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COMPARISON OF INTELLIGENT ALGORITHMS OF NEW RETAIL DISTRIBUTION CENTER

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Abstract

The relationship between the number and size of retail stores and the optimization ability of intelligent algorithms is analyzed by experiments. The location coordinates of retail stores are randomly generated by intelligent algorithm, and the location model with revenue as objective function is constructed. The numerical examples of chaotic-enhanced fruit fly optimization algorithm and particle swarm optimization algorithm are designed. The results show that under the same constraints, with the increase of the number of retail stores, chaotic-enhanced fruit fly optimization algorithm and particle swarm optimization algorithm show different optimization capabilities. That is to say, the relationship between the number and size of retail stores and the optimization effect of intelligent algorithms is not stable: when the number of retail stores is small or medium-sized, theparticle swarm optimization algorithmhas strong optimization ability; but when the number of retail stores continues to increase sharply, the chaotic-enhanced fruit fly optimization algorithm displays its prominent optimization ability.

Keywords: New Retail concept, New Retail distribution center, Chaotic-enhanced Fruit Fly Optimization Algorithm, Particle Swarm Optimization, intelligent algorithms.

Introduction

At present, there are 6.8 million small stores in the whole fast-food market in China, including husband and wife stores, community stores and grocery stores. The 6.8 million small stores account for 49.3% of the total domestic merchandise shipments (Ya, 2017). Han and Wang (2018) summarizethe current situation of new retail and believe that in the future, local suppliers and retailers will be integrated online for cloud computing. What's more, offline and logistics distribution will be combined to serve a large number of local supermarket terminals, so as to realize the full channel of online and offline access. Therefore, how to locate these new retail distribution centers has become a hot issue again. In addition, in recent years, intelligent algorithms have attracted much attention. Especially in the development of artificial intelligence, intelligent algorithms have been applied to the location of logistics distribution centers (Zhang, & Liu , 2018; Wan, Xi, Hu, & Wan, 2018; Duan, Xiao, & Tan, 2017).

As a novel bionic evolutionary swarm algorithm, fruit fly optimization algorithm(FOA) was first invented by professor Pan(2012), a Taiwanese scholar in China. The search process is based on simulating the process of fruit fly foraging. The optimal solution is obtained by iterating the search of food sources (Pan, 2012).Since Professor Pan put forward it, it has been used in various research fields because of its strong operability (Zhang, et al., 2018; Wan, et al., 2018; Duan, et al.,2017). However, the original fruit fly optimization algorithm is easy to fall into local optimum and converge prematurely, so some scholars try to improve the fruit fly optimizationalgorithm. For example, Yang, Wang, and Shao (2018) modified the fitness function by adding escape coefficient, which enlarged the search range of fruit fly; Gui, Ai, and Ding(2018) achieved an effective balance between the global and local search capabilities offruit fly optimization algorithm by changing the search radius of fruit fly population. Zhang, Chen,

and Ding(2018) proposed a dynamic search co-evolution fruit fly optimization algorithm, which further improved the original fruit fly algorithm; Similarly, Wang, Feng, Zhu, Chai, and Wu (2018) advanced a new fruit fly optimization algorithm based on global-local bidirectional drive, which also optimized the fruit fly optimization algorithm; In addition, Han and Liu (2013) raised the adaptive chaotic-enhanced fruit flyoptimization algorithm (ACFOA) as early as 2013. The simulation results showed that the chaotic fruit fly optimization algorithm had better global search ability, and its convergence speed, reliability and accuracy were better than the original fruit fly optimization algorithm.

To sum up, on the one hand, there are many studies on fruit fly optimization algorithm, and even it is widely used in various disciplines and fields (Zhang, Yang, & Wu,2015; Liu, Deng, Ren, Liu, & Liu, 2019; Zhou, Liu, Han, & Wang, 2018), however, few studies have focused on the application of fruit fly optimization algorithm in site selection.In contrast, particle swarm optimization (PSO) was proposed earlier than fruit fly optimization algorithm, and it was proposed by J. Kennedy and R. C. Eberhart, two foreign researchers, whilefruit fly optimization algorithm was proposed by professor Pan Wenchao, a Taiwanese scholar in China. Although both fruit fly optimization algorithm and particle swarm optimization (PSO) are based on swarm intelligence iteration, compared with fruit fly optimization algorithm, which is rarely used in site selection, there are abundant achievements in the field of site selection by using PSO in all walks of life(Zhang, Yang, & Wu, 2017; Peng, Manier, & Manier, 2017; Li, Zhang, Yan, & Zhang, 2019; Cheng, 2018; Cao, Zhang, Li, Zhou, Zhang, & Chaovalitwongse, 2018).

Therefore, this paper hopes to do a little bit for the research of this fruit fly optimization algorithm. This paper also tries to arouse a little ripple in the academic circles, as much as possible to attract more researchers' attention and explore the fruit fly optimization algorithm, after all, fruit fly optimization algorithm is an excellent research achievement creatively put forward by Chinese researchers. Although some scholars have applied fruit fly optimization algorithm to location problem (Yu, 2015), most of them focus on comparing the advantages and disadvantages of fruit fly optimization algorithm before and after the improvement, and this research idea about intelligent algorithm is currently more respected. Nevertheless, this paper attempts to compare chaotic fruit fly optimization algorithm with other algorithms, such as particle swarm optimization. On the other hand, most of the current studies focus on comparing the advantages and disadvantages of the algorithm under limited examples (Wu, Yang, Maheshwari, & Li, 2019; Zhou, Pang, Chen, & Chou, 2018; García-Nieto, López-Camacho, García-Godoy, Nebro, & Aldana-Montes, 2019), but considering that with the new concept of retail concepts proposed in China, the resources of offline physical stores, namely retail stores, will be re-integrated in the future. In the case of the sudden increase in the number of retail stores, the optimization ability of intelligent algorithms may also have its own limitations. For example, under different retailer sizes, two types of retailers may present different search capabilities. Therefore, this paper speculates that the location effect of distribution centers may vary with the number and scale of retail stores. Therefore, this paper attempts to explore the difference between the chaotic fruit fly optimization algorithm and particle swarm optimization algorithm in the location of new retail distribution centers. This paper tries to analyze the relationship between the number and size of retail stores and the optimization effect of intelligent algorithms.

Research Method

Earnings pattern

Former research scholars Zhang and Yan (2012) and Wang and Li (2010) studied vehicle routing problem according to different types and sizes, and then got different decision-making schemes. This paper assumes that cities in all regions need to build a logistics distribution center of a new retail store. However, based on the previous research experience, this paper considers that the number of retail stores in different cities may also affect the choice of decision-making options, and the number of chain retail stores in different cities is variable, and the location of chain retail stores in different cities is also different. However, in order to facilitate the experimental comparison, this experiment divides the number and scale of chain retail stores into three types. Similarly, in order to simulate the uncertain geographical location of retail stores, the coordinate positions of all chain retail stores are randomly generated by intelligent algorithms. In this paper, through the above way, this paper try to make a more general comparison between chaos fruit fly optimization algorithm (CFOA) and particle swarm optimization (PSO) algorithm in the case of retail stores of different size and location. To sum up, this paper assumes that the coordinate positions of all chain retail stores are randomly generated by intelligent algorithm, and the number of chain retail stores can be divided into three scales. The first scale is the number of small retail stores, which is 10 chain retailers. The second scale is 100 medium-sized retail stores, and the third scale is 1000 large-scale retail stores. Therefore, under the condition of the new retail concept, the problem of locating logistics distribution centers of chain new retail stores can be described as: Under the condition of single cycle, discrete time and fixed demand, i $(i=1,2,3,\ldots,n)$ retail stores are randomly generated, and then a logistics distribution center j $(j=1)$ is selected. The decision-making goal of this system is to maximize the total profit per unit distance between each retail store and the new retail distribution center, and satisfy the following constraints at the same time: The total quantity of goods required by each retail store is fixed at W（$W=a$）; the unit profit of the quantity of goods is fixed at P $(P=b)$; the new retail distribution center can meet the quantity of goods required by each retail store; the transportation cost and time penalty cost are not considered.

Based on the above assumptions, this paper takes the earnings as the objective function to establish earnings pattern, and the mathematical model of logistics distribution center location of chain retailers under the new retail concept can be described as follows:

$$R(i,j)=\sum\frac{W_{ij}\times P_{ij}}{D_{ij}} \quad (1)$$

$$D_{ij}=\sqrt{\left(X_i-X_j\right)^2+\left(Y_i-Y_j\right)^2} \quad (2)$$

$$\forall i,\ \forall j, W_{ij}=a \quad (3)$$

$$\forall i,\ \forall j, P_{ij}=b \quad (4)$$

Formula (1) is the objective function, and $R(\mathrm{i},\mathrm{j})$ refers to the sum of unit distance profit between retail distribution centers and retail stores.
Formula (2) refers to the distance between i retail stores and j $(j=1)$ new retail distribution centers. (X_i, Y_i) refers to the site selection of dispatch center; (X_j, Y_j) refers to location of each retailer.
Formula (3) is the fixed freight volume that each retail store i needs to transport from the new retail logistics distribution center j $(j=1)$, and a is a constant.
Formula (4) refers to the fixed profit per unit of goods transported from the new retail logistics distribution center j $(j=1)$ for each i retail store, and b is a constant.

Chaotic-enhanced fruit fly optimization algorithm (CFOA)

Fruit Fly Optimization Algorithm (FOA) was invented by Professor Pan (2012), a Taiwanese scholar in China. Fruit fly optimization algorithm is an intelligent algorithm, which seeks global optimization based on the deduction of Fruit fly foraging behavior. On the basis of the original Fruit flyoptimization algorithm invented by Professor Pan and the theory of chaos, Professor Yuan (2015) optimized the Chaotic-enhanced fruit fly optimization algorithms (CFOA). The operation steps are as follows:

Step 1:Initialization. Maximum number of iterations is $K\max$. The end point of chaotic search is $K1$, and the starting point of local search is $K2$. K=1. Initializing the chaotic sequence of fruit fly population location $M(\ )$

$$\begin{cases} X\_axis = X\min,i + M(\ )(X\max,i - X\min,i) \\ Y\_axis = Y\min,i + M(\ )(Y\max,i - Y\min,i) \end{cases} \quad (5)$$

Step 2: If $K \le K1$, global chaotic search is performed:

$$\begin{cases} X(i) = X\_axis + M(\ )\max\{(X\max - X\_axis),(X\_axis) - X\min)\} \\ Y(i) = Y\_axis + M(\ )\max\{(Y\max - Y\_axis),(Y\_axis) - Y\min)\} \end{cases} (6)$$

If not, fruit fly individuals are given random directions and distances for food search by smelling. $R(K)*M(\ )$ refers to the search distance.

$$\begin{cases} X(i) = X\_axis + R(K)*M(\ ) \\ Y(i) = Y\_axis + R(K)*M(\ ) \end{cases} \quad (7)$$

$$R(K) = (X\max - X\min)/2*((K\max - k)/K\max)^2$$

Step 3: Estimate the distance from the origin $(Dist)$.

Calculate the judgment value of smell concentration (S)

$$D(\mathrm{i}) = X(i)^2 - Y(i)^2 \quad (8)$$

$$S(\mathrm{i}) = D(i) \quad (9)$$

Step 4: Substitutethe value of smell concentration (S) into the odor concentration determination function $(Fitness\ function)$, the odor concentration ($Smell_i$) of the individual location of fruit fly was calculated.

$$Smell(i) = Function(S(i)) \quad (10)$$

Step 5: Find out the fruit fly with the highest odor concentration in this fruit flypopulation

$$[bestSmell\ bestindex] = \max(Smell) \quad (11)$$

Step 6: If $bestSmell >$ Smell$best$ or $K < K2$, step 7 is followed; if not, the local search method is performed as follows:

$$\begin{cases} X_L = 0.618*X\_axis + 0.3282*X(\mathrm{bestIndex}) \\ Y_L = 0.618*Y\_axis + 0.3282*Y(\mathrm{bestIndex}) \end{cases}$$

(12)

Calculate $Dist_L$, S_L and $Smell_L$.

If $SmellL >$ Smell$best$, Updatethe fitness function values, optimize variablevalues , and then follow step 7; otherwise, do as followed:

$$\begin{cases} X_C = X(\mathrm{bestIndex}) + 1.618*(X\_axis - X(bestIndex)) \\ Y_C = Y(\mathrm{bestIndex}) + 1.618*(Y\_axis - Y(bestIndex)) \end{cases} \quad (13)$$

Calculate $Dist_C, S_C, Smell_C$. Find better fitness function value, then update the search results.

Step7: Determine whether $Fitness$ is better than previous generations, and if so, keep the best flavor concentration value and x, y coordinates. At this time, the fruit fly population uses vision to fly to that location.

$$\begin{cases} X\_axis = X(\mathrm{bestindex}) \\ Y\_axis = Y(\mathrm{bestindex}) \end{cases}$$

(14)

Smell$best$ = $bestSmell$;

(15)

Step8: If $K\max \le K$, end the algorithm, if not, repeat step 2.

Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO)is an intelligent algorithm which regards an individual as a particle without mass and volume, and changes the speed and position of particles according to the size of fitness value. Zeng (2004) believed that the speed and location of each particle were determined not only by the historical best value of the particle itself, but also by the historical best value of the whole population. Therefore, the experience of particles is determined by the common experience of individuals and groups. It can be said that particle algorithm can effectively avoid local optimum value.

Parameter description: i refers to certain particle; j refers to dimension of the particle; a refers to algebra; C1, C2 refer to acceleration constant with value range of (0, 2); t1, t2 refer to two unrelated random functions.

X_i refers to position of particle i (i = 1, 2, 3...n),

V_i refers to fly velocity of particle i (i = 1, 2, 3...n),

P_i refers to the optimal position travelled by particle i (i = 1, 2, 3...n),

Assume minf(X) is the objective function, then the particle's current optimal position is as follows:

$$P_i(a+1)=\begin{cases} P_i(a)\text{若 } f(X_i(a+1))\geqslant f(P_i(a)) \\ X_i(a)\text{若 } f(X_i(a+1))\leqslant f(P_i(a)) \end{cases} \quad (16)$$

Assume the particle quantity is q, the optimal position travelled by the group is $P_g(a)$, the global optimal position, then

$$P_g(a)=\left\{\left\{P_0(a),P_1(a),\ldots P_q(a)\right| f(P_g(a))=\min\left\{f(P_0(a)),f(P_1(a)),\ldots f(P_q(a)\right\}\right\} \quad (17)$$

The evolution equation of the basic particle swarm optimization is as follows:

$$V_{ij}(a+1)=V_{ij}(a)+c_1t_{1j}(a)(P_{ij}(a)-X_{ij}(a))+V_{ij}(a)+c_2t_{2j}(a)(P_{pj}(a)-X_{ij}(a)) \quad (18)$$

$$X_{ij}(a+1)=V_{ij}(a)+V_{ij}(a+1) \quad (19)$$

Process of the basic particle swarm optimization is as follows:
Step 1: Assign the initial value on the particle velocity and position.
Step 2: Calculate each particle's fitness value based on fitness function.
Determine whether the fitness value calculated by step 2 is superior to the best historical fitness value of the particle itself or not, if yes, then proceed to step 3.
Step 3: Take the current fitness value as the particle own optimal position.
Determine whether the fitness value calculated by step 2 is superior to the best historical fitness value of the group or not, if yes, then proceed to step 4.
Step 4: Take the current fitness value as the group's optimal position.
Step 5: Adjust the particle's velocity and position as per the above equation (14) (15)
Step 6: Determine whether the end condition has been reached or not, if yes, end the algorithm, if not, repeat step 2 (Shi, 2008).

Empirical Result and Analysis

The equipment used in the experiment is as follows: Fujitsu LIFEBOOK (AH544) computer, processor 2.6 GHz Intel (R) Core (TM) i5, memory 8 GBDDR3, operating system 10 home version, and MATLAB version R2012a.The experiment was conducted under three scenarios: the first scenario assumes that 10 retail stores are small in size; the second scenario assumes that 100 retail stores are medium in size; and the third scenario assumes that 1000 retail stores are large in size.Each algorithm has 100 iterations.In this paper, the total amount of goods required by each retail store is set at 100, and the unit profit value of goods is set at 50. In this paper, the total profit per unit distance between the new retail distribution center and the retail stores can be obtained by two intelligent optimization algorithms, chaotic-enhanced fruit fly optimizationalgorithm and particle swarm optimization algorithm, under the conditions of three new retail chain stores of different sizes. Therefore, this paper tries to find a better algorithm by comparing the results of the two methods. The parameters are set as Table 1.

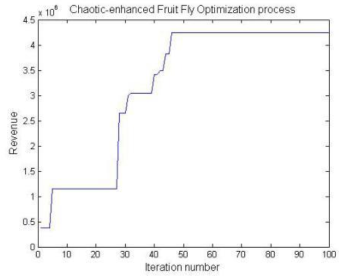
Table1: Description of parameters

Parameter symbol	Parameter	Parameter values
W	Freight volume required by each retailer	100
P	Profit earned by each unit of cargo	50
$Size1$	The first scale of the number of stores	10

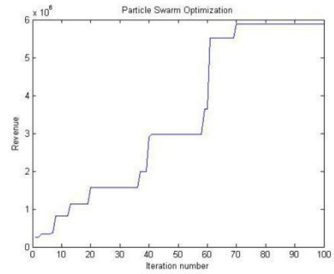
$Size2$	The second scale of the number of stores	100
$Size3$	The third scale of the number of stores	1000
$Maxgen$	The number of iterations.	100

Optimum search study of the two algorithms

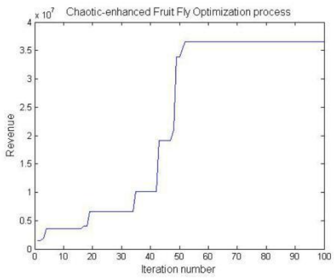
Preset the parameter iteration times are of 100; assume the retailer quantities are 10, 100 and 1000 respectively, employ Matlab program for operation based on CFOA, PSO,compare the optimal for the earning condition, and obtain the followedoperation conditions which are as shown in the followed figure 1:



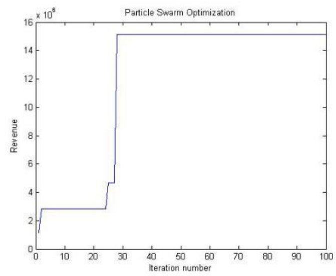
CFOA R



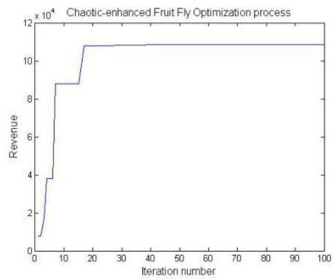
PSO R 10



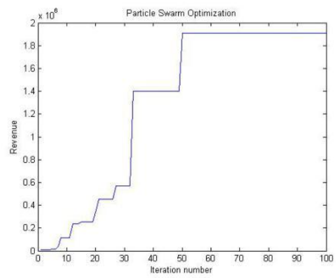
CFOA R 1



PSO R 100



CFOA R 10



PSO R 100

Figure1: Optimal iteration of two intelligent optimization algorithms

According to the Matlab operation effect diagram, in course of optimal site selection for the logistics dispatch center when there are 10 retailers, CFOA converges at iteration of 49 with 16 turning points, PSO converges at iteration of 50 with 25 turning points; while in course of optimal site selection for logistics dispatch center when there are 100 retailers, CFOA converges at iteration of 46 with 22 turning points, PSO converges at iteration of 70 with 30 turning points; and in course of optimal site selection for logistics dispatch center when there are 1000 retailers, CFOA converges at iteration of 52 with 24 turning points, PSO converges at iteration of 28 with 11 turning points.

Result statistics

The operation result statistics are as shown in the followed table2:

Table 2: The iterative results of two intelligent optimization algorithms

Scenario	Chaotic-enhanced Fruit Fly Optimization				Particle Swarm Optimization			
	Earnings	Turning points	Convergence Iteration Number	Operating time (seconds)	Earnings	Turning points	Convergence Iteration Number	Operating time (seconds)
10retail stores	10.8×10^4	16	49	0.77	19.1×10^5	25	50	0.15
100retail stores	42.4×10^5	22	46	0.44	58.8×10^5	30	70	0.20
1000retail stores	36.5×10^6	24	52	1.35	15.1×10^6	11	28	0.59

Under the pre-set condition of 10 or 100 retailers, the operation result of particle swarm optimization algorithm of revenues,computational speed and randomness are better than Chaotic-enhanced fruit fly optimization algorithm.

Under the pre-set condition of 1000 retailers, the operation result of Chaotic-enhanced fruit fly optimization algorithm of revenues, and randomness are better than particle swarm optimization algorithm. But Chaotic-enhanced fruit fly optimization algorithm needs to improve its iterative and computational speed.

CONCLUSION

Aiming at the location problem of new retail distribution centers, this paper established a model for the location of new retail distribution centers with revenue as the objective function. Under the three situations of retail store size, two intelligent optimization algorithms, chaotic-enhanced fruit fly optimizationalgorithm and particle swarm optimization algorithm, were used to compare and analyze the location of new retail distribution centers by using examples.

This paper drew the following conclusions through experiments: when the number of retail stores is small and medium-sized, the randomness, optimization ability and operation time of particle swarm optimization are better; when the number of retail stores is large, the randomness and optimization ability of chaotic-enhanced fruit fly optimizationalgorithmare better. Therefore, we could draw a preliminary conclusion that particle swarm optimization can be used when the number of retail stores is small and medium-sized, and chaotic-enhanced fruit fly optimization algorithm can be considered when the number of retail stores is large.

Considering the stability of the algorithm under the same constraints (Zhang and Chen, 2018), with the increase of the number of retail stores, chaotic-enhanced fruit fly optimization algorithm and particle swarm optimization algorithm show different optimization capabilities, that is, the relationship between the number of retail stores and the optimization effect of intelligent algorithm is not stable. Especially when the number of retail stores is large, the chaotic-enhanced fruit fly optimization algorithm performs better than the particle swarm optimization algorithm. Especially the new concept of retail proposed at present, the development of cloud computing technology in the future, and the combination of cloud computing and logistics technology, will produce more offline retail stores, and then the number of retail stores may increase sharply. Therefore, in the era of big data, the role of chaotic-enhanced fruit fly optimization algorithm will be fully embodied in the future when analyzing large sample data. One of the contributions of this paper is to use the chaotic-enhanced fruit fly optimization algorithm for large data experimental analysis, which extends the research of the chaotic-enhanced fruit fly optimization algorithm. However, the research on location of logistics distribution centers based on intelligent algorithms in this paper can be further expanded in the future, especially focusing on more different algorithms based on swarm intelligence iteration.

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