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Dynamic Matching Algorithms for Internet-based Logistics Brokerage Agents*

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ABSTRACT

In this paper, we present a dynamic matching methodology for the logistics brokerage agent that intermediates empty vehicles and freights registered to the logistics e-marketplace by car owners and shippers. In this matching methodology, two types of decisions should be made: one is when to match freights and vehicles and the other is how to match freights and vehicles at that time. We propose three strategies for deciding when to match, *i.e.* real time matching (RTM), periodic matching (PM), and fixed matching (FM) and use Hungarian method for solving the how-to-match problem. In order to compare the performance of the when-to-match strategies, computational experiments are done and the results show that the waiting-and-matching strategies, PM and FM, give better performance than real time matching strategy, RTM. We can expect that the suggested matching methodology may be used as an efficient and effective tool for the brokerage agent in the logistics e-marketplaces.

Keywords: Logistics, Matching, Brokerage, Agent

1. INTRODUCTION

The traditional off-line markets are radically changing to the on-line e-marketplace as the Internet is getting more popularly used. The ratio of logistics cost to total product cost is more than 11% (refer to www.mk.co.kr) and this fact means that one company should give more attention to the logistics area. For reducing costs

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and increasing efficiencies in the logistics area, many companies are changing their logistics process to the electronic one so called *e-logistics*, that is matched with the e-marketplace concepts such as e-procurement and supply chain management *etc.*

The traditional logistics companies that have performed the off-line businesses like parcel/package delivery, freight transportation, and house-moving services *etc.* are now moving their business area to the on-line business that informs estimate sheets for shipment orders of shippers or gets transportation orders from customers by the Internet. In addition, these companies expand the business area from the inside of the company itself to the companies (customers and suppliers) registered to the website of the company. By this expansion of the business area, they can give an elementary brokerage service between the shippers and vehicle owners by informing the freight information to the vehicle owners and the vehicle information to the shippers. Some advanced companies open a new field of enterprise so called *logistics brokerage business* to intermediate shippers and vehicle owners by using auction and counter-auction business models (refer to www.e4cargo.com). In these types of business models, however, most of the brokerage companies simply receive information such as freights' locations, destinations, and transportation due dates *etc.* from a company and then deliver the information the other company. We cannot say that this type of business model for brokering vehicles and freights is a completed one because the complete brokerage means not circulation of the information about freights and vehicles itself but matching freights and vehicles in an optimal manner. Therefore, we need to introduce an intelligent logistics brokerage agent to intermediate freights and vehicles in the electronic logistics marketplace for minimizing the total logistics cost.

In the past, various researches have been done for trying to increase efficiency of the logistics system and to reduce the related cost. These researches can be classified into two areas: vehicle scheduling and vehicle assignment [4, 5, 10]. In the area of the vehicle scheduling, many of the researchers try to solve the optimization problems, so called scheduling and routing problems, which are restricted by the given constraints such as schedules, starting points, destinations, loading capacities of the vehicles, and volumes of the freights *etc.* [1, 3, 8]. On the other hand, in the area of the vehicle assignment, many researchers have solved the assignment problems for deciding how the vehicles transport freights distributed here and there. The objective function of the assignment problem is minimizing the number of necessary vehicles or minimizing transportation times [2, 12]. Most of the traditional researches have been interested in the logistics problem occurred at the inside of a company (intra-company phenomena). Because of the rapid growth of Internet, many companies can share the logistics information about their empty vehicles and freights to be transported. Therefore, the logistics problem is extended to the area of inter-company phenomena from the traditional intra-company phenomena. However, we cannot solve the inter-company logistics problem by using only solution procedures for the traditional vehicle scheduling and assignment problems.

If we assume some companies having freights to be transported as customers and other companies having empty vehicles as suppliers, the inter-company logistics problem can be interpreted to the matching problem for intermediating customers and suppliers in the electronic commerce environment. In the area of brokerage agent, researchers have proposed some brokering methodologies such as electronic commerce agents using multiple criteria decision making (MCDM) techniques and simplified action agents using matching algorithms *etc.* [6, 7, 9, 11]. However, these methodologies can be utilized only when customers and suppliers are defined deterministically, that is, brokerage decisions are made for a given set of customers and suppliers at a given decision point. Since the brokerage point when to intermediate the customers and suppliers is not determined, therefore, we cannot directly use these methodologies for solving the inter-company logistics problem in which freights and vehicles dynamically arrive at the logistics brokerage market.

The logistics problem considered in this paper is different with the traditional problems in two aspects. One is that the problem is interested in intermediating freights and vehicles originated not from a single company but from multiple companies. The other is that the problem assumes that freights and vehicles are dynamically arriving at the brokerage market and hence we should decide when to intermediate the freights and vehicles, while the previous problems assume that all freights and vehicles arrived at the brokerage market already and hence we need not decide when to intermediate. In this paper, we propose an efficient and effective methodology for solving the logistics brokerage problem in which freights and vehicles originated from multiple companies dynamically arrive at the logistics market.

2. THE DYNAMIC MATCHING PROBLEM

2.1 Logistics brokerage

In the e-marketplace for logistics, three types of participants exist: a freight owner, a vehicle owner, and a brokerage agent. The freight owner is a people or a company who has freights to be transported from one place to other place. The vehicle owner is a people or a company who has vehicles to transport the freights. The brokerage agent is an information system to intermediate the freights to the vehicles using an efficient and effective matching methodology. As shown in Figure 1, the freight owners and vehicle owners input freight and vehicle information such as locations, volumes, and destinations to the brokerage agent. After receiving the information, the brokerage agent matches freights and empty vehicles to minimize total logistics costs using the received information and its own matching methodology. The logistics cost contains two types of costs: the transportation cost being proportional to the moving time of vehicles and the delay cost being proportional to the waiting time of freights (moving time and waiting time will be explained more detail at the end of this section).

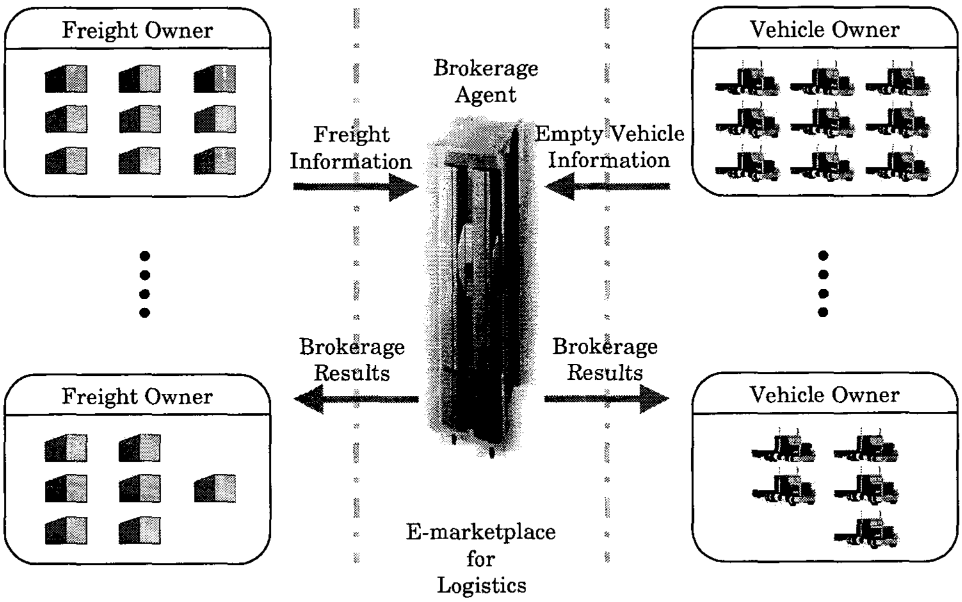

Figure 1. Logistics brokerage agent for freights and vehicles

In the e-marketplace, freights of shippers and empty vehicles of transporters arrive at different points of times, such as freight F#1 arrives at t_1, vehicle V#1 arrives at t_2, freight F#2 arrives at t_3 and so on as shown in Figure 2. A freight arrives in the marketplace means that the freight at a certain location becomes need to be transported by a vehicle and the owner of the freight registers the freight to the e-marketplace as a customer. A vehicle arrives in the marketplace also means that the vehicle becomes available at a certain location and the owner of the empty vehicle registers the vehicle to the e-marketplace as a vendor. At certain points of times (so called matching points), with the objective of minimizing the total logistics costs, the brokerage agent matches the freights and vehicles to have arrived before the point of time. In Figure 2, seven freights F#1 to F#7 and eights vehicles V#1 to V#8 have arrived before the matching point t_{16}, and hence the seven freights are matched with the eight vehicles at t_{16}. At the next matching point t_{21}, F#8, F#9, V#9, V#10 and a vehicle that were not matched at t_{16} will be matched with each other.

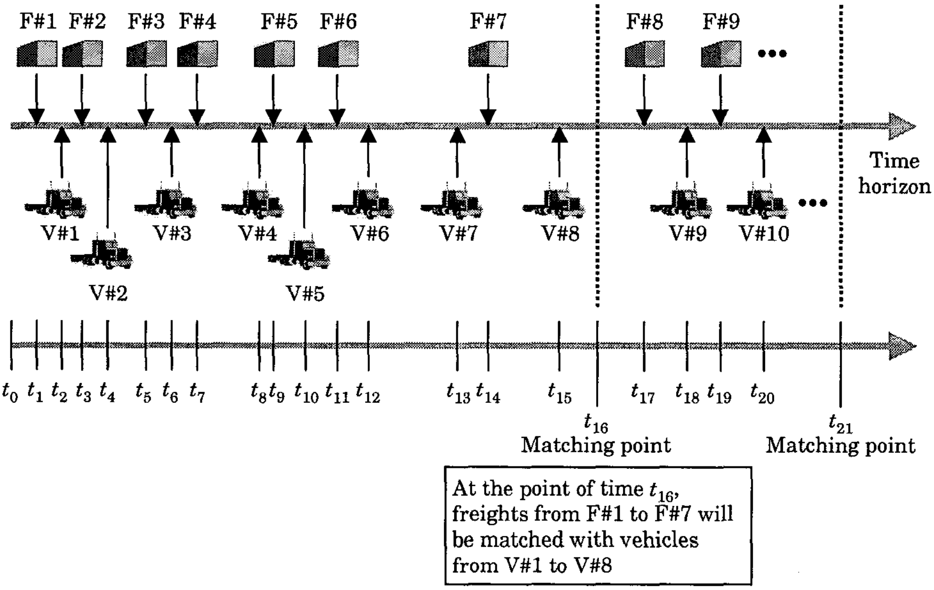

Figure 2. Dynamic view of the matching problem

Although the freights and vehicles arrive virtually at the same logistics e-marketplace, the physical locations where the freights are generated and the vehicles become available are different to each other. Therefore, a matching problem at a matching point can be represented as Figure 3, in which freights and vehicles are located at different locations. Figure 3 illustrates that freights F#1 and F#5, freights F#2 and F#3, and freights F#4, F#6, and F#7 have been generated at location 1, 2, and 3, respectively, and vehicles V#1 and V#2, vehicles V#3, V#6, and V#7, and vehicles V#4, V#5, and V#8 have also become available at location 3, 2, and 4 respectively. At the matching point, the problem is to decide pairs of freights and vehicles being located at various different sites, which make the total logistics costs to be minimized.

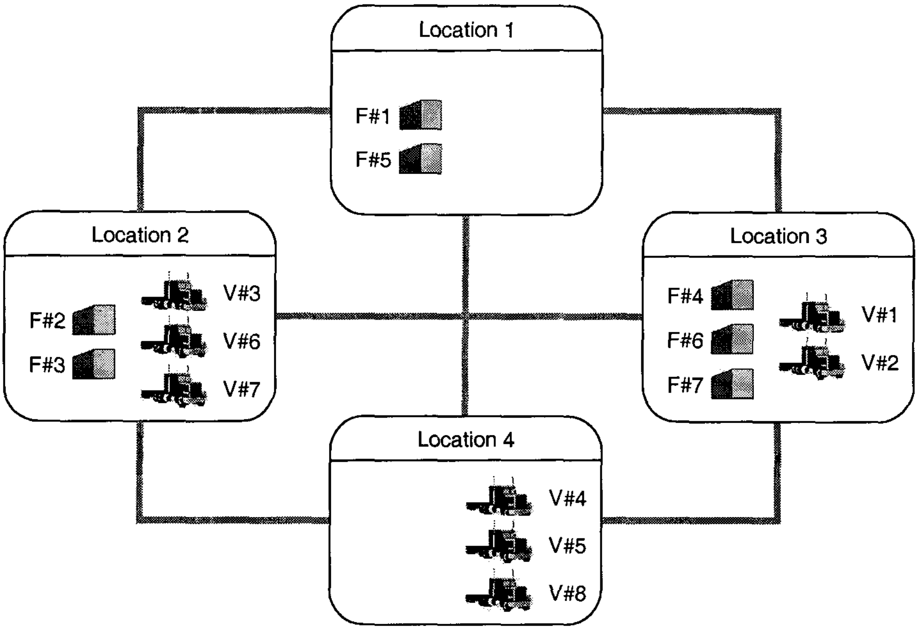

Figure 3. Static view of the matching problem at a given decision point

We call this type of the problem as a dynamic matching problem for internet-based logistics brokerage agent. In the problem, the logistics costs can be reduced if the following two types of time decrease. One is the *waiting time* occurred by waiting from the point of time when the freight arrives at a corresponding location to the matching point. For example, in Figure 2, the waiting time for freight F#5 is $t_{16} - t_9$. The other is the *moving time* occurred by moving from the current vehicle's location to the location where the matched freight is waiting. For example, in Figure 3, if the freight F#5 is matched with the vehicle V#4, the moving time is the time for moving from location 4 to location 1. After the vehicle arrives at the freight's location, the time needed for moving from the freight's current location to the destination location is constant for all vehicles since all vehicles are assumed to have the same performance and hence need the same moving time for the same distance.

If the time length between two matching points (so called matching period), for example $t_{16} - t_0$ and $t_{21} - t_{16}$ in Figure 2, becomes longer, there can exist more freights and vehicles at the matching point. Therefore, the freights have more chances to be matched with the vehicles located more close to the freights and hence the moving time can be reduced. On the other hand, the waiting time may increase because the freights should wait until the matching point comes. The trade off relationship embedded in the dynamic matching problem is that if the matching period becomes longer, the waiting time increases but the moving time can decrease, otherwise the waiting time decreases but the moving time can increase. Therefore, we need to consider the following two sub-problems for solving the dynamic matching problem.

- *When to match* freights with vehicles, that is, how to decide the matching points?
- *How to match* freights with vehicles at a given matching point?

2.2 The problem definition

In this section, we formally define the dynamic matching problem. The goal considered in this study for matching freights with vehicles is to minimize the total lead-time (the surrogate measure of the total logistics cost) for the freights to be transported by the vehicles. The lead-time is constituted of the *waiting time* and the *moving time* as described earlier. The constraints considered in this study are cardinality relationships between freights and vehicles. In this study, we assume that one freight can be carried by only one vehicle and one vehicle can carry only one freight. We can interpret the freight as a grouped freight, *i.e.* a set of small freights that can be aggregated and transported by using a single vehicle simultaneously. After a freight is matched with a vehicle, the cost for transporting the freight from the origination location to the destination location is constant whatever vehicles are selected. That is, the only difference in logistics costs is due to the moving time from the vehicle's location to the matched freight's origination location.

To describe the dynamic matching problem more clearly, we first give notations.

t_l The decision variable, matching point, when the matching decision is made, $l = 1, 2, \cdots, r$.

$C(t)$ The total lead-time of the matching problem at the point of time $t = t_1, t_2, \cdots, t_r$.

$n(t)$ The number of freights waiting for transportation at the point of time $t = t_1, t_2, \cdots, t_r$.

$m(t)$ The number of vehicles waiting for transportation at the point of time $t = t_1, t_2, \cdots, t_r$.

$x_{ij}(t)$ The decision variable, $x_{ij}(t) = 1$ if the freight i is matched with the vehicle j

at matching point t, $x_{ij}(t) = 0$ otherwise, $i = 1, 2, \cdots, n(t), j = 1, 2, \cdots, m(t), t = t_1, t_2, \cdots, t_r$.

$d_{ij}(t)$ The time distance between the site where the freight i is located and the site where the vehicle j is located, $i = 1, 2, \cdots, n(t), j = 1, 2, \cdots, m(t), t = t_1, t_2, \cdots, t_r$.

$t_i^f(t)$ The point of time when the freight i arrive (shipper registers the freight) at the e-marketplace, $t_i^f(t) \le t$, $i = 1, 2, \cdots, n(t), t = t_1, t_2, \cdots, t_r$.

As shown in Figure 4, the lead-time, $C(t)$, consists of the waiting time, $t - t_i^f(t)$, and the moving time, $d_{ij}(t)$. Using the above notations, the dynamic matching problem can be mathematically stated as follows.

$$\text{Minimize} \quad \sum_{t=t_1}^{t_r} C(t) \tag{1}$$

$$\text{Subject to} \quad C(t) = \sum_{i=1}^{n(t)} \sum_{j=1}^{m(t)} (t - t_i^f(t) + d_{ij}(t)) x_{ij}(t),\ t = t_1, t_2, \cdots, t_r \tag{2}$$

$$\sum_{i=1}^{n(t)} x_{ij}(t) = 1,\ j = 1, 2, \cdots, m(t),\ t = t_1, t_2, \cdots, t_r \tag{3}$$

$$\sum_{j=1}^{m(t)} x_{ij}(t) = 1,\ i = 1, 2, \cdots, n(t),\ t = t_1, t_2, \cdots, t_r \tag{4}$$

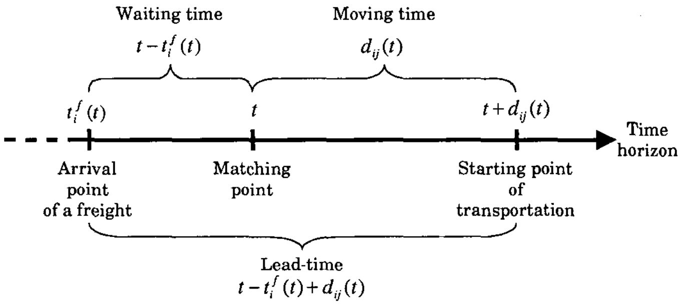

Figure 4. Definition of the lead-time

At time t, there are $n(t)$ freights and $m(t)$ vehicles to wait for being matched. Actually if $n(t)$ is less than equal to $m(t)$, $n(t)$ freight and vehicle pairs are matched with each other, otherwise $m(t)$ freight and vehicle pairs are matched with each other. The matching problem at the matching point t can be mathematically stated as an assignment problem.

$$\text{Minimize} \quad \sum_{i=1}^{n(t)}\sum_{j=1}^{m(t)} (t - t_i^f(t) + d_{ij}(t))x_{ij}(t) \tag{5}$$

$$\text{Subject to} \quad \sum_{i=1}^{n(t)} x_{ij}(t) = 1, j = 1, 2, \cdots, m(t) \tag{6}$$

$$\sum_{j=1}^{m(t)} x_{ij}(t) = 1, i = 1, 2, \cdots, n(t) \tag{7}$$

Equation (5) can be simplified as follows.

$$\sum_{i=1}^{n(t)}\sum_{j=1}^{m(t)} (t - t_i^f(t) + d_{ij}(t))x_{ij}(t) = t\sum_{i=1}^{n(t)}\sum_{j=1}^{m(t)} x_{ij}(t) - \sum_{i=1}^{n(t)} t_i^f(t)\sum_{j=1}^{m(t)} x_{ij}(t) + \sum_{i=1}^{n(t)}\sum_{j=1}^{m(t)} d_{ij}(t)x_{ij}(t)$$

$$= C_0(t) + \sum_{i=1}^{n(t)}\sum_{j=1}^{m(t)} d_{ij}(t)x_{ij}(t),$$

where $C_0(t)$ is a constant value for t, $C_0(t) = tn(t) - \sum_{i=1}^{n(t)} t_i^f(t)$ (8)

Therefore, the object function of the assignment problem at decision point t can be rewritten as follows.

$$\text{Minimize} \quad \sum_{i=1}^{n(t)}\sum_{j=1}^{m(t)} d_{ij}(t)x_{ij}(t) \tag{9}$$

The next section describes that a procedures to solve the defined dynamic matching problem for the internet-based logistics brokerage agent.

3. THE SOLUTION PROCEDURE

The dynamic matching problem can be solved using the following solution procedure constituted of three phases.

Phase 0: Make a strategy for deciding when to match freights with vehicles.

Phase 1: (When-to-match decision) Decide matching point when to match using the strategy to be made in Phase 0.

Phase 2: (How-to-match decision) Match freights with vehicles (make pairs of freights and vehicles) and go to Phase 1.

As noted earlier, two decision problems should be solved for the dynamic matching problem: one is when to match and the other is how to match. The former is to decide the matching point, $t = t_1, t_2, \ldots, t_r$, when to solve the matching problem. At the matching point, the latter is to solve the matching problem for a given set of $n(t)$ freights and $m(t)$ vehicles registered to the e-marketplace before the matching point t and not matched yet. We first describe the solution procedure for the former: when-to-match problem.

3.1 When to match

In this study, we propose three types of matching strategies for deciding the matching points as follows: Real Time Matching (RTM), Periodic Matching (PM), and Fixed Matching (FM).

RTM: Matching freights with vehicles as soon as a freight or a vehicle is registered at the e-marketplace.

PM: Matching freights with vehicles at an interval of the predetermined period, *i.e. matching period.*

FM: Matching freights with vehicles when the minimum of the number of freights waiting for transportation and the number of empty vehicles comes to the predetermined number, *i.e. matching amount.*

As shown in Figure 5, when using RTM strategy, matching decisions can be made at the points of time when a freight or a vehicle arrives, that is t_1 through t_{21} except for t_9 and t_{16}. When using PM strategy, matching decisions are made at the points of time, t_9 (= t_0 + matching period), t_{16} (= t_9 + matching period), and t_{22} (= t_{16} + matching period). When using FM strategy, matching decisions are made at the points of time, t_8 (if we assume the matching amount as 4, the 4th vehicle arrives at t_8 and hence the number of matching pairs of freights and vehicles comes to 4) and t_{18} (the 8th freight arrives).

For strategies PM and FM, we should determine the best matching period and matching amount. Figure 6 shows simulation results for investigating the relationship between the lead-time and the matching period and the matching amount. Although we cannot prove the convexity of the lead time function to the matching period and the matching amount, the lead time function looks like a convex function as shown in Figure 6. Based on this observation, we propose two simple gradient search algorithms for obtaining the best matching period and matching amount. To describe the search algorithms more clearly, we first give notations.

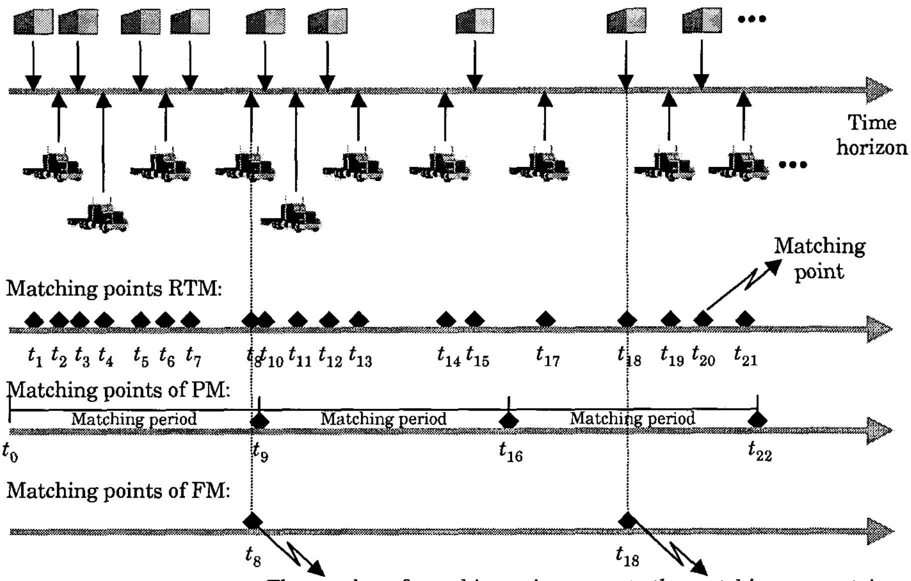

Figure 5. Matching points of the three matching strategies

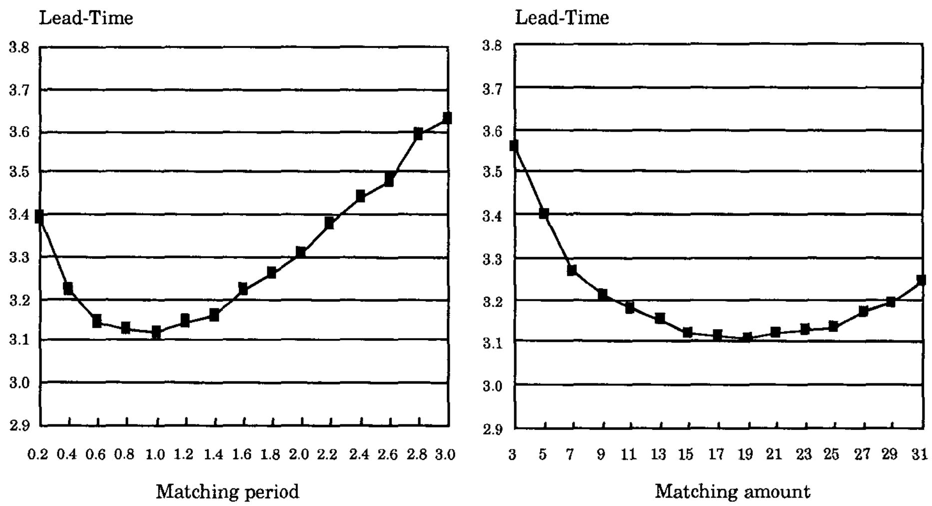

Figure 6. Relationship between the lead-time and the matching period and the matching amount

T Matching period, if we use matching period *T*, matching points are *T*, 2*T*, ⋯, and so on.

M Matching amount, if we use matching amount *M*, matching decisions are made at the points of time when the Mth freight or vehicle arrives, the $2M$th freight or vehicle arrives, and so on.

$C(T)$ The objective function value of the matching problem when matching period T is used for the PM strategy.

$C(M)$ The objective function value of the matching problem when matching amount M is used for the FM strategy.

Gradient search algorithm for the matching period

Step 0: Set T to an arbitrary value such as average inter-arrival time of the freight, Δ to $T / 2$, and ε to 0.01.

Step 1: If $C(T) - C(T + \Delta) > 0$ then set $T = T + \Delta$ and go to Step 3.

Step 2: If $C(T) - C(T - \Delta) > 0$ then set $T = T - \Delta$ and go to Step 3.

Step 3: If $\Delta > \varepsilon$ then set $\Delta = \Delta / 2$ and go to Step 1. Otherwise the best matching period $T^* = T$ and stop.

Gradient search algorithm for the matching amount

Step 0: Set M to an arbitrary value such as the multiplication of the mean arrival rate and the number of locations where freights are generated, Δ to $M / 2$, and ε to 1.

Step 1: If $C(M) - C(M + \Delta) > 0$ then set $M = M + \Delta$ and go to Step 3.

Step 2: If $C(M) - C(M - \Delta) > 0$ then set $M = M - \Delta$ and go to Step 3.

Step 3: If $\Delta > \varepsilon$ then set $\Delta = \Delta / 2$ and go to Step 1. Otherwise the best matching amount $M^* = M$ and stop.

3.2 How to match

Now we describe the solution procedure for the later problem: how to match problem. At the matching point t, this problem can be represented as a bipartite weighted matching problem, so called an assignment problem, as follows.

$$\text{Minimize} \quad \sum_{i=1}^{n(t)} \sum_{j=1}^{m(t)} d_{ij}(t) x_{ij}(t) \tag{10}$$

$$\text{Subject to} \quad \sum_{i=1}^{n(t)} x_{ij}(t) = 1, j = 1, 2, \cdots, m(t) \tag{11}$$

$$\sum_{j=1}^{m(t)} x_{ij}(t) = 1, i = 1, 2, \cdots, n(t) \tag{12}$$

$x_{ij}(t)$ is a binary variable, $i = 1, 2, \cdots, n(t), j = 1, 2, \cdots, m(t)$

In this paper, we use the famous Hungarian algorithm for solving the above problem. The Hungarian algorithm can be summarized as follows.

Hungarian algorithm

Step 0: If $n(t) < m(t)$ then make $m(t) - n(t)$ dummy freights and if $n(t) > m(t)$ then make $n(t) - m(t)$ dummy vehicles, and set time distances of the dummy freights and vehicles be zero, that is $d_{ij}(t) = 0$ for all dummy freights and vehicles. Make time distance matrix of which element is $d_{ij}(t)$ for $i, j = 1, 2, \cdots, n(t)$ (if $n(t) \geq m(t)$) or $m(t)$ (if $m(t) > n(t)$).

Step 1: For each row of the time distance matrix, subtract the minimum element in the row from each element in the row.

Step 2: For each column of the resulting matrix, subtract the minimum element in the column from each element in the column. The result is a reduced matrix.

Step 3: Draw the minimum number of lines through the rows and columns to cover all zeros in the reduced matrix. If the minimum number of lines is $n(t)$ (or $m(t)$), then an optimal solution is available. Otherwise, go to Step 4.

Step 4: Select the minimum uncovered element. Subtract this element from each uncovered element and add it to each twice-covered element. Go to Step 3.

4. COMPUTATIONAL EXPERIMENTS

4.1 Test problems and method

For the performance evaluation of the proposed algorithms, 54 problem sets were generated. These sets are characterized by {HOH, MAR, NOL, TDL}, where the terms in the brace represent the followings.

HOH (Homogenous Or Heterogeneous): whether the mean arrival rates of freights and vehicles at the locations are all same or different each other; HOH is homogenous or heterogeneous.

MAR (Mean Arrival Rate): the mean arrival rates of freights and vehicles at the locations; MAR is 0.5, 1, or 2.

NOL (Number Of Locations): the number of locations where freights and empty vehicles can be generated; NOL is 4, 7, or 10.

TDL (Time Distance Level): whether time distances between the locations are short, middle, or long, TDL is 1, 2, or 3.

For example, the problem set (Homogenous, 2, 10, 1) means that the mean arrival rates of all locations are same, the mean arrival rates of freights and vehicles are 2, the number of locations is 10, and the time distance level is short. After some preliminary investigations of the arrival process of vehicles and freights, we assume that freights and vehicles arrive in a certain location according to a Poisson process of rate λ = MAR and hence the inter-arrival time has an exponential distribution with a mean of $1 / \lambda$ = 1 / MAR. In the experiment, five problem instances were randomly generated per each problem set as follows.

When HOH is homogeneous, the inter-arrival times of freights are generated from **EXP**(1 / MAR), where **EXP**(a) is an exponential distribution with a mean of a. When HOH is heterogeneous, we first generate the mean arrival rate of the location k, MAR_k, from **U**(0.75 × MAR, 1.25 × MAR), where **U**(a, b) is an uniform distribution with a range a and b, and then the inter-arrival times of freights at location k are generated from **EXP**(1/MAR_k). The generation method of inter-arrival times of vehicles is the same as that of vehicles.

The x-coordinate and y-coordinate of location k are generated from **U**(0, 30). The time distance between location k and location l is calculated using the Euclidean distance, *i.e.* TDL × [(x-coordinate of location k – x-coordinate of location l)^2 + (y-coordinate of location k – y-coordinate of location l)^2]$^{1/2}$.

For each problem, three matching strategies RTM, PM, and FM are applied to the logistics brokerage. As noted earlier, the matching period and amount obtained from the gradient search algorithms may not be the best values because the convexity of the lead-time function cannot be proved. In order to test whether the proposed search algorithms for PM and FM find the best values and hence minimize the lead-time function or not, we add an enumeration method for PM which varies the matching period from 0.2 to 6.0 by increasing step by 0.2 and find the best matching period from the 30 trials (0.2, 0.4,$\cdots$, 6.0) and an enumeration method for FM which varies the matching amount from 2 to 60 by increasing step by 2 and find the best matching amount from the 30 trials (2, 4, $\cdots$, 60). Therefore matching strategy PM is classified into two strategies PM-G and PM-E, the former finds the best matching period using the proposed gradient search algorithm and the later find the best matching period using the enumeration method and matching strategy FM is also classified into two strategies FM-G and FM-E.

For each problem instance, ten replications (each replication is running during 100 time units and 200 ~ 2000 pairs of freights and vehicles are matched each other in a replication) are done for reducing bias due to random effects and the average value of the ten replications are used for comparing the matching strategies. C language is used for the simulation test and a personal computer with a Pentium IV processor (1.6 GHz) is used for the test.

4.2 Test results

The results of the computational experiments are shown in Table 1. Here, the relative deviation percentage (RDP) is used as a measure to compare the performance of the five strategies RTM, PM-G, PM-E, FM-G, and FM-E. The RDP of a strategy is computed with $100(C - C^*) / C^*$, where C is the objective value of the corresponding strategy and C^* is the minimum of the objective values of the five strategies. Therefore, the strategy with a small RDP is better than the one with a large RDP. To see (in)difference between the performances of each pair of strategies, paired t-test were done and the results are given in table 1. From the table, it can be seen that the strategies to wait and match such as PM and FM gave a considerably better performance than the strategy to match at once such as RTM. By matching after waiting some time to gather freights and vehicles, the objective function value, *i.e.* total lead-time for freights, can be reduced by more than 30%. This shows that the advantage of waiting-and-matching strategy, which is obtained from *increasing the chance for matching freights to vehicles that are more adequate.*

Table 1. RDPs and results of the paired t–test

	RDP	Average search time (Second)	T statistics			
			PM-E	FM-G	FM-E	RTM
PM-G	0.37%	273	3.545†	19.729†	21.603†	29.832†
PM-E	0.66%	930		17.637†	17.896†	29.217†
FM-G	2.26%	172			2.497††	27.779†
FM-E	2.42%	564				27.534†
RTM	33.99%	0				

Note: † There is a difference in two means at a significance level of 0.01.
†† There is a difference in two means at a significance level of 0.05.

The strategy PM gave a little better performance than the strategy FM. This can be explained as follows. When using the strategy PM, the matching points are determined by the value of matching period T to have a continuous value. On the other hand, when using the strategy FM, the matching points are determined by the value of matching amount M to have a discrete value. Therefore, the best matching points can be determined more accurately when using the strategy PM to use continuous values than when using the strategy FM to use discrete values. The strategy PM needed a longer search time than the strategy FM, however, since the strategy PM needs to find the best matching period to have a continuous value and hence should evaluate more candidate matching periods than the strategy FM to find the best matching amount from a set of limited discrete values. When using the strategies PM and FM, gradient-based methods PM-G and FM-G gave a slightly better performance than the enumeration-based methods PM-E and FM-E, because of the gap between two successive alternative parameter values, *i.e.* 0.2 for the matching period and 2 for the matching amount. If the best value exists between two successive alternative values the enumeration-based methods cannot find the best value more accurately.

To show the effects of the five factors (the matching strategy, HOH, MAR, NOL, and TDL) to the RDPs, ANOVA table is given in Table 2. As can be seen in the table, different performances were obtained if we used different matching strategies or MAR, NOL, and TDL were different. On the other hand, the performance of the logistics brokerage agent was not affected by HOH. Table 3 shows comparison of matching strategies with respect to the significant problem generation factors. As can be seen in the table, differences in performances of the strategy RTM and the others become large as MAR, NOL, and TDL are getting increase. If MAR and NOL have large values, the more freights and vehicles are generated during the same period and hence we have more chances to reduce the moving time by waiting some time and matching the freights to the more preferred vehicles.

Table 2. Analysis of variance for the mean difference percentage

Source of variation	Sum of squares	Degrees of freedom	Mean square	F statistics
Matching strategy	22.986	4	5.747	950.509†
HOH	0.000	1	0.000	0.023
MAR	0.165	2	0.082	13.612†
NOL	0.217	2	0.109	17.976†
TDL	1.077	2	0.539	89.086†
Error	8.089	1338	0.006	
Total	32.535	1349		

Note: † There is a difference in the effects at a significance level of 0.01.

Table 3. Comparison of matching strategies with respect to the problem generation factors

Matching strategy		PM-G	PM-E	FM-G	FM-E	RTM
MAR	0.5	0.36%	0.64%	2.61%	2.86%	26.30%
	1	0.32%	0.69%	2.39%	2.51%	34.13%
	2	0.43%	0.66%	1.77%	1.90%	41.53%
NOL	4	0.46%	0.76%	2.91%	3.32%	24.81%
	7	0.43%	0.68%	2.33%	2.32%	33.31%
	10	0.22%	0.56%	1.53%	1.62%	43.84%
TDL	1	0.11%	0.64%	1.83%	2.02%	17.02%
	2	0.31%	0.75%	2.38%	2.60%	35.38%
	3	0.70%	0.61%	2.57%	2.64%	49.56%

To show the effects of the four factors (HOH, MAR, NOL, and TDL) to the matching periods and amounts, ANOVA tables are given in table 4. As can be seen in the table, MAR, NOL, and TDL affects both the matching period and the matching amount. As shown in table 5, the best matching period tends to increase as NOL and TDL increase and MAR decreases on the contrary. This may be explained as follows. If MAR is a small value, during a certain period, the less freights and vehicles arrive at the logistics e-marketplace and hence the freights and vehicles have less chance for being matched with freights or vehicles waiting at near locations. For increasing the chance, therefore, the matching period should have a longer value. In addition, if NOL and TDL become large, moving times of vehicles to the freights' sites become increase and hence the matching period tends to increase for reducing the moving times by increasing the chance for being matched with freights waiting at near locations. The increasing rate of the matching period for the increase of NOL is less than the increasing rate of the matching period for the increase of TDL, however, since the waiting time also becomes increase if NOL becomes large. The best matching amount tends to increase as MAR, NOL, and TDL increase. For the NOL and TDL, this phenomenon may be explained similarly since the larger matching amount means the longer matching period. The best matching amount tends to increase as MAR increases, however, since the number of freights and vehicles increases more rapidly although the corresponding matching period tends to decrease. From the results of the computational experiments, we can see the relationship between the best matching period (T^*) and the best matching amount (M^*), $T^* = M^* / (\text{MAR} \times \text{NOL})$, where MAR × NOL means the number of freights or vehicles to be generated per unit time.

Table 4. Analysis of variance for matching periods and matching amounts

	Source of variation	Sum of squares	Degrees of freedom	Mean square	F statistics
Matching period	HOH	1.1530	1	1.153	3.3155
	MAR	93.1108	2	46.555	133.8737†
	NOL	6.7500	2	3.375	9.7051†
	TDL	127.6496	2	63.825	183.5332†
	Error	91.1121	262	0.348	
	Total	319.7756	269		
Matching amount	HOH	5.0704	1	5.070	0.1720
	MAR	9871.3407	2	4935.670	167.4208†
	NOL	12478.7852	2	6239.393	211.6438†
	TDL	9073.4741	2	4536.737	153.8887†
	Error	7723.9259	262	29.481	
	Total	39152.5963	269		

Note: † There is a difference in the effects at a significance level of 0.01.

Table 5. The best matching periods and matching amounts

		Matching period	Matching amount
MAR	0.5	2.790	10.27
	1	1.917	16.32
	2	1.363	25.00
NOL	4	1.857	9.28
	7	1.977	16.43
	10	2.236	25.88
TDL	1	1.119	9.83
	2	2.166	17.76
	3	2.785	24.00

5. CONCLUDING REMARKS

In this paper, we presented a methodology for matching freights and vehicles originated from multiple companies. In addition, we proposed three strategies for deciding the matching points, *i.e.* real time matching, periodic matching, and fixed matching, and compared the performance of the strategies through the computational experiments. The results showed that the waiting and matching strategies such as periodic matching and fixed matching could reduce the logistics costs more than the real time matching strategy.

For operating an e-marketplace for the logistics area, an efficient and effective matching algorithm for the logistics brokerage agent needs to be developed. Since the proposed methodology can give good matching solution within a short computation time, we can expect that the suggested methodology can be used as a useful tool in many logistics markets. The current research can be extended in several ways by relaxing the assumptions to be considered in this paper: one vehicle can transport several freights located at different sites simultaneously and volumes of the freights and capacities of the vehicles are different with each other. These problems are more difficult to solve since the matching problem and the vehicle routing problem are solved at the same time.

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