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PATH FLOW ESTIMATOR FOR PLANNING APPLICATIONS IN SMALL COMMUNITIES

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ABSTRACT

This paper presents an alternative planning framework to model and forecast network traffic for planning applications in small communities, where limited resources debilitate the development and applications of the conventional four-step travel demand forecasting model. The core idea is to use the path flow estimator (PFE) to estimate current and forecast future traffic demand while taking into account of various field and planning data as modeling constraints. Specifically, two versions of PFE are developed: a base year PFE for estimating the current network traffic conditions using field data and planning data, if available, and a future year PFE for predicting future network traffic conditions using forecast planning data and the estimated base year origin-destination trip table as constraints. In the absence of travel survey data, the proposed method uses similar data (traffic counts and land use data) as a four-step model for model development and calibration. Since the Institute of Transportation Engineers (ITE) trip generation rates and Highway Capacity Manual (HCM) are both utilized in the modeling process, the analysis scope and results are consistent with those of common traffic impact studies and other short-range, localized transportation improvement programs. Solution algorithms are also developed to solve the two PFE models and integrated into a GIS-based software called Visual PFE. For proof of concept, two case studies in northern California are performed to demonstrate how the tool can be used in practice. The first case study is a small community of St. Helena, where the city's planning department has neither an existing travel demand model nor the budget for developing a full four-step model. The second case study is in the city of Eureka, where there is a four-step model developed for the Humboldt County that can be used for comparison. The results show that the proposed approach is applicable for small communities with limited resources.

Keywords: travel demand forecasting; four-step planning model; path flow estimator; small communities

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1 INTRODUCTION

Transportation is critical to the social, environmental, and economic health of every metropolitan city. Because of its importance, federal regulations in the United States require each urbanized area over 50,000 in population to have a Metropolitan Planning Organization (MPO) responsible for transportation planning (Meyer and Miller, 2001). Yet, according to the U.S. Census, over 40 percent of all U.S. communities have populations less than 50,000. In California, there are 333 municipalities (out of 535 municipalities) that have a population less than 50,000 (U.S. Census Bureau, 2009). Such *small communities* usually do not have sufficient resources to conduct travel surveys or embark on model development and maintenance for carrying out various planning functions. Current practice in modeling network traffic is through a four-step travel demand forecasting model (i.e., trip generation, trip distribution, mode choice, and traffic assignment), commonly referred to as the four-step model, that requires travel surveys as input and specialized technical staffs to develop and estimate. Although such a modeling approach has been used in practice in major urban areas, Yan (1998) noted that many smaller communities usually do not have sufficient resources to conduct travel surveys, nor to house technical staffs for model development and maintenance. Without data from a travel survey in the study area, trip generation rates of various land use zones are often “borrowed” from such published data as *Trip Generation* of the Institute of Transportation Engineers (ITE) or reports of travel surveys performed in other areas. The unavailability of data on Trip Length Frequency Distribution (TLFD) of local travelers often forces modelers to skip the calibration of trip distribution models. Instead, calibration and validation of the overall model are often carried out by altering the friction factors and adding k-factors, in a trial-and-error fashion, to the trip distribution model such that the results of traffic assignment would match traffic counts on selective screenlines and critical links. The calibration process is usually a lengthy process and the resultant models often contain many factors that do not have the necessary behavioral foundation established from travel surveys. Schutz (2000) suggests that for those communities to meet the planning requirements, development of innovative methodologies is urgent and necessary. Many researchers and practitioners have proposed techniques for modeling networks in small communities. Turnquist and Gur (1979) introduced a method for estimating origin-destination (O-D) trip tables from observed link volumes for evaluation of short-range, sub-regional traffic improvement plans (e.g., quick response traffic impact analysis when improvement to the

transportation systems are proposed). They noted that estimating trip tables from traffic counts represents a cost-effective alternative to conventional trip generation and distribution models that depend on expensive, time-consuming surveys and labor-intensive data preparation and analyses. Because many jurisdictions regularly conduct traffic counts on streets and intersections, estimating trip tables from observed traffic volumes can also significantly reduce the effort and time associated with data collection. However, Turnquist and Gur's study deals exclusively with the estimation of trip table. It does not demonstrate how the method can be used in a modeling process when changes in land use and transportation network are expected. Many of the subsequent studies on the estimation of O-D trip tables continue to focus on the methods and applications in evaluating traffic operation strategies, which usually do not involve regional growth due to land use changes. As a result, planners and modelers dealing with forecasting network traffic involving land use development cannot easily apply the O-D estimation methods.

Path Flow Estimator (PFE), originally developed by [Bell and Shields \(1995\)](#) and further enhanced by [Chen et al. \(2005, 2009, 2010\)](#) and [Chootinan et al. \(2005\)](#), is a one-stage network observer capable of estimating path flows and path travel times using only traffic counts from a subset of network links. The core component of PFE is a logit-based route choice model ([Fisk, 1980](#)) that interacts with link cost functions to produce a stochastic user equilibrium (SUE) traffic flow pattern conforming with the traffic counts and other side constraints if available (e.g., intersection turning movement flows, target O-D flows, production flows, attraction flows, etc.).

The theoretical advantage of the nonlinear PFE is the single-level convex programming formulation with side constraints. Since the objective function is strictly convex with respect to the decision variables (path flows) and the constraints are all linear (equality and inequality) relationships, the optimization is guaranteed to yield unique path flows that can be used to derive other useful information at different spatial levels.

The basic idea of PFE is to find a set of unique path flows that can reproduce the observed link counts as well as other available side information, such as historical O-D patterns or link capacities, to increase the observability of the O-D trip table. The resulting path flows can be used to derive other flows, such as flows on unobserved links, intersection turning movement flows, O-D flows, production flows of a traffic zone, attraction flows of a traffic zone, and total travel demand in the entire network. The flexibility of aggregating path flows at different spatial levels allows us to develop a simplified PFE planning model that makes use of not only existing field data (e.g., traffic counts, intersection turning movement flows, etc.) but also planning data (e.g., socio-economic and land use data converted through the ITE trip generation rates (ITE, 2008) to obtain zonal production and attraction flows) for estimating and forecasting network traffic in small communities in the absence of trip generation models. Using the trip rates to capture the trip-making propensity of a given land use configuration in the study area is a common practice, and provides an economical and reasonable estimate when planning resources are limited.

The main objective of this paper is to develop a simplified planning framework that exploits the O-D estimation capability of the path flow estimator (PFE) to perform planning applications in small communities where limited planning resources hinder the development and application of a full four-step model. Two versions (i.e., base year and future year) of the PFE are proposed to address the specific transportation planning issues and needs of small communities. The base year PFE is used for estimating the O-D trip table using current year field measurement data (and planning data if any) as constraints, and the future year PFE is used for predicting network traffic conditions using future trip production and trip attraction and scaled base year (calibrated) O-D trip table as constraints. The unique features of PFE make the proposed framework less resource intensive than the conventional four-step process, and particularly suited for small communities with limited resources. These two versions for PFE are finally integrated into a GIS-based software tool called *Visual PFE* for planning applications in small communities.

The rest of the paper is organized as follows. The tailored PFE models developed for transportation planning in small communities are discussed in Section 2. Section 3 provides the solution algorithm for solving the two PFE models. Section 4 presents two case studies to

demonstrate how the *Visual PFE* tool can be used in practice. Section 5 provides some concluding remarks.

2 SIMPLIFIED PFE PLANNING TOOL

Figure 1 depicts the overall framework of using PFE as a simplified planning tool for estimating the base year O-D trip table and predicting future year network traffic conditions. The major thrust of the proposed approach is that model estimation and forecasting are each accomplished through PFE constrained by various field data and planning data. Specifically, the simplified PFE planning tool includes two modules as depicted in Figure 1: (a) a base year PFE for estimating and calibrating the origin-destination (O-D) trip table using current field data (e.g., traffic counts) and planning data (e.g., historical/target trip table, trip production, trip attraction) as constraints, and (b) a future year PFE for predicting network traffic conditions, taking into account future trip production and trip attraction and the scaled base year O-D trip table to match future total demand as constraints. When only field data (e.g., traffic counts) are available in the base year for model estimation, modeling network traffic with the base year PFE can be more efficient than with a traditional four-step model because it can produce estimates within an acceptable error bound in one estimation step. When field data are not available in the future, the scaled base year O-D trip table can be used as constraints to preserve the trip-making pattern in the future. These unique features of PFE make it a promising planning tool for modeling and forecasting network traffic for small communities with limited resources.

Figure 1 The PFE-based transportation planning framework

2.1 Input data for the base year PFE

Unlike the conventional four-step model which requires extensive surveys for each step (i.e., socio-economic and land use survey, household survey, roadside survey, internal and external survey, on-board transit survey, traffic counts, etc.), PFE just requires some existing field data and planning data that can be obtained in public domains. For details, we provide a description of each type of data and its mathematical expression associated with PFE as follows.

2.1.1. Observed traffic counts

Traffic counts on streets and intersections are regularly collected by various government agencies (e.g., State Department of Transportation, County, City, MPO, etc.). These observed traffic counts are collected in different formats: hourly traffic volume, annual average daily traffic (AADT), annual average weekday traffic (AAWT). Using the peak hour traffic (K-factor) and directional distribution (D-factor) (Roess et al., 2004), it is possible to convert them into a common and usable format for PFE. In addition, PFE does not require the estimated link flows to

reproduce the observed traffic counts exactly, but within an acceptable range defined by the error bounds (i.e., upper and lower bounds). More reliable counts will constrain the estimation to be within a smaller tolerance, whereas less reliable counts will allow for a larger deviation. The introduction of the user-defined error bounds in the traffic count constraints enhances the flexibility of PFE by allowing the user to incorporate local knowledge about the network conditions in the estimation process. The observed traffic count on a link is expressed as follows:

$$(1 - \varepsilon_a) \cdot v_a \leq x_a \leq (1 + \varepsilon_a) \cdot v_a, \quad \forall a \in M, \quad (1)$$

where v_a is the observed traffic volume on link a ; x_a is the estimated flow on link a ; ε_a is the percentage of measurement error allowed for the traffic count on link a ; M is the set of network links with measurements. The error bounds are inputs provided by the user. This typically involves knowledge and experience of the user to provide appropriate error bounds that reflect the traffic measurements within the study area. Alternatively, these error bounds can be specified according to the road functional classification (i.e., freeway, principle arterial, minor arterial, and collector) of roadways as suggested by the Federal Highway Administration (FHWA, 1990) and Cambridge Systematics (2010) in Table 1.

Table 1 Percentage error for daily traffic volumes by facility type

Facility Type	FHWA Targets
Freeway	+/- 7%
Major Arterial	+/- 10%
Minor Arterial	+/- 15%
Collector	+/- 25%

Source: FHWA (1990) and Cambridge Systematics (2010)

Similarly, turning movement counts at intersections can also be used in the base year PFE. Note that modeling intersection turning movements typically requires network expansion at each intersection in order to represent all turning movements. However, adding nodes and links to the network to model intersection turning movements is an expensive proposition. Consider a single intersection represented as a node (left Figure) as shown in Figure 2, to model the intersection turning movements would require adding 3 nodes and 12 links for each intersection (right Figure). For a network with 1,000 nodes and 4,000 links, this would require 4,000 nodes and

16,000 links to fully model all intersection turning movements in the network. This is a 4-fold increase in terms of nodes and links. For large-scale networks, this approach is infeasible.

Figure 2 Network representation of an intersection

In this study, we make innovative use of the path-flow solution to derive intersection turning movements without the need to expand the network. For the turning movements at an intersection, the orientations of links connected to intersection are needed so as to determine the individual turning movement (e.g., left, right, or through movement) from the used paths without the need to expand the network for representing turning movements (see [Chen et al. \(2012\)](#) for the procedure for deriving intersection turning movements using path flows). The observed intersection movement counts at an intersection can be expressed as follows:

$$(1 - \varepsilon_m^i) \cdot g_m^i \leq t_m^i \leq (1 + \varepsilon_m^i) \cdot g_m^i, \quad \forall m \in M_i, i \in \bar{I}, \quad (2)$$

where g_m^i is the observed traffic volume on turning movement m at intersection i ; t_m^i is the estimated flow on turning movement m at intersection i ; ε_m^i is the percentage of measurement error allowed for turning movement m from intersection i ; M_i is the set of turning movements at intersection i ; and $\bar{I}$ is the set of intersections with measurements. Similar to the traffic counts on a link, PFE does not require the estimated intersection movement flows to reproduce the observed intersection turning movement counts exactly, but within an acceptable range defined by the error bounds (i.e., upper and lower bounds). The user can incorporate local knowledge about the network conditions to provide these error bounds.

2.1.2 Zonal production and attraction flows

One of the features of PFE is that it can account for not only traffic counts, but also such planning data as zonal productions and attractions as inputs to the O-D estimation problem. Thus, it has the potential to be an alternative to the conventional trip generation and distribution models for the evaluation of short-range and sub-regional transportation plans. Unlike the traditional O-D estimation methods that use only observed traffic counts and prior O-D trips (or target trip table) to update the trip table, the zonal production and attraction constraints can reflect the spatial interactions of the land use development and travel patterns within a community. In the absence of trip generation models, existing socio-economic and land use information in the base year (e.g., population, employment, number of dwelling units, dwelling types, etc.) can be used to estimate zonal productions and zonal attractions as shown in Figure 3. This requires using the ITE trip generation rates ([ITE, 2008](#)) to convert the socio-economic and land use information to zonal productions and zonal attractions. The trip generation rates published by ITE are expressed in the unit of vehicle trips for: (1) an average weekday, Saturday and Sunday, (2) weekday morning and evening peak hours of the generator, and (3) the weekday morning and evening peak hours on the adjacent street traffic with the percentage of trip productions and attractions for each zone. Table 2 shows an example of applying the ITE trip generation rates. The entering and exiting trip ends are used to estimate vehicle trip attractions and productions, respectively.

Figure 3 Zonal production and attraction flows from socio-economic and land use data

Table 2 Example of trip production and trip attraction estimation using ITE trip rates

TAZ	Parcel ID	Land Use	Unit	Number	Trip Rate	Total Trip Ends	Entering (Attraction)	Exiting (Production)
1	1	General office	ksf	215	1.49	320	265	54
2	1	Single Family (Medium density)	acres	84	2.74	230	78	152
	2	Single Family (High density)	acres	23	3.74	86	29	57
8	1	Agriculture	ksf	60	2.01	121	61	60
23	1	General office	ksf	156	1.49	232	193	39
	2	Single Family	acres	3.2	2.74	9	3	6

ksf = Thousands of Square Feet

Using the trip rates to capture the trip-making propensity of a given land use configuration in the study area is a common practice, and it provides an economical and reasonable estimate when planning resources are limited. In the same manner as the traffic count constraints, the zonal production and zonal attraction constraints can be expressed as follows.

$$(1 - \varepsilon_r) \cdot O_r \leq P_r \leq (1 + \varepsilon_r) \cdot O_r, \quad \forall r \in \bar{R}, \quad (3)$$

$$(1 - \varepsilon_s) \cdot D_s \leq A_s \leq (1 + \varepsilon_s) \cdot D_s, \quad \forall s \in \bar{S}, \quad (4)$$

where O_r and D_s are the observed trip production of origin r and observed trip attraction of destination s obtained by converting land use data via the ITE trip rates; P_r and A_s are the estimated trip production of origin r and estimated trip attraction of destination s ; ε_r and ε_s are the error bounds allowed for trip production of origin r and trip attraction of destination s ; and $\bar{R}$ and $\bar{S}$ are the sets of zones with planning data. The introduction of error bounds in Eqs. (3) and (4) provides the flexibility to have differential land use developments among the different zones.

2.1.3 Prior O-D trip tables

It is well known that O-D estimation from traffic counts is a highly underspecified problem (i.e., the number of O-D demands to be estimated is much greater than the number of independent traffic counts). Therefore, there are multiple O-D trip table estimates that can reproduce the same link flows. In order to increase the observability of the O-D estimation problem from traffic counts, target (or outdated) O-D demands are commonly included to preserve the spatial distribution of the O-D demand pattern. Target (or prior) O-D flow in the base year can be expressed as follows:

$$(1 - \varepsilon_{rs}) \cdot z_{rs} \leq q_{rs} \leq (1 + \varepsilon_{rs}) \cdot z_{rs}, \quad \forall rs \in \bar{R}\bar{S}, \quad (5)$$

where z_{rs} is the target O-D flows between origin r and destination s ; q_{rs} is the estimated O-D flows between origin r and destination s ; ε_{rs} is the error bound allowed for the target O-D demands between origin r and destination s ; and $\bar{R}\bar{S}$ is the set of target (or prior) O-D pairs. Similar to the zonal production and attraction flows, reliable O-D pairs are constrained within a smaller tolerance, while less reliable O-D pairs can have a larger deviation.

2.1.4 Total demand

Total demand is a useful measure to assess the overall traffic demand level in the study area. It can be expressed as follows:

$$(1 - \varepsilon) \cdot F \leq T \leq (1 + \varepsilon) \cdot F \quad (6)$$

where F is the target total demand; T is the estimated total demand; and ε is the error bound allowed for the target total demand.

2.2 Base year PFE formulation

The core component of base year PFE is a logit-based route choice model with various side constraints as discussed above. Based on the equivalent mathematical programming formulation given by [Fisk \(1980\)](#), the base year PFE formulation can be formulated as a constrained convex program as shown in Figure 4.

Objective Function	
Minimize: $Z(\mathbf{f}) = \frac{1}{\theta} \sum_{rs \in RS} \sum_{k \in K_{rs}} f_k^{rs} (\ln f_k^{rs} - 1) + \sum_{a \in A} \int_0^{x_a} t_a(\omega) d\omega$	(7)
Constraints:	
Field Data	
Observed traffic counts from Eq. (1)	(Core data)
Intersection turning movement counts from Eq. (2)	(Optional data)
Planning Data	
Zonal production flows from Eq. (3)	(Optional data)
Zonal attraction flows from Eq. (4)	(Optional data)
Target O-D trip table from Eq. (5)	(Desirable data)
Total demand from Eq. (6)	(Optional data)
Others	
$x_a \leq C_a, \quad \forall a \in U$	(8)
$f_k^{rs} \geq 0, \quad \forall k \in K_{rs}, rs \in RS$	(9)
Definitional	
$x_a = \sum_{rs \in RS} \sum_{k \in K_{rs}} f_k^{rs} \delta_{ka}^{rs}, \quad \forall a \in A$	(10)
$t_m^i = \sum_{rs \in RS} \sum_{k \in K_{rs}} \sum_{a \in IN_i} \sum_{b \in OUT_i} f_k^{rs} \delta_{ka}^{rs} \delta_{kb}^{rs}, \quad \forall m \in M_i, i \in I$	(11)
$P_r = \sum_{s \in S} \sum_{k \in K_{rs}} f_k^{rs}, \quad \forall r \in R$	(12)
$A_s = \sum_{r \in R} \sum_{k \in K_{rs}} f_k^{rs}, \quad \forall s \in S$	(13)
$q_{rs} = \sum_{k \in K_{rs}} f_k^{rs}, \quad \forall rs \in RS$	(14)
$T = \sum_{rs \in RS} \sum_{k \in K_{rs}} f_k^{rs}$	(15)

Figure 4 Base year PFE formulation

where θ is the dispersion parameter in the logit model; f_k^{rs} is the flow on path k connecting O-D pair rs ; $t_a(\cdot)$ is the travel time on link a ; x_a is the estimated traffic volume on link a ; δ_{ka}^{rs} is the path-link indicator, 1 if link a is on path k between O-D pair rs and 0 otherwise; and the rest of the variables are previously defined.

The objective function (7) has two terms: an entropy term and a user equilibrium term. The entropy term seeks to spread trips onto multiple paths according to the dispersion parameter, while the user equilibrium term tends to cluster trips on the minimum cost paths. As opposed to the traditional logit-based SUE model, the base year PFE finds path flows that minimize the SUE objective function in Eq. (7) while simultaneously reproducing traffic counts on all observed links in Eq. (1), turning movement counts on all observed intersections in Eq. (2), zonal production and attraction of certain origin and destination in Eqs. (3) and (4), prior travel demands of certain O-D pairs in Eq. (5), and total demand in Eq. (6) within some predefined error bounds. These error bounds are essentially confidence levels of the observed data at different spatial levels used to constrain the path flow estimation. For the unobserved links, the estimated flows cannot exceed their respective capacities as indicated by Eq. (8). This constraint is incorporated for the same purpose as in the capacitated traffic assignment (Larsson and Patriksson, 1995), which is to prevent producing unrealistically high link flow estimates. Eq. (9) constrains the path flows to be non-negative. Eqs. (10), (11), (12), (13), (14) and (15) are definitional constraints that sum up the estimated path flows to obtain the link flows, intersection turning movement flows, zonal production flows, zonal attraction flows, O-D flows, and total demand, respectively.

2.3 Input data for the future year PFE

Since one cannot observe future traffic counts, the forecasting process for the future network traffic conditions needs to make full use of available planning data (i.e., future socio-economic and land use data) and the O-D demand pattern estimated in the base year.

2.3.1 Future zonal production and attraction flows

Similar to the base year PFE, future socio-economic and land use data can be used to generate future zonal production and attraction flow using the ITE trip generation rates. The future zonal production and zonal attraction constraints can be expressed as follows.

$$(1 - \varepsilon_r) \cdot O_r \leq P_r \leq (1 + \varepsilon_r) \cdot O_r, \quad \forall r \in \bar{R}, \quad (16)$$

$$(1 - \varepsilon_s) \cdot D_s \leq A_s \leq (1 + \varepsilon_s) \cdot D_s, \quad \forall s \in \bar{S}, \quad (17)$$

where O_r and D_s are the future zonal production of origin r and future zonal attraction of destination s obtained by converting future land use data via the ITE trip rates; P_r and A_s are the estimated future zonal production of origin r and estimated future zonal attraction of destination s ; ε_r and ε_s are the forecasting error bounds for trip production of origin r and trip attraction of destination s ; and $\bar{R}$ and $\bar{S}$ are the sets of zones with future data. The error bounds in Eqs. (16) and (17) provide the flexibility to have differential land use developments among the different zones to reflect the spatial interactions of the future land use development and travel patterns within a community.

2.3.2 Future target O-D trip table

Since future traffic counts are not available, it is necessary to make use of the base year spatial demand distribution as a guide to infer the trip-making pattern in the future year. Due to uneven land use changes, some O-D pairs may experience substantial changes in its demand relative to other O-D pairs, so the scaling over the base year O-D may not apply to all the O-D pairs in the same way. Figure 5 provides a graphical illustration of the steps used to compute future year target O-D trip table (or selected future target O-D pairs).

Figure 5 Derivation of future target O-D trips

With the scaling factors, the future target O-D flows can be expressed as follows:

$$(1 - \varepsilon_{rs}) \cdot z_{rs} \leq q_{rs} \leq (1 + \varepsilon_{rs}) \cdot z_{rs}, \quad \forall rs \in \bar{R}\bar{S}, \quad (18)$$

where z_{rs} is the future target O-D flows between origin r and destination s ; q_{rs} is the estimated future O-D flows between origin r and destination s ; ε_{rs} is the error bound allowed for the target O-D demands between origin r and destination s ; and $\bar{R}\bar{S}$ is the set of target O-D pairs. These future target O-D flow constraints can help to infer the spatial distribution of O-D demands.

2.3.3 Future total demand

Similar to the base year, future total demand can be included to constrain the estimated total demand as follows.

$$(1 - \varepsilon) \cdot F \leq T \leq (1 + \varepsilon) \cdot F, \quad (19)$$

where F is the future target total demand; T is the estimated future total demand; and ε is the error bound allowed for the target total demand.

2.4 Future year PFE formulation

The core component of the future year PFE is a logit-based route choice model with only planning data (i.e., future trip production and trip attraction) and the scaled base year O-D trip table to match future total demand as constraints for predicting future network traffic conditions. Similar to the base year PFE, the future year PFE can be formulated as a convex program with various side constraints as shown in Figure 6.

Objective Function	
Minimize: $Z(\mathbf{f}) = \frac{1}{\theta} \sum_{rs \in RS} \sum_{k \in K_{rs}} f_k^{rs} (\ln f_k^{rs} - 1) + \sum_{a \in A} \int_0^{x_a} t_a(\omega) d\omega$	(20)
Constraints:	
Planning Data	
Zonal production flows in Eq. (16)	(Core data)
Zonal attraction flows in Eq. (17)	(Core data)
Target O-D trip table in Eq. (18)	(Core data)
Total demand in Eq. (19)	(Optional data)
Others	
$f_k^{rs} \geq 0, \quad \forall k \in K_{rs}, rs \in RS$	(21)
Definitional	
$x_a = \sum_{rs \in RS} \sum_{k \in K_{rs}} f_k^{rs} \delta_{ka}^{rs}, \quad \forall a \in A$	(22)
$P_r = \sum_{s \in S} \sum_{k \in K_{rs}} f_k^{rs}, \quad \forall r \in R$	(23)
$A_s = \sum_{r \in R} \sum_{k \in K_{rs}} f_k^{rs}, \quad \forall s \in S$	(24)
$q_{rs} = \sum_{k \in K_{rs}} f_k^{rs}, \quad \forall rs \in RS$	(25)
$T = \sum_{rs \in RS} \sum_{k \in K_{rs}} f_k^{rs}$	(26)

Figure 6 Future year PFE formulation

3 SOLUTION ALGORITHM

The solution procedure for solving the two versions of PFE is depicted in Figure 7. It consists of three main modules: (1) an iterative balancing scheme, (2) column (or path) generation, and (3) output generation from path flows. The basic idea of the iterative balancing scheme is to sequentially scale the path flows to fulfill one constraint at a time by adjusting the dual variables. Once the scheme converges, the path flows can be analytically determined. A column generation is included in the solution procedure to avoid path enumeration for a general transportation network. Finally, an output generation procedure is used to derive information at different spatial levels using the PFE path-flow solution (e.g., link flows, turning movement flows for all intersections, production flows, attraction flows, O-D flows, and total demand).

Figure 7 Flowchart of the PFE solution algorithm

3.1 Iterative balancing scheme

Note that the iterative balancing scheme is demonstrated for the base year PFE with both field data and selected planning data. The same scheme can also be used to solve the future year PFE with only planning data as constraints. The steps are summarized as follows.

Step 1. Initialization

1.1 Set inner iteration $(n) = 0$

1.2 Set primal variables: $x_a^n, t_m^{i,n}, P_r^n, A_s^n, q_{rs}^n$ and $T^n = 0$,

1.3 Set dual variables: $(u_a^-)^n, (u_a^+)^n, (\tau_m^{i-})^n, (\tau_m^{i+})^n, (\rho_r^-)^n, (\rho_r^+)^n, (\alpha_s^-)^n, (\alpha_s^+)^n, (o_{rs}^-)^n, (o_{rs}^+)^n, (\psi^-)^n, (\psi^+)^n$ and $(d_a)^n = 0$.

where $u_a^-, u_a^+, \tau_m^{i-}, \tau_m^{i+}, \rho_r^-, \rho_r^+, \alpha_s^-, \alpha_s^+, o_{rs}^-, o_{rs}^+, \psi^-, \psi^+$ and d_a are the dual variables of constraints (1), (2), (3), (4), (5), (6) and (8), respectively.

Step 2. Compute Dual and Primal Variables

The values of $u_a^+, \tau_m^{i+}, \rho_r^+, \alpha_s^+, o_{rs}^+, \psi^+$ and d_a are restricted to be non-positive, while the values $u_a^-, \tau_m^{i-}, \rho_r^-, \alpha_s^-, o_{rs}^-$, and ψ^- must be nonnegative. $u_a^-, u_a^+, \tau_m^{i-}$ and τ_m^{i+} can be viewed as the corrections to the link travel times and intersection turning movement delays, respectively, by adjusting the estimated path flows to match with the link count and intersection turning movement count constraints specified by Eqs. (1) and (2). Similarly, $\rho_r^-, \rho_r^+, \alpha_s^-, \alpha_s^+, o_{rs}^-, o_{rs}^+, \psi^-$ and ψ^+ can be viewed as the corrections to the zonal production levels, zonal attraction levels, O-D travel times, and total demand level, respectively. These corrections can be used to steer the estimated path flows to match with the observed zonal production, zonal attraction, target O-D flow, and total demand constraints specified by Eqs. (3), (4), (5), and (6). d_a is related to the link queuing delay (Bell et al., 1997) when the estimated link flow reaches its capacity. These dual variables are zero if the estimated primal values (e.g., link flows, intersection turning movement flows, production flows, attraction flows, O-D flows, and total demand) are within an acceptable range defined by the measurement error bounds, non-zero if they are binding at one of the limits, and infinity (or very large positive or negative values) if there exists no solution that can fulfill

the constraints (Bell et al., 1997).

2.1 Update dual variables

- a. For each measured link ($a \in \mathbf{M}$), update the dual variables

$$(u_a^+)^n = \text{Min} \left\{ 0, (u_a^+)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 + \varepsilon_a) \cdot v_a}{x_a^n} \right) \right\}, \text{ and}$$

$$(u_a^-)^n = \text{Max} \left\{ 0, (u_a^-)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 - \varepsilon_a) \cdot v_a}{x_a^n} \right) \right\}.$$

- b. For each unmeasured link ($a \in \mathbf{U}$), update the dual variables

$$(d_a)^n = \text{Min} \left\{ 0, (d_a)^{n-1} + \frac{1}{\theta} \ln \left(\frac{C_a}{x_a^n} \right) \right\}.$$

- c. For each measured intersection ($i \in \bar{\mathbf{I}}$), update the dual variables

$$(\tau_m^{i+})^n = \text{Min} \left\{ 0, (\tau_m^{i+})^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 + \varepsilon_m^i) \cdot g_m^i}{t_m^{i,n}} \right) \right\}, \text{ and}$$

$$(\tau_m^{i-})^n = \text{Max} \left\{ 0, (\tau_m^{i-})^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 - \varepsilon_m^i) \cdot g_m^i}{t_m^{i,n}} \right) \right\}$$

- d. For each zonal production flow ($r \in \bar{\mathbf{R}}$), update the dual variables

$$(\rho_r^+)^n = \text{Min} \left\{ 0, (\rho_r^+)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 + \varepsilon_r) \cdot O_r}{P_r^n} \right) \right\}, \text{ and}$$

$$(\rho_r^-)^n = \text{Max} \left\{ 0, (\rho_r^-)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 - \varepsilon_r) \cdot O_r}{P_r^n} \right) \right\}$$

- e. For each zonal attraction flow ($s \in \bar{\mathbf{S}}$), update the dual variables

$$(\alpha_s^+)^n = \text{Min} \left\{ 0, (\alpha_s^+)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 + \varepsilon_s) \cdot D_s}{A_s^n} \right) \right\}, \text{ and}$$

$$(\alpha_s^-)^n = \text{Max} \left\{ 0, (\alpha_s^-)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 - \varepsilon_s) \cdot D_s}{A_s^n} \right) \right\}$$

- f. For each target O-D flow ($rs \in \bar{\mathbf{R}}\bar{\mathbf{S}}$), update the dual variables

$$(o_{rs}^+)^n = \text{Min} \left\{ 0, (o_{rs}^+)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 + \varepsilon_{rs}) \cdot z_{rs}}{q_{rs}^n} \right) \right\}, \text{ and}$$

$$(o_{rs}^-)^n = \text{Max} \left\{ 0, (o_{rs}^-)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 - \varepsilon_{rs}) \cdot z_{rs}}{q_{rs}^n} \right) \right\}$$

g. For the total demand, update the dual variables

$$(\psi^+)^n = \text{Min} \left\{ 0, (\psi^+)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 + \varepsilon) \cdot F}{T^n} \right) \right\}, \text{ and}$$

$$(\psi^-)^n = \text{Max} \left\{ 0, (\psi^-)^{n-1} + \frac{1}{\theta} \ln \left(\frac{(1 - \varepsilon) \cdot F}{T^n} \right) \right\}$$

2.2 Compute primal variables: path flows can be derived analytically as a function of path costs and dual variables.

a. Compute path flows

$$(f_k^{rs})^n = \exp \left(\theta \cdot \left(\begin{aligned} & - \sum_{a \in A} t_a (x_a^n) \delta_{ka}^{rs} + \sum_{a \in M} \left((u_a^-)^n + (u_a^+)^n \right) \cdot \delta_{ka}^{rs} + \sum_{a \in U} (d_a^n) \delta_{ka}^{rs} + \\ & \sum_{m \in M_i} \sum_{i \in I} \sum_{a \in IN_i} \sum_{b \in OUT_i} \left((\tau_m^{i-})^n + (\tau_m^{i+})^n \right) \cdot \delta_{ka}^{rs} \delta_{kb}^{rs} + (\rho_r^-)^n + (\rho_r^+)^n \\ & + (\alpha_s^-)^n + (\alpha_s^+)^n + (o_{rs}^-)^n + (o_{rs}^+)^n + (\psi^-)^n + (\psi^+)^n \end{aligned} \right) \right), \begin{aligned} & \forall k \in K_{rs}, \\ & \forall rs \in RS \end{aligned}$$

b. Compute link flows

$$x_a^n = \sum_{rs \in RS} \sum_{k \in K_{rs}} (f_k^{rs})^n \delta_{ka}^{rs}, \quad \forall a \in A$$

c. Compute intersection turning movement flows

$$t_m^{i,n} = \sum_{rs \in RS} \sum_{k \in K_{rs}} \sum_{a \in IN_i} \sum_{b \in OUT_i} (f_k^{rs})^n \delta_{ka}^{rs} \delta_{kb}^{rs}, \quad \forall m \in M_i, i \in I$$

d. Compute zonal production and attraction flows

$$P_r^n = \sum_{s \in S} \sum_{k \in K_{rs}} (f_k^{rs})^n, \quad \forall r \in R$$

$$A_s^n = \sum_{r \in R} \sum_{k \in K_{rs}} (f_k^{rs})^n, \quad \forall s \in S$$

e. Compute O-D flows

$$q_{rs}^n = \sum_{k \in K_{rs}} (f_k^{rs})^n, \quad \forall rs \in RS$$

f. Compute total demand

$$T^n = \sum_{rs \in RS} \sum_{k \in K_{rs}} (f_k^{rs})^n$$

Step 3. Convergence and divergence Test

$$\xi = \text{Max} \left\{ \begin{array}{l} \left| (u_a^+)^n - (u_a^+)^{n-1} \right|, \left| (u_a^-)^n - (u_a^-)^{n-1} \right|, \left| (d_a)^n - (d_a)^{n-1} \right|, \left| (\tau_m^{i+})^n - (\tau_m^{i+})^{n-1} \right|, \\ \left| (\tau_m^{i-})^n - (\tau_m^{i-})^{n-1} \right|, \left| (\rho_r^+)^n - (\rho_r^+)^{n-1} \right|, \left| (\rho_r^-)^n - (\rho_r^-)^{n-1} \right|, \left| (\alpha_s^+)^n - (\alpha_s^+)^{n-1} \right|, \\ \left| (\alpha_s^-)^n - (\alpha_s^-)^{n-1} \right|, \left| (o_{rs}^+)^n - (o_{rs}^+)^{n-1} \right|, \left| (o_{rs}^-)^n - (o_{rs}^-)^{n-1} \right|, \left| (\psi^+)^n - (\psi^+)^{n-1} \right|, \\ \left| (\psi^-)^n - (\psi^-)^{n-1} \right| \end{array} \right\}$$

If $\eta_0 \leq \xi < \eta$, where η_0 is a convergence tolerance (e.g., 10^{-6}) and η is the upper limit (e.g., 10^6) of change in dual variables, then set all parameters of the next iteration equal to those of the current iteration, set $\text{Inner}(n) = \text{Inner}(n+1)$, and go to step 2. If $\xi \geq \eta$ (detecting divergence) then set all parameters of the next iteration equal to those of the current iteration, set $\text{outer}(n) = \text{outer}(n+1)$, and go to column generation step. If $\xi \leq \eta_0$ then terminate, go to output step.

In the above procedure, we provide only the final form of the adjustment equations for different types of constraint (e.g., observed links, unobserved links, observed intersections, target O-D flows, etc.). The detailed derivations of the adjustment equations can be found in [Chen et al. \(2009, 2010\)](#), and convergence of the iterative balancing scheme is discussed in details in [Bell et al. \(1997\)](#) and [Bell and Iida \(1997\)](#).

3.2 Column generation

The above iterative balancing scheme assumes that a working path set is given. For large networks, it is not practical to enumerate a working path set in advance since the number of possible paths grows exponentially with respect to network size. To circumvent path enumeration, a column (or path) generation procedure can be augmented to the iterative balancing scheme. Basically, the algorithm introduces an outer loop (or iteration) to iteratively

generate paths to be added to the working path set as needed to replicate the observed interval constraints (e.g., link counts, turning movement counts, selected prior O-D flows, etc.), and to account for the capacity restraints for the unobserved links as well as the congestion effects, while the iterative balancing scheme iteratively adjusts the primal variables (e.g., path flows, link flows, intersection turning movement flows, O-D flows, etc.) and the dual variables in the inner loop for a given working path set from the outer loop. Note that the working path set is generated by a column generation scheme (or a shortest path algorithm) using the generalized link costs, which is based not only on the link costs but also on the dual variables from the active side constraints. The dual variables force the column generation scheme to generate paths that satisfy the side constraints. For additional discussions on the issue of using the generalized link costs to generate paths, refer to [Bell et al. \(1997\)](#) and [Chen et al. \(2009, 2010\)](#).

3.3 Output generation from path flows

The unique path-flow solution from PFE makes it possible to derive useful information at different spatial levels. Given the path-flow solution, the following information at different spatial levels can be derived:

- Total demand: the sum of all path flows from all O-D pairs gives the total demand utilizing the network.
- Zonal production: the sum of all path flows emanating from a given origin gives the zonal production.
- Zonal attraction: the sum of all path flows terminating at a given destination gives the zonal attraction.
- O-D flow: the sum of all paths flows connecting that O-D pair gives the O-D flow.
- Intersection turning movement flow: the sum of all path flows passing through that intersection turning movement gives the intersection turning movement flow.
- Link flow: the sum of all path flows passing through a given link gives the link flow.

3.4 Visual PFE software

Visual PFE is an integrated software suite that combines the Path Flow Estimator (PFE) with other software components to facilitate the base year estimation and future year forecasting, using a user-friendly Graphical User Interfaces (GUI) for inputting data and outputting results in

tabular and map formats. It is built to be an open source standalone software using an open source programmable Geographical Information Systems (GIS) software ([MapWindow, 2010](#)). MapWindow is a mapping tool, a GIS modeling system, and GIS application programming interface all in one convenient redistributed open source form. MapWindow was developed to address the needs for a GIS programming tool that could be used in engineering research and project software, without requiring end users to purchase a complete GIS system, or become GIS experts. With Visual PFE, users can:

- Run PFE with GUIs
- Convert the estimated O-D tables to Microsoft Excel Files
- Change the colors and zoom levels of the O-D table cells
- Interactively display and query O-D desire lines
- Interactively display and query paths between any pairs of O-D
- Convert the PFE outputs to GIS files
- Create thematic maps of network links and traffic analysis zones
- Generate diagnostic scatter plots
- Link the scatter plots to the network for identification of outliers
- Change network link attributes and export the network back to the PFE format for another estimation
- Create and edit PFE networks as text files
- Compare different scenarios

For additional details, readers are referred to [Zhang et al. \(2010\)](#) for a complete description of the Visual PFE software.

4 CASE STUDIES

For proof of concept, two case studies were conducted using two communities in northern California. The first case study is a small community in the city of St. Helena, where the city's planning department has neither an existing travel demand model nor the budget for a full model development. The second case study is in the city of Eureka, where there is a four-step travel

demand forecasting model developed for the Humboldt County Association of Government that can be used for comparison.

4.1 Case study 1: City of St. Helena

The City of St. Helena is located in the wine-producing region of Napa Valley in California, approximately 65 miles north of San Francisco. St. Helena is a full-service city with a population of 6,006 (as of January 1, 2005) within an area of 4 square miles. The City's development pattern is relatively compact. Commercial development and wineries concentrate along Highway 29 (Main Street) corridor and residential developments radiate out from Main Street (See Figure 8). The primary planning goal of the City is to preserve the rural, small town quality and agricultural character. Nevertheless, in the past few years, the City has been faced with pressures to grow as demand for service and commercial activities are rapidly rising with the increased number of tourists to the Napa Valley every year. The pressure for regional growth has caused serious concerns in the community with regard to deteriorating traffic conditions and the small town atmosphere. Continuous growth in most of the City is not expected, because there is a substantial difficulty in expanding the public utility systems. To cater to the need for development, the City designated an area within the city boundary as a specific plan area to carefully guide and support future development of properties within the area while maintaining the desired town characteristics. The specific plan proposes to relieve congestion on Highway 29 by extending a street (Oak Avenue) that runs parallel to the highway (see Figure 8). Oak Avenue is designated in the City's General Plan ([City of St. Helena, 1993](#)) as a collector street. The identification of potential traffic impacts and the decision-making for right-of-way preservation hinge upon a reliable forecast of design year traffic volumes on the extended street. However, the City's planning department has neither an existing travel model nor the budget for a full model development. The dilemma calls for innovative modeling approaches that can provide quick and reasonable responses with available resources.

4.1.1 Base year analysis

For the base year analysis, traffic counts collected since 2001 were retrieved for application of the proposed procedure. Link volumes collected during the evening peak hour, the time of day when traffic congestion on Highway 29 presents a serious issue, were assembled and a network

with 28 TAZs was coded with the observed link volumes. The network contains 113 links and 54 of the links do not have traffic count data. Turn penalties, based on the actual traffic conditions, were also applied in the network such that the shortest paths among TAZ centroids replicate actual travel patterns in the area. In addition, turning movement counts at two intersections (Fulton/Main and Mitchell Dr./Oak Ave.) were considered to assist the estimation (used as constraints in addition to link observation constraints). Figure 8 depicts the St. Helena network and locations of two intersections (Fulton/Main and Mitchell Dr./Oak Ave.) of which turning movement counts were considered to assist the estimation.

Figure 8 St. Helena network and locations of intersection turning movement counts

Figure 9 shows the scatter plots of observed and estimated link flows and turning movement flows, respectively. To measure the accuracy of estimated flows, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are adopted. As can be seen in the figure, both link flows and turning movement flows closely match the observed counts. All estimated flows are within $\pm 15\%$ of absolute errors of the observed values. MAE and RMSE between observed

counts and estimated flows are 15.55 and 25.12 in link flows, while 3.08 and 7.40 are computed for turning movement flows, respectively.

Figure 9 Comparison between observed and estimated flows

Figure 10 shows the estimated results in terms of link flows, production flows, and attraction flows to assess the overall flow pattern in the City. We observe that most flows are concentrated on Main Street, which agrees with the traffic condition in the City.

Figure 10 Base year flow pattern estimates

4.1.2 Future year analysis

Since future traffic counts are not available, future land use information and the base year O-D trip table were used to predict future network traffic conditions. Future land use data are generally available from the General Plan of each city. For this study, we obtained the land use data from the General Plan 2030 of the City of St. Helena ([City of St. Helena, 2010](#)). When land use changes are expected to impact trip production and attraction in the study area of future years, the additional number of trips can be estimated with the ITE trip generation rates to convert various land uses to trip productions and attractions. In general, the land use characteristics in St. Helena can be classified into four categories: residential areas, commercial and mixed use areas, business and industrial areas, and community and natural resource areas. Since no other potential development was expected elsewhere in the City, the additional trips produced from and attracted to TAZs in the specific plan area were added to the base year production and attraction to obtain the future production and attraction flows. Trip balancing was subsequently performed to ensure that the total production equals to the total attraction. Figure 11 graphically depicts the future year zonal production and attraction flows for the St. Helena network.

Figure 11 Future year zonal production and attraction flows

According to the specific plan proposed by City's general plan, two scenarios were set up as follows.

1. No build scenario
2. Build scenario (extending Oak Avenue)

The St. Helena planning network was revised according to the conceptual street design proposed in the specific plan (i.e., extending Oak Avenue). The future PFE was performed to forecast traffic volumes based on the land use and the two scenarios considered above. The forecasting process is essentially an O-D estimation constrained on the specific plan trip production and attraction and the scaled base year O-D trip table to preserve the spatial distribution patterns exhibited in the base year O-D trip table. Because there are no link counts to constrain the estimation, the trip production and attraction of the forecast O-D trip table match almost exactly the given future production and attraction flows. Since there are no observed future traffic conditions, the forecast results can only be assessed based on its reasonableness. Figure 12 shows the forecast results in terms of link flows and volume to capacity (V/C) ratios for the two scenarios. As expected, congestion level on Main Street is slightly higher in scenario 1 (no build scenario) compared to those in scenario 2 (build scenario). It appears that by extending Oak Avenue parallel to Main Street can help to alleviate some of the congestion on Main Street, particularly on the segments between Mitchell Dr. and Mills Lane (detailed level-of-service (LOS) analysis is provided in the next subsection).

Figure 12 Forecast link flows and V/C ratios for two scenarios

To further assess the build scenario (extending Oak Avenue), level of service (LOS) analysis is performed. Maintaining an acceptable LOS is one of the most important controls in roadway design. According to the Fourth Edition of A policy on Geometric Design of Highways and Streets by the American Association of State Highway and Transportation Officials ([AASHTO, 2001](#)), the number of lanes to be provided on urban collector streets with high traffic volumes should be determined from capacity analysis. This analysis should consider both intersections and mid-block locations, when appropriate, in assessing the ability of a proposed design to provide the desired LOS. The standard methodology in the Highway Capacity Manual 2000 ([TRB, 2000](#)) provided in Table 3 was used to determine the LOS on various segments on Main Street. To facilitate the analysis of average travel speed on the design street, forecasts of link volumes were derived from the future year PFE. The existing segments on Main Street can be classified as Class IV urban streets with a speed limit of between 25 mph and 35 mph. Table 4 summarizes the analysis results. All segments on Main Street appear to be acceptable with a LOS of C or better for both scenarios. However, the built scenario (scenario 2) has better LOS on some segments due to the extension of Oak Avenue.

Table 3 Urban street level of service

Urban Street Class	I	II	III	IV
Range of Free Flow Speeds (mph)	45 to 55	35 to 45	30 to 35	25 to 35
Typical Free Flow Speed (mph)	50	40	33	30
Level of Service	Average Travel Speed (mph)			
A	>42	>35	>30	>25
B	>34	>28	>24	>19
C	>27	>22	>18	>13
D	>21	>17	>14	>9
E	>16	>13	>10	>7
F	≤16	≤13	≤10	≤7

Source: *Highway Capacity Manual 2000*

Table 4 LOS analysis for Main Street

Street Segment (Scenario 1)		Volume (vph)	Time (sec)	Speed (mph)	LOS
Vintage Ave - Dowdell Lane	Northbound	1186	30	19	B
Dowdell Lane - Vintage Ave	Southbound	1258	30	19	B
Dowdell Lane - Mills Lane	Northbound	1294	21	19	B
Mills Lane - Dowdell Lane	Southbound	1512	22	18	C
Mills Lane - Charter Oak Ave	Northbound	1453	41	18	C

Charter Oak Ave - Mills Lane	Southbound	1564	42	17	C
Charter Oak Ave - Spring St.	Northbound	1391	50	18	C
Spring St.- Charter Oak Ave	Southbound	1590	54	17	C
Street Segment (Scenario 2)		Volume (vph)	Time (sec)	Speed (mph)	LOS
Vintage Ave - Dowdell Lane	Northbound	1199	30	19	B
Dowdell Lane - Vintage Ave	Southbound	1275	30	19	B
Dowdell Lane -Mills Lane	Northbound	1308	21	19	B
Mills Lane - Dowdell Lane	Southbound	1532	22	18	C
Mills Lane - Charter Oak Ave	Northbound	1241	39	19	B
Charter Oak Ave- Mills Lane	Southbound	1252	39	19	B
Charter Oak Ave- Spring St.	Northbound	1142	47	19	B
Spring St.- Charter Oak Ave	Southbound	1252	48	19	B

Volume = forecast of number of vehicles during the PM peak hour; Time = travel time (including delays) in seconds

Speed = segment speed in miles per hour; LOS = level of service for urban streets

4.2 Case study 2: City of Eureka

The City of Eureka is located in the Humboldt County in California, approximately 270 miles north of San Francisco. Eureka serves as a principal city for the County with a population of 26,097 (as of 2007). U.S. Route 101 extends north and south through the City. Harris St., Myrtle Ave, H St., and I St. are the main roads in the City of Eureka. State Route 299 (formerly U.S. Route 299) connects to U.S. Route 101 at the northern end of the nearby City of Arcata. Route 299 begins at that point and extends to the east as the major traffic artery for the Greater Eureka community (see Figure 13). There is a four-step travel demand forecasting model developed by [DKS Associates \(2006\)](#) for the Humboldt County Association of Government. For the trip generation step, a cross classification model is used with planning data including dwelling unit (single family and multi-family) and employment data for each traffic analysis zone (TAZ). In the trip distribution step, a doubly-constrained gravity model is adopted, while a probit-based stochastic user equilibrium (SUE) assignment model is used to conduct the traffic assignment step. Note that the modal split step is not considered in the four-step model. To demonstrate how to apply the base year and future year PFE to the Eureka network, comparisons between the results obtained from the four-step model and the PFE models were performed.

4.2.1 Input data preparation

The input data preparation for the Eureka network involves a number of steps: (a) subarea analysis, (b) zonal aggregation, and (c) land use and socio-economic data. The first step was to

perform subarea analysis by extracting the City of Eureka from the Humboldt County network using the Greater Eureka Area Travel Model (GEATM) developed by [DKS Associates \(2006\)](#). In the second step, zonal aggregation was performed to eliminate zones with very low demand or no demand. Finally, zonal production and attraction flows were estimated from the land use and socio-economic data. Figure 13 shows the extracted network in the City of Eureka with locations of traffic counts and TAZ after subarea analysis and zonal aggregation.

The number of observed counts in the City of Eureka is 136 or about 2% of the 6344 links in the extracted network. As can be seen, the number of observed counts is not sufficient to estimate a reliable O-D trip table. Many of the O-D pairs in the extracted network simply contain no information that can be used to estimate the O-D demand.

Figure 13 Traffic counts and aggregated TAZ locations in the Eureka network

Since traffic counts are not sufficient (about 2%) to estimate a reliable O-D trip table for the base year, land use and socio-economic data were used to increase the observability for estimating the base year O-D trip table as well as for predicting future network traffic conditions. Land use and socio-economic data are generally available from the General Plan of each city. For this case study, we obtained the data from the GEATM. Figure 14 presents a procedure using ITE trip rates to estimate zonal production and attraction trips for the aggregated TAZs, and Figure 15 shows the estimated zonal production and attraction flows for the base year (2005) and the future year (2030).

Figure 14 Procedure for converting land use data to zonal production and attraction trips

Figure 15 Estimated zonal production and attraction flows for years 2005 and 2030

4.2.2 Base year analysis

This section compares the results of the base year PFE to those of the four-step model obtained from the GEATM model: (a) zonal production and attraction flows, (b) O-D flows, and (c) link flows.

(a) Zonal Production and Attraction Flow Comparison for the Base Year

Figure 16 provides a graphical visualization of the estimated zonal production and attraction flows obtained from both models. Overall, both models produce similar trip generation patterns with higher zonal production and attraction flows concentrating on the major highways. The R^2 values between the results of the two models are 0.86 and 0.80 for production and attraction, respectively. Using the base year PFE typically underestimates the zonal production and attraction flows on the major highways while overestimates some of the internal zonal production and attraction flows within the City compared to those of the four-step model. Since traffic counts are not sufficient to estimate a reliable O-D trip table, the production and attraction flows based on the average trip rate values surveyed from various cities in North America were also used as constraints in the base year PFE. Therefore, these values may not be able to capture the specific characteristics of the local study area compared to trip generation model developed by GEATM.

Figure 16 Estimated zonal production and attraction flows for the base year

(b) O-D Flow Comparison for the Base Year

Figure 17 shows the percentage of O-D pairs by the absolute O-D flow difference between the base year PFE model and the four-step model. More than 70% of the O-D pairs are estimated within ± 1 trip, and more than 97% of the O-D pairs are within ± 10 trips. The overall match between the two models depicted by the correlation coefficient is 0.74.

Figure 17 Percentage of O-D pairs by the absolute O-D flow difference for the base year

(c) Link Flow Comparison for the Base Year

Figure 18(a) depicts the estimated link flow results for the four-step model and the base year PFE model. As can be seen, both models produce similar traffic patterns in terms of link flows and V/C ratios (i.e., higher congestion on the major highways). The four-step model estimated a slightly higher congestion level on U.S. 101 compared to those estimated by the base year PFE model. This discrepancy is due to the side constraints (i.e., both traffic counts on the major highways in Figure 13 and the zonal production and attraction flows in Figure 14(a)) used in the logit-based PFE model as opposed to the probit-based SUE assignment results of the four-step model. Figure 18(b) shows the scatter plots of observed and estimated link flows by roadway functional class. It shows that the base year PFE can replicate the observed link counts better than the four-step model. For the estimated flows by the base year PFE, the errors are within 20%, while some of the link flows estimated by the four-step model have more than 20% error. The correlation coefficients are 0.849 for the four-step model and 0.978 for the base year PFE model.

(a1) Four-step model

(a2) PFE model

(a) Estimated link flows and V/C ratios

(b1) Four-step model

(b2) PFE model

(b) Comparison between observed and estimated link flows

Figure 18 Link flow comparison for the base year

4.2.3 Future year analysis

Similar to the base year analysis, the forecast results from the future year PFE with those obtained from the GEATM model were compared for year 2030. Predicted zonal production and attraction flows shown in Figure 15 were used with selected (important) O-D pairs from the base

year trip table to constrain the relationship of travel impedance and trip interchange between each O-D pair in the future year PFE forecasting process.

(a) Zonal Production and Attraction Flows Comparison for the Future Year

Figure 19 provides a graphical visualization the forecast zonal production and attraction flows for year 2030. Both models produce similar trip generation patterns for the future year. The R^2 values are 0.97 and 0.93 for production and attraction, respectively. The core inputs to the future PFE model for predicting zonal production and attraction flows are the future planning data (i.e., dwelling unit for trip production and employment for trip attraction) and the scaled base year O-D trip table, and the figure shows that the predicted zonal flows by ITE trip rates generally agree with those predicted flows by the four-step model, with a slight advantage for production flows over attraction flows. The discrepancy mainly occurs for the low attraction flows (i.e., fewer than 50 trips), which is understandable given that PFE uses the average ITE trip rates to convert the forecast land use and socioeconomic data to trip productions and trip attractions.

Figure 19 Zonal production and attraction flow comparison for the future year

(b) O-D Flow Comparison for the Future Year

Figure 20 shows the percentage of O-D pairs by the absolute O-D flow difference between the future year PFE model and the four-step model. More than 87% of the O-D pairs are predicted within ± 1 trip, and more than 99% of the O-D pairs are within ± 10 trips. Compared to the base year, the overall match between the two models is much better with a correlation coefficient of 0.95.

Figure 20 Percentage of O-D pairs by the absolute O-D flow difference for the future year

(c) Link Flow Comparison for the Future Year

Figure 21 provides a graphical representation of the forecast link flows and V/C ratios obtained from the four-step model and the future year PFE model. From the figure, we can observe that both models produce similar traffic patterns (i.e., congestion on U.S. 101), indicating that both models are capable of capturing the overall congestion pattern in the Eureka network. However, the congestion magnitudes differ slightly between the two models. The future year PFE model appears to forecast a slightly higher congestion levels than those of the four-step model (e.g., some segments on U.S. 101, Myrtle Ave., H & I St., and Harris St.). This discrepancy is due to a higher demand estimate from future land use and socio-economic data (i.e., the total number of trips in PFE is about 1400 trips (or about 10% of 15,000 trips) higher than the total number of trips predicted by the four-step model). Figure 22 shows the percentage of links by the forecast V/C ratio for the two models. The forecast V/C ratios are grouped into three categories: (1) low-congestion links (e.g., V/C between 0.0 to 0.2), (2) medium-congestion links (V/C between 0.2 to 0.6), and (3) high-congestion links (e.g., V/C higher than 0.6). The number of links in the low-congestion level from the four-step model is higher, while using PFE model results in a higher number of links in the high-congestion level. However, the magnitude of these differences is minor.

(a) Four-step model

(b) PFE model

Figure 21 Forecast link flows and V/C ratios for the future year

Figure 22 Percentage of links by the forecast V/C ratio for the future year

5 CONCLUSIONS

In this paper, we presented a simplified methodology for planning applications in small communities by adapting the path flow estimator (PFE). Two versions of PFE were developed: a base year PFE for estimating the O-D trip table using current traffic counts, target trip table, and

trip production and trip attraction as constraints, and a future year PFE for predicting network traffic conditions using future trip production and trip attraction and scaled base year O-D trip table to match future total demand as constraints. To show proof of concept, two case studies were conducted using two small communities in northern California.

Some of the specific findings include:

- Based on the experience gained from the two case studies, the proposed simplified planning tool using Visual PFE is applicable for small communities with limited resources.
- In the absence of travel survey data, the proposed method uses similar data (traffic counts and land use data) as a four-step model for model development. The link flow estimates from Visual PFE generally match the observed data with a more satisfactory error bound than the link flow estimates from the four-step model. The results on the spatial distribution of trip making (i.e., O-D trip table) between the two models are satisfactory.
- Since both ITE trip generation rates and HCM are utilized in the modeling process, the analysis scope and results are consistent with those of common traffic impact studies and other short-range, localized transportation improvement programs.
- Future research is needed to enhance the proposed approach such that the impacts of long-range, area-wide growth can be modeled within the same framework. Mode choice should be included in the tool to assess the impact of adding a transit system and/or a non-motorized bicycle mode. In addition, more case studies should be conducted to further validate the usefulness of the simplified PFE planning tool and its applicability across different test areas.

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