European Journal of Operational Research 201 (2010) 123–128

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Production, Manufacturing and Logistics

Mining Pareto-optimal modules for delayed product differentiation

Zhe Song, Andrew Kusiak *

Intelligent Systems Laboratory, MIE, 3131 Seamans Center, The University of Iowa, Iowa City, IA 52242-1527, USA

ARTICLE INFO

Article history:
Received 1 June 2008
Accepted 12 February 2009
Available online 20 February 2009

Keywords:
Data mining
Evolutionary computations
Mass customization
Modularity
Delayed product differentiation
Multi-objective optimization

ABSTRACT

This paper presents a framework for finding optimal modules in a delayed product differentiation scenario. Historical product sales data is utilized to estimate demand probability and customer preferences. Then this information is used by a multiple-objective optimization model to form modules. An evolutionary computation approach is applied to solve the optimization model and find the Pareto-optimal solutions. An industrial case study illustrates the ideas presented in the paper. The mean number of assembly operations and expected pre-assembly costs are the two competing objectives that are optimized in the case study. The mean number of assembly operations can be significantly reduced while incurring relatively small increases in the expected pre-assembly cost.

1. Introduction

In the last decade, manufacturing has been moving from mass production to mass customization. The concept of developing product families and modular architectures are of interest to manufacturing companies in the quest to meet diverse customer requirements while maintaining an economy of scale (Farrell and Simpson, 2003).

In order to implement mass customization successfully, manufacturing companies have to balance their efforts through the life-cycle of their products. Roughly speaking, a product life-cycle can be divided into design and manufacturing. For each stage, different techniques can be adopted to implement the mass customization strategy. For example, during the design stage, modular design and product family concepts are widely used (Fujita and Yoshida, 2004; Huang and Kusiak, 1998; Jiao and Tseng, 1999; Kreng and Lee, 2004; Kusiak and Huang, 1996; Yigit et al., 2002). Basic ideas are to provide diverse products with low technical varieties. Different products can be easily obtained by different combinations of modules.

During manufacturing stage, commonality, postponement (Ma et al., 2002; Swaminathan and Tayur, 1999) are important methods for managing product diversity and maintaining low manufacturing costs. However manufacturing performance can still be affected by product variety (MacDuffie et al., 1996) especially when customer orders are so diverse. Fu et al. (2006) studied the inventory and production decisions for a single product with uncertain demand and assembly capacity. Lee and Tang (1997) considered the benefits and costs of the delayed differentiation strategy for two products. Hsu and Wang (2004) presented a dynamic programming model for determining the delayed differentiation point in a multi-stage production system. Jewkes and Alfa (2008) used a queueing model to analyze the benefits of delayed differentiation. Gunasekaran and Ngai (2009) reviewed models of make-to-order supply chain. Gupta and Benjaafar (2004) studied the trade-offs between the delayed differentiation, make-to-order, and make-to-stock strategies in the context of a multi-stage assembly system with limited production capacity. These researches provide insights into the manufacturing process under different configurations.

Most research literatures are focused on modular product design or product family design. But in order to improve manufacturing performance, such as delivery time, more researches are needed to develop new techniques to support mass customization in manufacturing stage.

Once a product is designed, it is ready to be manufactured and assembled according to customer orders. Internet-based configuration systems have been gaining popularity in recent years. Customers are able to configure products by selecting desired features, which result in many unique configurations. Maintaining a large number of different product configurations increases production complexity and extends delivery lead time (Da Cunha et al., 2007; Swaminathan and Tayur, 1998). To shorten the lead time, companies may follow a delayed differentiation strategy. The delayed differentiation strategy is a compromise between MTO (make-to-order) and MTS (make-to-stock) strategies (Gupta and Benjaafar, 2004; Swaminathan and Tayur, 1999, 1998). Following

* Corresponding author.
E-mail address: andrew-kusiak@uiowa.edu (A. Kusiak).

0377-2217/$ - see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.ejor.2009.02.013

the MTO strategy, a company assembles a final product only when a customer order arrives. In the MTS strategy, a company pre-assembles a set of complete products, and once a customer order arrives, the company will search the pre-assembled products. If a match is found, the product is shipped; otherwise, the customer order is assembled from the basic components. In the delayed differentiation strategy, maintaining a set of pre-assembled modules (sub-assemblies or semi-finished products) shortens the final assembly time (Da Cunha et al., 2007; Swaminathan and Tayur, 1998). Once a customer order arrives, the modules needed to assemble a product are retrieved. Then additional components may be assembled with the retrieved modules, if necessary, to make a complete product. Thus customer satisfaction is improved by reducing final assembly time.

Jiao and Zhang (2004) applied a genetic algorithm to solve a product portfolio optimization problem for generating complete product configurations. However finding semi-finished products is of interest for the manufacturing company. Determining a set of modules to be pre-assembled and stocked is a complex optimization problem (Da Cunha et al., 2007; Fu et al., 2006; Jiao and Zhang, 2004; Kusiak and Huang, 1996; Swaminathan and Tayur, 1998) in which multiple costs have to be considered and balanced. Da Cunha et al. (2007) developed a linear cost function and heuristic algorithms to find the optimal module combinations that could reduce the mean number of assembly operations. Swaminathan and Tayur (1998) developed an optimization model to determine inventory levels for the modules they selected under variable demand and fixed assembly capacity.

This paper extends and combined the concepts discussed in the literature (e.g. Da Cunha et al., 2007; Swaminathan and Tayur, 1998), by finding optimal modules for a product family described by a set of attributes, where each attribute is associated with a set of components. A multi-objective function is used to find a solution minimizing the mean number of assembly operations and expected pre-assembly cost simultaneously. The optimal solutions considered in this research are semi-finished products. Compared with previous research (Da Cunha et al., 2007), this optimization framework allows users to simultaneously consider multiple cost functions. There is no need to assign a weight for each cost component. In contrast to Swaminathan and Tayur (1998), the proposed solution is more focused on the selection of modules by using historical sales data. Mean assembly time and pre-assembly costs are considered to derive the modules.

This paper is organized in six sections. Section 2 formulates the multi-objective optimization problem. An evolutionary computation algorithm for finding Pareto-optimal solutions is introduced in Section 3. Section 4 discusses the incorporation of historical sales data into the model formulated in Section 2. The three objectives to be achieved are addressed in Section 5. Section 6 discusses an industrial case study based on a truck data set.

2. Problem formulation

A product can be described by a set of attributes (features). Each attribute usually represents a set of components (e.g., a sub-assembly) which the customer selects to create his or her desired configuration. Unlike previous research (Da Cunha et al., 2007; Swaminathan and Tayur, 1998), their configuration (a complete product) is described by a set of components. Each configuration is determined by binary choices, a component is either selected or not selected to be in the configuration.

Definition 1. A product is described by n attributes. Each attribute A_i ($i = 1,\ldots,n$) is a set of n_{A_i} components. $A_i(j)$ is the jth component of A_i, $j = 1,\ldots,n_{A_i}$.

Based on Definition 1, the following relationships are established:

(a) In the absence of assembly constraints among the components, there are $\prod_{i=1}^{n} n_{A_i}$ unique configurations.
(b) A module could be a single component, a partial configuration, or a complete configuration. There are total $\prod_{i=1}^{n}(n_{A_i}+1)-1$ unique modules in a product.
(c) The set of modules with only one component is expressed as $\bigcup_{i=1}^{n} A_i$.
(d) The set of modules with two components is expressed as $\bigcup_{i=1,j=1,i\neq j}^{n} A_i \times A_j$.
(e) The set of modules with three components is expressed as $\bigcup_{i=1,j=1,k=1,i\neq j\neq k}^{n} A_i \times A_j \times A_k$.
(f) The set of all complete configurations is expressed as $A_1 \times \cdots \times A_n$.

Definition 2. A module M_i $\left(i = 1,\ldots,\prod_{i=1}^{n}(n_{A_i}+1)-1\right)$ is a set of components drawn from different attributes.

There are two questions to be answered here. Which modules should be selected and assembled first? What are the inventory levels of these modules? There are numerous answers to these two questions depending on users' preferences. In this paper, the selected modules should have the ability to form a certain number of unique product configurations. In other words, most customer orders can be assembled from these modules. As we all know, assembling those modules costs a manufacturing company in terms of additional inventory and pre-assembly operations. Thus selecting those modules should also consider these costs.

The ultimate goal of forming these modules is to reduce the final assembly time and deliver products fast to customers. Besides, knowing these modules can help the company utilize its underused manufacturing resources by avoiding waiting for customer orders.

Definition 3. Let $\boldsymbol{M}$ be a set of modules selected from $\prod_{i=1}^{n}(n_{A_i}+1)-1$ unique modules. $\boldsymbol{M}(i)$ is the ith element of set $\boldsymbol{M}$, $i = 1,\ldots,n_M$. $\boldsymbol{M}(i)$ could be regarded as a set of components from different attributes.

Based on the previous definitions, the optimal set of modules can be determined by solving an optimization problem with multi-objectives. Without loss of generality, it is assumed that there are g objectives to be minimized, i.e., $y_1,\ldots,y_g$. Model (1) states that the optimal set of modules should minimize the g objective functions while satisfying all constraints:

$$\begin{aligned} &\min_{\boldsymbol{M}} \{y_1, y_2, \ldots, y_g\} \\ &\text{s.t.}\quad \text{Constraints.} \end{aligned} \tag{1}$$

The overall solution presented in this paper can be described as following steps:

1. Analyze historical sales data to estimate customer demand information and preferences.
2. Formulate different objective functions (cost functions) and constraints which the selected modules will optimize.
3. Use multi-objective evolutionary algorithms to solve the optimization problem.

Historical sales data contains important information about customer demand and preferences. For example, knowing which configurations (finished complete product) are frequently purchased by customers will help identify those semi-finished products. As a result, the final assembly time of complete products ordered by customers will be decreased.