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Dynamic Matching Algorithms for On-Time Delivery in e-Logistics Brokerage Marketplaces*

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ABSTRACT

In the previous research, we considered a logistics brokerage problem with the objective of minimizing total transportation lead time of freights in a logistics e-marketplace, in which a logistics brokerage agent intermediates empty vehicles and freights registered by car owners and shippers [7]. However, in the logistics e-marketplace, transportation due date tardiness is more important than the transportation lead time, since transportation service level is critically determined by whether the due date is met or not. Therefore, in this paper, we deal with the logistics brokerage problem with the objective of minimizing total tardiness of freights. Hungarian method based matching algorithms, real time matching (RTM), periodic matching (PM), and fixed matching (FM), are used for solving the problem considered in this paper. In order to test performance of the proposed algorithms, we perform computational experiments on a various problem instances. The results show that the waiting-and-matching algorithms, PM and FM, also give better performance than real time matching strategy, RTM, for the total tardiness minimization problem as the algorithms did for the total lead time minimization problem.

Keywords: Logistics, Periodic Matching, Fixed Matching, Brokerage Agent, Tardiness

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

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cost is more than 11% (refer to http://www.mk.co.kr) and this fact means that one company should give more attention to the logistics area. For reducing costs and increasing efficiencies in the logistics area, many companies are changing their logistics process to the electronic one so called *e-logistics*, that is correspondence with the e-marketplace concepts such as e-procurement and supply chain management *etc.*

In this trend, some companies introduce a *logistics brokerage* service between the shippers and vehicle owners by informing the freight information to the vehicle owners and the vehicle information to the shippers (refer to http://www.e4cargo.com and http://www.100-b.net). For these companies, we need to solve a logistics brokerage problem: how to intermediate freights of shippers to the appropriate vehicles of car owners. This type of problem is different from the traditional logistics problems in two aspects. One is that the problem is interested in intermediating freights and vehicles originated not from 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 the past, various researches have been done for trying to increase efficiency of the logistics system and to reduce the related cost [4, 5, 11]. These researches are mainly related to the problems so called vehicle scheduling/routing [1, 3, 9] and vehicle assignment [2, 13]. Most of these researches have been interested in the logistics problem occurred at the inside of a company (*intra-company* phenomena). Therefore, the *inter-company* logistics problem cannot be solved by using only the above algorithms for the traditional vehicle scheduling and assignment problems. In the area of brokerage agent, researchers also 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, 8, 10, 12]. 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.

Fortunately, an efficient dynamic matching algorithm has been proposed for solving for the logistics brokerage problem described above [7]. The algorithm is used for deciding when to match freights and vehicles and how to match freights and vehicles. The objective function of the problem is minimizing the transportation lead time (the arrival time of a freight to the destination site – the arrival time of the freight to the logistics brokerage e-marketplace). However, in the transportation industry, the transportation tardiness (maximum [0, the arrival time of a freight to the destination site – transportation due date of the freight]) is a more important performance measure for assessing the service level than the transportation lead time. In this paper, for the logistics brokerage problem described above, we propose and test algorithms for minimizing total tardiness of freights instead of total transportation lead time of freights.

This paper is organized as follows. First, we describe the logistics brokerage problem to be considered in this paper in the next section. In section 3, we describe the solution procedure for solving the logistics brokerage problem: the methods to decide when to match and how to match. To show the performance of the solution procedure, computational experiments are done on a number of problem instances, and test results are reported in section 4. Finally, we conclude this paper in section 5.

2. The Logistics Brokerage 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 input freight information such as locations, volumes, due dates, and destinations to the brokerage agent and vehicle owners also input vehicle information such as location and capacities to the brokerage agent. After receiving the information, the brokerage agent matches freights and empty vehicles to minimize total transportation tardiness (lateness) using the received information and its own matching methodology.

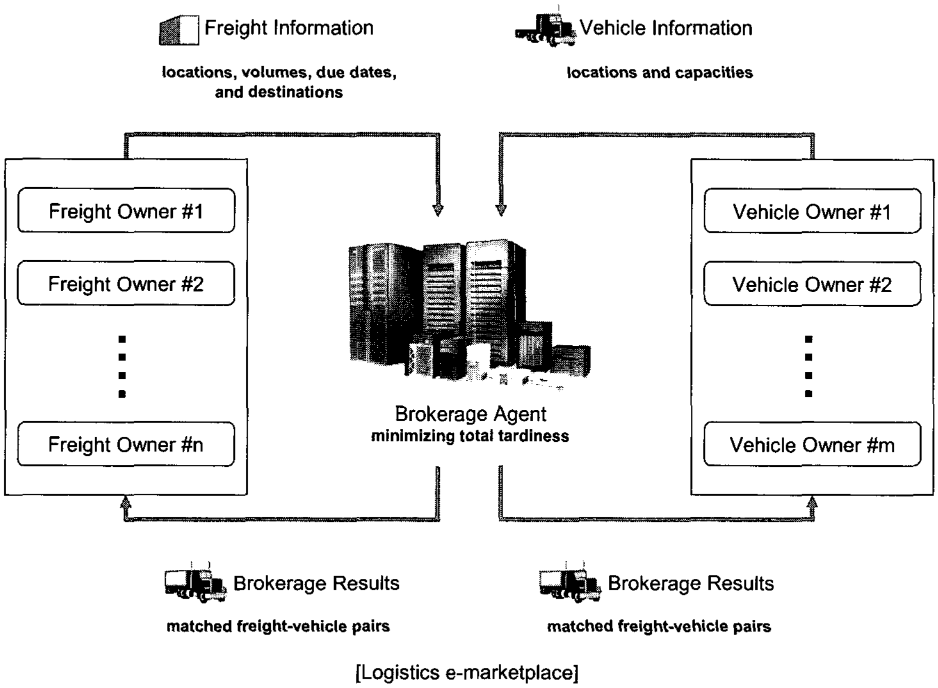

Figure 1. Brokerage agent in the logistics e-marketplace

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 supplier. At certain points of times (so called matching points), with the objective of minimizing the total tardiness, the brokerage agent matches the freights and vehicles to have arrived before the point of time. In Figure 2, freights F#1 to F#7 and vehicles V#1 to V#8 have arrived before the matching point t_{16}, and hence seven freights become matched with eight vehicles at t_{16}. Therefore, one vehicle, V#6, remains at the logistics e-marketplace being unmatched. At the next matching point t_{21}, two freights F#8 and F#9 become matched with three vehicles, *i.e.* one vehicle, V#6, which was not matched at t_{16} and two additional vehicles, V#9 and V#10, which were newly arrived at the logistics e-marketplace.

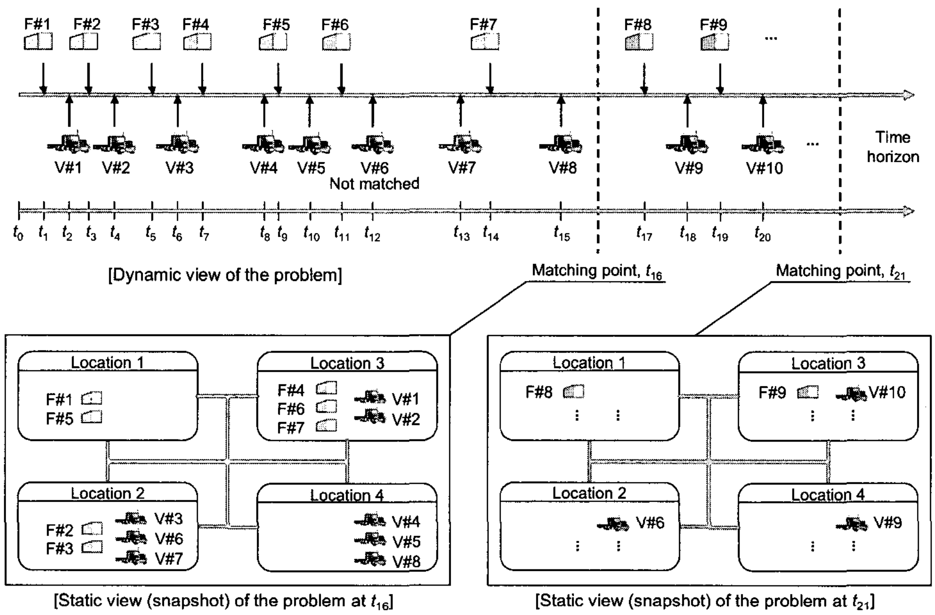

Figure 2. Dynamic and static views of the logistics brokerage problem

Although 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, at a matching point, t_{16}, the logistics brokerage problem can be represented as a snapshot in low-left part of Figure 2, in which freights and vehicles are located at different locations. This situation 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#3, V#6, and V#7, vehicles V#1 and V#2, and vehicles V#4, V#5, and V#8 have also become available at location 2, 3, and 4 respectively. A snapshot in low-right part of Figure 2 also illustrates static view of the problem at matching point, t_{21}. At the matching points, the problem is to choose pairs of freights and vehicles in order to minimize total transportation tardiness to be minimized. Therefore, we need to consider the following two sub-problems for solving the logistics brokerage problem in the logistics e-marketplace.

- Dynamic view: *When to match* freights with vehicles, that is, how to decide the matching points?
- Static view: *How to match* freights with vehicles at the given matching points?

2.2 The problem definition

In this section, we formally define the logistics brokerage problem. The goal considered in this study for matching freights with vehicles is to minimize the total tardiness for the freights to be transported by the vehicles. Tardiness of a freight depends on the transportation due date of the freight that is given by the freight owner and the arrival time of the freight to the destination site which is determined by *waiting time, moving time, transportation time* as described in Figure 3.

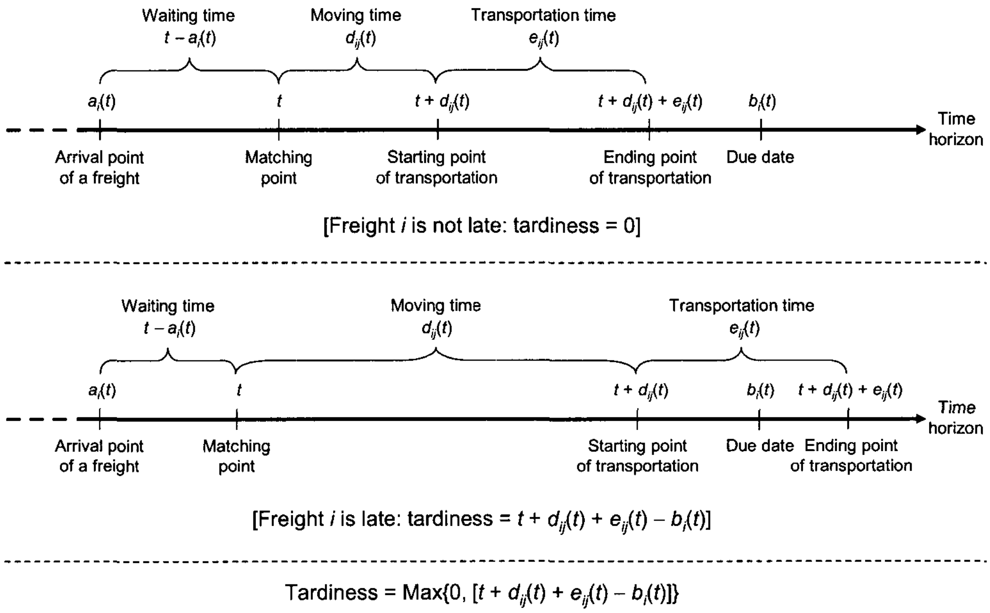

Figure 3. Definition of the transportation tardiness

Waiting time is defined as a time period, from the arrival point of a freight to the matching point. For example, in Figure 2, the waiting time for freight F#4 is $t_{16} - t_7$. Moving time is defined as a time period, from the matching point to the starting point of transportation of a freight. For example, in Figure 3, if freight F#4 is matched with the vehicle V#5, the moving time is the time for moving from location 4 to location 3. Transportation time is defined as a time period, from the starting point of transportation of a freight to the ending point of transportation of the freight. For example, in Figure 3, if destination site of freight F#4 is location 1, the transportation time is the time for moving from location 3 to location 1.

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 the matched vehicle arrives at the freight's location, the transportation time is constant for all vehicles, since all vehicles are assumed to have the same performance and hence need the same transportation time for the same distance. To describe the dynamic matching problem more clearly, we first give notations.

- t — The decision variable, matching point at which matching decision is made, $t = t_1, t_2, \cdots, t_r$.
- $C(t)$ — The total tardiness of the logistics brokerage 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 $t = t_1, t_2, \cdots, t_r$.
- $a_i(t)$ — The point of time when freight i arrives (shipper registers the freight) at the e-marketplace, $t \geq a_i(t)$, $i = 1, 2, \cdots, n(t)$, $t = t_1, t_2, \cdots, t_r$.
- $b_i(t)$ — The point of time when freight i should arrive at the destination (transportation due date of the freight i), $b_i(t) \geq a_i(t)$, $i = 1, 2, \cdots, n(t)$, $t = t_1, t_2, \cdots, t_r$.
- $d_{ij}(t)$ — The time distance between the site where freight i is located and the site where vehicle j is located, $i = 1, 2, \cdots, n(t)$, $j = 1, 2, \cdots, m(t)$, $t = t_1, t_2, \cdots, t_r$.
- $e_{ij}(t)$ — The time distance between the origination and the destination of freight i when vehicle j is used for the transportation, $i = 1, 2, \cdots, n(t)$, $j = 1, 2, \cdots, m(t)$, $t = t_1, t_2, \cdots, t_r$. As we assumed above, $e_{ij}(t)$ is the same for all j.
- $c_{ij}(t)$ — Tardiness of freight i, $c_{ij}(t) = \text{Max}\{0, [t + d_{ij}(t) + e_{ij}(t)] - b_i(t)\}$ if freight i is matched with vehicle j at a matching point t, $i = 1, 2, \cdots, n(t)$, $j = 1, 2, \cdots, m(t)$, $t = t_1, t_2, \cdots, t_r$.
- $x_{ij}(t)$ — The decision variable, $x_{ij}(t) = 1$ if freight i is matched with vehicle j at a matching point t, $x_{ij}(t) = 0$ otherwise, $i = 1, 2, \cdots, n(t)$, $j = 1, 2, \cdots, m(t)$, $t = t_1, t_2, \cdots, t_r$.

As shown in Figure 3, if freight i and vehicle j are matched with each other, the tardiness of freight i at time t can be defined as $\text{Max}\{0, [t+d_{ij}(t)+e_{ij}(t)]-b_i(t)\}$. Using the above notations, the logistics brokerage problem can be mathematically stated as follows.

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

$$\text{Subject to} \quad C(t) = \sum_{i=1}^{n(t)} \sum_{j=1}^{m(t)} \text{Max}\{0, [t+d_{ij}(t)+e_{ij}(t)]-b_i(t))\} x_{ij}(t),\ t = t_1, t_2, \cdots, t_r \tag{2}$$

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

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

$$x_{ij}(t) \text{ is a binary variable, } i = 1, 2, \cdots, n(t),\ j = 1, 2, \cdots, m(t),\ t = t_1, t_2, \cdots, t_r \tag{5}$$

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 logistics brokerage problem at a matching point t can be mathematically stated as an assignment problem.

$$\text{Minimize} \quad \sum_{i=1}^{n(t)} \sum_{j=1}^{m(t)} c_{ij}(t) x_{ij}(t) \tag{6}$$

$$\text{Subject to} \quad c_{ij}(t) = \text{Max}\{0, [t+d_{ij}(t)+e_{ij}(t)]-b_i(t)\} \tag{7}$$

$$\sum_{i=1}^{n(t)} x_{ij}(t) = 1,\ j = 1, 2, \cdots, m(t) \tag{8}$$

$$\sum_{j=1}^{m(t)} x_{ij}(t) = 1,\ i = 1, 2, \cdots, n(t) \tag{9}$$

$$x_{ij}(t) \text{ is a binary variable, } i = 1, 2, \cdots, n(t),\ j = 1, 2, \cdots, m(t) \tag{10}$$

The next section describes a procedure to solve the defined logistics brokerage problem in the logistics e-marketplace.

3. The Solution Procedure

As noted earlier, two decision problems should be solved for the logistics brokerage problem: one is when-to-match and the other is how-to-match. The former is to decide the matching point, $t = t_1, t_2, \cdots, t_r$, when to solve the how-to-match problem. At the matching points, $t = t_1, t_2, \cdots, t_r$, 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. Therefore, the logistics brokerage problem can be solved using a solution procedure constituted of two phases. First phase is when-to-match decision: the brokerage agent decides a matching point when to intermediate freights and vehicles. Second phase is how-to-match decision: the brokerage agent matches freights with vehicles (make pairs of freights and vehicles) and then go to the first phase. We first describe the solution procedure for the when-to-match decision.

3.1 When to match decision

In this study, we use three types of matching strategies for deciding the matching points as follows: Real Time Matching (RTM), Periodic Matching (PM), and Fixed Matching (FM). These strategies showed good performance for the logistics brokerage problem with the objective of minimizing total transportation lead time [7].

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 a predetermined period, *i.e. matching period.*

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

As shown in figure 4, 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 is 4, the fourth vehicle arrives at t_8 and hence the number of matching pairs of freights and vehicles comes to 4) and t_{18} (the eighth freight arrives).

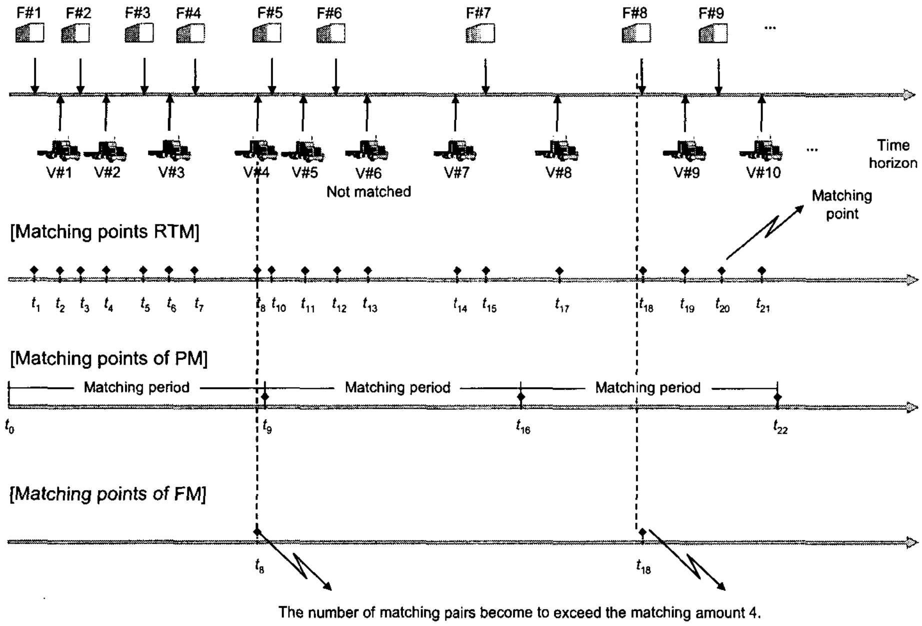

Figure 4. Matching points of the three matching strategies

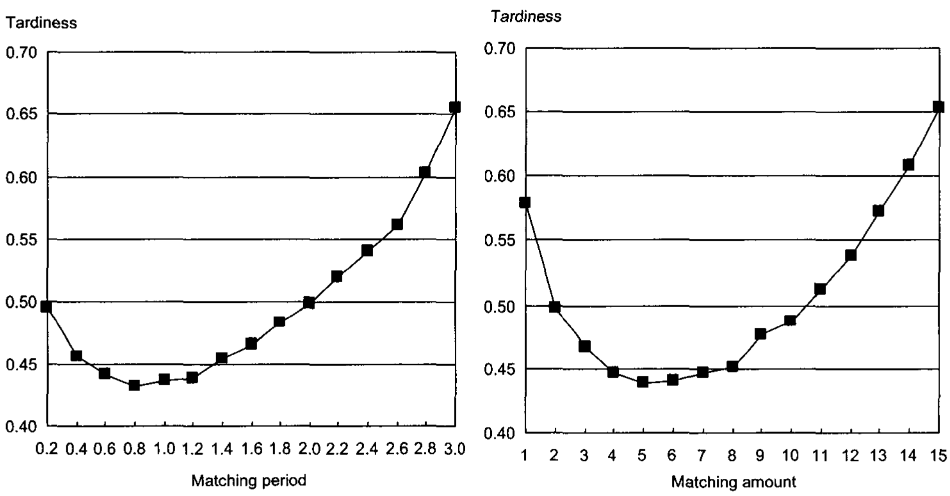

Figure 5. Relationship between the tardiness and the matching period and amount

For strategies PM and FM, we should determine the best matching period and amount. Figure 5 shows simulation results for investigating the relationship between the tardiness and the matching period and amount. In this simulation, since number of locations is 10 and mean arrival rate of freights is 0.5, matching period 1 is corresponded to matching amount $5 = 1\times 10\times 0.5$, matching period 2 is corresponded to matching amount $10 = 2\times 10\times 0.5$, and so on. Although we cannot prove the convexity of the tardiness function to the matching period and the matching amount, the tardiness function looks like a convex function as shown in Figure 5. Based on this observation, we propose a gradient search algorithm for obtaining the best matching period and amount.

To describe the algorithm more clearly, we first give notations.

- T Matching period, if we use matching period T, matching points are T, $2T, \cdots$ 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 problem when matching period T is used for PM strategy.
- $C(M)$ The objective function value of the problem when matching amount M is used for the FM strategy.

The gradient search algorithm for the matching period (matching amount) can be described as follows (the content in bracket [ ] are corresponding to the case of matching amount).

- Step 0: Set $T(M)$ to an arbitrary value such as average inter-arrival time of freights [mean arrival rate$\times$ number of locations], Δ to $T/2$ [$M/2$], and ε to 0.001 [1].
- Step 1: If $C(T)-C(T+\Delta)>0$ [$C(M)-C(M+\Delta)>0$] then set $T=T+\Delta$ [$M=M+\Delta$] and go to Step 3.
- Step 2: If $C(T)-C(T-\Delta)>0$ [$C(M)-C(M+\Delta)>0$] then set $T=T-\Delta$ [$M=M+\Delta$] and go to Step 3.
- Step 3: If $\Delta>\varepsilon$ then set $\Delta=\Delta/2$ and go to Step 1. Otherwise the best matching period $T^*=T$ [matching amount $M^*=M$] and stop.

3.2 How to match decision

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 defined in equations (6) to (10). In this paper, we use the famous Hungarian algorithm for solving the assignment problem. The Hungarian algorithm can be summarized as follows.

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 tardiness of the dummy freights or vehicles be zero, that is $c_{ij}(t) = 0$ for all dummy freights or vehicles. Make a tardiness matrix of which element is $c_{ij}(t)$ 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 tardiness 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, 162 problem sets were generated. These sets are characterized by {HOH, MAR, NOL, TDL, DTL}, where the terms in the brace represent the followings.

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

MAR (Mean Arrival Rate): mean arrival rates of freights at locations; MAR is 0.5, 1.0, or 2.0.

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

TDL (Time Distance Level): whether time distances between the locations are short, middle, or long, TDL is 0.5, 1.0, or 1.5.

DTL (Due date Tightness Level): whether transportation due dates of freights are tight, normal, or loose, DTL is 0.8, 1.0, or 1.2.

For example, the problem set (Homogenous, 2.0, 10, 1.0, 0.8) means that mean arrival rates of all locations are same, mean arrival rates of freights are 2.0, the number of locations is 10, the time distance level is middle, and due date tardiness level is tight. After some preliminary investigation of the arrival process of freights, we assume that freights 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 x-coordinate and y-coordinate of location k are generated from **U**(0, 10). 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]$^{1/2}$. In this case, note that average time distance between two locations is TDL× 10/2. Therefore, average time distance of a transportation, *i.e.* distance from vehicle's location to freight's starting location and distance from freight's starting location to freight's destination location, is 2× TDL× 10/2 = TDL× 10. Due dates of freights are determined as follows: freight's arrival time + time distance from freight's starting location to freight's destination location + DTL× TDL× 10/2.

A number of NOL× MAR× TDL× 10 vehicles exist in the logistics e-marketplace, which makes the arrival rate of freights is same as the service rate of vehicles, that is NOL× MAR = number of vehicles / (TDL× 10). The first arrival times of vehicles are generated from **EXP**(TDL × 10). After a vehicle arrives to the freight's destination location, the corresponding vehicle becomes available and the vehicle owner registers the empty vehicle to the brokerage e-marketplace.

For each problem instance, three matching strategies RTM, PM, and FM are applied to the logistics brokerage. As noted earlier, the gradient search algorithms may not give the best matching period and amount because the convexity of the tardiness 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 tardiness function or not, we add enumeration methods for PM and FM. PM enumeration method tries the matching period from 0.1 to 3.0 by increasing step by 0.1 and find the best matching period from the 30 trials (0.1, 0.2,$\cdots$, 3.0) and FM enumeration method tries the matching amount from 1 to 30 by increasing step by 1 and find the best matching amount from the 30 trials (1, 2,$\cdots$, 30). 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 desktop computer with a Pentium IV processor (3.0 GHz) is used for the test.

4.2 Test results

The results of the computational experiments are shown in table 1. Here, the relative improvement percentage (RIP) is used as a measure of comparing the performance of five strategies RTM, PM-G, PM-E, FM-G, and FM-E. The RIP of a strategy is computed with $100(C^* - C)/C^*$, where C is the objective value of the corresponding strategy and C^* is the maximum of the objective values of the five strategies. Therefore, the strategy with a large RIP is better than the one with a small RIP.

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

Strategy	RIP	Average search time (Second)	T statistics			
			PM-E	FM-E	FM-G	RTM
PM-G	48.28%	70	6.415†	15.400†	21.799†	61.754†
PM-E	47.29%	114		11.244†	18.035†	59.214†
FM-E	45.33%	103			12.781†	54.094†
FM-G	43.20%	28				50.302†
RTM	0.27%	0				

Note: † There is a difference in two means at a significance level of 0.001.

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. This result was same that of the previous research to deal with the logistics brokerage problem with the objective of minimizing total lead time [7]. By matching freights and vehicles after *waiting* for some time period so as to collect freights and vehicles enough, total tardiness for freights can be reduced by more than 40%. This shows the advantage of waiting-and-matching strategy to be obtained from increasing chance for matching freights with vehicles that are more appropriate to the freights (i.e. vehicles that can meet the transportation due dates of the freights).

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 strategy PM, the gradient-based method PM-G gave a slightly better performance than the enumeration-based method PM-E, because of the gap between two successive alternative parameter values of the strategy PM-G, *i.e.* 0.1 for the matching period. If the best value exists between two successive alternative values, the enumeration-based methods cannot give the best value. For example, if the best matching period is 1.035, PM-E can select the best value only from 1.0 or 1.1. However, when using the strategy FM, the enumeration-based method FM-E gave a slightly better performance than gradient-based method FM-G. This is explained as follows. If the best matching amount is in the range of from 1 to 30, FM-E searches all possible alternatives and select the best one but FM-G does not. If the gradient search algorithm FM-G falls in local optimum, FM-G may not give the best value.

Table 2. Analysis of variance for the mean improvement percentage

Source of variation	Sum of squares	Degrees of freedom	Mean square	*F* statistics
Matching strategy	136.853	4	34.213	2091.079†
HOH	0.115	1	0.115	7.055††
MAR	23.821	2	11.911	728.216†
NOL	33.124	2	16.562	1012.589†
TDL	34.424	2	17.212	1052.344†
DTL	10.562	2	5.281	322.872†
Error	66.013	4036	0.016	
Total	855.566	4049		

Note: † There is a difference in the effects at a significance level of 0.001.
†† There is a difference in the effects at a significance level of 0.01.

ANOVA table is given in Table 2, which shows the effects of the six factors (matching strategy, HOH, MAR, NOL, TDL, and DTL) to the RIPs. As can be seen in the table, different performances are obtained if we used different matching strategies or HOH, MAR, NOL, TDL, and DTL are different. However, we can see that HOH affects RIPs much smaller than other factors.

Table 3 shows comparison of RIPs of the matching strategies with respect to the problem generation factors. As can be seen in the table, differences in RIPs of the strategy RTM and the others become large as MAR, NOL, TDL, and DTL are getting increase. If MAR and NOL have large values, the more freights and vehicles are generated during the same time period and hence we have more chances to reduce the moving time by waiting for some time period and matching the freights to the more preferred vehicles. This phenomenon makes the difference in RIPs. As TDL is getting long (short), distance from vehicle's current location to freight's origination location, $d_{ij}(t)$, and distance from freight's origination location to freight's destination location, *i.e.* $e_{ij}(t)$, become large (small), and hence tardiness for the due date also becomes large (small) if we do not finish the transportation of the freight before the due date. Therefore, if TDL is large, the waiting and matching algorithms give larger RIPs than the case of which TDL is small. If DTL is tight, the waiting and matching algorithms give smaller RIPs, since tardiness for the due date cannot be reduced much although we use efficient and effective algorithms in this tight case. On the other hand, if DTL is loose, the waiting and matching algorithms give larger RIPs, since tardiness for the due date can be reduced much if we use efficient and effective algorithms in this loose case.

Table 3. Comparision of RIPs of the matching strategies with respect to the prblem generation factors

Influence factor		PM-G	PM-E	FM-E	FM-G	RTM
HOH	Homo	48.71%	47.78%	46.17%	44.17%	0.20%
	Hetero	47.84%	46.80%	44.48%	42.22%	0.35%
MAR	0.5	36.20%	35.72%	32.00%	29.61%	0.74%
	1	50.17%	48.70%	47.18%	45.28%	0.08%
	2	58.46%	57.44%	56.80%	54.70%	0.00%
NOL	4	34.70%	33.45%	30.08%	27.05%	0.68%
	7	49.52%	48.79%	47.06%	45.51%	0.13%
	10	60.62%	59.63%	58.84%	57.02%	0.01%
TDL	Short	33.67%	31.57%	29.57%	27.53%	0.75%
	Middle	51.10%	50.27%	48.17%	46.11%	0.07%
	Long	60.07%	60.02%	58.25%	55.95%	0.00%
DTL	Tight	39.76%	38.45%	36.92%	35.75%	0.07%
	Normal	49.41%	48.45%	46.65%	44.23%	0.50%
	Loose	55.67%	54.97%	52.41%	49.61%	0.26%

To show the effects of the five factors (HOH, MAR, NOL, TDL, and DTL) 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 amount.

As shown in Table 5, the best matching period tends to increase as TDL increases and MAR decreases on the contrary. This may be explained as follows. If MAR is a small value, during a certain period, less freights arrive at the logistics e-marketplace and hence the freights have less chance for being matched with freights or vehicles waiting at near locations. Note that matching with the vehicles located at near locations makes reduction in the moving time and hence makes reduction in the tardiness of freights. For increasing this chance, therefore, the matching period should have a longer value. In addition, if TDL becomes large, the moving times of vehicles to the freights' origination locations 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 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 amount (M^*) and the best matching period (T^*), $M^* \approx (\text{MAR} \times \text{NOL}) \times T^*$, where MAR × NOL means the number of freights to be generated per unit time. Note that average of MAR is (0.5 + 1.0 + 2.0) / 3 = 1.17 and average of NOL is (4 + 7 + 10)/3 = 7 in the experiments.

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	0.479	1	0.479	2.460
	MAR	3.642	2	1.821	9.351†
	NOL	2.650	2	1.325	6.804†
	TDL	153.129	2	76.564	393.158†
	DTL	0.426	2	0.213	1.095
	Error	155.794	800	0.195	
	Total	1189.930	809		
Matching amount	HOH	0.772	1	0.772	0.056
	MAR	11705.314	2	5852.657	427.315†
	NOL	5422.351	2	2711.175	197.949†
	TDL	8593.202	2	4296.601	313.704†
	DTL	85.780	2	42.890	3.132
	Error	10957.077	800	13.696	
	Total	109905.000	809		

Note: † There is a difference in the effects at a significance level of 0.001.

Table 5. The best matching periods and matching amounts

Influence factor		Matching period (T^*)	Matching amount (M^*)	Estimate of M^* = (MAR × NOL) × T^*
HOH	Homo	1.063	9.53	8.71 = 1.17 × 7 × 1.063
	Hetero	1.014	9.47	8.30 = 1.17 × 7 × 1.014
MAR	0.5	1.109	5.08	3.88 = 0.5 × 7 × 1.109
	1	1.058	9.07	7.41 = 1.0 × 7 × 1.058
	2	0.949	14.36	13.29 = 2.0 × 7 × 0.949
NOL	4	1.107	6.49	5.18 = 1.17 × 4 × 1.107
	7	0.967	9.22	7.92 = 1.17 × 7 × 0.967
	10	1.042	12.80	12.19 = 1.17 × 10 × 1.042
TDL	Short	0.490	5.30	4.01 = 1.17 × 7 × 0.490
	Middle	1.073	9.97	8.79 = 1.17 × 7 × 1.073
	Long	1.553	13.24	12.72 = 1.17 × 7 × 1.553
DTL	Tight	1.006	9.17	8.24 = 1.17 × 7 × 1.006
	Normal	1.057	9.39	8.66 = 1.17 × 7 × 1.057
	Loose	1.053	9.94	8.62 = 1.17 × 7 × 1.053

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 can reduce the transportation tardiness more than the real time matching strategy and hence increase customer service satisfaction level. 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 e-marketplaces.

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. However 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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