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APPLICATION of HYBRID ANT COLONY OPTIMIZATION (HACO) AlGORITHM for SOLVING CAPACITATED VEHICLE ROUTING PROBLEM (CVRP)

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***Abstract*— The Capacitated Vehicle Routing problem (CVRP) is a combinatorial optimization and nonlinear problem seeking to service a number of customers with a fleet of vehicles. CVRP isan important problem in the fields of transportation, distribution and logistics . Usually, the goal is delivering goods located at a central depot to customers who have placed orders. This transportation optimization problem is NP-hard ,which means that the computational effort required to solve it increases exponentially with the problem size. To solve it in an acceptable time some stochastic algorithms are needed. Here we proposed the algorithm Hybrid Ant Colony Optimization(HACO) which takes the advantage of Simulated Annealing(SA) to solve CVRP**

***Keywords*— CVRP,ACO ,SA,HACO.**

I. INTRODUCTION

Routing is the process used to determine route for packet travelling from source to destination. Routing is performed by the routers, which updates the routing tables with minimizing cost functions like physical distance, link delay, etc. The metric for optimization can be distance, number of hops or estimated transit time. The capacitated vehicle routing problem (CVRP) is defined as to service a set of delivery customers with known demands. The objective of CVRP is to provide each vehicle with a sequence of delivers so that all customers are serviced, and the travelling cost of vehicles is minimized [1–6]. It is hard to solve this problem directly when the number of customers is large [7, 8]. In real time logistics transportation is the key operation, model building and developing solution techniques for CVRP is the basic step to solve complex models. In enumeration CVRP requires very high computational operations and time to find the optimal solution hence it is declared as NP-hard problem. Many researchers use ACO to obtain near optimal solutions or even global optimal solutions for CVRP. Ant colony optimization(ACO) , a swarm intelligence based optimization technique , is widely used in network routing. These approach try to map the solution capability of swarms to mathematical and engineering problems.

In this paper, a hybrid ant colony optimization (HACO) is proposed to solve CVRP. It has both the advantage of SA, the ability to find feasible solutions, and that of ACO, the ability to avoid premature convergence and then search over the subspace.

The paper is organized as follows. In Sect. 2 describes the problem definition of CVRP. An ant colony optimization is given in Sect. 3. In Sect. 4 underlines the proposed algorithm. Finally, conclusions are presented in the last section.

II. CVRP

Capacitated Vehicle Routing Problem (CVRP) was defined (Cordeau *et al*., 2002; Lysgaard *et al*., 2004) as a Set of n customers served from the common depot or warehouse of 0 , for a non negative q_i customer demand by N number of vehicles of having capacity of Q and distance or cost of C_{ij} between two nodes of i and j by vehicle k. The objective of CVRP is to determine optimum route schedule which minimizes the distance or cost with the following constraints:

- Each customer is served exactly once by exactly one vehicle
- Each vehicle starts and ends its route at the warehouse
- The total length of each route must not exceed the constraint
- The total demand of any route must not exceed the capacity of the vehicle

The CVRP mathematical model was formulated based on previous study (Bodin *et al*., 1983) to explain the objective function, vehicle schedule with constraints. The objective function is expressed in Eq.1, which aims to minimize the sum of set the of routes visiting by the vehicles in the model. The customer is exactly visited only once by a vehicle and it is ensured by the Eq. 2 and 3, the vehicle visit between two customers is assigned as X_{ij}^k =1 otherwise "0" to obtain the objective function. The vehicle tour starts at warehouse, visit customers on sequence and finish with the warehouse. In this tour, the vehicle needs to visit the cities continuously and Eq. 4 ensures the continuity visit among the cities in the route.

$$\text{Min} \sum_{k=1}^{N}\sum_{i=0}^{n}\sum_{j=0}^{n} C_{ij}^k X_{ij}^k \qquad (1)$$

Subject to:

$$\sum_{k=1}^{N}\sum_{i=0}^{n} X_{ij}^k = 1,\ j=1,2,.............n \qquad (2)$$

$$\sum_{k=1}^{N}\sum_{j=0}^{n} X_{ij}^k = 1,\ i=1,2,.............n \qquad (3)$$

$$\sum_{i=0}^{n} X_{it}^k - \sum_{j=0}^{n} X_{tj}^k == 0,\ k=1,2............,\ N;\ t\ 1,2,.....n \quad (4)$$

III. ANT COLONY OPTIMIZATION(ACO) ALGORITHM

Ant colony optimization(ACO) ,a swarm intelligence(SI) based optimization technique , is widely used in network routing. General Characteristics of Swarm Intelligence(SI):

- SI provide network adaptive feature and generates multiple path for routing. SI algorithms are capable of adapting for change in network topology and traffic while giving equivalent performance [9].
- It relays on both passive and active information for gathering and monitoring. They collect non local information about the characteristics of solution set, like – all possible paths.
- It makes use of stochastic components. It uses stochastic component like pheromone table for user agents. User agents are autonomous and communicate each other through stigmergy [10].
- It sets path favoring load balancing rather than pure shortest path. The algorithm also supports for multiple paths, so that load balancing can be achieved.
- Fast route recovery - If optimal path fails, then packets can easily be sent to other neighbors by recomputing next hop probability, i.e., choosing second best path.
- Distributed and fault tolerance – SI algorithm are inherently distributed. There is no centralized control mechanism, so if any node or link fails, there is no heavy loss [11].
- Scalability and adaptation– Population of ants may change based on the size of network. The agents may die or reproduce, with little effect on performance.
- Speed – Change in the network can be adapted very fast.

The network under consideration is represented as G = (V, E), a connected graph with N nodes. The metric of optimization is number of hops between the nodes. The goal is to find the shortest path between source node V_s and destination V_d, where V_s and V_d belong to V. The path length is given by the number of nodes along the path. Each link/edge e(i,j) ε E of the graph connecting node V_i and V_j has a variable $\varphi_{i,j}$ indicating the artificial pheromone value. An ant located in node V_i uses pheromone $\varphi_{i,j}$ of node V_j belong to N_i to compute the probability of node V_j as next hop. N_i is the set of one hop neighbors of node V_i.The probability at node V_i can be computed as follows:

$$p_{i,j} = \varphi_{i,j} / (\Sigma\varphi_{i,j}) \text{ for } j \in N_i$$
$$= 0 \text{ for } j \text{ does not belong to } N_i \quad (5).$$

The probability $p_{i,j}$ of a node V_i has the constraint that The probability $p_{i,j}$ of a node V_i has the constraint that

$$\sum_{j \in N_i} p_{i,j} = 1$$

The value of $\varphi_{i,j}$ is incremented by Δ by the ant packet which move along the path V_i to V_j. ie $\varphi_{i,j} = \varphi_{i,j} + \Delta$. The concentration $\varphi_{i,j}$ indicates the usage of the link. As the concentration of the pheromone should decrease with time, at every constant interval t, the value of $\varphi_{i,j}$ between the nodes V_i to V_j is decreased by α ie $\varphi_{i,j} = \varphi_{i,j} - \alpha$. If $\varphi_{i,j}$ becomes less than zero, it is set to zero, indicating no pheromone. The rate of increase in pheromone (Δ) greater that the rate of decrease in pheromone (α).

The working of ACO algorithm divided into three phases:

- Route discovery phase – This phase finds all possible paths from source node to destination node.
- Route maintenance phase – This phase strengthens the path between the nodes.
- Route failure handling – If any node along the source to destination fails or moves away from the network, alternate paths will be generated [12].

A.ROUTE DISCOVERY

Route discovery is responsible for generating all possible routes between source and destination. It uses control packets called Forward Ant (FA) and Backward Ant (BA) to discover route. A FA establishes the pheromone track to the source node and BA establishes pheromone track to the destination. A forward ant is broadcast by the sender and relayed by the intermediate nodes till it reaches the destination. A node receiving a FA for the first time creates a record in its routing table. The record includes destination address, next hop and pheromone value. The node interprets the source address of the FA as the destination address, the address of the previous node as the next hop and computes the pheromone value depending on then number of hops the FA needed to reach the node. Then the node forwards the FA to its neighbors. FA packets have unique sequence number. Duplicate FA is detected through sequence number. Once the duplicate ants are detected, they are dropped by the nodes. When the FA reaches the destination, its information is extracted and it is destroyed. BA is created with same sequence number and sent towards the source. BA reserves the resources at along the nodes towards source. BA establishes path to destination node. Once the source receives the BA from the destination, the path is generated and the data can be sent along the path.

Working of this phase is as follows:

- At source node create FA and broadcast to nodes in neighbour list.
- At source node, wait for BA. If BA not received within timeout period, generate FA with new sequence number and broadcast to nodes in neighbour list. If BA is received within timeout period send data packets along the path generated.
- At any node, when it receives FA, it does the following if current node = destination node

{

• Set type of control packet to BA with same sequence number as FA.

• Reserve resource at current node

• Send BA to node from which it has received FA.

}

else

{

• hop count = hop count + 1

• $\varphi_{i,j} = \varphi_{i,j} + \Delta$

//update pheromone value

• send FA to nodes in neighbour list

}

• At any node, when it receives BA, it does the following

if (current node is not source node)

{

• Reserve resource at current node

• Send BA to node from which it has received FA

}

else //BA reaches source node

{

• Get pheromone values of all links using neighbour list.

• Compute probability for all nodes in neighbour list using Eqn 5.

• Send packets to that link which has highest probability value.

}

B. ROUTE MAINTENANCE

Route maintenance phase is responsible for the maintenance of the path generated during the discovery phase. This phase basically helps in maintaining the route which has already been established during route discovery phase. As the topology of the network changes, it is required to refresh the route between the nodes. Once the path between source and destination is set up, it is up to the data packets to maintain the route. When a node V_i forwards the data packet to node V_j to reach the destination V_d, it increments the pheromone value along the path V_j and V_d by Δ thus strengthening the path. An acknowledgement is sent to all the packets received. If acknowledgement is not received with in timeout period then the route error message is transmitted to previous node. Working of this module is as follows:

• At each node, when it receives data packet, it does the following

if current node = destination node

{

• Extract data

• Send packet (acknowledge packet) to previous node

}

else

{

• Get pheromone values of all links using neighbor list.

• Compute probability for all nodes in neighbor list using Eqn 5.

• Send packets to that link which has highest probability value.

• Increment pheromone value for the highest probability link.

}

• At regular intervals decrement pheromone value by α.

If the pheromone value = 0 for any destination then call route discovery phase.

• If acknowledgement is not received at current node before timeout send route error to previous node (handling by error handling phase)

• Refresh route after time out.

C ROUTE FAILURE HANDLING

This phase is responsible for generating alternative routes in case the existing route fails. Node mobility in ad hoc network may cause certain links to fail. Every packet is associated with acknowledgement; hence if a node does not receive an acknowledgement, it indicates that the link is failed. On detecting a link failure the node sends a route error message to the previous node and deactivates this path by setting the pheromone value to zero. The previous node then tries to find an alternate path to the destination. If the alternate path exists, the packet is forwarded on to that path else the node informs its neighbours to relay the packet towards source. This continues till the source is reached. On reaching the source, the source initiates a new route discovery phase. Ant algorithm provides multiple paths. If the optimal path fails, it leads to choosing next best path. Next best path will be that path with links having next highest pheromone value (second best path). Hence ant algorithm does not break down on failure of optimal path. This helps in load balancing. That is, if the optimal path is heavily loaded, the data packets can follow the next best paths. Working of this phase is as follows:

At any node if a route error message is received, it performs the following function

• If alternate path exist to reach destination send packets through other route

else

{

• Set pheromone = 0 in routing table //deactivate link

• Send route error message to previous node.

}

if route error message reaches source, it calls route discovery phase.

Study of Ant algorithm is concentrated mainly on two issues. One is Ant loss and other is resource reservation at nodes.

• Ant loss during transmission

There is a possibility of ant loss during the process of determining the reliable path. This can be of two types-the loss of the forward ant and the loss of the backward ant.

Loss of forward ant - Whenever a forward ant is lost, there will be a preset time-out period (say 6 seconds) at the source node within which if the backward ant does not return to the source, then a new forward ant with a different sequence number will be launched.

Loss of backward ant - Whenever a backward ant is lost after being dispatched from the destination node, the same time-out mechanism will be used at the source node to handle the ant loss. Another forward ant will be launched, or to make it more time efficient and dynamic, a backward ant with the same sequence number will be launched at the node where it was last seen thereby reducing the time taken for ant movement.

• Reserving memory at each node

Sometimes, it is necessary to store the packets at intermediate nodes in order to avoid packet or ant loss during transmission. Loss may be due to failure of links. If the packet is stored in the previous node, it can be retransmitted. Hence the algorithm stores packets at intermediate nodes during transmission in a fixed buffer of memory. In case of ant loss, it helps in regeneration of ants for path finding.

IV. HYBRID ACO(HACO)

The HACO algorithm takes the advantages of SA and ACO for solving CVRP. Given that a solution of CVRP is made of multiple routes, the depot is represented as 0 and the visited customers are denoted as integers from 1 to N. Supposed there are K vehicles and N customers. The representation of solution is the permutation of 1 to N and ($K - 1$) number of 0. The first vehicle sets out beforehand from the depot and gets back to the depot after visiting customers and other vehicles leave the depot in order. The arrangement of each vehicle's route is repeated until every customer has one vehicle visited.

Simulated annealing (SA) is a generic probabilistic metaheuristic for the global optimization problem of locating a good approximation to the global optimum of a given function in a large search space. It is often used when the search space is discrete (e.g., all tours that visit a given set of cities). Simulated annealing (SA) is one of the most flexible techniques available for solving hard combinatorial problems. The main advantage of SA is that it can be applied to large problems regardless of the conditions of differentiability, continuity, and convexity that are normally required in conventional optimization methods. SA is an intelligent stochastic strategy used in solving optimization problems. It was successfully applied to the optimization problems by Kirkpatrick [13, 14]. SA employs certain probability to avoid becoming trapped in a local optimum by allowing occasional alterations that increases the diversity of the particles in the swarm. In the search process, the SA accepts not only better but also worse neighbouring solutions with a certain probability. Such mechanism can be regarded as a trial to explore new space for new solutions, either better or worse. The probability of accepting a worse solution is larger at higher initial temperature. As the temperature decreases, the probability of accepting worse solutions gradually approaches zero. More specifically, starting from an initial state, the system is perturbed at random to a new state in the neighbourhood of the original one. Then the change ΔE of the fitness function value is calculated. For minimization problems, the new state is accepted with probability $min\{1, exp(-\Delta E /T)\}$, where T is a control parameter corresponding to the temperature in the analogy. The SA algorithm generally starts from a high temperature, and then the temperature is gradually lowered. At each temperature, a search is carried out for a certain number of iterations.

The proposed algorithm takes the advantages of SA and ACO for CVRP.

It first applies SA to obtain the initial best solution and then the initial value of pheromone trail for HACO.

Then, ants start from a randomly selected node of the route to construct solutions for CVRP.

In HACO, the concept of information is conducted to estimate the variation of the pheromone matrix. Each trail is a discrete random variable in the pheromone matrix. The information gain (info) of a random variable X is defined as

$$info(X) = -\sum_{k=1}^{k} P(x_k) \log P(x_k)$$

where X represents the trails in the pheromone matrix.

Since the initial pheromone for each trail has the same value, the probability is a uniform distribution as follows

$$P_1 = P_2 = \cdots = P_k = \frac{1}{K} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

For (6), the information gain is given by

$$info = -\sum_{k=1}^{k} P_k \log P_k = -\sum_{k=1}^{k} \frac{1}{K} \log \frac{1}{K} = \log K \ldots\ldots\ldots\ldots (7)$$

In HACO, the local search is performed to find the best solution. In the proposed algorithm, insertion method and swap method are performed as local search. The insertion method is done by randomly selecting the ith number of solution and inserting it into the position immediately preceding the j th number of solution. The swap method is done by randomly selecting two positions in the solution, and then exchanges the values of these two positions directly. In local search, the probabilities of choosing the swap and the insertion methods are equal. At each iteration, the information gain ($info_{iteration}$) is calculated and the gain ratio

$(G) = info_{iteration}/info_{max}$ is set to dynamically updated the heuristic parameter.

Finally, the proposed algorithm is repeated until it meets the termination condition.

V. CONCLUSION

The CVRP has been an important problem in the field of distribution and logistics. Since the delivery routes consist of any combination of customers, this problem belongs to the class of NP-hard problems. In this paper, a hybrid ant colony optimization is proposed for CVRP. It takes the advantages of simulated annealing and ant colony optimization. Ant colony optimization(ACO) ,a swarm intelligence based optimization technique , is widely used in network routing. SA based design optimization is simple, robust and reliable for design optimization problem. The proposed algorithm proved that it has better performance when compared to ACO and SA. The proposed algorithm can be applied to solve CVRP for both small-sized and large-sized instances.

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