Automating Redesign of Electro-Mechanical Assemblies

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Abstract

Automating redesign of electro-mechanical artifacts presents many difficult problems to the developers of intelligent CAD systems. To address this need requires we identify new AI technologies for representation and planning and effectively apply them to the manufacturing problem. In this paper, we present the redesign problem and outline some of the critical points; presenting how to bring existing AI research to bear in creating more effective CAD tools.

1 Introduction

Computer-aided design (CAD) and CAD software is fast becoming a ubiquitous component of the modern manufacturing workplace. The decreasing cost of computational power has made sophisticated software for tasks such as finite element and mechanism analysis essential for increasing engineering quality and productivity. Software tools designed to reduce time-consuming *build-test-redesign* iterations are becoming crucial components for supporting concurrent engineering.

Many of these are tools for design analysis and critiquing. For example, they might examine whether a candidate design violates manufacturing or functional constraints (such as stress, acceleration, and so forth); or they might attempt to find possible suggestions to the user about how to improve a design [12, 10, 16, 3, 21]. Other analysis tools might include those that help the designer foresee potential problems with product life-cycle considerations such as performance, producibility, reliability, maintainability, and so forth.

These design analysis and critiquing systems, in order to realize the advantages of collaborative engineering, must consider downstream manufacturing and life-cycle activities during the design phase. This has stretched the limits of traditional design activities and increased their complexity—presenting a variety of difficult computational problems such as the following:

- how to represent partial or incomplete design information;

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- how to reason with partial or incomplete design information;
- how to access and intelligently reuse legacy information (for example, in a corporate knowledge base);
- how to mediate conflicts to satisfy contradictory manufacturing constraints;
- how to provide quick responses for interactive computing environments.

The automated redesign problem cuts across all of these issues and is of increasing interest to researchers, in both academia and industry. While some commercial software tools exist (such as those to reduce the number of parts in an assembly), satisfying solutions to the general redesign problem have eluded researchers. Existing systems vary significantly by approach, scope, and level of sophistication, with most attempting to capture manufacturability problems as collections of rules or heuristics. However, it has proven difficult to capture subtle manufacturability problems with hard-coded and coarse rules. Many problems can only be detected at the manufacturing planning level; problems that are compounded when multiple artifacts interact, not only in assemblies, but across the manufacturing enterprise. As a further complication, design is an interactive process and thus all of these computations must be handled in real-time.

By building on our previous work in manufacturing and [15, 14, 20, 2, 13, 11] AI [18, 32, 5, 23, 27, 28, 7, 9, 17], we will identify promising new AI technologies for enabling redesign and outline how they may be effectively applied to the manufacturing problem. We anticipate that this work with serve to further the development of redesign systems by both expanding and improving the application of AI technologies to the problem; leading to the development of systematic methodologies for automated redesign. This will speed the introduction of automated designer's aides that capable of simultaneously considering design goals and manufacturing constraints, and identifying and alleviating manufacturing problems during the design stage.

2 Scenarios for Intelligent Automated Redesign

There are a variety of scenarios in which redesign is a necessary step in the product development cycle:

Changes in Functional Requirements. Consider the situation where the functional requirements of a new design have minor differences from those of an existing design. For example, modifying the design of an existing engine housing to accommodate a larger motor.

Incorporation of new manufacturing technology. In order to take full advantage of a new manufacturing process, existing products may require redesign. For example, engine blocks have traditionally been manufactured using a casting that is later machined. As die casting becomes increasingly economical, coupled with the pressure to construct lighter, more fuel-efficient automobiles, designers must plan for the possibility of die-casted engine blocks. While the function of the engine block will be identical, redesign will need to adjust existing engine block designs to suit the die casting process.

Changes to production resources. Manufacturing facilities for an organization will change over time and may often need to be rapidly reconfigured to adjust to abrupt changes in market forces. Other considerations that redesign may have to accommodate include equipment failure and the addition of new facilities and tools.

Redesign for improved manufacturability. During the design process, a design often goes through a cycle of analysis and review during which cost effectiveness and quality are constantly evaluated. Unfortunately, however, in many situations beneficial design modifications are discovered by experienced process planners and machinists only after the component enters the production cycle. Making automated tools for suggesting design revisions available during the design stage would reduce the product realization cost [2].

Ideally, an interactive and highly-automated redesign system will need to be capable of analyzing the artifact's design history, its relationship to similar parts in a company's corporate manufacturing knowledge bases or files, and the constraints imposed by the different interacting design and manufacturing teams working concurrently on the product.

3 Three Challenges

To enhance the intelligence and function of the next generation of redesign systems, we outline three focus areas that have potential for positive impact.

3.1 Plan Merging and Reuse

Consider the case where a design has one or more process plans associated with it. If the design gets modified, the brute force generative approach is to re-plan from scratch. In order to adjust plans based on design changes, techniques for plan reuse and plan merging [31, 30, 29, 18, 32] might be applied to isolate portion of the design that requires re-planning. Further, one might be able to adjust plans to accommodate changes in manufacturing process and production resources.

A different, but compatible approach, is to view design as an incremental process [5, 4] and modeled as an incremental planning task. As design information (such as tolerances, surface finish requirements, functional specifications and associations, relationships to manufacturing processes) is modified, these changes can be translated into modifications to process and production plan.

3.2 Reactive and Impartial Information Planning

Engineering design and manufacturing planning each are executed concurrently at several different levels of abstraction. For instance, design proceeds from conceptual level, through embodiment, eventually yielding a detailed design of the product. Similarly, manufacturing planning is done for individual machines, the level of the factory, and enterprise wide. At many stages of these processes, planning proceeds without having access to all of the relevant information.

Planning techniques for imperfect information domains [23, 22, 25, 24] can be used to represent partially completed designs and reason about their intermediate process plans.

In order to handle simultaneous planning at multiple levels of abstraction, work on architectures for reactive systems can be adapted to address the different types of goals that arise when performing initial process and production planning activities [26, 27].

3.3 High-Performance AI

Design is a highly interactive process. Hence, predicting characteristics such as design performance and manufacturability (i.e., product cost, quality, and lead time) ideally must be done in real-time. As the cost of high-performance machines and distributed networks of computers continues to drop, we need to carefully examine how to migrate applications to these architectures. In particular, methods for executing multi-processor search and knowledge queries can be directly applied to key problems in manufacturing planning:

Search. In the University of Maryland's Interactive Manufacturability Analysis and Critiquing System (IMACS) project [19, 15, 14], branch and bound search strategy to navigate the space of possible machining plans. IMACS generates and evaluations alterative plans in order to estimate manufacturing cost and calculate an optimal plan. Application of parallel search techniques [6, 28, 7] can lead to large performance increases for complex operation planning problems and for interactive applications.

Knowledge Management. Parallel search and knowledge representations can be applied to the searching of very large knowledge-bases of corporate design and manufacturing information (e.g. given a design's functional specifications, find similar parts and process plans from the company database) [1, 8, 9, 17]

4 Conclusion

As we move toward greater levels of automation in computer-aided engineering environments, greater amounts of information can be captured and reused. One of the areas with great potential is automated redesign.

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