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Dynamic Decision Making for Connected Vehicles in IoT System

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Abstract
Intelligent Transportation System (ITS) which focuses on dynamic decision making for IoT data processes using distributed and decentralized systems has attracted much attention in recent years. In this paper, we propose a novel approach for enabling computational intelligence into dynamic decision-making for connected vehicles to provide various applications of smart cities. The proposed approach is based on the ant colony optimization (ACO) approach, which is able to improve the performance of intelligent transportation systems. In addition, the simulated results are compared with previous works in the literature.
Keywords: *Internet of Things (IoT), Intelligent Transportation System (ITS), Connected Vehicles.*

1. Introduction
The Internet of Things (IoT) has emerged as a transformative technology paradigm, enabling the interconnection of billions of devices across various domains. IoT deployments encompass a diverse range of applications, including smart homes, healthcare monitoring, industrial automation, and smart cities. However, managing dynamic decision making in IoT-connected devices presents unique challenges that require innovative solutions to ensure optimal performance, reliability, and security. This paper provides an overview of the complexities associated with dynamic decision making in IoT environments and explores strategies to address these challenges effectively. In this paper, we introduce an innovative approach for dynamic decision making in IoT-connected devices based on Ant Colony Optimization (ACO). ACO, inspired by the collective behavior of ants searching for food, offers a decentralized and adaptive optimization technique suitable for dynamic IoT environments. We explore the application of ACO algorithms to address key challenges in routing, resource allocation, and task scheduling within IoT networks. Specifically, connected vehicles are equipped of smart transportation with Internet access that enables vehicles to communicate with the internal and external environments (e.g., Vehicle- to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Sensor (V2S), and Vehicle-to-Base Station (V2B)). Figure 1 shows the overview of cyber-physical architecture of smart transportation. In this regard, the objective of this study takes an investigation beyond the connections among connected vehicles to provide intelligent services in transportation management. Thereby, this study mainly focuses on answering the following questions: [1-4]

1. How connected vehicles communicated with each other?
2. What information is needed for applying ACO among connected vehicles?

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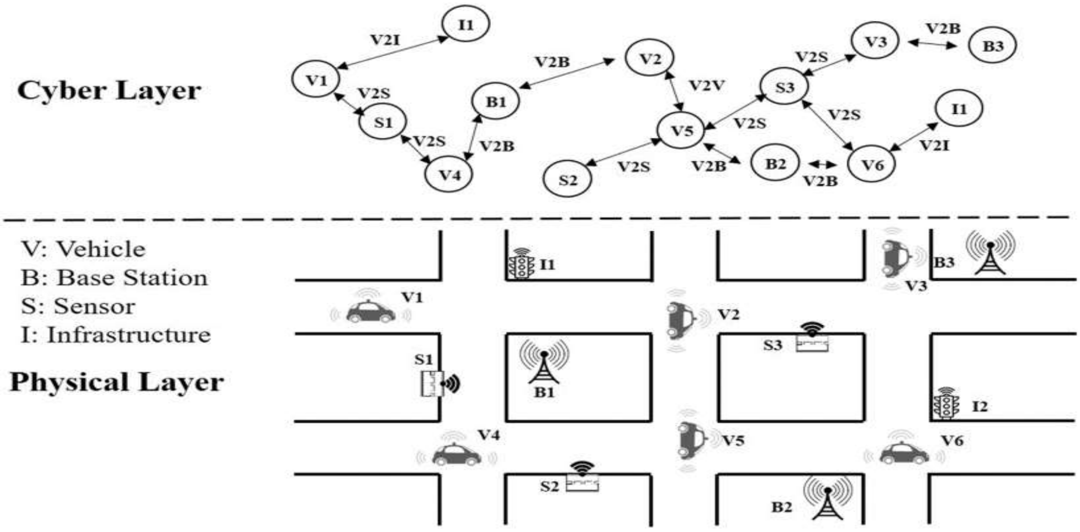

Figure 1 The Overview of Cyber-Physical Architecture of Smart Transportation

2. Method

2.1. Connected Vehicle for Intelligent Transportation System

V2X, which stands for 'vehicle to everything', is the umbrella term for the car's communication system, where information from sensors and other sources travels via high-bandwidth, low-latency, high-reliability links, paving the way to fully autonomous driving. Figure 2 shows V2X communications [5-9].

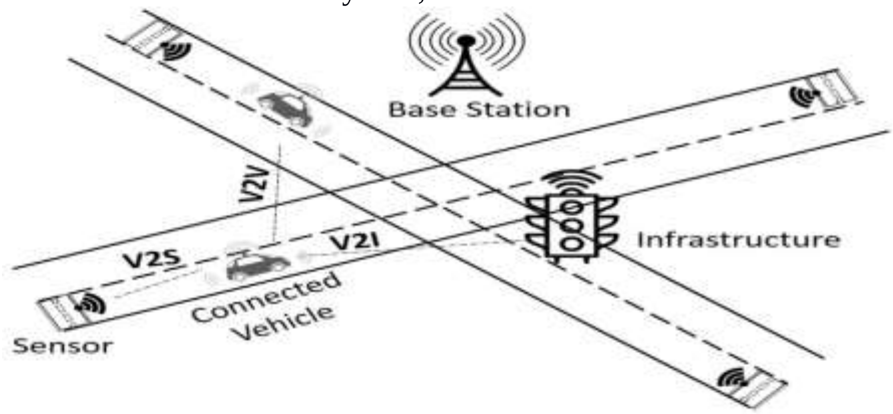

Figure 2 V2X Communications

Technically, a connected vehicle v can be represented by 4-tuples as follows:

v = (I, R, A, K)

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.

3. System Model

There are three statuses of a connected vehicle traversing v at a certain area, which are defined as follows: [10-13]

ARRIVING: the state when a vehicle arrives the area.

PASSING: the state when vehicle is moving on the area.

EXISTING: the state when vehicle exits the area.

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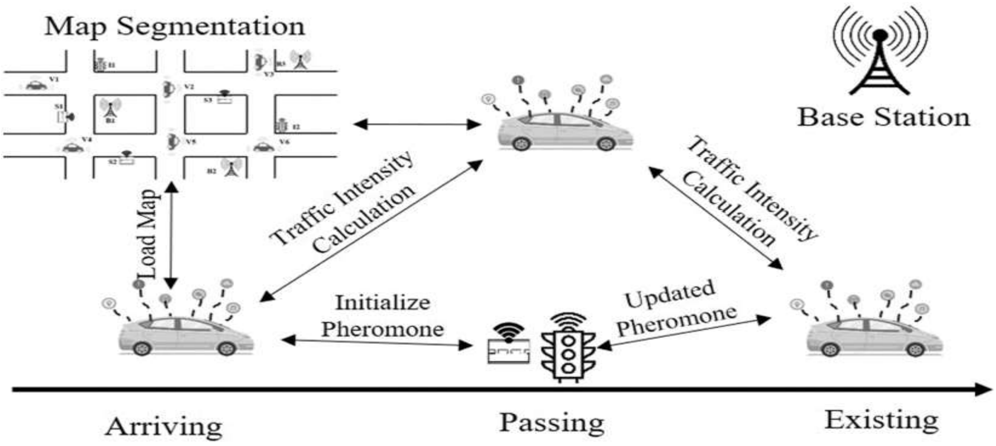

Figure 3 **The Process of Connected Vehicles Traversing a Given Area**

REQUEST- (IV, sv, dv, NV): when connected vehicles request to get information for calculating traffic intensity.

LOCAL − UP DAT E (IV, N, v, lv): when vehicles receive the request message, they response the local-updated message about their information.

GLOBAL − UP DAT E (IV, sv, dv, RV): when vehicles exit the area, they will send the global-updated message about their information for passing the route (e.g., paths and consuming time). [14-17]

Algorithm 1: Message Functions of a Connected Vehicle for Passing a Given Area.

```
Function Request(v, N_v)
while v_Status := Arriving; do
    Send request(I_v, s_v, d_v, N_v) ;
    time = time + 1;
    t_v = time;
    Send(request, t_v)
end
Function Local-update(v', N_v')
while Receve Request(I_v, s_v, d_v, N_v) do
    if N_v = N_v' then
        (Request, t_v):= recieve();
        time = max(t_v, time + 1) ;
        if v_Status != Existing then
            Send Local − Update(id_v, l_v', N_v') ;
        end
    end
end
Function Global-update(v)
if v_Status := Existing then
    Send Global − Update(id_v, s_v, d_v, R_v)
end
```

Figure 4 **The Algorithm**

Specifically, Algorithm 1 in Figure 4, depicts the movement functions of a connected vehicle during traveling a certain area by using message types. Figure 3 shows the process of connected vehicles traversing a given area. [18-20]

4. Evaluation

For evaluating the effectiveness of the proposed approach, we calculate the average waiting time of vehicles for passing a certain area. Regarding research question, we take into account three typical scenarios in transportation management systems which include:

Single Intersection: the scenario including different paths, enables vehicles to make the decision for moving at a given junction node.

Intersection with Multiple Lanes: the scenario is

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deployed with multiple-lanes in a path, for emphasizing the advantage of connected vehicles by sharing information with each other for real-time data processing.

Multiple Intersections: the scenario with multiple junction nodes evaluates the performance of our approach in terms of the large scale of the road network.

5. Discussion

Following figure how's the average waiting time following the increasing number of vehicles with the density in each direction equals *50%*. Our approach is able to effectively adapt with different situations of real-time traffic flow, comparing with the standard ACO approach.

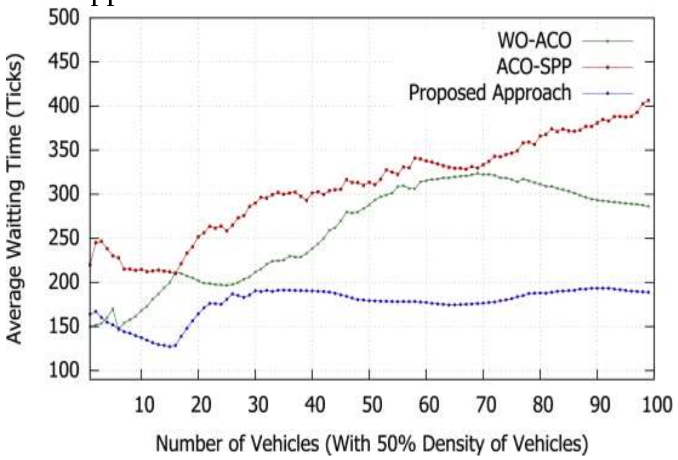

Figure 5 ACO Approach

Furthermore, for evaluating the effectiveness of the proposed approach, we have developed a scenario in terms of the large scale of the road network. Particularly, the scenario includes 3×3 road topology in which the vehicles move with different sources and destinations. In this regard, there are different routes for a vehicle passing from the source to the destination. Figure 5. 8depicts the average waiting times for passing a certain area with different approaches following different rates of density of vehicles from opposite sides. As a result, by dynamic decision making based on communication and collaboration among connected vehicles, our approach is able to deal with the dynamic traffic flow, especially in the case of high density. Specifically, with the increasing pheromone value, the number of vehicles moving on the same paths will increase. In this regard, in the case of high density, congestion will occur. In our approach, connected vehicles are able to self-balance pheromone values based on sharing information of real-time traffic flow to be able to make adaptive decisions for choosing a path with an effective cost (waiting time).

Conclusion

Dynamic decision making in IoT-connected devices is essential for enabling intelligent, autonomous, and adaptive behaviors in distributed systems. By addressing the challenges of resource constraints, data heterogeneity, real-time requirements, and security concerns, organizations can unlock the full potential of IoT technologies and harness actionable insights from vast amounts of sensor data. Future research directions include exploring synergies between machine learning, edge computing, and IoT security to develop holistic solutions for dynamic decision making in IoT environments.

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