Combination of Ant Algorithms and Simulated Annealing in solving Flow Shop Scheduling Problem*

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Abstract

Flow Shop Scheduling [5] belongs to the category of scheduling tasks. Given n job and m machines. During the problem, all jobs must be processed in the same machine order. A job can only be started on a given machine if the processing on the previous machine has already been completed and the machine is free. The common objective function of the problem is the minimization of the total completion time (C_{max}). The Flow Shop Scheduling task is applied in many industrial and service areas. It is used in problems where the workpieces move through the resources in the same technological order. The flow shop model is typically applicable in many logistics and service, manufacturing areas, such as automotive assembly lines, electronic component manufacturing, metalworking and surface treatment plants or packaging and administrative processes.

In this paper, two Hybrid Ant Algorithms were applied to the Taillard [6] benchmark dataset. These two algorithms are the Hybrid Ant Colony System with Simulated Annealing and the Hybrid Rank Based Version of Ant System with Simulated Annealing.

The Ant Colony System (ACS) [4] algorithm models the behavior of ants. Ants use pheromone trails to find short routes to food sources. During their journey, the ants deposit pheromone on each route. In the case of the algorithm, artificial ants build the solution step by step. The ants take each route pieces based on the

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pheromone content and a combination of a heuristic value (e.g. distance, cost). An important step of the algorithm is the local pheromone update, which recalculates the given edge after each route is created. During the global pheromone update, the pheromone of the best route will change.

The Rank Based Version of Ant System [3] is also an algorithm which belongs to the Ant Colony Optimization family. During the algorithm, pheromone updating is performed in a way that ants are given a greater role based on their rank. Solutions are ranked according to their fitness value, and pheromone updating is performed only by the best w ant.

Simulated Annealing [2] models the cooling process of metals. It is an algorithm that operates on a single solution and tries to reach a global optimum. During the algorithm, worse solutions are accepted to avoid getting stuck in local optima. The algorithm starts from an initial solution and then creates a neighboring solution. If the neighboring solution is better than the current solution, then the neighbor will be the current solution. If the neighboring solution is not better, the algorithm can still accept it as the current solution, but only with a certain probability. Initially, the algorithm is more likely to accept worse solutions. Therefore, as the temperature decreases, the probability of accepting bad solutions also decreases.

The Taillard [6] dataset is a widely known benchmark dataset for the Flow Shop Scheduling task. It was published by E. Taillard in 1993 and has since served as a reference for comparing the performance of various heuristics and metaheuristics. The dataset contains problems of different sizes, with different numbers of jobs and machines (e.g. 20×5, 20×10, 20×20, 50×5, 50×10, 100×20).

The article presents the test results of the Ant Colony System and Rank Based Version of Ant System algorithms on the Taillard dataset using Simulated Annealing hybridization. The hybridization of the Ant Colony System and Rank Based Version of Ant System algorithms was performed as follows. In each iteration, after the ants have constructed their path and the pheromones have been updated, the individual solutions are improved by Simulated Annealing. A similar hybridization technique has already been applied to the Discrete Bacterial Memetic Evolutionary algorithm [1], where good results were obtained on the benchmark dataset.

The test results show that the gap values are $0 - 0.5$ % for the 20×5 dataset, $0 - 1.5$ % for the 20×10 dataset, $0.5 - 2$ % for the 20×20 dataset and $0.6 - 3$ % for the 50×10 dataset.

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