Modeling of Optimal Adaptive Weighted Clustering Protocol for Vehicular Ad hoc Networks

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Abstract

Vehicular ad hoc network (VANET) is a mobile adhoc network widely used in intelligent transportation systems (ITS). Owing to the unique features of VANET like self-organized, recurrent link interruptions, and quick topology modifications, the design of an effective clustering protocol is a challenging problem. The clustering process is considered an optimization problem and can be solved using metaheuristic algorithms. Therefore, this paper presents an adaptive weighted clustering protocol with artificial fish swarm optimization (AWCP-AFSO) algorithm for VANET. The proposed AWCP-AFSO technique aims to select the CHs effectively and thereby accomplishes energy efficiency. To construct clusters, the AWCP-AFSO algorithm derives an objective function from electing an optimal set of CHs. A wide range of simulations are performed, and the results are investigated in terms of several performance measures. The experimental values showcased the betterment of the AWCP-AFSO technique over the recent techniques.

Keywords: VANET, Communication, Clustering, Metaheuristics, Fitness function, Weighted clustering algorithm

1. Introduction

Vehicular ad hoc network (VANET) is unlike mobile ad hoc network (MANET); hence, clustering algorithm developed for MANET could not be used for VANET. In classical VANET, infrastructures, such as roadside unit (RSU), is employed for providing network service to vehicular node, electing the optimum path and transferring information [1, 2]. These infrastructures provide road congestion, road safety data, climate condition to drivers, alternative directions. In urban areas in which RSU supports are accessible, VANET works effectively, however, in this area where infrastructures aren't accessible, VANET doesn't perform [3]. Alternatively, scalability is the main problem in VANET. Clustering is employed for solving the scalability problem, however, in the high speed platform on highway in which the vehicle speeds are quite fast when compared to urban area, the clustering doesn't perform well, result in degraded network efficiency because of the high rate of re-clustering [4, 5]. Present VANET clustering and routing methods are approximately extensive, hence needed to construct a heterogeneous routing method FANET aided VANET using lower routing overhead, effective use of computation resource, and higher network throughputs [6]. The adding of UAV in present VANET is a stimulating task since they contain different characteristics than vehicle or ground node. Other problems are the effective use of flight time of UAV since UAV carries constrained energy resource [7]. In VANET, partial framework supports are accessible by RSU; replace the RSU using UAV to make wholly adhoc networks are additional challenges to be tackled. Fig. 1 shows the VANET architecture.

Extensive applications and protocols based on VANET clustering to attain their objectives. E.g., clustering is used for various security applications for detecting intrusions and addressing security risks

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[8-10]. Moreover, various VANET routing protocol is presented according to clustering for mitigating scalability challenges [11]. As clustering permits an improved use of the network resource and scheduling of medium accessing, many MAC protocol uses the CH of every cluster for coordinating the medium accesses between the cluster members [12]. Furthermore, VANET security application benefits from clustering to distribute security messages with the provision of a successful transmission method [13], as well as various applications like QoS assurance and topology discovery [14]. In the past 30 years, a huge amount of clustering methods were developed in this study. But, validating and developing a clustering method appropriate for each condition and scenario is highly challenging which is exposed to the authors in VANET region [15].

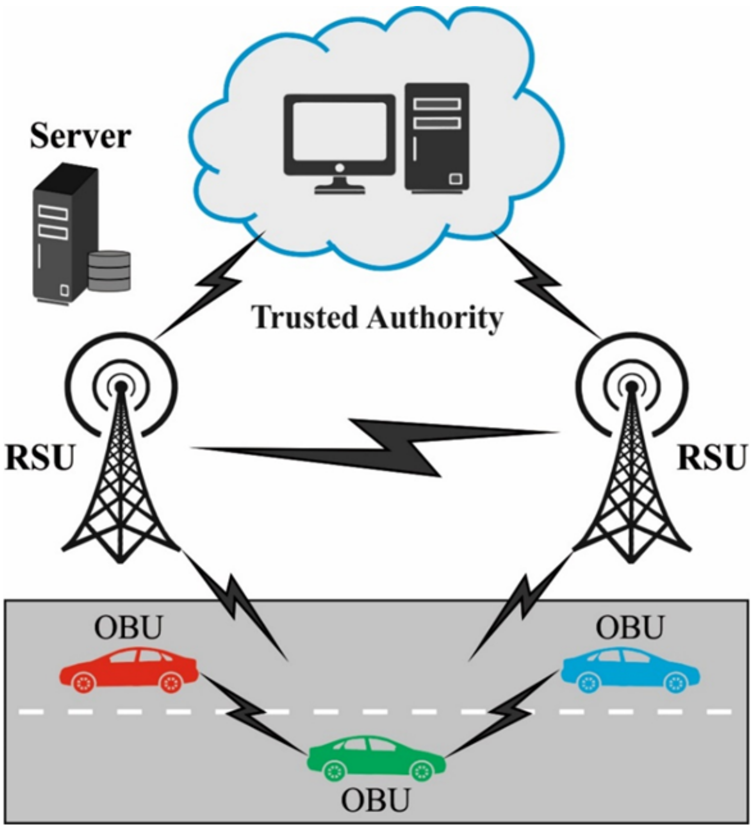

Fig. 1. Vehicular communication process

This paper presents an adaptive weighted clustering protocol with artificial fish swarm optimization (AWCP-AFSO) algorithm for VANET. The proposed AWCP-AFSO technique aims to select the CHs effectively and thereby accomplishes energy efficiency. In order to construct clusters, the AWCP-AFSO algorithm derives an objective function to elect an optimal set of CHs. A wide range of simulations are performed and the results are investigated interms of several performance measures. The experimental values showcased the betterment of the AWCP-AFSO technique over the recent techniques.

2. Related works

In [16], proposed a CACONET model. It forms enhanced cluster for strong transmission. It is related to advanced models such as MOPSO and CLPSO. Alsuhli et al. [17] proposed a comprehensive resilient DHC method for VANET. This presented method is a mobility based clustering method which uses applicable mobility matrices like vehicle position, direction, and speed, as well as other metrics' associated with the transmission link quality like LET and SNR. The presented approach has stability features and enhanced performance, particularly in the cluster maintenance stage, using a group of processes proposed for achieving this objective. [18] presented a K-Medoid Clustering method for clustering vehicle node and then, energy effective node is known to compel transmission. Using the anticipation of achieving energy effective transmission, effective node is familiar from every cluster with

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a Meta heuristic approach, e.g, EDA that enhances the parameters as minimal utilization of power in VANETs.

Cheng et al. [19] proposed a CP dependent DC method for VANET in urban areas. Initially, present a CP technique based on the feature of vehicular nodes and comparative characteristics amongst vehicular nodes. Later, create a DC method according to the connectivities amongst vehicle density and nodes. Lastly, introduce a DC method regarding routing approach for realizing stable transmission between vehicle nodes. In [20], a clustering routing protocol, called QMM-VANET, that considers QoS requirement, the mobility constraint, and distrust value parameter, is projected. The protocols specify reliable and stable clusters also increase the connectivity and stability in the course of communication. It is made up of 3 portions: (1) processing the QoS of vehicle and selecting trust vehicles as CH, (2) electing a group of suitable adjacent nodes as gateway for retransferring the packet, and (3) with gateway recovery method for choosing other gateway if the connection failures.

3. The Proposed Clustering Algorithm

AWCP-AFSO algorithm is highly beneficial for emerging models in unique intelligence for identifying global optimum solutions and doesn't acquire gradient details of objective functions. Here, an artificial fish explores food according to the foraging hierarchy of swarming nature as well as random behavior [21]. In addition, artificial fish enables mutual data communications till reaching a global optimal. The fundamental concept of AFSA is defined in the following: an *n*- dimension space, consider a fish swarm using N artificial fish. Consider $X = (x_1, x_2, \dots x_n)$ means the place of artificial fish, and $Y = f(X)$ signifies the fitness at Position X. Assume $d_{ij} = \|X_i - X_j\|$ is a distance among the position X_i and X_j, and *Step* and *Visual* imply the moving step and perceptive range of artificial fish, respectively.

Foraging behavior: Consider X_i is a recent position of artificial fish, and choose the position Xj arbitrarily from *Visual* range. When $Yj < Yi$, then artificial fish is moved a *Step* in directions of $(X_j - X_i)$. Else, decide a position Xj in random fashion for selecting whether it meets the forward criteria. When the condition is not satisfied, then random behavior is carried out. The foraging nature applies the given rule:

$$\tilde{X}_i = \begin{cases} X_i + Step \cdot \dfrac{X_j - X_j}{d_{jj}} \cdot rand, & if\ (Y_j < X_i) \\ random\ behavior, & otherwise \end{cases} \tag{1}$$

where $\tilde{X}_i$ means the upcoming position of an artificial fish, *rand* denotes uniform produced values from zero and one.

Swarming behaviour: In a fish swarm, artificial fish X_i has to search intermediate place X_c of N_F artificial fish in recent neighborhood (d_{ij} <Visual) . If $(Y_C/N_F > \delta Y_i)$, the artificial fish X_i moves forward into X_c. Numerical function of swarming behavior is provided below:

$$\tilde{X}_i = \begin{cases} X_i + Step \cdot \dfrac{X_c - X_i}{d_{i_C}} \cdot rand, & if\ (Y_c/N_F < \delta \cdot Y_i) \\ foragying\ behavior, & otherwise \end{cases} \tag{2}$$

Whereas $\delta \in (0,1)$ denotes the food concentrations.

Following behaviour: If X_{lbest} is a local optimal unit in present neighbourhood of X_i. Then, $(Y_{lbest}/N_F > \delta Y_i)$, the artificial fish X_i moves in a direction $(X_{lbest} - X_i)$. The arithmetic expression of this behavior is implied as:

$$\tilde{X}_i = \begin{cases} X_i + Step \cdot \dfrac{X_{lbest} - X_i}{d_{i,lbest}} \cdot rcmd, & if\ (Y_{lbest}/N_F < \delta \cdot Y_i) \\ foraging\ behavior, & otherwise \end{cases} \tag{3}$$

Random behaviour: The artificial fish decides a place arbitrarily from *Visual* state, and travels to the respective place. It is named as a default behavior.

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Behavior selection: In case of AF, the predefined behavior is performed and compared, correspondingly. Therefore, an optimal nature has been decided for upgrading recent state of AF.

Bulletin: It is applied for recording best state X_{best} in a fish swarm. Every AFs are compared with corresponding state using bulletin after a step. When the condition becomes normal, then a bulletin might be upgraded.

Therefore, AFSA applies a social nature of fish swarm to resolve the optimization issues, and it is extremely beneficial for fish self-information as well as environmental data for changing the searching direction in order to gain better diversity and convergence. Hence, AF gets a position where the food resource is maximum. Even though AFSA is supreme in global optimization model for optimization issues, it is still at risk in converging sub-optimum such as metaheuristics. It is named as premature convergence of complex optimization issues which results in reduced efficiency. Later, the AFSA method acquires a fitness function with the help of 3 input variables like distance to neighbours, energy for CH selection, and trust level [22].

Distance to neighbors: It is suitable for selecting CHs with minimum distance amongst neighbouring vehicles. At the time of intra cluster transmission procedure, sensor vehicle power consumption to CH communication. When the neighbouring vehicles distance is reduced, then the power of intra cluster communication is also minimalized.

Objective 1: Minimalize

$$f_1 = \sum_{j=1}^{m} \frac{1}{l_j} \left(\sum_{i=1}^{l_j} dis(CH_j, s_i) \right) \tag{4}$$

Trust factor (TF): Initially, the entire vehicle is described that TF is one. The value of TF is reduced by abnormal prediction module once the vehicle processes the anomalous task and vehicle is named as malicious vehicle.

Objective 2: Maximise

$$f_2 = \sum_{j=1}^{m} \frac{1}{m} (TF_j) \tag{5}$$

Energy: It is an amount of power utilized as CHs to RE of CHs. When a CH consumes less power usage as processes, sensing, and transmission processes also with high RE is gathered as low energy ratio. Hence low as energy ratio, the CH selection improves more possible.

Objective 3: Minimalize

$$f_3 = \sum_{j=1}^{m} \frac{E_c(CH_j)}{E_R(CH_j)} \tag{6}$$

In the proposed SHPC-SEMD technique, it could be vital to reducing the linear integration of an objective function. Thus, the potential energy function of SHPC-SEMD technique is implemented by:

$$Minimize\ Potiential\ energy\ function = \alpha_1 \times f_1 + \alpha_2 \times f_2 + \alpha_3 \times f_3 \tag{7}$$

Where $\alpha_1 + \alpha_2 + \alpha_3 = 1, \alpha_2 \geq (\alpha_1 + \alpha_3). Also\ 0 < f_1, f_2, f_3 < 1$.

4. Results and Discussion

Table 1 and Fig. 2 investigates the CH life duration (CHLD) analysis of AWCP-AFSO algorithm under distinct speed ranges. The results demonstrated that the AWCP-AFSO algorithm has accomplished proficient outcomes with the higher CHLD under all distinct ranges of speed. For instance, with the vehicle speed of 4m/s, the AWCP-AFSO algorithm has gained a higher CHLD of 87% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA techniques have provided a lower CHLD of 48%, 60%, 72%,

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and 82% respectively. Also, with the vehicle speed of 8m/s, the AWCP-AFSO technique has reached a maximum CHLD of 88% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA techniques have provided a minimal CHLD of 43%, 61%, 68%, and 83% correspondingly. Besides, with the vehicle speed of 16m/s, the AWCP-AFSO algorithm has achieved an increased CHLD of 90% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA techniques have given a lower CHLD of 50%, 54%, 71%, and 83% respectively. Moreover, with the vehicle speed of 24m/s, the AWCP-AFSO method has reached a higher CHLD of 94% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA manners have provided a lower CHLD of 52%, 58%, 64%, and 91% correspondingly. Furthermore, with the vehicle speed of 28m/s, the AWCP-AFSO methodology has gained a maximum CHLD of 91% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA techniques have offered a minimum CHLD of 59%, 58%, 73%, and 86% correspondingly.

Table 1 CHLD Analysis of AWCP-AFSO algorithm

CHLD (%)					
Speed (m/s)	**VCP**	**AWCP**	**AWCP-WA**	**AWCP-EWA**	**AWCP-AFSO**
4	48	60	72	82	87
8	43	61	68	83	88
12	52	53	63	79	90
16	50	54	71	83	90
20	49	61	68	86	91
24	52	58	64	91	94
28	59	58	73	86	91

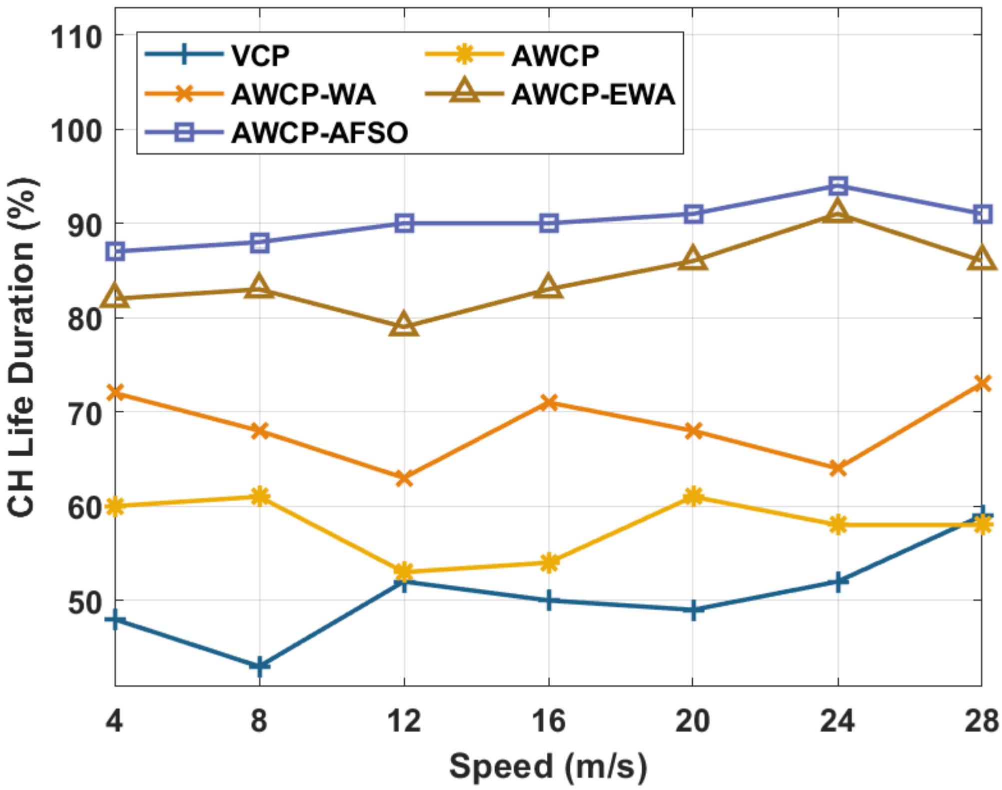

Fig. 2. Results analysis of AWCP-AFSO technique interms of CHLD

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Table 2 and Fig. 3 depict the OCHET analysis of the AWCP-AFSO algorithm with existing techniques under varying speeds. The results ensured the betterment of the AWCP-AFSO algorithm with the lower OCHET under all varying speeds of the vehicles. For instance, with the vehicle speed of 4m/s, the AWCP-AFSO algorithm has gained a reduced OCHET of 0.146 whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA techniques have provided an increased OCHET of 0.819, 0.894, 0.559, and 0.207 respectively. Similarly, with the vehicle speed of 8m/s, the AWCP-AFSO manner has attained a lower OCHET of 0.256 whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA methods have given an enhanced OCHET of 0.844, 0.819, 0.605, and 0.292 correspondingly. Likewise, with the vehicle speed of 16m/s, the AWCP-AFSO method has gained a decreased OCHET of 0.249 whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA systems have provided an improved OCHET of 0.669, 0.822, 0.413, and 0.299 respectively. Additionally, with the vehicle speed of 24m/s, the AWCP-AFSO algorithm has gained a reduced OCHET of 0.264 whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA methodologies have given a higher OCHET of 0.666, 0.762, 0.452, and 0.328 respectively. At last, with the vehicle speed of 28m/s, the AWCP-AFSO technique has gained a lower OCHET of 0.281 whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA methods have offered a superior OCHET of 0.684, 0.790, 0.427, and 0.345 correspondingly.

Table 2 OCHET Analysis of AWCP-AFSO algorithm

Optimal CH Election Time (OCHET) (m)					
Speed (m/s)	**VCP**	**AWCP**	**AWCP-WA**	**AWCP-EWA**	**AWCP-AFSO**
4	0.819	0.894	0.559	0.207	0.146
8	0.844	0.819	0.605	0.292	0.256
12	0.755	0.833	0.417	0.342	0.292
16	0.669	0.822	0.413	0.299	0.249
20	0.616	0.712	0.367	0.296	0.242
24	0.666	0.762	0.452	0.328	0.264
28	0.684	0.790	0.427	0.345	0.281

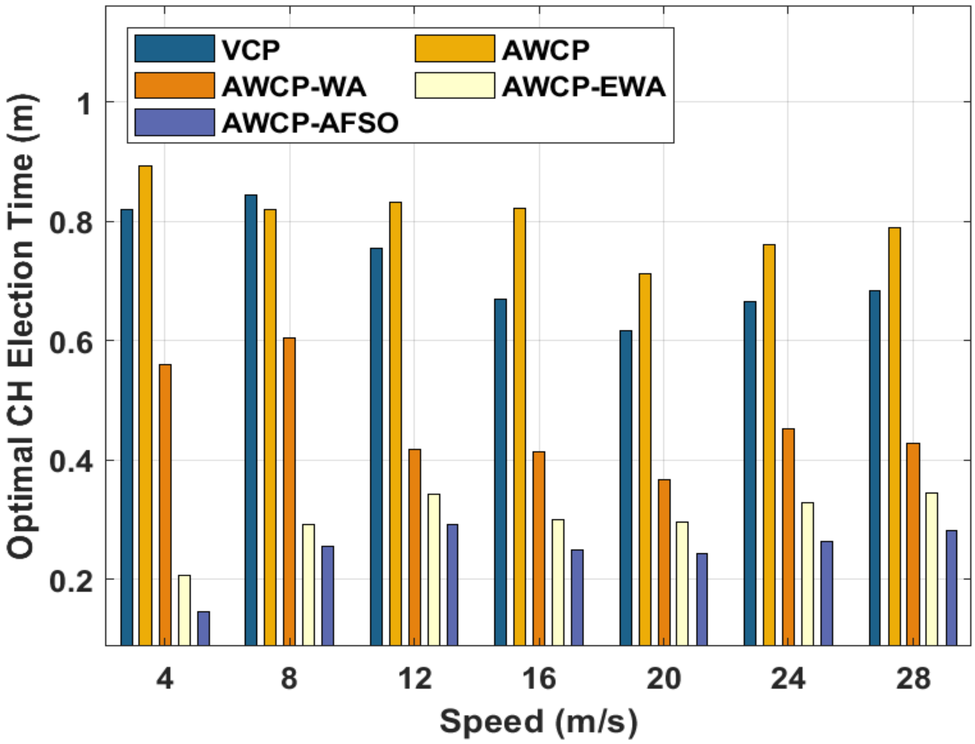

Fig. 3. Results analysis of AWCP-AFSO technique interms of OCHET

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Table 3 Comparison study of AWCP-AFSO technique interms of NLT

NLT (%)					
No. of Vehicle	**VCP**	**AWCP**	**AWCP-WA**	**AWCP-EWA**	**AWCP-AFSO**
25	69.12	81.85	95.00	110.27	115.36
50	78.45	100.09	92.45	121.72	128.94
100	62.33	83.12	88.63	98.39	109.00
125	48.75	56.39	71.66	94.15	103.48
150	58.51	72.09	99.24	124.27	133.60
175	65.72	70.82	103.06	128.94	134.00
200	78.45	91.60	114.51	132.75	138.27

Table 3 and Fig. 4 examines the NLT analysis of AWCP-AFSO technique under varying count of vehicle. The results outperformed that the AWCP-AFSO algorithm has accomplished proficient outcomes with the superior NLT under all varying ranges of speed. For instance, with vehicle 25, the AWCP-AFSO algorithm has reached a superior NLT of 115.36% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA techniques have to provide a lesser NLT of 69.12%, 81.85%, 95%, and 110.27% correspondingly. Afterward, with vehicle 50, the AWCP-AFSO manner has gained a maximal NLT of 128.94% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA approaches have provided a minimal NLT of 78.45%, 100.09%, 92.45%, and 121.72% correspondingly. Along with that, with vehicle 125, the AWCP-AFSO approach has reached a maximum NLT of 103.48% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA methods have given a lower NLT of 48.75%, 56.39%, 71.66%, and 94.15% correspondingly. In addition, with vehicle 175, the AWCP-AFSO approach has offered a lower NLT of 65.72%, 70.82%, 103.06%, and 128.94% correspondingly. Also, with vehicle 200, the AWCP-AFSO algorithm has achieved an increased NLT of 138.27% whereas the VCP, AWCP, AWCP-WA, and AWCP-EWA techniques have provided a least NLT of 78.45%, 91.60%, 114.51%, and 132.75% correspondingly.

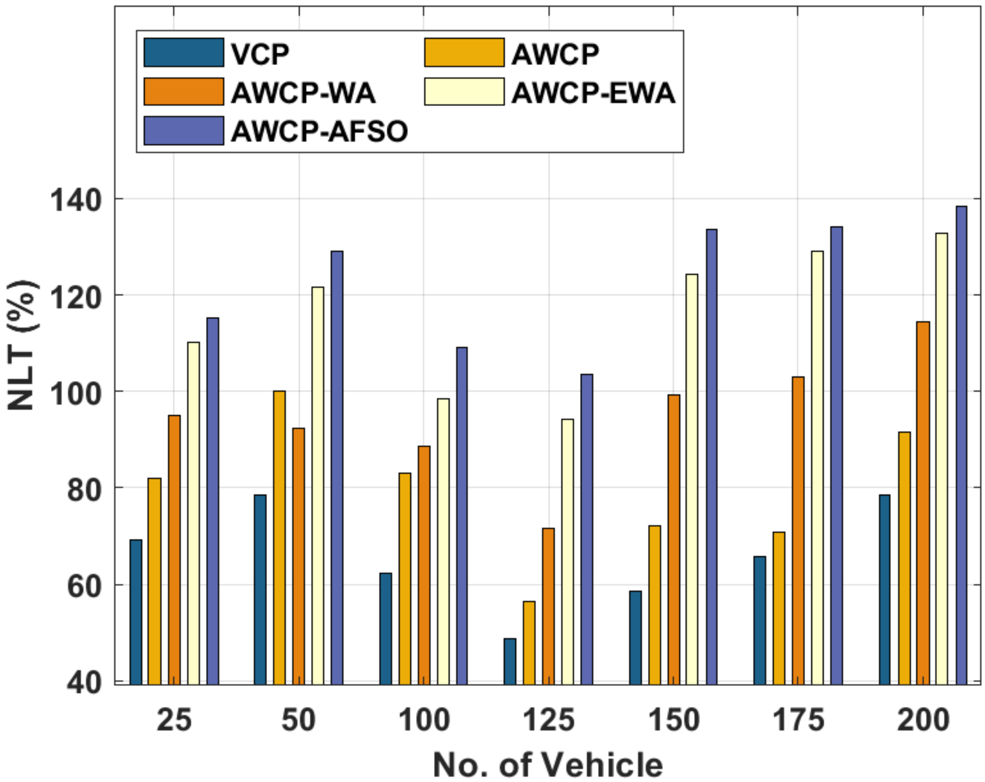

Fig. 4. Results analysis of AWCP-AFSO technique interms of NLT

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5. Conclusion

In this study, a new AWCP-AFSO algorithm is developed for accomplishing energy efficiency in VANET. The proposed AWCP-AFSO technique aims to select the CHs effectively and thereby accomplishes energy efficiency. In order to construct clusters, the AWCP-AFSO algorithm derives an objective function to elect an optimal set of CHs. A wide range of simulations are performed and the results are investigated interms of several performance measures. The experimental values showcased the betterment of the AWCP-AFSO technique over the recent techniques. As a part of future scope, the AWCP-AFSO technique can be designed to involve route planning techniques for effective vehicular communication.

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