2009 ISECS International Colloquium on Computing, Communication, Control, and Management

A Particle Swarm Optimization Algorithm for Grain Logistics Vehicle Routing Problem

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***Abstract*—Vehicle routing problems (VRP) arise in many real-life applications within transportation and logistics. This paper considers vehicle routing models in grain logistics (GLVRP) and its intelligent algorithm. The objective of GLVRP is to use a fleet of vehicles with specific capacity to serve a number of customers with fixed demand and time window constraints. In this paper, a novel real number encoding method of Particle Swarm Optimization (PSO) for Open Vehicle Routing Problem is proposed. The vehicle is mapped into the integer part of the real number; and the sequence of customers in the vehicle is mapped into the decimal fraction of the real number. They are used to optimize the inner or outer routes and modify illegal solutions. In the experiments, a number of numerical examples are carried out for testing and verification. The Computational results confirm the efficiency of the proposed methodology.**

Keywords-Particle Swarm Optimization (PSO); Vehicle routing problems (VRP); Efficiency and reliability

I. INTRODUCTION

The Vehicle Routing Problem (VRP) has been largely studied because of the importance of mobility in logistic and supply-chains management that relies on road network distribution. Many different variants of this problem have been formulated to provide a suitable application to a variety of real world cases, with the development of advanced logistic systems and optimization tools. The features that characterize the different variants aim on one hand to take into account the constraints and details of the problem, while on the other to include different aspects of its nature, like its dynamicity, time dependency and/or stochastic aspects. The richness and difficulty of this type of problem, has made the vehicle routing an area of intense investigation.

The VRP has attracted considerable research attention and a number of algorithms have been proposed for its solution, such as tabu search algorithm, simulated annealing algorithm, ant colony optimization, and genetic algorithm. Contrary to the VRP, the OVRP has only been studied by very few people. So far as we know, the first author to mention the OVRP was Schrage [1] in an article dedicated to the description of realistic routing problems, bringing attention to some of its applications. Sariklis and Powell [2] use the “Cluster First, Route Second” method, in the second phase, they generate open routes by solving a minimum spanning tree problem. Their method is rapid, but doesn’t get so good solution. Brandao et al. [3] apply the hybrid tabu Search algorithm for the problem. They generate the initial solution using a variety of methods including nearest neighbor heuristic and K-tree method. In the tabu search algorithm, they only use two types of simple trial moves, an insertion move and a swap move. Fu et al. [4] also use the tabu search algorithm. They develop a farthest first heuristic to generate an initial solution, and they develop four types of moves.

There are two problems existed in solution for OVRP. First, the applied methods are singleness. Many algorithms have not been attempted, such as particle swarm optimization, ant colony optimization and genetic algorithm. Second, the model of OVRP is simple. Some constraints in the practice have not considered in the model.

In the paper, we develop a particle swarm optimization algorithm for OVRP in order to exploit the research method. Particle swarm optimization is an evolutionary algorithm that simulates the social behavior of bird flocking to a desired place. Similar to metaheuristic methods, PSO starts with initial solutions and updates them from iteration to iteration. Updating of particle-represented solution is achieved through formulated equations that are able to exploit the searching experience of one particle itself or the best of all the particles. In addition to the advantages the metaheuristc methods have, including computational feasibility and effectiveness, PSO shows its uniqueness such as easy implantation and consistency in performance.

II. PROBLEM DESCRIPTION

A. Problem Description

The basic idea of grain logistics VRP can be expressed as follows: all the required grain depots must be served from a unique grain terminal, then the vehicle must return depot, the location of the grain depot is known, each grain depot asks for a quantity of goods and a vehicle of capacity is available to deliver goods. The objective is to minimize the vehicle distance and the sum of travel cost and waiting time needed to supply all depots in their required hours. The grain logistics VRP is the same problem that VRP with the additional restriction that in VRP a time window is associated with each grain depot, defining an interval wherein the grain depot has to be supplied. The grain logistics VRPTW is, characterized by the following restrictions: (1) every vehicle must start with central depot, then return central depot; (2) each required depot is visited

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only once by one vehicle; (3) the total tour demand is less than the capacity of a vehicle; (4) each route must start and end within the time window associated with the depot.

B. Mathematical Model

The vehicle routing problem has been an important problem in the field of distribution and logistics since at least the early 1960s [1]. It is described as finding the minimum distance or cost of the combined routes of a number of vehicles m that must service a number of customers n. Mathematically, this system is described as a weighted graph G=(V, A, d) where the vertices are represented by V={i},i=0,1, …,n, and the arcs are represented by A={(v_i,v_j),i ≠ j} A central depot where each vehicle starts its route is located at v_0 and each of the other vertices represents the n customers. The distances associated with each arc are represented by the variable d_{ij} which is measured using Euclidean computations. Each customer is assigned a non-negative demand q_i and each vehicle is given a capacity constraint Q_k. The problem is solved under the following constraints.

$$\min F = \{\sum_i \sum_j \sum_k d_{ij} x_{ij}^k\} \tag{1}$$

$$\sum_i q_i y_t^k \le Q_k, \forall k \tag{2}$$

$$\sum_i y_t^k = 1, i \in v \tag{3}$$

$$\begin{aligned} &\sum_i x_{ij}^k = y_j^k, j \in v, \forall k \\ &\sum_j x_{ij}^k = y_j^k, i \in v, \forall k \end{aligned} \tag{4}$$

$$\sum_{i,j \in s \times s} \sum x_{ij}^k \le |S| -1, S \subseteq v, 2 \le |S| \le n-1 \tag{5}$$

$$x_{ij}^k \in (0,1), y_{ij}^k = (0,1)$$

$$e_i + t_{ij} \le s_j \quad i, j \in 1, \cdots, n \tag{6}$$

$$\min M = \sum_{k=1}^{m} q_i \,/\, Q_k \tag{7}$$

$$\min N = \{\sum_i \sum_j \sum_k d_{ij} x_{ij}{}^k q_i\} \tag{8}$$

where objective function(1) is transports the way to be shortest; (2) is the vehicles limit; (3) guaranteed that each vehicles visit one time to each fixed point; (4), (5) is for can the looping and for G fixed-point integer. Objective function (7), (8), is the number of cars that use bulk grain at least, the minimum distance transport. On the three objectives of this function (1), (7), (8), the problem of logistic transporting multiple-objective optimization order: First the smallest of vehicles traveling path, that is, to minimize the number of vehicles required. Then the vehicles for transporting is least optimize the size of the total distance traveled and waiting time.

III. PARTICLE SWARM OPTIMIZATION FOR OVRP

A. Fundamental Principle of PSO

The Particle Swarm Optimization (PSO) algorithm is an adaptive algorithm based on a social-psychological metaphor. It was originally proposed by J.Kennedy [5].A population of individuals adapts by returning stochastically toward previously successful regions in the search space, which is influenced by the successes of their topological neighbors. PSO is related with Artificial Life, and specifically to swarming theories, and also with Genetic Algorithms (GA). PSO can be easily implemented and it is computationally inexpensive. Moreover, it does not require gradient information of the objective function under consideration, but only its values, and it uses only primitive mathematical operators. PSO has been proved to be an efficient method for many optimization problems, such as Design Combinational Logic Circuits, Evolving Artificial Neural Networks, Multiple Object Problems, and TSP.

Two versions of the PSO algorithm have been developed, one with a global neighborhood, and the other with a local neighborhood. The global version was used in the paper. Each particle moves towards its best previous position and towards the best particle in the whole swarm. On the other hand, according to the local version, each particle moves towards its best previous position and towards the best particle in its restricted neighborhood. The global version PSO algorithm can be described as follows: Suppose that the search space is D-dimensional, then the i-th particle of the swarm in the t-th iteration can be represented by a D-dimensional vector. The velocity of this particle can be represented by another D-dimensional vector. The best previously visited position of the particle in t-th iteration is denoted as Pi,t. The global best particle in t-th iteration denoted as Pg,t. Then the swarm is manipulated according to the following two equations:

$$Vi_{t+1} = c_1 Vi_t + c_2 * r_1(p_{i,t} - Xi_t) + c_3 * r_2 * (P_{g,t} - Xi_t) \tag{9}$$

$$Xi_{t+1} = Xi_t + Vi_{i+1} \tag{10}$$

Where i=1, 2…P, and P is the total number of particles in the swarm, i.e. the population size; t=1, 2…T, and T is the iteration limited; c1 is an inertia weight which is employed to control the impact of the previous history of velocities on the current one. Accordingly, the parameter c1 regulates the trade-off between the global (wide-ranging) and local (nearby) exploration abilities of the swarm. r1, r2 are random numbers, uniformly distributed in [0, 1]; c2, c3 are two positive constants, called cognitive and social parameter respectively. That proper fine-tuning these two parameters may result in faster convergence and alleviation of local minima. The details of tuning the parameters of PSO were discussed in [6]. Formula (9) is used to calculate a particle's new velocity according to its previous velocity and the distance from its current position to its local best and the global best. Formula (10) is used to calculate a particle's new position by utilizing its experience (i.e., local best) and the best experience of all particles (i.e., global best). Formulas (9) and (10) also reflect the information-sharing mechanism of PSO.

B. Real Number Encoding Method

In general, there are three encoding methods, i.e. real number encoding, integer encoding, and binary bit encoding. For the combination optimization problem, Clerc [7] presented the integer encoding PSO for Traveling Salesman Problem (TSP) firstly. Each particle's position was represented a permutation of integer and the velocity was different from continuous problem. Clerc defined a so-called "exchange number" to represent the velocity of particles. As described above, Clerc also defined the operation rules about the velocity, such as addition and subtraction. The advantages of integer encoding method are decoding and computing fitness conveniently. This encoding method, however, has not well used the advantages of PSO.

Ayed Salmen et al. [8] used the real number encoding of PSO for task assignment problem. They mapped an M-task assignment instance into corresponding M-coordinate particle position. Since values in a particle are processor numbers, a real value is meaningless. Therefore, in the decoding algorithm, they rounded these numbers to the closest processor number by dropping the sign and the fractional part. Li Ning et al. [9] applied PSO for Vehicle Routing Problem (VRP). They presented that each particle was encoded as a vector X with 2L dimensions, which represented L customers VRP. The one L dimensions Xv represented the vehicles of the customers; the other Xr represented the sequence of customers visited in the vehicle. Higher dimension is presented in the encoding method, and every dimension should be rounded the number closest integer and sorted. It operates difficult and consumes much CPU time. Meanwhile, if the position presents the infeasible solution, it is very difficult to be adjusted.

The paper presents a novel real number encoding method of PSO for OVRP. In the method, the dimension size of the particle's position equals to the number of customers. When the particle position is decoded, it only does once round the number to the closest integer and sort. Meanwhile, it is convenient for readjusting the particle position when updated. For L customers, each particle is encoded as a real number vector with L dimensions. The integer part of each dimension or element in the vector represents the vehicle. Thus, the same integer part represents the customer in the same vehicle. The fractional part represents the sequence of the customer in the vehicle.

Definition:

[X] represents the integer part of X.

{X} represents the fractional part of X.

The decoding procedure is:

(1) Each dimension of the particle's position gets the [X].

(2) Form different groupings according to the values of [X].

(3) Each particle gets {X} in the team.

(4) Build the sequence of the visited customer according to the values of {X}.

For example, if there are 7 customers and 3 vehicles in an OVRP instance, according to the encoding method, we can present encoding like:

Customer serial number: 1 2 3 4 5 6 7

Particle's position X: 4.1 1.86 1.53 1.12 1.24 3.29 3.05

Based on the decoding rules as above described, first, we round X to the closest integer by dropping the fractional part. The Xi, which is the same integer part, is assigned into the same team. We can get the three teams: (4.1), (1.86, 1.53, 1.12, 1.24), (3.29, 3.05). Second, Xi is arranged from small to big according to the fractional part in the same team. We can get the result as: (4.1), (1.12, 1.24, 1.53, 1.86), (3.05, 3.29) Finally the above position is mapped into the corresponding customer, and then, we can get the result of delivery plan which the position represents.

First route: 0-1

Second route: 0-4-5-3-2

Third route: 0-7-6

C. Hybridization of Particle Swarm Optimization with an Ant Colony Approach

This section describes the implementation of proposed improvement in particle swarm optimization using an ant colony approach. The proposed method, called, PSACO (particle swarm ant colony optimization) is based on the common characteristics of both PSO and ACO algorithms, like, survival as a swarm (colony) by coexistence and cooperation, individual contribution to food searching by a particle (an ant) by sharing information locally and globally in the swarm (colony) between particles (ants), etc. The implementation of PSACO algorithm consists of two stages. In the first stage, it applies PSO, while ACO is implemented in the second stage. ACO works as a search, wherein, ants apply pheromone-guided mechanism to refine the positions found by particles in the PSO stage. In PSACO, a simple pheromone-guided mechanism of ACO is proposed to apply as local search. The proposed ACO algorithm handles P ants equal to the number of particles in PSO. Each ant i generate a solution zit around the global best-found position among all particles in the swarm up to iteration count t as:

$$Z_t^i = N(P_t^g, \sigma) \tag{11}$$

In Eq. (11), we generate components of solution vector zit, which satisfy Gaussian distributions with mean pgt and standard deviation r, where, initially at t = 1 value of r = 1 and is updated at the end of each iteration as r = r . d, where, d is a parameter in (0.25, 0.997) and if $r < r_{min}$ then $r = r_{min}$, where, rmin is a parameter. Compute objective function value. This simple pheromone-guided mechanism considers, there is highest density of trails (single pheromone spot) at the global best solution of the swarm at any iteration. In each stage of ACO implementation and all ants P search for better solutions in the neighborhood of the global best solution. In the beginning of the search process, ants explore larger search area in the neighborhood of due to the high value of standard deviation r and intensify the search around as the algorithm progresses. Thus, ACO helps PSO process not only to efficiently perform global exploration for rapidly attaining the feasible solution space but also to effectively reach optimal or near optimal solution.

The pseudo-code of PSACO method is given in Eq. (11), the algorithm starts with initializing parameters of both PSO and ACO methods. The first stage consists of PSO, which generates P solutions using Eqs. (9) and (10). Objective function values are computed. ACO is applied in the second stage to update the positions of particles in the swarm. This process is repeated until iteration count as $t = t_{max}$.

D. Path Relinking

This approach generates new solutions by exploring trajectories that connect high-quality solutions by starting from one of these solutions, called the starting solution and generating a path in the neighborhood space that leads towards the other solution, called the target solution. The roles of starting and target solutions can be interchangeable. In the first one, the worst among the two solutions plays the role of the starting solution and the other plays the role of the target solution. In the second one, the roles are changing. There is a possibility for the two paths to simultaneously explore. A particle in particle swarm optimization can either follow its own way, or go back to its previous optimal solution, or go towards to the global optimal solution (to the best particle in the swarm).Thus, in the PSO-VRP when the particle decides to follow either the path to its previous optimal solution or the path to the global optimal solution, a path reliking strategy is applied where the current solution plays the role of the starting solution and the best particle of the swarm or the current best solution of the particle plays the role of the target solution. The trajectories between the two solutions are explored by simple swapping of two nodes of the starting solution if the decision corresponds to a routing or by closing a facility and opening another facility if the decision corresponds to a location until the starting solution becomes equal to the target solution. The paths are generated by choosing moves(swaps in the routing and opening or closing facilities in the location)in order to introduce attributes in the starting solution that are present in the guiding target solution. If in some step of the path reliking strategy a new best solution, either of the particle or of the whole swarm, is found then the current best (particle or swarm) solution is replaced with the new one and the algorithm continues.

IV. Experimental Results

In this experiment, the algorithms presented in article were implemented in JAVA language on a Toshiba notebook, as Pentium M 2.0G (T2500), 1024 MB machine running in Windows xp environment. The performance of the proposed PSACO algorithm is tested on several well-known Solomon standard data R102 [12] problems.

TABLE I. COMPARSION WITH OTHER METHOD

Algorithm	*Successful searching rate*	*average transport cost*	*average searching time*
PSO	57%	920.5	8.02
ACO	48%	912.4	7.91
PSOACO	67%	864.6	6.12

V. Conclusions

Although Vehicle Routing Problem has been developed for more than two decades, there are only a few incomplete solutions available. In the paper, based on PSO principle, a new solution-solving scheme for VRP is proposed. In consideration of a real number encoding method of PSO, the decoding rules of PSOs for VRP are developed. In order to improve the solution quality, several heurist methods are applied into the post-optimization procedure, such as Nearest Insertion algorithm, and GENI algorithm, which can optimize the inner or outer routes and modify the illegal solution. The performance of PSO algorithm is evaluated in comparison with some other heurists..

Acknowledgment

This work is partially support by The 11th Five Years Key Programs for Science and Technology Development of China (No.2008BADA8B03), Henan Program for New Century Excellent Talents in University (No. 2006HANCET-15).

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