FINAL REPORT

USING HISTORICAL DATA TO MEASURE TRANSPORTATION INFRASTRUCTURE CONSTRAINTS ON LAND USE

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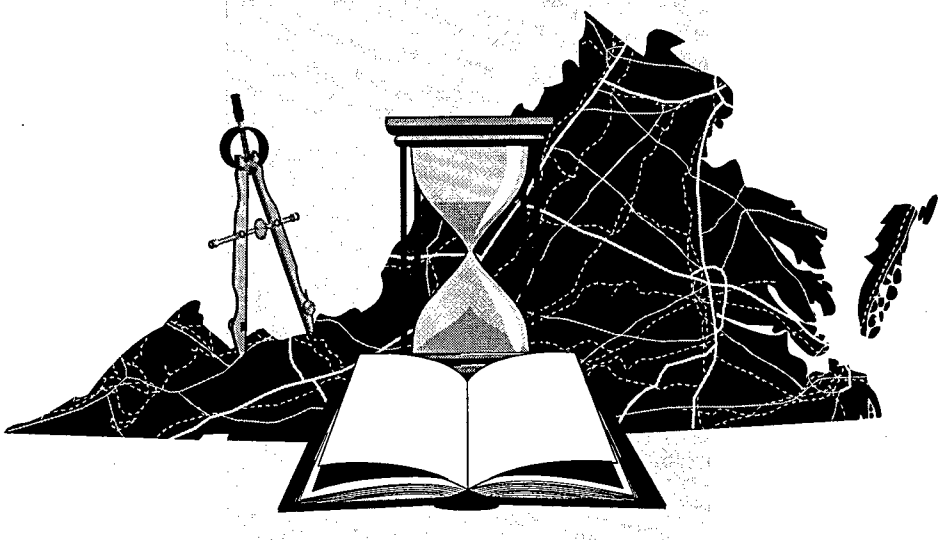

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16. Abstract

Conventional practice for developing transportation forecasts is to calibrate a model for base year conditions and then apply the model to identify future deficiencies. These models typically begin with an assumed land use and then project future traffic volumes. To determine limitations on land development as a function of the capability of the transportation system, this research effort reversed that direction, beginning with transportation system characteristics as the independent variable and calculating employment and population as dependent variables. To evaluate this process, a case study area was selected for which transportation planning data were available at three points in time over a 25-year period. This area is Charlottesville, Virginia, with imperfect snapshots of transportation and land use characteristics from 1967, 1979, and 1990.

A five-component modeling process was developed and applied to the Charlottesville area for the 1967 base year. This initial approach made intuitive sense, was built from models suggested by the literature, and worked reasonably well on a small theoretical network. The performance of one component, however, was extremely weak and led the authors to develop a direct estimation model instead. This revised technique directly estimates zonal trip ends based on transportation system variables that are influenced by link volumes, roadway types, travel distances, and the geographical position of the zone. Additionally, the authors regressed retail employment, nonretail employment, and population to zonal trip ends. Lessons learned with 1967 data were used to calibrate the model for the 1979 base year and apply it for the 1990 forecast year. For individual zones, errors on the order of 50% were obtained, with larger values for retail employment and smaller values for nonretail employment and population. For the aggregate study area, errors between 6% and 21% were obtained.

Suggestions about how this model formulation might be interpreted to yield land use limits as a function of traffic volumes are discussed. A simple finding for achieving convergence with the iterative entropy maximization method is stated. Recommendations for using historical data to predict the present, ensuring that these planning data are available for future efforts, and conducting a longitudinal study are presented. Issues associated with linking data from different time periods are explained.

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(The opinions, findings, and conclusions expressed in this report are those of the authors and not necessarily those of the sponsoring agencies.)

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FOREWORD

The research reported herein was the basis for Dr. Miller's dissertation entitled *Reversing the Direction of the Transportation Planning Process: Measuring Transportation Infrastructure Constraints on Land Use With Historical Data.* This report is an abridged version that focuses on the lessons learned and the modeling efforts that were finally used as a result of the larger effort.

Data development for this project was a labor-intensive task. For that reason, and because subsequent research using the same data sets is to be encouraged, the data used for this project are included in a separate volume entitled *Albemarle County/City of Charlottesville Transportation Planning Compact Disc* (VTRC 98-R33).

EXECUTIVE SUMMARY

Introduction

The typical transportation planning process entails dividing a study area into various sections, or zones, and then examining the land use characteristics of the zones. For example, a zone that consists primarily of residential detached houses with a density of four such units per acre has a substantially different land use than a zone in the center of a city that consists primarily of businesses and apartment buildings. Transportation planners often follow a modeling process through which they compute the number of trips each of these zones will generate, distribute, and receive. The product is an understanding of how much traffic will be on the roadway network throughout the study area. In sum, then, the typical transportation planning modeling sequence begins with a fixed land use and concludes with an estimate of transportation system usage, e.g., 24-hour traffic volumes for the various roadway segments.

A second feature of most planning studies is that they build a model based on current data and then forecast the future. By the time the "future" occurs, attention has been diverted from the original planning study. Then, analysts build a new model based on current information and again forecast the future. Planners rarely test a model by calibrating it to a point in the past and then seeing whether the predictions are accurate based on current data.

Purpose and Scope

This study had three goals:

1. To develop a method for reversing the planning process, such that we begin with transportation system usage and conclude with an indication of land use.

2. To validate this process by calibrating the model with historical data and then using it to predict the present.

3. To employ the modeling process to determine limits on land development that could arise as a result of constraints on the transportation infrastructure. That is, if a particular volume of traffic in a zone is generated as a result of the zone's population and employment, how much additional population and employment can the zone accommodate without physical improvements being made to the zone's roadway network?

Methods

To accomplish these goals, we performed five key tasks.

1. Review the literature, select the most promising concepts from the literature, and test these concepts on a small theoretical network. The outcome of this task was an understanding of which modeling tools had the most promise for reversing the direction of the planning process.

2. Select a case study area, and synthesize the data from this area over a 25-year period. The outcome of this task was a detailed understanding of the historical data available for analysis in the case study area. Data were available at three discrete points: 1967, 1979, and 1990. These data included land use/socioeconomic data (e.g., population, dwelling units, number of acres zoned as commercial usage, total number of acres in a zone), transportation data (e.g., number of lanes on each roadway segment, operating speeds, traffic volumes), and other planning data (e.g., a table that shows how trips are distributed among the various zones).

3. Construct a five-step approach for reversing the direction of the planning process. We built the approach from models identified in task 1 and tested it with a 1967 data set synthesized in task 2. Although the approach had shown promise on a theoretical network, only portions worked with the base year 1967 network. A critical step, determining an origin-destination (O-D) trip table from traffic counts, was unsuccessful. Extensive testing and variations to the approach did not improve performance, indicating the need to find a better methodology for deriving land use limits from transportation system usage. Note that in this task and the task that follows, the data span 30 years but the analysis methods employed are newer.

4. Develop a new approach, called the direct estimation method, for reversing the direction of the planning process. This task had three parts: (1) obtain the number of vehicle trips that begin or terminate in each zone as a function of transportation system characteristics, such as 24-hour traffic volumes; (2) use these vehicle trips to determine population, nonretail employment, and employment as a function of these zonal vehicle trips; and (3) formally test this approach, where data were calibrated for 1979 as the base year and then tested with 1990 as the forecast year.

5. Determine land use limits (e.g., maximum values of population, nonretail employment, retail employment) as a function of transportation system usage (e.g., 24-hour traffic volumes). We loaded the links of the roadway network to a 24-hour volume that would correspond to a level of service of C. From this application, we obtained corresponding employment and population values for each zone. These values were a function of not only transportation but also of other factors not encompassed by the model. Since the model was imperfect, we presented the predictions of employment and population as ranges. For example, we might present the population of the entire study area as the estimate plus or minus a tolerance of 21%. That tolerance reflects the imperfections of the model, the fact that factors in addition to transportation affect population and employment, and any data errors.

Findings

1. A slight modification to the computational method helped one of the algorithms converge. The five-step approach cited in Task 3 required a subroutine that derived an origin-destination table using the principle of entropy maximization. Before the modification was

made, there were instances when the software subroutine that implemented the algorithm oscillated between two answers rather than settling on a single answer.

2. When obtaining a trip O-D table from traffic counts, the type of technique employed affects the likely distribution of values within the table.

3. The initial five-step model has theoretical promise, even though it did not work well for this data set.

4. The new direct estimation approach for determining trip ends has real-world potential. Splitting employment into retail and nonretail categories augments this potential.

Conclusion

The key conclusion of this study is: It is possible to use historical planning studies, along with other data sources, to test the utility of planning models by using the past to predict the present. The specific application for this study, determining land use limits as a function of transportation infrastructure constraints, is just one of many possibilities for such testing. By beginning to validate planning models using historical data, the planning community may gain credibility with the public and those who make decisions. No model will be 100% accurate, but with historical analyses, planners can begin to put ranges or bounds on their forecasts.

Recommendations

1. When planning efforts are underway, document data as fully as possible, at least for smaller geographical areas where there will not be multiple agencies that have all of the planning data. These data should be archived such that they may be accessed for future studies.

2. Select one study area for which historical and present day data exist, and assess the validity of the original plan's forecasts.

3. For a set of base year data, run the planning process in both the forward and reverse directions, i.e., use the standard four-step process to derive traffic volumes from socioeconomic parameters, and separately use the reverse direction to determine socioeconomic parameters from traffic volumes.

4. Conduct a longitudinal study using transportation planning data and use the findings to evaluate how well one can respond to policy questions.

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INTRODUCTION

On January 27, 1997, U.S. District Court Judge Suzanne B. Conlon ruled against the Federal Highway Administration (FHWA), the U.S. Department of Transportation, and several individuals, concluding that an environmental impact statement submitted by the defendants for constructing a 12.5-mile toll road in Northern Illinois did not comply with relevant regulations.[1] In correspondence circulated by FHWA concerning this decision, agency personnel correctly pointed out that a possible interpretation of the ruling is that future planning studies must explicitly contain two sets of socioeconomic forecasts: one that assumes toll road construction and one that does not.[2]

This decision also contains enlightening tenets about how courts may interpret future controversial planning efforts. The decision pointed out that because the National Environmental Policy Act "does not require an agency to use the best scientific methodology available," the court does not require "that the final impact statement . . . contain a socioeconomic forecast that reflects the growth inducing effect of the tollroad."[1] The court gives the option of either incorporating such a forecast or stating within the environmental impact statement why such a forecast cannot be accomplished. It is this latter option that the use of historical planning data may address.

The issue of whether we "can" accomplish such a traffic volume forecast would logically focus on whether we could, with the data and resources at our disposal, either determine the "correct" forecast exactly or determine the forecast within acceptable limits of precision. That is, if the population of an area in 2005 was 123,456 persons, a model that predicted 123,455 persons would be viewed as acceptable. On the other hand, a model that predicted 999,999 persons would likely be viewed as useless. The question then becomes twofold: First, how accurate are the models, and second, is this level of accuracy acceptable?

One method to answer this question is to make predictions now, wait until the future, and then compare what was predicted to what existed. A timely alternative, though, is to use historical data to predict the current situation. Such an alternative is not exact, as historical data may not be as complete as current data, and the size, scope, and interactions of a geographic area will change. Yet, by attempting such a process, we can roughly determine the probable accuracy

of such forecasts. By then applying the forecasts, along with the associated error, to a land use or transportation decision, we can determine whether a reasonable decision can be made given the level of error generated by the model. This validation potentially allows us to know whether forecasts are "possible."

The question raised by this research refers to land use limits, where these are defined as the maximum amounts of population and employment that may be sustained by an area given its transportation system. It may be unrealistic to assume that employment and population growth are unconstrained by the capacity of the transportation system. Instead, it is reasonable to examine how transportation system constraints may constrain future development, given that right-of-way acquisition and infrastructure investments are becoming increasingly expensive. Yet, to what extent does transportation system capacity influence land use development, and more important, how well can this relationship be specified over time?

The standard planning process begins with an assumed land use and then derives a transportation system that can accommodate the expected needs of that land use. In this vein, a typical modeling procedure generates trips from employment and population sites, distributes these trips between various transportation analysis zones, and assigns these trips to the transportation network. This process is calibrated for the base year such that performance replicates base year conditions satisfactorily. Then, the calibrated model is applied for a forecast year, with the result being used to identify expected deficiencies in the transportation network. Steps can then be taken to remedy these deficiencies.

We sought to determine land use limits as a function of transportation system growth by reversing the direction of this planning process and applying the methodology to a set of historical data, with a point in time from the past being the base year and a point in time closer to the present being the forecast year. We sought to employ a methodology that began with transportation system characteristics, such as traffic volumes and speeds, and concluded with land use parameters, in the form of employment and population by zone.

PURPOSE AND SCOPE

This project had three objectives:

1. *To develop an approach that reverses the direction of the planning process.* That is, we sought to begin with transportation system characteristics as the independent variable and conclude with land use or socioeconomic characteristics as the dependent variable.

2. *To test this "reverse" approach with historical data.* We sought to apply this approach to a year from the past and see how well it "predicted" the present. This would indicate the accuracy of the approach.

3. *To use the approach to determine limits on population and employment as a function of transportation system growth.* To accomplish this, we apply the reverse approach

again, this time beginning with levels of congestion that users will tolerate. The resultant population and employment maximums may be termed *land use limits.*

We chose the case study area of Charlottesville, Virginia. We extracted information from base year data used in three major planning efforts that had been conducted over the past 30 years: 1965-1967, 1974-1985, and 1987-1990.

METHODS

First, we conducted a literature review. A macroscopic survey provided an understanding of planning paradigms at large, and a microscopic examination of selected articles provided a better understanding of specific models that were the most likely to be fruitful. This review helped us identify potentially useful models. Our experiments with very small networks suggested that some of these approaches had substantial promise.

Second, we synthesized the planning data from publications, memoranda, handwritten notes, unpublished drafts, and historical files for the case study area of Charlottesville, Virginia. We extracted this information from base year data used in three major planning efforts that had been conducted over the past 30 years: 1965-1967, 1974-1985, and 1987-1990. Reformatting these data to allow comparing land use and transportation characteristics over multiple time periods was a substantial challenge.

Third, we applied a five-step modeling approach we built from the literature and tested on theoretical networks to the 1967 study area. The results were abysmal, although repeated experiments allowed us to understand why the approach was not feasible for the case study area. The model structure allowed us to derive employment and population values from transportation system usage, but the performance of the model when compared to real world data was poor.

Fourth, in response to the failure of the initial five-step model, we developed a simpler but more workable methodology that showed promise both for the base year calibration and the forecast year prediction. Using base year data, we devised a model where we begin with base year transportation system characteristics, such as traffic volumes, lane widths, and travel speeds, and derive base year employment and population. These computations may be done for each zone of the study area. This process is repeated, except we may begin with forecast year traffic volumes and conclude with forecast year population and employment. In this latter application, we can measure how close the forecast year population and employment are to the actual population and employment.

Fifth, we made estimates about how well land use limits as a function of transportation system constraints may be determined. We highlight relevant concepts here; details are available in Miller.[3]

RESULTS

Task 1: Conduct a Literature Review

Transportation Planning Paradigms

The fact that transportation and land use are interrelated is well known. The questions that arise therefore focus not on whether a link exists but instead on how this link should be studied and explicitly employed in a planning context.

Alleged Purpose of Transportation Planning

Significant national attention has been focused on the issues of air quality and traffic congestion. The capacity of the transportation infrastructure has not been able to keep pace with increases in automobile usage, with the result being that many roads carry more traffic than they were designed to handle. Estimates are that by the year 2005, traffic in the United States will increase by 50% and capacity will increase by 5% as compared to 1990 levels, at an estimated cost of 7 billion vehicle-hours of delay annually.[4,5] The financial resources available to build more roads are insufficient to meet this increased demand.

Congestion relief is not the only challenge faced by the transportation community. A growing movement toward environmental protection, coupled with tying the availability of transportation funds to air quality levels, renders air quality a major consideration in transportation planning. For example, the Clean Air Act Amendments of 1990, which require metropolitan areas to attain minimum air quality standards as defined by the Environmental Protection Agency (EPA), have generated calls for improved transportation modeling procedures. Even though current research is addressing how air pollution levels may be modeled and reduced in the short term by transportation control and demand measures, questions are also being raised about how long-term land use might play a role in determining a region's level of air quality.[6] In this context, *land use* refers to the quantity, density, and mixture of residential, commercial, and employment-based development that is permitted to occur in a region.

Congestion and air quality may constrain future land development given the continued increase in automobile usage both in the United States and around the world (L.A. Hoel, unpublished data). *Air quality* refers to National Ambient Air Quality Standards established by the EPA for ground level ozone, and *congestion* refers to facility levels of service that commuters will tolerate.[7] Congestion can restrict land use initiatives by making traffic levels of service unacceptable, thereby thwarting residential and economic development. Poor air quality may restrict land use initiatives because the Clean Air Act Amendments mandate that a state attain specified emissions reductions to receive federal funding to implement desired transportation improvements.

In congested areas where the automobile is the only feasible mode of transportation for a large part of the population, many steps that may be required to limit the growth of single-occupant vehicle travel are politically unpopular. Concepts such as transportation control

measures and transportation demand measures have gained attention as methods of reducing single-occupant vehicle travel. These measures, which include ridesharing incentives and transit incentives, have had a very small impact on reducing trips and vehicle miles traveled.[8,9] Although market-based policies such as congestion pricing, emissions fees, and gasoline taxes are considered to have a stronger impact, they would likely be met with much public opposition.[10,11] One obstacle to changes in behavior was demonstrated in the San Diego HOV experiment: passes that allow single drivers to occupy an 8-mile stretch of HOV lanes on I-15 have sold out at a fee of $50 per month. Clearly, at least for such drivers who would rather pay $50 each month than carpool, changes in travel behavior without more severe economic penalties are hard to render.[12] In light of this, we need to understand just how much development can be accommodated by existing transportation infrastructure without expecting substantial changes in human choices.

Both planning models and the scope of transportation planning have been criticized. It has been argued that certain mathematical models are insensitive to policy options, such as transportation demand management or intelligent transportation system initiatives. In addition, the models themselves have been criticized as being irrelevant since a host of public goals, such as "community, environmental, and economic development," rather than transportation system performance, now drive investment decisions.[13] Finally, planning models need to be validated. Hartgen pointed out problems with a variety of transportation-related models (not just planning models) that include a disparity between actual and predicted values of 100% and the presentation of raw predictions without error estimation.[14]

Transportation Capacity and Land Use

One area of transportation planning deals with the direction of causality between capacity and travel behavior. Is increased highway capacity—an increase in the number of lanes of a facility, for example—simply a response to expected population and employment growth that would have generated travel demand in any event, or does additional highway capacity induce more travel that otherwise would not have taken place?[15]

Much public debate has occurred over the issue of how the addition of capacity, in the form of measures such as highway widening, signal improvements, and the construction of new facilities, affects the demand for motor vehicle travel. Numerous sources have commented on the capacity-travel relationship from a variety of angles, and the Transportation Research Board's synthesis of the state of the understanding of these issues illustrates why this phenomenon can be confusing.[15] Several factors are postulated to be responsible for an increase in travel over the past 50 years:

- *Demographics.* Not only have populations increased, which would increase travel, but also household sizes have decreased, resulting in the average person making more trips (we can even compare the number of trips per person made by a family of five with the number of trips per person made by five dwelling units, each containing one person).

- *Employment.* The number of jobs has grown even faster than the population, with more workers per household and the entry of women in the work force.

- *Disposable income.* Growth in disposable income has not only increased automobile ownership but has also provided the means for more leisure travel. The increase in automobile ownership is evident in that there are more vehicles per household.

- *Decentralization.* As people have moved further from the urban core because of a desire for more land or better schools, average trip lengths have tended to be longer, especially where high-speed roads are available.

- *Mode choice.* Development in lower density areas has increased automobile travel because the automobile is often the only mode of travel available unless great increases in travel time or out-of-pocket cost are incurred.

- *Monetary cost.* The increase in income and the decrease in real gasoline costs have also lowered real out-of-pocket (monetary) costs.

- *Travel time.* Although not explicitly stated, a logical extension of travel on higher speed facilities is that the impedance to travel is reduced, resulting in greater travel by users of the roadway network.

Clearly, capacity can affect some of these parameters to some degree, but capacity alone is not responsible for all changes in these parameters. For example, widening a highway from two to four lanes can decrease travel times but alone will not increase the population of a specific area if the highway does not improve accessibility for additional travelers. Changes in capacity can alter some of these parameters in the short term, such as route used, time of day travel occurs, and quantity of congestion. Over the long term, parameters such as mode, destination, and quantity of trips can be changed in part by highway capacity, whereas land use and automobile ownership may or may not.[15] Capacity thus induces some travel, but in many cases additional travel occurs as a result of other factors.

New highways and other capacity changes may redistribute growth in addition to or instead of stimulating growth.[15] Capacity changes thus ultimately affect the location and shape of land use development. For example, business location theory partly explains the expansion of suburbs since World War II. The construction of interstate highways has lowered travel costs from central business districts (CBD) to outlying areas. This improved accessibility, combined with the improved attractiveness of suburban land (initially lower prices), results in decentralization of both residences and businesses that value this abundant land (although some theorists argue that certain businesses would centralize because of a need for products and services that are centrally based). Thus, capacity alone can induce businesses or residents to relocate to newer areas, thereby encouraging development if the conditions are right. The item of interest in this study is that there is at least a theoretical basis for considering the impacts of capacity on land use, although capacity alone does not influence land use. Harvey and Deakin wrote that the "magnitude of the effect [of transportation improvements] remains unclear" and

that there is still debate about how modifications to transportation capacity affect demand for travel choices (e.g., trips being made, route taken, and mode used).[16]

Long-term Versus Short-term Impacts

A different argument found in the literature is that travel will change only slightly in spite of large changes in capacity, meaning that capacity will not substantially affect land use. At the regional level, the literature suggests that if we control for other growth-inducing factors, such as population increases and cheaper real prices of gasoline, even large changes in capacity will produce only small changes in travel over time.[17] The argument that travel is thus less sensitive to capacity may be extended to the effect of capacity on land use. The argument is that unless densities are very high (even greater than those found in most U.S. cities), even substantial changes in capacity will not affect land use in the short term (e.g., less than 10 years). The reason is that capacity will not affect land use where a basic level of accessibility has been established, at least within a short time. This explains why historical substantial transportation developments (e.g., invention of the streetcar and the subsequent rise of the automobile) greatly affected the layout of metropolitan areas, but why no change of that magnitude has since taken place. The same argument extends, however, into land use changes being affected in the long term (e.g., greater than 20 years) by capacity changes as these changes have a chance to multiply. Harvey and Deakin discussed the "long implementation horizon" associated with modifying the transportation network to guide urban form but also stated that concepts such as specifying development densities and development boundaries are strategies considered by planning organizations.[16]

Other opinions regarding the relationships among land use, transportation, and air quality persist. Kitamura explained that quantifying the impact of a change in capacity is difficult because the transportation system is composed of interdependent building blocks. The supply of the network drives land use, which together raise or lower the accessibility level of various destinations, and this accessibility determines how trips are generated. The catch is that land use changes occur over time, so the demand created by this network in turn drives the planning process, including the future supply of transportation.[17] Kitamura concluded that additional research in this area is needed, but his views seem to match Harvey's and Deakin's concept of a long implementation horizon, the duration of which is unknown. In contrast to the argument that capacity does not significantly drive land use, the Middlesex Somerset Mercer Regional Council concluded that within a 20-year horizon, changes in land use could reduce trip generation by as much as 60%, based on modeling results that applied various land use constructs (e.g., that certain densities would generate certain rates of trips).[18]

Substantial literature further discusses the relationships between transportation and land use. Burwell et al. cited a California study where denser single-family residences generated substantially fewer daily vehicle trips than less dense single-family residences.[19] Deakin also implied that improved construction techniques may have accelerated the development of suburbs, exurbs, and other areas where large amounts of land are available. As it became more cost-effective to construct entire neighborhoods rather than single homes, the large amounts of land with a single owner outside the city became more attractive to developers than smaller plots

with many owners inside the city. The tendency would then be for newer development to occur outside the central city, in addition to the reasons for suburbanization cited previously. The existence of "relationships among jobs, housing, and transportation" has influenced the direction of research both at the regional level and the more microscopic urban design scale.[20]

Historical land use/transportation studies have focused on other aspects of the planning process. For example, a recent California study investigated the link between highway spending and economic development over a 20-year period.[21] The unique part of the study was that economic development was examined both in counties where increased highway spending occurred and in counties that bordered counties where increased highway spending occurred. The result was that the extra highway funds resulted in greater economic growth for those counties in which the roads were situated (as expected) but lower economic growth in the counties that bordered those counties (not expected). In brief, the extra spending resulted in at least a partial redistribution of economic growth rather than a pure increase in economic growth.

Whether Capacity Effects Are Worth Examining

Clearly, the capacity issue is not resolved. On the one hand, if we believe changes in highway capacity can eventually drive land use development and motor vehicle travel, the implications for air quality and congestion are substantial. On the other hand, if capacity does not affect travel demand significantly, the primary reason for studying capacity improvements is to understand short-term consequences such as travel path selection. *TRB Special Report 245* noted that from an environmental perspective, "route diversion can result in traffic shifts toward or away from areas that are more sensitive to local air quality and noise impacts." The implications for congestion are also evident. For example, peak period traffic increases that occur when a congested highway's capacity is increased result, in the short term, from traffic being taken from other routes or other times of the day.[15]

In brief, although regional travel may not be substantially altered, there clearly is room for investigating whether travel shifts may occur. Particularly, suggestions where shifts of travel on a temporal basis would improve air quality are relevant; an example is Horowitz's graphic representation showing that changes in either nitrogen oxides or hydrocarbons may substantially affect ozone levels. These graphs show that ozone levels may increase if we reduce a precursor emission under certain conditions. Wayne also described this phenomenon.[22] Consequently, from a modeling framework, we need to understand how transportation system usage and capacity may affect land use limits. Two questions arise:

1. In the short term, how may capacity affect trip generation and trip distribution? In more theoretical terms: How does the supply of transportation services affect the demand for travel?

2. In the long term, how may capacity affect urban form, realizing that additional factors beyond capacity (e.g., perceptions of neighborhoods) also affect development? More theoretically: How does the supply of transportation services affect the location and availability of activities? (An *activity* is an event, service, or product, e.g., block of homes, theater, supermarket, that requires its patrons to consume transportation

services.) The question then is: What framework is acceptable for understanding the impacts of travel demand or capacity on land use?

Cause and Effect: Linking Land Use, Transportation, and Congestion

Land use is a function of usage, density, and degree of mixture. Zoning, a regulatory surrogate for land use, is an interesting phenomenon because it may be viewed through two perspectives. From the local (individual) standpoint, it constitutes only two of the three land use parameters: usage and density. For example, a developer may view a particular parcel as being zoned as residential with 40 dwelling units per acre. At the aggregate level, however, we perceive a third parameter: the degree of mixture of land uses. The residents of a large subdivision of townhouses may have substantially different trip making characteristics than the residents of an urban district characterized by a mixture of apartments and smaller business establishments. Land use limits therefore may be viewed as the quantity and type of development a geographical location can sustain, given the constraints of congestion that users will tolerate and emissions that are legally acceptable. These limits both influence and are influenced by changes in the transportation network.

Land use is also affected by the amount of access provided to transportation infrastructure; as stated previously, some have argued that this access (e.g., transportation capacity) has influenced the path of development. For example, one speaker at the 1994 International Road Federation/Institute of Transportation Engineers Executive Conference on Traffic Congestion Management commented that the construction of interstate highways that cut directly from what once were rural areas to the urban core was a substantial contributor to the increase in suburban development in the United States over the past three decades. The California Urban Futures Model supported this reasoning where under certain scenarios, home sales prices increase closer to transportation infrastructure.[23,24]

Finally, the temporal distribution of development should be considered a descriptor of land use. Putman alluded to this phenomenon, noting that a land use and a transportation system are never in equilibrium. Putman's reasoning complements a distinction suggested by Harvey and Deakin's "planning horizon" that some responses to capacity change, such as a varied traffic pattern, will take place much more quickly than other responses to capacity change, such as a shift in housing locations.[25] Obviously, the transportation network will constantly be affected by these short-term changes while a response to a longer term change is being formulated. Rodrigue also touched on this issue in his comparison of optimal and functional levels of interaction between transportation and land use systems.[26] (Not all aspects of land use can evolve at the same rate in response to changes in capacity. For example, with regard to a zone's square footage of commercial space and the number of employers in the zone, if access to the zone is decreased, the change in employers may occur more quickly than any noticeable change in the amount of commercial space in the zone.)

In conclusion, we realize that land use may be represented by the type of use, density, degree of mix, proximity to transportation services, and current state of development. Many researchers have used these concepts to develop simultaneous equations relating transportation

supply, transportation demand, and land use, although implementing such equations is more difficult than developing theory. Manheim diagramed interactions among the transportation system, activity system, and resultant flows of people and goods moving through the network.[27] Manheim went on to write a set of state equations that reflect these three systems, using service functions and demand functions to describe the supply and demand, respectively, placed on the transportation system. These equations may thus be solved simultaneously, although Manheim noted the distinction between short- and long-term equilibrium resulting from quick changes in vehicle routing contrasted with slower changes in urban form. Rodrigue argued for using neural networks to model interactions between transportation and land use, citing relationships among four key systems: land use, the transportation system, interactions, and socioeconomic characteristics. Like Manheim, Rodrigue pointed out the interrelationships among these systems.

Prior Information, Convergence, and Data Issues

Alternative Methods for Deriving a Trip Matrix from Traffic Counts

Although several steps are required to reverse the direction of the planning process, one of the most difficult is to obtain a trip distribution matrix from traffic counts. Generally, the available models assume a constant land use, a specified target trip table that guides the solution, or both. Two broad categories of techniques for moving from traffic counts to the trip distribution matrix are:

1. *Linear programming/cost minimization methods*, where some type of optimal function is sought (e.g., minimization of total travel time). Penalties in the form of artificial variables may be included to reflect the characteristics of the particular transportation network.

2. *Maximum entropy methods*, as developed by Van Zuylen and Willumsen (often referred to as the minimum information approach) and modified by others.[28]

A variety of additional methods are outlined in the literature, such as parameter calibration methods that employ regression analysis along with an assumption of how trips should be distributed.[29] The salient features of the two major techniques is that different assumptions are made in going backward from traffic counts to trip distribution matrices, as one set of traffic counts may give rise to many trip tables even if the traffic counts are replicated precisely.

In both cases, the constraints are the traffic volumes, and in the absence of prior information and presuming explicit path enumeration, we may write these respectively as

linear programming/cost minimization, **minimize:** $\sum_{ijk} C_{ijk} \bullet T_{ijk}$

entropy maximization, **maximize:** $-\sum_{ijk} (T_{ijk} \bullet \ln|T_{ijk}|) - \sum_{ijk} (T_{ni}) \bullet \ln(T_{ni})$

where C_{ijk} is the cost of traveling from zone i to zone j via path k, T_{ijk} is the number of trips using that path k from i to j, and T_{ni} represents the no traveled state for i. That is, T_{ni} reflects the fact that there may be persons in zone i who elect not to travel at all.

The entropy model uses a different philosophy than the cost minimization model. Rather than minimizing the total costs or user costs (depending on the path selection criteria), the entropy model seeks to maximize total entropy. In short, the entropy model will tend to spread things out rather than concentrate on assigning a value to the lowest cost variables. This is especially useful because of the results later obtained with the cost minimization model on the 1967 network, where many zonal interchanges were computed as zero.

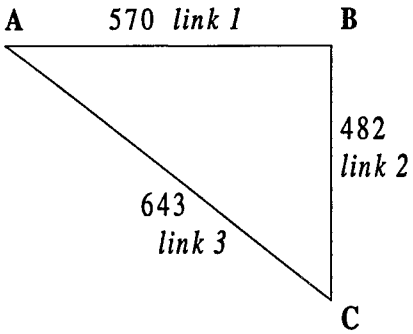
In other words, the cost minimization and entropy models represent two fundamentally different approaches, but both can be governed by constraints. The former seeks to minimize total travel costs, and the latter seeks to maximize the number of persons in each state. To pick one approach over the other arbitrarily would be incorrect. For example, the cost minimization approach uses speeds or a generalized function of travel cost. If we have relatively accurate measures of travel cost and reason to believe that travelers will tend to follow them, that approach is worth considering. On the other hand, if we do not have very much information about the network, the entropy approach may be preferable.

A relatively surprising example is shown with a simple three-link one-way network, where there is just one path between each origin zone and each destination zone. Further, travel is just one way. To go from zone **A** to zone **B,** we must traverse link 1, but to go from **B** to **A,** we must traverse link 2 and then link 3. For the cost minimization method, we can consider two scenarios: a short path favored approach, where the paths that use two links have a cost of 2.0 but the paths that use one link have a cost of 0.99, and a long path favored approach, where the paths that use two links have a cost of 2.0 but the paths that use one link have a cost of 1.01. Both versions of the cost minimization approach yield substantially different answers from the maximum entropy approach: the latter tends to spread out travelers into the various states, whereas the former concentrates trips into the lowest cost categories. These results are shown in Figure 1.

These results make intuitive sense. In each cost minimization approach, the path costs drive the solution, whereas in the entropy approach there is an attempt to distribute the values as much as the constraints will allow. Clearly, the choice of one of these approaches over the other depends on the amount of data available, the structure of the network, and the decisions of travelers.

To maximize the entropic function, it is often not the case that the function is optimized directly when the network is relatively large. Instead, iterative solutions can be employed. Unfortunately, this means addressing issues that arise with respect to how to accomplish the iterative method in terms of providing a starting solution and achieving convergence.

Sample Network



Volume of Trips Using Each Path

Path	Short Trips Favored	Long Trips Favored	Maximum Entropy
A to B	570	0	189
A to C	0	204.5	150
B to A	0	277.5	183
B to C	482	0	149
C to A	643	0	230
C to B	0	365.5	231

Figure 1. Comparision of Entropy and Cost Minimization Approaches

Use of Prior Information for Deriving an Origin-Destination Table (Trip Matrix)

Van Zuylen and Willumsen pointed out the possibility of using prior information to achieve an optimal solution, and this indeed is the common practice (e.g., The Highway Emulator Model).[28] For purposes of using traffic counts to update an old trip table whose basic purpose is then to develop new traffic counts, such an approach appears reasonable, as illustrated by much of the literature (e.g., Wang and Wilson).[30] Using an old origin-destination (O-D) table to determine a new one does not necessarily appear reasonable if changes from the former to the latter result from land use changes.

Van Zuylen and Willumsen suggested that based on previous work, a "target trip table" can help guide an entropy maximization scheme to a "correct" solution.[28] We, however, suggest that although such an application is useful when land use is constant, it does not appear appropriate for cases where land use may have changed since the creation of the target trip table.

For our purposes, it is relevant to consider how prior information is used in deriving a trip table. In other words, if we have no prior information, we simply seek to maximize entropy subject to the appropriate constraints, but with the prior trip table, we essentially adjust values obtained by the entropy method to match those from the prior table. The question is: Does this make sense? If land use parameters and other conditions that underlie the trip table remain constant, perhaps so. Yet, such an assumption is not valid if we consider that perhaps the "true" O-D table has changed not only as a direct result of linear growth in traffic counts but also as a result of travel patterns themselves. A trip table is a result of derived demand for travel, and indeed, planning studies are conducted often because the conditions that generated the previous study are no longer valid. In brief, if the socioeconomic and land use patterns that underlie trip distributions have changed, it is not appropriate to guide solutions necessarily toward an "old" trip table. Experiments with a hypothetical network illustrate this concept, where land use changes were superimposed and resultant traffic counts updated: a better estimation of the "real" trip table was obtained when an old trip table was not used. Whether an old trip table is more helpful than not will depend on how far the entropy solution differs from the correct solution in

the first place and the degree to which the underlying patterns have changed. In the extreme, however, we can quickly see the futility of such an approach, as with an area that grows where initially a zone has no activity. Increased traffic to and from that zone would mean it is producing or attracting trips, but the equations show how we could mistakenly assign the source of the activity elsewhere.

Methods for Relating the Trip Matrix to Expected Travel Impedance

If traffic counts are used to derive a trip matrix but no prior information regarding land use or a previous trip matrix is to be employed, there needs to be a method for deriving the trip matrix. One alternative is to derive the seed value for each t_{ijk} from the travel impedance of that path. Sen and Soot suggested a method that is relevant to this travel impedance determination.[31]

Sen and Soot outlined a method for determining the gravity model based simply on comparing observed flows between zones. Using an expanded form of the gravity model as $T_{ij} = P_i A_j M_i N_j F_{ij}$, where M is an adjustment factor for production zone i and N is an adjustment factor for attraction zone j, we may cancel out the A, P, M, and N terms such that we can write

$$(T_{ij} \bullet T_{ji})/(T_{ii} \bullet T_{jj}) = (F_{ij} \bullet F_{ji})(F_{ii} \bullet F_{jj})$$

The key advantage of this concept is that we may use a historical O-D trip table along with a least squares application to determine the friction factors, shown here as the F_{ij} terms. These friction factors are similar in meaning to those used in the traditional four-step planning process (which consists of trip generation, trip distribution, mode choice, and traffic assignment) although the method for deriving them as shown in the equation is slightly different from the iterative procedure typically used for gravity model calibration. The Appendix details this derivation of the friction factors.

Returning to the problem of deriving O-D trip matrices from traffic counts, Han and Sullivan noted an interesting phenomenon: even when a predicted and an actual trip table are substantially different, they may produce similar results when both are "assigned" to the network.[32] Hence, it is important to note how we are measuring performance: whether by predicting trip tables from traffic volumes or vice-versa. This affects the typical scheme of using traffic counts to update old O-D tables that are then assigned to the network: similar transportation performance measures can arise from very different O-D configurations.

Validation of Forecasts

Most of our literature review focused on methodologies for modeling transportation and land use relationships. Toward the conclusion of this effort, however, it became apparent that there was some discussion of attempts to measure the accuracy of forecasts generated by transportation planning models. In 1995, Hartgen identified deficiencies of large-scale models, one of which was an unrealistic statement of precision.[14]

In a review of land use allocation methods, Bajpai noted: "Almost no 'before and after' or ex-post evaluation results are available pertaining to the accuracy and quality of various forecasting and spatial allocation methods."[33] The author did mention a few exceptions, however. One is the San Francisco Project Optimization Land Information System (POLIS) model that, with a 5-year difference between the base year calibration and the forecast year, predicted housing and employment with R^2 values of 0.74 and 0.78, respectively. Further, using a 1980 base year and a 1985 forecast year, Putman obtained relatively good correlation between 1985 predicted values and 1985 actual values for employment and household type.[34] The same author also pointed out problems arising from data incompatibility, such as a disparity between how employment was classified in 1980 and 1985. In a retrospective examination of the 1962 Chicago Area Transportation Study, McDonald explained that 1980 travel demand forecasts were accurate: overestimates of population and employment were mitigated by underestimates of the number of trips per person. An example given for the city is that population was overpredicted by 23% and vehicle ownership was underpredicted by 24%. The accuracy of estimates by individual zone was not given, but aggregate estimates, such as the travel between all other zones and the CBD, are stated to be accurate.[35] Hence, this suggests a difference in accuracy between aggregate predictions and disaggregate computations.

Other works, although not explicitly calling for additional validation of transportation planning models with historical data, offer evidence implying such exercises could be worthwhile for specific aspects of the planning methodology. These works address forecasting issues with respect to specific components of urban travel demand forecasting, namely trip generation, mode choice, and traffic assignment. The examples that follow illustrate the compatibility of a "before" data set and an "after" data set.

In a review of forecast ridership levels for major rail transit projects, Pickrell pointed out that actual ridership levels were 28% to 85% less than what had been expected prior to the construction of the facility.[36] The long horizon between the base and forecast year is offered as a contributing factor to the disparity between actual and predicted ridership levels as it adds uncertainty to key independent variables that reflect employment and population patterns, automobile costs, or economic conditions. On a positive note regarding longitudinal data utility, Purvis reported that household surveys for the San Francisco Area from 1965, 1981, and 1990 were sufficiently compatible to warrant comparison of trip generation rates by various modes.[37] Purvis also stated that this exercise illustrates the need to update non-work trip generation models, since the number of such trips per household actually decreased over time.

Other studies using longitudinal data with mode choice models shed some light on the importance of historical validation. Seven mode choice models (for determining whether trips would be automobile, transit, or pedestrian) specified from a 1964 data set were tested with 1986 data for Toronto; the model that had the best fit with the 1964 calibration data did not perform the best with the 1986 data.[38] Those researchers suggested that the model suffered because of an overtraining phenomenon: it was so oriented to the 1964 data that changes in the urban environment were more detrimental to that model than to more generalizable models. With a smaller 5-year horizon, though, survey data from the Orlando area suggested that opinions regarding mode choice remained constant between 1973 and 1978. Similarly, from a data set prior to the construction of the Bay Area Rapid Transit (BART) System, a 1973-1974 survey, and a 1975 survey, it was concluded that the coefficient estimates of a model that predicted mode

choice for work trips would remain stable in the short run. A warning was given, though, that, as the planning horizon increases, it becomes less likely that a model will continue to reflect travel choices.[39]

Kannel and Heathington suggested that trip generation expressions based on 1964 household data (rather than zone data) could successfully make predictions based on 1971 data.[40] On the other hand, a comparison of survey data from 1960 and the late 1980s showed that trip generation rates could change markedly depending on whether stratification for the cross classification technique was by household size, income, or automobile ownership.[41] Although the aim of that study was to measure temporal stability of trip generation rates, the researchers acknowledged that the accuracy of long-range forecasts is not guaranteed even when temporal stability is achieved. They also noted at least three data compatibility issues: (1) the movement of the regional cordon line between surveys, (2) the fact that a person going to a convenience store on the way home from work would be recorded as a single home-based work trip in the 1960 survey versus "a non-home-based trip from work to shopping and a home-based shopping trip to reach home," and (3) the need to convert 1960 dollars to 1988 dollars. Further, over the past few decades, the distribution of trips by purpose has changed, with nonwork trips becoming more prevalent.[42]

Historical studies have also been accomplished with the trip distribution and traffic assignment steps. Levine, who compared San Francisco commuting patterns with data from 1981 and 1989, noted that there were "incompatibilities of data sources"; in spite of this, however, the author was able to study the relationships between commute distance and income that evolved over that 8-year period.[43] On the other hand, 1989 traffic levels predicted from a 1983 base year were substantially lower than the actual traffic levels.[44] The reason given was that the route choice parameters used to define user cost were initially developed in 1981 and had changed considerably since that point in time.

Thus, the results from the literature appear mixed with regard to measuring forecast year performance of models. Three potential obstacles can be observed: First, a study area must have data elements defined in a consistent manner over time such that one can make a meaningful comparison of their values. Second, as the planning horizon becomes larger it becomes more challenging to have forecast year predictions match what actually occurred. Third, for approaches that rely on multiple steps performed in sequence, errors in one step early in the process may propagate (and magnify) as additional computations are performed.

Task 2: Synthesize Data from Charlottesville Planning Studies

The Charlottesville area developed over a 200-year period and by 1940 had a population of approximately 20,000.[45] In 1947 and in 1957, two transportation-related studies were conducted, and then in 1967, 1979, and 1990, full-scale planning efforts were undertaken.[46] It was tempting to try to use the data from all five efforts, but there would have been substantial differences between the two earlier efforts and the three later planning projects; for example, there is no O-D trip table from the two oldest efforts. Thus, we chose to restrict the scope of the project to the three later studies, beginning with 1967 as the earliest year. An alternative for

future research would be to select the most central portion of the Charlottesville area and work with data from all five time periods, with the result being a study that was smaller in scope geographically but larger in scope temporally.

In retrospect, a big problem with this effort may have been the disparity between the base year when the socioeconomic parameters were developed and the base year where the traffic counts were taken. For example, a study we refer to as "1979" was fully initiated in 1974 and published in 1985. Census data from 1970 were extrapolated and sometimes collected for a 1974 socioeconomic year, but 1979 traffic counts appear to have been used for the study. Thus, a 5-year lag exists between counts and socioeconomic parameters for the 1979 planning study; this lag is substantial when compared to the 11-year lag between the dates of the actual studies. Compounding this issue is the fact that the 1979 study contains counts from 1984. Further examination of the unpublished 1981 technical report shows, however, that the 1984 study actually used 1979 counts to develop its future projections. Hence, the 1984 counts were merely cosmetic.

Finally, the "1967" study was initiated in 1965 and terminated in 1967, and the "1990" study was begun in 1987 and finished in 1990. Thus, the gap between the beginning and termination of these studies is not as large for these studies as is the gap for the 1979 study.

Data Preparation

We contacted a wide variety of persons for planning information regarding the study area. The Charlottesville Planning District Commission, Albemarle County Planning Office, Charlottesville City Planning Office, Virginia Department of Transportation's (VDOT) Central Office, VDOT's Charlottesville Residency, and individuals who had been involved with planning efforts provided data, insights, contacts, or comments. We also scoured institutions, libraries, planning studies, and census data for Charlottesville data. A variety of publications, electronic data files, software packages, unpublished drafts, and handwritten notes provided necessary information regarding traffic assignment, trip distribution, and trip generation within the study area for the 1967, 1979, and 1990 planning studies.

We then synthesized base year data by category: traffic assignment, trip distribution, trip generation, land use, and zonal linkage among the studies. We checked how well the data could be linked spatially and temporally. Although in some cases we had to estimate missing base year data, most of the time, we could obtain the necessary data directly from either base year planning studies or other agencies.

In this effort, we were dealing with two issues that do not normally arise in transportation planning studies. First, we were linking data collected at different times by different persons, with the attendant differences. Second, the scope of the study area evolved, such that transportation or land use elements considered "outside" the study area in the 1960s may have become much more important in 1990.

Traffic Assignment Data

We viewed transportation system data, such as link volumes, operating speeds, peak hour factors, and roadway types, as essential inputs for the base and forecast year models and thus sought them for all three time periods. The availability of these data varied with each study.

1967 Data

In the 1967 planning effort were 115 roadway segments totaling 60 miles in length within the City of Charlottesville and the County of Albemarle. For most of the links, the length, average operating speed, average daily travel, directional distribution, and peak hour volumes were directly available from the planning study.

For the few links for which the operating speed was not available, we used the 1963 *Charlottesville Traffic and Parking Survey* speed data for the link, if available.[47] For the remaining minority of links, we hypothesized that a link's operating speed would be a function of its geometric characteristics and congestion level. The geometric characteristics would be related to the number of lanes and the service volume, and the peak hourly volume and peak hour factor would help estimate the congestion level. For two-lane links only, we used the segments that did have complete data to develop three linear regression models to describe speed as a function of the volume-to-service volume ratio and the peak hour factor.

We generated three equations that predicted speeds based on roads with service volumes of 600 to 699 vehicles per hour (vph), 700 to 799 vph, and 1,100 to 1,199 vph, respectively. We dropped the peak hour factor from the equations, leaving only the peak hour volume as the independent variable; this resulted in an R^2 of 0.89 for predicting speeds when the service volume was between 1,100 and 1,199 vph and relatively low R^2 values for the other two cases. Therefore, we computed speeds for roadway segments with service volumes in the range of 1,100 to 1,199 vph using the regression equation, but for the other two cases we adopted similar speeds from close links in the network. For a few links where the use of other link speeds did not appear reliable, we used the 1965 *Highway Capacity Manual.*[48]

Finally, in a few cases, we treated two segments as one to facilitate comparison with other study periods. In those cases, we weighted the speed by link distance to determine overall speed as a function of total distance and travel time.

1979 Data

From the 1979 study, 390 roadway links were available in paper format, with only the length, number of lanes, and average daily travel (ADT) available. Speed data were not available from these reports. Fortunately, however, we found in VDOT's Fulton Warehouse handwritten notes that contained a link node map. We and a technician matched the node numbers on the map to node numbers from a computer output file provided by VDOT, which related speeds to traffic links. In one case where a link's speed could not be found, we used the

speed for an adjacent link. Although time-consuming and prone to error, this appeared to be the only method through which we could realistically derive operating speeds on the 1979 network.

In the appendix of the 1979 study, formally published in 1985, are several roadway segments where the year 2000 "projected" ADT is smaller than the 1984 "measured" ADT! For example, a 0.40-mile stretch of Route 29 from the city boundary to the Route 250 Bypass had a volume of 42,100 in 1984 but was projected to have a volume of 37,500 in the year 2000. Did planners really expect the traffic volume on Route 29 to decrease over time? In the unpublished 1981 technical report, we find a likely answer: the appendix shows the year 2000 projected volumes and the 1979 ADT and still projects the same volume as the 1985 report. The report shows a 1979 volume of 34,260. For all of the links we examined, the 1981 technical report and the 1985 published report have identical year 2000 projected volumes. It appears therefore that (1) the 1979 volumes were used to develop the year 2000 projections in the 1981 report and (2) these projections were not updated in 1985, but the planners chose to remove the 1979 volumes and replace them with 1984 volumes in the Appendix. This is our opinion and is not formally documented. In light of this, we used 1979 traffic volumes except for approximately 7% of the roadway links where only the 1984 volumes were available.

1990 Data

For the 1990 study, data were surprisingly limited. The *Route 29 Corridor Study* showed only some of the links with posted speeds, peak hour speeds, average travel speeds, and screen line counts.[49] (A screen line is an imaginary line traversing a large portion of the study area.) The electronic format for that study, however, showed distance, computed speed, volumes for a few links, and the number of lanes for each link.

Hence, for the estimated 214 links in the study, many link volumes were not known and many link speeds were not known. We obtained some volumes from VDOT records of traffic counts in 1988[50] and other from VDOT records of annual counts.[51] For 7 of the links, we used traffic assignment volumes, although inaccurate. For an additional 24 links, we used 1984 volumes, and for 3 links, we used 1979 data as 1984 counts were not available. Finally, for 5 links, we felt it acceptable to estimate a volume based on historical volumes and neighboring link volumes.

For determining operating speeds, we used the TSVA parameter shown in the MINUTP software package as we thought it provided a relatively reliable measure of speed. One could argue that we should have used the software's computed speed based on computed volume/road type estimations. However, computed speeds are often modified in the traditional forward four-step process to bring computed volumes in line with select real volumes. The four-step process consists of trip generation, trip distribution, mode choice, and traffic assignment. Therefore, we felt the TSVA parameter was more reliable since it was estimated prior to any changes to the computed vehicle speed.

Coding Decisions

For the 1967 network, for example, approximately 112 links were listed in the 1967 Charlottesville planning study. Thus, we created a node-based network, with each roadway segment coded as at least one link between two nodes. It was clear, however, that certain roadway segments listed in the 1967 network would need to be subdivided for comparison with the 1979 and 1990 networks. For example, the 1967 data described a 3.16-mile segment of U.S. Route 29 that ran between the Charlottesville city limits and the northernmost portion of the 1967 study area. Yet, this segment spanned several traffic zones from later studies, and future development would be such that it would not make sense to assume performance was uniform throughout the entire 3.16-mile segment. Thus, we subdivided this segment into five links, such that each could be analyzed separately. Details of this coding scheme are provided elsewhere.[3]

Trip Distribution Data

We thought the O-D trip table (affectionately referred to as the trip matrix, trip distribution table, or O-D matrix) to be essential at the outset of this effort, as it reflects either the number of vehicular trips or person trips. In retrospect, given that this table was not as important as expected, a future study might consider incorporating the two efforts from the 1940s and 1950s, which contain planning data but no such table. Unfortunately, a trip distribution table by purpose was not available for 1967 and 1979 data.

1967 Data

The 1967 study had a single 24-hour vehicle trip table with all purposes lumped together. The study also required expansion beyond its 43-zone study area boundary to make the study area compatible with our aggregate study area. To accomplish this, we used the 1963 Charlottesville Traffic and Parking Survey to estimate the number of trips, shown in 1967 as external stations, that were outside the 1967 study area but within the boundaries of the aggregate study area. From that 1963 study, we superimposed a GIS-based zonal map of Albemarle County over a photocopied map of 1963 voting districts. This relationship gave a measure of the external trips used by the 1963 survey that would have been within the aggregate study area, although these trips were relatively few.

1979 Data

The 1979 study contained a single aggregate person trip table between zones that had been thoroughly balanced from the unpublished 1981 technical report. Several computer files with mostly balanced trip tables were also available. After quickly checking the files against the technical report, we obtained a single trip interchange table for all 142 zones from the 1974 table. This trip table, unlike the 1967 trip table, is a person rather than a vehicle O-D trip table.[52] Unfortunately, it is not clear what auto occupancy rates the authors assumed to convert person trips to vehicle trips, although the "tested" rates ranged from 1.25 to 2.0.

1990 Data

The 1990 report had several items such as auto occupancy rates and friction factors, but the electronic format for trip tables was shown for all three purposes: home-based work, home-based other, and non-home based. Obtaining these data required their extraction from the electronic version and then conversion from a binary to ASCII format. As with the 1979 study, the trip table is a person trip table, with auto occupancy rates from 1.12 to 1.70 presumed.[49]

Conversion of 1979 and 1990 Person Trip Tables to Vehicle Trip Tables

It is a mild statement to say that we experienced consternation when faced with the task of deducing vehicle O-D trip tables from person O-D trip tables. For the 1979 study, various occupancy rates were tested but the results of these tests were not available. Hence, we examined historical efforts on a national scale that concerned vehicle occupancy rates.

On the surface, these would appear to be relatively high. For example, Pisarski wrote that such rates were, on average, 1.9 in 1977, 1.7 in 1983, and 1.6 in 1990, with work trips being less than average.[53] (Similarly, the National Public Transportation Survey [NPTS] cited figures of 1.89 in 1977, 1.75 in 1983, and 1.64 in 1990.[54]) On the other hand, these figures appear relatively high when compared to earlier cited field studies. For example, internal auto occupancy rates between 1958 and 1965 ranged from 1.42 to 1.70 for 19 areas throughout the United States, a strikingly low figure considering that rates have decreased since that time.[55] Likewise, rates over a 12-hour period prior to 1981 in the Atlanta area ranged from 1.35 to 1.56.[56]

The reason, perhaps, for the NPTS rates being high is that they include all types of trips, including vacation trips, for example, which would increase the overall total. Yet, the average of the Charlottesville 1990 occupancy rates for three types of trips is substantially lower than the 1990 NPTS overall figure, with the former being 1.64 and the latter being 1.53. If the NPTS category "social and recreational" is removed, however, the average is 1.53 from the NPTS compared to 1.52 from Charlottesville. Such a comparison should be taken with a grain of salt. The true number of vehicle trips is not known, and the averaging method is imperfect. Yet, this suggests that the occupancy rates used by planning studies do not attempt necessarily to include all types of trips, and we speculate that the key element here is that the occupancy rate will be lower than that used by the NPTS.

We divided by the NPTS figure of 1.53 to convert the 1990 person trips to vehicle trips. Similarly, the 1979 NPTS figure, an average of the 1977 and 1983 NPTS figures (minus the category of social and recreational), is 1.83. Likewise, we divided the person trip table by that figure to obtain the vehicle trip table for 1979.

Trip Generation Data

We sought socioeconomic data, such as number of students living in a particular zone, number of schools, labor, and employment, for all three study periods.

1967 Data

The 1967 study had a single aggregate table giving trip generation rates as a function of automobile ownership and persons per household. Fortunately, though, by zone, a large amount of socioeconomic information was available: population, dwelling units, blue collar and white collar workers, blue collar and white collar employment, school age population, school attendance, and retail sales.[57]

1979 Data

For the 1979 study, equations for trip productions and attractions by purpose, truck trips, and taxi trips were available from handwritten notes describing the computations. Further, for each zone, the population, dwelling units, retail and non-retail employment, students by zone of attendance, number of parks, and auto ownership were available directly from the 1979 study in paper format.

1990 Data

Zonal data for dwelling units, population, automobile ownership, retail and non-retail employment, and school attendance were available in an electronic format that could also be verified with spreadsheets obtained from the Albemarle County Planning Office.

We decided to exercise caution when presented with the option of using trip generation rates when it became clear that in some cases "adjustment factors" were used to make volumes match the O-D table. For example, the 1990 study noted that "Due to the under estimation of HBO [home-based other] & NHB [non-home based] trips, the productions for those two purposes will be multiplied by 1.7315. This factor was determined by looking at the under estimation after an initial assignment and determining a factor for the under reported purposes."[49] For that reason, we collected socioeconomic data but did not use the trip generation rates cited in the studies directly; instead, as explained in the modeling development, we computed trip generation rates using the data we could obtain.

Acreage and Activity Data by Zone

Determining zonal acreage and land use was one of the more challenging steps in the data preparation. Although some of this information was well documented in the 1979 and 1990

studies, we had to do a substantial amount of work to convert 1967 land use data for specific regions to values for specific transportation analysis zones.

1967 Data

Although zonal specific values were not available, a land use map of the 1967 study area, the land use by district, and memoranda showing which zones fit within which districts were available. The first step was to use the land use map to estimate the percentage of land use by type for each zone, where land use types were given as high density residential, low density residential, commercial, industrial, public, and open/recreational. Also, we gleaned the portions of each zone that were not developed from the map.[58] By overlaying transportation analysis zones over this general land use map, we could estimate visually percentages of each land use type for each zone.

Fortunately, though, there was a way to make this method more accurate for a portion of the study area. In 1967, the 43 zones were divided into 16 districts. Land use totals by acre were given for 10 of these districts (those within the city), and the district area was given in acres for all 16 districts.[59] The districts are referred to in the 1967 planning study and *Planning Projections and 1985 Land Use Plan* (Figure 2, page 3),[58] which details the same map. The 16 districts cover the total 1967 study area, with the first 9 districts appearing to correspond to census tracts, 1 district corresponding to the University of Virginia, and the remaining 6 districts covering portions of Albemarle County.

Further, a document retrieved from VDOT's Fulton Warehouse and labeled as *Tables 1-1j, Existing Land Use, Charlottesville, Virginia Urban Area, January 1, 1968,* showed which zones corresponded to which districts. We know this memorandum corresponds to the 1967 planning study because the zones matched up when we compared the 1985 projected populations in the memorandum and the same on page 69 of the planning study; the confusion is that the memorandum refers to zones 44, 45, 46, 47, and 48, which do not exist in the 1967 study.

We could then fit these estimated land use percentages (gleaned by examining the map) to the district land use totals that were known. The result was estimates of the number of acres in each zone that were used as high density residential, low density residential, commercial, industrial, recreational/open, undeveloped, and public for 32 of the 43 zones from the 1967 study area.

We can summarize this as the following formula:

$$A_{zL} = \frac{\text{(Percentage of developed } z \text{ that has land use } L) \cdot \text{(Percentage of } z \text{ that is developed)} \cdot \text{(Size of } z\text{/Size of the district)}}{\sum_{\text{all zones in the district}} \text{(Percentage of developed } z \text{ that has land use } L) \cdot \text{(Percentage of } z \text{ that is developed)} \cdot \text{(Size of } z\text{/Size of the district)}}$$

where A denotes the land use in acres, z denotes the zone, and L denotes the land use type.

Although these totals were not available for the remaining 6 districts, these districts tended to be less developed than the previous 6 and hence easier to decipher. Thus, the outcome

of these computations is the number of acres for each district by land use and a measure of the degree of "mix" of land uses.

1979 Data

We used several data sources to piece together zonal values. A computer printout entitled *Charlottesville Population Distribution Data: Sequential Run 1 of Population Distribution Program* dated 1/6/1976 showed the acreage for each zone and the amount of developed land. Handwritten notes showed both acreage and land use for the Albemarle County zones, and the acreage totals matched the computer printout totals. Finally, land uses were also shown in a memorandum for the City of Charlottesville.[60] These three items together produced the estimates of the 1979 land use by zone. These data were preferred over the comparable census data as they were zone specific.[61] The memorandum also came in handy because of a state policy "that dictates that employment data be withheld from the public if a situation exists where one firm has 80% or more of a traffic zone's employment or if one employment category has less than three firms in a traffic zone."[62] Thus, where these data were not available from the published planning study, they could be gleaned from the memorandum for transportation analysis zones within the City of Charlottesville.

1990 Data

In the 1990 study, for the zones in Albemarle County only, the area in acres, the type of land use, and an estimate of the number of structures were available. We asked the City of Charlottesville for these data but ultimately did not pursue this request as land use data were later shown not to be as necessary as socioeconomic data. Thus, land use data were the least detailed for the 1990 study, with only the "percent of land developed" being somewhat reliable.

To overcome this problem, we used electronic data files that covered the county area only to compute the percentage of each zone that was classified as "rural." This category, from the documentation available, did not include the 1967 categories (commercial, industrial, residential, open and recreation, and public) or the "service" categories. For zones within the city, we extrapolated the percentage of vacant land from census tracts, an imperfect but practical method.[63]

Zone Correspondence Between Planning Studies

Our initial attempts to overlay the study areas from 1967, 1979, and 1990 did not prove fruitful as there was not an integral correspondence among the zones (e.g., a parcel of land known as zone *a* in 1979 might have been designated as zones *b* and *c* in 1967 and zones *e*, *f*, and part of *g* in 1990). Thus, we examined streams, roads, jurisdictional boundaries, and other features within the 1990 GIS Tiger files until we could discern the 1990, 1979, and 1967 zonal structures. Likewise, we obtained the 1990 roadway network from a transportation planning package and deleted census road classes until the GIS information paralleled the 1990 roadway

network. Then, we deleted additional segments to obtain the 1979 and 1967 roadway classes. We used ArcInfo GIS software (version 7.0).[64,65] Figure 2 shows the study area in 1967, and Figure 3 shows the study area in 1990.

The application of GIS resulted in the development of a table that linked the various zones from the three major planning efforts. We used the table to convert land use and socioeconomic data from the 43-zone 1967 study, the 128-zone 1979 study, and the 228-zone 1990 study to the 50-zone aggregate study being conducted for this research. Figure 3 shows the zones, and Figure 4 shows the roadway network. Only zones 1 through 43 were present for the 1967 study. Further, in 1979, southernmost zone 43 was not part of the study! (For readers familiar with the 1967 effort, there is not a one-to-one correspondence between the zone numbering in that effort and that for the first 43 zones shown in Figure 3.)

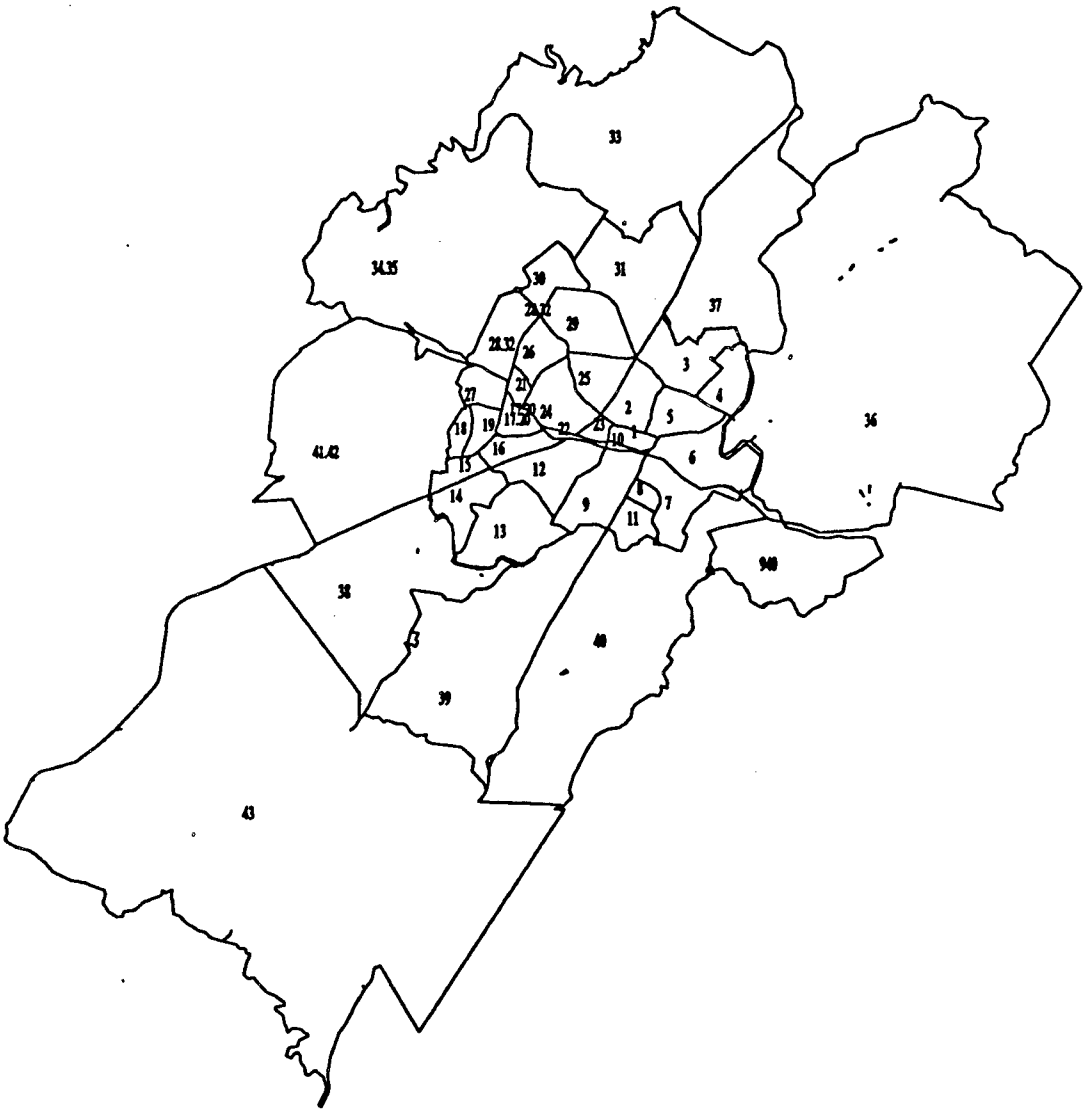


Figure 2. The Study Area in 1967

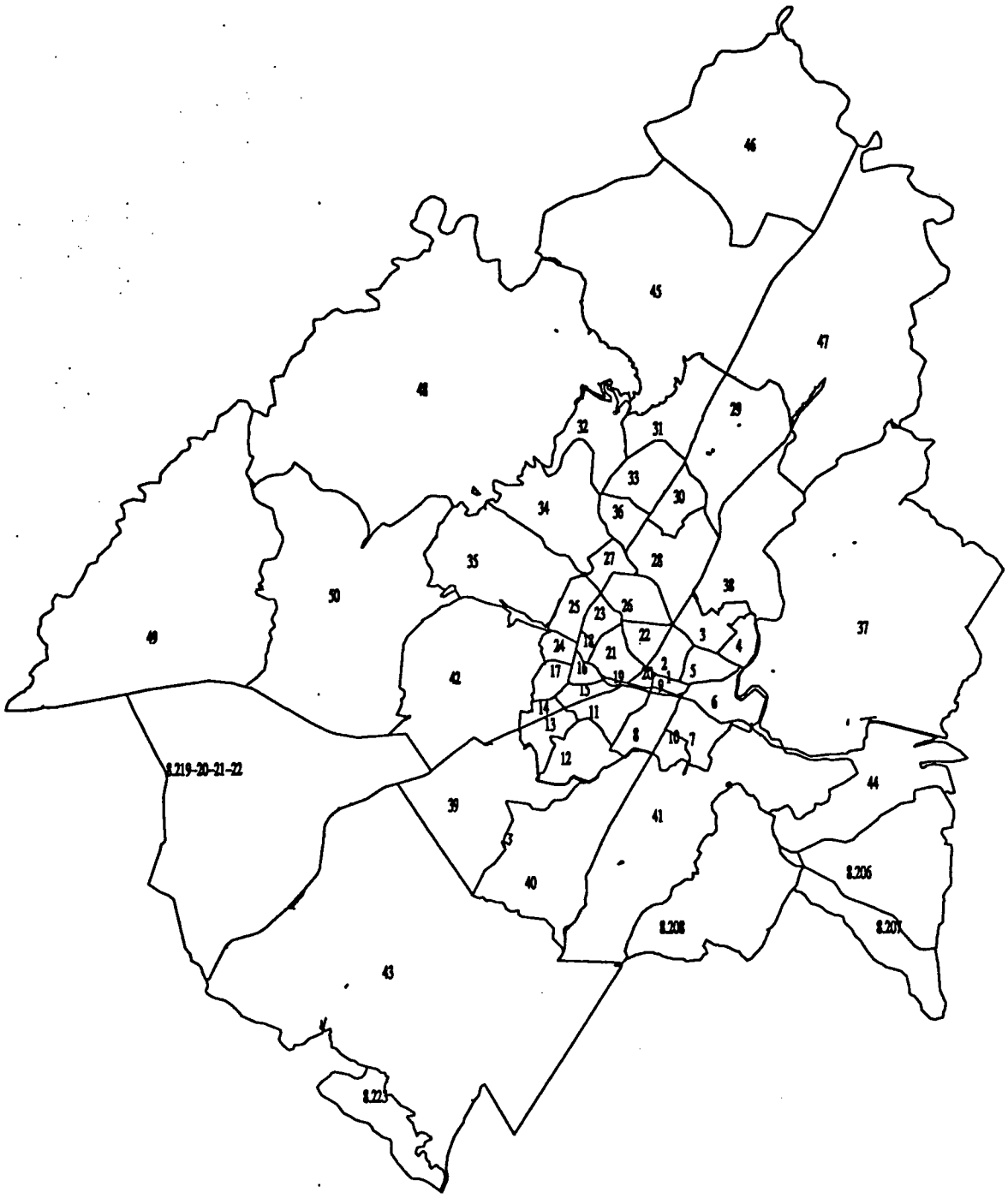


Figure 3. The Study Area Divided into 50 Zones

The outcome of this process is that for each zone in Figure 3, we have an estimate of the transportation, land use, and socioeconomic activity at three points in time. Although this aggregation masks some of the variance among the zones, the basic premise of this work was to evaluate the validity of forecasts. The fact that the study area would exhibit greater variance over time, and hence require a greater number of zones, was not known at the beginning of the

Figure 4. The Roadway Network for the Study Area

time period. Hence, the use of a 50-zone structure was a realistic concept for planners from the 1967 study.

Verification

The extensive processing combined with the continual discovery of errors led us to document how certain procedures were verified to avoid as many careless mistakes as possible (e.g., mistakes we made) and to remedy discrepancies within the data (e.g., mistakes made by

others). We checked data pertaining to land use, socioeconomic characteristics, trip distribution, traffic assignment, and travel path determination. The details of the verification scheme are given elsewhere, but two relevant examples, land use data and socioeconomic information, are included here.[3]

Land Use Data

Toward the conclusion of this effort, we found an opportunity to have a rough estimate of how well the zones had been overlaid between studies. As stated previously, census tract roads, streams, and jurisdictional boundaries had been selectively eliminated to create the 1967, 1979, and 1990 zonal overlays. This allowed us to know, for example, which 1979 zones corresponded to which 1967 zones, how those same zones related to the 1990 zones, and so on. For 10 of the 16 districts from 1967, where a district is a grouping of zones, the total amount of acreage from that district was available. Although the sizes of the 1967 zones could not be obtained, the sizes of the 1979 zones, in acres, were available. Thus, we compared the 1967 "given" district area totals to the 1967 "computed" area totals, where the latter was based on area totals by relating 1979 zones (whose areas are known) to 1967 zones (whose areas are not known). As shown in Table 1, discrepancies ranged from as low as 1% to as high as 14%.

Table 1. Estimated Land Use Errors Using 1967 and 1979 Data

District	Correct Area (acres)	Computed Area (acres)	Error (%)
1	156.7	177.3	13
2	519.2	539.8	4
3	862.9	826.0	4
4	892.9	926.7	4
5	1054.9	1121.6	6
6	216.0	245.4	14
7	1021.0	1042.5	2
8	1018.9	1033.6	1
9	571.9	544.4	5
10	346.3	324.6	6

For zones 44 through 50, we used both 1979 and 1990 zonal acreage from the two 1979 sources and the 1990 computer file courtesy of Albemarle County. Unfortunately, the same file was not available for Charlottesville city zones. Errors ranged from 5% to 21%. Thus, the aggregation posed challenges. Most troubling, perhaps, was that the detail did not clearly progress as the studies moved over time. For example, for zone 43, it was possible to obtain some socioeconomic data from 1967 but not from 1979.

Socioeconomic Information

Since the necessary task of zone aggregation and disaggregation contributed errors, we took steps to reduce them. When we used 1967 socioeconomic data from a computer file, we first verified them by hand. We found several inconsistencies in the computer data and in the

printed data. An example is that zone 6 was thought to have 7,611 dwelling units—a ridiculously large number. Comparison with the other values and the total led us to conclude that the "7" was a misprint. Similar problems were encountered with the other 1967 data. Other errors resulted from data being changed in the course of the studies undertaken at the time; for example, the speeds for the 1979 study may have been modified to accommodate the trip generation or trip distribution steps for that particular effort.

Aspects of the 1990 data were troubling. We had obtained a paper copy of the socioeconomic information from the Albemarle County Planning Office. We checked these data against an electronic file for the same study and, after manipulating the electronic file, obtained similar totals for employment, school attendance, and dwelling units. When we found a difference of 6 dwelling units (of more than 32,000) between the two formats, handwritten notes showed that the same phenomenon had occurred at the time of the study! Yet, the population and automobile totals were different, with those in the electronic format being lower. We speculate that this discrepancy resulted from a category in the electronic file that used "2 or more" automobiles or "4 or more" persons per household. Using the multiplier 2 wrought too low a total, but we found that using 2.51 instead of 2 for automobiles and 5.80 instead of 4 for population made the electronic and paper totals acceptably close. Although this is not proof that the multiplier is correct, this is a reasonable explanation as it matches how socioeconomic categories are often presented.

Clearly, data synthesis and data imperfections affected to some extent the performance of the approach. Although we do not know how much perfect data would have improved the performance of the models, the steps we took illustrate how to minimize the adverse impacts of imperfect data.

Task 3: Implement the Five-Step Modeling Approach

Our initial modeling approach entailed applying five key steps for the 1967 study area in Charlottesville. The detailed testing that led to the establishment of these five steps is described elsewhere.[3]

We give the mathematical derivations of these steps in the Appendix. Although those equations are important for replicating the steps, they are not essential to following the five-step procedure. Therefore, we present only the summary of the five steps here. The Appendix provides the actual expressions and definitions.

The five steps are given as:

1. *Determine the ideal "friction factors" between the various zones of the study area.* A friction factor between two zones represents the difficulty of traveling between the zones. The computation of the friction factors is based on the base year trip distribution matrix.

2. *Determine travel paths whose impedance matches the ideal friction factors.* At least one and usually many possible travel paths exist between two zones. A number of

factors can make one travel path seem more attractive than another, even if both have the same origin and destination. Travel speed, congestion, and the type of roadway facility, for example, may all influence whether one path is more attractive than another. For each O-D interchange, we can use the friction factor, computed in step 1, along with the various path characteristics to determine which paths may have been the most appealing. The mathematical formulation for accomplishing this is a form of regression where a few paths are selected and weights for these paths are determined.

3. *Determine the form of the entropy model to yield the trip O-D table.* Using the travel paths computed in step 2 along with various weights that reflect the attractiveness of each path, we may use either the entropy method or the cost minimization method described in the literature review. Applying the cost minimization method to the 1967 network, however, was futile: regardless of the weights employed, most of the O-D cells were (incorrectly) computed as zero. Thus, we pursued extensive experiments with the entropy formulation at this stage. Unfortunately, extensive availability of ground counts did not seem to improve the performance of this step.

4. *Compute adjustment parameters for each zone.* Variables that influence trip distribution that are not reflected in the friction factor from step 1 may be accounted for at this stage. The existence of these other effects is quantified in the form of a single adjustment parameter for each zone.

5. *Relate base year adjustment parameters and trip totals to socioeconomic information.* For each zone, we may derive values for employment, population, automobiles, and land use characteristics as a function of the trips generated by the zone (computed in step 3) and the zone adjustment parameter (computed in step 4).

One problem initially encountered with step 3 was that the algorithm did not always converge. As explained in the Appendix, this can be overcome by reducing the appropriate exponent within the computer code.

Task 4: Develop a New Approach for Reversing the Direction of the Planning Process: The Direct Estimation Approach

The five-step process represented the culmination of the literature review and theoretical development. Yet, substantial testing showed that step 3 performed poorly: no variant could reveal acceptable zone trip end values. (In this sense, a *trip end* is either a starting or terminating point of a trip.) In other words, neither the entropy maximization method nor the cost minimization method presented estimates of zonal trip ends that could be used to predict relevant socioeconomic parameters. Yet, these trip ends are necessary to have a workable approach for relating land use characteristics to transportation system characteristics. Hence, we considered a different technique for determining these zone trip end values that became the focus of this effort. We called this method the direct estimation method.

Developing this method had three parts: (1) obtain the number of vehicle trips that begin or terminate in each zone as a function of transportation system characteristics, such as 24-hour traffic volumes; (2) use these vehicle trips to determine population, nonretail employment, and employment as a function of these zonal vehicle trips; and (3) formally test this approach, where data were calibrated for 1979 as the base year and then tested with 1990 as the forecast year.

Direct Estimation Model Concept

One can try to predict zone trip ends directly from transportation system characteristics. Upon examination of the roadway network in conjunction with the transportation analysis zones, we can quickly see that some zones have many links with high volumes and others have only a few low-volume links. Intuitively, if the road characteristics of the two sets of highway segments are identical, we would expect the former to have more trip ends than the latter.

Yet, we could also quickly see that if the former were, say, interstate highway segments, it would be incorrect to presume that the counts were representative of trip ends for those particular zones. Instead, they would simply be trips that pass through but do not begin or terminate in those zones. On the other hand, if a segment were a one-way street with an average operating speed of 19 mph, we would expect that a substantial portion of vehicles on the segment represented trips that either began or terminated near the segment.

Unfortunately, most roads do not fall neatly into one of these two categories; e.g., a major arterial street with a speed of 45 mph may carry a mixture of through and local traffic. Further, we could not arbitrarily resolve which variables might be the most important for determining whether a link tended to represent local or through traffic. For example, the zone's position relative to other zones, as well as more definitive aspects such as the classification of the roadway and average travel speed, might or might not be significant. Further, many links were not neatly located within a single zone. Hence, at least two traffic count variables are worthy of consideration: one variable that represents volumes on links only if the link is completely within a particular zone and another variable that could include links that are partially within the zone as well.

Thus, although we knew that the maximum number of trip ends a zone may have would be the sum of all traffic counts on all the links within that zone, the next step was to develop a model that could be calibrated, using the base year traffic characteristics, to predict the current year trip ends. Therefore, we initially included several explanatory variables in the model for the base year calibration:

Variable A. Zone Position Information. We may characterize the position of the zone within the network in a variety of ways. Unfortunately, though, the CBD is not always located neatly in the true "center" of the study area. Further, zones may differ in size, shape, and accessibility. Hence, we employed five measures of position:

1. number of zones between each zone and the CBD
2. number of zones between each zone and the closest edge of the study area

3. number of zones that bordered each particular zone
4. our subjective and visual classification of the zone's centrality based on the zone's proximity to the CBD and the edge of the study area
5. shortest travel distance between the zone and the CBD.

We included item 4 because we hypothesized that a visual assessment might be more representative of a zone's position than the other four measures. Subsequent tests, discussed later, showed that this was not the case.

Variable B. Lane Parameters. Both the physical number of lanes and the corresponding roadway type (local versus through) affect the nature of the trips. We considered four variables in this category:

1. total number of links within a zone that are more than two lanes (which increases the likelihood they are for through traffic, with the exception of one-way segments)
2. this variable multiplied by the corresponding traffic counts on each such segment
3. number of links that are through routes (Routes 20, 29, 250, and later I-64)
4. this variable multiplied by the corresponding traffic counts.

Variable C. Speed Parameters. Likewise, as the operating speed increases, we may suspect that a particular link is more likely to be carrying through traffic. Yet, where should we draw the division? A graph of the speed distribution for the 1967 data suggests a bimodal distribution, with a large hump around 25 mph followed by a more gradual (plateaued and lower in magnitude) hump between 37 and 48 mph. A dip is evident around 32 mph; examination of the 1967 links suggested, though, that a 29 mph breakpoint might be feasible, with links below that operating speed being more likely to carry local trips and links operating above that speed carrying through traffic. Therefore, we used a breakpoint of 29.1 mph with both (1) a zonal variable (average speeds of all links in the zone) and (2) a link variable (positive link volume if the corresponding link was likely a local link [less than 29.1 mph] or negative link volume if the corresponding link was likely a through link [greater than 29.1 mph]).

The utility of these variables in prediction attempts is one indicator of whether the 29.1 mph breakpoint holds for the 1979 and 1990 data.

Variable D. Distance Parameters. We included three zone-based variables and a link-based variable:

1. total distance of all links in the zone
2. average link distance of links in the zone
3. number of links in the zone
4. link distance multiplied by link volume.

Variable E. Count Disparity. Examination of two intersecting links (e.g., two road segments that physically touch at one endpoint) with identical volumes suggests that no trips terminated between the two links. A change in volume suggests the opposite. Hence, we considered six variables in this category:

1. difference in volumes between the intersecting links at each node in the network
2. the same, but only for nodes that had exactly two links
3. number of volume measurements taken for a particular link in the planning study (This variable reflects the amount of activity expected by the planner; e.g., if we wanted to study Route 29, we might take 10 counts in an urban congested area but only 1 count over the same distance in a rural area, with the former choice reflecting more activity for the urban segment.)
4. the same variable as in item 3 except with divisions based on segments; e.g., if one segment had two divisions but only one volume, the segment would contribute a value of 1.0 to the E_3 parameter but a value of 2.0 to the E_4 parameter
5. a variable based on multiplying the link volume by E_3
6. a variable based on multiplying the link volume by E_4.

Thus, each zone had a particular value for the six variables. For example, zone 42 has five links with distances totaling 4.0; so for zone 42, variable D_1 has a value of 4.0.

In addition, we measured the total number of trip ends for each zone via two methods:

1. *Intrazonal counts:* sum of all link volumes that are completely within a zone; this variable is designated as $\mathbf{Count_I}$.

2. *Estimated counts:* intrazonal counts plus all link volumes partially within a zone; these partial link volumes were shared pro rata by the number of zones that share that particular segment; this variable is designated as $\mathbf{Count_E}$.

For example, only part of link 2 is within zone 6. Hence, for zone 6, $Count_I$ would not include the volume associated with this link whereas $Count_E$ would include this volume divided by the number of zones that share link 2. (For variables *A* through *E*, the link volumes were not normalized for simplicity.) Thus, the $Count_E$ variable would have more links than the $Count_I$ variable. (A complication for these definitions is the case where a link has endpoints that intersect two or more zones, such that the endpoints of both links fall within two or more zones.)

In sum, then, the initial model may be represented as

Trip ends in zone i = Function of ($\mathbf{Count_I}$, $\mathbf{Count_E}$, **A, B, C, D, E**)

where **A, B, C, D,** and **E** represent the multiple variables defined in this section. We used a linear regression model to select the most likely feasible independent variables and then used these to construct exponential and linear models. Many of these variables, as explained next,

were not significant. It is with this model that through trips are separated from local trips, and the performance of this model affects the degree to which this task can be accomplished.

Initial Model Calibration

For this new model, a linear fit using all of the variables to predict 1967 zonal trip ends resulted in a slight improvement over the original approach, with an R^2 of 0.40, based largely on the E_5 variable. We then ran a stepwise linear regression that included not only the independent variables but also the logarithmic transformation of all positive variables. This produced an R^2 of 0.79, based largely on one of the measures of zonal centrality (A_1). This variable is essential. Removing it reduces the best possible R^2 to 0.40, which is the same model as that obtained previously. Further, this variable is heavily dependent on the CBD. Removing the CBD from the 43 zones reduced R^2 to only 0.49. The fact that the A_1 variable along with the CBD value helps the model points to the importance of the CBD for predicting trip ends in 1967.

This is a critical finding: Of all the methodologies we employed for going from traffic counts to trip ends for the base year, the most successful was this last effort, and the reason is the role of the CBD as suggested by the A_1 variable. The traffic counts, as coded by us, are not very indicative in themselves of local trip generation, although they are the second most important independent variable in the model for which an adjusted R^2 of 0.79 was obtained. Still, for the 1967 base year, the most important variable is the number of zones between each zone and the CBD, reflected as A_1.

Table 2 presents the best models assuming the existence and nonexistence of the CBD. These comparisons are based on the mean absolute error (MAE) for each model. In addition, the rightmost column of the table reflects the number of zones where the model's MAE (e.g., the model's error) was greater than the total trip ends for that zone. Thus, for the first model with the 1967 network, there were 12 zones where the MAE was larger than the value of the trip ends the model is trying to predict. For comparison purposes, the best and worst of the maximum entropy models from step 3 of the five-component approach are shown in the last two rows of Table 2.

At this point, with the base year calibration, there should be no reason to exclude zone 1, the CBD, from the analysis, except that we know intuitively that the CBD will decrease in importance. Keeping in mind that we should imagine it is the base year (1967), however, we should go with the best fit of the model, since we are not clairvoyant. The second model, shown in Table 2, has 42 rather than 43 zones: including the CBD increases the MAE to more than 1,300.

Several variables had a value of 0. We addressed this in the following manner: for the A_5 parameter, we inserted 0.01 for zones with a value of 0. For the A_1 parameter, we gave zone 1 (the CBD) a value of 0.01. For the remaining variables, assuming 0 was the lowest value, we assigned a value of 0.5 when we encountered a 0. We did this to allow a logarithmic transformation without ignoring the zones with a zero value. It is reasonable for a zone to be

Table 2. Base Year Calibration of Trip Ends

Model	MAE	No. Zones Where MAE Larger Than Zonal Trip Ends (43 max)
Best model that includes CBD (zone 1) Trip ends = 1539 - 3320 • $\ln(A_1)$ + 0.088 • $Count_I$ + 1097 • A_1 - 0.116 • D_4	1099	12
Best model that does not include CBD (zone 1) Trip ends = exp(11.18 + 0.000099 • $Counts_E$ - 0.000036 • E_6 + 0.724 • $\ln(E_3)$ - 0.544 • $\ln(D_4)$)	960	11
Best iterative entropy method (from step 3 of 5-step model)	2516	25
Worst iterative entropy method (from step 3 of 5-step model)	3709	35

given a value of 0.5 instead of 0 when the remaining zones have values in the hundreds and thousands for the variable in question, as was the case with E_1.

Revising the Socioeconomic Model

Further experiments with predicting socioeconomic parameters from zonal trip ends, e.g., extending the work of step 5 in Task 3, showed two deficiencies. First, for some zones, a large number of trip ends corresponded to a large value of employment and a small value for population, or vice versa. Second, it became apparent that certain socioeconomic parameters, such as population, were correlated to other parameters, such as the number of automobiles. Extensive tests suggested the need for an improvement. It also became apparent that although predicting employment and population was feasible, forecasting land use by type was extremely difficult.

In response to this problem, we may combine employment and population or employment and dwelling units into a single expression and attempt to predict those combined variables using trip ends. This would essentially translate into a statement that trip ends predict some combination of home-based trips and non-home based trips and that someone is going to either a dwelling unit or a place of employment. A second option would be to let the zone trip ends be represented as a function of employment, dwelling units, and population in the base year. For example, we could write:

$$\text{Zone trip ends} = A \bullet (\text{employment}) + B \bullet (\text{dwelling units}) + C \bullet (\text{population}) + \text{constant}$$

and then compute A, B, and C in the base year via regression. Then, we could allow the land use limits to be of a form that combines employment, dwelling units, and population such that we would relate an aggregate variable composed of these three terms to forecast year zone trip ends. Such a model would also have an error term as there are a number of factors besides employment, dwelling units, and population that affect zone trip ends but are not included in the model.

Table 3 shows six sets of independent tests recalibrated for each of the three study periods. For all cases, we used the 1967 zone structure; e.g., only roads present in 1967 were

employed along with 43 zones that represented the 1967 study area, although the characteristics of these roads and zones were updated with 1979 and 1990 values as appropriate. The leftmost column shows the dependent variable, and the three right columns reflect the results for each of the study periods treated as a base year. In the first two sets of tests, we assumed that employment and population could simply be added, likely an unrealistic assumption, to produce a simple aggregate dependent variable. In the next three sets of tests, we attempted to use various formulations of the employment, population, and dwelling unit variables to predict the trip ends. The last set of tests tried to predict trip ends but with forcing the model through the origin.

Table 3. Prediction of Combined Work Trip/Home Trip Variable

Dependent Variable	1967 (R^2)	1979 (R^2)	1990 (R^2)
Employment, dwelling units	195 + 0.195 • trip ends (0.65)	192 + 0.276 • trip ends (0.78)	77 + 0.317 • trip ends (0.61)
Employment, population	762 + 0.234 • trip ends (0.44)	746 + 0.408 • trip ends (0.67)	531 + 0.428 • trip ends (0.69)
Trip ends (O_i) (employment, population, dwelling units available)	383 + 4.53 • employment + 1.44 • population - 2.02 • dwelling units (0.81)	None	None
Trip ends (O_i) (employment, dwelling units)	1200 + 4.38 • employment (0.74)	-84.6 + 2.60 • employment + 3.86 • dwelling units (0.80)	894 + 1.77 • employment + 3.46 • dwelling units (0.66)
Trip ends (O_i) (employment, population)	366 + 4.39 • employment + 0.789 • population (0.79)	-53.8 + 2.55 • employment + 1.25 • population (0.76)	754 + 1.81 • employment + 1.45 • population (0.69)
Trip ends (Oi) (employment, population) no intercept	4.52 • employment + 0.966 • population (0.88)	2.53 • employment + 1.23 • population (0.91)	1.95 • employment + 1.69 • population (0.90)

These results show that there is hope to combining home-based parameters and work-based parameters, letting the former be represented by the number of dwelling units or population, and allowing the latter to be represented by the number of employment positions. Clearly, it does not make sense, though, necessarily to write a function of employment, population and dwelling units as this combined variable. The 1967 model containing all three variables would falsely lead us to believe that increasing dwelling units would be linked to a decrease in trips!

The last four rows suggest what we could do if we decided not to define *a priori* how home-based trip ends and non-home based trip ends should be related to zone totals. Instead, we can try to develop a model that relates total trip ends for each zone to a combination of employment and population. Yet, the last two rows suggest the limits of this technique: even when the intercept is removed, the combinations of employment and population vary for each study period. That is, in 1967, the linear model might have suggested that every additional person would increase the number of trip ends by 1.0, whereas the 1979 and 1990 models would

suggest that every additional person would increase the number of trip ends by about 1.2 and 1.7, respectively. Similarly, the 1967 linear model suggests that every additional employment position would increase the number of trip ends by approximately 4.5, whereas the 1979 and 1990 models would suggest corresponding increases of only 2.5 and 2.0, respectively. There is a good theoretical reason for forcing the models through the origin: a zone with no population, no retail employment, and no nonretail employment would presumably not generate or attract any trip ends.)

Finally, we wondered if the variation in coefficients of population and employment over the three study periods could be explained by differentiating between types of employment. We would expect nonretail employment to attract mostly "work" trips and retail employment to attract some work trips but also a variety of nonwork trips. Therefore, we did regressions for the three studies with and without going through the intercept and restricting independent variables to retail employment, nonretail employment, and population in an effort to predict zonal trip end totals. Unfortunately, 1967 employment was divided only into blue collar employment and white collar employment with no classification of retail versus nonretail. Table 4 shows these results.

Table 4. Prediction of Combined Work Trip/Home Trip Variable With Split Employment

Variable	1967 (R^2)	1979 (R^2)	1990 (R^2)
O_i (intercept)	325 + 6.08 • white collar employment + 1.10 • population (0.80)	85.9 + 8.89 • retail employment + 1.53 • nonretail employment + 1.04 • population (0.98)	160 + 7.19 • retail employment + 1.42 • nonretail employment + 1.35 • population (0.94)
O_i (origin)	6.23 • white collar employment + 1.26 • population (0.89)	8.90 • retail employment + 1.56 • employment + 1.07 • population (0.99)	7.28 • retail employment + 1.45 • nonretail employment + 1.40 • population (0.98)

Yet, we can consider the 1979 and 1990 cases, both of which show employment and nonretail employment by zone: an increase in retail employment positions of 1.0 corresponds to an additional 8.9 trips in 1979 and an additional 7.3 trips in 1990, whereas a similar increase in nonretail positions meant an additional 1.6 trips in 1979 and 1.5 trips in 1990, which are relatively close. Similarly, an increase of a zone's population by 1.0 corresponds to an additional 1.1 trips in 1979 and an additional 1.4 trips in 1990. This suggests that there is some consistency in the relationship between trip ends and these socioeconomic parameters even for different time periods; such consistency is very useful if the relationship is to be used as a prediction tool. Considering that this is based on 1979 and 1990 networks with only 43 zones, we suspect there is hope for even more improvement if we include the entire network. The right two columns are shaded as these years not only represent high adjusted R^2 values for a linear model but also encompass similar structures and coefficients. In both cases, for example, the coefficient for population is relatively low compared to the coefficient for retail employment.

Certain dependent variables should not be analyzed separately in some situations. A case in point is the relationship of employment positions and population: some zones will have a high number of trip ends because of the former and some zones will have a high number of trip ends because of the latter. By combining these two variables, we have a better chance of developing a workable model; by not arbitrarily adding them but instead using a simple technique to see how

they relate to trip ends, we have a semi-rational basis for understanding how they combine to influence trip ends. By recognizing that two categories of employment have strongly different influences on trip making characteristics, we can better distinguish the import of changes in one type of employment versus another with respect to zonal trip ends.

Formulating the Final Model and Evaluating Its Performance

Model Summary

After tests with the 1967 base year (to predict 1979 trip ends) and the 1979 base year (to predict 1990 zonal trip ends), the 1979 base year trip end model is given as:

$$\text{Zonal trip ends} = -827 + 0.027 \bullet X_1 + 0.039 \bullet X_2 - 1{,}807 \bullet \ln(X_3) + 685 \bullet \ln(X_4) + 96.1 \bullet X_5 + 1{,}729 \bullet \ln(X_6) \qquad (eq\ 1)$$

where the variables are redefined for simplicity as:

X_1 = number of links that are through routes, such as interstates and major arterials, multiplied by the corresponding traffic counts

X_2 = sum of all link volumes that are completely within a zone

X_3 = number of zones between each zone and the CBD

X_4 = shortest travel distance between the zone and the CBD

X_5 = number of subdivisions a segment received in the base year planning study

X_6 = number of zones that bordered each particular zone.

Although we tested other models and variables, this formulation performed the best in the base and forecast years, and all variables were statistically significant. An initial concern had been that the formulation had too many variables that are dependent on the position of the zone, but this did not adversely affect the performance of the model.

The aggregate socioeconomic model is given as:

$$\text{Zonal trip ends} = 1.64 \bullet \text{nonretail employment} + 9.36 \bullet \text{retail employment} + 1.11 \bullet \text{population} \qquad (eq\ 2)$$

where the assumption is that the proportions of nonretail employment, retail employment, and population in the study area will remain constant from 1979 to 1990. We discuss the impact of this assumption on the model's performance later.

Base Year Calibration With 1979 Data

The trip end model was calibrated with base year 1979 data, yielding an adjusted R^2 of 0.77, and an MAE of that was approximately 27% of the average zonal trip end value (Figure 5). In the aggregate, however, the predicted number of trip ends for the entire study area was within 1% of the correct trip end total. (Thus, the MAE reflects the difference between computed and actual trip ends for the 1979 base year.)

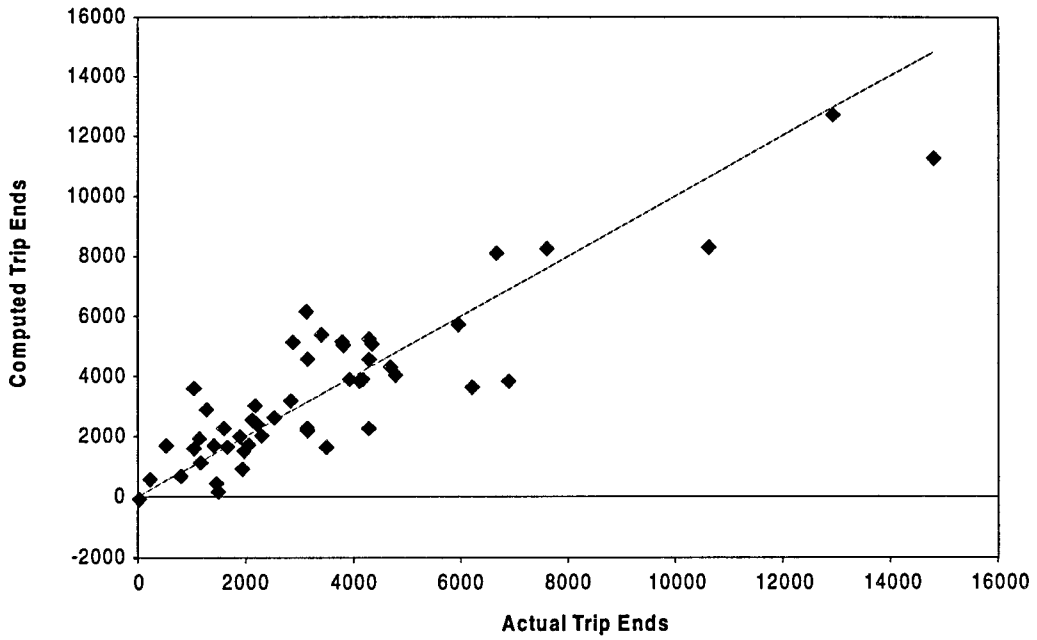


Figure 5. 1979 Base Year Calibration: Computed vs. Actual Trip Ends

For the socioeconomic model, we obtained an adjusted R^2 of 0.99 when forcing the model through the origin. This was done because it conceptually makes sense that a zone with no employment or population should not generate or attract any trips. This gave an MAE that is only about 8% of the average zonal value.

In a real-life application, we would use both models together, compounding the error. Doing so increases the MAE to approximately 31% of the average value for predicting zonal trip ends.

Forecast Year Prediction With 1990 Data

In the forecast year, we fed 1990 volumes into a trip end model built from 1979 data. The MAE jumped to approximately 38% of the average zonal trip end value, which is a noticeable increase from the 27% figure for the base year case. A scatter plot of predicted versus computed trip ends is shown in Figure 6, where an ideal fit would result in all the points being

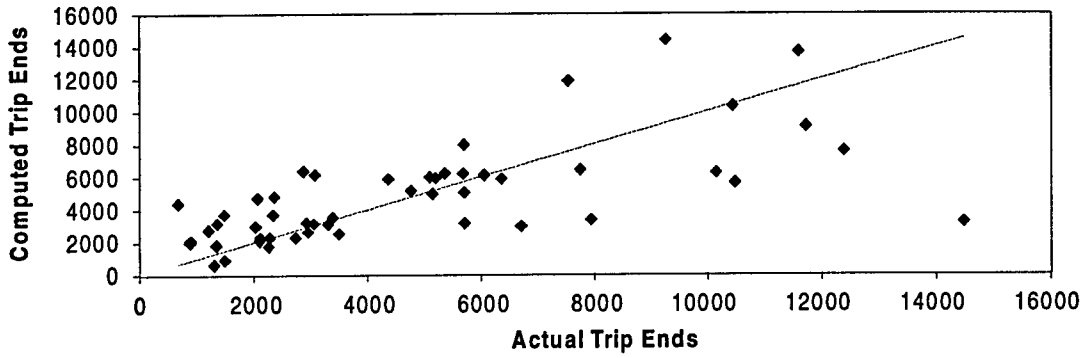


Figure 6. 1990 Predicted vs. Actual Trip Ends

directly on the line shown in the figure. Clearly, the variability in the computation of trip ends threatens to overshadow the predictive capability of the model. Again, however, the computed trip total for the study area was very close to the correct total, being off by less than 1%.

In the forecast year, using zonal trip ends to predict an aggregate socioeconomic measure of employment and population, via the socioeconomic model, produces an MAE that is approximately 15% of the average value if we use perfect trip ends. In the forecast year (in other words, the future), we do not know the trip ends with certainty: instead, we must use the computed (estimated) trip ends, which brings the MAE to 38% of the average value.

To determine individual socioeconomic parameters for each zone, we must assume that the proportions of population and employment will remain constant from year to year, which is not true, as discussed later. Prediction of retail employment performed the worst, where the MAE was approximately 63% of the average zonal value, and nonretail employment and population fared better, with the MAE being 43% and 48% of the average zonal values, respectively.

These figures show where the model needs improvement. The base year starts with error, that error grows in the forecast year, and the trip end and socioeconomic parameter models combined have an MAE that is about 38% of the average value. Using the assumption that the zonal ratios for population to employment will remain constant, we see the errors increase further, with retail employment being at 43% and nonretail employment being higher at 63%.

Diagnosis of Prediction Errors

Figure 7 shows a plot from 1990 of the real trip ends on the vertical axis against the aggregate socioeconomic variable (derived from the socioeconomic model). There is a substantial amount of variation, but a general linear trend may be discerned: as the number of trip ends increases, so does the aggregate socioeconomic variable. On the other hand, if we replace the actual trip ends on the *y* axis with the computed trip ends from the trip end model, then we obtain the graph shown in Figure 8. Unfortunately, the linear trend is much harder to observe as the rightmost two data points are responsible for the sudden downward shift.

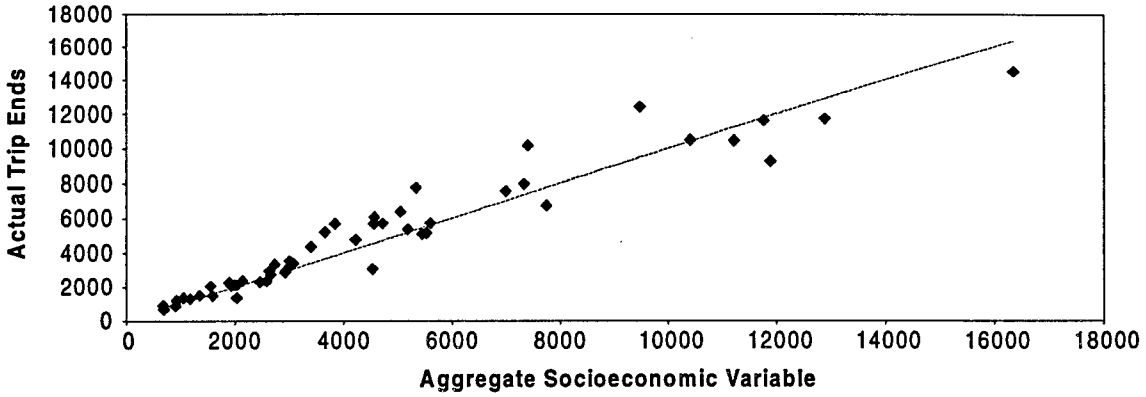


Figure 7. 1990 Actual Trip Ends vs. Aggregate Socioeconmic Variable

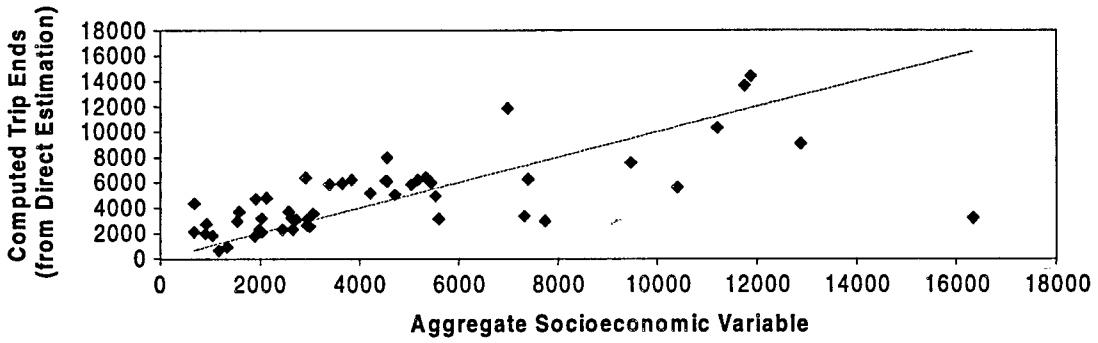


Figure 8. 1990 Computed Trip Ends vs. Agfgregate Socioeconimic Variable

In Figure 8, we can almost envision two regression lines: one for the first set of data points to the left of 6,000 on the horizontal axis, and a second to the right of the 6,000. The disparity between the two is that the left regression line would have a similar slope but would be "higher," whereas the right regression line would have a smaller slope and would overall tend to be "lower." Unfortunately, the 1979 data shown in Figure 7 do not categorically justify such a calibration approach in the base year: the few data points greater than 6,000, however, do suggest the possibility of such a trend. (This type of analysis could reveal, for example, that two functions are appropriate for relating zone trip ends to aggregate socioeconomic measures, with one function being appropriate for zones with a small number of trip ends and the other being appropriate for zones with a large number of trip ends.)

The reader may be curious about the point in the lower right corner of Figure 8, which has a high aggregate socioeconomic variable (well over 16,000) but a low number of computed trip ends (about 3,200). The same point is fairly close to the regression line in Figure 7 yet is far from the regression line in Figure 8. For that zone, trip ends were poorly estimated from 1990 traffic characteristics, as reflected by the poor fit shown in Figure 8. Yet, the point is very close to the regression line in Figure 7, meaning that the prediction of socioeconomic parameters from trip ends is quite appropriate for that zone. Examination of the network revealed that only a few

link volumes were available for that zone, which is a logical explanation for the difficulty in predicting the zonal trip ends from the trip end model.

Adjusted R^2 values and MAE measurements are only a few mechanisms through which we can determine whether a model is suitable. We used other techniques, such as plotting the data, detailed elsewhere.[3] We applied the *t* test and *F* test to both the trip end model and the aggregate socioeconomic model shown in (*eq 1*) and (*eq 2*) for the 1979 data. In the 1979 base year case, with 50 sampled values and the 95% confidence interval for a two-tailed estimate, for both models all coefficients were deemed significant using the critical value of $t(a/2, n - 2) = 2.011$. For the stepwise regression, we also set the *F* statistic at the 95% confidence interval. From these tests, we infer that the coefficients used in both models were statistically significant.

Whether Data Limitations Overshadow the Modeling Predictive Capabilities

Before moving into the application of these models for policy analysis, it is appropriate to reconsider both the performance of the models and the quality of the data set. The model's performance was weaker for individual zones and stronger for the study area as a whole. The data quality, as outlined in Task 2, is far from perfect, which may lead some readers to ask whether there is more variance between values as a result of data integrity rather than zonal differences. The appropriate response is that there is no definitive way to measure all aspects of these data, but they are at least as accurate as the state of the art for base year planning studies. For example, as indicated in Task 2, error will be introduced in matching land acreage among zones from different time periods. In some cases, it was possible to estimate the error, and these computations suggested errors between 1% and 14% for that category. Further, data were synthesized before the modeling attempts: any weaknesses in the data will adversely affect the predictive capabilities of the model. Thus, the weaknesses of the data set are reflected within the error measures of the model; we presume that with better data, we would obtain better predictive abilities, although the contribution of better data cannot be quantified at this stage. We addressed the impacts of the error bounds on policy analysis in the next task.

Task 5: Apply the Model to Determine Land Use Limits

Impacts of Assumptions

The use of historical data to predict the present allowed us to test the impacts of our assumptions. For example, we made three assumptions in the course of model building: (1) the CBD would remain as important as it was in 1967; (2) the ratios of population, nonretail employment, and retail employment would remain constant over time; and (3) the relationship between these parameters and trip generation rates would be constant. As discussed previously, the first assumption ruined the model, and this new information allowed development of a better 1979 base year model.

Table 5 shows that the latter two assumptions yielded errors from 35% to 40% for the three socioeconomic parameters for the individual zones, assuming trip ends for each zone could be known perfectly (e.g., if we could determine the actual trip ends without error). The second

Table 5. Error Computations Obtained With 1990 Forecast Year

Error Type	Nonretail Employment (%)	Retail Employment (%)	Population (%)
Individual zones (using perfect trip ends)	37	35	40
Individual zones (using computed trip ends)	43	63	48
Zone summation (using perfect trip ends)	10	21	27
Zone summation (using computed trip ends)	8	17	25
Aggregate study area (using perfect trip ends)	6	11	20
Aggregate study area (using computed trip ends)	6	11	21

row of the table illustrates how using modeled trip ends compounds the error in that case. Yet, if we were interested only in total population and employment, Table 5 also shows that the effect of the trip end error is not as drastic as it would be if we were interested in population and employment for individual zones: errors can be kept to between 6% and 21% for the aggregate case. In brief, although assumptions 2 and 3 are not ideal and can be detrimental at the zonal level, they are mitigated somewhat at the aggregate level. In the table, errors shown for individual zones are the MAE divided by the average value. Errors shown for zone summation are the difference between the computed and correct total divided by correct total for entire study area. These were derived by determining trip ends for each zone, computing employment and population for each zone, and summing population and employment for entire study area. Errors shown for aggregate study area are the difference between the computed and correct total divided by the correct total. We derived them by computing trip ends for the entire study area and deriving population and employment directly from this aggregate measure.

Policy Application: Load All Links to a Level of Service C

First, we define what level of traffic volumes might be viewed as acceptable to citizens. Although, we arbitrarily selected such a level, we could raise or lower it depending on what citizens of the study area desire.

Approach

Level of service is generally defined as the "relative value of ... travel time, frequency, comfort, reliability, convenience, and safety."[66] The manner in which we compute this variable depends not only on the transportation mode but also on the type of facility, with the manner of computation being different, for example, depending on whether we have a freeway segment or a signalized intersection. For this study area, we used service volumes defined in the 1990 study that would yield a level of service of C, which is generally viewed as an imperfect but tolerable vehicle density.

One may use the error bounds from Table 5 to load the links on the network to LOS C and then derive the corresponding land use limits. For example, zone 35 has seven links that are completely within the zone. One of these links, Old Ivy Road, is a two-lane road with a service

volume of 600 vehicles per hour per lane, assuming level of service C.[50] That is, this road can carry 1,200 vehicles per hour and maintain this level of service.

Yet, the traffic volumes available for this study were only 24-hour volumes. Hence, we needed to convert the hourly service volume of 1,200 vehicles per hour (for two lanes) to a 24-hour volume. Although we might simply multiply that service volume by 24 to obtain 28,800 vehicles per day, this is clearly unrealistic: it is unlikely that a road would be used equally during the midnight hour and the noontime hour. Hence, to determine a 24-hour volume that would correspond to an hourly service volume, it would be appropriate to compute a fraction of the total service volume.

From the 1994 *Highway Capacity Man*ual, several graphs of hourly variation in flow are available.[67] In spite of discrepancies based on geographical location, roadway type, and day of the week, several key trends may be discerned:

- The hours between midnight and 6 A.M. have extremely low volumes.
- Various shapes such as a single maximum, two maximums, and a horizontal line represent usage for the remaining 18 hours.
- A large portion of the area under the curve can be captured with a 12-hour portion.

Although the actual data that produced the graph are not available, we selected points that would appear to replicate the shape of the graph. This graph of 24-hour usage is shown in Figure 9. For convenience, the top is presumed to be the service volume of each road.

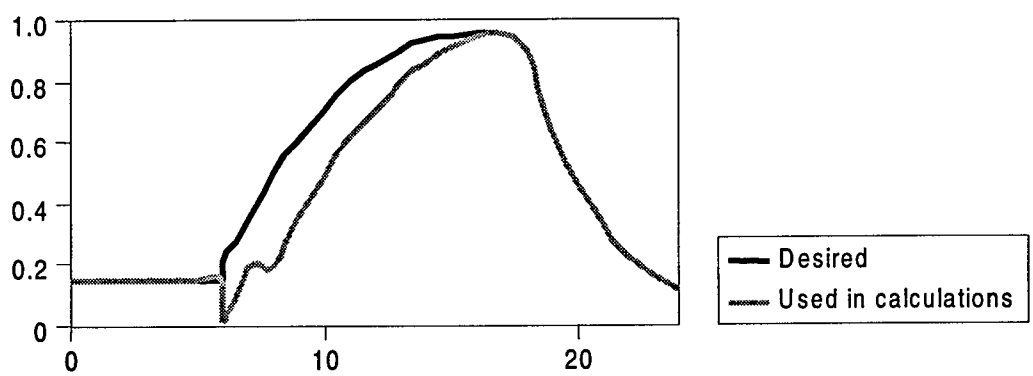


Figure 9. Synthetic 24-Hour Usage

We can quickly compute the area under the curve in Figure 9. Letting the leftmost portion be a horizontal line that presumes 15% of the service volume per hour, letting the middle section be a curve described by a power-three expression, and letting the rightmost section be described as a variant of the natural logarithm, we can find the total area as being

$$\int_0^6 0.15dx + \int_6^{17} (-1.29 + 0.33x - 0.015x^2 + 0.0002x^3)dx + \int_{17}^{24} (400\exp(-x/2.95)dx$$
$$= 12.44$$

Given that equal usage at the service volume for all 24 hours would yield an area of

$$\int_0^{24} dx = 24.0$$

we should assume that a typical use based on this curve is that 12.44 or approximately 50% of the maximum 24-hour volumes would reflect a level of service C.

Now, for each of the 214 segments in the 1990 study, we can compute the hourly service volume based on the number of lanes and the roadway type, where the following service volumes were taken from the 1990 planning study:

- *Interstates and major arterials:* 1,400 vehicles per hour per lane (vphpl)
- *Other four-lane divided roads:* 600 to 700 vehicles per hour per lane
- *Two-lane roads:* 375 or 600 vehicles per hour per lane depending on how classified by the 1990 planning study.

These service volumes are approximate: in some cases, it was not clear whether a road should have 600 or 700 vphpl as a service volume, whereas the 375 arises from our decision to classify all 300 and 400 vphpl service volumes at the 375 vphpl value. Using these values, we may recompute the volumes on each of the roadway segments:

24-hour capacity volume = Number of lanes • Hourly service volume • 12

To use the trip end model, however, it is also necessary to change the E_4 variable, which reflects the amount of attention paid to a particular segment. We changed this variable:

$$E_4^{\text{LOS C for 24 hours}} = (E_4^{1990} \bullet \text{LOS C volume})/1990 \text{ volume}$$

The effect is simply to make the E_4 variable realistic in terms of the higher volumes, as it refers to the number of divisions created in a segment for a planning study. Hence, as the volumes would increase, we would expect a similar increase in the number of divisions.

Results

Although only 24-hour volumes were available, we can use graphs of 24-hour travel variation along with link service volumes to determine what 24-hour traffic volumes correspond to a peak hour level of service of C. Using this methodology, the total number of trip ends for the entire study area is forecast as being 495,000, with the error bounds ranging from 269,000 to 772,000. That is, we could say that half a million trips would be forecast, plus or minus roughly

50%, after accounting for both the trip prediction error (derived from transportation characteristics) and the aggregate employment and population error (derived from trip ends).

The next problem is that although we do not explicitly know the ratios of nonretail employment, retail employment, and population, we do know the ratios of these values varied from one year to the next as shown in Table 6. (This table exhibits a challenge to using historical data: employment was categorized as white collar or blue collar only in 1967; these categories were replaced by retail and nonretail in 1979 and 1990.)

Table 6. Variation in Employment and Population Proportions for Aggregate Study Area

Ratio	1967	1979	1990
Population/employment	2.94	2.20	1.87
Nonretail employment/retail employment		4.95	4.15
White collar/blue collar employment	1.46		

In the aggregate, therefore, we can write

$$495{,}107 = 1.64 \bullet (\text{nonretail employment}) + 9.36 \bullet (\text{retail employment}) + 1.11 \bullet (\text{population})$$

$$= 1.64 \bullet (\text{nonretail}) + 9.36 \bullet (\text{nonretail})/4.15 + 1.11 \bullet 1.87 \bullet (\text{nonretail} + \text{nonretail}/4.15)$$

Thus, keeping the ratios the same as for 1990, we could solve for population, retail employment, and nonretail employment when all roadway links are loaded to level of service C. The precision of this method is constrained by two assumptions: that the ratios will remain constant over time and that the error bounds will remain proportionately constant; e.g., the errors we obtained in going from 1979 to 1990 would still propagate at the same rate from 1990 until the time the level of service C volumes were obtained. Further, in the zonal specific arena, a third source of error is that the interactions among zones may change over time.

Table 7 shows the land use limits that would result. For example, we would be constrained to a population of approximately 178,000 for the study area. Yet, by seeing that our lower and upper error bounds are 96,000 and 277,000, respectively, we can see that it would be misleading to tell citizens that we had forecast a single number. Instead, it would be more appropriate to give the answer as 180,000 plus or minus 50% using this method of error bounds analysis.

Table 7. Aggregate Values for Population and Employment When All Links at LOS C

Variable	Predicted Value	Low Error Bound	Upper Error Bound
Nonretail employment	76,508	41,560	119,302
Retail employment	18,436	10,015	28,748
Population	177,545	96,446	276,853

This range reflects the error that would result if we simply computed trip ends and then socioeconomic parameters for each zone individually. If we were interested in only the study area as a whole, then we could compute total trip ends first and then derive socioeconomic parameters from this single number. Since prediction of total trip ends was within 1% error, the tolerance would be much tighter than what is shown in Table 7. (The last two rows of Table 5 suggest that the error bounds would be between 6% and 21% depending on whether we were interested in nonretail employment, retail employment, or population for the entire study area.)

Table 7 was obtained by first deriving individual zonal socioeconomic values from individual zonal trip ends, as suggested by the first two rows in Table 5. In reality, were we interested in obtaining only aggregate nonretail employment, aggregate retail employment, and aggregate population, we would have simply added all zonal trip ends first and then computed retail employment, nonretail employment, and population for the entire study area, as suggested by the last two rows in Table 5. Such an action yields much tighter error bounds, as assisted by the close correspondence between total predicted trip ends and total actual trip ends for the 1990 forecast year.

Results of Loading All Links to Level of Service C for Specific Zone

Often, citizens will be interested in the impacts within a subset of the geographical area. Thus, we may attempt to determine land use limits for a specific zone. For example, for a single zone located near the edge of the study area (zone 50), the population to employment ratio is about 14. Placing all links at LOS C suggests that the existing infrastructure can support a population of slightly less than 14,000 give or take approximately 45%, as shown in Table 8, *if* the errors for computing population and employment were all similar. Yet, from 1979 to 1990, ratios for population and employment did not remain constant: the rapid growth in residential population for that zone meant that the model did a better job of predicting population but a much poorer job of predicting employment. Were the same change in population and employment ratios to occur in loading all links to LOS C, then the bounds shown in Table 8 could be tightened for population but would have to be substantially loosened for employment.

Table 8. Employment and Population Predictions for Particular Zone Presuming LOS C

Variable	Predicted Value	Low Error Bound	Upper Error Bound
Nonretail employment	698	401	1,040
Retail employment	271	156	405
Population	13,712	7,887	20,449

These reflect computations for zone 50.

Similarly, we can target specific roadway segments for a reduction in traffic volume. Further study of the trip end model allows us to examine how the individual variables within a zone would be affected by volume reductions. This also has useful implications for the consideration of newly constructed links.

To accomplish this, we select a specific zone and set of network links within that zone for the year 1990, place 1979 volumes on those links, compute trip ends as a function of those link volumes, and then compute population and employment from those trip ends. We then compare these computed 1979 population and employment figures with actual values. That is, we will make believe the base year is 1990 and the forecast year is 1979.

Therefore, we select zones 33 and 36, which are bordered by Route 29, Rio Road, and Hydraulic Road. We now employ the volumes on the roads within these zones for the base year and forecast years using the formulas for each zone and presuming the ratios of population, retail employment, and nonretail employment remain constant:

$$\text{Trips} = -827 + 0.027 \bullet X_1 + 0.039 \bullet X_2 - 1{,}807 \bullet \ln(X_3) + 685 \bullet \ln(X_4) + 96.1 \bullet X_5 + 1{,}729 \bullet \ln(X_6)$$

$$\text{Trips} = 1.64\ (\text{nonretail employment}) + 9.36\ (\text{retail employment}) + 1.11\ (\text{population})$$

We may now compute the correct values and computed values for trip ends and the socioeconomic variables for both the base year (which in this case is 1990) and the "forecast" year (which in this case is 1979). Recall that we are using a model that was originally developed with 1979 data; hence, now our "base" year of 1990 actually performs worse than the "forecast" year of 1979. But these errors give a feel of how well we can do when targeting a specific zone for overall reductions in volume. The computations indicated errors on the order of 33% for all three socioeconomic parameters in the base year.

One may use these error bounds to estimate the impacts of certain reductions on specific links. Realistically, we can see quickly that the error bounds become significant in relation to the reductions being computed. For example, suppose citizens wish to reduce the traffic volumes on the five Rio/Hydraulic links by 25%; analytically, this translates into a 15% trip reduction and a subsequent employment and population reduction of 10%. Yet, these figures are still within the 33% error bounds suggested previously. This is not to say that the effect cannot be noticed, but it does give a realistic impression of how accurately we may forecast certain impacts. (Although the regression model employed is not directly a causal model, this is a logical inference to be drawn since transportation is a derived demand from employment and population characteristics. The extent to which the models do not explain the transportation-socioeconomic relationship is reflected in the performance of the models in the forecast year. Therefore, predictive capability is aided not by the structure of the model but rather by the act of using historical data to validate the model, and the structure helps the analyst formulate questions pertaining to land use limits.)

Finally, one planner pointed out that in Virginia, modeling efforts are affected by population control totals established by the Virginia Employment Commission (R. Tambellini, personal communication). In such a case, we could use the application at the aggregate level, where population would be fixed and the number of trips and/or employment would be variable as shown in (*eq 2*).

SUMMARY OF WORK

Key efforts for each of the three purposes of this research were as follows:

1. *Develop a method to reverse the direction of the planning process.* As outlined in Task 3 and the Appendix, we developed and implemented a five-step approach after considering the various models we found in the literature review. Since this approach did not fare well in subsequent tests, we developed a direct estimation model as outlined in Task 4.

2. *Test the approach using historical data.* Synthesizing the planning data from different time periods, as outlined in Task 2, resulted in a data set we could use to test the proposed approaches. Although the initial five-step approach failed, Task 4 showed that the direct estimation approach had potential. This testing also gave an estimate of the precision of the direct estimation model: errors were large for specific zone computations but smaller for the study area.

3. *Apply the approach to determine land use limits.* As outlined in Task 5, we applied the direct estimation approach to determine zonal or study area constraints on population, retail employment, and nonretail employment as a function of 24-hour traffic volumes. The resultant "limits" were not a single number but rather a range of values, where the size of the range is proportionate to the accuracy of the model.

MAJOR FINDINGS

Five lessons become apparent as a result of this research effort. For clarity, the findings are listed in chronological order and appear in reverse order of importance.

1. *Using a modified version of the maximum iterative entropy method, we can alter the exponent used in the iterative solution to influence both the rate of convergence and the time to arrive at a solution.* As pointed out in the Appendix, we found that generally an exponent of less than 0.5 was needed to achieve convergence but that the lower the exponent the slower the solution time. Although others familiar with Gur's 1983 work may already be aware of this solution, it was not clear that this would be the case from the literature we examined.[68]

2. *For determining O-D trip tables, the entropy approach and the cost minimization approach have fundamentally different paradigms; the former tends to distribute trips more widely.* As explained in Task 1, although the entropy approach had more potential for this application, each may have its niche in specialized applications. However, the errors from both these approaches were too large to be useful for this study given the data available.

3. *A five-component model shows how we can begin with traffic counts and conclude with socioeconomic parameters.* The theoretical development of the five-step model outlined under Task 3 showed the model's potential, and base year tests highlighted its fatal flaw: the third step, where a reasonably accurate trip distribution matrix could not be obtained. Should others be able to improve the performance of this third step, however, we could reexamine the utility of using this approach. An example is the use of specific path types so that we could assess the impact of improving performance for various segments or even modes of transportation.

4. *We derived a model that directly estimates zonal trip ends from a variety of transportation system variables and tested it for a base year and two sets of forecast years.* As outlined under Task 4, the results show promise. Although substantial errors are obtained for many cases, the MAE is less than the average value for zonal trip ends. Some of the independent variables in the zonal trip end model are directly measurable traffic characteristics, and others are a surrogate for the amount of activity estimated by planners to occur on a particular segment. For determining this latter class of variables (e.g., the number of counts taken for a segment), techniques such as the Delphi method may be appropriate for further research.

5. *Errors associated with measuring select socioeconomic parameters separately could be overcome by aggregating nonretail employment, retail employment, and population.* As shown in Task 4, by regressing these variables to predict trip ends, we can estimate, with some error, the coefficients for these variables with the data. A weakness is that in predicting the future we had to assume that the ratios of these variables to one another would remain constant; however, it should also be shown that for the two time slices, the coefficients were similar when complete data were available (1979 and 1990). A characteristic of this model is that it is a one-to-many relationship: multiple combinations of population and employment values will generate the trip ends shown in (*eq 2*).

CONCLUSIONS

- *The framework as outlined in the application to the study area does address the impact of changes in traffic volumes on population and employment.* If a decision maker desires to change traffic volumes, a corresponding change in population and employment will also need to occur.

- *The predicted change will have substantial error arising from several sources,* e.g., imperfect measurement techniques, changes in the relationships among socioeconomic variables that are not captured by the model, and the fact that zonal trip ends are not the only contributors to traffic volumes in a zone.

- *Decision makers who are given these predictions should also be given an error range associated with them.* With the methods shown in this study, errors on the order of 50% can

be expected for socioeconomic parameters, with retail employment being higher (63%) and population and nonretail employment being lower (48% and 43%, respectively). In these cases, the percentages are the MAE divided by the average value of the variable being predicted.

- *The large error tolerances show that some of the more sensitive modeling questions, such as implementation of TDM strategies or small reductions in trip totals as a result of increased vehicle occupancies, will not be accurately captured by the approach we employed. On the other hand, the direct estimation techniques do stand the test of real world data over the passage of time and show what can be modeled with some confidence: gross changes in traffic volumes as they affect aggregate measures of population and employment.*

- *Historical planning studies, along with other data sources, can be used to test the utility of planning models by using the historical data as a calibration set and then using more recent data as the test data set.* By using historical data from the past and the present, we can better understand which relationships built into the model will be impervious to changing trends.

- *These conclusions are based on work with one study area.* To make the results more general, additional efforts are needed with other geographical areas. Of significance would be the available data, the structure of the zones, and the layout and size of the study area.

PHILOSOPHICAL CONSIDERATIONS

The opportunity to conduct this research allowed us to speculate about where we now stand with regard to urban transportation planning, where we are headed, and what we might want to change with regard to our planning goals. The following are inferences that seem evident from what transpired during the course of this research, and we offer them as suggestions that planners (and those deciding what planners should accomplish) might consider.

- *Planning studies are not usually validated for the forecast year.* Although base year calibration is standard procedure, transportation planning studies are usually developed, used to compare forecast year alternatives, and then completed, with no one later assessing how accurate the forecast year assumptions, projections, and calculations proved to be. The reason for this should be evident from the data preparation required to make studies from different time periods compatible: with such validation not required by legislation, it can be hard to justify spending the necessary resources when day-to-day problem solving takes precedence. *TRB Special Report 245* alluded to this phenomenon of trying to use historical data to predict the present, noting: "In a few metropolitan areas, the data exist to make such analyses possible."[15] Although limited forecast year validations are sometimes performed, it is surprising that, given the amount of funds required for detailed transportation planning models, measuring forecast year performance is not more routine.

- *Making accurate forecast year predictions may be difficult.* We applied two methodologies for reversing the direction of the transportation planning process: a five-step approach and a two-step direct estimation method. Although the latter was more successful, both had relatively large errors for the forecast year (e.g., testing data set). At the zonal level, the accuracy of the predicted socioeconomic parameters was around 50% and that at the aggregate level was between 6% and 25%. Unless other methods can yield better forecast year results, distinguishing between precision and accuracy is necessary. The former reflects the number of decimal points to which calculations are carried out, and the latter reflects the correctness of these calculated values in the first place. Thus, if we estimate a zone's population as 1,012 yet we know from previous tests that our forecast year populations are subject to a 20% error, the estimate is better represented as 1,000 $\pm$ 20%. Hartgen raised a similar point: too much emphasis on precision would be "to assert that a city's air pollution from autos 10 years in the future will be, say, 1,207,849 lbs."[14]

- *Planning is a continuous process.* Even though a transportation plan has a single set of recommendations based on network deficiencies, we may view the preparation of the various transportation plans as a continuum of events. For example, the *Major Arterial Street and Highway Plan*, produced in 1967, recommended a number of roadway improvements. Yet, just 4 years later, the Charlottesville City Council passed a resolution that both removed projects from the 1967 plan and requested that the Virginia Department of Highways conduct a new transportation study. Clearly, such modifications to transportation plans demonstrate that planning should be viewed as an ongoing process. This being the case, it is appropriate to envision a process where data considerations and modeling requirements are incrementally and periodically updated. That is, we can view a more "ideal" planning process as one where every year, 2 years, or 4 years—whatever time frame is appropriate—transportation plans are reformulated in light of data that became available since the creation of the last plan *and* historical projections are validated to provide guidance for modelers.

- *Alternative approaches to transportation modeling are possible.* In the 1950s and 1960s, when standard planning approaches were just getting underway, it made sense to have a few basic tools that could take advantage of the scarce computer power available at the time. Now that we have a host of planning data—for some urban areas we have data as far back as the 1960s—and substantially greater computer power, we have an opportunity to try alternative approaches. These approaches do not necessarily need to be more complex. We may find that a simple time series modeling, for example, is more effective than complex gravity type approaches. Yet, so long as data sets for urban areas can be archived and made accessible to those who can use them, it may indeed be possible to develop certain modeling applications that can forecast accurate results. If this is not feasible, then using historical data to predict the present can at least give decision makers an estimate of the validity of the forecasts presented by modelers.

RECOMMENDATIONS

1. *Document or archive base year data such that they may be more fully accessed for future studies.* A large amount of information is often lost from historical planning studies because this information is not published in the final report. Desired data include trip matrices by purpose (e.g., home-based work, home-based other, and non-home based), trip generation and attraction equations, and facility-specific data. Documentation of all data may prove very useful for future planning studies, even if the utility of the data is not apparent for present efforts. To implement this recommendation, we advise that language be added to consulting contracts that the planning data be archived in a suitable medium, e.g., CD ROM, that may be accessed for future research. VDOT's Transportation Planning Division should store these data until they can be appropriately integrated in VDOT's Data Warehouse Initiative underway in VDOT's Information Technology Division.

2. *Select one study area for which historical and present day data exist, and assess the validity of the original plan's forecasts.* A literature review would be appropriate in this effort. An in-depth study would logically focus on four key areas:

   - *The accuracy of the assumptions in the plan,* such as "givens" in the form of socioeconomic or land use projections.

   - *The accuracy of the computed variables in the plan,* such as forecast year trip distribution matrices and estimated traffic count projections. A subset of this item could be an assessment of when, for zones experiencing growth, traffic volumes met or exceeded forecast year projections.

   - *The degree to which the plan's recommendations were followed.* This would not be a judgment on the architects of the transportation plan but might give hindsight as to how often, and in what time frame, we can expect proposed transportation improvements to be accomplished. Even though transportation plans are viewed as single reference points in time from which decisions are made, the act of planning is a continuous process, and there may well be room within transportation plans to account for this fact.

   - *A longitudinal assessment of how the plan's goals and data requirements evolved.* Planning horizons, data categories, and objectives reflect the time at which the transportation plan is developed. The extent to which these aspects will remain constant over time is of interest.

3. *For a set of base year data, run the planning process in both the forward and reverse directions.* That is, use the standard four-step process to derive traffic volumes from socioeconomic parameters, and separately use the reverse direction to determine socioeconomic parameters from traffic volumes. Not only could we learn better which of these is easier to derive, but we could also develop a methodology to iterate between these two methods. This prediction tool might have the potential to help discern some of the hard decisions that must be made: for example, if zoning officials desire a low-density land use and business interests foresee a need for a high volume of truck traffic, then using both the

forward and reverse directions could pinpoint incompatibilities between these two visions. Identifying such pitfalls during the planning stages would give competing interests an opportunity to achieve agreement while there was still time to take action. Such a project would consist of five components:

- *forward direction application,* from socioeconomic parameters to traffic volumes
- *reverse direction application,* from traffic volumes to socioeconomic parameters
- *adjustment application,* enabling these two processes to converge, (e.g., what happens if the forward direction beginning employment does not equal the reverse direction terminating zone employment)
- *forecast year application,* where the process would be applied for a set of forecast year data
- *scenario application,* where we could assess the utility of shifting population and employment sites on reducing the need to travel; the end product would be the ability to test "what-if" applications with some sense of the accuracy of the projections.

4. *Conduct a longitudinal study using transportation planning data. TRB Special Report 245* pointed out that "the inherent methodological and data problems are formidable" for conducting such research.[15] Yet, with a substantial effort toward compiling historical data from several points in time, we may begin to have adequate information to conduct various types of analyses. Methodologies for conducting time-series models are available; one option is Gu's CityPlan software.[69] In such an application, the research question focuses on three areas:

   - Is the application feasible given the available data and subsequent performance of the model with these data?
   - How sensitive is the model to variables that can be controlled by feasible policy options?
   - What are the numerical values required for the calibration parameters, and do the values employed make intuitive sense?

   For the case study area we employed, for example, one finding was that the O-D trip table was less important than originally anticipated. There exists therefore the possibility of incorporating data from planning studies conducted in the 1940s and 1950s into such an effort: although the trip matrix is not available, other planning data from these earlier studies may prove useful.

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APPENDIX

THE INITIAL FIVE-STEP METHOD

As explained under task 3, the initial five-step method was unsuccessful because of the performance of its middle step. This approach, however, has theoretical interest as it may become useful if the third step can be improved.

Step 1: Determine ideal friction factors

The method outlined by Sen and Soot allows us to separate travel costs from other factors in the gravity model.[31] Thus, let the trips that begin in zone i and end in zone j be represented as T_{ij}, let the sum of all trips that originate in zone i be shown as O_i, and let F_{ij} be a friction factor that represents the difficulty of travel between zones i and j. Finally, let M_i and M_j be adjustment parameters for trips originating and terminating, respectively, in zone i. The normal convention is to use a terminology known as *productions* and *attractions* in place of trip ends O_i and O_j, but for simplicity, we avoided this terminology. In other words, M_i and M_j are zonal specific characteristics that affect the trip travel from any zone i to any zone j, and F_{ij} is the travel impedance between i and j and thus also affects the number of trips between i and j.

Letting $T_{ij} = O_iO_jM_iM_jF_{ij}$, we may isolate the friction factors, such that:

$$(Tij \bullet Tji)/(Tii \bullet Tjj) = (OiOjMiMjFij \bullet OjOiMjMiFji)/(OiOiMiMiFii \bullet OjOjMjMjFjj)$$
$$= (Fij \bullet Fji)/(Fii \bullet Fjj)$$

As Sen and Soot pointed out, if we assume the costs of intrazonal travel are the same for each zone and that travel from zone i to j costs the same as travel from zone j to i, then the formulation for determining "correct" friction factors simplifies to:

$$(T_{ij} \bullet T_{ji})/(T_{ii} \bullet T_{jj}) = (F_{ij})^2/(F_{ii} \bullet F_{jj})$$

If we assume all $F_{ii} = 1$, then we can write that $F_{ij} = (T_{ij} \bullet T_{ji}/T_{ii} \bullet T_{jj})^{0.5}$.

This gives great latitude in selecting a model, shown in step 2, to be equal to the friction factor (F_{ij}). We may also assign different numerical values to intrazonal friction factors (F_{ii}) if we wish them to be different but we do not want them to complicate the path selection process. In that case, the expression is:

$$F_{ij} = ([T_{ij} \bullet T_{ji} \bullet F_{ii} \bullet F_{jj}]/[T_{ii} \bullet T_{jj}])^{0.5}$$

Many readers will recall that the gravity model is usually presented as

$$Tij = (Pi)(Aj)(Fij)/\Sigma_j(Aj)(Fij)$$

The reason is that when one begins with the "original" gravity model, shown as

$$Tij = (Pi)(Aj)(Fij)(Mi)(Nj)$$

one can use, as shown by Stopher and Meyburg[70], simultaneous equations to derive M*i* and N*j* such as

$$Pi = \Sigma_j Tij = \Sigma_j(Pi)(Aj)(Fij)(Mi)(Nj) = (Pi)(Mi)\,\Sigma_j(Aj)(Nj)(Fij), \text{ and}$$
$$Aj = \Sigma_i Tij = \Sigma_i(Pi)(Aj)(Fij)(Mi)(Nj) = (Aj)(Nj)\,\Sigma_i(Pi)(Mi)(Fij)$$

Normally, one then sets the N_j value to 1.0. Subsequent computation of the parameter M_i and insertion into the original gravity model yields the more familiar expression shown as

$$T_{ij} = (P_i)(A_j)(F_{ij})/\,\Sigma_j\,(A_j)(F_{ij}).$$

Step 2: Determine travel paths whose impedance matches the ideal friction factors F_{ij}

We may generate various travel paths depending on how we suspect users perceive costs as a function of network parameters such as the number of lanes, travel speed, or congestion. We may then attempt to fit a model of the form:

$$F_{ij} = \prod_k Z_k \bullet C_{ijk}^{Xk} \bullet e^{(Yk \bullet Cijk)}$$

where C_{ijk} represents the cost, real or user perceived, of path k from i to j, and X, Y, and Z are numerical values. We may then select different types of paths for each zonal interchange. For example, path type 1 might be the fastest path based on travel time alone from i to j, and path type 2 might be a path that is slower in terms of travel time but involves higher speeds of travel. There are many possible type 2 paths from i to j, depending on how much importance is given to a fast travel speed. For example, we can compute the cost of each link in a path as travel time multiplied by (speed^{-A}), where a large value of A would make high speed paths very attractive yet a lower value would make such paths less desirable. Likewise, we may select path types based on the number of lanes and peak hour traffic volume. Using the F_{ij} values from step 1 and the C_{ijk} values for the various path types, regression enables us to determine X, Y, and Z parameters for the expression. An adjusted R^2 value of approximately 0.7 could be obtained with the best paths selected such that $k = 4$ in the expression.

Selection of these four best paths, however, required consideration of more than 150 potential paths for the 1967 network. These paths were intended to reflect different types of travelers. Examples are:

- true fastest path, t, = distance/average link travel speed
- facility-weighted path, t, = (distance/speed)/a

where a varies directly as a function of the number of lanes of the facility. The effect is to select paths for travelers who are biased toward larger facilities.

- speed-weighted path, t, = distance/speed • $(25/\text{speed})^b$

  Since 25 mph seemed to be an average link travel speed in 1967, links with speeds greater than 25 mph will appear exponentially more attractive to travelers.

- peak-hour avoidance path, t, = distance/speed • $(\text{phf}/0.095)^c$

  Since 0.095 was the average peak hour factor for the 1967 links, a link with a lower peak hour factor should be more "attractive" during the peak hour.

We also tested variations on these criteria, such as varying values for a, b, and c, substituting distance for speed, and varying the speed breakpoint.

Step 3: Determine the form of the entropy model

The code for accomplishing this in an iterative fashion is given elsewhere, both for a simple case and the 1967 base year network.[3] The T_{ijk} paths are those that are selected from step 2. The iterative method approximates a solution to the following expression, where the no-traveled state issue alluded to previously is reflected by the trip length, which in turn is reflected by the number of trips given in the seed expression

maximize: $-\sum_{ijk}(T_{ijk} \bullet \ln|T_{ijk}|) - \sum_{i} (T_{ni}) \bullet \ln(T_{ni})$ such that link volumes are replicated.

Part of solving the expression involves applying the following subexpression repeatedly:

$$\mathrm{T}ijk_{\text{current}} = \mathrm{T}ijk_{\text{prior}} \bullet \mathbf{X}$$

The maximization is achieved using an iterative method developed by Van Zuylen and Willumsen in conjunction with a modification to the improvement suggested by Gur.[28,68] The original algorithm entails a step where one modifies the Lagrangean multiplier based on the ratio of the actual link volume to the computed link volume. In 1983, Gur suggested using an

exponent of 0.5 for this ratio.[68] We found that in many instances a lower value, usually in the range of 0.1 to 0.25, was required to achieve convergence.

Step 4: Compute ideal *M* (zone adjustment) parameters

The correct base year trip distribution matrix may be used with the ideal friction factors and the method of least squares to compute *M* parameters based on the following equation:

$$T_{ij} = O_i O_j M_i M_j F_{ij}, \text{ or } \ln(M_i) + \ln(M_j) = \ln(T_{ij}/(O_i O_j F_{ij})$$

If morning and evening trip tables were available, however, one could have the O_j and M_j variables replaced by D_j and N_j such that that O_i and M_i would correspond to trip starting parameters and D_j and N_j would correspond to trip terminating parameters for each zone in the study area. In 1967, though, only 24-hour travel was recorded.

Step 5. Relate base year *M* parameters and trip totals to socioeconomic information

One may then use trip totals and *M* parameters to obtain land use or socioeconomic data, although in this particular case the only land use data that proved feasible were "percentage of the zone that has been developed." From the 1967 model calibration using the correct trip table and the correct socioeconomic parameters, we formulated the models for population, employment, dwelling units, automobiles, and percentage of land developed. For example, one potential model for predicting employment is

$$\text{Zone employment} = -116.15 + 0.171 \bullet \text{trips}$$

Although we also considered nonlinear models at this stage, further testing showed that linear models with a poorer base year fit performed better in the forecast year than did nonlinear models with a better base year fit.