Real-Time Multiple-Objective Path Search for In-Vehicle Route Guidance Systems

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The application of multiple-objective route choice for in-vehicle route guidance systems is discussed. A bi-objective path search algorithm is presented and its use demonstrated. A concept of trip quality is introduced that is composed of two objectives: minimizing travel time and minimizing trip complexity. Trade-offs between the objectives are examined. The concept is illustrated through simulation modeling on a test network. The experiments serve to demonstrate the effects on the trip performance of pretrip routing and dynamic routing strategies under full market penetration (an idealized condition) and under varying levels of demand and trade-offs between time and complexity.

The development of advanced traveler information systems (ATISs), particularly in-vehicle route guidance systems (IVRGSs), has led to increased research activity to better understand and model driver route-choice behavior. One method of modeling route choice is the use of multiple objectives (or criteria) in the context of performing path search through a network. Using multiple-objective shortest-path (MOSP) search is appealing on two levels. From a modeling perspective, such as traffic assignment, it enables a more realistic representation of driver route choice. From a user perspective, drivers may feel more comfortable that IVRGS is responsive to their actual travel preferences.

Several IVRGSs are being deployed in which personal computer–based routing software considers different path search strategies by allowing drivers to specify a particular single-objective search strategy. Some IVRGSs in development have attempted to base route selections on roadway classification (such as avoiding local streets) in an attempt to account for non-travel-time objectives. For example, a system might provide the capability to choose from among the following strategies: (*a*) minimum time path, (*b*) minimum distance path, (*c*) most direct path, (*d*) path that maximizes use of highway, and (*e*) path that avoids highways.

There are two apparent shortcomings in these systems. First, arc costs, such as travel times, are based on free-flow conditions and therefore do not use real-time information for searching the network and making route guidance decisions. Second, only a single objective is used in directing the path search and the only possible trade-off is in comparing resulting alternative routes generated from the different objectives. This either-or approach does not capture the fact that driver route-choice preferences may be shaped by multiple objectives, some of which may conflict. More desirable would be trade-offs in which the weighting of the relative importance of each objective reflects the driver's routing interests.

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This paper explores the use of such weighted trade-offs. The next section presents an overview of research and issues in MOSP search. This is followed by a presentation of a specific algorithm and approach for multiple-objective search that can be applied within IVRGS in real time. An example of a bicriterion formulation applied to a small network with idealized peak-period demand follows. The two objectives used for the study are minimizing path travel time and minimizing path complexity. Simulation is used to examine the effects of trading off these objectives.

BACKGROUND

Modeling driver route-choice behavior has focused extensively on identifying and quantifying the effect of multiple attributes (*1,2*). In addition to travel time, behavioral attributes that have been considered are distance, convenience, and safety (*2*). Distance is a simple metric to measure, but it is not obvious how to measure convenience and safety. Other research has identified distance, traffic signals, proportion of trips through scenic areas, and proportion of trips on highways (*3*). In route choice experiments it has been shown that minimizing turns is an important choice for drivers (*4*). Also, the recent introduction to the marketplace of in-vehicle route choice navigation systems brings to the fore new possibilities in the consideration of driver behavior goals.

An example of a new IVRGS-based goal is that of generating alternatives to the best path (*5*). In that work an algorithm gives a driver one path for the inbound trip and a substantially different path for the outbound trip. The algorithm allows no more than *k* similar arcs in the path, where *k* is set by the user. This approach gives a geometrically different path to the first one found. This geometric goal is akin to that of scenic optimization.

This research identifies an IVRGS-oriented metric that has not been considered previously and offers insight into another geometric goal, the *directness* of a driver's trip. This metric is termed "trip complexity," defined as the sum of turning movement costs. Trip complexity complements trip time as an objective, as the minimum trip complexity will not necessarily correspond to the shortest trip time. For example, this situation would occur when the most direct path—say, a straight path with minimal complexity—has considerable congestion. Some drivers would prefer the most direct path over a shorter time path for ease of decision making and maneuvering. Thus, trip complexity is akin to the convenience and safety goals mentioned in the literature (*2*) that have ambiguous definitions.

As a convenience goal, minimizing trip complexity gives drivers a more direct route. As a safety goal, it offers a less demanding route to those drivers who may be less comfortable with negotiating turns and other involved maneuvers. Though in-vehicle navigation equipment reduces the decision making by identifying turns for the driver, it does not make the actual maneuvering of the vehicle easier, an important consideration for many drivers. Commercial vehicle operators, especially those with large trucks, may wish to avoid paths with turns. Another situation can arise in which trip complexity would be useful to drivers who are comfortable with their vehicles. When trip complexity is invoked as a shared goal with trip time, the least complex of all the very good trip time paths would be the most favorable. Thus, minimizing trip complexity generally can produce convenience and safety improvements that are of potential interest to any driver.

In making trip complexity an objective, this research is purposefully pursuing an extension of the boundaries of knowledge about driver behavior and the effects of geometric goals on route choice and network performance. As such, it moves in the direction of including safety and convenience in the path search.

Few efforts have attempted to incorporate multiple criteria within route choice modeling and traffic assignment. Of note is work by Dial (*6*) and Leurent (*7*) in multiple-objective static traffic assignment (STA). Dial, for example, has formulated a bicriterion user equilibrium assignment based on out-of-pocket cost and trip time cost as the criteria of mode route choice, parking policy planning, or congestion pricing. Value of time is treated as a random variable. He concludes that this approach could be extended to dynamic traffic assignment as well.

Traffic assignment methods are useful as planning tools and are being developed for ATIS, but they are not directly applicable to modeling individualized routing decisions made with the aid of in-vehicle route guidance systems. Real-time route guidance with IVRGS can be accomplished by using a path search algorithm in conjunction with real-time data received from networks equipped with traffic sensors and communications technologies. The objective is to enable *autonomous* route choice by drivers in response to actual conditions. The IVRGS serves to collect real-time data from the network and provide the driver with more informed path search capabilities. By allowing for true multiple-objective search, which reflects drivers' preferences and trade-offs among competing goals, perceptions of trip quality and effectiveness of ATIS will be improved.

Methods for applying multiple-criteria decision making to network search problems are well established. Zeleny (*8*) and Steuer (*9*) provide a thorough introduction to the theory of multiple-criteria decision making. Development and application of MOSP algorithms able to handle both deterministic and stochastic problems are also well documented, as discussed by List et al. (*10*).

There have been few, if any, applications of multiobjective routing to ITS networks. A significant body of work applying MOSP algorithms exists in the area of routing hazardous materials. Application of MOSP algorithms to hazardous materials was begun by Cox (*11*), who explored routing and scheduling decisions. List and Mirchandani (*12*) have done multiple-objective routing and siting for hazardous materials and waste. Turnquist and List (*13*) have applied MOSP routing to emergency response in dealing with high-level radioactive waste shipments. List (*14*) has also studied emergency response team siting using four objectives: response time, risk, risk equity, and cost, where the objectives are combined using weights that sum to 1 ($\Sigma w_i = 1$), to form a generalized cost function. The multiobjective in-vehicle route choice algorithm used in this work is derived from the aforementioned work by List (*10,12–14*). This research substitutes other goals for route selection more appropriate to meet the quality of trip desired by ordinary drivers (i.e., those not involved in hazardous waste transport).

OVERVIEW OF BI-OBJECTIVE SEARCH APPROACH

Seaman (*15*) developed a theory of quality to define the trade-off of multiple objectives in support of meeting a goal. His work focused on identifying the best operating point from process inputs and controllers on-line, continuously and automatically. Extending this idea to traveler behavior and routing, trip quality can be thought of as a subjective concept measuring a degree of satisfaction of route choice under competing goals.

Consider two competing objectives that a driver might use in making route choice decisions. The first is minimizing travel time; the second is minimizing trip complexity. The former objective is a traditional and obvious goal; the latter is introduced to illustrate the trade-off between time and directness.

Trip Complexity

Complexity can be viewed as an increase in driving task associated with making road changes in a network. For example, freeway-to-freeway interchanges require lane changing, merging, and weaving movements. On surface streets, intersections require left and right turns, which have degrees of difficulty associated with them.

In this example, application deterministic complexity costs were assigned to arc-to-arc movements on the basis of the angle of the turn (in degrees) and the direction of the turn (left or right). The values assigned were arrived at empirically. For example, in moving straight ahead, there is a cost of 0. A right turn has a cost of 0.2 and a left, of 0.3. Table 1 gives a summary of complexity costs used.

Figure 1 gives an illustration of assigning trip complexities. In this network, Node 88 is a dummy entry node, used only to give a complexity cost to the vehicle's entry to the network. The complexity costs are shown for each turn of a path from Node 12 to Node 19. The trip complexity cost of Path 88-12-15-16-29 is 0.5. This cost includes 0.2 for entering and bearing left at Node 12 (88-12-15), 0.2 for bearing left again at Node 15 (12-15-16), and 0.1 for bearing right at Node 16 (15-16-19).

Trip Quality

A minimally complex path can take more time, and a minimum time path can be more complex. Drivers may aim for a compromised

TABLE 1 Turning Movement Complexity Costs

Turn Movement	Complexity Cost
0° turn (straight ahead)	0
45° right turn	0.1
90° right turn	0.2
135° right turn	0.3
45° left turn	0.2
90° left turn	0.3
135° left turn	0.4
180° turn (reverse direction)	0.5

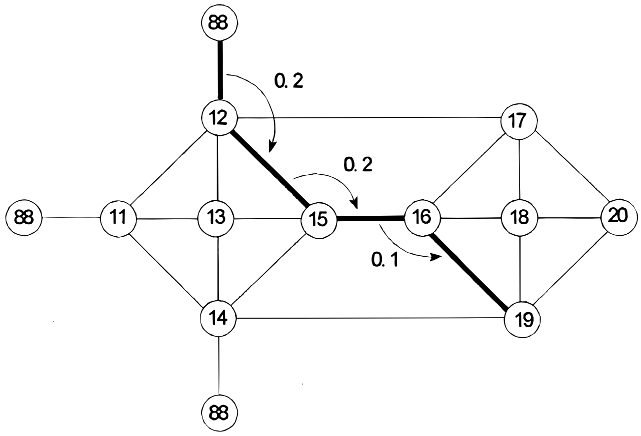


FIGURE 1 Illustration of trip complexity.

situation in which a path produces a good travel time and good trip complexity. The authors could define the concept *trip quality* to reflect the combination of both travel time and trip complexity:

$$Q = \alpha T + (1 - \alpha)C \tag{1}$$

where

Q = perceived cost of trip quality,
T = perceived value of trip having travel time t,
C = perceived value of trip having complexity c, and
α = trade-off parameter where $0 \leq \alpha \leq 1$.

The optimal-quality route is the multiple-objective route with the minimum quality cost. This treatment does not limit trip quality to trip time and complexity; the concept can clearly be extended to three or more objectives (*14*). The actual set of factors that constitute a driver's trip quality is left for behavior-oriented research. This paper offers trip time and trip complexity as working surrogates to illustrate the concept of multiple-objective routing.

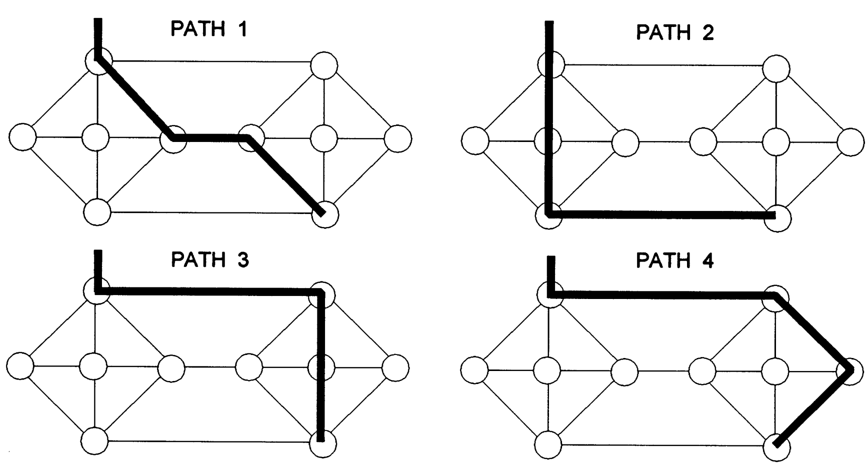
Lexicographic Ordering and Nondominated Solutions

Consider an example examining the effect of trip quality on route choice. Figure 2 presents a network that highlights four alternative paths, of many possible paths, for a given origin-destination pair. Each path differs by travel time and trip complexity. If only travel time were considered as the objective, Path 1, having the lowest travel time, would be considered optimal. However, if only trip complexity were considered as the objective, Path 2 would be considered optimal.

One way to treat the two objectives is to use a lexicographic ordering in which one objective is the primary search attribute and the second is used to break ties. Figure 2 illustrates a lexicographic ordering of the four paths with travel time as the primary objective. This search strategy does not allow for direct trade-offs in the values of the attributes. A more sensitive approach is to consider the attributes jointly, as in Equation 1, and look for nondominated paths. Under no circumstances would dominated paths be considered optimal. One issue for further research is developing search routines that can handle multiple objectives and dismiss dominated solutions efficiently.

MULTIPLE-OBJECTIVE PATH SEARCH ALGORITHM

The formulation presented here is for handling a bi-objective search problem, but it can easily be extended to multiple objectives. Define a graph $G(N,A,T,C)$ with set of nodes N, set of arcs A, set of arc travel times T, and turning movement complexities C. Unlike a traditional label setting approach in which each node is labeled with a minimum value and points to a predecessor node, it is possible under



Path	Travel Time	Complexity	Status
1	1.2	0.5	Nondominated
2	1.4	0.3	Nondominated
3	1.5	0.5	Dominated
4	1.6	0.6	Dominated

FIGURE 2 MOSP illustration.

multiple-objective search to reach a node from several partial paths. Each nondominated partial path must be stored. As a result, this algorithm uses a partial-path vector to store labels and predecessor pointers; labels are not assigned directly to nodes.

Let PPI[1 . . . K] be the partial-path vector with a maximum of K partial paths to be stored. Each vector consists of six record values:

TN = to-node
TLT = temporary label for time
TLC = temporary label for complexity
Q = trip quality = αTLT + $(1 - \alpha)$TLC
PL = permanent label = one of three values: ∞ if not yet reached, 1 if reached and scanned from, and 0 if reached and dominated
PRED = predecessor partial path, which holds an index pointing to a different record of the PPI

Let LAST be the last index of PPI set, and let R = set of nodes reached.

The algorithm is as follows:

- *Initialization*. Select origin node s. Let LAST = 1; for PPI[LAST] set TN = s; TLT, TLC, Q, PRED = 0; PL = ∞. Set $R = \varnothing$. Select value for α, where $0 \leq \alpha \leq 1$.
- *Iterations*.
  1. Of all records in PPI having PL = ∞ find the minimum Q. (If there are ties, see the note that follows.) Set its index to k. (Note: if a value of α is chosen such that $\alpha \neq 0$ and $\alpha \neq 1$, ties can be broken by arbitrarily selecting any index. If a value of 1 or 0 is chosen for α, the search routine should be modified to use a lexicographic ordering to break ties in the value of the primary attribute based on the value of the secondary attribute.)
  2. With PPI[k] set PL = 1; TLT = TLC = ∞. If PPI[k].TN $\notin$ R then R $\cup$ PPI[k].TN
  3. Get the associated TN of PPI[k] and associate it with I. Scan out from node I and assign for each reachable node j:
     LAST = LAST + 1;
     with PPI[LAST] set
     TN = j
     PRED = k.
     TLT = PPI[k].TLT + $T(I, j)$
     TLC = PPI[k].TLC + C(PPI[$k - 1$].TN, I, j)
  4. *Domination check*. For all nodes that have reached ($n \in R$) and having multiple TN entries in PPI, check for partial-path domination. For each node n in R find all entries in PPI where TN = n. For each entry k do:

If the pair (PPI[k].TLT, PPI[k].TLC) is dominated, then set PPI[k].PL = 0.

[Note: since complexity is a two-arc value (from-arc to to-arc, involving three nodes), each PPI[k].TLC must be treated carefully in tests for domination by making sure it is greater than a minimally safe value greater than the complexity of the largest nondominated value of complexity for that node n.]

- *Termination*. The algorithm terminates when there is no nondominated open node that could be scanned from and reach the terminal node t. The minimum path is identified by finding the minimum value of Q of all PPI records with PPI[k].TN = t. The actual minimum path is found by traversing the PRED label and reading off the TN label of all partial paths reached.

Using the network in Figure 1, the algorithm's search for an optimal path from Node 11 to Node 19 is illustrated. To limit the search to a manageable size, only the 12 nondominated nodes scanned by the algorithm are given in Table 2. The scan is done using time-based search. The path is read back from the nondominated destination node that has the minimum value of the search criterion. The table shows the two instances of Node 19, and the one with the time cost of 1.247 is the minimum for time-based search. The path is read from the to-node associated with the predecessor partial path (PPP) back to the partial-path index (PPI). The optimal path-related values are highlighted in the table. If a nomenclature of (PPI) to-node [PPP] is used, the path is read: 19[4]-(4)14[1]-(1)11, or Path 11-14-19 read forward. The path nodes selected are presented in Table 2 in the column "Path" with a "T" for time-based path. A complexity-based path or a multiple-objective path (Equation 1) would have a different scan, but the procedure would be the same,

TABLE 2 Path Search of Nondominated Nodes

PPI	To-Node	PPP	Time	Complexity	Path
1	**11**	0	0	0	T
2	12	1	0.527	0.4	
3	13	1	0.319	0	
4	**14**	**1**	0.528	0.2	T
8	15	3	0.639	0	
12	17	2	1.227	0.6	
16	**19**	**4**	**1.247**	0.6	T
20	16	8	0.939	0	
30	17	20	1.454	0.4	
31	18	20	1.235	0	
32	19	20	1.452	0.2	
44	20	31	1.554	0	

with the scans and the destination to-node choice based on the path search criterion in use.

SIMULATION EXPERIMENTS

Background

A set of simulation experiments was conducted to illustrate the application of a multiple-objective search for IVRGS. The goal was threefold: (*a*) to study the effect on network performance under single- and multiple-objective routing strategies, (*b*) to conduct sensitivity analysis for a range of α values, and (*c*) to compare pretrip route selection and dynamic rerouting strategies.

Since trip complexity and travel time are measured on different scales, the trip quality expression (Equation 1) was modified to include a scaling factor, γ, that makes the nondominated frontier less skewed and easier to interpret.

$$Q' = \alpha T + \gamma(1 - \alpha)C \quad (2)$$

In the simulation experiments that follow, trip quality was minimized over a range of α values with γ set to 2.0. When α = 1, the resulting search is referred to as "time-based"; when α = 0, the resulting search is referred to as "complexity-based." For both of these special cases, a lexicographic ordering is used in the path search algorithm as described earlier.

The network constructed for the analysis, along with the dynamic peak-period loading patterns and origin-destination splits, is shown in Figure 3. There are three origin nodes (11, 12, and 14). The maximum demand rate occurs midway into the 1-hr simulation period. To reveal the capabilities of the search strategies under differing levels of congestion, the peak volume loaded is varied from 800 to 1,895 vehicles per hour (vph). To compare routing strategies on an even platform, with minimal complicating effects, it is assumed that all vehicles are equipped with IVRGS and consist of a single user class in which all travelers use the same value of α. These assumptions are not considered realistic or necessary for IVRGS to be effective in improving network flows, but they are useful for a parametric comparison of routing strategies. The simulator used for the experiments was developed by Blue et al. and is presented in detail elsewhere (*16, 17*). The link performance function is based on Greenshields flow relationships with the capacity of each arc being 1,800 vph. Arcs are independent. To avoid inter-arc spillbacks, when the speed on any arc falls below 10 mph, the simulation terminates and the strategy is considered nonfunctional under those demand and trade-off conditions.

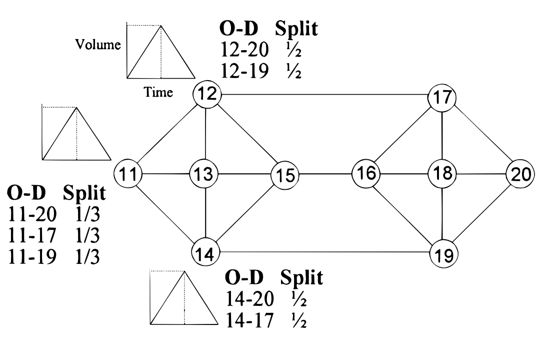


FIGURE 3 Bidirectional network under investigation.

Performance of Routing Strategies

To obtain statistically significant performance of the routing strategies, 20 replications of each strategy at each peak volume were simulated. Average values for the 20 replications were used in the following analysis.

Pretrip Versus Dynamic Routing

Pretrip routing (PR) represents the case in which at the start of the trip instantaneous values of travel times and deterministic values of complexity are used to compute an optimal path to the destination. The vehicle is constrained to this path for the duration of the trip; no en route path switching occurs. In dynamic routing (DR), a vehicle's prescribed path is reevaluated at each node reached on the basis of current conditions in the network.

Simulations were conducted at various peak demands and over the full range of α. Figures 4 and 5 illustrate the trade-off surfaces for the DR and PR strategies. In these figures, values of α = 1.0 are at the right. Each point on the trade-off surface for a particular demand indicates a decrease in α of 0.1. Values of α = 0.6 are identified as a guide in reading the chart; the arrowhead simply signifies the direction of increasing volume. In addition, α = 0.6 represents a high rate of change with adjacent values of α. It is a value for which there is a high rate of trade-off between objectives in the network's performance for all peak volumes in which this level of α is attainable. For higher demand levels, not all values of α can be simulated because of restrictions in the simulation. At lower levels of α and higher volumes, severe congestion occurs and a cutoff rule is implemented as trip travel times greatly increase.

Trade-off Surface for Dynamic Routing Figure 4 shows the trade-off surface of time and complexity for DR. The full range of α values is present at 800 vph. The value of 800 vph is the highest that will process a full range of α values from 0 to 1. For volumes higher than 800 vph, solutions could not be obtained for some small values of α. As volumes increase, path choices based on complexity are difficult to process. The value of 1,895 vph was the highest volume for which 20 replications were processed.

At 1,895 and 1,845 vph, DR has relatively large trade-offs in trip time for each downward step in α with almost no change in complexity. At 1,895 vph, DR has two points that have a vertical slope, a large trade-off between trip time and complexity. At 1,845 vph, DR still has a nearly vertical slope. This trading off of trip time without any improvement in trip complexity at a high volume is not advantageous. At 1,800 vph, DR is leveling off; at 1,675, DR begins to have parallel slopes.

Trade-off Surface for Pretrip Routing Figure 5 shows the trade-off surface of time and complexity for PR. PR is limited to volumes of 1,675 vph or less, and at 1,675 vph PR successfully performs simulations only for time-based search. Not until 1,500 vph is a meaningful range of α values simulated successfully. This shows a significant difference with DR that single-objective time-based charts would not point out. PR is rather limited in accommodating complexity as a goal on this network, primarily because of the overconcentration of vehicles on Arc 1516 that DR is capable of avoiding more successfully.

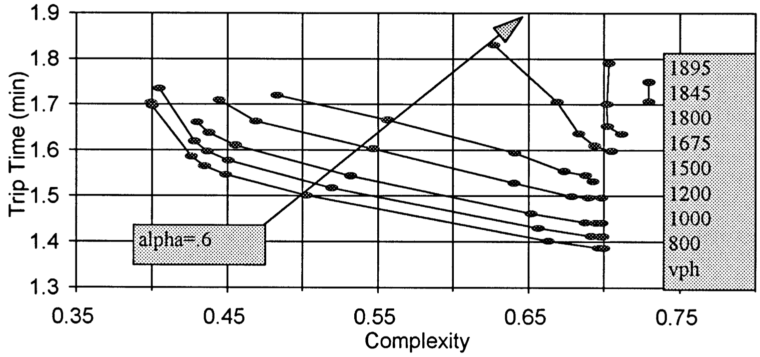


FIGURE 4 Trade-off surface of trip time and complexity for DR strategy with α-based multiple-objective search.

At 1,500 vph, the multiple-objective range of PR performance improves greatly. When superimposed on the DR chart, the PR curves are virtually identical to the DR curves. DR does not improve on PR except for volumes above 1,500 vph, but there is a significant difference thereafter. Since PR is virtually identical to DR until 1,500 vph and has only a very limited ability above 1,500 vph, there is little reason to continue discussion of PR.

Multiple-Objective Search Results for Trip Time and Complexity

It is interesting to investigate the values of each objective separately under the DR case. Figure 6 shows that a maximum average trip time of between 1.7 and 1.83 min is reached at each volume. There is a significant change in trip times over the α range, at low volumes especially, because of a larger range of α over which trip time can improve. For most of the volumes, trip time changes most rapidly (maximum slope of the curves) over the interval α = [0.5, 0.7]. In this range, drivers are more likely to consider alternative routes because trade-offs can be achieved in the objective space. Flat regions of the graph represent little difference in path choices among various values of α. Most notable are the low ([0, 0.2]) and high ([0.7, 1.0]) values of α.

Average trip complexity for DR is shown in Figure 7. The figure is very similar for DR and PR for the range of volumes over which they operate. The figure shows an S-curve with a narrow band of complexity values, virtually independent of peak volume for any given value of α. The DR strategy chooses on average nearly the same proportion of the available paths for each peak volume and value of α. In fact at α = 0.68 and complexity = 0.62, the curves appear to meet. At volumes of 1,800 vph or more, the DR strategy allows complexities to rise beyond this narrow band of values. In general, drivers will experience the greatest change in complexity over the α interval [0.5, 0.7]. Complexity is relatively unchanged in the two regions outside these limits.

These figures show that, with respect to travel time, sensitivity to α changes as demand increases. Less of an effect is seen for complexity. This results from the fact that travel time is a function of demand and higher levels of demand produce increased travel times. In turn, higher travel times induce route switching. With respect to complexity, low values of α reflect the goal of minimizing complexity. As α increases, and emphasis is shifted to travel time, complexity values may increase. However, for any given value of α, there is little variation for values of complexity over the range of demands.

CONCLUSIONS

This paper examined the use of multiple-objective routing strategies for in-vehicle route guidance systems. A multiple-objective search algorithm was presented. The goal of improving trip quality has been treated as optimal trade-offs of trip time and complexity for

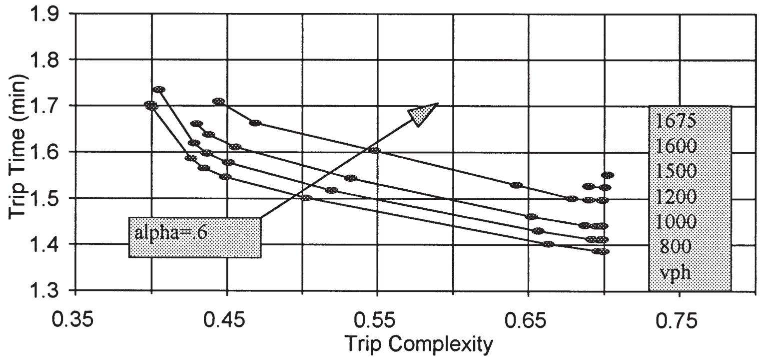


FIGURE 5 Trade-off surface of trip time and complexity for PR strategy with α-based multiple-objective search.

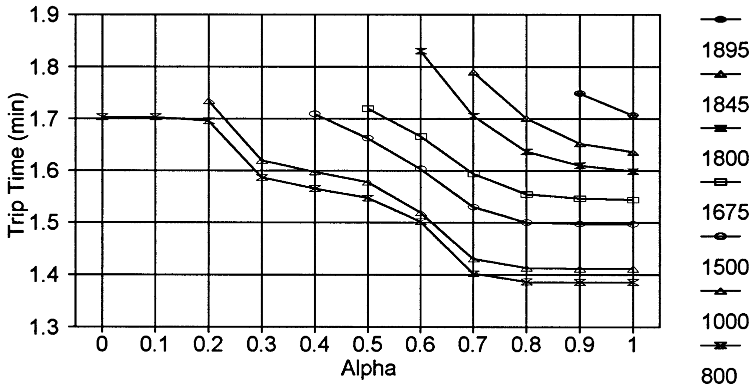


FIGURE 6 Average trip time for DR strategy with α-based multiple-objective search.

drivers. A simulation experiment was conducted to illustrate the effects of multiple objectives on network performance. It was shown how drivers can improve trip quality when a trade-off between trip time and trip complexity is desired. It was also demonstrated that substantial network flow improvements over PR are possible when DR is allowed. The trade-off surface of trip time and complexity for the full range of α stratified by peak volumes reveals transition points of the objectives and the range of α values at a given volume. DR showed significant advantages over PR over the entire α range above a peak volume of 1,500 vph. PR could be considered a special case of DR that occurs at lower volumes. At lower volumes there is less necessity for en route switching.

In the studied case, performance was assessed for an idealized network topology and peak-hour demand pattern. The effect of different peak volumes of the demand pattern was examined over an array of time-complexity trade-offs. Though the experiment was carefully constructed, the results are network- and demand-specific and are weighed against its special case nature. There are arc capacity, turning complexity costs, and other modeling assumptions to consider as well. Complexity was treated as a deterministic (average) value, but it could be extended to a more realistic probability density function, much as Dial has done with value of time (*6*). This is motivation for further study.

Driver behavior modeling is an area in which the concepts of multiple-objective search might be readily applied. It has been in an effort to capture driver interests that the multiple-objective approach was taken. Simulation experiments with finer-tuned cognitive psychological models of drivers using MOSP methods appears a fertile area for research. The experiments should aim to determine the travel attributes and values of α that constitute trip quality. Discovering the appropriate distributions for turning costs is an important area for more effective use of trip complexity as a driver interest in path choice.

In order to compare routing strategies, the experiments employed a single user class, with all drivers having IVRGS equipment and using the same value of α. Work is under way to explore the effect of varying the market penetration of IVRGS and the distribution of α among the user population. Further in-laboratory modeling studies are needed to justify the development of these IVRGS concepts for real-world driver populations. Performance for both drivers and network flows must be better understood before real-time multiobjective IVRG can be realized in the marketplace and on the road.

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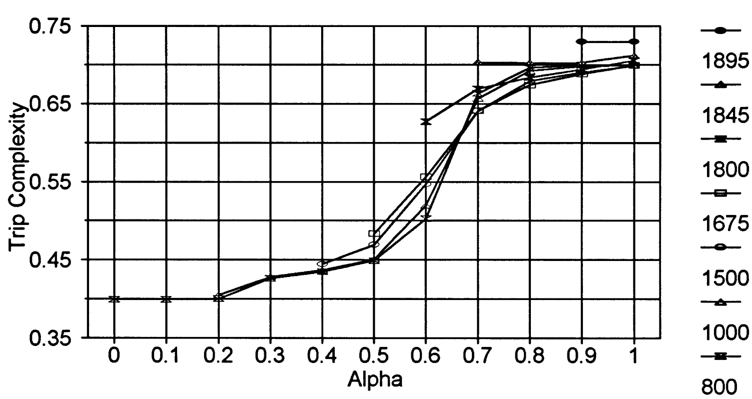

FIGURE 7 Average trip complexity for DR strategy with α-based multiple-objective search.

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