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A survey on Heuristic-based Routing Methods in Vehicular Ad-Hoc Network: Technical challenges and future trends.

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***Abstract*—Vehicular ad hoc network (VANET) is a set of vehicles trying to exchange security and comfort data even if they are not directly within radio range of each other. As VANET presented several challenges, the various contributions defined are not efficient to provide reliable services. Consequently,several researches and projects have beenlaunched to develop an intelligent transportation system that guarantees both safety and comfort for users. Although the use of metaheuristics seems to be the most convenient to overcome these issues, actually, to the best of our knowledge there are no studies addressing the uses of those approaches in VANET.**
This paper surveys and discusses different metaheuristics applied to solve the routing problem within VANET.Furthermore, technical challenges and future trends are treated and presented.

Keywords-Vehicular ad hoc netwo; routing protocol; metaheuristic;sensor; survey.

I. Introduction

Mobile ad hoc network (MANET) is a collection of mobile units interconnected by wireless technology without any predefined infrastructure. In this type of network, each node attempts to exchange data with others. For this, the source has to establish a direct connection with the destination or to pass its data through other relay nodes. [1].

As known, vehicular ad hoc network is a subgroup of MANET. Nevertheless, to apply any MANET routing protocol to VANET, substantial amendments have to be performed to overcome the flooding problem and the high mobility of vehicles. [2], [3].
The specific protocols for VANETs can be classified in different ways according to several criteria. Indeed, depending on the manner of the creation and the maintenance of routes, five classes of routing protocols are shown in Fig. 1

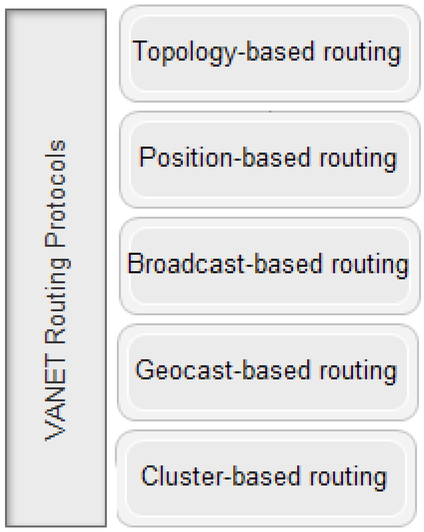

Fig. 1. Routing protocols in VANET.

The various protocols developed so far do not provide an optimal solution in polynomial time because of the high mobility of nodes and the diversity of routing environments (city, urban, residential, highway). Therefore, significant efforts have been done to find a reliable intelligent system that ensures efficient routing of messages from source to destination with less transmission problems.

For many reasons, the routing in vehicular networks can be reduced to an optimization problem looking for the best solution. Therefore, the need to reach the optimal solution with reasonable cost leads researchers to use approximate methods called metaheuristics.[4], [5].

In this paper we survey the uses of metaheuristic methods [6], [7] to achieve an efficient routing in vehicular ad hoc networks.

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Therefore, in Section 2 we explain how the researchers used metaheuristics to solve the problem of routing in VANET. In the third section we discuss the different methods used, giving the advantages and the disadvantages of each one. In section 4, the future trends in vehicular network are described.
Finally, in Section 5 we present a general conclusion with prospects of new directions for future research.

II. HEURISTIC APPROACH FOR VANET

To focus our study on the most effective used heuristics, we relied on a sample of 100 papers for mobile network and 30 papers for vehicular network.
According to this study, over than 90% of researchers used heuristics based population to resolve the routing problem in both MANET and VANET. Therefore, the remaining sections describe the main metaheuristics used to improve the routing within vehicular ad hoc network.

A. Using Particle Swarm Optimization (PSO) for VANET

PSO is a stochastic descent method that compares for any iteration the initial solution with all its neighbors to keep the best. This process is inspired from social behavior of fish schooling and bird flocking. [8], [9].
Each particle of the swarm moving within the search space is influenced by its own best previous position (personal Best) and the best previous position of the whole swarm (global Best). [10], [11].

a- *Modified-Optimized Link State Routing protocol (M-OLSR)*

(Zuriati &al, 2014) [12] used PSO to adjust the OLSR protocol in order to overcome the problem of the frequent change in VANET topology. The given solution improves the protocol performance in terms of the bandwidth capacity and the End to End Delay.

In M-OLSR, based on three performance metrics, the author used equation (1) to calculate the cost function of each new configuration. This cost will be the input of the PSO algorithm to provide the optimal parameter settings allowing OLSR to be appropriate for any VANET scenario.

$$Cost\ function = 0.2 * PL + 0.3 * E2ED + 0.2 * NRL - 0.3 * \frac{PDR}{4} \quad (1)$$

Where

- Pl: Packet Loss.
- E2ED: End to End Delay.
- NRL: Normalized Routing Load.
- PDR: Packet Delivery Ratio.

b- *Tuning of OLSR Routing protocol with Metaheuristic Algorithm for VANET*

In [13], (Anusha bandi & al, 2015) used metaheuristics to adjust the standard OLSR protocol to be convenient for vehicular network.

The proposed framework consists of two phases (optimization and simulation). In the first one, four techniques (GA, PSO, SA, DE) were conceived to find the optimal solution.
After the process of optimization, the new generated solution by the tuned OLSR will be evaluated according to three metrics (Packet Delivery Ratio (PDR), Normalized Routing Load (NRL), and Average End to End Delay (EED)).
Based on the fitness value (2), which is the output of simulation process, an iterative treatment will be launched until the stop condition is satisfied.

$$commu_{cos1} = we2 * NRL1 + we3 * E2ED1 - we * PDR1 \quad (2)$$

c- *Optimized DSDV using Particle Swarm Optimization*

The performance and the robustness of anyalgorithm are measured according to the right choice of the parameters configuration. [14].
For instance, in DSDV routing protocol there are more than 229 possible combinations of parameters. [15].
In this context (sanjiv Sharma &al, 2014) [16], suggested a tuning method based on the popular algorithm PSO to find out the optimal parameter configuration of DSDV protocol according to three metrics (PDR, AEED, and NRL).
The proposed framework consists of two phases:

- Optimization algorithm: Using the fitness function described below (3), PSO tries to find the best parameters configuration.
- Solution evaluation: Each solution generated in phase 1 will pass into DSDV.

Where, Fitness $= w1*NRL+w2*AEED-w3*PDR$ (3)

d- *Parameter Value Optimization of Ad-hoc on Demand Multipath Distance Vector Routing Using Particle Swarm Optimization*

Providing the best quality of service (QoS) in vehicular network counts on the accuracy of parameters used in.
In [17], (lobiyal & al, 2015), presented an algorithm based on PSO to get an optimal combination of parameters used in Ad hoc On Demand Multipath Distance Vector routing protocol (AOMDV) in case of VANET real scenario.
Because of the large number of possible combinations of values of the nine parameters of AOMDV, authors transform the challenge as a combinatorial optimization problem resolved using PSO.
The presented framework used three QoS parameters (PDR, AE2ED and NRL) and contains two phases (Optimization algorithm and Solution Evaluation).

- Optimization algorithm: Applying PSO to select the best value of parameters.
- Solution Evaluation: Calculating the Fitness Function defined according to the three QoS parameters selected above.

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e- *TS-PSO Time Seed Based Solution Using Particle Swarm Optimization*

In [18], the dynamic Vehicle Routing Problem (DVRP) can be identified into different aspects according to five objectives (customer ranking geographical ranking of the request, expected reachability time, satisfaction level of the customers and service time). To deal with this problem, (ampakasha & al, 2015) suggested a time set based solution based on the Particle Swarm Optimization (TS-PSO).

According to the proposed approach, the Multi-objective Dynamic Vehicle Routing Problem (M-DVRP) should be divided into many DVRP with smaller size depending on the degree of dynamism.

The solution of M-DVRP is reached by combining the solutions of all DVRP in many time seed.

f- *PSO_DREAM+SIFT: Particle Swarm Optimization_ Distance Effect Routing Algorithm for Mobility + Simple Forwarding over Trajectory*

To get a protocol with effective performance, (k.D .kalambe & al, 2015) [19] suggested the combination of the reactive protocol SIFT and the location based routing protocol DREAM.

Also to improve the efficiency of this hybrid model within large scale network as VANET, the PSO technique is used to skip the problem of centralized control.

g- *GeoPSO: Geocasting trough Particle Swarm Optimization*

In order to improve the quality of the selected next hop vehicle (NHV), (Omprakash & Sushil, 2014) [20] used PSO to optimize the constraints related with the selection of NHV.

Indeed, any particle is designed by a point of right semi-circle of transmission range, and the fitness function Q_{NHV} of each candidate solution is calculated as

$$Qnhv(\hat{P}\text{x,y}, \hat{S}, \hat{D}) = \varphi 1LD + \varphi 2PD - \varphi 3NL - \varphi 4ED - \varphi 5TP - \varphi 6HC \qquad (4)$$

Where $\varphi i,\ i = 1, 2, \dots 6$ represents the respective weights for

- LD: Link Disconnection probability.
- PD: Packet Delivery.
- ND: Network Load.
- ED: End-to-End delay.
- TP: Throughput.
- HC: Hop-Count.

The simulation shows that GeoPSO performs well than other techniques in the selection of NHV (peripheral node based NHV, voronoi diagram based NHV…) in terms of packet delivery and network load.

h- *PBPC: Particle swarm optimization Beacon Power Control*

For VANET environment, especially in dense situation, the large amount of safety messages exchanged between vehicles increases the collision in channel. [21], [22], [23].

To deal with this problem and to ensure an efficient channel management, (Ghassan&Tarek, 2013) [24] proposed PBPC as a transmission power control technique for safety message.

In PBPC, the dynamic control of beacon transmission power leads to reduce the collision of beacon packet. This decrease of collision makes the transmission channel fully used for safety message.

The lowering made in PSO algorithm depends on the parameters taken from the Active Beacon list (ABL) which contains all information of neighboring vehicle.

i- *DA-PSO: Data Aggregation for Vehicular Ad-hoc Network using Particle Swarm Optimization.*

The collection and the expression of data in a summary forms is known as “Data Aggregation”. This process has a great importance and can be defined as a general tool which manage data base complexity and enhance the performance benefits.

In [25], authors formulated the data aggregation for vehicular network as a multi-objective optimization problem that can be resolved using PSO.

The swarm population (N particles) randomly initialized will be updated through an iterative process according to the fitness function defined below:

$$fitness = \frac{IS}{IR}\,(transmission\ time * n) \qquad (5)$$

- IS: Information Similarity.
- IR: Information Loss.

Indeed, the success of DA-PSO depends on its capacity to find the best compromise between the two conflicting objectives (maximize the aggregation accuracy and minimize the delivery time).

B. Using Genetic Algorithm (GA) for VANET

Genetic algorithms are inspired from the evolution of species. Some individuals might adapt and evolve over time inheriting their characteristics to their offspring’s, the others will disappear gradually. [26].

Indeed, the GA is a polynomial time algorithm designed to find the best solution for any hard optimization problem without an exact algorithm. [27]. To improve the quality of individuals, genetic algorithm evolves an initial population for a predetermined number of iterations. At each one, a set of individuals will be eliminated from the population and others will be inserted to find the best feasible solution.

Five steps resume the GA process.

1. The creation of the initial population.
2. The evaluation of individuals.
3. The creation of new individuals by selection, crossover and mutation.
4. The insertion of new individuals within population.
5. Reiteration of the process.

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a- *Roadside Unit Deployment for Information Dissemination in a VANET: An Evolutionary Approach*

To get an accurate, fast and timely data dissemination, an efficient model that calculates the necessary number of road side units (RSUs) and defines their locations has to be developed.
In [28], (Evellyn S. Cavalcante & al, 2012), tried to find the best deployment of RSU in order to cover the largest possible number of cars.
To achieve this goal, the proposed model contains two phases:

- Formulating the problem of deployment as a Coverage Maximization Problem with threshold (MCTTP).
- Resolving this optimization problem using genetic algorithm.

b- *A Genetic Algorithm-Based Sparse Coverage Over Urban VANETs.*

To monitor and to manage the road traffic in urban VANET, the described approach in [29] contains three phases.

- For any given region the road network is clustered into various hotspots according to coverage value metric.
- Buffering operation is launched to define the deployment location of candidates based on geometry.
- The problem of Budgeted Sparse Coverage (BSC) for the road network is transformed to a maximization problem which can be resolved using genetic algorithm.

c- *A genetic algorithm for management data stream in VANET*

To overcome the data flow challenges in transportation system, several dissemination approaches are developed recently [30], [31].
Wherefore, (s. Raghay & al, 2011), [32] used genetic algorithm to determinate the appropriate number of vehicles able to generate cognition from gathered data. This model minimizes the consumption of bandwidth by decreasing the number of cars involved in generating and transporting data.

d- *Data Aggregation and Roadside Unit Placement for a VANET Traffic Information System*

Data aggregation is a fundamental challenge in vehicular ad hoc networks. To overcome this problem and to minimize the overall bandwidth used, (C. Lochert & al, 2008) [33] developed an optimized strategy based on GA to an aggregation scheme and to specify the best possible solutions for supporting units.
To achieve the navigation system, two steps are needed:

- Developing an aggregation scheme based on Hierarchical aggregation and Landmark routing.
- Using GA to evaluate the number and the placement of supporting units.

e- *An Intelligent Routing Protocol for Delay Tolerant Networks Using Genetic Algorithm*

In urban area where sub-networks are sparse, there is an urgent need to efficiently select the best vehicle able to carry data from one portion to another.
[S.A. Bitaghsir & al, 2011) [34] suggested an intelligent protocol based on genetic algorithm to cope with Delay Tolerant Network in urban environment.
To overcome the failure of the two traditional modes of forwarding (greedy forwarding, perimeter forwarding) in disconnected and sparse networks, the proposed protocol integrated DTN forwarding as a third mode to select the best DTN node.
The genetic algorithm is used to calculate the impact of each parameter in selecting the DTN node.

f- *An Improved Genetic Based Routing Protocol for VANETs*

Finding the best path with minimum delay from source to destination is a fundamental routing problem in vehicular networks.
Since GA is an effective technique to generate the shortest path between two nodes [35], (dicvaya & al, 2014), [36], proposed genetic based routing protocol to minimize the lateness from source to destination using routing tree and spanning tree.
This approach contains three phases:

- Applying Genetic Algorithm: GA is launched with a random population to find the best path from source node to destination and to construct the matrix weight containing fitness value of each node.
- Spanning Tree: According to the matrix generated above, the spanning tree is created to drop links which cause loop.
- Routing tree: In this phase, each link of the spanning tree is transformed to a node of routing tree.

g- *A Multi-Objectif Genetic Algorithm-Based Adaptive Weighted Clustering Protocol in VANET*

Clustering topology are applied to devise large network into smaller parts more stable [37], [38].
To improve the stability in vehicular network (Haddad &all, 2015) [39], exploit the geographic information of nodes to develop an Adaptive Weighted Clustering Protocol (AWCP).
The refinement of the proposed protocol is divided into three phases:

- Based on the known Weighted Clustering Algorithm (WCA), the clustering protocol (AWCP) is created.
- An optimization Multi Objective Problem is defined with AWCP's as an input.
- The defined MOPB is addressed by the Non dominated Sorted Genetic Algorithm II to decrease cluster overhead and increase the data delivery rate. In this contribution, two vehicles are considered as neighbors only if they have the same direction on the same highway.

h- *Improved AODV routing protocol for mitigating effects of Grayhole Attack in VANET using Genetic Algorithm*

The Gray hole Attack (pack drop attack), is a special case of denial service where malicious node pretends like normal one and starts dropping packet partially[40], [41]. In last few years, various security mechanisms are developed to prevent attack in vehicular network, [42], and [43].

In [44], (Gurleen & al, 2015) used GA to decrease the harm caused by gray hole attack on AODV routing protocol.
After creating initial population, the mutation value depends on the fitness function. Indeed, if the current feature set of the considered node is greater than its fit value then this node will be considered as gray hole one.

i- Generation of Realistic Mobility for VANETs Using Genetic Algorithms

The simulation is a set of computer calculations that replicates a physical phenomenon. It provides results close to reality without any human risk or material damage. [45]. Also, in any simulation, the more realistic inputs we have the more reliable outcomes we get. [46].
The VeHIlux model is able to generate realistic vehicular traces depending on two inputs: Map topology and basic traffic volume counts. [47].
In [48], considering those inputs, an optimization problem is formulated to find the parameters of VeHIlux. Also to provide realistic vehicular traces, (Marcin & al, 2012) used genetic algorithm to tune the parameters of this model.

C. Using Ant Colony Optimization (ACO) for VANET

Ant Colony Algorithms are a class of metaheuristics, inspired from the collective behavior of ants to solve NP-hard problems. The ants communicate with each other indirectly through the pheromones that deposit in their progression. Then, depending on the amount of pheromone previously deposited, the best directions to be followed are preferred and the others are ignored. [49]. Eight steps describe the behavior of ants to find the shortest path:

1. An ant randomly scans the surroundings of the colony.
2. When it finds a food source, the ant returns to the nest by dropping pheromones on its way back.
3. The ants that are close will follow more or less directly this path.
4. Returning to the nest, these ants will strengthen the path dropping more pheromones.
5. If there are two paths to reach the same food source, then, most ants follow the shortest path containing more pheromones.
6. The shortest path will be increasingly strengthened to be more attractive.
7. The longest path will disappear because the pheromone will evaporate.
8. Finally, the ants have succeeded in identifying and selecting the shortest path.

a- Mobility-aware Ant Colony Optimization Routing for Vehicular Ad Hoc Networks

In order to get a suitable model for vehicular ad-hoc network, (Correia& al, 2011) [50] tried to enhance the performance of the reactive protocol DYMO by recourse to the Ant Colony Optimization.
The proposed protocol (ACO-DYMO) contains two phases:

- Integrating additional information (position, speed …) into the Hello message of the DYMO protocol. This taskallowseach vehicle to predict the position of their neighbors at a given time t, also the hello message will be sent only when needed.
- Selecting the best path from the routing table according to its pheromone level, this is measured by the application of the two mechanisms of ACO (pheromone deposit and pheromone evaporation).

b- Routing Algorithm for Vehicular Ad Hoc Network Based on Dynamic Ant Colony Optimization

To mitigate the bad impact of environment's change in vehicular networks, (A.M. Orani & al, 2016) [51] proposed a new routing algorithm by coupling the DYMO protocol and the Ant Colony Optimization.
This model used the two mechanisms (Explorer Ant and Search ant) to create the path which connects it to the source, and to find the specific destination.
The RREQ of DYMO is improved by the use of a new search strategy that takes into account the quantity of pheromone in each path. Finally, the discovered path is evaluated and selected according to its reliability and its delay time.

c- QoS realization for routing protocol on VANETs using combinatorial optimization

In vehicular networks, the Quality of Service (QoS) is a measure based on several criteria (bandwidth, jitter, delay, packet delivery ratio…). This aspect is used to evaluate the performance of any given protocol. [52].
Also, to improve the QoS of the Ad hoc on Demand Vector routing protocol (AODV), (Uday & al, 2013) [53], tried to find the best parameter configuration through two steps

1. Applying ACO to fine tune the network layer of AODV.
2. Simulating the optimized AODV given in step1.

d- Application of Ant Colony Optimized Routing Algorithm Based on Evolving Graph Model In VANETs

The ACO-EG model of (Xueyarg & al, 2014) [54] is based on the use of both Evolving Graph (EG) and ACO as a solution for the network congestion and the frequent change in VANET topology.
When vehicles are occupied with GPS and wireless transceivers, their movements can be predicted, consequently the EG offers dynamic behavior of mobile network.
The predictable proposed algorithm can be customized into three parts:

1. Forward-ant: it generated periodically along all journeys and answerable to check the delay and the bandwidth of the journey.
2. Backward-ant: it propagates the pheromone into the routing table when coming to source via the opposite direction of the same path created by its corresponding forward-ant.
3. Routing table and packet forwarding: this table has to be maintained and updated by any node itself.

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e- *A Heuristic Algorithm Based on Ant Colony Optimization for Multi-objective Routing in Vehicle Ad Hoc Networks*

Routing in vehicular networks can be formulated as an optimization problem looking for the best path among all feasible solutions.
In [55], based on the popular ant colony optimization technique, authors tried to find the shortest path which ensures low disconnections.
Furthermore, to overcome the problem of having obstacles in VANET which adversely affects the communication between vehicles, (Rodrigo & al, 2013) used the enhancement of AntSensor algorithm proposed by Cunha [56] as a solution to find an alternative route.
The AntRS model is a heuristic multi-objective routing algorithm based on ACO, it contains two basic steps:

1. Finding all neighbors of each vehicle in the network.
2. Selecting the best route according to its level of pheromone, its number of hops, and the Euclidean distance between vehicles.

f- *Network Routing Using Zone Based Ant Colony Optimization in VANET*

To get a scalable protocol, robust to link failure and able to exploit the bandwidth efficiently, (Afna &al, 2015), [57] developed a hybrid multi-path Ant Colony routing algorithm that contains three phases:

1. Dividing the network into various zones, each vehicle must belong to one or two zones maximum.
2. Using proactive approach within zones and reactive approach between zones.
3. Developing a multi-path algorithm based on extra information (density, velocity, movement pattern of vehicles …) to select the shortest path.

g-*A trust based clustering with Ant Colony Routing in VANET*

To develop a convenient routing approach that is able to overcome critical issues in VANET, (Rashmi & al, 2012) [58] used the Ant Colony technique based on Trust.
At the beginning of this model, two basic algorithms are proposed to successfully create clusters and to elate the suited cluster head.Three processes resume this model:

1. Cluster formation: to join a given cluster, the vehicle must have the same direction of all other one belonging to this cluster, and their speed should be equal or less than the given sill value (Sth).
2. Cluster head selection : If the cluster contains a Road Side Unit, then the cluster head is that RSU,

Else the elated node should:

- Be a normal node,
- Be the slowest in the cluster,
- Have the greatest Trust value.

3. Ant Colony process: to establish the best path from source to destination, the malicious vehicle must be detected and their transmitted message should be removed from the network.

h- *Improving Vehicular Ad-Hoc Network Stability Using Meta-Heuristic Algorithms*

According to (M. fathian & al, 2014) in [59], the coupling of clustering technique and the Ant Colony System can be an efficient model to improve the stability in vehicular network.
The (ACS-BASED) algorithm includes five processes triggered after the initialization and the creation of clusters:
Process 1: Dividing clusters into sub-clusters,
Process 2: Affecting vehicles and objects into appropriate sub-clusters through the pheromone consistency,
Process 3: Merging clusters that have high similarity,
Process 4: Removing the great dissimilarity within each sub-cluster,
Process 5: Vehicle with minimum distance from Dmean (Tn) is selected as a cluster head.

i- *Cluster Based Ant Colony Optimization Routing For Vehicular Ad Hoc Networks*

In [60], (Balaji & al, 2013), combined clustering approach and ant colony optimization to invent and estimate bio-inspired procedure in urban VANET.In that model the needed information (vehicle's speed and position) are obtained by applying Kitnetic Graph Framework [61].

III. Comparative study

As mentioned above, more than 90% of researchers used metaheuristics based population to enhance the performance of well-known routing protocols.Hence, our comparison is made based on the main contribution, advantages and disadvantages of each approach in several scenarios (Table1, 2, 3).
Furthermore, a careful comparison is performed according to the most popular performances metrics. [62], [63].

A. Performance metrics

- **End-to-end Delay:**

The needed time to send packet from source to destination.
∑ (arrive time – send time) / ∑ Number of connections.

- **Packet delivery ratio:**

The ratio of delivered data packet to the destination.
∑ Number of packet received / ∑ Number of packet sent.

- **Network load:**

The total traffic received and transmitted within the network.

- **Bandwidth:**

The amount of data that can be sent through network.

B. Heuristic contributions for VANET routing

The given section has been designed to compare the effectiveness of various contributions based heuristics to improve the routing problem in vehicular network.

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Notation: +: Suitable, N/A: Not Available, - Not suitable.

TABLE I. THE USE OF PSO FOR VANET ROUTING.

Technique	Contribution	Algorithm	Mobility Model	Performance Metrics				Pros	Cons	Simulator
				E2ED	Net Load	PDR	BW			
Particle Swarm Optimization	Selecting the best Next Hop Vehicle.[20].	Geocast Protocol	Urban	N/A	+	+	N/A	Efficient in sparse environment.	Heavily influenced by link failure.	NS2
	Adjusting the OLSR parameters.[12].	M-OLSR	Urban	+	N/A	+	+	Makes network more stable.	Peer with high mobility.	NS2
	Dynamic control of beacon transmission power.[24]		Highway	N/A	+	N/A	+	Efficient use of the transmission channel.	Large dependance on the informations taken from the ABL.	Matlab
	Optimizing the data aggregation in VANET scenario. [25].		Downtown	+	+	+	N/A	Fast convergence toward optimal solution.	Minimizing the delivery time reduces the aggregation accuracy.	NS2
	Obviating the centralized control.[19].	SIFT + DREAM	Urban	+	+	N/A	+	Suitable for large scale network.	Small decrease in energy consumption.	NS2
	Tuning the parameters of OLSR protocol.[13].	OLSR	highway	+	+	+	N/A	Fast convergence toward optimal solution.	Less effective in large network.	NS2
	Finding the best parameters configuration of DSDV protocol.[16].	DSDV	Urban	+	+	+	N/A	Significant improvement of the QoS of DSDV.	No rules for determining the values of w1, w2 and w3.	NS2
	Dividing the M-DVRP into many DVRP with smaller size.[18].		Urban	+	+	N/A	+	Efficient even in dense case.	Largely influenced by the degree of dynamism	NS2
	Tuning the DSDV routing protocol parameters.[17].	AOMDV	Urban	+	+	+	N/A	Significant improvement in term of E2ED.	Drop in PDR in case of large map.	NS2

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TABLE II. THE USE OF GA FOR VANET ROUTING.

Technique	Contribution	Algorithm	Mobility Model	Performance Metrics				Pros	Cons	Simulator
				E2ED	Net Load	PDR	BW			
Genetic Algorithm	Adjusting the VeHIlux parameters to generate a realistic vehicular traces. [48].	VeHIlux model	Real case study	N/A	N/A	N/A	N/A	Efficient to provide realistic road traces	Limited effectiveness in rush hours.	NS3
	Minimizing the lateness using GA, spanning tree and routing tree.[35].	AODV MAODV	Highway	+	N/A	+	N/A	Convenient to find the best path between two nodes	Less effective in dense case	NS2
	Reducing number of vehicles used to generate cognition from gathered data.[32].		Urban	+	+	+	+	Performs best in case of diffusion	The choice of the effect parameters is not obvious	N/A
	Finding the optimal RSU deployment. [29].		Urban	+	N/A	N/A	+	Ensure a high network connectivity.	Sharp fall in coverage area when number of RSU decrease	NS2
	Minimizing the harm caused by Gray Hole Attack.[44].	AODV	Downtown	+	+	+	N/A	Prevent propagation of malicious message	Slight improvement in term of Bit Error Rate	Matlab
	Designing a new clustering protocol AWCP. [39].		highway	+	N/A	+	N/A	High stability of network	Not efficient in dense case	Ns2
	Optimizing the RSU deployment. [33].		Urban	N/A	+	+	+	Best deployment for supporting unit	Model tested for small environment	N/A
	Optimizing the number and the locations of the RSU. [28].		Urban	+	+	+	N/A	Significant improvement in vehicle coverage	Less efficient in very large scale network.	VISSIM
	Finding the best vehicle to carry and forward data from one part to another. [34].	GeoDTN + N/AV	Urban	+	N/A	+	N/A	Efficient for delay tolerant network		NS2

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TABLE III. THE USE OF ACO FOR VANET ROUTING.

Technique	Contribution	Algorithm	Mobility Model	Performance Metrics E2ED	Net Load	PDR	BW	Pros	Cons	Simulator
Ant Colony Optimization	Improving the efficiency of the DYMO protocol. [50].	DYMO	Urban	+	+	+	N/A	Effective to reduce the congestion within the network.	Generates more control traffic.	NS2
	Developing a multipath algorithm (MAZACORNET) to reduce broadcasting and congestion.[57]	AODV	Urban	N/A	+	+	+	Provide an effective use of bandwidth.	Less suitable for sparse environment.	NS2
	Improving the DYMO protocol to cope with the environment changes. [51].	DYMO	Urban	+	+	+	N/A	Able to face the problem of environments changing.	Less effective in dense environment.	NS2
	Minimizing network disconnectivity. [55].	Ant Sensor Algorithm	Urban	N/A	+	+	N/A	Ensures low disconnectivity even in high mobility.	Needsmore processing time which affect adeversely the E2ED.	C++
	Providing a new optimization strategy for AODV protocol.[53].	AODV	Highway	+	+	+	N/A	Efficient in dense case.	Not checked with real scenario.	NS2
	Ensure best commitment between Evolving Graph and ACO to improve the network communication. [54].		Highway	+	+	+	N/A	Rapid response to frequent topology change.	Some packets have to wait for a long time in transmit queue.	OpNet
	Efficient clustering with best election of cluster head. [58].		Highway	+	+	+	N/A	Ensure efficient communication in VANET scenario.	Less efficient when there is a large number of cluster.	N/A
	Fast and efficient clustering.[59]		Urban	N/A	+	+	N/A	Provide stable network.	Needs more processing time in dense scenario.	N/A
	Getting needed information for clustering based on kitnetic framework and ACO. [60].	DYMO	Urban	+	N/A	+	N/A	Convenient for urban scenario.	Doesn’t take into account proactive phase routing.	NS2

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TABLE IV. SUCCESS RATE OF HEURISTIC APPROACHES.

	E2ED	Net Load	PDR	BW
PSO	0.75	0.63	0.50	0.38
GA	0.67	0.44	0.67	0.44
ACO	0.78	0.67	1.00	0.11

As shown in table 4, the ACO achieved the highest rate in three performance metrics.
Indeed, 78% of contributions succeeded to minimize the needed time to deliver packet from sender to receiver (E2ED); 67% of contributions permit to lighten the network load, and all contributions are effective to prevent the data loss. Also it is clear that reaching such success was at the expense of bandwidth.

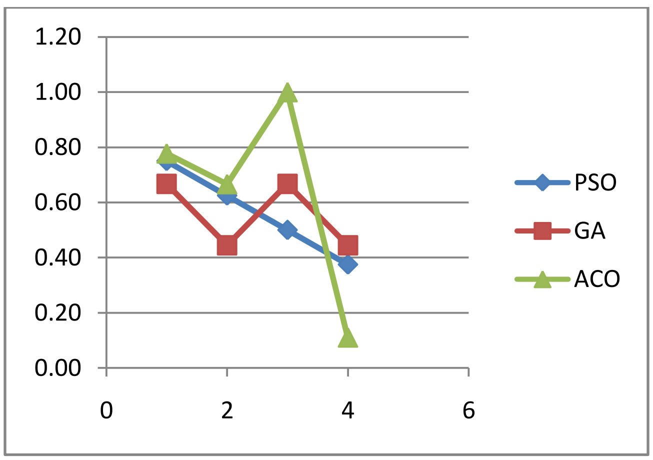

Fig.2. Comparison of heuristic approaches

"Fig.2" displays the efficacy of each approach over various performance metrics; it is clear that ant colony optimization is more appropriate to improve all metrics especially for dense scenario. This is because the pheromone density increases with the rise in the number of node. Indeed, ACO gives a realistic model based on both AODV and DYMO routing protocol.
On the other hand, the genetic algorithm is considered less efficient especially in dense case with the presence of obstacles. Except this, all heuristics based population are very efficient to improve VANET protocol and their performance is very close.

C. Heuristics performance over different scenarios

In this section, we compare the performance of each heuristic approach (PSO, GA, ACO) in urban and highway scenario.
Table 5and 6 show the rate of contributions that have managed to improve the various performance metrics.
Indeed, for any performance metric, higher value indicates better performance.

1)Urban scenario:

TABLE V. PERFORMANCE RATES IN URBAN SCENARIO

Heuristic	Performance metrics			
	E2ED	Net Load	PDR	BW
PSO	0.83	0.83	0.67	0.5
GA	0.8	0.6	0.8	0.6
ACO	0.5	0.83	1	0.17

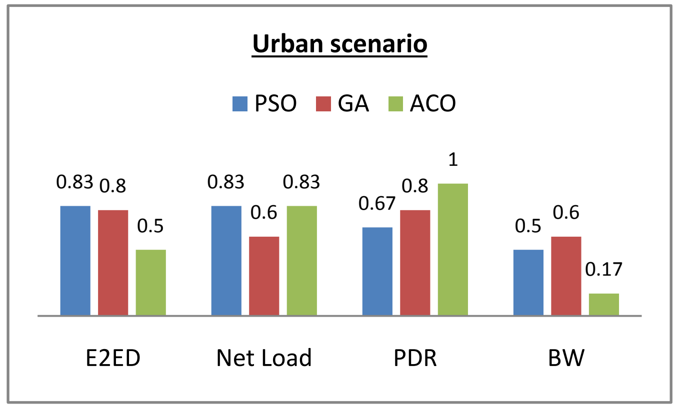

Fig.3. Heuristic performances in urban scenario

It is shown in "Fig. 3" that the use of heuristic approaches in VANET routing improves all performance metrics with the exception of bandwidth.This weakness is due to the density of vehicles in urban environments where the rational use of channel becomes the most significant challenge.For instance, we found out that 17% of contributions based on ACO had improved the bandwidth compared to 83 % failed to do it.

2) Highway scenario

TABLE VI. PERFORMANCE RATES IN HIGHWAY SCENARIO

Heuristic	Performance metrics			
	E2ED	Net Load	PDR	BW
PSO	0.5	1	0.5	0.5
GA	1	0	1	0
ACO	1	1	1	0

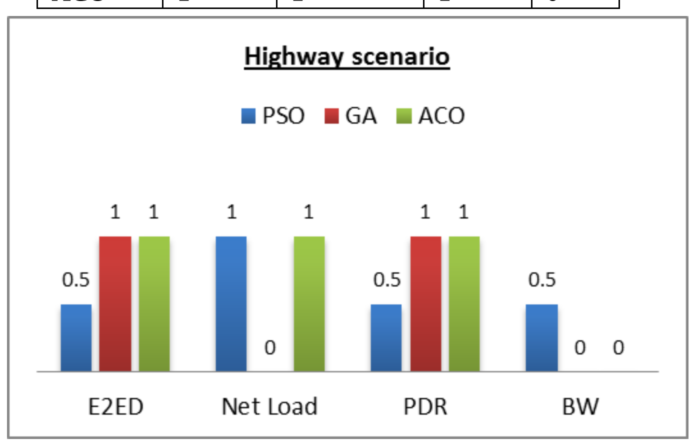

Fig.4. Heuristic performances in highway scenario

From the graph in "Fig. 4", we notice that the GA approach is the less appropriate under highway scenario. Also, in spite of the high performance of the ACO approach, it failed to get an effective use of the bandwidth.

We can come to a conclusion that:

- In highway scenario, where the density is low, the bandwidth is a flexible constraint which does not affect the quality of the solution. Wherefore, most contributions give a high priority to improve each of E2ED, network load and PDR
- In urban scenario, with high density, the bandwidth becomes a hard constraint that must be satisfied to avoid the network congestion and to reach a feasible solution.

IV. Future trends

As a result of the exponential growth in number of vehicles over the years, vehicular ad hoc networks received considerable momentum.

Thence, both researchers and car companies tried to provide an Intelligent Transportation System (ITS) able to improve comfort applications and road safety.

On the other hand, and due to the revolution in communication technology, there are still some possible futuristic trends that can be studied as follows:

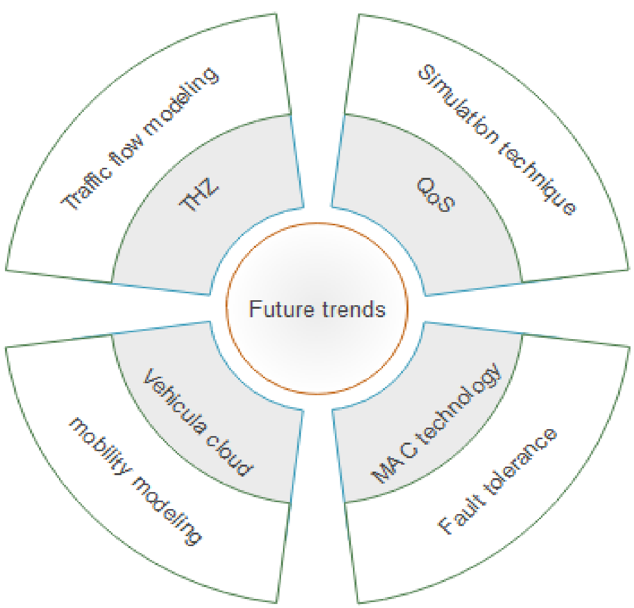

Fig. 5. Futur trends.

a. Mobility modeling

The high mobility of vehicles adversely affects the connectivity and decreases links life time. Thence more efforts are required to provide an effective mobility model able to overcome this challenge. [64].

b. Traffic flow modeling

To efficiently manage traffic in vehicular network, it is necessary to design a new model which takes into account traffic flow variability. The proposed model should be able to automatically interact with any unexpected transition from one environment to another.

c. MAC technology

To provide a more robust MAC layer within high speed vehicular scenario, the tendency is toward the use of the Dedicated Short-Range Communications technology (DSRC)

d. Simulation technique

In VANET, the experimental evaluation is very expensive; therefore providing an accurate simulator valuable for all scenarios is a persistent need.

e. Quality of service (QoS)

To provide an efficient safety system with high QoS, many problems related to coverage, forwarding and latency should be addressed.[65], [66].

f. Fault tolerance

In vehicular network, sudden malfunction of any vehicle may cause a fault in the whole system. So, future models have to consider that question:"How to design for fault tolerance?"

g. Vehicular cloud

Regarding the great advantages offered by cloud, it would be very beneficial to implement cloud computing in vehicular network.

h. THz for Vehicular Communication Networks

In a dense vehicular network, and with current wireless communication systems, the available frequencies become saturated and limited in capacity.

Thus, it becomes imperative to use the new THZ technology, which is very useful for many applications, especially in telecommunications to satisfy the increasing demand for higher speed wireless communication. [67].

V. Conclusion

In the last few years, there is an enormous potential worldwide for increase in vehicle use. Thus, developing an intelligent transportation system that support both safe driving and comfort application has received much attention for the automotive industry and government agencies. To reach this goal and to overcome the VANET challenges, many metaheuristics approaches have been used. Hence, this paper provides a comprehensive survey on the main uses of these methods with the challenges faced by VANET.

In this study, we have summarized the main contribution given by the most popular approaches which include Particle Swarm Optimization, Genetic Algorithm and Ant Colony Optimization.

A comparative study was presented to list the advantages and the disadvantages of those approaches based on four performance metrics (E2ED, PDR, Net Load, and Bandwidth).Thus, we recommend that heuristic approaches can effectively improve the performance of any routing protocol especially for VANET.

As a future scope, we have to check the effectiveness of each approach by a significant simulation on real case study.

Finally, although routing in vehicular network has a significant attention in recent years, providing an adaptive and reliable routing in VANET is still an open issue of research with many challenges.

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