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Analyze the Effectiveness of the Algorithm for Agricultural Product Delivery Vehicle Routing Problem Based on Mathematical Model

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ABSTRACT

With the recent development in the economic system, the requirement for logistic services has also increased gradually. This increased the demand for efficient and cost-effective delivery services without compromising the quality and timeliness. This has become a challenge to the logistic service providers to maintain the high-quality standards along with reliable delivery services. A mathematical equation model is proposed in this work to solve the problem of random quantity of agricultural products collected/distributed by working vehicle collection/distribution path planning. This article proposes a hybrid algorithm which combines the taboo algorithm search and the taboo hybrid algorithm to solve the problem. In the proposed algorithm, a large-scale problem is several small-scale problems to reduce the time complexity of the algorithm. Since randomness is much more complicated than certain types of problems, accurate algorithms can only be applied to a small range of problem types. The heuristic calculations involved in the development of algorithms make it a convenient simplified tool for the collection and distribution of random agricultural products. An average validation accuracy of 94% has been obtained for the proposed algorithm after completing 200 iterations while obtaining 94.37%, 94.57%, and 94.56% precision, recall, and F-score values, respectively.

KEYWORDS

Agricultural Products, Optimizing Work Car Allocation, Taboo Algorithm

1. INTRODUCTION

In the process of collecting and distributing agricultural products, there are generally several obvious characteristics: First, products with high water content, such as fruits and vegetables, etc., have high fresh-keeping standards. In the process, there is its own time limit and the moving time requirements are particularly high; secondly, agricultural products will use a large area of land, and the geographical scope is wide. The collection and delivery locations of the products will correspondingly increase and

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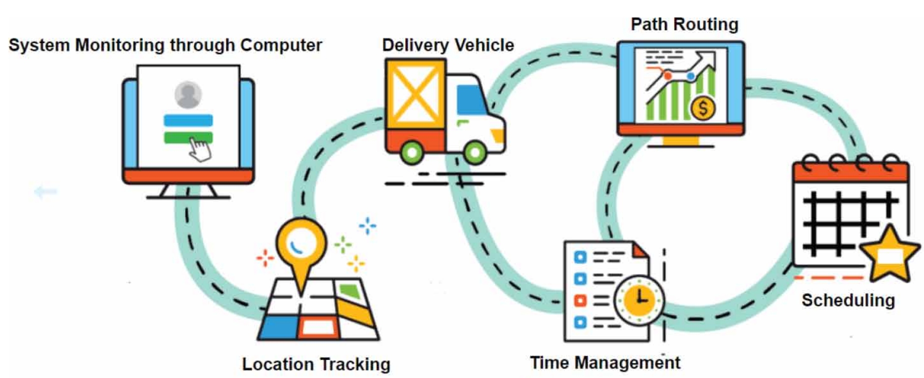
be too scattered, and unscientific vehicle movement will be Will greatly cause the waste of resources and transportation personnel, that is, the increase in production costs (Linfati et al., 2018). According to the characteristics of agricultural products, optimizing the collection and distribution routes and reducing the transportation time and vehicle fees of agricultural products have intuitive meaning. The large range and large number of demand locations will be transformed into distribution topics with scientific allocation of time; delays in the transmission of information at each production site, uncertainty in the production and ripening time of agricultural products, these topics are the research focus of logistics distribution planning. Taboo search algorithm is a branch after the expansion of local domain search. It is an algorithm that transforms from comprehensive to local optimal, and is an algorithm that simulates the human computing process (Feng et al., 2018; Jones et al., 2019). A general flow diagram of logistic distribution using vehicle routing is illustrated in Figure 1.

The major key problem in the process of logistic distribution is high transportation cost of vehicle routing and low efficiency. The development of science and technology has popularized the delivery of various commodities and electronic commerce and logistics. This industry has broad prospect and market potential with the involvement of intellect, information, networking and automation (Fan et al., 2014; He et al., 2015; Sharma and Kumar, 2019, 2017). The requirements of the clients are also increasing rapidly with the developing economy and gradual increase in the logistic services. The practical significance of routing problem for vehicles with different time frame consideration for distribution has become an important research area nowadays. This study explores the optimization framework for the distribution vehicle routing problem and minimizing the processing time as per the logistic characteristics.

This article focuses on the characteristics of the collection and distribution of agricultural products using an accurate path planning of the vehicle to establish a mathematical model, and design an intelligent algorithm for the same. This work is dedicated to solve the problem of randomization in the collection and distribution of agricultural products. Since randomness is much more complicated than certain types of problems, accurate algorithms can only be applied to a small range of problem types. It uses a hybrid of taboo search algorithms for solving the problem of random quantity of agricultural products collected / distributed by working vehicle collection / distribution path planning. In the proposed taboo algorithm, a large-scale problem can be divided into several small-scale problems that can be calculated at the same time by dividing a large-scale problem into a number of small-scale problems, which can reduce the time complexity of the algorithm. The heuristic calculations involved in the development of algorithms make it convenient simplified tool for the collection and distribution of random agricultural products.

The rest of this article is arranged as: section 2 presents the literature review of existing state-of-the-art techniques in this field; problem description and mathematical modeling is discussed in

Figure 1. General Flow diagram of Logistic Distribution



section 3 followed by section 4 detailing the proposed algorithmic part. The results and analysis along with the detailed discussion of the outcomes obtained are presented in section 5 followed by the conclusion and future scope of this research work in section 6.

2. LITERATURE REVIEW

Moradi, B. proposed a new multi-objective discrete learnable evolution model (MODLEM) to solve the problem of vehicle path with time window. The learnable Evolution Model (LEM) includes a machine-learning algorithm, like a decision tree, that can find the right direction of evolution and thus significantly improve an individual's fitness. A new priority-based LEM chromosome coding scheme is proposed, and the corresponding routing scheme is given. In order to improve the quality and diversity of the initial population, a good approximation of Pareto frontier can be obtained within a reasonable calculation time. In addition, a new heuristic operator is used to counter the formation of incomplete chromosomes in the instantiation process (Moradi, 2020). (Wang and Lu, 2019) proposed a competition-based meme algorithm (MAC) to solve the CGVRP. Based on the substitution array of travel agent problem (TSP) route, an effective decoding method for constructing CGVRP route is proposed. Based on the location information of customers, an initialization method based on K nearest neighbor is proposed. According to the characteristics of CGVRP, variable neighborhood search (VNS) framework and simulated annealing (SA) strategy are adopted to perform search operator on TSP path for all solutions. The validity of the competitive search and decode method is verified. A large number of comparison results show that this algorithm is more effective than the existing method in solving CGVRP. (Zhu and Li, 2018) studied the application of computer algorithm in agricultural products e-commerce, introduced agricultural products e-commerce and precision mining algorithm, constructed the characteristic information of consumer preference model, and constructed the agricultural product feature model and recommendation algorithm. The precise recommendation algorithm is studied from four aspects. Based on the characteristics of agricultural products, the optimization of traditional product recommendation process is helpful to improve the accuracy of recommendation.

The latest research emphasis is on the scheduling and optimization of delivery vehicles in order to provide the reduced cost and reliable delivery service (Bin and Xiao-Jun, 2015; Li, 2014; Xiao-yi, 2017). The vehicle routing problem was initially solved by using the Ant colony optimization algorithm (Shang et al., 2007). However, the technological advancement motivated the researchers to apply optimization algorithms in other industries (Li, 2014) while transferring the multi-dimensional optimization problem to one dimensional statics. The recent advent came in exploring the evolution optimization algorithms of ant colony optimization to view its potential growth (Balseiro et al., 2011). These algorithms have recently been applied to the network routing problems, vehicle routing, data mining, fault diagnosis, etc (Ramadhani et al., 2017). The potential of particle swarm optimization (PSO)has been studied in the recent years to deal with the continuous optimization problems in the domains like biological medicine, image processing, task scheduling, engineering application problems, etc. (Chávez et al., 2016; Kıran et al., 2012; Poongodi et al., 2019; Ramadhani et al., 2017; Sharma and Kumar, n.d.; Xu and Min, 2016; Xu et al., 2016). Various optimization algorithms have been used by different researchers like Zachariadis et al. presents a particle swarm algorithm (Zachariadis et al., 2009), and (Jin et al., 2007), (G and Peralta, 2009) and (Tasan and Gen, 2010) utilizes the taboo search algorithm combined with local search, ant colony algorithm and genetic algorithm respectively. The work using the Taboo search is impressive in terms of its approach towards the reduction of effective split delivery while minimizing the mileage of transportation with reasonable computational time.

3. PROBLEM DESCRIPTION AND MATHEMATICAL MODEL

The problem description and its mathematical modelling is presented in this section describing the vehicle routing problem.

3.1 General Description of the Problem

To address the issue of distribution of agricultural products collection and distribution routes, first conceptual description: in the two-dimensional transportation route map $G = (V, A)$, $V = [(v_0, v_1, v_2), ..., V_n]$ is the end point control. v_0 represents the planned product distribution center, where *m* working cars are placed for collection and distribution, and the distribution car returns whenever the distribution enters Stand by at this point. The remaining *vi* represents the locations all over the distribution area, that is, the distribution points. The distribution demand is set as a random variable ξ_i, and the agricultural products of the distribution points in all areas are completed by the distribution vehicles of the distribution center. $A=\{(v_i, v_j)|i\neq j,(v_i, v_j)\in V\}$ is a set of arcs, and each arc represents the route of two delivery points. $C=\{c_{ij}|(i,j)\in A\}$, c_{ij} represents the movement distance required for the operation of the two distribution points, oil consumption, depreciation, or time consumption (Nadir et al., 2019). Then set the moving speed of all vehicles in the distribution center as u, the loading and unloading time of each distribution point is t_s, and the loading and unloading time of the distribution vehicle in the distribution center is t_0. Set the delivery point to specify the maximum time T_i for the vehicle to reach this point. If it arrives late, the extra lost work fee is $f(t_i-T_i)$. If it arrives early, there is no lost work fee, and then set t_i represents the actual travel time used by the delivery vehicle. The models of all delivery vehicles are the same, and the highest operating capacity is Q. Then there is the fastest operation plan to find the total cost of distribution (the sum of moving expenses, delayed work time and fixed expenses).

3.2 The Minimum Number of Delivery Vehicles Required Under the Constraint of Opportunity

As mentioned above, the demand for distribution points is generated randomly, that is, random variables, so this problem belongs to the category of random distribution. In random distribution planning, the demand for delivery vehicles is generally determined for the first time based on opportunity constraints. Then, in the moving path τ with n delivery points that has been designed in a day, the maximum number of delivery points that a delivery vehicle can serve:

$$n_1 = \max\left\{ r \middle| p\left(\sum_{i=1}^{r} \xi \le Q_i\right) \ge p_a \right\} \tag{1}$$

Among them: r is a natural number, representing the number of delivery points that the delivery vehicle can serve; P_α is the chance constraint probability that a delivery vehicle can serve all delivery points on the set route without returning to the delivery point.

The minimum number of vehicles used in this model:

$$m\left[\frac{n}{n_1}\right]+1 \tag{2}$$

among them, $\left[\frac{n}{n_1}\right]$ means less than $\frac{n}{n_1}$, the largest integer.

3.3 Time When the Vehicle Arrives at the Demand Point

The route problem of the delivery vehicle is random. This type of problem is generally used to plan the route. For example, when the delivery vehicle starts to leave the station, first plan the delivery route, and then the delivery vehicle follows the planned route. The operation process is already empty and full in the middle, adjust the route. For example, if the delivery vehicle is empty and full in the middle, then first return to the distribution center to reload and unload, and then follow the previously set route to complete the remaining distribution points Delivery and pickup (Jones et al., 2019). If the delivery vehicle does not complete the pre-given planned tasks, that is, it does not pass through all the delivery points and must return with a full load, this situation becomes a route planning failure. In this model, the delivery vehicle must pass through each delivery point; when the delivery vehicle reaches the *i-th* delivery point, it can know the demand of the next delivery point $i+1$, so the remaining delivery capacity of the current delivery vehicle is not enough to complete the next delivery point. When there is a demand for a distribution point, the distribution vehicle returns to the distribution center from the current distribution point i in advance; each distribution vehicle is only allowed to have one route planning failure during the delivery; the planned path is equal, and d represents the movement between the two distribution points. Distance, $d_{ij} = d_{ji}$. The route of n delivery points can be obtained in the service process of delivery vehicle k, when there is no path planning failure during the operation process, the time to reach delivery point i:

$$t_{ik}^{0} = \frac{1}{u}\sum_{j=1}^{i-1} d_{j(j+1)} + \left(i-1\right)t_{s} \tag{3}$$

If the route planning that occurs at $j|j<i$ is not successful, the time for the delivery vehicle to reach i is:

$$t_{ik}^{j} = t_{ik}^{0} + t_{0} + \frac{\omega_{ik}}{u} \tag{4}$$

among them ϖ_{ik}.

The added value of the route due to the failure of route planning at point j:

$$\omega_{jk} = d_{j0} + d_{0(j+1)} - d_{j(j+1)} \tag{5}$$

The expected penalty value caused by the time delay is:

$$F\left(t_{ik}\right) = \left\{\sum_{j=1}^{i-1}\left[f\left(t_{ik}^{j} - T_{i}\right)p_{jk}\right] + f\left(t_{ik}^{0} - T_{i}\right)p\left(\sum_{h=1}^{i}\xi_{h} \le Q\right)\right\} \tag{6}$$

where p_{jk} is the probability of failure of route planning at point j:

$$p_{jk} = P\left(\sum_{r=1}^{j+1}\xi_{r} \succ 0\right) - P\left(\sum_{r=1}^{j}\xi_{r} \succ 0\right) \tag{7}$$

3.4 Path Cost Objective Function

The path cost value of the *k-th* vehicle:

$$E\left(\tau_k\right) = \sum_{i=1}^{n_k} d_{i,i+1} = \sum_{i=1}^{n-1_k} F\left(t_{ik}\right) \tag{8}$$

The objective function of path cost for m vehicles is as follows:

$$\min z = \sum_{k=1}^{m} E\left(\tau_k\right) + g\left(m\right) \tag{9}$$

where *g(m)* is the fixed investment cost related to the number of vehicles.

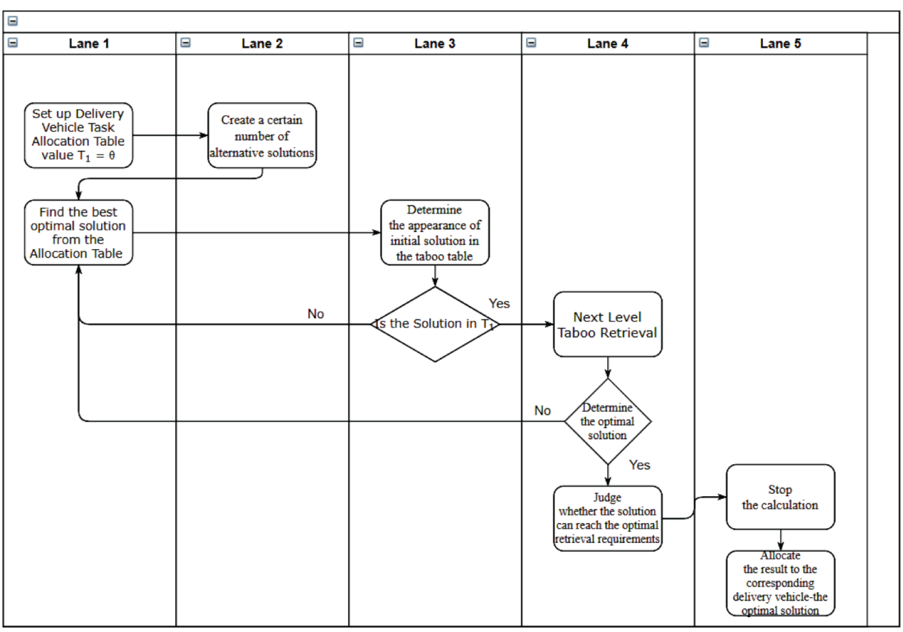
4. PROPOSED ALGORITHM

Compared with random programming, the precise algorithm requires strong mathematical skills when calculating, and the scale of problem distribution points that can be applied to this algorithm is relatively limited. Then compare with examples and algorithms. The flowchart of the proposed algorithm is given in Figure 2 and the algorithm is described as follows.

4.1 Taboo Search Algorithm

The taboo search algorithm is not suitable for large-scale problems. Therefore, in order to make the search scope wider, set a taboo table for all delivery vehicles-task allocation architecture, and then configure the monomer with the same allocation structure to enter the most Excellent route taboo

Figure 2. Flowchart of the Proposed Algorithm



search. Definition of the distribution structure: set $G_j=[g_1,g_2,...,g_m]$ represents the distribution vehicle corresponding to solution *j-task* distribution structure, g_i represents the delivery vehicle *i* is going to The number of delivery points. If the two sets are the same, then the two feasible solutions have the same delivery vehicle-task assignment architecture. For example, if there are 4 delivery vehicles, the distribution result of feasible solution 1 is 3-2-2-3, and the distribution result of feasible solution 2 is 2-2-3-3. Since the car models are the same, the two solutions have the same distribution structure.

Taboo algorithm steps:

Step 1: Set up delivery vehicle-task allocation framework taboo table T_1, initialize $T_1 = \varphi$.

Step 2: A certain number of alternative solutions will be generated from the above. The generation step of an alternative solution: first generate a random sequence of distribution points, and then take turns to randomize the demand of each distribution point to the distribution vehicle that can undertake the task (Arnon-Rips et al., 2019; Briones and Sarmah, 2018). This process is random Yes, if the demand of the distribution point assigned to a certain distribution vehicle exceeds the maximum loading capacity of the current distribution vehicle, then stop assigning tasks to the distribution vehicle. Then, the distribution points assigned to each distribution vehicle are connected into a route sequence, which is an alternative solution. Refer to similar documents for the specific method used. Repeat the above steps, when the generated alternative solutions reach a certain level, then select the excellent solutions in the front row from these alternative solutions as the initial solutions.

Step 3: In the initial solution selected in the previous stage, take turns to determine whether each delivery vehicle-task delivery structure in the initial solution has appeared in the taboo table. If there are duplicates, skip the search and judge the next initial solution; If there is no repetition, put the distribution structure into the taboo table T_1, use this solution as the initial solution of the next-level taboo retrieval algorithm, and go to the next step.

Step 4: The inner taboo retrieval algorithm refers to the use of the current feasible solution, the neighborhood change 2-opt (Nadir et al., 2019) (two distribution points replacement), select several candidate solutions with better results from the distribution set, and determine the candidates in turn is the optimal solution in this taboo? If there is no taboo, the corresponding taboo item is placed in the taboo table, and the current candidate is used as the current solution; if the taboo is triggered, it is judged whether it can trigger the breaking of the taboo. If the conditions for breaking the taboo are reached, the taboo is broken and the resultant is the current solution; if the condition of breaking the taboo is not met, it will be the next candidate solution for the judgment mentioned above. The number of candidates sets and the length of the taboo table are determined according to the running time of the program and the accuracy of the comprehensive calculation.

Step 5: Then judge whether the solution can reach the optimal retrieval requirements, if it meets the requirements, stop the calculation, and then allocate the result to the corresponding delivery vehicle-the optimal solution of the task delivery architecture.

Step 6: Whether the search has been completed in the initial solution set, return to Step 3 if it is not completed; if it has been completed, select the optimal value in the optimal solution of all the distribution vehicles-task distribution architecture as the final search result.

4.2 Genetic-Taboo Hybrid Algorithm

In order to get better calculation results, the premature nature of genetic algorithm and the limitations of taboo retrieval algorithm, the advantages of the two algorithms can be selected and combined into a hybrid algorithm. The hybrid algorithm in this article is a variation of genetic algorithm, which uses taboo retrieval mutation. The algorithm of genetic algorithm literature (Jones et al., 2019) is consistent, and the taboo retrieval algorithm is roughly the same as 2.1. When the number of delivery vehicles-task delivery architectures is huge, taboo retrieval will be used for all architectures, and the calculation time will increase. Therefore, it is possible to set taboo search only for some distribution architectures with good target values. In the program design, a variable mutation probability can be set. As the algebra of genetic evolution increases, the probability value gradually increases.

5. RESULTS AND DISCUSSION

The algorithm is applied on the agricultural product area and the results are computed for the proposed approach. In a 100×100 agricultural product area, 20 distribution points are set (coordinate points are shown in Table 1), the distribution center location is (50, 50), and the distribution of each service center is independent.

The distribution centers conform to the loose distribution $qi\sim p(\lambda=5)$, the maximum operation capacity of all delivery vehicles $Q=30$, the driving speed $u=60$, the operation time of each delivery point takes 113, the time point when the delivery vehicle starts to move is 0, and the maximum arrival of all delivery points. The time is randomly allocated by the computer. If the telephone time ti of the delivery vehicle arriving at the delivery point is greater than the time limit Ti, the penalty function is set to the maximum operating capacity of all vehicles $Q=30$, driving speed $u=60$, the service time of each point is 113, and the time when the vehicle starts to depart. Recorded as 0, the required arrival time of all demand points is randomly generated by the computer. When the earliest time ti of the vehicle's arrival at the service point exceeds the time limit Ti, the penalty function is set as f(ti-Ti) = 400(ti-Ti). The fixed investment cost is 1,000. The Coordinate points of the latest arrival time and demand points are presented in Figure 3.

In the improved mathematical model, the algorithm uses ordinal coding. After the mutation calculation, the auxiliary factor based on integer order can be used to solve the shortcomings of the mutation, and then the genes obtained after the mutation operation are all ordinal, which can do the rest. This is also the most important part of the improved mathematical model algorithm. It is conceivable that if other rounding methods are used, such as conventional rounding, rounding down or up cannot be all gene values Ordinal numbers cannot get effective results. The crossover factor is designed to follow the evolutionary algebra to automatically update the crossover factor. This crossover operation makes the algorithm in the initial stage of evolution, which can improve the algorithm's global retrieval ability, and can also strengthen the local retrieval ability in the later stage. The calculation outcomes achieved for the proposed algorithms are provided in Table 2.

Table 1. Coordinates of the latest arrival time and demand points

Serial number	coordinate	Latest arrival time	Serial number	coordinate	Latest arrival time
1	95.5	0.86	**11**	61.1	0.39
2	23.35	4.08	**12**	79.74	8.38
3	60.81	9.1	**13**	92.44	5.08
4	48.0	0.33	**14**	73.93	10.4
5	89.13	1.74	**15**	17.46	5.31
6	76.20	2.44	**16**	40.41	4.80
7	45.19	2.39	**17**	93.84	9.46
8	1.60	6.82	**18**	91.52	5.96
9	82.27	3.2	**19**	41.20	2.44
10	44.19	2.4	**20**	89.67	7.56

Figure 3. Graphical representation of latest arrival time and coordinates for respective demand points

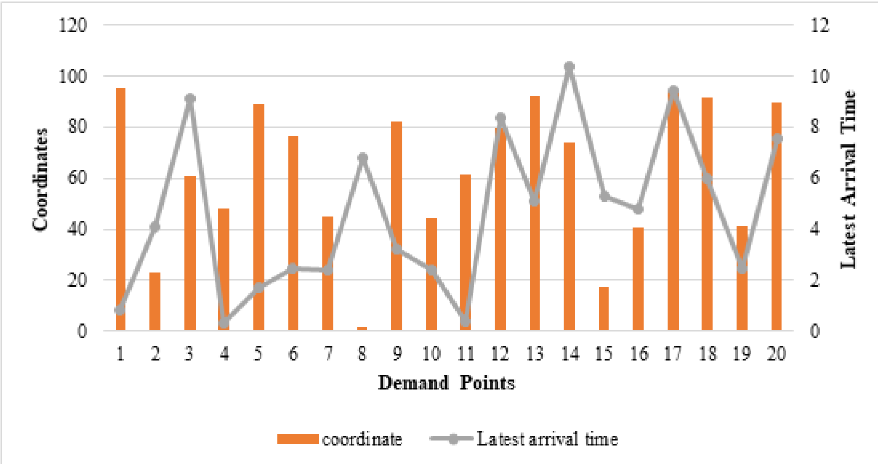


Table 2. Calculation results

		psize	st	st1	cn	maxv	minv	meanv	Standard deviation	time
n=10 m=2 m=3	GA	50			10	2618.9	2414.3	2500.8	60.9	3
	GA	80			10	2502.2	2394.5	2469.1	30.7	6
	TS	30	5	5	10	2414.3	2394.0	2398.4	8.4	20
	HA	50	5	2	10	2414.3	2394.0	2442.6	28.8	6
n=11 m=3 m=4	GA	50			10	3606.7	3494.2	3544.4	32.7	3
	GA	80			10	3599.1	3482.1	3543.9	36.9	9
	TS	30	8	8	10	3501.4	3470.2	3482.3	10.2	25
	HA	50	8	4	10	3506.3	3458.6	3478.8	16.6	6
n=16 m=4 m=5	GA	80			10	4842.9	4720.0	4779.8	37.5	8
	GA	12			10	4853.3	4750.2	4797.9	36.6	12
	TS	30	10	10	5	4620.5	4558.1	4598.7	25.4	30
	HA	80	10	4	10	4653.3	4570.3	4610. 8	24.1	16

Description: GA is a genetic algorithm; *psize* represents the number of initial solution sets; $m, \overline{m}$ refers to the minimum and maximum number of delivery vehicles respectively; the genetic algorithm has a crossover probability of 0.6 and a mutation probability of 0.2; *st* is the delivery vehicle-task delivery architecture; TS is the taboo retrieval algorithm; *st1* is the actual delivery vehicle task delivery architecture involved in the calculation; *cn* is the number of calculations; time: the approximate running time of the program, the unit is min, and the computer CPU frequency is 800; maxv, minv, meanv, and standard deviation are the maximum, minimum, and average expected values of the delivery vehicle's moving mileage after 10 calculations Value and standard deviation; HA is a genetic-taboo combined algorithm. From the analysis of the calculation results, the following conclusions are drawn.

The convergence of taboo algorithm can be used, and because it needs to retrieve each delivery vehicle-task distribution structure, the retrieval time is too long. Genetic algorithm has an advantage in computing time, but the convergence is not better than taboo algorithm. When the distribution vehicle-task distribution structure is relatively small, it is more appropriate to adopt the taboo retrieval algorithm; when there are many distribution structures, it is necessary to improve the algorithm, and a hybrid algorithm can also be used. After passing some better solutions expressly through genetic algorithm, and then retrieving these distribution-task distribution structures, the search time can be reduced. In practical applications, the taboo retrieval algorithm is used in small-scale cases, and the taboo retrieval algorithm is used in large-scale cases. If the time is too long, hybrid algorithms can be used. The results for 200 iterations after applying the proposed algorithms is depicted in Figure 4.

After carrying out a 200-ratio iterative procedure and 10 experiments, 40 delivery routes with the same performance were obtained. The best results can be achieved 94%. The total route length is 790km, and the collection can be completed with 3 delivery vehicles For the delivery task, the delivery route of the first delivery vehicle is 1-6-3-2-4-5, and then the actual loading capacity when leaving the distribution center is 8 tons, which can reach the full load state and return to the actual loading capacity of the distribution center It is also 8 tons and the route length is 215km. The delivery route of the second vehicle is: 0-1-3-4-0-6-2-5. The actual loading capacity when leaving the distribution center is also 8 tons, which is also fully loaded, and the loading capacity when returning to the distribution center It is 6.5 tons and the route length is 305km.

The outcomes are also evaluated in terms of different evaluation parameters like accuracy, precision, recall and F-score. These outcomes for different iterations are depicted in Figure 5.

A highest validation accuracy of 94.27% was obtained over 200th iteration count, while a high precision value of 94.37% was reported for the same. An average validation accuracy of 94% has been obtained for the complete algorithm. The other performance indices like recall and F-score provides 94.57% and 94.56% values for the proposed optimized approach.

Figure 4. Results after 200 iterations

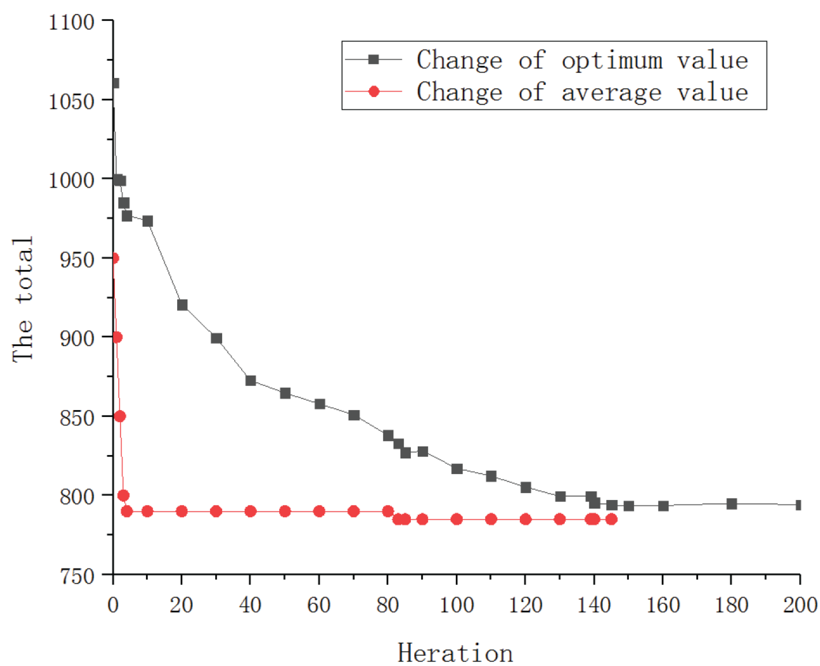
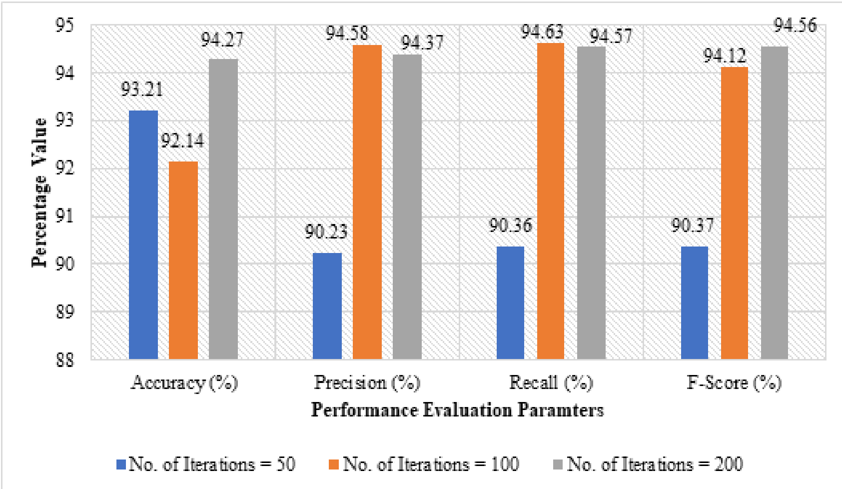


Figure 5. Performance Evaluation Parameters for different iterations



6. CONCLUSION

This paper combines the characteristics of the collection and distribution of agricultural products, carries out the optimization of the collection and distribution route of agricultural products with a time limit and uncertain number of delivery vehicles. The proposed approach gives the expected planning model by hybridizing the two methods of taboo retrieval algorithm and hybrid algorithm and focusing on the research on taboo retrieval algorithm. By adopting the double taboo of understanding set and route order in the algorithm, the shortcomings of taboo algorithm on large scale are solved. However, because randomness is much more complicated than certain types of problems, accurate algorithms can only be applied to a small range of problem types, and heuristic calculations in the development of algorithms makes the algorithm simplified for the collection and distribution of random agricultural products. This calculation result has a good effect on the similar topics mentioned in the taboo retrieval algorithm. The highest validation accuracy of 94.27% was obtained over 200th iteration count, while achieving the high precision, recall and F-score values of 94.37%, 94.57% and 94.56% respectively. The future perspective of this work lies in solving the randomness and complexity issue while doing the more in-depth research of the time and accuracy.

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