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UPDATING JUDGMENTS OF UNCERTAINTY IN TRAVEL DEMAND FORECASTS WITH MODEL OUTPUTS: EMPIRICAL RESULTS AND ANALYTICAL IMPLICATION

DISserTATION

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

By
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*****

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ABSTRACT

Travel forecasting is essential, since it affects the design and evaluation of transportation systems. Although mathematical models are used to assist in forecasting, travel demand cannot be predicted perfectly because the future is uncertain. We, therefore, investigate the uncertainty in travel forecasts of practitioners and academics and how prediction models used in the traditional "four-step travel demand forecasting process" help reduce this uncertainty.

We elicited subjective probability judgments about transportation events from 47 practitioners and academics before and after seeing the output of each model of the four-step process. We found that individuals felt most uncertain in the Trip Generation (TG) and Trip Distribution (TD) steps, and least uncertain in the Modal Split (MS) step. We also found that individuals were less uncertain about their predictions after observing the model outputs and had the most confidence in the Traffic Assignment (TA) model. They had the least confidence in the Modal Split (MS) model, but the uncertainty before seeing the MS model was already very small compared to the other three steps. Therefore, individuals seem to need better understanding about trip making behavior in the TG and
TD steps, and there seems to be more need to improve the TG and TD models than the MS and TA models.

We also investigated the degree to which the models reduce uncertainty in Total System Travel Time (TSTT), an outcome commonly estimated from the four-step process. We constructed a sequential prediction process to produce probability distributions of TSTT based on prior and posterior distributions of the four-step models. Analysis of the coefficient of variations of the TSTT distributions under various conditions showed that the TD, MS, and TA models reduced the uncertainty of TSTT only slightly; in contrast, the TG model reduced the uncertainty of TSTT markedly. This would imply that special attention should be given to the reduction of uncertainty in the TG step when the objective is to use the four-step process to calculate system-wide TSTT.
Dedicated to my parents and WanFang Cheng
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CHAPTER 1

INTRODUCTION

1.1 Motivation

Travel demand prediction is considered an essential element of the transportation planning process (FTA, 1992; Dickey, 1983; and Stopher and Meyburg, 1975), since it affects the design of transportation facilities or policies and enables planners to evaluate the costs and impacts of the projects. When planning for transportation service, planners must predict future travel on the transportation facilities under alternative policies. For example, they must predict the number of vehicles traveling in a corridor during an average weekday peak period 20 years in the future, under a policy in which the highway system is that which exists at the present time and under a policy in which a new freeway link is added to the system.

Unfortunately, predicting travel demand is a difficult task. Travel demand is a result of a complex interaction between the need for socioeconomic activity and the availability of transportation services. Behavioral, societal, economic, and physical factors all influence when and how people make trips (McCord and Maldonado, 1988).
In practice, planners use various kinds of prediction models to forecast travel demand. Models are, by definition, simplifications of reality. Travel demand models simplify the forecasting task by representing how people make trips in terms of mathematical specifications of the interactions among the travel related factors. The models help planners predict travel demand by efficiently integrating all the related factors through their mathematical specifications.

Even if present interactions could be modeled completely, the future is still uncertain, and future demand cannot be predicted exactly. The future interaction between the personal need for socioeconomic activities and the availability of transportation services may be much different from now. People may make more or fewer trips for their future needs. Destinations may become more attractive because of new market developments in the areas or less attractive because of developments elsewhere. The impedance to travel between specific origins and destinations may be reduced by a new freeway or increased because of congestion. Moreover, people may change their trip making behavior because of the change in their preferences of travel related factors. Since the future is uncertain, travel demand can only be referred to as an uncertain event.

Since travel demand forecasts are uncertain, any point estimate produced from prediction models will very likely be wrong. There are several reported examples of wrong forecasts. Pickrell (1990) found that the ratio of actual to predicted ridership of nine urban rail transit systems in the United States varied from 15 to 72 percent.
Johnston, Sperling and DeLuchi (1988) found similar results for the transit systems in Canada. Bovy and Jansen (1983) found that the difference of actual and predicted flows on urban streets varied from 43 percent to 87 percent. Mackinder and Evans (1981) found that highway and public transit trips were overestimated by 30 to 35 percent in forty-four British urban transportation studies.

Wrong forecasts can lead decision makers to choose solutions that turn out poorly because the future differs from the projections used in the decision making process. For example, ridership forecasts led decision makers of ten cities in the United States to select rail transit projects over bus systems and other Transportation System Management (TSM) programs. The decisions caused local and federal governments to spend about $15 billion (1988 dollars) on building those rail transit systems (Pickrell, 1990). Actual ridership, on average, was less than half of that forecast. A similar problem occurred in Dallas/Fort Worth, where a new multi-billion dollar airport carried fewer passengers than smaller airports in major cities around the United States (de Neufville, 1976).

Since the future is uncertain, it is better to recognize uncertainty in predictions than to ignore it (de Neufville, 1976). One way of recognizing uncertainty is to think carefully about the chance associated with each level of travel demand. When such chances are identified, uncertainty is recognized and can be quantified in terms of probabilities (Winkler, 1972). Ultimately, it would be useful to use the quantified
uncertainty in the planning process to allow for more informed decisions (Lewis, 1995; Morgan and Henrion, 1990; and Maldonado, 1986).

1.2 Research Objectives and Scope

In this study we investigate a preliminary step toward an understanding of uncertainty in travel demand forecasts. Specifically, we want to understand how transportation practitioners and academics judge uncertainty in travel demand forecasts and how these individuals change their judgments about future travel patterns when model forecasts are available.

In general, individuals make some prior judgments about travel demand in the future, but the individuals are uncertain. In this stage, we express these prior judgments as probability distributions over possible levels of travel demand and assess these distributions using subjective probability theory (Savage, 1954; de Finetti, 1937; and Ramsey, 1926).

Individuals normally try to reduce their uncertainty by collecting additional information so that they will feel more confident about the decisions they are going to make (Winkler, 1972; and Raiffa, 1968). The additional information considered in this study comes from the outputs of transportation prediction models. Due to the
questionable assumptions of the models and their inability to predict the demands accurately, it is interesting to know whether transportation practitioners and academics use the outputs of the models to change their prior judgments about future travel demand, and which parts of the models are most useful in reducing the uncertainty in their predictions. To investigate these issues, we show the individuals model outputs and reassess their probability distributions over the same levels of travel demand. We call these distributions posterior distributions, since they represent judgments after having seen model outputs. Changes from the prior to the posterior distribution are then attributed to the additional knowledge obtained when seeing the model output.

The change of judgments due to the model output provides some indication of the value of the model. If the output of the model does not change the prior judgment, the model has no value because the decision would be the same when using either the prior or posterior distribution. In contrast, if the model output changes the prior judgment sufficiently, the model will have a positive value (Clemen, 1990; Winkler, 1972; and Raiffa, 1968). This increase is because the information or the output of the model will lead to a different decision, one with a better value than what would have been experienced without the model output. When the cost of getting the model output is compared with the potential benefits from the change in the decisions, one can determine whether the model output is worth the investment of producing it.
We chose to investigate the change in judgments due to the output of model used in each step of the traditional “four-step travel demand forecasting process” (JHK & Associates and Dowling Associates, 1992; FTA, 1992; Dickey, 1983; US-DOT and FHWA, 1977). This four-step process is the most common process used for predicting travel demand in the urban transportation planning. The process divides the travel demand forecasting task into a series of four smaller tasks or steps: Trip Generation (TG), Trip Distribution (TD), Modal Split (MS), and Traffic Assignment (TA). In the Trip Generation step, the number of trips produced and attracted by each traffic analysis zone are estimated. In the Trip Distribution step, the number of trips originated from each zone are directed to the destination zones. In the Modal Split step, the number of trips between any pair of zones is divided among available modes of transportation. Finally, the Traffic Assignment step is concerned with finding the particular route selected by travelers going between each pair of zones on each mode of transport. Each of these steps is modeled separately, but the output of one model is used as an input to another.

Another objective of this study is to investigate the relative importance of the models used in the four-step process. Specifically, we compared the effects of models among the four steps to identify the step in which the greatest change of judgments occurred. In addition, we compared the effect of the changes in judgments due to the four models on the change in the predicted outcome of the modeling system to identify the model which reduced uncertainty in the predicted outcome the most. We chose Total System Travel Time (TSTT) as the predicted outcome for this investigation, since TSTT
is an outcome often calculated from the outputs of the four-step process. By comparing the effects of different models used in the four-step process, we hope to provide useful input for education and model development. For example, the information about the relative change in judgments due to the four models could help us identify which model individuals rely on. The information about the relative contribution of the models to the reduction of uncertainty in the predicted outcome (TSTT) may also help individuals identify which model is more likely to reduce the uncertainty of conclusions and, hence, would need more refinement to benefit the individuals in making decisions under uncertainty.

The specific research questions for this study are listed as follows:

a) Which step of the four-step process is considered to be most uncertain by individuals familiar with the process when predicting travel demand in the step?

b) Do individuals' judgments of uncertainty towards the transportation events predicted by the models of the four-step process change with the availability of the model outputs?

c) Which model in the four-step process changes the individuals' judgments toward uncertainty the most?

d) Which model in the four-step process contributes to the greatest reduction in the uncertainty of the predicted outcome of the modeling system (TSTT)?
1.3 Overview of Dissertation

This dissertation contains five chapters. Chapter 1 serves as an introduction to this dissertation. We describe the motivation of this study in Section 1.1 and present the research objectives, scope, and questions in Section 1.2. Finally, Section 1.3 provides an overview of chapters in this dissertation.

We present a general overview of common practice for travel demand forecasting in Section 2.1. Specifically, we describe the four-step process as well as the models that are commonly used in the process to predict travel demand. In Section 2.2, we describe why the point estimate from the models would likely be wrong and the problem of using wrong forecasts in making decisions when planning for transportation services. In Section 2.3, we present how to quantify uncertainty in travel demand forecasts. Specifically, we introduce subjective probability theory and demonstrate the techniques that we used to encode subjective probability distributions from individuals for this study.

In Chapter 3, we investigate the effect of prediction models on individuals' judgments toward uncertainty in travel demand forecasts. Specifically, we investigate how individuals change their intuitive judgments about future travel patterns when model forecasts are available. To investigate this issue, we conducted experiments with transportation practitioners and academics who were familiar with travel demand forecasts. We present an overview of the methodology used for the investigation in
Section 3.1. In Section 3.2, we present the experimental design of this investigation. In Section 3.3, we describe the questionnaire used to elicit probability statements that allowed us to answer the research questions posed above. We present the procedure for data collection in Section 3.4. In Section 3.5, we describe the analytical methods used to investigate the effect of the models on the individuals' judgments. Finally, we present the results of the investigation in Sections 3.6 and 3.7. In Section 3.6, we show the results of the investigation for all individuals, while in Section 3.7 we show the results based on some individuals' characteristics that lead to special cases or different conclusions than those that we found in Section 3.6.

In summary, we found the following. First, the individuals felt most uncertain in the Trip Distribution step and felt least uncertain in the Modal Split step both before and after seeing the model output. Second, we found that most individuals did change their judgments toward the uncertainty in the transportation events predicted from the models after observing the model output in each step of the four-step process. The individuals were less uncertain about their predictions after observing the model outputs. Third, we found that the different models of the four-step process had different effects on judgments toward uncertainty. The Traffic Assignment model was the one that reduced individuals' uncertainty in the predicted event the most, while the Modal Split model was the one that reduced uncertainty the least.
In Chapter 4, we investigate which of the four models reduced uncertainty in the prediction of the output of the four-step system the most. We choose Total System Travel Time (TSTT) as the predicted outcome to investigate, since TSTT is an outcome often calculated from the outputs of the four-step process. In Section 4.2, we construct a sequential prediction process based on the four-step process and use it to estimate uncertainty of TSTT. Specifically, we model uncertainty in model outputs of each step of the four-step process based on the “posterior distributions” of Chapter 3 and propagate these posterior uncertainties through the four-step process to develop a base-case probability distribution of TSTT. We then investigate the effect of each model in the four-step process. To investigate the effect of the Trip Generation (TG) model, for example, we model the uncertainty in the outputs of the TG model based on the “prior distribution” in the TG step of Chapter 3 and the uncertainty in the outputs of the other three models based on the “posterior distributions” of Chapter 3. We then propagate the prior TG uncertainties and the other (TD, MS, TA) posterior uncertainties through the four-step process to develop another distribution of TSTT. This distribution would have “larger uncertainty” than the base-case TSTT probability distribution, since the prior TG distribution would have “larger uncertainty” than the posterior TG distribution. We repeat this process using the “prior distribution” for each of the other steps of the four-step process, while using the “posterior distribution” for the other three steps. The changes of uncertainty in TSTT are compared to determine the relative importance of models used in the four-step process.
In summary, we found the following. First, the TG model was the model that led to the greatest reduction in the uncertainty of TSTT, while the TD model was the one that led to smallest reduction in the uncertainty of TSTT. Second, the reduction in the uncertainty of TSTT due to the TG model was much greater that that of the other three models (TD, MS, TA). Third, the TD model, the MS model, and the TA model reduced the uncertainty of TSTT very little.

In Chapter 5, we summarize the findings of this research and their implications for education and model development and propose areas for study. We conclude that individuals felt most uncertain in the TG and TD steps, and least uncertain in the MS step. In addition, individuals were less uncertain about their predictions after observing the model outputs and had the most and least confidence in the TA and MS models, respectively. Therefore, individuals seem to need better understanding about trip making behavior in the TG and TD steps, and there seems to be more need to improve the TG and TD models than the MS and TA models. We also conclude that the TD, MS, and TA models reduced the uncertainty of TSTT only slightly; in contrast, the TG model reduced the uncertainty of TSTT markedly. This implies that special attention should be given to the reduction of uncertainty in the TG step when the objective is to use the four-step process to calculate system-wide TSTT.
CHAPTER 2

UNCERTAINTY IN TRAVEL DEMAND FORECASTING

2.1 Travel Demand Forecasting

2.1.1 Introduction

Transportation planning has been a requirement for receiving Federal capital or operating assistance in the United States since 1962 (Dickey, 1983). The Surface Transportation Assistance Act of 1962 requires urbanized areas of over 50,000 population to have continuing, comprehensive and cooperative (3C) transportation plans if one wants to make use of U.S. federal funds. The act pushed city, state and federal agencies to develop standard techniques and processes for conducting transportation planning. Recent regulations, such as the Federal Clean Air Act of 1990 and the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991, have made transportation planning more comprehensive by requiring planners to consider more issues when planning for transportation service.
Travel demand prediction is thus considered an essential element of the transportation planning process (FTA, 1993; Dickey, 1983; and Stopher and Meyburg, 1975). When planning for transportation service, planners must predict future travel demand assuming the existence of facilities anticipated in the alternative future policies. For example, they must predict the number of vehicles using an existing freeway during a peak period on an average weekday 20 years in the future, with and without a new freeway. Travel demand will affect the design of transportation facilities or policies. It also will enable planners to evaluate the costs and impacts of the projects. As a result, future transportation plans can be properly designed and selected to meet the travel needs in an acceptable manner. We present a general overview of common practice for travel demand forecasting in Sections 2.1.2 to 2.1.7.

2.1.2 Travel Demand Modeling

Predicting travel demand is a difficult task, since travel demand is a result of a complex interaction among various kinds of factors. In practice, planners use various kinds of prediction models to predict travel demand. Models simplify the prediction process by representing how people make trips in terms of mathematical specifications of interactions among related factors. Planners can then compare alternative planning scenarios easily by changing the model inputs according to the alternative scenarios and observing the changes in model outputs.
Many governmental agencies and public organizations are involved in selecting transportation plans. The explicit nature of models can accelerate the planning process by allowing everyone to understand, in common terms, how the forecasts are estimated. Models, by themselves, are explicit because they have definite mathematical specifications. For this reason, models always produce exactly the same forecasts when using the same values of model inputs. Models also make forecasting explicit because they require values of model inputs from planners when forecasting travel demand. Planners must, therefore, be explicit about the values of model inputs in order to use the models.

Travel demand modeling was first developed in the early 1950's when computers capable of manipulating large amounts of data became available (Dickey, 1983). Today, there are many modeling techniques available to planners for forecasting travel demand. Arguably, the most widely used method is called the "four-step process." The popularity of the process is demonstrated by the fact that travel demand modeling is often referred to as the "four-step process" (JHK & Associates and Dowling Associates, 1992).

The "four-step process" divides the travel demand forecasting task into a series of four smaller tasks or steps: Trip Generation, Trip Distribution, Modal Split, and Traffic Assignment. Each of these steps is modeled separately, but the output of one model is used as an input to another. The outputs of the "four-step process" are usually link flows by transport modes (see Figure 2.1). In the Trip Generation step, the number of trips
produced and attracted by each traffic analysis zone are estimated. In the Trip Distribution step, the number of trips originated from each zone are directed to the destination zones. In the Modal Split step, the number of trips between any pair of zones is divided among available modes of transportation. Finally, the Traffic Assignment step is concerned with finding the particular route selected by travelers going between each pair of zones on each mode of transport. The following four sections describe state-of-the practice and concerns in the four-step demand modeling. More detailed description and examples can be found in JHK & Associates and Dowling Associates (1992); Dickey (1983); US-DOT and FHWA (1977); US-DOT, FHWA and UMTA (1977).

![Four-Step Travel Demand Forecasting Process](image)


Figure 2.1: The Four-Step Travel Demand Forecasting Process
2.1.3 Trip Generation

The Trip Generation step is the first step in the four-step process. In this step, trip productions and trip attractions for each zone are estimated. Trip productions and trip attractions are the number of person trips produced at and attracted to each zone, respectively. Trip Generation is a step representing an attempt to quantify the relationship between urban activities and travel. The number of trips is estimated by using information about land use, population and economic indicators. These estimates are usually made separately by trip purpose. Examples of the trip purposes are home-based work trips, home-based shopping trips, home-based other trips, non-home based trips, truck trips and taxi trips. Home-based trips are trips that begin or end at home, while non home-based trips are trips that neither begin nor end at home.

The most commonly used models for Trip Generation are the cross-classification model and the linear regression model (FTA, 1993; and JHK & Associates and Dowling Associates, 1992;). Both models can be used to estimate trip productions or trip attractions. However, the cross-classification model is more often used for estimating trip productions while the linear regression is more often used for estimating trip attractions. Different independent variables are used in the trip production and trip attraction models. Commonly used trip production variables are income, auto ownership, number of dwelling units and household size. Commonly used trip attraction variables are employment and floor space.
The cross-classification model estimates trips by multiplying the number of units (usually number of households or individuals) in certain groups with trip rates of the groups. First, the units of analysis (usually households) are stratified into a number of groups according to levels of socioeconomic variables. As mentioned above, commonly used variables are income, number of persons in a household, and auto ownership. The purpose of stratification is to create relatively homogeneous groups of households. Second, trips generated in each group are estimated by multiplying the number of households in the group with the trip rate of the group. Example trip rates are shown in Table 2.1. The rates are normally estimated from travel survey data. Finally, the number of trips generated in a zone are obtained by summing the number of trips generated by every group in the zone. The model has the following formula:

\[ T_i = \sum_{all\ j} HH(i, j) \times Rate(i, j), \] (2.1)

where \( T_i \) is the number of person trips generated in zone “i”; “j” is an indicator of specific socio-economic variables; \( HH(i, j) \) is the number of households (or individuals) located in zone “i” having “j” as an indicator of specific socio-economic variables; and \( Rate(i, j) \) is a trip rate or the number of person trips per household (or individuals) in zone “i” having “j” as an indicator of specific socio-economic variables (trip rates are usually estimated from travel survey data).
The other common type of model used for the Trip Generation step are regression models. This model links trips to some explanatory variables by using a linear equation:

$$T_i = a + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_n X_{in}$$ (2.2)

where $T_i$ is the number of person trips produced in or attracted to zone "i"; $X_{in}$ is the $n^{th}$ variable of zone "i"; "a" is a constant of the linear equation; and $\beta_n$ is a parameter for the $n^{th}$ variable.

Unlike the cross-classification model, the regression model is usually developed by using data at an aggregate level (usually zone) and used to estimate trips at the an aggregate level (zone). The constant (a) and parameters (\beta) are estimated from the model calibration process (see Section 2.1.7) by using travel survey data.

---

### Table 2.1: Example Trip Rates.

<table>
<thead>
<tr>
<th>Family Size</th>
<th>0</th>
<th>1</th>
<th>2 or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.19</td>
<td>2.57</td>
<td>1.70</td>
</tr>
<tr>
<td>2</td>
<td>1.43</td>
<td>3.16</td>
<td>2.17</td>
</tr>
<tr>
<td>3</td>
<td>1.45</td>
<td>4.55</td>
<td>4.74</td>
</tr>
<tr>
<td>4 or more</td>
<td>2.02</td>
<td>4.40</td>
<td>5.05</td>
</tr>
</tbody>
</table>

Unit: trips per household.
In the Trip Generation step, there is a need to balance trip productions and attractions. Conceptually, the total trip productions must equal the total trip attractions at the regional level. If not, some trips will be attracted that are not produced or produced that are not attracted. Since trip productions are estimated independently from trip attractions, imbalances between the two estimates can occur. A balancing routine adjusts trip attractions by zone so that the total number of trip attractions equals the total number of trip productions (US-DOT and FHWA, 1977).

2.1.4 Trip Distribution

The Trip Distribution step is the step by which zonal trip productions are distributed to attraction zones in the study area, including the production zone. As a result, trips between production zones and attraction zones are estimated. The Trip Distribution step is based on attempts to quantify the relationship between a choice of attraction zone and the relative attractiveness of attraction zones. The attractiveness of various zones is compared to determine the number of trip productions attracted to each zone. Conceptually, zones with higher degree of attractiveness receive higher numbers of trip productions. Trip Distribution is usually done separately by trip purposes.
The most commonly used model for Trip Distribution is the gravity model (JHK & Associates and Dowling Associates, 1992; and FTA, 1993). The general form of the model is as follows:

\[ T_{ij} = \frac{P_i \cdot A_j \cdot F_{ij} \cdot K_{ij}}{\sum_{all_j} A_j \cdot F_{ij} \cdot K_{ij}} \quad (2.3) \]

where \( T_{ij} \) is the number of person trip productions in zone "i" that attracted to zone "j"; \( P_i \) is the number of person trip productions in zone "i"; \( A_j \) is the number of person trip attractions in zone "j"; \( F_{ij} \) is a friction factor for trips produced at zone "i" and attracted to zone "j"; and \( K_{ij} \) is a socio-economic adjustment factor for trips produced at zone "i" and attracted to zone "j", usually assumed to be 1 (US-DOT and FHWA, 1977).

The gravity model distributes trip productions based on the attractiveness of the attraction zone and the spatial separation of the production zone to the attraction zone. The attractiveness of an attraction zone is measured by the number of trip attractions (\( A_j \)) of the zone. As seen in equation 2.3, an attraction zone with a larger number of trip attractions will receive a greater fraction of trip productions than one with a smaller number of trip attractions.

The spatial separation between a pair of zones has an inverse proportional relationship with the distributed trips (\( T_{ij} \)). An attraction zone having greater spatial separation from the production zone receives a lower fraction of the production trips.
Spatial separation is measured in terms of travel impedance (Cij). Examples of the travel impedance are travel time, distance, out-of-pocket cost, and a combination of travel time and cost. Larger travel impedance between zone “i” and “j” means greater spatial separation between zone “i” and “j” and, hence, smaller fraction of trip produced at zone “i” and attracted to zone “j”. The impedance is represented by friction factor (Fij) in the gravity model. The common functions for the friction factor (Meyer and Miller, 1984, p.251) are Fij = Cij^β; Fij = e^{-βCij}; alternatively, Fij can be a graphical function of Cij. The functions imply that the smaller the travel impedance (Cij), the larger the friction factor (Fij) and, hence, the larger fraction of trip produced in zone “i” that attracted to zone “j”. Note that β is a parameter of the friction factor function. It must be estimated from travel survey data in the model building process.

As with Trip Generation, there are “conservation” concerns when applying the gravity model. The outputs of the gravity model must be adjusted so that the number of trips produced at and attracted to each zone match the ones found in the Trip Generation process. An additional concern relates to the fact that the outputs of the gravity model are trips from production zones to attraction zones, while the desirable trips are the directional trips from origin zones to destination zones. Production-attraction trips are not always the same as origin-destination trips, since trips that originated from or ended at homes are always considered as trip produced at home (see explanation below). When the difference occurs, production-attraction trips must be converted to origin-destination trips before used as inputs to Modal Split model.
Note that homes are always considered as production zones even though they are places of destination. For example, a trip from a work place to home is considered as a trip originating at the work place and destined to home in an origin-destination format, while the trip is considered as a trip produced at home and attracted to the work place in a production-attraction format. As a result, trip conversion is necessary for all home-based trips, since the production and attraction zones are not the same as the origin and destination zones. In contrast, trip conversion is not necessary for trips that have neither origin nor destination at home (i.e., non home-based trip), since production and attraction zones are the same as the origin and destination zones.

Origin-destination trips can be obtained by applying directional trip factors to production-attraction trips from the gravity model. The factors can be derived from travel survey data (see for example SANDAG, 1995). In practice, a 50-50 split is assumed for the average daily analysis of all home-based trips (US-DOT and FHWA, 1977) implying that all trips originating at homes eventually return to homes on an average weekday.

2.1.5 Modal Split

The Modal Split step is the step by which trips between a given origin and destination are split into trips using various modes. Examples of the modes are automobile, bus and light-rail transit. The step represents an attempt to quantify the
relationship between a choice of modes and the relative benefits of using various modes. The benefits of using various modes are compared to determine which modes travelers choose. Modal Split is usually done separately by trip purposes.

The most commonly used model for Modal Split is the Logit model (JHK & Associates and Dowling Associates, 1992; and FTA, 1993). The general form of the model is as follows:

\[ P_n(i) = \frac{e^{U_{in}}}{\sum_{j} e^{U_{jn}}} , \]  

where \( P_n(i) \) is a probability of individual “n” choosing mode “i”; and \( U_{jn} \) is a utility of mode “j” for individual “n”.

The Logit model splits the trips among various modes based on the relative benefits of a traveler using a specific mode. The benefits are represented by the utility. The utility usually is a linear combination of factors affecting travelers' decisions on which mode to use for their travel needs. Examples of the factors are travel time and travel cost of a mode between an origin and a destination. The general form of the utility is as follows:

\[ U_i = a + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_n X_{ni} , \]  

23
where $U_i$ is a utility of mode “i”; $X_{ni}$ is the $n^{th}$ factor affecting a traveler decision about choosing mode “i”; “$a$” is a constant of the utility function; and $\beta_n$ is a parameter for the $n^{th}$ factor.

The factors ($X$), constant ($a$) and parameters ($\beta$) may be different from places to places reflecting the differences in travel behavior in different places. The constant ($a$) and parameters ($\beta$) must be estimated from travel survey data in the model building process.

In this step (US-DOT, FHWA and UMTA, 1977), person trips by autos must be converted to vehicle trips. The vehicle trips from different trip purposes are then combined to form a single vehicle trip table before used as an input to Traffic Assignment model. An auto occupancy model is used for converting auto person trips to vehicle trips. In practice, vehicle trips are obtained by applying fixed auto occupancy rates to auto person trips from the Modal Split model. Usually, different auto occupancy rates are used for different trip purposes. Examples of the rates can be found in SANDAG (1993).

2.1.6 Traffic Assignment

The Traffic Assignment step is a step by which trips between an origin and destination are assigned to the specific links on transportation network. The step
represents an attempt to quantify the relationship between a choice of routes and the relative cost or impedance of using various routes. The costs of using possible routes are compared to determine which routes travelers use. The Traffic Assignment step constitutes the most complex calculation in the four-step process, since the number of alternative routes is usually extremely large. Travel time is one of the most common factors of the cost of using a route. Different modeling techniques are used for assigning highway trips and transit trips, since highway systems provide travelers many more routes than transit systems do. In the next section, we present arguably the most well-known technique used for highway Traffic Assignment.

The most commonly used model for highway Traffic Assignment is the User-Equilibrium (UE) model (JHK & Associates and Dowling Associates, 1992; and FTA, 1993). The model assumes that (a) any traveler chooses a route to minimize his or her travel time between two zones; and (b) the level of flow on a link affects the travel time in the link (Sheffi, 1983). The model applies a procedure to search for the flow pattern at an equilibrium condition. The equilibrium condition is a condition in which any traveler going from his or her origin to his or her destination cannot go faster by switching to an alternate route. In 1963, Beckmann successfully transformed the User-Equilibrium Traffic Assignment problem into a nonlinear optimization problem. The transformation allows one to use optimization techniques to find a solution to the User Equilibrium Traffic Assignment problem. A commonly used technique is the Frank-Wolfe algorithm, which
involves an iterative process that guarantees convergence to the user-equilibrium solution (Sheffi, 1983).

The travel time on a highway segment is determined by a link performance function. The most common function is the function developed by the Bureau of Public Roads (1964):

\[ T_i(V_i) = T_{io} \left[ 1 + \alpha^*(V_i/C_i)^\beta \right], \]  

where \( T_i(V_i) \) is travel time on link "i" when traffic volume is \( V_i \); \( T_{io} \) is free flow travel time on link "i"; \( V_i \) is a traffic volume of link "i"; \( C_i \) is a practical capacity of link "i"; and \( \alpha \) and \( \beta \) are parameters of the function (the common values are \( \alpha = 0.15 \) and \( \beta = 4 \)).

Traffic flows during the peak hour are usually the desired forecasts in the transportation planning process. However, the traditional four-step process produces daily traffic flows. Peak hour demand can be obtained by multiplying daily demand with peak hour factors (PHF). Basically, there are two methods to apply the peak hour factors. The first method is to apply the factor after the Traffic Assignment step (US-DOT and FHWA, 1977). In this method, the outputs of the traditional four-step process, which are daily link flows, are multiplied by PHF to arrive at the peak hour link flows. The second method is to apply PHF before the Traffic Assignment step (JHK & Associates and Dowling Associates, 1992). In this method, daily vehicle trips from the Modal Split step
are multiplied by PHF before they are used in the Traffic Assignment step. This method may produce more realistic estimates because the method allows the use of a more realistic congestion level when assigning trips.

2.1.7. Building Travel Demand Models

Before forecasting travel demand, it is necessary to represent the study area with zones and network systems. Normally, the study area is divided into a set of small geographic areas called traffic analysis zones or, in short, zones. Also, the transportation systems available in the study area are coded in a network format. Any trip that might be made in a zone is then assumed to begin or end at the centroid of the zone. The centroids represent the center of activities of the zones. They are connected to the network system by a “dummy” network arc.

Zones vary in size and shape. Zones are usually developed so that they encompass homogeneous land use or urban activities, such as residential or commercial activities (US-DOT, FHWA and UMTA, 1977). Therefore, zones are usually small in dense areas or central business areas, and large in undeveloped or suburban areas. In practice, zone systems are designed with attention to the systems for which the travel related data are coded. As a result, zones are usually bounded by census tract boundaries, streets, or natural barriers. One might expect the forecast accuracy to increase with finer resolution.
of zones. However, small zones require more data and time in the model building stage and the forecasting process.

The network systems usually consist of highway and transit networks. Other available transportation systems (such as express bus, subway, and ferry) can be coded in the network format as well. The network uses links to represent highway segments or transit segments and nodes to represent highway intersections or transit stations. Links and nodes provide data representing the level of service of the transportation systems in the study area. For highway networks, links provide data about travel times on the link, average speeds, capacity, and direction. Nodes provide data about intersections and the location of the node.

The mathematical networks are models of the real system and do not show all actual links and nodes. These mathematical networks must, therefore, be designed and tested in the travel demand modeling process to ensure that the forecasts based on the networks are reasonably accurate. Networks with too few links may result in too many trips predicted on the major links (JHK & Associates and Dowling Associates, 1992). Networks with too many links will require more data and time in the model building stage and the forecasting process.

After representing the study area with zone and network systems, a considerable effort must be made to build models to be used as a forecasting tool. As mentioned above,
planners usually build a set of models for each step of the four-step process. Then, the models are combined so that the outputs of models in one step are inputs to models in the next step. Typically, building a model includes three tasks: model specification, model calibration, and model validation (JHK & Associated and Dowling Associates, 1992; and US-DOT, FHWA and UMTA, 1977). A brief description of each task is presented below.

In model specification, the mathematical formulation must be defined and variables must be selected. Furthermore, the level of the analysis for which the models are going to be used must be specified. For example, it must be decided whether the model is to represent individual travel behavior or a larger group's behavior. For the four-step process, there is a need to design how models in one step relate to models in the next step. Note that the specifications of the models depend on the transportation problem of interest and limitations, such as the availability of data, time, and money.

In model calibration, the parameters of the model are estimated from available travel data, called base year data. The calibration process searches for the values of the parameters that allow the model using such parameters to reasonably duplicate travel patterns of the base year data. Different calibration techniques are used to calibrate the model parameters, since different models are used in different steps of the four-step process.
In model validation, the predictive accuracy of the model is evaluated to determine the usefulness of the model. Model validation is done by comparing the model forecasts with the base-year travel data. The model should produce forecasts that reasonably duplicate the base-year travel behavior; otherwise the model should not be used as a forecasting tool. It is recommended that the validation data be different from those used in the calibration process. (JHK & Associated and Dowling Associates, 1992).

2.2 Uncertainty in Travel Demand forecasts

2.2.1 Sources of Uncertainty

The future is uncertain; therefore, future travel demand cannot be predicted exactly. Travel demand is a result of complex interactions between the need for socioeconomic activity and the availability of transportation services. People may make more or fewer trips due to their future socioeconomic needs. Destinations may become more attractive because of new market developments in the areas or less attractive because of developments elsewhere. The impedance to travel between specific origins and destinations may be reduced by a new freeway or increased because of congestion. Moreover, people may change their trip making behavior because of the change in their preferences of travel related factors. Since the future is uncertain, travel demand can only be referred to as an uncertain event.
In practice, planners need forecasts 15 to 25 years into the future for their long-range transportation planning process. For examples, planners must forecast how many vehicles will be on a specific freeway 25 years from now. For such a long period, no model can predict future demand exactly, and forecasts from models can be highly uncertain. The uncertainty is a result not only of uncertain model inputs but also in the inability of models themselves to predict human behavior.

Uncertainty in model inputs is one source of uncertainty in model outputs. Planners must estimate future values of model inputs when using models to predict future travel demand. For example, the Trip Production model in the Trip Generation step would require planners to estimate future values of income, auto ownership, number of dwelling units and household size. Planners cannot know the values of these inputs 15 to 25 years into the future. In practice, planners frequently disagree about the values of these inputs: different planners may view the future from very different perspectives.

The inability of models to predict human behavior is another source of uncertainty in model outputs. Planners build models based on incomplete knowledge about how people make trips. Different planners may have different ideas in designing models to represent trip making behavior. They do not always agree on model specifications: the structures of the models, the functional forms of the models, the parameters of the models, and the variables of the models. As mentioned in Section 2.1, travel demand models simplify trip making behavior as a function of a few variables. Planners may be
able to build models that adequately simulate the general travel patterns of the past. However, these may simply be "fits" to data and not truly capture behavior. If behavior is not captured, the models can not predict future travel patterns correctly. Moreover, there is no guarantee that behavior will not change in the future.

2.2.2 Problems due to Uncertainty

Since travel demand forecasts are subject to uncertainty in the future, any estimate from prediction models will very likely be wrong. In fact, there are many reported examples of wrong forecasts. Horowitz and Emslie (1978) found that the forecast traffic volumes of urban interstate highways overestimated the actual volumes by 21 percent on average. Mackinder and Evans (1981) found that highway and public transit trips were overestimated by 30 to 35 percent on average in forty-four British urban transportation studies. Bovy and Jansen (1983) found that the differences between actual and predicted flows varied from 43 percent to 87 percent depending on the level of network aggregation. Janson, Thint and Hendrickson (1986) found that the differences between actual and predicted flows along two screen lines varied from 16 to 28 percent. Mathew (1987) found that there was an average of 28 percent in variation between actual flows and predicted flows from the best method among eight models (PlanPac-UTPS). Pickrell (1990) found that the ratio of actual to predicted ridership of nine urban rail transit systems in the United States varied from 15 to 72 percent. Johnston, Sperling and
DeLuchi (1988) found that ratio of actual to predicted ridership of nine urban rail transit systems in North America varied from 11 to 117 percent. De Neufville (1976) found that forecasts of US-Domestic and international air traffic were exceeded by 20% on average after six years.

Wrong forecasts can lead to financial disasters for local and federal governments, as well as for private investors. The costs of providing transportation facilities are usually very high. Tables 2.2 and 2.3 show the costs of providing some highway and transit facilities in urban areas across the United States. Wrong forecasts can lead decision makers to choose solutions that turn out poorly because the future differs from the projections used in the decision making process. For example, ridership forecasts led decision makers of ten cities in the United States to select rail transit projects over bus systems and other Transportation System Management (TSM) programs. The decisions caused local and federal governments to spend about $15 billion (1988 dollars) on building those rail transit systems. Actual ridership, on average, was less than half of that forecasts (Pickrell, 1990). A similar problem occurred in Dallas/Fort Worth, where a new multi-billion dollar airport carried fewer passengers than smaller airports in major cities around the United States (de Neufville, 1976).
### Table 2.2 Costs of Providing Selected Urban Highway Facilities

<table>
<thead>
<tr>
<th>Urban Highway Facility</th>
<th>Total Cost</th>
<th>Miles</th>
<th>Cost per Miles</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-66 Arlington, Virginia</td>
<td>233</td>
<td>10.1</td>
<td>23</td>
</tr>
<tr>
<td>1-635 Kansas City, Kansas</td>
<td>25</td>
<td>16.5</td>
<td>2</td>
</tr>
<tr>
<td>1-270 St. Louis</td>
<td>153</td>
<td>35.6</td>
<td>4</td>
</tr>
<tr>
<td>I-695 Baltimore</td>
<td>154</td>
<td>30.8</td>
<td>5</td>
</tr>
</tbody>
</table>

**In Design Stage (costs in millions of 1979 US dollars)**

<table>
<thead>
<tr>
<th>Urban Highway Facility</th>
<th>Total Cost</th>
<th>Miles</th>
<th>Cost per Miles</th>
</tr>
</thead>
<tbody>
<tr>
<td>I-478 Westway, New York City</td>
<td>1400</td>
<td>6.1</td>
<td>229</td>
</tr>
<tr>
<td>I-90 Seattle, Washington</td>
<td>904</td>
<td>7.5</td>
<td>120</td>
</tr>
<tr>
<td>I-105 Century, Los Angeles</td>
<td>1600</td>
<td>17.2</td>
<td>93</td>
</tr>
<tr>
<td>I-696 Vine St., Philadelphia</td>
<td>168</td>
<td>2.5</td>
<td>67</td>
</tr>
<tr>
<td>I-670 Columbus, Ohio</td>
<td>199</td>
<td>10.5</td>
<td>19</td>
</tr>
<tr>
<td>I-595 Ft. Lauderdale, Florida</td>
<td>457</td>
<td>13.4</td>
<td>34</td>
</tr>
</tbody>
</table>

Source: John W. Dickey, Metropolitan Transportation Planning, p.46, 1983.

### Table 2.3 Costs of Providing Selected Urban Transit Facilities

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Heavy Rail Transit Projects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Washington, D.C.</td>
<td>7968</td>
<td>199.9</td>
</tr>
<tr>
<td>Atlanta</td>
<td>2720</td>
<td>40.3</td>
</tr>
<tr>
<td>Baltimore</td>
<td>1289</td>
<td>21.7</td>
</tr>
<tr>
<td>Miami</td>
<td>1341</td>
<td>37.5</td>
</tr>
<tr>
<td><strong>Light Rail Transit Projects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buffalo</td>
<td>722</td>
<td>11.6</td>
</tr>
<tr>
<td>Pittsburgh</td>
<td>622</td>
<td>8.1</td>
</tr>
<tr>
<td>Portland</td>
<td>266</td>
<td>5.8</td>
</tr>
<tr>
<td>Sacramento</td>
<td>188</td>
<td>6.9</td>
</tr>
<tr>
<td><strong>Downtown People Mover (DPM) Projects</strong></td>
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<td></td>
</tr>
<tr>
<td>Miami</td>
<td>175</td>
<td>4.6</td>
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<tr>
<td>Detroit</td>
<td>215</td>
<td>10.9</td>
</tr>
</tbody>
</table>

Since the future is uncertain, it is better to recognize uncertainty in prediction than to ignore it (de Neufville, 1976). Historically, planners ignore uncertainty in predictions in order to appear confident when planning for transportation service. It would be useful to quantify uncertainty and use it in the planning process to allow for more informed decisions (Lewis, 1995; Morgan and Henrion, 1990; and Maldonado, 1986). One way of recognizing uncertainty is to think carefully about the chance associated with each level of travel demand. Such chances are frequently quantified in terms of probabilities (Lewis, 1995 and Winkler, 1972). We explain methods for quantifying uncertainty in terms of probability in the following section.

2.3 Quantifying Uncertainty

2.3.1 Uncertainty and Probability

The probability of an event can be interpreted as a numerical measure of a person's degree of belief that an event will occur (Morgan and Henrion, 1990; Winkler 1972). In other words, probability is a quantified belief. The probability of any event is scaled between zero and one. The probability equals zero when the event will not occur and equals one when the event will certainly occur. Any intermediate value represents an
intermediate degree of belief on the outcomes of the uncertain event. For example, an event is equally likely to occur or not occur when the probability is 0.5.

Probability is a popular means of quantifying uncertainty. It is popular because probability quantifies personal degree of belief with number. Representing any degree of belief with a number has several advantages over representing any degree of belief with an expression. First, a probability of an uncertain event (such as 0.3 and 0.5) has a specific meaning, while an expression of an uncertain event (such as “probable” and “likely”) may have several meanings across individuals. Second, probabilities or numbers are easier to use than expressions in comparisons. For example, it is easier to elucidate the difference between 0.3 and 0.5 than to elucidate the difference between “probable” and “likely.” Third, probabilities, unlike expressions, can be scaled into small intervals to precisely represent various degrees of beliefs.

2.3.2 Objective and Subjective Probabilities

Probability can be derived by two methods: objective (or classical) and subjective, or Bayesian (Wright and Ayton, 1994; Winkler, 1972; Savage, 1954; and de Finetti, 1937). We introduce the two methods here and explain why we use the subjective method to quantify uncertainty in this study.
According to an objective method, a long-run relative frequency is used as an interpretation of probability for an uncertain event. Conceptually, probability is viewed as the value to which the long-run frequency would converge as the number of experiments increases toward infinity (Winkler, 1972). It is implied that the events must be the outcomes of repeatable phenomena (for example, tossing a coin, drawing a white ball from an urn having 25 black and 10 white balls). For this reason, we must be able to observe the event of interest under identical conditions in order to obtain the probability of the event.

Although, future travel demand can be thought about in a probabilistic sense, it cannot be thought of in terms of a relative frequency. We cannot observe many repetitions of the transportation events under identical conditions. For example, we may want to know the chance that the number of cars on a specific freeway one year from today during the a.m. peak hour will be 3,500. We may have past information about the number of cars on that specific freeway. And, we may be lucky enough that there were some days in the past that the number of cars on that street during the a.m. peak hour was exactly 3,500. However, it is very doubtful that the condition leading to travel in the past were identical to those one year from now. In fact, travel conditions change daily. The conditions may change because some travelers may be ill and not make trips, or they may want to try different destinations, or they may change their departure time or arrival time. For these reasons, there is no information available, in terms of observed frequencies, about the transportation event of interest.
In this case, we must use subjective methods to estimate probability of future travel demand. According to this method, a personal degree of belief is used as an interpretation of probability of an uncertain event. Subjective probability theory (Savage, 1954; de Finetti, 1937; and Ramsey, 1926) allows an individual to quantify his or her judgment and to use it as an interpretation of probability. The theory was developed based on Ramsey's work on notation of measurement and de Finetti's early work on quantification of personal belief. Savage, then, showed that the theory satisfies axioms of probability theory. According to Ramsey's notation, a degree of belief is a measure of an individual's propensity to take action, in the same way that the mass of an object is a measure of a propensity of an object to act against resistance under gravity force. According to de Finetti's work, degree of belief can be quantified from an individual's decisions on simple bets or lotteries.

There are no right or wrong probability distributions when thinking in terms of subjective probability, since probability is interpreted in terms of personal degree of belief. The individual expresses his or her belief by relying on available information and heuristic principles (Tversky and Kaneman, 1982). Different people may have different degrees of beliefs regarding certain events and, hence, will express different probabilities.

Subjective probabilities have been widely used as an important element in the analysis of various kinds of decision problems for years (Winkler et. al., 1995; Corner
and Kirkwood, 1991; Morgan and Henrion, 1990; Keeney and von Winterfeldt, 1989; de Neufille, 1976; and Raiffa, 1968). In many cases, subjective methods are the only methods that allow planners to quantify the uncertainty of the events of interest.

Many studies show that subjective probability forecasts can be reasonably accurate. Murphy and Winkler (1977a) studied 24,859 precipitation probability forecasts made subjectively by meteorologists in Chicago during the four-year period ending June 1976. They found that the forecasts were exceptionally accurate (see Figure 2.2). For example, it rained about 30% of the time when meteorologists predicted that there was a 30% chance of rain. Yates (1990) found the overall accuracy of subjective probability forecasts in weather forecasting, business forecasting and medicine diagnoses to be reasonably accurate.

In this study, we shall use subjective probability theory to quantify planners' judgments towards uncertainty in predicting transportation events.
2.3.3 Techniques for Encoding Subjective Probabilities

Several procedures and methods have been proposed for encoding subjective probabilities (e.g. Winkler et al., 1995; Keeney and von Winterfeldt, 1991; Merkhofer, 1987; Wallsten and Budescu, 1983; Spetzler and von Holstein, 1975; Hampton, Moore, and Thomas, 1973; and Winkler, 1967). However, there is no standard method. The available methods may be different in their details, but they share the same goals, namely: (a) reducing the effect of cognitive and motivational biases often held by subjects; (b) helping experts provide probability distributions that accurately represent their
judgments; and (c) making the assessment of subjective probability distributions formal and explicit.

In general, the encoding procedures include three main parts: (a) preparation for encoding, (b) encoding, and (c) verifying. In the first part, the subject is conditioned to avoid cognitive and motivational biases. Subjects usually are given training in encoding probability judgment and are given explanation of the importance of their judgments. Also in this part, the uncertain event is clearly defined, and the subjects are given the relevant information used to help them think about the uncertain quantity associated with the event. In the second part, the subjective probability distribution for the uncertain event is actually encoded. The judgment is quantified in this part. The methods used for quantifying the judgment will be explained in the following paragraphs. In the last part, the subject is asked to review his or her assessed probability distribution. The purpose of this part is to make sure that the subject really believes his or her quantified judgment. If the quantified judgments do not reflect his or her beliefs, the subject is allowed to make adjustments to the assessed distribution.

In general, the encoding methods are based on questions for which the answers can be represented as points on a cumulative distribution function, CDF, (Spetzler and von Holstein, 1975). Subjects are usually asked to assign values that correspond to the points on the CDF, for example, 0.25, 0.50, and 0.75. Subjects may be asked directly for
the numbers that correspond to the points on the CDF (direct mode) or asked indirectly by choosing between simple bets (indirect mode).

Research shows that the indirect mode is preferable to the direct. Most people seem to experience difficulty in giving directly the numbers that correspond to the points on the CDF (direct mode) and those who are capable of giving directly the numbers are later found to have little confidence in their initial numerical responses (Merkhofer, 1987; and Spetzler and von Holstein, 1975). The widely used indirect methods are based on the use of a probability wheel or a bisection procedure. They are popular because they are easy to explain and understand and, therefore, should lead to more representative responses.

The Probability Wheel method (Spetzler and von Holstein, 1975; Merkhofer, 1987) requires a subject to compare a chance that an event will occur with a chance that the pointer of a probability wheel will land in a target area when the pointer spun. A point on a CDF can be found by either adjusting the target area, as represented by a dark area, or the value of the event until the subject feels that the chances of the event occurring and of the pointer falling in a target area are equally likely. The relative amount of target area is then assigned as the probability of the event. An example of a probability wheel is shown in Figure 2.3.
To illustrate the method, assume that we want to encode a 50-percentile level of
tomorrow’s reported high temperature in Columbus, Ohio. First, we must set the target
area such that it covers 50 percent of the total wheel’s area (see Figure 2.4). We then
would ask a subject to compare two events at a time and ask which event he believes is
more likely. The two events are (a) the tomorrow’s reported high temperature in
Columbus will be below a certain level, for example 0 °F; and (b) the pointer will land in
the target area of the probability wheel when the wheel spun. If the subject believes it is
more likely that the pointer will land in the target area, we would change the temperature
from 0 °F to a higher level, for example 50 °F, and ask the subject to compare the two
events again. If, in the original question, the subject believed that the temperature was more likely to be below 0 °F, we would change the temperature from 0 °F to a lower level, for example -10 °F, and ask the subject to compare the two events again. We would keep asking the same question but change the number (temperature) until we would find the temperature at which the subject thought it equally likely that the high temperature tomorrow would be below that number and the pointer would fall in the target area when the pointer spun. The number would be the temperature that represents the subject’s 50-percentile level on a probability distribution.

![Figure 2.4: A Probability Wheel with a 50 percentage of Target Area](image)

The bisection method (Spetzler and von Holstein, 1975; Merkhofer, 1987), also known as the interval or fractile method, requires the division of an interval into subintervals or fractiles such that the event is equally likely to occur in any subinterval.
Typically, the median value is determined first by dividing the range of possible values into two equally likely regions. Then, values for the 25 and 75 percent points on the CDF are found by subdividing each of those regions.

To illustrate the bisection method, assume that we again want to encode a 50-percentile level of the high temperature. We would begin the encoding session by presenting the subject a range of possible temperatures. We then may ask the subject directly the number (temperature) at which he believes it divides the range of possible values into two equally likely regions. It may be necessary to guide some subjects to such number. We may start the encoding session by picking a number (temperature) at a low level, for example 0 °F, and asking the subject whether tomorrow's high temperature is more likely to be below or above 0 °F. If the subject believed it more likely to be above that number, we would change the number (temperature) from 0 °F to a higher level, for example 50 °F and then ask the same question. If the subject believed it likely to be below that number, we would change the number from 0 °F to a lower level, for example -10 °F and then ask the same question. We would keep asking the same question but change the number (temperature) until we would find the temperature at which the subject thought it equally likely that the high temperature tomorrow would be below or above that number. The number would be the temperature that represents the subject's 50-percentile level on a probability distribution.
In this research, we use a combination of Probability Wheel and Bisection methods to encode subjective probability from our subjects. We use the Probability Wheel technique to assess the values for the 25 percent and 50 percent points (Median) on the CDF. We then use the bisection technique to verify that median found from the probability wheel method. We present a detailed description of the procedure and methods used for encoding expert judgments for this study in Section 3.3.
CHAPTER 3

EFFECT OF MODELS ON JUDGMENTS TOWARD UNCERTAINTY

3.1 Overview of Methodology

In this chapter, we investigate the effect of prediction models on individuals' judgments toward uncertainty in travel demand forecasts. Specifically, we investigate how individuals change their intuitive judgments about future travel patterns when model forecasts are available. To investigate this issue, we conducted experiments with individuals familiar with transportation forecasts. In these experiments, we specified transportation events of interest (see Section 3.4.2 for details) and elicited the individuals' judgments about the events. We used subjective probability theory to encode two kinds of judgments: prior and posterior judgments. The prior and posterior judgments, respectively, were the judgments before and after the individuals observed the outputs of the models. Differences between the prior and posterior judgments were used to indicate the change in judgments due to the model outputs.
The change of judgments due to the model output provides some indication of the value of the model. If the output of the model does not change the prior judgment, the model has no value because the decision would be the same when using either the prior or posterior distribution. In contrast, if the model output changes the prior judgment sufficiently, the model will have a positive value (Clemen, 1990; Raiffa, 1968; and Winkler, 1972). This is because the information or the output of the model will lead to a different decision, one with a better value than what would have been experienced without the model output.

In this study, we investigated the effects of the traditional transportation prediction models used in the four-step travel demand forecasting process. The four steps are Trip Generation (TG), Trip Distribution (TD), Modal Split (MS) and Traffic Assignment (TA). We also compared the effects of models among the four steps to identify the step in which the greatest change of judgments occurred. By comparing the effects of different models used in the four-step process, we hope to provide useful input for education and model development.

The methodology for this investigation can be summarized as follows. First, we designed our experiment so that we could have data to find the answers to our research questions. The data were probability judgments from local planners, consultants, and academics familiar with travel forecasting. Second, we designed a questionnaire to be used for encoding the probability judgments. We pre-tested the questionnaire on 57
students at The Ohio State University and a few planners. Based on this pretest, we made slight modifications to the questionnaire. Third, we designed how to collect data. This included the design of the interview process for each subject, selection of subjects, and selection of the specific techniques for eliciting judgments from each subject. Finally, we designed methods for analyzing the assessed judgments of individuals to find the answers to our research questions. The details involved in each step are addressed in the following sections.

3.2 Experimental Design

3.2.1 Subjects

The subjects in this study were practitioners and academics familiar with transportation forecasting models. Due to time and budget constraints, we collected data from practitioners and academics in the Columbus, Ohio, area only. All subjects were voluntary subjects. They were classified into one of three groups according to their places of employment: governmental agency, private consulting company, or academic institution. In this experiment, our subjects consisted of 21 planners from six different governmental agencies, 18 planners from 12 different private consulting companies, and 8 academics, all from The Ohio State University.
3.2.2 Requirements for Data Collection

We decided to collect data through personal interviews. Based on extensive testing with 57 students who registered for graduate-level courses in transportation program at The Ohio State University, we found that an interaction between interviewer and participant was necessary to get reliable results. Personal interviewing had many advantages. First, we could answer questions that might arise in any stage of the assessment. Second, we could clearly explain to participants the tasks, the questions, the assumptions and the basic information necessary to make probability judgments. This was very important in assessing the subjective probability distribution for this study, since we did not want vagueness in the questions, assumptions, or information to contribute to uncertainty of the events of interest. Third, we could help participants use the information quickly. Fourth, we could help participants express their judgments. Finally, we could check for consistency in responses and resolve inconsistencies when they occurred.

The data sought were the individual’s subjective probability distributions before and after he or she observed the outputs of models normally used in a step of the four-step process. Ideally, it would be best to collect data from a large number of individuals and to assess, for each individual, the complete probability distributions of the transportation events associated with each step of the four-step process. However, it would not be possible to find many volunteers with the patience to provide this amount of data.
Especially since the participants all participated voluntarily, we designed the experiment to limit the time required.

We decided to try to limit interview sessions to 30 minutes. Based on several tests with the students, we found that it took approximately 25 to 35 minutes to collect enough data to find results for our research questions. Therefore, we knew we only needed to refine the interview protocol. This strategy worked very well. We asked 54 local individuals to participate in this study. Ninety-one percent of those individuals (49 individuals) participated in this study. However, only 47 individuals were available during the data collection period. Since we limited the interview session to 30 minutes, we had to balance our desire for data against the time constraints for data collection. Based on the several tests with the students, we decided to collect data from each individual as described in the following.

For each individual, we collected judgments about two transportation events associated with two different steps of the four-step process — e.g., Trip Generation and Trip Distribution. We collected data for two different steps in order to allow us to make comparisons among the different models at the individual (disaggregate) level. We believed that the interview process would be easier if the individual was asked to provide judgments on the event about which he or she had more knowledge. Therefore, we asked each individual to select a pair of steps with which he or she felt most familiar. Note that there are six possible pairs of steps in the four-step process: (TG and TD), (TG and MS),
(TG and TA), (TD and MS), (TD and TA) and (MS and TA). To allow an increased number of observations in each pair, however, we limited the choices to four pairs of steps: (TG and TD), (TG and MS), (TD and TA) and (MS and TA).

For each step of the four-step process, we assessed the prior judgment and posterior judgment from the individual. We assessed the prior judgment from the individual, first. We then showed the model output and assessed the individual's posterior judgment. For both the prior and posterior judgments, we asked the individual to provide two values that corresponded to the 25% fractile and 50% fractile of the cumulative distribution function (CDF) of his or her judgment. The difference between the 25% fractile and 50% fractile was used to represent the uncertainty of the judgment. The details of the procedure and method for assessing the individual's judgments are presented in Section 3.4.

3.2.3 Designing the questions

We tried to design the experiment in such a way that it allowed comparisons of the changes in judgments among the four steps on "equal footing." First, we carefully chose transportation events for each step such that they were comparable to each other in terms of the difficulty in predicting the events. We describe this issue in detail in Section 3.2.4. Second, we gave approximately the same amount of information used in predicting
the event in each step of the four-step process. We describe this issue in Sections 3.3.1 and 3.3.2. Finally, for each step of the four-step process, after assessing the prior judgment and before assessing the posterior judgment, we provided a “model output” to the individual that was set at the median of the individual’s prior judgment. We describe this issue in the following subsections.

The underlying assumption is that individuals change their judgments based on how much confidence they have in the model and in how “surprising” (how much relevant information) the model contains. In general, the more the individuals believe in a model, the more likely it is they would change their judgments after they observed the model outputs. In contrast, individuals would not change their judgments if they did not believe in the model. Moreover, if individuals believed the model, the change in their judgments would be very different if their judgments (e.g., the medians of their prior judgment) were at the model output than if they were very different from the model output.

We were interested in the first issue -- the confidence in the model -- as opposed to how well individuals’ prior judgments corresponded to model outputs. Specifically, we wanted to investigate the relative confidence among the various steps of the four-step process. To investigate this issue and control for the “surprise” factor when prior judgments differed from model outputs, we set the “model output” at the median of the prior judgment when assessing the posterior judgment. That is, we did not produce real
results from a model but told the individual to assume that the model was run and produced a result equal to his or her prior median.

Setting the model output at the median of any prior judgment had several advantages. First, we did not need the real values of model outputs when asking for the posterior judgments. Second, for a given step of the four-step process, we controlled for the effect of surprise when comparing across individuals in terms of the change in their confidences due to the model. Third, for a given individual, we controlled for the effect of surprise when comparing across steps of the four-step process in terms of the change in his or her confidences due to the models.

3.2.4 The Transportation Events of Interest

In Section 3.2.2, we mentioned that we wished to obtain data from each subject within a 30-minute interview session. To achieve this goal, we had to choose the events such that they required minimal psychological tasks from individuals when making subjective predictions. Therefore, we chose events about which general transportation planners and academics had knowledge and which were easy to describe during the interview session.
We also tried to design the transportation events so that the comparison of the changes in judgments among individuals and among the four steps would be on "equal footing." We, therefore, tried to make the events as simple as possible so that they were equally difficult to predict. For this reason, we chose to ask individuals to predict travel demand that they normally predict in practice. In addition, we chose to ask individuals to predict the demand for the areas where many studies for transportation improvement programs were conducted so that individuals would be more familiar with the events of interest.

Therefore, we used the typical outputs of each step of the four-step travel demand forecasting process. For the Trip Generation step, the event was the number of person work trips originating from homes in Clintonville on an average weekday in the year 2020. For the Trip Distribution step, the event was the number of person work trips originating from homes in Clintonville and going Downtown on an average weekday in the year 2020. For the Modal Split step, the event was the number of person work trips leaving homes in Clintonville for Downtown and made by automobiles during the AM peak hour (7:30-8:30A.M.) on an average weekday in the year 2020. For the Traffic Assignment step, the event was the number of vehicles going southbound on the interstate I-71 between Hudson Street and Seventeenth Avenue during the AM peak hour (7:30-8:30A.M.) on an average weekday in the year 2020. (Note that we were interested in the number of vehicles on I-71, which is a result of travel demand from all over the
Columbus, not only from Clintonville to Downtown.) These events are summarized in Table 3.1.

<table>
<thead>
<tr>
<th>Steps of The Four Step Process</th>
<th>The Transportation Events of Interest</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Trip Generation</td>
<td>The number of person work trips originating from homes in Clintonville on average weekday in 2020.</td>
<td>Person Trips per Day</td>
</tr>
<tr>
<td>2. Trip Distribution</td>
<td>The number of person work trips originating from homes in Clintonville and going Downtown on average weekday in 2020.</td>
<td>Person Trips per Day</td>
</tr>
<tr>
<td>3. Modal Split</td>
<td>The number of person work trips leaving from homes in Clintonville for Downtown and made by automobile during the AM peak hour on average weekday in 2020.</td>
<td>Person Trips per Hour</td>
</tr>
<tr>
<td>4. Traffic Assignment</td>
<td>The number of vehicles going southbound on I-71 between Hudson St. and 17th Ave. during the AM peak hour on average weekday in 2020.</td>
<td>Vehicles per Hour</td>
</tr>
</tbody>
</table>

Table 3.1: The Transportation Events for this Study

Work trips are the portion of person trips representing travel to and from work. We chose to investigate travel demand for work trips, since work trips usually constitute the biggest portion of total demand in cities around the country (Hu and Young, 1993; Hu and Young, 1994) and create most of the congestion on roadways. Congestion usually is at its peak during the period in which work trips occur because demand for travel is at its highest. Also, because of their importance, we believed that individuals would have more experience and knowledge with this kind of trips than others.
We chose to investigate travel demand in Trip Generation and Trip Distribution steps in an average weekday unit because the unit is the one that individuals normally predict for demand in these two steps in practice. We chose to investigate demand in Modal Split and Traffic Assignment steps in peak-hour unit for the same reason.

We simplified the events by investigating only the demand in the year 2020 of two traffic zones in Columbus, Ohio. The two zones are Clintonville and Downtown (see Figure 3.1). By investigating the same events for the same areas, all individuals were constrained to refer to the same transportation events. Note that we were not looking at individuals' uncertainty in predicting events but at how models changed the uncertainty. Specifically, we were looking at the relative difference between prior and posterior judgments in each step of the four-step process. Therefore, it was not necessary that individuals had to know travel conditions in Columbus, Ohio well.

We used Clintonville and Downtown as our study areas for three reasons. First, work trips were the major trips between these two areas (COTA Long Range Plan, 1990). Clintonville is considered a residential area with stable and mature neighborhoods, while Downtown is considered the major work place of Columbus, Ohio. Second, travelers between these areas are able to choose to travel either by car or transit. Finally, both zones are in an area where many studies have been conducted for transportation improvement programs. These studies made our study easier in terms of providing more realistic forecasts for the information we needed in questionnaire.
We used the events in the year 2020 because much of the information needed in our questionnaire was available for this year from the Mid-Ohio Regional Planning Commission (MORPC). In this study, we had to estimate values of some information in the year 2020 and present them to individuals so that they could express their judgments about the events of interest. We also used the year 2020 because planners often estimate demand over a ten to twenty year planning horizon when preparing transportation plans.

3.3 Questionnaire Design

There were two objectives when we designed the questionnaire. The first objective was to construct a questionnaire that could help the interview process go smoothly and quickly. This objective was essential in maintaining individuals' attention while collecting a sufficient amount of valid information within the 30-minute interview session. We believed that the less we had to probe, explain, or clarify, the smoother and faster the interview process would go and the better the data we would obtain. The second objective was to make the comparison of the changes in judgments fair among individuals as well as among steps of the four-step process. We already addressed this second objective in Sections 3.3.1 and 3.3.2.
Figure 3.1: Areas Investigated in the Columbus, Ohio Region
Designing the questionnaire involved (a) selecting the questions and assumptions needed to meet the research objectives; (b) selecting background information to present to individuals to allow them to make probability judgments; and (c) selecting a way to present the information during the interview. We explain each issue in more detail in the following subsections. We tested various sets of questions, assumptions, and information on students to make sure that the questions could be answered within a certain limit of time. We also tested various ways of presenting them so that all information in the questionnaire could be assessed and used easily and effectively.

Constructing the questionnaire for this study required several stages of writing and revising. We tested the questionnaire with 40 students who registered for graduate-level transportation planning courses at The Ohio State University. Early versions of the questionnaire contained questions and assumptions that were confusing and overloaded with information. The pretest was meant to identify these problems. We observed how the tested subjects interacted with the questionnaire under development and used the information to redesign the questionnaire. We rewrote questions, added and dropped certain information, and changed presentation formats until we obtained a questionnaire that seemed to fit our needs.

After having the fully developed questionnaire, we tested the questionnaire with an additional 17 students and a few transportation planners. The purpose of this test
was to make sure that the questionnaire could help us obtain the desired data within the 30-minute time constraint before it was used to collect the real data.

In summary, we found the following items helpful in making an effective questionnaire for our study:

a) making sentences and phrases as short as possible;
b) using standard words and terms whenever possible;
c) avoiding technical terms so that the least technical respondent could understand easily;
d) keeping background information presented to only that which was required;
e) using illustrations along with words to help subjects understand the definitions of the events and assumptions;
f) using different fonts for words and different colors with pictures to highlight the important words and ideas;
g) presenting the assumptions, questions, and information in a consistent manner for each of the steps of the four-step process so that they could be easily accessed and used;
h) using realistic estimates for the information presented in the questionnaire to avoid any potential confusion or conflict.
3.3.1 Designing questions and assumptions on the transportation events

We developed several sets of assumptions and questions, and tested them with 41 students to make sure that the questions could be answered. We encoded subjective probability distributions from the students by using these early versions of assumptions and questions. We observed whether the tested subjects had any problem with them. For example, the subjects might misunderstand or misinterpret questions because they might be confusing, vague, or poorly worded. We discussed the meanings of the assumptions and questions during the tests. Such discussions helped identify the problems mentioned above.

We selected the questions based on two criteria. First, they were meant to ask for the transportation events of interest. Second, respondents had to be able to quickly understand and answer the questions.

In each step of the four-step process, the background assumptions were the travel demand outputs from the previous step. For example, when assessing information at the MS step, we had the individuals assume that the number of person trips between Clintonville and Downtown during the A.M. peak-hour in the year 2020 (i.e., an output of the TD step) would be exactly 1,300. We gave the subjects the demand from the previous step because we wanted them to predict only the transportation event of the step under investigation. By conditioning on error-free demands from the previous step, the
comparison of the changes in judgments due to the models could be made fairly among individuals and among steps of the four-step process. The following were the assumptions and the questions that we used in the questionnaire.

For the Trip Generation step, the assumption was, “Assume: exactly 35,000 workers will live in Clintonville in 2020.” The question was, “How many average weekday person work trips will be originating from homes in Clintonville in 2020?”.

For the Trip Distribution step, the assumption was, “Assume: on the average weekday in 2020, there will be (a) exactly 800,000 person work trips per day in Columbus area; (b) exactly 33,000 person work trips per day (4% of total work trips) originating from homes in Clintonville for any part of Columbus; and (c) exactly 100,000 person work trips per day (13% of total work trips) going Downtown from all over Columbus.” The question was, “How many of the person work trips per day originating from homes in Clintonville will go Downtown?”.

For the Modal Split step, the assumption was, “Assume: exactly 1,300 average weekday person work trips will be leaving homes in Clintonville for Downtown during the A.M. peak hour (7:30-8:30A.M.) in 2020.” The question was, “How many of these person work trips will be made by automobiles?”.
For the Traffic Assignment step, the assumption was, "Assume: during the average weekday A.M. peak hour (7:30-8:30 A.M.) in 2020, there will be (a) exactly 200,000 vehicle work trips in the Columbus area; and (b) exactly 1,200 vehicle work trips leaving homes in Clintonville for Downtown." The question was, "How many vehicles will be going southbound on the interstate I-71 between Hudson Street and 17th Avenue during the A.M. peak hour (7:30-8:30 A.M.) on an average weekday in the year 2020?".

3.3.2 Designing the basic information

We also provided some information related to the transportation events of interest. The role of the information was to help individuals predict the event of interest more rapidly and to control the state of knowledge among individuals. We developed several sets of information and tested them with the students. We discussed with the tested subjects how they came up with their answers. Such discussions helped identify the information needed for subjects to quickly make probability judgments. We found that providing more information to the subjects did not necessarily mean that the subjects could give the prediction of the events more quickly. The more information we gave to the subjects, the more time we used to explain the information to the subjects and the more time the subjects used to understand the information.
We selected the basic background information based on two criteria. First, the information had to be available to individuals in practice to avoid any potential confusion or conflict during the interview. Second, the amount of information was to be approximately equal among steps of the four-step process. Equal amount of information is important because we wanted to have data such that the comparisons of the changes in judgments could be made fairly among individuals as well as among steps of the four-step process.

Based on several tests with the students, we found it effective to provide the subjects the base rates associated with the event under investigation. To illustrate the idea, consider the Trip Generation step. We asked the subjects for subjective probability information about the number of average weekday person work trips originating from homes in Clintonville in the year 2020. We also told the subjects to assume that there would be exactly 35,000 workers living in Clintonville in 2020. To help individuals predict the event, we gave individuals background information on journey-to-work characteristics of the past (see Table 3.2): the numbers of workers in Clintonville in the past and the rates (percentage) of the workers who left their homes to work. This information is available in the census data. Together the information could give the subjects an idea about the number of trips in the past and its trend as a function of the number of workers. With this information, we found that the tested subjects were able to quickly provide statements about the event of interest: the number of average weekday person work trips originating from homes in Clintonville in the 2020.
On a usual day 1980 census 1990 census

1. Number of workers living in Clintonville 28,416 30,865

2. Number of workers living in Clintonville who left their homes to work 26,131 28,245

3. Percentage of workers living in Clintonville who left their homes to work 0.920 0.915

Table 3.2: The Basic Information in the Trip Generation step

We used the above idea to design the basic background information in the other three steps of the four-step process. For the Trip Distribution step, the basic information was (a) the total number of workers living in Columbus who left their homes to work; (b) the number of workers living in Clintonville who left their homes to work; (c) the number of workers who went to work in Downtown; and (d) the number of workers living in Clintonville who left their homes to work in Downtown. We also provided percentages of (d)/(a), (d)/(b), and (d)/(c).

For the Modal Split step, the basic information was (a) the number of workers living in Clintonville who left their homes to work in Downtown; (b) the numbers of these workers who went to work by automobiles; and (c) the percentage of these workers who went to work by automobiles.
For the Traffic Assignment step, the basic information was (a) the total number of workers living in Columbus who left their homes to work by automobiles; (b) the number of workers living in Clintonville who left their homes to work in Downtown by automobiles; (c) the number of vehicles going southbound on the specific section of I-71; (d) the capacity of the specific section of I-71; and (e) the volume-capacity ratio of the I-71 section. We also provided the rates of (c)/(a) and (c)/(b). The details can be found in Appendix A.

We did not use actual estimates for the basic information presented in the questionnaire because we did not have the data at the time of the interviews. Instead, we used realistic data. The data were estimated based on several transportation studies that were conducted for the area covering our study areas of Clintonville and Downtown. Our data were realistic because all data could be obtained from the census data or local transportation planning agencies, and the numbers used were consistent with actual studies.

3.3.3 Designing the format and layout of the questionnaire

The goals of designing the format and layout of the questionnaire were to make the questionnaire look attractive to individuals and to allow us to guide them to use all
information in the questionnaire effectively. We tested various formats and layouts with
the students. The resulting questionnaire is shown in Appendix A.

The layout of the questionnaire could be described as follow. In general, we
consistently organized the assumptions, questions, and information among steps of the
four-step process so that they could be easily accessed and used. Specifically, all
information in any step of the four-step process was presented in two pages. The first
page contained the assumption and question regarding the event of interest. We also
included a picture along with words to help individuals quickly understand the definitions
of the event and assumption. (We needed to provide two more pictures in the Traffic
Assignment step to help describe the event and its assumption in this step.) The second
page contained basic information to help individuals make judgments. The information
was organized such that individuals could easily observe the changes of values from 1980
to 1990. In addition, we use different fonts for words and different colors with pictures to
highlight the important words and ideas.

3.4 Data Collection

We used the procedure described in this section to encode subjective probability
distributions of individuals. In summary, we encoded the probability judgments in such a
way that was consistent with past research and accepted practice regarding assessments of
probability judgments. We encoded prior and posterior distributions of two transportation events from each individual. For each event, we presented the individual the basic information and assessed his or her prior distribution. Subsequently, we presented the model output and assessed his or her posterior distribution. We describe the procedure in detail in the following subsections.

3.4.1 Procedure before the Interview.

We first developed a list of prospective subjects based on personal contacts. We then sent the prospective subjects a letter explaining the nature of our research and asking for their participation. The letter is shown in Appendix B. A few days after sending the letter, we called the subjects and asked for their participation. A total of 54 individuals were contacted and 49 individuals voluntarily participated in this study. Of these, 47 individuals were available during the data collection period.

To increase a chance of success in encoding reliable probability judgments, we faxed a second letter (see Appendix B) to each individual who was willing to participate in this study. We did this a few days before we were to interview the individual. In this letter, we reminded the individual of the interview date and time, and we provided more information about the interview. Specifically, we provided information explaining the objective of the study, the tasks that would be required, and a brief description of
subjective probability theory. We also introduced the method of encoding probability judgment through an exercise. The exercise was designed to give the individual a feel for the type of questions that would be used to assess judgments on travel demand during the interview session. In the exercise, we showed how we would encode probabilistic judgment about the following day's reported high temperature in Columbus, Ohio. We used an exercise based on weather forecasting because we believed that it was familiar enough to allow an understanding of the concepts without biasing results by presenting numbers associated with tasks that were to be performed in the actual interviews.

3.4.2 Procedure for Encoding Probability Judgments

The procedure for encoding probability judgments consisted of the following eight steps.

Step 1: Motivation In this step, we gave individuals the background information explaining the objective of the study and the encoding tasks. We also reminded the individuals of the usefulness and worthiness of their judgments. We then motivated the idea of uncertainty in prediction to combat overconfidence that often occurs in probabilistic judgments.
Step 2: Preparation. In this step, we demonstrated how individuals could make probability judgment through an exercise. We also used the exercise to introduce them to the type of questions that would be used to assess their judgments during the interview. The exercise was the one that was sent with the second letter. We requested individuals to review the exercise before the interview so that the exercise would not take much time to complete. In this step, we actually encoded judgments about the following day’s reported high temperature in Columbus, Ohio. The process was designed to take five minutes or less to complete.

Step 3: Structuring. In this step, we explained to the individuals the exact definition of the transportation event of interest and its units as well as any assumption about the event. Since we did not want vagueness to contribute to uncertainty of the events of interest, we tried to ensure that the individuals clearly understood the event and the assumptions before encoding the uncertainty of the event.

Step 4: Conditioning. In this step, we presented to the individuals the basic background information associated with the transportation event. We then asked them to review the information and to think carefully about their judgments on the event. Note that the information was different among the transportation events of interest.

Step 5: Encoding. In this step, we quantified the individuals’ judgments in the probabilistic terms. First, we asked individuals to express subjectively their prior
judgments about the event after considering the assumptions and the basic information. Specifically, we asked the individuals for the values first of the median and then of the 25% fractile (or the first quartile) of the probability distribution that represented their prior judgments about the event. Subsequently, we presented the individuals with the "model output," along with a brief description of how it was estimated. After considering the model output, we asked the individuals to express their posterior judgments about the event. Again, we only asked the individuals for the values of the median and the 25% fractile of the probability distributions. We used a combination of the Probability Wheel method and Bisection method (as described in Section 2.3.3) to encode the individuals' judgments. Specifically, we used the Probability Wheel method to encode the median and the 25% fractile of the distribution. We then used the Bisection method to verify the median found from the Probability Wheel method. We developed worksheets and used them to aid the encoding process. The worksheets are shown in Appendix C. Recall that we did not use the real output from the model when encoding the posterior judgments of the individuals. We simply set the value of the "model output" to the median of the prior judgments of the individuals (see Section 3.2.3).

Step 6: Verification. In this step, we asked individuals to verify the judgments that we encoded from them. The purpose of this step was to make sure that they really believed in their quantified judgments. We allowed them to make adjustments to their judgments.
Step 7. We repeated step 4, 5, and 6 to obtain the prior and posterior judgments about the second event of interest from each individual.

Step 8. We asked individuals to fill out questions on respondent characteristics to complete the interview.

3.4.3 The Interview Data

We collected data from a total of 47 individuals. Twenty-one individuals were from six different governmental agencies, eight were from one academic institution, and eighteen were from twelve different private consultant companies. For each individual, we encoded his or her judgments for two steps of the four-step process or more. The data are shown in Table 3.3. To illustrate, consider record 1 of Table 3.3. Record 1 contains data that we collected from subject 1. We obtained the prior and posterior judgments about the events in the Trip Distribution (TD) step and the Traffic Assignment (TA) step. For the Trip Distribution step (i=TD), we obtained from subject 1 the 25% fractile and the median of his or her prior distribution -- $X_{25_{TDi}}=4,800$ and $X_{50_{TDi}}=5,000$, respectively -- as well as the 25% fractile and the median of his or her posterior distribution -- $X_{25_{TDi}'}=4,800$ and $X_{50_{TDi}'}=4,900$, respectively. For the Traffic Assignment step (i=TA), we obtained from subject 1 the 25% fractile and the median of his or her prior distribution -- $X_{25_{TAi}}=6,300$ and $X_{50_{TAi}}=6,800$, respectively -- as well as, the 25% fractile and the
median of his or her posterior distribution -- $X_{25T} = 6,300$ and $X_{50T} = 6,500$, respectively. Note that certain subjects -- namely 11, 24, 29, 37, 38, and 46 -- allowed us to elicit their judgments for more than two steps of the four-step process.

3.5 Analytical Methods

In this section, we present the methods used to analyze the effect of travel demand models on the uncertainty in travel demand forecasts. We present the two statistics that we used to depict the uncertainty expressed in the subjective probability distribution and describe how we determined the step of the four-step process in which individuals felt most uncertain about the forecasts. Then, we discuss how we investigated the effect of model on the individuals' judgments in each step of the four-step process. Finally, we describe how we compared the effects of models between steps in order to draw a conclusion as to the step in which the judgments were changed most due to the model.

Note that we were not interested in the expertise of the subjects, as measured by how close the probability distributions were to the "true" values of transportation events of interest. There were no "true" values of future events.
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Table 3.3: The Interview Data
### Table 3.3: The Interview Data (continued)

3.5.1 Representing the Assessed Probability Distributions

From the survey, we obtained the 25% and 50% (median) fractiles of the prior and posterior probability distributions. We refer to the "quartile range" as the difference between the median and the 25% fractile (first quartile) of the distribution. The median
and the quartile range were used later in our analysis as summary statistics of the assessed probability distribution. We chose the median because it represented the central tendency of the distribution. The median reflects an individual's belief in the level of outcome for which there is an equal chance for the random variable to be above or below this value. We chose the quartile range because it showed the dispersion of the distribution, which reflected how uncertain an individual was. The larger the quartile range, the higher the individual's degree of uncertainty.

To demonstrate the idea, consider the assessed probability statements obtained from individuals in Table 3.3. The statements corresponding to the prior distribution for the TD step in record 1 of Table 3.3 result in a median (X_{50}^{TD}) of 5,000 trips per day, and a quartile range (X_{50}^{TD} - X_{25}^{TD}) of 200 trips per day. Similarly, the statements corresponding to the posterior distribution for the TD step in record 1 result in a median (X_{50}^{TD}) of 4,900 trips per day and a quartile range (X_{50}^{TD} - X_{25}^{TD}) of 100 trips per day.

3.5.2 Investigating the Judgments toward Uncertainty

One of the research questions in this study was to investigate the individuals' judgments toward uncertainty. Specifically, we wanted to know the step of the four-step travel demand forecasting process in which individuals felt most uncertain about the forecasts. To investigate this issue, we compared the dispersions in subjective probability
distributions among the four steps. Comparing the dispersions of distributions is often done by comparing the variances or standard deviations of the distributions. However, the distributions must satisfy two conditions: (a) the distributions have the same units of measurement and (b) the means of the distributions are approximately equal. Neither of these conditions was met in our transportation events of interest. For example, a subject might believe that there would be 33,000 work trips originating from homes in Clintonville area on an average weekday in the year 2020 and might believe that there would be 6,500 cars using the specified section of an interstate I-71 during A.M. peak-hour on an average weekday in the year 2020.

To compensate for these effects, one may use a more relative measure of dispersion such as the coefficient of variation (CV). This measure can be used in comparing the variability of distributions that do not meet the two conditions mentioned above (Daniel and Terrell, 1992). The Coefficient of Variation is defined as:

\[
CV = \frac{\text{Standard Deviation}}{\text{Mean}}. \tag{3.1}
\]

Since we only obtained the first quartile (X25) and the median (X50), we could not calculate the standard deviation and mean (and, therefore, the CV) without further assumptions. Therefore, instead of using the CV, we used a relative measure which we called the variation index (VI):
\[ VI_{ik}^j = \frac{(X50_{ik}^j - X25_{ik}^j)}{X50_{ik}^j}, \]  

(3.2)

where \( VI_{ik}^j \) is the variation index of individual k's judgments in step i under condition j;

- \( i \) is the step of the sequential prediction process
  - \( i = \text{TG} \) for the Trip Generation step;
  - \( i = \text{TD} \) for the Trip Distribution step;
  - \( i = \text{MS} \) for the Modal Split step;
  - \( i = \text{TA} \) for the Traffic Assignment step;

- \( j = 0 \) before the model output is presented (corresponding to the prior);
- \( j = 1 \) after the model output is presented (corresponding to the posterior);

\( X50_{ik}^j \) is the median (0.50 fractile) of a probability judgment in step i under condition j of individual k, which we assumed equals the model output;

\( X25_{ik}^j \) is the first quartile (0.25 fractile) of a probability judgment in step i under condition j of individual k.

Note that the variation index (VI) is the CV when one replaces the standard deviation and the mean in the formula of coefficient of variation (CV) with the quartile range \((X50_{ik}^j - X25_{ik}^j)\) and the median \(X50_{ik}^j\), respectively.

Like the coefficient of variation, the variation index is a relative measure of dispersion that is independent of the units of measurement. Since both the quartile range \((X50_{ik}^j - X25_{ik}^j)\) and the median \(X50_{ik}^j\) are expressed in the same units, these units cancel out in the calculation of ratio. We used the variation index to indicate the variability in
the distribution, scaled by the value of the median. The higher the value of VI, the larger
the variation of the distribution as compared to median. Hence, the more the individual
was uncertain about the event of interest.

In the analysis, we calculated the variation index ($VI_{ik}^j$) for every assessed
distribution from every individual using equation 3.2. We then classified these $VI_{ik}^j$ into
four groups according to the steps of the four-step process (TG, TD, MS, TA), and
calculated the average value of VI for the group ($VI_i^j$) using:

$$VI_i^j = \frac{1}{K} \sum_{k=1}^{K} VI_{ik}^j / K,$$  \hspace{1cm} (3.3)

where $VI_i^j$ is the average variation index of judgments on step $i$ under condition $j$;
$VI_{ik}^j$ is the variation index of judgments in step $i$ under condition $j$ of
individual $k$;
$K$ is the total number of individuals in step $i$;
$i = TG, TD, MS, TA$;
$j$ is defined as before.

To investigate the step in which individuals felt most uncertain about the forecasts, we
compared the average value of VI ($VI_i^j$) among the four groups. The step in which
individuals felt most uncertain about the forecasts is the one that produced the highest
$VI_i^j$. 

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3.5.3 Investigating the Changes in Judgments due to the Models

To investigate the change in individuals' judgments, we observed the relative change of assessed probability distributions due to the outputs of the models by comparing the prior and posterior distributions. Recall that the prior and posterior judgments, respectively, were the judgments before and after the individuals observed the outputs of the models. If the outputs of models changed the individuals' judgments, their posterior distributions would differ from the prior ones.

In this study, we investigated the change in the prior judgment by observing the relative changes in the central tendency and the relative change in the variation of the distribution. We used two measures to represent these relative changes. They were the Percentage Change in the Median (PCM) and the Percentage Change in the Quartile Range (PCQ), respectively. We define the two measures as follows:

\[
P_{\text{CM}} = 100 \times \frac{X_{50i} - X_{500}}{X_{500}}, \quad (3.4)
\]

\[
P_{\text{CQ}} = 100 \times \frac{(X_{50i} - X_{25i}) - (X_{500} - X_{250})}{(X_{500} - X_{250})}, \quad (3.5)
\]

where \( P_{\text{CM}} \) is the percentage change in the median in step i of individual k;

\( P_{\text{CQ}} \) is the percentage change in the quartile range in step i of individual k;

\( X_{25i} \) and \( X_{50i} \) are defined as before.
These measures can help us determine the direction of the change in individuals' judgments, as well as whether and by how much the model outputs change the individuals' prior judgments toward uncertainty in travel demand forecasts.

As in the previous analysis, we classified the assessed probability distributions into four groups (TG, TD, MS, TA) according to the step of the four-step process. Then, we calculated PCM\textsubscript{ik} and PCQ\textsubscript{ik} for each individual in each group. By looking at PCM\textsubscript{ik} and PCQ\textsubscript{ik} of every individual in each group, we were able to conclude whether the output of the model used in each step of the four-step process changed the individuals' prior judgments. When either the value of PCM\textsubscript{ik} or PCQ\textsubscript{ik} was not equal zero, we concluded that the model changed the individuals' judgments toward uncertainty in predicting travel demand. We also concluded that individuals were more uncertain when the value of PCQ\textsubscript{ik} was positive and less uncertain when the value of PCQ\textsubscript{ik} was negative. Note that PCQ\textsubscript{ik} would have a positive value when the quartile range of the posterior judgment (X\textsubscript{50,ik} - X\textsubscript{25,ik}) was larger than that of the prior judgment (X\textsubscript{50,ik\textdegree} - X\textsubscript{25,ik\textdegree}). In contrast, PCQ\textsubscript{ik} would have a negative value when the quartile range of the posterior judgment (X\textsubscript{50,ik} - X\textsubscript{25,ik}) was less than that of the prior judgment (X\textsubscript{50,ik\textdegree} - X\textsubscript{25,ik\textdegree}).

In addition, we used the values of PCM and PCQ to investigate the degree to which the model outputs affected the individuals' prior judgments. The values had a positive relationship with how much the model changed prior judgments. That is, the
larger the positive or negative values of $\text{PCM}_{ik}$ and $\text{PCQ}_{ik}$, the more the changes in the individuals' judgments due to the model.

3.5.4 Comparing the Changes in Judgments among Steps

We are also interested in which step of the four-step process the model changed the individuals' prior judgments most. To investigate this issue, we classified the assessed probability distributions into four groups as before, and we compared among the groups the average effect of model on individuals.

Two measures were used for this purpose. We define them as follows:

$$
\text{AAPCM}_i = \frac{\sum_{k=1}^{K} |\text{PCM}_{ik}|}{K}, \quad (3.6)
$$

$$
\text{APCQ}_i = \frac{\sum_{k=1}^{K} \text{PCQ}_{ik}}{K}, \quad (3.7)
$$

where $\text{AAPCM}_i$ is the Average Absolute Percentage Change in the Median of individuals in group "i"; $\text{APCQ}_i$ is the Average Percentage Change in the Quartile range of individuals in group "i"; $K$ is the total number of individuals in group "J"; $i = \text{TG, TD, MS, TA}$
PCM\(_{ik}\) and PCQ\(_{ik}\) are defined as before.

Note that we use the absolute value of PCM\(_{ik}\) to calculate the average change in medians of the distributions (AAPC\(_{i}\)). Unlike PCQ\(_{ik}\), PCM\(_{ik}\) could have a positive or negative value which reflects the direction of the change in the median of the distribution. We must use the absolute value of PCM\(_{ik}\) in equation 3.6 to calculate the average effect of the model otherwise equation 3.6 would produce meaningless results.

The AAPC\(_{i}\) and APCQ\(_{i}\) have a positive relationship with the level of change in prior judgments due to the model. The higher the values of AAPC\(_{i}\) or APCQ\(_{i}\), the greater the change in individuals’ judgments due to the model. Therefore, we identified the step in which the model affected the prior judgments most by looking at the values of AAPC\(_{i}\) and APCQ\(_{i}\). The model whose output resulted in the highest values of AAPC\(_{i}\) or APCQ\(_{i}\) was the one that changed the prior judgments most.
3.6 Results of Data Analysis

We analyzed the data in Table 3.3 using the methods describe in Section 3.5. Specifically, for each record, we calculated the prior variation index \( V_{ik}^0 \) and the posterior variation index \( V_{ik}^1 \) using equation 3.2, the Percentage Change in Median \( \text{PCM}_{ik} \) using equation 3.4, and the Percentage Change in Quartile Range \( \text{PCQ}_{ik} \) using equation 3.5. The results of this analysis are shown in Table 3.4. To illustrate, consider record 1 of Table 3.4 which contains the analysis results for data in record 1 of Table 3.3. For the Trip Distribution step \( i=\text{TD} \), we obtained \( V_{\text{TD}i}^0=0.040 \) and \( V_{\text{TD}i}^1=0.020 \) from equation 3.2, \( \text{PCM}_{\text{TD}i}=-2.0\% \) from equation 3.4, and \( \text{PCQ}_{\text{TD}i}=-49.0\% \) from equation 3.5. For the Traffic Assignment step \( i=\text{TA} \), we obtained \( V_{\text{TA}i}^0=0.074 \) and \( V_{\text{TA}i}^1=0.031 \) from equation 3.2, \( \text{PCM}_{\text{TA}i}=-4.4\% \) from equation 3.4, and \( \text{PCQ}_{\text{TD}i}=-58.2\% \) from equation 3.5.

We then classified \( V_{ik}, \text{PCM}_{ik}, \) and \( \text{PCQ}_{ik} \) into four groups according to the steps of the four-step process. Finally, for each group, we calculated the average variation index \( V_i^j \) using equation 3.3, the Average Absolute Percentage Change in Median \( \text{AAPCM}_i \) using equation 3.6, and the Average Percentage Change in Quartile Range \( \text{APCQ}_i \) using equation 3.7. The results of this analysis are shown in Table 3.5.

We looked at the results in Table 3.4 and 3.5 to answer research questions for the experiment. The first question is concerned with the step of the four-step process in which individuals felt most uncertain about the forecasts. The second question refers to
whether or not the models change the individuals' judgments and in which step the judgments were changed most due to the model.

In summary, we found the following. First, the individuals felt most uncertain in the Trip Distribution step and felt least uncertain in the Modal Split step both before and after seeing the model output. Second, we found that most individuals did change their subjective probability distributions after observing the model output in any step of the four-step process. The individuals were less uncertain about their predictions after observing the model outputs. Third, we found that the models changed the distributions differently among the steps of the four-step process. The Traffic Assignment model was the one that reduced uncertainty in the individuals' judgments the most, while the Modal Split model was the one that reduced uncertainty in the judgments the least. As for the change in the central tendency of the distribution (median), the Trip Generation model was the one that led to the greatest change in the medians, while the Modal Split step was the one that led to the smallest changes in the medians. However, the change in the central tendency of the distribution was not obvious. The results of data analysis are described in more detail in the following sections.
<table>
<thead>
<tr>
<th>Record</th>
<th>Subject (k)</th>
<th>First Step (i)</th>
<th>Results of Data Analysis for the First Step</th>
<th>Second Step (i)</th>
<th>Results of Data Analysis for the Second Step</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$V_{1k}$</td>
<td>$V_{2k}$</td>
<td>PCM$_{1k}$</td>
</tr>
<tr>
<td>1</td>
<td>TD</td>
<td>0.040</td>
<td>0.020</td>
<td>-2.0%</td>
<td>-49.0%</td>
</tr>
<tr>
<td>2</td>
<td>TG</td>
<td>0.241</td>
<td>0.107</td>
<td>-3.4%</td>
<td>-55.6%</td>
</tr>
<tr>
<td>3</td>
<td>TG</td>
<td>0.127</td>
<td>0.127</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>4</td>
<td>TG</td>
<td>0.290</td>
<td>0.118</td>
<td>9.7%</td>
<td>-59.5%</td>
</tr>
<tr>
<td>5</td>
<td>TD</td>
<td>0.195</td>
<td>0.189</td>
<td>-9.8%</td>
<td>-3.0%</td>
</tr>
<tr>
<td>6</td>
<td>MS</td>
<td>0.042</td>
<td>0.041</td>
<td>2.1%</td>
<td>-2.0%</td>
</tr>
<tr>
<td>7</td>
<td>MS</td>
<td>0.116</td>
<td>0.101</td>
<td>0.9%</td>
<td>-12.8%</td>
</tr>
<tr>
<td>8</td>
<td>TG</td>
<td>0.286</td>
<td>0.129</td>
<td>-1.6%</td>
<td>-54.8%</td>
</tr>
<tr>
<td>9</td>
<td>TG</td>
<td>0.179</td>
<td>0.179</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>10</td>
<td>MS</td>
<td>0.111</td>
<td>0.089</td>
<td>0.0%</td>
<td>-20.0%</td>
</tr>
<tr>
<td>11</td>
<td>TG</td>
<td>0.169</td>
<td>0.162</td>
<td>4.6%</td>
<td>-4.4%</td>
</tr>
<tr>
<td>12</td>
<td>TD</td>
<td>0.167</td>
<td>0.063</td>
<td>0.0%</td>
<td>-62.5%</td>
</tr>
<tr>
<td>13</td>
<td>TG</td>
<td>0.115</td>
<td>0.103</td>
<td>-4.9%</td>
<td>-9.9%</td>
</tr>
<tr>
<td>14</td>
<td>TD</td>
<td>0.180</td>
<td>0.180</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>15</td>
<td>TG</td>
<td>0.091</td>
<td>0.086</td>
<td>5.5%</td>
<td>-5.2%</td>
</tr>
<tr>
<td>16</td>
<td>MS</td>
<td>0.048</td>
<td>0.048</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>17</td>
<td>TG</td>
<td>0.233</td>
<td>0.115</td>
<td>-13.3%</td>
<td>-50.5%</td>
</tr>
<tr>
<td>18</td>
<td>MS</td>
<td>0.087</td>
<td>0.043</td>
<td>0.0%</td>
<td>-50.0%</td>
</tr>
<tr>
<td>19</td>
<td>TG</td>
<td>0.024</td>
<td>0.024</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>20</td>
<td>TG</td>
<td>0.161</td>
<td>0.048</td>
<td>0.0%</td>
<td>-70.0%</td>
</tr>
<tr>
<td>21</td>
<td>TD</td>
<td>0.104</td>
<td>0.095</td>
<td>9.4%</td>
<td>-8.6%</td>
</tr>
<tr>
<td>22</td>
<td>TG</td>
<td>0.194</td>
<td>0.145</td>
<td>-7.5%</td>
<td>-25.2%</td>
</tr>
</tbody>
</table>

Subjects from a Governmental Agencies

<table>
<thead>
<tr>
<th>Record</th>
<th>Subject (k)</th>
<th>First Step (i)</th>
<th>Results of Data Analysis for the First Step</th>
<th>Second Step (i)</th>
<th>Results of Data Analysis for the Second Step</th>
</tr>
</thead>
<tbody>
<tr>
<td>23</td>
<td>TG</td>
<td>0.164</td>
<td>0.164</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>24</td>
<td>TG</td>
<td>0.175</td>
<td>0.121</td>
<td>4.8%</td>
<td>-30.6%</td>
</tr>
<tr>
<td>25</td>
<td>TG</td>
<td>0.241</td>
<td>0.154</td>
<td>-10.3%</td>
<td>-36.3%</td>
</tr>
<tr>
<td>26</td>
<td>MS</td>
<td>0.087</td>
<td>0.087</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>27</td>
<td>TG</td>
<td>0.241</td>
<td>0.154</td>
<td>-10.3%</td>
<td>-36.3%</td>
</tr>
<tr>
<td>28</td>
<td>TD</td>
<td>0.400</td>
<td>0.240</td>
<td>0.0%</td>
<td>-40.0%</td>
</tr>
<tr>
<td>29</td>
<td>MS</td>
<td>0.021</td>
<td>0.021</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>30</td>
<td>TG</td>
<td>0.098</td>
<td>0.049</td>
<td>0.0%</td>
<td>-50.0%</td>
</tr>
<tr>
<td>31</td>
<td>TD</td>
<td>0.134</td>
<td>0.115</td>
<td>-7.1%</td>
<td>-14.0%</td>
</tr>
<tr>
<td>32</td>
<td>TG</td>
<td>0.214</td>
<td>0.151</td>
<td>0.0%</td>
<td>-29.4%</td>
</tr>
<tr>
<td>33</td>
<td>TG</td>
<td>0.250</td>
<td>0.129</td>
<td>-3.1%</td>
<td>-48.4%</td>
</tr>
<tr>
<td>34</td>
<td>MS</td>
<td>0.043</td>
<td>0.022</td>
<td>-2.1%</td>
<td>-48.9%</td>
</tr>
<tr>
<td>35</td>
<td>TG</td>
<td>0.250</td>
<td>0.129</td>
<td>-3.1%</td>
<td>-48.4%</td>
</tr>
<tr>
<td>36</td>
<td>TD</td>
<td>0.310</td>
<td>0.237</td>
<td>1.7%</td>
<td>-23.5%</td>
</tr>
</tbody>
</table>

Subjects from an Academic Institution (The Ohio State University)

Table 3.4: The Results of Data Analysis at the Individual Level
<table>
<thead>
<tr>
<th>Record</th>
<th>Subject (k)</th>
<th>First Step (i)</th>
<th>Results of Data Analysis for the First Step</th>
<th>Second Step (i)</th>
<th>Results of Data Analysis for the Second Step</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>V1k^0</td>
<td>V1k^1</td>
<td>PCMk</td>
<td>PCQk</td>
</tr>
<tr>
<td>37</td>
<td>TD</td>
<td>0.167</td>
<td>0.154</td>
<td>8.3%</td>
<td>-7.7%</td>
</tr>
<tr>
<td>38</td>
<td>TD</td>
<td>0.063</td>
<td>0.021</td>
<td>-2.1%</td>
<td>-66.0%</td>
</tr>
<tr>
<td>39</td>
<td>MS</td>
<td>0.043</td>
<td>0.043</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>40</td>
<td>MS</td>
<td>0.021</td>
<td>0.021</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>41</td>
<td>TG</td>
<td>0.233</td>
<td>0.207</td>
<td>-3.3%</td>
<td>-11.3%</td>
</tr>
<tr>
<td>42</td>
<td>TG</td>
<td>0.179</td>
<td>0.179</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>43</td>
<td>TD</td>
<td>0.063</td>
<td>0.063</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>44</td>
<td>TG</td>
<td>0.182</td>
<td>0.091</td>
<td>0.0%</td>
<td>-50.0%</td>
</tr>
<tr>
<td>45</td>
<td>TD</td>
<td>0.186</td>
<td>0.186</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>46</td>
<td>TG</td>
<td>0.250</td>
<td>0.125</td>
<td>0.0%</td>
<td>-50.0%</td>
</tr>
<tr>
<td>47</td>
<td>MS</td>
<td>0.042</td>
<td>0.021</td>
<td>0.0%</td>
<td>-50.0%</td>
</tr>
<tr>
<td>48</td>
<td>TG</td>
<td>0.250</td>
<td>0.125</td>
<td>0.0%</td>
<td>-50.0%</td>
</tr>
<tr>
<td>49</td>
<td>TD</td>
<td>0.174</td>
<td>0.174</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>50</td>
<td>MS</td>
<td>0.114</td>
<td>0.114</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>51</td>
<td>TG</td>
<td>0.258</td>
<td>0.174</td>
<td>-1.6%</td>
<td>-32.7%</td>
</tr>
<tr>
<td>52</td>
<td>TG</td>
<td>0.290</td>
<td>0.147</td>
<td>9.7%</td>
<td>-49.3%</td>
</tr>
<tr>
<td>53</td>
<td>TG</td>
<td>0.141</td>
<td>0.121</td>
<td>3.1%</td>
<td>-13.8%</td>
</tr>
<tr>
<td>54</td>
<td>TG</td>
<td>0.167</td>
<td>0.107</td>
<td>-6.7%</td>
<td>-35.7%</td>
</tr>
<tr>
<td>55</td>
<td>TG</td>
<td>0.077</td>
<td>0.032</td>
<td>-4.6%</td>
<td>-58.1%</td>
</tr>
<tr>
<td>56</td>
<td>MS</td>
<td>0.071</td>
<td>0.038</td>
<td>0.0%</td>
<td>-47.1%</td>
</tr>
<tr>
<td>57</td>
<td>TG</td>
<td>0.231</td>
<td>0.167</td>
<td>-7.7%</td>
<td>-27.8%</td>
</tr>
<tr>
<td>58</td>
<td>MS</td>
<td>0.064</td>
<td>0.064</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>59</td>
<td>TG</td>
<td>0.231</td>
<td>0.167</td>
<td>-7.7%</td>
<td>-27.8%</td>
</tr>
<tr>
<td>60</td>
<td>TD</td>
<td>0.245</td>
<td>0.151</td>
<td>0.0%</td>
<td>-38.5%</td>
</tr>
<tr>
<td>61</td>
<td>TD</td>
<td>0.364</td>
<td>0.309</td>
<td>0.0%</td>
<td>-15.0%</td>
</tr>
</tbody>
</table>

Table 3.4: The Results of Data Analysis at the Individual Level (continued)
Table 3.5: Average Variation Index (VI\text{\textdegree}), Average Percentage Change in Quartile Range (APCQi), and Average Absolute Percentage Change in Median (AAPCMi) by Step of the Four-Step Process

<table>
<thead>
<tr>
<th>Step of the Four-Step Process (i)</th>
<th>Average Variation Index</th>
<th>APCQi</th>
<th>AAPCMi</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>without the use of model (VI\text{\textdegree})</td>
<td>with the use of model (VI\text{\textdegree})</td>
<td></td>
</tr>
<tr>
<td>Trip Generation (i=TG)</td>
<td>0.1947</td>
<td>0.1261</td>
<td>-31.9%</td>
</tr>
<tr>
<td>Trip Distribution (i=TD)</td>
<td>0.2104</td>
<td>0.1544</td>
<td>-25.9%</td>
</tr>
<tr>
<td>Modal Split (i=MS)</td>
<td>0.0651</td>
<td>0.0523</td>
<td>-19.4%</td>
</tr>
<tr>
<td>Traffic Assignment (i=TA)</td>
<td>0.1243</td>
<td>0.0705</td>
<td>-45.5%</td>
</tr>
</tbody>
</table>

Figure 3.2 shows the comparison of the average variation index (VI\text{\textdegree}) among steps of the four-step process. We observed that the Trip Distribution step has the highest average variation index both before and after seeing the model output: $VI_{TD}^\text{\textdegree}=0.210$ and $VI_{TD}^\text{\textdegree}=0.154$. This means that individuals felt most uncertain in the Trip Distribution step (TD) in both conditions. We also observed that individuals felt least uncertain in the Modal Split step (MS) in both conditions, since the average variation indexes of the MS step in both conditions are the lowest ones among those of the other three steps: $VI_{MS}^\text{\textdegree}=0.065$ and $VI_{MS}^\text{\textdegree}=0.052$.

As shown in Figure 3.2, the average variation index of the TG step in both before and after seeing the model outputs are obviously higher than the ones in the MS step and
the TA step. This means that individuals felt more uncertain in the TG step than in the MS and TA steps.

Since we had judgments about two events associated with two different steps from every individual, we made comparisons of the variation index between pairs of steps at the individual level. The data that we had allowed us to make the comparisons for four pairs of steps: (TG and TD), (TG and MS), (TD and TA), and (MS and TA). The results are shown in Table 3.6 and Figures 3.3 to 3.6.
Results of the analysis at the individual level supported the statements above. First, the TD step was the step in which individuals felt more uncertain about their predictions when compared to the other steps. Figures 3.3 and 3.4 show the variation index of judgments in the TD step ($V_{TD}$) in comparison with the ones in the TG step ($V_{TG}$) and the TA step ($V_{TA}$), respectively. We found that 11 of the 17 individuals who provided judgments for the events in the TG and TD step had variation index in the TD step greater than that in the TG step both before and after seeing the model outputs. In addition, 10 of the 14 individuals who provided judgments for the events in the TD and TA steps had variation index in the TD step greater than that in the TA step both before and after seeing the model outputs.

Second, the MS step was the step in which individuals felt least uncertain about their predictions when compared to the other steps. Figures 3.5 and 3.6 show the variation index of judgments in the MS step ($V_{MS}$) compared to that in the TG step ($V_{TG}$) and the TA step ($V_{TA}$), respectively. We found that all of the 15 individuals who provided
judgments for the events in the TG and MS steps had variation index in the MS step less than that in the TG step before seeing the model outputs, and 12 of them had variation index in the MS step less than that in the TG step after seeing the model outputs. In addition, 12 of the 14 individuals who provided judgments for the events in the MS and TA steps were less uncertain in the MS step than in the TA step before seeing the model outputs, and 9 of them had variation index in the MS step less than that in the TA step after seeing the model outputs.

Figure 3.3: Comparison of the Variation Index in the TG step and the TD step -- Individual Analysis

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Figure 3.4: Comparison of the Variation Index in the TD step and the TA step -- Individual Analysis

Figure 3.5: Comparison of the Variation Index in the TG step and the MS step -- Individual Analysis
3.6.2 Changes in Judgments due to the Models

We investigated the change in judgments by observing the relative changes in subjective probability distributions after the individuals saw model outputs. We used Percentage Change in Quartile Range (PCQ$_{ik}$) to measure the relative change in the dispersion of the distribution, and used Percentage Change in Median (PCM$_{ik}$) to measure the relative change in central tendency of the distribution.

Table 3.4 shows the results of this investigation at the individual level. We found that most individuals did change their subjective probability distributions after observing
the model output in any step of the four-step process. None of the individuals who
changed their distribution were more uncertain about their predictions after observing the
model outputs. The individuals were obviously less uncertain about their predictions after
seeing the model outputs as observed by a reduction in the dispersions of individuals’
probability distributions and, hence, a negative PCQ_{ik}. Column 4 of Table 3.5 shows the
average reduction in the dispersions of distributions for each step of the four-step process.
The average reductions are 31.9% in the TG step, 25.9% in the TD step, 19.4% in the MS
step, and 45.5% in the TA step.

We conducted the analysis of the reduction in the dispersions of the distributions
due to the model in each step of the four-step process at the individual level. We show the
numerical results in Table 3.7 and graph the results in Figure 3.7. We observed the
following.

<table>
<thead>
<tr>
<th>Steps of the Four-Step Process</th>
<th>Number of Observations</th>
<th>Number of Observations with Positive PCQ_{i}</th>
<th>Number of Observations with Negative PCQ_{i}</th>
<th>Number of Observations with PCQ_{i}=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip Generation (TG)</td>
<td>28</td>
<td>0</td>
<td>23</td>
<td>5</td>
</tr>
<tr>
<td>Trip Distribution (TD)</td>
<td>26</td>
<td>0</td>
<td>18</td>
<td>8</td>
</tr>
<tr>
<td>Modal Split (MS)</td>
<td>26</td>
<td>0</td>
<td>15</td>
<td>11</td>
</tr>
<tr>
<td>Traffic Assignment (TA)</td>
<td>24</td>
<td>0</td>
<td>24</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3.7: Numbers of Observations with Positive, Negative, and Zero Percentage Changes in Quartile Range (PCQ_{i}) in the TG, TD, MS, and TA Step
In the TG step, 23 of the 28 individuals who provided prior and posterior judgments for the event were less uncertain about their subjective predictions after seeing the model outputs. The other 5 individuals were equally uncertain about their predictions after seeing the model outputs. In the TD step, 18 of the 26 individuals who provided judgments for the event were less uncertain about their predictions after seeing the model outputs. The other 8 individuals were equally uncertain about their predictions after seeing the model outputs. In the MS step, 15 of the 26 individuals who provided judgments for the event were less uncertain about their predictions after seeing the model outputs. The other 11 individuals were equally uncertain about their predictions after seeing the model outputs. In the TA step, all of the 24 individuals who provided the judgments for the event were less uncertain about their predictions after seeing the model outputs.
(a) Percentage Change in Quartile Range in the TG step (PCQ_{TG})

(b) Percentage Change in Quartile Range in the TD step (PCQ_{TD})

(c) Percentage Change in Quartile Range in the MS step (PCQ_{MS})

(d) Percentage Change in Quartile Range in the TA step (PCQ_{TA})

Figure 3.7: Percentage Change in Quartile Range in the TG, TD, MS, and TA steps -- Individual Analysis
As for the change in the central tendency of the distribution (median), we found that not many individuals changed the medians of their distributions (see column 6 and 11 of Table 3.4). For those who changed their medians, they changed their medians only slightly. This was observed by the small magnitudes of the positive or negative PCMikS. Column 5 of Table 3.5 shows the average change in the medians of distributions for each step of the four-step process. The average changes are 4.0% in the TG step, 2.6% in the TD step, 0.8% in the MS step, and 3.5% in the TA step. Note that since we set the "model output" to the median of the prior distribution, we would expect only small changes in the median (due to measurement or round-off error) unless the subjects thought the models were biased and incorporated this bias when transforming their prior distributions into posterior distributions.

We conducted the analysis of the change in the median due to the model in each step of the four-step process at the individual level. We found the following. In the TG step, 18 of 28 individuals giving their judgments for the event changed their medians. In the TD step, 13 of 26 individuals giving their judgments for the event changed their medians. In the MS step, 9 of 26 individuals giving their judgments for the event changed their medians. In the TA step, 14 of 24 individuals giving their judgments for the event changed their medians.
3.6.3 Comparing the Changes in Judgments between Steps

The other research question in this study is that concerning the step of the four-step process in which the model changed the individuals' prior judgments most. To investigate this issue, we classified the assessed probability distributions into four groups as before, and we compared among the groups the average effect of model on individuals. We used two measures for this purpose: Average Absolute Percentage Change in Median (AAPCMi) and Average Percentage Change in Quartile Range (APCQi). The measures are described in Section 3.5.4.

Figure 3.8 shows the comparison of the change in the subjective probability distributions due to the models among steps of the four-step process at the aggregate level. We found that models changed the distributions differently among the steps of the four-step process. The Traffic Assignment model was the one that reduced uncertainty in the individuals' judgments the most. This is because the TA step had the largest Average Percentage Change in Quartile Range (APCQTA) of -45.5%. We also observed that the Modal Split model was the one that reduced uncertainty in the judgments the least, since the MS step had the smallest APCQMS of -19.4%. Finally, we observed that the TG model reduced uncertainty in individuals' judgments more than the TD model did at the aggregate level.
As for the change in the central tendency of the distribution (median), the Trip Generation model was the one that led to the greatest change in the medians, with Average Absolute Percentage Change in Median ($AAPCM_{TG}$) of 4.0%, while the Modal Split step was the one that led to the smallest changes in the medians with $AAPCM_{MS}$ of 0.8%. As shown in Figure 3.8, the Average Percentage Change in Median of the distribution in any step ($AAPCM_i$) was very small when compared to the average change in the dispersion of the distributions of the step ($APCQ_i$). This was not surprising, since we set the "model output" to the median of the prior distribution.

![Figure 3.8: AAPCM and APCQ of Probability Distributions -- Aggregate Analysis](image_url)
Since we had judgments about two events associated with two different steps from every individual, we compared changes in the dispersions of the distribution between pairs of steps at the individual level (PCQ_{ik}). Again, the data that we had allowed us to make the comparisons of PCQ_{ik} for four pairs of steps: (TG and TD), (TG and MS), (TD and TA), and (MS and TA). The results are shown in Table 3.8 and Figures 3.9 to 3.12.

Results of the analysis at the individual level supported the statements above. First, the TA model was the one that reduced uncertainty in the individuals' judgments the most when compared to the models in the other steps. Figures 3.9 and 3.10 show the percentage change in quartile range of the TA step (PCQ_{TAk}) in comparison with the ones in the TD step (PCQ_{TDk}) and the MS step (PCQ_{MSk}), respectively. We found that 13 of the 14 individuals providing judgments for the events in the TA and TD steps had greater quartile range percentage changes in the TA step than in the TD step. In addition, all of the 14 individuals providing judgments for the events in the TA and MS steps had greater quartile range percentage changes in the TA step than in the MS step.

Second, the MS model was the one that reduced uncertainty in the individuals' judgments the least when compared to the models in the other steps. Figures 3.10 and 3.11 show the percentage change in quartile range of the MS step (PCQ_{MSk}) in comparison with the ones in the TA step (PCQ_{TAk}) and the TG step (PCQ_{TGk}), respectively. We found that all of the 14 individuals providing judgments for the events in the TA and MS step had lower quartile range percentage changes in the MS step than
in the TA step. In addition, 11 of the 15 individuals providing judgments for the events in the TG and MS steps had lower quartile range percentage changes in the MS step than in the TG step.

Figure 3.12 shows the comparison of the percentage change in quartile range of the 17 individuals providing judgments for the events in the TG and TD steps. We found that 8 individuals had greater quartile range percentage changes in the TG step greater than in the TD step, while 8 individuals had quartile range percentage changes in the TG step lower than in the TD step and one individual had percentage change in quartile range equal zero in both steps. For this reason, we could not make a conclusion as to which of the two models (the TG model and the TD model) reduced uncertainty in the subjective predictions more. Additional data may be able to help determine whether the TG model reduces uncertainty in subjective predictions more or less than the TD model does.

<table>
<thead>
<tr>
<th>Steps Compared</th>
<th>Number of Comparisons</th>
<th>Number of Times the First Step listed had Greater PCQi</th>
<th>Less PCQi</th>
<th>Equal PCQi</th>
</tr>
</thead>
<tbody>
<tr>
<td>TD vs. TA</td>
<td>14</td>
<td>0</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>MS vs. TA</td>
<td>14</td>
<td>0</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>TG vs. MS</td>
<td>15</td>
<td>11</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>TG vs. TD</td>
<td>17</td>
<td>8</td>
<td>8</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3.8: Comparison of Percentage Change in Quartile Range (PCQi) in the Four-Step Process
Figure 3.9: Percentage Change in Quartile Range (PCQ) of Judgments due to the Traffic Assignment (TA) Model vs. the Trip Distribution (TD) Model — Individual Analysis

Figure 3.10: Percentage Change in Quartile Range (PCQ) of Judgments due to the Traffic Assignment (TA) Model vs. the Modal Split (MS) Model — Individual Analysis

Figure 3.11: Percentage Change in Quartile Range (PCQ) of Judgments due to the Trip Generation (TG) Model vs. the Modal Split (MS) Model — Individual Analysis
3.7 Results of Additional Data Analysis

Additional analyses were performed to examine the relationship between characteristics of the individuals and the uncertainty in individuals' judgments or the change in the individuals' judgments due to the models. We conducted this analysis because we wanted to know whether the results found in Section 3.6 held across different characteristics of individuals.

We collected individual characteristics using "questions on respondent characteristics" in the questionnaire in Appendix A. The data are shown in Table D.1 in Appendix D. We conducted an analysis to determine the characteristics of our subjects. The results of this analysis are shown in Appendix D. For each characteristic, we observed the numbers of individuals associated with different levels of the characteristic. We then classified the individuals into two or three groups such that the number of
individuals in each group was large enough to allow us to do the analysis that we did in Section 3.6. Based on the information that we obtained, we classify individuals as follows:

- According to the first question on respondent characteristic, individuals were classified into three groups according to their places of work: (a) governmental agency, (b) private consulting company, and (c) academic institution;

- According to the second question, individuals were classified into two groups: those who had been working at present positions for (a) 5 years or less, and (b) more than 5 years;

- According to the third question, individuals were classified into two groups: those who had worked in the positions responsible for or dealing with travel demand forecasting for (a) 10 years or less, and (b) more than 10 years;

- According to the fifth question, individuals were classified into two groups: those who felt that (a) there is no difference, and (b) there is a difference in their familiarity with the use of the two models under investigation;

- According to the sixth question, individuals were classified into two groups: those who were (a) not very familiar (chose 1, 2, 3 or 4 on the scale), and (b) very familiar (chose 5 on the scale) with the transportation system in Columbus, Ohio;

- According to the seventh question, individuals were classified into two groups: those who were (a) not familiar or somewhat familiar (chose 1, 2 or 3 on the scale), and (b) familiar or very familiar (chose 4 or 5 on the scale) with probability theory;
According to the eighth question, individuals were classified into two groups: those who had (a) been exposed to subjective probability theory before the interview, and (b) never been exposed to the theory.

Note that we did not classify individuals according to the characteristic associated with the fourth question, which is “Have you had any training in travel demand forecasting during or after your university studies?,” because every individual had training.

For each group of characteristic, we conducted the same type of analysis described in Section 3.6. Specifically, for individuals in the group of a specific characteristic, we compared uncertainty in the individuals' judgments between steps using the variation index ($V_{i|k}$) and compared the change in the judgments between steps due to the models using the Percentage Change in Quartile Range ($PCQ_{ik}$). The data that we had allowed us to make the comparison at the individual level for four pairs of steps: (TG and TD), (TG and MS), (TD and TA), and (MS and TA). The results are shown in Tables D.2 to D.9 in Appendix D.

In general, we found that the results lead to the same conclusions that we have in Section 3.6. First, the individuals felt most uncertain in the Trip Distribution step and felt least uncertain in the Modal Split step both before and after seeing the model output. Second, we found that individuals were less uncertain about their predictions after
observing the model outputs. Third, the Traffic Assignment model was the one that reduced uncertainty in the individuals' judgments the most, while the Modal Split model was the one that reduced uncertainty in the judgments the least. In addition, we found that analysis based on some characteristics led to special cases or different conclusions that we have in Section 3.6. We present them in the following sections.

3.7.1 Uncertainty in Subjective Probability Distributions.

The individuals from an academic institution showed that they were definitely less uncertain in the TG step than in the TD step both before and after seeing the model outputs. As shown in Table 3.9, all of the 4 individuals from The Ohio State University who provided judgments for the events in the TG and TD steps had prior and posterior variation indexes in the TG step less than those in the TD step. For the other groups (private consulting company and governmental agency), we were not able to conclude whether individuals were more or less uncertain in the TG step than in the TD step before and after individuals saw the model outputs. As shown in Table 3.9, 3 of the 7 individuals from private consulting companies had prior and posterior variation indexes in the TG step greater than those in the TD step, while the other 4 individuals had prior and posterior variation indexes in the TG step less than those in the TD step. Similarly, 3 of the 6 individuals from governmental agencies had prior and posterior variation indexes in
the TG step greater than those in the TD step, while the other 3 individuals had prior and posterior variation indexes in the TG step less than those in the TD step.

The individuals who had been at the present position for more than 5 years were less uncertain in the TG step than in the TD step before and after seeing the model outputs. As shown in Table 3.9 and D.3, only 8 of 12 such individuals who provided judgments for the events in the TG and TD steps had prior and posterior variation indexes in the TG step less than those in the TD step before and after seeing the model outputs. Only 2 of these 12 such individuals had prior and posterior variation indexes in the TG step greater than those in the TD step. Note that one of these 12 such individuals had variation index in the TG step greater than that in the TD step before but not after seeing the model outputs, and one of these 12 such individuals had variation index in the TG step less than that in the TD step before but not after seeing the model outputs.

The individuals who had been in the position responsible for dealing with travel demand forecasting for more than 10 years were less uncertain in the TG step than in the TD step before seeing the model outputs. As shown in Table 3.9, 7 of the 9 such individuals who provided judgments for the events in the TG and TD steps had prior variation indexes in the TG step less than those in the TD step before seeing the model outputs, and the other two individuals had prior variation indexes in the TG step greater than those in the TD step.
The individuals who had been exposed to subjective probability theory before having the interview were less uncertain in the TG step than in the TD step both before and after seeing the model outputs. As shown in Table 3.9 and D.9, 5 of the 7 such individuals who provided judgments for the events in the TG and TD steps had variation indexes in the TG step less than those in the TD step before seeing the model outputs, and the other two individuals had variation indexes in the TG step greater than those in the TD step. In addition, 6 of these 7 individuals had variation indexes in the TG step less than those in the TD step after seeing the model outputs, and the other individual had variation index in the TG step greater than that in the TD step. Note that 1 of these 7 individuals had variation index in the TG step greater than that in the TD step before but not after seeing the model outputs.
### Table 3.9: Comparison of Variation Index between the Trip Generation (TG) and Trip Distribution Step—Classified by Four Characteristics of Individuals

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Number of Records</th>
<th>Number of Times the TG Step had Greater Prior VI</th>
<th>Less Prior VI</th>
<th>Equal Prior VI</th>
<th>Greater Posterior VI</th>
<th>Less Posterior VI</th>
<th>Equal Posterior VI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Places of Work</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Private Consultant Company</td>
<td>7</td>
<td>3</td>
<td>4</td>
<td>0</td>
<td>3</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>• Governmental Agency</td>
<td>6</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>• Academic Institution</td>
<td>4</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td><strong>Number of Years at the Present Position</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• 5 years or less</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>0</td>
<td>3</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>• More than 5 Years</td>
<td>12</td>
<td>3</td>
<td>9</td>
<td>0</td>
<td>3</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td><strong>Number of Years at the Position Responsible for or Dealing with Travel Demand Forecasting</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• 10 years or less</td>
<td>8</td>
<td>4</td>
<td>4</td>
<td>0</td>
<td>2</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>• more than 10 years</td>
<td>9</td>
<td>2</td>
<td>7</td>
<td>0</td>
<td>4</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td><strong>Whether or not been Exposed to the Subjective Probability Theory before the Interview</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Exposed</td>
<td>7</td>
<td>2</td>
<td>5</td>
<td>0</td>
<td>1</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>• Not Exposed</td>
<td>10</td>
<td>4</td>
<td>6</td>
<td>0</td>
<td>5</td>
<td>5</td>
<td>0</td>
</tr>
</tbody>
</table>

3.7.2 Comparison of the Changes in the Dispersions of Judgments between Steps

For individuals who felt that there was no difference in their familiarity with the TG model and the TD model, the TG model reduced uncertainty in their predictions more than the TD model did. As shown in Table 3.10, 7 of the 11 such individuals who provided judgments for the events in the TG and TD steps had the magnitude of PCQ<sub>TG</sub> smaller than that of PCQ<sub>TD</sub>, 3 of the individuals had the magnitude of PCQ<sub>TG</sub> larger than that of PCQ<sub>TD</sub>, and one of the individuals had PCQ<sub>TG</sub> and PCQ<sub>TD</sub> equal zero. We also found that the TD model reduced the uncertainty in the individuals' predictions more than
the TG model did when individuals felt that they were more familiar with the TG model than the TD model. As shown in Table 3.10, 5 of 6 such individuals who provided judgments for the events in the TG and TD had the magnitude of $PCQ_{TG}$ smaller than that of $PCQ_{TD}$, and the other individual had the magnitude of $PCQ_{TG}$ larger than that of $PCQ_{TD}$.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Number of Records</th>
<th>Number of Times the Magnitude of $PCQ_{TG}$</th>
<th>Greater than that of $PCQ_{TD}$</th>
<th>Smaller than that of $PCQ_{TD}$</th>
<th>Equal to that of $PCQ_{TD}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Familiarity with the TG and TD model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• No Difference in familiarity with the two models</td>
<td>11</td>
<td>3</td>
<td>7</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>• More familiar with the TG model than the TD model</td>
<td>6</td>
<td>1</td>
<td>5</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>• Less familiar with the TG model than the TD model</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Familiarity with the probability theory</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Not familiar or somewhat familiar</td>
<td>8</td>
<td>3</td>
<td>5</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>• Familiar and very familiar</td>
<td>9</td>
<td>5</td>
<td>3</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.10: Comparison of Percentage Change in Variation in the Trip Generation (TG) and Trip Distribution Step—Classified by Two Characteristics of Individuals.

We found that individuals providing judgments for the events in the TG and TD steps changed the uncertainty in their judgments differently, depending on how familiar they were with probability theory. For the individuals who were not familiar or somewhat familiar with the probability theory, the TD model reduced uncertainty in their predictions.
more than the TG model did. As shown in Table 3.10, 5 of 8 such individuals had the magnitude of $PCQ_{TG}$ smaller than that of $PCQ_{TD}$, and the other three individuals had the magnitude of $PCQ_{TG}$ larger than that of $PCQ_{TD}$. In contrast, for those who were familiar or very familiar with probability theory, the TG model reduced uncertainty in their predictions more than the TD model did. As shown in Table 3.10, 5 of 9 such individuals had the magnitude of $PCQ_{TG}$ larger than that of $PCQ_{TD}$, three of the individuals had the magnitude of $PCQ_{TG}$ smaller than that of $PCQ_{TD}$, and the other individual had $PCQ_{TG}$ and $PCQ_{TD}$ equal zero.
CHAPTER 4

IDENTIFICATION OF RELATIVE IMPORTANCE
OF THE FOUR-STEP MODELS

4.1 Overview of Methodology

In this chapter, we investigate the relative importance of the models used in the four-step travel demand forecasting process. The models are the Trip Generation (TG) model, the Trip Distribution (TD) model, the Modal Split (MS) model and the Traffic Assignment (TA) model. Specifically, we want to investigate which of the four models reduces uncertainty of predicted consequences most. The information may help individuals decide upon which models need more refinement to benefit them in making decisions under uncertainty.

We chose total system travel time (TSTT) as the predicted consequence to analyze for this investigation. TSTT is a consequence often calculated from the outputs of the four-step process. TSTT is defined as:
\[ TSTT = \sum_{a} V_a t_a. \]  

(4.1)

where \( V_a \) is the number of vehicles on arc \( a \);
\( t_a \) is the average travel time on arc \( a \).

We wish to investigate which of the models in the four-step process would lead to greatest reduction in the uncertainty in TSTT.

The methodology used in this investigation can be summarized as follows. We constructed a sequential prediction process and used it to estimate uncertainty of TSTT. The process was based on the four-step process. Specifically, we modeled uncertainty in model outputs of each step of the four-step process based on the "posterior distributions" of Chapter 3 and propagated these posterior uncertainties through the four-step process to develop a base-case probability distribution of TSTT. We then investigated the effect of each model in the four-step process. To investigate the effect of the TG model, for example, we modeled the uncertainty in the outputs of the TG model based on the "prior distribution" in the TG step of Chapter 3 and the uncertainty in the outputs of the other three models based on the "posterior distributions" of Chapter 3. We then propagated the prior TG uncertainties and the other (TD, MS, TA) posterior uncertainties through the four-step process to develop another distribution of TSTT. This distribution would have "larger uncertainty" than the base-case TSTT probability distribution, since the prior TG distribution would have "larger uncertainty" than the posterior TG distribution. We
repeated using the "prior distribution" for each of the other steps of the four-step process, while using the "posterior distribution" for the other three steps. The changes of uncertainty in TSTT were compared to determine the relative importance of models used in the four-step process. The details involved in each step are addressed in the following sections.

4.2 The Sequential Prediction Process

We developed the sequential prediction process and used it to produce a probability distribution of TSTT. The process used the same models and structure as the traditional four-step process. The distinction between our process and the four-step process was that we imposed uncertainty on the outputs of each step of the four-step process. We then propagated the uncertainties through the process to simulate the uncertainty of TSTT.

In each step of the four-step process, we approximated uncertainty of any model output with a probability distribution. Specifically, we considered the deterministic output produced by the model to be the median of the distribution. We then approximated the dispersion of the distribution with the average (taken across individuals interviewed) dispersion of the probability judgments associated with that step. Note that we used
model output as the median of the distribution because we wanted to investigate only the
effect of the change in uncertainty on the predicted consequence, TSTT.

To simulate the condition when a model would be used and it would not be used,
we set the dispersions of distributions at the average dispersion of posterior and prior
judgments, respectively. Recall that prior and posterior judgments represent judgments
before and after the individuals observed the model outputs, respectively. We obtained
the judgments from transportation practitioners and academics in Columbus, Ohio (see
Chapter 3).

We measured the average dispersion in terms of the average variation index,
defined as:

\[ V_{I_j} = \frac{1}{K} \sum_{k=1}^{K} V_{I_k} / K, \]  (4.2)

where \( V_{I_j} \) is the average variation index of judgments on step i under condition j;
\( V_{I_k} \) is the variation index of judgments on step i under condition j of
individual k (see equation 3.2 in Section 3.5.2);
\( K \) is the total number of individuals in step i for which judgments were
assessed;
i is the step of the sequential prediction process
(i=TG for the Trip Generation step; i=TD for the Trip Distribution step;
Table 4.1 shows the average variation indexes used in each step of the sequential prediction process for this investigation.

<table>
<thead>
<tr>
<th>Step of the Four-Step Process (i)</th>
<th>Variation Index (VI$_{ij}$) without the use of model (j=0)</th>
<th>with the use of model (i=1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip Generation (i=TG)</td>
<td>0.1947</td>
<td>0.1261</td>
</tr>
<tr>
<td>Trip Distribution (i=TD)</td>
<td>0.2104</td>
<td>0.1544</td>
</tr>
<tr>
<td>Modal Split (i=MS)</td>
<td>0.0651</td>
<td>0.0523</td>
</tr>
<tr>
<td>Traffic Assignment (i=TA)</td>
<td>0.1243</td>
<td>0.0705</td>
</tr>
</tbody>
</table>

Table 4.1: The Variation Index of Travel Demand with and without the Use of Models

We used Monte Carlo simulation to approximate the probability distributions of the model outputs in each step as well as the distribution of TSTT. With this technique, a random sample was generated from each probability distribution of the model output in each step of the four-step process. The random samples were then propagated through the sequential prediction process to produce TSTT. The entire process was repeated N times, producing N independent values of model outputs in each step of the four step process, as
well as \( N \) independent values of TSTT. These \( N \) values of TSTT constituted random
samples from the probability distribution over TSTT induced by random samples from
the probability distributions over the model outputs in each step of the four-step process.

In the following sections, we illustrate the methodology by applying the sequential
prediction process and Monte Carlo simulation to a small network example. We then
show the results of the application of the methodology to an extended network example.
We use the extended network example to illustrate the methodology in a more realistic
setting. We are also interested in seeing whether results found for the small network hold
for this larger network.

The small network example is shown in Figure 4.1. In this example, there are four
traffic analysis zones, two of which are origin zones (zone 1 and zone 2) and two of
which are destination zones (zone 3 and zone 4). The transportation network for this
element consists of six links and five nodes.
Figure 4.1: A Small Network Example

The extended network example is shown in Figure 4.2. In this example there are 42 traffic analysis zones, 399 links, and 134 nodes. The transportation network for this example is based on major highway system in Columbus, Ohio.
4.2.1 Trip Generation

First, consider the small network example. We assumed base-case origin person trips $O_r^{(b)}$ (where $r=1$ and 2) and base-case destination person trips $D_s^{(b)}$ (where $s=3$ and 4). These trips were the outputs of trip generation (TG) model. Since we assumed the trips were uncertain, we approximated each $O_r^{(b)}$ and each $D_s^{(b)}$ with a probability
distribution that had a median equal to $O_r^{(b)}$ and $D_s^{(b)}$, respectively. We then assumed that
the distribution had a variation index equal to the average variation index of the
individuals' judgments in the TG step ($VI_{TG}$). Specifically, we assumed the distribution
had the variation index of 0.1947 when the TG model was not used ($VI_{TG}^0=0.1947$) and
of 0.1261 when the TG model was used ($VI_{TG}^1=0.1261$).

We applied a procedure, similar to that used in Hidalgo (1997), to obtain the
probability distributions of trips with desired $VI$ ($VI_{TG}^0$ or $VI_{TG}^1$). First, we imposed
random errors ($e_{TG,g}$ where $g=1,2,3,4$) on the base-case trips ($O_r^{(b)}$ and $D_s^{(b)}$) to obtain
realizations of origin person trips ($O_r$) and destination person trips ($D_s$):

\[
O_r = O_r^{(b)} (1+e_{TG,r}), \quad r=1,2
\]
\[
D_s = D_s^{(b)} (1+e_{TG,s}), \quad s=3,4
\]

where $e_{TG,g}$ ($g=1,2,3,4$) are independent random errors with $N(0, \eta_{TG})$.

Since the errors ($e_{TG,g}$, $g=1,2,3,4$) were generated independently, the sum of
origin person trips ($O_r$) may not equal the sum of destination person trips ($D_s$). We had to
balance the origin person trips and the destination person trips to ensure conservation of
trips. We, therefore, adjusted the trips using the following formula:

\[
O'_r = O_r[(\Sigma_r O_r + \Sigma_s D_s)/2]/\Sigma_r O_r, \quad r=1,2 \text{ and } s=3,4
\]
\[
D'_s = D_s[(\Sigma_r O_r + \Sigma_s D_s)/2]/\Sigma_s D_s, \quad r=1,2 \text{ and } s=3,4
\]
Table 4.2 shows the results of the application of this procedure to our small network example. Consider, for example, the trips from an origin zone 1 (O\(_1\)). In this example, we had 5,066 base-case origin person trips (O\(_1^{(b)}\)= 5,066) from the TG model. We imposed a random error (\(\epsilon_{TG,1} = -0.2834\)) on the base-case trips using equation 4.3a; as a result, we obtained a realization of origin person trips (O\(_1\)) equal to 3,630 (O\(_1\)=5,066*(1+(-0.2834))). We applied equation 4.3a to the other origin zone (zone 2) and equation 4.3b to the destination zones (zone 3 and zone 4). Note that (O1+O2) \(\neq\) (D1+D2). We therefore adjusted the trips by using equation 4.4a; as a result, we obtained the adjusted origin person trips (O\(_1^{(')}\)) equal to 4,582 (O\(_1^{(')}\)=3,630* [(7,393 + 11,269)/2]/7,393). The adjusted trips, shown in column 5 of Table 4.2, were then used as inputs to the trip distribution (TD) model in the next step of the sequential prediction process.

<table>
<thead>
<tr>
<th>Zone (r or s)</th>
<th>Base-Case Trips (O(_r^{(b)}) or D(_s^{(b)}))</th>
<th>Realization of Random Error ((\epsilon_{TD,r,s}))</th>
<th>Realized Trips (O(_r) or D(_s))</th>
<th>Adjusted Trips (O(_r^{(')}) or D(_s^{(')}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>r=1</td>
<td>O(_1^{(b)})=5066</td>
<td>-0.2834</td>
<td>3630</td>
<td>4582</td>
</tr>
<tr>
<td>r=2</td>
<td>O(_2^{(b)})=5557</td>
<td>-0.3229</td>
<td>3763</td>
<td>4749</td>
</tr>
<tr>
<td>s=3</td>
<td>D(_3^{(b)})=5393</td>
<td>0.0465</td>
<td>5644</td>
<td>4673</td>
</tr>
<tr>
<td>s=4</td>
<td>D(_4^{(b)})=5230</td>
<td>0.0755</td>
<td>5625</td>
<td>4658</td>
</tr>
</tbody>
</table>

Table 4.2: Trip Generation (TG) Example.
We achieved the probability distributions of trips with the desired variation index of TG through the choice of standard deviation ($\eta_{TG}$) of the error term in the TG step ($\varepsilon_{TG}$). Specifically, we randomly generated 2,000 sets of errors ($\varepsilon_{TG,g}, g=1, 2, 3, 4$) from a normal distribution, $N(0, \eta_{TG})$, and used equation 4.3a and 4.3b to obtain 2,000 sets of the realized origin trips ($O_r$) and destination trips ($D_d$). For each set of $O_r$ and $D_d$, we adjusted the trips using 4.4a and 4.4b and calculated the VI. We averaged VI over the 2,000 set of $O_r$ and $D_d$ to obtain VI of TG ($V_{TG}$). We experimented with the values of $\eta_{TG}$ until we obtained the desired VI of TG ($V_{TG}^0$ or $V_{TG}^1$). In the small network example, we found that $\eta_{TG}=0.325$ yielded $V_{TG}^0=0.1947$ and $\eta_{TG}=0.211$ yielded $V_{TG}^1=0.1261$ (see Figure 4.3).

![Figure 4.3: Simulated Variation Index (VI) in the Trip Generation Step as a Function of Standard Deviation of the Error Term in the Trip Generation Step ($\eta_{TG}$)](image)
We used 2,000 samples of errors in the Trip Generation step ($\varepsilon_{TG}$) to find $\eta_{TA}$.

Determining the best number of samples is outside the scope of this research. We determined our number of samples based on the following procedure. We also applied this procedure to find the number of samples used for calibrating standard deviations of errors in trip distribution step ($\eta_{TD}$) and in traffic assignment step ($\eta_{TA}$).

To illustrate the procedure, assume that we want to find $\eta_{TG}$ for the small network example. Note that there are two desired VIs in the TG step: $V_{TG}^0 = 0.1947$ and $V_{TG}^1 = 0.1261$. The average of these two values is 0.1604. We started the procedure by arbitrarily picking a value of $\eta_{TG}$ and a large number of samples. For this example, we started with $\eta_{TG} = 0.25$ and 100,000 samples. We then changed $\eta_{TG}$ and continued to generate 100,000 samples for each $\eta_{TG}$ chosen until we found VI that approximately equaled the average VI of 0.1604. For the small network example, we found that $\eta_{TG} = 0.270$ yielded $V_I = 0.1604$. We then checked the stability of the VI against the number of samples. In this case, we found that the calibration process was very stable after approximately 2,000 (see Figure 4.4). Therefore, we assumed the calibration process was stable with 2,000 samples, and used 2,000 samples to develop the curve in Figure 4.3, from which we estimated $V_{TG}^0$ and $V_{TG}^1$. 

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For the extended network example, Hidalgo (1997) applied the same procedure for calibrating $\eta_{TG}$ and found that the standard deviation of the adjusted trips ($\sigma_{TG}$) was very close to the standard deviation of error in TG ($\eta_{TG}$). To obtain $\sigma_{TG}=0.25$, for example, the errors in equation 4.3a and 4.3b had to be generated from $N(0, \eta_{TG}=0.2519)$ for a case with low demand for travel and from $N(0, \eta_{TG}=0.2488)$ for a case with high demand for travel. The required $\eta_{TG}$ was very close to $\sigma_{TG}$ because the extended network example (42 zones) had a large number of degrees of freedom for the adjustment procedure to guarantee the conservation of total trips.
For this reason, we directly chose $\eta_{\text{TG}}$ that corresponded to the desired VI in the TG step. Specifically, we chose $\eta_{\text{TG}}$ such that $N(0, \eta_{\text{TG}})$ had a dispersion, as measured by VI, equal to the desired VI in the TG step. Using a relationship between fractiles and the standard deviation of the normal probability distribution, we found that $\eta_{\text{TG}} = 0.2890$ and $\eta_{\text{TG}} = 0.1861$ corresponded to $V_{\text{TG}}^0 = 0.1947$ and $V_{\text{TG}}^1 = 0.1261$, respectively.

4.2.2 Trip Distribution

In trip distribution (TD) step, we used the gravity model to estimate origin-destination (OD) person trips. The model has the following formula:

$$T_{rs} = \frac{O'_r \cdot D'_s \cdot F_{rs}}{\sum_{s} D'_s \cdot F_{rs}}, \quad (4.5)$$

where

- $T_{rs}$ is the number of person trips originating in zone “r” destined for zone “s”;
- $O'_r$ is the number of adjusted origin person trips in zone “r” from the TG step;
- $D'_s$ is the number of adjusted destination person trips in zone “s” from the TG step;
- $F_{rs}$ is the “friction factor” between zone “r” and zone “s”.

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Table 4.3 shows the friction factors \( (F_{rs}) \) used for the small network example. The factors were those used in Hidalgo (1997). Table 4.3 also shows the resulting OD person trips \( (T_{rs}) \) from the gravity model for the Trip Generation example in Table 4.2. The model used the adjusted origin person trips \( (O'_r) \) and destination person trips \( (D'_s) \) from the TG step (from column 5 of Table 4.2) and the friction factors \( (F_{rs}) \) to estimate OD person trips \( (T_{rs}) \).

Note that the OD person trips from the gravity model \( (T_{rs}) \) may not preserve the number of origin person trips \( (O'_r) \) or destination person trips \( (D'_s) \), output from the TG model. We, therefore, must balance the OD person trips \( (T_{rs}) \) to satisfy the conservation of \( O'_r \) and \( D'_s \). We used an iterative row and column factoring procedure (Fotheringham and O’Kelly, 1989) to balance the trips. The resulting balanced OD person trips, called base-case OD person trips \( (T_{rs}^{(b)}) \), are shown in column 5 of Table 4.3 for the example begun in Table 4.2.

<table>
<thead>
<tr>
<th>Origin Zone (r)</th>
<th>Destination Zone (s)</th>
<th>Friction Factor ( (F_{rs}) )</th>
<th>OD Trips from the Model ( (T_{rs}) )</th>
<th>Balanced Base-Case OD trips ( (T_{rs}^{(b)}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>0.0000000306</td>
<td>2295</td>
<td>1218</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>0.0000000306</td>
<td>2287</td>
<td>3364</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0.000335000</td>
<td>4184</td>
<td>3455</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>0.000045400</td>
<td>565</td>
<td>1294</td>
</tr>
</tbody>
</table>

Table 4.3: Friction Factors and Origin-Destination Trips for the Small Network Example
Similar to what we did in the TG step, we modeled the uncertainty in base-case OD person trips \(T_{rs}^{(b)}\) with a probability distribution that had a median equal to \(T_{rs}^{(b)}\), the model outputs. We then assumed the distribution had a dispersion equal to the average dispersions of the individuals’ judgments in the TD step. Specifically, we assumed the distribution had a variation index of 0.2104 when the TD model was not used \((VI_{TD}^0=0.2104)\) and of 0.1544 when the TD model was used \((VI_{TD}^1=0.1544)\).

To obtain the probability distributions of OD person trips with the desired VI, we imposed random errors \(\epsilon_{TD,rs}, rs=13, 14, 23, 24\) on the base-case OD person trips \(T_{rs}^{(b)}\) to obtain realizations of OD person trips \(T_{rs}^{(r)}\):

\[
T_{rs}^{(r)} = T_{rs}^{(b)} (1+\epsilon_{TD,rs}), \ rs=13, 14, 23, 24
\]

(4.6)

where \(\epsilon_{TD,rs} (rs=13, 14, 23, 24)\) are independent random errors with \(N(0, \eta_{TD})\).

For illustration, consider the person trips originating in zone 1 that are destined for zone 3 \((T_{13}^{(r)})\) in column 6 of Table 4.4. We had 1218 base-case OD person trips \(T_{13}^{(b)}=1218\) from the gravity model. Consider that we imposed a random error \(\epsilon_{TD,13}=-0.3114\) on the base-case trips. Equation 4.6 indicated that we would obtain a realization of OD person trips \(T_{13}^{(r)}\) equal to 839 \((T_{13}^{(r)}=1218*(1+(-0.3114)))\). We would continue to apply equation 4.6 to the other pairs of origins and destinations. Examples are presented in Table 4.4. We then balanced the OD person trips \(T_{13}^{(r)}\) using the same iterative row and
column factoring procedure. As a result, we obtained 1,413 balanced person trips for OD pair 1-3 ($T'_{13}$). The balanced OD person trips for the example begun in Table 4.2 are shown in column 6 of Table 4.4. The trips were then used as inputs to the Modal Split (MS) model in the next step of the sequential prediction process.

<table>
<thead>
<tr>
<th>Origin Zone (r)</th>
<th>Destination Zone (s)</th>
<th>Base-Case OD Trips ($T_{rs}^{(b)}$)</th>
<th>Realization of Random Error ($e_{TD,rs}$)</th>
<th>Realized OD Trips ($T'_{rs}$)</th>
<th>Balanced OD trips ($T''_{rs}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>1,218</td>
<td>-0.3114</td>
<td>839</td>
<td>1,413</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>3,364</td>
<td>-0.6974</td>
<td>1,018</td>
<td>3,169</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>3,455</td>
<td>0.3097</td>
<td>4,526</td>
<td>3,260</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>1,294</td>
<td>-0.1352</td>
<td>1,119</td>
<td>1,489</td>
</tr>
</tbody>
</table>

Table 4.4: Trip Distribution (TD) Example

We obtained the probability distributions of OD person trips with the desired variation index of TD through the choice of standard deviation ($\eta_{TD}$) of the error term in the TD step ($e_{TD}$). We found $\eta_{TD}$ through the use of 100,000 samples of error. Specifically, we randomly generated 100 sets of sample errors in the TG step ($e_{TG}$) from a normal distribution, $N(0, \eta_{TG})$. We then used equations 4.3 and 4.4 to obtain realizations of origin trips ($O'_{r}$) and destination trips ($D'_{s}$). Then, for each of 100 sets of $O'_{r}$ and $D'_{s}$, we randomly generated 100 sets of sample errors in the TD step ($e_{TD,rs}$) from a normal distribution, $N(0, \eta_{TD})$, and calculated VI of $T''_{rs}$. We averaged VI of $T''_{rs}$ over the 100
sets of $O'$ and $D'$, to obtain the VI of TD. We changed $\eta_{TD}$ until we obtained the desired VI of TD. In the small network example, we found that $\eta_{TD}=0.525$ yielded $VI_{TD}^0=0.2104$ and $\eta_{TD}=0.418$ yielded $VI_{TD}^1=0.1544$ (see Figure 4.5).

Note that there were two desired $\eta_{TG}$ in the TG step: $\eta_{TG}=0.325$ for $VI_{TG}^0=0.1947$ and $\eta_{TG}=0.211$ for $VI_{TG}^1=0.1261$. We generated the 100 sets of sample errors in the TG step by using $\eta_{TG}=0.268$ which was the average values of the desired $\eta_{TG}$, i.e., 

$$(0.325+0.211)/2.$$ 

Figure 4.5: Simulated Variation Index (VI) in the Trip Distribution Step as a Function of Standard Deviation of the Error Term in the Trip Distribution Step ($\eta_{TD}$)
We used the procedure described in Section 4.2.1 to obtain the number of samples needed for calibrating $\eta_{TD}$. To illustrate the procedure, assume that we want to find $\eta_{TD}$ for the small network example. We started the procedure by arbitrarily picking a value of $\eta_{TD}$ and a large number of samples. We started with $\eta_{TD} = 0.25$ and 1,000,000 samples. Specifically, for each of 1,000 randomly generated sets of origin trip (O's) and destination trips (D's), we randomly generated 1,000 sets of sample errors ($\varepsilon_{TD,rs}$, $rs=13, 14, 23, 24$) from $N(0, \eta_{TD})$. We then changed $\eta_{TD}$ until we found $VI$ approximately equal to 0.1824, which was the average of the prior and posterior $VI$'s in the TD step, i.e., 
\[(0.2104 + 0.1544)/2\]. For the small network example, we found that $\eta_{TD} = 0.472$ yielded $VI \approx 0.1824$. We then checked the stability of $VI$ against the number of samples. In this case, we found that the calibration process was stable after the number of samples reached approximately 100,000 (see Figure 4.6). Therefore, we assumed the calibration process was stable with 100,000 samples, and we then used 100,000 samples to estimate $VI_{TD}^0$ and $VI_{TD}^1$. 

For the extended network example, Hidalgo (1997) applied the same procedure for calibrating $\eta_{TD}$ and found that the standard deviation of the balanced OD trips ($\sigma_{TD}$) was very close to the standard deviation of error in TD ($\eta_{TD}$). To obtain $\sigma_{TD} = 0.25$, for example, the errors in equation 4.6 had to be generated from $N(0, \eta_{TD} = 0.2480)$ for the low demand case and from $N(0, \eta_{TD} = 0.2515)$ for the high demand case. The required $\eta_{TD}$ was very close to $\sigma_{TD}$ because the OD matrix of the extended network example (42 zones
by 42 zones) had a large number of degrees of freedom in the adjustment procedure that guaranteed the conservation of origin trips ($O'$) and destination trips ($D'$).

For this reason, we could analytically determine $\eta_{TD}$ that corresponded to the desired VI in the TD step. Specifically, we directly chose $\eta_{TD}$ such that $N(0, \eta_{TD})$ had a variation index (VI) that equaled the desired VI in the TD step. Using a relationship between fractiles and standard deviation of the normal probability distribution, we found
that \( \eta_{TD} = 0.3145 \) and \( \eta_{TD} = 0.2345 \) corresponded to \( V_{TD} = 0.2104 \) and \( V_{TD} = 0.1544 \), respectively.

### 4.2.3 Modal Split

To estimate OD vehicle trips for any pair of zones, we considered:

\[
q_{rs}^{(b)} = T_{rs}^{*} \cdot P_{rs}(Auto) \cdot (\text{Occupancy Rate}),
\]

where \( q_{rs}^{(b)} \) is the base-case number of vehicle trips originating in zone “r” destined for zone “s”;

\( T_{rs}^{*} \) is the balanced person trips originating in zone “r” destined for zone “s”, as determined in the TD step;

\( P_{rs}(Auto) \) is a probability that random individuals going from zone “r” to zone “s” choose to travel by autos, from the modal split (MS) model;

(\text{Occupancy Rate}) is the average number of persons per vehicle, assumed to be 1 in this study.

To estimate base-case OD vehicle trips \( q_{rs}^{(b)} \), the model used the balanced OD person trips \( T_{rs}^{*} \) from the trip distribution step (as shown column 6 of Table 4.4), the
probability of trips made by automobiles \( (P_{rs}(\text{Auto})) \) from the MS model and the occupancy rate. Table 4.5 shows the resulting \( q_{rs}^{(b)} \) from one set of realizations in the MS step for the small network example.

As with trip generation and trip distribution, we approximated the uncertainty in the base-case OD vehicle trips \( (q_{rs}^{(b)}) \) with a probability distribution that had a median equal to \( q_{rs}^{(b)} \). We also assumed the distributions had their dispersions equal to the average dispersion of individuals' judgments in the MS step. Specifically, we assumed the distributions had a variation index of 0.0651 when the MS model was not used \( (VI_{MS}^0=0.0651) \) and of 0.0523 when the MS model was used \( (VI_{MS}^1=0.0523) \).

We applied the following procedure to obtain the probability distributions of vehicle trips with the desired VI of MS. First, we imposed independent random errors \( (\varepsilon_{MS,rs} \text{ where } rs=13, 14, 23, 24) \) on the base-case OD vehicle trips \( (q_{rs}^{(b)}) \) to obtain realizations of OD vehicle trips \( (q'_{rs}) \):

\[
q'_{rs} = q_{rs}^{(b)} (1+\varepsilon_{MS,rs}), \quad rs=13, 14, 23, 24
\]  

(4.8)

where \( \varepsilon_{MS,rs} \) are independent random errors with \( N(0, \eta_{MS}) \), \( rs=13, 14, 23, 24 \).
Table 4.5 shows the results of the application of this procedure to our small network example. Consider, for example, the OD vehicle trips from zone 1 to zone 3 ($q'_{13}$). We had 1,130 base-case OD vehicle trips ($q_{13}^{(b)} = 1130$). We imposed a random errors ($\epsilon_{MS,13} = 0.0352$) on the base-case OD vehicle trips using equation 4.8. As a result, we obtained a realization of OD vehicle trips ($q'_{13}$) equal to $1,170$ ($q'_{13} = 1,130 \times (1 + 0.0352)$). We then applied equation 4.8 to the other pairs of origins and destinations. The resulting OD vehicle trips ($q'_{rs}$) for the example begun in Table 4.2 are shown in column 7 of Table 4.5. The trips were then used as inputs to the traffic assignment model in the next step of the sequential prediction process.

<table>
<thead>
<tr>
<th>Origin Zone (r)</th>
<th>Destination Zone (s)</th>
<th>Balanced OD Person Trips ($T_{rs}^{'}$)</th>
<th>Prob. of using Auto ($P_{rs}(\text{Auto})$)</th>
<th>Base-Case OD vehicle Trips ($q_{rs}^{(b)}$)</th>
<th>Realization of Random Error ($\epsilon_{MS,rs}$)</th>
<th>Realized OD vehicle Trips ($q'_{rs}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>1,413</td>
<td>0.80</td>
<td>1,130</td>
<td>0.0352</td>
<td>1,170</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>3,169</td>
<td>0.90</td>
<td>2,852</td>
<td>0.0480</td>
<td>2,989</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>3,260</td>
<td>0.95</td>
<td>3,097</td>
<td>0.0667</td>
<td>3,304</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>1,489</td>
<td>0.85</td>
<td>1,266</td>
<td>0.0750</td>
<td>1,360</td>
</tr>
</tbody>
</table>

Table 4.5: Modal Split (MS) Example

We obtained the probability distributions of OD vehicle trips with the desired VI ($VI_{MS}^0$ and $VI_{MS}^1$) through the choice of standard deviation of error in MS ($\eta_{MS}$). Since
there was no need to modify the resulting OD vehicle trips (q'_{rs}) to satisfy the conservation of OD person trips (T''_{rs}), the standard deviation of the OD vehicle trips (\sigma_{MS}) equals \eta_{MS}. Therefore, we directly chose \eta_{MS} that corresponded the desired VI of MS. Specifically, we chose \eta_{MS} such that N(0, \eta_{MS}) had a dispersion, as measured by VI, equal to the desired VI. Using a relationship between fractiles and standard deviation of the probability distribution, we found that \eta_{MS}=0.0948 and \eta_{MS}=0.0772 corresponded to VI_{MS}=0.0651 and VI_{MS}=0.0523, respectively.

4.2.4 Traffic Assignment

In the traffic assignment (TA) step, we used the User-Equilibrium (UE) model to estimate traffic volumes on arcs. The model used the OD vehicle trips (q'_{rs}) from the Modal Split (MS) step and average travel time on arcs (t_a) to estimate traffic volumes of arcs (V_a). We used the common Bureau of Public Roads (Sheffi, 1984) arc performance function to estimate travel time on each arc:

$$t_a = t_{oa} [1 + 0.15(V_a/C_a)^4], \quad (4.9)$$

where $t_a$ is the average travel time on arc $a$; $V_a$ is the number of vehicles on arc $a$; $C_a$ is the practical capacity of arc $a$;
\( t_{oa} \) is the free-flow time on arc \( a \).

We applied the technique developed by Hidalgo (1997) to obtain the probability distributions of arc volumes with the desired VI of TA. In this technique, uncertainty in arc flows was produced by modeling uncertainty in the free-flow times of arcs, \( t_{oa} \). We approximated the uncertainty of \( t_{oa} \) with a normal probability distribution. The distribution was assumed to have a median equal to a base-case free-flow travel time \( (t_{oa}^{(b)}) \) and a standard deviation equal to \( (t_{oa}^{(b)} \cdot \eta_{TA}) \). The uncertainties were then propagated through the UE model. In this way, the probability distributions of arc volumes were generated while retaining the structure of the OD vehicle matrix and the incidence relationships relating arc and path volumes (see McCord, et. al., 1997; Hidalgo, 1997).

We applied the following procedure to obtain the probability distribution of arc volumes with the desired VI of TA. First, we imposed random errors \( (e_{TA,a}) \) on the base-case free-flow time of each arc \( (t_{oa}^{(b)}) \) to obtain realizations of the free-flow time of the arc \( (t'_{oa}) \):

\[
t'_{oa} = t_{oa}^{(b)} (1 + e_{TA,a}), \quad a=1,2,3,4,5,6
\]  

(4.10)

where \( t'_{oa} \) is the realized free-flow time on arc \( a \);

\( t_{oa}^{(b)} \) is the base-case free-flow time on arc \( a \);
\( \varepsilon_{TA,a} (a=1, 2, 3, 4, 5, 6) \) are independent random errors with \( N(0, \eta_{TA}) \).

For illustration, consider the arc volumes associated with the realized OD vehicle trips from the Modal Split step (column 7 of Table 4.5). First, we imposed a random error \( \varepsilon_{TA,a} = -0.0133 \) on the base-case free-flow time of arc 1 \( (t_{01}^{(b)}) \) using equation 4.10. As a result, we obtained realization of free-flow time of arc 1 \( (t_{01}^{'} \)) equal 9.8671 \( (t_{01}^{'} = 10.0 \times (1+(-0.0133))) \). Consequently, we used equation 4.9 to estimate the realization of the average travel time on arc 1 \( (t_{1}^{''}) \). We continued to apply equations 4.9 and 4.10 to the other arcs of the network. We then used the UE traffic assignment model to find the arc volumes \( (V_a) \) associated with the OD vehicle trips. The resulting arc volumes \( (V_a) \) are shown in column 6 of Table 4.6.

Note that the UE traffic assignment model uses the average travel time of arcs \( (t_{a}^{''}) \) and the OD vehicle trips from the MS step \( (q''_{ns}) \) to calculate the time used for traveling from any origin "r" to any destination "s". The model (Sheffi, 1984) assumes that every traveler tries to minimize his travel time and that the travel times of each arc depend on the number of vehicles on the arc \( (V_a) \) (see also equation 4.9).
Table 4.6: Traffic Assignment (TA) Example

We use 1,562,500 samples of errors in free-flow time (\( \eta_{TA} \)) for calibrating the standard deviation of error in free-flow time (\( \eta_{TA} \)). Specifically, in the TG step, we randomly generated 25 sets of \( \varepsilon_{TG} \) from \( N(0, \eta_{TG}) \) and used equations 4.3 and 4.4 to estimate \( \Omega^r \) and \( D^s \). In the TD step, we applied the gravity model (equation 4.5) for each set of \( \Omega^r \) and \( D^s \) and balanced the model outputs to obtain \( T^r_n \). We then randomly generated 25 sets of \( \varepsilon_{TD} \) from \( N(0, \eta_{TD}) \) for each \( T^r_n \). We used equation 4.6 to obtain \( T^r_n \) and then re-balanced the \( T^r_n \) to obtain a balanced OD matrix, \( T''_n \). As a result, 625 sets of \( T''_n \) were generated at the end of the TD step. In the MS step, we calculated \( q_{rs}^{(b)} \) for each \( T''_n \) using equation 4.7. We then randomly generated 25 sets of \( \varepsilon_{MS} \) from \( N(0, \eta_{MS}) \) for each \( q_{rs}^{(b)} \) and estimated \( q'_{rs} \) using equation 4.8. This created 15,625 sets of vehicle trips matrix, \( q'_{rs} \), at the end of the MS step. In the TA step, for each \( q'_{rs} \), we randomly generated 100 sets of \( \varepsilon_{TA} \) from \( N(0, \eta_{TA}) \) and used equations 4.9 and 4.10 to...
obtain $t_a$. We then performed UE traffic assignment for each set of $\varepsilon_{TA}$ to estimate arc volumes for the $q^*$. Finally, we calculated the VI of arc volumes over the 100 sets of $\varepsilon_{TA}$. We then averaged the VI over the 15,625 sets of $q^*$ to obtain VI of TA.

Note that there were two desired standard deviations of errors in the TG step: $\eta_{TG}=0.325$ for $VI_{TG}^0=0.1947$ and $\eta_{TG}=0.211$ for $VI_{TG}^1=0.1261$. We used the average values of the two $\eta_{TG}$ (i.e., $0.268=(0.325+0.211)/2$) to generate the 25 sets of errors in the TG step ($\varepsilon_{TG}$). Similar to the TG step, we used the average values of the two desired standard deviations of errors in the TD step ($\eta_{TD}$), i.e., $0.472=(0.525+0.418)/2$, to generate the 25 sets of errors in the TD step ($\varepsilon_{TD}$) and the average values of standard deviations of errors in the MS step ($\eta_{MS}$), i.e., $0.086=(0.095+0.077)/2$, to generate the 25 sets of errors in the MS step ($\varepsilon_{MS}$).

We achieved the probability distributions of arc volumes with the desired VI of TA through the choice of standard deviation ($\eta_{TA}$) of the error term in free-flow time ($\varepsilon_{TA}$). We changed $\eta_{TA}$ until we obtained $VI_{TA}^0=0.1243$ and $VI_{TA}^1=0.0705$, the average variation indexes of the prior and posterior judgments in the TA step from subjects in Chapter 3. In the small network example, we found that $\eta_{TA}=0.348$ yielded $VI_{TA}^0=0.1243$ and $\eta_{TA}=0.198$ yielded $VI_{TG}^1=0.0705$ (see Figure 4.7).
We used 1,562,500 samples to find $\eta_{TA}$ because it was practical for us to find the desired $\eta_{TA}$ through the iterative process described above. A larger number of samples would cover more realizations of arc volumes ($V_a$), and might yield better estimations of $\eta_{TA}$. We also realized that the number of samples needed may depend on the value of desired VI of TG, TD and MS and may vary as a function of the transportation network, as well as the levels of OD vehicle trips ($q_{rs}$). However, determining the best number of samples is outside the scope of this research.

We used the procedure describe in Section 4.2.1 to obtain the number of samples needed for calibrating $\eta_{TA}$. To illustrate the procedure, assume that we want to find $\eta_{TA}$ for the small network example. We started the procedure by arbitrarily picking a value of $\eta_{TA}$ and a large number of samples. Specifically, we started with $\eta_{TA} = 0.25$ and 2,700,000
samples, which were a combination of 30 sets of errors in TG and 30 sets of errors in TD and 30 sets of errors in MS and 100 sets of errors in TA. We then changed $\eta_{TA}$ until we found VI of TA approximately equal to 0.0974, which is the average variation indexes of the prior and posterior judgments in the TA step from subjects in Chapter 3 (i.e., $(0.1243+0.0705)/2$). For the small network example, we found that $\eta_{TA}=0.240$ yielded VI=0.0968. We then checked the stability of VI against the number of samples. As shown in Figure 4.8, the calibration process was very stable. We chose to calibrate with $\eta_{TA}$ with 1,562,500 samples because it was practical for us to do the calibration. We then assumed the calibration process was stable with 1,562,500 samples and we used 1,562,500 samples to find the two desired VI in TA. Note that 1,562,500 samples were a combination of 25 sets of errors in TG and 25 sets of errors in TD and 25 sets of errors in MS and 100 sets of errors in TA.

![Graph showing the simulated variation index (VI) in the traffic assignment step as a function of numbers of samples for the small network example.](image-url)

**Figure 4.8**: Simulated Variation Index (VI) in the Traffic Assignment Step as a Function of Numbers of Samples--The Small Network Example
In the extended network example, we used the same calibration technique to find the desired $\eta_{TA}$. However, we reduced the number of samples to 4,375 because of the increased computational time required for running UE traffic assignment for the extended network. The samples were the combination of 5 sets of errors in TG, 5 sets of errors in TD, 5 sets of errors in MS and 35 sets of errors in TA. We found that $\eta_{TA}=0.172$ yielded $VI_{TA}^0=0.1243$ and $\eta_{TA}=0.055$ yielded $VI_{TA}^1=0.0705$ (see Figure 4.9).

Figure 4.9: Simulated Variation Index (VI) of the Traffic Assignment Step as a Function of Standard Deviation of the Error Term in Free-Flow Time ($\eta_{TA}$) -- The Extended Network Example
4.2.5 Procedure for Estimating Total System Travel Time

We used the results from the sequential prediction process to estimate the probability distribution of total system travel time (TSTT). Specifically, we used the process to obtain traffic volumes of arcs and their associated travel time. We then applied equation 4.1 to estimate TSTT.

In summary, we used the following Monte Carlo simulation procedure to obtain the distribution of TSTT:

**Step 0:** Assume base-case trips in the TG step ($O_{r}^{(b)}$ and $D_{s}^{(b)}$); friction factors ($F_{rs}$) in the TD step; probability of trips made by automobiles ($P_{rs}$(Auto)) in the MS step; and base-case free-flow time of arcs ($t_{os}^{(b)}$) and practical capacities of arcs ($C_{a}$) in the TA step; also select number of simulation runs for the TG step ($R_{TG}$), the TD step ($R_{TD}$), the MS step ($R_{MS}$), and the TA step ($R_{TA}$);

**Step 1:** Randomly generate a set of $\epsilon_{TG}$ from $N(0, \eta_{TG})$ and estimate $O'_{r}$ and $D'_{s}$ by using equations 4.3 and 4.4;

**Step 2:** Apply the gravity model (equation 4.5) with $O'_{r}$ and $D'_{s}$ and balance the model outputs to obtain $T_{rs}^{(b)}$;

**Step 3:** Randomly generate a set of $\epsilon_{TD}$ from $N(0, \eta_{TD})$ to produce $T'_{rs}$ by using equation 4.6; then re-balance $T'_{rs}$ to obtain $T''_{rs}$;

**Step 4:** Apply equation 4.7 with $T''_{rs}$ to obtain base-case OD vehicle trips ($q_{rs}^{(b)}$);
Step 5: Randomly generate a set of $\varepsilon_{MS}$ from $N(0, \eta_{MS})$ and estimate $q'_{n}$ by using equation 4.8;

Step 6: Randomly generate a set of $\varepsilon_{TA}$ from $N(0, \eta_{TA})$ and perform the UE Traffic Assignment to estimate arc volumes and arc travel time;

Step 7: Calculate TSTT by using equation 4.1;

Step 8: Repeat 6 and 7 $R_{TA}$ times;

Step 9: Repeat 5-8 $R_{MS}$ times;

Step 10: Repeat 3-9 $R_{TD}$ times;

Step 11: Repeat 1-10 $R_{TG}$ times.

The procedure would produce $R_{TG} \times R_{TD} \times R_{MS} \times R_{TA}$ random realizations of TSTT. These realizations constituted random samples from the probability distribution over TSTT induced by random samples from the probability distributions over the model outputs in each step of the four-step process. We assumed each realization would occur with equal probability. From these realizations, we calculated the coefficient of variation (CV) of the distribution of TSTT. We then used the CV to represent the uncertainty in TSTT.

We describe in the next section how we used the above procedure to develop several distributions of TSTT. We compared the CVs of the distributions and made a conclusion on which of the four-step models reduced uncertainty in TSTT the most.
4.3 Analytical Method

We first modeled uncertainty in model outputs of each step of the four-step process based on the “posterior distributions” of Chapter 3 and propagated these posterior uncertainties through the four-step process to develop a base-case probability distribution of the Total System Travel Time (TSTT) in the network. Specifically, the base-case distribution of TSTT is developed by applying the procedure in Section 4.2.3 with $\eta_{TG}$, $\eta_{TD}$, $\eta_{MS}$, and $\eta_{TA}$ that corresponded to the posterior distributions of Chapter 3. The values of $\eta_{TG}$, $\eta_{TD}$, $\eta_{MS}$, and $\eta_{TA}$ are shown in Table 4.7. To develop the base-case distribution of TSTT, we used $\eta_{TG}=0.211$, $\eta_{TD}=0.418$, $\eta_{MS}=0.077$, $\eta_{TA}=0.198$ for the small network example, and we used $\eta_{TG}=0.186$, $\eta_{TD}=0.235$, $\eta_{MS}=0.077$, $\eta_{TA}=0.055$ for the extended network example. Once the base-case distribution of TSTT was developed, we calculated the coefficient of variation of the distribution, called $CV_{BASE}$, and used it to represent the base-case uncertainty of TSTT.

<table>
<thead>
<tr>
<th>Steps of the Four-Step Process (i)</th>
<th>Prior Distribution</th>
<th>Posterior Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Desired $VI_i$</td>
<td>Derived $\eta_i$</td>
</tr>
<tr>
<td>Results of the Small Network Example</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip Generation ($i=\text{TG}$)</td>
<td>0.1947</td>
<td>0.325</td>
</tr>
<tr>
<td>Trip Distribution ($i=\text{TD}$)</td>
<td>0.2104</td>
<td>0.525</td>
</tr>
<tr>
<td>Modal Split ($i=\text{MS}$)</td>
<td>0.0651</td>
<td>0.095</td>
</tr>
<tr>
<td>Traffic Assignment ($i=\text{TA}$)</td>
<td>0.1243</td>
<td>0.348</td>
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<tr>
<td>Results of the Extended Network Example</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip Generation ($i=\text{TG}$)</td>
<td>0.1947</td>
<td>0.289</td>
</tr>
<tr>
<td>Trip Distribution ($i=\text{TD}$)</td>
<td>0.2104</td>
<td>0.315</td>
</tr>
<tr>
<td>Modal Split ($i=\text{MS}$)</td>
<td>0.0651</td>
<td>0.095</td>
</tr>
<tr>
<td>Traffic Assignment ($i=\text{TA}$)</td>
<td>0.1243</td>
<td>0.172</td>
</tr>
</tbody>
</table>

Table 4.7: The Desired Variation Index ($VI$) and the Derived Standard Deviation of Error Term ($\eta$) for the Prior and Posterior Distributions of the Steps of the Four-Step Model for Small and Extended Network Examples

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To investigate the effect of the TG model, we modeled the uncertainty in the outputs of the TG model based on the “prior distribution” in the TG step of Chapter 3 and the uncertainty in the outputs of the other three models based on the “posterior distributions” of Chapter 3. We then propagated the prior TG uncertainties and the other (TD, MS, TA) posterior uncertainties through the four-step process to develop another distribution of TSTT. This new distribution of TSTT was obtained by applying the procedure in Section 4.2.3 with the same $\eta_{TD}$, $\eta_{MS}$, $\eta_{TA}$ that we used in developing the base-case distribution of TSTT and with a different $\eta_{TG}$. Specifically, we replaced $\eta_{TG}=0.211$ with $\eta_{TG}=0.325$ for the small network example and replaced $\eta_{TG}=0.186$ with $\eta_{TG}=0.289$ for the extended network example. Once the new distribution of TSTT was developed, we calculated the coefficient of variation of the distribution, called $CV_{TG}$. $CV_{TG}$ would be larger than $CV_{BASE}$, since the prior TG distribution had “larger uncertainty” than the posterior TG distribution.

To investigate the effect of the TD model, we developed another distribution of TSTT by applying the procedure in Section 4.2.3 with the same $\eta_{TG}$, $\eta_{MS}$, $\eta_{TA}$ that we used in developing the base-case distribution of TSTT and with a $\eta_{TD}$ that corresponded to the “prior distribution” in the TD step of Chapter 3. Specifically, we used $\eta_{TD}=0.525$ for the small network example and used $\eta_{TD}=0.315$ for the extended network example. Once the new distribution of TSTT was developed, we calculated the coefficient of variation of the distribution, called $CV_{TD}$. Again, $CV_{TD}$ would be larger than $CV_{BASE}$, since the prior TD distribution had “larger uncertainty” than the posterior TD distribution.
To investigate the effect of the MS model, we developed another distribution of TSTT by applying the procedure in Section 4.2.3 with the same $\eta_{TG}$, $\eta_{TD}$, $\eta_{TA}$ that we used in developing the base-case distribution of TSTT and with a $\eta_{MS}$ that corresponded to the "prior distribution" in the MS step of Chapter 3. Specifically, we used $\eta_{MS}=0.095$ for both network examples. Once the new distribution of TSTT was developed, we calculated the coefficient of variation of the distribution, called $CV_{MS}$. $CV_{MS}$ would be larger than $CV_{BASE}$, since the prior MS distribution had "larger uncertainty" than the posterior MS distribution.

Finally, to investigate the effect of the TA model, we developed the other distribution of TSTT by applying the procedure in Section 4.2.3 with the same $\eta_{TG}$, $\eta_{TD}$, $\eta_{MS}$ that we used in developing the base-case distribution of TSTT and with a $\eta_{TA}$ that corresponded to the "prior distribution" in the TA step of Chapter 3. Specifically, we used $\eta_{TA}=0.348$ for the small network example and used $\eta_{TA}=0.172$ for the extended network example. Once the new distribution of TSTT was developed, we calculated the coefficient of variation of the distribution, called $CV_{TA}$. Again, $CV_{TA}$ would be larger than $CV_{BASE}$, since the prior TA distribution had "larger uncertainty" than the posterior TA distribution.

We investigated the relative importance of the models used in the four-step process by observing the relative difference between $CV_{BASE}$ and the other four $CV$s, namely $CV_{TG}$, $CV_{TD}$, $CV_{MS}$, and $CV_{TA}$. The difference between $CV_{BASE}$ and $CV_i$ ($i=\{TG$, $TD$, $MS$, $TA\}$)
TD, MS, TA) indicated how much the model in step "i" reduced uncertainty of TSTT. The more the difference between $CV_{\text{BASE}}$ and $CV_i$, the more the model in step "i" reduced the uncertainty of TSTT and the more the important the model in the four-step travel demand forecasting process. Recall that we selected TSTT as the predicted consequence of the four-step process in this study.

4.4 Results

In this section, we present results of the analysis (described in Section 4.3) for the small network example and the extended network example. We show the coefficient of variation (CV) results in Table 4.8 and graph the results in Figures 4.10 and 4.11. We investigate for 5, 10, 15, and 30 “runs in each step (R)” for the small network example, and 5, 10, 15 “runs in each step (R)” for the extended network example. By “runs in each step (R),” we meant that we generate R random realizations of outputs in each step for each output produced in the previous step. For example, 5 “runs in each step” means that we simulate the distribution of TSTT using 5 sets of errors in the TG step, 5 sets of errors in the TD step for each of the 5 TG outputs, 5 sets of errors in the MS step for each of the $5 \times 5 = 25$ outputs of the TD step, and 5 sets of errors in the TA step for each of the $5 \times 5 \times 5 = 125$ outputs of the MS step. The procedure would, therefore, produce $5 \times 5 \times 5 \times 5 = 625$ random realizations of TSTT. From these realizations, we calculated the coefficient of variations.
variation (CV) of the distribution of TSTT. We then used the CV to represent the uncertainty in TSTT.

<table>
<thead>
<tr>
<th>Number of Runs in each step (R)</th>
<th>Base-Case CV (CV_{BASE})</th>
<th>Coefficient of Variation without Using Model</th>
<th>TG model (CV_{TG})</th>
<th>TD model (CV_{TD})</th>
<th>MS model (CV_{MS})</th>
<th>TA model (CV_{TA})</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Results of the Small Network Example</strong></td>
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</tr>
<tr>
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<td>0.4290</td>
<td>0.4546</td>
<td>0.4396</td>
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<tr>
<td>10</td>
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<td>0.5730</td>
<td>0.3469</td>
<td>0.3588</td>
<td>0.3837</td>
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<tr>
<td>15</td>
<td>0.3301</td>
<td>0.5037</td>
<td>0.3326</td>
<td>0.3443</td>
<td>0.3584</td>
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<tr>
<td>30</td>
<td>0.4243</td>
<td>0.6634</td>
<td>0.4419</td>
<td>0.4500</td>
<td>0.4896</td>
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</tr>
<tr>
<td><strong>Results of the Extended Network Example</strong></td>
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<td></td>
<td></td>
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<tr>
<td>5</td>
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<td>0.2119</td>
<td>0.1436</td>
<td>0.1454</td>
<td>0.1440</td>
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<tr>
<td>10</td>
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<tr>
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<td>0.1096</td>
<td>0.1090</td>
<td>0.1122</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.8: Coefficient of Variation of Total System Travel Time for Base-Case and "Without Using" each Step of the Four-Step Model.

As mentioned before, the difference between CV_{BASE} and CV_i \ (i=\text{TG, TD, MS, TA}) indicated how much the model in step "i" reduced uncertainty of TSTT. To measure the reduction in uncertainty of TSTT, we define

\[ RU_i = CV_i - CV_{BASE}, \quad i = \text{TG, TD, MS, TA}, \] (4.10)

where \( RU_i \) is the reduction in uncertainty of TSTT when using the model in step "i";

\( CV_i \) is the coefficient of variation of TSTT when not using the model (i.e., using the prior distribution of Chapter 3) in step "i" but using model (i.e., using the posterior distribution of Chapter 3) in the other steps;

\( CV_{BASE} \) is the coefficient of variation of TSTT when using the models (i.e., using
the posterior distribution of Chapter 3) in all four steps of the four-step process.

We calculate $RU_i$ for 5, 10, 15, and 30 "runs in each step (R)" for the small network example, and 5, 10, 15 "runs in each step (R)" for the extended network example. The results are shown in Table 4.9. In summary, we found the following. First, the TG model was the model that led to the greatest reduction in the uncertainty of TSTT, while the TD model was the one that led to smallest reduction in the uncertainty of TSTT. This statement is true for all cases, (i.e., for both network examples and for any "runs in each step (R)" that we tested). Second, in all cases, the reduction in the uncertainty of TSTT due to the TG model was much greater than that of the other three models (TD, MS, TA). Third, the TD model, the MS model, and the TA model reduced the uncertainty of TSTT very little, almost unnoticeably in the case of the extended network. Fourth, there was little difference in the level of the reduction in the uncertainty of TSTT among the numbers of runs for the four models (see Figures 4.10 and 4.11). The difference was almost unnoticeable in the extended network case.

4.4.1 Results of the Small Network Example

Table 4.8, Table 4.9 and Figure 4.10 show the results of the analysis for the small network example. It is obvious that the TG model reduced uncertainty of TSTT more than any of the other three models. As shown in Table 4.9, the reduction in the uncertainty of
TSTT due to the TG model varied from 0.1737 when the number of runs in each step equaled 15 to 0.2391 when the number of runs equaled 30. We also found that the TD model always led to the smallest reduction in uncertainty of TSTT. The reductions varied from 0.0000 when the number of runs in each step equaled 10 to 0.0176 when the number of runs in each step equaled 30.

<table>
<thead>
<tr>
<th>Number of Runs in each step (R)</th>
<th>Base-Case CV (CV_{base})</th>
<th>Reduction in Uncertainty of TSTT when using</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>TG model (RU_{TG})</td>
</tr>
<tr>
<td>5</td>
<td>0.4288</td>
<td>0.2134</td>
</tr>
<tr>
<td>10</td>
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<td>15</td>
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<td>0.1737</td>
</tr>
<tr>
<td>30</td>
<td>0.4243</td>
<td>0.2391</td>
</tr>
</tbody>
</table>

Table 4.9: Reduction in Uncertainty of TSTT for each Step of the Four-Step Model, by Number of Runs in each Step

As shown in Table 4.9 and Figure 4.10, the reductions of uncertainty in TSTT due to the TD model, MS model, and TA model are very small. There is also little difference when comparing the reduction of the uncertainties of TSTT across the “use of” the three models (TD, MS, TA). However, as we shall see, the differences are greater than those in the extended network example. The TA model reduced the uncertainty of TSTT the most among these three models except for the 5-run case. However, the difference is not large,
and the reduction in uncertainty of TSTT due to the TA model is still far smaller than that due to the TG model. We also observe little change in the level of the reduction in uncertainty of TSTT among the four steps as the number of runs in each step increased.

4.4.2 Result of the Extended Network Example

Table 4.8, Table 4.9 and Figure 4.11 show the results of the analysis for the extended network example. Again, the TG model is the one that reduced uncertainty of TSTT the most. Although the differences between the value of $CV_{TG}$ and those of the other three steps are not as big as in the small network example, the value of $CV_{TG}$ is still considerably higher than those of $CV_{TD}$, $CV_{MS}$, and $CV_{TA}$ for any number of runs that we tested. As shown in Table 4.9, the reduction in the uncertainty of TSTT due to the TG
model varied from 0.0557 when the number of runs in each step equaled 15 to 0.0684 when the number of runs equaled 5. Again, we also found that the TD model always led to the smallest reduction in uncertainty of TSTT except for the 15-run case. The reductions vary from 0.0000 when the number of runs in each step equaled 5 to 0.0018 when the number of runs in each step equaled 15. As shown in Table 4.9 and Figure 4.11, the reductions of uncertainty in TSTT due to the TD model, MS model, and TA model are very small. There is also very little difference in the level of the reduction of the uncertainty in TSTT due to the use of each of these three models (TD, MS, TA). Unlike in the small network example, the difference in the extended network example is almost unnoticeable. We also observe very little change in the pattern of the reduction in uncertainty of TSTT among the four steps as the number of runs in each step increased.

Figure 4.11: Coefficient of Variation (CV) of TSTT for Base-Case and “Without Using” each Step of the Four-Step Model -- the Extended Network Example
CHAPTER 5

SUMMARY AND CONCLUSIONS

Travel demand forecasting is considered an essential element of the transportation planning process, since it affects the design of transportation facilities or policies and enables planners to evaluate the costs and impacts of the projects. Unfortunately, forecasts are uncertain, since the future is uncertain. Individuals normally try to reduce their uncertainty in forecasts by collecting additional information. The additional information considered in this study comes from the outputs of models used in the four-step process. The four-step process is the most common process used in predicting travel demand in urban transportation planning. The process divides the travel demand forecasting task into a series of four steps called Trip Generation (TG), Trip Distribution (TD), Modal Split (MS), and Traffic Assignment (TA). Due to the questionable assumptions of the models and their inability to predict the demands accurately, we wanted to see whether the models actually help reduce uncertainty in individuals’ judgments about future travel demand and which models help most.
To accomplish the goals of this study, we elicited judgments from 47 transportation practitioners and academics about hypothetical, but realistic transportation events that would be forecast from the “four-step process” models. We elicited the individuals’ judgments before and after seeing the output of the model used in each step of the four-step process. The judgments were expressed as fractiles on probability distributions over possible levels of travel demand. We elicited the judgments in a manner consistent with subjective probability theory and compared the variation indices of the probability judgments to see how uncertain the individuals were among steps of the four-step process. We then investigated how much models reduced uncertainty in the judgments by observing the change in variation indices of posterior compared to prior judgments. The prior and posterior judgments, respectively, are the judgments before and after the subjects saw the model output. We found the following.

The individuals felt most uncertain in the Trip Generation (TG) and Trip Distribution (TD) steps and felt least uncertain in the Modal Split (MS) step. The uncertainty in the TD step was slightly higher than that of the TG step and markedly higher than that of the other two steps (MS and TA) both before and after seeing the model outputs. This implies that it is more difficult for individuals to predict the events in the TG and TD steps both without and with the use of models. Therefore, there seems to be more need for research that would help individuals have a better understanding about trip making behavior in the TG and TD steps and more need to improve the TG and TD models. Moreover, it would be useful to inform students, who are studying travel demand
forecasting, that individuals familiar with transportation planning appear most uncertain in their forecasts of the TG and TD steps.

We also found that transportation practitioners and academics were less uncertain about their predictions after observing the outputs of models used in the four-step process than before seeing them. That is, the individuals did find the models helpful. Therefore, the models can be used in practice not only to get rough estimates of predictions but to reduce uncertainty in predictions.

Moreover, we found that the models changed the individuals' judgments differently among the steps of the four-step process. In our experiment, transportation practitioners and academics reduced the uncertainty in their judgments, as measured by the Average Percentage Change in the Quartile Range (APCQ), by 32%, 26%, 19%, and 46% in the TG, TD, MS and TA steps, respectively. Based on this measure, the individuals had most confidence in the TA model and least in MS model. Therefore, the TA model seems to be performing best. Based on these results, more work seems to be warranted to develop better TD models, since individuals seem to have the biggest uncertainty in their predictions about an event in the TD step and the TD model seems to help reduce uncertainty in the predictions only slightly. Although individuals had the least confidence in the MS model, more work does not seem to be justified to develop better MS models, since the uncertainty associated with the event in the MS step was already very small compared to the other three steps.
We also investigated which of the four models most reduced the uncertainty of Total System Travel Time (TSTT), an outcome often calculated from the outputs of the four-step process. We constructed a sequential prediction process and used it to produce probability distributions of TSTT under the condition in which all the four-step models were “used” and under four other conditions in which each of the four-step models was “not used,” while the other three models were. By “used” and “not used,” we mean that we modeled uncertainty in model outputs of the step under consideration based on the “posterior distributions” and “prior distributions” of Chapter 3, respectively.

Based on analysis of the Coefficient of Variation of TSTT distributions under various conditions, we found that the reduction in the uncertainty of TSTT due to the use of the TG model was much greater than that of the other three models (TD, MS, TA). In addition, we found that the reduction of uncertainty in each of the other three steps (TD, MS, TA) due to the use of the model in that step reduced the uncertainty of TSTT only slightly. These results held for both a simple illustrative network and a more realistic, extended highway network. It would appear, then, that practitioners should pay special attention to reduce uncertainty in the Trip Generation step if they are concerned with reducing uncertainty of TSTT.

In addition to the findings related to our original research objectives, we also thought it interesting that the transportation practitioners and academics in our
experiment were able to provide subjective probability forecasts with little effort, although many had never been exposed to subjective probability before the interview. This would indicate the potential for using subjective probability in practice. If it is truly better to recognize uncertainty in forecasts than to ignore it, the use of the subjective probability may be a means to explicitly recognize it. Ultimately, it would be helpful to use the quantified uncertainty in the planning process to allow for more informed decisions.

We also believe that the distribution assessed could be useful for other work. For example, McCord, Goel, O’Kelly, and Hidalgo (1997) and Hidalgo (1997) formulated a framework for estimating the value of improved forecasting models in a specific transportation planning problem. The study assumed that the uncertainties of the events in each step were the same. However, the results of the work presented here show that the uncertainties of the events estimated subjectively in each step are not the same. Therefore, the use of the results from this study may be useful in other research.

We also see areas that warrant further study. Confirming the results in other settings would be useful. In this study, we investigated the effect of models for a base-case policy. Specifically, we assumed that there would be no change in transportation and land use policies when eliciting judgments about the transportation events. Different policies may make certain models more important. For example, when considering a policy such as whether or not to build a light-rail-transit system, the Modal Split model...
may stand out as the model that requires more work. Or, when considering a policy such as whether or not to build a new freeway, the relative effect of the Traffic Assignment model may become greater.

Finally, we recommend studies that would encode other points of the subjective probability distribution. To reduce assessment time, we only encoded points that correspond to the 25% fractile and the median of the subjective probability distribution. If the data collection must still be conducted within the time limits we set, one could repeat this experiment while encoding points that correspond to the median and 75% fractile. It would be interesting to see if the same results held for the other sides of the distributions. Moreover, when simulating the distribution of total system travel time with the sequential prediction process, we were forced to assume that the probability distributions of model outputs in each step were symmetrical. Encoding the other sides of the distributions would support or refute this assumption. One could also simulate the TSTT distributions using the information of the other sides of the distributions and see if the results were similar to those obtained in this study. Alternatively, if assessment time could be extended, one could assess 25%, 50% (median), and 75% fractiles from the same individuals and investigate the symmetrical assumption of probability distributions at the individual level.

In conclusion, it seems clear that the future is uncertain and that, therefore, travel demand can never be predicted exactly. Although, models such as those used in the four-
step process are used widely, these models all have questionable assumptions. This study is the first to our knowledge that investigates how uncertain transportation practitioners and academics truly are in their judgments about travel demand forecasts and how the models of the four-step process help reduce the uncertainty. Moreover, we found that the individuals felt markedly more uncertain in their forecasts in one step than in others. We also found that the models helped reduce the uncertainty in individuals’ judgments and that the different models of the four-step process reduced the uncertainty by different amounts. We hope that the results of this study will be a step toward further research and practical guidelines for developments in travel demand forecasting and transportation planning in an uncertain world.
REFERENCES


Maldonado, J. *The Effects of Model Information on the Opinion of Individuals and Their Implications for Uncertainty in Urban Transportation Planning and Forecasting*. Master Thesis, Civil Engineering, The Ohio State University, Columbus, Ohio, 1986.


APPENDIX A

Questionnaire
Map of Columbus, Ohio
Highway and Transit networks
(as of March 1992)
Please make the forecasts with the assumption that there will be no change in policy toward transportation supply and land use.

For examples, there are
- no new policies on land use or zoning;
- no changes in highway network;
- no changes in transit network, headway, fare (adjusted for inflation), and etc.
TRIP GENERATION

Assume: Exactly 35,000 workers will live in Clintonville in 2020.

Question: How many Average Weekday person work trips will be originating from homes in Clintonville in 2020?
**Basic Information:**

-From 1980 and 1990 censuses, Clintonville had the following Journey-to-Work characteristics.

**Table 1**

<table>
<thead>
<tr>
<th>On a usual day</th>
<th>1980 census</th>
<th>1990 census</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Number of workers living in Clintonville</td>
<td>28,416</td>
<td>30,865</td>
</tr>
<tr>
<td>2. Number of workers living in Clintonville who left their homes to work</td>
<td>26,131</td>
<td>28,245</td>
</tr>
<tr>
<td>3. Percentage of workers living in Clintonville who left their homes to work</td>
<td>92.0%</td>
<td>91.5%</td>
</tr>
</tbody>
</table>
TRIP DISTRIBUTION

Assume: On the Average Weekday in 2020, there will be

(a) exactly 800,000 person work trips per day in the Columbus area;

(b) exactly 33,000 person work trips per day (4% of total work trips) originating from homes in Clintonville for any part of Columbus.

(c) exactly 100,000 person work trips per day (13% of total work trips) going Downtown from all over Columbus.

Question: How many of the person work trips per day originating from homes in Clintonville will go Downtown?
Basic information:

-From 1980 and 1990 censuses, Clintonville and Downtown had the following Journey-to-Work characteristics.

Table 2

<table>
<thead>
<tr>
<th>On a usual day</th>
<th>1980 census</th>
<th>1990 census</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Total number of workers living in Columbus who left their homes to work</td>
<td>395,670</td>
<td>505,381</td>
</tr>
<tr>
<td>2. Number of workers living in Clintonville who left their homes to work</td>
<td>26,131</td>
<td>28,245</td>
</tr>
<tr>
<td>3. Number of workers who went to work in Downtown</td>
<td>71,368</td>
<td>79,029</td>
</tr>
<tr>
<td>4. Number of workers living in Clintonville who left their homes to work in Downtown</td>
<td>4,165</td>
<td>4,307</td>
</tr>
<tr>
<td>5. Percentage of</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) / (1)</td>
<td>1.1%</td>
<td>0.9%</td>
</tr>
<tr>
<td>(4) / (2)</td>
<td>15.9%</td>
<td>15.3%</td>
</tr>
<tr>
<td>(4) / (3)</td>
<td>5.8%</td>
<td>5.4%</td>
</tr>
</tbody>
</table>
**Assume:** Exactly 1,300 Average Weekday person work trips will be leaving homes in Clintonville for Downtown during the AM peak hour (7:30-8:30 A.M.) in 2020.

**Question:** How many of these person work trips will be made by automobiles?
MODAL SPLIT

Basic information:

- From 1980 and 1990 censuses, Journey-to-Work trips from Clintonville had the following characteristics.

Table 3

<table>
<thead>
<tr>
<th>On a usual day during the peak hour</th>
<th>1980 census</th>
<th>1990 census</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Number of workers living in Clintonville who left their homes to work in Downtown</td>
<td>1,198</td>
<td>1,238</td>
</tr>
<tr>
<td>2. Number of these workers who went to work by automobiles</td>
<td>1,060</td>
<td>1,125</td>
</tr>
<tr>
<td>3. Percentage of these workers who went to work by automobiles</td>
<td>88.5%</td>
<td>90.9%</td>
</tr>
</tbody>
</table>
Assume: During the Average Weekday AM peak hour (7:30-8:30A.M.) in 2020, there will be
(a) exactly 200,000 *vehicle work trips* in the Columbus area;
(b) exactly 1,200 *vehicle work trips* leaving homes in Clintonville for Downtown.

**I-71 Freeway**

Question: How many *vehicles* will be going southbound on Interstate I-71 between Hudson St. and 17th Ave. during *the AM peak hour (7:30-8:30A.M.)* on an *Average Weekday in 2020*?
TRAFFIC ASSIGNMENT

Highway Network and Major Trip Generators in the North Corridor.

I-71 between Hudson St. and 17th Ave.
Desire Lines: showing the magnitude of vehicle trip interchanges on the shortest airline distances between the terminal points of trips.
### TRAFFIC ASSIGNMENT

**Basic information:**
- From 1980 and 1990 censuses, and reports from Mid-Ohio Regional Planning Commission (MORPC), it is found that

#### Table 4

<table>
<thead>
<tr>
<th>On a usual day during the peak hour</th>
<th>1980</th>
<th>1990</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Total number of workers living in Columbus who left their homes to work by automobiles.</td>
<td>100,000 (census)</td>
<td>140,000 (census)</td>
</tr>
<tr>
<td>2. Number of workers living in Clintonville who left their homes to work in Downtown by automobiles.</td>
<td>1,060 (census)</td>
<td>1,125 (census)</td>
</tr>
<tr>
<td>3. Number of vehicles going southbound on the specific section of I-71</td>
<td>4,000 (MORPC)</td>
<td>5,000 (MORPC)</td>
</tr>
<tr>
<td>4. Ratio of ((3)/(1)) ((3)/(2))</td>
<td>0.040</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>3.773</td>
<td>4.444</td>
</tr>
<tr>
<td>5. Capacity of the specific section of I-71 (vehicles per hour)</td>
<td>6,600* (assumption)</td>
<td>6,600* (assumption)</td>
</tr>
<tr>
<td>6. Volume-Capacity Ratio (V/C)</td>
<td>0.61</td>
<td>0.76</td>
</tr>
</tbody>
</table>

**Note:**
*Assuming 2,200 automobiles per hour per lane.
Questions on respondent characteristics

Although your responses will remain anonymous, we wish to correlate them with some general descriptive information. Please answer the following questions as best as possible. Thank you.

1. You consider your current position to be primarily (check one):

<table>
<thead>
<tr>
<th>Private</th>
<th>Government</th>
<th>Academic</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2. Approximately how long have you been at your present position?

______________ Years

3. Not including university studies, approximately how long have you been in position that is responsible for travel demand forecasting?

______________ Years

4. Have you had any training in travel demand forecasting during or after your university studies?

_____ YES _____ NO

5. How familiar would you consider yourself with the following steps of the so-called four-step travel demand forecasting process? Please circle the associated number for each step.

<table>
<thead>
<tr>
<th>Not familiar at all</th>
<th>somewhat familiar</th>
<th>very familiar</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

5.1 Trip Generation

5.2 Trip Distribution

5.3 Modal Split

5.4 Traffic Assignment

181
Questions on respondent characteristics

6. How familiar are you with the transportation system in Columbus, OH?

<table>
<thead>
<tr>
<th>Not familiar at all</th>
<th>somewhat familiar</th>
<th>very familiar</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

7. How familiar would you consider yourself with the probability theory?

<table>
<thead>
<tr>
<th>Not familiar at all</th>
<th>somewhat familiar</th>
<th>very familiar</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

8. Have you ever been exposed to subjective probability before having this interview?

______YES______NO
APPENDIX B

Letters for Contacting the Subjects
December 4, 1996

Mr. Test Subject
XYZ Company
111 Test Street
Columbus, Ohio 43222

Dear Mr. Subject:

My Ph.D. students and I are conducting research on effective use of travel demand models. One step is to investigate how transportation planners and engineers change their intuitive judgments about future travel patterns when model forecasts are available. By comparing the effects of different models used in the traditional "4-step process," we hope to provide useful input for education and model development.

We are collecting judgments from practitioners and academics associated with transportation forecasting models. We collect these judgments through personal interviews and are kindly asking you to participate in this study. All responses will, of course, be anonymous. The interview should take 30 minutes or less, and one of my graduate students, Tony Lao, will conduct this interview at your office for your convenience.

In the interview, you will only need to compare two events at a time and say which event you feel is more likely. Such comparisons are commonly used in business studies and have also been used in specific transportation applications. However, this is the first time to our knowledge that this methodology is being used in a systematic research effort in the transportation field. The comparisons are meant to indicate your beliefs about the relative likelihood of events before and after you see model outputs. We will not be trying to see "how well" or "how accurately" you can predict the future; we do not know what will happen in the future either. We are only interested in assessing the relative likelihood given by individuals, such as yourself, who have some experience with transportation forecasting models.
Tony will be calling you soon, hopefully to confirm your willingness to participate in this study and to arrange for a convenient time for the interview.

Thank you for your anticipated cooperation.

Sincerely,

Dr. Mark R. McCord
Associate Professor
Civil Engineering
City & Regional Planning
January 4, 1997

Mr. Test Subject
XYZ Company
111 Test Street
Columbus, Ohio 43222

Dear Mr. Subject:

I am writing to remind you that my Ph.D. student, Tony Lao, will interview you on Wednesday, January 7 at 2:00 P.M., as scheduled by telephone. If you must change the appointment, please contact Tony at (614) 781-1122 or by e-mail at "laosirihongthong.2@osu.edu". The interview should take 30 minutes or less to complete, and Tony will conduct this interview at your office for your convenience.

I would like to take this opportunity to provide more information on the interview. **Purpose:** The purpose of this interview is to collect the data for research on effective use of travel demand models. One step in this research is to investigate how transportation planners and engineers change their intuitive judgments about future travel patterns when model forecasts are available. By comparing the effects of different models used in the traditional “4-step process” (Trip Generation, Trip Distribution, Modal Split, and Traffic Assignment), we hope to provide useful input for education and model development. We are collecting empirical judgments from practitioners and academics associated with transportation forecasting models. We collect these judgments through personal interviews.

**Interview:** We will assess your judgments toward the uncertainty involved in forecasting the numbers of trips made in Columbus, Ohio, in the year 2020. You do not need to know anything about Columbus to perform tasks required in this interview. We will provide you with the basic information required to form judgments. We will ask you to state your judgments before and after you see 4-step model outputs.

To quantify your judgments, we will ask questions in a manner consistent with the "Subjective Probability" method. According to this method, we will present you with two events at a time and ask which you feel is more likely to occur. One of the attractions of this method is that the expert (you) does not need to know anything about the method to
answer the questions. Only the analyst (us) has to know the details to translate your answers into meaningful measurements.

First, we will introduce the method to you through an exercise designed to give you a feel for the type of questions that will be used to assess your judgments on travel demand. The introductory exercise will have the format presented in the attachment to this letter. I would kindly ask you to read the attachment before Tony arrives so that your session will go smoothly. Please feel free to contact Tony or me with any question, comments, or feedback. Thank you in advance for participating in this experiment.

Sincerely,

Dr. Mark R. McCord
Associate Professor
Civil Engineering
City & Regional Planning
We present this example to give you a feel for the type of questions that will be used to assess your judgments during the interview. The actual interview question will deal with travel forecasting, but to illustrate the type of question we present an example based on weather forecasting. Basically, we will present you with two events at a time and ask which you feel is more likely to occur. The questions will have the following format:

"Do you believe, it is more likely
(a) that tomorrow’s reported high temperature in Columbus will be below -10 °F; or
(b) that the pointer will land in the shaded area of the probability wheel when I spin the wheel?"

You probably would say it is more likely that the pointer will land in the shaded area, right? If you agree, we would change the number from -10 °F to a higher level -- for example 50 °F -- and ask the same type of question. That is, we would then ask, "Do you believe, it is more likely
(a) that tomorrow’s high temperature will be below 50 °F; or
(b) that pointer will land in the shaded area of the probability wheel when I spin the wheel?"

If, in the original question, you believe that it was more likely to be below -10 °F than to fall in the shaded area, that would be OK, too, since there are no right or wrong answers at the time we ask you the question; we are trying to measure your beliefs. We would simply change the number from -10 °F to a lower level -- for example -20 °F -- and ask the same type of question. That is, we would then ask, "Do you believe, it is more likely
(a) that tomorrow’s high temperature will be below -20 °F; or
(b) that pointer will land in the shaded area of the probability wheel when I spin the wheel?"

We would keep asking the same question but change the number (temperature) until we would find the temperature at which you think it is approximately just as likely that the high temperature tomorrow would be below that number and the pointer would fall in the shaded area when the wheel is spun. This would be your 50-percentile level on a probability distribution. (However, you do not need to know this interpretation; you only
need to know which of two events you consider more likely, or whether you consider them approximately equally likely.)

It is important in this experiment that you respond as you think. There are no right or wrong answers. We are not trying to see "how well" or "how accurately" you can predict the future; we do not know what will happen in the future either. We are trying to see how your judgments are affected by forecasts - e.g., "the Weather Service forecasts a high temperature for tomorrow of 40 °F" in the weather forecasting example; "the output of a travel demand model is X trips" in the interview we will be conducting. You have only to consider the information provided in each case and respond honestly.
APPENDIX C

Worksheets for Encoding Probability Judgments
Assessing Median

Assume Clintonville will have exactly 35,000 workers in 2020.

An un-colored area shows the possible range.
Assessing 25% Fractile

Assume Clintonville will have exactly 35,000 workers in 2020.

An un-colored area shows the possible range.
Assessing Median

Assume 33,000 average weekday person work trips originating from homes in Clintonvilles in 2020.

An un-colored area shows the possible range.

An un-colored area shows the possible range.
Assessing 25% Fractile

Assume 33,000 average weekday person work trips originating from homes in Clintonvilles in 2020.

An un-colored area shows the possible range.

An un-colored area shows the possible range.
Assessing Median

Assume there will be exactly 1,300 average weekday person work trips from Clintonville to Downtown in 2020.

An un-colored area shows the possible range.

An un-colored area shows the possible range.

195
Assessing 25% Fractile

Assume there will be exactly 1,300 average weekday person work trips from Clintonville to Downtown in 2020.

An un-colored area shows the possible range.

<table>
<thead>
<tr>
<th>0</th>
<th>100</th>
<th>1,280</th>
<th>1,300</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0%)</td>
<td>(1%)</td>
<td>(98%)</td>
<td>(100%)</td>
</tr>
</tbody>
</table>

An un-colored area shows the possible range.

<table>
<thead>
<tr>
<th>850</th>
<th>950</th>
<th>1,050</th>
<th>1,150</th>
<th>1,250</th>
</tr>
</thead>
<tbody>
<tr>
<td>(65%)</td>
<td>(73%)</td>
<td>(81%)</td>
<td>(88%)</td>
<td>(96%)</td>
</tr>
<tr>
<td>800</td>
<td>900</td>
<td>1,000</td>
<td>1,100</td>
<td>1,200</td>
</tr>
<tr>
<td>(62%)</td>
<td>(69%)</td>
<td>(77%)</td>
<td>(85%)</td>
<td>(92%)</td>
</tr>
</tbody>
</table>
Assessing Median

An un-colored area shows the possible range.

An un-colored area shows the possible range.
TRAFFIC ASSIGNMENT

Assessing 25% Fractile

An un-colored area shows the possible range.

4,000 4,500 5,000 5,500 6,000 6,500 7,000 7,500 8,000 8,500 9,000 9,500 10,000
APPENDIX D

Results of Data Analysis

on Individuals’ Characteristics
<table>
<thead>
<tr>
<th>Subject</th>
<th>Questions on Respondent Characteristics*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>**2</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
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<td>2</td>
<td>1</td>
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<tr>
<td>47</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: * see the description of each question and the associated unit of the data from the questionnaire in Appendix A; ** “1” for “Private Consulting Company”, “2” for “Government Agency”, and “3” for “Academic Institution”; *** “1” for “YES” and “2” for “NO.”

Table D.1: Interview Data on Individual Characteristics.

200
Figure D.1: Results of the Analysis of Individuals' Characteristics

201
Figure D.1: Results of the Analysis of Individuals’ Characteristics (continue)
Histogram of Question 6 on Respondent Characteristic.

<table>
<thead>
<tr>
<th>Familiarity</th>
<th>Frequency</th>
<th>Cumulative %</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>.00%</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>.00%</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>8.02%</td>
</tr>
<tr>
<td>4</td>
<td>22</td>
<td>44.26%</td>
</tr>
<tr>
<td>5</td>
<td>34</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Histogram of Question 7 on Respondent Characteristic.

<table>
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<th>Frequency</th>
<th>Cumulative %</th>
</tr>
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<td>1</td>
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<td>6</td>
<td>11.48%</td>
</tr>
<tr>
<td>3</td>
<td>19</td>
<td>42.52%</td>
</tr>
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<td>4</td>
<td>24</td>
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<td>11</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Histogram of Question 8 on Respondent Characteristic.

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<th>Frequency</th>
<th>Cumulative %</th>
</tr>
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<tbody>
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<td>27</td>
<td>44.26%</td>
</tr>
<tr>
<td>No</td>
<td>34</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Figure D.1: Results of the Analysis of Individuals' Characteristics (continue)
Note: Results are Sorted according to the Steps of the Four-Step Process and Table D.2: Results of Data Analysis on Characteristic#1 from Question#1

<table>
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<th>Second Step (l)</th>
<th>Results of Data Analysis for the Second Step</th>
<th>Question #1</th>
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<td>PCQi</td>
<td>Post-PCQi</td>
<td>Prior VI</td>
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<td>0.207</td>
<td>-3.3%</td>
<td>-11.3%</td>
<td>TD 0.182</td>
</tr>
<tr>
<td>42</td>
<td>35</td>
<td>TG 0.179</td>
<td>0.179</td>
<td>0.0%</td>
<td>0.0%</td>
<td>TD 0.200</td>
</tr>
<tr>
<td>43</td>
<td>37</td>
<td>TG 0.182</td>
<td>0.091</td>
<td>0.0%</td>
<td>-50.0%</td>
<td>TD 0.185</td>
</tr>
<tr>
<td>46</td>
<td>38</td>
<td>TG 0.250</td>
<td>0.125</td>
<td>0.0%</td>
<td>-50.0%</td>
<td>TD 0.174</td>
</tr>
<tr>
<td>52</td>
<td>41</td>
<td>TG 0.290</td>
<td>0.147</td>
<td>9.7%</td>
<td>-49.3%</td>
<td>TD 0.206</td>
</tr>
<tr>
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<td>42</td>
<td>TG 0.141</td>
<td>0.171</td>
<td>3.1%</td>
<td>-13.9%</td>
<td>TD 0.333</td>
</tr>
<tr>
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<td>46</td>
<td>TG 0.231</td>
<td>0.167</td>
<td>-7.7%</td>
<td>-27.8%</td>
<td>TD 0.245</td>
</tr>
<tr>
<td>48</td>
<td>46</td>
<td>TG 0.250</td>
<td>0.125</td>
<td>0.0%</td>
<td>-50.0%</td>
<td>MS 0.042</td>
</tr>
<tr>
<td>51</td>
<td>40</td>
<td>TG 0.258</td>
<td>0.174</td>
<td>-1.6%</td>
<td>-32.7%</td>
<td>MS 0.065</td>
</tr>
<tr>
<td>54</td>
<td>43</td>
<td>TG 0.167</td>
<td>0.107</td>
<td>-6.7%</td>
<td>-35.7%</td>
<td>MS 0.064</td>
</tr>
<tr>
<td>55</td>
<td>44</td>
<td>TG 0.077</td>
<td>0.032</td>
<td>-4.6%</td>
<td>-58.1%</td>
<td>MS 0.045</td>
</tr>
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<td>45</td>
<td>TG 0.231</td>
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<td>-7.7%</td>
<td>-27.8%</td>
<td>MS 0.064</td>
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<tr>
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<td>50</td>
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<td>-7.7%</td>
<td>TA 0.185</td>
</tr>
<tr>
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<td>51</td>
<td>TG 0.063</td>
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<td>-2.1%</td>
<td>-66.9%</td>
<td>TA 0.004</td>
</tr>
<tr>
<td>59</td>
<td>52</td>
<td>TG 0.063</td>
<td>0.063</td>
<td>0.0%</td>
<td>0.0%</td>
<td>TA 0.127</td>
</tr>
<tr>
<td>60</td>
<td>53</td>
<td>TG 0.186</td>
<td>0.186</td>
<td>0.0%</td>
<td>0.0%</td>
<td>TA 0.074</td>
</tr>
<tr>
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<td>53</td>
<td>TG 0.174</td>
<td>0.174</td>
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<td>0.0%</td>
<td>TA 0.123</td>
</tr>
<tr>
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<td>53</td>
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<td>-38.9%</td>
<td>TA 0.067</td>
</tr>
<tr>
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<td>54</td>
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<td>0.0%</td>
<td>-15.0%</td>
<td>TA 0.138</td>
</tr>
<tr>
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<td>55</td>
<td>MS 0.043</td>
<td>0.043</td>
<td>0.0%</td>
<td>0.0%</td>
<td>TA 0.186</td>
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<td>MS 0.021</td>
<td>0.021</td>
<td>0.0%</td>
<td>0.0%</td>
<td>TA 0.139</td>
</tr>
<tr>
<td>57</td>
<td>57</td>
<td>MS 0.042</td>
<td>0.021</td>
<td>0.0%</td>
<td>-50.0%</td>
<td>TA 0.123</td>
</tr>
<tr>
<td>58</td>
<td>58</td>
<td>MS 0.114</td>
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<td>0.0%</td>
<td>TA 0.111</td>
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<tr>
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<td>58</td>
<td>MS 0.064</td>
<td>0.064</td>
<td>0.0%</td>
<td>0.0%</td>
<td>TA 0.067</td>
</tr>
</tbody>
</table>

Note: Results are Sorted according to the Steps of the Four-Step Process and Classified into three groups: (a) "1" for "private consulting company", (b) "2" for "Government Agency", and (c) "3" for "Academic Institution"; Table D.2: Results of Data Analysis on Characteristic#1 from Question#1

204
Note: Results are Sorted according to the Steps of the Four-Step Process and Classified into two groups: (a) five years or less and (b) more than five years.

| Question #2 | Table D.3: Results of Data Analysis on Characteristic#2 from Question#2 | 205 |
Note: Results are Sorted according to the Steps of the Four-Step Process and Classified into two groups: (a) ten years or less and (b) more than ten years.

Table D.4: Results of Data Analysis on Characteristic #3 from Question #3

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<th>Question #3</th>
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<td>Posterior VI</td>
<td>Prior VI</td>
<td>Posterior VI</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>TG</td>
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<td>0.107</td>
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<td>-55.6%</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>TG</td>
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<td>0.118</td>
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<td>10</td>
</tr>
<tr>
<td>15</td>
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<td>5.5%</td>
<td>-2.2%</td>
<td>10</td>
</tr>
<tr>
<td>19</td>
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<td>0.0%</td>
<td>0.0%</td>
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</tr>
<tr>
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<td>TG</td>
<td>0.250</td>
<td>0.125</td>
<td>0.0%</td>
<td>-50.0%</td>
<td>8</td>
</tr>
<tr>
<td>52</td>
<td>TG</td>
<td>0.290</td>
<td>0.147</td>
<td>9.7%</td>
<td>-49.3%</td>
<td>10</td>
</tr>
<tr>
<td>53</td>
<td>TG</td>
<td>0.141</td>
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<td>-13.8%</td>
<td>1</td>
</tr>
<tr>
<td>57</td>
<td>TG</td>
<td>0.231</td>
<td>0.167</td>
<td>-7.7%</td>
<td>-27.9%</td>
<td>5</td>
</tr>
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<td>0.129</td>
<td>-1.6%</td>
<td>-54.8%</td>
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</tr>
<tr>
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<td>-9.9%</td>
<td>1.5</td>
</tr>
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<td>TG</td>
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<td>0.115</td>
<td>-13.3%</td>
<td>-50.5%</td>
<td>9</td>
</tr>
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<td>TG</td>
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</tr>
<tr>
<td>22</td>
<td>TG</td>
<td>0.194</td>
<td>0.145</td>
<td>-7.5%</td>
<td>-35.2%</td>
<td>4</td>
</tr>
<tr>
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<td>TG</td>
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<td>-50.6%</td>
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<td>0.125</td>
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<td>-50.0%</td>
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</tr>
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<td>51</td>
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<td>-1.6%</td>
<td>-32.7%</td>
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</tr>
<tr>
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<td>TG</td>
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<td>0.167</td>
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<td>-27.5%</td>
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</tr>
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<td>5</td>
</tr>
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<td>-15.0%</td>
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</tr>
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<td>TG</td>
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<td>-14.0%</td>
<td>10</td>
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<td>0.0%</td>
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</tr>
<tr>
<td>39</td>
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<td>0.0%</td>
<td>2</td>
</tr>
<tr>
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<td>-60.4%</td>
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</tr>
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<td>9</td>
<td>TG</td>
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<td>0.0%</td>
<td>0.0%</td>
<td>15</td>
</tr>
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<td>TG</td>
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<td>-4.4%</td>
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<td>0.0%</td>
<td>30</td>
</tr>
<tr>
<td>25</td>
<td>TG</td>
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<td>0.154</td>
<td>-10.3%</td>
<td>-36.3%</td>
<td>13.5</td>
</tr>
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<td>TG</td>
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<td>-50.0%</td>
<td>15</td>
</tr>
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<td>0.250</td>
<td>0.129</td>
<td>-3.1%</td>
<td>-48.4%</td>
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<td>41</td>
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<td>0.0%</td>
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<td>0.0%</td>
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<td>16</td>
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<td>0.154</td>
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<td>-36.3%</td>
<td>13.5</td>
</tr>
<tr>
<td>35</td>
<td>TG</td>
<td>0.250</td>
<td>0.129</td>
<td>-3.1%</td>
<td>-48.4%</td>
<td>15</td>
</tr>
<tr>
<td>54</td>
<td>TG</td>
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<td>0.032</td>
<td>4.6%</td>
<td>-58.1%</td>
<td>15</td>
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<td>45</td>
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<td>0.077</td>
<td>0.032</td>
<td>4.6%</td>
<td>-58.1%</td>
<td>15</td>
</tr>
<tr>
<td>12</td>
<td>MS</td>
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<td>0.0%</td>
<td>0.0%</td>
<td>15</td>
</tr>
<tr>
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<td>MS</td>
<td>0.168</td>
<td>0.140</td>
<td>1.9%</td>
<td>-26.8%</td>
<td>15</td>
</tr>
<tr>
<td>24</td>
<td>TD</td>
<td>0.400</td>
<td>0.240</td>
<td>0.0%</td>
<td>0.0%</td>
<td>15</td>
</tr>
<tr>
<td>36</td>
<td>TG</td>
<td>0.310</td>
<td>0.237</td>
<td>1.7%</td>
<td>-23.5%</td>
<td>15</td>
</tr>
<tr>
<td>37</td>
<td>TG</td>
<td>0.167</td>
<td>0.154</td>
<td>8.3%</td>
<td>-7.7%</td>
<td>25</td>
</tr>
<tr>
<td>31</td>
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<td>0.093</td>
<td>0.021</td>
<td>2.1%</td>
<td>-60.0%</td>
<td>22</td>
</tr>
<tr>
<td>43</td>
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<td>0.063</td>
<td>0.0%</td>
<td>0.0%</td>
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<tr>
<td>45</td>
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<td>0.186</td>
<td>0.0%</td>
<td>0.0%</td>
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### Table D.5: Results of Data Analysis on Characteristic #4 from Question #4

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Note: Results are Sorted according to the Steps of the Four-Step Process.
Note: Results are Sorted according to the Steps of the Four-Step Process.

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Table D.6: Results of Data Analysis on Characteristic#5 from Question#5

Note: Results are Sorted according to the Steps of the Four-Step Process.
Note: Results are Sorted according to the Steps of the Four-Step Process and Classified into two groups: (a) 1&2&3&4 and (b) 5.

Table D.7: Results of Data Analysis on Characteristic #6 from Question #6
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<td>PCQI</td>
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<td>TG 0.141</td>
<td>0.141 3.1% -13.8% TA 0.333</td>
<td>0.167 0.0% -50.0%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>51</td>
<td>40</td>
<td>TG 0.238</td>
<td>0.238 -1.6% -32.7% MS 0.256</td>
<td>0.145 -4.3% -30.3%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>35</td>
<td>4</td>
<td>MS 0.083</td>
<td>0.083 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.043</td>
<td>0.043 -0.0% 0.0%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>TG 0.127</td>
<td>0.127 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.049</td>
<td>0.049 0.0% 0.0%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>8</td>
<td>TG 0.286</td>
<td>0.286 -1.6% -54.8% MS 0.025</td>
<td>0.017 -0.8% -32.8%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>21</td>
<td>TG 0.194</td>
<td>0.194 -7.5% -35.2% MS 0.052</td>
<td>0.039 0.4% -25.3%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>23</td>
<td>TG 0.175</td>
<td>0.175 4.8% -30.6% MS 0.068</td>
<td>0.067 2.3% -2.2%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>35</td>
<td>29</td>
<td>TG 0.250</td>
<td>0.250 -3.1% -48.4% MS 0.043</td>
<td>0.022 -2.1% -48.9%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>43</td>
<td>40</td>
<td>TG 0.167</td>
<td>0.167 -6.7% -36.7% MS 0.064</td>
<td>0.043 -2.1% -31.9%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>43</td>
<td>36</td>
<td>TD 0.063</td>
<td>0.063 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.127</td>
<td>0.095 0.0% -25.0%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>36</td>
<td>29</td>
<td>TD 0.310</td>
<td>0.310 1.7% -23.5% TA 0.118</td>
<td>0.060 -15.5% -49.3%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>45</td>
<td>37</td>
<td>TG 0.186</td>
<td>0.186 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.074</td>
<td>0.029 0.0% -80.0%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>39</td>
<td>MS 0.114</td>
<td>0.114 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.111</td>
<td>0.108 3.2% -3.1%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>MS 0.042</td>
<td>0.042 2.1% -2.0% TA 0.063</td>
<td>0.030 3.1% -51.5%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>MS 0.111</td>
<td>0.111 0.0% -20.0% TA 0.186</td>
<td>0.143 0.0% -23.1%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>15</td>
<td>MS 0.048</td>
<td>0.048 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.172</td>
<td>0.105 -18.0% -39.9%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>17</td>
<td>MS 0.087</td>
<td>0.087 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.113</td>
<td>0.046 0.0% -57.1%</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>34</td>
<td>29</td>
<td>MS 0.043</td>
<td>0.043 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.118</td>
<td>0.060 -15.5% -49.3%</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>33</td>
<td>MS 0.021</td>
<td>0.021 0.0% 0.0% 0.0% 0.0% 0.0% 0.0% TA 0.139</td>
<td>0.097 0.0% -30.0%</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

Note: Results are Sorted according to the Steps of the Four-Step Process and Classified into two groups: (a) 1&2&3 (b) 4&5.

Table D.8: Results of Data Analysis on Characteristic#7 from Question#7
Note: Results are Sorted according to the Steps of the Four-Step Process and Classified into two groups: (a) exposed to subjective probability theory before the interview, and (b) not exposed to subjective probability theory before the interview.

Table D.9: Results of Data Analysis on Characteristic#8 from Question#8
APPENDIX E

Computer Programs and some Data Files
Demand Data File for the Small Network Example

13 NARC: # OF LINKS
4 NCENT: # OF CENTROIDS
9 NNOD: # OF NODES

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<tr>
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<td>0.0001</td>
<td>10000.0</td>
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<td>4</td>
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<td></td>
</tr>
<tr>
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<td>100.0000</td>
<td>1.0</td>
<td>7</td>
<td>5</td>
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</tr>
<tr>
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<tr>
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<td>10.0000</td>
<td>500.0</td>
<td>7</td>
<td>13</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>4.0000</td>
<td>4.0000</td>
<td>3000.0</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>5.0000</td>
<td>5.0000</td>
<td>3000.0</td>
<td>7</td>
<td></td>
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<td>0.0001</td>
<td>10000.0</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.0000</td>
<td>0.0001</td>
<td>10000.0</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Network Data File for the Small Network Example

4

| 5066.00 | 0.00 | 403.6027 | 0.000000 |
| 5557.00 | 0.00 | 1.0074 | 0.000000 |
| 0.00 | 5393.00 | 0.0000 | 0.65287 |
| 0.00 | 5230.00 | 0.0000 | 1.85785 |

1.000000000000 | 0.0000 |
0.000000000000 | 0.0000 |
0.000000000000 | 0.8000 |
0.000000000000 | 0.9000 |
0.000000000000 | 0.0000 |
1.000000000000 | 0.0000 |
0.000000000000 | 0.9500 |
0.000004500000 | 0.8500 |
0.000000000000 | 0.0000 |
0.000000000000 | 0.0000 |
1.000000000000 | 0.0000 |
0.000000000000 | 0.0000 |
0.000000000000 | 0.0000 |
0.000000000000 | 0.0000 |
1.000000000000 | 0.0000 |
Typical Job Control File

// JOB,
// REGION=9216K,TIME=(150,0)
*/JOBPARM LINES=90000,DISKIO=40000
// EXEC VSF2CLG,
// PARM.FORT='DC(FRS, TFRS, OD, ARCDT, ODST, ID, FST, SPT),OPT(2)'
// PARM.LKED='AMODE=31, RMODE=ANY',TIME=(150,0)
// FORT.SYIN DD DSN=TLAOSI.TSTT.FOR, DISP=SHR
// GO.FT11F001 DD DSN=TLAOSI.DEMANDB.DAT, DISP=SHR
// GO.FT13F001 DD DSN=TLAOSI.NETB.DAT, DISP=SHR
// GO.FT12F001 DD DSN=TLAOSI.NOMS.DAT, DISP=SHR
// GO.FT22F001 DD DSN=TLAOSI.NOMS101.OUT,
// DISP=(NEW, CATLG, DELETE), UNIT=USERAll, SPACE=(TRK, (100, 10), RLSE),
// DCB=(LRECL=80, BLKSIZE=15440, RECFM=FB)
// GO.FT32F001 DD DSN=TLAOSI.NOMS102.OUT,
// DISP=(NEW, CATLG, DELETE), UNIT=USERAll, SPACE=(TRK, (100, 10), RLSE),
// DCB=(LRECL=80, BLKSIZE=15440, RECFM=FB)
// GO.FT33F001 DD DSN=TLAOSI.NOMS103.OUT,
// DISP=(NEW, CATLG, DELETE), UNIT=USERAll, SPACE=(TRK, (100, 10), RLSE),
// DCB=(LRECL=80, BLKSIZE=15440, RECFM=FB)

Typical Input- Data File

10
0.186000
0.186000
0.235000
0.0772000
10
0.055000
0.090000 0.750000
1
0.0000 0.0000 0.0000 0.0000 0.0000 SIGMA/MU TIME, FUEL, CO, HC, NOX
Program for evaluation change in coefficient of variation (COV) in total system travel time (TSTT)

C PROGRAM FOR EVALUATING CHANGE IN COEFFICIENT OF VARIATION (COV) IN TOTAL SYSTEM TRAVEL TIME (TSTT)

->MAX. #RUNS IN EACH STEP OF THE FOUR-STEP PROCESS IS 30<-

->MAX. #LINKS=399 AND MAX. #ZONES=42<-

COMMON /FRS/ FRS
COMMON /TFRS/ TFRS,MS,MSPLIT
COMMON /OD/ O,D,SDFIJ
COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
COMMON /ODDT/ TOD,AMT
COMMON /FST/ FS,ODLK
COMMON /ALBET/ ALP,BET,ALPl,TYP
COMMON /ID/ IDNODE
COMMON /DMPDT/ NDMP,DMP,NREA,NREB,NREC,NRATT,SETI,SEFU,SECO,
SEHC,SEN0X,AA,AB
REAL L (399),C(399),V (399),FL(399),COST (399),NFL (399)
REAL ALP (18),BET(18),ALPl(18),V C R (399)
REAL TTIME (399),NEWT(399),TLTT (399),TTIM (399)
INTEGER TOO(399),FS (399),TYP(399),VC1 (399), VC2 (399)
INTEGER IDNODE(1000) , ODLK(2000), D M P (101),TOD (1764),CRUNS
REAL ETA (3),ETG (3),EOD (3),EAS (3),P(42),A(42)
REAL FRS(1764,30),TFRS(1764,30),MS,MSPLIT
REAL AMT (1764),TTT (810000),MTSTT
DOUBLE PRECISION FIJ(1764),MSIJ (1764), AK(42),BK(42)
REAL O(42,30),D(42,30),SUO (42),SUD(42)
REAL SDFIJ(42,30)
REAL MO(42),MD(42),SDO(42),SDD(42)
REAL MOD(1764),SUOD (1764),SDOD(1764),CVO (1764),CVD(1764)
REAL FLOW(399,900),SFLOW(900),MFLOW (900),SDFLOW(900)
REAL SSFL,CVFLOW (900)
REAL SSTA(1000),SSSTA (1000)
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,*) SDDI
READ(12,*) SDMS
READ(12,*) NDMP
READ(12,*) NRTA
READ(12,*) SDAS
READ(12,*) AA,AB
READ(12,*) NRATT
READ(12,*) SETI,SEFU,SECO,SEHC,SEN0X
WRITE(33,*) NREPE,NRTA,NRATT
WRITE(33,*) SDPR,SDAT,SDDI,SDMS,SDAS

***READ PRODUCTIONS, ATTRACTIONS, PARAMETERS GRAVITY MODEL***
READ(11,*) NCENT
DO 3108 I = 1, NCENT

215
READ(11,3119) P(I),A(I),AK(I),BK(I)
CONTINUE
DO 3109 I=1, NCENT*NCENT
READ(11,3121) FIJ(I),MSIJ(I)
WRITE(33,3121) FIJ(I),MSIJ(I)
CONTINUE
FORMAT(2F10.2,F13.10,F10.7)
FORMAT(F14.12,F8.4)
***READ NETWORK DATA***
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 CONTINUE
format(11i6)
810 continue
ALP(7) = 0.15
BET(7) = 4.
ALP(I) = 0.15
DO 20 I=1,51
DMP(I) = I - 1
20 CONTINUE
DO 3110 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)
100 CONTINUE
continue
DO 8125 I= 1, TRUNS
TTT(I) = 0
8125 CONTINUE
do 8125 I=1, TRUNS
TTF(I) = 0
SAMPLING FOR ERROR IN PRODUCTIONS/ATTR ACTIONS

CALL RNSET(10000)
DO 3159 NREA=1,NREPE
   TO=0
   TD=0
   DO 3140 J=1,NCENT
      EP=1+SDPR*RNNOF()
      IF(EP.LE.0) EP=0.00001
      EA=1+SDAT*RNNOF()
      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)
   WRITE(22,*) NREA,J,EP,EA
3140 CONTINUE

BALANCING ORIGINS AND DESTINATIONS

TT=(TO+TD)/2
PO=TO/TT
PD=TD/TT
DO 3150 J=1,NCENT
   O(J,NREA)=O(J,NREA)/PO
   D(J,NREA)=D(J,NREA)/PD
   WRITE(22,*) NREA,J, O(J,NREA), D(J,NREA)
3150 CONTINUE
3159 CONTINUE

CALCULATE SUMMARY STATISTICS IN TRIP GENERATION STEP

SSO=0
SSD=0
COUNTO=0
COUNTD=0
DO 3160 J=1,NCENT
   SUO(J)=0
   SUD(J)=0
   DO 3161 NREA=1,NREPE
      SUO(J)=SUO(J)+O(J,NREA)
      SUD(J)=SUD(J)+D(J,NREA)
3161 CONTINUE
   MO(J)=SUO(J)/NREPE
   MD(J)=SUD(J)/NREPE
   IF(MO(J).NE.0) GOTO 1001
   SDO(J)=0
   CVO(J)=0
   COUNTO=COUNTO+1
1001 SSO=SSO+CVO(J)
   IF(MD(J).NE.0) GOTO 1004
   SDD(J)=0
   CVD(J)=0
1002 SDO(J)=(SUO(J)/(NREPE-1))**0.5
   CVO(J)=SDO(J)/MO(J)
   SSO=SSO+CVO(J)
1003 SDD(J)=0
   CVD(J)=0
1004
COUNTD=COUNTD+1
GOTO 1005
1004
SUD(J)=0
DO 1009 NREA=1,NREPE
   SUD(J)=(MD(J)-D(J,NREA))*(MD(J)-D(J,NREA))+SUD(J)
1009 CONTINUE

SDD(J)=(SUD(J)/(NREPE-1))**0.5
CVD(J)=SDD(J)/MD(J)
SSD=SSD+CVD(J)
1005 CONTINUE
WRITE(22,3169) J,MO(J),SDO(J),MD(J),SDD(J),CVO(J),CVD(J)
3160 CONTINUE
3169 FORMAT(16,4F10.2,2F10.4)
SSO=SSO/(NCENT-COUNTO)
SSD=SSD/(NCENT-COUNTD)
ASS=(SSO+SSD)/2
WRITE(22,*)
SST=SSSSTA=0
DO 3333 NREA=1,NREPE
   SSSSTA(NREA)=0
3333 CONTINUE
NSEED=20000
VCRAT=0
VCRTTTT=0
DO 3300 NREA=1,NREPE
   CALL RNSET(NSEED)
3300 CONTINUE
TO=0
TD=0
WRITE(22,*),'FLOWS FROM GRAVITY MODEL WITHOUT BALANCE'
DO 3158 JJ=1,NCENT
   DO 3157 KK=1,NCENT
      SDFIJ(JJ,NREA)=D(KK,NREA)*FIJ(KK+NCENT*(JJ-1))
   CONTINUE
3157 CONTINUE
3158 CONTINUE
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))
      FRS(K+NCENT*(J-1),NREA)=O(J,NREA)*D(K,NREA) *FIJ(K+NCENT*(J-1))/SDFIJ(JJ,NREA)
      IF(FRS(K+NCENT*(J-1),NREA).NE.0) WRITE(22,*),J,K,FRS(K+NCENT*(J-1),NREA)
5170 CONTINUE
WRITE(22,*)
C BALANCING OF THE O-D MATRIX
---
CV=0.051
IT=1
3175 IF(IT.EQ.21) GOTO 3185
IF(CV.LT.0.0001) GOTO 3185
CV=0.001
---
218
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)
3167 CONTINUE
PT=TO/O(J,NREA)
IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
DO 3171 K=1,NCENT
FRS(K+NCENT*(J-1),NREA)=FRS(K+NCENT*(J-1),NREA)/PT
3171 CONTINUE
3168 CONTINUE
DO 3174 K=1,NCENT
TD=0
IF(D(K,NREA).LT.0.01) GOTO 3174
DO 3172 J=1,NCENT
TD=TD+FRS(K+NCENT*(J-1),NREA)
3172 CONTINUE
PT=TD/D(K,NREA)
IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
DO 3173 J=1,NCENT
FRS(K+NCENT*(J-1),NREA)=FRS(K+NCENT*(J-1),NREA)/PT
3173 CONTINUE
3174 CONTINUE
IT=IT+1
GOTO 3175
3185 CONTINUE
C
WRITE(22,*) 'FLOWS FROM GRAVITY MODEL WITH BALANCE'
DO 3301 J=1,NCENT
DO 3301 K=1,NCENT
IF(FRS(K+NCENT*(J-1),NREA).NE.0) WRITE(22,*) J,K,
3301 CONTINUE
C
C
SAMPLING OF ERROR IN TRIP DISTRIBUTION MODEL

WRITE(22,*) 'FLOWS AFTER ERROR IN DISTRIBUTION W/O BALANCE'
DO 3191 J=1,NCENT
DO 3191 K=1,NCENT
EF=RENNDF()**SDDI+1
IF (EF.LE.0) EF=0.00001
TFRS(K+NCENT*(J-1),NREB)=FRS(K+NCENT*(J-1),NREA)*EF
IF(TFRS(K+NCENT*(J-1),NREB).NE.0)
WRITE(22,*) NREB,J,K,EF,TFRS(K+NCENT*(J-1),NREB)
3191 CONTINUE
3192 CONTINUE
C
ADJUSTMENT FOR CONSERVATION OF ORIGINS AND DESTINATIONS
C
CV=0.051
IT=1
3193 IF(IT.GT.21) GOTO 3205
IF(CV.LT.0.0001) GOTO 3205
CV=0.001
DO 3198 J=1,NCENT
TO=0
IF(O(J,NREA).LT.0.01) GOTO 3198
DO 3197 K=1,NCENT
  TO=TO+TFRS(K+NCENT*(J-1),NREB)
CONTINUE
3197
PT=TO/O(J,NREA)
IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
DO 3200 K=1,NCENT
  TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT
CONTINUE
3200
DO 3201 K=1,NCENT
  TD=0
  IF(D(K,NREA).LT.0.01) GOTO 3201
  DO 3202 J=1,NCENT
    TD=TD+TFRS(K+NCENT*(J-1),NREB)
  CONTINUE
  PT=TD/D(K,NREA)
  IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
  DO 3203 J=1,NCENT
    TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT
  CONTINUE
3201
IT=IT+1
GOTO 3193
3205
C  WRITE(22,*)
C  WRITE(22,*) 'FLOWS AFTER ERROR IN DISTRIBUTION WITH BALANCE'
DO 3206 J=1,NCENT
  DO 3206 K=1,NCENT
    SSOD(K+NCENT*(J-1))=0
    SDOD(K+NCENT*(J-1))=0
  CONTINUE
DO 3230 NREB=1,NREPE
  DO 3230 J=1,NCENT
    DO 3230 K=1,NCENT
      SUOD(K+NCENT*(J-1))=SUOD(K+NCENT*(J-1))+TFRS(K+NCENT*(J-1),NREB)
    CONTINUE
    C  WRITE(22,*)
    C  WRITE(22,*) 'AVERAGE FLOWS'
    DO 3240 J=1,NCENT
      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
        WRITE(22,*) J,K,MOD(K+NCENT*(J-1))
        IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB,J,K,
          TFRS(K+NCENT*(J-1),NREB)
    CONTINUE
3240
C  WRITE(22,*)
C  WRITE(22,*) 'CALCULATION OF SUMMARY STATISTICS IN TRIP DISTRIBUTION STEP
-----------------------------------------------------------------------------------------------------------------
CALL RNGET(NSEED)
SSOD=0
CNTOD=0
DO 3211 J=1,NCENT
  DO 3211 K=1,NCENT
    SUOD(K+NCENT*(J-1))=0
    SDOD(K+NCENT*(J-1))=0
  CONTINUE
DO 3230 NREB=1,NREPE
  DO 3230 J=1,NCENT
    DO 3230 K=1,NCENT
      SUOD(K+NCENT*(J-1))=SUOD(K+NCENT*(J-1))+TFRS(K+NCENT*(J-1),NREB)
    CONTINUE
    DO 3239 NREB=1,NREPE
      DO 3239 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
        WRITE(22,*) J,K,MOD(K+NCENT*(J-1))
        IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB,J,K,
          TFRS(K+NCENT*(J-1),NREB)
      CONTINUE
3239
C  WRITE(22,*)
C  WRITE(22,*) 'AVERAGE FLOWS'
DO 3240 J=1,NCENT
  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
    WRITE(22,*) J,K,MOD(K+NCENT*(J-1))
    IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB,J,K,
      TFRS(K+NCENT*(J-1),NREB)
  CONTINUE
3240
C  WRITE(22,*)
C  WRITE(22,*) 'AVERAGE FLOWS'
DO 3240 J=1,NCENT
  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
    WRITE(22,*) J,K,MOD(K+NCENT*(J-1))
    IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB,J,K,
      TFRS(K+NCENT*(J-1),NREB)
  CONTINUE
3240
C  WRITE(22,*)
C  WRITE(22,*) 'AVERAGE FLOWS'
DO 3240 J=1,NCENT
  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
    WRITE(22,*) J,K,MOD(K+NCENT*(J-1))
    IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB,J,K,
      TFRS(K+NCENT*(J-1),NREB)
  CONTINUE
3240
C  WRITE(22,*)
C  WRITE(22,*) 'AVERAGE FLOWS'
DO 3240 J=1,NCENT
  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
    WRITE(22,*) J,K,MOD(K+NCENT*(J-1))
    IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB,J,K,
      TFRS(K+NCENT*(J-1),NREB)
CONTINUE
CONTINUE
WRITE(22, *) 'STANDARD DEVIATION AND SIGMA/MU'
DO 3250 J=1,NCENT
   DO 3250 K=1,NCENT
      WRITE(22, *)
      WRITE(22, *) 'AUTO TRIPS (TRIPS IN MODAL SPLIT STEP) ARE'
      ******************************************************************************
      START MODAL SPLIT MODEL (LOOPED IN TRIP DISTRIBUTION) <<<<
      ******************************************************************************
      DO 3329 NREB=1,NREPE
         DO 3328 NREC=1,NREPE
            DO 3270 J=1,NCENT
               DO 3270 K=1,NCENT
                  MSPLIT = TFRS(K+NCENT*(J-1), NREB)* MSIJ(K+NCENT*(J-1))
                  EMS=RNNOF()*SDMS+1
                  IF (EMS.LE.O) EMS=0.00001
                  MS= MSPLIT*EMS
                  IF(MS.NE.O)
                     WRITE (22, 3266) NREA, NREB, NREC, J, K, MSPLIT, EMS, MS
                  3266 FORMAT(5I6,F15.5,F15.8,F15.5)
               3270 CONTINUE
            C  SAMPLING OF ERROR IN MODAL SPLIT MODEL
      3270 CONTINUE
      >>>>START MODAL SPLIT MODEL (LOOPED IN TRIP DISTRIBUTION) <<<<
      C  PREPARE DATA FOR TRAFFIC ASSIGNMENT STEP
      C  INITIALIZE & SAMPLING OF ERROR IN "FREE FLOW TRAVEL TIME"
      SSOD=0
      VCRTTT=0
      DO 3271 N=1,NARC
         SFLOW(N)=0
      3271 CONTINUE
      COFL=0
      SSFL=0
      VCRATT=0
      C  SAMPLING OF ERROR IN TRAFFIC ASSIGNMENT MODEL
      C  >>>>START TRAFFIC ASSIGNMENT MODEL <<<<
      C (LOOPED IN TRIP DISTRIBUTION AND MODAL SPLIT)
      C  PREPARE DATA FOR TRAFFIC ASSIGNMENT STEP
      C  INITIALIZE & SAMPLING OF ERROR IN "FREE FLOW TRAVEL TIME"
      SSOO=0
      VCRATT=0
      DO 3271 N=1,NARC
         SFLOW(N)=0
      3271 CONTINUE
      EPS=1.E-3
      CALL UE(EPS, NARC, NNOD, NCENT, ITER, NFL, TSTT)
      CALL RNSET(I*NARC*NREA*NREB*NREC*10)
      CALL RNSET(NARC*NREA*NREB*NREC*10)
      DO 3285 N=1,NARC
         ET=RNNOF()*SDAS+1
         IF(ET.LE.O) ET=0.00001
         TTIME(N)=TIM(N)*ET
         WRITE(32, 3283) NREA, NREB, NREC, I, N, ET, TTIME(N)
      3283 FORMAT(18,3I6,12,F15.8,F15.8)
      3285 CONTINUE
      3281 CONTINUE
      3280 I=1,NRTA
      CALL RNSET(I*NARC*NREA*NREB*NREC*10)
      DO 3285 N=1,NARC
         ET=RNNOF()*SDAS+1
         IF(ET.LE.O) ET=0.00001
         TTIME(N)=TIM(N)*ET
         WRITE(32, 3283) NREA, NREB, NREC, I, N, ET, TTIME(N)
      3283 FORMAT(18,3I6,12,F15.8,F15.8)
      3285 CONTINUE
      EPS=1.E-3
      CALL UE(EPS, NARC, NNOD, NCENT, ITER, NFL, TSTT)
      221
***PREPARE DATA FOR CALCULATING MEAN & SD & COV OF TSTT***

CRUNS = CRUNS + 1
TSTT(CRUNS) = TSTT
STSTT = STSTT + TSTT

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
3275 CONTINUE
VCRATT=VCRAT/NARC+VCRATT
VCRAT=0

3280 CONTINUE
VCRATT=VCRATT/NRTA+VCRATT
VCRATT=0

CALCULATE STATISTICS IN TRAFFIC ASSIGNMENT STEP

DO 3289 N=1,NARC
MFLOW(N)=SFLOW(N)/NRTA
WRITE(32,*) 'AVERAGE FLOW FOR LINK #', N, MFLOW(N)
SFLOW(N)=0
3289 CONTINUE

DO 3290 N=1,NARC
DO 3290 I=1,NRTA
SFLOW(N)=SFLOW(N)+(FLOW(N,I)-MFLOW(N))**2
3290 CONTINUE
SSTA(NREB)=0
DO 3291 N=1,NARC
CVFLOW(N)=0

IF(C(N).EQ.1) GOTO 3291
IF(C(N).GT.9999) GOTO 3291
IF(MFLOW(N).EQ.0) GOTO 3291

SDFLOW(N)=(SFLOW(N)/(NRTA-1))*0.5
CVFLOW(N)=SDFLOW(N)/MFLOW(N)
SSTA(NREB)=CVFLOW(N)+SSTA(NREB)
SFLOW(N)=0
COFL=COFL+1
3291 CONTINUE
IF(COFL.EQ.0) GOTO 3293
SSTA(NREB)=SSTA(NREB)/COFL
SSSTA(NREA)=SSSTA(NREA)+SSTA(NREB)
SDTA=0
DO 3292 N=1,NARC

**TAKE OUT DUMMY LINKS AND LINKS WITH ZERO FLOW**

IF(C(N).EQ.1) GOTO 3292
IF(C(N).GT.9999) GOTO 3292
IF(MFLOW(N).EQ.0) GOTO 3292

SDTA=SDTA+(CVFLOW(N)-SSTA(NREB))**2
3292 CONTINUE
SDTA=(SDTA/(COFL-1))**0.5

WRITE(32,*) NREA, NREB, SSTA(NREB), SDTA
CONTINUE
COFL=0
CONTINUE
VCRTTTT=VCRTTTT+VCRTTT/NREPE
VCRTTT=0
WRITE(32,*) SSSTA(NREA)=SSSTA(NREA)/NREPE
SDTA=0
DO 3310 NREB=1,NREPE
SDTA=SDTA+(SSSTA(NREA)-SSTA(NREB))**2
CONTINUE
SDTA=(SDTA/(NREPE-1))**.5
WRITE(32,*)'AVERAGE AND SIGMA/MU ARE',SSSTA(NREA),SDTA
WRITE(32,* ) SSSTA=SSSSTA+SSSTA(NREA)
CONTINUE

-------------------------------------------------------------------
*** CALCULATE MEAN OF TOTAL SYSTEM TRAVEL TIME (TSTT)***
MTSTT = STSTT/CRUNS
WRITE(33,*)'TOTAL NUMBER OF SIMULATION RUNS =',CRUNS
WRITE(33,*)'AVERAGE TSTT =',MTSTT
-------------------------------------------------------------------
***CALCULATE STANDARD DEVIATION OF TSTT***
STSTT = 0
DO 3350 1 = 1,CRUNS
STSTT = STSTT + (TTT(I ) -MTSTT)**2
CONTINUE
SDTSTT = (STSTT/(CRUNS-1))* * 0.5
WRITE(33,*)'STANDARD DEVIATION OF TSTT =',SDTSTT
-------------------------------------------------------------------
***CALCULATE COEFFICIENT OF VARIATION (COV)***
COV = SDTSTT/MTSTT
WRITE(33,*)'COV OF TSTT =', COV
-------------------------------------------------------------------
***CALCULATE OTHER STATISTICS***
VCRTTTT=VCRTTTT/NREPE
SSSOD=SSSOD/NREPE
WRITE(22,*)
WRITE(22,3400) SSSOD
3400 FORMAT('SUMMARY STATISTIC O-D FOR ALL REPETITIONS, SSSOD= ',F10.4)
SSSSTA=SSSSTA/NREPE
SDTA=0
DO 3405 NREA=1,NREPE
SDTA=SDTA+(SSSSTA-SSSTA(NREA) )**2
CONTINUE
SDTA=(SDTA/(NREPE-1))* * .5
WRITE(33,3410) SSSSTA,SDTA
3410 FORMAT('SUMMARY STATISTIC TRAFFIC ASSIGNMENT ',F10.4,F10.4)
WRITE(32,3411) VCRTTTT
3411 FORMAT('AVERAGE VOLUME CAPACITY V/C RATIO',F10.7)
STOP
END
-------------------------------------------------------------------
** END OF THE MAIN PROGRAM **
-------------------------------------------------------------------
SUBROUTINE UE(EPS, NARC, NNOD, NCENT, ITER, NFL, TSTT)
COMMON /ARCDT/ TOO, L, C, V, FL, COST, TTIME, NEWT, TLTT
COMMON /ODDT/ TOD, AMT
COMMON /DMPDT/ NDMP, DMP, NREA, NREB, AA, AB
COMMON /FST/ FS, ODLK
COMMON /ALBET/ ALP, BET, ALP1, TYP
REAL L(399), C(399), V(399), FL(399), COST(399)
REAL NFL(399)
REAL ALP(18), BET(18), ALP1(18), XN
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), TOD(1764), FS(399), ODLK(2000)
INTEGER TYP(399), DMP(101)
REAL AMT(1764)
CALL AON(FL, NARC, NNOD, NCENT, ITER)
K=1
ITER=0
FOBJ=0.
DO 70 I=1, NARC
A1=ALP1(TYP(I))
B1=BET(TYP(I))
FOBJ=FOBJ+FINT(TTIME(I), C(I), FL(I), A1, B1)
70 CONTINUE
CONTINUE
CONV=2.*EPS
10 IF(CONV.GT.EPS) GO TO 30
15 CALL DUMP(ITER, NNOD, NCENT, NARC, NFL, TSTT)
RETURN
30 CONTINUE
IF(ITER.NE.NDMP) GO TO 40
GO TO 15
40 ITER=ITER+1
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+FINT(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(399), C(399), V(399), FL(399), COST(399)
REAL NFL(399), SP(8000)
REAL ALP(18), BET(18), ALP1(18)
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), TOD(1764), FS(399), ODLK(2000)
224
INTEGER TYP(399), PRED(1000), INTERNO
REAL AMT(1764)  
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(I .EQ. 1.) THEN
ENDIF
60 J1=PRED(J)
IF(J1.EQ.0) GO TO 30
N1=FS(J1)
N2=FS(J1+1)-1
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)
COMMON /ARCDT/ TOO, L, C, V, FL, COST, TTIME, NEWT, TLTT
COMMON /FST/ FS, ODLK
COMMON /ALBET/ ALP, BET, ALP1, TYP
REAL L(399), C(399), V(399), FL(399), COST(399), NFL(399)
REAL ALP(18), BET(18), ALP1(18)
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), FS(399), TYP(399), ODLK(2000)
AMN=0.
AMX=1.
10 AMD=(AMX+AMN)/2.
IF((AMX-AMN).LE.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)
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
NFL(N)=FL(N)+AMD*(NFL(N)-FL(N))
RETURN
END
FUNCTION COSTFN(TIME, C, FL, A, B)

C
SUBROUTINE BISECT(NFL, NARC)
COMMON /ARCDT/ TOO, L, C, V, FL, COST, TTIME, NEWT, TLTT
COMMON /FST/ FS, ODLK
COMMON /ALBET/ ALP, BET, ALP1, TYP
REAL L(399), C(399), V(399), FL(399), COST(399), NFL(399)
REAL ALP(18), BET(18), ALP1(18)
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), FS(399), TYP(399), ODLK(2000)
AMN=0.
AMX=1.
10 AMD=(AMX+AMN)/2.
IF((AMX-AMN).LE.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)
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
NFL(N)=FL(N)+AMD*(NFL(N)-FL(N))
RETURN
END
FUNCTION COSTFN(TIME, C, FL, A, B)

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

FUNCTION FINT(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)
C THIS SUBROUTINE COMPUTES SHORTEST PATHS
C FROM R TO ALL OTHER NODES. PRED(I) CONTAINS PREDECESSOR OF NODE
C 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(399),C(399),V(399),FL(399),COST(399),SP(8000)
REAL TTIME(399),NEWT(399),TLTT(399)
INTEGER TOO(399),FS(399),PRED(SOOO),CL(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
60 CL(NT)=K
NT=K
CL(K)=NNOD+1
GO TO 40
50 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
C

---

226
SUBROUTINE DUMP(ITER, NNOD, NCENT, NARC, NFL, TSTT)
COMMON /ARCDT/ TOO, L, C, V, FL, COST, TTIME, NEWT, TLTT
COMMON /FS/ FS, ODLK
COMMON /ALP/ ALP, BET, ALP1, TYP
COMMON /ID/ IDNODE
COMMON /DMPDT/ NDMP, DMP, NREA, NREB, AA, AB, NRATT, SETI, SEFU, SECO, 
* SEHC, SENOX
REAL L(399), C(399), V(399), FL(399), COST(399), NFL(399)
REAL ALP(18), BET(18), ALP1(18), VCR(399)
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), BET(18), ALP1(18), VCR(399)
INTEGER IDNODE(1000), ODLK(2000), DMP(101)
REAL RD(1000, 5), FUEL, HC, CO, NOX
C  WRITE(32, 101) ITER
C  WRITE(*, 101) ITER
101 FORMAT(IX, 'NO. OF ITERATIONS = ', I6)
VCRATT = 0
K = 0
STX = 0
SLX = 0
IX = 0
DO 10 I = 1, NNOD
J1 = FS(I)
J2 = FS(I + 1) - 1
IF(J1.GT.J2) GO TO 10
DO 20 J = J1, J2
K = K + 1
NFL(K) = FL(J)
IF(C(J).NE.0) VCR(K) = FL(J)/C(J)
IF(C(J).EQ.0) VCR(K) = 0
VC1(K) = IDNODE(I)
VC2(K) = IDNODE(TOO(J))
IF(FL(J).EQ.0.) GO TO 20
IF(VC1(K).LE.NCENT) GO TO 20
IF(VC2(K).LE.NCENT) GO TO 20
IX = IX + 1
A1 = ALP(TYP(J))
B1 = BET(TYP(J))
C
CST = COSTFN(TTIME(J), C(J), FL(J), A1, B1)
NEWT(J) = CST
STX = STX + CST*FL(J)
SLX = SLX + L(J)*FL(J)
20 CONTINUE
10 CONTINUE
TSTT = 0
CALL RNSET(NRC*NREA*NREB*1000)
DO 201 I = 1, NARC
TSTT = TSTT + NEWT(I)*NFL(I)
201 CONTINUE
104 FORMAT(3I6, F15.2)
DO 23 I = 1, NARC
C  WRITE(32, 103) NREA, NREB, I, NFL(I), NEWT(I), TLTT(I), VCR(I)
102 FORMAT(16, F13.2, F9.5, F10.2, 2I7)
103 FORMAT(3I6, F13.2, F9.5, F14.3, F10.7)
23 CONTINUE
RETURN
END
Program for calibrating standard deviation of the error term in the Trip Generation step ($\eta_{Tg}$)

C
C CALIBRATION FOR TRIP GENERATION MODEL
C
COMMON /OD/ O,D
COMMON/ODDT/ OSORT,DSORT
REAL P(50),A(50)
REAL O(50,10000),D(50,10000)
REAL OSORT(50,10000),DSORT(50,10000)
REAL M0(50),MD(50),S0(50),SDD(50)
REAL M025(50),MD25(50)
REAL CVO(50),CV(50)
EXTERNAL RNSET,RNNOF

C ***READ SCENARIO: NUMBER OF REPETITIONS, PROBABILITIES***
C
READ(12,*) NREPE
WRITE(22,*) NREPE
READ(12,*) SDPR
READ(12,*) SDAT

C ***READ PRODUCTIONS, ATTRACTIONS***
C
READ(11,*) NCENT
DO 3108 I=1,NCENT
   READ(11,3119) P(I),A(I)
3108 CONTINUE
3119 FORMAT(2F10.2)

C ***********************************************************
C ****** END OF READING INPUT DATA  ******
C ***********************************************************
C >>>START TRIP GENERATION/ATTRACTION MODELS<<<
C
KK=0
KKK=0

C SAMPLING FOR ERROR IN PRODUCTIONS/ATTRACTIONS
C
CALL RNSET(10000)
DO 3159 NREA=1,NREPE
   TO=0
   TD=0
   DO 3140 J=1,NCENT
      EP=1+SDPR*RNNO(())
      IF(EP.LE.0) EP=0.00001
      EA=1+SDAT*RNNO(())
      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)
      WRITE(22,*) NREA,J,EP,EA
3140 CONTINUE

C 3159 CONTINUE
C
C BALANCING ORIGINS AND DESTINATIONS
C
C
\[ TT = \frac{(TO + TD)}{2} \]

\[ PO = \frac{TO}{TT} \]

\[ PD = \frac{TD}{TT} \]

\[ DO \quad 3150 \quad J = 1, NCENT \]

\[ O(J, NREA) = O(J, NREA) / PO \]

\[ D(J, NREA) = D(J, NREA) / PD \]

WRITE(22, *) NREA, J, O(J, NREA), D(J, NREA)

3150 CONTINUE

WRITE(22, *)

3159 CONTINUE

---------------------------------------------------------------------------------------------------

\textbf{CALCULATE SUMMARY STATISTICS IN TRIP GENERATION STEP}
---------------------------------------------------------------------------------------------------

\[ SSO = 0 \]

\[ SSD = 0 \]

\[ COUNTO = 0 \]

\[ COUNTD = 0 \]

\[ IX25 = NREPE / 4 \]

\[ IX50 = NREPE / 2 \]

\[ IX75 = 3 \times NREPE / 4 \]

***BEGINNING OF SORTING O AND D***

DO 3160 J = 1, NCENT

\[ ID = 0 \]

DO 3161 I = 1, NREPE

\[ ID = ID + 1 \]

\[ OSORT(J, ID) = 0.00 \]

\[ DSORT(J, ID) = 0.00 \]

\[ OMIN = 1000000 \]

\[ DMIN = 1000000 \]

DO 3163 K = 1, NREPE

IF (O(J, K) .LT. OMIN) THEN

\[ OMIN = O(J, K) \]

\[ KK = K \]

ENDIF

IF (D(J, K) .LT. DMIN) THEN

\[ DMIN = D(J, K) \]

\[ KKK = K \]

ENDIF

3163 CONTINUE

\[ OSORT(J, ID) = OMIN \]

\[ O(J, KK) = 1000000 \]

\[ DSORT(J, ID) = DMIN \]

\[ D(J, KKK) = 1000000 \]

3161 CONTINUE

*****END OF SORTING O AND D*****

\[ \text{CALCULATE 25\%-FRACTILES, MEDIANS AND 75\%-FRACTILES OF O AND D} \]

\text{NOTE THAT THE FORMULA REQUIRE NUMBER OF SIMULATIONS IS AN EVEN NUMBER)}

\[ MO(J) = \frac{(OSORT(J, IX50) + OSORT(J, (IX50 + 1)))}{2} \]

\[ MO25(J) = \frac{(OSORT(J, IX25) + OSORT(J, (IX25 + 1)))}{2} \]

\[ MD(J) = \frac{(DSORT(J, IX50) + DSORT(J, (IX50 + 1)))}{2} \]

\[ MD25(J) = \frac{(DSORT(J, IX25) + DSORT(J, (IX25 + 1)))}{2} \]

\text{CALCULATE VARIATION INDEX OF O AND D AND THEIR AVERAGE VALUES}
IF(MO(J).NE.0) GOTO 1001
  SDO(J)=0
  CVO(J)=0
  COUNTO=COUNTO+1
GOTO 1003

1001  SDO(J)=MO(J)-MO25(J)
  CVO(J)=SDO(J)/MO(J)
  SSO=SSO+CVO(J)

1003  IF(MD(J).NE.0) GOTO 1004
  SDD(J)=0
  CVD(J)=0
  COUNTD=COUNTD+1
GOTO 1005

1004  SDD(J)=MD(J)-MD25(J)
  CVD(J)=SDD(J)/MD(J)
  SSD=SSD+CVD(J)

1005 CONTINUE
C WRITE(22,3169) J,MO(J),SDO(J),MD(J),SDD(J),CVO(J),CVD(J)
3160 CONTINUE

3169 FORMAT(I6,4F10.2,2F10.4)
  SSO=SSO/(NCENT-COUNTO)
  SSD=SSD/(NCENT-COUNTD)
  ASS=(SSO+SSD)/2
C WRITE(22,"*")
WRITE(22,3164) SSO,SSD,ASS
3164 FORMAT('SIGMA/MU: SSO=',F10.4,' SSD=',F10.4,' AVERAGE=',F10.4)
C WRITE(22,"*")
STOP
END
C *************************************************
C ********** END OF THE PROGRAM *****************
C *************************************************
program for calibrating standard deviation of the error term in the trip distribution step (\( \eta_{TD} \))

C

CALIBRATION FOR TRIP DISTRIBUTION MODEL

C COMMON /FRS/ FRS
COMMON /TFRS/ TFRS,ODSORT
COMMON /OD/ O,D,SDFIJ
COMMON /DMPDT/ NREA,NREB

C REAL P(4),A(4)
REAL FRS(16,100000),TFRS(16,100000)
REAL ODSORT(16,100000)
DOUBLE PRECISION FIJ(16),AK(4),BK(4)
REAL O(4,100000),D(4,100000)
REAL SDFIJ(4,100000)
REAL MOD25(16)
REAL MOD(16),SUOD(16),SDOD(16)
EXTERNAL RNSET,RNNOF

C

***READ SCENARIO: NUMBER OF REPETITIONS, PROBABILITIES***

READ(12,*) NREPE
WRITE (22,*) 'NUMBER OF RUNS EQUAL TG=100 * TD=',NREPE
READ(12,*) SDPR
READ(12,*) 5DAT
READ(12,*) SDDI

C

***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
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,F8.4)

C

END OF READING INPUT DATA

C

>>>START TRIP GENERATION/ATTRACTION MODELS<<<

C

C

SAMPLING FOR ERROR IN PRODUCTIONS/ATTRACTIONS

C

CVOD=0
CALL RNSET(10000)
DO 3159 NREA=1,100
TO=0
TD=0
DO 3140 J=1,NCENT
EP=1+SDPR*RNNOF()
IF(EP.LE.0) EP=0.00001
EA=1+SDAT*RNNOF()
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)
WRITE(22,* ) NREA,J,EP,EA
CONTINUE
C
BALANCING ORIGINS AND DESTINATIONS
------------------------------------------------------------------------------------------------------------------------
TT=(TO+TD)/2
PO=TO/TT
PD=TD/TT
DO 3150 J=1,NCENT
O(J,NREA)=O(J,NREA)/PO
D(J,NREA)=D(J,NREA)/PD
WRITE(22,* ) NREA,J,O(J,NREA),D(J,NREA)
CONTINUE
C
WRITE(22,* )
CONTINUE
C
<<<START TRIP DISTRIBUTION MODEL<<<
------------------------------------------------------------------------------------------------------------------------
NSEED=20000
IRUNS=0
KK=0
SSSD=0.0
DO 3300 NREA=1,100
CALL RNSET(NSEED)
TO=0
TD=0
C
WRITE(22,* ) 'FLOWS FROM GRAVITY MODEL WITHOUT BALANCE'
DO 3158 JJ=1,NCENT
DO 3157 KK=1,NCENT
SDFIJ(JJ,NREA)=D(KK,NREA)*FIJ(KK+NCENT*(JJ-1))
SDFIJ(JJ,NREA)
CONTINUE
C
CONTINUE
C
FRS(K+NCENT*(J-1),NREA)=AK(J)*O(J,NREA)
FRS(K+NCENT*(J-1),NREA)=D(K,NREA)*FIJ(K+NCENT*(J-1))
FRS(K+NCENT*(J-1),NREA)=O(J,NREA)*D(K,NREA)
FRS(K+NCENT*(J-1),NREA)=FIJ(K+NCENT*(J-1))/SDFIJ(JJ,NREA)
FRS(K+NCENT*(J-1),NREA)
IF(FRS(K+NCENT*(J-1),NREA).NE.0) WRITE(22,* ) J,K,FRS(K+NCENT*(J-1),NREA)
CONTINUE
C
WRITE(22,* )
C
BALANCING OF THE O-D MATRIX
------------------------------------------------------------------------------------------------------------------------
CV=0.051
IT=1
3175 IF(IT.EQ.21) GOTO 3185
IF(CV.LT.0.0001) GOTO 3185
CV=0.001
DO 3168 J=1,NCENT
TO=0
IF(O(J,NREA).LT.0.01) GOTO 3168
DO 3167 K=1,NCENT

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TO = TO + FRS(K+NCENT*(J-1), NREA)
CONTINUE
PT = TO/0(J, NREA)
IF(ABS(PT-1) .GT. CV) CV = ABS(PT-1)
DO 3171 K = 1, NCENT
    FRS(K+NCENT*(J-1), NREA) = FRS(K+NCENT*(J-1), NREA)/PT
CONTINUE
3168 CONTINUE
DO 3174 K = 1, NCENT
    TD = 0
    IF(D(K, NREA) .LT. 0.01) GOTO 3174
    DO 3172 J = 1, NCENT
        TD = TD + FRS(K+NCENT*(J-1), NREA)
    CONTINUE
    PT = TD/D(K, NREA)
    IF(ABS(PT-1) .GT. CV) CV = ABS(PT-1)
    DO 3173 J = 1, NCENT
        FRS(K+NCENT*(J-1), NREA) = FRS(K+NCENT*(J-1), NREA)/PT
    CONTINUE
3174 CONTINUE
IT = IT + 1
GOTO 3175
3185 CONTINUE
C WRITE(22, *)
C WRITE(22, *) 'FLOWS FROM GRAVITY MODEL WITH BALANCE'
DO 3301 J = 1, NCENT
    DO 3300 K = 1, NCENT
        IF(FRS(K+NCENT*(J-1), NREA) .NE. 0) WRITE(22, *) J, K, FRS(K+NCENT*(J-1), NREA)
3300 CONTINUE
3301 CONTINUE
C SAMPLING OF ERROR IN TRIP DISTRIBUTION MODEL
C-----------------------------------------------
C WRITE(22, *)
DO 3210 NREB = 1, NREPE
    WRITE(22, *) 'FLOWS AFTER ERROR IN DISTRIBUTION W/O BALANCE'
    IRUNS = IRUNS + 1
    DO 3192 J = 1, NCENT
        DO 3191 K = 1, NCENT
            EF = RNNOF() * SDDI + 1
            IF(EF .LE. 0) EF = 0.00001
            TFRS(K+NCENT*(J-1), NREB) = FRS(K+NCENT*(J-1), NREA) * EF
            IF(TFRS(K+NCENT*(J-1), NREB) .NE. 0)
                WRITE(22, *) NREB, J, K, EF, TFRS(K+NCENT*(J-1), NREB)
4391 CONTINUE
3192 CONTINUE
C ADJUSTMENT FOR CONSERVATION OF ORIGINS AND DESTINATIONS
C---------------------------------------------------------------------
CV = 0.051
IT = 1
3193 IF(IT .GT. 21) GOTO 3205
IF(CV .LT. 0.0001) GOTO 3205
CV = 0.001
DO 3198 J = 1, NCENT
    TO = 0
    IF(O(J, NREA) .LT. 0.01) GOTO 3198
    DO 3197 K = 1, NCENT
        TO = TO + TFRS(K+NCENT*(J-1), NREB)
3197 CONTINUE
PT=TO0(J,NREA)
IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
DO 3200 K=1,NCENT
  TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT
ENDO
3200 CONTINUE
3198 CONTINUE
DO 3201 K=1,NCENT
  TD=0
  IF(D(K,NREA).LT.0.01) GOTO 3201
  DO 3202 J=1,NCENT
    TD=TD+TFRS(K+NCENT*(J-1),NREB)
  ENDDO
3202 CONTINUE
PT=TD/D(K,NREA)
IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
DO 3203 J=1,NCENT
  TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT
ENDO
3203 CONTINUE
3205 CONTINUE
IT=IT+1
GOTO 3193
3205 CONTINUE
C WRITE(22,*)
C WRITE(22,*) 'FLOW S AFTER E R R O R  IN DISTRIBUTION W ITH  BALANCE'
DO 3206 J=1,NCENT
  IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB,J,K,
     TFRS(K+NCENT*(J-1),NREB)
3206 CONTINUE
C WRITE(22,*)
3210 CONTINUE
C -----------------------------------------------
C CALCULATION OF SUMMARY STATISTICS IN TRIP DISTRIBUTION STEP
C -----------------------------------------------
SSOD=0
CNTOD=0
IX25=NREPE/4
IX50=NREPE/2
C ***BEGINING O F SORTING O-D TRIPS***
C WRITE(22,*) 'AVERAGE F L O W S'
DO 3240 J=1,NCENT
  DO 3240 K=1,NCENT
    JJ= K+NCENT*(J-1)
  ENDDO
3240 CONTINUE
ID=0
DO 3217 NREB=1,NREPE
  ID=ID+1
  ODSORT(JJ,ID)=0.00
  ODMIN=100000
  DO 3215 KNREB=1,NREPE
    IF (TFRS(JJ,KNREB).LT.ODMIN) THEN
      ODMIN=TFRS(JJ,KNREB)
      KK=KNREB
    ENDIF
  ENDDO
3215 CONTINUE
  ODSORT(JJ,ID)=ODMIN
  TFRS(JJ,KK)=100000
3217 CONTINUE
****END OF SORTING O AND D****

**CALCULATE 25%-FRACTILES, MEDIANS AND 75%-FRACTILES OF O AND D**

(Note that the formula require number of simulations is an even number)

MOD(JJ) = (ODSORT(JJ, IX50) + ODSORT(JJ, (IX50 + 1)))/2
MOD25(JJ) = (ODSORT(JJ, IX25) + ODSORT(JJ, (IX25 + 1)))/2

IF (MOD(JJ).LT.0.01) GOTO 3240
WRITE(22,*) J, K, MOD(JJ)
3240 CONTINUE

**CALCULATE VARIATION INDEX OF O AND D AND THEIR AVERAGE VALUES**

WRITE(22,*') 'STANDARD DEVIATION AND SIGMA/MU'
DO 3250 J = 1, NCENT
    DO 3250 K = 1, NCENT
        JJ = K + NCENT*(J-1)
        IF (MOD(JJ).NE.0) GOTO 3248
        CNT0D = CNT0D + 1
    GOTO 3250
3248 SDOD(JJ) = MOD(JJ) - MOD25(JJ)
    CVOD = SDOD(JJ)/MOD(JJ)
WRITE(22,*) J, K, SDOD(JJ), CVOD
    SSOD = CVOD + SSOD
    SDOD(JJ) = 0
3250 CONTINUE
IF (CNT0D.NE.NCENT**2) SSOD = SSOD/(NCENT*NCENT-CNT0D)
SSSOD = SSOD + SSSOD
WRITE(22,3260) SSOD
3260 FORMAT('SUMMARY STATISTIC O-D ONE REPETITION, SSOD= ',F10.4)
3300 CONTINUE
WRITE(22,*) 'TOTAL RUNS IS', IRUNS
SSSD = SSOD/100
WRITE(22,*) SSSSD
3400 FORMAT('SUMMARY STATISTIC O-D FOR ALL REPETITIONS, SSSOD= ',F10.4)
3412 STOP

END
Program for calibrating standard deviation of the error term in the Traffic Assignment step ($\eta_{TA}$)

C CALIBRATION FOR TRAFFIC ASSIGNMENT MODEL

C COMMON /FRS/ FRS
COMMON /TFRS/ TFRS,MS,MSPLIT
COMMON /OD/ O,D,SDFIJ
COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
COMMON /ODDT/ TOD,AMT
COMMON /FST/ FS,OCLK
COMMON /ALBET/ ALP,BET,ALPL,TYP
COMMON /ID/ IDNODE
COMMON /DMPDT/ NDM,DM,P,NREB,NREC,NRATT,SETI,SEFU,SECO,SEH,SENOX,AA,AB
REAL L(399),V(399),FL(399),COST(399),NFL(399)
REAL ALP(18),BET(18),ALPL(18),VCR(399)
REAL TTIME(399),NEWT(399),TLTT(399),TTIM(399)
INTEGER TOO(399),FS(399),TYP(399),VC(399),VC2(399)
INTEGER IDNODE(1000),OCLK(2000),DM(101),TOD(1764),CRUNS
REAL ETA(3),ETG(3),EOD(3),EAS(3),P(42),A(42)
REAL FRS(1764,25),TFRS(1764,25),MS,MSPLIT
REAL AMT(1764),MSLTT
DOUBLE PRECISION FIJ(1764),MSIJ(1764),AK(42),BK(42)
REAL O(42,25),D(42,25),SUO(42),SUD(42)
REAL SDIJ(42,25)
REAL MO(42),MD(42),SDO(42),SDD(42)
REAL MOD(1764),SUOD(1764),SDDOM(1764),CVO(1764),CVD(1764)
REAL FLOW(399,625),MFLOW(625),SDFLOW(625),MTA,MMTA
REAL FSORT(399,625),MF25(625)
REAL SSSL,CVFLOW(625)
REAL SSSTA(625),SSSTA(625)
DOUBLE PRECISION VCRAT
EXTERNAL RNSET,RNUNF,RNNOF,RNGET

C ***READ SCENARIO: NUMBER OF REPETITIONS, PROBABILITIES***

C READ(12,*),NREPE
WRITE(22,*),NREPE
READ(12,*),SDPR
READ(12,*),SDAT
READ(12,*),SDDI
READ(12,*),SDMS
READ(12,*),NDMP
READ(12,*),NRAT
READ(12,*),SDAS
READ(12,*),AA,AB
READ(12,*),NRATT
READ(12,*),SETI,SEFU,SECO,SEH,SENOX
WRITE(33,*),NREPE,NRTA
WRITE(33,*),SDPRT,SDAT,SDDI,SDMS,SDAS

C ***READ PRODUCTIONS, ATTRACTIONS, PARAMETERS GRAVITY MODEL***

C READ(11,*)NCENT
DO 3108 I = 1, NCENT
   READ(11,3119) P(I),A(I),AK(I),BK(I)
3108 CONTINUE

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DO 3109 I=1, NCENT*NCENT
   READ(11,3121) FIJ(I),MSIJ(I)
C   WRITE(33,3121) FIJ(I),MSIJ(I)
3109 CONTINUE
3119 FORMAT(2F10.2,F13.10,F10.7)
3121 FORMAT(F14.12,F8.4)
C
C     ***READ NETWORK DATA***
C
READ(13,*) NARC
READ(13,*) NCENT
READ(13,*) NNOD
C     WRITE(*,*) '# OF ARCS =',NARC
C     WRITE(*,*) '# OF CENTROIDS =',NCENT
C     WRITE(*,*) '# OF NODES =',NNOD
DO 810 I = 1, NNOD/11+1
   READ(13,811) (IDNODE( (I-1)*11+IJ) , IJ = 1 , 11)
C  »>INITIALIZE VARIABLES USED IN CALCULATING MEAN & SD & COV OF TSTT<<
C
CRUNS = 0
STSTT = 0
MTSTT = 0
SDTSTT = 0
COV = 0
C
C  >>>START TRIP GENERATION/ATTRACTION MODELS<<<
C  ******************************************************
C
SAMPLING FOR ERROR IN PRODUCTIONS/ATTRACTIONS

CALL RNSET(10000)
DO 3159 NREA=1,NREPE
   TO=0
   TD=0
   DO 3140 J=1,NCENT
      EP=1+SDPR*RNNOF()
      IF(EP.LE.0) EP=0.00001
      EA=1+SDAT*RNNOF()
      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)
   C
3140 CONTINUE
C
BALANCING ORIGINS AND DESTINATIONS

TT=(TO+TD)/2
PO=TO/TT
PD=TD/TT
DO 3150 J=1,NCENT
   O(J,NREA)=O(J,NREA)/PO
   D(J,NREA)=D(J,NREA)/PD
C
3150 CONTINUE
C
WRITE(22,*) NREA,J,O(J,NREA),D(J,NREA)
C
3159 CONTINUE
C
--------------------------------------------------------------------------
CALCULATE SUMMARY STATISTICS IN TRIP GENERATION STEP

DO 3160 J=1,NCENT
   SUO(J)=0
   SUD(J)=0
   DO 3161 NREA=1,NREPE
      SUO(J)=SUO(J)+O(J,NREA)
      SUD(J)=SUD(J)+D(J,NREA)
   CONTINUE
   MO(J)=SUO(J)/NREPE
   MD(J)=SUD(J)/NREPE
   IF(MO(J).NE.0) GOTO 1001
   SDO(J)=0
   CVO(J)=0
   COUNTD=COUNTD+1
   GOTO 1003

   SUO(J)=0
   DO 1002 NREA=1,NREPE
      SUO(J) = (MO(J) - O(J,NREA)) * (MO(J) - O(J,NREA)) + SUO(J)
   CONTINUE
   SDD(J)=(SUO(J)/(NREPE-1))**0.5
   CVD(J)=SDO(J)/MO(J)
   SSO=SSO+CVO(J)
   IF(MD(J).NE.O) GOTO 1004
   SDD(J)=0
   CVD(J)=0
   COUNTD=COUNTD+1
   GOTO 1005

   SUD(J)=0
   DO 1009 NREA=1,NREPE
      SUD(J)=(MD(J)-D(J,NREA)) * (MD(J)-D(J,NREA)) + SUD(J)
   CONTINUE
   SSD(J)=(SUD(J)/(NREPE-1))**0.5
   CVD(J)=SDD(J)/MD(J)
   SSD=SSD+CVD(J)

C WRITE(22,3169) J,MO(J),SDO(J),MD(J),SDD(J),CVO(J),CVD(J)

CONTINUE

3160 CONTINUE

3169 FORMAT(16,4F10.2,2F10.4)
   SSO=SSO/(NCENT-COUNTO)
   SSD=SSD/(NCENT-COUNTD)
   ASS=(SSO+SSD)/2
C WRITE(22,'(SSOS=','F10.4,',' SSD=','F10.4,',' AVERAGE=','F10.4))
C WRITE(22,*)

3164 FORMAT('SIGMA/MU: SSO=','F10.4,' SSD=','F10.4,' AVERAGE=','F10.4)
C WRITE(22,*)

C >>>>START TRIP DISTRIBUTION MODEL<<<
C *********************************************
C SSO=0
C SSSSTA=0
C DO 3333 NREA=1,NREPE
C SSSSTA(NREA)=0

3333 CONTINUE

NSEED=20000
VCRAT=0

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VCRTTTT=0
MMTA=0
SDTA=0
DO 3300 NREA=1,NREPE
   CALL RNSET(NSEED)
   TO=0
   TD=0
C WRITE(22,*),'FLOWS FROM GRAVITY MODEL WITHOUT BALANCE'
C
DO 3158 JJ=1,NCENT
   DO 3157 KK=1,NCENT
      SDFIJ(JJ,NREA)=D(KK,NREA)*FIJ(KK+NCENT*(JJ-1))
      +SDFIJ(JJ,NREA)
   CONTINUE
3157 CONTINUE
3158 CONTINUE
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))
   +FRS(K+NCENT*(J-1),NREA)=O(J,NREA)*D(K,NREA)
   *FIJ(K+NCENT*(J-1))/SDFIJ(J,NREA)
   IF(FRS(K+NCENT*(J-1),NREA).NE.0) WRITE(22,*) J, K, FRS(K+NCENT
   *(J-1),NREA)
   CONTINUE
3170 CONTINUE
C WRITE (22,*)
C
BALANCING OF THE 0-D MATRIX
C
CV=0.051
IT=1
3175 IF(IT.EQ.21) GOTO 3185
IF(CV.LT.0.0001) GOTO 3185
CV=0.001
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
3167 CONTINUE
   PT=TO/O(J,NREA)
   IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
   DO 3171 K=1,NCENT
      FRS(K+NCENT*(J-1),NREA)=FRS(K+NCENT*(J-1),NREA)/PT
   CONTINUE
3171 CONTINUE
3168 CONTINUE
   DO 3174 K=1,NCENT
      TD=0
      IF(D(K,NREA).LT.0.01) GOTO 3174
      DO 3172 J=1,NCENT
         TD=TD+FRS(K+NCENT*(J-1),NREA)
      CONTINUE
3172 CONTINUE
   PT=TD/D(K,NREA)
   IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
   DO 3173 J=1,NCENT
      FRS(K+NCENT*(J-1),NREA)=FRS(K+NCENT*(J-1),NREA)/PT
   CONTINUE
3173 CONTINUE
3174 CONTINUE
   IT=IT+1
   GOTO 3175
3185 CONTINUE
C WRITE(22,*)
WRITE(22,*) 'FLOWS FROM GRAVITY MODEL WITH BALANCE'
DO 3301 J=1,NCENT
   DO 3301 K=1,NCENT
      IF(FRS(K+NCENT*(J-1),NREA).NE.0) WRITE(22,*)J,K,
      FRS(K+NCENT*(J-1),NREA)
   3301 CONTINUE
SAMPLING OF ERROR IN TRIP DISTRIBUTION MODEL
WRITE(22,*)
DO 3210 NREB=1,NREPE
   C WRITE(22,*) 'FLOWS AFTER ERROR IN DISTRIBUTION W/O BALANCE'
   DO 3192 J=1,NCENT
      DO 3191 K=1,NCENT
         EF=RNNOF() * SDDI + 1
         IF (EF.LE.0) EF=0.00001
         TFRS(K+NCENT*(J-1),NREB)=FRS(K+NCENT*(J-1),NREA) * EF
      3191 CONTINUE
   3192 CONTINUE
ADJUSTMENT FOR CONSERVATION OF ORIGINS AND DESTINATIONS
CV=0.051
IT=1
3193 IF (IT.GT.21) GOTO 3205
   IF(CV.LT.0.0001) GOTO 3205
   CV=0.001
   DO 3198 J=1,NCENT
      TO=0
      IF(O(J,NREA).LT.0.01) GOTO 3198
      DO 3197 K=1,NCENT
         TO=TO+TFRS(K+NCENT*(J-1),NREB)
      3197 CONTINUE
      PT=TO/0(J,NREA)
      IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
      TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT
   3198 CONTINUE
   DO 3201 K=1,NCENT
      TD=0
      IF(D(K,NREA).LT.0.01) GOTO 3201
      DO 3200 J=1,NCENT
         TD=TD+TFRS(K+NCENT*(J-1),NREB)
      3200 CONTINUE
      PT=TD/D(K,NREA)
      IF(ABS(PT-1).GT.CV) CV=ABS(PT-1)
      TFRS(K+NCENT*(J-1),NREB)=TFRS(K+NCENT*(J-1),NREB)/PT
   3201 CONTINUE
   IT=IT+1
   GOTO 3193
3205 CONTINUE
WRITE(22,*) 'FLOWS AFTER ERROR IN DISTRIBUTION WITH BALANCE'
DO 3206 J=1,NCENT
   DO 3206 K=1,NCENT
240
C        IF(TFRS(K+NCENT*(J-1),NREB).NE.0) WRITE(22,*) NREB, J, K,
C        TFRS(K+NCENT*(J-1),NREB)
3206 CONTINUE
C WRITE(22,*)
3210 CONTINUE
C
C CALCULATION OF SUMMARY STATISTICS IN TRIP DISTRIBUTION STEP
C
C CALL RNGET(NSEED)
SSOD=0
CNTOD=0
DO 3211 J=1,NCENT
   DO 3211 K=1,NCENT
      SUOD(K+NCENT*(J-1))=0
      SDOD(K+NCENT*(J-1))=0
3211 CONTINUE
DO 3230 NREB=1,NREPE
   DO 3230 J=1,NCENT
      DO 3230 K=1,NCENT
         SUOD(K+NCENT*(J-1))=SUOD(K+NCENT*(J-1))
            +TFRS(K+NCENT*(J-1),NREB)
3230 CONTINUE
C WRITE(22,*)
C WRITE(22,*) 'AVERAGE FLOWS'
   DO 3240 J=1,NCENT
      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,*)
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))
   C WRITE(22,*) J, K, CVOD, SDOD(K+NCENT*(J-1))
   SDOD(K+NCENT*(J-1))=0
3249 CONTINUE
3250 CONTINUE
C IF(CNTOD.NE.NCENT**2) SSOD=SSOD/(NCENT**2-CNTOD)
   SSOD=SSOD+SDOD
3260 FORMAT('SUMMARY STATISTIC O-D ONE REPETITION, SSOD= ',F10.4)
C WRITE(22,*)
C WRITE(22,*) 'AUTO TRIPS (TRIPS IN MODAL SPLIT STEP) ARE'
C >>>START MODAL SPLIT MODEL (LOOPED IN TRIP DISTRIBUTION)<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<
   DO 3329 NREB=1,NREPE
   DO 3328 NREC=1,NREPE
   DO 3370 J=1,NCENT
   241
DO 3270 K=1, NCENT
MSPLIT = TFRS(K+NCENT*(J-1), NREB)* MSIJ(K+NCENT*(J-1))
C
C  SAMPLING OF ERROR IN MODAL SPLIT MODEL
C
EMS=RNNOF() *SDMS+1
IF (EMS.LE.0) EMS=0.00001
MS= MSPLIT*EMS
IF(MS.NE.O)
C  * WRITE(22, 3266) NREA, NREB, NREC, J, K, MSPLIT, EMS, MS
3266 FORMAT(5I6,F15.5,F15.8,F15.5)
C
C  PREPARE DATA FOR TRAFFIC ASSIGNMENT STEP
C
AMT(K+NCENT*(J-1)) = MS
3270 CONTINUE
C
C  *****************************************************.****.*
C  » » S T A R T TRAFFIC ASSIGNMENT M O D E L««
C  (LOOPED IN TRIP DISTRIBUTION AN D MOD A L SPLIT)
C  *****************************************************.****.*
C
C  INITIALIZE & SAMPLING OF ERROR IN "FREE F L O W TRAVEL TIME"
C
SSOD=0
VCRTTT=0
COFL=0
SSFL=0
VCRATT=0
C
C  SAMPLING OF ERROR IN TRAFFIC ASSIGNMENT MODEL
C
DO 3280 I=1, NRTA
   CALL RNSET(I*NARC*NREA*NREB*NREC*10)
DO 3285 N=1, NARC
   ET=RNNOF() *SDAS+1
   IF(ET.LE.0) ET=0.00001
   TTIME(N)=TTIM(N)*ET
WRITE(32,3283) NREA, NREB, NREC, I, N, ET, TTIME(N)
3283 FORMAT(I8,3I6,I12,F15.8,F15.8)
3285 CONTINUE
C
C  WRITE(32, *)
EPS=1.E-3
CALL UE(EPS, NARC, NNOD, NCENT, ITER, NFL, TSTT)
CRUNS=CRUNS+1
C
C  PREPARE DATA FOR CALCULATING STATISTICS
C
DO 3275 N=1, NARC
   FLOW(N, I)=NFL(N)
3275 CONTINUE
3280 CONTINUE
C
C  CALCULATE SUMMARY STATISTICS IN TRAFFIC ASSIGNMENT STEP
C
SSF=0
MTA=0
COUNTF=0
IX25=NRTA/4
IX50=NRTA/2
C
242
**BEGINNING OF SORTING 0 AND D**

```fortran
DO 3289 J=1,NARC
   ID=0
   DO 3290 I=1,NRTA
      FSORT(J,ID)=0.00
      FMIN=1000000
      DO 3291 K=1,NRTA
         IF (FLOW(J,K).LT.FMIN) THEN
            FMIN=FLOW(J,K)
            KK=K
         ENDIF
      3291 CONTINUE
      FSORT(J,ID)=FMIN
      FLOW(J,KK)=100000
   3290 CONTINUE
C *****END OF SORTING FLOW FOR ARC "J"*****
C
C >>>CALCULATE 25%-FRACITILE AND MEDIANS OF FLOW ON ARC J<<<
C (THE FORMULA REQUIRE NUMBER OF SIMULATIONS IS AN EVEN NUMBER)
C
MFLOW(J)=(FSORT(J,1X50)+FSORT(J,(1X50+1)))/2
MF25(J)=(FSORT(J,1X25)+FSORT(J,(1X25+1)))/2
C
C>>>CALCULATE UM OF FLOW ON ARC J AFTER >NRTA< RUNS<<<
C
C ***TAKE OUT DUMMY LINKS AND LINKS WITH ZERO FLOW***
IF (C(J).EQ.1) GOTO 3292
IF (C(J).GT.9999) GOTO 3292
IF (MFLOW(J).EQ.0) GOTO 3292
C
SDFLOW(J)=MFLOW(J)-MF25(J)
CVFLOW(J)=SDFLOW(J)/MFLOW(J)
GOTO 3293
C
3292 SDFLOW(J)=0
CVFLOW(J)=0
COUNTF=COUNTF+1
GOTO 3289
C
3293 SSF=SSF+CVFLOW(J)
MTA=MTA+MFLOW(J)
C3288 WRITE(33,3294) J,MFLOW(J),SDFLOW(J),CVFLOW(J)
3294 FORMAT(16,2F10.2,F10.4)
3289 CONTINUE
C
C>>>CALCULATE VARIATION INDEX OF FLOWS ON ALL ARCS FOR ALL RUNS<<<
C
MTA=MTA/(NARC-COUNTF)
SSF=SSF/(NARC-COUNTF)
C
WRITE(33,*) 'AVERAGE FLOW AND UM FOR >NRTA RUNS< ARE',MTA,SSF
C
WRITE(33,*) 'TOTAL NUMBER OF SIMULATION RUNS = ',CRUNS
```

243
MMTA = MMTA/NREPE**3
SDTA = SDTA/NREPE**3
WRITE(33,3165) MMTA, SDTA
3165 FORMAT(' A V E R A G E  F L O W  A N D  U M  F O R  <ALL RUNS> A R E  A R E ',2F10.4)
C STOP
END
C **************************** END OF THE MAIN PROGRAM ****************************
C
SUBROUTINE UE(EPS,NARC,NNOD,NCENT,ITER,NFL,TSTT)
COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
COMMON /ODDT/ TOD,AMT
COMMON /DMPDT/ NDM, DMP,NREA,NREB,AA,AB
COMMON /FST/ FS,ODLK
COMMON /ALBET/ ALP,BET,ALP1,TYP
REAL L(399),C(399),V(399),FL(399),COST(399)
REAL NFL(399)
REAL ALP(18),BET(18),ALP1(18),XN
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), TOD(1764), FS(399), ODLK(2000)
INTEGER TYP(399), DMP(101)
REAL AMT(1764)
CALL AON(FL,NARC,NNOD,NCENT,ITER)
K=1
ITER=0
FOBJ=0.
DO 70 I=1,NARC
A1=ALP1(TYP(I))
B1=BET(TYP(I))
FOBJ=FOBJ+FINT(TTIME(I), C(I), FL(I), A1,31)
70 CONTINUE
CONV=2.*EPS
10 IF(CONV.GT.EPS) GO TO 30
15 CALL DUMP(ITER,NNOD, NCENT,NARC,NFL,TSTT)
RETURN
30 CONTINUE
IF(ITER.NE.NDMP) GO TO 40
GO TO 15
40 ITER=ITER+1
CALL AON(NFL,NARC,NNOD,NCENT,ITER)
CALL BISECT(NFL, NARC)
CONV = SQRT(CONV)
IF(D . EQ. 0.) GO TO 10
CONV=CONV/D
GO TO 10
END
C
---------------------------------------------------------------------
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(399),C(399),V(399),FL(399),COST(399)
REAL NFL(399),SP(8000)
REAL ALP(18),BET(18),ALP1(18)
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), TOD(1764), FS(399),ODLK(2000)
INTEGER TYP(399),PRED(IOOO), INTERNO
---------------------------------------------------------------------
REAL AMT(1764)
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
60 J1=PRED(J)
IF(J1.EQ.0) GO TO 30
N1=FS(J1)
N2=FS(J1+1)-1
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)
COMMON /ARCDT/ TOO,L,C,V,FL,COST,TTIME,NEWT,TLTT
COMMON /FST/ FS,ODLK
COMMON /ALBET/ ALP,BET,ALPl,TYP
REAL L(399),C(399),V(399),FL(399),COST(399),NFL(399)
REAL ALP(18),BET(18),ALPl(18)
REAL TTIME(399),NEWT(399),TLTT(399)
INTEGER TOO(399),FS(399),TYP(399),ODLK(2000)
AMN=0.
AMX=1.
10 AMD=(AMX+AMN)/2.
IF((AMX-AMN).LE.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)
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
NFL(N)=FL(N)+AMD*(NFL(N)-FL(N))
40 RETURN
END

FUNCTION COSTFN(TIME,C,FL,A,B)
COSTFN=TIME

245
IF (FL .LE. 0.01) COSTFN = COSTFN
IF (C .NE. 0.) COSTFN = COSTFN * (1. + A * (FL / C)**B)
RETURN
END

C---------------------------------------------------------------
FUNCTION FINT(TIME, C, FL, A, B)
FINT = TIME * FL
IF (C .NE. 0.) FINT = FINT * (1. + A / (b + 1) * (FL / C)**B)
RETURN
END
C---------------------------------------------------------------
SUBROUTINE SHPATH(R, PRED, SP, NNOD)
C THIS SUBROUTINE COMPUTES SHORTEST PATHS FROM R TO ALL OTHER NODES. PRED(I) CONTAINS PREDECESSOR OF NODE I.
C SP(I) CONTAINS LENGTH OF PATH TO NODE I.
C COMMON /ARCDT/ TOO, L, C, V, FL, COST, TTIME, NEWT, TLTT
COMMON /FST/ FS, ODLK
REAL L(399), C(399), V(399), FL(399), COST(399), SP(8000)
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), FS(399), 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)
   IAI = FS(I)
   IF (IAI .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
40 CL(K) = CL(I)
   CL(I) = K
40 CONTINUE
   ICL = CL(I)
   CL(I) = -1
   I = ICL
   IF (I . LE. NNOD) GO TO 20
RETURN
END
C---------------------------------------------------------------
SUBROUTINE DUMP (ITER, NNOD, NCENT, NARC, NFL, TSTT)
REAL L(399), C(399), V(399), FL(399), COST(399), NFL(399)
REAL ALP(18), BET(18), ALP1(18), VCR(399)
REAL TTIME(399), NEWT(399), TLTT(399)
INTEGER TOO(399), FS(399), TYP(399), VC1(399), VC2(399)
INTEGER IDNODE(1000), ODLK(2000), DMP(101)
REAL FUEL, HC, CO, NOX

WRITE(32,101) ITER
101 FORMAT(IX,'NO. OF ITERATIONS = ',I6)
VCRATT=0
K=0
STX=0
SLX=0
IX=0
DO 10 I=1,NNOD
J1=FS(I)
J2=FS(I+1)-1
IF(J1.GT.J2) GO TO 10
DO 20 J=J1,J2
K=K+1
NFL(K)=FL(J)
IF(C(J).NE.0) VCR(K)=FL(J)/C(J)
IF(C(J).EQ.0) VCR(K)=0
VC1(K)=IDNODE(I)
VC2(K)=IDNODE(TOO(J))
IF(FL(J).EQ.0.) GO TO 20
IF(VC1(K).LE.NCENT) GO TO 20
IF(VC2(K).LE.NCENT) GO TO 20
IX=IX+1
A1=ALP(TYP(J))
B1=BET(TYP(J))

C
CST=COSTFN(TTIME(J),C(J),FL(J),A1,B1)
NEWT(J)=CST
STX=STX+CST*FL(J)
SLX=SLX+L(J)*FL(J)
20 CONTINUE
10 CONTINUE
TSTT=0
DO 201 I=1,NARC
TSTT = TSTT + NEWT(I)*NFL(I)
201 CONTINUE
104 FORMAT(3I6,F15.2)
DO 23 I = 1, NARC
WRITE(32,103) NREA, NREB, I, NFL(I), NEWT(I), TLTT(I), VCR(I)
102 FORMAT(I6,F13.2,F9.5,F10.2,2I7)
103 FORMAT(3I6,F13.2,F9.5,F14.3,F10.7)
23 CONTINUE
RETURN
END