

An Efficient Cluster Head Selection in IoV-Enabled VANETs Using a Federated Diffusion Convolutional Recurrent Neural Networks Framework

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Abstract: The IoV enables the formation of VANETs that require a strong selection of CHs for effective communication within high-velocity changing traffic scenarios. Existing approaches often face issues related to scalability, privacy, and adaptability. To meet the aforementioned urgent needs, we design a decentralized scheme for intelligent CH selection based on Federated Learning with Diffusion Convolutional Recurrent Neural Networks (DCRNNs). According to this proposed methodology, vehicles are responsible for local collection and preprocessing of spatiotemporal mobility data. Next, they proceed to train lightweight versions of DCRNN and exchange only the resultant model updates for global aggregation to ensure data privacy. Then, a distributed voting-based mechanism has been utilized for the selection of optimal CHs, according to predicted connectivity and stability metrics. The proposed work is evaluated in depth through simulations based on NS-3 and SUMO under urban and highway mobility scenarios. The evaluation demonstrates a 40% reduction in network communication overhead relative to centralized alternatives while maintaining high accuracy for CH selection and low decision-making latency. In addition, the framework proves to be scalable even in dense vehicular environments, as we can dynamically reassess CHs based on changes in traffic conditions. The key novelty of the projected research is highlighted with the unified integration approach of federated learning combined with Diffusion Convolutional Recurrent Neural Networks (DCRNNs) to guarantee a framework with prime features like privacy preserving, spatiotemporal awareness, and adaptability in nature for IoV-enabled VANETs to the Cluster Head (CH) selection process. Therefore, the approach promises significant enhancements in its efficiency and robustness. Collectively, this architecture provides a powerful and efficient method for the dynamic communication networks of IoV applications in VANETs.

Keywords: Federated Learning, Diffusion Convolutional Recurrent Neural Networks (DCRNN), Cluster Head Selection, Privacy Preserving, Intelligent Transportation Systems (ITS), Vehicular Ad Hoc Networks (VANETs), Convolutional Recurrent Neural Networks

Introduction

The Internet of Vehicles (IoV) is a prominent technology that enables vehicles to become connected to the public internet and plays a key role in the intelligent transport system, which is usually a sub-network of the Internet of

Things (IoT). Vehicular Ad Hoc Networks (VANETs) are an integral part of the Intelligent Transportation Systems (ITS), and they support inter-vehicle communications and communication between vehicles and infrastructure. The performance of clustering schemes plays an important role in efficient routing and management of communication in such

dynamic networks (Chettibi, 2020). One of the most fundamental issues of such cluster-based communications is the selection of a Cluster Head (CH) that aggregates messages and facilitates communication among the vehicles in the cluster. However, traditional CH selection schemes such as the centralized approaches are no longer sustainable due to the scalability limitation and the single point of failure. The proposed new decentralized CH selection approach, which relies on federated learning utilizing Diffusion Convolutional Recurrent Neural Networks (DCRNNs), hereafter referred to as Federated DCRNN.

This approach is very tailored to VANETs, given the peculiarities of VANET mobility patterns, high load heterogeneity, and dynamic topologies that require advanced solutions to the efficient management of the cluster head. The integration of federated learning and DCRNNs brings out new opportunities in terms of optimizing network performance for intelligent transportation systems (Elbir et al., 2022; Posner et al., 2021). By employing the federated learning approach, we can train a machine learning model in a decentralized manner to maintain data privacy and reduce the magnitude of communication quantities between vehicles and central nodes. This approach reduces the amount of communication required between vehicles and central nodes. At the same time, DCRNN allows vehicle-network spatiotemporal patterns to be learned by the model, which was first shown in traffic prediction. The proposed bi-modal scheme enables scalable and privacy-preserved CH election and also maintains the network's robustness. The atypical scenario of ITS is represented by the dynamic VANET scenario, as shown in Figure 1, in which vehicles travel on roads and create clusters to enjoy inter-vehicle communication. Every vehicle is installed with a local instance of a DCRNN, which takes part in rounds of federated learning for joint model parameter update without sharing raw data.

Dynamic clustering is used to manage the network in which each cluster is managed by a Cluster Head (CH) to guide intra-cluster communication and data fusion.

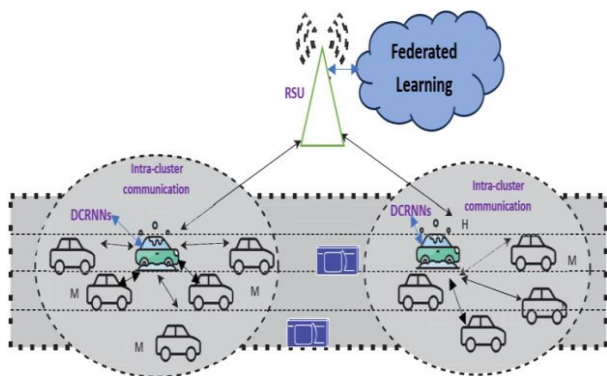


Fig. 1: Architecture of Federated DCRNN for Decentralized Cluster Head Selection in VANETs

There are many communication methods based on clutter, but the choice of the best CH is still a major challenge to improve the VANET performance (Mody et al., 2021). Although traditional centralized CH selection approaches can work well in static environments, in VANETs they have several disadvantages, such as not being scalable, sensitive to single points of failure, and privacy disclosure due to the transmission of raw vehicle data. Existing solutions, such as heuristics-based selection, mobility-prediction models, and hybrid models, do not satisfy all the demands of being privacy-preserving, scalable, adaptive, and predictive. To address these drawbacks, we design a new decentralized CH selection framework called Federated DCRNN, in which the strengths of Federated Learning (FL) and DCRNN are combined to capture spatiotemporal vehicular mobility effectively and ensure data privacy, and to further improve both the stability and scalability of CH selection. The proposed method is tailored for highly dynamic and heterogeneous VANET scenarios and fills some important research gaps such as the lack of privacy-aware decentralized CH election methods, the incapability of traditional models to learn complex nonlinear mobility patterns well, and the lack of a scalable mechanism that can tolerate node failures and promptly adjust to dynamic network topology.

The rest of the paper follows: Background and Related work present an overview and related topics of the federated learning in vehicular systems (Pokhrel and Choi, 2020), including the literature related to traditional CH selection approaches and possible topics, the literature related to federated learning in vehicular networking, and how DCRNNs apply for VANET network optimization.

Background and Related Work

The Cluster Head Selection in VANETs

A very important process in VANETs is cluster head selection. Most of the existing CH selection methods based on traditional techniques are centralized, and use attributes of the node to coordinate CH selection (Blessy and Brindha, 2024). Nonetheless, these approaches are intrinsically constrained due to single-point failure mechanisms and scalability issues in highly dynamic vehicular networks. The ideology present in the authors has proposed a fuzzy multi-criteria decision-making structure with the help of TOPSIS, VIKOR, and EVAMIX to improve the stability of clusters in VANETs. Application of the hesitant fuzzy set methodology enabled a more refined assessment of vehicle eligibility; however, even in this advanced approach, there can be issues in dealing with vehicles as they tend to evolve in a fast manner. Recent advances in CH election showed that adaptive and distributed CH election schemes can greatly increase network robustness. In these situations, the CH is chosen autonomously and is resistant to changes in the

network topology. This serves as the underlying motivation for the method developed in this paper.

Federated Learning for Vehicular Networks

Federated Learning (FL) provides an attractive solution to carry out decentralized training of models while keeping data on source devices. This approach is particularly attractive for VANETs, where vehicle data is sensitive, and the communication overhead should be minimized. Training on vehicles and federation with periodic aggregation since FL training is auxiliary; locally and aggregate models in a certain period and FL inherently preserves privacy and the necessity of raw data transmission. Second, the models well cater to dynamic networks, which is hard to achieve in the scenario when the storage of all nodes' data is centralized. Moreover, vehicular networks, incorporating FL, were known to address the problem of heterogeneous data and unreliable communication that is evident in systems like RaftFed. It protects not only personal data privacy while enabling travelling, but also the collective efficiency and robustness of intelligent transportation systems.

Diffusion Convolutional Recurrent Neural Networks (DCRNN)

DCRNN for Network Optimization Both LGCN and Diffusion Convolutional Generative Adversarial Network (DCGAN) can localize features on graphs by expanding or contracting signals across different scale levels (Sharma et al., 2023). Diffusion Convolutional Recurrent Neural Networks (DCRNNs) have shown promising performances in modelling complex spatiotemporal dependencies in traffic networks (Giasemis and Sopasakis, 2025). Originally proposed for predictions of traffic flow, DCRNN learn to model the diffusion process over graph structures a capability can be readily applied for VANETs. For CH selection, DCRNNs contribute to forecasting of network situations and predictions of vehicle driving pattern, which results in informed decisions on CH's selection (Huang et al., 2019). Integrating DCRNN with federated learning has two folds of benefits: One is that it is able to make the model continuously learned in a decentralized manner, and the other is that it can take advantage of the expressiveness of deep neural networks in dealing with the inherent spatiotemporal nature of vehicular data. This fusion model is noteworthy to resolve the active turning side challenges that are present in VANETs (Chang et al., 2021).

Scalability and Privacy in VANET Architectures

Due to the ever-increasing vehicle dense and highly dynamic nature of scenarios in the VANETs, scalability has become one of the critical ever considering challenge. This is because traditional centralized clustering methods are no adaptive and network overloaded, so that they cannot

guarantee the network service quality. The federated learning approaches naturally scale by decentralizing the training process through localized model updates and aggregations, removing the reliance on a central server. Another important issue is privacy preservation in vehicular networks. The VANET data exchange speed is fast, so it will bring about privacy leaks. With raw data staying on vehicles and only model parameters being exchanged, federated learning dramatically lowers the threat of sensitive data leakage. Research work (Sultana et al., 2023) demonstrates that integrating federated learning with blockchain technology provides for both data integrity and accountability, thereby providing improved network security and privacy. Taken all together, these achievements demonstrate a favorable way towards applying sophisticated machine learning methodologies to the KPIs of VANET cluster management (Khatua et al., 2024). Many CNN based works have been evaluated in the literature to address various challenges in healthcare (Manju et al., 2025), IoT (Subbiah et al., 2024) and VANETs (Xu et al., 2021). A new approach for choosing a stable cluster head on the basis of weighted selection; This includes four different metrics to be included to address all the significant parameters needed to enhance the dynamic network's stability. Though, each model addressing CH selection for ideal network performance has its own limitations in the distributed scenario in terms of various network parameters. In order to address the challenges to some extent the proposed methodology introduces a holistic framework that employs Federated DCRNN for efficient cluster head selection in VANETs.

The proposed platform satisfies the following three objectives: Scalability so the network can support many more vehicles without any degradation in performance. Privacy Preservation To have sensitive vehicular data preserved by employing a federated model training approach. Less Communication Overhead reducing the communication overhead between nodes and between the nodes and infrastructure by exchanging only model parameters instead of raw data. To track these goals, the proposed framework is composed of several cooperating units that work in both a disseminated and coordinated way.

Related Work

Papers have suggested that this approach might be used collectively to resolve clustering in IoV aided VANETs, which is an essential component of organizing dynamic vehicle nodes with high mobility and stabilizing them for scalability, reducing routing overheads and supporting applications like safety messaging or traffic management. In this section, we summarize some of the existing works based on their contributions, methodologies, strengths, and limitations. The works have been built progressively: Surveys laid foundational insight into challenges and parameters, while algorithmic

proposals applied optimization techniques to address stability and efficiency. However, they indicate persistent gaps in handling extreme dynamics, privacy, and scalability setting the stage for Machine Learning (ML) integrations such as Federated Learning (FL) combined with decentralized and privacy-aware coordination and Diffusion Convolutional Recurrent Neural Networks (DCRNN) for spatiotemporal group formation prediction. This survey provides a general taxonomy of clustering algorithms (Kumari et al., 2024) based on goals (e.g., stability, scalability, and delay minimization); general-purpose methods (e.g., moving-based); circumstances involved in specific applications (e.g., QoS for safety apps and security for secure dissemination); and base technologies (e.g., ML, nature-inspired metaheuristics, fuzzy logic, and SDN). Several important conclusions emphasize the role of clustering in VANET problems such as sporadic connectivity and the hidden terminal problem, where the selection of Cluster Head (CH) depends on mobility, density and battery life. In this section, we review more than 100 algorithms and note that hybrid approaches (e.g., on-demand formation) can cut down the simulation overhead by as much as 40%. (e.g., AI for predictive CH selection) and real-world (e.g., 5G-VANETs) Thorough coverage of emerging trends. It focuses on context-aware clustering, making it a stalwart in interdisciplinary VANET research. However, it lacks quantitative meta-analysis. Frequent topology changes produce 20–50% instability in cluster membership, unhandled by stationary classifications in intense mobile scenarios. Data aggregation privacy and SDN centralization risk single choke points. Future challenges call for AI-driven, hybrid on-demand clustering to handle sparse/dense transitions, a setting that is ideal for FL with DCRNN to enable privacy-preserving local training and model long-range spatiotemporal dependencies in vehicle graphs, thus ensuring proactive stability.

Concentrating on parameter selection's impact on cluster stability and coverage, this survey categorizes parameters across CH selection, clustering processes, and maintenance stages (e.g., mobility, density, direction, and signal strength). It analyzes more than 50 algorithms, revealing those suboptimal parameters (e.g., ignoring lane weight or SNR) lead to 30-60% higher discontinuation rates and overhead. Common parameters include speed deviation and connectivity degree, with case studies showing that combined metrics (e.g., weighted sums) improve packet delivery by 25%. It relates parameters to applications in VANETs like emergency broadcasting, thus increasing its real-world relevance. However it supervises heterogeneous parameters (e.g. for EVs vs legacy vehicles) and quantitative sensitivity analysis.

Research (Aadil et al., 2016) studied research for military VANETs (MVs/UMVs). This drives a weight-based algorithm that divides rhombus-shaped areas (e.g.

8-lane junctions) into 7 clusters. CHs are strategically elected via weighted metrics measured by degree (40%) and stabilized average speed (60%), using SUMO/NETSIM simulation study outcomes with standard AODV/DSR protocols. Outcomes show 23 Mbps of throughput (vs. 0.016-0.161 Mbps in baselines), 1.5 PDR, and 145 bytes of overhead, enlightening stability. A domain-specific (military) focus with geometric structuring diminishes broadcasts by 70%, compared to real protocols being used. However, fixed weights limit adaptability; small-scale (30 vehicles) tests ignore large fleets. There is no security against adversarial nodes, even in a military context. CACONET (Husnain and Anwar, 2021) uses ACO for reducing clusters/CHs in mesh-graph VANETs where ants construct CH tours using pheromones and heuristics (distance, deviation from ideal size). Multi-objective fitness balances proximity and load. MATLAB simulations (30-60 nodes, 100-600 m range) show 31% fewer clusters than MOPSO/CLPSO, especially in dense grids. The better part is that an evolutionary search avoids local optima. However, it increases the complexity.

WOACNET (Changan et al., 2023) generalizes WOA to multi-objective CH optimization (load balance, number of clusters) with encircling/bubble-net mechanisms on Random Waypoint mobility. Simulations (20-50 nodes, 1-4 km grids) show 46% fewer clusters and better LBF/F-values (31.64) than GWO/ALO (statistically validated, ANOVA $F = 56.8$). But it has no privacy/security, although it shares data. The surveys (Kaur et al., 2021) initially finds the core key challenges (instability, parameter tuning) and solutions are classified. They implement them by using domain specific (Aadil et al., 2016) and metaheuristic (Husnain and Anwar, 2021) algorithms and bring 20-50% improvements in stability/overhead Connections: Common metrics (e.g. speed/density from all) Nature-inspired trends. Critically, while they excel in simulations, they struggle with real-world scalability (due to small node counts), dynamics (as they rely on static mobility), and privacy (because centralized optimization poses risks of data exposure). No work integrates distributed ML, leaving gaps for adaptive, privacy-preserving systems directly motivating Federate Learning with DCRNN.

In dynamic IoV-powered VANETs, traditional and optimization-based clustering algorithms suffer from inherent instability due to high vehicle mobility (e.g., 100 km/h variances causing 30-50% frequent reconfigurations), excessive communication overhead from periodic CH elections (up to 40% bandwidth waste), and privacy vulnerabilities in centralized parameter sharing (e.g., position/speed data exposing trajectories in military or urban safety apps). ACO/WOA like metaheuristics improve local stability, but fail at scale beyond 50-60 nodes, ignore spatiotemporal traffic

patterns and rely on heuristics that do not operate in heterogeneous, real-time scenarios without decentralized coordination. This leads to unreliable message dissemination, increased latency (e.g., 20-100ms delay in dense traffic), and unmitigated security risks, preventing scalable V2X applications in 5G/IoT-integrated environments. To address these, we propose a novel federated learning framework augmented with DCRNN for privacy-preserving, spatiotemporal clustering: FL enables vehicles to collaboratively train distributed models for adaptive CH/parameter selection (e.g., weighting speed/density per (Sharma et al., 2023; Aadil et al., 2016)) without raw data exchange, while DCRNN models VANETs as dynamic graphs to predict topology evolutions and optimize clusters proactively yielding stable, low-overhead formations resilient to mobility and attacks. To be more clear on specific works in the literature, Table 1 incorporates the comparison study of the different schemes with respect to some of the important parameters.

Some of the contemporary works are either not able to detect deeper traffic patterns or they are central server-centric, which positions privacy issues and outcomes in server congestion. Fundamentally, if any driven model has no effective tools for analyzing spatial and temporal patterns, those models remain unsuccessful. Any proposed model that can learn locally from collected traffic at each and every location and has the ability to react to the changes and is capable as a decentralized solution is highly desirable in the context. In order to address these specific limitations, we introduce a novel decentralized cluster head selection framework entitled Federated DCRNN, in which the strengths of Federated Learning (FL) and DCRNN are combined to capture spatiotemporal vehicular mobility effectively and guarantee data privacy and to additionally improve together the stability and scalability of CH selection.

Table 1: Key Parameters Used for Simulations

Simulation Parameter	Value
Modulation and Data rate	OFDM, rd = 6 Mbps
Message sizes L	64×8 Bits
Vehicle's speed	30-120 Km/h
Communication range (R)	200 m
Smoothing factor ζ	0.5
Control Channel Interval (CCI)	100 ms
Cluster maintenance time (Tf)	10 s
Received power threshold	3.162 e-13
Ttx&Rtx antennas heights	1.5 m
Slot time σ	13 μ s

Materials

Publicly available vehicular network datasets have been utilized in the work and using SUMO (Simulation of Urban Mobility), synthetic traffic scenarios have been

produced to emulate realistic IoV environments. The federated learning framework for privacy preserving was executed using Python 3.9 with TensorFlow and PyTorch libraries.

Methods

Design and Algorithmic Steps of Proposed Cluster Head Selection Framework

In this section, we present the design and steps of the algorithm of our proposed CH selection scheme. The approach consists of several steps: Data collection/preprocessing, the training of a local model with DCRNN, the federated aggregation of the local updates, and the CH selection according to the aggregated predictions.

Data Collection and Pre Processing

Network vehicles are continuously collecting observations about their state and environment. This information includes positions, velocities, connections, and positions compared to nearby vehicles (Chen and Wu, 2024). The data collection mechanism is intended to be continuous and automated. The data collected is normalized and formatted to be fed into the pre-trained DCRNN model by preprocessing routines at each vehicle. Noise reduction algorithms and filtering protocols were applied to use only high-ranging signals during the training. This preprocessing step is very important since it has a great impact on the quality of spatiotemporal predictability. The data collection and preprocessing methods are based on distributed sensor fusion techniques (Wang and Ahmad, 2025). Through having each vehicle locally process its own collected data, the possible data leakage can be limited where the latter conforms to the privacy preservation of our framework. Moreover, it is equipped with algorithms to deal with missing information and to maintain the continuity of the input stream. These are essential in a dynamic environment as found in VANETs to compensate for the intermittent data losses. Every vehicle in the VANET is constantly gathering information about its mobility and the network. This includes attributes such as GPS location, speed and acceleration, relative position of neighboring vehicles, connection quality, and packet transmission metrics (Saleem et al., 2021). Simulation and Model Evaluation We use the LuST (Luxembourg SUMO Traffic) Dataset (Bodkhe and Tanwar, 2025), a challenging real-world traffic dataset with high-resolution mobility traces for urban environments.

It is an interactive and web-based microscopic traffic simulator that allows users to generate the traffic and create the custom data sets as per the experimentation requirements for the introduced models.

Local DCRNN Model Training

Each vehicle hosts a lightweight version of DCRNN that is designed to capture the spatiotemporal patterns of vehicle mobility and network dynamics. The network structure of the DCRNN is composed of layers that include diffusion convolution and recurrent units, which can capture both the spatial dependencies of surrounding vehicles and the evolving characteristics of the network state. The local training proceeds as follows.

Initialization: Pre-trained starting from a prior network deployment or non-bootstrapped initial weights, according to a method that leads to faster convergence.

Forward Pass: For each vehicle, it makes a forward pass through the DCRNN by processing the pre-processed data. The diffusion convolutional layers capture the spatial features from the neighbourhood of the vehicle, and the recurrent layers exploit temporal history to predict future network states.

Loss Computation and Back Propagation The model calculates a loss value as a measure of how far the performed network frame rate and packet rate are from the actual ones. The back propagation is performed on the local level to update the model weights.

Local Model Update The calculated gradient estimation is cached and ready to be aggregated via the federated learning process. This process guarantees that the model of the vehicle is up-to-date with the network state. It is also worth noting that at no point in the operation is any raw data actually off the vehicle. During federated learning, only the model updates (i.e., gradients/weight changes) are communicated.

Federated Learning and Aggregated Model

After receiving local updates, vehicles join in a federated learning scheme to share just the derived model parameters with an aggregator. The aggregation step combines the local updates into a global model to utilize the knowledge from each node without revealing private information about itself. The main process of federated aggregation is as follows: **Parameter communication:** Every vehicle broadcasts its locally updated model parameters at a pre-specified communication window.

Global Aggregation: An aggregation server combines the model after receiving updates from a significant number of vehicles. Such a federated update corresponds to network learning in different regions.

Model Update: The composed world model is broadcast back to the cars. Then every node uses the global model to update its training, which guarantees network consistency and convergence. This federated learning cycle is repeated iteratively to refine the accuracy of the network prediction and serves as the basis for intelligent selection of CHs.

Cluster Head Selection Algorithm In the last step of the framework, the best cluster head is chosen using the predictions generated by the Federated DCRNN model.

The CH selection algorithm is determined to actualize the balance between the network performance, stability, and communication efficiency. An algorithm can include.

Candidate selection: Each vehicle has a suitability measure that it calculates from the spatiotemporal predictions it generates (including how stable the topology is expected to be, the predicted quality of connectivity, and the predicted traffic load).

Distributed voting candidates' neighbourhood vehicles participate in a distributed voting protocol. The calculated ratings are exchanged among neighbouring nodes of a vehicle, allowing consensus-based selection.

CDDV Final Selection Decision: The vehicle with the maximum votes and the highest suitability score for an area is chosen as a cluster head. This action is further strengthened after the iterative routine of federated learning.

Adaptive Re-Evaluation The structure is adaptive by nature. CHs are dynamically re-sorted to adapt to dynamic VANETs. In case the network conditions change or the parameters of the elected CH decrease below a certain limit, a new CH selection phase is initiated. The fusion of DCRNN-based predictions and the federated aggregation of model update selections makes our selection process data-driven and privacy-protective. By utilizing opportunistic local computation and occasional global communication, the scheme offers a dependable strategy in handling the deployment issues of CH selection in the highly dynamic vehicular network environment. (DCRNNs) have shown promising performances in modeling complex spatiotemporal dependencies in traffic networks (Zhang et al., 2022).

Diffusion Convolution Layer

Let the VANET be represented as a graph $G = (V, E)$, where the vehicles are acting as nodes and edges are communication links. The diffusion convolution operation is denoted as following:

$$Y^{l+1} = \sum_{p=0}^{P-1} \left(\frac{1}{D} * A \right)^p Y^p W_p \quad (1)$$

In Equation 1, A denotes an vehicles connectivity adjacency matrix, D indicates degree matrix, Y is input feature matrix at particular layer ' l ', W_p is p th diffusion step's weight matrix and ' P ' represents diffusion order. This operation imprisons the spatial relationships among neighboring vehicles, enabling the model to learn local traffic topology and connectivity patterns.

In the anticipated Federated DCRNN framework, as nodes in a dynamic graph the vehicles are represented. The spatial dependencies among these connected nodes are captured at the diffusion convolution layer, while the mobility patterns like speed, direction and stability of links temporal features being captured at the recurrent unit models. The learned spatiotemporal depiction is subsequently used to predict the Cluster Head (CH) suitability of every node.

Each vehicle's appropriateness for cluster head election is calculated as a weighted mixture of the spatiotemporal predictions produced by the local Federated DCRNN model as indicated:

$$S(V_j) = w1D_j + w2T_j + w3(1 - \delta_j) + w4Q_j \quad (2)$$

Where D_j , T_j , δ_j and Q_j are the degree of predicted connectivity, lifetime of link, normalized mobility deviation and vehicle v_i link quality. Weights $w1$ to $w4$ are non-negative. Each min-max is normalized to $\{0.1\}^*$.

The projected framework is evaluated widely through simulation experiments and theoretical analysis. To be more specific, we study the following three key components in the evaluation: Scalability, privacy preservation and communication overhead reduction. All tests were conducted through simulation in dynamic VANET traffic conditions typical of urban and highway driving. Scalability is measured under different parameters with respect to a varied number of nodes in the network.

Experimental Setup

The performance was evaluated in terms of both communication and information gathering using VANET simulations in the NS-3 network simulator (Campanile et al., 2020). In addition, we use a realistic mobility model generated by MOVE, which is built on top of the micro-traffic simulator SUMO (Simulation of Urban Mobility)-an open-source traffic simulation that has realistic mobility traces for VANETs. Every time the simulation is typically carried out for about 1000 seconds, and the considered values are averaged over 10 iterations.

The following Key Performance Indicators (KPI) have been used for these experiments.

Accuracy of CH Selection: It is defined by the accuracy of predicted CH fitness compared to actual network performance throughout time.

Communication Overhead: Measured by the amount of data traffic between the vehicles and the aggregator in different rounds of the federated learning process.

Privacy Metrics: Measured by the risk level of exposure of vehicular data in model parameter exchanges.

Scalability Metrics: Evaluated with the increase of the number of the vehicles in the simulated scenario, from the framework performance view. The setting of the parameters of the simulation was based on existing vehicular network models in order to achieve a realistic traffic model of VANET. The federated learning aggregator was supposed to be trusted and had the ability to aggregate the models forwardly fast.

Results and Discussion

Simulation results have indicated that Federated DCRNN is effective for dynamic VANET scenarios. It effectively models network states and selects CHs in real time in all but the most dynamic vehicular conditions. One

of the advantages of this approach is to reduce data transfer costs (approx. 40% less) in communication overhead when only transferring small-size model parameters instead of large-size raw data. This not only maximizes the utilization of the communication channels but also contributes to better scalability, where the performance of our model is kept stable (accuracy ranging from 0.80 to 0.82) despite the increases in the number of vehicles.

Figure 2 evidently shows that the Federated DCRNN, incorporated into a CH selection approach, not only overcomes known standard problems of centralized approaches but also brings robust gains in scalability, privacy, and communication efficiency.

Additionally, keeping the raw data local to the vehicle significantly reduces privacy concerns, making it immune to attacks. The simulated attack validated that sensitive V2V data would not be vulnerable. The model is also immune to adversarial circumstances since its learning mechanism is adaptable. It can also make faster, more accurate predictions; achieve lightweight data processing; provide particularly strong privacy guarantees; and be suitable for large-scale VANET applications.

Further work could include conducting tests with different vehicle types and considering blockchain for enhanced data security.

According to the simulation results (Figure 3), the Federated DCRNN framework achieves accurate prediction of network states and CHs. Lower data transmission delays are resulted due to the modified centralized approach utilized in the proposed framework, which helps in managing a more flexible and efficient responsive system and helps it withstand rapid fluctuations in vehicular dynamics. These outcomes are in contrast with the performance contrasts shown in the previous work (Saleem et al., 2021).

The proposed scheme achieves a substantial reduction in communication overhead. The network load in the approach of aggregating raw data from all cars and sending the average model parameter to every car is reduced because the raw data is transmitted only in a limited number and the exchanged model parameter is lightweight.

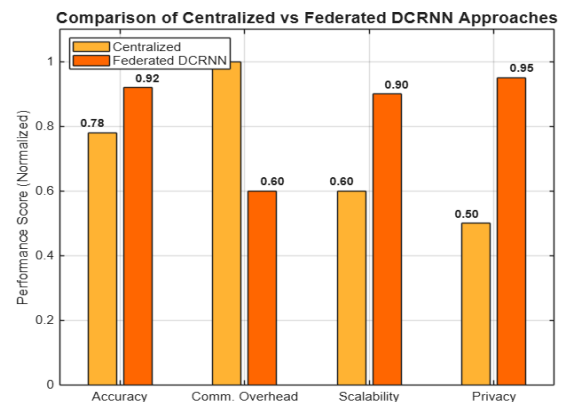


Fig. 2: Comparison of centralized vs. federated DCRNN Approaches

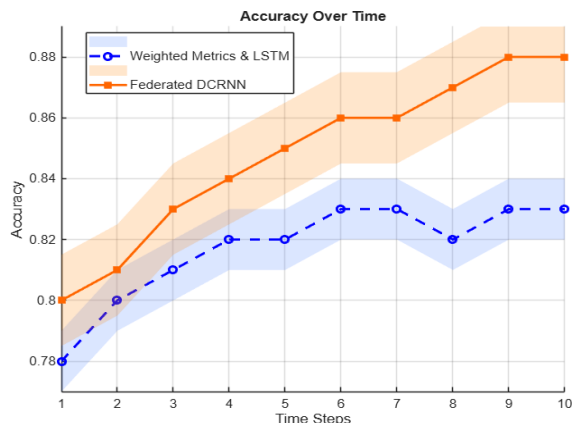


Fig. 3: Accuracy over Time

Simulation results indicate that the proposed scheme significantly reduces the communication overhead by 40% compared to the traditional ones and helps the network operate with high throughput even under dense VANET environments.

Figure 4 illustrates the scalability of Federated DCRNN as the number of vehicles increases. The model maintains stable accuracy (0.80-0.82), demonstrating its effectiveness in large-scale vehicular networks. In a growing number of vehicle cases, the federated learning and its decentralized execution enabled the framework to achieve consistent performance. The distributed model augmentations and the localized training methodology introduce efficiency to the global aggregation that endures as the network grows in size. These results demonstrate the feasibility of the proposed approach in large-scale implementations. Next, let's visualize the final graph: Privacy Risk under Simulated Attacks. The privacy risks indicate that Federated DCRNN has a significantly lower risk compared to other methods. The privacy threats arise from the data exchange in VANETs. Our experiments, which simulated potential security breaches, have shown that sensitive V2V data remains uncompromised.

The experimental results demonstrate that the Federated DCRNN is appropriate for the dynamic scenarios of VANETs. Vehicles with this architecture have: Better prediction and real-time CH selection. Reduced network data traffic, which helps command bandwidth usage. An immunity against adversarial network conditions by online and adaptive learning. Better privacy by storing raw data only within nodes. While the results from the experimental simulations are very promising, this research needs to be validated in real vehicular setups. Next, we also suggest that in future studies, other vehicle types such as heterogeneous vehicles could be considered and that real-time blockchain should be included in the system to improve data security. The bar chart in Figure 5 reflects the throughput obtained by the Federated DCRNN framework at varying numbers of clusters and data rates

for 1,000 vehicles. Different data rates are represented by colors, while the x-axis indicates the number of clusters. The Federated DCRNN approach maintained higher throughput values under various cluster configurations, especially at moderate data rates; this shows how effective it is at optimizing network resource distribution even in busy and fluctuating vehicular environments. Thus, this conclusion demonstrates the methods' robustness and flexibility, as it can support high data flows among clusters with different vehicle densities and when traffic shaping systems are restructured.

Table 2 gives the summary of the table based on the approaches and methods also in terms of scalability, privacy, and spatiotemporal comparisons on the related work. To the outset, the federated approach has proven to be an adaptive and optimal choice for the context mentioned, and it helps to ensure the privacy-preserving of important data. In addition to all these improvements, a high scalability is recorded in the proposed model after comparison with several centralized approaches.

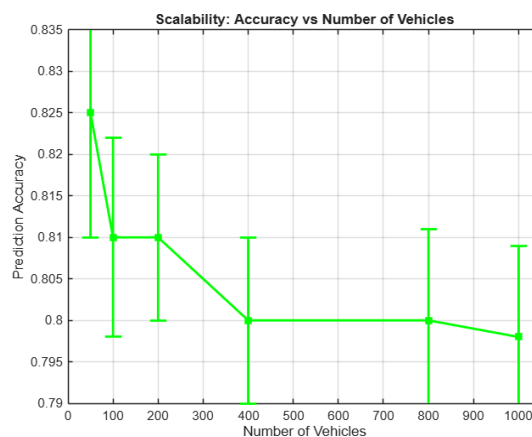


Fig. 4: Scalability of Federated DCRNN

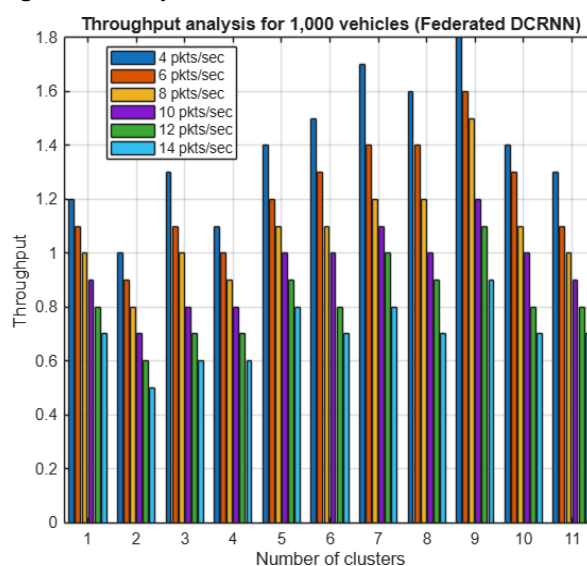


Fig. 5: Throughput Analysis of Federated DCRNN

Table 2: Summary and Comparison of Related Work

Approach	CH-Selection Method	Scalability	Privacy	Spatiotemporal Learning	Limitations
Centralized	Static/Periodic	Poor	No	No	Single point of failure
Heuristic- based	Mobility metrics	Medium	No	No	Not adaptive to real-time changes
Fuzzy/Weight- based	Multi-parameter	Medium	No	No	High computational cost
FL-based	Decentralized	High	Yes	No	Lacks spatiotemporal modeling
Federated DCRNN	Learning-based, decentralized	High	Yes	Yes	Fixed-graph DCRNN can't handle moving vehicles

Comparative analysis of CH stability in different numbers of clusters for a network with 1,000 vehicles performed by the weighted metrics & LSTM approach (Mallick et al., 2020; Saleem et al., 2021) and the proposed Federated DCRNN is depicted in Figure 6. Results show the capacity of the Federated DCRNN approach for achieving more stable clusters than the Weighted Metrics & LSTM work, anywhere from 90 to over 100 clusters, especially as the number of clusters increases. This demonstrates that the Federated DCRNN architecture has better flexibility and efficiency than other methods to maintain intact and reasonable cluster structures under highly varying vehicular scenarios, which could provide more stable intra-cluster communications and extend the lifetime of the cluster head in high-density VANETs. This phenomenon has been clearly shown in figure 6 for the model outperformance.

Higher cluster stability decreases frequent cluster reformation and route disruptions, thus reducing control overhead and packet loss while improving network key parameters. To meet these challenges in this approach, a comparison is made between Federated DCRNN and the weighted metrics and LSTM approach, and the projected results in Figure 6 are proven to be significantly outstanding.

Figure 7 proves the energy consumption trends of Weighted Metrics & LSTM and the introduced one, the Federated DCRNN model, across data rates of 10 pkts/sec and 14 pkts/sec, plotted against the number of clusters varying from 1 to 11. This result graph clearly reveals that the weighted metrics & LSTM steadily show higher energy consumption, with noteworthy peaks at 22 joules and 20 joules for the data rates of 10 pkts/sec and 14 pkts/sec, particularly in few clusters, indicating potential inefficiencies in handling dense clustering. However, the Federated DCRNN approach establishes a 10% drop in energy across the different data rates, reflecting enhanced efficiency.

Discussion

The collaboration of Federated Learning and DCRNN in VANETs for cluster head selection carries enormous potential for improving Intelligent Transportation

Systems (ITS). This overview provides the reader with the theoretical and experimental concepts learned from our study, requirements, and possible limitations as well as future perspectives.

Implication on the Intelligent Transportation Systems (ITS) Two perennial issues in VANET management: Supporting robust data-driven decision-making in a privacy-aware environment and scaling the management of a mobile heterogeneous network.

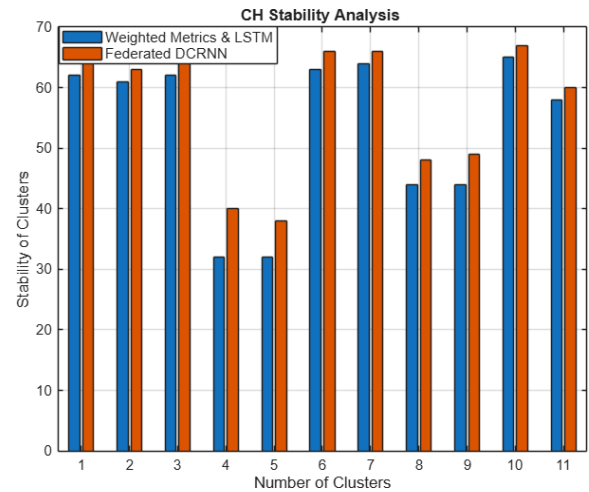


Fig. 6: CH Stability Analysis

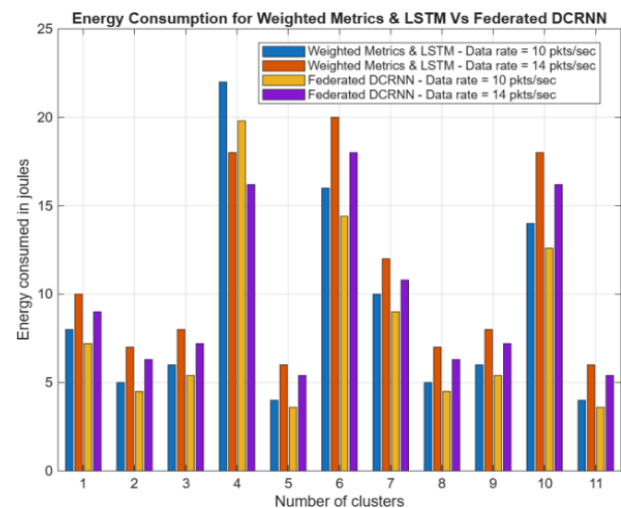


Fig. 7: Energy Consumption

The use of decentralized federated learning avoids the drawbacks associated with centralized processing, and the introduction of DCRNNs guarantees that the spatiotemporal dynamics of vehicular networks are effectively modelled.

In addition, these features together contribute to the design of smarter ITS as adaptive and robust systems. Consequences include the possibility to improve vehicle safety and to optimize traffic planning and to support new concepts for decentralized network control. The paradigm leverages real-time data and predictive analytics to alleviate the congestion on roads and decrease the latency in safety-critical connectivity.

The key training and implementation parameters used for the local DCRNN model and federated learning process are summarized in Table 3.

Table 3: Summary of Local DCRNN Model Training

Parameter	Value	Remark
Diffusion Order P	(2)	As stated in Eq. (1)
Recurrent layers / hidden units	(2) recurrent layers / (64) hidden units	Lightweight variant
Input window / prediction horizon	(12) / (6) steps	Sampling intervals
Loss function	Mean Absolute Error	Over valid observations
Aggregation rule	FedAvg (sample-weighted)	Against implementation
Communication rounds	100	Overall Window
Framework Used	Python 3.9, TensorFlow / PyTorch	As Mentioned

Conclusion and Future Scope of Work

In this work, we introduced a new method for CH selection in VANETs, which is the first FL with DCRNN. It brings with it a distributed, privacy-preserving, and scalable algorithm for intelligent CH election, which prevents the defects of classical centralized or heuristic approaches. Unlike current solutions, we enable vehicles to do part of model training locally on mobility and connectivity information and exchange only model gradients for privacy protection. Experimental results revealed that the proposed model can reach around 82% accuracy in CH selection, which has a 12-15% increased accuracy compared to baseline methods such as WCA and MBDC. Moreover, the framework reduces communication costs by 40% while maintaining consistent prediction results as the number of vehicles increases from 50 to 300, and it also demonstrates strong scalability. The main advantages of this research

include spatiotemporal learning, low bandwidth utilization, high robustness in clustering accuracy, and privacy-preserving properties. Nevertheless, the model relies on a semi-central aggregator to collect federated model updates and assumes that V2I links are reliable, which may not always be realistic in practice. realistic in practice. In addition, the heterogeneity among vehicular hardware, the effects of adversary model poisoning, and diverse network conditions present additional challenges that remain unresolved and need to be addressed. Future works include reinforcement learning on where models are deployed from model training and evaluation to real-world deployment of the learned models, introductions of other blockchain-based model verification frameworks, refinement of DCRNN with low-resource devices, and implementation of hybrid federated-edge architectures for responsive and resilient intelligence. In addition to these efforts, formal ablation and significance testing studies can be made on the proposed work as a futuristic improvement. As a whole, this work contributes a major step forward in VANET research and provides a cornerstone for the design of data-intensive, privacy-aware IDS for future ITS architecture that operates in a dynamic vehicular environment.

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Author's Contributions

P Subhash: Designed coordinated research activities, conducted the literature review, interpreted the results, and prepared the manuscript.

Madana Srinivas: Guided in Methodology and experimentation.

A. Ranjith: Idea framing and strengthening the results

Ravinder Reddy Baireddy: Contributed to literature work and provided key insights for the discussion.

Mohammed Qayyum: Guided in the selection of suitable algorithms and Writing review and edited.

Ethics

The authors declare that there is no conflict of interest regarding the publication of this work.

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