Ant Colony Optimization with Adaptive Heuristics Design

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ABSTRACT
Heuristics design, including definitions of heuristic information and parameter settings that control the impact of heuristic information, has significant influence on the performance of ant colony optimization (ACO) algorithms. However, in complex real-world problems, it is difficult or even impossible to find one heuristics design that suits all problem instances. Besides, static heuristics design biases ACO to search certain areas of the solution space constantly, which makes ACO less explorative and increases the risk of prematurity. This paper proposes a heuristics design adaptation scheme (HDAS) for addressing the above problems in ACO. With HDAS, each ant defines a profile of heuristics design to guide its solution construction procedure. Such profiles are adaptively adjusted towards the most suitable heuristic design according to the search experience of ants.The ACO with HDAS (HDA-ACO) is validated on a set of benchmarks of flexible job-shop scheduling problems (FJSP). Experimental results show that the HDA-ACO outperforms the original ACO.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods, scheduling.*

General Terms
Algorithms, Management, Experimentation

Keywords
Ant colony optimization (ACO), adaptation, flexible job-shop scheduling

1. INTRODUCTION
The performance of ant colony optimization (ACO) algorithms is significantly influenced by heuristics design[1]-[4], which contains two aspects: definition of heuristic information and settings of parameters that control the influence of heuristic information. The definition of heuristic information is usually based on empirical rules that lead to good solutions. However, the more complex the problem is, the more difficult it is to find an empirical rule that bring benefits in all problem instances. The parameter settings determine to what extent the search is biased towards solution components with good heuristic values. For obtaining good results, the requirement for bias strength varies from one instance to another. It is also difficult to find a parameter combination suitable for all problem instances. From the above, we can know that it would be more desired if the algorithm can automatically choose a suitable heuristics design according to traits of the problem instance at hand.

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On the other side, the use of heuristic information can bias ACO to search areas that are considered promising according to the definition of heuristic information. Such bias accelerates ACO in finding high-quality solutions, but also makes ACO less explorative and thus increases the chance of getting trapped in local optima. Besides, different heuristics design may be required at different stages in the search procedure. Therefore, a dynamic heuristics design that can adapt to the need of the search procedure is more desired than the traditionally used static design.

Aiming at achieving the above two desires, this paper proposes an adaptation scheme for the heuristics design of ACO. The proposed adaptation scheme, named as heuristics design adaptation scheme (HDAS), enables ACO to learn the currently appropriate design from the searching experience of ants. In order to examine the proposed HDAS, we develop an ACO algorithm with HDAS (termed as HDA-ACO) for solving flexible job-shop scheduling problem (FJSP). FJSP is the generalization of job-shop scheduling problem. Many real-world problems can be modeled into FJSP. Therefore, finding an effective and efficient way to address FJSP is a research topic of both theoretical and practical importance. Experimental results on benchmarks are compared with those of the same ACO algorithm without using HADS. The comparison reveals the effectiveness and efficiency of the proposed HDAS.

2. HDA-ACO FOR FJSP
Detailed design of the ACO algorithm for FJSP is not presented here due to page limit. In this section, we focus on introducing the implementation of HDAS in the ACO algorithm for FJSP.

2.1 Heuristic Information
The ACO algorithm defines six types of heuristic information for each node in the solution construction graph. The definitions are briefly described as follows:

- *Time-based Heuristics(TH)*: assign one operation to the machine that uses the shortest time to complete it.
- *Remainder-based Heuristics (RH)*: prioritize jobs with more remaining operations.
- *Flexibility-based Heuristics (FH)*: prioritize operations with less flexibility, that is,schedule operations with fewer choices of machines first.
- *Start-time-based Heuristics (STH)*: prioritize operations with earlier start time.
- *Complete-time-based Heuristics (CTH)*: prioritize operations with earlier complete time.
- *Workload-based Heuristics (WH)*: assign operations to the machine with minimum workload.

2.2 The Proposed HDAS
The fundamental idea of HDAS is to learn proper heuristics design from previous search. For achieving this, HDAS assigns a

profile of heuristics design to each ant in ACO algorithms. The profile contains both definitions of heuristic information and settings of parameters that control the influence of heuristic information. Each ant follows its own profile to guide its solution construction procedure. Fitness of the resulting solutions, paired with the corresponding profiles, is kept in an external archive set up by HDAS. The ants adjust their own profiles by mining the relationship between fitness and profiles in the archive.

With respect to the proposed ACO-FJSP, the heuristic information is defined based on the six types of heuristic information in Section 2.1, and the heuristic strength is controlled by two parameters: q_0 and β. Therefore, the profile $P^{(a)}$ of an ant a is defined as

$$P^{(a)} = < \boldsymbol{h}^{(a)}, q_0^{(a)}, \beta^{(a)} > . \quad (1)$$

In (1): $q_0^{(a)}$ and $\beta^{(a)}$ denotes the parameter values of q_0 and β used by the ant a; $\boldsymbol{h}^{(a)}$ is a binary vector of six dimensions, in which the i-th element $h_i^{(a)}$ indicates whether the i-th type of heuristic information is used ($h_i^{(a)} = 1$) or not ($h_i^{(a)} = 0$). Given a node v_l in the candidate set $\boldsymbol{C}$, the ant a follows its own profile $P^{(a)}$ and calculates the heuristic value of v_l as

$$\eta_l = \boldsymbol{h}^{(a)} \times \begin{bmatrix} \eta_l^{\mathrm{TH}} & \eta_l^{\mathrm{RH}} & \eta_l^{\mathrm{FH}} & \eta_l^{\mathrm{STH}} & \eta_l^{\mathrm{CTH}} & \eta_l^{\mathrm{WH}} \end{bmatrix}^{\mathrm{T}} \Big/ \sum_{i=1}^{6} h_i^{(a)} . \quad (2)$$

From (1) and (2), it can be known that the profile allows the ants to choose every possible heuristics design, which provides a basis for finding the optimal one. The profile of each ant is initialized with pheromone at the beginning of the algorithm. In initialization, the profile of each ant a is generated at random.

The profiles of the ants are adjusted every G iterations of the algorithm. First, a subset $\boldsymbol{R}$ of the external archive is selected for covering the best λ% solutions. Then the definition of heuristic information in the profile of each ant a is adjusted as

$$h_i^{(a)} = \begin{cases} 1, & \text{if } r \le 0.9 \times \sum_{P^{(k)} \in \boldsymbol{R}} h_i^{(k)} \Big/ (|\boldsymbol{R}| + 1) \\ 0, & \text{otherwise} \end{cases}, \ 1 \le i \le 6, \quad (3)$$

where $r \in [0,1]$ is a normalized random number. The parameter values are also adjusted by the following equations:

$$q_0^{(a)} = Cauchy(\mu_{q_0}, \sigma_{q_0}) \quad (4)$$

$$\beta^{(a)} = Cauchy(\mu_{\beta}, \sigma_{\beta}) \quad (5)$$

Where $Cauchy(\mu, \sigma)$ is a function returning a random value subject to the Cauchy distribution with an average μ and a standard deviation σ. After adjusting the profile of each ant, the current round of profile adjustment is finished. HDAS empties the external archive for the next learning period.

3. EXPERIMENTAL RESULTS

The proposed HDA-ACO is tested on the ten FJSP benchmarks in Brandimarte dataset [6]. Experimental results are compared with those of the ACO approach that doesn't use HDAS. For the sake of fairness, both algorithms are tested for 10 independent times on each benchmark.

Table 1. Benchmarks in Brandimarte Dataset

Case Name	HDA-ACO	ACO$^{\mathrm{TH}}$-FJSP	ACO$^{\mathrm{CTH}}$-FJSP
Mk01	**40**	42†	41.9‡
Mk02	**27**	28†	28.1‡
Mk03	**204**	**204**	**204**
Mk04	**63.9**	71.8†	70.4‡
Mk05	**173.5**	177.9†	177.9‡
Mk06	**63.9**	76.2†	76.6‡
Mk07	**144.1**	147.9†	149.6‡
Mk08	**523**	529.5†	532‡
Mk09	**307**	347.2†	343.6‡
Mk10	**215**	251.2†	254.9‡

†: *t*-test shows that ACO$^{\mathrm{TH}}$-FJSP is significantly worse with 95% confidence.
‡: *t*-test shows thatACO$^{\mathrm{CTH}}$-FJSP is significantly worse with 95% confidence.

4. CONCLUSION

This paper proposes an adaptation scheme (HDAS) for ACO to adaptively adjust the heuristics design according to the problem at hand and the need of the optimization procedure. The ACO with HDAS (named as HDA-ACO) is applied to an NP-hard problem, FJSP. Experiments show that HDA-ACO significantly outperforms the original ACO algorithm. For future work, we will further investigate the performance of HDA-ACO, including the influence of parameter G in HDAS. We will also apply HDA-ACO to complex real-world problems for testifying its effectiveness and efficiency in practical use.

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