ROUTING PROBLEM FOR PARALLEL ROUTE BASED MAX-MIN ANT SYSTEM

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Abstract

The proposed work presented a modified MAX-MIN Ant System (MMAS) algorithm to solve the routing problem, in which known demand are supplied from a store house with parallel routes for new local search. Routing Problem is an optimization problem and solved to nearly optimum by heuristics. The objective of routing issues is to use a fleet of vehicles with specified capacity to serve a number of users with dissimilar demands at minimum cost, without violating the capacity and route length constraints. Many meta-heuristic approaches like Simulated Annealing (SA), Tabu Search (TS) and An Improved Ant Colony System (IACS) algorithm are compared for the performance result analysis.

The real life problems deal with imperfectly specified knowledge and some degree of imprecision, uncertainty or inconsistency is embedded in the problem specification. The well-founded theory of fuzzy sets is a special way to model the uncertainty. The rules in a fuzzy model contain a set of propositions, each of which restricts a fuzzy variable to a single fuzzy value by means of the predicate equivalency. That way, each rule covers a single fuzzy region of the fuzzy grid. The proposed system of this thesis extends this structure to provide more general fuzzy rules, covering the input space as much as possible. In order to do this, new predicates are considered and a Max-Min Ant System is proposed to learn such fuzzy rules.

1. Introduction

The system has shown that Ant Colony System (ACS) is competitive with other nature-inspired algorithms on some relatively simple problems. Heuristic approaches to the routing can be classified as path constructive heuristics and path improvement heuristics.

The most used and well-known path improvement heuristics are 2-optimization and 3-optimization, and Lin-Kernighan [3] in which respectively two, three, and a variable number of edges are exchanged. It has been experimentally shown that, in general, path improvement heuristics produce better quality results than path constructive heuristics. A general approach is to use path constructive heuristics to generate a solution and then to apply a path improvement heuristic to locally optimize it. It has been shown recently that it is more effective to alternate an improvement heuristic with updation of the last (or of the best) solution produced, rather than iteratively executing a path improvement heuristic starting from solutions generated randomly or by a constructive heuristic.

An example of successful application of the above alternate strategy is the work by Freisleben and Merz [1] in which a genetic algorithm is used to generate new solutions to be locally optimized by a path improvement heuristic. ACS is a path construction heuristic which, like genetic algorithm, each iteration produces a set of feasible solutions which are in some sense an updation of the previous best solution. It is therefore a reasonable guess that adding a path improvement heuristic to ACS could make it competitive with the best algorithms.

The system has therefore added a path improvement heuristic to ACS. In order to maintain ACS ability to solve both ROUTING and Adaptive routing problems the system have decided to base the local optimization heuristic on a restricted 3-optimizationprocedure that, while inserting/removing three edges on the path, considers only 3-optimizationmoves that do not revert the order in which the cities are visited. The resulting algorithm is called ACS-3-optimization. In this way the same procedure can be applied to symmetric and asymmetric routing, avoiding unpredictable path length changes. In addition, when a candidate edge (r ,s) to be removed is selected, the restricted 3-optimizationprocedure restricts the search for the other two edges to those nodes p belonging to edge (p,q) such as $\delta(r,q)<\delta(r,s)$. This project proposes an ant colony optimization algorithm for tuning generalization of fuzzy rule.

2. Routing Problem Analysis

2.1 Routing Problem

The vehicle routing problem is a very complicated combinatorial optimization problem that has been worked on since the late fifties, because of its central meaning in distribution management. The vehicle routing problem can be described as follows n customers must be served from a depot. Each customer asks v for a quantity qi of goods. A fleet of vehicles, each vehicle with a capacity Q, is available to deliver goods. A service time ti is associated with each customer. It represents the time required to service him/her. Therefore, a vehicle routing problem solution is a collection of tours. The VRP can be modeled in mathematical terms through a complete weighted digraph $G = (V,A)$, where $V = \{0,1..,n\}$, is a set of nodes representing the depot (0) and the customers $\{0,1..,n)$ and $A = \{(i;j)\ i,\ j\ V\ \}$ is a set of arcs, each one with a minimum travel time tij associated. The quantity of goods $q\ I$ requested by each customer i (i >0) is associated with the corresponding vertex with a label. Labels $Q1..,Q2$ corresponding to vehicles capacities are finally associated with vertex 0 (the depot).

3. Max-Min Ant System

The modified MAX–MIN Ant System (MMAS) algorithm achieves a strong exploitation of the search history by allowing only the best solutions to add pheromone during the pheromone trail update. Also, the use of a rather simple mechanism for limiting the strengths of the pheromone trails effectively avoids premature convergence of the search. Finally, modified MMAS can easily be extended by adding local search algorithms. In fact, the best performing ACO algorithms for many different combinatorial optimization problems improve the solutions generated by the ants with local search algorithms. As our empirical results show, modified MMAS is currently one of the best performing ACO algorithms for the routing issues. One of the main ideas introduced by max–min Ant System, the utilization of pheromone trail limits to prevent premature convergence, can also be applied in a different way, which can be interpreted as a hybrid between MMAS and Ant Colony System (ACS).

4. Experimental Evaluation of Modified Max-Min Ant on routing issues

In our research, apply modified MMAS for routing problem include three steps that are described as follows: The first steps, requires that a colony of ants is activated to find the shortest route by the procedure finds a feasible solution by an algorithm based on nearest neighbor and determine the initialized a number of vehicles (*nv*), capable to cope with all demand (*nv*). To simply determine by the total demand divided into vehicle capacity. The MMAS used the amount of ant colonies equal to the number of vehicles plus one (*nv* + 1) to construct routes.

Number of vehicle (nv) = Total demand of customers / maximum load of vehicle

The second, an ant constructs routes using as multi colonies. In every generation, each ant *k* constructs one feasible solution by starting at the depot and successively choosing a next node or customer from the set of feasible nodes. An ant works can be analyzing each node with respect to the constraints imposed by the model, each ant builds list of feasible movements and chooses the one indicated by the probabilistic rule. Finally, after an ant has constructed its solution, apply a local search to improve the solution quality. In particular, apply 2-Opt and Or-Opt by exchanging a customer of route with a customer of another route. For constructing phases, improved MMAS used the amount of ant colonies equal to the number of vehicles plus one (*nv* + 1) to construct routes. It is an extension of the algorithm for ant colony construct routes in two frameworks between sequential and parallel constructions.

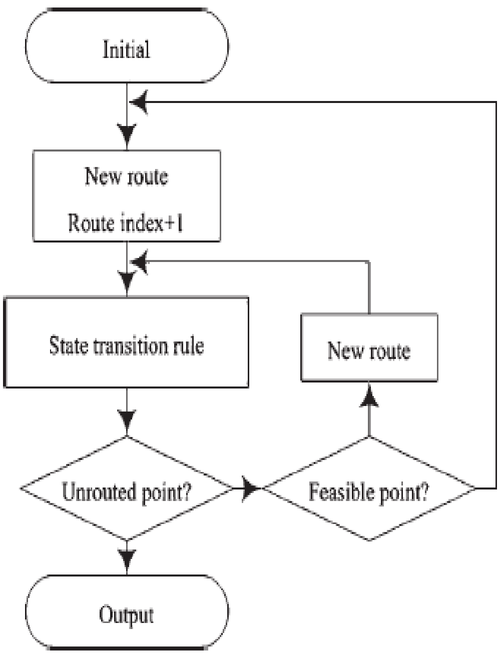

Fig 1: MMAS Algorithms for parallel route

The sequential route construction, a route for a vehicle is constructed one at a time. When either the number of constructed routes or the total capacity a vehicle spent has reached the maximum number allowed a new route is initiated. The sequential construction phase ends if all gather points have been assigned to vehicles. On the other hand, in the parallel route construction the first route of the parallel method is constructed for every vehicle at the same time. However, each tour must be not violated conditions of any routes or vehicles.

5) Performance Evaluation of modified max-min ant for routing problem

The proposed MMAS algorithm was applied to the identification of the analytical function using equally distributed fuzzy partitions with triangular membership functions for all input and output fuzzy domains and with five sets each of the routing issues. The experiment consisted on the identification of the system with randomly generated training sets with three different sizes (30, 50 and 70 examples), and the subsequent run of the proposed MMAS algorithm over the identified fuzzy model. In this respect, the original Ant System version was implemented, which applies a random proportional rule for selecting each step and whose pheromone deposit mechanism is run once the solution is completed.

Two measures were used in order to analyze both the generality and accuracy results of the method. On the one hand, the number of rules describing the model together with the averaged complexity of the premises was considered for evaluating its generality. On the other hand, the normalized mean square error between the model and the system output was obtained for accuracy evaluation. The experiment was run 10 times for each training set size and the average results were obtained. It can be observed that the generalization capability of the MMAS algorithm is better than the one provided by the Ant Colony Optimization system. It shows the average generality of the fuzzy models expressed as the average number of rules describing them and, the average complexity of the premises in the rules.

Again, the MMAS algorithm provides fuzzy models described with a lower number of rules when compared with the initial fuzzy models and these rules had also have a low complexity. In addition, practically no case needed the maximum number of cycles, NC_{max}, to obtain the best solution and, in average; about 8 cycles were enough which proves the solidarity of the MMAS system compared to the Ant colony optimization system. Table 1 summarizes the experiment results. Compared with the variety of list scheduling and the force-directed scheduling method, the MMAS algorithm generates better results consistently over all testing cases. For some of the testing samples, it provides significant improvement on the schedule latency. The biggest saving achieved is 23%. This is obtained when LWID is used as the local heuristic for our algorithm and also as the heuristic for constructing the priority list for the traditional list scheduler.

Though the results of force-directed scheduler are generally superior to that of the list scheduler, our algorithm achieves even better results. On average, comparing with the force-directed approach, our algorithm provides a 6.2% performance enhancement for the testing cases, while performance improvement for individual test sample can be as much as 14.7%. Finally, compared with the optimal scheduling results computed by using the integer linear programming model, the results generated by the proposed algorithm are much closer to the optimal than those provided by the list scheduling heuristics and the force directed approach. The MMAS algorithm improves the average schedule latency by 44% comparing with the list scheduling heuristics.

(Resource Labels: a=alu, fm=faster multiplier, m=multiplier, i=input, o=output)

(Heuristic Labels: IM=Instruction Mobility ID=Instruction Depth, LWID=Latency Weighted Instruction Depth, SN=Successor Number)

Resources	Latency/ runtime	Force Directed	List scheduling				Proposed MMAS (Average over 5 runs)				Existing ACO			
			IM	ID	LWID	SN	IM	ID	LWID	SN	IM	ID	LWID	SN
1a, 1fm, 1m, 3i, 3o	8/32	8	8	8	9	8	8	8	8	8	6	6	6	6
2a, 1fm, 2m	11/22	11	11	11	13	13	11	11	11	11	9	9	9	9
1a, 1fm, 1m	27/24000	28	28	31	31	28	27.2	27.2	27	27.2	25.8	25.8	25	25
2a, 2m, 3i, 3o	13/232	19	19	19	19	18	17.2	17.2	17	17.8	15.5	15.5	15	15.2
1a, 1fm, 1m, 3i, 3o	14/11560	19	19	21	21	21	16.2	16.4	16.2	17	14.8	14.6	14.8	14
2a, 2m, 1fm, 3i, 3o	-	18	19	20	18	18	17.4	18.2	17.6	17.6	15.6	16.8	15.4	15.4
2a, 2m, 1fm, 3i, 3o	-	23	23	23	23	23	21.2	21.2	21.2	21.2	19.8	19.8	19.8	19.8

Table 1: Evaluation Results

The performance of traditional list scheduler heavily depends on the input. This is echoed by the data in Table 1. Meantime, it is easy to observe that the proposed algorithm is much less sensitive to the choice of different local heuristics and input applications. This is evidenced by the fact that the standard deviation of the results achieved by the new algorithm is much smaller than that of the traditional list scheduler. Based on the data shown in Table 1, the average standard deviation for list scheduler over all and different heuristic choices is 0.8128, while that for the MMAS algorithm is only 0.1673. In other words, user can expect to achieve much more stable scheduling results on different application regardless the choice of local heuristic. This is a great attribute desired in practice.

Use as lower limit T_{min} , the probability that a specific arc is chosen may become very small, but will be still greater then zero. The trail limits alleviate the problem associated with the early stagnation of search especially for long runs, that leading to a higher degree of exploration. The trail strength in MMAS is initialization to T_{max} for all arcs. After each iteration the evaporation will reduce the trail strength by a factor ρ only the trail on arcs participating in the best tours are allowed to increased their intensities or maintain them at a high level. Thus the trail strength on bad arcs decreases slowly and only good arcs can maintain a high level of trail strength and will therefore be selected more often by the ants.

The performance of MMAS improves considerably over Ant System. Despite of using maximum and minimum trail limits, long runs of the modified MMAS still can show stagnation behavior. If the mean 0.05-branching factor approaches very low values only few new tours are built, leading to very limited exploration of possible better. To avoid this, we added the trail-smoothing mechanism: In case of stagnation of the search as indicated by mean branching factor, we adjust the trail intensities according to a portion all y update: the trail intensity in increased proportional to the different between T_{max} and the current trail intensity $T_{ij}(t)$ on the arc (I,j)

$$\text{Increase} \sim T_{max} - T_{ij}(t)$$

As an advantage of the proportional update, we do not completely forget the trails learned so far. Its overall effect is that by increasing the trail intensities, the probability distribution for the selection of the exploration of new tours is higher. We call this approach smoothing of the trail as the differences between high and low trail intensities become less pronounced, i.e. smoothing. With approach the solution quality for longer runs increased significantly.

6. CONCLUSION

The proposed modified MMAS for solving routing problem efficiently find the good solutions and also evaluated the performance of our results with other heuristics such as Simulated Annealing (SA) Tabu Search (TS) and Improved Ant Colony System (IACS) method. The MMAS method outperformed SA and TS but in some cases feable to IACS. The results indicate that this method performed as well in terms of the solution quality and run time consumed by compared with other heuristic approach. Our results demonstrate that MMAS achieves a strongly performance for the routing issues.

In this work, MMAS algorithm has been proposed to increase the generality of the fuzzy rules by searching for its structure to be maximal**.** With this aim, the method searches good descriptions by means of compound rules of fuzzy models initially expressed with conventional single rules. The construction graph allows representing each solution as a sequential addition of labels to the premises in the antecedent, and from the cooperative behavior of the ants good combinations of compound rules emerge.

The MMAS model presents an exponential pheromone deposition approach to improve the performance of classical ant system algorithm which employs uniform deposition rule. A simplified analysis using differential equations is carried out to study the stability of basic ant system dynamics with both exponential and constant deposition rules. A roadmap of connected cities, where the shortest path between two specified cities are to be found out, is taken as a platform to compare max-min ant system model (an improved and popular model of ant system algorithm) with exponential and constant deposition rules. Extensive simulations are performed to find the best parameter settings for non-uniform deposition approach and experiments with these parameter settings revealed that the above approach outstripped the traditional one by a large extent in terms of both solution quality and convergence time.

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