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Review Article

A Study to Enhance the Route Optimization Algorithm for the Internet of Vehicle

Ritesh Dhanare,[1] **Kapil Kumar Nagwanshi**,[1] **and Sunita Varma**[2]

[1]*Department of CSE, Amity School of Engineering and Technology, Amity University Rajasthan, Jaipur, India*
[2]*Department of Computer Engineering, Shri G. S. Institute of Technology and Science, Indore, India*

Correspondence should be addressed to Kapil Kumar Nagwanshi; dr.kapil@ieee.org

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In the Internet of Things (IoT), the advancement of the new modern era of Internet-off driving, known as the Internet of Vehicles (IoV), is aimed at the Intelligent Transportation System (ITS) to improve road safety and traffic. Therefore, IoV is better for traffic management. But perhaps, the main challenges in this type of network are that timely decision to make adequate decisions by a driver under certain conditions of rapid change in topology, high vehicular mobility, and frequent link failures is hard to improve road safety. Therefore, an optimized and congestion-free route is required to collect real-time data from vehicles. Thus, some of the latest bioinspired optimization routing algorithms in the IoV environment are presented in this study. Hence, monitoring speed limits, pollution checks, and emergency responses to traffic accidents should also be considered while performing vehicle routing to avoid traffic problems. In the previous decades, many route-directing protocols for the IoV environment have been proposed that can handle the requirements of reliability and security. But such routing of protocols suffers from high complexity and scalability limitations in big-scale networks, routing overlays, etc. Therefore, their strengths, weaknesses, and critical characteristics are compared using various criteria for such algorithms. Then, a suggestion is made to propose a prescribed combined model of a multimodular bioinspired approach to IoV routing. Finally, the main future directions of research in this sector are highlighted.

1. Introduction

In recent years, there has been a growing interest in the transport industry and academic researchers in improving road safety by delivering fast and reliable information to vehicle drivers and navigation entities [1, 2]. Integrating road traffic data over mobile or wireless networks with the minimum infrastructure offered by the Intelligent Transportation System (ITS) is one approach to enhancing road safety. ITS provides a wide range of real-time applications like real-time diversion route calculation; blind crossing; traffic flow control; monitoring traffic; collision avoidance; vehicle safety; finding the nearby restaurant, gas station, or hotel; and automatic toll payment [3, 4].

Despite much progress in sustainable development traffic, transmitting data to a broadcast medium like mobile gateways has limitations like high asset prices and geographic confines, particularly in rural areas such as deserts, mountains, and islands. As a result, many telecommunication services are severely limited in their ability to cover a wide range of networks. Moreover, due to the speed of the traffic, the connections offered by these basic network connections are affected by the unreliable connectivity of the network and are more prone to interruptions [5]. Furthermore, infrastructure-based vehicle networks have a significant disadvantage in terms of the expense of deploying several fixed devices and units on the street.

Because of these vehicular network restrictions, all cars must participate in a multihop or unicast routing procedure with each other as well as with fixed and stationary gateways. Therefore, vehicular ad hoc networks (VANETs) have been developed to provide traffic users with reliable network coverage, extensive connectivity, and minimum communication costs [6].

Several surveys addressing various elements of routing in vehicular networks have been suggested in previous research. The majority of them are concentrated based on the density, velocity, direction of motion, and so on, whereas other categorizations of VANET routing protocols are based on information dissemination mode [7]. In particular, in [8], the authors categorized the protocols devoted to VANETs based on V2I and V2V structures, and they also discussed the future potential of considering vehicle density in the routing algorithm. But, they ignore the hybrid construction that employs both V2I, V2V, and V2O, whereas in [9], the authors proposed a conceptual taxonomy based on various factors of the unicast protocol. They first divide them into two major categories. The route-dependent and route-routing systems vary in data forwarding and path selection. In addition, to highlight the advantages and shortcomings of protocols, the authors proposed a conceptual taxonomy based on fundamental functions such as relay selection, recovery strategy, inference logic, probing objective, probing scope, and routing techniques. In [10], a taxonomy of VANET routing protocols is presented, with categorization based on data fusion, opportunism, clustering, hybridity, and geography.

The VANET routing protocols described in [11] are divided into two primary categories: geographic-based routing and topology-based routing. In the paper presented here [12], the authors are interested in position-based routing methods for VANETs and examine position determination issues. They present some relevant work on the advancement of position assessment system solutions and list the position-based protocols, along with their benefits and a worldwide qualitative comparison of the protocols. From this study, the authors classify routing protocols that employ decision metrics. Furthermore, they provided privacy, security, and delay in view.

The network topology of VANETs is continually and rapidly changing, which creates several challenges and unclear instructions like bandwidth scarcity, channel instability, and communication delays when the network is implemented on a broad scale. While a greater number of nodes create a more stable route, a too dense population might induce network congestion and packet collisions. To reduce delays and enhance the efficiency and dissemination distance, several techniques such as cluster-based routing, geographic position, reactive, proactive, machine learning, bioinspired, probabilistic, broadcast, and unicast are utilized [13, 14].

However, due to a lack of processing capacity for global information by VANET and vehicle telematics, there is a need for an open-integrated network framework system. So, nowadays, VANET, vehicle telematics, and other vehicle networks are associated with IoV [15]. IoV is considered to be a large network capable of providing services for large cities and countries [16]. IoV is particularly an open and incorporated network framework system that consists of many more users, vehicles, network organizations, and things in accommodation with controllability and high management. The key goal of IoV is to interact with the human-vehicle environments and things to limit social cost, ensure human satisfaction, promote efficient transportation, and improve the service levels in cities [17]. The basic model of IoV is shown in Figure 1.

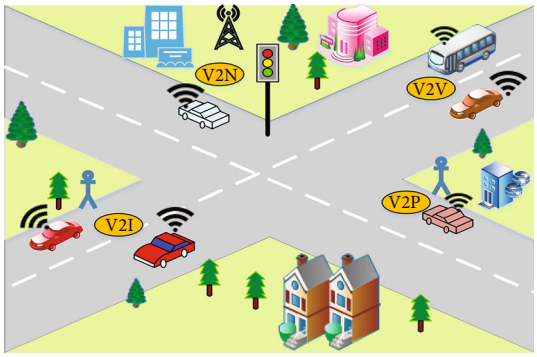

Figure 1: Architecture of IoV.

Advances in IoV technology can reduce the travel time of passengers or drivers by finding a shorter route. There are numerous routing protocols for a vehicle to find a better route path. But some of the paths become invalid as slight changes occur in their topology. To mention the prediction of a path failure, before finding a new path, a novel estimation of the path duration routing protocol is necessary to enhance the performance of the network [18]. Several classic-type routing protocols and the vehicle's properties by some geographic-type protocols that come from MANET studies are used, such as Destination Sequenced Distance Vector (DSDV), Dynamic Source Routing (DSR), Ad hoc On-Demand Distance Vector (AODV), Greedy Perimeter Stateless Routing (GPSR), and Greedy Perimeter Coordinator Routing (GPCR). However, it should be noted that the majority of routing algorithms are only suitable for a limited scale [19]. For such issues, an optimization algorithm is the best way to find the shortest path and the fastest convergence speed. Many models inspired by nature have been developed to solve optimization problems that arise in different areas of life. Bioinspired approaches such as swarm intelligence (SI), genetic algorithms (GA), and neural networks like artificial neural network (ANN) are used to solve complex optimization problems [20, 21]. An evolutionary system deals with the collective behavior of groups of worms, birds, ants, and bees. Individuals in the group develop traits based on their specific characteristics, i.e., where to feed and where to breed. Bees and ants use this information to find new food sources. Cuckoo Search, Bat Algorithm, firefly algorithm (FA), etc. are swarm intelligence established methods utilized to solve complex real-life issues [22–24]. Ant Colony Optimization (ACO) makes extensive use of routing paths. The Quality of Service (QoS) multicast problem is solved by the bee colony routing optimization algorithm. All of evolutionary computing has found a wide range of solutions to many real-world problems that include graph colorization problems, vehicle routing problems (VRP), back-packing problems, and work-planning problems [25].

With the popularisation of nature-inspired optimization algorithms over the last decade, our survey offers a solution

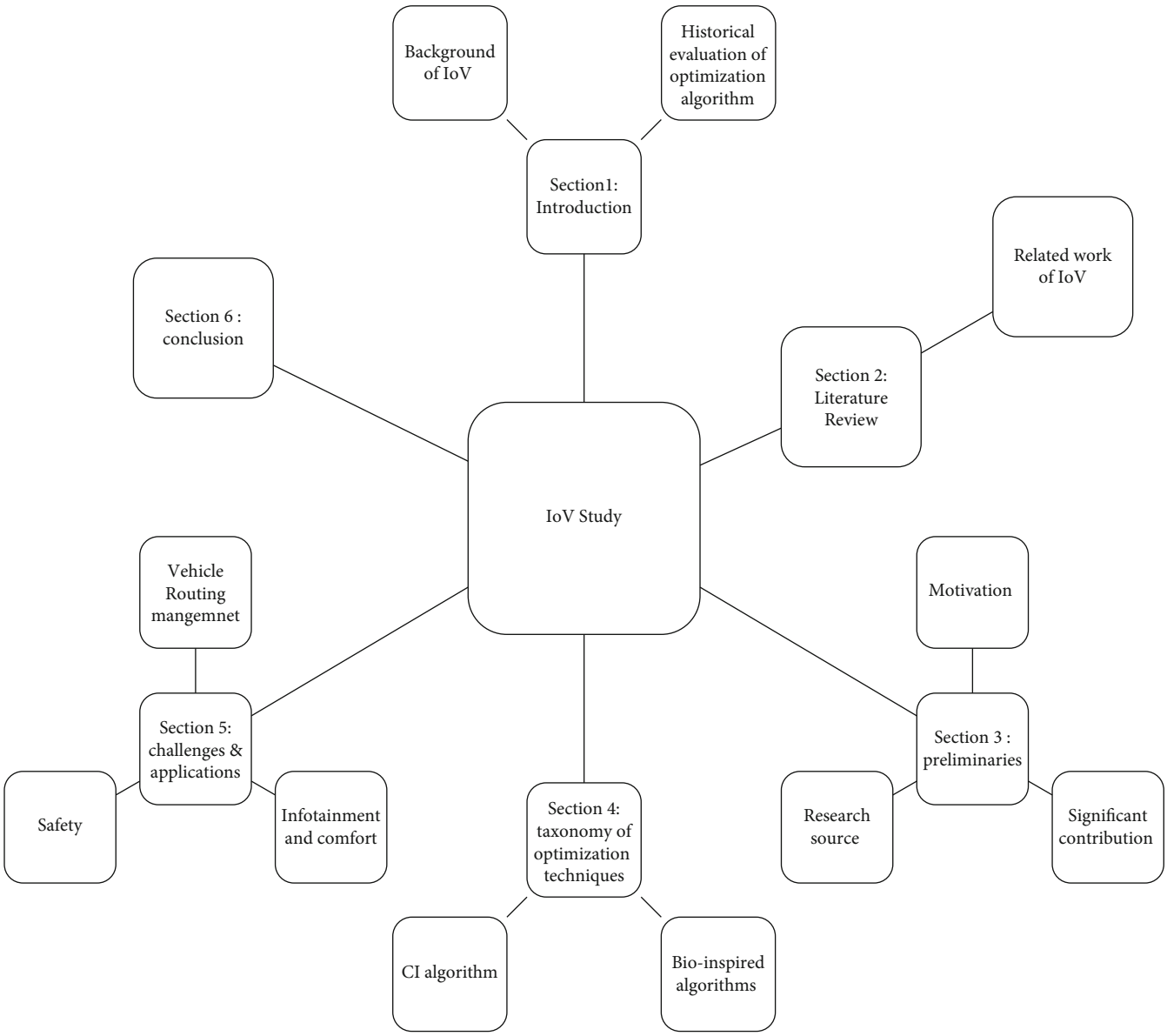

Figure 2: Organization of survey.

to validate recent progress in the bioinspired VANET based on emerging research issues that can be further expanded to contribute to optimal routing in VANET.

The organization of this survey is structured in Figure 2. In Section 2, we provide the existing review of IoV. The preliminaries of review are explained in Section 3. The taxonomy of optimization algorithms in IoV is discussed in Section 4. We also discussed the challenges and applications of this survey there. Finally, at the end of the paper, the conclusion to this review is provided in Section 6.

2. Literature Review

Numerous sorts of examinations have been conducted in the field of IoV in ITS. From that, a small portion of the overall challenges of finding the shortest route path to reach the endpoint by the existing routing algorithms is clarified underneath.

Hussain et al. [26] have reviewed the end-to-end service in the IoV scenario and the quality service of IoV. The agglomeration is critical in IoV for vehicle communication, processing, integrating, and sensing. Due to the additional devices connected and communicating, there will be a huge vehicle load on the network. Hence, IoV needs accurate end-to-end delivery without any compromise and with QoS parameters such as latency, jitter, delay, and bandwidth. In IoV, QoS is utilized to enhance the network service and satisfy customer needs. The parameters of QoS provide dedicated bandwidth and reduce the characteristics of packet loss, which are some of the main goals of IoV. In IoV, since the vehicles are dynamic and move from one place to another at a very high speed, the network requirements are unpredictable. Yet, it is very difficult to manage and

integrate all these features into the network while providing the IoV service, which is dynamic in nature. The main challenge in IoV is that when the vehicles move from one place to another network, there could be packet loss when the vehicle network is autonomous. The end-to-end services are in collaboration with the IoV network. The vehicles are treated as nodes and change dynamically with varying conditions. From this review, they conclude that they can develop the optimal solution using QoS parameters and their measurements.

Cheng et al. [27] have surveyed the details of IoV-based routing algorithms. For this purpose, the IoV uses a general protocol for the horizontal networking process in order to realise IoV. Initially, they categorize the transmission scheme into three types, such as broadcast ones, unicast ones, and geocast ones. In much of the work, they discussed the routing protocols referring to the unicast category. The application of this category is emergency vehicle preemption and information about the road conditions. The balance type of routing algorithms is used in the last category. Based on these details, they classify the information into four categories: map, position, path-based one, and topology for the communication process in vehicular networks. Yet, the nature of the geographic nature of these protocols prevents them from forecasting the topology holes in the distributing nodes. Moreover, many routing protocols only work in one- or two-dimensional scenarios and have the worst performance in the real-time third-dimensional scenario. They also discussed the reliability of the communication between the vehicles. For this communication, a heterogeneous vehicular network process is needed. Therefore, the researcher needs a set of well-defined routing protocols, which are used to address the issues caused by the heterogeneous nature of IoV and large scale. Finally, they suggest the researchers certify the studies in small-scale homogeneous networks. Furthermore, the large-scale heterogeneous networks make the vehicles dependent on road information after the social environment.

Kayarga and Kumar [28] presented the details of the IoV network model, and they reviewed IoV technologies in different applications. Mostly, they concentrate on the bioinspired algorithms, which are used between vehicles, things, and humans. For these different applications, the IoV contains various steps to take the vehicles into the IoV integrated network by using wireless access technology. To maintain this technology, the IoV has aspects such as encoding, virtual network, and data awareness that play the main role in switching the control message to the IoV. With this type of maintenance, each topology is also maintained in intervehicle networks. The main routing topology is an ad hoc network-based topology. This technology is more effective for wireless vehicle communication. It is also essential for a credible and manageable IoV. The solution of IoV considers vehicle communication in the complex city. Sophisticated technology is utilized to develop the ability of IoV communication by using a variety of technologies for IoV. Hence, vehicular communication over big data can enhance the network burden. Effective optimization techniques are also needed to develop the service to enhance the suitability of mobile nodes in the global network. Furthermore, many challenges are focused on the VANET of IoV from multiple vehicles, things, and users, because IoV goes beyond telematics, intelligent transportation, and ad hoc networks by integrating sensors, vehicles, and mobile devices to enable different services.

Tuyisenge et al. [29] have surveyed the IoV on the market opportunities in the field of city transport communication systems. It faces huge challenges and problems such as traffic congestion, safety problems, pollution, and commercialization. This is all forecasted, and it is evident that the IoV component will create a huge amount of data and huge real-time IoV applications and requires fast routing. They also reviewed the existing protocols, namely, IEE, 3GPP, and VANET, which are used for IoV vehicle communication, and further, they used protocol stack analysis. From this survey, they finally provide some information about the future work related to the mechanism of IoV between various networks.

Ksouri et al. [30] conducted a review of suitable VANET routing techniques and multioptimization algorithms. They suggest new criteria for the routing process in the dynamic environment. The survey shows that new innovations in IoV applications and the presentation of autonomous vehicles in networking provide new security and QoS challenges in the VANET network. They classify the routing algorithms based on the forward criteria to maintain the macro classification. In the routing protocol, the macro classification is a third family. It is named "hybrid routing," which is a combination of both geographically based routing and topology-based modeling. The function of this process represents the merging of both the routing processes. Secondly, they discussed the geographical routing techniques. This VANET routing model is capable of taking specific route materials based on the vehicle's environment. This model is more suitable for large-scale vehicular communication network processes and the performance of improving the node's security and safety. Then, they survey the forward process. It allows the packets to move from one node to another. This stage is an important core part of the IoV routing process. It has two substages, such as the forward selection stage and the packet relaying stage. Then, they review the optimization techniques used for routing to enhance the overall routing process, such as relay, path discovery, cluster head selection, and routing FR. The routing optimization algorithm is more effective than the IoV routing algorithm. Finally, they discussed the large-scale IoV routing techniques, including the marine domains, terrestrial and aerial, for future study.

Many traditional optimization algorithms for traffic management in IoV to optimize deterministic problems have been proposed. But those algorithms have not shown their ability to tackle the inherent randomness in traffic systems. Therefore, to handle such efficient and random situations efficiently, a better bioinspired optimization algorithm is needed, because bioinspired optimization algorithm has an ability to combine biological and natural characteristics that can be easily adapted to frequently changing environments. Table 1 provides the comparative analysis with an existing survey on vehicular routing techniques.

Table 1: Comparative analysis with existing survey.

Author	Year	Taxonomy	Application	Findings
Hussain et al. [26]	2019	QoS-based routing	Multimedia application	It is critical to provide best end-to-end services with networks because the cars treated as nodes change constantly in response to changing network circumstances. As a result, there is a need to design efficient methods for dealing with mobile nodes, such as automobiles.
Cheng et al. [27]	2015	Topology-based, position-based, map-based, and, path-based routing	Road condition, accident warnings, and infotainment applications	To make IoV function in the real world, the authors recommend that researchers test their findings not just in small-scale omogeneous systems but also in large-scale heterogeneous networks.
Kayarga and Kumar [28]	2021	Genetic algorithm	Traffic message management, routing decision	The hybridization of machine learning and swarm intelligence gives better routing efficiency.
Tuyisenge *et al.* [29]	2018	Architecture-based routing	—	It is projected and obvious that IoV components would generate large amounts of data at high rates, extremely sensitive to delay, and demand rapid big data processing and dependable fast response. As a result, efficient and dependable network designs that support efficient IoV installation in real-time are required.
Ksouri *et al.* [30]	2020	Geographical routing, optimization-based routing	Prediction-based applications	Information interchange across the various IoV domains like marine, aerial, and terrestrial should be facilitated to allow for greater collaboration and the adoption of innovative solutions.

3. Preliminary of the Survey

This section discusses the motivation for conducting this review, as well as the contribution of the primary survey. The main motivation of the review is to show the following issues and challenges present in performing a vehicle routing algorithm in the IoV: to achieve that, some sources of papers are selected by using some string words to select papers based on our work.

3.1. Motivation of the Study. The main motivation for this study is as follows:

(i) To find an optimal path between the network nodes to find the shortest routes, thus reducing the travel time

(ii) To gain real-time road traffic information for providing optimal routing to improve travel comfort for drivers

(iii) Hence, the use of bioinspired optimization routing algorithms for the IoV environment boosts the robustness of the IoV network while performing optimal path routing at the time of network disruptions. The chosen path should satisfy the routing constraints such as packet delivery ratio, distance, congestion, connection probability, cost, transmission delay, and variance introduced by the algorithm

3.2. Contribution. The main contribution of this review is to recognize the sorts of issues that occur when trying to find an optimized path to travel from a source to a destination, and that chosen path should satisfy the following needs to mitigate them: packet delivery ratio, distance, congestion, connection probability, cost, transmission delay, and variance. The main purpose of IoV routing is to afford a correct path of routing direction by a network in avoidance of traffic to their final destination. So the contribution of the review falls within a study of the IoV routing protocol in an extreme or complex urban environment. This review paper addresses the need for bioinspired optimization routing algorithms in IoV, which can be able to tolerate low-/high-density traffic networks with little throughput and delay variation.

3.3. Search Criteria. The papers collected are manually searched, particularly journal papers and conference proceedings since 2001.

3.3.1. Selection of Sources. For the systematic review of existing issues, we searched the Springer, IEEE, Elsevier, and Wiley Online Library databases using the following search string words: IoV, route optimization, challenges and issues, VANET, and machine learning. The search engine selection for this survey is listed in Table 2, and the search strategy is illustrated in Figure 3.

3.3.2. Exclusion Criteria. The articles are excluded on the following basis:

(i) Publication not related to IoV routing

(ii) If the entire content of the paper is not available

Table 2: Selection of search engines for this study.

Search engine	Source address
IEEE Xplore	http://ieeexplore.ieee.org/
Springer	http://link.springer.com/
Elsevier	http://www.elsevier.com/
Wiley Online Library	http://www.WileyOnlineLibrary.com/
Hindawi	https://www.hindawi.com/
ACM	https://dl.acm.org/

(iii) The papers published before 2001

(iv) Same papers available in different journals

(v) Papers not written in English

4. Taxonomy of Optimization Techniques of IoV

This section holds the taxonomy of overall bioinspired optimization techniques and solutions used to overcome the issues in IoV routing. The overall taxonomy of IoV optimization techniques is illustrated in Figure 4.

4.1. Taxonomy of Bioinspired Optimization Algorithms in IoV. There are some optimization algorithms to handle such problems, where the correct path is determined by the actual solution rather than the best solution. Nature is such an inspiring, immense set of solutions that deal with all real-time problems. This has motivated many researchers to use nature-inspired algorithms to solve such complex-related issues. Therefore, algorithms inspired by nature are also called "bioinspired algorithms" [31]. Such algorithms are nowadays used to optimize the routing problem in networking. Hence, these algorithms are considered to find the global optimal solution. Bioinspired route optimization algorithms carry an assortment of optimization algorithms in terms of using biological principles to cover a wide range of networks. Such types of algorithms include Ant Colony Optimization (ACO), Bat Algorithm (BA), Cuckoo Search (CS), Particle Swarm Optimization (PSO), bee colony optimization (BCO), firefly algorithms (FA), Flower Pollination Algorithm (FPA), and the Krill Herd (KH) algorithm. Nowadays, a variety of new classes of algorithms are applied, such as genetic algorithms (GA), evolutionary algorithms (EA), neural networks (NN), and simulated annealing (SA) [32].

The following types of optimization methods are used for solving NP-hard and NP-complete optimization problems: the hard optimization approach presents a huge number of candidate solutions that can attain a global optimal solution at a reasonable time. Hence, finding an optimal solution by bioinspired means in the case of a substantial solution is well known.

The bioinspired algorithms are extra flexible in operating larger-scale vehicular ad hoc networks because of some similarity in the manner of finding routes to satisfy their natural needs. As a result, one of its main advantages is that it generates less complexity, making it suitable for use in computational problems [33]. Also, it is improved to maintain a satisfactory routing performance over time despite network disruptions [29]. As a result, bioinspired route optimization techniques are bringing in more essentials in the IoV. The classification and subclassification of algorithms are shown in Figure 3. Accordingly, algorithms are classified into three foremost categories: Swarm Intelligence Algorithms (SIA), EA, and other biologically inspired algorithms. Their detailed explanations are discussed below.

The first category of routing algorithms is motivated by swarm intelligence like birds, bees, and ants, and the three subclasses of ACO, BCO, and PSO are explained. Most of the VANET routing protocols use ACO routing, inspired by the behavior of ants while searching for the shortest route to reach the destination. This is done by a chemical substance called pheromone. Ants communicate with each other via pheromone trails. In [33], they introduced a mobility-aware ACO routing protocol in VANET to find optimal routes between source and destination nodes while estimating each vehicle's flexibility in terms of spot and speed [34].

The second category of the EA is inspired by the computational natural behavior of mutation, crossover, and inheritance, and aimed at finding the shortest route between the transmitter and the receiver. From this, two subclasses are carried out: Parallel Genetic Algorithms (PGA) and Sequential Genetic Algorithms (SGA). The SGA is aimed at evaluating only one objective taken into consideration by the geographical routing protocol based on intersection [31] to increase the possibility of connection among vehicles and the Internet. PGA optimizes multiobjective transmission benchmarks such as power consumption and by performing automatic configuration using the routing protocol of Optimized Link State Routing (OLSR) to VANET. Evolution for bioinspired-based vehicular routing algorithms is shown in Figure 5.

4.1.1. Performance of Swarm Intelligence-Based Bioinspired Algorithms in IoV for Vehicle Routing. The purpose of bioinspired optimization algorithms is to exist in different applications. This subsection is primarily concerned with investigating its application in IoV at vehicle routing as those discussed below.

(1) Grey Wolf Optimization Algorithm (GWO). The aim of GWO is to follow the natural predation behavior of grey wolves, such as hunting their food in a cooperative way. GWO is based on the clustering algorithm in IoV. It copycats fully the social and hunting performance of grey wolves. Clustering is done in VANETs and IoV for certain features such as vehicle location, speed, position, and direction. A GWO-based clustering algorithm for VANETs is implemented [35]. In this approach, the social behavior of the wolves is pictured into four levels: alpha, beta, gamma, and omega. An alpha is such a dimension that it has a position of basic leadership in the pack. Beta, the subordinate wolf's terms, as the second dimension, helps in settling a choice for alpha. Delta is the subordinate wolf's term for the

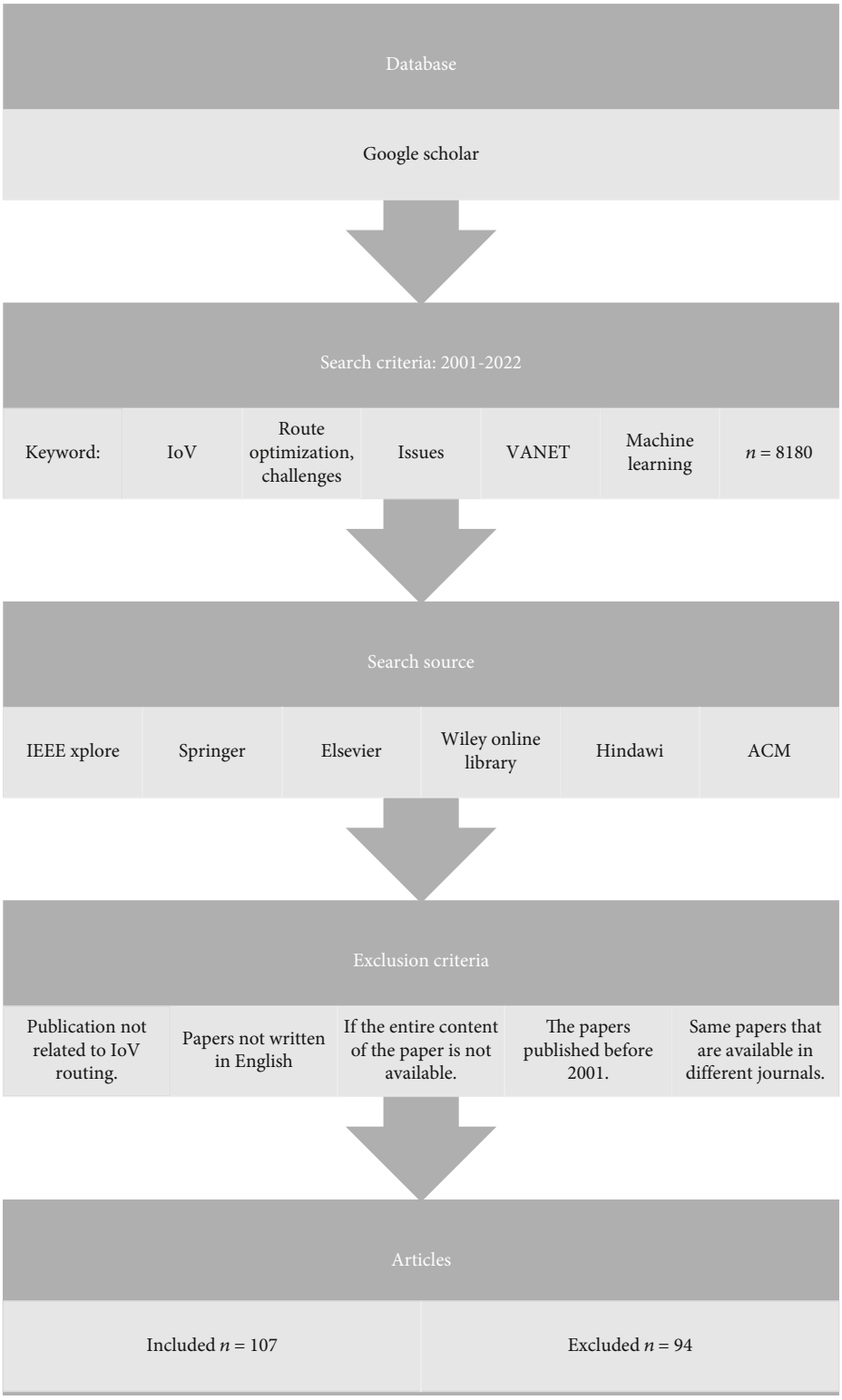

Figure 3: Search strategy.

third dimension used for classification. Omega is the most minimal dimension which helps the grey wolves remember the prey position capacity. Then, hunting for problems over the network is converted into a mathematical model to easily understand the behavior of the algorithm. From this concept, an appropriate form of cluster is extracted to optimize the mentioned problem. Finally, the alpha, beta, and gamma direct the hunting while their position ought to be by the omega wolves by three best-arrangement considerations [36].

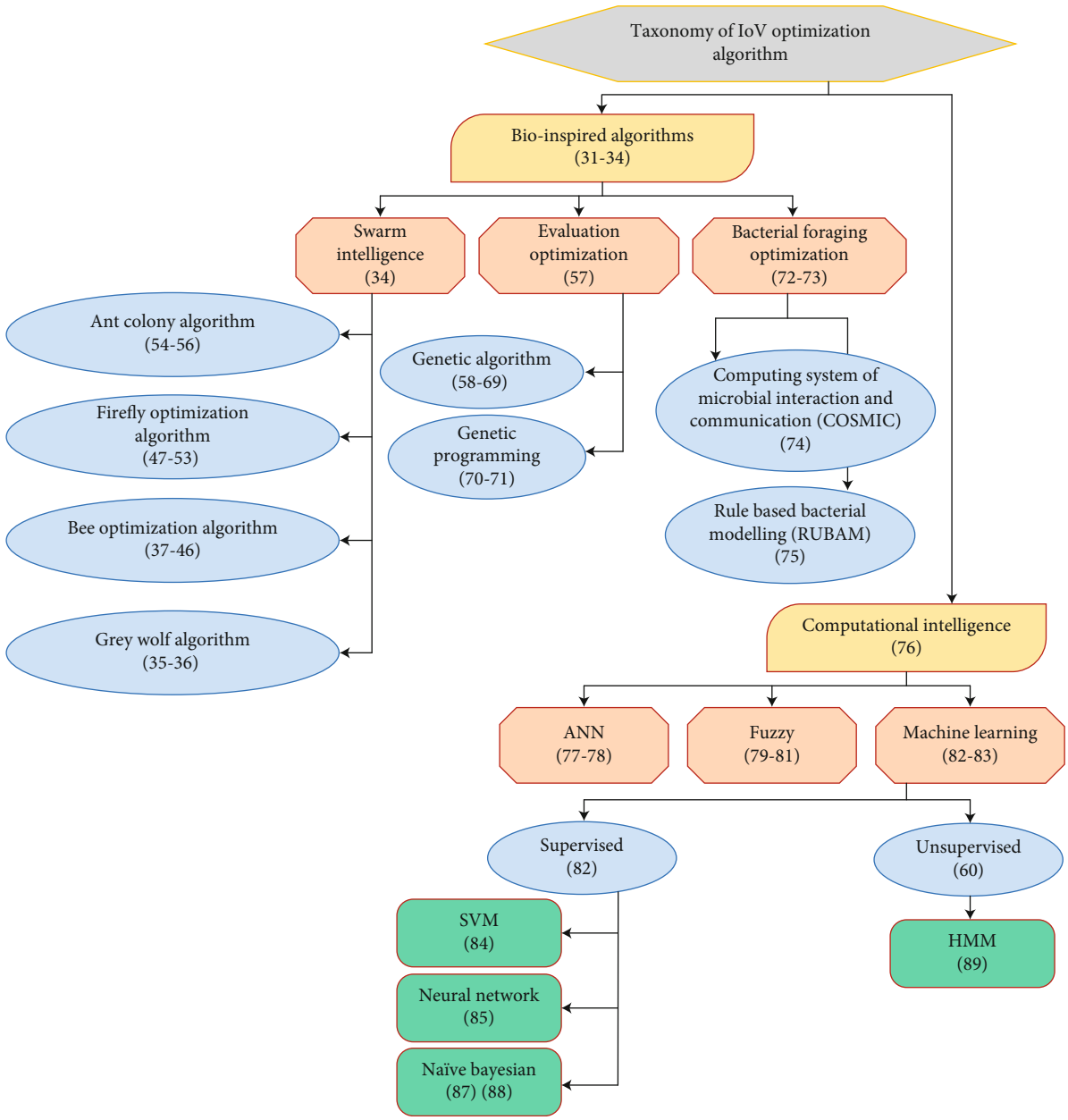

Figure 4: Taxonomy of various vehicle routing optimization algorithm used in IoV (give the complete types for the taxonomy).

(2) Honey Bee Algorithm (HBA). HBA admits to being interested in the nature of bees. In a period of looking for food, the bees leave their hives. When the food is situated at the hour of voyaging, it passes on the message to different honey bees in a type of waggle movement. This cycle of passing on is considered a neighborhood (shifty) and worldwide (explorative) look. Researchers in [37] have developed a HBA-propelled QoS directing convention for VANETs and taught about the value transmission of data among conveying hubs and vehicles to suggest honey bee's versatility. There are four unique types of honey bee-roused calculations in tackling vehicle directing issues [38]. Such calculations are isolated into two subclasses dependent on honey bee conduct and are depicted as follows. Among them, one is the Artificial Bee Colony (ABC) calculation, and later, some adjustments have been made by Basturk and Karaboga in order to tackle numeric capacity streamlining issues. The ABC model derives full motivation for planning from the scavenging conduct of bees. The first ABC to tackle vehicle steering issues was finished by Banharnsakun, who picked the Traveling Salesman Problem as the fundamental issue. Then, at that point, Karaboga utilized the ABC approach as a universally useful streamlining model to take care of the vehicle directing issue [39–42]. The accompanying ABC calculation works by utilizing three sorts of specialists (honey bees, for example, are passerby honey bees, utilized honey bees, and scout honey bees). Each one of them is utilized for explicit stages in the calculation. Next, honey bee-roused calculation of BCO is proposed by Nakrani and Tovey. To take care of a way portion issue in the

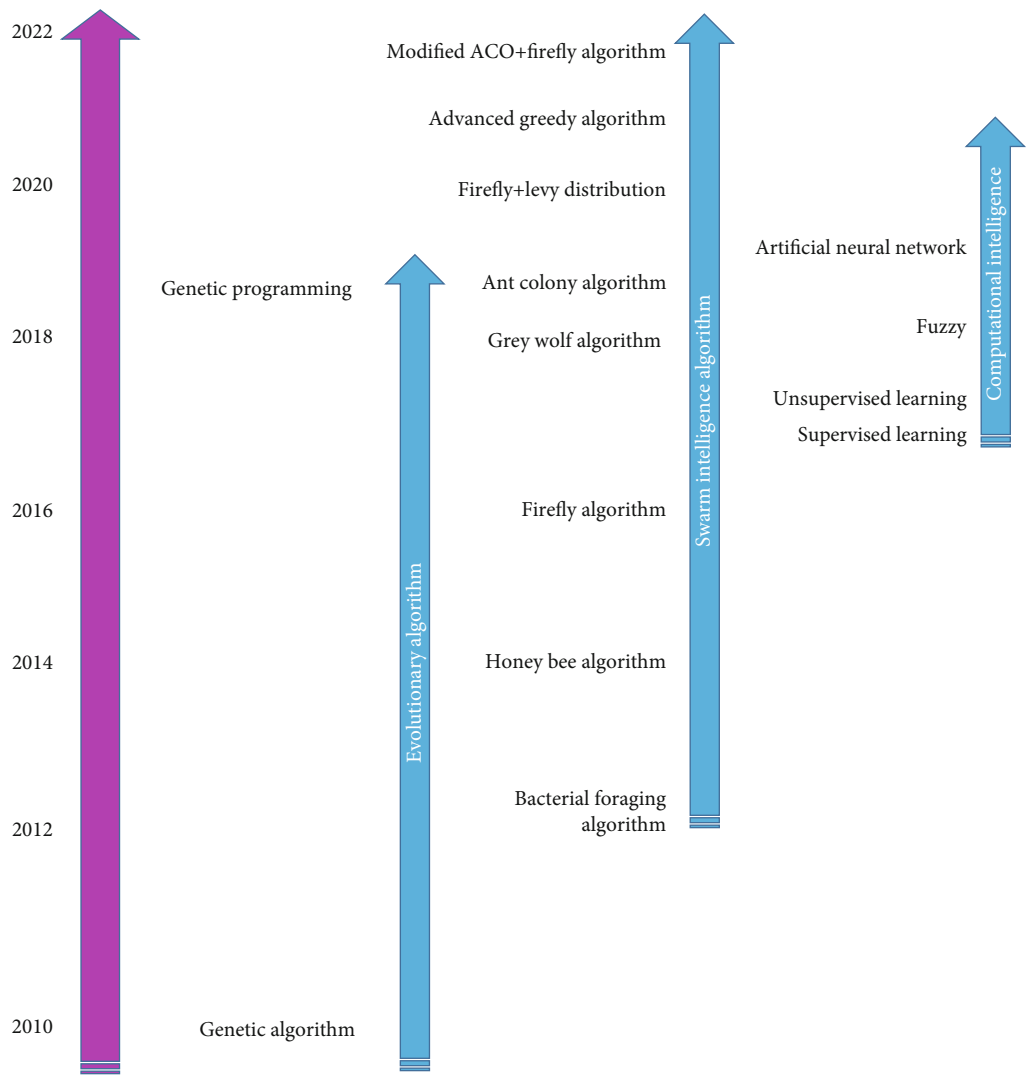

Figure 5: Evolution of bioinspired and CI algorithms in vehicular routing.

organization and a little alteration made in the first calculation to tackle the directing issue by Wong and Zhou later, the Marriage in Honeybee Optimization (MHBO) model is presented by Abbass. The MHBO conveys four types of specialists at performing enhancement, including sovereigns, robots, broods, and workers [43–46].

(3) Firefly Algorithm. Fireflies are otherwise called lightning bugs. The function of the firefly approach depends on the conduct of fireflies. Fireflies act as a sign, and they deliver short and cadenced blazes to speak with different fireflies. The protocol for each group is based on the routing in IoV and was planned by researchers in [47] dependent on the firefly model. The firefly approach is used for spreading messages among vehicles during a crisis, so reasonable connections are chosen for quick message dissemination.

The FA is a BI algorithm dependent on the social mating conduct of fireflies [48]. This approach has a place in the class of multitudes of knowledge procedures that depend on the bioluminescence blazing conduct of fireflies, which goes about as a flagging framework to draw in different fireflies created by Yang [49]. With this approach, each of the fireflies streaks a certain level of brilliance. This makes other fireflies adjoin, and each of their fascinations is impacted by their distance [50]. The two fireflies that are near one another are considered to have a higher appreciation of one another. Each firefly represents having a certain point in a pursuit space, and therefore, the target work is indicated by the engaging quality level of every firefly. The real natural behavior of each firefly needs to be moved towards its neighbors by its most noteworthy fascination. One of the fundamental parts of FA is the distinction of light force, and the other is by means of their drawing quality. From this view, the fascination of every firefly is estimated by its light intensity [51–53].

(4) Ant Colony Optimization (ACO). This kind of ACO algorithm is a type of bioinspired algorithm, used to mimic the natural behavior of ants. An ant can find a small path from the source location to the food location by discharging a

pheromone along the path. The ACO technique for optimization can be used to improve vehicle routing problems in IoV.

The function of ACO is based on the routing algorithm efficiency for VANET and IoV. It depends on the nature of ants. Their behavior is based on evaporation and pheromone redeposition. Ants are not interested in traveling along similar paths more than once, so circular dependence between vehicles is developed. The main benefit of ACO is that it can reduce the overall delay and also increase the packet delivery.

Kumar et al. [54] have proposed the IoV-based traffic management method, which is used to prevent traffic congestion and accidents. Here, they separate the street map into small submaps. Initially, they used the ACO algorithm for each submap to find the optimal route path. The optimal solution is based on the rod length and moving vehicles with the help of IoV technology. In ACO, the forward ant's process is utilized to find the optimal solution. Its functional equation is given below:

$$\overset{K}{_{IJ}}(T) = \begin{cases} \dfrac{A(\partial_{IJ}) + B(1-\eta_{IJ})}{\sum_{H \notin TABU_K} A(\partial_{IJ}) + B(1-\eta_{IJ})} \times \left(\dfrac{1}{1+(1/n_J)}\right), & \text{if } J \notin TABU_K, \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where ∂_{IJ} denotes the pheromone value of ant in nodes I and J, η_{IJ} denotes the instantaneous fuzzy function, A denotes the weight value of ∂_{IJ}, B is the weight value of η_{IJ}, n_J denotes the number of the nearest node, $TABU_K$ denotes the node set not visited by the ant. Then, the fuzzy function is designed to calculate the intensity of the vehicle in heavy traffic. The experimental result of this method is compared with some existing methods.

Nguyen et al. [55] have proposed addressing the dynamic IoV traffic routing issues with multisource and multidestination in an IoV environment. This proposed model is designed to solve the vehicle traffic in the IoV. Initially, they proposed the decentralized ACO routing model to connect the vehicles. By using this algorithm, the coloured ants are utilized for traffic flow between the sources and destination. This ACO algorithm design is used to develop communication and is also proposed to exchange data among infrastructure and connected vehicles. The functional equation of ACO is given below:

$$\Delta_{t_{IJ}}^{\upsilon_{\lambda D}}(T) = \frac{1}{l_{IJ}^{\upsilon\lambda_D}(T)} + \frac{1}{k_{IJ}^{\upsilon\lambda_D}(T)} + \frac{1}{d_{IJ}^{\upsilon\lambda_D}(T)}, \tag{2}$$

where $l_{IJ}^{\upsilon\lambda_D}(T)$ is the length of each edge, $k_{IJ}^{\upsilon\lambda_D}(T)$ is the vehicle traveling time, and $D_{IJ}^{\upsilon\lambda_D}(T)$ represents the density of vehicles. The simulation result of this proposed method was performed with a multi-intersection scenario in the NetLogo platform. This result shows that the ACO algorithm is better for the routing process than the non-ACO algorithms.

In the IoV model, Jabri et al. [56] present multiaccess edge-based vehicular fog computing. The goal of this model is to exploit both the infrastructure equipment and vehicles to bring the users close to the cloud. The function of this proposed model has two main steps. Firstly, the Multiaccess Edge Computing (MEC) technology is used to provide centralized control of the vehicular fog. They used various modules in this architecture. But here, they particularly focus on the selection gateway module. Then, in the context of the vehicular cloud, they access the MEC server. It will allow all vehicles to connect directly to the cloud, increasing radio resources and increasing traffic congestion and collision rates. Initially, they utilized fuzzy logic for the gateway selection process based on some parameters. The values of each parameter are collected through the IoV communication between vehicles. Then, they use the ACO algorithm to solve the gateway selection with the uncovered vehicles. Therefore, the issues are divided into two steps: first, the connection of the covered node to the gateways and secondly, connecting the uncovered nodes to the covered node. This proposed model provides an important node ratio, particularly for static vehicles. The functional comparison of SIA is discussed in Table 3.

(5) Hybrid Algorithm. To address the multicast routing problem, a firefly with Levy distribution (FF-L) technique was proposed by [57]. The Levy distribution is used in the FF algorithm to prevent it from being trapped in local optima. A set of tests on three distinct scenarios is used to validate the FF-L algorithm in VANET. This method showed less cost, jitter, and delay compared to other methods. To improve the performance of IoV, a bioinspired advanced greedy hybrid routing protocol was proposed in [58], where a bee colony optimization combined with a greedy algorithm is used to choose the best route with high service quality and select a route with the minimum overflow. The simulation outcomes show that this protocol works well in both V2I and V2V environments and has a significant impact on enhancing delay and packet delivery ratio while maintaining a minimum hop count across all vehicles and reasonable overhead. However, various challenges exist, such as determining the quickest path between the source and the final destination, excessive delays, poor connection, congestion, and low packet delivery ratios. To overcome these issues, the work presented in [59] provides a hybrid optimization strategy that combines firefly optimization and modified ant colony to determine the average

Table 3: SI-based bioinspired algorithm advantage, simulation tool, evaluation parameter, and application.

Swarm intelligence-based bioinspired optimization algorithm	Advantage	Simulation tool	Evaluation parameter	Application
ACO	It provides highly optimized routing and is fault-tolerant	NS2	Packet delivery ratio, loss, and throughput	Routing
FA	The delivery ratio of each packet proposed protocol is quite improved	NS2	End-to-end delay and propagation delay	Routing
HBA	Outperformance of this approach is better than the protocols like AODV and DSR	NCTUns6.0	Throughput and packet loss	Routing
GWO	The outcome of this model illustrates that performance of cluster heads is good	MATLAB	Transmission range, grid size, and number of nodes	Routing
Hybrid	Selects the best path and cut trip time	MATLAB	Delay, packet delivery ratio, connectivity	Routing

speed and discover the optimum path to the destination. Here, the algorithm used pheromones and attractiveness to select the best path and cut trip time.

4.1.2. Performance of Evolutionary Algorithm-Based Bioinspired Algorithms in IoV for Vehicle Routing. In the taxonomy of bioinspired algorithms, the evolutionary algorithm is the first type of approach. It is utilized to solve problems in the diverse domain of science and real-time applications. It is used to obtain an exact optimal solution for a multimodal function. The function of evolutionary algorithms is loosely based on the metaphors of biological processes. The function of EA is based on a random search approach with some metaheuristics. This technique consists of population-based functions; it represents the search point and feasible solution, and it is unprotected from the collective learning process, which is performed from one generation to the next. The EA population is randomly initialised and subjected to selection; then, the recombination process and mutation process will be performed over several generations [60]. The classification techniques of EA are discussed below.

(1) Genetic Algorithm. Because the vehicle routing problem (VRP) is a complex NP-hard problem, it has attracted the attention of many scholars from various fields. Using a traditional method is unsatisfactory for VRP to get a global optimal solution. Hence, a global method based on genetic theory and selection theory of genetic algorithms has been introduced. GA is a natural selection-based process that carries out three operations: selection, crossover, and mutation [61]. Therefore, the researchers presented a genetic-based routing protocol for IoV to forward the data with the least amount of rate from source to destination vehicle. But GA itself has some problems, such as slow convergence and premature termination. Hence, improving its convergence speed and, at the same time, maintaining population diversity in solving VRP are considered a main goal [62, 63]. Therefore, they proposed an improved GA to solve VRP by including SA into the GA in terms to avoid premature and convergence issues. Zirour introduced a GA to solve the vehicle routing problem with time windows (VRPTW) to reduce the aggregate distance and delay time of each customer's vehicle path under time violation, whereas utilizing GA algorithms to solve such a problem includes two steps. First, they use the initial solution to reduce the expenses in two steps, and then, the expenses in the next step will fail. Hence, this research proved the solutions that are close to the best solutions. Then, GA with a crossover operator was used to solve the VRPTW problem. Then, the same improved GA-based crossover operator algorithm was used [64] that was used there. The crossover operator chooses an individual from the whole population to generate offspring. Rather than using a traditional method of presenting offspring, the swap node operator has been used for random selection. After testing with other algorithms, the improved GA algorithm presented the best optimal solution and illustrated that their outcomes were competitive. There have been multiple objective functions in VRPTW. From the following objective function, some of the common considerations of the objective function used for minimization are (i) total travel distance of the vehicles, (ii) total number of vehicles, (iii) total travel time, and (iv) maximum QoS. In [65], we chose five objective functions for multiobjective routing problems, such as total delay time, total waiting time, total travel distance, and makespan. To deal with such problems, nondominated sorting GA (NSGA-II) will be introduced to deal with vehicle routing problems (VRP). Then, Zhong-yue et al. and Castro-Gutierrez [66, 67] applied such an optimization algorithm in VRP with two kinds of demand, focusing on the number of vehicles and makespan. The optimization process considers the similarity set of nondominated solutions. Later, Jozefowiez proposed an improved version of NSGA-II optimization by including two enhancement processes: parallelization and elitist diversification. This type of approach is applied in VRP problems to tackle where to limit the travel distance between the shortest and longest routes. Next, Wei passed this algorithm in a real-world test case in the USA, considering three objectives: distribution time, travel distance, and set of vehicles. Bullinaria and Garcia-Najera used NSGA-II performance, which is related to another algorithm, an MOEA that includes two of the same measures: edit distance and Jaccard parallel coefficient [68–70]. The

performance was assessed using the travel distance and number of vehicles. A GA-based parallelization method for the Traveling Salesman Problem (TSP) in VRP is presented. The approach has been used to solve time-constrained issues of IoV routing and autonomous vehicle control in IoV [71, 72].

(2) Genetic Programming (GP). GP is a populace-based inquiry calculation propelled by normal development. It begins with creating a populace of people (as a rule, indiscriminately) who are IoV for the target issue [73]. Then, at that point, every individual is assessed and doled out with a wellness score that demonstrates how well this up-and-comer tackles or verges on taking care of the current issue. Until an end standard is fulfilled, new populations are created iteratively by utilizing determination, hybrid, and transformation administrators, as in normal advancement. These hereditary administrators are used to provide better services to the new population. The vast majority of bioadvanced calculations used in impromptu organizations are classified into two types: centralized with global (online) information and decentralized with local (offline) information. The executives of every vehicle handled by VANETs assess the trust esteem dependent on the neighborhood data while continuing on with the organization. The most trusted board models are fundamentally used in impromptu organizations to ensure secure and solid correspondence. As a result, the GP for introducing trust in the executive model in VANET deals with the powerful changing geography and events [74].

4.1.3. Performance of Bacterial Foraging-Based Bioinspired Algorithms in IoV for Vehicle Routing. Bacterial foraging optimization (BFO) utilizes the regular scavenging procedures of Escherichia coli bacterium cells and makes an essential move to augment the energy used per unit of time spent on searching. From that point forward, BFO has been applied effectively to multitarget issues. A versatile BFO is introduced for addressing VRPTW. The VRPTW is defined as a collection of vehicles used to collect the user's time windows [75]. It starts at the warehouse and ends at the station. Thus, every one of the clients ought to be served precisely once. In the event that vehicles show up before the time window "opens" or after the time window "closes," there will be hanging tight for costs and late expenses to limit the total expense of fulfilling all correspondence and disparity requirements.

The objective function of total cost is taken into consideration. The variables have various pieces of information, such as distribution strategist, vehicle routing, and the arrival time for every customer. The dimension of each variable is based on the vehicles [76].

(1) Computing System of Microbial Interactions and Communication (COSMIC). COSMIC was created in 2004 by Saunders et al. The guidelines for this model are based on the processing framework. It was mainly introduced for the bacterial simulation process for COSMIC-Rules by Saunders et al. in the year of 2006. The models of the following development changes occur in cells while utilizing discrete time waves and a pseudoconstant space model. Each of the cells contains genomes that are associated with real time, etc. COSMIC contains three remarkable levels of stages, including the genome, the cell, and the climate occupied by cells. The fundamental aim is to contemplate the advancement or variation of microscopic organisms and to foresee the conduct of pathogenic microorganisms [77].

(2) Rule-Based Bacterial Modeling (RUBAM). RUBAM was designed by [78]. The function of RUBAM is a combination of GA and GP algorithms. The function of RUBAM is based on the bacteria. It acts as a data unit process which maps action and message. The data from the real-time applications is mapped to take them again. This process is not static because it makes it possible to continuously change the environment, ensure real life, and also enhance the reproduction process. The main goal of this model is to grasp the bacteria and their behavior and features. The model can balance the computational demands and complexity. Moreover, it has a set of interconnection mechanisms and a collection of artificial organisms that also set the operators for the evolution process. The overall knowledge contains artificial organisms. In multimodal search space, this model can get optimal results. But the other optimization algorithms can interact with the real-time environment applications and also calculate the fitness value. The best outcomes are shared with various processes [79]. The feature comparison of bioinspired algorithms is illustrated in Table 4.

4.2. Taxonomy of Computational Intelligence-Based IOV Algorithms. Computational intelligence (CI) is based on artificial intelligence and computer systems. The methodology of CI is a biooriented computation model. It is used for some real-time applications in dynamic and static environments in which mathematical or traditional modeling and reasoning are too complex and are uncertain, and the process will be stochastic in nature [80]. The CI process is controlled in a modified way. The main principles of the CI technique are listed in Figure 3.

4.2.1. Artificial Neural Network (ANN). ANN is a CI-based technique; its functions are based on biological networks. Data flows through the affected ANNs as a neural network (NN) changes—or learns in a certain way—based on the input and output. ANN is a framework to design a biologically inspired algorithm. Various kinds of networks have been used, including self-organizing networks, single-layer networks, recurrent networks, and multilayer networks. It is effectively applied in many fields to find vehicular communication details such as predictions, pattern classifications, traffic density estimations, and robotics. In addition, this is one of the most effective methods for nonlinear, uncertain, and time-based models. However, it is also utilized for short-term route forecasting systems [81]. The NN has the ability to predict various traffic routing parameters, as well as these parameters are based on the minimum and maximum changes in the lane, length of the road segment, vehicle flow, etc. The ANN has been applied successfully to reduce and solve several problems in the IoV [82].

Table 4: Summarize of bioinspired algorithm features.

Author/year	Bioinspired algorithm	Features					Protocol
		Mobility	Scalability	Delay	Packet delivery ratio	Energy awareness	
Fahad *et al.* [35] (2018)	GWO algorithm	✓	✓	_	✓	_	_
De Rango et al. [36] (2020)	GWO algorithm	✓	_	✓	_	_	Routing protocol
Jung and Mu'azu [37] (2014)	Bee optimization algorithm	✓	_	✓	✓	_	Routing protocol
Sachdev *et al.* [47] (2016)	Firefly algorithm	✓	_	✓	✓	✓	_
Ramachandran Pillai and Arock [53] (2021)	Firefly algorithm	_	_	✓	_	_	Routing protocol
Nguyen and Jung [55] 2020	ACO algorithm	_	_	✓	✓	_	_
Jabri *et al.* [56] 2019	ACO algorithm	✓	_	✓	✓	✓	Routing protocol
Khan *et al.* [69] (2019)	Genetic algorithm	_	_	✓	✓	✓	Routing protocol
Hadded *et al.* [71] (2015)	Genetic algorithm	✓	_	_	✓	_	Routing protocol
Aslan and Sen [74] (2019)	Genetic programming	✓	_	✓	_	_	_
Mehta *et al.* [76] (2016)	Bacterial foraging	✓	_	✓	✓	_	Routing protocol

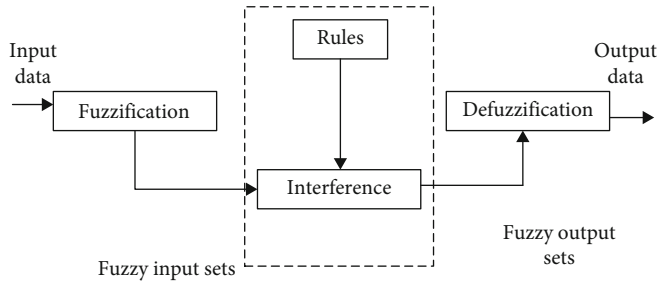

Figure 6: Block diagram of the fuzzy system.

4.2.2. Fuzzy. "Fuzzy" is an uncertainty within "crisp logic" in which it has two reasons, i.e., true or false, while "fuzzy logic" reasons approximately or to a degree of true or false. Fuzzy logic has arisen from the growth of the fuzzy set. A fuzzy system is a type of CI technology that uses fuzzy theory to solve issues in many fields [83].

It is applied for the successful control system, home applications, vehicle communication, etc. Nowadays, it is mainly used for IoV prediction and density estimation. Fuzzy logic is often utilized to address different issues in control, system identification, and signal processing. Fuzzy modeling is one of the most crucial issues in blazing research. In the previous years, research and theoretical study focused on research systems from the application-original perspective [84].

Figure 6 illustrates the functional structure of a fuzzy system. It has four stages: fuzzification, fuzzy rule base, fuzzy inference engine, and defuzzification. In the fuzzification phase, each section of the input data converts one or more member functions into member degrees by one view. There are rules that are based on unclear logic, including inappropriate relationships between inputs and outputs. These fuzzy rules are based on IF-THEN statements. The fuzzy release engine takes into consideration all the intricate rules of the zero rule base and learns how to change a set of measures for the relevant results [48]. In the end, the resulting fuzzy logic outflows are transformed from an incomplete exhaust engine to a series of defuzzification processes [85].

4.2.3. Machine Learning (ML). Machine learning is an important learning technique that is utilized in a real-time environment. It is the subsection of AI for the development and understanding of techniques and algorithms that allow machines to learn [86]. The learning method provides good IoV, with high-density dependencies of explicit variables and dramatic downtime for vehicle communication on major networks. Thus, it outperforms and makes better predictions than other learning methods. ML is categorized into supervised and unsupervised learning [87]. The functional overview of ML algorithms and the features of each algorithm are compared in Tables 5 and 6.

(1) Supervised Learning (SL). SL inputs and their required outputs and a general rule that maps the entries to outputs. SL is widely used for classification problems. The SL methods are divided into classification and regression. It is one of the important techniques for decision tree networks and NN training processes. The SL method is broadly used for IoV. SL involves introducing extra layers between input and output that change the manual functions with some algorithms and the extraction of hierarchical properties [86]. The taxonomy method determines an error in the NN and minimizes it. The SL algorithm takes a set of IoV routing input data and trains the model to make forecasts for responding to new data.

(2) Support Vector Machine (SVM). An SVM is a supervised technique used for classification. SVM defines the dimensional hyperplane to separate the dataset into two sets. Network weight can be achieved by solving a quadrature programmatic problem that has simple limitations, rather than removing arbitrary migration problems, as well as training for basic neural networks. The SVM model has a large amount of memory usage and terms of time. In contrast, the converting approaches NN, SVM, and non-parametric regression are utilized for IoV routing path forecasting because of their complex arcades and self-learning characteristics. SVM can also achieve a globally optimal solution without limiting it to a local minimum point, which gives strong resistance to unnecessary problems and high alert performance [88].

(3) Neural Network (NN). Neural networks have been widely utilized in the IoV area. In many cases, the traffic network will have a single output variable, although, in the case of multistate classification issues, this may relate to multiple output units. There are various applications of NN in the IoV forecasting area: multilayer perceptrons, time-delayed recurrent neural networks, multirecurrent neural networks, state-space neural networks, etc. There are also some hybrid neural network applications in the field of traffic forecasting. Neural networks are the most widely applied models to the traffic prediction problem because they are capable of modeling nonlinear and dynamic processes well. Many extensions of the basic concept have been implemented to improve prediction accuracy and/or reduce computational effort [89]. Among NN, backpropagation networks are widely applied because of their ability to model complex nonlinear relationships among continuous variables. These multilayer networks perform supervised learning. NN's architecture is based on models and predictions of the evolution of traffic congestion based on global positioning system

Table 5: Comparison of machine learning algorithms.

Techniques	Overview	Limitation	Application
SVM	The SVM performs the coordination of individual observation. The result of this model creates an optimal hyperplane that separates classes.	The training and testing function of SVM is slow.	Context-aware security of IoV
Neural network	It is an ANN biological NN and is organized in layers that are made up of several interconnected "nodes."	It takes a large time to process and requires a large dataset.	Speed forecasting in IoV
Naive Bayesian	It is a bioinspired neural system organized in layers that are connected with each other node.	The function of Bayesian is dependent on hardware and is repeatedly faced with inexplicable behavior.	Fast vehicular communication
K-nearest neighbor (KNN)	This algorithm is used to utilize a database to categorize into several classes for forecasting the sample point.	Its learning process is low.	Communication of IoV is fast
HMM	The function of HMM is processed only on the partially observable.	It needs a large amount of computational time.	Best routing process

Table 6: Summary of CI algorithm features.

Author/year	Bioinspired algorithm	Features					
		Mobility	Scalability	Delay	Packet delivery ratio	Energy awareness	Protocol
Karabulut *et al.* [82] (2019)	ANN algorithm	_	_	✓	✓	_	_
Alsarhan *et al.* [84] (2019)	Fuzzy model	_	✓	✓	✓	_	Routing protocol
Bylykbashi *et al.* [85] 2019	Fuzzy model	_	_	✓	_	✓	Routing protocol
Wu *et al.* [88] (2018)	SVM algorithm	✓	_	✓	_	_	_
Xu *et al.* [89] (2020)	Neural network	✓	_	_	_	✓	_
Yin *et al.* [90] (2020)	Neural network	✓	_	✓	_	_	_
Yao *et al.* [93] (2017)	HMM	✓	_	✓	✓	_	_

data. The backpropagation (BP) algorithm is an effective algorithm, but it has some issues that can be resolved by it. The backpropagation model has become one of the vital NN models [90].

(4) Naive Bayesian Network (NBN). The NBN is classified using Bayes theory and forecasting and is frequently obvious to the problem solver. This method is widely used in practice due to its low computational effort and ease of use. A small amount of training data is required to estimate the parameters required for classification. NBN can be trained in a controlled learning system. In a number of real-time applications, the IoV routing paths are predicted for the NBN model, which uses the highest probability method [91]. In the NBN, the data from adjacent links is considered informative for the link currently under investigation. However, this method is used in the real-time IoV system. The process of NBN is related to the adjacent road links and statistical data. From this NBN, the nearest node can be used in reasoning about some features of the present node. The NBN explicitly adopts the data from the adjacent links to provide IoV communication and prediction. The traffic flow forecast here can be considered as a reference to the Bayesian network [92].

(5) Unsupervised Learning (UL). UL is the training of a CI algorithm using IoV data that is neither categorized nor labeled and allows the algorithm to act on that information without guidance. If it has no results given to the UL algorithms, then it finds the structure in its input. The aim of UL is to detect hidden patterns in the data. In today's environment, ML approaches are mainly applicable to transportation issues. In this review, we divided the techniques under the UL base algorithm for the IoV routing process [63].

(6) Hidden Markov Model (HMM). An HMM is based on a Markov chain, which is only partially noticeable in the state. Observation functions are associated with the state of the system, but they are usually not enough to accurately determine the state. In HMM-based IoV estimation approaches, the communication state on a road segment is a latent state that can be estimated in accordance with the conditions of road sections having similar traffic characteristics. The HMM was developed and calibrated using a large amount of real-world IoV vehicle communication surveillance data. It is broadly used for the routing process. The IoV has been defined as the first- and second-rate statistics on vehicular communication observations, as well as within the shortest time frame, local variations, and traffic trends [93].

5. Challenges and Application of This Survey

IoV is the combination of hardware pieces with different types of networks, which is used to allow pedestrians, cars, and other units under RSU to interchange real-time information. IoV is one of the super versions of VANET. In general, conventional VANET allows cars to form a wireless connection with other vehicles. Therefore, all vehicles nearby IoV have a reliable connection to the local infrastructure. The main working principle of IoV technology is to form a social IoV with smart infrastructure. The five types of IoV infrastructure are vehicle-to-roadside (V2R) unit, vehicle-to-human (V2H), vehicle-to-sensors (V2S), vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I). In addition, in IoV, many issues are encountered when the routing protocols for vehicular communication and traffic enhancement are created. Some of these challenges are quick variation of topology, high mobility, and network fragmentation. Other issues are related to IoV, such as storage, as the huge number of connected vehicles and the large volume of data processing take place; thus, managing the network is a challenging task, which can be solved [94].

The application of IoV is categorized into three types: safety applications, infotainment and comfort, and management of vehicle routing and efficiency.

5.1. Safety-Related Application. The aim of the IoV application is to be utilized to reduce and avoid road accidents. The safety application is used to provide a head warning to the vehicle drivers. Also, this application is utilized to avoid mishaps from occurring in any case.

(i) Traffic signal violation warning: it is used to manage the infrastructure for vehicles' routing to pass the message between vehicles in any hazard case

(ii) Intersection collision avoidance: based on dedicated short-range communication, it is used to reduce accidents and improve road safety. Moreover, it establishes secure links to provide prior information in any accident, thus alerting the driver to take appropriate action

5.2. Management of Vehicle Routing and Efficiency (MVRE). The MVRE application is designed to prevent road mishaps by optimizing the traffic flow and ignoring the traffic congestion. In this application, the vehicles forward the notification about the traffic situation based on the Roadside Unit (RSU) and On-Board Unit (OBU), and accordingly, the drivers might change their vehicle routes.

(i) Intersection management: this is a technique for improving the efficiency of vehicle intersections. In smart cities, vehicles passing through the intersection area are dangerous. During that period, spared roadside-to-vehicle communication will provide more notifications about the traffic flow prediction and the current traffic situation

(ii) Vehicle routing traffic management: this management is used to manage the flow of vehicle traffic and reduce congestion in traffic routing. In this turn, it increases the capacity of routing efficiency and prevents vehicle traffic jams

5.3. Infotainment and Comfort. The comfort and infotainment applications are designed to improve the vehicle's driving comfort. This IoV application can be tolerated for information losses and delays. In IoV, the unicast routing is used for infotainment applications, which are used to search for the nearest locations and pass the information between vehicles to vehicles, etc. [57–59, 95, 96].

6. Conclusion

In the new era of IoT, the evolution of Internet-based driving, named IoV, supports ITS, telematics, and ad hoc vehicular networks. The bioinspired approach in IoV has proven to be more efficient for large-scale vehicular networks in performing routing in terms of greater scalability and less complexity. In addition, it is more robust and flexible and ensures better routing performance even when the networks drop down. Therefore, this article will discuss a comparative study of various bioinspired algorithm techniques in IoV routing to support ITS applications. After discussing the background of the IoV routing, the basic concept and operations of some recently implemented bioinspired algorithms are mentioned in the taxonomy section, which is classified into three categories: evolutionary algorithms, swarm intelligence, and bacterial foraging. These three categories include some subclasses of algorithms such as PSO, BCO, fuzzy logic, ACO, and GA. Research projects were reviewed, classified, and compared for each category using the essential scheme and routing criteria, such as complexity, robustness, scalability, and mobility model employed QoS. To find the convergence in bioinspired applications in the IoV, a suggestion to propose a unified formal model for managing multiple solutions is discussed. From this consideration, the suggested model is better suited for a bioinspired approach than the existing procedures, which can address different routing aspects. The final part of the review ends with some lessons learned, future trends, and opportunities for the IoV route.

Notations

A: Weight of ∂_{IJ}
B: Weight value of η_{IJ}
∂_{IJ}: Pheromone value of ant in nodes I and J
η_{IJ}: The instantaneous state of fuzzy
n_J: Number of nearest nodes
$TABU_K$: Node set not visited by the ant
$\Delta_{t_{IJ}}^{\upsilon_{\lambda D}}(T)$: Pheromone dropped by the vehicle
$l_{IJ}^{\upsilon\lambda_D}(T)$: Length of the edge
$k_{IJ}^{\upsilon\lambda_D}(T)$: Traveling time of vehicle
$D_{IJ}^{\upsilon\lambda_D}(T)$: Density of vehicles.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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