

Intelligent DoS Attack Detection with Congestion Control Technique for VANETs

R. Gopi¹, Mahantesh Mathapati², B. Prasad³, Sultan Ahmad⁴, Fahd N. Al-Wesabi⁵,
Manal Abdullah Alohal^{6,*} and Anwer Mustafa Hilal⁷

¹Department of Computer Science and Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur, 621 212, India

²Department of Computer Science and Engineering, RajaRajeswari College of Engineering, Bengaluru, 560074, India

³Department of Information Technology, Vignan's Institute of Information Technology, Visakhapatnam, 530049, India

⁴Department of Computer Science, College of Computer Engineering and Sciences, Prince Sattam Bin Abdulaziz University, Alkharj, 11942, Saudi Arabia

⁵Department of Computer Science, College of Science & Arts at Mahayil, King Khalid University, Muhayel Aseer, 62529, Saudi Arabia & Faculty of Computer and IT, Sana'a University, Sana'a, 15347, Yemen

⁶Department of Information Systems, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh, 11564, Saudi Arabia

⁷Department of Computer and Self Development, Preparatory Year Deanship, Prince Sattam bin Abdulaziz University, Al-Kharj, 16278, Saudi Arabia

*Corresponding Author: Manal Abdullah Alohal. Email: maalohaly@pnu.edu.sa

Received: 02 September 2021; Accepted: 01 November 2021

Abstract: Vehicular Ad hoc Network (VANET) has become an integral part of Intelligent Transportation Systems (ITS) in today's life. VANET is a network that can be heavily scaled up with a number of vehicles and road side units that keep fluctuating in real world. VANET is susceptible to security issues, particularly DoS attacks, owing to maximum unpredictability in location. So, effective identification and the classification of attacks have become the major requirements for secure data transmission in VANET. At the same time, congestion control is also one of the key research problems in VANET which aims at minimizing the time expended on roads and calculating travel time as well as waiting time at intersections, for a traveler. With this motivation, the current research paper presents an intelligent DoS attack detection with Congestion Control (IDoS-CC) technique for VANET. The presented IDoS-CC technique involves two-stage processes namely, Teaching and Learning Based Optimization (TLBO)-based Congestion Control (TLBO-CC) and Gated Recurrent Unit (GRU)-based DoS detection (GRU-DoSD). The goal of IDoS-CC technique is to reduce the level of congestion and detect the attacks that exist in the network. TLBO algorithm is also involved in IDoS-CC technique for optimization of the routes taken by vehicles via traffic signals and to minimize the congestion on a particular route instantaneously so as to assure minimal fuel utilization. TLBO is applied to avoid congestion on roadways. Besides, GRU-DoSD model is employed as a classification model to effectively discriminate the compromised and genuine vehicles in the network. The outcomes from a series of simulation analyses highlight the supremacy of



This work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

the proposed IDoS-CC technique as it reduced the congestion and successfully identified the DoS attacks in network.

Keywords: VANET; intelligent transportation systems; congestion control; attack detection; dos attack; deep learning

1 Introduction

Vehicular Ad hoc Network (VANET) is one of the advanced and established networks and is named so, since the location of the vehicle alters at all instances of time. The normal speed of vehicular nodes differs from 40 to 80 km/h [1]. This heavy arbitrariness, in terms of position exposes VANET to each form of cyber threat and attacks, particularly hybrid DoS attack. Uncertainties, like hybrid DoS attack, are the main reason for cyber threats. VANET makes use of vehicles as mobile nodes and is a subclass of Mobile Adhoc Network (MANET) to communicate with and amongst the nearby vehicles closer to equipment/roadside unit (RSU). However, it differs from other networks in terms of its features [2]. Mainly, the vehicles (nodes) are insufficient for road topology while stirring. So, the vehicle's upcoming location could be anticipated since the data of the road is accessible. According to IEEE 1471-2000 and ISO/IEC 42010 architecture standard principles, VANET system could be classified into three types such as generic domain, mobile domain, and infrastructure domain. Fig. 1 shows the structure of VANET. Mobile domain transfers the data and communicates with the infrastructure domain. It makes use of IEEE 802.11p signals and beacons that process the information and move on to modulation process [3]. Later, the infrastructure domain communicates with generic domain and exchanges the data. The flow of the information between stationary and the mobile resources leads to efficient usage of the road with users who use IEEE 802.11p beacon transmission standards.

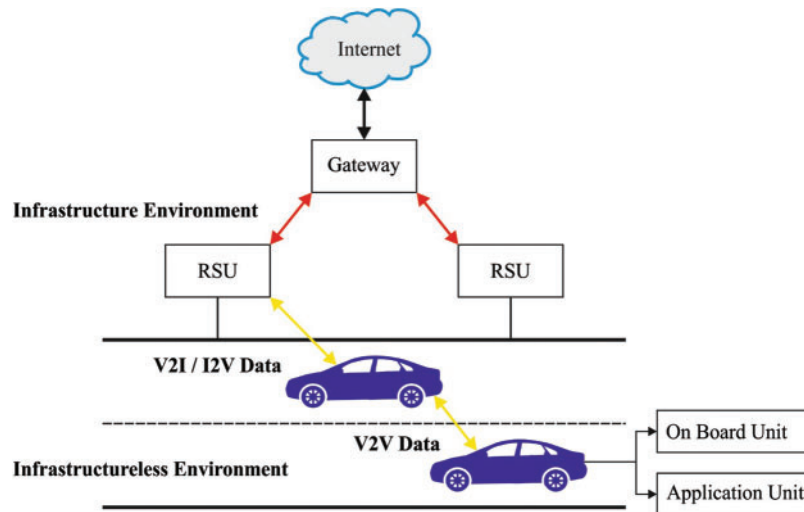


Figure 1: Overview of VANET

The current work considered the broadcast rate of data for real-time IEEE 802.11p data delivery in VANET to be 30 Mbps. Also in VIA, the vehicle co-operation occurs in the group motion for

frequent exchange of the sporadic broadcast of security messages [4]. Such transmission carries the data about vehicle's speed and its location while using IEEE 802.11p beacons-devoted channel [5]. Beacon losses tend to occur at the time of standard operations of IEEE 802.11p MAC protocol with arbitrary access requirements. This could be featured as the damage to wireless networks (viz., beacon transmission overlaps the results from various vehicles that could lead to congestion or collision). Collision/Congestion (CC) could be decreased on the basis of suitable selection of MAC protocol real-time broadcast method. This method includes key distribution algorithm and secure authentication methods whereas secure broadcast range model could be placed in VIA network. Depending on this, efficiency parameters are used like real-time end-to-end delay sensitivity to implement the neighbouring node successfully.

In VANET, the consistency of vehicular nodes is measured based on its cooperation, which considers the amount of participation with transmission packets from their neighbors. This is because of absence of centralized control points for transmission [6]. However, the degree of collaborations, provided by the vehicular node, to transmit the packets reduces the existence of malicious activities such as DDoS attacks. Because these attacks unintentionally/intentionally utilize the resources and reduce the efficiency of network so as to stay active in the network with no genuine reason [7]. The existence of DDoS attack possibly decreases the rate of throughput and packet delivery, despite the acquisition of total overhead, great level of delay, and control overhead. In previous years, a substantial amount of mitigation approaches presented DDoS attacks and methods to overcome it.

VANET is a highly scalable network with differing amounts of nodes (vehicles) and RSUs (infrastructure) that keeps changing from time to time. Further, its network topology also gets altered regularly, since the node moves with changeable speed. VANET is incorporated in smart transportation systems [8] to decrease the time consumed on road which includes both waiting time and travel time at the intersection, for a commuter. Travel time could be decreased with the help of shortest paths between two nodes. However, when each vehicle elects the shortest path, then it would create congestion on that path. Therefore, the shortest routes are mostly not the optimum routes [9]. Commuters might select a slightly longer route. However, their primary focus is to evade congestion in their routes by having less number of traffic signals and less waiting time for smoother mobility.

Khoza et al. [10] introduced an IHACO approach to decrease congestion in smart cities. The aim is to select and recommend an optimal route during rush hours. Also, the system follows IHACO approach to improve the QoS to ITS. This method (IHACO) is different than other approaches, for instance PSO, due to pheromone upgrade process that makes it highly effective. In Jindal et al. [11], a new MACO-P approach was presented to reduce the total travelling time. MACO approach was utilized to avoid the congested route by sensing the pheromone trail. The inclusion of pre-emption in the presented MACO approach would lead to decrease in normal queue length at intersections, therefore, lesser waiting times ensure smoother mobility.

Erskine et al. [12] used VFC incorporation with hybrid OA and SI algorithm including CSA, ABC, and GA to provide a real-time recognition of DoS attacks in IEEE 802.11p. In this method, VFC was used for achieving a secured smart vehicular network. The vehicle moves at a particular speed and the data gets transferred at 30 Mbps. FFBPNN approach was utilized in this study as a classifier to distinguish between genuine and the attacked vehicles. Chang et al. [13] proposed a distributed broadcast power adjustment approach to enhance the awareness and transmission congestion control to address the transmission congestion issues that occur in VANET. The aim is to offer maximal awareness of nearby vehicles, when preserving a communication channel load, within the threshold allowed. By altering the broadcast range of the vehicle gradually, on the basis of communication

channel load of its neighbouring vehicles, this approach detects the optimum broadcast range that can offer maximum awareness without the congestion of resultant communication. Furthermore, the presented method properly controls the channel load in a reasonable way without sacrificing the awareness of certain vehicles during congested condition.

Sangaiah et al. [14] presented a LACC approach to enhance the advantages of greedy routing and DDM algorithm. LACC focuses on electing receiver vehicles by measuring its end-to-end service capability and connection stability preference. Kumar et al. [15] presented an effective traffic control scheme using IoV technique. The presented approach was implemented in the work area of Vellore district, Tamil Nadu, India. The street map was divided into smaller sections of different maps. ACO approach was employed in all the maps to find the optimum path. Furthermore, FL algorithm-based traffic intensity evaluation function was also presented for modelling heavy traffic conditions. The presented IoV-based path election approach is related to the present shortest route election methods like Dijkstra, Kruskal, and Prim algorithms.

Lyu et al. [16] proposed a DBCC system to control the beacon activities by considering the condition of links such as vehicles with additional neighbours and better condition of link with its neighbours, so that the system would be allocated with high beacon rates. First, the authors used two ML algorithms namely, NB and SVM to train the features and a classification method was conducted online with NLoS links to forecast the output. Using link data, the authors created L-SBM problems of rate adaption under TDMA transmission MAC which is otherwise known as NPhard. A greedy heuristic approach was presented for L-SBM and the efficiency of the method was calculated. In Selvi et al. [17], an ASPBT algorithm was presented as an efficient and reliable emergency message communication technique. This protocol vigorously changes the amount of partitions and the periodicity of beacons to reduce the amount of recommunication. In this method, partition size is defined by network density and the broadcast schedule for all partitions is evaluated by LOA approach. It is a bio-inspired optimization based on the features of lions.

The current research article presents an Intelligent DoS attack Detection with Congestion Control (IDoS-CC) technique for VANET. The presented IDoS-CC technique has two stages namely, Teaching and Learning-Based Optimization (TLBO)-based Congestion Control (TLBO-CC) and Gated Recurrent Unit (GRU)-based DoS detection (GRU-DoSD). IDoS-CC technique includes TLBO algorithm to optimize the routes taken by vehicles via traffic signals and minimize the congestion instantaneously on a particular route which in turn to assure minimal fuel utilization. Besides, GRU-DoSD model is also employed as a classification model to effectively distinguish the compromised as well as genuine vehicles in network. A series of simulation analyses was conducted and the results attained by IDoS-CC technique established its supremacy in terms of reduced congestion and successful identification of DoS attacks in the network.

2 The Proposed Model

In this study, a new IDoS-CC technique is designed for VANET. The goal of IDoS-CC technique is to reduce the level of congestion and to detect the attacks that exist in network. It includes a two-stage process namely, TLBO-CC based Congestion Control and GRU-DoSD-based attack detection. The following sections detail the working of these sub-processes.

2.1 Design of TLBO-CC Technique

This approach is inspired by knowledge transfer that occurs between students and the teachers during education period. Assume that two teachers, T1 & T2, teach a topic using identical data to

same merit level learners in two dissimilar classes. The mark distributions among the learners of two classes were validated with the teacher. Curve 1 & 2 illustrate the mark attained by the learners who were taught by the teachers, T1 & T2 correspondingly. The standard distributions are considered for the attained mark. But, in real time, it might be skewness. The standard distributions are demonstrated as follows.

$$f(X) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (1)$$

where σ^2 represents the variance, μ denotes the mean and x indicates the value where the standard distribution functions are needed. Curve 2 indicates the optimum efficiency related to curve 1 and so it is supposed that T2 value is higher than T1 in terms of teaching. An essential variant amongst the efficiency is measured by calculating the mean between them (M_1 for Curve 1 and $1M_2$ for Curve 2). For instance, an excellent teacher achieves optimal means from the result of learner. Also, the learner learns from communication amongst them and it also assists them to improve the outcomes [18]. There are two major levels in TLBO approach i.e., 'Learner Phase' (learns through their communication) and 'Teacher Phase' (learns from teacher).

2.1.1 Teacher Phase

The mean of class increases in M_A to M_B based upon the decent teacher. Teachers are supposed to be optimum, if his/her learner is up to her/his level, depending upon their knowledge. However, it is not possible essentially and the teachers could shift the mean of class up to a certain level based on the ability of class. Let M_i indicates the mean and T_i represents the teacher during all iterations i . T_i shifts the efforts to the mean M_i near their individual level. Hence, the novel means would be T_i which is called as M_n . The solutions get upgraded based on the variant between the present and novel mean compared as follows.

$$\text{Difference_Mean}_i = r_i(M_n - T_F M_i) \quad (2)$$

In which T_F stands for teaching feature, calculated as a mean value that should be changed. Further, r_i denotes an arbitrary amount between zero and one. The value of T_F is one or two, i.e., again it is a heuristic phase and is definite in an arbitrary method with similar likelihood as $T_F = \text{round}[1 + \text{rand}(0, 1) \{2 - 1\}]$. This difference modifies the present solution based on the equation given below.

$$X_{n, i} = X_{o, i} + \text{Difference_Mean}_i \quad (3)$$

2.1.2 Learner Phase

The learner enhances their skill utilizing two ways: input by the teachers and their communications with students. The learner endures interface with rest of the learners through group discussion, presentation, and so on. The learners learn novel things, if other learners are highly skilled with regards to the subject. The learner's alteration is given herewith.

For $i = 1: P_n$

Randomly select two learners X_i and X_j , in which $i \neq j$

Iff $f(X_i) < f(X_j)$

$$X_{n, i} = X_{o, i} + r_i(X_i - X_j)$$

Otherwise

$$X_{n,i} = X_{o,i} + r_i(X_j - X_i)$$

End If

End For

Agree X_n once optimal function values are attained.

At the time of journey, a commuter spends their main time in waiting, because of traffic signals at the intersection or congestion *en route* created by accident, few researches, and so forth. Therefore, to reduce the total travel time, one should decrease the waiting time in these areas concurrently. The current study presents a TLBO-CC approach in VANET to reduce the travel time in the course of road trips. The presented approach decreases the waiting time at intersection through route optimization i.e., by evading congestion *en route*. This results in travel cost reduction due to decrease in the consumption of fuel and mitigated health hazards like skin disease or asthma or lung-related disorders or irritation to eyes that occur as a result of engine emission and so on. In current situation, vehicles should wait for a long period of time to get their turn to cross the connections, because of pre-timed signal or actuated signal with predetermined time estimation method. This method does not take into account the actual vehicle density. In general, each driver tends to select the shortest route to reach the destination which in turn increases the congestion in that specific route, owing to huge number of vehicles, utilizing the specific route. So, in current study, this parameter is optimized concurrently with TLBO-CC approach to reduce the trip time. In the presented method, TLBO-CC approach is enhanced by integrating preemptive traffic signals instead of average traffic signals faced during travel to the destination. Once the TLBO-CC approach is executed, the commuters are capable of reducing their waiting time at the intersection with non-congested optimized path. This results in lesser travel time that additionally decreases the traveling cost to reach the destination, due to low consumption of fuel.

A fitness function is assumed which is dependent upon various parameters like network throughput, residual energy, and packet loss rate to control congestion in VANET:

$$\text{Fitness function } (f_j) = \sum_{i=1}^N (w_1 * \tau_i + w_2 * (1 - P_{L_i}) + w_3 * E_i + w_4 * d_{j,i}) \quad (4)$$

where i implies the iteration in the range of [1-N] (entire number of nodes),

$w_1, w_2, w_3,$ and w_4 represent the weights supplied to this technique,

τ refers to the throughput of networks, P_L represents the normalization packet lost rate from the network

$d_{j,i}$ signifies the distance between node i as well as j

E stands for residual energy of all the nodes in the network.

2.2 Design of GRU-DoSD Technique

GRU method is generally used in the allocation of appropriate class labels for DoS attacks. RNN signifies Neural Network (NN) with one or more recurrent layers in hidden layers. However, it differs from other networks in its reception of input data. It is commonly employed for series data and is approximately connected with data regarding time order, language, weather, and stock price. RNN is a feedback framework that attains and employs the outcome of completed layers as its input. Therefore, the previous data affects the outcome. RNN is planned well to process the time order data; it employs

weight as well as bias frequently by passing the data into cyclic vectors. It gains an input vector X and makes the resultant vector, y . It is considered as output as well as input with unrestricted length and Fully Connected (FC) designs. The network of many styles and shapes is developed by changing its structure. The current RNNs are a long-term dependency problem [19]. The weight converges at zero while it deviates at infinity as the time lag increases. Hence, LSTM is projected to resolve the long-term dependence issue of existing RNNs. It can be a modified structure of RNN and is considered as the occurrence of cell state. LSTM contains output, input, and forget gates. All the gates control values using sigmoid layer and pointwise multiplication. LSTM has an outstanding ability to remember long term dependence. So, it gets a long time to train the manner, due to its difficult framework. Thus, GRU is projected to speed up the trained method. It is a type of RNN framework that utilizes gate approach and is enthused by LSTM and east framework.

GRU is different from LSTM while the latter contains three gate functions that are dependent upon RNN network such as output, input, and forgetting gates to resultant values, control input, and memory correspondingly. However, the two gates are projected in GRU manner i.e., reset and upgrade gates. But σ represents the gating function. Fig. 2 illustrates the framework of GRU.

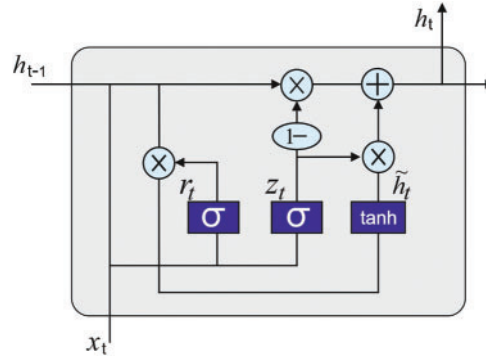


Figure 2: Structure of GRU

GRU integrates input as well as forgetting gates of LSTM for single upgrade gate. These procedures effectually reduce the amount of computations and the probabilities of gradient explosion/disappearance. In particular, the functioning approach is provided as follows

$$Z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z), \quad (5)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r), \quad (6)$$

$$h'_t = \tanh(W \cdot [r_t * h_{t-1}, x_t] + b_h), \quad (7)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * h'_t, \quad (8)$$

$$y_t = \sigma(W_0 \cdot h_t), \quad (9)$$

While Z_t and r_t imply the reset and upgrade gates correspondingly, W_z , W_r , W and W_0 signify the weight parameters of input data, h_{t-1} denotes the output of prior layer, and x_t refers to the input of current layer. b_z , b_r and b_h demonstrate the biases, σ stands for sigmoid function whereas \tanh is employed to change the value flow by networks. The resultant values i.e., σ and \tanh functions are organized between (0, 1) and (-1, 1) correspondingly

Then, the final outcome is obtained and the loss value is evaluated with the help of loss function.

$$E_t = \frac{1}{2}(y_d - y_t^0)^2, \quad (10)$$

$$E = \sum_{t=1}^T E_t \quad (11)$$

where E_t refers to the loss of single sample at a certain time, y_d signifies the real label data, y_t^0 demonstrates the resultant value of primary iteration, and E implies the loss of single instance at always.

BP technique is employed in this study to learn the networks. So, the partial derivatives of loss function are evaluated to all the parameters. Then, the parameter is upgraded and the loss convergence is iteratively defined.

In order to optimally alter the hyperparameters present in GRU technique, NADAM optimizer is utilized. NADAM optimizer has tried to integrate Nesterov's accelerated adaptive moment estimate with Adam. An essential advantage of this combined technique is that the employed adaptive moment estimation assists in the execution of most precise stage in a gradient way. This occurs by upgrading the process variables with momentum phase, before the calculation of gradient [20]. The upgrade rule of NADAM is demonstrated herewith.

$$w_t = w_{t-1} - \alpha \times \frac{\bar{m}_t}{\sqrt{\hat{v}_t + \varepsilon}}, \quad (12)$$

But

$$\bar{m}_t = (1 - \beta_{1,t})\hat{g}_t + \beta_{1,t+1}\hat{m}_t,$$

$$\hat{m}_t = \frac{m_t}{1 - \prod_{i=1}^{t+1} \beta_{1i}}, \quad (13)$$

$$\hat{g}_t = \frac{g_t}{1 - \prod_{i=1}^{t+1} \beta_{1i}}.$$

3 Performance Validation

The current section demonstrates the results of the analysis attained by the presented algorithm in terms of reduced travel time and detection of DoS attacks. The proposed model was simulated using MATLAB tool. The results were examined under varying number of vehicles and prediction intervals. [Tab. 1](#) and [Fig. 3](#) shows the results of Total Distance Covered (TDC) analysis of TLBO-CC method with recent techniques under varying number of vehicles in metres. The results show that the proposed TLBO-CC approach accomplished effectual outcomes with the least TDC value under distinct vehicle counts. For instance, with 300 vehicles, TLBO-CC technique produced a low TDC of 3316 m, whereas ACO, EACO, MACO, and HAPO techniques achieved high TDC values such as 5793, 6831, 7442, and 7042 m respectively. Besides, with 1200 vehicles, the proposed TLBO-CC approach accomplished a less TDC of 7674 m, whereas ACO, EACO, MACO, and HAPO methods got improved TDC values like 9629, 16450, 18920, and 17193 m correspondingly. With 2100 vehicles, the proposed TLBO-CC technique attained a low TDC of 18382 m, whereas other techniques such as ACO, EACO, MACO, and HAPO obtained superior TDC values such as 20841, 28693, 32465, and 28577 m respectively. Furthermore, with 3300 vehicles, TLBO-CC method yielded a low TDC of 32047 m, whereas ACO,

EACO, MACO, and HAPO schemes achieved enhanced TDC values namely, 34946, 44422, 49271, and 43659 m correspondingly. Moreover, with 4500 vehicles, the proposed TLBO-CC method produced a reduced TDC of 40657 m, whereas ACO, EACO, MACO, and HAPO algorithms accomplished the maximum TDC values such as 43048, 55976, 61569, and 55319 m correspondingly.

Table 1: Results of TDC analysis accomplished by TLBO-CC technique (m)

Total distance covered (in m)					
No. of vehicles	ACO	EACO	MACO	HAPO	TLBO-CC
300	5783	6831	7442	7042	3316
600	6685	8427	9207	8669	4098
900	7593	12469	14254	12960	4754
1200	9629	16450	18920	17193	7674
1500	13596	19788	23660	20986	11240
1800	18724	24274	27984	24688	16429
2100	20841	28693	32465	28577	18382
2400	24642	32972	37503	32887	22323
2700	27917	36965	41907	36741	25136
3000	30235	42984	47916	42677	27914
3300	34946	44422	49271	43659	32047
3600	37480	46996	52843	46583	34765
3900	39663	50849	56415	50392	36927
4200	41859	53142	57987	52405	39920
4500	43048	55976	61569	55319	40657

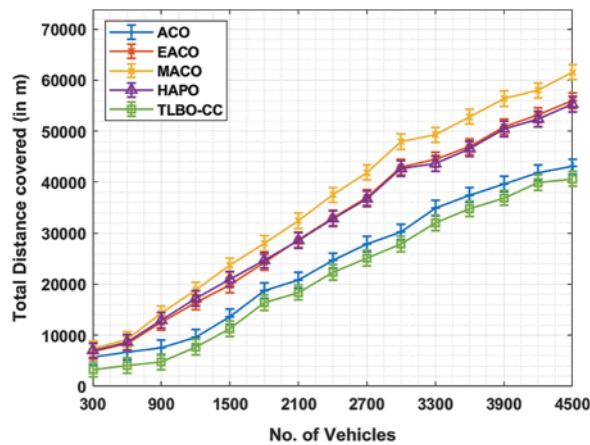


Figure 3: TDC analysis of TLBO-CC model under different counts of vehicles

Tab. 2 and Fig. 4 shows the results from Total Travel Time (TTT) analysis achieved by the proposed TLBO-CC technique against recent methods under varying number of vehicles. The results show that the proposed TLBO-CC algorithm outperformed other methods and produced effective

outcomes with the least TTT under varying vehicle counts. For sample, with 300 vehicles, TLBO-CC approach resulted in a reduced TTT of 279 s, whereas ACO, EACO, MACO, and HAPO methods accomplished enhanced TTT values such as 578, 564, 513, and 498 s respectively. Similarly, with 1200 vehicles, TLBO-CC technique produced a low TTT of 773 s, whereas ACO, EACO, MACO, and HAPO methods accomplished superior TTT values such as 1328, 1115, 1303, and 1027 s respectively. Likewise, with 2100 vehicles, TLBO-CC technique achieved a low TTT of 1339 s, whereas ACO, EACO, MACO, and HAPO approaches offered increased TTT values such as 2147, 1892, 2034, and 1634 s respectively. In addition to these, with 3300 vehicles, TLBO-CC method resulted in a decreased TTT value of 1808 s, whereas ACO, EACO, MACO, and HAPO techniques produced high TTT values such as 3109, 2450, 2718, and 2162 s respectively. Finally, with 4500 vehicles, the proposed TLBO-CC method accomplished a low TTT of 2404 s, whereas ACO, EACO, MACO, and HAPO approaches obtained high TTT values namely, 3841, 2935, 3547, and 2743 s correspondingly.

Table 2: Results of TTT analysis accomplished by TLBO-CC technique (sec)

Total travel time (sec)					
No. of vehicles	ACO	EACO	MACO	HAPO	TLBO-CC
300	578	564	513	498	279
600	820	746	742	685	454
900	1195	988	1025	932	668
1200	1328	1115	1303	1027	773
1500	1792	1389	1569	1362	961
1800	2026	1647	1835	1549	1241
2100	2147	1892	2034	1634	1339
2400	2278	2063	2117	1735	1411
2700	2498	2159	2211	1906	1551
3000	2642	2246	2313	1987	1666
3300	3109	2450	2718	2162	1808
3600	3295	2514	2924	2348	1937
3900	3478	2768	3136	2531	2053
4200	3710	2871	3342	2689	2295
4500	3841	2935	3547	2743	2404

Tab. 3 and Fig. 5 shows the results of Prediction Variance (PV) analysis accomplished by IDoS-CC technique against state-of-the-art algorithms under varying prediction intervals in 100 nodes. The results demonstrate that the proposed IDoS-CC algorithm accomplished effective outcomes with the worst PV under different vehicle counts. For instance, with 10 intervals, the IDoS-CC method produced a low PV of 154.08 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOA methods achieved the highest PV values namely, 170.36, 169.90, 167.42, and 156.34 s correspondingly.

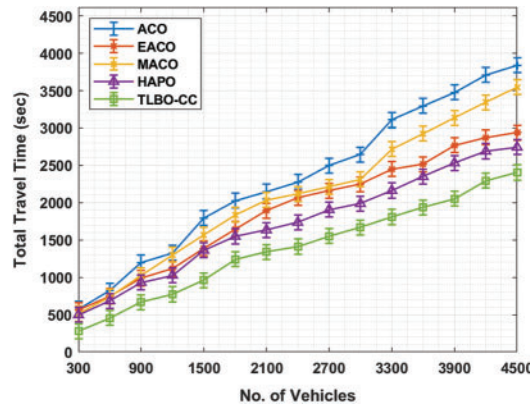


Figure 4: TTT analysis of TLBO-CC model under different counts of vehicles

Table 3: Results of the analysis of IDoS-CC technique in terms of Prediction Variance (PV) under 100 nodes

Prediction variance (meters)					
Prediction interval (sec)	CA-PSO	CA-GA	CA-ACOA	CA-IACOIA	IDoS-CC
10	170.36	169.90	167.42	156.34	154.08
20	178.95	176.91	173.52	161.54	157.92
30	187.31	184.82	183.24	164.25	160.64
40	194.09	188.67	189.57	167.19	163.35
50	213.08	193.87	197.26	171.94	167.42
60	212.63	198.61	204.49	175.10	170.13
70	225.52	210.37	207.66	179.17	173.75
80	230.94	215.79	210.14	182.34	175.56
90	237.95	221.67	214.21	187.99	178.50
100	238.17	224.84	218.28	192.51	181.43

Likewise, with 30 intervals, IDoS-CC technique produced a reduced PV value of 160.64 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA techniques offered increased PV values such as 187.31, 184.82, 183.24, and 164.25 s respectively. Also, with 50 intervals, the proposed IDOS-CC technique resulted in a reduced PV value of 167.42 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA algorithms accomplished enhanced PV values namely, 213.08, 197.26, 171.94, and 167.42 s respectively. In addition to these, with 70 intervals, IDoS-CC technique resulted in a reduced PV value of 173.75 s, whereas other techniques namely, CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA achieved high PV values such as 225.52, 210.37, 207.66, and 179.17 s respectively. Eventually, with 100 intervals, IDoS-CC technique produced a less PV value of 181.43 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA methodologies obtained improved PV values namely, 238.17, 224.84, 218.28, and 192.51 s correspondingly.

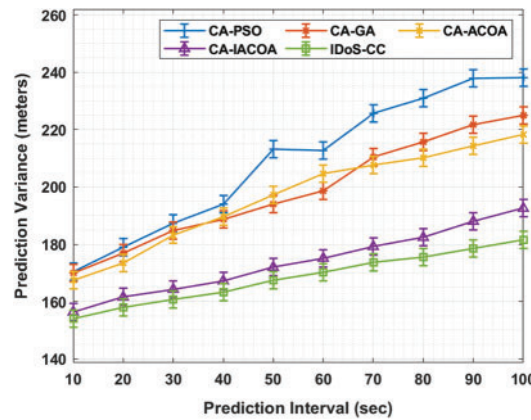


Figure 5: Prediction variance analysis results of IDoS-CC model under 100-nodes

Tab. 4 and Fig. 6 shows the results of PV analysis attained by IDoS-CC method against recent algorithms under varying prediction intervals in 200 nodes. The results showcase that IDoS-CC manner accomplished effectual outcomes with the least PV under varying vehicle counts. For instance, with 10 intervals, IDoS-CC technique produced a less PV of 155.79 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACO techniques achieved high PV values namely, 170.66 s, 168.89 s, 189.28 s, and 161.79 s correspondingly. Followed by, with 30 intervals, IDoS-CC technique resulted in a reduced PV value of 160.62 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACO algorithms presented superior PV values namely, 187.28, 184.40, 203.91, and 167.56 s correspondingly. Along with these, with 50 intervals, the proposed IDOS-CC technique resulted in a reduced PV value of 165.81 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACO methods obtained improved PV values such as 212.99, 194.60, 209.89, and 175.76 s correspondingly. Furthermore, with 70 intervals, the proposed IDoS-CC algorithm accomplished a low PV value of 175.88 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACO techniques offered the maximum PV values namely, 225.85, 210.78, 217.87, and 182.85 s respectively. At the same time, with 100 intervals, IDoS-CC method resulted in a reduced PV value of 189.13 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACO approaches accomplished high PV values such as 238.04, 224.52, 244.91, and 197.04 s correspondingly.

Table 4: Results of the analysis of IDoS-CC technique in terms of Prediction variance (PV) under 200 nodes

Prediction variance (meters)					
Prediction interval (sec)	CA-PSO	CA-GA	CA-ACOA	CA-IACO	IDoS-CC
10	170.66	168.89	189.28	161.79	155.79
20	179.30	176.87	197.48	164.45	157.46
30	187.28	184.40	203.91	167.56	160.62
40	193.93	189.28	207.45	172.43	164.50
50	212.99	194.60	209.89	175.76	165.81
60	213.44	198.59	213.88	179.08	169.09

(Continued)

Table 4: Continued

Prediction variance (meters)					
Prediction interval (sec)	CA-PSO	CA-GA	CA-ACOA	CA-IACOIA	IDoS-CC
70	225.85	210.78	217.87	182.85	175.88
80	230.95	216.32	222.08	188.83	178.84
90	238.71	221.64	233.83	192.38	183.38
100	238.04	224.52	244.91	197.04	189.13

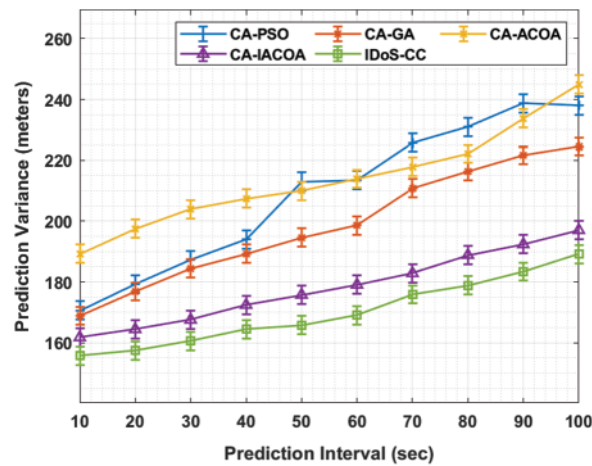


Figure 6: Prediction variance analysis of IDoS-CC model under 200-nodes

Fig. 7 shows the results of PV analysis accomplished by IDoS-CC method against other state-of-the-art approaches under varying prediction intervals in 100 nodes. The results portray that the proposed IDoS-CC approach accomplished an effectual outcome with the least PV under distinct vehicle counts. For instance, with 10 intervals, the proposed IDoS-CC technique resulted in a low PV of 5.24 s, whereas other techniques such as CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA accomplished increased PV values namely, 5.80, 5.71, 5.53, and 5.37 s correspondingly. Moreover, with 30 intervals, IDoS-CC technique achieved a low PV of 5.22 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA techniques offered the maximum PV values such as 5.62, 5.64, 5.45, and 5.27 s respectively. Similarly, with 50 intervals, the proposed IDOS-CC technique resulted in a reduced PV value of 5.15 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA techniques achieved increased PV values namely, 5.48, 5.54, 5.36, and 5.22 s respectively. Besides, with 70 intervals, IDoS-CC method resulted in a reduced PV value of 5.11 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA techniques accomplished high PV values namely, 5.44, 5.46, 5.29, and 5.16 s correspondingly. Likewise, with 100 intervals, the IDoS-CC technique resulted in a reduced PV value of 4.74 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA techniques achieved high PV values such as 5.36, 5.36, 5.21, and 4.98 s correspondingly.

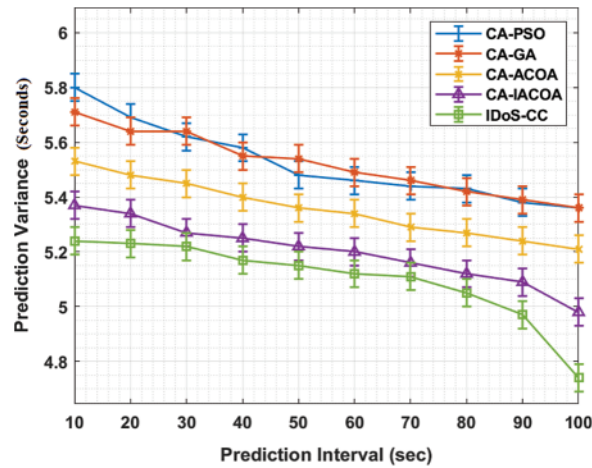


Figure 7: Prediction variance analysis of IDoS-CC model under 100-nodes

Tab. 5 explores the results accomplished during PV analysis by IDoS-CC technique against recent algorithms under different prediction intervals in 200 nodes. The results show that the proposed IDoS-CC method outperformed other methods through its effectual outcomes with the least PV under distinct vehicle counts.

Table 5: Results of the analysis of IDoS-CC technique in terms of Prediction Variance (PV) under 200 nodes

Prediction variance (Seconds)					
Prediction interval (sec)	CA-PSO	CA-GA	CA-ACOA	CA-IACOIA	IDoS-CC
10	5.60	5.70	5.50	5.22	5.15
20	5.55	5.62	5.45	5.21	5.14
30	5.45	5.61	5.40	5.18	5.09
40	5.42	5.53	5.35	5.16	5.07
50	5.40	5.51	5.31	5.13	5.04
60	5.38	5.44	5.28	5.08	5.00
70	5.34	5.42	5.23	5.04	4.97
80	5.31	5.38	5.21	5.01	4.90
90	5.27	5.34	5.18	4.89	4.81
100	5.23	5.31	5.15	4.85	4.78

For instance, with 10 intervals, the proposed IDoS-CC technique resulted in a reduced PV value of 5.15 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA techniques accomplished high PV values namely, 5.60, 5.70, 5.50, and 5.22 s correspondingly. Followed by, with 30 intervals, the IDoS-CC method produced a low PV of 5.09 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOIA techniques achieved improved PV values such as 5.45, 5.61, 5.40, and 5.18 s respectively. Also, with 50 intervals, the proposed IDOS-CC technique resulted in a low PV value of 5.04 s, whereas CA-PSO,

CA-GA, CA-ACOS, and CA-IACOA schemes offered increased PV values namely, 5.40, 5.51, 5.31, and 5.13 s respectively. Likewise, with 70 intervals, IDoS-CC technique attained a low PV of 4.97 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOA techniques obtained high PV values such as 5.34, 5.42, 5.23, and 5.04 s correspondingly. Eventually, with 100 intervals, the proposed IDoS-CC technique resulted in a reduced PV of 4.78 s, whereas CA-PSO, CA-GA, CA-ACOS, and CA-IACOA techniques offered high PV values namely, 5.23, 5.31, 5.15, and 4.85 s correspondingly. A series of simulation analyses was conducted and the results are discussed above which highlight the better outcomes of IDoS-CC technique. The proposed technique reduced the congestion and successfully identified DoS attacks in the network.

4 Conclusion

In current research work, a new IDoS-CC approach is designed for VANET. The goal of the proposed IDoS-CC technique is to reduce the level of congestion and detect the attacks that exist in the network. It includes two-stage processes namely TLBO-CC based congestion control and GRU-DoSD based attack detection. IDoS-CC technique includes TLBO algorithm to optimize the routes taken by vehicles via traffic signals and to minimize the congestion instantaneously on a particular route so as to assure minimal fuel utilization. TLBO is applied to avoid congestion on roadways. Besides, GRU-DoSD model is also employed as a classification model to effectively distinguish the compromised as well as genuine vehicles in the network. A series of simulation analyses was conducted and the outcomes illustrate the supremacy of the proposed IDoS-CC technique. The proposed method reduced the congestion and successfully identified DoS attacks in the network. In future, the hyperparameter tuning of the GRU model can be derived by multi-objective TLBO algorithm in order to improve detection accuracy.

Funding Statement: The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work under grant number (RGP 2/23/42). This research was funded by the Deanship of Scientific Research at Princess Nourah bint Abdulrahman University through the Fast-Track Research Funding Program.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

- [1] S. K. Erskine and K. M. Elleithy, "Real-time detection of dos attacks in ieee 802.11p using fog computing for a secure intelligent vehicular network," *Electronics*, vol. 8, no. 7, pp. 776, 2019.
- [2] D. Gupta, A. Khanna, S. K. Lakshmanaprabu, K. Shankar, V. Furtado *et al.*, "Efficient artificial fish swarm based clustering approach on mobility aware energy-efficient for MANET," *Transactions on Emerging Telecommunications Technologies*, vol. 30, no. 9, pp. 1–10, 2019.
- [3] S. Sharma and A. Kaul, "A survey on intrusion detection systems and honeypot based proactive security mechanisms in VANETs and VANET cloud," *Vehicular Communications*, vol. 12, pp. 138–164, 2018.
- [4] I. V. Pustokhina, D. A. Pustokhin, E. L. Lydia, M. Elhoseny and K. Shankar, "Energy efficient neuro-fuzzy cluster based topology construction with metaheuristic route planning algorithm for unmanned aerial vehicles," *Computer Networks*, vol. 196, pp. 108214, 2021.
- [5] C. Campolo and A. Molinaro, "Multichannel communications in vehicular Ad Hoc networks: A survey," *IEEE Communications Magazine*, vol. 51, no. 5, pp. 158–169, 2013.

- [6] T. Vaiyapuri, S. N. Mohanty, M. Sivaram, I. V. Pustokhina, D. A. Pustokhin *et al.* “Automatic vehicle license plate recognition using optimal deep learning model,” *Computers, Materials & Continua*, vol. 67, no. 2, pp. 1881–1897, 2021.
- [7] K. D. Thilak and A. Amuthan, “Cellular automata-based improved ant colony-based optimization algorithm for mitigating ddos attacks in vanets,” *Future Generation Computer Systems*, vol. 82, pp. 304–314, 2018.
- [8] S. Manne, E. L. Lydia, I. V. Pustokhina, D. A. Pustokhin, V. S. Parvathy *et al.* “An intelligent energy management and traffic predictive model for autonomous vehicle systems,” *Soft Computing*, vol. 25, pp. 11941–11953, 2021.
- [9] A. Rajagopal, G. P. Joshi, A. Ramachandran, R. T. Subhalakshmi, M. Khari *et al.* “A deep learning model based on multi-objective particle swarm optimization for scene classification in unmanned aerial vehicles,” *IEEE Access*, vol. 8, pp. 135383–135393, 2020.
- [10] E. Khoza, C. Tu and P. Owolawi, “Decreasing traffic congestion in vanets using an improved hybrid ant colony optimization algorithm,” *Journal of Communications*, vol. 15, no. 9, pp. 676–686, 2020.
- [11] V. Jindal and P. Bedi, “Preemptive maco (maco-p) algorithm for reducing travel time in vanets,” *Applied Artificial Intelligence*, vol. 31, no. 2, pp. 174–196, 2017.
- [12] S. K. Erskine and K. M. Elleithy, “Real-time detection of dos attacks in ieeee 802.11p using fog computing for a secure intelligent vehicular network,” *Electronics*, vol. 8, no. 7, pp. 776, 2019.
- [13] H. Chang, Y. E. Song, H. Kim and H. Jung, “Distributed transmission power control for communication congestion control and awareness enhancement in VANETS,” *PLoS ONE*, vol. 13, no. 9, pp. e0203261, Sep. 2018.
- [14] A. K. Sangaiah, J. S. Ramamoorthi, J. J. P. C. Rodrigues, M. A. Rahman, G. Muhammad *et al.* “LACCVoV: Linear adaptive congestion control with optimization of data dissemination model in vehicle-to-vehicle communication,” *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–10, 2020.
- [15] P. M. Kumar, U. Devi, G. Manogaran, R. Sundarasekar, N. Chilamkurti *et al.* “Ant colony optimization algorithm with internet of vehicles for intelligent traffic control system,” *Computer Networks*, vol. 144, pp. 154–162, 2018.
- [16] F. Lyu, N. Cheng, H. Zhou, W. Xu, W. Shi *et al.*, “DBCC: Leveraging link perception for distributed beacon congestion control in vanets,” *IEEE Internet Things Journal*, vol. 5, no. 6, pp. 4237–4249, 2018.
- [17] M. Selvi and B. Ramakrishnan, “Lion optimization algorithm (LOA)-based reliable emergency message broadcasting system in VANET,” *Soft Computing*, vol. 24, no. 14, pp. 10415–10432, 2020.
- [18] M. Singh, B. K. Panigrahi and A. R. Abhyankar, “Optimal coordination of directional over-current relays using teaching learning-based optimization (TLBO) algorithm,” *International Journal of Electrical Power & Energy Systems*, vol. 50, pp. 33–41, 2013.
- [19] M. H. Jeong, T. Y. Lee, S. B. Jeon and M. Youm, “Highway speed prediction using gated recurrent unit neural networks,” *Applied Sciences*, vol. 11, no. 7, pp. 3059, 2021.
- [20] G. Bargshady, X. Zhou, R. C. Deo, J. Soar, F. Whittaker *et al.*, “The modeling of human facial pain intensity based on temporal convolutional networks trained with video frames in hsv color space,” *Applied Soft Computing*, vol. 97, pp. 106805, 2020.