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**A Unifying Collection of Models and Techniques  
for  
ISTEA Management Systems**

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13. ABSTRACT (Maximum 200 words)  This report describes how two operations research decision making tools, Multicriteria Decision Making (MCDM) and Risk Analysis (RA), may be used in conjunction with transportation system modeling techniques to select amongst alternative transportation corridor improvement options. Each corridor improvement option is defined to have certain consequences with respect to the decision maker's goals. The measures of the consequences are estimated or forecast by the UMTA four-step modeling process and by traffic simulations using NETSIM. Air quality measures are estimated using MOBILE5a. Uncertainty in the future operating environment is also included in the procedure. The procedure is demonstrated through a simple hypothetical application in which two alternatives are compared. The example shows that the concepts involved are relatively easy to learn and use. Off-the-shelf software, which is available to implement these tools, provides useful sensitivity analysis features which are discussed as part of this paper.
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## INTRODUCTION

### Background

The 1991 Intermodal Surface Transportation Efficiency Act (ISTEA) mandated that each state develop and implement management systems for highway pavements, bridges, safety, congestion, public transportation and intermodal analysis. ISTEA also required eventual integration of the systems in the sense that the capability must exist for trade-offs to be analyzed across the six systems. The models and techniques embedded in some of the systems, such as pavement management and bridge management, are well-established since such systems have been operational for many years. However, other systems, such as congestion management, do not have widely-accepted paradigms. In addition, techniques for considering trade-offs across the six systems are still in the early stages of development and it is safe to say that no state transportation agency has developed true system integration. The results of this fragmented approach are inefficiency and sub-optimal solutions.

Integration across the six systems is important because there are many important decisions that cut across multiple systems. Consider, for example, a corridor study where various alternatives for transportation system improvement are being considered. The decisions that are made for that corridor will have effects related to congestion, safety, and perhaps public transportation and intermodal management. For major decisions such as this, individual management systems cannot be used in isolation; there must be some mechanism for integrating them so that they can be simultaneously considered when making major transportation system decisions. This need for integration also exists at the strategic, state- or region-wide levels of planning. The scope of the present study was limited to the corridor level of planning. Integration across systems was limited primarily to the congestion and safety management systems.

The project involved collaboration between the Universities of Connecticut (UConn) and New Hampshire (UNH). The major congestion management effort and integration across systems was the main thrust of the effort at UConn while the activity at UNH concentrated on developing a highway safety rating system and other considerations involved with safety management.

As more fully described below, two techniques of operations research, which are widely used in the private sector, were adapted and integrated for application to congestion management. The techniques, multi-criteria decision making (MCDM) and risk analysis (RA), are members of a larger family of decision support systems which are intended to promote orderly and expedient decision making.

Besides improved decision-making, reported benefits of decision support systems include:

- improved communication
- clarification of issues for stakeholders
- facilitation of informed debate

- assistance in building consensus
- identification of new approaches
- provision of defensible approaches to decision making
- assistance in handling unavoidable value trade-offs

The last item listed above is especially significant if the Congestion Management System (CMS) is to be integrated with one or more of the other management systems. Integration of these systems will necessitate an approach that incorporates the relevant multiple criteria that span across the six systems. Because MCDM can explicitly consider multiple criteria, its application within a congestion management system can facilitate that system's integration with the other systems.

It cannot be over-emphasized, however, that the techniques are intended to *assist* the decision maker, not *replace* him. Accordingly, informed involvement of all stakeholders is critical at all stages of the process. Conceptually, the potential benefits of application of MCDM and RA to any of the management systems is rather obvious; the unique contribution of the present research is the manner in which the two techniques are linked together and supported by other modeling (e.g. traffic and air quality).

An additional observation is in order at this point. Although the ISTEA management systems are now optional, the need for the systematic approach remains. Indeed, much of what would be required for project level congestion management is required of a major investment analysis (MIA). Moreover, ConnDOT notes that "...as substantial effort has gone into developing a CMS, including extensive coordination with MPOs, this Department will continue to produce this document. Additionally, the MPOs have found it to be useful, and they have endorsed its continuation."\* According to a recent article in "Congestion Management News", most states have similar views.<sup>1</sup>

Following a review of the literature in the next section, this report describes the methodology in detail. Two appendices give detailed descriptions of predictive modeling for highway crashes and delay, respectively. A third appendix discusses interactions between congestion and air quality.

## **State-of-the-Practice**

### *ISTEA System Implementation*

The status of implementation of the ISTEA management systems as of September 1996 was summarized in a 1997 report to congress<sup>2</sup>. This status is shown in Figures 1 through 7. While only 24 states were implementing all six systems, the remaining states indicated that they were developing and implementing at least three of the systems. Almost all states indicated that

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\* Richard Martinez, Chief of the Bureau of Planning, in a letter to Carl Gottschall, Assistant Division Administrator, FHWA, March 5, 1996.



safety and congestion management systems (the primary subjects of the present report) were either being implemented or under development. In many cases, states were developing systems tailored to their own needs. It is interesting to note also, that a primary thesis of our research, i.e., the need to integrate across systems, was recognized by over half of the states.

### *Congestion Management Systems*

Efforts to manage congestion pre-date ISTEA. For example, Nash<sup>3</sup> describes California legislation of 1989 and 1990 allocating funds for congestion management. Similarly, Kurtz<sup>4</sup> reviews efforts in Los Angeles County in the late '90s. Activity in other states since the passage of ISTEA is described by Mcleod<sup>5</sup> (Florida), the Texas Department of Transportation<sup>6</sup>, the North Carolina Department of Transportation<sup>7</sup>, Arnold<sup>8</sup>, and O'Brien and Jacobson<sup>9</sup>. The need for CMSs as well as a discussion of their general features is described by numerous authors, such as Hoefft<sup>10</sup> Lindley<sup>11</sup> Orski<sup>12</sup>, Arnott and Smal<sup>13</sup> Flynn<sup>14</sup> and Fleet<sup>15</sup>. The use of geographic information systems (GIS) as a tool for implementing management systems in general is described by Johnson and Demetsky<sup>16</sup>.

A description of CMS and discussion of performance measures and strategy evaluation is given in the text of a three day training course by the Federal Highway Administration (FHWA)<sup>17</sup>. The FHWA also published a Technical Report<sup>18</sup> giving case studies for several states and discussing performance measures. Performance measures are also described by Levinson et al.<sup>19</sup>. The proposed guidelines for the development of CMSs in Connecticut are given in a 1994 paper<sup>20</sup>.

### *Safety Management Systems*

Broad reviews of highway safety research in general are given by Judycki<sup>21,22</sup>. Strategic planning for highway safety was the subject of a 1987 workshop.<sup>23</sup> The accepted procedure for identifying and eliminating hazardous locations is given by Laughland et al.<sup>24</sup>. Safety management systems in particular are discussed by Hall<sup>25</sup> and Zogby<sup>26</sup>. Guidance on the implementation of *Safety Management Systems* is given by Wallen<sup>27</sup> and Bray<sup>28</sup>.

### *Multi-Criteria Decision Making and DRA*

The application of MCDM to transportation projects has been reported by a number of investigators. Won<sup>29</sup>, applied three different MCDM methods; concordance analysis, goals achievement matrix, and compromise solution, to auto restraint in Seoul. Giuliano<sup>30</sup> used a slightly modified concordance analysis to investigate nineteen transportation alternatives for the Santa Ana transportation corridor in Orange County, California, a source of prolonged peak hour congestion. Bielli<sup>31</sup> makes a case for the use of DSSs in dealing with the complexity of urban traffic systems with a large number of conflicting goals. Gomes<sup>32</sup> describes a MCDM technique that is easily understood by transportation decision makers and is particularly well suited for situations that require the participation of the public in the process. Kulkarni<sup>33</sup> and his associates used a formal decision analysis technique to evaluate alternative alignments for a proposed project wherein the main differences between the alternatives were the environmental and socio-economic

impacts of each. The linking of MCDM and DRA is described in a simplified example by Ossenbruggen<sup>34</sup>, who introduces the element of uncertainty in the design of a flood protection system. The element of uncertainty associated with transportation decisions is discussed by, among others, Khisty<sup>35</sup> and Lewis<sup>36</sup>. Finally, much of the work described herein builds on previous work by three of the present principal investigators<sup>37</sup>.

## METHODOLOGY

### Multicriteria Decision Making

As the name implies, MCDM involves deciding between several alternative solutions to a problem based on a tradeoff between multiple criteria or goals. For example, consider the design of an intersection. Further, assume that the design *alternatives* under consideration are (a) left turn bay and (2) no left-turn bay. Depending on the design chosen, a *consequence* will result. For the simple example, we might express the consequence in terms of construction cost, operating cost, air pollution, fuel consumption, and traffic accidents. Presumably, we would choose the design that would minimize each of the five components of the consequence. Unfortunately, in all likelihood, no such design would exist and we would need to make tradeoffs. The basic tool for displaying the tradeoffs is a *goals hierarchy*. The goals hierarchy for the intersection design is shown in Figure 1. Note that the overall goal is to select the "best design" and that several of the goals have been grouped. This grouping allows the goals to be more easily weighted. Also note that the original six components are represented by ellipses. We will refer to these as *measures* and to the higher level entities (rectangles) as *goals*.

The numbers shown next to the goals and measures shown in Figure 1 correspond to a set of weights which have been assigned. The set of weights chosen will be unique to each individual decision maker and must sum to one across a given level of the hierarchy. Shown inside of the ellipses are values of the measures that would be associated with a given design. It immediately becomes apparent that multiplying the measure values by weights would be meaningless. To overcome this difficulty, the concept of *utility* is introduced and the disparate measures are converted into common units termed *utils* which vary from zero (least preferred) to one (most preferred). The determination of the appropriate conversion functions is often one of the major tasks in the MCDM process.

Having established the appropriate utility functions, weights, and measurement values, the process of evaluating each alternative is straightforward. Each of the alternative solutions is evaluated by calculating its overall utility. The alternative having the highest utility is then the "best". While, as noted above, the technique is not intended to replace the experience and judgement of the decision maker, it can be a powerful tool when used to support the decision

making process.

## Risk Analysis

One of the shortcomings of standard MCDM techniques is that they cannot explicitly handle the uncertainties and sequential decision making that RA methods can handle. However, there is no reason why MCDM methods cannot be used in conjunction with RA tools like decision trees and influence diagrams. This type of approach is likely to be appropriate for transportation system planning in general and congestion management in particular because key future events (such as the availability of federal funding and regulations, and predictions made by the transportation modeling process) have a significant degree of uncertainty, and major decisions are likely to depend on the outcomes of these events. For models to be useful in practice, such dependencies must be explicitly incorporated into the analysis.

The basic tool of RA is the *decision tree*, shown schematically in Figure 2. The decision-maker (DM) must choose between alternatives  $a$  and  $a'$ . Depending on the alternative selected, a "consequence",  $C$  or  $C'$  is reached. The DM would select the alternative leading to the most preferred consequence. In general, the consequence would be represented by a vector of attributes, i. e.,

$$C : [x_1, x_2, \dots, x_i, \dots, x_n] = X \quad (1)$$

where the  $x_i$  are in disparate units of measurement. In our simple intersection example, the  $x_i$  are the five measures. As noted earlier, the disparate measure values must be converted into utilities so that the weighting can be made.

## MCDM and RA Combined

Figure 3 shows, conceptually, how MCDM and RA can be coupled. Note that each end of a branch of the decision tree represents the *state of nature* arising from the indicated sequence of decisions and chance occurrences along the branch. In the tree shown, the top entry is the utility of having made decision A and then experiencing the outcome 1 of the chance event 1 followed by outcome 1 of the chance event 2. Knowing the state of nature, an overall utility can be obtained using the techniques of Section 3.1. The *expected* overall utility of each alternative is obtained by working backwards, weighting the overall utilities by the various probabilities.

Perhaps the most challenging aspect of using MCDM is obtaining inputs to build the model from those persons most knowledgeable about the decision at hand. The next subsection summarizes the interactions that occurred to obtain inputs needed for the development of the congestion management model.

## MODEL BUILDING

### The Cooperative Effort

In response to ISTEA, ConnDOT proposed the following two-tiered approach for a congestion management system:

Tier 1: a statewide system of annual reporting and monitoring;

Tier 2: 15 separate regional systems for the purposes of evaluating and implementing congestion reduction strategies.

Under this proposed approach, tier 2 is the joint responsibility of ConnDOT and each MPO (Metropolitan Planning Organization). The present project explored the applicability of MCDM and RA techniques to congestion management decisions with an eye towards incorporating the techniques as part of the second tier of ConnDOT's proposed system.

The specific objectives of this project were as follows:

- A) To build an integrated MCDM and RA model that could be useful for supporting congestion management decisions.
- B) To adopt one or more of these models to assist in decision-making for a specific congestion management application within one of the state's MPOs.
- C) To present the results of the application described above to other MPOs as a way of encouraging additional use of D&RA techniques for other congestion management applications.

Throughout the project, the research team worked closely with personnel from the ConnDOT Bureau of Planning and CRCOG. Following a literature review of the state-of-the-practice of congestion management, the team reviewed alternatives, evaluation criteria, and performance measures that have been identified as being relevant to congestion management.

### The Integrated Models

The linking of models and the flow of information for the overall process are shown in Figure 4. Note that two models have been added - a traffic simulation model (NETSIM) and an air quality model (MOBILE5a). These models are required to transform network characteristics and origin/destination tables for the various *alternative/scenario combinations* into measurement values required as input to the MCDM model. Additional measurement values, not related to traffic modeling, are input directly. In the term *alternative/scenario combination*, *alternative* refers to a particular congestion management strategy, e.g. increased transit, and is the choice of

the decision maker. The term *scenario* refers to a state of nature defined by specified outcomes of all chance events.

Output from the MCDM model consists of utility scores for all alternative/scenario combinations. This output, along with user supplied probabilities, is then input to the RA model which determines the "best" alternative. Because commercially available software packages are available used for the MCDM and RA modeling, that part of the overall process can be completed with relative ease.

### **AN EXAMPLE - THE ROUTE 99 CORRIDOR**

The 3-mile Route 99 corridor in the Town of Whethersfield, Connecticut, shown in Figure 5, served as a test application of the process. The City of Hartford is to the immediate north of the corridor.

Because the cooperating agencies did not want to complicate on-going studies, several of which are controversial, the approach taken for this test case was a retrospective one. The corridor had recently undergone improvements and the process was applied to the conditions existing in the corridor *prior* to the improvements. At that time, Route 99 was a two lane major urban arterial with numerous commercial developments and strip shopping centers on both sides. Note also that Interstate 91 shares the corridor and that Route 99 would serve as a diversion route should an incident occur on Interstate 91.

The goals hierarchy for the MCDM portion of the process is shown in Figure 6. Note that there are 17 measures arranged in six major groups reflecting tradeoffs beyond just congestion. For this example, only two alternatives were considered - do-nothing and increased transit. The uncertainties involved were projected economic growth of the region (high or low) and, in the case of the transit alternative, transit demand (high, medium or low).

Table 1 gives the values of the measures for each alternative/scenario combination. As noted earlier, those measures related to traffic, e.g., person mph and emissions, were obtained from the simulation model NETSIM and, in the case of emissions, the air quality model MOBILE5a. Many of the other values were assumed for this simple example. Measures such as citizen reaction and environmental justice are on user defined-ordinal scales varying from 1 (no impact) to 5 (large impact). Figure 7 shows the utility functions assumed for these two measures. Note that both of the curves are monotonic decreasing, reflecting a decrease in utility with an increase in impact. The utility function for citizen reactions shows an accelerated decrease in utility with increased impact. The weights used are shown in Figure 8. Note that the weights under the "Overall Utility" goal sum to one. The weights given for the various measures under the eight sub-goals sum to their respective weights under the overall goal. For example, the sum of the "Air Quality" weights is 0.15.

The output of the MCDM model is shown in Table 2 for each alternative/scenario

combination. It can be seen that the highest utility (0.7846) is associated with the do-nothing alternative with low economic growth. In order to determine the preferred alternative, however, it is necessary to account for the uncertainties involved. This is done using the decision tree shown in Figure 9(a), where the probabilities shown on each of the branches have been assumed. The analyzed decision tree is shown in Figure 9(b). As may be seen, the resulting preferred alternative is do-nothing with an expected utility of 0.7335.

## 6. Summary and Conclusions

Even though the prescribed ISTEA management systems are no longer required, most states and MPOs have experienced benefits from developing and implementing them. This paper describes an application of two operations research decision making tools, MCDM and RA, for the implementation of a congestion management system for selecting among corridor improvement options. The concepts underlying these tools are well proven in other application areas in the operations research literature. They are quite helpful for choosing among competing alternatives when the decision maker is forced to satisfy several potentially conflicting objectives in the face of uncertainty about the future operating environment.

These two tools were combined along with transportation system modeling techniques. Each alternative is defined to have certain consequences with respect to the decision maker's goals. These consequences are then represented by one or more measures which gauge compliance with the goals. The measures are estimated or forecast by appropriate models; here congestion and vehicle travel measures are modeled using trip tables generated by the UMTA Four-step modeling process and by traffic simulations generated using NETSIM. Other quantities are forecast using Air Quality models, or are estimated. Uncertainty in the future operating environment is also included in the procedure.

The procedure is demonstrated through a simple application in a suburban Connecticut highway corridor. Two alternatives were compared, an improvement in transit service in the corridor, and doing nothing. The procedure was applied, considering traveler response to the improved transit service and the preferred alternative was revealed. This limited example shows how the procedure can be applied to other corridors, with more alternatives and with more complicated modeling of measures.

This method has been demonstrated to recommend an optimal alternative for a transportation system investment decision considering multiple objectives as well as forecast and conditional uncertainties, both prevalent in transportation investment decisions. The concepts involved are easy to learn and require no mathematics beyond simple arithmetic. Off-the-shelf software is available to implement these tools; this software is easy to install and use, as it is designed for management professionals with little computer expertise. The software also provides sensitivity analysis along with the optimal decision to show the factors and objectives to which the estimated utility ratings are most sensitive. This helps the decision maker to judge which goal weights are most critical to establish with greater certainty.

There are several ways in which this procedure can be made more effective for ongoing implementation. Use of Geographic Information System coverages would make reporting of information to stakeholders more convenient and provide the interactive capability required to achieve consensus. Full integration of the traffic and air quality forecasting models into the procedure would permit smoother application. The procedure, as described here, must be set up individually for each traffic corridor to be studied. Implementation of the suggested enhancements might permit the procedure to model an entire region, with subareas extracted as needed without excessive labor involved with setting up the modeling framework.

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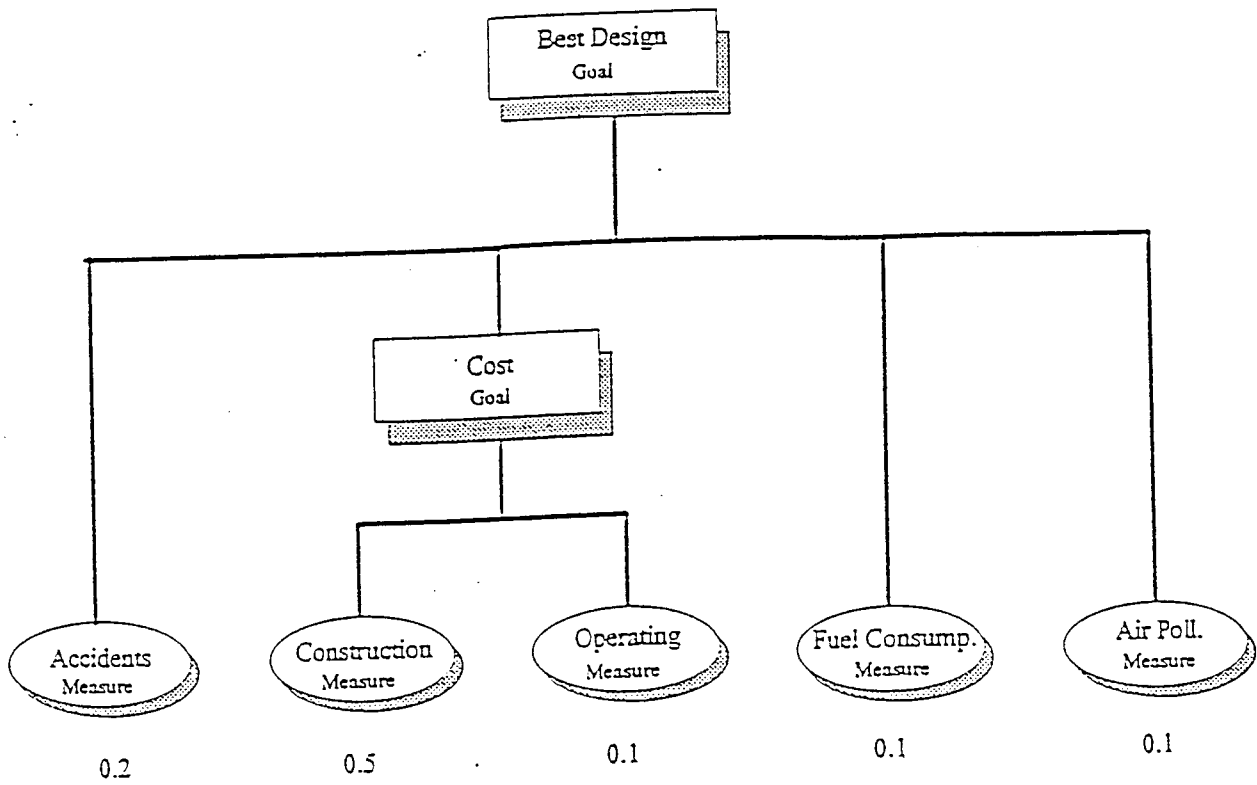


Figure 1. Goals hierarchy for intersection design.

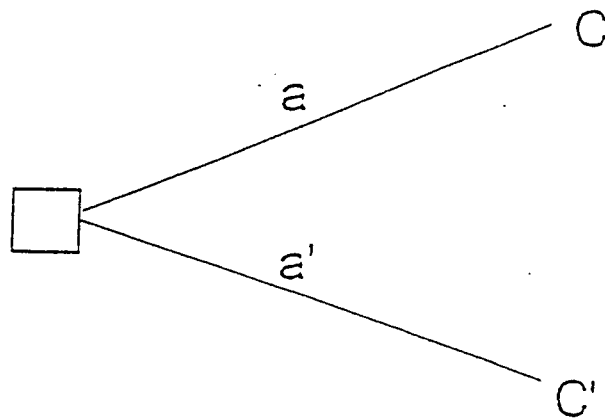


Figure 2. Simple decision tree.

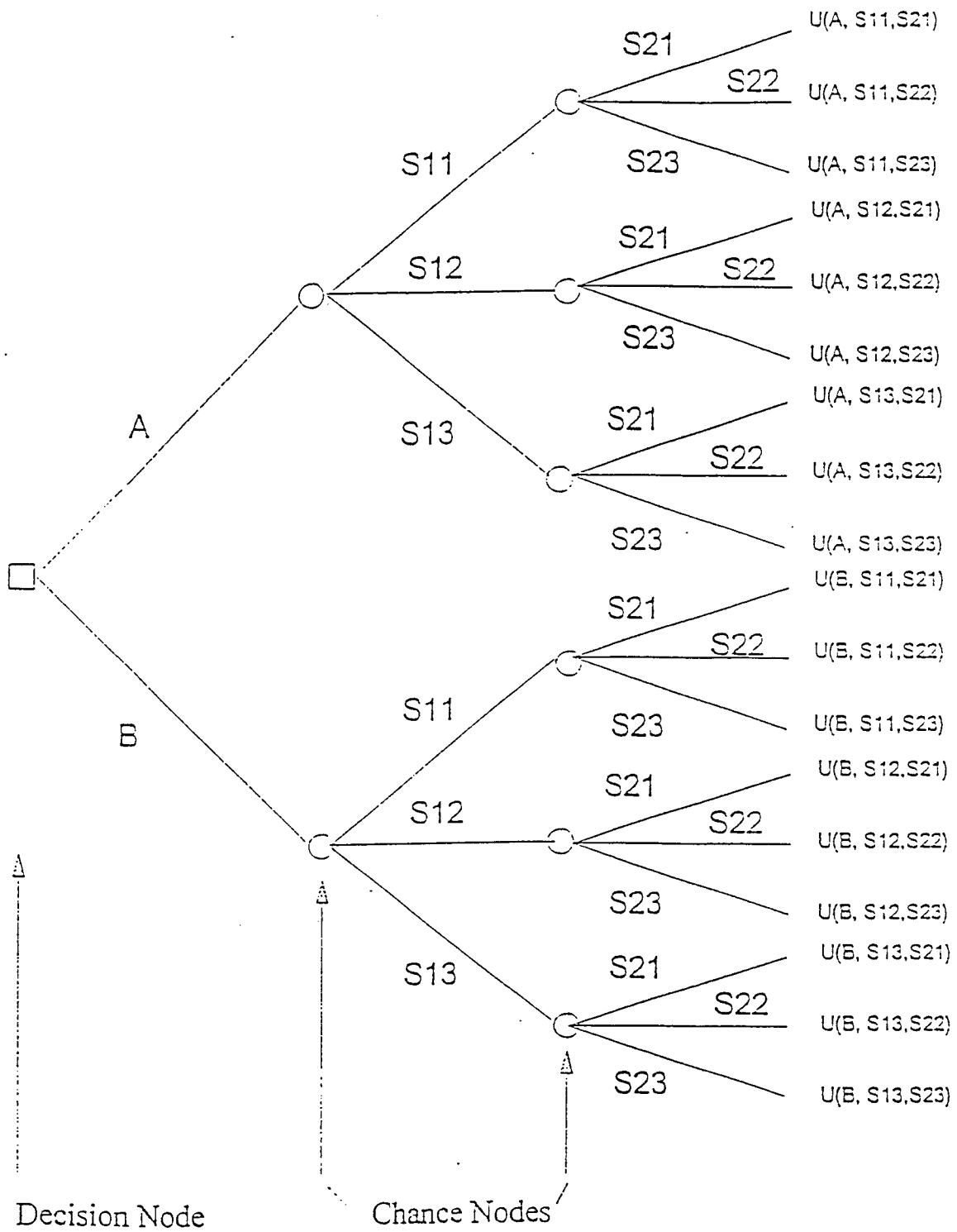


Figure 3. Coupling of MCDM and RA.

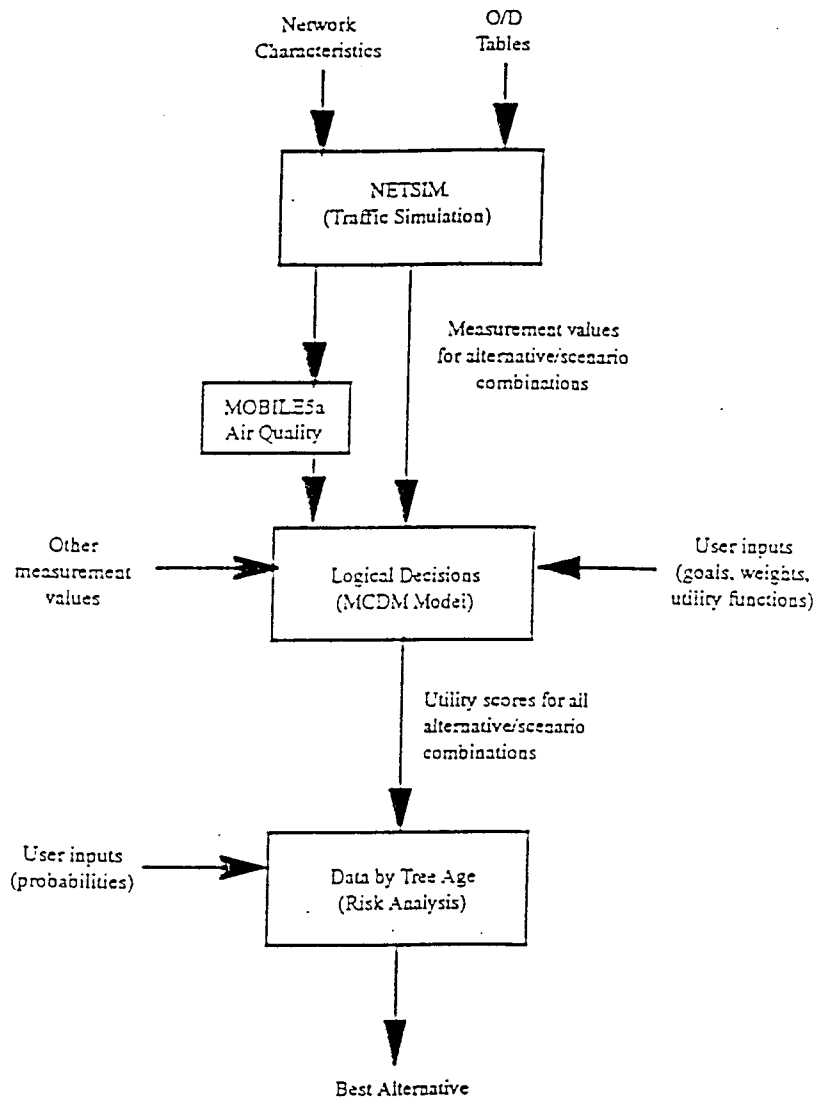


Figure 4. Modelling framework.

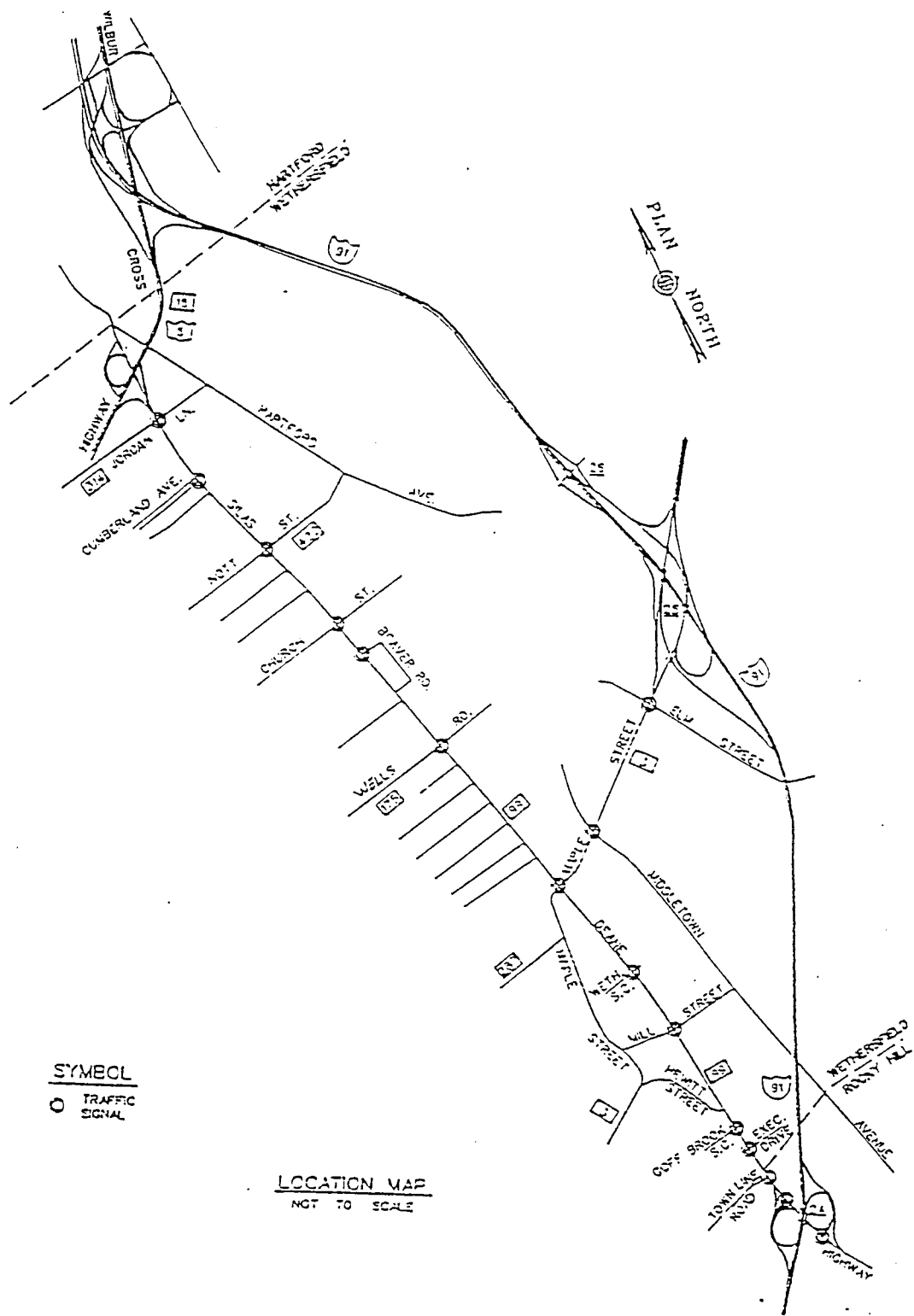


Figure 5. The Route 99 corridor.

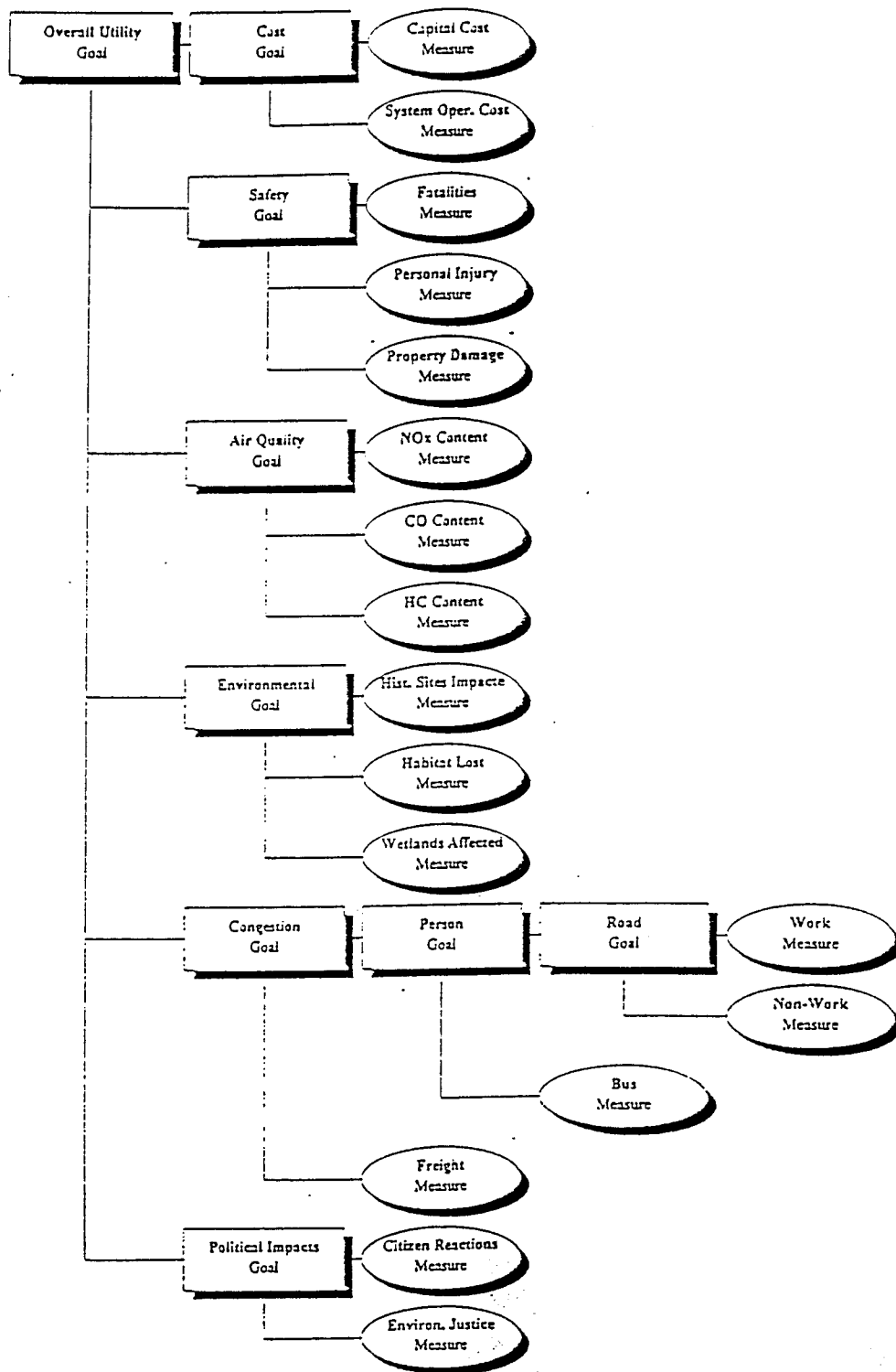


Figure 6. Goals hierarchy for the MCDM Model.

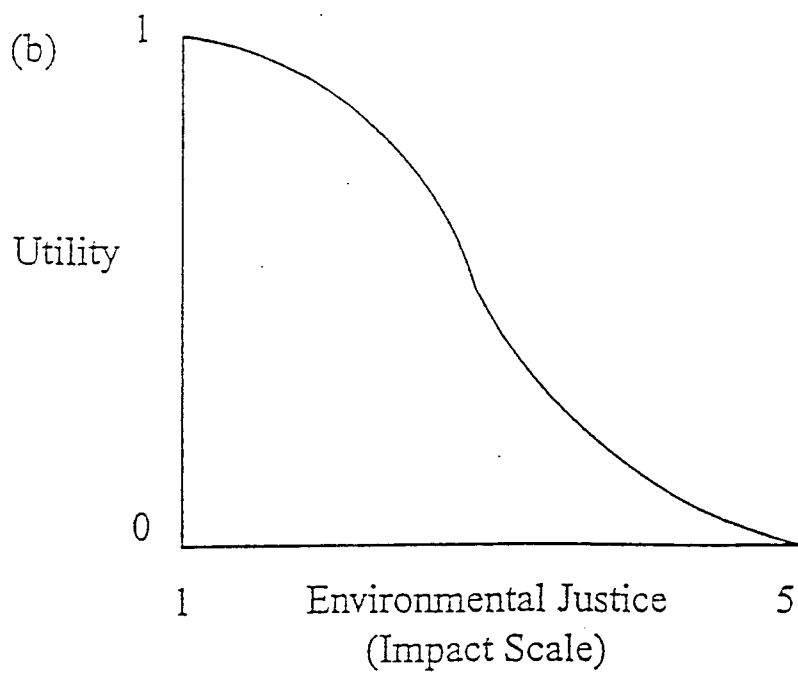
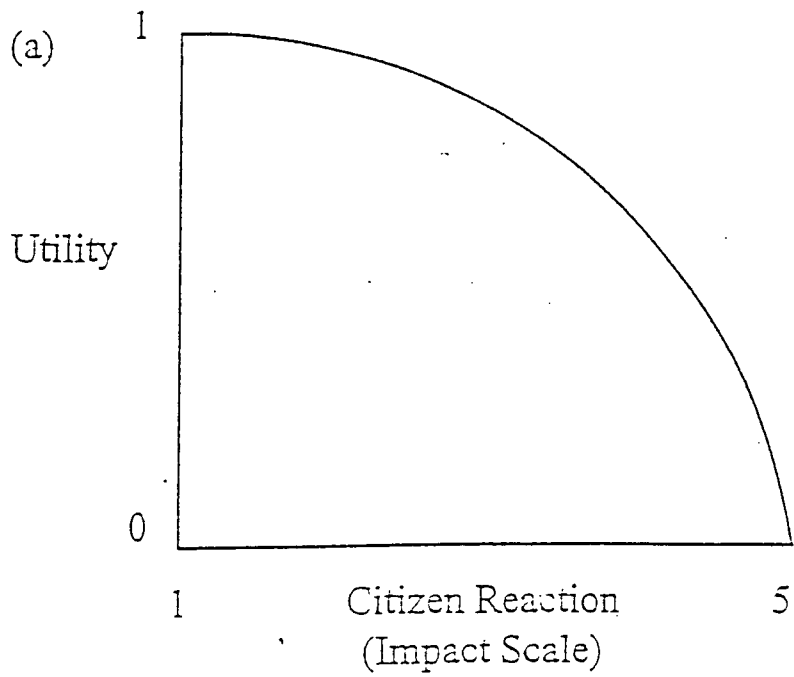


Figure 7. Utility functions for (a) Citizen Reaction and (b) Environmental Justice.



Weights under Overall Utility Goal

Congestion Goal weight = 0.30  
Air Quality Goal weight = 0.15  
Cost Goal weight = 0.15  
Safety Goal weight = 0.15  
Environmental Goal weight = 0.15  
Political Impacts Goal weight = 0.10

Weights under Congestion Goal

Person Goal weight = 0.2100  
Freight Measure weight = 0.0900

Weights under Air Quality Goal

NOx Content Measure weight = 0.0500  
CO Content Measure weight = 0.0500  
HC Content Measure weight = 0.0500

Weights under Cost Goal

Capital Cost Measure weight = 0.0750  
System Oper. Cost Measure weight = 0.0750

Weights under Safety Goal

Fatalities Measure weight = 0.0900  
Personal Injury Measure weight = 0.0450  
Property Damage Measure weight = 0.0150

Weights under Environmental Goal

Wetlands Affected Measure weight = 0.0600  
Hist. Sites Impacts Measure weight = 0.0450  
Habitat Lost Measure weight = 0.0450

Weights under Political Impacts Goal

Citizen Reactions Measure weight = 0.0700  
Environ. Justice Measure weight = 0.0300

Weights under Person Goal

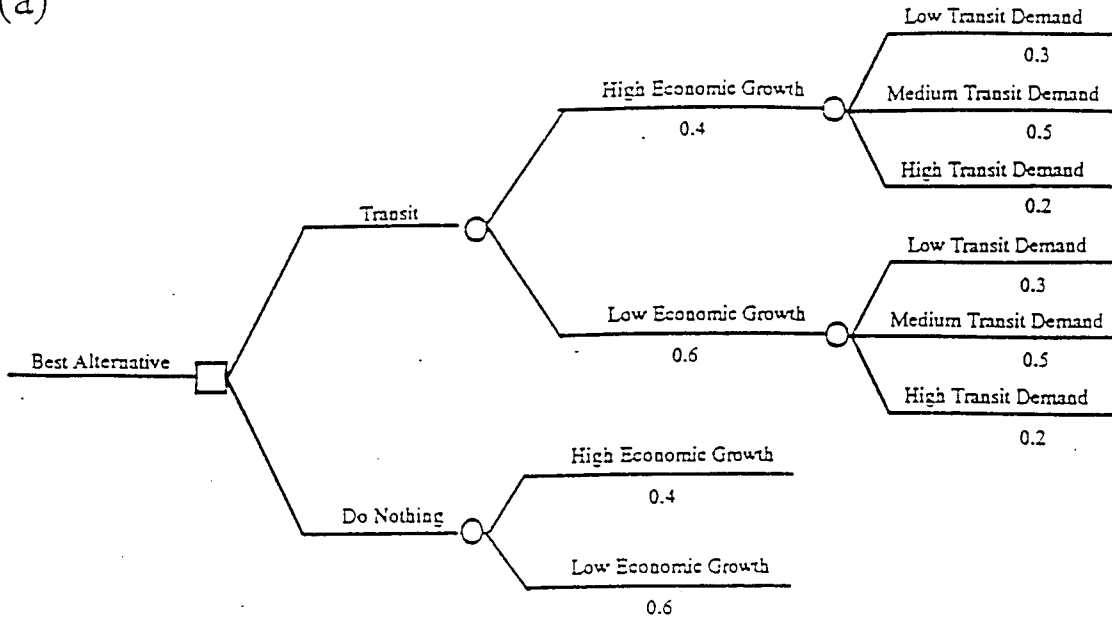
Road Goal weight = 0.1260  
Bus Measure weight = 0.0840

Weights under Road Goal

Work Measure weight = 0.0832  
Non-Work Measure weight = 0.0378

Figure 8. Example of weights for MCDM model.

(a)



(b)

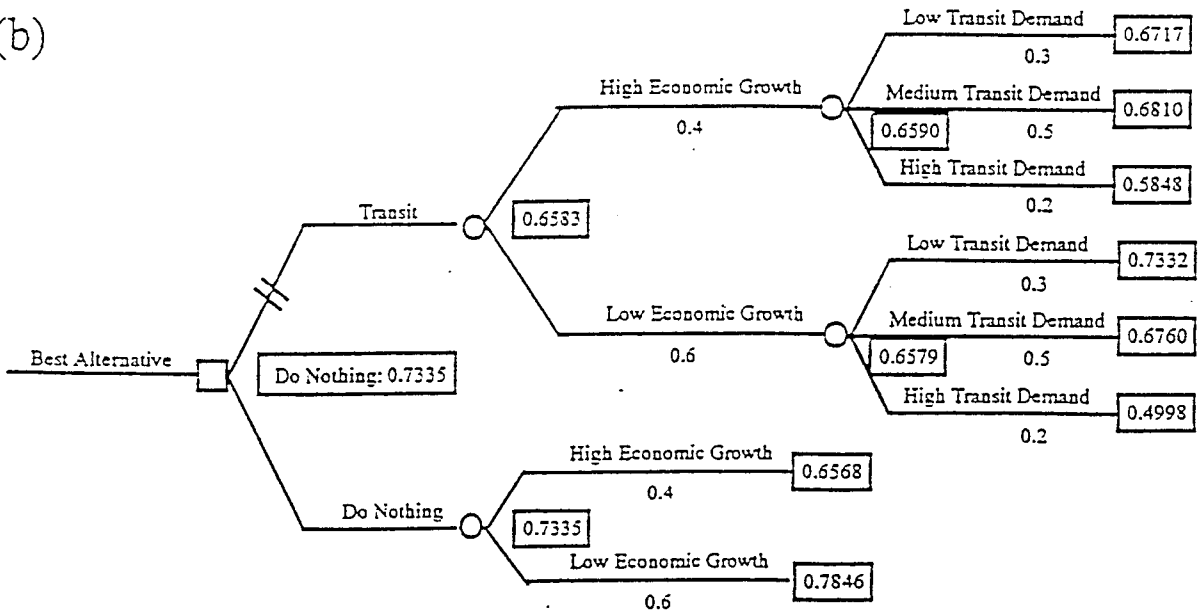


Figure 9. (a) Decision tree and (b) analyzed decision tree.

Table 1. Measure values.

	Do Nothing		Transit					
	High Econ	Low Econ	High Economic Growth			Low Economic Growth		
			High demand	Med demand	Low demand	High demand	Med demand	Low demand
Capital Cost (\$M)	0	0	25	25	25	25	25	25
Sys Oper Cost (\$M)	0	0	1	1	1	1	1	1
Fatalities (/year)	3	3	1	1	1	1	1	1
Pers (Inj/yr)	8	7	3	3	3	3	3	3
NOx (1000gm)	4.053	3.951	5.824	4.694	4.046	5.174	4.560	3.947
CO (1000gm)	24.816	22.658	24.191	24.171	24.186	24.937	23.280	22.894
HC (1000gm)	4.656	4.323	4.648	4.637	4.668	4.356	4.461	4.390
Hist Sites Impacted	1	1	2	2	2	2	2	2
Habitat Lost	1	1	2	2	2	2	2	2
Wetlands Affected	0	0	10	10	10	10	10	10
Freight (pers-mph)	5696	5827	5623	5786	5772	5489	5696	5782
Work (pers-mph)	60303	60610	56048	58929	60035	54708	58014	60133
Non-work (pers-mph)	140707	141423	130779	137502	140083	127653	135366	140310
Bus (pers-mph)	39173	40471	195262	120560	40088	190546	118686	40152
Citizen Reaction	1	1	1	1	1	1	1	1
Environ. Justice	2	2	2	2	2	2	2	2
Property Damage (\$/year)	30000	30000	10000	10000	10000	10000	10000	10000

Table 2. Example of utility score output from MCDM Model.

Ranking for Overall Utility Goal

Alternative/Scenario	Utility
Do Nothing/High Econ	0.6563
Do Nothing/Low Econ	0.7846
Transit/High Econ/Low Demand	0.6717
Transit/High Econ/Medium Demand	0.6310
Transit/High Econ/High Demand	0.5343
Transit/Low Econ/Low Demand	0.7332
Transit/Low Econ/Medium Demand	0.6760
Transit/Low Econ/High Demand	0.4993

## APPENDIX A

### Effectiveness of Progression Quality Estimation Procedures for Signalized Intersections<sup>1</sup>

The Highway Capacity Manual (HCM) (1) embodies the most complete and authoritative collection of empirical techniques for assessing the quality of highway traffic flow available. Originally published in 1950, the manual has been revised numerous times and is, with some rare exceptions, universally accepted in the U.S. Chapter 9 of the HCM, dealing with signalized intersections, is probably the most widely used chapter. In the present (1994) version of the HCM, the performance of an intersection is quantified by the *capacity* and by the *level of service* of each intersection approach individually and of the intersection as a whole. The level of service is based on the average stopped delay (seconds per vehicle).

When the intersection being analyzed is part of a coordinated system, a very important determinant of performance is the quality of progression in the system. If the intersection is in existence at the time of the analysis, the quality of progression may be readily determined by field observations. If it is not, some technique must be used for estimating the progression quality. Several techniques for making this estimate have been suggested. Whichever technique is used, effort is involved in collecting data and carrying out the analysis. Thus, the questions arise:

- Is there any difference in the predictive capability of the available techniques?
- If so, which of the techniques is best under a given set of conditions?

Moreover, since the entire calculation of delay is itself an estimate, we might also reasonably ask how large the progression quality prediction error must be before it significantly affects the overall results. The research described below was directed at answering these questions.

#### BACKGROUND

The HCM gives the following empirical equations for estimating delay:

$$d = d_1 DF + d_2 \quad (1)$$

$$d_1 = 0.38C \frac{[1 - (g/C)]^2}{[1 - (g/C) \{ \text{Min}(X, 1.0) \}]} \quad (2)$$

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<sup>1</sup> Taken largely from: Braun, S. M., *The Effectiveness of Using Traffic Signal Progression Quality Estimation Procedures in Conjunction with the 1994 Highway Capacity Manual Signalized Intersection Delay Model*, M.S. Thesis, University of Connecticut, 1994, 82 pp.

$$d_2 = 173 X^2 \left[ (X - 1) + \sqrt{(X - 1)^2 + (mX/c)} \right] \quad (3)$$

where:

- $c$  = capacity of lane group (vph);
- $C$  = cycle length (sec)
- $d$  = average stopped delay per vehicle in lane group (sec);
- $d_1$  = uniform delay per vehicle in lane group (sec);
- $d_2$  = incremental delay per vehicle in lane group (sec);
- $DF$  = delay adjustment factor for quality of progression or control type;
- $g$  = effective green time (sec);
- $m$  = an incremental delay calibration term, accounting for the effect of arrival type and degree of platooning;
- $X$  = volume to capacity ratio.

For coordinated signals for either non-actuated lane groups of semi-actuated approaches, or for pre-timed approaches,  $DF$  is equal to the progression factor,  $PF$ . In the previous (1985) version of the HCM,  $PF$  was selected from a table based on arrival type,  $AT$ , controller type, and  $X$  for the lane group. However, research by Fambro, Chang, and Messer (2) suggested that approach was flawed and that a new equation for predicting  $PF$  would eliminate discrete thresholds due to the use of tabular values. Thus, they suggested estimating  $PF$  from:

$$PF = \frac{(1 - P) f_p}{[1 - (g/C)]} \quad (4)$$

Here,  $f_p$  is an adjustment factor for the arrival of the front of the platoon during the cycle. It takes on discrete values depending on "Arrival Type" (See Ref. 1)

However, the user was still left with the problem of determining a value for  $P$ . Fambro, et al. presented two techniques for the prediction of  $P$  when field data are not available. The first of these was developed by Courage et al. (3). The second model presented in the report by Fambro, et al. was proposed by Bonneson and is based on a model suggested by Rouphail (4). The remainder of this paper describes research that, in essence, examines the conditions under which either or both of these procedures are appropriate.

## METHOD

As noted, the purpose of this research was to examine how sensitive the HCM delay model is to  $P$ , and to determine what effect the use of an estimation procedure for  $P$ , rather than field measurement, would have on the final estimated delay as compared to the measured delay. First, measured delay was calculated from field data. Next, HCM procedures were used to estimate delay based on the field conditions and the measured  $P$  value. Delay estimates were then recalculated with an increased or decreased  $P$  value until a statistically significant change in the

mean delay error (MDE) of the HCM estimates (versus measured delay) occurred. This change in  $P$  would then be the largest allowable error in an estimate of  $P$  that would not cause a statistically significant change in MDE.

Two techniques were then used to predict  $P$  for these same approaches. The predicted  $P$  values for the two techniques were then compared to the measured  $P$ , and the average error determined for each procedure. These results were then compared to the allowable error in  $P$  from the sensitivity analysis to see if the procedures are able to predict  $P$  well enough that a statistically significant change in the MDE does not occur. Finally, the procedures were evaluated based on three main criteria: the level of accuracy of the predictions, the relative ease of computation, and data requirements.

The final result of this research is a set of recommendations of when and how to predict  $P$  when field measurements of it are not readily available. This is most useful for an operational analysis of an intersection, but may also apply to planning or future volume scenarios. Significant savings in time and effort may be achieved for the same level of confidence in delay, depending on the characteristics of the approach in question.

### **Data Collection**

Eight consecutive intersections along the Silas Deane Highway (Route 99) in the Town of Wethersfield, Connecticut were the subject of this study. Route 99 is a four-lane, undivided, major urban arterial connecting the Town of Rocky Hill in the south with the City of Hartford to the north. Left-turn bays are provided at all of the intersections studied. There is extensive commercial development, mostly in the form of strip shopping centers, on both sides of the highway. All of the signals are semi-actuated and coordinated. These intersections are shown in Figure 1.

For each intersection, the following basic data (in addition to turning movement counts) were gathered from field investigations and construction plans:

- Cycle length (sec);
- Green time for each movement (sec);
- Geometry; and
- Offsets and coordination plan between signals.

### *Sample Size*

Collection of field data first required a selection of the level of confidence and sampling error required for a statistically significant sample. These values were then used to determine the required sample size. Based on a 95% confidence interval, a sampling error of plus or minus 0.5 seconds per vehicle, and assuming a sample standard deviation of 2.0 sec/veh, the required number of samples (or approaches to be studied) was sixty-one.

In order to achieve 95% confidence with an allowable error of 0.10 in the estimate of  $P$  (assuming  $P \approx 0.5$ ), the required vehicle sample size was found to be 384. This is roughly the 15-minute flow rate on Route 99. Thus, field samples consisted of a 15-minute period of video-recorded data for an approach over which results were aggregated. Since a total data acquisition time period of one hour for Route 99 approaches was used, each intersection yielded eight samples (four fifteen-minute periods in each direction). Eight intersections were therefore sufficient to obtain a statistically significant sample of 64 approaches.

### *Videotaping*

Each approach serving mainline Route 99 was videotaped for a period of one hour, from 4:30 P.M. to 5:30 P.M. on different days. From the videotape, the following data were gathered for each approach and aggregated over fifteen-minute intervals:

- Flow rate for each movement (vph);
- Percent of heavy vehicles;
- Pedestrian flow rates;
- Percent of vehicles arriving on green; and
- Number of vehicles queued at every twenty-second interval.

### **Sensitivity Analysis**

The sensitivity of HCM delay equations to the percent of vehicles arriving on green,  $P$ , was the first item to be determined.

### *Effects of Green Ratio and Degree of Saturation*

In a preliminary investigation of how  $P$  affects the delay calculations of the HCM, graphs of delay versus  $P$  for different  $g/C$  ratios and  $X$  values (for an arbitrary intersection with a 90 second cycle length) were created. These show that small changes in the  $P$  value may in some instances change the output level of service (LOS) for the analysis. Figure 2 shows one of these graphs for  $X = 0.4$ . As shown in Figure 2, the slopes of the lines become more negative with decreasing  $g/C$ . Since with a constant  $X$  a decreasing  $g/C$  implies a decreasing volume, under these conditions the delay is more sensitive to  $P$ . Similar plots for other values of  $X$  show the same trend. Note also that the lines lose linearity in the region where  $P$  is equal to  $g/C$ . This is due to the non-continuous adjustment factor  $f_p$  (Equation 4) which changes from 0.93 for Arrival Type 2, to 1.00 for Arrival Type 3, to 1.15 for Arrival Type 4.

To further illustrate these results, a linear regression was carried out to determine an average slope of the plot of delay versus  $P$ . The average slope of each line was then divided by the maximum slope of all lines (of all  $g/C$ ,  $X$  combinations), to determine the relative change in delay per unit change in  $P$  value for each combination of  $g/C$  and  $X$  value. The results again seem to indicate that the low  $g/C$ , high  $X$  value approaches should be most sensitive to changes in  $P$ . However, to determine if a change is statistically significant, the variances must be considered.



Thus, the statistical significance of a change in  $P$  is proportional to the change in the mean delay error (MDE) and inversely proportional to the square root of the sum of the variances. The preceding analysis does not take into account the variances of the delay errors for each group of approaches. As the approach delay increases, the delay errors in the HCM predictions increase as well (assuming that the average error of the HCM predictions is a percentage of the actual delay), increasing the variance. Larger variances are found for intersections that are closer to failing (LOS C or D) than for low delay (LOS A) intersections. These variances are critical in determining whether or not a statistically significant change has occurred in the error of the delay predictions. While it is apparent that the combination of  $g/C$  and  $X$  of the approaches will affect the results, the discussion above only accounts for half of the analysis. It does not capture the true sensitivity of the HCM equations to changes in the  $P$  value. The sensitivity analysis which follows will determine the interaction between the change in MDE and the variances to examine the effect on the critical change in  $P$ .

### *Data Set Description*

The field data were divided into different groups based on  $X$  and  $g/C$  ratio. Figure 3 plots the  $g/C$  and  $X$  for each of the 64 approaches observed in this study. Note that there are three distinct groupings, and that some points overlap on the graph. Group 1, with 16 approaches, has low  $g/C$  ratios (0.26 - 0.38) and high  $X$  values (0.55 - 0.95). The approaches function at LOS C and D. Group 2 consists of eight approaches with a  $g/C$  of 0.53, and  $X$  values ranging from 0.4 to 0.6. These approaches are functioning at LOS B and C. Group 3 (forty approaches) has very high  $g/C$  values (0.67 - 0.75) and low  $X$  values (0.25 - 0.40) and are all functioning at LOS A.

Figure 3 shows that the data seem to roughly fall along a line, implying a relationship between  $g/C$  and  $X$ . The reason for this relationship is that the capacity of a lane is a function of the geometry of the approach and the green time allotted to it. Since all of the intersections have very similar geometry,  $X$  should be linearly related to  $g/C$ . All of the data points in Figure 3 represent intersections of the same arterial with side streets of varying geometry, vehicle flow rates, and green time requirements. As the side streets require more green, less is available to the main line, thus increasing its  $X$ .

Data points in Group 1 represent intersections of the selected arterial with another major route. In this instance, heavy flows are found on all approaches, thus a relatively shorter green time on the arterial and large  $X$  values. Group 3 represents intersections of the arterial with side streets that experience relatively low vehicle volumes. For these approaches, the majority of the green time goes to the arterial due to the semi-actuation, and therefore relative low  $X$  values are found on these approaches. Group 2 represents intersections of the arterial with collector roads. Volumes are larger than on side streets, but not as great as on arterials, so  $g/C$  ratios and  $X$  values are in between the other two groups.

Other areas of this chart are theoretically possible, but not for this arterial under the existing conditions. The lower left portion of the chart (denoted Region 4) represents

intersections similar to those from Group 3, where the characteristics of the *side* street are plotted on the chart rather than the arterial. For these approaches flow rates are small, so *g/C* ratios for these intersections would be low due to the semi-actuation of the signals. The upper right portion of this chart, (region 5, high *g/C* and high *X* values) would be represented by any of the Group 3 approaches under extremely congested conditions. Under these conditions, even a very large *g/C* ratio is not enough to move the high volume of traffic, most likely due to under-designed geometry of the approaches.

Using data observed for eight coordinated signalized intersections on Route 99, the procedures from HCM for calculation of delay were applied. A spreadsheet applying this technique was developed because HCM computer software uses a look-up table to determine *PF* based on the given *P*. This precluded examination of the full benefits of the new equation for *PF* implemented in HCM.

### *Critical Change in P*

Predicted delay ( $d_{ij}$ ) for the *i*<sup>th</sup> fifteen minute interval of approach *j* using the measured *P* (here denoted  $P_m$ ) was computed for each approach and fifteen minute interval using the HCM delay equations. The technique described by the Federal Highway Administration (FHWA)(5) for determination of stopped delay per vehicle based on field measurements was then applied. Thus:

$$d_{ij} = 0.92 \sum_{k=1}^N \frac{v_k l}{V} \quad (5)$$

where:

$d_{ij}$	=	measured delay for approach <i>i</i> during 15 minute interval <i>j</i> ;
$N$	=	number of intervals in analysis period;
$v_k$	=	number of vehicles stopped during 20 second interval <i>k</i> ;
$l$	=	the length of the interval (20 sec.);
$V$	=	total volume passing through the approach during the entire analysis period;

and the correction factor of 0.92 accounts for over-estimation of stopped delay by this method.

The error in the delay prediction ( $DE$ ) =  $d_{ij} - d_{ij}$  was then determined for each *i,j* pair and the mean of the delay errors, MDE, calculated from

$$MDE = \frac{1}{mn} \sum_{j=1}^m \sum_{i=1}^n (d_{ij} - d_{ij}) \quad (6)$$

It was then required to determine what change in  $P_m$  would cause a statistically significant change in the MDE. This was carried out in the following manner: Delay was predicted for each *i,j* pair again except that the *P* value used in the HCM delay equations was  $P_x$ , computed as:

$$P_x = P_m \pm x \quad (7)$$

where:

$$0.01 \leq x \leq \Delta P_{cr}$$

$\Delta P_{cr}$  = the decimal change in  $P_m$  for which the corresponding  $P_x$  causes a significantly significant change in the MDE.

The resulting new delay term, denoted  $d_{xjp}$  is the predicted delay for the i,j pair with  $P$  set equal to  $P_x$ .

For increasing values of  $x$  from 0.01 to  $\Delta P_{cr}$  (both positive and negative), a new mean delay error,  $MDE_x$  was calculated as before. The MDE and  $MDE_x$  were then tested to determine  $\Delta P_{cr}$ , the smallest change in  $P$  that would have a statistically significant effect on the error in the delay predicted by the HCM equations.

### Comparison of Techniques

As noted earlier, the two techniques for predicting  $P$  were developed by Courage et al. (3) and by Bonneson (based on work by Rouphail (4)). For brevity, we will refer to the two techniques as "band ratio" and "platoon", respectively.

#### *Band Ratio*

This method is the simpler of the two techniques examined. Using a time space diagram as a starting point, it assumes that traffic approaches a signal with one of two platoon densities that can be represented by the proportion of vehicles entering at the upstream signal on the artery and on the cross street.

Then:

$$\begin{aligned} P_a &= \text{the proportion of traffic entering upstream from the artery, and} \\ 1 - P_a &= \text{the proportion of traffic entering upstream from the cross street.} \end{aligned}$$

With this simplifying assumption, the arrivals at the downstream intersection would be at relative density  $P_a$  within the band and at a relative density  $1 - P_a$  outside of the band. Based on this, the proportion of vehicles arriving on green at the downstream signal within the band ( $P_1$ ) is expressed as:

$$P_1 = P_a \frac{B}{G_o} \tag{8}$$

where:

$$\begin{aligned} B &= \text{Bandwidth (sec); and} \\ G_o &= \text{green time at the origin signal (sec).} \end{aligned}$$

The proportion of vehicles arriving on green at the downstream signal outside of the band,  $P_2$ , will be:

$$P_2 = \frac{(1 - P_a)(G_d - B)}{G_o} \quad (9)$$

where:

$G_d$  = green time at the downstream signal, and  
the other symbols are as previously defined.

The total proportion of vehicles arriving on green at the downstream signal will be the sum of  $P_1$  and  $P_2$ . Thus:

$$P = p \frac{B}{g_i} + (1 - p) \left( \frac{g - B}{C - g_i} \right) \quad (10)$$

where:

$p$  = the proportion of arrival traffic at the downstream signal that originates from the coordinated phase at the upstream signal.

### *Platoon*

This method of estimating  $P$  is the more complicated of the two techniques. It uses the following ten steps:

1. Establish platoon window.
2. Determine platoon flow rate.
3. Compute smoothing factor.
4. Determine cyclic platoon dispersion overlap flow rate.
5. Determine time of platoon arrival.
6. Determine flow rate within the platoon window.
7. Calculate flow rates at the downstream intersection.
8. Determine the duration of downstream green experiencing platoon arrivals.
9. Determine arrival rate during green phase.
10. Calculate percent arriving on green.

### *Comparison*

The described calculations were carried out for both procedures for fourteen coordinated approaches, seven northbound and seven southbound on Route 99. These were compared to the  $P$  value measured in the field for the selected fifteen minute interval. The other approaches (northbound at Maple Avenue, and southbound at Wethersfield Shops) in the study area were not coordinated with each other, and were assumed to have random arrivals for the purpose of these

calculations. For each procedure, the average error in  $P$  over the approaches was determined, as well as the standard deviation, and the 95% confidence interval for the average error over the approaches.

The errors in the estimations based on these two techniques were then compared to the allowable errors as determined by the sensitivity analysis. These two techniques were then rated based on comparison of their errors to the allowable error  $\Delta P_{cr}$ , data requirements, and the level of complexity of the calculations.

## RESULTS

### Sensitivity Analysis

Table 1 summarizes the results obtained from the sensitivity analysis for both the positive and negative values of  $\Delta P_{cr}$  for each subset of the data, and the range for the  $g/C$  and  $X$  values.

When averaged over positive and negative changes in  $P$ , the average critical changes in the  $P$  value by group are 32.6 % for LOS C and D (15 to 40 seconds of stopped delay) approaches (Group 1), 13.9% for LOS B (5 to 15 seconds) approaches (Group 2), and 6.1% for the LOS A (0 to 5 seconds) approaches (Group 3). This indicates that as the performance of an intersection increases (better LOS), HCM equations become increasingly sensitive to changes in  $P$ . In order to use an estimated  $P$  with equal confidence to that of a measured  $P$ , the estimated  $P$  must be within 6.1 percent of its actual value for the LOS A approaches, 13.9 percent for the LOS B approaches, and 32.6 percent for the LOS C and D approaches. These values represent the allowable error criteria against which the two procedures for prediction of  $P$  may be compared. These results may now be compared to the predictions of  $P$  by each of the two techniques to determine if the procedures will produce predictions of  $P$  within the allowable error described by the sensitivity analysis.

It is interesting to note that for the poorer performing intersections, the equations are less sensitive when the  $P$  value is under estimated. A larger change in the negative direction is required to cause a statistically significant change in the MDE. A procedure that consistently underestimates  $P$  (actual progression is better than estimated) is therefore allotted more leeway in its predictions than one that overestimates  $P$  (actual progression is worse than estimated). If either the platoon or band procedures tends to underestimate, they can be held to less strict allowable error, which will have bearing on the final results of the effectiveness of the equations in predicting  $P$ .

### Estimation of $P$ Using Band Ratio and Platoon Procedures

These two procedures were used to estimate the percent arriving on green for one of the fifteen-minute intervals in the data set. Not all four fifteen-minute periods were used for this portion of the analysis because the predicted  $P$  values for the different fifteen minute intervals of the same

intersection were not significantly different from each other.

Table 2 shows the results of the estimations using the band ratio and platoon procedures, the measured  $P$  value, the error in the prediction, and the average error per approach and 95 percent confidence interval for the average. Wethersfield Shops southbound and Maple Avenue northbound do not have entries, because these intersections were not coordinated with each other, and therefore had  $P$  values representing random arrivals.

The average error for the band ratio and platoon procedures for estimating  $P$  are ten percent and nine percent respectively. Comparing these findings to the results of the sensitivity analysis, it would indicate that either of these procedures is valid for both the Group 1 approaches (LOS C and D) and the Group 2 approaches (LOS B). However, neither is adequate for predicting  $P$  within the very small tolerance (6.1 %) required by the Group 3 approaches.

### **Evaluation of Band Ratio and Platoon Procedures**

#### *Accordance with Allowable Error Criteria*

In order to better explain how well these procedures meet the allowable error criteria, we may compare the errors from Table 2 for each procedure to the results of the sensitivity analysis shown in Table 1. Table 3 summarizes the results of this analysis. The actual error observed for each approach is compared to the average  $\Delta P_{cr}$  (average over positive and negative changes in  $P$ ) for the group with which each approach was analyzed. An estimation is considered valid if it meets the allowable error criteria for its LOS group for HCM equations, and is denoted with a check mark ( $\checkmark$ ). The last four rows of the table are statistics on the number of valid observations / total observations for each group of samples.

Although the average error for both the band ratio and platoon procedures appear on average to meet the allowable error criteria for both Groups 1 (LOS C/D) and 2 (LOS B), Table 3 shows that this is really not the case. The summary statistics in Table 3 indicate that while both band ratio and platoon procedures predict all 3 of the LOS C and D approaches within the allowable 33 percent error, each only predicts 1 of the 2 LOS B approaches within the allowable 14 percent error. The Platoon Method predicted 4 of the 9 LOS A approaches within allowable error, and the Band Ratio Method 3 of 9. This indicates that some loss of accuracy would be incurred if these procedures were used to estimate  $P$  for the HCM model on LOS A or B approaches. However, both could be used for LOS C and D approaches without detriment to the delay results. Figure 4 plots the approaches used in this analysis by  $g/C$  and  $X$  value and demonstrates the regions over which the two procedures are useful in conjunction with the HCM procedures.

One additional item to note is that both procedures tend to underestimate  $P$  as opposed to overestimate it (Band Ratio 9 / 14, Platoon 10 / 14 under-estimations). This makes the average  $\Delta P_{cr}$  a conservative estimate of the allowable error in  $P$ . It may therefore be that the procedures

are good for LOS B approaches as well, but more investigation of where exactly to draw the line in terms of intersection performance is required.

#### *Data Requirements for Both Procedures*

The only significant difference in data requirements between the two procedures is in the saturation flow rate ( $s$ ), and the traffic volume ( $q$ ). These are both required by the platoon procedure, but not by the band ratio procedure. However, both of these values need to be computed during the HCM analysis regardless of which procedure is used, so no extra effort is expended in obtaining those data.

The other difference is in how the procedure quantifies the progression scheme. The band ratio procedure uses  $B$ , the progression bandwidth. Calculating this value requires the progression speed and the distance between intersections as well as the offsets, green times, and cycle lengths. The platoon procedure uses travel times (a function of distance and average speed) in addition to the other values. This is essentially the same information expressed in a different way.

#### *Complexity of Procedures*

The Platoon procedure was computationally far more complex. The main benefit of this procedure was the ease with which the entire procedure lends itself to computation with a spreadsheet. While a few initial hours are spent programming a spreadsheet to carry out the procedure, once it is programmed it takes only minutes to enter the data and produce a result.

The band ratio procedure equations are significantly less complex than the platoon procedure, so the amount of time programming the spreadsheet was very small. However, a separate time space diagram would be required to determine the progression bandwidth for each group of coordinated intersections on which the band ratio procedure is used. This would require additional programming of a spreadsheet, or some additional computer software. For routine application, the marginal effort expended for each additional intersection or arterial is much less for the Platoon procedure than for the Band Ratio procedure.

## **CONCLUSIONS AND FUTURE RESEARCH**

### **Conclusions**

The HCM model for determining the level of service (LOS) of a signalized intersection is based on average delay per vehicle. According to this model, this delay value is dependent on many things, including the green time available to each approach, the demand volume, and the geometry of the intersection (number of lanes, and lane widths).

Traffic signals on arterial streets are often included in coordinated systems to minimize wasted green time on the mainline and to improve the movement of platoons of vehicles through

the area. Whenever traffic signals are included in this type of system, it is important to account for the quality of the progression between the intersections when computing delay. The HCM indicates that the most important variable for quantifying progression quality is  $P$ .

For the intersections studied, this research has shown that when computing intersection delay using the HCM equations, two of the procedures given in the literature for estimating  $P$  may be effectively used in lieu of field measurements of  $P$  for approaches that are functioning at LOS C and D, with  $g/C$  values in the range of 0.26 to 0.38, and  $X$  values in the range of 0.55 - 0.95. Neither procedure was able to predict  $P$  accurately enough for approaches operating at LOS A or B; however, this is not a serious problem since delay studies are not frequently required in the absence of existing serious delays at an intersection.

### **Recommendations for Future Research**

One recommendation for future research is related to the Group 2 (mid-range  $g/C$ , mid-range  $X$ ) approaches. During the course of this research, eight approaches of this type were analyzed. This is not a large enough data set to prove whether or not using the two estimation procedures for these approaches would cause a statistically significant change in the results of the HCM model. Development and analysis of a larger data set of mid-ranged  $X$  and  $g/C$  approaches would allow for a more thorough examination of this issue, and could prove that the two estimation procedures for  $P$  may be used for these approaches as well.

The other issue that came up during this research was the subject of the required duration for measuring  $P$  in the field in order to get a value representative of the field conditions. During this study,  $P$  was measured over a period of one hour. The data were then divided into fifteen-minute intervals for the purpose of analysis. The results of an analysis of variance (ANOVA) for the four fifteen-minute intervals for the sixteen approaches showed that the  $P$  values between fifteen-minute intervals were not significantly different from each other for fourteen of the sixteen approaches. This indicates that measurement of the  $P$  value over fifteen minutes could result in a reasonable representation of the one hour field conditions, however this is based on limited data and analysis. Further investigation into this matter is recommended.

### **ACKNOWLEDGMENTS**

This research was sponsored by the New England Region University Transportation Center and was conducted at the Connecticut Transportation Institute at the University of Connecticut.

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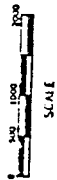
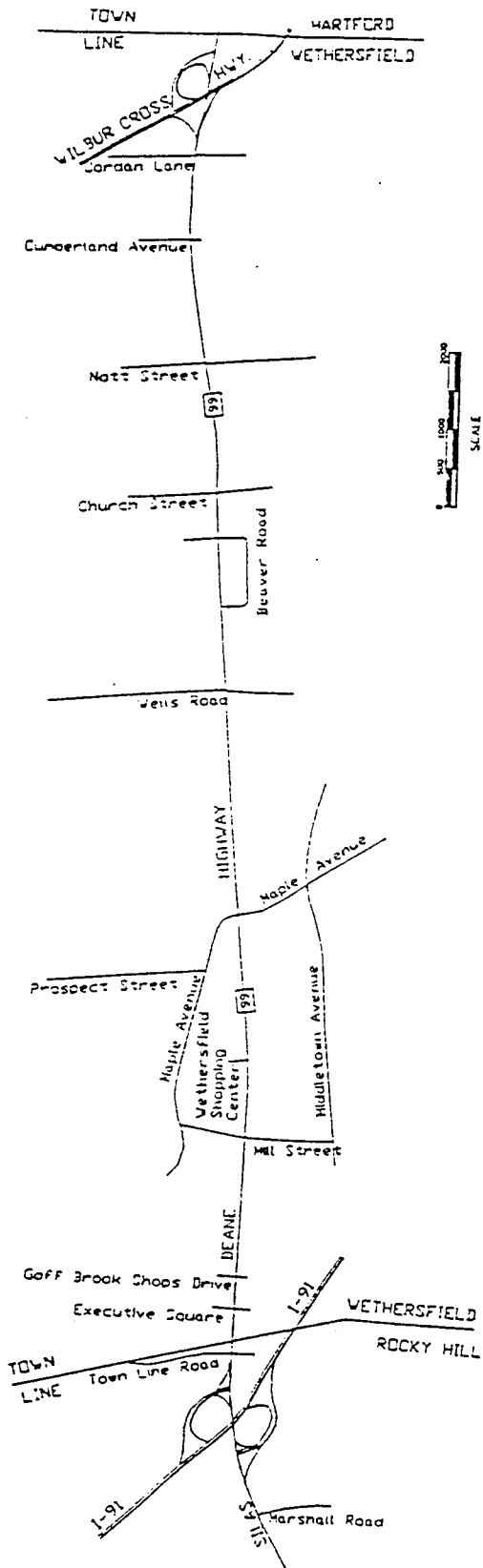


FIGURE 1. Relative Locations of Intersections

Delay vs. P by g/C for X=0.4

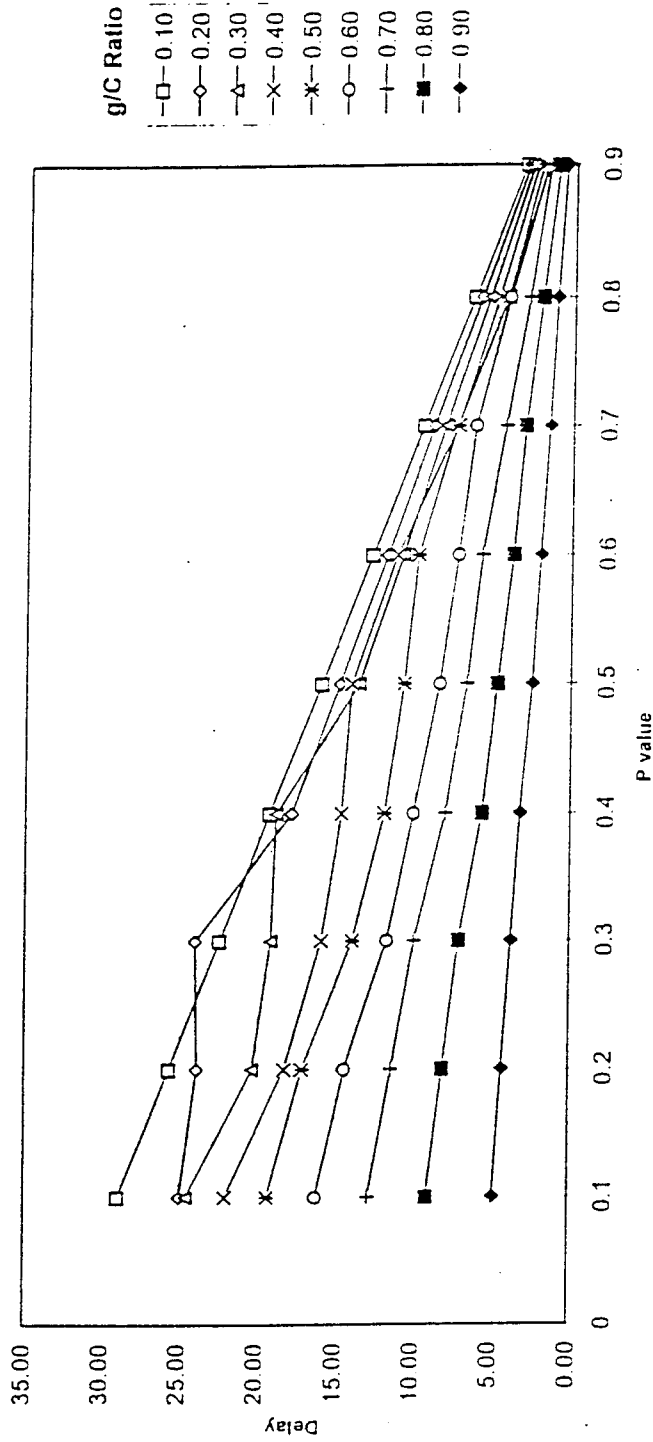


FIGURE 2. Delay vs. P by G/C for X = 0.4

Approach Descriptions

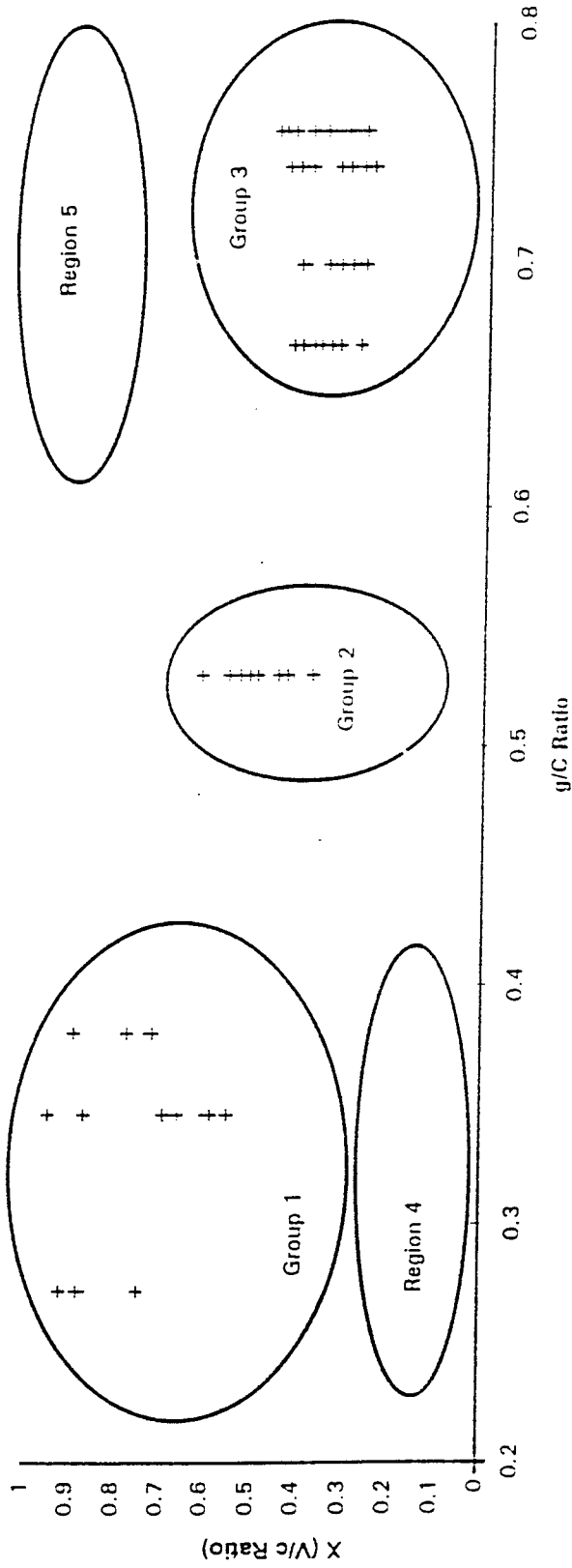


FIGURE 3. Approach Descriptions

Areas of Compatibility for Bonneson, Courage Procedure With HCM94

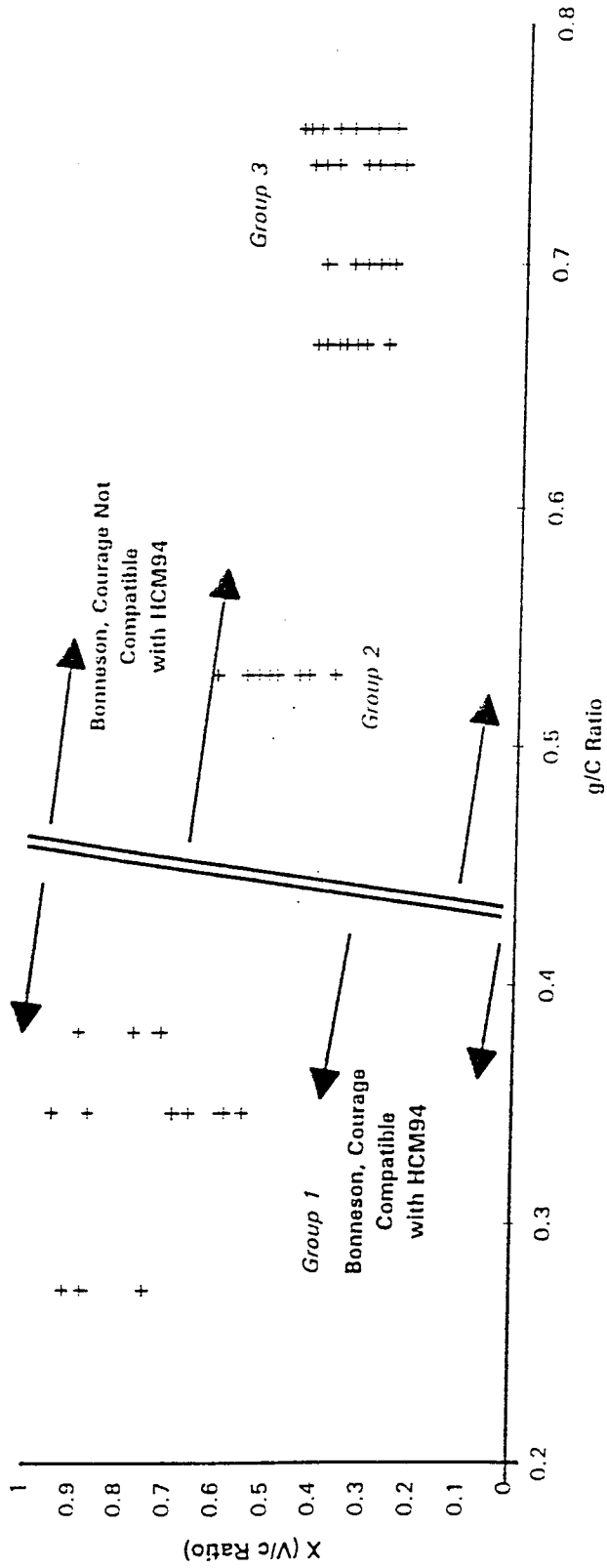


FIGURE 4. Areas of Compatibility with HCM94

**TABLE 1. Summary of Sensitivity Analysis Results**

Grouping of Data Set	$\Delta P_{cr}$	Range	Range
		g/C	X
1. 16 low g/C, high X approaches	+0.279	0.26 - 0.38	0.55 - 0.95
	-0.373	0.26 - 0.38	0.55 - 0.95
2. 8 mid g/C, mid X approaches	+0.115	0.53	0.38 - 0.62
	-0.162	0.53	0.38 - 0.62
3. 40 high g/C, low X approaches	+0.062	0.67 - 0.75	0.25 - 0.40
	-0.060	0.67 - 0.75	0.25 - 0.40

**TABLE 2. Results of Estimation Procedures**

INTERSECTION NAME	DIR	Measured P	Bonneson		Courage	
			P pred.	P error	P pred.	P error
EXECUTIVE SQUARE	NB	0.91	0.87	-0.04	0.81	-0.10
	SB	0.84	0.89	0.05	0.83	-0.01
GOFF BROOK	NB	0.95	0.90	-0.05	0.81	-0.14
	SB	0.86	0.71	-0.15	0.78	-0.08
MILL STREET	NB	0.71	0.59	-0.12	0.82	0.11
	SB	0.71	0.67	-0.04	0.66	-0.05
WETHERSFIELD SHOPS	NB	0.95	0.88	-0.07	0.80	-0.15
	SB	0.83	*	*	*	*
MAPLE AVENUE	NB	0.23	*	*	*	*
	SB	0.36	0.21	-0.15	0.42	0.06
WELLS ROAD	NB	0.49	0.45	-0.04	0.40	-0.09
	SB	0.30	0.41	0.11	0.39	0.09
BEAVER ROAD	NB	0.80	0.88	0.08	0.96	0.16
	SB	0.85	0.95	0.10	0.91	0.06
CHURCH STREET	NB	0.65	0.59	-0.06	0.54	-0.11
	SB	0.64	0.43	-0.22	0.40	-0.25
Overall Average Error				0.09	0.10	
95% Confidence Interval				0.02	0.03	

\* denotes a non-coordinated approach that had random arrival patterns.

**TABLE 3. Number of Valid Predictions of  $P$  by Each Procedure**

INTERSECTION NAME	DIR	Group	Aver. $\Delta P_{cr}$	Bonneson		Courage		
				$P$ error	Valid	$P$ error	Valid	
EXECUTIVE SQUARE	NB	3	0.06	-0.04	√	-0.10		
	SB	3	0.06	0.05	√	-0.01	√	
GOFF BROOK	NB	3	0.06	-0.05	√	-0.14		
	SB	3	0.06	-0.15		-0.08		
MILL STREET	NB	3	0.06	-0.12		0.11		
	SB	3	0.06	-0.04	√	-0.05	√	
WETHERSFIELD SHOPS	NB	3	0.06	-0.07		-0.15		
	SB	3	0.06	*		*		
MAPLE AVENUE	NB	1	0.33	*		*		
	SB	1	0.33	-0.15	√	0.06	√	
WELLS ROAD	NB	1	0.33	-0.04	√	-0.09	√	
	SB	1	0.33	0.11	√	0.09	√	
BEAVER ROAD	NB	3	0.06	0.08		0.16		
	SB	3	0.06	0.10		0.06	√	
CHURCH STREET	NB	2	0.14	-0.06	√	-0.11	√	
	SB	2	0.14	-0.22		-0.25		
Group 1 (LOS C and D)					3 / 3		3 / 3	
Group 2 (LOS B)					1 / 2		1 / 2	
Group 3 (LOS A)					4 / 9		3 / 9	
Total Valid Predictions					8 / 14		7 / 14	

## APPENDIX B

### Interactions among Land Use, Area Type, Congestion Mitigation Strategies, and Air Quality<sup>1</sup>

#### *Abstract*

The study performs a microscopic analysis of the impacts of individual projects on air quality. The rationale is that even though the overall impact of a state-wide or regional-wide transportation improvement programs is needed for the final conformity analysis, it is also important to learn the contributions of individual projects to assist in selecting among projects competing for funding. This study examines four types of projects commonly encountered in air quality analysis, here referred to as "congestion mitigation strategies." These strategies are studied in the context of different types of land use, development density and traffic control to see how these variations affect the resulting air quality and traffic operations.

#### *Introduction*

It is widely known that traffic congestion has negative impacts on air pollution. Lyons *et al.* [1] found that as vehicle congestion and, thus, acceleration-deceleration cycles increase, harmful gas production exceeds that of normal operating levels. Mitigating congestion, however, does not reduce air pollution if it enables motorists to drive at high speeds, because tail pipe emissions of most air pollutants are the lowest at intermediate speeds.

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<sup>1</sup>Taken largely from: Ivan, J. N. and M. R. Kusuma, Interactions among Land Use, Area Type, Congestion Mitigation Strategies, and Air Quality, in *Transportation, Land Use, and Air Quality: Making the Connection*, Proceedings of the Conference sponsored by A.S.C.E., May 1998, pp. 729-736.



The effect of applying specific congestion mitigation strategies depends heavily on the *transportation system characteristics* of the area, such as land use density, area type, and signalized intersection frequency. For example, the impact of adding an exclusive left turn lane in a densely developed business zone will be different from the impact of installing one in a suburban residential zone with predominantly through traffic.

This research studies how varying several transportation system characteristics affects the success of congestion mitigation strategies in reducing traffic congestion and air pollution. Finding a clear, integrated relationship between these transportation system characteristics, congestion, and air pollution reduction measures will assist decision-makers in selecting the appropriate congestion mitigation strategy.

### Background

As noted previously, alleviating congestion does not always reduce air pollution. The interaction between congestion analysis and air quality is complicated because congestion and air quality are not optimized at the same speed, as shown in Figure 1.

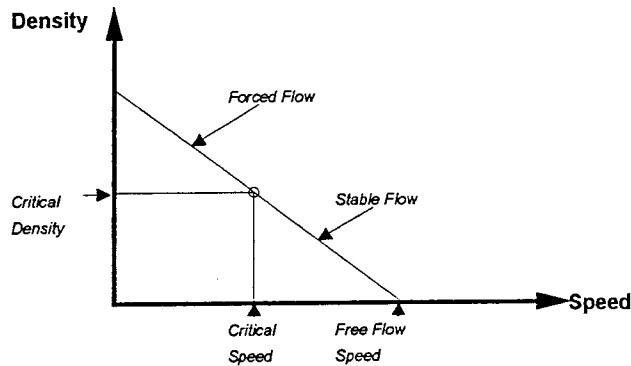


Figure 1a. Speed - density relationship.

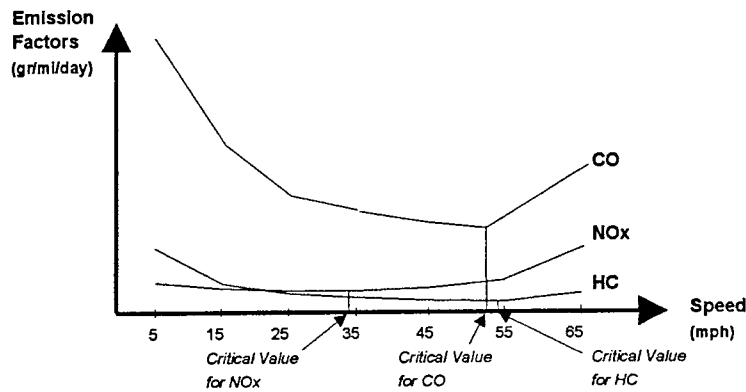


Figure 1b. Speed - emission factors relationships.

Figure 1a depicts the generalized speed-density function derived by Greenshields [2]. Density (vehicles per mile) is a good measure of the degree of congestion. When density is reduced, average travel speed increases. The logical extreme is to reach the free flow speed (observed when density is zero).

Optimizing air quality, on the other hand, requires increasing speed only to critical values as shown in Figure 1b. This figure depicts typical relationships between speed and exhaust Carbon Monoxide (CO), Hydrocarbon (HC), and Volatile Organic Compounds (VOC) derived from a popular emission factor model, MOBILE 5a\_h [3]. Selection of a congestion mitigation strategy should consider this complicated relationship between congestion and air pollution, being certain to reduce both.

### *Congestion Mitigation Strategies*

Building new roads is still often the most obvious solution and nearly always produces immediate results. This solution, however, often only relieves traffic congestion temporarily. New facilities induce new traffic demand and reduce average vehicle occupancies. They fill up with traffic almost as soon as the new facilities are opened [4]. This not only brings back traffic congestion, but also worsens the values of other criteria such as fuel consumption and air pollution. Despite these discouraging consequences, many still believe that adding supply is the most effective way to mitigate congestion, as was found by Arnold [5], who surveyed transportation engineers in Virginia. Arnold listed several alternatives for managing traffic congestion, including: intersection improvements (channelization and turn lanes), removing or restricting on street parking, and other traffic signal improvements.

This study investigates four congestion mitigation strategies:

1. Adding a left turn lane at signalized intersections with protective left turn phasing,
2. Adding a lane in each direction and a left turn lane at every intersection with protective left turn phasing,
3. Same as Alternative 1, but with permissive left turn phasing, and
4. Same as Alternative 2, but with permissive left turn phasing.

### *Mobile Sources*

Motor vehicles are responsible for a large number of harmful gasses emitted into the atmosphere. These gases include CO, HC, and NO<sub>x</sub>. CO concentrations in the vicinity of emission sources tend to be higher when the air is stable than when it is turbulent. This is because reduced turbulence decreases the rate at which pollutants mix and dilute into the air. In the winter, atmospheric conditions tend to be more stable and wind speeds tend to be lower than in other seasons. CO emissions also tend to be higher in low rather than high temperatures. These two factors cause the highest CO concentrations to occur in winter [6].

The term HC normally refers strictly to compounds of carbon and hydrogen. However, in air quality studies, the class is often extended to include a variety of

other volatile organic substances, such as aldehydes and alcohols [6]. The importance of HC stems mainly from its role in atmospheric chemical reactions to form harmful secondary gases, such as ozone and nitrogen dioxide.

NO<sub>x</sub> consists of all oxides of nitrogen and can react chemically in the air to form acidic substances. NO<sub>x</sub> and HC react photochemically to form Ozone. Ozone concentrations vary from time to time in the same day. The concentration usually reaches its highest value in the afternoon, when the temperature is also at its highest value. The formation of ozone increases on summer days, with long hours of intense sunlight. Accordingly, the production of HC and NO<sub>x</sub> become more important in the summer than in the winter and in areas with higher temperatures.

Emission studies in this research are limited only to summer settings, that is, the emissions of the three pollutants, including CO, are analyzed using summer data. Even though we are aware that it is more useful to analyze CO emissions in the winter, the winter analyses of CO emissions are not included here. We will include these in our future study, which is still in progress.

### *The Analysis Network and Transportation System Characteristics*

A hypothetical four-lane undivided roadway with a length of 3.2 kilometers and seventeen intersection spaced evenly two hundred meters apart is used as the model network for this study. This roadway corridor is assumed to exist in a suburban setting. Figure 2 depicts this roadway network.

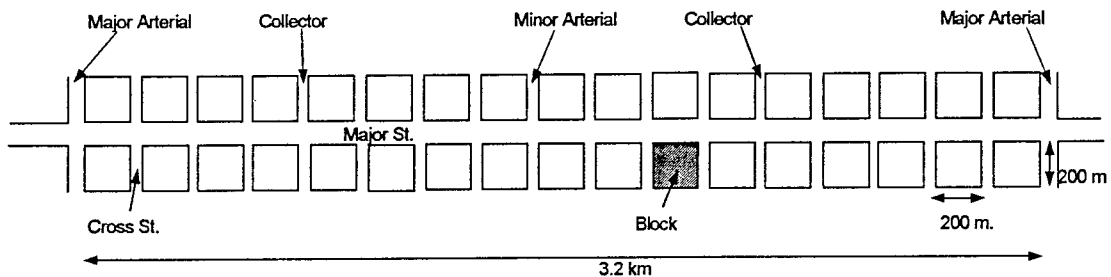


Figure 2a. Analysis network

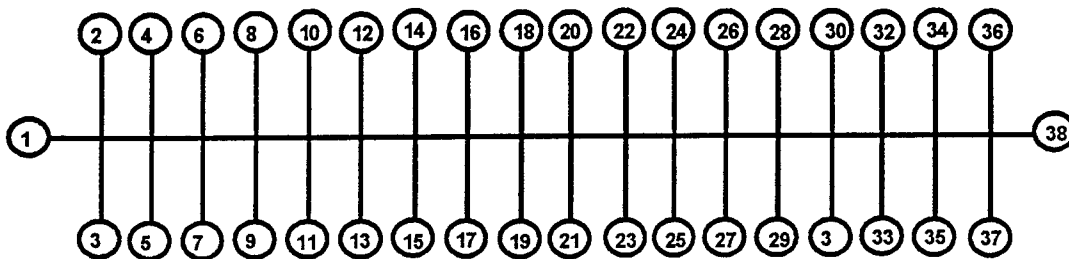


Figure 2b. Network representation.

There are sixteen blocks at each side of the major street inside the study area. A block is an area bounded by two adjacent cross streets and major streets, and has a size of two hundred meters wide by two hundred meters deep.

Analysis scenarios for comparing CMAQ strategies are defined by varying the three transportation system characteristics: area type, land use density, and signalized intersection frequency. Area type affects traffic patterns in the area, especially turning movements, which, in turn, affect traffic congestion. Three types of land use are assumed to exist in the study area: retail, office, and housing. The land use coding system follows the numbering system given by the Institute of Transportation Engineers' (ITE) *Trip Generation* [7]. Retail is represented by "Shopping Center" (land use 820) and "Supermarket" (850). Office comprises "General Office Building" (710), "Research and Development Center" (760), and "Business Park" (770). Housing includes "Apartments" (220), "Residential Condominiums and Townhouses" (230), and "Single-Family Detached Housing" (210). The proportions of these three land use types define the area type. For example, the residential type includes mainly housing, with some retail and office use and the commercial type includes mainly office and retail uses with a small amount of housing. The six land use categories are:

1. Commercial A: 80% retail – 10% office – 10% housing,
2. Commercial B: 100% retail,
3. Business/Industrial A: 10% retail – 80%-office-10% housing,
4. Business/Industrial B: 100% office,
5. Residential: 10% retail – 10% office – 80% housing, and
6. Mixed: 30% retail – 30% office – 40% housing.

Land use density affects the magnitude of traffic occupying the roadways in the area. We define three levels of land use density: medium, high, and very high, based on total gross floor or gross leasable area (GLA) and the number of housing units in the area. High density land use has a total floor area approximately 1.5 times that of the medium density land use, and extremely high density land use has twice as much area floor as the medium density land use, with average floor areas (FAR) of 2.5, 3.75, and 5.0. With assumed block areas, GLA is computed by multiplying the FAR by the block area. A FORTRAN program was written to randomly assign land use type and land use density to each block according to its average FAR (with a tolerance of  $\pm 25\%$ ).

Signalized intersection frequency indicates the distance between two signalized intersections. This feature affects stopped delay, which in turn, affects pollution levels. Five, nine, and seventeen signals placed evenly along the roadway corridor represent three types of signalized intersection frequency to be studied.

Fifteen hundred external vehicle trips are fed into the corridor through all possible channels (cross roads and main road) during the analysis period. The analysis period is a typical summer afternoon peak hour, defined as the single busiest one hour period between 4:00 P.M. and 6:00 P.M. [7]. These trips represent: (a) external-external or pass-through trips, (b) external-internal trips, and (c) internal-external trips.

## Measures of Effectiveness

Five measures of effectiveness (MOEs) are used in this study:

1. Average system travel time is the average of overall travel time in the study network, including travel times in major and cross streets;
2. Average major street travel time is selected because congestion mitigation strategies are applied only to major street;
3. HC emissions inventory during summer PM peak hour;
4. CO emissions inventory during summer PM peak hour; and
5. NOx emissions inventory during summer PM peak hour.

## Methodology

The analysis procedure consists of the following six-steps: (1) determination of area type and land use density, (2) generation of trip ends, (3) distribution of trip ends into a trip table, (4) simulation of traffic operations, (5) calculation of emission factors and emission inventories, and (6) analysis of results.

The first step has been explained thoroughly in the previous section. Once land use type and GLA are assigned for each block in the study area, the number of trips produced by and attracted to those blocks can be determined using ITE trip generation formulas. These trip ends are later distributed to all zones using the gravity model to obtain an origin-destination (O-D) table. This O-D table, signal timings and other geometric information are coded into a network to be analyzed using the TRAF-NETSIM traffic simulation package [8]. Signal timings are optimized using PASSER IV-94 [need a reference here].

TRAF-NETSIM is used here because of its capability to simulate traffic condition microscopically. TRAF-NETSIM is stochastic rather than deterministic, so random processes within the model influence its output. Because it represents driver behavior randomly, TRAF-NETSIM results will vary from one run to another depending on the random number seed used in the model, even though the same input values are used. Multiple model runs produce more reliable results than a single model run, because averaging output from multiple model runs increases the confidence level of the results. The number of runs needed for each scenario depends on the desired confidence level; Hale [9] suggests the following formula to determine the number of runs needed for each scenario:

$$N_2 = N_1 \left[ t_{(N_1-1),\alpha} \times \sqrt{S^2_{N_1}/N_1} \right] / (CI \times X_{N_1}) \quad (1)$$

Where:

$N_1$  is the number of executions for the initial run

$N_2$  is the number of executions needed for the model with level of confidence  $\alpha$

$t_{(N_1-1),\alpha}$  is the critical t-distribution value for  $N_1 - 1$  degrees of freedom and level of confidence  $1 - \alpha$

$S^2_{N_1}$  is the sample variance computed for the initial run

CI is the confidence interval fraction, e.g., 0.1 allowing 10% deviation from the sample mean

$X_{N_1}$  is the sample mean for the initial run

Using twenty-five initial executions, the model needs nine repetitions to achieve 90% confidence interval on the average travel time on the major street. Using this criterion and an initial run of twenty-five independent executions, we determined that we need to run nine executions for each scenario and alternative combination to achieve a confidence interval within 10% with 90% confidence.

TRAF-NETSIM outputs congestion measures such as average system travel time, average major street travel time, average link speed, and link volumes. Average link speeds are input to Mobile5a\_h to calculate emission factors of CO, HC, and NO<sub>x</sub>. Emission inventories are then calculated using the following formula:

$$\text{Emission Inventory} = \text{Emission Factor} \times \text{Link Distance} \times \text{Link Volume} \quad (2)$$

Emission factors are determined using emission control file for Greater Connecticut area.

### *Analysis of Results*

Simulation results will give congestion and emission measure values (travel time and emission inventories, respectively) for each congestion mitigation strategy under each scenario. We will deduce the following effects of each transportation system characteristic on the MOEs for each strategy:

1. How a single transportation system characteristic affects each MOE given constant values for the other two characteristics; and
2. Which combinations of characteristics optimize each MOE, and under what other conditions.

The analysis will be carried out using an analysis of variance (ANOVA) framework with the transportation system characteristics used as experimental factors. These factors are set at levels corresponding to the six area types defined earlier. The improvements in traffic congestion and air pollution measures relative to the do-nothing alternative are the dependent variables for the model. One-way, two-way and three-way factorial experiments will be used to carry out the analysis separately for each MOE, and repeated for each congestion mitigation alternative.

As was established earlier, we expect the congestion and air quality measures to be optimized under different conditions, and thus, that not all alternatives will optimize the same MOEs. Furthermore, we also expect the optimal alternative for each MOE to vary with the combinations of system characteristics. It is possible, however, that certain alternatives may dominate others under some combinations. In any case, the ability to produce a non-dominated set of alternatives that offer a range of reductions in both congestion and air pollution would be useful for planners and decision-makers for initial screening of alternatives, thus reducing the number of alternatives that require detailed analysis.

## Conclusions

At this point, simulation runs are being conducted, but insufficient runs have been completed to report any tangible results. Ultimately, we plan to validate our findings with a case study applied to a simulation of an actual traffic network in a suburb of Hartford, Connecticut. We expect our findings to be useful for decision-makers involved in studying, analyzing and selecting congestion mitigation and air quality improvement strategies.

One useful outcome of this research will be the establishment of a format to jointly evaluate traffic congestion and air quality that is simpler than the one used in current practice. While not as detailed as the current procedure, it will permit decision-makers to quickly forecast congestion and air quality improvements expected from applying specific strategies. Another useful outcome will be the application of this procedure as a screening tool for paring down lists of potential congestion mitigation and air quality improvement alternatives.

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## APPENDIX C

### Prediction of Traffic Accident Rates Using Poisson Regression<sup>1</sup>

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<sup>1</sup>Taken largely from: O'Mara, P., *Prediction of Traffic Accident Rates Using Poisson Regression*, M.S. Thesis, University of Connecticut, 1996, 71 pp.



## **INTRODUCTION**

Reflecting on the history of transportation engineering, James Foley noted that since its beginning, safety and efficiency have been primary goals (1). In 1994 40,676 people were killed on U.S. highways (2). More people have been killed in traffic accidents in the U.S. than in all the wars in which this nation has been involved (3). Overall, accidents represent about fourteen percent of the cost of highway travel, creating a loss ratio that most business and industrial activities could not support. Additionally, the social and humanitarian costs are high since sixty percent of those who die and nearly seventy percent of those injured are in the highly productive fifteen to forty-five year old age group (4).

One of the six management systems required by the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 is a Safety Management System (SMS). According to the Federal Highway Administration, a SMS should ensure that all opportunities to improve highway safety are identified, considered, implemented as appropriate (including roadway, human, and vehicle safety elements), and evaluated in all phases of highway planning, design, construction, maintenance, and operation (5).

Therefore, based on a sample of Connecticut's highways and their accident experiences, this paper describes an investigation to determine the features that most influence Connecticut highway accidents. Traffic and geometric variables that significantly affect accident rates on Connecticut highways are identified using Poisson regression analysis of accident, traffic and geometric data collected from the Connecticut Department of Transportation.

## **PREVIOUS RESEARCH**

### **Factors Affecting Highway Accident Rates**

A number of studies have attempted to quantify the effect of highway geometric design variables on accident rates. Dart and Mann studied rural highway accidents in Louisiana over a five-year period (1962-1966) (6). They found the accident rate (accidents per million vehicle miles) to increase with traffic volume and number of conflicts (intersections and driveways), and to decrease with lane width. Another finding, unique to this study, was that roadways with flat cross slopes tended to have higher accident rates than those with steeper slopes, a significant finding for areas like Louisiana with heavy rainfall.

Agent and Deen attempted to identify high-accident locations with respect to the functional type and geometry of the highway, using accident and volume data from rural highways in Kentucky collected from 1970 through 1972 (7). Accident, injury and fatality rates were all proportional to the number of conflict points on a roadway and the volume of traffic. Consequently, four-lane undivided highways, which frequently carry high volumes of traffic with numerous conflict points, experienced the highest accident, injury, and fatality rates.

A study of shoulder widths on two-lane roadways in Oakland County, Michigan, determined that there is no significant difference in accident frequency between roadways with shoulder widths that meet AASHTO guidelines of eight feet and those that do not (8). A similar study of rural two-lane road accidents compared roadways with the same shoulder widths and found that accident rates generally decrease with increasing lane width, especially on roadways without shoulders (9). This study also found that for the same lane widths accident rates tended to decrease as shoulder width increased, but increases in lane width reduced accident rates more than the same increases in shoulder width. Another investigation into the effects of geometric conditions found degree of curve to clearly be the geometric feature that most adversely affects both accidents and vehicle operations on horizontal curves, compared with lane and shoulder widths, superelevation, and gradient (10).

Space-wise, at-grade intersections are a relatively small part of the total roadway network, but over one-half of the motor vehicle accidents in the United States occur at intersections (9). Research has also found the vertical alignment of a roadway to be a factor influencing roadway accidents, as dangerous speed differentials between heavy trucks and other vehicles can lead to potential rear-end accidents.

### **Accident Prediction Methods**

Researchers have generally used two approaches to estimate accident rates based on traffic and geometric variables: multiple linear regression (11, 12, 13) and Poisson regression (14, 15, 16). Gupta modeled accident rates using multiple linear regression with accidents observed over a five-year period from July 1964 to June 1969 on over two thousand miles of Connecticut highway (11). A study of over seven thousand miles of roadway logs in the state of Utah used linear regression to predict the truck accident involvement rate per kilometer per year based on AADT per lane, truck ADT per lane, shoulder width, horizontal curvature, and vertical gradient (12). This study found that the truck involvement rate increases with AADT, truck ADT, degree of curvature and gradient.

Another study used both multiple linear regression and Poisson regression models to estimate truck accident rates using a given set of independent traffic and geometric variables (13). The Poisson regression model described the relationship between large-truck-involved accidents and the associated traffic and geometric variables better than the linear regression model. Miaou and Hu *et al.* proposed the use of Poisson regression to establish empirical relationships between truck accidents and key highway geometric design variables (14). Using geometric and traffic data from the Highway Safety Information System (HSIS) they applied Poisson regression to 8,779 miles of roadway on which there were nine hundred thirty-three large truck accidents during a three year period. For each road section, they tested three surrogate measures for horizontal and vertical alignment (curvature change rate, mean absolute curvature, and maximum absolute curvature). Results of the modeling indicate that the surrogate measures Mean Absolute Curvature (for horizontal alignment) and Mean Absolute Grade (for vertical alignment) are the most appropriate variables for estimation.

A study in Seattle used Poisson regression to estimate accident frequency and to identify the characteristics unique to a specific day that might increase or decrease the number of expected accidents to inform decisions about allocating resources in Seattle's accident management system (15). Hadi and Aruldhus *et al.* used negative binomial regression to estimate accident rates for various types of rural and urban highways with different traffic levels (16). The negative binomial regression model is related to the Poisson model, but releases the Poisson model restriction that the mean and variance be equal. Higher AADT levels and the presence of intersections are associated with higher crash frequency, while wider lanes and shoulders are effective in reducing crash rates.

In most studies AADT is the variable used to indicate traffic conditions and congestion. One shortcoming of AADT is that it only provides the number of vehicles traveling on a particular highway, not the resulting level of congestion. The highway volume-to-capacity ratio should also be examined to explain possible effects of highway congestion on accident rates. Another factor influencing traffic accidents is vehicle speed differentials introduced where the posted speed limit differs from the design speed. This paper examines the effect of both these variables on accident rates.

## DATA COLLECTION

This investigation of the influence of traffic and roadway geometric characteristics on accidents requires the selection of roadway locations having reliably recorded crash data, corresponding traffic volume data, and roadway inventory or characteristic information. The accident data for this study were obtained from the Connecticut Department of Transportation (CONNDOT) Traffic Accident Surveillance Report (TASR) for the three year period from January 1, 1991 to December 31, 1993. The geometric information was obtained from the CONNDOT Highway Performance Monitoring System (HPMS). Both data sets were made available by CONNDOT's Office of Planning Inventory and Data.

The TASR provides traffic accident rates for two types of locations: *spots*, which are intersections or highway segments less than one-tenth of a mile in length, and *sections*, which are segments greater than one-tenth mile. The entire length of each Connecticut highway route is segmented and accounted for in this report. Each segment is described by the following features:

- Presence of a traffic signal;
- Rural or urban location;
- Roadway type (*e.g.*, divided or undivided, number of lanes, limited access);
- Intersection type;
- Total number of accidents from 1991 to 1993;
- Total three-year traffic volume (AADT multiplied by three times 365);
- Vehicle miles traveled on the highway segment from 1991 to 1993, in millions;
- Actual accident rate (accidents per mvm);
- Average accident rate for the highway and surrounding land use type; and

- Critical accident rate, used for testing the safety of the segment, a function of the segment length, traffic volume, time period, and the average accident rate for that particular highway.

Locations selected for this study were chosen from a list of over three thousand sites monitored by the HPMS. The HPMS list provides the route number, starting milepost, length of section, roadway type, rural or urban classification and the town in which the roadway is located. Once the sites were selected, the additional geometric and roadway information was obtained from the Office of Planning Inventory and Data at the Connecticut Department of Transportation.

The geometric and traffic information provided for each HPMS location include: lane widths, shoulder width, AADT, number of at-grade intersections (signalized, stop signs or other), speed limit, peak-hour volume to capacity ratio, roadway type, horizontal curvature, vertical gradient, etc. Table 1 defines thirteen categories of horizontal curvature. The length of each curve within a given section is recorded into one of these thirteen curve classifications. The vertical gradient is separated into six categories based on the percent grade, also defined in Table 1. The length of each vertical curve segment at a site is also recorded in one of the appropriate six groups. Sites were selected to acquire a representative sample of Connecticut roadways, providing a variety of terrain and traffic conditions, also with a fair representation across the state.

This study considers four geometric variables: shoulder width, horizontal curvature, vertical gradient, and intersections per mile. Lane widths were not considered for this study since nearly all of the HPMS sites had lane widths of twelve feet. The traffic variables analyzed include: AADT, speed limit, and volume/capacity ratio. Sites selected for this study are from state numbered or U.S. numbered routes only, since the accident records were found to be better documented on these roadways than on the local road system. Therefore, results from this study will only apply to state and US highways.

Because the location of an accident is often estimated and occasionally assigned to the nearest milepost on the route, segments larger than three tenths of a mile were selected, thereby increasing the probability that the reported accident occurred within that section. Assigning vehicle accidents to very short road sections is more susceptible to locational error than assigning accidents to longer road sections (14). Furthermore, these sections were selected independently of the accident data to avoid any accident bias. Therefore, a few zero accident locations are present in the database.

There are a total of three hundred forty-four miles of arterial and collector roadways in this Connecticut sample, most of which are two-lane arterial segments varying in length from three tenths of a mile to 3.86 miles long. Following are additional statistics describing the data set:

- 344 miles of roadway on 446 segments
- Average segment length of 0.77 miles; shortest: 0.30; longest: 3.86
- Rural / urban mileage split of 47 / 53 percent

- Lowest AADT of 300 vehicles; highest of 45,500 vehicles
- Average segment accident rate of 3.5 accidents per mvm; lowest: 0.0; highest: 20.3

## EXPLORATORY DATA ANALYSIS

Descriptive statistics were computed for the data set to find critical relationships between the dependent variable (accidents per mvm over the three year study period) and the independent variables (geometric design and traffic conditions). The total accident rate includes fatality, personal injury, and property damage accidents; traffic characteristic variables for each highway segment included in the analysis are:

AADT	Annual Average Daily Traffic (thousands of vehicles)
SPDLMT	posted speed limit (mph)
DESGSPD	design speed (mph)
DIFFSPD	speed differential (design speed less the posted speed limit, mph)
VOLCAP	volume to capacity ratio

Geometric design variables are:

HC	horizontal curve classification
VC	vertical gradient classification
RT SHLDR	right shoulder width (feet)
INT	number of intersections (signalized and unsignalized) per mile

Each highway section is not homogeneous with respect to its curvature or gradient. Therefore, to classify the characteristics of each section, three surrogate measures for horizontal curvature classification and three surrogate measures for vertical gradient classification were used:

HCAVG and VCAVG	Mean absolute horizontal curvature and vertical gradient classification
HCMAC and VCMAX	Maximum absolute horizontal curvature and vertical gradient classification
HC85 and VC85	Eighty-fifth percentile horizontal curvature and vertical gradient classification

These measures are similar to those used by other researchers (13, 14).

Table 2 provides the Pearson correlation coefficients for the variables in this model with the dependent variable along with other descriptive statistics. Intersections per mile has the greatest influence on accident rates; the relationship is depicted on Figure 1, where accident rate increases monotonically with intersections per mile. Note also that accident rate is greater for principal arterials than for minor arterials for the same intersection density category. The higher accident rates on the principal arterials may be caused by greater numbers of vehicle interactions associated with greater traffic volumes.

Posted speed limit has the second highest correlation with accident rate. Figure 2 shows that as the speed limit increases from twenty-five to fifty mph, the accident rate per million vehicle miles traveled decreases from 6.3 to 1.5. This relationship is understandable since highways with higher speed limits generally have higher design speeds and fewer access points. Both AADT and the volume/capacity ratio of the highway as traffic condition variables were included to determine which variable is more appropriate; volume/capacity ratio is slightly better correlated with accident rate than AADT.

The three measures for vertical gradient and horizontal curvature are not well correlated with accident rate, nor is right shoulder width. Computation of the mean accident rates for different shoulder widths indicated no significant increase or decrease in accidents with increasing shoulder width. Similarly, there were no significant increases or decreases in accident rate between different horizontal and vertical curve classes, and none of these variables were correlated well with the dependent variable.

Based on these tests, the variables INT and SPDLMT appear to be good variables for accident prediction modeling, followed by VOLCAP, AADT, and DIFFSPD. It should be noted that during modeling, the estimated coefficient value for SPDLMT should be negative since it has displayed a negative correlation with accident rates.

## POISSON REGRESSION METHOD

Poisson regression estimates parameters for predicting the probability of a given event as follows (14):

$$\text{Prob } [Y = y] = e^{-\lambda} (\lambda t)^y / y! \quad y = 0, 1, 2, \dots \quad (1)$$

where:  $\lambda = e^{\beta x}$

(2)

and Y is a discrete random variable representing the number of events over a period of time;

$\lambda$  is the expected mean number of events (number of accidents / mvm), a function of the regressor variables  $x$ ;

$x$  is a vector representing the explanatory variables; and

$\beta$  is a vector representing the parameters to be estimated.

Poisson regression was chosen for this study over multiple linear regression because it possesses several favorable qualities. First, multiple linear regression sometimes estimates a large negative constant coefficient value which can produce negative accident rate predictions. Poisson regression uses the natural log to predict accident rates, thereby ensuring that only non-negative rates are predicted.

Second, multiple linear regression assumes a normal distribution for the dependent variable. This is inappropriate for modeling highway accident rates, which are positively skewed

due to the number of highway sections having very few or no reported accidents during a given study period. The Poisson model accounts for positively skewed distributions.

Finally, multiple linear regression for accident rate prediction is a normal approximation of a discrete process. For example, a prediction from a linear model may be 6.7 accidents per mvm (a non-discrete value). The Poisson model is capable of recognizing safety in terms of accident involvement rates and accident probabilities. For a given highway segment the Poisson model will provide the accident rate per million vehicle miles traveled along with the probability of observing a given number of accidents within a certain period of time.

The Poisson regression regressor variables of equation (2) are the geometric and traffic characteristics of each highway segment. The equation parameters are found using maximum likelihood estimation (MLE), which here was performed using the LIMDEP statistical software package (17). Once the parameter values have been estimated, the expected accident rate ( $\lambda$ ) of each highway section is computed from its traffic and geometric conditions, and Equation (1) is used to calculate the probability of observing a discrete number of accidents ( $y$ ) for the section over a specified period of time.

Poisson regression assumes the variance of the dependent variable to be equal to its mean. One shortcoming of this assumption is the possibility of extra variation or overdispersion in the dataset, which occurs when the observed variance is actually greater than the mean. Overdispersion in the Poisson model was tested using a simple least squares regression test proposed by Cameron and Trivedi and recommended by the LIMDEP User Manual (18). Overdispersion does not affect coefficient estimates, but does cause their standard errors to be underestimated, thus overstating the significance of the model (14). Agresti suggested dividing the t-statistic values by the square root of the overdispersion parameter in order to correct the significance levels of the regression coefficients (19).

The following criteria were used for testing models:

- the selected model should have the expected signs for all estimated coefficients;
- each individual parameter is accepted according to its t-statistic; and
- the selected model should have a minimum Akaike Information Criterion (AIC) value (described later).

The t-test determines whether or not parameter estimates are significantly different from zero. The t-statistic is computed as:

$$t^* = \frac{\beta}{\text{S.E.}(\beta)} \quad (3)$$

where:  $\beta$  = parameter estimate

S.E. ( $\beta$ ) = the standard error of the parameter estimate

Given a large number of observations (greater than two hundred fifty), the null hypothesis that a parameter value is equal to zero can be rejected at a significance of five percent if the absolute value of the t-statistic is greater than 1.96. If the model displays overdispersion, these t-statistic values should be divided by the square root of the overdispersion parameter before determining significance.

AIC uses a theoretical information-criterion to identify the optimal model. Unlike other model evaluation methods, AIC identifies the “best approximating” model among a class of competing models with different numbers of parameters without specifying a significance level (20). AIC is defined as follows:

$$AIC = -2 * ML + 2 * K \quad (4)$$

where: ML = the maximum log - likelihood  
K = the number of free parameters in the model

The best model has the minimum AIC value.

## RESULTS

Table 3 shows estimation results for five models testing the independent variables having the greatest correlation with accident rate. Model 1 statistics indicate that INT is significant. Model 2 is better than Model 1, having a smaller AIC value, and SPDLMT is also significant. Models 3 and 4 are rejected since the DESGSPD and DIFFSPD are insignificant at five percent. AADT and VOLCAP (Models 5 and 6) are both significant at one percent, but Model 5 (AADT) is better according to the AIC.

The geometric design variables of horizontal curvature, vertical gradient and the width of the right-hand shoulder were then added to Model 5; results are in Table 4. Model 7 includes RT SHLDR and Models 8 through 10 includes the three surrogate horizontal curve and vertical gradient variables. All of these variables have very small coefficients and are insignificant at five percent. Additionally, none of the models provided a better AIC value than Model 5.

In addition to these variables, the effects of area-type and functional classification of the highway on Connecticut highway accident rates were examined. Dummy variables indicating principal or minor arterial highway classification and rural area type were added to Model 5. All variables are significant except for the minor arterial indicator. As shown in Table 5, principal arterials tend to produce higher accident rates than minor arterials (higher coefficient value for the principal arterial indicator). The negative coefficient value for the rural highway variable indicates that the average accident rate for rural highways is 0.212 accidents per mvm less than on urban highways. These results may be partially explained by the fact that urban highways and principal arterials generally have higher AADT levels and that urban highways have lower design speeds as a result of being constrained to a narrow right-of-way.



These results suggest that the geometric characteristics may have a significant influence only on rural or high speed highways (posted speed limit at least forty mph), conditions where these characteristics are more critical than others (such as the number of intersections). Therefore, a segmented dataset with sections tending to have fewer intersections may permit the highway geometric design variables to become more important. The correlation coefficients between accident rates and the geometric design variables for rural highway and high speed highways were first calculated. Table 6 shows a small improvement in correlation coefficients for the surrogate measures of horizontal curvature and vertical gradient. Models were then tested using only the rural and the high speed highway data; these results appear on Tables 7 and 8. Results of these models show the geometric design variables to remain insignificant at five percent.

All models were tested for overdispersion using the regression based test introduced earlier. Results indicate that there is some overdispersion; for Model 5 the overdispersion parameter ( $\tau$ ) was estimated to be 1.20. Dividing the t-statistic values by 1.2 provides more accurate t-statistics; all four coefficients remain significant at five percent.

Using Model 5, a comparison was made between the observed accident rates and the predicted accident rates. Figure 3 shows a fairly equal distribution of predictions about the "Fit Line." For observed accident rates less than four accidents per mvm the model tends to slightly overpredict.

## CONCLUSIONS AND RECOMMENDATIONS

Poisson regression was chosen to predict Connecticut highway traffic accidents based on geometric characteristics and traffic condition data collected from Connecticut's HPMS and 1991-1993 TARS. INT, SPDLMT and AADT were found to be the best variables for explaining highway accident rates. Geometric variables were found to be insignificant. Compared to VOLCAP, AADT proved to be a better estimator. Similarly, compared to DIFFSPD and DESGSPD, SPDLMT proved to be better for explaining traffic accidents. Adjustments were made to the significance levels of the estimated coefficients to account for some overdispersion displayed in the model.

The effects of geometric characteristics may be indirectly accounted for by SPDLMT. This would help explain the negative coefficient on SPDLMT, since highways with higher posted speed limits generally have higher design speeds (*i.e.*, better geometric characteristics). Raising the speed limit above the design speed may actually increase the number of accidents. In order to significantly determine the effect of the geometric design variables on highway accidents, the data set could be segmented into several categories according to SPDLMT, AADT and INT, permitting variation of geometric characteristics within these categories to be analyzed.

DIFFSPD was used to represent the highway vehicle speed differential, but did not prove to be significant for predicting accident rate. An alternative representation might compare observed speeds with the design speed. Also, INT proved to be a critical variable for accident

predicting, although it does not distinguish between signalized and unsignalized intersections. Further research should consider the possibility of different effects for signalized and unsignalized intersections.

Occasionally, an accident within a given highway segment is caused by characteristics of the upstream highway section. Inconsistencies along a highway segment may contradict a driver's expectations, thereby causing an accident. For this particular type of situation, how might the cause and location of the accident be identified? Future research should focus on methods for improving accident location accuracy. This may be accomplished through improving methods for reporting accident locations.

Earlier in this study it was mentioned that the minimum section length is three tenths of a mile in order to reduce the probability of location error. Further research should identify those conditions where there should be a maximum section length. At what point do the effects of the highway geometric characteristics on accident rates become diluted due to the length of the section?

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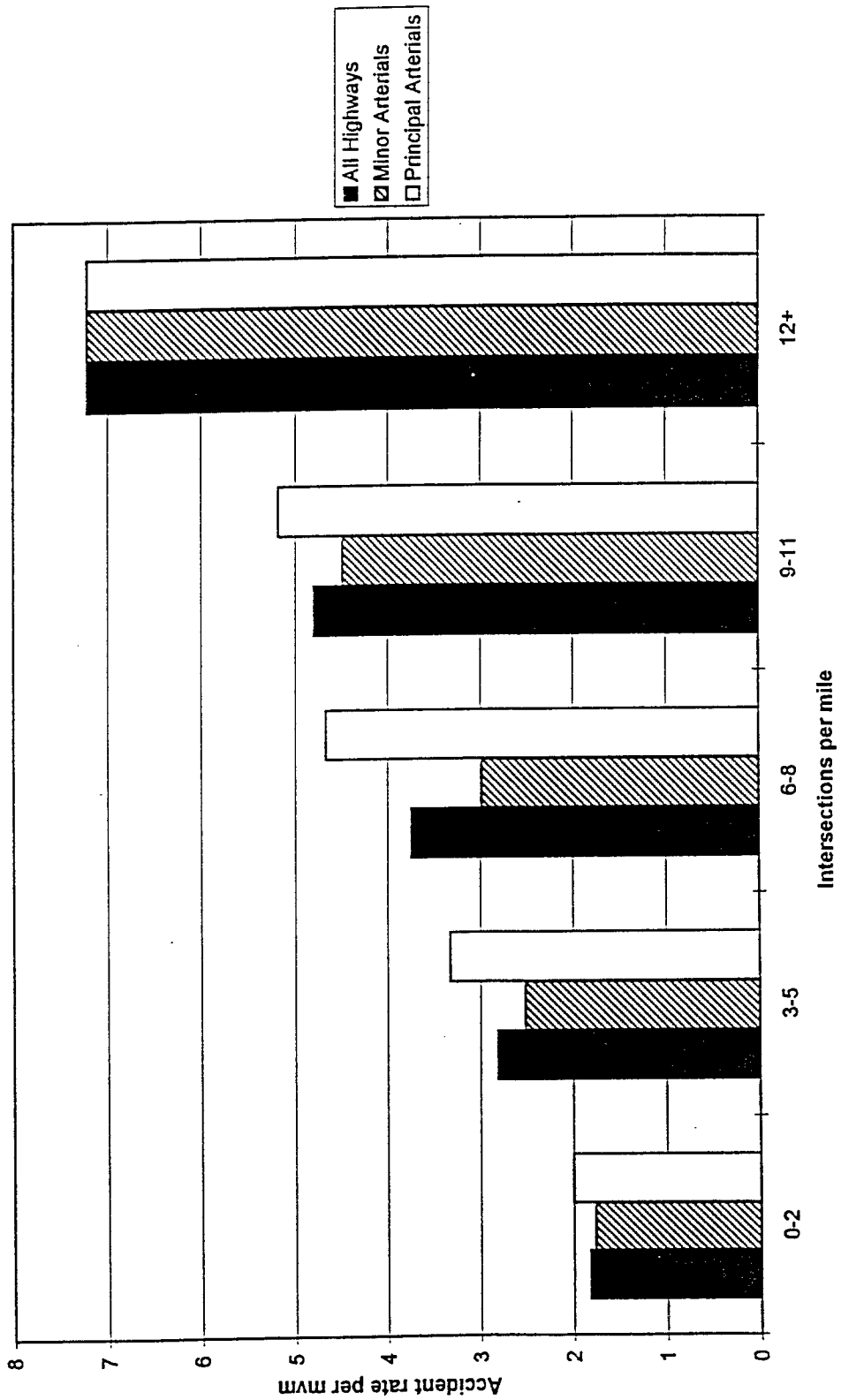


Figure 1. Effect of Intersections on Accident Rate

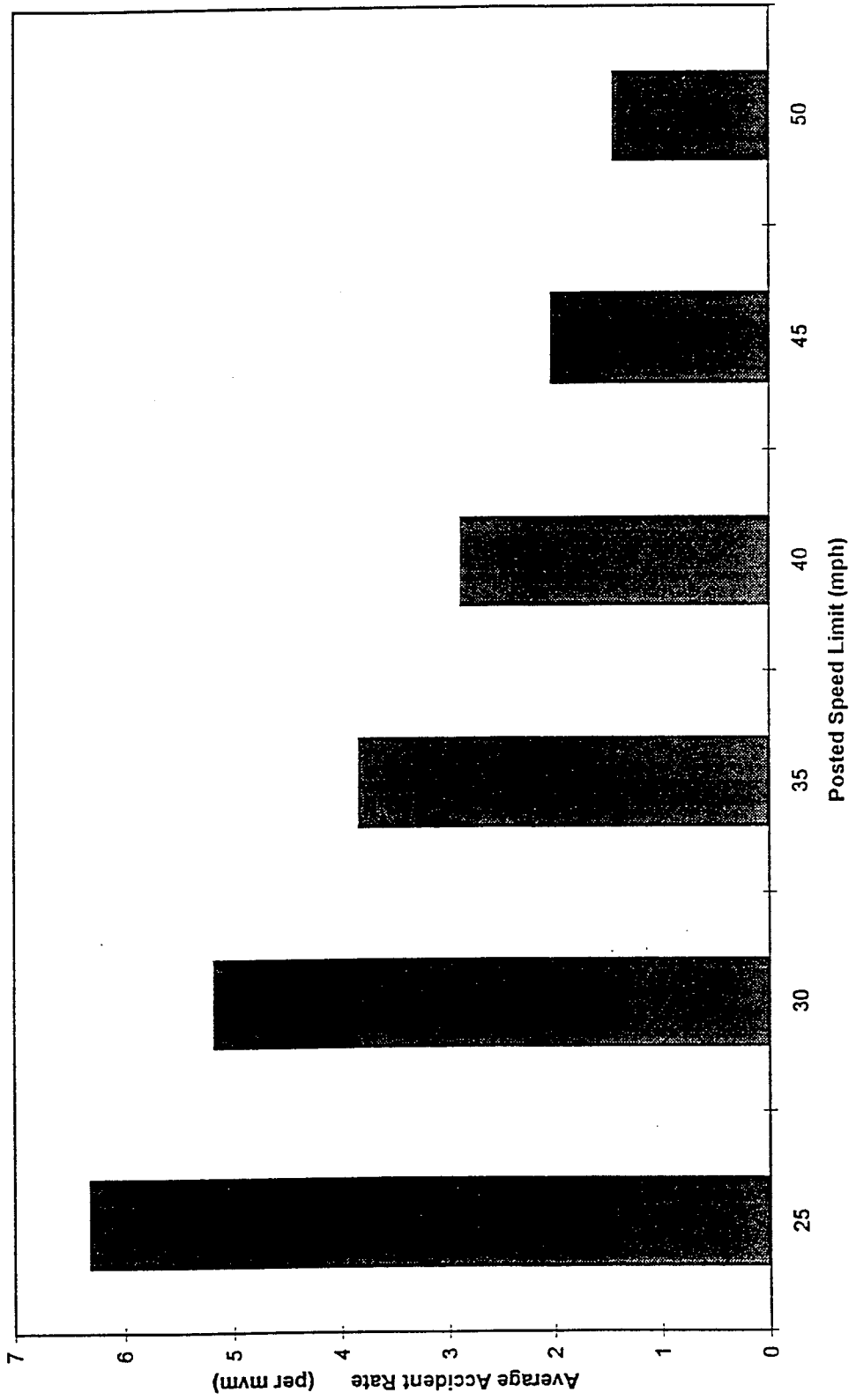


Figure 2. Accident Rate vs. Posted Speed Limit

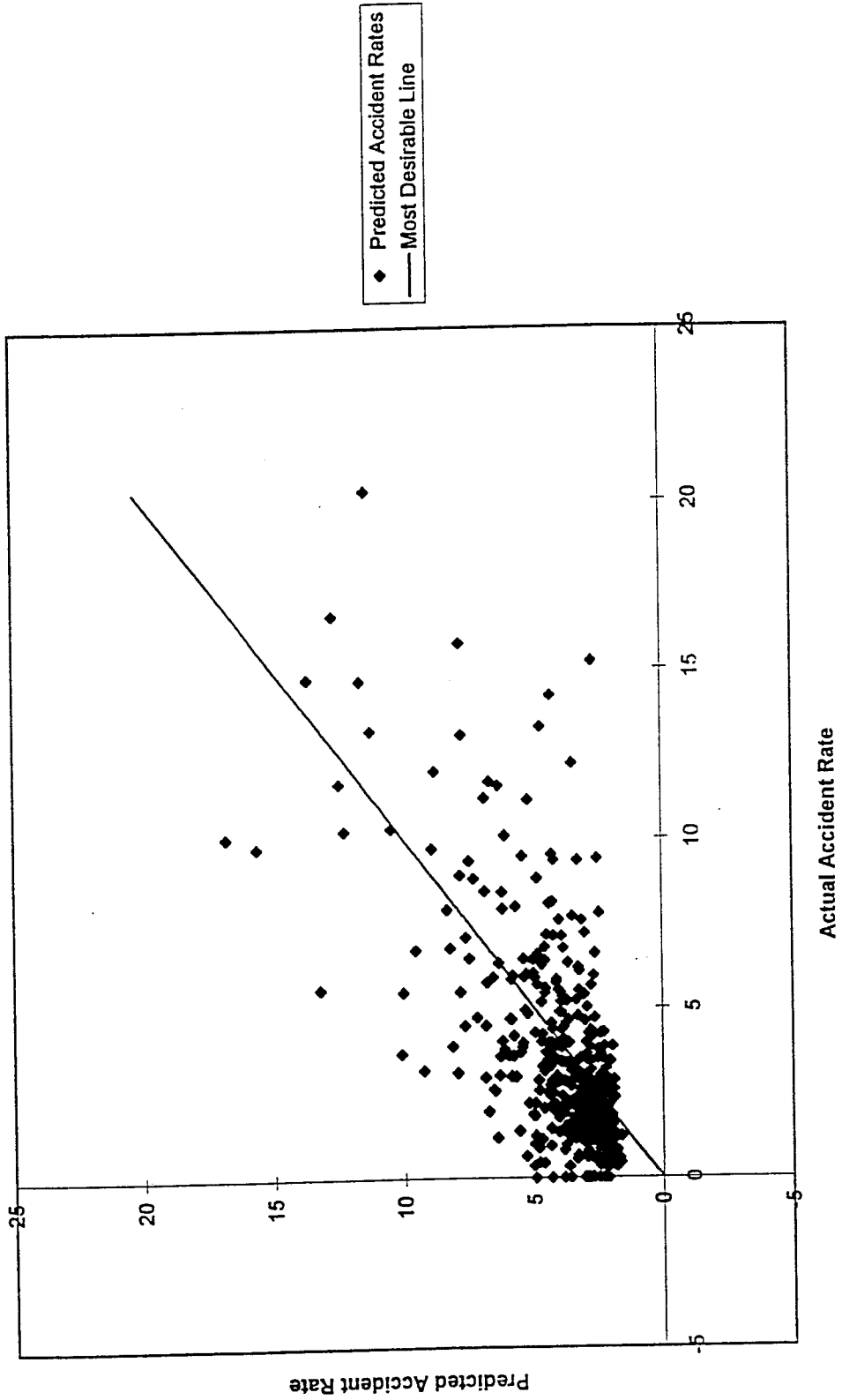


Figure 3. Predicted vs. Observed Accident Rates

**TABLE 1 Horizontal Curvature and Vertical Grade Classification Codes**

Horizontal Curve Class	Degree of Curvature	Vertical Grade Class	Percent Grade
A	0.0 - 0.4	A	0.0 - 0.4
B	0.5 - 1.4	B	0.5 - 2.4
C	1.5 - 2.4	C	2.5 - 4.4
D	2.5 - 3.4	D	4.5 - 6.4
E	3.5 - 4.4	E	6.5 - 8.4
F	4.5 - 5.4	F	8.5 +
G	5.5 - 6.9		
H	7.0 - 8.4		
I	8.5 - 10.9		
J	11.0 - 13.9		
K	14.0 - 19.4		
L	19.5 - 27.9		
M	28 +		

**TABLE 2 Statistical Summary of Model Variables**

	Correlation with Accident Rate	Average Value	Minimum Value	Maximum Value
Accident Rate	1.0000	3.45	0.00	20.30
INT	0.5853	5.85	0.00	32.00
AADT (thousands)	0.2378	9.74	0.30	45.50
DIFFSPD (mph)	0.2359	20.92	-5.00	45.00
SPDLMT (mph)	-0.4380	37.95	25.00	50.00
VOLCAP	0.2537	0.49	0.05	1.37
RT SHLDR (ft)	0.0682	2.60	0.00	12.00
HC AVG	0.0327	0.5 - 1.4 deg.	0.0 - 0.4 deg.	7.0 - 8.4 deg.
HCMAX	-0.0715	2.5 - 3.4 deg.	0.0 - 0.4 deg.	19.5+ deg.
HC 85	-0.0042	2.5 - 3.4 deg.	0.0 - 0.4 deg.	19.5+ deg.
VC AVG	-0.0702	0.5 - 2.4 %	0.0 - 0.4 %	8.5+ %
VC MAX	-0.1018	2.5 - 4.4 %	0.0 - 0.4 %	8.5+ %
VC 85	-0.0732	2.5 - 4.4 %	0.0 - 0.4 %	8.5+ %

**TABLE 3 Poisson Regression Results: Traffic Variables**

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.742 (18.77)	1.966 (11.41)	0.737 (17.85)	0.737 (17.58)	1.960 (11.37)	1.888 (10.79)
INT	0.070 (19.79)	0.054 (12.82)	0.070 (19.69)	0.070 (19.71)	0.047 (10.28)	0.049 (10.85)
SPDLMT		-0.030 (-7.20)			-0.030 (-7.33)	-0.030 (-7.33)
DESGSPD			-0.00002 (-0.47)*			
DIFFSPD				-0.00002 (-0.40)*		
AADT					0.019 (5.37)	
VOLCAP						0.262 (3.20)
Overdispersion	1.66	1.49	1.66	1.67	1.44	1.47
Log - likelihood	-954.95	-928.68	-954.84	-954.87	-914.84	-923.63
AIC	1913.90	1863.36	1915.68	1915.74	1837.68	1855.26

Values in parentheses are original t-statistics (not adjusted for overdispersion).

\* Value is not significant at 95% confidence level.

Model 1:  $\ln \lambda = 0.742 + 0.007 \text{ INT}$

Model 2:  $\ln \lambda = 1.966 + 0.054 \text{ INT} - 0.030 \text{ SPDLMT}$

Model 3:  $\ln \lambda = 1.966 + 0.074 \text{ INT} - 0.00002 \text{ DESGSPD}$

Model 4:  $\ln \lambda = 0.737 + 0.070 \text{ INT} - 0.00002 \text{ DIFFSPD}$

Model 5:  $\ln \lambda = 1.960 + 0.047 \text{ INT} - 0.031 \text{ SPDLMT} + 0.019 \text{ AADT}$

Model 6:  $\ln \lambda = 1.888 + 0.049 \text{ INT} - 0.031 \text{ SPDLMT} + 0.262 \text{ VOLCAP}$



**TABLE 4 Poisson Regression Results: Traffic and Geometric Design Variables**

Variable	Model 5	Model 7	Model 8	Model 9	Model 10
Constant	1.960 (11.37)	1.951 (11.28)	2.008 (10.89)	2.008 (10.90)	2.033 (11.04)
INT	0.047 (10.28)	0.047 (10.27)	0.046 (10.00)	0.046 (9.99)	0.046 (9.95)
SPDLMT	-0.031 (-7.33)	-0.031 (-7.96)	-0.035 (-7.93)	-0.035 (-7.94)	-0.035 (-8.02)
AADT	0.019 (5.37)	0.018 (4.80)	0.018 (4.91)	0.018 (4.91)	0.017 (4.79)
RT SHLDR		0.0052 (0.52)*			
HCAVG			0.00005 (0.74)*		
HCMAX				0.00005 (0.74)*	
HC85					0.00007 (1.12)*
VCAVG			0.00003 (0.24)*		
VCMAX				0.00003 (0.21)*	
VC85					-0.00004 (- 0.64)*
Overdispersion	1.44	1.44	1.44	1.44	1.44
Log-likelihood	-914.84	-914.70	-914.44	-914.45	-914.16
AIC	1837.68	1839.40	1840.88	1840.90	1840.32

Values in parentheses are original t-statistics (not adjusted for overdispersion).

\* Value is not significant at 95% confidence level.

**TABLE 5 Poisson Regression Results: Locational and Highway Type Variables**

Variable	Model 5	Model 11	Model 12	Model 13
Constant	1.960 (11.37)	1.882 (10.79)	1.832 (9.10)	1.935 (11.16)
INT	0.047 (10.28)	0.047 (10.28)	0.046 (9.88)	0.046 (10.01)
SPDLMT	-0.031 (-7.33)	-0.029 (-6.31)	-0.033 (-7.82)	-0.034 (-7.88)
AADT	0.019 (5.37)	0.014 (3.78)	0.013 (3.24)	0.014 (3.49)
RUR-IND		-0.212 (-2.89)		
MIN-IND			0.118 (1.01)*	
PRIN-IND			0.280 (2.27)*	0.170 (2.92)
Overdispersion	1.44	1.40	1.39	1.39
Log - likelihood	-914.84	-910.58	-910.05	-910.57
AIC	1837.68	1831.16	1832.10	1831.14

*Values in parentheses are original t-statistics (not adjusted for overdispersion).*

*\* Value is not significant at 95% confidence level.*

RUR-IND = Variable indicating rural highway

MIN-IND = Variable indicating minor arterial

PRIN-IND = Variable indicating principle arterial

**TABLE 6 Correlation Between Model Variables and Accident Rate for Different Types of Highway**

	All Highways	Rural Highways	Urban Highways	Highways with Speed Limit > 40 mph	Highways with Speed Limit < 40 mph
Accident Rate	1.0000	1.000	1.000	1.000	1.000
INT	0.5853	0.3923	0.5661	0.3182	0.5837
AADT	0.2378	0.2651	0.1229	0.2018	0.3200
DIFFSPD (mph)	0.2359	0.0638	0.0926	0.1013	0.1725
SPDLMT (mph)	-0.4380	-0.2734	-0.3821	-0.1930	-0.2755
VOLCAP	0.2537	0.2328	0.1168	0.2021	0.2588
RT SHLDR (ft)	0.0682	0.0932	-0.0138	0.0250	0.1154
HC AVG	0.0327	0.1427	0.0846	0.0614	-0.0396
HCMAX	-0.0715	0.0052	0.0226	-0.0687	0.0050
HC 85	-0.0042	0.0912	0.0649	0.0085	-0.0714
VC AVG	-0.0702	-0.0097	-0.0272	0.0081	-0.0277
VC MAX	-0.1018	-0.0144	-0.0314	-0.0184	0.0072
VC 85	-0.0732	0.0236	-0.0381	0.0087	-0.0101

**TABLE 7 Poisson Regression Results for Rural Highways**

Variable	Model 5	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19
Constant	1.960 (11.37)	1.517 (3.61)	1.555 (3.72)	1.529 (3.65)	1.505 (3.34)	1.509 (3.36)	1.555 (3.46)
INT	0.047 (10.28)	0.048 (3.28)	0.059 (4.48)	0.057 (4.32)	0.059 (4.37)	0.059 (4.37)	0.058 (4.30)
SPDLMT	-0.031 (-7.33)	-0.026 (-2.70)	-0.026 (-2.62)	-0.026 (-2.66)	-0.025 (-2.40)	-0.025 (-2.41)	-0.025 (-2.48)
AADT	0.019 (5.37)	0.021 (1.86)					
RT SHLDR				0.026 (0.86)*			
HCAVG					-0.00003 (-0.22)*		
HCMAX						-0.00004 (-0.21)*	
HC85							-0.00001 (-0.09)*
VCAVG					0.00012 (0.38)*		
VCMAX						0.00012 (0.34)*	
VC85							0.00010 (0.29)*

Values in parentheses are original t-statistics (not adjusted for overdispersion).

\* Value is not significant at 95% confidence level.

**TABLE 8 Poisson Regression Models for High Speed Roadways**

Variable	Model 5	Model 20	Model 21	Model 22	Model 23	Model 24
Constant	1.960 (11.37)	2.614 (4.68)	2.565 (4.53)	2.701 (4.78)	2.698 (4.78)	2.693 (4.79)
INT	0.047 (10.28)	0.051 (4.66)	0.050 (4.61)	0.050 (4.57)	0.050 (4.56)	0.050 (4.61)
SPDLMT	-0.031 (-7.33)	-0.049 (-3.75)	-0.047 (-3.57)	-0.050 (-3.82)	-0.050 (-3.82)	-0.050 (-3.81)
AADT	0.019 (5.37)	0.014 (2.81)	0.016 (2.76)	0.013 (2.41)	0.013 (2.41)	0.012 (2.21)
RT SHLDR			-0.012 (-0.65)*			
HCAVG				0.00013 (1.10)*		
HCMAX					0.00012 (1.10)*	
HC85						0.00018 (1.55)*
VCAVG				-0.00013 (-0.54)*		
VCMAX					-0.00014 (-0.59)*	
VC85						-0.00037 (-1.89)*

Values in parentheses are original t-statistics (not adjusted for overdispersion).

\* Value is not significant at 95% confidence level.

