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A GA-based Multi-Objective Decision Making for Optimal Vehicle Transportation

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In this study, a genetic algorithm is applied to obtain the best combination of transportation parameters for vehicle dispatching. The searching mechanism based on genetic algorithm can find several feasible solutions of dispatching parameters to proceed with transportation plan within constrained conditions. Besides, the concept of fuzzy due time is applied to replace that of time window so as to meet customers' preferences and demands much better. A fuzzy vehicle routing and scheduling problem (FVRSP) is formulated with five attributes: space utility, service satisfaction, waiting time, delay time, and transportation distance and proposed to solve it with a pure genetic algorithm method. In addition, the system can simultaneously calculate the residual loading capacity of weight and volume of each vehicle in order to provide the dispatcher with options to tune the dispatching operation. With the help of this system of acquiring the optimal solution to vehicle transportation, the promotion of the efficiency of transportation can thus be achieved.

Keywords: vehicle transportation, fuzzy due time, genetic algorithm, time window, fuzzy vehicle routing and scheduling

1. INTRODUCTION

It is more challenging for an enterprise to keep and increase profits today than ever. Logistics management [1] includes the process of planning, implementing and controlling the efficient, cost effective flow and storage of raw materials, in-process inventory, finished goods, and related information from point-of-origin to point-of-consumption for the purpose of conforming customers' requirements. Transportation planning is one of the important components of supply chain management. Transportation planning [2, 3], is concerned with deriving a demand-driven, feasible plan for transportation resources that are required to move inventory from one location in the supply chain to another. The transportation problem was originally proposed by Hitchcock in 1941 [4]. Since then the research on the problem has received a great deal of attention and various variants of the basic transportation problems have been investigated. Transportation and logistics organizations often face large-scale combinatorial problems on both operational and strategic levels. In such problems, you must examine all possible combinations of decisions and variables to find a solution; consequently, no partial-enumeration-based exact algorithm can consistently solve them.

In real life, the transportation-dispatching problem is very complicated. A good transportation plan must content with several requirements like capacity constraints and

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dynamic routing. As the plan is about to execute, decision on load consolidation, mode/ carrier selection, routing and scheduling need to be made. Using information within manufacturing planner, transportation planner consolidates orders or shipments into loads, to select the appropriate mode and carrier, as well as schedules and routes the loads. Each planning is made according to constraints of the transportation system including container capacity, equipment availability, and transit times. The goal of transportation is to allocate the supply availability at each origin to optimize a criterion to satisfy the demand at each destination. The usual objective function is to minimize the total transportation cost or total weighted distance or to maximize the total profit contribution from the allocation [5]. Therefore, a dispatcher always faces the complicated problem to meet all essential demands under certain specific constrained conditions.

The vehicle routing problem (VRP) involves the design of a set of minimum cost routes, originating and terminating at a central depot, for a fleet of vehicles which service a set of customers with known demands. Each customer is serviced exactly once and, furthermore, all customers must be assigned to vehicles without exceeding the capacities [6-9]. Among variants of VRP with capacity and time window constraints, called the vehicle routing problem with time windows (VRPTW) has been widely studied in the last decade [10-13]. The vehicle routing problem with time window constraints (VRPTW) is an important generalization of the VRP. In the VRPTW, each customer has a time window (or time interval formed with deadline and the earliest time constraints) in which he/she must be served. When time windows are presented, the problem involves a combination of routing and scheduling components. Routes must be designed in order to minimize total transportation cost, but, at the same time, scheduling must be performed in order to ensure time feasibility.

VRPTW can be further divided into two classes known as hard time window constraints and soft time window constraints. Hard time window constraints strictly request customers' delivery time falling between earliest and latest time constraints with no violation. When a vehicle arrives at a customer location before its earliest service time, the vehicle must wait to start a service until the earliest service time. It is inefficient in searching within the feasible region of the VRP with hard time window (VRPHTW) when the constraints are tight. Moreover, in many real-world situations, constraints of time window can be violated to some extent. We treat time window constraints as soft in this paper. When a vehicle arrives at a customer location before its earliest service time, it must wait (*i.e.*, a "waiting time" penalty function is used) to start service until the earliest service time. On the other hand, when a vehicle arrives later than the latest service time, a "delay time" penalty function is used. Besides, the service time that to unload and load the cargo at each customer is not taken into account in the paper.

The VRPTW has a wide range of applications such as bank deliveries, postal deliveries, school bus routing and so on, and it has been a subject of intensive research focused mainly on heuristic and metaheuristic approaches [1, 14, 15] Among recent approaches are a GA search based on Pareto ranking technique by Ombuki *et al.* [16], a two-stage hybrid local search by Bent and Van Hentenryck [17], a hybrid genetic algorithm by Berger, Barkaoui and Bräysy [18] and Pérez [19], a reactive variable neighborhood search by Bräysy [20], a two-phase hybrid metaheuristic algorithm by Gehring *et al.* [21], Alvarenga *et al.* [22], and Lu *et al.* [23], a variable neighborhood decent with constraint-based operators by Roussean, Gendreau and Pesant [24] and so on.

In many practical applications, the concept of time window does not model the customer's preference very well. Thangiah, Vinayagamoorthy, and Gubbi [25] have investigated vehicle routing problems with time deadlines and had a problem of destroying subtours in chromosome during decoding to let evolution lose its meaning. The objective is to minimize the number of vehicles and the travel for servicing a set of customers without exceeding the capacity or being tardy. They proposed a kind of cluster-first route-second heuristic procedure. Genetic algorithms are used to cluster customers (or assign vehicles to customers). The customers within each cluster (or vehicle) are then routed with a cheapest insertion heuristic. The solutions obtained from this heuristic are further improved with a standard 2-opting post-processing of the customers to determine if some should be serviced from neighboring clusters.

Recently, application of fuzzy set to VRP to help find optimal (or near optimal) solution is widely spreading. The research reported in [25] proposed a novel genetic algorithm with multiple species in dynamic regions, each of which occupies a dynamic region determined by the weight vector of a fuzzy adaptive hamming neural network. An optimization system developed specially for dynamic real-time schedules by using self-organizing fuzzy logic to create a controller to manage the computational time available to ensure the fast insertion of appropriate new jobs were investigated in [26]. Moreover, a fuzzy set was used to partition customers into fuzzy regions according to quantity supplied and the length of paths using genetic algorithm in [27]. The experimental results on the vehicle routing problem with time windows show good performance of the proposed genetic algorithm.

Even though customers are asked to provide a fixed time window for service, they really hope to be served at a desired time (*i.e.*, due time) if possible. In such a case, the preference information of customers normally represents as a fuzzy number with respect to the satisfaction for service time. For instance, customers' preferences may be various such as (a) tolerable for lateness but less tolerable for earliness (b) tolerable for earliness but less tolerable for lateness (c) tolerable for both earliness and lateness; and (d) less tolerable for both earliness and lateness. The various satisfactions for customers can be defined by specific membership function of satisfaction. The term set of linguistic variable "satisfaction" is different for customers and can be determined by a membership function based on the requests for service time from customers. The more approaching to 1 for the calculated value of membership function and the closer to the customer satisfied level it is.

Cheng and Gen [27, 28] suggested to use the concept of fuzzy due time to replace that of time window because it can describe customers' preferences better than fixed time window. When seeking a scheduling under the consideration of fuzzy due time, they are interested not only in the feasibility of service time for all customers as the conventional one does but also the reasonability of service time in the sense that they enforce the service time for each customer to approach his due time as close as possible. A fuzzy vehicle routing problem (FVRP) is formulated and proposed to solve it with a genetic algorithm, which is complex with a post-processing heuristic method. A push-bump-throw post-procedure is proposed to find the best service time for each customer.

In this study, we propose a single global solution procedure using a pure GA approach rather than several separated phases using a heuristic method [27-33] as proposed before. With the pure GA approach, an optimal or a nearly optimal solution of transportation with the minimal number of vehicles, maximal delivery efficiency (*i.e.*, the maximal vehicle space utility U, defined as the average of ratios of the current loaded weight to the maximum for all the vehicles in use), maximal customer service satisfaction, minimal overall waiting time and delay time of vehicles, and minimal transportation distances can be obtained directly by decoding the chromosome without any post-processing after several generations. Thus, we can effectively find the optimal solution or a nearly one under constrained conditions necessary for the transportation problem mentioned above. With the assistance of this developed methodology, a dispatcher can more efficiently determine how to distribute the shipments to serve customers by available vehicles. Thus, the management efficiency of logistics can be promoted and so as its competency.

2. FUZZY ROUTING AND SCHEDULING MODEL

It is always mainly focused on minimizing the number of vehicles in use as to set the dispatching strategy. Nevertheless, there are other attributes to be concerned with when determining the optimal dispatching strategy, such as minimizing the total transportation distance and the waiting time, and maximizing the service satisfaction. A sacrifice of increasing the total transportation distance is always made during minimizing the number of vehicles used for transportation. For promoting the average service satisfaction, it is sometimes necessary to increase the total waiting time or delay time of vehicles as well. The fuzzy membership function applied in this study for approaching the exact expected service time is nothing like the traditional way only to meet the already-set allowed service time range. Moreover, we try to accomplish minimizing the number of vehicles used not only with a minimal total transportation distance but also a maximal overall customer service satisfaction, and a minimal overall waiting time and delay time of vehicles. There are five attributes for the optimal vehicle-dispatching model proposed in this paper. They are space-utility, service satisfaction, waiting time, delay time, and transportation distance. Each of them is illustrated as follows.

2.1 Space Utility

The traditional dispatching method always loads the commodity for the same customer on the same vehicle. A vehicle loaded with various customers' commodities cannot go beyond the limit of its loading weight or volume. It is necessary to take all these into consideration. Applying genetic algorithm to search for the most (or almost) appropriate dispatching strategy to transport the commodities with maximal loading performance of the fleet, it is necessary to take the term into consideration, *i.e.*, maximizing the space utility U. The bigger U is and the better space utility for the fleet is. By maximizing U, the maximum loading performance of the fleet can thus be evaluated and obtained by Eq. (1).

Maximizing

$$U = \frac{\sum_{j=1}^{N'} f_j/F_j}{N'}, \tag{1}$$

where

N: the number of total vehicles;
N′: the number of vehicles used for transporting;
f_j: total weight (volume) of the commodities for customers served by vehicle *j*;
F_j: the loading capacity (weight or volume) of vehicle *j*.

The space utility *U* is defined to make good use of the space of a vehicle as complete as possible, in other words, sparing the loading space of a vehicle as little as possible. If space utility *U* is calculated based on weight in Eq. (1), constrains are evaluated based on volume and vice versa. The space utility *U* is calculated based on weight in this paper.

2.2 Service Satisfaction

Nowadays, it is getting more important for logistics to enhance the competition in a supply chain. Various companies cooperate to achieve this by strategic unifying. Service quality is always a crucial competition factor for a company. The only way for a company everlasting is improving its service quality to consumers. Based on the definition of service quality [34], "expectation" is the key point for consumer aware of the service quality good or not. There is a "tolerance area" between "essential" level and "satisfying" level for the service quality. The service quality outside the "tolerance area" makes customer depressed and lessen the loyalty. On the contrary, the one not only inside but beyond "tolerance area" satisfies and surprises the customer to enhance his/her loyalty.

In the past, only if the consumer's allowable time window could be offered, the service quality could be accepted. The tolerable interval of service time for consumer *i* is described by $[e_i, l_i]$, where e_i is the earliest time and l_i is the latest.

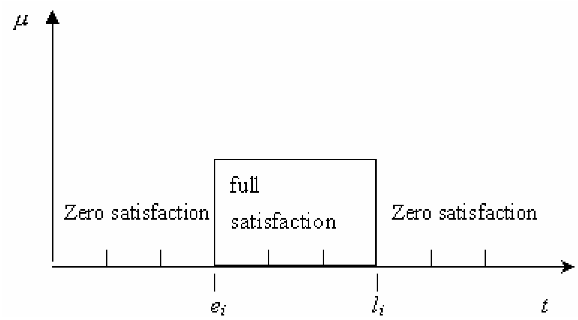

Fig. 1. Time window.

Conventional approaches just consider the tolerance of customers and represent it as a time window shown in Fig. 1. The grade of satisfaction of service is 1 (full satisfaction) if the service time falls within the range of a time window; otherwise, the grade of satisfaction of service is 0 (no satisfaction). The grade of service satisfaction $\mu_i(t)$ can be defined for any service time *t* ($t > 0$) as

$$\mu_i(t) = \begin{cases} 1, & \text{if } e_i \le t \le l_i. \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Nowadays, the service satisfaction is getting more and more emphasized in logistics. We intend to substitute time window to fuzzy due time. In order to manipulate customers' preferences further beyond crisp set as mentioned above. A fuzzy set, defined originally by Zadeh [35], is an extension of a crisp set and applied in this study to represent the grade of satisfaction for service time. A triangular fuzzy number (TFN) with respect to the grade of satisfaction for service time can be defined by the triple (e_i, u_i, l_i). The service time is described by the due time u_i and generally, $e_i \leq u_i \leq l_i$. The membership function of the fuzzy due time of the customer i by $\mu_i(t_i)$ can be shown as Eq. (3) and illustrated in Fig. 2, where w_j denotes the waiting time occurring at customer j and r_{ij} denotes the required time transporting from customer i to j. If a customer is served at his/her desired due time, the grade of satisfaction for him/her is 1 (full satisfaction); otherwise, the grade of satisfaction gradually decreases with the increase of difference between the service time and his/her desired due time. The grade of satisfaction will be 0 (no satisfaction) if the service time falls outside the time interval.

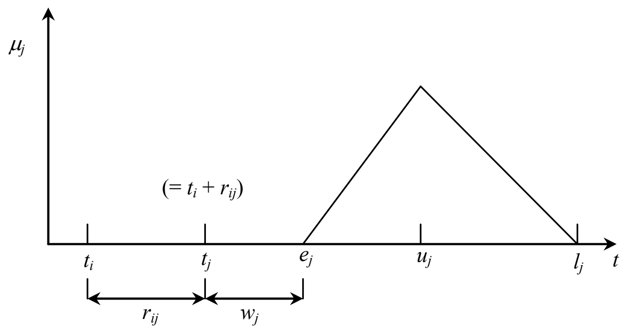

Fig. 2. Fuzzy due time and waiting time.

$$\mu_i(t_i) = \begin{cases} 0, & t_i < e_i, \\ \dfrac{t_i - e_i}{u_i - e_i}, & e_i \leq t_i \leq u_i, \\ \dfrac{l_i - t_i}{l_i - u_i}, & u_i \leq t_i \leq l_i, \\ 0, & t_i > l_i. \end{cases} \tag{3}$$

where

t_i: service time for customer i;
e_i: the earliest service time for customer i;
l_i: the latest service time for customer i;
u_i: the best services time for customer i.

The overall degree of service satisfaction of vehicle j to all its service customers (*i.e.*, S_j) can be calculated by Eq. (4). We can find out the maximal service satisfaction of vehicle j to all its service customers through maximizing the value of S_j.

Maximizing

$$S_j = \sum_{k=1}^{n_{cj}} \mu_{jk}(t_{jk}), \tag{4}$$

where

$\mu_{jk}(t_{jk})$: the service satisfaction of vehicle j to customer k at service time t_{jk};
t_{jk}: service time of vehicle j to customer k;
n_j^c: the number of customers served by vehicle j.

2.3 Waiting Time and Delay Time

In addition to decreasing the cost of transportation, promoting service quality is another critical means to enhance the competency. With the service satisfaction improved, the number of vehicles, total waiting time, or total delay time occurring under only certain amount of vehicles available for service probably increases at the same time. The more emphasized it is, the more seriously increasing they are. It is worth increasing the vehicles or the waiting time occurring under only specific number of vehicles available for service to promote the service quality. On the other hand, in order to reduce the cost of vehicles, it is always mainly focused on minimizing the number of vehicles in use, which is likely to result in increasing the delay time during serving the customer. The relationship of the service time between two different customers of a vehicle is illustrated in Fig. 2. After finishing serving customer i at the service time t_i, the vehicle arrives and starts to serve customer j at t_j. The time r_{ij} denotes the required transport time from customer i to customer j. A waiting time exists while the service time (*i.e.*, t_j) of customer j is earlier than the earliest time wanted and a delay time occurs while the service time (*i.e.*, t_j) of customer j is later than the latest time allowed. The waiting time w_j and the delay time dl_j can be shown as Eqs. (5) and (6) respectively.

$$w_j = e_j - (t_i + r_{ij}), \text{ if } t_j < e_j, \tag{5}$$
$$dl_j = (t_i + r_{ij}) - l_j, \text{ if } t_j > l_j, \tag{6}$$

where

$$t_j = t_i + r_{ij}$$

t_i: service time of customer i;
t_j: service time of customer j;
e_j: the earliest time of service time for customer j;
l_j: the latest time of service time for customer j;
r_{ij}: the required time transporting from customer i to j.

Once the minimal number of vehicles is used with the least waiting time and delay time, the most effective transportation solution can be reached. With respect to a customer k, which is served by vehicle j and needs waiting time (delay time), the ratio of his waiting time (delay time) to the maximum can be calculated by $w_{jk}/w^0_{\max}$ ($dl_{jk}/dl^0_{\max}$), where w_{jk} (dl_{jk}) denotes the waiting time (delay time) of the customer k served by vehicle

j and $w^0{}_{\max}$ ($dl^0{}_{\max}$) denotes the maximum waiting time (delay time), whose value is set flexibly on how long all the customers need to be completely served. In this study, $w^0{}_{\max}$ ($dl^0{}_{\max}$) is set to 24 (hr), *i.e.*, all the customers are served completely within 24 hours. Through the ratio of each waiting time (delay time) to the maximum (*i.e.*, $w_{jk}/w^0{}_{\max}$ and $dl_{jk}/dl^0{}_{\max}$) being calculated, the average (*i.e.*, W_j and DL_j) of all ratios of waiting time (delay time) of the customer k served by vehicle j to the maximal waiting time (delay time) can be obtained with Eq. (7) (Eq. (8)). We can find out the minimal waiting time (delay time) for vehicle j during distributing through minimizing the value of $W_j(DL_j)$.

Minimizing

$$W_j = \frac{1}{n_j^c}\sum_{k=1}^{n_j^c}\frac{w_{jk}}{w_{\max}^0}. \tag{7}$$

Minimizing

$$DL_j = \frac{1}{n_j^c}\sum_{k=1}^{n_j^c}\frac{dl_{jk}}{dl_{\max}^0}, \tag{8}$$

where

n_j^c: the number of customers served by vehicle j;
w_{jk}: the waiting time of the customer k served by vehicle j;
dl_{jk}: the delay time of the customer k served by vehicle j;
$w^0{}_{\max}$: the maximum waiting time;
$dl^0{}_{\max}$: the maximum delay time.

2.4 Transportation Distance

Apart from decreasing the required number of vehicles, there is another effective way to reduce the cost of transportation by shortening the distance. But, with the decreasing of the number of vehicles, the total transportation distance will be probably increased in the meantime. Once the shortest transportation distance with the minimal number of vehicles in use is found, the lowest cost for transportation can be reached.

Through the ratio of each distance to the maximum (*i.e.*, $d_{jk}/d_{\max}$) calculated, the average ratio (*i.e.*, D_j) for all transportation distance to the maximum can be obtained by Eq. (9), in which d_{j0} denotes the transportation distance between the 0th customer (*i.e.*, distribution center) and the 1st customer; $d_{jn_j^c}$ denotes that between the n_j^cth customer (*i.e.*, the last customer) and the 0th customer (*i.e.*, distribution center). Thus, there are totally $n_j^c + 1$ transportation distances included in the transportation route for each vehicle in serving n_j^c customers. We can find out the shortest transportation route of vehicle j through minimizing the value of D_j.

Minimizing

$$D_j = \frac{\sum_{k=0}^{n_j^c}(d_{jk}/d_{\max})}{(n_j^c+1)}, \tag{9}$$

where

n_j^c: the number of customers served by vehicle j;
d_{jk}: the transportation distance between the kth customer and the $(k + 1)$th customer by vehicle j;
$d_{\max}$: the maximum transportation distance among all the distance between customers served by all the vehicles.

3. DEVELOPMENT OF THE MODEL AND THE SOLUTION APPROACH

The main goal of this study is to explore an effective way to help a dispatcher obtain several appropriate combination sets of ways immediately. Each set is composed of parameters of the various commodities and their quantities, vehicles available for shipping, and various destinations (or customers) to serve. With the shipment of vehicles available, all commodities required are exactly provided at the service time as close as to the due time.

3.1 Searching Mechanism

We adopt a search method, genetic algorithm (GA) [36, 37], to the combination sets. To solve a problem, the GA randomly generates a set of solutions for the first generation. Each solution is called a chromosome that is usually in the form of a binary string. These strings (*i.e.*, chromosomes) can be altered to produce children (new solutions) using genetic operators. One of these genetic operators is crossover, in which a randomly chosen sequence of bits is exchanged between two strings to produce two new strings. Another operation is mutation, which randomly alters bits within a single string to produce a new string. The new population is evaluated, a new reproducing population is chosen, and the process of crossovers and mutations repeats for a predetermined number of iterations, or until an acceptable evaluation level is reached. The roulette wheel approach [36], creating a biased roulette wheel where each current string in the population has a roulette wheel slot sized in proportion to its fitness, is adopted as the selection mechanism to reproduce the chromosome of next generation in the paper.

According to a fitness function, a fitness value is assigned to each solution. The fitness values of these initial solutions may be poor, however, they will rise as better solutions and survive in the next generation. A new generation is produced through the following three basic operations [27, 32].

(1) Randomly generate an initial solution set (population) of N strings and evaluate each solution by fitness function.
(2) If the termination condition does not meet, do
    Repeat {Select parents for crossover.
        Generate offspring.
        Mutate some of the numbers
        Merge mutants and offspring into population.
        Cull some members of the population.}

(3) Stop and return the best fitted solution

3.1.1 Chromosome representation

A main difference between genetic algorithms and more traditional optimization search ones is that the former work with a coding of the parameter set and not the parameters themselves. Thus, before any type of genetic search can be performed, a coding cheme must be determined to represent the parameters in the problem in hand. In finding solutions, consisting of proper combination of the three transportation parameters, *i.e.*, vehicle, customer, and time, a coding scheme for three parameters must be determined and considered in advance. A multi-parameter coding, consisting of three sub-strings, is required to code each of the three variables into a single string. In a direct problem representation, the transportation variables themselves are used as a chromosome. A list of vehicle/customer/start time is used as chromosome representation, which represents the permutation of vehicles associated with assigned customers and start time. A gene is an ordered triple (vehicle, customer, and start time).

3.1.2 Crossover

Crossover is the main genetic operator. It operates on two chromosomes at a time and generates offspring by combining both chromosomes' features. A simple way to achieve crossover would be to choose a random cut-point and generate the offspring by combing the segment of one parent to the left of the cut-point with the segment of the other parent to the right of the cut-point, as shown in Fig. 3. In other words, the operator creates a new transportation solution configuration by switching sub-strings between parents at a random cut-point.

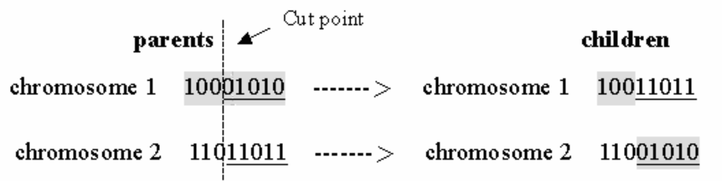

Fig. 3. Illustration for crossover and mutation operation.

3.1.3 Mutation

One parent is selected from the mating pool and an arbitrary gene of the parent chromosome is randomly changed. A simple way to achieve mutation would be to alter one or more genes. The operator causes a very little 'local' change, and therefore is used at a very low rate.

3.2 Objective Function

Mathematically, a multi-objective decision making (MODM) problem can be represented as follows [38]:

$$\left.\begin{array}{l}\text{Maximize } \{f_i(X), i = 1, \ldots, l\}, \\ \text{Subject to: } g_j(X) \leq b_j,\ j = 1, 2, \ldots, m.\end{array}\right\}$$

where X is a vector of decision variables. Combining multiple objectives and genetic algorithms, multi-objective genetic algorithm (MOGA) [39] is applied in this paper. The target is to maximize the space utility and customers' service satisfactions and to minimize the waiting time, delay time, and transportation distance. We can find out the maximum values of U and $\sum S_j$, and the minimum values of $\sum W_j$, $\sum DL_j$, and $\sum D_j$ by approaching fitness value to 1. The objective function can be illustrated as follows.

Objective: To maximize Fitness.

$$\left.\begin{array}{l}Fitness = \rho_1 \times U + \rho_2 \times S + \rho_3 \times (1 - W) + \rho_4 \times (1 - DL) + \rho_5 \times (1 - D), \\ U = \dfrac{\sum_{j=1}^{N'} f_j / F_j}{N'},\ S = \dfrac{1}{n^{v'}} \sum_{j=1}^{n^{v'}} S_j,\ W = \dfrac{1}{n^{v'}} \sum_{j=1}^{n^{v'}} W_j,\ DL = \dfrac{1}{n^{v'}} \sum_{j=1}^{n^{v'}} DL_j,\ D = \dfrac{1}{n^{v'}} \sum_{j=1}^{n^{v'}} D_j.\end{array}\right\} \quad (10)$$

Subject to:

(1) Loading weight of vehicle ≤ 100%.
(2) Loading volume of vehicle ≤ 100%.
(3) Each customer served by the same vehicle and only once.
(4) Each customer's demand is just completely provided.

where $n^{v'}$ denotes the number of vehicle in use for service and $\sum \rho_i = 1$, $\rho_i \geq 0$, $i = 1, 2, 3, 4, 5$. The values of U, S_j, W_j, DL_j, and D_j can be obtained by Eqs. (1), (4), (7) - (9). The U, related with the condensation degree of commodity's loading on vehicles and the space utilities of vehicles, is used to maximize the loading capacity of the fleet. The S, W, and DL are applied to evaluate the customer service satisfaction, the waiting time, and the delay time respectively. The D is utilized to evaluate the shortest route for the vehicle routing design. However, it requires the provision of weights for each objective while applying the additive form of objective function.

The usual objective function is to minimize the total transportation cost or total weighted distance or to maximize the total profit contribution from the allocation [5]. Transportation dispatching is a complex problem. First of all, a dispatcher must figure out the way to keep all commodities for a consumer on the same vehicle, without exceeding whose maximum loading capacity. Secondly, to find a way to minimize the number of vehicles used. Thirdly, to make a feasible schedule with the minimum waiting time and without tardiness for all the vehicles used to serve consumers. Finally, make sure more further to meet the maximum service satisfaction for all the consumers.

The emphasis is placed on the objective average grade of customer satisfaction. This may lead to the increase of total waiting time for vehicles, so a dispatcher also needs to make a tradeoff between average grade by customers and total waiting time by vehicles. There are tradeoffs between objectives. Thus, the transportation problem can only be found with a compromise (*i.e.*, nearly optimal) solution for considering different objectives at the same time. It is easier for a dispatcher to acquire a best compromise solution by minimizing the overall cost of objectives (*i.e.*, fleet size, average of grade of customer satisfaction, waiting time, delay time, and travel distance). In other words, the minimum overall cost can be reached through satisfying the larger costs of objectives but sacrificing the smaller ones. The cost coefficients $\rho_1 \sim \rho_5$ of objectives in Eq. (10) depend on the cost ratios of them to the overall cost based on cost estimates [40]. Based on the historical data, the total cost can be estimated by a multiple regression equation [41], *e.g.*, $T_{cost} = a + b_1U + b_2S + b_3(1 - W) + b_4(1 - DL) + b_5(1 - D)$, where a is the intercept, and $b_1 \sim b_5$ are the slope. It can be reformed into $Y = \rho_1U + \rho_2S + \rho_3(1 - W) + \rho_4(1 - DL) + \rho_5(1 - D)$, where $\sum\rho_i = 1$, $i = 1, 2, 3, 4, 5$. Thus the cost coefficients $\rho_1 \sim \rho_5$ of objectives in Eq. (10) can be estimated and obtained.

4. AN APPLICATION OF REAL WORLD CASE

The developed system based on the proposed model is applied in a paper supplier that delivers printing paper shipment to customers. There are three kinds of paper package size for delivery and the requested amount of them needs satisfying. Moreover, all of them need to be sent at due time to each customer. Nowadays, the business competitiveness among suppliers is more serious than ever. The key point for enhancing the competency is to provide a high quality service to the customer. This developed system can help vehicle dispatcher determine the required number of vehicles and route for each vehicle so as to arrive at the required due time for each customer as close as possible.

The paper supplier confronts a transportation problem, which consists of a fleet of 4 vehicles, 3 items of commodity (*i.e.*, three kinds of paper package size), and 8 customers located in the northern Taiwan, and is illustrated as Table 1. The objective is to design a dispatching strategy for all the required number of each item of commodity distributed to the 8 customers by these 4 vehicles in the least total delivery cost. The cost coefficients $\rho_1 \sim \rho_5$ for objectives are all set at 0.2 to reach the least overall cost based on the supplier's cost estimates. The weight (volume) loading capacity of vehicle and size of commodity are shown as Table 2. The required quantity of commodity is shown as Table 3.

Table 1. Required, known, and constrained conditions.

<table>
<tr><td>Application</td><td colspan="6">Required & known conditions</td><td>Set target</td></tr>
<tr><td rowspan="7">Vehicle dispatching</td><td>(1) 4 vehicles</td><td colspan="5">Table 2</td><td rowspan="5">The minimal total delivery cost</td></tr>
<tr><td>(2) 8 customers</td><td colspan="5">Table 3 & Table 4</td></tr>
<tr><td>(3) 3 Items</td><td colspan="5">Table 2</td></tr>
<tr><td rowspan="2">(4) cost coefficients</td><td>ρ_1</td><td>ρ_2</td><td>ρ_3</td><td>ρ_4</td><td>ρ_5</td></tr>
<tr><td>0~1</td><td>0~1</td><td>0~1</td><td>0~1</td><td>0~1</td></tr>
<tr><td colspan="7">Constrained conditions</td></tr>
<tr><td colspan="7">(1) Loading weight of vehicle ≤ 100%.
(2) Loading volume of vehicle ≤ 100%.
(3) Each customer served by the same vehicle and only once.
(4) Each customer's demand is just completely provided.</td></tr>
</table>

Table 2. Vehicle loading capacity and commodity size.

Vehicle	Vehicles			
	VH_1	VH_2	VH_3	VH_4
Weight loading capacity (kg)	1000	1500	2000	2000
Volume loading capacity (m^3)	6	8	14	14

Commodity	Items		
	I_1	I_2	I_3
Weight (kg/#)	5	10	15
Volume (m^3/#)	0.05	0.10	0.15

Table 3. Required number of commodity for customers.

Destinations (Customers)	C_1			C_2			C_3			C_4		
Items	I_1	I_2	I_3	I_1	I_2	I_3	I_1	I_2	I_3	I_1	I_2	I_3
Required number (#)	9	5	8	8	9	2	5	2	3	2	4	6
Destinations (Customers)	C_5			C_6			C_7			C_8		
Items	I_1	I_2	I_3	I_1	I_2	I_3	I_1	I_2	I_3	I_1	I_2	I_3
Required number (#)	3	4	9	1	3	5	2	3	1	4	6	3

Table 4. Transit distance (km) between distribution center and customers.

Destinations (Customers)	Distribution center	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Distribution center	0	10	15	8	5	10	15	20	10
C_1	10	0	5	5	10	15	20	15	15
C_2	15	5	0	10	15	20	5	10	5
C_3	8	5	10	0	20	5	8	5	20
C_4	5	10	15	20	0	8	10	20	15
C_5	10	15	20	5	8	0	5	15	20
C_6	15	20	5	8	10	5	0	20	15
C_7	20	15	10	5	20	15	20	0	8
C_8	10	15	5	20	15	20	15	8	0

Table 5. Required service time schedules.

Destinations (Customers)	C_1			C_2			C_3			C_4		
Service time	e_1	u_1	l_1	e_2	u_2	l_2	e_3	u_3	l_3	e_4	u_4	l_4
Required time (#)	8:30:00	9:00:00	10:00:00	9:00:00	10:00:00	11:00:00	10:00:00	11:00:00	11:30:00	12:30:00	13:00:00	14:00:00
Destinations (Customers)	C_5			C_6			C_7			C_8		
Service time	e_5	u_5	l_5	e_6	u_6	l_6	e_7	u_7	l_7	e_8	u_8	l_8
Required time (#)	13:00:00	14:00:00	15:00:00	14:00:00	15:00:00	16:00:00	15:00:00	16:00:00	17:00:00	16:00:00	17:00:00	17:30:00

The transit distances among customers are shown as Table 4. The transit time (hr) needed between each two customers is calculated based on Table 4 by setting the average speed of vehicle to 10 km/hr. With respect to the customer's service satisfaction, it can be evaluated by the membership function of the fuzzy due time of customer *i* by $\mu_i(t_i)$ shown as Eq. (3). Using a triangular fuzzy number (TFN) shown as Fig. 2, the grade of satisfaction can be defined by the triple (e_i, u_i, l_i). The required service time schedule for customers is shown as Table 5, where customer 1 and customer 4 are more tolerable for lateness but less for earliness; customer 3 and customer 8 are more tolerable for earliness but less for lateness; the others are tolerable for both earliness and lateness.

4.1 Effect of Visit Order to the Shortest Route

Because it is essential that all commodities for the same customer delivered by the same vehicle, we encode the customer instead of the commodity. The encoded value of customer C_{jk} being '1' denotes all commodities of the customer *k* are delivered by vehicle *j*. Otherwise, being '0' denotes none of them is delivered by vehicle *j*. The service route for each vehicle can be obtained through linking all its service nodes (*i.e.*, customers). For instance, a vehicle with 3 customers is of a service sequence as distribution center → customer 1 → customer 2 → customer 3 → distribution center. The total transportation distance (*i.e.*, $D = d_{01} + d_{12} + d_{23} + d_{30}$) can be obtained. It is never to find out the shortest distance of the service route if the gene of customers in chromosome is positioned on a fixed place. Probably there is a shorter route than the above-mentioned (*i.e.*, distribution center → customer 1 → customer 2 → customer 3 → distribution center) for the vehicle such as distribution center → customer 2 → customer 1 → customer 3 → distribution center. But for the gene of customers is positioned on a fixed place, it is impossible to find the shortest route. Thus, it is necessary to set a subgen segment included in the chromosome to determine the service sequence of a vehicle to its customers. Fig. 4 shows the chromosome scheme, in which a gene segment for visiting orders of vehicles is added. The service sequence for each vehicle to its customers is determined by ranking the decoded values of them. The vehicle serves its customers according to the ranking order of the decoded values from the biggest to smallest. If any decoded values happen to be the same, the customer with the smallest ordinal number is the first. For instance, the decoded values for vehicle 1 (*i.e.*, $O_{11} \sim O_{18}$) in the segment of the service sequence for vehicle 1 to all its customers are shown as follows.

Customers (*i.e.*, $C_{11} \sim C_{18}$) :	$\underline{C_{18}}$	$\underline{C_{17}}$	$\underline{C_{16}}$	$\underline{C_{15}}$	$\underline{C_{14}}$	$\underline{C_{13}}$	$\underline{C_{12}}$	$\underline{C_{11}}$
The decoded (*i.e.*, $O_{11} \sim O_{18}$) :	7 -	6 -	1 -	4 -	8 -	2 -	5 -	3

The service sequence for vehicle 1 to its 8 possible customers can be determined based on the ranking result and shown as the following: 8 (*i.e.*, C_{14}) → 7 (*i.e.*, C_{18}) → 6 (*i.e.*, C_{17}) → 5 (*i.e.*, C_{12}) → 4 (*i.e.*, C_{15}) → 3 (*i.e.*, C_{11}) → 2 (*i.e.*, C_{13}) → 1 (*i.e.*, C_{16}). Thus, the service sequence for each vehicle to its possible customers can be determined through ranking the decoded values of the genes in the segment for service sequence. Next, judging from the decoded values (*i.e.*, "0" denotes none of the commodities is delivered by the vehicle) of genes for vehicle to customers, we can decide which customers are visited. For instance, the decoded values of genes (*i.e.*, $C_{11} \sim C_{18}$) for vehicle 1 to its customers are a bit-string of "01011110", in which the bit from right to left represents C_{11}, C_{12}, …, and C_{18} respectively. We can determine customer 2, 3, 4, 5, and 7 are visited by vehicle 1. Eventually, the service route with a sequence is obtained and shown as the following: 8 (*i.e.*, C_{14}) → 6 (*i.e.*, C_{17}) → 5 (*i.e.*, C_{12}) → 4 (*i.e.*, C_{15}) → 2 (*i.e.*, C_{13}).

4.2 Chromosome Design

Fig. 4 shows the structure of chromosome for 4 vehicles and 8 customers. There are three gene segments included in the chromosome, *i.e.*, the segment of vehicles for customers, the service segment for the vehicle to all its customers, and the start shipping time for vehicles from the right to the left respectively. The string length of chromosome depends on the number of vehicles in the fleet and customer to serve. In this study, a binary coding is utilized and the bit size of encoding for the 32 variables (*i.e.*, C_{11} ~ C_{18}, C_{21} ~ C_{28}, C_{31} ~ C_{38}, and C_{41} ~ C_{48}) in the 1st segment (*i.e.*, segment of vehicles for customers) is set to 1 bit, of which the decoded '1' denotes all the commodities of the respective customer are delivered by the vehicle and '0' denotes none of them is delivered. Next, the bit size of encoding for the 32 variables (*i.e.*, O_{11} ~ O_{18}, O_{21} ~ O_{28}, O_{31} ~ O_{38}, and O_{41} ~ O_{48}) in the 2nd segment (*i.e.*, segment of service sequence for the vehicle to all its customers) is set to 3 bits for each of them because of 8 possible options (*i.e.*, customers) for each vehicle to serve. Table 6 illustrates the relationship between the encoded (*i.e.*, bit string) and the decoded (*i.e.*, customer). Finally, the bit size of encoding for the 4 variables (*i.e.*, T_{VH1}, T_{VH2}, T_{VH3}, and T_{VH4}) in the 3rd segment (*i.e.*, segment of start shipping time) is set to 8-bit precision for the range of [0, 24] (*i.e.*, 24 hr/(2^8 – 1) = 0.0941 hr = 5.6460 min).

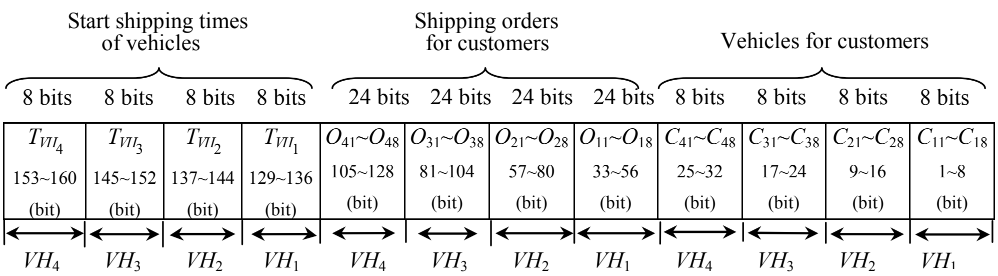

Fig. 4. Structure of chromosome for a practical problem.

Table 6. Encoding and decoding for visit order segment in chromosome.

the encoded	000	001	010	011	100	101	110	111
the decoded	1	2	3	4	5	6	7	8

The chromosome for transportation problem (4 vehicles × 8 customers) in this study consists of three parts. One is composed of genes of vehicle 1~vehicle 4 (1 ~ 32 bits), which are decoded to determine which ones of customers are served by the vehicle. Another is composed of genes of segment of the service sequence for vehicle 1 (33 ~ 56 bits), vehicle 2 (57 ~ 80 bits), vehicle 3 (81 ~ 104 bits), and vehicle 4 (105 ~ 128 bits).

The other is composed of genes of start shipping time of vehicle 1 (129 ~ 136 bits), vehicle 2 (137 ~ 144 bits), vehicle 3 (145 ~ 152 bits), and vehicle 4 (153 ~ 160 bits) respectively.

In addition to the 32 bits (*i.e.*, 1 bits × 8 customers × 4 vehicles) for the genes of the segment of vehicles for consumers, there are another 96 bits (*i.e.*, 3 bits × 8 customers × 4 vehicles) for the genes of segment of the service sequence for the vehicle to all its customers, and the other 32 bits (*i.e.*, 8 bits × 4 vehicles) for the genes of the start shipping time for vehicles. Thus, a chromosome bit string consisting of 160 bits can be formed. The bit-string size of the chromosome depends on the problem size. The more numbers of vehicles (customers) are, the larger the bit-string size of the chromosome becomes.

4.3 Fitness Function

Fitness is calculated based on the objective function shown as Eq. (10). Usually the emphasis is placed on the objective of minimizing fleet size, but the tradeoff between fleet size and travel cost must be considered. For the fuzzy vehicle routing problem, besides these objectives, another three objectives must be considered: (1) maximizing the average grade of customer satisfaction, (2) minimizing total waiting time over vehicles, and (3) minimizing total delay time over vehicles. There are tradeoffs between objectives. Thus, the transportation problem can only be found with a compromise (*i.e.*, nearly optimal) solution for considering different objectives at the same time. It is easier for a dispatcher to acquire a best compromise solution by minimizing the overall cost of objectives. He/She can satisfy the bigger costs of objectives but sacrifice the smaller to minimize the overall cost. The cost coefficients $\rho_1 \sim \rho_5$ of objectives in Eq. (10) can be determined by the cost ratios of them to the overall cost based on cost estimates. For instance, based on the company's specific cost estimates, the contribution ratio for each of them is 0.6 for fleet size (*i.e.*, ρ_1), 0.25 for service satisfaction (*i.e.*, ρ_2), 0.05 for waiting time (*i.e.*, ρ_3), delay time (*i.e.*, ρ_4), and transportation distance (*i.e.*, ρ_5). Once the cost coefficients of objectives are determined through cost estimation, Eq. (10) can be conversed into a total cost measure function. The user can find the optimal (near optimal) solution by maximizing the fitness value.

4.4 Necessity to Set Constrained Conditions

Regarding genes of the generated chromosome, one should firstly check if none of the total loading weights (or volumes) of vehicles goes beyond the maximum loading capacity. Secondly, make sure each consumer is served by the same vehicle and only once. Thirdly, confirm each customer's demand is just completely provided. Finally, keep the service times of a vehicle for consumers at the range of $[e_i, l_i]$. These above-mentioned constrained conditions are illustrated in Table 1. If anything happens to violate the above-mentioned 1st, 2nd and 3rd cases, the fitness of the chromosome is set at "0" to prevent from occurring the bad evolution for the next other generations. As for the last case, when a vehicle arrives at a customer location before its earliest service time, it must wait (*i.e.*, a "waiting time" penalty) until the earliest service time. If the vehicle arrives at a customer location after its latest service time, an extra cost is imposed to penalize the solution. Therefore, there is a "waiting time" penalty function (*i.e.*, $1 - W$) and a “delay time” one (*i.e.*, $1 - DL$) included in the objective function shown as Equation 10 instead of directly setting the fitness at “0”. The service times for customers in the obtained solutions can eventually stay in the range of $[e_i, l_i]$ after generations. Thus, the solution acquired from evolutions can converge to fit into the practical application.

4.5 Experiment Results

Following the above-mentioned steps by using a binary coding method, we encode the unknown parameters. Through proceeding with the search mechanism of GA, we can decode and obtain the dispatching parameters for transportation, *i.e.*, $C_{11} \sim C_{48}$, $O_{11} \sim O_{48}$, and $T_{VH1} \sim T_{VH4}$. The basic setting of weights for the fitness function is given in Table 7. Fitness function simulation runs with the crossover, mutation, and reproduction operations under conditions of crossover probability, mutation probability, random seed, and initial population being set as 0.3, 0.033, 0.8 and 80 respectively.

Based on the above-mentioned basic GA settings, the weights of objective function (*i.e.*, Eq. (10)) are varied as shown in Table 7 to investigate how they impact on the final decision. Fig. 5 shows the simulation graph for the best fitness and average fitness of the 500 generations based on setting 1 in Table 7. There comes up with feasible solutions through the 103rd generation of GA. The other five weight settings (*i.e.*, setting 2 ~ 6) go quite the same as the 1st one.

Table 7. Various set weights for searching.

Settings	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5
1	**0.80**	0.05	0.05	0.05	0.05
2	0.05	**0.80**	0.05	0.05	0.05
3	0.05	0.05	**0.80**	0.05	0.05
4	0.05	0.05	0.05	**0.80**	0.05
5	0.05	0.05	0.05	0.05	**0.80**
6	**0.60**	**0.25**	0.05	0.05	0.05

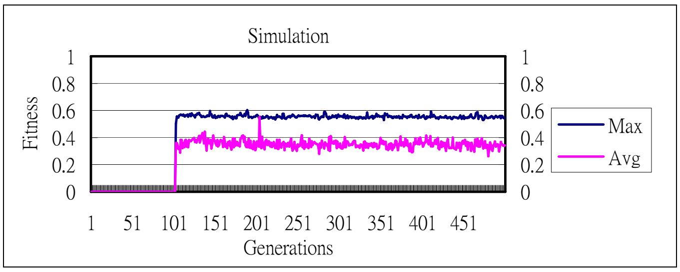

Fig. 5. Simulation results.

We experiment runs of simulation, there comes up with the same trend results. Table 8 shows the survey result for each setting over 5 runs of 500 generations. From setting 1 to setting 6, all of them can result in the expected outcomes. There is a bigger *U* value 0.5425 (*i.e.*, a better loading performance of the fleet) for setting 1, a bigger *S* one

Table 8. Searched results based on the set weights.

Settings	*U*	*S*	*W*	*DL*	*D*	Fitness
1	0.5425	0.0230	0.0596	0.0686	0.3909	0.5592
2	0.2625	0.1208	0.0590	0.0624	0.4393	0.2317
3	0.2633	0.0265	0.0000	0.0866	0.4214	0.8891
4	0.1833	0.0313	0.1229	0.0000	0.5094	0.8791
5	0.2294	0.0226	0.0662	0.1269	0.3429	0.6286
6	0.4000	0.0469	0.0939	0.2208	0.5333	0.3593

0.1208 (*i.e.*, a better service satisfaction) for setting 2, a smaller *W* one 0.0000 (*i.e.*, little waiting time for vehicles) for setting 3, a smaller *DL* one 0.0000 (*i.e.*, little delay time for vehicles) for setting 4, and a smaller *D* one 0.3429 (*i.e.*, a shorter path for delivery) for setting 5, and two bigger *U* and *S* ones 0.4000 and 0.0469 (*i.e.*, better loading performance and service satisfaction) for setting 6 respectively as expected. In general, it leads to some how changes for logistics when emphasizing on certain objectives. For instance, it leads to the increase of the total travel distance (*i.e.*, a bigger *D* value 0.3909) due to emphasis on the objective of good loading performance (*e.g.*, setting 1: $\rho_1 = 0.80$), the increase of the total travel distance (*i.e.*, a bigger *D* value 0.4393) due to emphasis on the service satisfaction (*e.g.*, setting 2: $\rho_2 = 0.80$). Emphasizing on the objective of total transportation distance (*e.g.*, setting 5: $\rho_5 = 0.80$) leads to the decrease of the grade of service satisfaction (*i.e.*, a smaller *S* value 0.0226) and the space utilization of the fleet (*i.e.*, a smaller *U* value 0.2294). All the above-mentioned results are well in accordance to experiment ones shown in Tables 7 and 8.

Based on the above-mentioned basic GA settings, the loading performance of the fleet, the service satisfaction, the waiting time for vehicles, delay time for vehicles, and total travel distance do be affected by specific set weights of objective function (*i.e.*, Eq. (10)) as shown in Table 7 to improve the respective values of *U*, *S*, *W*, *DL*, and *D* as illustrated in Table 8. However, it may not be very helpful in practice for a dispatcher to acquire an optimal (near optimal) solution by setting specific values for the parameters. For example, the fitness values for parameter settings in Table 8 are different from one another. The setting 3 (*i.e.*, $\rho_1 = \rho_2 = \rho_4 = \rho_5 = 0.05$, $\rho_3 = 0.80$) produces the best objective function value (fitness = 0.8891). Nevertheless it is hard to tell if it is a better solution than the other five because it produces a smaller *U* (= 0.2633) value and larger *DL* (= 0.0866) and *D* (= 0.4214) ones than those (*i.e.*, *U* = 0.5425, *DL* = 0.0686, and *D* = 0.3909) of the setting 1 (*i.e.*, $\rho_1 = 0.80$, $\rho_2 = \rho_3 = \rho_4 = \rho_5 = 0.05$). A conversion of the solution to a cost measure may be more direct and useful for the user.

The compensation between objectives for an additive form of the objective function (*i.e.*, Eq. (10)) is unavoidable during searching stage of GA. Based on the policy of "sacrifice the less valued to satisfy the more valued", the utmost profit (least cost) can be obtained as expected. The cost coefficients $\rho_1 \sim \rho_5$ of objectives can be determined by the cost ratios of them to the overall cost based on cost estimates. For instance, based on the company's specific cost estimates, the contribution ratio for each of them is 0.2 for fleet size (*i.e.*, ρ_1), 0.2 for service satisfaction (*i.e.*, ρ_2), 0.2 for waiting time (*i.e.*, ρ_3), 0.2 for delay time (*i.e.*, ρ_4), and 0.2 for transportation distance (*i.e.*, ρ_5). Once the cost coefficients of objectives are determined through cost estimation, Eq. (10) can be conversed

Table 9. A generated solution without tardiness.

Chromosome
0101010101001010001010010100111010101100011111000011100011100100010010011111 11011101111001010000100101011001101001100001001100010001000110100100000010 10010000000

VH_1								VH_2								VH_3								VH_4							
C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}	C_{28}	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	C_{37}	C_{38}	C_{41}	C_{42}	C_{43}	C_{44}	C_{45}	C_{46}	C_{47}	C_{48}
0	0	0	0	0	0	0	**1**	0	0	**1**	0	**1**	0	0	0	0	0	0	**1**	0	0	**1**	0	**1**	**1**	0	0	0	**1**	0	0
O_{1}	O_{12}	O_{13}	O_{14}	O_{15}	O_{16}	O_{17}	O_{18}	O_{21}	O_{22}	O_{23}	O_{24}	O_{25}	O_{26}	O_{27}	O_{28}	O_{31}	O_{32}	O_{33}	O_{34}	O_{35}	O_{36}	O_{37}	O_{38}	O_{41}	O_{42}	O_{43}	O_{44}	O_{45}	O_{46}	O_{47}	O_{48}
010	100	001	001	100	001	101	001	011	101	100	000	010	001	111	101	011	111	111	100	100	000	001	111	000	111	000	110	111	000	011	101
3	5	2	2	5	2	6	2	4	6	5	1	3	2	8	6	4	8	8	5	5	1	2	8	1	8	1	7	8	1	4	6
0	0	0	0	0	0	0	2	0	0	5	0	3	0	0	0	0	0	0	5	0	0	2	0	1	8	0	0	0	1	0	0

T_{VH_1}	T_{VH_2}	T_{VH_3}	T_{VH_4}
01001110	00101001	01001010	01010101
7.3412	3.8588	6.9647	8.0000

Fitness
0.5143

Weight left (kg)				Volume left (m^3)			
VH_1	VH_2	VH_3	VH_4	VH_1	VH_2	VH_3	VH_4
875	1220	1805	1515	4.8	5.2	12.0	9.1

Path			
Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
0→8→0	0 → 3 → 5 → 0	0 → 4 → 7 → 0	0→2→ 1→6→0

U	S	W	DL	D
0.1629	0.0156	0.1600	0.0000	0.4469

Initial population: 80 generations: 500 crossover: 0.3 mutation: 0.033 random seed:0.8

cost coefficients: $\rho_1 = 0.2$, $\rho_2 = 0.2$, $\rho_3 = 0.2$, $\rho_4 = 0.2$, $\rho_5 = 0.2$

into a total cost measure function. The user can find the optimal (near optimal) solution simply by maximizing the fitness value.

Table 9 illustrates a generated chromosome (*i.e.*, solution) without delivery tardiness (*i.e.*, $DL = 0$) after 5 runs of 500 generations based on setting cost coefficients $\rho_1 \sim \rho_5$ at 0.2 as above-mentioned. Its results live up to the required conditions without violating any of them shown in Table 1. There are four vehicles used for serving customers, vehicle 1 for customer 8, vehicle 2 for customer 3 and 5, vehicle 3 for customer 4 and 7, and vehicle 4 for customer 2, 1, and 6. The start shipping times for vehicle 1, 2, 3, and 4 are 7.3412 (*i.e.*, 07:20:28), 3.8588 (*i.e.*, 03:51:32), 6.9647 (*i.e.*, 06:57:53), and 8.0000 (*i.e.*, 08:00:00) respectively. Each vehicle visits its customers based on an average speed of 10 km/hr. For instance, it takes 0.8 hour (based on an average speed of 10 km/hr) for vehicle 2 to arrive at the location of customer 3 from the distribution center. By leaving at 03:51: 32 (*i.e.*, $T_{VH2} = 3.8588$) from the distribution center, the arrival time of vehicle 2 is 04:39:32 (= 3.8588 + 0.8), which is earlier than the earliest service time (*i.e.*, 10:00:00) of customer 3. Thus, there is a waiting time during vehicle 2 serving customer 3. Vehicle 2 has to wait until the earliest time (*i.e.*, e_3 = 10:00:00) of customer 3. The service time

Table 10. Results between GA-based method and currently used approach.

(1) GA-based Method	Fitness							
	0.5143							
	Weight left (kg)				Volume left (m^3)			
	VH_1	VH_2	VH_3	VH_4	VH_1	VH_2	VH_3	VH_4
	875	1220	1805	1515	4.8	5.2	12.0	9.1
	Path							
	Vehicle 1		Vehicle 2		Vehicle 3		Vehicle 4	
	0 → 8 → 0		0 → 3 → 5 → 0		0 → 4 → 7 → 0		0 → 2 → 1 → 6 → 0	
	U	*S*	*W*	*DL*	*D*			
	0.1629	0.0156	0.1600	0.0000	0.4469			
(2) Currently Used Method (based on dispatcher's experiences)	Fitness							
	?							
	Weight left (kg)				Volume left (m^3)			
	VH_1	VH_2	VH_3	VH_4	VH_1	VH_2	VH_3	VH_4
	1000	1500	2000	910	6	8	14	3.1
	Path							
	Vehicle 1		Vehicle 2		Vehicle 3		Vehicle 4	
	0→?→….→ 0		0→?→…. → 0		0→?→…. → 0		0→?→…. → 0	
	U	*S*	*W*	*DL*	*D*			
	?	?	?	?	?			

Initial population: 80 generations: 500 crossover: 0.3 mutation: 0.033 random seed: 0.8
cost coefficients: $\rho_1 = 0.2$, $\rho_2 = 0.2$, $\rho_3 = 0.2$, $\rho_4 = 0.2$, $\rho_5 = 0.2$

that to unload and load the cargo at each customer isn't taken into account in this paper. After finishing serving customer 3, vehicle 2 launches at 10:00:00 to serve customer 5. It takes 0.5 hour to reach there. The arrival time is 10:30:00, which is earlier than the earliest service time (*i.e.*, e_5 = 13:00:00). A waiting time occurs during vehicle 2 serving customer 5 as well. The results show it has a fitness of 0.5143 and values of *U*, *S*, *W*, *DL*, and *D* as 0.1629, 0.0156, 0.1600, 0.0000, and 0.4469 respectively. There is no delivery tardiness during serving customers for vehicles.

If the dispatcher is not yet satisfied with them after 500 generations, he can just reset, say at 1000, the generations. The same (but not necessary to be the same) initial population, crossover probability, and mutation probability of 80, 0.3, and 0.033, respectively, remain, and he/she can then run the system again to search for another combination of bit strings. He/She expects that there is a chromosome with a better fitness value for a better dispatching way for transportation.

Table 10 shows the results between the GA-based method and the current approach used by the company for the problem illustrated in Table 1. The company currently used method firstly mainly focuses on maximizing the loading performance of the fleet (*i.e.*, lessening the number of vehicles in use as much as possible) and then tries to adjust the spare vehicle available to meet the other objectives by trial and error based on the dispatcher's expertise and experiences. Besides maximizing the space utility, there are targets, which need taking into account such as to maximize customers' service satisfactions and to minimize the waiting time, delay time, and transportation distance. Based on the consideration of maximizing the space utility, all the required commodities for customer 1 ~ 4, whose total amount of weight (volume) is 1,090 kg (10.9 m^3), can be loaded on a single vehicle, *e.g.*, vehicle 4 (F_4 = 2,000 kg (14 m^3)) without violating the limited weight (volume) capacity of the vehicle. Next, the dispatcher has to consider distributing certain customer's commodities to the spare vehicles available so as to meet the demands from the other objectives. There are so many alternatives (the question mark in Table 10) for the dispatcher to determine. In other words, it is extremely hard for a dispatcher to deal with because there is a variety of compromised solutions can be found. However, with the assistance of this developed GA-based system, there are many sets of feasible solution, consisting of parameters (*i.e.*, $C_{11} \sim C_{48}$, $O_{11} \sim O_{48}$, and $T_{VH1} \sim T_{VH4}$) obtained in a short time for the dispatcher to make decision much easier than ever during exploring feasible dispatching strategy. Through selecting the solutions with larger fitness values but without service tardiness from the evolved chromosome, a dispatcher can obtain several feasible solutions to refer. The preset dispatching goal without violating all constrains can be achieved. Besides, the dispatcher can be free from conflicting with the limit of maximum capacity in weight and volume of vehicle during dispatching process. Furthermore, in case none of them satisfies the dispatcher, he/she can still continue proceeding with the GA for another generation until there comes up with a feasible one.

5. CONCLUSIONS

In this study, we have successfully set up a searching mechanism based on pure genetic algorithm without any post-processing for efficiently finding appropriate combination sets of the transportation parameters including, space utility, service satisfaction, waiting time, delay time, and transportation distance applied in vehicle dispatching. The searching mechanism is of a promising performance of searching capacity to facilitate a dispatcher to obtain feasible solutions consisting of dispatching parameters. With this developed system, a dispatcher can efficiently obtained several feasible solutions to refer based on setting determined weights of object function. Thus, the complex logistics dispatching problem, existing multi-objectives to meet under constraints, can be more easily solved. This study demonstrates the GA methodology a promising way to promote the efficiency of transportation in a practical application.

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