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Research on TSP Problem in E-Commerce Tourist Based on Ant Colony Algorithm

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Abstract

In recent years, e-commerce recommendation systems become more mature which is widely used. E-commerce tourist routes recommendation system realize the personalized design in the ant colony algorithm based on tourist routes. In the past few years, research on ant colony optimization algorithm is widely used in the TSP problem. In this paper we propose the Branching Ant Colony with Dynamic Perturbation (DP) algorithm under the electronic commerce environment .The algorithm introduces dynamic disturbance to select cities. Experiments show that the algorithm can effectively improve the disadvantages of long search time and easy to fall into local minima in basic ant colony algorithm. This method helps the tourists choose the travel route under the environment of e-commerce more effectively,

Keywords: *E-commerce, TSP, E-commerce, Routes recommendation*

1. Introduction

Online consumption becomes more and more important to the business in the world. Researchers have paid more and more attention to E-customers online consumer behavior. At the same time, tourism has gradually become an important part in people's life, and the tourism market is becoming more and more popular. Tourism electronic commerce does not have a precise definition in the world. The general recognition of this concept of tourism e-commerce being given by the definition of World Tourism Organization is proposed in the publication of "E-Business for Tourism". Electronic commerce is improved by enhancing information exchange business activities and it uses the Internet technology to improve or change the core business process. From the combination of these two aspects we know electronic commerce is improved through the advanced information technology means (through intranet) and external (via the Internet) connectivity for tourism destination management and tourism enterprises. From a general point of view, tourism electronic commerce can improve the inter agency between tourism enterprises and the inter agency upstream suppliers in the tourism industry. It also strengthens the contact between tourism enterprises and tourists in exchange and transaction.

A combination of tourism industry and electronic commerce has also attracted the attention of many scholars: Li studied the impact of e-commerce in Chinese Tourism [1],Wu and Chang discusses the credibility problem for electronic commerce environment of Tourism [2].Hsien, Jyh-Jeng Wu, *et al.,* studied tourism strategy for Taiwan Tourism under the electronic commerce environment [3, 4], Jesse W. J., Weltevredena, Orit and Rotem-Mindali researched on C2C tourism for Holland economic evaluation method under the environment of e-commerce [5]. But in the face of numerous tourist attractions, how to choose constantly

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travel tour plan? With the rapid development of information technology, intelligent technology in e-commerce recommendation system is becoming more and more popular. It opens up a new way for the design of tourist routes. In early 90's of last century, Italy scholar M. Dorigo, *et al.,* proposed a simulated evolutionary algorithm model - ant colony algorithm (Ant Colony Algorithm, ACA) [6]. They applied the algorithm to the well-known traveling salesman problem (Traveling Salesman Problem, TSP), and the experimental results got better, but at the same time there are some problems in this algorithm such as slow convergence speed, and stagnation behavior [7]. Aiming at the shortcomings of the algorithm, many scholars proposed [8-10] the improving ant colony algorithm. The convergence speed of the algorithm is improved to a certain extent and eliminates stagnation in the algorithm. Ant colony optimization algorithm is widely used in QAP (Quadratic Assignment Problem) [11], VRP (Vehicle Routing Problem) [12] and JSP (Job -shop Scheduling Problem) [13], Talb, Roux and Fonlupt applied ant colony algorithm in the two assignment problem[14], Bullnheimer and Bell eta applied in the vehicle route planning problem[15, 16]. McMullen eta solve multi objective JIT sorting with using this algorithm [17], AhnSH and Lee using ant colony algorithm to complete the graph coloring [18], Shelokar established system modeling and estimate the parameter [19]. TSP (Traveling Salesman Problem) is a hot research topic, especially in tourist problem.

The TSP problem is a typical NP problem, it can be represented as an undirected complete connected graph $G = (V, A)$, of which $V = \{v_1, v_2, \cdots, v_n\}$ for the city, (point) set, and $A = \{arc(r, s) | r, s \in V\}$ connection diagram in any two city (point) set of arc, d_{rs} arc $arc(r, s)$ in length, and $d_{rs} = d_{sr}$ in generally. TSP problem is to find the shortest length of the Hamilton loop in G . The literature describes multiple traveling salesman problems (MTSP) and introduces concepts and practical application in detail the process of heuristic MTSP [20]. The literature made a lot of research on ant colony algorithm for solving TSP problems. Many scholars put forward the improvement measures of ant colony algorithm. HAO Jin and Shi Li designed a novel random perturbation strategy [21]. FENG Zu hong, XU Zong ben used climbing algorithm improved TSP problem [22]. Xiong Weiqing, Yu Shunhao, Zhao Jieyu proved that the mutation operator in ant algorithm can significantly improve the results [23]. Cheng -Fa Tsai, Chun -Wei Tsai, and Ching –Chang Tseng solve the TSP problem with dividing the paths into several, so all the ants can exchange between populations of pheromone [24]. However, the above literature is a strategy or rule to make improvements on the ant colony algorithm, and does not take into account the relationship between the policies or rules. If we only change a policy or rule, it is difficult to achieve good result without a corresponding change associated with policies or rules.

The branching ant colony with dynamic perturbation algorithm (DP) is applied to e-commerce tourist routes recommendation system in the background of E-Business for Tourism. This method takes into account the interaction strategy or rule changes, can introduce branching strategy selection of city and the introduction of dynamic disturbance strategy. Experiments show that the algorithm can effectively improve the disadvantages of basic ant colony algorithm such as searching long time and being easy to fall into local minima.

2. The Basic Algorithm

We list the relevant variables:

n - the scale of the TSP problem, namely the number of city'

m -The number of the ants in the colony;

k -Symbol of each ant in the colony; $k = 1, 2, \cdots, n$;

$\tau(r,u)$ -the ant pheromone density of $Arc(r,u)$ at the moment of t, the initial state is τ_0;

$d(r,u)$ - The European length of $Arc(r,u)$

$\eta(r,u)$ -The heuristic function value of $Arc(r,u)$, equal to $1/d(r,u)$),obviously , $\eta(r,u) = \eta(u,r)$

$H(r,u)$ -The hybrid heuristic information density of $Arc(r,u)$, equal to $[\tau(r,u)]^{\alpha}[\eta(r,u)]^{\beta}$;

α -The relative importance of ant pheromone density, $\alpha \geq 0$;

β -The relative importance of heuristic function, $\beta \geq 0$;

ρ -The evaporation coefficient of the ant pheromone, $0 < \rho < 1;$;

q -The random numbers obeying [0,1] interval uniform distribution;

$L_{global-best}$ -The optimal solution length;

$V_{global-best}$ -The current optimal path;

$J_k(r)$ -the set of the city r which the ant $k(k \in [1,n])$ has not visited at the moment of t;

$MaxIter$ -The maximum cyclic algebra algorithm specified;

$iter$ -Current loop algebra algorithm, $1 \leq iter \leq MaxIter$;

V_{iter} -The optimal path generation $iter$ cycle created;

v_{iter}^{j} -The points of $V_{iter}, J \in [1,n], v_{iter}^{n+1} := v_{iter}^{1}$;

L_{iter} -The length of V_{iter};

$V(k)_{iter}$ -The travelling path of the ant k in the $iter$ generation cycle;

$v(k)_{iter}^{j}$ - The points of $V(k)_{iter}, J \in [1,n], v(k)_{iter}^{n+1} := v(k)_{iter}^{1}$;

$L(k)_{iter}$ - The length of $V(k)_{iter}$;

t ;- Times of the optimal solution generated in the current algorithm ;

V_t -The current optimal path, $1 \leq t \leq iter$;

v_t^{j} - The points of $V_t, J \in [1,n], v_t^{n+1} := v_t^{1}$;

L_t -The length of V_t;

2.1. TSP Prototype

Assume the set of city $V = (v_1, v_2, \cdots, v_n)$, The arbitrary distance between the two city i, j is d_{ij}, seek a path which cross each city only once $\pi = (\pi(1), \pi(2), \cdots, \pi(n))$.,s.t:.

$$\min[\sum_{i=1}^{n-1} d_{\pi(i),\pi(i+1)} + d_{\pi(n),\pi(1)}]$$

2.2. The Principle of Ant Colony Algorithm

At present, there are many kinds of model about ant colony algorithm. For example, Ant System (AS), Ant Colony System (ACS), MAX-M1NAS (MMAS) .The main idea is the simulation of ant foraging swarm intelligence. The ant movement will be on the path to release a material can be called "pheromone". The ant colony behavior with self-organization is very efficient by the pheromone "path information exchange". The ant movement formed a positive feedback mechanism and the final optimal path is found through collective catalytic behavior of ant colony. Ant colony algorithm mainly includes two basic stages: stage adaptation and stage collaboration. In the adaptation phase, each candidate solutions constantly adjusted its structure according to the accumulated pheromone: more road ants passed, information element quantity is larger and it is easier to choose the path; the longer the time, the information obtained is less. In cooperation period, the candidate solutions have better performance to the desired solution through the exchange of information. Here in ACS, the results can be popularized to other ant colony algorithm as a representative of the ant colony algorithm.

2.3. The Model of the Algorithm and the Main Steps

When ant k current located in the city of r and visit the city the next s, follow the state transition rule:

$$s\begin{cases}\arg\max_{u\in J_k(r)}\{[\tau(r,u)]^{\alpha}\cdot[\eta(r,u)]^{\beta}\}, if & q\le q_0\\ S & otherwise\end{cases} \quad (1)$$

Among them, $q_0(0\le q_0\le 1)$ is the given probability in algorithm, S is subject to (2) the probability distribution of random variables:

$$p_k(r,s)\begin{cases}\dfrac{[\tau(r,u)]^{\alpha}\cdot[\eta(r,u)]^{\beta}}{\sum_{u\in J_k(r)}[\tau(r,u)]^{\alpha}\cdot[\eta(r,u)]^{\beta}} if & s\in J_k(r)_0\\ 0 & otherwise\end{cases} \quad (2)$$

When ant k is in each round, according to the local updating rules update the pheromone in the arc visited,

$$\tau^{new}(r,s)\leftarrow(1-\rho)\cdot\tau^{old}(r,s)+\rho\cdot\tau_0$$

When all ants have completed a tour at the end of each loop, if there is produced new optimal solution, we updates to the global optimal solution of the arc pheromone according to the global updating rule

$$\tau^{new}(r,s)\leftarrow(1-\rho)\cdot\tau^{old}(r,s)+\rho\cdot\Delta\tau \quad (3)$$

$$\Delta\tau(r,s)=\begin{cases}1/L_{blobal-best} & if\ (r,s)\in V_{blobal-best}\\ 0 & otherwise\end{cases} \quad (4)$$

The basic ant colony algorithm steps can be described as:

Step 1: Initialize each arc of the pheromone density and heuristic function, m ant randomly placed on n vertices;

Step 2: In order to find a feasible solution ,each ant sequentially using the state transition rule (1) or (2) type and update the feasible solutions corresponding to the arc on the pheromone according to (3);

Step 3: All the ants get the feasible solution is compared with the known optimal, if there is a new optimal solution, we update the pheromone on the arcs corresponding to the optimal solution according to (4);

Step 4: Turn to Step2, until meet the termination conditions in the cycle;

3. The Improved Algorithm

Definition: To solve a specific problem, the feasible solution is defined as "the current optimal solution", if it can meet the requirement of the objective function more suitable than the previous feasible solutions in the process of operation. So far as we known, the most satisfactory solution was defined as "the global optimal solution"; all the current optimal solution which did not reach the global optimum solution of the optimal solution we called the "local optimal solution".

The new algorithm improved the basic ant colony algorithm state transition rule and pheromone update strategy .And this new algorithm creatively introduces dynamic branch strategy , the condition of perturbation strategy and combining the variation strategy of genetic algorithm. The solution of the problem has been improved. During the operation of TSP algorithm, all the arcs on the pheromone density must be maintained in the interval $[\tau_{\min},\tau_{\max}]$, among $\tau_{\min}:=\tau_0,\tau_{\max}:=1/m$. For the symmetric TSP, $\tau(r,u)=\tau(u,r)$ is more conducive to the convergence of the algorithm. Assuming the algorithm runs in M

generation, its complexity is $O(M \cdot n^2 \cdot m)$, and the basic ant colony algorithm complexity is the same, but the new algorithm is more robust.

We assume that the algorithm has been circulating $iter$ generation and it has produced t current optimal solutions. It is easy to understand the current optimal solution V_t , if $arc(v_t^j, v_t^{j+1})$ length is longer, and then $H(v_t^j, v_t^{j+1})$ is smaller, so it is abandoned in the construction of the new optimal solution most likely. So in the beginning of the loop $(iter+1)$ generation, we first sort the mixed heuristic information $H(v_t^1, v_t^2), H(v_t^2, v_t^3), \cdots, H(v_t^n, v_t^1)$ of the n arcs on the v_t .and then select the minimum m (when the disturbance is n) heuristic information values $H(v_t^{j1}, v_t^{j2}), \cdots, H(v_t^{jm}, v_t^{jm+1})$, these values correspond to the vertices of the branch point arc as the current optimal solution $v_t^{je}(e=1,\cdots,m)$. The branch strategy significance is: if there is a better solution in current problems, it is easier to find better solutions if ants search the road from the branch point in a certain state transition rule, and the search range of ants is more relative concentration.

In the DP algorithm, we should apply branch strategy in the current optimal path to find the branch point set $\{v_t^{je} \mid e=1,\cdots,m\}$ when there is a new optimal solution. Once a cycle begins, each ant at the branch point randomly selected a branch point as the travel path of the starting point from the branch set, but also the end of the path.

In basic ant colony algorithm, the arc length is shorter, the pheromone density will be larger and the state transition probability is bigger after a certain algebraic cycles. So the possibility was selected for the optimal solution is greater. But from observing (2), we can be found the value of the denominator is determined for a given point $s \in J_k(r)$. The actual molecular decided by transition probability of the s point.

Combining the better information and search for the optimal path, DP algorithm designed a state transition rules simply. Let J_k denote the vertex r in V_t position, is:

$$s\begin{cases} V_t^{j_r+1} & if \quad q > q_0, and \quad r \in V_t \\ \arg \max\limits_{u \in J_k(r)} H(r,u) otherwise \end{cases} \tag{5}$$

When $q \le q_0$ or $q > q_0$ and r is not in V_t , ant k search the new path, select arc hybrid heuristic information maximum adjacent vertices connected r with no access; When $q > q_0$ and r on V_t , using the current optimal path existing, ant k will visit the adjacent vertex of r unvisited on V_t .

Considering the randomness, we take q_0 as the inverted index function $a \cdot e^{b/iter}, a>0, b>0$ .By the properties of converse exponential curve know, q_0 value of the final approach a , b determines the speed of a curve approach. With the increase in cyclic algebra $iter$, the current optimal solution closes to the global optimal solution, but are more and more similar; At the same time by (5) type know, , the ant will increasingly use the current optimal path on the arc to construct a new optimal solution with inverted index function value decreasing.

Definition: The ant search to get the feasible solution according to certain rules. The length is called "invalid solution" of not less than the path to the current optimal solution or "invalid path", namely the V_{iter} ,s.t $L_{iter} \ge L_t$. Ant search process which generates invalid solution is known as "invalid search". Before finding the global optimal solution, each cycle of each ant search around the path alone are not necessarily better than the current optimal solution, and some even very poor. If ants directly the release pheromone in the path, it is likely to mislead the next search process, produce a lot of invalid solution and increase the invalid search time. The variation strategy of genetic algorithm in local search advantage, mutating the travel path of each ant, can improve the quality of solution.

We define $v(k)_{iter}^{j}$ is v^{j}. Variation method is: Choose any point v^{j} on $V(k)_{iter}$,change its original position and insert it at any point on $V(k)_{iter}$ after $v^{P}(j+1 \leq P \leq n-1)$ or before any point $v^{Q}(1 \leq Q \leq j-1)$,then get the variation of solution $V'(k)_{iter}$ .If the length of $V'(k)_{iter}$ is less than $V(k)_{iter}$, this means it is variance to improve the quality of the solution ,then $V(k)_{iter} := V'(k)_{iter}$.

For the ants in the $V(k)_{iter}$, releasing pheromones can make the information known as the direction on the path relative better.

Improved DP algorithm for the path using local pheromone update rule (6), and ensure that the $\tau(r,s)$ increase after all ants mutated travel. In every generation of the end of the cycle, the algorithm makes improvements on the global pheromone updating rule.

$$\tau^{new}(r,s) \leftarrow (1-\rho)\cdot\tau^{new}(r,s) + \rho\cdot 1/L_t \tag{6}$$

Step 1 : If $L_{iter} < L_t$,get the new optimal solution then $V_{t+1} := V_{iter}$ in order to strengthen the optimum path information. Without causing too fast convergence, all the local optimal paths $V_i(i=1,2,\cdots,t+1)$ update pheromone, not just to update the current optimal path pheromone on V_{t+1} +

$$\tau^{new}(r,s) \leftarrow \tau^{old}(r,s) + \gamma \cdot \Delta\tau(V_i) \tag{7}$$

$$\Delta\tau(V_i) = \begin{cases} 1/L_i(r,s) \in V_i \\ o \qquad otherwise \end{cases}$$

ρ and γ parameters satisfy certain conditions, if $\rho \cdot \gamma$,it is difficult to play a role in strengthening, is too small it may accelerate the stagnation. We think the $5 \leq \rho/\gamma \leq 10$ value range is quite satisfactory.

Step 2: If $L_{iter} \geq L_t$, show that the estimated solution has not been improved and the algorithm stagnates. We introduces the ant pheromone communication strategy, remember $\tau(k)$ for the current ant k around the pheromone density, θ is exchange coefficient,

$$\begin{cases} \tau(m) = (1-\tau)\cdot\tau(1) + \theta\cdot\tau(m) \qquad if \qquad k = m \\ \tau(k) = (1-\tau)\cdot\tau(k+1) + \theta\cdot\tau(k) \qquad otherwise \end{cases} \tag{8}$$

So, this algorithm narrows the gap of each ant pheromone travel path through the exchange of information. According to the branch strategy, there may be produced new bifurcation point; the ant is likely to search out the local optimal path new.

3.2. The Condition of the Dynamic Disturbance Strategy

Each arc section of pheromone density continuous differentiation and the range of searching focus on certain optimum path after several cycles in DP algorithm. Hybrid heuristic information on arcs has different degrees of growth with the increasing of cyclic algebra and the density of mixed heuristic information is high on shorter length whit rapid growth; vice versa. Thus, the arc gap between the hybrid heuristic information become more and more big and the range of ant search is more and more concentrated in a few arc of larger density. If we fall into the local minimum, only depending on the algorithm is very difficult to improve the quality of the solution, also waste a lot of resources because of invalid search. So we introduce the disturbance to change some parameters and iteration rule. The objective is to narrow the gap hybrid heuristic information of each arc and expand the scope of the search ant. These above measures can effectively guide the algorithm jump out of local minimum areas and continue to the global optimum approximation.

Because the disturbance weakened the advantage of current optimal solution, and neutralize the optimum path and poor gap between the actual path, actually degenerate the solution, therefore the introduction of disturbance should not be too frequent, and must meet certain conditions.

Theoretically, it may be considered that the operation of stagnation if algorithm traverses all the possible solution space and still can’t seek out a satisfactory solution. We study the structure of DP algorithm and find the space all ants need to search for is $Z = m(n-1)/2$ in each cycle; and we found local optimal solution in the search for new local optimal solution after $Z/5$ generation cycle.

Based on this, we set a counter CS_1 and record invalid search algebra, and the conditions of introducing a perturbation is: invalid search frequency $\geq m(n-1)/(2 \cdot 5)$), namely $CS_1 \leq Z/5$. Dynamic disturbance strategy using the improving algorithm with the search process disturbance time dynamic changing, but also periodical and continuous.

Step 1: When $CS_1 = Z/5$, all arcs on the pheromone density $\tau(i, j)$ is set to the current optimal solution length, namely $1/L_t$ .At the same time start another counter CS_2 and record disturbance after continuous invalid search algebra, once generate the new local optimal solution, the CS2 is equal to zero.

Step 2: When $CS_1 > Z/5$, we only use local information (3) to the average travel path length of all ants which is greater than $V(k)_{iter}$ in $L(k)_{iter}$ in one cycle ,While the pheromone density on other shorter road the ants travel decrease according to the volatile coefficient . For delay the degenerate of the better information i.e.:

$$\rho = In(-a \cdot X + b)$$

Among them, the X is not a valid search frequency after introducing perturbations; $b = \exp$ (The initial disturbance of the value of ρ). Mean ρ decline as the logarithmic curve from the initial value. This makes the ants search the new path with the increase of the invalid search times and pheromone volatilization speed faster. If the disturbance improve the current optimal solution, we do not set the CS_1 zero but till allow the disturbance continues, in order to further improve the solution to the contrary.

Step 3: When $CS_1 = Z/5$, we think the algorithm has been difficult to improve the solution according to the existing rules. So we set the CS_1 zero, ρ recovery initial value, disturbance termination and recovery of local information disturbance before the update rules. When the CS_1 reaches $Z/5$. We introduce the disturbance second time. N is a natural number. We determined experience value by the experiment, and it is inversely proportional to the problem size.

The algorithm improves the ability of searching better solutions after introducing perturbations. The figure below shows the convergence in the disturbance and non-convergence of two different kinds of disturbances, each experimental cycle 50 generation and each running 10 times the average, then solid line in the figure at a standstill after some generations having an obvious decline process. It makes the algorithm can quickly search the global optimal solution of evolution with disturbance.

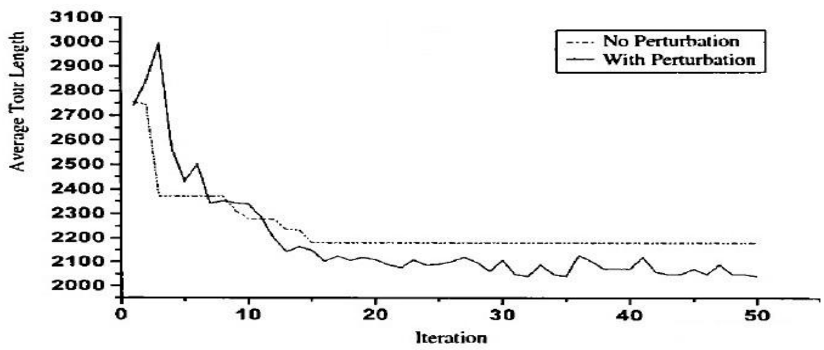


Figure 1. The Different Convergence

4. Experiments, Results Analysis and System Structure Design

4.1. Parameter Value

We set $m = n/4, \tau_0 = 1/(n \cdot L_{nn})$, Where L_{nn} is the Tsp of the maximum distance between any two nodes, $\alpha = 1, \beta = 2, \rho = 0.1, \gamma = 0.01$, $q_0 = x\exp(0.01/iter)$. Then, we use the Basic-ACO algorithm; ACOMAC+DNN and model based on DP algorithm to compare several computational results of the algorithm with randomly generated 50-city, 75-city and 150- city TSP through the simulation research. Each TSP operates 20 times and takes the average worth to table 1. The terminating condition of the loop is to achieve the optimal solution or reach the maximum cycle number specified. In Table 1, "optimal solution times" means to be able to search the optimal solution of the number in a total of 20 cycles, “the fastest search time" refers to the earliest time to find the optimal solution in algorithm.

Table 1. Experimental Results of the DP Algorithm for Solving TSP Problem

Name	The optimal solution	The number of optimal solutions	The average search results to the quick search	The fastest search time
50-city	426	5 /20	426·8	0·39
75-city	538	9 /20	538·1	0·469
100-city	14379	18 /20	14379	1·094

Table 2. The Results of the Three Algorithms

algorithm	50-city		75-city		100-city	
	average	The best results	average	The best results	average	The best results
Basic-ACO algorithm	434.2	430.4	552.3	549.9	3201.6	3150.4
ACOMAC+DNN	428.9	428.5	548.6	545.8	2550.3	2461.0
model based on algorithm	427.5	427.3	544.6	543.0	2408.6	2306.8

Study on the Table 1, we can find the DP algorithm can quickly search the optimal solution of TSP problem, and multiple search results dispersion is very small. Table 1 show that the improved algorithm is efficient to solve the TSP problem. In Table 2, Basic-ACO algorithm, ACOMAC+DNN, DP algorithm are used to solve several problems. The DP algorithm is superior to Basic-ACO algorithm, and better than ACOMSC-DNN.

The reason is that the DP algorithm combine the direction and random organically. For example, we select the branch point as the search starting point the ants search next in the current optimal path, only in the mutated ant traveled path update pheromone and update the optimal path pheromone for all the locals and so on. The purpose is to guide the algorithm towards the optimal direction of evolution. But the given probability q_0 is set as a random number, improve the state transition rules and increase the path selection diversity, and introduce disturbance each arc pheromone density difference and so on, these purpose is to increase the possibility of ants selecting the. To strengthen the direction can make the algorithm converge faster and increase the randomness can expand the scope of the search algorithm. Combination of the two can quickly search the global optimal solution and can effectively avoid the local minimum.

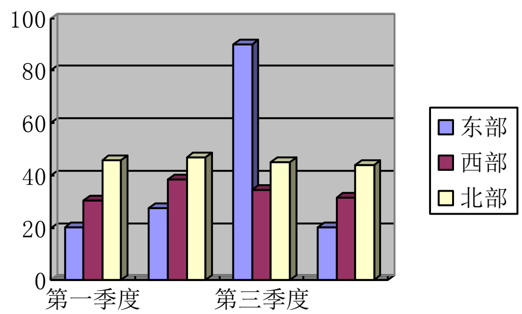
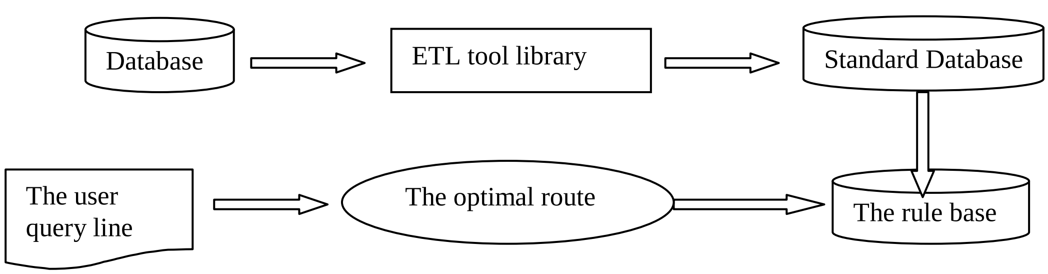


Figure 2. The System Structure Design of TSP Problem in E-Commerce Environment



The system is a subsystem of tourism management system, which has two functional modules for improving algorithm module and the recommendation module respectively.

(1) The DP algorithm module using the ETL (cleaning, conversion, and loading) tools drawn from the original database loading data to generate standard data for mining the next step. The rule is written to the rule base.

(2) Recommendation module function is directly to access the system service for the users through the web. It records the user access to tourist sites, as input data module and the visitors to the site without the knowledge. There is no need to provide additional information, because it can provide the service for the users and users don't have to worry about personal information leakage. This reflects the intelligent features of ARTRMS. Through the

association rules module using the record access to records for processing and feedback the results to the recommendation module, recommendation module will feedback rules in a certain form back to the system and users get the recommended results through the access system

5. Conclusion

In our daily life, the application of e-commerce has been integrated into our daily life, not only in shopping, but also in payment and other aspects. E-commerce has opened up a new field in the tourism industry. Electronic commerce has broken the monopoly of individual enterprises, so that every enterprise survives in the fierce competitive environment. E-commerce has become tourism value net coordinators, strengthen the cooperation with various enterprises, and constantly improve every tourist consumer demand.

In people's daily visit, route choice problem is always a trouble and important problem, so tourist routes recommendation system is introduced in e-commerce. Customer only need to input the places they want to go, tourist routes recommendation system can choose the optimal path.

This paper puts forward branching ant colony with dynamic perturbation algorithm, the algorithm to improve the basic ant colony algorithm and solve the disadvantage of basic ant colony algorithm: prematurity, stagnation and slow convergence through some rules. We introduce several new search strategies to strengthen the random and directional ant search make the ant colony algorithm has better convergence, stability and faster search speed. In the travel path selection, can be faster and more accurate selection of the optimal path .But as we see, when the problem is large, the result of the algorithm is not ideal. The reason may be the disturbance influencing the relationship between pheromone density and arc length. When the problem is large, reduces the ability of the ants to search the new path. This has become a key problem to solve the related algorithm and improved algorithm for the next step.

So far, the tourism electronic commerce is just in the initial stage. The industry has not formed a set of system of industry chain. Therefore, the application of mobile technology in the tourism industry should not be expected in the market and be accepted too quickly. The bottleneck factor demand and tourism services should pay more attention to the tourists, the maximum and the traditional service combination. Constantly enrich tourism services can promote the comprehensive development of tourism mobile commerce based on electronic commerce.

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