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VALUE OF PERFECT INFORMATION OF TRANSPORTATION
FORECASTING MODELS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for
the Degree Doctor of Philosophy in the Graduate
School of The Ohio State University

By

Dario Hidalgo, M.S.

*****
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1997

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ABSTRACT

The Value of Perfect Information (VOPI) on predictions from various transportation models is formulated in the context of building improvements. This study is justified by a perceived need to assess the value of the information produced from increasingly sophisticated transportation models against their costs and lack of such assessments in evaluation-based transportation prediction models.

A framework is developed to calculate: i) cumulative VOPI, or the VOPI of the outcomes of each step of a sequential forecasting process; ii) marginal VOPI, or the VOPI of each step given that the inputs are known with certainty; and iii) model VOPI, or the VOPI of each step given that the inputs to this step are uncertain.

A simulation-based, sequential prediction model is also developed. This model considers uncertainty in the outputs in addition to the inputs of the different steps. The model includes trip generation, trip distribution, traffic assignment and five attributes models: system travel time, fuel consumption, and hydro-carbon (HC), carbon monoxide (CO) and nitrous-oxides (NOx) emissions.

The VOPI framework is applied to different network, congestion and cost of construction conditions. The results indicate that all VOPIs peak when the difference in expected utilities between alternatives is zero and increase with the level of congestion.
The results also show that the marginal VOPI of the attribute models is larger than that of the traffic assignment model, and that the latter is larger than marginal VOPI of trip distribution model for most conditions. Additionally, for most cases, the model VOPI is very close to zero, suggesting that, in general, there is little value in improving a single step in the forecasting process. Sensitivity analyses on relevant input factors reveal that VOPI values are most sensitive to pollution-related preference parameters and traffic assignment uncertainty.

Calculating model uncertainty an calculating VOPI are computationally intensive, requiring extensive simulation. Several areas of further research are suggested, including more sophisticated sensitivity analysis, improving the numerical procedures, investigating the uncertainty of the prediction model components and formulating the value of imperfect information.
"Dejo a los varios povenires (no a todos)
mi jardín de los senderos que se bifurcan
--I leave to the many futures (not all)
my garden of the forking paths."

Jorge Luis Borges (1942)

Dedicated to Maria Constanza and our upcoming baby
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CHAPTER 1

INTRODUCTION

In this study we formulate the Value of Information (VOI) on predictions from various transportation models in the context of a simple planning problem: to build or not to build a highway improvement. The concept of VOI (Sengupta, 1982; SRI, 1977; Raiffa, 1968) is a well-established means of assessing whether the benefits of pursuing additional information outweigh the costs. It can also be used to indicate which types of additional information should receive highest priority. Yet, we have only seen limited application of the VOI concept to evaluation-based transportation prediction models.

There are two types of information: perfect and imperfect. The value of perfect information (VOPI) provides the value that would be associated if the information is error-free. Although no information would be error-free, VOPI is easier to determine and is, therefore, often used as a first-cut indication of an upper bound on the value of more realistic information. The value of imperfect information (VOII) provides the value that would be associated if the information has a given level of uncertainty. Although we introduce the basic concepts for VOII calculation, we concentrate on VOPI. We first formulate a framework to calculate it, and then we apply this formulation to illustrative...
examples. We explain the implications of our results, explore the issues associated with the application of this formulation and recommend extensions to our work.

This study is justified by a perceived need to assess the value of the information produced from increasingly sophisticated transportation models against the cost of producing this information. We address trip generation, trip distribution, traffic assignment and impact prediction models. We formulate the VOI assessment in the context of evaluating transportation alternatives under uncertainty.

In the following sections we provide some background on evaluating transportation alternatives evaluation and uncertainty associated with the predictions of transportation alternatives impacts. We close this chapter with a brief description of the remainder of this document.

1.1. Evaluation of Transportation Alternatives

In normative decision making, transportation alternatives are evaluated through their projected impacts. These impacts are multiple because transportation affects the quality of life and the economy in many different ways (Meyer and Miller, 1984; Dickey, 1983). Transportation improvements may affect the community-at-large (e.g., noise, pollution), travelers (e.g., travel time, travel cost), businesses (e.g., accessibility of workers and clients, shipment costs), government agencies (e.g., cost, image), and so on.

These multiple impacts are recognized in the processes with which transportation projects must comply to be eligible for federal funding. At the planning stages --that is,
in the selection of alternatives at the project level— these requirements are dictated by the National Environmental Policy Act (NEPA). At the implementation stages --that is, in the selection of projects to be included in regional and state programs and plans-- the processes are dictated by the Intermodal Surface Transportation Efficiency Act (ISTEA) and the Clean Air Act Amendments (CAAA).

According to the NEPA process, most highway investments need an Environmental Impact Statement (EIS) to be eligible for federal funding. An EIS should evaluate all reasonable alternatives to the investment, considering the project’s purpose, need, consistency with the goals and objectives of any local urban plan, and the social, economic, environmental and other impacts of the project (23 CFR Parts 635, 640, 650, 712, 790; 49 CFR Part 622; 23 CFR Part 771).

In the federal regulations no specific methodology is recommended to evaluate the alternatives. The values (impacts) that are considered important in the decision-making process should be identified in a Record of Decision (ROD), along with the reasons some values were considered more important than others. The decision, then, represents a balancing of the values, and this balancing should be reflected in the ROD.

To facilitate the process FHWA has issued guidelines for preparing the NEPA process documents (FHWA, 1987). These guidelines include ways to identify alternatives and list possible impacts. Four types of alternatives are recommended for consideration: no-action (no-build), implementing transportation system management alternatives (TSM), establishing mass transit based alternatives, and building highways.
Several options might be evaluated within each type of alternative, especially for building highways (e.g., different alignments, design features, etc.).

The list of possible environmental consequences discussed in the guidelines is extensive. It includes:

- land use impacts and relationship with area’s development plan,
- farmland impacts,
- social impacts (e.g., neighborhoods, travel patterns and accessibility, school districts, safety, groups affected),
- relocation impacts (including anticipated problems and proposed solutions),
- economic impacts (regional & local economy; tax revenues/expenditures, employment opportunities, accessibility, and retail sales),
- joint development,
- considerations relating to pedestrians and bicyclists,
- air quality impacts (impacts on regional conformity and project carbon oxides analysis),
- noise impacts,
- water quality impacts,
- permits (EPA, Corps of Engineers, Coast Guard),
- wetland impacts,
- water body modification and wildlife impacts,
- floodplain impacts,
• wild and scenic rivers,
• coastal barriers,
• coastal zone impacts,
• threatened or endangered species,
• historic and archeological preservation,
• hazardous waste sites,
• visual impacts,
• energy,
• construction impacts,
• relationship of local short-term uses vs. long-term productivity,
• irreversible and irretrievable commitment of resources.

FHWA recommends discussing the applicable impacts for each alternative in the EIS and using state-of-the-art methodologies to quantify measurable impacts.

The NEPA process is considered concluded when the EIS is approved or disapproved. Approving the EIS does not commit FHWA to approve any future grant request to fund the preferred alternative. It is, though, a requisite for such funding approval. As indicated above, implementation (funding) decisions follow processes regulated under ISTEA and CAAA.

The planning process leading to funding is collaborative, comprehensive, continuing and flexible (ISTEA). Projects are first introduced in the state’s Long Term Plan (LTP), which is a list of projects indicating the priority investments over a period of 20 years. Projects that have completed the NEPA Process and have received approval of
the final EIS are eligible for implementation (i.e., final engineering design, construction and operation). The priority projects are then listed in the state's Transportation Improvement Program (TIP). This TIP is updated every five years by designated Metropolitan Planning Organizations (MPOs). The TIP must conform to the CAAA, be financially "reasonable," be consistent with the long-range plan, and address fifteen factors spelled out in ISTE A section 103(f) (Younger, 1994). Conformity to the CAAA implies that both the LTP and TIP meet the regional air quality emissions targets (Shrouds, 1992). These targets are aimed at limiting the severity and reducing the number of violations of the National Amended Air Quality Standards (NAAQS).

As a result, the process to select projects for the LTP and the TIP should include several impacts and is constrained by the air quality compliance requirements and the availability of funds. Accordingly, some States and MPOs have developed multi-criteria methods. We provide (Table 1.1) three examples of these multi-attribute selection methods: Albany, NY, San Francisco Bay Area, CA and the Ohio Department of Transportation (ODOT).

The processes have in common an attempt to rationalize the selection process according to specified sets of objectives. The point systems (San Francisco, ODOT) explicitly indicate the trade-offs among choices. The MPO mechanisms (Albany, San Francisco) reflect a multimodal view of the transportation system and are based on the expected impacts of the projects. The ODOT methodology concentrates on highways and uses current conditions as indicators of most of the impacts.
<table>
<thead>
<tr>
<th>Agency (Source)</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital District Transportation Committee, Albany, NY (Younger, 1994)</td>
<td>Project Cost (Federal Share) [$1000/yr]</td>
</tr>
<tr>
<td></td>
<td>Total User Savings [$1000/yr]</td>
</tr>
<tr>
<td></td>
<td>Safety Benefits [$1000/yr]</td>
</tr>
<tr>
<td></td>
<td>Travel Time Savings [$1000/yr]</td>
</tr>
<tr>
<td></td>
<td>Energy and User Cost Savings [$1000/yr]</td>
</tr>
<tr>
<td></td>
<td>Life Cycle Cost Savings [$1000/yr]</td>
</tr>
<tr>
<td></td>
<td>Congestion Relief</td>
</tr>
<tr>
<td></td>
<td>Daily Excess Vehicle Hours of Delay Saved</td>
</tr>
<tr>
<td></td>
<td>Air Quality</td>
</tr>
<tr>
<td></td>
<td>Hydrocarbon Emission Reductions</td>
</tr>
<tr>
<td></td>
<td>Noise Reduction</td>
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<tr>
<td></td>
<td>Residential Traffic</td>
</tr>
<tr>
<td></td>
<td>Community and Ecological Disruption</td>
</tr>
<tr>
<td></td>
<td>Access to the Public Transportation System</td>
</tr>
<tr>
<td></td>
<td>Modal Integration</td>
</tr>
<tr>
<td></td>
<td>Provision of Alternate Modes</td>
</tr>
<tr>
<td></td>
<td>System Linkage</td>
</tr>
<tr>
<td></td>
<td>Economic Development</td>
</tr>
<tr>
<td></td>
<td>Other</td>
</tr>
<tr>
<td>Metropolitan Transportation Commission, San Francisco Bay Area, CA (Younger, 1994)</td>
<td>Maintain/Sustain the Transportation System (30 points)</td>
</tr>
<tr>
<td></td>
<td>Rehabilitations and Replacements Based on Management System (up to 30)</td>
</tr>
<tr>
<td></td>
<td>Not based on Management System or for Support Infrastructure (up to 20)</td>
</tr>
<tr>
<td></td>
<td>Improve Efficiency and Effectiveness (30 points)</td>
</tr>
<tr>
<td></td>
<td>Safety and Security</td>
</tr>
<tr>
<td></td>
<td>Score based on magnitude and impact</td>
</tr>
<tr>
<td></td>
<td>Congestion Relief</td>
</tr>
<tr>
<td></td>
<td>Score based on magnitude and impact</td>
</tr>
<tr>
<td></td>
<td>Cost-Effectiveness</td>
</tr>
<tr>
<td></td>
<td>Score based on annualized travel time and cost savings/project cost (normalized by the median cost effectiveness of all projects submitted)</td>
</tr>
<tr>
<td></td>
<td>Freight Movement</td>
</tr>
<tr>
<td></td>
<td>Points assigned based on facility type and nature of project</td>
</tr>
<tr>
<td></td>
<td>Expand System (meeting demand) (15 points)</td>
</tr>
<tr>
<td></td>
<td>Score based on existing ADT and LOS and impact</td>
</tr>
<tr>
<td></td>
<td>External Impacts (25 points)</td>
</tr>
<tr>
<td></td>
<td>Air Quality (Implement Transportation Control Measures)</td>
</tr>
<tr>
<td></td>
<td>Land Use Policy Support (Foster modal shift from single occupant vehicle trips on regional facilities)</td>
</tr>
<tr>
<td></td>
<td>Energy Conservation (Demonstrate energy conservation)</td>
</tr>
<tr>
<td></td>
<td>Americans with Disabilities Act enhancements</td>
</tr>
<tr>
<td></td>
<td>Total 100 points (prorated according to nearness and necessity of planning project to direct and immediate transport improvements)</td>
</tr>
</tbody>
</table>

Table 1.1 Examples of Multi-Criteria Procedures Used to Prepare Transportation Improvement Programs
Table 1.1 continued

<table>
<thead>
<tr>
<th>Agency (Source)</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ohio Department of Transportation (ODOT, 1995)</td>
<td>Traffic [ADT] (15 points)</td>
</tr>
<tr>
<td></td>
<td>Congestion [Volume/Capacity] (15 points)</td>
</tr>
<tr>
<td></td>
<td>Safety [No. Accidents] (15 points)</td>
</tr>
<tr>
<td></td>
<td>Readiness [Planning Stage] (5 points)</td>
</tr>
<tr>
<td></td>
<td>Importance [Road Type] (8 points)</td>
</tr>
<tr>
<td></td>
<td>Regional Impact [Level] (3 points)</td>
</tr>
<tr>
<td></td>
<td>Impact Freight Transportation [Belongs to Access Ohio] (8 points)</td>
</tr>
<tr>
<td></td>
<td>Jobs Creation [No. of Jobs Created/Retained] (8 points)</td>
</tr>
<tr>
<td></td>
<td>Joint Development [$ Private Investment] (8 points)</td>
</tr>
<tr>
<td></td>
<td>Private/Local Participation [Level] (3 points)</td>
</tr>
<tr>
<td></td>
<td>Total 89 Points</td>
</tr>
</tbody>
</table>

In summary, project planning and implementation selection processes (NEPA, ISTEA) recognize the existence of multiple impacts. They provide a great deal of flexibility on how to evaluate alternatives and recommend the use of the best mechanisms available to quantify (predict) the impacts. The application of these policies in the transportation planning practice has resulted in different types of evaluation mechanisms, according to the needs and preferences of the local and regional decision making authorities. Examples of these mechanisms are rather deterministic and give an illusion of precision in prediction (Younger, 1994). Nevertheless, forecasted impacts are inevitably uncertain. We discuss the inherent uncertainty in impact prediction in the next section.
1.2. Uncertainty in Prediction of Transportation Impacts

Transportation impacts cannot be predicted with certainty. Uncertainty is the result of the future nature of the events and the use of imperfect models (Hartgen, 1995; de Neufville, 1976). Transportation systems are implemented for the long term; consequently, the impacts have to be predicted for a long time horizon (e.g., 15-25 years). There is no way to predict exactly what will happen in such long periods. Moreover, forecasting is done through models that inevitably have input, specification and estimation errors (Ben Akiva and Lerman, 1985). Input errors come from the measurement techniques or from other forecasting models. Specification errors arise when relevant variables are not considered or model assumptions do not entirely reflect the actual behavior of the system. Estimation errors are the result of the parameter calculation techniques. After combining the future nature of the events and the inevitable errors in the models, the predictions become highly uncertain.

Some of the impacts, such as delay, emissions and noise, depend on the predicted flows. Hence, a great deal of effort is commonly employed in predicting flows. But these flows are also uncertain. Indeed, empirical studies have documented large differences between predicted and actual transportation flows. Table 1.2 lists a sample of documented comparisons for rail transit, highway and air transportation. This table indicates the wide range of errors for particular applications. For highway models, the comparisons are reported for current traffic. Forecasted highway traffic is likely to be even further from the realized traffic.
<table>
<thead>
<tr>
<th>Study</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pickrell (1991)</td>
<td>Ratio of actual to forecasted ridership ranged from 15% to 72% in ten selected rail projects in the USA.</td>
</tr>
<tr>
<td>McCord and Maldonado (1991)</td>
<td>UE traffic assignment model underestimated the traffic on a link of a network with respect to actual volume by 36%. Experts overestimated the volume by 32% on average before seeing UE model outcome and 22% after doing so.</td>
</tr>
<tr>
<td>Johnston et al. (1989)</td>
<td>Ratio of actual to forecasted ridership varied between 11% and 117% in nine transit projects in North America.</td>
</tr>
<tr>
<td>Mathew (1987)</td>
<td>Best method among 8 models (PlanPac-UTPS) showed a 28% average variation in arc flows between actual and predicted highway flows.</td>
</tr>
<tr>
<td>Janson, Thint and Hendrickson</td>
<td>Equilibrium assignment highway flows were 16% to 28% different from observed link counts along two screen lines.</td>
</tr>
<tr>
<td>(1986)</td>
<td></td>
</tr>
<tr>
<td>Bovy and Jansen (1983)</td>
<td>Average error between actual and predicted highway flows ranged between 87% and 43% depending on the level of network aggregation.</td>
</tr>
<tr>
<td>de Neufville (1976)</td>
<td>Forecasts of national and international air traffic were exceeded by approximately 20% on average after six years. Diverse national air traffic forecasts were on target for some periods but 20%-25% off target for other periods. Forecasts of traffic for specific airports showed more uncertainty than the national projections.</td>
</tr>
<tr>
<td>Florian and Nguyen (1976)</td>
<td>System-wide average concordance between predicted and observed volumes in a highway equilibrium assignment is good. Nevertheless, there is considerable scatter, partially caused by day-to-day variations in traffic data.</td>
</tr>
</tbody>
</table>

Table 1.2 Examples of Comparisons Between Predicted and Actual Transportation Flows
The traditional modeler's reaction to observed discrepancies between predictions and realizations is a desire to increase the sophistication in the prediction models, usually by attempting to increase their physical and behavioral realism (de Neufville, 1976). Nevertheless, the more sophisticated models that result will still be imperfect due to, for example, inability to model and forecast human behavior completely, changes in competitive facilities or modes, changes in interrelation among variables, uncertainty in exogenous variables and changes in the political landscape (Hartgen, 1995).

Moreover, increased sophistication usually means increased data requirements and operational complexity, which usually comes at an increased cost (Hartgen, 1995; de Neufville, 1976). Therefore, it seems reasonable to evaluate the value of the information produced from the increasingly sophisticated models against the cost of producing this information. Since model data are used to support decision making, such evaluation should be made in the context of the decisions being made.

1.3 Summary of the Chapters of the Dissertation

In the next chapter we explain the foundations of the framework to calculate the Value of Information (VOI). We start by introducing the decision theoretic evaluation framework in which VOI is embedded. For this application we chose Multi-Attribute Utility Theory (MAUT). We provide some background on MAUT and illustrate its application using a simple corridor example. The corridor example is divided in two parts: first, we show
how MAUT is used to select among alternatives; second, we show how to calculate Value of Perfect Information VOPI of the link volumes. We also present the calculation of Value of Imperfect Information VOII using the corridor example.

We then introduce mechanisms to calculate VOPI in the context of a sequential transportation forecasting process including trip generation, trip distribution, traffic assignment and travel time estimation. We define three types of VOPI: Cumulative VOPI, Marginal VOPI and Model VOPI. The Cumulative VOPI, which we call VOPI for simplicity, is the value of perfect information of the outcomes of the forecasting sequence up to a given step. Marginal VOPI is the value of perfect information of a given step given that the inputs to that step are known with certainty. Model VOPI is the value of perfect information of a given step given that the inputs to that step are uncertain. We use a small network example to illustrate the three types of VOPI. Finally, we summarize the elements involved and indicate what would be required to extend the calculation frameworks to more realistic applications. For this illustrative applications we use assumed discrete probability distributions.

In Chapter 3 we develop a sequential prediction model. One important and innovative characteristic of this model is that we consider uncertainty in the outputs of the different steps in addition to uncertainty in the inputs. We define an uncertainty measure of the outputs for each step and show how we use Monte Carlo simulation to obtain the desired levels of this measure. The model includes trip generation, trip distribution, traffic assignment and five attributes models: system travel time, fuel
consumption, and hydro-carbon (HC), carbon monoxide (CO) and nitrous-oxides (NOx) emissions. We illustrate the application of this process using the small network example.

In Chapter 4 we present the results of the application of the prediction and VOPI calculation methodologies to the simple network example. We first present the inputs to the process, i.e., preference model and inputs to the prediction model. We then present VOPI of the Attributes, Arc Volumes, OD Matrix, and Productions-Attractions, and Marginal VOPI of the Attribute Models, Traffic Assignment and Trip Distribution. As a preliminary investigation of sensitivity, we present our results as a function of the number of attribute vector samples, and as a function of the difference between the expected utilities of the No-Build and Build alternatives for two levels of demand.

We repeat these calculations for an extended network example in Chapter 5. This extended network corresponds to the main roadways network of Columbus, Ohio. In addition to the VOPI and Marginal VOPI we calculate the Model VOPI, that is the value of perfect information on a given conditional model given that its inputs are uncertain. We also present a sensitivity analysis of the preference and prediction models parameters.

Finally, in Chapter 6, we discuss issues associated with the VOPI framework components: the preference model and the prediction model. We also discuss the main numerical results for our preliminary analyses and propose topics for further research.

We indicate that our basic assumptions about the preferences could be restrictive, especially the assumed additive functional form of the utility function and linear single attribute utilities. Nevertheless, we indicate mechanisms to relax these assumptions and demonstrate that the results are fairly insensitive to most of the utility related parameters.
We see that the shape of the single attribute utility function of the different attributes dealing with vehicle emission may affect substantially the expected utilities and VOPI levels. The remaining parameters of the preference model analyzed --i.e., marginal rates of substitution and shape parameter of the utility of time-- have little impact on the VOPI according to the preliminary sensitivity analysis.

We also discuss possible ways to modify the prediction model and the possible impacts on the complexity of the prediction and the VOPI analysis. We stress the importance of obtaining expert-based uncertainty measures of the different models. We also indicate that the assumption of unbiased normal errors of the different model outcomes should be studied in further detail.

Additionally, we present on the main numerical results from our illustrative applications. We observe that the results follow intuition, and hence, that the methods are correctly implemented. We note that our results are fairly consistent across the different network topologies and demand levels. For instance, we observe that VOPI increases with the level of congestion. We also note that the Marginal VOPI of the Attribute Models is larger than the Marginal VOPI of Traffic Assignment and Marginal VOPI of Trip Distribution for most conditions. The Marginal VOPI of Traffic Assignment is larger then the Marginal VOPI of the Attribute Models only when we consider high demand for the extended network example and the difference in expected utilities for the No-Build and Build alternatives is very close to zero.

We also observe that for most cases the Model VOPI --i.e., the value of perfect information of a given step given that the inputs remain uncertain-- is very close to zero.
Only when the difference in expected utilities for the No-Build and Build alternatives is very close to zero, does the Model VOPI become significant. This suggests that, in general, there is no value in improving a single step in the forecasting process. Given that the cumulative VOPI of the attribute models is greater than zero for a wide range of values of the difference in the expected utilities, it would seem more appropriate to improve all the steps at the same time.

Finally, we suggest areas of research to continue the methodological and practical aspects of the evaluation of the value of information of transportation models. We group the recommended studies in six areas: sensitivity analysis using the current modeling assumptions; computational aspects; changes to the preference model; changes in the prediction model; calculation of the value of imperfect information, and determination of the model uncertainty measures from expert opinion.
CHAPTER 2

VALUE OF INFORMATION ELEMENTS

The Value of Information (VOI) concept is embedded in a decision theoretic evaluation framework where there are four major components: 1) options, 2) preference model, 3) prediction model, and 4) decision rules. The options consist of the alternatives $X_i, i=1,...,N,$ being considered. The preference model consists of a vector of attributes $Y=(Y_1,...,Y_M)$ and preferences for these vectors. The prediction model consists of predicting the attributes levels that would result if the alternatives were implemented $(Y|X_i), i=1,...,N$. The decision rules consist of the logic used to order preferences among the alternatives based on predicted attribute levels.

We use Multi-Attribute Utility Theory (MAUT) (de Neufville, 1990, Keeney and Raiffa, 1976) as the underlying decision framework. MAUT has the advantage of explicitly incorporating uncertainty, being arguably operational, and explicitly considering the preferences of the decision maker in a manner rigorously derived from intuitive underlying assumptions or axioms.

MAUT has been applied to evaluate diverse problems. Keeney and Raiffa (1976) list MAUT applications in air pollution control, instructional programs, fire department operations, management policies, siting and licensing of nuclear power
facilities, safe aircraft landing policies, frozen blood policies, sewage sludge disposal, job selection, transport of hazardous substances, medical treatments, water quality indexes development, foreign policy, and forest pest management. Additional transportation related MAUT applications include airport location (Keeney and Raiffa, 1976), coal transportation routing (Stone, 1984), pavement rehabilitation policies (Mohan and Bushnak, 1985), medical emergency helicopter fleet sizing (McCord, Franzese and Sun, 1992), urban transportation systems evaluation (Hidalgo, 1994; Bee and Sargious, 1981), hazardous materials routing (McCord and Leu, 1993), and weigh in motion technology evaluation (Leu, 1996).

In MAUT preferences are modeled by utility functions over the attribute vectors $U(Y)$, and predictions are given by probability distributions of the attributes, given specific alternative $f(Y|X_i)$. The alternatives are then evaluated according to the expectation of the utility of the attributes, which we denote $EU[X_i]$ for simplicity. The expectation, in general, is given by:

$$EU[X_i] = \int_{y_1}^{\cdot} \int_{y_M}^{\cdot} U(Y|F(Y|X_i))dy_1, \ldots, dy_M. \quad (2.1)$$

If the utilities indicate increasing degree of preference, the alternatives $X_i$, $i=1, \ldots, N$, can be ranked in terms of preference by their $EU[X_i]$ values. The preferred alternative, hence, will be the alternative $X^*$ satisfying:
In the next section, we illustrate the application of MAUT. We then introduce Value of Perfect Information (VOPI) and Value of Imperfect Information (VOII). We use simple examples for illustrative purposes.

2.1 Selection of the Preferred Alternative

Consider, for example, a decision between not building \((X_1)\) or building \((X_2)\) a highway segment between nodes \(r\) and \(s\), when there is currently one route between these nodes (see Figure 2.1).

\[
EU[X^*] = \max_{X_1, X_2, \ldots, X_n} \{EU[X_1], EU[X_2], \ldots, EU[X_n]\} \tag{2.2}
\]

---

Figure 2.1 Corridor Example
We evaluate these alternatives according to two attributes (M=2): annual equivalent cost $Y_1$ expressed in [million dollars/year], and total system travel time $Y_2$ expressed in [min/peak-hour]. The total system travel time ($Y_2$) is defined in the typical fashion (Sheffi, 1984) as:

$$Y_2 = \sum_{a=1}^{N} \nu_a t_a$$

(2.3)

where $\nu_a$ and $t_a$ are flow (volume) and travel time, respectively, on arc $a$ during the peak hour, and $N$ is the number of arcs in the network. To model preferences, we assume an additive multi-attribute utility function (de Neufville, 1990; Keeney and Raiffa, 1976):

$$U[Y] = \sum_{m=1}^{2} k_m u_m(Y_m), \quad \sum_{m=1}^{2} k_m = 1,$$

(2.4)

where $k_m$ is a scaling parameter and $u_m(Y_m)$ are single attribute utility functions. The additive form of the multi-attribute utility function implies that the preferences are independent among attributes, that is, the tradeoffs between a given pair of attributes do not depend on the levels of the rest of the attributes.

We further assume that the single attribute utility functions are given by

$$u_m(Y_m) = 1 - \left[ \frac{Y_m - Y_m^{(min)}}{Y_m^{(max)} - Y_m^{(min)}} \right]^{a_m}, \quad m=1,2.$$  

(2.5)
In (2.5) \( Y_m^{(\text{min})} \) and \( Y_m^{(\text{max})} \) are bounds on the minimum and maximum levels of attribute \( Y_m \), and \( \alpha_m \) is a shape parameter. The functional form of the single attribute utilities implies that the single attribute utilities are monotonically decreasing in attribute level. That is, it assumes we want to maximize utility, but that more cost (\( m=1 \)) or total system travel time (\( m=2 \)) leads to less utility.

For simplicity, in the corridor example we assume linear single attribute utilities, i.e., \( \alpha_m=1, m=1,2 \). Using this in (2.5) and combining with (2.4), the utility function can be written as:

\[
U[Y] = k \left[ 1 - \frac{Y_1 - Y_1^{(\text{min})}}{Y_1^{(\text{max})} - Y_1^{(\text{min})}} \right] + (1 - k) \left[ 1 - \frac{Y_2 - Y_2^{(\text{min})}}{Y_2^{(\text{max})} - Y_2^{(\text{min})}} \right]. \tag{2.6}
\]

Let us consider \( Y_1^{(\text{min})}=\$0.0 \text{ million/year}, Y_1^{(\text{max})}=\$14.63 \text{ millions/year}, Y_2^{(\text{min})}=212,750 \text{ min/peak-hr}, Y_2^{(\text{max})}=388,333 \text{ min/peak-hr} \) and \( k=0.5 \). Note that these parameters lead to values with economic and behavioral meaning if one considers marginal rates of substitution of total system travel time and project cost. The derivatives of the utility with respect to the attributes are:

\[
\frac{\partial U[Y]}{\partial Y_1} = 0.5 \left[ \frac{-1}{14.63 - 0.00} \right] = \frac{-0.5}{14.63} \text{ [$\text{million} / \text{year}$]} \tag{2.7a}
\]

\[
\frac{\partial U[Y]}{\partial Y_2} = (1 - 0.5) \left[ \frac{-1}{388,333 - 212,750} \right] = \frac{-0.5}{175,583} \text{ [min / peak-hr]} \tag{2.7b}
\]
The marginal rate of substitution of time and cost \( (MRS_{Y_2,Y_1}) \) is the ratio of these derivatives

\[
MRS_{Y_2,Y_1} = \frac{\partial U[Y]}{\partial Y_2} \bigg/ \frac{\partial U[Y]}{\partial Y_1}. \tag{2.8}
\]

Substituting the values from (2.7) in (2.8) we find:

\[
MRS_{Y_2,Y_1} \bigg|_{\text{Y}_1=14.63, Y_2=175,163} = 5.00 \text{ [$/hr]}. \tag{2.9}
\]

Assuming 1,000 peak-hours/year, we have

\[
MRS_{Y_2,Y_1} \bigg|_{\text{Y}_1=14.63, Y_2=175,163} \times \frac{10^6}{1000} \times \frac{1}{14.63} \times \frac{1}{175,163} = 5.00 \text{ [$/hr]}. \tag{2.10}
\]

The prediction model requires probability distributions for cost \( (f[Y_i|X_i]) \) and system travel times \( (f[Y_2|X_i]) \) conditioned on alternative \( X_i \), \( i=1,2 \), being implemented.

For our introductory example, we assume that the annual equivalent cost \( Y_i \) is deterministic and equal to $14.1 million if the new link is built and $0.00 if the new link is not built. That is, \( E[Y_i|X_i]=0.00 \text{ million} \) and \( E[Y_i|X_i]=14.1 \text{ million} \).

The probability distribution of the total system travel time \( f[Y_2|X_i] \) is the result of the combined prediction of the arc travel times and volumes. In this introductory
example we predict each arc travel time $t_a$ as a function of the volume $v_a$ assigned to the arc using a BPR link performance function (Sheffi, 1984):

$$t_a = t_{0a} [1 + 0.15 (v_a/C_a)^4],$$  \hspace{1cm} (2.11)

where $t_{0a}$ and $C_a$ are, respectively, the free flow time and practical capacity of the arc $a$.

For our example, these parameters are given in Figure 2.1. We also consider that the total demand $q_{rs}$ between $r$ and $s$ is known with certainty to be 18,000 vehicles in the peak hour.

Now we introduce uncertainty in the problem by considering two possible traffic assignment ($TA$) results if the new link is built (alternative $X_2$): $TA_1$ yields $v_1^{(1)} = 12,378$ veh/h, $v_2^{(1)} = 5,622$ veh/h; and $TA_2$ yields $v_1^{(2)} = 10,904$ veh/h, $v_2^{(2)} = 7,096$ veh/h, where $v_i^{(n)}$ means the volume on link $i$, $i=1,2$, given traffic assignment $T_{An}$, $n=1,2$. We further assume that $TA_1$ and $TA_2$ occur with probabilities 0.60 and 0.40, respectively. (Note that the expected volumes, $E[v_1|X_2] = 11,708$ veh/h and $E[v_2|X_2] = 6,212$ veh/h, correspond to user equilibrium assignment.) If the alternative is not built (alternative $X_1$), the 18,000 vehicles would use arc 1 with probability 1.00.

At this point, we assume no uncertainty in the time-volume functions given by (2.11). Hence, the traffic assignments $TA_1$ and $TA_2$ under alternatives $X_1$ and $X_2$, would, respectively, result in

$$Y_2(TA_n, X_1) = \sum_{a=1}^{2} v_a^{(i,n)} t_{0a} \left(1 + 0.15 \left(\frac{v_a^{(i,n)}}{C_a}\right)^4\right), \hspace{1cm} n = 1,2, \hspace{1cm} i = 1,2,\hspace{1cm} (2.12a)$$
\[ Y_2|(TA_1, X_1) = 18,000 \left( 10 \left( 1 + 0.15 \left( \frac{18,000}{10,800} \right)^4 \right) \right) \]

\[ = 388,333 \text{ [min/peak-hr]}, \] (2.12b)

\[ Y_2|(TA_1, X_2) = 12,378 \left( 10 \left( 1 + 0.15 \left( \frac{12,378}{10,800} \right)^4 \right) \right) + 5,622 \left( 12 \left( 1 + 0.15 \left( \frac{5,622}{12,000} \right)^4 \right) \right) \]

\[ = 223,768 \text{ [min/peak-hr]}, \] (2.12c)

\[ Y_2|(TA_2, X_2) = 10,904 \left( 10 \left( 1 + 0.15 \left( \frac{10,904}{10,800} \right)^4 \right) \right) + 7,096 \left( 12 \left( 1 + 0.15 \left( \frac{7,096}{12,000} \right)^4 \right) \right) \]

\[ = 212,749 \text{ [min/peak-hr]}, \] (2.12d)

Using these values and the deterministic value of cost \((Y_1=14.1)\) in (2.6), we find that the utilities of the different outcomes:

\[ U[(Y_1, Y_2), X_1] = 0.5 \left( 1 - \frac{0.0}{14.63} \right) + 0.5 \left( 1 - \frac{388,333 - 212,750}{175,583} \right) = 0.5000, \] (2.13a)

\[ U[(Y_1, Y_2)|(TA_1, X_2)] = 0.5 \left( 1 - \frac{14.1}{14.63} \right) + 0.5 \left( 1 - \frac{223,768 - 212,750}{175,583} \right) = 0.4876, \] (2.13b)

\[ U[(Y_1, Y_2)|(TA_2, X_2)] = 0.5 \left( 1 - \frac{14.1}{14.63} \right) + 0.5 \left( 1 - \frac{212,750 - 212,750}{175,583} \right) = 0.5178. \] (2.13c)

We can now use a decision tree to illustrate the decision process (Figure 2.2). In the decision tree the chance nodes are represented by circles, and the decision nodes are represented by squares. The dynamic programming algorithm used to "solve" the decision tree, known as "average out and fold back" (Raiffa, 1968) consists of calculating the expected values at the chance nodes and selecting the choice with the
maximum expected value at the decision nodes, starting from the right hand side of the tree.

\[
\begin{array}{cccc}
\text{Pr} & Y_1 & Y_2 & U(Y_1,Y_2) \\
\hline
\text{TA}_1: & v_1=12,378;v_2=5,622 & 0.6 & 14.1 & 223,768 & 0.4876 \\
\text{TA}_2: & v_1=10,904;v_2=7,096 & 0.4 & 14.1 & 212,749 & 0.5178 \\
\text{TA}_3: & v_1=18,000 & 1.0 & 0.0 & 388,333 & 0.5000 \\
\end{array}
\]

Figure 2.2. Decision Tree for Selecting the Preferred Alternative in the Corridor Example

In our example, we start by calculating the expected utilities at the chance nodes

\[EU[X_2]=0.6 \times 0.4876 + 0.4 \times 0.5178 = 0.499 \quad \text{and} \quad EU[X_1]=1.0 \times 0.500 = 0.500. \]

Then, we select the alternative with the greatest utility, that is \(X^*\) such that

\[EU[X^*]=\max_{X_1,X_2} \{EU[X_1]=0.500, \quad EU[X_2]=0.499\}. \tag{2.14}\]

Hence, the selected alternative would be \(X^*=X_1\), with \(EU[X^*]=0.500\). This expected utility is also the expected utility of not conducting studies on the traffic flows \((EU[\text{No Study}]=EU[X^*]=0.500)\).
2.2 Value of Information on Traffic Flows

The Value of Information on traffic flows would be given by the maximum cost of a study $S$ that a decision maker would be willing to pay to conduct a study that would provide information about the traffic flows. This information would be used to make the decision on whether or not to build the highway segment under consideration. This cost of study $S$ would correspond to the value of $S$ that makes the decision maker indifferent between conducting the study and not conducting the study (Sengupta, 1984):

$$\text{VOI} = S \mid \{ EU[\text{No Study}] = EU[\text{Study}] \}$$ (2.15)

The Value of Perfect Information (VOPI) on traffic flows would correspond to the maximum cost that the decision maker would be willing to pay for a study that provides error-free information on these traffic flows. The probability of occurrence of the potential outcomes of this study would have probabilities associated with the current level of knowledge, i.e., the prior probability distribution.

Consider, for example, that in the corridor example one can commission a study at annualized cost $S$ to produce perfect information on whether traffic assignment $TA_1$ or $TA_2$ will occur. The prior probability distribution given above has two possible outcomes: $TA_1$ with probability 0.6, and $TA_2$ with probability 0.4. Therefore, this perfect information study would reveal $TA_1$ as the true assignment with probability 0.6.
and $TA_2$ as the true assignment with probability 0.4. Once the study reveals which outcome will be realized, one can decide to build the new segment or not. Again, building (not building) the segment is preferred if $EU[X_2] > (<) EU[X_1]$.

If we assume that the cost of the study $S$ can be combined with other cost elements ($Y_i$), we can then use (2.6) to show that:

\[
U[(Y_1+S,Y_2)(X_1,TA_1)] = 0.5\left(1 - \frac{0.0+S}{14.63}\right) + 0.5\left(1 - \frac{388,333 - 212,750}{175,583}\right) = 0.5000 - \frac{S}{29.26}\text{. (2.16a)}
\]

\[
U[(Y_1+S,Y_2)(X_2,TA_1)] = 0.5\left(1 - \frac{14.1+S}{14.63}\right) + 0.5\left(1 - \frac{223,768 - 212,750}{175,583}\right) = 0.4867 - \frac{S}{29.26}\text{. (2.16b)}
\]

\[
U[(Y_1+S,Y_2)(X_2,TA_2)] = 0.5\left(1 - \frac{14.1+S}{14.63}\right) + 0.5\left(1 - \frac{212,749 - 212,750}{175,583}\right) = 0.5181 - \frac{S}{29.26}\text{. (2.16c)}
\]

Note that for $X_1$, there is only one TA pattern.

The decision tree for evaluating the study on perfect information is displayed in Figure 2.3. The upper part of the tree is equivalent to the tree in for selecting the preferred alternative (Figure 2.2). Hence, the expected utility of no study is the utility that occurs when you chose $X_1$, that is $EU[\text{No Study}] = EU[X_1] = 0.500$.

The lower part of the tree shows the possible outcomes of the study and the decision being made after the result of the study is known. Note that the utilities include the cost $S$ of performing the study. As before, the study branch of the tree is "solved" by averaging-out and folding-back. First we select between the build and no build alternatives given that the result of the study is $TA_1$.

\[
\text{Max}\{EU[X_1|TA_1],EU[X_2|TA_1]\} = EU[X_1|TA_1] = 0.500 - S/29.26.
\]
Then we select between the build and no build alternatives given that the result of the study is $TA_2$, $\max\{EU[X_1|TA_2], EU[X_2|TA_2]\} = EU[X_2,TA_2]=0.5181-S/29.26$. We then calculate the expected utility by multiplying these maxima by the corresponding probabilities $EU[Study]=0.6\times(0.500-S/29.26)+0.4\times(0.5181-S/29.26)=0.50724-S/29.26$. The value of $S$ that makes the upper and lower branches indifferent is the value of perfect information. Therefore, VOPI is found by solving $EU[Study]=0.50724-S/29.26=0.500$ for $S$, and we find
Note that if the study cost $S$ is greater than $212,000$, $EU[Study]$ would be less than the preferred alternative in which no study is conducted, and not conducting the study would be preferred. If the study cost $S$ is less than $212,000$, $EU[Study]$ would be greater than the preferred alternative in which no study is conducted, and conducting the study would be preferred. In this way VOPI is the maximum one should pay for study on perfect information on the traffic assignment.

In case the information provided by the study is not perfect, we can still calculate the value of information. We would call Value of Imperfect Information (VOII) the cost that the decision maker would be willing to pay for a study that would provide information with a given level of uncertainty.

Figure 2.4 displays a possible decision tree corresponding to the VOII in the introductory corridor example. As noted in this figure, the outcomes of the study would be the same ones of a perfect information study. However, there would be a chance that the result of the study would be true or not. In this example, we use a probability $p$ of being correct to illustrate the level of uncertainty. For illustrative purposes we use $p=0.9$. Again, we average-out and fold-back starting from the right hand side of the tree. The upper branch (No Study) is not changed; hence $EU[No Study]=0.500$. In the lower branch we first calculate the expected utilities given that the chosen alternative is $X_i$, $i=1,2$, and the result of the study is $TA_i$: 

$$VOPI=0.212 \text{ million}. \quad (2.17)$$
\[ EU[X_2|TA_1] = 0.9 \times (0.4876 - S/29.26) + 0.1 \times (0.5178 - S/29.26) = 0.49062 - S/29.26, \quad (2.18a) \]

\[ EU[X_1|TA_1] = 0.5000 - S/29.26. \quad \] (2.18b)

**Figure 2.4. Decision Tree for Calculating VOII of Traffic Flows in the Corridor Example**
Then, we calculate the maximum of these utilities,

\[ \text{Max}[EU|TA_1] = \text{Max} \{0.49062 - S/29.26, 0.5000 - S/29.26\} = 0.5000 - S/29.26. \] (2.18c)

We repeat these operations for \(X_i\), \(i = 1,2\), and \(TA_2\):

\[ EU[X_2|TA_2] = 0.1 \times (0.4876 - S/29.26) + 0.9 \times (0.5178 - S/29.26) = 0.51478 - S/29.26, \] (2.19a)

\[ EU[X_1|TA_2] = 0.5000 - S/29.26, \] (2.19b)

\[ \text{Max}[EU|TA_1] = \text{Max} \{0.51478 - S/29.26, 0.5000 - S/29.26\} = 0.51478 - S/29.26. \] (2.19c)

Finally, the expected utility of the Study alternative would be equal to the weighted average of these maxima:

\[ EU[\text{Study}] = 0.6 \times (0.5000 - S/29.26) + 0.4 \times (0.51478 - S/29.26) = 0.5059 - S/29.26. \] (2.20)

The VOII would be the value of \(S\) that makes \(EU[\text{Study}] = EU[\text{No Study}]\), that is \(0.5059 - S/29.26 = 0.5000\). Solving for \(S\) we find

\[ \text{VOII} = \$0.173 \text{ million/year}. \] (2.21)

As it might be expected VOII is smaller than VOPI. Note, also, that VOPI is a special case of VOII when the probability \(p\) of being correct is 1.0. The previous example illustrate the elements required to calculate the value of information: alternatives, preferences, predictions and decision rules. We also used decision trees to illustrate the processes in the cases of No-Study and Study with and without perfect information. Finally, we showed how to average-out and fold-back the decision trees.
The application of these concepts to more realistic transportation models would require special considerations. In the next section we discuss the conceptual calculation of value of information in the context of a sequential forecasting model including trip generation, trip distribution, traffic assignment and travel time prediction components. We illustrate the considerations using the build-no-build decision for a highway embedded in a simple network.

2.3 Value of Information of the Components of a Sequential Forecasting Model

The classical four-step urban transportation forecasting sequence (Dickey, 1983) uses Trip Generation (TG), Trip Distribution (TD), Modal Split (MS), and Traffic Assignment (TA) models to predict the flows on the links of a transportation network. These flows are then used to calculate traffic related impacts, such as travel time, travel cost, fuel consumption, noise, pollutant emissions, and safety. As discussed in Chapter 1, the traffic related impacts are used in conjunction with non-traffic related impacts, such as infrastructure costs, wetlands impacts, neighborhood effects, and economic development, in the evaluation of the alternatives and selection of projects for implementation.

In this section we use a sequential process derived from the four step-process to predict the traffic volumes on a simple network (Figure 2.5) and then estimate the travel times on the links. We use these link travel times to calculate the total system travel time, which we use in conjunction with the infrastructure cost to evaluate a No-Build vs. Build
decision for a link embedded in the simple network. Hence, the choices consist of \( X_1 \) (No-Build; i.e., do not build link 7) and \( X_2 \) (Build; i.e., build link 7).

We assume the same preference model for this example as that used in sections 2.1 and 2.2. The attributes are: \( Y_1 \) (Cost) and \( Y_2 \) (Total System Travel Time). The utility function is again given by (2.6):

\[
U[Y] = k \left[ 1 - \frac{Y_1 - Y_1^{(min)}}{Y_1^{(max)} - Y_1^{(min)}} \right] + (1 - k) \left[ 1 - \frac{Y_2 - Y_2^{(min)}}{Y_2^{(max)} - Y_2^{(min)}} \right] .
\] (2.22)

In this network example we use simple predictions consisting of 2 different production-attraction patterns, 2 distinct O-D tables for each production-attraction pattern, 2 diverse traffic assignments (link volume vectors) for each O-D table and
alternative $X_i$, i=1,2, and 2 possible total system travel times realizations for each link volume-alternative vector. As a result we consider $2^4$ "states of nature" for alternative $X_i$ (No Build) and $2^4$ "states of nature" for alternative $X_2$ (Build).

In Table 2.1 we present the alternative production-attraction patterns considered in our network example. We have two origins (r=1 and r=2) and two destinations (s=3 and s=4). We assume that production-attraction pattern one (PA₁), which consists of 13,076 total vehicle-trips/peak-hour, occurs with 0.6 probability and that PA₂, which consists of 11,614 total vehicle-trips/peak-hour, occurs with 0.4 probability.

For each one of these production-attraction patterns, we consider two trip distribution patterns or Origin-Destination (OD) matrices. The matrices are represented by $OD_{m}^{l}$: the m<sup>th</sup> OD matrix conditioned on the l<sup>th</sup> production-attraction pattern, with m=1, 2, and l=1, 2. We present the assumed matrices in Table 2.2.

<table>
<thead>
<tr>
<th></th>
<th>Vehicle trips/peak-hour</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PA₁ Pr=0.6</td>
<td>PA₂ Pr=0.4</td>
<td></td>
</tr>
<tr>
<td>r=1</td>
<td>3,149</td>
<td>2,585</td>
<td></td>
</tr>
<tr>
<td>r=2</td>
<td>3,389</td>
<td>3,222</td>
<td></td>
</tr>
<tr>
<td>s=3</td>
<td>3,352</td>
<td>3,267</td>
<td></td>
</tr>
<tr>
<td>s=4</td>
<td>3,186</td>
<td>2,540</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.1 Production-Attraction Patterns in the Network Example
We further assume that $OD_1^l$ occurs with 0.55 probability and $OD_2^l$, occurs with 0.45 probability, for both $l=1$ and $l=2$. Additionally, we consider two traffic assignment patterns (link volume vectors), $TA_m$, $m=1,2$, for each one of these OD tables and alternatives $X_i$, $i=1,2$. We represent these link volume vectors by $^iV_{n,m,l}^l$: the $n^{th}$ link volume vector conditioned on the $i^{th}$ alternative, the $m^{th}$ OD matrix and $l^{th}$ production-attraction pattern, and $n=1,2$; $i=1,2$; $m=1,2$ and $l=1,2$. We present the assumed link volume vectors in Table 2.3. We further assume that $^1V_{1,m,l}^l$; occurs with 0.7 probability and $^2V_{2,m,l}^l$ occurs with 0.3 probability, for all $i=1,2$, $m=1,2$, and $l=1,2$.

Finally, we consider two different levels of total system travel time ($Y_2=TSTT$) for each traffic assignment pattern, as shown in Table 2.4. We represent the conditional $Y_2$ using $^oV_{2,n,m,l}^l$ the $o^{th}$ TSTT conditioned on alternative $X_i$ and the $n^{th}$ link volume
pattern, the m\textsuperscript{th} OD matrix and the l\textsuperscript{th} PA pattern. We assign a 0.65 probability to the first of these TSTT (o=1) and 0.35 to the second (o=2), for all i=1,2, n=1,2, m=1,2 and l=1,2.

<table>
<thead>
<tr>
<th>Volume Vector</th>
<th>Links</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7(^{(2)})</th>
</tr>
</thead>
</table>
| Pr=0.7
| \(V_{1,1}^{1,1}\) | 2317.00 | 832.00 | 2701.33 | 687.67 | 2520.00 | 2498.33 | - |
| \(V_{2,1}^{1,1}\) | 1841.68 | 617.60 | 2633.32 | 755.68 | 2734.40 | 1740.60 | 689.72 |
| Pr=0.3
| \(V_{1,1}^{1,2}\) | 2317.00 | 832.00 | 2568.37 | 820.63 | 2520.00 | 2365.37 | - |
| \(V_{2,1}^{1,2}\) | 1840.99 | 570.32 | 2520.00 | 869.00 | 2781.68 | 1579.32 | 737.68 |
| Pr=0.7
| \(V_{1,2}^{2,1}\) | 2477.00 | 672.00 | 2680.00 | 709.00 | 2680.00 | 2477.00 | - |
| \(V_{2,2}^{2,1}\) | 1721.71 | 672.00 | 2680.00 | 709.00 | 2680.00 | 1721.71 | 755.29 |
| Pr=0.3
| \(V_{1,2}^{2,2}\) | 2477.00 | 672.00 | 2680.00 | 709.00 | 2680.00 | 2477.00 | - |
| \(V_{2,2}^{2,2}\) | 1662.54 | 672.00 | 2687.05 | 701.95 | 2680.00 | 1669.59 | 814.46 |
| Pr=0.7
| \(V_{1,1}^{2,2}\) | 1682.06 | 902.94 | 2388.95 | 853.05 | 2364.06 | 1686.95 | - |
| \(V_{2,1}^{2,2}\) | 1098.25 | 767.58 | 2574.15 | 647.85 | 2499.42 | 1172.98 | 719.18 |
| Pr=0.3
| \(V_{1,2}^{2,2}\) | 1715.68 | 869.32 | 2263.69 | 958.31 | 2397.68 | 1581.69 | - |
| \(V_{2,2}^{2,2}\) | 901.76 | 821.26 | 2423.58 | 798.42 | 2445.74 | 879.60 | 861.98 |
| Pr=0.7
| \(V_{1,1}^{2,2}\) | 1882.00 | 703.00 | 2564.00 | 658.00 | 2564.00 | 1882.00 | - |
| \(V_{2,1}^{2,2}\) | 1077.62 | 703.00 | 2564.00 | 658.00 | 2564.00 | 1077.62 | 804.38 |
| Pr=0.3
| \(V_{1,2}^{2,2}\) | 1882.00 | 703.00 | 2564.00 | 658.00 | 2564.00 | 1882.00 | - |
| \(V_{2,2}^{2,2}\) | 1059.65 | 703.00 | 2564.00 | 658.00 | 2564.00 | 1059.65 | 822.35 |

\(^{(1)}\) i=1,2, PA pattern; m=1,2, OD pattern given PA, pattern; n=1,2, volume vector pattern given OD, Alternative X; \(i=1,2\), alternative (Build, No-Build)

\(^{(2)}\) Link 7 does not exist in No-Build Alternative

Table 2.3 Link Volume Vectors for each OD Pattern and Build, No-Build Alternative for the Network Example
<table>
<thead>
<tr>
<th>( i_n^{Y,m,l} )</th>
<th>( i_n^{Y,n,m,l} )</th>
<th>( Y_{PA,1} )</th>
<th>( Y_{PA,2} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( i_1^{Y,m,l} )</td>
<td>( i_1^{Y,n,m,l} )</td>
<td>No Build ( i=1 )</td>
<td>107,383</td>
</tr>
<tr>
<td>Build ( i=2 )</td>
<td>99,403</td>
<td>74,478</td>
<td>81,193</td>
</tr>
<tr>
<td>( i_2^{Y,m,l} )</td>
<td>( i_2^{Y,n,m,l} )</td>
<td>No Build ( i=1 )</td>
<td>93,236</td>
</tr>
<tr>
<td>Build ( i=2 )</td>
<td>86,378</td>
<td>76,207</td>
<td>82,202</td>
</tr>
<tr>
<td>( i_1^{Y,m,l} )</td>
<td>( i_1^{Y,n,m,l} )</td>
<td>No Build ( i=1 )</td>
<td>108,736</td>
</tr>
<tr>
<td>Build ( i=2 )</td>
<td>108,412</td>
<td>98,527</td>
<td>61,622</td>
</tr>
<tr>
<td>( i_2^{Y,m,l} )</td>
<td>( i_2^{Y,n,m,l} )</td>
<td>No Build ( i=1 )</td>
<td>107,329</td>
</tr>
<tr>
<td>Build ( i=3 )</td>
<td>95,246</td>
<td>99,523</td>
<td>80,722</td>
</tr>
</tbody>
</table>

(1) Link Volume Vector \( n^a \), conditioned on \( i^a \) alternative, \( m^a \) OD pattern and \( l^a \) PA pattern
(2) Total System Travel Time \( Y_2 \) conditioned on \( i^a \) alternative, \( n^a \) volume vector, \( m^a \) OD pattern and \( l^a \) PA pattern.

Table 2.4 Total System Travel Time \( (Y_2) \) [minutes/peak-hour] as a Function of Alternative, Link Volumes, OD Matrices and Production-Attraction Pattern in the Network Example

We use these TSTT \( (Y_2) \) combined with a deterministic cost \( (Y_1) \) to evaluate the alternatives and estimate the value of information of the components of the sequential prediction model. We assume a cost \( (Y_1) \) of $0.0 million/year for alternative \( X_1 \), No Build, and $0.5 million/year for alternative \( X_2 \), Build. Note that the sequential forecasting procedure used in this example yields 32 potential outcomes, where an outcome is defined by the combination of \( Y_1 \) and \( Y_2 \). In the next sub-sections we present mechanisms to select the preferred alternative and to calculate the VOPI of the different steps in the sequential forecasting process.
2.3.1 Preferred Alternative

As before, we evaluate the alternatives using the expected utility, which is the probability weighted average of the utilities of the different outcomes. Recall that the utility is given by (2.6). We use the following parameters for the utility function: $k=0.3203$, $Y_1^{(\text{max})}=2.00$ [million/year], $Y_2^{(\text{min})}=61,622$ and $Y_2^{(\text{max})}=112,540$ [min/peak-hr]. Substituting in (2.6):

$$U(Y_1, Y_2) = 0.3203 \left[ 1 - \frac{Y_1}{2.00} \right] + 0.6797 \left[ 1 - \frac{Y_2 - 61,622}{112,540 - 61,622} \right].$$

We obtain $Y_2^{(\text{min})}$ and $Y_2^{(\text{max})}$ from Table 2.4 The other parameters, i.e., $k$ and $Y_1^{(\text{max})}$, are chosen in such a way that the marginal rate of substitution of time and cost (2.8), is equal to $\$5$/hour when considering 1,000 peak-hours per year, as before.

In Figure 2.6 we present the decision tree used to calculate the expected utility of each alternative. We calculate the utilities $U(Y_1, Y_2)$ of each of the 32 potential outcomes by replacing $Y_1$ and $Y_2$ in (2.23). We assume $Y_1 = 0.0$ for $X_1$ and $Y_1 = 0.5$ for $X_2$. We obtain $Y_2$ from Table 2.4. As before, we solve the decision tree by averaging-out and folding back starting at the right hand side of the tree.

The expected utility of each alternative $X_i$, $i=1,2$, is then given by the expression:

$$EU[X_i] = \sum_{l=1}^{2} \Pr(PA_l) \left( \sum_{m=1}^{2} \Pr(OD_{mi}) \left( \sum_{n=1}^{2} \Pr(V_{n,i}^{m,l}) \left( \sum_{o=1}^{2} \Pr(Y_{2,o}^{n,m,l}) U(Y_1, Y_{2,o}^{n,m,l}) \right) \right) \right).$$

(2.24)
Figure 2.6 Decision Tree for Selecting the Preferred Alternative in the Network Example
Note that equation (2.24) is equivalent to (2.1) for the conditions of the network example. Using this equation we find that $EU[X_1]=0.5599$ and $EU[X_2]=0.5729$; hence, the preferred alternative is $X_2$ (Build).

2.3.2 VOPI at the Sequential Forecasting Steps

In section 2.2 we illustrated the mechanism to calculate VOPI of the link volumes in a simple corridor example. We can use the same type of mechanism to calculate the VOPI of production-attraction patterns, O-D matrices, the link volumes and total system travel times ($Y_j$) in our network example, i.e., the cumulative VOPI at each one of the sequential forecasting steps, which we will continue calling VOPI for simplicity.

As before, the decision will be made after knowing the outcome of the study. Each outcome of the study would have a probability of occurrence equal to the prior probability of the component being evaluated. For example, when calculating VOPI of Production-Attraction, the potential outcomes of the study would be $PA_1$ and $PA_2$ with 0.6 and 0.4 probabilities respectively. The decision to build or not would follow the result of the study, and then the rest of chance nodes will follow, as shown in Figure 2.7.

The expected utility of the study branch for production-attraction would then be given by:

$$EU[PA \text{ Study}] = \sum_{i=1}^{2} Pr(PA_i) \left( \sum_{i=1}^{2} Pr(OD_{ij}) \left( \sum_{j=1}^{2} Pr(Y_{nmj}) \left( \sum_{m=1}^{2} Pr(Y_{2,mj}) U(Y_1 + S_{12,mj}) \right) \right) \right) \right) \tag{2.25}$$
Figure 2.7 Decision Tree for Calculating the Expected Utility of a Perfect Study on Production-Attraction Patterns

40
Note that we include the cost of the studies $S$ in the utility function, and that we assume that this cost is added to the predicted costs $Y_i$.

This equation results in $EU[PA\ Study] = 0.584613 - 0.3203 S/2.00$. The VOPI on the production-attraction (PA) pattern is the maximum cost the decision maker is willing to pay for the studies, which is equivalent to the cost $S$ that makes the expected utility of the No-Study branch equal to the expected utility of the Study branch. Hence, to find VOPI of PA we solve $EU[No\ Study] = EU[PA\ Study]$. The $EU[No\ Study]$ is equal to the maximum expected utility between the build and no-build alternative.

As shown in the previous sub-section, the maximum expected utility between $X_1$ and $X_2$ corresponds to $X_1$ and is equal to 0.5729. Hence, $EU[No\ Study] = 0.5729$. Solving for $S$ we find $VOPI(PA) = 0.073$ $\text{million/year}$.

To calculate the VOPI on the OD patterns we consider that a study yields one of the four potential OD matrices displayed in Table 2.2 with probability $Pr(PA_i) \times Pr(OD_{m_l}^l)$, $m=1,2$, $l=1,2$. The decision maker would decide whether to build or not to build link 7 after learning which OD would be realized for certain. Then, the rest of chance nodes (i.e., volumes and total system travel times) will follow. The decision tree corresponding to the perfect information study on the OD is shown in Figure 2.8.

The expected utility would then be:

$$EU[OD\ Study] = \sum_{l=1}^{2} Pr(PA_l) \left( \sum_{m=1}^{2} Pr(OD_{m_l}^l) \left( Max_{i=1,2} \left( \sum_{n=1}^{2} Pr\left( Y_{n,s}^l \right) \left( \sum_{o=1}^{2} Pr\left( Y_{o,n}^l \right) U\left( Y_1 + S_i, Y_{o,n}^l \right) \right) \right) \right) \right)$$

$$= 0.597355 - 0.160155. \quad (2.26)$$
Figure 2.8 Decision Tree for Calculating the Expected Utility of a Perfect Study on Origin-Destination Patterns
Finding $S$ such that $EU[$OD Study$] = EU[$No Study$] = 0.5729$ yields $\text{VOPI(OD)} = 0.153$ million/year. This value is the maximum cost the decision maker is willing to pay for a study on perfect information on the OD pattern.

Similarly, to calculate the VOPI on the link volumes, we consider a study yields paired vectors of volumes for the no-build and build alternatives. That is, for each OD matrix $OD^l_m$, $m=1,2$, $l=1,2$, the study would tell which combination of link volume vectors $(V_{m_1}^{n_1}, V_{m_2}^{n_2})$, $n_1=1,2$, $n_2=1,2$, would occur for certain. Note that if we assume that the traffic assignment for alternative $X_i$ is independent of the traffic assignment for alternative $X_j$, there would be four link vector combinations for each OD matrix (i.e., $n_1=1$, $n_2=1$; $n_1=1$, $n_2=2$; $n_1=2$, $n_2=1$; and $n_1=2$, $n_2=2$; for all $m=1,2$, $l=1,2$). These combinations would be obtained from Table 2.3.

The probability of each combination would be given by

$$\text{Pr}(PA_l) \times \text{Pr}(OD^l_m) \times \text{Pr}(V_{m_1}^{n_1}) \times \text{Pr}(V_{m_2}^{n_2})$$

for $n_1=1,2$, $n_2=1,2$, $m=1,2$, $l=1,2$. The decision maker would decide between the build and no build alternatives after learning the result of the study on link volumes. Then, the remaining chance node (i.e., total system travel time) would follow. A portion of the decision tree for a perfect information study on the link volumes is shown in Figure 2.9.

The expected utility of this study would then be:

$$EU[VL \text{ Study}] = \sum_{i=1}^{2} \text{Pr}(PA_i) \left( \sum_{m=1}^{2} \text{Pr}(OD^l_m) \left( \sum_{n_1=1}^{2} \sum_{n_2=1}^{2} \text{Pr}(V_{m_1}^{n_1}) \text{Pr}(V_{m_2}^{n_2}) \left( \max_{i=1,2} \left[ \sum_{o=1}^{2} \text{Pr}(V_{l_o}^{n_o}) U(Y_{i} + S_{l_o}^{n_o}) \right] \right) \right) \right) \right)$$

$$= 0.621141 - 0.160155.$$

(2.27)
Figure 2.9 Part of the Decision Tree for Calculating the Expected Utility of a Perfect Study on Link Volume Patterns
Finding S such that \( \text{EU[VL Study]} = \text{EU[No Study]} = 0.5729 \) yields \( \text{VOPI(VL)} = 0.301 \text{[\$million/year]} \). This value is the maximum cost the decision maker is willing to pay for a study on perfect information on the link volume pattern.

Finally, to calculate the \( \text{VOPI} \) on the total system travel time, we consider a study yields paired levels of the TSTT for the no-build and build alternatives. That is, for each paired volume vectors \( (1_{n_1}^{m, l}, 2_{n_2}^{m, l}) \), \( n_1=1,2, n_2=1,2, m=1,2, l=1,2 \), the study would indicate which combination of TSTT \( (1_{2, o_1}^{n_1, m, l}, 2_{2, o_2}^{n_2, m, l}) \), \( o_1=1,2, o_2=1,2 \) would occur for certain. Note, again, that if we assume that the TSTT for alternative \( X_1 \) is independent of the TSTT for alternative \( X_2 \), there would be four link vector combinations for each paired volume vectors (i.e., \( o_1=1, o_2=1; o_1=1, o_2=2; o_1=2, o_2=1; \) and \( o_1=2, o_2=2; \) for all \( n_1=1,2, n_2=1,2, m=1,2, l=1,2 \)). These combinations would be obtained from Table 2.4.

The probability of each combination would be given by

\[
\text{Pr}(P_{Ai}) \times \text{Pr}(OD_{n_1}^i) \times \text{Pr}(1_{n_1}^{m, l}) \times \text{Pr}(2_{n_2}^{m, l}) \times \text{Pr}(1_{2, o_1}^{n_1, m, l}) \times \text{Pr}(2_{2, o_2}^{n_2, m, l}) , o_1=1,2, o_2=1,2, n_1=1,2, n_2=1,2, m=1,2, l=1,2.
\]

The decision maker would decide between the build and no build alternatives after learning the result of the study on TSTT.

A portion of the decision tree for a perfect information study on the link volumes is shown in Figure 2.10. The expected utility of this study would then be:

\[
\text{EU[TSTT Study]} = \sum_{l=1}^{2} \text{Pr}(P_{Ai}) \left( \sum_{m=1}^{2} \text{Pr}(OD_{n_1}^l) \left( \sum_{n_1}^{2} \sum_{n_2}^{2} \text{Pr}(1_{n_1}^{m, l}) \text{Pr}(2_{n_2}^{m, l}) \left( \sum_{o_1}^{2} \sum_{o_2}^{2} \text{Pr}(1_{2, o_1}^{n_1, m, l}) \text{Pr}(2_{2, o_2}^{n_2, m, l}) \left( \text{Max}_{i=1,2} \left( U(i_S + S, i_{2, o_1}^{n_1, m, l}) \right) \right) \right) \right) \right).
\]
Figure 2.10 Part of the Decision Tree for Calculating the Expected Utility of a Perfect Study on Total System Travel Time
Hence,

\[ EU[TSTT \; Study] = 0.632172 + 0.160155S. \]  

Finding \( S \) such that \( EU[TSTT \; Study] = EU[No \; Study] = 0.5729 \) yields \( VOPI(TSTT) = 0.395 \) [$\text{million/year}$. This value is the maximum cost the decision maker is willing to pay for a study on perfect information on the total system travel time levels.

In summary, the VOPI at each step of the sequential forecasting process are 

\[ VOPI(PA) = 0.073, \; VOPI(OD) = 0.153, \; VOPI(VL) = 0.301 \] and \( VOPI(TSTT) = 0.395 \) [$\text{million/year}$. for production-attraction, origin-destination, link volume and total system travel time respectively. These values indicate the maximum cost of studies the decision maker is willing to pay for perfect information at each step of the forecasting sequence.

It is also possible to calculate the VOPI of each step, that is, the VOPI of the models used in the sequential forecasting process: trip generation (TG), trip distribution (TD), traffic assignment (TA) and travel time (TI). We present mechanisms to calculate VOPI of each step in the next section.

### 2.3.3 VOPI of the Forecasting Steps

In this sub-section we present two mechanisms to calculate the VOPI of each modeling step in the sequential forecasting process: Marginal VOPI and Model VOPI. We define the Marginal VOPI as the cost the decision maker is willing to pay to obtain perfect
information at each step, given that s/he already has perfect information at the previous step. That is, Marginal VOPI of step i would be the difference between the VOPI at step i and the VOPI at step (i-1). For example, the Marginal VOPI of trip distribution (TD) would be equal to the difference between VOPI(OD) and VOPI(PA).

In the previous section we showed that VOPI(OD)=0.153 and VOPI(PA)=0.073 for the network example; hence the Marginal VOPI(TD)=0.153-0.073=0.080 [$\text{million/year}$]. Similarly, the Marginal VOPI of Traffic Assignment (TA), would equal to VOPI(VL)-VOPI(OD)=0.301-0.153=0.148 [$\text{million/year}$]. Finally, the Marginal VOPI of Travel Time (TI), would be equal to VOPI(TSTT)-VOPI(VL)=0.395-0.301=0.094 [$\text{million/year}$].

Alternatively, we define Model VOPI as the cost the decision maker is willing to pay to obtain perfect information at each step given that the previous step outcomes remain uncertain. Consider, for example, that we want to calculate the Model VOPI of the trip distribution step, given that the production-attraction pattern is unknown. In this case, a perfect information study would provide the trip distribution patterns (i.e., OD matrices) for any possible production-attraction pattern. As a result there would be $M^L$ potential outcomes of this perfect information study, where $L$ is the number of production-attraction patterns and $M$ the number of trip distribution patterns for each production-attribution problem $l=1,...,L$. In our example $L=2$ and $M=2$, hence there would be four outcomes of the perfect information study:

Outcome 1 (TD Study): $OC_1=(OD_1^1,OD_1^2)$,
Outcome 2 (TD Study): $OC_2=(OD_1^1,OD_2^2)$,
Outcome 3 (TD Study): \( OC_3 = (OD_1^1, OD_1^2) \),
Outcome 4 (TD Study): \( OC_4 = (OD_2^1, OD_2^2) \),

where \( OD_m^l \), \( m=1,2, l=1,2 \), corresponds to the \( m \)th origin-destination pattern given the \( l \)th production-attraction (PA) pattern. If we assume that the origin-destination pattern for PA is independent of the origin-destination pattern for PA, the probability of occurrence of each outcome \( OC_q \) would be:

\[
\begin{align*}
\Pr(OC_1) &= \Pr(OD_1^1) \times \Pr(OD_1^2) = 0.55 \times 0.55 = 0.3025 \\
\Pr(OC_2) &= \Pr(OD_1^1) \times \Pr(OD_2^2) = 0.55 \times 0.45 = 0.2475 \\
\Pr(OC_3) &= \Pr(OD_2^1) \times \Pr(OD_1^2) = 0.45 \times 0.55 = 0.2475 \\
\Pr(OC_4) &= \Pr(OD_2^1) \times \Pr(OD_2^2) = 0.45 \times 0.45 = 0.2025
\end{align*}
\]

In Figure 2.11 we show the decision "branch" for one of the outcomes of the perfect information trip distribution study. There would be four of these branches (i.e., outcomes \( OC_q \)) in the study portion of the decision tree. Note that there is a chance node for the production-attraction pattern after the decision node (No-build-Build).

We solve each decision branch by averaging-out and folding-back, as before. The expected utility of the perfect trip distribution study would be the probability weighted average of the four branches (Outcomes \( OC_q, q=1,\ldots,4 \)):

\[
EU[TD\ Study] = \sum_{q=1}^{4} \Pr(OC_q) \left( \max_{l=1,2} \left[ \sum_{i=1}^{2} \Pr(TG_i) \left( \sum_{m=1}^{2} \Pr(i \rightarrow n_{q,l} \mid m) \left( \sum_{o=1}^{2} \Pr(i \rightarrow n_{2,o} \mid q) U(Y_i + S, i \rightarrow n_{2,o}) \right) \right) \right] \right). \tag{2.30}
\]
Figure 2.11 Part of the Decision Tree for Evaluating a Perfect Information Study on Trip Distribution Given that Production-Attraction Pattern is Unknown

Note that the index \( m \), which indicates the conditional OD pattern, depends on the outcome \( q \). Replacing the variables in (2.30) with their corresponding values we find that \( EU_{\text{TD Study}} = 0.58809 - 0.3203 \times 2.00 \). Solving \( EU_{\text{TD Study}} = EU_{\text{No Study}} = 0.5729 \) for \( S \) we find that Model \( V_{\text{OPI(TD)}} = 0.095 \) (\$million/year). This value is the maximum cost the decision maker is willing to pay for a perfect information study on trip distribution given that the production-attraction pattern is unknown.

Similarly, we can formulate the expected utility of perfect information studies on traffic assignment (TA) given that the origin-destination (OD) pattern is unknown. In this case, a perfect information study would provide the volume vectors for any possible
OD pattern and alternative $X_i$, $i=1,2$. There would be $N^{L,M}$ potential outcomes of this perfect information study where $L$ is the number of production-attraction patterns, $M$ the number of origin-destination patterns for each production-attraction pattern, $N$ is the number of link volume vectors conditioned on each OD matrix, and $2$ is the number of alternatives (Build, No-Build). In our example $L=2$, $M=2$, and $N=2$; hence, there would be 264 outcomes of the perfect information study:

$$OC_1 = (1^l V_1^{1,1}, 2^l V_1^{1,2}), (1^l V_1^{2,1}, 2^l V_1^{2,2}), (1^l V_2^{1,1}, 2^l V_2^{1,2}), (1^l V_2^{2,1}, 2^l V_2^{2,2})$$

$$OC_2 = (1^l V_1^{1,1}, 2^l V_1^{1,2}), (1^l V_1^{2,1}, 2^l V_1^{2,2}), (1^l V_1^{2,1}, 2^l V_1^{2,2}), (1^l V_2^{2,1}, 2^l V_2^{2,2})$$

$$...$$

$$OC_{264} = (1^l V_2^{1,1}, 2^l V_2^{1,2}), (1^l V_2^{2,1}, 2^l V_2^{2,2}), (1^l V_2^{2,1}, 2^l V_2^{2,2}), (1^l V_2^{2,1}, 2^l V_2^{2,2})$$

where, $^l V_n^{m,i}$ correspond to the $n^{th}$ volume vector for alternative $X_i$, $i=1,2$, conditioned on the $m^{th}$ OD pattern for the $l^{th}$ production-attraction (PA) pattern. If we assume that the traffic assignment for alternative $X_1$ is independent of the traffic assignment for alternative $X_2$, and that they are also independent of the OD matrix, the probability of occurrence of each outcome is:

$$Pr(OC_q) = Pr(1^l V_1^{1,1}) \times Pr(1^l V_1^{2,1}) \times Pr(2^l V_2^{1,2}) \times Pr(2^l V_2^{2,2}) \times Pr(1^l V_2^{1,2}) \times Pr(1^l V_2^{2,2}) \times Pr(2^l V_2^{1,2}) \times Pr(2^l V_2^{2,2})$$

(2.31)
where \( n_{m,i} = 1,2 \) for \( m=1,2, i=1,2 \), indicates the index to be used in each term of this equation. As a result we have that the probabilities of the different outcomes would be:

\[
\begin{align*}
Pr(OC_1) &= 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.7 = 0.057648 \\
Pr(OC_2) &= 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.3 = 0.024706 \\
& \quad \vdots \\
Pr(OC_8) &= 0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.3 \times 0.3 \times 0.3 = 0.0045379 \\
& \quad \vdots \\
Pr(OC_{264}) &= 0.3 \times 0.3 \times 0.3 \times 0.3 \times 0.3 \times 0.3 \times 0.3 \times 0.3 = 0.00006561
\end{align*}
\]

We show one branch of the decision tree used to calculate the expected utility of the traffic assignment (TA) study in Figure 2.12. Note that there are chance nodes for the PA and OD patterns after making the decision between \( X_1 \) and \( X_2 \). Note also that, for a given outcome of the perfect information study, the link volume vector we only have one possible volume vector for each OD pattern.

As before, we "solve" the tree by averaging-out and folding-back. The expected utility of the study on perfect traffic assignment is then given by:

\[
EU[TA \text{ Study}] = \sum_{q=1}^{264} Pr(OC_q) \left[ \max_{i=1,2} \left( \sum_{j=1}^{2} Pr(TG_i) \left( \sum_{m=1}^{2} Pr(OD_{m}^{i}) \left( \sum_{o=1}^{2} Pr(y_{i,o}^m, l) U \left( \chi_i + S, y_{i,o}^m, l \right) \right) \right) \right) \right] \\
= 0.58862 - 0.16015 S. \quad (2.32)
\]

Note that the index \( n \), which indicates the conditional link volume vector, depends on the outcome \( q \) of the study. To find the Model VOPI(TA) we solve \( EU[TA \text{ Study}] = EU[No \ldots) \)
Study\(]=0.5729\) for \(S\), as before. We find that \(\text{VOPI}(\text{TA})=0.098\) \([$\text{million/year}$\]). This is the maximum value the decision maker would be willing to pay for a perfect information study on traffic assignment when the OD pattern remains unknown.

\[
\begin{array}{c|c|c|c|c}
X_i & P_{Ai} & Pr & OD_m^i & Pr \\
\hline
\text{No Build} & i=1 & 0.6 & m=1 & 0.55 \\
& & & m=2 & 0.45 \\
& i=2 & 0.4 & m=1 & 0.55 \\
& & & m=2 & 0.45 \\
\text{Build} & i=2 & & & \\
\end{array}
\]

\[
\begin{array}{c|c|c|c|c|c}
 & & & & & U(Y_i,Y_j) \\
\hline
\text{OC}_1 & l^1 & l^2 & l^3 & 0.0576 & \\
\hline
\text{No Build} & i=1 & 0.6 & m=1 & 0.55 & n=1 & 1.0 \\
& & & m=2 & 0.45 & n=1 & 1.0 \\
& i=2 & 0.4 & m=1 & 0.55 & n=1 & 1.0 \\
& & & m=2 & 0.45 & n=1 & 1.0 \\
\text{Build} & i=2 & & & & \\
\end{array}
\]

Figure 2.12 Part of the Decision Tree for Evaluating a Perfect Information Study on Traffic Assignment Given that the OD Pattern is Unknown

In the following section we summarize the required elements for the calculation of the value of information, and especially VOPI.
2.4 Summary of the Required Elements

To calculate value of information we need to define alternatives, $X_i$, $i=1,\ldots,N$; establish a preference model, which consists of a vector of attributes $\mathbf{Y}=(Y_1,\ldots,Y_M)$ and a preference function over this vector; develop prediction models $(\mathbf{Y}|X_i)$, $i=1,\ldots,N$, to determine the attributes levels that would result if the alternatives are implemented; and, finally, define decision rules to order preferences among the alternatives based on predicted attribute levels. In this study we use a multi-attribute utility function $U[\mathbf{Y}]$ to model the preferences and expected utilities $EU[X_i]$ to arrange the alternatives in order of preference.

To calculate the value of perfect information (VOPI), it is assumed that it is possible to conduct a study to obtain perfect information upon an uncertain future realization (e.g., a set of link volumes). The probability distribution of the results of such a study is the same prior probability distribution of the uncertain future realization being considered (e.g., probability distribution on link volumes). The VOPI is then defined as the cost of the study $S$ that makes the expected utility of the alternative in which the study is conducted equal to the expected utility of the most preferred alternative in which the study is not conducted. We illustrated how to calculate VOPI in a simple and a sequential forecasting process, including trip generation, trip distribution, traffic assignment and time estimation, using a corridor and a network example, respectively.
In the sequential forecasting process we are able to calculate the VOPI at each step and VOPI of each modeling step. When calculating VOPI at each step, we assume it is possible to conduct a study that provides perfect information up to the given point in the forecasting sequence, e.g., production-attraction patterns, OD matrices, link volumes and total system travel times. We use the prior probabilities to determine the likelihood of occurrence of each possible outcome of the study.

When calculating VOPI of each model we use two approaches. We first consider the Marginal VOPI, that is, the additional cost the decision maker is willing to pay to obtain perfect information on the outcome of a given modeling step given that s/he knows the outcome of the previous step for certain. To calculate the Marginal VOPI we subtract the VOPI at the previous step from the VOPI at the selected step; (e.g., to calculate Marginal VOPI of traffic assignment we subtract the VOPI(OD) from the VOPI(Link Volumes).

We then consider the Model VOPI, defined as the cost the decision maker is willing to pay to obtain perfect information of the outcome of a given modeling step given that s/he does not know the outcome of the previous step. To calculate Model VOPI we assume that it is possible to conduct a study that provides perfect information on the model outcomes at the current step for any possible realization of the previous step. For example, the study would provide the OD matrix that would be realized for any possible realization of the production-attraction pattern. In this case, there would be as many study outcomes as potential combinations of the current step potential realizations and the previous step potential realizations (i.e., the number of study outcomes would be 55.
\( A^B \), where \( A \) is the number of possible realizations of the current step and \( B \) is the potential number of realizations of the previous step). As shown through the network example in this chapter, there are large number of outcomes to consider in the perfect information studies on the modeling steps.

We also illustrated how to calculate value of imperfect information VOII using the corridor example. For this calculation we required additional information on the level of uncertainty of the imperfect information study.

To illustrate the concepts, the examples used in this chapter used assumed discrete probability distributions with very few "states of nature." We also considered that the preference model only contained two attributes: cost and total time. In the next chapter we develop a sequential prediction scheme to obtain probability distributions of the attributes. We also include additional attributes: fuel consumption and pollution emissions.
CHAPTER 3

SEQUENTIAL PREDICTION PROCESS

The prediction model consists of predicting the attributes levels that would result if the alternatives were implemented \( \{Y_i X_j \}, i=1, \ldots, I \). In this chapter we present a sequential prediction process, based on the traditional four-step urban forecasting sequence (Dickey, 1983), energy consumption models (FHWA, 1995) and air quality analysis models (US-EPA, 1995). This process is used to find probability distributions of the attributes depending on two alternatives: No-Build \( X_1 \), and Build \( X_2 \). For illustration, we continue using the network from chapter 2 (Figure 3.1). We predict probability distributions for the following attributes:

- \( Y_1 \) = annualized cost [millions of dollars]
- \( Y_2 \) = system travel time [min/peak-hr]
- \( Y_3 \) = system fuel consumption [gallons/peak-hr]
- \( Y_4 \) = vector of vehicle emissions = \( (Y_{4,1}, Y_{4,2}, Y_{4,3}) \)
  - \( Y_{4,1} \) = hydro-carbons (HC) emissions [kg/peak-hr]
  - \( Y_{4,2} \) = carbon monoxide (CO) emissions [kg/peak-hr]
  - \( Y_{4,3} \) = nitrous oxides (NOx) emissions [kg/peak-hr]
We model the cost attribute $Y_I$ as not depending on the realized arc volumes, and develop its probability distribution separately. We model the other attributes as depending on the realized arc volumes and obtain their joint probability distribution by first developing the arc volumes distribution, then the attributes distribution conditioned on the arc volumes.

We approximate the distributions with Monte Carlo simulation. Specifically, for a given alternative ($X_1$ or $X_2$) we randomly generate $N_v$ arc volume vectors $v$ and assume that each vector occurs with probability $1/N_v$. For each arc volume vector we randomly generate $R_{y|v}$ attribute vectors, and assume that each occurs with probability $1/R_{y|v}$, conditional on flow pattern $y$ having occurred. Next, we detail how we simulate the flow and attribute distributions.
3.1 Probability Distribution of the Arc Volumes

To develop the probability distributions of the arc volumes, we model the volumes as being produced from a sequence of "conditional models": Vehicle Trip Generation (TG), Vehicle Trip Distribution (TD) and Vehicle Traffic Assignment (TA), denoted \( cm = 1, 2, 3 \), respectively. By considering vehicle trips immediately in this example, we avoid the Modal Split (MS) component of the traditional 4-step process (Dickey, 1983). This could be easily incorporated in other applications. We call the models conditional, since they produce outputs conditional upon inputs from the preceding model in the sequence. We consider TG as the first model in the sequence here, but in general TG would use outputs from other models. Therefore, we also consider it a conditional model.

The important distinction between our modeling approach and traditional risk analysis applied to flow prediction (i.e., Lewis, 1995; Rose, 1985; Pell, 1984) is that, in addition to considering inputs and parameters uncertain, we consider the mapping of inputs to outputs --i.e., the model itself-- to be uncertain. For example, even if we could predict the vehicle origin-destination matrix and model congestion perfectly, we still could not predict arc volumes perfectly; i.e., the conditional traffic assignment process is not known perfectly. We, therefore, consider uncertainty as a function of the conditional model outputs, as opposed to conditional model inputs.

In general, one run of conditional model \( cm \) will produce a vector of outputs \( OP(cm) = (OP(cm)_1, OP(cm)_2, \ldots, OP(cm)_{N(cm)}) \). In our network example, the TG (\( cm = 1 \)) model produces \( N(1) = 4 \) outputs --the number of origins at nodes 1 and 2 and the number
of destinations at nodes 3 and 4; the TD (cm=2) model produces $N^{(2)} = 4$ outputs --the number of trips $q_{rs}$ from node $r$ to node $s$, $r=1,2; s=3,4$; and the TA (cm=3) produces $N^{(3)} = 6$ outputs in the no-build ($X_2$) and $N^{(3)} = 7$ in the build ($X_1$) options --the volume on each arc of the network.

We define a measure to determine the average dispersion in the probability density function of the outputs of each conditional model. This dispersion can be a function of the inputs. For example, the dispersion in the probability density function of each arc volume is expected to be a function of the OD pattern used as input. Hence, we define the uncertainty measure $UM_h^{(cm|cm-1)}$ of model $cm=2, 3$, as the average of the estimated standard deviation $ESD_{i,h}^{(cm|cm-1)}$ divided by the estimated mean $EM_{i,h}^{(cm|cm-1)}$ of the $i^{th}$ output of model $cm$, conditioned on the $h^{th}$ output vector $OP_{h}^{(cm-1)}$ serving as input to $cm$. The average is taken over all $N^{(cm)}$ outputs produced by a run of $cm$, and the estimates of the conditional means and standard deviations are taken over $R^{(cm)}$ runs of $cm$. That is:

$$UM_h^{(cm|cm-1)} = \frac{1}{N^{(cm)}} \sum_{i=1}^{N^{(cm)}} \frac{ESD_{i,h}^{(cm|cm-1)}}{EM_{i,h}^{(cm)}} , \quad cm=2,3; h=1,...,R^{(cm-1)},$$ (3.1a)

with:
\[ EM_{i,h}^{(cm|cm-1)} = \sum_{j=1}^{R^{cm}} \frac{OP_{j,i}^{(cm)} | OP_{h}^{(cm-1)}}{R^{(cm)}}, \quad cm=2,3; \quad i=1,...,N^{(cm)}; \quad h=1,...,R^{(cm-1)}, \quad (3.1b) \]

and:

\[ ESD_{i,h}^{(cm|cm-1)} = \left[ \frac{R^{(cm)}}{\sum_{j=1}^{R^{cm}}} \frac{\left( \frac{OP_{j,i}^{(cm)} | OP_{h}^{(cm-1)}}{R^{(cm)} - 1} \right)^2}{\left( R^{(cm)} - 1 \right)} \right]^{1/2}, \quad cm=2,3; \quad i=1,...,N^{cm}; \quad h=1,...,R^{cm-1}, \quad (3.1c) \]

We define the uncertainty measure \( UM^{cm} \) of model \( cm=2,3 \), by "unconditioning" over the input vectors of model \( cm-1 \):

\[ UM^{(cm)} = \frac{R^{(cm-1)}}{\sum_{h=1}^{R^{(cm-1)}}} \frac{UM_{h}^{(cm|cm-1)}}{R^{(cm-1)}}, \quad cm=2,3, \quad (3.2) \]

In this study the trip generation model \( TG (cm=1) \) is the first step of the sequential forecasting process; hence, it is not conditioned on different outputs of a previous model as TD \( (cm=2) \) and TA \( (cm=3) \). We, then, define the uncertainty measure \( UM^{1} \) of TG directly as the average over the \( i^{th} \) outcomes of the estimated standard deviation \( ESD_{i}^{(1)} \) to the estimated mean \( EM_{i}^{(1)} \) ratio:

\[ UM^{1} = \frac{1}{N^{1}} \sum_{i=1}^{N^{1}} \frac{ESD_{i}^{1}}{EM_{i}^{1}}, \quad (3.3a) \]
where,

\[ EM^1_i = \sum_{j=1}^{R^1} \frac{O^1_{j,i}}{R^1}, \quad i=1,\ldots,N^1, \quad (3.3b) \]

and

\[ ESD^1_i = \left[ \sum_{j=1}^{R^1} \left( O^1_{j,i} - EM^1_i \right)^2 \right]^{1/2}, \quad i=1,\ldots,N^1. \quad (3.3c) \]

Our approach consists of imposing random error while retaining the conditional model structure to achieve a specified value of \( \mathcal{UM}^{em} \). We detail our approach for each one of the conditional models in the next sections.

3.1.1 Trip Generation (TG)

For TG we assume base case origin flows \( O_r^{(b)}, \ r=1,2 \) and destination flows \( D_s^{(b)}, \ s=3,4 \). We simulate realizations of \( O_r \) and \( D_s \) by imposing random errors on these base case values:

\[ O_r = O_r^{(b)} (1 + \epsilon_{TG,r}), \quad r = 1, 2; \quad (3.4a) \]

\[ D_s = D_s^{(b)} (1 + \epsilon_{TG,s}), \quad s = 3, 4; \quad (3.4b) \]

with \( \epsilon_{TG,g} \sim N(0, \eta_{TG}), \ g=1,2,3,4. \)
We assume independent errors \( \varepsilon_{TG,g}, g=1,2,3,4 \). Generating errors in this way will not guarantee that the sum of the origin flows equals the sum of the destination flows. We, therefore, adjust the resulting flows using:

\[
O_r' = O_r \frac{[\sum_r O_r + \sum_s D_s]/2}{\sum_r O_r}; \quad r=1,2; \quad s=3,4; \tag{3.5a}
\]

\[
D_s' = D_s \frac{[\sum_r O_r + \sum_s D_s]/2}{\sum_s D_s}; \quad r=1,2; \quad s=3,4. \tag{3.5b}
\]

Consider, for example, base case flows and realizations of the random error given in columns two and three of Table 3.1. The resulting number of vehicles originating or ending at each centroid, and the adjusted flows are also shown in this table. For example, for origin 1 we have that \( O_1=3,100*(1+0.0048)=3,115 \) and \( O_1'=3,115\frac{[6,467+6,610]/2}{6,467}=3149 \). The adjusted flows, shown in column 5 of Table 3.1, are then input to the conditional TD model.

<table>
<thead>
<tr>
<th>Origin-Destination</th>
<th>Base Case Flows ( O_r^{(b)} )</th>
<th>Realization of Random Error ( \varepsilon_{TG,g} )</th>
<th>Realized Flows ( O_r = O_r^{(b)} (1+\varepsilon_{TG,r}) )</th>
<th>Adjusted Flows ( O_r', D_s' )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r=1 )</td>
<td>3,100</td>
<td>0.0048</td>
<td>3,115</td>
<td>3,149</td>
</tr>
<tr>
<td>( r=2 )</td>
<td>3,400</td>
<td>-0.0141</td>
<td>3,352</td>
<td>3,389</td>
</tr>
<tr>
<td>( s=3 )</td>
<td>3,300</td>
<td>0.0270</td>
<td>3,389</td>
<td>3,352</td>
</tr>
<tr>
<td>( s=4 )</td>
<td>3,200</td>
<td>0.0067</td>
<td>3,221</td>
<td>3,186</td>
</tr>
</tbody>
</table>

Table 3.1 Trip Generation (TG) Model Example

We achieve the uncertainty measure on trip generation \( UM^{(1)} \) through the choice of \( \eta_{TG} \). Specifically, for our \( O_r^{(b)} \)'s and \( D_s^{(b)} \)'s (Table 3.1), we generated 2,000 sets of
random errors with a given $\eta_{TG}$ and calculated $UM^{(1)}$. We then changed the $\eta_{TG}$ until we obtained the desired $UM^{(1)}$. Using this iterative procedure, we got the values shown in Figure 3.2. Note, for example, that $\eta_{TG}=0.276$ yielded $UM^{(1)}=0.25$. The values of $\eta_{TG}$ and $UM^{(1)}$ differ because of the conservation of flow constraint. That is, if we did not need to guarantee that the sum of origins $\Sigma O_r=\Sigma D_r$, $\eta_{TG}=0.25$ would result in $UM^{(1)}=0.25$.

![Figure 3.2 Uncertainty Measure of the Trip Generation Model Output $UM^{(1)}$ as a function of the Standard Deviation of the Error in Trip Generation $\eta_{TG}$](image)

3.1.2 Trip Distribution ($TD$)

For the $TD$ model we use the $TG$ outcomes and a gravity model to estimate conditional origin-destination flows $q_{rs}, r=1,2, s=3,4$.

Specifically, the gravity model can be written as:
\[ q_{rs} = A_r O'_r B_s D'_s F_{rs} \]  

(3.6)

where \( F_{rs} \) is the impedance for traveling from \( r \) to \( s \), \( A_r \) and \( B_s \) are equilibration parameters, and \( O'_r \) and \( D'_s \) are the total vehicle trips originated at \( r \) and destined to \( s \), respectively (Fotheringham and O'Kelly, 1989). The assumed parameters of the gravity model for the illustrative example are shown in Table 3.2.

<table>
<thead>
<tr>
<th></th>
<th>( s=3 )</th>
<th>( s=4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r=1 )</td>
<td>( F_{13}=3.06E-7 )</td>
<td>( F_{14}=3.06E-7 )</td>
</tr>
<tr>
<td>( r=2 )</td>
<td>( F_{23}=3.35E-4 )</td>
<td>( F_{22}=4.54E-5 )</td>
</tr>
<tr>
<td></td>
<td>( B_3=0.6529 )</td>
<td>( B_4=1.858 )</td>
</tr>
</tbody>
</table>

Table 3.2. Parameters of the Gravity Model

The resulting \( q_{rs} \) values will not necessarily satisfy conservation of origin and destination flows. Therefore, we use an iterative row and column factoring procedure (Fotheringham and O'Kelly, 1989) to adjust \( q_{rs} \) and obtain base case flows \( q_{rs}^{(b)} \) which guarantee that \( \Sigma_s q_{rs}^{(b)} = O'_r \) and \( \Sigma_r q_{rs}^{(b)} = D'_s \). The procedure can be summarized as:

Step 1. Calculate \( q_{rs}^{(0)} = A_r O'_r B_s D'_s F_{rs} \), set \( i=0 \)

Step 2. Set \( i=i+1 \), \( q_{rs}^{(i)} = q_{rs}^{(i-1)} \).

Step 3. Calculate row adjustment factor \( \text{raf}_{r}^{(i)} = \Sigma_s q_{rs}^{(i)}/O'_r \), \( r=1,2 \).
Step 4. Divide \( q_{rs}^{(i)} \) of each row by the corresponding row adjustment factor to find
\[ q_{rs}^{(i)} = q_{rs}^{(i)} / r_{af}^{(i)}. \]
If maximum \(|1 - r_{af}^{(i)}| < \varepsilon = 0.006\) stop; else, continue to Step 5.

Step 5. Calculate column adjustment factor \( c_{af_s}^{(i)} = \sum_r q_{rs}^{(i)} / D_s', s = 3,4. \)

Step 6. Divide \( q_{rs}^{(i)} \) on each column by the corresponding column adjustment factor to find
\[ q_{rs}^{(i)} = q_{rs}^{(i)} / c_{af_s}^{(i)} \]
If maximum \(|1 - c_{af_s}^{(i)}| < \varepsilon = 0.006\) stop; else, go to Step 2.

The resulting flows from the adjustment procedure are the base case flows \( q_{rs}^{(b)} \). This procedure usually converges after only a few iterations, and it is guaranteed to converge if \( \Sigma O_r = \Sigma D_s'. \)

Consider, for example, the application of the gravity model to the origins and destination flows from the trip generation example (Table 3.1):

Step 1. \( q_{rs}^{(0)} = A_r \cdot O_r \cdot B_s \cdot D_s' \cdot F_{rs} \); for example: \( q_{13}^{(0)} = 403.6 \times 3.149 \times 0.6529 \times 3.352 \times 3.06E-7 = 851.13 \). Continuing for the other flows yield \( q_{14}^{(0)} = 2,302.16 \); \( q_{23}^{(0)} = 2,502.05 \); \( q_{24}^{(0)} = 917.17 \).

Step 2. \( i=1, q_{rs}^{(1)} = q_{rs}^{(0)}. \)

Step 3. \( r_{af}^{(1)} = \Sigma q_{rs}^{(1)} / O_r' \); for example \( r_{af_1}^{(1)} = (851.13 + 2,302.16) / 3.149 = 1.001364. \)
Continuing for \( r=2 \) yields \( r_{af_2}^{(1)} = 1.0008917. \)

Step 4. \( q_{rs}^{(1)} = q_{rs}^{(1)} / r_{af}^{(1)} \); for example \( q_{13}^{(1)} = 851.13 / 1.001364 = 849.97. \) Continuing for the other flows yield \( q_{14}^{(1)} = 2,299.03 \); \( q_{23}^{(1)} = 2,479.94 \); \( q_{24}^{(1)} = 909.06 \). The maximum \(|1 - r_{af}^{(1)}| \) is then 0.008917 which is larger than 0.006. As a result, we continue to step 5.
Step 5. \( \text{caf}_s(1) = \frac{\sum \text{q}_{rs}(1)}{D_s'} \); for example \( \text{caf}_3(1) = \frac{(849.97 + 2,479.94)}{3,352} = 0.99341 \).

Continuing for \( s = 4 \) yields \( \text{caf}_4(1) = 0.996508 \).

Step 6. \( \text{q}_{rs}(1) = \frac{\text{q}_{rs}}{\text{caf}_s(1)} \); for example \( \text{q}_{13}(1) = \frac{849.97}{0.99341} = 855.61 \). Continuing for the other flows yield \( \text{q}_{14}(1) = 2,307.09; \text{q}_{23}(1) = 2,496.39; \text{q}_{24}(1) = 912.25 \). The maximum \( \mid 1 - \text{caf}_s(1) \mid = 0.00659 > 0.006 \); hence we go to step 2.

Continuing until convergence is achieved we find that the equilibrated base case flows are \( \text{q}_{13}^{(b)} = 852 \text{ q}_{14}^{(b)} = 2,297; \text{q}_{23}^{(b)} = 2,482; \text{q}_{24}^{(b)} = 907 \). We now introduce uncertainty in the conditional TD model by adding a random error to these base case values:

\[
q_{rs}' = q_{rs}^{(b)} (1 + \varepsilon_{TD,rs}), \quad r = 1, 2; s = 3, 4, \quad (3.7)
\]

where \( \varepsilon_{TD,rs} \) are independent random errors with \( \varepsilon_{TD,rs} \sim N(0, \eta_{TD}) \). Again, the resulting \( q_{rs}' \) do not necessarily satisfy conservation of origins and destinations. Therefore, we use the same adjustment procedure to find \( q_{rs}'' \), \( r = 1, 2; s = 3, 4 \), so that \( \Sigma_s q_{rs}'' \approx O_{r}' \) and \( \Sigma_r q_{rs}'' \approx D_{s}' \).

For example, consider the base case adjusted gravity model flows and random error realizations shown in Table 3.3. These errors led to the O-D pair realizations shown in column 4 of the same table. For instance, \( q_{12}' = 852 \times (1 + 0.0211) = 870 \). Note that, for example, \( \Sigma_{q_{12}}' = 870 + 2,304 = 3,149 \). Therefore, we need to adjust the realized flows using row and column factoring. This results in the balanced flows displayed in column
5. These balanced flows $q''_{rs}$ serve as inputs to the conditional traffic assignment $TA$ model.

<table>
<thead>
<tr>
<th>$r, s$</th>
<th>Base Case Flows $q_{rs}^{(b)}$</th>
<th>Realization of Random Error $\in TD_{rs}$</th>
<th>Realized Flows $q'_{rs}$</th>
<th>Balanced Flows $q''_{rs}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r=1, s=3$</td>
<td>852</td>
<td>0.0211</td>
<td>870</td>
<td>832</td>
</tr>
<tr>
<td>$r=1, s=4$</td>
<td>2,297</td>
<td>0.0030</td>
<td>2304</td>
<td>2317</td>
</tr>
<tr>
<td>$r=2, s=3$</td>
<td>2,482</td>
<td>-0.0040</td>
<td>2472</td>
<td>2522</td>
</tr>
<tr>
<td>$r=2, s=4$</td>
<td>907</td>
<td>-0.1080</td>
<td>809</td>
<td>867</td>
</tr>
</tbody>
</table>

Table 3.3. Trip Distribution Example

As with $TG$, we achieve $UM^{(2)}$ through the choice of $\eta_{TD}$. Specifically, for each of 100 randomly generated sets of $O_r'$ and $D_s'$ from the TG model we found $q_{rs}^{(b)}$. Then, for each $q_{rs}^{(b)}$ we randomly generated 100 sets of errors with a given $\eta_{TD}$ to find $q'_{rs}$ and calculated $UM^{(2)(1)}$. We averaged over the 100 sets of $O_r'$ and $D_s'$ to find $UM^{(2)}$. We then changed $\eta_{TD}$ until we obtained the desired $UM^{(2)}$. Using this iterative procedure, we found the values shown in Figure 3.3. We see, for example, that $\eta_{TD} = 0.362$ yielded $UM^{(2)} = 0.25$. Again, $\eta_{TD}$ and $UM^{(2)}$ differ because of conservation constraints. That is, if we did not need to guarantee that $\Sigma_s q_{rs} = O_r$, and $\Sigma_r q_{rs} = D_s$, $r=1,2, s=1,2$, $\eta_{TG} = 0.25$ would result in $UM^{(2)} = 0.25$. 

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3.1.3 Traffic Assignment (TA)

A realization of the conditional TD model is an origin-destination matrix, i.e., \( q''_{rs} \), \( r=1,2, \ s=3,4 \). These are inputs to the conditional TA model. The uncertainty in the conditional TA model would be the result of uncertainty in free flow times, capacities, volume-delay relationships, and route choice. Probabilistic modeling of traffic assignment usually assumes a given route choice behavior (e.g., the user equilibrium principles) and uncertainty in the other inputs (e.g., Rose, 1985; Pell, 1984). Uncertainty on route choice also has been addressed; for example, see the models discussed by Cantarella and Cascetta (1995); Mahmassani and Chang (1988); Ben Akiva, et. al (1986), Sheffi (1984), and Daganzo and Sheffi (1977). Nevertheless, we believe that no model, or combination of models, will capture route choice behavior completely. As a result, we
consider that there will still be a level of uncertainty in the traffic volumes after considering the uncertainty on the inputs.

In the introductory example, the small number of paths and arcs might allow one to impose errors on the arc volumes output from a given TA algorithm and develop a balancing procedure similar to those used in TD and TG. This could be done, for example, by adding-up the flows between a given OD pair for all the possible paths between these origin and destination, and then factoring the link flows according to the error between the OD flows and these sums. This would require enumeration of all the possible paths for a given O-D pair.

However, the combinatorially large number of paths in a realistic network would make this infeasible, in general. Therefore, rather than imposing error on the outputs, we impose error on the travel time as a means to achieve the desired UM(3) while retaining the structure of the OD matrix and the incidence relations relating arc and path volumes. Specifically, we assume that arc \( a \) performance function is:

\[
t_a = t'_{oa} (1 + 0.15 (v_{\alpha} C_a)^a),
\]

where

\[
t'_{oa} = t_{oa} (1 + \varepsilon_{TAa}).
\]

and \( \varepsilon_{TAa} \) are independent random errors with \( \varepsilon_{TAa} \sim N(0, \eta_{TA}) \). Note that we do not claim that the travel time error models uncertainty in the physical time-flow relationship. We simply use it as a mechanism to achieve the desired level of output uncertainty of TA.
We then determine arc volumes \( v_a \) with a user equilibrium (UE) assignment. For our illustrative example we consider the network topology and link performance parameters shown in Figure 3.1. The basic free flow travel times for each arc are also shown in Table 3.4.

For illustration, consider the two sets of realizations of random errors shown in Table 3.4 for the No-Build \((X_1)\) and Build \((X_2)\) alternatives (columns 3 and 7). These realizations were generated with \( \eta_{TA} = 0.281 \) and \( \eta_{TA} = 0.070 \) for the No-Build \((X_1)\) and Build \((X_2)\) alternatives, respectively. The realized free flow times \( t'_{oa} \) are then obtained using \( t'_{oa} = t_{oa}(1 + \varepsilon_{TAa}) \). For example, for arc 1 under the No-Build \((X_1)\) alternative, we have \( t'_{01} = t_{01}(1 - 0.2484) = 7.516 \). Continuing for all the arcs under alternatives \( X_1 \) and \( X_2 \) yield the realized free flow travel times displayed in columns 4 and 8 of the same table. Using these free flow travel times one can perform UE to find the arc volumes displayed in columns 5 and 9 of the same table.

As before, we achieve \( UM^{(3)} \) through the choice of the standard deviation of the random error \( \eta_{TA} \). Specifically, for each of 10,000 randomly generated sets of \( q' \) we randomly generate 100 sets of \( \varepsilon_{TAa} \) errors with a given \( \eta_{TA} \) and calculated \( UM^{(3)} \). We averaged over the 10,000 \( q' \) sets to obtain \( UM^{(3)} \). We then modified \( \eta_{TA} \) until we achieved the desired \( UM^2 \). We obtained the values indicated in Figure 3.4. See for example, that \( \eta_{TA} = 0.281 \) and \( \eta_{TA} = 0.070 \) yielded \( UM^2 = 0.25 \) for alternatives \( X_1 \) and \( X_2 \) respectively.
Table 3.4. Traffic Assignment Example

<table>
<thead>
<tr>
<th>a</th>
<th>Basic Free Flow Time $t_{oa}$</th>
<th>Realization of Random Error $e_{oa}$</th>
<th>Realized Free Flow Time $t'_{oa}$</th>
<th>Arc Volumes $v_a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.0</td>
<td>-0.2484</td>
<td>7.5160</td>
<td>3149.00</td>
</tr>
<tr>
<td>2</td>
<td>15.0</td>
<td>0.1551</td>
<td>17.3265</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>4.0</td>
<td>0.1789</td>
<td>4.7156</td>
<td>2754.24</td>
</tr>
<tr>
<td>4</td>
<td>10.0</td>
<td>-0.0326</td>
<td>9.6740</td>
<td>631.76</td>
</tr>
<tr>
<td>5</td>
<td>4.0</td>
<td>-0.2012</td>
<td>3.1916</td>
<td>3354.00</td>
</tr>
<tr>
<td>6</td>
<td>5.0</td>
<td>0.5119</td>
<td>7.595</td>
<td>2552.24</td>
</tr>
</tbody>
</table>

Preliminary analysis leads us to believe that network topology causes different $\eta_{TA}$'s for the Build ($X_1$) and No-Build ($X_2$) alternatives. The introduction of the additional link in the simple network increases the number of paths. Hence, small relative variations in the travel time among the paths cause important variations in the

Figure 3.4 Uncertainty Measure of the Trip Distribution Model Output $UM^{(2)}$ as a function of the Standard Deviation of the Error in Traffic Assignment $\eta_{TA}$

![Graph showing uncertainty measure UM^2 as a function of ETA]

$\eta_{TA}$
traffic volume assigned to the paths. As a result, the required standard deviation $\eta_{TA}$ in the link times error required to produce a given uncertainty measure $UM^{(3)}$ of the arc volumes (e.g., $UM^{(3)} = 0.25$) is larger for the No-Build ($X_1$) than for the Build ($X_2$) alternative (e.g., $\eta_{TA} = 0.28$ and $\eta_{TA} = 0.07$, respectively). This result deserves a more detailed analysis, which is beyond the scope of this study.

Note also that we used a large number of repetitions to obtain a stable uncertainty measure $UM^{(3)}$. Figures 3.5 and 3.6 display the variation in $UM^3$ as a function of the number of combinations of the TG, TD, TA random model outputs for the No Build ($X_1$) and Build ($X_2$) alternatives, respectively. In this graphs, $\eta_{TA} = 0.28$ for No-Build ($X_1$) and $\eta_{TA} = 0.07$ for Build ($X_2$).

![Figure 3.5](image)

**Figure 3.5** Uncertainty Measure $UM^{(3)}$ as a Function of the Number of Combinations of TG, TD and TA Random Model Outputs for the No-Build ($X_1$) Alternative
We increased the number of combinations until the uncertainty measure showed stability (i.e., $100^3$ combinations). This large number of combinations required for stability in $UM^{(3)}$ seems to be a result of the large sensitivity of the user equilibrium arc volumes to the arc travel times in the small network.

3.1.4 Summary of the Procedure to Obtain the Arc Volumes Probability Distribution

In summary, to obtain the probability distribution on the arc volumes, we used the following Monte Carlo simulation approach:
Step 0. Assume \( O_t^{(b)}, D_s^{(b)}, r=1, \ldots, number \ of \ origins, \ s=1, \ldots, number \ of \ destinations; \)

gravity model parameters; and uncertainty measures \( UM_c^m, cm=1, 2, 3. \)

Step 1. Find \( \eta_{TG}, \eta_{TD}, \eta_{TA}, \) to yield \( UM_c^m, cm=1, 2, 3. \)

Step 2. Generate \( \epsilon_{TG,r}, \epsilon_{TG,s} \) from \( \epsilon_{TG} \sim N(0, \eta_{TG}), \) apply (4) and (5) to obtain \( O', r, \) and \( D', s. \)

Step 3. Apply gravity model, equation (6), and adjust outputs to obtain \( q_{rs}^{(b)}. \)

Step 4. Generate \( \epsilon_{TD,rs}, \epsilon_{TD,s} \) from \( \epsilon_{TD} \sim N(0, \eta_{TD}), \) apply (7), and adjust to obtain realized OD matrix \( q''_{rs}. \)

Step 5. Generate \( \epsilon_{TA,a}, a=1, \ldots, number \ of \ links, \) from \( \epsilon_{TA} \sim N(0, \eta_{TA}), \) apply (8), and perform UE traffic assignment with \( q''_{rs} \) to get realized volumes \( v_a. \)

Step 6. Repeat step 5 \( R_{TA} \) times;

Step 7. Repeat steps 4-6 \( R_{TD} \) times;

Step 8. Repeat steps 2-7 \( R_{TG} \) times.

This procedure is performed for each alternative \( X_i, i=1,2. \) To approximate the arc volumes probability distributions, we assume each realization would occur with probability \( 1/(R_{TA} \times R_{TD} \times R_{TG}). \) In the case of the illustrative example presented in the previous sub-sections, we consider two origins (\( r=1 \) and \( r=2 \)) and two destinations (\( s=3 \) and \( s=4 \)), as shown in Table 3.1, the gravity model parameters shown in Table 3.2, and uncertainty measures \( UM_c^{(1)} = UM_c^{(2)} = UM_c^{(3)} = 0.25. \) We find \( \eta_{TG}=0.27, \eta_{TD}=0.36, \eta_{TA}=0.28 \) for No-Build (\( X_1 \)) and \( \eta_{TA}=0.07 \) for Build (\( X_2 \)). We then apply steps 2-8 with.
Note that this yields \( R_{TA} \cdot R_{TD} \cdot R_{TG} = 30^3 \) random realizations of arc volumes; hence each arc volume vector realization is assumed to occur with \( 1/30^3 \) probability. We chose the number of simulated outcomes in such a way that we obtain a large, and still manageable, sample of the arc volumes.

3.2 Attribute Distributions

In our framework we consider that attributes \( Y_m, m=2, 3, 4 \), (total system time, total fuel consumption and total pollution emissions) depend on the arc volumes \( v \), which depend on the alternative \( X_i \). We assume that attribute \( Y_1 \) (cost) is independent of \( v \). We again use Monte Carlo simulation to estimate these attribute distributions. In summary, for each \( v \) generated using the methodology presented above, we generate \( R_{LV} = 30 \) realizations of \((Y_2, Y_3, Y_4)\) vectors. We, therefore, generate \( R_{TG} \cdot R_{TD} \cdot R_{TA} \cdot R_L = 30^4 \) attribute vectors for both the build and no-build options, and approximate the joint probability distributions by assuming that realizations occur with equal probability. We use conditional travel time, fuel consumption, and emission models, define uncertainty measures \( UM^m \) similar to (3.1)-(3.3), and impose random errors to achieve a desired \( UM^m \).

In the following sub-sections we detail the attribute models used for our network example. We start by showing the procedures to estimate total system travel time, total system fuel consumption and total system pollution emissions. We illustrate the application of these procedures with examples. The resulting attribute vectors, in
conjunction with the cost \(Y_1\) are then used to evaluate the alternatives and calculate VOPI. We present the evaluation and the value of information calculations in Chapter 4.

### 3.2.1 Total System Travel Time

We model the total system travel time \(Y_2\) as

\[
Y_2 = \sum_{a=1}^{N} v_a t'_a
\]  

(3.10)

where \(v_a\) and \(t'_a\) are the volume and average travel times on arc \(a\), respectively, and \(N\) is the number of arcs \((N=7\) for \(X_1\) and \(N=6\) for \(X_2\) in the illustrative example). We use a BPR type performance function to model the average travel time \(t_a\) on the arcs:

\[
t_a = t'_{oa} (1 + 0.15(v_a/C_a)^{4/3}),
\]

(3.11)

where the realized free flow time \(t'_{oa}\) is given by (3.9). We incorporate uncertainty in travel time \(t_a\) calculation by adding a random variable \(\varepsilon_{Y_{1a}}\) with \(\varepsilon_{Y_{1a}} \sim \mathcal{N}(0, \eta_{Y_1})\):

\[
t'_a = t_a (1 + \varepsilon_{Y_{1a}}).
\]

(3.12)

As opposed to the previous conditional models, the link travel time model only has one output \((t'_a)\). There is also no need for adjustment to comply with modeling restrictions (i.e., conservation of flow in trip generation, trip distribution and traffic assignment models). As a result the uncertainty measure \(\text{UM}^{Y_1} = \eta_{Y_1}\).
Examples of the travel time calculation for the build and no-build alternatives are presented in Table 3.5. We use the realized free flow travel times $t'_{oa}$ and arc volumes $v_a$ obtained in the traffic assignment example (Table 3.4) to calculate the average travel times $t_a$ using (3.11). For example, the travel time $t_1$ in arc 1 for the No-Build ($X_I$) alternative would be $t'_{o1}(1+0.15(v_1/C_1)^4)=7.5160(1+0.15(3,149/2,500)^4)=10.350$. We then introduce errors in travel time with $\epsilon_{Y_1a}$ with $\epsilon_{Y_1a}$-N(0,$\eta_{Y_1}$), and $\eta_{Y_1}=0.25$. For example, for arc 1, a random realization of the error is $\epsilon_{Y_11}=-0.0131$. Replacing the value in (3.12) we get $t'_1=10.225$. Continuing for the other links conditioned on $X_1$ and all the links conditioned on $X_2$ we get the travel times $t'_a$ shown in column 6 of Table 3.5.

<table>
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<tr>
<th>No-Build Alternative ($X_I$)</th>
<th>Realized Free Flow Time</th>
<th>Arc Volumes</th>
<th>Average Time</th>
<th>Realization of Random Error $Y_1$</th>
<th>Realized Time</th>
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<table>
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<th>Arc Volumes</th>
<th>Average Time</th>
<th>Realization of Random Error $Y_1$</th>
<th>Realized Time</th>
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Table 3.5 Travel Time Calculation Example
We add up the realized arc travel times $t_a$ to obtain the total system travel time $Y_2$ (3.10). In this example $Y_2$ is equal to 98,724 min/peak-hr for the No-Build Alternative ($X_1$) and 73,189 min/peak-hr for the Build Alternative ($X_2$). Note that these values are conditioned on particular realizations of the errors in trip generation, distribution, traffic assignment and travel time. The link travel times would also be inputs to the fuel consumption and emission models.

3.2.2 Total System Fuel Consumption

The Total System Fuel Consumption ($Y_3$) would be the sum over all the arcs of the network of the fuel consumption on each link ($TF'_a$):

$$Y_3 = \sum_{a=1}^{N} TF'_a.$$  

(3.13)

To obtain $TF'_a$ we use a fuel consumption model given by:

$$FA_a = 14.4525 + 0.0038751 s_a + 0.020496 s_a^2 - 0.000376 s_a^3 + 0.0000022845 s_a^4;$$  

(3.14a)

$$FT_a = 25.0947 + 4.24873 s_a - 0.17624 s_a^2 + 0.0036927 s_a^3 - 0.00002266 s_a^4;$$  

(3.14b)

where $FA_a$ and $FT_a$ are the fuel consumed per second by an automobile and a truck, respectively, traveling at an average speed equal to $s_a$ miles/hour. These equations were estimated from speed-fuel consumption tables inside CORSIM Traffic Simulation Software (FHWA, 1995) and are given in $10^{-5}$ gal/sec/vehicle. A detailed derivation of
these models is presented in Appendix A. We obtain the speed \( s_a \) by dividing the arc length \( l_a \), by the realized travel time \( t'_a \), that is

\[
s_a = \frac{l_a}{t'_a / 60}. \tag{3.15}
\]

The total fuel consumed on an arc \( a \) (TF\(_a\) [gal/peak-hr]) would then be the weighted average of fuel consumed by any vehicle on that arc \(-i.e.,\)

\[ p_a F A_a + (1 - p_a) F T_a \text{ [gal/sec/veh]}, \]

where \( p_a \) is the proportion of autos and \((1-p_a)\) is the proportion of trucks on arc \( a \)-- multiplied by the arc flow \( q_a \) [veh/peak-hr] and the realized time \( t'_a \) [min] multiplied by 60 [sec/min]:

\[
TF_a = \left( \frac{p_a F A_a + (1 - p_a) F T_a}{10^5} \right) q_a \left[\frac{\text{gal}}{\text{sec/veh}}\right] \times \left[\frac{\text{veh}}{\text{peak-hr}}\right] \times \left[\frac{\text{sec}}{\text{min}}\right]. \tag{3.16}
\]

Note that the results are given in gal/peak-hr.

We introduce uncertainty in fuel modeling at the arc level by adding a random variable \( \varepsilon Y_{2a} \) with \( \varepsilon Y_{2a} \sim N(0, \eta_{Y2}) \). The realized arc fuel consumption is then given by:

\[
TF'_a = TF_a (1 + \varepsilon Y_{2a}). \tag{3.17}
\]

As in the link travel time model, the fuel consumption conditional model uncertainty measure \( UM^{Y2} = \eta_{Y2} \). As before, the outcome is a single scalar and there is no need to adjust it for restrictions such as conservation of flow.
In our illustrative example we consider two types of highways: freeways and arterials. We consider arcs 1, 3, 5, and 6 as freeways and arcs 2, 4, and 7 as arterials. We assume that the proportion of autos is 75% ($p_a=0.75$) and 90% ($p_a=0.90$) on freeways and arterials, respectively. We assume that this proportion does not depend on the traffic assignment.

### No-Build Alternative ($X_1$)

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### Build Alternative ($X_2$)

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Table 3.6. Fuel Consumption Calculation Example

Table 3.6 displays a fuel consumption calculation example. See, for example that the speed on arc 1 under the No-Build ($X_1$) alternative is $s_1=l_1/(t_1/60)=10.00/(10.225/60)=58.68$ mph. Replacing $s_1$ in (3.14a) we find $F_A=36.363$ and $F_T=145.022 \ \text{[10^6 gal/sec]}$. 

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Inserting these values, $p_f=0.75$ and $v_f=3149.00$. in (16), we get $TF_f=1227.30$ [gal/peak-hr]. Finally, introducing $e_{Y_{21}}=0.2354$, we find $TF'_f=1516$ [gal/peak-hr]. Continuing for the other links in $X_1$ and all the links in $X_2$, we get the values displayed in the last column of Table 3.6. In this example, the total system fuel consumption $Y_3$, i.e., sum of the arc fuel consumption realizations (3.13), is $Y_3=3,029$ gal/peak-hr for the No-Build Alternative ($X_1$) and $Y_3=3,077$ gal/peak-hr for the Build Alternative ($X_2$).

### 3.2.3 Total System Pollution Emissions

The procedure to estimate the Total System Pollution Emissions ($Y_4$) is similar to the one used for Total System Fuel Consumption ($Y_3$). We consider three types of pollutants: hydro-carbons (HC), carbon monoxide (CO), and nitrous-oxides (NOx). The total system HC, CO and NOx emissions are denoted by $Y_{4,1}$, $Y_{4,2}$ and $Y_{4,3}$, respectively. These total emissions are equal to the sum of the total arc emissions:

\[
Y_{4,1} = \sum_{a=1}^{N} THC'_a , \quad (3.18a)
\]

\[
Y_{4,2} = \sum_{a=1}^{N} TCO'_a , \quad (3.18b)
\]

\[
Y_{4,3} = \sum_{a=1}^{N} TNOx'_a , \quad (3.18c)
\]

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where $THC'_a$, $TCO'_a$ and $TNOx'_a$ are the total realized arc HC, CO and NOx emissions, respectively. To estimate the arc HC emissions we use:

$$HC_{1a} = 4.47291567 - 0.22554054s_a + 0.00650787s_a^2 - 9.5662E^{-5}s_a^3 + 5.7207E^{-7}s_a^4, \quad (3.19a)$$

$$HC_{2a} = 5.53680395 - 0.2860775s_a + 0.00830099s_a^2 - 1.2115E^{-4}s_a^3 + 7.1416E^{-7}s_a^4; \quad (3.19b)$$

where $HC_{1a}$ and $HC_{2a}$ are the HC emissions in [grams/mile/vehicle] for freeways and arterials, respectively, and $s_a$ is the average vehicle speed in [miles/hour], as given in (3.15). Similarly, we estimate arc CO and NOx emissions in [grams/mile/vehicle] using:

$$CO_{1a} = 46.52000643 - 2.07396692s_a + 0.04755901s_a^2 - 7.0355E^{-4}s_a^3 + 5.1987E^{-6}s_a^4, \quad (3.19c)$$

$$CO_{2a} = 55.40320111 - 2.52101554s_a + 0.05919692s_a^2 - 8.7213E^{-4}s_a^3 + 6.3032E^{-6}s_a^4, \quad (3.19d)$$

$$NOx_{1a} = 3.08717843 - 0.2413613s_a + 0.01462959s_a^2 - 4.26E^{-4}s_a^3 + 5.8535E^{-6}s_a^4 - 2.953E^{-8}s_a^5, \quad (3.19e)$$

$$NOx_{2a} = 3.19685831 - 0.2505566s_a + 0.01592302s_a^2 - 4.74E^{-4}s_a^3 + 6.6012E^{-6}s_a^4 - 3.372E^{-8}s_a^5. \quad (3.19f)$$

These equations were estimated from the output of MOBILE 5a (US-EPA, 1995), with input parameters corresponding to Columbus-Ohio. Again, we present details of the derivation of these models in Appendix A. To estimate the total emissions on an arc we use:

$$THC_a = \begin{cases} 
HC_{1a}v_al_a & \text{if the arc is a freeway} \\
HC_{2a}v_al_a & \text{if the arc is an arterial} 
\end{cases} \quad (3.20a)$$
where $THC_a$, $TCO_a$ and $TNOx_a$ are the HC, CO and NOx arc emissions in [grams/peak-hr], respectively, $v_a$ is the arc volume [vehicles/peak-hr], $l_a$ is the arc length [miles].

We introduce uncertainty in the emission models by adding random variables to the emission models (3.19) and (3.20) as follows:

$$THC'_a = THC_a (1 + \epsilon_{Y_{4,1a}})$$

$$TCO'_a = TCO_a (1 + \epsilon_{Y_{4,2a}})$$

$$TNOx'_a = TNOx_a (1 + \epsilon_{Y_{4,3a}})$$

We assume that the random variables $\epsilon_{Y_{4,ua}} \sim N(0, \eta_{Y_{4,ua}})$, $u=1,2,3$. Note that, as with the arc time (3.12) and arc fuel consumption (3.17) probabilistic models, the arc pollution emission models (3.21) yield a single value and do not require adjustment; hence, the uncertainty measure $UM_{Y_{4,ua} = \eta_{Y_{4,ua}}}$, $u=1,2,3$.

We present an example of the pollution emissions calculation in Table 3.7. Most inputs to the pollution models (i.e., arc length $l_a$, volume $v_a$ and average speed $s_a$) are the same used for fuel consumption estimation. These values are displayed in Table 3.6. To calculate the emissions we first check if the arc is an arterial or a freeway. Recall that in
<table>
<thead>
<tr>
<th>Arc</th>
<th>THC(_a) ([\text{grams/peak-hr}])</th>
<th>THC(_a) ([\text{grams/peak-hr}])</th>
<th>TCO(_a) ([\text{grams/peak-hr}])</th>
<th>THC(_a) ([\text{grams/peak-hr}])</th>
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</table>

Table 3.7 Pollutant Emissions Calculation Example

the illustrative example we consider arcs 1, 3, 5, and 6 as freeways and arcs 2, 4, and 7 as arterials. Then, we use the speeds \(s_a\) to calculate the vehicle emissions using (3.19). For instance, for arc 1 under the No-Build \((X_1)\) alternative, we replace \(s_1=58.68\) mph in (3.19b), (3.19d) and (3.19e) and find that the arc HC, CO and NO\(x\) emissions are 1.3214, 13.4137, 2.3566 [grams/mile/vehicle]. These results are multiplied by the length \(l_1=10\) [miles] and volume \(v_f=3149\) [veh/peak-hr] to obtain the emissions per link \(THC_1'=41,511\), \(TCO_1'=442,396\) and \(TNO_x=74,209\) [grams/peak-hr] respectively.

We then introduce the random errors \(\varepsilon_{Y_{4,ua}}\) with \(UM^{Y_{4,ua}}=\eta_{Y_{4,ua}}=0.25\) for \(u=1,2,3\), for example \(\varepsilon_{Y_{4,11}}=-0.0721\), \(\varepsilon_{Y_{4,21}}=0.3104\) and \(\varepsilon_{Y_{4,31}}=-0.0566\), and use (3.21) to find
Continuing for the other links in $X_1$, and all the links in $X_2$ we find the set of realizations of arc emissions displayed in columns 4, 7 and 10 of Table 3.7.

The total system pollutant emissions are equal to the sum over all the links of the estimated emissions on each link (3.17). For our illustrative example, the set of realizations of the total HC, CO and NOx are $Y_{4,1}=120.4$ kg of HC/peak-hr, $Y_{4,2}=1,248.1$ kg of CO/peak-hr, and $Y_{4,3}=194.9$ kg of NOx/peak hr for the No-Build Alternative ($X_1$), and $Y_{4,1}=109.6$ kg of HC/peak-hr, $Y_{4,2}=1,142$ kg of CO/peak-hr, and $Y_{4,3}=155.0$ kg of NOx/peak-hr, for the Build Alternative ($X_2$).

3.2.4 Annualized Cost $Y_I$

We assume that the cost attribute does not depend on the traffic assignment. We can estimate the annualized cost using

$$Y_i|X_i = CT|X_i (1 + \varepsilon_{Y_i}),$$

(3.22)

where $CT|X_i$ is the expected annualized cost conditioned on the alternative $X_i$, and $\varepsilon_{Y_i}$ is a random error in estimation of the cost, with, for example, $\varepsilon_{Y_i} \sim N(0, \eta_{Y_i})$. However, if we assume an additive multi-attribute utility function and a linear single attribute utility function (chapter 4) it can be shown (Keeney and Raiffa, 1976) that one can use the expected annualized cost values rather than the entire cost probability distribution. This is based on the observation that

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\[ EU[X_i] = EU[(Y_1, Y_2, Y_3, Y_4) | X_i] \]
\[ = E[k_1u_1(Y_1) + k_2u_2(Y_2) + k_3u_3(Y_3) + k_4u_4(Y_4) | X_i] \]
\[ = k_1E[u_1(Y_1 | X_i)] + E[k_2u_2(Y_2) + k_3u_3(Y_3) + k_4u_4(Y_4) | X_i], \]

(3.23)

and that linear single attribute utility \( u_1(Y_1) \) means

\[ E[u_1(Y_1)] = E \left[ 1 - \frac{Y_1 - Y_1^{(\text{min})}}{Y_1^{(\text{max})} - Y_1^{(\text{min})}} \right] \]

(3.24)

For the simple network example, we assume an expected annualized cost \((E[Y_i | X_i] = CT | X_i, i=1,2)\) of $0.0 million/year for the No-Build Alternative \((X_1)\) and $5.0 million/year for the Build Alternative \((X_2)\). In the next chapter we present the evaluation using MAUT and value of information calculations.
CHAPTER 4

NUMERICAL RESULTS - SMALL NETWORK EXAMPLE

We present numerical results of the application of the value of information framework to a small network illustrative example. This example corresponds to the same network employed to illustrate the VOPI calculation in Chapters 2 and the attribute prediction methodology in Chapter 3. In this chapter we first describe the inputs to the VOPI calculation, i.e., alternatives, attributes, preferences and predictions. We then present the results of the expected utility calculation, the VOPI and marginal VOPI of each step of the prediction process. We also present VOPI calculations as a function of the difference in the expected utility of the alternatives.

4.1 Inputs for the Calculation of VOPI in the Small Network

As before, we consider two alternatives: $X_1 = \text{do not build highway segment}$ and $X_2 = \text{build highway segment}$, embedded in the network shown in Figure 4.1. The segment considered is the direct arc 7, indicated by the dashed line, from node 1 to node 4. The parameters of the arcs in the network are also indicated in Figure 4.1.
4.1.1 Preference Model for the Small Network Example

We use a preference model with the following attributes:

\[ Y_1 = \text{annualized cost [millions of dollars]} \]
\[ Y_2 = \text{system travel time [min/peak-hr]} \]
\[ Y_3 = \text{system fuel consumption [gallons/peak-hr]} \]
\[ Y_4 = \text{vector of vehicle emissions} = (Y_{4,1}, Y_{4,2}, Y_{4,3}) \]
\[ Y_{4,1} = \text{hydro-carbons (HC) emissions [kg/peak-hr]} \]
\[ Y_{4,2} = \text{carbon monoxide (CO) emissions [kg/peak-hr]} \]
\[ Y_{4,3} = \text{nitrogen oxides (NOx) emissions [kg/peak-hr]} \]

We model the preferences using an additive multi-attribute utility function (Keeney and Raiffa, 1976):

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where the single attribute utilities of cost $Y_1$, total system travel time $Y_2$, total fuel consumption $Y_3$ and are given by

$$u_m(Y_m) = 1 - \left[ \frac{Y_m - Y_m^{(min)}}{Y_m^{(max)} - Y_m^{(min)}} \right]^{\alpha_m}, \quad m=1, 2, 3. \quad (4.2)$$

The utility of the pollution vector $Y_4$ is also given by an additive utility function:

$$u_4(Y_4) = \sum_{p=1}^{3} k_{4,p} u_{4,p}(Y_{4, p}), \quad \sum_{p=1}^{3} k_{4,p} = 1, \quad (4.3)$$

where the utilities for the pollution emission attributes, total HC ($Y_{4,1}$), total CO ($Y_{4,2}$) and total NOx ($Y_{4,3}$), are:

$$u_{4,p}(Y_{4, p}) = 1 - \left[ \frac{Y_{4, p} - Y_{4, p}^{(min)}}{Y_{4, p}^{(max)} - Y_{4, p}^{(min)}} \right]^{\alpha_{4,p}}, \quad p=1, 2, 3. \quad (4.4)$$

The parameters of the single attribute utilities are summarized in Table 4.1. The bounds on the parameters (i.e., $Y_j^{(max)}$ and $Y_j^{(min)}$, $j=1, 2, 3, 4, 1, 4, 2$ and $4, 3$) are selected from the sampled attributes vectors using the Monte Carlo simulation procedure detailed in chapter 3. Specifically, we perform the simulation $30^4$ times and select the
maximum and minimum values of each attribute across all the simulations. We do this for two different sets of productions and attractions (Table 4.2) considering uncertainty levels $UM^{cm}=0.375$, $cm=1,...,8$.

<table>
<thead>
<tr>
<th>Attribute $Y_j$</th>
<th>Shape Parameter $\alpha_j$</th>
<th>Minimum $Y_j^{(min)}$</th>
<th>Maximum $Y_j^{(max)}$</th>
<th>Scaling Parameter $k_j$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost ($Y_1$) [$\text{million/year}$]</td>
<td>1.00</td>
<td>0.00</td>
<td>80.0</td>
<td>0.05085</td>
</tr>
<tr>
<td>Total System Travel Time ($Y_2$) [minutes/peak-hr]</td>
<td>1.00</td>
<td>55,749.4</td>
<td>1,052,850.0</td>
<td>0.05282</td>
</tr>
<tr>
<td>Total Fuel Consumption ($Y_3$) [gal/peak-hr]</td>
<td>1.00</td>
<td>863.8</td>
<td>23,476.3</td>
<td>0.02156</td>
</tr>
<tr>
<td>Utility of Emissions $U(Y_4)$</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.87477</td>
</tr>
<tr>
<td>HC Emissions ($Y_{4,1}$) [kg/peak-hr]</td>
<td>1.00</td>
<td>13.0</td>
<td>961.6</td>
<td>0.08877</td>
</tr>
<tr>
<td>CO Emissions ($Y_{4,2}$) [kg/peak-hr]</td>
<td>1.00</td>
<td>221.8</td>
<td>9,349.4</td>
<td>0.85412</td>
</tr>
<tr>
<td>NOx Emissions ($Y_{4,3}$) [kg/peak-hr]</td>
<td>1.00</td>
<td>10.7</td>
<td>621.0</td>
<td>0.05711</td>
</tr>
</tbody>
</table>

Table 4.1. Shape Parameters and Bounds on the Attributes for the Small Network Example

For this analysis we assume linear single attribute utilities (i.e., $\alpha_j=1.0$, $j=1, 2, 3, 4, 4, 4, 2$ and 4, 3). We acknowledge that some of these utilities may be non-linear. For example, we could assume a concave shape for the utility of total system time (i.e., $\alpha_2<1.0$) if we believe that a unit of time savings is more "valuable" at low levels of time than at high levels of time. That is, saving a minute when the total trip time is 10 min may be considered better than saving a minute when the total trip time is 60 min.
Similarly, we could assume convex utility functions (i.e., $\alpha_j > 1.0$, $j = 1, 2, 3$) for the pollution emission attributes HC ($Y_{41}$), CO ($Y_{42}$) and NOx ($Y_{43}$) if we believe that higher concentrations of pollutants are disproportionately more harmful to human health, materials and plants than lower concentrations of pollutants (Horowitz, 1982). As a result, we could assume that the marginal contribution of a unit of pollutant is higher at high levels of pollution than at low levels of pollution (i.e., $\alpha_j > 1.0$, $j = 1, 2, 3$).

Given that we do not have literature-based information on the shape of the single attribute utilities of total system time and total pollution at this time, we selected the simplest case, that is, $\alpha_j = 1.0$, $j = (2), (4, 1), (4, 2), (4, 3)$. We test the sensitivity of the outcomes of the VOPI calculation process to changes in these shape parameters in chapter 5.

On the other hand, considering linear single attribute utility of cost ($Y_1$) and total fuel consumption ($Y_3$), i.e. $\alpha_j = 1.0$, $j = 1, 3$, seems adequate. For instance, it appears appropriate to consider that the marginal contribution to the utility of cost of an extra unit of cost is the same at any level of cost. Similarly, it seems proper to assume that the marginal contribution to the utility of total fuel consumption of an extra unit of fuel is the same at any level of fuel consumption for the range considered in this example. Even if the utility of fuel for national consumption is not linear, the range of fuel consumption considered in this example is so small, compared with the national levels, that we would be dealing with a nearly linear portion of this utility.

The extremes and shape parameters of the single attribute utility functions (Table 4.1) in conjunction with marginal rates of substitution are used to derive the scaling
(tradeoff) parameter values \( (k_j, j=1,2,3,4) \). The marginal rate of substitution (see, for example, Ben Akiva and Lerman, 1985) is derived to be the negative of the derivative of the utility \( U(Y) \) with respect to one attribute divided by the derivative of the utility \( U(Y) \) with respect to the other. For example, the marginal rate of substitution of time and cost is given by:

\[
MRS_{Y_1Y_2} = \frac{\partial Y_1}{\partial Y_2} = -\frac{\partial U(Y)/\partial Y_1}{\partial U(Y)/\partial Y_2}.
\]  

(4.5)

Taking the derivatives of (4.1) and (4.2) we have:

\[
MRS_{Y_1Y_2} = \frac{-k_2(-\alpha_2)}{k_1(-\alpha_1)} \frac{\left[ Y_2 - Y_2^{(\text{min})} \right]^{\alpha_2-1}}{\left[ Y_2^{(\text{max})} - Y_2^{(\text{min})} \right]^{\alpha_2}} \frac{\left[ Y_1 - Y_1^{(\text{min})} \right]^{\alpha_1-1}}{\left[ Y_1^{(\text{max})} - Y_1^{(\text{min})} \right]^{\alpha_1}},
\]  

(4.6)

where \( k_j \) are the tradeoff parameters, \( \alpha_j \) are the single attribute utility shape parameters, \( Y_j^{(\text{max})} \) and \( Y_j^{(\text{min})} \) are the bounds on \( Y_j \), and \( j=1,2 \).

We assume a marginal rate of substitution of cost and time \( MRS_{Y_2Y_1} \) of -5.00/hr, which is equivalent to \(-8.33 \times 10^{-5} \) \([\text{($million/year)/(minutes/peak-hour)]}\) when we consider 1,000 peak hours/year:

\[
MRS_{Y_2Y_1} = -5.00 \left[ \frac{\$}{hr} \right] \times \frac{1000}{10^6 \times 60} \left[ \frac{\text{peak-hours/year}}{\text{S$/million x min/hour}} \right] = -8.33 \times 10^{-5} \left[ \frac{\text{S$million/year}}{\text{minutes/peak-hr}} \right].
\]  

(4.7)

Substituting this marginal rate of substitution and the bounds and shape parameters from Table 4.1 in (4.6) we have:
\[
MRS_{Y_1Y_2} = -0.00008333 = \frac{-k_2(-1)(Y_2 - 55,749)^0 / (1,052,850 - 55,749)^1}{k_1(-1)(Y_1 - 0)^0 / [80 - 0]^1},
\]

(4.8)

As a result, the tradeoff parameter \( k_2 \) can be expressed as

\[ k_2 = 1.0386k_1. \]

(4.9)

Note that, when the single attribute utility of time is linear, the coefficient of \( k_1 \) does not depend on the point \( Y_2 \) in which we calculate the marginal rate of substitution. In the general case in which this utility is not linear the point of calculation would become relevant. We need to consider this in the sensitivity analysis of chapter 5.

For the tradeoff parameter of the utility of fuel \( k_3 \), we have that the marginal rate of substitution of cost and fuel is:

\[
MRS_{Y_1Y_3} = \frac{\partial Y_1}{\partial Y_3} = -\frac{\partial U(Y)/\partial Y_3}{\partial U(Y)/\partial Y_1},
\]

(4.10)

or,

\[
MRS_{Y_1Y_3} = \frac{-k_3(-\alpha_3)[Y_3 - Y_3^{(\min)}]^{(\alpha_3 - 1)} / [Y_3^{(\max)} - Y_3^{(\min)}]^\alpha_3}{k_1(-\alpha_1)[Y_1 - Y_1^{(\min)}]^{(\alpha_1 - 1)} / [Y_1^{(\max)} - Y_1^{(\min)}]^\alpha_1}.
\]

(4.11)

We assume a marginal rate of substitution of cost and fuel consumption \( MRS_{Y_3Y_l} \) of -\$1.50/gal, equivalent to \(-1.5 \times 10^{-3} \) \([(\text{\$million/year})/(\text{gal/peak-hr})], \) at 1,000 [peak-hours/year]:
Substituting this marginal rate of substitution, and the shape parameters and bounds indicated in Table 4.1 in (4.11) we have:

\[ MRS_{Y_3} = -1.50 \left[ \frac{\text{\$}}{\text{gal}} \right] \times \frac{1000}{10^6} \left[ \frac{\text{peak-hrs/year}}{\text{\$/$million gal}} \right] = -1.50 \times 10^{-3} \left[ \frac{\text{\$millions/year}}{\text{gal/peak-hr}} \right]. \] (4.12)

Hence, we can express \( k_3 \) as

\[ k_3 = 1.64187k_1 \] (4.14)

The relationship between the tradeoff parameters of the utility of pollution \( k_1 \) and the utility of cost \( k_1 \) is derived from a study performed by the National Academy of Sciences and reported by Horowitz (1982). The study estimates the total annual savings for a 90% reduction in pollutants emitted in 1973 in the US. The savings correspond to the monetary equivalent of human lives, health problems, and materials and plant damages. These savings range between \$0.96 billion and \$4.8 billion in 1973 dollars. We transform these dollar amounts into 1996 units using

\[ \text{US\$}(1996) = \text{US\$}(1973)^{\frac{462.5}{127.7}}, \] (4.15)
where 462.5 is the consumer price index in January of 1996 and 127.7 is the consumer price index in January 1973 as reported by the Bureau of Labor Statistics (http://www.bls.gov). Hence, we consider savings ranging from $3.477 billion/year to $17.384 billion/year. For this study we use the mid-point savings, i.e., $10.431 billion/year. The level of pollutants in 1973 was calculated to be $9.8 \times 10^6$ kg, $73.8 \times 10^6$ kg, and $6.4 \times 10^6$ kg, for HC, CO and NOx, respectively (Horowitz, 1982). Assuming, again, 1,000 [peak-hr/year], we have 9,800, 73,800 and 6,400 [kg/peak-hr] of HC, CO and NOx. We can use these pollution levels and monetary savings to express the following utility equivalency:

\[
U[Y_1, Y_2, Y_3, (9800, 73800, 6400)] = U[Y_1 + 10431, Y_2, Y_3, (9800, 73800, 6400)], \quad (4.16)
\]

where the utility on the left hand side corresponds to the pollutant levels in 1973 and the utility in the right hand side to the utility on the pollutant levels reduced by 90%. Note also that the cost in the right hand side includes the cost the society is willing to pay to achieve the reduction in pollution. Using (4.1), this identity can be expressed as

\[
k_1u_1(Y_1) + k_2u_2(Y_2) + k_3u_3(Y_3) + k_4u_4(9800, 73800, 6400) \\
= k_1u_1(Y_1 + 10431) + k_2u_2(Y_2) + k_3u_3(Y_3) + k_4u_4(9800, 73800, 6400), \quad (4.17)
\]

and then

\[
k_4 = \frac{u_1(Y_1) - u_1(Y_1 + 10431)}{u_4(9800, 73800, 6400) - u_4(9800, 73800, 6400)} k_1, \quad (4.18)
\]
where

\[ u_1(Y_1) = 1 - \left[ \frac{Y_1}{Y_1^{(\text{max})}} \right], \quad u_1(Y_1 + 10431) = 1 - \left[ \frac{Y_1 + 10431}{Y_1^{(\text{max})}} \right] = 1 - \left[ \frac{Y_1}{Y_1^{(\text{max})}} \right] - \left[ \frac{10431}{Y_1^{(\text{max})}} \right] \quad (4.19) \]

\[ u_4(Y_4) = k_{41} \left( 1 - \left[ \frac{Y_{41} - Y_{41}^{(\text{min})}}{Y_{41}^{(\text{max})} - Y_{41}^{(\text{min})}} \right]^{\alpha_{41}} \right) + k_{42} \left( 1 - \left[ \frac{Y_{42} - Y_{42}^{(\text{min})}}{Y_{42}^{(\text{max})} - Y_{42}^{(\text{min})}} \right]^{\alpha_{42}} \right) + k_{43} \left( 1 - \left[ \frac{Y_{43} - Y_{43}^{(\text{min})}}{Y_{43}^{(\text{max})} - Y_{43}^{(\text{min})}} \right]^{\alpha_{43}} \right) \quad (4.20) \]

Replacing the parameters from Table 4.1, and using \( k_{41} = 0.08877, \ k_{42} = 0.85412 \) and \( k_{43} = 0.05711 \) (see derivation below), one can show that \( u_4(9800, 73800, 6400) = -7.3989 \) and \( u_4(980, 7380, 640) = 0.18079 \). As a result, the tradeoff parameter of the utility of cost is given by

\[ k_4 = \frac{-10431/80}{-7.3989 - 0.1879} = 17.2018 k_1 \quad (4.21) \]

We also have, from (4.1), that \( k_1 + k_2 + k_3 + k_4 = 1 \). If we substitute (4.9), (4.14) and (4.21) and solve for \( k_1 \), we have

\[ k_1 = \frac{1}{(1 + 1.038646 + 0.423984 + 17.2018)} = 0.050853. \quad (4.22) \]

Replacing \( k_1 = 0.05085 \) in (4.9), (4.14) and (4.21) we obtain \( k_2 = 0.05282, \ k_3 = 0.02156 \) and \( k_4 = 0.874767 \), respectively.
The tradeoff parameters within the utility function for the pollution emissions $u_i(Y_i)$ are also obtained from marginal rates of substitution among the different pollutants. As a base case we assume that, all other attributes being equal, reducing one kilogram of HC is equivalent to reducing one kilogram of CO or reducing one kilogram of NOx. As a result, we have that the base case marginal rates of substitution of HC for CO and HC for NOx are $MRS_{Y_4,Y_2} = -1$ and $MRS_{Y_4,Y_5} = -1$, respectively. We test the sensitivity of VOPI to changes in these assumptions in chapter 5.

Again, developing the derivatives in the definition of the marginal rate of substitution we have

$$MRS_{Y_4,Y_2} = \frac{-k_{41}(-\alpha_{41})\left[Y_{41} - Y_{41}^{(\min)}\right]^{(\alpha_{41} - 1)} / \left[Y_{41}^{(\max)} - Y_{41}^{(\min)}\right]}{k_{42}(-\alpha_{42})\left[Y_{42} - Y_{42}^{(\min)}\right]^{(\alpha_{42} - 1)} / \left[Y_{42}^{(\max)} - Y_{42}^{(\min)}\right]}^{\alpha_{41}}. \quad (4.23)$$

Replacing the marginal rate of substitution and the shape parameters and bounds from Table 4.1 we have that $k_{42}$ can be expressed as

$$k_{42} = \frac{-(-1)^0\left[Y_{42} - 221.8\right] / \left[9,349.4 - 221.8\right]}{(-1)(-1)^0\left[Y_{41} - 13.0\right] / \left[961.6 - 13.0\right]} = 9.6222k_{41}. \quad (4.24)$$

Similarly, we have

$$MRS_{Y_4,Y_2} = \frac{-k_{41}(-\alpha_{41})\left[Y_{41} - Y_{41}^{(\min)}\right]^{(\alpha_{41} - 1)} / \left[Y_{41}^{(\max)} - Y_{41}^{(\min)}\right]}{k_{42}(-\alpha_{42})\left[Y_{42} - Y_{42}^{(\min)}\right]^{(\alpha_{42} - 1)} / \left[Y_{42}^{(\max)} - Y_{42}^{(\min)}\right]}^{\alpha_{42}}. \quad (4.25)$$

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Replacing the marginal rate of substitution, the bounds and shape parameters from Table 4.1 we have that $k_{43}$ can be expressed as

$$k_{43} = \frac{-(1)[Y_{43} - 10.7]^0 / [621.0 - 10.7]^1}{(-1)(-1)[Y_{41} - 13.0]^0 / [961.6 - 13.0]^1} = 0.64337k_{41}. \quad (4.26)$$

We then use the definition of the additive multi-attribute utility function (4.3), $k_1 + k_2 + k_3 = 1$, to calculate

$$k_{41} = \frac{1}{1 + 9.6222 + 0.64337} = 0.08877 \quad (4.27)$$

Substituting $k_{41}=0.08877$ in (28) and (30) we have $k_{42}=0.85412$ and $k_{43}=0.05711$, respectively.

These tradeoff parameters complete the specification of the parameters of the preference model (Table 4.1). Note that the we derived the tradeoff parameters from the bounds on the attributes, the shape of the single attribute utilities, the selected marginal rates of substitution among attributes and the points in which the marginal rates of substitution are calculated.

### 4.1.2 Prediction for the Small Network Example

To obtain the attribute distribution we use the prediction model described in Chapter 3. The two sets of inputs to the trip generation model are shown in Table 4.2. Note that in
the low demand case (A) we have 8,641 total vehicle trips and in the high demand case (B) we have 10,623 vehicle trips. These demand scenarios lead to deterministic weighted averages of the volume to practical capacity ratio (i.e., \( \frac{\sum \left[ \frac{V_j}{C_j} \right] V_j}{\sum V_j} \)) of 1.29 in case A and 1.60 in case B.

We also consider an uncertainty measure of trip generation \( \Delta M^{(1)} = 0.25 \). We used an approach described in chapter 3 to find that this level of uncertainty is achieved with an error in trip generation \( \varepsilon_g \sim N(0, 0.2918) \) for the low demand case (A) and \( \varepsilon_g \sim N(0, 0.2923) \) for the high demand case (B).

<table>
<thead>
<tr>
<th>Origin-Destination</th>
<th>Low Demand (A) ( O_r^{(b)} - D_s^{(b)} )</th>
<th>High Demand (B) ( O_r^{(b)} - D_s^{(b)} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r=1 )</td>
<td>4,121</td>
<td>5,066</td>
</tr>
<tr>
<td>( r=2 )</td>
<td>4,520</td>
<td>5,557</td>
</tr>
<tr>
<td>( s=3 )</td>
<td>4,387</td>
<td>5,393</td>
</tr>
<tr>
<td>( s=4 )</td>
<td>4,254</td>
<td>5,230</td>
</tr>
</tbody>
</table>

Table 4.2 Demand Scenarios for Small Network Example

The outputs of the trip generation model (i.e., production-attraction vectors \( PA \)) are the inputs to the trip distribution model. We use the same set of parameters of the trip distribution (gravity) model for the low demand case (A) and the high demand case (B). These parameters are shown in Table 4.3. In this table \( F \) represent the impedance of traveling from origin \( r \) to destination \( s \), and \( A_r \) and \( B_s \) are equilibration parameters (Fotheringham and O'Kelly, 1989). We consider an uncertainty measure in trip distribution \( \Delta M^{(2)} = 0.25 \). Again we used the procedure of chapter 3 to find this level of
uncertainty with an error in trip distribution equal to $\varepsilon_{sd} \sim N(0, 0.3646)$ for Demand A
$\varepsilon_{sd} \sim N(0, 0.3644)$ for Demand B.

<table>
<thead>
<tr>
<th>$s$</th>
<th>$r=1$</th>
<th>$s=3$</th>
<th>$F_{13}=3.06E-7$</th>
<th>$F_{14}=3.06E-7$</th>
<th>$A_1=403.6$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r=2$</td>
<td></td>
<td>$F_{23}=3.35E-4$</td>
<td>$F_{22}=4.54E-5$</td>
<td>$A_2=1.007$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$B_3=0.6529$</td>
<td>$B_4=1.858$</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3. Parameters of the Trip Distribution (Gravity) Model

Again, the outputs of the trip distribution model (i.e., Origin-Destination Tables OD) are the inputs to the traffic assignment model. For traffic assignment we use a user equilibrium based procedure as discussed in chapter 3. The network topology and basic arc characteristics (i.e., free flow travel time $t^*$, and practical capacity $C^*$) are shown in Figure 4.1. We consider an uncertainty measure in traffic assignment $UM^{(3)}=0.25$. Again, we used the method described in chapter 3 to find that this level of uncertainty is achieved with an error in time $\varepsilon_{su} \sim N(0, 0.2919)$ for the no-build alternative $X_i$ and $\varepsilon_{su} \sim N(0, 0.3137)$ for the build alternative $X_j$ in the case of the low demand case (A); and $\varepsilon_{su} \sim N(0, 0.2233)$ for the no-build alternative $X_i$ and $\varepsilon_{su} \sim N(0, 0.2893)$ for the build alternative $X_j$ in the case of the high demand (B).

The resulting outputs of the traffic assignment model (i.e., arc volumes $V_L$) are the inputs to the different attribute models. We use the attribute models detailed in chapter 3 and uncertainty measures $UM^{(4)}=UM^{(5)}=UM^{(6)}=UM^{(7)}=UM^{(8)}=0.25$. As
discussed also in chapter 3, we obtain these uncertainty measures with normally distributed errors (i.e., N(0, 0.25)) for each model.

We sample the same number of realizations of each conditional model, i.e., \( N_{tg}=N_{td}=N_{ta}=N_{at}=R \); hence, we obtain \( N_{\gamma}=R^4 \) attribute vectors. To sample the \( N_{at}=R \) attributes from each one of the \( N_{tg} \times N_{td} \times N_{ta}=R^3 \) arc volume patterns, we sample \( R \) sets of arc travel times and one set of arc fuel consumptions and arc pollution emissions (HC, CO and NOx) for each one of these arc travel time sets.

4.2 Results for the Small Network Example

We present the expected utilities of the no-build and build alternatives, VOPI at the different prediction steps (i.e., VOPI of the Attributes, Arc Volumes, Origin-Destination Tables and Production-Attraction Vectors) and marginal VOPI of each step (i.e., attribute models, traffic assignment, trip distribution, trip generation). We perform this illustrative analysis for two levels of the basic demand. We also calculate VOPI as a function of the difference between the Expected Utilities.

4.2.1 Expected Utilities for No-Study Case

We calculate expected utilities \( EU[X_1] \) and \( EU[X_2] \) for the no-build and build alternatives when no study to improve the current level of information is performed. As indicated above, we assume a fixed level of the uncertainty measure \( UM^{cm}=0.25, cm=1, \ldots, 8 \), two
demand scenarios (A and B, see Table 4.2) and a basic cost $Y_1|X_1=0.0$ and $Y_1|X_2=50.0$ [$\text{millions/year}$] for the no-build and build alternatives, respectively. The expected utilities as a function of the number of attribute vectors sampled ($R^4$) are displayed in Figures 4.2 and 4.3 for demand A and demand B, respectively.

We observe that the expected utility as a function of the number of attributes sampled is more stable for demand A (low) than for demand B (high). We also observe a change in the preferred alternative. While the no-build alternative yields a higher expected utility than build for demand A (low), the build alternative yields higher expected utility than no-build for demand B (high). For example, the expected utilities for $30^4$ samples of the attribute vectors are $\text{EU}[X_1]=0.8649$ and $\text{EU}[X_2]=0.8431$ for demand A and $\text{EU}[X_1]=0.7744$ and $\text{EU}[X_2]=0.7807$ for demand B. Additionally, we note a wider "gap" between the expected utilities of the no-build $X_1$ and build $X_2$ alternatives for Demand A than Demand B. For instance, for $30^4$ samples of the attribute vectors, the difference in expected utilities is $0.0218$ for demand A and $-0.0064$ for demand B. Note that the preferred alternative does not depend on the number of samples.

4.2.2 Value of Perfect Information for the Small Network Example

We calculate the value of perfect information (VOPI) of knowing the attributes (AT), arc volumes (VL), origin destination tables (OD) and production-attraction pattern (PA). We also calculate the marginal VOPI of the prediction models, that is the difference between the VOPI at each prediction step and the VOPI at the preceding step.
Figure 4.2 Expected Utilities as a Function of the Number of Attribute Vectors Sampled in the Small Network Example and Demand A

Figure 4.3 Expected Utilities as a Function of the Number of Attribute Vectors Sampled in the Small Network Example and Demand B
For example, the marginal VOPI of traffic assignment (TA) is defined to be the difference between the VOPI of the arc volumes (VL) and the VOPI of the OD matrices. We also use a basic cost \( Y_{1|X_1}=0.0 \) and \( Y_{1|X_2}=50.0 \) [dollars/million/year] for the no-build and build alternatives, respectively. The results of the VOPI of AT, VL, OD and PA calculations as a function of the number of samples of the attribute vectors are displayed in Figures 4.4 and 4.5.

As would be expected, we observe that VOPI increases as you move closer to the end of the forecasting sequence; that is, \( \text{VOPI}[\text{AT}] > \text{VOPI}[\text{VL}] > \text{VOPI}[\text{OD}] > \text{VOPI}[\text{PA}] \). We also observe that, for demand A and 30th Attribute Samples, \( \text{VOPI}[\text{AT}]=12.796 \), \( \text{VOPI}[\text{VL}]=6.3765 \), \( \text{VOPI}[\text{OD}]=4.0296 \) and \( \text{VOPI}[\text{PA}]=3.7252 \) [dollars/million/year]. The corresponding values for demand B are \( \text{VOPI}[\text{AT}]=35.1063 \), \( \text{VOPI}[\text{VL}]=24.5562 \), \( \text{VOPI}[\text{OD}]=19.8574 \) and \( \text{VOPI}[\text{PA}]=18.5646 \) [dollars/million/year]. That is, perfect information at any prediction step is much more valuable in the case of the higher level of congestion (Demand B) than the lower level of congestion (Demand A) for the same cost of construction of the build alternative \( Y_{1|X_2}=50 \) [dollars/million/year].

According to these results, a decision maker would be willing to pay a maximum of \$35.1 million/year (70% of the construction cost) for perfect information on the attributes before making the decision between the alternatives (build, no-build) when the demand is high (B). Similarly, s/he would be willing to pay \$18.6 million/year (37% of the construction cost) for perfect information on the production-attraction pattern in the high demand case.
Figure 4.4 VOPI at Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Small Network Example with Demand A

Figure 4.5 VOPI at Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Small Network Example with Demand B
These high values of perfect information seem to be the result of the high level of uncertainty when making the decision with the expected utilities. Note that when the expected utilities of build and no-build are further apart (demand A), the willingness to pay reduces substantially. For instance, the decision maker would be willing to pay $12.8 million/year for perfect information on the attributes and $3.7 million/year for perfect information of the production attraction patterns in the case of low demand; that is 2.7 times and 5.0 times less than in the high demand case.

We also calculate the marginal VOPI of the each modeling step, i.e., attribute models (AM), traffic assignment (TA), trip distribution (TD), and trip generation (TG). As indicated before, the marginal VOPI is defined as the difference between the VOPI at a given modeling step minus the VOPI at the previous step. marginal VOPI is then the value of obtaining perfect information given that there is perfect information on the previous step. Hence, the marginal VOPI[AM]=VOPI[AT]-VOPI[VL], marginal VOPI[TA]=VOPI[VL]-VOPI[OD] and marginal VOPI[TD]=VOPI[OD]-VOPI[PA]. We present the marginal VOPI as a function of the number of attribute vector samples in Figures 4.6 and 4.7 for Demand A and Demand B respectively.

For 30⁴ attribute vector samples marginal VOPI[AM] = 6.4195, marginal VOPI[TA] = 2.3470, and marginal VOPI[TD] = 0.3044 for demand A; and marginal VOPI[AM] = 10.5501, marginal VOPI[TA] = 4.6988, and marginal VOPI[TD] = 1.2928 for Demand B. We note that the values are much larger for demand A than for demand B. We also observe the same ordering of the marginal VOPI for demand A and demand B.
Figure 4.6 Marginal VOPI of Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Small Network Example with Demand A

Figure 4.7 Marginal VOPI of Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Small Network Example with Demand B
The greatest marginal VOPI corresponds to attribute models (AM), followed by Traffic Assignment (TA), then Trip Distribution (TD).

Finally, we also note that, according to the figures, it seems necessary to increase the number of attribute vectors sampled to obtain greater accuracy. Accuracy could also be improved by using a different sampling strategy. For example, by increasing the number of samples of one step while decreasing the number of samples from another. In this illustrative example we continue to report the results with $R^* = 30$ attribute vectors.

4.2.3 VOPI as a Function of the Expected Utility Differences

We investigate the sensitivity of the value of perfect information to the difference between the expected utilities of the no-build ($X_1$) and build ($X_2$) alternatives. To modify the relative utilities we use the cost $Y_1$ of the build alternative $X_2$ while keeping the cost $Y_1$ of the no-build alternative $X_1$ equal to 0.0. Since the other attributes do not depend on it, we use the same set of attribute vectors to obtain the expected utilities and VOPIs for different levels of cost $Y_1$ of build $X_2$. That is, we perform the Monte Carlo simulation procedure to generate $R^* = 30$ attribute vectors only once for demand $A$ and once for demand $B$, and we use these attribute vectors to calculate the expected utilities and VOPIs for different levels of cost.

Figures 4.8 and 4.9 show the VOPI of the attributes (AT), arc volumes (VL), O-D matrix (OD) and production-attraction vectors (PA). In these figures, the left extreme
corresponds to the maximum difference in expected utility. This point is achieved by making the cost \( Y \), given \( X_2 \) equal to zero. The point in which the expected utilities are equal, i.e., \( \text{EU}[X_1] - \text{EU}[X_2] = 0 \), is achieved by making the cost \( Y \), given \( X_2 \) equal to 15.7103 (demand A) and cost \( Y \), given \( X_2 \) equal to 59.8919 (demand B).

We observe that the VOPIs of the different modeling steps peak at \( \text{EU}[X_1] - \text{EU}[X_2] = 0 \). This is expected, since the additional information provided by the perfect information studies would help the decision maker the most when the alternatives appear equally good.

We also observe that at any \( \text{EU}[X_1] - \text{EU}[X_2] \) it seems that VOPI(\( \xi \)) given demand B is larger than VOPI(\( \xi \)) given demand A for all the outcomes \( \xi \) (i.e., attributes, arc volumes, OD matrix, PA pattern). For example, when \( \text{EU}[X_1] = \text{EU}[X_2] \) VOPI(\( \text{AT} \)) = 25.0840 for demand A and VOPI(\( \text{AT} \)) = 40.4592 for demand B. Hence, it seems more valuable to conduct studies when the congestion is high (B) than when the congestion is low (A). This appears reasonable given that the level of the outcomes of the conditional models is larger with the increased demand. Since we want the same uncertainty measure for both levels of demand (A and B), we would need a larger outcome error variance, and, hence, the associated value of knowing perfectly the outputs of the conditional models would be larger.

Additionally, we observe that the values are not completely symmetric around \( \text{EU}[X_1] - \text{EU}[X_2] = 0 \). For example, in the low demand case (A), VOPI(\( \text{AT} \)) = 17.5861 at \( \text{EU}[X_1] - \text{EU}[X_2] = -0.01 \) and VOPI(\( \text{AT} \)) = 18.5584 at \( \text{EU}[X_1] - \text{EU}[X_2] = +0.01 \).
Figure 4.8 VOPI at Each Prediction Step as a Function of the Difference Between the Expected Utilities of the Alternatives for the Small Network Example with Demand A.

Figure 4.9. VOPI at Each Prediction Step as a Function of the Difference Between the Expected Utilities of the Alternatives for the Small Network Example with Demand B.
This asymmetry is more noticeable for demand B. For instance, VOPI[AT]=35.1063 at EU[X₁]-EU[X₂]=−0.006 and VOPI[AT]=36.3201 at EU[X₁]-EU[X₂]=+0.006. This indicates that studies may be more valuable when the preferred alternative using the expected utility is no-build [X₁], especially under congested conditions (demand B).

Using the VOPI at each prediction step we calculate the marginal VOPI. We display the marginal VOPI of each step as a function of the difference between the expected utilities of the alternatives in Figures 4.10 and 4.11 for demand A and demand B, respectively. In this case, we again observe a peak when the difference in expected utility between the alternatives is close to zero. We also note that the ordering of the marginal VOPIs does not depend on the difference between the expected utilities and the demand. That is, the marginal VOPI of the attribute models is larger than the marginal VOPI of traffic assignment and the marginal VOPI of traffic assignment is larger than the marginal VOPI of trip distribution for all the values of the difference in expected utility and for demand A and demand B.

Additionally, we note a slight asymmetry around EU[X₁]-EU[X₂]=0. We see, for example that the marginal VOPI of the attribute models is 9.4902 when EU[X₁]-EU[X₂]=−0.01 and 10.1637 when EU[X₁]-EU[X₂]=+0.01 for demand A. For demand B we have that the marginal VOPI of the attribute models is 10.5501 when EU[X₁]-EU[X₂]=−0.006 and 10.2349 when EU[X₁]-EU[X₂]=+0.006.
Figure 4.10 Marginal VOPI of Each Prediction Step as a Function of the Difference Between the Expected Utilities of the Alternatives for the Small Network Example with Demand A

Figure 4.11 Marginal VOPI of Each Prediction Step as a Function of the Difference Between the Expected Utilities of the Alternatives for the Small Network Example with Demand B
These observations may indicate that the greatest marginal improvements in the information seem to be produced by the attribute models, followed by the traffic assignment model and then by the trip distribution model. This seems to hold for any level of the difference in expected utilities caused by changes in the cost $Y_1$ of the build alternative $X_2$. 

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CHAPTER 5

NUMERICAL RESULTS - EXTENDED NETWORK EXAMPLE

The extended network example is intended to illustrate the application of the value of information framework to a more realistic setting. We are also interested in seeing whether results found for the small network seem to hold for this larger network. We use the major highways of the Columbus, Ohio, transportation network. We first present the inputs to the prediction and preference models; then we show the value of information for different steps of the sequential forecasting model used in this study; and finally, we elaborate a sensitivity analysis to selected inputs to the preference model.

5.1 Inputs for the Calculation of VOPI in the Extended Network Example

In the extended network example we analyze the same type of decision used in the small network, i.e., no-build $X_1$ or build $X_2$ improvements to the highway network. In this example we use improvements to the major highway network of the Columbus, Ohio, consisting of new east-west expressway links (patterned on a Interstate 670 extension) north of the downtown area. The network is shown in Figure 5.1.
Some characteristics of the network are displayed in Table 5.1. Note that in this example we are considering 14 additional links in the build alternative. These links represent the total length of the proposed I-670 extension, and the new ramps to connect this expressway links to the existing network. The complete set of link characteristics -- namely, lengths, practical capacities and free flow travel times-- are listed in the input files to the simulation program in the appendix B.
<table>
<thead>
<tr>
<th>Network Characteristics</th>
<th>No-Build (X₁)</th>
<th>Build (X₂)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number of Links</td>
<td>399</td>
<td>413</td>
</tr>
<tr>
<td>Arterial Links</td>
<td>175</td>
<td>177</td>
</tr>
<tr>
<td>Freeway Links</td>
<td>140</td>
<td>152</td>
</tr>
<tr>
<td>Centroid Connectors</td>
<td>84</td>
<td>84</td>
</tr>
<tr>
<td>Total Nodes</td>
<td>134</td>
<td>142</td>
</tr>
<tr>
<td>Centroids</td>
<td>42</td>
<td>42</td>
</tr>
</tbody>
</table>

Table 5.1 Selected Network Characteristics for the Extended Network Example

5.1.1 Preference Model for the Extended Network Example

We use the same attributes as before, i.e., cost \( Y₁ \), total system travel time \( Y₂ \), total fuel consumption \( Y₃ \), and total emissions \( Y₄ \), --HC emissions \( Y₄₁ \), CO emissions \( Y₄₂ \), and NOx emissions \( Y₄₃ \).

We also use the same functional forms of the utility functions:

\[
U[Y] = \sum_{m=1}^{4} k_m u_m(Y_m), \quad \sum_{m=1}^{4} k_m = 1, \quad (5.1a)
\]

\[
u_m(Y_m) = 1 - \left[ \frac{Y_m - Y_m^{(min)}}{Y_m^{(max)} - Y_m^{(min)}} \right]^\alpha_m, \quad m = 1, 2, 3, \quad (5.1b)
\]

\[
u_4(Y_4) = \sum_{p=1}^{3} k_{4,p} u_{4,p}(Y_{4,p}), \quad \sum_{p=1}^{3} k_{4,p} = 1, \quad (5.1c)
\]

\[
u_{4,p}(Y_{4,p}) = 1 - \left[ \frac{Y_{4,p} - Y_{4,p}^{(min)}}{Y_{4,p}^{(max)} - Y_{4,p}^{(min)}} \right]^\alpha_{4,p}, \quad p = 1, 2, 3. \quad (5.1d)
\]
The inputs used to derive the parameters of the utility functions, i.e., marginal rates of substitution, shape parameters, extreme values are displayed in Table 5.2. The marginal rates of substitution are the same ones used in the previous chapter. We also use linear single attribute utilities for all the attributes (i.e., \( \alpha_j=1, j=1, 2, 3, 4,1, 4,2, 4,3 \)) as a first-cut approximation. Nevertheless, we use different bounds to those used in the small network example, and, as a result, the scaling (tradeoff) parameters \( k_j \) change.

<table>
<thead>
<tr>
<th>Attribute ( Y_j )</th>
<th>Marginal Rate of Substitution ( MRS_{Y_iY_j} )</th>
<th>Shape Parameter ( \alpha_j )</th>
<th>Minimum on ( Y_j )</th>
<th>Maximum on ( Y_j )</th>
<th>Tradeoff ( k_j )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost ( (Y_1) )</td>
<td>( 1.00 ) ([\text{million/year}/\text{million/year}])</td>
<td>( 1.00 )</td>
<td>( 0.00 )</td>
<td>( 80.0 )</td>
<td>( 0.01537 )</td>
</tr>
<tr>
<td>Total Time ( (Y_2) )</td>
<td>( -8.33 \times 10^{-5} ) ([\text{million/year}/\text{minutes/peak-hr}])</td>
<td>( 1.00 )</td>
<td>( 1,422,697 )</td>
<td>( 5,390,265 )</td>
<td>( 0.06353 )</td>
</tr>
<tr>
<td>Total Fuel Consumption ( (Y_3) )</td>
<td>( -1.50 \times 10^{-3} ) ([\text{million/year}/\text{gallons/peak-hr}])</td>
<td>( 1.00 )</td>
<td>( 32,782 )</td>
<td>( 102,445 )</td>
<td>( 0.02008 )</td>
</tr>
<tr>
<td>Total Pollution ( (Y_4) )</td>
<td>( 1.36489 ) ([\text{million/year}/u_4(Y_4)])</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>( 0.90102 )</td>
</tr>
<tr>
<td>( (Y_{4,1}) )</td>
<td>HC</td>
<td>( -1.00 ) ([\text{kg HC/kg HC}])</td>
<td>( 1.00 )</td>
<td>( 1,301.3 )</td>
<td>( 4,171.2 )</td>
</tr>
<tr>
<td>( (Y_{4,2}) )</td>
<td>CO</td>
<td>( -1.00 ) ([\text{kg CO/kg HC}])</td>
<td>( 1.00 )</td>
<td>( 11,716.3 )</td>
<td>( 42,712.1 )</td>
</tr>
<tr>
<td>( (Y_{4,3}) )</td>
<td>NOx</td>
<td>( -1.00 ) ([\text{kg NOx/kg HC}])</td>
<td>( 1.00 )</td>
<td>( 1,468.1 )</td>
<td>( 4,015.3 )</td>
</tr>
</tbody>
</table>

Table 5.2. Marginal Rates of Substitution, Shape Parameters Bounds on the Attributes and Tradeoff Parameters for the Extended Network Example
We obtained the bounds on the attributes from sampled attribute vectors using the Monte Carlo simulation procedure detailed in chapter 3 as before. Specifically, we sampled 15 attribute vectors for extreme sets of inputs and then selected the maximum and minimum values of each attribute across all the samples. The extreme sets of inputs are given by the demand level, the alternative, and the selected uncertainty measures. To obtain the maximum we performed the simulations with an input set consisting of a high demand level, the no-build alternative and uncertainty measures \( U_{cm}=0.375, \ cm=1,\ldots,8 \). To obtain the minimum we performed the simulations with an input set consisting of a low demand level, the build alternative and uncertainty measures \( U_{cm}=0.375, \ cm=1,\ldots,8 \). The high and low demand levels are detailed in section 5.1.

We calculate relationships among the tradeoff parameters of cost and time and cost and fuel using the same marginal rates of substitution of cost and time and cost and fuel used in chapter 4 and the new extremes. As a result we have:

\[
MRS_{Y_2, Y_1} = -8.33 \times 10^{-5} = \frac{\partial U}{\partial Y_2} \bigg/ \frac{\partial U}{\partial Y_1} = \frac{-k_2(80.0-0.0)}{-k_1(5,390,256-1,422,697)} \therefore k_2 = 4.13288k_1, \ (5.2a)
\]

\[
MRS_{Y_3, Y_1} = -1.5 \times 10^{-3} = \frac{-k_3(80.0-0.0)}{-k_1(102,444-32,782)} \therefore k_3 = 1.30617k_1. \ (5.2b)
\]

We obtain the tradeoff parameters within the pollution utility function using marginal rates of substitution among HC and CO and HC and NOx equal to -1.00 as before. Using the new extremes we have:
From (5.1c) we have

\[ 1 = k_{41} + k_{42} + k_{43}, \]  

hence,

\[ k_{41} = \frac{1}{(1 + 10.8003 + 0.88756)} = 0.078815, \quad k_{42} = 0.85123, \quad k_{43} = 0.06995 \]  

We use these tradeoff parameters to calculate the relationship between \( k_i \) and \( k_i \) from given pollution reduction benefits discussed in chapter 4:

\[ U[Y_1, Y_2, Y_3, (9800, 73800, 6400)] = U[Y_1 + 10431, Y_2, Y_3, (980, 7380, 640)]. \]  

which is equivalent to

\[ k_1 u_1(Y_1) + k_4 u_4(9800, 73800, 6400) = k_1 u_1(Y_1 + 10431) + k_4 u_4(980, 7380, 640). \]  

As a result

\[ k_4 = \frac{-u_1(10431)k_1}{u_4(9800, 73800, 6400) - u_4(980, 7380, 640)} = \frac{-130.387k_1}{-1.07383 - 1.1506} = 58.613k_1 \]  

Using (5.1a) we have

\[ 1 = k_1 + k_2 + k_3 + k_4 = k_1 (1 + 4.13288 + 1.306172 + 58.6129) \]  

\[ k_1 = 0.01537, \quad k_2 = 0.0635, \quad k_3 = 0.0201, \quad k_4 = 0.9010 \]
5.1.2 Prediction for the Small Network Example

The inputs to the prediction model are the basic production-attraction pattern, the gravity model parameters, the network characteristics and the error parameters. We perform the value of information analysis for two congestion levels. We establish the congestion level by providing two production-attraction patterns or demand levels. Demand level A, consists of 94,332 trips and yields a deterministic weighted average of the volume to practical capacity ratio \( A[DV_a/C_a] = 1.31 \) for the No-Build (X1) network. We calculate this average as follows:

\[
A[DV_a/C_a] = \frac{\sum_{a=1}^{NARC} (DV_a/C_a)DV_a}{\sum_{a=1}^{NARC} DV_a},
\]

where \( DV_a \) are the arc volumes after user equilibrium traffic assignment without error in travel time, \( C_a \) are the arc practical capacities (i.e., the volumes that make the arc travel time to increase by 15%), and NARC is the number of arcs in the network (excluding centroid connectors).

Demand level B consists of 106,319 trips and yields \( A[DV_a/C_a] = 1.61 \). It consists of the production-attraction vectors of demand level A multiplied by 1.25. These production-attraction vectors are listed in the demand files included in appendix B. We consider an uncertainty measure of trip generation \( UM^{(U)} = 0.25 \). We use the procedure of
chapter 3 to achieve this uncertainty measure with an error $e_{tg} \sim N(0,0.2519)$ for the low demand case (A) and $e_{tg} \sim N(0,0.2488)$ for the high demand case (B).

We note that the standard deviation in the errors in trip generation are closer to the desired uncertainty measure than those of the small network example ($\eta_{tg} = 0.2918$ for low demand and $\eta_{tg} = 0.2923$ for high demand). In the extended network case the vectors are much larger (42 centroids), hence there are more degrees of freedom in the adjustment procedure used to guarantee conservation of flow. As a result, the required error has a standard deviation very similar to the desired uncertainty measure level.

We use the same parameters of the gravity model used in the trip distribution step for both levels of demand. These parameters are also included in demand files presented in appendix B. We also consider an uncertainty measure in trip distribution $UM^{(2)} = 0.25$. Using the procedure detailed in chapter 3 to achieve this uncertainty measure with $e_{ud} \sim N(0,0.2480)$ for the low demand case (A) and $e_{ud} \sim N(0,0.2515)$ for the high demand case (B).

We note, again, that the standard deviations of the errors in trip distribution for this example are closer to the desired uncertainty measures than those of the small network example (i.e., $\eta_{ud} = 0.3646$ for low demand and $\eta_{ud} = 0.3644$ for high demand). We also believe that the larger size of the OD matrix results in an increased number of degrees of freedom for the flow conservation adjustment procedure and, hence, the required standard deviations are closer to the desired uncertainty measure.

The traffic assignment requires the network topology and arc characteristics (i.e., free flow travel time $t_{fa}$, and practical capacity $C_a$ as inputs). We provide a list of the
network topology and characteristics for the no-build and build alternatives in the network files of appendix B. We consider an uncertainty measure in traffic assignment $\text{UM}^{(0)}=0.25$. Again, we use the procedure in chapter 3 to achieve this uncertainty measure with an error in time $\epsilon_{ta} \sim \text{N}(0,0.1255)$ for the no-build alternative $X_1$, $\epsilon_{ta} \sim \text{N}(0,0.1048)$ for the build alternative $X_2$ in the case of the low demand case (A); and $\epsilon_{ta} \sim \text{N}(0,0.2695)$ for the no-build alternative $X_1$, $\epsilon_{ta} \sim \text{N}(0,0.2226)$ for the build alternative $X_2$ in the case of the alternative demand (B).

We note that unlike in the TG and TD conditional models ($cm=1,2$) the values differ from the desired UM uncertainty measures. We also observe that the required errors are very different from UM for the low demand case and much closer for the high demand case. The required standard deviations are also smaller for the build network than for the no-build network in both cases. These effects are different than those observed in the small network example. In that case we observed that we required larger standard deviations for the low demand case and larger standard deviations for the build alternative ($\eta_{ta}=0.2916$ for no-build and $\eta_{ta}=0.3137$ for build for low demand, $\eta_{ta}=0.2233$ for no-build and $\eta_{ta}=0.2893$ for build for high demand). These results indicate that the effects of errors in the travel time on the uncertainty measure may depend on a combination of the level of congestion and the network topology. This issue would require further exploration, which is beyond the scope of this study.

The outputs of the traffic assignment model (i.e., arc volumes $VL$) are the inputs to the different attribute models. We use the attribute models detailed in chapter 3 and uncertainty measures $\text{UM}^{(cm)}=0.25$, $cm=4,...,8$, which we obtain with normally distributed
errors (i.e., $N(0,0.25)$). We sample the same number of realizations of each conditional model, i.e., $N_{tg}=N_{td}=N_{ta}=N_{at}=R$; hence, we obtain $N_y=R^4$ attribute vectors. As in chapter 4, the $N_{at}=R$ conditional samples of the attributes are obtained from $R$ samples from the travel time model for each arc of the network and one sample from the fuel consumption and emissions (HC, CO, NOx) models for each travel time sample.

5.2 Results for the Extended Network Example

As with the small network example, we present the expected utilities of the no-build and build alternatives, VOPI at the different prediction steps (i.e., VOPI of the attributes, arc volumes, origin-destination tables and production-attraction vectors) and marginal VOPI of each step (i.e., attribute models, traffic assignment, trip distribution, trip generation). We also present results of the calculation of model VOPI, that is the value of information of a given modeling step given that the inputs to this step remain uncertain. We perform this analysis for two levels of the basic demand. We also calculate VOPI, marginal VOPI and model VOPI as a function of the difference between the expected utilities.

5.2.1 Expected Utilities for No-Study Case

We calculate expected utilities $EU[X_j]$ and $EU[X_j]$ for the no-build and build alternatives when no study to improve the current level of information is performed. As indicated above, we assume a fixed level of the uncertainty measure $UM^{cm}=0.25, cm=1,...,8$, two
demand scenarios (A and B) and a construction cost $Y_1|X_1=0.0$ and $Y_2|X_2=50.0$ [millions/year] for the No build and build alternatives, respectively. The expected utilities as a function of the number of attribute vectors sampled ($R^*$) are displayed in Figures 5.2 and 5.3 for demand A and demand B, respectively.

According to these graphs, it seems that the expected utility values stabilize faster than for the small network example. We observe that the preferred alternative, according to the expected utility, is the same for the two levels of demand. The build alternative yields a higher expected utility than no-build alternative in both cases. For example, the expected utilities for $15^4$ samples of the attribute vectors are $EU[X_1]=0.9146$ and $EU[X_2]=0.9219$ for demand A and $EU[X_1]=0.6233$ and $EU[X_2]=0.6416$ for demand B. The expected utilities are higher for low demand than for high demand for the same construction cost $Y_1$ of the build alternative. This is expected since all the non-cost attributes tend to increase with the level of demand and this results in lower expected utility.

Additionally, we note a slightly wider "gap" between the expected utilities of the no-build $X_1$ and build $X_2$ alternatives for demand B than demand A. For instance, for $15^4$ samples of the attribute vectors, the difference in expected utilities is -0.0073 for demand A and -0.0183 for demand B. This would also be expected since the build alternative is better than no-build for low congestion and its expected utility is moved more than the expected utility of no-build as congestion increases.
Figure 5.2 Expected Utilities as a Function of the Number of Attribute Vectors Sampled in the Extended Network Example and Demand A

Figure 5.3 Expected Utilities as a Function of the Number of Attribute Vectors Sampled in the Extended Network Example and Demand B
These results are different than those of the small network. In that case we observed a change in the preferred alternative, and a wider “gap” between the expected utilities for demand A than demand B. For the small network and low congestion (i.e., A[DV/C]=1.3) the no-build alternative is preferred (i.e. EU[X₁]>EU[X₂]). When congestion is increased (i.e., A[DV/C]=1.6), the expected utility of build increases more than the expected utility of no-build, resulting in a change in the preferred alternative (i.e., EU[X₂]>EU[X₁]). It also results in a reduction in the difference between the expected utilities.

5.2.2 Value of Perfect Information for the Extended Network Example

As with the small network example, we calculate the value of perfect information (VOPI) of knowing the attributes (AT), arc volumes (VL), origin-destination tables (OD) and production-attraction pattern (PA). We also calculate the marginal VOPI of the prediction models, that is the difference between the VOPI at each prediction step and the VOPI at the preceding step. Additionally we calculate the model VOPI, that is the value of information of a modeling step given that the inputs to this step remain uncertain. We also use a basic cost $Y_{i|X₁}=0.0$ and $Y_{i|X₂}=50.0$ [millions/year] for the No build and build alternatives, respectively. The results the VOPI of AT, VL, OD and PA calculations as a function of the number of samples of the attribute vectors are displayed in Figures 5.4 and 5.5.
Figure 5.4 VOPI at Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Extended Network Example with Demand A

Figure 5.5 VOPI at Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Extended Network Example with Demand B
We observe that, for demand A and 15 attribute Samples, VOPI[AT]=24.4335, 
VOPI[VL]=7.4242, VOPI[OD]=4.0580 and VOPI[PA]=0.3228 [$millions/year]. The 
corresponding values for demand B are VOPI[AT]=32.9447, VOPI[VL]=14.9841, 
VOPI[OD]=1.0640 and VOPI[PA]=0.0000 [$millions/year]. These results make sense 
given that further down the modeling process leads to more value of the information.

These results also indicate that the information on the attributes and link volumes 
is more valuable in case of high level of congestion (demand B) than low level of 
congestion (demand A) for the same cost of construction of the build alternative 
$Y_2|X_2=50 [$million/year]. On the other hand, information on the OD matrix and 
production attraction patterns is more valuable for the low level of congestion than for the 
high level of congestion. This is different than the result for the small network example, 
where information on all the outcomes of the prediction models was more valuable for 
the high congestion level.

According to these results, a decision maker would be willing to pay a maximum 
of $24.4 million/year (49% of the construction cost) for perfect information on the 
attributes before making the decision between the alternatives (build, no-build) when the 
demand is low (A). Similarly, s/he would be willing to pay $0.3 million/year (0.6% of 
the construction cost) for perfect information on the production-attraction pattern in the 
low demand case. This big difference in the values of perfect information appears to be 
the result of the high level of uncertainty accumulated through the forecasting process.

We also note that when the congestion increases (demand B), the difference 
between the VOPI of the attributes and the VOPI of the production-attraction pattern is
even bigger. In the high demand case the decision maker would be willing to pay $32.9 million/year for perfect information on the attributes and $0.0 million/year for perfect information of the production attraction patterns. It seems that congestion increases the level of uncertainty as one progresses through the forecasting process.

We also calculate the marginal VOPI of the each modeling step, i.e., attribute models (AM), traffic assignment (TA), trip distribution (TD), and trip generation (TG). As indicated before, the marginal VOPI is the difference between the VOPI at a given modeling step minus the VOPI at the previous step. We present the marginal VOPI as a function of the number of attribute vector samples in Figures 5.6 and 5.7 for Demand A and Demand B respectively.

For $15^4$ attribute vector samples marginal VOPI[AM] = 17.0093, marginal VOPI[TA] = 3.3662, and marginal VOPI[TD] = 3.7353 for demand A; and marginal VOPI[AM] = 17.3271, marginal VOPI[TA] = 13.9202, and marginal VOPI[TD]=1.0640 for demand B. We note that marginal VOPI[AM] given demand A is approximately equal to the marginal VOPI[AM] given demand B. Also, we see that marginal VOPI[TA] given demand A is much less than marginal VOPI[TA] given demand B. Finally, we observe that marginal VOPI[TD] given demand A is much more than marginal VOPI[TD] given demand B. This differs from the small network example, where all the marginal VOPI values are much larger for demand A than for demand B.
Figure 5.6 Marginal VOPI of Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Extended Network Example with Demand A

Figure 5.7 Marginal VOPI of Each Prediction Step as a Function of the Number of Attribute Vector Samples for the Extended Network Example with Demand B
We also observe different ordering of the marginal VOPI for demand A and demand B. The greatest marginal VOPI corresponds to attribute models (AM) in both demand cases. Nevertheless, the marginal VOPI[TA] = marginal VOPI[TD] for demand A, while marginal VOPI[TA] > marginal VOPI[TD] for demand B. This may suggest that congestion makes traffic assignment more relevant.

5.2.3 VOPI as a Function of the Difference Between the expected utilities of the alternatives in the Extended Network Example

We repeat the sensitivity test of the value of perfect information to the difference between the expected utilities of the no-build \( X_i \) and build \( X_j \) alternatives performed for the small network example. As before, we generate two sets of 15 attribute vectors, one for demand A and the other for demand B. We then use these vectors with different levels of cost \( Y_1 \) of the build \( X_j \) alternative to calculate the expected utilities and the VOPIs. Figures 5.8 and 5.9 show the VOPI of the attributes (AT), arc volumes (VL), O-D matrix (OD) and production-attraction vectors (PA). In these figures, the left extreme corresponds to the maximum expected utility of the build alternative (i.e., Cost \( Y_1|X_2=0 \)), and \( EU[X_1]-EU[X_2]=0 \) corresponds to a construction cost \( Y_1|X_2=87.8727 \) and \( Y_1|X_2=145.2359 \) for demand A and demand B, respectively.

We observe that, in the same way to that of the small network example, at any \( EU[X_1]-EU[X_2] \) it seems that VOPI[\( \xi \)] given demand B is larger than VOPI[\( \xi \)] given demand B for all the outcomes \( \xi \) (i.e., attributes, arc volumes, OD matrix, PA pattern).
Figure 5.8 VOPI at Each Prediction Step as a Function of the Difference Between the Expected Utilities of the Alternatives for the Extended Network Example with Demand A

Figure 5.9 VOPI at Each Prediction Step as a Function of the Difference Between the Expected Utilities of the Alternatives for the Extended Network Example with Demand B
For example, when $EU[X_1]=EU[X_2]$ $VOPI[AT]=40.774$ for demand A and $VOPI[AT]=70.803$ for demand B. Hence, it seems more valuable to conduct studies when the congestion is high than when the congestion is low. We already mention that this may be caused by the larger uncertainty that results from larger attribute levels.

We also observe that, as before, the values are not completely symmetric around $EU[X_1]-EU[X_2]=0$. For example, for low demand (A) $VOPI[AT]=10.7430$ at $EU[X_1]-EU[X_2]=-0.02$, and $VOPI[AT]=11.3091$ at $EU[X_1]-EU[X_2]=+0.02$. For demand B $VOPI[AT]=32.944$ at $EU[X_1]-EU[X_2]=-0.02$, and $VOPI[AT]=33.484$ at $EU[X_1]-EU[X_2]=+0.02$. This indicates, as before, that studies may be more valuable when the preferred alternative using the expected utility is no-build $[X_i]$.

Again, using the VOPI at each prediction step we calculate the marginal VOPI. We display the marginal VOPI of each step as a function of the difference between the expected utilities of the alternatives in Figures 5.10 and 5.11 for demand A and demand B, respectively. As with the VOPI at each prediction step, we observe that the marginal VOPI peaks when the difference in expected utility between the alternatives is zero. Recall that for the small network example the peak was close but not necessarily at $EU[X_1]=EU[X_2]$. We also observe that the marginal VOPIs decrease faster for the large network than they do for the small network.

We also note that the ordering of the marginal VOPI depends on the difference between the expected utilities and the demand. That is, the marginal VOPI of the attribute models is larger than the marginal VOPI of traffic assignment and VOPI of trip distribution for all the values of the difference in expected utility when the demand is low.
Figure 5.10 Marginal VOPI of Each Prediction Step as a Function of the Difference Between the expected utilities of the alternatives for the Extended Network Example with Demand A

Figure 5.11 Marginal VOPI of Each Prediction Step as a Function of the Difference Between the expected utilities of the alternatives for the Extended Network Example with Demand B

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(A) but only for some values of this difference for high demand (B). Also, the marginal VOPI of traffic assignment is almost equal to the marginal VOPI of trip distribution for all the values of the difference in expected utility when the demand is low (A), but is larger than VOPI of trip distribution for all the values of this difference when the demand is high (B). Finally, we observe that the marginal VOPI of traffic assignment is larger than the marginal VOPI of the attribute models when the difference of the expected utilities is close to zero and the demand is high (B).

These observations may indicate that the marginal VOPI follows roughly the same ordering as the VOPI at the different modeling steps for the two networks and two demand levels. Nevertheless, we observe that the ordering can change for some values of the difference in expected utility.

Again, we also note a slight asymmetry around $\text{EU}[X_1] - \text{EU}[X_2] = 0$. We see, for example, that the marginal VOPI of the attribute models is 10.743 when $\text{EU}[X_1] - \text{EU}[X_2] = -0.02$ and 11.309 for $\text{EU}[X_1] - \text{EU}[X_2] = +0.02$ for demand A. For demand B we have that the marginal VOPI of the attribute models is 32.94 when $\text{EU}[X_1] - \text{EU}[X_2] = -0.02$ and 33.48 for $\text{EU}[X_1] - \text{EU}[X_2] = +0.02$. As before, these results may imply that marginal improvements in the information are more important when the no-build alternative is preferred to the build alternative.
5.2.4 Model VOPI Calculation for the Extended Network Example

We define Model VOPI as the value of an error free conditional model, i.e., a model that provide perfect outcomes conditioned on any given uncertain inputs. For the calculation of model VOPI we randomly sample the potential results of an ideal study that yields perfect outcomes for any given input. In chapter 2 we showed that the potential number of outcomes of this ideal study is very large.

For instance, we showed that the potential number of outcomes of a perfect information study on trip distribution would be \( M^L \), where \( L \) is the number of production-attraction patterns and \( M \) the number of OD matrices for each \( l=1,...,L \). For traffic assignment we have \( N^{2LM} \) potential outcomes of this perfect information study, where \( N \) is the number of link volume vectors conditioned on each OD matrix, and \( 2 \) is the number of alternatives (build, no-build). Finally, for the attribute models we have \( O^{N2ML} \) potential outcomes, where \( O \) is the number of attribute vectors for each link volume vector.

Given that these numbers are computationally unmanageable, we "sample" a subset of the outcomes. In Figure 5.12 we present the model VOPI as a function of the number of samples drawn from each ideal perfect information study. We calculate the model VOPI for the high demand case (B) and the cost that makes \( \text{EU}[X_t]=\text{EU}[X_s] \). We observe that the number of samples required for a stable value of model VOPI is around 500 for trip distribution and 2,500 for traffic assignment and attribute models.
Figure 5.12 Model VOPI as a Function of the Number of Samples of the Perfect Information Studies of Each Modeling Step for the Extended Network Example with High Demand (B) and $EU[X_1] - EU[X_2] = 0$

We then calculate model VOPI as a function of $EU[X_1] - EU[X_2]$ for low demand (A) and high demand (B) using 2,500 samples for each perfect information study (attribute models, traffic assignment, trip distribution). We present the results in figures 5.13 and 5.14.

We observe that model VOPI peaks at $EU[X_1] - EU[X_2] = 0$ and decreases very fast with the increase in the absolute value of this difference. Model VOPI only yields some value greater than zero when the difference in expected utilities is very close to zero (i.e., $|EU[X_1] - EU[X_2]| < 0.0004$ for model VOPI > 0.1 for demand A). In general, this absolute difference is expected to be larger; hence, it is possible to say that for most cases model VOPI ≈ 0 [$\text{million/year}$]. In other words, a decision maker will not be willing to pay any
Figure 5.13 Model VOPI as a function of the difference between the Expected Utilities for the Extended Network Example and Demand A

Figure 5.14 Model VOPI as a function of the difference between the Expected Utilities for the Extended Network Example and Demand B
money for having an error free conditional model when the inputs to that model are uncertain.

In the special cases in which $\text{EU}[X_1]-\text{EU}[X_2]=0$ we observe that trip distribution yields the largest model VOPI for both demand A and B. We also note that model VOPI of traffic assignment is higher than model VOPI of the attribute models for both demand A and B. Nevertheless, for low demand (A) the model VOPI[T_A] values are only slightly larger than the model VOPI[T_D].

This result may imply that, in case the expected utilities are very close to each other, it may be more valuable to invest in improving the models in the early stages of the forecasting process (i.e. trip distribution) than in the last stages (i.e. attribute models). We note that this implication is different to that of the marginal VOPI. In that case we observed that, for most cases, the last step (i.e., attribute models) contributed the most to the cumulative VOPI of the attribute vector.

5.3. Sensitivity Analysis to the Preference Model Parameters

We perform a sensitivity analysis to the preference model parameters to investigate which of them may affect the VOPI the most. We perform this analysis on the extended network example with high demand. With this analysis we would be able to indicate how changes in the preference model assumptions may affect the VOPI ordering and values.

We perform the analysis in three phases. In the first phase we select a group of preference model parameters for sensitivity analysis. In the second phase we modify
these selected parameters one at a time to identify the direction in which they affect the responses and the relative magnitudes of their influence. We use the elasticity concept (Kleijnen, 1987) to identify the relative influences. In the third phase we design and apply an experiment consisting of a selected group of combinations of variations of these inputs. The responses of these experiments --i.e., expected utilities, VOPI and Marginal VOPI-- are then used as dependent variables in the estimation of preliminary metamodels consisting of single interactions (Kleijnen, 1987).

5.3.1 Parameters Selected for the Sensitivity Analysis on the Preference Model

The input factors to the preference model are the marginal rates of substitution among the attributes, the shape parameters, the extremes of the single attribute utility functions, and, when the shape parameters are different from one, the point at which we calculate the marginal rates of substitution.

In this analysis we consider the effect of nine factors: 1) the marginal rate of substitution of cost to time (MRS_{Y,1/Y,2}); 2) the marginal rate of substitution of cost to fuel (MRS_{Y,1/Y,3}); 3) the estimated costs of not reducing some given pollution levels (Pollution Cost, see discussion in section 4.1); 4) the marginal rate of substitution of HC to CO (MRS_{Y,4/Y,2}); 5) the marginal rate of substitution of HC to NOx (MRS_{Y,4/Y,3}); 6) the shape parameter of the single attribute utility of total system travel time (\alpha_2); 7) the shape parameter of the single attribute utility of total HC emissions (\alpha_4); 8) the shape
parameter of the single attribute utility of total CO emissions ($\alpha_{42}$); and, 9) the shape parameter of the single attribute utility of total NOx emissions ($\alpha_{43}$).

We use two levels for each factor in this sensitivity analysis. These levels are indicated in Table 5.3. Level 1 corresponds to the values used in the previous sections. Level 2 corresponds to a 50% increase in the values in Level 1 for factors 1 to 5. For factors 6 to 9 (i.e., shape parameters), we calculate the parameter $\alpha_i$ that changes the utility of the midpoint of the range by 50%. For total system travel time, we consider a 50% reduction of the utility of the midpoint. This is because, in case of non linearity, we might expect a concave utility function for total system travel time (see discussion in section 4.1). For the single attribute utility of the different pollutants, we consider a 50% increase of the utility of the midpoint of the range. This is because, in case of non linearity, we might expect convex utility functions for the pollutants (again, see discussion in section 4.1).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Level 1</th>
<th>Level 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MRS$_{YY}$</td>
<td>8.33E-05</td>
</tr>
<tr>
<td>2</td>
<td>MRS$_{YY}$</td>
<td>0.0015</td>
</tr>
<tr>
<td>3</td>
<td>Pollution Cost</td>
<td>1.043E+10</td>
</tr>
<tr>
<td>4</td>
<td>MRS$_{4142}$</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>MRS$_{4143}$</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>$\alpha_2$</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>$\alpha_4$</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>$\alpha_{42}$</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>$\alpha_{43}$</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 5.3 Factors and Levels Considered in the Preference Model Sensitivity Analysis
We do not consider the sensitivity of the outcomes to changes in the shape parameters of cost and fuel consumption. In section 4.1 we argued that the assumption of a linear utility function for these attributes is reasonable. Hence, we do not consider it necessary to test the sensitivity of the outcomes to these parameters. Additionally, we do not consider sensitivity to changes in the ranges of the attributes. The tradeoff parameters calculated with different extremes should change in such a way that the relative expected utilities of the alternatives would remain unchanged. Hence, neither the preferred alternative nor the VOPI are expected to change with changes in the bounds on the single attribute utilities.

Finally, it is important to mention that for non-linear single attribute utilities the point of calculation of the marginal rate of substitution becomes relevant. We calculate the marginal rates of substitution at the expected values of the different attributes for the No-Build ($X_1$) alternative and high demand (B), i.e., $E[Y_{I}|X_1,B]=1,978,759$; $E[Y_{II}|X_1,B]=1,579$; $E[Y_{III}|X_1,B]=14,206$; and $E[Y_{IV}|X_1,B]=1,695$. We calculate these values from $15^4$ simulated attribute vectors (see section 5.1). We expect that many of the actual realizations of the attributes would occur around these expected values. We do not test the sensitivity to the selection of a different point to calculate the marginal rates of substitution. The inputs and outputs of the sensitivity analyses described below are detailed in appendix C.
5.3.2. Sensitivity Analysis for Changes of One Preference Factor at a Time

We perform nine experiments changing one factor at a time. That is, for experiment 1 we use Level 2 for factor 1 (i.e., MRS_{Y1Y2}=0.000125) and Level 1 for the remaining factors. For experiment 2 we use Level 2 for factor 2 (i.e. MRS_{Y1Y2}=0.000225) and Level 1 for the remaining factors. We continue in this way for the other seven factors to complete the nine experiments. We calculate the expected utilities, VOPI and Marginal VOPI for each one of these experiments using the same paired sets of 15^4 attribute vectors for the No Build and Build Alternatives. For each experiment we calculate the ratio of the proportional change in the outcome to the proportional change in the income or outcome-factor elasticity:

\[
Elasticity(Outcome, factor) = \frac{\Delta Outcome / Outcome}{\Delta factor / factor},
\]

(5.11)

where \(\Delta Outcome\) is the change in the outcome from a base case situation (i.e., all the outcomes at Level 1) to the new situation (i.e., experiments 1 to 9), and \(\Delta factor\) is the change in the factor from Level 1 one to Level 2. We consider the following outcomes: 1) expected utilities of the alternatives (EU[X_1], EU[X_2]), 2) difference in expected utilities (EU[X_1]- EU[X_2]), 3) VOPI of attributes, arc volumes, and OD matrix, and 4) Marginal VOPI of attribute models, traffic assignment and trip distribution.

We graphically display the results of this sensitivity analysis on the expected utilities using this elasticity concept in Figure 5.15. The results are also tabulated in
appendix C. We observe that the expected utilities are fairly insensitive (i.e., |Elasticity[EU, factor]|<0.05) to factors 1 to 7, and are more sensitive (i.e., |Elasticity[EU, factor]|>0.05), for factors 8 and 9, especially for the shape parameter \( \alpha_{42} \) of CO emissions (factor 8). This indicates that it would be necessary to assess the pollution emissions single attribute utility functions more carefully.

![Figure 5.15 Elasticity of the Expected Utility to Preference Model Factors Using One Factor at a Time Changes](image)

We also calculate the elasticity of the difference between the expected utilities to the nine factors. We graphically display these elasticities in Figure 5.16 and tabulate them in appendix C. We observe that this elasticity is negative for \( \text{MRS}_{v41, v42}, \alpha_{41}, \alpha_{42} \) and \( \alpha_{43} \). This indicates that the difference in expected utilities may decrease with increments in
these factors. We also observe that the difference in expected utilities seems more sensitive to the factors than do each of the expected utilities alone. The absolute value of the elasticity is larger than 0.05 for all the factors but MRS_{Y1Y3} and MRS_{Y4Y43}, and it is larger than 2.0 for \( \alpha_{41} \) and \( \alpha_{42} \). This large elasticity for the shape parameters of the utilities of HC and CO indicates, again, that these factors may be critical in the determination of the expected utilities.

Figure 5.16 Elasticity of the Difference in the Expected Utilities to Preference Model Factors Using One Factor at a Time Changes

We graphically display the elasticity of VOPI of the model outcomes to the nine factors in Figure 5.17 and tabulate it in appendix C. We observe larger sensitivities of the VOPI to changes in Pollution Cost, \( \alpha_{41} \) and \( \alpha_{42} \) than for the other factors. These results
reinforce the need to consider the parameters associated with pollution carefully. The signs of the VOPI elasticity for Pollution Cost are also interesting. While an increase in this factor causes increases in the VOPI of Attributes and VOPI of Volumes, it results in a decrease in the VOPI of the OD Matrix. Similarly, increase in the shape parameter of the utility of NOx results increase in the VOPI of the OD matrix and decrease in the VOPI of the attributes.

![Elasticity of the VOPI to Preference Model Factors Using One Factor at a Time Changes](image)

Figure 5.17: Elasticity of the VOPI to Preference Model Factors Using One Factor at a Time Changes

Finally, we calculate the elasticity of the Marginal VOPI to changes in the preference model factors. We graphically display these results in Figure 5.18 and tabulate them in appendix C. We observe that these elasticities follow a similar pattern to
that to of the elasticities for VOPI, that is larger sensitivities of the VOPI to changes in Pollution Cost, \( \alpha_{41} \) and \( \alpha_{42} \) than for the other factors. We also observe that an increase in Pollution Cost causes increases in Marginal VOPI of Attributes and Traffic Assignment, but a decrease in Marginal VOPI of Trip Distribution. Similarly, an increase in the shape parameter of the utility of NOx results in an increase in the Marginal VOPI of the OD matrix and a decrease in the Marginal VOPI of Traffic Assignment and Attribute models.

![Figure 5.18 Elasticity of the Marginal VOPI to Preference Model Factors Using One-Factor-at-a-Time Changes](image)

In summary, the results of this preliminary sensitivity analysis indicate the need to consider the preference parameters associated with pollution carefully, especially pollution cost and shape parameters for the utilities of HC and CO. The results also
suggest that the expected utilities and VOPI calculations seem not very sensitive to changes in the other parameters (i.e., marginal rates of substitution of cost to time, cost to fuel, HC to CO, HC to NOx, and shape parameter of the utility function of total system travel time). For those attributes that cause significant changes in the outcomes, we observe that the directions of the changes are diverse. For instance, positive changes in pollution cost cause positive changes in VOPI of Attributes and Volumes and Marginal VOPI of Attribute Models and Traffic Assignment, and cause negative changes in VOPI of OD Matrix and Trip Distribution. Investigating if these changes are caused by the specific numerical estimates resulting from our simulations, or by more general underlying relationships among the multiple components of the VOPI framework is beyond the scope of this study. We recommend further analysis.

5.3.3 Estimation of Metamodels for Expected Utilities and VOPI as a Function of the Preference Parameters

A metamodel is an approximation of the simulation model (Montgomery, 1991; Kleijnen, 1987). It summarizes in a simple equation the complex relationships embedded in the simulation. It also allows the judgment of the importance of the different factors. The construction of a metamodel consists of determining a response surface. A recommended first step in the determination of the response surface is to consider single interactions and linear terms only (Montgomery, 1991; Kleijnen, 1987). In this analysis we desire to obtain
where $F(z)$ is the desired outcome and $z$ is the vector of factors $(z_1, z_2, ..., z_9)$. We can use regression analysis to estimate the parameters $\beta_i$, $i=0, ..., 9$ from simulation outcomes for different factor level combinations. In general, we would need many combinations to obtain good estimates of these parameters. Hence many simulation experiments would be required. Since determining VOPI is computationally expensive with the procedures developed in this thesis, this could be very time consuming. However, if the factor-level combinations are chosen carefully, only few experiments are required.

We use a Plackett-Burman resolution III design (Montgomery, 1991) to define 12 experiments that we use to estimate the parameters in (5.12). We assume that the response surface consists only of linear terms with no interactions. In case this assumption is not correct, that is, the metamodel involves interactions and quadratic effects, the estimated parameters would be biased (Kleijnen, 1987).

To reduce possible bias, in addition to the 12 factor-level combinations resulting from the Plackett-Burman design, we use the base case (i.e., all factors at Level 1), the nine one-factor-at-a-time experiments considered in section 5.3.2, and an extra experiment considering factors 1-6 at Level 1 and factors 7-9 at Level 2. As a result we have a total of 23 experiments. We show the experiment design in Table 5.4. In this table, experiment 1 corresponds to the base case, experiments 2-13 to the Placket-Burman combinations, experiments 14-22 to the one-at-a-time combinations, and experiment 23 to the extra experiment.
The experiments consist of calculating $EU[X_1]$, $EU[X_2]$, $\{EU[X_1]-EU[X_2]\}$, $VOPI[AT]$, $VOPI[VL]$, $VOPI[OD]$, $VOPI[PA]$, Marginal $VOPI[AM]$, Marginal $VOPI[TA]$ and Marginal $VOPI[TD]$ using the inputs to the preference model indicated in Table 5.4, while keeping the remaining inputs to the calculation framework constant at the base case levels (see section 5.1). The factor levels are then used as independent variables to estimate the parameters of linear models given by (5.12) using ordinary least squares (Montgomery, 1991). The regression statistics results of the ordinary least squares estimation procedure are provided in Table 5.5. We show the P-values of the F
statistic for each model, the parameter values and their t-statistics P-values. We consider that the assumptions for the statistical tests on the model and the parameters hold, that is: 1) the matrix of independent variables is not collinear, 2) the regression model is linear in its parameters β, 3) the simulation responses have constant variance, 4) the responses are independent and normally distributed, and 6) the regression model is valid (Kleijnen, 1987). We do not test the validity of these assumptions in this preliminary analysis, hence, we are cautious with the result interpretation.

<table>
<thead>
<tr>
<th>P-value F Stat.</th>
<th>P-value t-statistic</th>
<th>β₀</th>
<th>β₁</th>
<th>β₂</th>
<th>β₃</th>
<th>β₄</th>
<th>β₅</th>
<th>β₆</th>
<th>β₇</th>
<th>β₈</th>
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</tr>
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<tbody>
<tr>
<td>EU[X1]</td>
<td>0.0000 0.0000</td>
<td>0.0077</td>
<td>0.2097</td>
<td>0.1259</td>
<td>0.6843</td>
<td>0.1332</td>
<td>0.0271</td>
<td>0.3161</td>
<td>0.0000</td>
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</tr>
<tr>
<td>EU[X2]</td>
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<td>0.0027</td>
<td>0.2407</td>
<td>0.0031</td>
<td>0.7295</td>
<td>0.1341</td>
<td>0.0170</td>
<td>0.7554</td>
<td>0.0000</td>
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</tr>
<tr>
<td>EU[X1] -E[X2]</td>
<td>0.1435 0.6780</td>
<td>0.6028</td>
<td>0.4609</td>
<td>0.0244</td>
<td>0.7718</td>
<td>0.4688</td>
<td>0.4712</td>
<td>0.1152</td>
<td>0.1054</td>
<td>0.9983</td>
<td></td>
</tr>
<tr>
<td>VOPΙ[AT]</td>
<td>0.0042 0.0178</td>
<td>0.5433</td>
<td>0.4254</td>
<td>0.0006</td>
<td>0.3379</td>
<td>0.2300</td>
<td>0.4131</td>
<td>0.0112</td>
<td>0.0508</td>
<td>0.5234</td>
<td></td>
</tr>
<tr>
<td>VOPΙ[VL]</td>
<td>0.0598 0.0457</td>
<td>0.2655</td>
<td>0.3331</td>
<td>0.0245</td>
<td>0.2118</td>
<td>0.2080</td>
<td>0.2658</td>
<td>0.0177</td>
<td>0.4659</td>
<td>0.7467</td>
<td></td>
</tr>
<tr>
<td>VOPΙ[OD]</td>
<td>0.1124 0.3771</td>
<td>0.4367</td>
<td>0.7360</td>
<td>0.1740</td>
<td>0.0990</td>
<td>0.5540</td>
<td>0.2382</td>
<td>0.1206</td>
<td>0.0252</td>
<td>0.3012</td>
<td></td>
</tr>
<tr>
<td>VOPΙ[PA]</td>
<td>0.0752 0.5471</td>
<td>0.0859</td>
<td>0.2379</td>
<td>0.0491</td>
<td>0.0390</td>
<td>0.3165</td>
<td>0.5497</td>
<td>0.2541</td>
<td>0.0602</td>
<td>0.9608</td>
<td></td>
</tr>
<tr>
<td>Marginal</td>
<td>VOPΙ[AM]</td>
<td>0.0012</td>
<td>0.0220</td>
<td>0.9767</td>
<td>0.6479</td>
<td>0.0001</td>
<td>0.6447</td>
<td>0.3739</td>
<td>0.7276</td>
<td>0.0248</td>
<td>0.0098</td>
</tr>
<tr>
<td>Marginal</td>
<td>VOPΙ[TA]</td>
<td>0.0020</td>
<td>0.0261</td>
<td>0.3015</td>
<td>0.2530</td>
<td>0.0004</td>
<td>0.5928</td>
<td>0.1682</td>
<td>0.4706</td>
<td>0.0192</td>
<td>0.0098</td>
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<tr>
<td>Marginal</td>
<td>VOPΙ[TD]</td>
<td>0.0448</td>
<td>0.3291</td>
<td>0.8437</td>
<td>0.1334</td>
<td>0.5576</td>
<td>0.3074</td>
<td>0.8828</td>
<td>0.0232</td>
<td>0.0978</td>
<td>0.0258</td>
</tr>
</tbody>
</table>

Table 5.5 Ordinary Least Squares Regression Statistics for Preliminary Metamodels of the Response Surfaces for Selected Preference Parameters
We observe that the P-values of the F Statistic (column 2) is greater than 0.05 for the estimated models of EU[X1]-EU[X2], VOPI[VL], VOPI[OD], and VOPI[PA]. Hence, we cannot reject the hypothesis that all the parameter values are equal to zero for that confidence level. We may conclude that the linear model specification is not adequate for these response surfaces. On the other hand, the P-values of the F statistics are less than 0.05 for the other models. We can reject the hypothesis that all the parameters are zero with that confidence level for the remaining models.

For those models where the linear specification seems better than no model, the P-values of the t-statistics of the estimated β parameters indicate to which factors the outcomes are the most sensitive. For example, for EU[X1] we cannot reject the hypothesis that β equals zero at a 0.05 confidence level for MRS_{Y1Y2}, α_2, α_{42} and α_{43}. Similarly, we cannot reject β=0 at a 0.05 confidence level for MRS_{Y1Y2}, pollution cost, α_2, α_{42} and α_{43} for EU[X2]; pollution cost,α_{41} and α_{42} for marginal VOPI[AM] and marginal VOPI[TA]; and α_2 and α_{42} for marginal VOPI[TD]. Some of the estimated β parameters for the marginal VOPI models are shown in table 5.6.

<table>
<thead>
<tr>
<th>Marginal VOPI</th>
<th>β0 (Intercept)</th>
<th>β3 (Pollution Cost)</th>
<th>β6 (α_2)</th>
<th>β7 (α_{41})</th>
<th>β8 (α_{42})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attribute Models</td>
<td>15.8982</td>
<td>9.7035E-10</td>
<td>-0.9557*</td>
<td>-3.9899</td>
<td>-4.7530</td>
</tr>
<tr>
<td>Traffic Assignment</td>
<td>10.1363</td>
<td>5.7701E-10</td>
<td>-1.3177*</td>
<td>-2.7733</td>
<td>-3.1402</td>
</tr>
<tr>
<td>Trip Distribution</td>
<td>1.8761*</td>
<td>-3.3188E-11*</td>
<td>-2.0896</td>
<td>-0.8484*</td>
<td>1.1964</td>
</tr>
</tbody>
</table>

*Non Significant 95%

Table 5.6 Parameter Estimates for Marginal VOPI Models of Preference Parameters
This table shows those parameters that are significant for one or more of the marginal VOPI models. We observe that the marginal VOPI of Attribute Models and Traffic Assignment increase with increases in pollution cost and decrease with increments on the shape parameters of the utilities of HC and CO. We also observe that the marginal VOPI of Trip Distribution decreases with an increment in the shape parameter of the utility of total time and increase with an increment in the shape parameter of the utility of CO. The signs of these parameters coincide with the direction of the changes caused with the one-at-a-time changes analyzed in the previous section. It would be interesting to investigate whether the signs of these parameters are a result of the specific samples used in this study or more general underlying relationships.

In summary, the results of this sensitivity analysis indicate that the linear specification with single effects does not work for some outcomes (i.e., difference in expected utility and VOPI of Volumes, OD Matrix and Production Attraction patterns). It also indicates that those outcomes that are better modeled by a linear specification than no model at all are sensitive to the shape parameter of single attribute utility of CO, and most of them are sensitive to the pollution cost and to the shape parameters of the utility and HC. If there is an interest to pursue higher level metamodels of the Marginal VOPI (i.e., those including paired and quadratic effects), one can recommend to screen out the marginal rates of substitution of cost to time, fuel to time, HC to CO, HC to NOx, and the shape parameter of the utility of NOx.
5.4. Sensitivity Analysis to the Prediction Model Parameters

We also perform a sensitivity analysis to selected prediction model parameters to establish which of them may affect the outcomes of the VOPI calculation the most. As before, we perform this analysis on the extended network example with high demand using three phases: 1) selection of parameters for sensitivity analysis, 2) elasticity analysis using one-at-a-time changes, and 3) regression analysis using a single interaction model. We use a cost of $145,236 million/year, that is the cost that yields $\text{EU}[X_i]=\text{EU}[X_j]$ for $\text{UM}^{(cm)}=0.25$, $cm=1,...,8$ and the preference model parameters given in table 5.2 (i.e., linear single attribute utilities).

We analyze the sensitivity of the different VOPIs to changes in the assumed uncertainty measures $\text{UM}^{(cm)}$ of the eight conditional models $cm$ (chapter 3): trip generation ($cm=1$), trip distribution ($cm=2$), traffic assignment ($cm=3$), time model ($cm=4$), fuel consumption model ($cm=5$), HC emissions model ($cm=6$), CO emissions model ($cm=7$) and NOx emissions model ($cm=8$). We leave all the other prediction model inputs unchanged in this analysis. We define two levels for these 8 prediction factors: $\text{UM}^{(cm)}=0.125$ (Level 1) and $\text{UM}^{(cm)}=0.375$ (Level 2).

5.4.1 Sensitivity Analysis for Changes of One Prediction Factor at a Time

We perform nine experiments changing one factor at a time. For experiment 1 we use Level 2 for factor 1 (i.e., $\text{UM}^{(1)}=0.375$) and Level 1 for the remaining factors (i.e.,
UM_{cm}^1=0.125, \text{ cm}=2,\ldots,8). For experiment 2 we use Level 2 for factor 2 (i.e. \(UM_{cm}^{(2)}=0.375\)) and Level 1 for the remaining factors (i.e., \(UM_{cm}^1=0.125, \text{ cm}=1,3,\ldots,8\)).

We continue in this way for the other six factors to complete eight experiments. Finally, we set all the factors equal to Level 1 (i.e., \(UM_{cm}^1=0.125, \text{ cm}=1,\ldots,8\)).

Each experiment consists of three parts: 1) calibration of the input standard deviations of the errors of the conditional models, 2) generation of the attribute vectors, and 3) calculation of outcomes (Expected Utilities and VOPIs). In part 1, we use the Monte Carlo simulation procedure detailed in chapter 3 to calculate the uncertainty measures from given standard deviations of the errors of trip generation, trip distribution and traffic assignment. We change the values of these standard deviations until we obtain the desired uncertainty measure levels. The resulting standard deviations are displayed in Table 5.7. In part 2, we use the resulting standard deviations to sample 15^4 attribute vectors for the No Build and Build alternatives using, again, Monte Carlo simulation. In part 3, we use these attribute vectors to calculate the outcomes.

For each experiment we calculate the ratio of the proportional change in the outcome to the proportional change in the input factor or outcome-factor elasticity (5.11). We consider the following outcomes: 1) expected utilities of the alternatives (EU[X_1], EU[X_2]); 2) difference in expected utilities (EU[X_1]- EU[X_2]); 3) VOPI of attributes, arc volumes, and OD matrix; 4) Marginal VOPI of attribute models, traffic assignment and trip distribution; 5) Model VOPI of attribute models, traffic assignment and trip distribution. The base level for the calculation of the elasticity is the outcome of experiment 10 (i.e., \(UM_{cm}^1=0.125, \text{ cm}=1,\ldots,8\)).
Table 5.7 Standard Deviations in the Errors of the Conditional Models to Obtain Desired Levels of the Uncertainty Measure UM\(^{(cm)}\), cm=1,..3

We graphically display the results of the sensitivity analysis on the expected utilities and the difference in expected utilities using the elasticity concept in Figure 5.19 and tabulate them in appendix C. We observe that the elasticity of the expected utilities is very close to zero for all the uncertainty measures. The highest elasticity corresponds to the elasticity of the expected utility of No Build to the uncertainty measure of traffic assignment \((\Delta EU[X_2]/EU[X_2])/(\Delta UM^{(3)}/UM^{(3)}) = -0.056\). These results indicate that, the preference for the alternatives do not change significantly as a result of changes in the prediction parameters. This might be expected since we are only changing the dispersion around the mean and we are using linear single attribute utilities.

Despite this, we observe that the elasticity of the difference in expected utilities is only zero for UM\(^{(3)}\) (fuel model), UM\(^{(7)}\) (CO model) and UM\(^{(8)}\) (NOx model), and less than zero for the other factors. The highest elasticity corresponds to the elasticity of the difference in expected utilities to the uncertainty measure in trip generation, \(\Delta(EU[X_1])\)-
EU[X₁]/(EU[X₂]-EU[X₁])/{ΔUMᵢ(0)/UMᵢ(0)} = -0.36, followed by the elasticity to traffic assignment (0.33). This indicates that the difference in expected utilities is more sensitive to changes in the uncertainty measure than the expected utilities alone for most factors, and that increases in the level of uncertainty tend to slightly increase the absolute value of the difference in expected utilities.

![Graph showing elasticity of the Expected Utility and Difference in Expected Utility to Prediction Model Factors Using One-Factor-at-a-Time Changes](image)

Figure 5.19 Elasticity of the Expected Utility and Difference in Expected Utility to Prediction Model Factors Using One-Factor-at-a-Time Changes

We plot the elasticity of VOPI of the model outcomes to the eight factors in Figure 5.20 and tabulate it in appendix C. We observe that, as it would be expected, the larger the uncertainty measures the larger the VOPI. We also observe larger sensitivities of the VOPI to changes in the uncertainty measure of traffic assignment, especially for the VOPI of arc volumes, where the elasticity to the uncertainty measure of traffic
assignment \((U^M)\) is equal to 2.0. That indicates that a positive change of one unit in the uncertainty measure of traffic assignment results in a change of two units in the VOPI of the arc volumes. We observe that VOPI is not sensitive (elasticity≈0) to the uncertainty measure in trip distribution, fuel consumption, CO emissions and NOx emissions.

We also calculate the elasticity of the Marginal VOPI to changes in the predictions model factors. We plot these results in Figure 5.21 and tabulate them in appendix C. The results are similar to those obtained for VOPI. The Marginal VOPIs of Traffic
Assignment is sensitive to the uncertainty measure of traffic assignment, but not very sensitive to the other factors. The Marginal VOPI of Trip Distribution is sensitive to the uncertainty measures of Traffic Assignment and HC models, and in lesser degree to the uncertainty measures of trip generation and a time models. The Marginal VOPI of the Attribute Models is sensitive to the uncertainty measures of HC models and total system travel time, and in lesser degree, traffic assignment model. We note that this latter influence is negative, i.e., an increase the in the uncertainty measure of traffic assignment results in a decrease in the marginal VOPI of the Attribute Models. This results from a bigger change in the VOPI of arc volumes than the change in the VOPI of attributes.

Figure 5.21 Elasticity of the Marginal VOPI to Prediction Model Factors Using One-Factor-at-a-Time Changes
Finally, we graphically display the results of the elasticity analysis of the Model VOPI with respect to the eight prediction factors in Figure 5.22. These results are also tabulated in appendix C. We observe that Model VOPI of traffic assignment is sensitive to the uncertainty measures of trip generation and trip distribution models, and to a lesser degree to the uncertainty measure of the time model. These elasticities are negative, indicating that Model VOPI tends to decrease with increases in these uncertainty measures. Model VOPI of trip distribution is also sensitive to the uncertainty measures of trip generation, trip distribution and time models. The Model VOPI of the attribute models, on the other hand, is very sensitive to the HC model and Time Model, and in smaller degree to the trip generation, trip distribution and traffic assignment models.

![Elasticity of the Model VOPI to Prediction Model Factors Using One-Factor-at-a-Time Changes](image)

Figure 5.22 Elasticity of the Model VOPI to Prediction Model Factors Using One-Factor-at-a-Time Changes
We also note that the Model VOPI of traffic assignment increases with positive changes in the uncertainty measures of trip generation, trip distribution and HC emission models, and decreases with an increase in the uncertainty measure of traffic assignment and travel time models.

In summary, the results of this preliminary sensitivity analysis indicate that none of the outcomes is significantly sensitive to the uncertainty measures of the fuel consumption, CO emissions and NOx emissions models. Sensitivity to the other uncertainty measures depends on the output being analyzed. For instance, the Marginal VOPIs of traffic assignment and trip distribution are very sensitive to the uncertainty measure of Traffic Assignment, but Model VOPI of TA and Model VOPI of TD are not. Again, it would be interesting to investigate whether the direction of the changes of Marginal VOPIs and Model VOPIs is a result of the samples used or of the underlying relationships of the VOPI framework.

5.4.2 Estimation of Metamodels for Expected Utilities and VOPI as a function of the Prediction Parameters

As before, in this analysis we desire to obtain

\[ F(Z) = \beta_0 + \beta_1 z_2 + \beta_2 z_2 + \ldots + \beta_8 z_8 \]  \hspace{1cm} (5.13)
where \( F(z) \) is the outcome (e.g., VOPI of arc volumes) and \( z \) is the vector of factors \( (z_1, z_2, \ldots, z_8) \). We can use regression analysis to estimate the parameters \( \beta_i, i=0,\ldots,8 \) from simulation outcomes for different factor level combinations.

Again, we use a Plackett-Burman resolution III design (Montgomery, 1991) to define 12 experiments that we use to estimate the parameters in (5.13). To reduce possible bias, in addition to these 12 factor-level combinations, we use the base case (i.e., \( U M^{(cm)}=0.25, cm=1,\ldots,8 \)), the eight one-factor-at-a-time experiments considered in section 5.4.1, and an extra experiment considering factors 1-3 at Level 2 and factors 4-8 at Level 1. As a result we have a total of 22 experiments. We show the experiment design in Table 5.8. In this table, experiment 0 corresponds to the base case, experiments 1-8 to the one-at-a-time combinations, 9-20 to the Placket-Burman combinations, experiment 21 to the extra experiment. We also include in Table 5.7 the estimated standard deviations of trip generation, trip distribution and traffic assignment (No Build and Build cases) required to obtain the desired uncertainty measures. We recall that the standard deviations of the other models (i.e., time, fuel, pollution) are equal to the desired uncertainty measures.

As before, the experiments consist of: 1) obtaining the standard deviations leading to the desired uncertainty measures; 2) sampling \( 15^4 \) attribute vectors; and 3) calculating \( \text{EU}[X_1], \text{EU}[X_2], \{\text{EU}[X_1]-\text{EU}[X_2]\}, \text{VOPIs}, \text{Marginal VOPI}, \text{and Model VOPI} \) using the inputs to the prediction model indicated in Table 5.7, while keeping the remaining inputs to the calculation framework constant at the base case levels (see section 5.1). The factor
levels are then used as independent variables to estimate the parameters of linear models given by (5.13) using ordinary least squares (Montgomery, 1991).

| Experiment | UM\(^{(1)}\) | UM\(^{(2)}\) | UM\(^{(3)}\) | UM\(^{(4)}\) | UM\(^{(5)}\) | UM\(^{(6)}\) | UM\(^{(7)}\) | UM\(^{(8)}\) | \(\eta_{lg}\) | \(\eta_{ld}\) | \(\eta_{lg|x_1}\) | \(\eta_{lg|x_2}\) |
|------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1          | 0.250       | 0.250       | 0.250       | 0.250       | 0.250       | 0.250       | 0.250       | 0.250       | 0.2488      | 0.2515      | 0.2695      | 0.2230      |
| 2          | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.3753      | 0.1243      | 0.0374      | 0.0221      |
| 3          | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.1263      | 0.3706      | 0.0527      | 0.0373      |
| 4          | 0.125       | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.1263      | 0.1250      | 0.5016      | 0.4620      |
| 5          | 0.125       | 0.125       | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.1263      | 0.1250      | 0.5043      | 0.0373      |
| 6          | 0.125       | 0.125       | 0.125       | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       | 0.1263      | 0.1250      | 0.5043      | 0.0373      |
| 7          | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.375       | 0.125       | 0.125       | 0.1263      | 0.1250      | 0.5043      | 0.0373      |
| 8          | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.375       | 0.125       | 0.1263      | 0.1250      | 0.5043      | 0.0373      |
| 9          | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.375       | 0.1263      | 0.1250      | 0.5043      | 0.0373      |
| 10         | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.375       | 0.3753      | 0.1243      | 0.4913      | 0.4503      |
| 11         | 0.375       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.375       | 0.3753      | 0.3679      | 0.4919      | 0.4501      |
| 12         | 0.125       | 0.375       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.3753      | 0.3706      | 0.5017      | 0.4633      |
| 13         | 0.375       | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.3753      | 0.1243      | 0.4913      | 0.4503      |
| 14         | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.3753      | 0.3679      | 0.0354      | 0.0216      |
| 15         | 0.375       | 0.375       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.3753      | 0.3679      | 0.4919      | 0.4501      |
| 16         | 0.125       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.1263      | 0.3706      | 0.5017      | 0.4633      |
| 17         | 0.125       | 0.125       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.1263      | 0.1250      | 0.5015      | 0.4620      |
| 18         | 0.125       | 0.125       | 0.125       | 0.375       | 0.375       | 0.375       | 0.375       | 0.375       | 0.1263      | 0.1250      | 0.5043      | 0.0373      |
| 19         | 0.375       | 0.125       | 0.125       | 0.125       | 0.375       | 0.375       | 0.375       | 0.375       | 0.3753      | 0.1243      | 0.0374      | 0.0221      |
| 20         | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       | 0.375       | 0.375       | 0.375       | 0.1263      | 0.3706      | 0.0527      | 0.0373      |
| 21         | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.1263      | 0.1250      | 0.5043      | 0.0373      |
| 22         | 0.375       | 0.375       | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       | 0.3753      | 0.3679      | 0.4919      | 0.4501      |

Table 5.8 Experiments Selected for Preliminary Metamodel Estimation of the Response Surfaces for Prediction Parameters

The regression statistics from the ordinary least squares estimation procedure are provided in Table 5.9. We show the P-values of the F statistic for each model, the parameter values and their t-statistics P-values. Again, we consider that the assumptions for the statistical tests on the model and the parameters hold.

We observe that the P-values of the F Statistic (column 2) is greater than 0.05 for the estimated models of EU\([X1]\)-EU\([X2]\), and Model VOPI (AM, TA and TD). Hence,
we cannot reject the hypothesis that all the parameter values are equal to zero for that confidence level. We may conclude that the linear model specification is not adequate for these response surfaces. On the other hand, the P-values of the F statistics are less than 0.05 for the other models. We can reject the hypothesis that all the parameters are zero with that confidence level for the remaining models.

<table>
<thead>
<tr>
<th>F Statistic</th>
<th>P-value</th>
<th>P-value t-statistic</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_0$</td>
<td>$\beta_1$</td>
<td>$\beta_2$</td>
</tr>
<tr>
<td>EU[X1]</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>EU[X2]</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>EU[X1] - E[X2]</td>
<td>0.2199</td>
<td>0.0010</td>
<td>0.4188</td>
</tr>
<tr>
<td>VOP[AT]</td>
<td>0.0000</td>
<td>0.0505</td>
<td>0.0349</td>
</tr>
<tr>
<td>VOP[VL]</td>
<td>0.0000</td>
<td>0.0435</td>
<td>0.0376</td>
</tr>
<tr>
<td>VOP[OD]</td>
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<td>0.0073</td>
<td>0.0820</td>
</tr>
<tr>
<td>VOP[PA]</td>
<td>0.0000</td>
<td>0.0024</td>
<td>0.2447</td>
</tr>
<tr>
<td>VOP[AM]</td>
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<td>0.7919</td>
<td>0.9386</td>
</tr>
<tr>
<td>VOP[TA]</td>
<td>0.0000</td>
<td>0.1943</td>
<td>0.0321</td>
</tr>
<tr>
<td>VOP[TD]</td>
<td>0.0000</td>
<td>0.1107</td>
<td>0.0158</td>
</tr>
<tr>
<td>Model VOP[AM]</td>
<td>0.9998</td>
<td>0.7497</td>
<td>0.8233</td>
</tr>
<tr>
<td>Model VOP[TA]</td>
<td>0.9999</td>
<td>0.7848</td>
<td>0.9433</td>
</tr>
<tr>
<td>Model VOP[TD]</td>
<td>0.9934</td>
<td>0.6241</td>
<td>0.9759</td>
</tr>
</tbody>
</table>

Table 5.9 Ordinary Least Squares Regression Statistics for Preliminary Metamodels of the Response Surfaces for Selected Prediction Parameters
For those models where the linear specification seems better than no model, the P-values of the t-statistics of the estimated \( \beta \) parameters indicate to which factors the outcomes are the most sensitive. For example, for EU\([X_i]\) and EU\([X_j]\) we cannot reject the hypothesis that \( \beta = 0 \) at a 0.05 confidence level for UM\(^{(5)}\), UM\(^{(6)}\), UM\(^{(7)}\), and UM\(^{(8)}\). Similarly, we cannot reject \( \beta = 0 \) at a 0.05 confidence level for UM\(^{(2)}\), UM\(^{(5)}\), UM\(^{(7)}\), UM\(^{(8)}\) for VOPI (AT, VL, OD, PA) and Marginal VOPI (AM, TA, TD). We also observe that UM\(^{(1)}\) is not significant for VOPI[PA] and Marginal VOPI[AM], UM\(^{(4)}\) is not significant for VOPI[VL] and Marginal VOPI[TA] and [TD], and UM\(^{(6)}\) is not significant for VOPI[VL].

In table 5.10 we show some estimated coefficients of the prediction factors for the VOPI and Marginal VOPI metamodels. This table includes the parameters that are significant at 95% for one or more metamodels. We observe that, with the exception of the intercept, all the VOPI metamodels coefficients are positive. This indicates that VOPI increases with increase in the underlying uncertainty, as it might be expected.

Additionally, we note that the VOPI of the Attribute Vector is the most sensitive to changes in the uncertainty measures, followed by VOPI of Arc Volumes, OD Matrix and Production-Attraction Patterns. We also observe that the VOPIs are more sensitive to changes in the uncertainty measure of the traffic assignment model (UM\(^{(3)}\)), than they are to changes in the other uncertainty measures. With respect to Marginal VOPI, we observe that the direction of change depends on the uncertainty measure being considered. For instance, Marginal VOPI of the Attribute Models decreases with increases in UM\(^{(3)}\), but
increases with increments in $UM^{(4)}$ and $UM^{(6)}$; Marginal VOPI of Traffic Assignment increases with increments in $UM^{(1)}$ and $UM^{(3)}$, but decreases with increments in $UM^{(6)}$; and Marginal VOPI of Trip Distribution increases with increments in $UM^{(1)}$, $UM^{(3)}$ and $UM^{(6)}$. The signs of the parameters are consistent with the direction of changes observed in the one-factor-at-a-time experiments. Again, it would be interesting to investigate whether these signs are the result of the samples used or the underlying relationships.

<table>
<thead>
<tr>
<th></th>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Intercept)</td>
<td>($UM^{(1)}$ TG)</td>
<td>($UM^{(3)}$ TA)</td>
<td>($UM^{(6)}$ TT)</td>
<td>($UM^{(8)}$ HC)</td>
</tr>
<tr>
<td>VOPI[AT]</td>
<td>-17.2366</td>
<td>40.9990</td>
<td>127.9916</td>
<td>63.3321</td>
<td>97.8995</td>
</tr>
<tr>
<td>VOPI[VL]</td>
<td>-17.9896</td>
<td>40.5216</td>
<td>166.5699</td>
<td>25.4234*</td>
<td>15.2745*</td>
</tr>
<tr>
<td>Marginal VOPI[AM]</td>
<td>0.7530*</td>
<td>0.4774*</td>
<td>-38.5783</td>
<td>37.9087</td>
<td>82.6250</td>
</tr>
<tr>
<td>Marginal VOPI[TA]</td>
<td>-6.8465*</td>
<td>26.1184</td>
<td>113.5579</td>
<td>0.1824*</td>
<td>-31.5649</td>
</tr>
<tr>
<td>Marginal VOPI[TD]</td>
<td>-2.3156*</td>
<td>8.1702</td>
<td>22.8764</td>
<td>4.4889*</td>
<td>22.7610</td>
</tr>
</tbody>
</table>

*Non Significant at 95%

Table 5.10 Parameter Estimates for VOPI and Marginal VOPI Metamodels of Prediction Parameters

In summary, the results of this sensitivity analysis indicate that the linear specification with single effects does not work for some outcomes (i.e., difference in expected utility and Model VOPIs). It also indicates that those outcomes that are better modeled by a linear specification than no model at all are very sensitive to the uncertainty measure of the traffic assignment model. Most of these calculations are also sensitive to the uncertainty measure of the HC emissions model, and the uncertainty measure of the
trip generation model. All the VOPI and Marginal VOPI are not sensitive to the uncertainty measures of trip distribution, fuel consumption, CO emissions and NOx emissions models. These parameters could be screened out when constructing higher order metamodels. It is also noteworthy the fact that the VOPI is the most sensitive to changes in the uncertainty measure of the traffic assignment conditional model.
In this study we developed a methodology for calculating the value of perfect information (VOPI) over the outcomes of a sequential forecasting process. This VOPI is calculated in the context of a common urban transportation decision problem: to build or not to build a given highway improvement within a transportation network.

We recognized that planning decisions in the transportation arena are complex; they require the prediction of multiple attributes whose actual realizations are highly uncertain. We observed that this complexity and uncertainty have resulted in highly sophisticated models that, despite their demands on input information and computational resources, are still unable to predict the attributes accurately. This lack of accuracy is the result of the intrinsic imperfection of models (i.e., input, estimation, and measurement errors), the unforeseen characteristics of the underlying human behavioral component of transportation systems, and the fact that they are future events depending on variable circumstances. As a result we perceived a need to evaluate the value of the information produced from the increasingly sophisticated models against the cost of producing this information.
The main contribution of this study is the formulation of a method to determine the value of perfect information (VOPI) for a sequential forecasting process. We also developed a probabilistic sequential forecasting process considering errors in the outputs of the modeling steps as opposed to errors in the inputs. Additionally, we applied the VOPI framework and the sequential forecasting process to different network characteristics and congestion levels and observe the presence or absence of trends. In this chapter we discuss issues associated with the VOPI framework components: the preference model and the prediction model (i.e., the sequential forecasting process). We also discuss the main numerical results for our preliminary analyses and propose topics for further research.

6.1 Value of Information Framework

We distinguished two types of information: perfect and imperfect. The value of perfect information (VOPI) corresponds to the value that would be associated with error-free information. Although no information would be error-free, VOPI is easier to determine and is, therefore, used as a first-cut indication of and upper bound on the value of more realistic information. The value of imperfect information (VOII) corresponds to the value that would be associated if the information has a given level of uncertainty. Although we formulated the basic elements of VOII, in this study we concentrated on VOPI.

We developed mechanisms to calculate three types of VOPI in the context of a sequential forecasting process: Cumulative VOPI, Marginal VOPI, and Model VOPI.
The Cumulative VOPI, which we call VOPI for simplicity, is the value of perfect information of the outcomes of the forecasting sequence up to a given step. Marginal VOPI is the value of perfect information of a given step given that the inputs to that step are known with certainty. Model VOPI is the value of perfect information of a given step given that the inputs to that step are uncertain.

The VOPI concept is embedded in a decision theoretic evaluation framework. We use Multi-Attribute Utility Theory (MAUT) as the underlying decision framework (see, for example, Keeney and Raiffa, 1976). MAUT has the advantage of explicitly incorporating uncertainty, being arguably operational, and explicitly considering the preferences of the decision maker in a manner rigorously derived from intuitive underlying assumptions or axioms. In MAUT preferences are modeled by utility functions over the attribute vectors, and predictions are given by probability distributions of the attributes for each alternative. The alternatives are then evaluated according to the expectation of the utility of the attributes.

6.1.1 Preference Model

The preference model determination for the VOPI calculation can be cumbersome. It would require the involvement of actual decision maker(s), the use of fairly extensive interviews and some level of training of this (these) decision maker(s). As a first cut approximation, we adopted a simple utility function: limited number of attributes and an
additive utility function specification with linear single attribute utilities. We derived the tradeoff parameters from intuitive and literature-based marginal rates of substitution.

The attributes selected for the numerical examples (i.e., construction cost, total system travel time, total system fuel consumption and total system HC, CO and NOx emissions) are routinely considered in transportation planning applications. As a result, we selected them for our illustrative applications. Nevertheless they are only a subset of the impacts of transportation improvements. Considering additional attributes would result in more complex utility function specifications and in a need for additional forecasting models.

The additive utility function assumption implies that the relative preferences for any given pair of attributes are independent of the levels of the remaining attributes. Assuming preference independence can result in bias in the expected utility and VOPI calculation. It would be interesting to assess the preference model from an actual decision maker (or group of decision makers) and check the validity of this assumption. A non-additive utility function would result in numerical issues for VOPI calculation.

For instance, if the construction cost utility is not independent of other attributes more computations would be required. In our applications it was possible to separate the utility function into utility for cost and utility for non-cost attributes, and find VOPI in a closed form. If the utilities are not independent an iterative process would be required to find VOPI, and hence more computational time would be required.

Finally, the linear single attribute utility assumption considered in this study seems appropriate for some attributes but inappropriate for others. For instance,
assuming linear utility of cost appears proper since monetary units have the same purchasing power at any level of cost. Also, linear utility of fuel seems adequate given that fuel consumption is associated with the national energy demand levels. Even if the preferences for these national energy demand levels are non-linear, the ranges of fuel consumption for most of the urban areas in the country are small compared to the national levels. As a result, we would be dealing with a nearly linear portion of the national fuel consumption utility.

In the other hand, linear utility for total system travel time appears to be inadequate but not important. One might expect that the "value" of a unit of time savings depends on the total trip length, i.e., one minute saved in a 10 minute trip is more valuable that one minute saved in a 60 minute trip. Hence, the utility of total system travel time would exhibit a decreasing slope as the total time increases, i.e., a shape parameter $\alpha_2<1.0$. The actual number used for this shape parameter would depend on the ranges of the total system travel time. We did not have enough information to assume a given number for this shape parameter, hence we selected $\alpha_2=1.0$ and tested the influence of decreasing it in a preliminary sensitivity analysis. We observed that while the expected utilities were sensitive to this parameter, the VOPI calculation was not. Hence, assuming linear utility of travel time seems acceptable for VOPI estimation.

Linear utilities seem to be inadequate for the pollutant emissions also. They appear important as well. It seems that pollutants are more harmful at high levels of concentration than at low levels of concentration. Hence, one might expect that the utility of the pollutants would exhibit an increasing slope as the pollutant levels increase, i.e.
shape parameters $a_j > 1.0$, $j = 1, 2, 3$. Again, we did not have enough information to assume a given number of these shape parameters, hence we selected $a_j = 1.0$, $j = 1, 2, 3$, and tested the influence of increasing them in a preliminary sensitivity analysis. We observed that the expected utilities and the VOPI calculations were very sensitive to them. Consequently, we recommend a more detailed analysis of which pollution utility function parameters to use for evaluation and VOPI calculation.

Another element used in the determination of the preference model were intuitive and literature-based marginal rates of substitution. We used them to determine the tradeoff parameters among the single attribute utilities. We also tested their influence in the expected utility and VOPI calculation in a preliminary sensitivity analysis. We found that the expected utilities and VOPI levels were not very sensitive to most of the assumed marginal rates of substitution. There only was a relatively strong influence of the assumed cost of not reducing pollution. As a result, we would recommend to use the best available marginal rates of substitution for cost and time, cost and fuel and among pollutants without a great concern on biases in the outcome. We would recommend, though, to perform a more detailed analysis to find the marginal rate of substitution of cost and pollution levels.

6.1.2 Prediction Model

The prediction model used in this study is different from other risk analysis models we have seen in the past (Lewis, 1995; Rose, 1985; Pell, 1984) in that it considers
uncertainty on the model component outputs in addition to the model component inputs. We believe that models are not able to replicate behavior completely, even if they consider the right inputs. We defined a metric, called uncertainty measure, to determine the level of precision of a given model. The uncertainty measure estimates the average accuracy of the conditional model outputs. For the base case results in this study we set the uncertainty measure to a given level (i.e., $UM^{(cm)}=0.25, cm=1,...8$, where $cm$ is the conditional model) and investigated the sensitivity of VOPI to changes in these values. We do not have, at this time, estimates of the actual or perceived accuracy of transportation models. This would be an interesting area for further research.

We achieved the desired level of the uncertainty measure by setting the parameters of probability distribution of the error on the outputs. To calibrate these parameters we performed Monte Carlo simulations with different inputs until we obtained the desired output.

We list the modeling assumptions and types of inputs to the sequential prediction model in Table 6.1. We used a pure sequential process; that is, we did not include feed back loops. We also considered auto trips directly; that is, we did not include modal split in this model. The introduction of modal split would cause an increase in the complexity of the problem. Other changes in the modeling assumptions could include the introduction of feed-back loops to model the effect of the estimated travel times in step 4 on trip generation, trip distribution, and traffic assignment.
<table>
<thead>
<tr>
<th>Conditional Model</th>
<th>Modeling Assumptions</th>
<th>Inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip Generation</td>
<td>Balancing Mechanism</td>
<td>Basic Production-Attraction Pattern</td>
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<td>Normal Probability Distribution of the Error in Trip Generation</td>
<td>Standard Deviation Probability Distribution of the Error in Trip Generation</td>
</tr>
<tr>
<td>Trip Distribution</td>
<td>Gravity Model</td>
<td>Gravity Model Parameters</td>
</tr>
<tr>
<td></td>
<td>Doubly Constraint Balancing Mechanism</td>
<td>Convergence Criteria Balancing Mechanism</td>
</tr>
<tr>
<td></td>
<td>Normal Probability Distribution of the Error in Trip Generation</td>
<td>Standard Deviation Probability Distribution of the Error in Trip Generation</td>
</tr>
<tr>
<td>Traffic Assignment</td>
<td>User Equilibrium Traffic Assignment with probabilistic free flow travel time</td>
<td>Network Topology</td>
</tr>
<tr>
<td></td>
<td>BPR Type Link Performance Function</td>
<td>Arc Characteristics (Free Flow Time and Practical Capacity)</td>
</tr>
<tr>
<td></td>
<td>Normal Probability Distribution of the Error in Free Flow Travel Time</td>
<td>Parameters Link Performance Function</td>
</tr>
<tr>
<td></td>
<td>Convergence Criteria</td>
<td>Standard Deviation Probability Distribution of the Error in Travel Time</td>
</tr>
<tr>
<td>Total System Travel Time</td>
<td>BPR Type Link Performance Function</td>
<td>Parameters Link Performance Function</td>
</tr>
<tr>
<td></td>
<td>Normal Probability Distribution of the Error in Travel Time</td>
<td>Standard Deviation Probability Distribution of the Error in Travel Time</td>
</tr>
<tr>
<td>Total System Fuel Consumption</td>
<td>Fuel Consumption Model from CORSIM (free flow)</td>
<td>Fuel Consumption Model Parameters (coefficients, % trucks arterials, freeways)</td>
</tr>
<tr>
<td></td>
<td>Normal Probability Distribution of the Error in Fuel Consumption</td>
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</tr>
<tr>
<td>Total System HC Emissions</td>
<td>HC Emissions Model from MOBILESa</td>
<td>HC Emissions Model Parameters (coefficients)</td>
</tr>
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<td>Normal Probability Distribution of the Error in HC Emissions</td>
<td>Standard Deviation Probability Distribution of the Error in HC Emissions</td>
</tr>
<tr>
<td>Total System CO Emissions</td>
<td>CO Emissions Model from MOBILESa</td>
<td>CO Emissions Model Parameters (coefficients)</td>
</tr>
<tr>
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<td>Normal Probability Distribution of the Error in CO Emissions</td>
<td>Standard Deviation Probability Distribution of the Error in CO Emissions</td>
</tr>
<tr>
<td>Total System NOx Emissions</td>
<td>NOx Emissions Model</td>
<td>NOx Emissions Model Parameters</td>
</tr>
<tr>
<td></td>
<td>Normal Probability Distribution of the Error in NOx Emissions</td>
<td>Standard Deviation Probability Distribution of the Error in NOx Emissions</td>
</tr>
</tbody>
</table>

Table 6.1 Modeling Assumptions and Inputs to the Prediction Model

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We observe, though, that the modified model should capture the fact that even if the traffic assignment is known with certainty, the travel times would remain uncertain due to variations among drivers, times of the day, days of the week, or months of the year.

We could also use other models within the steps. For instance, we could use discrete choice models for trip distribution, or a different fuel consumption models. That would require different input parameters and procedures, i.e., modification of the current estimation procedure.

We also assumed that the model errors are normal and unbiased, i.e., the errors in the outputs are Normal(0, \(\eta\)). Non-normality and bias could be important issues for non-linear utilities. In those cases the difference in expected utilities would change, and, consequently, the VOPI values. If bias does not depend on the alternative and the utilities are linear, it is probable that the expected utilities are simply scaled by the same amount, and VOPI would not change. Nevertheless, normality and bias would require further consideration.

Changes in the inputs would affect the numerical values of the expected utilities and VOPI. We observed the effects of variations on the network topology and basic demand (production-attraction pattern) levels in the numerical results chapters. We also tested the sensitivity to changes in the uncertainty measures. We comment some of these results in the next section.
6.2 Numerical Results Findings

The main purposes of the numerical examples was to observe the presence or absence of trends under various conditions, and to identify the practical issues of applying the prediction and VOPI calculation framework. We showed in chapters 5 and 6 the results of applying the prediction models and VOPI to a small network and an extended network for two different levels of the basic demand.

We observed that the results of VOPI were consistent with the a-priori intuition. We noted that the VOPI of the outcomes of the each step in the process are larger than the VOPI of the outcomes of the previous step. Moreover, we saw that VOPI peaks when the difference between the expected utilities of the alternatives is zero. In that case it is expected that additional information would help the most in making the right decision. We also observed that VOPI increases with the level of congestion.

In addition, we observed that the Marginal VOPI of the last step (i.e., Attribute Models) was larger than the Marginal VOPI of the other steps for almost all cases of topology, demand and expected utility. Only when we considered the extended network with high demand and the expected utilities were very close to zero we did observe that the Marginal VOPI of Traffic Assignment was larger than the Marginal VOPI of the Attribute Models. This may imply, that for most situations, a decision maker would be willing to pay more to improve the information from perfect arc volumes to perfect attributes than s/he is willing to pay to improve the information from perfect OD matrix to perfect traffic assignment.
A different way to compare the relative value of the different models is the willingness to pay to have perfect information on a given model when the inputs to this model are uncertain, which we call Model VOPI. We observed that Model VOPI is very small (close to zero) for most cases. Its value increases only when the difference in expected utilities is very close to zero. This suggests that, in general, there is no value in improving a single step in the forecasting process. Given that the VOPI of the attributes is relatively high compared with the cost of construction, it seems more appropriate to improve all the models at the same time.

In the rare case in which the expected utilities are very close to zero, the Model VOPI of Trip Distribution is larger than Model VOPI of Traffic Assignment and Model VOPI of Attribute Models. In this case, it seems better to improve the information of the early stages.

These results may depend on the preference model and prediction model assumptions and inputs. We performed a preliminary sensitivity analysis to the preference model and note that the values of the expected utilities and VOPI are fairly insensitive to most of the inputs. Only the shape parameters of the pollution emission utilities and the assumed pollution cost seem to substantially affect the results.

We also performed a preliminary sensitivity analysis to the prediction model. We observed that, for the base case utility parameters, VOPI and Marginal VOPI are most sensitive to changes in the uncertainty of the traffic assignment model, less sensitive to changes in the uncertainty of trip generation, travel time and HC pollution models, and
not sensitive to changes in the uncertainty of trip distribution, fuel consumption, CO pollution, and NOx pollution models.

Other important findings of the numerical examples are related to the practical issues of applying the sequential forecasting process and VOPI calculation. Our procedure is designed in three steps. In the first step we used series of Monte Carlo simulations to obtain the standard deviation of the errors in the conditional models that yield desired levels of uncertainty. In the second step we used these standard deviations to obtain a number of attribute vector samples. In the third step we used these attribute vector samples to calculate the expected utilities and VOPI (evaluation).

The separation of attribute vector sampling and VOPI calculation into different processes was very convenient. In this way we were required to perform the attribute vectors sampling only once. We could then use the same simulation outcome (i.e., attribute vectors samples) to calculate the expected utilities and VOPI for different costs and different preference model parameters.

For our examples we tried to simulate enough samples to produce stable estimates. We observed, though, that stability was hard to achieve; that is, we required a large number of samples from the conditional models to obtain stable uncertainty measures, expected utilities and VOPI estimates. This was especially critical for the calibration of standard deviations of the errors used in the traffic assignment model. It was also more difficult for the small network than for the extended network, probably as a result of the larger number of degrees of freedom on the latter.
We were not interested in this study in determining the optimal run length or the accuracy of the outcomes of the simulation. It would be interesting to develop statistical procedures to determine these characteristics.

The standard deviations obtained were interesting in themselves and deserve closer examination. We needed to obtain these standard deviations to get desired levels of the uncertainty measure. We recall that the uncertainty measure is a metric designed to indicate the precision of the conditional model. We observed, for example, that the standard deviations for the errors in trip generation and trip distribution were closer to the desired uncertainty measures for the large network example than for the small network example. Again, this could be the result of the number of degrees of freedom for the adjustment procedure.

6.3 Recommendations for Further Research

We have already mentioned a series of potential studies to continue the study of the value of information of transportation models. These recommended studies can be arranged into six groups: 1) sensitivity analysis using the current modeling assumptions; 2) computational aspects; 3) changes to the preference model; 4) changes in the prediction model; 5) calculation of the value of imperfect information, 6) determination of the model uncertainty measures from expert opinion.

There are several areas that could be analyzed using the current modeling assumptions. These analyses would consist on testing the sensitivity of the procedures
described here for variations in the numerical inputs. We already performed a preliminary sensitivity analysis to the preference and prediction model inputs. We concentrated on the single factor effects on the expected utilities and VOPI measures. We found that the results were very sensitive to the pollution related parameters, especially the shape parameters of the single attribute utilities. We also observe high sensitivity to changes in the uncertainty measure of traffic assignment.

We did not test for higher order effects, i.e., combined factor and quadratic effects. Testing for these effects may require additional experiments, including additional factor levels. The preliminary analysis would help in screening the factors to be considered for higher order metamodels. For instance, we could recommend to exclude the following factors: marginal rates of substitution of cost and time, fuel and time, HC and CO, and HC and NOx, and the shape parameter of the utilities of total system time and total system NOx emissions, as well as the uncertainty measure of the trip distribution model.

We also tested the effect of changing the network topology and the basic demand levels. We tried to control most of the conditions in these experiments; nevertheless, we observed that these types of changes in the inputs resulted in relatively complex responses. Additional tests of the effects of changes in demand and topology could be designed and performed, taking into account the subtle relationships. These studies would possibly confirm our preliminary numerical findings regarding the direction of changes and ordering of the VOPIs.
A second group of potential studies is concerned with the computational issues. On the one hand there is room for improvement of the computer codes to make them more efficient. On the other hand the simulation procedures are cumbersome. A study on the optimal run length and the accuracy of the outcomes of the simulation process would be required to improve the efficiency of the process and the quality of the results.

The third group of potential studies deals with changes to the preference model. We already indicated that the preference model could be obtained from actual decision makers, and that this process could be cumbersome. This would be necessary to establish whether or not the additive specification is applicable.

If the additive specification is not applicable, more general preference models would be used, for example models that account for influences of combined attributes (e.g., a multiplicative utility specification; de Neufville, 1990). These changes may result in computational changes (i.e. iterative procedures as opposed to the current single loop calculation procedure) and extra complexity (e.g., more complicated formulas to calculate the tradeoff parameters from marginal rates of substitution).

The fourth group of recommended studies concentrates on changes to the prediction model. We have mentioned changes to the modeling assumptions, for example using different models for the steps (e.g., discrete choice models for trip distribution, or different attribute prediction models), including feed-back loops (i.e., effects of travel time changes from the travel time prediction model on the previous steps), including more modeling steps (e.g., land use models, modal split models), or
using different error probability distributions (e.g., non-normal, biased errors). These changes would affect the complexity of the problem.

The fifth group of recommended studies includes the development of mechanisms to calculate the value of imperfect information (VOII) or alternatively, the value of reducing the uncertainty level. We introduced VOII for the simplest corridor as the cost that the decision maker would be willing to pay for a study that would provide information with a given level of uncertainty. The application of this concept to the sequential forecasting process seems subtle. It would require, for example, the definition of metrics to indicate the degree of imperfection. Nevertheless, it would provide very interesting comparative information for investment on the development of transportation models.

Last, but not least, there is an important input to the prediction process that requires study. That is the actual values of the uncertainty measures. We consider that these measures can be obtained from expert opinion. Nevertheless, their assessment may not be easy. Laosirihongtong (1995) has proposed mechanisms to find subjective probability distributions for the outcomes of the four-step process and is currently performing interviews of different transportation experts to assess them. These distributions could potentially lead to expert-opinion-based uncertainty measures.
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APPENDIX A

FUEL CONSUMPTION AND POLLUTION EMISSION MODELS

In this appendix we provide some details on the fuel consumption and pollution emission models used in the sequential prediction process (Chapter 3). These models were estimated from fuel consumption tables within CORSIM (FHWA, 1996) and emission tables estimated through MOBILE5a (US-EPA, 1996). We used these tables to fit polynomial equations on the speed for different types of vehicles (fuel) and types of roads (emissions).

A.1 Fuel Consumption Models

CORSIM (FHWA, 1995) is a traffic simulation software widely used in the design and evaluation of traffic operations such as single intersection signals and area traffic control systems. The main measure of performance provided by CORSIM is the total system vehicle delay. It also is able to provide total system fuel consumption and pollutant emissions. For this, the software uses fuel and emission consumption tables as a function of speed, acceleration, and vehicle type. The user can choose from default tables and user defined tables.
The default tables are provided for three vehicle types, a range of speed varying from 0 to 70 miles/hour and a range of acceleration varying from -10 feet/sec/sec to +10 feet/sec/sec. We extracted the tables using one of the printing options of the software. Specifically, we set the option to print the fuel and emission tables to one, and ran a small example (i.e. single intersection). The output of the example was given in a plain text file that we used to extract the tables for fuel for the desired vehicle types, speed range and acceleration level.

For our study we used two vehicle types: automobiles and trucks, and the full speed range provided in the tables. We also used an acceleration of 0 feet/sec/sec, which was consistent with the steady state assumption of the traffic assignment procedure used to determine the arc volumes (Chapter 3).

We imported the text file containing the fuel table to a spreadsheet with regression capabilities (MS-EXCEL 7.0) and created tables containing the speed \( s \), \( s_2 \), \( s_3 \), \( s_4 \) and the fuel consumption for an acceleration equal to 0 feet/sec/sec (Table A.1). Then we run standard least square regression procedures for the specification:

\[
F = \beta_0 + \beta_1 s_a + \beta_2 s_a^2 + \beta_3 s_a^3 + \beta_4 s_a^4, \quad \text{(A1)}
\]

where \( F \) is the Fuel Consumption \([10^{-4} \text{ gal/sec}]\), \( s_a \) is the speed \([\text{miles/hour}]\), and \( \beta_i \), \( i=0,\ldots,4 \), are the equation parameters to be estimated. The summary output of the regression procedure for Auto and Trucks is provided in Table A.2.
The fuel consumption models are then given by:

\[ FA_a = 14.4525 + 0.0038751s_a + 0.020496 s_a^2 - 0.000376 s_a^3 + 0.000022845 s_a^4; \quad (A.2a) \]
\[ FT_a = 25.0947 + 4.24873 s_a - 0.17624 s_a^2 + 0.0036927 s_a^3 - 0.00002266 s_a^4; \quad (A.2b) \]

where \( FA_a \) and \( FT_a \) are the fuel consumed by an automobile and a truck, respectively, traveling at an average speed equal to \( s_a \) miles/hour. In Figures A1.1 and A1.2 we display the fuel consumption as a function of speed for autos and trucks respectively according to the data from CORSIM (FHWA, 1995) shown in Table A.1 and the estimation equations (A.2).

A.2 Pollution Emission Models

We extract the pollution emission models from the outputs of MOBILE5a (US-EPA, 1995). This software is used to establish the pollution emissions from mobile sources for evaluation of transportation projects and air quality attainment determination of transportation programs and plans (see chapter 1). The inputs of the program include, among others, the fleet composition, the proportion of cold starts, the usage of different fuels, and temperature ranges. We used outputs generated with characteristics corresponding to Columbus, Oh, in 1996, as provided by staff members of the Mid-Ohio Regional Planning Commission. The basic input file used to generate the factors is presented in Figure A.3.
The output file contains hydro-carbons (HC), carbon monoxide (CO) and Nitrous-Oxides (NOx) emission factors in [grams/mile] as a function of speed for two types of roads: freeways and arterials, and each one of the hours of the day. We chose 8:00-9:00 am as the peak-hour; hence, we extracted the outputs corresponding to this hour from the output files of MOBILE5a.

Again, the output data was imported to a spreadsheet with regression capabilities (MS-EXCEL 7.0), where we created a tables containing the speed \( s_a, s_a^2, s_a^3, s_a^4, s_a^5 \) and the emission factors for each one of the pollutants and road types (Table A.3). Then we run standard least square regression procedures for the specifications:

\[
HC = \beta_0 + \beta_1 s_a + \beta_2 s_a^2 + \beta_3 s_a^3 + \beta_4 s_a^4 ,
\]

(A.3a)

\[
CO = \beta_0 + \beta_1 s_a + \beta_2 s_a^2 + \beta_3 s_a^3 + \beta_4 s_a^4 ,
\]

(A.3b)

\[
NOx = \beta_0 + \beta_1 s_a + \beta_2 s_a^2 + \beta_3 s_a^3 + \beta_4 s_a^4 + \beta_5 s_a^5
\]

(A.3c)

where \( HC, CO \) and \( NOx \) are the emissions of each pollutant [grams/mile], \( s_a \) is the speed [miles/hour], and \( \beta_i, i=0,...,5 \), are the equation parameters to be estimated. The summary output of the regression procedure for each pollutant, arterials and freeways is provided in Tables A.4, A.5, and A.6 for HC, CO, and NOx respectively.

The pollution emission models are then given by:

\[
HC_{fa} = 4.47291567 - 0.22554054 s_a + 0.00650787 s_a^2 - 9.5662E^{-5} s_a^3 + 5.7207E^{-7} s_a^4 , \quad (A.4a)
\]
\[ HC_{2a} = 5.53680395 - 0.2860775s_a + 0.00830099s_a^2 - 1.2115E^{-4}s_a^3 + 7.1416E^{-7}s_a^4; \quad (A.4b) \]
\[ CO_{1a} = 46.52000643 - 2.07396692s_a + 0.04755901s_a^2 - 7.0355E^{-4}s_a^3 + 5.1987E^{-6}s_a^4; \quad (A.4c) \]
\[ CO_{2a} = 55.4032011 - 2.52101554s_a + 0.05919692s_a^2 - 8.7213E^{-4}s_a^3 + 6.3032E^{-6}s_a^4; \quad (A.4d) \]
\[ NOx_{1a} = 3.08717843 - 0.24136138s_a + 0.01462959s_a^2 - 4.26E^{-4}s_a^3 + 5.8585E^{-6}s_a^4 - 2.953E^{-8}s_a^5; \quad (A.4e) \]
\[ NOx_{2a} = 3.19685831 - 0.2505566s_a + 0.015923026s_a^2 - 4.74E^{-4}s_a^3 + 6.6012E^{-6}s_a^4 - 3.372E^{-8}s_a^5; \quad (A.4f) \]

where \( HC_{1a} \) and \( HC_{2a} \) are the HC pollution emissions; \( CO_{1a} \) and \( CO_{2a} \) are the CO pollution emissions, and \( NOx_{1a} \) and \( NOx_{2a} \) are the NOx pollution emissions as a function of speed \( s_a \) for arterials (1) and freeways (2), respectively.

We plot the data and the estimated models of pollution emission in figures A.4, A.5 and A.6 for HC, CO, and NOx, respectively. We note that HC and CO emission rates decrease with speed in the range 10-55 mph, and increase with seed when the speed is greater than 55 mph. We also note that the NOx emission rates are slightly decrease with speed when speed is less than 20 mph, slightly increase with speed when speed is between 20 and 50 mph and have a larger increase when speed is larger than 50 mph.
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Table A.1. Fuel Consumption Table
Table A.1 continued

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Source: CORSIM Traffic Simulation Software (FHWA, 1995) default fuel consumption tables for 0 feet/sec/sec
### Dependent Variable = Fuel Consumption Auto

**Regression Statistics**

| Multiple R | 0.9863849 |
| R Square   | 0.97295516 |
| Adjusted R Sq. | 0.97131608 |
| Standard Error | 1.44097332 |
| Observations | 71 |

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**Regression Statistics**

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| Adjusted R Sq. | 0.97926941 |
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Table A.2 Summary Output Regression Procedure for Fuel Consumption
Figure A.1 Fuel Consumption Automobiles

Figure A.2 Fuel Consumption Trucks
Figure A.3 Input File for MOBILE5a

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Source: Mid-Ohio Regional Planning Commission, 1996
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Table A.3 Pollution Emissions Table
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Source: Output of MOBILESa for Columbus, OH, characteristics.
### Dependent Variable = HC Arterial

**Regression Statistics**

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**ANOVA**

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<th>F</th>
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<tr>
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**Coefficients**

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### Dependent Variable = HC Freeway

**Regression Statistics**

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**ANOVA**

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**Coefficients**

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Table A.4 Summary of the Output of the Regression Procedures for HC
### Dependent Variable = CO Arterial

#### Regression Statistics

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#### ANOVA

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#### Coefficients

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### Dependent Variable = CO Freeway

#### Regression Statistics

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#### ANOVA

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#### Coefficients

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Table A.5 Summary of the Output of the Regression Procedures for CO
### Table A.6 Summary Output of the Regression Procedures for NOx

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<th>t Stat</th>
<th>P-value</th>
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<th>Upper 95%</th>
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Table A.6 Summary Output of the Regression Procedures for NOx

205
Figure A.4 HC Emission Rates as a Function of Speed

Figure A.5 CO Emission Rates as Function of Speed
Figure A.6 NOx Emission Rates as Function of Speed
APPENDIX B

COMPUTER IMPLEMENTATION

The prediction process and the value of perfect information (VOPI) calculation mechanisms were coded in FORTRAN 77 and implemented in a IBM 3270 Mainframe. This appendix includes listings of these computer programs. It also includes examples of inputs and outputs to and from these programs.

B.1 Prediction Process

The program used to generate random samples of the attribute vectors depending on the link volumes is listed in Figure B.1. The inputs to this program are the basic production-attraction vector and gravity model parameters (Figure B.2); the network topology and characteristics (Figures B.3); and the standard deviations in the errors and the number of samples of and from each conditional mode (Figure B.4).

The production-attraction vectors and gravity model parameters listed in Figure B.2 correspond to a portion of the low level of demand file considered for the extended network example (chapter 5). The first row indicates the number of centroids \((r=s=42)\). Rows 2-43 are organized as follows: column 1 is the production vector \((O^)\); column 2 is
the attraction vector \( (D_j) \); column 3 is the \( A \) parameter of the gravity model, and column 4 is the \( B \) parameter of the gravity model. The remaining rows (44-1808) contain the 1764 impedance factors \( F_{\alpha} \) of the gravity model. These factors are listed sequentially by rows and then by columns of the impedance matrix. Only few entries of this matrix are shown.

A portion of the network topology and characteristics file listed in Figure B.3 corresponds to the No-Build network used in the extended network example. The first three lines indicate the number of links, number of centroids and number of nodes, respectively. Lines 14-17 provide labels to the nodes. The remaining lines (18-417) the link characteristics and network topology structure: column 1 is the length of the link in miles; column 2 is the label of the end node of the link; column 3 is the free flow travel time in minutes; column 4 is the practical capacity in vehicles/hour; column 5 is the label for the link performance function; and column 6 is the forward star vector. Only a portion of the file is listed.

The scenario file listed in Figure B.4 correspond to a level of 15 samples for each conditional model and yields uncertainty measures \( UM^{(cm)}=0.25 \), \( cm=1,\ldots,8 \), for the low demand (Figure B.2) case. The first row in this file indicates the number of samples to generate of the production-attraction (PA) vectors and the origin-destination (OD) matrices conditioned on each PA pattern (15). Row 2 and 3 are the standard deviations in the errors in trip generation and trip attraction. The same error in generation and attraction was used in the illustrative applications (0.2159). Row 4 is the standard deviation in the error in trip distribution (0.24798). Row 5 is the maximum number of iterations for the
traffic assignment program (10). Row 6 the number of link volumes sampled for each one of the OD matrices. In Row 7 two figures are provided indicating the estimated percent of autos in arterials and freeways, respectively.

We also list the job file required to run the program on the IBM 3270 Mainframe (Figure B.5). This job file includes the maximum time allocated to use the program (90.0 min), the name of the code file (SIMULA.FOR) the names of the input files (DEMAND.DAT, NETWORK.DAT, SCENARIO.DAT, for the basic production-attraction pattern and gravity model parameters file, network file, and scenario file, respectively), and the names of the output files (GENATTR.OUT, TRAASSIG.OUT, ATTRIBUTE.OUT for the generation-attraction/distribution steps, traffic assignment step and attribute generation step, respectively). It also includes Job Control Language (i.e. the operational system commands for the IBM 3270 Mainframe) instructions that indicate the characteristics of the input and output files, and compilation options.

We list portions of the output files for the trip generation and trip distribution steps (Figure B.6); traffic assignment step (Figure B.7) and attribute prediction step (Figure B.8).

The output file of the trip generation and trip distribution step (Figure B.6) contains intermediate and final calculations of the uncertainty measure of the trip generation model and the trip distribution model. The first row indicates the number of samples for each of the two steps (15). The second row show three figures: the uncertainty measure for the trip production cells, the uncertainty measure for the trip attraction cells, and the average between the first two. This number is the uncertainty
measure for the trip generation step. Rows 3-18 show the uncertainty measure of trip
distribution conditioned on each trip generation pattern (e.g.; 0.2471 for the pattern 1, and
0.2470 for pattern 15). Row 19 shows the average between the conditional uncertainty
measure for the 15 trip production-attraction patterns (0.2469).

The output of the traffic assignment step (Figure B.7) contains information for the
calculation of the uncertainty measure of traffic assignment, the uncertainty measure and
the average volume/capacity ratio. The first rows (1-5985) contain five columns. These
rows contain link information for the 15 samples of the traffic volumes conditioned on
the first sampled OD matrix (i.e., 15 times 399 links). Column 1 is the link label (see for
example link 398), column 2 the sampled flow (61.00), column 3 the sampled link travel
time (5.32536), column 4 the link travel time plus a random error in travel time (4.886,
i.e., first sample for attributes distribution) and column 5 the volume/capacity ration
(0.0266118). The following rows, (i.e., 5986-6000), contain the uncertainty measure of
traffic assignment and the standard deviation of this uncertainty measure across all the
links conditioned on the 15 OD matrix for the first PA pattern (e.g., 0.2216 and 0.4671
for OD 1). Rows 6001-6015 contain the uncertainty measures of traffic assignment and
the standard deviation of these uncertainty measures across OD matrices for each PA
pattern (e.g., 0.2239 and 0.0149 for PA 1) . The next to last row (6016) contains the
uncertainty measure of TA (0.2287) and the standard deviation of this measure across the
PA patterns (0.0141). The last row (6017) contains the average volume/capacity ratio
(1.3765) across all the realizations of PA, OD and flows, and links (excluding centroid
connectors).
The attributes file (Figure B.8) contains the number of repetitions of each step (15). The following rows contain the attributes depending on the volumes estimation. Column 1 is a sample of the total system travel time (i.e., 210965.0 for the first sample); column 2 is a sample of the total system fuel consumption (i.e., 42236.3); column 3 a sample of the total system HC emissions (i.e., 1620.8), column 4 a sample of the total system CO emissions (i.e., 14934.9); and column 5 a sample of the total system NOx emissions.

B.2 Expected Utilities and VOPI Calculation

The program used for expected utilities and VOPI calculation is presented in Figure B.9. The inputs to VOPI calculation are an input file (Figure B.10), an extremes and averages file (Figure B.11), and the attribute files (from the prediction process for the two alternatives (No-Build and Build), like the one shown in Figure B.8.

The input file to VOPI calculation (Figure B.10) contains information for the determination of the tradeoff parameters (row 1), the shape parameters of the utility functions (row 2), the tradeoff parameters for emission utilities (row 3), the expected cost of construction (row 4) and the maximum cost of construction (row 5). It provides the option to calculate model VOPI (row 10; 1 do not calculate Model VOPI, 2 calculate Model VOPI). If Model VOPI is calculated, the number of samples for its calculation shall be provided (rows 6, 7 and 8, for Model VOPI in trip distribution, traffic assignment and attribute models, respectively). Also, the tradeoff parameters may be provided
externally (row 9). If option 1 is provided, the program will calculate the tradeoffs using
the marginal rates of substitution provided in row 1; if option 2 is provided the program
will use the tradeoff parameters provided in row 11.

The extremes and averages file (Figure B.11) contains the maximum and
minimum for each attribute (excluding cost) and the averages to calculate the marginal
rate of substitution when the utilities are not linear (see discussion in section 4.1).
Column 1 corresponds to total system travel time, column 2 corresponds to total system
fuel consumption, and columns 3, 4 and 5 correspond to HC, CO, and NOx total system
emissions respectively. To obtain the extremes we use attribute vectors files generated
under exceptional conditions (i.e., high or low demand and high uncertainty).

The job file to use the expected utilities and VOPI calculation program in the IBM
3270 Mainframe computer is shown in Figure B.12. This file contains the control
commands and the names of program file (VOPIALL.FOR) and the input and output
files. Input files are MAXMIN.OUT, ATTRIBU1.OUT, ATTRIBU2.OUT, and
INPUT.DAT, which correspond to the extremes and averages file, the No-Build attributes
file, the Build attributes file and the input file, respectively. The output file (VOPI.OUT)
contains the input data, extremes, expected utilities, and VOPI calculations.

An example of an output file is provided in Figure B.14. The first rows replicate
the data from the input file (i.e., marginal rates of substitution, shape parameters, tradeoff
for emissions preference model, cost build alternative, maximum cost, number of samples
for Model VOPI calculation, and options chosen for tradeoff calculation and Model VOPI
calculation). The next rows replicate the extremes and average inputs (see Figure B.11).
Then, the tradeoff parameters, total system travel time, total system fuel consumption, utility of pollution emissions and cost, are shown. In this output file the expected utility of Build is 0.921918 and the expected utility of No Build 0.914611. The expected utility of no test is the maximum between these values, i.e., 0.921918. The VOPI of Attributes is 24.4335, the VOPI on the flow patterns is 7.4246, the VOPI of the OD matrix is 4.0580, and the VOPI of trip generation (production-attraction patterns) is 0.3238.

A special program (Figure B.14) is used to obtain extremes and averages to use as input to VOPI calculation. The file used as input to VOPI calculation has the same layout than the output of the extremes calculation program (Figure B.11); nevertheless, it is actually formed from various sources and edited by hand. The Job file to use the extremes and averages calculation program is shown in Figure B.15. The extremes and averages calculation program (MAXMIN.FOR) uses two sets of attributes (ATTRIBU1.DAT, ATTRIBU2.DAT). The output, which is similar to Figure B.11, displays the maximum and minimum of each attribute across all the attributes samples and the averages for the first attribute set and the second attribute set.
MONTECARLO SIMULATION TRIP GENERATION, TRIP DISTRIBUTION, TRAFFIC ASSIGNMENT AND ATTRIBUTES (TIME, FUEL, EMISSIONS)

COMMON /FRS/ FRS
COMMON /TFRS/ TFRS
COMMON /OD/ O, D
COMMON /ARCDT/ TOO, L, C, V, FL, COST, TTIME, NEWT, TLTT
COMMON /ODDT/ TOD, AMT
COMMON /FST/ FS, ODLK
COMMON /ALBET/ ALP, BET, ALP1, TYP
COMMON /ID/ IDNODE

COMMON /DMPDT/ NDMP, DMP, NREA, NREB, AA, AB, NRATT, SETI, SEFU, SECO, SEHC, SENOX
REAL L(IOOO), C(IOOO), V(IOOO), FL(IOOO), COST(IOOO), NFL(IOOO)
REAL ALP(18), BET(18), ALP1(18), VCR(1000)
REAL TTIME(IOOO), NEWT(IOOO), TLTT(IOOO), TTIM(IOOO)
INTEGER TOO(IOOO), FS(IOOO), TYP(IOOO), VC1(IOOO), VC2(IOOO)
INTEGER IDNODE(IOOO), ODLK(2000), DMP(101), TOD(2500)
REAL ETA(3), ETG(3), EOD(3), EAS(3), P(10), A(100)
REAL FRS(2500, 1000), TFRS(2500, 1000)
REAL AMT(2500)
DOUBLE PRECISION FJ(2500), AK(100), BK(100)
REAL O(100, 1000), D(IOOO, 1000), SUO(100), SUD(100)
REAL MO(100), MD(IOOO), SDQ(100), SD(100)
REAL MOD(2500), SUOD(2500), SDL(2500), CVO(1000), CVD(IOOO)
REAL FLOW(500, 1000), SFLOW(1000), MDL(100), SFL(1000)
REAL SSFL, CVFLOW(IOOO)
REAL SSSTA(IOOO), SSSTA(IOOO)
REAL RA(100), RB(100)
DOUBLE PRECISION VCRAT
EXTERNAL RNSET, RNUNF, RNNOF, RNGET

READ SCENARIO: NUMBER OF REPETITIONS, PROBABILITIES
READ(12,*) NREPE
WRITE (22,*) NREPE
READ(12,*) SDPR
READ(12,*) SDAT
READ(12,*) SDII
READ(12,*) NDMP
READ(12,*) NRATA
READ(12,*) SDAS
READ(12,*) AA, AB
READ(12,*) NRATT
READ(12,*) SETI, SEFU, SECO, SEHC, SENOX
WRITE (33,*) NREPE, NRAT, NRATT

READ PRODUCTIONS, ATTRACTIONS, PARAMETERS GRAVITY MODEL
READ(11,*) NCENT
DO 3108 I= 1, NCENT
   READ(11,3119) P(I), A(I), AK(I), BK(I)
3108 CONTINUE

continued

Figure B.1 Computer Program for Random Sampling of Attribute Vectors
DO 3109 I=1, NCENT*NCENT
   READ(11,3121) FIJ(I)
3109 CONTINUE
3119 FORMAT(2F10.2,F13.10,F10.7)
3121 FORMAT(F14.12)
READ(13,*) NARC
READ(13,*) NCENT
READ(13,*) NNOD
WRITE(*,*) '"# OF ARCS =', NARC
WRITE(*,*) '"# OF CENTROIDS =', NCENT
WRITE(*,*) '"# OF NODES =', NNOD
DO 810 I = 1, NNOD/11+1
READ(13,811) (IDNODE((I-1)*11+IJ),IJ=1,11)
811 format(11l6)
810 continue
   ALP(7) = 0.15
   BET(7) = 4.
   ALP(I) = 0.15
   DO 20 I = 1,51
      DMP(I) = I - 1
   CONTINUE
   DO 21 I = 1, NARC
      READ(13,100,END=10000) TOO(I),L(I),TTIM(I),C(I),TYP(I),FS(I)
      WRITE(*,100) TOO(I),L(I),TTIM(I),C(I),TYP(I),FS(I)
   CONTINUE
   DO 3110 I = 2, NCENT
      ODLK(I) = ODLK(I-1) + NCENT
      ODLK(NCENT+1) = ODLK(NCENT) + NCENT
   CONTINUE
   TRIP GENERATION/ATTRACTION MODEL
   CALL RNSET(10000)
   DO 3159 NREA=1,NREPE
      TO=0
      TD=0
   CONTINUE
   DO 3140 J=1,NCENT
      EP=1+SDPR*NNOD()
      IF(EP.LE.0) EP=0.00001
      EA=1+SDAT*NNOD()
      IF(EA.LE.0) EA=0.00001
      O(J,NREA)=P(J)*EP
      D(J,NREA)=A(J)*EA
      TO=TO+O(J,NREA)
      TD=TD+D(J,NREA)
   DO 3140 continue
Figure B.1 continued

3140    CONTINUE
C
3150    BALANCING ORIGINS AND DESTINATIONS
C
3151    \( TT = (TO + TD) / 2 \)
3152    \( PO = TO / TT \)
3153    \( PD = TD / TT \)
3154    DO 3150 J=1,NCENT
3155        \( O(J,NREA) = O(J,NREA) / PO \)
3156        \( D(J,NREA) = D(J,NREA) / PD \)
3157    C
3158    WRITE (22,*), J, O(J,NREA), D(J,NREA)
3159    CONTINUE
C
3160    SUMMARY STATISTICS
C
3161    \( SSO = 0 \)
3162    \( SSD = 0 \)
3163    \( COUNTO = 0 \)
3164    \( COUNTD = 0 \)
3165    DO 3160 J=1,NCENT
3166        \( SUO(J) = 0 \)
3167        \( SUD(J) = 0 \)
3168    DO 3161 NREA=1,NREPE
3169        \( SUO(J) = SUO(J) + O(J,NREA) \)
3170        \( SUD(J) = SUD(J) + D(J,NREA) \)
3171    CONTINUE
C
3172    CONTINUE
C
3173    \( MO(J) = SUO(J) / NREPE \)
3174    \( MD(J) = SUD(J) / NREPE \)
3175    IF (MO(J).NE.0) GOTO 1001
3176        \( SDO(J) = 0 \)
3177        \( CVO(J) = 0 \)
3178        \( COUNTO = COUNTO + 1 \)
3179        GOTO 1003
3180    GOTO 1001
1001    \( SUO(J) = 0 \)
1002    DO 1002 NREA=1,NREPE
1003    \( SDD(J) = (SUO(J) / (NREPE-1)) ** 0.5 \)
1004    \( SDO(J) = (SUO(J) / (NREPE-1)) ** 0.5 \)
1005    \( CVO(J) = SDO(J) / MO(J) \)
1006    \( SSO = SSO + CVO(J) \)
1007    \( CVDO(J) = 0 \)
1008    \( COUNTD = COUNTD + 1 \)
1009    GOTO 1003
C
1010    CONTINUE
C
1011    \( SDD(J) = (SDD(J) / (NREPE-1)) ** 0.5 \)
1012    \( SDO(J) = (SDD(J) / (NREPE-1)) ** 0.5 \)
1013    \( CVDO(J) = SDO(J) / MD(J) \)
1014    SSD=SSD+CVO(J)
1015    SSD=SSD+CVD(J)
1016
continued
Figure B.1 continued

CONTINUE
WRITE(22,3169) J, MO(J), SDO(J), MD(J), SDD(J), CVO(J), CVD(J)
FORMAT(I6,4F10.2,2F10.4)
SSO=SSO/(NCENT-COUNTO)
SSD=SSD/(NCENT-COUNTD)
ASS=(SSO+SSD)/2
WRITE(22,*)
WRITE(22,3164) SSO, SSD, ASS
FORMAT('AVERAGE SIGMA/MU: SSO',F10.4,' SSD',F10.4,F10.4)
TRIP DISTRIBUTION MODEL
SSSOD=0
SSSSTA=0
DO 3333 NREA=1,NREPE
SSSTA(NREA)=0
CONTINUE
NSEED=20000
VCRAT=0
VCRTTTT=0
DO 3300 NREA=1,NREPE
CALL RNSET(NSEED)
TO=0
TD=0
WRITE(22,*)'FLOWS FROM GRAVITY MODEL'
DO 3170 J=1,NCENT
DO 3170 K=1,NCENT
FRS(K+NCENT*(J-1),NREA) =AK(J)*O(J,NREA)
*BK(K)*D(K,NREA)*FIJ(K+NCENT*(J-1))
IF(FRS(K+NCENT*(J-1),NREA).NE.0)
CONTINUE
WRITE(22,*)
CONTINUE
WRITE(22,*)
BALANCING OF THE O-D MATRIX
CV=0.051
IT=1
3175 IF(IT.EQ.21) GOTO 3185
IF(CV.LT.0.02) GOTO 3185
CV=0.019
DO 3168 J=1,NCENT
TO=0
IF(O(J,NREA).LT.0.01) GOTO 3168
DO 3167 K=1,NCENT
TO=TO+FRS(K+NCENT*(J-1),NREA)
CONTINUE
PT=TO/O(J,NREA)
IF(ABS(PT-1).LT.CV) CV=ABS(PT-1)
DO 3171 K=1,NCENT
FRS(K+NCENT*(J-1),NREA) =FRS(K+NCENT*(J-1),NREA)/PT
continued
Figure B.1 continued

<table>
<thead>
<tr>
<th>Line</th>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>3171</td>
<td>CONTINUE</td>
<td>00211000</td>
</tr>
<tr>
<td>3168</td>
<td>CONTINUE</td>
<td>00212000</td>
</tr>
<tr>
<td>3174</td>
<td>DO 3174 K=1,NCENT</td>
<td>00213000</td>
</tr>
<tr>
<td></td>
<td>TD=0</td>
<td>00214000</td>
</tr>
<tr>
<td></td>
<td>IF(D(K,NREA).LT.0.01) GOTO 3174</td>
<td>00215000</td>
</tr>
<tr>
<td></td>
<td>DO 3172 J=1,NCENT</td>
<td>00216000</td>
</tr>
<tr>
<td></td>
<td>TD=TD+FRS(K+NCENT*(J-1),NREA)</td>
<td>00217000</td>
</tr>
<tr>
<td>3172</td>
<td>CONTINUE</td>
<td>00218000</td>
</tr>
<tr>
<td></td>
<td>PT=TD/D(K,NREA)</td>
<td>00219000</td>
</tr>
<tr>
<td></td>
<td>IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)</td>
<td>00220000</td>
</tr>
<tr>
<td></td>
<td>DO 3173 J=1,NCENT</td>
<td>00221000</td>
</tr>
<tr>
<td></td>
<td>FRS(K+NCENT*(J-1),NREA)=FRS(K+NCENT*(J-1),NREA)/PT</td>
<td>00222000</td>
</tr>
<tr>
<td>3173</td>
<td>CONTINUE</td>
<td>00223000</td>
</tr>
<tr>
<td>3174</td>
<td>CONTINUE</td>
<td>00224000</td>
</tr>
<tr>
<td></td>
<td>IT=IT+1</td>
<td>00225000</td>
</tr>
<tr>
<td></td>
<td>GOTO 3175</td>
<td>00226000</td>
</tr>
<tr>
<td>3185</td>
<td>CONTINUE</td>
<td>00227000</td>
</tr>
<tr>
<td></td>
<td>WRITE(22,*)</td>
<td>00228000</td>
</tr>
<tr>
<td></td>
<td>C WRITE(22,*) 'ESTIMATED FLOWS (WITHOUT ERROR)'</td>
<td>00229000</td>
</tr>
<tr>
<td></td>
<td>C DO 3301 J=1,NCENT</td>
<td>00230000</td>
</tr>
<tr>
<td></td>
<td>C DO 3301 K=1,NCENT</td>
<td>00231000</td>
</tr>
<tr>
<td></td>
<td>C IF(FRS(K+NCENT*(J-1),NREA).NE.0) WRITE(22,*) J,K</td>
<td>00232000</td>
</tr>
<tr>
<td></td>
<td>C FRS(K+NCENT*(J-1),NREA)</td>
<td>00233000</td>
</tr>
<tr>
<td>3301</td>
<td>CONTINUE</td>
<td>00234000</td>
</tr>
<tr>
<td></td>
<td>C SAMPLING OF ERROR IN TRIP DISTRIBUTION MODEL</td>
<td>00235000</td>
</tr>
<tr>
<td></td>
<td>C WRITE(22,*)</td>
<td>00236000</td>
</tr>
<tr>
<td></td>
<td>C DO 3210 NREB=1,NREPE</td>
<td>00237000</td>
</tr>
<tr>
<td></td>
<td>C WRITE(22,*) 'FLOWS AFTER ERROR IN DISTRIBUTION W/O BALANCE'</td>
<td>00238000</td>
</tr>
<tr>
<td></td>
<td>C DO 3192 J=1,NCENT</td>
<td>00239000</td>
</tr>
<tr>
<td></td>
<td>C DO 3191 K=1,NCENT</td>
<td>00240000</td>
</tr>
<tr>
<td></td>
<td>C EF=RNNOF() SDDI+1</td>
<td>00241000</td>
</tr>
<tr>
<td></td>
<td>C IF(EF.LE.0) EF=0.00001</td>
<td>00242000</td>
</tr>
<tr>
<td></td>
<td>C TFRS(K+NCENT*(J-1),NREB)=FRS(K+NCENT*(J-1),NREA)*EF</td>
<td>00243000</td>
</tr>
<tr>
<td></td>
<td>C IF(TFRS(K+NCENT*(J-1),NREB).NE.0)</td>
<td>00244000</td>
</tr>
<tr>
<td></td>
<td>C WRITE(22,<em>) J,K,TFRS(K+NCENT</em>(J-1),NREB)</td>
<td>00245000</td>
</tr>
<tr>
<td>3191</td>
<td>CONTINUE</td>
<td>00246000</td>
</tr>
<tr>
<td>3192</td>
<td>CONTINUE</td>
<td>00247000</td>
</tr>
<tr>
<td></td>
<td>C ADJUSTMENT FOR CONSERVATION OF ORIGINS AND DESTINATIONS</td>
<td>00248000</td>
</tr>
<tr>
<td></td>
<td>C TO=0</td>
<td>00249000</td>
</tr>
<tr>
<td></td>
<td>TD=0</td>
<td>00250000</td>
</tr>
<tr>
<td></td>
<td>CV=0.021</td>
<td>00251000</td>
</tr>
<tr>
<td></td>
<td>IT=1</td>
<td>00252000</td>
</tr>
<tr>
<td>3193</td>
<td>IF(IT.GT.50) GOTO 3205</td>
<td>00253000</td>
</tr>
<tr>
<td></td>
<td>IF(CV.LT.0.02) GOTO 3205</td>
<td>00254000</td>
</tr>
<tr>
<td></td>
<td>CV=0.019</td>
<td>00255000</td>
</tr>
<tr>
<td></td>
<td>DO 3198 J=1,NCENT</td>
<td>00256000</td>
</tr>
<tr>
<td></td>
<td>IF(0(J,NREA).LT.0.01) GOTO 3198</td>
<td>00257000</td>
</tr>
<tr>
<td></td>
<td>DO 3197 K=1,NCENT</td>
<td>00258000</td>
</tr>
</tbody>
</table>

continued
TO=TO+TFRS(K+NCENT*(J-1),NREB) 00263000
3197 CONTINUE 00264000
PT=TO/O(J,NREA) 00265000
IF(ABS(PT-1)>CV) CV=ABS(PT-1) 00266000
DO 3200 K=1,NCENT 00267000
TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT 00268000
3200 CONTINUE 00269000
TO=0 00270000
3198 CONTINUE 00271000
3199 DO 3201 K=1,NCENT 00272000
700 DO 3202 J=1,NCENT 00273000
 TD=TD+TFRS(K+NCENT*(J-1),NREB) 00274000
700 CONTINUE 00275000
PT=TD/D(K,NREA) 00276000
IF(ABS(PT-1)>CV) CV=ABS(PT-1) 00277000
DO 3203 J=1,NCENT 00278000
TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT 00279000
3203 CONTINUE 00280000
TD=0 00281000
3201 CONTINUE 00282000
IT=IT+1 00283000
GOTO 3193 00284000
3205 CONTINUE 00285000
C WRITE(22,* ) 00286000
C WRITE(22,* ) ' FLOWS AFTER ERROR IN DISTRIBUTION WITH BALANCE' 00287000
C DO 3206 J=1,NCENT 00288000
C DO 3206 K=1,NCENT 00289000
C IF(TFRS(K+NCENT*(J-1),NREB)-NE.0) WRITE(22,* ) J,K, 00290000
C * TFRS(K+NCENT*(J-1),NREB) 00291000
C3206 CONTINUE 00292000
C WRITE (22,* ) 00293000
C WRITE (22,* ) 00294000
C 3210 CONTINUE 00295000
C 00296000
C CALCULATION OF SUMMARY STATISTICS 00297000
C 00298000
C CALL RNGET( NSEED) 00299000
SSOD=0 00300000
CNTOD=0 00301000
DO 3211 J=1,NCENT 00302000
DO 3211 K=1,NCENT 00303000
SUOD(K+NCENT*(J-1))=0 00304000
SDOD(K+NCENT*(J-1))=0 00305000
3211 CONTINUE 00306000
DO 3230 NREB=1,NREPE 00307000
DO 3230 J=1,NCENT 00308000
DO 3230 K=1,NCENT 00309000
SUOD(K+NCENT*(J-1))=SUOD(K+NCENT*(J-1)) 00310000
* TFRS(K+NCENT*(J-1),NREB) 00311000
3230 CONTINUE 00312000
C WRITE (22,* ) 00313000
C WRITE (22,* ) ' AVERAGE FLOWS' 00314000
DO 3240 J=1,NCENT 00315000
continued
Figure B.1 continued

```
DO 3240 K = 1, NCENT
MOD(K+NCENT*(J-1)) = SUOD(K+NCENT*(J-1))/NREPE
IF(MOD(K+NCENT*(J-1)).LT.0.01) GOTO 3240
C WRITE(22,*) J, K, MOD(K+NCENT*(J-1))
DO 3239 NREB = 1, NREPE
   SDOD(K+NCENT*(J-1)) = SDOD(K+NCENT*(J-1)) +
   (TFRS(K+NCENT*(J-1), NREB) - MOD(K+NCENT*(J-1))) ** 2
3239 CONTINUE
3240 CONTINUE
C WRITE(22,*) 'STANDARD DEVIATION AND SIGMA/MU'
DO 3250 J = 1, NCENT
   DO 3250 K = 1, NCENT
      IF(SDOD(K+NCENT*(J-1)).NE.0) GOTO 3248
      CNTOD = CNTOD + 1
   GOTO 3249
3248 SDOD(K+NCENT*(J-1)) = (SDOD(K+NCENT*(J-1))/(NREPE-1)) ** 0.5
   CVOD = SDOD(K+NCENT*(J-1))/MOD(K+NCENT*(J-1))
   WRITE(22,3260) J, K, SDOD(K+NCENT*(J-1)), CVOD
SSOD = CVOD + SSOD
SDOD(K+NCENT*(J-1)) = 0
3249 CONTINUE
3250 CONTINUE
IF(CNTOD.NE.NCENT**2) SSOD = SSOD / (NCENT*NCENT - CNTOD)
SSSOD = SSSOD + SSOD
WRITE(22,3260) SSOD
3260 FORMAT('SUMMARY STATISTIC O-D ONE REPETITION, SSOD= ',F10.4)
SSOD = 0
VCRATT = 0
DO 3260 NREB = 1, NREPE
DO 3270 J = 1, NCENT
   DO 3270 K = 1, NCENT
      AMT(K+NCENT*(J-1)) = (TFRS(K+NCENT*(J-1), NREB))
3270 CONTINUE
C TRAFFIC ASSIGNMENT MODEL
C DO 3271 N = 1, NARC
   SFLOW(N) = 0
SFC = 0
SSFL = 0
VCRATT = 0
DO 3280 I = 1, NRTA
   CALL RNSET(I*NARC*NREA*NREB*10)
   DO 3285 N = 1, NARC
      ET = RNNOF() * SDA + 1
   IF(ET.LE.0) ET = 0.00001
   TTIME(N) = TTIME(N) * ET
C IF(TTIME(N).NE.0) WRITE(32,*) N, TTIME(N)
   TTIME(N) = TTIME(N)
   CONTINUE
   EPS = 1.0E-3
3285 CONTINUE
```

continued
CALL UE(EPS, NARC, NNOD, NCENT, ITER, NFL)
DO 3275 N=1,NARC
 FLOW(N, I)=NFL(N)
 SFLOW(N)=SFLOW(N)+NFL(N)
 IF(C(N).GT.0) VCRAT=(NFL(N)/C(N)) +VCRAT
 CONTINUE
3275 
 VCRATT=VCRAT/NARC+VCRATT
 VCRAT=0
3280 
 CONTINUE
 VCRATT=VCRATT/NRTA+VCRATT
 VCRATT=0
 DO 3289 N=1,NARC
 MFLOW(N)=SFLOW(N)/NRTA
 WRITE(32,*) 'AVERAGE FLOW ',MFLOW(N)
 SFLOW(N)=0
 CONTINUE
 DO 3290 N=1,NARC
 DO 3290 1 = 1 ,NRTA
 SFLOW(N)=SFLOW(N)+(FLOW(N,I)-MFLOW(N))**2
 CONTINUE
 SSTA(NREB)=0
 DO 3291 N=1,NARC
 CVFLOW(N)=0
 IF(SFLOW(N).LT.0.01) GOTO 3291
 SDFLOW(N)=SDFLOW(N)/MFLOW(N)
 SSTA(NREB)=CVFLOW(N)+SSTA(NREB)
 SFLOW(N)=0
 COFL=COFL+1
 CONTINUE
3291 
IF(COFL.EQ.0) GOTO 3293
 SSTA(NREB)=SSTA(NREB)/COFL
 SSSTA(NREA)=SSSTA(NREA)+SSTA(NREB)
 SDTA=0
 DO 3292 N=1,NARC
 IF(CVFLOW(N).EQ.0.) GOTO 3292
 SDTA=SDTA+(CVFLOW(N)-SSTA(NREB))**2
 CONTINUE
3292 
 SDTA=(SDTA/(COFL))**.5
 IF(NREA.EQ.1) WRITE(32,*) 'SSTA=',SSTA(NREB),SDTA
 CONTINUE
3293 
 COFL=0
3329 CONTINUE
 VCRATT=VCRATT/NREPE
 CONTINUE
 C WRITE(32,*) 'AVERAGE FLOW ',MFLOW(N)
 CONTINUE
3329 
 CONTINUE
 SSTA(NREA)=SSSTA(NREA)/NREPE
 SDTA=0
 DO 3310 NREB=1,NREA
 SDTA=SDTA+(SSSTA(NREA)-SSTA(NREB))**2
 CONTINUE
3310 
 SDTA=(SDTA/(NREPE-1))**.5
 WRITE(32,*) 'AVERAGE SIGMA/MU TA ',SSSTA(NREA),SDTA
 continued
Figure B.1 continued

```fortran
C WRITE(32,*), 00421000
SSSSTA=SSSSTA+SSSTA(NREA), 00422000
3300 CONTINUE, 00423000
VCRTTTT=VCRTTTT/NREPE, 00424000
SSSOD=SSSOD/NREPE, 00425000
WRITE(22,*) , 00426000
WRITE(22,3400) SSSOD, 00427000
3400 FORMAT('SUMMARY STATISTIC O-D FOR ALL REPETITIONS, SSSOD= ',F10.4), 00428000
SSSSTA=SSSSTA/NREPE, 00429000
SDTA=0, 00430000
DO 3405 NREA=1,NREPE, 00431000
SDTA=SDTA+((SSSSTA-SSSTA(NREA))**2, 00432000
3405 CONTINUE, 00433000
SDTA=(SDTA/(NREPE-1))**.5, 00434000
WRITE(32,3410) SSSSTA,SDTA, 00435000
3410 FORMAT('SUMMARY STATISTIC TRAFFIC ASSIGNMENT ',F10.4,F10.4), 00436000
WRITE(32,3411) VCRTTTT, 00437000
3411 FORMAT('AVERAGE VOLUMEN CAPACITY V/C RATIO',,F10.7), 00438000
STOP, 00439000
END, 00440000
C 00441000
SUBROUTINE UE (EPS,NARC,NNOD,NCENT, ITER,NFL), 00442000
COMMON /ARCDT/ TOO, L, C, V, FL, COST,TTIME,NEWT, TLTT, 00443000
COMMON /ODDT/ TOD,AMT, 00444000
COMMON /DMPDT/ NDMP,DMP,NREA,NREB,AA,AB, 00445000
COMMON /FST/ FS,ODLK, 00446000
COMMON /ALBET/ ALP,BET,ALP1 , TYP, 00447000
REAL L(IOOO) ,C (1000) ,V (1000) ,FL (1000) ,COST(IOOO), 00448000
REAL NFL(IOOO) 00449000
REAL ALP(18) ,BET(18),ALP1 (18),XN, 00450000
REAL TTIME(IOOO),NEWT(IOOO),TLTT(IOOO), 00451000
INTEGER TOO(IOOO),TOD(2500),FS(IOOO),ODLK(2000), 00452000
INTEGER TYP(IOOO),DMP(IOOO), 00453000
REAL AMT(2500) 00454000
CALL AON (FL,NARC,NNOD,NCENT,ITER), 00455000
K=1, 00456000
ITER=0, 00457000
FOBJ=0., 00458000
DO 70 I=1,NARC, 00459000
A1=ALP1(TYP(I)), 00460000
B1=BET(TYP(I)), 00461000
FOBJ=FOBJ+FIN(TTIME(I),C(I),FL(I),A1,B1), 00462000
70 CONTINUE, 00463000
CONV=2.*EPS, 00464000
10 IF(CONV.GT.EPS) GO TO 30, 00465000
15 CALL DUMP(ITER,NNOD,NCENT,NARC,NFL), 00466000
RETURN, 00467000
30 CONTINUE, 00468000
IF(ITER.NE.NDMP) GO TO 40, 00469000
GO TO 15, 00470000
40 ITER=ITER+1, 00471000
```

continued
Figure B.1 continued

CALL AON (NFL, NARC, NNOD, NCENT, ITER)
CALL BISECT (NFL, NARC)
CONV=0.
FOBJ=0.
D = 0
DO 20 N=1,NARC
A1=ALP1 (TYP(N))
B1=BET(TYP(N))
FOBJ=FOBJ+FIN T(TTIME(N), C(N), NFL(N), A1, B1)
XN=ABS(NFL(N)-FL(N))
XN = XN * XN
IF (XN .EQ. 0.) GO TO 20
D= D + FL(N)
CONV=CONV+XN
FL(N)=NFL(N)
20 CONTINUE
CONV = SQRT(CONV)
IF (D . EQ. 0.)  GO TO 10
CONV=CONV/D
GO TO 10
END

SUBROUTINE AON (NFL, NARC, NNOD, NCENT, INTERNO)
COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
COMMON /ODDT/ TOD,AMT
COMMON /FST/ FS,ODLK
COMMON /ALBET/ ALP,BET,ALP1, TYP
REAL L(1000),C(1000),V(1000),FL(1000),COST(1000)
REAL NFL(1000),SP(8000)
REAL ALP(18),BET(18),ALP1(18)
REAL TTIME(1000),NEWT(1000),TLTT(1000)
INTEGER TOO(1000),TOD(2500),FS(1000),ODLK(2000)
INTEGER TYP(1000),PRED(2500),INTERNO
REAL AMT(2500)
DO 10 N=1,NARC
A1=ALP(TYP(N))
B1=BET(TYP(N))
NFL(N)=0
COST(N)=COSTFN(TTIME(N), C(N), FL(N), A1, B1)
10 CONTINUE
DO 20 I=1,NCENT
I1=ODLK(I)
I2=ODLK(I+1)-1
IF (I1.GT.I2) GO TO 20
CALL SHPATH(I, PRED, SP, NNOD)
DO 30 K= I1,I2
J=TOD(K)
IF (J .EQ. 1 ) THEN
ENDIF
30 CONTINUE
J1=PRED(J)
IF(J1.EQ.0) GO TO 30
N1=FS(J1)
N2=FS(J1+1)-1
continued
Figure B.1 continued

```fortran
DO 40 N=N1,N2
  IF (TOO(N) .EQ. J) GO TO 50
40  CONTINUE
50  NFL(N) = NFL(N) + AMT(K)
    J = J1
    GO TO 60
30  CONTINUE
20  CONTINUE
    RETURN
END

SUBROUTINE BISECT(NFL,NARC)
C COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
C COMMON /FST/ FS,ODLK
C COMMON /ALBET/ ALP,BET,ALP1,TYP
REAL L(IOOO),C(IOOO),V(IOOO),FL(IOOO),COST(IOOO),NFL(IOOO)
REAL ALP(IOOO),BET(IOOO),ALP1(IOOO)
REAL TTIME(IOOO),NEWT(IOOO),TLTT(IOOO)
INTEGER TOO(IOOO),FS(IOOO),TYP(IOOO),ODLK(IOOO)
AMN=0.
AMX=1.
AMD=(AMX+AMN)/2.
IF ((AMX-AMN)*0.0005) GO TO 20
D=0.
DO 30 N=1,NARC
  X=FL(N)+AMD*(NFL(N)-FL(N))
  A1=ALP(TYP(N))
  B1=BET(TYP(N))
  CST=COSTFN(TTIME(N),C(N),X,A1,B1)
  D=D+CST*(NFL(N)-FL(N))
30  D=D+CST*(NFL(N)-FL(N))
  IF (D.GT.0.) AMX=AMD
  IF (D.LE.0.) AMN=AMD
  GO TO 10
20  DO 40 N=1,NARC
40  NFL(N) = FL(N) + AMD*(NFL(N)-FL(N))
    RETURN
END

FUNCTION COSTFN(TIME,C,FL,A,B)
COSTFN=TIME
IF (FL.LE.0.01) COSTFN = COSTFN
IF (C.NE.0.) COSTFN=COSTFN*(1.+A*(FL/C)**B)
RETURN
END

FUNCTION FIN(TIME,C,FL,A,B)
FINT=TIME*FL
IF (C.NE.0.) FINT=FINT*(1.+A/(B+1)*(FL/C)**B)
RETURN
END

SUBROUTINE SHPATH(R,PRED,SP,NNOD)
```

continued
THIS SUBROUTINE COMPUTES SHORTEST PATHS FROM R TO ALL OTHER NODES. PRED(I) CONTAINS PREDECESSOR OF NODE I. SP(I) CONTAINS LENGTH OF PATH TO NODE I.

COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
COMMON /FST/ FS,ODLK
REAL L(1000),C(1000),V(1000),FL(1000),COST(1000),SP(8000)
REAL TTIME(1000),NEWT(1000),TLTT(1000)
INTEGER TOO(1000),FS(1000),PRED(8000),ODLK(2000),R
DO 10 I=1,NNOD
   SP(I)=1.E20
   PRED(I)=0
   CL(I)=0
10 CONTINUE
   SP(R)=0
   CL(R)=NNOD+1
   I=R
   NT=R
20 IA=FS(I+1)-1
   S=SP(I)
   IA1=FS(I)
   IF(IA1.GT.IA) GO TO 30
   DO 40 IR=IA1,IA
      K=TOO(IR)
      SD=S+COST(IR)
      IF( R. EQ. 1) THEN
         ENDIF
      IF( SD.GE.SP(K)) GO TO 40
      PRED(K)=I
      SP(K)=SD
      IF( R. EQ. 1) THEN
         ENDIF
      IF(CL(K)) 50,60,40
   50 CL(NT)=K
   NT=K
   CL(K)=NNOD+1
   GO TO 40
   60 CL(K)=CL(I)
   CL(I)=K
40 CONTINUE
30 ICL=CL(I)
   CL(I)=1
   I=ICL
   IF(I.LE.NNOD) GO TO 20
   RETURN
   END

SUBROUTINE DUMP(ITER,NNOD,NCENT,NARC,NFL)
COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
COMMON /FST/ FS,ODLK
COMMON /ALBET/ ALP,BET,ALP1, TYP
COMMON /ID/ IDNODE
COMMON /DMPDT/ NDMP,DMP,NREA,NREB,AA,AB,NRATT,SETI,SEFU,SECO,
Figure B.1 continued

```plaintext
*    SEHC,SEN0X
REAL L(1000),C(1000),V(1000),FL(1000),COST(1000),NFL(1000) 00631000
REAL ALP(18),BET(18),ALP1(18),VCR(1000) 00632000
REAL TTIME(1000),NEWT(1000),TLTT(1000) 00633000
INTEGER TOO(1000),FS(1000),TYP(1000),VC1(1000),VC2(1000) 00634000
INTEGER IDNODE(1000),OLK(2000),DMP(101) 00635000
REAL RD(1000,5),FUEL,HC,CO,NOX 00636000
C WRITE(32,101) ITER 00637000
C WRITE(*,101) ITER 00638000
101 FORMAT(1X,'NO. OF ITERATIONS = ',I6) 00639000
VCRATT=0 00640000
K=0 00641000
STX=0 00642000
SLX=0 00643000
IX=0 00644000
DO 10 I=1,NNOD 00645000
J1=FS(I) 00646000
J2=FS(I+1)-1 00647000
IF(J1.GT.J2) GO TO 10 00648000
DO 20 J=J1,J2 00649000
K=K+1 00650000
NFL(K)=FL(J) 00651000
IF(C(J).NE.0) VCR(K)=FL(J)/C(J) 00652000
IF(C(J).EQ.0) VCR(K)=0 00653000
VC1(K)=IDNODE(I) 00654000
VC2(K)=IDNODE(TOO(J)) 00655000
IF(FL(J).EQ.0.) GO TO 20 00656000
IF(VC1(K).LE.NCENT) GO TO 20 00657000
IF(VC2(K).LE.NCENT) GO TO 20 00658000
IX=IX+1 00659000
A1=ALP(TYP(J)) 00660000
B1=BET(TYP(J)) 00661000
C COST=COSTFN(TTIME(J),C(J),FL(J),A1,B1) 00662000
NEWT(J)=CST 00663000
STX=STX+CST*FL(J) 00664000
SLX=SLX+L(J)*FL(J) 00665000
CONTINUE 00666000
20 CONTINUE 00667000
10 CONTINUE 00668000
DO 202 NRC=1,NRATT 00669000
TSTT=0 00670000
TSFC=0 00671000
TSHC=0 00672000
TSCO=0 00673000
TSONO=0 00674000
CALL RNSET(NRC*NREA*NREB*1000) 00675000
DO 201 I=1,NARC 00676000
TLTT(I) = NEWT(I)*1+SETI*RNNOF() 00677000
IF(TLTT(I).EQ.0) GOTO 231 00678000
IF(L(I)/TLTT(I)*60.GT.70) TLTT(I)=L(I)*60/70 00679000
IF(L(I)/TLTT(I)*60.LT.10) TLTT(I)=L(I)*60/10 00680000
TSTT = TSTT + TLTT(I)*NFL(I) 00681000
```

continued
S = L(I) / TLTT(I) * 60

IF (S.GT.70) S = 70

FUEL = 14.4525 + 0.0038751 * S + 0.0020496 * S ** 2 - 0.000376 * S ** 3

* + 0.0000022845 * S ** 4

FUELT = 25.0947 + 4.24873 * S - 0.17624 * S ** 2 + 0.036927 * S ** 3

* - 0.00002266 * S ** 4

IF (C(I).GT.1500) GOTO 150

FUEL = (FUELA * AA + FUELT * (1-AA)) * TLTT(I) * 60 * NFL(I) / 10 ** 5

HC = (4.47291567 - 0.22554054 * S + 0.00650787 * S ** 2 - 0.00095662 * S ** 3

* + 0.0000057207 * S ** 4) * L(I) * NFL(I)

CO = (46.5200643 - 2.0739692 * S + 0.04755901 * S ** 2 - 0.00070355 * S ** 3

* + 0.0000051987 * S ** 4) * L(I) * NFL(I)

NOX = (3.08717843 - 0.2413613 * S + 0.01462959 * S ** 2 - 0.000426 * S ** 3

* + 0.0000059858 * S ** 4 - 0.000000022952 * S ** 5) * L(I) * NFL(I)

GOTO 180

150 CONTINUE

FUEL = (FUELA * AB + FUELT * (1-AB)) * TLTT(I) * 60 * NFL(I) / 10 ** 5

HC = (5.53680 - 0.2860775 * S + 0.00830099 * S ** 2 - 0.00012115 * S ** 3

* + 0.00000071416 * S ** 4) * L(I) * NFL(I)

CO = (55.4032011 - 2.52101554 * S + 0.05919692 * S ** 2 - 0.00087213 * S ** 3

* + 0.0000063062 * S ** 4) * L(I) * NFL(I)

NOX = (3.19695831 - 0.25055566 * S + 0.01592326 * S ** 2 - 0.000474 * S ** 3

* + 0.0000066012 * S ** 4 - 0.00000003372 * S ** 5) * L(I) * NFL(I)

GOTO 180

180 CONTINUE

FUEL = FUEL * (1 + SEFU * RNNOF())

HC = HC * (1 + SEHC * RNNOF())

CO = CO * (1 + SECO * RNNOF())

NOX = NOX * (1 + SENOX * RNNOF())

IF (FUEL.GT.O) TSFC = TSFC + FUEL

IF (HC.GT.O) TSHC = TSHC + HC

IF (CO.GT.O) TSOC = TSOC + CO

IF (NOX.GT.O) TSN0X = TSN0X + NOX

GOTO 201

201 CONTINUE

WRITE (3,104) TSTT, TSFC, TSHC/1000, TSOC/1000, TSN0X/1000

104 FORMAT (SF14.1)

202 CONTINUE

IF (NREA.NE.1) GOTO 24

IF (NREB.NE.1) GOTO 24

DO 23 I = 1, NARC

WRITE (32,103) I, NFL(I), NEWT(I), TLTT(I), VCR(I)

23 CONTINUE

24 CONTINUE

RETURN

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Figure B.3 Portion of the Network File for the Extended Network Example No-Build Alternative
15 REPETITIONS 00001000
0.251900 STANDARD DEVIATION ERROR IN GENERATION 00002000
0.251900 STANDARD DEVIATION ERROR IN ATTRACTION 00003000
0.247981 STANDARD DEVIATION ERROR IN DISTRIBUTION 00004000
10 NUMBER OF ITERATIONS TRAFFIC ASSIGNMENT 00005000
15 NUMBER OF REPETITIONS TRAFFIC ASSIGNMENT 00006000
0.125581 STANDARD DEVIATION ERROR IN TIME (TA) 00007000
0.90000 0.75000 PERCENTAGE OF AUTOS IN ARTERIALS/FREeways 00008000
15 NUMBER OF REPETITIONS ATTRIBUTE SIMULATION 00009000
0.2500 0.2500 0.2500 0.2500 0.2500 SIGMA/MU TIME,FUEL,CO,HC,NOX 00010000

Figure B.4 Example of a Scenario File for Random Sampling of the Attribute Vectors Program

// JOB,
// REGION=6144K, TIME=(90,0)
/* JOPARM LINES=90000,DISKIO=40000
 // EXEC VSF2CTLG,
 // PARM.FORT=’DC(FRS,TFRS,OD,ARCDT,ODDT,ALBET,ID,FST,SPT),OPT(2)’,
 // PARM.LKED=’AMODE=31,MODE=ANY’, TIME=(90,0)
 // FORT.SYSIN DD DSN=DHIDAL.SIMULA.FOR,DISP=SHR
// G0.FT11F001 DD DSN=DHIDAL.DEMAND.DAT,DISP=SHR
// G0.FT13F001 DD DSN=DHIDAL.NETWORK.DAT,DISP=SHR
// G0.FT12F001 DD DSN=DHIDAL.SCENARIO.DAT,DISP=SHR
// G0.FT22F001 DD DSN=DHIDAL.GENDISTR.OUT,
// DISP=(NEW,CATLG,DELETE),UNIT=USER80,SPACE=(TRK,(100,10),RLSE),
// DDB=(LRECL=80,BLKSIZ=15440,RECFM=FB)
// G0.FT32F001DD DSN=DHIDAL.TRAAASSIG.OUT,
// DISP=(NEW,CATLG,DELETE),UNIT=USER80,SPACE=(TRK,(100,10),RLSE),
// DDB=(LRECL=80,BLKSIZ=15440,RECFM=FB)
// G0.FT33F001DD DSN=DHIDAL.ATTRIBUT.OUT,
// DISP=(NEW,CATLG,DELETE),UNIT=USER80,SPACE=(TRK,(100,10),RLSE),
// DDB=(LRECL=80,BLKSIZ=15440,RECFM=FB)

Figure B.5 Example of a Job File for Using the Random Sampling of the Attribute Vectors Program

231
AVERAGE SIGMA/MU: SSO 0.2442 SSD 0.2358 0.2400

SUMMARY STATISTIC O-D ONE REPEATITION, SSOD = 0.2471

SUMMARY STATISTIC O-D ONE REPEATITION, SSOD = 0.2482

SUMMARY STATISTIC O-D ONE REPEATITION, SSOD = 0.2470

SUMMARY STATISTIC O-D FOR ALL REPETITIONS, SSSOD = 0.2469

Figure B.6 Example Trip Generation and Trip Distribution Steps Output File

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Figure B.7 Example Traffic Assignment Step Output File

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AVERAGE SIGMA/MU TA 0.250944793 0.142863393E-01

SUMMARY STATISTIC TRAFFIC ASSIGNMENT 0.2287 0.0141

AVERAGE VOLUMEN CAPACITY V/C RATIO 1.3765001

232
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Figure B.8 Example Attributes Step Output File
Figure B.9 Computer Program for Expected Utility and VOPI Calculation

234
Figure B.9 continued

IF (NNOPT.EQ.2) WRITE(30,*).'OPT 2, CALCULATE MODEL VOPI' 00051000
IF (NNOPT.EQ.1) WRITE(30,*).'OPT 1, DO NOT CALCULATE MODEL VOPI' 00052000
27  FORMAT(F10.2, 'COST BUILD ALTERNATIVE') 00053000
    WRITE(30,*).'MAXIMUM AND MINIMUM FOR EACH ATTRIBUTE' 00055000
    READ(11,12) MAXI(1),MAXI(2),MAXI(3),MAXI(4),MAXI(5),X 00056000
    WRITE(30,12) MAXI(1),MAXI(2),MAXI(3),MAXI(4),MAXI(5),MAXI(6) 00057000
    READ(11,12) MINI(1),MINI(2),MINI(3),MINI(4),MINI(5),X 00058000
    WRITE(30,12) MINI(1),MINI(2),MINI(3),MINI(4),MINI(5),0 00059000
    READ(11,*) 00060000
    WRITE(30,*).'AVERAGE FOR EACH ATTRIBUTE' 00061000
    READ(11,12) AVEA(1),AVEA(2),AVEA(3),AVEA(4),AVEA(5),X 00062000
    WRITE(30,12) AVEA(1),AVEA(2),AVEA(3),AVEA(4),AVEA(5),0 00063000
    READ(11,12) AVEB(1),AVEB(2),AVEB(3),AVEB(4),AVEB(5),X 00064000
    WRITE(30,12) AVEB(1),AVEB(2),AVEB(3),AVEB(4),AVEB(5),CT 00065000
    WRITE(30,*) 00066000
12  FORMAT(6F13.1) 00067000
    IF(NOPT.EQ.2) GOTO 13 00068000
        CALCULATE TRADEOFF PARAMETERS
        K2K1=(RSCT*(MAXI(1)-MINI(1))**AA)/(AA*MAXI(6)*
             (AVEA(1)-MINI(1))**(AA-1)) 00071000
        K3K1=(RSCP*(MAXI(2)-MINI(2))**AB)/(AB*MAXI(6)*
             (AVEA(2)-MINI(2))**(AB-1)) 00073000
        K4K1=MAXI(6)/RSCP 00075000
        KD=1/(1+K2K1+K3K1+K4K1) 00076000
        KA=KD*K2K1 00077000
        KB=KD*K3K1 00078000
        KC=KD*K4K1 00079000
        GOTO 14 00080000
      CONTINUE 00081000
    WRITE(30,15) KD,KA,KB,KC 00082000
14  WRITE(30,*).'TRADEOFF PARAMETERS' 00083000
    WRITE(30,15) KA,KB,KC,KD 00084000
15  FORMAT(4F10.5) 00085000
    WRITE(30,*) 00086000
    KK=0 00087000
    MM=0 00088000
    CALCULATE THE VALUE OF INFORMATION
    FOR TOTAL TRIPS 00090000
    EUA=0.0000000000000000000000 00091000
    EUB=EUA 00092000
    EUAA=EUA 00093000
    EUBB=EUA 00094000
    EUAAA=EUA 00095000
    EUBBB=EUA 00096000
    EUAT=EUA 00097000
    EUATT=EUA 00098000
    continued
Figure B.9 continued

```
EUATTTT=EUA 00104000
EUATTTT=EUA 00105000
EUT=EUA 00106000
EUTT=EUA 00107000
EUTTT=EUA 00108000
EUOD=EUA 00109000
EUODD=EUA 00110000
EUTG=EUA 00111000
EUODDD=EUA 00112000
DO 18 M=1,NREPE 00113000
DO 17 J=1,NREPE 00114000
DO 16 K=1,NRTA 00115000
DO 19 L=1,NRATT 00116000
READ (12,*) TIA, FUA, HCA, COA, XNOA 00117000
READ (13,*) TIB, FUB, HCB, COB, XNOSB 00118000
UTA = KA*U(TIA, AA, 1) + KB*U(FUA, AB, 2) + KC* (MA*U(HCA, AE, 3) 00119000
  + MB*U(COA, AF, 4) + MC*U(XNOA, AG, 5)) + KD*U(0, AD, 6) 00120000
UTB = KA*U(TIB, AA, 1) + KB*U(FUB, AB, 2) + KC* (MA*U(HCB, AE, 3) 00121000
  + MB*U(COB, AF, 4) + MC*U(XNOSB, AG, 5)) + KD*U(0, AD, 6) 00122000
EUA = UTA + EOA 00123000
EUB = UTB + EOB 00124000
EUAA = EUA/NRATT + EUAA 00125000
EUBB = EUB/NRATT + EUBB 00126000
UTA (IND (L, K, J, M)) = UTA 00127000
UTB (IND (L, K, J, M)) = UTB 00128000
CONTINUE 00129000
19 CONTINUE 00130000
EUAA = EUA/NRATT + EUAA 00131000
EUBB = EUB/NRATT + EUBB 00132000
EUA = 0.0000000000000000 00133000
EUB = EUA 00134000
CONTINUE 00135000
16 CONTINUE 00136000
DO 42 KAA = 1, NRTA 00137000
DO 42 KBB = 1, NRTA 00138000
DO 43 L = 1, NRATT 00139000
EUA = UTIA (IND (L, KAA, J, M)) + EUA 00140000
EUB = UTIB (IND (L, KBB, J, M)) + EUB 00141000
43 CONTINUE 00142000
EUT = RMATAX (EUA/NRATT, EUB/NRATT, 0) + EUT 00143000
EUA = 0.0000000000000000 00144000
EUB = EUA 00145000
DO 44 LAA = 1, NRATT 00146000
DO 44 LBB = 1, NRATT 00147000
EUT = RMATAX (UTIA (IND (LAA, KAA, J, M)), UTIB (IND (LBB, KBB, J, M))) 00148000
44 CONTINUE 00149000
EUATT = EUAT + (NRATT*NRTA)*EUATT 00150000
EUATT = 0.0000000000000000 00151000
CONTINUE 00152000
42 CONTINUE 00153000
EUATTT = EUATT + (NRAT*NRTA) + EUATTT 00154000
EUATT = 0.0000000000000000 00155000
EUATT = EUATT + (NRAT*NRTA) + EUATTT 00156000
EUT = 0 00157000
EUOD = RMATAX (EUAA/NRTA, EUBB/NRATT, 0) + EUOD 00158000
EUAAA = EUAA/NRATT + EUAAA 00159000
EUBBB = EUBB/NRATT + EUBBB 00160000
continued
```
EUAA=0.0000000000000000 00157000
EUBB=0.0000000000000000 00158000
17 CONTINUE 00159000
EUATTTT=EUATTT/NREPE+EUATTTT 00160000
EUATTT=0.0000000000000000 00161000
EUTT=EUTT/NREPE+EUTT 00162000
EUTT=0.0000000000000000 00163000
EUTG=MAX(EUAAA/NREPE, EUBBB/NREPE,0)+EUTG 00164000
EUODD=EUOD/NREPE+EUODD 00165000
EUOD=0.0000000000000000 00166000
EUAAA=EUAAA/NREPE+EUAAA 00167000
EUBBBB=EUBBB/NREPE+EUBBBB 00168000
EUAAA=0.0000000000000000 00169000
EUBBB=0.0000000000000000 00170000
18 CONTINUE 00171000
EUNB=EUAAAA/NREPE 00172000
EUU=EUBBBB/NREPE 00173000
EUNT=RMAX(EUNB, EUU, 0) 00174000
WRITE(30,*) 'EXPECTED UTILITY BUILD ', EUU, 'NO BUILD ', EUNB 00175000
WRITE(30,*) 'EXPECTED UTILITY NO TEST ', EUNT 00176000
WRITE(30,*) 00177000
EUATR=EUATTT/NREPE 00178000
WRITE(30,*) 'EXPECTED UTILITY TEST ATTRIBUTES ', EUATR 00179000
VOPI=MAXI(6)*(EUATR-EUNT)/KD 00180000
WRITE(30,*) 'VALUE OF INFORMATION ATTRIBUTES ', VOPI 00181000
EUTE=EUTT/NREPE 00182000
WRITE(30,*) 'EXPECTED UTILITY TEST FLOW PATTERNS ', EUTE 00183000
VOPI=MAXI(6)*(EUTE-EUNT)/KD 00184000
WRITE(30,*) 'VALUE OF INFORMATION FLOW PATTERNS ', VOPI 00185000
EUTEOD=EUOD/NREPE 00186000
VOPI=MAXI(6)*(EUTEOD-EUNT)/KD 00187000
WRITE(30,*) 'EXPECTED UTILITY TEST OD MATRIX ', EUTEOD 00188000
WRITE(30,*) 'VALUE OF INFORMATION OD MATRIX ', VOPI 00189000
WRITE(30,*) 'MARGINAL VALUE OF INFORMATION TRAFFIC ASSIGNMENT ', 00190000
* VOPI-VOPIO 00191000
WRITE(30,*) 00192000
IF(NNOPT.EQ.1) GOTO 300 00193000
CALL RNSET(10000) 00194000
EUT=0 00195000
DO 90 NS=1,NSAT 00196000
DO 91 M=1,NREPE 00197000
DO 92 J=1,NREPE 00198000
DO 93 K=1,NRTA 00199000
L=INT(RNUNF() *NRATT)+1 00200000
IF(L.GT.NRATT) L=NRATT 00201000
EUA=UTIA(IND(L, K, J, M))+EUA 00202000
continued
Figure B.9 continued

L = INT (RNUNF () * NRATT) + 1
IF (L .GT. NRATT) L = NRATT
EUB = UTIB (IND (L, K, J, M)) + EUB
93 CONTINUE
EUAA = EUA / NRTA + EUAA
EUBB = EUB / NRTA + EUBB
EUAA = 0.0000000000000000
EUBB = 0.0000000000000000
92 CONTINUE
EUAA = EUA / NREPE + EUAA
EUBB = EUB / NREPE + EUBB
EUAA = 0.0000000000000000
EUBB = 0.0000000000000000
91 CONTINUE
EUT = RMAX (EUAAA / NREPE, EUBBB / NREPE, 0) + EUT
EUAAA = EUAA / NREPE + EUAAA
EUBBB = EUBB / NREPE + EUBBB
EUAA = 0.0000000000000000
EUBB = 0.0000000000000000
90 CONTINUE
EUT = EUT / NSAT
WRITE (30.96) EUT, NSAT
96 FORMAT ('EXPECTED UTILITY ATTRIBUTES STUDY USING SAMPLING', F10.6, 0.230000
* ' SAMPLES', (5))
VOPI = (EUT - EUNT) * MAXI (6) / KD
WRITE (30.97) VOPI
97 FORMAT ('VOPI ATTRIBUTES STUDY USING SAMPLING', F10.6)
WRITE (30, *)
EUT = 0.0000000000000000
CALL RNSET (10000)
DO 216 NS = 1, NSTA
DO 217 M = 1, NREPE
DO 218 J = 1, NREPE
DO 219 L = 1, NRATT
K = INT (RNUNF () * NRTA) + 1
IF (K .GT. NRTA) K = NRTA
EUAA = UTIA (IND (L, K, J, M)) + EUA
K = INT (RNUNF () * NRATT) + 1
IF (K .GT. NRATT) K = NRATT
EUB = UTIB (IND (L, K, J, M)) + EUB
219 CONTINUE
EUAA = EUA / NRATT + EUAA
EUBB = EUB / NRATT + EUBB
EUAA = 0.0000000000000000
EUBB = 0.0000000000000000
218 CONTINUE
EUAAA = EUAA / NREPE + EUAAA
EUBBB = EUBB / NREPE + EUBBB
EUAA = 0.0000000000000000
EUBB = 0.0000000000000000
217 CONTINUE
EUT = RMAX (EUAAA / NREPE, EUBBB / NREPE, 0) + EUT
EUAAA = 0.0000000000000000
EUBBB = 0.0000000000000000
continued

238
Figure B.9 continued

216 CONTINUE 00262000
EUT=EUT/NSTA 00262000
WRITE(30,221) EUT,NSTA 00264000
221 FORMAT('EXPECTED UTILITY TA STUDY USING SAMPLING',F10.6, 00265000
* 'SAMPLES',I5) 00266000
VOPI=(EUT-EUNT)*MAXI(6)/KD 00267000
WRITE(30,222) VOPI 00268000
222 FORMAT('VOPI TA USING SAMPLING',F12.6) 00269000
WRITE(30,*) 00270000
EUT=0.0000000000000000 00271000
CALL RNSET(10000) 00272000
DO 270 NS=1,NSOD 00273000
DO 271 M=1,NREPE 00274000
DO 272 K=1,NRTA 00275000
DO 273 L=1,NRATT 00276000
J=INT(RUNUF()*)NREPE)+1 00277000
IF(J.GT.NREPE) EUTA=UTIA(IND(L,K,J,M)) 00278000
J=INT(RUNUF()*)NREPE)+1 00280000
IF(J.GT.NREPE) EUTB=UTIB(IND(L,K,J,M)) 00282000
273 CONTINUE 00283000
EUAA=EUAA/NRATT+EUA 00284000
EUBB=EUBB/NRATT+EUB 00285000
EUAA=0.0000000000000000 00286000
EUBB=0.0000000000000000 00287000
272 CONTINUE 00288000
EUAA=EUAA/NRTA+EUAA 00289000
EUBB=EUBB/NRTA+EUBBB 00289000
EUAA=0.0000000000000000 00290000
EUBB=0.0000000000000000 00291000
271 CONTINUE 00292000
EUT=MAX(EUAA/NREPE,EUBBB/NREPE,0)+EUT 00293000
EUAA=0.0000000000000000 00294000
EUBB=0.0000000000000000 00295000
EUAA=0.0000000000000000 00296000
270 CONTINUE 00297000
EUT=EUT/NSOD 00298000
WRITE(30,*) 00299000
WRITE(30,275) EUT,NSOD 00300000
275 FORMAT('EXPECTED UTILITY TD STUDY USING SAMPLING',F10.6, 00301000
* 'SAMPLES',I5) 00302000
VOPI=(EUT-EUNT)*MAXI(6)/KD 00303000
WRITE(30,276) VOPI 00304000
276 FORMAT('VOPI TD STUDY USING SAMPLING',F10.6) 00305000
WRITE(30,*) 00306000
EUT=0.0000000000000000 00307000
END 00308000
C
FUNCTION IND(L,K,J,M) 00310000
COMMON /REP/ NRTA,NREPE,NRATT 00312000
IND=L+(K-1)*NRTA+(J-1)*NRATT+(M-1)*NRTA*NREPE*NRATT 00313000
RETURN 00314000
continued
FUNCTION RMAX(A,B,C)
DOUBLE PRECISION A,B,C,RMAX
RMAX=A
IF(B.GT.RMAX) RMAX=B
IF(C.GT.RMAX) RMAX=C
RETURN
END

FUNCTION U(ATT,A,I)
COMMON /M/ MAXI,MINI
DOUBLE PRECISION MAXI(6),MINI(6)
IF (ATT.GT.MINI(I)) GOTO 5
U=1
GOTO 6
5 U=1-((ATT-MINI(I))/(MAXI(I)-MINI(I)))**A
6 RETURN
END
Figure B.10 Input File for Expected Utility and VOPI Calculation

<table>
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<tr>
<th>JOB,</th>
<th>REGION=6144K,TIME=(90,0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>/JOBPARMLINES=90000,DISKIO=40000</td>
<td></td>
</tr>
<tr>
<td>// EXECVSF2CLG, PARM.FORT='DC(M,EU,REP,UTIA,UTIB),OPT(2)',</td>
<td></td>
</tr>
<tr>
<td>// PARM.LKED='AMODE=31,RMODE=ANY',TIME=(90,0)</td>
<td></td>
</tr>
<tr>
<td>// FORT.SYSIN DD DSN=SHCHEN.VOPIALL.FOR,DISP=SHR</td>
<td></td>
</tr>
<tr>
<td>//GO.PT11F001 DD DSN=SHCHEN.MAXMIN.OUT,DISP=SHR</td>
<td></td>
</tr>
<tr>
<td>//GO.PT12F001 DD DSN=SHCHEN.ATTRIB1.OUT,DISP=SHR</td>
<td></td>
</tr>
<tr>
<td>//GO.PT13F001 DD DSN=SHCHEN.ATTRIB2.OUT,DISP=SHR</td>
<td></td>
</tr>
<tr>
<td>//GO.PT14F001 DD DSN=SHCHEN.INPUT.DAT,DISP=SHR</td>
<td></td>
</tr>
<tr>
<td>//GO.PT30F001 DD DSN=SHCHEN.VOPI.OUT,</td>
<td></td>
</tr>
<tr>
<td>//DISP=(NEW,CATLG,DELETE),UNIT=USER80,SPACE=(TRK,(100,10),RLSE),</td>
<td></td>
</tr>
<tr>
<td>//DCB=(LRECL=80,BLKSIZ=15440,RECFM=FB)</td>
<td></td>
</tr>
</tbody>
</table>

Figure B.11 Extremes and Averages Input File for VOPI Calculation

| MAXIMUM AND MINIMUM FOR EACH ATTRIBUTE | 5390265.0 | 102444.6 | 4171.2 | 42712.1 | 4015.3 |
| AVERAGE OF EACH ATTRIBUTE | 1422697.0 | 32782.1 | 1301.3 | 11716.3 | 1468.1 |
| 1978756.8 | 41059.8 | 1579.4 | 14205.6 | 1695.2 |
| 2032463.6 | 42178.9 | 1687.1 | 16134.7 | 1868.6 |

Figure B.12 Example of a Job File for Using Expected Utility and VOPI Calculation Program
Figure B.13 Example of an Output File from the Expected Utility and VOPI Calculation Program
PROGRAM TO CALCULATE MAXIMUM AND MINIMUM OF THE ATTRIBUTES

DOUBLE PRECISION MINI(6), MAXI(6)
DOUBLE PRECISION AVEA(6), AVEAA(6), AVEB(6), AVEBB(6)
DOUBLE PRECISION AVEAAA(6), AVEBBB(6), AVEAAAA(6), AVEBBBB(6)

READ(12,*) NREPE, NRTA, NRATT
READ(13,*) N1, N2, N3
IF (N1.EQ.NREPE) GOTO 2
IF (N2.EQ.NRTA) GOTO 2
IF (N3.EQ.NRATT) GO TO 2
WRITE(20,*) 'NUMBER OF REPETITIONS DIFFERENT FOR BUILD AND NO
BUILD SCENARIOS'
GOTO 300
CONTINUE

READ ATTRIBUTES FOR EACH NETWORK
DO 3 I=1,6
    MINI(I) = 90000000
    MAXI(I) = 0
    AVEA(I) = 0
    AVEB(I) = 0
    AVEAA(I) = 0
    AVEBB(I) = 0
    AVEAAA(I) = 0
    AVEBBB(I) = 0
    AVEAAAA(I) = 0
    AVEBBBB(I) = 0
CONTINUE

DO 10 M=1,NREPE
    DO 8 J=1,NREPE
        DO 6 K=1,NRTA
            DO 4 L=1,NRATT
                READ(12,*) TIA, FUA, HCA, COA, XNOA
                READ(13,*) TIB, FUB, HCB, COB, XNOB
                MINI(1) = RMIN(TIA, TIB, MINI(1))
                MINI(2) = RMIN(FUA, FUB, MINI(2))
                MINI(3) = RMIN(HCA, HCB, MINI(3))
                MINI(4) = RMIN(COA, COB, MINI(4))
                MINI(5) = RMIN(XNOA, XNOB, MINI(5))
                MAXI(1) = RMAX(TIA, TIB, MAXI(1))
                MAXI(2) = RMAX(FUA, FUB, MAXI(2))
                MAXI(3) = RMAX(HCA, HCB, MAXI(3))
                MAXI(4) = RMAX(COA, COB, MAXI(4))
                MAXI(5) = RMAX(XNOA, XNOB, MAXI(5))
                AVEA(1) = TIA/NRATT+AVEA(1)
                AVEA(2) = FUA/NRATT+AVEA(2)
                AVEA(3) = HCA/NRATT+AVEA(3)
                AVEA(4) = COA/NRATT+AVEA(4)
                AVEA(5) = XNOA/NRATT+AVEA(5)
                AVEB(1) = TIB/NRATT+AVEB(1)
                AVEB(2) = FUB/NRATT+AVEB(2)
                AVEB(3) = HCB/NRATT+AVEB(3)
                AVEB(4) = COB/NRATT+AVEB(4)
                AVEB(5) = XNOB/NRATT+AVEB(5)
            CONTINUE
        CONTINUE
    CONTINUE
CONTINUE
Figure B.14 Program for Extremes and Averages Determination

continued
Figure B.14 continued

\[ AVEB(4) = \frac{COB}{NRATT} + AVEB(4) \]
\[ AVEB(5) = \frac{XNOB}{NRATT} + AVEB(5) \]
\[ AVEB(6) = \frac{CTB}{NRATT} + AVEB(6) \]

CONTINUE

DO 5 I = 1, 5
\[ AVEA(I) = AVEA(I) / NRATT + AVEAA(I) \]
\[ AVEBB(I) = AVEBB(I) / NRATT + AVEBB(I) \]
\[ AVEA(I) = 0 \]
\[ AVEB(I) = 0 \]

CONTINUE

DO 7 I = 1, 5
\[ AVEAAA(I) = AVEAA(I) / NREPE + AVEAAA(I) \]
\[ AVEBBB(I) = AVEBB(I) / NREPE + AVEBBB(I) \]
\[ AVEAA(I) = 0 \]
\[ AVEBB(I) = 0 \]

CONTINUE

DO 9 I = 1, 5
\[ AVEAAAA(I) = AVEAA(I) / NREPE + AVEAAAA(I) \]
\[ AVEBBBB(I) = AVEBB(I) / NREPE + AVEBBBB(I) \]
\[ AVEAAA(I) = 0 \]
\[ AVEBBB(I) = 0 \]

CONTINUE

DO 11 I = 1, 5
\[ AVEA(I) = AVEAAAA(I) \]
\[ AVEB(I) = AVEBBBB(I) \]

WRITE(20, *) 'MAXIMUM AND MINIMUM FOR EACH ATTRIBUTE'
\[ MAXI(1), MAXI(2), MAXI(3), MAXI(4), MAXI(5) \]
\[ MINI(1), MINI(2), MINI(3), MINI(4), MINI(5) \]
WRITE(20, *) 'AVERAGE OF EACH ATTRIBUTE'
\[ AVEA(1), AVEA(2), AVEA(3), AVEA(4), AVEA(5) \]
\[ AVEB(1), AVEB(2), AVEB(3), AVEB(4), AVEB(5) \]
FORMAT(5F13.1)

FUNCTION RMAX(A, B, C)
\[ RMAX = A \]
IF (B.GT.RMAX) RMAX = B
IF (C.GT.RMAX) RMAX = C
RETURN
END

FUNCTION RMIN(A, B, C)
\[ RMIN = A \]
IF (B.LT.RMIN) RMIN = B
IF (C.LT.RMIN) RMIN = C
RETURN
END
/* JOBPARMLINES=90000,DISKIO=40000
 // EXECVSP2CLG, PARM.FORT='DC(REP, TI, FU, HC, CO, NOA, NOB, CTA, CTB), OPT(2)',
 // PARM.LKED='AMODE=31, RMODE=ANY', TIME=(20,50)
 // FORT.SYSIN DD DSN=SHCHEN.MAXMIN.FOR, DISP=SHR
 // GO.FT12F001 DD DSN=SHCHEN.ATRIB1.OUT, DISP=SHR
 // GO.FT13F001 DD DSN=SHCHEN.ATRIB2.OUT, DISP=SHR
 // GO.FT20F001 DD DSN=SHCHEN.MAXMIN.OUT,
 // DISP=(NEW, CATLG, DELETE), UNIT=USER80, SPACE=(TRK, (100, 10), RLSE),
 // DCB=(LRECL=80, BLKSIZE=15440, RECFM=FB)

Figure B.15 Example of a Job File for Using Extremes and Averages Calculation Program
APPENDIX C

SENSITIVITY ANALYSIS NUMERICAL RESULTS

This appendix contains some inputs and outputs of the sensitivity analysis performed on the extended network (chapter 5). They are included for future reference and analysis. Table C.1 contains the scaling (tradeoff) parameters for each one of the experiments performed to test the sensitivity of the preference model (section 5.3). Row one shows the basic tradeoff parameters, rows 2-13, show the tradeoff parameters for the Plackett-Burman design, rows 14-22 show the tradeoff parameters for one-at-a-time factor modifications, and row 23 and the tradeoff parameters for an extra experiment conducted to reduce the possible bias of the metamodel parameter estimates. Experiment 1 is also used as the base case for the elasticity analysis.

Table C.2 contains the expected utilities, VOPIs and Marginal VOPIs estimated for each one of the experiments changing the preference model parameters. All these results were obtained with a single set of 15^4 attribute vectors for the no-build alternative, and a single set of 15^4 attribute vectors for the build alternative for the extended network example with high demand.

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Table C.3 contains the input standard deviations for each one of the prediction model sensitivity analysis experiments. Row 1 contains the base case, rows 2-9 contain the one-factor-at-a-time experiments, row 10-21 the Plackett-Burman design experiments, and row 22 an extra experiment. Each set of standard deviations (i.e., each row) is used to sample $15^4$ attribute vectors for the build scenario and $15^4$ attribute vectors for the no build scenario. These paired sets are then used to estimate the expected utilities and VOPIs with a fixed set of preference parameters (base case). Experiment 21 in is used as the base case for the elasticity analysis.

Tables C.4 and C.5 contain the expected utilities and VOPIs for the prediction model traffic sensitivity analysis experiments.
<table>
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<th>Experiment</th>
<th>$k_1$</th>
<th>$k_2$</th>
<th>$k_3$</th>
<th>$k_4$</th>
<th>$k_{41}$</th>
<th>$k_{42}$</th>
<th>$k_{43}$</th>
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<td>0.06353</td>
<td>0.02008</td>
<td>0.90102</td>
<td>0.07681</td>
<td>0.85123</td>
<td>0.06995</td>
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<tr>
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<td>0.04719</td>
<td>0.05862</td>
<td>0.86427</td>
<td>0.11374</td>
<td>0.81896</td>
<td>0.06730</td>
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<td>0.02591</td>
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<td>0.09968</td>
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Table C.1 Tradeoff Parameters for the Preference Model Sensitivity Analysis Experiments
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Table C.2 Expected Utilities, VOPIs and Marginal VOPIs for the Preference Model
Sensitivity Analysis Experiments
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|------|-------------|-------------|----------------|----------------|-------------|-------------|-------------|-------------|-------------|
| 1    | 0.24880     | 0.25148     | 0.26945        | 0.22265        | 0.25        | 0.25        | 0.25        | 0.25        | 0.25        |
| 2    | 0.37530     | 0.12432     | 0.03741        | 0.02209        | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       |
| 3    | 0.12631     | 0.37059     | 0.05265        | 0.03728        | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       |
| 4    | 0.12631     | 0.12500     | 0.50151        | 0.46196        | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       |
| 5    | 0.12631     | 0.12500     | 0.05431        | 0.03729        | 0.375       | 0.125       | 0.125       | 0.125       | 0.125       |
| 6    | 0.12631     | 0.12500     | 0.05431        | 0.03729        | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       |
| 7    | 0.12631     | 0.12500     | 0.05431        | 0.03729        | 0.125       | 0.125       | 0.375       | 0.125       | 0.125       |
| 8    | 0.12631     | 0.12500     | 0.05431        | 0.03729        | 0.125       | 0.125       | 0.125       | 0.375       | 0.125       |
| 9    | 0.12631     | 0.12500     | 0.05431        | 0.03729        | 0.125       | 0.125       | 0.125       | 0.125       | 0.375       |
| 10   | 0.37530     | 0.12432     | 0.49129        | 0.45029        | 0.125       | 0.125       | 0.125       | 0.375       | 0.375       |
| 11   | 0.37530     | 0.36794     | 0.49188        | 0.45014        | 0.375       | 0.125       | 0.125       | 0.125       | 0.375       |
| 12   | 0.12631     | 0.37059     | 0.50173        | 0.46332        | 0.125       | 0.375       | 0.125       | 0.125       | 0.125       |
| 13   | 0.37530     | 0.12432     | 0.49129        | 0.45029        | 0.375       | 0.125       | 0.375       | 0.125       | 0.125       |
| 14   | 0.37530     | 0.36794     | 0.03568        | 0.02165        | 0.375       | 0.125       | 0.375       | 0.125       | 0.125       |
| 15   | 0.37530     | 0.36794     | 0.49188        | 0.45014        | 0.125       | 0.375       | 0.375       | 0.125       | 0.125       |
| 16   | 0.12631     | 0.37059     | 0.50173        | 0.46332        | 0.375       | 0.125       | 0.375       | 0.125       | 0.125       |
| 17   | 0.12631     | 0.12500     | 0.50151        | 0.46196        | 0.375       | 0.125       | 0.375       | 0.125       | 0.125       |
| 18   | 0.12631     | 0.12500     | 0.05431        | 0.03729        | 0.375       | 0.375       | 0.375       | 0.125       | 0.375       |
| 19   | 0.37530     | 0.12432     | 0.03741        | 0.02209        | 0.125       | 0.375       | 0.375       | 0.375       | 0.125       |
| 20   | 0.12631     | 0.37059     | 0.05265        | 0.03728        | 0.125       | 0.375       | 0.375       | 0.375       | 0.375       |
| 21   | 0.12631     | 0.12500     | 0.05431        | 0.03729        | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       |
| 22   | 0.37530     | 0.36794     | 0.49188        | 0.45014        | 0.125       | 0.125       | 0.125       | 0.125       | 0.125       |

Table C.3 Input Standard Deviations for the Prediction Model Sensitivity Analysis Experiments
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Table C.5 VOPIs for the Prediction Model Sensitivity Analysis Experiments