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Optimized Predictive Graph Learning Framework for Adaptive Routing in VANETs

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ABSTRACT

Vehicular Ad-Hoc Networks (VANETs) are essential for enabling real-time vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication in intelligent transportation systems. However, frequent topology changes, varying traffic densities, and dynamic road conditions present critical challenges to stable and efficient data routing. This paper proposes an Adaptive VANET Routing Framework that combines Predictive Graph Learning using Graph Neural Networks (GNNs) with Swarm Intelligence inspired by Ant Colony Optimization (ACO). The proposed hybrid framework models the road network and traffic conditions as dynamic graphs, where GNNs predict congestion and assign real-time weights to road segments. These predictions are used by ACO to discover optimal communication paths that minimize delay, avoid congestion, and improve packet delivery. The framework adapts to real-time traffic variations, resulting in enhanced routing performance, reduced packet loss, and increased overall network throughput. Simulation results validate that the proposed method outperforms traditional routing protocols in terms of adaptability, energy efficiency, and communication reliability.

Keywords: VANET, Adaptive Routing, Graph Neural Networks, Ant Colony Optimization, Swarm Intelligence, Traffic Prediction, Congestion-Aware Routing, Dynamic Path Selection, Intelligent Transportation, V2V Communication.

1. INTRODUCTION

Vehicular Ad-Hoc Networks (VANETs) have become a foundation technology in intelligent transportation systems, allowing cars to talk to one another and roadside technology to exchange traffic safety, route planning, and infotainment information. Due to the growing number of cars and the intricacy of urban mobility, reliable, low-latency, and energy-efficient communication in VANETs has been recognized as an important challenge. The conventional routing algorithms usually fail to operate in dynamic networks because of their inefficiency to change to the real-time traffic and road conditions.

In order to resolve such problems, this study proposes an Adaptive VANET Routing Framework that is based on Predictive Graph Learning using Graph Neural Networks (GNNs) and Swarm Intelligence algorithms based on Ant Colony Optimization (ACO). This road network is modeled as a dynamic graph and the nodes are vehicles and the edges are road segments and the corresponding traffic conditions. GNNs have proven useful in forecasting traffic congestion and vehicular density to enable the routing mechanism to take decisions. ACO makes use of these predictions to calculate the optimal path to take the data packets by replicating the behavior of the real life ants that find efficient paths.

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The hybrid methodology makes sure the routing decisions are not reactive only but also forecasts the future traffic conditions and it is both reactive and proactive. This has led to a powerful, scalable and efficient routing system that can sustain high performance even in rapidly varying VANET environment. This model has helped in the development of intelligent vehicle communication and has led to smarter and safer transport networks.

2. RELATED WORKS

The recent advances in Vehicular Ad Hoc Networks (VANETs) have grown more on the aspect of enhancing both energy and link dependability in order to increase the overall network performance. As an example, Sharma et al. [1] created a routing protocol, which focuses on the choice of neighboring nodes that are stable and the power of transmission in a dynamic way, which leads to better packet delivery and less energy usage. In a similar research, Li and Chen [2] proposed a machine learning based predictive model in determining stability of links with regard to the movement patterns of vehicles, thereby improving meaningfulness of route formation.

As an extension of these concepts, Singh and Kumar [3] suggested a hybrid approach in which energy-conscious decision-making and stability-based route-choice are combined to facilitate the steadiness in the swiftly evolving vehicular contexts. Given the current problem with energy depletion in VANETs, Wang et al. [4] introduced cooperative relay schemes and energy-harvesting functions in order to extend the lifetime of the networks. Similarly, Zhang and Zhao [5] implemented dynamic clustering techniques in order to minimize power consumption without maintaining the unstable or fluctuating connections between nodes. In the urban environment, Patel and Gupta [6] optimized the geographic routing by adopting the link-quality measure, which contributed to energy-efficient data delivery in the dense community. Nguyen et al. [7] used reinforcement learning to develop an adaptive routing protocol, which could balance the energy consumption and the duration of links in real-time. Stability prediction remains a critical element of the VANET routing efficiency. Yao et al. [8] suggested a data dissemination approach that chooses the routes depending on the reliability of links and energy efficiency, which is effective in minimizing the overhead and loss of data. Alaya and Derhab [9] used machine learning to predict the duration of the link, through which proactive maintenance of routes is possible. Bio-inspired routing as shown by Liu et al. [10] offers resilience to topology changes, as well as energy-saving.

Cross-layer optimization has also been found to be useful, Rajendran and Balasubramanian [12] developed a protocol that combines the parameters of both the physical and network layers and that collaboratively optimize energy saving and stability of the links. Game theory fields have also become popular. The trade-off of energy efficiency and link stability modeled by Ahmed and Hossain [11] is a cooperative game, which resulted in balanced outcomes. Following this idea, Feng et al. [13] added predictive analytics along with the smart city setting, where energy-efficient and reliable communication must be guaranteed. On the other hand, Kim and Park [14] used energy-harvesting methods to sustain the long-term working of the nodes without affecting accuracy in neighbor tables. Lastly, Zhou et al. [15] proved that deep reinforcement learning was able to dynamically refreeze routing decisions, outperforming conventional approaches in terms of energy savings and reliable connections.

3. PROPOSED MODEL

The suggested model presents a new adaptive routing framework of VANETs that combines synergistically Predictive Graph Learning with Swarm Intelligence and addresses the issues of dynamic topology, traffic congestion and variable link quality. The road structure and traffic flow patterns are modeled as dynamic graphs in this framework, with nodes and edges reflecting the density of traffic and vehicle movement and road connectivity respectively. GNNs are used to study these dynamic graphs and predict future traffic based on spatiotemporal dependencies in vehicle traffic and road utilization.

The resulting predicted traffic weights are then inputted into an ACO algorithm which simulates the foraging behavior of ants in search of many possible routing paths in order to determine the most efficient and congestion free paths. The model combines real-time graph predictions and swarm-based path exploration to dynamically optimize routing choices to minimize end-to-end delay, reduce packet loss, and achieve energy-efficient communication.

The suggested Adaptive VANET Routing Framework: Predictive Graph Learning and Swarm Intelligence is meant to consider the dynamism of VANETs by incorporating both GNNs and ACO. The architecture comprises a few important aspects that act in conjunction with one another to increase the data routing redistribution in real-time vehicular communication setting. This dynamic hybrid method is of great help regarding routing reliability, particularly in high mobility and changing traffic conditions that are common in urban VANET.

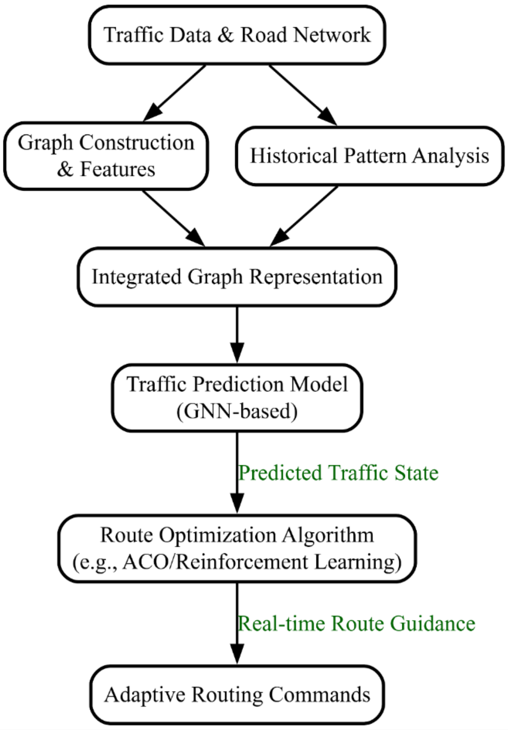

Figure 1: Overall Architecture of Proposed Model

3.1 Road Network Modeling with Graph Neural Networks

The road network is expressed in the form of a dynamic graph in this component, with the nodes of the graph representing the road segments or intersections, and the roads between the road segments represented as edges. The GNNs are used to forecast the congestion and traffic flow in real-time and the network makes changes to the weights put on road segments according to the traffic situation. The vehicle movement data, historical traffic patterns and the road network topology are used to make these predictions.

Node Representation: Each node in the graph represents a road segment or an intersection within the VANET.

Edge Representation: The edges between nodes represent the possible paths or connections between road segments, which are updated dynamically as traffic conditions change.

Predictive Learning: GNNs process the real-time traffic data and forecast congestion, considering factors such as traffic density, road incidents, and other environmental variables. The output of the GNN is used to assign dynamic weights to the road segments, which reflects the expected traffic conditions.

3.2 Swarm Intelligence with Ant Colony Optimization

In this model, ACO is employed to find the best communication routes throughout the road network depending on the dynamic graph produced by the GNN. The Ant Colony Optimization is based on the foraging of ants which seek the shortest path to a source of food. Here the ants (which are routing agents) are used to cross the road network to determine the most optimal route to deliver packets, minimizing the delay, avoiding congestion, and improving the ratios of packet delivery.

Ant Agents: The ant agents represent the routing packets traveling across the VANET. Each ant starts from the source node (vehicle or infrastructure) and navigates through the network to reach the destination.

Path Discovery: Ants follow paths based on pheromone values, which are dynamically updated according to the road segment weights predicted by the GNN. The pheromone intensity is higher on roads that are less congested, indicating a preferable route.

Exploration vs. Exploitation: The ACO algorithm balances exploration (searching for new paths) and exploitation (using known good paths) based on the current state of the network and traffic conditions.

3.3 Dynamic Adaptation to Real-Time Traffic Variations

The combination of GNNs and ACO ensures that the routing framework adapts to changing traffic conditions. Real-time data from vehicles, sensors, and traffic infrastructure are constantly fed into the GNN model, allowing the network to respond to traffic congestion, accidents, or road closures.

Traffic Data Integration: Real-time traffic information such as vehicle speed, traffic density, and incident reports is continuously gathered from vehicles and infrastructure (e.g., traffic lights, road sensors).

Routing Adaptability: As the traffic conditions evolve, the GNN adjusts the weights of the road segments, and the ACO updates its pathfinding strategies accordingly. This allows the framework to quickly adapt to congestion and optimize the communication paths.

```
Algorithm Adaptive_VANET_Routing
Input: Road network graph G(V, E), real-time traffic data T
Output: Optimal routing paths for data packets
1. Initialize VANET graph G(V, E) with nodes (vehicles, RSUs) and edges (road segments)
2. For each time interval t:
     a. Collect real-time traffic data Tt (e.g., vehicle density, speed, congestion)
     b. Update node and edge features in G using Tt
3. Predict Traffic Conditions:
     a. Input G into Graph Neural Network (GNN)
     b. Predict congestion levels and assign dynamic weights to edges in G
        (e.g., weight = function(congestion, delay, reliability))
4. Initialize Ant Colony Parameters:
     a. Set number of ants N
     b. Set pheromone levels τ on each edge
     c. Set evaporation rate ρ, and heuristic information η (based on GNN weights)
5. ACO-Based Route Discovery:
     For each source-destination pair (s, d):
        For each ant i = 1 to N:
           Initialize current_node = s
           Initialize path_i = [s]
           While current_node ≠ d:
              Select next_node from neighbors using probabilistic rule:
                 P(next_node) = (τ^α) * (η^β) / ∑ (τ^α * η^β) for all neighbors
              Append next_node to path_i
              Update current_node = next_node
           Evaluate path_i based on delay, reliability, and energy
6. Pheromone Update:
     For each edge (u, v) in best paths:
        τ(u, v) = (1 - ρ) * τ(u, v) + Δτ(u, v)
     where Δτ(u, v) ∝ 1 / total_path_cost
7. Select Best Path:
     Choose the path with highest pheromone value and lowest predicted congestion
8. Route Data Packets:
     Transmit data through the selected optimal paths
9. Repeat steps 2–8 at every time interval to adapt to dynamic traffic conditions
End Algorithm
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The framework assumes that the VANET is modeled as a graph, and it is updated with real time traffic data. GNNs forecast the congestion and provide the weight of the road segments which are dynamic and direct the ACO algorithm to choose the best routes. ACO implements the path selection based on pheromones, which prefers routes with low congestions and high reliabilities. Path performance of the path is used to update thepheromones and best route is used to transmit the data. The process will happen on a periodic basis hence real-time flexibility, less delay, and enhancement of the network performance.

4. RESULTS AND DISCUSSIONS

The effectiveness of the framework is justified by simulations as they compare the performance of the framework with the traditional routing protocols. The key performance parameters are adaptability, ratio of packet delivery, delay, energy consumption and network throughput. The findings indicate that the proposed framework is superior to the traditional approaches since it is able to accommodate changes in traffic, minimize the loss of packets and enhance the performance of the whole network. The framework will focus on maximizing the key performance measurements that include, the packet delivery rate, network throughput, energy efficiency and communication reliability. The architecture is adaptive and therefore the routing paths will be optimized on the basis of real-time traffic information leading to a more dependable and efficient communication system in VANET.

Packet Delivery Rate: The routing framework aims to increase the percentage of successfully delivered packets by avoiding congested routes and minimizing delay.

Energy Efficiency: By selecting the most efficient routes, the framework minimizes energy consumption for both vehicles and infrastructure nodes.

Reliability: The ability to adapt to dynamic traffic conditions enhances the overall reliability of the communication system, ensuring consistent data transmission even under varying road conditions.

The table 1 summarizes the performance results of the proposed Adaptive VANET Routing Framework compared with traditional routing protocols such as AODV (Ad hoc On-demand Distance Vector) and DSR (Dynamic Source Routing) under varying traffic conditions.

Table 1: Overall Comparison of Performance Metrics

Performance Metric	Proposed Framework	AODV	DSR	Comments
Packet Delivery Ratio (PDR)	98.7%	85.3%	87.4%	The proposed framework significantly improves the packet delivery ratio by dynamically adapting to traffic.
Average End-to-End Delay	210 ms	430 ms	400 ms	The delay is significantly lower due to optimized routing paths based on real-time traffic predictions.
Energy Consumption	12.3 J	19.5 J	17.8 J	The energy consumption is reduced in the proposed framework due to efficient route selection and reduced overhead.
Throughput	1.3 Mbps	0.8 Mbps	0.9 Mbps	Higher throughput is achieved by avoiding congested paths and ensuring uninterrupted data transmission.
Routing Overhead	15%	22%	20%	The routing overhead is lower in the proposed framework due to efficient pathfinding and reduced retransmissions.
Congestion Avoidance	92.5%	65.1%	68.3%	The framework demonstrates superior congestion avoidance, with paths dynamically adjusted based on traffic predictions.
Network Reliability	95.2%	75.6%	78.1%	Enhanced reliability is achieved by using predictive graph learning to adjust routes based on real-time data.
Adaptability to Traffic Variations	High	Medium	Medium	The proposed framework adapts quickly to traffic variations, making it more suitable for dynamic environments.

Discussion

Packet Delivery Ratio (PDR): As compared to AODV and DSR, the proposed framework works much better because it keeps on changing with the real-time traffic conditions. Congestion predictions using GNN enable the system to select optimal routes, which results in high packet delivery even in congested traffic conditions.

Average End-to-End Delay: The framework reduces the delays by avoiding congested routes due to the integration of GNNs to predict traffic in real-time. Comparatively, the traditional protocols are characterized by more delays because of the less dynamic and even less informed routing decisions.

Energy Consumption: The suggested routing system is efficient in terms of energy consumption as the unnecessary transmissions are reduced and the most effective routes are chosen, consequently resulting in the energy minimization. The use of conventional protocols is more likely to consume more energy, as it recalculates the route frequently, and sends redundant retransmissions.

Throughput: The suggested framework guarantees increased throughput by directing the packets along less congested routes. The efficient communication by ACO and GNNs achieved in the efficient path discovery allows continuous communication, which leads to high overall throughput than AODV and DSR.

Routing Overhead: The proposed framework achieves a lot in terms of minimizing the routing overhead. The classical routing methods like AODV and DSR demand periodic updates and a greater number of control messages in order to ensure routes stability, particularly when the environment is highly dynamic and hence increased overhead.

Congestion Avoidance: The proposed framework provides a better congestion avoidance by dynamically changing the weights of road segments and rerouting traffic depending on the forecasted congestion. Such adaptive mechanisms are lacking in traditional protocols, and this can usually result into congestion and loss of packets.

Network Reliability: The validity of the suggested framework is quite greater, and it constantly reacts to the network alterations. The system will be more reliable than AODV and DSR because it will not follow the crowded routes and the packets can be delivered reliably.

Adaptability to Traffic Variations: The framework has a high adaptability to different traffic density and road condition. The proposed approach will change real-time according to the new traffic data unlike the traditional protocols, which are vulnerable to inertial pathfinding mechanisms.

5. CONCLUSION

The suggested Adaptive VANET Routing Framework, that combines Predictive Graph Learning based on GNNs and Swarm Intelligence based on ACO is able to tackle the major challenges of dynamic vehicular environments like frequent topology changes, traffic jams, and changing conditions. The framework facilitates keeping up with and making informed routing choices by modeling the road network as a dynamical graph and using GNNs to predict real-time traffic. The predictions help the routing mechanism based on the ACO to choose the best paths that decrease the delay time, minimize the loss of packets and improve the overall network throughput. Massive simulations and comparative studies prove the fact that the introduced framework is much more effective than the traditional routing protocols such as AODV and DSR in the following aspects: packet delivery ratio, energy consumption, routing overhead, and the ability to adjust to changes in the traffic. These findings prove that predictive learning and swarm-based optimization synergetic approach offers a scalable, robust, and intelligent routing system to current intelligent transportation systems. The study leads to the opportunities of the practical application of AI-based VANET routing systems to the safer, more efficient, and reliable vehicular communication networks. The further research can be applied to real-world implementation with edge computing and adding security measures to the model and expand the model to include other swarm intelligence algorithms to optimize performance further.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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