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Travel Time Prediction-Based Routing Algorithms for Automated Highway Systems

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ABSTRACT This study investigates routing algorithms for automated highway systems (AHS). In AHS, the central system manages decisions regarding routing for all vehicles and the distribution of traffic volume. We define an automated highway routing problem, of which the objective is to minimize the average travel time of vehicles through the target highway network. We propose four routing approaches considering (1) distance, (2) current traffic conditions, (3) predicted travel time, and (4) probabilistic route selection with predicted travel time. In the third and fourth approaches, the predicted travel time is obtained from an empirical speed–density relationship. AnyLogic, an agent-based simulation software, is used to simulate the behavior of individual cars. Four approaches are tested on a sample highway network and we found that the routing approach considering the predicted travel time difference exhibits the best performance.

INDEX TERMS Automated highways, prediction algorithms, routing, simulation.

I. INTRODUCTION

Traffic congestion is one of the most important unsolved problems of modern society. Although transportation infrastructure is constructed considering current and future traffic demand, traffic congestion often occurs owing to changes in demand and the failure of forecasting. Transportation infrastructure, particularly highways, cannot easily respond to changes in traffic demand. Constructing a new highway or extending existing highway requires significant cost and time and, in some cases, it is not feasible owing to environmental and political issues. Therefore, it is important to utilize the current infrastructure efficiently. An automated highway system (AHS) is one tool that could be used to increase performance of the traffic system.

In an AHS, the central system can manage decisions about routing for all vehicles and the distribution of the traffic volume. Once vehicles enter the AHS and specify their destination, drivers do not need to drive and select their route. The AHS can decide the routes of vehicles and the autonomous vehicles are operated by communicating with the AHS. The introduction of AHS is expected to significantly improve the highway traffic performance.

There are many studies about routing considering human drivers and intelligent support systems, but there are few studies that the central system controls the entire vehicle operations (i.e., AHS). Our study focuses on this case and proposes efficient routing algorithms for AHS. The objective of the routing algorithms is to minimize the average travel time of vehicles through the target highway network. However, to implement routing algorithms in the real world, travel time difference between vehicles must also be considered. If several vehicles with the same destination depart at the same time, their arrival times should be as close as possible even if their assigned routes are different. Thus, we consider the travel time difference between vehicles whose origin and destinations are the same. To evaluate the travel time difference of individual vehicles, we use an agent-based simulation model for routing algorithms. The proposed algorithms or approaches are tested on a sample highway network and their performances are compared.

The rest of the paper is organized as follows. Section II reviews AHS and relevant routing studies. Section III defines the automated highway routing problem (AHRP). Section IV describes our proposed approaches for the AHS routing problem. Section V discusses the simulation experiment results and Section VI concludes the paper.

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II. RELATED WORK

In this section, we review previous literature on AHS and routing. Baskar *et al.* [1] summarized ongoing research on AHS. In an AHS, vehicles and roadside infrastructure have their own intelligence systems and communicate with each other. An intelligent vehicle (IV) supports its driver or drives itself using sensors and assisting systems, such as adaptive cruise control (ACC) and route guidance systems. ACC is a system that automatically adjusts the speed of the equipped vehicle and distance to the car in front using sensors. Route guidance systems provide the best route to the destination using static information such as distance and dynamic information such as traffic congestion and accident information. The roadside infrastructure includes roadside sensors and traffic management systems. They classified AHS into five types depending on the level of automation of vehicle and roadside infrastructure and introduced control methods and frameworks of AHS.

Among the research areas related to the AHS, platooning is the topic that has seen the most progress. Platooning in an AHS means that several vehicles move at the same speed and spacing in the same lane. Hedrick *et al.* [2] discussed various components and methods for realizing platooning. Broucke and Varaiya [3] stated that platooning can increase the total capacity of a highway by collision-free operation and reduction of unnecessary acceleration and deceleration, and thereby reduce harmful gas emissions by one-half.

Eskafi *et al.* [4] presented an AHS simulator package called SmartPath. The simulator consists of automated lanes and transition lanes. Whereas vehicles are automatically controlled by the central system when they are in the automated lanes, vehicles in the transition lanes are controlled manually.

There are few studies related to the routing or route guidance problem for AHS. Baskar *et al.* [5] proposed two approaches for the route selection problem for AHS. The first approach is an approximated mixed-integer linear programming (MILP) model for road network flows. The model considered pre-defined link travel times, link capacities, and waiting times in the queues at the boundary and inside of the network. The objective function of the model is to minimize the total time spent in the network. They compared the result of the model with the case where each vehicle takes the shortest distance route to its destination. The second approach is based on METANET model, which is a second-order macroscopic traffic flow model [6], [7]. It represents traffic dynamics at an aggregate level using macroscopic variables such as density, mean speed, and flow. Baskar *et al.* [5] proposed macroscopic traffic flow characteristics for platooning in AHS. The ACC-equipped IVs with platooning have a different speed–density relationship from that of human driving cars. They extended the METANET model using the proposed platoon characteristics and compared the performance of the three cases: uncontrolled case with human drivers, controlled case with human drivers, and controlled case with platoons.

Our study is similar to that of Baskar *et al.* [5] in that we attempt to control the routes of all the vehicles optimally in the AHS. However, our approach is different from theirs. The first difference is in the level of details in the model. Baskar *et al.* [5] used a mathematical model and a macroscopic flow model, and their decisions are flow and flow splitting rate for each time interval. On the other hand, our study controls individual vehicles rather than aggregated traffic flow. We attempt to improve the efficiency of the highway network as well as to minimize the travel time difference between individual vehicles. We would like to propose a control logic that makes the arrival time as close as possible when several vehicles with the same destination depart at the same time, even if their selected routes are different. Macroscopic aggregated flow models are not sufficient to achieve this goal. We develop an agent-based simulation model for AHS and test several control logics. The second difference is the prediction methods used for future traffic flow. Baskar *et al.* [5] solved their macroscopic flow model for a given prediction time horizon, applied the result to the next time horizon, and repeated the procedure. In this study, we propose a travel time prediction method based on the empirical speed–density relationship. This method can predict future states of the road network for the entire time and the best route for each vehicle can be determined based on the future states.

The routing problem for AHS is closely related to dynamic traffic assignment (DTA) research. The inputs of the traffic assignment problem are a description of the transportation system and a matrix of interzonal trip movements (demands), and the outputs of the problem are traffic volumes, traffic times, and costs [8]. The DTA problem is a traffic assignment problem that considers time-varying transportation system and demands. There are two main objectives of DTA: the user equilibrium (UE) and the system optimum (SO) objectives [9]–[11]. The UE corresponds to vehicles' behavior that minimize their own travel time. As a result of the UE condition, the travel times of the routes used tend to be equal, while the routes unused have equal or greater travel times. The SO, in contrast, corresponds to social behavior that minimizes the total cost of the entire network system (i.e., total time spent).

The approaches of DTA can be used in the routing problem for AHS. Peeta and Ziliaskopoulos [10] classified the DTA approaches into four groups: mathematical programming, optimal control, variational inequality, and simulation-based approaches. The first three were further labeled as analytical approaches. Simulation-based approaches are used to implement complex traffic dynamics that are difficult to represent with analytical approaches. For those approaches, various traffic simulators including CONTRAM [12], DYNASMART [13], and DynaMIT [14], [15] have been used. Furthermore, to support detailed behavior, agent-based traffic simulators such as DTALite [16] and POLARIS [17] have been used. In our study, we also use an agent-based simulation software, AnyLogic 7.3, to simulate the routing behavior of an AHS. AnyLogic is an agent-based simulation software and it supports the road traffic library and JAVA programming. By using this library, we develop the components of an AHS: roadside infrastructure, intelligent vehicles, central system, and communication systems.

There are other similar studies on solving routing or route guidance problem in traffic systems other than AHS. However, our study is differentiated by the fact that the AHS controls all the vehicles individually. Individual vehicle-level route control results in a change in overall flow. We propose travel time prediction methods and routing alternatives for an AHS and validate them using an agent-based simulation software.

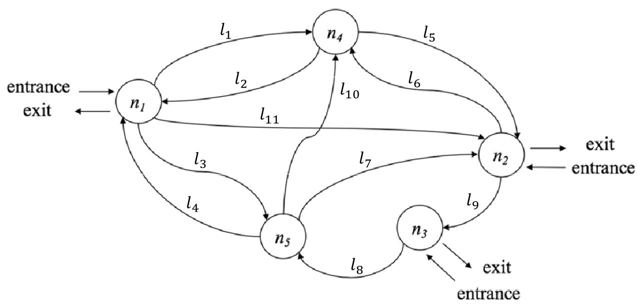

FIGURE 1. **Network structure of an example AHS.**

III. PROBLEM DESCRIPTION

In an AHS, a road network such as Figure 1 is given. A road network consists of directional links and nodes. Let L_l and N_l be the length and number of lanes of link l, respectively. Nodes, n_1, n_2, n_3, n_4, and n_5 in the example case, are junctions where two or more links intersect. Some nodes, n_1, n_2, and n_3 in the example case, have toll gates and cars enter and leave the AHS through them.

We assume that vehicles follows first-in, first-out (FIFO) rule in the link and junction. Vehicles continuously enter the highway system through toll gate nodes. The i th vehicle entering the system is denoted by v_i, and it has information about the entrance time denoted by t_i and its origin–destination (OD) denoted by (o_i, d_i). For example, suppose that vehicle v_7 enters the highway through node 3 at 9:30:45 AM and its destination is node 4. Then, t_7 is 9:30:45 AM and (o_7, d_7) is (3, 4).

In this study, we assume that the AHS does not have intersections or traffic signals. Roads are connected by junctions without traffic signals. Each vehicle has a preferred speed and it does not exceed this speed. If the vehicle speed is lower than the preferred speed, the vehicle will attempt to accelerate to the desired speed.

Let e_i be the exit time from the highway of vehicle v_i. Then, τ_i, the travel time of vehicle v_i, is $(e_i - t_i)$. By assigning an appropriate route to each vehicle, we would like to achieve the minimization of the average travel time of vehicles on highways. At the same time, we will consider the travel time difference between routes. We call this problem the automated highway routing problem (AHRP).

IV. SOLUTION APPROACHES

In this section, we propose four route control approaches for the AHRP.

A. ROUTE CONTROL WITH SHORTEST DISTANCE

In the route control with shortest distance (RCSD) approach, each vehicle v_i always takes the shortest distance route for its OD pair (o_i, d_i). This approach can be considered an uncontrolled case because it is the naivest approach.

B. ROUTE CONTROL WITH INSTANTANEOUS TRAVEL TIME

The instantaneous travel time can be defined as the travel time of a virtual vehicle travelling along a given route facing the current traffic conditions [11]. The AHS continually measures the current mean speed of each link. Based on this data, the AHS can find a minimum travel time route for a vehicle v_i at entrance time t_i. This route control with instantaneous travel time (RCIT) approach assumes that the traffic conditions at t_i do not change until the vehicle exit time e_i. The Dijkstra's algorithm [18] is used to find the minimum instantaneous travel time route for each vehicle.

C. ROUTE CONTROL WITH TRAVEL TIME PREDICTION

If traffic conditions change rapidly or the routes are too long to ensure the stability of traffic conditions, route control with travel time prediction (RCTP) may perform better than the previous two approaches. In this study, we use a vehicle speed–density relationship for travel time prediction. Vehicle speed is affected by the number of nearby vehicles. When the number of vehicles is low, vehicles can travel at their maximum speed, but the speed decreases as the number of vehicles increases.

Various formula-based speed–density models have been suggested, including Greenshields' model [19], Greenberg's logarithm model [20], Underwood's exponential model [21], the Northwestern model [22], and the logistic model [23]. Each model has one or more parameters, and their values are estimated from actual vehicle traveling data. Empirical speed–density models can also be used. An empirical model can directly represent the speed–density relationship as data is gathered. In the AHS, because real-time data can be gathered, and it is better to adjust the speed–density relationship dynamically to estimate the travel time more accurately, we use empirical speed–density models rather than existing formula-based speed–density models.

We assume that each highway link has its own speed–density relationship. Roess and Prassas [24] suggested that the preferred speed of a multi-lane highway depends on the number of lanes, lane width, and roadside access points. The speed limit of highways varies from link to link. For accurate travel time prediction, we assume that each link has an individual speed–density relationship. The generation of the empirical speed–density relationship and the prediction of travel time are described in the following.

1) DATA COLLECTION AND GENERATION OF THE EMPIRICAL SPEED–DENSITY RELATIONSHIP

For each link (or segment, which is a division of a link), the AHS records the following data whenever a vehicle arrives at the end of the link: (1) the total number of vehicles on the link; and (2) travel time of that vehicle on the link. Then, the mean travel time is obtained for each number of vehicles on the link. The number of vehicles can be converted into density, and the mean travel time can also be converted into the mean speed. As a result, the collected data can generate and update the empirical speed–density relationship for the link in real time.

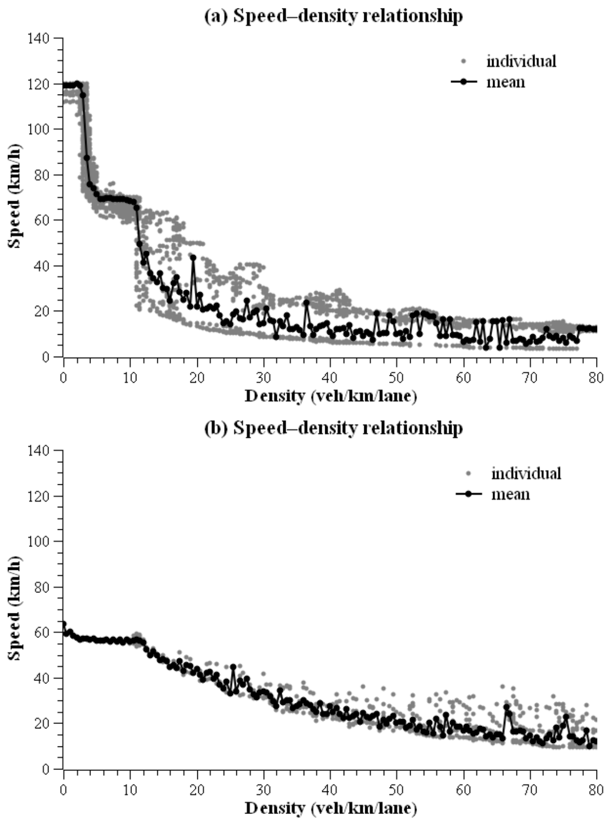

FIGURE 2. Speed–density relationship: (a) two-lane link and (b) one-lane junction link.

In this study, data for any link is collected in 1 km segment units. For the junction link (which is described in detail in Section V-A), data is collected without segmenting. Using collected data for a straight link or junction link, the empirical speed–density relationship is generated. An example of an empirical speed–density relationship of our AHS simulation model is shown in Figure 2. Figure 2(a) shows the result of a two-lane straight link and Figure 2(b) shows the results of a one-lane junction link. In the graph, ''individual'' denotes the speed–density relationship of each vehicle and ''mean'' denotes the average speed at each density. In Figure 2, as the density increases the speed of both straight links and junction links decreases. Junction links have a lower speed than straight links at low density.

2) PREDICTED NUMBER OF VEHICLES

The predicted number of vehicles $m_{(l,j),k}$ has two indices. The space index (l, j) indicates segment j of link l. The length of segment j of link l is $L_{l,j}$. The time index k indicates the time interval. The AHS continually updates and maintains $m_{(l,j),k}$ data.

3) TRAVEL TIME PREDICTION AND ROUTE SEARCH

When vehicle v_i enters the first segment of link l at time index k, the predicted travel time $\tau_{i,(l,1),k}$ becomes

$$\tau_{i,(l,1),k} = \frac{L_{l,1}}{U(m_{(l,1),k})} \tag{1}$$

where $U(m_{(l,1),k})$ is speed at $m_{(l,1),k}$ vehicles at the link. The density is obtained from $m_{(l,1),k}$, $L_{l,1}$, and N_l. The speed is obtained from the density and the empirical speed–density relationship of link l. Then, the time index of entrance of the next segment can be obtained. By repeating this process from the first segment of link l to the last segment of link l, $\tau_{i,l,k}$, which is the predicted travel time of vehicle v_i of link l at entrance time index k, can be obtained. The minimum predicted travel time route can also be obtained by Dijkstra's shortest path algorithm because vehicles follows FIFO rule in the link. Whereas the instantaneous travel time is used to calculate the shortest path route for each vehicle in RCIT, the predicted travel time explained above is used in RCTP.

4) UPDATING THE PREDICTED NUMBER OF VEHICLES

After a route is selected, $m_{(l,j),k}$ values are updated. Following the selected route, the AHS increases the $m_{(l,j),k}$ value by 1 following the route and the predicted travel time.

D. ROUTE CONTROL WITH TRAVEL TIME PREDICTION AND RANDOM ROUTE SELECTION

The proposed route control approach in Section IV-C might have prediction errors. In real traffic, it is difficult to predict the exact movement of all the vehicles. For example, the travel time of two vehicles entering at the same time may be differ by their lane allocation. As a result, the number of predicted vehicles and average predicted speed in the prediction process can be differ from the actual arrival. Furthermore, there might be a time delay to reflect the actual traffic flow in the prediction model. Consequently, there is a possibility that the selected route for a vehicle is not always the actual minimum travel time route. Thus, it is better to select another route for some vehicles, rather than a route with the minimum predicted travel time but which might be congested. To implement this idea, we propose a predicted travel time based random route selection approach. For the route control with travel time prediction and random route selection (RCTPR) approach, the following probability function of route selection is used:

$$p_{i,r} = \frac{\tau_{i,max} - \tau_{i,r} + \alpha_{(o,d)}\tau_{i,min}}{\sum_r (\tau_{i,max} - \tau_{i,r} + \alpha_{(o,d)}\tau_{i,min})} \tag{2}$$

where $\tau_{i,r}$ is the predicted travel time of route r of (o, d), $\tau_{i,max}$ and $\tau_{i,min}$ are the maximum and the minimum predicted travel time of routes, respectively, and $\alpha_{(o,d)}$ is a weight parameter. All the routes for (o, d) can be considered, but in the case of a complex road network, only appropriate routes can be pre-selected and considered. The probability $p_{i,r}$ increases as $\tau_{i,r}$ decreases and vice versa. A weight parameter $\alpha_{(o,d)}$ adjusts the difference between the route selection probabilities. When $\alpha_{(o,d)}$ is zero, $p_{i,r}$ of the route with the maximum predicted travel time is always zero and $p_{i,r}$ of other routes is a positive value. When $\alpha_{(o,d)}$ is a positive value, $p_{i,r}$ of the route with the maximum predicted travel time is also a positive value. The appropriateness of the value of $\alpha_{(o,d)}$ depends on the road network structures and traffic conditions. If the travel time difference between routes is large, $\alpha_{(o,d)}$ needs a low value or to be zero. If the travel time difference is small, $\alpha_{(o,d)}$ needs a high value to reduce the probability difference. It is difficult to find an appropriate value of $\alpha_{(o,d)}$ theoretically, but the value can be obtained by experientially. In this study, the value is obtained from preliminary simulation experiments.

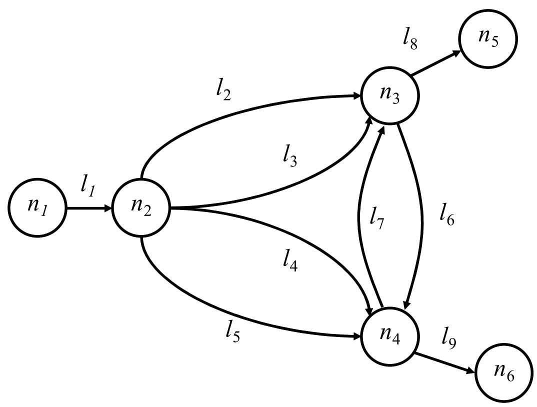

FIGURE 3. Road network design of the case study (Baskar *et al.*, 2013).

V. SIMULATION STUDY

A. CASE STUDY SCENARIOS

To test the route control approaches proposed in the previous section, we consider the road network of the AHS presented in Figure 3. The basic network structure is adopted from Baskar *et al.* (2013), but the length and number of lanes of links are adjusted to our agent-based simulation. There is one entrance node n_1, two exit nodes n_5 and n_6, and three junction nodes n_2, n_3, and n_4. The length of l_1, l_8, and l_9 is 5 km. The lengths of l_2 to l_7 are 20, 18, 12, 14, 4, and 4 km, respectively. The number of lanes of l_1 is eight, and the number of lanes of all other links is two. Note that l_1 is assumed to have eight lanes because it is used to generate incoming traffic to the network and many lanes are required to generate enough cars for the simulation in AnyLogic. It is assumed that the interarrival times of the OD pair cars (n_1, n_5) and (n_1, n_6) follow exponential distributions.

We developed the simulation model using AnyLogic 7.3, whose traffic library is used to model physical parts such as the road network and vehicles and Figure 4 shows part of the model. The links are connected to junctions. A junction is composed of several junction links, which connect two link lines. Logical parts such as the data collection system, data communication system, and route controller are developed in JAVA.

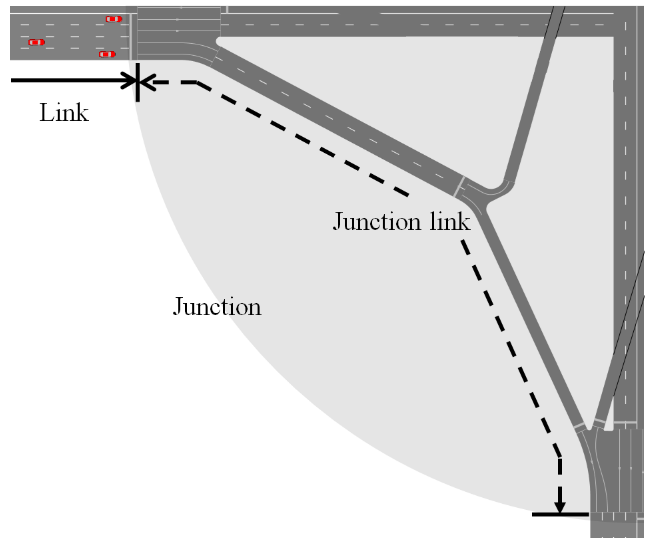

FIGURE 4. Link and junction link.

We consider the following three scenarios for the simulation.

- **Scenario 1**:
  OD pair (n_1, n_5) with 2.4 s mean interarrival time (25 veh/min).
- **Scenario 2**:
  OD pair (n_1, n_5) with 3.6 s mean interarrival time (16.7 veh/min) and OD pair (n_1, n_6) with 7.2 s mean interarrival time (8.3 veh/min).
- **Scenario 3**:
  OD pair (n_1, n_5) with 2.4 s mean interarrival time (25 veh/min) and OD pair (n_1, n_6) with 4.8 s mean interarrival time (12.5 veh/min).

For all the scenarios, it is assumed that the length of a vehicle is 5 m and the preferred speed of the vehicles is 120 km/h. The total simulation time horizon is 6 h. The simulation for each scenario is conducted 10 times.

B. SIMULATION RESULTS

1) SCENARIO 1

In Scenario 1, there are four possible routes to choose: $l_1 - l_2 - l_8$ (from now on, only numbers are used as, e.g., 1–2–8), 1–3–8, 1–4–7–8, and 1–5–7–8. Figure 5 shows the results of the four approaches proposed in Section IV. In the graph, (x, y) of each point indicates (departure time of vehicle v_i at the entrance node, total travel time of v_i). The travel times of the vehicles that do not arrive at the destination node until simulation end time (6 h) are not shown.

In the RCSD approach, because all the vehicles consider their shortest distance route, the vehicles with the same OD

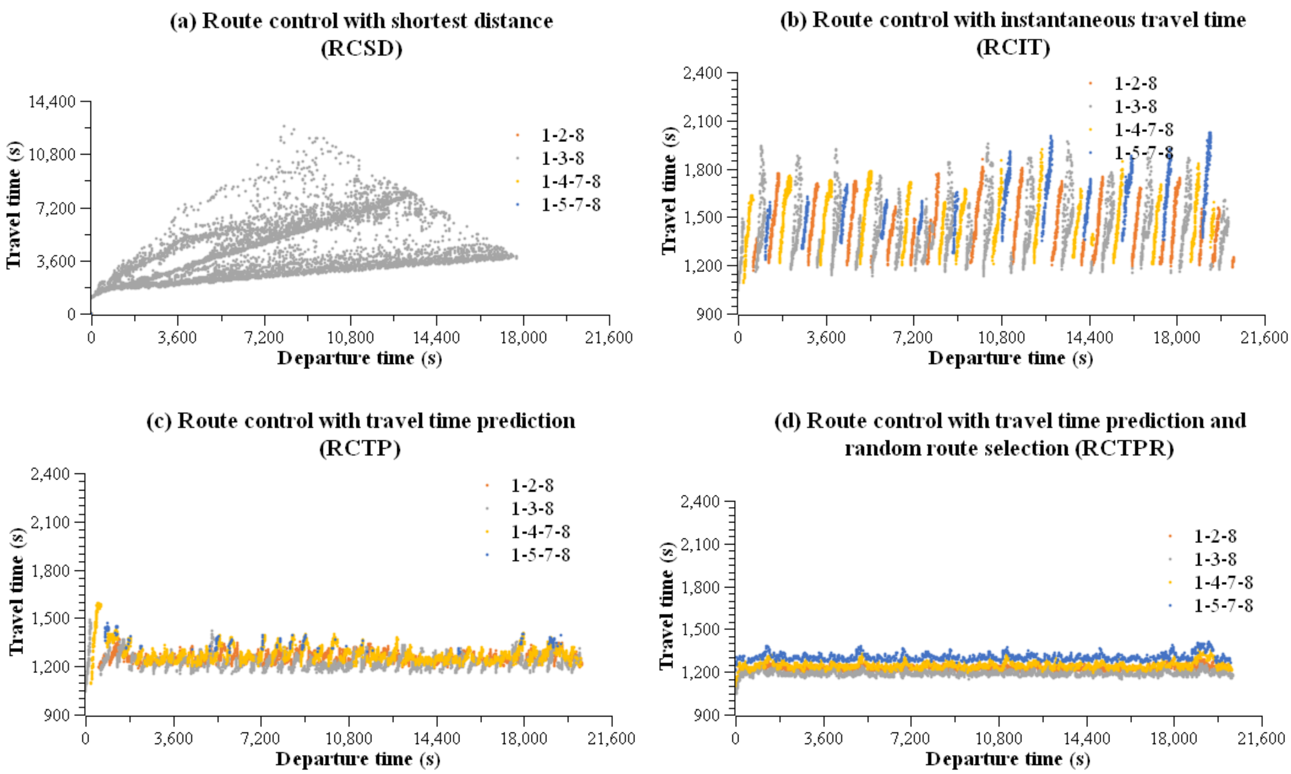

FIGURE 5. Simulation results of Scenario 1.

TABLE 1. Simulation results of Scenario 1 (average of 10 simulations).

Route	Average travel time (s)				Number of vehicles			
	RCSD	RCIT	RCTP	RCTPR	RCSD	RCIT	RCTP	RCTPR
1–2–8	-	1,457.4 (28.5)	1,258.5 (5.5)	1,228.4 (2.2)	-	2,136.8 (52.4)	2,639.8 (39.2)	2,252.9 (83.9)
1–3–8	4,136.9 (76.1)	1,455.1 (28.0)	1,232.7 (3.9)	1,192.9 (1.8)	5,972.7 (5.0)	2,685.5 (88.0)	2,902.3 (42.1)	2,916.3 (54.6)
1–4–7–8	-	1,485.1 (17.6)	1,283.8 (7.1)	1,248.7 (3.6)	-	2,060.2 (115.2)	2,756.5 (51.6)	1,949.9 (79.5)
1–5–7–8	-	1,607.6 (46.5)	1,373.5 (17.3)	1,307.2 (3.4)	-	1,455.7 (117.5)	137.6 (52.7)	1,323.0 (21.6)
Total	4,136.9 (76.1)	1,490.4 (13.1)	1,259.7 (5.3)	1,233.2 (2.4)	5,972.7 (5.0)	8,338.2 (114.3)	8,436.2 (100.8)	8,442.1 (102.4)
Max–Min	-	171.5 (34.3)	140.9 (18.0)	114.4 (2.6)				

Note. Standard deviations are given in parentheses.

pair select the same route. When the flow exceeds the capacity of the links, as shown in Figure 5(a), the vehicles are congested, and their travel time continuously increases. Note that Figure 5(a) has a larger vertical scale than the other graphs.

In the RCIT approach, the shortest distance route is used initially as in the RCSD approach. However, if congestion occurs and the instantaneous travel time of the previously used route is greater than the other route, the AHS selects the route with the minimum instantaneous travel time for the next incoming vehicle. Figure 5(b) shows the result of the approach. It is clearly better than Figure 5(a), but we can observe another problem. Figure 5(b) shows that the routes being used are distinct by time intervals. This means that the shortest travel time route is not changed for a while and the same route is chosen continuously for incoming vehicles. This happens because the vehicles entering a road link do not immediately affect the driving time of the road, and there is a time delay between the entering of vehicles and recognizing their effects. The instantaneous travel time on a road link reflects the road condition at the moment when a vehicle enters at the origin node. However, when the vehicle arrives at a road link on the route, the road conditions have changed from the observed conditions at the origin node. The instantaneous travel time of that road link is updated by these vehicles and the update occurs later as the road link is farther away from the origin node. Such time delay causes the delay in route change.

The RCTP approach is proposed to overcome the time delay problem of the RCIT approach. Using the RCTP approach, the duration of using only one route is reduced and the average travel time of vehicles decreases significantly as listed in Table 1. Furthermore, the RCTPR approach shows better results than the RCTP approach. In Table 1, the Max–Min row, which lists the travel time difference between maximum and minimum travel time routes, shows that RCTP and RCTPR approaches are also effective for the minimization of the travel time difference between routes.

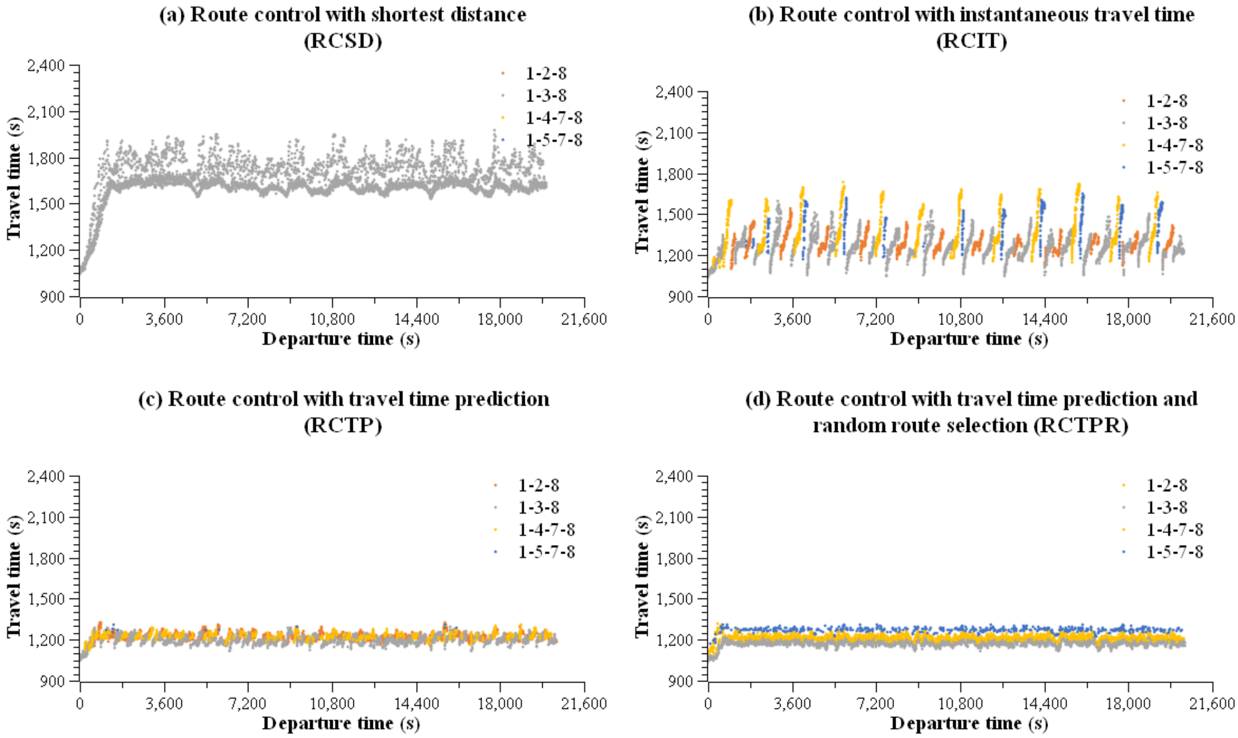

FIGURE 6. Simulation results of Scenario 2: OD pair (n_1, n_5).

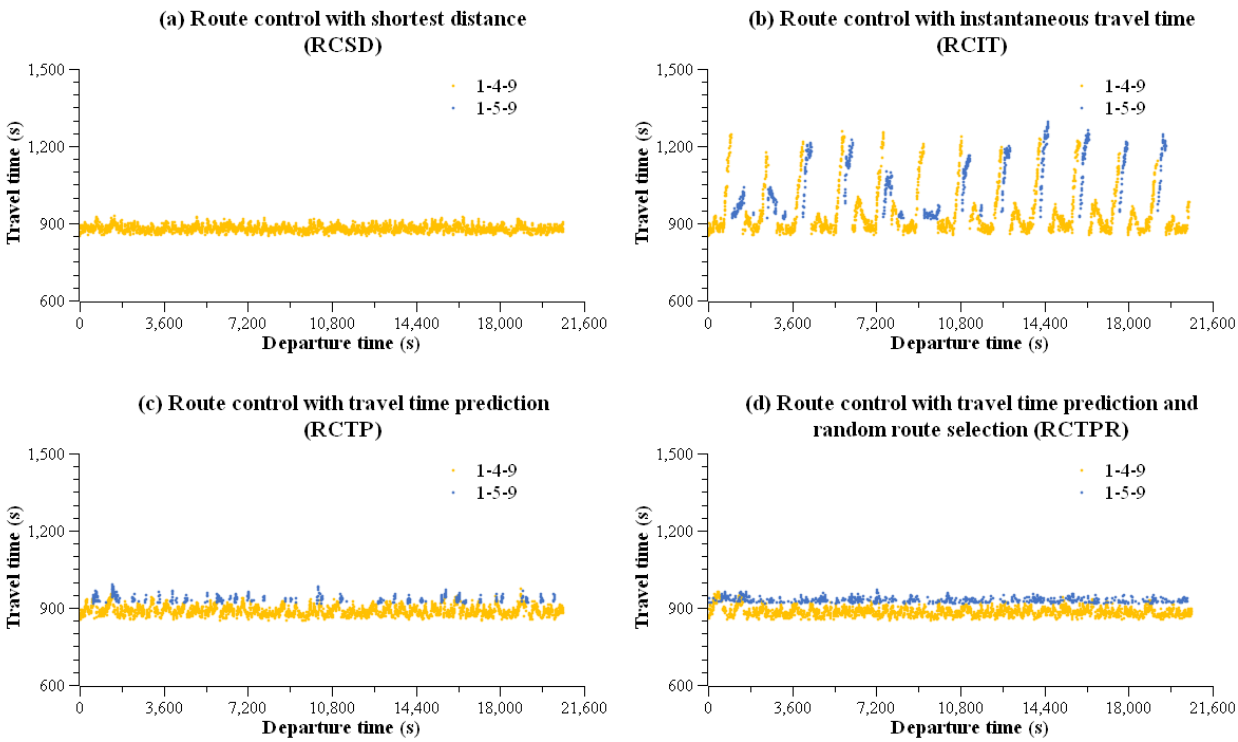

FIGURE 7. Simulation results of Scenario 2: OD pair (n_1, n_6).

The main difference between the results of the RCTP and RCTPR approaches is the usage ratio of (1–4–7–8) and (1–5–7–8) routes. These two routes share link l_7 and the total number of vehicles traveling through both routes is similar in the two approaches. However, the usage ratio of the two routes is very different. Whereas the usage ratio of the RCTP

TABLE 2. Simulation results of Scenario 2 (average of 10 simulations).

Route	Average travel time (s)				Number of vehicles			
	RCSD	RCIT	RCTP	RCTPR	RCSD	RCIT	RCTP	RCTPR
1–2–8	-	1,305.9 (14.0)	1,229.8 (2.3)	1,211.9 (1.9)	-	1,333.9 (54.9)	2,183.9 (40.9)	1,437.3 (171.1)
1–3–8	1,642.4 (9.5)	1,268.4 (8.0)	1,199.3 (2.3)	1,176.4 (1.7)	5,553.6 (55.6)	2,634.8 (56.2)	2,748.8 (54.2)	2,857.3 (66.8)
1–4–7–8	-	1,389.6 (7.2)	1,243.3 (9.6)	1,222.3 (1.9)	-	1,249.7 (42.3)	701.3 (50.5)	888.0 (42.5)
1–5–7–8	-	1,428.9 (15.0)	1,287.2 (5.1)	1,273.0 (1.2)	-	431.3 (70.0)	39.7 (17.4)	494.9 (103.4)
Total	1,642.4 (9.5)	1,316.3 (6.3)	1,217.1 (2.5)	1,201.0 (2.8)	5,553.6 (55.6)	5,649.7 (54.7)	5,673.7 (58.7)	5,677.5 (62.7)
Max–Min		160.5 (14.5)	87.9 (6.4)	96.6 (1.2)				
1–4–9	880.8 (0.6)	941.5 (6.4)	892.0 (1.9)	886.3 (0.7)	2,902.9 (44.0)	2,131.4 (73.8)	2,420.5 (79.6)	2,258.8 (64.9)
1–5–9	-	1,042.4 (24.5)	936.5 (1.0)	931.7 (1.4)	-	767.9 (89.8)	481.6 (65.5)	643.5 (56.5)
Total	880.8 (0.6)	967.5 (4.8)	899.3 (2.4)	896.3 (1.4)	2,902.9 (44.0)	2,899.3 (45.4)	2,902.1 (439)	2,902.3 (45.3)
Max–Min	-	100.9 (28.4)	44.5 (1.9)	45.4 (1.3)				

Note. Standard deviations are given in parentheses.

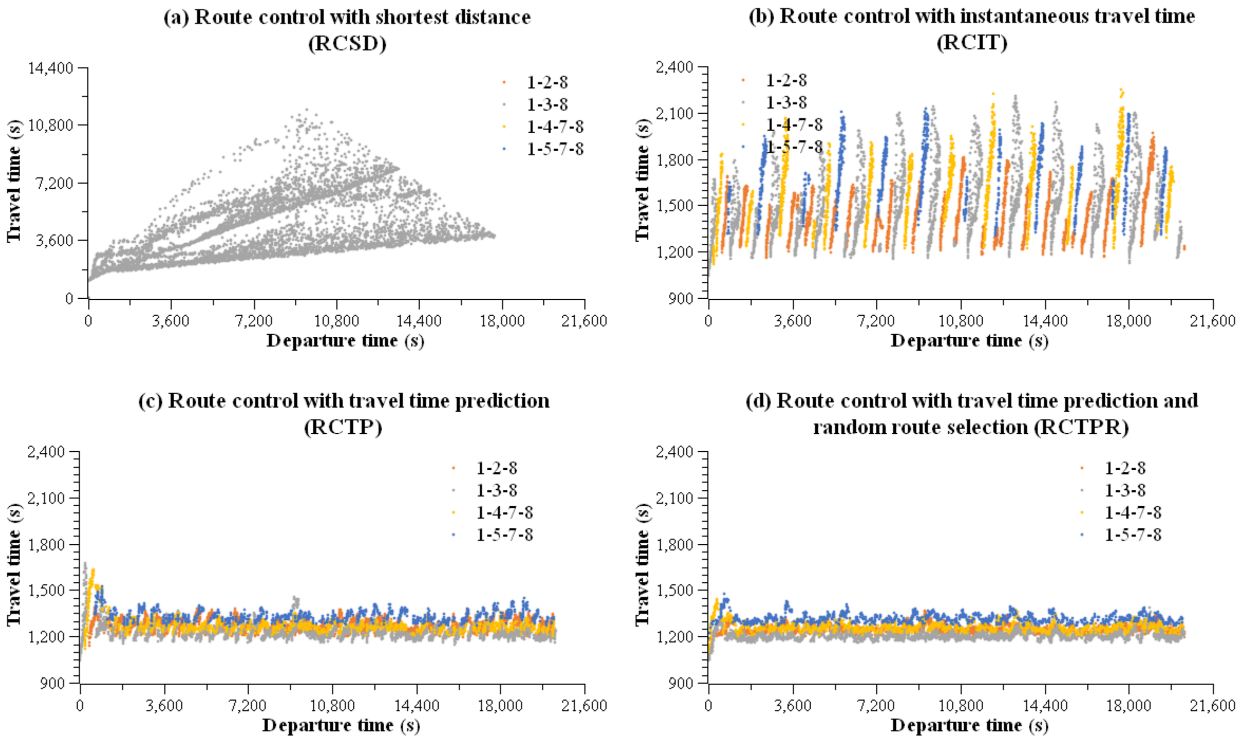

FIGURE 8. Simulation results of Scenario 3: OD pair (n_1, n_5).

result is 20:1, that of the RCTPR result is 3:2. Note that in the RCTPR approach, the weight parameter $\alpha_{(1,5)}$ is set to 0.028. The value was obtained from preliminary simulation experiments with all the possible values between 0 and 0.040 at 0.002 intervals. In other scenarios, each $\alpha_{(o,d)}$ is also obtained in a similar manner.

2) SCENARIO 2

Scenario 2 is obtained by changing the OD pair of some vehicles to OD pair (n_1, n_6) from Scenario 1. The total vehicle flow rate is the same as Scenario 1, but one-third of the vehicles are assigned to OD pair (n_1, n_6). Figure 6 shows the results of the OD pair (n_1, n_5) and Figure 7 shows the results of the OD pair (n_1, n_6). Table 2 lists the summary. For OD pair (n_1, n_6) vehicles, only (1–4–9) and (1–5–9) routes are considered. Although both (1–2–6–9) and (1–3–6–9) routes are also possible, they are not considered as appropriate routes because their total distances are significantly longer than (1–4–9) and (1–5–9) routes.

As a result of the decrease in the vehicles of OD pair (n_1, n_5), there was no serious congestion even though only one route was used in the RCSD approach (Figure 6(a)). The results of the RCIT, the RCTP, and the RCTPR approach (Figure 6(b), (c), and (d)) are similar to Scenario 1 but the average travel time has decreased compared with Scenario 1. The results of the OD pair (n_1, n_6) are similar to the OD pair (n_1, n_5) case, except for the available routes (Figure 7). The weight parameters $\alpha_{(1,5)}$ and $\alpha_{(1,6)}$ in the RCTPR approach are set to 0.006 and 0.010.

3) SCENARIO 3

Scenario 3 is obtained by adding the flow for OD pair (n_1, n_6) from Scenario 1. The ratio of flow rate of two OD pairs is the same as the ratio in Scenario 2. Figures 8 and 9 and

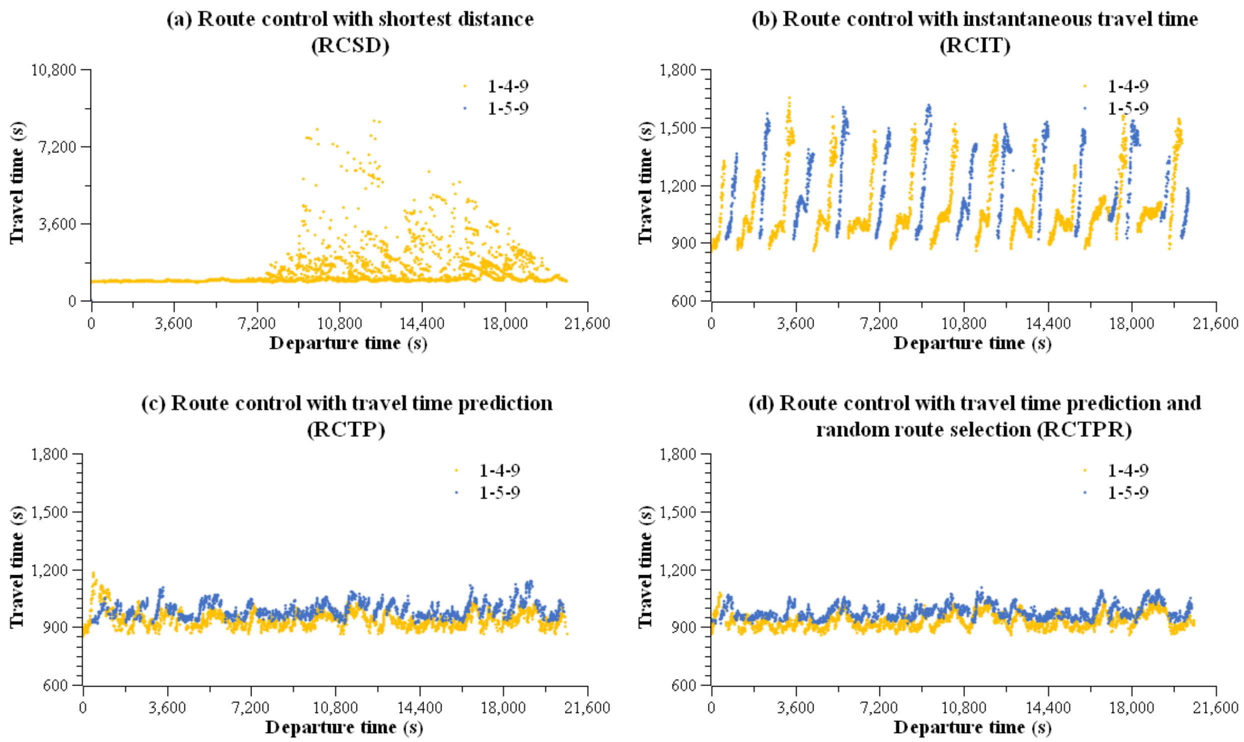

FIGURE 9. Simulation results of Scenario 3: OD pair (n_1, n_6).

TABLE 3. Simulation results of Scenario 3 (average of 10 simulations).

Route	Average travel time (s)				Number of vehicles			
	RCSD	RCIT	RCTP	RCTPR	RCSD	RCIT	RCTP	RCTPR
1–2–8	-	1,522.3 (36.8)	1,277.8 (4.1)	1,252.9 (4.0)	-	2,492.8 (101.6)	2,869.4 (40.5)	2,865.2 (47.9)
1–3–8	4,179.2 (86.8)	1,495.2 (23.1)	1,236.0 (3.7)	1,214.6 (4.2)	5,969.1 (4.9)	2,965.8 (64.0)	3,300.0 (29.6)	3,101.6 (29.4)
1–4–7–8	-	1,592.8 (13.2)	1,282.2 (10.1)	1,269.0 (3.0)	-	1,638.7 (91.5)	1,195.4 (55.1)	1,392.2 (48.6)
1–5–7–8	-	1,708.4 (18.4)	1,346.4 (6.8)	1,322.2 (4.1)	-	1,230.8 (90.3)	1,089.2 (67.2)	1,105.1 (45.1)
Total	4,179.2 (86.8)	1,554.2 (15.1)	1,271.0 (4.1)	1,250.5 (4.0)	5,969.1 (4.9)	8,328.1 (102.7)	8,454.0 (93.2)	8,464.1 (92.9)
Max–Min	-	222.0 (28.4)	110.4 (8.1)	107.6 (3.6)				
1–4–9	1,279.1 (103.1)	1,084.3 (14.6)	949.3 (7.6)	947.6 (9.0)	4,057.9 (88.3)	2,713.5 (92.5)	2,583.7 (77.7)	2,436.1 (58.4)
1–5–9	-	1,204.8 (17.4)	1,007.2 (8.8)	994.3 (11.1)	-	1,529.2 (118.3)	1,705.1 (41.5)	1,852.3 (38.8)
Total	1,279.1 (103.1)	1,127.3 (9.5)	972.3 (7.8)	967.8 (9.6)	4,057.9 (88.3)	4,242.7 (73.4)	4,288.8 (67.9)	4,288.4 (67.9)
Max–Min	-	120.5 (28.3)	57.9 (3.4)	46.7 (3.9)				

Note. Standard deviations are given in parentheses.

Table 3 display the results. The results of the OD pair (n_1, n_5) are similar to the results of Scenario 1. However, except in the RCSD approach, average travel times have increased because the vehicles of the OD pair (n_1, n_6) that share link l_4 and l_5 are added. The results of the OD pair (n_1, n_6) are similar to the OD pair (n_1, n_6) of Scenario 2. As the traffic flow rate of Scenario 3 is greater than Scenario 2, average travel times of the OD pair (n_1, n_6) have increased; in the RCSD approach, heavy congestion occurs as shown in Figure 9(a), and this is similar with OD pair (n_1, n_5) in Figure 8(a).

Although the flow has increased, the RCTP approach shows significantly better results than the RCIT approach, and the RCTPR approach also shows better results than the RCTP approach (Table 3). The weight parameters $\alpha_{(1,5)}$ and $\alpha_{(1,6)}$ in the RCTPR approach are set to 0.014 and 0.010.

VI. CONCLUSION

This study has investigated the routing algorithm for an AHS. We defined the AHRP and suggested four approaches: RCSD, RCIT, RCTP, and RCTPR. The RCSD approach, which takes the shortest distance route, corresponds to an uncontrolled case. The RCIT approach corresponds to a non-prediction case. It measures the current mean speed and takes the minimum travel time route. Both the RCTP and the RCTPR approaches consider predicted travel time, but the RCTP approach considers only the minimum predicted travel time route and the RCTPR approach considers the predicted travel time of all routes and selects routes with probability. We have developed an AHS model using an agent-based simulator and applied the suggested approaches. The experimental results show that the RCTPR approach is the best among the four.

Note that if the relevant traffic information is collected and appropriately shared and the human drivers follow the guidelines (suggested route selection) generated by the algorithm, the proposed approaches can be applied to even today's highway networks.

This research can be extended in many directions. First, the RCTPR approach requires an efficient and automatic parameter setting method for $\alpha_{(o,d)}$. In the current RCTPR approach, we tested various values through preliminary simulations, and then selected the best value among them. To apply the approach to dynamic traffic demand and various road networks, the parameters should be determined automatically. We plan to use machine learning techniques such as reinforcement learning for the automatic parameter setting. Second, the proposed approaches need to be validated on much larger road network models with more complicated OD pairs.

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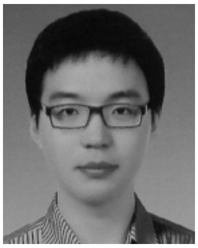

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