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SUPPORT SYSTEMS FOR DECISION AND NEGOTIATION PROCESSES

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CONCURRENT ENGINEERING: MODELING THE NEGOTIATION PROCESS

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ABSTRACT: Concurrent design should reduce the duration of a design project, development cost, and provide a better quality of final design. However, due to the diversified problem-solving knowledge and different goal-settings among design agents, it may increase the number of conflicts and make design process more difficult to manage. In this paper, a goal-driven negotiation model based on decision analysis for resolving conflicts in a multi-agent environment is presented. The proposed model generates the negotiation sets, analyzes the utilities derived from each agent, and evaluates them based on the three heuristic rules. The goal-driven negotiation model attempts to maximize the system objectives and satisfy design constraints. It also reduces the interaction required among agents. An example of the poppet relief valve is used to demonstrate the negotiation concept.

Keywords: Concurrent engineering, negotiation, engineering design, decision analysis.

1. Introduction

Concurrent engineering attempts to incorporate various constraints related to the product life cycle, i.e., manufacturability, quality, reliability, and so on, in the early design stages. It aims at improvement of the product quality and reducing the development time and cost. However, due to the diversified design knowledge, concurrent design needs to incorporate numerous views of multi-discipline specialists (called in this paper design agents). Typically, an individual agent is narrow-focused and has only limited knowledge about other disciplines. Each agent tends to view problem-solving goals from a local perspective. The diversified knowledge and different goal-settings among individual agents lead to conflicts in the design process. To maintain consistency and produce an acceptable design, the conflicting goals between design agents need to be negotiated. A successful design can be viewed as a compromise that incorporates tradeoffs, such as cost, manufacturability, reliability, maintainability. The global goal is to produce an acceptable design that is synthesized from contributions of different perspectives.

Negotiation involves finding a compromise solution for multiple conflicting goals. It is an ill-structured, complex, dynamic, and iterative process. The research in decision science has lead to the development of quantitative models of the negotiation process (DeSanctis and Gallupue 1987, Chatterjee et al. 1991). Depending upon the assumptions considered, it is possible to apply multiobjective decision techniques such as: game theory (Kannapan and Marshek 1993), decision analysis (Sycara 1988). Artificial intelligence approaches use mostly logic-based deduction modeling (Rosenschein and Breese 1989, Bond 1989, ChaibDraa and Millot 1990), case-based reasoning (Sycara 1991), genetic algorithms (Matwin et al. 1991), or constraint-directed search (Fox 1989) to resolve conflicts.

In this paper, a goal-driven negotiation model based on decision analysis (Keeney and Raiffa 1976) is proposed for resolving multiple conflicts among individual design agents. The proposed model generates all possible alternatives, analyzes them, and chooses the most satisfying solution. The evaluation is based on three heuristic rules. The multi-attribute utility theory is applied to set the preference of possible decisions for each design agent. A blackboard architecture is used as a modeling environment.

The paper is organized as follows. A goal-driven negotiation model based on parametric design for conflict resolution is presented in Section 2. In Section 3, a design example is discussed. Section 4 concludes the paper.

2. The Analytical Model of Design Negotiation

2.1 Assumptions of rationality

In a concurrent design environment, design agents specializing in different fields interact through a global database or blackboard (Nii 1986). The design agents suggest, critique, and implement changes to the product design. To resolve the conflicts between agents, three rationality assumptions are made:

1. Individual rationality

   The negotiation set must be represented at least as favorably as the conflict situation without any agreement; i.e. the compromise solution should be satisfied each of the agents.

2. Joint rationality

   The compromise represents a situation that the joint solution could not be improved any further by both design agents. The joint rationality is also called in the literature the pareto optimal set (Yu 1985).

3. Non-benevolent rationality

   Each agent has its goals and does not necessary help another agent with information or actions. As conflicts among agents exist, there is often a potential for a compromise and mutually beneficial actions. Some agents might be capable of interacting even when their goals are not compatible.

Based on these three assumptions, design agents compromise with each other in order to resolve conflicts and produce an acceptable design that satisfy possibly all constraints.

2.2 Analytical approach to conflict resolution

Many analytical solution approaches have been proposed in game theory (Luce and Raiffa 1958) and multi-criteria decision-making, such as: pareto-optimality, feasibility, uniqueness. In the design negotiation process, an alternative that would be the most preferable to one agent may be the least preferable to another one, since their goals are in conflict. Hence, the selection of a compromise solution that will be potentially acceptable to all design agents becomes important.

To model the preference structure of each agent, multiattribute utility theory (MAUT) is used which is one of the most effective and widely used procedures for modeling human preferences (Keeney and Raiffa 1976). The concept of utility is the basis for selecting among several alternatives and for evaluating past actions. Each alternative is evaluated in terms of the number of attributes that a decision maker considers important in order to select one with the maximum overall utility. However, it is difficult to construct a utility function, when the evaluation problem has multiple dimensions.

In this paper, three heuristic rules for guiding the problem solver in selection of the "best" compromise solution are considered.

Notation:

m = number of agents

n = number of alternatives

$\mu_{ij}(x_1, x_2, ..., x_k)$ = utility function of agent i for alternative j based on attributes $x_1, x_2, ..., x_k$; for $i = 1, ..., m$; $j = 1, ..., n$

μ_{m_j} = mean utility of alternative j, which is defined as

$$\mu_{m_j} = \frac{1}{m}\sum_{i=1}^{m} \mu_{ij}(x_1, x_2, ..., x_k); \text{ for } j = 1, ..., n$$

U_j = joint utility of alternative j; for $j = 1, ..., n$

U_{d_j} = deviation of utility for alternative j; for $j = 1, ..., n$

U_{c_j} = compromise utility for alternative j; for $j = 1, ..., n$

(1) The Maximum Joint Utility Rule

Due to the simplicity, the maximum joint utility rule is one of the most frequently used techniques for aggregation of preferences. The rule maximizes:

$$U_j = \sum_{i=1}^{m} \mu_{ij}(x_1, x_2, ..., x_k) \quad (1)$$

(2) The Minimum Deviation Rule

The purpose of this rule is to estimate the "mean utility" of alternative j, μ_{m_j} ($j = 1, ..., n$). The difference between the agent utility and mean utility is calculated from the following formula:

$$U_{d_j} = \sum_{i=1}^{m} | \mu_{ij}(x_1, x_2, ..., x_k) - \mu_{m_j} | \qquad (2)$$

The alternative that minimizes individual utility differences (U_{d_j}) is selected.

(3) The Compromise Utility Rule

The rule minimizes the deviation and maximizes the joint utility, i.e., maximizes U_{c_j}, where:

$$U_{c_j} = U_j - U_{d_j} \qquad (3)$$

Once the difference U_{c_j} for each alternative is calculated, the alternative that maximizes U_{c_j} is selected.

2.4 Goal-driven negotiation model

The structure or attributes of the artifact being designed can be characterized by a set of design variables. Each design agent is allowed to make decisions independently on certain variables, called decision variables. The design variables that measure the performance of a system or subsystem (goals of the system or agent) are called performance variables. The design variables that are determined by more than one design agent are called shared variables. The variables that are determined by individual agent are called private variables. Determining the value of shared variables is critical in design, because of different goals associated with agents. Values of some private and shared variables might be specified in the design requirements phase.

In this section, a goal-driven negotiation model, where all agents possess individual, joint, and non-benevolent rationality, is proposed to resolve conflicts in a multi-agent design environment. An agent is defined as a system or component capable of making decisions. Each design agent has its own goal and considers its contribution towards the system-level objective.

The formal description of the design negotiation procedure is shown next.

Design Negotiation Procedure

The negotiation procedure for design agents is described as follows:

Step 1: Detect the conflict variables and determine the performance variables that are affected by the conflict variables.

Step 2: For each design agent, set a satisficing goal.

Step 3: For each design agent, identify the scaling constants of performance variables involved in the negotiation process.

Step 4: For each design agent, construct the multi-attribute utility function $\mu(x_1, x_2, ..., x_n)$, where x_i, $i = 1, ..., n$, is the performance variable involved in the negotiation process.

Step 5: Identify the negotiation set for each conflict variable. The negotiation set is defined as follows:

$S_i \in [a_i, b_i]$, where:

m = the number of conflict variables

n = the number of design agents

S_i = the negotiation set for conflict variable c_i, for $i = 1, ..., m$

$a_i = \operatorname{Min}_{j=1}^{n}\{c_i\}$, for $i = 1, ..., m$

$b_i = \operatorname{Max}_{j=1}^{n}\{c_i\}$, for $i = 1,..., m$

Step 6: Generate the possible alternatives for the set of conflict variables and propagate the change back to the decision variables and other related design variables. The alternatives are produced by dividing the range of each conflict variable into pieces and combining all the endpoint values derived from the division. The alternatives that do not satisfy the design constraints are ignored. Two heuristics used for determining the decision variables for propagation are as follows:

(1) select decision variables that do not affect other conflict variables.

(2) select the related decision variable with the minimum number of propagation paths.

Step 7: Calculate the utility value for each alternative according to the utility function built in Step 4. Evaluate all alternatives based on three heuristic rules and select the best alternative.

Step 8: Check with the goal set for each design agent involved in the negotiation process:

(1) If each design agent's utility is greater than its corresponding goal utility, then stop:

(2) If utility of agent i is less than the goal, then modify the proposed solution so it becomes more acceptable to agent i and go to Step 6. This can be done by reducing the negotiation set S_i to S_i' for conflict variable c_i, in which the range of S_i' is between the proposed solution and the solution suggested by design agent i.

(3) Otherwise, the following three strategies can be used:

- go to Step 2 to reset the satisficing goal of each design agent.
- go to Step 3 to rescale the preference structure for each agent.
- modify some of the design specifications.

3. Application of the Design Negotiation Model - Design of a Poppet Relief Valve

In this section, the concept of design negotiation is illustrated with the example of a poppet relief valve (Lyons 1982, Kannapan and Marshek 1993). Figure 1 shows the schematic of a poppet relief valve which includes a poppet valve, poppet valve stem, and helical compression spring enclosed in a pipe (Kannapan and Marshek 1993).

Assume that design of the poppet relief valve is performed by three design agents (DAs) as shown in Figure 2: the valve DA, helical-spring DA, and pipe-enclosure DA. Note that, the design agents are not completely independent because some variables should be considered by more than two agents, such as variables δ, F_c, F_t, and K_{act} shared by valve design agent and helical-spring design agent. Three agents have to interact with each other in order to reach the compromise values for shared variables that define the geometry, material, and configuration of the poppet relief valve.

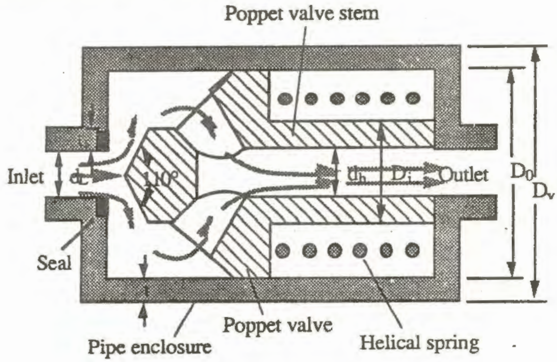

Figure 1. Schematic of a poppet relief valve

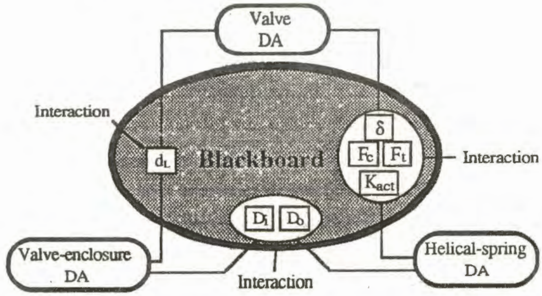

Figure 2. Three design agents and their relationship in design of a poppet relief valve

The system goal, goals for each design agents, and constraints are defined as follows:

System goals: design a relief valve for optimum flow

Subgoals:

Valve DA: minimize the flow area

Helical-Spring DA: minimize the weight of the helical spring (V_H) and maximize the spring stability (r_s)

Valve-Enclosure DA: minimize the volume of the valve enclosure (V_E)

The design constraints are listed in Kusiak and Wang (1992).

Assume that the solution for each agent is determined and two conflict variables D_o and D_i, which are belong to pipe-enclosure DA and helical-spring DA, are observed (see Kusiak and Wang (1992) for details). Pipe-enclosure DA suggests the value of 2.476 for the outer diameter of the spring enclosure (D_o); however, the value of 2.055 is more favorable to the helical-spring DA. For the inner diameter of spring enclosure (D_i), larger diameter is preferable to helical-spring DA (1.639 > 1.545). It is assumed that the satisficing goals for both agents are 85%. The multi-attribute utility functions for valve-enclosure DA and helical-spring DA are defined as follows:

Helical-spring DA: $\mu_H = 0.35\ \mu_{V_H} + 0.65\ \mu_{r_s}$

Valve-enclosure DA: $\mu_V = 1.0\ \mu_{V_E}$

For the conflict variable D_o, the possible compromise solution should be between 2.055 and 2.476, which are obtained from helical-spring DA and valve-enclosure DA individually. According to the rationality assumptions, the negotiation sets for both conflict variables:

$$S_{D_o} = [2.055, 2.476] \qquad S_{D_i} = [1.545, 1.639]$$

Subdividing the range [2.055, 2.476] of D_o and the range [1.545, 1.639] of D_i into four parts results in 25 alternatives. The decision variables r_{c1}, r_{c2}, A_1 and A_2 are chosen for negotiation (see Kusiak and Wang (1992) for details). The utility value for each alternative is determined, according to the utility functions for the performance variables (V_H, r_s, and V_E). Hence, twenty-five alternatives are evaluated based on three heuristic rules. Using equation (1) to analyze the alternatives, the maximum joint utility is:

$$U_{max} = \mu_H + \mu_E = 1.0 + 1.0 = 2.0,$$

where:

$$D_o = 2.476, \quad D_i = 1.639, \quad r_{c1} = 0.3339, \quad r_{c2} = 0.0367$$

$$A_1 = 0.0101, \quad A_2 = 0.0094$$

Two design agents are fully satisfied the final solution (see Kusiak and Wang 1992 for details).

4. Conclusions

In this paper, a design methodology for resolving multiple conflicts in a multi-agent environment was presented. The negotiation strategy is goal-driven, i.e., each agent compromises with other agents and attempts to maximize the system goal at the same time. Hence, design of a component maximizes the system objectives and satisfies design constraints. Also, the goal-driven negotiation reduces the interaction required among agents so that the complexity of the system is reduced.

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