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CIRP Annals Manufacturing Technology

Journal homepage: www.elsevier.com/locate/cirp

Generating alternative process plans for complex parts

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Balancing the load in workshops of versatile machines can be significantly improved if parts are processed through alternative routings. The paper presents an automated process planning method that departing from the geometric part model and the description of machining resources generates a portfolio of executable process plans with the objective to maximize the throughput of a workshop. Parts may have rotational, planar and freeform surfaces. A new model is suggested for the macro planning phase where a combination of geometric reasoning and constrained combinatorial optimization generates alternative setups, resource assignments and operation sequences. The method is demonstrated in industrial setting.

Manufacturing, Computer automated process planning (CAPP), Optimization

1. Introduction

The generic objective of the presented research was to improve the efficiency of workshops having various types of machining resources through the integration of traditionally separated planning functions of production engineering like Computer-Aided Manufacturing (CAM), Computer Automated Process Planning (CAPP), and production scheduling. The key idea was to exploit the potential of *alternative routings* over flexible Computer Numerical Control (CNC) machines. In the first phase of the research, efficient *load balancing* and *operation sequencing* methods were developed to schedule flexible job shops by using alternative routings (i.e., process plans) for producing the same parts. The method that maximized a workshop's *throughput* proved to be robust and applicable even in large-scale industrial scenarios [1]. The second phase of the research was aimed at generating for any product such a *portfolio of process plans* that contains high-quality plans and facilitates a proper balancing of the load on a set of machines with mixed capabilities (e.g., milling, turning, advanced freeform machining).

For the details of the industrial motivation and background, as well as the selected approach to integrating process planning and scheduling, the reader is referred to [1]. This paper reports on a novel approach for solving the problem of process planning.

2. Related works

In general, CAPP departs from the models of the blank and finished part, as well as the description of the available technological resources, and generates an ordered set of technological operations that upon execution produce the part as required by its design specification [2]. Since the very inception of the field [3], CAPP has always been considered the weakest link in manufacturing automation, and there is a common understanding that so far CAPP had only limited impact on industrial practice [4][5]. The crux of process planning is to provide passages between the worlds of ideas and their realization: between design and production. The planner's knowledge and competence must embrace a wide variety of fields, from geometry and tolerances, material properties, technologies, resources and capacities up to business objectives [6]. Hence, CAPP is considered for long a "wicked" problem [2] whose solution calls for the "efficient use of deficient knowledge" [7] and the stringent application of some of the main principles of production engineering.

Aggregation is one of them suggesting a hierarchical decision scheme that separates macro- and micro- levels of planning [8]. While *macro planning* is responsible for the selection of resources, the definition and ordering of setups and operations, *micro planning* involves the selection of particular tools, generation of tool paths and setting the process parameters. Research in the latter field proved to be successful and resulted in a number of industry-proof CAM systems [5] [9] (even though the machining of freeform surfaces is still considered an issue [10]). As rare options to this traditional decision scheme, recently the distinctions between generic (i.e., machine neural) and machine specific planning [11], as well as rough-cut and detailed planning [6] have been suggested.

Decomposition is the principle unanimously applied in macro planning. The semantic units of decomposition are almost without exception manufacturing (form) *features* such as holes, slots, or faces that define local, small worlds of machining with their definite geometric properties, shapes and applicable manufacturing processes [5][12]. Features provide general remedy for the complexity of planning: help structure domain knowledge, organize them into ontologies and use this knowledge efficiently in solving local problems. However, getting a feature-based model as input is still one of the main bottlenecks of CAPP, let it be done either by feature recognition on 3D CAD models or by any design-by-feature method [5]. Even though features may provide multiple interpretations for the same part [13], planners are typically committed to a single feature-based model.

In the global context of the part, features interact both in negative and positive ways resulting in constraints that have to be satisfied and opportunities (such as the removal of several features in a common setup or operation) that could be exploited during planning. Hence plan synthesis heavily relies on the use of constrained optimization techniques, such as mathematical [14] or constraint programming [15]. Combinatorial complexity called for the application of rule-based techniques [16], emergent synthesis methods [17], genetic algorithms [18] and a host of other meta-heuristics (for a comprehensive review, see [5]).

A recent direction to get out of the complexity trap is *adaptive* process planning which stresses the re-use of earlier solution patterns [9][11][14]. Though, most methods sacrifice general applicability and narrow the scope of planning to particular part and/or machine types [4]. A vast majority of CAPP solutions handles rotational or prismatic parts on some 3-axis machinery and do not concern freeform machining. In fact, this severely hinders the take-up of research results in industries that produce complex machined products. An integrative effort is suggested in [19] that extends 2.5D feature models by the application of *volume-based decomposition* towards freeform features. Volume-based decomposition is used also in a hybrid feature recognition system for detecting and merging analytic surfaces [13]. Mainstream feature-based CAPP has recently been challenged by a proposal using shape grammars in a design-to-fabrication system [20]. Here, the actual domain knowledge of the relationship between CNC machining processes and shapes they can produce is represented in form of a shape grammar. The approach gives some room for optimization by allowing the combination of volumes to be removed by a single movement of the tool but does not tackle the problem of selecting appropriate machining resources.

3. Problem statement

3.1. Main principles of the CAPP model

By adopting the principle of aggregation, the CAPP model presented here is structured into macro and micro planning. Since there are readily applicable solutions for the micro planning problem, further discussion is confined to macro planning where the complexity of planning is concentrated. Decomposition is also used, but not in the sense how features are taken to divide and conquer the problem at hand. Along with the ultimate goal of this research (which is improving the throughput of a workshop via alternative process plans) various machine, setup and operation alternatives are considered. In fact, the model allows for multiple interpretations of the part to be manufactured. Finally, during plan synthesis the initial commitment of decomposition can be revised and elements of the model are re-composed in different ways, resulting in a portfolio of plan variants.

3.2. Part, process and resource models

Parts to be manufactured have complex surface geometry composed of *planar*, *cylindrical* and *freeform sculptured* surfaces. The model of both the *blank* and the *finished part* is given in terms of the *Standard Tessellation Language* (STL) format that is a triangular mesh representation of a 3D surface geometry. No specific information on material, surface quality, as well as tolerances (on dimensions, parallelism, shape, etc.) is given because it is assumed that the modelled resources are capable to make the products with such detailed specifications. The blank part (or stock) could be of any shape provided that it completely surrounds the final part geometry.

As for machining *processes*, the basic assumption is that *turning* and *milling* type operations are only to be performed in the workshop. Both kinds of processes may be applied both for roughing and finishing. The workshop consists of turning and milling *machines* of different, partly overlapping *capabilities*: CNC lathes, 3-axis milling machines, multitasking machines as well as advanced freeform machining centres. While the time necessary for changing tools can be neglected, *setup* and *machine change* times are fixed and depend only on the actual machine. Multitasking machines can execute one operation at a time, i.e., planning parallel operations are out of scope. Each machine is characterised by its *volume removal speed* (VRS), the maximal volume of part material that can be removed per time unit. VRS is an aggregate property of the machine that is calculated on the basis of its spindle speed, feed-rate and potentially applicable tools, as well as of the material of the product. While *tools* are not explicitly considered during macro-level planning, tool geometry and parameters implicitly determine the VRS of machines. Finally, *capacity* of each machine type is given in terms of the number of its available instances.

Albeit fixture design is out of the scope of this work, basic information related to *fixturing* is essential for determining setups as well as tool approach directions of operations. Specifically, fixturing determines in any case a *setup plane* that dissects the working space of the machine tool into a positive and a negative half-space. Operations can be executed only in the positive half-space, while the negative half-space is forbidden for any movement of the tool.

3.3. The CAPP model

The key concepts of the proposed CAPP model are as follows:

- Planning is performed considering a set of pre-defined *machine types*, with given technological capabilities.
- The material to be removed is decomposed into *volume primitives* (VPs), i.e., elementary units that can be removed by some of the available machines.
- *A setup* defines how the part is grasped in the workspace of the machine. It determines the accessibility relations of VPs on a particular machine type.
- An elementary technological step (which may or may not be included in the computed plan) is called a *process element* (PE). It refers to the removal of a single volume primitive by a given machine type in a given setup.
- An *operation* is a series of PEs executed on one machine in a single setup, without interruption. The use of a single tool or the continuity of the removed volume is not required.
- *Accessibility constraints* state that in order to execute a process element, some other volume primitives must be removed in a previous or in the current operation.

A solution of the CAPP problem consists of selecting a subset of the process elements and assigning them into operations in such a way that all VPs are removed, and the accessibility constraints are respected. A series of operations executed on one machine (but not necessarily in one setup) without interruption is called *meta-operation*. A *process plan* is a sequence of (meta-)operations that produce the final part from the initial stock. The *total processing time* of a plan is the sum of the machine and setup change times, and the operation times. The ultimate goal of planning is to generate such a *portfolio* of process plans whose elements maximize the *throughput* of the workshop under different, anticipated load conditions. As a consequence, a specific process plan will maximally concentrate the (meta-) operations on the selected machines.

3.4. Working example

As an example, consider the manufacturing of the sample part presented in Figure 1 in a workshop with four types of machines, namely 3-axis machining centres, freeform milling machines, turning machines, and multitasking machines that are able to execute turning and milling without a setup change in between them (see Table 1). The blank part is a rod modelled as a tessellated cylinder. The final part's surface can be subdivided into two external and two internal planar faces, and three independent freeform surface sections, located sequentially along the main axis of the part. Setup planes are generated with the assumption that parts can be grasped on each machine in a jaw fixturing chuck. While finishing the freeform surfaces requires using a freeform milling machine, it is possible to perform roughing (and, in case of the faces, even finishing) by any of the machines. This implies that a variety of substantially different process plans exists, and different process plan alternatives may perform well under different workshop loads.

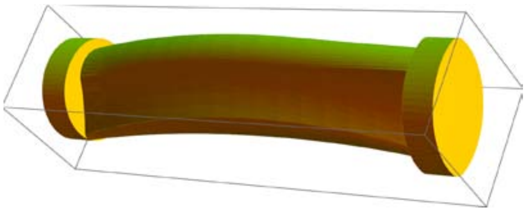

Figure 1. The sample part.

Table 1. Properties of available machine types: M1: 3-axis machining centre; M2: freeform milling machine; M3: turning machine; M4:multi-tasking machine.

Machine type	VRS [m^3/s]	Change time [s]		Capacity
		Setup	Machine	
M1	250	3000	1500	8
M2	100	5000	1500	8
M3	250	3200	1000	2
M4	200	3500	1500	1

4. Solution of macro planning

4.1. Part analysis and model building by geometric reasoning

The first phase of macro planning is *part analysis* that generates the main elements and relations of a CAPP problem by *geometric* and *technological reasoning*. First, considering the part geometry, available machining resources and their process capabilities, alternative setups are defined for machining the part. Next, the problem is decomposed into volume primitives that can be processed by the available machining resources. By exploiting locality, alternative ways of machining processes are then assigned to VPs, forming this way the process elements. Finally, geometry and technology related knowledge is manifested in terms of accessibility constraints between VPs and PEs.

Material to be removed by machining is the difference of the volume of the blank and finished part. This volume is *decomposed* into the elementary units of VPs. VPs are disjoint and their union exactly makes up the total material volume to be removed. The region between the surfaces of the blank and the finished part are subdivided into VPs by two kinds of *segmentation rules*:

- Decomposing the material to be removed into *layers* that are akin to peels of material around the finished part. Layers are given as offset bounding areas around the part that contain material of a given thickness to be removed. While there is no theoretical upper bound on the number of layers, engineering common sense suggests using only a couple of layers. For the sample part, by means of two offset bounding boxes an external (roughing) and an internal (finishing) layer was generated.
- Segmenting volumes defined by layers into smaller regions by appropriate *planes* that ensue from the part, fixture and machine geometry. Any operation may be performed only in the positive half-space of a plane. *Setup planes* capture consequences of fixturing and define the working area of machining. *Tool approach planes* "shadow" some of the part's geometry, supposing a given machine type and setup. In case of the sample part, planes are typically (but not necessarily) perpendicular or parallel to its dominating axis.

Consequently, VPs are delimited by surfaces of the blank and finished part, as well as of the layers and planes. There is an important difference between VPs and manufacturing form features: while features have pre-determined geometrical forms, like a face, step, pocket, or a shoulder, the geometry of VPs is not defined in advance. Instead, the segmentation rules of VPs are given that capture a major body of manufacturing expertise.

Given a set of planes, the working area where operations can be performed at all is the intersection of the positive half-spaces of the planes. All other areas are forbidden or impossible to reach for any movement of the tool. In the CAPP model a *setup* is formally defined by a *set of setup and tool approach planes*. Of course, machine tools and setups are mutually interrelated: each setup is assigned to all the machine tools that are able to work on the part in the given setup. The result of geometric reasoning is represented in a *tree of volume primitives* where the *root* of the tree is the complete volume to be removed, the *edges* are segmentation rules, and the leaves denote VPs (see Figure 2).

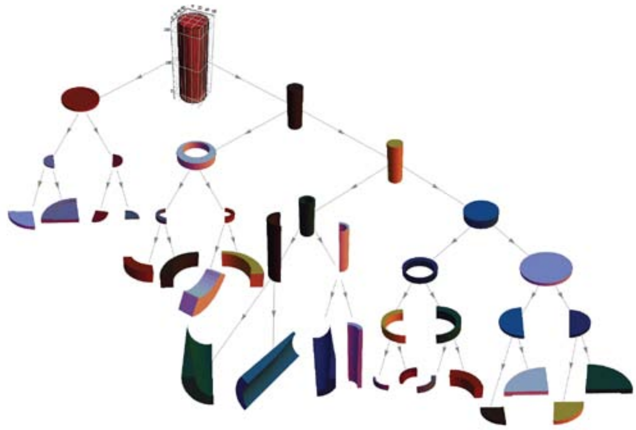

Figure 2. VP decomposition of the external layer of the sample part.

Process elements (PEs) enrich the so far purely geometric entities of VPs with machining related information. PEs specify the alternative ways of machining VPs by the available resources. VPs may have several alternative PEs, but so as to warrant feasibility of process plans, each VP has at least one PE. Each process element ξ is given in terms of the volume primitive $v(\xi)$ it can remove, the actual $j(\xi)$ machine, the actual $s(\xi)$ setup on machine $j(\xi)$ where ξ can be removed, its estimated processing time $t(\xi)$, and the *accessibility set* of its volume primitive, $A(\xi)$. $A(\xi)$ defines conditions of executing ξ in terms of the set of those VPs that should be removed before or together with $v(\xi)$. Processing time $t(\xi)$ is calculated for ξ based on the volume of $v(\xi)$, and the maximal VRS of the assigned $j(\xi)$ machine.

The *accessibility* of VPs implies *precedence constraints* on the PEs. Note that these constraints relate to PEs and do not imply a universal order of the removal of VPs. Accessibility is basically determined by the *line-of-sight*: e.g., VPs in an inner layer are accessible only if the VPs covering them in the outer layers have already been removed. Hence, when performing a PE ξ by removing $v(\xi)$, each volume primitive in $A(\xi)$ should have been already removed by an earlier operation, or must be removed together with $v(\xi)$ in the same operation.

The *logic* for determining accessibility sets differs by machine types, but $A(\xi)$ can always be generated by local geometric reasoning. For 3-axis machining centres, $A(\xi)$ contains the VPs in the line-of-sight according to the tool approach direction. For turning machines, $A(\xi)$ holds the VPs along the same or an outer perimeter than $v(\xi)$. E.g., in the left of Figure 3, access to V_4 for turning requires that V_1, V_2, and V_3 are processed earlier or in the same operation. The accessibility set is analogous for V_3, i.e., there exists a directed cycle of accessibility relations between V_3, and V_4, implying that these two VPs can only be turned together. For freeform milling machines, accessibility relations point from VPs of the outer layer to VPs of the inner layer (e.g., in the right of Figure 3, access to V_2 assumes that V_1 is clear). Finally, the PEs assigned to a multitasking machine are determined as a union of 3-axis milling and turning PEs, together with their corresponding accessibility sets.

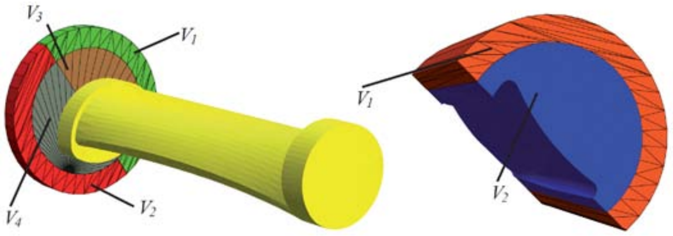

Figure 3. Examples for accessibility in case of turning and milling.

4.2. Process planning by combinatorial optimization

The second phase of macro planning takes the model built by geometrical reasoning, and applies *combinatorial optimization* techniques to compute a portfolio of process plans to maximize the *workshop throughput*. Each plan in the portfolio contains a selection of PEs, organized into a sequence of (meta-)operations that altogether produce the final part from the initial stock. Plans are added to the portfolio one-by-one, by constructing a plan in each step that complements the current portfolio the best. The latter requirement is captured by minimizing the *weighted total processing time* of the plan, with different weights in each iteration, set according to the algorithm presented in Section 4.3. Constructing a single, optimal plan with given weights is represented as a *mixed-integer linear program* (MIP) (see Table 2 for the notation):

Minimize

$$T + \varepsilon b \tag{1}$$

subject to

$$z_{\mu,\omega,\xi} \le y_{\mu,\omega,j(\xi),s(\xi)} \qquad \forall \mu,\omega,\xi \tag{2}$$

$$y_{\mu,\omega,j,s} \le x_{\mu,j} \qquad \forall \mu,\omega,j,s \tag{3}$$

$$\sum_{j} x_{\mu,j} \le 1 \qquad \forall \mu \tag{4}$$

$$\sum_{j,s} y_{\mu,\omega,j,s} \le 1 \qquad \forall \mu,\omega \tag{5}$$

$$\sum_{\mu,\omega,\xi:\, v(\xi)=v} z_{\mu,\omega,\xi} = 1 \qquad \forall v \tag{6}$$

$$z_{\mu,\omega,\xi} \le \sum_{\mu',\omega',\xi':\, v(\xi')=v \,\wedge\, (\mu>\mu' \,\vee\, \mu=\mu' \wedge \omega \ge \omega')} z_{\mu',\omega',\xi'} \qquad \forall \mu,\omega,\xi, v \in A(\xi) \tag{7}$$

$$T = \sum_{\mu,j} w_j h_j x_{\mu,j} + \sum_{\mu,\omega,j,s} w_j d_j y_{\mu,\omega,j,s} + \sum_{\mu,\omega,\xi} w_{j(\xi)} t(\xi) z_{\mu,\omega,\xi} \tag{8}$$

$$b = \sum_{\mu,j} x_{\mu,j} + \sum_{\mu,\omega,j,s} y_{\mu,\omega,j,s} + \sum_{\mu,\omega,\xi} (\mu+\omega) z_{\mu,\omega,\xi} \tag{9}$$

$$x_{\mu,j},\, y_{\mu,\omega,j,s},\, z_{\mu,\omega,\xi} \in \{0,1\} \qquad \forall \mu,\omega,\xi,j,s \tag{10}$$

The objective (1) is minimizing the (weighted) total processing time of the plan, perturbed by a small tie-breaking expression. Constraints (2) and (3) state that a process element can only be executed in a (meta-) operation only if the proper machine type and setup are selected for that (meta-)operation. Inequalities (4) and (5) ensure that at most one machine type and one setup will be selected for each (meta-)operation. Note that for (meta-) operations that do not contain any PE, no machine or setup must be selected. Equalities (6) state that each VP must be removed exactly once. Inequalities (7) encode the accessibility constraints, stating that the access volumes of a PE must be removed by an earlier operation or by the same operation. Line (8) defines the total processing time, composed of the machine change times, setup change times and processing times. Finally, line (9) determines the tie-breaking expression and (10) defines the domains of the binary variables.

Table 2. Notation used in the description of the CAPP problem.

Indices	
j	A machine type
s	A setup
v	A volume primitive
μ	A meta-operation
ω	An operation
ξ	A process element
Parameters	
w_j	Weight of machine type j
h_j	Machine change time for machine type j
d_j	Setup change time for machine type j
K_j	Capacity of machine type j
$v(\xi)$	The volume primitive removed by process element ξ
$j(\xi)$	Machine type on which process element ξ can be executed
$s(\xi)$	The setup in which process element ξ can be executed
$t(\xi)$	Processing time for process element ξ
$A(\xi)$	The set of access volumes for process element ξ
ε	A small constant, e.g., 0.01
Variables	
$x_{\mu,j}$	Indicates whether meta-operation μ uses machine type j (binary)
$y_{\mu,\omega,j,s}$	Indicates whether meta-operation μ, operation ω uses machine type j and setup s (binary)
$z_{\mu,\omega,\xi}$	Indicates whether process element ξ is executed in meta-operation μ, operation ω (binary)
Objectives	
T	(Weighted) total processing time of the process plan
b	Tie-breaking expression

4.3. Generating an efficient portfolio of plans

The *weights* w_j in the above MIP representation can be used to parameterize the problem in order to generate multiple alternative plans. The weight w_j can be considered as the relative hourly cost of using machine type j. Using unit weights, i.e., for $\forall j$ w_j=1 results in a plan with minimal total processing time. Intuitively, increasing w_j results in less, while decreasing it leads to more load on j. However, defining a set of weight vectors in such a way that the resulting portfolio optimizes a given performance measure is not a trivial task. The method used for maximizing the workshop throughput is as follows. It is assumed that the precedence constraints can be relaxed and for each machine type j a constant capacity K_j is given. Let Π be the (potentially enormous) complete set of all possible process plans for the given product. Let α_π, $\pi \in \Pi$ be decision variables, where α_π determines the fraction of products following plan alternative π in the production. The load incurred by plan π on machine type j is denoted by $q_{j,\pi}$. Then, the throughput maximization problem can be formulated as shown in the following linear program (LP):

Minimize

$$L \tag{11}$$

subject to

$$\sum_{\pi \in \Pi} \alpha_\pi = 1 \tag{12}$$

$$\sum_{\pi \in \Pi} q_{j,\pi} \alpha_\pi \le L K_j \qquad \forall j \tag{13}$$

The objective (11) is minimizing the average time L to produce a unit of the product, which is the multiplicative inverse of the workshop throughput. Constraint (12) states that the fraction of products using the various alternative plans must sum up to 1. Inequalities (13) encode the capacity constraint for the given machine types.

Since the size of Π can be enormous, this LP is solved by *column generation* [1]. Namely, let Π' be an initial set of alternatives containing a single plan that minimizes the total processing time, received by solving the CAPP problem with weights $\forall j\ w_j=1$. Now, let $LP(\Pi')$ denote the restriction of LP to the columns Π' instead of Π. The small size $LP(\Pi')$ is solved to optimality. Then, following the rules of column generation, a new plan alternative is sought, where the machine weights w_j are determined by the optimal dual variables of the corresponding capacity constraints (Eq. 13). The plan found is added to Π', and the procedure is continued until no further plan can improve the portfolio, and therefore an optimal portfolio has been found. In case there are multiple capacity profiles given, the column generation algorithm is re-started using the current portfolio as the initial portfolio Π'.

5. Implementation and testing

5.1 Architecture of the integrated CAPP and scheduler system

The architecture of the implemented CAPP system and the connected scheduler is depicted in Figure 4. The input of the system consists of the definition of the machine tools and the CAD model of the part. The overall CAPP and scheduling framework, the user interface and the geometrical reasoner have been implemented in Wolfram's Mathematica. The CAPP optimizer, which computes the optimal portfolio of macro-level plans from the CAPP model, is implemented as a C++ application and uses the IBM ILOG Cplex MIP solver. The CAPP post-processor produces the scheduling problem definition from the macro-level plans, while the Scheduler solves the detailed scheduling problems. The Scheduler uses the Coin-OR CBC branch-and-cut solver [1]. The set of VPs that are removed in one operation are passed to the Esprit CAM system that generates the micro-level plans. Micro-level plans could be used to refine the processing time values in the scheduling problem definition, although this functionality is currently not fully integrated.

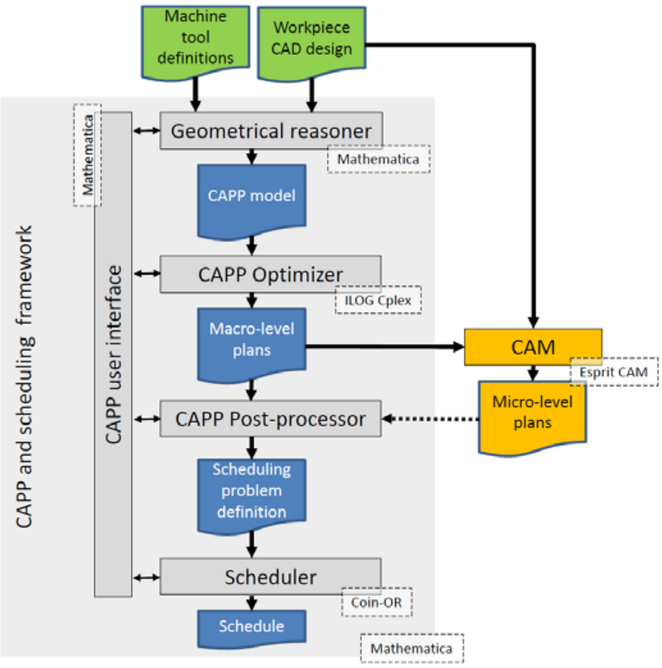

Figure 4. Architecture of the CAPP and scheduling system.

5.2 Experimental results: plan quality

The validity of the computed plans was assessed by expert evaluation. The plan portfolio obtained for the sample part maximizes the throughput in a workshop that contains machines as given in Table 1. The first plan uses a turning machine for roughing and a freeform milling machine for finishing. Note that though VPs of the sample part are not of rotational geometry, the planning method re-composed some of them so that they could be removed together by turning (see Figure 2). This plan has the lowest possible total processing time (30262 seconds), however, with the given capacity profile, it overloads the turning machines. Further plans are therefore computed that perform roughing on different machines (finishing can only be performed on freeform milling machines). Among them, plan#5, displayed in Figure 5, performs roughing on a 3-axis machining centre, and has a total processing time of 39064 seconds. The complete, optimal portfolio consists of seven plans. The portfolio is shown in Figure 6, which presents the load incurred by the alternative plans on the different machine types.

To demonstrate the benefits of using a portfolio of plans instead of a single plan, the production of 100 pieces of the sample part was scheduled using the scheduler [1]. In the case when all the parts had to be manufactured according to plan#1 (i.e., the plan with minimal throughput time), the time required to produce them was 8.79 days. In contrast, when all the seven plan alternatives could be used, this time decreased by 25.69%, to 6.53 days. Further research will investigate the gains of using plan portfolios in a workshop producing different parts in parallel.

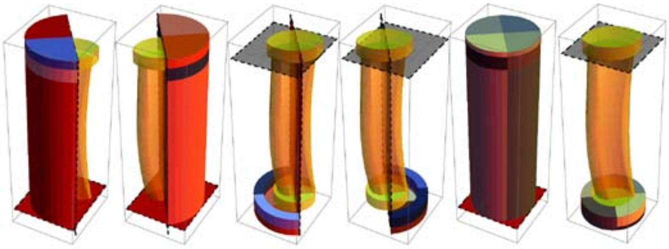

Figure 5. Plan#5: roughing on a 3-axis machining centre in 4 setups. Next, finishing on a freeform milling machine in 2 setups. Each figure displays the volume removed in the given setup.

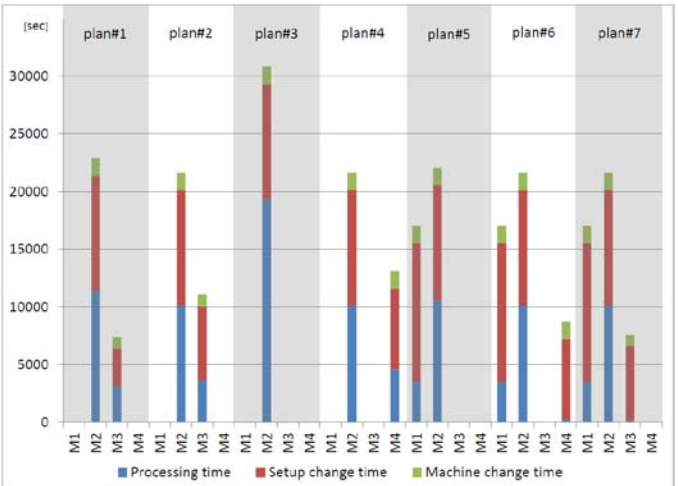

Figure 6. A comparison of the machine loads incurred by the different plan alternatives. Columns correspond to machine types as follows: M1: 3-axis machining centre; M2: freeform milling machine; M3: turning machine; M4: multitasking machine.

5.3 Experimental results: computational efficiency

The efficiency and scalability of the macro-level planning procedure were investigated in a series of computational experiments. In order to obtain problems of different complexity and characteristics, a couple of original industrial CAD models were altered, parameters of geometric reasoning were varied, and numerical parameters such as VRS and machine/setup change times were modified. Two types of scenarios were considered: (1) The CAPP optimizer was run with pre-defined machine weight vectors, denoted by **W**. (2) The column generation procedure determined the weight vectors automatically, and called the MIP solver to generate further plans until an optimal plan portfolio was reached. These scenarios are denoted by **C**. The characteristics of the instances, together with the experimental results are shown in Table 3. The number of VPs ranged from 20 to 60. In all cases, the 4 machine types (MTs) have been taken with up to 10 different setups. These resulted in PEs ranging from 76 to 368. Column **Scen** displays the applied optimization scenario, i.e., the number of weight vectors (W-type instances) or the number of capacity profiles (C-type instances). Column **Alt** contains the number of different plan alternatives found. The last two columns display the average and the maximum time required for finding a single process plan in seconds, or the time limit of 600 seconds where this limit was hit.

Table 3. Problem instances and experimental results. The asterisk (*) indicates the instances where a time-out occurred. For such instances, the average computation time is displayed both over the scenarios successfully solved to optimality and over all scenarios.

VPs	MTs	Setups	PEs	Scen.	Alt.	Avg. time	Max. time
20	4	4	76	W17	9	0.63	4.13
20	4	4	78	W17	8	0.41	1.39
40	4	10	224	W17	7	25.59	358.39
40	4	10	288	W17	7	6.40/ 41.68*	600.00*
40	4	10	160	C1	3	2.14	6.10
40	4	10	160	C1	5	7.53	27.10
40	4	10	160	C2	2	2.22	7.11
40	4	10	160	C2	6	7.78	23.63
60	4	10	368	W17	14	74.08	271.61
60	4	10	368	C1	5	41.04	133.06
60	4	10	368	C5	11	173.98/ 202.38*	600.00*

The experimental results demonstrate that the approach is suitable for solving problem instances of industrially relevant size. The characteristic computation time to generate one plan is well below 1 minute for 40 volume primitives, and it is a couple of minutes for 60 volume primitives. For the two scenarios where the solver could not find proven optimal plans, the gap between the lower and the upper bounds was around 1%.

6. Conclusions

This paper proposed a new generic CAPP model as an alternative to the traditional feature-based models. Geometric and technological reasoning prepares the ground for planning by generating elementary VPs, PEs, and accessibility relations with the use of local, domain specific knowledge. While VPs are defined by rules with much less assumptions towards geometry and manufacturing processes, the proposed decomposition method can be applied to mesh-type part models only. The selection of resources, setups and operations, as well as their sequencing is performed in a single plan synthesis phase, which is the key for optimization and for generating essentially different plan alternatives. All these developments have been made possible by relying on the increased representation power and computational efficiency of generic CAD modelling, geometric reasoning and combinatorial optimization techniques.

The CAPP model can account for other geometric entities like holes and slots, and consider more than one cutting condition per machine. Extension of the declarative model with additional industrial expert advice is also possible. E.g., a rule like “one must not leave thin walls when removing the material” can be represented in the mathematical model. Macro planning takes quasi-standard CAD models as input and provides micro planning with all relevant data for NC code generation. As the experiments have shown, the generated portfolio of plan alternatives greatly improves the throughput of a workshop if applied with proper load balancing and sequencing methods [1]. The overall study confirmed the main assumption that was suggested both by theoretical investigations and engineering's best practice: the integration of the product- and production-oriented aspects of production engineering at higher levels of abstraction and decision levels can provide new opportunities for productivity gains.

Acknowledgements

The Hungarian authors thank for the NKTH OMFB-01638/200 and the TÁMOP-4.2.1/B-09/1/KMR-2010-0002 grants.

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