CARAVAN: Congestion Avoidance and Route Allocation Using Virtual Agent Negotiation

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***Abstract*—Traffic congestion becomes a cascading phenomenon when vehicles from a road segment chaotically spill on to successive road segments. Such uncontrolled dispersion of vehicles can be avoided by evenly distributing vehicles along alternative routes. This paper proposes a practical multiagent-based approach, which is designed to achieve acceptable route allocation within a short time frame and with low communication overheads. In the proposed approach, which is called congestion avoidance and route allocation using virtual agent negotiation (CARAVAN), vehicle agents (VAs) in the local vicinity communicate with each other before designated decision points (junctions) along their route. Cooperative route-allocation decisions are performed at these junctions. VAs use intervehicular communication to propagate key traffic information and undertake its distributed processing. Every VA exchanges its autonomously calculated route preference information to arrive at an initial allocation of routes. The allocation is improved using a number of successive virtual negotiation "deals." The virtual nature of these deals requires no physical communication and, thereby, reduces communication requirements. In addition to the theory and concept, this paper presents the design and implementation methodology of CARAVAN, including experimental results for synthetic and real-world road networks. Results show that when compared against the shortest-path algorithm for travel time improvements, CARAVAN offers 21%–43% gain (when traffic demand is below network capacity) and 13%–17% gain (when traffic demand exceeds network capacity), demonstrating its ability to regulate overall system traffic using local coordination strategies.**

***Index Terms*—Cooperative systems, dynamic traffic assignment, multiagent systems (MAS), traffic congestion management.**

I. Introduction

TRAFFIC congestion can be caused by physical bottlenecks, traffic incidents, work zones, and special events. Most of the existing congestion control techniques, such as variable message signs or traffic information systems, advise vehicles to detour, thereby dispersing them unevenly along alternative routes and often overloading only a few popular routes. For quick dissipation of traffic and congestion avoidance, the vehicles need to be evenly distributed along alternative routes; this requires a vehicle to have knowledge of the route choices of the surrounding vehicles to make an informed decision about whether to take its intended route. This information exchange can be facilitated by intervehicular communication (IVC) and/or by installing a roadside infrastructure unit for collecting and transmitting useful traffic information. However, given the vast expanse of road networks, it is impractical to have infrastructure units on every road segment/intersection due to prohibitive costs. IVC allows efficient and real-time information exchange where vehicles acting as mobile nodes form a wireless vehicular ad hoc network (VANET). VANETs employ single-hop and multihop topologies for communication with vehicles in close proximity or in the surrounding area. IVC can enable traffic safety applications, such as collision avoidance and hazard detection, and nonsafety applications, such as traffic and parking management and infotainment services. IVC is facilitated by wireless communication technologies (e.g., cellular networks and dedicated short-range communication).

Effective management of congestion requires timely processing of traffic information (made available via IVC) and coordinated execution of control actions via traffic control entities. The control entities should be able to learn and adapt from the effects of their previous control actions. In addition to timely processing, coordination, and learning, any traffic management solution should be also cost effective in terms of communication overhead and infrastructure requirements. Existing traffic management solutions that are implemented within roadside infrastructure units and vehicular onboard units lack some or most of these characteristics. Multiagent systems (MAS), which are distributed systems consisting of a number of autonomous agents (software entities), possess the characteristics of being adaptive and collaborative. MAS, in combination with IVC technology, can overcome the disadvantages of conventional traffic management techniques.

The main contributions of this paper are 1) articulating the need for cooperative route allocation for effective congestion management; 2) proposing a multiagent-based collaborative congestion management solution using IVC, which employs a virtual negotiation technique to reduce communication overheads; and 3) presenting a detailed evaluation of the proposed solution for synthetic and real road networks, demonstrating its effectiveness for congestion management.

This paper is organized as follows: Section II reviews related work in cooperative traffic management. Section III describes the application of multiagent-based resource allocation (MARA) to the route assignment problem and introduces the concept of satisficing agents. Section IV presents the design and implementation of congestion avoidance and route allocation using virtual agent negotiation (CARAVAN). Section V presents a detailed experimental evaluation of CARAVAN. Section VI concludes this paper with future research directions.

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II. Related Work

This section reviews existing VANET- and MAS-based congestion management techniques and explains the relevance of satisficing solutions for the traffic assignment problem.

A. *Congestion Management Techniques Using* VANETs

Detailed information about the traffic conditions propagated using VANETs can be used for real-time prediction of travel time [1], which could be used by travelers to choose their preferred travel paths and by intelligent software entities to analyze travel routes and recommend best travel routes to drivers. Kraus *et al.* in [2] and Leontiadis *et al.* in [3] used VANET-based gossiping (communication) for traffic information propagation. The simulation outcome in [2] showed that only 20%–30% of vehicles (gossiping agents) resulted in average travel time similar to that when the information was obtained from a centralized information center. However, further increase in the number of gossiping agents increased the travel time as most of the agents tried to follow the same alternate path. The results in [3] showed that 64% of gossiping agents save on time; however, due to lack of coordination, the vehicles can congest the second best path. In [4], vehicles exchanged their average speed information with other vehicles in their vicinity and updated their travel route based on the derived traffic situation. Simulation results showed 50% reduction in travel time with 80% equipped vehicles. However, this approach involves extensive use of IVC and does not consider driver preferences. In [5], a vehicle requests traffic information for its probable travel routes using vehicular communication and uses this to select the least congested travel route. Simulation results showed that such information propagation helps reduce congestion. In all these approaches, VANETs facilitate real-time information propagation. However, on getting congestion alerts, the vehicles may unevenly disperse along the same alternate routes, ultimately overcrowding them. Hence, for a robust solution, a cooperative route-allocation strategy that does not require excessive communication is needed.

B. *MAS-Based Congestion Management Techniques*

MAS are well suited to the problem of traffic management, which is geographically distributed, dynamic in nature, and requires coordination between constituent traffic entities [6]. In the bio-inspired MAS approach in [7], ants deposit a chemical substance called pheromones of varying intensities to mark the shortest path between the nest and the food. Computational results showed improvement in traffic flow with the application of this approach. Another approach in [8] is inspired by food foraging in ant colonies, where vehicle agents (VAs) use exploration ants to identify all possible paths between the source and the destination. Experimental results showed 35% gain in travel time when compared with normal drivers or those drivers using real-time data made available by *traffic messaging channel* services. The market-inspired road intersection management approaches in [9] and [10] consist of infrastructure agents, which provide intersection space reservation to driver agents. The driver agents choose the route based on the current prices of the reservations, personal travel time preferences, and the involved monetary costs. In [10], the intersection managers compete for the supply of the reservations. The driver agents participate in the allocation of road network capacity through a combinatorial auction-based mechanism. Experimental evaluation showed 30% reduction in the delay for the drivers who submitted high-value bids. The hierarchical cooperative MAS-based route guidance approach in [11] consists of three types of agents for 1) providing traffic information, 2) satisfying drivers' route choice, and 3) focusing on overall network stability. Here, conflicting objectives of driver satisfaction and network stability were handled using an interagent negotiation technique. Experimental results suggested that the negotiation can achieve good network performance and increase driver satisfaction by allocating drivers evenly along the network.

C. *Satisficing Solutions for Traffic Assignment*

Evenly distributing traffic is key to avoiding congestion. The measure of evenly distributed traffic can be quantified in terms of system equilibrium (SE) or user equilibrium (UE). UE or user optimal (UO) flow is achieved when traveler's route choices are influenced so as to minimize the total trip time [12]. System optimal (SO) flow minimizes the overall travel time, resulting in SE. As stated in [13], the UE model is more suited to a deterministic environment, and the SO flow pattern cannot be achieved without coordinated decisions of motorists to minimize the total system travel time. An even distribution of traffic can be only obtained by evaluating permutations and combinations of all possible assignments of routes to vehicles while also considering road speed limit variations and driver preferences. Overall, this process can take too long to reach an optimal solution. Such an exhaustive search approach is computationally intensive and not appropriate for dynamic traffic scenarios, where the VA software running within an onboard unit may have limited processing capacity, and the solution must be generated in limited time. Moreover, as it is not practically feasible to get an accurate real-time view of the global traffic situation, real-time decision-making is frequently based on incomplete traffic information. Consequently, the SO and UO flow patterns cannot be effectively applied to a stochastic and dynamic traffic environment. In this case, the systematic exploration of the entire search space for computing an optimal solution can prove to be expensive; here, a practical approach is to adopt a suboptimal satisficing solution [14].

III. Theory Underlying CARAVAN: Multiagent-Based Resource Allocation and Virtual Deals

A. *MARA*

CARAVAN addresses the problem of route allocation using MARA. The resource-allocation problem can be defined as the problem of allocating a set of resources among a set of entities that have preferences over this resource set to maximize an objective function [15]. In the context of MAS, the problem of route allocation can be stated as a MARA problem, in which

TABLE I
ALLOCATIONS RESULTING FROM ADD, SWAP, AND DROP DEALS FOR INITIAL ALLOCATION: $\{v1-r5; v2-r5; v3-r2; v4-r1\}$

Deal Type	Final Allocation
ADD (assign r2 to v1)	*{v1-r2, v2-r5, v3-r2, v4-r1}*
SWAP (between v1 and v3)	*{v1-r2, v2-r5, v3-r5, v4-r1}*
DROP (between v1 and v3)	*{v1-r2, v2-r5, v3-r1, v4-r1}*

**vi-ri means vehicle/agent vi is allocated route ri*

there is a finite number of agents (vehicles) and a finite number of indivisible but sharable resources (routes). Agents in the given traffic scenario have preferences for various assignments of the resources, which can be expressed as utility functions. An agent's utility for a route depends on its own preference value for that route and the cost it incurs by taking that route. If the number of vehicles being assigned to a certain route is greater than its threshold capacity value, the cost incurred in traversing that route will increase with the number of vehicles.

Centralized or decentralized MARA techniques are widely used in scheduling, network routing, logistics, and airport traffic management applications [16]. Centralized approaches will be less effective for the distributed traffic environment as these are primarily based on combinatorial auctions wherein the agents report their preference to a central auctioneer, which then does the final allocation. Allocation in decentralized approaches is facilitated by local deals (trading of resources) or negotiation between the involved agents as in [17]. Negotiation is a way of coordinating, resolving conflicts [18], and reaching a mutual agreement over a common goal [19].

B. Virtual Negotiation Using Virtual Deals

In the decentralized MARA approaches in [15], agents are interconnected in various topologies to facilitate the exchange of resources via extensive communication to reach a solution. This is difficult to realize in vehicular environments due to the dynamic nature of traffic flow with limited time for communication and solution determination. To address these problems, we propose the concept of virtual negotiation by means of the so-called "virtual deals" that require actual communication only at the start and end of the route-allocation process. In a virtual deal, an agent does not actually communicate with other agents but only enacts the process of interagent communication in its "mind." After the exchange of preferences, every VA is assigned a route in the form of an initial allocation. To improve the allocation in terms of the overall utility (social welfare), individual utility (rational welfare), or both (mixed welfare), every agent internally plays out the deals with other agents. A "deal" between agents i and j, which is represented as $\delta\ (i,j) = (\sigma, \sigma')$, can be defined as the transition from allocation σ to σ'. An acceptable deal is one that results in gain in the utility, i.e., $\Delta u > 0$. Every VA autonomously carries out virtual negotiation in the form of ADD, SWAP, or DROP virtual deals. An example of the deals presented in Table I shows the final allocations obtained after performing each of the deals on a given initial allocation: 1) ADD deal, i.e., an agent virtually assigns itself one of its preferred routes (v1 assigns itself to route r2); 2) SWAP deal, i.e., an agent exchanges its route with another agent (v1 and v3 swap routes); 3) DROP deal, i.e., an agent assigns itself a route that has been currently assigned to some other agent, whereas the other agent is assigned a random route from the available set of routes (v1 is assigned the route of v3, and v3 is assigned a random route r1).

As the actual communication only happens at the start and end of the route-allocation process in virtual negotiation (to exchange route preferences and final resulting allocations), communication costs are not incurred for intermediate steps. The post-deal acceptance of an allocation is based on the type of welfare adopted by the system. A deal is acceptable if it results in increased utility of the individual agent (for rational and mixed welfare) and/or increased overall utility of the allocation (for social and mixed welfare). The process of deals is iterative, and eventually, better allocations result from successful deals. The final allocations obtained by agents are exchanged among them, and the best allocation in terms of utility value is accepted by all agents. The virtual deal mechanism does not require a central control entity for managing allocations, further reducing the constraints on communication costs.

C. Problem Statement

The route-allocation problem can be expressed as a MARA [20], in the form of a 5-tuple: $(V, R, \{a_i \mid i \in V\}, \{c_{i,r} \mid i \in V, r \in R\}, \{p_{i,r} \mid i \in V, r \in R\}$, where V is the set of n vehicles (agents), R is the set of m routes, a_i is the allocation strategy for agent i, $c_{i,r}$ is the cost experienced by agent i when using route (resource) r, and $p_{i,r}$ is a preference-based utility value that agent i holds for route r. Every VA is assigned a single route, provided that the assignment does not exceed road capacity. *Road capacity* is defined as the potential number of vehicles that can traverse a road at a speed that is either equal to free-flow speed per unit time (if road capacity equals the practical road capacity) or below free-flow speed per unit time (if road capacity exceeds the practical road capacity). *Practical/threshold capacity* of a road is the number of vehicles that can traverse the road at free-flow speed per unit time, and beyond which, congestion starts to build up.

To calculate the average travel time denoted by $S_k(vol_k)$ for a vehicle on link "k," we use the link (arc) congestion function provided by the Bureau of Public Roads [21], i.e.,

$$S_k(vol_k) = t_k \left(1 + \frac{\alpha}{\beta + 1}\left(\frac{vol_k}{c_k}\right)^{\beta}\right) \quad (1)$$

where parameter α is very small and $5 >= \beta > 1$, t_k is the free-flow travel time on link "k" per unit of time, vol_k is the volume of traffic on link per unit of time, and c_k is the practical or the threshold capacity of link "k" per unit of time. When flow vol_k is much less than c_k, ratio vol_k/c_k is negligible, and hence, $S_k(vol_k) \approx t_k$, which means that the average travel time is equal to the free-flow travel time. For larger values of vol_k, the effects of congestion start to become visible.

D. Utility of Allocation/Solution Space

Let $n_r(\sigma)$ be the number of agents that use resource (route) r in allocation σ. The cost experienced by agent i on route r

in allocation σ due to $n_r(\sigma)$ number of VAs is $c_{i,r}(n_r(\sigma))$, and $p_{i,r}(\sigma)$ is the preference utility index of agent i for route r in solution space σ. The cost depends on the number of vehicles taking the route and the average travel time on that route, which is calculated using (1). Here, p and c are the constant multipliers for $p_{i,r}(\sigma)$ and $c_{i,r}(n_r(\sigma))$, respectively. Hence, the utility u_i of solution space σ for agent i can be given as

$$u_i(\sigma) = p * p_{i,r}(\sigma) - c * c_{i,r}\left(n_r(\sigma)\right). \tag{2}$$

From (2), the utility of the allocation/solution space is given as the aggregate of the utilities of all the agents in that allocation, i.e.,

$$u(\sigma) = \sum_{i=1}^{n} u_i(\sigma). \tag{3}$$

E. VAs *as Satisficing Agents*

Amongst the negotiation models, the game-theoretic model aims to find an *optimal* strategy, whereas the heuristic model attempts to find a *suboptimal* strategy. As stated in [22], for computationally intractable problems (such as the traffic assignment problem), adopting a suboptimal satisficing solution will be practical. The agents that try to achieve such a solution are called satisficing agents. Satisficing solutions are a result of tradeoffs that favor benefit over cost [23]. In our case, benefit refers to maximizing an agent's preference utility index, and cost refers to minimizing the communication and computation time required to reach an acceptable allocation and the cost of using the assigned route.

IV. Congestion Avoidance and Route Allocation Using Virtual Agent Negotiation (CARAVAN)

This section presents our proposed CARAVAN solution, which is designed for dynamic traffic management scenarios. It uses interagent communication to perceive the surrounding traffic situation and uses local neighborhood decision-making via interagent cooperation and negotiation.

A. *Functional Prototype*

Fig. 1 is a functional block diagram of CARAVAN, which describes the primary steps of the algorithm and the flow of information between its components. Here, every VA, starting from source A and destined to reach destination G, exchanges its autonomously calculated route preferences for routes between decision points B and G and uses this information to arrive at an initial allocation of routes. For conflicting route allocations, each VA performs a given fixed number of virtual negotiation deals to improve upon the initial allocation. The resulting allocation is exchanged, and the final allocation is cooperatively chosen based on the welfare type. The main modules of CARAVAN are 1) *graphical user interface*, which provides a user interface to visualize vehicular mobility; 2) *mobility model*, which works as the "perception unit" and detects the vehicles in range and controls the creation of VAs and their mobility;

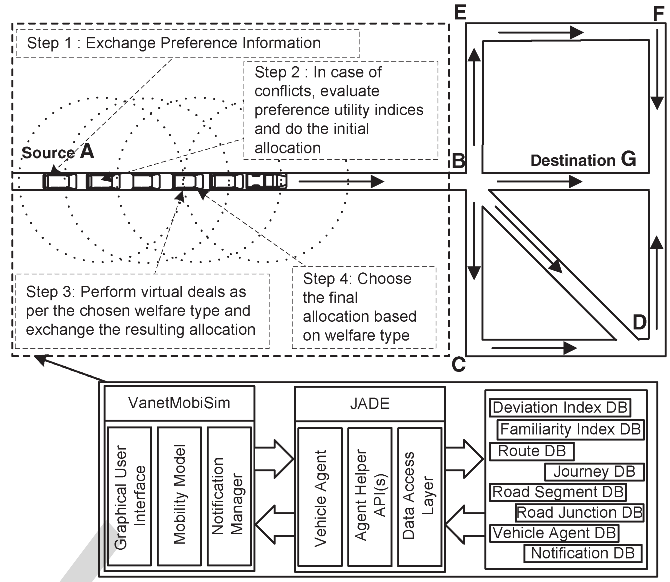

Fig. 1. Functional block diagram of CARAVAN.

3) *notification manager*, which conveys agent creation information from VanetMobiSim [24] to Java Agent Development Framework (JADE) [25] and route allocation information from JADE to VanetMobiSim; 4) *VA*, which represents the core software module residing within vehicle onboard units and is responsible for analyzing perceived traffic conditions, deriving traffic patterns, interagent cooperation, and carrying out virtual deals for route allocation; and 5) *data access layer*, which is responsible for interacting with the internal database for storage and retrieval of user preferences, road network data, and final route allocation information.

B. *Route Preference Representation*

Driver behavioral studies have shown that drivers do not always choose quicker routes, and route preference also depends on factors such as route familiarity, road conditions, road characteristics (e.g., toll roads and route complexity), and driver demographics [26]. Other than the preferred route, the most common criterion for acceptance of an alternate route is that it should not exceed the delay threshold (time limit to reach the destination). In this paper, these route choices have been characterized into more generic classifications, i.e., shortest time (ST), shortest distance (SD), and familiar (F) routes. These have been further classified into primary preference (PP) and secondary preference (SP) routes.

In CARAVAN, vehicles exchange route preference information that is used in negotiation and the route-allocation process. Here, route preferences represented as weighted routes are first classified into a number of preference bands. This basic preference information is further processed to obtain relative ranking between preferences, which is represented as the preference utility index. Each vehicle computes and maintains a preference list L_i (where $i \in V$), which is the list of preferred routes in decreasing order of preference utility index.

Preference Utility Weight: p_w is calculated by a VA for every alternate route under consideration between the given source

TABLE II
PARAMETERS FOR CALCULATION OF PREFERENCE UTILITY WEIGHT

Parameter and its Possible Values/Range of Values	Comments
Choice of Alternate Route 'a' Value=1 : if alternate route exists Value=-1 : if alternate route does not exist	If a=-1, none of the remaining parameter values are calculated and p_w equals -1, indicating that the route is invalid for that vehicle as it does not lead to its destination.
Previous Compliance 'c' Value=0: if driver complied more number of times than the threshold Value=1: if driver complied less number of times than the threshold	Ensures that a vehicle is not made to compromise on its route choice repeatedly, as this might lead to driver non-compliance. In this work, threshold is assumed to be 2.
Deviation Index 'i' Value range:0-1	Calculated as the ratio of the number of times a vehicle has deviated from its primary preference route to the total number of journeys undertaken. The smaller the index, the more flexible is the vehicle with its route choice.
Time Tolerance 't' Value=0: if current route travel time exceeds threshold Value=1: if current route travel time is less than the threshold	The threshold is calculated as the average of excess travel times encountered (over all previous route traversals) as compared to 'Shortest Time' route.
Distance Tolerance 'd' Value=0: if travel distance exceeds threshold Value=1: if travel distance is less than the threshold	The threshold is calculated as the average of excess travel distance encountered (over all the previous route traversals) as compared to the 'Shortest Distance' route.
Familiarity Index 'f' Value range: 0-1	Calculated as the ratio of the number of times a particular route is taken to the total number of journeys undertaken on it and any of its alternate routes.

and destination. Its value is calculated on the basis of a weighted combination of parameters, as described in Table II.

The final preference utility weight p_w (for all values of $a \neq -1$) is calculated as

$$p_w = a * w1 + c * w2 + (1-i) * w3 + t * w4 + d * w5 + f * w6 \quad (4)$$

where $w1, \ldots, w6$ are the respective weight multiplying factors such that $w3 = w4 = w5 = w6$, signifying that all of them are of equal importance. Constants $w1$ and $w2$ are equal to and greater than all of the other weight factors, signifying their relative importance. The sum of weights $w1, \ldots, w6$ is 1, and the value of p_w for valid routes ranges between 0 and 1. For the simulation experiments, the value for $w3, \ldots, w6$ is assumed to be 0.1 and that for $w1$ and $w2$ to be 0.3. Thus, the higher the preference utility weight, the more preferable is that route.

Preference Bands: Depending on the preference utility weights, the agent route choices are classified into preference bands. Preference bands convey the preferences in a succinct format without significant loss of information while also limiting the amount of information to be exchanged. Here, we classify the preference utility weights into six preference bands; the first five band values are between 0 and 1 (at intervals of 0.2), and the sixth band value is -1, indicating an invalid route. Table III shows an example p_w matrix for routes $r5$, $r2$, and $r1$ according to the band classification for vehicles $v1-v4$.

TABLE III
PREFERENCE UTILITY WEIGHT MATRIX WITH BAND VALUES

Vehicle	Route – Band Value for Bands B1 – B6					
ID	B1	B2	B3	B4	B5	B6
v1	r5 - 0.85	r2 - 0.65	r1 - 0.50			
v2	r5 - 0.90		r2 - 0.45			
v3		r5 - 0.75	r2 - 0.50	r1 - .25		
v4		r5 - 0.65	r1 - 0.50			

Preference Utility Index: To ensure fairness in allocation, the importance of a route for a vehicle is determined not only by the preference utility weight given by (4) but by the relative importance of that route to a vehicle as well, as compared with its other route choices. For example, vehicle v_x with a single route choice in band B1 should be given higher priority than vehicle v_y with three route choices in band B1, as v_y can choose from any of its three route choices, whereas v_x has only a single route choice. Moreover, this increases the probability of driver compliance (driver following the assigned route). In CARAVAN, each vehicle individually calculates the preference utility index for every route in each band based on the following parameters (see Table III): 1) $rank$—rank of the route, e.g., rank of $r5$ for $v1$ is 1 as it is the most preferred route; 2) $band$—band number to which the route belongs, e.g., band of $r2$ for $v1$ is B2, i.e., 2; 3) alt—number of alternate routes in that band, e.g., number of alternatives to route $r2$ for $v1$ is 0; and 4) $dist$—if the band number of the current route is 2 and the next best route falls in band 3, the value of this term is 1. Preference utility index p_i is calculated as the weighted sum of the given parameters having equal weight multiplying factors, signifying equal importance. Thus

$$p_i = 0.25 * (rank + band + alt + dist). \quad (5)$$

The value of the weighting factors sums to 1. The higher the preference utility index, the more preferred is the route. The index values calculated are "band values" for the vehicles.

C. Welfare Strategies

Welfare strategies (social, rational, and mixed) determine which utility the agents tend to maximize—individual, group, or a combination of both. In addition to utility evaluation, the welfare strategies also govern the choice of final allocation.

Social welfare is related to social agents. A *social agent* is an altruistic agent; it accepts only those deals that increase the overall welfare of the allocation irrespective of its individual welfare. For social agent i, if σ is the initial allocation and σ' is the final allocation, then the overall utility of final allocation $u(\sigma')$ is greater than the overall utility of initial allocation $u(\sigma)$, which is given as $u(\sigma') > u(\sigma)$. In this type of welfare, every agent performs negotiation deals to maximize the overall utility of the allocation. The welfare of the allocation is evaluated as the sum of the individual utilities of all agents in the allocation, as given in (3). This is referred to as multilateral or group decision-making and results in a multilateral satisficing set [23]. At the end of negotiation deals, every agent exchanges its obtained allocation, and the allocation with the maximum utility value is chosen by all agents.

Rational welfare relates to rational agents. A *rational agent* is a selfish agent. It accepts only those deals that increase its

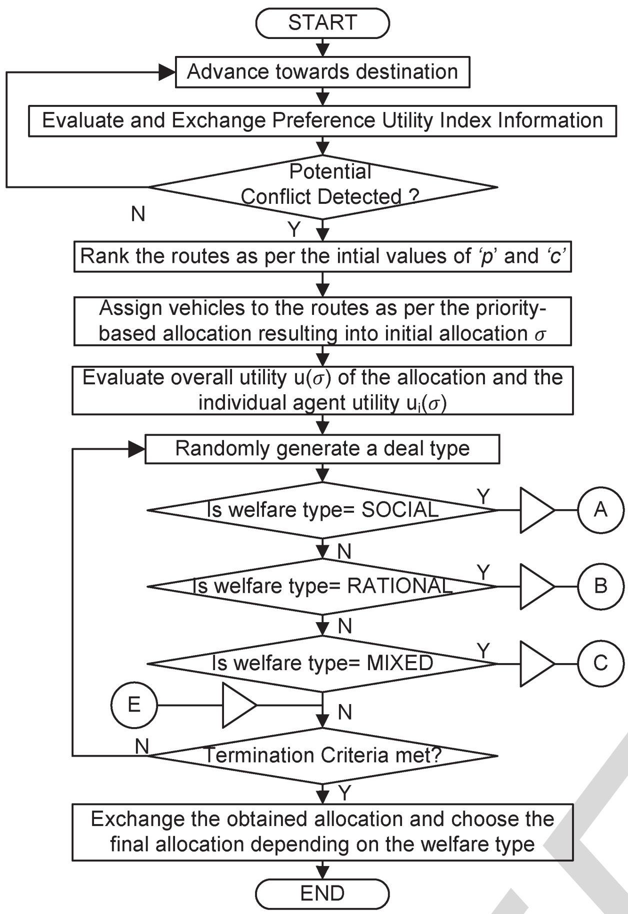

Fig. 2. Algorithm for CARAVAN.

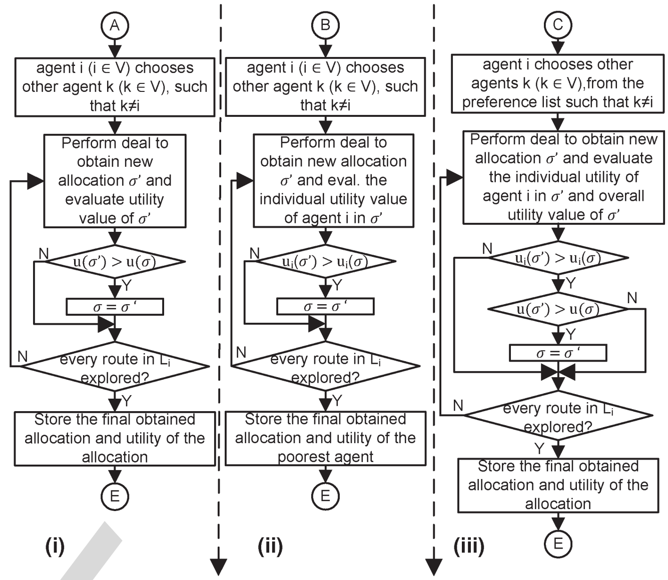

Fig. 3. Algorithm for (i) social welfare, (ii) rational welfare, and (iii) mixed welfare types of CARAVAN.

individual utility value calculated using (2). If σ is the initial allocation and σ' is the final allocation, then the individual utility $u_i(\sigma')$ of the rational agent in the final allocation is greater than its utility in initial allocation $u_i(\sigma)$, which is given as $u_i(\sigma') > u_i(\sigma)$. In this type of welfare, every agent performs negotiation deals to maximize its own utility even at the cost of overall welfare. This is referred to as unilateral decision-making and results into a univariate satisficing set [23]. At the end of negotiation deals (iterations), every VA exchanges its allocation. The final choice of the allocation will depend on the egalitarian welfare criterion [16], which ensures individual welfare of the poorest agent in an allocation. *Poorest agent* in allocation σ refers to an agent with the least utility value.

Mixed welfare aims to maximize both individual and overall welfare. An agent in mixed welfare performs negotiation deals to maximize its individual welfare but not at the cost of the overall welfare of the allocation. At the end of negotiation deals, every agent exchanges its obtained allocation, and the allocation with the maximum utility value is chosen by all agents.

D. Algorithm

Figs. 2 and 3 describe the functionality of CARAVAN. Fig. 3 outlines the algorithms for each of the social, rational, and mixed welfares. The algorithm is initiated when the agents detect the necessity of coordinated routing after the initial exchange of preference information on the road segment far prior to the decision point (junction); this is termed the *initiation criteria*. Every VA starts with an initial solution based on *priority-based allocation* consisting of routes being ranked as per their priority. The allocation for different values of constants p and c in (2) is done as 1) $c = p$ and $c \neq 0$, i.e., the routes are ranked in decreasing order of preferences and increasing order of travel time; 2) $p = 0$ OR $c \neq 0$, $p \neq 0$ $c > p$, i.e., the routes are ranked in increasing order of travel time; and 3) $c = 0$ OR $c \neq 0$, $p \neq 0$ $p > c$, i.e., the routes are ranked in decreasing order of preference utility value. Allocations are done starting with the agent with the highest preference index value being assigned to the highest priority route. The allocation can result in an agent being assigned a route for which it has zero preference utility with which to start. The algorithm terminates either after the preset number of iterative deals or at a given distance before the junction (based on the Global Positioning System location), whichever is earlier; this is the *termination criteria*. Here, we use 20 iterations preset as the termination criteria (empirically found to be acceptable). At the end of all iterations, the agents exchange the resulting allocation and its utility value. The best solution, depending on the type of welfare chosen, is adopted by all the agents.

V. Evaluation of CARAVAN

CARAVAN was simulated using JADE as the agent simulator and VanetMobiSim as the mobility simulator, as described in Fig. 1. Various road networks were configured in VanetMobiSim using scenario Extensible Markup Language files, and agent behavior (embodying CARAVAN solution) was simulated on JADE. CARAVAN was extensively simulated in the following scenarios: 1) varying values of p and c for a single-junction synthetic road network, 2) varying number of junctions and vehicles for a multijunction synthetic road network, 3) varying number of vehicles—below and above the road capacity for a seven-junction real road network, and

TABLE IV
PERFORMANCE OF CARAVAN FOR A SINGLE-JUNCTION SCENARIO

Gain in % Travel Time over	Social Welfare	Rational Welfare	Mixed Welfare
Shortest Path Algorithm	24	22	23
Preference Based Algorithm	14.1	15	15.7
Preference Based Shortest Path Algorithm	22.5	22.5	22.5

4) scaling to a wider real road grid network with high vehicle count.

A. *Scenario 1: Synthetic Road Networks*

Single-Junction Road Network: In this scenario, we compare the performance of CARAVAN with three noncooperative algorithms: *shortest-path algorithm* (where $p = 0$), *preference-based algorithm* (where $c = 0$), and *preference-based shortest-path algorithm* (where p and c are equal, and $p \neq 0$). The simulation was carried out for a simple synthetic road network with 13 vehicles and with average capacity of 10 vehicles. For preference evaluation, the roads are characterized as being ST, SD, or F routes or a combination of them. Every VA is randomly designated a primary and a secondary route preference. The longest of the three road segments is taken to be 17% longer than the shortest time route and takes 16.87% more time to reach the destination than the shortest distance route. The travel speed of a road segment reduces if its occupancy exceeds threshold capacity, where the effects of congestion start to become visible. The travel speed further drops when road occupancy exceeds road capacity, and this is when the vehicles travel at an extremely slow speed.

In the shortest-path algorithm, all vehicles take the path with the least amount of travel time between the source and the destination, disregarding absolute road capacity (i.e., traffic congestion cannot be avoided via cooperation as vehicles do not "talk" to each other in this algorithm). The utility of an allocation in CARAVAN is calculated using (2), and for this scenario, multiplier p is set to zero. Hence, the utility of taking a route solely depends on the cost of traveling on it.

In preference-based allocation, routes are allocated to the VAs as per agent preferences. The vehicles take their best route choice, disregarding road capacity. There is no IVC involved. The utility of the allocation in CARAVAN is evaluated using (2), and for this scenario, multiplier c is set to zero. Hence, the utility of taking a route solely depends on the preference index of the route allocated to that agent.

In preference-based shortest-path allocation, the vehicles take the shortest of their preferred route choices, disregarding road capacity. There is no IVC involved. The utility of an allocation in CARAVAN is calculated using (2), and for this scenario, both p and c are equal, and each has a nonzero value.

Discussion: Table IV presents the results of the simulation with 13 vehicles and compares the total cumulative travel time gain obtained using CARAVAN against the three noncooperative algorithms. It is evident that cooperative traffic assignment using CARAVAN leads to reduction in the overall travel time and offers the highest gains ranging from 22% to 24% when compared against the shortest-path algorithm. In

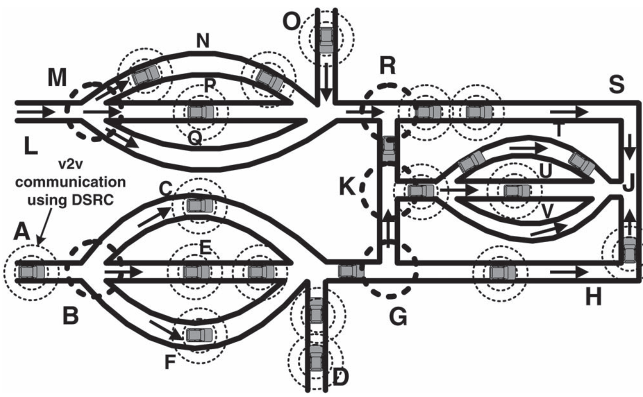

Fig. 4. Five-junction synthetic road network.

CARAVAN, the vehicles communicate and cooperatively distribute themselves along the alternate routes to minimize travel time costs. All vehicles in the shortest-path algorithm only resort to the shortest route (irrespective of road capacity constraints), which is the key cause of congestion. Preference-based and preference-based shortest-path algorithms are driven by user preferences (who may not always prefer one route). This, in effect, tends to distribute a percentage of the vehicles along the alternate paths instead of crowding the single shortest route. Hence, for most cases, the gain obtained against the shortest-path algorithm is seen to be better than the gain obtained against the preference-based algorithm (which is around 15%) and the preference-based shortest-path algorithm (which is 22.5%). For the preference-based allocation algorithm, the percentage gain in travel time is slightly higher for mixed welfare than for social welfare. Here, agents using the social welfare strategy try to increase the overall value of the preference utility index to satisfy more agents, leading to increased travel times. However, the mixed welfare strategy is restrictive as it accepts deals that increase the individual and overall utility.

Multijunction Road Network: In this scenario, the road network was scaled up to five, 10, and 15 junctions to observe the performance of CARAVAN on a wider scale. Fig. 4 shows the five-junction road network with junctions M, B, R, G, and K denoted by dark dotted circles. The roads in this network are single-lane roads and run from left to right and have speed limits. Every junction splits into two or three alternate routes, each of which differs from the other in terms of length, road capacity, and/or speed limit. The simulation was run for one, three, five, 10, and 15 junctions with A, L, D, and O as the source nodes and J as the destination node. The vehicles exchange information and undertake negotiation and route allocation before reaching each of the junctions. Complexity of the road network, traffic dynamics, and absence of infrastructure nodes make it impractical to predict the exact number of vehicles arriving from different road segments that would meet at a common junction at a given point in time. For this scenario, accurate traffic information was assumed, and vehicles assumed full knowledge of the traffic joining at the forthcoming junctions.

Discussion: From the simulation results in Table V, it can be seen that for the multijunction road network, CARAVAN offers significant gain ranging from 21% to 43% in terms of

TABLE V
PERFORMANCE OF CARAVAN FOR A MULTIJUNCTION SCENARIO
(% GAIN IN TRAVEL TIME OVER NONCOOPERATIVE SHORTEST PATH)

No. of Junctions	No. of Vehicles	Social Welfare	Rational Welfare	Mixed Welfare
15	36	36.42	36.12	36.31
10	36	34.04	33.60	33.90
	30	38.79	38.64	38.72
5	36	33.81	33.21	33.68
	30	34.27	33.98	34.12
	24	43.31	43.29	43.31
3	18	32.91	32.64	32.64
	15	32.96	32.38	32.65
	12	38.31	38.30	38.31
1	16	26.07	25.22	25.22
	13	24.00	22.00	23.00
	10	21.26	21.26	21.26

travel time over the noncooperative shortestpath algorithm. The percentage gain in travel time increases with more junctions available for negotiation and route optimization (it is 21%–26% for a single junction and around 36% for 15 junctions). This indicates that CARAVAN's local decision-making at every junction helps to reduce the overall travel time as it leads to a better distribution of vehicles along the road network.

For single-junction scenarios, when the number of vehicles increases, vehicles employing the shortestpath algorithm experience increase in their travel time (as they tend to saturate their shortest paths). However, in CARAVAN, vehicles are allocated along the alternate paths instead of congesting the shortest path. Hence, for a single-junction scenario, the gain in percentage travel time increases with the number of vehicles (it is around 21% for 10 vehicles and around 26% for 16 vehicles; the capacity of the key shortestpath segment is 10) when compared with the shortestpath algorithm. From the results of the social welfare strategy, it can be also noted that the gain increases from around 21% (single junction) for 10 vehicles to around 43% (five junctions) for 24 vehicles. The average network capacity being about 30 for the five-junction network, the gain decreases with the presence of 30 or more vehicles. Even in the case of increased vehicles (e.g., five-, 10-, and 15-junction scenarios with 36 vehicles), it can be observed that increasing the number of junctions offers tangible improvement in travel time when using CARAVAN.

B. Scenario 2: Real Road Networks

In this scenario, CARAVAN was applied to a model of a seven-junction real road network and an 8×4 real road grid network adjoining the Melbourne Central Business District. For the purpose of simulation, the network sizes were reduced to scale while maintaining the original topology and speed limits. The capacities of routes were also proportionally reduced to approximate values to simplify simulation and evaluation.

Seven-Junction Real Road Network: Fig. 5 shows the Google maps traffic view of the area under simulation. The simulations were carried out for a set of vehicles starting from origin "A" and "C," respectively, and traveling toward "B," where the net road capacity of alternate routes (toward "B") is 30. The simulations were carried out for two scenarios: 1) 22 vehicles

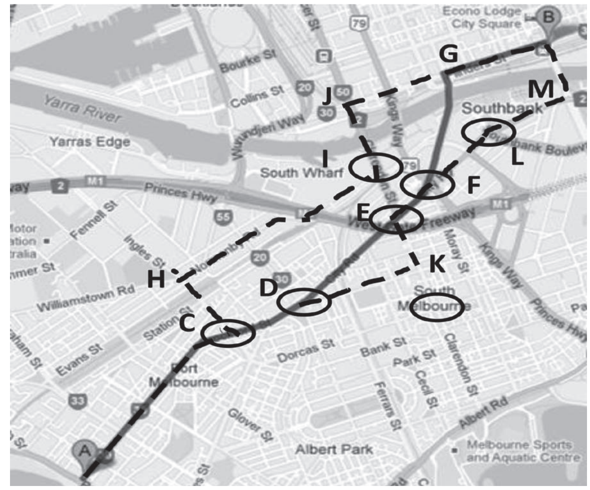

Fig. 5. Road network near the Melbourne Central Business District. (Ovals) Seven junctions. (Continuous line) Shortest path from A to B (A-C-D-E-F-G-B). (Dotted lines) Paths from applying CARAVAN for random vehicles #13 (A-C-H-I-J-G-B) and #19 (A-C-D-K-E-F-L-M-B).

TABLE VI
PERFORMANCE (IN % GAIN) WITH CARAVAN FOR A SEVEN-JUNCTION REAL ROAD NETWORK AS COMPARED WITH THE SHORTESTPATH ALGORITHM

No. of Junctions	No. of Vehicles	Social Welfare	Rational Welfare	Mixed Welfare
7	33	15.26	17.74	13.60
	25	24.88	25.65	24.52
1	22	23.86	23.63	23.63

interacting at a single decision point "C" and 2) 25 and 33 vehicles for seven-junction scenarios. (Each decision point is highlighted as an oval in Fig. 4.) These simulations evaluate the performance of CARAVAN for single- and multijunction decision-making and for network demands that are below and above network capacity. To allow a more realistic evaluation (unlike synthetic scenarios), vehicles on this network were not allowed to have accurate real-time information about traffic on forthcoming routes (further away from the neighborhood negotiation zone) and used static traffic information about average traffic on those road segments. Fig. 4 compares the paths obtained by applying the shortestpath algorithm for the randomly selected vehicles #13 and #19 (continuous line) and also the paths taken by these vehicles after the application of CARAVAN (dotted lines).

Discussion: Table VI presents the results obtained from the application of CARAVAN with all three welfare types in terms of percentage gain in travel time over the shortestpath algorithm. For scenarios that involve vehicles less than the network capacity, the gain in travel time obtained is around 23%–25%, whereas for the scenario involving vehicles that are more than the network capacity, the percentage gain in travel time is between 13% and 17%. It can be seen that for the seven-junction scenario (unlike previous simulation scenarios), the rational welfare strategy performs slightly better than the social and mixed welfares. This can be attributed to the lack of available accurate traffic information about forthcoming routes and corresponding successive local decision-making with estimated information. Here, while the agents using the rational welfare

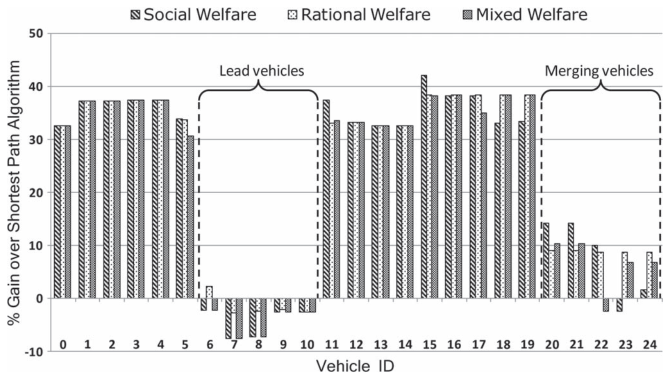

Fig. 6. Comparing % Gain in travel time of 25 vehicles for the three welfare types of CARAVAN with the shortest-path algorithm for the seven-junction real road network.

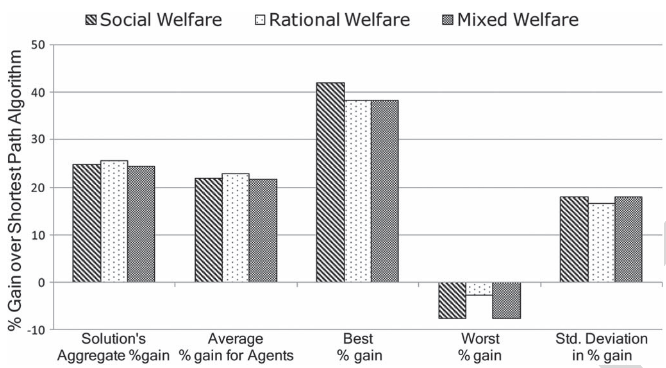

Fig. 7. Comparing % Gain in travel time for the three welfare types of CARAVAN with the shortest-path algorithm for the seven-junction real road network.

strategy perform selfish allocation of least cost routes, the other two welfare types resort to a defensive allocation mechanism to avoid forthcoming traffic.

In the 33 vehicles and the seven-junction scenario, the road network demand exceeds the network capacity of key roads leading toward destination "B." In this scenario, vehicles will experience unavoidable congestion on arterial roads.

However, CARAVAN performs well even in this situation, giving a gain of around 15% over the shortest-path algorithm. Fig. 6 presents the percentage gain in travel time for the three welfare types for all 25 vehicles from the seven-junction scenario from Table VI. It is expected that the lead vehicles (#6 to #10) enjoy smooth travel before congestion starts building up and, hence, will see an insignificant or no gain. Vehicles #20 to #24 join the traffic flow at junction "C" and, thus, take less time to reach destination "B" as compared with the rest of the vehicles starting at junction "A," and as a consequence, these vehicles showed less gain. Majority of the vehicles are individually gaining from the adoption of the rational welfare. For the small percentage of vehicles not gaining from CARAVAN, the change is negligible. Fig. 7 compares the performance of the three welfare types in terms of aggregate percentage gain, average percentage gain, best percentage gain, worst percentage gain, and the standard deviation in percentage gain. The standard deviation indicates high variability; however, gains obtained are significant, and worst percentage gains are low,

TABLE VII
PERFORMANCE (IN % GAIN) WITH CARAVAN FOR FIVE RANDOM ORIGIN–DESTINATION PAIRS FOR AN 80-VEHICLE REAL GRID NETWORK

	Scenario No.				
	1	2	3	4	5
% Gain in travel time over Shortest Path Algorithm	31.26	36.53	25.12	23.74	27.70

indicating that vehicles not gaining from CARAVAN are not heavily penalized.

The 80-Vehicle Real Grid Network: To validate the stability and scalability of CARAVAN, it was applied to a wider 8×4 real grid network with 80 vehicles. Five scenarios with a random variety of origin–destination pairs were simulated. Table VII compares the performance of CARAVAN (social welfare strategy) and the shortestpath algorithm in terms of percentage gain in travel time for five simulation scenarios.

Discussion: As seen in Table VII, even for a wider road network with higher vehicle count, CARAVAN consistently provides 23%–36% gain in travel time over the shortestpath algorithm. It was also observed that the travel time gain increased with the increase in total travel distance and the number of junctions encountered as the vehicles got more opportunity to negotiate and arrive at a better allocation.

VI. CONCLUSION AND FUTURE WORK

We have described CARAVAN, which is a cooperative MAS-based congestion management algorithm, where the VAs exchange preference information and use virtual negotiation for collaborative route allocation. Use of virtual negotiation is aimed at reaching an acceptable suboptimal solution within a short time frame with very low communication overhead. Depending on the welfare type, the agents try to maximize either the individual or overall utility or both. CARAVAN involves complete autonomy of VAs where they individually explore the solution space. The process of virtual deals is highly individualistic, but it affects or sometimes increases the utility of other agents involved in the deal. Thus, the utility of more than one agent can be maximized using these one-step deals.

The simulation results for CARAVAN suggest that MAS-based local cooperation and negotiation is a promising strategy for the traffic route-allocation problem. The results presented compare the performance of CARAVAN with the shortestpath algorithm under different utility maximization conditions, such as social, rational, and mixed welfares. For the single-junction scenario, for different parameter values of p and c, CARAVAN outperformed all three types of noncooperative algorithms. For synthetic road network scenarios (with 3–15 junctions), CARAVAN was seen to offer 21%–43% gain in travel time when compared with shortest-path algorithm. In addition to the social welfare strategy (which maximizes overall utility and was expected to offer gains), even selfish strategies (rational/mixed welfares) were found to offer consistent gains with CARAVAN. When applied to real road networks, CARAVAN was shown to offer around 23%–36% gain in travel time, where traffic demand was below the network capacity. Furthermore, even when traffic demand exceeded the network capacity, CARAVAN continued to offer consistent gains in the range of 13%–17%. It was also observed that, in congested network conditions, the performance of CARAVAN improves with the increase in decision points (junctions) available for negotiation. In the absence of real-time accurate traffic information, the selfish rational welfare strategy was seen to perform slightly better than the "social" welfare strategy, showing the dependence of the latter on accurate traffic information. To validate the stability and scalability of CARAVAN, it was applied to a wider grid network with higher vehicle count (80 vehicles) and simulated for five random source–destination pairs. Here, CARAVAN was found to consistently perform, offering a gain of 23%–36% in travel time over the shortestpath algorithm. The results demonstrate that a series of local decision-making can consistently offer overall global gains. CARAVAN's cooperative routing proves to be effective as it exhibits adaptive characteristics while acting autonomously and in a decentralized manner. This solution requires no infrastructure units and is based on a novel concept of virtual negotiation that reaches an acceptable solution in a short time frame and with low communication overheads. This makes CARAVAN a practical and a relatively low-cost solution, which can contribute toward overall traffic management.

Future work will study the algorithm for various preference utility weight parameter configurations, varying number, and placement of junctions, studying the effect of varying the percentage of nonequipped vehicles and noncompliant drivers on total travel time.

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