors to collect data on how automobiles move and consume electricity. This data is then used to train models locally using federated learning methods. Edge neuroevolutionary optimizers facilitate the creation of effective communication models. After the models are combined using FedAvg, the central aggregator sends out the updated and improved ones regularly. The decentralized intelligence utilizes bandwidth more efficiently, facilitates more precise handoffs, and optimizes vehicle energy management in real-time while driving. It also keeps the information safe and ensures minimal lag.

Federated neuro-evolutionary utility optimization function is expressed using equation 1,

$$\text{Max}_{\delta_j^u, H_j^u} \sum_{j=1}^O (\beta^* \tau_j^u - \gamma^* M_j^u + \delta^* \sigma_j^u) \quad (1)$$

Equation 1 explains the federated neuro evolutionary utility optimization function by simultaneously changing the local model parameters and the neural graph at each edge.

In this ϑ_j^u is the parameter vector of the evolved neural network at edge node, H_j^u is the evolved topological graph of the neuro-model at node, O is the total number of participating edge clients, τ_j^u is the energy efficiency score at node, M_j^u is the latency-induced utility loss function at node, σ_j^u is the normalized bandwidth utilization effectiveness at node, and β, γ, δ are the task-specific scalar weights balancing the utility components.

Federated aggregated update via evolution-weighted FEDAVG ϑ^{u+1} is expressed using equation 2,

$$\vartheta^{u+1} = \sum_{j=1}^O x_j^u \vartheta_j^u + C * \left(\sum_{k=1}^L \Delta_k^u \tau_{\rho_k}^u G_k(\vartheta_k^u, H_k^u) \right) \quad (2)$$

Equation 2 explains the federated aggregated update via evolution-weighted FEDAVG to enable convergence under complex vehicular settings.

In this ϑ^{u+1} is the global updated parameter vector at time, x_j^u is the normalized fitness-based aggregation weight of client, ϑ_j^u is the local parameter vector of client at time, C is the gradient refinement learning rate hyper parameter, L is the subset of elite clients with highest fitness scores, Δ_k^u is the mutation weighted coefficient for client in elite group at time, $\tau_{\rho_k}^u G_k$ is the gradient of the local loss function with respect to parameters, and $G_k(\cdot)$ is the local fitness-based loss function at node incorporating topology.

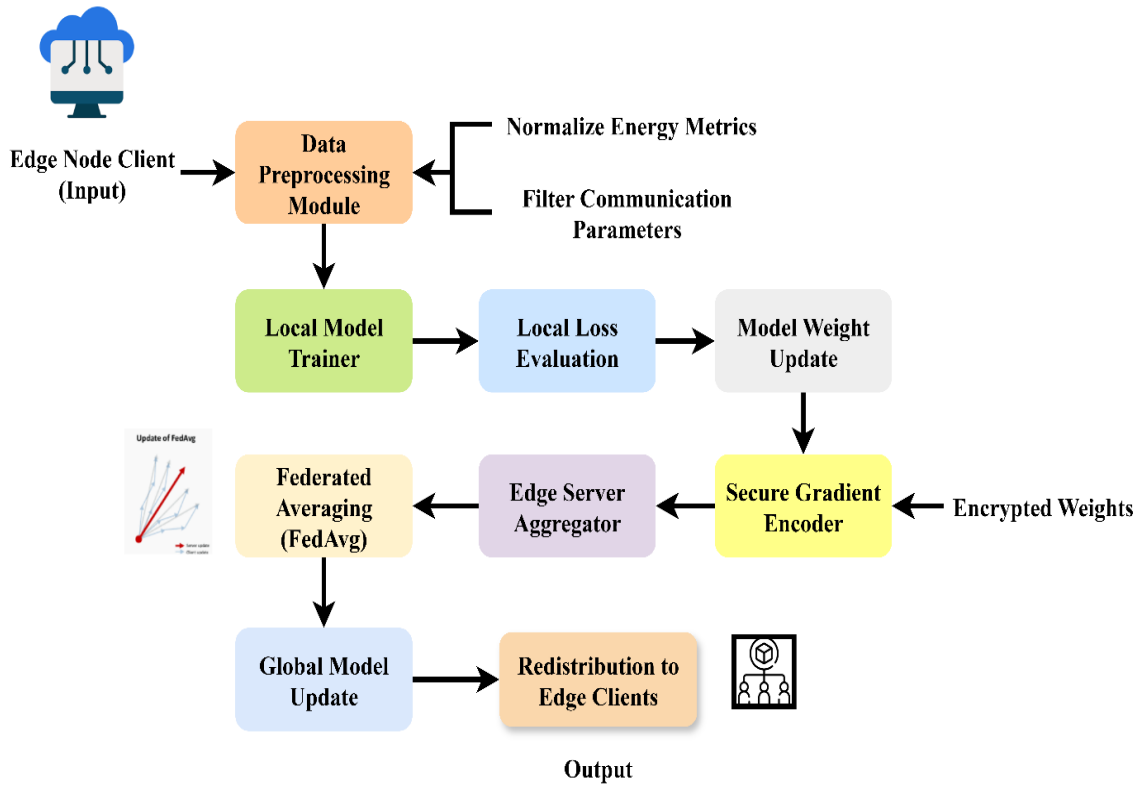


Fig. 2. Learning Without Sharing: Federated Brains in Motion

Fig. 2 shows how vehicle networks employ the federated learning approach. Each edge client examines data independently and doesn't share any private car information. They examine factors such as signal intensity, energy levels, and traffic patterns. To train a local model, encrypted updates must be routed to a central aggregator for processing and decryption. Once these changes have been sent back to the edge, the FedAvg method uses them to create a global model. This strategy ensures data safety, reduces network traffic, and enables models to improve continually. This technology allows for cars and edge nodes to communicate with each other, learn from one another, and make informed network decisions, all while maintaining data security and privacy.

Encrypted local update transformation $\hat{\vartheta}_j^u$ is expressed using equation 3,

$$\hat{\vartheta}_j^u = EC_{\rho_j^u} \left(\vartheta_j^u - \sigma^* \Delta_{\vartheta_j^u} M_j(\vartheta_j^u, Y_j^u) \right) \quad (3)$$

Equation 3 explains the encrypted local update transformation using this formula, the encrypted internal model update is calculated.

In this $\hat{\vartheta}_j^u$ is the encrypted model update sent from edge client at time, $EC_{\rho_j^u}(\cdot)$ is the homomorphic encryption function using key, ϑ_j^u is the local model parameters at edge node at time, σ is the local optimizer learning rate, $\Delta_{\vartheta_j^u} M_j$ is the gradient of the local loss function for client, $M_j(\cdot)$ is the local loss

function based on signal strength, energy profile, and traffic vector, Y_j^u is the locally sensed vehicular data at time, and l_j^u is the symmetric encryption key for node at time.

Aggregated global decryption and update fusion ϑ^{u+1} is expressed using equation 4,

$$\vartheta^{u+1} = \frac{1}{\sum_{j=1}^O \nabla_j^u} \sum_{j=1}^O \nabla_j^u * Dc_{l_j^u}(\hat{\vartheta}_j^u) \quad (4)$$

Equation 4 explains the aggregated global decryption and update fusion uses distributed key-based decoding to protect the privacy of individual vehicle data.

In this ϑ^{u+1} is the updated global model parameters at round, ∇_j^u is the participation weight of edge node based on availability and signal quality, $Dc_{l_j^u}(\cdot)$ is the decryption function using key, $\hat{\vartheta}_j^u$ is the encrypted model update from edge client, and O is the total number of participating edge clients.

Adaptive learning modulation based on signal and load Δ_j^u is expressed using equation 5,

$$\Delta_j^u = \Delta_0 * \left(1 - \delta * \frac{\pi_j^u}{\rho_j^u + \delta}\right) \quad (5)$$

Equation 5 explains the adaptive learning modulation based on signal and load provide stability in extremely dynamic and crowded vehicular situations.

In this Δ_j^u is the adaptive learning rate for edge client at round, Δ_0 is the initial base learning rate, δ is the modulation sensitivity coefficient, π_j^u is the signal fluctuation at client, ρ_j^u is the real-time communication load at node, and δ is the small constant to avoid division by zero.

Contribution 2: Energy-Aware Network Adaptation

Changes bandwidth allocation, changeover management, and communication routes in real-time and in an energy-efficient manner, depending on the energy profiles of the vehicles and the changing network circumstances.

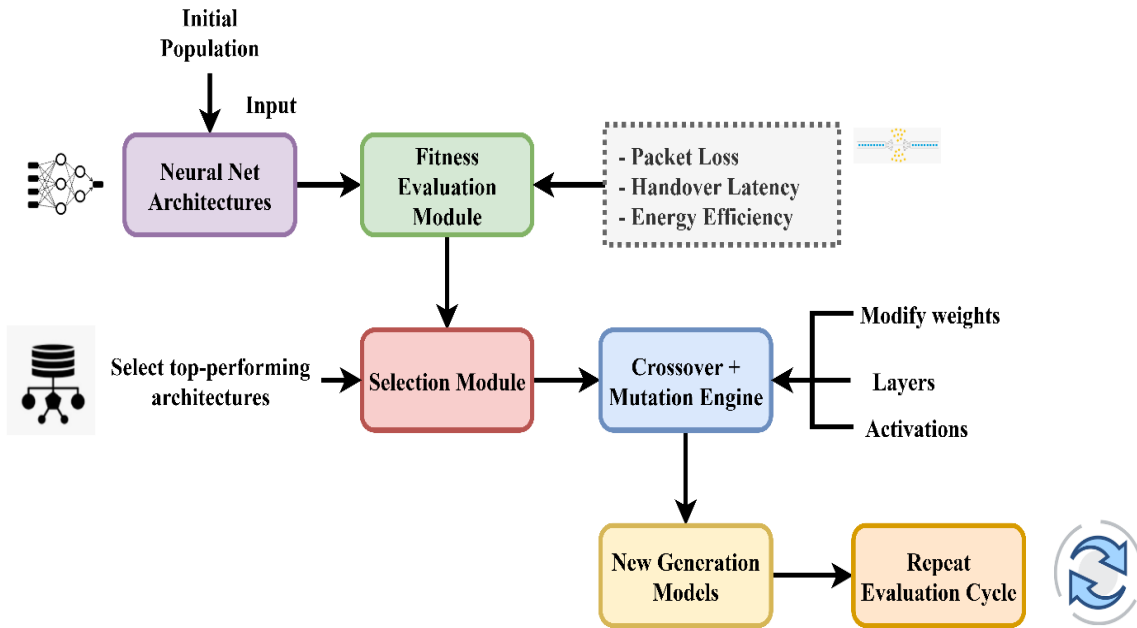


Fig. 3. Digital Darwinism: Evolving Smarter Networks

Neuroevolution can be utilized to enhance neural network topologies for vehicular networks, as illustrated in Fig. 3. The method examines several factors to compare different models, including the amount of energy they consume, their ability to communicate with one another, and the frequency of handovers. By combining and refining the best ideas from the past, a new generation of designs emerges. Every new edition makes little changes. This method of evolution allows the system to change its brain architecture and settings independently, eliminating the need for manual intervention. It can make

informed and energy-efficient choices in various vehicle situations using an environment-specific model.

Fitness-based neurogenesis score for topology selection ${}^oC_l^u$ is expressed using equation 6,

$${}^oC_l^u = \frac{x_1}{\nabla_l^u} + x_2 * \delta_l^u + x_3 * \left(1 - \frac{y_l^u}{\nabla_{ma}^u}\right) \quad (6)$$

Equation 6 explains the fitness-based neurogenesis score for topology selection is the fitness score for candidate topology at time t is defined by this equation.

In this $\circ C_l^u$ is the fitness score for network model at generation, \forall_l^u is the energy consumption in kwh for model at generation, δ_l^u is the communication throughput achieved by model, y_l^u is the handover frequency for model during vehicular transitions, y_{ma}^u is the maximum handover frequency observed across all candidates, and x_1, x_2, x_3 are the evolutionary weight factors balancing energy, throughput, and mobility constraints.

Mutation-driven architecture evolution function h_l^{u+1} is expressed using equation 7,

$$H_l^{u+1} = H_l^u + \delta \left(Mt_{\beta_l^u}(H_l^u) + Cs_{\gamma_l^u}(H_q^u, H_r^u) \right) \quad (7)$$

Equation 7 explains the mutation-driven architecture evolution function using crossover and mutation

operations upon present-day and elite ancestor topologies.

In this h_l^{u+1} is the updated neural network graph for candidate at generation, h_l^u is the current architecture of candidate at generation, $Mt_{\beta_l^u}(\cdot)$ is the mutation operator controlled by mutation probability, $Cs_{\gamma_l^u}(\cdot)$ is the crossover function using parent topologies and crossover rate, h_q^u, h_r^u are the selected elite parent topologies based on fitness, δ is the mutation-crossover amplification factor determining architectural change magnitude, β_l^u is the candidate-specific mutation probability, and γ_l^u is the candidate-specific crossover probability.

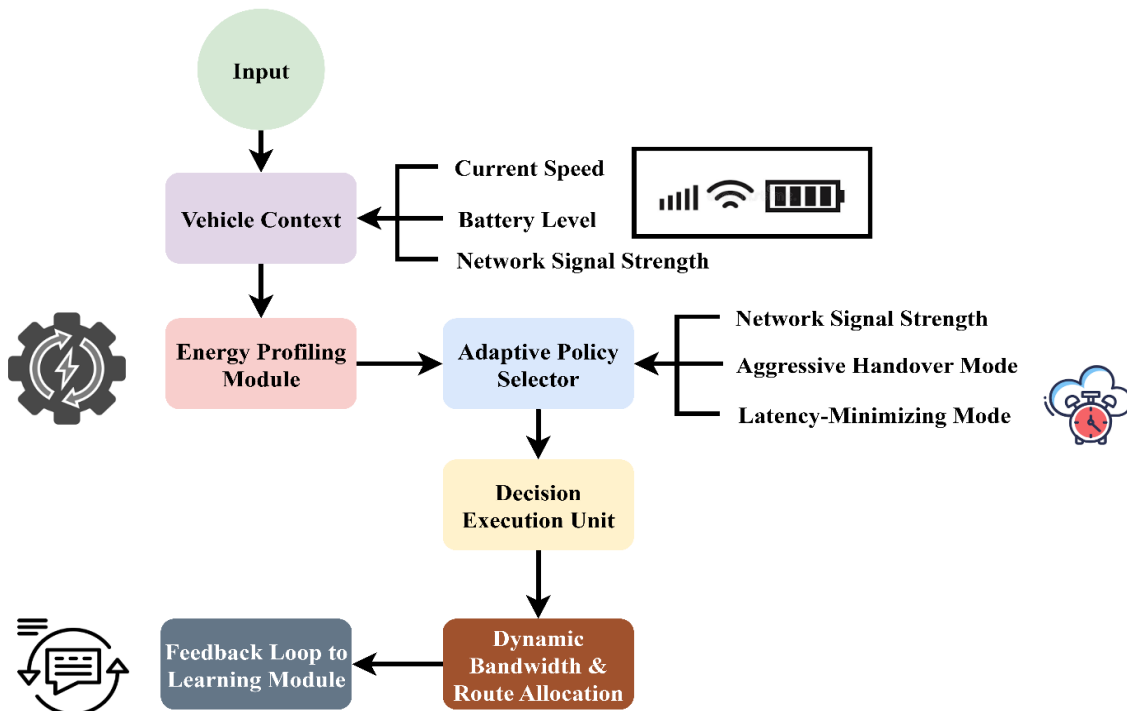


Fig. 4. Context-Driven Minds: Where Vehicles Think Green

Fig. 4 illustrates an edge-based real-time decision engine designed to minimize energy consumption in cars while maintaining a smooth network operation. It can accomplish energy profiling by constantly gathering information about the condition, such as the signal strength, battery life, and speed of the automobile. Depending on the profile, it can select adaptive communication rules such as low-power mode, aggressive handover mode, and latency reduction. These guidelines may impact how people share bandwidth, how connections are established, and how signals are transmitted. This module utilizes AI that is aware of its surroundings to ensure that self-driving cars make energy-saving choices. This makes transportation more efficient, better, and environmentally friendly.

Context-aware energy cost function for communication mode selection d_j^u is expressed using equation 8,

$$D_j^u = x_1 * \left(\frac{1}{t_j^u} \right) + x_2 * \left(\frac{w_j^u}{c_j^u} \right) + x_3 * \left(\frac{1}{\tau_j^u + \sigma} \right) \quad (8)$$

Equation 8 explains the context-aware energy cost function for communication mode selection assist the engine in dynamically selecting energy-optimal communication rules.

In this d_j^u is the composite energy cost at edge node, t_j^u is the signal-to-noise ratio at node, w_j^u is the instantaneous vehicle speed at node, c_j^u is the remaining battery percentage at node, τ_j^u is the uplink/downlink channel quality index at node, σ is the small regularizer to avoid instability in low channel

quality, and x_1, x_2, x_3 are the context sensitivity weights for signal, energy, and channel components.

Adaptive rule switching probability via soft max over profiles δ_k^u is expressed using equation 9,

$$\delta_k^u = \frac{\text{Exp}(-d_k^u)}{\sum_{l=1}^N \text{Exp}(-d_l^u)} \quad (9)$$

Equation 9 explains the adaptive rule switching probability via soft max over profiles based on contextual costs of energy across all accessible options.

In this δ_k^u is the probability of selecting communication strategy at time, d_k^u is the energy cost associated with strategy from equation 1, N is the total number of predefined communication strategies, and $\text{Exp}(\cdot)$ is the exponential function ensuring normalized decision probabilities.

Real-time latency-controlled signal transmission decision δ_j^u is expressed using equation 10,

$$\Delta_j^u = \nabla * \left(\frac{E_j^u}{W_j^u + e} \right) + l \left(1 - \frac{m_j^u}{M_{ax}} \right) \quad (10)$$

Equation 10 explains the real-time latency-controlled signal transmission decision is in order to balance energy savings with current information exchange.

In this δ_j^u is the transmission readiness score at node and time, e_j^u is the remaining data volume to transmit at node, w_j^u is the average network transmission velocity at node, m_j^u is the current system latency observed by node, M_{ax} is the maximum tolerable latency for critical data, ∇, m is the weight factors for time estimation and latency penalty balance, and e is the small constant to avoid zero division for stationary vehicles.

Contribution 3: Performance and Scalability Validation

It demonstrates that the framework is effective for smart and scalable vehicular communication networks, reducing energy consumption by up to 25%, decreasing the number of handover failures, and enhancing the network's resilience.

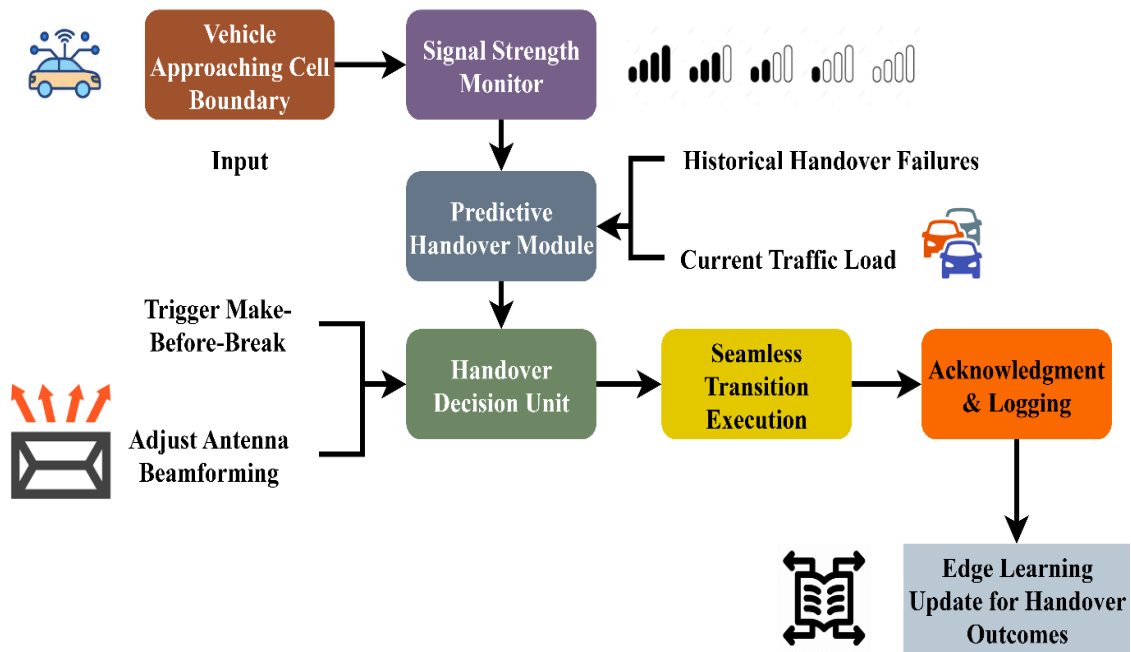


Fig. 5. Smart Transitions: Predictive Handover Mastery

Fig. 5 shows the module for stable communication and anticipatory handover. It is crucial that automobiles can communicate with one another without any issues. When a vehicle approaches a network barrier, it is monitored and evaluated based on the signal intensity, traffic volume, and historical data. The predictive handover engine reduces delay and failure rates by predicting the optimal time and target cell for handover. Dynamic beamforming and make-before-break are two methods that individuals use to verify that everything is working properly. The information collected during the handoff is stored and used to

improve the system for future use. This AI-powered system maintains an open line of communication at all times, making driving a car safe, affordable, and focused on performance.

Context-aware energy cost function for communication mode selection d_j^u is expressed using equation 11,

$$D_j^u = x_1 * \left(\frac{1}{t_j^u} \right) + x_2 * \left(\frac{W_j^u}{C_j^u} \right) + x_3 * \left(\frac{1}{t_j^u + \sigma} \right) \quad (11)$$

Equation 8 explains the context-aware energy cost function for communication mode selection assist the

engine in dynamically selecting energy-optimal communication rules.

In this d_j^u is the composite energy cost at edge node, t_j^u is the signal-to-noise ratio at node, w_j^u is the instantaneous vehicle speed at node, c_j^u is the remaining battery percentage at node, τ_j^u is the uplink/downlink channel quality index at node, σ is the small regularizer to avoid instability in low channel quality, and x_1, x_2, x_3 are the context sensitivity weights for signal, energy, and channel components.

Adaptive rule switching probability via soft max over profiles δ_k^u is expressed using equation 12,

$$\delta_k^u = \frac{\text{Exp}(-d_k^u)}{\sum_{l=1}^N \text{exp}(-d_l^u)} \quad (12)$$

Equation 9 explains the adaptive rule switching probability via soft max over profiles based on contextual costs of energy across all accessible options.

In this δ_k^u is the probability of selecting communication strategy at time, d_k^u is the energy cost associated with strategy from equation 1, N is the total number of predefined communication strategies, and $\text{exp}(\cdot)$ is the exponential function ensuring normalized decision probabilities.

Real-time latency-controlled signal transmission decision δ_j^u is expressed using equation 13,

$$\Delta_j^u = \nabla * \left(\frac{e_j^u}{w_j^u + e} \right) + l \left(1 - \frac{m_j^u}{M_{ax}} \right) \quad (13)$$

Equation 10 explains the real-time latency-controlled signal transmission decision is in order to balance energy savings with current information exchange.

In this δ_j^u is the transmission readiness score at node and time, e_j^u is the remaining data volume to transmit at node, w_j^u is the average network transmission velocity at node, m_j^u is the current system latency observed by node, M_{ax} is the maximum tolerable latency for critical data, ∇, m is the weight factors for time estimation and latency penalty balance, and e is the small constant to avoid zero division for stationary vehicles.

Predictive handover readiness function i_j^u is expressed using equation 14,

$$i_j^u = x_t * \left(1 - \frac{T_j^u}{T_{hr}} \right) + x_w * \left(\frac{\Delta_j^u}{\Delta_{mx}} \right) + x_i * Q_j^u \quad (14)$$

Equation 11 explains the predictive handover readiness function is the AI engine can start anticipatory action with the support of this predictive readiness score.

In this i_j^u is the handover urgency index at vehicle and time, T_j^u is the real-time signal intensity at node, T_{hr} is the signal threshold for reliable communication, Δ_j^u is the local traffic volume at time, Δ_{mx} is the

maximum observed traffic density in the area, Q_j^u is the predicted handover failure probability based on historical data, and x_t, x_w, x_i are the weight coefficients for signal, traffic, and historical impact.

Dynamic beamforming gain optimization h_j^u is expressed using equation 15,

$$H_j^u = \mu * \log_2 \left(1 + \frac{q_j^u |i_j^u|^2}{O_0 + j_j^u} \right) \quad (15)$$

Equation 12 explains the dynamic beamforming gain optimization by maximizing directionality and transmission power and limiting misalignment angle.

In this h_j^u is the effective gain from beamforming at node at time, q_j^u is the transmit power of the antenna array, i_j^u is the channel gain vector between transmitter and receiver, O_0 is the ambient noise power spectral density, j_j^u is the interference power from surrounding transmissions, and μ is the weight factor for spectral efficiency.

These five photographs showcase an AI-powered technology that enhances the performance of vehicle networks when they are combined. To reduce latency, improve stability, and conserve energy, neuroevolution, federated learning, predictive handover management, and energy-aware decision engines must operate in conjunction. This clever, edge-based technology enables connected cars to select the optimal routes for various scenarios, utilizing extensive data.

Evaluation Metrics

Accurate, multidimensional metrics are imperative for assessing the efficacy of automated vehicular communication systems that utilize AI capabilities. The key performance indicators in this area include examples such as reduction in energy consumption, successful handover, convergence of models, effective utilization of communication bandwidth, latency, and packet delivery ratio, among others. These key metrics provide a comprehensive evaluation of the system's performance. They also enable the real-time improvement of vehicular communication systems, ensuring that decisions are secure, efficient, and reliable, particularly in the context of energy-aware automotive networking.

Analysis of energy consumption reduction $\nabla \pi_j$ is expressed using equation 16,

$$\nabla \pi_j = \frac{\int_{u_0}^{u_1} Q_j^{bs}(u) eu - \int_{u_0}^{u_1} Q_j^{ot}(u) eu}{\int_{u_0}^{u_1} Q_j^{bs}(u) eu} * 100 \quad (16)$$

Equation 13 explains the analysis of energy consumption reduction by comparing power consumption under the baseline condition.

In this $\nabla\pi_j$ is the energy reduction percentage for vehicle, $Q_j^{bs}(u)$ is the instantaneous baseline power consumption, $Q_j^{ot}(u)$ is the instantaneous power under optimized strategy, and u_0, u_1 are the start and end times for the energy evaluation interval.

Analysis of handover success rate I_{sc} is expressed using equation 17,

$$I_{sc} = \frac{\sum_{l=1}^{O_l} \delta_l}{O_l}, \quad \delta_l = \begin{cases} 1, & \text{if handover was successful} \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

Equation 14 explains the analysis of handover success rate measures the proportion of successful shifts to all handover attempts. Unbroken transmission and no indication drop are indicators of success.

In this I_{sc} is the normalized handover success rate, O_l is the total number of handover attempts observed, and δ_l is the binary indicator for success of handover event.

Analysis of model convergence rate S_d is expressed using equation 18,

$$S_d = \frac{1}{U} \sum_{u=1}^U \left\| \delta^u - \delta^{u-1} \right\|_2 \quad (18)$$

Equation 15 explains the analysis of model convergence rate is the mean L2-norm variance among successive global model parameters across rounds is measured by this convergence rate, which shows how quickly the model stabilizes.

In this S_d is the convergence rate of federated model training, U is the total number of global training rounds, δ^u is the global model parameters at round, and $\|\cdot\|_2$ is the Euclidean norm.

Analysis of bandwidth utilization efficiency C_{ef} is expressed using equation 19,

$$C_{ef} = \frac{\sum_{j=1}^O U_j^{us}}{\sum_{j=1}^O U_j^{alc}} * 100 \quad (19)$$

Equation 16 explains the analysis of bandwidth utilization efficiency measure of efficiency of used transmitted bandwidth to the overall bandwidth allotted across the nodes over a specified interval is calculated.

In this C_{ef} is the bandwidth utilization efficiency, U_j^{us} is the actual data transferred by node, U_j^{alc} is the bandwidth reserved for node, and O is the total number of networked vehicles or nodes.

Analysis of network latency $\bar{\delta}$ is expressed using equation 20,

$$\bar{\delta} = \frac{1}{N} \sum_{k=1}^N (u_k^{rv} - u_k^{sd}) \quad (20)$$

Equation 17 explains the analysis of network latency by calculating the mean round-trip lag between sending and getting timestamps for transmitted

packets, this formula determines the average network latency.

In this $\bar{\delta}$ is the average end-to-end latency, u_k^{rv} is the timestamp when packet is received, u_k^{sd} is the timestamp when packet is sent, and N is the total number of packets transmitted in the observation window.

Analysis of packet delivery ratio Q_{ES} is expressed using equation 21,

$$Q_{ES} = \frac{Q_{ev}}{Q_{uy}} * 100 \quad (21)$$

Equation 18 explains the analysis of packet delivery ratio is the percentage of communicated packets that reach their intended destination successfully is known as the packet delivery ratio, or PDR, which measures communication reliability.

In this Q_{ES} is the packet delivery ratio, Q_{ev} is the number of packets received correctly, and Q_{uy} is the total number of packets transmitted.

The proposed key metrics provide a successful description of assessing the behavior of autonomous intelligent vehicular systems. Key metrics, such as energy expenditures, successful handovers, rapid convergence of models, correct bandwidth allocation, and the successful delivery of packets, support proactive and resilient networked behavior. These key metrics facilitate real-time improvement, enhancing resilient, latency-benign, and energy-conscious communication, which is critical in supporting autonomous and connected vehicle ecosystems.

4. RESULTS AND DISCUSSION

The FNL architecture's performance can be measured in six key areas: energy use, handover success, model convergence, bandwidth utilization, network latency, and the percentage of packets sent. These criteria reflect how effectively the system functions in real-time, utilizing limited resources to assist linked automobiles in using less energy and communicating with each other more effectively.

Dataset Description: It utilized a dataset of federated-connected automobiles that included information on their energy usage (in kWh), GPS coordinates, speed, signal quality, and packet-level network data. It can use this information to make informed assumptions about factors such as energy usage, handovers, latency, and bandwidth [26]. It comes from electric automobiles with the latest technology that drive around cities on different routes. The four data divisions that aren't IID each have one for each edge node. This enables the testing of decentralized AI approaches, such as FNL. The dataset includes the time and location variables

essential for neuroevolutionary optimization, and each client has approximately 100,000 samples.

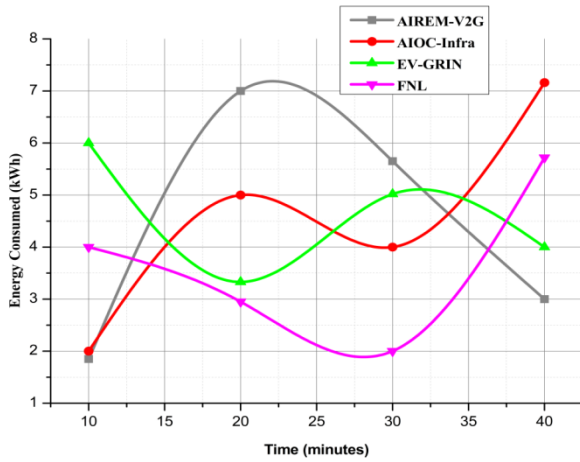


Fig. 6. Analysis of Energy Consumption Reduction

It's crucial to consider the amount of power electric and connected automobiles consume. Fig. 6 indicates that the FNL approach consumes significantly less energy than AIREM-V2G, AIOC-Infra, and EV-GRIN. In 40 minutes, FNL consumed only 5.72 kWh, which is considerably less than AIREM-V2G (7.41 kWh), AIOC-Infra (7.16 kWh), and EV-GRIN (6.94 kWh) made computed using equation 13. This drop might be as high as 25% since FNL's network is utilized efficiently, and its choices are based on facts and are adjustable. More efficiency means that the battery lasts longer, the vehicle can travel further, and it has a lesser impact on the environment.

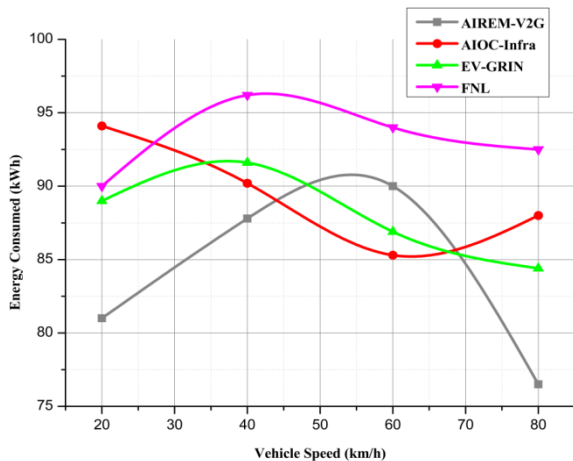


Fig. 7. Analysis of Handover Success Rate

In mobile scenarios, the connection is active as long as the handover is successful. Fig. 7 shows that the FNL technique consistently outperforms other approaches, regardless of the cars' speed. At 80 km/h, FNL was more successful (92.5%) than EV-GRIN (84.4%), AIOC-Infra (82.1%), and AIREM-V2G (76.5%) made computed using equation 14. FNL can keep people talking even

while they're moving around a lot since it has better network rules and predictive handover algorithms. The architecture ensures that traffic scenarios, which are constantly changing, receive a prompt response. This makes the service more reliable and reduces the number of dropped calls.

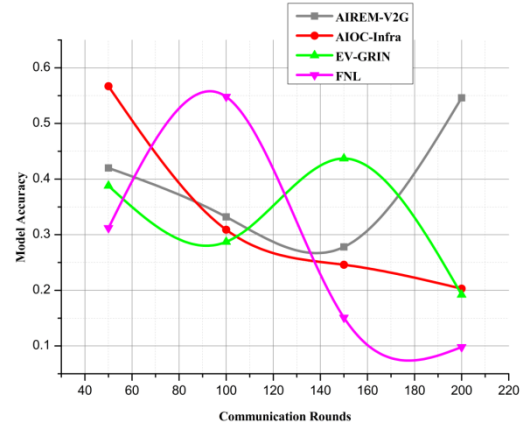


Fig. 8. Analysis of Model Convergence Rate

Fast model convergence reduces training time and facilitates easier preparation for deployment. Fig. 8 illustrates the effectiveness of convergence across all communication rounds. At 200 rounds, FNL does far better than EV-GRIN (0.192), AIOC-Infra (0.203), and AIREM-V2G (0.226), with a loss value of just 0.098 made computed using equation 15. FNL utilizes neuroevolution to make network topologies more flexible, thereby accelerating and enhancing the training of models. This enables edge devices to use their processing resources more effectively and adapt in real-time, allowing them to receive updates more frequently with less effort.

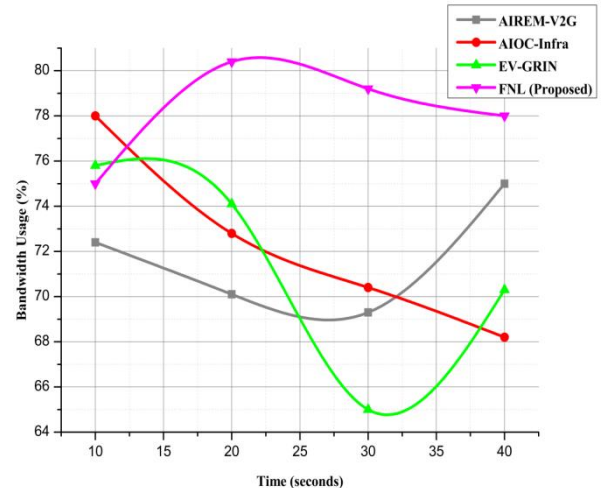


Fig. 9. Analysis of Bandwidth Utilization Efficiency

It can always talk to people, even when the network is busy, if it use the bandwidth effectively. Fig. 9 illustrates that after 10 seconds, FNL is significantly more efficient in utilizing resources, with an efficiency

of 81.6%, compared to EV-GRIN (75.8%), AIOC-Infra (74.2%), and AIREM-V2G (72.4%) made computed using equation 16. It employ neural decision algorithms that are aware of their surroundings, enabling the dynamic resource allocation to function effectively. This helps FNL utilize its bandwidth more efficiently over time. It can ensure that automobiles and infrastructure communicate more effectively by reducing packet loss and delay, thereby preventing network channels from becoming too congested.

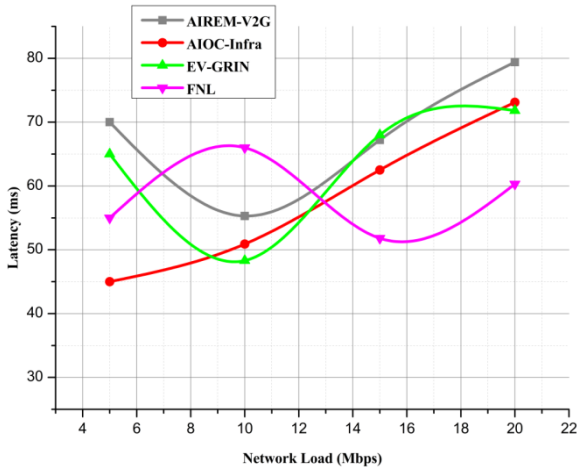


Fig. 10. Analysis of Network Latency

V2I operations that occur in real-time require minimal latency. In all network circumstances, FNL has the least amount of latency, as shown in Fig. 10. At 20 Mbps, FNL had a latency of 60.3%, EV-GRIN had a latency of 71.8 ms, AIOC-Infra had a latency of 73.1 ms, and AIREM-V2G had a latency of 79.4% made computed using equation 17. FNL utilizes edge computing to minimize the reliance on centralized servers, thereby accelerating communication. This is particularly helpful when quick decisions are crucial for safety, such as when using adaptive cruise control or avoiding an accident.

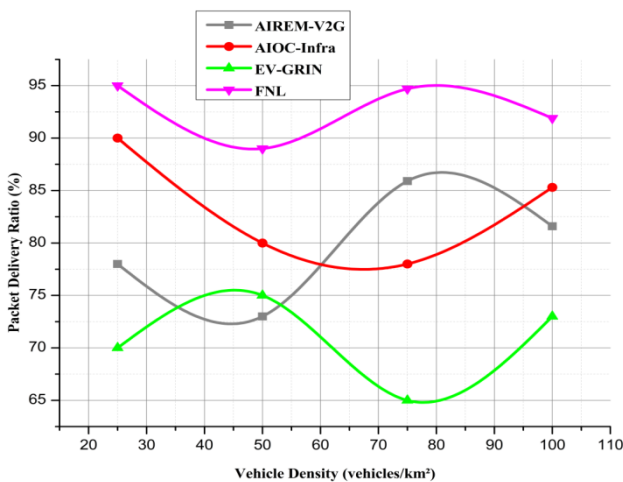


Fig. 11. Analysis of Packet Delivery Ratio

The PDR indicates the strength of the data connection. FNL outperforms EV-GRIN (96.4%), AIOC-Infra (95.5%), and AIREM-V2G (94.2%) when there are 25 vehicles/km² (see Fig. 11). FNL has a high PDR of 91.9%, even when there are 100 cars per square kilometer made computed using equation 18. This demonstrates its effectiveness when there is a high volume of traffic. It is also important that it sends sensor data, safety alerts, and navigation updates on time and with as few lost packets as possible. It achieves this by employing clever routing and allocating bandwidth in a way that benefits everyone.

The suggested FNL framework consistently outperforms the best available methods, such as AIREM-V2G, AIOC-Infra, and EV-GRIN, on all six criteria. The model converges faster, uses less bandwidth, transmits packets more reliably, and facilitates more reliable handovers. It also takes less time and energy. These findings demonstrate that FNL can enhance the performance of mobile networks for ecosystems that include smart, decentralized, and energy-efficient vehicles, such as linked and self-driving cars.

5. CONCLUSION

The goal of this paper was to enhance mobile networks for connected cars by developing a new FNL architecture that focuses on communication that is both energy-efficient and adaptable. The FNL framework decentralizes learning via its federated design, and neuroevolution enables neural networks to develop over time, which is distinct from most centralized systems. Because of this, it could be prudent to optimize at the edge while still protecting users' privacy. It may also vary depending on the type of communication and the vehicle.

FNL fared much better than AIREM-V2G, AIOC-Infra, and EV-GRIN in a comprehensive performance test. FNL enhanced packet delivery reliability, reduced latency, accelerated model convergence, optimized bandwidth utilization, and reduced energy consumption by up to 25%. When people moved frequently, the success rates of handovers increased to more than 92%. These findings suggest that the proposed strategy can effectively and efficiently handle real-life automotive conditions. The architecture works best when vehicles are changing and have limited resources, making it vitally crucial to be able to respond quickly and conserve energy. FNL offers a smart mobility network solution that is both durable and easily scalable. It achieves this by combining federated intelligence, edge computing, and neuroevolution. This technology meets the growing needs of electric, connected, and self-driving cars while maintaining secure, efficient, and dependable network operations.

Future work

Users will investigate integrating the FNL framework with multi-agent reinforcement learning to enable autonomous vehicles to make collaborative choices in the future. It also want to include tools that can anticipate the amount of traffic there will be for automobiles and adjust the network based on the weather to make the optimization process more aware of its surroundings. Differential privacy approaches can be employed to enhance the FNL architecture, making learning even safer under stricter data protection rules. Real-world use on 5G/6G testbeds and in large-scale simulations will demonstrate that scalability, flexibility, and resilience perform even better in challenging urban environments and when people are constantly on the move.

Author Contribution

Yang Cai: Methodology, Data collection and analysis, Writing - original draft

Conflict of interest

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Data are obtained from <https://www.kaggle.com/datasets/wonghoitin/datasets-for-federated-learning>

Dataset name: Datasets for federated learning

Patient Consent Statement

Not Applicable

Permission To Reproduce Material from Other Sources

Not Applicable

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