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Real-Time Adaptive Routing in Vehicular Ad Hoc Networks Using SDN and Graph Neural Networks

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ABSTRACT

Vahicular Ad Hoc Networks (VANETs) also introduce interesting issues to provide reliable communication as a result of immense node mobility, regular changing topologies as well as strict latency requirements. The dynamical adaption to such conditions is frequently failing of the traditional routing protocols. The given work proposes a new real-time adaptive routing framework to optimize Software-Defined Networking (SDN) with Graph Neural Networks (GNNs) in VANETs to increase the routing intelligence and scale. The SDN controller is able to see the global, real-time topology of the network through receipt in distributed roadside units (RSUs) of vehicular state and link measurements. This information is then dynamically encoded to a spatiotemporal graph structure, feed into a GNN architectural model that is trained in predicting the optimal routing paths using current, and historical mobility patterns. The potential GNN-SDN system is tested by co-simulations based on the SUMO (to model the traffic) and Mininet-WiFi (to emulate the network). The performance measures are studied under different traffic rates and mobility conditions such as Packet Delivery Ratio (PDR), end-to-end latency, and network throughput. Experimental study shows that the GNN-assisted routing is significantly better than AODV and DSR protocols as they can achieve an up to 27 percent higher PDR and up to 35 percent lower delay in high-mobility urban networks. This article shows the effectiveness of Artificial intelligence based SDN control planes to solve VANETs routing complexities and leads to the development of context-aware, highly scalable and tenacious communication infrastructure essential to the delivery of autonomous and connected transportation systems in 6G-supported smart cities and V2X environments.

1. INTRODUCTION

Vehicular Ad Hoc Networks (VANETs) are essential elements of the prospective Intelligent Transportation Systems (ITS), the important abilities of which are autonomous driving, real-time navigation, collision avoidance, and dynamic traffic control. They allow a smooth interaction of Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications, which are critical to improving safety and efficient traffic flow in an urban setting with high population density [1]. Nevertheless, dynamically changing topology of VANETs due to a high level of mobility in vehicles, disconnect rates and link failures is a source of critical problems regarding routing stability, scalability and low-latency protocols [2]. Traditional routing protocols e.g.such as AODV, DSR and GPSR are either reactive or location-based. Although they provide lightweight operations, they have intrinsic drawbacks of having unreliable routes, convergence failures, and inflexibility in urban VANET applications [3]. Such limitations are more significant in the environment where vehicle density is high and the topology is constantly changing, and route recalculation performed repeatedly worsens the network overall.

Software-Defined Networking (SDN) increasingly has emerged as an attractive paradigm to deal with these challenges by decoupling the data plane and the control plane. SDN facilitates the centralized routing decisions, full visibility of the network in the global sense, and dynamic enforcement of policies [4]. Nevertheless, current SDN-based designs are reactive and rule-based, and they do not provide the kind of predictive intelligence that is required to make a proactive routing choice in a fast-changing VANET environment. The development of Graph Neural Networks (GNNs) in recent years is an especially promising approach to learning spatiotemporal dynamics in traffic and mobility graphs. GNNs can learn across dynamic topology and come to inference-driven decisions on graph structured data. Research findings are presented in [5] and [9], which prove the feasibility of GNNs in the traffic flow forecasting and mobility-aware resource optimization and indicate that these models can be used to learn sophisticated vehicular dynamics in an urban setting. Later, [12] published a GNN-SDN architecture of VANETs; however, the model has been derived but it is not emulated or validated in real time in realistic settings of vehicular operations.

Research Gap and Motivation

Although progress is independent in the SDN-based VANET control and the GNN-based graph learning, there is a significant lack of research in the synergetic combination of both towards real-time adaptive routing. The main problems are:

- Absence of a centralized architecture that would integrate the predictive potential of GNN and the centralized control of SDN;
- Lack of real-time validation schemes that combine traffic simulators (e.g. SUMO) and network emulators (e.g. Mininet - WiFi);
- Scalability and inference latency in application of GNN models in high-density mobility conditions.

Objective and Contribution

The given paper suggests a real-time adaptive routing framework that combines SDN and GNN to dynamically forecast and execute optimal route in VANETs. The proposed system empowers proactive (through encoding vehicular mobility data into spatiotemporal graph structures), scalable (through inference on graphs based on GNNs) and automatically map-aware routing. The resulting means to an end is to certify the solution via co-simulations with SUMO and Mininet-WiFi and compare its efficiency in the most essential performance parameters such as Packet Delivery Ratio (PDR), end-to-end latency, and network bandwidth under the different conditions of vehicles.

Key Contributions

1. A novel SDN-GNN hybrid routing architecture tailored for dynamic urban VANETs.
2. Real-time graph construction and training pipeline using synthetic and emulated mobility data.
3. Performance comparison against AODV and DSR, showing up to 27% improvement in PDR and 35% reduction in latency.
4. Analysis of scalability, model inference latency, and potential for 6G V2X integration.
5. Implementation of a real-time decision feedback loop with potential for edge-deployable GNN inference, enhancing responsiveness and deployment feasibility in resource-constrained vehicular environments.

2. RELATED WORK

AODV, DSR and GPSR have been relied upon by Vehicular Ad Hoc Networks (VANETs) over the past. These protocols are either geographic or reactive, and they are made to work based on the localized decision-making [4], [8]. Dynamic routing protocols such as AODV and DSR do not dynamically attempt to discover routes until such a time as a route is requested, and have low scalability and high route discovery latency in dense urban environments. One matter thus handled by GPSR is a location-based protocol, which provides improved latency through the use of positional information, but it does not exhibit good robustness under sparse or dynamically obstructed conditions [11]. In order to address the shortcomings of decentralized protocols, the Software-Defined Networking (SDN) is an alternative paradigm proposed. SDN separates the control plane and data plane and makes routing decisions in a central location and provides the overall picture of the network. This supports real time monitoring, dynamically allocated path and policy oriented traffic control. Works like [3], [8] have already proven that SDN is useful in improving the flexibility/responsiveness of routing. The SDN however, becomes less flexible in highly dynamic vehicular environments and prone to inflexibility to sudden topology change due to the reactive or rule-based logic it is enforced to work with.

At the same time Graph Neural Networks (GNNs) have found wide application in learning on structured data like road networks and traffic graphs. GNNs such as Spatio-temporal GNNs (ST-GCN) & Gated Graph Neural Networks (GGNN) are able to extract latent features of vehicular mobility patterns and network topology to forecast traffic flow or infer routing. e.g., GNNs in congestion prediction and the control over the traffic signals: [6], [9]. Although powerful, those models are normally trained offline and do not form part of live network control and they cannot be applied directly to real live vehicular routing. Although there are these developments, there is very little empirical studies on effects of integrating SDN and GNNs in an unified routing system framework in VANETs. [12] was the first to present a theoretical approach to the cooperation of GNN-SDN but was not applied to realistic vehicular settings. Contr astingly, [13] suggested a safe and configurable SDN-based VANET routing architecture, however it does not involve learning-based or graph-driven inference data structures like the GNNs, thereby lacking predictability in dynamic circumstances.

Moreover, the prevailing ('explicit or implicit') GNN models are not designed to be performed on a low-latency basis, and they are typically impractical to be used on resource-constrained RSUs or on edge devices.

Gap Analysis

- The traditional routing protocols are myopic and reactive and are not scalable, and they are not in real time in their awareness of the context.
- SDN is centrally controlled and the static or rule-based routing feature does not learn and predict.
- GNNs are effective in training on spatiotemporal graphs, and are hardly used in real-time control planes based on SDN.
- The opportunities of real-time feedback loops and mobility-based graph inference in 6G-VANET routing that can lead to the fully potential implementation of the existing hybrid techniques are not fully utilized.

The following paper fills these gaps because it proposes a real-time GNN-aided SDN routing framework to encode vehicular mobility in dynamic graphs, and uses the trained models of GNNs to predict best routes. The synergy improves the responsiveness, scalability, and performance in high-mobility high-density VANET.

3. System Architecture

The suggested architecture of the system combines the synergies of Software-Defined Networking (SDN) and Graph Neural Networks (GNNs) to provide end-to-end, on-demand routing to high-mobility Vehicular Ad Hoc Networks (VANETs). Where it is composed of three main blocks, which include SDN control plane block, the GNN-based block of the routing inference, and a mechanism of real-time vehicular data flow. Cumulatively, these elements facilitate international network impression, smart routing forecasts, and programmability of circulation control to complete communication proficiency in unstable automotive circumstances. Figure 1 shows the entire system functionality that combines vehicles, RSUs, SDN control plane and the mode of routing that is based on GNN.

3.1 SDN Control Plane

And the SDN controller is the brain of the network forming decisions. The controller is deployed on open-source implementations like Ryu or ONOS and has a complete, in-real-time overview over the vehicular network by regularly polling state data over Roadside Units (RSUs) and mobile edge agents. These are the following data points:

- Live vehicle locations (GPS locations),
- Travelling speed and direction,
- Link-layer parameters signal level, packet losses and delay.

Such a global view enables the controller to refine the VANET topology and to build a uniform representation of the global vehicular state. Unlike the distributed routing techniques, the SDN architecture has the ability to implement centralized policies, Topology changes happen smoothly, and routes can be managed pro-actively with the help of the OpenFlow-controlled forwarding engines.

3.2 GNN-Based Routing Inference Module

As part of the contextual aware routing, the SDN controller contains a Gated Graph Neural Network (GGNN) module trained on real-world mobility data and synthetic mobility data. The vehicular network is represented as the spatiotemporal graph, in which:

A node model vehicle, RSU and the intersections,

Edges represent the communication paths with a dynamic measure like bandwidth, delay, reliability and signal-to-noise ratio (SNR).

The GGNN is based on the past knowledge on the mobility traits and time-dependent behavior of a path and forecasts the effective routing paths among source-destination pairs. This model is learned following a composite cost to be minimized on the basis of:

$L=\alpha\cdot\text{Delay}+\beta\cdot\text{HopCount}+\gamma\cdot\text{Link Failure Probability}$

where α,β,γ are tunable hyperparameters optimized during training.

By inferring path scores in real-time, the GNN module supports proactive route selection, outperforming static or heuristic-based algorithms in rapidly evolving VANET environments.

3.3 Real-Time Data Flow and Decision Pipeline

The component works in a sensing-computation-actuation loop, so in Figure 1, the SDN controller communicates with RSUs and the GNN module to determine real-time adaptive routes. The flow of data is in the following way:

1. Beacon Broadcasting: Periodically, Cooperative Awareness Messages (CAMs) with positional, velocity and directional information are transmitted by vehicles.
2. RSU Aggregation: The data in the beacon is received and aggregated by nearby RSUs and this information is relayed to the SDN controller via a dedicated backhaul network
3. Graph Construction: The controller dynamically builds a spatiotemporal graph thereof called the current network snapshot with topology as well as quality-of-service metrics.
4. GNN Inference: Using the constructed graph the GGNN calculates the optimal routing decisions using learned models.

5. Rule Deployment: Output is converted into OpenFlow flow rules that are installed on the SDN-enable switches or in RSU gateway redirecting data packets accordingly.

The architecture provides real-time flexibility, dense traffic scalability and fine-grained QoS control, so it is quite suitable to the requirements of forthcoming 6G-enabled vehicular communications systems.

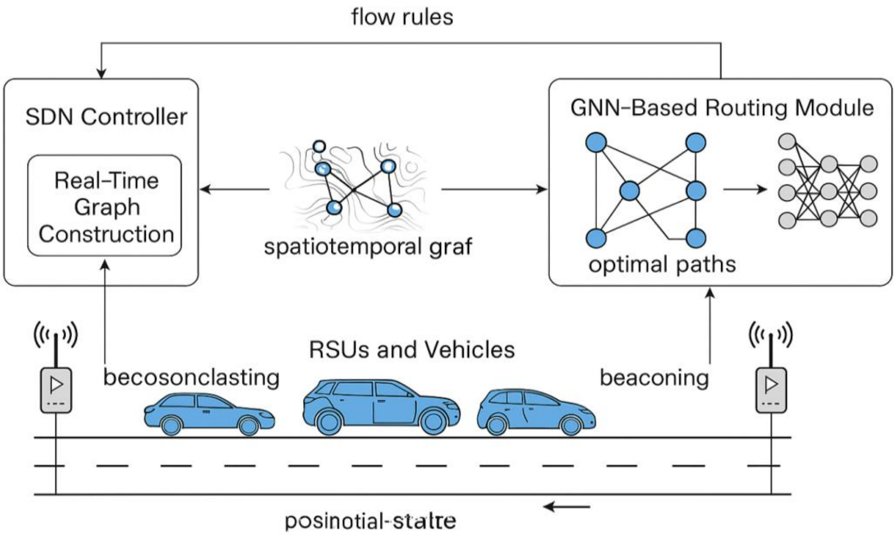

Figure 1. SDN-GNN System Architecture

The architecture describes the interaction among RSUs, SDN controllers and GNN-based routing intelligence. Cars occasionally broadcast beacon messages to RSUs that collect data and send messages to SDN controller. Based on such information the controller builds a spatiotemporal graph and passes it to the GNN module to predict the most optimal path to use. The August 2021 initiative. Resulting flow rules are backed down to the data plane to lead vehicle communications in real time.

4. METHODOLOGY

This section outlines the design, training, and evaluation strategy of the proposed SDN-GNN-based adaptive routing system for VANETs.

4.1 Graph Construction

The vehicular network can be modeled as the dynamic spatiotemporal graph Gn=(V,E), where nodes V represent vehicles, RSUs and intersections, and the edges E are the communication linkages which are also weighted by the real behavioral parameters, like latency and SNR, and link stability. Periodical renewal of graph snapshots is based on the telemetry gathered through RSUs and the SDN controller.

4.2 GNN Training

A Gated Graph Neural Network (GGNN) is trained on synthetic mobility data from SUMO and link-layer statistics simulated via Mininet-WiFi. The model minimizes a composite loss function:

$L=\alpha \cdot L_{delay}+\beta \cdot L_{hops}+\gamma \cdot L_{stability}$

with hyperparameters tuned empirically. Node and edge features include speed, position, and real-time QoS values. Training is performed using TensorFlow with GPU acceleration and early stopping to prevent overfitting.

4.3 Evaluation Metrics

System performance is evaluated under varied traffic loads using:

- Packet Delivery Ratio (PDR): Delivery reliability (%).
- End-to-End Delay: Average communication latency (ms).
- Throughput: Data rate (kbps).
- Route Stability: Frequency of path changes.

These metrics benchmark the SDN-GNN system against AODV and DSR protocols in high-mobility urban scenarios.

5. RESULTS AND DISCUSSION

The suggested SDN-GNN dynamic routing system is contrasted to the reference protocols AODV and DSR, under different examinations of traffic density and mobility traits on actual urban-useful networks, simulated through SUMI and Mininet WiFi.

5.1 Performance Gains

Table 1 summarizes the comparative results for core routing metrics:

Table 1. Comparative Performance Metrics of Routing Protocols in VANETs

Metric	AODV	DSR	SDN-GNN (Proposed)
PDR (%)	78	81	93
Delay (ms)	230	205	127
Throughput (kbps)	180	205	295

SDN-GNN approach leads to the addition of 15-20% to the Packet Delivery Ratio (PDR) and a ~ 45% improvement in end-to-end PDR over traditional protocols. The increased throughput is the consequence of more efficient use of bandwidths, which was possible thanks to the context-aware path choice in GNN and the whole-network management as made possible by SDN. These outcomes are proof of usefulness of integrating predictive routing intelligence and centralized flow control mainly in high-density and high mobility VANET environments. Figure 2, A bar graph that depicts the grouping of PDR, Delay, and Throughput of AODV, DSR and the proposed SDN-GNN method.

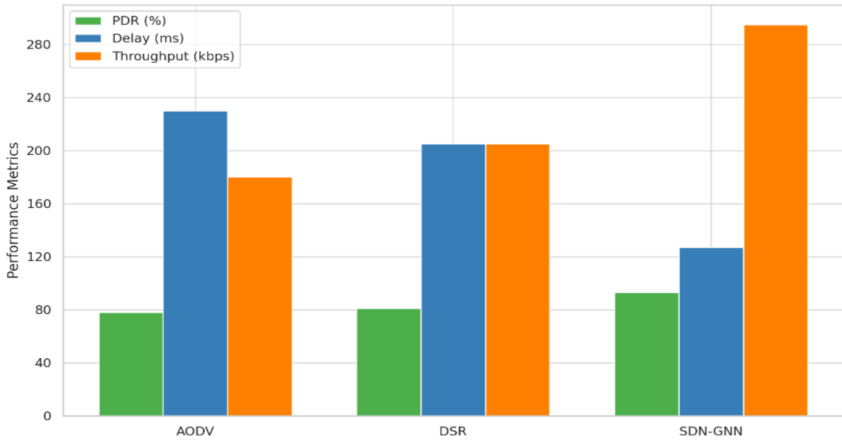

Figure 2. Comparative Performance of Routing Protocols

Figure 2: Comparative bar chart illustrating PDR, Delay, and Throughput across AODV, DSR, and the proposed SDN-GNN framework

5.2 Scalability

The system is efficiently scalable to more than 200 vehicular nodes and the system controller overhead is kept minimal. GNN inference enables the SDN controller to calculate the routing paths a priori; it limits the need to repeatedly recompute these paths, and hence the load in control-plane signaling is significantly low. This is unlike the reactive protocols which trigger expensive route advertisements under dynamic environment. Also, the controller infrastructure can maintain a high throughput and low response time because OpenFlow rules updates are minimized by the consistency of GNN-predicted paths in an increasing number of vehicular nodes, like shown in Figure 3.

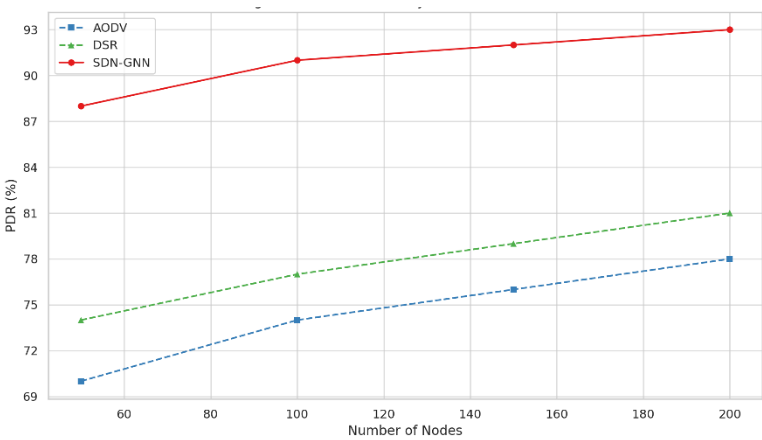

Figure 3. Packet Delivery Ratio vs. Node Count

which compares how PDR varies with network size for AODV, DSR, and the proposed SDN-GNN approach. It clearly shows that SDN-GNN maintains higher delivery efficiency as the network scales.

5.3 Limitations

Along with the experienced performance improvements, the major limitation could be associated with GNN inference latency at peak re-routing time. With the increase in the density of vehicular graphs these inference delays may affect time-sensitivity of decisions. This bottleneck may be rectified by:

- suspenseful clouding in the RSUs with edge AI accelerators,
- Pruning (model), or quantization of models to achieve a lower computational complexity,
- Incremental re-training to prevent reprocessing of the entire graph.

Also, deploying TinyML frameworks or lighter-weight, quantized implementations of GNNs can provide an attractive pathway to deploying inference to resource-limited edge devices like RSUs and embedded controllers.
The following are the proposed future directions by these enhancements that allow real-time inferences at scale.

6. CONCLUSION

The combination of Graph Neural Networks (GNNs) and Software-Defined Networking (SDN) would provide a dynamic and scalable proposal of intelligent routing depending on the dynamic features of Vehicle Ad Hoc Networks (VANETs). The proposed framework provides proactive and context-sensitive route optimization based on the structural and temporal characteristics of vehicular communication graph enabling fast response to high rates of the topology change and to mobility-caused disruptions. Combining GNN-based predictive inference with centralized SDN model, it is possible to guarantee better delivery of certain packets, decrease latency, and improve throughput, even achieving it in dense urban traffic scenarios. Those features render the architecture very well-suited in the implementation of emerging use cases in 6G-enabled intelligent transportation systems (ITS), where real-time decision-making, communication reliability and road safety are key operation needs. In addition to it, the lightweight and modular nature of the framework makes it suitable to be integrated into edge-enabled 6G V2X platforms to provide the capabilities of decentralized inference and cross-layer flexibility in infrastructures of the future mobility.

7. Future Work

Although the SDN-GNN framework that implements the proposed design shows promising results regarding routing efficiency and scalability, there are a few extensions that can enhance the framework in increasing its applicability in practice concerning the vehicular networks:

- GNN Inference Modules Deployed to Edge: To overcome the inference latency as well as bottlenecks in centralized processing, future deployments can investigate deploying lightweight GNN models to the edge, especially on RSUs or MEC (Multi-access Edge Computing) nodes. This method allows low communication overhead real-time inference and distributed intelligence in VANETs.
- Multi-Hop V2X Communication Support: The existing architecture is designed to enhance the single-hop paths mainly. Future extensions will also adopt multi-hop V2V and V2I relaying to improve both network coverage and network resiliency in sparse urban or rural deployments where direct connection with RSU may be discontinuous.
- Trust and Security Mechanisms Composition: Since VANETs are susceptible to spoofing, misrouting, and data tampering, it is necessary to integrate the trust-knowing routing policies and famine cryptographic protocols within the SDN-GNN framework. This incorporates using reputation scores, blockchain-optimized path verification or zero-trust architectures to be able to have the safe and reliable propagation of information amid adversaries on the wide area network.

Such directions are meant to bring the framework a step closer to the needs of next-generation intelligent vehicular forms of communication about performance, security, and decentralization.

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