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A Pareto improved artificial fish swarm algorithm for solving a multi-objective fuzzy disassembly line balancing problem

Zeqiang Zhang[a,*], Kaipu Wang[a], Lixia Zhu[a], Yi Wang[b]

[a] School of Mechanical Engineering, Southwest Jiaotong University, Chengdu, 610031, China
[b] Department of Mathematics and Computer Science, Auburn University at Montgomery, Montgomery, AL, USA

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ABSTRACT

To better reflect the uncertainty existing in the actual disassembly environment, the multi-objective disassembly line balancing problem with fuzzy disassembly times is investigated in this paper. First, a mathematical model of the multi-objective fuzzy disassembly line balancing problem (MFDLBP) is presented, in which task disassembly times are assumed as triangular fuzzy numbers (TFNs). Then a Pareto improved artificial fish swarm algorithm (IAFSA) is proposed to solve the problem. The proposed algorithm is inspired from the food searching behaviors of fish including prey, swarm and follow behaviors. An order crossover operator of the traditional genetic algorithm is employed in the prey stage. The Pareto optimal solutions filter mechanism is adopted to filter non-inferior solutions. The proposed model after the defuzzification is validated by the LINGO solver. And the validity and the superiority of the proposed algorithm are proved by comparing with a kind of hybrid discrete artificial bee colony (HDABC) algorithm using two test problems. Finally, the proposed algorithm is applied to a printer disassembly instance including 55 disassembly tasks, for which the computational results containing 12 non-inferior solutions further confirm the practicality of the proposed Pareto IAFSA in solving the MFDLBP.

1. Introduction

In the process of rapid development of social economy, it has become increasingly important to improve the utilization rate of natural resources, while reducing the environment pollution. Recycling, as an effective way of dealing with used or broken products for reusing and remanufacturing, has been gradually popularized in the manufacturing industry. Therein disassembly, being the first crucial step of recycling process that affects both the environment and economic benefits of enterprises, has become a hotspot in the related research filed. Disassembly operation performed at one single workstation is inefficient and cannot be adapted to the demand in large quantities, and the *disassembly line* (Kalayci & Gupta, 2013b) was consequently introduced as an efficient way to achieve scale and automation disassembly production (Gungor & Gupta, 2002). However, there exists a high degree of unbalance problems in the disassembly line, which has brought out a large amount of research about the disassembly line balancing problem (DLBP).

Gungor, Gupta, Pochampally, and Kamarthi (2000) firstly proposed the disassembly line balancing problem. Subsequently, a mathematical model of the DLBP considering the characteristics of the disassembly line was formulated, and, a heuristic method was applied for acquiring the appropriate task assignment schemes by Gungor and Gupta (2002). A greedy algorithm (Mcgovern & Gupta, 2003) and a 2-opt heuristic method (Mcgovern & Gupta, 2004) presented were both applied to the DLBP. The advantage of the heuristic algorithm is that the principle is intuitionistic and easy to grasp. The disadvantage is that the effect of the solution is uncertain. In order to guarantee the accuracy of the solution, Altekin and Kandiller (2012) and Altekin, Kandiller, and Ozdemirel (2008) used the mixed integer programming method to solve the profit-oriented incomplete disassembly line balance problem.

Since the problem of disassembly line balance is NP-complete problem (McGovern & Gupta, 2007), the solving difficulty will increase geometrically with the increase of the problem scale. Therefore, the mathematical programming method is not suitable for solving large-scale disassembly line balancing problems, and the meta-heuristic method with good performance is widely used, such as ant colony algorithm (Agrawal & Tiwari, 2008), reinforcement learning method (Tuncel, Zeid, & Kamarthi, 2014), simulated annealing algorithm (Kalayci, Gupta, & Nakashima, 2011b), particle

* Corresponding author.
E-mail addresses: zhangzq@home.swjtu.edu.cn (Z. Zhang), wkp20106981@163.com (K. Wang), m18200289139@163.com (L. Zhu), ywang2@aum.edu (Y. Wang).

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swarm algorithm (Kalayci & Gupta, 2012), variable neighborhood search algorithm (Kalayci, Polat, & Gupta, 2015), tabu search algorithm (Kalayci & Gupta, 2011b)and so on. On the basis of the traditional disassembly line balance problem, Kalayci et al. proposed a sequence-related disassembly line balance problem according to the mutual interference between the tasks existing in the actual disassembly, and designed a variety of meta-heuristic algorithms to solve the problem, such as genetic algorithm (Kalayci, Polat, & Gupta, 2016), ant colony algorithm (Kalayci & Gupta, 2013a), artificial bee colony algorithm (Kalayci & Gupta, 2013b), simulated annealing algorithm (Kalayci & Gupta, 2013c), particle swarm algorithm (Kalayci & Gupta, 2013d), tabu search algorithm (Kalayci & Gupta, 2013e) and so on. The Riggs, Jin, and Hu (2015) considered a model of incomplete disassembly, and proposed a two-stage optimization strategy to adjust the sequence of operations.

Although the above-mentioned meta-heuristic algorithms have considered multiple decision-making objectives when establish the mathematical model, the multi-objective problem has been transformed into a single-objective problem with prioritization in the actual solution. However, the decision-making objectives are generally conflicting with each other in the actual production, thus this approach cannot guarantee the equilibrium of the optimization of the all objectives. Ding, Feng, Tan, and Gao (2010) used the ant colony algorithm based on Pareto solution set to optimize the multi-objective DLBP, and can get a variety of optimization schemes and realize the equilibrium among the all objectives.

The DLBP is not simply a reverse process of the assembly line balancing problem. The DLBP is more complex owing to uncertain factors due to uncertain features of recycled products, which may lead to variations of task disassembly times in the disassembly line. Therefore, *a kind of DLBP considering fuzziness was proposed in this paper*. Early in the year 1995, Gen et al presented a single product assembly line balancing problem with fuzziness (Gen, Tsujimura, & Li, 1996; Tsujimura, Gen, & Kubota, 1995). Later, Hop (2006) investigated a fuzzy mixed-model assembly line balancing problem and used a heuristic method to solve it. In addition, Tapkan, Ozbakir, and Baykasoglu (2012) discussed a fuzzy multi-objective two-sided assembly line balancing problem and applied a bee colony algorithm to solve it. Compared to the assembly line balancing problem, there was little study on fuzzy disassembly times for a disassembly line balancing problem in previous studies. Paksoy, Gungor, Ozceylan, and Hancilar (2013) firstly proposed a binary fuzzy goal programming and fuzzy multi-objective programming approaches for a mixed-model disassembly line balancing problem. Besides, Kalayci, Hancilar, Gungor, and Gupta (2014) researched the MFDLBP in which the disassembly time was supposed as a TFN and used a kind of HDABC to solve it. Therein a fixed weighted evaluation mechanism was employed to deal with multiple optimization objectives, which resulted in an unbalance among optimization objectives.

Based on the studies in the literature, a Pareto improved artificial fish swarm algorithm (IAFSA) is presented, aiming at the multi-objective fuzzy disassembly line balancing problem (MFDLBP). The artificial fish swarm algorithm is an optimization method based on fish's behavior of searching food. The artificial fish swarm algorithm simulates the prey, swarm, follow and random behavior of fish to achieve the optimization. The algorithm possesses the advantages of fast convergence speed and strong global search ability and strong robustness (Cheng, Li, & Bao, 2016). The algorithm exhibits excellent performance in solving the traveling salesman problem (Cheng et al., 2016; Yang, 2014), redundancy allocation problem (He, Hu, Ren, & Zhang, 2015), QoS routing problem (Zhao & Du, 2015), distribution center location problem (Fei, Zhang, Sun, Chen, & Ren, 2016), short term hydrothermal scheduling problem (Fang, Zhou, Zhang, Liu, & Zhang, 2014), 0–1 knapsack problem (Azad, Rocha, & Fernandes, 2014a; Azad, Rocha, & Fernandes, 2014b; Azad, Rocha, & Fernandes, 2015) and many other discrete combinatorial optimization problem. As far as we know, the application of the AFSA to the MFDLBP has not been mentioned yet. On the other hand, to avoid the deficiency of the basic artificial fish swarm algorithm in solving the MFDLBP, a Pareto improved artificial fish swarm algorithm is introduced to solve the MFDLBP in this paper.

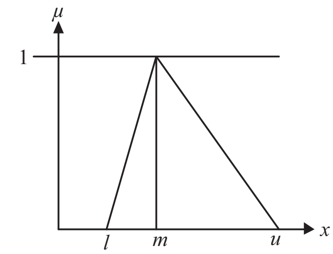

Fig. 1. The membership function of a TFN $\tilde{A}$.

The rest of the paper is organized as follows. Section 2 describes the DLBP and formulated the mathematical model of the problem. Section 3 introduces the proposed improved Pareto IAFSA in detail. In Section 4, the proposed algorithm is tested by a 25-task disassembly case and a 47-task disassembly case, and further by a printer disassembly instance including 55 disassembly tasks. The validity and the superiority of the proposed algorithm are identified and confirmed. At the end of this paper is a summary of the research work.

2. Problem definition and formulation

2.1. Triangular fuzzy number

In this paper, the fuzzy-oriented disassembly time is to genuinely reflect the actual situation of the disassembly production. To this end, both the cycle times and disassembly times are both described as TFNs. Let $\tilde{A}$ be a TFN. The TFN $\tilde{A}$ is described by a triplet $(l,\ m,\ u)$ (Zacharia & Nearchou, 2012), where, l and u are the least and largest values of $\tilde{A}$, respectively, and m is the most likely value of $\tilde{A}$ of which the membership degree μ is 1. Fig. 1 is a diagram of the membership function of a TFN $\tilde{A}$, where the x-axis represents the value in the interval $[l, u]$ of the universe of the TFN $\tilde{A}$, and, the vertical axis represents the membership degree μ $(0 \le \mu \le 1)$ corresponding to each value in the interval $[l, u]$. The membership function indicates the quantitative description of a fuzzy concept.

Let $\tilde{A} = (\alpha_1,\ \alpha_2,\ \alpha_3)$ and $\tilde{B} = (\beta_1,\ \beta_2,\ \beta_3)$. The operation rules of TFNs are performed according to Eqs. (1) ~ (4),

$$\tilde{A} + \tilde{B} = (\alpha_1 + \beta_1,\ \alpha_2 + \beta_2,\ \alpha_3 + \beta_3), \tag{1}$$

$$\tilde{A} - \tilde{B} = ((\alpha_1 - \beta_3) \vee 0,\ \alpha_2 - \beta_2,\ \alpha_3 - \beta_1), \tag{2}$$

$$\tilde{A} \times \tilde{B} = (\alpha_1 \times \beta_1,\ \alpha_2 \times \beta_2,\ \alpha_3 \times \beta_3), \tag{3}$$

$$\widetilde{\frac{A}{B}} = \left(\frac{\alpha_1}{\beta_3},\ \frac{\alpha_2}{\beta_2},\ \frac{\alpha_3}{\beta_1}\right), \tag{4}$$

where, the notation $(x \vee y)$ means taking the maximum of two real numbers x and y.

2.2. Notation

Notations used in the mathematical model are listed as follows.