CARAVAN: Congestion Avoidance and Route Allocation Using Virtual Agent Negotiation

Prajakta Desai, Member, IEEE, Seng W. Loke, Aniruddha Desai, Member, IEEE, and Jack Singh, Member, IEEE

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. 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 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.
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 148 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, 156 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 166 or user optimal (UO) flow is achieved when traveler’s route choices are influenced so as to minimize the total trip time. 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→r; v2→r; v3→r; v4→r\}

<table>
<thead>
<tr>
<th>Deal Type</th>
<th>Final Allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADD (assign r2 to v1)</td>
<td>v1→r2, v2→r2, v3→r2, v4→r2</td>
</tr>
<tr>
<td>SWAP (between v1 and v3)</td>
<td>v1→r2, v2→r3, v3→r2, v4→r2</td>
</tr>
<tr>
<td>DROP (between v1 and v3)</td>
<td>v1→r2, v2→r3, v3→r1, v4→r1</td>
</tr>
</tbody>
</table>

\(vi\rightarrow ri\) means vehicle/agent \(vi\) is allocated route \(ri\)

---

201 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 and other agents’ preferences for the same route.

202 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.

203 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].

204 B. Virtual Negotiation Using Virtual Deals

205 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 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 \(\sigma\) to \(\sigma'\). 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 route \(v3\) or \(v1\) is assigned to a random route \(r1\)).

As the actual communication only happens at the start and end of the route-assignment 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.

206 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 allocation value that agent \(i\) holds for route \(r\).

Every VA is assigned a single route, provided that the assignment does not exceed the 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 \(S_k(\text{vol}_k)\) for a vehicle on link “\(k\),” we use the link (arc) congestion function provided by the Bureau of Public Roads [21], i.e.,

\[
S_k(\text{vol}_k) = t_k \left(1 + \frac{\alpha}{\beta + 1} \left(\frac{\text{vol}_k}{c_k}\right)^\beta\right)
\]

(1)

where parameter \(\alpha\) is very small and \(5 \geq \beta > 1\), \(t_k\) is the free-flow travel time on link “\(k\)” per unit of time, \(\text{vol}_k\) 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 \(\text{vol}_k\) is much less than \(c_k\), \(\text{ratio} \ (\text{vol}_k/c_k)\) is negligible, and hence, \(S_k(\text{vol}_k) \approx t_k\), which means that the average travel time is equal to the free-flow travel time. For larger values of \(\text{vol}_k\), the effects of congestion start to become visible.

D. Utility of Allocation/Solution Space

Let \(n_v(\sigma)\) be the number of agents that use resource (route) \(r\) in allocation \(\sigma\). The cost experienced by agent \(i\) on route \(r\) is...
in allocation \( \sigma \) 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 \( \sigma \). 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 \( \sigma \) for agent \( i \) can be given as
\[
 u_i(\sigma) = p \cdot p_{i,r}(\sigma) - c \cdot c_{i,r}(n_r(\sigma)).
\]

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.,
\[
 u(\sigma) = \sum_{i=1}^{n} u_i(\sigma).
\]

\[E. \text{ VAs as Satisficing Agents}\]

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.

\[IV. \text{Congestion Avoidance and Route Allocation}\]

\[\text{Using Virtual Agent Negotiation (CARAVAN)}\]

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.

\[A. \text{Functional Prototype}\]

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 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; 3) notification manager, which conveys agent creation information from VanetMobiSim to Java Agent Development Framework (JADE) 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.

\[B. \text{Route Preference Representation}\]

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.

\[\text{Preference Utility Weight:}\]

\( p_{i,r} \) is calculated by a VA for every alternate route under consideration between the given source and destination.
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 \( a \neq 382 - 1 \)) is calculated as

\[
p_w = a \times w1 + c \times w2 + (1 - i) \times w3 + t \times w4 + d \times w5 + f \times w6
\]

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 \( v1 \) \( \rightarrow v4 \).

### 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 405 importance of that route to a vehicle as well, as compared 406 with its other route choices. For example, vehicle \( v_y \) with a 407 single route choice in band B1 should be given higher priority 408 than vehicle \( v_y \) with three route choices in band B1, as \( v_y \) 409 can choose from any of its three route choices, whereas \( v_x \) 410 has only one route choice. Moreover, this increases the 411 probability of driver compliance (driver following the assigned 412 route). In CARAVAN, each vehicle individually calculates the 413 preference utility index for every route in each band based on the following parameters (see Table III): 1) \( rank \) — rank of the 414 route, e.g., \( rank \) of \( r5 \) for \( v1 \) is 1 as it is the most preferred route; 416 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; 419 and 4) \( dist \) — if the band number of the current route is 2 and 420 the next best route falls in band 3, the value of this term is 1. 421 Preference utility index \( p_i \) is calculated as the weighted sum of the given parameters having equal weight multiplying factors, signifying equal importance. Thus

\[
p_i = 0.25 \times (rank + band + alt + dist).
\]

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

### 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 \( \sigma \) is the initial allocation and \( \sigma' \) 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 satisfying 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 welfare.
individual utility value calculated using (2). If \( \sigma \) is the initial allocation and \( \sigma' \) 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 \( \sigma \) 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 utility 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.

### 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 501 VanetMobiSim using scenario Extensible Markup Language 502 files, and agent behavior (embodying CARAVAN solution) was 503 simulated on JADE. CARAVAN was extensively simulated 504 in the following scenarios: 1) varying values of \( p \) and \( c \) for 505 a single-junction synthetic road network, 2) varying number 506 of junctions and vehicles for a multijunction synthetic road 507 network, 3) varying number of vehicles—below and above 508 the road capacity for a seven-junction real road network, and 509
In preference-based shortest-path allocation, the 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 CARA V AN 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 CARA V AN 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 CARA V AN 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 CARA V AN against the 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 CARA V AN 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 CARA V AN 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 CARA V AN 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 CARA V AN against the 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 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 CARA V AN 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 CARA V AN is calculated using (2), and for this scenario, both $p$ and $c$ are equal, and each has a nonzero value.
TABLE V

<table>
<thead>
<tr>
<th>No. of Junctions</th>
<th>No. of Vehicles</th>
<th>Social Welfare</th>
<th>Rational Welfare</th>
<th>Mixed Welfare</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>36</td>
<td>36.42</td>
<td>36.12</td>
<td>36.31</td>
</tr>
<tr>
<td>10</td>
<td>36</td>
<td>34.04</td>
<td>33.60</td>
<td>33.90</td>
</tr>
<tr>
<td>5</td>
<td>36</td>
<td>38.79</td>
<td>38.64</td>
<td>38.72</td>
</tr>
<tr>
<td>3</td>
<td>36</td>
<td>33.81</td>
<td>33.21</td>
<td>33.68</td>
</tr>
<tr>
<td>1</td>
<td>18</td>
<td>32.91</td>
<td>32.64</td>
<td>32.64</td>
</tr>
<tr>
<td>1</td>
<td>15</td>
<td>32.96</td>
<td>32.38</td>
<td>32.65</td>
</tr>
<tr>
<td>1</td>
<td>12</td>
<td>38.31</td>
<td>38.30</td>
<td>38.31</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>26.07</td>
<td>25.22</td>
<td>25.22</td>
</tr>
<tr>
<td>1</td>
<td>13</td>
<td>24.00</td>
<td>22.00</td>
<td>23.00</td>
</tr>
<tr>
<td>1</td>
<td>10</td>
<td>21.26</td>
<td>21.26</td>
<td>21.26</td>
</tr>
</tbody>
</table>

The percentage gain in travel time over the noncooperative shortest path algorithm 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 CARA V AN’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 shortest path algorithm experience an increase in their travel time (as they tend to saturate their shortest paths). However, in CARA V AN, 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 shortest path algorithm. From the results of the social welfare strategy, it can be also noted that the gain increases from around 21% (single junction) to around 43% (five junctions) for 24 vehicles. The average network capacity being around 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 CARA V AN.

B. Scenario 2: Real Road Networks

In this scenario, CARA V AN 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 two scenarios: 1) 22 vehicles 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 CARA V AN 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 shortest path algorithm for the randomly selected vehicles #13 and #19 (continuous line) and also the paths taken by these vehicles after the application of CARA V AN (dotted lines).

Discussion: Table VI presents the results obtained from the application of CARA V AN 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
670 strategy perform selfish allocation of least cost routes, the other 671 two welfare types resort to a defensive allocation mechanism to 672 avoid forthcoming traffic.

673 In the 33 vehicles and the seven-junction scenario, the road 674 network demand exceeds the network capacity of key roads 675 leading toward destination “B.” In this scenario, vehicles will 676 experience unavoidable congestion on arterial roads.

677 However, CARA V AN performs well even in this situation, 678 giving a gain of around 15% over the shortest-path algorithm.

679 Fig. 6 presents the percentage gain in travel time for the three welfare types for all 25 vehicles from the seven-junction 680 scenario from Table VI. It is expected that the lead vehicles 681 (#6 to #10) enjoy smooth travel before congestion starts building 682 up and, hence, will see an insignificant or no gain. Vehicles 683 #20 to #24 join the traffic flow at junction “C” and, thus, take 684 less time to reach destination “B” as compared with the rest 685 of the vehicles starting at junction “A,” and as a consequence, 686 these vehicles showed less gain. Majority of the vehicles are in- 687 dividually gaining from the adoption of the rational welfare. For 688 the small percentage of vehicles not gaining from CARA V AN, 689 the change is negligible. Fig. 7 compares the performance 690 of the three welfare types in terms of aggregate percentage gain, 691 average percentage gain, best percentage gain, worst percent- 692 age gain, and the standard deviation in percentage gain. The 693 standard deviation indicates high variability; however, gains 694 obtained are significant, and worst percentage gains are low, 695 indicating that vehicles not gaining from CARA V AN are not 696 heavily penalized.

697 The 80-Vehicle Real Grid Network: To validate the sta- 698 bility and scalability of CARA V AN, it was applied to a wider 699 8 × 4 real grid network with 80 vehicles. Five scenarios with 700 a random variety of origin–destination pairs were simulated. 701 Table VII compares the performance of CARA V AN (social welfare strategy) and the shortestpath algorithm in terms of 702 percentage gain in travel time for five simulation scenarios.

703 Discussion: As seen in Table VII, even for a wider road 704 network with higher vehicle count, CARA V AN consistently 705 provides 23%–36% gain in travel time over the shortestpath 706 algorithm. It was also observed that the travel time gain in- 707 creased with the increase in total travel distance and the number 708 of junctions encountered as the vehicles got more opportunity 709 to negotiate and arrive at a better allocation.

VI. CONCLUSION AND FUTURE WORK

We have described CARA V AN, which is a cooperative MAS- 713 based congestion management algorithm, where the VAs ex- 714 change preference information and use virtual negotiation for 715 collaborative route allocation. Use of virtual negotiation is 716 aimed at reaching an acceptable suboptimal solution within 717 a short time frame with very low communication overhead. 718 Depending on the welfare type, the agents try to maximize 719 either the individual or overall utility or both. CARA V AN 720 involves complete autonomy of VAs where they individually 721 explore the solution space. The process of virtual deals is highly 722 individualistic, but it affects or sometimes increases the utility 723 of other agents involved in the deal. Thus, the utility of more 724 than one agent can be maximized using these one-step deals. 725

The simulation results for CARA V AN suggest that MAS- 726 based local cooperation and negotiation is a promising strategy 727 for the traffic route-allocation problem. The results presented 728 compare the performance of CARA V AN with the shortestpath 729 algorithm under different utility maximization conditions, such as social, rational, and mixed welfare. For the single-junction 731 scenario, for different parameter values of $p$ and $c$, CARA V AN 732 outperformed all three types of noncooperative algorithms. 733 For synthetic road network scenarios (with 3–15 junctions), 734 CARA V AN was seen to offer 21%–43% gain in travel time when 735 compared with shortest-path algorithm. In addition to the social 736 welfare strategy (which maximizes overall utility and was 737 expected to offer gains), even selfish strategies (rational/mixed 738 welfare) were found to offer consistent gains with CARA V AN. 739 When applied to real road networks, CARA V AN was shown 740 to offer around 23%–36% gain in travel time, where traffic de- 741 mand was below the network capacity. Furthermore, even when 742 traffic demand exceeded the network capacity, CARA V AN 743
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.

References


Aniruddha Desai (M’04)

He is an Associate Director for Innovation and a Senior Research Fellow with La Trobe University, Melbourne, Australia. He is the Head of the R&D program with the Centre for Technology Infusion, La Trobe University, which has produced smart energy management technology for Australia’s first zero-emission house and intelligent transportation systems (ITS) technology for one of the world’s largest level crossing safety trial of ITS. He is a Principal Inventor of a number of patent applications. His research interests include modeling and simulation, intelligent systems, data analytics, system software, computer architecture, and embedded and real-time systems.

Mr. Desai has won various national/international innovation awards.

Jack Singh (M’05)

He is a Research Professor with and the Director of the Centre for Technology Infusion, La Trobe University, Melbourne, Australia. For years, he has been involved in research, education, and industry development projects of national/international significance, such as the Australian Telecommunications Cooperative Research Centre (CRC), one-chip radio, smart sensor, the Square Kilometer Array radio telescope, the Advanced Automotive Technology CRC, Chipskills project, intelligent transport systems for safety at level crossing, and the National Networked TeleTest facility, among others. He has extensively published in his areas of interest and regularly delivers keynote/invited talks. His research interests include wireless systems, smart sensors, radio frequency/analog, intelligent transportation systems, embedded systems, and information and communications technology.
AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

AQ1 = Please provide educational history of Seng W. Loke.
AQ2 = Please provide educational history of Aniruddha Desai.
AQ3 = Please provide educational history of Jack Singh.

END OF ALL QUERIES