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Review

Soft Computing Techniques Aware Clustering-Based Routing Protocols in Vehicular Ad Hoc Networks: A Review

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Abstract: The vehicular ad hoc network is an emerging area of technology that provides intelligent transportation systems with vast advantages and applications. Frequent disconnections between the vehicular nodes due to high-velocity vehicles impact network performance. This can be addressed by efficient clustering techniques. Several recent studies have attempted to develop optimal clustering algorithms to improve network performance metrics using soft computing techniques. Although sufficient work on soft computing techniques has been carried out, it seems less commonplace to find an analysis of various algorithms' network parameters together. This paper provides a systematic analysis of the clustering-based routing protocols used in vehicular networks that are aware of soft computing techniques. The categorization is performed according to various soft computing techniques: particle swarm optimization, k-means, neural networks, artificial bee colony, genetic algorithm, firefly algorithm, and fuzzy logic. A comparative study of soft computing strategies is also provided in the survey with a focus on their objectives, along with their strengths and limitations. This survey makes it easier for researchers to pick the required soft computing technique used in vehicular networks in order to improve metrics such as packet delivery ratio, end-to-end delay, throughput, cluster lifetime, and message overhead.

Keywords: VANET; routing protocols; k-means; soft computing; PDR; cluster

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1. Introduction

Vehicle ad hoc networks (VANET) are often referred to as networks on wheels, which are used to provide connectivity between vehicle nodes. It is an outgrowth of mobile networks. Vehicular nodes are self-organized and connect with each other in a less environmentally sound infrastructure. The IEEE Committee has established the IEEE 802.11p standard for VANETs, recognizing that the ad hoc vehicle network is essential for the provision of safety-associated applications in the Intelligent Transportation System. For short-range transmission, the US Federal Communication Commission (FFC) has allotted 75 MHz of bandwidth at 5.9 GHz between vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I). The main objective of VANETs is to create an intelligent framework for transport. In building V2V and V2I communications, Dedicated Short Range Communication (DSRC) may play an important role. DSRC has a range of around one thousand meters. Inter-networking via VANETs has received huge attention over the past few years. Realizing its increasing importance, academia, major automotive manufacturers, and government agencies are making efforts to develop VANETs [1,2]. VANET has mobile nodes, sensor vehicles, static networks, fixed roadside access points (RSAP), and wireless links such as V2V, V2I, and point-to-a-vehicle access (I2V). Depending on the coverage requirements, this wireless communication device consists of a combination of GPS and a cellular communication system using either one- or multi-hop mode. One of this technology's main services is to support drivers with protection so that road injuries can be reduced. Providing protection for onboard passengers is the main service offered by this form of network. A VANET's key requirements are high processing power, large storage space, adequate energy, and node movement estimation [3,4]. This technology facilitates a variety of applications that affect daily human life, such as infotainment, traffic management services, and security, as displayed in Figure 1. Due to their unique characteristics, several clustering schemes have been proposed for VANETs in previous years. Due to technological advancement in vehicle mobility, protocols that utilize multiple network parameters have been revealed to be highly appropriate for VANETs. The authors selected parameters such as distance, density, connection stability, velocity, and location in soft computing techniques for their review work. In addition, VANETs have received a lot of consideration in industry a0nd are predicted to be introduced in the near future, thus attaining data sharing between vehicles and organizations that enable different mobile vehicle services such as safety, traffic performance, urban detection, driver support, and vehicle user entertainment [5]. Vehicles can create intra-vehicle, V2V, V2I, and still vehicle-to-everything (V2X) transmission, in particular, in such a VANET to partially reduce the load of data traffic while meeting the maintenance requests of vehicle users nearby [6].

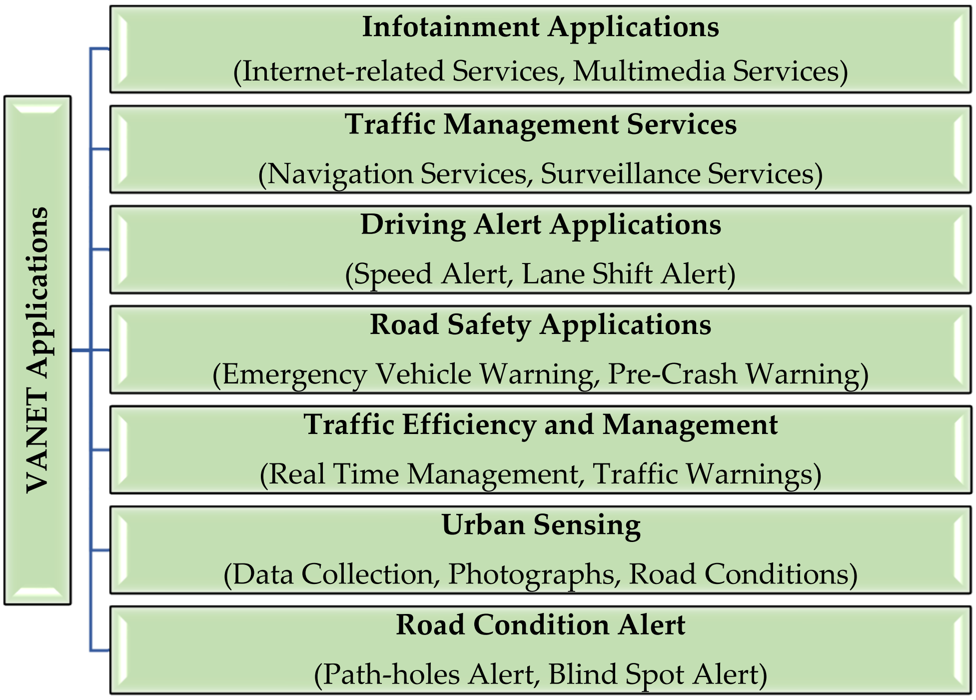

Figure 1. VANET Applications with Examples.

The traffic flowing through a vehicular network increases with the vehicular nodes, resulting in network congestion. Routing in the network then becomes a challenging task which affects throughput, delay, and packet loss and hence reduces the overall efficiency of the network.

In past years, Particle Swarm Optimization (PSO), K-means, Neural Networks (NN), Artificial Bee Colony (ABC), Genetic Algorithm (GA), Firefly Algorithm (FA), and Fuzzy Logic (FL) have been proposed to upgrade the efficiency in wireless sensor networks with the rapid expansion of soft computing techniques [7].

To provide versatility and strength to network failure, complex network topology, and flexible channel requirements in VANETs, soft computing techniques are found to be the best optimal solution in a vehicular environment. This survey, therefore, discusses the recently proposed clustering protocols based on soft computing techniques in the literature that have provided optimum performance in VANETs. The major contributions of this survey are reviewed as below:

1. We present an outline of architecture and characteristics associated with VANET.
2. A comprehensive overview of issues and challenges involving vehicular communication is presented.
3. A detailed analysis of soft computing-based clustering protocols in VANETs with their goals, strategies, and comparison.
4. We present a comparative evaluation of soft computing techniques emphasizing their strengths and limitations.
5. Future research directions that can enhance the efficiency of VANETs are introduced.

The remainder of the paper is laid out as follows: The architectural design of VANETs is discussed in Section 2. The characteristics and challenges of VANETs are discussed in Sections 3 and 4, respectively. In Section 5, clustering protocols based on soft computing techniques are briefly addressed. A comparative analysis of the examined protocols is provided in Section 6. Finally, Section 7 introduces the potential future scope and Section 8 represents the conclusion.

2. Architecture of VANETs

VANETs adopt similar concepts of connectivity and design as MANETs. VANET communication can be divided into three major categories: (1) V2V communication, where vehicles can link immediately to disseminate messages to each other; (2) V2I communication [8], in which the vehicle can connect with infrastructure-based networks for exchanging data wirelessly; and (3) Infrastructure-to-Infrastructure (I2I) networks to contribute to major vehicular applications, as shown in Figure 2. A wireless connection exists between the infrastructure and nearby vehicles, where it can relay data in both directions (e.g., V2I and I2V) [9]. The infrastructure offers up-to-date information and internet access to vehicles through this connection. As a result, they will receive major updates on current events as well as traffic on nearby highways. VANET architecture includes communication between the onboard unit (OBU) installed on vehicles with the Roadside Unit (RSU), which are mostly static in nature and are installed at the roadside. The synchronization between all the units provides improved results in the form of delivery, throughput, and efficiency.

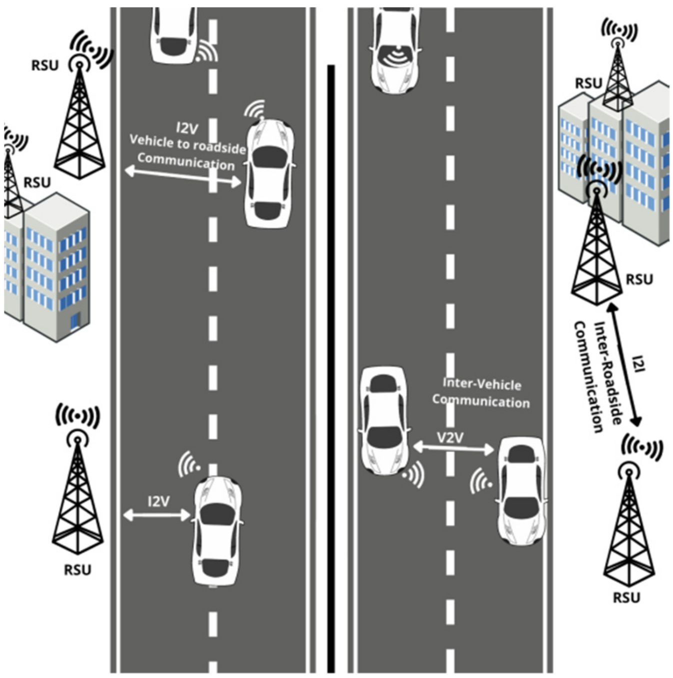

Figure 2. VANET Architecture.

The Roadside Unit (RSU) and an onboard unit (OBU) are the key elements used for VANET [10]. Normally, the RSU is static all along the paths, while the OBU is housed inside the vehicle. All RSUs are interconnected with each other along the route. The key RSU functions include: (i) Expanding the range of VANET communication [11] by sending messages to another OBUs and RSUs. (ii) Applications for running protection, such as traffic situation coverage or accident alerts. (iii) Supplying OBUs with internet access.

The OBU, on the other hand, handles contact between vehicles and the RSUs on the network [12], as shown in Figure 3. An OBU comprises a processor, memory, network unit, and sensors for resource commands. Later, the OBU observes and collects the data to create messages delivered via wireless media to nearby vehicles [13].

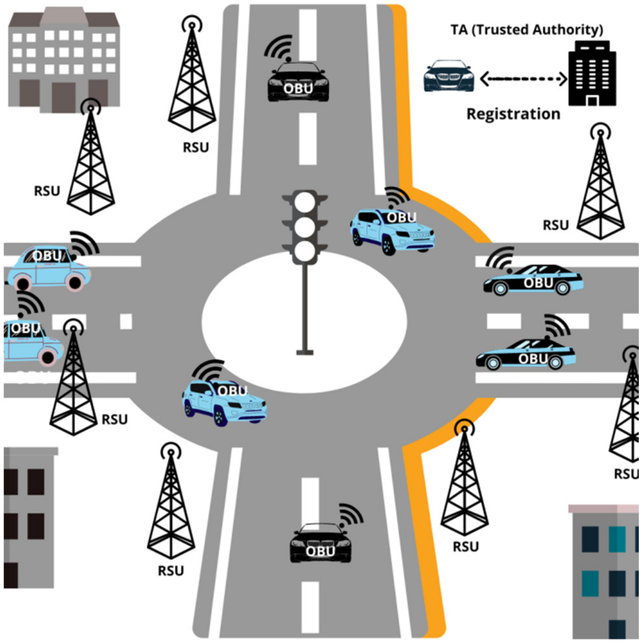

Figure 3. VANET Components.

3. Characteristics of VANETs

Since VANETs are used in so many monitoring and safety applications, they have a number of hardware and communication device characteristics [14] that affect VANET communication. The following is a list of the most significant characteristics that affect VANET communication [15]:

- Estimate of movement: The movement of vehicles is limited by the urban structure, such as sidewalks, crossings, and roads, thereby possible vehicle activities can be predictable [16].
- Power constraints: Because every vehicle is fitted with prolonged battery life, the VANETs do not have any power limitations.
- Variable network density: Network density depends upon the traffic in roadside scenarios; in rural areas the density is low, whereas in traffic jams and highly populated urban areas, the density is high.
- Mobility: In VANETs, vehicles usually drive at high velocity. A slight delay in V2V transmission can also lead to several problems.
- Variable Network Topology: Due to the extreme mobility of vehicles, the topology of VANETs varies rapidly. This makes VANETs susceptible to attacks and the detection of malicious vehicles is difficult [17].
- Real-time restrictions: In VANETs, the communication of data has a fixed time threshold range. This is intended to provide ample time for the recipient to make determinations and take necessary actions quickly.

- Processing and storage capacity: In VANETs, it is common to manage vast quantities of data between vehicles and infrastructures. Therefore, the capacity to compute and store is a daunting problem.
- Volatility: It is common for the interactions between two nodes in VANETs to arise only once because of their versatility. The links between nodes will stay within a few wireless hops for a restricted duration of time. Thus, the protection of personal contacts at VANET will be difficult to ensure.
- High processing capacity: Compared to other mobile nodes, operational vehicles can utilize much higher processing, networking, and sensing abilities [18].
- Conventional mobility: Vehicles have motions that are more convenient than traditional MANETs. Vehicles travel only on highways. From GPS technology, roadway information is available.
- Wide scale: With several participants, VANETs could span a whole road network. Its area of coverage can vary from a neighborhood to a whole town.

4. Challenges of VANETs

In Intelligent Transport System (ITS), which varies from traffic protection applications to infotainment applications, different applications are used. Such a set of applications presents different specifications for protocols for vehicular communication [19]. Such requirements lead to new challenges:

- Bandwidth limitations: VANETs endure channel overcrowding, particularly in a high-density zone, because of the absence of a central controller that handles the use of restricted bandwidth and comfortable activity [20].
- Delay constraints: Frequent topology changes in VANET have rigorous time rules. Hence, it is important to consider a fair time delay in designing effective vehicle transmission protocols.
- Privacy rights: Vehicular contact must resolve the tradeoff between privacy and accountability. Each car has to believe the source of the data it receives.
- Cross-layering protocols: Real-time applications have rigorous limitations in terms of time and place. The routes are often altered due to the complex topology. Thus, delivering reliable links via the transport layer is effective in such a situation.
- Security threats: Because of the open environment of VANETs, vast amounts of attacks can be targeted. Therefore, it is a challenging problem to discover new incidents related to vehicular interaction and protect the clustering protocols compared to such attacks [21].
- High dynamic and disconnected topology: In order to deal with such conditions, a new research model is therefore implemented called Vehicular Delay Tolerant Networks [22].

5. Taxonomy of Soft Computing Techniques Aware Clustering-Based Routing Protocols in VANETs

Soft computing delivers an adaptive mechanism that generates intelligent behavior in a dynamic and complex environment such as VANETs. With the quick growth of soft computing techniques, cluster-based routing protocols based on PSO, neural networks, firefly algorithm, fuzzy logic, ABC, and GA have been widely accepted to ensure effective clustering and routing in VANETs. Such clustering protocols have been demonstrated to work well under VANET-specific requirements such as network failures, dynamic topology, and node mobility [23]. In this section, we will discuss soft computing-based clustering routing protocols in VANET. This is represented in Figure 4.

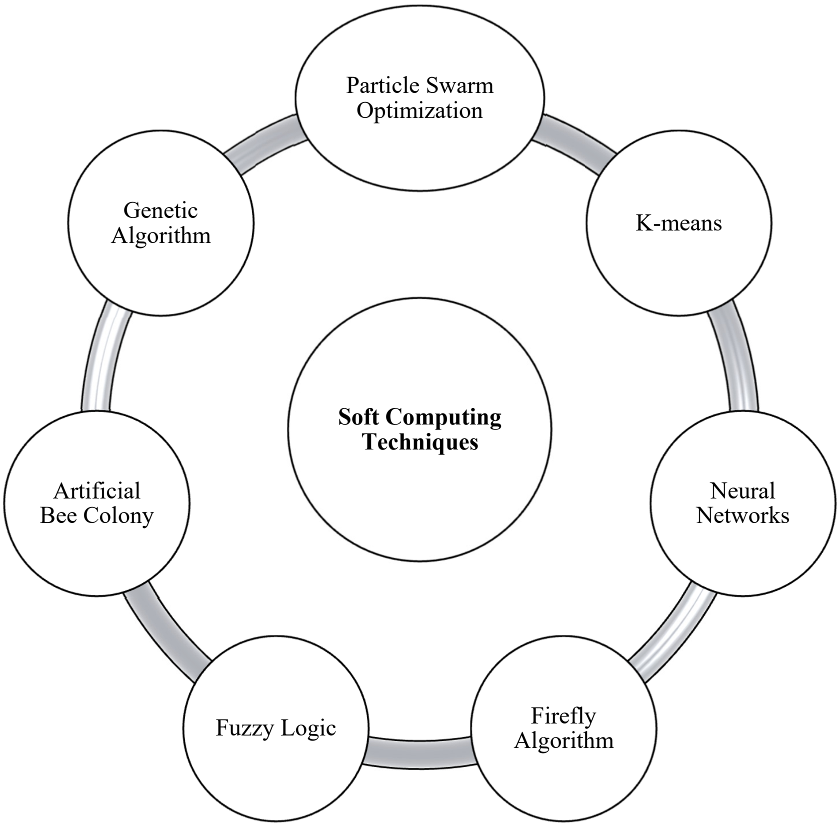

Figure 4. Soft Computing Techniques in VANETs.

5.1. Particle Swarm Optimization

PSO is replicated by the social behavior of bird flocking. It includes a swarm of particles in search space, in which a particle captures a position and a velocity in a global search area. Figure 5 shows how a particle achieves the best optimal solution. Throughout the search time, each particle displays its own individual best named as $pBest_i$ and a global best named as $gBest$. Later obtaining the $pBest_i$, $gBest$, and particle P_i revises its velocity and position in every iteration by utilizing the following equations:

$$V_{i,d}(t+1) = w \times V_{i,d}(t) + c_1 r_1 (pBest_{i,d} - X_{i,d}(t)) + c_2 r_2 (gBest - X_{i,d}(t)) \quad (1)$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \quad (2)$$

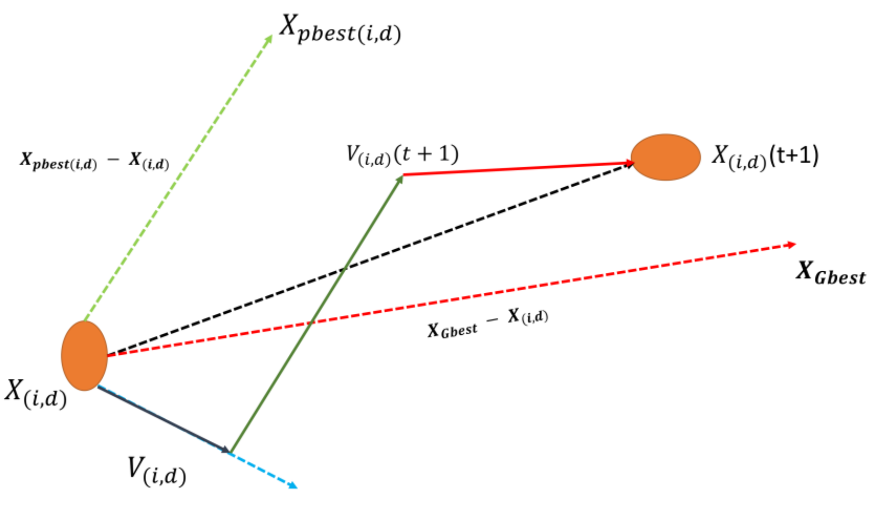

Figure 5. Particle representation in PSO.

Where w suggests the inertial weight, r_1, r_2 show two evenly dispersed random digits and c_1, c_2 suggest two non-negative factors called acceleration factor, generally set to 2.0. After finding a new location in every iteration, the $pBest_i$ and $gBest$ of particle P_i is updated by calculating the fitness function. This method is repeated until a static amount of iterations $I_{\max}$ is achieved.

Bao et al. [24] proposed a PSO-based efficient clustering V2V routing (CRBP) scheme in VANETs to increase the execution of V2V. The protocol consists of cluster formation, particle coding of the path, and cluster routing. Initially, vehicles are identified with identical changing routes, and the CHs are chosen. Second, the route particle and its velocity, iteration procedures, and fitness functions are intended for optimal routing. Thirdly, methods are suggested that can considerably enhance the effectiveness of routing. In order to create a stable cluster, the position, velocity, and neighbors of the nodes are gathered, and the link fitness is determined so that the optimal route can be found immediately. The results of the simulation signify that node density, node contact radius, and maximum hops among the CH and any member node have a significant impact on CRBP performance; CRBP has a 20% increase in PDR compared to CBVRP and QoS-OLSR and a 47% decline in delay.

In summary, the PSO-based clustering algorithm improves the stability of the clusters, reduces the delay, improves the efficiency of transmission, and finds the best optimal route from source to destination. However, the no infrastructure traffic environment is assumed with all vehicle nodes having GPS devices and an identical communication radius only.

5.2. K-Means Algorithm

It is a centroid-based algorithm, which means that each cluster has its centroid. The main goal of this algorithm is to reduce the number of distances between data points and the clusters to which they belong. The algorithm takes an unlabeled dataset as input, divides it into k-number of clusters, and repeats the procedure until no better clusters are found. In this algorithm, the value of k should be predetermined. The k-means clustering algorithm primarily accomplishes two goals:

- Uses an iterative approach to find the best value for K center points or centroids.
- Assigns each data point to the K center that is nearest to it. A cluster is formed to data points that are closed to a specific K center.

Hence, each cluster has data points with some commonalities, and is away from other clusters. However, the K-means clustering [25] approach has been used significantly to solve a variety of VANET problems.

In summary, the PDR and throughput are improved with reduced delay, which is a major finding in the research [25]; however, the nodes are limited from 50–100, with a fixed communication range and less vehicle speed.

Elhoseny et al. [26] proposed a clustering-based optimization approach to extend the energy efficiency of V2V communication. This paper introduced the model of the k-medoid to cluster the vehicles, and the energy-efficient nodes are accepted for convincing transmission. The successful node identification of VANETs was introduced in this paper, considering at least the energy utilization factor. A k-means algorithm recognizes effective nodes from each cluster with the probability of achieving energy-efficient transmission. The k-medoid process groups the vehicles in various modifications and selects any nodes in some rounds as CHs. It has the potential to decrease the amount of communicated messages from each node to other, saving the network more resources. At that point, through the evolution of the network factor (EC) using the EDA algorithm, the optimal path for V2V transmission was acquired between the vehicles in VANETs.

The proposed clustering-based optimization technique improves the energy efficiency in the networking nodes with less execution time. However, the work can be taken forward to maximize QoS by proposing efficient clustering and optimization techniques.

Ramalingam et al. [27] suggested a dynamic grouping that fits well with VANET's dynamic topology characteristics by K-implies. The suggested strategy fits admirably with the number of bunches referred to in advance and even the mysterious number of categories. The user has the opportunity to resolve the number of bunches needed in this method. This measure demonstrates the new focus of the bunch by increasing the unit counter by one in each concentration until the goal work is accomplished. The same can be established and it is possible to overcome the ideal CHs and the connection between CMs and CHs. There is a dynamic weighting potential for dynamic k-means. The detailed analysis shows that the proposed computation produces fine improvements in the main VANET factors. This calculation decreases the number of messages and further increases the proportion of package transport.

K-implies allow dynamic grouping of cluster members which improves its connectivity with the cluster head for the dynamic topology of VANET, but choosing the best cluster head in the different scenarios is still a challenging task.

Khan et al. [28] proposed a new Triple Cluster Based Routing Protocol (TCRP) for CH selection utilizing the revised K-Means & Floyd–Warshall algorithm. The updated k-means divide the vehicle nodes inside their velocity confidence variety into three clusters. For all VANET pairs of vehicles, the Floyd–Warshall algorithm determines the smallest path. A vehicle with the lowest average distance to the other and the smallest velocity variation will be chosen. The modified k-means algorithm for cluster formation is also proposed, considering the distance and cluster size. The results of the simulation demonstrate that the TCRP keeps the cluster structure constant and prevents CH reselection in-coming rounds, thus creating reasonably stable vehicle clusters. By eliminating message flooding, TCRP gains control over the network's excessive overhead.

The major focus is on maintaining the stability of the cluster which also decreases the message overhead and is more suitable for limited-speed vehicles. High-speed vehicles may affect cluster stability, which is a major area of research.

5.3. Neural Network

A NN is a vast network of interconnected elements formed by human neurons. A neuron performs a small number of processes, and the weighted amount of these is the total process. A known set of inputs must condition a neural network to produce the required outputs. Training is usually conducted by feeding teaching patterns into the system and allowing the network to alter its weighting function according to certain learning rules previously developed. There may be supervision or unmonitored learning. An ANN comprises three layers: input, secret layer, and output, where nodes may have numbers in each layer. This measures the neural network's performance against the target output, and the weights among layers are changed and the procedure is repeated until a minor fault remains if the results are not as expected [29].

The focused review leads to several important issues related to the neural network. However, further research can be performed to develop more efficient and effective methods in neural model and feature variable combination.

Bagherlou et al. [30] proposed a clustering-based reliable routing algorithm with stable implementations. In this way, simulated annealing was used for suitable clustering of nodes, and the parameters such as node degree, network coverage, and capacity were taken into account. The radial base function (RBF) neural network is utilized to choose the best cluster head (CH), and an effective fitness value based on velocity and free buffer size is employed. The pseudo-code algorithm is also proposed, which includes cost function, and implements RBF to select the best CH. Every cluster has two gateways that are utilized for the transmission of a packet as the communication interface. The simulation results showed the effectiveness in terms of route detection rate and transmission rate of packets.

The authors proposed simulated annealing for clustering of vehicular nodes with the parameters of the velocity of nodes, buffer size, and coverage. However, the scope of hybrid networks for controlling congestion and data aggregation still needs to be addressed.

Mohammadnezhad et al. [31] proposed a clustering-based routing protocol in which nodes are grouped by using an imperialistic algorithm based on motion parameters such as node degree and vehicle speed. The CH is then selected according to the sum of available buffer space and predicted communication count based on the radial base function neural network algorithm. A node will be selected as CH in a given cluster if it has the highest free space and the least estimated communication count. They proposed an algorithm including an objective function that selects the node based on vehicle position, speed, and direction. Simulation results suggested that the proposed protocol enhances PDR, throughput, and end-to-end (E2E) delay.

The proposed scheme improves the PDR, throughput, and delay since the algorithm still depends on predefined conditions in the network, so this area still has scope to work for the researchers under the dynamic conditions of VANET.

5.4. Firefly Algorithm

Firefly Algorithm (FA) imitates the characteristics and twinkling behavior of tropic firefly swarms. FA has two essential resources, which makes it better than other computational algorithms. The exceptional characteristics of the FA are local attractions and automatic regrouping. Since light strength and distance are proportionate, the attraction among the fireflies tends to be global or regional based on the absorption coefficient. This allows both global and regional modes to be visited. FA can sub-split and regroups based on the neighboring attractiveness, this merit of FA becomes more acceptable for clustering issues [32].

Joshua et al. [33] proposed a Reputation-based Weighted Clustering Protocol (RWCP). To stabilize the VANET topology, the RWCP is enclosed by considering the path of vehicles, location, speed, neighboring vehicles, and the status of each node. The work uses a multi-objective issue that takes the considerations of the RWCP as the feedback and intends to provide an improved cluster lifespan, enhanced packet distribution ratio, and decreased overhead of the cluster. An evolutionary approach, the multi-objective firefly algorithm (MOFA), is used to optimize the factors of the RWCP. The suggested objective function uses an algorithm to initialize the fireflies, and random walk to find the best solution and sort for best estimation techniques. The TETCOS NetSim simulator and MOFA structure have been used to refine simulations. With similar evolutionary optimization methods, the results are tested. The simulation results indicate that the suggested Mean Cluster Lifespan, PDR, and Control Packer Overhead technique performs well.

The proposed algorithm enhances the lifetime of the cluster, PDR, and reduces the overhead. Still, improvements can be carried out by reducing computational time and to cater for areas with more vehicular density.

5.5. Fuzzy Logic

Fuzzy Logic (FL) is a numerical tool developed to convey approximate human thought. FL produces intermediary standards centered on inference rules and linguistic variables, instead of a conventional set theory in which the outputs are either real or untrue. There are four fundamental components of a fuzzy logic scheme: fuzzification, defuzzification, a fuzzy rule base, and a fuzzy inference engine, as shown in Figure 6. The fuzzification component plans the device responses to the appropriate fuzzy sets. It designates every fuzzy set, which is defined by a language word, such as “high”, “low”, “moderate”, “small”, and “large” membership degree.

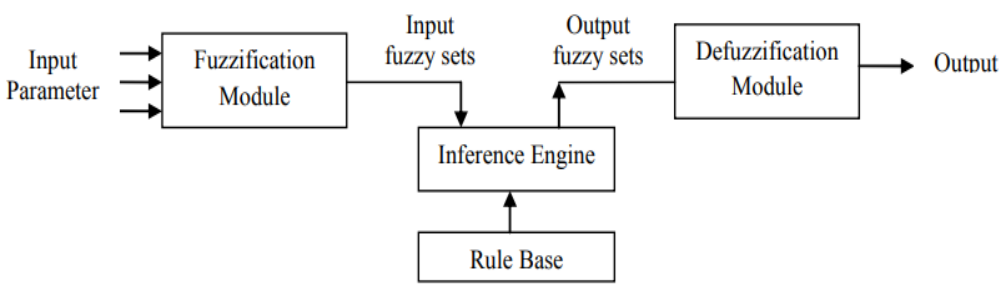

Figure 6. Fuzzy Logic System.

If-then rules are stored by the fuzzy inference engine, from which the fuzzified values with the aid of the fuzzy rule are mapped to linguistic output variables. The results obtained from the inference scheme are translated using defuzzification, such as the averaging technique and centroid technique, into crisp values [34].

Moridi et al. [35] suggested a stable multilevel clustering routing protocol in VANETs. It is an expansion of the AODV protocol at the first level, which has been strengthened by using fuzzy logic to establish efficient routing between members of the cluster. For routing among CHs and destinations, Tabu search was used at a higher level. This approach is used to solve problems with hybrid optimization and utilizes a cost function to choose a resolution from a range of potential solutions. Node size, node velocity, node angle, and reliability are the efficient metrics utilized for selecting the optimum path. The simulation result showed an improved transmission rate of packets and reduced average E2E delays. The number of packet failures contrasted with previous protocols.

The proposed protocol uses fuzzy logic to improve the routing between the cluster members. The parameters taken for the research work are distance, direction, and velocity. However, more parameters may be considered for future work, looking toward the dynamic scenario in VANET.

5.6. Artificial Bee Colony

The ABC algorithm uses the foraging performance of honey bees to optimize the multi-variable function problem. Honey bees' forage can be organized into three assemblies in the ABC for food sources: working, onlookers, and scout bees. Based on local data, the forager bees take advantage of a food source within their surroundings. Though, suppose the fitness value related to the new food source is improved compared to the previous one. In that case, the bees consider the new position and ignore the previous one. Afterward, the entire quest is completed by every employed forager bee. Through a waggle dance, they share the food source's fitness details such as path, distance, and productivity with the onlooker bees. An onlooker bee analyzes the fitness value given by each bee and selects a source of nutrition with a greater probability of finding nectar. When any of the current food sources desert the bees after several forages, scout bees start looking randomly around the hive for new food sources [36].

Fekair et al. [37] suggested a QoS-based unicast clustering algorithm for VANETs. This protocol considers two methods: a clustering algorithm that arranges and optimizes data transmission according to QoS constraints, and an ABC that discovers the best routes based on QoS criteria from a source to a destination. Clusters are built in our approach around cluster-heads chosen based on QoS consideration: usable bandwidth, E2E delay, jitter, and expiration time of the connection. Via simulation shows that, by selecting routes based on the QoS parameters, the method can greatly improve routing efficiency in VANET. The findings show that optimal route selection enhances PDR, E2E delay, and network overhead.

The proposed algorithm finds the best optimal route between the source and destination based on QoS criteria. The results show route selection improves the PDR; the end-to-end delays leave scope to add more network performance metrics for the researchers to work upon.

5.7. Genetic Algorithm

GA is an evolutionary process that replicates the mechanism of evolution in order to produce optimized solutions. Figure 7 displays the GA flowchart. According to the problem, it begins with the randomly produced population of people, called chromosomes. An individual chromosome is a set of genes containing a portion of the solution. Based on a specific issue, the fitness value is estimated. The chromosomes related to large fitness costs are chosen in the next generation for the reproduction process. In the next phase, chromosome recombination is carried out through the use of a crossover process to replicate original children. In order to produce new offspring, the crossover process combines the genetic features of two parents. A mutation procedure is executed on the chosen chromosomes to produce new children by arbitrarily altering the genes of the specific chromosomes. This process is repeated until an optimal solution is attained [38].

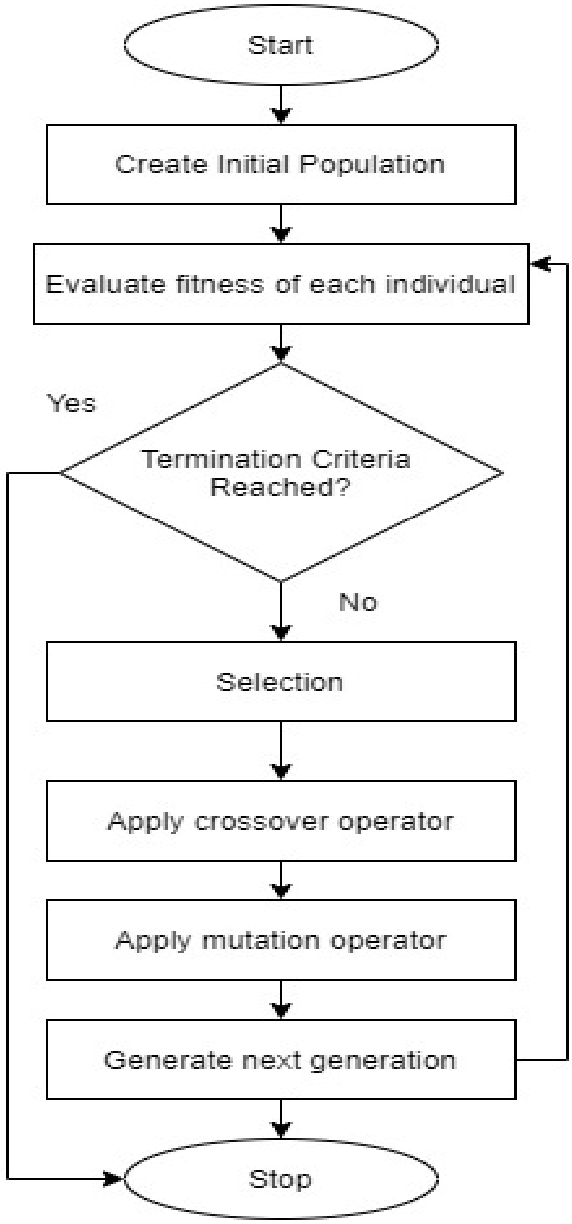

Figure 7. Flowchart of Genetic Algorithm.

Hadded et al. [39] proposed an Adaptive Weighted Clustering Protocol (AWCP) to enhance the stability of the network topology, which considers vehicle direction, location, speed, and the number of neighboring vehicles. The numerous parameters of AWCP consider this problem as non-trivial. The authors describe a multi-objective problem to optimize the protocol whose goals are: delivering stable cluster architectures, optimizing the rate of data transmission, and minimizing overhead clustering. The authors fix this multi-objective issue with version 2 of the Non-dominated Sorted Genetic Algorithm (NSGA-II). The simulation results show that AWCP achieves considerable improvement in terms of the arrangement, distribution, and inverse generational distance.

Efficiency is improved by assigning the responsibility to the cluster head to improve the network performance metrics; however, the channel efficiency can further be improved by the development of a cross-layer model where bandwidth assignment responsibility can be given to the cluster head.

6. Comparative Analysis

This section offers a comparative analysis of clustering protocols based on various soft computing techniques in VANETs. The soft computing systems, and clustering parameters of the checked clustering protocols, are highlighted in Table 1. This section will also allow researchers to quickly evaluate the different soft computing techniques examined in this paper and choose the appropriate technique depending on their benefits and drawbacks, as presented in Table 2. Figure 8 depicts the graphical representation of various performance metrics addressed by surveyed clustering protocols. It is noted that PDR, E2E delay, and clustering overheads are the most addressed performance metrics over the recent years as per the clustering protocols included in this survey.

Table 1. Comparative Analysis of Bio-inspired Techniques Based Routing Protocols.

Protocols	Soft Computing Technique	Issue Addressed	Parameters	Metrics
Bao et al. [24]	PSO	Provide efficient and reliable information exchange	Node's position Node's velocity Node's neighbors	PDR E2E delay
Elhoseny et al. [26]	K-means	Improve node lifetime and link lifetime	Distance	Energy consumption
Ramalingam et al. [27]	K-means	Provide effective information transmission between vehicles	Distance	PDR
Khan et al. [28]	K-means	Minimize the traffic overhead	Average distance	Energy consumption Delay
Bagherlou et al. [30]	NN	Provide a stable and reliable communication	Node degree Coverage ability	Route discovery rate PDR
Mohammadnezhad et al. [31]	NN	Manage the dynamic nature of vehicle nodes and unstable wireless links	Node degree Speed of vehicles	PDR Throughput E2E delay
Joshua et al. [33]	FA	Efficiently handle the changing topology of VANETs	Vehicle direction Location Speed Nearby vehicles Status of each node	Mean cluster lifetime PDR Control packet overhead
Moridi et al. [35]	FL	Enhance the stability of the network topology	Node's distance Velocity Angle Reliability	PDR E2E delay Packet loss rate
Fekair et al. [37]	ABC	Provide a higher level of quality of services (QoS) for real-time applications	Existing bandwidth E2E delay Jitter Connection expiration period	PDR E2E delay Network overhead
Hadded et al. [39]	GA	Improve AODV routing between cluster members.	Highway ID Vehicle direction Location Speed Neighboring vehicles	Data delivery rate Clustering overheads

Table 2. Summary of bio-inspired techniques.

CI Techniques	Advantages	Disadvantages
PSO	Because of its simplicity in executing on hardware or software, and highly optimum result, PSO is the most prevalent soft computing technique used in VANETs.	The PSO's iterative design does not make it ideal for real-time services.
K-means	Comparatively easy to implement. Guarantees convergence.	Difficult to approximate K-value. It did not fit properly with a global cluster.
NN	NNs will deal with incomplete sets of data. NNs are useful for prediction.	In complex ANN systems, excessive training can be needed.
FA	For determining the fitness function, the FA has relatively fewer parameters.	It is not successful in defining the high-performing regions in the search space for complicated issues.
FL	The least system improvement cost, design time, and computing memory are needed to execute FL.	Fuzzy laws do not conform to the complexities of the network and need to be re-learned under difficult network circumstances.
ABC	The ABC algorithm attains global optimization through discovery by artificial scouts, while local optimization is achieved by exploitation of onlookers and employed bees.	Because of the random solution, ABC has a sluggish convergence issue.
GA	The inherent parallel environment makes GAs appropriate for the process of data collection.	GA has a slow speed of convergence that limits its execution in real-time applications.

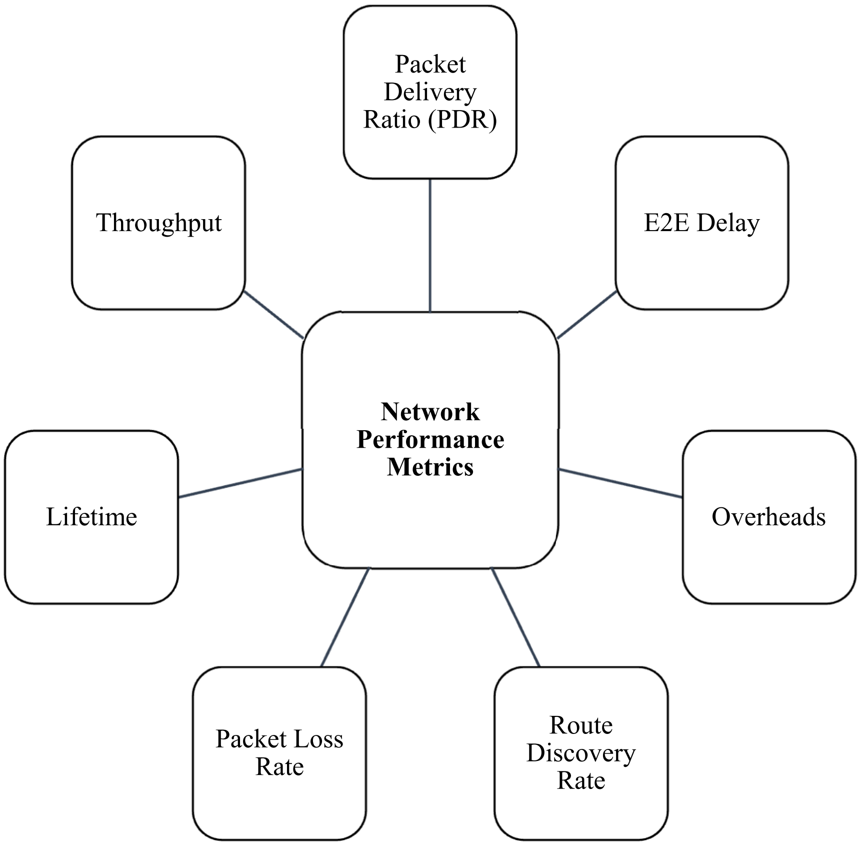

Figure 8. Network performance metrics.

7. Future Scope

This paper discusses most of the current clustering algorithms based on soft computing techniques, with their merits and limitations, to meet the need for applications. Nevertheless, we find several study gaps where the science is either not studied or not completely utilized to its maximum potential:

- In VANET, due to high-speed network situations, the location of vehicles often changes. In an uneven VANET vehicle density structure, clustering protocols should have a greater ability to predict the exact vehicle location. Clustering techniques based on traffic density may be implemented. The role of the cluster protocol in an uneven vehicle density scenario for precise location prediction may be comprehensively analyzed and can be worked upon.
- In the trustworthiness verification process, vehicles require to discover the requested data. It is hard to handle both trust and user privacy for such procedures. Therefore, to guarantee the trade-off between privacy and trust, a need for a robust cluster-based architecture motivates the researchers to work in this emerging area.
- The proposal on clustering protocols has taken into account urban or highway situations in the literature work. Although, for a hybrid road scenario, a special investigation is needed to improve various network performance parameters. Further, a hybrid approach can also include the real highway speed vehicles in a bidirectional road scenario.

8. Conclusions

This paper addressed various soft computing technique-based clustering routing protocols in VANETs and summarized some explicit suggestions based on existing research work. A thorough review of various algorithms was carried out for the clustering techniques in VANET. The significance of soft computing techniques was represented using a detailed analysis of different clustering schemes, emphasizing their objectives to improve network metrics. This survey allows researchers to quickly evaluate the different soft computing techniques, depending on their benefits and drawbacks, and choose the appropriate technique to extend their research as suggested in future work.

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