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Traffic Aware Routing using Multi-Objective Delay Centric Enhanced Artificial Ecosystem-Based Optimization for VANET

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Abstract: A vehicular Ad hoc Network (VANET) is generally a heterogeneous wireless network generated between vehicles. The vehicles of the VANET have wireless transceivers and computerized control for allowing the vehicles to operate as network nodes, hence the vehicles can communicate in a VANET environment. However, the communication of VANET is affected because of the higher network congestion and energy usage caused by the dynamic topology of VANET. Therefore, an effective Traffic-Aware Routing (TAR) approach is required to be developed to enhance communication. In this paper, the Multi-Objective Delay Centric Enhanced Artificial Ecosystem-based Optimization (MDCEAEO) is proposed to develop a TAR in VANET. The End to End Delay (EED) is considered as primary cost in the MDCEAEO to develop the TAR where a vehicle's average predicted speed is utilized for identifying the traffic in VANET. The developed MDCEAEO-TAR method is used to improve data transmission by avoiding collisions. The performances of MDCEAEO-TAR are evaluated using EED, energy consumption, Packet Delivery Ratio (PDR), and the routing overhead. The existing research such as LARgeoOPT, DREAMgeoOPT, ZRPgeoOPT, Improved Harmony Search (IHS) and Enhanced Distance, Residual energy based Congestion Aware Ant Colony Optimization (EDR-CAACO), Artificial Ecosystem-based Optimization (AEO), Fixed Step Average and Subtraction Based Optimizer (FS-ASBO) and Three Influential Members Based Optimizer (TIMBO) are used to evaluate the MDCEAEO-TAR. The PDR of the MDCEAEO-TAR is 0.9836 at 1000s, which is high when compared to the IHS.

Keywords: Dynamic topology, Multi-objective delay centric enhanced artificial ecosystem-based optimization, Packet delivery ratio, Traffic aware routing approach, Vehicular ad hoc network.

1. Introduction

VANET is a discrete type of mobile ad hoc network in that vehicles are considered nodes and an entire communication usually occurs between vehicles [1, 2]. VANET doesn't require any fixed architecture, but the fixed network nodes i.e., Road Side Unit (RSU) are deployed in the network. These RSU helps to provide different services for vehicular networks such as spreading the data on the sparse network and functioning as a gateway to link to the Internet [3]. VANET has two important components such as vehicles and roadside architectures. These components generally create communication among the vehicles which is defined as Vehicle to Vehicle (V2V) or among vehicle and Vehicle to Infrastructure (V2I) communications [4]. One more type of VANET communication is a hybrid network where the network integrates both the V2V and V2I network. The vehicle creates the link with the infrastructure either directly or via a V2V connection using the multi-hop connection which is referred to as hybrid architecture in VANET [5]. The important objective of this VANET is to develop an Intelligent Transport System (ITS). The ITS is a wireless technology used in transportation systems to route data between vehicles in an intelligent way to enhance road safety [6, 7].

The VANET applications are ITS, permitting smart city operations, parking slots management, health care services, advertising products, autonomous driving systems and so on. Moreover, essential services developed by VANETs are hazard control systems and emergency handling services [8, 9]. Generally, the VANET is a decentralized wireless ad hoc network, so it doesn't have a predefined architecture in the network. Hence, the nodes in the VANET generate the routing infrastructure for broadcasting the data to the destination without having any prior global information about the network [10, 11]. The VANET is having some special restrictions and features such as frequent variation of data, higher mobility of vehicular nodes, faster variations in network topology, and unstable connectivity which affects data transmission [12]. The energy usage and network congestion are extensively maximized due to the higher dynamic topology of VANET that affects the VANET performances. Consequently, energy consumption minimization and traffic maintenance are considered challenging tasks in mobility-based VANET [13, 14]. The communication link among the vehicles is extremely unstable because of the faster movement that causes performance degradation in the routing process [15].

The contributions of this work are concise as follows:

- The conventional Artificial Ecosystem-based Optimization (AEO) is converted into EAEO with multiple objectives to develop traffic aware routing. In EAEO, an additional operator is incorporated for enhancing the balance between exploitation and exploration which is used to improve the search progress.
- The proposed MDCEAEO developed the TAR by considering the EED as the primary cost function where the average predicted speed of the vehicle is used to identify the traffic of the VANET topology. Therefore, the MDCEAEO is used to minimize congestion and energy utilization over the VANET.

The remaining paper is structured as follows: Section 2 delivers the related work done using the routing over the VANET. The explanation of the MDCEAEO-based TAR is given in Section 3. The outcomes of the MDCEAEO-TAR are provided in Section 4 whereas the conclusion is presented in Section 5.

2. Related work

Singh [16] presented Hybrid Genetic Firefly Algorithm (HGFA) based routing to obtain faster data delivery in VANET. The fitness function considered in HFGA was retransmission time and propagation time. Here, the genetic algorithm's features were combined with the firefly approach for achieving reliable communication. The developed HGFA was required to consider the residual energy and distance for achieving the energy-efficient routing over the network.

Husain [17] developed the geocast routing approaches using Particle Swarm Optimization (PSO). Three different routing approaches were developed such as LARgeoOPT, DREAMgeoOPT, and ZRPgeoOP. Here, the PSO was used with the next vehicle approach for minimizing the delay and improving the data delivery. The developed geocast routing was not developed traffic aware path which led to creating the collision.

Saravana Kumar [18] evaluated the Road-Based using Vehicular Traffic Reactive (RBVT-R) and Geographic Source Routing (GSR) protocols for VANET. Next, the Glow Worm Swarm Optimization (GSO) was used to optimize the RBVT-R for improving performance. The developed GSO-RBVT-R was chosen as the ideal path by considering the various Quality of Service (QoS) parameters that comprised an average number of hops, packet delivery, and average delay. The PDR of GSO-RBVT-R was less when there was an increment in the packet rate.

Ramamoorthy and Thangavelu [19] presented Enhanced Distance and Residual energy based Congestion Aware Ant Colony Optimization (EDR-CAACO) for discovering the optimum shortest path. The EDR-CAACO considered the vehicle's residual, distance and congestion levels for evaluating the pheromone levels. The roulette wheel was used to choose the route based on fitness which was used to identify the route without congestion. The developed EDR-CAACO doesn't consider delay while discovering the route. Because the consideration of delay was used to identify the route with less transmission time.

Chandren Muniyandi [20] developed the Improved Harmony Search (IHS) to solve the optimization issue of the Optimized Link State Routing (OLSR) approach. The optimization process of IHS was performed by embedding two different selection approaches such as the roulette wheel and the tournament choosing approach. The definition of optimum parameter values of OLSR optimization was used to enhance the QoS. The TAR was required to be considered in IHS to avoid collision while broadcasting the data packets.

In recent times, there are huge amount of optimization approaches are developed for different real time applications. In this section, three different optimization approaches such as AEO [21], FS-ASBO [22] and TIMBO [23] are developed to solve the optimization issues. AEO [21] was inspired based on energy flow in the ecosystem over the earth where this AEO was replicated the three distinct actions of existing organisms which comprised of production, consumption, and decomposition. FS-ASBO [22] was developed from the typical Average And Subtraction-Based Optimizer (ASBO). The developed FS-ASBO was replaced the randomized step size in the directed motion along with the fixed step size. If the new candidate was failed to discover an appropriate solution, the exploration was incorporated after the directed motion in an each iteration. The TIMBO [23] was used three different population members such as best member, worst member, and member as mean population for enhancing the population member's location. The TIMBO was doesn't required any control parameters that stated that there was no necessary for controlling the TIMBO's parameter. However, the AEO, FS-ASBO and TIMBO was developed for single objective functions, hence it was difficult to achieve an optimal performances when it was processed with optimization issues.

The limitations found from the related work are inappropriate cost function selection, less PDR, routing without traffic consideration and single objective optimization. These limitations are overcome by developing the traffic aware routing using MDCEAEO that used to avoid the collisions while broadcasting the data. Thus leads to enhance the PDR and delay over the VANET.

3. MDCEAEO-TAR method

In this research, the TAR is developed by using an MDCEAEO to improve the data delivery of the VANET. The MDCEAEO achieves a good balance between exploitation and exploration which is used to improve the search progress. The developed MDCEAEO-TAR method is used to minimize collisions by selecting the route with less traffic. Moreover, the energy consumption of the nodes is minimized by developing the shortest path. Therefore, the MDCEAEO-TAR also achieves energy efficiency in the VANET. The block diagram of the MDCEAEO-TAR method is shown in Fig. 1.

3.1 Network model

VANET network is determined as a special type of network that provides different types of services to the users, e.g., driver forecast, infotainment, and message alerts. In this research, the sensors (i.e., vehicles) are considered as randomly moved in the lane of the network. Therefore, there is a high requirement of developing traffic-aware routing using the proposed method to achieve reliable communication over the VANET. The EAEO and routing using delay-centric EAEO are explained in the following sections.

3.2 Overview of EAEO

The EAEO is established from the conventional AEO [21] to enhance the performances. In general, AEO [21] is one of the metaheuristic optimization approaches which mimics the energy flow of the ecosystem in three phases. In the first phase, most of the producers are green plan category, therefore it is not required to obtain energy from any other creatures which help to improve the exploitation and exploration. The animals are denoted as consumers in the second phase where consumers do not generate their food. Subsequently, the animal gets the vitamin

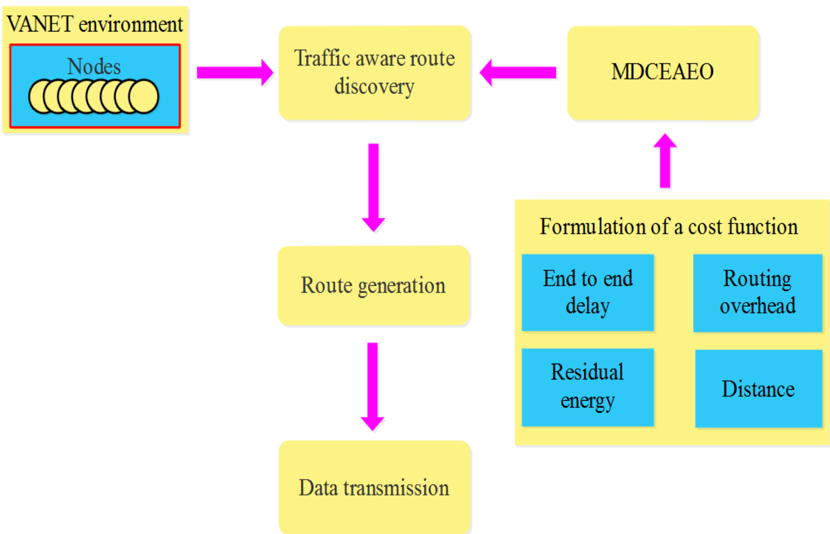

Figure. 1 Block diagram of the MDCEAEO-TAR

and energy from the producer/ remaining consumers. This consumption is utilized for improving the exploration. The final stage is decomposers that are used to feed the producers/ consumers and it is used to improve exploitation. In EAEO, the modification is performed in the production phase which is used for searching locally in the search space. The second phase is used to perform the global search which is referred to as exploration. Global minima are assured and the search space is decreased via these phases that are used to avoid the EAEO from stuck in local minima. In the production phase, an extra operator is incorporated to enhance the balance between exploitation and exploration. The EAEO algorithm has only one producer and one decomposer whereas the remaining individuals are considered consumers.

3.2.1. Producer

The updated individual is created randomly among the finest individual (x_n) and random individual (x_{rand}) which originated in the search space. An optimal individual (i.e., Decomposer) and lower & upper limits of search space are utilized for updating the worst individual (i.e., Producer). Further, this updated individual is used to lead the remaining individuals for searching in diverse regions. The producer phase is expressed in Eq. (1).

$$x_1(t+1) = (1-a)x_n(t) + a x_{rand}(t) \quad (1)$$

Where, a and x_{rand} of Eq. (1) is expressed in Eqs. (2) and (3).

$$a = (1 - t/MaxIt) \times r_1 \quad (2)$$

$$x_{rand} = r \times (UP - LW) + LW \quad (3)$$

Where, the maximum iteration is denoted as $MaxIt$; r and r_1 defines the generated random value among $[0,1]$; the coefficient value utilized for the linear weighting is denoted as a; n denotes the population count and the lower & upper limits are represented as LW & UP, respectively.

In this EAEO, a new operator G is incorporated for improving the balance between exploitation and exploration. This operator G reduces linearly through iterations from 2 to 0 based on Eq. (4).

$$G = 2 \times (1 - It/MaxIt) \quad (4)$$

Where, the current iteration is denoted as It. The derived operator G is incorporated in the production which is expressed in Eq. (5).

$$x_2(t+1) = x_2(t) + G \times C \times [x_2(t) - x_1(t)] \quad (5)$$

Where, the operator C denotes the Levy flight and it is expressed in Eq. (6).

$$C = 0.5 \times (v_1/|v_2|) \quad (6)$$

Where, $v_1 \sim N(0,1)$; $v_2 = N(0,1)$ that denotes the normal dissemination.

3.2.2. Consumption

An individual solution of EAEO is updated using the consumption phase which helps to improve the exploration. This phase comprises three different consumers such as herbivores, carnivores and omnivores. The herbivore type eats both the producers and consumers; consumers with higher energy level is eaten by a carnivore; the remaining consumer with higher energy level and/ or producers are eaten by an omnivore. Subsequently, a random selection is used for the consumer to categorize into any one type of aforementioned consumers.

The consumer when it is chosen as herbivore, carnivore and omnivore is denoted in Eqs. (7) to (9).

$$x_i(t+1) = x_i(t) + C[x_i(t) - x_1(t)], \quad i \in [3, \dots, n] \quad (7)$$

$$x_i(t+1) = x_i(t) + C\left[x_i(t) - x_j(t)\right], \quad i \in [3, \dots, n], j = randi\,([2 \;\; i-1]) \quad (8)$$

$$x_i(t+1) = x_i(t) + C\left[r_2\big(x_i(t) - x_1(t)\big) + (1 - r_2)\Big(x_i(t) - x_j(t)\Big)\right], \quad i \in [3, \dots, n], j = randi([2\; i-1]) \quad (9)$$

Where, r_2 defines the random value among $[0,1]$.

3.2.3. Decomposition

An optimum solution is utilized to update the solution at the decomposition phase. The decomposition factor D and weight variables h & e are used to accomplish the decomposition which is used to enhance the exploitation. The decomposer x_n is used for updating the position of individual x_i as shown in Eq. (10).

$$x_i(t+1) = x_n(t) + D[e x_n(t) - h x_i(t)] \quad (10)$$

Where, $D = 3u,\ u \sim N(0,1)$; $e = r_3 \times randi([1\;2] - 1)$; $h = 2r_3 - 1$ and random number generated between $[0,1]$ is r_3.

3.3 Traffic aware route discovery using MDCEAEO

In this phase, the route from the transmitter node to the receiver node is discovered using the MDCEAEO. The optimal traffic-aware route is selected to improve the data delivery over the VANET.

3.3.1. Population initialization

The MDCEAEO begins with the initialization of individuals by using the possible route from transmitter to receiver. Each individual's dimension is equal to the number of relay nodes that exist in the route. Let, the individual i is $x_i = (x_{i,1}(t), x_{i,2}(t), .., x_{i,dim}(t))$, where each location $x_{i,loc}, 1 \leq loc \leq dim$ defines the successive relay node in the route.

3.3.2. Formulation of a cost function

This proposed method uses unique cost functions such as EED, routing overhead (RO), energy (E) and distance $(Dist)$ to achieve the traffic aware routing over the VANET. The formulated cost function is expressed in the following Eq. (11).

$$Cost = \alpha_1 \times EED + \alpha_2 \times RO + \alpha_3 \times E + \alpha_4 \times Dist \quad (11)$$

Where, the values of $\alpha_1 - \alpha_4$ defines the weight values allocated to each cost value. Because, all the cost values are non-conflicting, those multiple cost values are converted into single cost values.

The details about each cost function are derived as follows:

- EED is one of the essential cost metrics which is evaluated using traffic prediction. The delay is required to be less, hence the cost function is effective during the routing process. Here, the EED is computed according to the vehicle's average speed and the length of the road segment is expressed in Eq. (12).

$$EED = \sum_{\substack{Id=1 \\ i=1}}^{m^{Id}} \frac{l^{Id}}{AS_i^{Id}(U)} \quad (12)$$

Where, l^{id} represents the length of the road segment Id; i is the time; m is the total amount of vehicles; the average predicted speed of vehicle U is denoted as $AS_i^{Id}(U)$. The traffic is less on the road, when the EED is less.

- Routing overhead is defined as the ratio of a number of packets sent and EED during the transmission is expressed in Eq. (13).

$$RO = \frac{Number\ of\ packets\ sent}{EED} \times 100 \quad (13)$$

- The residual energy is considered an important metric in the cost function. The node with higher residual energy is preferred while generating the traffic-aware route in VANET. Because the relay nodes in the route have to transmit and receive the data with adjacent nodes. Eq. (14) expresses the residual energy (RE) of the node.

$$RE = \sum_{j=1}^{dim} E_j \quad (14)$$

Where, the remaining energy of the node j is denoted as E_j.

- The Euclidean distance $(Dist)$ is considered to identify the route with less transmission distance. Because, the higher the distance increases the energy consumption of the nodes.

3.3.3. Iterative process

The routes are initialized as individuals in the MDCEAEO which are updated in the producer phase according to Eq. (1). In the producer phase, an operator G is introduced for an effective balance between exploitation and exploration. This operator G used along with levy flight and x_1 to update the second individual (x_2). Subsequently, the consumer phase is performed as shown in Eqs. (7)to (9) whereas the position update of herbivore, carnivore and omnivore is determined according to the random number. After performing the consumer phase, the decomposer phase is enabled based on Eq. (10). The cost function of Eq. (11) is used to identify the optima individual that results in the optimal TAR over the VANET.

4. Results and discussion

The outcomes of the MDCEAEO-TAR method are provided in this section. The design and simulation of the MDCEAEO-TAR method are done in MATLAB R2020a where the system is operated with 16GB RAM and an i7 processor. The MDCEAEO-TAR method is used to perform the traffic-aware routing in the dynamic topology of the VANET. The developed MDCEAEO-TAR method analyzed 50 nodes deployed in the VANET topology

Table 1. Simulation parameters

Parameters	Values
Routing method	MDCEAEO-TAR
Area	$500m \times 500m$
Number of nodes	70
Transmission range	150 m
Speed range (Mobility)	$70\ and\ 100\ km/h$
Packet size	512 bytes

of $500m \times 500m$. The specifications of the MDCEAEO-TAR method are mentioned in Table 1.

4.1 Performance analysis

The performance analysis of the MDCEAEO-TAR method is analyzed as EED, energy consumption, PDR, and routing overhead. Here, the performance of the MDCEAEO-TAR method is analyzed with the conventional AEO [21], FS-ASBO [22] and TIMBO [23] methods.

4.1.1. End-to-end delay

EED represents the delay between the time at which the transmitter sends the information and the time received by the receiver. The EED comparison among the MDCEAEO-TAR, AEO [21], FS-ASBO [22] and TIMBO [23] is shown in Fig. 2. This analysis shows that the MDCEAEO-TAR achieves lesser delay when compared to the AEO [21], FS-ASBO [22] and TIMBO [23]. The main reason to achieve lesser delay for MDCEAEO-TAR is by developing traffic aware path based on the vehicle speed. The lesser control packets are only required during the route discovery of MDCEAEO-TAR that is further used to minimize the EED.

4.1.2. Energy consumption

Energy consumption expressed in Eq. (15) defines how much energy is spent by each node in the network.

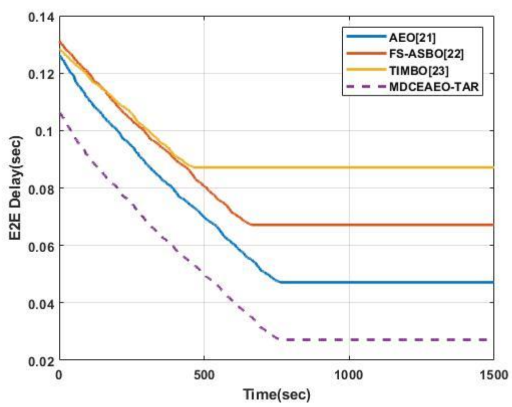

Figure. 2 End-to-end delay

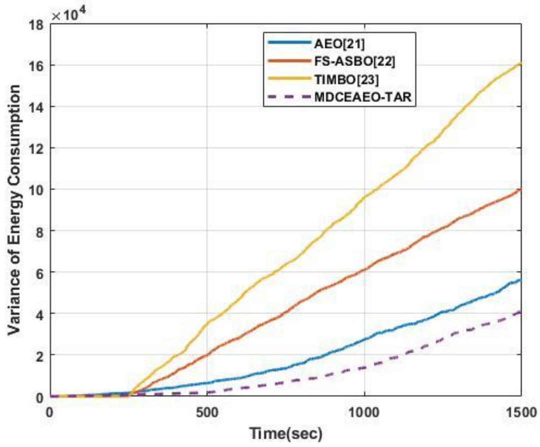

Figure. 3 Energy consumption

$$\mu(Y) = \frac{\sum_{k=1}^{N}(y_k - \mu)^2}{N-1} \quad (15)$$

Where, μ represents the mean value of all node's energy usage ($i.e., \mu = mean(y)$); the amount of nodes is denoted as N; energy used by kth node is denoted as y_k.

Fig. 3 shows the energy consumption comparison for MDCEAEO-TAR with AEO [21], FS-ASBO [22] and TIMBO [23]. Fig. 3 shows that the MDCEAEO-TAR has lesser energy consumption than the AEO [21], FS-ASBO [22] and TIMBO [23]. The identification of the shortest path using the MDCEAEO-TAR helps to minimize the node's energy utilization over the network.

4.1.3. Packet delivery ratio

PDR is defined as the ratio between the number of received packets and transmitted packets which is expressed in Eq. (16).

$$PDR = \frac{Number\ of\ received\ packets}{Number\ of\ transmitted\ packets} \times 100 \quad (16)$$

The PDR comparison among the MDCEAEO-TAR, AEO [21], FS-ASBO [22] and TIMBO [23] is shown in Fig. 4. This analysis shows that the MDCEAEO-TAR achieves higher PDR when compared to the AEO [21], FS-ASBO [22] and TIMBO [23]. The PDR of MDCEAEO-TAR increased based on the following reasons: 1) the Development of TAR used to avoid collisions which reduce the loss and 2) The mitigation of node failure in route discovery increases the data transmission.

4.1.4. Routing overhead

Routing overhead is the ratio of routing packets and the data packets transmitted where each hop is individually counted in the network. Fig. 5 shows the

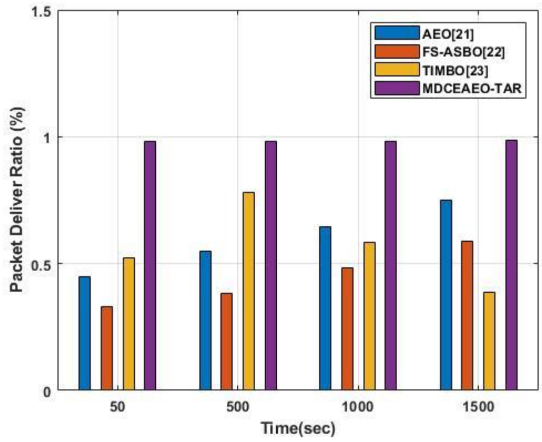

Figure. 4 Packet delivery ratio

routing overhead comparison for MDCEAEO-TAR with AEO [21], FS-ASBO [22] and TIMBO [23]. Fig. 5 shows that the MDCEAEO-TAR has lesser routing overhead than the AEO [21], FS-ASBO [22] and TIMBO [23]. The routing overhead of MDCEAEO-TAR is minimized by identifying routes with less control packets. The requirement of control packets is minimized by using effective cost-function measures such as EED, RO, residual energy and distance.

4.2 Comparative analysis

The existing methods such as LARgeoOPT [17], DREAMgeoOPT [17], ZRPgeoOPT [17], EDR-CAACO [19] and IHS [20] are used to compare the efficiency of MDCEAEO-TAR. Here, the comparison is provided with two different cases. Table 2 and 3 shows the comparative analysis of the MDCEAEO-TAR for Case 1 and Case 2 respectively, where NA represents the values which are not available in those researches. From the tables, it is concluded that the MDCEAEO-TAR achieves better performance than the LARgeoOPT [17], DREAMgeoOPT [17], ZRPgeoOPT [17], EDR-CAACO [19] and IHS [20]. The PDR of MDCEAEO-TAR is improved by avoiding the congestions over the VANET. On the other hand, avoiding a node failure also used to enhance the data delivery. The usage of lesser control packets in MDCEAEO-TAR helps to minimize the delay and routing overhead. Further, the shortest path generation using MDCEAEO-TAR also used to minimize the delay and energy consumption.

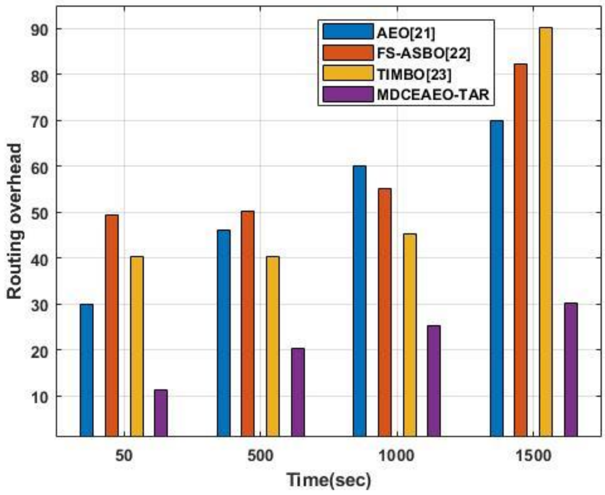

Figure. 5 Routing overhead

Table 2. Comparative analysis of MDCEAEO-TAR for case 1

Performance measures	Methods	Time(sec)			
		50	500	1000	1500
Routing overhead	IHS [20]	17	38.02	39.5	41
	MDCEAEO-TAR	11.23	20.231	25.25	30.2649
EED (sec)	IHS [20]	0.16	0.12	0.17	0.19
	MDCEAEO-TAR	0.0991	0.0498	0.0271	0.0271
Energy consumption (J)	IHS [20]	0.1×10^5	0.31×10^5	1.9×10^5	3.05×10^5
	MDCEAEO-TAR	0.0107×10^4	0.1924×10^4	1.3917×10^4	4.1078×10^4
PDR	IHS [20]	0.48	0.46	0.47	0.461
	MDCEAEO-TAR	0.9820	0.9821	0.9836	0.9867

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Table 3. Comparative analysis of MDCEAEO-TAR for case 2

Performance measures	Methods	Vehicles		
		30	40	50
Routing overhead	EDR-CAACO [19]	0.15	0.17	0.19
	MDCEAEO-TAR	0.032	0.053	0.085
EED (sec)	EDR-CAACO [19]	0.08	0.09	1.4
	MDCEAEO-TAR	0.007	0.006	0.005
PDR (%)	LARgeoOPT [17]	NA	74	NA
	DREAMgeoOPT [17]	NA	67	NA
	ZRPgeoOPT [17]	NA	56	NA
	EDR-CAACO [19]	99.01	98	97
	MDCEAEO-TAR	99.231	98.36	98.67

5. Conclusion

VANET is recognized as a modern technology that is extensively utilized in autonomous systems. In this paper, the MDCEAEO-TAR method is developed for discovering the traffic-aware route over vehicular networks. Here, the MDCEAEO is optimized with distinct cost functions such as EED, RO, residual energy, and distance. The discovered route with less traffic is used to avoid collisions while transmitting the data packets. Moreover, the shortest path generation of MDCEAEO is used to minimize the energy consumption of the nodes. Hence, the data delivery of the MDCEAEO is enhanced based on TAR while minimizing energy consumption. From the results, it is concluded that the MDCEAEO-TAR achieves better performance than the AEO, FS-ASBO, TIMBO, LARgeoOPT, DREAMgeoOPT, ZRPgeoOPT, IHS and EDR-CAACO. The PDR of the MDCEAEO-TAR is 0.9836 at 1000s, which is high when compared to the IHS. In future, the novel optimization algorithm can be used to improve the data transmission over the VANET.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper background work, conceptualization, methodology, dataset collection, implementation, result analysis and comparison, preparing and editing draft, visualization have been done by first author. The supervision, review of work and project administration, have been done by second and third author.

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