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Efficient Multi-Objective Optimization Method for the Mixed-Model-Line Assembly Line Design Problem

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Abstract

This paper presents a mathematical model and an adaptation of the Strength Pareto Evolutionary Algorithm II (SPEA2) for the Mixed-Model Assembly Line balancing and equipment selection problem. The SPEA2 was enriched with a task and equipment reassignment procedure and aims at supporting the planners to find better solutions in the earliest phases of a production system planning project.

Keywords: Assembly Line Design problem; balancing problem; equipment selection; Mixed Model Line; Multi-objective; SPEA2

1. Introduction

Nowadays, due to the current levels of globalization, competition and deregulation that have engendered a changeable, dynamic and uncertain global market with greater need for flexibility and responsiveness [1], the ability of a company to compete effectively is influenced to a large extent by its capacity to produce an increased number of customer based products in a timely manner [2]. Shorter product life cycles; high flexible, dynamic and efficient production systems are required, engendering an increased complexity in all factory domains. To handle this complexity, methods of Operations Research are often used to support the decision maker to plan flexible and optimal assembly lines. Assembly lines that allow a low cost production, reduced cycle times and accurate quality levels, can be classified into three variants: (i) the Single Model Line, designed to carry out a single product, (ii) the Mixed Model Line, designed to produce similar models of a product in sequence or batch and (iii) the Multi Model Line, designed to produce various similar or different models in large batches. Several standard scientific problems relating to these three variants have been formulated in the literature, such as the optimal process planning, facility layout, line balancing, buffer allocation, equipment selection, etc. [3]. While the Single and Multi Model Line are the least suited production systems for high variety demand scenarios, the Mixed Model Line is better appropriated to respond to these requirements of flexibility and efficiency. This paper deals with the resolution of a multi-objective problem, namely with the line balancing problem and equipment selection problem, also called Assembly Line Design Problem, for a Mixed-Model-Line. While the line balancing problem is related to the decision problem of optimally partitioning or balancing the assembly tasks among stations, the equipment selection problem is associated to the decision problem of optimally selecting the equipment for each assembly task.

In the next section, the basic concepts of multi-objective problems will be presented, followed by a state of the art in the field of the Assembly Line Design Problem, in which the weaknesses of the current available methods will be presented. Our efficient multi-objective optimization method will be presented in the last sections.

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2. State of the Art

2.1. Multi-Objective Optimization

2.1.1. Basic Concepts and Terminology

A multi-objective optimization problem (MOP) is a problem in which at least two objectives need to be simultaneously optimized. In mathematical terms, a MOP can be formulated as follows:

$$min\, \mathrm{f(x)} = [f_1(x), \dots, f_k(x)]^T \quad (1)$$

$$\text{s.t. } g_j(x) \le 0 \qquad j = 1, \dots, m \quad (2)$$

$$h_l(x) = 0 \qquad l = 1, \dots, e \quad (3)$$

Where $k > 1$ denotes the number of objective functions, m is the number of inequality constraints, and e the number of equality constraints.

Due to the multi-objective nature of most real-life problems (e.g. in finance, scheduling, engineering design and medical treatment [4]), MOPs have been a rapidly growing area of research and application. Generally, these objectives are in conflict, implying that by improving one objective, another objective will become worse. MOPs with such conflicting objective will provide many optimal solutions, instead of only one. The reason for the optimality of more than one solution is that no one can be considered to be better than any other with respect to all objectives [5]. These optimal solutions are known as the Pareto-optimal solutions [6]. A solution $x^* \in X$, where X is the feasible region, is defined as either a Pareto-optimal solution or a non-dominated solution, if it does not exist another point, $x \in X$, such as $f(x) \le f(x^*)$ and $f_i(x) \le f_i(x^*)$ for at least one function, where $X = \{x | g_j(x) \le 0 \; and \; h_l(x)\}$ $\forall\, j = 1, \dots, m$ and $i = 1, \dots, e$. A solution $x^* \in X$ is defined as Weakly Pareto-optimal, if there does not exist another point, $x \in X$, such as $f(x) < f(x^*)$.

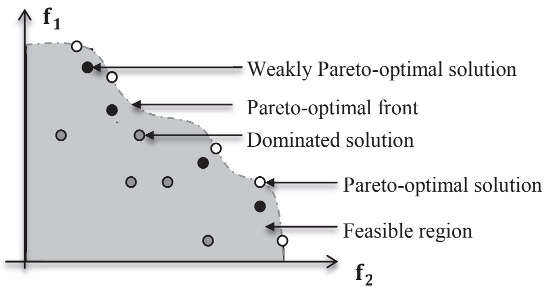

Fig. 1. Illustrative example of Pareto optimality

2.1.2. Approaches to Solve Multi-objective Optimization Problems

There exist many methods and algorithms for solving MOPs. These methods and algorithms can be divided in two categories: (i) classical methods which use direct or gradient-based methods following some mathematical principles and (ii) non-classical methods which follow some natural or physical principles [7,8]. Classical methods mostly attempt to scalarize multiple objectives and perform repeated applications to find a set of Pareto-optimal solutions. In this first category, methods such as the weighted-sum method or scalarization method, ε-Constraints method, Goal-programming, Goal-attainment method and min-max optimization can be found. What has made these methods attractive and why they have been so popular can be attributed to the fact that a wide range of well-studied algorithms for single-objective optimization problem (SOP) can be used. The main criticism of most of these methods is that although they may converge to one Pareto-optimal solution, these methods have to be applied many times in order to get more than one solution. This implies a systematic variation of weight vectors or ε parameters that does not guarantee a good diversity in the set of solutions and thus an inefficient search. In this iterative process, the systematic variation of parameters may also lead to an important CPU time. Moreover, some of these techniques may be sensitive to the shape of the Pareto-optimal front. Indeed, non-convex parts of the Pareto set cannot be reached by optimizing convex combinations of the objective functions [9]. Furthermore, as the solutions mainly depend on parameters such as, weights and upper/lower bounds, these methods also require certain knowledge in order to find Pareto-optimal solutions. Mainly due to these reasons the Multi-Objective Evolutionary Algorithms (MOEA), that stand for a class of stochastic optimization methods, have risen up. Schaffer [10] published the earliest work in the field of MOEA. He proposed a Vector Evaluated Genetic Algorithm (VEGA) based on the traditional Genetic Algorithm by using a modified selection. Since this first publication, the development of MOEA has successfully evolved, producing better and more efficient algorithms, due to in some way the incorporation of the elitism concept, which ensures that the number of non-dominating individuals in the population increases. According to their performances and characteristics, the MOEA can be classified in the following two groups: (i) First Generation, where the Multi-Objective Genetic Algorithm (MOGA), the Niched-Pareto Genetic Algorithm (NPGA) and the Non-dominated Sorting Genetic Algorithm (NSGA) can be found, and (ii) Second Generation, where the Strength Pareto Evolutionary Algorithm (SPEA), SPEA2 [11], the Memetic Pareto Achieved Evolution Strategy (M-PAES), the Pareto Envelope-based Selection Algorithm (PESA), PESA-II and the NSGA-II can be found.

Two major problems must be addressed when an evolutionary algorithm is applied to solve MOP: (i) minimizing the distance to the optimal front and (ii) maximizing the diversity of the generated solutions. In this context, two fundamental issues have to be taken into consideration: (i) the mating selection and (ii) the environmental selection. The first issue is related to the question of how to guide the search towards the Pareto-optimal front, while the second deals with the question of which individuals should be kept in the evolution process. The general concept, common to all these algorithms, is shown in Fig. 2.

First an initial population, representing the starting point of the evolution process, is created at random (or according to a predefined scheme such as heuristics). In the fitness evaluation step, the fitness - reflecting the quality of a solution - is attributed. Afterwards, a binary tournament is normally used for the mating selection process. Here, the mating pool is filled up by individuals that have the best fitness values