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Article

Optimization of electric vehicle distribution routes for multiple distribution centers based on biomechanic principles and improved Plant Growth Simulation Algorithm (PGSA)

Xingyao Zhou[1], Fujun Wan[1,*], Qiaohui Wang[1], Zhongyu Li[2]

[1] China National Institute of Standardization, Beijing 100193, China
[2] Talent Development Institute of Shandong High-speed Group Co., Ltd, Jinan 250000, China
*** Corresponding author:** Fujun Wan, wanfujun@126.com

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Abstract: This study focuses on the optimization of electric vehicle delivery routes for multiple distribution centers, proposing a dynamic route optimization model based on an improved Plant Growth Simulation Algorithm (PGSA). Inspired by the growth mechanisms of plants in nature, PGSA simulates the growth behavior of plants under light and resource distribution. According to the knowledge of molecular and cellular biomechanics, the growth process of plants can be seen as a series of mechanical and biological responses. By simulating this growth behavior, PGSA optimizes path selection through phototropism and resource acquisition, providing novel insights for the design of electric vehicle delivery routes. This paper enhances PGSA by introducing a variable step-size search mechanism, simulating the pattern of plant branches growing from long to short, gradually narrowing the search scope to improve search efficiency. Simultaneously, it randomly rearranges auxin concentration to mimic the dynamic changes in hormone concentration at plant growth points, enhancing search diversity and avoiding local optima. Through simulation experiments, the improved PGSA significantly reduces computation time and iteration counts when solving large-scale dynamic route optimization problems for multiple distribution centers, offering an efficient and intelligent solution for electric vehicle delivery route optimization. By integrating biological principles with optimization algorithms, this study not only expands the application domain of PGSA but also lays the foundation for further research on bio-inspired algorithms in logistics optimization.

Keywords: multiple distribution centers; dynamic route optimization; plant growth simulation algorithm; phototropism; bio-inspired algorithm

1. Introduction

With the rapid development of industry, global climate issues have become increasingly prominent, and the strategy of energy transformation has gained depth. Issues such as low carbon, energy conservation, and environmental protection have attracted widespread attention. In 2021, China proposed building a new power system centered on renewable energy. Using electric vehicles for logistics and distribution has become the direction and trend of future logistics development. Electric vehicles have low energy consumption and low noise, but they are greatly constrained by long charging times and the current shortage of charging stations. How to reasonably dispatch electric vehicles has become a hot topic of discussion [1,2]. In the context of increasingly severe global climate issues, countries are taking energy transition strategies to reduce greenhouse gas emissions and dependence on fossil fuels. Electric vehicles, as low-carbon and environmentally friendly transportation tools, can not only improve delivery efficiency but also effectively reduce carbon emissions. In 2023, China's oil imports reached approximately 564 million tons, with an import value of 337,494 billion US dollars, of which 94% of gasoline consumption is used by passenger vehicles. China's high dependence on oil urgently requires promoting electric vehicles and optimizing their delivery routes to reduce reliance on imported oil and enhance energy security.

Vehicle Routing Problem (VRP) was proposed by Dantzig and Ramser in 1959 [3]. There have been continuous studies on VRP optimization by scholars, and rich research achievements have been achieved in interference management, logistics distribution, transportation and other fields [4–6]. In addition, scholars also use genetic algorithm, ant colony algorithm, emergency search algorithm and other heuristic algorithms to solve VRP problems. VRP refers to arranging appropriate vehicle routes so that vehicles meet constraints, pass through a series of delivery points and/or delivery points, and achieve certain goals. VRP is mainly divided into dynamic vehicle routing problem and static vehicle routing problem. The latter refers to the arrangement of vehicle routing when information such as vehicle, time, personnel and customer needs are determined. However, in the real world, customers' demands, traffic conditions, weather, personnel, vehicles and other information are uncertain, and some information is in a constantly changing state [7]. For example, after the vehicle has set off, there may still be new customer service requests or customer information changes. The dispatching system needs to respond quickly to the update of information and dynamically arrange the route of the vehicle according to the constantly updated system information. This is the dynamic vehicle routing problem (DVRP) [8].

In addition, with the development of modern information technology, real-time vehicle routing optimization has become possible. Technological tools such as geographic information systems (GIS), Global Positioning Systems (GPS), intelligent transportation systems (ITS), mobile e-commerce platforms (MCS) and the Global System for Mobile Communications (GSM) can help people access dynamic information in real time. The dispatching center needs to constantly combine new information to generate a new distribution plan when each dynamic event occurs [9]. The process of information acquisition is as follows: MCS is used to obtain customer demand and demand point location information, ITS is used to obtain real-time traffic information, GPS is used to locate vehicles, and GIS is used to obtain the actual distance between any two customers. Based on the above real-time information, after each dynamic event occurs, the distribution depot can generate a new distribution route, and its instructions are sent to drivers through GSM.

According to the number of distribution depots, the vehicle scheduling problem can be divided into single distribution depot VRP problem and multi-distribution depot VRP problem. With the expansion of urban scale, the customer demand points of urban distribution are numerous and unevenly distributed, the number and demand of customers are constantly changing, and the traffic situation is complicated. Considering the above problems, the initial distribution scheme of single distribution depot cannot meet the needs of customers and enterprises, and cannot guarantee the minimum total distribution cost and the highest customer satisfaction [10]. Therefore, real-time information based multi-distribution depot vehicle routing optimization has important practical significance. Multi-Deport Vehicle Routing Problem (MDVRP) refers to the use of multiple distribution depots to distribute to customers. There are two ways to solve it. The first one is decomposition method, which means that the vehicle scheduling problem of multiple distribution depots is transformed into the vehicle scheduling problem of multiple single distribution depots; the second is the holistic method, which sets a virtual depot, and its distribution point covers all the actual depot and distribution point. It stipulates that the distribution vehicle must start from the set virtual depot and complete the distribution task towards the distribution point of the virtual depot [11]. Xiao, Tan, Zhou and Zeng converted the problem into vehicle scheduling problem of single distribution depot by using boundary allocation method, and solved the optimal scheduling scheme of cross-regional distribution by using genetic algorithm and ant colony algorithm [12]. Based on the analysis of the penalty function of time window, Shi, Wang and Ge established a multi-distribution depot vehicle scheduling model with time window. Based on the model, they designed a two-stage solution algorithm, firstly dividing customers into different distribution depots by scanning algorithm, and then using improved genetic algorithm to solve the vehicle scheduling model of single distribution depot with time window [13]. Chen adopted the two-stage method. He first established a mathematical model of multi-distribution depot vehicle scheduling according to the characteristics of multi-distribution depots, then used fuzzy membership degree method to classify customers to determine the customers distributed by distribution depots, and adopted improved immune clone selection heuristic algorithm to solve the problem of vehicle scheduling [10]. Ge Xianlong studied the open VRP problem of multi-distribution depot dynamic demand across regions. In his research, he proposed sharing and joint distribution strategies of distribution vehicles, established vehicle routing optimization models conforming to the actual situation, and improved genetic algorithm by using cloud model theory to solve the model and obtained good results [14].

Dynamic vehicle routing optimization in multiple distribution depots based on real-time information is a nonlinear integer optimization problem [15]. It requires a large-scale nonlinear integer programming algorithm because of its complex constraint conditions. At the same time, the calculation speed of the algorithm needs to be improved to ensure that the distribution route of vehicles can be adjusted in real time. Plant Growth Simulation Algorithm (PGSA) is an intelligent optimization algorithm proposed by Li et al. in 2005. It is derived from the phototropism mechanism of plants and is suitable for global optimization of integer programming problems [16].

However, traditional PGSA has limitations, such as excessive iterations and long computation time, which are not conducive to real-time vehicle optimization. In this research, biomechanic principles were introduced into the improved Plant Growth Simulation Algorithm for dynamic vehicle scheduling in multiple distribution centers. With leveraging biomechanics principles, a variable step-size mechanism was also designed in the improved algorithm. This design can significantly improve the search efficiency and reduce the number of iterations. Moreover, based on biomechanic-inspired concepts, randomly rearranging auxin concentration in the algorithm will enhance the search diversity. By applying bi-level programming, the algorithm can effectively deal with complex constraints. And then it can improve both the computational speed and the quality of solutions in real-time optimization scenarios. At present, PGSA has been applied to solve travel agents [17], shop scheduling [18], facility location [19], emergency management [20], power systems [21], and other combinatorial optimization problems [5,22]. When it comes to solving the multi-distribution depot dynamic vehicle scheduling problem based on real-time information, the original algorithm still has some shortcomings. And it is improved in this research.

In summary, scholars at home and abroad have conducted in-depth research on real-time optimization of electric vehicle routing, dynamic vehicle routing and multi-distribution depot vehicle routing. At the same time, they have made useful attempts and made great achievements in terms of theory, model and algorithm. However, there are few research results on multi-distribution depot based on real-time information. Most studies are based on the occurrence of dynamic events for real-time route optimization, or on the condition of customer information to determine the multi-distribution depot vehicle scheduling problem optimization, and have not considered the real-time route optimization under the condition of dynamic events. And at the same time, it fails to take into account the national requirements for green and low-carbon delivery. On this basis, the paper constructs a two-layer programming model of new energy vehicle delivery routes. Firstly, it uses fuzzy membership degree method to partition customers. Secondly, based on real-time information, it introduces virtual customers and transforms electric vehicle dynamic routing problem into static vehicle routing problem, thus constructing a real-time optimization model of multi-distribution depot dynamic vehicle routing with the lowest distribution cost and the highest customer satisfaction as the goal. According to the characteristics of the model and algorithm, this study designed an improved algorithm to simulate plant growth. It establishes the initial distribution route, and makes real-time optimization and comparison of the route, which proves the effectiveness of the model and algorithm.

2. Problem description and model construction

2.1. Problem description and analysis

In analyzing the dynamic routing problem of electric vehicles in multiple distribution centers, we can draw on the optimization path selection mechanisms found in biological systems. From the perspective of Biomechanic Principles, organisms in nature adapt to their environments and choose optimal paths to acquire resources, which can provide insights for the design of electric vehicle delivery routes. The growth patterns of plants, which are influenced by biomechanical factors (gravity and the distribution of nutrients), offer valuable insights for the design of electric vehicle delivery routes. By introducing the Plant Growth Simulation Algorithm (PGSA), which mimics the growth behavior of plants under light and resource distribution, we can effectively optimize delivery paths. Additionally, with the integration of Biomechanic Principles, the algorithms can be improved again. Like plants adjust their growth rate based on environmental factors in a biomechanical sense, this variable step size in the algorithm allows for more efficient exploration of the solution space, reducing the number of unnecessary iterations. Inspired by the randomness in the distribution of biological substances in organisms, in the next research stage, we plan to randomly rearrange the auxin concentration in the algorithm, enhancing the search diversity. The multi-distribution depot electric vehicle dynamic routing problem based on real-time information can be described as: there are multiple distribution depots to provide distribution services for customers, and the total inventory of multiple distribution depots can meet the needs of all customers. Customers are zoned and served by different distribution depots. When dynamic events (changes in the number of customers, changes in demand, traffic congestion and breakdown of delivery vehicles) occur, the system re-partitions customers and arranges the driving route of delivery vehicles, aiming at the lowest total delivery cost and the highest customer satisfaction.

This paper can be transformed into a dynamic vehicle scheduling problem for multiple vehicle types in multiple distribution depots. Assume that all distribution depots have the same vehicle models, the maximum deadweight is Q tons, and the maximum driving distance is L; The vehicle in the distribution route has completed Q_r tons of goods distribution, and the $Q - Q_r$ tons of goods remain on the vehicle, its maximum driving distance is $L - L_r$. Therefore, a vehicle departing from a distribution depot after a dynamic event occurs and a vehicle in transit can be regarded as a different vehicle type.

In this study, a two-layer programming model is adopted to further transform the dynamic vehicle scheduling problem of multi-vehicle model and multi-distribution depot into a static vehicle routing problem of single-vehicle model and single-distribution depot. Firstly, it adopts decomposition method to decompose multiple distribution depots into multiple single distribution depots, and carries out route optimization respectively. Secondly, this study sets a virtual customer at the current location of vehicle h undergoing distribution, whose demand is Q_h. The distance between the virtual customer and the distribution depot is Q_h, and the in-transit distribution vehicle is constrained to serve its corresponding virtual customer first. By applying the Improved Plant Growth Simulation Algorithm with Biomechanic Principles, the complex constraints in this process can be better handled, improving the computational speed and the quality of the optimized routes.

2.2. Upper level model—customer classification for multiple distribution depots

This paper adopts the customer division method of multi-distribution depot in literature [8], that is, the fuzzy membership degree method is used to classify customers. According to the maximum membership degree between the customer and the distribution depot, this study determines the distribution relationship between distribution depot and the customers. Firstly, by using the fuzzy method, based on the location of the customer and the distribution depot, this study determines the membership degree of a customer to each distribution depot. The greater the degree of customer membership to the distribution depot, the more distribution should be carried out by the distribution depot. The membership function is as follows:

$$\mu_{P_i} = 1 - \frac{d(K_j, P_i)}{\sum_{i=1}^{m} d(K_j, P_i)} \tag{1}$$

where K_i represents customer i, P_j represents distribution depot j, and $d(K_i, P_j)$ represents the distance between customer i and distribution depot P_j.

When the difference between the maximum membership degree and the second largest membership degree of A customer is greater than β, then the customer should be distributed by the corresponding distribution depot. Other customers are fuzzy customers and need to be classified again.

The secondary classification determines whether the distribution is carried out by the same distribution depot according to the fuzzy membership degree among customers. The classification method is as follows:

$$P(m) = min \sum_{i=1}^{K-1} \sum_{j=1}^{K-1} (d(k_m, k_i) + d(k_m, k_j)) \tag{2}$$

$$k_i, k_j \in P \tag{3}$$

$$k_i \neq k_m, k_j \neq k_m \tag{4}$$

where, K represents customer, k_m represents fuzzy customer, $d(k_m, k_i)$ represents the distance between k_m and k_m, k_i and k_m require the same distribution depot for distribution.

2.3. Lower level model—multi-distribution depot dynamic vehicle routing optimization model

(1) Analysis of Energy Consumption and Charging Demand for Electric Vehicles

The power consumption of electric vehicles is not only related to the inherent properties of the vehicle but also influenced by the actual driving distance and speed. Therefore, for an electric vehicle h with a maximum actual load of q traveling at a speed of v, the operating power can be calculated as follows:

$$E(Q_h, v) = \frac{(q + Q_h)g\varepsilon v + \frac{C_d A v^3}{21.15}}{3600\eta} \tag{5}$$

g represents the acceleration of gravity; η represents the mechanical efficiency of the transmission system; ε, C_d, A respectively represent the rolling resistance coefficient, air resistance coefficient, and frontal area of the vehicle.

The amount of electricity consumed by the electric vehicle on the transportation route is:

$$M_{ijh} = E(Q_h, v_{ij}) t_{ij} \tag{6}$$

M_{ijh} represents the power consumption of electric vehicle h from node i to node j. When the remaining battery capacity of the electric vehicle is insufficient to serve the next customer, rapid charging is required during the delivery process. The charging time of the electric vehicle at the charging station is:

$$r = \sum_{j=0}^{m\sum_{jh}} \sum_{h=1}^{n\sum} \frac{Mjh_{max}}{L} \tag{7}$$

$M_{\max}$ represents the maximum battery capacity of the electric vehicle; M_{jh} represents the remaining battery capacity of electric vehicle h at node j; L represents the charging frequency of the electric vehicle.

For the calculation of charging costs, when the remaining battery capacity of the delivery vehicle is insufficient to serve the next customer, rapid charging mode needs to be adopted during transportation. The electricity cost is proportional to the charging time.

$$c_2 = lk \tag{8}$$

(2) Model establishment

Symbol definition:

P represents $K_1 = \{1,2,\ldots,n'\}$ the distribution depot;

Followings are the set of customers that have been served:

$K_2 = \{1,2,\ldots,n\}$ represents the set of customers that have not been served yet;

$K = \{1,2,\ldots,n',\ldots n' + n\}$ represents the set of all customers;

$N = \{1,2,\ldots,n,\ldots n + o + p\}$ represents the set of all current nodes (customers that have not been served yet, virtual customer, distribution depot);

$H = \{1,2,\ldots,m\}$ represents the set of distribution vehicles;

h_p represents the number of distribution vehicles of the p distribution depot;

Q represents the maximum loading capacity of the distribution vehicles;

q represents the tare weight of the electric delivery vehicle;

L represents the maximum traveling distance of the distribution vehicles;

v represents the average speed of the distribution vehicles;

c represents the unit transportation cost;

c_0 represents the fixed cost of vehicles providing distribution services;

c_1 represents the fixed cost required for the vehicle to perform delivery services;

c_2 represents the charging cost of the delivery vehicle;

d_{ij} represents the distance between any two nodes;

q_i represents the demand of customer i;

t_i represents the time when a vehicle begins to serve customer i;

S_i represents the service time of customer i;

r_{phi} represents customer i in the route of vehicle h of distribution depot p;

k_{h_p} represents the number of customers served by vehicle h of distribution depot p;

$[E_i, L_i]$ represents the time window required by a customer;

$[a_i, b_i]$ represents the service time window that customer i can tolerate;

The following decision variable has been introduced:

$$x_{ijh} = \begin{cases} 1, \text{Vehicle } h \text{ visit customer } j \text{ from node } i \\ 0, \text{ other} \end{cases}$$

Typically, penalty costs are applied in vehicle delivery problems with time windows. But in practice, the deviation of service time can only lead to the reduction of customer satisfaction, but does not lead to the penalty cost. Therefore, the trapezoidal fuzzy time window in literature [23] is adopted in this paper to establish the membership degree function $\mu i(ti)$ of service starting time, which is defined as the satisfaction of customer i, as shown in Equation (9).

$$\mu i(ti) = \begin{cases} 0, & \mathrm{t}i < E_i \\ (\mathrm{t}i - E_i)/(a_i - E_i), & E_i < ti < a_i \\ 1, & ai < ti < bi \\ (L_i - ti)/(L_i - b_i), & b_i < ti < L_i \\ 0, & \mathrm{t}i > L_i \end{cases} \tag{9}$$

Multi-distribution depot dynamic vehicle routing model based on real-time information:

$$max\, Z\, 1 = \frac{1}{n}\sum_{i=1}^{n} \mu i(ti) \tag{10}$$

$$min\, Z\, 2 = (C_0 + \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{h=1}^{m} c \cdot xijh) \tag{11}$$

$$\mathrm{s.t.}$$

$$\sum_{i \in N}\sum_{j \in N} q_i x_{ijh} \leq Q\,,\ \ h \in H \tag{12}$$

$$\sum_{i \in N}\sum_{j \in N} d_{ij} x_{ijh} \leq L \tag{13}$$

$$\sum_{h \in H}\sum_{i \in N} x_{ijh} = 1\,,\ \ i \in N \tag{14}$$

$$\sum_{h \in H}\sum_{j \in N} x_{ijh} = 1\,,\ \ j \in N \tag{15}$$

$$\sum_{p \in P}\sum_{h_p \in H} k_{h_p} \tag{16}$$

$$R_{ph} = \{r_{phi} | r_{phi} \in N\}, i = 1,2, \ldots, k_{ph_p} \tag{17}$$

$$\sum_{i \in N} x_{ijh} - \sum_{j \in N} x_{ijh} = 0\,,\ \ i \in N,\ \ h \in H \tag{18}$$

$$\sum_{h \in H}\sum_{p \in P}\sum_{j \in N, j \neq 0} x_{pjh} = \sum_{h \in H}\sum_{p \in P}\sum_{i \in N, i \neq 0} x_{iph} = m \tag{19}$$

$$x_{pjh} = 1,\ \ n + 1 \leq j \leq n + o,\ \ h \in H \tag{20}$$

The meanings of the equations in the above model are:

Objective function (10) represents the highest average customer satisfaction as the goal;

Objective function (11) represents the lowest total distribution cost as the goal;

Constraint (12) ensures that the loading capacity of each vehicle is within the maximum loading capacity;

Constraint (13) ensures that the total driving distance of each vehicle does not exceed its maximum driving distance;

Constraints (14) and (15) ensure that each customer can only be served once;

Constraint (16) represents the total number of customers distributed by all distribution depots;

Constraint (17) represents the combination of customers on each route;

Constraint (18) means that on each route, the number of vehicles leaving each node is equal to the number of vehicles entering the node;

Constraint (19) ensures that the starting point and ending point of all distribution vehicles are the same distribution depot;

Constraint condition (20) indicates that each vehicle executing the task must first serve the corresponding virtual customer, so that the distribution path is transformed into a simple circle.

3. Algorithm design

3.1. The basic idea of the plant growth simulation algorithm

The Plant Growth Simulation Algorithm (PGSA) is inspired by the growth mechanisms of plants in nature, particularly how plants optimize themselves through phototropism and resource acquisition. By simulating the growth process of plants under different environmental conditions, PGSA can dynamically adjust delivery routes and optimize resource allocation, thereby achieving more efficient logistics scheduling. The plant growth simulation algorithm (PGSA) is an optimization algorithm inspired by the light growth of plants in nature, and it is a simulation of plant growth characteristics [16]. Let the length of the trunk of A plant be M, the length of its branches be m, and there are K growing points on the trunk, which are represented as $S_M = (S_{M1}, S_{M2}, \cdots, S_{Mk})$. The auxin concentration at these growth points is $P_M = (P_{M1}, P_{M2}, \cdots, P_{Mk})$, and there are q growth points on the branches, which are represented as $S_m = (S_{m1}, S_{m2}, \cdots, S_{mq})$. The corresponding morph concentration at these growth points is $P_m = (P_{m1}, P_{m2}, \cdots, P_{mq})$. Based on the above conditions, the morphactin concentration at each growth point on the trunk and branches of this plant can be calculated by the following formula:

$$P_{Mi} = \frac{f(x_0) - f(S_{mi})}{\sum_{i=1}^{K}(f(x_0) - f(S_{Mi})) + \sum_{i=1}^{q}(f(x_0) - f(S_{mj}))} \tag{21}$$

$$P_{Mj} = \frac{f(x_0) - f(S_{m1})}{\sum_{j=1}^{K}(f(x_0) - f(S_{Mi})) + \sum_{j=1}^{q}(f(x_0) - f(S_{mj}))} \tag{22}$$

Where: x_0 is the root point of the plant (i.e. the initial base point); $f()$ represents the environment information function at this growth point (i.e. the objective function in the optimization problem). The smaller its value is, the more favorable the growth environment conditions at this point are for growth, and the more conducive to the growth of new stems and leaves. It can be seen from Equations (21) and (22) that morphin concentration at each growth point on the plant is determined by its relative location and the environmental information at that point. From these two formulas, it can be further inferred that:

$$\sum_{i=1}^{K}\sum_{j=1}^{q}\left(P_{Mi}+P_{Mj}\right)=1 \tag{23}$$

Random numbers between $[0,1]$ are generated by computer simulation. When the generated random number falls in the state space between, the growth point corresponding to this state space will grow new branches and leaves before other growth points. When this branch grows, the morphactin concentration value of the growth point will be redistributed and regenerated into a new random number corresponding to the growth priority of the growth point. This process iterates until no new branches are created.

3.2. Algorithm improvement

The advantage of the plant growth simulation algorithm is that it can find the optimal solution in the global scope. Compared with other optimization algorithms, it has no limitations in parameter setting [24,25]. However, when solving large-scale problems, due to its large growth space, the solving run time will be longer. When solving the electric vehicle dynamic routing problem of a multi-distribution depot, the solution space will be very large because there are many customers and distribution vehicles involved and the scheduling situation is complicated. This requires high computational speed, so it is necessary to improve the original algorithm [26]. Since both customer distribution and vehicle distribution routes affected by dynamic events need to be adjusted, the idea of two-layer programming should be introduced into the algorithm. Specific improvement measures are as follows:

(1) In the variable step search operation, the search scope depends on the step size every time the growing point is searched. In the original algorithm, assuming that the main stem is grown first, the step size is an integer greater than 1. The branches are followed, and the steps are all set to 1. This step size design can ensure that the local optimal solution close to the growth point can be searched without missing, but the search efficiency is greatly reduced. If the initial solution is far away from the optimal solution, the number of growth will increase, so it cannot converge to the optimal solution quickly [27]. In order to solve this problem, this paper draws on the following characteristics: the length of the branches is different each time the plants grow, and they grow first and then grow short. On this basis, this study will calculate the step size gradually decreasing from long to short until it finally reduces to 1, so as to search for the change of the step size of the solution. The specific operation steps are as follows: for the given interval length of objective function D, take step size λ_1 as $[D/2]-1$, take λ_2 as $[\lambda_1/2]-1$, and finally $\lambda_k=1$ as the minimum branch length. After adopting the variable step size design, the number of iterations is greatly reduced, and the search efficiency and calculation speed are improved.

(2) As for the random ordering of auxin concentration, the distribution and arrangement sequence of auxin concentration set in the original algorithm remained

unchanged from beginning to end. This parameter setting method may cause a certain growth point to be repeatedly selected, resulting in the decrease of search efficiency and the increase of calculation time, which is not conducive to obtaining the optimal solution in a short time [28]. In fact, as new shoots are produced, the auxin concentration at each node of the plant decreases as the number of growing points increases, and the order of auxin concentration changes accordingly [29]. Therefore, in this paper, the order of auxin concentration is randomly rearranged in each cycle, so as to reduce the probability of repeated selection of a certain growth point and shorten the calculation time.

(3) When solving the problem of multiple independent variables, the two-layer growth primitive algorithm assumes that each independent variable is independent of each other, so it cannot define the relationship between each variable by changing each chromosome parameter like genetic algorithm, so it is difficult to effectively solve the problem of multiple independent variables being interrelated [30]. In the model established in this paper, two variables, namely dynamic events and multi-distribution depot scheduling affected by dynamic events, need to be considered at the same time, and the two variables are closely related, so it is necessary to use the idea of two-layer programming to divide them into two layers.

3.3. Algorithm design

Let x_0^n, the location where dynamic event n occurs, and $a_k = (x_0^n, q_0^n)$, the quantity change q_0^n in demand, be the growth point BBB of the upper layer, and CC, the location of nodes in the initial distribution scheme, and q_0^m, the demand, be the growth point $b_k = (x_0^m, q_0^m)$ of the lower layer. If the customers need to be reclassified after the occurrence of dynamic event n, the growth point of the lower layer is first grown; If there is no need to reclassify customers after the occurrence of dynamic event n, the growth point of the upper layer is first grown.

Step 1: Input the original data, including the location and demand of each node, classify the customers, and determine the initial distribution scheme. The scheme must meet the constraints of electric vehicles' loading capacity, maximum driving distance and time window. Then, input the location x_0^n of dynamic event n and the quantity of demand changes q_0^n, and determine the location growth step λ_x^n of distribution depot, the number of distribution vehicles growth step λ_q^n and the initial objective function $f(x_0)$.

Step 2: Determine the initial growth point location. If the customers need to be reclassified after the occurrence of dynamic event n, the growth points of the lower layer are first grown, and then go to Step 3. If there is no need to reclassify customers after the occurrence of dynamic event n, the growth point of the upper layer will first grow, and then go to Step 6.

Step 3: Take (x_0^n, q_0^n) as the base point and $(\lambda_x^n, \lambda_q^n)$ as the step length, $2n$ new growth points were obtained after growth, and the new growth points meeting the constraint conditions were incorporated into the set of growth points; calculate the function value of each growth point, and the growth point whose objective function value is less than $f(x_0^n, q_0^n)$ is retained to find the growth point with the smallest objective function.

Step 4: Calculate the growth probability (morphactin concentration) of points to be grown, and calculate the morphactin concentration $P_1, P_2, \cdots, P_n$ of all points to be grown in the set of points to be grown. The calculation method is as shown in the above section, and the corresponding growth point is randomly selected on $(0,1)$ as the new base point.

Step 5: Calculate the feasible solution range of dynamic event n, namely the service distribution depot location D_x^n, the number of vehicles D_q^n, and then calculate the new step sizes λ_x^n and λ_q^n;

Step 6: Take the position x_0^m of each node in the initial distribution scheme and the demand q_0^m as the base point, and take $(\lambda_x^n, \lambda_q^n)$ as the step size to get $2n$ new growth points, and incorporated the new growth points meeting the conditions into the growth point set; calculate the function values of and growth points, retained the growth points whose objective function values were less than $f(x_0^m, q_0^m)$, and determined the minimum value of the objective function of each growth point and its growth point.

Step 7: Calculate the growth probability $P_1, P_2, \cdots, P_n$ and randomly select the corresponding growth point on $(0,1)$ as the new base point.

Step 8: Judge whether the number of search iterations reaches the set maximum number of cycles, and whether there is only the set of minimum points of the objective function value in the growth point set. If the value of the objective function of all the growing points in the growing points set becomes stable, then finish the calculation; otherwise, let $\lambda_0 = [\lambda_0/2] - 1$ and return to Step 2.

Step 9: End.

4. Example simulation

This article demonstrates through simulation results that the proposed Plant Growth Simulation Algorithm effectively solves the electric vehicle delivery route optimization problem. It explores how these solutions resonate with optimization strategies in biological systems, utilizing simulations of biological growth patterns to optimize the service area division of distribution centers. In this paper, with reference to Chen's study, the simulation data is designed as follows: A company has three distribution depots: $P_1(2,8)$, $P_2(9,14)$ and $P_3(16.5,10)$, each with five electric vehicles of the same model, providing distribution services for 15 customers. The maximum carrying capacity of the vehicle is 10 t, the maximum driving distance of each vehicle is 200 km, and the speed is 20 km/h. We roughly calculate 1/3 of the demand as the service time of the demand point, the transportation cost is 10 yuan/km, and the fixed cost of delivery service for each vehicle is 100 yuan. $a_i = E_i - 2$, $b_i = E_i + 2$, customers with conditions for secondary classification are $\beta = 0.1$. Specific information is shown in **Table 1**.

Table 1. Customers' demand.

No.	Coordinate	Demand (t)	Time window	No	Coordinate	Demand (t)	Time window
1	(2.9, 13.4)	2.8	(1, 3)	11	(10.5, 10.8)	0.8	(1, 3.5)
2	(6.5, 7.3)	1.9	(3, 5)	12	(10, 19.3)	2.8	(3, 7)
3	(15, 16.5)	0.9	(2, 5)	13	(13.6, 8)	2.7	(3, 6)
4	(7, 14.3)	1.8	(3.5, 6)	14	(19.1, 8.5)	2.7	(2, 4)
5	(2.1, 4.4)	2.8	(2, 4.5)	15	(11.7, 8.4)	1.8	(3, 5)
6	(3, 1.4)	2.5	(1, 4)	16	(19.2, 12.4)	2.8	(3, 5)
7	(3.9, 9.1)	1.2	(1.5, 5)	17	(11.7, 16.9)	1.6	(2.5, 5)
8	(0.3, 11.5)	2.8	(2, 4)	18	(12.8, 12.2)	1.8	(1.5, 3)
9	(12.3, 0.4)	2.7	(2, 5)	19	(17, 14)	2.7	(1.5, 5)
10	(2.3, 15.9)	2.5	(0.5, 4)	20	(17.6, 1)	2.5	(1, 5)

4.1. Initial distribution scheme

Using the above improved simulation plant growth algorithm, this study solved the model. In a computer with a Window10 system and 4G memory, the researcher used MATLAB 2020a to complete the calculation.

(1) Area division of customers

Customers are divided into different areas for distribution, and the membership degree of each customer to the distribution depot is solved. The membership degree and the initial classification results are as shown in **Table 2**.

Table 2. Membership degree and initial classification of the initial distribution scheme.

No.	Membership degree to P1	Membership degree to P2	Membership degree to P3	Classification	No.	Membership degree to P1	Membership degree to P2	Membership degree to P3	Classification
1	0.786	0.761	0.453	P1,P2	11	0.517	0.81	0.673	P2
2	0.794	0.676	0.531	P1	12	0.547	0.824	0.629	P2
3	0.459	0.774	0.768	P2,P3	13	0.489	0.667	0.845	P3
4	0.608	0.901	0.491	P2	14	0.459	0.636	0.905	P3
5	0.883	0.617	0.5	P1	15	0.537	0.704	0.759	P2,P3
6	0.818	0.619	0.563	P1	16	0.44	0.674	0.886	P3
7	0.9	0.677	0.423	P1	17	0.484	0.845	0.671	P2
8	0.867	0.69	0.443	P1	18	0.423	0.791	0.786	P2,P3
9	0.657	0.625	0.719	P1, P3	19	0.427	0.716	0.857	P3
10	0.739	0.77	0.491	P2, P3	20	0.59	0.627	0.823	P3

According to the above calculation results, the researcher conducted a secondary classification of customers 1, 3, 9, 10, 15 and 18. The calculation results according to Equation (2) are as shown in **Table 3**.

Table 3. Second classification of the initial distribution scheme.

No.	Membership degree to P1	Membership degree to P2	Membership degree to P3	Classification
1	0.786	0.761	0.453	P1
3	0.459	0.774	0.768	P2
9	0.657	0.625	0.719	P3
10	0.739	0.77	0.491	P1
15	0.537	0.704	0.759	P3
18	0.423	0.791	0.786	P2

Through calculation, customers of P1 distribution depot include 1, 2, 5, 6, 7, 8, 10; customers of P2 include 3, 4, 11, 12, 17, 18; customers of P3 include 9, 13, 14, 15, 16, 19, 20.

(2) Initial distribution route

After calculation, the initial distribution route is obtained as follows **Table 4**:

Table 4. Initial distribution scheme.

Distribution depot	Route	Total length	Transportation cost	Transportation volume	Loading rate	Customers' satisfaction
P1	P1-8-10-1-P1	16.77	267.7	8.1t	81%	80%
	P1-5-6-2-7-P1	18.95	289.5	8.4t	84%	78%
P2	P2-4-12-17-3-11-18-P2	25.17	351.7	8.6t	86%	63%
P3	P3-14-16-19-P3	13.65	236.5	8.2t	82%	85%
	P3-20-9-15-13-P3	27.89	378.9	9.7t	97%	64%

The total driving route of each distribution depot is 102.43 km, the transportation cost is 1524.3 yuan, the loading rate is 86%, and the customer satisfaction rate is 74%.

4.2. Real-time optimization of distribution routes

Due to the limitation of length, this paper only takes the change of customer number and demand as an example for route optimization based on real-time information.

At T = 1 h 30 min, the following dynamic event occurs: Old customer 14 reduces demand by 0.5 t, old customer 17 increases demand by 1 t, old customer 2 cancels order, and new customers 21, 22, 23, 24, 25, 26 emerge. At this time point, the customers that need to be served are as shown in **Table 5**.

Table 5. Customers' demand.

No.	Coordinate	Demand (t)	Time window	No.	Coordinate	Demand (t)	Time window
1	(2.9, 13.4)	2.8	(1, 3)	15	(11.7, 8.4)	1.8	(3, 5)
3	(15, 16.5)	0.9	(2, 5)	17	(11.7, 16.9)	2.6	(2.5, 5)
7	(3.9, 9.1)	1.2	(1.5, 5)	18	(12.8, 12.2)	1.8	(1.5, 3)
9	(12.3, 0.4)	2.7	(2, 5)	21	(2.5, 11.4)	1.6	(0, 2.5)
10	(2.3, 15.9)	2.5	(0.5, 4)	22	(4.6, 6.2)	2.8	(2, 3.5)
11	(10.5, 10.8)	0.8	(1, 3.5)	23	(7.2, 8.6)	2.5	(0.5, 3)
12	(10, 19.3)	2.8	(3, 7)	24	(9.2, 9.8)	2.2	(2, 4)
13	(13.6, 8)	2.7	(3, 6)	25	(15.5, 4)	0.9	(3.5, 5)
14	(19.1, 8.5)	2.2	(2, 4)	26	(19.9, 11.8)	1.7	(1.5, 3)

(1) Area division of customers

Based on the real-time information, the researcher once again divides the customers into different areas. Customers' membership degree and classification are as shown in **Table 6**.

Table 6. Membership degree and initial classification of the distribution scheme in real-time optimization.

No.	Membership degree to P1	Membership degree to P2	Membership degree to P3	Classification	No.	Membership degree to P1	Membership degree to P2	Membership degree to P3	Classification
1	0.786	0.761	0.453	P1,P2	15	0.537	0.704	0.759	P2, P3
3	0.459	0.774	0.768	P2,P3	17	0.484	0.845	0.671	P2
7	0.9	0.677	0.423	P1	18	0.423	0.791	0.786	P2, P3
9	0.657	0.625	0.719	P1, P3	21	0.86	0.714	0.426	P1
10	0.739	0.77	0.491	P2, P3	22	0.872	0.636	0.492	P1
11	0.517	0.81	0.673	P2	23	0.743	0.72	0.537	P1, P2
12	0.547	0.824	0.629	P2	24	0.608	0.778	0.614	P2
13	0.489	0.667	0.845	P3	25	0.561	0.628	0.81	P3
14	0.459	0.636	0.905	P3	26	0.45	0.666	0.884	P3

According to the above calculation results, the researchers conducted a secondary classification of customers 1,3,9,10,15,18,23. The results of calculation according to Equation (2) are shown in **Table 7**. After adding new customers, customer 15 has a relatively high degree of attachment to distribution depot P2, so distribution depot P2 is assigned to provide services for this customer.

Table 7. Secondary classification of the distribution scheme in real-time optimization.

No.	Membership degree to P1	Membership degree to P2	Membership degree to P3	Classification
1	0.786	0.761	0.453	P1
3	0.459	0.774	0.768	P2
9	0.657	0.625	0.719	P3
10	0.739	0.77	0.491	P1
15	0.537	0.704	0.759	P2
18	0.423	0.791	0.786	P2
23	0.743	0.72	0.537	P2

Through calculation, customers of P1 distribution depot include 1, 7, 10, 21, 22; P2 customers include 3, 11, 12, 15, 18, 23, 24; The customers of P3 are 9, 13, 14, 25, 26.

(2) Real-time optimized distribution routes

By using the plant growth simulation algorithm, the researcher reconstructed the distribution route, and the distribution scheme obtained is as shown in **Table 8**, and the optimal solution obtained is as shown in **Figure 1**.

Table 8. Real-time optimized distribution scheme.

Distribution depot	Route	Total length	Transportation cost	Transportation volume	Loading rate	Customers' satisfaction
P1	P1-8-10-1-21-P1	18.52	192.6	9.7 t	97%	85%
	P1-5-6-22-7-P1	16.97	184.85	9.3 t	93%	88%
P2	P2-4-12-17-3-18-P2	23.15	215.75	9.9 t	99%	75%
	P2-23-24-15-11-P2	17.11	185.55	7.3 t	73%	85%
P3	P3-19-16-26-14-P3	14.07	170.35	9.4 t	94%	89%
	P3-20-25-9-13-P3	28.79	243.95	8.8 t	88%	65%

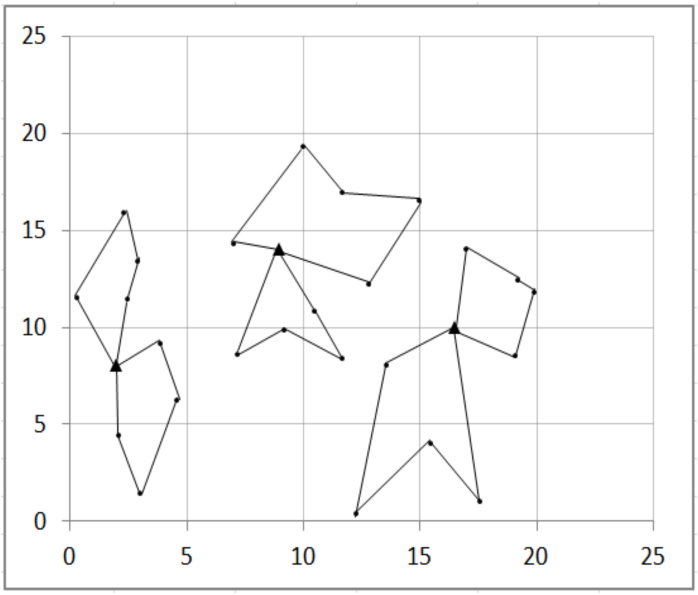

Figure 1. Best route.

The total length of all driving routes of each distribution depot is 118.61 km, the transportation cost is 1786.1 yuan, the loading rate is 90.67%, and the customers' satisfaction is 81%.

4.3. Comparative analysis

(1) Comparison with the static distribution scheme

After dynamic events occur, if the traditional static vehicle scheduling method is used, the scheduling scheme is as shown in **Table 9**.

Table 9. Static scheduling method.

Distribution depot	Route	Total length	Transportation cost	Transportation volume	Loading rate	Customers' satisfaction
P1	P1-8-10-1-P1	16.77	267.7	8.1 t	81%	80%
	P1-5-6-2-7-P1	18.95	289.5	8.4 t	84%	78%
	P1-22-21-P1	12.21	222.1	4.4 t	44%	85%
P2	P2-4-12-17-3-11-18-P2	25.17	351.7	8.6 t	86%	63%
	P2-23-24-P2	12.23	222.3	4.7 t	47%	86%
P3	P3-14-16-19-P3	13.65	236.5	8.2 t	82%	85%
	P3-20-9-15-13-P3	27.89	378.9	9.7 t	97%	64%
	P3-24-25-P3	18.89	288.9	2.6 t	26%	75%

The total length of all routes of each distribution depot is 145.76 km, the transportation cost is 2257.6 yuan, the loading rate is 68.38%, and the customer satisfaction rate is 77%.

By comparing the real-time optimal scheduling scheme with the static scheduling scheme, it can be seen that when dynamic events occur, the multi-distribution depot dynamic vehicle scheduling model based on real-time information established in this paper can reduce the total distribution cost by 471.5 yuan, reduce the total distribution distance by 27.15 km, and increase customer satisfaction by 4%.

(2) Comparison with the genetic algorithm

In order to further analyze and improve the performance of the plant growth simulation algorithm, the researcher compared its calculation results with those of the genetic algorithm. The initial population of the genetic algorithm was set as 20, the crossover probability was set as 0.5, and the mutation rate was set as 0.01. The experimental comparison results are as shown in **Table 10**. The total driving distance of the improved plant growth simulation algorithm was reduced by 11.01 km, the total distribution cost was reduced by 210.2 yuan, and the customer satisfaction was increased by 2%. The convergence of the improved PGSA and GA is referenced in **Figure 2**.

Table 10. Comparison of the calculation results of the improved plant growth simulation algorithm and the genetic algorithm.

Algorithm	Total driving distance	Total cost	Loading rate	Customers' satisfaction
PGSA	118.61	1786.1	90.67%	81%
GA	129.63	1996.3	77.71%	79%

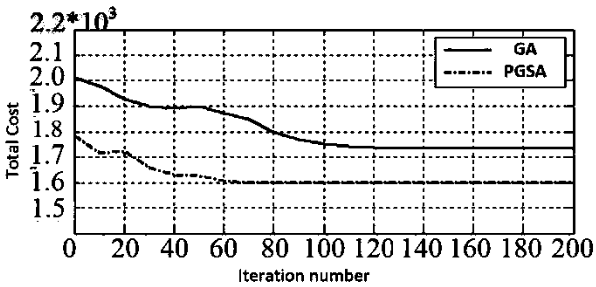

Figure 2. Convergence of the improved PGSA and GA.

5. Conclusions

This study focuses on the electric vehicle scheduling problem of multiple distribution depots affected by dynamic events. It mainly studies how to use real-time information to coordinate the electric vehicle scheduling of multiple distribution depots under the circumstances of dynamic events such as changes in the number of customers, changes in demand, traffic jams, and vehicle breakdowns. Aiming at the highest customer satisfaction and the lowest distribution cost, this paper constructs a multi-distribution depot electric vehicle dynamic scheduling model based on real-time information. By introducing virtual customers and classifying customers with fuzzy membership degrees, this study transforms the dynamic vehicle scheduling problem of multi-distribution depots under real-time information into the vehicle scheduling problem of multiple static single distribution depots, making the problem better match the real-life distribution [31]. In this study, the improved plant growth simulation algorithm was used to optimize the model in real time, and the optimal distribution scheme was obtained. On this basis, the results are compared with static scheduling schemes and genetic algorithms. The comparison results have shown that the model and algorithm proposed in this study can reduce the distribution cost quickly and effectively and improve customer satisfaction.

The improved model and algorithm in this paper have limitations in practical applications, particularly under extreme weather, traffic congestion, or emergencies, which may affect optimization effectiveness. The model primarily targets uniform electric vehicle models and does not account for performance differences among various vehicle types, limiting its applicability in diverse fleets. To enhance adaptability for distribution centers of different scales, optimization strategies can include introducing adaptive mechanisms for real-time parameter adjustments and expanding the model to incorporate different vehicle characteristics. From a biomechanics-related perspective, future research could also analyze the mechanical stress and energy consumption differences of different vehicle types in the distribution process. Future research should analyze the applicability of models for small, medium, and large distribution centers, addressing their unique challenges. By developing specialized optimization strategies tailored to each scale, overall delivery efficiency and customer satisfaction can be significantly improved.

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