

# An Analytical Model of Traffic Equilibrium with Stochastic Demands

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## **An Analytical Model of Traffic Equilibrium with Stochastic Demands**

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### **INTRODUCTION**

Evaluating uncertainty of traffic networks is very important for network design. One of the methods of assessing the uncertainty theoretically is an equilibrium model that can estimate probability distributions of travel times or traffic flows.

Stochastic User Equilibrium (SUE), introduced by Daganzo & Sheffi (1977), is one of the most important network equilibriums. SUE is regarded as Wardrop's equilibrium (Wardrop, 1952) with route choice based on random utility models. The (route) utility in route choice of SUE has an error term. The interpretation of the error term is disputable. The error term does not seem to reflect variation or uncertainty of travel time on the route. It is natural that the error term is interpreted as "perceptual" error (or effect of the components that are not considered in the model). Furthermore, network flows in SUE are not stochastic but deterministic as means of flows (Hazelton, 2000). In SUE of Daganzo & Sheffi (1977), variation of flows is supposed to be insignificant and deterministic because the weak law of large numbers can be applied. But, it is possible that route flows are reformulated to follow a multinomial distribution exogenously based on route choice probabilities or route choice proportions the random utility models give (Sheffi, 1985).

There have been several other studies about uncertainty of network flows. Mirchandani & Soroush (1987) assumed that free-flow travel time is random, and proposed a network equilibrium model with probabilistic travel times. Arnott et al. (1991) and Chen et al. (2002) introduced random capacity to network equilibrium. These three studies assumed exogenous randomness. Cascetta (1989) and Cascetta & Canterella (1991) formulated day-to-day dynamics of network flows as a Markov process. The convergent distribution of network flow could be interpreted as network equilibrium with stochastic flow. Watling (2002) extended SUE and presented a second order stochastic network equilibrium. He assumed route choice based on random utility theory and stochastic flow variables. The travel demands are assigned based on the mean cost. Cascetta (1989), Cascetta & Canterella (1991), and Watling (2002) consider stochastic route choice, but the travel demand is fixed. One of the main causes of network uncertainty is variation of travel demands. Stochastic demand should be incorporated

into network equilibrium models.

In this study, we assume stochastic demand as well as stochastic route choice, and formulate a stochastic network equilibrium model under stochastic demands. This model enables us to examine network reliability under uncertain demands.

## CONDITIONAL FLOW DISTRIBUTION

We assume that a driver chooses a route stochastically. This represents a combination of choices with probabilities. For example, Choice 1 is adopted with probability 0.5 and Choice 2 with 0.5. This type of choice is called mixed strategy in game theory. In Watling (2002), the route choice probabilities are given by the random utility models. In this study, for simplicity, the route choice probabilities are given by the logit model.

Let  $i$  ( $i = 1, 2, \dots, I$ ) denote an origin-destination (OD) pair in the network and  $n^i$  the demand of the  $i$ th OD pair. Let  $j$  denote a route, where the total number of routes is  $J$  and the number of routes linking the  $i$ th OD pair is  $J_i$ . Let  $a$  denote a link, where the total number of links in the network is  $A$ .

Assume that each driver who travels between the  $i$ th OD pair chooses the  $j$ th route with probability  $p_{ij}$ ; that is,  $p_{ij}$  is the probability of choosing the  $j$ th route between the  $i$ th OD pair.

Clearly,  $\sum_{j=1}^{J_i} p_{ij} = 1$ . The joint probability of route flows between the  $i$ th OD pair follows a multinomial distribution if the route choice probability is common among drivers (Sheffi, 1985, p. 281, Watling, 2002). That is,  $\mathbf{Y}_i \sim \text{Mn}(n_i, \mathbf{p}^i)$  where  $\mathbf{Y}_i$  is the vector of random variables of route flows between the  $i$ th OD pair when the demand is  $n_i$  and which follows a multinomial distribution,  $\mathbf{p}^i$  is the vector of route choice probabilities between the  $i$ th OD pair, and  $\text{Mn}(\cdot)$  is a multinomial distribution.

We can obtain the probability of a single route flow as the marginal probability of the multinomial distribution. The probability mass function of the flow on the  $j$ th route between the  $i$ th OD pair is expressed as:

$$\begin{aligned} f_{Y_{ij}|n_i}(y_{ij}) &= \sum_{y_{i1}} \cdots \sum_{y_{ij-1}} \sum_{y_{ij+1}} \cdots \sum_{y_{iJ_i}} \frac{n_i!}{\prod_{j=1}^{J_i} y_{ij}!} \prod_{j=1}^{J_i} (p_{ij})^{y_{ij}} \\ &= \frac{n_i!}{y_{ij}!(n_i - y_{ij})!} p_{ij}^{y_{ij}} (1 - p_{ij})^{n_i - y_{ij}} \end{aligned} \quad (1)$$

where  $f_{Y_{ij}|n_i}(y_{ij})$  is the probability mass function of flow on the  $j$ th route between the  $i$ th OD pair when the demand is  $n_i$ ,  $\frac{n_i! \prod_j p_{ij}^{y_{ij}}}{\prod_j y_{ij}!}$  is a probability mass function of multinomial distribution,  $y_{ij}$  is the realized value of the  $j$ th route flow, and  $Y_{ij}$  is the component of  $\mathbf{Y}_i$ . This is a binomial distribution. The flow on a single route follows the binomial distribution  $\text{Bn}(n_i, p_{ij})$ , where  $\text{Bn}(\cdot)$  denotes a binomial distribution.

## STOCHASTIC DEMAND

Travel demand variation is one of the main causes of network uncertainty. Stochastic demand should be incorporated. Assume a latent demand (or potential demand) which is the number of drivers who has the possibility of making a trip. Let  $q_i$  and  $\pi_i$  denote the latent demand between the  $i$ th OD pair and the probability that the demand make trips, respectively. In this case, the demand follows a binomial distribution. The mean and variance of the binomial distribution,  $\text{Bn}(q_i, \pi_i)$ , are  $q_i \pi_i$  and  $q_i \pi_i (1 - \pi_i)$ , respectively. Let  $\lambda_i$  be the mean,  $q_i \pi_i$ . Then, the variance is  $\lambda_i (1 - \pi_i)$ . Therefore,  $0 \leq \lambda_i (1 - \pi_i) \leq \lambda_i$  because  $0 \leq \pi_i \leq 1$ . In many cases, coefficient of variance of traffic volumes is from 5% to 20%. When  $\lambda_i$  is large, the variance of the binomial distribution may not be enough. For example, the maximum of the variance is  $1/30$  ( $\approx 3.3\%$ ) when  $\lambda_i = 900$ . In such a case, a negative binomial distribution is useful. The negative binomial distribution is the compound of a binomial distribution and beta distribution. Imagine that the probability of making a trip is distributed among the demand. Also, assume that the probability of making a trip follows a beta distribution. Then, the demand follows a negative binomial distribution.

Assume that travel demand follows a negative-binomial distribution,  $\text{NgBn}(\alpha, \beta)$ . Negative binomial distributions are discrete and always take positive values unlike normal distributions. The probability mass function of the demand,  $g_{N_i}(n_i)$ , is:

$$g_{N_i}(n_i) = \frac{\Gamma(\alpha_i + n_i)}{\Gamma(\alpha_i) n_i!} \left( \frac{1}{1 + \beta_i} \right)^{\alpha_i} \left( \frac{\beta_i}{1 + \beta_i} \right)^{n_i} \quad (2)$$

where  $\Gamma(\cdot)$  denotes a gamma function, and  $\alpha_i$  and  $\beta_i$  are constant parameters and specify the demand of the  $i$ th OD pair. The mean and variance of  $g_{N_i}(n_i)$  are  $\alpha_i \beta_i$  and  $\alpha_i \beta_i (1 + \beta_i)$ , respectively.

The route flows between the same OD pair are given as a compound distribution of a multinomial distribution and a negative binomial distribution. That is, the route flows in which the demand follows  $g_{N_i}(n_i)$  are given by  $f_{\mathbf{y}_i|n_i}(y_i) g_{N_i}(n_i)$ .

$$\begin{aligned} f_{\mathbf{y}_i}(\mathbf{y}_i) &= f_{\mathbf{y}_i|n_i}(\mathbf{y}_i) g_{N_i}(n_i) \\ &= \frac{\Gamma(\alpha_i + n_i)}{\Gamma(\alpha_i) n_i!} \left( \frac{1}{1 + \beta_i} \right)^{\alpha_i} \left( \frac{\beta_i}{1 + \beta_i} \right)^{n_i} \frac{n_i!}{\prod_{j=1}^{J_i} y_{ij}!} \prod_{j=1}^{J_i} p_{ij}^{y_{ij}} \\ &= \frac{\Gamma(\alpha_i + n_i)}{\Gamma(\alpha_i) \prod_j y_{ij}!} \xi_{i0}^{\alpha_i} \prod_j \xi_{ij}^{y_{ij}} \end{aligned} \quad (3)$$

where  $n_i = \sum_j y_{ij}$ ,  $\xi_{i0} = 1/(1 + \beta_i)$ ,  $\xi_{ij} = \beta_i p_{ij}/(1 + \beta_i)$ . This is a negative-multinomial distribution. Means and variances and covariance are given by:

$$\mu_{ij} = \alpha_i \beta_i p_{ij} \quad (4a)$$

$$\sigma_{ij}^2 = \alpha_i \beta_i p_{ij} (1 + \beta_i p_{ij}) \quad (4b)$$

$$\sigma_{ij,j'} = \alpha_i \beta_i^2 p_{ij} p_{ij'} \quad (4c)$$

Thus, route flows of each OD pair follow a negative-multinomial distribution under negative-binomial distributed demands.

Each route flow follows a negative binomial distribution. The flow on the  $j$ th route between the  $i$ th OD pair is given by  $\sum_{y_{ij} \cdots \sum_{y_{ij-1}} \sum_{y_{ij+1}} \cdots \sum_{y_{i,j_i}} f_{Y_i}(\mathbf{y}_i)$ . The p.d.f.,  $f_{Y_{ij}}(y_{ij})$ , is:

$$f_{Y_{ij}}(y_{ij}) = \frac{\Gamma(\alpha_i + y_{ij})}{\Gamma(\alpha_i) y_{ij}!} \frac{(\beta_i p_{ij})^{y_{ij}}}{(1 + \beta_i p_{ij})^{\alpha_i + y_{ij}}} \quad (5)$$

In order to calculate mean travel time,  $p_{a,i}$  is defined as  $\sum_j \delta_{a,ij} p_{ij}$ . This  $p_{a,i}$  means the probability that drivers between the  $i$ th OD pair travel on the  $a$ th link. Let  $X_{a,i}$  denote  $\sum_j \delta_{a,ij} Y_{ij}$  and  $x_{a,i}$  denote the realized value of  $X_{a,i}$ .  $X_{a,i}$  follows the negative binomial distribution  $\text{NgBn}(\alpha_i, \beta_i, p_{a,i})$ .

$$f_{X_{a,i}}(x_{a,i}) = \frac{\Gamma(\alpha_i + x_{a,i})}{\Gamma(\alpha_i) x_{a,i}!} \frac{(\beta_i p_{a,i})^{x_{a,i}}}{(1 + \beta_i p_{a,i})^{\alpha_i + x_{a,i}}} \quad (6)$$

## MEAN TRAVEL TIME

Let  $x_a$  denote the traffic volume on the  $a$ th link and  $X_a$  its random variable.  $X_a$  is  $\sum_i \sum_j \delta_{a,ij} Y_{ij}$ , where  $\delta_{a,ij}$  takes a value of 1 if the  $a$ th link is part of the  $j$ th route; otherwise its value is 0. As mentioned in the previous section, the link flow follows a probability distribution. The mean travel time on a link is calculated as follows:

$$E[T_a] = E[t_a(X_a)] = \sum_{x_a=0}^{\infty} t_a(x_a) \cdot f_{X_a}(x_a) \quad (7)$$

where  $f_{X_a}(\cdot)$  is the probability mass function of flow on the  $a$ th link,  $T_a$  is the random variable of travel time on the  $a$ th link,  $t_a(x_a)$  is the travel time function of the  $a$ th link, and  $E[\cdot]$  is the expectation operator.

In this study, we adopt a BPR-type travel time function for calculating travel time;  $t = t_f(1 + c'(x/C)^b)$  where  $t$  is the link travel time,  $t_f$  is the free-flow travel time,  $x$  is the link flow, and  $b$  and  $c'$  are positive parameters. For simplicity, we express link travel times as  $h + c \cdot x^b$ , where  $b$ ,  $c$ , and  $h$  are positive constant parameters. When  $b$  is an integer (4.0 is usually used), the mean link travel time can be calculated using moment generating functions.

A moment generating function,  $M(s)$ , is defined as  $E[e^{sX}]$  (e.g., Ang & Tang, 1977;

Papoulis, 1965). The moment generating function of the sum of independent random variables is the product of their moment generating functions. The  $a$ th link flow,  $X_a$ , is  $\sum_j X_{a,i}$ .  $X_{a,i}$  is mutually independent because the demand is independent among OD pairs. Let  $M_{a,i}(s)$  denote the m.g.f. (moment generating function) of  $X_{a,i}$  and  $M_a(s)$  denote the m.g.f. of the  $a$ th link.  $M_a(s) = \prod_i M_{a,i}(s)$ . As a property of the moment generating function,  $E[X^b] = d^b M_a(s)/ds^b|_{s=0}$ . The mean travel time on the  $a$ th link is given as:

$$E[T_a] = h + c \cdot \left. \frac{d^b M_a(s)}{ds^b} \right|_{s=0} \quad (8)$$

where  $M_a(s)$  is the moment generating function of the  $a$ th link.

The variance of link travel time,  $\text{Var}[T_a]$ , is  $E[T_a^2] - \{E[T_a]\}^2$ , and  $E[T_a^2]$  is also calculated using moment generating functions.

## FORMULATION

Assume that each driver choose a route stochastically based on the logit model as follows:

$$p_{ij} = \frac{\exp(-\theta \bar{c}_{ij}(\mathbf{p}))}{\sum_{j' \in J_i} \exp(-\theta \bar{c}_{ij'}(\mathbf{p}))} \quad \forall i \forall j \quad (9)$$

where  $v_{ij}$  is the mean travel time of the  $j$ th route between the  $i$ th OD pair,  $\mathbf{p}$  the vector of the routes,  $\theta$  a positive parameter. We can incorporate toll fee, risk attitude and so on into  $v_{ij}$ .

Define  $\mathbf{g} = (g_{11}, \dots, g_{1J_1}, g_{21}, \dots, g_{IJ_I})^T$ . The component of  $\mathbf{g}$ ,  $g_{ij}$ , is:

$$g_{ij}(\mathbf{p}) = \frac{\exp(-\theta \bar{c}_{ij}(\mathbf{p}))}{\sum_{j' \in J_i} \exp(-\theta \bar{c}_{ij'}(\mathbf{p}))} \quad (10)$$

where  $\mathbf{p}$  is the vector of all route flows and is  $(p_{11}, \dots, p_{1J_1}, p_{21}, \dots, p_{IJ_I})^T$ .

A logit-based stochastic network equilibrium model can be formulated as a fixed point problem as follows:

$$\mathbf{p} = \mathbf{g}(\mathbf{p}) \quad (11)$$

The above can also be formulated as the following complementary problem:

$$\begin{aligned} \text{Find } \mathbf{z}^* = \begin{bmatrix} \mathbf{p} \\ \boldsymbol{\kappa} \end{bmatrix} \in R_+^J \times R_+^I \\ \text{such that } \langle \mathbf{z}, \mathbf{f}(\mathbf{z}) \rangle = 0, \mathbf{f}(\mathbf{z}) \geq \mathbf{0}, \mathbf{z} \geq \mathbf{0} \end{aligned} \quad (12)$$

$$\mathbf{f}(\mathbf{z}) = \begin{bmatrix} \mathbf{0} & -\Lambda^T \\ \Lambda & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{p} \\ \boldsymbol{\kappa} \end{bmatrix} + \begin{bmatrix} \bar{\mathbf{c}} + \ln(\mathbf{p})/\theta \\ -\mathbf{I} \end{bmatrix} \quad (13)$$

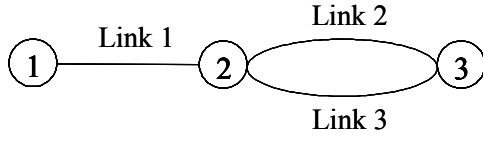


Fig. 1. Example Network

Table 1. Demand

	OD 1 between node 1&3	OD 2 between node 2&3
distribution	NgBn(40, 40)	NgBn(20, 50)
mean	1600	1000
variance	65600	51000
S.D.	256.1	225.8

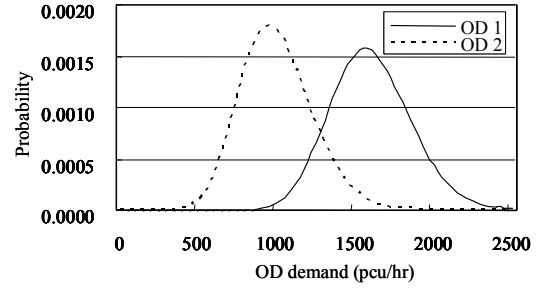


Fig. 2. Demand's Probability Function

Table 2. Travel Time Function

	Free-flow travel time	Capacity
Link 1	10	2000
Link 2	10	2000
Link 3	5	1000

where  $\mathbf{p} = (\mathbf{p}_1, \dots, \mathbf{p}_i, \dots, \mathbf{p}_l)^T$ ,  $\mathbf{p}_i = (p_{i1}, \dots, p_{il})^T$ ,  $\mathbf{ln}(\mathbf{p}) = (\ln p_{11}, \dots, \ln p_{ll})^T$ ,  $\bar{\mathbf{c}}(\mathbf{p}) = (\bar{c}_{11}(\mathbf{p}), \dots, \bar{c}_{ll}(\mathbf{p}))^T$  mean route travel times and  $\boldsymbol{\kappa}$  the vector of minimum mean route travel times,  $\Lambda$  OD-route incident matrix,  $\langle \mathbf{x}, \mathbf{y} \rangle$  the inner product,  $\mathbf{I}$  the unit vector,  $\mathbf{0}$  the null vector,  $T$  transition for vectors or matrices.

### EXAMPLE

As an illustration of the above equilibrium model under stochastic demand, a simple network example is presented, consisting of two OD pairs and three links. Fig. 1 shows the example network. Table 1 presents the distributions of OD demands and Fig. 2 illustrates the probability mass functions. The link travel time functions are given in Table 2.

In order to consider drivers' risk attitude, route disutility,  $U_j$ , in the logit model is defined as  $E[T_{ij}] + \eta \sqrt{\text{Var}[T_{ij}]}$  instead of  $E[T_{ij}] = \bar{c}_{ij}$ . We set the diversion parameter,  $\theta$ , and the risk attitude parameter,  $\eta$ , at both 1.0.

We could obtain the route choice probabilities by solving the problem written in the previous section. Table 3 shows the results of the example network. Link 1 and Link 2 are the same link. The (mean) flow on Link 1 is greater than that on Link 2, and the S.D. and variance on Link 1 are greater than those on Link 2. The capacity of Link 3 is half of Link 1 and Link 2, and the flow on Link 3 fluctuates more largely than Link 1 and Link 2. So, S.D. and variance of Link 3 are greater than Link 1 and Link 2 although mean flow on Link 3 is the least. We can also calculate covariance between link travel times. Thus, we can evaluate network's uncertainty using the model presented.

**Table 3. Link Travel Time in the Example**

	Link 1	Link 2	Link 3
Mean	16.56	14.40	13.40
S.D.	2.11	1.18	2.24

	Link 1 & 2	Link 1 & 3	Link 2 & 3
C.C.	0.73	0.75	0.95

## CONCLUSION

Evaluating uncertainty of traffic networks is very important for network design or traffic management. We assume that drivers choose their routes stochastically based on the logit model and that the travel demands are negative-binomial-distributed. A network equilibrium model with stochastic route choice under stochastic demands is formulated as a fixed point problem and a complementary problem. Then, the model is applied to a simple example. As a future work, we have to examine the properties of the equilibrium under gamma-distributed demand are discussed. Also, for applying for a large-scale network, an algorithm should be developed.

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