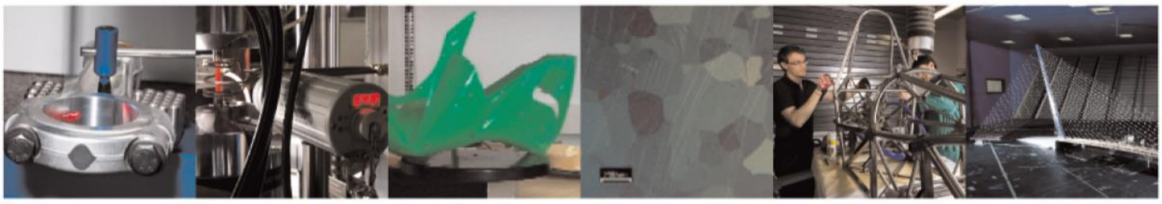

A nested partitioning-based approach to integrate process planning and scheduling in flexible manufacturing environment

Mohapatra, P.; Kumar, N.; Matta, Andrea; Tiwari, M. K.

This is an Accepted Manuscript of an article published by Taylor & Francis in INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING on 01 Oct 2014, available online: http://www.tandfonline.com/10.1080/0951192X.2014.961548.

A nested partitioning-based approach to integrate process planning and scheduling in flexible manufacturing environment

P. Mohapatra[a], N. Kumar[a], Andrea Matta[b] and M.K. Tiwari[a]*

[a]*Industrial & Systems Engineering, Indian Institute of Technology, Kharagpur, India;* [b]*Politecnico DI Milano, Dipartimento di Meccanica, DI Milano, Italy*

(*Received 23 June 2012; accepted 31 August 2014*)

1. Introduction

Manufacturing companies in the twenty-first century are facing frequent and unpredictable market changes driven by global competition, including the rapid introduction of new products and constantly varying product demand. To remain competitive, companies must design manufacturing systems that not only produce high-quality products at low cost, but also allow for rapid response to market changes and consumer needs. For this reason, process planning and scheduling are considered two important functions and their integration plays an important role in manufacturing system.

Process planning is a manufacturing system function that translates the design data into the best method to manufacture a part. In other words, process planning is defined as a systematic determination of methods by which a product needs to be manufactured (Chen and Khoshnevis 1990). The process planning first generates process plan for each part which includes determining the suitable manufacturing resources (machines and tool), selecting set-up plans and sequencing the machining operations. Process planning provides the fundamental input to the scheduling. Scheduling is another manufacturing function which attempts to assign manufacturing resources to the operations indicated in the process plans in such a way that some relevant criteria, such as due dates, are met (Gere 1966). Scheduling specifies the schedule of manufacturing resources on each operation for the part according to the importance of jobs, availability of resources and time constraint.

Earlier process planning and scheduling are considered separately, each having its own aims and optimisation norms. The main objective of process planning is to analyse the design requirement and overlook the potential of integration with scheduling function. Limited attention has been paid to the effect of shop floor conditions may have on the desirability of process plans. Similarly, research on scheduling has been primarily focused on construction of efficient algorithms to different types of scheduling problems: flow shop, job shop, scheduling parallel machines and so on. Most of the scheduling problems are nested partition (NP)-hard in nature (Tan and Khoshnevis 2000). Over the last few years, there are several methods which attempts to integrate process planning and scheduling, but the integration is limited functionality or compensated in computational efficiency due to the NP-hard nature in the problem.

Set-up planning is the critical bridge between process planning and detailed operation planning in machine shop; it is also intimate upstream for fixture planning (Zhang and Lin 1999). The purpose of set-up planning for a part is to ensure its stability during machining and more

*Corresponding author. Email: mkt09@hotmail.com
Present address for P. Mohapatra is School of Mechanical Engineering, Kalinga Institute on Industrial Technology (KIIT), Bhubaneswar, India.
Present address for Andrea Matta is School of Mechanical Engineering, Shanghai Jiao Tong University, China.

importantly guarantee the precision of the machining process. The production control activities in a machine shop consist of scheduling, job dispatching and status monitor-ing where the set-up is most commonly used for the dispatching and scheduling unit of machining task (Bauer et al. 1994). Set-up planning is part of process plan which determines the number of sequence and set-up (including machining features grouping in each set-up) and part orientation in each set-up based on availability of machine tools. An approach is proposed to generate auto-matically feasible set-ups and select optimal set-up plan for machining feature of a prismatic part (Hebbal and Mehta 2008). Set-up planning also considers the designing detail of the part, changing shop floor conditions, which includes the availability and capability of machine tools. However, opti-misation of a process plan after set-up planning is limited to a specific machine and determined by scheduling system, because scheduling generally is performed after process planning. Thus, set-up plan plays an important role for integration of process planning and scheduling. In this arti-cle, an adaptive set-up planning (ASP) algorithm is devel-oped to correlate process planning and scheduling. In brief, the decomposed process plans are embedded into group of generic set-ups and merged to form a specific set-up that meets the scheduling requirement (machining cost, make-span and machine utilisation) according to the availability and capability of machines of the given scheduling system.

The ASP problem under examination is an ideal combinatorial optimisation problem and is NP-hard (Cai, Wang, and Feng 2009). There are many parameters involved (machines, machining features, tool approach direction [TAD], primary locating surfaces [PLSs], etc.) in such problem which leads to large solution space. In order to find an optimal solution from the large solution space, a NP approach is adapted and reported in the paper. This method tends to cluster good solutions together, and the computational effort is mainly concentrated in the corresponding subregions after the partition. Hence, this method is especially efficient for problems where the feasible region can be partitioned. This method partitions the feasible region into subregions and calculates the promising index for each of these subregions. It moves by selecting the most promising region based on the promising index generated. This method records the most promising region in each iteration, and the number of feasible sample solutions is generated. Hence, both the computational time and effort are reduced by quite an extent. The rest of the article is organised as follows. Section 2 reviews the related literature. Section 3 describes the problem statement. Section 4 presents mathematical model. Section 5 details the proposed nested partitioning method. Sections 6 and 7 illustrate the applicability of the proposed approach through examples, discussions and analysis. Finally, Section 8 concludes the research finding with suggested future research.

2. Literature review

In the past few years, a lot of research has been done in the field of integration of process planning and scheduling. The existing approaches for these two methods are broadly categorised into two types: the progressive/enumerative approach and the simultaneous/centralised approach. A true integrated idea was first proposed by Chen and Khoshnevis (1990). The simultaneous/centralised approach considers the problem in a broader scope and formulates the two problem domains of process planning and scheduling into a unified whole as a single optimisation problem. The approach of considering alternative process plans and avail-able resources simultaneously and selecting an optimal plan according to certain scheduling criteria was adapted and extended by Chen and Khoshnevis (1993) and Tan and Khoshnevis (2000). Some works have introduced two-level hierarchical method structures to formulate the integration problem. Plausible schedules are determined at a high level of the structure based on the effective adjustments of some cost-efficient process plans generated and maintained a low level of the structure (Brandimarte and Calderini 1995; Zhang, Saravanan, and Fuh 2003). Brandimarte and Calderini (1995) represented both the process planning and scheduling in linear mixed integer programming forms. A process planning module for each part based on genetic algorithm (GA) and simulated annealing (SA) was devel-oped in the work of Zhang, Saravanan, and Fuh (2003), which generates an optimal or near-optimal process plans with minimum manufacturing cost. A scheduling module generates a schedule based on some given criteria after taking the optimal or near-optimal plans of each part. The efficient unified optimisation models and algorithms have been developed to further enhance the performance of the algorithm (Morad and Zalzala 1999; Kim, Park, and Ko 2003; Yan et al. 2003; Zhang and Yan 2006). A GA-based integration scheme was evolved by Morad and Zalzala (1999), in which process plans represented as chromosomes underwent crossover and mutations operations to develop other alternative process plans. The performance criteria to choose a plausible schedule from the process plans might be the minimum makespan, the minimum total cost or the maximum utilisation. The integration of process planning and scheduling was performed by a single optimisation model developed by Kim, Park, and Ko (2003). An optimisation model established by Yan et al. (2003) and Zhang and Yan (2006) combined the specifications from process planning and scheduling, such as the production cost, the tardiness time, the set-up cost and the early finish time. On this basis, a Tabu Search (TS)-based approach (Yan et al. 2003) and an improved hybrid GA-based approach (Zhang and Yan 2006) have been developed to optimise both planning and scheduling simultaneously.

The progressive/enumerative approach lessens the computational complexity of the problem and provides a higher flexibility to the whole system. This approach divides a large optimisation problem into several steps and gradually carries out the decision-making and optimisation. Huang, Zhang, and Smith (1995) proposed a progressive three-phased approach that brings out the interaction between process planning and scheduling starting from a more global level and ending at a more detailed level. The activities in each phase (preplanning, paring planning and final planning) occur in a different time interval. Saygin and Kilic (1999) proposed a structure consisting of four integrated stages with the primary objective of reducing the completion time, increasing system performance and deci-sion-making by consideration of process flexibility, sequence flexibility and alternative machine tools. Li and McMahon (2007) developed a simulation-based approach to optimise the integration of process planning and sche-duling. In this approach, three strategies, which include process flexibility, operation sequencing flexibility and scheduling flexibility, are adapted to explore the search space to support the optimisation process effectively. The framework presented by Jain, Jain, and Singh (2006) can quickly integrate both functions and can be implemented in a company without disrupting and reorganising existing process planning and scheduling departments. A hybrid approach using knowledge-based rule and geometric rea-soning rule is developed for the machining feature sequen-cing in a distributed process planning (Li and Wang 2007). The integration of process planning and scheduling is one of the significant features of the distributed process plan-ning system (Wang, Feng, and Cai 2003).

The two major constraints in set-up planning originate from design specifications and manufacturing resources. Zhang and Lin (1999) presented the idea of a hybrid graph theory and applied tolerance as the crucial constraint in set-up planning. Zhang et al. (2001) used tolerance decomposition, fixture design and manufacturing resource capability to set-up planning. Ong, Ding, and Nee (2002) introduced a hybrid approach to set-up planning optimisation using GAs, SA and a precedence relationship matrix. An integrated approach to automatic set-up planning was also presented by Huang and Xu (2003), which considers various components: geometry, precedence constraint, kinematics, force and tolerance methodically. Gologlu (2004) applied component geometry, dimensions and tolerances to derive constraints-imposed precedence relations amongst features and also considered fixturing strategies. The second constraint generally deals with terms of cost, quality, lead time and agility under the consideration of available machine tools at the optimisation stage. Yilmaz et al. (2007) recently introduced set-up grouping strategies for minimisation of make-span, and Yao et al. (2007) proposed automated set-up planning at both single part level and machine station level.

The cross-machine ASP problem is a typical NP-hard combinatorial optimisation problem. This cross-machine ASP deals with a total of I, 3-axis based set-ups ($ST^i_{3-\mathrm{axis}}$, $i \in [1, I]$), K PLSs (PLS_k, $k \in [1, K]$) and a total number of L machine tools (MT_l, $l \in [1, L]$) available in the shop. Hence, the maximum solution space is $I! \times K! \times L!$. For the case studies undertaken in this article, the solution space is huge as $2.69007299 \times 10^{13}$ (for $I = 13$, $K = 6$, $L = 3$).

Artificial intelligence techniques such as GA and SA are generally used to solve this optimisation problem to find near-optimal solutions. Chen, Zhang, and Nee (1998) developed a new approach for set-up planning of a prismatic part using Hopfield neural net coupled with SA. Singh and Jebaraj (2005) developed a feature-based design environment module that is used for the design, modelling, synthesis, representation and validation of the component for machining application. An object-oriented manufacturing resource modelling and agent-based process planning is proposed by Zhang et al. (1999). Amaitik and Kiliç (2007) presented an intelligent process planning system using STEP features for prismatic parts. Hybrid approach techniques like neural network, fuzzy logic and rule-based are used as the inference engine of the developed system. Shen, Wang, and Hao (2006) submitted a state-of-the-art survey of agent-based distributed manufacturing process planning and sche-duling. A multiagent architecture of an integrated and dynamic system for process planning and scheduling for multiple jobs is developed (Tehrani, Sugimura, and Iwamura 2011). Chen, Du, and Huang (2010) developed a scheduling problem on parallel batch processing machine in the presence of dynamic and job arrival and nonidentical job sizes, which is NP-hard in nature. Two meta-heuristics, GA and ACO, are proposed to solve this problem. Nested parti-tioning algorithm is applied to the multimachine set-up planning or the cross-machine ASP problem in order to find the exact optimal solution. Shi and Ólafsson (2000) proposed a new method known as NP method, which sys-tematically partitions the feasible region and concentrates on the search reason that is the most promising area, for solving the global optimisation problem. Shi, Chen, et al. (1999) investigated the nested partition framework, which combines optimal computing budget allocation to solve the discrete resource allocation problem. Shi et al. (2004) introduced a NP framework for solving large-scale multicommodity facil-ity location problems, which is capable of efficiently produ-cing very high-quality solution. Ólafsson and Gopinath (2000) proposed a nested partition method which system-atically partitions the feasible region and concentrate the search in the most promising area. This method combines both global and local search. Zhou, Zheng, and Wang (2011) proposed a methodology for assembly sequence planning for a complex component which consists of three phases: assembly-based modular design, assembly subsequence generation for each module and assembly sequences merging. NP method is used to merge the assembly subsequences, which is an effective method for assembly sequence planning of complex product. Shi, Ólafsson, et al. (1999) proposed a randomised optimisation framework, the nested partitioning approach to solve the travelling salesman pro-blem. Chew et al. (2009) proposed an approach using nested partitioning method to search promising solution and multi-objective optimal computing budget allocation algorithm to identify nondominated solution for a differentiated service inventory problem with multiple demand classes. A nested partition method is presented for assembly sequence plan-ning for complex components, which consists of assembly-based modular design, assembly subsequence generation for each model and assembly merging (Zhao et al. 2010). Chauhdry and Luh (2012) adapted a NP algorithm for global optimisation to solve the nonconvex optimisation problem in nonlinear model predictive control. Su and Wang (2011) proposed a novel algorithm named as weighted NP based on differential evolution (WNPDE) to solve a scheduling problem of parallel batch processing machines. Hence, the NP algorithm is applied to the cross-machine ASP problem and multimachine set-up planning with the help of a case study reported in this article.

3. Problem statement

The consideration of tool accessibility direction is the most critical part of ASP problem. The input data in the ASP are the part information in the form of 3-axis-based set-ups obtained by applying the feature grouping algorithms (Wang, Jin, and Feng 2006) The machine configurations (3-axis with indexing table, 4-axis machine and 5-axis machine) are represented by its tool orientation space (TOS), showing the available motion range on a unit spherical surface. In this article, we have modelled the ASP problem differently than other researchers by including the following aspects such as machining time, set-up time and tool change time. In earlier paper (Wang et al. 2010), these are considered as unity, that is, the variability of these factors is not taken into account. Therefore, our problem can be stated as minimisation of makespan, minimisation of cost and maximisation of machine utilisation subjected to satisfying all the constraints, whereas the variable pertaining to machining time, tool change time, etc. will give specific solution.

The formulation presented in the paper is NP-hard in nature. The flexibility and adaptability of set-up plans are what we are targeting. A nested partitioning approach is presented by integrating tool accessibility examination for the optimal set-up plan generation considering the variety of machines.

4. Cross-machine ASP

The primary objective of cross-machine ASP for each available machine configuration, machine combination and other requirement from a scheduling system is to generate an optimal or near-optimal set-up plan for a part-based config-uration and capability. The primary motive of a cross-machine ASP is depicted in Figure 1, where the inputs to the ASP are 3-axis-based set-ups and the TOS of available machines. The yield of the ASP is the optimal set-up plan corresponding to a selected objective for optimisation.

All the notations used are given in the Table 1.

4.1. *Objective function*

(1) The minimisation of the total makespan of the part.

The makespan TS_p is the difference between the starting point and the finishing point during the manufacture of the part. In case of a multimachine set-up, the makespan is calculated as

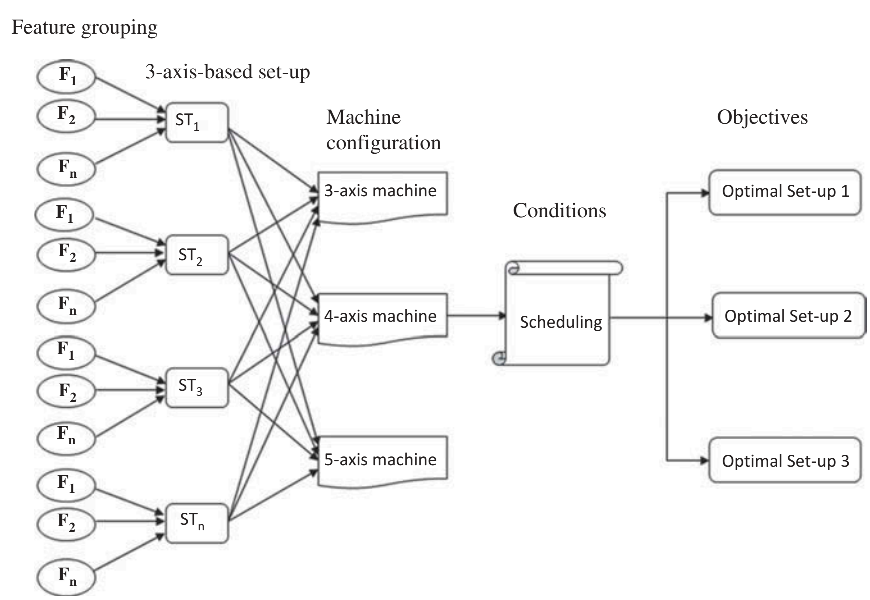

Figure 1. Cross-machine adaptive set-up planning.

Table 1. Notation of variables.

Variables	descriptions
PLS_k	The primary locating surface k, k = 1,2,3, … , p
MT_l	The machine tool l, l = 1,2, …, L
MU_l	The utilisation of MT_l
UF_l	The utilisation factor of MT_l
ST^i_{3-axis}	3-axis-based set-up I, I = 1, 2, …, L
STP_p	The set-up plan p, p = 1,2, . . . , P
$S_{\min}$	The minimum value of S_p
S_l	The number of set-ups on MT_l
ST^s_p	The set-up s in set-up p, s = 1,2, …,S_p
SM_l	The set-up merging matrix for MT_l
TCT_f	Tool change time for feature f
T_ID_f	Tool ID used for machining feature f
TCT_index_f	Index of tool change time for feature f
TCC_f	Tool change cost for feature f
TCC_index_f	Index of tool change cost for feature f
TC_p	Total cost for set-up plan p
TS_p	Total makespan for set-up plan p
TU_p	Total system utilisation for set-up plan p
Q^s_p	The number of machining features grouped in ST^s_p
lf^s_p	The locating factor of ST^s_p
UC^s_p	The unit cost of the machine tool to be used for ST^s_p
MC_p	The machining cost of STP_p
$MC_{\min}$	The minimum value of MC_p
MS_p	The makespan of STP_p
$MS_{\min}$	The minimum value of MS_p
LF_p	The locating factor of STP_p
GF_p	The grouping factor of STP_p
CF_p	The cost factor of STP_p
MF_p	The makespan factor of STP_p
UF_p	The utilisation factor of STP_p
W_L	The weight factor of LF_p
W_G	The weight factor of GF_P
W_C	The weight factor of CF_p
W_M	The weight factor of MF_p
W_U	The weight factor of UF_p
σ_i	Representation of ith subregion after first partition
$\sigma_j{}'$	Representation of jth subregion after second partition
x^j_i	ith sample in the jth subregion after first partition
y^k_i	ith sample in the kth partition after second partition

$$TS_p = \max_{MTl/l\in[1,l]} \sum_{s=1}^{Sl} \left(ST_s + \sum_{f=1}^{Q^s_p} (MT_f + TCT_f)\right) \tag{1}$$

$$\Omega(X,Y) = \begin{cases} 0 & ; \quad X = Y \\ 1 & ; \quad X \neq Y \end{cases}$$

$$TC_f = \Omega(T\_ID_{f-1}, T\_ID_f)$$

$$TCT_f = TC_f \times TCT\_index_f$$

where S_l is the number of set-ups on machine l, ST_s is the set-up time for set-up s, L is the total number of available machines, MT_f is the respective machining time of feature f, TCT_f is the respective tool change time for feature f, Q^s_p is the number of machining features in set-up s, and T_ID_f is the tool ID for feature f.

(2) The minimisation of the total cost incurred in producing the part.

The total cost TC_p of a set-up plan p can be calculated as:

$$TC_p = \sum_{s=1}^{S_p} \Big(ST_s \times MC_l + \sum_{f=1}^{Q^s_p} (MT_f \times MC_l + TCC_f)\Big) \tag{2}$$

$$TCC_f = TC_f \times TCC\_index_f$$

where S_p is the number of set-ups in set-up plan p, TCC_f is the tool change cost for feature f, and MC_l is the machining cost index for machine l.

(3) The maximisation of the system utilisation.

The utilisation of a system is calculated as the sum of machining time of the features and the utilisation of the various set-ups.

$$TU_p = \sum_{s=1}^{S_l} \Big(ST_s \times SU_s + \sum_{f=1}^{Q^s_p} MT_f\Big) \tag{3}$$

where SU_s is the respective utilisation of set-up s.

Some definitions:

(i) Locating factor:

The locating factor determines the quality of a PLS. Locating factor of a set-up plan p is given by the expression,

$$LF_p = \frac{\sum_{s=1}^{S_p} (Q^s_p \times lf^s_p)}{\sum_{s=1}^{Sp} Q^s_p} \tag{4}$$

where lf^s_p is the locating factor of set-up s within set-up plan p (Cai, Wang, and Feng 2008).

(ii) Grouping factor:

The effect of PLS also depends on the number of machining features. The machining features are grouped into various set-ups, and the grouping factor is defined as follows

$$GF_p = \frac{S_{\min}}{S_p}, \; S_{\min} \xrightarrow{\text{theorically}} 1 \tag{5}$$

where $S_{\min}$ is the minimum value of S_p amongst all alternative set-up plans. $S_{\min} \overset{\text{theorically}}{\longrightarrow} 1$. If all machining features can be grouped in one set-up in one perfect machine, the grouping factor provides a relative ratio for evaluating set-up plan p in terms of set-up number minimisation.

(iii) Cost and makespan factors:
The cost and makespan factors are the relative rates for evaluating set-up plan p and are given as,

$$CF_p = \frac{TC_{\min}}{TC_p} \tag{6}$$

$$MF_{\min} = \frac{TS_{\min}}{TS_p} \tag{7}$$

where $TC_{\min}$ is the minimum cost incurred when a low-end machine with a cheap unit cost is used, and $TC_{\min}$ is the shortest makespan if the job gets evenly distributed amongst all available machines.

(iv) Utilisation factor:
The utilisation factor UF_l for each of the machines is given by the ratio of total utilisation to the available time for this machine

$$UF_l = \frac{TU_l}{AT_l} \tag{8}$$

and the utilisation factor for the set-up plan p is the arithmetic mean of utilisation factors of all machines.

$$UF_p = \frac{1}{L} \times (\sum_{l=1}^{L} UF_l) \tag{9}$$

The overall objective function for the adaptive set-up plan is given by

$$OSP = \max_{p \in [1 \ldots P]} (W_l \times LF_p + W_g \times GF_p + W_c \times CF_p + W_m \times MF_p + W_u \times UF_p) \tag{10}$$

where W_L, $W_{G,}$ W_C, W_M and W_U are the respective weight factors of LF_P, GF_P, CF_P, MF_P and UF_P for the set-up plan p under considerations.

Hence, OSP can further be written as

$$OSP = \max_{p \in [1 \ldots P]} \left(W_L \times \frac{\sum_{s=1}^{S_p} \left(Q_p^s \times lf_p^s \right)}{\sum_{s=1}^{S_p} Q_p^s} + W_G \times \frac{S_{\min}}{S_p} + W_C \times \frac{TC_{\min}}{TC_p} + W_M \times \frac{TS_{\min}}{TS_p} + W_U \times \left(\frac{1}{L} \times \left(\sum_{l=1}^{L} UF_l \right) \right) \right) \tag{11}$$

4.2. *Constraints and assumptions*

The following constraints and assumptions are considered as basis for the objective function given in Equation (11):

Constraint 1

$$ST^i_{3-\text{axis}} \in L_l \ \ (i = 1, 2, 3, \ldots, I \text{ and } l = 1, 2, 3)$$

The final set-up plan may involve set-ups for a single machine configuration or for more than one machine configurations.

Constraint 2

$$\text{if } f_j \in ST^i_{3-\text{axis}}, \ \ j \in J \text{ and } i \in I$$

$$\text{then } f_j (\text{does not belong to}) ST^{i'}_{3-\text{axis}} \forall\, i' \in I \text{ and } i \neq i'$$

$$ST^i_{3-\text{axis}} \cap ST^{i'}_{3-\text{axis}} = \phi \ \forall\, i \in I,\ i' \in I \text{ and } i \neq i' \ ST$$

All machining features are first grouped into 3-axis-based set-ups, and no single machining feature can be grouped into more than one 3-axis-based set-up, that is, the same features.

Constraint 3
All 3-axis-based set-ups can be merged into fewer set-ups, and each 3-axis-based set-up can only be merged into one final set-up.

$$\text{if } ST^i_{3-\text{axis}} \in PLS_m, \text{ then } ST^i_{3-\text{axis}} \notin PLS_p$$

where p = {1,2,3,4,5,6} − {m}

$$PLS_p \ = p\text{th primary locating surface}$$

Constraint 4
Each of the machines may use all of the tools available for the production of the required part.

5. Nested partitions algorithm

This algorithm attempts to partition the most promising region of the solution space into a number of subregions. The first step includes partitioning the whole solution space so that to identify the most promising region initially. A number of random sample solutions are generated in each of the subregions, and the corresponding fitness values for each of these solutions are calculated according to the considered objective function. From each of the subregions, the best fitness value and the sample solution generating this value are selected. The best fitness values from each of the subregions are compared to extract the best fitness values from all of the subregions. The sample solution that has the best fitness value of all the subregions is the most promising subregion. Next, the most promising region determined is selected and the same processes are applied upon this subregion as were applied upon the previous most promising region. This whole procedure is repeated for a number of iterations, and the best solution is derived by comparing the best solutions from each of the iteration.

5.1. A nested partitions algorithm–based approach

The objective of this cross-machine ASP is to select the available machine configurations and PLSs and to assign the features grouped under the set-ups to the various PLSs and hence the machines so as to maximise the formulated objective function as well as to satisfy the constraints for a definite test part. This ASP for the test part under consideration defines a solution space that comprises of selecting available machines, PLSs grouped under selected machines and all of the 3-axis-based set-ups grouped under the chosen PLSs. There are three machine configurations, six PLSs and the 3-axis-based set-ups grouping the various machining features of the test part available for the generation of any set-up plan.

5.1.1. Partitioning

Two-step partitioning is performed on the solution space for generating the optimal set-up plan. The first partition is based on the selection of machine configurations and the second on the selection of PLSs. Initially, the whole solution space consisting of all the machine configurations, PLSs and the 3-axis-based set-ups is considered to be the most promising region. First, this solution space is partitioned into L subregions consisting, respectively, of randomly selected 1, 2, 3 … L machine configurations out of the available L. The next most promising region would now include the fixed machine configurations to be included in the set-up plan. The next partition of this region is based on the number of randomly selected PLSs out of the available P. Since each machine configuration has to have at least one PLS assigned to it, so the first subregion is partitioned into P subparts, the second into $P-1$, the third into $P-2$ and so on up to $P-L+1$.

The set of machines $M = \{1,2,3,\ldots,L\}$ and the set of PLSs $PLS = \{1,2,3,\ldots,P\}$. The L subregions after the first partition:

$$\sigma_1 = \{i\};\ \ i \in M, \quad \sigma_2 = \{a, b\};\ a, b \in M(a \neq b)$$

$$\sigma_3 = \{a, b, c\};\ a, b, c \in M(a \neq b \neq c), \quad \sigma_L = \{1, 2, 3, ..., L\}$$

And the surrounding region except for σ_j is aggregated into another region σ_{L+1}.

The subparts after the second partition are:

$$\sigma_j{}' = \{p_1, p_2, ..., p_n\},$$

where $j, n = [1, 2, ..., P]$ if σ_1 is partitioned,
$j, n = [2, 3, ..., P]$ if σ_2 is partitioned, ……
$j, n = [L, ..., P]$ if σ_L is partitioned,
and $p_i \in PLS$, $p_i \neq p_j \quad if \quad i \neq j$.

And the surrounding region except for $\sigma_j{}'$ is aggregated into another region σ'_{P+1}.

5.1.2. Random sampling

The subregions obtained as a result of first partition of the total sample space consist of fixed machine configurations. In each of these subregions, a number of random sample set-up plans are generated using uniform sampling techniques. A variable number of PLSs out of the available six are selected and are randomly assigned to the selected machines. The assignment is done in a way such that no individual PLS is assigned to more than one machine configuration. Then, all the 3-axis-based set-ups which group the machining features of the part are randomly assigned to the selected PLSs while taking care that no two PLSs have a similar set-up assigned to them. Next, the corresponding fitness values of the set-up plans generated in each subregion are calculated according to the formulated objective function.

m sample solutions are generated in each of the subregions σ_j:

$$x^j_1, x^j_2, ..., x^j_m, \text{ where } x^j_i \text{ is a function defined as}$$

$$x^j_i = f(\sigma_j, p, ST), \text{ where } ST = [ST^1_{3-\text{axis}}, ST^2_{3-\text{axis}}, ..., ST^q_{3-\text{axis}}]$$

q = number of 3-axis-based set-ups.

$$p = \{p_1, p_2, ..., p_n\}, \text{ where } n \in \begin{cases} 1, 2, ..., P; \ when\ j = 1 \\ 2, 3, ..., P; \ when\ j = 2 \\ 3, 4, ..., P; \ when\ j = 3 \\ ...... \\ P - L, ...P; \ when\ j = L \end{cases}$$

The corresponding fitness values are:

$$o(x_1^j), o(x_2^j), ..., o(x_m^j)$$

where $o(f)$ denotes the objective function value or the fitness value for set-up plan f.

A number of random samples are also generated for the subparts obtained as a result of the partition of the most promising subregion. The machine configurations and the PLSs in these subparts are fixed. All available 3-axis-based set-ups are randomly assigned to the various PLSs in the considered subpart such that each individual set-up is not assigned to more than one PLS at a time. This is done for all the subparts. Now, the corresponding performance values for each of these set-up plans are calculated.

m sample solutions are also generated in each of the subparts $\sigma_k\prime$

$$y_1^k, y_2^k, ..., y_m^k, \text{ where } y_i^k \text{ is a function defined as}$$

$$y_i^k = f(\sigma_j, \sigma_k', ST);$$

where $j \in \{1, 2, 3, ..., L\}$, and $ST = \left[ST_{3-\text{axis}}^1, ST_{3-\text{axis}}^2, ..., ST_{3-\text{axis}}^q\right]$

$$k = \begin{bmatrix} 1, 2, ..., P; & if\ j = 1 \\ 2, 3, ..., P; & if\ j = 2 \\ ..... & \\ P - L, 4, ..., P; & if\ j = L \end{bmatrix}$$

The corresponding fitness values are:

$$o(y_1^k), o(y_2^k), ..., o(y_m^k)$$

5.1.3. *Promising index calculation*

After the first partition, the promising index for each of the subregions is determined as the best fitness value (maximum objective function value) out of those generated by all set-up plans where the machine configurations are kept fixed and the PLSs and 3-axis-based set-ups are randomly selected and assigned. After the second partition, the set-up plan out of those consisting of fixed machines, PLSs and randomly assigned set-ups to the PLSs generating the best fitness value is considered to be the index for the most promising subpart.

The promising index for the subregions after the first partition is calculated as:

$$I(\sigma_j) = \max_{i=1,2,...,m}(o(x_i^j)), \text{where } j = [1, 2, 3, 4]$$

The index $j = 4$ is for the aggregated surrounding region after first partition, and for the subparts after the second partition is calculated as:

$$I(\sigma_k\prime) = \max_{i=1,2,...,m}(o(y_i^k)), \text{where } k = \begin{bmatrix} 1, 2, ..., 6, 7 \ ; \ if\ j = 1 \\ 2, 3, ..., 6, 7 \ ; \ if\ j = 2 \\ 3, 4, ..., 6, 7 \ ; \ if\ j = 3 \end{bmatrix}$$

The index $k = 7$ is for the aggregated surrounding region after second partition.

If two or more regions are equally promising, the tie can be broken arbitrarily.

5.1.4. *Backtracking*

If the promising index corresponds to a region that is a subregion of some particular region in the current iteration, then it will be the most promising region in the next iteration. Otherwise, if the index corresponds to the surrounding region, the algorithm backtracks to the super region of the current most promising region.

After the first partition, if the promising index corresponds to the index $j = 4$, the solution will backtrack to the previous solution space where the whole solution space will include the machine configurations as well.

If $j < 4$, then

$$\sigma_k' = \sigma_j \text{ where } I(\sigma_j) = \max_{i=1,2,...,m}(o(x_i^j))$$

else,

$\sigma_k' =$ the original total solution space including the machine configurations.

After the second partition, if the promising index corresponds to the index k=7, the solution will backtrack to the previous solution space where the whole solution space will include the machine configurations as well.

If $j < 4$, then

$$\text{the most promising region} = \sigma_k' \text{ where } I(\sigma_k') = \max_{i=1,2,...,m}(o(y_i^k))$$

else,

the most promising region is the subregion selected after first partition.

5.1.5. Movement

The most promising subregion after the first partition is selected as the region having the maximum value of promising index out of all the three. After the second partition, the most promising subpart is chosen based on the comparison of the promising indices of all subparts generated as a partition of the subregion selected and selecting the subpart with the maximum promising index value. Now, random samples are generated in the selected subpart by random assignment of available set-ups to the already-fixed PLSs. The corresponding performance values are calculated for the generated sample solutions and compared to deduce the sample solution with the maximum fitness value.

Most promising region after first partition:

$$\sigma_j \text{ such that } \max_{j=1,2,3}(I(\sigma_j)).$$

Most promising region after second partition:

$$\sigma_k{}' \text{ such that } \max_k(I(\sigma_k{}'));\ k = \begin{bmatrix} 1,2,...,6 & ; & if\,j=1 \\ 2,3,...,6 & ; & if\,j=2 \\ 3,4,...,6 & ; & if\,j=3 \end{bmatrix}$$

This sample solution is determined to be the best amongst all the set-up plans generated after partitioning the whole sample solution twice and random selection and assignment of machine configurations, PLSs and 3-axis-based set-ups. This best sample solution is noted. This above sequence of operations is run iteratively for a definite number of times, and the noted sample solutions from each of the iterations are compared. This comparison is done to find the maximum fitness value solution out of the noted solutions from all the iterations. This solution with the maximum fitness value after running the above sequence of operations for definite number of iterations is the exact optimal set-up plan for the cross-machine ASP. The flowchart of nested partition algorithm is shown in Figure 2.

6. Case study

For the validation of proposed approach, a prismatic part is considered as shown in Figure 3. The test prismatic part consists of six PLSs (Table 2) and 31 machining features with their TAD machining time are shown in Table 3. The 31 machining features are grouped into 13 3-axis-based set-up-based TAD. All the 3-axis-based set-ups' set-up times are shown in the Table 4. Three different machine configurations (3-axis, 4-axis and 5-axis) are taken considered for machining operations given in the Table 5. Eight different machining tools are used which are listed alongside their time index and cost index for tool change in the Table 6.

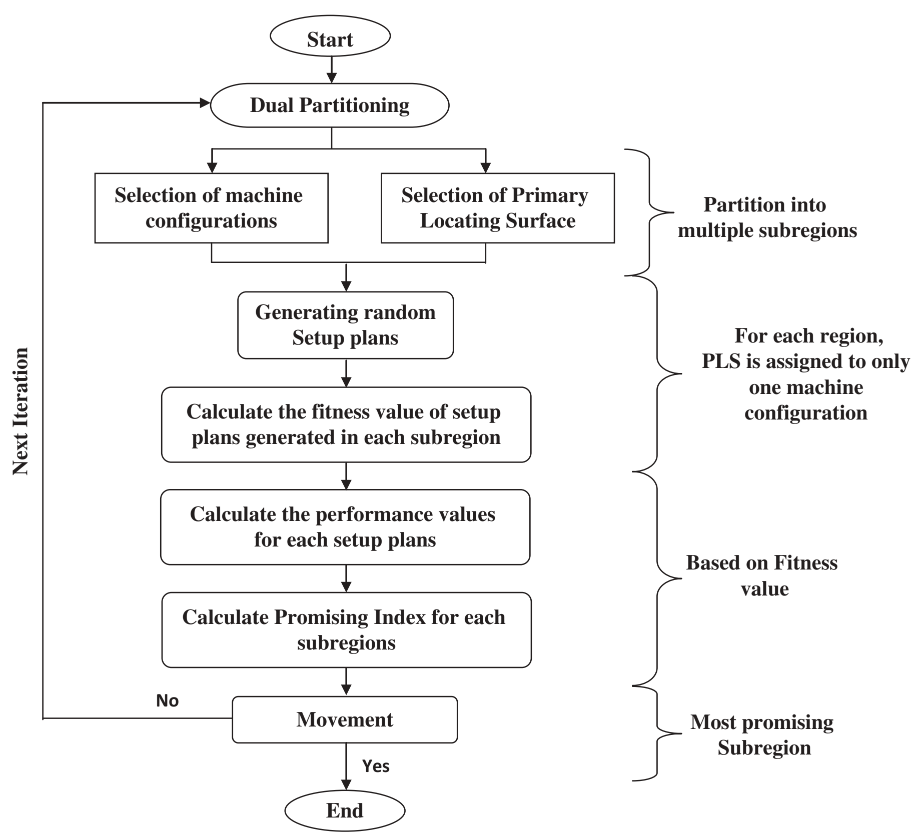

Figure 2. Steps in nested partition algorithm.

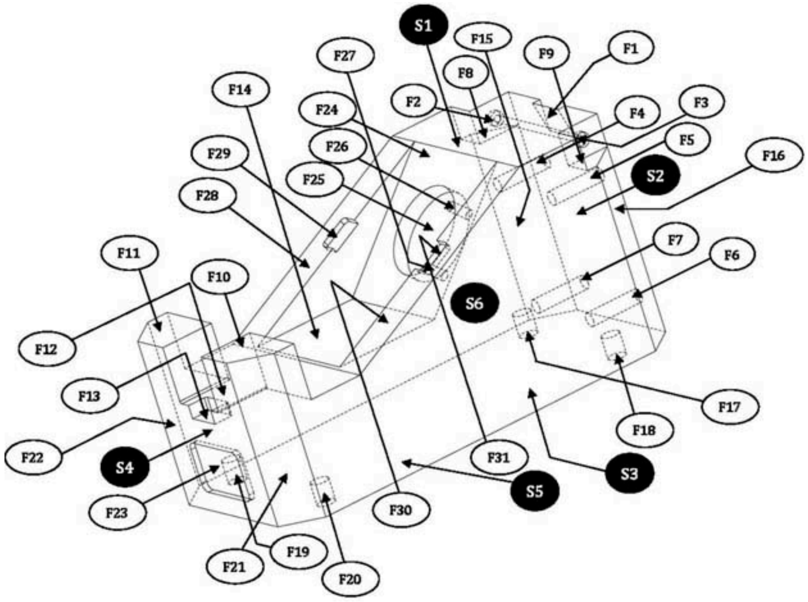

Figure 3. Part feature to be tested.

Table 2. PLS candidates of the test part.

Surface ID	Surface normal	Surface area (inch^2)	Surface accuracy grade
S_1	(0, 0, 1)	1.7294	1
S_2	(0, 1, 0)	2.6383	1
S_3	(1, 0, 0)	7.7388	1
S_4	(0, 0, –1)	1.4127	1
S_5	(0, –1, 0)	5.1505	1
S_6	(−1, 0, 0)	5.1505	1

6.1. Parameter tuning

After encoding, it is important in NP algorithm to use the right parameters for finding the appropriate results. The required parameters in our problem are the number of random samples generated in each partition and the total number of generations. For the given case studies, there are 300 generations and 100 random samples are generated in each partition in the case study.

7. Results and discussions

The five parameters considered while evaluating the objective function (Equation (11)) are locating factor, grouping factor, cost factor, makespan factor and machine utilisation factor. Cautious and proportionate adjustment of the weights (W_L, W_G, W_C, W_M and W_U) allows the variety of scheduling configurations to be efficiently served by this problem. In a standard situation, with the presumption that the ASP is integrated with a scheduling

Table 3. Tool approach direction of machining features of test part.

Feature ID	Tool approach direction	Machining time	Tool ID
F_1	(0, –cos 10^0, –sin 10^0)	15	7
F_2	(1, 0, 0)	5	7
F_3	(−1, 0, 0)	7	2
F_4	(0, −1, 0)	8	3
F_5	(0, −1, 0)	6	4
F_6	(0, −1, 0)	11	4
F_7	(0, −1, 0)	10	1
F_8	(0, 0, −1)	9	5
F_9	(0, 0, −1)	8	8
F_{10}	(0, 0, −1)	7	8
F_{11}	(0, 0, −1)	7	6
F_{12}	(0, 0, −1)	5	6
F_{13}	(0, 0, −1)	10	2
F_{14}	(0, 0, −1)	10	1
F_{15}	(cos 45^0, –sin 45^0, 0)	12	3
F_{16}	(–cos 45^0, –sin 45^0, 0)	13	4
F_{17}	(0, 0, 1)	9	6
F_{18}	(0, 0, 1)	15	8
F_{19}	(0, 0, 1)	8	3
F_{20}	(0, 0, 1)	6	2
F_{21}	(–cos 45^0, sin 45^0, 0)	6	4
F_{22}	(cos 450, sin 450, 0)	11	1
F_{23}	(0, 1, 0)	10	1
F_{24}	(0, cos 45^0, –sin45^0)	14	3
F_{25}	(0, cos 45^0, –sin45^0)	13	2
F_{26}	(0, cos 45^0, –sin45^0)	10	5
F_{27}	(0, cos 45^0, –sin45^0)	7	6
F_{28}	(0, sin 30^0, –cos 30^0)	8	7
F_{29}	(0, sin 30^0, –cos 30^0)	12	8
F_{30}	(0, sin 30^0, –cos 30^0)	14	1
F_{31}	(0, sin 30^0, –cos 30^0)	11	7

Table 4. 3-axis-based machine set-up for test part.

Set-up	Tool approach directions	Features	Set-up time	Set-up utilisation
$ST^1_{3-\text{axis}}$	(0, –cos10^0, sin10^0)	F1	5	2
$ST^2_{3-\text{axis}}$	(1, 0, 0)	F_2	6	3
$ST^3_{3-\text{axis}}$	(−1, 0, 0)	F_3	6	4
$ST^4_{3-\text{axis}}$	(0, −1, 0)	F_4, F_5, F_6, F_7	9	1
$ST^5_{3-\text{axis}}$	(0, 0, −1)	F_8, F_9, F_{10}, F_{11}, F_{12}, F_{13}, F_{14}	10	2
$ST^6_{3-\text{axis}}$	(cos 45^0, –sin 45^0, 0)	F_{15}	7	3
$ST^7_{3-\text{axis}}$	(–cos 45^0, –sin 45^0, 0)	F_{16}	10	4
$ST^8_{3-\text{axis}}$	(0, 0, 1)	F_{17}, F_{18}, F_{19}, F_{20}	5	2
$ST^9_{3-\text{axis}}$	(–cos 45^0, sin 45^0, 0)	F_{21}	5	1
$ST^{10}_{3-\text{axis}}$	(cos 45^0, sin 45^0, 0)	F_{22}	8	2
$ST^{11}_{3-\text{axis}}$	(0, 1, 0)	F_{23}	7	3
$ST^{12}_{3-\text{axis}}$	(0, cos 45^0, –sin45^0)	F_{24}, F_{25}, F_{26}, F_{27}	9	4
$ST^{13}_{3-\text{axis}}$	(0, sin 30^0, –cos 30^0)	F_{28}, F_{29}, F_{30}, F_{31}	8	1

Table 5. Machine configuration.

Machine ID	Machine type	Orientation	Cost	Available time
1	3-axis	(0,0,0,0,0,0)	35	15
2	4-axis	(−90,90,0,0,0,0)	55	20
3	5-axis	(−90,90,0,0,0,360)	75	25

Table 6. Index of tool.

Tool ID	Tool change time index	Tool change cost index
1	2	9
2	3	8
3	4	10
4	4	10
5	4	9
6	3	9
7	3	8
8	2	9

system, the scheduling system can determine the values of the weights which are then forwarded to ASP for set-up planning. This makes this underlying problem viable for application to a real-world situation.

To verify this approach, the results of each and every weight factor are affirmed individually. The explicit plot described above is then worked out using GA approach. The results generated by using the two algorithms and their comparison are given in Table 7.

Table 7. Comparison of nested partition approach–based ASP and GA.

Condition	Nested partitions	GA
$W_L = W_G = 1,\ W_C = W_M = W_U = 0$	1.376923	1.332771
$W_L = W_G = 1,\ W_C = 1,\ W_M = W_U = 0$	1.709348	1.606788
$W_L = W_G = W_M = 1,\ W_C = W_U = 0$	1.519748	1.494947
$W_L = W_G = W_C = W_M = W_U = 1$	3.007043	2.590981
$W_L = W_G = 1,\ W_C = 2,\ W_M = W_U = 0$	2.041773	1.721056

Table 8. Comparison of computational time.

Condition	Nested partitions	GA
$W_L = W_G = 1,\ W_C = W_M = W_U = 0$	54	62.540
$W_L = W_G = W_C = 1,\ W_M = W_U = 0$	41.2	68.235
$W_L = W_G = W_M = 1,\ W_C = W_U = 0$	43.34	71.421
$W_L = W_G = W_C = W_M = W_U = 1$	39.2	66.869
$W_L = W_G = 1,\ W_C = 2,\ W_M = W_U = 0$	45	58.524

As far as time is concerned, the actual computation time is shown in Table 8. All computations are done by personal computer (Dell Studio, 500 GB HD, 4 GB RAM and Core (TM) 2 2.20GH processor). From the table, it is clear that the proposed NP method computation is relatively stable for different weight assignment.

This article presents five different scenarios that are selected from a number of numerical results in addition to the above verifications.

Scenario 1: To utilise the most capable machines first

$$W_L = W_G = 1,\ W_C = W_M = W_U = 0$$

In this condition, there are no weights given to the constraints of cost factor, makespan factor and machine utilisation factor. The only constraints being considered are the locating factor and grouping factor. Thus, the PLS with the highest number of features is selected which in this case is the third one. Also, all the set-ups and hence all the grouped features merge down to the 5-axis machine in accordance to satisfy the considered constraints. The optimum set-up plan is given in Table 9, and the optimum result is shown in Figure 4.

Scenario 2: To reduce cost while keeping minimum set-ups

$$W_L = W_G = W_C = 1,\ W_M = W_U = 0$$

This case deals with the weights given to the constraints of locating factor, grouping factor and cost factor. It requires the reduction in the total production cost as well

Table 9. Optimal set-up plan of features for part for Scenario 1.

Machine configuration	PLS	Feature
5-axis machine	PLS3	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}, F_{17}, F_{18}, F_{19}, F_{20}, F_{21}, F_{22},F_{23}, F_{24}, F_{25}, F_{26}, F_{27}, F_{28}, F_{29}, F_{30}, F_{31}

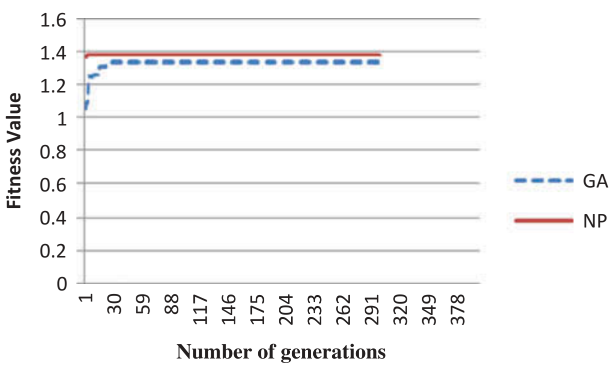

Figure 4. The comparison of fitness of nested partition verses GA for Scenario 1.

Table 10. Optimal set-up plan of features for part for Scenario 2.

Machine configuration	PLS	Feature
3-axis machine	PLS3	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}, F_{17}, F_{18},, F_{19}, F_{20}, F_{21}, F_{22}, F_{23}, F_{24}, F_{25}, F_{26}, F_{27}, F_{28}, F_{29}, F_{30}, F_{31}

as the optimal grouping of set-ups onto the given PLSs. This simultaneous optimality condition of cost and grouping leads to all the set-ups and the features grouped under them getting merged to the third PLS and the 3-axis machine configuration. The optimum set-up plan is given in Table 10, and the optimum result is shown in Figure 5.

Scenario 3: To produce the part as soon as possible

$$W_L = W_G = W_M = 1,\ W_C = W_U = 0$$

In this case, a minimum makespan (or a quick production time) along with optimal grouping of set-ups onto various PLSs is required. This leads to the distribution of final set-ups amongst three different PLSs which in turn are allocated to the three different machine configurations. Machining time, tool change time and set-up time are the major concerns. The optimum set-up plan is given in Table 11, and the optimum result is shown in Figure 6.

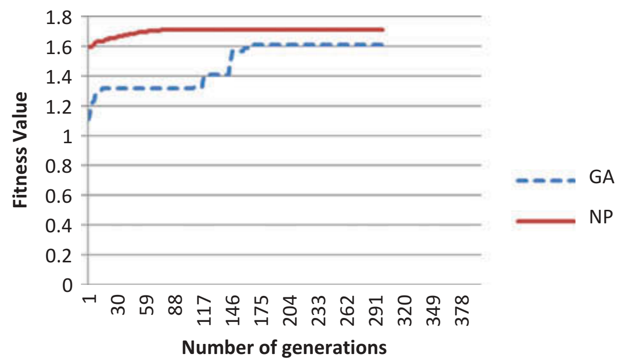

Figure 5. The comparison of fitness of nested partition verses GA for Scenario 2.

Scenario 4: To trade-off between all optimisation criteria

$$W_L = W_G = W_M = W_C = W_U = 1$$

This is a trade-off situation existing due to the simultaneous consideration of cost, makespan and machine utilisation factors along with the locating and grouping factors. No single criterion is fully satisfied. All the set-ups consisting of various features are further grouped under the first, third and sixth PLSs which are finally allocated to the 5-axis machine configuration in order to

Table 11. Optimal set-up plan of features for part for Scenario 3.

Machine configuration	PLS	Feature
3-axis machine	PLS6	F_1, F_2, F_3, F_4, F_5, F_6, F_7
4-axis machine	PLS3	F_8, F_9, F_{10}, F_{11}, F_{12}, F_{13}, F_{14}, F_{15}, F_{16}, F_{17}, $F_{18,}$ $F_{19,}$ F_{20}
5-axis machine	PLS5	F_{21}, F_{22},F_{23}, F_{24}, F_{25}, F_{26}, F_{27}, F_{28}, F_{29}, F_{30}, F_{31}

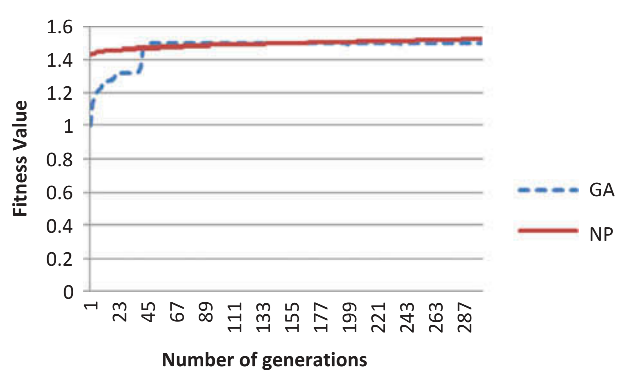

Figure 6. The comparison of fitness of nested partition verses GA for Scenario 3.

Table 12. Optimal set-up plan of features for part for Scenario 4.

Machine	Primary locating surface	Features
5-axis machine	PLS_1	F_{16}, F_{21}
	PLS_3	F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_{15}, F_{17}, F_{18}, F_{19}, F_{20}, F_{22}, F_{23}, F_{24}, F_{25}, F_{26}, F_{27}
	PLS_6	F_8, F_9, F_{10}, F_{11}, F_{12}, F_{13}, F_{14}, F_{28}, F_{29}, F_{30}, F_{31}

Table 13. Optimal set-up plan of features for part for Scenario 5.

Machine	Primary locating surface	Features of final set-up plan
3-axis machine	PLS_1	F_{17}, F_{18}, F_{19}, F_{20}
	PLS_5	F_4, F_5, F_6, F_7
4-axis machine	PLS_2	F1, F_8, F_9, F_{10}, F_{11}, F_{12}, F_{13}, F_{14}, F_{23}, F_{24}, F_{25}, F_{26}, F_{27}
	PLS_4	F_{21}, F_{28}, F_{29}, F_{30}, F_{31}
	PLS_5	F_2, F_3, F_{15}, F_{16}, F_{22}

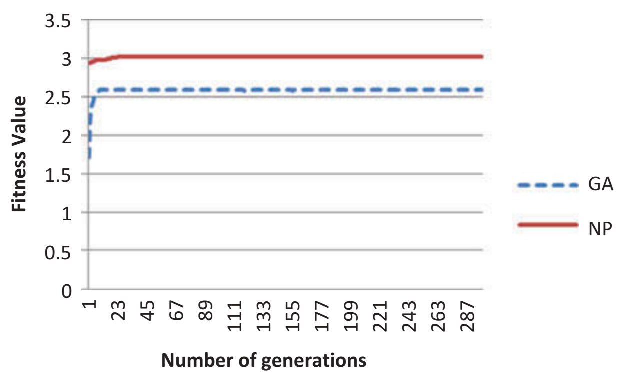

Figure 7. The comparison of fitness of nested partition verses GA for Scenario 4.

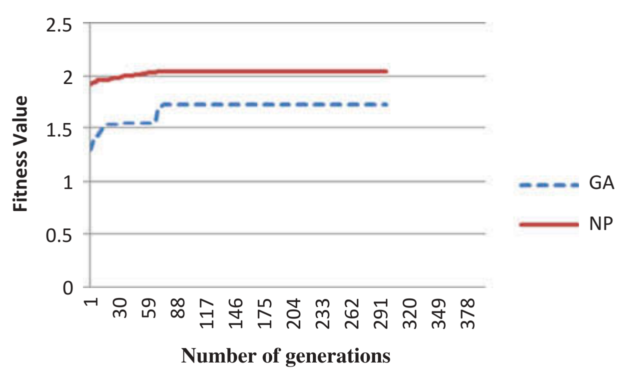

Figure 8. The comparison of fitness of nested partition verses GA for Scenario 5.

satisfy the constraints under speculation. The optimum set-up plan is given in Table 12, and the optimum result is shown in Figure 7.

Scenario 5: To minimise cost as much as possible

$$W_L = W_G = 1,\ W_C = 2,\ W_M = W_U = 0$$

This final case considers the weight of the cost factor getting doubled. The features of final set-up plan goes to 3-axis and 4-axis machines in all parts due to the effect of grouping factor that strives to reach a minimum number of final set-up. The optimum set-up plan is given in Table 13, and the optimum result is shown in Figure 8.

8. Conclusion

The current scenario requires an integration of ASP with dynamic scheduling which is definitely provided to some extent by the NP-based approach reported in this article. It first attains the adaptive processes and then by dynamic scheduling, on a requirement it generates machine characteristic set-ups. This kind of a plan does both obtaining the scheduling requirements of cost, makespan and machine utilisation and implementing the process plans on the specific machines. The NP-based approach has been adopted which partitions the solution space, and the most promising region is selected based on the promising indices. Thus, the computational effort is mostly concentrated in the most promising region and hence minimised. Also this algorithm generates exact optimal solutions on the basis of partitioning and sampling which is quite effective and feasible. This approach being based on tool accessibility examinations makes ASP preferred to support integration of process planning and scheduling within the imposed time period.

One of the distinct advantages of NP-based ASP is that less time is required for replanning and rescheduling when adaptive machining is treated to random changes. NP-based ASP promotes the efficient information exchange and integration between process planning and scheduling with reduction in lead time and improvement in production rate. As the extension of our work is to interface the ASP planned to use reconfigurability index as a base to integrate process planning and scheduling in distributed manufacturing environment.

References

Amaitik, S. M., and S. E. Kiliç. 2007. "An Intelligent Process Planning System for Prismatic Parts Using STEP Features." *The International Journal of Advanced Manufacturing Technology* 31: 978–993. doi:10.1007/s00170-005-0269-5.

Bauer, A., R. Bowden, J. Browne, J. Duggan, and G. Lyons. 1994. *Shop Floor Control Systems – From Design to Implementation*. London: Chapman & Hall.

Brandimarte, P., and M. Calderini. 1995. "A Hierarchical Bicriterion Approach to Integrated Process Plan Selection and Job Shop Scheduling." *International Journal of Production Research* 33 (1): 161–181. doi:10.1080/00207549508930142.

Cai, N., L. Wang, and H.-Y. Feng. 2008. "Adaptive Setup Planning of Prismatic Parts for Machine Tools with Varying Configurations." *International Journal of Production Research* 46 (3): 571–594. doi:10.1080/00207540600849125.

Cai, N., L. Wang, and H.-Y. Feng. 2009. "GA-Based Adaptive Setup Planning toward Process Planning and Scheduling Integration." *International Journal of Production Research* 47 (10): 2745–2766. doi:10.1080/00207540701663516.

Chauhdry, H. M., and P. B. Luh. 2012. "Nested Partitions for Global Optimization in Nonlinear Model Predictive Control." *Control Engineering Practice* 20: 869–881. doi:10.1016/j.conengprac.2012.05.003.

Chen, H., B. Du, and G. Q. Huang. 2010. "Metaheuristics to Minimise Makespan on Parallel Batch Processing Machines with Dynamic Job Arrivals." *International Journal of Computer Integrated Manufacturing* 23 (10): 942–956. doi:10.1080/0951192X.2010.495137.

Chen, J., Y. F. Zhang, and A. Y. C. Nee. 1998. "Setup Planning Using Hopfield Net and Simulated Annealing." *International Journal of Production Research* 36 (4): 981–1000. doi:10.1080/002075498193480.

Chen, Q., and B. Khoshnevis. 1990. "Integration of Process Planning and Scheduling Functions." *Journal of Intelligent Manufacturing* 1 (3): 165–176.

Chen, Q., and B. Khoshnevis. 1993. "Scheduling with Flexible Process Plans." *Production Planning and Control* 4 (4): 333–343. doi:10.1080/09537289308919455.

Chew, E. P., H.-L. Lee, S. Teng, and H.-C. Koh. 2009. "Differentiated Service Inventory Optimization Using Nested Partitions and MOCBA." *Computers & Operations Research* 36 (5): 1703–1710. doi:10.1016/j.cor.2008.04.006.

Gere, W. S. 1966. "Heuristics in Job Shop Scheduling." *International Journal of Management Science* 13 (3): 167–190.

Gologlu, C. 2004. "Machine Capability and Fixturing Constraints-Imposed Automatic Machining Setups Generation." *Journal of Materials Processing Technology* 148 (1): 83–92. doi:10.1016/j.jmatprotec.2004.01.043.

Hebbal, S. S., and N. K. Mehta. 2008. "Setup Planning for Machining the Features of Prismatic Parts." *International Journal of Production Research* 46 (12): 3241–3257. doi:10.1080/00207540601070937.

Huang, S. H., and N. Xu. 2003. "Automatic Setup Planning for Metal Cutting: An Integrated Methodology." *International Journal of Production Research* 41 (18): 4339–4356. doi:10.1080/0020754031000153351.

Huang, S. H., H.-C. Zhang, and M. L. Smith. 1995. "A Progressive Approach for the Integration of Process Planning and Scheduling." *IIE Transactions* 27 (4): 456–464. doi:10.1080/07408179508936762.

Jain, A., P. K. Jain, and I. P. Singh. 2006. "An Integrated Scheme for Process Planning and Scheduling in FMS." *The International Journal of Advanced Manufacturing Technology* 30: 1111–1118. doi:10.1007/s00170-005-0142-6.

Kim, Y. K., K. Park, and J. Ko. 2003. "A Symbiotic Evolutionary Algorithm for the Integration of Process Planning and Job Shop Scheduling." *Computers and Operations Research* 30 (8): 1151–1171. doi:10.1016/S0305-0548(02)00063-1.

Li, W. D., and C. A. McMahon. 2007. "A Simulated Annealing-Based Optimization Approach for Integrated Process Planning and Scheduling." *International Journal of Computer Integrated Manufacturing* 20 (1): 80–95. doi:10.1080/09511920600667366.

Li, Z., and L. Wang. 2007. "Sequencing of Interacting Prismatic Machining Features for Process Planning." *Computers in Industry* 58: 295–303. doi:10.1016/j.compind.2006.07.003.

Morad, N., and A. Zalzala. 1999. "Genetic Algorithms in Integrated Process Planning and Scheduling." *Journal of Intelligent Manufacturing* 10 (2): 169–179. doi:10.1023/A:1008976720878.

Ólafsson, S., and N. Gopinath. 2000. "Optimal Selection Probability in the Two-Stage Nested Partitions Method For Simulation-Based Optimization." In *Proceedings of the 2000 Winter Simulation Conference*. doi: 10.1109/WSC.2000.899787.

Ong, S. K., J. Ding, and A. Y. C. Nee. 2002. "Hybrid GA and SA Dynamic Setup Planning Optimization." *International Journal of Production Research* 40 (18): 4697–4719. doi:10.1080/00207540210155864.

Saygin, C., and S. E. Kilic. 1999. "Integrating Flexible Process Plans with Scheduling in Flexible Manufacturing Systems." *The International Journal of Advanced Manufacturing Technology* 15 (4): 268–280. doi:10.1007/s001700050066.

Shen, W., L. Wang, and Q. Hao. 2006. "Agent-Based Distributed Manufacturing Process Planning and Scheduling: A State-Of-The-Art Survey." *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)* 36 (4): 563–577. doi:10.1109/TSMCC.2006.874022.

Shi, L., C. H. Chen, E. Yucesan, P. A. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans. 1999. Simultaneous Simulation Experiments and Nested Partition For Discrete Resource Allocation in Supply Chain Management." In *Proceedings of the I999 Winter Simulation Conference*. doi:10.1145/324138.324257.

Shi, L., R. R. Meyer, M. Bozbay, and A. J. Miller. 2004. "A Nested Partitions Framework for Solving Large-Scale Multicommodity Facility Location Problems." *Journal of Systems Science and Systems Engineering* 13 (2): 158–179. doi:10.1007/s11518-006-0159-x.

Shi, L., and S. Ólafsson. 2000. "Nested Partitions Method for Global Optimization." *Operations Researches* 48 (3): 390–407. doi:10.1287/opre.48.3.390.12436.

Shi, L., S. Ólafsson, and N. Sun. 1999. "New Parallel Randomized Algorithms for the Traveling Salesman Problem." *Computers and Operations Research* 26: 371–394. doi:10.1016/S0305-0548(98)00068-9.

Singh, D. K. J., and C. Jebaraj. 2005. "Feature-Based Design for Process Planning of Machining Processes with Optimization Using Genetic Algorithms." *International Journal of Production Research* 43 (18): 3855–3887. doi:10.1080/00207540500032160.

Su, G., and X. Wang. 2011. "Weighted Nested Partitions Based on Differential Evolution (WNPDE) Algorithm-Based Scheduling of Parallel Batching Processing Machines (BPM) with Incompatible Families and Dynamic Lot Arrival."

International Journal of Computer Integrated Manufacturing 24 (6): 552–560. doi:10.1080/0951192X.2011.562545.

Tan, W., and B. Khoshnevis. 2000. "Integration of Process Planning and Scheduling – A Review." *Journal of Intelligent Manufacturing* 11 (1): 51–63. doi:10.1023/A:1008952024606.

Tehrani, H., N. Sugimura, and K. Iwamura. 2011. "Agent-Based Dynamic Integrated Process Planning and Scheduling in Flexible Manufacturing Systems." *International Journal of Production Research* 49 (5): 1373–1389. doi:10.1080/00207543.2010.518741.

Wang, L., N. Cai, H. Yung, and J. Ma. 2010. "ASP: An Adaptive Setup Planning Approach for Dynamic Machine Assignment." *IEEE Transactions on Automation Science and Engineering* 7 (1): 1–14.

Wang, L., H.-Y. Feng, and N. Cai. 2003. "Architecture Design for Distributed Process Planning." *Journal of Manufacturing Systems* 22 (2): 99–115. doi:10.1016/S0278-6125(03)90008-2.

Wang, L., W. Jin, and H. Y. Feng. 2006. "Embedding Machining Features in Function Blocks for Distributed Process Planning." *International Journal of Computer Integrated Manufacturing* 19 (5): 443–452. doi:10.1080/09511920500399060.

Yan, H. S., Q. F. Xia, M. R. Zhu, X. L. Liu, and Z. M. Guo. 2003. "Integrated Production Planning and Scheduling on Automobile Assembly Lines." *IIE Transactions* 35 (8): 711–725. doi:10.1080/07408170304348.

Yao, S., X. Han, Y. Yang, Y. Rong, S. H. Huang, D. W. Yen, and G. Zhang. 2007. "Computer Aided Manufacturing Planning for Mass Customization: Part 2, Automated Setup Planning." *The International Journal of Advanced Manufacturing Technology* 32: 205–217. doi:10.1007/s00170-005-0328-y.

Yilmaz, I. O., M. Grunow, H.-O. Günther, and C. Yapan. 2007. "Development of Group Setup Strategies for Makespan Minimisation in PCB Assembly." *International Journal of Production Research* 45 (4): 871–897. doi:10.1080/00207540600690735.

Zhang, H.-C., and E. Lin. 1999. "A Hybrid-Graph Approach for Automated Setup Planning in CAPP." *Robotics and Computer-Integrated Manufacturing* 15 (1): 89–100. doi:10.1016/S0736-5845(98)00031-3.

Zhang, X. D., and H. S. Yan. 2006. "Integrated Optimization of Production Planning and Scheduling for a Kind of Job-Shop." *International Journal of Advance Manufacturing Technology* 26(7–8): 876–886.

Zhang, Y., S. C. Feng, X. Wang, W. Tian, and R. Wu. 1999. "Object Oriented Manufacturing Resource Modelling for Adaptive Process Planning." *International Journal of Production Research* 37 (18): 4179–4195. doi:10.1080/002075499189727.

Zhang, Y., W. Hu, Y. Rong, and D. W. Yen. 2001. "Graph-Based Setup Planning and Tolerance Decomposition for Computer-Aided Fixture Design." *International Journal of Production Research* 39 (14): 3109–3126. doi:10.1080/00207540110056171.

Zhang, Y. F., A. N. Saravanan, and J. Y. H. Fuh. 2003. "Integration of Process Planning and Scheduling by Exploring the Flexibility of Process Planning." *International Journal of Production Research* 41 (3): 611–628. doi:10.1080/0020754021000037874.

Zhao, F., Y. Hong, D. Yu, Y. Yang, and Q. Zhang. 2010. "A Hybrid Particle Swarm Optimisation Algorithm and Fuzzy Logic for Process Planning and Production Scheduling Integration in Holonic Manufacturing Systems." *International Journal of Computer Integrated Manufacturing* 23 (1): 20–39. doi:10.1080/09511920903207472.

Zhou, W., J. R. Zheng, and J. F. Wang. 2011. "Nested Partitions Method for Assembly Sequences Merging." *Expert Systems with Applications* 38: 9918–9923. doi:10.1016/j. eswa.2011.02.038.