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Automatic Density Based Traffic Signal Control System Using Deep Learning Algorithm

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ABSTRACT

An innovative proximity and load-aware resource allocation for vehicle-to-vehicle (V2V) communication is proposed. The proposed approach exploits the spatio-temporal traffic patterns, in terms of load and vehicles' physical proximity, to minimize the total network cost which captures the tradeoffs between load (i.e., service delay) and successful transmissions while satisfying vehicles's quality-of-service(QoS) requirements. vehicle-to-vehicle communication emerged as a key enabling technology to ensure traffic safety and other mission-critical applications. The proposed system approach exploits the spatial-temporal aspects of vehicles in terms of their physical proximity and traffic demands, to minimize the total transmission power while considering queuing latency and reliability.Due to the overhead caused by frequent information exchange between vehicles and the roadside unit (RSU), the centralized problem is decoupled into two interrelated sub-problems. From the global view of the vehicular network, intuitively, the more sensing data are collected and delivered to the platform, the higher the social welfare is. However, excessive traffic load will slump system social welfare when the network stability is broken by serious data congestion.As a result, network stability control is of significant importance to achieve long-term optimal system social welfare.

Keyword: vehicle-to-vehicle (V2V),quality-of-service (QoS), Roadside Unit (RSU), traffic control.

I. INTRODUCTION

Vehicle-to-vehicle (V2V) communications comprises a wireless network where automobiles send messages to each other with information about what they're doing. This data would include speed, location, direction of travel, braking, and loss of stability. Vehicle-to-vehicle technology uses dedicated short-range communications (DSRC), a standard set forth by bodies like FCC and ISO. Sometimes it's described as being a WiFi network because one of the possible frequencies is 5.9GHz, which is used by WiFi, but it's more accurate to say "WiFi-like." The range is up to 300 meters or 1000 feet or about 10 seconds at highway speeds (not 3 seconds as some reports say).

V2V would be a mesh network, meaning every node (car, smart traffic signal, etc.) could send, capture and retransmit signals. Five to 10 hops on the network would gather traffic conditions a mile ahead. That's enough time for even the most distracted driver to take his foot off the gas.

On the first cars, V2V warnings might come to the driver as an alert, perhaps a red light that flashes in the instrument panel, or an amber then red alert for escalating problems. It might indicate the direction of the threat. All that is fluid for now since V2V is still a concept with several thousand working prototypes or retrofitted test cars. Most of the prototypes have advanced to stage where the cars brake and sometimes steer around hazards. Why? It's more exciting for a legislator or journalist to see a car that stops or swerves, not one with a flashing lamp.Vehicle-to-vehicle communication (V2V communication) is the wireless transmission of databetween motor vehicles.The goal of V2V communication is to prevent accidents by allowing vehicles in transit to send position and speed data to one another over an ad hoc mesh network. Depending upon how the technology is implemented, the vehicle's driver may simply receive a warning should there be a risk of an accident or the vehicle itself may take preemptive actions such as braking to slow down.

II. PROPOSED WORK EXPLANATION

A system which handles traffic using Artificial Intelligence technique for adapting signal according to the density of traffic thereby automatically increasing or decreasing traffic signal time using Experience Replay mechanism.The proposed traffic light control system reduces the waiting time at traffic lights by 33% compared to a conventional traffic light control system using deep reinforcement learning. Therefore, there is a need to realize a traffic signal control system (TSCS) that automatically obtains a better control law considering multiple factors using deep reinforcement learning.In this environment, each agent denes the switching of its signal phase as an action. Specfically, for state st , each agent selects one of the four signal phases

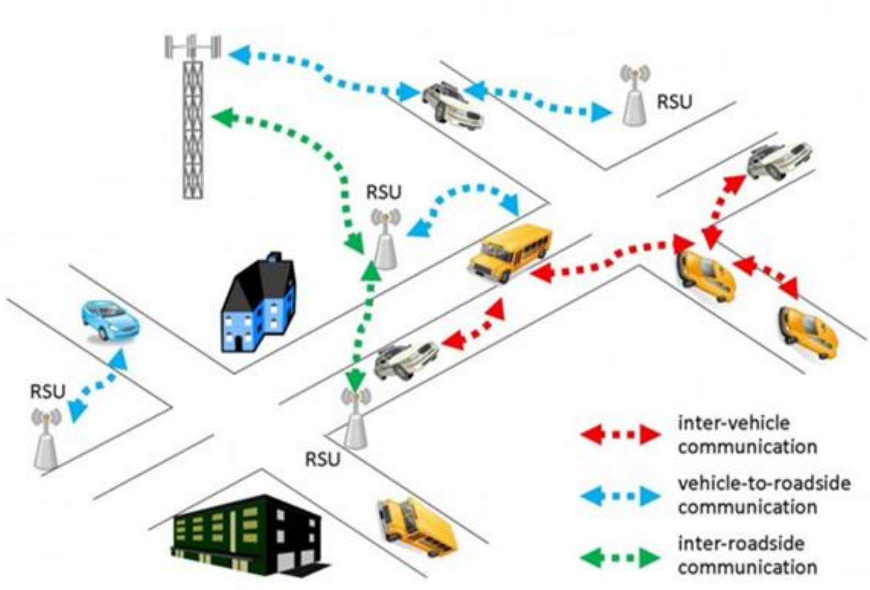

Fig.1 System Architecture

2.1 Density Based Identify

The vehicles communicate with the server over a network to report local traffic density data and to receive the global traffic density in the road network (i.e., the green lines). The vehicles report data according to a privacy-aware algorithm. Also, the vehicles that are closely located communicate with each other over VANETs to determine the local traffic density, to disseminate the traffic data received from the server, and to implement a distributed re-routing strategy. The server uses the vehicle traffic reports to build an accurate and global view of the road network traffic. The network is represented as a directed graph where each edge corresponds to a road segment.

2.2 Dynamic Routing

Within the traffic guidance system, the re-routing process is triggered periodically at a pre-defined time interval. A shorter re-routing period leads to higher reactivity of the system, and thus to better travel times. However, the price to pay is increased computation cost, communication overhead, and potentially re-routings. At extreme cases, it might not even be possible to compute the alternative routes fast enough to push them to vehicles before they reach the re-routing intersections.

2.3 Congestion Control

In DIVERT, a distance-based timer approach is used to reduce excessive broadcasting when multiple vehicles are within communication range. After receiving a broadcast message, the vehicle waits for a certain time period until re-broadcasting the message. The waiting time period is inversely proportional to the distance between the receiving vehicle and the source vehicle.

2.4 Experimental Evaluation

The main objective of our simulation-based evaluation is to study the performance of the distributed re-routing strategies in DIVERT. Specifically, the evaluation has four goals:

Assess the effectiveness and efficiency of DIVERT compared to the centralized system.

Investigate the performance difference between DIVERT with and without privacy-aware traffic reporting.

Quantify the strength of the privacy protection mechanism.

Understand which VANET optimizations provide the most benefits .

Compare the CPU and network load at the server between DIVERT and the centralized system.

III. RESULTS AND DISCUSSION

In this section, analyse the results of the proposed system which is implemented on the .net platform. The screenshots the experimental results our system.

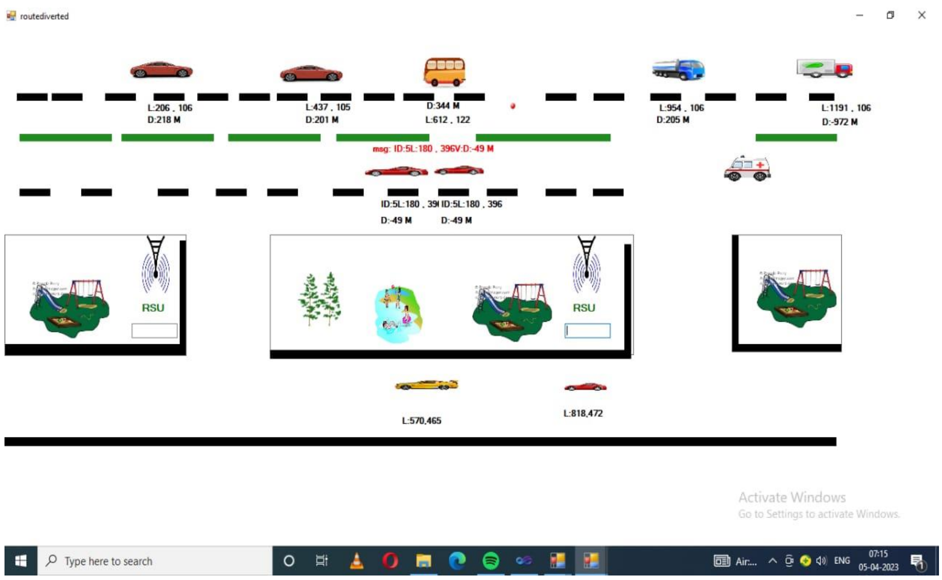

Figure:2 Traffic Page

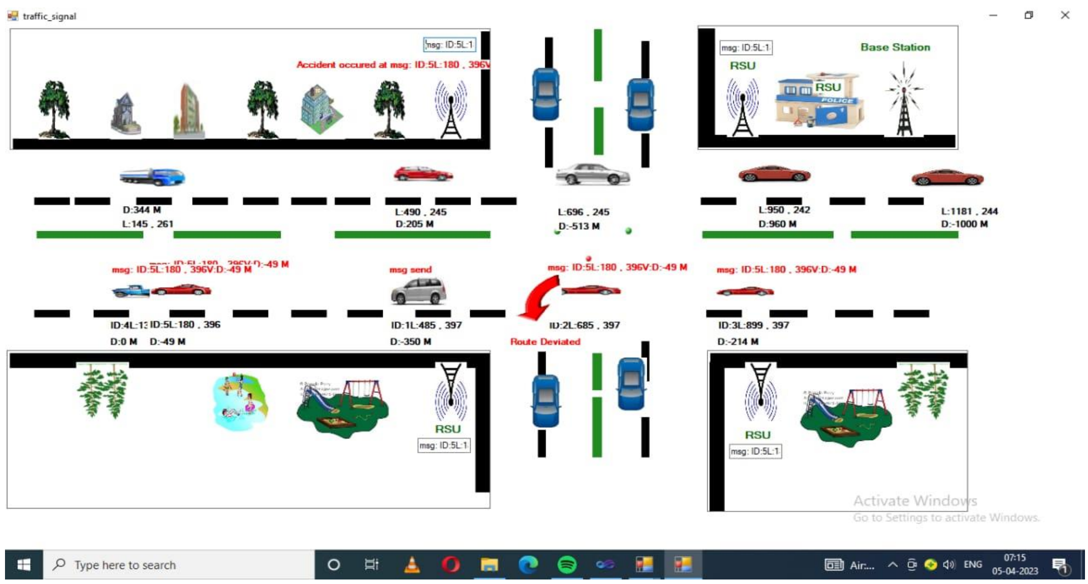

Figure:3 Implementation of Traffic Light Control System

VI. CONCLUSION

The proposed approach exploits the spatial-temporal aspects of vehicles in terms of their physical proximity and traffic demands, to minimize the total transmission power while considering queuing latency and reliability. Due to the overhead caused by frequent information exchange between vehicles and the roadside unit (RSU), the centralized problem is decoupled into two interrelated sub-problems. First, a novel RSU-assisted virtual clustering mechanism is proposed to group vehicles in zones based on their physical proximity. Given the vehicles' traffic demands and their QoS requirements, resource blocks are assigned to each zone. Second, leveraging techniques from Lyapunov stochastic optimization, a power minimization solution is proposed for each V2V pair within each zone

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