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A hybrid biogeography-based optimization algorithm for job shop scheduling problem

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ABSTRACT

In this paper, a hybrid biogeography-based optimization (HBBO) algorithm has been proposed for the job-shop scheduling problem (JSP). Biogeography-based optimization (BBO) is a new bio-inpired computation method that is based on the science of biogeography. The BBO algorithm searches for the global optimum mainly through two main steps: migration and mutation. As JSP is one of the most difficult combinational optimization problems, the original BBO algorithm cannot handle it very well, especially for instances with larger size. The proposed HBBO algorithm combines the chaos theory and "searching around the optimum" strategy with the basic BBO, which makes it converge to global optimum solution faster and more stably. Series of comparative experiments with particle swarm optimization (PSO), basic BBO, the CPLEX and 14 other competitive algorithms are conducted, and the results show that our proposed HBBO algorithm outperforms the other state-of-the-art algorithms, such as genetic algorithm (GA), simulated annealing (SA), the PSO and the basic BBO.

1. Introduction

Knowledge and services have been emphasized in modern manufacturing in the present decade. Many enterprises are facing challenges of unprecedented and abrupt changes, such as intense global competition, rapid IT infrastructure changes and development of advanced management technologies. Due to its importance in the field of manufacturing industries, the job-shop scheduling problem (JSP) attracts considerable attention (Ma, Chu, & Zuo, 2010; Michael et al., 2013; Zhang, 2010).

The JSP is one of the most difficult combinatorial optimization problems and it has been well known as an NP-hard problem (Lawler et al., 1982; Xia & Wu, 2005). The JSP can be described briefly as follows. There are a number of jobs that need to be processed on a number of machines. Each job has several operations which have to be processed in a predefined sequence on different machines and each machine can only process one job at a time (Sels et al., 2012). The goal is to schedule the jobs on the machines to minimize the completion time needed for processing all jobs.

Because of the practical importance of the JSP, huge research effort has been devoted to fields of engineering, computer science, management science and business. Numerical efficient methods have been proposed, such as guided local search with shifting bottleneck (SB) (Balas & Vazacopoulos, 1998), tabu search (TS) (Azzouz et al., 2012; Brucker & Neyer, 1998; Eshlaghy & Sheibatolhamdy, 2011; Eugeniusz & Czesław, 2005; Nowicki & Smutnicki, 1996; Watson, Christopher Beck, Howe, & Darrell Whitley, 2003) and simulated annealing (SA) (Atabak et al., 2011; Van Laarhoven, Aarts, & Lenstra, 1992). Since that biologically inspired techniques have been advanced in the literature (Duan, Shao, Su, & Zhang, 2010; Duan, Xu, & Xing, 2010; Liu, Duan, & Deng, 2012; Sun, Duan, & Shi, 2013; Xu, Duan, & Liu, 2010; Yu & Duan, 2013; Zhang & Duan, 2014), there are also many bio-inspired optimization algorithms applied to the JSP, such as genetic algorithm (GA) (Azzouz et al., 2012; De Giovanni & Pezzella, 2010; Pezzella, Morganti, & Ciaschetti, 2007; Sun et al., 2010; Zhang, Shao, Lia, & Gao, 2009), particle swarm algorithm (PSO) (Gu, Tang, & Zheng, 2012; Lian, Jiao, & Gu, 2006; Xia, Wu, Zhang, & Yang, 2004), ant colony algorithm (ACO) (Anitha & Karpagam, 2013; Azzouz et al., 2012; Chen & Zhang, 2013; Xing & Chena, 2010), and artificial bee colony (ABC) algorithm (Deming, 2012; Tasgetiren et al., 2011; Wang, Duan, & Luo, 2013; Wang, Wang, Yu, & Zhang, 2013). In this paper, a hybrid biogeography-based optimization (HBBO), which takes advantages of the chaos theory (Xu et al., 2010) and the "searching around the optimum" strategy, is structured to solve the JSP.

Biogeography-based optimization (BBO) (Simon, 2008) is a new algorithm, which emulates the geographical distribution and the migration of species in an ecosystem. In this method each feasible

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solution is represented by a habitat. The habitat suitability index (HSI) is utilized to measure the goodness of the habitat. In order to find a solution with the best aspects, the concepts and models of biogeography are applied. The basic BBO works mainly based on the two mechanisms: migration and mutation. With the migration mechanism, poor solutions can accept a lot of new features, which may improve the quality of those solutions. Furthermore, solutions do not have the tendency to clump together in similar groups due to the new type of mutation operation. Elitism operation (Simon et al., 2009), which retains the best solutions in the population from one generation to the next, can also make the basic BBO algorithm more efficient in the both aspects of migration and mutation.

The chaos theory and "searching around the optimum" strategy are integrated into the basic BBO. Therefore, the exploration ability of the algorithm can be enhanced and the diversity of population can be improved. Furthermore, premature converge can be avoided. Thus the potential weakness lying in the basic method is avoided. We verify experimentally that our proposed HBBO approach outperforms the basic BBO approach, and is significantly better than the PSO and several state-of-art approaches.

The remainder of this paper is organized as follows. In Section 2, the JSP is formulated. In Section 3, the main principle of the basic BBO with elitism is presented. Section 4 describes the chaos theory and the principle of the "searching around the optimum" strategy. In Section 5, the detailed implementation procedures of the HBBO algorithm for the JSP are specified. In Section 6, a series of comparative experiments are given to verify that the HBBO approach outperforms the CPLEX, the PSO, the basic BBO and numerical existing algorithms. Our concluding remarks are contained in the final section.

2. The mathematical description of the JSP

Suppose that there are m machines $M = \{M_1, M_2, \ldots, M_m\}$ and n jobs $J = \{J_1, J_2, \ldots, J_n\}$, where job i has p operations $O_i = \{O_{i1}, O_{i2}, \ldots, O_{ip}\}$, $i = 1, 2, \ldots, n$. In this paper we make the number of the operations in each job the same, and it is also same to the number of the machines. Thus, $ip = m$, $i = 1, 2, \ldots, n$ and the operation set can be described as $O = \{\sigma_1, \sigma_2, \ldots, \sigma_{n\times m}\}$. Makespan $C_{\max}$ is the total time cost in completing operations of all jobs under conventional assumptions. The conventional assumptions can be described as following (Allaoui & Artiba, 2004; Wang, Duan, et al., 2013; Wang, Wang, et al., 2013).

(1) Each operation of one job must be processed exactly once on each of m machines.
(2) Each job is routed through the m machines in a given order to ensure that the j-th operation of job i O_{ij} will be processed only when the processing of the $(j-1)$-th operation O_{ij-1} has been finished.
(3) Every machine can process only one job at any time, and every operation cannot be interrupted.
(4) The machines cannot be breakdown.
(5) The jobs are independent from each other.

Matrix $S\,(m^*n)$ is developed to represent that the s_{ij}-th operation of the job i is processed on machine j, s is the element of the matrix, and i is the column and j is the row of the matrix.

$$S = \begin{bmatrix} s_{11} & s_{12} & \ldots & s_{1m} \\ s_{21} & s_{22} & \ldots & s_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \ldots & s_{nm} \end{bmatrix}$$

Another matrix $T\,(m^*n)$ is developed to represent the time cost t_{ij} of the j-th operation of the job i, i is the column and j is the row of the matrix.

$$T = \begin{bmatrix} t_{11} & t_{12} & \ldots & t_{1m} \\ t_{21} & t_{22} & \ldots & t_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n1} & t_{n2} \ldots & t_{nm} & \end{bmatrix}$$

The processing of operation σ_j on the machine i is denoted by G_{ij}. Suppose that the p-th operation on machine i, G_{ip}, is directly connected by the q-th operation G_{iq}, the relation can be represented by the operator $G_{ip} \to G_{iq}$. The completion time of $G_{ip} \to G_{iq}$ can be calculated with $C_{iq} = C_{ip} + t_{iq} + t_k$, where t_{iq} is the time cost of the operation σ_q on the machine i and t_k is the space time on machine i during the convert of the two operations. Thus the completion time of all the jobs can be computed as $C_{\max} = \max_{allG_{ij}}(C_{ij})$. Therefore, the aim of the JSP is to make the makespan $C_{\max}$ minimized.

3. Biogeography-based optimization

3.1. Principles of the basic BBO algorithm

BBO is a bio-inspired computation algorithm inspired by the geographical distribution and the migration of species in an ecosystem. The problem can be of any area in life (Engineering, Economics, Medicine, Business, Urban Planning, Sports, etc.) as long as we have a qualitative measure of the suitability of a given solution (Bansal et al., 2013; Jain et al., 2012; Jamuna & Swarup, 2011; Li, Wang, Zhou, & Yin, 2011; Ma & Simon, 2011; Sayed, Saad, Emara, & Abou El-Zahab, 2013; Silva, Coelho, Lebensztajn, & Lebensztajn, 2012; Wang & Duan, 2013). The BBO technique is utilized to solve the JSP in this paper.

BBO is developed based on the mathematics models of biogeography, which explains how species emigrate and immigrate within the habitats, how new species arise, and how species become extinct. A quantitative performance index HSI is used to evaluate if a habitat is suitable for biological survival. Features that correlate with HSI include such factors as rainfall, diversity of vegetation, diversity of topographic features, land area and temperature (Simon, 2008). The variables that characterize habitability are named suitability index variables (SIVs). SIVs are the independent variables of the habitat, while HSI are the dependent variable.

A set of habitats is used to present the candidate solutions in the BBO. The basic BBO works mainly on two mechanisms, migration and mutation. HSI is the evaluation criteria to measure if a solution is good, analogous to fitness in other population-based optimization algorithms. The species migrate from one habitat to other habitats that have good geographical conditions. Habitats with a high HSI tend to have a larger number of species, more species that emigrate to nearby habitats, and a lower species immigration rate. The solutions with high HSI tends to share their features with those with low HSI, and poor solutions can accept a lot of new features from good solutions. Mutation is a probabilistic operator that randomly modifies habitat SIVs based on the habitats a priori probability of existence. Suppose that we have a habitat H, a vector of SIVs, following the migration and mutation steps to reach the optimal solution. In this way, new candidate habitat is generated from all of the salutation in population.

3.2. The migration strategy

BBO migration is a probabilistic operator that adjusts each solution H_i by sharing features between solutions. In the BBO, the migration strategy is similar to the evolutionary strategy in which many parents can contribute to a single offspring (Li et al., 2011).