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Research Article

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Vehicle routing problem using colony and Markov algorithm

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ABSTRACT

There exist several limitations associated with the traditional theory. Releasing the restricted conditions of traditional VRP has become a research focus in the past few decades. The vehicle routing problem is a well-known optimization issue in transportation and logistics network systems. The vehicle routing problem with split deliveries and pickups is particularly proposed to release the constraints on the visiting times per customer and vehicle capacity, that is, to allow the deliveries and pickups for each customer to be simultaneously split more than once. Few studies have focused on the VRPSPDP problem. In this paper we propose colony and Markov algorithm method integrating the initial colony algorithm to study the VRPSPDP problem. The computational results indicated that the proposed algorithm is superior to these three algorithms in terms of total travel cost and average loading rate.

Keywords: vehicle routing problem; logistics network systems; vehicle capacity

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INTRODUCTION

With the rapid development of urban economy,logistics companies are seeking an effective andefficient solution to manage and optimize the flow ofresources in order to satisfy customers' demands(Wanget al., 2012). Vehicle routing optimization isconsidered one critical countermeasure to reduce costand improve service quality for logistics operators(Chepuri and Homem-de-Mello, 2005; Mitra, 2005).The classic vehicle routing problem (VRP) is acombinatorial optimization procedure (Baldacci et al.,2010; Wang et al., 2013), and can be described as:Several vehicles depart from the depot, serve a seriesof customers, and return to the same depot. Theobjective of VRP is to determine the optimal set ofroutes with minimized various costs (e.g., total traveldistance and the number of vehicles).

Genetic ant colony algorithm

The basic theory of ant colony algorithm

The ant colony algorithm is a new search algorithm which imitates the process model of ant collective cooperation to find food, and has better research results applied to the combinatorial optimization problem. In the experimental model of double bridge, the assumption is that in an asymmetric type of bridge, the remainder pheromone of the ants in the walking path is proportional to the number of ants at the end of the bridge, the more ants are on the bridge, the more the residual information is, and the others select path according to retained information. Example assumes that short bridge is A, the long is B, A_m and B_m is the number of ants across two bridges respectively, and $A_m + B_m = m$, If m ants have come two bridges, the probability of the m + 1th across A bridge meets:

$$P_A(m) = \frac{(A_m + k)^h}{(A_m + k)^h + (B_m + k)^h} \qquad (1)$$

In the formula, A and B are parameters for matching the real data. The probability of the m + 1th across A bridge meets:

$$P_B(m) = 1 - P_A(m) \quad (2)$$

When ants are across two bridges, according to (1) calculates the probability $P_A(m)$ across the A bridge, and then generates a φ random number uniformly distributed $[0,1]$. If $\varphi \le P_A(m)$, the ants are across the A bridge, or across the B bridge.

The parameter selection of ant colony algorithm

Time will make artificial ant residual path information of a memory capacity gradually evaporate. The parameter ρ of residual pheromone volatilization, not only directly affects the convergence speed of the algorithm, also influences its global search ability, and $\rho \in [0,1]$ in algorithms. The ants are choosing the same path, the algorithm stop to enter the local optimal solution. The smaller volatile parameters ρ is, the less the volatile of path pheromone residue is, and then the longer ants choosing the same path is. However, if ρ is larger, the repeatability of routing select between ants will abate, which makes random selective enhancement of ants.

Because the distribution of the residual pheromone is evener, which reduces the positive feedback of information, at the same time increases the randomness of the algorithm. But if the ant number m is too small, it is easily into the algorithm stagnation, which abates the global, and improves the convergence of the algorithm. When the number of cities is n, the number of ants m, meets $m \in [0.75n, 1.5n]$, is the most reasonable.

Information inspired parameter ∂, expresses a random intensity of effect in ant search path, mapping a relative key of ant's accumulation of information in group search. The greater information inspired parameter ∂ is, the greater the chance of choosing the same path for ants is, which makes the algorithm search the randomness abate, and easily into the local optimal solution. However, if inspired parameter ∂ is too small, algorithmic search randomness will be enhanced, but it will hinder the algorithm to obtain the optimal solution.

The basic principle of genetic algorithm

Genetic algorithm is a kind of algorithm of random probability iterative search, which is based on Darwin's classical theory of "natural selection, survival of the fittest". The basic idea is the genetic variation of species evolution applied to calculating the optimal solution. Being left in the process of evolution is the most adaptable to environment, and the calculation for iteration can obtain far the most optimal solution.

Genetic algorithm is based on the population formed by potential solutions to resolve problems as a starting point, and each population contains a certain number of individuals, and these individuals are encoded by genes, making individuals into a chromosome of characteristics of individual entities. Genetic algorithm simplifies coding work and based on "survival of the fittest, survival of the fittest" theory, it continuously iterates and evolves better approximate solutions. Select individual is decided by individual fitness function of the problem domain and applies genetic operators to achieve crossover and mutation, and produce new stocks set until the iteration works out the best individual, that is, it finds the approximate optimal solution.

Genetic algorithm is mainly used to choose, crossover and mutation operations form. It is the first to random initialization of a certain amount of the parent individual, and gets its individual fitness function. In accordance with the optimizing principles, evolution produces new offspring, according to the fitness function choice and cross parent individuals generates new individuals. Offspring is to implement mutation. Then offspring fitness is again calculated, which is cycled until the best individual is produced.

Model analysis

Sets the state space of random sequence $\{X_n; n \ge 0\}$ to S, if $\forall\ n \in N_0$, and

$i_0, i_1, \ldots, i_n, i_{n+1} \in S$, $P\{X_0 = i_0, X_1 = i_1, \ldots X_n = i_n\} > 0$,

$$P\{X_{n+1} = i_{n+1} \mid X_0 = i_0, X_1 = i_1, \ldots X_n = i_n\}$$

$$= P\{X_{n+1} = i_{n+1} \mid X_n = i_n\}$$

So, $\{X_n; n \ge 0\}$ is Markov chain.

each individual produces j new offspring in a probability of $p_j\,(j = 0,1,2,3\ldots)$ at the end of the life, and the number of offspring produced by other individuals is independent of each other. Initial number of individuals is represented by X_0, known as the 0th generation total, the descendants of the 0th generation constitute the first generation, its total number to X_1, every individual with equal distribution of first generation produces the second generation,......, in General, X_n is the total number of the nth generation, the Markov chain $\{X_n = 1, \quad n = 0,1,2...\}$ is called branching process.

So it makes an assumption that X_n is the number of individuals of the nth generation in the colony, and $n \geq 0$, as well as individual "children" are independent and identically distributed random variables. Here, $Z_i^{(n)}$ is the number of the i th member of the nth generation, and setting is

$$P\{Z_i^{(n)} = j\} = p_j, j = 0,1,2..., p_0 > 0, p_0 + p_1 < 1$$

Here, “ $p_0 > 0$ ” indicates that it may produce that the "child" number of a member is 0, “ $p_0 + p_1 < 1$ ” indicates the number of the "children" of a member is 2,3 , …, which may happen. From the above assumptions there is:

$$X_{n+1} = \sum_{i=1}^{x_n} Z_i^{(n)}$$

Here, the formula indicates the number of members of the n+1th generation is the sum of numbers of "children" of all members. Obviously, when X_n is known, X_{n+1} is not related to $X_{n-1}, X_{n-2}, \ldots X_0$, so{ X_n , $n \geq 0$ } is Markov chain. When $X_0 = 1$, the probability of the colony extinction is:

$$p_k(n) = P\{X_1 = k\} = P\{Z_1^{(0)} = k\} = p_k \text{, as } p_k(n) = P\{X_n = k\}, k, n = 0,1,2, \ldots ,$$

Studying only finite or infinite non-negative random variables, it is more convenient that the value generating function is used to replace the characteristic function.

Extinction probability analysis

We assume that{ ξ_n } is a branching process, and $E(\xi_n) = \mu^n$, $n \geq 0$. Where, $\mu = E(\zeta)$ is the average of descendant s of each individual. So

$$E(\xi_n) \xrightarrow[(n\to\infty)]{} \begin{cases} 0, \mu < 1; \\ 1, \mu = 1; \\ \infty, \mu > 1. \end{cases}$$

Where, $\mu < 1$ means average number of descendants reproduced by individuals is less than previous generations' deaths, which will lead to colony extinction, $\mu > 1$ means that individual reproductive average is higher than that of previous generations' deaths, which will lead to colony explosion.

When X_0 =1, the above probability π_0 of colony extinction is the minimum positive root of the formula $s = A(s)$. Where, $A(s)$ is $Z_1^{(0)}$, which is PGF of X_1. And the sufficient and essential condition of the colony extinction is the number of the average "children" of a member does not exceed the number 1(shown as Figure 3—1). It is that

$$\pi_0 = 1 \Leftrightarrow \mu \leq 1$$

Where, $\mu = E(Z_1^{(0)}) = E(X_1) = E[Z_i^{(n)}]$, $n = 0,1,2, \ldots$, i =1,2...

EXPERIMENTAL MODEL

WechooseNS-2which developed by South California University as platform[17],and use the throughput and delay of transmission time as indicators, and select the algorithm OSPF (OpenShortest PathFirst)[18],SPF (ShortestPathFirst) and BF for comparison.

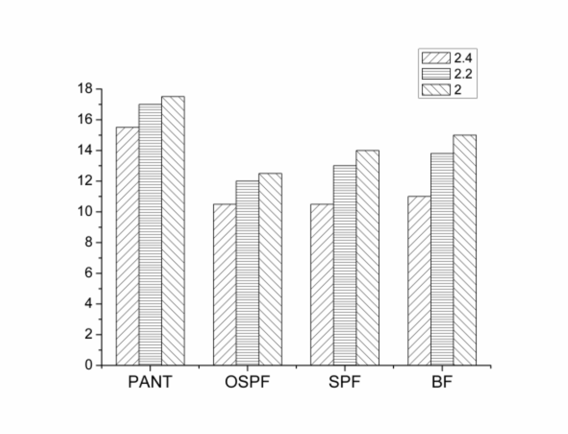

FIGURE1Averagethroughput

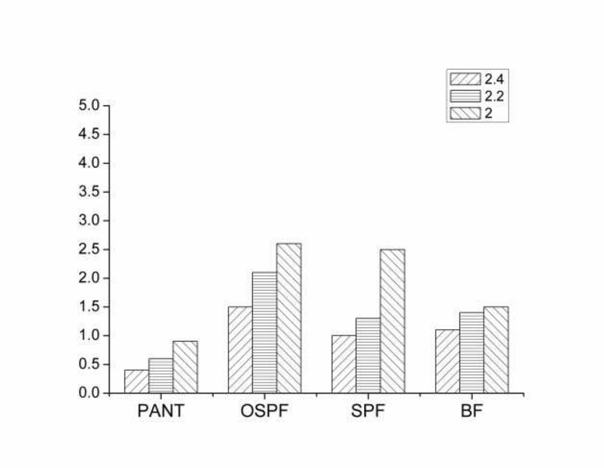

FIGURE2The Performance of packet delay

From FIGURE1 and FIGURE2, we can find that the polymorphic ant colony algorithm performances better than the other three in throughput and delay of transmission time. And through the experiment, we can also find that in the algorithm based on polymorphic ant colony, if the inspired factor is too small, convergence will be slow and, easily fall into local optimum; if inspired factor is too large, pheromone' weight will be heavy in scouting, and causes premature convergence. If expected factor is too small, the ant colony will lead
Into purely random searching, and difficult to find the optimal solution; if it is too large, the speed of convergence be faster, but convergence tends to be bad.

If pheromone evaporation factor is too large, previously searched path had possibility of researching, and it will affect the algorithm's randomness and global searching capability; if pheromone enhancement factor Qislarger, accumulation of pheromone will be faster, and it can enhance capability of the positive feedback insearching, and fasten the convergence; when Q is too large, the algorithm of the global search capability will deteriorate, easy to fall into local optimal solution, and cause the loops.

REFERENCE

[1] C. Coello, S. de Computación and C. Zacatenco, "Twenty years of evolutionary multi-objective optimization: A historical view of the field", *IEEE Computational Intelligence Magazine,* vol. 1, no. 1, (**2006**).

[2] L. J. J. Wismans, E. C. van Berkum and M. C. J. Bliemer, "Comparison of Multiobjective Evolutionary Algorithms for Optimization of Externalities by Using Dynamic Traffic Management Measures", Transportation Research Record: *Journal of the Transportation Research Board*, vol. 2263, (**2011**).

[3] Krainyukov A, Kutev V, Opolchenov D **2010** *Transport and Telecommunication* 11(4)14–28。

[4] Xue Changjiang **2007** The Steel Supply Chain of Forging Stability - Re-recognition of Current Relationship for

Steel and Steel Production. *China's steel industry* 33-35.
[5] Wang Wei, Wu Min, Chen Xiao-Fang, Gui Wei-Hua **2003** Raw Material Stock Optimization System Based on Multiple Parallel Genetic Algorithm *Control Engineering of China* 10(1) 33-37.
[6] Liu Guo-Li, Tang Li-Xin, Zhang Ming **2007** *Journal Of Northeastern University (Natural Science)* 28(2) 172-175.