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Two-tiered Decentralized Simulation Model to Regulate Urban Freight Trucks Operation

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Abstract: Time windows and vehicle restrictions are widespread urban freight trucks regulations around the world which result in substantial social and economic losses many times. A two-tiered decentralized simulation model was developed to regulate freight trucks to access the urban area. This model met the different freight demands of municipal sub-areas based on their own evolving traffic capacity and introduced a level of readiness to direct freight trucks access priority. Furthermore, its sustainable system goals included travel cost within an urban area and satisfaction of user's expectations. Beijing was taken as a case study to illustrate how to calibrate the demand and capacity of sub-areas. And its simulation results showed temporal regulation plans for each user which was very instructive for the authorities to efficiently and dynamically regulate freight trucks into the congested urban area.

Key words: Urban logistics, freight transport, trucks restriction, simulation

INTRODUCTION

Time windows and vehicle restrictions are popular urban freight transport policy measures in various mega cities around the world (Quak and de Koster, 2008), keeping designated streets or areas free of freight traffic during particular time. And usually all transport service types have to respect the same time constraints (Ibeas *et al*., 2012). Restrictive delivery windows might bring substantial social and economic losses (Holguin-Veras, 2008), e.g., a decrease in the efficiency of deliveries, in terms of number of trips or the load factor (Stathopoulos *et al*., 2012) and as a consequence increase in traffic congestion, fuel consumption and emissions (Quak and de Koster, 2008). Sathaye *et al*. (2010) demonstrated that adjusting freight transportation to the night-time hours may increase the average pollutant density discharged by diesel engine. Whereas, no limits on freight trucks during the daytime cause traffic congestion on city roadways and suffering for city dwellers (Bhuiyan *et al*., 2010). All the routes in the city are not really congested during every hour of the day and some roads definitely can allow a few freight trucks to go through. Furthermore, with the information and communications technology revolution and widely practice of Intelligent Transportation Systems (ITS), the urban freight transportation structure could be greatly changed to meet dynamic demand with the evolving traffic conditions (Grzybowska and Barcelo, 2012).

To dynamically regulate freight trucks access congested urban areas and take advantage of road network traffic capacity within different sub-areas, this study introduced a two-tiered decentralized distribution structure through literature review, developed a tactics simulation model to regulate freight trucks access sub-areas within the city center regarding their own variant traffic capacity and finally took Beijing as a case study to illustrate its application.

TWO-TIERED DECENTRALIZED MODEL OF URBAN TRUCKS REGULATION

A two-tiered decentralized distribution structure: Distribution Centers (DCs) may be stand-alone facilities situated close to the city access or beltway, or may be part of air, rail, or navigation terminals with enhanced functionality to provide coordinated and efficient freight movements within the urban zone (Crainic *et al*., 2004). They provide a place near the urban center for truckers to wait out peak traffic periods (Regan and Golob, 2005). Therefore, it is increasingly common that tours from a DC to a service area start with a connecting distance, often along a primary highway system, then followed by the tour itself in the service area (Figliozzi, 2007) and extensive use of these facilities may improve traffic and freight delivery in the city (Suksri and Raicu, 2012). DC influence area is divided into service areas that can be attended to by a route (Figliozzi, 2006).

Freight flows are mainly pulled by end-consumer demand. From the aspect of socio-economic characteristics and commercial structure, this study defined commodity-based models to capture spatial patterns characterizing the urban freight distribution and calibrated the requirements in terms of productions and

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attractions at each of the transportation analysis zones (Holguin-Veras, 2000). When combined with traffic, freight demand analysis should consider the time sensitivity and value of the product itself, namely freight classification and properties, e.g., the composition of product flow and the distribution of daily product flows per freight types, even shipment size by freight type (Ibeas *et al*., 2012).

Description on simulated participants behavior and general equations: T: Set of time, t, t_e, $t_f \in T$, t_e demand expected and t_f demand failed. Freight are grouped into a number of homogeneous products, P: Set of products, $p \in P$. Due to time window restriction, all products to users are waiting and served by the nearest depot (namely DC), S: Set of depots, $s \in S$, without the capacity constraint. A user corresponds to a cluster of locations where freight actually delivered within a restricted area. Each user is assumed to be heterogeneous with respect to its population density, land use and the commercial profile. U: Set of users, $u \in U$.

Given a 24 h timeframe, at time t:

- User u expects demand $\hat{D}_u^p(t)$ of product p which captures the aggregate supply and demand of the service coverage for certain kind of product and its actual arrival volume $D_u^p(t)$. $\hat{D}_u^p(t)$ is scheduled by the user u to arrive at depot s in advance with the average travel time $\overline{\tau}_{su}^p(t)$, namely arrival volume $A_{su}^p(t-\overline{\tau}_{su}^p(t)) = \hat{D}_u^p(t)$. $Q_{su}^p(t)$, product p waiting in the depot s for user u, $Q_{su}^p(t) = Q_{su}^p(t-1) + A_{su}^p(t) - X_{su}^p(t)$ and corresponding average waiting time is $\overline{\delta}_{su}^p(t)$
- $X_{su}^p(t)$, product p departure from depot s to user u, is decided by the maximized benefit B_{su} as Eq. 1. In general, low value-low time sensitive products or low value-high time sensitive products, are driven by distinct trade-offs between inventory and transport/order costs (Figliozzi, 2007). So, the level of readiness $L_{su}^p(t)$ for trucks with product p to departure was introduced. And Eq. 1 subject to Eq. 2 and 3:

$$\max_{X_{su}^p(t)} B_{su} = \sum_p L_{su}^p(t) \times X_{su}^p(t) \forall t \tag{1}$$

$$\text{s.t} \sum_p X_{su}^p(t) \le f_{su}(t) \times C_{su}(t) \tag{2}$$

$$X_{su}^p(t) \le Q_{su}^p(t-1) + A_{su}^p(t) \tag{3}$$

$$L_{su}^p(t) = \omega^p \times (A^p + \frac{\log(1+\overline{\delta}_{su}^p(t))}{\log B^p})$$

ω^p is static departure priority decided by products physical features; A^p, B^p are parameters.

Equation 2, trucks that get the permit to leave the depot is decided by the remaining capacity of the sub-area $C_{su}(t)$ and permit ratio $f_{su}(t)$. If $f_{su}(t) = 0$, the sub-area is closed for trucks, e.g., peak hours during workdays.

Equation 3, the departure number of trucks is subject to its number of queuing in line and current arriving.

- $X_{su}^p(t)$ arrive at user u after average travel time $\overline{\tau}_{su}^p(t)$ which is based on historical statistics, so arrival volume $Y_{su}^p(t+\overline{\tau}_{su}^p(t)) = X_{su}^p(t)$

The system cost has travel cost within an urban area and satisfaction of user's expectations. And the latter has two parts, namely the task fulfilled and totally failed. If still stay in depots after simulation timeframe, penalty β_p is applied to distinguish types of products. α_1, α_2 and α_3 are weighting parameters:

$$\begin{aligned} \min_{f_{su}(t)} C_{system} &= \sum_t \sum_u \sum_p \alpha_1 X_{su}^p(t) \times \overline{\tau}_{su}^p(t) \\ &+ \sum_{t_e} \sum_u \sum_p \alpha_2 \left| \hat{D}_u^p(t_e) - D_u^p(t_e) \right| \\ &+ \sum_{t_f} \sum_u \sum_p \alpha_3 \beta^p \left| \hat{D}_u^p(t_f) - D_u^p(t_f) \right| \end{aligned} \tag{4}$$

Minimize the system cost Eq. 4 and get the optimal output, permit ratio $f_{su}(t)$.$f_{su}(t) \times C_{su}(t)$ provides the number of permits the authorities will issue to every user within 24 h.

Equation 5 and 6 are system flow conservations:

$$\sum_t A_{su}^p(t) = \sum_t X_{su}^p(t) \tag{5}$$

$$\sum_t Y_u^p(t) = \sum_t D_u^p(t) \tag{6}$$

RESULTS AND DISCUSSION ON BEIJING CASE STUDY

Calibrate input data of the simulation system: Beijing, as the capital of China, illegal freight operation are driven by great profits, like selling the freight permit or using fake freight permit although Beijing Municipal Commission of Transport (BMCT) specifies time windows and vehicle restrictions (Wang, 2013). So, this simulation model was employed to dynamically issue permits and timely coordinated the demand and traffic capacity in different sub-areas.

Urban center was divided into 6 districts (users) within the downtown 5th Ring Road and assigned their corresponding "depots" according to highways layout and density of their freight traffic as Table 1.

Table 1: Users and their corresponding depots

User	Center distance (km)	Depot ID
DC	17	1
XC	15	3
HD	31	2
CY	16	1
FT	32	2
SJS	22	2

Table 2: Users freight trucks demand grouped by products types

	Wholesale		Retail		
User	Produce	Others	Residents daily necessary	Food and beverages	Society maintenance
DC	892	3570	1352	386	193
XC	1009	4037	1234	352	176
HD	2276	9103	2047	585	292
CY	2334	9335	3603	1029	515
FT	372	1490	1026	293	147
SJS	150	600	497	142	71

Table 3: Time window expected and parameters of the $L^p_{su}(t)$

Products	Time window expected	ω^p	A^p	B^p
Produce	0:00~24:00	1.0	2.8	1.2
Others	22:00~5:00	0.6	1.0	2.0
Residents daily necessary	8:00~18:00	0.8	2.0	1.8
Food and beverages	6:00~9:00	0.9	2.5	1.5
Society maintenance	0:00~24:00	1.0	3.0	1.2

Table 4: Beijing freight volume and trips percentage grouped by time window (%)

	Urban center		Within 4th ring road	
Time window	Volume	Trips	Volume	Trips
23:00~6:00	38.0	18.7	34.1	16.4
9:00~16:00	45.3	69.7	51.1	73.1
6:00~9:00 and 16:00~23:00	16.7	11.7	14.9	10.5

Table 5: $C_{su}(t)$ and the average speed (km h^{-1}) of every Monday, March, 2013

	$C_{su}(t)$ (trucks)						Average speed (km h^{-1})					
Time window	DC	XC	HD	CY	FT	SJS	DC	XC	HD	CY	FT	SJS
0:00~5:45	123	131	135	151	142	142	42	44	45	50	47	47
6:00~11:45	41	48	76	84	85	105	26	27	33	34	34	38
12:00~13:45	71	78	109	116	116	126	31	32	38	40	40	42
14:00~21:45	47	52	80	81	93	110	27	28	33	33	35	39
22:00~23:45	105	113	123	132	133	137	37	39	42	44	44	46

In 2010 Beijing downtown daily freight volume was 275,100 tons, of which 170,600 tons daytime (6:00-23:00); daily freight trips 99,700, of which 81,100 daytime. Here gave 280,000 tons as the average daily freight volume demand, via 5-tons trucks, 56,000 vehicles needed and assumption of which 70% as the wholesale demand and 30% as the retail. Refer 2012 Beijing Statistical Yearbook, got the wholesale and retail of the 6 users and calculated their percentage as the weight of vehicles demand. Users demand profile as Table 2.

And users generally have their own preferred time windows to receive products and products with physical and social characteristics. According to the product classification, Table 3 gave time window expected by users and parameters of the $L^p_{su}(t)$.

Distribution of $\hat{D}^p_u(t_e)$ within the time window expected referred "Survey Report on Freight Demand of Beijing Urban Centers" (BMCT, 2011) as Table 4 which unevenly distributed day and night, urban center and downtown area. Furthermore, $\hat{D}^p_u(t_e)$ evenly distributed (every 15 min) within time window expected in Table 3.

Sarker and Baylot (2012) employed the concept of average speed on a linked road to estimate the throughput rate of the vehicles. Equation 7 calculated hourly sub-area remaining capacity $C_{su}(\nu)$ in one direction, if $\nu \le \nu_0$, the road congested $C_{su}(\nu) = 0$. And the relationship between ν and ϕ referred Wang (2013):

$$C_{su}(\nu) = \frac{1000}{\frac{1}{3.6} + \frac{\nu}{254\phi} + \frac{14}{\nu}} - \frac{1000}{\frac{1}{3.6} + \frac{\nu}{254\phi} + \frac{14}{\nu_0}} \tag{7}$$

$$(\nu > \nu_0,\ \nu_0 = 20 \text{ km h}^{-1})$$

Usually workdays and weekends have different traffic characteristics and Friday differs from the other workdays. Here took every Monday in March of 2013 as an example. Table 5 listed their capacity of trucks in four directions and the average speed (km h^{-1}). The time window was clustered by historical data. The speed was collected every 15 min from BMTC website (http://www.bjjtw.gov.cn/bmfw/jtzs/index.htm) and accordingly $C_{su}(t)$ calculated with Eq. 7. Suppose that road capacity and increased trucks have no impact on travel time. And there are no shared arcs between depots to sub-areas.

RESULTS

This model was programmed by MATLAB (R2010a) and solved with the optimal toolbox GA (population 50 and elite count 5), $\alpha_1 = 0.5$, $\alpha_2 = 0.1$, $\alpha_3 = 0.4$, $\beta^p = [8\ 4\ 6\ 6\ 7]$, $Lb \le f_{su}(t) \le Ub$, for each sub-area Lb = [5 0 0 0 5], Ub = [5 0.5 1.5 0.5 5].

Simulated the 6 users as a whole, although on Monday the total capacity 56000 is greater than the aggregate demand 49108, there were still 7369 trucks failed users' demand with the minimum system cost 63046.

Individual simulation got Table 6. And the summation of discrete system cost 63222.7 is bigger than 63046. FT and SJS met all the demand. For DC and XC, regardless of the fact that their demand is smaller than their own capacity, they still respectively failed 1109 and 944 trucks. This might be explained by the demand distribution diversification on dissimilar products. As Table 4, freight volume and trips during daytime are far greater than the late night (almost doubled), especially have highly demand during 9:00~16:00. In contrast, road capacity is abundant during the night especially 22:00~6:00.

Table 6: Capacity, demand, demand failed and system cost of each sub-area

	Total (trucks)			
User	Capacity	Demand	Demand failed	System cost
DC	6848	6394	1109	8485.1
XC	7488	6808	944	6429.0
HD	9480	14303	1996	24280.4
CY	10216	16815	3416	16888.6
FT	10416	3328	0	5699.6
SJS	11552	1461	0	1440.0

Table 7: Temporal regulation ratio for every user $f_{su}(t)$

Time	Simulation as a whole results						Individual simulation results					
window	DC	XC	HD	CY	FT	SJS	DC	XC	HD	CY	FT	SJS
0:00~5:45	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
6:00~11:45	0.50	0.50	0.49	0.50	0.49	0.45	0.50	0.49	0.49	0.46	0.49	0.24
12:00~13:45	0.92	0.85	1.49	1.34	0.74	0.90	1.00	1.23	1.06	1.50	0.43	0.6
14:00~21:45	0.48	0.48	0.49	0.49	0.50	0.46	0.45	0.48	0.49	0.44	0.48	0.43
22:00~23:45	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00

Table 7 presented temporal regulation $f_{su}(t)$ for every user corresponding simulated as a whole and individually. When referred Table 5, different users got their own tailored regulation plan as $f_{su}(t)\times C_{su}(t)$.

DISCUSSION

Case study revealed the general procedure on how to find the custom regulation plan for each user. And the demand profiles quoted Statistical Yearbook and Survey Report which might be improved by a thorough field survey, e.g., the time window expected or preferred by the user and the expression and parameters of $L^p_{su}(t)$. Furthermore, the choice behavior of depots and their capacity constraint could be described by a survey. As regulation ratios, the initial values of Lb and Ub should have a further study, not only to compromise the great disparity between capacity and demand but also understand the actual departure behavior $X^p_{su}(t)$. α_i, β^p should also be carried on a comparative analysis and adjusted.

The consequences of this model are affected by: (1) The features of GA, like individuals, fitness function, crossover and mutation randomly generated, (2) In Eq. 1, $X^p_{su}(t)$ sometimes are determined by constraints and don't have the optimal solution.

On assumption that road capacity and increased trucks have no impact on travel time which should have in-depth discussions on the break point of sub-area truck flow base capacity $C_{su}(t)$ and consider shared arcs between depots to sub-areas, even the real road network.

In addition, this model is possible to extend by the user to well organize the freight arrival schedule at the depot and its outflow constraint. Now there are still some leftover after simulation, namely failed demand which will be adjusted to satisfy all the demand with reasonable system cost.

CONCLUSION

On a tactical level, this paper proposed a decentralized daily simulation model to issue truck permits to access sub-areas which comprised the level of readiness $L^p_{su}(t)$ for trucks with product p to departure. And this provided the authorities with custom regulation plans $f_{su}(t)\times C_{su}(t)$ for each user based on historical traffic information.

This method can be applied to all kinds of big cities. Nonetheless, it should be noted that different cities have totally different spatial and socio-economic structure feature, resulting in the adjustment of essential parameters. So, a dynamic coordination system by Matlab Java Builder is suggested base on this simulation algorithm to support the diverse authorities effectively integrating urban logistics market supply and demand as well as alleviate traffic congestion, by dynamically and economically regulating the freight vehicles permits to access downtown areas.

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