Energy Efficient Optimal Routing for Communication in VANETs via Clustering Model

Mohamed Elhoseny and K. Shankar

Abstract Vehicular Ad Hoc Network (VANET) is a kind of extraordinary remote ad hoc network, which has high node portability and quick topology changes. Clustering is a system for gathering nodes, making the network increasingly vigorous. With no consciousness of nodes, at some point, it comes up short on energy which causes execution issues in network and topology changes. At that point, it emerges a primary issue of energy in routing protocol, which endeavor node lifetime and link lifetime issues in the network. To broaden the energy effectiveness of V2V communication, proposed a clustering based optimization technique. This paper presents K-Medoid Clustering model to cluster the vehicle nodes and after that, energy efficient nodes are recognized for compelling communication. With the expectation of accomplishing energy efficient communication, efficient nodes are recognized from each cluster by a metaheuristic algorithm, for example, Enhanced Dragonfly Algorithm (EDA) which optimizes the parameter as minimum consumption of energy in VANET. The outcome exhibits that the V2V communication improves the energy efficiency in all vehicle nodes additionally it accomplishes less execution time contrasted with existing algorithms.

Keywords VANET · Vehicle nodes · Energy efficient routing · K-Medoid clustering · EDA and minimum energy consumption

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1 Introduction

Nowadays, roads can be viewed as huge frameworks which incorporate computers, sensors, road-side foundation components, and vehicles. VANETs give the stage to data trade between road clients and roadside foundation components without requiring any network supplier [1]. Many research endeavors that have explored different issues identified with V2I, V2V, and VRC territories on account of the vital job they are relied upon to play in Intelligent Transportation Systems (ITSs) [2]. With the exponential development of energy utilization in remote communications, Green communication has been drawing increasingly more consideration in recent year [3]. The technique set comprises of the dimension of transmission power and the sending probability. In each round, nodes pick the energy consumption to send traffic; at that point, nodes will refresh the sending likelihood dependent on the convictions [4]. Another protocol enhances energy efficiency and decreases the number of dead nodes in large-scale Wireless Sensor Networks (WSNs). The algorithm is to locate the base inactivity and energy efficient way in a lossy network [4, 5]. The energy saving protocol attempts to diminish the energy utilization of the network in the WSN and accordingly increment the operational lifetime, which additionally, as a rule, leads to the use of the shortest routing paths [6, 25]. The energy balancing protocol, then again, endeavors to adjust the energy utilization to anticipate partitioning of the network [7, 26]. Be that as it may, the VANET joins a dynamic topology with an outsized and variable network estimate, and, obviously, it's to help quick nature of vehicles [8, 27]. From the clustering and optimization model the optimal path through which data is transmitted [9] from a source node to a goal node and decide if to utilize the moving vehicles as a versatile transfer to transmit data dependent on the bearing of movement just as the areas of the source node and the destination node [8]. Indeed, different VANET ventures have been executed by different governments, businesses, and academic establishments around the globe in the most recent decade or so [1].

2 Review of Existing Research Papers

With the expansion in demand for information download among the vehicular clients, control utilization, both at vehicle end and the roadside unit is additionally expanding relatively by Shrivastava et al. [10]. An improved multicast based energy efficient artful information scheduling algorithm. We gauge optimum data rate and an optimum number of clients having great channel conditions, in this way deterring the need to know the channel state data at the transmitter. The most testing features in VANETs are their dynamic topology and versatility, where vehicles are moving at variable high speeds and in various directions. Conversely, the test in the WSN is in dealing with the constrained energy assets of the nodes, since the execution of WSNs emphatically relies upon their lifetime by Mohaisen et al. [11]. To conquer these difficulties, this exploration researches the impacts of various Quality of Service (QoS) parameters on forwarding decisions in an efficient distributed position based routing protocol and spotlights on data transmission estimation.

Despite that VANET is considered as a subclass of MANET, it has for disposition the high versatility of vehicles delivering the successive changes of network topology that include changing of the road and fluctuating node thickness of vehicles existing in this road by Samira Harrabi et al. in 2017 [12]. Limiting network overhead value, number of created clusters and had not considered the vehicles intrigues which characterized as any related information used to separate vehicle from another. In Sharma et al. [13], It's to assesses enhanced AODV course data based IEEE 802.11 g ad hoc network consolidating OFDM radio network interfaces along with DCF-MAC protocol by methods for OPNET Modeler TM to understand an energy-efficient IEEE 802.11 g network. A novel methodology of load adjusted routing is proposed to improve the network strength and battery lifetime in individual nodes by Agarwal et al. [14], Assuming variable energy dimensions of transmission in every vehicle, our examination builds up some upper limits on the partition of two back to back RSUs for almost load adjusted routing. The issue has been characterized for a straight network with uniform dissemination of vehicles more than the 1-D road.

2.1 The Significance of Energy Efficient Routing

The increase in traffic once a day is a major test for the general population of developing nations. Accordingly, the experts capable should concentrate on road security to make the road traffic as efficient as could reasonably be expected [17–20]. Because of IT advancement, the communication among vehicles over expansive spaces has coordinated the consideration of scientists towards efficient road traffic the executives [21]. Information broadcasting from such a large number of sources with the limitation of opportune and conveyance of message causes blockage issue in vehicular communication, in this way guaranteeing packet dropping, low energy efficiency and broadened delay [22–24]. The proposed research work has been committed to the optimal routing structure in an energy-efficient way by optimizing the energy consumption parameter.

3 System Model

This model we will analyze the Vehicular communication framework by energy efficient routing process, it's solved by the help of optimization. Essentially, build up the vehicle network topology for V1R communication or V2V communication model. Before finding the energy efficient routing, clustering and cluster head selection is performed, the detail examination of our inventive model intricately talked about in the underneath area.

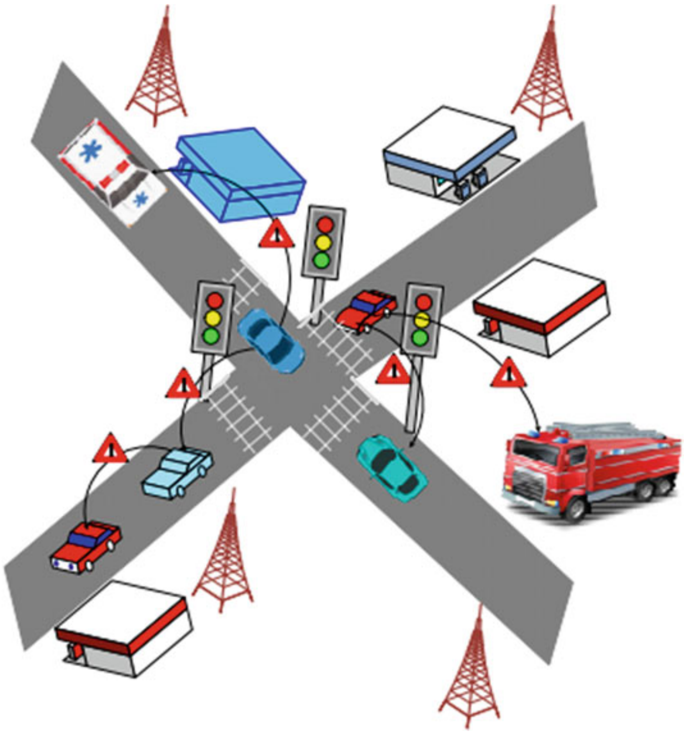

Fig. 1 Network topology

4 Network Topology

The network topology of networks can be viewed as a subset of the city map and the developments of vehicles are confined along the streets and by the traffic conditions. Here we have utilized 200 vehicle nodes, the ordinary nodes portrayed in gray color trade data among one another without GPS. Be that as it may, so as to have a decent knowledge of position data of the entire network, a couple of reference nodes are outfitted with GPS reliable and low-control communications are simultaneously considered and examined in light of the impedance of the jammers. The road separates the plane into two sections. The source node and destination node are on either side of the road, separately; the systematical model is exhibited in Fig. 1.

4.1 Vehicle Clustering

A few clustering strategies for VANET have been proposed in the literature. The cluster individuals and utilize the VANET clustering systems to frame the clusters, none of them took speed contrast into thought for clusters arrangement in VANET. Here we are utilized K-medoid clustering model to clusters the 200 vehicle nodes, from the group with fewer individuals are rejected and its cluster head joins the neighboring group, while different individuals begin group development process in the event that they can't join any close-by groups.

4.1.1 K-Medoid Clustering

This clustering model chooses "k" information things as beginning medoids to represent the k clusters. The various residual things are incorporated into a cluster which has its medoid nearest to them. From that point, another medoid is resolved which can represent the cluster better. K clusters are framed which are focused on the medoids and every one of the information individuals is put in the proper cluster dependent on closest medoid [15].

Initialization: Chooses K value of the n data points as the medoids

Medoids Selection: The medoid value is chosen by evaluating the distance between every two data points of all considered objects. Here, the distance measure is calculated by

$$\mathrm{Dist} = \sum_{i=1}^{n} (F_i - S_i)^2 \tag{1}$$

Generation of Cluster: The initial cluster is formed by assigning each object to the closest medoid value.

Update the Selected Medoids: The role of calculating new medoid in each cluster is, it minimizes the total distance between objects in the cluster.

Vehicle Nodes into Each Medoid: By appointing each object to the closest medoid, the clustering result will be achieved. Assess the total sum of the separation from all objects for example instated n objects to their medoids. In the event that the calculated sum is equivalent to the past one, at that point end the execution of the clustering algorithm. Or else, rehash the method of K-medoid algorithm from the medoid determination step. By utilizing the K-medoid algorithm, 200 vehicle nodes are gathered dependent on their distance measure. The clustering process of V2V communication is represented in Fig. 2.

4.2 Head Selection

The determination criteria for the formation of cluster head mostly rely on the portability measurements (speed, position, and acceleration) of vehicle nodes.

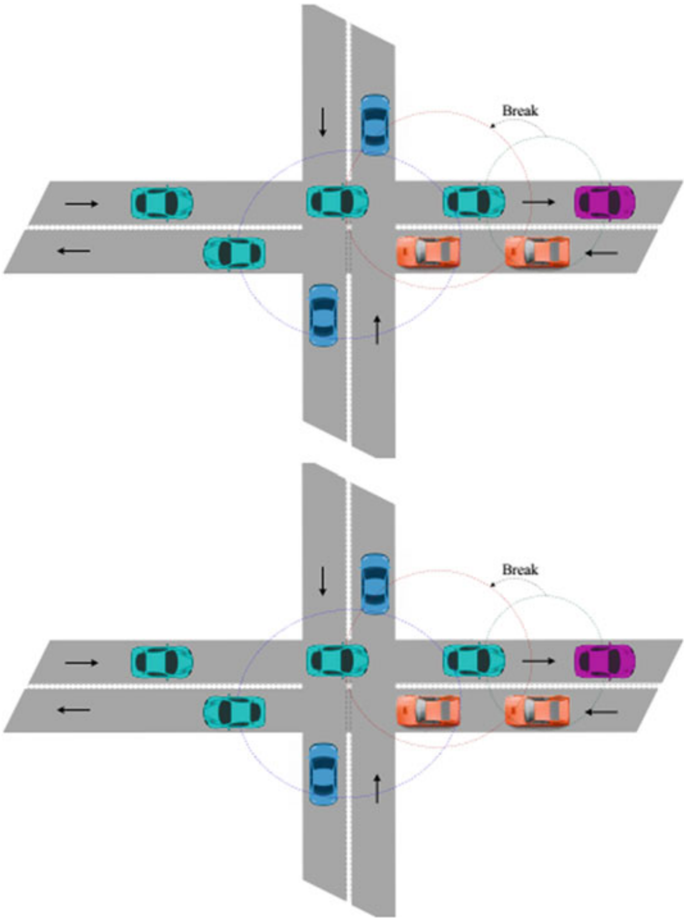

Fig. 2 Vehicle clustering

- A vehicle with the smallest average distance among a cluster is picked as the cluster head.
- *Closest Position to Average*: A vehicle endeavors to pick as its cluster head arranged by the absolute difference of candidate's position to the normal position of every single proximal vehicle.
- *Closest Velocity to Average*: A vehicle endeavors to pick as its cluster head arranged by the absolute difference of candidate's velocity to the average velocity of every single proximal vehicle.

4.3 Energy Efficient Optimization Model

We explore the optimal routing path configuration in traffic areas by considering the per-node most extreme energy effectiveness. Here, the energy efficiency between vehicular nodes is improved by the AODV protocol. The optimal energy efficient routing way is chosen by the parameter as minimum energy utilization.

4.3.1 Optimal Energy Efficient Route Selection

The primary objective is to build up a V2V communication with efficient routing by the network parameter optimization. The fitness work is determined dependent on the network parameter by minimizing the energy utilization of vehicular nodes. The target work is expressed as in condition (2).

$$OF(V2V) = \{\min(EC)\} \tag{2}$$

The preferred minimized value is obtained by the use of inspired optimization technique i.e. Enhanced Dragonfly Algorithm (EDA).

Dragonfly Algorithm (DA): Dragonflies are considered as little predators that chase practically all other small insects in nature. The fundamental motivation of the DA algorithm starts with static and dynamic swarming practices [16]. These two swarming practices are fundamentally the same as the two principle periods of optimization utilizing meta-heuristics: exploration and exploitation.

Enhanced Function: The Cauchy mutation operator is acquainted with disregard to fall into a neighborhood ideal. Into a nearby optimum, this mutation operator is well ready to minimize the possibility of catching. The mutation probability for the worldwide best is equivalent to zero and it upgrades with diminishing the fitness by applying this new mutation probability.

Implementation Steps of EDA

(i) Initialization: Initialize the population of dragonflies (vehicle nodes) in terms of V_i

$$V_i = V_1, V_2, V_3, \ldots\ldots..V_n,\ \text{where i} = 1, 2, 3 \ldots \text{n}. \tag{3}$$

(ii) Behavior Analysis of DA

The behavior of Dragonflies: The behavior of dragonflies can be explained in five steps, namely, separation, alignment, cohesion, attraction towards a food source and distraction outwards an enemy (Table 1).

Parameter Description: In separation, $Se_i \rightarrow$ indicates the separation of i-th individual, V is the current position of the individual, V_k is the position of k-th individual, N is the total number of neighboring individual in the search space. In alignment, $Al_i \rightarrow$ indicates the alignment of i-th neighboring individual, v_k is the

Table 1 The behavior of dragonfly's calculation

Behavior of Dragonflies	Formula
Separation	$Se_i = \sum_{k=1}^{N} V - V_k$
Alignment	$Al_i = \frac{\sum_{k=1}^{N} v_k}{N}$
Cohesion	$Co_i = \frac{\sum_{k=1}^{N} V_k}{N} - V$
Attraction towards a food source	$Food_i = V^+ - V$
Distraction outwards an enemy	$Enemy_i = V^- + V$

velocity of k-th individual. In food source and enemy, V^- indicates the position of the enemy, V^+ indicates the position of food source.

(iii) ***Updation process***: To update the position of artificial dragonflies in an inquiry space and reproduce their developments, two vectors are considered: step (ΔD) and position (V). The progression vector closely resembles the speed vector in Particle Swarm Optimization (PSO), and the DA algorithm is created dependent on the framework of the PSO algorithm. The progression vector demonstrates the course of the development of the dragonflies and characterized as pursues:

$$\Delta V_{t+1} = (sSe_i + aAl_i + cCo_i + fFood_i + eEnemy_i) + w\Delta V_t \tag{4}$$

where s signifies the separation weight, a signifies the alignment weight, c is the cohesion weight, f signifies the food factor, e signifies enemy factor, w signifies inertia weight, t shows iteration count.

The position vector can be calculated as

$$V_{t+1} = V_t + \Delta V_{t+1} \tag{5}$$

During the enhancement procedure, different explorative and exploitative practices can be accomplished. At the point, there is no neighboring solution; the situation of dragonflies is refreshed by Cauchy mutation probability. Along these lines, the position vectors V are determined as:

$$V_{t+1} = V_t + M_p V_t \tag{6}$$

The neighborhood area is expanded and at last, at the conclusive period of the optimization process, the swarm becomes just a single gathering. Food source and the enemy are chosen from the best and the most exceedingly bad arrangements got in the entire swarm at any moment. This leads the assembly towards the promising locales of pursuit space and in the meantime, it leads dissimilarity outward the non-promising territories in inquiry space. The flow diagram of the EDA is shown in Fig. 3.

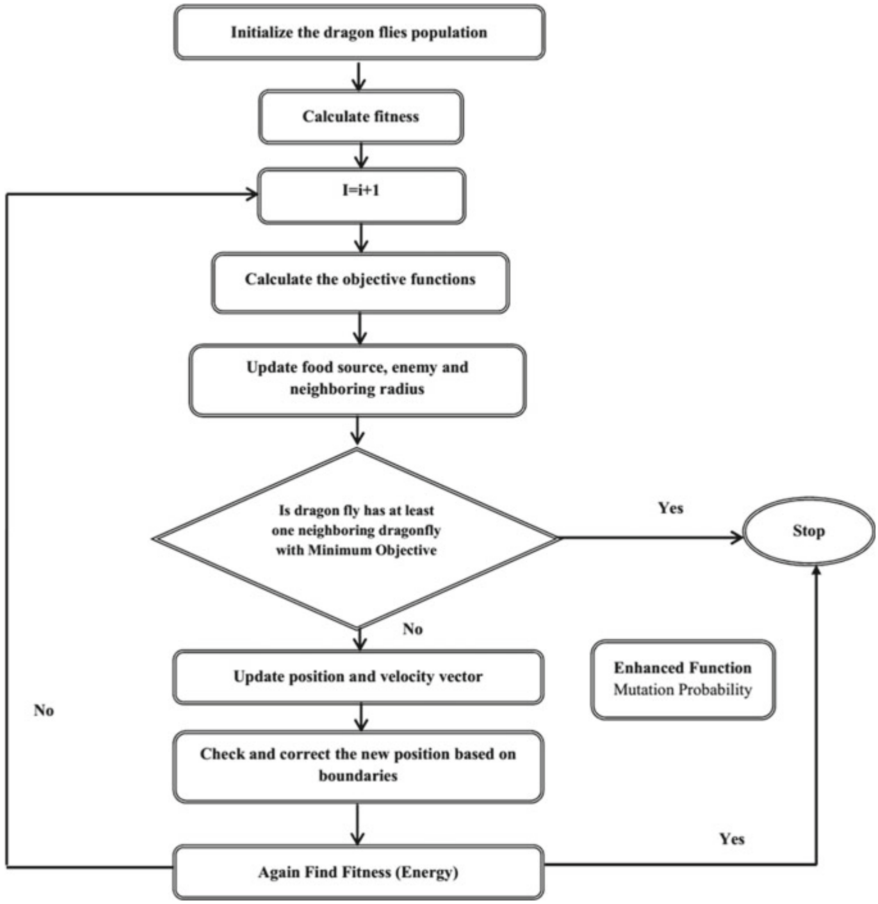

Fig. 3 Flowchart of EDA

In view of the achieved optimal parameter as minimized Energy utilization, the efficient vehicle nodes with its routing way are chosen. In course disclosure process, the trust module encourages the destination node to introduce the threshold value for the energy-factor and it additionally inspects the energy-factor of the nodes to incorporate or dismiss the nodes in the course.

5 Result and Discussion

In the result analysis part, the performance of the K-medoid clustering and optimization model is investigated by examining the network parameters in terms of energy consumption, packet delivery ratio, network lifetime and throughput. The execution of the proposed study is analyzed with the help of Network Simulation Tool-Version 2 (NS2). The simulation results of the proposed work are described in this section.

5.1 Evaluation Metrics

Throughput: Network throughput can be defined as the accomplishment of acknowledged packets over a communication channel.

Packet to the Delivery ratio (PDR): It can be described as a number of packets delivered successfully and correctly to the number of packets delivered over communication.

Energy Consumption: It is referred to as total energy depleted during data transmission of packets from source to destination.

Table 2 clarifies the outcome examination of a proposed model for an alternate number of vehicle nodes. In light of the node quality (efficient course), vehicles are clustered utilizing K-medoid clustering model. The execution of the proposed model is analyzed as far as throughput PDR, NLT, and EC. Contrasted with existing models, the energy efficient routing for V2V communication is practiced in K-medoid with EDA model.

In the throughput analysis, these parameters are analyzed dependent on the clustering and optimization procedures; showed in Fig. 4a. Compared to the customary Dragonfly algorithm, the enhanced Dragonfly algorithm gives the better throughput for 50, 100, 150 and 200 quantities of vehicles in the information transmission. The Packet to Delivery Ratio (PDR) for various quantities of the vehicle is exhibited in Fig. 4b. On contrasting the proposed model and the current methodology, the presented clustering K-medoid with EDA accomplishes high PDR for the 50, 100, 150 and 200 quantities of vehicles.

Figure 4 clarifies the execution of the vehicular network by estimating throughput, NLT, PDR, and EC individually under the diverse vehicle nodes. Figure 4c portrays the Network lifetime (days) for different numbers of a vehicle like 50, 100, 150 and 200 based optimization systems. At 50 quantities of vehicles, the k-medoid with EDA accomplishes the network lifetime as 8.5 days, k-medoid with EDA as 4 days. So also, for different quantities of the vehicle (100−200) the NLT is dissected and

Table 2 Performance Metrics Results

No. of Vehicles	Throughput (kbps)		PDR (%)		NLT (Day)		EC (J)	
	Existing	Proposed	Existing	Proposed	Existing	Proposed	Existing	Proposed
50	8524	10547	59.55	92.75	6.5	10	252	189
100	7284	8247	61.75	89.64	7	9.2	242	156
150	7124	8045	49.28	78.44	8.5	9.5	308	227
200	7025	8115	56.72	69.78	4.8	10.5	342	220

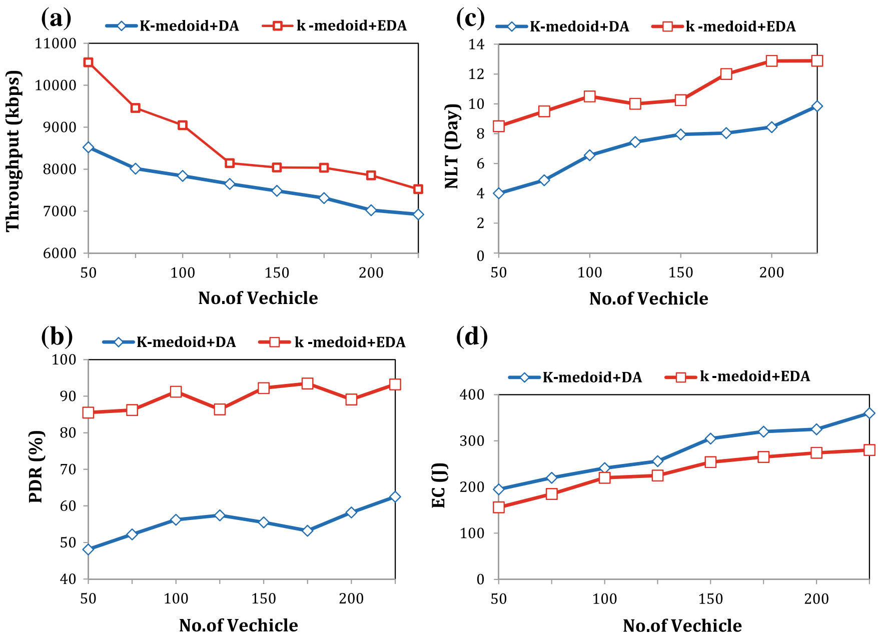

Fig. 4 Performance analysis **a** Throughput, **b** PDR, **c** NLT and **d** EC

compared. At long last, the diagram finishes up the proposed methodology achieves the most extreme lifetime in the V2V communication.

At whatever point the node transmission control is more, at that point, the number of bounces in between source to destination will be generally less. This thusly results in diminished control overhead and expanded feasible throughput. In any case, expanded node control utilization may lead to impedance with part nodes which results in packet loss because of crashes. So as to lessen the energy utilization of V2V communication between vehicle nodes, we proposed k-medoid clustering with EDA optimization. Figure 4d demonstrates the energy utilization rate of 50, 100, 150 and 200 vehicle nodes based communication. Contrasted with existing advancement, K-medoid clustering with EDA expends the least energy.

The percentage analysis of EC for a number of vehicle nodes is illustrated in Fig. 5. For 25 numbers of vehicles, k-medoid + DA consume 83% energy in data transmission and k-medoid + EDA consumes 49%. Similarly, 50, 75, 100, 125, 150, 175 and 200 numbers of vehicles are illustrated in the figure. The bar graph concludes that the proposed approach (k-medoid with EDA) achieves minimum energy consumption compared to k-medoid + DA approach.

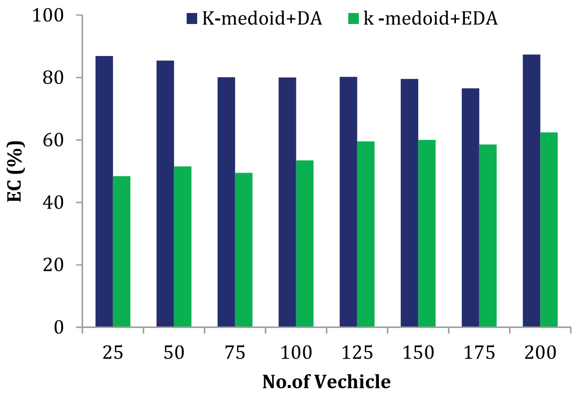

Fig. 5 Percentage analysis of EC

6 Conclusion

This paper introduced the efficient node identification of VANETs considering with energy utilization factor at least. This goal was accomplished by the clustering algorithm, for example, K-medoid algorithm along with optimization. It groups the vehicle nodes in various adjusts and choosing any nodes as cluster heads in certain rounds, it has the capacity to diminish the number of transmitted messages from every node to various nodes and to the base station, saving more energy in the network. At that point, the energy efficient route for V2V communication was obtained among the clustered nodes in VANETs by the advancement of network parameter (EC) utilizing the EDA algorithm. From the simulation examination, the proposed algorithm k-medoid + EDA give the minimum energy consumption, contrasted with the k-medoid + DA method. Later on, we can also broaden this work by improving energy efficiency regarding limited expense and maximized QoS by proposing progressively efficient clustering and optimization strategies.

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