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Simulation of Multi-Agent based Cybernetic Transportation System

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A B S T R A C T

A Cybernetic Transportation System (CTS), composed of a fleet of driverless vehicles, is able to provide public transport services with on-demand and door-to-door capabilities. Of course, fleet planning is essential for system performance. This research uses a distributed fleet planning algorithm based on Multi-Agent System, which is suitable for the Cybernetic Transportation System. Each agent represents one driverless vehicle and transport tasks can be completed more efficiently through cooperation and competition among the agents. Furthermore, a simulated model of the Cybernetic Transportation System based on Multi-Agent System has been developed. The simulation results demonstrate that the effectiveness of the proposed algorithm is better than that of the traditional centralized planning algorithms investigated. The effects of the number of driverless vehicles and the road topology on the proposed fleet planning algorithm have also been investigated.

1. Introduction

Although the application of public transport systems in urban areas has a long history, traditional public transport systems have been unwilling to meet passenger demands in some areas due to the lack of sufficient economic incentive. Examples may include areas such as university campuses, resorts, and industrial parks. Passenger demands may go unmet for reasons such as inconsistent passenger flow, randomly generated transportation demands, or complex transportation tasks.

A Cybernetic Transportation System (CTS) composed of road vehicles with fully automated driving capabilities has been proposed as a possible solution to the transport needs in such areas. A fleet of such vehicles could form a transportation system for passengers or goods on a road network with on-demand and door-to-door capability [1].

Cybernetic Transportation System fleet planning, including task allocation and routing, is an important factor affecting system performance. To address randomly arriving transportation demands and random conflicts between vehicles, dynamic planning is needed and such research is in high demand. Fleischmann et al. [2] has studied the framework for dynamic vehicle routing based on online traffic information. Powell [3] has introduced a hybrid model for dynamic vehicle allocation (DVA). Yang et al. [4] has presented some optimization-based policies for the real-time truckload pickup and delivery problems (TPDP). Andréasson [5] has studied the reallocation of empty Personal Rapid Transit (PRT) vehicles. In these previous researches, most of the proposed algorithms are centralized and the fleet is controlled by a management center. Moreover, each vehicle can carry out only one job at a time. A Cybernetic Transport System, however, provides each driverless vehicle with the capacity to act and plan for itself. Therefore, each vehicle could be regarded as an agent, and the fleet operation of this Multi-Agent based system has the characteristic needed for distribution.

Characteristics of a single agent include reactivity, autonomy and interactivity [6]. The Multi-Agent System (MAS) is composed of loosely coupled agents who can resolve complex issues in dynamic environment through interacting with

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one another [7]. Due to its high efficiency and stable characteristics in distributed, open and dynamic environments, Multi-Agent System technology has seen wide use in such areas as telecommunications, business process modeling, multi-robot control and transportation management [8]. The Multi-Agent based planning algorithm has been researched in several recent investigations. Zutt and Witteveen [9] have provided a Multi-Agent planning framework including several phases in planning process. Krogt and Weerdt [10] have addressed the problem of Multi-Agent System coordination through plan repair method. Hoen et al. [11] has established a Multi-Agent model for logistics management, based on market mechanism. In practice, fleet planning is required to consider the allocation of tasks, the planning of routes and the status of vehicles. However, most previous studies have only considered some of the factors mentioned above.

In this paper, we propose a distributed hierarchical fleet planning algorithm based on a Multi-Agent System for Cybernetic Transportation System with task allocation, route planning and vehicle status considered in the planning process. Each driverless vehicle can be regarded as an agent with the ability to search transportation demands and act independently. The distributed hierarchical fleet planning algorithm can be divided into three layers: the pre-plan layer, the coordination layer, and the re-plan layer. The effectiveness of the algorithm we proposed has been evaluated in simulation study by comparing it with the traditional centralized planning algorithms.

The remaining parts of this paper are organized as follows: We begin with a description of the Cybernetic Transportation System. We then present the design of vehicle agent in Section 3. Section 4 addresses the distributed fleet planning algorithm for Cybernetic Transportation System. The simulation study with numerical results, based on the case study, is the subject of Section 5. Finally, we draw conclusions and give some directions for future research in Section 6.

2. System description

The external environment and the components of the Cybernetic Transportation System are formally stated in the following:

Road network: The simple notation for a transit network of a local area is graph $G = (S,E)$, where $S = \{s_1, s_2, \ldots, s_N\}$ is the set of N stations, and $E = \{e_{i,j} | i = 1, 2, \ldots, N;\ j = 1, 2, \ldots, N;\ i \neq j\}$ is the set of lanes between N stations.

Passengers: Passengers with transportation demands arrive at origin stations randomly and queue for driverless vehicles. The waiting passengers at the same origin station may have different destinations, thus forming different queues according to their destinations.

Queue: The queue with origin station i and destination station j is denoted by queue $Q_{i,j} = [q_1, q_2, \ldots, q_k, \ldots]$, where q_k corresponds to the information of kth passenger. The total number of passengers in queue $Q_{i,j}$ is denoted by $\mathrm{NQ}_{i,j}$. Let $\mathrm{TQ}_{i,j}$ denote the wait time of a queue, which is the total waiting time of passengers in queue $Q_{i,j}$.

Driverless vehicles: The driverless vehicles used in the Cybernetic Transportation System are small low-cost electric vehicles. The set of these vehicles is $V = \{v_1, v_2, \ldots, v_M\}$, where M is the number of vehicles. Each driverless vehicle has the same performance parameters and a capacity of C seats.

Shortest route: The shortest route from station i to station j can be determined by the Dijkstra algorithm and can be simply denoted by function

$$\mathrm{str}_{i,j} = \mathrm{SR}(i,j), \tag{1}$$

where $\mathrm{str}_{i,j}$ is a string composed of the IDs of stations in the shortest route by order. For example, $\mathrm{str}_{\mathrm{i,j}} = s_\mathrm{i} s_\mathrm{n} s_\mathrm{j}$ denotes the route $s_i \to s_n \to s_j$. Both passengers and vehicles determine their routes by formula (1).

The operation of the Cybernetic Transportation System is as follows: randomly arriving passengers declare their destination stations at their origin stations. Then these transportation demands are broadcasted in the area via the communication facility of the Cybernetic Transportation System. Each driverless vehicle can receive transportation demands and plan transportation task by itself. These driverless vehicles can communicate with each other and resolve the underlying conflicts between them. In this MAS based system, each vehicle agent has the desire to complete as many transportation tasks as possible, and the overall performance optimization of the Cybernetic Transportation System can be achieved.

The objective of the MAS based fleet planning algorithm is to minimize the wait time and the total travel time of passengers. The planning of each vehicle agent includes task planning and route planning. Due to the underlying conflicts between vehicle agents, the coordination of these vehicle agents should be considered in this fleet planning algorithm.

3. The design of vehicle agent

3.1. The structure of vehicle agent

The vehicle agent structural design is based on the BDI (Belief–Desire–Intention) model [12]. The function of the "Belief" portion is to perceive the local environment information and the internal state information of an agent. The environment information includes the broadcasted transportation tasks and the status of other vehicles. The "Desire" portion corresponds to the goal of the vehicle agent to complete as many transportation tasks as possible. The "Intention" portion generates the intent of a vehicle agent, and plans the task and the route.

3.2. Task planning of vehicle agent

The vehicle agent begins planning a task when it arrives at a station. A queue at the current station will be selected as the planning task, and passengers in this queue will be picked up. The number of passengers that a driverless vehicle can pick up is restricted by its capacity. The task planning method of an empty vehicle is different from that of a non-empty vehicle. These two task planning methods are addressed as follows.

3.2.1. Task planning of an empty vehicle

If a driverless vehicle is empty, it will select the queue with the longest wait time at the current station as the planning task. Assume the current station that vehicle arrives at is *i*th station, and the planning task is Q_{p}, then

$$Q_p = Q_{i,j} \text{ if } \mathrm{TQ}_{i,j} = \max_{1 \leqslant n \leqslant N}\{\mathrm{TQ}_{i,n}\}. \tag{2}$$

3.2.2. Task planning of a non-empty vehicle

For a non-empty vehicle, it can select the planning task from queues whose planning routes are consistent with that of the vehicle agent.

Definition 1. Assume that *k*th vehicle agent arrives at *i*th station, the planning route of *k*th vehicle agent is str_k and the planning route of queue $Q_{\mathrm{i,j}}$ is $\mathrm{str}_{\mathrm{i,j}}$. Both $\mathrm{str}_{\mathrm{k}}$ and $\mathrm{str}_{\mathrm{i,j}}$ are non-empty strings. If $\mathrm{str}_{\mathrm{k}} \subseteq \mathrm{str}_{\mathrm{i,j}}$, or $\mathrm{str}_{\mathrm{i,j}} \subseteq \mathrm{str}_{\mathrm{k}}$, that is, all the stations in $\mathrm{str}_{\mathrm{k}}$ belong to $\mathrm{str}_{\mathrm{i,j}}$, or all the stations in $\mathrm{str}_{\mathrm{i,j}}$ belong to $\mathrm{str}_{\mathrm{k}}$, then the planning route of queue $Q_{\mathrm{i,j}}$ is consistent with the planning route of *k*th vehicle agent.

All the queues whose planning routes are consistent with *k*th vehicle form a set S_{k} at the current station of *k*th vehicle agent. If there is more than one element in S_{k}, the vehicle agent will select the queue with the longest wait time as its planning task. Assume the current station that vehicle agent arrives at is *i*th station, then

$$Q_p = Q_{i,j} \text{ if } Q_{i,j} \in S_k \text{ and } \mathrm{TQ}_{i,j} = \max_{1 \leqslant n \leqslant N}\{\mathrm{TQ}_{i,n}\}. \tag{3}$$

3.3. Route planning of vehicle agent

When a vehicle agent arrives at a station, it plans its route after pick-up or drop-off. The current station must be set as its origin station before route planning. The key issue of route planning is to determine the destination station. The route planning method of an empty vehicle is different from that of a non-empty vehicle. These two route planning methods are addressed as follows:

3.3.1. Route planning of an empty vehicle

For an empty vehicle, if it stays at the current station and waits for oncoming passengers, the waiting passengers at the other stations can not get timely transport services. In a dynamic situation with competitive vehicle agents, if an empty vehicle chooses a destination station away from its current station, the planned transport task in the destination may have been completed by some other vehicle agents when it arrives at the destination. Moreover, the efficiency of the Cybernetic Transportation System cannot be improved and empty mileage of vehicle will increase. Therefore, the area from where the destination can be chosen should be balanced. A solution to this issue is that an empty vehicle can select its destination from its envelope. Let S^k_{en} denote the envelope of *k*th vehicle agent. S^k_{en} is a set of stations including the vehicle agent's current station and all the adjacent stations (see Fig. 1). For example, the current station of *k*th vehicle in Fig. 1 is station 11, and the envelope of *k*th vehicle agent is $S^k_{\mathrm{en}} = \{s_6, s_{10}, s_{11}, s_{12}\}$.

Assume that *k*th vehicle is empty and is at *i*th station. The current station and the destination station of this vehicle agent are denoted by s_{i} and s_{d}, respectively. According to the distribution of passengers in the envelope of *k*th vehicle agent, the destination station of this vehicle agent can be determined in the following cases.

Case 1: If there are passengers at the current station, the current station will be selected as the destination of the empty vehicle, that is, an empty vehicle needs no route planning in this situation. Then

$$s_d = s_i \text{ if } \sum_{j=1}^{N} \mathrm{NQ}_{i,j} > 0, \tag{4}$$

where $\sum_{j=1}^{N}\mathrm{NQ}_{i,j}$ is the number of waiting passengers at *i*th station.

Case 2: If there is no passenger at the current station, the adjacent station with the most waiting passengers in the envelope will be selected as the destination. Then

$$s_d = s_m \text{ if } s_m, s_n \in S^k_{\mathrm{en}} \text{ and } \sum_{j=1}^{N} \mathrm{NQ}_{m,j} = \max_n\left\{\sum_{j=1}^{N} \mathrm{NQ}_{n,j}\right\}, \tag{5}$$

where $\sum_{j=1}^{N}\mathrm{NQ}_{m,j}$ and $\sum_{j=1}^{N}\mathrm{NQ}_{n,j}$ are the numbers of waiting passengers at *m*th and *n*th station, respectively.

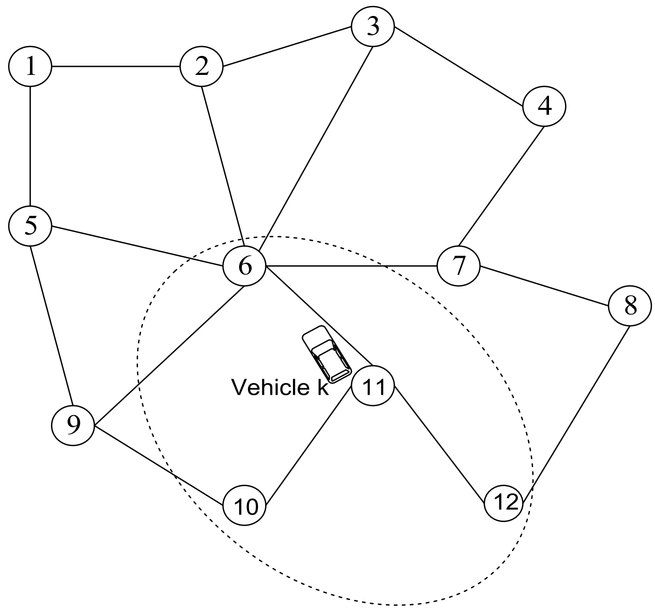

Fig. 1. Sketch of the envelope of *k*th vehicle agent.

Case 3: If there is no waiting passenger in the envelope, the vehicle agent can randomly select an adjacent station in its envelope with small probability and set this station as its destination. The vehicle agent generates a random number τ between 0 and 1, and compares τ with a predefined small threshold ϕ, then

$$s_d = \begin{cases} s_r & \text{if} \quad \tau < \phi, s_r \in S^k_{\text{en}} \\ s_i & \text{else} \end{cases} \tag{6}$$

where s_{r} is an adjacent station randomly selected and s_{i} is the current station of the empty vehicle. The mechanism in this case enables an empty vehicle agent to roam to an adjacent station in small probability and thus improves its activity.

Once the destination station has been determined, the empty vehicle agent can plan its route according to formula (1). If the destination of the vehicle agent is its current station, the route planned by formula (1) will be empty and the empty vehicle will stay at the current station.

3.3.2. Route planning of a non-empty vehicle

For a non-empty vehicle, if it picks up some passengers at a station, the planning route of these passengers may not be the same as that of this vehicle agent. Since only passengers whose planning routes are consistent with that of the vehicle agent can be picked up, their planning route may exceed that of the vehicle agent, and this situation can be formally stated as follows. Assume the planning route of a group of newly picked-up passengers is $\text{str}_{\text{i,j}}$ and the planning route *k*th vehicle agent is str_{k}, then $\text{str}_{\text{k}} \subset \text{str}_{\text{i,j}}$ if the planning route of passengers exceeds that of the vehicle. In this situation, *k*th vehicle agent must extend its planning route according to

$$\text{str}^*_k = \text{str}_k \cup \text{str}_{i,j}. \tag{7}$$

If the planning route of the newly picked passengers does not exceed that of *k*th vehicle, or there is no newly picked passenger, the *k*th vehicle agent does not need to revise its planning route.

4. Multi-Agent based distributed architecture of fleet planning

The distributed architecture of fleet planning consists of three layers: the pre-plan layer, the coordination layer and the re-plan layer (see Fig. 2). Fleet planning of the Cybernetic Transportation System is processed in a circular manner in the flowchart of Fig. 2. All information of the real-time transportation demands and the states of vehicle agents are broadcasted in the Cybernetic Transportation System via wireless communication facility.

4.1. Pre-plan

A vehicle agent addresses pre-plan when it arrives at a station. In the pre-plan layer, each vehicle agent plans its transportation task by itself, according to the method proposed in Section 3.2. For each vehicle agent, the states of other vehicle

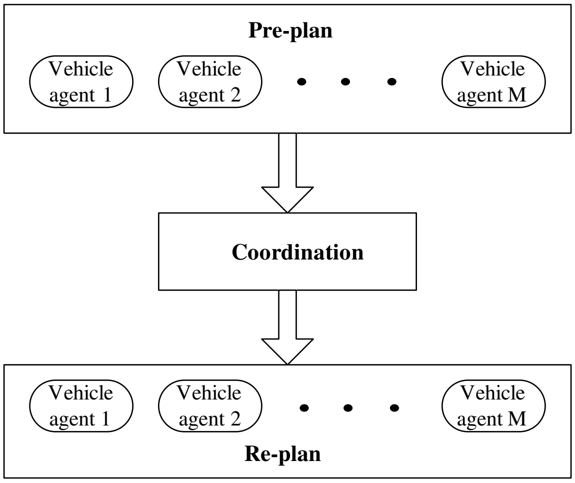

Fig. 2. Fleet planning flowchart.

agents are not considered in this process. Those vehicle agents, in transit, need not address pre-plan until they arrive at stations. Transportation tasks planned through all vehicle agents are sent to the coordination layer after the pre-plan.

4.2. Coordination

Tasks coordination should be carried out when the same queue is selected as the planning task by more than one vehicle agent. An auction mechanism is adopted which chooses the vehicle agent with the maximum ability as the winner. The ability of kth vehicle agent corresponding to queue $Q_{i,j}$ is defined as

$$\mathrm{cap}_{k,i,j} = \frac{1}{|\mathrm{NQ}_{i,j} - \mathrm{ava}S_k| + k_0}, \tag{8}$$

where $\mathrm{ava}S_k$ is the number of the available seats of kth vehicle agent, k_0 is a constant positive value introduced to prevent the denominator from becoming zero. If more than one vehicle agent submits the same ability, their IDs will be compared in auction. For the bidding vehicle agents participating in the coordination, the winner will get a positive reply and the others will get negative replies. These replies are sent to the re-plan layer after coordination.

4.3. Re-plan

In this layer, each vehicle agent refreshes its intention according to the reply from the coordination layer. If a vehicle agent gets a positive reply, it will keep the pre-plan intention and pick up passengers in the queue corresponding to its planning task. Otherwise, it must abandon the pre-planned intention and prepare for the pre-plan in the next cycle. After the re-plan, each vehicle agent can plan its route according to the method mentioned in Section 3.3 and run along the route.

5. Tests and results

An online test of fleet planning algorithms has the disadvantage that the scenarios cannot be reproduced. To evaluate the performance of the proposed MAS based fleet planning algorithm, we have developed a discrete event simulation system for the Cybernetic Transportation System. Driverless vehicles in this system plan transportation tasks and routes independently. Each driverless vehicle has a constant speed of 50 km/h and its capacity is 4 seats. There are 12 stations in this simulation system. Location of these stations is given in Table 1 and the coordinate origin is at *1*th station. Each station can provide a berth for more than one driverless vehicle at one time. Dual lanes between stations enable two-way traffic of driverless vehicles.

The assumptions we made for this simulation system are as follows: Passengers' move time from the queue to the vehicle and the move time of drop-off are negligible and, therefore, ignored. Passengers take a vehicle on a first-in, first-out (FIFO) basis. The driverless vehicles never experience failures.

Simulation tests are carried out in scenarios with different passenger flows and different O–D (original–destination) distributions. Passengers arrive at this simulation system in groups that vary in size of one to two, uniformly distributed. The average time between arrivals of two successive groups is exponentially distributed. Two kinds of O–D (original–destination) distributions used in the test scenarios are: the uniform O–D distribution and the non-uniform O–D distribution. For the uniform O–D distribution, both passengers' origins and destinations are uniformly distributed. For the non-uniform O–D

Table 1
Location of the stations

The number of station	Location		The number of station	Location	
	X (m)	Y (m)		X (m)	Y (m)
1	0	0	7	1360	800
2	680	−120	8	2160	760
3	1480	−120	9	0	1320
4	2120	80	10	600	1640
5	−120	680	11	1320	1360
6	560	560	12	2280	1480

distribution, the origin of each passenger is uniformly distributed, but the destinations of all passengers are the same. To evaluate the performance of the proposed MAS based fleet planning algorithm, we have compared this algorithm with two classical centralized planning algorithms in the same situations. In addition, the effects of the number of driverless vehicles and the road topology on the performance of the proposed fleet planning algorithm have also been investigated.

5.1. Comparison of the MAS based fleet planning and the centralized fleet planning algorithms

The centralized fleet planning algorithms we use here are the assignment algorithm and the insertion algorithm. The assignment algorithm assigns newly arrived transport orders to the available vehicles. The insertion algorithm inserts new transport orders into the current route of each driverless vehicle dynamically. A detailed explanation of these algorithms has been described in [2]. Both dense passenger flow and sparse passenger flow are adopted in the comparison tests. For the dense passenger flow, the average time between arrivals of two successive groups is 10 s. For the sparse passenger flow, the average time between arrivals of two successive groups is 30 s. The road topology used in the comparison tests is shown in Fig. 3.

5.1.1. Case 1 – dense passenger flow, uniform O–D distribution

In this case, the dense passenger flow and the uniform O–D distribution are used. The number of passengers arriving at the transport area is 1000. The fleet consists of thirty driverless vehicles. Passengers' wait time, total travel time (the sum of wait time and travel time), and the corresponding statistics have been tested and the results are presented in Tables 2 and 3.

5.1.2. Case 2 – dense passenger flow, non-uniform O–D distribution

Differences between the test conditions of Case 2 and Case 1 are the passengers' destinations. In Case 2, the destinations of all passengers are the same, namely, the 7th station. The test results of passengers' wait time, total travel time, and the corresponding statistics are presented in Tables 4 and 5.

5.1.3. Case 3 – sparse passenger flow, uniform O–D distribution

In this case, the sparse passenger flow and the uniform O–D distribution are used. The number of passengers arriving at the transport area is 500. The fleet consists of twenty five driverless vehicles. Passengers' wait time, total travel time, and the corresponding statistics have been tested and the results are presented in Tables 6 and 7.

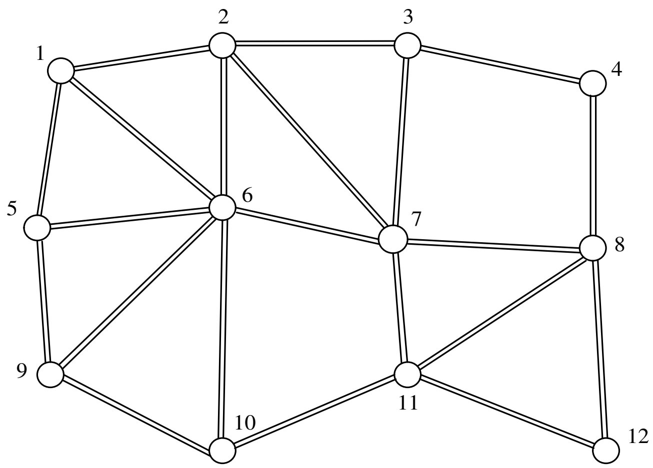

Fig. 3. Road topology used in the comparison tests.

Table 2
Statistics of passengers' wait time (Case 1)

	Average wait time (min)	Longest wait time (min)	Standard deviation of wait time (min)
MAS based fleet planning	0.73	5.56	0.69
Assignment fleet planning	1.0	9.70	1.18
Insertion fleet planning	0.98	8.73	1.05

Table 3
Statistics of passengers' total travel time (Case 1)

	Average total travel time (min)	Longest total travel time (min)	Standard deviation of total travel time (min)
MAS based fleet planning	2.62	8.18	1.09
Assignment fleet planning	2.86	12.2	1.47
Insertion fleet planning	2.87	11.82	1.35

Table 4
Statistics of passengers' wait time (Case 2)

	Average wait time (min)	Longest wait time (min)	Standard deviation of wait time (min)
MAS based fleet planning	0.54	3.48	0.53
Assignment fleet planning	0.92	8.65	1.17
Insertion fleet planning	0.77	7.85	0.90

Table 5
Statistics of passengers' total travel time (Case 2)

	Average total travel time (min)	Longest total travel time (min)	Standard deviation of total travel time (min)
MAS based fleet planning	1.98	5.43	0.76
Assignment fleet planning	2.94	10.50	1.35
Insertion fleet planning	2.24	9.65	1.08

Table 6
Statistics of passengers' wait time (Case 3)

	Average wait time (min)	Longest wait time (min)	Standard deviation of wait time (min)
MAS based fleet planning	0.49	2.07	0.44
Assignment fleet planning	0.85	7.15	1.07
Insertion fleet planning	0.80	6.02	0.92

Table 7
Statistics of passengers' total travel time (Case 3)

	Average total travel time (min)	Longest total travel time (min)	Standard deviation of total travel time (min)
MAS based fleet planning	2.40	5.70	0.98
Assignment fleet planning	2.74	9.85	1.42
Insertion fleet planning	2.72	9.77	1.29

5.1.4. Case 4 – sparse passenger flow, non-uniform O–D distribution

Differences between the test conditions of Case 4 and Case 3 are the passengers' destinations. In Case 4, the destinations of all passengers are the same, namely, the 6th station. Passengers' wait time, total travel time, and the corresponding statistics have been tested and the results are presented in Tables 8 and 9.

The results from Case 1 to Case 4 show that in different passenger flow and different O–D distribution scenarios, comparing with the two traditional fleet planning algorithms, the proposed MAS based fleet planning algorithm can decrease the wait time and the total travel time of passengers. The standard deviations of wait time and total travel time corresponding to the MAS based planning algorithm are smaller than those corresponding to the traditional planning algorithms. Therefore, the proposed MAS based fleet planning algorithm is more suitable for the Cybernetic Transportation System than the traditional centralized fleet planning algorithms that we have investigated.

Table 8
Statistics of passengers' wait time (Case 4)

	Average wait time (min)	Longest wait time (min)	Standard deviation of wait time (min)
MAS based fleet planning	0.55	2.7	0.49
Assignment fleet planning	1.04	13.6	1.41
Insertion fleet planning	1.06	16.5	1.81

Table 9
Statistics of passengers' total travel time (Case 4)

	Average total travel time (min)	Longest total travel time (min)	Standard deviation of total travel time (min)
MAS based fleet planning	2.06	5.3	0.90
Assignment fleet planning	2.57	16.5	1.76
Insertion fleet planning	2.58	19.4	2.18

5.2. The effects of the number of driverless vehicles and the road topology

The number of driverless vehicles and the road topology are factors that may affect the performance of the MAS based fleet planning algorithm. The effects of these factors on the performance of the proposed planning algorithm have been investigated, respectively.

5.2.1. The effect of the number of driverless vehicles

The relationship between the number of driverless vehicles and the average wait time has been tested in two different cases, which correspond to uniform and non-uniform O–D distributions, respectively. The average time between arrivals of two successive groups of passengers is 30 s. The number of passengers arriving at the transport area is 500. The road topology used here is the same as that of Section 5.1. Fig. 4 shows the relationship between the number of driverless vehicles and the average wait time of passengers in different scenarios, which correspond to different O–D distributions.

The results from Fig. 4 clearly show that the average wait time decreases with an increase in the number of driverless vehicles in the fleet. When the number of driverless vehicles is small, the increase in the number of vehicles can decrease the average wait time significantly; however, the decrease on the average wait time will slowdown when the number of vehicles is more than a certain value.

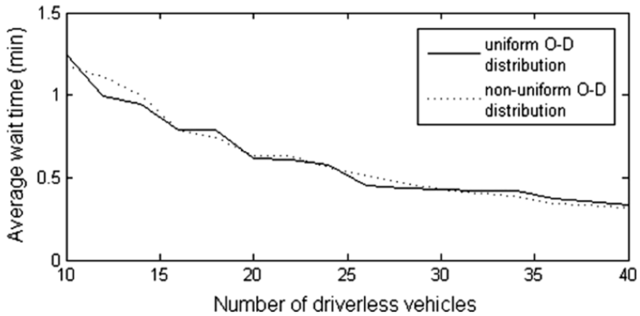

Fig. 4. The relationship between number of driverless vehicles and average wait time.

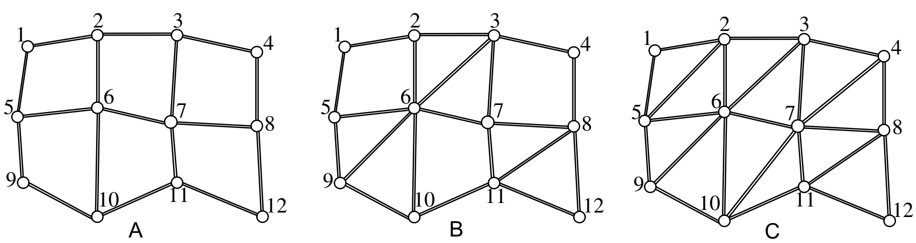

Fig. 5. The topologies of different road networks.

Table 10
Statistics of passengers' wait time corresponding to different road topologies

Road topology	Average wait time (min)	Longest wait time (min)	Standard deviation of wait time (min)
A	0.73	3.37	0.66
B	0.69	3.55	0.61
C	0.56	2.75	0.53

5.2.2. The effect of the road topology

To evaluate the effect of the road topology on the performance of the proposed fleet planning algorithm, three different kinds of road topologies (see Fig. 5) are used in the tests. Road topology A is the sparsest road network and road topology C is the densest road network in these road topologies. The average time between arrivals of two successive groups of passengers is 10 s. O–D distributions in test scenarios are uniform. The number of passengers arriving at the transport area is 1000. The fleet consists of thirty driverless vehicles. Table 10 presents the statistics of passengers' wait time corresponding to different road topologies in the same scenario.

The results from Table 10 indicate that the statistics of passengers' wait time have not varied remarkably with the change of the road topology. Therefore, the performance of the proposed fleet planning algorithm is not closely related to the road topology.

6. Conclusions

The Cybernetic Transportation System (CTS) is a new branch of the Intelligent Transportation System (ITS), which can provide flexible transportation services for university campuses, resorts, and industrial park. Fleet planning is critical for the operation of Cybernetic Transportation System. A distributed fleet planning algorithm based on Multi-Agent System (MAS) is proposed for this dynamic system. Compared with the traditional centralized fleet planning algorithms investigated, the proposed MAS based fleet planning algorithm can decrease the wait time and the total travel time of passengers in various scenarios. Meanwhile, the standard deviations of passengers' wait time and total travel time can also be decreased by using this algorithm, thus more reliable service can be provided. Therefore, the proposed fleet planning algorithm is suitable for the operation of the Cybernetic Transportation System. Simulation results show that in scenarios with a given passenger flow, the increase in the number of vehicles can decrease the average wait time significantly when the number of driverless vehicles is small; however, the decrease on the average wait time will slowdown when the number of vehicles is more than a certain value. Test results indicate that road topology does not significantly affect the performance of Cybernetic Transportation System using the proposed fleet planning algorithm. This MAS based fleet planning algorithm can also be used in other applications, such as the operation of dial-a-ride transport, local courier, express services, and taxis. The extended applications of this fleet planning algorithm are among our future research goals.

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