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SUPPLY CHAIN SIMULATION FOR MODELING THE INTERACTIONS IN FREIGHT MOVEMENT

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Abstract: Freight movement is a dynamic process involving with complex interaction among many agents by which the commodities are flowed through supply chains. Simulation based model allows such dynamic and complex interaction system to be undertaken. Simulation based multi-agent approach is therefore utilized to model the behaviors of agents and their interactions in supply chains in order that the mechanism of freight movement is better demonstrated. This model simulates day-to-day activities of agents (including, retailers, manufacturers, and suppliers) in product acquisition, production, and distribution. Systematic framework of the proposed model permits wide variety of application. Feedback and learning of freight agents and variation in freight traffic demand can be captured by the proposed model. This paper discusses the on-going research of supply chain simulation and provides the modeling framework, mathematical formulation, and the application of the model to the supply chain of food industry in the Tokyo Metropolitan Area.

Key Words: Freight demand model, Supply chain, Simulation, Multi-agent

1. INTRODUCTION

A freight transportation model is a necessary tool to access to the decision making on freight transportation systems. However, modeling of freight transportation system is very difficult since freight transportation system involves very complex linkages among many freight agents (for example, shippers, customers, and freight forwarders). The heterogeneity of freight transportation also includes the characteristics of commodities that vary in volume, weight, and shape. As computer technology has been dramatically developed and, as of recently, has reached a very high performance level, it is becoming more practical to develop freight models at the microscopic level. Microscopic models deal with each individual behavior instead of dealing with a zone as in macroscopic models. The individual can be a truck, an office, or a company depending on the level of modeling considered in each model. The current freight demand modeling tends to the microscopic level as it results in a more realistic and policy sensitive model comparing with the macroscopic one. An example of the microscopic models is the GoodTrip model for urban freight movement in supply chains proposed by Beorkamps et al. (1999, 2000). Models for mode choice and vehicle routing also belong to the microscopic modeling level. The examples of this type of model are the freight mode choice model using adaptive stated preferences developed by Shinghal and Fowkes (2002) and the freight routing model of time-definite delivery developed by Lin (2001). Micro-simulation is an analysis approach to modeling the behavior of an individual, which is used for expanding the survey data to all the individuals from their distribution. Due to this characteristic, micro-simulation is applicable to the wide area. The research of Vovsh et al (2002) is an example of the application of micro-simulation to transportation demand model. The other examples of the micro-simulation models applying to urban freight transportation are the researches of Hosoya et al. (2001, 2003) and Wisetjindawat and Sano (2003).

Freight flows are originally the results of the interaction among many freight agents in supply chains. Modeling of freight movement should take into account this characteristic. Supply chain simulation simulates activities involved in the movement of commodities and interactions among agents in a supply chain. Up to recent, supply chain simulation is widely used in the field of operation research and is mostly used for prediction supply chain performance of a single company. It is possible to extend the area of supply chain simulation to modeling of the urban freight movement. This paper aims to outline the model framework of the ongoing research and demonstrate an example of the proposed model applied to simulate the freight movement of food industry in the Tokyo Metropolitan Area.

Section 2 provides general background about supply chain simulation and related work done previously. Section 3 discusses in details the concept of the proposed model. Mathematical formulation is also presented in this section. Section 4 demonstrates the application of the proposed model to a scenario. Finally, Section 5 provides conclusions and recommendations on the proposed model.

2. SUPPLY CHAIN SIMULATION

Supply chain is a dynamic and complex system involving the behavior of several participants. Due to its applicability of dealing with the interaction among agents, supply chain simulation is suitable for modeling the interaction among agents in supply chain through information and material flows. Supply chain simulation is widely applied in the field of supply chain management. Numerous studies have been done for the purpose of supply chain management of a single company. Supply chain simulation is a useful tool to observe supply chain performance. Many models use the simulation for predicting and design of the appropriate supply chain for each particular industry. For the purpose of supply chain design, Reiner and Trcka (2004) used simulation to design the supply chain structure for a production company in food industry. Supply chain simulation also used for study production, inventory, and distribution policies. Siprelle et al (2003) utilized a supply chain simulation to study inventory allocation. In addition, supply chain simulation is utilized to study several phenomena in economic, such as bullwhip effect, boom and bust, and phantom demand. Higuchi and Troutt (2004) studied the phenomena occurred with the short product life cycle case of Tamagotchi, which is the first of the virtual pet toys.

Up to recent, supply chain simulation efforts mainly focus on the improvement of the performance in term of responsiveness, complexity, and inventory control. However, due to the attractive performances of supply chain simulation, we believe that supply chain simulation can be extended to the area of freight transportation planning.

3. MODEL FRAMEWORK

Freight agents interact with each other by two types of the flows through a supply chain including information and material flows. The proposed model simulates the day-to-day activities of agents of the entire supply chain involving in product acquisition, production, and distribution. Agents, including retailers, wholesalers, manufacturers, suppliers, and carriers, are rational and all their activities are based on the concept of minimization of the total costs. Agent forecasts demand and examines the proper policies to control inventory, production, and product distribution. The policies are revised periodically according to the demand forecasting to be suited for the actual demand. From the demand of final consumers, we simulate everyday the amount of products being sold by each retailer. Based on the actual sale, agent reviews its own inventory level at the end of each day. The information flow is started either when it is found that the inventory level has reached reorder position or when it is the time for order at the proper frequency. The agent then places the order of the products to the upper level of the supply chain (shipper agent). After the shipper has received the orders, material flow will be started; the products are loaded to trucks and transferred to the customers. During product distribution, shipments are treated according to the transportation policies of the shipper agent. The shipment is decided for the type of truck to be used and whether the shipment will be delivered by freight forwarder or by shipper itself. Then, the transport agent makes the delivery route to visit customers at the minimized travel costs. Finally, the truck trip OD matrices at each time period can be obtained.

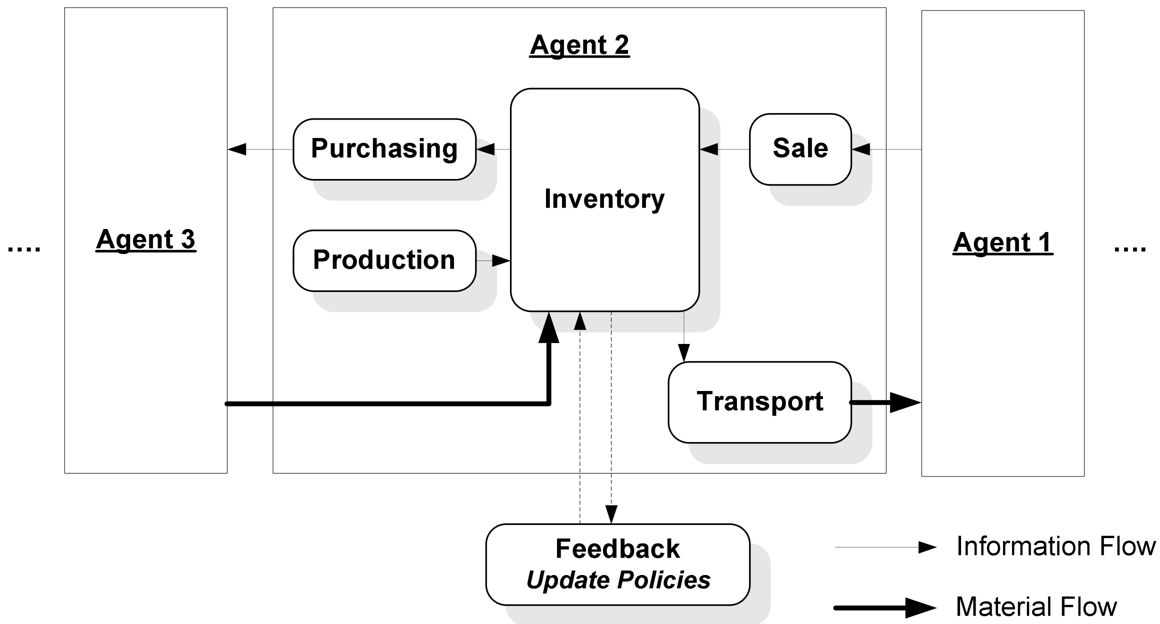

Figure 1. Model Structure

The proposed model structure is shown as Figure 1. Agents are sorted by level according to the position in supply chain structure. Considering Agent 2 in the supply chain in Figure 1, Agent 1 is located at its immediate downstream node and Agent 3 is located at its immediate upstream node. For example, Agent 1 might be a retailer; Agents 2 and 3 could be a manufacturer and a supplier respectively. In each agent, the decision process consists of six modules for dealing with each of the activities. The decision modules are listed as follows:

- Sale module.
- Production module.
- Purchasing decision module.
- Inventory module.
- Transportation module.
- Feedback module.

3.1. Sale Module

Demands of commodities of the end users at each of the retailers are assumed follow a normal distribution with mean and variance estimated from the survey data. The daily sale (d_i^t) of each retailer i at time t, which is assumed follow normal distribution with mean $\bar{d}_i$ and standard deviation ε_i, is simulated using Monte-Carlo simulation concept.

$$d_i^t = N(\bar{d}_i, \varepsilon_i) \tag{1}$$

For other agents from which the end users do not directly purchase, the sale demand depends on the orders received from agents at the lower level of the supply chain.

3.2. Production Module

Each firm makes the decision of its production controls, saying that the amount of commodity will be produced. The average monthly amount of commodities produced by each firm is estimated using regression techniques from the characteristics of firms as shown in Equation 2. The variables can be any attributions of the firm, which in this case are number of employees and floor area.

$$G_i = f(x_{1i}, x_{2i}, \cdots, x_{ki}) \tag{2}$$

where,

G_i is the monthly amount of produced commodities of firm *i*.

x_{ki} are the attributions of firm *i*, such as number of employees, floor area, and other related attributes.

3.3. Purchasing Decision Module

A firm can purchase a commodity from many sources; purchasing decision module determines the fraction of commodity to be purchased from each source. The purchasing fraction is a multiplication of three parts: distribution channel choice, location choice, and shipper choice as shown in Equation 3.

$$P(i) = P(C) \cdot P(z|C) \cdot P(i|C, z), \quad i \in C, z \tag{3}$$

Distribution Channel Choice, $P(C)$

To select the industry type from which the firm purchases, we assume that the firm's decision is based on the attractiveness of each industry type. A multinomial logit model is used to explain the decision behavior from the attractiveness variables, which in this study are the amount of production and number of firms of that industry type.

$$P(c) = \frac{\exp(V_C)}{\sum_{C' \in \hat{C}} \exp(V_{C'})} \tag{4}$$

$$V_C = f(x_{1C}, x_{2C}, \cdots, x_{kC}) \tag{5}$$

where,

$P(C)$ is the fraction of commodity purchased from industry type *C*.

V_C is the utility function of industry type *C*.

x_{kC} are the attributes representing the attractiveness of industry type C, such as the total amount of total production and number of firms.

Location Choice, $P(z|C)$

The locations of the shippers to be selected are assumed based on the attractiveness of the zones. The location choice is also determined using a multinomial logit model. The zonal attractiveness variables (such as number of firms in the zone and total commodity production in the zone) and zonal impedance variables (such as distance between customer zone and shipper zone) are used to explain the attractiveness of the zones.

$$P(z|C) = \frac{\exp(V_z)}{\sum_{z' \in Z} \exp(V_{z'})} \tag{6}$$

$$V_z = f(x_{1z}, x_{2z}, \cdots, x_{kz}) \tag{7}$$

where,

$P(z|C)$ is the fraction of commodity purchased from industry type C that located in zone z.

V_z is the utility function of zone z.

x_{kz} are the attributes representing the attractiveness of the zone z, such as number of firms in the zone, total commodity production in the zone, and distance between customer and shipper zones.

Shipper Choice, $P(i|C, z)$

Similarly, shipper choice is used for identifying the shippers from which a customer purchases. The choice decision process is designed using a multinomial logit model formulated as a function of the attractiveness of shipper, such as the total commodity production of each firm.

$$P(i|C,z) = \frac{\exp(V_i)}{\sum_{i' \in I} \exp(V_{i'})} \tag{8}$$

$$V_i = f(x_{1i}, x_{2i}, \cdots, x_{ki}) \tag{9}$$

where,

$P(i|C,z)$ is the fraction of commodity purchased from shipper i of industry type C that locates in zone z.

V_i is the utility function of shipper i.

x_{ki} are attributes of the attractiveness of shipper i, such as the total production amount of commodity.

3.4. Inventory Module

Inventory module is the main module to decide whether or not the other modules will be activated. Once the inventory level arrives to the reorder point, the production and purchasing modules is activated to acquire the products. Likewise, when the order is placed, the transport module is launched to delivery the product to customers.

Each firm makes decision on the inventory – the inventory level will be kept, the ordering lot size and frequency, the safety stock level, and other policies. The decisions of each firm are assumed to minimize the total inventory costs including holding costs, ordering costs, and transportation costs. In actual situation, there are several strategies related to inventory control and should be considered in the analysis, such as Just-In-Time policies and so on. However, for simplicity of analysis, this study assumed that each firm's order is a fixed frequency. The optimum ordering frequency is then formulated as follows:

$$F_{ij} = \sqrt{\frac{Q_{ij}}{\gamma \cdot D_{ij}}} \tag{10}$$

where,

F_{ij} is the ordering frequency of firm i requested to firm j.

Q_{ij} is the monthly commodity purchased by firm i from firm j.

D_{ij} is the distance between firm i and firm j.

γ is the parameter for inventory model.

3.5. Transportation Module

Each time the information flows from customers to shippers, transportation module is activated to distribute the commodities from shippers to their customers. Transportation module consists of two sub modules: carrier and vehicle choices and vehicle routing. When shipper delivers commodities to customers, firstly, it decides the choices whether delivery by itself or delivery by using a freight forwarder company. After deciding the carrier and truck choices, the commodities are loaded to trucks and delivered to each customer according to the order of visiting customers from vehicle routing.

Shipper is assumed to select their carrier and vehicle preference based on the minimization of the total transportation costs. The choices are structured as a two level-nested logit model of carrier choice (between private and business trucks) and vehicle choice (between large and small trucks). The small truck category includes trucks that have maximum carrying weight less than five tons. The choice decision depends on the characteristics of shippers and customers (such as industry type and number of employees), the attributes of commodities (such as commodity type, lot size and frequency) and other characteristics related to the commodities.

$$P_{ij}(LP) = \frac{\exp(V_P)}{1+\exp(V_B)} \cdot \frac{\exp(V_L + V_P^{'} \cdot \mu_P)}{1+\exp(V_L + V_P^{'} \cdot \mu_P)} \tag{11}$$

$$V_P = f(Nc_i, Emp_i, L_{ij}, F_{ij}, TT_{ij}) \tag{12}$$

$$V_P^{'} = \ln\left[\exp(V_P) + \exp(V_B)\right] \tag{13}$$

where,

$P_{ij}(LP)$ is the probability of selecting a large private truck.
V_P is the utility function of a private truck.
V_B is the utility function of a business truck.
V_L is the utility function of a large truck.
V_B is the utility function for a business truck.
Nc_j is the number of customers for shipper *i*.
Emp_j is the number of employees for shipper *i*.
L_{ij} is the lot size delivered from shipper *i* to customer *j*.
F_{ij} is the delivery frequency from shipper *i* to customer *j*.
TT_{ij} is the travel time between shipper *i* and customer *j*.
$V_P^{'}$ is the log-sum variable of the nested logit model.
μ_P is the scale parameter for private truck

Vehicle routing provides an order to visit customers. The delivery route is decided in the way that minimizes the total route travel time, which is constrained by the maximum working hours of a truck driver and limited carrying weight of a truck. The total travel time includes the staying time at customer's location for parking, commodity loading and unloading. The formulation can be written as:

Min $$TC_i = \sum_{m=1}^{n}\sum_{l=1}^{n}((TT_{l,m} + ST_m) \cdot x_{l,m}) \tag{14}$$

Subject to: $$\sum_{m=1}^{n} x_{l,m} = 1 \tag{15}$$

$$\sum_{l=1}^{n} x_{l,m} = 1 \tag{16}$$

$$\sum_{m=1}^{n}\sum_{l=1}^{n}((TT_{l,m} + ST_m) \cdot x_{l,m}) \le HR_{\max} \tag{17}$$

$$\sum_{m=1}^{n}\sum_{l=1}^{n}(L_{l,m}\cdot x_{l,m})\le WT_{\max} \tag{18}$$

$$x_{l,m}\in\{0,1\} \tag{19}$$

where,

TC_i is the total travel time of a delivery route for shipper i.

$TT_{l,m}$ is the travel time between customer l and customer m.

ST_m is the staying time at customer m.

n is the number of customers

$HR_{\max}$ is the maximum working hours of a driver

$WT_{\max}$ is the maximum carrying weight of a truck

3.6. Feedback Module

The implementations of all the above policies can feedback the agent's decisions. Each time the firms receive the orders, they revise their demand prediction and the decisions about production, purchasing, inventory, and transportation policies. Firm predicts demand in order to revise the inventory policies. We assume that the firm utilizes moving average as the demand prediction method. When the predicted demand changes, the ordering frequency is also adjusted to suit for the demand in order to avoid backlogging or over stock.

4. SUPPLY CHAIN SIMULATION

The proposed model was applied to the simulation test bed of the supply chain of food industry in the Tokyo Metropolitan Area. The supply chain of food industry is chosen for analysis of this paper because it is one of the main commodities of urban freight movement. The number of truck trips of food products is the largest which is about 17 percent of the total number of trips of all commodity types. Based on the data of Tokyo Metropolitan Goods Movement Survey (TMGMS, 1982, 1994), the supply chain structure of food industry can be obtained as shown in Figure 2.

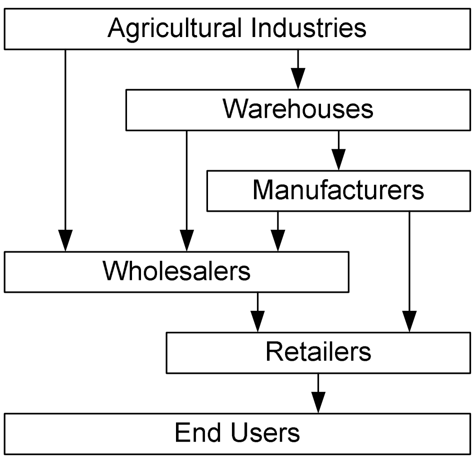

Figure 2. Supply Chain Structure of Food Industry

The model presented here is the ongoing research and still have some limitations. For simplicity of analysis and simulation, we focus on some part of supply chain as shown as Figure 3. The model was applied to 250 simulated firms of retailers, manufacturers, and warehouses over the Tokyo Metropolitan Area.

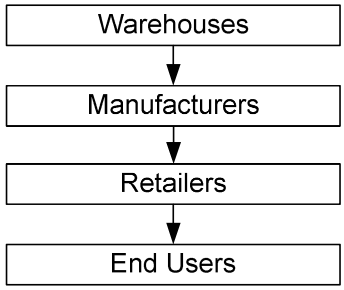

Figure 3. Supply Chain Structure Considered in this Paper

4.1. Simulation Parameters

The daily sale rate of a retailer is approximated from the TMGMS survey data as shown in Table 1. Retailers are categorized into eight groups according to the number of employees. The daily sale of retailer in each employee group is assumed follows a normal distribution with mean and standard variation as shown in the table.

Table 1. Distribution of Daily Sale of Retailers

Group	**Number of Employees (persons)**	**Mean (kg/day)**	**SD (kg/day)**
1	1-4	45	38
2	5-9	210	55
3	10-19	429	76
4	20-29	747	108
5	30-49	1,671	483
6	50-99	3,784	559
7	100-299	9,916	4,562
8	more than 300	15,789	25,174

The model parameters are calibrated and validated using the data set of the TMGMS data to estimate the firm's capacity on production, inventory and transportation costs, purchasing and vehicle choices and so on. The calibration results of the production models are summarized as shown in Table 2. The production capacity of warehouse depends on the number of employees, whereas the production capacity of manufacturer mainly depends on the floor area of the firm. Retailer, which does not produce any commodity and only purchases the commodities from manufacturers, is not considered for its production model.

Table 2. Estimated Parameters of Production Models

Industry	**Production (kg/month)**		**R**
Warehouses	$G_i = 37{,}485 Emp_i$	t-value = 5.2	0.84
Manufacturers	$G_i = 45 Flr_i$	t-value = 25.8	0.99

Purchasing decision model consists of three parts: distribution choice, zone choice, and shipper choice. Firstly, the choice of industry to be selected, in this case, is equal to one because we are considering a single supply chain. Secondly, the calibrated parameters of the choice of a zone to be selected are shown in Table 3. The total zone production has a positive sign indicating that a bigger purchase amount comes from the zone producing a higher amount of commodity. On the other hand, distance has a negative sign, which implies that customers prefer purchasing larger amounts from nearer zones. Comparing the distance parameters among three industry types, the parameter of warehouse is larger than that of manufacturer and the parameter of manufacturer is also larger than that of retailer. It means that retailer prefers to purchase a bigger lot from the nearer zones comparing with manufacturer and warehouse in which the commodities are distributed in the longer distance.

Table 3. Estimated Parameters of Purchasing Choice Models

Industry	Utility Function of Zone z	ρ^2
Warehouses	$V_z = 0.114\sqrt{G_z} - 0.026D_{IJ}$ t-value = 147.9, -6.7	0.182
Manufacturers	$V_z = 0.198\sqrt{G_z} - 0.033D_{IJ}$ t-value = 108.3, -9.1	0.228
Retailers	$V_z = 0.245\sqrt{G_z} - 0.054D_{IJ}$ t-value = 79.0, -12.3	0.267

The estimated γ of Equation (7) of ordering frequency are summarized in Table 4. The value of warehouses is larger than that of manufacturers and the value of manufacturers is also larger than that of retailers. This indicates that retailer prefers to purchase at higher frequency comparing with manufacturer and warehouse. Likewise the manufacturer prefers to order a higher frequency comparing with warehouse.

Table 4. Estimated Parameters of Ordering Frequency Models

Industry	Ordering Frequency		R
Warehouses	$\gamma = 22.17$	t-value = 10.6	0.47
Manufacturers	$\gamma = 10.54$	t-value = 11.9	0.41
Retailers	$\gamma = 0.88$	t-value = 11.9	0.41

The estimated parameters of carrier and vehicle choices are summarized in Table 5. For warehouses, the sign of employee parameter ($Emp - P$) is positive meaning that the larger warehouse tends to use private truck rather than business truck. For the sign of travel time parameters, $TT - P$ is negative and $TT - L$ is positive indicating that large business truck is preferred in case of the delivery for the longer distance. For manufacturers, the sign of employee parameter ($Emp - P$) is negative indicating that the larger manufacturer's preference tends to the usage of business truck. The sign of parameters $Nc - L$ and $Lot - L$ are positive confirms the fact that large truck is used for delivery to the large number of customers and lot sizes. For the far distance delivery, manufacturers use a large business truck. For retailers, the larger company prefers using business truck which indicated by the negative sign of the employee parameter ($Emp - P$). For the delivery for the longer distance, the preference changes to the usage of business truck.

Table 5. Estimated Parameters of Carrier and Vehicle Choices Models

Industry Type	Variables	Private and Business Truck		Large and Small Truck		N	ρ^2	Hit Ratio
Warehouses	*First Level Choice*					7,448	0.621	0.777
	Const-PL	4.14	*(20.5)*					
	Const-PS	-4.519	*(-23.1)*					
	Nc-P	0.002695	*(1.9)*					
	Emp-P	0.0004848	*(2.0)*					
	TT-P	-0.005047	*(-6.5)*					
	Second Level Choice							
	Const-L			-33.83	*(-2.3)*			
	Nc-L			-0.02482	*(-1.7)*			
	TT-L			0.02837	*(2.3)*			
	Lot-L			0.0004918	*(16.9)*			
	μ_P			0.12	*(1.9)*			
Manufacturers	*First Level Choice*					26,965	0.559	0.743
	Const-PL	5.635	*(50.1)*					
	Const-PS	-2.231	*(-31.7)*					
	Nc-P	-0.004543	*(-9.4)*					
	Emp-P	-0.0004132	*(-12.1)*					
	TT-P	-0.01068	*(-30.1)*					
	Lot-P	-0.0001377	*(-16.1)*					
	Second Level Choice							
	Const-L			-9.125	*(-17.8)*			
	Nc-L			0.003883	*(4.1)*			
	TT-L			0.006735	*(12.2)*			
	Lot-L			0.00000998	*(5.5)*			
	Frq-L			0.02175	*(14.)*			
	μ_P			0.53	*(8.7)*			
Retailers	*First Level Choice*					32,351	0.814	0.913
	Const-PL	4.234	*(35.3)*					
	Const-PS	-2.838	*(-22.6)*					
	Nc-P	-0.0009187	*(-7.2)*					
	Emp-P	-0.002464	*(-20.3)*					
	TT-P	-0.009531	*(-9.2)*					
	Second Level Choice							
	Const-L			-6.341	*(-15.2)*			
	Nc-L			-0.001268	*(-5.5)*			
	Emp-L			0.0004808	*(6.6)*			
	Frq-L			0.03365	*(3.8)*			
	μ_P			0.54	*(8.4)*			

Note: t-value in parentheses.

4.2. Simulation Results

All modules in supply chain simulation are programmed using Visual Basic. The simulation is started with the daily sale of retailer simulated from the distribution as shown in Table 1. From the sale demand at each day, the retailer updates the inventory levels. Assuming that the firm utilizes fixed frequency policy for ordering the commodities from manufacturers, the ordering frequency is the optimum frequency obtained from the inventory model. When it is the time to order, the retailer places an order to manufacturer using "order up to level" policy.

After the manufacturer receives the orders, the inventory level is reviewed and the ordered commodities are prepared for delivery. To deliver the commodities to customers, manufacturer selects the proper carrier and vehicle choices which will minimize the delivery costs. Then, the delivery route is simulated to visit each customer in the way that will minimize the total delivery costs. Manufacturer also orders the commodities from warehouse at the fixed frequency as same as warehouse updates the inventory and deliveries the commodities. The optimum ordering frequency is revised at each time the products are sold in order that the ordering policy will be suited for the actual demand. Finally, from the vehicle routes, the OD of truck trips by each truck type can be obtained.

With the simulation period of 60 days, the daily variation in number of truck trips for transportation of food industry of the 250 simulated firms is shown in Figure 4. The average number of all truck trips is 351 trips per day. For each truck type, the average numbers of truck trips of all Origin-Destinations by truck types are 72 trips per day and 278 trips per day for small and large trucks respectively. Figure 5 demonstrates the variation on the share of truck trips between small and large trucks. In this simulation, large trucks are the main vehicles used for delivery in which about 80 percent of all truck trips are occupied by large trucks. This is because the preferences of manufacturers and warehouse mainly tend to the usage of large trucks. From the daily variation of truck demand, the number of truck trips at the peak time is much more than the mean value, which is about 3 to 4 times of the average value. This circumstance is occurred because the ordering frequencies of customers are synchronized. If we increase the number of simulated firms and the variation in ordering frequency and lead time, this large amplitude at the peak time could be reduced and the model results would be more realistic. The present application provides a rough figure of the output and capability of the proposed model but has not yet validated with the actual truck ODs since only the small number of simulated firms of the supply chain of food industry are simulated. If the scope of study is extended to cover all supply chain types and industry types, the model can be validated with the actual truck trips OD from the survey data. These subjects will be taken into account in the future improvement.

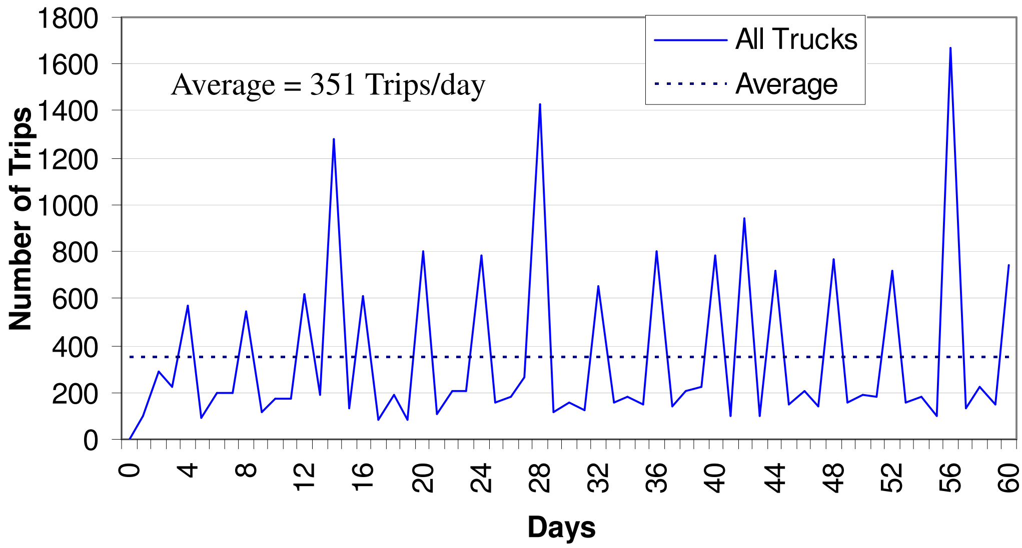

Figure 4. Daily Variation of the Number of Total Truck Trips for All ODs
(For Transport of Food Products of 250 Warehouses, Manufacturers, and Retailers)

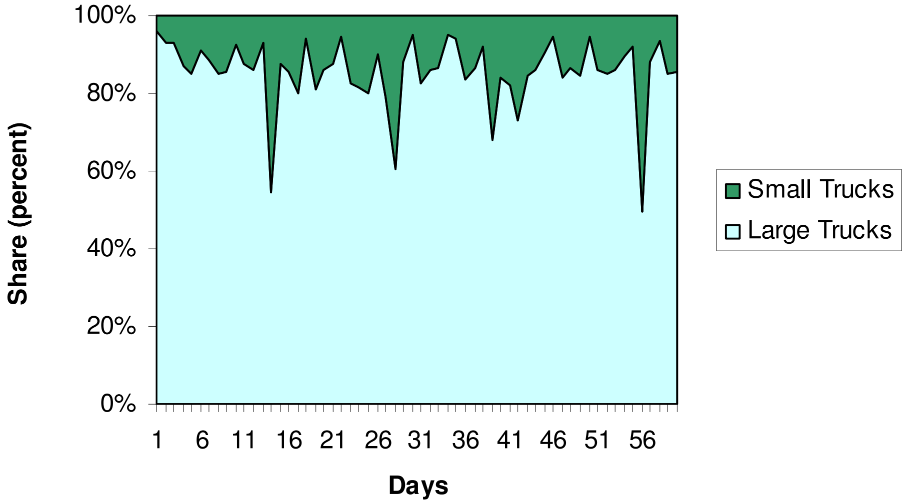

Figure 5. Variation in Share of Number of Small and Large Trucks

The ability to demonstrate the traffic variation is an important characteristic. Since static models result only the mean values which sometimes does not enough to be the good representative values. Not only for truck trip demand but also the behaviors of freight agents (for example, production and inventory behaviors, purchasing choice, vehicle choice, and so on) are dynamic. Freight agents do not always purchase the commodities at the same amounts, or order the commodities at the same frequency all the times, or use the same truck at all the times for delivery. These kinds of characteristics are yet considered in static models. The ability of the proposed model is not limited to only the result in the variation in truck trip demand but also capture the feedback and learning of agents in response to the decisions and behaviors of the other agents. Agents learn from experience the appropriated inventory level, the production rate, carrier and vehicle type, and other policies. Such complex system of freight movement is very difficult to be captured by static models while a dynamic supply chain simulation model relax such difficulties and allows incorporating the complex relationships and interactions among freight agents in a supply chain. Since the proposed model is a dynamic supply chain simulation, the model is able to overcome all the above deficiencies of static models.

5. CONCLUSION

This paper has presented an overview of the proposed supply chain simulation for freight movement with an example of the model application to the urban freight movement of food industry in the Tokyo Metropolitan Area. The proposed model is a dynamic multi-agent modeling system which systematically incorporates the interactions among the freight agents through the decision process. The model takes into account the feedback in which an agent is influenced by the behaviors of the other agents in the supply chain. The flexible modeling framework causes the model to be applicable to the wide variety of application area. The model framework can be adapted to various supply chain structures and include many more number of the involved agents. The model can be adjusted to meet the requirement of transportation planners at the more sophisticated level. In addition, the proposed model is a dynamic system considering the dynamic of freight agent's behaviors not only the mean values as static models. The proposed model therefore could better represent the mechanism of the complex system and capture the variation in freight traffic demand.

Various aspects in freight transportation are, however, still not considered in the present research. Variation in production rate and lead time among different manufacturers causes different freight movement patterns. The interaction with freight forwarders on commodity delivery, the different processes for dealing with raw materials and finished products in manufactures, and other innovations in freight movement (such as Just-In-Time, Third-Party Logistics, and so on) are needed to be improved in the future research.

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