Bio-inspired based Optimization on Internet of Vehicles in Vehicular Adhoc Communication

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Abstract. In the era of Industrial Revolution 4.0, the revolution of Internet of Things (IoT) is massively evolving in bringing new themes into life. This area involves intelligent transportation, smart housing, smart mobility, and smart health. The development of smart cities is being powered by this transition, which is centered on smart transportation. The earlier mobile-based vehicular adhoc networks (VANETs) is being replaced by the Internet of Vehicles (IoV) in order to achieve this goal. Vehicular networking and content distribution is considered as important components in disseminating messages to their intended recipients. However, the current IoV network faced an issue in the communication channel in order to receive messages with no or less delay. Thus, to solve the issue addressed, the optimization of Internet of Vehicles (IoV) using Particle Swarm Optimization (PSO) is introduced as an approach to enhance vehicular adhoc communication systems. By leveraging the principles of PSO, which is a bio-inspired computational method, this approach aims to improve the efficiency, reliability, and overall performance of the communication networks within IoV systems. The goal of PSO algorithm is to optimizes the parameter of the IoV network to achieve better performance in increasing the throughput and reducing delay, thus improves connectivity among vehicles, leading to a more robust and effective vehicular network. The simulation results obtained verify that the proposed work improves the Quality of Service (QoS) of the IoV network in terms of throughput and delay.

Keywords: Traffic congestion, Internet of Vehicles (IoV), Particle Swarm Optimization (PSO).

1 Introduction

Communication networks are the main support of Intelligent Transportation System (ITS) since they connect application areas as well as connect individual components of the system [1]. Previously, Vehicular Adhoc Networks (VANETs) were established as a way to disseminate important messages in ITS in order to reduce congestion, share data, and provide effective traffic management. However, network traffic tends to be

N. A. S. Abdullah et al. (eds.), *Proceedings of the International Conference on Innovation & Entrepreneurship in Computing, Engineering & Science Education (InvENT 2024)*, Advances in Computer Science Research 117,
https://doi.org/10.2991/978-94-6463-589-8_44

congested and it require a lot of bandwidth to deliver message when too many cars are streaming over the same traffic network [2]. Another issue to be addressed is although VANETs is well-known with its additional features such as high mobility and high topology rate, the conventional VANETs have limited access and coverage. The mobility constraints and the number of connected vehicles is the issues raised in VANETs make it unstable [2]. Therefore, this problem leads towards the introduction of Internet of Vehicles (IoV).

IoV which is the expansion technology of Internet of Things (IoT) from the previous conception of VANETs, is defined as an open and integrated network system equipped with the features of high manageability, controllability, operationalization and credibility. It has the capability to obtain, manage and compute large scale of data. The goal of IoV development is to capture in-depth integration of human-vehicle-thing-environment, to reduce social cost, to promote efficiency of transportation and to minimize the services of a city. It is a formed of multiples nodes including host and neighboring vehicles, things and network [3-5]. IoV has a significant impact in the development of smart cities due to the growing numbers of vehicles circulating on the road. IoV is used to deliver important messages to road users to avoid congestion, which include safety and non-safety messages such as alert on accidents, collisions, emergency vehicle warning, route optimization etc [6-7]. These messages are disseminated through V2X vehicular communications; mainly Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I). It is based on the IEEE1609 Family of Standards for Wireless Access in Vehicular Environments (WAVE) which dependent on IEEE802.11p for Information Technology, telecommunications and information exchange among systems [4][8].

Due to the advantages of high-speed mobility, delay sensitivity uninterrupted network connection, robust and more secure network, IoV has been deployed in several areas, such as smart home, smart energy, smart healthcare, smart environment, smart transportation and smart city [4]. It was introduced as a layered network model which basically consists of the interaction in the network within the vehicles (nodes), the users (humans) and the sensors [4][9]. In IoV terminology, *human* refers to any anyone who uses or provides IoV services or applications. Humans include not only those who operate vehicles, such as drivers and passengers, but also those who are in the surrounding environment of IoV, such as cyclists, pedestrians, and the relatives of drivers while *vehicles* refer to any type of vehicle that uses or offers IoV services or applications [10]. The architecture of basic IoV is illustrated in Figure 1 and the communication is shown in Figure 2.

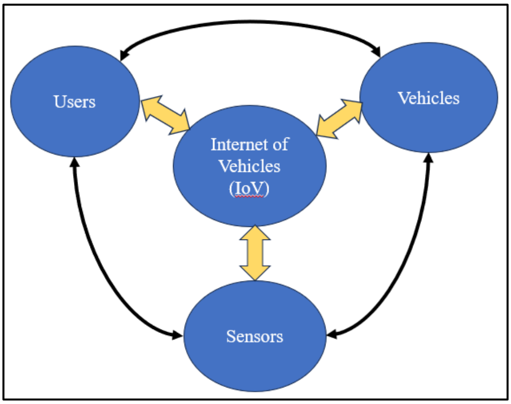

Fig.1. The basic architecture of IoV [4], [10], [11]

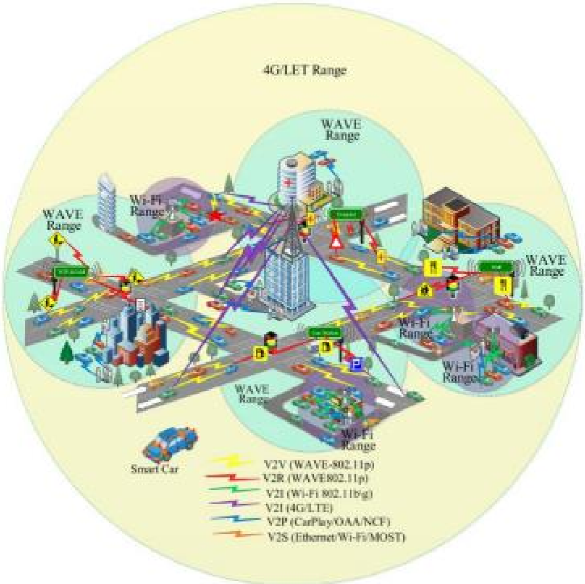

Fig. 2. V2X connections in IoV [8]

Although IoV is proved to be promising for improving the network, however the issue such as traffic congestion and communication problem remains unsolved when the network becomes congested due to the transmitted packet loads during a period of intensive traffic exceed the capacity of the buffer. Consequently, it leads to a loss of network quality of service (QoS) by affecting its metrics such as throughput, end-to-end latency, packet delivery ratio etc. [4], [12-15]. The goal of this work is to optimize the IoV network using the bio-inspired algorithm which is Particle Swarm Optimization (PSO) to increase the QoS parameters performance especially in maximizing throughput and minimizing the delay. The paper is structured as follows; Section 2 will discuss on the PSO algorithm as the method of IoV optimization. In section 3, further elaboration on the simulation setup, the parameters used and the contribution of the end-to-end delay as the objective function will be presented. In Section 4, we will illustrate and explain the simulation result of the IoV model. Finally in Section 5, we present our conclusion of the proposed work.

2 Particle Swarm Optimization (PSO) as the bio-inspired optimization procedure

Particle Swarm Optimization (PSO) is a population-based optimization technique inspired by the social behavior observed in bird flocking and fish schooling. This bio-inspired algorithm was introduced by Kennedy and Eberhart in 1995 [16-17]. PSO offers several advantages, including insensitivity to the scaling of design variables, simple implementation, ease of parallelization for concurrent processing, a derivative-free approach, minimal algorithm parameters, and highly efficient global search capabilities. These attributes make PSO a promising method for solving a wide range of optimization problems.

PSO is made up of many particles that resemble birds. Every particle has a specific location within the search space. It has a fitness function that it uses to determine each particle's fitness, which is a measurement for the quality of the position. The particles travel at a specific speed over the search space. Every particle possesses an internal state connected via a social network. Additionally, the velocity depends on its personal best position called *pbest*, the best solution called *lbest* that has been found thus far by its social neighbors, and the global best called *gbest*. The swarm will then gather at the best locations [16-18]. In this study, the phases involve in PSO is shown in Figure 3.

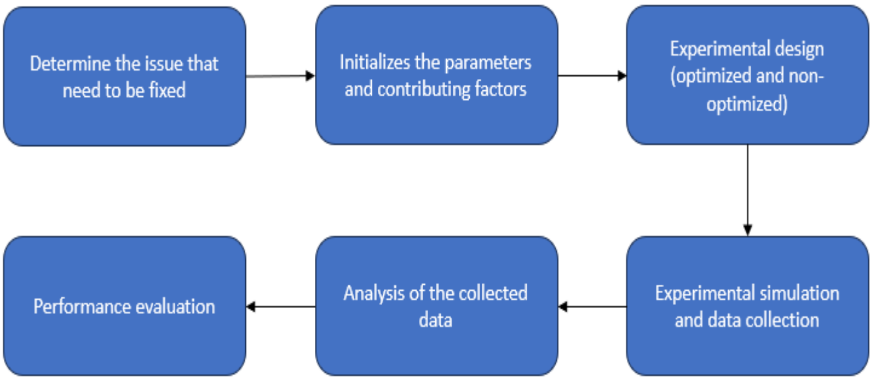

Fig. 3. Phases in PSO

There are several previous research that implement PSO-based optimization method on IoV. Authors in [19] implemented clustering approach (hash-based detection) to reduce users' travel time on the road in case traffic congestion occurs. Authors in [20] introduced moth flame clustering algorithm (MFCA-IoV) to generate optimized clusters for transmission. Authors in [21] used metaheuristic dragonfly-based clustering algorithm (CAVDO) for cluster-based packet route optimization. Authors in [22] solved the offloading strategy problem of multiuser and multi-objective nodes using PSO based joint optimization approach (offloading decision of vehicles, resource allocation by RSUs and offload ratio of vehicles). Authors in [5] presented allocation of bandwidth resources using multi-domain Virtual Network Embedding Algorithm (VNE) in IoV. However, there are some preoccupied considerations on the performance of the QoS parameters especially the throughput and the delay. The PSO algorithm designed for this work is illustrated in Figure 4.

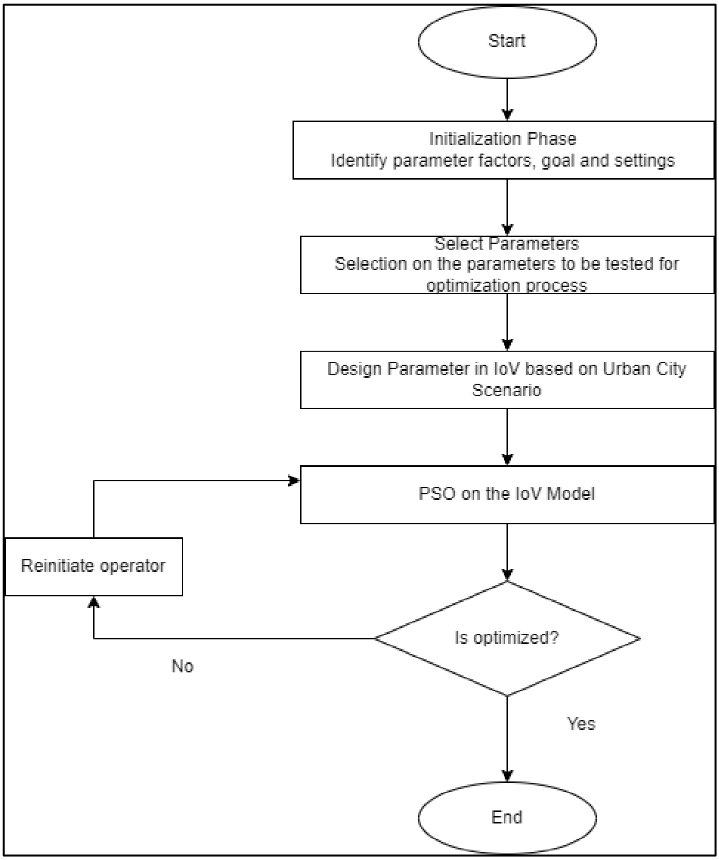

Fig. 4. Proposed PSO Algorithm

3 Research Method

Simulation of Urban Mobility (SUMO) 0.28.0 was used for the traffic simulation in order to assess the parameters required for identifying and predicting traffic flow and congestion [23]. The OMNeT++ 5.6.2 simulator is then used to conduct the traffic network experiments [22-23]. This open-source software is categorized as a software-defined network (SDN) which allow system network framework optimization by means of design that takes user perception of the suggested framework into account. The INET framework [24] and Veins of the OMNET++ form the basis of all MAC and routing protocols.

The input data used to evaluate the traffic generator is user datagram protocol (UDP). The simulation scenario was carried out in a setting with wireless vehicular mobility up to 250 seconds with random initial point and random node movement.

Table 1. Simulation parameters

Parameter	Value
Network range	1000x1000m
Number of nodes	100-250
Node initial placement	Random
Node movement model	Random waypoint
Traffic type	UDP
.wlan	IEEE 802.11p
Simulation time	50s - 250s

The necessary parameters of the simulation modules in this network, together with other simulation elements like bit rate, rate limit, mobility speed, and transmit interval, would be used and set using a *.ini* file. Relay units and other single modules are coupled by gates to form compound modules, which are then combined to create a hierarchical style.

Table 2. PSO parameters

Parameter	Value
Population size	100
Inertia weight, w	0.7
Learning factor, c1, c2	0.2, 0.6

For the network optimization of the work, several parameters were identified as in table 2. The vector of position and the vector of velocity can be indicated as $Xpos = (x1, x2, x3,..., xN)$ and $Velo = (v1, v2, v3,..., vN)$, respectively, where N is the number of particles. The personal best of each particle is denoted by *Pbest = (p1, p2, p3, ..., pN)*, whereas *Gbest* represents the global best position. The inertia weight is denoted as *w* and in this case, *c1* and *c2* are two constants, referred to as the acceleration coefficients, that define the weight of *Pbest* and *Gbest*, respectively. The two random numbers, *r1* and *r2*, are each generated independently using a uniform distribution in the interval [0,1]. The velocity and position of the particles are updated periodically according to following equation in (1) and (2) [14]. Equation (3) is the first objective function of each particle's fitness evaluation. The value of α and β is the weights of *F1* and *F2* indicates the shortest path and the smoothest path respectively. It is a novel idea introduced for the purpose of network optimization.

$$Velo(t+1) = wVelo(t) + c1r1(Pbest - Xpos(t)) + c2r2(Gbest(t) - Xpos(t)) \tag{1}$$

$$Xpos(t+1) = Xpos(t) + Velo(t+1) \tag{2}$$

$$x(t) = \alpha * F1 + \beta * F2 \tag{3}$$

As mentioned previously, this research used PSO to optimize the average delay of the network. In PSO, every particle needs to have a boundary in order to reduce search time. For simplicity, the lower bound is set to one whereas the upper bound is set to 10 [13][16]. The second objective function is defined as in equation (4).

$$f(x) = 1/x(t) \tag{4}$$

Although *f(x)* does not explicitly demonstrate the average delay of the network, it is linear to the end-to-end delay of the network. Therefore, reducing *f(x)* is equivalent to reducing the end-to-end delay.

4 Result and Discussion

This section explained the results of the research and at the same time it provides a comprehensive discussion. Performance metrics being evaluated and observed in this proposed work are the end-to-end delay and the throughput. It is evaluated for before and after optimization. As mentioned previously, PSO is implemented in the IoV model to minimize the delay of each node while transmitting the messages. The result is shown in Figure 5 and Figure 6.

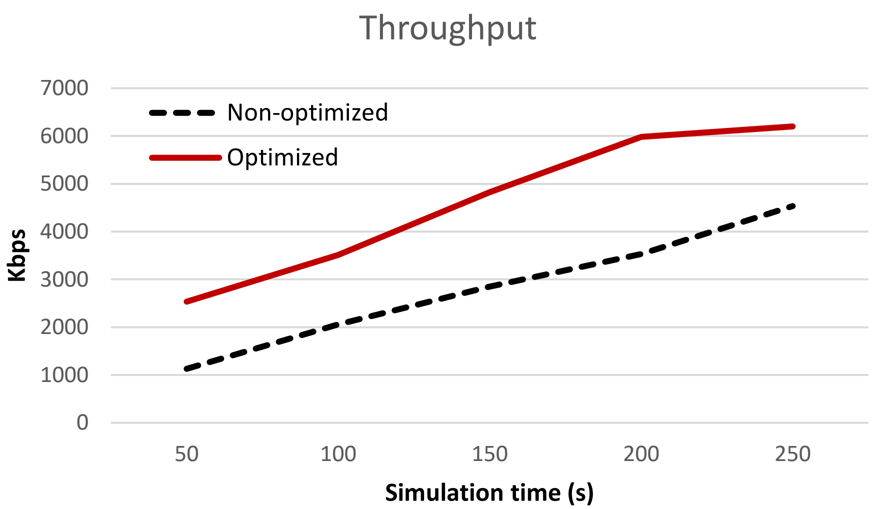

Fig. 5. Performance throughput for optimized and non-optimized network

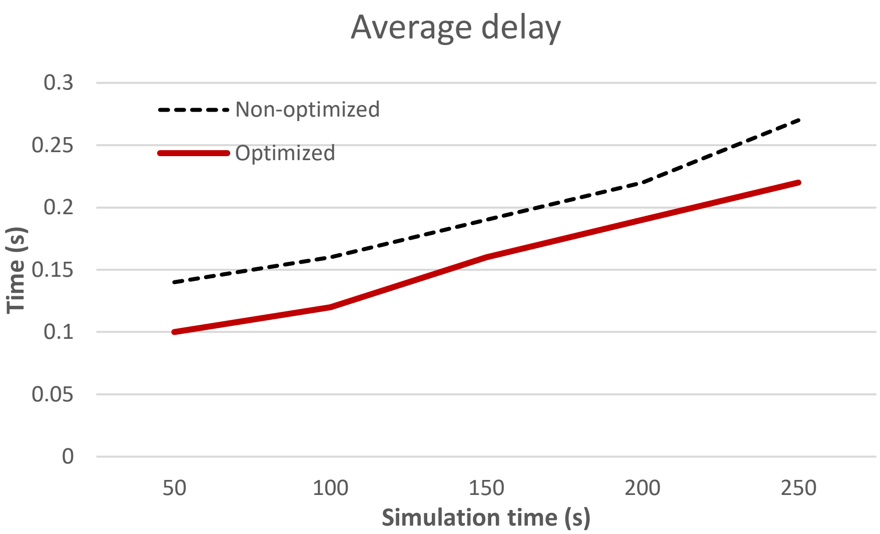

Fig. 6. Performance average delay for optimized and non-optimized network

Figure 5 illustrates the result of the throughput and Figure 6 shows the average delay of the network before and after optimization. Initially, the network scenario starts with a lower average delay compared to the optimized network. The optimized IoV consistently shows lower average delay compared to the non-optimized across all data points. This result indicates that the optimized scenario significantly improves performance, by means reducing the delay. Based on Table 3, it is identified that there are improvements of 23.13% on the throughput and decrement of 12.22% on the average delay respectively. Thus, this result indicates that the amount of packet loss is also reduced.

Table 3. Normalization percentage of network improvement

Simulation Time(s)	50	100	150	200	250	Average
Throughput	14.04	15.54	31.94	32.49	21.66	23.13
End-to-end delay	13.85	21.82	10.31	8.92	6.19	12.22

5 Conclusion

In this study, an enhanced Particle Swarm Optimization (PSO) algorithm is proposed to increase the performance of IoV model by optimizing the end-to-end delay to produce better performance result in terms of the throughput and average delay. By comparing and analyzing the results, we reached to a conclusion that PSO based IoV produced excellent performance which means it excelled in increasing the throughput value and decreasing the average delay of the transmission packets. End-to-end delay was identified and used as the objective function of the proposed PSO. The growing difference in delays between the two scenarios as the input increases highlights the effectiveness of the optimization of PSO algorithm on IoV. The proposed PSO method in this paper has strong global search ability, where the distance and the smoothest fit particles were considered but it needs further improvement in jumping out of local search capability by adjusting the parameters of the algorithm. It is also suggested that there is potential of conducting in-depth research on the speed of the algorithm with different QoS parameters.

Acknowledgments. The authors wish to thank Universiti Teknologi MARA, Malaysia and Ministry of Higher Education of Malaysia for funding this research.

Disclosure of Interests. The authors of this paper have no competing interests.

References

1. Hahn, D. A., Munir, A., & Behzadan, V.: Security and Privacy Issues in Intelligent Transportation Systems: Classification and Challenges. IEEE (2019).
2. Hatim, S. M., Elias, S. J., Awang, N., & Darus, M. Y.: VANETs and Internet of Things (IoT): A discussion. Indonesian Journal of Electrical Engineering and Computer Science, 12(1), 218–224 (2018).
3. Yang, F., Wang, S., Li, J., Liu, Z., Sun, Q.: An Overview of Internet of Vehicles. China Communications, 11(10), pp. 1–15. https://doi.org/10.1109/CC.2014.6969789 (2014).

4. Hatim, S. M., Elias, S. J., Ali, R. M., Jasmis, J., Aziz, A. A., Mansor, S.: Blockchain-based Internet of Vehicles (BIoV): An Approach Towards Smart Cities Development. 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE), pp. 1-4 (2020).
5. Zhang, P., Wang, C., Aujla, G. S., Kumar, N. & Guizani, M.: IoV Scenario: Implementation of a Bandwidth Aware Algorithm in Wireless Network Communication Mode. IEEE Transactions on Vehicular Technology (2022).
6. Elias, S. J., Hatim, S. M., Darus, M. Y., Abdullah, S., Jasmis, J., Badlishah, R. A., & Wong, Y. K.: Congestion Control in Vehicular Adhoc Network: A Survey. Indonesian Journal of Electrical Engineering and Computer Science, Vol. 13, No. 3, pp. 1280-1285 (2019).
7. Dandala, T., Krishnamurthy, V. & Alwan, R.: Internet of Vehicles (10 V) for Traffic Management. IEEE International Conference on Computer, Communication and Signal Processing (2017).
8. Kaiwartya, O., Abdullah, A. H., Cao, Y., Altameem, A., Prasad, M., Lin, C. T., & Liu, X.: Internet of Vehicles: Motivation, Layered Architecture, Network Model, Challenges, and Future Aspects. IEEE Access, 4, pp. 5356–5373 (2016).
9. Contreras-Castillo, J., Zeadally, S. & Ibáñez, J. A. G.: A seven-layered model architecture for Internet of Vehicles. Journal Of Information and Telecommunication, Vol. 1, No. 1, pp. 4–22 (2017).
10. Yang, F., Wang, S., Li, J., Liu, Z., & Sun, Q.: An Overview of Internet of Vehicles. China Communications, 11(10), pp. 1–15 (2014).
11. Sharma, S., Ghanshala, K. K. & Mohan, S.: Blockchain-Based Internet of Vehicles (IoV): An Efficient Secure Ad Hoc Vehicular Networking Architecture, IEEE International Conference on Advanced Networks and Telecommunications (2019).
12. Hahn, D. A., Munir, A., & Behzadan, V.: Security and Privacy Issues in Intelligent Transportation Systems: Classification and Challenges. IEEE (2019).
13. Taie, S., & Elazb, A.: Challenge of Intelligent Transport System. International Journal of Modern Engineering Research (IJMER), 6(10) (2016).
14. Royyan, M., Ramli, M. R., Lee, J.-M., & Kim, D.-S.: Bio-Inspired Scheme for Congestion Control in Wireless Sensor Networks. 14th IEEE International Workshop on Factory Communication Systems (WFCS). doi: 10.1109/WFCS.2018.8402366 (2018).
15. Ferdowsi, A., Challita, U., & Saad, W.: Deep Learning for Reliable Mobile Edge Analytics in Intelligent Transportation Systems. IEEE (2017).
16. Cai, J., Peng, P., Huang, X., & Xu, B.: A Hybrid Multi-phased Particle Swarm Optimization with Sub Swarms. International Conference on Artificial Intelligence and Computer Engineering (ICAICE). IEEE (2020).
17. Masehian, M. & Sedighizadeh, D.: A Multi-Objective PSO-based Algorithm for Robot Path Planning. IEEE International Conference on Industrial Technology (2010).
18. Li, J., Sun, Y., & Hou, S.: Particle Swarm Optimization Algorithm with Multiple Phases for Solving Continuous Optimization Problems. Discrete Dynamics in Nature and Society, Vol. 21 (2021).
19. Rawat, D. B., Garuba, M., Chen, L. & Yang, Q.: On the Security of Information Dissemination in the Internet-of-Vehicles. Tsinghua Science and Technology, Vol. 22, No. 4, pp. 437-445 (2017).
20. Khan, M. F., Aadil, F., Maqsood, M., Bukhari, S. H. R., Hussain, M. & Nam, Y.: Moth Flame Clustering Algorithm for Internet of Vehicle (MFCA-IoV). IEEE (2018).
21. Aadil, F., Ahsan, W., Rehman, Z. U., Shah, P. A., Rho, S. & Mehmood, I.: Clustering Algorithm for Internet of Vehicles (IoV) based on Dragonfly Optimizer (CAVDO). Journal of Super Computing (2018).

22. Lin, L. & Zhang, L.: Joint Optimization of Offloading and Resource Allocation for SDN-Enabled IoV. Hindawi Wireless Communications and Mobile Computing, Special Issue (2022).
23. Gunasekaran, R., Dhanasekaran, P., Anbalagan, S., Ganapathisubramaniyan, A. & Bashir, A. K.: SDN-enabled Traffic Alert System for IoV in Smart Cities (2020).
24. Hatim, S. M., Haron, H., Elias, S. J., & Bashah, N. K.: Smart optimization in 802.11p media access control protocol for vehicular ad hoc network. International Journal of Electrical and Computer Engineering (IJECE), Vol. 13, No. 2, pp. 2206-2213 (2023).