# AI Planning Versus Manufacturing-Operation Planning: A Case Study<sup>\*</sup>

Dana S. Nau†SatyarComputer Science Department and<br/>Institute for Systems Research<br/>University of MarylandRobe<br/>CarnegieUniversity of Maryland<br/>College Park, MD 20742<br/>nau@cs.umd.eduskgupta

Satyandra K. Gupta

Robotics Institute ( Carnegie Mellon University Pittsburgh, PA 15213 skgupta@isl1.ri.cmu.edu

William C. Regli<sup>‡</sup> Computer Science Department and Institute for Systems Research University of Maryland College Park, MD 20742 regli@cs.umd.edu

### Abstract

Although AI planning techniques can potentially be useful in several manufacturing domains, this potential remains largely unrealized. In order to adapt AI planning techniques to manufacturing, it is important to develop more realistic and robust ways to address issues important to manufacturing engineers. Furthermore, by investigating such issues, AI researchers may be able to discover principles that are relevant for AI planning in general. As an example, in this paper we describe the techniques for manufacturing-operation planning used in IMACS (Interactive Manufacturability Analysis and Critiquing System), and compare and contrast them with the techniques used in classical AI planning systems. We describe how one of IMACS's planning techniques may be useful for AI planning in general-and as an example, we describe how it helps to explain a puzzling complexity result in AI planning.

# 1 Introduction

AI planning techniques can potentially be useful in several manufacturing domains. However, with the exception of manufacturing scheduling, previous applications of AI planning technology to manufacturing (cf. [Famili et al., 1992]) generally have had little impact on manufacturing practices [Ham and Lu, 1988; Nevins and Whitney, 1989; Shah et al., 1994].

One reason for this difficulty appears to be the different world views of AI planning researchers and manufacturing planning researchers. The first author works in both worlds—and his work on manufacturing planning has significantly influenced his research on AI planning,

<sup>†</sup>Also with the University of Maryland Institute for Advanced Computer Studies (UMIACS).

and vice versa—but this influence is not particularly evident in the publications themselves, because they were written to address two different audiences, who have different ideas of what the important problems are and how they should be solved:

- Since AI planning researchers are usually more interested in general conceptual problems than domain-dependent details, the AI approach to manufacturing planning has typically been to create an abstract problem representation that omits unimportant details, and look for ways to solve the abstract problem. From the viewpoint of the manufacturing engineer, these "unimportant details" often are very important parts of the problem to be solved—and this can lead manufacturing engineers to view AI planning techniques as impractical.
- Manufacturing planning researchers typically want to solve a particular manufacturing problem, and present their research results within the context of this problem, without discussing how the approach might generalize to other planning domains. For AI researchers, this makes it difficult to see what the underlying conceptual problems are, or whether the approach embodies a general idea that can be applied to other problems. This can lead AI planning researchers to view manufacturing planning as a domain full of ad-hoc, domain-specific programs rather than general principles and approaches.

Some of the issues arising in manufacturing planning are similar to issues investigated in AI planning, and others are distinctly different. Some of the former may amenable to the use of existing AI planning techniques and some of the latter may lead to new principles useful in AI planning. However, to investigate such issues, AI researchers will need a better understanding of manufacturing problems and concerns, so as to get better ideas of what the interesting generalizations are, and which techniques from AI might best be applied to realistic manufacturing problems.

In this paper we attempt to provide a step in this direction, by describing the planning techniques used in IMACS, a computer system for helping designers produce designs that are easier to manufacture [S. Gupta *et al.*, 1994b; S. Gupta and Nau, 1995]. IMACS analyzes the manufacturability of proposed designs for machined parts by generating and evaluating operation plans for

<sup>\*</sup>This work was supported in part by NSF Grants DDM-9201779, IRI-9306580, and NSFD EEC 94-02384. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

<sup>&</sup>lt;sup>2</sup>Also with: National Institute of Standards and Technology, Manufacturing Systems Integration Division, Building 220, Room A-127, Gaithersburg, MD 20899.

definitions of machining features; as shown in Figure 4, we consider a machining feature to include information about the type of machining operation, the material removal volume (the volume of space in which material can be removed), and the accessibility volume (the volume of space needed for access to the part).

#### 2.2 Feature Extraction

Although much past work on integrating design with manufacturing planning has involved feature-based design techniques in which users specified designs directly as sets of form features, most researchers have become convinced that a single set of features cannot satisfy the requirements of both design and process planning instead, some form of feature extraction is needed. For IMACS, we have developed algorithms to extract machining features directly from the CAD model [Regli et al., 1994; S. Gupta et al., 1994a].

There can be many—sometimes infinitely many different machining features capable of creating various portions of a given part. Of these, we define a *primary* feature to be a feature that contains as much of the stock as possible without intersecting with the part, and as little space as possible outside the stock. Figure 5 shows examples of primary and non-primary features; for a detailed definition see [S. Gupta and Nau, 1995].

As described in [S. Gupta *et al.*, 1995; Regli *et al.*, 1995], in every operation plan that IMACS will ever want to consider, each machining operation will create either a primary feature or a truncation of a primary feature and the number of primary features for a part is always finite (in fact, polynomial). Thus, IMACS's first step is to find the set  $\mathcal{F}$  of all primary features for P and S. For example, for the socket  $P_0$  the set  $\mathcal{F}$  contains 22 primary features, a few of which are shown in Figure 6.

In AI terms, machining operations are elementary actions and machining features are tasks.  $\mathcal{F}$  is the set of all tasks that might ever be relevant for achieving the goal. Unlike most AI planners, IMACS finds this set in advance before it begins to generate plans—but as we discuss later, this technique may be useful in a number of AI planning problems.

### 2.3 Generating Incomplete Plans

Figure 6 shows that the features in  $\mathcal{F}$  may overlap in complicated ways, and not all of them are needed to create the part (for example, we do not need to machine both s1 and s2). A feature-based model (FBM) is any irredundant subset of features  $F \subseteq \mathcal{F}$  such that subtracting those features from S produces P. For example, Figure 7 shows an FBM, FBM1, for the socket  $P_0$ .

In AI planning terminology, an FBM is an incomplete plan: if we can machine the features in it, this will create the part. Since each FBM is a subset of  $\mathcal{F}$ , FBM's can be generated using set-covering techniques, but there can be exponentially many FBM's. As an example, for the socket  $P_0$ ,  $\mathcal{F}$  contains 22 primary features from which one can form 512 FBM's. In general, we usually will not want to generate all of these FBM's, for only a few of them will lead to good operation plans. Thus IMACS does a depth-first branch-and-bound search to generate and test FBM's one at a time, pruning unpromising







Figure 6: A few of the 22 primary features for the socket  $P_0$ . s1, s2, s9, and s10 are end-milling features; h1 and h2 are drilling features.



Figure 7: Feature-based model FBM1 for the socket  $P_0$ .

machining feature			
setup operation	machining operation process details	finishing operation	
Figure 9: Task decomposition in IMACS.			

• Modify goals. Suppose features f and g overlap, and f precedes g in some total ordering. Then when we machine f, we are also machining part of g. We don't want to machine that same portion of g again later in the sequence, because we would merely be machining air. Thus, IMACS truncates g to remove the portion covered by f. As an example, several of the features shown in Figure 8(a) were produced by truncating the corresponding features in FBM1.

• Unlinearize. Once the truncated features have been produced, several of the resulting FBM's may have identical features but different precedence constraints. In such cases the precedence constraints that differ can be removed, translating the total orders into partial orders. For example, Figure 8(b) shows the partial order for the FBM of Figure 8(a).

#### 2.5 Additional Steps

To obtain an operation plan from the partially-ordered FBM, IMACS uses the following steps:

- Incorporate finishing operations. For faces with tight surface finishes or tolerances, IMACS adds finishing operations, with precedence constraints to make them come after the corresponding roughing operations. Currently, one finishing operation per face is allowed.
- Determine setups. On a three-axis vertical machining center, features cannot be machined in the same setup unless they have the same approach direction. This and the partial ordering constraints can be used to determine which features can be machined in the same setup, as shown in Figure 8(b). Although the specific computations are different, the problem is a special case of what is known to AI researchers as the plan-merging problem [Yang et al., 1992; Foulser et al., 1992; Britanik and Marefat, 1995].
- Determine process details. To select cutting parameters such as those shown in Figure 8(c), IMACS uses the recommendations of the Machinability Data Center's handbook [Machinability Data Center, 1980]. The maximum recommended cutting parameters are used, rather than attempting to select optimal cutting parameters; thus IMACS's estimates involve considerable approximation.

As shown in Figure 9, these steps correspond to a task decomposition somewhat analogous to that used in HTN planning [Sacerdoti, 1977; Tate, 1977; Wilkins, 1990; 1988; Yang, 1990; Kambhampati and Hendler, 1992; Erol et al., 1995a; 1994].

Since each FBM can lead to several different operation plans, IMACS does the above steps inside a depthfirst branch-and-bound search, evaluating the plans as

Table 1: Estimated production time for the operation plan shown in Figure 8.

Operation	Time (min)	Operation	Time (min)
drill h1	2.3	mill s2	5.0
drill h3	0.3	mill s4	5.0
drill_h5	0.3	mill s6	5.0
drill h7	0.6	mill s8	5.0
drill h9	0.6	mill s9	4.0
drill h11	0.3	mill s10	4.2
drill h12	0.3	3 setups	6.0

Total Time: 39 minutes

described in Section 2.6 in order to find the optimal operation plan. For example, Figure 8 shows the operation plan IMACS finds for the socket  $P_0$ .

### 2.6 Operation Plan Evaluation

Once IMACS has found an operation plan, it evaluates whether the plan can achieve the design tolerances. To verify whether a given operation plan will satisfy the design tolerances, IMACS must estimate what tolerances the operations can achieve. Typical approaches for computer-aided tolerance charting are computationally very intensive, and only consider limited types of tolerances [Ji, 1993; Mittal *et al.*, 1990]. Thus, IMACS simply evaluates the manufacturability aspects of a wide variety of tolerances without getting into optimization aspects, as described in [S. Gupta and Nau, 1995]. As an example, the operation plan shown in Figure 8 satisfies the tolerances shown in Figure 3, and thus is an acceptable way to make  $P_0$  from  $S_0$ .

If the plan can achieve the design tolerances, then IMACS estimates the plan's manufacturing time. The total time of a machining operation consists of the cutting time (when the tool is actually engaged in machining), plus the non-cutting time (tool-change time, setup time, etc.). Methods have been developed for estimating the fixed and variable costs of machining operations; our formulas for estimating these costs are based on standard handbooks related to machining economics, such as [Winchell, 1989; Wilson and Harvey, 1963]. As an example, Table 1 shows the estimated production time for the operation plan of Figure 8.

# 2.7 Efficiency Considerations

As described in [S. Gupta *et al.*, 1994b; S. Gupta and Nau, 1995], IMACS uses a depth-first branch-and-bound search to generate and evaluate FBM's and plans one at a time. By evaluating them as they are being generated and keeping track of the best one it has seen so far, IMACS can discard FBM's and plans that look unpromising, even before they have been fully generated. For example, from the 22 primary features shown in Figure 6 one can form 512 FBM's for the socket  $P_0$ , but IMACS generates only 16 of these FBM's. Below are some of IMACS's pruning criteria, which can be thought of as similar to critics in HTN planning:

• IMACS will discard an FBM if it contains features whose dimensions and tolerances appear unreasonable. Examples would include a hole-drilling operation having too large a length-to-diameter ratio;

5

- [N. Gupta and Nau, 1991] N. Gupta and D. S. Nau. Complexity results for blocks-world planning. In *Proc. AAAI-91*, 1991. Honorable mention for the best paper award.
- [N. Gupta and Nau, 1992] N. Gupta and D. S. Nau. On the complexity of blocks-world planning. Artificial Intelligence, 56(2-3):223-254, Aug. 1992.
- [S. Gupta and Nau, 1995] S. K. Gupta and D. S. Nau. A systematic approach for analyzing the manufacturability of machined parts. *Computer Aided Design*, 27(5), 1995, to appear.
- [S. Gupta et al., 1994a] S. K. Gupta, T. R. Kramer, D. S. Nau, W. C. Regli, and G. Zhang. Building MRSEV models for CAM applications. Advances in Engineering Software, 20(2/3):121-139, 1994.
- [S. Gupta et al., 1994b] S. K. Gupta, D. S. Nau, W. C. Regli, and G. Zhang. A methodology for systematic generation and evaluation of alternative operation plans. In [Shah et al., 1994], pages 161-184.
- [S. Gupta et al., 1994c] S. K. Gupta, W. C. Regli, and D. S. Nau. Integrating DFM with CAD through design critiquing. Concurrent Engineering: Research and Applications, 2(2), 1994.
- [S. Gupta et al., 1995] S. Gupta, W. Regli, and D. Nau. Manufacturing feature instances: Which ones to recognize? In ACM Solid Modeling Conference, 1995, to appear.
- "Ham and Lu, 1988] Inyong Ham and Stephen C.-Y. Lu. Compute-aided process planning: The present and the future. Annals of the CIRP, 37(2):591, 1988.
- [Hayes, 1995] C. Hayes. Using a manufacturing constriant network to identify cost critical areas of designs. Artificial Intelligence in Engineering Design and Manufacturing (special issue on innovative approaches to concurrent engineering), May 1995, to appear.
- [Ji, 1993] Ping Ji. A tree approach for tolerance charting. International Journal of Production Research, 31(5):1023-1033, 1993.
- [Kambhampati and Hendler, 1992] S. Kambhampati and J. Hendler. A validation structure based theory of plan modification and reuse. Artificial Intelligence, May 1992.
- [Kambhampati et al., 1992]
- S. Kambhampati, M. Cutkosky, J. Tenenbaum, and S. H. Lee. Integrating general purpose planners and specialized reasoners: Case study of a hybrid planning architecture. *IEEE Trans. on Systems, Man and Cybernetics* (special issue on planning and scheduling), 1992.
- [Machinability Data Center, 1980] Machinability Data Center. Machining Data Handbook. Metcut Research Associates, Cincinnati, Ohio, third edition, 1980.
- [Mittal et al., 1990] R. O. Mittal, S. A. Irani, and E. A. Lehtihet. Tolerance control in the machining of discrete components. Journal of Manufacturing Systems, 9(3):233-246, 1990.

- [Nau and Chang, 1986] D. S. Nau and T. C. Chang. Hierarchical representation of problem-solving knowledge in a frame-based process planning system. *Jour. Intelligent Systems*, 1(1):29-44, 1986.
- [Nau, 1987] D. S. Nau. Automated process planning using hierarchical abstraction. TI Technical Journal, pages 39-46, Winter 1987. Award winner, Texas Instruments 1987 Call for Papers on AI for Industrial Automation.
- [Nevins and Whitney, 1989] J. L. Nevins and D. E. Whitney, editors. Concurrent Design of Products & Processes. McGraw-Hill, 1989.
- [Opas and Mäntylä, 1994] Jussi Opas and Martti Mäntylä. Feature-based part
- programming. In [Shah et al., 1994], pages 239-260.
- [Regli et al., 1994] W. C. Regli, S. K. Gupta, and D. S. Nau. Feature recognition for manufacturability analysis. In K. Ishii, editor, ASME Computers in Engineering Conference, pages 93-104, 1994.
- [Regli et al., 1995] W. C. Regli, S. K. Gupta, and D. S. Nau. Extracting alternative machining features: An algorithmic approach. Research in Engineering Design, 1995, to appear.
- [Sacerdoti, 1977] E. D. Sacerdoti. A Structure for Plans and Behavior. American Elsevier, 1977.
- [Shah et al., 1994] J. Shah, M. Mäntylä, and D. S. Nau, editors. Advances in Feature Based Manufacturing. Elsevier/North Holland, 1994.
- [Tate, 1977] A. Tate. Generating project networks. In Proc. IJCAI-77, 1977.
- [Vandenbrande and Requicha, 1993] J. H. Vandenbrande and A. A. G. Requicha. Spatial reasoning for the automatic recognition of machinable features in solid models. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 15(12):1269, Dec. 1993.
- [Wilkins, 1988] D. E. Wilkins. Practical Planning: Extending the Classical AI Planning Paradigm. Morgan Kaufmann, San Mateo, CA, 1988.
- [Wilkins, 1990] D. E. Wilkins. Domain-independent planning: Representation and plan generation. In J. Allen, J. Hendler, and A. Tate, editors, *Readings in Planning*, pages 319-335. Morgan Kaufmann, 1990. Originally appeared in Artificial Intelligence 22(3), April 1984.
- [Wilson and Harvey, 1963] F. W. Wilson and P. D. Harvey. Manufacturing Planning and Estimating Handbook. McGraw Hill, 1963.
- [Winchell, 1989] W. Winchell. Realistic Cost Estimating for Manufacturing. Society of Manufacturing Engineers, 1989.
- [Yang et al., 1992] Q. Yang, D. S. Nau, and J. Hendler. Merging separately generated plans with restricted interactions. Computational Intelligence, 8(2):648-676, Feb. 1992.
- [Yang, 1990] Q. Yang. Formalizing planning knowledge for hierarchical planning. Computational Intelligence, 6:12-24, 1990.