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A New Routing Method Based on Ant Colony Optimization in Vehicular Ad-hoc Network

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Abstract
Vehicular Ad hoc Networks (VANETs) face significant challenges in providing high-quality service. These networks enable vehicles to exchange critical information, such as road obstacles and accidents, and support various communication modes known as Vehicle-to-Everything (V2X). This research paper proposes an intelligent method to improve the quality of service by optimizing path selection between vehicles, aiming to minimize network overhead and enhance routing efficiency. The proposed approach integrates Ant Colony Optimization (ACO) into the Optimized Link State Routing (OLSR) protocol. The effectiveness of this method is validated through implementation and simulation experiments conducted using the Simulation of Urban Mobility (SUMO) and the network simulator (NS3). Simulation results demonstrate that the proposed method outperforms the traditional OLSR algorithm in terms of throughput, average packet delivery rate (PDR), end-to-end delay (E2ED), and average routing overhead.

Keywords VANET; Routing; OLSR; Artificial intelligence; Ant Colony Optimization.

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1. Introduction

The domain of the Internet of Vehicles (IoV) has garnered significant research attention due to its focus on enhancing safety in urban environments through the use of Vehicular Ad hoc Networks (VANETs). This last one are a specialized subset of Mobile Ad hoc Networks (MANETs), are characterized by high vehicle mobility and rapidly changing network topologies. In VANETs, vehicles exchange information with other vehicles and base stations. Each vehicle maintains a routing table that contains traffic path information, and multiple paths are proposed for reaching a destination. The selection of the optimal path relies on a routing algorithm. In this paper, we propose an efficient routing algorithm to enhance the quality of service in VANETs. To achieve this, we integrate an artificial intelligence (AI) algorithm, specifically a swarm intelligence (SI) algorithm. Swarm intelligence, a widely adopted AI technique (1), encompasses a range of 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). In the context of vehicle routing problems, ACO can be applied to search for optimal solutions to specific optimization problems. Its adaptability to dynamic changes in topology and ability to ensure Quality of Service (QoS) make ACO particularly well-suited for MANETs (5).

Topology-based routing protocols in MANETs can be classified into three categories: proactive, reactive, and hybrid protocols. The difference between these categories lies in the routing algorithm employed. Proactive routing

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protocols, also known as table-driven protocols, require an overall understanding of the network topology. Routing tables are constructed in advance, even before a packet transmission request is made. In contrast to proactive protocols, reactive routing protocols, or on-demand protocols, do not rely on any prior knowledge of the network topology. Routing table construction occurs dynamically in response to a node's request. Hybrid routing protocols combine the mechanisms of both proactive and reactive 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).

The main objective of this paper is to introduce an intelligent method, named OLSRACO, for selecting an optimal path in a vehicular network. This method combines the Optimized Link State Routing (OLSR) protocol with a swarm intelligence technique called Ant Colony Optimization (ACO).

The OLSRACO approach leverages the capabilities of OLSR to detect one-hop and two-hop neighbors and to gather a comprehensive view of the network topology. By utilizing OLSR, the method can obtain essential information about the network structure.

To determine the optimal path, the ACO algorithm is employed. ACO is chosen due to its advantages in terms of low cost, scalability, and robustness. This swarm intelligence-based algorithm offers a practical and efficient solution for path selection, taking into account the dynamic nature of vehicular networks.

By combining the strengths of OLSR and ACO, the OLSRACO method aims to improve the efficiency and effectiveness of path selection in vehicular networks, ultimately enhancing the overall performance of the network.

As already introduced, ACO is well-suited for MANETs due to its inherent capability to adapt to dynamic changes in network topology and maintain Quality of Service (QoS) even in the presence of link failures (5). In this paper, we highlight the principal ideas discussed as follows:

- Dynamic Topology Adaptation: MANETs experience frequent changes in network topology due to node mobility. ACO algorithm can dynamically adjust the routing paths based on real-time information, ensuring efficient routing even in highly dynamic environments.
- Resilience to Link Failures: MANETs are prone to link failures due to node movements or environmental factors. ACO's distributed nature and adaptive behavior enable it to quickly identify and reroute around failed links, minimizing disruptions and maintaining network connectivity.
- Scalability and Low Cost: ACO is known for its scalability and low overhead. The algorithm relies on local pheromone updates and probabilistic decision-making, making it efficient in terms of computational resources and communication overhead.

By leveraging the strengths of ACO, our research aims to harness its dynamic adaptability, resilience to link failures, scalability, and cost-effectiveness to improve the overall performance and reliability of MANETs.

The contributions of this work can be summarized as follows:

- Discussion of Recent and Related Works: The paper provides a comprehensive review and discussion of recent works in the field of vehicular networks and routing protocols. This helps to establish the research context and identify the gaps that the proposed work aims to address.
- Introduction of the Pheromone Metric: A new metric (the pheromone) is introduced to enhance the reputation of vehicles in the network. The pheromone metric takes into account the behavior and reliability of vehicles when selecting routes, which contributes to more accurate and efficient path selection.
- Integration of ACO in the OLSR Protocol: The paper proposes the integration of the Ant Colony Optimization (ACO) algorithm into the Optimized Link State Routing (OLSR) protocol. This integration enables the OLSRACO protocol, which selects the optimal path based on the dynamic behavior of the network and the pheromone metric.
- Development of Simulated Scenario: A simulated scenario of the city of KENITRA, Morocco, is developed to evaluate the performance of the OLSR and OLSRACO protocols. This scenario provides a realistic environment for testing and comparison purposes.
- Evaluation of Routing Process: The paper evaluates the routing process by comparing the performance of the OLSR and OLSRACO protocols. The analysis focuses on metrics such as throughput, average packet

delivery rate (PDR), end-to-end delay (E2ED), and overhead. This evaluation helps to assess the effectiveness and efficiency of the proposed OLSRACO protocol.

The remaining sections of the paper are organized as follows: Section 2 presents an overview of the relevant works and research conducted in the field of vehicular networks and routing protocols. It provides a comprehensive review of the existing literature, highlighting the key findings, approaches, and limitations of previous studies. In section 3, the methodology of the proposed work is discussed in detail. It covers the conceptual framework, algorithms, and techniques employed in integrating the ACO algorithm into the OLSR protocol. The steps involved in path selection, the use of the pheromone metric, and the overall design of the OLSRACO protocol are explained. Section 4 provides a summary of the simulation details. The parameters and configurations used in the simulations are described. Additionally, the results of the simulations are presented and analyzed, focusing on the metrics of throughput, average packet delivery rate (PDR), end-to-end delay (E2ED), and overhead. The paper concludes with section 5, where the main findings, contributions, and implications of the proposed work are summarized. The conclusion section also highlights the potential future research directions and improvements that can be explored in the field of vehicular networks and routing protocols.

2. Related works

This section presents an overview of some achievements reported in the literature that motivated this study.

In (8), the authors presented a new modified ant colony optimization method with pheromone mutation (ACOPM) to address the trapping problem in local optima. Comparative simulation results between ACOPM and the traditional AODV protocol demonstrate that ACOPM outperforms AODV, showcasing its superior performance.

In (9), the authors introduced an improved mechanism for the fuzzy logic-based ACO protocol in VANET. The proposed protocol, F-Ant, was evaluated through simulations using the NS-2 network simulator. The results demonstrate that F-Ant achieves enhanced performance in terms of Packet Delivery Ratio (PDR) and End-to-End Delay (E2ED) compared to traditional routing algorithms such as ACO and AODV.

In (10), the authors introduced an application of Ant Colony Optimization (ACO) in solving the routing problem and reducing travel time for electric vehicles. Through simulations, the authors demonstrated that their proposed ACOEVRP (Ant Colony Optimization for Electric Vehicle Routing Problem) approach is effective in generating feasible routes that optimize energy consumption. The results indicate that the ACOEVRP approach has the potential to improve energy efficiency in electric vehicle routing, thereby reducing travel time."

In (11), the authors proposed a novel routing protocol that builds upon the ACO-AODV protocol. The proposed protocol, named SCL-ACO-AODV, incorporates selective cross-layer optimization to address the route selection problem in vehicular networks. By integrating the ACO algorithm, the new approach aims to improve the efficiency of route selection. The multi-layer design proposed in this work selectively optimizes the exchange of information between different layers in the vehicular network. This cross-layer approach enables enhanced performance and efficiency by leveraging relevant data from different layers during the routing process. Simulation experiments were conducted to compare the performance of SCL-ACO-AODV with several other routing protocols, namely CL-AODV, CL-WPR, CO-GPSR, and LAR, in both urban and highway scenarios. The results of the simulations demonstrated that the proposed SCL-ACO-AODV protocol outperforms the other protocols in terms of packet delivery ratio, throughput, average delay, and routing efficiency. This indicates that the SCL-ACO-AODV protocol provides better overall performance in different network scenarios.

In (12), the authors introduced the improved hybrid ant colony optimization algorithm (IHACO) with the aim of improving the quality of service of Intelligent Traffic Systems (ITS). The simulation results, carried out using the Matlab simulator, show better performance in terms of throughput and other parameters.

In (13), the authors proposed a solution for optimizing QoS in multipath wireless multimedia sensor network (WMSN) based on a priority-based multipath routing algorithm (PBMRA). The proposed algorithm is composed of three modules: neighborhood selection, multipath construction and priority selection. The proposed algorithm is compared with other existing algorithms. The experimental results show that the PBMRA algorithm increases the packet reception rate and provides a robust route compared to the existing algorithms.

In (14), the authors presented a new improved hybrid ant colony optimization routing protocol (EHACORP) to enhance vehicular network performance. EHACORP offers several advantages over existing protocols, including faster packet processing, rapid convergence speed, enhanced throughput, and improved PDR. The simulation results showed that EHACORP outperforms the other protocols in terms of various measurement parameters.

In (15), the authors proposed a method based on the artificial neural network (ANN) by using the OLSR protocol to enhance the PDR. The simulation was performed using MATLAB simulator to test a set of performance measures such as Routing Overhead Ratio (ROR), E2ED, Energy Consumption (EC) and PDR. The simulation results revealed that the ANN-based OLSR protocol effectively increases network lifetime, reduces energy consumption and increases PDR.

In (16), the authors proposed the extension of OLSR protocol in the heterogeneous ad hoc network (composed of MANET, VANET and FANET devices) with multiple paths (MHAR OLSR). This new protocol enables new functionalities: node identification, path computation, path classification and path selection. Experimental results using NS-3 and BonnMotion show performance enhancement (PDR, E2ED and energy consumption) over the conventional routing protocol.

In (17), the authors presented the new approach for integrating parallelism into the genetic algorithm (GA), with the objective to solve the routing problem in ad-hoc network containing 40 nodes. The results obtained show the better quality of solutions for 40 nodes. On the contrary, among the limits of this approach is: can we integrate this method in a network with high mobility, where there is the large change of topology and the large number of nodes.

“Table 1” summarizes the existing work based on ACO.

3. Methodology

In this paper, we propose a solution to enhance routing quality in VANETs based on the OLSR protocol and the ACO algorithm. The objective is to find an optimal path between a source vehicle and a destination vehicle, aiming to improve the overall performance of the network. The proposed solution is the utilization of the OLSR protocol and ant colony optimization (OLSRACO) to optimize the performance of VANETs. The following subsections provide a description of the OLSR routing protocol and a detailed explanation of the ACO algorithm. Following that, we present our novel approach that combines OLSR and ACO to enhance the performance of VANETs.

3.1. Optimized Link State Routing

The OLSR protocol is a proactive topology-based routing protocol that was developed at INRIA and standardized by the IETF MANET working group in the RFC3626 draft. This protocol aims to reduce the overhead in ad-hoc networks by optimizing the traditional link-state technique and introducing the concept of MultiPoint Relays (MPRs).

In the OLSR protocol, each node maintains a routing table that consists of several fields including Destination Node Address (R_dest_addr), Next Hop Node Address (R_next_addr), Distance (R_dist), and Interface Address (R_iface_addr). These fields are used for routing decisions and maintaining the network topology.

The routing process in the OLSR protocol begins with the exchange of HELLO messages between neighboring nodes. These HELLO messages serve to detect and establish links with neighboring nodes. By exchanging HELLO messages, each node can determine its set of MPRs, which are a subset of its neighbors that help in forwarding packets and reducing the control message overhead.

In general, the OLSR protocol optimizes the routing process in ad-hoc networks by minimizing control message overhead and efficiently establishing and maintaining the network topology through the use of MultiPoint Relays (18).

Algorithm 1 describes the routing process in the OLSR protocol. Algorithm 2 discusses the procedure for defining MPRs.

Table 1. Existing ACO-based Works.

References	Proposed idea	Paper objective	Performance metrics	Simulation tools
(8)	ACOPM	solve the trapping problem in the local optimum.	Best fitness value, Success round.	TSP Library
(9)	F-Ant	Present an enhanced fuzzy logic-based mechanism for VANET.	PDR, E2ED.	NS-2
(10)	ACOEVRP	Solve the routing problem and reduce the travel time of electric vehicles.	Total Travel Time (TTT), waiting Time (WT).	EVRP benchmark instances
(11)	SCL-ACO-AODV	Solve the route selection problem.	PDR, throughput, Average Delay, Routing efficiency.	NS-2.32
(12)	IHACO	Enhance the quality of service of intelligent traffic systems.	Reliability, E2ED, Distance, Throughput.	Matlab
(13)	PBMRA modified	propose a solution for optimizing QoS in WMSN.	Throughput, PDR, delivery delay.	NS3
(14)	EHACORP	Enhance vehicular network performance.	Throughput, PDR, packet processing, convergence speed.	NS2
(15)	ANNOLSR	Enhance the PDR in MANET.	Routing Overhead Ratio, E2ED, PDR, Energy Consumption.	MATLAB
(16)	MHAROLSR	OLSR extension with new functionalities: nodes identification, paths calculation, paths classification and paths choice.	PDR, E2ED, energy consumption.	NS-3 and BonnMotion
(17)	parallelism into the genetic algorithm (GA)	Solve the routing problem in ad-hoc network containing 40 nodes.	Mutation Rate, Crossover Rate, Number of Threads.	API

Algorithm 1 OLSR process

Input : Network Model;
Output: Routing table computations;
for $(i = 0; i < Nb\_Nodes\_MAX; i++)$ **do**
  Discover_neighboring_nodes();
  Select_optimum_MPRset ();
  TC_Broadcast();
  Construct_routing_table();
  Manage_routing();
end for

Algorithm 2 MPR selection algorithm

$MPR(s) = \varnothing$;
N1(s)=1-hop neighborhood of s;
N2(s)= 2-hop neighborhood of s;
for $\forall$ node x $\in$ 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 $\in$ 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

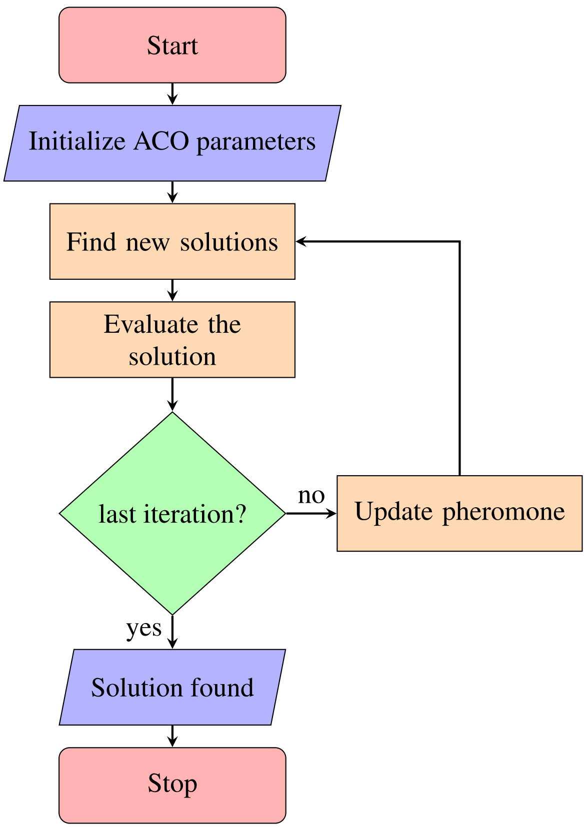

Figure 1. Flowchart of the ACO algorithm.

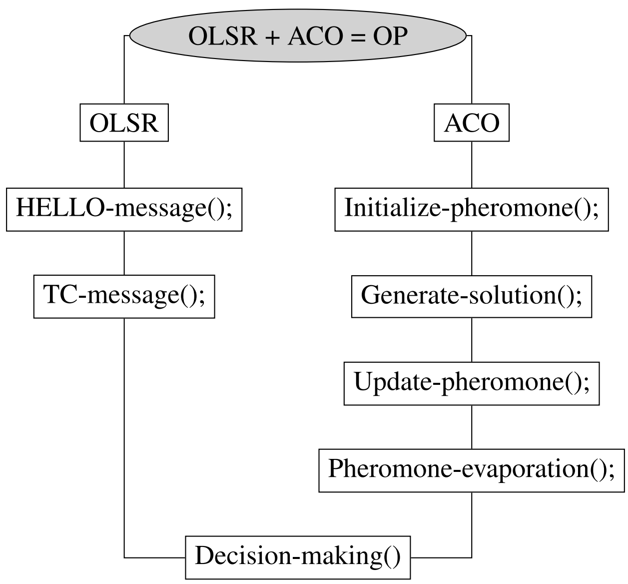

Figure 2. Our approach architecture in VANET.

"Fig. 1" presents the execution steps of the ACO algorithm.

3.2. ACO

In the literature, various definitions of the ACO have been proposed. According to the paper by Jayalakshmi et al. (19)), ACO is described as a method inspired by the behavior of ants in their search for food resources. In the paper by Kanti et al. (20), ACO is defined as an intelligent technique utilized to find an optimal path in a graph.

Ants in a colony communicate with each other by depositing and following chemical trails called pheromones. They collectively find the shortest path to food sources by depositing more pheromones on shorter paths, thus attracting other ants to follow those paths. This collective behavior allows ants to efficiently explore and exploit resources in their environment.

The ACO algorithm adopts this principle and applies it to optimization problems. It utilizes a virtual ant colony to search for the optimal solution by iteratively building and updating pheromone trails that represent the quality of different solution components. The pheromone trails guide the search process, with higher pheromone values indicating better solutions. Through the iterative process, the algorithm converges towards the optimal solution based on the collective behavior of the virtual ants.

3.3. Proposed algorithm description

The proposed algorithm in this paper aims to enhance the OLSR protocol's route selection process by integrating the Ant Colony Optimization (ACO) algorithm. The objective of the algorithm is twofold: optimizing the network performance and selecting the optimal path (OP).

To achieve this objective, a new metric called pheromone (phvalue) is introduced as part of the route selection process. The phvalue represents the amount of pheromone associated with a particular path. It is used to guide the ants (representing nodes) in the network towards the optimal path. The higher the phvalue, the more attractive the path becomes to the ants. The phvalues are updated dynamically based on the quality and performance of the paths.

The OLSR protocol combines Dijkstra's algorithm for finding the shortest path with the MPR selection algorithm. By integrating the ACO algorithm, the proposed approach leverages the concept of pheromone trails to influence the route selection process. The proposed algorithm aims to optimize the network performance and select the most optimal path for data transmission (not necessarily the shortest path).

The "Fig. 2" below presents our proposed approach.

We can formulate our problem as a combinatorial optimization problem represented by a graph. In this graph, the vehicles are represented as vertices, and the links between vehicles are represented as edges. The graph can be denoted as G = (V, E), where V represents the set of vertices and E represents the set of edges.

$$G = \{V, E\} \tag{1}$$

The optimal path (OP) is the outcome of integrating the ACO algorithm into the OLSR protocol. A path is defined as a sequence of vehicles denoted as $V_1, V_2, \ldots, V_n$, where V_1 represents the source vehicle and V_n represents the destination vehicle.

$$OP = \{V_1, V_2, \ldots, V_n\} \tag{2}$$

The proposed approach initiates by initializing various parameters necessary for selecting the optimal path. These parameters include N, T, τ, α, β, ρ, ζ, and m. The specific meanings of these parameters can be found in Table 3.

In this approach, each vehicle begins by broadcasting hello messages to detect neighboring vehicles in the network. Subsequently, a TC message is sent to gain a global understanding of the network topology.

To replace the basic routing table of the OLSR protocol, a new routing table is introduced, which incorporates an additional metric called pheromone (phvalue). This modified routing table, referred to as the ACO-OLSR routing table, is presented in the following format (refer to "Table 2").

Table 2. New routing table.

Dest-vehicle	Neighbor-vehicle	Interface	Distance	phvalue

After constructing the global topology representation, we assign each vehicle the role of an ant, which serves as a computational agent in the Ant Colony Optimization (ACO) algorithm. During a particular iteration, an ant moves from one vertex to another within the network. During this movement, the ant leaves a trail of pheromone on the edge it traverses. The equation (3) represents the general formula to use to calculate the quantity of pheromone to be deposited by an ant on a given edge.

$$\Delta\tau_{ij} = \frac{Q}{L_{\text{ant}}} \tag{3}$$

Where: $\Delta\tau_{ij}$ is the amount of pheromone deposited on the edge between vertices i and j by the ant. Q is a constant representing the pheromone deposit factor or the quantity of pheromone released by each ant. L_{ant} is the cost of the ant's tour. The update process can be represented as in the equation "(4)".

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k}^{m} \Delta\tau_{i\ j}^{k} \tag{4}$$

The equation (5) calculates the probability of an ant choosing to move from vertex i to vertex j based on the pheromone and attractiveness values of the available paths. The values of α and β determine the relative importance of pheromone and attractiveness in the ant's decision-making process.

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

such as

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

Where:
$P_{i\ j}^{k}$ is the probability of the ant k moving from vertex i to vertex j.
$\tau_{i\ j}^{\alpha}$ 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	Population 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
$P_{i\ j}^{k}$	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 : Initializes parameters
N, T, τ, α, β, ρ, ζ, m ;
Phase 02: Discovering neighboring vehicles and topology
Hello-message();
TC-message();
Phase 03: find the optimal path
for 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
```

4. Experimental results

4.1. Simulation Setup

This section presents the simulation and performance analysis of two routing protocols: OLSR and OLSRACO (the approach proposed in this paper). The simulations were implemented using the NS3 network simulator, with the road scenario created using the urban mobility simulation tool SUMO. The objective of the simulation is to evaluate the efficiency of the proposed algorithm under varying vehicle densities. The simulation considers vehicle densities of 20, 40, 60, 80, and 100. Given the high mobility and dynamic topology of the network, vehicles may frequently join or leave the network.

To conduct the simulation, the urban environment of KENITRA-Morocco was chosen, and the map was obtained using Open Street Map (OSM), as depicted in Figure 3. Figure 4 illustrates the road traffic scenario generated by SUMO.

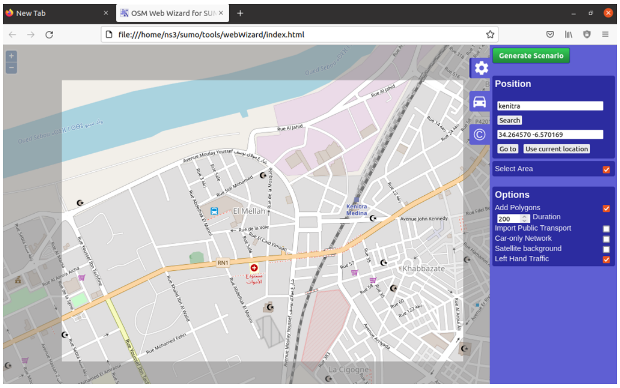

Figure 3. Scenario generated for the region of KENITRA, Morocco.

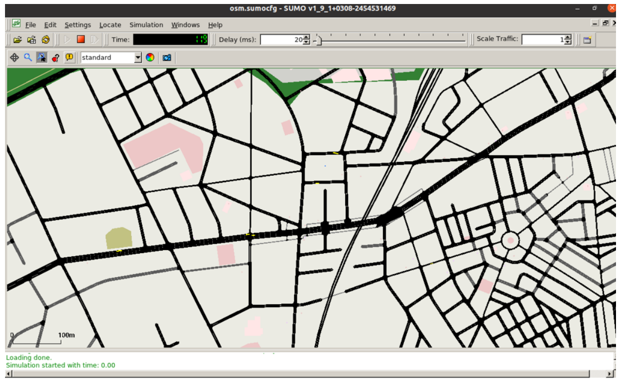

Figure 4. Road traffic scenario generated by SUMO.

"Fig. 5" presents in detail the simulation process.

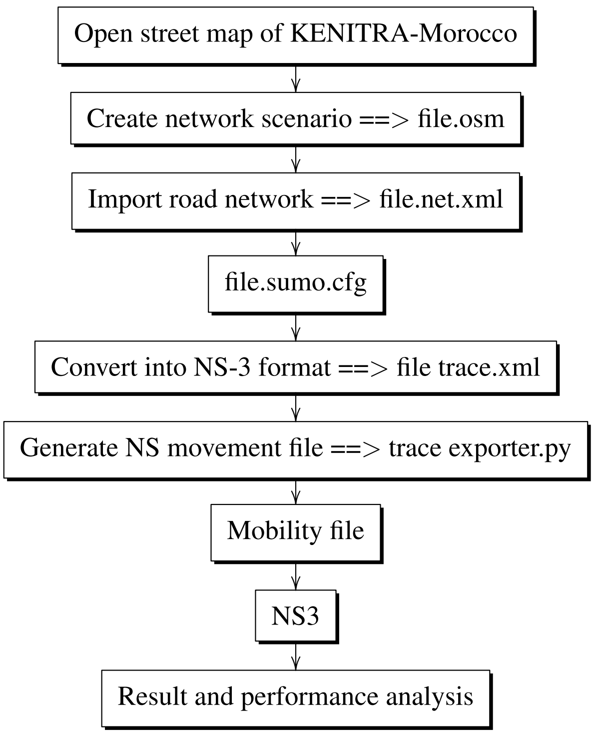

Figure 5. Simulation steps.

The simulation parameters used for OLSRACO in VANET are shown in the "Table 4"

Table 4. Simulation parameters.

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 of KENITRA-Morocco
Simulation time SUMO	200 seconds
Simulation time NS-3.33	100 seconds
Iteration count	10
Number of repetitions for each run	10

4.2. Parameters

The evaluation of the performance of the OLSR and OLSRACO protocols in the vehicular network is based on several parameters, which are summarized in Table 5. The table provides an overview of the notations used in the performance evaluation.

Table 5. Summary of notations.

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

Throughput is a metric that measures the amount of digital data transmitted per unit time. It is typically expressed in bits per second (bps). A higher value of throughput indicates a more efficient network. The mathematical calculation of throughput is shown in Equation (7)

$$Throughput(Kbps) = TotalP_R/(T_L - T_F) \tag{7}$$

Packet Delivery Ratio (PDR) is a metric that measures the ratio between the number of packets successfully received and the total number of packets sent. A higher PDR value indicates better network routing quality. The mathematical calculation of the PDR can be obtained using Equation (8).

$$PDR(\%) = (TotalP_R/TotalP_S) * 100 \tag{8}$$

End-to-End Delay (E2ED) is a metric that measures the time taken for data to travel from the source node to the destination node (21). A lower value of E2ED indicates better routing quality. The mathematical calculation of E2ED can be obtained using Equation (9).

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

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

Overhead This metric indicates the saturation level of the network. We say the network has less overhead when the value of this metric is minimum. The Overhead is calculated using equation “(10)”:

$$OvH = (TotalPHY_S - TotalAPP_S)/TotalPHY_D \tag{10}$$

The density degree is the ratio between the number of vehicles and the size of the simulation area. Density is calculated using the equation “(11)”:

$$Degree_{density} = NB_{Vh}/SimulationArea \tag{11}$$

4.3. Simulation results

Based on the simulation results, as depicted in Fig. 6, it is observed that the throughput rate is nearly identical for both the OLSR (Optimized Link State Routing) basic approach and the proposed approach, OLSRACO (OLSR with Ant Colony Optimization).

The comparable throughput rates achieved by both protocols can be attributed to their respective routing strategies. OLSR selects the shortest path, which aims to minimize the number of hops between nodes, while OLSRACO selects the optimal path using the ant colony optimization algorithm, which considers factors such as link quality, congestion, and other metrics.

Despite the different path selection mechanisms, the performance of both protocols in terms of throughput remains similar. This suggests that the proposed OLSRACO approach effectively finds paths that are as efficient as the shortest paths chosen by OLSR.

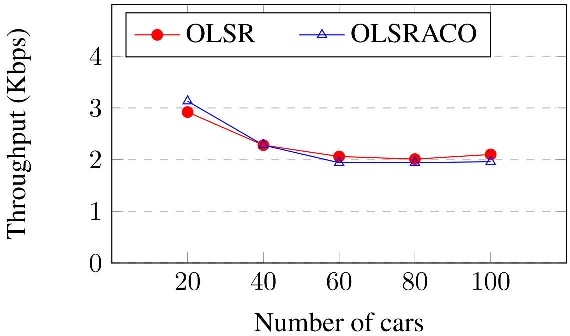

Figure 6. Throughput analysis of OLSR and OLSRACO in a vehicular network.

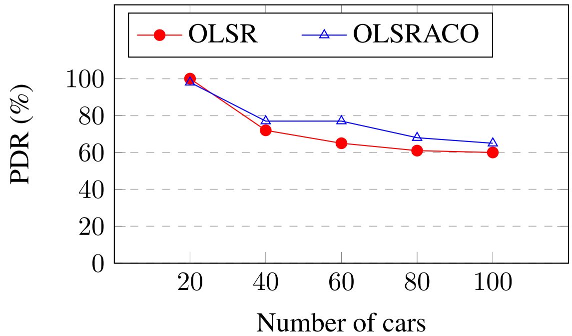

Figure 7. PDR analysis of OLSR and OLSRACO in a vehicular network.

Based on the provided simulation results in Fig. 7, it is observed that the packet delivery rate achieved by the proposed approach, OLSRACO, is higher than that of OLSR when the number of vehicles in the network increases.

The improvement in packet delivery rate obtained by OLSRACO can be attributed to its ability to select an optimal path with a low communication cost.By leveraging the ant colony optimization algorithm, OLSRACO can consider multiple factors such as link quality, congestion, and other metrics when determining the optimal path for packet transmission. This allows OLSRACO to dynamically adapt to changes in the network conditions and select paths that are more likely to deliver packets successfully. On the other hand, OLSR, which selects the shortest path, may not always take into account the communication cost associated with this path. Therefore, in scenarios with higher number of vehicles in the network, the performance of OLSR in terms of packet delivery rate is lower.

Based on the provided simulation results in Fig. 8, it can be observed that the proposed approach, OLSRACO, achieves significantly lower E2ED values compared to OLSR as the number of vehicles in the VANET increases.

The minimal E2ED values obtained by OLSRACO indicate its effectiveness in reducing the end-to-end delay experienced by packets transmitted in the network. This improvement can be attributed to the optimal path selection strategy employed by OLSRACO, which takes into account various factors. By considering these factors, OLSRACO can dynamically adapt to the network conditions and choose paths that minimize delays. On the other hand, OLSR, which selects the shortest path, may not always consider the potential delay associated with that path. Hence, as the number of vehicles increases, the performance of OLSR in terms of E2ED values may be comparatively higher.

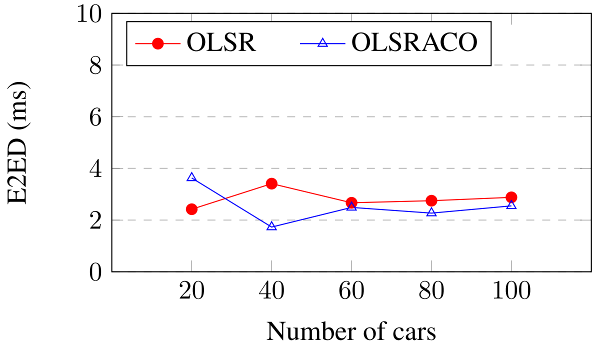

Figure 8. E2ED analysis of OLSR and OLSRACO in a vehicular network.

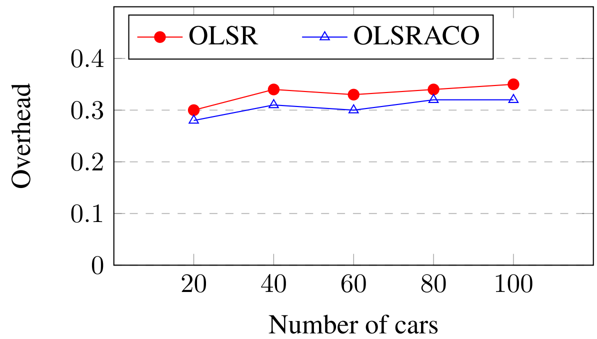

Figure 9. Overhead analysis of OLSR and OLSRACO in a vehicular network.

Based on the information provided, it can be inferred from Fig. 9 that the proposed approach, OLSRACO, achieves optimized results in terms of network overhead compared to the OLSR. This improvement can be attributed to the intelligent path selection mechanism of OLSRACO. On the contrary, OLSR, which relies on selecting the shortest path, may not always consider the potential impact on network overhead.

"Fig. 10", "Fig. 11", "Fig. 12", and "Fig. 13" illustrates the analysis of Throughput, PDR, E2ED, and Overhead in the VANET with a density degree equal to 0.01 by varying the number of cars depending on the simulation area. The results obtained show that the approach proposed in this paper is more motivating. In terms of throughput, the OLSRACO approach shows a small increase. At the level of PDR, E2ED, and Overhead always the proposed approach is more efficient.

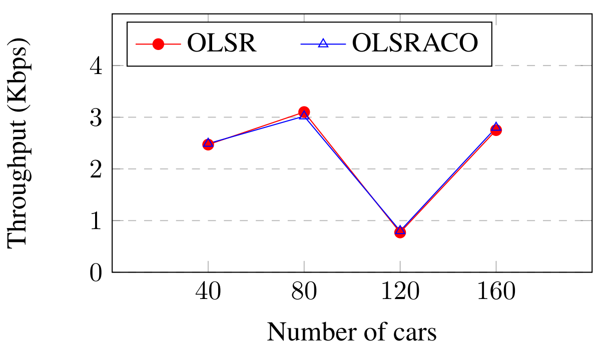

Figure 10. Throughput analysis with density degree=0.01.

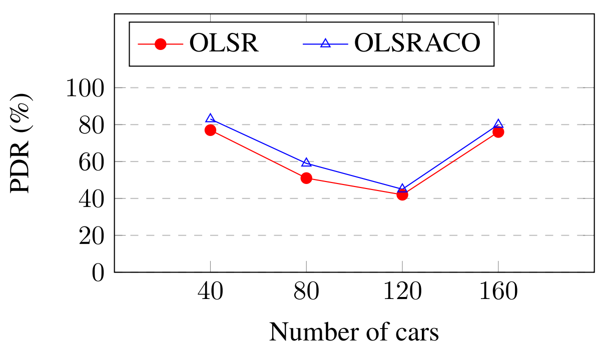

Figure 11. PDR analysis with density degree=0.01.

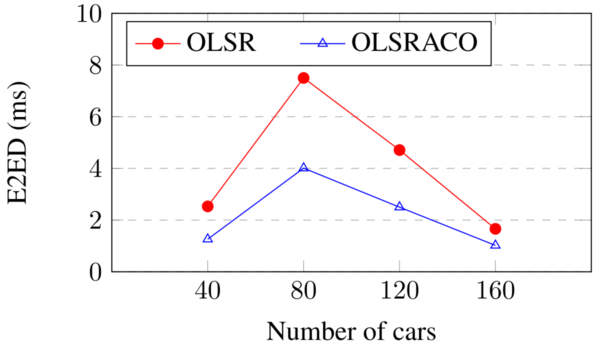

Figure 12. E2ED analysis with density degree=0.01.

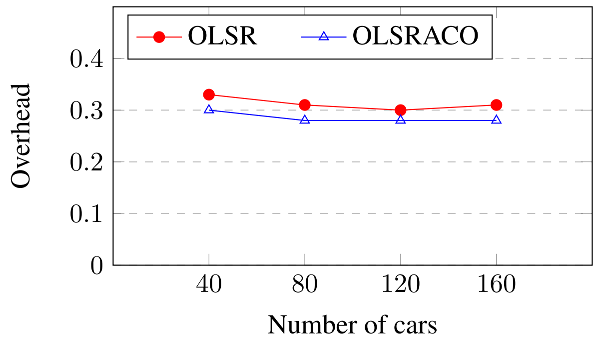

Figure 13. Overhead analysis with density degree=0.01.

5. Conclusion

This paper introduces a new approach called OLSRACO for VANETs. The proposed scheme combines OLSR to gather information about the network topology and ACO to find optimal paths. In this approach, the optimal path is defined as a shorter path that improves the performance of the vehicular network and reduces communication costs.

The simulation results conducted on the city of KENITRA, Morocco, demonstrate that the OLSRACO approach outperforms the OLSR protocol in terms of throughput, PDR, E2ED, and network overhead. This suggests that the intelligent path selection mechanism of OLSRACO, using ACO, effectively improves the overall performance of the VANETs.

In future work, we will simulate the OLSRACO approach in scenarios involving larger cities or highways. This would provide insights into the performance of the approach in more complex and diverse network environments. Additionally, we aim to explore multi-objective optimization of the OLSR protocol specifically tailored for VANETs. This indicates a desire to further enhance the performance of OLSRACO by considering multiple optimization objectives simultaneously.

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