Optimal Collaborative Design in Supply Chains

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INTRODUCTION

Most modern industrial products are manufactured through supply chains. Competition, rapid product upgrading, and demand for customized products make design and redesign important activities in supply chains. From the manufacturing perspective, a supply chain consists of a set of *manufacturers* that cooperate in the design and production of a final product or multiple related products. Each pair of manufacturers directly involved in the supply chain form a supplying relation, with one of them being the *supplier* and the other being the *consumer*. In this chapter, we use the term *consumer* to refer to a manufacturer in the above sense, and we refer to people who purchase and consume the product as *end-users*, who are regarded as outside the supply chain. A manufacturer R_1 may be the consumer relative to another manufacturer R_2, but acts as the supplier to a third manufacturer R_3 in the same supply chain.

Product design in supply chains are dominated by *component-centered design*, in which a final product is designed as a set of components. In computer design, a processor chip is a component, and so is a hard-disk drive. Lower level components may be composed into a higher level component. For instance, a desktop system unit is a component assembled from month-board, processor chips, etc. Under component-centered design and production, each supplier supplies one or more components to one or more consumers.

Contemporary design in supply chains is essentially top-down (Huang et al., 2000). The manufacturer R of final product decomposes it into components. For each component C to be supplied to R, a supplier S further decomposes C into sub-components, and the process continues. With top-down design, consumers play dominant roles and suppliers are passive. Such designs are unlikely to be optimal, because consumers are usually not in the best position to judge options available to suppliers.

This chapter presents a computational framework for collaborative design where suppliers play equally active roles in shaping design. In particular, we describe a multiagent framework, where manufacturers are collaborative designers aided by intelligent agents. The objective is to produce an overall optimal design by distributed decision making. The multiagent system and decision algorithm are elaborated.

BACKGROUND

A product has a design space described by a set D of variables. Each variable in D is a *design parameter*. Type of processor used in a smart appliance is a design parameter. We assume that each parameter is associated with a discrete domain of possible values, and a naturally continuous parameter is discretized. A *partial design* is an assignment of values to variables in a proper subset of D, and a *complete design* assigns values to all variables in D.

A design is subject to a set of constraints. For instance, if length of a computer case is L and length of the motherboard is L', then L>L' should hold. A constraint involves a subset $S \subset D$ of

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variables and specifies allowable assignments for S. A design is *valid* if it satisfies all constraints.

Different valid designs result in products with different performances. Maximum speed is a performance measure of a car. For simplicity, we refer to performance of a product resultant from a design as performance of the design. *Performance space* of a product is described by a set M of variables, each being a *performance measure*. We assume that each measure is associated with a discrete domain.

Performance of a product also depends on environment in which it operates. For instance, high level of humidity may cause a computer to fail. We describe such *environmental factors* by a set T of discrete variables.

People differ in preference over a given product performance. Subjective preference of stake-holders (manufacturer or end-user) over design is represented by utility functions (Keeney & Raiffa, 1976). For clarity, we assume that utility is directly dependent on performance of product, not directly on design parameters. Hence, we denote the utility function U(M). An overview of methods for utility function assessment is given in (Farquhar, 1984).

We assume that U(M) can be decomposed additively (Keeney & Raiffa, 1976) as follows: Partition performance measures into groups M_1, M_2, ... Each M_i is associated with a utility function $U_i(M_i) \in [0,1]$. The overall utility function satisfies

$$U(M) = \Sigma_i\ \omega_i\ U_i(M_i),$$

where each weight $\omega_i \in (0,1)$ such that $\Sigma_i\ \omega_i = 1$. As argued in (Keeney & Winterfeldt, 2007), when decision objectives are properly chosen, additive utility decompositions are widely applicable.

Design cannot ensure performance deterministically, due to uncertainty in product life-cycle. We evaluate expected utility of design instead. Denote a design by $D = \underline{d}$. Denote an assignment of performance measures of resultant product by $M = \underline{m}$. $P(\underline{m}|\underline{d})$ is the probability of performance $\underline{m}$ of product resultant from design $\underline{d}$. Expected utility of $\underline{d}$ relative to $U_i(M_i)$ is

$$EU_i(\underline{d}) = \Sigma m\ U_i(proj(\underline{m}, M_i))\ P(\underline{m}|\underline{d}), \qquad (1)$$

where $proj(\underline{m}, M_i)$ is projection of $\underline{m}$ to M_i. Expected utility of $\underline{d}$ is

$$EU(\underline{d}) = \Sigma_i\ \omega_i\ (\Sigma m\ U_i(proj(\underline{m}, M_i))\ P(\underline{m}|\underline{d})). \qquad (2)$$

Given (D, T, M, U), the problem of decision-theoretic design is to find a valid design $\underline{d}$* that maximizes $EU(\underline{d})$.

Deterministic design assumes typical maximum loads and minimum material property. It often leads to overdesign and inability to risk analysis. Probabilistic design optimizes in face of uncertainties (Batill et al., 2000). We extends probabilistic design to decision-theoretic, which incorporates stake-holder preference, and to collaborative design by distributed decision-making. Collaborative design may be viewed as distributed constraint satisfaction problems (DisCSPs), e.g., (Meisels & Zivan, 2007). However, DisCSPs involve finding constraint satisfying solutions, but not optimization among them. The limitation is overcome by distributed constraint optimization (DCOP). However, most research on DCOP, e.g., (Petcu & Faltings, 2005) is not decision-theoretic. Below, we present a multiagent framework for decision-theoretically optimal, collaborative design (Xiang et al., 2004).

MAIN FOCUS

To compute $EU(\underline{d})$ effectively, we represent a centralized design problem as a graphical model, called *design network (DN)*. We then represent a design problem on supply chain as a *collab-*

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