MICHIGAN OHIO UNIVERSITY TRANSPORTATION CENTER

Alternate energy and system mobility to stimulate economic development.

Report No: MIOH UTC SC42 2012-Final

ENHANCING JIT FREIGHT LOGISTICS IMPACTED BY TRANSPORTATION SYSTEM PROJECTS UNDER ITS

FINAL REPORT

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EXECUTIVE SUMMARY

We developed an analysis methodology to support effective planning of Just-In-Time (JIT) freight logistics in transportation networks impacted by system improvement projects. To achieve this goal, our project and plan's mile-stones are the following:

Mile-stone #1: Develop methods for efficient estimation of dynamic Origin-Destination (OD) matrices using traffic flow data readily available from Intelligent Transportation Systems (ITS) systems

Mile-stone #2: Given the transportation improvement project scope and extent/corridor, estimate future state network traffic flows through equilibrium / traffic assignment models

Mile-stone #3: Apply dynamic routing algorithms on future state traffic flow network to plan JIT freight logistic operations

These components are integrated into existing JIT freight planning models/tools. We give additional details regarding these components importance, novelty, and requirements under the methodology heading of the first section.

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ABSTRACT

We developed an analysis methodology to support effective planning of JIT freight logistics in transportation networks impacted by system improvement projects. Currently, shippers and carriers do not have the necessary tools to predict and account for the traffic congestion impact of construction projects. Existing models used by shippers/carriers rely on historical traffic flow/congestion data from ITS and other sources. There is need for predictive tools that can be used for assessing the congestion and traffic flow impact of construction projects. These predictive tools are integrated within route planning models of shippers/carriers. We designed practical, scalable tools that use readily available and up to date traffic flow data from ITS operators such as Traffic.com and Michigan Intelligent Transportation Systems (MITS) Center (our collaborators). The flow data is used to estimate OD matrices at the source/sink nodes of the network under consideration. Given the transportation improvement project scope and extent/corridor, we use estimated OD matrices for estimation of the future state of network traffic flows through equilibrium / traffic assignment models. The methods are designed for seamless integration into existing JIT freight planning models/tools.

1. Introduction

Over the last two decades, transformation in supply chains from a culture of mass production and distribution to a culture of pull-based demand sensing and response have necessitated efficient supply chain (SC) operations such as JIT deliveries and reduction of inventories, both in-transit and in facilities (Anderson et al 2003, Simchi-Levi et al 2000). For example, our collaborator, Ford MP&L, reports that nearly 80% of all parts and assemblies supplied to vehicle assembly plants in the Detroit metropolitan area are JIT based and involve 5 to 6 deliveries per day per part (with no more than 3 hours of inventory in most cases). More broadly, SRI (2004) reports that SC inventories have decreased by more than 20% in the last two decades, while offering more product variety under shorter product lifecycles. This transition has increased the importance of reliability and efficiency throughout the SC operations including sourcing of goods, transportation, manufacturing, and distribution. While reliability and efficiency of supply and manufacturing processes can be ensured through best practices, the reliability of logistics operations is most affected by inefficiencies in the transportation network (TTI 2005, FHWA Report)[3]. Examples of transportation inefficiencies are late/early pickup/delivery and longer transportation times, causing increased fuel costs and driver costs. These inefficiencies have "direct" effects on the economics of logistics operations, but more importantly, they more significantly affect SC operations through missed deliveries, idled capacity/labor, and increased schedule nervousness (McKinnon 2004, Rao et al 1991).

[3] Texas Transportation Inst.: 2005 Urban Mobility report. FHWA report "An Initial Assessment of Freight Bottlenecks on Highways"

For example, Ford's MP&L reports the cost of "idling" a final vehicle assembly plant due to part shortages and missed deliveries to be $50-$60 thousand/hour. The enormity of all these costs, estimated at $200 billion a year, and the critical need to mitigate traffic congestion effects, are presented in the Department of Transportation's (DOT) 2006 report. [4]

The inspiration for this project comes from conversations with our industry collaborators and a recent meeting (May 17, 2010 at U.D. Mercy) led by Dr. Leo Hanifin, Director, Michigan Ohio University Transportation Center titled *"Predicting the Traffic and Economic Impact of Multiple Major Transportation Projects in the Detroit-Toledo-Windsor Region"* with stakeholders from the Ohio Department of Transportation, the Michigan Department of Transportation, transportation agencies, local governments, Detroit Chamber of Commerce, and researchers from multiple universities. The main theme of the meeting was to reduce the negative impact of the upcoming major transportation projects in Southeast Michigan (SE-MI) on traffic flow through the development of novel methods/tools for modeling and analysis.

Our vision with this research project is to address the effect of "non-recurrent congestion" due to "work zones" on the delivery reliability within JIT supply chain operations in SE-MI. Many of the pavements on national highways have exceeded their design lives. To carry current and future high traffic volume of travel and freight, many highway segments in the urban areas including SE Michigan are undergoing "4-R" projects: restoration, resurfacing, rehabilitation and reconstruction. AASHTO[5] reports that 10% of all traffic congestion in urban areas is directly related to work zones (not because of traffic volumes). The negative influence of work zones would be even higher on urban areas roadways that are already near or above capacity flow.

2. Literature Review

Dynamic Routing Algorithms: The problem of dynamic routing with stochastic and time-dependent travel times for a single user has been studied by various researchers (Hall 1986, Miller-Hooks and Mahmassani 2000 and 2003, Bander and White 2002). There are also studies that consider real-time information for dynamic routing of a user (Psaraftis and Tsitsiklis 1993, Polychronopoulos and Tsitsiklis 1996, Azaron and Kianfar 2003, Fu 2001, Waller and Ziliaskopoulos 2002, Gao and Chabini 2006, Kim et al. 2005, Thomas and White 2007). These studies to do not effectively account for recurrent and non-recurrent congestion information available from ITS systems. We have addressed these gaps in our previous project. However, none of the earlier studies have considered the impact of large scale construction projects on route planning. This study furthers this research by accounting for the construction project impact within dynamic routing.

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[4] DOT's 2006 report, "National Strategy to Reduce Congestion on America's Transportation Network" in May 2006

[5] The American Association of State Highway and Transportation Officials (www.aashto.org)

Estimation of Origin-Destination Matrix: The OD matrix has information on the travel volume by transportation mode between different zones of a region. The OD matrix is difficult and often costly to obtain by direct measurements/interviews or surveys. However, link flows as monitored by ITS network of sensors may constitute an important data source for the estimation of "reasonable" OD matrices.

The solution approaches in the literature to estimate OD matrices based on link flows can be classified into two. The first class is traffic modeling approaches which directly or indirectly assume that the trip making behavior is represented by a certain trip distribution model (e.g., Fisk 1988, Kawakami et al. 1992, Yang 1994). The other class is statistical inference approaches which assume that the traffic volumes as well as the "target OD matrix"[6] are generated by known probability distributions (Abrahamsson, 1998). The statistical inference approaches include the Maximum Likelihood Estimation (Spiess, 1987), Generalized Least Squares (e.g., Cascetta and Nguyen, 1988, Yang et al. 1992), and Bayesian Inference (Maher, 1983).

Based on the time dimension of the problem, the OD estimation approaches can be classified as static (flows are assumed to be stable and given for a certain period of time) and dynamic (flows are assumed to be time-dependent). Dynamic OD matrix estimation methods are becoming increasingly important due to more demanding needs for Intelligent Transportation Systems (ITS) and Advanced Traveler Information Systems (ATIS). Several methods have been proposed to solve the problem of dynamic OD matrix estimation (Cremer and Keller 1987, Sherali and Park 2001, Zhou and Mahmassani 2007, and Ásmundsdóttir 2008).

Network Equilibrium and Traffic Assignment: During construction period, users may change their route or may be advised for detours. To develop an effective tool, we need to estimate the new network equilibrium and corresponding traffic assignment solution. The demand-supply interaction can be captured by a conventional dynamic traffic assignment (DTA) model in deterministic networks (Peeta and Ziliaskopoulos, 2001). There are also user equilibrium traffic assignment models where users make dynamic routing decisions in stochastic time-dependent networks (Ukkusuri and Patil 2006 and Gao 2008).

3. Methodology

We aim to develop an analysis methodology to support effective planning of JIT freight logistics in transportation networks impacted by system improvement projects. To achieve this goal, our project and plan's components are the following:

1. Develop methods for efficient estimation of dynamic OD matrices using traffic flow data readily available from ITS systems

[6] Target OD matrix is a-priori information that may come from household surveys or road interviews. In statistical approaches the target OD matrix is typically regarded as an observation of the "true" OD matrix to be estimated. In traffic model based approaches, the target OD matrix is normally assumed to be an old OD matrix and use "minimum information" from that.

2. Given the transportation improvement project scope and extent/corridor, estimate future state network traffic flows through equilibrium / traffic assignment models
3. Apply dynamic routing algorithms on future state traffic flow network to plan JIT freight logistic operations

These components are integrated into existing JIT freight planning models/tools. We give additional details regarding these components importance, novelty, and requirements below.

3.1. Estimation of OD Matrices

Given an OD matrix, one can "assign" the demand of traffic between every pair of zones to the links of the network and predict the flow according to the assignment. Thus, the problem of OD matrix estimation from given link flows, is considered as the "inverse" of the assignment problem. However, there may be a large number of OD matrices that reproduces the same observed traffic flow. To overcome this problem, estimation procedures often use a-priori information. This a-priori flow information is often provided as a "target OD matrix" that may come from household surveys or road interviews.

Among several solution approaches available for estimation of OD matrices, we employed a maximum likelihood estimation approach that can handle time-dependent dynamic traffic flows which is adapted from R. He (2010).

3.1.1. Model Formulation

Consider a transportation network with n nodes and m directed links. Suppose that we observe the traffic system over N homogeneous, independent time periods. For example, these measurement periods could be 8:00am to 12:00pm or 4:00pm to 8:00pm on a sequence of Tuesdays. N is basically the number of repeated samples. The length of each measurement period should be sufficiently large so that a typical journey can be finished during that period. Since we are studying dynamic traffic condition, we discretize time and use our sampling interval h as time unit. The maximum number of sampling intervals in one measurement period is T, so the sampling intervals are [1, 2, ..., h, ..., T].

Start with standard assumption of $q^{rs}(t)$, the total OD demand from origin r to destination s during departure time t, as a standard Poisson random variable with the following expectation and variance:

$$E\left(q^{rs}(t)\right) = \lambda^{rs}(t)$$

$$Var\left(q^{rs}(t)\right) = \lambda^{rs}(t)$$

Let route flow $f_k^{rs}(t)$ be the part of traffic $q^{rs}(t)$ that takes path k (one of the K paths between r and s) during departure time t, and is multinomially distributed with the following probability distribution function:

$$P\left\{F_k^{rs}(t) = f_k^{rs}(t), "k\right\} = q^{rs}(t)\prod_{k=1}^{K}\frac{[p_k^{rs}]^{f_k^{rs}(t)}}{f_k^{rs}(t)!}$$

and

$$\sum_{k=1}^{K} f_k^{rs}(t) = q^{rs}(t)$$

with mean and variance-covariance as follows:

$$E\left(f_k^{rs}(t)\right) = q^{rs}(t)\, p_k^{rs}(t)$$
$$Var\left(f_k^{rs}(t)\right) = q^{rs}(t)\, p_k^{rs}(t)\left(1 - p_k^{rs}(t)\right)$$

$$Cov\left(f_k^{rs}(t), f_{k'}^{r's'}(t')\right) = 0, \; if \; (rs) \neq (r's') \; or \; t \neq t'$$
$$= -q^{rs}(t)\, p_k^{rs}(t)\, p_{k'}^{rs}(t), \; if \; (rs) = (r's'), \, t = t', \, k \neq k'$$

where $p_k^{rs}(t)$ is the probability of traffic $q^{rs}(t)$ that takes path k (one of the K paths between r and s) departing at time t.

Utilizing the properties of Poisson and Multinomial distributions, the mean and variance of unconditional path flows F can be determined as follows:

$$E\left(f_k^{rs}(t)\right) = \lambda^{rs}(t)\, p_k^{rs}(t)$$
$$Var\left(f_k^{rs}(t)\right) = \lambda^{rs}(t)\, p_k^{rs}(t)$$
$$Cov\left(f_k^{rs}(t), f_{k'}^{r's'}(t')\right) = 0$$

where $p_k^{rs}(t)$ probability (proportion) of travelers choosing route k from r to s departing at time t. k = 1, 2, ..., K (K is the number of routes from r to s).

Define link flows X as linear combinations of path flows F:

$$X = \Delta \square F$$

where Δ is the link-route incidence matrix.

Then, link flows X are random variables with mean:

$$E(X) = \Delta \bullet E(F)$$

and variance-covariance matrix, Σ_X :

$$\Sigma_X = \Delta \cdot \Sigma_F \cdot \Delta^T$$

The link-route incidence matrix is as follows:

$$\Delta = \left(\delta_{k,h}^{a,t} \right)_{k,h,a,t}$$

where a — link, k — route, h — time interval [1, ..., T], t — departure time.

The link flows on link a for sampling interval h are combinations of route flows:

$$x_a(h) = \sum_{k,t \le h} \delta_{k,h}^{a,t} f_k(t)$$

To obtain the estimation of dynamic OD and route choice parameters, it is needed to maximize the likelihood function of link flow X. However, maximization of the likelihood function

$$L(\lambda, P) = Lik\left(x \middle| E\left(X \middle| P, \lambda \right), \Sigma_X\left(P, \lambda \right) \right)$$

is only computationally feasible for very small-scale examples. When dealing with large transportation systems, a natural way of attempting to overcome computational problems is to use a multivariate normal approximation. Taking log of the likelihood function of link flows and omitting additive constants, the following objective function is obtained:

$$\log L - \frac{1}{2} \sum_{n=1}^{N} \left(x^{(n)} - E\left(X \middle| P, \lambda \right) \right)^T \left(\Sigma_X\left(P, \lambda \right)(\lambda, P) \right)^{-1} \left(x^{(n)} - E\left(X \middle| P, \lambda \right) \right)$$

subject to $1 \ge p \ge 0$ and $\lambda \ge 0$. $x^{(n)}$ is the link traffic count for sample n. Then, above equation is simplified as:

$$\log L - \frac{1}{2} \sum_{n=1}^{N} \left(x^{(n)} - E\left(X \middle| P, \lambda \right) \right)^T S^{-1} \left(x^{(n)} - E\left(X \middle| P, \lambda \right) \right)$$

subject to $1 \ge p \ge 0$ and $\lambda \ge 0$.

3.2. Equilibrium/Traffic Assignment

Once the OD matrix is obtained, we map OD flows to links on the new network (network impacted by construction). This task is known as the Traffic Assignment problem. There are three common ways to this task: Static Traffic Assignment (STA), Dynamic Traffic Assignment (DTA), or direct estimation of path-flows. DTA differs from STA in that it captures the dynamic nature of traffic and is more reliable in assignment solution. DTA generally consists of a route choice model and a dynamic network loading model as illustrated in the figure below from Van Zuylen et al., (2006).

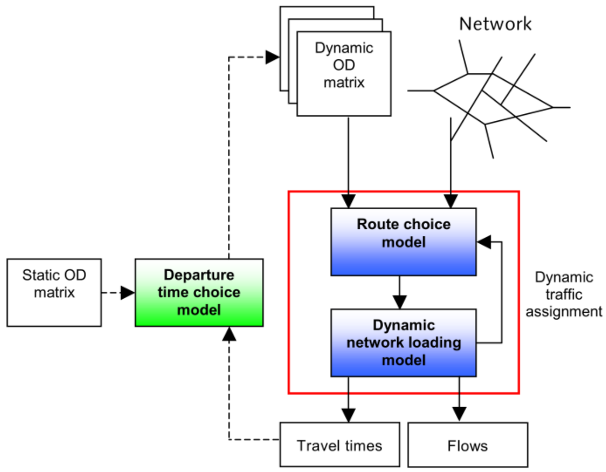


Figure 1. Dynamic Assignment Framework
(Van Zuylen et al., 2006)

3.3. Dynamic Routing Algorithms Utilizes Predicted Traffic Flow

We have already developed and extended several dynamic models in the previous project. During this phase, we applied our already developed dynamic routing algorithms to the network with estimated traffic flows resulting from DTA analysis.

4. Results

In this section we will demonstrate our proposed algorithm and methods solution quality on a stylized freeway network. We illustrated the network in Figure 2 and give the details in

All algorithm and methods were coded in Matlab 7 and executed on a Pentium IV machine with 1.6 GHz speed processor and 1024 MB RAM under the Microsoft Windows XP operating system environment.

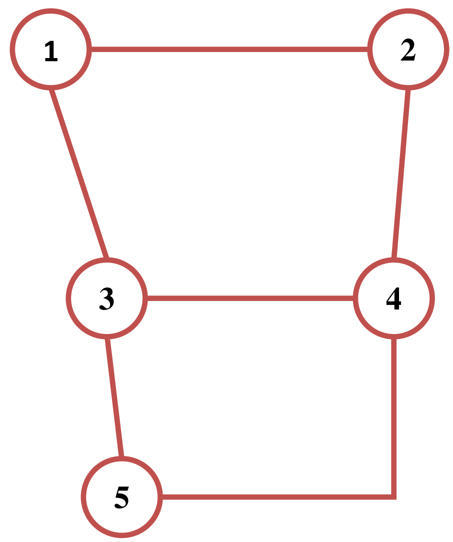


Figure 2. Road Network Considered for Experimental Study

We assume that all the arcs of the network have a capacity of 30 vehicles per minute (vpmin) under normal conditions. Also, we assume in-flow traffic arrival rate for each arc is a Poisson random variable with parameter 25 vpmin during these operation times.

Table 1. Information Regarding the Road Network Nodes and Arcs

Arc ID	From Node	To Node	Length (miles)	Capacity (vpmin)
1	2	1	1.75	30
2	4	3	1.32	30
3	2	4	3.13	30
4	4	5	2.81	30
5	1	3	3.26	30
6	3	5	1.42	30

Path One:

The link route incidence matrix is determined through travel times on links and travel times are calculated with Bureau of Public Road (BPR) function:

$$T_a(h) = t_{a,ff}\left[1 + A_a\left(\frac{x_a(h)}{c_a}\right)^{R_a}\right]$$

where $t_{a,ff}$ is free flow link travel time, A_a and R_a are constants. We take A_a =0.15 and R_a =4 along with the literature. We assume free flow link travel time is average travel

We take node 2 as the origin and node 5 as the destination. From origin 2 to destination 5 there are 3 different path options could be taken. (path 1: 2-1-3-5; path 2: 2-4-3-5 and path 3: 2-4-5). With our origin-destination estimation method we will first estimate the trip distribution (the proportion of traffic on each path) when there is no construction on the network.

As we discussed earlier, the length of each measurement period (T) should be sufficiently large so that a typical journey can be finished during that period. Thus, we determined this measurement period based on the travel time on the longest path based on the BPR function given the random sample count of the links on that path. This leads that T=8.

P= [	0.24	0.22	0.23	0.24	0.20	0.25	0.23	0.22	0.24
	0.34	0.35	0.38	0.35	0.34	0.31	0.31	0.35	0.29
	0.42	0.43	0.39	0.41	0.46	0.44	0.45	0.43	0.47]

Now, we assume there is construction on arcs 3 and 4 which reduces the capacity of those arcs to 18 vpmin and the demand between origin 2 and destination 5 doesn't change. After re-calculating the proportions of paths when there is a construction in the network we get the below results.

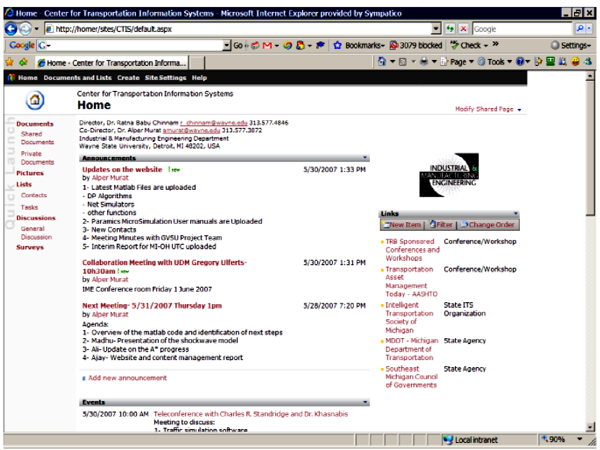
P= [	0.38	0.32	0.35	0.37	0.37	0.35	0.36	0.38	0.39
	0.33	0.33	0.28	0.3	0.31	0.29	0.31	0.29	0.33
	0.29	0.35	0.37	0.33	0.32	0.36	0.33	0.33	0.28]

The change in the proportions suggests that construction cause to reduce the proportion of vehicles using path 3 and increases path 1. The interrelation between travel time and volume of links governs the path proportions.

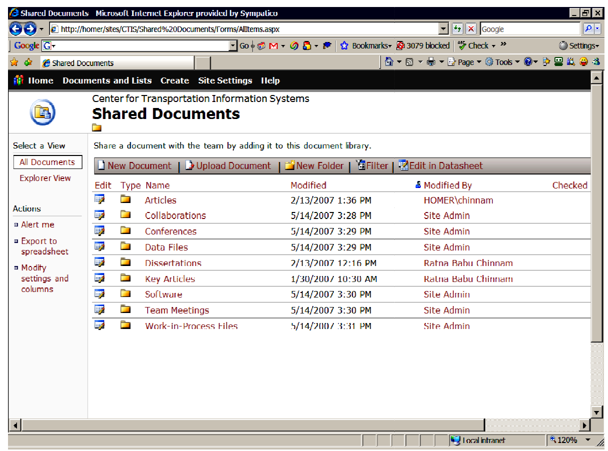
5. Results Dissemination

We have established a Microsoft SharePoint Website for the project that helps us track/store all project related documents/information in one place. Currently, it carries all our literature, data sets, code, weekly research group meeting minutes, long-term mile-stones, short-term tasks, calendar, and contacts. While we currently control access to this website through password protection, we are in the process of opening parts of the website for anonymous access. The screen shots below highlight different parts of our website.

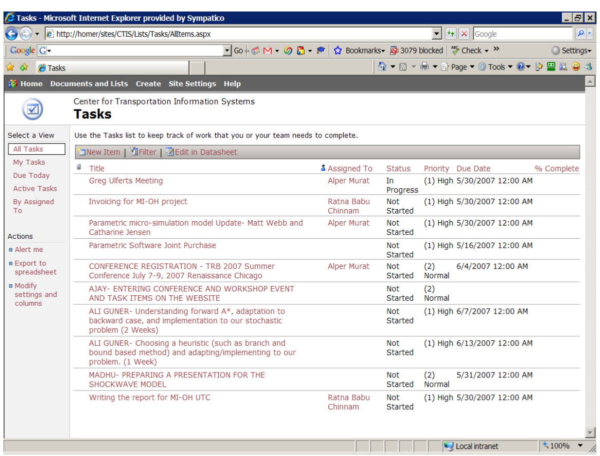
Homepage



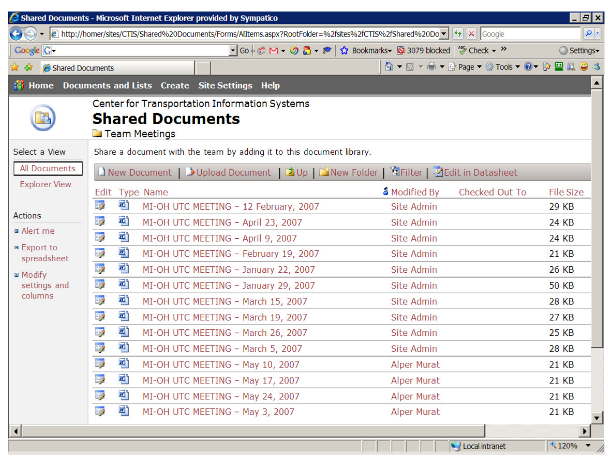
Literature



Tasks



Meeting Minutes



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7. Acronyms

AASHTO	American Association of State Highway and Transportation Officials
ATIS	Advanced Traveler Information Systems
BPR	Bureau of Public Road
DOT	Department of Transportation
DTA	Dynamic Traffic Assignment
JIT	Just-in-Time
MITS	Michigan Intelligent Transportation Systems
OD	Origin-Destination
ITS	Intelligent Transportation Systems
SC	Supply Chain
SE-MI	Southeast Michigan
STA	Static Traffic Assignment