DT-VAR: Decision Tree Predicted Compatibility-Based Vehicular Ad-Hoc Reliable Routing

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***Abstract*—Reliable routing and efficient message delivery in vehicular ad-hoc networks (VANETs) is a significant challenge owing to underlying environment constraints, such as dynamic nature, mobility, and limited connectivity. With the increasing number of machine learning (ML) applications in wireless networks, VANETs can benefit from these data-driven predictions. In this letter, we innovate and investigate ML-based classifications in VANETs to predict the most suitable path with the longest compatibility time and trust using a fog node based VANET architecture. The proposed scheme in SUMO VANET traces achieves up to a 16% packet delivery ratio (PDR) with a 99% accuracy and longer connectivity with only 3 $\sim$ 4 hops, compared with existing AOMDV and TCSR solutions with merely a 4% PDR.**

***Index Terms*—Ad-hoc routing, decision tree, machine learning, reliable routing, VANET.**

I. Introduction

In THE era of high-speed 5G and B5G communications, efficient message delivery and routing in dynamic and highly mobile networks such as vehicular ad-hoc networks (VANETs) and unmanned aerial vehicles is a significant challenge [1], [2]. With the advent in communications technologies such as dedicated short-range communication (DSRC) 802.11p on a physical/media access control layer and the wave short message protocol 1609 on the network layer, vehicle-to-vehicle (V2V) and vehicle-to-any (V2X) communications share more than merely emergency messages. A connected VANET enables applications like efficient emergency response, smart traffic congestion control, cooperative driving, and safety [3]. However, the high mobility and dynamic nature of VANET traffic can stifle communications technology performance, thereby hindering future applications. Legacy routing solutions focus on the network throughput, hop count, etc. based routing while overlooking underlying VANET characteristics [4], [5]. Moreover, highly dynamic and agile VANETs require pro-active solutions for better performances [6]. Increasing interest in artificial intelligence and machine learning (ML) applications for smart and swift decision making has resulted in many efficient solutions. ML methods are promising in VANET, such as in predicting resource allocation [7], preemptive road safety measures, power allocation [8], security challenges, and routing [2], [9]. We are the first to hypothesize that an efficient predictive message routing can significantly increase network performances.

A reinforcement learning-based study in [7] proposed a multi-parameter 5G resource allocation strategy for vehicular networks. A similar deep reinforcement learning-based solution suggested the efficient selection of the relay and the transmission power levels in 5G mmWave based networks [8]. The study in [10] predicts the mobility of vehicles using an SDN-based artificial neural network for, a source and a destination that are both in the same base station coverage. The proposed scheme utilizes mobility prediction to estimate topology changes, transmission successes and delays at the base stations, and roadside units. The proposed network operated routing prediction requires global network information availability at the SDN controller. An interesting study in [11] combines geographical knowledge of road segments and distributed Q-learning with greedy forwarding to achieve reduced delivery delay and higher packet delivery ratios (PDRs). However, the solution requires each vehicle to perform Q-learning for V2V while considering each packet as an agent, thereby incurring a high cost for each vehicle. The authors of [12] investigated an AODV based solution with ant colony optimization to achieve a multiple QoS aware routing in vehicular networks. The AODV control messages were modified to carry pheromone and QoS metrics information, which was then used for route evaluation and selection. The authors of [13] proposed a multi-objective packet reception probability-based routing protocol, which prioritizes packet reception probability to select the optimal path using particle swarm optimization. The study in [14] investigates a multi-metric fuzzy Q-learning based routing decision making, in which a vehicle's relative movement estimation, available bandwidth, and link quality are considered. Each metric is assigned three labels, and the combination using output membership function is ranked as perfect, good, non-preferable, bad, or very bad. The proposed approach relies on AODV control messages for link evaluation.

In the dynamic VANET, message delivery is a tedious task and requires several intermediate nodes to successfully transmit messages. Frequent topological changes and vehicular movements result in-efficient message delivery, unreliable paths, path re-calculation, and/or message re-transmission. Our thorough literature review indicates that an efficient routing protocol that considers major VANET characteristics such as

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compatibility time, speed, distance, and direction, is urgently required. In this letter, we developed the decision tree predicted compatibility based vehicular ad-hoc reliable routing (DT-VAR), which focuses on two major parameters, i.e., a longer compatibility time (CT) and trustworthiness. DT and random forest classification (RFC) have been identified as being highly accurate than other ML techniques in our evaluations because of their recursive partitioning heuristic, and divide and conquer nature. However, DT supersedes the RFC in terms of training and testing time. Considering the potential of ML in VANETs, we utilized roadside units and/or base stations as fog nodes (FNs) to train and predict vehicular compatibility. However, vehicles unable to access FNs can estimate the same using our offline mathematically tractable equations. We define compatibility of two vehicles in terms of their communication duration using their distance, relative velocity and direction with respect to each other. The proposed route selection scheme chooses a route based on its end-to-end communication compatibility which increases the network performance by reducing packet drop and retransmissions. Fig. 1 illustrates the proposed architecture, where FNs collect vehicular environment data for training and communicate with vehicles for prediction. We evaluated four ML classification techniques in the VANET environment to predict the CT of vehicles and selected the best technique. Moreover, we evaluated the feasibility of two existing variations of AODV based solutions, ad-hoc on-demand multipath distance vector(AOMDV) [4] and trust cryptographic secure routing (TCSR) [5]. Our major innovative contributions are 1) Distance, speed, and direction based compatibility prediction/ estimation using ML in VANETs, 2) practical (online-offline), and efficient message routing in high mobility networks, and 3) we formulate vehicular reliability as a function of trust and connectivity duration for efficient communications in high mobility scenario, 4) we are the first to develop a reliable routing scheme based on vehicular mobility and trust, using a hybrid of accurate compatibility calculation (locally, analytical) and prediction (FN based, ML predictions).

II. Proposed DT-VAR Scheme

Analytical Model: Each vehicle was assumed to be equipped with the dual connectivity of DSRC to communicate locally and to access networks globally by the cellular network. In DSRC, vehicles share basic safety messages (BSMs) with each other; the messages contain information such as location, velocity, direction, and vehicle type. Using BSM messages, the Euclidean distance λ_{ij} between two vehicles (i and j) having velocity φ_i, φ_j and locations $l_i(x_i, y_i), l_j(x_j, y_j)$ can be calculated as follows:

$$\lambda ij = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

The relative velocity ΔV_{ij} of vehicle *j* as seen by vehicle *i*, can be estimated as:

$$\Delta V_{ij} = \sqrt{(\varphi_i - \varphi_j)^2} + 1 \tag{2}$$

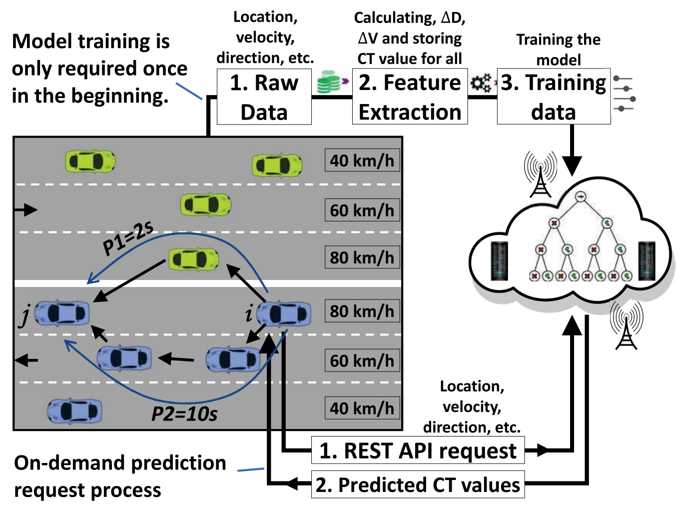


Fig. 1. DT-VAR architecture.

In this letter, we focus on establishing reliable routes for efficient message delivery in a multi-hop vehicular environment. A reliable route maintains its connectivity between a source and a destination for a longer period of time with adequate trustworthiness. Utilizing information available on the media access control layer through BSM messages, a cross-layer information exchange can facilitate efficient routing decisions on the network layer. The compatibility time (CT_{ij}) between two vehicle *i* and *j* with local communication range *R* can be estimated as follows [12]:

$$CT_{ij} = \frac{R - \lambda ij}{\Delta V_{ij}} = \frac{R - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sqrt{(\varphi_i - \varphi_j)^2} + 1} \tag{3}$$

To estimate the accurate CT and accommodate various dynamic scenarios of vehicular movement, position, and direction, we considered two weights, ω and ϑ, in the equation above, as:

$$CT_{ij} = \frac{R - \omega\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sqrt{(\varphi_i - \vartheta\varphi_j)^2} + 1} \tag{4}$$

The ω and ϑ configurations can facilitate the estimation of the CT. When vehicle *i* is ahead of vehicle *j*, $\omega = 1$ and $\vartheta = 1$; when *i* is behind *j*, $\omega = -1$ and $\vartheta = 1$; when *i* and *j* are approaching each other, $\omega = -1$ and $\vartheta = -1$; when *i* and *j* are moving away from each other, $\omega = 1$ and $\vartheta = -1$.

Learning Model and Data Features: Supervised learning classification can identify and segregate a specified test case into designed classes. In our case, we assume that any vehicle can request to predict the compatibility level (CT^L_{ij}) of another vehicle using the following labels/classes.

$$CT^L_{ij} = \left\{ \begin{array}{l} L0 \ \text{ if } CT_{ij} == 0 \\ L1 \ \text{ if } CT_{ij} > 2 \ \& \ CT_{ij} \leq 5 \\ L2 \ \text{ if } CT_{ij} > 5 \ \& \ CT_{ij} \leq 10 \\ L3 \ \text{ if } CT_{ij} > 10 \ \& \ CT_{ij} \leq 15 \\ L4 \ CT_{ij} > 15 \end{array} \right\} \tag{5}$$

Algorithm 1 DT-VAR on-Demand Message Protocol

```
Broadcast Route Request (RReq)
Receive Route Reply (RRep) = {NextHop, MinCT, }
if Msg Type is private then
    for all RRep do
        Calculate T_ix for RRep_x
        if T_ix > τ then
            Request FNs/Calculate CT_ix
            Calculate MinCT_iz^{RRep_x}
        end if
    end for
else
    for all RRep do
        Request FNs/Calculate CT_ix
        Calculate MinCT_iz^{RRep_x}
    end for
end if
Path selected with MaxMinCT_iz
```

Above mentioned classes are designed keeping in mind of emergency communications ($L1$ and $L2$) and entertainment transmissions such as images, video, and live broadcasts ($L3$ and $L4$); however, these classes are programmable. The column headings in our learning model training (dataset) and testing (prediction query) include $\lambda_{ij}, \Delta V_{ij}$, Direction difference ($\Delta\theta_{ij}$), Direction difference label ($\Delta\theta_{ij}^{L}$), and tendency ($Tend_{ij}$). λ_{ij} and ΔV_{ij} are estimated using Equation (1) and (2), respectively. $\Delta\theta_{ij}^{L}$ has three possible values, which represent the directions of vehicle *i* and *j*, as follows:

$$\Delta\theta_{ij}^{L} = \begin{Bmatrix} 0(\text{Same}) & \text{if } \Delta\theta_{ij} \leq 60 \\ 2(\text{Opposite}) & \text{if } \Delta\theta_{ij} \geq 120 \\ 1(\text{Neither}) & \text{otherwise} \end{Bmatrix} \tag{6}$$

where $\Delta\theta_{ij} = |((\theta_i - \theta_j + 180)\%360 - 180)|$ and θ_i is the angle of vehicle *i*'s direction, whereas the north points to 90° at al times.

The $Tend_{ij}^{L}$ label signifies if vehicles *i* and *j* are moving toward each other or moving away. This helps the model to identify the difference between vehicles that are at the same distance but moving in different directions.

$$Tend_{ij}^{L} = \begin{Bmatrix} 0 & \text{if } \Delta\theta_{ij}^{L} == 2 \ \& \ \lambda_{ij}(t2) - \lambda_{ij}(t1) < 0 \\ 1 & \text{if } \Delta\theta_{ij}^{L} == 2 \ \& \ \lambda_{ij}(t2) - \lambda_{ij}(t1) > 0 \end{Bmatrix} \tag{7}$$

where $\lambda_{ij}(t1)$ and $\lambda_{ij}(t2)$ represent the distances between vehicles *i* and *j* at time epochs t1 and t2, respectively. It is noteworthy that these column headings are calculated as prediction-preprocesses using the raw data from BSM messages, i.e., the location, direction, and speed only.

Proposed Scheme: We herein propose the DT-VAR, which utilizes a hybrid mechanism to efficiently predict or calculate the compatibility of a path. Fig. 1 illustrates a high mobility scenario where communication between vehicle *i* and *j* has path $P1\{$one intermediate node, 2s CT$\}$ and $P2\{$two intermediate nodes, 10s CT$\}$. Our DT-VAR routing scheme considers CT as a path selection metric which leads to selecting $P2$ as a communication route and thus ensuring longer connectivity in high mobility scenario with fewer retransmission and packet loss. Vehicle *i* can calculate CT value for each path either using Equation (4) or requesting a FN using our two steps (request and response) on-demand prediction process. The FN model is trained once by collecting raw data of vehicular environment to extract feature for ML model training. Moreover, if the message is confidential, then a vehicle can opt for trust as a metric along with compatibility. The trustworthiness of the next-hop *j* for vehicle *i* (T_{ij}) is estimated using peer opinion a_{ij} and forwarding ratio b_{ij} with transitivity (A trusts B, B trusts C, and then A trusts C), as follows below [5]:

Fig. 2. Fog node response module.

$$T_{ij} = \phi a_{ij} + (1 - \phi) b_{ij} \tag{8}$$

where $\phi \in [0, 1]$ is the weight assigned to the direct forwarding ratio (b_{ij}) and indirect forwarding ratio (a_{ij}), estimated as:

$$a_{ij} = \frac{\sum_{k=1\&k\neq i}^{CP_{ij}} b_{kj}}{CP_{ij}} \tag{9}$$

$$b_{ij} = \frac{msgs_{ij}^{f}}{Total\ msgs_{ij}} \tag{10}$$

where CP_{ij} represents the number of common peers, $msgs_{ij}^{f}$ the number of messages (both control and data) successfully forwarded by *j* from *i*, and $Total\ msgs_{ij}$ the total messages sent by *i* to j. Therefore, a vehicle must establish trust by forwarding control and non private data packets.

Algorithm 1 outlines the proposed DT-VAR on-demand message protocol, where vehicle *i* initiates by broadcasting the route request (RReq) message, provided that no destination route exists. After receiving route reply (RRep) messages, vehicle *i* calculates T_{ix} using Equation (8) where *x* is the next-hop vehicle. The trust is only calculated if the source vehicle identifies that the message is confidential. A path (RRep) is considered viable or trustworthy if the trust from the source to the next hop (T_{ix}) is higher than a predefined threshold (τ). Nevertheless, for every RRep, the vehicle determines the minimum compatibility time value throughout the multi-hop path ($MinCT_{iz}^{RRep_x} = \arg\min(CT_{ix}, CT_{xz})$), where *x* is an intermediate node between vehicles *i* and *z*. Utilizing BSM information (location, direction and speed), vehicle *i* can request the FNs to predict the CT_{ix} or calculate it using Equation (4). The prediction (online) or calculation (offline) of CT_{ix} relies on the accessibility and availability of the FNs. In response to the CT prediction request, the FN performs feature extraction to formulate the appropriate query ($\lambda_{ij}, \Delta V_{ij}, \Delta\theta_{ij}, \Delta\theta_{ij}^{L}, Tend_{ij}$) for the prediction model. The FN communicates with the requesting vehicle and shares the predicted CT value(s) (CT_{ij}^{L}), as outlined in Fig. 2. Finally, a path is selected using the maximum CT value from all η RRep values as follows:

$$MaxMinCT_{iz} = \arg \max(MinCT_{iz}^{RRep_1}, MinCT_{iz}^{RRep_2}, \ldots, MinCT_{iz}^{RRep_\eta}), \tag{11}$$

where η is the number of total received RRep messages.

Fig. 3. Sumo trace scenario at Seoul, South Korea.

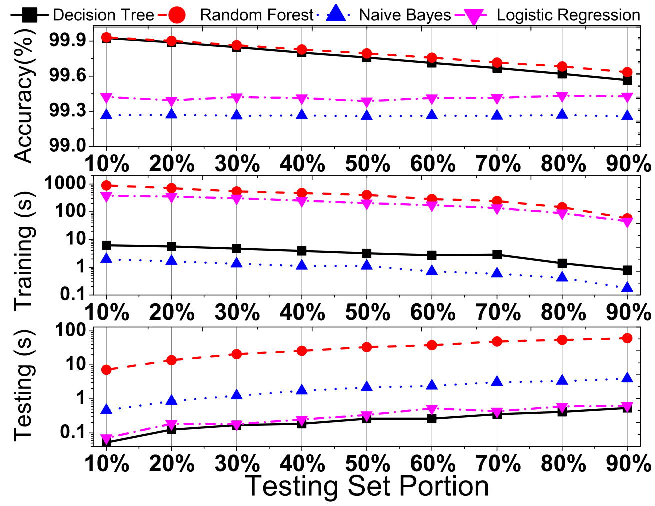


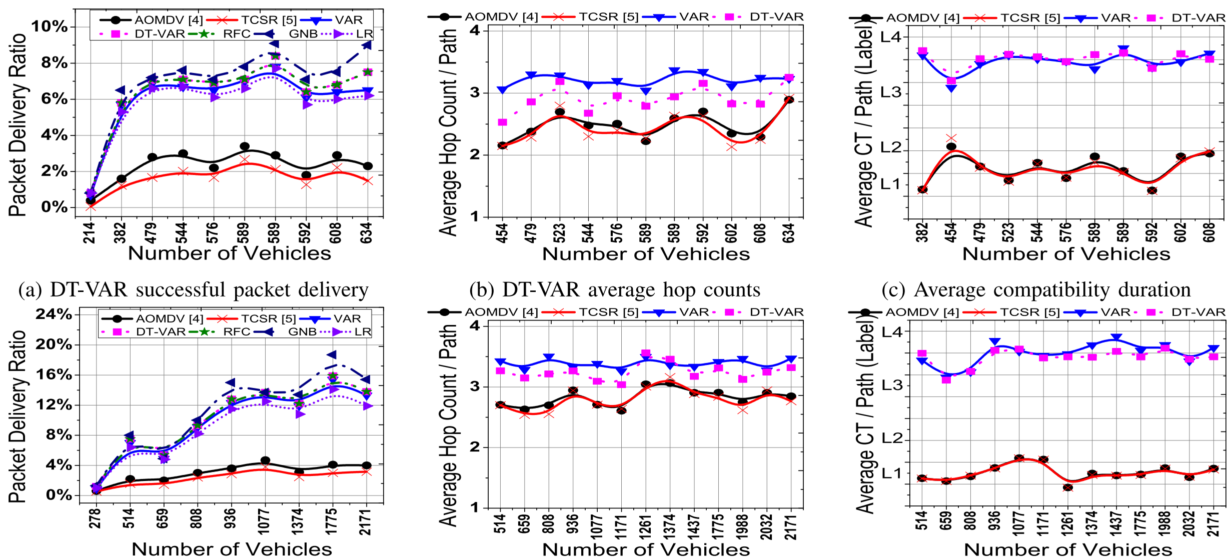
Fig. 4. Comparative evaluation of supervised learning models in the vehicular network SUMO dataset.

III. PERFORMANCE EVALUATION AND OBSERVATIONS

Considering ML classification varieties, we evaluated the decision tree (DT), random forest classification (RFC), Gaussian naive Bayes (GNB), and logistic regression (LR) in terms of accuracy and time consumption (training and testing). The dataset in [15], observes the SUMO traffic trace (illustrated in Fig. 3) for up to 500 s to identify the CT_{ij}^L for each vehicle at every second. The dataset contains six column headings ($\lambda_{ij}, \Delta V_{ij}, \Delta\theta_{ij}, \Delta\theta_{ij}^L, Tend_{ij}, CT_{ij}^L$) and more than 8,148,004 samples, where each row identify the relation between two vehicles at time t (out of 500 s). We evaluate dataset with various train/test split sizes. Fig. 4 shows that all classification methods achieved more than 99% accuracy in CT_{ij}^L prediction, regardless of the train/test split size. There is a small decline of 0.3% in both DT and RFC accuracy due to smaller training set portion (10%) which is a result of fewer split points for predictor variables. There is no impact of testing data set portion increase on LR and GNB because of their probabilistic based nature. However, the time consumption for training and testing shows that RFC and LR required longer times. Meanwhile, the DT achieved better accuracy than GNB with a slight difference in time consumption. The high accuracy in DT and RFC is a result of efficient split points at predictor variables which allows discarding false values using divide and conquer. Particularly, in vehicular networks dataset, the nature of our feature set supports binary split decisions. RFC creates a number of decision trees for prediction which can be useful for a complex dataset; However, in our vehicular dataset, DT outperforms RFC in terms of time consumption. Considering the comparative evaluation for the vehicular networks dataset, we believe that the DT classification can outperform other ML techniques in terms of accuracy and practicality. Our simulation setting in the SUMO trace at Seoul, South Korea included 30+ intersections spanning over an area measuring 2.5 km x 1.5 km for a total of 3600 s. The simulation environment is generated from real traces available on OpenStreetMap and subsequently populated with simulated vehicles. Each vehicle among a total of 2500 vehicles was equipped with DSRC having 1 Mbps bandwidth for up to a 50 m range and cellular network communications for FN access. We evaluated the performance of the proposed scheme in terms of the PDR, the average number of hops to reach the destination, and the average time a selected path remains in contact (CT_{ij}^L), in two different vehicular densities (medium and high). Moreover, variations of the proposed scheme depending on the CT value calculation included the following: a) vehicular ad-hoc reliable routing using analytical calculation only (VAR); b) DT-VAR, which uses predicted CT values; c) RFC forecasting; d) GNB prediction; and e) LR methods, as compared to existing f) AOMDV [4] and g) TCSR [5] schemes.

Fig. 5(a) shows that the GNB and DT-VAR based solutions achieved PDRs that were 10% higher than those of other variations and existing schemes of AOMDV (2∼4%) and TCSR (1∼3%). The proposed analytical solution VAR outperformed the LR based prediction and achieved a 6 to 8% PDR. However, the ML solutions (DT-VAR, RFC, GNB, and LR) were advantageous in terms of PDR and had an upper hand on analytical route selection (VAR). The difference was a trade-off between independent route estimation or FN-based path selection. Nevertheless, the proposed hybrid DT-VAR algorithm utilized both analytical and predictive methods depending on the FN availability. Meanwhile, the proposed analytical (VAR) and predictive (DT-VAR) methods chose a higher number of hops on average compared with the existing hop based AOMDV and TCSR schemes, as illustrated in Fig. 5(b). However, Fig. 5(c) shows that the proposed solution considered longer connectivity as opposed to the hop counts and achieved an average of 10∼15s (L3 and L4 CT_{ij}^L labels) compatibility between a source and a destination. The labels L1, L2, L3 and L4 are defined in Equation (5) as L1=2-5s, L2=5-10s, L3=10-15s, and L4≥15s. Fig. 5 (d, e, and f) shows that the proposed scheme (DT-VAR) in a dense environment achieved up to a 16% PDR, with 3∼4 average hops, and connectivity higher than 15 s for the average selected path. With a higher number of vehicles, the existing AOMDV and TCSR schemes involved more average hops per path with only a 4% PDR and a short communication time of up to 5s (L1).

It is noteworthy that the proposed analytical (VAR) and simulated (DT-VAR) results differ only slightly in terms of PDR, hops, and CT. The results in Fig. 5 shows slight



(a) DT-VAR successful packet delivery (b) DT-VAR average hop counts (c) Average compatibility duration

(d) DT-VAR successful packet delivery (e) DT-VAR average hop counts (f) Average compatibility duration

Fig. 5. Comparative analysis in data set with medium (a, b, and c) and high (d, e, and f) vehicular density, where L1=2-5s, L2=5-10s, L3=10-15s, L4≥15s.

fluctuation which is due to the fact that each epoch is nor dependent neither connected with the previous epoch. Our exhaustive simulation considers 3600 epochs, each having 1000 packet generated between two randomly selected vehicles (source and destination). Moreover, the low PDR is due to the random selection of source and destination out of sparsely distributed vehicles in our realistic SUMO traces. The proposed scheme opts for longer paths with a high number of intermediate nodes, thereby resulting in propagation delays. However, the selected path remains in contact for a significant amount of time. Moreover, the proposed hybrid solution (offline and online-based) allows practicality, where a vehicle can either request an FN for predicting or self-calculating of the CT value. We believe that the proposed solution with DT prediction is the most suitable route selection scheme for connected and futuristic vehicular networks.

IV. Conclusion

In this letter, we investigated the efficiency of supervised classification on SUMO vehicular network traces and proposed the DT-VAR protocol. Our solution considered (offline) analytical and (online) prediction based vehicular compatibility (four classifications: DT, GNB, RFC, and LR) to select the best message routing path with the highest connectivity time. The proposed DT-VAR achieved up to a 16% PDR with a continuous connectivity that was loner than 15 s between a source and a destination and only 3 ∼ 4 average hops. In the existing schemes, shorter paths were selected in terms of average hops, resulting in a low PDR of only 4% and a short connectivity of only 2 to 5 s. Our future work includes developing purely ML based routing by contrasting it with existing ML based solutions for VANETs.

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