Gorilla Troops Optimizer with Deep Learning-based Multi-Criteria Decision Making for Traffic Analysis in V2X Networks

Djamal Lhiani[1,*], Othman Al-basheer[2]

[1]Department Of Mathematics, University Of Blida 1, Blida, Algeria

[2]Sudan University of Science and Technology, Faculty of Science, Khartoum, Sudan

Emails: lhanibest13@gmail.com, othmanzolbasheer@gmail.com

Abstract

Multi-criteria decision-making (MCDM) is employed for analyzing traffic in a Vehicle-to-Everything (V2X) network. V2X suggests communication among vehicles and other entities, containing pedestrians, infrastructure, and other vehicles. Traffic analysis and management in V2X networks need effectual decision-making approaches, which assume several conditions. MCDM contains estimating and choosing alternatives depending on several conditions or objectives. In the context of traffic analysis in V2X networks, MCDM algorithms are employed for decision-making concerning traffic flow optimizer, resource allocation, route planning, and congestion management. Deep learning (DL) approaches are trained to analyze massive counts of data gathered from several sources from the V2X network. These sources contain traffic sensors, GPS data, vehicle-to-infrastructure (V2I) communication, and historical traffic designs. By processing this data, DL approaches extract useful insights and create informed decisions depending on various conditions. Therefore, this article proposes a gorilla troops optimizer with deep learning-based MCDM for traffic analysis (GTODL-MCDMTA) technique in the V2X network. The purpose of the GTODL-MCDMTA algorithm is to identify the traffic flow prediction for improving route planning and resource allocation with the consideration of various factors into account. In the presented GTODL-MCDMTA technique, the input data is pre-processed to remove noise and normalize it for analysis. Next, the GTO algorithm is used for the feature selection process. Besides, the deep extreme learning machine (DELM) model is used for the forecast of traffic movement. Finally, the seeker optimization algorithm (SOA) has been utilized for the parameter tuning of the DELM technique. A brief set of simulation outcomes can be applied to emphasize the promising outcomes of the GTODL-MCDMTA technique. The experimental outcome demonstrates the efficiency and efficiency of the GTODL-MCDMTA approach in handling the complexity and dynamic nature of V2X network traffic analysis.

Keywords: Sustainable transport; V2X Networks; Traffic analysis; Deep learning; Multi-criteria decision-making

1. Introduction

Decision-makers within the logistics, mobility, and transportation sectors must be taken into consideration for a large number of conflicting data from actors with diverse interests and backgrounds [1]. Sustainability reflects the fundamental human desire to protect and enhance our earth. It highlights the complex nature of human activities and thus the necessity for coordinated decisions amongst distinct groups, jurisdictions, and sectors [2]. The sustainability concept has a powerful grip on people. Attainment of sustainable transportation system is desirable, but many problems lie along the path to attaining such a system [3]. The nation's transportation system has a better quality of life through increased access to education, health care, recreation, employment, and a large number of consumer goods.

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On highways, traffic flow shows an active occurrence in operational setting [4]. The sustainability model in transport engineering can be described by the multi-criteria decision-making analysis (MCDA), a self-control of Operation Research (OR) that is in a vast number of practices and applications in realtime traffic trade [5]. The concept of vehicles-to-everything (V2X) employs the new generation of information and communication technology (ICT) to recognize vehicle-to-infrastructure (V2I), omnidirectional vehicle-to-vehicle (V2V), vehicle-to-network/cloud (V2N/V2C) network connections, and vehicle to pedestrian (V2P). This technique connects the different components of transportation namely vehicles, roads, pedestrians, and cloud environment [6]. V2X is supported in promoting an intelligent transportation system (ITS) and promoting the emergence of novel forms and novel modes of automobiles and transport services, and supporting vehicles to attain further details and endorse the application and innovation of automated drive technology. It is very important to reduce pollution, improve traffic effectiveness, save resources, improve traffic management, and reduce the incidence of accidents. Intelligent connected vehicles, automated driving, and Intelligent transportation are the applications of V2X [7]. A wide range of applications has a number of requirements for safety, latency, user density, throughput, and reliability of the V2X environments.

Recently, the DL algorithm becoming ever more common since it can rapidly solve some types of complex challenges in various uses supervised and unsupervised learning techniques [8]. It relies on multi-layer neural networks (MLNN) and techniques that deal with wide-ranging datasets and some techniques outperform typical artificial neural networks (ANN) in processing the prior data. The advances of existing DL assure solving of previously unsolvable, highly complex problems [9]. DL algorithm is of great significance to predict traffic behaviors because it is acquired in huge data counts and more accurately recognizes patterns than other techniques. Potential traffic prediction enables performances to enhance the quality of service (QoS) beforehand it droplets [10]. Since DL exploits previous data to achieve higher accuracy and enhance its decision-making for predicting analysis. A secure network can be allowed by forecasting a massive potential occurrence of data flow at an unusual time that is more accurately defined as data stream-based intrusion.

This article proposes a gorilla troops optimizer with deep learning-based MCDM for traffic analysis (GTODL-MCDMTA) technique in the V2X network. In the presented GTODL-MCDMTA technique, the input data is pre-processed to remove noise and normalize it for analysis. Next, the GTO algorithm is used for the feature selection (FS) process. Besides, the deep extreme learning machine (DELM) model is used for the forecast of traffic movement. At last, the seeker optimization algorithm (SOA) has been utilized for the parameter tuning of the DELM technique. A brief set of simulation outcomes can be carried out to demonstrate the promising results of the GTODL-MCDMTA technique with respect to different measures.

2. Related Works

A short-term traffic predictive system that depends on difficult NN under the environments of the V2X transmission system was proposed in [11]. At first, a traffic perception model of a multi-media sensor depending on V2X transmission was designed and proposed. Then, a mobile edge computing (MEC)-aided structure was proposed in the V2X system to assist the computational and perceptual capabilities of the network. Furthermore, the GRU, the soft-attention model, and the graph convolutional network (GCN) are combined for extracting spatiotemporal characteristics of the traffic condition and incorporate them for upcoming forecasts. In [12], a DL algorithm based on the unidirectional LSTM technique was introduced for predicting traffic in the V2X network.

Qiu et al. [13] introduced a novel system that could precisely forecast the density and traffic flow in the city used for avoiding the V2X transmission flash crowd scenarios. The study employs a Topological GCN (ToGCN) by the Sequence-to-sequence (Seq2Seq) architecture for predicting future density and traffic flow with temporal correlation by fusing the present graph-and-grid-based traffic flow predictive techniques. Li et al. [14] devised an end-edge-cloud framework for the deployment of ML-driven techniques at network edges for predicting future trajectories of the vehicles that are further used for providing a robust safety message dissemination system. The traffic safety messages are distributed to appropriate vehicles and were forecast to pass over accident regions that could avoid unnecessary interference and considerably decrease the network data transmission overhead.

The authors [15] present a traffic flow predictive method that depends on WOA optimized BiLSTM_Attention mechanism for resolving these problems. First, the traffic flow can be predicted by the BiLSTM_Attention mechanism, which is enhanced by WOA for obtaining its 4 fittest parameters, such as count of nodes of 2 hidden states, learning rate, and training times. Lastly, to construct a WOA_BiLSTM_Attention mechanism, the four fittest parameters are used. The presented architecture was compared to the NN and CNN models enhanced by

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the WOA. In [16], proposed a traffic routing-based computational divesting system in cybertwin-driven IoV for V2X application where cybertwin is the network software functions and network hardware devices. At last, the enhanced Heterogeneous Earliest Finish Time (eHEFT) model was introduced to prevent inconsistency between the vehicle's movement and the data transmission direction that presents the gradient routing into the classical HEFT model.

Chu et al. [17] designed a semi-persistent resource distribution system utilizing the least minimum mean square error (LMMSE) traffic forecast in 2-tier networks. The proposed model comprises multiple roadside units (RSU) and central macro base station (MBS). In this work, the MBS pre-assigns persistent resources to RSUs dependent upon traffic forecasts, and later assign dynamic resource on real-time request in the vehicles by RSU. In [18], the past vehicle GPS data establishes the traffic prediction mechanism. At first, the Clustering in QUEst (CLIQUE)-based clustering model V-CLIQUE was introduced for analyzing the historical data of vehicle GPS. Afterwards, an ANN-based forecast technique was presented. At last, the study proposed an ANN-based weighted shortest path mechanism, A-Dijkstra.

3. The Proposed Model

In this article, we mainly designed a novel GTODL-MCDMTA technique to mechanize and effective traffic analysis in the V2X networks. The main purpose of the GTODL-MCDMTA system is to recognize the traffic flow prediction for improving route planning and resource allocation with the consideration of various factors into account. In the presented GTODL-MCDMTA technique, several subprocesses are involved namely pre-processing, GTO-based FS, DELM prediction, and SOA-based parameter tuning. Fig. 1 demonstrates the overall flow of the GTODL-MCDMTA method.

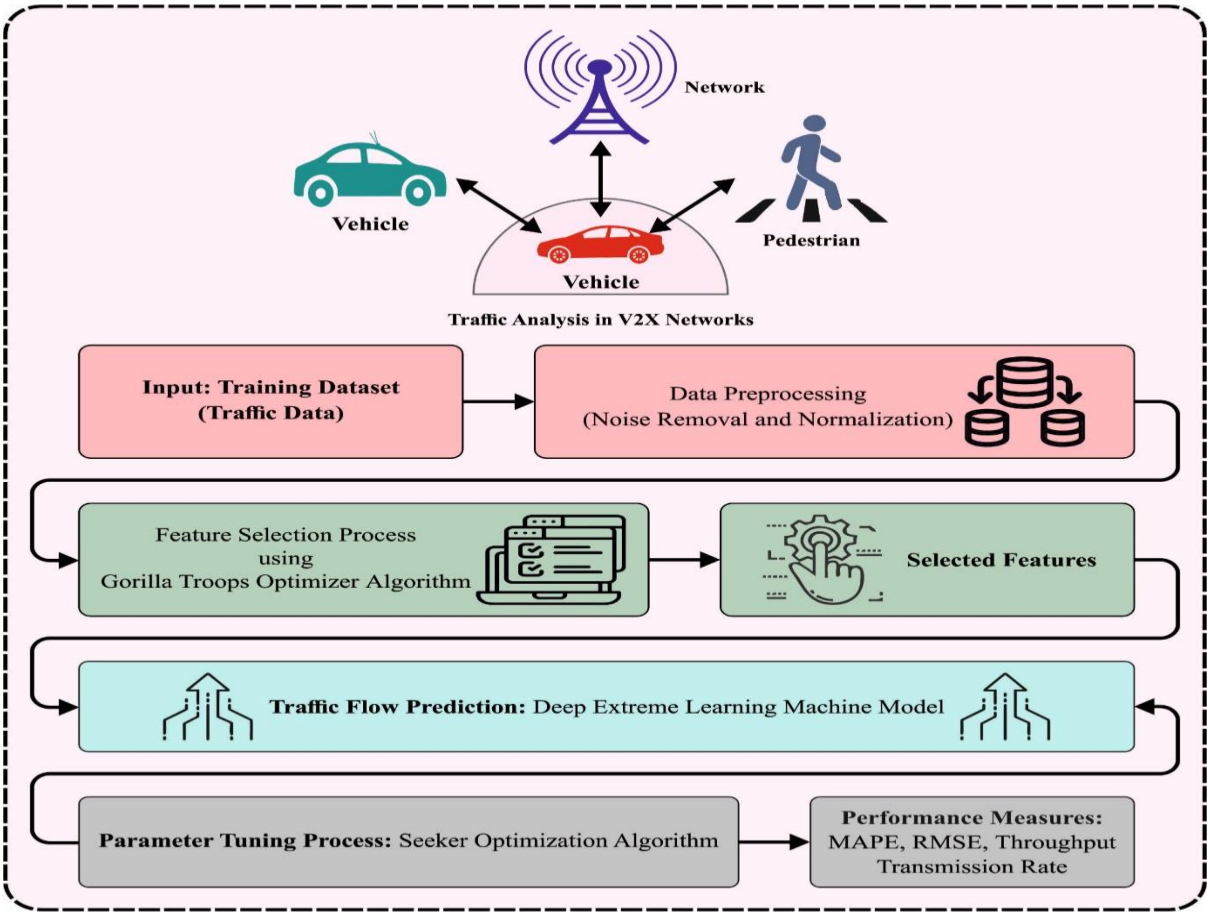

Fig. 1. Overall flow of GTODL-MCDMTA method

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3.1. GTO-based Feature Selection

For the selection of optimal features, the GTO algorithm is used. Artificial GTO is a new metaheuristic optimization algorithm based on gorilla behaviors [19]. The GTO optimizer demonstrates outstanding efficiency and accuracy in resolving several engineering issues. Moreover, the GTO technique has acceptable performance and a great potential to produce desirable outcomes for the system dimension by rising the number of search abilities. Also, it outperforms other optimizers in each dimension because the efficiency of other optimizers degrades as the dimension count rises. Another advantage of the GTO is that balances exploration and exploitation abilities in the surface of largescale difficulties.

In this stage, all the gorillas are set as a contestant for the fittest solution in all the iterations, with the better solution named silverback. The 3 dissimilar models are summarized in Eq. (1).

$$GX(t-1)=\begin{cases}(U_r-L_r)r_1+L_r & if\ rand<0\\ (r_2-D)X_r(t)+S\times V & if\ rand\geq 0.5\\ X(i)-S\left(S\big(X(t)-GX_r(t)\big)+r_3\big(X(t)-GX_r(t)\big)\right) & if\ rand<0.5\end{cases} \quad (1)$$

In Eq. (1), O denotes the parameter to migrate towards the unknown site. $GX(t-1)$ indicates the candidate of gorilla vector location from the following iteration, $rand$ shows the arbitrary parameter, $X(t)$ shows the gorilla location of existing vectors, and $X(i)$ denotes the candidate gorilla member numbers. Moreover, Lr and ur represent the lowest and uppest boundaries of the problem variable, correspondingly. $GX_r(t)$ shows the location of the arbitrarily selected gorilla candidate, and $X_r(t)$ denotes the location of these arbitrary gorillas. Moreover, the randomly generated variables r_1, r_2, and r_3 fall within [0,1]. The subsequent formula has been employed for calculating the V and S parameters.

$$D=N\times\left(1-\frac{t}{MaxIt}\right) \quad (2)$$

$$S=D*R \quad (3)$$

$$V=\frac{T}{X(i)} \quad (4)$$

Where $MaxIt$ denotes the maximal amount of iterations, R specifies the random integer within [−1, 1], and T shows the random integer ranges from $[-D,D]$. The male gorilla in the group is familiar with the silverback to search for food. During this step, "silverback" is the optimum solution found. These behaviors can be mathematically modelled by the following expression:

$$G_x(t+1)=S*\left(\left|1\backslash N\sum_{J-1}^{N}G_j\,(t)\right|\right)^{1/2^S} \quad (5)$$

$$G_x(t+1)=Y_{silverback}-\big(Y_{silverback}-Y(t)\big)*(2*rand-1)*A \quad (6)$$

Where $Y_{silverback}$ denotes the fittest location of the candidate solution, and A represents the constant parameter.

Lastly, in the exploitation stage, the fitness function (FF) solution was upgraded using a better solution. The major steps of GTO Algorithm 1 are given below:

1. Generate a population with an arbitrary position.
2. Fixed the D, S, L, U, and MaxIt parameters.
3. Define the gorilla's location utilizing Eq. (1).
4. Estimate all the FFs of gorillas.
5. Fixed the fittest solution as silverback's position.
6. Upgrade the gorilla location dependent upon values of D and W based on Eq. (6).
7. Display the better gorilla keep and posture the FF upgraded still the maximal iteration counts are attained.

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As previously stated, all the solutions are comprised of random floating point values within [0, 1] for estimating the FF score for all the solutions. The objective of FF is needed for evaluating the individual solution in FS. The main objective of FS is to improve prediction accurateness while reducing the amount of features. Especially, the objective function (OF) that integrates both conditions is given below:

$$OF\ (O) = \alpha * classification_{error} + (1-\alpha) * \frac{LS}{L} \tag{7}$$

In Eq. (8), $classification_{error}$ denotes the error rate of the learning algorithm, LS represents the length of the feature sub-string, L shows the unique dimensional, and α denotes the control parameter for the effects of feature size and classifier accuracy.

Algorithm 1: Pseudocode of GTO Algorithm

For each Gorilla Oi do
Change the location of the gorilla
Utilize the sigmoid function for turning the gorilla position as to probability values
Based on Eq. (6), for computing the candidate gorilla location in the separate domain
End for
For I=1to Ndo
Calculate OF of all the gorilla candidates (Gi)
If Gi is better than Oi, then exchange it,
End for
Set the better place as the Silverback
For each Gorilla Oi do
if $D \geq W$ then
Based on Eq. (6) to change the Gorilla's position
Else
Based on Eq. (5) altering the Gorilla's position
End if
End for
For $I = 1to$ Ndo
Calculate OF of all the candidate gorillas (Gi)
Exchange Oi if Gi is better, whereas G refers to the candidate Gorilla position
End for
Set better position as a Silverback
End for

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3.2. Traffic Prediction using DELM

In this work, the DELM model is utilized for the forecast of traffic movement. The ELM is established by Huang et al. to set the slow speed of learning of FFNNs [20]. The researchers recognized the slow speed of learning to utilize gradient descent (GD)-based learning approaches to train NNs and such methods iteratively tune the NN parameters. The DELM takes great generalized capability with very fast learning. Fig. 2 depicts the framework of DELM.

In different typical NNs, the hidden state parameters of DELM can be arbitrarily created without being iterative tuned, thus decreasing the learning method to just computing the better resultant weight β. To the given database $(x_j, t_j)_{(j=1)}^{N}$, whereas N implies the sample counts and SLFN has L hidden node, the activations function $g(x)$ is formulated as:

$$\sum_{i=1}^{L} \beta_i \, g(w_i . x_j + b_i) = t_j \tag{8}$$

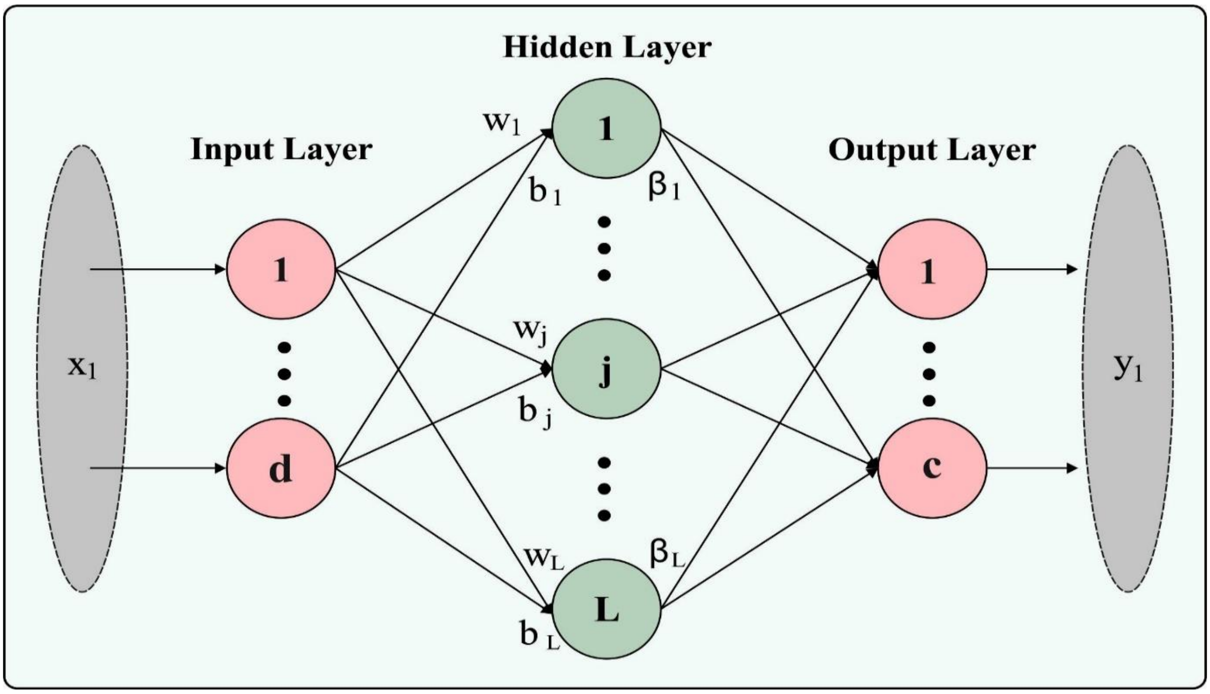

Fig. 2. Architecture of DELM

whereas t_j stands for the outcome of the network, $w_j = [w_{i1}, \ldots, w_{in}]^T$ signify the input weighted, b_i represents the bias of i^{th} hidden node, $\beta_i = [\beta_{i1}, \ldots, \beta_{im}]^T$ represents the weighted vector attaching the i^{th} hidden node with resultant nodes, and $w_{i^{x}j}$ exemplifies the inner product of w_i and x_i. Eq. (8) is modified in the compact matrix procedure as:

$$H\beta = T \tag{9}$$

In which, H indicates the resultant matrix of hidden state, and its mathematical model is written as:

$$H(w_1, \ldots, w_{N'} b_1, \ldots, b_{N'} x_1, \ldots, x_N) = \begin{bmatrix} g(w_i \cdot x_i + b_i) & \ldots & g(w_N \cdot x_i + b_i) \\ \vdots & \ddots & \vdots \\ g(w_1 x_N + b_1) & \ldots & g(w_N \cdot x_N + b_N) \end{bmatrix}_{N \times N} \tag{10}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix}_{N \times m} \quad and \quad \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N \times m} \tag{11}$$

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3.3. SOA-based Parameter Tuning

Finally, the SOA adjusts the parameters related to the DELM model. In SOA, the optimum solution can be accomplished by utilizing a seeker population [21]. There are 3 sub-populations for the whole population. The steps included in SOA are given below:

The search direction $d_{ij}(t)$ was evaluated at all the time steps t. Now, i specifies the population number and j indicates the amount of optimizer parameters. There exist two kinds of cooperative behaviours: (i) egotistic, and (ii) altruistic. The egotistic direction of i^{th} seekers is shown as follows.

$$\vec{d}_{i,ego}(t) = sign\left(\vec{p}_{i,best}(t) - \vec{X}_i(t)\right) \tag{12}$$

Where sign $(.)$ denotes the signum function.

In altruistic performance, the seeker shows pro-group behaviours. The 2 selective altruistic directions are provided as follows.

$$[\vec{d}_{i,alt\ 1}(t)] = \left[sign\left(\vec{g}_{best}(t) - \vec{x}_i(t)\right)\right] \tag{13}$$

$$\left[\vec{d}_{i,alt\ 2}(t)\right] = \left[sign\left(\vec{l}_{best}(t) - \vec{x}_i(t)\right)\right] \tag{14}$$

Where $\vec{g}sr(t)$ denotes the prior optimum location in neighborhood· $\vec{l}_{best}(t)$ implies the present optimal location of neighbours.

An empirical direction, viz., pro-activeness direction, shown in (15), is used for all the Seekers.

$$\vec{d}_{i,pro}(t) = \left[sign\left(\vec{\overline{x_i}}(t_1) - \vec{\overline{x_i}}(t_2)\right)\right] \tag{15}$$

Where $t_1, t_2 \in \{t, t-1, t-2\}$ and $\vec{\overline{x_i}}(t_1)$is better than $\vec{\overline{x_i}}(t_2)$.

The j^{th} component $of\,\vec{d}(t)$ was chosen by executing the proportional selection rule, as follows.

$$d_{ij} = \begin{cases} 0, & if\ r_j \leq p_j^{(0)} \\ +1, & if\ p_j^{(0)} \leq r_j \leq p_j^{(0)} + p_j^{(+1)} \\ 1, & if\ p_j^{(0)} + p_j^{(+1)} < r_j \leq 1 \end{cases} \tag{16}$$

Where r_j indicates the random integer that ranges from zero to one, $p_j^{(m)}(m \in \{0, +1-1\}$ shows the number of "m" from the set of values of $\{d_{ij,ego}, d_{ij,alt1}, d_{ij,alt2}, d_{ij,pro}\}$ on all the variables j, viz., $p_j^{(m)} = \frac{m}{4}$.

The input for fuzzy reasoning is considered from the consecutive number 1 to S. μ_i represents a linear membership function.

$$\mu_i = \mu_{\max} - \frac{S - I_i}{S - 1}(\mu_{\max} - \mu_{\min}) \tag{17}$$

Where I_i indicates the sequence number of $\vec{x}_i(t)$, the maximal membership degree ($\mu_{\max}$) is fixed to 0.95, and the minimal value $\mu_{\min} = 0.0111$ [1011] is considered.

Bell membership function, $\mu(x) = e^{-x^2/2\delta^2}$ is exploited for defuzzification. The $\vec{\delta}$ parameter can be determined as follows:

$$\vec{\delta} = \omega \times abs(\vec{x}\,best - \vec{x}) \tag{18}$$

In Eq. (15), ω is differed in [0.9-0.1] at all the iterations, and abs $(\cdot)$ returns the resultant vector. The best seeker was represented as $\vec{x}$ optimum and the arbitrarily chosen seeker is indicated as $\vec{x}$ where the i^{th}seeker belongs.

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Eq. (19) represents the step length (α_{ij}) for all the elements j.

$$\alpha_{ij} = \delta_j \left[\sqrt{-\ln\left(RAND(\mu_i, 1)\right)} \right] \tag{19}$$

Whereas $RAND\ (\mu_i, 1)$ denotes the randomly generated value within $[\mu_i, 1]$.

The place for j^{th} component of the i^{th} seekers is updated as follows:

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t) \times d_{ij}(t) \tag{20}$$

In all the subpopulations, the best one and worst seeker from the subpopulation was combined via the binomial crossover operator as follows:

$$x_{k_n j,worst} = \begin{cases} x_{lj}, best, & if\ rand_j \le 0.5 \\ x_{k_n j,worst}\,, & else \end{cases} \tag{21}$$

In Eq. (21), $rand_j$ denotes the randomly produced value within $[0,1], x_{lj,best}$, shows the j^{th} parameter of the better location in the l^{th} subpopulations. $x_{k_n j,worst}$ shows the parameter of the n^{th} worst location in the k^{th} subpopulation. Now, $n, k, l = 1,2, \ldots\ldots, K-1$ and $k \neq l$.

The SOA develops a main function dependent upon MSE and it can be employed for predicting the testing outcome of the DELM technique. It could be demonstrated as:

$$MSE = \frac{\sum_N^i |y_i - \hat{y}_i|^2}{N} \tag{22}$$

where y represents the round counts, y_i indicates the experimental value, and $\hat{y}_i$ defines the forecast values correspondingly.

4. Results and Discussion

In this part, the experimental validation of the GTODL-MCDMTA technique is examined under different aspects. In Table 1 and Fig. 3, the experimental outcome of the GTODL-MCDMTA technique is investigated under varying packets. The obtained values inferred that the GTODL-MCDMTA methodology attains effectual prediction results. For instance, on 4 packets, the GTODL-MCDMTA model gets MAPE, RMSE, and processing time of 8.89, 0.3213, and 72s respectively. Also, on 6 packets, the GTODL-MCDMTA model accomplishes MAPE, RMSE, and processing times of 9.71, 0.4309, and 61s correspondingly. Besides, on 10 packets, the GTODL-MCDMTA algorithm understands MAPE, RMSE, and processing time of 19.88, 1.0055, and 59.76s correspondingly. Besides, on 12 packets, the GTODL-MCDMTA methodology gains MAPE, RMSE, and processing time of 20.51, 1.0907, and 53.70s respectively. Finally, on 4 packets, the GTODL-MCDMTA system achieves MAPE, RMSE, and processing time of 26.66, 1.0899, and 95.35s correspondingly.

Table 1: Classifier outcome of GTODL-MCDMTA approach with changing packets

Packets/s	MAPE	RMSE	Processing Time (s)
4	08.89	0.3213	72.00
6	09.71	0.4309	61.00
8	13.63	0.6595	69.93
10	19.88	1.0055	59.76
12	20.51	1.0907	53.70
14	26.66	1.0899	95.35

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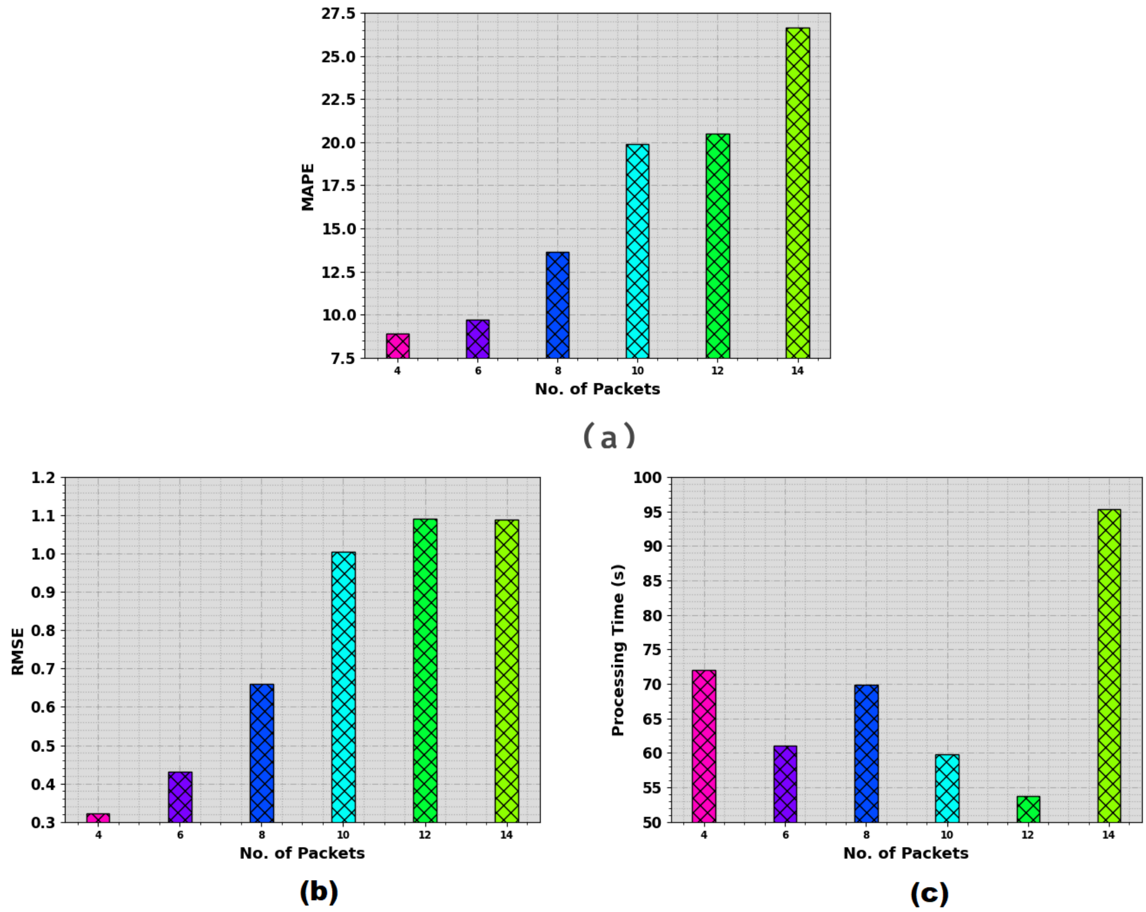

Fig. 3. Classifier outcome of GTODL-MCDMTA approach (a) MAPE, (b) RMSE, and (c) PT

In Table 2 and Fig. 4, the forecast consequence of the GTODL-MCDMTA technique has been examined under varying time frames and transmission rates. The simulation values signified that the GTODL-MCDMTA method attained effectual prediction performance over all transmission rates. For instance, under the transmission rate of 4 packets with 3s, the GTODL-MCDMTA technique has attained a predicted value of 0.57 for the actual 0.66. Meanwhile, under the transmission rate of 6 packets with 3s, the GTODL-MCDMTA algorithm has obtained a predicted value of 0.77 for the actual 0.83. Moreover, under a transmission rate of 8 packets with 3s, the GTODL-MCDMTA system has reached a predicted value of 0.74 for the actual 0.70. Furthermore, under a transmission rate of 14 packets with 3s, the GTODL-MCDMTA method has accomplished a predicted value of 0.70 for the actual 0.68.

Table 2: Prediction outcome of GTODL-MCDMTA approach under varying time frames and transmission rate

Times (sec)	Actual	Predicted	Actual	Predicted
Transmission Rate of 4 Packets/s			**Transmission Rate of 6 Packets/s**	
3	0.66	0.57	0.83	0.77
6	0.43	0.43	0.59	0.55
9	0.49	0.39	0.54	0.20
12	0.10	0.17	0.14	0.05
15	0.00	0.09	0.15	0.02
Transmission Rate of 8 Packets/s			**Transmission Rate of 10 Packets/s**	
3	0.70	0.74	0.69	0.49
6	0.26	0.31	0.43	0.32

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9	0.23	0.56	0.30	0.11
12	0.17	0.05	0.16	0.03
15	0.13	0.03	0.12	0.02
Transmission Rate of 12 Packets/s			**Transmission Rate of 14 Packets/s**	
3	0.77	0.80	0.68	0.70
6	0.47	0.51	0.50	0.26
9	0.53	0.58	0.43	0.05
12	0.17	0.48	0.19	0.03
15	0.13	0.39	0.19	0.05

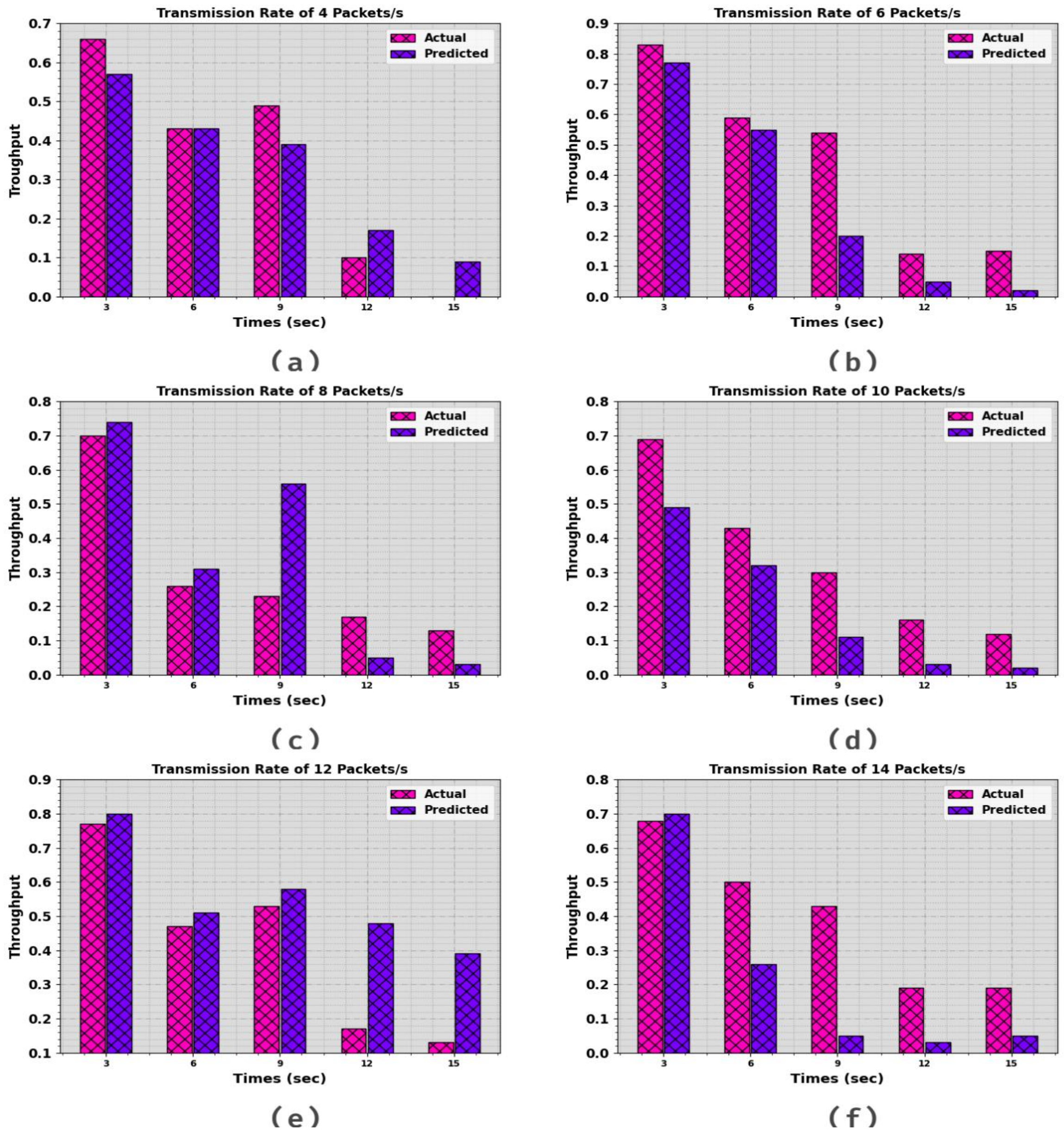

Fig. 4. Prediction outcome of (a) TR of 4 packets/s, (b) TR of 6 packets/s, (c) TR of 8 packets/s, (d) TR of 10 packets/s, (e) TR of 12 packets/s, and (f) TR of 14 packets/s

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Table 3 is a detailed comparison study of the GTODL-MCDMTA technique with recent models [12]. Fig. 5 inspects the MAPE results of the GTODL-MCDMTA algorithm with existing systems. The experimental values stated that the DBN, NB, and K-means approaches have reported minimal MAPE of 30.89, 27.90, and 28.46 respectively. Along with that, the CSORBM-TA, ELM, and DT models have accomplished moderate MAPE of 17.21, 20.34, and 23.81 respectively. Nevertheless, the GTODL-MCDMTA methodology attains effective values with the least MAPE of 16.55.

Table 3: Comparative outcome of GTODL-MCDMTA algorithm with existing systems

Methods	MAPE	RMSE	Processing Time (s)
GTODL-MCDMTA	16.55	0.77	68.62
CSORBM-TA	17.21	0.89	78.08
ELM Model	20.34	0.94	87.04
Decision Tree	23.81	1.08	92.40
Naïve Bayes algorithm	27.90	1.42	83.10
K-Means	28.46	1.49	82.61
DBN Model	30.89	1.21	75.81

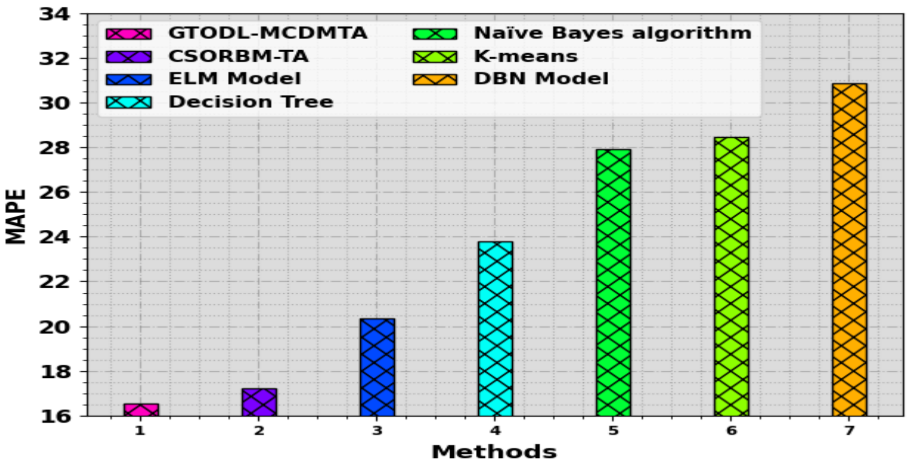

Fig. 5. MAPE outcome of GTODL-MCDMTA approach with other systems

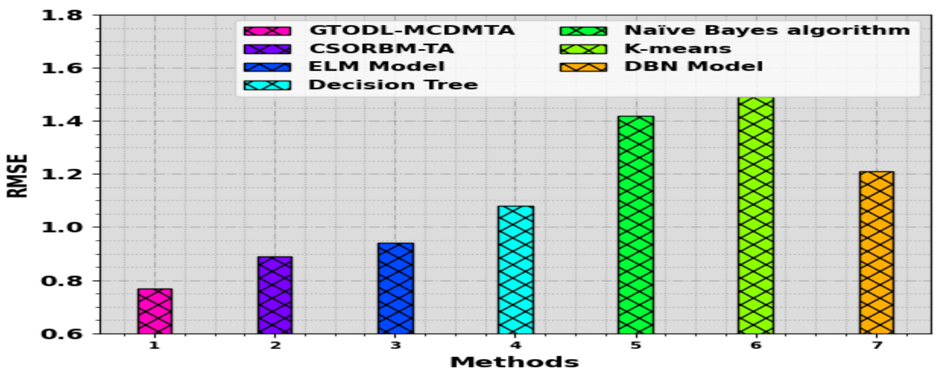

Fig. 6. RMSE outcome of GTODL-MCDMTA approach with other systems

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Fig. 6 investigative the RMSE study of the GTODL-MCDMTA technique with existing approaches. The experimental results implied that the NB, K-means, and DBN approaches have reported lesser RMSE of 1.42, 1.49, and 1.21 correspondingly. Followed by, the CSORBM-TA, ELM, and DT methods have obtained moderate RMSE of 0.89, 0.94, and 1.08 correspondingly. Yet, the GTODL-MCDMTA methodology reaches effective performance with a minimal RMSE of 0.77.

Fig. 7 examines the processing time (PT) outcome of the GTODL-MCDMTA algorithm with existing methods. The simulation result inferred that the DT, ELM, and NB approaches have reported lesser PT of 92.40s, 87.04s, and 83.10s correspondingly. Afterwards, the K-means, CSORBM-TA, and DBN systems attained moderate PT of 82.61s, 78.08s, and 75.81s correspondingly. But, the GTODL-MCDMTA algorithm achieves efficient performance with a lower PT of 68.62s.

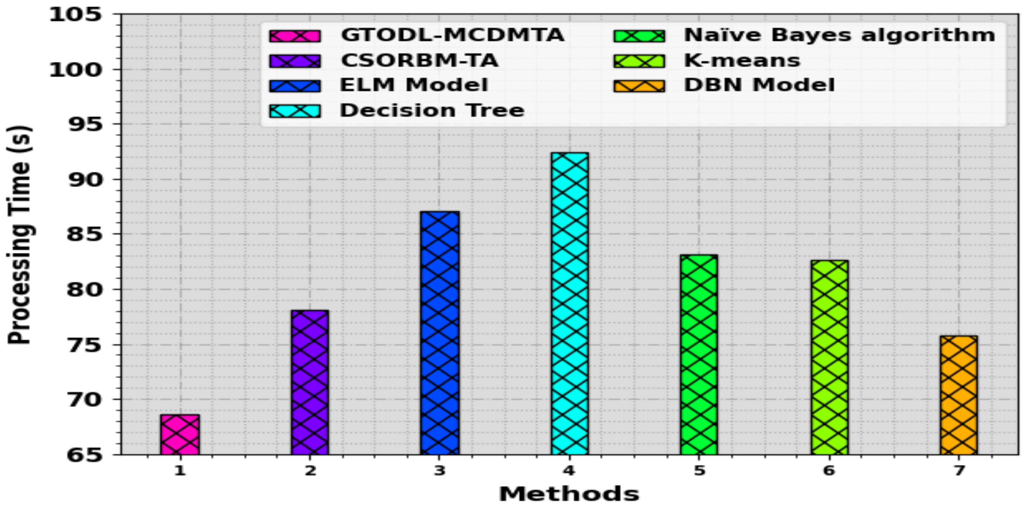

Fig. 7. PT outcome of GTODL-MCDMTA approach with other systems

These results stated the enhanced performance of the GTODL-MCDMTA technique on the traffic prediction process.

5. Conclusion

In this article, we mainly designed a novel GTODL-MCDMTA technique for automated and effective traffic analysis in the V2X networks. The main purpose of the GTODL-MCDMTA system is to recognize the traffic flow prediction for improving route planning and resource allocation with the consideration of various factors into account. In the presented GTODL-MCDMTA technique, several sub-processing stages are included such as pre-processing, GTO-based FS, DELM prediction, and SOA-based parameter tuning. A brief set of simulation outcomes are applied to demonstrate the promising outcomes of the GTODL-MCDMTA technique. The simulation outcome demonstrates the effectiveness and efficiency of the GTODL-MCDMTA approach in handling the complexity and dynamic nature of V2X network traffic analysis. By leveraging DELM and MCDM techniques, the GTODL-MCDMTA technique enhances the decision-making process in V2X networks, leading to more effective traffic management and a better overall commuting experience.

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