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Machining process sequencing and machine assignment in generative feature-based CAPP for mill-turn parts

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Abstract: Process selection and sequencing, as one of the most complex issues when evaluated from a mathematical point of view and crucial in CAPP, still attract research attention. For the current trend of intelligent manufacturing, machining features (MFs) are the information carriers for workpiece geometry and topology representation. They are basically derived from CAD models and are used by downstream engineering applications. A feature-based reasoning approach for generating machining sequences in terms of part setups and the assignment of machine alternatives is presented. The approach suggested in this research assumes a heavy reliance on a data input model incorporating functional requirements for parts and in particular GD&T references. An extended feature taxonomy corresponding to the needs of the rational process plan selection for the addressed category of part types is proposed. It is meant to be applicable to machining of both rotational and prismatic features using machines of various configurations. The developed taxonomy is based on the working directions for MFs and includes the identification of their location with respect to datum references. The developed taxonomy that involves feature tolerance relationships is at the core of the information data model utilised by the original algorithm which was aimed at generic process sequencing for the definite category of mechanical parts. Through the developed algorithm, adequate process alternatives can be generated by adaptive setup merging on a single machine or across multiple available machines under consideration of their respective process capabilities. The approach has been validated through an illustrative case study using a sample mill-turn part of considerable complexity.

Keywords: CAPP, machining feature, process selection and sequencing, generic setup, machine assignment, reasoning scheme

1. Introduction

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Up-to-date manufacturing is realised in a dynamically changing environment by an increased demand for the development of customised, high quality products in reduced time cycles and with shortened lifecycles [1, 2]. The efficiency of machining processes can be remarkably enhanced with the use of highly sophisticated CNC multi-axis, or mostly multi-tasking machine tools [3]. Machines of such configurations have enabled the realisation of the concept of one-hit machining, sometimes termed complete machining, that basically minimise the number of setups [4]. It might particularly refer to mill-turn part types, which contain both rotational and prismatic features. Both types of machining features (MFs) are most suitable for fabrication using multi-purpose machines. This machining technology can significantly reduce the number of necessary part setups. Thus, it decreases the length of the process. Unlike its working time, however, this method usually consumes much more time for process planning, as long as its component tasks are performed manually. Hence, attempting to shorten the process-planning time implies the need to further automate its individual tasks while also tackling the entire problem in an integrative manner in order to respond quickly to current industrial demands. This might be particularly valid as far as process sequencing and machine selection issues are concerned which are addressed in this study with respect to mill-turn parts manufacturing.

Process sequencing (operation sequencing) is a complex activity, especially when referring to the recognised MFs, and is the essential part of process planning. A proper MF sequence is fundamental for attaining process efficiency and high quality products [5]. For the current trend of manufacturing, MFs are the basic information carriers for workpiece geometry and topology representation as derived from CAD models. In the latest concepts MFs have been supplemented with attributes of extended Geometric Dimensioning & Tolerancing (GD&T) as annotations in Product and Manufacturing Information (PMI) representation [6, 7]. Hereby, they form a suitable foundation for solving crucial tasks of CAPP, including setup planning and machine selection.

As reported, process plans are often generated regardless of resource availability on a definite shop floor. This is due to the missing interconnection with the downstream engineering functions like: scheduling or job dispatching [8, 9]. The recently launched concept of distributed process planning (DPP) implies however that process plans are created at the supervisory planning level by grouping features into setups based on tool access directions (TADs) which is done independently of machines. Next, the generic setups and MFs within them are sequenced [10, 11].

Most existing methods and algorithms crucial to CAPP are developed on the foundation of knowledge-focused reasoning rules and heuristics utilising best applied manufacturing practices, as in expert-like systems. MF precedence in sequencing procedures is essentially determined in this manner, where part geometry and all tolerance annotations are represented in the underlying data model [12]. Such means of supporting the decision-making process exhibit numerous constraints and shortcomings. Firstly, the adopted rules tend to be subjective and are often disputable, especially while the conditions of tolerancing and MF interactions are considered. The difficulty with determining a proper machining sequence caused by MF interrelations are clearly presented in e.g. [13]. Ambiguity might also arise when selecting the appropriate TAD for multi-TAD features, in order to determine their precedence and assign to defined setups, as discussed by Manafi and Nategh [14] and Mokhtar and Xu [15]. Secondly, the rules lack of generic applicability, as these can fail to be suitable for some parts with particular geometry and topology characteristics. Therefore, to avoid ambiguity with interpreting the precedence of interrelated MFs, impartial and more reliable decision making schemes in CAPP are needed, that also involve using unified criteria.

Targeting solving the above mentioned problems, the objective of this research is to develop a robust reasoning approach for adaptive process sequencing in terms of setups with relevant datum selection, along with machine assignment alternatives, under conditions of distributed environment of parts manufacture. Moreover, the approach utilises the proposed classification scheme, and matrix representations of input data structures that enables optimised setup plan selection. Those are particularly intended to enable the avoidance of possible conflicts between geometric and technological rules based on attributes of processing technologies applied to machining mill-turn parts.

The reminder of this paper is organised in the following order. Section 2 contains a brief review of research performed in the area of automated process planning, and particularly with regard to machining process sequencing within CAPP framework. In Section 3, a decision making framework for rational process plan selection is reported, including a feature-based reasoning approach involving the designed algorithms for generating process sequence in terms of setups, along with the assignment of machine alternatives. A novel feature classification for mill-turn part types considering processing capabilities of contemporary multi-axis

CNC machine tools is also proposed. Our approach is validated through a complex sample workpiece consisting of both turning and milling MFs. Finally, the authors’ contributions are summarised in Section 4.

2. Review of related research work

Despite more than two decades of intense research and remarkable progress, there is still considerable need for further research in many aspects of automated process planning. This largely concerns the issue of operation selection and process sequencing in the framework of CAPP [16]. Tackling the issues of operation sequencing encounters particular difficulties and still remains a challenge due to their inherent complexity and adherence to the class of non-deterministic polynomial-time hard problems [15]. This finds its full confirmation in a state-of-the art review on CAPP for machining provided by Xu et al. [17], with a clear emphasis on the role played by feature-based technologies in its recent developments. A number of different approaches and algorithms have been proposed in the area of machining process sequencing, and various categories of research can be singled out. The majority of those is associated with the use of dedicated search techniques including integer programming, branch-and-bound, or dynamic programming.

For process sequencing, a tree-structured precedence graph was assumed to represent the precedence relations and alternative operations [18]. Next, suitable algorithms were suggested that iteratively search for optimal or near-optimal solution for operation sequences, expressed in terms of total cost. Lee et al. [19] outlined a process planning scheme in which operation sequences are generated based on the topological sorting of recognised MFs and searching in adequate graph models.

Other authors [11] discussed a method for process selection and sequencing in the context of developed approach to generating alternative process plans in integrated manufacturing. The objective function in this optimisation selection task was to minimise the fabrication time and cost, considering the constraints of processing capability for respective MFs in a knowledge-based fashion. Chung & Suh [20] considered operation sequencing termed as non-linear process planning in [17], involving process alternatives for complex machining instances based on STEP-NC and graph modelling. They developed an optimisation algorithm minimising the total cycle time, using the branch-and-bound method and heuristics from engineering insights. STEP-NC entities can be utilised for the representation of manufacturing process structure as shown in [21].

Studying existing literature on machining process sequencing, it can be seen that much effort was also given to the use of AI methods. More recently [22], a GA algorithm was directly adopted for optimal operation sequencing in CAPP aimed at minimising cots. Precedence-constrained operation sequencing problem was formulated in there into a mixed integer programming model, incorporating a definite set of principles deduced from manufacturing capability. The edge selection-based encoding strategy was applied that significantly improve the converging efficiency of the reasoning scheme. In a manufacturing practice, decision-making frequently deals with uncertain and imprecise information.

Setup planning, as one of pivotal functions in process sequencing in particular, has recently attracted the research attention. Accordingly, process plans are generically constructed in the unit of setups [14, 22]. Moreover, the setup planning activity plays an operating role, which deals with the optimisation of the shop-floor operations [23], to cope with increased product diversification in dynamic markets [24, 25]. Thus, some researchers have often taken into account the manufacturing resources in decision-making, and assumed MF-based planning with alternatives [17]. One notable approach, in response to the problems, was performed by Zhang & Lin [4], who utilised hybrid-graph theory, considering tolerance analysis as a critical step of setup planning. More importantly, Yao et al. [24, 25] introduced a procedure for setup planning that was based on not only the tolerance analysis but also the analysis of machine processing capabilities, including fixture planning and design. In [26] a setup planning module was reported for automatically generating the proper alternatives, through the identification of best datum surfaces, while considering machine capabilities and fixturing strategies. In parallel, rule-based MF sequencing approaches has gained ground in setup sequencing, as feature interactions became a critical factor for achieving the established goals.

With reference to the given aspect [1, 3], an adaptive setup planning (ASP) was proposed as applicable to various configurations of machine tools, and thus suitable for the conditions of dynamic system operation. The framework envisaged adaptive setup merging on both a single machine and across different machines, and the feasible setups for a given part are defined by examining the tool accessibility. To search effectively for an optimal or near-optimal solution an extended GA approach was applied to handle setup-specific issues. Later research reported by Ji et al [27] provided an interesting reachability based method for MF sequencing of increased adaptability which aims to reduce the number of tool changes and meet specific machining demands. This method utilised an MF path graph, an adjacency matrix, and a reachability matrix, that were generated using appropriate mapping principles based on MF geometry, and also non-geometric technological attributes.

In the field of feature-based CAPP, the issues of distributed or adaptive process planning [10, 11, 28], and its integration to the scheduling function [8, 9] have attracted the most of research attention. The latest research on distributed process planning focused, among others, on the implementation of functions blocks (FB) defined in an International Electrotechnical Commission (IEC) standard for process control systems, named IEC 61499 [29, 30]. This approach assumes that the generic process data be separated from the machine-specific ones with the use of advanced machine monitoring techniques. Wang was among those who as the first used in the concept of FB for feature-based process planning and CNC machining [28].

As widely reported, Cloud manufacturing might predominate as a trend of future manufacturing since it could provide cost effective, flexible and scalable solutions to companies by sharing manufacturing resources as services with lower support and maintenance costs [29, 30]. Targeting the Cloud manufacturing, Wang in **[**29**]** proposed an Internet **-** and Web-based system for machine availability monitoring and adaptive process planning. Particularly, this paper develops a tiered service-oriented framework and introduces an event-driven approach using IEC 61499 function blocks. The services include generating non-linear process plans and data acquisition from shop-floor machine tools through sensors, input from operators, and machine schedules. Next, the monitoring data undergo processing by an information fusion technique provided to feed the process planning function with the real-time status, specifications, and availability time windows of machine resources. The approach was further extended by Mourtzis et al. in [8].

A new Cloud-based approach for monitoring the manufacturing resources using a sensor network, dispatching jobs to the selected CNC machines, and generating the optimum part machining code is presented by Tapoglou et al. in [30]. A data acquisition system, as a component of the proposed system architecture, is utilized for monitoring the status of the manufacturing equipment which is determined after the analysis of acquired data. Event driven FBs with embedded optimization algorithms on the manufacturing equipment are employed that enable the optimal cutting parameters to be selected and the required toolpaths for parts machining to be generated while considering the latest information of the available machines and cutting tools.

One of the newest concept of dynamic machining feature which integrates the feature definition of a part to the capabilities of the selected machining resources was proposed by Liu et al. in [28]. By applying the event driven model of composite FBs, features can be generated adaptively and automatically during the whole dynamic manufacturing lifecycle and may be different in roughing, semi-finishing and finishing operations. This is of importance with regard to complex parts consisting of intersecting features. The dynamic feature concept is extended in such a way that each interim feature model of a part is defined along with the selected machine, cutter and cutting parameters, and updated adaptively according to changes to these machining resources. Changes of the selected resources and cutting parameters are sent as input events to the FB. In consequence, features of the un-machined geometry can be updated adaptively and automatically to support optimal process planning.

The relevance of these trends and goals and the essence of proposed methodical solutions have been adequately demonstrated in the most recent reports on the outcomes of the implementation of the EU-funded FP7 research project entitled “Collaborative and Adaptive Process Planning for Sustainable Manufacturing Environments - CAPP-4-SMEs”.

Another notable direction of research in the area concerned is represented by studies focussed on systematic modelling and reusing of process knowledge. Research papers of Zheng et al. [2], and later of Liu et al. [31] can be given as appropriate examples. While the former proposed a visual approach to rapid process configuration by reusing knowledge-based rules, the latter outlined an algorithmic approach for reusing the manufacturing information in MF- based process creation, under conditions of changing part geometry.

The possibilities for machining the mechanical components are directly determined by the functional characteristics of machine tools available for manufacturing. And so mill-turn machine tools are a subset of multi-tasking machines that can accomplish both milling and turning operations. Hereby, part types with both rotational turning and prismatic milling MFs are termed as mill-turn parts [3]. These part types have been also defined as prisronal ones in [32]. Mill-turn machines, being equipped with driven tools and increasingly utilized in metal-cutting industry, allow mill-turn parts to be completely machined in one single machine. As a result, work transfer between two (or even more) turning and milling machines can be avoided. The work transfer might be required, however, when a process alternative assume the use a mill-turn machine of insufficient number of CNC-controlled axes. Since TAD is the inherent attribute of various machining technologies [25], the significant issue with setup grouping is the proper assignment of relevant TAD to MFs. There are valid rules discussed in references that manage feature precedence and respective sequencing for setups [4]. It might be related to features having more than one TAD. TADs should be assigned to every feature according to the priorities of tight tolerance feature relationships, the number of features, and finally good machining practices. As reported also by the same authors, providing more TADs by a machine tool can reduce the number of needed setups. However, MFs of one TAD are not necessarily machined in one setup, and MFs machined in one setup are not necessary accessible from the same TAD. Most of the research work on machining feature sequencing focused either on prismatic or rotational parts [3, 33]. In any of the instances machining a feature requires the lining up between its working direction and machine tool *Z*-axis that coincides with the spindle direction -the tool axis [26]. The feature working direction is equivalent to the TAD vector located along the machine spindle axis. Like e.g. in [23] as well as in [34] in regards to large- size parts, it can be represented by the direction cosines computed with respect to an assigned workpiece linear coordinate system. In this regard, planning potential part setups within machining process sequencing is affected by workpiece placement and its orientation in machine working space. The decision making on selecting a potential setup is in particular of importance with regard to machining features, whose working directions are rotated with respect to the workpiece coordinate system. It might be referenced to this kind of features made on both multi-axis milling centres and mill-turn (multi-purpose) machines. In the latter case in particular, machining prismatic features on four- or five-axis machines need a proper part orientation with regard to the spindle axis of the driven milling or drilling tools. To sum up, many researchers have focused on feature sequencing problem but among the existing research only a few envisaged the machine-neutral (generic) formulation of feature clusters for adaptive CAPP. Commonly used TAD information seems to be insufficient for the effective setup planning and operation sequencing. Proposed by the authors, the unique information data model is based on formalised description of machining features for mill-turn parts. Consecutive setups as groupings of features are rapidly formulated in iterative fashion considering the factors of TAD and additionally the feature location as well as geometrical dimensioning and tolerance specification. Setups generated at supervisory level, are next merged on a single machine or across different machines in execution control, considering the availability and processing capabilities of machine resources.

3. Decision-making framework for optimal process plan selection in generative CAPP

Coming ahead the advocated decentralisation in CAPP system architecture and the concept of DPP for increased system responsiveness in dynamic environments, a two-stage hierarchical approach to setup planning in generative CAPP was proposed by the authors (**Fig. 1**). Its former stage is primarily for generic process sequencing which involves grouping features into clusters correspondingly to formed setups. Machining process precedence is therein determined, using appropriate machine-neutral reasoning scheme based on MF attributes, part functional relationships as well as rules underlying applied machining technologies (strategies). The latter stage in turn, is meant to make machine-specific decisions, associated with adaptive setup merging and alternative machine allocation to definite setups, with more focus on such dynamic issues, as: the capability of available machine resources as well as real-time operational scheduling constraints. The setup-related planning stages are followed by machine-specific operation planning, once the determined setup plans are downloaded to appropriate CNC controllers via the execution control function of DPP. Apart from the detailed planning of operation, the two-tier hierarchy of supervisory CAPP might be considered suitable for separating generic decisions from those specific to machines. In the present paper a feature-based reasoning approach is provided for generating machining sequence in the units of work setups, along with the associated assignment of machine alternatives (shown as shaded boxes in Fig.1), and presented in detail through following sections.

3.1. Generic machining process sequencing scheme

Capturing only geometric information of MFs themselves from a CAD model is insufficient for DPP, which also requires knowledge of technological rules and their suitable formalization. More recently, PMI representation is provided with modern CAD software to specify GD&T data which contains datum references, associated with edges and faces of a related part model. GD&T annotations become, after exporting to a STEP file, a part of the input information for CAPP. Digital form of PMI representation, associated with a CAD model, allows automated usage of represented GD&T data by CAPP functions to designate the feature precedence and to set datum references. The approach suggested in this research also assumes heavily reliance on input data model incorporating part functional requirements and in particular GD&T references. In this regards, currently available and suggested solutions, concerning the provision of necessary input data for supervisory CAPP have been outlined in **Fig. 2**.

The supervisory planning function of CAPP for machining the definite category of part types has been boiled down to determining generic setups, sequencing these setups and their constituent MFs. Generic process planning is accomplished in this research in the units of setups, utilising developed classification scheme (presented in the following section), based on the differentiators related to geometric properties and spatial relations among features of a workpiece as well as those associated with applied machining strategies. Features in particular are grouped into subsequent setups based on respected working directions, predefined ranked datum references, correspondingly to workpiece locating directions (setup orientation). Sequencing setups and feature precedence are decided based on the trade-off among the known and often conflicting geometry- and technology-related rules, given in adequately formalised form. In essence, this applies mainly to the multi-TAD features.

An extended feature classification for mill-turn part types, a.e. including both rotational and prismatic features was developed in this research, considering process capabilities of contemporary multi-axis CNC machine tools. The classification framework was assumed as underlying the reasoning approach to optimised process plan selection for parts with relatively high degree of complexity, commonly found in industrial practice.

3.1.1. Mill – turn parts related feature taxonomy

For process planning efficiency reasons, the authors propose an extended feature classification scheme correspondingly to the needs of rational process plan selection for addressed category of part types. It is meant to be applicable to machining rotational and prismatic features present in those parts, considering the use of machines of various configurations, and including advanced multi-axis milling or turning centres as well as multi-purpose machines. As indicated yet, adaptive setup defining in computer supported process sequencing boils itself to examining the tool accessibility for different types of machine tools. Hence, the developed classification scheme is based on such attributes: as feature working directions and their location, to perform all the working steps required by a given work part.

Thus, an individual feature F_i of a definite type can be denoted as an ordered four-tuple:

$$\boldsymbol{g_i} = [\cos\{\boldsymbol{TAD_i}, x_{wp}\}, \cos\{\boldsymbol{TAD_i}, y_{wp}\}, \cos\{\boldsymbol{TAD_i}, z_{wp}\}, L_{id}] \qquad (1)$$

where: $\cos\{\boldsymbol{TAD_i}, x_{wp}\}$, $\cos\{\boldsymbol{TAD_i}, y_{wp}\}$, $\cos\{\boldsymbol{TAD_i}, z_{wp}\}$ are the cosines of the angles between the axes of the workpiece coordinate system and the **TAD** of the feature (feature *z*-axis), and L_{id} – the numeric differentiator of feature location, set to 1 or 0: L_{id} = 1 if the feature symmetry axis/plane coincide with part datum axis or plane respectively, L_{id} = 0 if the tool axis during cutting or the feature symmetry axis or plane be off-datum axis or off-datum plane (positional features) or if the feature is asymmetric.

According to the feature location and orientation, commonly found turning and prismatic features can be classified into independent affiliation groups $\boldsymbol{g_h}$. As a result, the finite set G is formed of the generic feature affiliation groups $\boldsymbol{g_h}$, as follows:

$$G = \{g_h\}, \text{ where } h = 1, \ldots, h_{\max} \quad (2)$$

In the wake of the above, based on the analysis of processing capabilities of contemporary multi-axis CNC machines applied to machining mill-turn parts and related technological knowledge, a definite set of appropriate generic feature groups and classes could be designated, as reported in **Table 1**. Correspondingly, a mill-turn part shown in **Fig. 3** was used as an example to illustrate the concept of the implied classification scheme. According to the workpiece coordinate system in Fig.3 there exist three working directions (3 TADs) for machining the sample part. Two of them, and namely +*Z* and –*Z* also termed as “left” and “right” working directions respectively, coincide with the axis of part rotation (the datum axis). The third one defined as “side” direction is perpendicular to the other two, that is basically typical for part types under consideration. It is to be noted that such a part orientation allows to machine the rotated features, placed on part circumference, by means of a mill-turn machine. The work part selected includes distinctive features of various type and specific placement, which can be adequately assigned to the distinguished groups and classes, as shown in Table 1. There are typical turning features placed in-datum axis (L_{id} = 1) and accessible to a tool either from +*Z* or –*Z* TADs, falling into the groups $\boldsymbol{g}_1$ or $\boldsymbol{g}_2$ respectively, that require at least 2-axis lathes to be machined. Different values of the direction cosine (cos {$\boldsymbol{TAD}$, z_{wp}}) related to those feature imply the need for a setup change either by using a counter spindle or changing the work part position in the chuck by 180° for clamping it of the other side. Hence, a face (F_2), an axial hole (F_3) and an outer cylindrical surface (F_5) might be assigned to the group $\boldsymbol{g}_1$, while a face (F_1), outer cylindrical surface (F_4) along with the F_3 since it can be also accessed by a tool from -Z direction, to the group $\boldsymbol{g}_{2.}$ Due to the presence of features that have more than one TAD, like e.g. the feature F_3 mentioned above, the adequate reasoning schema based on GD&T, technological rules and good manufacturing practices must be followed. This is intended in order to ensure the appropriate assignment of each feature to a definite TAD, and will be discussed later in the following sections. Two more groups, as $\boldsymbol{g}_3$ and $\boldsymbol{g}_4$ of the C_2 class generally include typical milling or drilling positional features with off-datum axis location (L_{id} = 0), and with tool accessibility along the axis of part rotation. Such features can be symmetric or asymmetric and might require a 3-axis lathe equipped with driven tools or a 3-axis milling machine at the least, to be machined. The exemplary compound feature F_6 of four holes (Fig. 3) might be attributed both to the group $\boldsymbol{g}_3$ (cos {$\boldsymbol{TAD}_6$, z_{wp}} = 1) and to $\boldsymbol{g}_4$ (cos {$\boldsymbol{TAD}_6$, z_{wp}} = -1). The alternative assignments for F_6 are allowed because of same reason like in case of the F_3 feature, where the most suitable feature allocation be decided considering precedence relations that arise from tolerance and technological constraints. As seen, the rectangular pocket (F_7) has been assigned to the group g_4 (L_{id} = 0) even though its symmetry plane coincides with datum axis plane since while machining, the tool axis will move beyond the datum plane. The other two groups: $\boldsymbol{g}_5$ and $\boldsymbol{g}_6$, technologically similar to $\boldsymbol{g}_3$ and $\boldsymbol{g}_4$, are dedicated to features whose working directions are principally perpendicular to the main datum axis of a mill-turn part. Machining features attributed to the group $\boldsymbol{g}_5$ in particular would require at least a 3-axis lathe with driven tools or a 3-axis milling machine. The through slot F_8 (Fig. 3) whose symmetry plane passes through the part datum axis is due to be classified to $\boldsymbol{g}_5$ with L_{id} = 1, since the tool axis while its machining will be always in-datum axis. Wider slots whose machining need multi-passes of a tool in *y-z* plane would be qualified to the group $\boldsymbol{g}_6$ with L_{id} = 0, like the compound feature F_9 of two off-axis plane holes. Features affiliated to group $\boldsymbol{g}_6$ might be symmetric or asymmetric and require the use of at least a 4-axis turning centre with driven tools or a 4-axis milling machine for a complete part machining. The last of the listed features F_{10} which is a plane surface might be the representative one for a few groups including not only the most suitable $\boldsymbol{g}_3$ but also $\boldsymbol{g}_5$ or $\boldsymbol{g}_6$ groups. As suggested before its appropriate allocation would be chiefly decided by feature GD&T based relations, and manufacturing resource capabilities as indicated yet with regard to the assignment of the features F_3 or F_6.

A proposed method of a description of features composing mill-turn parts is relatively simple and based on commonly used, mostly in 3-axis machining, TAD with additional identification of their location with respect to datum features. It is devoted to mill-turn parts with typical turning and milling features by STEP-standard (AP224, AP 242). Its open architecture, however, allows for adding further groups and auxiliary identification numbers for new features of more complex parts requiring extended possibilities of machine tools like 5-axis lathes or milling machines. It can be also developed individually for specific set of available machine tools.

3.1.2. Representation scheme of feature relationships in an input data model

As mentioned earlier feature relationships strictly depend on the PMI representation with annotations related to GD&T data extracted from CAD models as the part of the input data for CAPP. The sample mill-turn workpiece, consisting of 16 MFs of definite technological requirements, is presented in **Fig. 4**. It is further used as an illustrative case study to explain the operation of developed reasoning approach to process selection and sequencing. The topological information accessible from a CAD model enables the determination of feature precedence relationships. For the sample workpiece, those relationships are represented by feature precedence graph and encoded in the feature precedence matrix FPM of 16 columns and 2 rows (**Fig. 5**). The matrix is formulated as: **FPM** = $[f_{ij}]_{i \le m,\, j \le n}$, where: m – the maximum number of required preceding features for a specific feature, n – the total number of features, and $f_{ij} < n$, as proposed by authors in [5]. The value of a single element of **FPM** matrix f_{ij} is strictly correlated with the readiness for machining corresponding feature #*j*. The numerical value 0 is assigned to the all initial features (of the highest level), in the first row of the **FPM** matrix. The child features are given then the values correspondingly to the numbers of directly preceding features. Hence, if the feature #*u* needs the feature #*v* to be completed, the value of $f_{1,u} = v$; and if the feature #*u* has more than one parent, e.g. the features: #*v* and #*w*, two elements: $f_{1,u} = v$, and $f_{2,u} = w$ occur in the column #*u*. The value of -1 for f_{ij} with $1 < i \le m$, $j \le n$, indicates no other relationships apart from those coded in the first row (i = 1).

In order to determine the feature precedence, the data input model needs to be supplemented with working directions for individual MFs and related positional tolerances, such as: circular and total run-out, parallelism, perpendicularity, angularity, position, concentricity, symmetry as well as angle and linear dimensional tolerances. This supplementary input information acquired from STEP file and associated with the test part is given in Table 2.

Clearly, interacting features make the determination of proper machining precedence more difficult. Hence, the detailed analysis of GPS specification is needed to streamline a decision making in generative setup planning and process sequencing. An appropriate datum reference frame (DRF) is designated as a reference coordination system, selected to secure the location of other features in the workpiece [26, 35, 36]. Owing to this, MFs with functional relationships, expressed in terms of tolerance types can be grouped together to be machined in specific single setups. Considering the above, based on the GPS specification and using adequate good machining practices, all the reference features for the test part were identified. The established datum features are given in the last column of **Table 2.** As it can be noted in the drawing of a sample work part (Fig. 4), the axis of feature F_3 coincides with the rotational reference axis of the part (indicated as the datum A). This might justify pointing out this entity as the primary datum axis. Moreover, machining features: F_1 and F_3 (as the adjacent face) were therefore selected as the primary locating surfaces. Those MFs are to be machined at the beginning of the process, with the reference to raw feature faces F_2 and F_6 located on the blank, which in turn were chosen as setup datum of a first rank.

3.1.3. Algorithm for generic machining process selection and sequencing

The alternative (generic) setup planning in CAPP applications not only needs to reason on the low-level CAD geometric and topology information including GD&T annotations but it also requires taking into account specific technological data. As indicated in the previous section (Table 2), it involves in particular the need for the specification of such attributes for each of the part feature, as: the working direction and its location as well as the determination of feature datum references within the DRF. As suggested in this research, the former attribute is denoted by means of the ordered four-tuple. The latter one in turn, associated with feature datum references might be assigned also by the user, accordingly to GD&T data specification, based on tolerance relationships and the adequate rules of machining technology.

A relevant algorithm for generic setup planning and process sequencing for the definite category of mechanical parts is discussed in this section, and depicted in the form of a flowchart in **Fig. 6**. Consequently, the developed algorithm utilises the implied input data components, along with the FPM matrix as its inseparable part, while assuming the procedure for simultaneous feature clustering and forming subsequent setups of generated process plan.

In order to enable an appropriate MF grouping and take control over the entire decision making process in the algorithm, the sequence of the datum references for a work part and their dependency has to be determined. Hence, at its preliminary stage, the datum dependency hierarchy is formulated using the matrix **DHM** = $[f_{rs}]_{r \le r\max,\, s \le s\max}$, with the numbers of designated features as its entries, where: r – the rank of datum reference termed respectively, as: primary –, secondary datum reference, etc., s – the number of reference (datum) features creating the specific datum reference. The related hierarchy of datum references (the rank order) can be established based on rules of machining practice and graph theory formulations [4]. The related task can be also accomplished by a suitable sorting algorithm, as reported in e.g. [1], where the item located at the top of sorting results would be the primary datum reference. As a matter of fact, a definite reference feature (RF) encompasses the set of all reference elements (faces). The appropriate **DHM** matrix determined by tolerance relationships among the MFs, and created for the illustrative instance based in particular on the specific data of Table 2, is given formally in **Fig. 7**.

It can be noted that for technological reasons, the reference faces (raw surfaces) of feature F_6 and F_2 have been selected as preliminary datum reference (of rank $r = 1$) and correspondingly a primary direction for workpiece locating, in prior to machined surfaces of F_3 and F_1 which constitute the primary datum reference ($r = 2$).

Thus, forming consecutive setups is strictly arranged according to the rank of datum references. Moreover, a significant role is attributed to the initiated feature placement and orientation matrix **FPOM o**f 4x4 dimensions. Therein, MF placement and orientation are determined within the workpiece coordinate system, defined through a set of workpiece linear coordinates and the direction cosines (each MF *z*-axis). Using that dummy matrix, respective features can be clustered by their attributes (the working direction and placement) into created subset(s) s_l associated with a relevant affiliation group (AG), and then the subsequent setups su_i. The iterative clustering procedure entails checking the involved features for readiness and the accessibility to be machined. The former is associated with considering constraints included in the **FPM** matrix, and the latter with the check of respective RFs for the envisaged feature, and consistently with those given in the **DHM** matrix. It should be noted that the expected transition to the next setup occurs with the change of working direction, whereas the entire reasoning process is continued until the respective set of features is emptied. As a result, the iterative reasoning framework designated as inherent for mill-turn parts, assumes searching for adequate features accessible to tools first along the direction parallel to rotational reference axis, and next along the direction perpendicular to it. The respective analysis could further incorporate the direction oblique to the part rotational axis, however, considering the extended need for intelligent process planning for five axis mill-turn part components, using multi-purpose machine tools. The developed algorithm used for the data related to the illustrative case generates seven subsets s_l of features forming the set SU of four setups su_i as it is shown in **Table 3**. Rank of the datum reference is the key index controlling feature clustering into subsets and setups. For a preliminary datum reference (of rank $r = 1$) two subsets s_1 and s_2 forming a subsequent setup su_1 are generated during two first iterations of a loop FOR ($k = 1, 2$). No subset is generated for a preliminary datum reference when the loop FOR repeats for $k = 3, 4$, although attributes of features F_{14}, F_{15} and F_{16} are coincided with adequate vectors $\mathbf{v} = \mathbf{FPOM}(k, :)$. Consecutive subsets $s_3 \div s_7$ are found and setups $su_2 \div su_4$ formed during iterations of a loop FOR after three successive changes of the working direction with respect to the reference z axis, using the formula ($\mathbf{FPOM}$(1:2, 3) = ($\mathbf{FPOM}$(1:2, 3)*(-1). In the illustrative case, the rank of the datum reference frame must be also changed ($r = r + 1$) after the transformation of the working direction, otherwise there is no access to the un-machined features. The detailed procedure of the proposed algorithm with the elements of Matlab code is presented numerically in Appendix A.

3.2. Setup merging for machining process alternatives

Setup is the commonly used job dispatching unit to assigned machines which is the domain of CAM. In this context the matter of importance was the consideration of the possibility for linking setups among machine tools available in a definite machining facility.

3.2.1. Modelling capabilities of machine resources

With regard to machine-specific level of the implied process planning scheme, it is assumed that machines available and taken into account in the planning procedure for analysed mill-turn parts constitute a finite set M:

$$M = \{m_n\},\ n = 1,\ldots,n_{\max}. \tag{1}$$

The process capability of a single machine m_n from the set M can be defined in terms of machining feasibility of generic feature groups g_h, what can be formally written in a vector $\mathbf{CM_n}$:

$$\mathbf{CM_n} = [g_{n,1}, \ldots, g_{n,h}]\ \forall m_n \in M,\ \forall g_h \in G \tag{2}$$

where: $g_{n,h} = 1$ if a group g_h is feasible on a machine m_n, and $g_{n,h} = 0$, if otherwise.

It allows in turn to assess the unique distribution of processing capabilities among different machine tools available in an existing machining facility in terms of shared and exclusive sets of definite feature groups and classes [37]. That is particularly essential for adaptive process planning and in particular appropriate process plan selection.

Referring to a set of analysed feature affiliation groups g_h (Table 1) the capabilities of four machine tools of a set M were defined using the notation of a vector $\mathbf{CM_n}$:

m_1: $\mathbf{CM}_1 = [1\ 1\ 1\ 1\ 1\ 1]$ – four-axis mill-turn (M-T) centre with controlled axes $\{x, y, z, c\}$

m_2: $\mathbf{CM}_2 = [1\ 1\ 1\ 1\ 1\ 0]$ – three-axis mill-turn (M-T) centre with controlled axes $\{x, z, c\}$,

m_3: $\mathbf{CM}_3 = [0\ 0\ 1\ 1\ 1\ 1]$ – three-axis milling centre M with controlled axes $\{x, y, z\}$,

m_4: $\mathbf{CM}_4 = [1\ 1\ 0\ 0\ 0\ 0]$ – two-axis lathe T with controlled axes $\{x, z\}$.

The generic description of machine capabilities in terms of determined feature affiliation groups shows that a four-axis mill-turn centre (m_1) has the highest technological possibilities and can be utilised for complete machining of mill-turn parts consisted of any feature corresponding to the set G – as outlined in **Fig. 8**. A two-axis lathe (m_4) is limited to typical turning features and a three-axis milling centre (m_3) to typical milling features. A three-axis mill-turn centre (m_2) does not provide all necessary **TAD**s for machining parts composed by any feature from a group g_6. Complete machining of such parts is infeasible on a machine m_2 and requires another machine tool: m_1 or m_3.

3.2.2. Adaptive setup merging and machine assignment

Adequate process alternatives can be generated through adaptive setup merging, under consideration of availability and processing capabilities of machine tools. The relevant algorithm developed and appropriated for machine assignments to generated setups is depicted in **Fig. 9**. This algorithm explores the possibility for allotting individual machines from a set M, with the capabilities encoded in the vector $\mathbf{CM}_n$, to the set SU of consecutive (generic) setups su_i formed by the algorithm outlined in section 3.1.3. Accordingly, the single setup su_i is included into the newly created set S_n related to a definite machine m_n if all associated features belonging to the specific generic group(s) g_h (see Table 3) can be machined on it. Merging the determined setups on a single machine m_n is feasible if all setups from SU can be realised on that machine. Merging setups across different machines allows to distinguish other process alternatives, only if machining all designated features is feasible using those machines. If this condition is not met, such a concept of setup merging is infeasible in a specified system.

The following sets S_n of setups su_i, feasible on available machines respectively, are created by the algorithm for the illustrative case of machining a mill-turn part:

$S_1 = \{su_1, su_2, su_3, su_4\}$ for m_1,

$S_2 = \{su_1, su_2, su_3\}$ for m_2,

$S_3 = \{ su_3, su_4\}$ for m_3,

$S_4 = \varnothing$ for m_4.

Under the circumstance, both types of setup merging can be considered in studied case. As seen, merging the setups su_i on a single machine is feasible only for m_1, as the set S_1 has the cardinality of $i_{max} = 4$. After excluding m_1 from the set M, other process alternatives are possible with merging setups across machines m_2 and m_3 due to the condition $|S_2 \cup S_3| = 4$. Setup realisation is impossible on m_4 because the set S_4 has the cardinality of 0, although features from the subsets s_1 and s_3 can be made on that machine. Process capabilities of machines available for part fabrication in the provided case study are depicted in Table 4. Consequently, all the feasible process sequences for the exemplary part of the demonstrative case study can be depicted in the form of a graph model, based on formalism of the Business Process Modelling Notation (BPMN) [38], as shown in **Fig. 10**. Accordingly, the sequence model contains, in particular, such routing constructs, as: XOR decision gateways for selecting one out of a set of mutually exclusive machine alternatives for the determined (generic) part setups (i.e. XOR – split) as well as XOR merge gateways (XOR – join) for joining the mutually exclusive machine alternatives into a definite process sequence. As a result, 24 process alternatives might be discerned for the discussed instance, which are denoted as adequate machine sequences. Among them, there are 15 combinations of process sequences without unnecessary backtracking part moves to machines previously used in machining the part (machine repetitions). The proper decision on machine allocation to consecutive setups under the circumstances of nonlinear process planning and dynamic environment is due to be made based on the criteria of maximised process efficiency and/or minimised total cost, as proposed in [13]. Searching for the optimum machine assignment alternatives can be accomplished by means of a branch and bound method that was successfully applied to solve this type of task in [5, 20].

Machining shops might be considered as Flexible Manufacturing Systems (FMSs) with inherent routing flexibility that basically operate in dynamic conditions and follow the Make-to-Order (MTO) strategy for handling orders in selected time periods. Thus, in the proposed approach, due-date short-term scheduling strategy is envisaged that allows for the resource pre-emptions. Therein, relevant schedules are developed at the stage of execution control, considering the constantly monitored status of available machine resources.

Consequently, operation sequencing can be successfully performed using the rule of minimum remaining slack, as the priority rule of parts at time t [39].

The rule can be formally defined, as given below:

$$Z_k(t) = D_k - t - P_{k,j(t)} \rightarrow \min \qquad (3)$$

where: t – time at which a scheduling decision is to be made, k –part type index, j – operation index, D_k – due date of a part of type k, and $P_{k,j(t)}$ – sum of processing times for all operations following (and including) the j-th operation of a part type k.

The Work-in-Next-Queue (WINQ) heuristic widely used with regard to operational planning of FMSs [39] is suggested as job dispatching rule to available machine tools. It entails selecting that machine to process the next operation for a definite part which has the least work, i.e. the machine with minimum priority value of $Z_m(t)$ at time t, defined as follows:

$$Z_m(t) = W_{k,j+1,m}(t) \quad for \quad m \in M_{k,j+1}, \qquad (4)$$

where: m – machine index, $M_{k,j+1}$ – subset of machines capable of processing the ($j+1$)-th operation of the k-th part type, $W_{k,j+1,m}(t)$ – total work content of the m-th machine queue, i.e., the sum of the imminent operation times of the $N_{k,j+1,m}(t)$ parts in that queue, correspondingly to the ($j+1$)-th operation of the k-th part type at time t.

The developed approach assumes that decisions on merging generated setups into operations are made in a dynamic manner, based on the event driven approach. Thus, the remaining slack times for parts are computed at time intervals, determined by the termination time of consecutive part setups, and included in the prototyped schedule. The specific optimisation task boils itself to finding the best way of distributing the generic process plan among available machines and proper merging the assigned setups together. Thereby, the objective function of the optimization model is aimed at the minimising the total number of machine changeovers. In this light, the appropriate alternatives of process sequencing with respect to machining the part type used in the illustrative case study have been outlined in **Fig. 11**, as the excerpts of prototyped operational schedules.

4. Discussions

In production engineering practice, process planning is often accomplished irrespective of resource availability on a definite shop floor. This is due to the missing interconnection with the downstream engineering functions including scheduling or job dispatching. Hence, targeting decentralisation in CAPP system should be recognised as the appropriate strategy. Considering the above and the class of parts represented by the test part of the case study, a multi-level hierarchical approach to setup planning and operation sequencing in generative CAPP was developed by the authors. The proposed algorithmic framework possesses similar functionalities, including the aspects of adaptability, as compared to systems presented in outcomes of the EU-funded FP7 project, and reported in detail in e.g. [3, 28-30]. It remains in effect except for the issues related to monitoring the manufacturing resources via a sensor network which is beyond the scope of the research work. The novelty of the proposed system, relative to aforementioned ones, lies in supporting process planning activity with the use of the data information model that includes machine related feature taxonomy and the generic description of the machine tool capabilities in terms of determined feature affiliation groups. The consecutive benefit of our approach is a dynamic merging generated setups into operations at the execution control level considering capability and availability of machine resources. This can significantly increase the productivity owing to rapid adjustment to changing manufacturing environment. As a result, machines downtime in a machining facility and the impact of uncertainty can be minimised under dynamic environment of system operation. Machine alternatives in routing constructs are denoted with the use of XOR decision gateways. Those might be readily implemented using the technology of FBs with embedded optimization algorithms on the manufacturing equipment, as advocated in papers dealing with distributed adaptive CAPP based on FBs and Cloud concept [3, 28-30].

5. Conclusions

The feature-based reasoning approach for generating machining sequence along with the dynamic assignment of machine alternatives is provided in this research considering the adaptability as the essential principle. It assumes the reliance on input data model incorporating part functional requirements and GD&T references. The extended feature classification for addressed category of part types, with the unique encoding manufacturing and topological information as an ordered four-tuple are proposed. It is meant to be applicable to machining of both rotational and prismatic features present in mill-turn parts, with regard to the use of machines of various configurations. The developed classification scheme is based on such attributes as feature working directions and their location, to efficiently perform all the working steps required by a given work part. With the use of the proposed taxonomy and based on the analysis of processing capabilities of contemporary multi-axis CNC machines applied to machining mill-turn parts and related technological knowledge, a definite set of appropriate generic feature groups and classes could be designated.

Data related to machining and the attributes of datum features, represented in numerical form and used in the relevant algorithm, allow for the allocation of MFs to determined affiliation groups, and generating subsequent of setups. Moreover, a unique algorithm, appropriated for the assignment of machine resources to generated setups has been proposed. Adequate alternatives of process solutions can be generated through adaptive setup merging on a single machine or across available machines under consideration of related processing capabilities. As a result, machines downtime in a machining facility and the impact of uncertainty can be minimised under dynamic system operation environment. The main contribution and benefits of this work can be summarised as:

- Unique information data model based on formalised description of machining features for mill-turn parts, including feature tolerance relationships as well as the feature location and orientation irrespective of machine tool coordinate system;
- Rapid formulation of generic consecutive machine-neutral (generic) setups as feature clusters by established working directions, using the reasoning scheme of an iterative algorithm;
- Provision of robust process planning and job dispatching facility under consideration of the availability and the capabilities of machine resources in order to minimize machines downtime and the impact of the uncertainty factor under dynamic environment of the system operation;
- Possibility for merging generated setups into operations in a dynamic manner, based on the event driven approach and FMS-related mechanical parts manufacturing;
- Development of relevant operational schedules for machines at the execution control level, considering their capabilities and the availability status in definite time frames.

Our further research aims at coupling the developed process selection and sequencing approach with DPP activities, through expanding the modelling scheme and in particular the extension of proposed feature classification by more complex multi-axis parts. Part routings modelled with the use of XOR decision gateways can be transformed into event driven FBs with embedded optimization algorithms on the manufacturing equipment. The application of an appropriate data acquisition system as a supplement to the developed framework might allow for the utilization of a Cloud-based manufacturing approach to support optimal process planning.

Appendix A

The following calculations with the elements of Matlab code describe the developed algorithm presented in Figure 6, using numerical data related to the illustrative case.

Acknowledgments

Computations carried out with the use of software and computers from Academic Computer Centre in Gdansk - TASK (http://www.task.gda.pl).

Figure and Table captions:

Fig. 1. Outline of the system solution for optimal process plan selection in CAPP applications

Fig. 2. Extracting the input data from CAD models for supervisory process planning

Fig. 3. Exemplary mill-turn sample part type inclusive various feature types and the working directions (designated as the vectors of computed direction cosines), and used with MF taxonomy

Fig. 4. A sample work part used in an illustrative case study with selected technological and some geometrical requirements, along with the specification of present machining features F_i

Fig. 5. Feature precedence graph (a) and the related **FPM** matrix for the sample workpiece (b), utilised as an illustrative case study

Fig. 6. Flowchart of the algorithm for generic process selection and sequencing for mill-turn parts

Fig. 7. Datum dependency hierarchy matrix (**DHM**) for the instance case study

Fig. 8. Distribution of individual machine capabilities in terms of definite feature affiliation groups (and classes)

Fig. 9. Flowchart of the algorithm for the assignment of machine alternatives to generated setups

Fig. 10. Graph model of alternative process sequences for the workpiece of the illustrative case study

Fig. 11. Prototype schedule solutions with alternative process sequences related to machining the part of the case study; merging all setups into a single operation performed on m_1 machine (a), merging setups across m_2 and m_3 machines and forming two operations (b), a variant with setup merging across m_2 and m_3, with the pre-emption of the former resource (c)

Table. 1. Specification of distinctive (generic) feature affiliation groups and classes

Table. 2. Machining feature oriented information data model of the test part

Table. 3. Results of feature clustering and their assignment into the setups determined in the provided case study

Table. 4. Process capabilities of available machine tools with respect to part setups determined in the illustrative case study research

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Figure 1

Figure 1

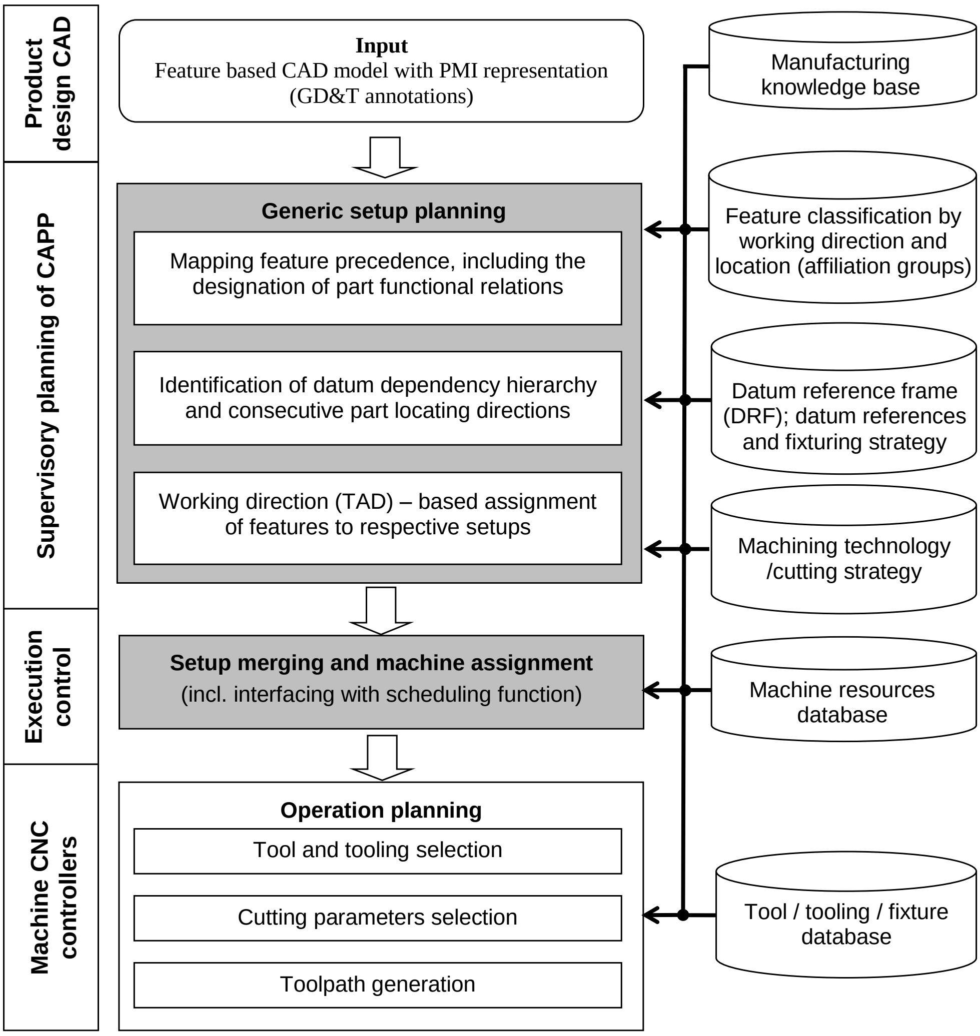

Fig. 1. Outline of the system solution for optimal process plan selection in CAPP applications

"Machining process sequencing and machine assignment in generative feature-based CAPP for mill-turn parts"

M. DEJA & M.S. SIEMIATKOWSKI

Figure 2

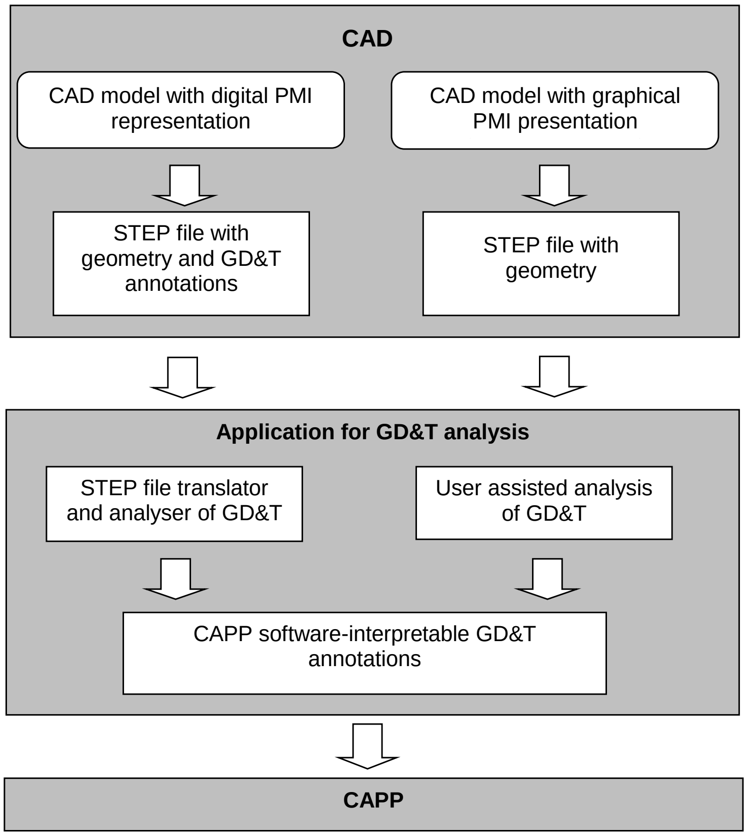

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Figure 3

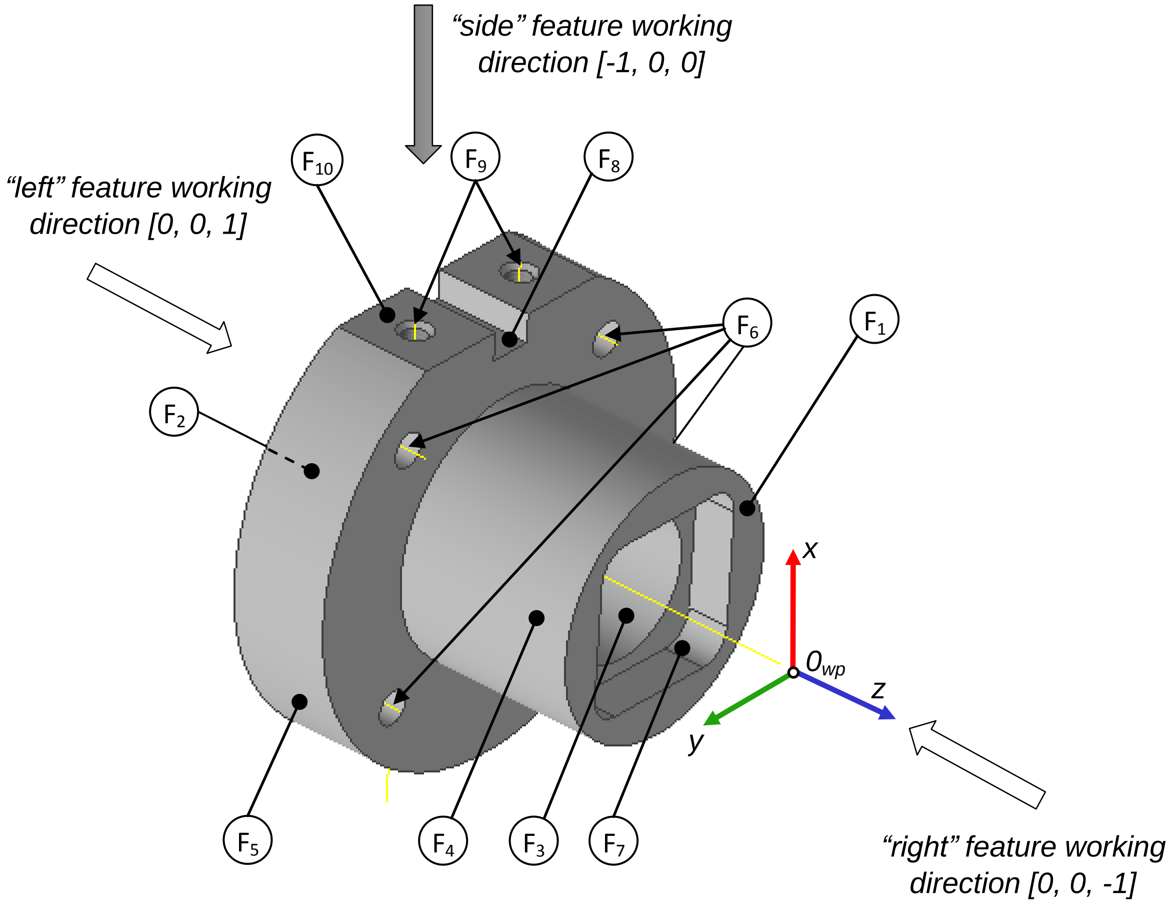

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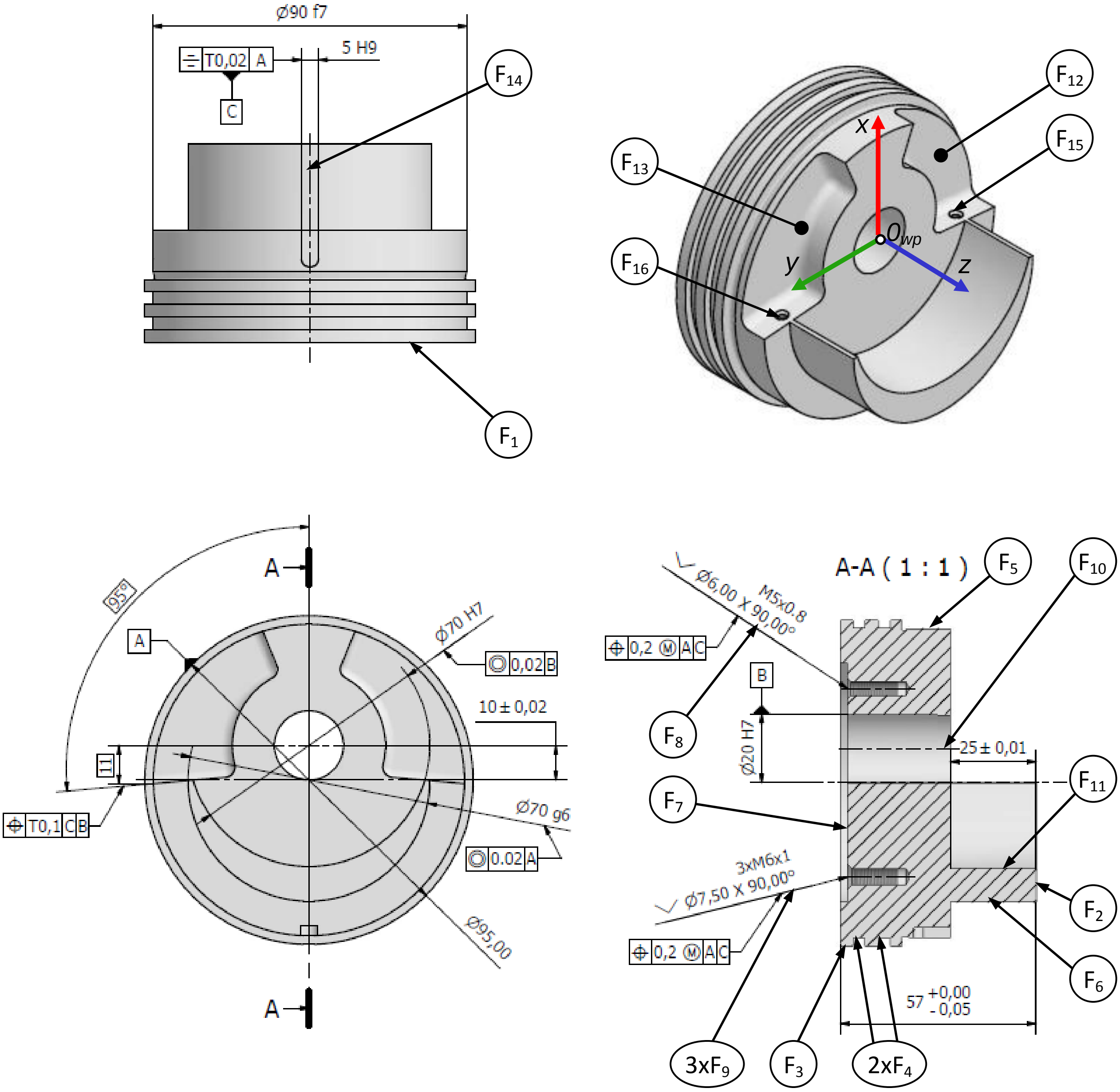
Figure 4



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“Machining process sequencing and machine assignment in generative feature-based CAPP for mill-turn parts”

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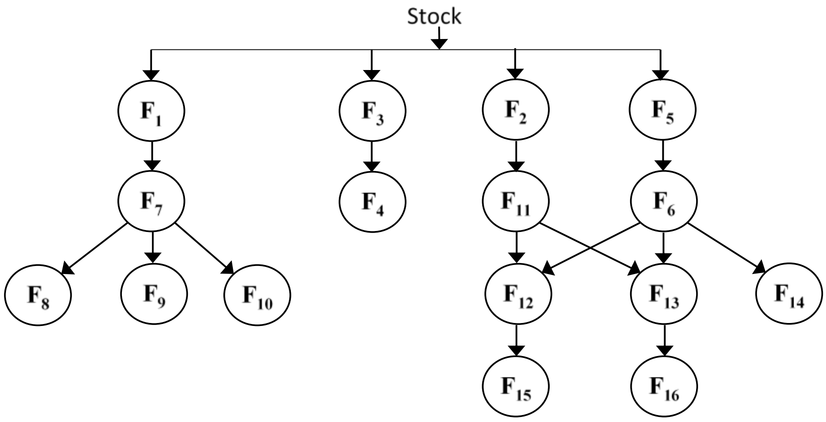
Figure 5

a)



b)

Feature #	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}	F_{13}	F_{14}	F_{15}	F_{16}
FPM =	0	0	0	3	0	5	1	7	7	7	2	6	6	6	12	13
	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	11	11	-1	-1	-1

Fig. 5. Feature precedence graph (a) and the related **FPM** matrix for the sample workpiece (b), utilised as an illustrative case study

"Machining process sequencing and machine assignment in generative feature-based CAPP for mill-turn parts"

M. DEJA & M. S. SIEMIATKOWSKI

Figure 6

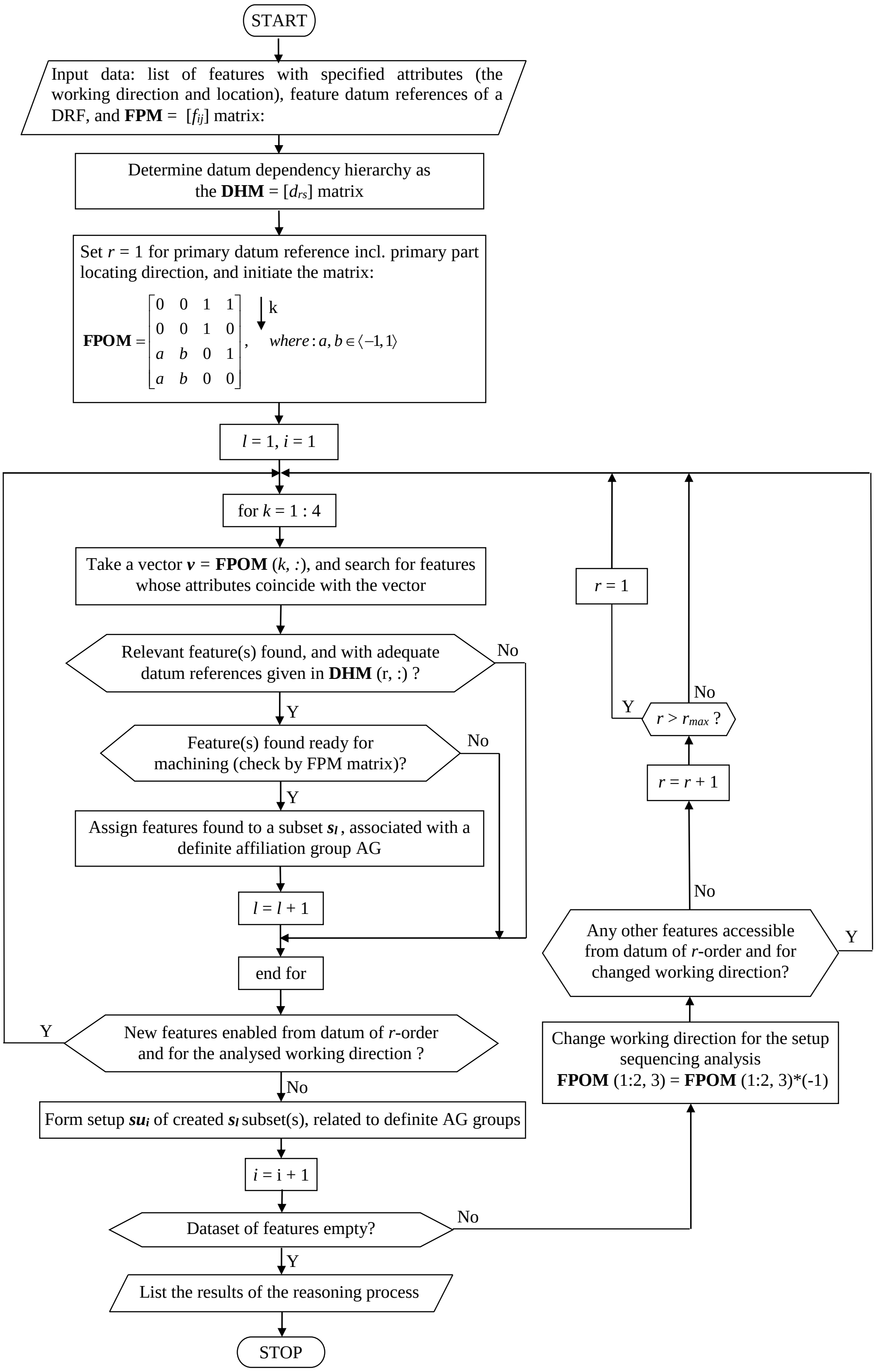


Fig. 6. Flowchart of the algorithm for generic process selection and sequencing for mill-turn parts

“Machining process sequencing and machine assignment in generative feature-based CAPP for mill-turn parts”

Figure 7

$$\mathbf{DHM} = \begin{bmatrix} 6\,(\boldsymbol{raw}) & 2\,(\boldsymbol{raw}) & 0 \\ 3 & 1 & 0 \\ 6 & 2 & 14 \\ 10 & 1 & 14 \end{bmatrix}$$

Fig. 7. Datum dependency hierarchy matrix (**DHM**) for the instance case study

"Machining process sequencing and machine assignment in generative feature-based CAPP for mill-turn parts"

M. DEJA & M. S. SIEMIATKOWSKI

Figure 8

Figure 8

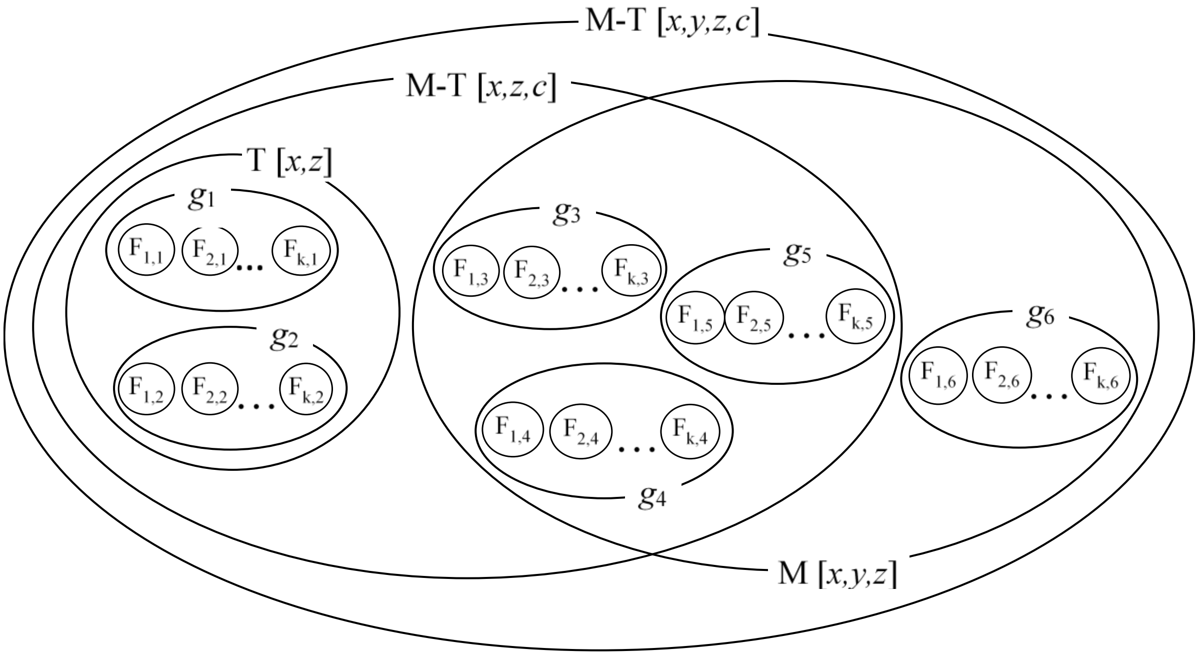


Fig. 8. Distribution of individual machine capabilities in terms of definite feature affiliation groups (and classes)

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Figure 9

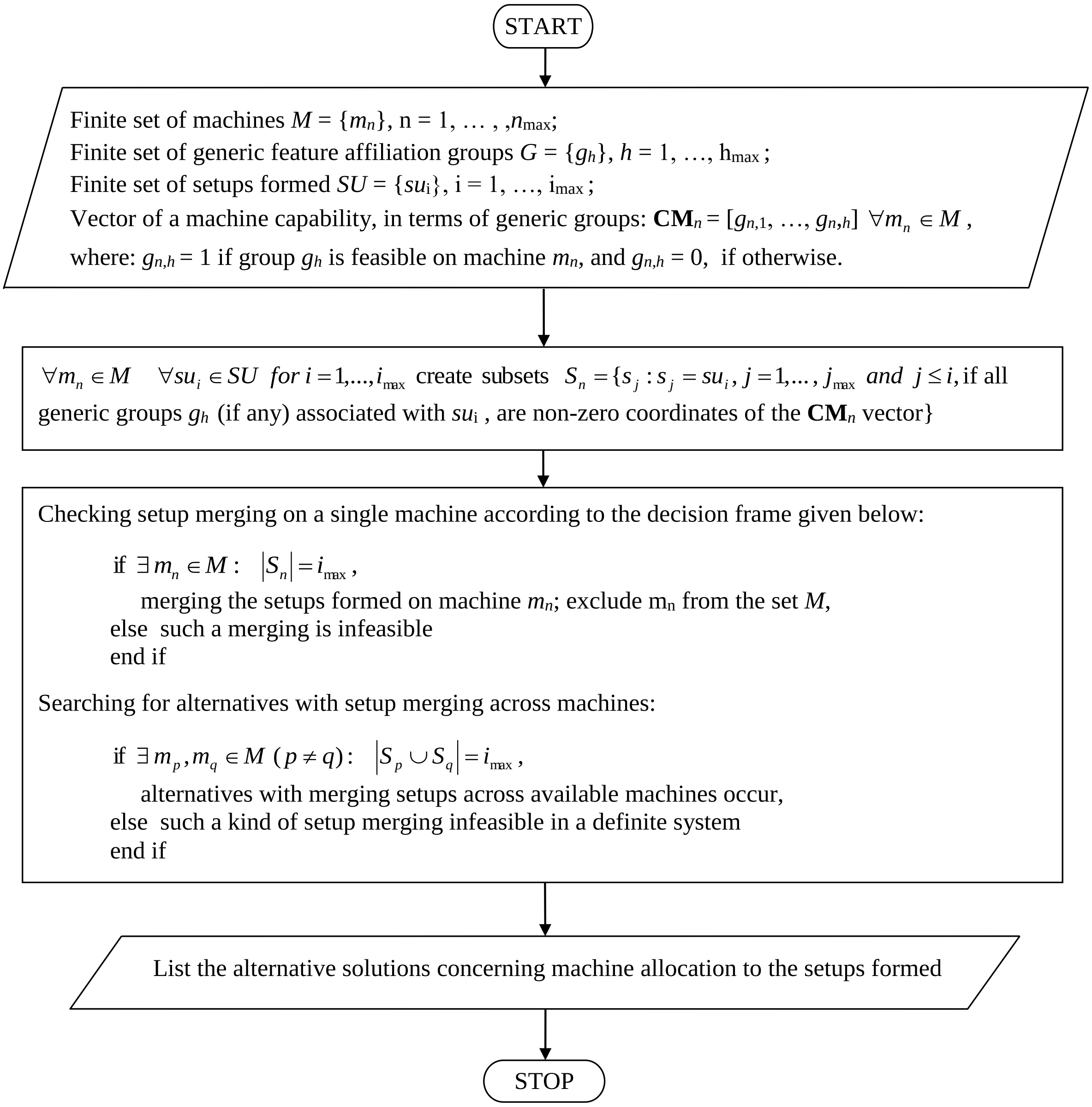

Fig. 9. Flowchart of the algorithm for the assignment of machine alternatives to generated setups

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Figure 10

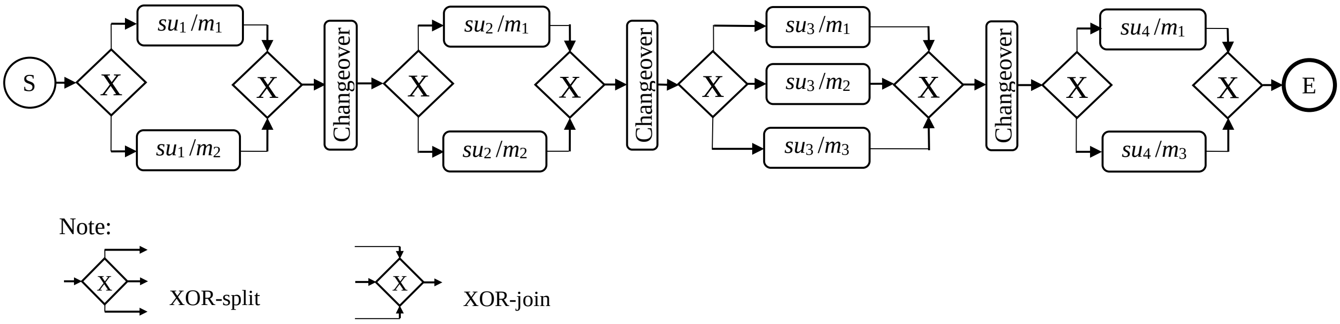

Fig. 10. Graph model of alternative process sequences for the workpiece of the illustrative case study

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Figure 11

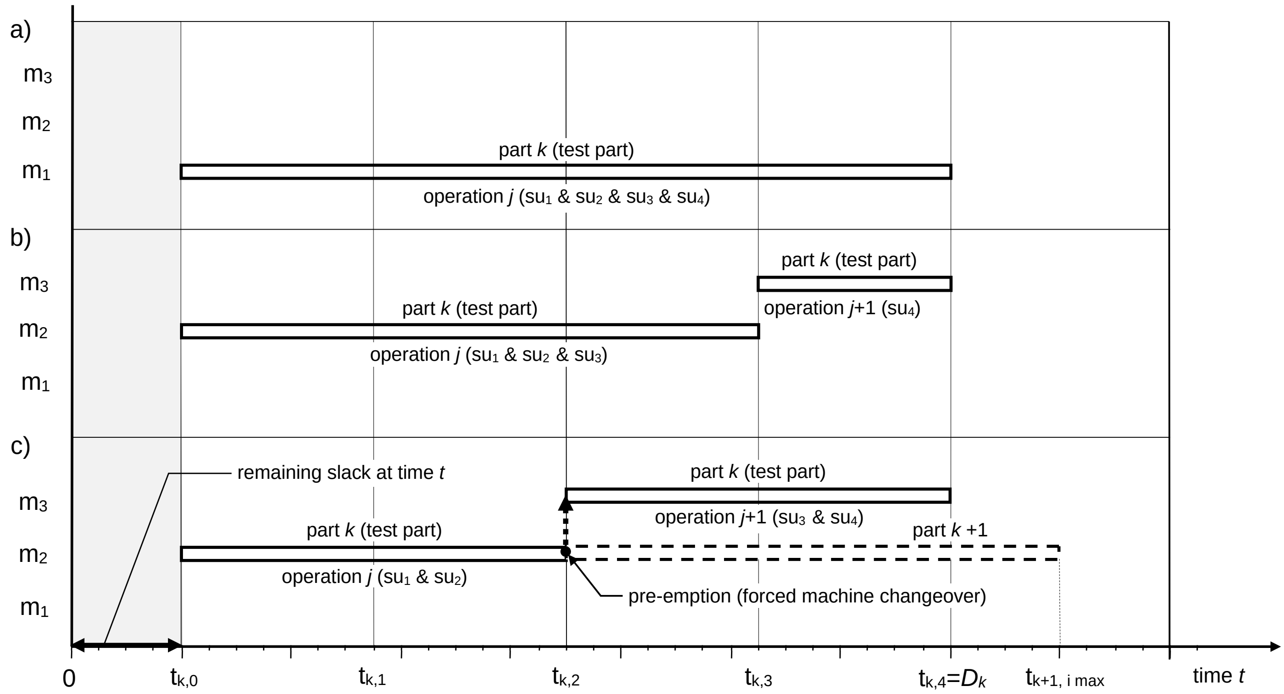

Fig. 11. Prototype schedule solutions with alternative process sequences related to machining the part of the case study; merging all setups into a single operation performed on m_1 machine (a), merging setups across m_2 and m_3 machines and forming two operations (b), a variant with setup merging across m_2 and m_3, with the pre-emption of the former resource (c)

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Table 1

Table. 1. Specification of distinctive (generic) feature affiliation groups and classes

Feature class and affiliation group		Feature working direction and location*)	Representative features denoted for a sample part in Fig. 3
C_1	g_1	[0, 0, 1, 1]	F_2, F_3, F_5
	g_2	[0, 0, -1, 1]	F_1, F_3, F_4
C_2	g_3	[0, 0, 1, 0]	F_6, F_{10}
	g_4	[0, 0, -1, 0]	F_6, F_7
C_3	g_5	[a, b, 0, 1]	F_8, F_{10}
C_4	g_6	[a, b, 0, 0]	F_9, F_{10}

*) given with respect to workpiece linear coordinate system O_{wp}, as the ordered four-tuple; $a, b \in <-1, 1>$

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Table 2

Table 2. Machining feature oriented information data model of a test part

Feature surface face #/ type	Feature attributes (working direction and feature placement) as an ordered four-tuple: [x, y, z, location id.]	Feature relationships by GPS specification in GD&T scheme given as a tolerance type						Reference (datum) feature(s) in determined DRF
		Angle / linear dimensional tolerance	Positional tolerance					
			Orientation tolerance		Location tolerance			
			⊥	//	◎	⌖	⌯	
1	2	3	4	5	6	7	8	9
F_1/Face**	[0, 0, 1, 1]	F_2 (raw)	F_3					F_6 (raw) $\wedge$ F_2 (raw)
F_2/Face**	[0, 0, -1, 1]	F_1		F_1				$F_3 \wedge F_1$
F_3/outer cylindrical*	[0, 0, 1, 1]	F_6 (raw)						F_6 (raw) $\wedge$ F_2 (raw)
F_4/cylindrical outer groove	[0, 0, 1, 1]	F_1			F_3			F_6 (raw) $\wedge$ F_2 (raw)
F_5/ outer cylindrical	[0, 0, -1, 1]	F_2			F_3			$F_3 \wedge F_1$
F_6/ outer cylindrical*	[0, 0, -1, 1]	F_2			F_3			$F_3 \wedge F_1$
F_7/cylindrical pocket	[0, 0, 1, 1]	F_1						F_6 (raw) $\wedge$ F_2 (raw)
F_8/compound feature (3 tapped holes)	[0, 0, 1, 0]	F_7				F_{14}		$F_6 \wedge F_2 \wedge F_{14}$
F_9/tapped hole	[0, 0, 1, 0]	F_7				F_{14}		$F_6 \wedge F_2 \wedge F_{14}$
F_{10}/off-datum axis hole*	[0, 0, 1, 0]	F_3	F_1	F_3				F_6 (raw) $\wedge$ F_2 (raw)
F_{11}/eccentric hole	[0, 0, -1, 0]	F_2			F_{10}			$F_{10} \wedge F_1 \wedge F_{14}$
F_{12}/three-sided pocket	[0, 0, -1, 0]	F_{10}, F_{11}				F_{14}		$F_{10} \wedge F_1 \wedge F_{14}$
F_{13}/three-sided pocket	[0, 0, -1, 0]	F_{10}, F_{11}				F_{14}		$F_{10} \wedge F_1 \wedge F_{14}$
F_{14}/blind slot in datum axis plane***	[1, 0, 0, 1]	F_5					F_3	$F_3 \wedge F_1$
F_{15}/off-axis plane hole	[-0,9962, -0,0872, 0, 0]	F_{10}, F_{11}						$F_{10} \wedge F_1 \wedge F_{14}$
F_{16}/off-axis plane hole	[-0,9962, 0,0872, 0, 0]	F_{10}, F_{11}						$F_{10} \wedge F_1 \wedge F_{14}$

Note: *) – primary datum axis, incl. A&B; **) – secondary datum plane; ***) – tertiary datum feature (C)

Table 3

Table. 3. Results of feature clustering and their assignment into the setups determined in the provided case study

Rank of the setup datum and related feature(s)	Generic feature affiliation group (g_h)	Feature cluster	Feature subset designated (s_l)	Setup # (su_i)
r = 1: F_6 (raw) $\wedge$ F_2 (raw)	g_1	{F_1, F_3, F_4, F_7}	s_1	su_1
	g_3	{F_{10}}	s_2	
r = 2: $F_3 \wedge F_1$	g_2	{F_2, F_5, F_6}	s_3	su_2
	g_5	{F_{14}}	s_4	
r = 3: $F_6 \wedge F_2 \wedge F_{14}$	g_3	{F_8, F_9}	s_5	su_3
r = 4: $F_{10} \wedge F_1 \wedge F_{14}$	g_4	{F_{11}, F_{12}, F_{13}}	s_6	su_4
	g_6	{F_{15}, F_{16}}	s_7	

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Table 4

Table. 4. Process capability of available machine tools with respect to part setups determined in the illustrative case study research

Determined setup # (su_i)	Machine set M			
	m_1	m_2	m_3	m_4
su_1	s_1	s_1		s_1
	s_2	s_2	s_2	
su_2	s_3	s_3		s_3
	s_4	s_4	s_4	
su_3	s_5	s_5	s_5	
su_4	s_6	s_6	s_6	
	s_7		s_7	

where: m_1 - 4-axis mill-turn centre, {x, y, z, c}; m_2 - 3-axis mill-turn, {x, z, c}, m_3 – 3-axis mill centre, {x, y, z}, m_4 – CNC lathe {x, z}

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Appendix A

START

INPUT:

Feature attributes	Datum features
a=0.9962	
b=0.0872	
F_ATTR=[...	F_Datum=[...
0 0 1 1	-6 -2 0
0 0 -1 1	3 1 0
0 0 1 1	-6 -2 0
0 0 1 1	-6 -2 0
0 0 -1 1	3 1 0
0 0 -1 1	3 1 0
0 0 1 1	-6 -2 0
0 0 1 0	6 2 14
0 0 1 0	6 2 14
0 0 1 0	-6 -2 0
0 0 -1 0	10 1 14
0 0 -1 0	10 1 14
0 0 -1 0	10 1 14
1 0 0 1	3 1 0
-a -b 0 0	10 1 14
-a b 0 0]	10 1 14]
FPM =[0 0 0 3 0 5 1 7 7 7 2 6 6 6 12 13 ... -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 11 11 -1 -1 -1]	

Step #1: *Determination of DHM matrix – explained in a text*

```
DHM=[...
    -6 -2  0
     3  1  0
     6  2 14
    10  1 14]
```

Step #2: r=1

```
FPOM=[...
      0 0 1 1
      0 0 1 0
      a b 0 1
      a b 0 0], where: a,b <-1,1>
```

Step #3: l = 1, i = 1

START loop ***for***

Actual datum references: **DHM**(r,:) = **DHM**(1,:) = [-6 -2 0]

First iteration of a loop ***for***, k = 1
v = **FPOM**(k,:) = **FPOM**(1,:) = [0 0 1 1]

Relevant features found?

function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)

```
function [F_number] = relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)
F_number=find(F_ATTR(:,1)==FPOM(k,1)& F_ATTR(:,2)==FPOM(k,2)...
    & F_ATTR(:,3)==FPOM(k,3) & F_ATTR(:,4)==FPOM(k,4) ...
    & F_Datum(:,1)==DHM(r,1) & F_Datum(:,2)==DHM(r,2) ...
    & F_Datum(:,3)==DHM(r,3))
end

F_number =

     1
     3
```

4
7

Yes: F_1, F_3, F_4, F_7

Features ready for machining?

Checking FPM matrix – the detailed algorithm in (Deja & Siemiatkowski 2013)

```
FPM =[ 0  0  0  3  0  5  1  7  7  7  2  6  6  6 12 13 ...
      -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 11 11 -1 -1 -1]
```

Yes: F_1, F_3, F_4 (after F_3), F_7 (after F_1)

$s_l = s_1 = \{ F_1, F_3, F_4, F_7\}$

l = 2

second iteration of a loop ***for***, *k* = 2

v = **FPOM**(k,:) = **FPOM**(2,:) = [0 0 1 0]

Relevant features found?

function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)

Yes: F_{10}

Features ready for machining?

Checking FPM matrix

```
FPM =[ 0  0  0  3  0  5  1  7  7  7  2  6  6  6 12 13 ...
      -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 11 11 -1 -1 -1]
```

Yes: F_{10} (after F_7)

$s_l = s_2 = \{F_{10}\}$

l = 3

Third iteration of a loop ***for***, *k* = 3

v = **FPOM**(k,:) = **FPOM**(3,:) = [a b 0 1], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?

function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)

```
function [F_number] = relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)
F_number=find(F_ATTR(:,1)>=-1 & F_ATTR(:,1)<=1 & F_ATTR(:,2)>=-1 ...
    & F_ATTR(:,2)<=1 & F_ATTR(:,3)==FPOM(k,3) & F_ATTR(:,4)==FPOM(k,4) ...
    & F_Datum(:,1)==DHM(r,1) & F_Datum(:,2)==DHM(r,2) ...
    & F_Datum(:,3)==DHM(r,3))
end

ans =
   Empty matrix: 0-by-1
```

No

Fourth iteration of a loop ***for***, *k* = 4

v = **FPOM**(k,:) = **FPOM**(4,:) = [a b 0 0], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?

function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)

No

END loop *for*

Step #4: New non-machined features enabled? **No**

Step #5: $su_i = su_1 = \{s_1, s_2\}$

Step #6: *i* = 2

Step #7: Dataset of non-machined features empty? **No**

Step #8: **FPOM**(1:2,3)=**FPOM**(1:2,3).*(-1)

```
FPOM=[...
      0 0 -1 1
```

```
0 0 -1 0
a b  0 1
a b  0 0], where: a,b <-1,1>
```

Step #9: Any other features accessible from datum of r-order? NO

Step #10: r **=** 2

Step #11: r > r_{max}? NO

START loop ***for***

Actual datum references: **DHM**(r,:) = **DHM**(2,:) = [3 1 0]

First iteration of a loop ***for***, k = 1
v = **FPOM**(k,:) = **FPOM**(1,:) = [0 0 -1 1]

Relevant features found?
function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)
Yes: F_2, F_5, F_6

Features ready for machining?
Checking FPM matrix

```
FPM =[  0   0   0   3   0   5   1   7   7   7   2   6   6   6  12  13 ...
       -1  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1  11  11  -1  -1  -1]
```

Yes: F_2, F_5, F_6 (after F_5)

s_l = s_3 = {F_2, F_5, F_6}

l = 4

Second iteration of a loop ***for***, k = 2
v = **FPOM**(k,:) = **FPOM**(2,:) = [0 0 -1 0]

Relevant features found?
function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)
No

Third iteration of a loop ***for***, k = 3
v = **FPOM**(k,:) = **FPOM**(3,:) = [a b 0 1], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?
function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)
Yes: F_{14}

Features ready for machining?
Checking FPM matrix

```
FPM =[  0   0   0   3   0   5   1   7   7   7   2   6   6   6  12  13 ...
       -1  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1  11  11  -1  -1  -1]
```

Yes: F_{14} (after F_6)

s_l = s_4 = {F_{14}}

l = 5

Fourth iteration of a loop ***for***, k = 4
v = **FPOM**(k,:) = **FPOM**(4,:) = [a b 0 0], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?
function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)
No

END loop *for*

Step #4; New non-machined features enabled? NO

Step #5; su_i = su_2 = {s_3, s_4}

Step #6; i = 3

Step #7; Dataset of non-machined features empty? NO

Step #8; **FPOM**(1:2,3)=**FPOM**(1:2,3).*(-1)

```
FPOM=[...
      0 0 1 1
      0 0 1 0
      a b 0 1
      a b 0 0], where: a,b <-1,1>
```

Step #9; Any other features accessible from datum of r-order? NO

Step #10; r **=** 3

Step #11; r > r_{max}? NO

Actual datum references: **DHM**(r,:) = **DHM**(3,:) = [6 2 14]

First iteration of a loop ***for***, k = 1
v = **FPOM**(k,:) = **FPOM**(1,:) = [0 0 1 1]

Relevant features found?
function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)
No

second iteration of a loop ***for***, k = 2
v = **FPOM**(k,:) = **FPOM**(2,:) = [0 0 1 0]

Relevant features found?
function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)
Yes: F_8, F_9

Features ready for machining?
Checking FPM matrix

```
FPM =[  0   0   0   3   0   5   1   7   7   7   2   6   6   6  12  13 ...
       -1  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1  11  11  -1  -1  -1]
```

Yes: F_8(after F_7), F_9 (after F_7)

s_l = s_5 = {F_8, F_9}

l = 6

Third iteration of a loop ***for***, k = 3
v = **FPOM**(k,:) = **FPOM**(3,:) = [a b 0 1], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?
function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)
No

Fourth iteration of a loop ***for***, k = 4
v = **FPOM**(k,:) = **FPOM**(4,:) = [a b 0 0], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?
function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)
No

END loop *for*

Step #4; New non-machined features enabled? NO

Step #5; su_i = su_3 = {s_5}

Step #6; i = 4

Step #7; Dataset of non-machined features empty? NO

Step #8; **FPOM**(1:2,3)=**FPOM**(1:2,3).*(-1)

```
FPOM=[...
      0 0 -1 1
      0 0 -1 0
      a b  0 1
      a b  0 0], where: a,b <-1,1>
```

Step #9; Any other features accessible from datum of r-order? NO

Step #10; *r* **=** 4

Step #11; *r* > r_{max}? NO

Actual datum references: **DHM**(r,:) = **DHM**(4,:) = [10 1 14]

First iteration of a loop ***for***, k = 1
v = **FPOM**(k,:) = **FPOM**(1,:) = [0 0 -1 1]

Relevant features found?
function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)
No

Second iteration of a loop ***for***, *k* = 2
v = **FPOM**(k,:) = **FPOM**(2,:) = [0 0 -1 0]

Relevant features found?
function: relevant1(r,k,F_ATTR,FPOM,F_Datum,DHM)
Yes: F_{11}, F_{12}, F_{13}

Features ready for machining?
Checking FPM matrix

```
FPM =[ 0  0  0  3  0  5  1  7  7  7  2  6  6  6 12 13
      -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 11 11 -1 -1 -1]
```

Yes: F_{11} (after F_2), F_{12} (after F_6 and F_{11}), F_{13} (after F_6 and F_{11})

$s_l = s_6 = \{F_{11}, F_{12}, F_{13}\}$

$l = 7$

Third iteration of a loop ***for***, *k* = 3
v = **FPOM**(k,:) = **FPOM**(3,:) = [a b 0 1], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?
function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)
No

Fourth iteration of a loop ***for***, *k* = 4
v = **FPOM**(k,:) = **FPOM**(4,:) = [a b 0 0], a>=-1 & a<=1, b>=-1 & b<=1

Relevant features found?
function: relevant2(r,k,F_ATTR,FPOM,F_Datum,DHM)
Yes: F_{15}, F_{16}

Features ready for machining?
Checking FPM matrix

```
FPM =[ 0  0  0  3  0  5  1  7  7  7  2  6  6  6 12 13
      -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 11 11 -1 -1 -1]
```

Yes: F_{15} (after F_{12}), F_{16} (after F_{13})

$s_l = s_7 = \{F_{15}, F_{16}\}$

$l = 8$

END loop *for*

Step #4; New non-machined features enabled? NO

Step #5; $su_i = su_4 = \{s_6, s_7\}$

Step #6; $i = 5$

Step #7; Dataset of non-machined features empty? YES

Listing of the reasoning process results:

Feature subsets:

$s_1 = \{F_1, F_3, F_4, F_7\}$
$s_2 = \{F_{10}\}$
$s_3 = \{F_2, F_5, F_6\}$
$s_4 = \{F_{14}\}$
$s_5 = \{F_8, F_9\}$
$s_6 = \{F_{11}, F_{12}, F_{13}\}$
$s_7 = \{F_{15}, F_{16}\}$

Setups:

$su_1 = \{s_1, s_2\}$
$su_2 = \{s_3, s_4\}$
$su_3 = \{s_5\}$
$su_4 = \{s_6, s_7\}$

STOP