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A multi-agent approach to cooperative traffic management and route guidance

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Abstract

This paper explores the use of cooperative, distributed multi-agent systems to improve dynamic routing and traffic management. On the supply-side, real-time control over the transportation network is accomplished through an agent-based distributed hierarchy of system operators. Allocation of network capacity and distribution of traffic advisories are performed by agents that act on behalf of information service providers. Driver needs and preferences are represented by agents embedded in intelligent in-vehicle route guidance systems. Negotiation between ISP and driver agents seek a more efficient route allocation across time and space. Results from simulation experiments suggest that negotiation can achieve more optimal network performance and increased driver satisfaction.

Keywords: Transportation management; Route guidance; Intelligent agents

1. Introduction

Adler and Blue (2002) developed the conceptual framework of a Cooperative Traffic Management and Route Guidance System (CTMRGS) based around the integration of multi-agent

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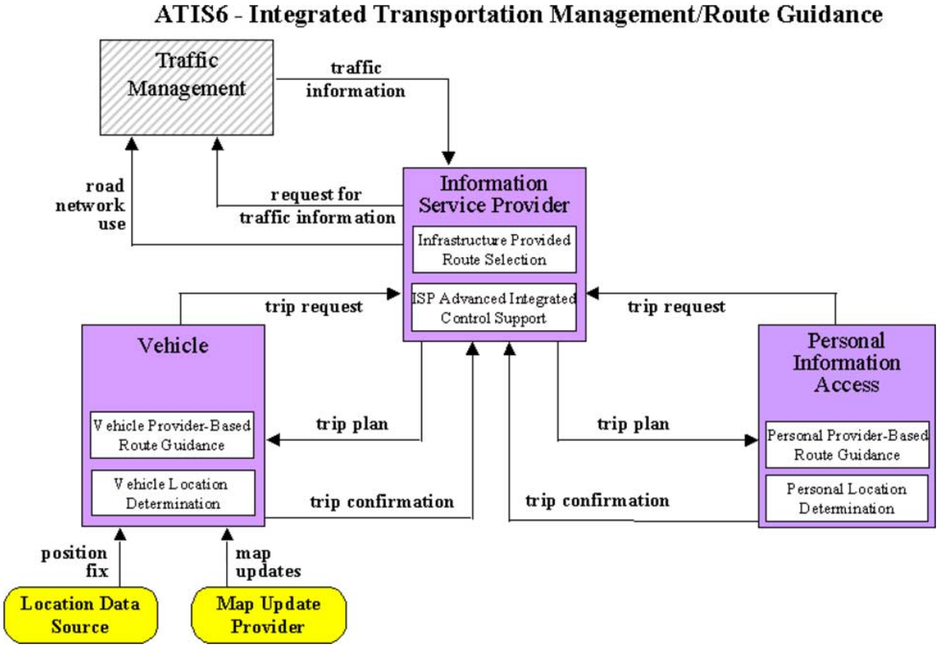

Fig. 1. Market Package for Integrate Traffic Management/Route Guidance showing allowable subsystems, terminators, architecture flows, and equipment packages (The ITS National Architecture Version 3.0, 2000).

systems and principled negotiation (PN). The CTMRGS [3] is proposed as an approach that can realize the vision of Market Package ATIS 6-Integrated Transportation Management/Route Guidance of the National ITS Architecture. ATIS6, shown in Fig. 1, is conceived as an approach to enhance transportation management through better cooperation between network managers, information service providers, and travelers.

Creating a cooperative environment between network managers and travelers is a difficult problem because their respective goals are often in conflict. The challenge is to find and implement solutions that achieve an efficient reallocation of network capacity over time and space without seriously violating any individual user's preferences for mode, routing, departure, and/or arrival time. Solutions must also balance the need for user responsiveness with preserving privacy and individual rights.

The CTMRGS, shown in Fig. 2, seeks to overcome the forecasting and compliance concerns while establishing a framework that seeks to satisfice both system and driver-side objectives. The CTMRGS extends the ITS National Architecture Market Package ATIS6 by adding a layer of distributed intelligence that is comprised of agents and protocols. The CTMRGS seeks to improve network performance by systematically allocating demand across capacity in a manner that satisfies both driver and system operator interests. The CTMRGS focuses on the interactions

[3] Readers are encouraged to refer to this paper as it provides the motivation for the CMTRGS and a full discussion of multi-agent systems for modeling traffic management systems.

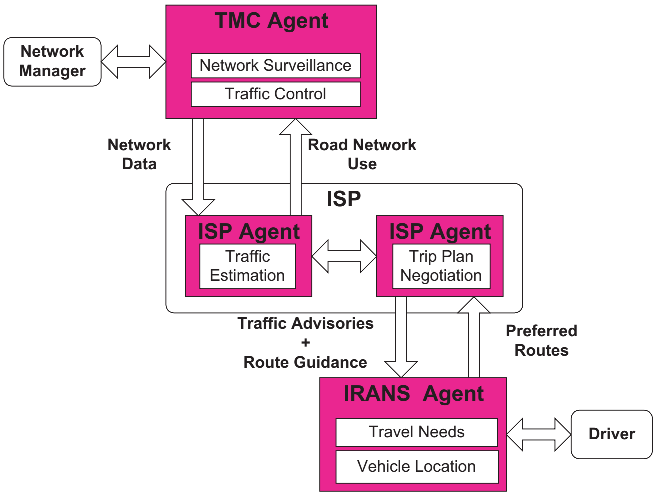

Fig. 2. Conceptual view of CTMRGS.

between agents that represent drivers (Agent-IRANS), information service providers (Agent-ISP), and system operators (Agent-TMC). Principled negotiation is used to guide interactions between Agent-IRANS and Agent-ISP. It provides the structure for ensuring that route choice and capacity allocation satisfy the objectives of both drivers and system operators.

Testing of the CTMRGS requires software that provides the ability to model multi-agent systems within traffic simulation. Intelligent Automation Inc. (IAI) has demonstrated the use of autonomous agents for traffic simulation and control (Erols et al., 1998; Manikonda et al., 2001) and developed a simulation framework by integrating their OpenCybele software with AASIM (Autonomous Agent Simulation)—a Java-based traffic simulation software developed by ITT under contract from Federal Highway Administration. Together, the authors have collaborated under NSF/DOT exploratory grant (Miriam et al., 2002) to create a working prototype of the CTMRGS model that has been tested within the integrated OpenCybele–AASIM framework created by IAI.

This paper describes both the analytical framework of this prototype model and results of the initial simulation testing. The primary motivation for this research is to explore a new, innovative approach to vehicle routing that simultaneously improve user acceptance while enhancing network performance. The CTMRGS satisfies these objectives by:

- encouraging the use of multiple objective decision-making into the routing problems,
- forcing supply-side operators to focus on individual route choice,
- promoting measuring network performance in terms of driver expectations and evaluation.

A key assumption for the CMTRGS is that vehicles are equipped with intelligent agent-based IRANS that are capable of learning, defining, and calibrating driver route choice and trip planning preferences. The vision for intelligent IRANS is discussed in a previous paper by Adler and Blue (1998).

2. Multiple objective formulation to assess agent satisfaction

The CMTRGS provides a holistic approach to modeling Route Choice Behavior and Traffic Management. The goal of the system is to simultaneously improve network performance and travel conditions relative to the needs and perceptions of drivers, ISPs, and system operators. To measure these needs and perceptions, a multiple objective utility model is adopted. A set of criteria to define link-based and path-based performance is used to define the goals and measure performance across the links and paths of the network.

2.1. Evaluation criteria

Nine objectives were identified as critical to the decision-making behavior of the Agent-IR-ANS, Agent-ISP, and Agent-TMC. These types of goals were selected based on previous work by the authors (Adler and McNally, 1994; Blue et al., 1997; Adler and Blue, 1998):

Travel time-based objectives
(t) minimize travel time: actual time from origin to destination;
(s) minimize schedule delay: difference between actual arrival time and desired arrival time.

Driving complexity-based objectives
(d) minimize travel distance;
(a) minimize use of arterial streets (distance on surface streets/total distance traveled);
(r) minimize number of turns (road changes);
(c) minimize roadway classification changes: going from highway to arterial or three-lane to two-lane etc.

Network traffic management objectives
(q) minimize expected standing queue delay;
(v) minimize (average) volume to capacity ratio;
(f) minimize (average) free flow to link velocity ratio.

2.2. Linear normalized weighted utility maximization model

Many utility models have been proposed to measure driver or system satisfaction with network, route, and link performance. For the CTMRGS prototype, a linear normalized weighted utility maximization model was used. This model is easy to understand and provides a straight forward way to normalize evaluation criteria that have different scales.

Weights are assigned across the set of goals that comprise the utility function such that the total sum of all weights is equal to 100. To allow objectives with different scales to be used in a weighted function, each objective is normalized to a scale from 0 to 1 through a logistic transformation. This approach follows previous work by Adler et al. (1993).

Perceived path performance is assessed through a linear normalized weighted utility maximization model. The path preference for each agent is measured on a scale of 1–100 by the following function:

$$U^{ip} = \sum_g W_g^i N_g^{ip}$$
$$\sum_g W_g^i = 100 \tag{1}$$

where i = agent, p = path, g = goal g, U = utility, W_g^i = weight assigned to goal g by agent i, N_g^i = normalized score for goal g by agent i.

Weights are assigned across the set of goals that comprise the utility function such that the total sum of all weights is equal to 100. To allow objectives with different scales to be used in a weighted function, each objective is normalized to a scale from 0 to 1 through a logistic transformation. This approach follows previous work by Adler et al. (1993).

$$N_g = \frac{1}{1 + \mathrm{e}^{V_g}}$$
$$V_g = \alpha_g + \beta_g x_g^p \tag{2}$$

where N_g = normalized score [0...1] for goal g, α_g, β_g = parameters for logistic function estimated from ideal and threshold points, x_g^p = the value for goal g for path p.

The shape of the logistic normalizing curve is estimated based on two anchor points that identify the linear portion of the curve and represent "ideal" and "minimum threshold" utilities. The logistic functions works as a normalizing function because between a set of "anchor points", the shape is (almost) linear and outside these points, the curve is asymptotic. The area between the anchor points exhibits linear correlation between performance and score. Outside the anchor points, the asymptotic characteristic of the curve indicates diminishing returns. Anchor points are specific to an agent based on its needs and preferences. Previous work by Adler et al. (1993), suggest that reasonable ranges for the ideal point is [0.75–0.90] and for minimum threshold between [0.25–0.35].

Once a set of anchor points have been established for a goal, any standard estimation approach (e.g., Newton–Raphson) can be used to generate the actual equation of the value function ($V_g = \alpha_g + \beta_g x_g$) that will be transformed into the normalizing logistic function. A typical normalizing function is depicted in Fig. 3.

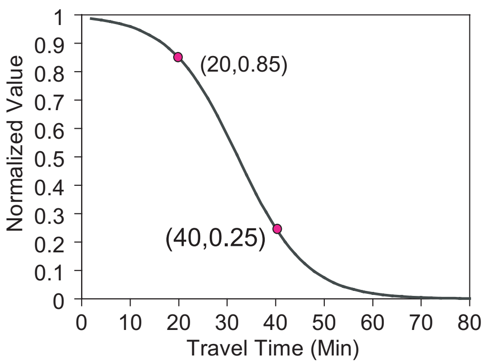

Fig. 3. Example logistic normalizing function.

3. Agent behavior models for pre-trip planning

The three primary agent systems, Agent-IRANS, Agent-ISP, and Agent-TMC, have independent goals and decision-making strategies. The following sections define these behavioral models for pre-trip planning.

3.1. Agent-IRANS model

The CTMRGS is envisioned to function in an environment where some or all of the vehicles are equipped with Agent-IRANS that are capable of planning route and interacting with Agent-ISPs as shown in Fig. 3. It is assumed that an Agent-IRANS is capable of accurately understanding driver route choice preferences and aiding with pre-trip route choice. IRANS are conceived as intelligent traveler information systems that use machine learning and artificial intelligence to learn driver. Readers are encouraged to refer to the paper by Adler and Blue (1998) that describes functionality of IT IS/IRANS.

Route selection model for Agent-IRANS is defined by two key parameters: (1) the set of weights across the goals ($\mathbf{W}_g$) and (2) the set of anchor points to define the normalization curve ($\mathbf{A}_g$). For pre-trip planning, the Agent-IRANS uses the linear normalized weighted utility maximization model with the particular set of weights and anchor points to compute the utility of all paths. The difference in utility between two paths is used to determine the strength of selection bias. Larger differences in utility suggest stronger preference.

To help Agent-ISP identify the boundary of negotiation space the Agent-IRANS must provide some indication of path indifference—the willingness to negotiate and consider paths that do not result in the absolute maximum utility. This is captured by introducing two additional threshold parameters: (1) a path utility indifference threshold ($\mathbf{U}_d^i$) and (2) weight change tolerance threshold ($\mathbf{\Psi}_g^i$).

The path utility indifference threshold is used to define the set of paths for the Agent-IRANS that the driver is indifferent to the optimal path (path with maximum utility). Given the path with maximum utility, the indifference threshold provides a range to identify the set of paths that the Agent-IRANS considers equally preferable. From the perspective of the CMTRGS, the indifference threshold is a key input value because it will define the range over which alternative paths may negotiated.

Consider two Agent-IRANS and their computed path utility over five identical paths as shown in Table 1. For both Agents, paths 3–5 are better than paths 1–2. However, for Agent-IRANS1, the low indifference threshold of 3 indicates that path 5 is clearly preferred over path 4. For Agent-IRANS2, the higher indifference band suggests that paths 3–5 are all viewed as essentially equal and Agent-IRANS2 would be willing to travel on any of these three paths.

Table 1
Example of path utilities and indifference thresholds

	Path 1	Path 2	Path 3	Path 4	Path 5	U_d
Agent-IRANS1	55	70	85	90	95	3
Agent-IRANS2	55	70	85	90	95	10

Table 2
Sample weight change tolerances

	Goal 1		Goal 2		Goal 3		Goal 4		Goal 5	
	W_1	ψ_1	W_2	ψ_2	W_3	ψ_3	W_4	ψ_4	W_5	ψ_5
Agent-IRANS1	20	(+5,0)	30	(+10,−5)	15	(0,−15)	25	(+10,−5)	10	(+0,−10)
Agent-IRANS2	20	(+5,−5)	20	(+5,−5)	20	(+5,−5)	20	(+5,−5)	20	(+5,−5)

The weight change tolerance thresholds will be used during negotiation to help define the solution space for the Agent-IRANS. It determines the boundaries over which the agent will allow his set of weights to be adjusted during negotiations. In this example, as depicted in Table 2, the weight tolerance assigned to each goal helps to shape an understanding of how each agent might approach negotiation. The weight tolerances for Agent-IRANS1 indicate a stronger preference for goals 1, 2, and 4 and a willingness to cede goals 3 and 5. On the contrary, the tolerances for Agent-IRANS2 indicates that the five goals are valued almost equally.

3.2. Agent-TMC model

The model for network management is based on previous work at IAI on dynamic traffic control (Manikonda et al., 2001). It is assumed that the Agent-ISP pulls network information from the Agent-TMC and uses it as the basis for negotiations with Agent-IRANS.

If the network contains arterial streets with traffic signals, then TMC can apply either fixed-time phase control strategy (based on offline analytical tools) or dynamic phase control strategy (assuming capability to monitor the flow rate through intersection). In both cases, it is assumed that TMC has the capability to monitor and predict the length of the standing queue (q_l) and its size (q_n), and the departure rate (r_d). Given this data collected at every intersections at the end of every phase, the link velocity between two intersections, with the second intersection being yield, exit or split between highways, the traveling time for that link of length l is given by:

$$(l - q_l)/V_q(l, q_l) + q_n/r_\mathrm{d} \tag{3}$$

$V_q(l, q_l)$ is a velocity model for a link of length l with a standing queue length q_l. The model adopted by various traffic simulation states that the velocity of a vehicle entering the link is the speed limit specified for the link if the q_l is less than a threshold value specific to the link, and decreases at certain rate if the q_l is greater than the threshold. The first term of the equation calculates the time taken to arrive at the standing queue and second term calculates the time taken to leave the queue.

If the link end is an intersection light, then TMC uses t_g (green light phase), t_r (red light phase), and r_n (the number of vehicles leave during the green light phase) in the estimation of the travel time for such links:

$$(l - q_l)/V_q(l, q_l) + (q_n/(r_\mathrm{d} \times t_\mathrm{g})) \times [t_\mathrm{g} + t_\mathrm{r}] \tag{4}$$

3.3. ISP agent model

Agent-ISP is the mediator between Agent-TMC and Agent-IRANS. Agent-IRANS agent negotiates with Agent-ISP for preferred route that satisfies the driver's objective criteria and the network managers' objective criteria. Typically, from a network manager's point of view, the objective is to maximize the throughput (i.e., traffic flow rate) through a network. This is possible by reducing the travel time between any two points in the network or on any (arterial or highway) link and directing the drivers through a low congested route between two points so that the traffic flow rate through the network can be maximized. In the process, network manager can also reduce the standing queues on any links at a given time.

Similar to Agent-IRANS, an Agent-ISP has its set of weights on the goals that appropriately reflect network manager's criteria. Given a set of paths for an origin and destination pair, the Agent-ISP can find utility values of the path based on these weights, which are called Agent-ISP utility values. The Agent-ISP utility value of the paths need not be the same as the Agent-IRANS utility value of those paths. However, if the order of the paths preferences based on Agent-ISP and Agent-IRANS utility values are exactly same then both Agent-ISP and Agent-IRANS entirely agree with each other. Otherwise, they need to negotiate for mutually agreeable path. This is the condition under which knowing the path indifference and weight change tolerances is critical.

4. Negotiation model for pre-trip route assignment

The CMTRGS proposes that the parties use goals rather than positions to achieve an efficient reallocation of network capacity over time and space without seriously violating any individual user's preferences for mode, routing, departure, and/or arrival time. The goal is to achieve a more efficient metering of scarce roadway capacity by steering drivers toward paths that will still satisfy their individual needs while also improving overall network performance. A good solution derived from negotiation between IRANS and ISP agents will result in drivers being satisfied that their needs and preferences were achieved by their resultant trip itinerary and the TMC being satisfied with improved system-wide performance.

This section describes the negotiation model. It begins by defining the basic process flow of the negotiation process. This is followed by detailed description of the analytical models that represent the decision logic for (1) assessing Agent-IRANS' submitted routes, (2) determining alternative driver compliant routes, and (3) updating of the option space.

4.1. Negotiation process flow model

Fig. 4 illustrates the basic negotiation Flow. The Agent-IRANS and Agent-ISP each have a set of goals over which path utility is measured. These goals may or may not overlap. For a given trip, the Agent-ISP and Agent-IRANS have a set of goal weights $\mathbf{W}$ and set of anchor points $(\mathbf{a}, \mathbf{b})$ used to estimate the normalized value of goals and utility of the paths for an origin–destination pair.

Fig. 4 indicates the PN flow for 1 decisioning instance, it does not show knowledge flow. A feedback loop is required to update both the IRANS and ISP Systems:

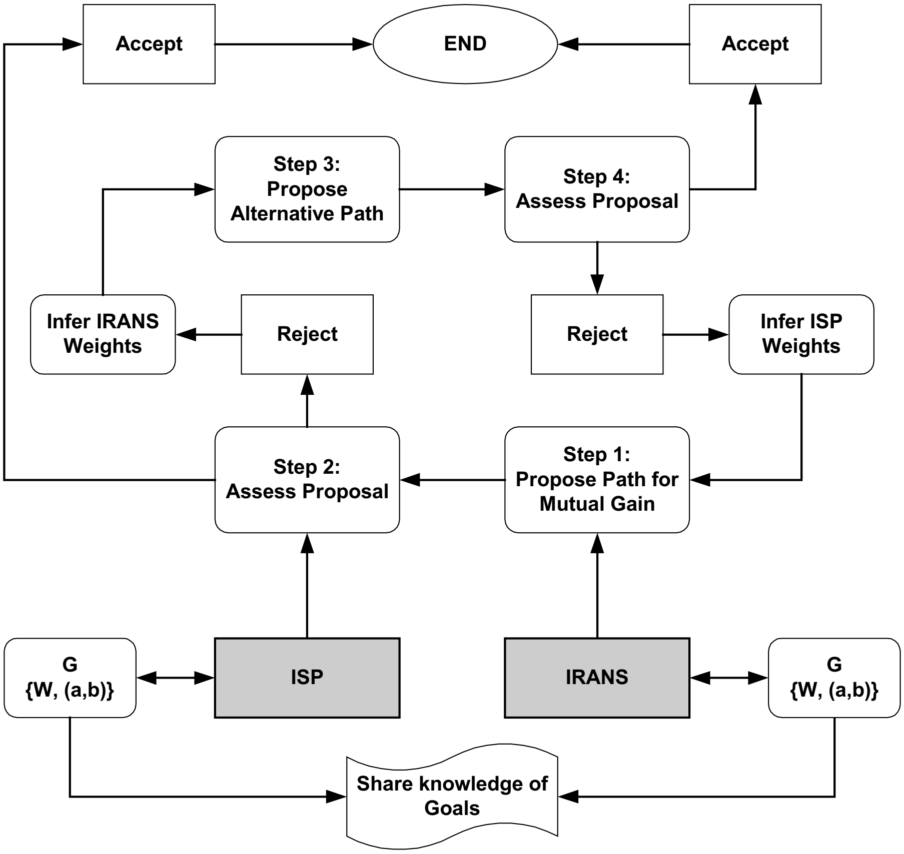

Fig. 4. Principled negotiation process flow.

ISP updating. The ISP will update their knowledge in two ways:

(a) Feedback on negotiation with individual drivers—the ISP should learn and be ready to anticipate requests from specific IRANS. All requests and results of negotiations with specific IRANS should be recorded. After trips are concluded the ISP could poll the IRANS to inquire hop well the trip "satisficed" the driver
(b) Network performance—ISP knowledge on driving conditions and network performance is updated continually.

IRANS: After each trip, IRANS updates its knowledge about the driver's goals, route preferences and weights.

Step 1: Pre-trip analysis and proposal by Agent-IRANS. The process begins by the Agent-IRANS planning a trip. Given its declared goals, weights, and associated anchor points, the Agent-IRANS assesses the network and generates a set of non-dominated routes. The Agent-IRANS contacts Agent-ISP to schedule a route assignment and submits the set of preferred routes, the sets of goals, weights and anchor points, and the option space consisting of utility indifference range and weight change tolerances.

Step 2: Agent-ISP analysis. The Agent-ISP assesses the data submitted by Agent-IRANS and determines whether to accept the route proposal or respond with a carefully calculated counter-offer. The analysis consists of comparing the set of preferred routes submitted by the Agent-IRANS agent with its own most desired routes for the Agent-IRANS agent (to follow) calculated using its own set of weights and anchor points. If the sets are similar then it accepts the proposed routes.

Step 3: Agent-ISP counter-proposal. If the Agent-ISP rejects the initial route offer, it generates an alternative route choice that falls within the realm of both Agent-IRANS option space and its own option space. If the Agent-ISP cannot determine a routing choice that is satisfied by the Agent-IRANS option space, then it offers a route choice that is satisfied by its option space, yet closest to the Agent-IRANS' option space. However, the Agent-ISP records this possible disagreement to statistically update its own option space for future usage.

Step 4: Agent-IRANS' evaluation of the counter-proposal. Agent-IRANS evaluates the Agent-ISP offered routes. An Agent-IRANS agent is most likely to accept if the offered routes satisfy its option space, which will ensure driver's compliance. If the offered choices do not satisfy its option space, then the Agent-IRANS agent will leave route choice at the discretion of the driver. If the driver, at all, chooses Agent-ISP offered route, then Agent-IRANS agent statistically updates its option space for future usage.

4.2. Analysis of the PN model

4.2.1. Agent-ISP's analysis of Agent-IRANS' submitted routes

Let $R^i = \left\{r_1^i, r_2^i, \ldots, r_k^i\right\}$ be the set of k preferred routes submitted by an Agent-IRANS agent i. Let $R^s = \left\{r_1^s, r_2^s, \ldots, r_k^s\right\}$ be the set of k routes that Agent-ISP desires the Agent-IRANS agent to follow. The set R^s is calculated by Agent-ISP using its own set of weights and anchor points that appropriately represents TMC's interest and all the Agent-IRANS agents as a whole. Let the utility indifference range that defines the option space of the Agent-ISP to be u_d^s. That means, the Agent-ISP is indifferent between two routes if the difference between the Agent-ISP's utility values of the two routes is less than and equal to u_d^s. Based on Agent-ISP's utility indifference range, let $R_{u_d^s}^s = \left\{r_1^s, r_2^s, \ldots r_{k'}^s\right\}$ be the ordered set of k' routes such that difference between the Agent-ISP's utility values of any of these routes and the route r_1^s is less than and equal to u_d^s. The set $R_{u_d^s}^s$ is the set of most desired routes that the Agent-ISP expects the Agent-IRANS to select. If the route r_1^i does not belong to the set $R_{u_d^s}^s$ then Agent-ISP must offer alternate route that the driver is most likely to comply.

4.2.2. Developing alternative driver compliant routes

Agent-ISP uses the Agent-IRANS submitted option space to determine alternative routes. Let u_d^i be the utility indifference range of the Agent-IRANS agent i. Based on this indifference range, let $R_{u_d^i}^i = \{r_1^i, r_2^i, \ldots, r_{k''}^i\}$ be the ordered set [4] of k'' routes such that difference between the Agent-

[4] The set is ordered by the Agent-IRANS calculated utility value of each route.

IRANS calculated utility values of any of these routes and the route r_1^i is less than and equal to u_d^i. If any of the routes in $R_{u_d^i}^i$ appears in the set $R_{u_d^s}^s$, then those routes are agreeable to both Agent-ISP and Agent-IRANS. If the intersection of the sets $R_{u_d^i}^i$ and $R_{u_d^s}^s$ is a non-null set, then the Agent-ISP offers the intersecting set of routes to the Agent-IRANS. The routes in the intersecting set are ordered by the Agent-IRANS calculated utility values.

If none of the routes in $R_{u_d^i}^i$ appears in the set $R_{u_d^s}^s$, then the Agent-ISP searches Agent-IRANS's second option space specified by the weight change tolerance. Let $W_1^i, W_2^i, \dots, W_g^i$ be the weights of the goals used by the Agent-IRANS agent i to calculate the utility value of the preferred routes. Let $\pm\psi_g^i$ be the weight tolerance on each goal g of the Agent-IRANS agent i. The objective of the Agent-ISP is to calculate Agent-IRANS utility value (given the anchor points) of the routes by altering Agent-IRANS weights on the goals within the specified tolerance such that intersection of newly calculated set $R_{u_d^i}^i$ and $R_{u_d^s}^s$ is not a null set. In fact the intersection set with largest number of elements must be sought as the optimal solution. Finding such a set is a difficult problem. The following optimization problem is formulated that approximately finds such a solution, if it exists.

The following max–max optimization problem is solved for each route r' in $R_{u_d^s}^s$ to determine a set of weights $\overline{W}_1^i, \overline{W}_2^i, \dots, \overline{W}_g^i$ within the specified tolerance.

$$\mathrm{Max}\left(\mathrm{Max}_{\mathrm{over}\, r \in R^i}\left(\sum_g \overline{W}_g^i N_g^{ir}\right) - \sum_g \overline{W}_g^i N_g^{ir'}\right) \tag{5}$$

subject to:

$$\left|\mathrm{Max}_{\mathrm{over}\, r \in R^i}\left(\sum_g \overline{W}_g^i N_g^{ir}\right) - \sum_g \overline{W}_g^i N_g^{ir'}\right| \leqslant u_d^i \tag{6}$$

$$|\overline{W}_g^i - W_g^i| \leqslant \psi_g^i \quad \forall g \tag{7}$$

$$\sum_g \overline{W}_g^i = 100 \tag{8}$$

The rationale for maximizing the difference between the Agent-IRANS utility value of the route r' and the maximum Agent-IRANS utility value of any route (both calculated using $\overline{W}_1^i, \overline{W}_2^i, \dots, \overline{W}_g^i$) is based on an assumption that by doing so a new set $R_{u_d^i, r'}^i$ can be found that contains maximum number of routes. Furthermore, it is also assumed that given the set $R_{u_d^i, r'}^i$ is a higher order set, the intersection of the set $R_{u_d^i, r'}^i$ and $R_{u_d^s}^s$ will be large. These assumptions are not validated.

For each max–max problem solved for each route r' in $R_{u_d^s}^s$, an intersecting set of $R_{u_d^i, r'}^i$ and $R_{u_d^s}^s$ is determined. The intersecting set with highest cardinality is sent to the Agent-IRANS as suggested routes. Since the intersecting set is determined from Agent-IRANS given option space, the suggested routes in the set is more likely to be acceptable by the Agent-IRANS.

If all the max–max problems solved for all the routes in $R_{u_d^s}^s$ becomes infeasible (i.e., no feasible $\overline{W}_1^i, \overline{W}_2^i, \dots, \overline{W}_g^i$ can be found subject to constraints to determine a set $R_{u_d^i, r'}^i$) and/or the intersecting set of each $R_{u_d^i, r'}^i$ and $R_{u_d^s}^s$ is a null set, then Agent-ISP cannot find a route in Agent-IRANS given option space. In such case, Agent-ISP will use the same optimization problem on a different $R_{u_d^s}^s$.

The set $R^s_{u^s_d}$ is the set of most desired routes for the Agent-IRANS i that is calculated using Agent-ISP's utility indifference range u^s_d. Agent-ISP is indifferent to selection of any routes in $R^s_{u^s_d}$ by the Agent-IRANS. Let $\overline{R}^s_{u^s_d}$ be the *second* most desired set of routes. It means that difference between the Agent-ISP utility value of the route with maximum Agent-ISP utility value in $\overline{R}^s_{u^s_d}$ and the route r^s_1 in $R^s_{u^s_d}$ is the smallest compared to any other routes that does not belong to the set $R^s_{u^s_d}$. However, the difference is greater than the Agent-ISP's utility indifference range u^s_d. Let this be route be denoted by $\bar{r}^s_1$. Agent-ISP is indifferent to the choice of any of the routes in the set $\overline{R}^s_{u^s_d} = \{\bar{r}^s_1, \bar{r}^s_2, \ldots, \bar{r}^s_{k'}\}$ when compared to the route $\bar{r}^s_1$. Note that the set $\overline{R}^s_{u^s_d}$ must not contain any route that belongs to $R^s_{u^s_d}$, though there may be routes in $R^s_{u^s_d}$ such that Agent-ISP is indifferent to choice of those routes when compared to the route $\bar{r}^s_1$ (based on the definition of indifference). Similar to first set of max–max problems solved for each route r' in $R^s_{u^s_d}$, the max–max problem is solved for each route r' in $\overline{R}^s_{u^s_d}$. The set $\overline{R}^i_{u^i_d,r'}$ is determined for each max–max problem is solved for each route r' in $\overline{R}^s_{u^s_d}$. The intersecting set of sets $\overline{R}^i_{u^i_d,r'}$ and $\overline{R}^s_{u^s_d}$ with highest cardinality is sent to the Agent-IRANS as suggested routes. Let $\overline{W}^i_1, \overline{W}^i_2, \ldots, \overline{W}^i_g$ be the weights on the goals that is determined while solving for $\overline{R}^i_{u^i_d,r'}$ that results in an intersecting set of the highest cardinality. The Agent-ISP records these weights for the Agent-IRANS agent i.

If the max–max problems are still infeasible or Agent-ISP cannot find non-null the intersecting set of any $R^i_{u^i_d,r'}$ and $\overline{R}^s_{u^s_d}$, then the Agent-ISP simply accepts (not necessarily agrees) Agent-IRANS submitted set of preferred routes $R^i = \{r^i_1, r^i_2, \ldots, r^i_k\}$. However, Agent-ISP maintains the record of such disagreements in terms of the weights and anchor points used by the Agent-IRANS agent to calculate set of preferred routes R^i. The Agent-ISP uses these weights recorded for these special Agent-IRANS agents to update its own weights.

The max–max problem can be reduced to a simple linear maximization problem as follows:

$$\begin{aligned}
&\mathrm{Max}\left(\mathrm{Max}_{\mathrm{over}\, r\in R^i}\left(\sum_g \overline{W}^i_g\left(N^{ir}_g - N^{ir'}_g\right)\right)\right)\\
&\mathrm{Max}_{\mathrm{over}\, r\in R^i}\left(\sum_g \overline{W}^i_g\left(N^{ir}_g - N^{ir'}_g\right)\right)
\end{aligned} \tag{9}$$

4.2.3. ISP option space update

The Agent-ISP's option space can be defined by its utility indifference range u^s_d. In order to modify its option space to appropriately represent driver's demands and TMC requirement, the Agent-ISP uses the weights and route utilities that it records at each of the three stages while searching for alternative routes for the Agent-IRANS. Note that the Agent-ISP resorts to the search for alternative routes, only if the assessment fails in finding the Agent-IRANS submitted most preferred route in its own option space. These three stages are:

The Agent-ISP searches the Agent-IRANS option space to determine a set of routes that matches/intersects with its calculated desired set of routes for the Agent-IRANS. If the Agent-ISP determines such a set, then it sends that set as set of suggested routes and records nothing. We expect this to be the case for most of the Agent-IRANS agents.

If the Agent-ISP cannot find any such set, then it tries to determine a set of routes that matches/intersects with its *second* set of desired routes for the Agent-IRANS as mentioned in the previous section. If it finds any such set in the second stage, then it records the weights of the goals searched within the Agent-IRANS specified weight change tolerance and the Agent-ISP utility value of the route with the largest Agent-ISP utility value in the *second* set of desired routes (i.e., the route $\bar{r}_1^s$). The difference between the Agent-ISP utility value of the most desired route in the set R^s (i.e., r_1^s) and the Agent-ISP utility value of the route $\bar{r}_1^s$ is recorded as the utility indifference range that the Agent-ISP should have considered for the particular Agent-IRANS agent i—denoted by $u_d^s(i)$.

If the Agent-ISP cannot determine any set at the second stage, then it simply accepts the Agent-IRANS preferred set of routes. In this case, the Agent-ISP records the weights used by the Agent-IRANS in the calculation of its preferred set of routes and the Agent-ISP utility value of the Agent-IRANS' most preferred route. The difference between this utility value and the Agent-ISP utility value of the most desired route in the set R^s (i.e., r_1^s) is recorded as the utility indifference range that the Agent-ISP should have considered for the particular Agent-IRANS agent i—denoted by $u_d^s(i)$.

Let a term period be a time interval during which the traffic behavior in terms of the choice of origin–destination pair of the driver and driver's microscopic behavior (e.g., lane change behavior, speed, and aggressiveness) is repeated. Examples of the period are—peak morning period, afternoon peak period, mid day etc. Given that the Agent-ISP records the weight and utility indifference change made to offer alternate route to certain set of drivers in certain period, the Agent-ISP uses this information to update weights to be used for the same next period (i.e., from Monday peak morning period to next Monday morning period with same weather and traffic influx conditions). At the end of one period, let J number of Agent-IRANS agents were offered alternate route at the first stage and K number of Agent-IRANS agents were offered alternate route in the second stage and L number of Agent-IRANS agents were offered alternate route in the third stage. The Agent-ISP's weight of a goal g for the same next period may be updated to:

$$\left(\sum_J W_g^s + \sum_K \overline{W}_g^i + \sum_L W_g^i\right) \Big/ (J + K + L) \tag{10}$$

where W_g^s, $\overline{W}_g^i$, and W_g^i are the weight of the goal of Agent-ISP, weight of goal adjusted in the second stage and weight of the goal of the Agent-IRANS respectively. Similarly, the utility indifference range for the same next period may be updated to:

$$\left(\sum_J u_d^s + \sum_K u_d^s(i) + \sum_L u_d^s(i)\right) \Big/ (J + K + L) \tag{11}$$

4.2.4. IRANS option space update

The Agent-IRANS agent is not expected to update its weights on the goals after the path acceptance by the Agent-ISP. However, Agent-IRANS can use different weights for different period. For example, it may assign higher weight to complexity related goals during the evening trip and higher weight to the schedule delay during the morning trip. The weight assigned by

Agent-IRANS will be specific to the time frame and geographic region. It is not necessary that an Agent-IRANS agent, which has used a set of weights in requesting for a path on a Monday morning, must use the same weights when it requests for path on the next Monday morning.

5. Simulation experiments

The Agent-IRANS, Agent-ISP and Agent-TMC are modeled on OpenCybele version 1.2-agent infrastructure (Satapathy et al., 2000) available at http://www.opencybele.org under open source license agreement. The agent-based implementation of CTMRG is integrated with a Java-based traffic simulation software developed by ITT under contract from Federal Highway Administration called Autonomous Agent Simulation (AASIM). AASIM has been demonstrated to show accurate simulated behavior of traffic on highways (no arterial streets) compared to CORSIM. One of the primary reasons to select AASIM over CORSIM is that it is difficult to model to drivers in CORSIM by assigning them with a particular path to take. Furthermore, it is easier to integrate AASIM with other Java application, such as CTMRG being modeled on OpenCybele Java-based infrastructure.

5.1. Agent-IRANS initialization

Each vehicle created within the simulation represents one instance of Agent-IRANS. When an Agent-IRANS is created, it is assigned a random set of goal weights, anchor points, and thresholds. Goal weights are generated from a uniform distribution with mean and deviation values provided in Table 3. The weights are normalized to ensure that sum of weights is 100.

All Agent-IRANS share the same set of anchor points. These are listed in Table 4. Minimum OD path distance is found from analyzing the network. Minimum OD path travel times are generated from instantaneous network volumes when the vehicle is set to start a trip.

The utility indifference range of any Agent-IRANS was randomly generated based on a range of (27.5 ± 12.5). The weight preference tolerance for any Agent-IRANS was randomly generated based on $W_i \times (0.325 \pm 0.125)$.

5.2. Agent-ISP initialization

In this experiment, a single Agent-ISP is used. Tables 3 and 5 present the weights and anchor points used to define its goals and preferences.

Table 3
Initial weighting matrix for Agent-ISP and Agent-IRANS

Goals	Agent-ISP weights	Distribution of Agent-IRANS weights
Travel time	0	40 ± 10
Schedule delay	0	25 ± 5
Path distance	0	7.5 ± 2.5
Route complexity	0	5 ± 5
Average path volume to capacity	55	15 ± 10
Average path to free-flow velocity	45	20 ± 10

Table 4
Agent-IRANS anchor points

Goals	Ideal (0.85)	Threshold (0.25)
Travel time	Minimum OD path travel time	$1.75 * \text{minimum OD path travel time}$
Schedule delay	0	Desired travel time
Path distance	Minimum OD path distance	$1.5 * \text{minimum OD path distance}$
Route complexity	0	2
Average path volume to capacity	0.01	0.9
Average path to free-flow velocity	1.5	0.5

Table 5
Agent-ISP anchor points

Goals	Ideal (0.85)	Threshold (0.25)
Travel time	N/A	N/A
Schedule delay	N/A	N/A
Path distance	N/A	N/A
Route complexity	N/A	N/A
Average path volume to capacity	0.0001	0.75
Average path to free-flow velocity	1.25	0.5

5.3. Realization of the negotiation model

When an Agent-IRANS is ready to start a trip through the network it computes the normalized utilities of all routes between its origin and destination nodes. The preferred set of satisficing routes is packaged along with the weights, anchor points, and thresholds and sent to the Agent-ISP.

The Agent-ISP computes its own ranking of the paths between the origin and destination based on its weights on different goals. If the ISP rankings and IRANS rankings match as is required by the negotiation model, then ISP accepts IRANS rankings. If not, ISP searches IRANS option space using IRANS utility indifference range. If still no match is found as is required, then the ISP uses a simplex routine to search IRANS weight space and solve the linear optimization problem by maximizing the objective function (9).

The solution is used by Agent-ISP to calculate new rankings on the path set. The new ranking and computed weights (resulted from the solution to the linear optimization problem) is sent back to Agent-IRANS via a message. The Agent-IRANS stores the new weights (so that after the trip has been made, the actual trip utility can be computed and compared with estimated pre-trip utility to compute driver's satisfaction) and computes its adjusted set of best routes.

5.4. Flow of information between AASIM-CTMRG

The information flow or cycle is depicted in Fig. 6 and can be summarized as follows:

Step 1: TMC/AASIM manager launches AASIM. It extracts list of all paths for each origin–destination pair, link travel time and velocity from AASIM. AASIM manager also obtains list of drivers with their origin and destination to be injected into the system.

Steps 2–3: For each driver to be injected, AASIM manager creates an Agent-IRANS unless the driver and his vehicle are re-used. The AASIM manager sends the path, travel time and velocity information to Agent-ISP and the Agent-IRANS agents.

Step 4: Each Agent-IRANS negotiates with Agent-ISP to determine their preferred route. The Agent-IRANS sets the route of driver object to the preferred route.

Step 5: Agent-IRANS informs AASIM manager about the completion of its negotiation.

Step 6: Agent-ISP informs the time when the drivers will be entering different links (network usage) to AASIM manager. AASIM manager can use this information to control traffic lights, if the network is changed to a combination of arterial and highways (note: this feature is not utilized in this experiment).

Step 7: AASIM manager notifies AASIM that the routes of the drivers has been selected and it can proceed to simulate next discrete time step.

5.5. Network description

A five-node network was created for testing the CTMRGS. The network consists solely of highways—two highways crossing each other and one beltway. The beltway considered is a three-lane highway and all other highways are two-lane highways. The complete length of the beltway is

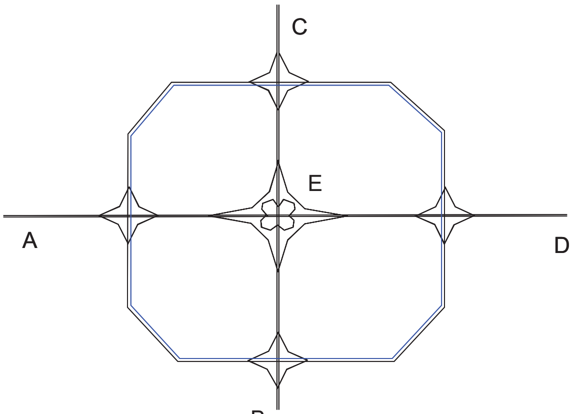

Fig. 5. Test network.

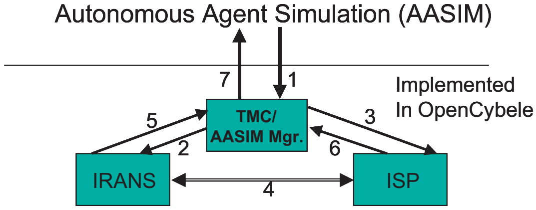

Fig. 6. CTMRG implemented in OpenCybele and interfaced AASIM simulation.

Table 6
Scenarios

Scenarios	Origin nodes	Destination nodes	Available routes
1	D	A	D–E–A, D–C–A
2	D	A, C	D–E–A, D–C, D–C–A
3	D	A, B, C	D–E–A, D–C, D-B, D–C_A
4	D, C	A	D–E–A, D–C–A, C–A, C–E–A
5	D, C, B	A	D–E–A, D–C–A, C–A, C–E–A, B–E–A

40 miles. The direct route highway from D to A, A to D, B to C and C to B is 15.15 miles. All the ramps are one-lane exits or entry links. The speed limit on beltway and highway was set to fixed 65 mph. There are no clover leaf exits or entry between highways and beltways. There are clover leaf exits only at the intersection of the two highways. The network is depicted in Fig. 5.

5.6. Simulation case scenario description and validation

Five different travel scenarios, as shown in Table 6, were created for testing purposes. Each scenario was simulated under low (1800 vph), moderate (3600 vph) and heavy (4800 vph) traffic conditions where vph is the injection rate unit expressed in vehicles per hour.

Each of the 18 resulting scenario–vph combinations was used to test and compare the performance between demand-side equipped routing and negotiation-based routing:

Demand-side equipped routing (IRANS-routing): All drivers have Agent-IRANS that operate independently. Under this scenario, every Agent-IRANS are informed of the current link travel time and velocity, volume, and capacity using which they select a path with maximum utility.

Negotiation-based routing: Under this scenario, each of the Agent-IRANS negotiates with the Agent-ISP to jointly establish the preferred route. This scenario is expected to produce high degree of drivers satisfaction and reasonably high (though not the best) system performance.

Supply-side system performance is measured by the following metrics:

1. *Throughput*: the number of drivers reaching their destination in the simulation period. It can be also reported by the ratio of number of drivers who reached their destination to drivers injected into the system.
2. *Average volume-to-capacity ratio* on every link of the network. A low value will imply low utilization of the link, but it is not the worst case, unless certain links are over utilized and others are under utilized.
3. *Average velocity-to-free-flow ratio* on every link of the network. A high value of the utilization of a link does not improve the system performance unless the average velocity to free-flow ratio of the same link is close to one. Similarly, a high velocity to free flow does not imply high system performance if the utilization is pretty low.

5.7. Measuring driver satisfaction

Agent-IRANS (driver) satisfaction is estimated by capturing and comparing pre-trip and post-trip utility values. The pre-trip utility values are calculated based on the real-time instantaneous values of the traffic provided by AASIM just prior to the start of the trip. The post trip utility values are calculated from the actual traffic conditions experienced by the driver during the entire course of its trip.

Demand-side equipped routing: Trip utility is measured as the difference between pre-trip and post-trip utility

$$\text{trip satisfaction} = (U_{\text{pre}}) - (U_{\text{post}}) \tag{12}$$

Negotiation-based routing: In the case of negotiation-based routing, the Agent-IRANS utility indifference threshold must be incorporated in the computation:

$$\begin{aligned} &\text{if } |U_{\text{pre}} - U_{\text{post}}| \leqslant u_d, \quad \text{then satisfaction} = 0 \\ &\text{if } |U_{\text{pre}} - U_{\text{post}}| > u_d, \quad \text{then satisfaction} = u_d - |U_{\text{pre}} - U_{\text{post}}| \end{aligned} \tag{13}$$

For these experiments, an average value for U_d was set to 12.5. This was used as a baseline for determining how many trips were made that resulted in a positive trip satisfaction. For both utility comparisons, the smaller (more negative) the utility difference, the better the solution.

5.8. Results from the experiments

Table 7 presents the summary of results for the single origin scenarios; Table 8 presents the results for the two single-destination scenarios. The key indicators are average utility difference and percentage of drivers who switched to a negotiated path.

5.8.1. Scenario #1: single origin–single destination

In this scenario, the two available paths are D–E–A and D–C–A. Both the IRANS-routing and CMTRGS approaches led to significant improvements in driver utility over all three volume levels. However, IRANS-routing produced more pronounced utility differences at all three volume levels. With limited path choices and low volumes there is less ability to improve path choice through negotiation.

5.8.2. Scenario #2: single origin–two destinations

The second scenario opened the network to two destination nodes, A and C and two travel paths for each destination (D–E–A, D–C–A, D–E–C, D–C). Three OD splits were run for each of the three network volumes. In seven of the nine experiments, the negotiation-based model produced better results. For volume = 1800 vph, the improvement of the negotiation-based model is larger. This is also reflected by a larger percentage of drivers who followed the negotiated path. For the larger volumes, the negotiation-based model produced slightly better results for the 50-50 and 75-25 splits. When more OD volume was routed toward node C, the IRANS model produced larger utility differences. In these cases the percentage of drivers who took the negotiated path was a minimum.

5.8.3. Scenario #3: single origin–three destinations

When the network access is expanded to three destination nodes almost identical results are realized. At the 1800 vph demand level, the negotiation-based approach produced larger utility differences for all three OD split cases. As volume is increased, the negotiation results in larger utility differences when more demand is targeted for destination A.

Table 7
Summary of experiments with single origin

Scenario O–D	vph	Demand distribution (percent vph from D to)			Average utility difference		Percentage of drivers who took negotiated path
		A	C	B	IRANS-routing	CMTRGS	
D → A	1800	100			−0.73	−0.15	16.01
	3600	100			−1.62	−1.36	12.35
	4800	100			−2.68	−2.14	10.86
D → A, C	1800	50	50		−0.16	−1.42	19.04
		25	75		−0.75	−2.00	17.91
		75	25		−0.29	−1.27	20.19
	3600	50	50		−1.58	−1.77	11.94
		25	75		−1.94	−1.79	10.38
		75	25		−1.43	−1.48	11.69
	4800	50	50		−2.14	−2.19	12.00
		25	75		−2.30	−2.11	10.20
		75	25		−1.94	−2.07	11.98
D → A, C, B	1800	40	30	30	−0.12	−1.06	16.64
		60	20	20	−0.13	−1.17	18.32
		30	40	30	−0.14	−1.06	17.02
	3600	40	30	30	−1.03	−1.27	14.08
		60	20	20	−1.15	−1.19	13.29
		30	40	30	−1.20	−1.47	12.82
	4800	40	30	30	−1.71	−1.62	10.55
		60	20	20	−1.83	−1.95	11.83
		30	40	30	−1.90	−1.75	12.80

Table 8
Summary of experiments with single destination

Scenario O–D	vph	Origin distribution (vph to A)			Average utility difference		Percentage of drivers who took negotiated path
		D	C	B	IRANS-routing	CMTRGS	
D, C → A	1800	900	900		−0.31	−1.26	16.55
	2700	1800	900		−0.89	−1.44	15.83
	4500	3600	900		−1.21	−1.09	10.06
	5400	3600	1800		−1.20	−1.56	9.33
D, C, B → A	1800	900	450	450	−0.30	−1.51	11.10
	2700	1800	450	450	−0.86	−1.61	16.70
	4500	3600	450	450	−1.64	−1.82	13.15
	5400	3600	900	900	−1.81	−2.16	9.44

5.8.4. Scenario #4: two origin–one destinations

In three of the four variations tested, the average utility difference for the negotiation-based routing is more pronounced. The improvement decreases as volume increases. This is also reflected by the percentage of drivers who take the negotiated path. This number decreases as volume increases.

5.8.5. Scenario #5: three origin–one destinations

In this scenario the negotiation-based approach yields preferable results in each of the four scenario variations tested. Again, the difference between the IRANS-routing and negotiation-based routing is larger when volumes are smaller.

5.9. General observations

There is an inverse relationship between the demand load (vph) and trip satisfaction results between the negotiation-based and IRANS-routing models. At lowest volumes, the utility difference is the largest. This can be explained by looking at the utility function and the manner in which path choice is determined. At lower volumes, link speeds are higher and there is greater variation between path utilities. Negotiation can be used to shift larger percentages of drivers while maintaining preferable path conditions.

The average utility difference or trip satisfaction numbers between negotiation-based and IRANS-routing models are practically same; although it has not been statistically validated (this analysis is planned for the next set of experiments). The same trip satisfaction numbers for all scenarios indicate that CTMRGS-based routing does not undermine the drivers satisfaction compared to IRANS-routing, and hence increase the chances of driver's compliance.

The average percentage of the drivers, who selected a different route ranges from 12% to 16% depending on the congestion conditions. There appears to be no direct correlation between drivers who switched paths and load volume. However it is theorized that there is a strong correlation between this metric and the IRANS negotiation space—weight tolerance and utility indifference range. If this space is created specific to the driver depending on his/her origin and destination reflecting a real-world case (instead of random), it should be expected that this percentage would rise.

6. Conclusions

This paper described the analytical framework and simulation modeling for a Cooperative Traffic Management and Route Guidance System. The objective was also to test the model against IRANS-based routing to determine if negotiation between drivers and ISPs compromises driver's expected trip utility. The results from preliminary simulation experiments show that CTMRGS-based routing does not compromise driver's pre-trip and post-trip utility difference when compared to IRANS-routing model. In fact preliminary results reported in the final report submitted to NSF by Satapathy and Adler (Satapathy et al., 2002) indicate the system/TMC performance in CTMRGS-based routing measured by utilization and throughput improves compared to IRANS-routing.

By successfully taking advantage of drivers' negotiation space, CTMRGS allocates drivers more evenly over the network than IRAN-routing without hampering drivers' satisfaction (in fact, the experience of the driver population may be enhanced). This brings negotiation-based approach close to system performance results expected from idealistic supply-side routing, which although may not guarantee drivers compliance. Supply-side routing approaches, such as DTA, were not considered for this preliminary experiment.

Results from this preliminary experiment suggest that further testing and model refinement be explored. More detailed testing of the model is being conducted by the authors to evaluate statistical differences between the negotiation-based model and the IRANS-routing model of assignment. These experiments seek to better understand how sensitive the model is as key parameters (e.g., weight preference tolerance, utility indifference range) are varied. Testing against DTA or other supply-side models will reveal whether a negotiated approach can better satisfy network operations preferences of the TMC.

Understanding how the model performs under various distributions of informed and uninformed drivers is crucial and most critical to achieve desirable results. Probably distribution of information as well as negotiations should be handled in different ways depending on the portion of informed drivers and complexity of the transportation network.

The linear weighted approach to measure utility was useful for building the prototype but may be too simplistic. It was derived from earlier work by the authors and was a convenient approach that was easy to embed in the CTMRGS. Work is needed to explore other models, such as Pareto-sets, that may be better suited to model short and longer-term changes in driver behavior and travel preference.

Formulating this search as a combinatorial optimization problem (see Eq. (9)) is fine for small sample networks. However, for large networks, it can create a very large search space that could be computationally intensive. Identifying methods, such as those based on evolutionary strategies, to move efficiently through the solution space is needed. Satisficing or variants of non-dominated k-shortest path algorithms are an alternative.

It is more likely that rule or case based approaches are better choices. In the spirit of principled negotiation, a rules-based or case-based reasoning approach might be more applicable. Rule-based system are appealing because rules can define appropriate responses and they lend themselves to transparency (easy to trace rules that fire and develop explanatory text in support). The authors are working on a rule-based approach to principled negotiation.

The availability of intelligent IRANS is needed to realize the vision for the CMTRGS. As machine learning and AI technology evolve, the creation and use of intelligent IRANS will increase significantly. Developers will find ways to enhance the ''AI'' to better capture and represent driver's true objectives and behavior.

The negotiation model described in this paper is derived from the principled negotiation model first proposed by Adler and Blue (2002). Work is underway to develop a purely rule-based principled negotiation model that allows for more direct negotiation between Agent-IRANS and Agent-ISP. In the past several years, many negotiation models have been devised for use in multiagent systems. These are worth reviewing.

It will also be valuable to explore extensions of the negotiation model. Infusion of real-time congestion pricing and/or pricing redistribution (see Adler and Cetin, 2001) concepts into the negotiation process may prove to aid acceptance of negotiated path choice. Allowing an ISP to adjust spatial and temporal demand by offering or charging a usage fee, may urge drivers to participate in negotiation for path choice scheduling. Adler and Cetin suggest a model whereby drivers that take a less than optimal path would receive a direct payment from those who are tolled for using the ''best'' route.

Electronic Toll Collection technology has revolutionized toll collection and reduced delays across the nation. Time is rapidly approaching when network operators will use this technology to combine intelligent routing and pricing redistribution to enhance travel performance. The State of Virginia recently initiated a pay-to-ride program, dubbed "Bridge Bucks" that is designed to remove 1000 vehicles from the travel lanes of the Woodrow Wilson Bridge that is undergoing reconstruction. The first-year cost to the state is estimated at about $745,000. The goal is to "pay drivers to get out of their cars and into buses, trains and vanpools" (Washington Post, 2004).

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