Journal of Information Systems Engineering and Management
2025, 10(25s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

An Innovative Router Method for Ad-hoc Vehicle Networks Employing Ant Colony Optimization

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ARTICLE INFO

Received: 02 Jan 2025

Revised: 22 Feb 2025

Accepted: 02 Mar 2025

ABSTRACT

Providing high-quality service is one of the biggest issues faced by Vehicular Ad hoc Networks (VANETs). These networks support a variety of Vehicle-to-Everything (V2X) communication modalities and enable automobiles to send and receive crucial data, such as road impediments and accidents. This investigation intends to minimize network overhead and promote routing efficiency by offering an ingenious method to enhance path selection between vehicles and raise service excellence. The Optimized Link State Routing (OLSR) protocol combines Ant Colony Optimization (ACO) through the proposed technique. Through implementation and simulation studies using the network simulator (NS3) and Simulation of Urban Mobility (SUMO), the efficacy of the above approach is verified. The suggested approach surpasses the conventional OLSR algorithm with regard to of throughput, end-to-end delay (E2ED), and average packet delivery rate (PDR), and other indicators, in accordance with simulation data.

Keywords: Ant Colony Optimization, Artificial intelligence, The Optimized Link State Routing, Routing, Vehicular Adhoc Network.

INTRODUCTION

The Internet of Vehicles (IoV) topic has been receiving a lot of scientific attention because it focuses on employing Vehicular Ad hoc Networks (VANETs) to enhance safety in urban environments. High vehicle mobility and swiftly fluctuating network topologies describe this most recent kind, which is a specific subset of Mobile Ad hoc Networks (MANETs). Throughout VANETs, automobiles interact with base stations and other automobiles. Numerous routes have been suggested to reach a destination, one and all vehicle keeps a table for routing with information of traffic for specific paths. An algorithm known as routing is used to choose the best route. Our goal in this research is to improve the VANETs' quality of service through the implementation of an efficient routing algorithm. We incorporate an (AI) artificial intelligence algorithm—more accurately, a (SI) swarm intelligence algorithm—to do this. We incorporate an artificial intelligence (AI) (1) algorithm—more precisely, a swarm intelligence (SI) algorithm—to do this. Swarm intelligence, a prevalent technique in Artificial Intelligence (1), includes many optimization algorithms such as Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) (2).

ACO (3) is a bio-inspired metaheuristic approach that draws inspiration from the behavior of ants. It is a probabilistic search algorithm commonly used to address the route selection problem (4). Applying ACO, one could search for the best remedies regarding specific optimization issues in the larger context of automotive routing issues. Its adaptability to dynamic changes in topology and ability to ensure Quality of Service (QoS) make ACO particularly wellsuited for MANETs (5).

Different type of three topology-based routing protocols exist in Moblie Adhoc Network: proactive, reactive, and hybrid protocols. The routing technique used distinguishes these groups from one another. Table-driven protocols, another name for proactive routing techniques, need a general grasp of the network architecture. Routing tables are built beforehand, even prior to a request for packet delivery. Reactive routing protocols, also known as on-demand protocols, don't depend on any prior understanding of the network structure, in contrast to proactive protocols. Construction of the routing table proceeds dynamically in response to a node's request. Proactive and reactive routing strategies' techniques are combined in hybrid routing protocols.

In this paper, our focus will be on proactive routing, specifically the Optimized Link State Routing (OLSR) protocol (6). OLSR is recognized as an intelligent routing protocol recommended for use in VANETs (7).

This paper's primary goal is to present OLSRACO, an intelligent approach for choosing the best route in a vehicle network. This approach combines a swarm intelligence methodology known as Ant Colony Optimization (ACO) with the Optimized Link State Routing (OLSR) protocol.

OLSRACO protocol makes use of OLSR's ability to identify one-hop and two-hop companions and to compile an extensive topology picture of the network. The approach can extract important network structure information by using OLSR. The ACO algorithm is utilized to ascertain the most advantageous route. ACO is selected because of its benefits in terms of resilience, scalability, and low cost. A realistic and effective routing selection that takes inside consideration the evolving attribute of mobile vehicle networks is provided by this swarm intelligence-based algorithm. The OLSRACO methodology seeks to enhance the efficacy and efficiency of path selection in vehicular networks by merging the advantages of OLSR and ACO, thereby improving the network's overall performance. As mentioned earlier, ACO's intrinsic capacity to adjust to dynamic changes in network topology and preserve Quality of Service (QoS) even in the event of link failures (5) makes it a good fit for MANETs. In this work, we emphasize the main points raised in the following manner.

.**Variable structure Adaptation:** Because of node mobility, MANETs frequently see changes in their network structure. Even in extremely dynamic contexts, the ACO algorithm can provide effective routing by dynamically adjusting the routing pathways depending on real-time input.

• **Resistance to Connection Breakdowns:** MANETs are vulnerable to link failures brought on by node migrations or external circumstances. Because ACO is distributed and adaptable, it can immediately detect and reroute around broken links to minimize disturbances and maintain network connectivity.

• **Restricted Cost and Scalability**: ACO is renowned for having minimal overhead and scalability.

The approach is efficient in terms of processing resources and communication overhead since it is based on probabilistic decision-making and local pheromone updates.

Our research intends to increase the overall performance and reliability of MANETs by utilizing the features of ACO, including its cost-effectiveness, scalability, resistance to link failures, and dynamic flexibility.

The following sums up this work's contributions:

• An Overview of Parallel and current Works: The study offers a thorough analysis and discussion of current developments in the fields of routing protocols and vehicular networks. This aids in defining the study setting and pointing out the gaps that the suggested work seeks to fill.

• Pheromone statistic: To improve the standing of cars in the network, a new statistic called the pheromone is created. When choosing routes, the pheromone metric considers the dependability and behavior of the cars, which helps to provide more precise and effective path selection.

• Incorporation of Ant Colony Optimization (ACO) with the Optimized Link State Routing (OLSR) Protocol: This work suggests incorporating the Ant Colony Optimization (ACO) method into the OLSR protocol. The optimal path is determined using the OLSRACO protocol using the pheromone metric and the dynamic behavior of the network., is made possible by this integration.

• Creation of Simulated Scenario: To assess how well the OLSR and OLSRACO protocols function, a simulated scenario of the Moroccan city of KENITRA is created. For testing and comparison, this scenario offers a realistic setting.
• Routing Mechanism Evaluation: The effectiveness of the OLSR and OLSRACO protocols is compared as to assess the routing process in this research. The investigation is centered on parameters like average packet size and throughput. This assessment aids in determining the efficacy Along with the effectiveness of the suggested OLSRACO procedure.

The paper's leftover data get arranged: A detail of pertinent task and investigation in the areas of routing protocols and vehicular networks is provided in Section 2. It offers a overall analysis of the body of research, stressing the vast and complete result, methodologies, and constraints of earlier investigations. The planned work's methodology is covered in depth in section 3. The conceptual framework, algorithms, and methods used to incorporate the ACO algorithm into the OLSR protocol are covered. The OLSRACO protocol's general architecture, the path selection process, and the application of the pheromone metric are all described. A overview of the specifics of the simulation is given in Section 4. There is a description of the simulations' settings and parameters. Furthermore, the simulation results are examined and presented with special attention to the measurements of overhead, average packet delivery rate (PDR), end-to-end delay (E2ED), and throughput. Section 5 serves as the paper's conclusion and provides a summary of the primary conclusions, contributions, and implications of the suggested study. The potential future directions and advancements in the field of routing protocols and vehicular networks are also highlighted in the conclusion section.

2. RELATED WORKS

An overview of some of the accomplishments mentioned in the literature that inspired this study is given in this section. To solve the trapping issue in local optima, the authors of (8) introduced a novel modified ant colony optimization technique with pheromone mutation (ACOPM). Simulation studies comparing ACOPM with the conventional AODV protocol reveal that ACOPM works better than AODV, demonstrating its improved performance.
An enhanced method for the fuzzy logic-based ACO protocol in VANET was presented by the authors in (9). The NS-2 network simulator was used to run simulations in order to assess the proposed protocol, F-Ant. The findings show that when compared to more established routing algorithms like ACO and AODV, F-Ant performs better in terms of Packet Delivery Ratio (PDR) and End-to-End Delay (E2ED).

The authors of the paper (10) presented the use of Ant Colony Optimization (ACO) to solve the routing issue and shorten the journey time for electric cars. The authors showed through simulations that the ACOEVRP (Ant Colony Optimization for Electric Vehicle Routing Problem) method they presented is a practical means of producing routes that maximize energy use. The findings suggest that the ACOEVRP method may save trip times by increasing energy efficiency in electric vehicle routing.

The developers of (11), which expands upon the ACO-AODV protocol, put forth a unique routing system. SCL-ACO-AODV is the suggested protocol that uses selective cross-layer optimization to solve the vehicular network route selection problem. The goal of the new strategy is to increase route selection efficiency by using the ACO algorithm. The multi-layer architecture put forward in this study optimizes information sharing across the various tiers of the vehicular network in a targeted manner. Enhanced performance and efficiency are made possible by this cross-layer technique, which uses pertinent data from many levels to aid in routing. In both urban and highway situations, simulation studies were carried out to evaluate the effectiveness of SCL-ACO-AODV against a number of other traversal methodology , including CL-AODV, CL-WPR, CO-GPSR, and LAR. According to the simulation findings, the suggested SCL-ACO-AODV protocol performs better than the other protocols in terms of throughput, average latency, packet delivery ratio, and traversal performance. Therefore suggests that in many network settings, the SCL-ACO-AODV protocol offers superior overall performance.
The authors of (12) presented the enhanced hybrid ant colony optimization algorithm (IHACO) in an effort to raise the standard of Intelligent Traffic Systems (ITS) service. Better performance in terms of throughput and other factors is demonstrated by the simulation results, which were generated using the Matlab simulator.

The authors of (13) suggested a method based on a priority-based multipath routing algorithm (PBMRA) for multipath wireless multimedia sensor network (WMSN) QoS optimization. Neighborhood selection, multipath construction, and priority selection are the three modules that make up the suggested algorithm. The algorithm that is being suggested is in comparison to other current methods. In comparison to the other algorithms, the testing findings demonstrate that the Priority Based Multipath Routing Algo methodology improves reception rates of packet and offers a reliable track.

To boost vehicular network performance, the authors of (14), introduced an enhanced hybrid ant colony optimization routing protocol (EHACORP). Compared to current protocols, EHACORP has a number of benefits, such as quicker packet processing, quicker convergence, higher throughput, and better PDR. According to the simulation findings, EHACORP performs better than the other protocols in a number situations

The authors of (15) suggested a technique that uses the OLSR protocol in conjunction with an artificial neural network (ANN) to improve PDR. The Routing Overhead Ratio (ROR), E2ED, Energy Consumption (EC), and PDR were among the performance metrics tested in the simulation, which was run using the MATLAB simulator. The ANN-based OLSR protocol successfully extends lifespan of network, lowers Consumption of energy, and raises PDR, according to the simulation findings.The authors of (16) suggested expanding the OLSR protocol to include multiple pathways in a heterogeneous ad hoc network made up of MANET, VANET, and FANET devices (MHAR OLSR). Node identification, path calculation, path categorization, and path selection are among the new functions made possible by this new protocol. Performance enhancement (PDR, E2ED, and energy usage) is demonstrated by the experimental findings utilizing NS-3 and BonnMotion.

In order to address the routing issue in an ad hoc network with forty nodes, the authors of (17) proposed a novel method for incorporating parallelism into the genetic algorithm (GA). The outcomes demonstrate the higher caliber of solutions for 40 nodes. Conversely, one of this approach's limitations is whether it can be applied in a highly mobile network with a lot of nodes and frequent topology changes. "Table 1" provides an overview of the current ACO-based activities.

METHODOLOGY

In this research, we offer an OLSR protocol and ACO algorithm based solution to improve routing quality in VANETs. The goal is to enhance the network's overall performance by determining the best route between a source and a destination vehicle. Using the Optimized Link State Routing methodology with Ant Colony Optimization (OLSRACO) to maximize VANET efficiency is the suggested remedy. The OLSR routing protocol is described in depth and the ACO algorithm is explained in detail in the next subsections. Then, we introduce a unique method to improve VANET performance by combining OLSR with ACO.

3.1 Optimized Link State Routing

In the RFC3626 draft, the IETF MANET working group standardised the the Optimized Link State Routing methodology, a proactive topology-based routing technology that was created on INRIA. By expanding upon the established link-state approach and adding the notion of MultiPoint Relays (MPRs), this protocol seeks to minimize the overhead in ad hoc networks.

The Destination Node Address (R dest addr), Next Hop Node Address (R next addr), Distance (R dist), and Interface Address (R iface addr) are among the data that each node in the OLSR protocol keeps track of. To maintain the network topology and make routing decisions, these variables are needed.

In the OLSR protocol, the HELLO message exchange between adjacent nodes initiates the routing process. The purpose of these HELLO messages is to locate and connect to nearby nodes. Each node may identify its set of MPRs—a subset of its neighbors—through the exchange of HELLO messages. These neighbors assist in packet forwarding and lower control message overhead.

Generally speaking, by reducing control message overhead and effectively creating and preserving the network topology through the use of MultiPoint Relays, the OLSR protocol enhances the routing process in ad-hoc networks (18)(22).

The OLSR protocol's routing procedure is explained in Algorithm 1. Algorithm 2 talks about how to define MPRs.

Table 1 Current work based on ACO.

The Sources	Working idea	Goal of Paper	Efficiency parameters	Tools used for simulation
1	ACOPM	resolve the local optimum's trapping issue .	Best bargain for fitness, overall success.	TSP Library
2	F-Ant	Display an improved fuzzy logic-based mechanism forVANET.	Packet Delivery Ratio, End to End Delivery .	Network Simulator -2
3	ACOEVRP	Resolve the routing issue and shorten the electric cars' trip time.	TTT:- Total Travel Time, WT:- waiting Time.	reference examples of EVRP
4	SCL-ACO-AODV	Address the route Selection Problem	PDR, throughput, Average Delay, Routing efficiency.	Network Simulator -2
5	IHACO	Raise the standard of intelligent traffic systems' services.	dependability, End to End Delivery, Distance, Throughput.	Matlab
6	PBMRA modified	propose a solution for opti-mizing QoS in WMSN.	Throughput, PDR, delivery delay.	NS3
7	EHACORP	Enhance vehicular network performance.	Throughput, PDR, packet processing, convergence speed.	NS2
8	ANNOLSR	Enhance the PDR in MANET.	Routing Overhead Ratio, E2ED, PDR, Energy Con-sumption.	MATLAB
9	MHAROLSR	OLSR extension featuring new features: identification of nodes, computation of pathways, categorization of paths, and selection of paths.	PDR, E2ED, energy con-sumption.	NS-3 and BonnMo-tion
10	The Genetic Algorithm (GA)	Address the routing issue in an ad-hoc network of 40 nodes.	Mutation Rate, Crossover Rate, Number of Threads.	API

Methodology 1:- Open Link State Routing Process

Provided by: Networking Topology

The result is Calculations for routing tables;

for $(j = 0; j < Nb\ \ Nodes\ MAX; j++)$ do

Identify adjacent nodes ();

Choose the most efficient MPR set ();

Transmit tolplogy Control Broadcast();

Build routing table();

Handle routing operation ();

end Loop

Fig 1 : ACO Methodology Flow chart

Methodolgy 2 Selection Algorithm for Multipoint Relay

```
MPR(s) = ∅;
N1(s)=1-hop neighborhood of s;
N2(s)= 2-hop neighborhood of s;
for ∀ node x ∈ N1(s) do
  if x cover isolated nodes of N2(s) then
    Add node x to MPR(s);
    Update(N1(s) and N2(s));
  end if
end for
for y ∈ N2(s) do
  if y not covered by the selected MPR then
    select y which covers the highest number of non-covered nodes in N2(s);
    Add node y to MPR(s);
    Update(N1(s) and N2(s));
  end if
end for
```

Fig 2 The architecture framework we employ in VANET

3.2 ACO

Different definitions of the ACO have been offered in the literature. ACO is defined by technique referred by ant behavior by its hunt for food resources in the work by Jayalakshmi (19). According to (20), ACO is an intelligent method for locating the best path across a graph.

Pheromones are chemical trails that ants in a colony leave behind and follow to communicate with one another. By placing more pheromones along shorter roads, they entice other ants to follow them and work together to discover the quickest path to food sources. Ants are able to effectively seek and utilize resources in their surroundings because of their collective behavior.

This idea is taken up by the ACO algorithm and used to solve optimization issues. It builds and updates pheromone trails, which indicate the quality of various solution components, iteratively using a virtual ant colony to find the best solution. Higher pheromone values indicate better solutions, and the pheromone trails direct the search. Based on the joint behavior of the simulated ants, the description iteratively converges towards the best solution.

3.3 Proposed Algorithm Description

This work proposes an approach that integrates (ACO) Ant Colony Optimization algorithm to improves,route selection process of the OLSR protocol. The algorithm seeks to achieve two goals: choosing the best path (OP) and maximizing network performance.

As part of the route selection procedure, a new metric known as pheromone (phvalue) is created in order to accomplish this goal. The pheromone concentration connected to a certain route is represented by the phvalue. It is employed to direct the network's ants, which stand in for nodes, along the best route. The ants find the trail more appealing the higher the phvalue. Phvalues are dynamically modified according to the pathways' performance and quality.

The MPR selection method and Dijkstra's shortest path algorithm are combined in the OLSR protocol. The suggested method makes use of the idea of pheromone trails to impact the path selection procedure by including the ACO algorithm. The suggested method seeks to maximize network performance and choose—rather than always using the shortest path—the most ideal one for data transfer. The suggested method is shown in "Fig. 2" below.

Our issue may be formulated as a graph-representative combinatorial optimization problem. The relationships between the cars are shown as edges in this graph, while the vehicles themselves are represented as vertices. G = (V, E) is a notation for the graph in which V stands for the set of vertices and E for the set of edges.

$$Graph\ (G) = \{V, E\} \qquad (1)$$

The result of incorporating the Ant Colony Optimization algorithm into the OLSR protocol is the optimum route (OP). A route is a series of vehicles with the designations V1, V2,..., Vn, where V1 stands for the first inline vehicle and Vn for the destination vehicle.

$$\text{Optimum Route} = \{V_1, V_2, \ldots, V_n\} \qquad (2)$$

Suggested method starts by setting up the different criteria that are needed to choose the best course. τ, α, β, ρ, ζ,N,T and M are some of these values reference . Table 3 contains the detailed meanings of these characteristics. According to this method, every car starts out by sending out hello signals to find other cars in the network. The next step is to send a TC message to acquire a global picture of the topology mentioning the network. A new routing table that includes the pheromone (phvalue) metric is presented to replace the OLSR protocol's basic routing table. The format of this updated routing table, also known as the ACO-OLSR routing table, is as follows (see "Table 2").

Table 2. New routing table.

Dest-vehicle	Neighbor-vehicle	Interface	Distance	phvalue

We first establish the global topological representation, and then we simulate the behavior of an ant, which is a computational agent in the Ant Colony Optimization (ACO) method, on each vehicle. An ant travels around the network, from one vertex to another, within a certain iteration. The ant tracks a pheromone along the edge it passes through during its maneuver. To determine the amount of pheromone that an ant will deposit on a certain edge, utilize equation (3) as a general formula

$$\Delta\tau_{ij} = \frac{Q}{L_{ant}} \qquad (3)$$

Here Δτij is the quantity of pheromone that the ant has left behind on the edge that connects vertices i and j. The quantity of pheromone emitted by each ant is represented by the constant Q, which stands for pheromone deposit factor. The price of the ant's excursion is Lant. Equation "(4)" can be used to illustrate the updating process.

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k} \Delta\tau_{ij}^{k} \qquad (4)$$

The likelihood that an ant will decide to go from vertex I to vertex J is determined by equation (5), which takes into account the pheromone and attraction values of the possible routes. The relative significance of pheromone and attractiveness in the ant's decision-making process is determined by the values of α and β.

$$P_{ij}^{k} = \frac{(\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta})}{\sum_{l \in N_i^k} (\tau_{il}^{\alpha} \cdot \eta_{il}^{\beta})} \tag{5}$$

such as

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{6}$$

Where:

P_{ij}^{k} is the probability of the ant k moving from vertex i to vertex j.

τ_{ij}^{α} represents the total amount of pheromone deposited on the path between vertices i and j raised to the power of α.

η_{ij}^{β} is the value or attractiveness of the path between vertices i and j raised to the power of β.

$\sum_{l \in N_i^k} (\tau_{il}^{\alpha} \cdot \eta_{il}^{\beta})$ represents the sum of the pheromone values multiplied by the attractiveness values of all the neighboring paths of vertex i for ant k.

Algorithm 3 summarizes our proposed approach.

"Table 3" contains all the notations used in this section.

Table 3. Symbols and notations

Symbols	Description
N	Vehicle size
T	Number of iteration
τ	Pheromone initial value
α	Pheromone exponential weight
β	Pheromone heuristic weight
ρ	Evaporate rate
ζ	Scaling parameter
m	Number of discrete value
P^{K}_{ij}	Probability of moving from vehicle i to j
τ_{ij}	Total pheromone deposit by ant on path ij

Algorithm 3 Algorithm of the proposed approach

Input:

$G = \{V, E\}$;

Phase 01 : Parameters Initialized

τ, α, β, ρ, ζ, M, N, T, ;

Phase 02: Discovering neighboring vehicles and topology

Hello-message();

TC-message();

Phase 03: Find the optimal pathfor i=1 to T do

Deposits-pheromone();

Compute probability values of edges of vehicles using equation "(5)";Calculate fitness value of edge;

if Path pheromone value is bigger then

Update the existing path with the new path;

end if

Pheromone-Evaporates();

Update-Pheromone using equation “(4)”;i=i+1;

end for

EXPERIMENTAL RESULTS

4.1 Simulation Setup

The simulation and performance analysis of two routing protocols—OLSR and OLSRACO, or the method suggested in this paper—are shown in this section. The NS3 network simulator was used to carry out the simulations, while the urban mobility simulation program SUMO was used to build the road scenario. The simulation's goal is to assess the suggested algorithm's effectiveness at different vehicle densities. In the simulation, vehicle concentrations of 20, 40, 60, 80, and 100 are taken into account. Vehicles may join and exit the network often because to its dynamic structure and high mobility. The urban setting of KENITRA, Morocco was selected for the simulation, and Open Street Map (OSM) was used to create the map, as shown in Figure 3. The scenario of traffic on the roads produced by SUMO

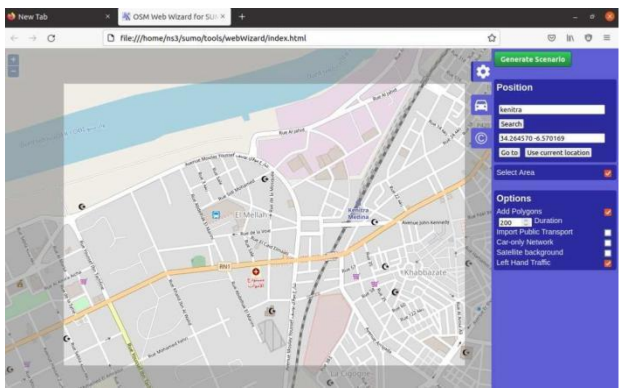

Figure 3. Scenario generated for the region of KENITRA,Morocco.

“Fig. 5” presents in detail the simulation process.

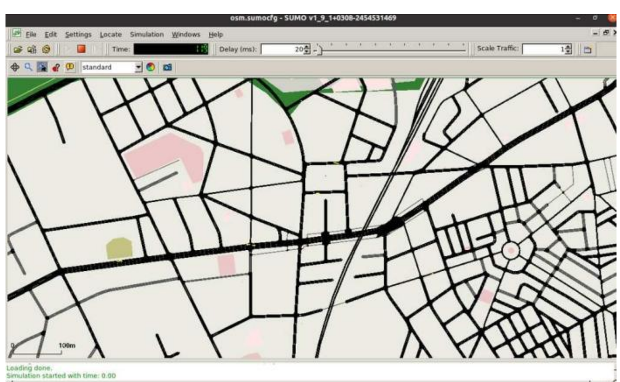

Figure 4. Road traffic scenario generated by SUMO.

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Parameter	*VALUE*
Simulators	NS-3.33, SUMO
Number of Cars	20,40,60,80,100

Node Speed	20 m/s
Routing Protocol	OLSR, OLSRACO
IEEE Scenario	VANET (802.11p)
Mobility Model	Urban Mobility ofKENITRA-Morocco
Simulation time SUMO	200 seconds
Simulation time NS-3.33	100 seconds
Iteration count	10
Number of repetitions for each run	10

Table 4 : The Simulation Parameter used for OLSRACO

4.2 Parameters

Several factors, which are compiled in Table 5, are used to assess how well the OLSR and OLSRACO protocols function in the vehicular network. An overview of the notations used in the performance evaluation is given in the table.

Notation	Signification
P_R	Packet Received
P_S	Packet Sent
PDR	Packet Delivery Ratio
T_L	Duration of data reception
T_F	Duration of data sending
$E2ED$	End-to-End Delay
T_{Delays}	Total Delays
OvH	Overhead
PHY_S	Lower layer data sent
PHY_S	Upper layer data sent
PHY_S	Lower layer data received
NB_{Vh}	Quantity of automobiles

Table 5. Summary of notations.

The quantity of digital data sent in a given length of time is measured by a statistic called throughput. Usually, it is stated in bits per second (bps). A network that is more efficient is indicated by a greater throughput value. Equation (7) illustrates the throughput computation mathematically.

$$Throughput(Kbps) = TotalP_R/(T_L - T_F) \qquad (7)$$

A statistic called the packet delivery ratio (PDR) calculates the proportion of successfully received packets to all packets transmitted. The network routing quality is greater when the PDR value is *higher. Equation (8) can be used to determine the PDR's mathematical computation.*

$$PDR(\%) = (TotalP_R/TotalP_S) * 100 \qquad (8)$$

A metric called End-to-End Delay (E2ED) calculates how long it takes for data to go from a source node to a destination node (21). Better routing quality is indicated by a lower E2ED value. Equation (9). This allows for the mathematical computation of E2ED to be produced.

$$E2ED(ms) = T_{Delays}/TotalP_R \qquad (9)$$

where T_{Delays} is the sum of all received packet delays.

Overhead This measure shows how saturated the network is. When this statistic has the lowest value, we claim the network has least overhead. Equation "(10)" is used to compute the overhead:

$$OvH = (TotalPHY_S - TotalAPP_S)/TotalPHY_D \quad (10)$$

The ratio of cars to the simulation area's size is known as the density degree. To compute density, use equation "(11)":

$$Degree_{density} = NB_{V\,h}/SimulationArea \qquad (11)$$

4.3 Simulation Results

The throughput rate for both the standard OLSR (Optimized Link State Routing) strategy and the suggested OLSRACO (OLSR with Ant Colony Optimization) technique is about the same, according to the simulation results, which are shown in Fig. 6.
Both protocols' equivalent throughput rates can be ascribed to the different routing schemes they employ. When choosing a path, OLSR chooses the shortest path, which tries to reduce the number of hops between nodes, whereas OLSRACO uses the ant colony optimization method to choose the best path, taking into account metrics like connection quality and congestion. The throughput performance of both protocols is comparable despite their distinct path selection algorithms. This suggests that the proposed OLSRACO approach effectively finds paths that are as efficient as the shortest paths chosen by OLSR

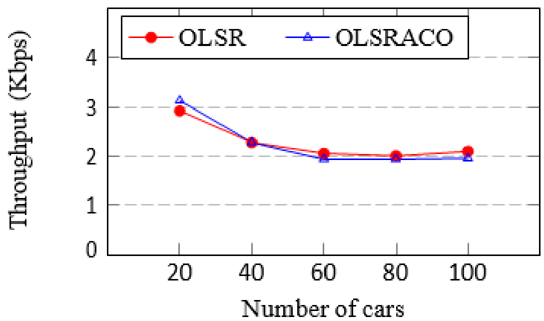

Figure 6. Throughput analysis of OLSR and OLSRACO in a vehicular network.

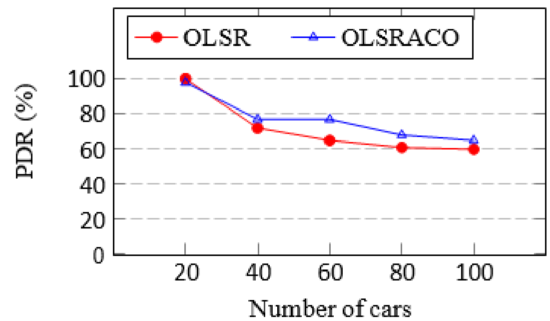

Figure 7. PDR analysis of OLSR and OLSRACO in a vehicular network.

As the number of cars in the network rises, the packet delivery rate attained by the suggested strategy, OLSRACO, is shown to be greater than that of OLSR, based on the simulation results shown in Fig. 7. The enhanced packet delivery rate attained by OLSRACO can be ascribed to its capacity to choose an ideal path that incurs minimal communication expenses.When deciding on the best path for packet transmission, OLSRACO may take into account a variety of parameters, including congestion, connection quality, and other metrics, by utilizing the ant colony optimization method. This enables OLSRACO to choose pathways that have a higher chance of effectively delivering packets and dynamically adjust to changes in the network environment. However, the shortest path is chosen using OLSR, which does not always consider the communication cost of this route. As a result, in situations when there are more cars on the network, OLSR performs worse in terms of packet delivery rate. As the number of cars in the VANET rises, the suggested strategy, OLSRACO, obtains much lower E2ED values compared to OLSR, according to the simulation results shown in Fig. 8.

The lowest E2ED values that OLSRACO was able to achieve show how effective it is in lowering the end-to-end latency that packets traveling over the network encounter. This improvement is attributable to OLSRACO's optimum path selection technique, which considers a number of variables.

OLSRACO can select pathways that minimize delays and dynamically adjust to network circumstances by taking these considerations into account. However, the shortest path is chosen using OLSR, which does not always take the path's possible delay into account. Therefore, the performance of OLSR in terms of E2ED values may be relatively greater as the number of cars grows.

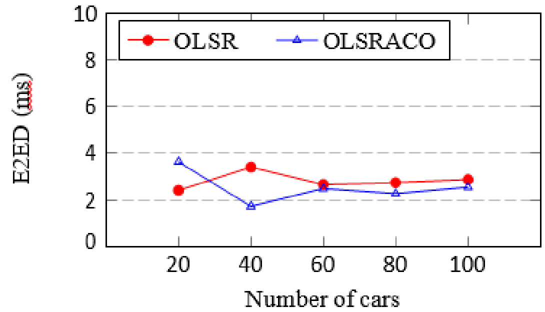

Figure 8. E2ED analysis of OLSR and OLSRACO in a vehicular network.

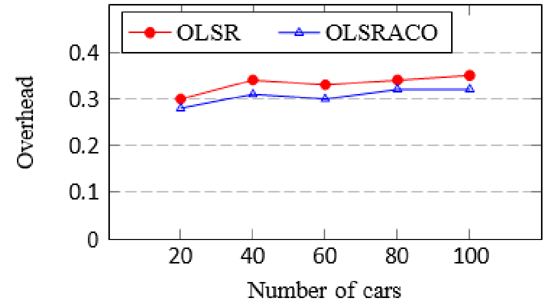

Figure 9. Overhead analysis of OLSR and OLSRACO in a vehicular network.

Based on the available data, Fig. 9 suggests that, in comparison to the OLSR, the suggested strategy, OLSRACO, achieves optimum outcomes in terms of network overhead. The OLSRACO's intelligent path selection mechanism is responsible for this advancement. Conversely, OLSR, which depends on choosing the shortest path, might not always take network cost into account.

By altering the number of vehicles based on the simulation area, "Figs. 10", "Fig. 11", "Fig. 12", and "Fig. 13" show the analysis of Throughput, PDR, E2ED, and Overhead in the VANET with a density degree equal to 0.01. The outcomes demonstrate how much more compelling the strategy suggested in this research is. The OLSRACO technique demonstrates a little boost in throughput. In terms of PDR, E2ED, and overhead, the suggested method is consistently more effective.

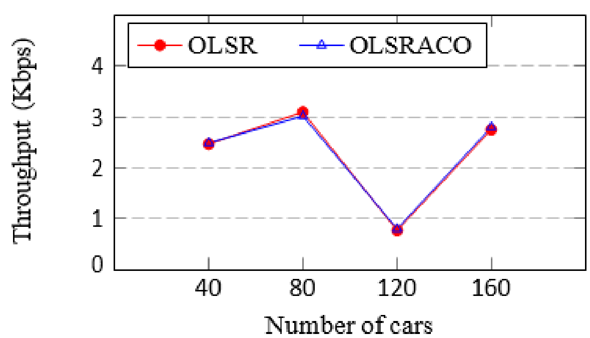

Figure 10. Throughput analysis with density degree=0.01.

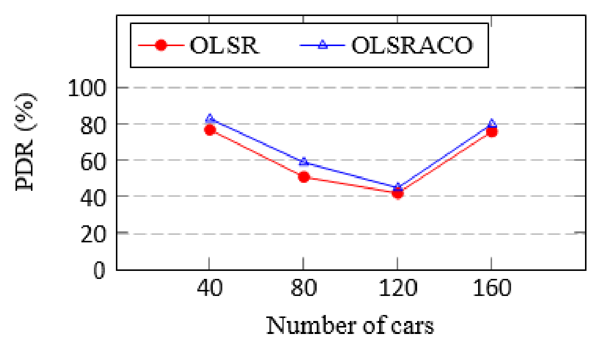

Figure 11. PDR analysis with density degree=0.01.

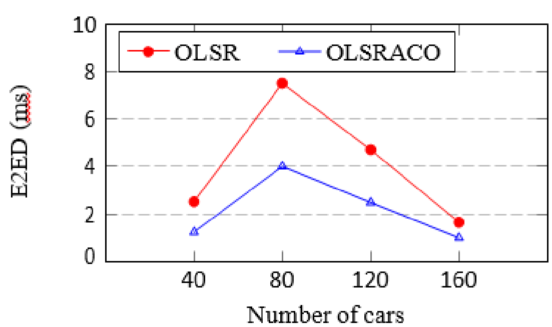

Figure 12. E2ED analysis with density degree=0.01.

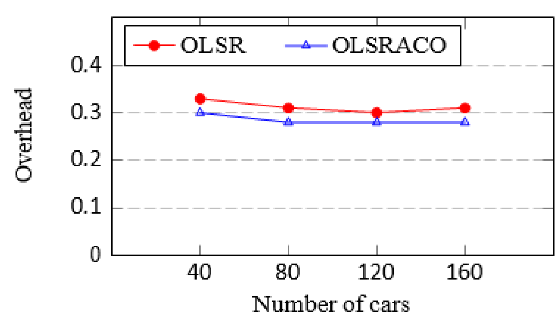

Figure 13. Overhead analysis with density degree=0.01.

CONCLUSION

This study presents a novel OLSRACO method for VANETs. The suggested method uses ACO to identify the best pathways and OLSR to collect network topology data. According to this method, a shorter way that enhances vehicular network efficiency and lowers communication costs is the ideal option.

The results of the simulation run on the Moroccan city of KENITRA show that in terms of throughput, PDR, E2ED, and network overhead, the OLSRACO method performs better than the OLSR protocol. This implies that OLSRACO's intelligent path selection technique, which makes use of ACO, successfully raises the VANETs' overall performance. We plan to simulate the OLSRACO technique in bigger city or highway settings in future work. This would offer light on how well the strategy works in more intricate and varied network contexts. Furthermore, we intend to investigate the OLSR protocol's multi-objective optimization with a focus on VANETs. This suggests an attempt to significantly improve OLSRACO's performance by taking into account several optimization goals at once.

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