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ORIGINAL ARTICLE

ACO-based traffic routing method with automated negotiation for connected vehicles

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Abstract
Most traffic control systems are centralized, where all the collected data can be analyzed to make a decision. However, there are problems with computational complexity and, more seriously, real-time decision-making. This paper proposes a decentralized traffic routing system based on a new pheromone model of ant colony optimization algorithm and an automated negotiation technique in a connected vehicle environment. In particular, connected vehicles utilize a new pheromone model, namely the inverted pheromone model, which generates a repulsive force between vehicles and gives negative feedback to the congested roads. They also perform a collective learning-based negotiation process for distributing traffic flows throughout the road networks, reducing traffic congestion. Via extensive simulations based on the Simulation of Urban Mobility, the proposed system shows that it can significantly reduce travel time and fuel consumption compared to existing systems.

Keywords Ant colony optimization · Automated negotiation · Connected vehicle · Traffic routing · Inverted pheromone

Introduction

The rising urban population generates a significant volume of traffic, which exacerbates traffic congestion. Congestion not only reduces traffic efficiency but also raises energy consumption and emissions of vehicles [1]. Therefore, urban traffic control is a notable concern for alleviating road congestion, enhancing road network capacity, and establishing an efficient and smooth traffic system. With increasing urbanization and the most recent advancements in the Internet of Things (IoT), Vehicles-to-Everything (V2X) communications, Artificial Intelligence (AI), and autonomous technologies, transportation research has evolved to more intelligent systems known as Intelligent Transportation Systems (ITS) [2]. The primary purpose of ITS is to offer participants safe, efficient, and sustainable transportation networks. Some key research topics, including optimal traffic signal control, traffic flow optimization, planning, and vehicle decision-making, can be investigated for this goal. As an essential part of ITS, connected vehicles have gained great attention from academia and industry [3]. Connected vehicles outfitted with contemporary sensors, controllers, actuators, and other devices, can perceive the surrounding environment and make smart decisions [3]. Control technologies are rapidly evolving, ensuring the safe functioning of connected vehicles in traffic networks. Furthermore, reliable communication and computing technologies guarantee that connected vehicles can share data effectively with other vehicles and infrastructure.

With the cutting-edge technologies, the existing studies have developed efficient traffic routing systems under the connected vehicle environment [4–7]. However, some issues need to be considered further to improve the effectiveness of the traffic routing systems. For example, most studies have taken centralized approaches to perform routing for connected vehicles in traffic networks [4,5]. However, in centralized models, there are two major issues: scalability (as a single central controller gathers information and makes decisions for all vehicles, resulting in a high communication and computing burden, confronting single-point failures) and privacy (as the vehicles have to share all information with the centralized server) [6,7]. To overcome these issues, connected vehicles can leverage the ant colony optimization (ACO) algorithm, a well-known meta-heuristic approach in swarm intelligence, to achieve decentralized and self-organized transportation systems [8–15]. However, without

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cooperation between vehicles, many vehicles may select the same path for travel; hence, the path will likely get congested shortly.

Motivated by the benefits of decentralized traffic routing models and the limitations of existing studies, in this paper, we develop a decentralized cooperative traffic routing method for coordinating connected vehicles in traffic networks. The main contributions can be summarized as follows.

- We propose a new pheromone model, called the inverted pheromone model, including occupancy time and fuel consumption rate pheromones. It gives negative feedback to the congested road segments. The pheromone-based traffic routing method minimizes travel time, fuel consumption, and emissions by avoiding congested routes and finding alternative routes with more environmentally friendly.
- We investigate the cooperative negotiation between vehicles in traffic routing to enhance traffic efficiency further. Vehicles collaborate when they are near, they effectively spread themselves out among different routes, preventing traffic jams on the same paths.
- Extensive simulations based on the Simulation of Urban Mobility (SUMO) simulator were conducted to demonstrate the effectiveness of the proposed framework under various traffic conditions. The results of simulations show that the system greatly increases traffic efficiency.

The rest of this paper is structured as follows. "Background and related work" reviews the background and related works in the field of smart transportation. "ACO-based traffic routing method with automated negotiation" introduces a new pheromone-based method with an automated negotiation technique for solving a traffic routing problem under the connected vehicle environment. "Performance evaluation" presents performance evaluation of the proposed method. Finally, conclusion remarks are provided in "Conclusion".

Background and related work

Decentralized intelligent transportation systems

IoT interconnects numerous digital things over the Internet as current communication technologies advance, culminating in an intelligent and large global infrastructure for an information-driven society [16]. Many applications employ IoT technology to improve our daily lives, including smart cities, smart homes, healthcare, energy management, and transportation [3,16,17]. The development of IoT requires decentralizing and distributing to maximize flexibility, agility, and reliability. As an IoT application in urban transportation, connected vehicles are potential solutions for the implementation of ITS in the near future [3]. As shown in Fig. 1, benefiting from V2X communications such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), connected vehicles quickly broadcast real-time traffic data to other vehicles or Roadside Units (RSU). Intelligent control algorithms for coordinating vehicles can enhance the effectiveness of transportation and reduce traffic congestion.

Swarm intelligence can be utilized to achieve edge intelligence in decentralized IoT systems. It is based on the self-organized collective behavior of natural agents (e.g., ant colonies, a flock of birds, bee swarm), which can develop decentralized systems [17]. Swarm intelligence-based decentralized systems can be applied for different domains such as transportation [15], energy management [17], and healthcare [18]. ACO is a widely used algorithm in swarm intelligence-based algorithms. It is prompted by the foraging actions of social ant species, which use pheromone trails to locate the shortest path between the nest and food sources [19,20]. Each ant represents a feasible solution to the problem. With existing pheromone trails and heuristic information, the solution is produced probabilistically. Ants share a pheromone database that is constantly updated. The greater the pheromone concentrations, the better the solution is. After several iterations, all ants pick the optimal path with the highest pheromone concentrations.

Automated negotiation techniques are promising solutions for implementing decentralized systems [21]. Negotiation techniques have been used in decentralized AI or multi-agent systems for decentralized problem-solving [22, 23]. During a negotiation, objects may change their local plans or relax their constraints to agree with other objects on a specific problem by following a negotiation protocol. Contract Net Protocol (CNP) is a well-known negotiation protocol in which the network is assumed to be made up of asynchronous objects, with each connected object communicating with others via message transmission [23,24]. Some studies were used automated negotiations for solving various problems, e.g., supply chain management [25], intersection traffic control [23], vehicle route allocation [26], and smart home energy management [23]. It can be shown that decentralized agents can interact locally, either directly or indirectly, while regulating overall outcomes in global optimization or an acceptable solution. As V2X communication evolves, connected vehicles can be considered intelligent objects that can work together to solve traffic control problems.

Traffic routing optimization

A traffic routing problem (also known as a traffic assignment problem) is the process of allocating traffic demand to routes on a road network. The complexity and unpredictability of the transportation networks make it difficult. For traffic

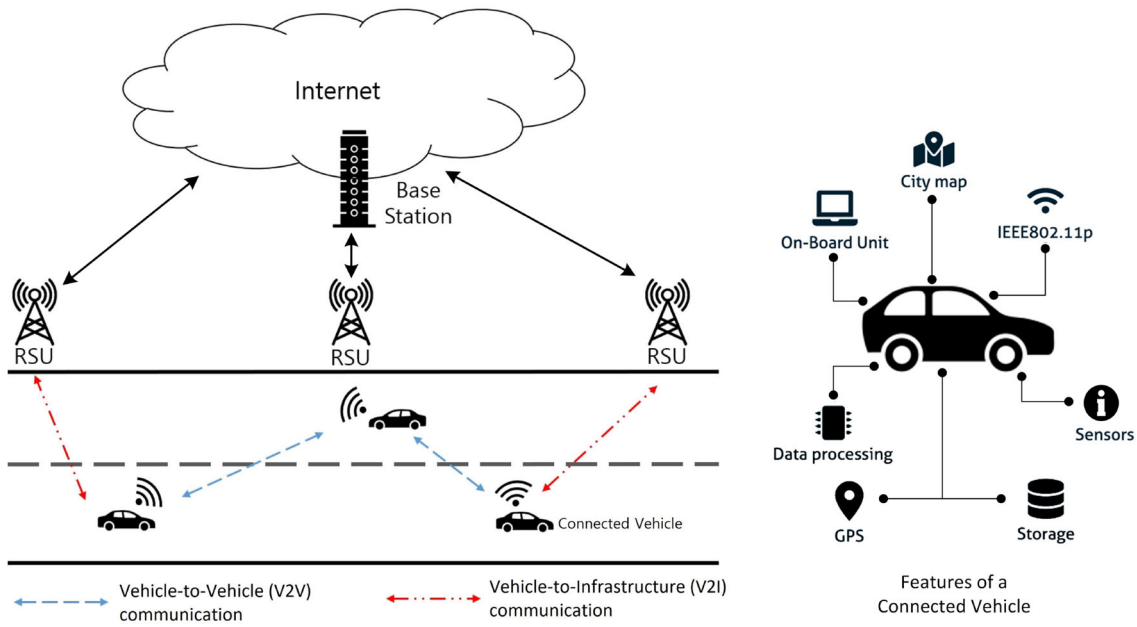

Fig. 1 Connected vehicle environment

assignment, there are two equilibrium concepts: user equilibrium (users prioritize the individual cost minimization) and system optimum (users prioritize global cost or the average travel time) [27]. These concepts can design routing systems that optimize an entire traffic system. In the early stages of tackling traffic routing issues, some research focused on path planning and routing vehicles under static circumstances, such as route distances and speed limits. For example, the Dijkstra and A* algorithms find the shortest path without considering the dynamic features of other road networks. On the other hand, dynamic traffic assignment (DTA) techniques can approximate user equilibrium with time-varying traffic flows using a centralized iterative simulation procedure [28,29]. However, the DTA algorithms have several practical challenges, including high computing resource needs, tractability for large-scale road networks, real-time routing capabilities, effective congestion control, and the ability to function when certain vehicles do not follow routing recommendations.

With connected vehicle technology, decentralized management systems can distribute the workload among vehicles in exchange for a higher effort for synchronizing communications. In particular, via indirect communications, ACO algorithms are investigated in decentralized and dynamic traffic routing issues under the connected vehicle environment [8–15]. While vehicles are moving on the roads, they send their digital pheromones, which usually represent the speed, travel time, and road density, to the corresponding RSU. The incoming vehicles obtain the pheromone information and execute route choice decision-making to disperse traffic flows over the road network and minimize trip time. In dynamic traffic routing, the vehicles can be rerouted to avoid congested roads with the help of sharing information between vehicles and road infrastructure. However, if many vehicles reroute to the same path, it can create traffic congestion in other places. Hence, negotiation between vehicles can be considered to improve traffic efficiency further.

ACO-based traffic routing method with automated negotiation

This section defines the urban transportation model and formulates the traffic routing problem. Then, we present a traffic routing method inspired by a new pheromone model in the ACO algorithm and an automated negotiation technique (Fig. 2).

Transportation model

The traffic network is represented as a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where $\mathcal{N} = \{i | i = [1, n]\}$ denotes a set of nodes or intersections and $\mathcal{E} = \{(i, j) | i, j \in N, i \neq j\}$ denotes a set of edges or road segments (two separate directions of a road are regarded as two distinct road segments). l_{ij} denotes the length of (i, j). R denotes a set of RSU, where $r_{ij} \in R$ is the RSU of (i, j).

Letting $\mathcal{V}$ to be the set of connected vehicles, which have entered the road transportation network. Each vehicle $v_k \in \mathcal{V}$ has the attributes as

$$v_k = \langle \mathrm{ID}_k, \mathrm{src}_k, \mathrm{dst}_k, p_k \rangle \tag{1}$$

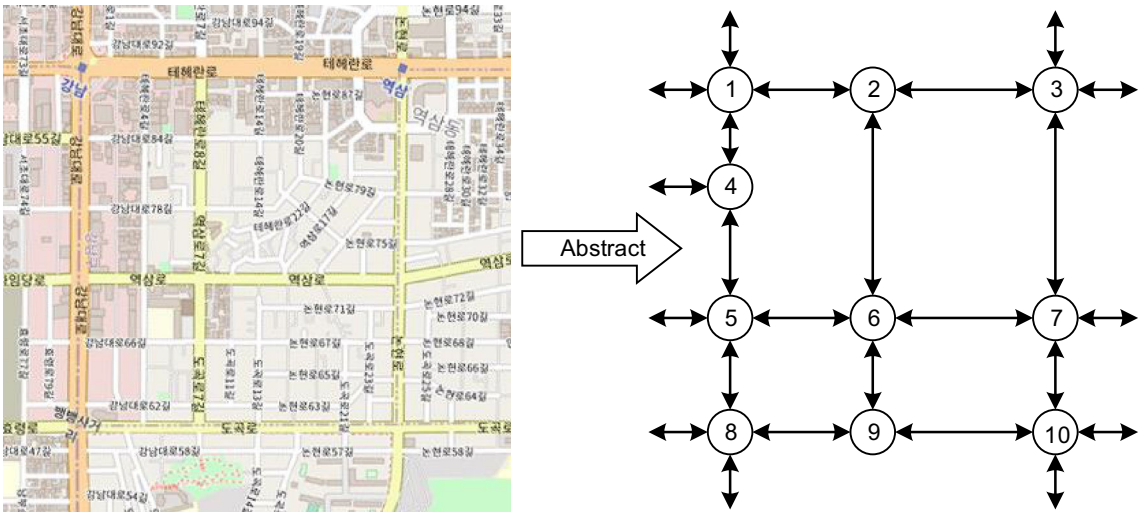

Fig. 2 Graph representation of traffic network

where ID_k is the vehicle identifier, src_k and dst_k is the source and destination of v_k in the road network, and p_k is the current travel path of v_k.

Achieving sustainability in transportation will significantly enhance the sustainability of cities. Hence, the emissions and fuel consumption of vehicles should be considered. Because of its processing efficiency and accuracy, the Emissions from Traffic (EMIT) model was chosen to assess vehicle emissions and fuel consumption [30]. The model first calculates the instantaneous tractive power P_{tr} using vehicle speed s (m/s) and acceleration a (m^2/s) as

$$P_{\mathrm{tr}} = A \cdot s + B \cdot s^2 + C \cdot s^3 + M \cdot a \cdot s + M \cdot g \cdot \sin \vartheta \cdot s \quad (2)$$

where A denotes rolling resistance (kW/m/s), B denotes speed correction (kW/(m/s)^2), C denotes air drag resistance (kW/(m/s)^3), M denotes vehicle mass (kg), g denotes gravitational constant (9.81 m/s^2), and ϑ denotes road grade (degrees). Based on P_{tr} value, the fuel consumption rate FR (l/s) is estimated by

$$FR = \begin{cases} \alpha + \beta \cdot s + \gamma \cdot s^2 + \delta \cdot s^3 + \zeta \cdot a \cdot s, & \text{if } P_{tr} > 0 \\ \alpha', & \text{if } P_{tr} = 0 \end{cases} \quad (3)$$

where α, β, γ, δ, and ζ denote constants corresponding to individual vehicles. They are derived by the use of ordinary least square linear regressions. The EMIT model estimates the engine-out pollutant emissions E (g/s) by

$$E = \lambda + \mu \cdot \mathrm{FR} \quad (4)$$

where λ and μ denote the greenhouse gas-specific emission index parameters. Carbon dioxide (CO_2) is the primary pollutant emitted by full combustion of fuel, and its level is proportionate to fuel consumption. Therefore, when analyzing the environmental impacts of vehicles, the expressions CO_2 emission and fuel consumption are equivalent.

Dynamic traffic routing problem

The traffic routing problem refers to assigning traffic demand to routes on the traffic network. Unlike typical traffic assignment problems, the dynamicity and unpredictability of traffic networks are considered. In other words, there is no prior knowledge of future traffic demand or vehicle schedules entering the road network. Thus, connected vehicles have to perform routing computations adaptively to avoid busy road segments without a centralized controller. Fuel consumption of vehicles is related to their travel times. Therefore, the main goal of the traffic routing problem is to minimize the average travel times of all vehicles. The global cost or the objective function is defined as

$$\min f_G = \sum_{v_k \in V} \sum_{(i,j) \in p_k} t_{ij}^k \quad (5)$$

where $(i, j) \in p_k$ is the road segment that belongs to the travel path p_k of v_k and t_{ij}^k is the travel time of vehicle v_k on (i, j).

Traffic flow models, e.g., Greenshields, Greenberg, and Underwood models, represent the relationship of speed and traffic density [31,32]. They are fundamental for estimating travel time in traffic networks. The Greenshield model is a well-known model for representing the uninterrupted traffic flow [31]. It is extensively utilized in traffic assignment models [4,32]. Hence, we apply the Greenshield model to estimate the travel time. The Greenshield model considers

the linear relationship between speed and traffic density as

$$\bar{s}_{ij} = s_{ij}^{\max} \cdot \left(1 - \frac{V_{ij}}{C_{ij}}\right) \tag{6}$$

where $\bar{s}_{ij}$ denotes the estimated average speed, $s_{ij}^{\max}$ is the speed limit, V_{ij} is the current number of vehicles moving on (i, j), and C_{ij} is the capacity of (i, j). C_{ij} is calculated as

$$C_{ij} = \frac{l_{ij} \cdot \text{lanes}_{ij}}{\bar{l}_v + \bar{l}_{\text{gap}}} \tag{7}$$

where l_{ij} is the length of (i, j), lanes_{ij} is the lanes number of (i, j), $\bar{l}_v$ and $\bar{l}_{\text{gap}}$ are the average length of vehicles and safety gap between vehicles, respectively. According to the average speed, the travel time is estimated as

$$t_{ij} = \frac{l_{ij}}{\bar{s}_{ij}}. \tag{8}$$

Based on the estimated travel time of each road segment, the vehicle v can find the shortest travel time path as a travel path p_k. Hence, the total travel time of the travel path p_k may be represented as

$$f_L(p_k) = \sum_{(i,j) \in p_k} t_{ij} \tag{9}$$

where $f_L(p_k)$ represent the local cost or total travel time of the path p_k of v_k, and $(i, j) \in p_k$ is the road segment that belongs to the current travel path p_k.

We proposed a new decentralized cooperative traffic routing strategy inspired by a new pheromone model in the ACO algorithm and an automated negotiating mechanism for tackling the dynamic traffic routing issue. The vehicles perform traffic routing in a decentralized paradigm rather than a centralized model. Centralized traffic routing systems have two key disadvantages: scalability (when dealing with large-scale traffic networks, the centralized controller necessitates significant computing and communication) and privacy (vehicles have to share all information with the centralized server) [6,7]. Decentralized models increase system scalability by reducing server computing utilization, and the number of messages exchanged between the server and the vehicles [6]. Furthermore, because decentralized models do not require extra infrastructure, they can reduce deployment costs and eliminate centralized controller failure [7].

Inverted pheromone-based traffic routing

In the ACO algorithm, pheromones on an ant's route entice other ants to follow and reinforce that route [19]. In connect vehicle environment, each vehicle can be modeled as an ant agent interacting with all others using digital pheromones stored by RSU [8–15]. However, the routing systems may give the same optimal path for many vehicles, causing congestion and lowering overall traffic efficiency. To overcome this issue, we present a new pheromone model, called the inverted pheromone model, that generates a repulsive force between vehicles and gives negative feedback to the congested roads. We consider two types of pheromones: occupancy time pheromone and fuel consumption rate pheromone.

Definition 1 (*Occupancy time pheromone*) Occupancy time pheromone of a vehicle is defined by the value of occupancy time, which is the amount of time necessary to travel the length of the vehicle at the current speed as

$$\tau_{\text{OC},ij}^k(t) = \frac{l_k}{s_k(t)} \tag{10}$$

where l_k denotes the length of v_k and s_k denotes the current speed of v_k on (i, j) at time t.

Definition 2 (*Fuel consumption rate pheromone*) Fuel consumption rate pheromone of a vehicle is the value of the fuel consumption rate of the vehicle moving on the road segment as

$$\tau_{\text{FR},ij}^k(t) = \text{FR}_{ij}^k(t) \tag{11}$$

where $\text{FR}_{ij}^k(t)$ denotes the fuel consumption rate of v_k on (i, j) at time t.

Definition 3 (*Inverted pheromone model*) The inverted pheromone model is defined as

$$\tau_{ij}^k(t) = \tau_{\text{OC},ij}^k(t) \cdot \tau_{\text{FR},ij}^k(t) \tag{12}$$

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \rho \cdot \sum_{k \in \mathcal{K}} \tau_{ij}^k(t) \tag{13}$$

where τ_{ij}^k represents the inverted pheromone of v_k deposited on (i, j), τ_{ij} represents the inverted pheromone deposited by all vehicles moving on (i, j), $\rho \in (0, 1)$ denotes the evaporation rate, and $\mathcal{K}$ denotes the set of vehicles moving on (i, j).

The inverted pheromone is periodically updated with the ACO hyper-cube framework [20]. The value of this pheromone confines the range [0, 1], and the evaporation rate determines the degree of the inverted pheromone's effect. Thus, in the paths with fewer inverted pheromones, the vehicles move faster, and the number of vehicles is lower than those with higher inverted pheromones. Traffic congestion detection is utilized to trigger the dynamic routing process. The RSU monitors traffic density in the corresponding road

segment to detect traffic congestion. The traffic density D_{ij} of (i, j) at time t is computed by

$$D_{ij}(t) = \frac{V_{ij}(t)}{C_{ij}} \tag{14}$$

where V_{ij} denotes the number of vehicles moving on (i, j) and C_{ij} denotes the capacity of (i, j). When the traffic density on a road segment exceeds a specified congestion threshold value (typically, 0.7 [4]), the road segment is considered congested.

If congestion is observed on the arriving road segment, the vehicle v_k finds alternative P_k paths at intersection i using the K-shortest path algorithm with the estimated travel times as costs [33]. The vehicle then chooses a path based on the inverted pheromone model. The probability $P^k_{i,p}$ for the vehicle v_k to select a path $p \in P_k$ is described as

$$P^k_{i,p}(t) = \frac{e^{-\tau_{i,p}(t)}}{\sum_p^{P_k} e^{-\tau_{i,p}(t)}} \tag{15}$$

where $\tau_{i,p}$ denotes the total of inverted pheromone values of road segments along the path p. The final path can be selected by the decision function as

$$p_k = \arg\max_{\forall p} \left\{ X \cdot P^k_{i,p}(t) \right\} \tag{16}$$

where $X \sim \cup([0, 1])$ is a random variable with a uniform distribution. The random variable improves traffic balance and lowers route flapping, which occurs when traffic shifts from one road to another when a large number of vehicles follow the same route suggestion.

The inverted pheromones are kept in the RSU, and the vehicles' pheromones are updated via V2V and V2I communications [8–15]. In specifically, in a traffic network, the RSU exchange their pheromone information in order to construct global pheromone information. When a vehicle receives a traffic congestion alarm message from the RSU, it uses the pheromone information to make routing decisions, then updates its pheromone to the RSU when it exits the road section. This procedure is continued till the vehicle arrives at its destination.

Cooperative negotiation-based traffic routing

The path selection process still relies on the probability function in the inverted pheromone-based traffic routing method. To further reduce the possibility of creating a new congestion spot in the rerouting process, the vehicles should facilitate cooperative negotiation in routing decisions when the traffic congestion is detected in nearby road segments.

To perform the coordination and optimize the path selection, vehicles employ the Iterative Economic Planning and Optimized Selections (I-EPOS)[1] algorithm as a multi-agent, decentralized, self-organizing, and privacy-preserving optimization method [34,35]. Each I-EPOS agent has a list of alternative paths generated by the corresponding vehicle. I-EPOS coordinates and chooses a subset of vehicles' paths to minimize the average travel time. I-EPOS agents self-organize in a tree-topology to structure their interactions, enable cost-effective path aggregation and perform coordinated optimization and decision-making. The Contract Net Protocol can be used for exchanging the solutions between vehicles [23]. I-EPOS executes consecutive learning iterations. Each iteration consists of the bottom-up (leaves to root) and top-down (root to leaves) phases. In particular, the vehicle agents self-organize into a tree topology. Since a tree topology allows for coordinated bottom-up and top-down incremental interactions, self-adaptive learning can be repeated similarly to the hierarchical topology of a neural network. During the bottom-up phase of each iteration, vehicle v_k selects the path p_k to achieve the optimization objective

$$p_k = \arg\min_{m=1}^{|P_k|} \left(\omega_1 \cdot f_G\left(p_k^m\right) + \omega_2 \cdot f_L\left(p_k^m\right)\right) \tag{17}$$

where

- $|P_k|$ represents the number alternative paths of vehicle v_k,
- $f_G(p_k^m)$ denotes the global cost of selecting p_k^m, which is the average of estimated travel times of different paths.
- $f_L(p_k^m)$ denotes the local cost of selecting p_k^m, which is the estimated travel time of the path p_k^m.
- ω_1 and ω_2 parameters (with $\omega_1, \omega_2 \in \{0, 1\}$ and $\omega_1 + \omega_2 = 1$) represent the preferences of vehicles for global cost and local cost, respectively. A vehicle with $\omega_1 = 1$ is an altruistic agent that reduces all vehicles' total cost or average journey time. In contrast, a vehicle with $\omega_2 = 1$ prioritizes minimizing its local cost or travel time.

Starting with the leaf agents, parents chose the selected planning paths of their children based on their children's possible planning paths and the aggregated selections of the agents in the branch underneath. During the top-down phase, agents are informed of their selected planning paths summed up at the root. The vehicle agents adjust their selected planning paths to minimize the cost relative to the previous iteration until the global cost no longer changes or a set number of iterations are completed. Previous papers on I-EPOS have more elaboration [34,35].

[1] https://epos-net.org/.

Fig. 3 Yeouido island traffic network scenario (around 4.15 km^2)

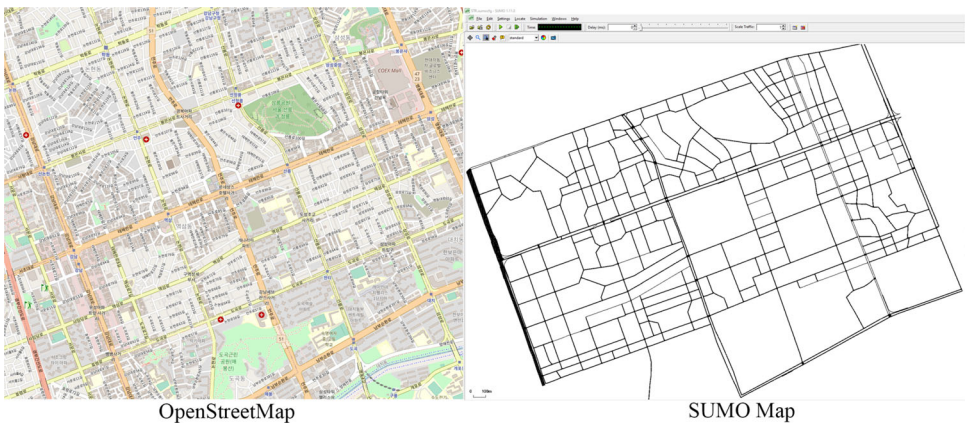

Fig. 4 Gangnam district traffic network scenario (around 12.60 km^2)

Performance evaluation

Simulation settings

The simulations were implemented with Python and SUMO 1.11.0[2] [36]. SUMO is a microscopic traffic simulator, open-source and portable. Moreover, through the Traffic Control Interface (TraCI), SUMO allows users to interact with the simulation environment using Python. We conducted the evaluations on two traffic networks with different sizes obtained from OpenStreetMap.[3] Particularly, we selected two well-known locations in Seoul, South Korea: the Yeouido island traffic network (Fig. 3), which can be downloaded via OpenStreetMap at the coordinates of (37.5257,126.9238), and the Gangnam district traffic network (Fig. 4), which can be downloaded via OpenStreetMap at the coordinates of (37.50262, 127.04294). We evaluate the traffic routing methods in a small-scale traffic network (Yeouido island scenario with the area of 4.15 km^2) and a large-scale traffic network (Gangnam district scenario with the area of 12.60 km^2).

In SUMO, the NETCONVERT tool transforms the traffic networks obtained from the OpenStreetMap into a SUMO map. Simulation scenarios and settings were conducted to test traffic routing strategies under various traffic demand levels. Traffic demand (vehicles per hour, veh/h) is the number of vehicles entering the traffic network in 1 h. Traffic demand is one of the most important aspects influencing the effectiveness of the control strategies. They are created at random using Poisson distribution supported by the RANDOMTRIPS tool in SUMO. It avoids uniform distribution of traffic demand and generates more realistic traffic demands. In an hour (3600 s) of simulation, the traffic demand is generated until it meets the maximum capacity of the traffic scenario. Each simulation is run ten times using a new random seed each time. Reported results are the mean values with standard deviations.

The proposed traffic routing method was compared with two non-cooperative traffic routing algorithms and an optimal traffic assignment method.

- Shortest Time Routing Method (**ShortRoute**): Vehicles follow the shortest path based on the free-flow travel time determined by the route's length and speed limit, ignoring road capacity and traffic density.
- Pheromone-based Routing Method (**PheRoute**) [8–10]: The method allows vehicles to choose a route identified by greater pheromone concentrations based on probabil-

[2] https://www.eclipse.org/sumo/.

[3] https://www.openstreetmap.org/.

ity. The free-flow travel time and traffic density determine pheromone values.

- Inverted Pheromone-based Routing Method (**IPheRoute**): The routing method is based on the inverted pheromone model, which includes occupancy time and fuel consumption information.
- Inverted Pheromone-based Routing with Cooperative Negotiation Method (**IPheNegoRoute**): This is the proposed routing method, which integrates the inverted pheromone model, the cooperative negotiation technique, and the traffic density-based congestion detection mechanism. All vehicles cooperate to minimize the global cost (i.e., $\omega_1 = 1$ and $\omega_2 = 0$ for all vehicles).
- Dynamic Traffic Assignment Method (**DTA**) [28,29]: Through an iterative simulation procedure, the method can approximately achieve user equilibrium. However, it is not suited for real-time and practical route recommendations due to its substantial computational overhead and requirement for a complete understanding of the traffic system. Nevertheless, it can provide the optimal routing results for comparison in a small-scale traffic scenario. The DTA tool in SUMO is used with default settings.

To assess traffic routing strategies, two performance indicators were used: **average travel time** (s) taken by all vehicles from source to destination, and **average fuel consumption** (ml) expended by all vehicles during their trips. The fuel consumption is estimated using the EMIT model [30], which is implemented in SUMO. The simulation parameters in the traffic network scenario are shown in Table 1.

Since the proposed framework is based on the decentralized model, it requires a greater number of exchanging messages than the centralized model [7,37]. However, the number of messages can be reduced by grouping mechanisms of vehicles in the decentralized model [38]. Furthermore, the decentralized model is more scalable than the centralized one since it reduces server-side processing and the number of messages exchanged in server-vehicle communications [6]. Also, the decentralized model does not need extra infrastructure, which reduces deployment costs and eliminates the single point of failure [7]. As a result, rather than evaluating the communication and model deployment aspects, the simulations focused on evaluating the traffic efficiency of the routing methods.

Table 1 Simulation settings

Parameters	Value
Simulator	SUMO 1.12.0
Simulation steps	3600 s
Road networks	Yeouido, Gangnam areas
Vehicle size	5 m
Vehicle gap	2.5 m
Vehicle emission class	HBEFA3/PC_G_EU4
Fuel consumption model	EMIT
Congestion threshold value	$\phi = 0.7$
Pheromone evaporation rate	$\rho = 0.5$

Results and discussion

Yeouido island traffic network

Figure 5 shows the average travel time results of the traffic routing methods in the Yeouido island traffic network scenario. The DTA method achieves the best performance since it is based on the iterative simulation process requiring high computational power and prior knowledge of traffic flows, which is impractical. The IPheNegoRoute method can greatly reduce the average travel time compared to the remaining methods. In particular, in the traffic demand scenario of 4000 veh/h, the IPheNegoRoute method decreases the average travel time by 21.89%, 8.99%, and 3.37% compared to the ShortRoute, PheRoute, and IPheRoute methods, respectively. Compared with the optimal solution of the DTA method, the average travel time of the IPheNegoRoute method is lower by 7.44%. This is expected since the DTA method relies on an iterative procedure to improve the solution for each iteration.

Figure 6 illustrates the average fuel consumption results of the traffic routing methods in the Yeouido island traffic network scenario. In the ShortRoute method, many vehicles travel on the same path, creating traffic congestion on the path. The average fuel usage of the ShortRoute method is significantly increasing with the increase in traffic demand because of the stop-and-go behavior of the vehicles moving on congested road segments. In contrast,

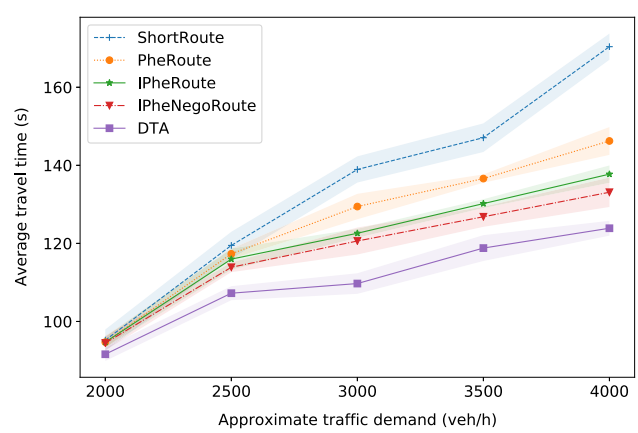

Fig. 5 Average travel time results of traffic routing methods in the Yeouido island traffic network scenario

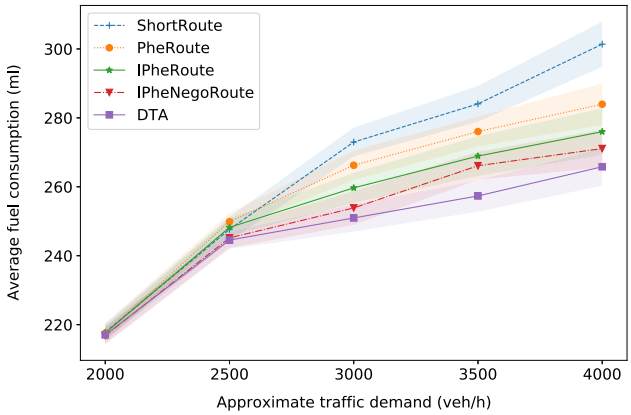

Fig. 6 Average fuel consumption results of traffic routing methods in the Yeouido island traffic network scenario

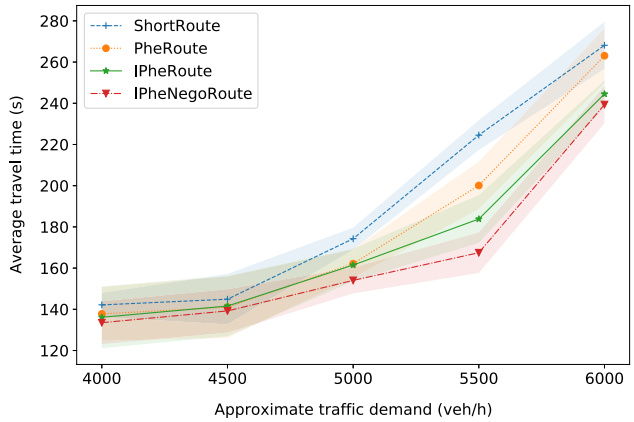

Fig. 7 Average travel time results of traffic routing methods in the Gangnam district traffic network scenario

with the dynamic routing mechanism, the routing methods with pheromone and inverted pheromone models (PheRoute, IPheRoute, and IPheNegoRoute methods) can reduce fuel consumption significantly. The IPheNegoRoute method, which includes the inverted pheromone model and automated negotiation technique, achieves the best performance. As a result, the IPheNegoRoute method can obtain near-optimal solutions compared to the DTA method. In the traffic demand scenario of 4000 veh/h, the average fuel consumption of the IPheNegoRoute method is better than that of the ShortRoute, PheRoute, and IPheRoute methods by 10.05%, 4.53%, and 1.78%, respectively. Also, the average fuel consumption of the IPheNegoRoute method is lower than that of the DTA method by 1.99% in the traffic demand scenario of 4000 veh/h (see Table 2).

It can be observed that the IPheNegoRoute technique can get results that are very near to the ideal outcomes of the DTA method. However, the DTA method cannot perform in a large-scale traffic network scenario since it requires all traffic information and performs an iterative simulation process. Hence, in the following, the other traffic routing strategies are further evaluated in a large-scale traffic network scenario.

Gangnam district traffic network

Figure 7 shows the performance of the traffic routing methods in the Gangnam district traffic network scenario. The routing methods with pheromone and inverted pheromone models (PheRoute, IPheRoute, and IPheNegoRoute methods) perform better than the traditional shortest path routing method (ShortRoute). The PheRoute method guides the vehicles to follow the optimal paths based on pheromone values from previous traveling vehicles; however, if many vehicles move to the same path, it creates new traffic congestion. On the other hand, the IPheRoute method presents traffic conditions by the inverted pheromone model based on vehi-

Table 2 Numerical results of traffic routing methods in the Yeouido island traffic network scenario

Method	Traffic demand (veh/h)		
	2500	3500	4000
Average travel time (s)			
ShortRoute	119.48 ± 3.49	147.08 ± 3.66	170.40 ± 3.34
PheRoute	117.32 ± 1.30	136.61 ± 1.06	146.24 ± 3.56
IPheRoute	115.97 ± 2.74	130.19 ± 1.12	137.74 ± 2.22
IPheNegoRoute	113.88 ± 1.24	126.82 ± 2.57	133.10 ± 3.77
DTA	**107.24 ± 1.79**	**118.80 ± 3.30**	**123.88 ± 1.90**
Average fuel consumption (ml)			
ShortRoute	247.66 ± 3.59	284.06 ± 5.18	301.39 ± 6.55
PheRoute	249.88 ± 2.49	276.03 ± 4.36	283.96 ± 6.02
IPheRoute	248.23 ± 2.65	268.91 ± 5.81	275.99 ± 6.83
IPheNegoRoute	245.18 ± 2.92	266.11 ± 4.10	271.09 ± 5.50
DTA	**244.54 ± 2.58**	**257.35 ± 4.55**	**265.81 ± 5.49**

The bold values indicate the best results

Table 3 Numerical results of traffic routing methods in the Gangnam district traffic network scenario

Method	Traffic demand (veh/h)		
	4000	5000	5500
Average travel time (s)			
ShortRoute	142.14 ± 5.87	174.27 ± 5.34	224.54 ± 7.21
PheRoute	137.79 ± 13.10	162.15 ± 7.00	200.11 ± 11.50
IPheRoute	136.13 ± 14.97	161.47 ± 7.96	183.82 ± 11.61
IPheNegoRoute	**133.51 ± 10.41**	**154.04 ± 6.29**	**167.46 ± 9.82**
Average fuel consumption (ml)			
ShortRoute	311.94 ± 8.85	347.23 ± 13.12	392.00 ± 10.05
PheRoute	307.78 ± 17.96	330.89 ± 7.47	370.62 ± 13.10
IPheRoute	306.45 ± 20.46	330.43 ± 7.11	352.47 ± 14.09
IPheNegoRoute	**303.00 ± 14.61**	**323.91 ± 10.00**	**336.73 ± 12.99**

The bold values indicate the best results

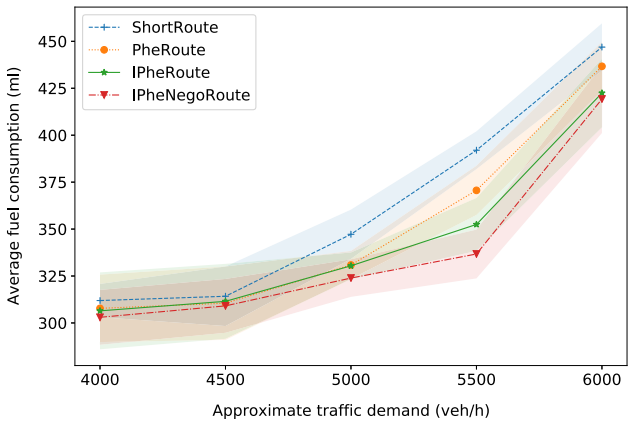

Fig. 8 Average fuel consumption results of traffic routing methods in the Gangnam district traffic network scenario

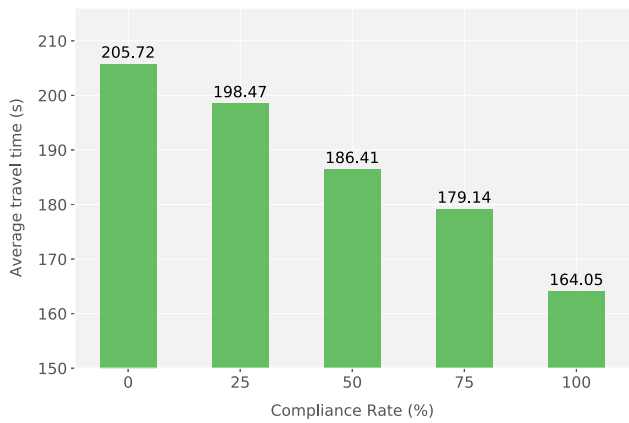

Fig. 9 Performance of the IPheNegoRoute method under different compliance rates

cles' occupancy time and fuel consumption rate. With the inverted pheromone model, the vehicles select paths with fewer vehicles moving at slow speeds and high fuel consumption rates. In addition, the IPheNegoRoute method lets vehicles negotiate in the path selection process by the collective learning algorithm. As a result, the IPheNegoRoute method achieves the best performance under various traffic demands (see Table 3).

The time of vehicle spending on the roads strongly correlates with vehicle fuel consumption and emissions. Figure 8 shows the average fuel consumption results of the traffic routing methods in the Gangnam district traffic network scenario. The IPheNegoRoute method saves fuel more than the others. Since the vehicles negotiate to select different paths for travel, creating new congestion is minimized. Hence, it reduces the fuel consumption of vehicles since the stop-and-go behaviors of vehicles on congested roads are reduced. In the ideal case (i.e., traffic demand of 5500 veh/h), the IPheNegoRoute method saves the average fuel consumption by 9.14–14.1% compared to the others (see Table 3).

In the IPheNegoRoute method, it is assumed that all vehicles are altruistic agents which prioritize minimizing the global cost or average travel times of vehicles. However, the vehicles may not fully comply with the routing method in practice. Therefore, the IPheNegoRoute is evaluated under different compliance rates with the traffic demand of 5500 veh/h in the Gangnam district traffic network. The compliance rate is the percentage of vehicles that adhere to the route guidance. As shown in Fig. 9, the more vehicles cooperate as the increase of compliance rate, the more average travel time can be reduced. The vehicles complying with others can receive fairly good routes, which improves traffic for the remaining vehicles and, as a result, reduces congestion on the road network.

Overall, in the non-cooperative routing methods (ShortRoute, PheRoute, and IPheRoute methods), the driver can obtain the optimal routes at the time of the routing recommendation. However, if many vehicles select the same optimal routes for travel, these routes can be congested soon. With the cooperation among vehicles, as in the IPheNegoRoute

method, traffic demands are distributed throughout the traffic network, reducing the probability of creating new congestion. Via the simulation results, the proposed traffic routing system has advantages in lowering the average travel times of vehicles. Furthermore, since fuel consumption and emissions are directly related to vehicles' travel times, the proposed system also implicitly reduces the negative effect of vehicles on the environment.

Conclusion

Traffic congestion and the dynamic nature of traffic systems are the challenging issues in urban traffic networks for developing ITS. This work focused on how a transportation system and vehicles can be coordinated to reduce travel times and fuel consumption in a decentralized manner. Based on the idea of swarm intelligence, connected vehicles deposit inverted pheromones, which are a new type of digital pheromones that deliver negative feedback for busy road segments. When traffic congestion is observed, using the inverted pheromone model and the decentralized collective learning algorithm, the vehicles redirect to new paths that maximize the social benefit of all vehicles, i.e., average travel time minimization. Thus, a route traveling by many vehicles simultaneously can be avoided by the vehicles communicating and collaborating. The proposed traffic routing method is shown effective via the simulations conducted on SUMO.

In future work, some issues could be taken into account. Travel time estimation and prediction problems are important and challenging in smart transportation systems. Hence, to improve the routing methods, these topics should be investigated. Performance comparison with other traffic routing methods could also be conducted further. In addition, due to the limitations of the SUMO simulator, communication aspects of the proposed method are not investigated in the paper. Hence, the SUMO simulator can be coordinated with a network simulator (e.g., NS3,[4] NetSim[5]) for further evaluation of the proposed method in terms of communication performance measures.

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[4] https://www.nsnam.org/.

[5] https://www.tetcos.com/.

Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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