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A PLANT GROWTH SIMULATION ALGORITHM FOR DYNAMIC VEHICLE SCHEDULING PROBLEM WITH TIME WINDOW

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Abstract. *We are concerned with dynamic vehicle scheduling problem with time window (VSPTW). Based on practical situations that outsourcing vehicles are limited, delivery staff often work overtime and customer demand is random, a dynamic model based on the time axis is established to minimize the total delivery cost, that is, in this work we extend the classical VSPTW to a dynamic vehicle scheduling problem with time windows. In addition, the plant growth simulation algorithm (PGSA) is designed to solve the formulated dynamic VSPTW. Finally, with a specific example, the designed PGSA is compared with the genetic algorithm. Comparison results show that the algorithm can not only obtain the optimum solution but also improve the efficiency.*
Keywords: Dynamic vehicle scheduling problem with time windows, Plant growth simulation algorithm, Outsourcing vehicles, Overtime delivery

1. **Introduction.** Vehicle scheduling problem (VSP) was first proposed by Dantzig and Ramser in 1959 [1], which is an important task at logistics delivery centers. In the contemporary world, with the development of social economy and the enhancement of information techniques, the information content in logistics will grow increasingly and change with the varying customer demand. Thus, dynamic vehicle scheduling problem with time windows (DVSPTW) is an important development of vehicle scheduling problem, which has attracted attention in latest VSP literature. In order to implement the research into the real-world operations, it is necessary to consider more actual situations to extend the dynamic VSPTW for improving practical delivery systems.

Since dynamic travelling salesman problem (TSP) [2] was put forward, scholars have made a lot of research on dynamic VSP. Huisman et al. [3] proposed a robust solution that used new mathematical formulations for the VSP problems. Xiao and Konak [4] studied the time-dependent vehicle routing & scheduling problem with CO_2 emissions optimization (TD-VRSP-CO_2). Monroy-Licht et al. [5] considered adjustments to the initial routes and presented a rescheduling arc routing problem. Han et al. [6] integrated appointment scheduling with vehicle routing problem with soft time windows to deal with attended home deliver with no-show and random response time. Ghannadpour et al. [7] proposed a multi-objective VSP model where the total number of required vehicles, the total travel distance and the vehicle waiting time were minimized, and the total customers' service satisfaction was maximized. Mandziuk and Swiechowski [8] considered the traffic jams to formulate a dynamic version of the capacitated vehicle routing problem and applied the upper confidence bounds applied to trees method for solving the problem. Zhang et al. [9] analyzed the recovery transport links of industrial waste recycling, built a vehicle scheduling optimization model, and used ant colony optimization algorithm to achieve good results. As we can see, extant studies have made a lot of efforts on solving DVSP. The dynamic conditions involve change of delivery demand, uncertain travelling time and damaged delivery vehicles. Since DVSP is an NP-hard problem, corresponding heuristic algorithms such as genetic algorithm [4] and intuitive heuristic dynamic programming [6] are designed to solve the DVSP models. However, in response to these dynamic conditions, not all the customers are in the same urgency degree which depends on various factors such as customers' time sensitivity. Thus, one difference of this work over the above related studies is that we consider the customers with dynamic requests are with different priorities. In the proposed model, a set of dynamic requests is received over time, and the planner does not have any information regarding their locations and sizes until they arrive. Moreover, the routing model aims to satisfy different customers according to their specific time windows which are predefined by an expert as being very important, casual or unimportant.

The plant growth simulation algorithm (PGSA) is a kind of intelligent optimization algorithm which was proposed by Li et al. in 2005 to solve the nonlinear integer programming problem [10]. Because the PGSA is simple and easy to determine the parameters, it has a good application prospect and has been applied in the field of engineering and technology. Wang and Cheng [11] compared the PGSA with other optimization algorithms in transmission network planning, whose results showed that the PGSA can produce the best solutions. In Bhattacharjee et al.'s paper [12], the nature-inspired PGSA has been applied to optimizing the image processing technique of object localization in leukocyte images. Li et al. [13] presented a nonlinear programming model based on PGSA. Zhou et al. [14] presented another version of plant growth computing algorithm and applied it into path planning.

Scholars also have gradually established a variety of dynamic vehicle routing models such as VSP based on the probability of network changes and time-dependent VSP. At the same time, some optimization methods based on A-priori optimization and real-time optimization are proposed. However, the delivery tasks in practical companies often fluctuate, and decision-makers do not tend to buy more vehicles or recruit more delivery staff to deal with temporary task increases. Some common measures are often taken, such as outsourcing additional delivery tasks to external vehicles and letting internal drivers work overtime. Thus, we should not only study the single DVSPTW model caused by the uncertainty of demand prediction but also consider some uncertain factors affecting the model, including vehicle outsourcing services, drivers working overtime, and so on. Meanwhile, in this paper the PGSA is adopted with the advantages that the adaptive optimization model and parameter determination of simulated plants to light source are very simple and it is easy to establish the randomness of dynamic models. In one previous work [15], authors also applied PGSA algorithm into the DVSP problem. In comparison with [15], two different contributions are made in our work. First, we present a different idea to deal with dynamic requests, that is, we introduce time axis and key points into the optimization model of DVSP; second, the objective and constraints considered are different.

In sum, this paper is based on the research of DVSPTW, aiming at dealing with the situation with service outsourcing, work overtime, and dynamic customer points. A cost optimization model is established with the objective of minimizing the total delivery cost. We also make full use of the advantages of the PGSA in solving combinatorial optimization problems and the ability of global optimization, and design a PGSA for the formulated DVSPTW. Finally, an example is given to compare the results of PGSA and genetic algorithm.

The rest of the work is organized as below. Section 2 presents the problem and mathematical model. Section 3 gives the designed PGSA. In Section 4, comparison results are given to show the effectiveness and advantage of our work. Section 5 concludes the work with some future research directions.

2. **Problem Description and Mathematical Model.**

2.1. **Problem description.** VSPTW can be described as below. Given a number of customers and limited service vehicles at the delivery center, let vehicles start from the center, serve the customer points orderly, and finally return to the center, so that the total transportation cost is minimal. Based on practical situations, some constraint conditions are as follows:

a) Site constraint: Every vehicle should start from the delivery center and must return to the center after completing its delivery task;

b) Capacity constraint: The sum of all customers' demand on each delivery route should not exceed the load of the vehicle;

c) Time window constraint: The vehicle should start the service between the earliest start time and the latest start time requested by each customer;

d) Access uniqueness constraint: Each customer should be served only by one vehicle and can only be served once;

e) Considering the limitation of the number of vehicles at the center and the requirement of overloaded delivery tasks, outsourcing vehicles and delivery personnel overtime are allowed in the work.

DVSPTW means that: In the process of the initial scheduling operation, because of the emergence of new demands, scheduling system needs to change the original routes or rearrange the routes to deal with dynamic customers. In order to solve DVSPTW, we introduce two related concepts: time axis and key points, as Figure 1 shows.

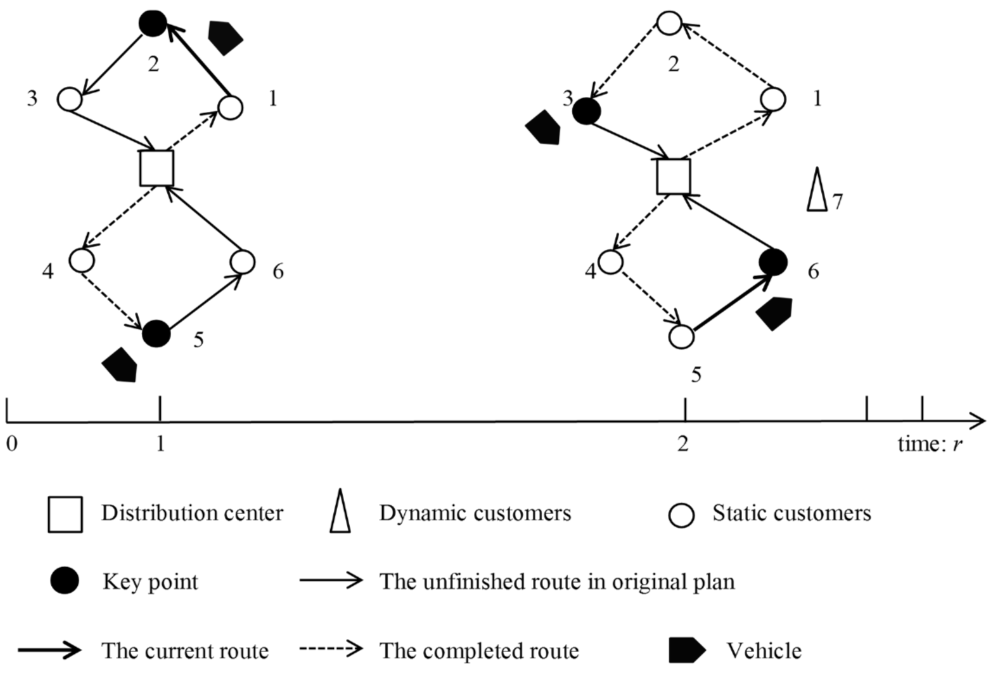


Figure 1. Schematic diagram of time axis and key points

In the dynamic scheduling system, it is possible to build the scheduling cycle such as a working day into a time axis. The time when the new customer is requested is denoted as r. Since the information on the dynamic customer point and the static customer point at time r is known, the dynamic model can be represented by its corresponding static model SubM(r).

At time r, according to the locations of all vehicles, the demand information can be divided into 4 categories: a) The completed customer points; b) The customer points being served or to whom delivery vehicles are on the way; c) Unfinished customer points; d) New customer points. The customers in the c) category cannot be changed in the task, so this kind of points are called as the key points of the sub model, such as customers 2 and 5 at time 1, and customers 3 and 6 at time 2 in Figure 1. As we can see, we can establish a series of static sub models in the time axis to represent the dynamic problems. Global positioning system (GPS) can be used to obtain the real-time locations of vehicles and geographic information system (GIS) can provide the road network information, so we can use GPS and GIS techniques to identify the key points at each time r.

2.2. **Mathematical model.** In order to help readers clearly check and understand the mathematical model, we first give out the notation list used in the following text:

$N_{c(r)}$ is a set of all the key points at time r;

$N_{c0(r)}$ is a set of all the key points and the delivery center at time r;

$N_{u(r)}$ is a set of all the unfinished customer points and new customer points at time r;

$N_{u0(r)}$ is a set of all unfinished customer points, new customer points and the delivery center at time r;

$N_{cu0(r)}$ is a set of all the key points, unfinished customer points, new customer points and the delivery center at time r;

K is the total number of vehicles to complete all the demands;

Q is the maximum load of each vehicle;

$Q_{ik(r)}$ is the cumulative load of vehicle k when departing from customer point i at time r (If the vehicle starts from the delivery center, $Q_{0k(r)} = 0$);

q_i is the demand of customer point i;

t_i is the time when the vehicle reaches to customer point i;

s_i is the service time at customer point i;

T_{ij} is the travel time from customer point i to customer point j;

$[E_i, L_i]$ is the time window of customer point i, where E_i means the earliest start time and L_i means the latest start time;

α is the driving cost per unit time;

β is the vehicle waiting cost per unit time;

CR_k is the regular labor cost per unit time for vehicle k;

CO_k is the overtime labor cost per unit time for vehicle k;

CF_k is the fixed cost for vehicle k;

CF_{ok} is the fixed cost for outsourced vehicle k;

T_{sk} is the departure time of vehicle k from the delivery center;

T_{ok} is the return time of vehicle k to the delivery center;

TO_k is the overtime of vehicle k, $TO_k = \max(T_{ok} - T_{sk} - 8, 0)$;

TR_k is the regular work time of vehicle k, $TR_k = \min(T_{ok} - T_{sk}, 8)$;

The definition of two binary variables is as below:

$$x_{ijk} = \begin{cases} 1, & \text{Vehicle } k \text{ is from customer point } i \text{ to customer point } j; \\ 0, & \text{Vehicle } k \text{ is not from customer point } i \text{ to customer point } j. \end{cases}$$

$$y_{ik} = \begin{cases} 1, & \text{Vehicle } k \text{ serves customer point } i; \\ 0, & \text{Vehicle } k \text{ does not serve customer point } i. \end{cases}$$

Then, the sub model SubM(r) at time r is obtained as follows. The optimization objective of the model is to minimize the total delivery cost, that is,

$$\begin{aligned} f(x_{ijk}, y_{ik}) = \min \Bigg(& \alpha \sum_{i \in \mathrm{N}_{cu0(r)}} \sum_{j \in \mathrm{N}_{u0(r)}} \sum_{k=1}^{K} x_{ijk} T_{ij} + \beta \sum_{i \in \mathrm{N}_{cu(r)}} \max(\mathrm{E}_i - t_i, 0) \\ & + \sum_{k=1}^{K} CF_k y_{ik} + \sum_{k=k_{y+1}}^{K} CF_{ok} y_{ik} + \sum_{k=1}^{K} CR_k TR_k + \sum_{k=1}^{K} CO_k TO_k \Bigg) \end{aligned} \tag{1}$$

where the first item $\alpha \sum_{i \in \mathrm{N}_{cu0(r)}} \sum_{j \in \mathrm{N}_{u0(r)}} \sum_{k=1}^{K} x_{ijk} T_{ij}$ is the total vehicle travel cost for all the customer points, the second item $\beta \sum_{i \in \mathrm{N}_{cu(r)}} \max(\mathrm{E}_i - t_i, 0)$ is the total vehicle waiting cost, the third item $\sum_{k=1}^{K} CF_k y_{ik}$ is the fixed cost for regular vehicles, the fourth item $\sum_{k=k_{y+1}}^{K} CF_{ok} y_{ik}$ is the fixed cost for outsourced vehicles where k_{y+1} denotes the first outsourced vehicle, the fifth item $\sum_{k=1}^{K} CR_k TR_k$ is the total regular labor cost, and the sixth item $\sum_{k=1}^{K} CO_k TO_k$ is the total overtime labor cost.

The constraints of the model are as below:

$$\sum_{i \in N_{u0(r)}} \sum_{j \in N_{c(r)}} x_{ijk} = 1, \quad k = 1, 2, \ldots, K \tag{2}$$

$$\sum_{i \in \mathrm{N}_{c(r)}} \sum_{j \in \mathrm{N}_{u0(r)}} x_{ijk} = |N_c|, \quad k = 1, 2, \ldots, K \tag{3}$$

$$\sum_{i \in \mathrm{N}_{u(r)}} x_{ijk} = \sum_{i \in \mathrm{N}_{u(r)}} x_{jik} = y_{ik}, \quad j \in N_{u(r)}, \quad k = 1, 2, \ldots, K \tag{4}$$

$$\sum_{k=1}^{K} y_{ik} = 1, \quad i \in N_{u(r)} \tag{5}$$

$$\sum_{i \in \mathrm{N}_{cu(r)}} q_i y_{ik} \le Q - Q_{jk(r)}, \quad j \in N_{c0(r)}, \quad k = 1, 2, \ldots, K \tag{6}$$

$$E_i \le t_i \le L_i, \quad i \in N_{cu0(r)} \tag{7}$$

In the above, constraints (2) and (3) guarantee only one vehicle starts from each key point and the vehicle finally goes back to the delivery center after completing its remaining task (The function $|N_c|$ returns the number of elements in the set N_c); constraint (4) is the flow balance which means the vehicle to one customer point should leave from the customer point; Formula (5) guarantees the access uniqueness constraint: each customer point can only be served by one vehicle and can only be served once; Formula (6) guarantees the capacity constraint: the sum of all customers' demand on each path should not exceed the load capacity of each vehicle; Formula (7) guarantees the time window constraint: the access time to each customer point should fall into its time window.

3. **The Designed PGSA.** In recent years, intelligent algorithms have made great achievements in solving VSPTW. PGSA is a kind of intelligent optimization algorithm based on the mechanism of plant growth response to light. Because the algorithm is simple and has a good application prospect, it has been applied in many engineering fields such as power network planning [11], medical image localization [12], and path planning [13].

3.1. **Plant growth mechanism.** The plant can be regarded as a system consisting of a large number of branches and nodes. The way to simulate the growth of plants is to describe, analyze and develop the formal language which is called L-system [16].

In order to better carry out the photosynthesis of plants in the growth process, plants must get enough sunshine and strive upward to produce more branches and leaves, which need increase the contact surface area with the sun as large as possible. In the process of plant growth, the general state of the plant shows properties of the fractal theory. The plant growth process and characteristics of L-system are as follows:

a) A stem firstly emerges whose some sections (called growth points) break out into new branches;

b) Most of the branches grow out new branches, and this behavior repeats;

c) Different branches have similarity to each other, and the whole plant has the self-similar structure.

Based on the above plant growth characteristics, the mechanism of plant growth is simulated from the mathematical view. Let the trunk length of a tree be M and the branch length of the tree be m; There are K growth nodes on the trunk, that is, $S_M = (S_{M1}, S_{M2}, \ldots, S_{Mk})$ whose corresponding morphactin concentration set is $P_M = (P_{M1}, P_{M2}, \ldots, P_{Mk})$; There are q growth nodes on the branch, that is, $S_m = (S_{m1}, S_{m2}, \ldots,$ $S_{mq})$ whose corresponding morphactin concentration set is $P_m = (P_{m1}, P_{m2}, \ldots, P_{mq})$. The morphactin concentration of each growth nodes on the trunk and branch is:

$$P_{Mi} = \frac{f(x_0) - f(S_{Mi})}{\sum\limits_{i=1}^{K} (f(x_0) - f(S_{Mi})) + \sum\limits_{j=1}^{q} (f(x_0) - f(S_{mj}))} \tag{8}$$

$$P_{mj} = \frac{f(x_0) - f(S_{mj})}{\sum\limits_{i=1}^{K} (f(x_0) - f(S_{Mi})) + \sum\limits_{j=1}^{q} (f(x_0) - f(S_{mj}))} \tag{9}$$

In Formulas (8) and (9), x_0 is the root point (initial base point) and $f(*)$ is environmental information function (objective function). Smaller objective function value means the environment of the corresponding node is better, so this node will grow into a new branch in bigger chance.

Formulas (8) and (9) show that the morphactin concentration of each growth node is determined by the relative position of each node to the root of the tree and the environmental conditions of the position. This model describes the relationship between the morphactin concentration of growth nodes and the corresponding environmental conditions, which is consistent with the formation mechanism of the plant cell. From Formulas (8) and (9), we can get:

$$\sum_{i=1}^{K} \sum_{j=1}^{q} (P_{Mi} + P_{mj}) = 1 \tag{10}$$

We can use computers to generate random numbers between $[0, 1]$. If the random number falls into a state space $(P_1, P_2, \ldots, P_{K+q})$, corresponding growth node will get the preferential right to grow. After a new branch comes out, the morphactin concentration of all growth nodes will change. The calculation formula will update with the consideration of the new branch and the removal of the corresponding growth node until no new trunks or branches are produced.

3.2. **Simulation steps of plant growth algorithm.** Based on the dynamic vehicle scheduling model, the objective function is to minimize the total delivery cost, the control variable is a multi-dimensional column vector of all conditional routes, and the constraint conditions are processed as follows: The possible solutions are verified in turn using the constraints such as vehicle load, travel distance and time window; The solutions meeting the constraints are retained and others are deleted directly. Thus, the plant growth simulation algorithm is used to solve the dynamic vehicle scheduling problem using the following steps.

Step 1: Determining the initial delivery routes (the root) x_0. Using the natural number coding method, we can generate the random code string. Then, the objective function value corresponding to the initial delivery scheme can be obtained, that is, $f(x_0)$. At this step, the optimal solution and the corresponding objective function value are $x_{\min} = x_0$ and $f_{\min}(x_{\min}) = f(x_0)$, respectively.

Step 2: Generating new growth nodes. Using x_0 as the basis, the 2N neighborhood search is used to generate new growth nodes. Then, the constraints of new growth nodes are verified, and the delivery routes that do not satisfy the constraint conditions are deleted.

Step 3: Updating the current optimal solution. The function value of each growth node is obtained and compared with the function value of the initial solution $f(x_0)$. Thus, the nodes whose objective function values are greater than $f(x_0)$ are further removed, and the remaining new growth nodes are merged into the growth node set. The minimum objective function value among the new growth nodes is compared with $f_{\min}(x_{\min})$, and if this value is smaller than $f_{\min}(x_{\min})$, then replace $x_{\min}$ and $f_{\min}(x_{\min})$.

Step 4: Inputting the dynamic information. The whole time axis is divided into a number of time periods, and all dynamic customer points at each time period are inserted into the growth node set.

Step 5: Calculating the morphactin concentrations. Using (8) and (9), we can get the morphactin concentrations of all the growth nodes in the current growth node set.

Step 6: Selecting next growth nodes. A probability space of $[0, 1]$ is established, and the growing node is selected based on the random number randomly generated by the computer.

Step 7: Repeating Step 2-Step 6 until no new growth nodes are generated or the number of iterations is reached.

The above procedure is shown in Figure 2.

4. **Application and Results.** We take a logistics company's delivery tasks and the time constraints of customer points as the example to solve the model. The detailed situation is as below: The delivery center is located at O; There are two owned vehicles and two outsourcing vehicle with a maximum load of 8 tons; The fixed cost for each owned vehicle is 150 yuan, and the fixed cost for each outsourcing vehicle is 200 yuan; The regular labor cost is 15 yuan per hour, and the overtime labor cost is 30 yuan per hour; The time window of the delivery center is $[0, 12]$; There are eight fixed customer points and two dynamic customer points on one day; The demand q_i, service time S_i, and time window $[E_i, L_i]$ of each customer point, and customer occurrence time r are shown in Table 1; Vehicle travel time T_{ij} (unit: hour) among customer points and the distribution center are shown in Table 2; Vehicle driving cost α is 50 yuan per hour, and waiting cost β is 20 yuan per hour.

Using Matlab 2015 to achieve the above algorithm, a notebook computer with Intel (R) Core (TM) I5-7200U CPU and 8GB memory is used to simulate the designed PGSA for the above case. We run the algorithm 80 times and the average running time is 10.6s. The minimum cost of serving all the above customer points is 2076.93 yuan, and the optimal delivery needs 4 vehicles as Figure 3 shows where Figure 3(a) represents a static solution and Figure 3(b) is the dynamic solution. In both the static solution and the dynamic one,

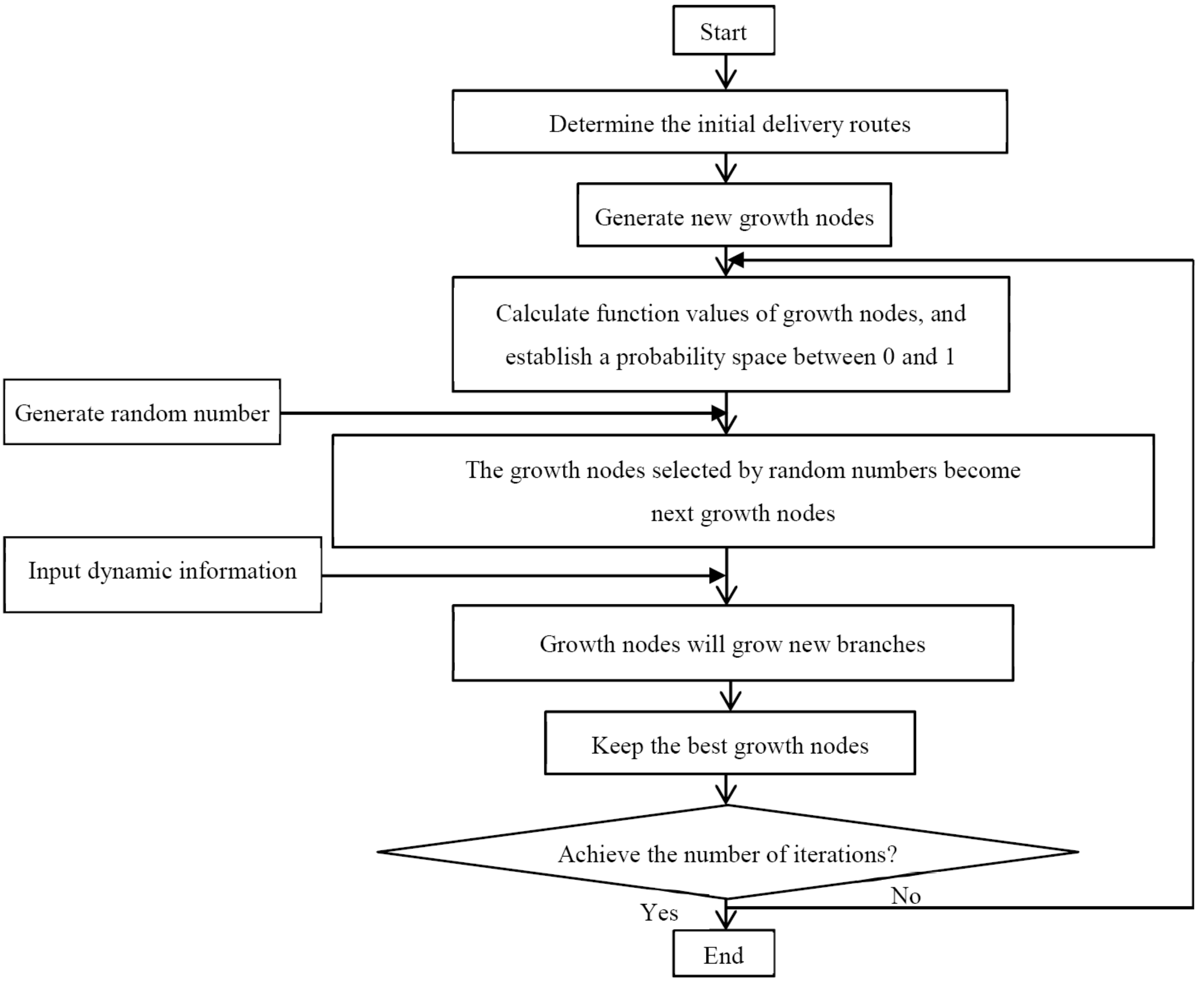


Figure 2. The flow of PGSA

Table 1. Customer point attributes

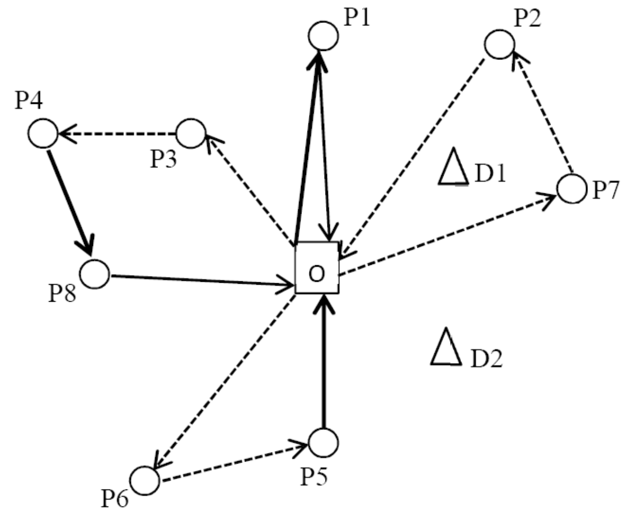
Customer point	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	D_1	D_2
q_i	2.0	1.5	4.5	1.5	2.5	3.0	4.0	3.0	2.5	1.5
S_i	1.0	2.0	1.0	2.0	3.0	0.8	2.5	3.0	1.0	2.0
$[E_i, L_i]$	$[1, 4]$	$[4, 6]$	$[1, 2]$	$[3, 5.5]$	$[5, 8]$	$[1.5, 4]$	$[2, 5]$	$[4, 7]$	$[5.5, 7]$	$[6.5, 8]$
r	0	0	0	0	0	0	0	0	2	4

four vehicles, that is, two owned vehicles and two outsourcing vehicles, are used. By the comparison, we can see the dynamic solution has a higher efficiency of vehicles.

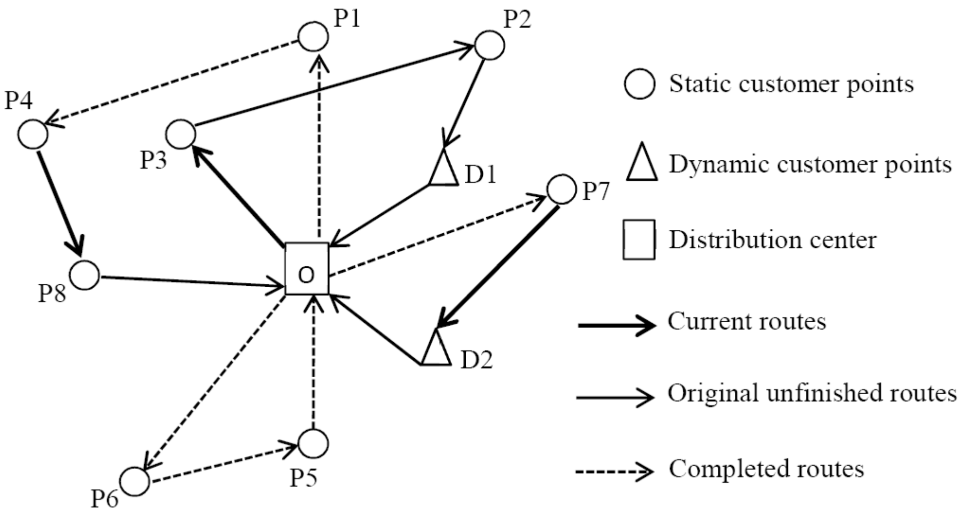
To further analyze the performance of PGSA, we compare the computational results of PGSA with traditional genetic algorithm (GA) [17]. The GA is set with population size being 30, crossover rate being 0.6 and the mutation rate being 0.05. The GA used the same constraint conditions and computer configuration to calculate, which ran 80 times with the average search time being 56.08s. The average minimum cost to complete all the customers is 2202.84 yuan, using 5 vehicles, as Figure 4 shows. Figure 4(a) represents the static results, and Figure 4(b) represents the dynamic results. By comparing the dynamic solution by GA with that by PGSA, we can see one more vehicle has to be used in the solution by GA. This additional vehicle also results in the increase of total delivery cost,

TABLE 2. Travel time among customer points and the delivery center T_{ij}

Customer point	O	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	D_1	D_2
O	0	0.8	1.2	1.5	4.0	3.2	1.6	2.0	1.8	0.6	2.0
P_1	0.8	0	1.3	0.8	1.0	2.2	2.0	1.5	2.0	1.0	1.8
P_2	1.2	1.3	0	1.5	2.0	1.5	1.5	1.5	2.0	1.0	1.0
P_3	1.5	0.8	1.5	0	1.0	1.8	3.0	1.8	2.0	1.5	1.5
P_4	4.0	1.0	2.0	1.0	0	2.0	1.5	2.0	1.5	2.5	2.0
P_5	3.2	2.2	1.5	1.8	2.0	0	1.8	1.5	1.4	0.8	1.6
P_6	1.6	2.0	1.5	3.0	1.5	1.8	0	2.0	2.0	1.2	2.0
P_7	2.0	1.5	1.5	1.8	2.0	1.5	2.0	0	1.5	1.4	0.8
P_8	1.8	2.0	2.0	2.0	1.5	1.4	2.0	1.5	0	2.5	2.0
D_1	0.6	1.0	1.0	1.5	2.5	0.8	1.2	1.4	2.5	0	3.0
D_2	2.0	1.8	1.0	1.5	2.0	1.6	2.0	0.8	2.0	3.0	0



(a) The static solution



(b) The dynamic solution

FIGURE 3. The optimal delivery routes by our PGSA

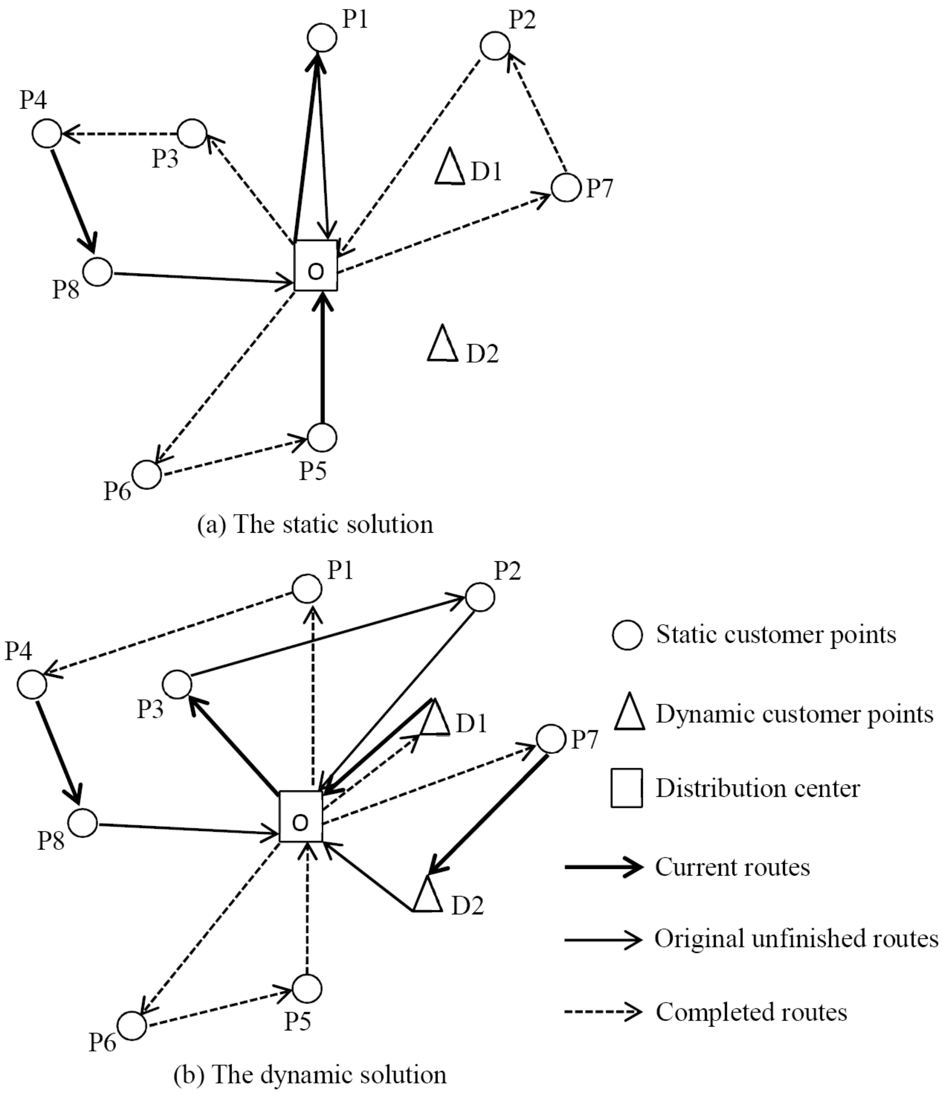


Figure 4. The optimal delivery routes by GA

that is, from 2076.93 yuan by our PGSA to 2202.84 by GA. These comparisons show the advantage of our PGSA over GA.

From the comparison in Table 3, we can find that our PGSA has higher efficiency than traditional genetic algorithm, and can converge to the global optimal solution in a relatively short time. PGSA avoids the disadvantages of premature and slow convergence problems which often occurred in genetic algorithm, and can quickly obtain the optimal solution for dynamic vehicle scheduling problem with time window, as Figure 5 shows. The in-depth reason of the advantage is that it is easy to determine the parameter of the PGSA algorithm, while GA algorithm involves more parameters such as selection and mutation operators.

5. **Conclusions.** Based on the analysis of dynamic vehicle scheduling problem, we used the plant growth simulation algorithm to solve dynamic vehicle scheduling problem with time window. The practical application results show that the PGSA algorithm can effectively solve the dynamic vehicle scheduling problem with time window. Therefore, the plant growth simulation algorithm has important influence and practical value for the optimization of logistics distribution system.

Table 3. The comparison results of PGSA and GA

Algorithm	Delivery routes	Total cost (yuan)	Average search time (s)
PGSA	O→P3→P2→D1→O O→P1→P4→P8→O O→P6→P5→O O→P7→D2→O	2076.93	10.06
GA	O→P3→P2→O O→P1→P4→P8→O O→P6→P5→O O→P7→D2→O O→D1→O	2202.84	56.08

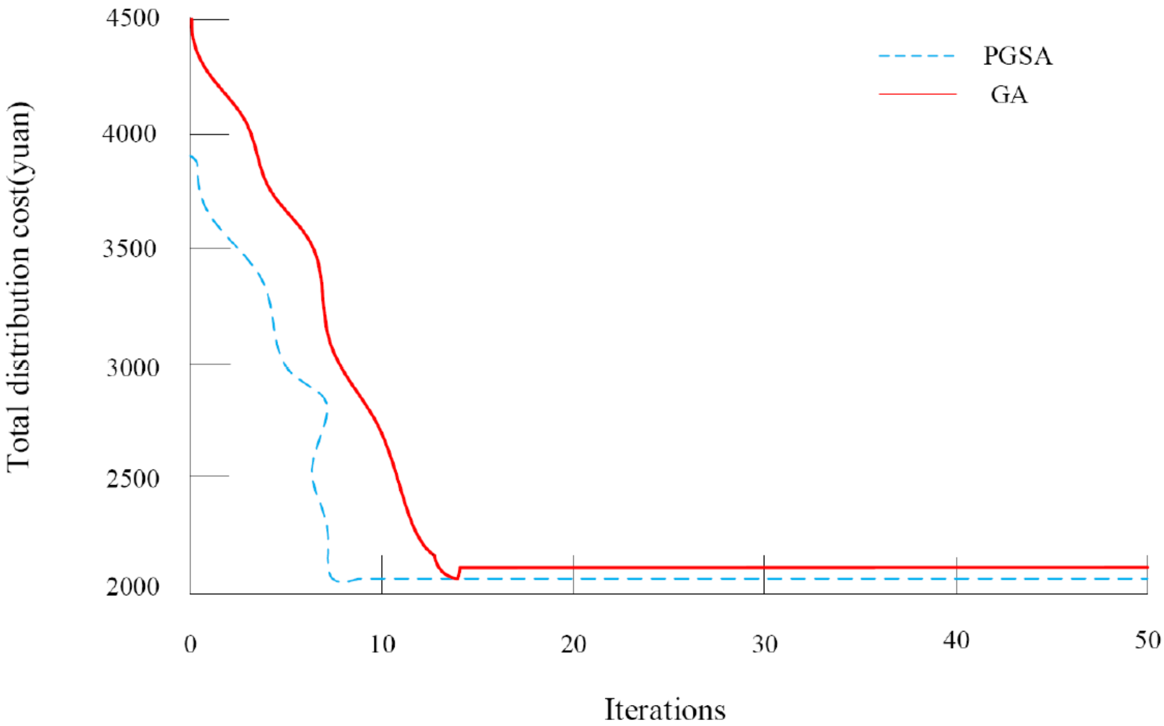


Figure 5. The convergence process of PGSA and GA

Based on the dynamic vehicle scheduling model, a plant growth simulation algorithm is designed and compared with the traditional genetic algorithm. Compared with the genetic algorithm, the plant growth simulation algorithm can process the objective function and constraints separately. There is no penalty coefficient, crossover rate and mutation rate, and the solution has good stability, which can quickly search for the optimal solution and effectively solve the vehicle scheduling problem.

Future research directions can focus on extending the work into more complicated situations such as the vehicle scheduling problem with fuzzy time window and the vehicle scheduling problem with uncertain travel time.

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