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A Hybrid Optimization Algorithm for Traveling Salesman Problem Based on Geographical Information System for Logistics Distribution

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Abstract

This paper presents a hybrid algorithm for traveling salesman problem. The algorithm is a combination of the genetic algorithm and simulated annealing algorithm; in other words, it is a hybrid algorithm. The combination overcomes the deficiencies of the two algorithms when acting separately. The real distance between customers has been used on the basis of geographical information system (GIS) in order to make the result more suitable in real-life. The algorithm has tested on the examples of international standards. We made a comparison with the result of second nearest neighbor algorithm and genetic optimization algorithm. The test showed that the algorithm proposed in this paper has improved the results.

Keywords: *traveling salesman problem, genetic-simulated annealing algorithm, geographical information system*

1. Introduction

On the basis of technology of Geographic Information System (GIS), this paper integrates optimization method with spatial database and proposes a hybrid intelligent optimization algorithm for traveling salesman problem (TSP). The algorithm aims at providing a cost-efficient and time-saving strategy that can use in real-life for logistics delivery.

In the paper, we consider that in the traveling salesman problem for distribution centers that the number of customers, order quantity and traffic are uncertain every day. In this paper, through the algorithm, we can get a better result: shorter line with less cost. The results on the standard examples show that the algorithm is valid and rational. After validation, the algorithm has also been tried out in practical as that the writer integrates the algorithm with GIS and customer order system. The strength of the algorithm is that it can get a cost-effective plan faster which we can use in daily actual delivery work. It means the optimization of time, path length, sequence and cost.

Traveling salesman problem (TSP) in distribution center can be defined like that: for a given set of customers to determine the appropriate delivery vehicle routes. The delivery process involves loading points and or unloading points, so that starting from the distribution center then in an orderly manner, through them, and finally return to the distribution center. During the process, we need to meet certain constraints, such as vehicle capacity, customer demand, time limits, mileage restrictions constraints, and to achieve goals of minimizing the total cost of transportation, minimizing the vehicle mileage or the delivery time. A variety of algorithms have been devised to solve TSP in

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recent years, and the algorithm concludes approximation algorithms and exact algorithm [1].

Though researchers have pay lots of efforts on the exact algorithm and many achievements [9-11] researchers achieved. According to algorithm complexity of TSP, the computational cost of an exact algorithm will grow exponentially with the expansion of the whole question, so that the exact algorithm is difficult to solve the problem efficiently or that the exact algorithms cannot guarantee a result within an acceptable time. While the requirements of algorithm speed and stability are increasing, as a result, in recent years more and more scholars use approximation algorithm to solve TSP problem. Furthermore, approximation algorithm can be divided into traditional and modern heuristic algorithms.

There are many traditional heuristic algorithms for TSP have been proposed, such as Improving-Exchange algorithm [12], [13], Saving-Inserting algorithm [14], [15-16], Mathematical Programming Based algorithm [17] and interactive method [18].

In 1980s, a number of modern heuristic algorithms such as artificial neural networks, genetic algorithms, simulated annealing and tabu algorithm [19-22] has been presented. Rabbani et al. has presented GA-PSO method [23]. They have developed by revealing or simulating natural phenomena and processes. The thoughts of these algorithms involve physics, mathematics, artificial intelligence and other aspects, and provide new methods and means to solve the large-scale complex problem. In the field of optimization, because these algorithms construction reflects the intuitive and natural mechanism, it is called intelligent optimization algorithm or meta-heuristic algorithms.

We compare several TSP algorithms and briefly analysis the main advantages and disadvantages of the various algorithms, as shown in Table 1.

Table 1. Comparison of TSP Algorisms

Classification		*Name of the algorithm*	*Advantages*	*Disadvantages*
Exact algorithm			We can get the optimal solution for small-scale problem.	High computational complexity, for complex practical problems involved solving within an acceptable time.
Heuristic algorithm	Basic algorithm	Saving algorithm	Algorithm is simple, with good expansion capability.	Sorted according to the size of the savings value, but the value of similar size to save a point location might be very far in practice so that the point on the same line within a division possibly in a far place and extended distribution distance cannot get a satisfactory solution.
		Nearest Neighbor algorithm	Algorithm is simple, the initial solution can be obtained with adjacent table in a relatively short period of time and the result of network is relatively dense.	Easy premature convergence and easy to fall into local optimum.
		Nearest inserted algorithm	Algorithm is simple, use the adjacent table search, we can obtain an the	Easy premature convergence, consume more time than the nearest neighbor algorithm which is easy to fall into a local optimum.

Classification	*Name of the algorithm*		*Advantages*	*Disadvantages*
			initial solution in a relatively short period of time, the algorithm is more accurate than the nearest solution obtained.	
		Scanning method	Algorithm is simple in principle, is a group first then line heuristics algorithm.	Urban roads and rivers are complex, points within the region may be divided into a dead end or very far away, but there are big difference in the intensity of the workload and generated line dividing with big difference.
	Improved algorithm	Simulated annealing algorithm	For small and medium-sized VRP sub-optimal solution can be obtained.	Algorithm is complex, has large amount of computation and involves complex neighborhood conversion and solving strategy.

2. GIS in Logistics and Distribution

Geographic Information System is a new technology and interdisciplinary between information science, space science and earth science and it integrated financial database systems and computer graphics in geospatial data processing and computer systems technology. Through system operation and correlation analysis with establishment of model generate useful information on aspects of regional planning, resource environment decision and management decisions. Complete GIS at least three major components: GIS hardware and software systems, IS geospatial data and related operations and management system.

Firstly, the point positioning and location.

GIS technology can manage spatial data such as distribution centers' and customer points' location coordinates messages. Logistics activities as objects move in time and space dimension, is an organic collection of time and space. The GIS has been used in logistics planning to improve logistics because of its powerful geospatial data analysis features.

When planning urban logistics distribution system, it is able to easily access the location coordinates of distribution center and customers. In the process of the selection of distribution center, we can take advantage of the spatial analysis and topological analysis automatically avoids interference and other obstacles. Therefore, it can be used to determine one or more nodes' locations. In the logistics system, distribution centers and delivery routes together form a logistics and distribution network, distribution centers is the nodes of the network. How to meet the actual needs of customers while improving distribution efficiency, reducing distribution costs, establishing a reasonable number of warehouses or other logistics facilities in the region, determining the specific location and scale of each facility and determining the relationship between logistics and the various facilities and so on at the same time. These issues can be solved more easily with GIS model.

Secondly, the optimization of TSP.

Road network data in logistics and distribution belongs to spatial information, and GIS is based on graphical and attribute data management. Model-based analysis has the advantage of information visualization and can provide more clear

expression for the user. At the same time it is able to display, capture, store, retrieve and analyze a variety of spatial and dynamic information to assist decision making.

Introduction of GIS facilitates the transport management and road network information process. With GIS ,we can not only add a variety of road network information needed , such as road's distance, road's type and road's traffic attributes and other information, but can also add various logistics distribution center points and customer points. All kinds of information involved in GIS can be visible and continent for decision-makers. Both in one-to-multi distribution and under multi-to-multi mode it can give a scientific and rational path planning. The program can also be adjusted on the visualized map flexibly when the automatic routes plan for a distribution center is not realistic.

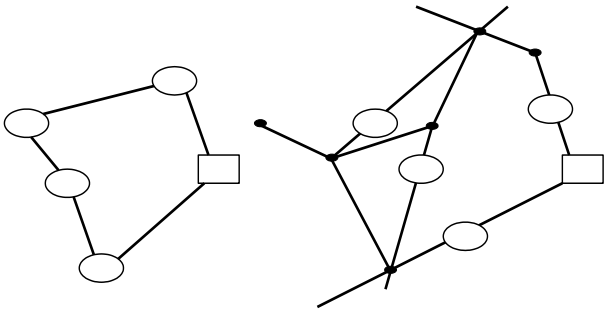
According to domestic development of international logistics practice, GIS-based integrated logistics and distribution system is the inevitable direction of modern distribution. However, according to current research, there is a lack of research in TSP optimization on the basis of GIS. In most applications of GIS systems, it's just been used in GPS but lack of assisting decision-making in logistics distribution.

3. Model Based on GIS

The traditional definition of TSP problem is: A distribution center with various vehicles and deliver multiple customers and vehicles are not full loads. It means that a delivery truck can serve multiple customers and the entire cargo less or equal than the maximum capacity of the vehicle. The hypothesis is that: each customer's location, distance from the area and the logistics center between any two clients, are known. Decision makers need to determine how to arrange vehicles and sequence. The optimal objective function is the lowest total cost or alike.

As shown in figure 1. (b), network diagram of GIS-based TSP model is constructed by the intersection of the paths, the starting point, the end point node, the location point of customers and relative paths. It is an undirected graph. The data structure not only includes the distance and the client nodes number, location and other information for all paths, but also includes the capacity of the path. The geographic features make the network diagram information much richer than the traditional one, and also more realistic.

The traditional TSP model established is relatively simple when traversing the network, and it is a undirected graph which take customer as nodes and paths as edge as shown in Figure 1. (a). Path distance and the client nodes constructed data structure.



(a) (b)

Figure 1. Comparison of Two TSP Network Diagram

Network graph builds process is as follows.

Step 1: Construction of GIS-based road network map.

GIS platform is with object-oriented spatial data management capabilities. Attribute database and spatial database can be designed and built under the support. The established GIS road attribute data constructed in this paper is made of the two, one is information collection E of path information and the other is information collection V of intersections of paths, while the two are divided into several sub-items correspondingly. The specified content as the following steps:

Step1.1: Store related path-based information to form an essential path information collection (E). The path information collection E includes road's unique identifications: encode, name, traffic factor and road grade information.

Step1.2: Store intersection information of the path to form a path intersection collection V. The intersection of the path not only includes the crossover point between any two roads, but also includes isolated endpoint of the road. In the actual distribution process to go through any one-customer point must firstly pass through the intersection of several paths before arrive. During the pretreatment process of the road network map, the intersections of paths are equally important information with customer's geographical location information. The route group V includes the serial number in the information collection E, the latitude and longitude coordinates of intersections of paths.

Step 2: Mapping customer Information on the road network.

After collection of customers' latitude and longitude information with the help of satellite location equipment, the exact GIS information is confirmed. We can see the customer points on maps when overlying all customers' latitude and longitude information on the map on designed electronic map. When applying it in the actual distribution system, there is a certain distance from the marked customer points to the main road. The advantage of the process method is on one hand the mapping process and on the other hand to facilitate the subsequent clustering to optimize the distribution division of the region. Customer service data processing steps are as follows:

Step 2.1: Firstly, create and store the customer's necessary information. The information collection includes the following information:

- Unique customer code (to identify customers)
- Latitude and longitude data (obtained by the GPS satellite location equipment)
- Volume of customer history distribution amount (in nearly three months as the initial cluster-based rationing amount)
- Customers' name and customers' contacts

Step 2.2: Map all customers' points in the digital map. Take vertical mapping to the map, if a customer point in the graph can be mapped to two roads, and then select one of the shorter vertical distances, according to the actual situation of artificial micro adjustment.

Step 2.3: Store location information of all customers including all mapped point location information of customers thus forming a collection of all clients mapping point C'. Customer mapping points collection include two coordinates of customer's location before and after the mapping, the serial number in the collection E, mapping points and the serial number of the customer in the group V.

Step 3: Construct the network.

It is needed to decide the delivery route and optimal sequence by using a heuristic algorithm solved one by one in each distribution area, after the completion of dividing the complex and large-scale distribution network into a number of small regions under the restriction of workload balance. That means use the improved two-stage K-means clustering algorithm (this is not within the research area of this paper) to complete partition of distribution areas. The problem of multi-vehicle

travel from one-distribution center to multi-customers transforms into k similar problems of a single-car travel to several customers in the distribution area.

The network diagram of the problem is: $G = [C', E, V, W]$

$C' = \{0,1,2,\cdots,n\}$ are Point sets, 0 means the distribution center, the other points shows customers. V means the collection of intersection of all paths. $C = \{c_{ij} \mid (i,j) \in A\}$ is the distance matrix c_{ij} which indicates that the corresponding arc (i, j) length. $E = \{(i,j) \mid i,j = 0,1,2,\cdots,n, i \neq j\}$ is arc set which means that all line segments vehicles may travel.

W is the positive set of real numbers $(W : E \rightarrow IR^{+})$ that indicates the corresponding path weights.

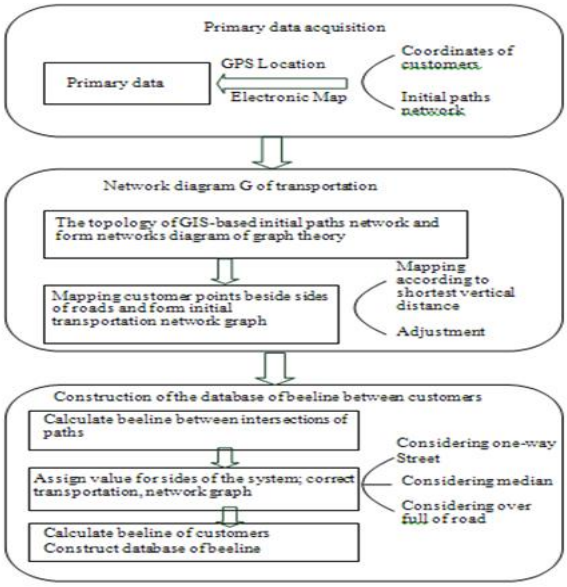


Figure 2. Geographic Information Builds Process of GIS-based TSP Problems

4. Algorithm

4.1. The Basic Idea of the Hybrid Algorithm

The intention of working with the TSP algorithm in this paper is to explore the potential for a global optimal solution for the initial population generated by the genetic algorithm, and then the simulated annealing process carried independently in each population. The TSP algorithm is a combination of the genetic algorithm and simulated annealing algorithm; in other words, it is a hybrid algorithm. The central idea of the hybrid algorithm is to harness the strong global search ability of the genetic algorithm and the high local search capability of the simulated annealing algorithm. The combination overcomes the deficiencies of the two algorithms acting separately in the optimization.

4.2. The Key Points of Genetic Algorithm

There are four key points in the genetic algorithm: fitness function, encoding scheme, genetic operator of crossover and mutation.

Encoding Scheme.

Encoding is an essential step in the design of the genetic algorithm and is the main problem in the application of the genetic algorithm. This paper uses sequence coding, with the implementation as follows:

We got the customer order of traversal as the coding mode. For example, in the case of 8 nodes, the nodes' codes are (A~H). The distribution center code is 0. When we encode an individual as 0ABCDEFGH0, this means that the vehicle travels from the initial node 0 followed by A, B, C, D, E, F, G, H and finally returns to the initial node. We added more nodes to represent the distribution center in accordance with the number of vehicles it sent out.

Fitness Function.

The genetic algorithm search according to the fitness function. The algorithm uses the fitness value of each in the population to search. In general, the fitness function is the direct transformation of the objective function, or the scale transformation of the objective function. Typically, the higher the fitness value, the better. However, in the actual logistics distribution process, if the fitness value is the length of all paths, it is the smaller value that is preferable. In order to make the fitness of the TSP problem consistent with the fitness in the genetic algorithm, the paper takes the reciprocal of path length as the fitness. The expression of the fitness function is as follows:

$$fitness = K * \frac{1}{\sum_{i-1}^{n-1} c_{ij}} \quad (1)$$

Where c_{ij} is the length of the section (i, j). K is the proportional coefficient, selected according to the particular problems.

Crossover Operator.

The paper uses the order crossover (OX). The condition of crossover is that the crossover probability of the parent body is smaller than P_c. We chose a part of the parent individual A, while preserving the relative order of nodes in the parent individual B to generate children individuals.

We then used the frequency of crossover probability P_c to control crossover operation. The greater value represents, the greater search capacity of the genetic algorithm. However, at the same time, it is easy to damage the high-performance individuals. If the P_c is too low, the search ability of the genetic algorithm will also be too low. Therefore, we set the individual i and individual j as a pair of cross individuals. The fitness values are f_i and f_j, where $\max f$ represents the maximum fitness of individuals. In order to protect real performance individuals, the crossover probability is defined as follows:

$$p_c(i, j) = \frac{\max f - \max(f_i, f_j)}{\max f} \quad (2)$$

Since the crossover probability should not be too small or too large, we set the range of crossover probability as $0.7 \le P_c \le 0.9$. When the crossover probability beyond this range, we take the corresponding boundary to be a substitution.

Mutation Operator.

The mutation operator is used to assist the genetic operators and also to maintain the diversity of the population. It aids the implementation of local search and prevents premature convergence. This paper uses the overturn mutation operator of the genetic algorithm. Firstly, we generated two random positions. Then we flipped the information of the two positions according to the mutation operator P_m.

Under normal circumstances, P_m is small. The main reason for maintaining it as such is to prevent the loss of an essential gene in the population. The paper uses the adaptive operator P_m to adjust the value according to the fitness value.

$$p_m(i) = k_1 \frac{\max f - f_i}{\max f} \tag{3}$$

Where: k_1 is in the range of 0.01-0.05.

As described, the first step in the process of applying the hybrid algorithm was to use the genetic algorithm to undertake a global search. The next step is to use the single iteration simulated annealing algorithm.

4.3. The Key Step of Simulated Annealing Algorithm

In the simulated annealing algorithm, the effect depends on the selection of a group of control parameters. The key elements include the expression of the state, movement, heat balance and cooling control.

The Expression of the State.

In the simulated annealing algorithm, a state corresponds to a solution of the problem. The energy function of the state corresponds to the objective function of the problem.

Movement.

We set i as the current solution and j as a solution in its neighborhood. Their fitness functions are f_i and f_j respectively. We took Δf to represent the object increment. $\Delta f = f_i - f_j$, moving from i to j when $\Delta f < 0$.

The Heat Balance.

The heat balance is equivalent to the physical annealing. It refers to the process of achieving a state of equilibrium under a given temperature. It is an inner loop process in the simulated annealing algorithm. To guarantee the achievement of an equilibrium state, the number of inner loops should be large enough to reach equilibrium in theory; however, in practice, this is impossible, and can only come close to the results. In the light of this, we set the inner circle to a constant at each temperature and conducted the inner loop iteration the same number of times.

Cooling Function.

The cooling function is used to control the temperature decreased, which is the external circulation process in the simulated annealing algorithm. This paper selects the cooling function:

$$T_{k+1} = T_k \cdot r \tag{4}$$

Where $r \in (0.95, 0.99)$, the greater the r, the more slowly the temperature decreased.

4.4. Steps of Hybrid Algorithm Implementation

The hybrid algorithm steps of TSP are as follows:

Step1: To determine the population size p, choose the initial temperature T_0, temperature coefficient of retreat r, as well as crossover and the probability coefficient of variation and termination rules; set the iteration counter $n = 0$.

Step2: Generate an initial population and calculate the fitness of each chromosome. $S = \max f$, $\max f$ is the maximum initial optimal fitness value in the original population; mark the best chromosome as R.

Step3: Implement the genetic algorithm according to the crossover probability, mutation probability of crossover and mutation operations. Implement optimal retention policy respectively.

Step4: Produce the next generation of groups under the replication strategy of genetic guidelines.

Step5: Run the simulated annealing for the next generation of the individual groups respectively, and produce a new generation group.

Step6: Calculate the fitness value of the new generation of groups, setting $S' = \max f$, and the corresponding chromosomes as R'.

Step7: Determine whether S' bigger than S: If yes, set $S = S'$, $R = R'$ If not, do not update the best individual.

Step8: Determine whether n bigger than the maximum number of iterations, while the final solution output is S, and stop counting if it is. Otherwise, $n = n + 1$ then return to Step 3.

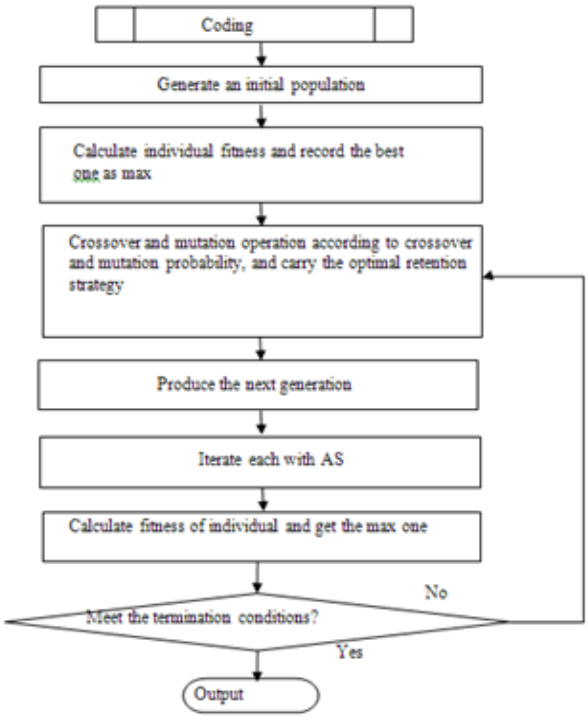


Figure 3. The Hybrid Algorithm Flow Chart

4.5. Computational Comparison

Do simulation test on ten instances of TSPlib and compare the results with the results of quadratic nearest algorithm and genetic algorithm. The results as shown in

the table. The average value of the hybrid algorithm is an average value of ten times random, and the average value of the genetic algorithm is an average value of ten times random run of it. The table shows that the hybrid algorithm gets better results than the quadratic nearest algorithm and ordinary genetic algorithms.

Following these steps, we conducted a simulation test on 10 instances of TSPlib and compared the results with the results of the quadratic nearest algorithm and genetic algorithm. The results show in table 1. The average value of the hybrid algorithm is an average value of ten times random, and the average value of the genetic algorithm is an average value. The table shows that the hybrid algorithm achieves better results than the quadratic nearest algorithm and ordinary genetic algorithms.

Table 2. Contrast of Algorithm Results

Instance	The secondary adjacent algorithm	Hybrid algorithm	Genetic algorithm
Att48	65294	35321	37496
Pr124	594620	86130	94780
Swiss42	2172	1390	1463
Berlin52	12448	86805	89268
Burma14	38.39	31.2269	31.485
Pr107	630710	510170	527827
Pr226	145430	119010	130869
Pr76	478230	122460	135550
Rat99	1751	1486	1510
Kroc100	39094	25079	26923

Simulation instance data sources：http//elib.zib.de/pub/mp-testdata/tsp/tsplib/tsp/index.html

5. Conclusions

This paper firstly compared the similarities and differences of GIS-based TSP with traditional issues, and then build a GIS-based geographic information constraints and road network and map customer information on the road. Then the computational complexity of the TSP is analyzed on the basis of a constructed network diagram. There is a hybrid algorithm combined advantages of both genetic algorithm and simulated annealing algorithm has been used to solve optimization of TSP. Through simulation experiment, we validate the effectiveness and its advantage.

In all, this paper improved the efficiency of the algorithm with a hybrid intelligent algorithm for TSP and get better results. We take advantages of actual road distance based on GIS that makes it applicable to optimizing the actual delivery vehicle path. Finally, the study breaks the status that TSP research stagnation in theoretical research and cannot be applied to practice in China.

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