Assessing Driver and Network Performance Under Bi-Objective Route Guidance Systems

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ABSTRACT

This paper explores the effects on driver route choice and network performance when real-time in-vehicle route guidance systems assume a viable market penetration. A bi-objective route choice model is adopted whereby drivers select routes based on minimizing trip quality costs, a performance measure that represents a linear bi-objective combination of trip time and route complexity costs. Network simulation is performed to evaluate network performance under low and high peak volumes and a range of market penetration levels. It is shown that when travel time is traded off for lower path complexity the network experiences slightly higher travel times. However, the total quality cost per driver decreases by over 20%, even at 100% market penetration. The findings suggest that the perceived value of route guidance systems will be enhanced if they can more accurately reflect drivers' multiple objective routing preferences. At the network level the bi-objective approach requires that the more complex perspectives and analytical approaches presented in this paper are needed to fairly compare supply-side to demand-side costs and benefits. Also, this bi-objective approach can overturn some of the prototypical results previously found in single-objective ITS network analysis for both drivers and networks.

Key Words: Route Guidance, Traveler Information Systems, Multiple Objectives, and Route Choice Behavior

1. INTRODUCTION

Providing drivers with real-time route guidance and/or traffic advisories is a central focus within Intelligent Transportation Systems (ITS). Over the past decade there has been an increased push to develop in-vehicle route guidance systems (IVRGS). To date, much of the design and evaluation of IVRGS has focused on the effects of providing drivers with single objective route guidance. For example, within several IVRGS, drivers may choose from among several route choice criteria, such as shortest path, most direct path, or a path that avoids freeways. However, the actual path search conducted by the device utilizes the single objective chosen. There are few existing IVRGS capable of providing true multicriteria path search based on explicit driver preferences. It is contended that the viability of IVRGS will be greatly improved with the ability to truly capture multiple criteria route choice behavior. Drivers who participated in the ADVANCE ITS demonstration project in Chicago wished to have more control over the route planning and to set their own criteria. The drivers suggested that computer learning of their route selection criteria or of their favorite routes would be desirable (Schofer et al., 1997).

From a systems perspective the most benefit to be gained is by effecting more efficient (i.e. lower travel time) route choice behavior across the driver population. There is an interest to determine the extent of improvement in system-wide performance should a significant number of vehicles be equipped to receive shortest time path guidance. Simulation studies have been conducted to investigate the effects of IVRGS devices on driver behavior and network performance. For example, Jayakrishnan et al. (1994) employed a simulation framework to study the effects of increased market penetration of IVRGS on network performance. A boundedly rational model of route choice is employed. Simulation studies were conducted on two moderately sized networks, Austin, being sparser and less congested, and Anaheim; more dense and higher congested. Improvements to network performance were realized on both networks; however, beyond 30% penetration rate the marginal improvement in system performance degraded. Lee (1994) argues that when market penetration of IVRGS is high under a centralized traffic control system, providing dynamic minimum time path route guidance will have an adverse impact on network performance, as too many vehicles will be routed onto the same shortest path. He advocates the use of a multiple-path routing strategy whereby the k-minimum time path is solved and vehicles are randomly provided with route guidance for one of the 'k' best paths.

Several researchers argue that route choice behavior is inherently a multiple objective decision making process and while using travel time as a single objective is convenient, it may detract from the potential benefits of IVRGS. Garling et al., (1986) showed that people generally do not try to minimize travel time when traveling. Golledge (1993) demonstrated that drivers consider other criteria such as shortest distance, minimizing the number of turns, or fewest traffic lights that are applied in tandem with time minimization to develop routing strategies. Based on empirical studies, Antoinisse et al., (1989) suggest that there may be several criteria that influence route choice including, but not limited to, minimum time and minimum distance. Bovy and Stern (1990) indicate that route choice behavior is influenced by characteristics of the driver, the network, the trip, and other special circumstances. Drivers evaluate paths on both effort and comfort related attributes.

It is important to realize that there are several benefits to be derived by individual drivers who own and use IVRGS. By focusing only on the supply-side impacts of IVRGS there is a potential to overlook or underestimate the real benefits. For example, one might argue that the ability of IVRGS to reduce stress and anxiety by helping drivers make path choices is a real benefit to the consumer. Private developers of IVRGS systems clearly recognize that the market is consumer driven and many of the IVRGS currently available for purchase include provisions for drivers to select one of several criteria for path guidance. Also, real-time IVRGS has been in development for some time. NAVTECH and SmartRoute Systems in the United States have combined interests and recently tested a working system.

The purpose of this research is to gain insights into the supply and demand-side benefits of IVRGS that are capable of providing route guidance based on multiple criteria. Market penetration has important impacts on understanding both driver and network effects due to bi-objective IVRGS. Traffic simulation is used to explore changes in system performance under different rates of IVRGS market penetration. Sensitivity analysis is provided for ranges of traffic volumes and various relative weighting schemes for the multiple criteria specification. This research is an extension of previous work to examine the application of bi-objective path search for full-market penetration (Blue, 1996, Blue, et al., 1997). A formulation for multiple-objective user equilibrium was developed to enable the market penetration analysis. The paper begins by presenting some background on the proposed bi-criteria approach. This is followed by a description of the simulation framework and experimental design. The results of the experiment are then presented along with discussion of the study's implications and plans for further study.

2. BI-CRITERIA FORMULATION

Route choice is taken to be dependent on the perception of two route attributes, travel time and route complexity. Travel time is measured as in-vehicle travel time between the origin and destination. Path complexity represents a 'catch-all' category for representing effects that impact upon both the safety and comfort of the driving task. Paths having high complexity would include many turns and road changes, lane changing, interactions with pedestrians, maneuvering through complex merging/weaving movements. It can also represent travel on a path with unstable flow conditions resulting in 'stop and go' conditions and requiring braking or accelerating behavior.

A linear weighted additive sum of travel time and complexity is adopted:

$$Q_j = \alpha T_j + \gamma (1- \alpha) C_j \tag{1}$$

Where

Q_j = Trip Quality for a path j

T_j = Travel time on path j

C_j = Complexity of path j

γ = Scaling factor, here set to 2.0 to scale evenly with the trip times

α = Relative weighting (tradeoff) parameter in the range [0,1]

This functional form suggests a primary travel objective of minimizing trip quality cost. Q is interpreted as the inverse of trip quality. γ is used to scale Q to account for different units on T and C. This scaling improves the ability to interpret the non-dominated frontier of potential solutions. α provides for shifting driver routing preference. At $\alpha = 1$, route choice is based only on minimizing travel time; for $\alpha = 0$, only complexity is considered.

A linear function with two objectives is used for demonstration purposes only. It is not suggested that this function is representative of all drivers' behavior. In fact, it is likely that there are several objectives to be considered and a non-linear scaling function may be better suited to model driver choice. Also, a multi-class formulation may be warranted to capture variations in route choice behavior among different drivers. This is beyond the scope of this demonstration study. The purpose of this work is to examine the difference between using travel time as the sole path attribute of interest and incorporating a second attribute that captures a trade-off of travel time.

3. A BI-OBJECTIVE SHORTEST PATH ALGORITHM

Methods for applying multiple criteria decision making to network search problems are well established. Zeleny (1982) and Steuer (1986) provide a thorough introduction to the theory of multiple criteria decision making. Development and application of multiple objective shortest path (MOSP) algorithms able to handle both deterministic and stochastic problems are also well documented.

Within transportation, a significant body of work developing and applying MOSP algorithms exists in the area of routing hazardous materials (List et al., 1991). Application of MOSP algorithms to hazardous materials began with Cox (1984) who explored routing and scheduling decisions. List and Mirchandani (1991) used multiple-objective routing and siting for hazardous materials and waste. Turnquist and List (1993) have applied MOSP routing to emergency response in dealing with high-level radioactive waste shipments. List (1993) has also done emergency response team siting using four objectives: response time, risk, risk equity, and cost where the objectives are combined using weights that sum to one.

Blue et. al. 1997 devised a bi-objective path search algorithm that could be used to accommodate the goal to minimize trip quality cost as discussed in the previous section. This algorithm is derived from the above-mentioned work by List (1991, 1993), with added functionality to account for the turn costs used in the route complexity portion of the algorithm. Route complexity is estimated for a path based on the number of turning movements where each turning movement is assigned a cost, relative to an implied complexity level. For example, a straight link-to-link connection has a zero cost but a right or left turn would incur a cost based on the intersection type and turning difficulty. Permitted left turns would incur a higher cost than right turns. The total complexity cost is derived as an additive sum of all turning costs accrued on the path.

The algorithm presented here is specifically designed for the bi-objective search problem described above, 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 multiple-objective search to reach a node from several non-dominated partial paths. Thus each non-dominated partial path must be tracked.

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

TN = to-node
TLT = temporary label for time
TLC = temporary label for complexity
Q = trip quality = $\alpha TLT + (1-\alpha)TLC$
PL = permanent label that takes on one of three values: ∞ if the node has not yet been 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

In addition, the algorithm tracks the last index of the PPI vector (LAST) and the set of nodes that have been reached (R).

The algorithm is as follows:

(1) Initialization: Select origin node s. Let LAST=1; for PPI[LAST] set TN = s; TLT = 0, TLC = 0;Q, = 0; PRED = 0; PL = ∞. Set R = $\emptyset$. Select value for α, where $0 \leq \alpha \leq 1$.

(2) Iterations:

Step 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.

Step 2. With PPI[k] set PL = 1; TLT = TLC = ∞. If PPI[k].TN $\notin$ R then R = R $\cup$ PPI[k].TN

Step 3. Let i = PPI[k].TN. Find all nodes j adjacent from node i and assign for each reachable node j:

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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)
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Step 4. Domination Check: For all nodes 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 non-dominated value of complexity for that node n.

(3) Termination: The algorithm terminates when there is no non-dominated 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.

4. EXPERIMENT DESIGN

Simulation experiments were conducted to gain insights on the effects of bi-criteria routing on network performance. A small test network of 8 nodes and 15 bi-directional arcs was generated and is shown in Figure 1. This network has three origin nodes (11, 12, and 14) and a three destination nodes (17,19,20). A bottleneck scenario is created in arc 15-16 as most of the drivers would prefer a path that uses this arc. This network is representative of having three parallel roads, the middle one being the main facility that is also most attractive to drivers. It is flanked on either side by roads that at low demands are less attractive. A simulation period of one hour is used and departure rates are defined as triangular distributions that peak in the middle of the hour.

This small test network was designed to afford examination of travel patterns around a bottleneck scenario without the distracting effects of a larger network. The number of O-D pairs is limited as is the scope of routing options but there are distinct parallel paths that serve to handle transients from the primary paths that traverse the bottleneck arc. In this light, the network is representative of a real ITS-scenario in which drivers use IVRGS to reroute around congested links. The experiment, albeit based on a small network, is useful to demonstrate the supply-demand interplay that arises in ITS networks.

A microscopic traffic simulator developed by Blue (1996) is used to study the system. This simulation models the travel of equipped and unequipped vehicles through the network. Two user classes are defined for the experiment: equipped (vehicles with IVRGS) and unequipped. For each simulation run a single value of alpha is assumed for all travelers. The alpha value may be considered as the average over a distribution of drivers. This uniform alpha value assumption is not considered realistic or necessary for IVRGS to be effective in improving network flows, but permits a useful parametric comparison of routing strategies. Effects on market penetration are examined for two levels of alpha: 1.0 and 0.6. The former corresponds to the single objective travel time minimization routing strategy; the latter allows for some tradeoff of travel time for improvement in complexity.

Equipped Drivers: Dynamic Routing (DR)

When drivers equipped with IVRGS enter the network they are assigned an initial shortest path based on instantaneous travel times. The current path is reevaluated at each node based on updated travel conditions. Path search is accomplished with the multiple-objective path search algorithm (MOPSA) described above. Because of the tradeoff between travel time and complexity it is possible to generate several non-dominated paths between the origin and destination. Post hoc, the quality cost is derived for each non-dominated path from equation 1 above. The path having the minimum quality cost is selected as being optimal.

Unequipped Drivers: Equilibrium Routing (ER)

For a specific volume and value of alpha, a bi-criteria equilibrium assignment is performed off-line, before the simulation is run, to identify the best paths between each O-D pair. This is consistent with the approach used by Jayakrishnan et al. (1994). The assignment routine by Wu (1999) is based on Dial's (1996) bicriterion traffic assignment model. Dial proposed a value of time (VOT) formulation based on a linear generalized cost model. For this experiment, a generalized quality cost function formulation based on equation 1 above was implemented. Because the test network is small, the bi-criteria assignment was generated using AMPL, a programming tool designed to handle linear and nonlinear optimization. The results of the off-line assignment are a set of path splits, percentages of trips assigned to each route between an origin and destination pair. These splits are uploaded to the simulator and used to assign unequipped vehicles to specific routes as they enter the network. Path choice is not revisited for these drivers as they follow their pre-assigned paths to the destination.

5. SIMULATION RESULTS AND DISCUSSION

Simulation experiments were conducted for two levels of dynamic peak volumes: (a) free flow (800 vph) and (b) more congested flow (1500 vph). In order to obtain statistically significant performance of the stochastically applied departures and ER 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. The results are presented in the following section. The performance of equipped drivers (DR), unequipped drivers (ER), and the entire population (All) were processed post-hoc. The results for the unequipped drivers at 0% market penetration (all drivers are unequipped) were used as the baseline for analysis and the performance of the other two groups are computed relative to the ER group.

5.1 Free Flow Conditions under Low Volumes (800 vph)

Figures 2-5 show the simulation results over a range of market penetration rates for the network operating under low volume. Figure 2 depicts quality cost for the two driver classes and the aggregate at alpha = 1.0 (routing under travel time only). In this case there is essentially no difference in quality for DR and ER drivers. The small 0.15% variation can be attributed to noise resulting from the stochastic assignments of driver type (ER and DR) and paths used by ER drivers from their externally found assignments. This should be expected as under free flow conditions all drivers can use the least cost paths. At low volumes there is little benefit to using IVRGS for path selection.

Figures 3-5 indicate a comparison of DR, ER, and All drivers under the bi-objective case specified by setting alpha = 0.6. Here too, there is virtually no difference in quality cost over the three classes although some differences in travel time and complexity are evident. At low market penetration rates the improvement in travel times for equipped drivers is the highest (4.2% reduction for 10% market penetration). As market penetration increases, travel time benefits decrease where at 100% penetration there is a 2.7% improvement over the base case. The reason drivers with information do much better is that there is less interest in the minimum time routes by all drivers. The complexity values show that drivers with information reroute considerably– up to 20 percent more that the baseline initially and 10 percent more with full market penetration. The relative differences in ranges of trip time and trip complexity account for the large percent differences. The capability of using trip complexity as a measure of rerouting shows that it is also a useful performance measure of the changes in rerouting that occur as well as a driver goal to reduce.

5.2 Congested Flow (1500 vph)

IVRGS are expected to provide the most benefit during congested times. A second set of simulation runs was conducted at higher volumes. Figure 6 depicts the quality cost for alpha = 1. Over the ranges of market penetration there are slight benefits for equipped drivers. ER drivers experience same level of performance over the range and all drivers taken together consistently improve as penetration increases.

More significant savings are seen for alpha = 0.6. As is depicted in Figure 7, the quality cost for all drivers decreases for market penetration levels from 0% to 40% then they begin to rise. Equipped vehicles are better off until about 70% penetration. It is interesting to note that everyone is better off for all levels of penetration. Shifting vehicles to alternate paths provides benefits for the unequipped drivers as well.

Figure 8 shows savings in travel time for equipped drivers at alpha = 0.6. At 10% penetration equipped drivers enjoy a 5.6 percent improvement in travel time. Even until 100% penetration, equipped drivers do very well. The results for the alpha = 0.6 tradeoff between time and complexity is distinguished by a 5.6 percent improvement initially and a 2.7 percent improvement in travel time at full market penetration. ER drivers improve too and the entire system levels off at 40-50 percent market share. Complexity results, shown in Figure 9 are virtually identical to the 800 vph. case where DR vehicles are seen as diverting to more complex paths to achieve lower trip times and net quality improvements.

5.3 Comparing the bi-criteria case (alpha = 0.6) with the base case of (alpha = 1.0) at higher volumes

Figures 6-9 provide comparisons of DR and ER relative to the ER case at the given alpha level. The do not, however, depict the savings gained by going from alpha = 1.0 to alpha = 0.6. Figures 10-12 illustrate the savings when alpha = 0.6 is introduced. In these graphs, the results of the experiments with alpha = 0.6 are graphed against the base case of alpha = 1.0 and all unequipped vehicles.

Figure 10 illustrates the change in network performance, measured in quality cost, gained by moving to a bi-criteria approach. The level of improvement ranges from 21-22%. At market penetration of 0%, total quality cost for the case of alpha = 0.6 is 78% of the cost for unequipped drivers at alpha = 1.0 and market penetration level of 0%. In other words, the introduction of quality cost for alpha = 0.6 results in a 22% reduction in quality cost. In addition, the system enjoys improvements in performance until 40% penetration. Figures 11 and 12 portray the values for travel time and complexity under alpha = 0.6. It shows that under trade-off conditions, drivers are assigned to paths having slightly longer travel times but lower complexities. This result in lower overall quality costs as illustrated in Figure 10. For example, at a market penetration of 20%, the quality cost for equipped drivers is about 77% of the base ER. The average travel time is 3.5% higher but the average complexity is roughly 18% lower.

The simulation experiments reported in this paper attempt to show the differences in network performance when a bi-criteria approach to path choice is taken. Trip quality, measured as a linear combination additive function of travel time and trip complexity, is used to determine route selection. The alpha parameter is used to control path choice decisions between using travel time as the sole objective (alpha = 1.0) and adding trip complexity as a second determinant (alpha = 0.6).

From a pure systems perspective in which minimizing travel time is the primary objective, moving from alpha = 1.0 to alpha = 0.6 produces disbenefits. Travel times increase, albeit, by less than 10%. However, from the ATIS user community's perspective, the analysis indicates the opposite effect. Drivers who really tradeoff secondary attributes (such as complexity, number of turns, scenic route, etc.) realize significant benefits in trip quality. In this small-scale experiment, the quality cost decreases 22% from the single objective case. The small increase in travel time is offset by significant reduction in path complexity.

These results are significant on two levels. First, developers of IVRGS have become more sensitive to providing drivers with options to specify path choice objectives other than travel time. Tarry (1996), states "a number of private companies have begun to develop ITS which are not necessarily of benefit to the whole network but are aimed at specifically reducing the adverse effects of congestion to individual vehicles. ." Enabling drivers to select from multiple objectives enhances the “value” of these systems in the driver’s perspective. Second, it underscores the need to carefully evaluate benefits from ITS. Although it appears that the supply-side gets disbenefits because travel times across the network increase, it can be argued that drivers may really better off under this scenario. In a consumer driven market, the needs of IVRGS customers impact network operations and are critical to understanding and evaluating the system-wide benefits.

6. CONCLUSIONS

This paper expanded the set of parameters used in representing driver needs and evaluated the effect of bi-criteria route guidance on driver and network performance. It was shown that adopting a bi-criteria approach leads to significant benefits in user performance while incurring small increases in network-wide travel times. The results suggest that somewhat more complex norms are needed to represent and fairly evaluate individual user perceived benefits. Furthermore, since many drivers do not strictly aim to minimize travel time, more emphasis is needed on incorporating multiple-objective path search than is used in present-day network simulation and evaluation tools. As shown in this paper, the concept of trip quality is useful for describing driver’s perceptions of improvements in wayfinding.

Several simulation studies have been conducted over the years to explore changes in network performance arising from varied levels of ATIS market penetration. A majority of these studies based route choice on a single criterion -- minimizing travel time. The purpose of this study was to explore the effects of assuming a bi-criteria-based routing model. The simulation focused on only two user classes, with all drivers sharing the same travel objective tradeoffs. The effort was undertaken to examine and promote the concept of multiple criteria path choice and estimating demand-side benefits. It is recognized that the test network is rather small and the analysis confined by several simplifying assumptions. The arising supply-demand dynamics shown to exist in this test network are highly specific. Applying these specific experimental results to other networks is inadvisable. However, the methodology presented offers important insights in the context of IVRGS and network performance. From assuming that multiple objectives are important to drivers, we have simulated and analyzed of the effects of bi-objective route choice and determined that these bi-objective findings can overturn some of the prototypical results previously found in single-objective ITS network analysis for both drivers and networks.

Experiments on larger networks and with varying behavioral considerations across the driver population are appropriate and are planned. Work is underway to test assignments based on a larger set of non-dominated solutions, on other norms, on multiple norms, an on a distribution of the linear function to identify the best path. Using multiple norms is akin to Lee’s (1994) approach of k-shortest path assignment. In addition, experiments to explore the importance of route complexity with stated-preference surveys and/or interactive computer simulation are being considered.

It is recognized that travel choice behavior varies over the driver population. For IVRGS to make a significant impact, these systems will need to be more intelligent and capable of representing, if not understanding, the goals and tradeoffs of drivers. Adler and Blue (1998) discuss the evolution from ATIS to ITIS (Intelligent Traveler Information Systems). It is envisioned that intelligent systems that can learn and adapt to changes in driver behavior and network conditions will enable drivers to reap greater improvements in trip quality. These systems will also be capable of handling demands for multi-criteria route guidance. The work presented in this paper to model the effects of bi-criteria route guidance is relevant to bringing these ITIS systems on-line.

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Figure 1: Test Network

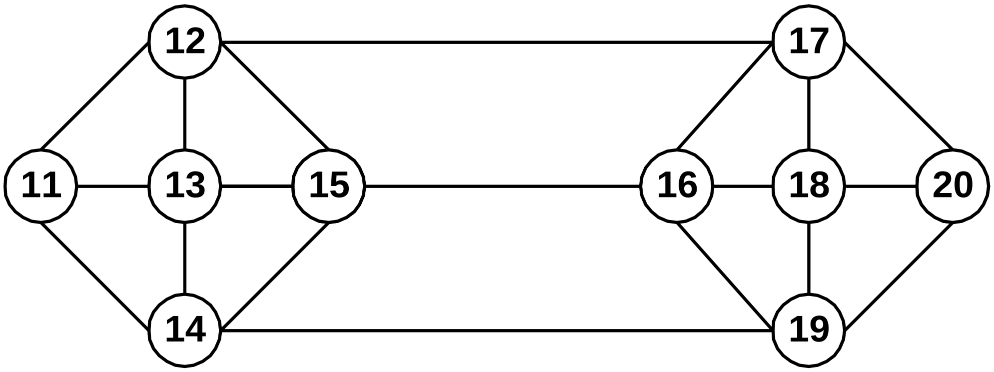

Figure 2: Quality Cost; 800 vph; alpha = 1.0

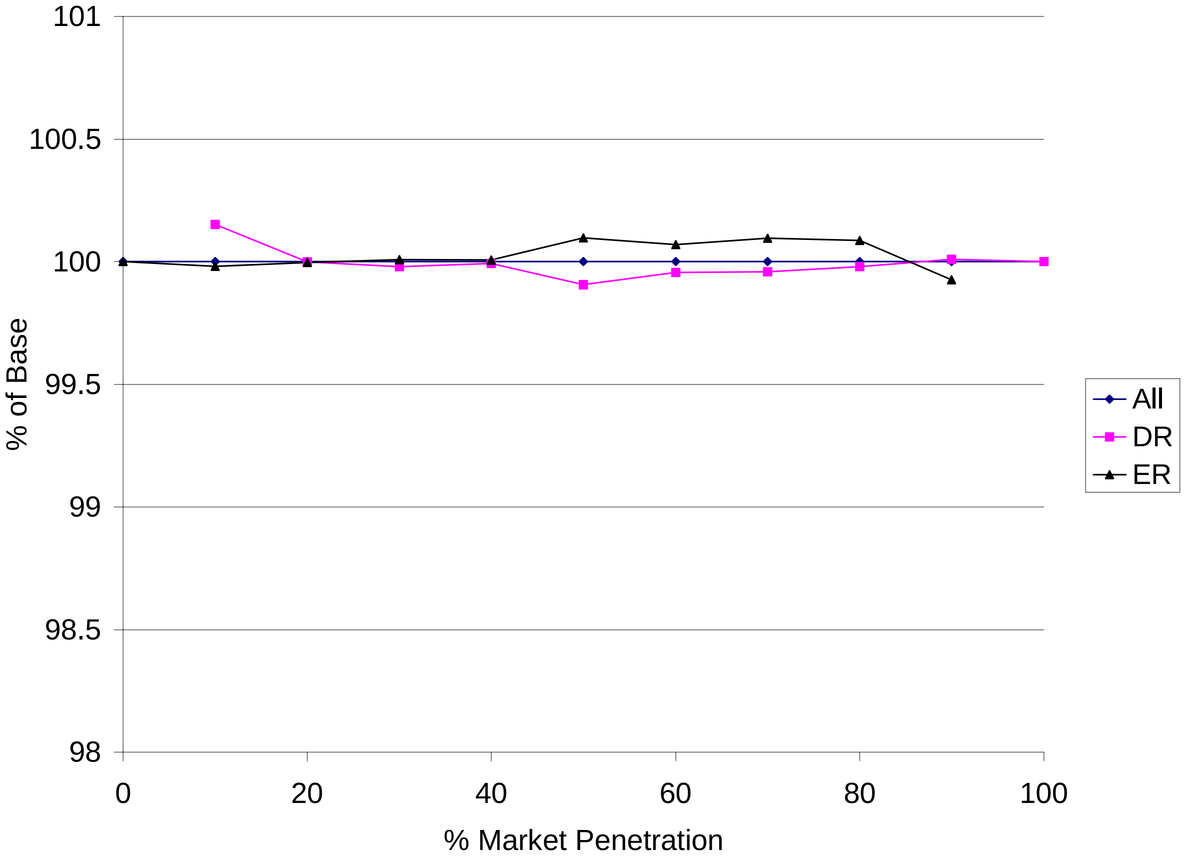

Figure 3: Quality Cost; 800 vph; alpha = 0.6

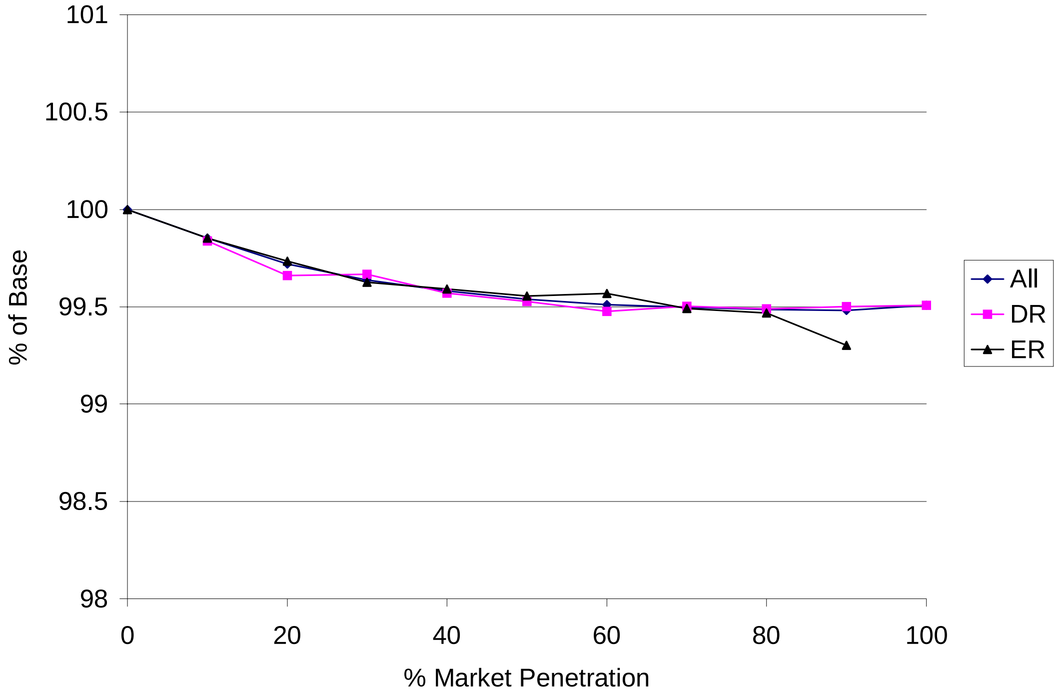

Figure 4: Travel Time; 800 vph; alpha = 0.6

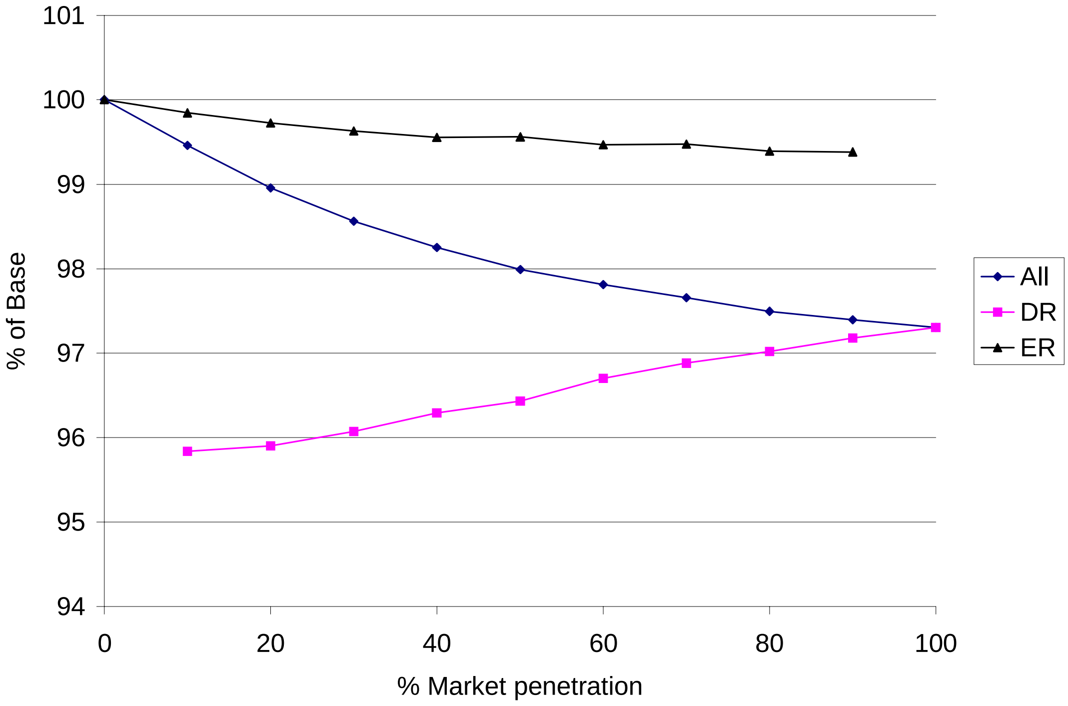

Figure 5: Complexity; 800 vph; alpha = 0.6

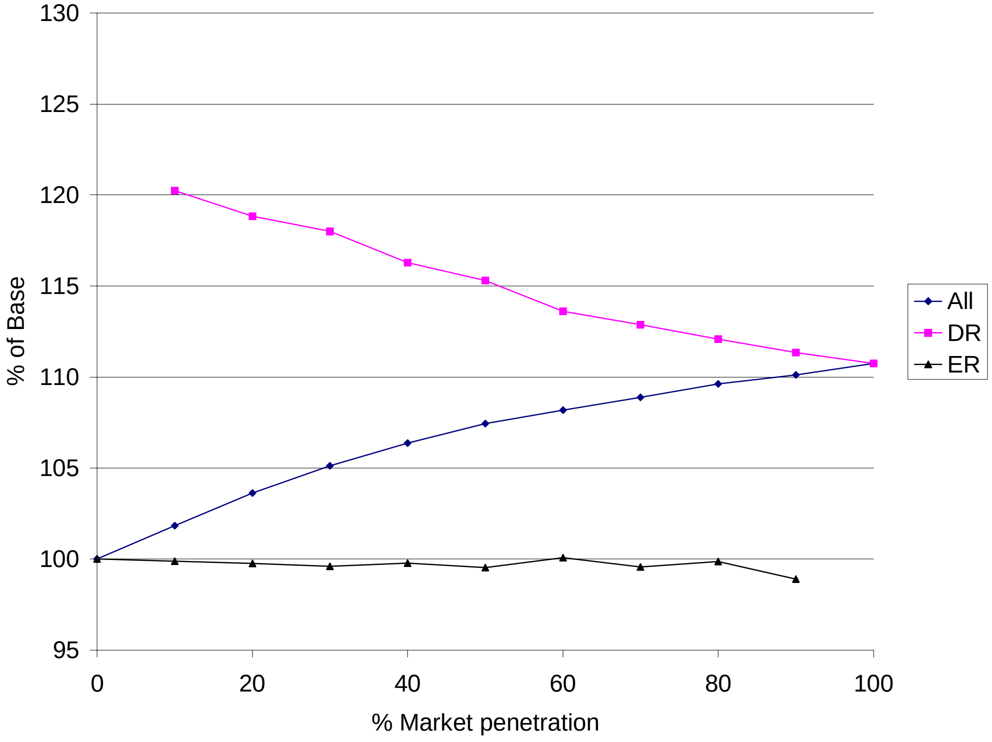

Figure 6: Quality Cost; 1500 vph; alpha = 1.0

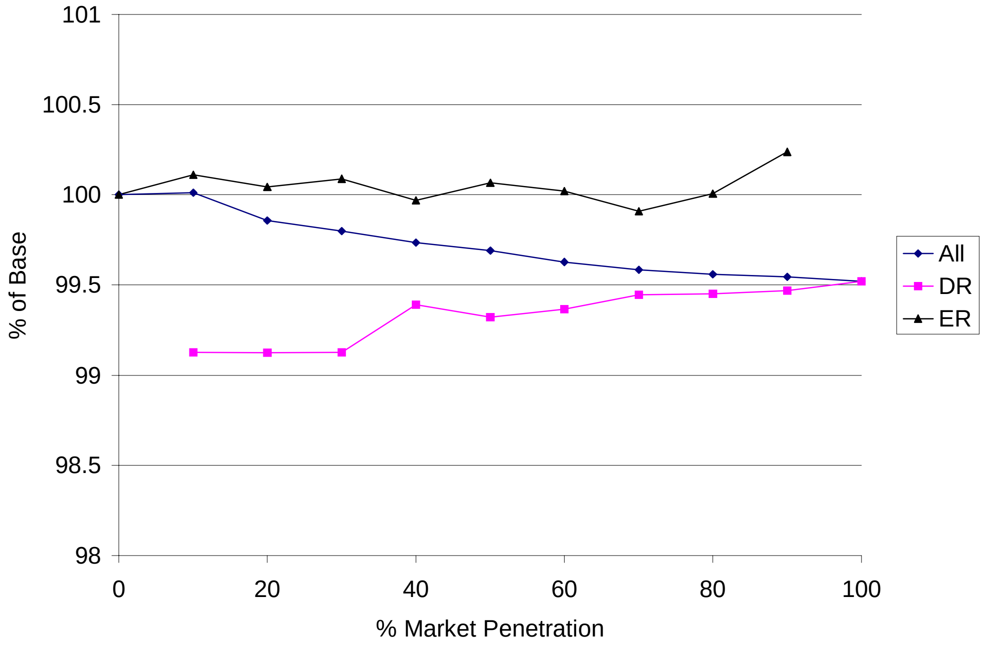

Figure 7: Quality Cost; 1500 vph; alpha = 0.6

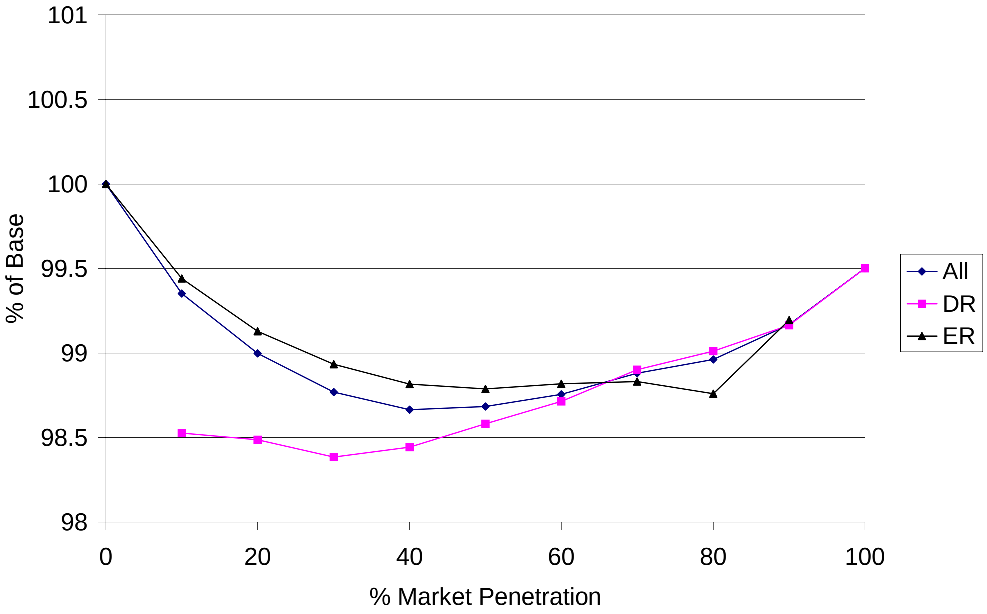

Figure 8: Travel Time; 1500 vph; alpha = 0.6

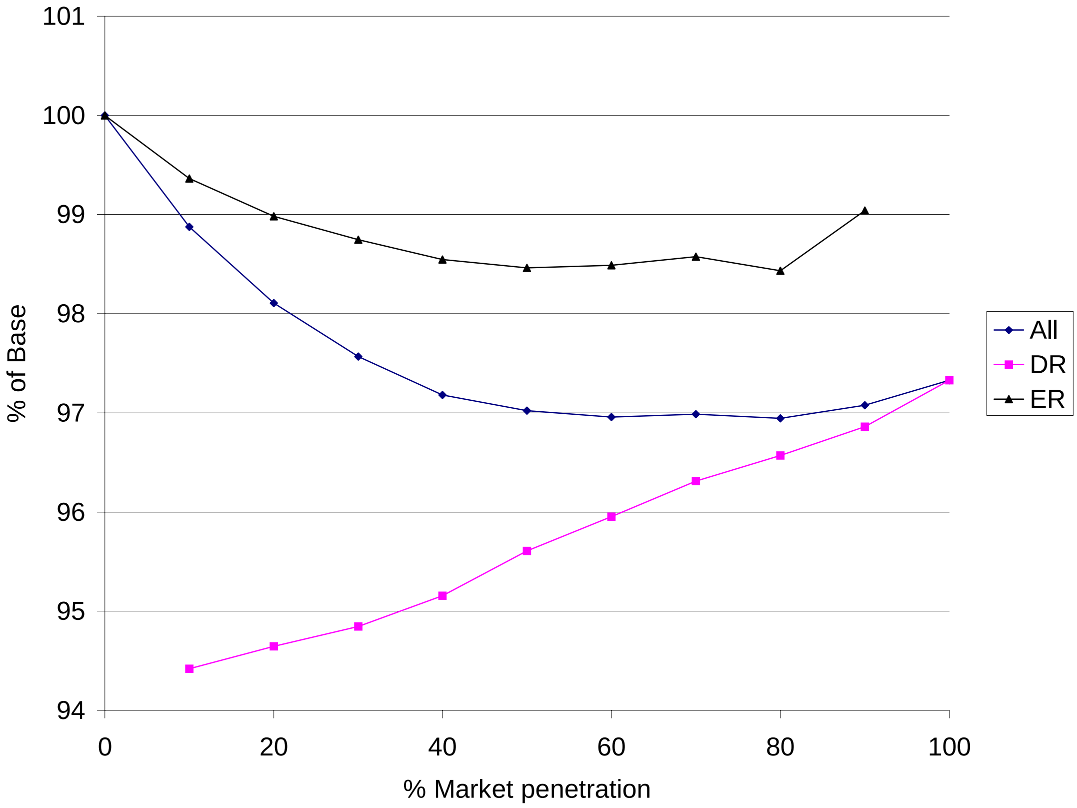

Figure 9: Complexity; 1500 vph; alpha = 0.6

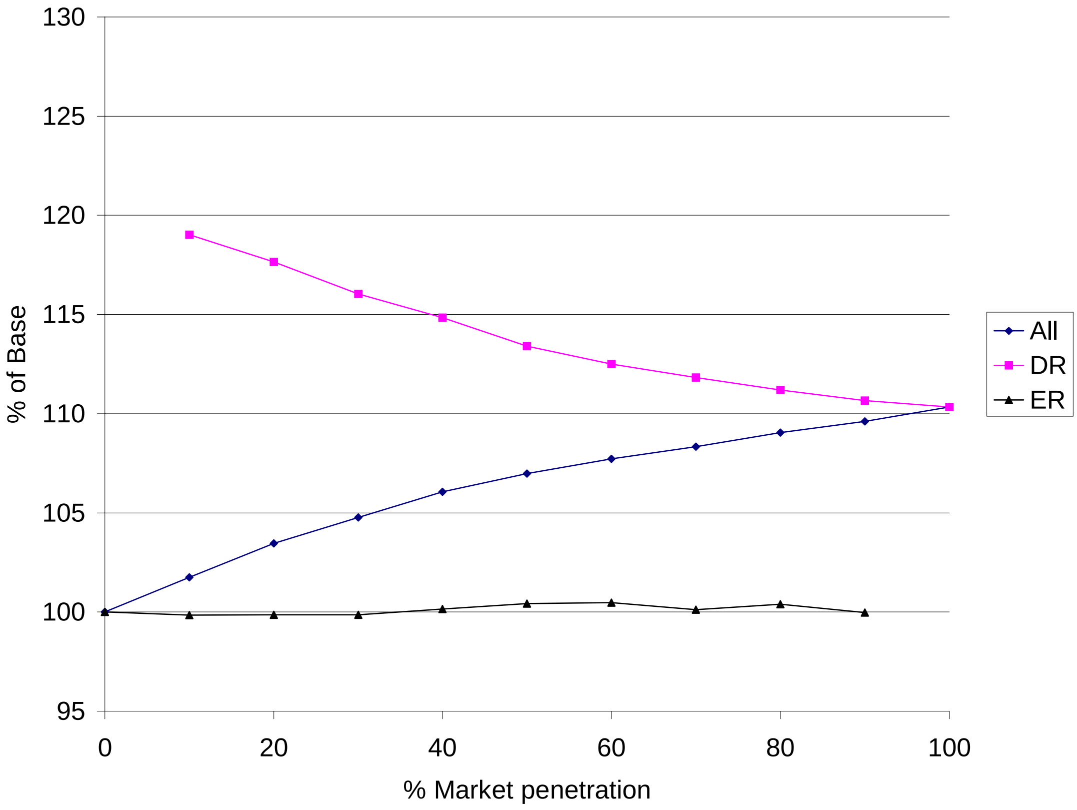

Figure 10: Quality Cost Comparison – 1500 vph

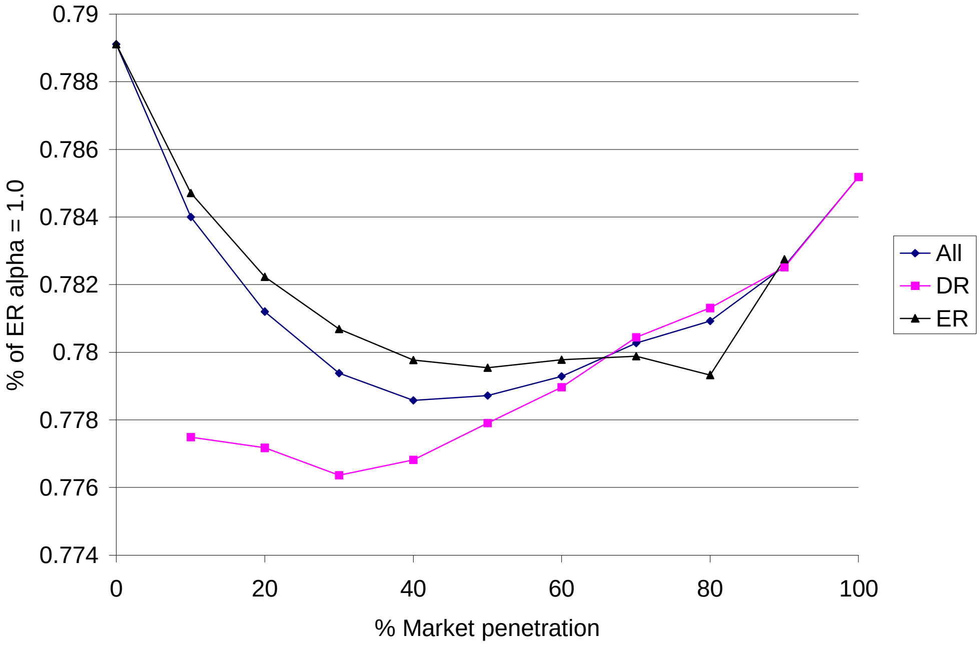

Figure 11: Travel Time Comparison – 1500 vph

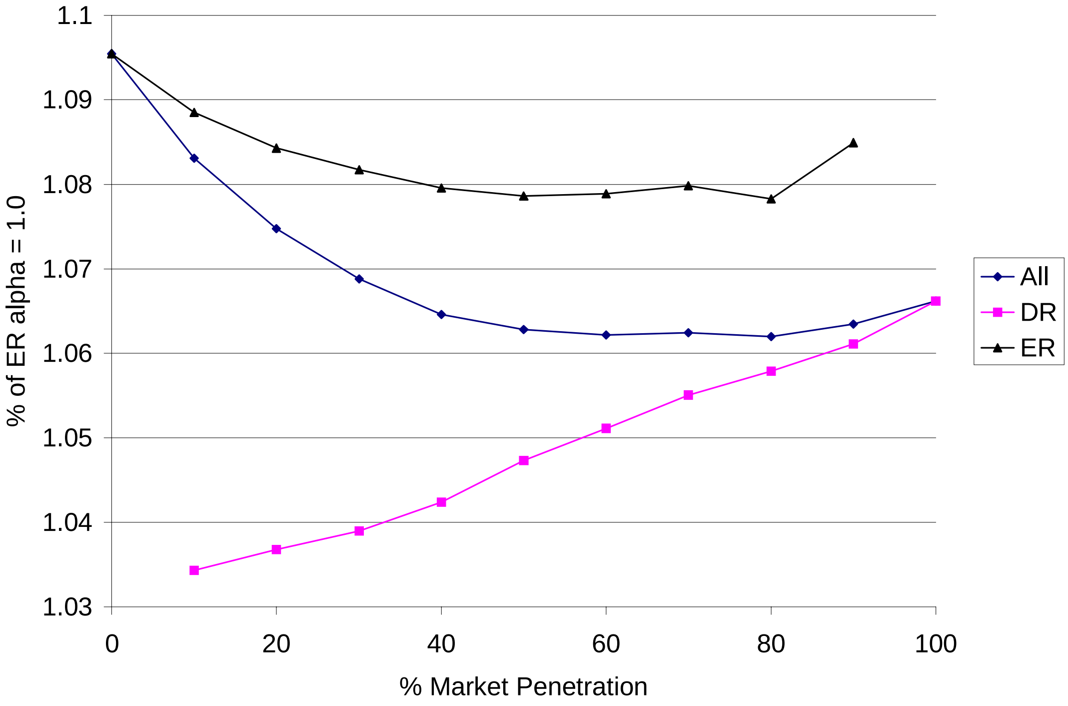

Figure 12: Complexity Comparison – 1500 vph