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Abstract

The research described in this paper is motivated by the complexity surrounding the development of decision support systems (DSSs) for collaborative design processes. If one realizes that each design agent engaged in a collaborative design process may have a unique theory of product behavior, a distinct language of communication, ami a specific model of decision making, the complexity of building a DSS for such a design process is obvious. In this paper, we propose that machine learning is probably the only feasible approach to build a DSS for certain classes of collaborative design problems. We discuss high-level requirements for such a DSS and then propose a conceptual solution to build such a DSS based on a machine learning approach.

1 Introduction

New approaches (which go under different names, such as concurrent engineering, simultaneous engineering, and collaborative engineering) have been proposed to improve product development processes by bringing relevant considerations as early as possible into die product development process. In most of these approaches, collaborative design is central to the research.

Collaborative design is a design process which encompasses multiple design agents who: 1) view the design product from different perspectives; 2) concurrently engage in decision making about the design product; and 3) are concerned with different design objectives. Each design perspective may be based on a unique theory of product behavior, a distinct language of communication, and a specific model of decision making with respect to the objectives of that perspective.

Computational environments that are being built to support collaborative design processes need **to answer an important question:** ***to what degree will the environment support collaborative decision*** *making processes?* To build a unifying theory or a model from first principles to support collaborative design processes seems infeasible when faced with heterogeneous, complex knowledge resources and incompatible communication languages across design perspectives.

As an alternative, we propose the use of machine learning approaches to develop empirical models of product behaviors, which may then be used to support decision making processes in collaborative design. Such empirical models may be built from a representative collection of product designs. These product designs may be historical design cases that embody important design expertise or could be generated by using perspective-specific design tools (i.e., simulation, knowledge-based, and analytic tools) to describe a collection of important design concepts. By developing empirical models for each design perspective, one may obtain a model of die design space.

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Such a model may be utilized for exploration of design alternatives within a perspective and with respect to its objectives. By providing interaction links among the empirical models, one may buUd a composite model of product behavior for use in collaborative design. Such a model would allow decisions within a perspective to impact decisions across all perspectives.

In Section 2 we discuss the requirements for a DSS for early stages of collaborative design. Then, in Section 3 we propose a conceptual solution for a machine learning-based DSS that meets these requirements. In Section 4 we summarize the contents of this paper.

2 Requirements for a Decision Support System for Early Collaborative Design

Many research papers on computational support for collaborative design fail to identify requirements for which these systems are developed. However, identification of these requirements is important for analyzing the tradeoffs for the alternative approaches to building these support systems. We first provide a compilation of requirements for support systems for collaborative design from a number of sources [Beggs 92, Finger 93, Hill 91, Kahaner 93, Prasad 93]. Then, we identify in detail the requirements that are specific to DSSs for early collaborative design. We focus on the operational requirements for a DSS for collaborative design. This means that organizational, cultural, sociological, and other issues are not covered, though equally important.

2.1 General Requirements for Decision Support Systems for Collaborative Design

2.1.1 Requirements Arising from the Multiplicity of Design Agents

Multiplicity of Perspectives. Fundamental to the operations of a DSS in collaborative design is a capability to support decision making of multiple agents viewing the product from different perspectives.

Concurrency. A DSS needs to allow design agents to engage in their respective decision making processes in parallel while communicating the decisions across all interested perspectives.

Common Understanding. A DSS needs to provide a way for design agents to become aware of how their decisions affect the decision making processes in other perspectives. Finding means for this "expanded understanding" of a design problem for all design agents is a hard task to achieve without introducing information overload.

Availability of Information. Collaborative design implies sharing of information among the design agents. Relevant information needs to be available in a timely manner. A special case of the requirement is a support for information abstraction: detailed design records need to be used in the early design stages by abstracting relevant information from the minute details.

2.1.2 Requirement Arising from the Early Stages of Decision Making

Management of Risk and Uncertainty. In early design stages, design information is often incomplete. Hence, a DSS needs to handle partial information in a manner which allows the evaluation of uncertainties and risks associated with proposed decisions. Failure to handle situations where partial data is available means inability to act in realistic design situations.

2.1.3 Requirements Arising from the Nature of Design Process

Management of Change. A DSS needs to take into account that the technological advances and changes in environmental influences and regulations may all affect the decision making processes. Depending on the dynamics of these changes and sensitivities of the product developer to these changes, different approaches for building a DSS may be more or less suitable.

Integration. A DSS that operates independently of the rest of the information management system of a product developer may prove to be beneficial. However, only through the overall integration of the information management resources can all the benefits of the DSS be realized: 1) responsiveness to market demands; 2) shorter time to market; and 3) increase in productivity.

Generation and Evaluation of Design Alternatives* A DSS needs to provide services to a design agent for generation and evaluation of design alternatives from the agent's perspective. This requirement translates in the need to support generative and evaluative inferences in a design process. (For a discussion of relevance of this requirement see [Hemming 93] and [Ivezic 92].)

Design History Capture and Reuse. A DSS needs to allow for recording, communicating, and sharing relevant information across the perspectives. Past designs (both successes and failures) need to be used to prevent the recurrence of the same design errors and to identify good designs.

22 Specific Requirements for Decision Support Systems for Collaborative Design

The following requirements apply specifically to a DSS for early stages of collaborative design. At the same time, we identify the elements of(he decision problem that appear in the eaiiy collaborative design. We believe that a DSS needs to recognize these categories of elements in the early collaborative design process. To illustrate these requirements, we describe them for a DSS for the collaborative design of industrial prefabricated buildings.

22.1 Context: Collaborative Design of Industrial Prefabricated Buildings

Suppose that a company is involved in manufacturing, assembly, and marketing of prefabricated industrial buildings. At least three design perspectives may be identified: structural design, manufacturing design, and construction planning. Support of decision making in early stages of design and within these design perspectives is the overall goal in developing a DSS. Decision makers (henceforth, design agents) in each of these perspectives are concerned with *objectives* specific to their perspectives; for example, the structural designer is concerned with structural safety and the manufacturing engineer with cost-efficiency of the manufacturing process. Each design agent deals with *decisions* that traditionally belong to his or her perspective: the structural designer selects the geometry and material for the structural components and the construction engineer selects equipment to be used for assembly of the product. In addition, a design agent needs to consider the *external actions* in his or her decision making process. For example, the structural designer needs to consider design loads. The overall design objectives (e.g., cost-efficiency of the project) are traditionally a matter of concern of the project manager. Figure 1 shows the perspectives of the three design agents and of the manager with the elements of the design problem classified into three classes: 1) design decisions; 2) external actions; and 3) design objectives.

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Evaluation of Decision Making. Interpretation of design objectives is very much context-dependent and subjective. Hence, there has to exist a measure of design performance as a basis for design evaluation. These measures of design performances (henceforth, *design performances)* are simply agreed-upon and are conventional measures of some aspects of design that carry information relevant to some objective. For example, the strength of a designed component is a conventional measure applied to obtain a measure of structural safety. Design performances are shown in Figure 2. With the introduction of this decision element, four inferences need to be supported in solving a design problem (also shown in Figure 2 and illustrated with arrows).

Constraints on Design Decisions. The last type of element in the decision model is the *compatibility constraint.* These elements identify constraints that are consequences of technological or regulatory restrictions imposed on valid ranges of design decisions. For example, there exist constraints on the geometry of structural components that can be feasibly manufactured. Figure 2 shows these decision elements and the inference that needs to be supported.

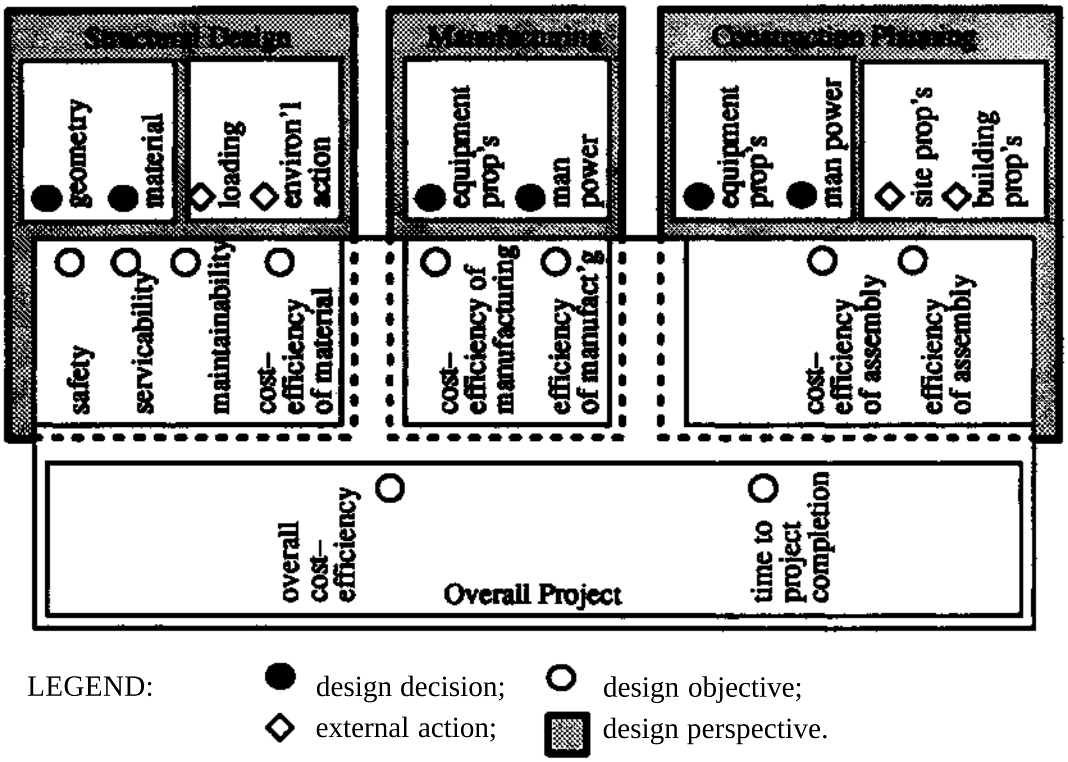


Figure 1 — Elements of the Design Decision Problem (Initial Version)

Natural Design Inferences. Decision support protocol provided by the DSS needs to allow a natural process of decision making within each perspective and the whole project. This requirement translates into a need to support different design protocols with as few constraints on the actual decision process as possible.

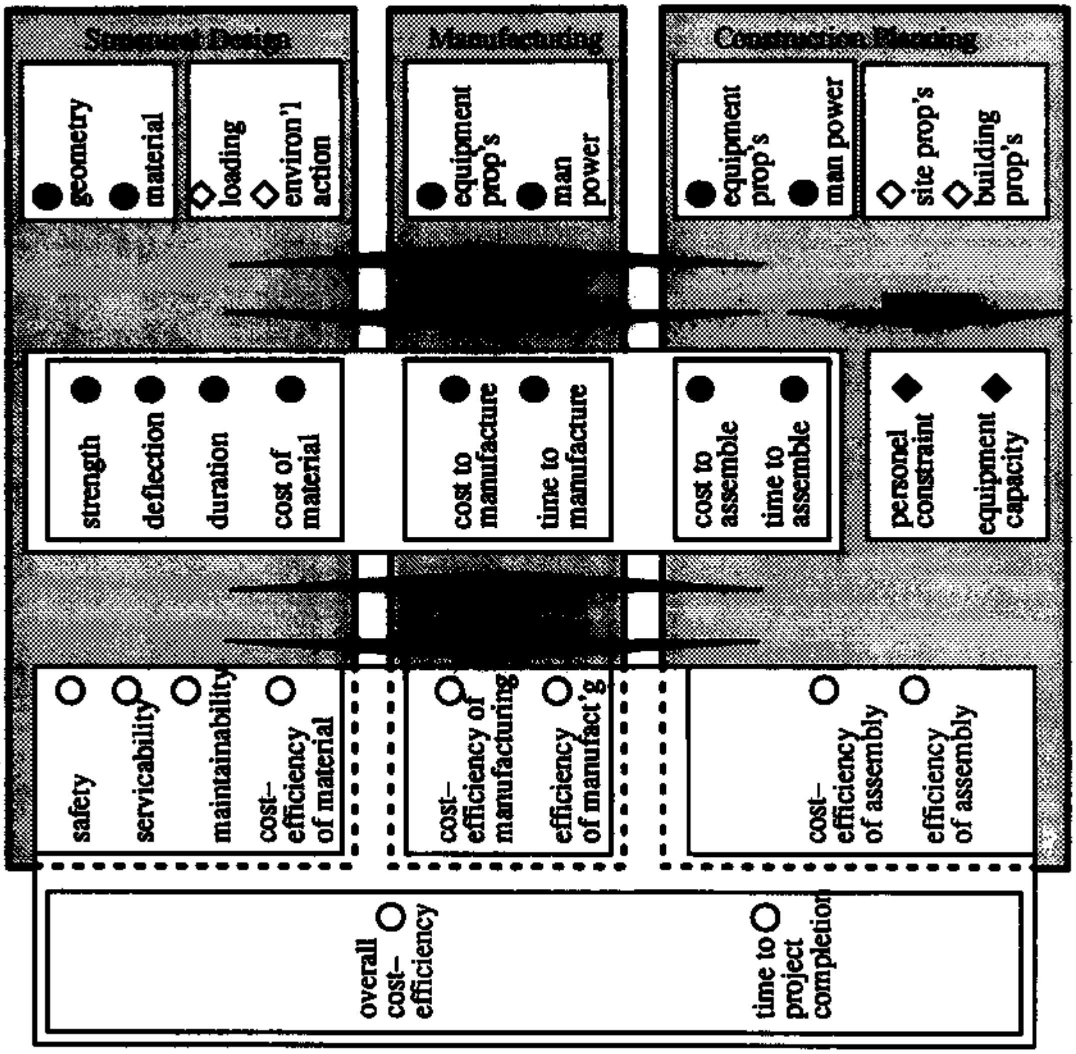
Communication of Design Decisions. Each design agent needs to be aware how his or her design decisions affect design objectives across perspectives. For example, the structural designer needs to be aware how decisions about the geometry of structural components influence cost-efficiency of manufacturing which, in turn, affects the overall cost-efficiency objective. To this end, each design agent needs to be able to communicate decisions across perspectives to other agents.

Effective Consideration of Global Objectives. Simultaneous consideration of objectives across the perspectives and the overall project must be supported.

Negotiation of the Decision Process. Since it is likely that conflicts in the interpretations of objectives will arise, negotiation of the decision process must be supported between design agents and the manager as well as among design agents.

3 A Machine Learning-Based Decision Support System for Collaborative Design

The intent of our approach is to build empirical models of design product behaviors with respect to each perspective in the collaborative design process. Each model will estimate the performances of the design product from a specific perspective and will have interaction links with other perspective models to allow for propagation of influences of decision making across perspectives. In the course of the design process, design agents and the project manager will interact with these models to search the design space for good designs conditional on external actions and perfor-



LEGEND: 0 design decision; O design objective; ● design performance.
0 external action; | j l design perspective;
^ compatibility constraint; design inference;

Figure 2 — Elements of the Design Decision Problem (Final Version)

mance constraints. (See [Ivezic 92] for related ideas based on using machine learning for engineering design synthesis and [Yerramareddy 93] for a similar approach.)

3.1 Key Decisions for Conceptual Design of a DSS

Neural Network Learning Approach. This is our principal approach to building the empirical models of design product behavior. We have selected this approach because of the capability of neural netwoik learning methods to approximate any functional relationship, its proven capability to leam empirical models through inductive learning, and its capability to support a number of uncertainty management approaches (i.e., probability, *fuzzy* logic). The shortcoming of the approach—limited representational capabilities—we believe is not a serious defect for the support of decision making in early design stages where compact representations (i.e., nominal, ordinal, and continuous variables) are desirable for the inference process.

Probabilistic framework. In order to manage uncertainty and to allow for evaluation of risks associated with decision making, a probabilistic framework and inference mechanism were selected. The benefit of this choice is that the probabilistic approach is well supported by theoretical statistical and machine learning research, it provides formalized interpretation of the notion of behavior (i.e., causality), and it integrates well with our choice of machine learning approach—neural network learning. The shortcoming of this choice — its substantial demand for data on which it derives its power—may be handled in two ways: 1) by requiring sufficient data resources to be generated or gathered in design perspectives; and 2) by incorporating prior knowledge about the design perspective in the probabilistic model.

Integrated Information Management As can be seen from the requirements, a DSS needs to have close links to other parts of the design information system. This decision—to design and implement a DSS and the rest of the information management system in an integral manner—we believe to be very important for the usefulness and usability of the DSS in the collaborative environment In spite of the increase of costs in this approach as compared to the independent development of a DSS and the rest of information management system, the evidence from the current practice indicates that a holistic approach is in the long run more beneficial [Stark 92].

3.2 Overview **of** Functionality and Implementation Techniques

We illustrate the basic functionalities and implementation techniques enabling these functionalities in the context of using the DSS for early design of prefabricated buildings. The DSS consists of a number of DSS modules, each module encompassing the empirical model for the corresponding perspective and the utility functions to allow for communication of the design agent with other design agents and the project manager. Assume that a four member team (including a structural designer, a manufacturing designer, a construction engineer and the project manager) is assigned a task to estimate value ranges for key decisions for a new project and the expected cost and time to complete the project The DSS provides the following functionalities to support the collaborative design decision process:

Input of Design Specifications **and** Decisions. A specific value or a desired range may be specified for any decision element both in the initial design specification stage and during the design decision process. For example, the structural designer may specify constraints on the geometry of structural components and on the component strengths (reflecting, say, code provisions).

Request **for** Relevant Out-of-Perspective Decisions. At any point in time a design agent may make a request for the state of decisions from perspectives that affect that agent's decision process. For example, a manufacturing designer may make a request for decisions about the geometry of the structural components as these decisions are relevant to the cost of the manufacturing process.

Test **for** Feasibility of Design Decisions. At any point the empirical model may be invoked by the design agent to perform a test for feasibility of design state. Taking the current constraints on the value ranges of decision elements (as specified by the agent) and the relevant out-of-perspective decisions, the empirical model estimates the probability distributions over the ranges of its decision elements. In the case when the probability over the allowed range of a decision element is estimated to be zero, the agent is warned of a possible infeasible collection of design decisions. For example, the empirical model corresponding to the structural design may estimate the probability of the user-specified range of material costs to be zero. In that case the structural design agent must understand that the combination of decisions about the geometry of the components, the material for the components, and constraints on the ranges for material costs, are contradictory to the relationships among these decisions embodied in the design cases used for building this empirical model. Estimates of these probability distributions is achieved by using Monte Carlo simulation techniques and by sampling the inputs to the neural network from the allowed ranges.

Prediction of Decision Element Values. As a direct support for the decision making process, a DSS module provides prediction capability for the corresponding design perspective. Predictions for the values of all decision elements are available for any combination of current design decisions. For example, in the structural design perspective, given the constraints on the geometry, material, and o>sts of the material, the s t m ^ral DSS module may predict the expected values, variances and other relevant statistics for the values of external loading that conform to these constraints. Hence, the agent may take the predicted values as an advice.

Sensitivity Analysis of Performances. An agent may find the sensitivities of performances with respect to specific decisions. For example, the structural agent may need to know how sensitive manufacturing costs are to decisions about the geometry of the components. The neural network-based empirical model allows these sensitivities to be computed through experimentation.

Specification of Overall Objectives. The project manager interacts with the DSS and the rest of the project team by imposing the overall project objectives on the decision process. While a design agent translates an objective within a perspective into one or more design performances *within that perspective,* the project manager deals with the overall objectives by interpreting them in terms of design performances *across one or more perspectives.* For example, the structural designer translates the cost-efficiency of material into a constraint on the cost of materials and the manager interprets the overall cost-efficiency objective in terms of constraints on the material cost, manufacturing cost, and assembly cost.

Negotiation of **the** Decision Process. The negotiation process is supported by the weights associated with design performances (as supplied by the project manager) and sensitivities of the design performances with respect to different design decisions.

33 **Attributes** of **the** Machine Learning **Approach** for DSS vs. **General** Requirements

The general requirements for a DSS for early collaborative design are addressed by attributes of all three aspects of the conceptual solution: neural network learning, probabilistic framework, and integrated information management. Neural network machine learning approaches result in *distributed* and *modular* computational systems. Common understanding using these approaches is obtainable at no extra cost as these approaches base their inferences on the syntactic, not semantic content of the information. The capability of the integrated modular neural network-based systems to communicate among themselves over interaction links allows for the building of a DSS system in which the effects of decisions are readily available to all agents.

The probabilistic framework allows for the handling of uncertainty and risk related to the decision process. Management of change is addressed by: 1) the machine learning approach through its adaptability and capability to generalize and predict based on a limited amount of training cases; 2) the probabilistic framework in which estimates of confidence in the predicted values can be made; and 3) the integrated system to gather or generate design cases from which adaptation of the learning system takes place. The integrated design case generation system allows for the vertical integration within design perspectives and, consequently, the capability for abstraction of relevant design information.

4 Summary

Building decision support systems for collaborative design processes is a highly complex task. Machine learning approaches have a potential to manage this complexity and effectively support building of these DSSs.

In this paper, we first discussed the operational requirements for such a DSS. The general requirements for a collaborative design support system included support for different perspectives, concurrency, common understanding, information availability, management of risk and uncertainty, management of change, vertical integration, generation and evaluation of design alternatives, and design history capture and reuse. The requirements specific to DSSs for early collaborative design included support for evaluation of decision making, constraints on design decisions, natural design inferences, communication of design decisions, consideration of global objectives, and negotiation of decision process.

We then discussed how these requirements might be met by a machine learning-based approach. In the proposed approach empirical models of design product are built foreach design perspective involved in the collaborative design process. These empirical models form the basis for decision support within each design perspective as they represent searchable models of design space. By providing communication links among the empirical models across design perspectives, a DSS for collaborative design is created. These communication links allow the effects of decision making within each perspective to be propagated to all other perspectives. Powerful functionalities are possible in the proposed DSS model: early tests for feasibility of design decisions, prediction of decision element values, sensitivity analysis of performances, and negotiation support.

5 Acknowledgments

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