

Developing an Approach for Tehran Residential Land Use Relocation Based on Equilibrium Trip Pattern

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Abstract: This paper addresses developing an approach to identify building orientation by using an important central concept of understanding the land use-transportation connection named Accessibility Measurement Index (AMI). In order to obtain AMIs for each Traffic Analysis Zone (TAZ) in Tehran metropolitan, the Combined Trip Distribution and Assignment Model (CTDAM) is applied. We valid used CTDAM, while the results are compared to the User-Equilibrium Assignment Model (UEAM) as well as the real observed Origin-Destination (O-D) data. The yardstick in the comparison study is the error of each method to predict observed links flow. Obtained AMIs from both CTDAM and UEAM and average land price are used to define Development Potential (DP) of residential location for each TAZ. The results show that if a TAZ has more distance from CBD, then it has more priority to increase residential density except marginal TAZ.

Keywords: Combined Model, Residential Relocation, Accessibility Measurement Index, Development Potential.

1. Introduction

Interaction between transport planning, land-use planning and regional economy is highly complex. The numerous feedback loops within and between transport, land use and economy are effective on different temporal and spatial levels. As a result even effects caused by the change of a single policy instrument can be difficult to predict. Especially as, in reality, most decision-making processes have to take into account a combination of different policy instruments (1).

The traditional transportation modeling approach (four-step model) represents response of transportation to land use condition; but response of land-use to change in transportation is, however, not represented. In the other words, land use or land development is assumed to have no response to change in transportation condition.

Furthermore, this four-step model has an inherent weakness. One important shortcoming of this model as a traditional approach is

inconsistency among steps. For example, the Origin-Destination (O-D) travel time output from a traffic assignment may not be the same as the travel time input to the mode choice model. Another problem is the lack of behavioral theory behind the traditional model (2). These deficiencies have motivated some attempts in order to predict four steps simultaneously. Modelers then began to ask how to combine these steps into a more consistent method. Because of this irony of history, this literature is widely known today as “combined models” (3).

The first of such models appeared in the elastic demand traffic assignment problem model of Beckmann et. al (1956) (4). Evans (1976) extended the formulation to include trip distribution, assuming fixed trip generation and an entropy model for trip distribution (5). Evans proposed a very efficient algorithm in order to solve her combined trip distribution and network assignment model. This technique is related to the Frank-Wolfe algorithm but only constructs a partial linearization of the objective function in finding a search direction (6). Recently, several attempts have been made to apply combined models to real urban areas (7, 8 and 9). In the land use modeling context, there are three main theories explaining the rationales underlying especially urban residential location: bid rent theory, travel cost and housing cost trade-off theory, and travel cost minimization theory (10).

Classical travel cost minimization theory with

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residential locations decision variables assumes households select locations in way their travel cost to be minimized.

In reality, the travel cost is not the only residential location factor affecting the decisions of households and other factors such as land price, housing price, open space and quality of housing are important. Nevertheless, travel cost minimization theory does have some relevance to household location (particularly through the notion of accessibility).

The purpose of this study is to develop a novel approach by using a new form of travel cost minimization theory in shape of Combined Trip Distribution and Assignment Model (CTDAM). CTDAM is used to predict trip distribution and trip assignment simultaneously. We apply the CTDAM to metropolis of Tehran and compare the results to User-Equilibrium Assignment Model (UEAM) in the Sequential Procedure. Before using CTDAM, dispersion parameter need to be calibrated with real observed O-D data. To evaluate CTDAM model applied to Tehran, UEAM is used as another alternative. Two models are assessed by real observed link flows of Tehran transportation network. Consequently the out put of both models and Traffic Analysis Zone (TAZ) land price distribution are used to define residential building orientation in future. The paper is organized in the following manner. The next section deals with developing CTDAM. Section 3 describes the application of extended Evans algorithm to solve CTDAM.

Calibration of dispersion parameter comes up in Section 4. Section 5 deals with accessibility measurement framework to assess the impact of CTDAM on land-use. In the sixth section we carry out case study of CTDAM to Tehran and present idealized future development priorities of residential location for the Tehran regional. Finally, Section 7 concludes and suggests some future lines of research.

2. Development of Proposed Procedure

To expound explicitly the basic theories and assumptions that underline the CTDAM, we first describe each of combined model components separately, then combine all the components into a single formulation.

2.1. Trip Distribution

In this research, trip distribution is concerned with the estimation of the number of trips per unit of time from each origin zone to each destination zone into which an urban area is partitioned. The most common form of trip distribution model is the gravity model. The gravity model can be singly-constrained to either productions or attractions or doubly-constrained to both productions and attractions. The attraction constrained gravity model may be considered to be a residential location model (10). A number of specifications for the cost function are possible, but the most common ones used in transport analysis are exponential function (6). The general form of the attraction-constrained distribution gravity model is given by:

$$q_{rs} = D_s \cdot \frac{P_r \cdot \exp(-\theta \cdot t_{rs})}{\sum_z P_z \cdot \exp(-\theta \cdot t_{zs})} \quad (1)$$

Where

q_{rs} = number of trips from origin zone r to destination zone s

t_{rs} = travel time from zone r to zone s

D_s = fixed and known total number of trips attracted to zone s

P_r = total number of trips produced by zone r

θ = model parameter

2.2. Trip Assignment

The trip assignment model adopted Wardrop's User-Equilibrium (UE) principle (11). This principle states that, at equilibrium, the average travel cost on all used paths connecting any given r - s pair will be equal, and the average travel cost will be less than or equal to the average travel cost on any of the unused paths (6). In this research, there is an assumption that the UE conditions would hold over networks. Thus, the mathematical expression equivalent to the UE conditions can be stated as follows:

$$h_p^{rs} [t_p^{rs} - u_{rs}] = 0 \quad \forall (r \in R, s \in S, p \in P) \quad (2)$$

$$[t_p^{rs} - u_{rs}] \geq 0 \quad \forall (r \in R, s \in S, p \in P) \quad (3)$$

Where

h_p^{rs} = person trips from r to s using path p

t_p^{rs} = average travel cost from origin r to

destination s using path p
 u_{rs} = minimum (or equilibrium) travel cost
 from r to s

Equations 2 and 3 state that if the (person) trip flow from r to s by path p be positive, then the travel cost for that path equals travel costs of all other path combinations chosen from r to s ; and that if the trip flow on a path combination from r to s is zero, its travel cost is no less than the cost on any chosen path combination.

When Equations 2 and 3 are combined with the flow conservation conditions, it can be write:

$$\sum_{p \in P} h_p^{rs} = q_{rs} \quad \forall (r \in R, s \in S) \quad (4)$$

And the flow non negativity constraints,

$$h_p^{rs} \geq 0 \quad \forall (p \in P) \quad (5)$$

They constitute a quantitative statement of Wardrop's UE principle (11). These equilibrium conditions can be interpreted as the Karush-Kuhn-Tucker (KKT) optimality conditions for an equivalent minimization problem, which is:

$$\text{Minimize } Z(f) = \sum_{a \in A} \int_0^{f_a} t_a(z) dz \quad (6)$$

Subject to Constraints 4 and 5, and a definitional constraint,

$$f_a = \sum_r \sum_s \sum_p \delta_{ap}^{rs} h_p^{rs} \quad (7)$$

Where

f_a = flow of person trips on link a

t_a = travel time function on link a at person flow

$\delta_{a,p}^{rs} = 1$ if path p from r to s includes link a , 0 otherwise.

2.3. CTDAM Formulation

Previous discussion has treated each model component as a separate entity. Thus, the trip distribution model would involve fixed zone-to-zone travel costs, whereas the trip assignment model would consider a fixed distribution of trips. In the former case travel costs are not affected by congestion resulting from increased demand for traveling to particular destinations, whereas in the latter case, because of the demand is constant, travelers do not alter their choice of destination even when travel to that destination entails additional costs (6).

This counter-intuitive location and travel

behavior leads to the consideration of a CTDAM with which the problems travel choice are solved jointly.

The proposed CTDAM is specified as follows:

$$q_{rs} = D_s \cdot \frac{P_r \cdot \exp(-\theta \cdot t_{rs})}{\sum_z P_z \cdot \exp(-\theta \cdot t_{zs})} \quad (8)$$

$$h_p^{rs} [t_p^{rs} - u_{rs}] = 0 \quad \forall (r \in R, s \in S, p \in P) \quad (9)$$

$$[t_p^{rs} - u_{rs}] \geq 0 \quad \forall (r \in R, s \in S, p \in P) \quad (10)$$

$$\sum_{p \in P} h_p^{rs} = \frac{q_{rs}}{\eta} \quad \forall (r \in R, s \in S) \quad (11)$$

$$h_p^{rs} \geq 0 \quad \forall (p \in P) \quad (12)$$

$$f_a = \frac{1}{\eta} \sum_r \sum_s \sum_p \delta_{ap}^{rs} h_p^{rs} \quad (13)$$

Equations 8-13 constitute a quantitative statement of UE conditions for the CTDAM. These equilibrium conditions state that at equilibrium conditions, a set of O-D trip flows and path flows must satisfy the following requirements:

1. The O-D trip flows satisfy a distribution model of Equation 8.
2. The flows are distributed in accordance with the user-equilibrium criterion (Equations 9 and 10).
3. The number of trips on all paths connecting a given OD pair equal the total trips distributed from r to s (Equation 11)
4. Each path flow is nonnegative nature (Equation 12).
5. The number of trips from all possible origins r to a given destination s is equal to the total trips attracted to s (resulting from summation over r on both sides of Equation 8)
6. The definitional relationship between path and link flows is satisfied (Equation 13).

2.4. Equivalent Minimization Problem

The idea of the equivalent optimization problem approach is to construct an intermediate model built around a convenient objective function and the original constraints (or a subset of them) that would permit to recover the model equations from the conditions of optimality of the minimization or maximization problem (12).

To solve the equilibrium of the CTDAM, the approach is to show that an Equivalent

Minimization Problem (EMP) exists whose solutions satisfy the equilibrium conditions (Equations 8-13). Consider the following minimization problem:

$$\begin{aligned} \text{Minimize } Z(q, f) = & \eta \cdot \sum_{a \in A} \int_a^f t_a(z) dz \\ & + \frac{1}{\theta} \sum_r \sum_s q_{rs} \left(Ln \frac{q_{rs}}{P_r} - 1 \right) \end{aligned} \quad (14)$$

Subject to

$$\sum_{p \in P} h_p^{rs} = \frac{q_{rs}}{\eta} \quad (15)$$

$$\sum_r q_{rs} = D_s \quad (16)$$

$$h_p^{rs} \geq 0 \quad (17)$$

In this formulation, the objective function (Equation 14) comprises two components. The first component can be represented by:

$$F(f) = \eta \sum_{a \in A} \int_a^f t_a(z) dz \quad (18)$$

And the second component can be written as:

$$G(q) = \frac{1}{\theta} \sum_r \sum_s q_{rs} \left(Ln \frac{q_{rs}}{P_r} - 1 \right) \quad (19)$$

The function $F(f)$ has as many terms as the number of links in a transportation network. Each term is a function of the traffic flows over all possible paths that share a given link a , which implied by the link-path incidence relationships (Equation 13).

A parameter η is added to the objective function term representing auto costs; it represents the ratio of auto occupants to autos (persons per vehicle), and is called auto occupancy. The second term, $G(q)$, has as many terms as the number of O-D pairs in the transportation network.

The function $G(q)$, corresponds to the Wilson's "entropy maximizing" "singly-constrained spatial interaction model (6).

The parameter of θ in the objective function is assumed to be given exogenously. Equations 15 and 16 are the flow conservation constraints. Equation 17 is the flow non negativity constraints required to ensure the solution of the program physically meaningful.

The importance of the EMP is that even with very mild assumptions imposed upon the demand and link cost functions, it is a convex

program and has a unique solution that is equivalent to the CTDAM. The objective function (Equation 14) is strictly convex, since both terms are strictly convex functions. Therefore, there is a unique equilibrium solution. The theorem of equivalence can be proved based on the Lagrangian equation and the KKT optimality conditions for the EMP (6).

3. Solution Algorithm

Implementation of the CTDAM requires an algorithm for obtaining solutions for the EMP. Because of the EMP is a convex programming problem with linear constraints, it can be solved efficiently by either Evans or Frank-Wolfe algorithm. The Evans algorithm is preferred. It is because; this algorithm requires less iteration than the Frank-Wolfe algorithm in order to obtain suitable solutions.

Moreover, each iteration of the Evans algorithm computes an exact solution for the equilibrium conditions, while in the Frank-Wolfe algorithm; none of the equilibrium conditions is met until the final convergence (13). This has an important implication in the large-scale network applications because it is often unlikely that either the Evans or the Frank-Wolfe algorithm will be run to exact convergence due to the high computational costs involved.

The Evans algorithm applied to the EMP can be summarized as follows (14):

Step 0: Initialization

Find an initial feasible solution
 $\{ q_{rs}^0 = 1, f_a^0 = 0 \}$. Set $n:=0$

Step 1: Travel cost update

Set $t_a^n := t_a(f_a^{n-1})$, $n:=n+1$; and compute minimum cost paths $\{ u_{rs}^n \}$ on the basis of updated link costs, for every O-D pair.

Step 2: Direction finding

(a) Solve a singly constrained gravity model as a function of the shortest path costs,

$$V_{rs}^n : V_{rs}^n = D_s \cdot \frac{P_r^n \cdot \exp(-\theta \cdot u_{rs}^n)}{\sum_z P_z^n \cdot \exp(-\theta \cdot u_{zs}^n)}, \quad \text{applying}$$

the dimensional balancing method. (b) Perform an all-or-nothing assignment of demand $\{ V_{rs}^n \}$ to

the shortest paths computed with the updated link costs $\{t_a^n\}$.

This yields $\{y_a^n\}$. The V_{rs}^n and y_a represent the auxiliary flow, variables corresponding to q_{rs}^n and f_a^n , respectively.

Step 3: Convergence check

Compute the Relative Gap and test for convergence:

$$Gap^{n-1} = \eta \cdot \sum_{a \in A} t_a (f_a^{n-1}) \cdot (y_a^n - f_a^{n-1}) + \frac{1}{\theta} \sum_r \sum_s V_{rs}^n (Ln \frac{q_{rs}^n}{P_r} - 1) - \frac{1}{\theta} \sum_r \sum_s q_{rs}^{n-1} (Ln q_{rs}^{n-1} \frac{q_{rs}^{n-1}}{P_r} - 1) \quad (20)$$

$$LB^{n-1} = Z(T^{n-1}, f^{n-1}) + Gap^{n-1}$$

$$BLB = \max_{n-1} (LB^{n-1})$$

$$Relative \ Gap^{n-1} = \frac{Gap^{n-1}}{BLB}$$

Is the Relative Gap $< \epsilon$? If YES, STOP; otherwise continue.

Step 4: Step-size determination

Find α_n that solves

$$Min \ Z(\alpha_n) = \eta \sum_{a \in A} \int_b^{f_a^{n-1} + \alpha_n (y_a^n - f_a^{n-1})} t_a(z) dz + \frac{1}{\theta} \sum_r \sum_s [q_{rs}^{n-1} + \alpha_n (V_{rs}^n - q_{rs}^{n-1})] (Ln \frac{q_{rs}^{n-1} + \alpha_n (V_{rs}^n - q_{rs}^{n-1})}{P_r} - 1) \quad (21)$$

subject to

$$0 \leq \alpha_n \leq 1$$

Step 5: Flow update

Revise trip flows as following

$$q_{rs}^n = q_{rs}^{n-1} + \alpha_n (V_{rs}^n - q_{rs}^{n-1}) \quad (22)$$

$$f_a^n = f_a^{n-1} + \alpha_n (y_a^n - f_a^{n-1}) \quad (23)$$

Step 6: Convergence check

Retest the updated value of the objective function for convergence. If the Relative Gap is acceptable, STOP; otherwise go to Step 1.

4. Calibration of Dispersion Parameter

The dispersion parameter d is positively related to the level of O-D flow dispersion and it can be calibrated from data when observed O-D counts are available.

All of the calibration procedures use the base year production-attraction matrix and the impedance matrix to generate the Observed Trip Length Distribution (OTLD), and the aim is to calibrate the model such that this OTLD is reproduced as closely as possible.

It has been shown in the case of an exponential function calibration that a particularly robust and efficient calibration method is achieved by comparing, at each iteration, the mean impedance of the forecast to the observed mean time, in which the mean impedance (t^*) is defined as (16):

$$t^* = \frac{\sum_{rs} q_{rs} t_{rs}}{\sum_{rs} T_{rs}} \quad (24)$$

Each iteration of the calibration procedure consists of the following steps:

1. Compute the friction factor matrix based on the current estimate of the function parameter p_i . The initial parameter (p_i) is taken as the inverse of the base year mean time t^* .
2. Evaluate a gravity model constrained to the base year productions and/or attractions. This produces a new trip flow matrix.
3. Compute the mean impedance \bar{t}_i (at iteration i) and comparing it to t^* . If $|\bar{t}_i - t^*| < \epsilon$, then the procedure stops.
4. Compute a new estimate of the parameter estimate based on p_{i-1} , \bar{t}_{i-1} , \bar{t}_i , and t^* using the following equation:

$$p_{i+1} = \frac{(\bar{t}_i - t^*) p_{i-1} - (t^* - \bar{t}_{i-1}) p_i}{\bar{t}_i - \bar{t}_{i-1}} \quad (25)$$

Unless it's the first iteration, in which case the following equation is used:

$$p_{i+1} = \frac{\bar{t}_i \cdot p_i}{t^*} \quad (26)$$

5. Return to the first step.

5. Accessibility measurement framework to assess the impact of CT DAM on land-use

The notion of accessibility is a key ingredient in many of the individual components of a land use– transportation models.

Accessibility may be broadly defined as the ease with which activities at a given destination may be reached from an origin location using a particular mode of transport.

Couched in land use terms, accessibility determines the profitability and utility of locating a use in a given area of the urban expanse by affecting the cost of movement in terms of distance, time, and convenience. Put simply, the greater the accessibility of a particular location, and the greater the importance of accessibility to a specific land use, the higher the valuation afforded a piece of land (10).

Mathematically, there exists a diversity of mechanisms for describing accessibility. The basic format of Measurement Accessibility Index (MAI) is defined as a function of opportunities in a destination zone and the cost of travel between an origin and its destination.

One way of expressing accessibility mathematically includes measures based on *gravity* formulations:

$$MAI_r = \frac{\sum_{s=1}^n D_s \exp(-\theta t_{rs})}{\sum_{s=1}^n D_s} \quad (27)$$

Identifying building orientation, we define Development Potential (DP) as follow:

$$DP_r = 100 \cdot \left(\frac{\Delta_r}{\sigma_{\Delta}} \right) / \left(\frac{p_r}{\sigma_{p_r}} \right) \quad (28)$$

$$\Delta_r = MAI_r(c) - MAI_r(e) \quad (29)$$

Where

$MAI_r(c)$ = MAI value for current situation of r th TAZ that obtains from UEAM.

$MAI_r(e)$ = MAI value for equilibrium condition r th TAZ that obtains from CT DAM.

p_r = an index related to average land price of an origin zone r

σ_m = standard deviation of parameter m ,

$m = \Delta_r, p_r$

If the $|DP|$ for one TAZ become small,

residential land-use relocations remain without change.

The other extracted roles are presented in Table 1.

Table 1 The qualitative concept of (DP) measure for residential building orientation.

DP measure changes	Residential land use relocation
$ DP \leq 100$	Without any changes
$DP > 100$	Area of residential building must be decreased
$DP < -100$	Area of residential building must be increased

6. Case Study-In Tehran region

6.1. Description of Tehran Transportation Network

The research area in Tehran Comprehensive Traffic and Transportation Studies (TCTTS) consists of 22 municipal districts and 560 Traffic Analysis Zones (TAZ). The number of external TAZ is 15. This network is composed of 8363 directed links, representing streets, and 5523 nodes, which generally represent intersections. Each link is described by its beginning node, ending node, length, mode (always auto), link type (i.e., freeway, expressway, principal arterial..., and the facility type, i.e., one-way, two-way undivided, two-way divided, ...), and finally number of lanes and volume delay function (15).

6.2. Volume Delay Function

In order to formulate the traffic assignment problem as an EMP the Jacobian matrix of the cost function must be symmetric. A stronger assumption is made, that the link costs are separable. To ensure uniqueness of the equilibrium link flows, it is assumed that link cost functions are monotonically increasing (14).

These assumptions are satisfied by the most commonly applied BPR-type functions with

$$t_a(f_a) = t_a^f \left[1 + 0.15 \left(\frac{f_a}{C_a} \right)^4 \right] \quad (30)$$

Where

t_a^f = the free flow travel time

C_a = the link capacity, as well as by many

variants of the BPR function. A total of 19 different calibrated and adjusted volume delay functions provided by TCTTS were used as a link performance functions model.

6.3. Solution Procedure and Comparative Results

All computations are limited to the morning peak period; the total flow for trips is approximately 1,425,000 person trips per hour. Auto occupancy is considered equal 1.5 from travel survey data (15). In order to calibrate the CTDAM and compare two models (UEAM and CTDAM) for base year (2003) that we have O-D survey; we solve them in the following way;

1. The dispersion parameter estimation procedure is applied in the way that described in Section 4. Using zone-to-zone travel times, and the base year (2003) O-D matrix to solve the trip distribution model dispersion parameter would be $d = 34.7222$.
2. In UEAM we assign observed O-D matrix (from 2003 survey) on Tehran network by using TransCAD package. The UEAM converges after 60 iterations ($\epsilon = 0.01$) in Frank-Wolf algorithm. The outputs of assignment are links flow and travel times.
3. We apply CTDAM on Tehran transportation network, using $d = 34.7222$ and trips production and attraction of TAZ (from 2003 survey) by extended Evans algorithm.

Our comparative analysis is based on comparing the predicted daily links flow by each model with observed morning peak hourly links flow, where we have 203 links with observed traffic counts in 2003 data from TCTTS screen line survey. When we apply linear regression for the outputs of the CTDAM on observed link flows, in case the regression line crosses from origin, the coefficient regression would be 0.9235, and its confidence interval with $\alpha = 0.05$ is [0.8691 0.9778], the p-value of hypothesis pair t test while null hypothesis is difference of observed link flows and predicted link flows is zero by CTDAM would be 0.7153. When we apply linear regression for the outputs of the UEAM on observed link flows, in case the regression line crosses from origin, the coefficient regression would be 0.8689, and its confidence interval with $\alpha = 0.05$ is [0.7885 0.9493], the p-value UERCM is 0.1779. Fig.1 shows the scatter plots

and regression lines of both models on 203 observed link flows.

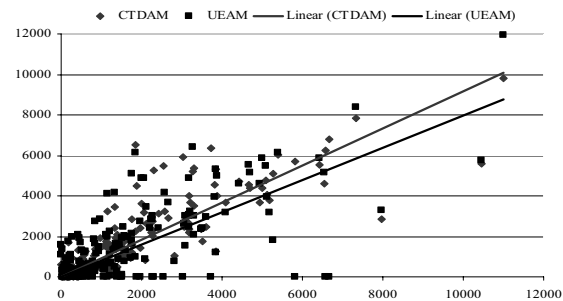


Fig. 1 Link flows solution of the CTDAM and the UEAM versus observed link flows.

Table 2 presents the statistical view of the using CTDAM and UEAM.

SSTO is the total sum of square that is $SSTO = \sum_{i=1} (observed\ link\ flow - mean\ of\ observed\ link\ flow)^2$

SSE is the sum of square error that is $SSE = \sum_{i=1} (observed\ link\ flow - predicted\ link\ flow)^2$.

SSR is SSTO-SSE.

Table 2 The results of comparison of CTDAM and UEAM with 203 observed link flows.

Model→ Statistics ↓	CTDAM	UEAM
SSTO	6.9492e+008	6.9492e+008
SSE	1.9785e+008	4.0440e+008
SSR	4.9707e+008	2.9424e+008
R^2	0.7153	0.4212
P-value of pair test	0.7321	0.1779

The results in Table 2 point out, the CTDAM has better performance to predict the links flow and the simultaneous prediction of trip distribution and assignment in future is notable advantage of the CTDAM rather than using the UEAM and a trip distribution model.

To obtain MAI & DP for each TAZ the following steps were applied:

1. Applying CTDAM & UEAM on Tehran transportation network, using $d = 34.7222$, trips production and attraction of TAZs and O-D matrix (predicted data for 2007) by extended Evans algorithm and Frank-wolf algorithm respectively.

Fig. 2 shows the Traffic volumes which obtained from the CTDAM during a peak hour for Tehran network in 2007.



Fig. 2 Traffic volumes obtained from the CTDAM during a peak hour for Tehran network in 2007.

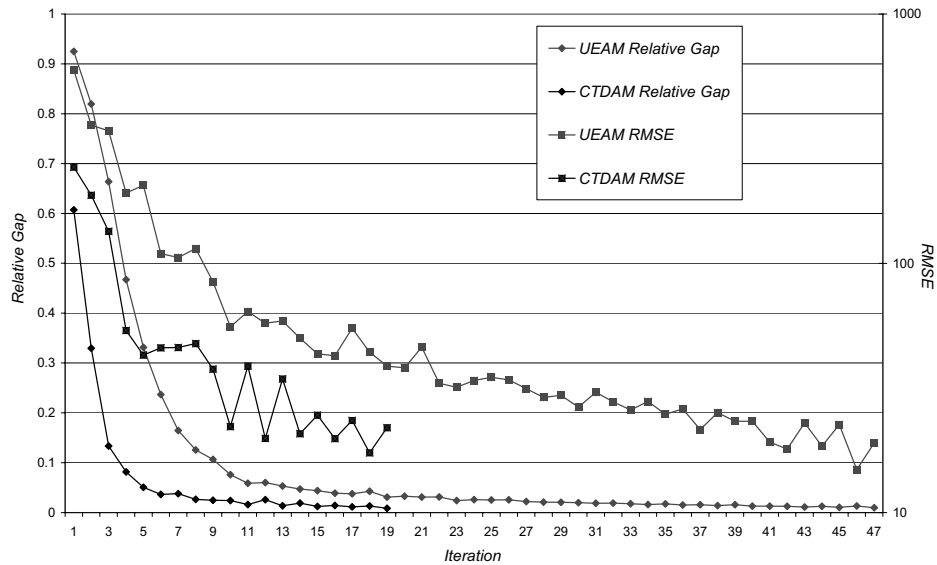


Fig. 3 Relative Gap and RMSE for CTDAM and UEAM.

Fig. 3 shows the convergence of the basic measures as a function of iteration for the Tehran Regional Network. This figure demonstrates the superior performance of the Evans algorithm, and the inferior performance of the Frank-Wolf procedure. After 19 iterations, the Evans algorithm reached relative gap and optimal step size of 0.008438 and 0.12044 respectively. While after 47 iterations, the UEAM produces a solution with relative gap of 0.009725 and optimal step size of 0.045705 that satisfy the

requirement. Another convergence criterion that was considered is the Root Mean Square Error (RMSE) for each predicted flow iteration n which is given by (17):

$$RMSE_n = \sqrt{\frac{\sum_{aeA} (f_a^n - f_a^{n-1})^2}{n-1}} \quad (31)$$

Similar trends were observed for this parameter. The CTDAM and UEAM produce solutions with RMSE (using the log scale to facilitate the comparison) less than 22 and 20 respectively.

2. The zone-to-zone travel times calculated by the matrix operations for CTDAM and UEAM. Total number of trips attracting to zone s was used to compute D_s due to lack of data to obtain amount of employment in zone s . At the end of this process for all TAZ the AMI (for equilibrium and current situation) is calculated and by using equation 28 and 29 we found the DP measure of all TAZ.

Fig. 4 shows idealized future development priorities of residential location for the Tehran region.

The implications of this figure reveal that the residential densities should be increased with an increase of the distances from the residential locations to the CBD except for marginal TAZ. This inference corresponds to the conventional suburban sprawl limitation of activities. Sprawl suggests unfettered growth rather than growth which is consciously planned and built by human intention (1).

The other finding is that the closer the CBD

implies a higher residential land use decreasing priorities.

According to this figure, the variation of residential densities is highly sensitive to the average land price. As for northeast zones with high land price, there isn't any changes recommendation.

7. Conclusions and Model Extensions

Land use is the key for transportation systems to be sustainable in the future. However, lack of understanding of land use transportation interactions from the government has led communities to choose the location for their activities based on patterns contrary to their own particular interests.

This paper addresses developing an approach to identify building orientation by using AMI. In order to obtain AMIs for each TAZ in Tehran metropolitan, the CTDAM was applied. We validated used CTDAM, while the results are compared to the UEAM as well as the real observed O-D data.

We conclude the CTDAM performs better than UEAM for following reasons:

1. The CTDAM converge in less iteration rather than the UEAM.



Fig. 4 Idealized Residential Land Use Priorities for Tehran TAZ.

2. The sum of square error $/R^2$ for the CTDAM is less/greater than sum of square error/ R^2 for the UEAM.
3. The p-value of null hypothesis test (the observed link flows – the predicted link flows =0) in the CTDAM is greater than its corresponding value in the UEAM significantly.
4. The simultaneous prediction of trip distribution and assignment in future is notable advantage of the CTDAM rather than using the UEAM and a trip distribution model.

Obtained *AMIs* from both CTDAM and UEQM and average land price were used to define DP of residential location for each TAZ. The results show that:

1. If a TAZ has more distance from CBD, then it has more priority to increase residential density except marginal TAZ.
2. The variation of residential densities is highly sensitive to the average land price. As for northeast zones with high land price, there isn't any changes recommendation.

At the end, several avenues for future research emerge from this study. First, it would be very productive to reformulate and apply the combined model so that it consists of modal split step.

Second, in this research no capacity restraint mechanism involving residential location changes in the proposed procedure. Finally, some research efforts directed to fully integrate employment location and residential location choice in the combined model would be valuable.

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