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Research Article

Enhancing The Route Optimization Using Hybrid Optimization Algorithm For The Internet Of Vehicle's

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ABSTRACT

The rapid advancement of the Internet of Things (IoT) has catalyzed the integration of connected vehicles into smart logistics, reshaping the transportation landscape. This research explores the development of a distributed intelligent traffic system by endowing connected vehicles with decision-making capabilities to navigate intricate traffic scenarios like roundabouts and intersections. Proposing a model for the next-generation Intelligent Transportation System (ITS), the study emphasizes dynamic decision-making rooted in ant colony optimization, a cornerstone algorithm in Swarm Intelligence (SI). A communication framework facilitates the exchange of traffic flow information among connected vehicles, while SI principles treat these vehicles as artificial ants, enabling adaptive decision-making in real-time traffic dynamics. Furthermore, the research introduces an effective order-aware hybrid genetic algorithm for the capacitated vehicle routing problem in the IoT context, characterized by an improved initialization strategy and a problem-specific crossover operator. Simulations validate the efficacy of the proposed approach in optimizing routing for capacitated vehicles within smart logistics networks.

Keywords: Dynamic Decision Making, Connected Vehicles, Intelligent Transportation System (ITS), Internet of Things (IoT), Swarm Intelligence (SI), Ant Colony Optimization, Capacitated Vehicle Routing Problem, Hybrid Genetic Algorithm.

1. INTRODUCTION

The ever-growing demands for transportation solutions in the face of increasing urbanization and population expansion have propelled the need for innovative approaches to enhance mobility, safety, and efficiency on the roads. As cities expand and become more complex, the challenges of managing transportation systems have become paramount. The advent of connected vehicles, enabled by Internet of Things (IoT) technology, presents a transformative opportunity to revolutionize the way we navigate urban environments and address the pressing issues of traffic congestion, road safety, and environmental sustainability. In response to the burgeoning challenges posed by urbanization and population growth, the quest for innovative transportation solutions has intensified, prompting researchers and policymakers to explore novel approaches to enhance mobility, safety, and efficiency on the roads. As cities expand and traffic complexities escalate, managing transportation systems becomes increasingly challenging, necessitating the adoption of advanced technologies to address these issues effectively. One such transformative technology is the emergence of connected vehicles, made possible by the Internet of Things (IoT). Connected vehicles offer a promising avenue to revolutionize urban mobility, presenting solutions to alleviate traffic congestion, improve road safety, and promote environmental sustainability. By harnessing IoT connectivity, vehicles can communicate with each other, infrastructure, and centralized systems, enabling them to gather and analyze real-time data on road conditions, traffic patterns, and potential hazards. Armed with this information, connected vehicles can autonomously make informed decisions, dynamically adapting to changing driving scenarios. Central to this paradigm shift are dynamic decision-making algorithms inspired by Swarm Intelligence principles, such as Ant Colony Optimization (ACO), which enable vehicles to navigate complex traffic situations with agility and precision.

This paper explores the convergence of dynamic decision-making algorithms, IoT technology, and intelligent transportation systems, with a focus on enhancing the capabilities of connected vehicles in urban environments. By designing innovative hybrid algorithms and communication frameworks, blending the strengths of multiple approaches, this research endeavors to optimize transportation management, improve traffic flow, and pave the way for smarter, more sustainable urban mobility solutions. Through an in-depth analysis of the challenges and opportunities in this domain, this study aims to contribute to the advancement of intelligent transportation systems and the realization of a safer, more efficient transportation ecosystem for future generations.

1.1 Challenge Statement

In this study, the Capacitated Vehicle Routing Problem (CVRP) is formulated as a graph G(V, E), where V represents the distribution center and order nodes, with v_0 denoting the center and n representing the number of orders. Each order nodev_i (where (i = 1, 2, ..., n)) is associated with a non-negative demand d_i.The set E consists of arcs connecting each pair of nodes, with each arc having an associated cost c_{ij} (symmetrically, c_{ij} c_{ij}). A fleet of m vehicles, each with a capacity C, is considered. Decision variables x_{ijk} are introduced, where $x_{ijk} = 1$ if vehicle k travels from node i to node j, and 0 otherwise. The objective is to minimize the total distribution cost while satisfying the following constraints: 1) Each route begins and ends at the distribution center, 2) Each order is served exactly once by a vehicle, and 3) The total demands of each route do not exceed the vehicle's capacity. The model aims to optimize the routing of vehicles to efficiently fulfill orders while considering capacity constraints and minimizing distribution costs.

$$\text{Min } \sum_{i=0}^{n} \sum_{i=0}^{n} \sum_{i=0}^{n} C_{ij} x_{ijk}$$

$$\sum_{i(j)=0}^{n} \sum_{k=1}^{m} x_{ijk} = 1$$

$$\sum_{i(j)=0}^{n} \sum_{k=1}^{m} d_i x_{ijk} \leq C$$

$$\sum_{i=0}^{n} \sum_{j=1}^{m} x_{ijk} \leq |v| - 1$$

1.2 Distributed Optimization Techniques for IoT

The rise of edge analytics within the Internet of Things (IoT) landscape marks a significant shift, bringing software-based artificial intelligence to the forefront of real-world applications. This trend, driven by advancements in machine learning, enables connected objects to undergo real-time optimization and computational intelligence at the system level. However, the inherent complexity and dynamic nature of IoT systems pose challenges, particularly in decentralized management. Swarm Intelligence (SI)-based algorithms offer a promising solution by enhancing data processing efficiency and reducing time consumption. Notably, applications like Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC) algorithms have found utility in optimizing smart systems such as connected vehicles and energy management. These algorithms leverage decentralized, self-organized management inspired by the collective behavior of social insects, thus improving the overall performance and consumer experience of IoT applications and services. Ongoing research efforts continue to explore the integration of SI-based algorithms into IoT systems, with a focus on addressing the complexities of decentralized management and enhancing efficiency across various domains, including smart homes, energy management, and e-health.

1.2.1 Smart Mobility Solutions

The advancement of vehicle technologies has facilitated seamless communication and collaboration among vehicles, both with each other and with infrastructure elements such as road infrastructure (V2I) and other vehicles (V2V). This capability holds immense potential for revolutionizing the landscape of Intelligent Transportation Systems (ITS), paving the way for the development of intelligent transportation networks. Endeavors have honed in on leveraging connected vehicles to introduce a plethora of smart traffic management applications, aiming to optimize traffic flow, enhance safety, and improve overall efficiency. Fig illustrates the communication framework of a connected vehicle, showcasing its ability to address routing problems effectively. This model is particularly designed to optimize travel time, leveraging factors such as distance (D) and traffic density (Φ) to determine the shortest and most efficient route to a given destination. The objective function of the Shortest Path Problem (SPP) revolves around selecting a route (R) that minimizes the overall weight (T) of the journey, ensuring expedited travel while navigating varying traffic conditions.

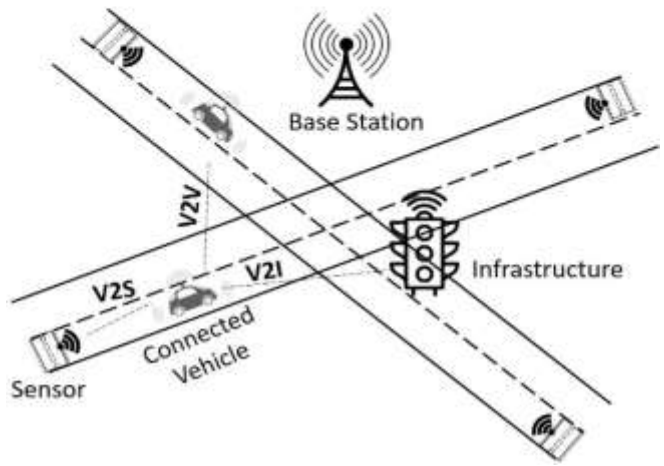

Figure 1. V2X communications

This approach represents a significant advancement in the realm of intelligent transportation, harnessing the power of swarm intelligence to address the complex challenges inherent in modern transportation systems. Through the integration of ACO and connected vehicle technology, we pave the way for a future where vehicles autonomously and intelligently navigate road networks, ushering in a new era of efficient and sustainable transportation. A connected vehicle v can be represented by 4-tuples as follows:

$v = \langle I, R, A, K \rangle$

where

I: is the id of the vehicle (e.g., number plate).

R: is the set of relay ports.

K: indicates the knowledge base about the environment.

A: is the set of actions based on computational analysis

ACO for Shortest Path Problem:

The road network can be effectively modeled as a connected graph G, represented as follows:

$G = < N, E, D >$

where N is the set of nodes, E is the set of directed edges, and this model is to find the shortest time for traveling to get the destination of vehicles which depend on the distance D and traffic density Φ. The objective function of SPP is to choose a path to destination which minimizes the weight T of route R which can be defined as follows:

$$T_R = \sum_{i=1}^{N} \sum_{j=1}^{N} a_{i,j}\, T_{i,j}$$
$$\forall i \neq j, i, j \epsilon N$$
$$a_{i,j} = \begin{cases} 1 \; if \; E_{i,j} = 1, \\ 0 \; otherwise, \end{cases}$$

The Ant Colony Optimization (ACO) algorithm applied to the Shortest Path Problem (SPP) in transportation systems, the determination of the time $T_{i,j}$ for traveling between two vertices i and j is crucial. This time is influenced by factors such as distance and traffic density, where higher traffic density leads to increased travel times, particularly in urban areas. Leveraging advanced vehicle technologies such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Sensor (V2S) communication, the ACO algorithm has emerged as a promising approach for improving traffic flow efficiency. In this framework, connected vehicles collaborate with each other to identify the shortest path to their destination, analogous to the foraging behavior of ants in nature. However, a key distinction lies in the decision-making process: while ants select paths with the highest pheromone concentration, representing the shortest route, the SPP algorithm chooses paths with lower traffic density to minimize travel times. The pheromone value $E_{i,j}$ on an edge between vertices i and j is updated based on the arrival time of backward information, reflecting the efficiency of the chosen route. This iterative process allows the ACO algorithm to adaptively update pheromone levels on edges, guiding subsequent iterations towards routes with lower traffic density and improved travel times.

$$\delta_{i,j}^{v} = \frac{a_{i,j}^{v}}{t_{i,j}^{v}} + \frac{a_{i,j}^{v}}{D_{i,j}}$$

Where $t_{i,j}^{v}$ represents for the time of vehicle v traverses $E_{i,j}$

Ant Colony Optimization (Aco) Algorithm

the ACO algorithm. Each node in the graph represents one operation of the jobs to be scheduled. Two more nodes are added into the graph, representing the starting and ending points. In the algorithm, each ant starts to visit all the nodes one-by-one from the starting node and complete its journey at the ending node. The schedule of the operations to be executed is constructed based on the sequence of the nodes that the ant has visited. All the operations are re-indexed from (0, 1, 2, N, N + 1), where 0 and (N+1) are the starting and ending nodes, respectively. The value te is the pheromone on the path that connects nodes rand s. The arrowhead lines indicate the precedence constraints between the operations within the same job. For example, the arrowhead line connecting nodes 1 and 2 indicates that the ant must visit node 1 before it can visit node 2. In other words, the operation O_{11}, must be executed before the operation O_{12}.

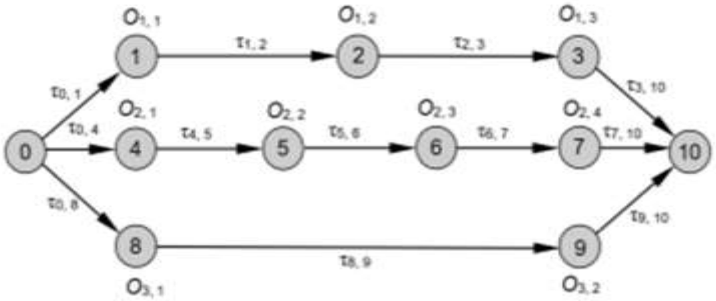

Figure 2. Disjunctive graph of Ant Colony Optimization (ACO) algorithm

1.3 Problem Formulation and Assumptions

Urban Congestion Challenges: Despite significant advancements in vehicular technologies aimed at managing traffic, urban congestion remains a pervasive issue, particularly in densely populated areas. This congestion not only leads to time inefficiencies but also contributes to environmental pollution and increased stress levels among commuters. As cities continue to grow and vehicle populations increase, finding effective solutions to alleviate congestion becomes paramount. Automated and connected vehicles emerge as promising components of Intelligent Transportation Systems (ITS), offering potential solutions through enhanced communication and collaboration among vehicles.

Research Objective: This research endeavors to address the pressing issue of urban congestion by proposing an innovative approach that empowers connected vehicles to autonomously navigate specific areas while making adaptive decisions. The primary goal is to develop an intelligent algorithm that enables connected vehicles to seamlessly interact and respond to dynamic traffic conditions in real-time. By leveraging the capabilities of connected vehicles within an Internet of Things (IoT) framework, the study aims to optimize traffic flow and mitigate congestion in urban environments.

Role of Swarm Intelligence and Ant Colony Optimization: In pursuit of this objective, the study draws inspiration from the principles of Swarm Intelligence (SI), where collective behaviors emerge from the interactions of individual agents. Specifically, Ant Colony Optimization (ACO), a prominent SI-based algorithm, is explored for its efficacy in addressing the Shortest Path Problem (SPP) within the context of urban traffic management. By simulating the foraging behavior of ant colonies, ACO offers a decentralized approach to route optimization, making it well-suited for applications in ITS.

Addressing Decentralized Connected Vehicle Operations: While existing research primarily focuses on utilizing ACO to improve overall traffic flow, this study uniquely emphasizes the role of connected vehicles in enabling decentralized traffic management systems. By treating connected vehicles as artificial ants capable of exchanging information in real-time, the proposed approach aims to enhance the adaptability and responsiveness of urban traffic systems. Through seamless Vehicle-to-Everything (V2X) communication, connected vehicles can collaboratively optimize route selection and traffic navigation, thereby mitigating congestion hotspots and improving overall traffic efficiency.

Assumptions and Considerations: To facilitate the development and evaluation of the proposed algorithm, certain assumptions are made regarding the reliability and efficiency of V2X communication channels. Additionally, the study assumes rapid computational capabilities for processing and analyzing real-time traffic data, enabling timely decision-making by connected vehicles. These assumptions lay the foundation for the creation of an effective decentralized traffic management system that addresses the complexities of urban congestion comprehensively.

2 RELATED WORK

Patrali Pradhan, Chandana Roy et.al (2023) In this study, we introduce Dec-Safe, a real-time decision generation mechanism aimed at delivering adaptive safety-linked decisions dynamically to users within the context of road transportation. Unlike existing models in the field, Dec-Safe addresses the critical issue of providing customized and safety-related information to users, thereby enhancing the overall safety-as-a-service (Safe-aaS) platform. Dec-Safe offers users the flexibility to choose between static and dynamic approaches for accessing safety services. In the static approach, the values of decision parameters remain relatively constant over time, with users having the option to request additional parameters as needed, albeit at an extra cost. To optimize computation complexity and reduce memory space at the server end, we employ relationship mapping to associate generated decisions with user-requested parameters. Conversely, the dynamic approach allows decision parameters to dynamically vary from origin to destination. **Jinzhu Wang, Zhixiong Ma, Xichan Zhu, et.al (2022)** In this study, to improve the application range of decision-making systems for connected automated vehicles, this paper proposes a cooperative decision-making approach for multiple driving scenarios based on the combination of multi-agent reinforcement learning with centralized planning. Specifically, the authors derived driving tasks from driving scenarios and computed the policy functions for different driving scenarios as linear combinations of policy functions for a set of specific driving tasks. Then, the authors classified vehicle coalitions according to the relationships between vehicles and used centralized planning methods to determine the optimal combination of actions for each coalition. Finally, the authors conducted tests in two driving scenarios considering different traffic densities to evaluate the performance of the developed approach. Simulation results demonstrate that the proposed approach exhibits good robustness in multiple driving scenarios while enabling cooperative decision making for connected automated vehicles, thereby ensuring safe and rational decision making. **Pin Lv, Jin Han, Jiangtian Nie, et.al (2023)** The paper proposes a scheme where CAVs indicate optimal emergency destinations to avoid collisions, introducing the task of predicting the optimal collision avoidance destination. This scheme employs a deep reinforcement learning (DRL) model to evaluate potential collision avoidance destinations, with the evaluation results depicted using a safety evaluation map (SEM). The cooperative ability of CAVs is integrated into the scheme, and a carefully designed reward function is utilized to train the DRL model. Experimental results demonstrate the effectiveness of the proposed model in accurately evaluating potential collision avoidance destinations and reducing traffic accident rates and accident damage in various traffic emergencies compared to state-of-the-art baseline methods**. Lina Yao, Xiaodong Xu, Muhammad Bilal, Huihui Wang (2022**) In this study, developments in the Internet of Vehicles (IoV) enabled the myriad emergence of a plethora of data-intensive and latency-sensitive vehicular applications, posing significant difficulties to traditional cloud computing. Vehicular edge computing (VEC), as an emerging paradigm, enables the vehicles to utilize the resources of the edge servers to reduce the data transfer burden and computing stress. Although the utilization of VEC is a favourable support for IoV applications, vehicle mobility and other factors further complicate the challenge of designing and implementing such systems, leading to incremental delay and energy consumption. In recent times, there have been attempts to integrate deep reinforcement learning (DRL) approaches with IoV-based systems, to facilitate real-time decision-making and prediction. Specifically, the dynamic computation offloading problem is constructed as a Markov decision process (MDP). Then, the twin delayed deep deterministic policy gradient (TD3) algorithm is utilized to achieve the optimal offloading strategy. **Peng Hang1, Chen Lv1, Chao Huang1 et.al (2021)** In this study, to address the safety and efficiency issues of vehicles at multi-lane merging zones, a cooperative decision-making framework is designed for connected automated vehicles (CAVs) using a coalitional game approach. Firstly, a motion prediction module is established based on the simplified single-track vehicle model for enhancing the accuracy and reliability of the decision-making algorithm. Then, the cost function and constraints of the decision making are designed considering multiple performance indexes, i.e. the safety, comfort and efficiency. Besides, in order to realize human-like and personalized smart mobility, different driving characteristics are considered and embedded in the modeling process. Furthermore, four typical coalition models are defined for CAVS at the scenario of a multi-lane merging zone. Then, the coalitional game approach is formulated with model predictive control (MPC) to deal with decision making of CAVs at the defined scenario. **Teng Liu, Xiaolin Tang, Jinwei Zhang, et.al (2020)** In this study, as a typical vehicle-cyber-physical-system (V-CPS), connected automated vehicles attracted more and more attention in recent years. This paper focuses on discussing the decision-making (DM) strategy for autonomous vehicles in a connected environment. First, the highway DM problem is formulated, wherein the vehicles can exchange information via wireless networking. Then, two classical reinforcement learning (RL) algorithms, Q-learning and Dyna, are leveraged to derive the DM strategies in a predefined driving scenario. Finally, the control performance of the derived DM policies in safety and efficiency is analyzed. Furthermore, the inherent differences of the RL algorithms are embodied and discussed in DM strategies. Khac-Hoai Nam Bui1 et.al (2019) In this study, proposed model aims to advance the field of intelligent transportation systems by leveraging Ant Colony Optimization, a Swarm Intelligence (SI)-based algorithm, to enable connected vehicles to make adaptive decisions based on real-time traffic conditions. The study also highlights the development of a communication framework among connected vehicles for sharing traffic flow information and the simulation of traffic scenarios within an Internet of Things (IoT) environment to evaluate the effectiveness of the proposed approach. The abstract suggests promising results from simulations, indicating the potential of the proposed model in improving transportation systems. **Shujuan Tian1, Deng Xianghong1 et.al (2021)** In this study, the rapid advancement of 5G technology, the proliferation of mobile applications such as autonomous driving, video streaming, and vehicle-based online games has surged, leading to an exponential increase in data exchanges and service requests for portable terminal devices. However, this unprecedented growth in data has placed a significant strain on roadside units (RSUs) and networks, jeopardizing the quality of user services provided by cellular networks. In response to these challenges, vehicle fog computing has emerged as a promising solution for enhancing the efficiency and reliability of vehicle networks. Nevertheless, the high mobility of vehicles and the intricate nature of traffic present formidable obstacles to communication and computing within vehicle fog computing environments. To address these issues, this study introduces a novel approach comprising a Vehicle Movement Model (VMM) to capture the dynamics of vehicles in traffic environments. The VMM utilizes a four-lane dual carriageway to simulate urban traffic scenarios. Furthermore, to optimize user service quality by minimizing task response times, we propose the KMM algorithm, which employs a two-step selection mechanism to choose offload servers and utilizes the Kuhn-Munkras algorithm for final decision-making. Additionally, we present the GMDC algorithm, which adapts to the dynamic nature of traffic environments by allocating feasible offload servers to user vehicles through a combination of random selection and a greedy algorithm. Experimental results demonstrate that our proposed algorithms outperform existing methods, increasing task offloading rates by 5% and reducing RSU utilization rates by 45%, while simultaneously improving task response times by 3% compared to the TOPM algorithm. **Rodrigo Silva et.al (2020)** In this study, Demand from different actors for extended connectivity where vehicles can exchange data with other devices have pushed vehicle manufacturers to invest in embedded solutions, which paves the way towards Cooperative Intelligent Transportation Systems (C-ITS). Cooperative vehicles enable the development of an ecosystem of services around them. Due to the heterogeneousness of such services and their specific requirements, for ubiquitous connectivity it is necessary to combine existing wireless technologies, providing applications with a communication architecture that hides such underlying access technologies specificities. Moreover, due to vehicles' high velocity it is needed a Decision Maker (DM) mechanism capable to take into account the short-term prevision about network environment in order to better manage all flow communications. Based on the Intelligent Transportation Systems (ITS) architecture proposed by International Organization for Standardization (ISO), we proposed the Ant-based Decision Maker for Opportunistic Networking (AD4ON), a modular decision maker mechanism capable to choose the best available access network for each data flow in an heterogeneous and dynamic network environment. **Edyta Kucharska1, Katarzyna Grobler-Dębska1 et.al (2019**) In this study, a collective decision making in dynamic vehicle routing problem. In contrast to the static problem, a part or all of the customers' companies are revealed dynamically during the design or execution of the routes. The problem is modelled using the algebraic-logical meta-model (ALMM) methodology, which enables making collective decisions in successive process stages, not separately for individual vehicles. ALMM is considered to be the rule according to which the availability of companies is determined. The steps and schematics of the general algorithm that take into account the dynamic appearance of new companies are shown. The proposed approach belongs to trajectory-based metaheuristics methods. A method called localized genetic algorithm (LGA) was raised by **Ursani et al. (2017)** to deal with CVRP. The results on benchmark instances indi- cated that LGA was feasible, but its performance deteriorateswhen orders in each route increased. **Wang and Lu (2009)** gavea novel HGA to optimize CVRP, and the response surface methodology (RSM) was first applied to tune the parame- ters. This algorithm was tested on benchmarks instances andtwo practical problems in the military domain. **Nazif et.al (2012)** proposed an optimized crossover genetic algo- rithm (OCGA) to address CVRP. This method integrated optimized crossover into the classical genetic algorithm, and results showed that OCGA was competitive regarding the quality of the solutions.

3. THE OHGA

In this section, the focus shifts to the proposed Order-aware Hybrid Genetic Algorithm (OHGA), unveiling its intricate components that drive the evolution process. The OHGA, tailored for addressing the Capacitated Vehicle Routing Problem (CVRP), integrates classical genetic algorithm elements alongside a novel population initialization strategy and a specialized crossover operator. The initialization strategy, a fusion of the sweep algorithm and randomness, swiftly generates constructed solutions to expedite convergence while ensuring population diversity. Meanwhile, the crossover operator, enriched with neighborhood search heuristics, meticulously crafts offspring with minimal cost, meticulously checking constraints to sidestep the generation of infeasible solutions, thus obviating the need for additional repair procedures. The OHGA executes seamlessly, guided by a straightforward process outlined in Algorithm 1. It commences by configuring crucial parameters such as the probability of crossover (Pc), the probability of mutation (Pm), the population size (S), the maximum iteration (MI), and the vehicle's capacity (C). Subsequently, the population initialization process unfolds using the innovative strategy proposed herein. Recombination of individuals follows suit, guided by the meticulously crafted crossover operator, while partial solutions undergo mutation as per the designated operator. A tournament strategy then selects potential solutions, iterating through the process for MI cycles until the optimal individual emerges triumphant, signifying the completion of the OHGA's evolutionary journey.

Algorithm 1 The OHGA

- **Input:** An Intuitionistic Fuzzy Graph (IFG) named G with specific properties (V, U, DVS Xβ, β = μβ, νβ).
- **Output:** The minimized value of expression,

- **Steps:** The algorithm outlines six steps (1-6) for achieving the minimized expression.
  - Step 1: Begins the algorithm execution.
  - Step 2: Constructs β0 using a product (∏) operation over a defined condition.
  - Step 3: Constructs the expression ΦD using a product (⊗) operation with multiple conditions. Comments explain the meaning of ξjik and pi.
  - Step 4: Constructs another version of the expression ΦD using a product (⊗) operation.
  - Step 5: Computes the final minimized expression using a product (∏) operation.
  - Step 6: Ends the algorithm execution.

3.1 THE CROSSOVER OPERATOR OF THE OHGA

This study proposes a novel crossover operator tailored for the Capacitated Vehicle Routing Problem (CVRP), integrating neighborhood search heuristics to produce offspring with minimal cost and ensured feasibility. The operator operates in two stages: removal and insertion. Initially, two parent solutions are randomly selected, each comprising several sub-routes. Subsequently, orders and related arcs from the chosen sub-routes in one parent are removed, and the missing orders are then inserted into the offspring, ensuring vehicle capacity constraints are met. The process iterates until feasible offspring are generated. The algorithm's pseudocode and visualization of the crossover process are provided, showcasing its efficacy in producing feasible solutions with minimal overlaps. Constraints, particularly vehicle capacity, are rigorously verified during each insertion, ensuring solution feasibility. This approach presents a significant advancement in addressing CVRP challenges, offering potential for efficient route optimization in logistics and transportation management scenarios.

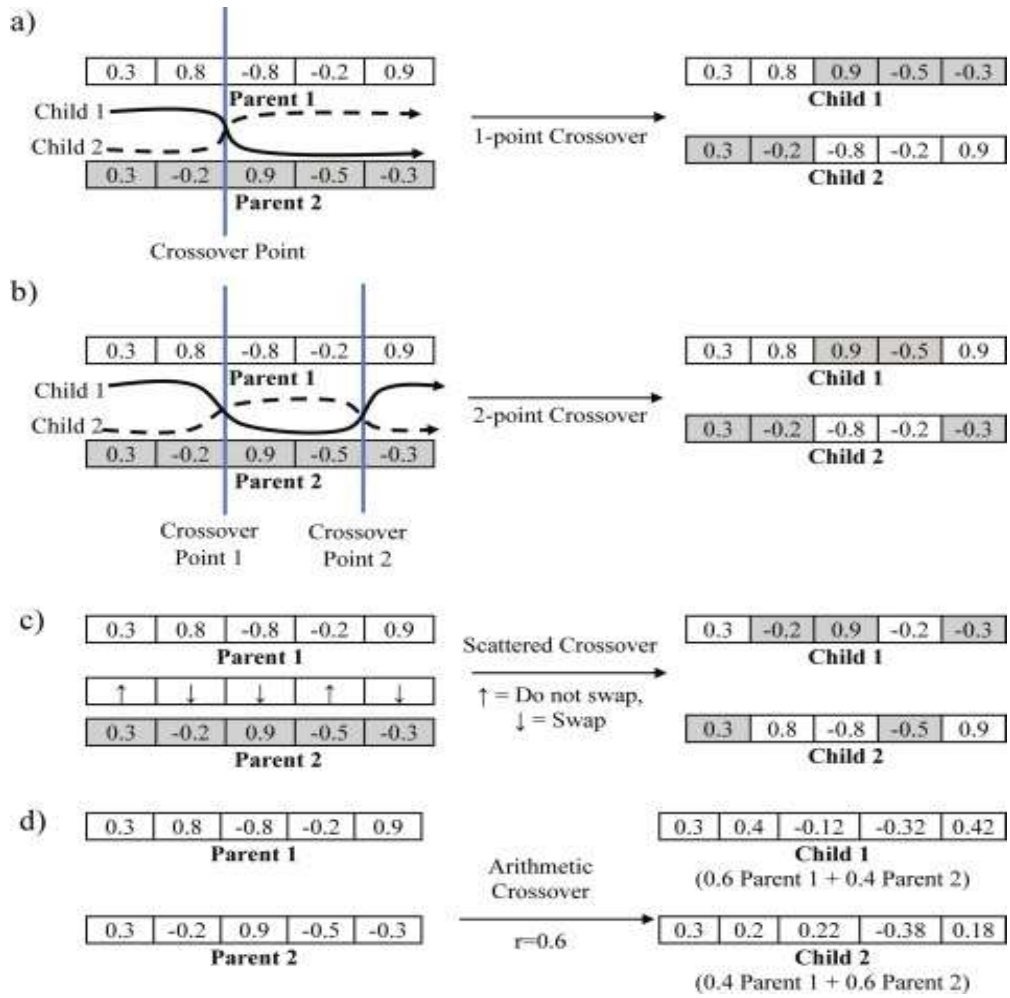

Figure 3. The insertion stage of the crossover operator.

Algorithm 3 The Crossover Operator
Input: An IFG G = (V, U) with intuitionistic DVS Xβ; β = μβ, νβ being degree of domination. Output: Minimized expression (7).
1. Begin
2. Construct β0 = W ∏ p (xj, xr) for all xj such that * 1 ≤ j ≤ n * xr ∈ V - {xj} * p (xj, xr) ≠ (0, 1) for all xr ∈ V - nxj
3. Construct the expression: ΦD = ⊗ (pi ∨ ⊗ (pj & ξjik)) for i = 1 to n * j = 1 to n * ξjik represents μ (xi, xj) ≥ μβ oR ν (xi, xk) ≤ νβ and pi = 1 if xi ∈ Xβ and 0 otherwise
4. Construct the expression: ΦD = ⊗ (Wi * pj & ξjik) for i = 1 to n * j = 1 to n

5. Compute the expression: $\Phi D = \prod (W_i * (p_{1i} \& p_{2i} \& ... \& p_{ki} \& \beta_i))$ for i = 1 to n
6. End

3.2 THE MUTATION OPERATOR OF THE OHGA

In contrast to the crossover operation, mutation in the context of the Capacitated Vehicle Routing Problem (CVRP) involves modifying a single individual, rendering it comparatively simpler. Classical mutation techniques, such as the exchange mutation operator (EX), have been found suitable for CVRP without yielding infeasible solutions. Studies, like the one conducted by Karaka tic and Podgorelec, have demonstrated the superiority of the EX operator over other mutation methods. This paper adopts the EX mutation approach, wherein two genes are randomly exchanged within a single sub-route, as illustrated in Figure 4.

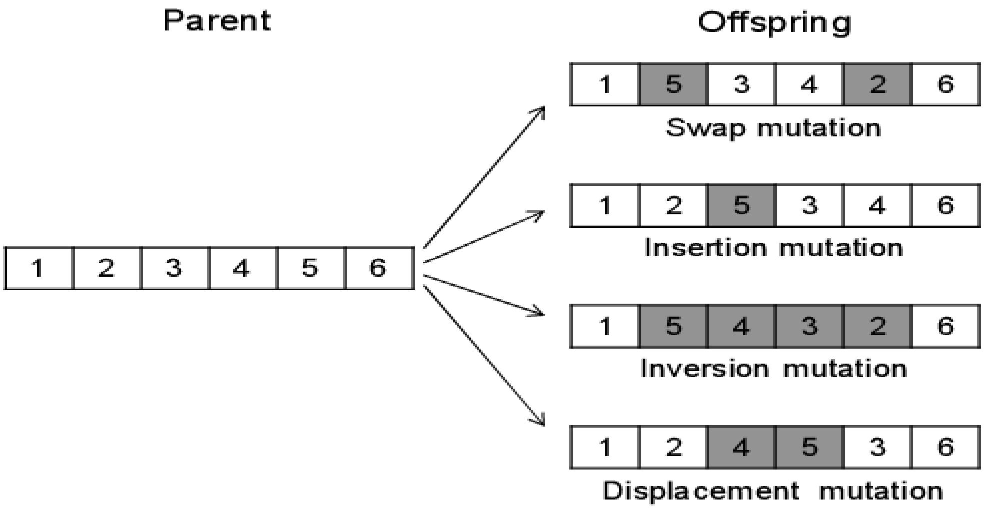

Figure 4. MUTATION OPERATOR

4. Aco Algorithm for Connected Vehicles System Model

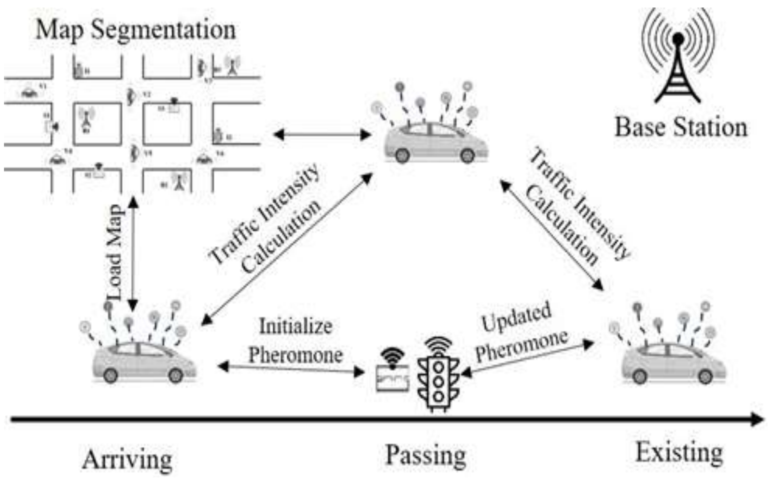

Figure 5. The process of connected vehicles traversing a given area

In Fig, the traversal process of connected vehicles within a designated area is illustrated. Upon entering the area, vehicles access and load maps to gather information necessary for navigating through the region. These maps are divided into discrete segments, each representing a distinct path that encapsulates the dynamic traffic flow within the area. Unlike traditional approaches that consider the entire road network, the computation of traffic intensity enables the independent determination of optimal routes for each segment, enhancing efficiency and adaptability. When a connected vehicle v seeks to transition from node i to node j, the decision regarding the next path is made using the Ant Colony Optimization (ACO) algorithm. This decision is guided by a probability calculation, which takes into account various factors such as pheromone levels, heuristic information, and traffic conditions, ultimately influencing the likelihood of selecting a particular path. By leveraging ACO, connected vehicles can navigate the area intelligently, selecting routes that minimize travel times and optimize overall traffic flow. This decentralized approach to route selection contributes to the efficiency and effectiveness of transportation systems, particularly in densely populated urban environments.

$$P_{i,j}^{v} = \frac{T_{i,j}^{a} \cdot \eta_{i,j}^{\beta}}{\sum_{k \epsilon N_i} T_{i,k}^{a} \cdot \eta_{i,k}^{\beta}}$$

Where,

$T_{i,j}^{a}$ indicates the backward pheromone values which is calculated

$\eta_{i,j}$ represents the traffic congestion estimation of instan- tenuous state of traffic intensity

α and β are the weigh for the importance of $T_{i,j}^{a}$ and $\eta_{i,j}$, respectively.

N_i represents the allowable moves from node i.

the pheromone values $T_{i,j}^{a}$ and the instan-tenuous state of traffic $\eta_{i,j}$, can be calculated based on the communication among connected vehicles which is defined in the following section. Specifically, for calculating the arrival time of backward ants, we apply the pheromone update rule in to make an update to the pheromone table. In this regard, the Eq. can be re-calculated as follows:

$$T_{ij} = (1-\lambda)T_{i,j}^{pre} + \lambda \sum_{v=1}^{M} \delta_{i,j}^{v}$$

The degree of traffic congestion is quantified as the ratio of the average vehicle speed within a path to the maximum speed permitted on that path. Consequently, the service rate $s_{i,j,l}$ of a lane within path $E_{i,j}$ can be estimated as follows:

$$s_{i.j.l} = \frac{C_{i,j}^{i} + 1 - V_{i,j}^{i}}{C_{i,j}^{i}}$$

where $V_{i,j}^{i}$ denotes the number of vehicles in the lane in $E_{i,j}$. $C_{i,j}^{i}$ indicates a capacity of the l-th lane in $E_{i,j}$ which can be calculated as follows:

$$C_{i,j}^{i} = \left[\frac{D_{i,j}}{\overline{L^{v}} + \overline{L^{g}}}\right]$$

where $D_{i,j}$ refers to the distance of $E_{i,j}$, Lv indicates the average length of vehicles, and Lg denotes the average length of gaps between vehicles. To estimate $\eta_{i,j}$, we aggregate service rates of lanes in $E_{i,j.}$ In practical, based on the destinations of vehicles, there are not all the lanes in $E_{i,j}$ which are always available. In this regard, supporting $L_{i,j,l}$ is the l-th lane in $E_{i,j}$, it can define an indicator function for determining whether $L_{i,j,l}$ have connectivity with any lane q in the neighboring nodes. Specifically, $I\,(L_{i,j,l})$ can be formulated as follows:

$$I(L_{i,j,l}) = \max_{q \epsilon N_i} I(L_{i,j,l}, q)$$

where N_j represents the allowable moves from node j, and

$$I(L_{i,j,l}) = \begin{cases} 1 \; if \; L_{i,j,l} \; has \; connectivity \\ 0 \quad otherwise \end{cases}$$

let's consider a scenario where we have two lanes within path $E_{i,j}$, and ten vehicles are traversing this path. If the vehicles are evenly distributed across the lanes, with five vehicles in each lane, we would have to wait for five vehicles to pass before we can proceed. However, if all ten vehicles are concentrated in one lane, we can utilize the other lane freely. To address this issue and avoid edges with evenly distributed service rates, we incorporate entropy loss into our calculations. The entropy loss is computed as follows:

$$L_{i,j} = -\sum_{t=1}^{L_{i,j}} I(L_{i,j,l}). S_{i,j,l} \,.\, log \; S_{i,j,l}$$

In this regard, the traffic congestion estimation of instant- nous state of traffic intensity can be calculated as follows;

$$\eta_{i,j} = -\sum_{t=1}^{L_{i,j}} I(L_{i,j,l}). S_{i,j,l} \cdot \frac{1}{L_{i,j} + 1}$$

Traffic Intensity Calculation based on Communication among Connected Vehicles:

In this present a novel methodology for calculating traffic intensity based on V2V communication among connected vehicles. Leveraging advanced vehicular technologies, vehicles share crucial information such as their current location, destination, and average speed. Introduce three distinct statuses of a connected vehicle within a given area: ARRIVING, PASSING, and EXITING, each accompanied by specific actions depicted in Fig. 3. Upon arrival, vehicles initiate a message exchange by requesting information from other vehicles passing through the area. In response, vehicles provide locally updated information. Upon exiting the area, vehicles transmit global-update messages containing comprehensive route information. It defines three types of message exchanges: REQUEST, LOCAL UPDATE, and GLOBAL UPDATE. Algorithm 1 outlines the movement functions of connected vehicles during traversal, incorporating these message types. This framework enables efficient communication and collaboration among vehicles, facilitating the calculation of traffic intensity and enhancing overall traffic management within intelligent transportation systems.

Algorithm 3: Message functions of a connected vehicle for passing a given area
Function Request (v, N_v):
while status: = Arriving do
Send request (v, sv, dv, N_v);
time = time + 1;
t_v = time;
Send (request, t_v);
end while
Function Local-update (v', N_v'):
while Receive Request (Iv, sv, dv, N_v) do
if N_v = N_v' then
(Request, t_v): = receive ();
time = max (t_v, time + 1);
if v_{status}! = Existing then
Send Local-Update (i_{dv}, lv', N_v);
end if
end if
end while
Function Global-update(v):
if v_{status}!: = Existing then
Send Global-Update (i_{dv},sv, dv, N_v);:);
end if

Algorithm 4: ACO-based Dynamic Decision Making for Connected Vehicles
while status: = Arriving do
Send request (v, sv, dv, N_v);
time = time + 1;
t_v = time;
Send (request, t_v);
end while
while Receive Request (Iv, sv, dv, N_v) do
if N_v = N_v' then
(Request, t_v): = receive ();
time = max (t_v, time + 1);
if v_{status}! = Existing then
end Local-Update (i_{dv}, lv', N_v');
end if
end if
e S nd while
if v_{status}!: = Existing then
Send Global-Update (i_{dv}, sv, dv, R_v);
end if

5. Simulated Scenarios and Parameter Setting

Three typical scenarios are considered within transportation management systems to assess the effectiveness of proposed approaches:

- **Single Intersection Scenario**: This scenario involves different paths and enables vehicles to make decisions for movement at a given junction node. By simulating interactions at a single intersection, researchers can analyze how connected vehicles respond to changing traffic conditions and make decisions to optimize their routes efficiently.
- **Intersection with Multiple Lanes Scenario**: In this scenario, multiple lanes are deployed along a path to emphasize the advantage of connected vehicles in sharing information with each other for real-time data processing. By simulating interactions in environments with multiple lanes, researchers can evaluate the effectiveness of connected vehicle systems in managing complex traffic patterns and lane-specific congestion.
- **Multiple Intersections Scenario:** This scenario involves multiple junction nodes and evaluates the performance of proposed approaches on a larger scale road network. By simulating interactions across multiple intersections, researchers can assess the scalability and robustness of connected vehicle decision-making algorithms in handling complex urban traffic scenarios.

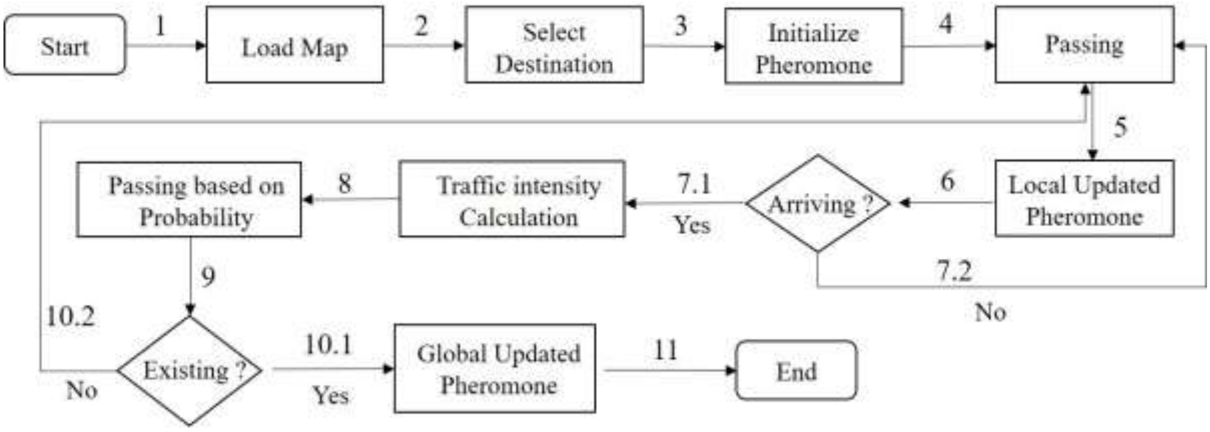

Figure 6. Diagram of ACO-based dynamic routing for connected vehicles passing a given area

The modeling environment described entails the utilization of NetLogo, a platform primarily written in Scala with supplementary components in Java, operating efficiently on a PC equipped with an Intel Core i7-4790 CPU clocked at 3.6 GHz and 16GB of RAM. Simulation parameters, as outlined in Table I, utilize "Tick" as the time unit for computing the average waiting time of vehicles. Vehicles are introduced randomly within simulated areas, adhering to varying densities ranging from 10% to 60% in each direction every 10 ticks, simulating real-world traffic conditions. Notably, congestion is observed to manifest when the density exceeds 60%. This setup facilitates the examination of traffic dynamics and congestion patterns under different vehicle density scenarios, aiding in the development of strategies for congestion mitigation and traffic management.

Table I Simulated Parameters:

Parameters	**Values**
Simulator	NetLogo V6.0.4
Unit of time	Ticks
Execute Time (per run)	1000 ticks
Speed of Vehicle	8-16 patches/10 ticks
Acceleration of vehicle	0.5-2 patches/10 ticks
Evaporation rate (λ)	0.8
Vehicle's appearance rate	10 ticks
Density of Vehicles	10% to 60% / direction
α, β	0.5

5.1 simulation result

In Fig. 5, the average waiting time comparison between method, ACO, and ACO-SPP is illustrated, with vehicle appearance intervals set at 10 ticks. Through ACO implementation, observe a notable reduction in average waiting times, leveraging pheromone values derived from backward traffic flow information. Interestingly, the difference between ACO-SPP and our approach is minimal in this context, as there's a lack of significant traffic flow in opposing directions, thereby mitigating the influence on pheromone values. This underscores the efficacy of approach and its similarity to ACO-SPP under specific traffic conditions.

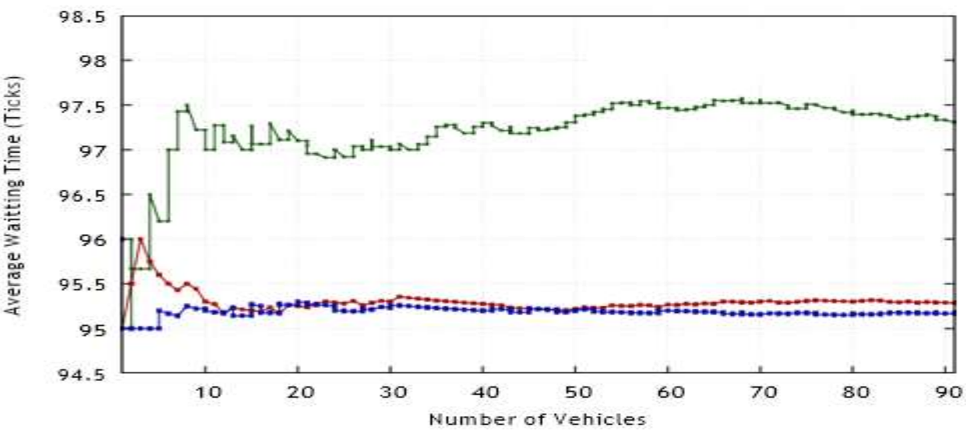

Figure 7. Traffic flow of single junction node

In the second simulation, introduced a scenario with multiple lanes in each path and varied sources and destinations within the same junction node, enhancing the complexity of the environment. Fig. 6 displays the traffic flow results at an intersection, illustrating the superiority of our approach over ACO-SPP. Our method integrates both backward and forward information, enabling connected vehicles to dynamically adjust their decisions. Fig. 7 further demonstrates this advantage by showcasing the average waiting time across increasing vehicle numbers with a density of 50% in each direction. Our approach exhibits superior adaptability to real-time traffic flow variations compared to the standard ACO approach, highlighting its effectiveness in diverse traffic scenarios.

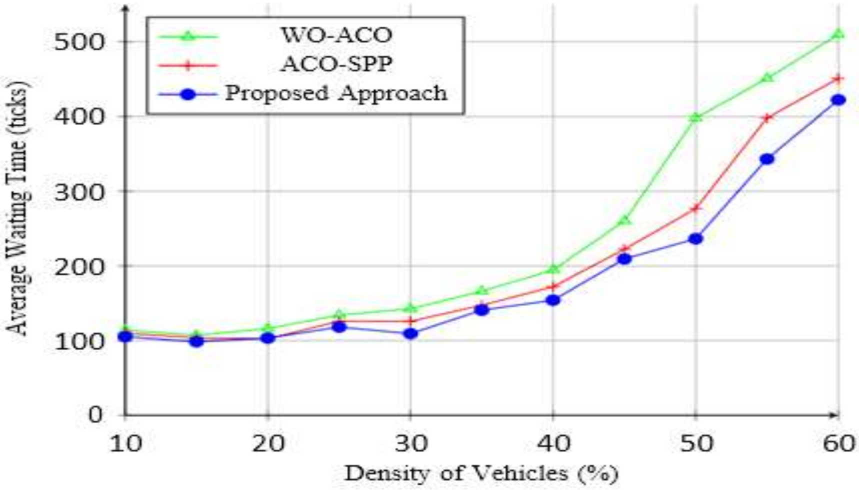

Figure 8. Traffic flow with multiple lanes

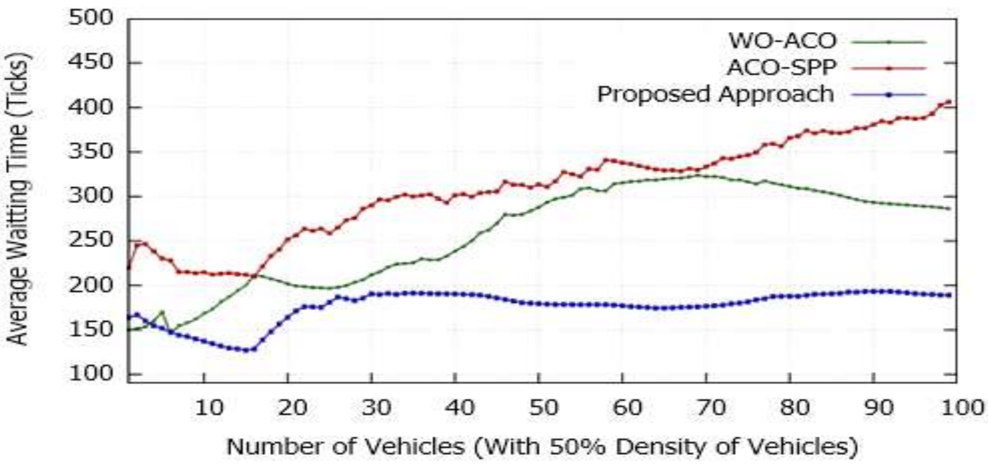

Figure 9. Traffic flow with multiple lanes

In our evaluation of the proposed approach, we constructed a scenario featuring a large-scale road network with a 3x3 road topology, accommodating vehicles with various sources and destinations. Fig. 8 showcases the average waiting times across different approaches as the density of vehicles from opposite sides varies. Our approach leverages dynamic decision-making through communication and collaboration among connected vehicles, effectively managing dynamic traffic flows, particularly under high-density conditions. Notably, as the pheromone value increases, more vehicles are inclined to follow the same paths, potentially leading to congestion during high-density periods. However, our approach enables connected vehicles to self-regulate pheromone values by sharing real-time traffic flow information, facilitating adaptive path selection with optimized costs (waiting time). This adaptive behavior enhances the efficiency and effectiveness of our approach in navigating complex road networks.

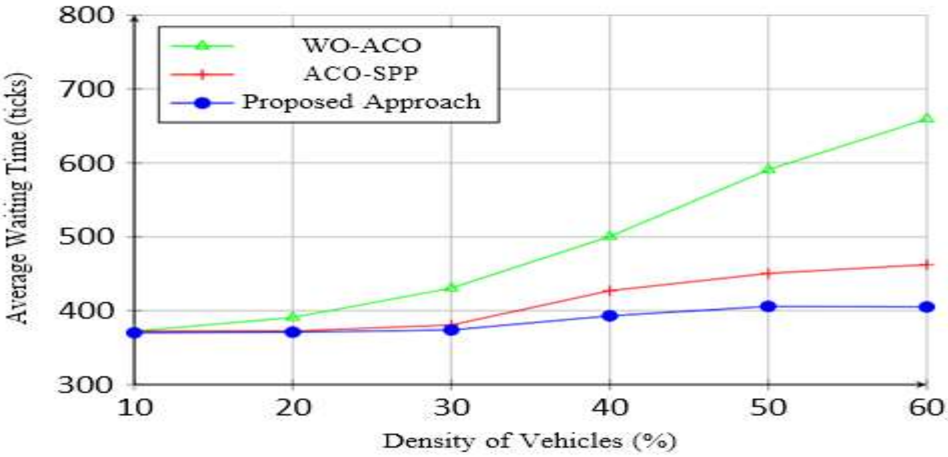

Figure 10. Traffic flow of multiple junction nodes with different densities

Fig. 9 provides a detailed insight into the average waiting time concerning the rising number of vehicles, maintaining a 60% density in alternate paths. Notably, in the ACO-SPP approach, as the number of vehicles sharing a path increases, recalculating pheromone values becomes time-consuming. Conversely, our approach capitalizes on the exchange of traffic flow information, incorporating both backward (T) and forward (η) information. This strategic fusion empowers vehicles to adaptively navigate the dynamic traffic environment, ensuring prompt and informed decision-making processes. Consequently, our approach demonstrates superior responsiveness and efficiency in handling varying traffic conditions compared to the conventional ACO-SPP method.

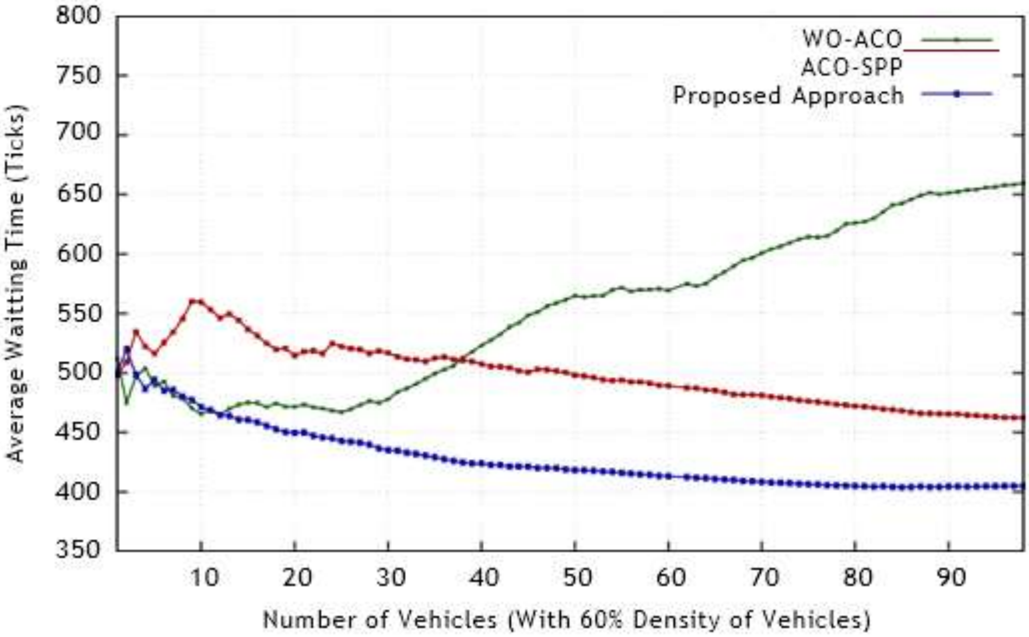

Figure 11. Traffic flow of multiple junction with the number of vehicles

6. CONCLUSION

In conclusion, our research contributes to the evolving landscape of Intelligent Transportation Systems (ITS) by proposing an innovative approach to dynamic decision-making for connected vehicles within an Internet of Things (IoT) environment. By leveraging computational intelligence and advancements in vehicular technology, we have developed a robust framework that facilitates real-time communication and collaboration among connected vehicles. Our integration of Ant Colony Optimization (ACO) concepts, combined with the order-aware hybrid genetic algorithm (OHGA), empowers vehicles to make informed decisions when navigating through complex traffic scenarios, thereby enhancing overall road safety and efficiency. Through simulated results across various scenarios, we have demonstrated the effectiveness of our approach, laying the foundation for further exploration and application in diverse ITS contexts. Looking ahead, future research endeavors will involve the application of our proposed approach to larger-scale ITS scenarios and the exploration of Swarm Intelligence (SI)-based hybrid algorithms to unlock additional capabilities within the transportation system. This study underscores the potential of integrating computational intelligence at the edge, including OHGA hybrid mode, to revolutionize the way we navigate urban environments and addresses the pressing challenges of traffic congestion, road safety, and environmental sustainability.

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