# Dynamic Matching Algorithms for Internet-based Logistics Brokerage Agents

정근채 (kcjeong@cbnu.ac.kr)
충북대학교 공과대학 구조시스템공학과

**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

## 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 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 web site 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

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. 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.

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. The other is the *moving time* occurred by moving from the current vehicle's location to the location where the matched freight is waiting. 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), 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?

## 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 when to solve the matching problem. At the matching point, the latter is to solve the matching problem for a given set of freights and vehicles registered to the e-marketplace before the matching point 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.*

For strategies PM and FM, we should determine the best matching period and matching amount. Figure 1 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 1. 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.

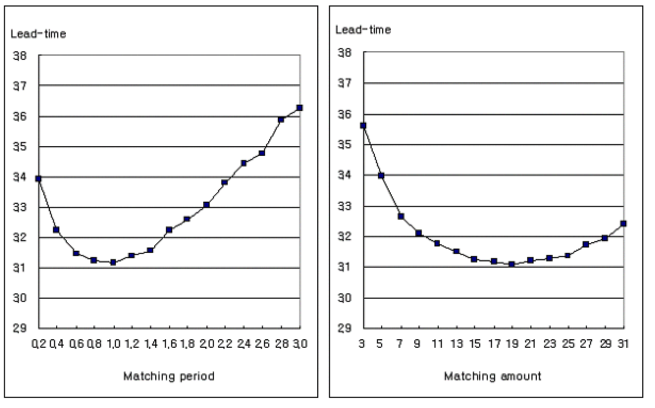


Fig 1. Relationship between the lead-time and decision variables

| | |
|---|---|
| $T$ | Matching period, if we use matching period $T$, matching points are $T$, $2T$, and so on. |
| $M$ | Matching amount, if we use matching amount $M$, matching decisions are made at the points of time when the $M$th 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, $\Delta$ to $T$ / 2, and $\varepsilon$ 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, $\Delta$ to $M$ / 2, and $\varepsilon$ 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. In this paper, we use the famous Hungarian algorithm for solving the above problem.

## 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 $\lambda$ = 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, ..., 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, ..., 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.

| | RDP | Average search time (Second) | 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 | | | | |

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

## 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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