A Road-aware Approach for Hierarchical Routing in IoV based on Intents and Q-values

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***Abstract*—Nowadays, intelligence is paving its ways into the IoV domain. With the need of improvement in intelligence in this area, the need of self-organizing network management systems for providing V2X communication is also of vital importance, which current systems lack. Current routing solutions for IoV are complex and require intelligence embedded in the form of closed-loop systems. To this, an intent-based system is designed, which takes high level requirements for routing in IoV. The routing approach is road-aware and widens the scope of road-awareness to vehicles from multiple edge domains. Another problem with the current routing schemes in IoV is that their network management systems are not self-organizing. A self-organizing management system is of high importance and requires a closed-loop system. To this, an intent-based approach is followed integrated with a reinforcement learning model that supports the creation of a routing policy, which is further applied to the orchestrator and enables a road-aware and hierarchical routing approach. The proposed system is shown to be efficient in terms of data rate and the number of packet flows managed per unit time, in the management of vehicular networks.**

I. Introduction

In VANET, the vehicles are connected to each other by an adhoc network. With the increase in number of vehicles day by day, traffic congestion is also arising. An exemplar platform to provide connectivity among the vehicles is shown in [1], which comprises of a data collection module, controlling and management module. As the IoV is an advancement to the V2V communication, so it comes up with new challenges such as routing for a variety of networks.

By keeping the introduction of different challenges in routing at the edge under consideration, the routing algorithm makes the use of a kalman filter based model for predicting the vehicle locations accurately. This accurate estimation of future location helps the proposed routing algorithm to stabilize and enhance the V2X network. The proposed system addresses the problem of domain scope for routing, and increases the scope of routing to be aware across the multiple road segments, zones.

Different mechanisms to optimize the use of resources at the edge nodes along with the user vehicles are being proposed and implemented for the multi-hop routing. The efficient usage of the spectrum can lead to a drastic improvement in the 5G networks. Architectures for D2D communication between proximity service (ProSe) function and home subscriber server (HSS) are also proposed [2]. Also, the usage of virtual on-board unit (vOBU) makes the vehicular communication use cases to perform close to real-time shown in this work.

II. Literature Review

Routing is also an important aspect of network management, especially when wireless networks are considered. It is a complex management task, which makes it more complicated in the domain of wireless networks. A 2 tier-based routing algorithm [3] is limited to wired networks only. In contrast, the proposed work considers the wireless adhoc networks where the mobility of vehicles is very dynamic in nature.

A use case related to predictive QoS [4] is described and is reflected to the proposed system. The concept of predicting new location of a vehicle is one such use case. Article [5], provides the information on how the prediction of handover time for a connected car can be derived and implemented using a proactive road-aware approach. Following the idea of prediction to support the proactive road-aware routing algorithm [6] [7] based on kalman filter [8], a proactive and stable routing IoV framework at the edge is proposed.

Two modules [8] used in the system to enable proactive decision making to install the flow rules related to the vehicles. The two modules are geographic information system (GIS) and routing in software-defined internet of vehicle (SD-IoV). And at last, the results are shown to evaluate the performance of a test bed based on a software-defined networking (SDN) controller, mininet for the emulation of vehicular network hosts, and open virtual switch (OVS) switches acting as RSU, switches and moving vehicles.

An overview of LTE-assisted D2D trial implementation under the 3GPP standards [9] is explained. An architecture is also proposed as a PoC to implement a ProSe function and makes it accessible to the evolved packet core (EPC). The interactions between the ProSe and EPC are also described in detail.

III. System Details

This section provides the highlight of the proposed system. The architecture is shown in fig. 1, which reflects several standards related to MEC, V2V, and ProSes. A stable path routing algorithm is embedded into the central Intent-based networking (IBN) application, which enables the high-level routing configurations in the form of routing policies. The features of the proposed routing algorithm are its proactiveness and road-awareness. It also follows the approach of closed-loop systems, which enables the property of self-organizing networks for IoV. Further, the proposed system is pictorially shown in fig. 1 as follows:

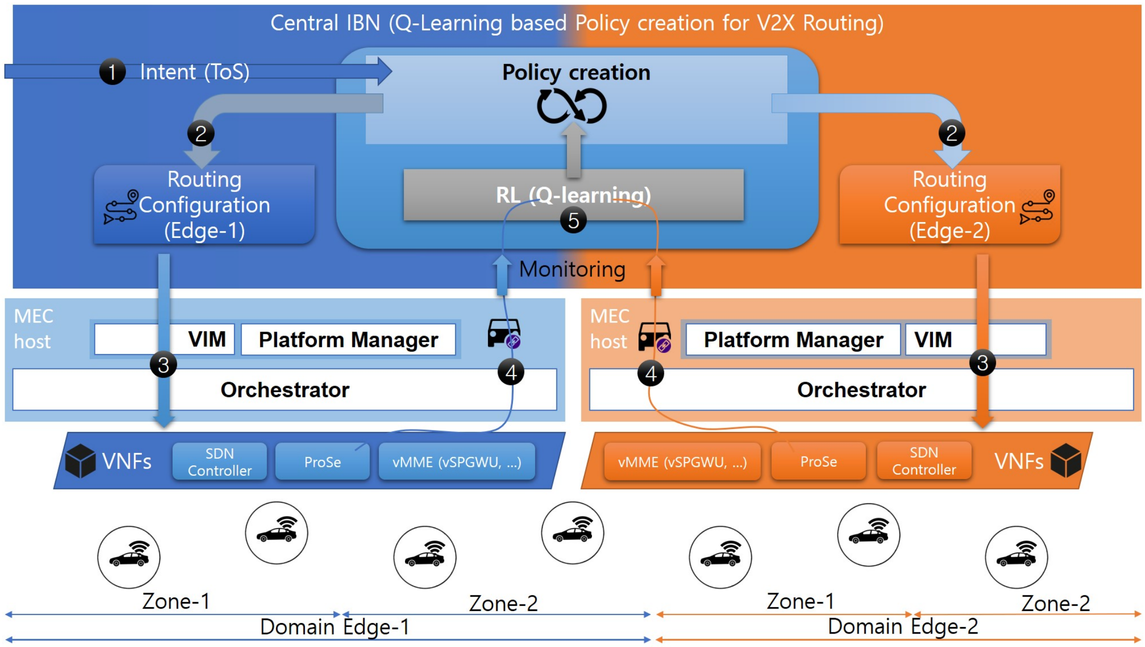

Fig. 1. System Architecture

A. IBN

IBN-based system shown in fig. 1, has the responsibility to translate the user-defined intent containing a high-level requirement. The inputs to the intent translation module are received either from the intent defined by the network operator to request a specific type of service (ToS) or from the monitored information of vehicles that comes from the orchestrator.

Firstly, the intent translation module's job is to translate the high-level policy into a low level or system understandable configurations. The user intent is converted into a policy which is further passed onto the orchestrator, which is responsible to orchestrate it onto the specific domain it was targeted for.

Secondly, the reinforcement learning (RL) [10] module embedded into the intent translation module predicts the best vehicle to be connected for data transfer. These predictions for every vehicle in each edge and zone are given as an input to the policy creation module which generates the route for each vehicle in the path.

There are two possible inputs to the intent translation module. The first possibility is that it gets the intent of a user in the form of high-level requirement, which it must be converted into a low-level configurable requirement. The second possibility is that it may receive the monitoring information of vehicles and it passes it onto the reinforcement learning module which predicts the next location of vehicle. The output of RL model and the other monitored information are considered to create a policy which is passed onto the lower-level orchestrator which installs flow rules betweeb vehicles.

B. Reinforcement learning

The RL model takes the monitored information and some of the inputs come from proximity services. The q-value shown in fig. 2 represents the delay-value of a packet to arrive on another vehicle.

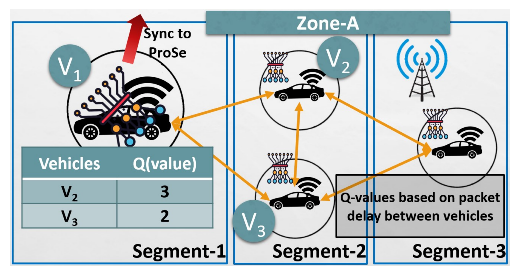

Fig. 2. Q-value synchronization

Besides the q-value representing the delay of packet transmission from one vehicle to another, other monitored information such as position, velocity, and direction are taken into consideration to decide the possible actions. All possible actions shown in fig. 3 are applied to the RL model, which gives the corresponding q-value, of which the best action is selected and the associated predicted location of vehicles. Markov decision process (MDP) is used in the proposed system. Then routing determines the path based on the best prediced location. The shape of road is also utilized in order to select the best path for the V2X path. To define the policy, IBN module plays its role and orchestrates as explained in Section III-A

C. Proposed V2X scenarios

The proposed scenarios are explained here. The scenario 1 showcases a connectivity example in which both of the vehicles are under the same cell. Second scenario, both are

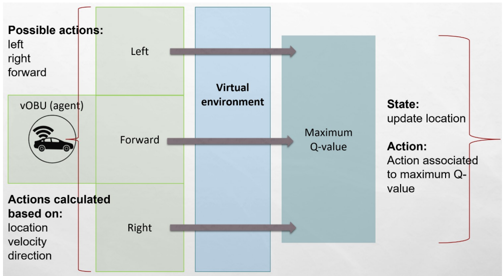

Fig. 3. Reinforcement learning model mechanism

TABLE I
DATA RATE AND PACKET FLOWS MANAGED.

Scenario number	Performance metrics			
	Data rate	Packet flows managed		
		low	medium	high
Scenario 1	21	7	11	10
Scenario 2	19			
Scenario 3	33			
Scenario 4	42			
Scenario 5	23			
Scenario 6	21			

under same cell but out of coverage. Third scenario, the vehicles are in range but under different cell. Fourth scenario, the vehicles are out of coverage and under different cell. Fifth and sixth scenarios demonstrate the proactiveness of the proposed routing algorithm, which is shown effective where the cells are not involved even in case where source and destination vehicles are under different cells. This is due to proactiveness and road-awareness property of proposed system.

IV. EVALUATION AND RESULTS

The experiments were conducted on a development workstation running Ubuntu 20.04.2 long term support (LTS) with 256 gigabytes (GBs) of random access memory (RAM) and running on Intel Xeon gold 6230r shown in table 3. 3 virtual machines (VMs) are created. The primary VM (master node) manages the other two VMs (edge nodes). The master node is assigned 16 processors with 30 GB RAM, with the help of which it manages each edge node, and each edge node is assigned 26 processors with 60 GB RAM.

Table I shows a comparison of data rates and number of packet flows managed by proposed solution. The comparison is made between the solutions based on no-prediction, prediction based on vehicle trajectory [8], and proposed method.

The results for number of packet flows managed are shown in fig. 4. The x-axis has different routing solutions applied for all six scenario average values. The y-axis represents the number of packet flows managed for each routing solution. Each comparison can be seen in the graph where the blue color is the data rate for the routing that is not based on a prediction and the orange color is the data rate for the routing based on prediction. Whereas the green color is the data rate for the proposed proactive and stable path routing approach using the reinforcement learning. A clear difference can be depicted from the graphs shown in fig. 4 that the shown number of packet flow managed for the proposed routing are lesser than the reactive forwarding. Overall performance of the proactive and stable routing algorithm integrated with the RL-based model proves to be beneficial in terms of performance.

The results for number of data rates are shown in fig. 5. It shows a comparison of data rates between different solutions based on no-prediction, prediction [8], and the proposed routing solution integrated with the RL model. The x-axis shows different routing solutions applied for all the scenarios. Y-axis represents the data rates for each routing solution mapped on x-axis. Each comparison can be seen in the graph where the blue color is the data rate for the routing that is not based on a prediction and the orange color is the data rate for the routing based on prediction. Whereas the green color is the data rate for the proposed proactive and stable path routing approach. A clear difference can be depicted from the graphs shown in data rate results. It depicts that the shown data rates for the proposed routing are far better than the reactive forwarding. It instead provides a direct V2V connection for the scenarios shown in fig. 5(e) and (f), when the vehicles are predicted to be closer and under the same cell. Overall, the performance of the routing algorithm integrated with the RL model shows better performance as compared to the previous approaches.

V. CONCLUSION

Efficiently managed vehicular networks provide a stable connection. In addition, as the future use cases to be addressed require a lot of bandwidth and are dependent on telecommunication networks. The increase in number of vehicles and the wide coverage of telecommunication networks drive the need of improvement in hybrid v2x network connectivity. To address this problem, a ton of data to be transferred on daily basis, efficient management of spectrum and channels in a hybrid approach using the proposed system can have significant impact on the resource usage and operating expenses (OPEX). The results provided in terms of data rates and number of packet flows managed proves to be intelligent in terms of provisioning of proactive and a stable connection. This reduces the load of cellular spectrum and provides a wide coverage of area using the proposed system with features of intelligent awareness of the road vehicle states. With the high-level required inputs in the form of intent leads to more open options in the IoV domain. This closed-loop system will also enable the zero touch systems, which also lead to the reduction in management cost of vehicular networks.

The number of packet flows managed and data rate results in the Section IV provide such a v2x network, which is reduces the burden of cellular networks with the help of wireless v2x connections based on direct short range communication (DSRC). The results of routing overhead and packet delivery ration both mapped against vehicle speed reflect the improvement in vehicular networks using the proposed methodology.

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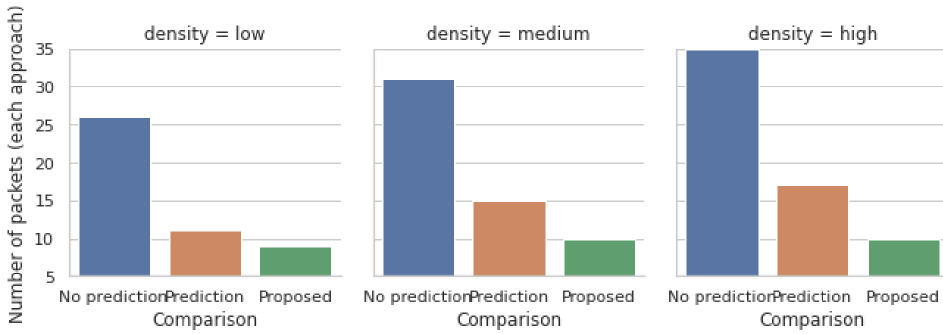

Fig. 4. Number of packet flows managed - A comparison

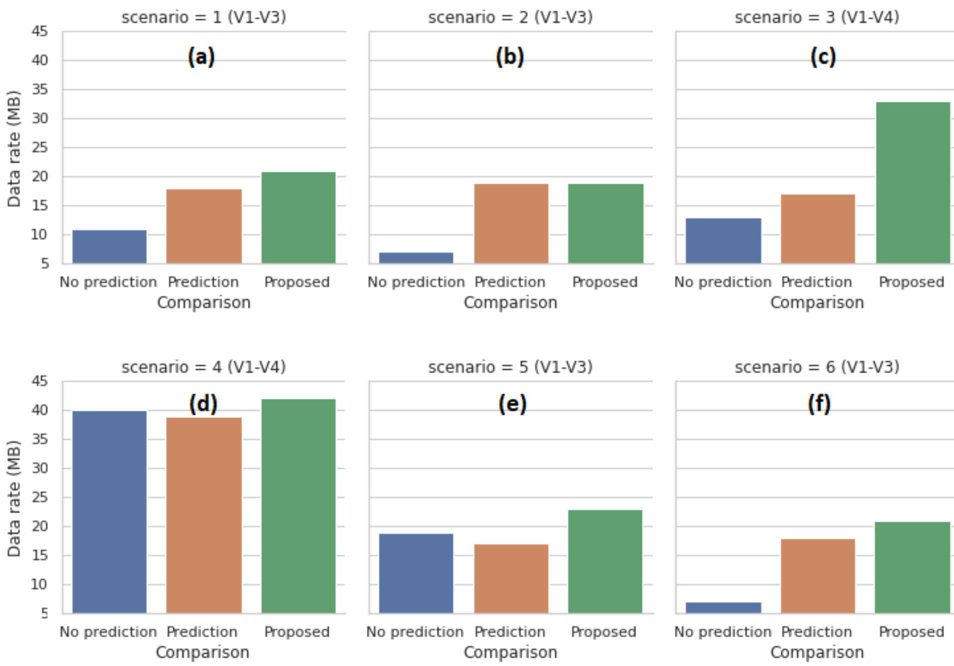

Fig. 5. Data rates - A comparison

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