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RECONFIGURING PROCESS PLANS: A MATHEMATICAL PROGRAMMING APPROACH

by

Ahmed A. Azab Ismail

A Dissertation

Submitted to the Faculty of Graduate Studies through
Industrial and Manufacturing Systems Engineering
in Partial Fulfillment of the Requirements for
the Degree of Doctor of Philosophy at the
University of Windsor

Windsor, Ontario, Canada

2008

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ABSTRACT

Increased global competition and frequent unpredictable market changes are current challenges facing manufacturing enterprises. Unpredictable changes of part design and engineering specifications trigger frequent and costly changes in process plans, which often require changes in the functionality and design of the manufacturing system. Process planning is a key logical enabler that should be further developed to cope with the changes encountered at the system level as well as to support the new manufacturing paradigms and continuously evolving products. Retrieval-based process planning predicated on rigid pre-defined boundaries of part families, does not satisfactorily support this changeable manufacturing environment. Since purely generative process planning systems are not yet a reality, a sequential hybrid approach at the macro-level has been proposed. Initially the master plan information of the part family's composite part is retrieved, then modeling tools and algorithms are applied to arrive at the process plan of the new part, the definition of which does not necessarily lie entirely within the boundary of its original part family. Two distinct generative methods, namely Reconfigurable Process Planning (RPP) and Process Re-Planning were developed and compared.

For RPP, a genuine reconfiguration of process plans to optimize the scope, extent and cost of reconfiguration is achieved using a novel 0-1 integer-programming model. Mathematical programming and formulation is proposed, for the first time, to reconfigure process plans to account for changes in parts' features beyond the scope of the original product family. The computational time complexity of RPP is advantageously polynomial compared with the exponentially growing time complexity of its classical counterparts. As for Process Re-Planning, a novel adaptation of the Quadratic Assignment Problem (QAP) formulation has been developed, where machining features are assigned positions in one-dimensional space. A linearization of the quadratic model was performed. The proposed model cures the conceptual flaws in the classical Traveling Salesperson Problem; it also overcomes the complexity of the sub-tour elimination constraints and, for the first time, mathematically formulates the precedence constraints, which are a corner stone of the process planning problem.

The developed methods, their limitations and merits are conceptually and computationally, analyzed, compared and validated using detailed industrial case studies. A reconfiguration metric on the part design level is suggested to capture the logical extent and implications of design changes on the product level; equally, on the process planning level a new criterion is introduced to evaluate and quantify impact of process plans reconfiguration on downstream shop floor activities. GAMS algebraic modeling language, its SBB mixed integer nonlinear programming solver, CPLEX solvers and Matlab are used. The presented innovative new concepts and novel formulations represent significant contributions to knowledge in the field of process planning. Their effectiveness and applicability were validated in different domains.

DEDICATION

To my late father, my beloved mama and Hosam.

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It is difficult to express my appreciation and gratitude to my Ph.D. supervisor, Prof. Hoda A. ElMaraghy. Prof. H. ElMaraghy was not just my thesis advisor, but a mentor, a teacher and a friend, who was always there for me during hard and good times. With her enthusiasm and dedication at work, my ambitions grew to perform state-of-the-art research for my doctoral thesis. I was inspired and motivated by her valuable guidance, sound advice and insightful comments. Prof. H. ElMaraghy invested massively in me with her precious time, effort, and the list goes on. I am deeply indebted and owe her a great deal. Her leading character, managerial skills and professional attitude had enriched me on personal and professional levels. At the Intelligent Manufacturing Systems (IMS) Centre, through ongoing seminars and research meetings and her excellent FMS course, Dr. H. ElMaraghy provided us with background on manufacturing system, which we were lacking; this was fundamental to our research at the IMS centre. I also learnt a lot from Dr. H. ElMaraghy's matchless writing skills through the endless editing process of the several publications we have written together, and in the period of my thesis writing where she put a lot of effort and long nights of reading so we could achieve what we did. It is a long journey and I am so grateful.

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our conversations and scientific arguments; he was always generous answering all my questions; I benefited greatly from taking his courses. Clearly, I am grateful to all faculty of Industrial and Mechanical Engineering at University of Windsor, in particular Dr. Walid Abdul Kader and Dr. Guoqing Zhang. I would also like to thank my friends and colleagues and all members of the IMS and the department of Industrial and Manufacturing Systems Engineering (IMSE) for creating a very healthy environment for research especially, Ms. Zaina Batal, Ms. Jacquie Mummery and Ms. Brenda Schreiber. Ms. Batal was very generous, providing all the help and assistance that I needed; also the two administrative staff of IMSE, Ms. Mummery and Ms. Schreiber were always considerate and nice to me and did their best to finish for us all the administrative and paper work we needed. I would like to recognize my professors at Cairo University in shaping me and my thinking; I believe I had an excellent undergraduate education in one of the most prestigious engineering schools all over the Middle East. Many thanks to Dr. Ashraf Nassef, who was always a friend and above all my first Optimization teacher and to my Masters' advisor, the late Dr. Mohamed F. Hassan, may Allah have mercy on his soul, who first educated me about Industrial Engineering and always stressed the importance of linking research to practice.

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LIST OF ABBREVIATIONS

B&B	Branch & Bound
CAD	Computer Aided Design
DFA	Design For Assembly
FMS	Flexible Manufacturing Systems
FPG	Features Precedence Graph
GA	Genetic Algorithm
GD&T	Geometric Dimensioning & Tolerancing
MINLP	Mixed Integer Non-Linear Programming
MIP	Mixed Integer Programming
OPG	Operations Precedence Graph
QAP	Quadratic Assignment Problem
RI _{Design}	Design Reconfiguration Index
RI _{Plan}	Plan Reconfiguration Index
RMS	Reconfigurable Manufacturing Systems
RMT	Reconfigurable Machine Tool
RPP	Reconfigurable Process Planning
SA	Simulated Annealing
TAD	Tool Access Direction
TSP	Traveling Salesperson Problem

NOMENCLATURE

Reconfigurable Process Planning (RPP) Model:

- n n is RPP problem size and it is the total number of decision variables and it could also be interpreted as the total number of machining features including the new machining feature to-be-inserted.
- C $C=[c_{i,j}]$ is the $n \times (n-1)$ precedence penalty matrix. A row would be assigned to each possible insertion position. For each row, a relatively large value would be assigned if the precedence between the feature/operation to be inserted and each feature/operation of the original sequence, at a time, is violated.
- S $S=[s_{i,j}]$ is the $n \times (n-1)$ work piece repositioning time matrix. A row would be assigned to each possible insertion position. For each row, the time required to reposition the work piece on the given fixtures (setups) in order to be able to switch between each pair of the successive features/operations of the new possible permutation, i.e after the insertion of the new feature/operation to be.
- Os $Os=\{Os_i\}$ is the $1 \times n$ old work piece repositioning time vector, which is a vector of the time required to reposition the work piece on the given fixtures (setups) in order to be able to switch between pairs of successive features/operations of the original sequence (i.e. not to include the new feature/operation) after subtracting the missing features/operations.
- Tr $Tr=\{Tr_i\}$ is the $1 \times n$ right tool change time vector (i.e. the tool change between the new to-be-inserted feature/operation and every feature/operation in the old sequence from the right side).
- Tl $Tl=\{Tl_i\}$ is the $1 \times n$ left tool change time vector (i.e. the tool change between the new to-be-inserted feature/operation and every feature/operation in the old sequence from the left side).
- Ot $Ot=\{Ot_i\}$ is the $1 \times n$ old tool change time vector, which is a vector of the tool change time in order to be able to switch between pairs of successive features/operations of the original sequence after subtracting the missing features/operations, i.e. not including the new feature/operation to-be-inserted.
- x_i 0-1 integer decision variable, where i runs from 1 to n . 1 if new feature is inserted at position i ; 0 otherwise. The position i takes the value 1 when the new feature is inserted right before the first feature of the original array of features and takes the value n when it is positioned right after the last feature of the original array, i.e. feature f_{n-1} .

Quadratic Assignment Problem (QAP) Model:

- m QAP problem size, which is defined as the total number of decision variables. It is also the total number of machining features to be sequenced; that is as far as the physics of the problem goes.
- T $T = [t_{i,j}]$ is an $m \times m$ symmetric handling time matrix.
- $y_{i,k}$ 0-1 integer decision variable, where both i and k run from 1 to n . The value of the decision variable is 1 if the feature i is positioned in location k ; otherwise it is zero.
- $q_{i,j,k}$ A new 0-1 decision variable $q_{i,j,k}$ is introduced in the linearized QAP model; the variable holds all three indices of the problem: i and j the features' indices and k the position index.

Simulated Annealing-based Heuristic:

- P Precedence constraint matrix, where every element in the matrix represents a precedence relationship between a pair of two features/operations. Each row is composed of two features/operations IDs representing a predecessor successor relationship.
- T $T = [t_{i,j}]$ is an $m \times m$ symmetric handling time matrix.
- t t is the annealing temperature; initial annealing temperature is t_0 .
- B Search current point.
- N New search point after applying the SA operator, where a move is randomly chosen to one of the neighboring solutions.
- S Outer loop counter, whose ceiling (upper limit) is S_{max} .
- z Inner loop count; it decreases by α , where $0 < \alpha < 1$. For the first loop it starts with a value z_{max} .
- j Inner loop counter.
- BestSoFar A variable to store the best search point visited so far.
- ObjFn Value of the objective function for a given sequence.
- ΔE $\Delta E = \text{ObjFn}(N) - \text{ObjFn}(B)$.

General Metrics:

- RI_{Design} Design Reconfiguration Index, which is a metric that measures the extent of design changes on the product (part/assembly)

level; it is an input to the process planning problem and is used to select the most suitable planning method accordingly.

RI_{Plan} Process Plan Reconfiguration Index, which is a metric that measures the percentage change, i.e. reconfiguration of the original master or existing process plan, due to adding and/or removing feature(s).

1. INTRODUCTION

In this chapter, the motivation behind the current work, the proposed approaches, and an overview of the dissertation is briefly given. Evolution of both product families and manufacturing systems are briefly overviewed. Physical and logical enablers for advanced state-of-the-art manufacturing systems are presented. Finally, an important soft enabler- process planning- the subject of this work is discussed.

1.1 Evolvable Products & Part Families

Manufacturers worldwide are faced with increased competition and major challenges to achieve agility, responsiveness and cost-effectiveness. They need to respond promptly to customer needs and to quickly introduce cost-competitive products to the market. Product families have become more dynamic; i.e., part families' definitions are not rigid anymore. A part family is the collection of all part instances obtained by varying the composite part features' parameters within its feasible range set by the designer (Huang and Yip-Hoi 2003). Parametric modeling has become a widely accepted mechanism for generating data set variants for product families. These data sets include geometric models and process plans. These ranges denote the extent or envelope of the product family, which is continuously changing, as clear product evolution has been witnessed. After a few generations, new product families gradually lose their roots (missing features) and develop new and different branches (additional features). The extent of difference between product generations depends of the number and nature of feature changes (ElMaraghy 2006 and ElMaraghy *et al.* 2008).

ElMaraghy *et al.* (2008) suggested that this evolution occurs in two modes. The first is a chronological mode, where change develops gradually over time and represents a unidirectional natural progression as more knowledge and better technology become available. This type of evolution is unidirectional because as new and better solutions are obtained, it does not make sense to revert to older inefficient or flawed designs. The second type is functional evolution, which is caused by a significant and major change in requirement, which is normally forced by many factors. It is often selective and discrete,

although a major overhaul is also possible. This type of change may be bi/multi-directional as the new product fulfills different functional requirements, but does not necessarily render previous designs obsolete.

1.2 Changeable Manufacturing Systems

Mass customization and agile manufacturing are paradigms that have emerged quite recently to face the new challenges due to highly customized and rapidly varying products. As explained in section 1.1, products are continuously evolving beyond the boundaries of their original part families. Different types of manufacturing systems with unique characteristics and scope exist.

At the design level, product variety and new product introductions are not usually considered for flow lines. Dedicated manufacturing systems enable mass production and economy of scale. A Flexible Manufacturing System (FMS) overcomes the rigidity of flow lines by having all the needed functionality built-in a priori; however, this results in high initial capital investments as well as relatively lower utilization. For mass customization and economy of scope, FMS are best suited.

In order to stay competitive, new responsive manufacturing systems and their enablers are beginning to emerge to support new business paradigms such as mass customization and agile manufacturing (ElMaraghy 2005). Reconfigurability is an engineering technology that deals with cost-effective, quick reaction to market changes (Koren *et al.* 1999). Reconfigurable Manufacturing Systems (RMS) are achieved by incorporating basic process modules that can be rearranged or replaced quickly and reliably to adjust the production capacity and functionality, in response to new market conditions and new process technology. Modularity, integrability, customization, convertibility, and diagnosability are its distinct characteristics (Mehrabi *et al.* 2000a). When these characteristics are embedded in the system design, a high degree of reconfigurability is achieved (Koren and Ulsoy 2002). This new type of manufacturing system allows flexibility not only in producing a variety of parts, but also in changing the system itself. These systems will be open-ended and will run less risk of becoming

obsolete, because they will enable rapid changes of system components and rapid addition of application-specific software modules (Mehrabi *et al.* 2000b). Reconfigurability aims at achieving more competitiveness by exploiting new technology and supporting business paradigms (ElMaraghy 2005). Gradually, RMS is becoming a reality, and is being deployed by many mid-to-large volume manufacturers (Li *et al.* 2006).

Wiendahl *et al.* (2007) commented on the differences between FMS and RMS. According to them, it is necessary to clearly define the boundaries between flexibility and reconfigurability. In summary, flexibility is interpreted as the ability of a system to change its behavior without changing its configuration, where reconfigurability is conversely interpreted as the ability to change the behavior of a system by changing its configuration. These definitions can be used only if the boundary of the system is clearly defined. Depending on the defined borders, change can be interpreted as either reconfigurability or flexibility. It was concluded that: “it is better to refer in general statements to the term changeability which encompasses both characteristics”. Therefore, changeability in this context is defined as characteristics to accomplish early and foresighted adjustments of the factory’s structures and processes, on all levels, to change responsively and economically.

1.3 Changeability Enablers

Reconfiguration could be achieved at the system or machine levels and it may be classified as soft (logical) or hard (physical) in nature (ElMaraghy 2005). Hard/physical changes require corresponding major changes in the soft and logical support functions, whether in the planning and control of individual machines, complete cells, and systems as well as the individual processes and production. Logical or soft reconfiguration includes many aspects of flexibility that can be achieved through good system design and software solutions. Products, technology and hardware changes using presently available technology require that soft/logical enablers, such as process planning, not only be in place, but also be easily adaptable and reconfigurable (ElMaraghy 2005). Soft/logical enablers allow manufacturers to cope with changes in products, process technologies or

capacity of the changeable manufacturing systems and equipment. The soft/logical enablers of change can extend the usability and life of any manufacturing system and increase productivity, competitiveness and profitability.

1.4 Process Planning

Process planning is an important soft type enabler for such changeable systems. It is an essential function for the smooth operation of any manufacturing system running under the variable conditions described earlier. Bedworth *et al.* (1991) defined process planning as a set of instructions that describe how to fabricate a part or build an assembly that will satisfy engineering design specifications. The resulting set of instructions may include any or all of the following: operation sequence, machines, tools, materials, tolerances, notes, operating parameters, processes, jigs, fixtures, time standards, setup details, inspection instructions, gauges, and graphical representations of the part in various stages of processing.

Process planning is the interface between design and manufacturing. It translates the design specifications into process and operations sheets. Process planners or process planning systems should be capable of querying all geometric, feature, and functional information about the product. Process planning systems are usually developed for a single manufacturing process, limiting themselves in some instances to certain geometry like prismatic or cylindrical parts. Metal Cutting is the primary area of investigation; however, assembly and inspection processes are also included.

The current process planning approaches, particularly the retrieval-based methods with their rigid definition of the boundaries of part families, do not satisfactorily support both the current advances and evolution of both manufacturing systems and product families. Since truly generative process planning systems are not yet a reality, a hybrid sequential process planning methodology is proposed in this work, where new planning methods, concepts and novel mathematical programming models have been developed for process planning in changeable and reconfigurable manufacturing at a macro-level (Azab and ElMaraghy 2007c). The proposed methodology reconfigures process plans to

support both the current trends in product design and evolution of part families and manufacturing systems. For the generative portion of the developed approach, two distinct approaches are presented to reconfigure process plans namely: Reconfigurable Process Planning (RPP) and Process Re-Planning.

1.5 Research Hypotheses

The main hypotheses of the current research are:

1. Mathematical modeling and programming are crucial solution methods in the field of process planning. Moreover, they are fundamental because they also serve as a conceptual basis for the rest of the non-traditional methods in the field.
2. Variant process planning, with its rigid definition of part families' boundaries, is not best suited for the current manufacturing environment with its evolvable part families and changeable manufacturing systems. Pure generative process planning on the other hand is not yet a reality. Therefore, a hybrid semi-generative process planning that is variant in nature, but yet also able to generate process plans for new parts that are not members of the original part family's master plan would, best match the current challenging manufacturing trends.
3. For low- to mid-volume job shops and batch production, it would be better to reconfigure existing or master process plans than to re-plan them from scratch, and hence, cause the least change and disruption in all the downstream activities on the shop floor.

1.6 Overview of the Dissertation

The following is an outline of the dissertation:

- Chapter Two presents the related different research directions in the literature. A thorough critique is provided.
- Chapter Three sketches the overall planning methodology, in which retrieval of master or existing plans, followed by generative processing by means of algorithmic and optimization methods takes place. The different variant and generative phases of the proposed approach are outlined.

- Chapter Four presents the first developed process plan reconfiguration method. Details of the proposed mathematical model are provided. A benchmark problem from the literature was used to illustrate the entire iterative reconfigurable method.
- Chapter Five describes an alternative proposed Process Re-Planning method. Both mathematical programming and non-traditional optimization methods are presented. Linearization of the developed quadratic model is carried out. Non-traditional optimization is also used to solve instances of large size. The same illustrative problem is used to demonstrate the models and methods proposed.
- Chapter Six presents a machining case study of a single cylinder front engine cover family.
- Chapter Seven is dedicated to verification in domains other than metal cutting. Two case studies in assembly and inspection planning are given.
- Chapter Eight concludes the dissertation with a brief discussion and a list of the research findings and conclusions.

The dissertation has two appendices. Appendix A provides more details of the Reconfigurable Process Planning (RPP) formulations. Appendix B provides details of the Quadratic Assignment Problem (QAP) formulations.

2. CRITICAL LITERATURE REVIEW

This chapter provides primarily a review of the literature with the most relevance to the problem of reconfiguring a process plan. Also, work related to the problem of Process Re-Planning with emphasis on mathematical modeling and programming approaches is covered. Besides metal cutting, the primary field of investigation, both assembly and inspection planning were also considered. A chronological order was generally followed. Critique and gaps in this area of research are highlighted.

2.1 Introduction

Very few publications had tackled the problem of reconfiguring a process plan. Zaeh *et al.* (2006) suggested that agility is necessary in process planning in order to be able to produce individualized products for the constantly reconfiguring companies structures (Warnecke 1993). ElMaraghy (2006) classified the various process planning concepts and approaches, based on their levels of granularity, degrees of automation, and scope. The new concept of “Evolving Parts/Products Families” was introduced. The need for “Evolvable and Reconfigurable Process Plans”, which are capable of responding efficiently to both subtle and major changes in “Evolving Parts/Products Families” and changeable and Reconfigurable Manufacturing Systems was indicated.

The most relevant process planning approaches that support, to varying degrees, changeable and agile manufacturing paradigms are reviewed in the following sections. Also emphasis on mathematical modeling and programming was provided. Finally, application in both assembly and inspection planning is demonstrated.

2.2 Macro- Versus Micro-Level Process Planning

Process planning has two distinguished levels, Macro- and Micro-level planning (ElMaraghy 1993). At the Macro-level, planning is concerned with identifying the main tasks and their best sequence and the type of manufacturing processes. Micro-level planning details process parameters, required tools and setups, process time and

resources. Macro-level process planning is difficult because of its dependence on declarative process knowledge including part geometry, tools, machine tools, fixtures and technological requirements and also its implied time-dependency represented by the order in which the given features should be machined. The optimization criteria used range from minimizing transportation of parts between and within machine tools to minimizing change of cutting conditions and rapid tool-traverse. The problem had traditionally been solved through rule-based knowledge that was acquired from machining practices (Lin *et al.* 1998). Most of the available research utilized geometric information and constraints for precedence creation for sequencing of operations. Almost all mathematical models developed for the classical macro-level process planning problem are based on the Traveling Sales-Person (TSP) problem formulation (e.g. Lin & Wang 1993). Refer to section 2.5 for a thorough critical review of process planning modeling.

2.3 Variant- Versus Generative-Type Process Planning

Process planning can also be classified as either variant or generative. Retrieval-type process planning techniques, based on a master template of a composite part, lend themselves to RMS predicated on a defined part family. However, this approach results in less than optimum process plans, because of the lack of specificity, precision, refinement and optimization possible at this high level of abstraction. Hetem (2003) discussed research, development and deployment of concepts and technologies to develop variant process planning systems for RMS. Bley and Zenner (2005) proposed another variant concept - an integrated management concept that allows meeting requirements of different markets and changing needs by generating a generalized product model. Both papers presented a strictly variant type system, which did not support the introduction of new features into the part family caused by changing demands.

Generative process planning is better able to handle products variety by generating process plans from scratch using rule-based and knowledge-based systems, heuristics and problem specific algorithms. Pure generic generative systems are not yet a reality. In most of the literature, mathematical formulations and programming are not used, but

rather informal procedural methods (Azab 2003) that are solved using either non-traditional optimization methods or search heuristics.

There is a dearth of literature that offers generative process planning solutions for changeable Reconfigurable Manufacturing Systems (RMS). Xu *et al.* (2004) presented a clustering method for multi-part operations. Based on analysis of process plans for Reconfigurable Machine Tool (RMT) design, a tolerance-based and concurrent-machining-based clustering method for a single part was proposed. The mathematical model and algorithm of the pattern recognition for recognizing the similar sub-operation groups within the entire part family was established. Shabaka and ElMaraghy (2005) proposed an approach for selecting different types of machines and their appropriate configurations to produce different types of parts and features, according to the required machines capabilities. The structures of the machine tools were represented by a kinematic chain that showed the number, type and order of different axes of motion on both the tool and the work piece sides of the machine. More than one minimum machine configuration for a single operation cluster was generated and, hence, increased the flexibility in machine tool selection and operations assignment (Shabaka and ElMaraghy 2007). This approach was not limited to RMS, and is applicable to any manufacturing system where dynamic and flexible process planning and machine assignments are required. Shabaka and ElMaraghy (2006) also developed a Genetic Algorithm (GA) method for operation selection and sequencing that could serve as a tool in aiding the machine assignment/selection activities. The proposed method guaranteed that operations that have related tolerance or logical constraints, are clustered together and manufactured on the same machine. Jin *et al.* (2007) introduced a novel method of process route and layout design to accelerate and rationalize the reconfiguration process of an RMS. A directed network model of process planning based on graph theory was constructed. The Dijkstra algorithm was applied to select the optimal process route in the established network model. Song *et al.* (2007) presented a dynamic Computer Aided Process Planning (CAPP) system structure to support RMS, where a strategy of dynamic decision of manufacturing resource allocation using neural networks is suggested.

In this work, generative mathematical models and solution algorithms based on mathematical programming and non-traditional optimization methods using Simulated Annealing (SA) search heuristics are presented and compared. Hence, application of SA in process planning is briefly reviewed.

Simulated Annealing (SA), sometimes combined with Genetic Algorithms, was adopted for solving the process planning problem. Lee *et al.* (2001) proposed four SA algorithms to solve the operations sequencing problem. Ma *et al.* (2000) reported an SA algorithm for operations selection and sequencing. Ma *et al.* (2002) presented the development of a computer-aided process planning (CAPP) system based on genetic algorithm and simulated annealing. Brown *et al.* (1997), Li *et al.* (2002), Shan *et al.* (2006), Li *et al.* (2002) developed hybrid GA-SA optimization approaches process plans, setup plans and operations sequencing in multiple domains such as metal cutting and assembly planning.

2.4 Dynamic and Adaptive Versus Non-linear Planning

Besides changeability of manufacturing systems, dynamicity of the plant and shop floor has always been a key factor in process planning. According to Ssemakula and Cloyd (1994) dynamic process planning is an approach where both the static and the dynamic capabilities of the manufacturing shop floor are taken into consideration. Integration of production scheduling and process planning was envisioned to support the dynamic nature of the factory floor. Hancock (1988) defined adaptive process planning as the capability of making efficient process planning, machine routing, and job shop scheduling decisions in a wide range of actual settings. Conversely, according to the literature, non-linear process planning entails the generation and ranking of alternative process plans for a given part prior to production independent of the resource status on the shop floor. It is important to note, however, that the term “non-linear” is not very accurate, since non-linear process planning is not based on concepts of linearity or non-linearity and principles of superposition and homogeneity.

Usher and Fernandes (1996a) proposed a dynamic process planning approach, where planning activities were carried out in two levels: static and dynamic. The static phase was concerned with the generation of generic alternative plans. The planning at this phase involved the selection, assignment, and sequencing of processes and machines that could potentially be used if available. The output of this phase would be a set of alternative macro-level plans. The dynamic planning phase would take place only when a job was released for production to the shop floor. Then, the developed macro-level plans would be retrieved and planning would be completed taking into consideration the availability of the shop-floor resources. Usher and Fernandes (1996b) focused on the implementation of the dynamic phase of planning and its integration with scheduling. The output of this phase would be a set of ranked feasible alternative plans. Usher and Fernandes (1999) considered tool selection within this dynamic process planning approach.

Usher and Bowden (1996) considered operation sequencing as one part of distributed process planning, where planning is performed in two stages: floor resource independent planning followed by resource dependent planning. The purpose of the resource independent stage was to provide a means for determining and archiving the best set of plans for a part, independent of the status of the shop floor resources' availability. Then, later when production of that part was released to the shop floor, the resource dependent planning phase completed the planning tasks. Features were classified by the author as primary and secondary features, with the primary features defining the basic shape of the part, while secondary features provide detailed shape aspects like threads. Kiritsis and Porchet (1996) presented a Petri net based approach for dynamic process planning and sequencing, where the reachability analysis is performed and a reachability tree is automatically created. Zhang *et al.* (1999) believed that accurate description of resources and their availability is a key element of an adaptive and practical process planning system. Ohashi (1999) proposed a hierarchical approach for dynamic process planning of palletized work pieces. At level one, group technology methods were applied to solve work piece grouping problem to combine similar machining operations for several work pieces. At level two, a model was formulated to optimally allocate the work pieces on a

pallet. Finally, at the last level, sequencing and scheduling of machining operations for the grouped work pieces were performed.

Chen and Liu (2001) developed an adaptive GA, where the genetic operator probabilities were varied in run-time. Joo *et al.* (2001) presented a conceptual framework for adaptive and dynamic process planning, where machine, cutting tool and machining parameters selection were considered. Cheraghi *et al.* (2006) adaptively modified process routing. A mathematical model was proposed to generate operational tolerances, machine assignments, and to provide a measure of plans feasibility, identify sources of infeasibility, recommend alternative machines, and identify the required process capabilities to make an infeasible plan feasible. Cai *et al.* (2008) developed an adaptive setup planning approach for various multi-axis machine tools focusing on kinematic analysis of tool accessibility and optimal setup plan selection.

On the other hand, for non-linear process planning, Kruth *et al.* (1996) presented several methods that would cut down its response time. One method was to classify the features into important and non-important, which resembles the reasoning pattern that a human process planner would adopt. Another method for performance improvement was to group features that have strong resemblance. Jang *et al.* (2003) provided methods to validate non-linear process plans and hence, correct them. The authors expressed the need to validate the generated process plans created manually or by CAPP against various criteria, such as the final shape of the finished part, features interaction and interference, features manufacturability, etc. Metrics had been provided to quantify the degree of invalidity of the process plan.

2.5 Mathematical Modeling in Process Planning

The problem of sequencing n sub-operations while satisfying a set of precedence constraints has the structure of the famous Traveling Salesperson Problem (TSP) (Lin and Wang 1993, Irani *et al.* 1995, Kim and Suh 1998). Papadimitriou and Steiglitz (1982) defined TSP as: given n (where n is an integer and $n > 0$) distance between every pair of n cities, and a tour as a closed path that visits every city exactly once, then the problem is to

find a tour with minimal total length. Lin and Wang (1993), Irani *et al.* (1995) and Kim and Suh (1998) stated that the problem is equivalent to that of extracting the Hamiltonian path of least cost that visits all of the features once and only once. Rardin (1998) proposed a Quadratic Assignment Problem (QAP) formulation for TSP. Lin *et al.* (1998) stated that an operation sequence had traditionally been determined through rule-based knowledge that was acquired from machining practices. Halevi and Weill (1992) enumerated the different types of precedence constraints as: (1) accessibility of a feature by the tool, taking into consideration the tool axis (approach) direction which is denoted as a vector approaching to the feature, (2) logical sequence of operations (e.g. drilling is done after center drilling, and boring is done after drilling), and (3) dimensional Precedence, for example a machined feature may be used as the reference datum from which another machining feature is to be measured (A surface being dimensioned in relation to another surface).

The modeling of the problem at hand is relatively difficult because it is not only dependent on the declarative process knowledge including part geometry, tools, machine tools, fixtures and technological requirements, but also time dependent, as it is heavily dependent on the order of the different sub-operations and their precedence. Most of the models in the literature, if not all, are based on the popular TSP. Criteria used in the literature are many and diverse, ranging from minimal transportation of parts between and within machine tools to the minimal change of cutting conditions. Chiang and Yang (1991) formulated and presented a technique to determine the optimal operation sequence for manufacturing a part using a saw derived by a robot. The criterion of optimization was minimizing the total manufacturing cost. The manufacturing cost was categorized into transition and direct cost. Transition cost was the cost of changing the manufacturing process from one to another. This included three items: tool exchange, traveling, and priority. The authors have included the direct processing cost of each sub-operation as an objective, although operations sequencing is independent of that cost component.

Lin and Wang (1993) had included operations sequencing as the fourth step in a four-step approach for operation planning. The problem was solved in two steps. Tooling

requirements were first considered, and then machining steps are sequenced in an effort to minimize tool changes. A Modified Traveling Salesperson Problem model was developed. The authors proposed a new sub tour elimination constraint; however the constraint prevents only subtours of size two from taking place; subtours of size greater than or equal to three could result. Moreover, the authors used two additional sub-indices for tools, where only two would suffice since tools were implicitly represented by the cost coefficients. Koulamas (1993) combined the problem of determining the operation sequence and cutting speeds. The problem was initially formulated as a continuous nonlinear optimization problem combined with a discrete combinatorial scheduling problem. As for Irani *et al.* (1995), they took the following criteria in consideration: machining parameter change, cutting tool change and setup change. The term 'setup change' was mistakenly used to denote the repositioning of the work piece or fixture. The problem was formulated as an unconstrained optimization problem where a penalty objective function was used. Penalty functions were improperly modeled. The TSP model can only model immediate predecessor-successor constraints. Hence, the author artificially tried to assign very large values to all indirect precedence in the cost matrix that would lead to the prohibited precedence, which is itself a search problem worthy of research. Irani *et al.* (1995), Bhashkara Reddy *et al.* (1999), Dereli and Feliz (1999), Qiao *et al.* (2000) and Gan *et al.* (2001) had adopted the same flawed method of applying penalties in order to model precedence constraints. The error in modeling precedence was obvious in a number of their published works as manifested by the infeasible plans generated.

Wong and Siu (1995) represented the necessary precedence of operations using a sequence tree structure, which was used to generate the final operations sequence using a refinery and linearization algorithm. Bhashkara Reddy *et al.* (1999) had adopted the same classification of features adopted by (Usher and Bowden, 1996). The fact that a secondary feature was defined as residing on a primary feature dictated that the machining of primary features must have come first. The authors had used a multi objective function where the minimal number of repositioning of work piece or fixture, tool changes, tool travel and finally good machining practice were all taken into

consideration. A scoring method was devised to rate each objective on a scale from 0 to 1. The square of the weighted sum of these scores was used to determine the overall objective function value. A single time objective function could have been used instead, where all the above stated criteria could be combined.

Gu et al. (1997) suggested that feature prioritization should be performed before operations sequencing could begin. After feature prioritization, operation sequencing of the important features, those with high priority, could be carried out first within a much smaller search space and then the operations of the less important features could be arranged easily due to reduced constraints. Although the authors mentioned that the importance of a feature was evaluated according to two aspects: the design function of the feature and the manufacturability or the manufacturing difficulty of the feature, however their work only focused on the analysis of the manufacturability of the part stating that the functional importance of a feature was generally quite well correlated with its manufacturability.

Kim and Suh (1998) performed optimal grouping and sequencing by minimizing non-cutting time in a multistage machining system. The authors considered medium to large size batch of products, where a flow line in which processing time in each stage was limited. An integer programming model based on TSP was developed to minimize non-cutting time. The authors had introduced additional integer decision variables to express the order of an operation, and hence model precedence constraints. Order in a TSP problem is not defined since the output of a TSP model is a tour with no start and no end. Also, the term non-cutting time proposed by the authors is not very accurate, since non-cutting time include other components than handling that could not be optimized such as servicing time, and fatigue time for instance.

A number of researches had tackled the operations sequencing problem for simultaneous machining. An example of the work done on parallel machining is Chiu *et al.* (1999). The author proposed a mixed integer programming model. The proposed mixed integer program sought the minimum cycle time (completion time) of the

corresponding operation sequence for a given work piece. The model was formulated under the assumptions that turrets are equipped with live tools and that automated tool change time was negligibly small. The computational complexity of the problem was not considered.

2.6 Process Planning for Non-Cutting Operations

The primary field of investigation of this research is metal cutting. However, the developed concepts, models, and methods are also tested and verified in other domains of application such as assembly and inspection. A brief review of both process planning for assembly and inspection is provided respectively in the following subsections.

2.6.1 Assembly Planning

The time spent on the design and assembly planning for a new product is quite considerable. For products with long life cycles, which are produced in rather large quantities and often assembled manually, such time investments are justifiable (Laperriere and ElMaraghy 1994). However, present market conditions demand that products be produced with much shorter life cycles and in smaller volumes. Therefore, the time spent on product development, at large, including that spared in assembly planning activities has to be reduced. Furthermore, as explained in chapter one, the current manufacturing environment with its continuously evolvable product and part families as well as its advanced changeable manufacturing systems dictate the development of new process planning concepts, models and tools for all manufacturing processes, including assembly operations.

The main objective of assembly planning is usually to determine the feasible optimal assembly sequence that minimizes assembly handling time. This is mainly composed of two components: 1) time required repositioning the different subassemblies in-process on the fixtures; 2) time required to perform tool changes in case of automated assembly systems. The assembly planning problem is a combinatorial optimization problem. Hence, in the last two decades, increased application of non-traditional optimization methods such as GA, SA, Tabu Search, Ants Colony, etc. is witnessed. Chen (1990) proposed Hopfield neural networks to solve a Traveling Salesperson Problem (TSP) formulation of the automated planning problem, where AND/OR precedence relationships were mapped into networks of neurons. The problem with the AND precedence relationship could be solved using a traditional second-order Hopfield network, whereas higher-order Hopfield networks are used to solve those with the OR

precedence relationships (Chen 1992). The cost of the prohibited precedence is artificially set to a very large value to guarantee the satisfaction of the specified constraints. This concept of restricting the movement of the next states was inaccurately called, by Chen (1990 & 1992), State-Constrained Traveling Salesman Problem. A ten-part gear box assembly was used for verification.

Park and Chung (1991) graphically modeled the problem, where all possible planning alternatives were exhaustively enumerated. Parallelism of assembly tasks, whether by the use of multiple robots or workers, is taken into account. A graph-theoretic approach was also employed by Laperriere and ElMaraghy (1994) to generate the assembly sequence. Only the feasible search space was considered, by including the precedence constraints when generating the search graph. An A* algorithm was used, where the evaluation of assembly-related criteria as the search graph expands, guides the search towards an optimal solution. Huang and Wu (1995) argued that a backward search would be more efficient than a forward search by converting the problem of finding how to assemble a given product into an equivalent problem of finding the same product can be disassembled. Zhao and Masood (1999) employed a graph set technique for creating an assembly model.

Guan *et al.* (2002) presented a hierarchical evolution algorithm approach, where a compound chromosome encoding was constructed to represent the abundant assembly process information. Geometric reasoning was used to distinguish the geometric feasibility of the chromosomes. Del Valle *et al.* (2003) developed a model to support multi-robotic assembly environments. The established criterion was the minimization of the total assembly makespan. Assembly times, available resources, tool change time, and the delays due to the transportation of intermediate subassemblies between different workstations were all issues taken into consideration. The authors included both GA and a greedy algorithm for solution. Galantucci *et al.* (2004) proposed a hybrid fuzzy logic GA method to plan the automatic assembly and disassembly operations. The suggested GA-Fuzzy Logic approach was implemented onto two levels. First, fuzzy controller

parameters were optimally determined by using GA. Second, a fuzzy function is used to determine the optimal sequence or disassembly plan.

Tseng *et al.* (2007) considered the global logistic supply chain aspect of the assembly planning problem, where a product could be designed and manufactured at different plants at multiple locations. A mathematical programming model was formulated to evaluate all the feasible multi-plant assembly sequences. The objective was to minimize the total cost of assembly.

2.6.2 Inspection Planning

The main purpose of inspection processes is to compare a product against its design specifications. Effective planning of inspection processes is to obtain the best timely and good quality product. Artificial intelligence, neural network, fuzzy rules and non-traditional optimization are all tools to optimize inspection processes (Mohib *et al.* 2008). Sample publications that are believed to be representative of the work done in the last decade are surveyed in this section.

EIMaraghy and Gu (1989) presented the first expert system for planning inspection operations for a Coordinate Measurement Machine (CMM). The developed system was generative in nature and feature-based. Chan and Gu (1993) developed an object-oriented knowledge-based inspection planner; however, the planning problem was not solved for optimality. The issues involved in CAD-directed inspection planning were examined; the task of inspection process planning is decomposed into several modules. An inspection planning system was designed as a multi-module knowledge-based system; each of these modules had its own knowledge base. Moroni *et al.* (1998) developed an expert system to generate touch probe configurations and to select the most suitable probe for CMM dimensional inspection. The considered optimization criteria are minimization of probe changes (tip, stylus, probe and accessories) and probe orientation changes. A depth-first strategy was adopted by means of priority scores assigned to the inspection rules.

Lu *et al.* (1999) used an artificial Neural Network technique for multi-component inspection path management. Genetic Algorithms were applied to reduce the distance moved by the probe to obtain a collision-free path. Hwang *et al.* (2004) proposed a CMM inspection planner to arrange the inspection feature measurement sequence by minimizing part repositioning on the given setups/fixtures and probe orientation changes, using a greedy heuristic and continuous Hopfield Neural Network. Hwang *et al.* (2002) developed a knowledge-based inspection planning system using a hybrid Neuro-Fuzzy method with weight parameters optimized using Genetic Algorithms. Beg and Shunmugam (2002 and 2003) developed an object-oriented planner using Fuzzy Logic to select and sequence part and probe orientations for the inspection of prismatic parts. Ketan *et al.* (2002) developed a feature-based geometric reasoning approach for planning the inspection of prismatic parts. Cho *et al.* (2005) developed a series of heuristic rules by analyzing the feature information, such as the nested relation and the possible probe approach directions to inspect work pieces having many primitive features.

2.7 Summary & Conclusions

Dynamic and adaptive process planning considers change of the manufacturing system due to the inherent dynamicity of the shop floor environment by adaptively configuring the current process plans according to manufacturing resources availability. Non-linear process planning, on the other hand, generates alternative process plans a priori to account for those sudden plant floor breakdowns.

Hetem (2003), Xu *et al.* (2004), Bley and Zenner (2005), etc., considered the changeability of the current and future manufacturing systems. Most of the work proposed strict variant-type systems because RMS in principle is, like FMS, built for a given part family. However, this pure retrieval-based approach does not support the introduction of new features into the part family caused by the changing demands, unpredictability and turbulence of today's globalized markets. Shabaka and ElMaraghy (2005, 2006 and 2007) addressed the problem of reconfiguring machine tools to account for these new changes on the part level. Song (2007) suggested dynamic adaptive process planning systems for RMS. In conclusion, none of the work surveyed genuinely

considered continuous change and evolution of parts and products families. No genuine reconfiguration of the process plan was proposed.

In summary, the existing methods for adapting process plans may be classified as pre-planning or re-planning approaches. Non-linear process planning is an example of pre-planning scenarios, where alternate process plans are developed and stored ahead of time in anticipation of potential future changes. There is an obvious cost and computational burden involved in this approach for changes that may not materialize. Total re-planning, where for every change a whole new process plan is re-created, with limited benefit from available plans with its existing fixtures (setups) and tooling, also represents a major cost for manufacturers. Re-planning should be carefully optimized, and new approaches developed to improve its effectiveness and reduce resulting direct and indirect cost.

As for mathematical modeling and programming for process planning, most, if not all, the models in the literature were based on the popular symmetric TSP model. However, applying TSP for process planning was not very successful. Hence, most of the work in the literature relied on non-traditional and non-mathematical programming methods. To begin with, it is wrongly believed (e.g., in Lin and Wang (1993), Irani *et al.* (1995), and Kim and Suh (1998)), that the problem of sequencing while satisfying a set of precedence constraints best takes the structure of the TSP problem. The output of a TSP is a tour and not a sequence with a start and an end. As for the precedence relationships, which are a corner stone of the problem in hand, TSP is limited to modeling immediate predecessor-successor constraints. Also, the TSP is well known for the complexity of its sub-tour elimination constraints. Moreover, the few formulated TSP-based models contained major flaws. Lin and Wang (1993) suggested a new sub-tour elimination constraints that only prevent subtours of size two from taking place. Irani *et al.* (1995), Bhaskara Reddy *et al.* (1999), Dereli and Feliz (1999), Qiao *et al.* (2000) and Gan *et al.* (2001) had adopted an incorrect method of applying penalty functions in an effort to model precedence constraints. The authors had artificially assigned very large values in the cost matrix to all indirect precedence predecessor-successor relationships

that would lead to the prohibited precedence, which appears itself to be a search problem worthy of research. Kim and Suh (1998) had dependent additional integer decision variables to their TSP-based formulation defining the order of operations. The authors failed to notice that order in TSP is not defined in the first place since the output is a cyclic tour.

Another line of research in the literature had adopted multi-objective optimization approaches such as utility functions, goal programming, etc. A single, time objective function, would have been better to use, where all the stated criteria are expressed in units of time. In some instances, direct machining cost was also mistakenly included as a criterion. Direct cost components could only contribute when simultaneous machining, multi-robot assembly, etc., are in question. Finally, some of the terminology used was not accurate. For example, the term “setup change” was used to denote the repositioning of the work piece on the jigs and fixtures. Non-linear process planning is not based on the concepts of linearity/non-linearity and principles of superposition and homogeneity. Non-cutting time was also inaccurately used on some occasions, where time components other than the handling time exist, such as operator fatigue and service/maintenance activities, which are not to be minimized by the optimization problem at hand.

3. SEQUENTIAL PROCESS PLANNING

This chapter presents an overview of the overall methodology developed for process planning, which is based on Azab and ElMaraghy (2007c). Continuous evolution of parts and product families and the paradigm shift in manufacturing systems and their increased flexibility, reconfigurability and changeability requires corresponding responsiveness in the underlying support functions to achieve cost-effective adaptability. Process planning is a significant logical enabler at the production planning and control level. Azab and ElMaraghy (2007c) argued that variant process planning systems, with their rigid definition of part families' boundaries, are not best suited for RMS and that generative process planning has more potential as an enabler of such new technology. In generative process planning, all plan details including the operations sequence are developed based on numerical algorithms, mathematical modeling and programming, decision tables and trees, etc., as well as possessed and stored manufacturing knowhow; pure generative systems do not presently exist. Instead, semi-generative process planning systems are developed, where a pre-process plan is generatively prepared and then further developed and refined by a process planner. Therefore, since purely generative process planning systems are not yet a reality, a hybrid semi-generative process planning system would be more suitable and achievable (Azab *et al.* 2006 2007).

3.1 Conceptual Framework

The need to have process planning techniques and methodologies that are capable of coping with frequent changes in design specifications, material, production technologies and manufacturing resources in an efficient and cost effective manner has always been expressed by process planners regardless of the type of the targeted manufacturing system. Its importance has been heightened by the continuous evolution of products and manufacturing systems and the emergence of new manufacturing system paradigms, where change is becoming the norm and the availability of enablers such as process plans that are easily adaptable to changes is proving to be an essential support function.

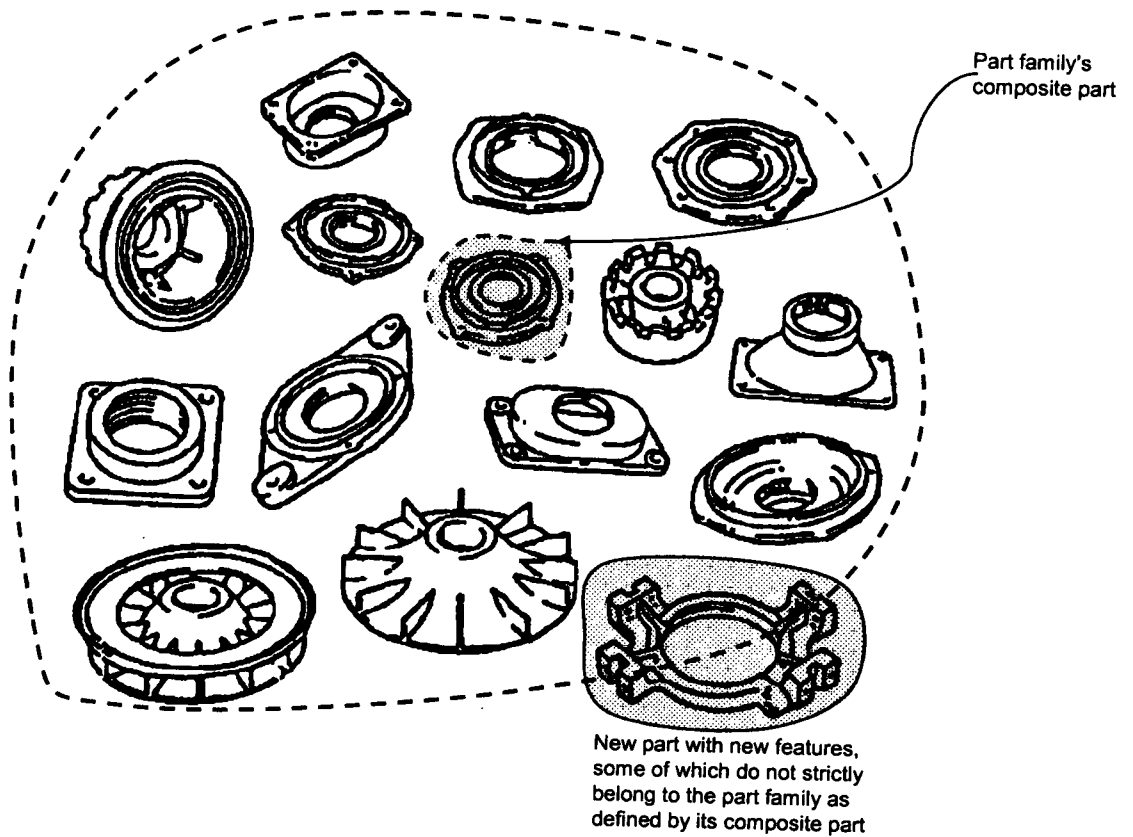


Figure (3.1) Step one of the proposed sequential methodology: retrieval of the closest master plan to the new part (the line drawing illustration of the part family is taken from Groover (2000)).

Variant process planning lends itself to changeable manufacturing systems including FMS as well as RMS, which are usually designed for a certain part family but with wider scope. However, generative process planning systems are better able to handle unplanned product variations. Therefore, it is believed that a hybrid process planning approach that is both variant in nature as well as capable of generating process plans for parts with features beyond those present in the current part family's composite part can best meet these current challenges. Therefore, a new part would typically have new as well as missing features/operations. Such an approach is sequential in nature; firstly, variant process planning is applied where the master process plan of the part family's composite part is retrieved as illustrated in Figure 3.1; precedence graphs and their associated data structures, which depict the precedence relationships and other declarative knowledge of the features/operations, are manipulated. Secondly, generative modeling tools and algorithms are then applied, as illustrated in Figure 3.2, to arrive at an

optimal process plan for the new parts, whose definition do not necessarily lie entirely within the rigid boundary of their respective part family.

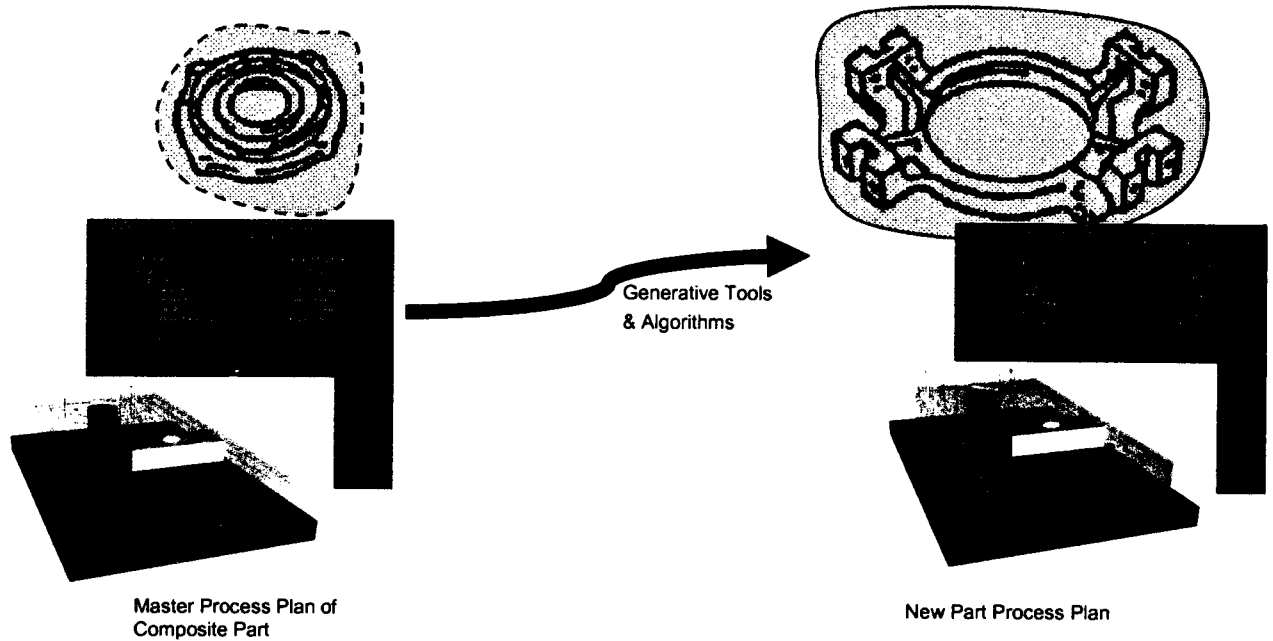


Figure (3.2) Step two of the proposed sequential methodology: generation of the new part's process plan starting from the composite part's master plan using reconfiguration or re-planning methods.

This work focuses on two different methods for the generative processing portion of the proposed methodology, namely Reconfigurable Process Planning (RPP) and Process Re-Planning.

3.2 Step I: Knowledge Retrieval and Manipulation

Presently, in most industries, the basic input to process planning is the part CAD feature-based model including the part's form features attributes, the working Geometric Dimensions and Tolerances (GD&T) and surface finish specifications. Initially, the new part's CAD model is analyzed, and the part family with which the new part could be most closely identified is determined. All the declarative knowledge associated with the composite part of that part family, including knowledge of available manufacturing resources (e.g. fixtures and tools), precedence, sequences and different data structures, are retrieved. The large number of interactions that exists between the different form features constituting the part complicates the problem. These interactions between the

different features generate precedence constraints for related features and operation and are modeled using Feature Precedence Graphs (FPG) and Operation Precedence Graphs (OPG), which are tree-like structures (directed graphs), where machining features and operations are mapped onto nodes; arcs between nodes represent features precedence. The following notation is also used to model precedence constraints (FeatureX→FeatureY), which means Feature X has to precede Feature Y; the wild card * means all features or operations; for example (Face101→{*}) means feature Face101 precedes all other features as shown in the FPG given by Figure 3.3 where Face and Bore were abbreviated as F and B respectively. In generating FPGs/OPGs, redundancy among precedence relationships was considered; for example for the following two precedence constraint sets (Face101→{*}), (Bore103→{Bore109, Bore110, Bore111, Bore112}), the precedence constraint Face101→Bore112 was implied by the following constraints: Face101→Bore103 and Bore103→Bore112; and hence, it was not included. Another key characteristic of the problem at hand is the handling time/cost matrix, where each element represents the handling time/cost between a pair of successive features/operations, which approximates the handling tasks to be performed between possible consecutive features/operations. This matrix could be represented in units of time or cost depending on the objective function used, whether it would be a cost- or time-objective function; see example handling time matrices in Chapters Five and Seven.

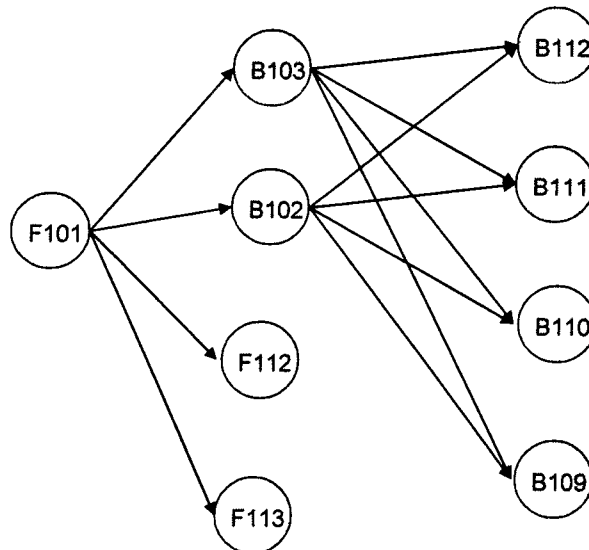


Figure (3.3) An example Feature Precedence Graph.

For the composite part or the existing parts on the shop floor, FPG/OPGs are retrieved and edited by adding and removing nodes and arcs. Only logical changes on the part level are taken into account; features which exhibit design changes not yet translated into modifications in the logical precedence relationships are not considered changes. See section 7.2.1 for clarification through an example.

There exist different types of precedence constraints (or the so called anteriorities by Halevi and Weill (1995)) for which certain sequences cannot be reversed. The following precedence constraints must be satisfied otherwise the feasibility boundaries would be violated:

- Accessibility of the feature by the tool: this constraint deals mainly with the positioning of the part and with the fixturing system. For each operation to be machined, the position of the part has to allow the cutting tool to access the feature for machining.
- Technological constraints: these constraints have to be respected in order to execute sequences of operations properly. For example considering the drilling and milling of a surface, a typical technological constraint is that the drilling must come before the finish surface milling of the surface.
- Dimensional and geometric constraints: these constraints refer to situations in which a feature acts as a datum point for other features. The case of a dimensional precedence is when the position of a feature refers to another feature; the case of a geometric constraint is when there is a geometrical relationship (i.e. co-axiality, perpendicularity, etc.) between two features and one is acting as datum for the other.
- Economic constraints: these constraints are considered in order to reduce production costs and wear or breakage of costly tools, etc.
- Non-destruction constraints: the non-destruction constraint ensures that subsequent machining operation does not destroy the properties of features produced in previous machining operations.

Feature Precedence Graphs (FPGs) are manipulated by adding and removing nodes in order to accommodate additional as well as missing machining features in the new parts. It is translated into an Operation Precedence Graph (OPG), where each feature corresponds to one or more machining operation. A machining feature is defined in this work as a geometrical feature that requires processing by one or more operation. Sequencing is carried out on the machining features level, taking the following into consideration: Within each feature, a logical sequence of operations is used to order the feature's sub-operations. Some features are represented by more than one node in exceptional cases, due to interdependence on precedence relationships with other features. The ratio of the time required to position the work piece on a different fixture (composed mainly of unloading the work piece, cleaning the setup and loading the work piece) to the tool change time is taken as 2:1 based on practical experience.

3.3 Step II: Generative Planning

In the following sub-sections two conceptually and mathematically/computationally different methods for the generative portions of the developed process planning methodology are introduced. They are for: a) optimal local reconfiguration, and b) optimal global re-planning.

3.3.1 Reconfigurable Process Planning (RPP)

Reconfigurable Process Planning (RPP) is realized for the most part by optimal reconfiguration of the precedence graphs in terms of reconfiguration scope and cost by inserting/removing features iteratively using a novel 0-1 integer programming model (Azab and ElMaraghy 2007). Mathematical programming and formulation is presented, for the first time, to genuinely reconfigure process plans to account for changes in parts' features beyond the scope of the original product family as was pictured in Chapter One. The proposed RPP mathematical scheme scales better with problem size compared with classical process planning models. The reconfiguration process is iterative in nature as will be explained in Chapter Four. The formulation of the mathematical model at each iterative step of reconfiguration has been automated. A process plan and part reconfiguration indices have been introduced to capture the extent of changes on the part

and plan levels respectively and their implications and significance have been introduced and discussed. A prismatic benchmark is used to demonstrate the method. Chapters Six and Seven are dedicated for validation and testing by solving industrial case studies in metal cutting and assembly. The computational behavior and advantages of the proposed model are discussed, analyzed and compared with classical models.

3.3.2 Process Re-Planning

A Process Re-Planning model based on the Quadratic Assignment Problem (QAP) formulation, where machining features are assigned positions in one-dimensional space is introduced. The proposed model overcomes the complexity of the sub-tour elimination constraints in the classical Traveling Salesperson Problem (TSP) and, for the first time, mathematically formulates the precedence constraints, which are a corner stone of the process planning problem. Linearization of the quadratic model was performed. The problem at hand is a combinatorial optimization problem. Hence, non-traditional optimization is also used to solve large instances of the problem. Application is illustrated with an example from the literature. The new process planning model is compared against other models such as TSP and RPP.

3.4 Summary

In this chapter the underlying overall developed methodology was outlined. Sequential Process Planning is a hybrid semi-generative approach where both variant and generative planning are applied sequentially. The proposed approach overcomes the shortcomings of the two fundamental planning approaches, namely variant and generative. Initially retrieval and manipulation of master or existing plans, and related declarative knowledge and graphs take place by adding and removing nodes in order to account for the new and missing features of the new part. This step is followed by generative processing of the retrieved information. Master precedence graphs and data structures, which depict the precedence relationships between features/operations are manipulated after retrieval and before applying generative processing by adding/removing nodes and their associated attributes. The generative portion of the

proposed approach, which consists of either Reconfiguration or Re-Planning, is discussed in Chapters Four and Five respectively.

4. RECONFIGURABLE PROCESS PLANNING

This chapter is based on Azab and ElMaraghy (2007a) and Azab and ElMaraghy (2007c). The paradigm shift in manufacturing systems and their increased flexibility, and changeability require corresponding responsiveness in support functions to achieve cost-effective adaptability. Reconfigurable Process Planning (RPP), the subject of this chapter, is envisioned as the enabler of changeability for evolving products and systems on the process planning level. Section 4.1 highlights the conceptual framework behind RPP. In Section 4.2, mathematical programming and formulation is presented, for the first time, to reconfigure process plans to account for changes in parts' features beyond the scope of the original product family. Reconfiguration of precedence graphs to optimize the scope and cost of process plans reconfiguration is achieved by inserting/removing features iteratively using a novel 0-1 integer programming model.

The model's computation complexity is discussed in Section 4.3. Two metrics that capture the extent of changes in the part and plan and their implications have been introduced in Section 4.4. Section 4.5 presents a prismatic benchmark that is used for illustration and verification. The computational behavior and advantages of the proposed model are discussed, analyzed and compared with classical models.

4.1 Conceptual Basis

Reconfigurable Process Planning (RPP) is the development of a process plan for a new part some features of which are not within the boundaries of the existing parts family or its composite part and master plan, i.e., the new part belongs to an evolving parts family (ElMaraghy 2006). Reconfigurable Process Planning is a differential method, where a master or existing plan is iteratively reconfigured to meet the requirements of the new part and its added features. New portions of the process plan, corresponding to the new additional features (and their machining operations), are generated and optimally positioned within the overall process plan.

If the sequence of features processing, which respects precedence constraints, is thought of as a genetic sequence, the added new features would represent mutation of that sequence by optimally inserting new genes (See Figure 4.1). This is consistent with the concept of evolving parts families. An innovative mathematical formulation using 0-1 integer programming is developed and algorithms have been written to automate the tedious and time-consuming formulation process.

A new part/product contains a set of new and/or missing features compared with the original existing part/product. In this model, the missing features/operations in the new part are subtracted from the original sequence, and the set of the new features/operations are inserted. It is important to note that the problem is still subject to precedence constraints and an objective function of minimizing the additional handling time spent mainly in repositioning the work piece or fixture and tool changes. The handling time changes are to reduce the changes of setup and tooling, and consequential implications on the shop floor such as possible machine tool reconfiguration, the need to retrain personnel on new plans, possible resulting quality errors, downtime, and opportunity cost. A work piece is defined in this context as the stock in process in-case of metal cutting or the assembly in-process in case of assembly. This combined generative/retrieval process plan reconfiguration is summarized as follows:

1. Retrieve the macro-level master process plan for the family's composite or existing part/product on shop floor, which contains the collection of feature/operation precedence graphs and their sequence, knowledge of available manufacturing resources (e.g. fixtures and tools) and their sequence.
2. Compare the new part with the composite/existing part to identify new and missing features.
3. For missing features, subtract the fragments corresponding to these features from the master plan.
4. For new/added features, formulate and apply iteratively the proposed mathematical model for generative reconfiguration by subsequent insertion of the new features in the original sequence of the existing/composite part.

5. For common features, retain the corresponding features graph portions.

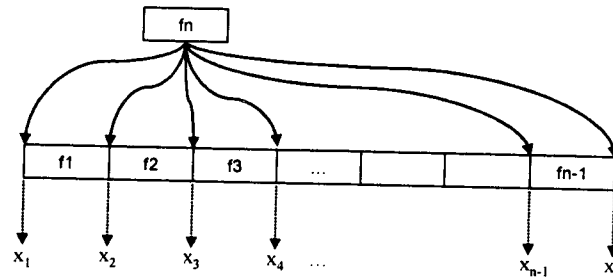


Figure (4.1) Illustration for finding the best position for a new added feature/operation (f_n) in the master original sequence using the evolving process planning sequence and genetic mutation metaphors.

4.2 Reconfigurable Process Planning Mathematical Modeling & Programming

The problem of macro-level process planning has long been modeled as a sequencing problem. The concept used in the proposed RPP is totally different. The objective is to determine the best location to insert the new feature(s) in the existing sequence while optimizing objective criteria and without violating specified constraints.

4.2.1 Assumptions & Notations

The assumptions made in this model are as follows:

1. The considered precedence constraints include:
 - a) Accessibility of the feature by the tool.
 - b) Logical sequence of operations.
 - c) Geometric Dimensioning & Tolerancing (GD&T) constraints.
 - d) Non-destruction of completed operations & features.
 - e) Machined fixture datum points on the part.
 - f) Good manufacturing practices and knowledge.
2. Feature Precedence Graph (FPG) is used to model the interactions and precedence relations, i.e., constraints that exist among the different features. An FPG is a tree-like structure graph where machining features are mapped to nodes and precedence constraints to arcs.

3. A machining feature is defined in this work as a geometrical feature that requires processing by one or more operation.
4. Sequencing is carried out on machining features taking the following into considerations:
 - a) Within each feature, a logical sequence of operations is used to order the feature's sub-operations.
 - b) Some features are represented by more than one node in exceptional cases due to interdependence on precedence relationships with other features.
5. Operation selection was done in advance.
6. Work piece repositioning on setups/fixtures, and tool information required for each operation was specified and given in advance.
7. The ratio of the time required to position the work piece on a different fixture (composed mainly of unloading the work piece, cleaning the setup and loading the work piece) to the tool change time is assumed to be 2:1.

The notations used are as follows:

- n denotes the problem size and it is the total number of decision variables and it could also be interpreted as the total number of machining features including the new machining feature to-be-inserted.
- $C=[c_{i,j}]$ is the $n \times n$ precedence penalty matrix. A row would be assigned to each possible insertion position. For each element in a row, a relatively large value (i.e. of different order of magnitude) would be assigned if the precedence between the feature to be inserted and each feature of the original sequence, at a time, is violated.
- $S=[s_{i,j}]$ is the $n \times n$ work piece repositioning time matrix. A row would be assigned to each possible insertion position. For each row, the time required to

reposition the work piece on the given fixtures (setups) in order to be able to switch between each pair of the successive features of the new possible permutation, i.e., after the insertion to be of the new feature/operation.

- $O_s = \{O_{s_i}\}$ is the $1 \times n$ old work piece repositioning time vector, which is a vector of the time required to reposition the work piece on the given fixtures (setups) in order to be able to switch between pairs of successive features of the original sequence (i.e. not to include the new feature) after subtracting the missing features.
- $Tr = \{Tr_i\}$ is the $1 \times n$ right tool change time vector (i.e. the tool change between the new to-be-inserted feature and every feature in the old sequence from the right side).
- $Tl = \{Tl_i\}$ is the $1 \times n$ left tool change time vector (i.e. the tool change between the new to-be-inserted feature and every feature in the old sequence from the left side).
- $O_t = \{O_{t_i}\}$ is the $1 \times n$ old tool change time vector, which is a vector of the tool change time in order to be able to switch between pairs of successive features/operations of the original sequence after subtracting the missing features/operations, i.e., not including the new feature/operation to-be-inserted.

The decision variables are:

x_i is a 0-1 integer variable, where i runs from 1 to n . 1 if new feature is inserted at position i ; 0 otherwise. The position i takes the value 1 when the new feature is inserted right before the first feature of the original array of features and takes the value n when it is positioned right after the last feature of the original array, i.e. feature f_{n-1} (see Figure 4.1).

4.2.2 Formulation

Two criteria are considered: 1) time for repositioning the work piece on different fixtures, and 2) time for tools change. The objective is to minimize the non-cutting time.

The time spent for rapid tool traverse from one feature to the other is ignored due to its relatively minor contribution. Also the time required for transportation of the work piece between different machine tools as well as that spent to adjust machining conditions are also ignored since these detailed parameters are not determined at this macro-level. The objective function is given by equation 4.1.

$$\min. \sum_{i=1}^n \sum_{j=1}^{n-1} C_{i,j} . x_i + \sum_{i=1}^n \left(\sum_{k=1}^{n-1} S_{i,k} \right) . x_i - \sum_{i=1}^n O_{s_i} . x_i + \sum_{i=1}^n (Tr_i + Tl_i) . x_i - \sum_{i=1}^n O_{t_i} . x_i \quad (4.1)$$

The first term represents the penalty for violating precedence constraints, where the precedence relation between every feature in the original sequence and the inserted new feature is checked. The second term represents the time required to reposition the work piece on the given fixtures (i.e. setup change time as commonly referred to in the literature). The first summation of $S_{i,k}$ over k represents the work piece repositioning time on the given fixtures/setups associated with a new sequence, i.e. between every pair of preceding features in each new permutation. The terms Tr_i and Tl_i with their summation over i from 1 to n depict the tool change cost. They account for the new precedence cost due to the insertion of the new feature between two existing features in the original sequence- one to the right (Tr_i) and one to the left (Tl_i). Finally, the O_{s_i} and O_{t_i} terms represent the handling time change incurred due to changing the original precedence between the two features in the original sequence after subtracting the missing features that are to be separated by inserting the new feature, and hence, the old work piece repositioning and tool change time components are subtracted.

The constraints system of the RPP model is advantageously simple and is represented by equation 4.2 as follows:

$$\sum_{i=1}^{n+1} x_i = 1 \quad (4.2)$$

This constraint prevents a feature from being inserted more than once at any position.

4.3 Computational Time Complexity

The comparison of the computational time complexity of the proposed model with the classical re-planning using a TSP model raises some interesting observations. The TSP model is a network of nodes representing different features of a part connected by arcs that represent the routes between them. The decision variable is the value associated with the arc; if the value is 1 then the route represented by this arc is in use; it is 0 otherwise. An arc in use means that the two features are sequenced consecutively. This model is characterized by its exponentially growing solution space and the complexity of the sub-tour elimination constraints. The picture is completely different for the proposed RPP model. The time complexity for inserting an m feature into an original sequence of size n grows polynomially. For one iteration, the solution space is n ; the total solution space is of the form $n+(n+1)+\dots+(n+m)$. The RPP optimization problem is by far more tractable since it offers a computational time complexity of $O(n)$ compared with the NP-complete exponentially growing classical TSP counterpart. Hence, typical industrial problems can be easily solved for optimality using the RPP model.

4.4 Reconfiguration Indices

Two different indices are formulated in this section to evaluate the extent of reconfiguration at the part and the process plan levels respectively. The Design Reconfiguration Index is primarily used to evaluate the extent of the input design changes on the product level, before generating a new process plan to help determine the appropriate planning methods best suitable for process planning the product in question, which could be a part or a complete assembly depending on the domain of application (see case studies in Chapters 6 and 7 for more details and explanation). The Plan Reconfiguration Index is used to evaluate the quality of the generated process plans in terms of the extent of reconfiguration and changes of the reconfigured plans. This is used for comparing several solutions and selecting the best reconfigured plan that would cause the least disruption in downstream activities.

4.4.1 Design Reconfiguration Index

As explained in chapter one, parts and product families undergo continuous change and evolution due to changes in consumer's requirements and market forces and demands. Product evolution and the continuously changing and moving boundaries of the existing part families are the primary motives and drivers behind the current study. Hence, it was very important to develop a metric that would measure the extent of changes in the problem inputs, i.e. the changes on the product level, and hence decide on the planning methods to use.

The proposed Design Reconfiguration Index (RI_{Design}) quantifies the extent of design change on the product level from a logical point of view. It consists of three different components as given by Equation 4.3: 1) ratio of the number of introduced new features in the new product to be planned to the number of features in the original existing or composite part, 2) ratio of number of missing features in the new product to the number of features in the original existing or composite part, and finally 3) ratio of number of new precedence relationships to the number of precedence relationships in the original existing or composite part. Larger weights are assigned to the first and the third component since it was noticed that missing features contribute the least to the resulting planning reconfiguration effort. Missing features are simply subtracted and, hence, cause the least changes in the planning logic. The newly added features result in a far more substantial optimal iterative insertion procedure (an arbitrary value of 0.6 is assigned to the β coefficient). Furthermore, the newly developed precedence relationships complicate this insertion process. The increase in the complexity of the precedence constraints is measured by counting the number of added arcs in the Feature Precedence Graph (FPG) of the new part; an arbitrary value of 0.3 is assigned to α . If input data is only available on the operation level in form of OPGs and related information, they may be taken as a rough measure of the changes on the design features level.

$$RI_{\text{Design}} = \left(\begin{array}{l} \beta \frac{\text{Number of added new features in new part/product design}}{\text{Total number of features of master or existing plan}} + \\ \alpha \frac{\text{Number of added new arcs in new FPG/OPG in new product/part design}}{\text{Total number of arcs of master or existing plan}} + \\ (1 - \alpha - \beta) \frac{\text{Number of missing features in new product/part design}}{\text{Total number of features of master or existing plan}} \end{array} \right) \cdot 100 \quad (4.3)$$

4.4.2 Plan Reconfiguration Index

A master process plan is reconfigured to arrive at a new plan for a new part using the proposed methodology and mathematical model. A new performance index is proposed to measure the percentage of change, i.e., reconfiguration of the original master or existing process plan due to the additional inserted feature(s). The Plan Reconfiguration Index (RI_{Plan}), as expressed by Equation 4.4, measures the amount of added work, time and hence cost that is needed to reconfigure the original process plan. RI_{Process} consists of two components: repositioning of work piece on the given fixtures/setups and tool changes. Weights are used to normalize the index and to reflect the relative importance of its respective terms.

$$RI_{\text{Plan}} = \left(\begin{array}{l} \alpha \frac{\text{Number of new/missing acts of repositioning the work piece in new plan}}{\text{Total number of work piece repositioning of master plan}} + \\ (1 - \alpha) \frac{\text{Number of added/missing tool changes in new plan}}{\text{Total number of tool changes of master plan}} \end{array} \right) \cdot 100 \quad (4.4)$$

The higher the value of RI_{process} , the more extensive is the process plan reconfiguration and its associated cost. For the coefficient α , it takes a value proportional to the average amount of time to reposition the work piece on a new fixture relative to the time required to change a tool. For example, if the ratio of time to reposition a work piece on a new fixture to that to change a tool is presumed to be 3:1, then α would take a value of $3/(4+1)=0.75$.

4.5 Illustrative Example

A handspike/lever (Bhaskara Reddy *et al.* 1999) is assumed to be the new part with a new feature. It is composed of 8 features (Table 1). For simplicity, the composite part is the same part less feature B and the tapping operations associated with features D, E and F are disregarded. Table 1 shows the features setup and tooling data. Figure 2 shows the FPGs for both the composite and the new part. The process sequence for the composite part is obtained using the exact optimal algorithm developed in (Azab 2003). The obtained sequence is $\{A_r, G, C, A_f, E, D, F\}$. Feature A is divided into sub-features A_r and A_f for the reasons explained in section 4.1 and clearly justified by the FPGs shown in Figure 4.2.

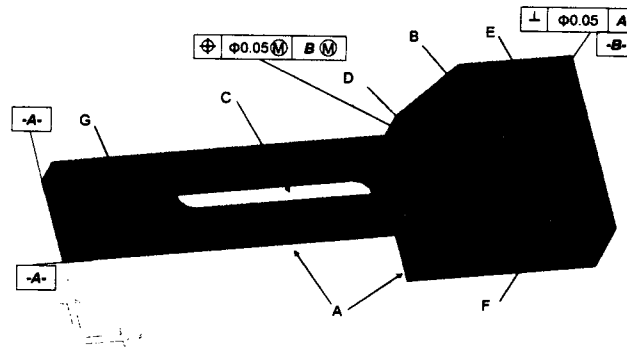


Figure (4.2) Model of the new handspike family member, adapted from Bhaskara Reddy *et al.* [1999].

The problem is formulated and solved using Xpress-MP. Feature B was inserted at position 3 in the process plan sequence, i.e. $x_3 = 1$. The new reconfigured sequence is $\{A_r, G, B, C, A_f, E, D, F\}$. The penalty, work piece repositioning and tool change time matrices and vectors are given in Tables 4.2- 4.13, and are derived from the setup/tooling information in Table 4.1. An element C_{ij} represents the penalty between a pair of two features; one always being the inserted feature. For example, Tables 4.2 and 4.3 show that there is a penalty of M if A_r is preceded by B, and 0 otherwise. For the rest of the coefficient matrices/vectors, an element would represent the tool change or the work piece repositioning time between a pair of features/operations. Unlike the C matrix, for the rest of the matrices the work piece repositioning/tool change time of a given feature/operation pair and its transpose have the same values since the order does not affect the tool change time or work piece repositioning time on a fixture. For example in

Table 4.12 the tool change time of having A_r being preceded by B or vice versa is the same. Note that the first and last elements of the old work piece repositioning vector O_s and those of the tool change vector O_t are always zero since if the new feature is inserted right before all the features or after them, no old setup cost has to be considered. Also, the first element of the left tool change time vector and the last element of the right tool change time element have to be zeros, because for the left tool change the new feature is inserted such that the original features come to the left and hence the first decision variable would not be associated with any of its elements. However, note that the values of the left tool change time vector are exactly the same as the right tool change time vector, but shifted by one element.

Table (4.1) Setup/Tooling data for the handspike.

Feature Name	Fixtures (Setup)	Tooling
A_r	S1	T1
C	S1	T2
D	S2	T3
E	S2	T3
F	S2	T3
G	S1	T4
A_f	S1	T5
<i>B</i>	<i>S2</i>	<i>T6</i>

Note that B in table 4.1 is the new feature for the new part; other features exist in both the composite and new part.

Table (4.2) Precedence penalty matrix C.

BA_r	BC	BD	BE	BF	BG	BA_r
A_rB	BC	BD	BE	BF	BG	BA_r
A_rB	CB	BD	BE	BF	BG	BA_r
A_rB	CB	DB	BE	BF	BG	BA_r
A_rB	CB	DB	EB	BF	BG	BA_r
A_rB	CB	DB	EB	FB	BG	BA_r
A_rB	CB	DB	EB	FB	GB	BA_r
A_rB	CB	DB	EB	FB	GB	A_rB

Table (4.3) Filled-in precedence penalty matrix C.

M	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	M	0	0	0	0	0
0	0	M	M	0	0	0	0
0	0	M	M	M	0	0	0
0	0	M	M	M	0	0	0
0	0	M	M	M	0	M	0

Table (4.4) Old work piece repositioning time vector Os.

0	A _r C	CD	DE	EF	FG	GA _F	0
---	------------------	----	----	----	----	-----------------	---

Table (4.5) Filled-in old work piece repositioning time vector Os.

0	0	S	0	0	S	0	0
---	---	---	---	---	---	---	---

Table (4.6) Old tool change time vector Ot.

0	A _r C	CD	DE	EF	FG	GA _F	0
---	------------------	----	----	----	----	-----------------	---

Table (4.7) Filled-in old tool change time vector Ot.

0	T	T	T	T	T	T	0
---	---	---	---	---	---	---	---

Table (4.8) Left tool change vector Tl.

0	A _r B	CB	DB	EB	FB	GB	A _F B
---	------------------	----	----	----	----	----	------------------

Table (4.9) Filled-in left tool change vector Tl.

0	T	T	T	T	T	T	T
---	---	---	---	---	---	---	---

Table (4.10) Right tool change time vector Tr.

BA _r	BC	BD	BE	BF	BG	BA _F	0
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Table (4.11) Filled-in right tool change time vector Tr.

T	T	T	T	T	T	T	0
---	---	---	---	---	---	---	---

Table (4.12) Work piece repositioning time matrix S.

BA_r	A _r C	CD	DE	EF	FG	GA _r
A_rB	BC	CD	DE	EF	FG	GA _r
A _r C	CB	BD	DE	EF	FG	GA _r
A _r C	CD	DB	BE	EF	FG	GA _r
A _r C	CD	DE	EB	BF	FG	GA _r
A _r C	CD	DE	EF	FB	BG	GA _r
A _r C	CD	DE	EF	FG	GB	BA_r
A _r C	CD	DE	EF	FG	GA _r	A_rB

Table (4.13) Filled-in work piece repositioning time matrix S.

S	0	S	0	0	S	0
S	S	S	0	0	S	0
0	S	0	0	0	S	0
0	S	0	0	0	S	0
0	S	0	0	0	S	0
0	S	0	0	0	S	0
0	S	0	0	S	S	S
0	S	0	0	S	0	S

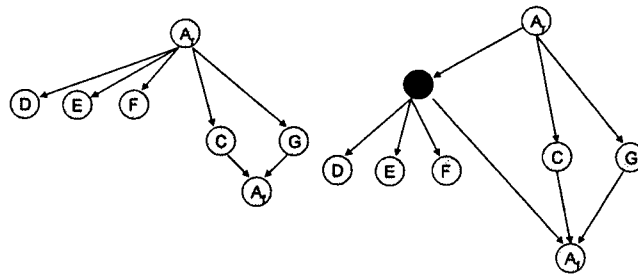


Figure (4.3) Features Precedence Graphs (FPGs) for the composite part and new handspike.

The formulation coefficient matrices/vectors are shown with the feature pairs to illustrate the method and then with their corresponding values as shown in Tables 2-13. The work piece repositioning objective function component is 'S', the tool change objective function component is 'T', while 'M' is a very high positive value representing a penalty. Cells in both the C penalty cost matrix and the S setup cost matrix are highlighted to demonstrate the repeatability of the different elements. One is not required to fill in all the elements for both matrices. In fact for matrix C, only the first row and the diagonal are filled in and the rest is simply a repetition. The diagonal is highlighted; all the elements below the diagonal are identical and equal to its respective diagonal elements. All the elements above a diagonal element are the same as the cells in the

matrix first row. As for the S matrix, there is a diagonal band with a width of two identical elements. The elements below the band are identical to their respective diagonal elements. The elements above the band are the same as those of the first row. Populating these matrices, although straightforward, can be error prone and tedious for relatively large size problems. Therefore, the process of generating the different penalty, setup and tool change time coefficient matrices has been automated using algorithms implemented in Matlab and fed to Xpress-MP using an input data file.

4.6 Summary

Reconfiguration of precedence graphs to optimize the scope and cost of process plan reconfiguration is achieved by inserting/removing features iteratively, using a novel 0-1 integer programming model. The formulation of the mathematical model at each iterative step of reconfiguration has been automated. Computational complexity was discussed. The proposed RPP mathematical scheme scales better with problem size compared with classical process planning models. Reconfiguration indices at both the part and the process plan levels were introduced to quantify the extent of change and reconfiguration, evaluate the newly developed plans, and advise on which methods to choose. A benchmark from Bhaskara Reddy *et al.* (1999) is used to illustrate the application of the developed model and method.

5. PROCESS RE-PLANNING

As explained in chapter one, manufacturers worldwide are faced with increased competition and major challenges to achieve agility, responsiveness and cost-effectiveness, and respond promptly to customer needs by providing cost-competitive products to the market. On the systems' side, changeability supported the increased dynamicity of part families and their witnessed evolution. Therefore, appropriate process planning concepts and methods should be developed to support this new agile changeable manufacturing environment. In this chapter, generative Re-Planning mathematical programming and non-traditional optimization is developed. For higher production volumes, when it is desired to arrive at highly optimized global plans, Re-Planning methods would be used to avoid the inherent locality of the RPP method implied by its objective of limiting the extent of plan changes and by the adoption of a specific sequence of insertion for the added new features. A benchmark problem has been solved to illustrate the proposed method and model. Industrial case studies are conducted in Chapters Six and Seven. This chapter is based on Azab and ElMaraghy (2007b, 2007c).

5.1 Quadratic Assignment Problem Mathematical Modeling & Programming

The objective is to sequence a global set of machining operations of a given part, subject to a number of precedence constraints, in order to minimize the total idle time spent mainly in repositioning the work piece or fixture and tool changes. The Quadratic Assignment Problem (QAP) is the problem of assigning a set of n objects to another set of n objects in order to minimize the sum of the costs associated with pairs of assignment (Erdogan and Tansel 2007). Some of the most common cases producing quadratic assignment models arise in facility layout planning, where a collection of machines, offices, departments or stores are to be arranged within a facility, and a set of locations within which they must fit. The problem is usually solved in two-dimensional space where a very common objective is to minimize the material handling cost or in other

words the flow-distance, i.e., the product of flow volumes between facilities and the distances between their assigned locations.

Since the process planning/operations sequencing is conceptually different from the 2-D or 3-D layout problems, a novel adaptation of the QAP is proposed. In process planning, it is required to assign n objects, which are the machining features of the part to be process-planned to n positions; in one-dimensional space representing the sequence of machining operations / features. These differences have been translated into variations in the objective function, where the cost coefficient matrix is no longer a function of the locations to which the objects would be assigned. Also, precedence constraints for the process planning problem have been formulated.

5.1.1 Assumptions

The assumptions made in this model are summarized as follows:

- A Feature Precedence Graph (FPG) is used to model the interactions and precedence relations, i.e. constraints that exist among the different features. A machining feature is defined in this work as a geometric feature that requires processing by one or more operations.
- Sequencing is carried out on machining features taking the following into consideration:
 - Within each feature, a logical sequence of operations is used to order the feature's sub-operations.
 - Some features are represented by more than one node in exceptional cases due to their interdependence on precedence relationships with other features.
- Operation selection was done in advance.
- Setup, and tool information required for each operation was specified and given in advance.
- The tool magazine of the machine tools used has enough capacity to hold all the required tools as well as the redundant tools used for back-up.
- Tool changes do not take place during loading and unloading of the part.

The considered precedence constraints include:

- Accessibility of the feature by the tool.
- Logical sequence of operations.
- GD&T constraints.
- Non-destruction of surfaces and features completed by preceding operations.
- Machined fixture datum points on the part.
- Good manufacturing practices and knowledge.

5.1.2 Notation

- $y_{i,k}$ is the problem decision variable; it is a 0-1 integer variables, where both i and k runs from 1 to m . The value of the decision variable is 1 if the feature i is positioned in location k ; otherwise it is zero.
- m denotes the problem size defined as the total number of decision variables. It is also the total number of machining features to be sequenced; that is as far as the physics of the problem goes.
- T is the symmetric handling time matrix $[t_{i,j}]$.

5.1.3 Formulation

Two criteria are considered: 1) time for repositioning the work piece on different fixtures, and 2) time for tool changes. The objective is to minimize the non-cutting time. The time spent for rapid tool traverse from one feature to the other is ignored due to its relatively minor contribution. The time required for transportation of the work piece between different machine tools as well as that spent to adjust machining conditions are also ignored since these detailed parameters are not determined at this macro-level. Therefore, the objective function is defined as in equation 5.1.

$$\min. \sum_{i=1}^m \sum_{j=1}^m T_{i,j} \sum_{k=1}^{m-1} y_{i,k} \square y_{j,k+1} \quad (5.1)$$

Subject to:

$$\sum_{k=1}^m y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, m\} \quad (5.2)$$

Equation 5.2 is a feasibility constraint that ensures that a manufacturing feature is only assigned once.

$$\sum_{i=1}^m y_{i,k} = 1 \quad \forall k \in \{1, 2, \dots, m\} \quad (5.3)$$

Equation 5.3 is a feasibility constraint that ensures that no more than one manufacturing feature is assigned to position k.

$$\sum_{k=1}^l y_{i,k} \geq \sum_{k=1}^l y_{j,k} \quad \forall l \in \{1, 2, \dots, m\} \quad (5.4)$$

For a pair of machining features i and j, this precedence constraint ($i \rightarrow j$) mandates that feature i be assigned a position in the plan sequence before feature j. The decision variable $y_{i,k}$ would be equal to one when feature i is placed at position k. For that to take place, the machining features i and j, $y_{i,k1}$ and $y_{j,k2}$ would equal one when the index k1 is less than the index k2 as demonstrated by Figure 5.1. Hence, the summation of $y_{i,k}$ over k would must always be greater than or equal that of $y_{j,k}$ over k. The summation would run n times where each time it stops at a different value; it starts with 1 and ends at n. Therefore, for every precedence constraint a set of n inequalities represented by equation-5.4 have to be defined.

k	1	2	3	4	5	6	...	n
$x_{i,k}$	0	1	0	0	0	0	...	0
$x_{j,k}$	0	0	0	0	1	0	...	0

Figure (5.1) Values of the decision variables for a precedence constraint ($i \rightarrow j$) between machining features i and j

$$y_{i,k} = (0,1) \quad \forall i,k \in \{1,2,\dots,m\} \quad (5.5)$$

5.2 Illustrative Example

A handspike/lever, shown in Figure 4.2, (Bhaskara Reddy *et al.* 1999) is assumed to be the new member part of the handspike part family that contains a new feature. It is composed of 8 features. For simplicity, the composite part is considered to be the same part less feature B and the tapping operations associated with the three small holes (features D, E and F) are disregarded. Table 5.1 shows the features setup and tool change data. The FPGs for both the composite and the new part is shown in Figure 4.3.

Table (5.1) Setup/Tooling data for the handspike

Feature	Setup	Tooling
A _r	S1	T1
C	S1	T2
D	S2	T3
E	S2	T3
F	S2	T3
G	S1	T4
A _f	S1	T5
B	S2	T6

**Note: B is the new feature for the new part; other features exist in both the composite and new part.*

5.2.1 The Composite Part

As explained earlier, the composite part is the model shown in Figure 4.2 without feature B. The handling time matrix T is listed in Table 5.2. Only the upper part of the matrix is filled since the C matrix is symmetric. In Table 5.2, S denotes the time required to reposition the work piece on a different setup, while T denotes the tool change time. The ratio S:T is taken as 3:1.

Table (5.2) Handling time matrix T for the Handspike composite part

	A _r	C	D	E	F	G	A _f
A _r	-	T	S+T	S+T	S+T	T	T
C		-	S+T	S+T	S+T	T	T
D			-	0	0	S+T	S+T
E				-	0	S+T	S+T
F					-	S+T	S+T
G						-	T
A _f							-

*Note: Matrix is symmetric.

Equations- 5.6-5.16 represent the formulation for the composite part. Sample constraints and the objective function are also expanded for the composite part in the Appendix to clearly demonstrate the model constraint equations and inequalities.

$$\min. \sum_{i=1}^7 \sum_{j=1}^7 T_{i,j} \sum_{k=1}^6 y_{i,k} \square y_{j,k+1} \quad (5.6)$$

Subject To:

$$\sum_{k=1}^7 y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, 7\} \quad (5.7)$$

$$\sum_{i=1}^7 y_{i,k} = 1 \quad \forall k \in \{1, 2, \dots, 7\} \quad (5.8)$$

For precedence constraint A_r→D, where features A_r and D are represented by indices 1 and 3:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{3,k} \quad \forall l \in \{1, 2, \dots, 7\} \quad (5.9)$$

For precedence constraint A_r→E, where features A_r and E are represented by indices 1 and 4:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{4,k} \quad \forall l \in \{1, 2, \dots, 7\} \quad (5.10)$$

For precedence constraint $A_r \rightarrow F$, where features A_r and F are represented by indices 1 and 5:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{5,k} \quad \forall l \in \{1, 2, \dots, 7\} \quad (5.11)$$

For precedence constraint $A_r \rightarrow C$, where features A_r and C are represented by indices 1 and 2:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{2,k} \quad \forall l \in \{1, 2, \dots, 7\} \quad (5.12)$$

For precedence constraint $A_r \rightarrow G$, where features A_r and G are represented by indices 1 and 6:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{6,k} \quad \forall l \in \{1, 2, \dots, 7\} \quad (5.13)$$

For precedence constraint $C \rightarrow A_f$, where features C and A_f are represented by indices 2 and 7:

$$\sum_{k=1}^l y_{2,k} \geq \sum_{k=1}^l y_{7,k} \quad \forall l \in \{1, 2, \dots, 7\} \quad (5.14)$$

For precedence constraint $G \rightarrow A_f$, where features G and A_f are represented by indices 1 and 3:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{3,k} \quad \forall l \in \{1, 2, \dots, 7\} \quad (5.15)$$

$$y_{i,k} = (0, 1) \quad \forall i, k \in \{1, 2, \dots, 7\} \quad (5.16)$$

The QAP process planning model was solved using GAMS algebraic modeling language and the SBB solver. SBB is a new GAMS solver for Mixed Integer Nonlinear Programming (MINLP) models. It is based on a combination of the standard Branch and

Bound (B&B) method known from Mixed Integer Linear Programming and some of the standard Nonlinear Programming (NLP) solvers already supported by GAMS.

The obtained near-optimal solution is $\{A_r, G, C, A_f, F, E, D\}$, where $y_{1,1}, y_{2,3}, y_{3,7}, y_{4,6}, y_{5,5}, y_{6,2}, y_{7,4}$ are equal to one; the rest are zero. The obtained corresponding value of the objective function is 7 time units.

5.2.2 The New Member Part

The new handspike part is the model shown in Figure 4.2. The handling time matrix T for the new part is listed in Table 5.3.

Table (5.3) Handling time matrix T for the handspike new part.

	A_r	C	D	E	F	G	A_f	B
A_r	-	T	S+T	S+T	S+T	T	T	S+T
C		-	S+T	S+T	S+T	T	T	S+T
D			-	0	0	S+T	S+T	T
E				-	0	S+T	S+T	T
F					-	S+T	S+T	T
G						-	T	S+T
A_f							-	S+T
B								-

**Note: Matrix is symmetric.*

Equations 5.17-5.29 represent the formulation for the composite part. For the new feature highlighted in the FPG in Figure 4.3, five new precedence constraints represented by equations 20, 23-26 are formulated. The model is also solved using GAMS and the SBB solver and the values of the following decision variables ($y_{1,1}, y_{2,2}, y_{3,6}, y_{4,4}, y_{5,5}, y_{6,7}, y_{7,8}, y_{8,3}$) were equal to one; the rest was zeros, i.e., the obtained sub-optimal plan sequence is $\{A_r, C, B, E, F, D, G, A_f\}$. The highlighted features represent the features in the sequence whose order was completely changed when compared with the original

master plan sequence of the composite part. By assuming the same ratio of 3:1 time units between S and T, the objective function value obtained is 11 time units.

$$\min. \sum_{i=1}^8 \sum_{j=1}^8 T_{i,j} \sum_{k=1}^7 y_{i,k} \square y_{j,k+1} \quad (5.17)$$

Subject To:

$$\sum_{k=1}^8 y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, 8\} \quad (5.18)$$

$$\sum_{i=1}^8 y_{i,k} = 1 \quad \forall k \in \{1, 2, \dots, 8\} \quad (5.19)$$

For precedence constraint $A_r \rightarrow B$, where features A_r and B are represented by 1 and 8:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{8,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.20)$$

For precedence constraint $A_r \rightarrow C$, where features A_r and C are represented by 1 and 2:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{2,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.21)$$

For precedence constraint $A_r \rightarrow G$, where features A_r and G are represented by 1 and 6:

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{6,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.22)$$

For precedence constraint $B \rightarrow D$, where features B and D are represented by 8 and 3:

$$\sum_{k=1}^l y_{8,k} \geq \sum_{k=1}^l y_{3,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.23)$$

For precedence constraint B→E, where features B and E are represented by 8 and 4:

$$\sum_{k=1}^l y_{8,k} \geq \sum_{k=1}^l y_{4,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.24)$$

For precedence constraint B→F, where features B and F are represented by 8 and 5:

$$\sum_{k=1}^l y_{8,k} \geq \sum_{k=1}^l y_{5,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.25)$$

For precedence constraint B→A_f, where features B and A_f are represented by 8 and 7:

$$\sum_{k=1}^l y_{8,k} \geq \sum_{k=1}^l y_{7,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.26)$$

For precedence constraint C→A_f, where features C and A_f are represented by 2 and 7:

$$\sum_{k=1}^l y_{2,k} \geq \sum_{k=1}^l y_{7,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.27)$$

For precedence constraint G→A_f, where features G and A_f are represented by 6 and 7:

$$\sum_{k=1}^l y_{6,k} \geq \sum_{k=1}^l y_{7,k} \quad \forall l \in \{1, 2, \dots, 8\} \quad (5.28)$$

$$y_{i,k} \in \{0, 1\} \quad \forall i, k \in \{1, 2, \dots, 8\} \quad (5.29)$$

5.3 QAP Linearization

The Quadratic Assignment Problem (QAP) presented in section 5.1 is a non-linear model since it holds a quadratic objective function. This section presents a linearized version of the QAP model. A procedure adopted from (Taha 1987) for linearizing integer programming models has been applied. The two models are equivalent and produce exact

optimal results. A new 0-1 decision variable $q_{i,j,k}$ is introduced with all three indices of the problem: i and j the features' indices and k the position index. This new decision variable $q_{i,j,k}$ replaces the original QAP objective function quadratic term. Two extra constraints, represented by equations 5.34 and 5.35 for each objective function term are added to ensure that the new decision variable would have a value 1 only if both original variables $y_{i,k}$ and $y_{j,k+1}$ equal 1. Solutions provided by the linearized model are guaranteed to be exact global optimal solutions; however, it is important to note that only instances of limited size can be solved for optimality since the problem at hand is of a combinatorial nature, as is explained in more detail in Section 5.5. The linearized model can be solved by almost all commercial optimization packages and solvers. GAMS algebraic modeling language and the CPLEX solver were used.

$$\min. \sum_{i=1}^m \sum_{j=1}^m T_{i,j} \sum_{k=1}^{m-1} q_{i,j,k} \quad (5.30)$$

Subject to:

$$\sum_{k=1}^m y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, m\} \quad (5.31)$$

Equation 5.31 is a feasibility constraint that ensures that a manufacturing feature is only assigned once.

$$\sum_{k=1}^m y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, m\} \quad (5.32)$$

Equation 5.32 is a feasibility constraint that ensures that no more than one manufacturing feature is assigned to position k .

$$\sum_{k=1}^l y_{i,k} \geq \sum_{k=1}^l y_{j,k} \quad \forall l \in \{1, 2, \dots, m\} \quad (5.33)$$

Equation 5.33 expresses precedence constraints of the form $(i \rightarrow j)$ as explained in section 5.1.

$$y_{i,k} + y_{j,k+1} - 2q_{i,j,k} \geq 0 \quad \forall i, j, k \quad (5.34)$$

$$y_{i,k} + y_{j,k+1} - q_{i,j,k} \leq 1 \quad \forall i, j, k \quad (5.35)$$

As explained above, equations 5.34, and 5.35 ensure that the new decision variable $q_{i,j,k}$ would only have a value when both original decision variables $y_{i,k}$ and $y_{j,k+1}$ equal 1 as in the original model.

$$y_{i,k}, q_{i,j,k} = (0,1) \quad \forall i, j, k \in \{1, 2, \dots, m\} \quad (5.36)$$

5.4 Conceptual Comparison of Proposed QAP Model, Classical TSP and Latest RPP Models

In this section, the proposed QAP-based process planning model is compared with the classical TSP as well as the RPP model introduced in Chapter 4. As mentioned earlier, several mathematical models have been presented in the literature for process planning. Many of them were informal procedural models (Azab 2003), and the few mathematical formulations were based on the popular symmetric (Traveling Salesperson Problem) TSP model. In this chapter, a novel adaptation of the QAP model has been proposed and developed for use in process planning (Azab and ElMaraghy 2007).

The QAP model is entirely conceptually different compared to its earlier TSP-based counterparts. First of all, as shown in Figure 5.2, the TSP model formulates the problem as a search for the optimal tour with the minimal distances between its cities. A tour has no start and no end, while the required sequence has. Lin and Wang (1993), Irani *et al.* (1995) and Kim and Suh (1998) stated that the problem is equivalent to that of extracting the Hamiltonian path of least cost that visits all of the features once and only once.

However, conceptually a tour remains equivalent to a cyclic closed sequence with one more route between the start and the end city. Hence, a slightly different problem with one more route is being optimized. On the other hand, QAP optimally allocates the manufacturing features/operations to a one-dimensional array, i.e., a sequence.

TSP fails to model properly precedence constraints, which are a corner stone of the process planning problem. As explained earlier in Chapter Two, the only precedence constraints that could be specified in the TSP model are immediate predecessor successor relationships. Some endeavors have been made to model precedence by applying penalty functions; however, it was not completely conceptually sound and in most cases resulted in infeasible solutions (see critique given in Chapter Two). As for the QAP model, rigorous general precedence constraints were mathematically modeled properly. Finally, the proposed QAP model overcomes the complex sub-tour elimination constraints of the TSP formulation. In contrast, the QAP is a non-linear model, i.e. near optimal solutions are expected. Therefore, linearization of the quadratic model was carried out in section 5.3.

The proposed QAP-based scheme offers a novel method of process re-planning, which could be conveniently used when products and systems are reconfigured. Re-Planning addresses the same problem that has been approached by Reconfigurable Process Planning (RPP) (Azab and ElMaraghy 2007). As explained in Chapter Four, RPP is the development of a process plan for a new part, some features of which are not within the boundaries of the existing parts family or its composite part and master plan, i.e., the new part belongs to an evolving parts family (ElMaraghy 2006). The master plan would be modified to meet the requirements of the new part and its added features. New portions of the process plan, corresponding to the new additional features (and their machining operations), are generated and optimally positioned within the overall process plan. If the sequence of features processing, which respects precedence constraints, is thought of as a genetic sequence, then the added new features would represent mutation of that sequence by optimally inserting new genes (Azab and ElMaraghy 2007). Reconfiguring Process Plans (RPP) offers locally reconfigured solutions. Solutions

obtained are minimally reconfigured compared with the existing or master plans. The localized solutions minimize the extent of reconfiguration and the impact on the related downstream shop floor activities. Hence, they would incur less reconfiguration costs, cause less disruptions and minimal changeover effort. This, in turn, would decrease the time required to introduce new products to the market, i.e., less opportunity cost. Minimal time and cost required for labor training on the new plans would be required and hence, possibly less mistakes that would affect product quality. All these factors could prove to be an important edge for relatively low- to medium-volume production and agile manufacturing, where products evolve and are customized frequently or when engineering changes are numerous, which is typical in present manufacturing environments during the product/process development phase.

On the other hand, the proposed QAP-based method conversely re-configures the process plan for the new part by re-planning. The problem is re-solved by mathematical programming after having the original model of the composite part re-formulated for the new part. One advantage of this approach is that the solution is a global exact optimal, whereas that offered by RPP seeks to partially reconfigure the process plan. Globally highly optimized solutions are obtained by Re-Planning, which would be more appropriate to use for higher volume of production.

The RPP approach is also an iterative algorithm where the RPP mathematical model is solved n times corresponding to the n new features of the new part. However, the computational time complexity of the RPP model is superior since each iteration is solved in polynomial time. Hence, the RPP model has by far a better computational time complexity polynomial function than the NP-complete QAP.

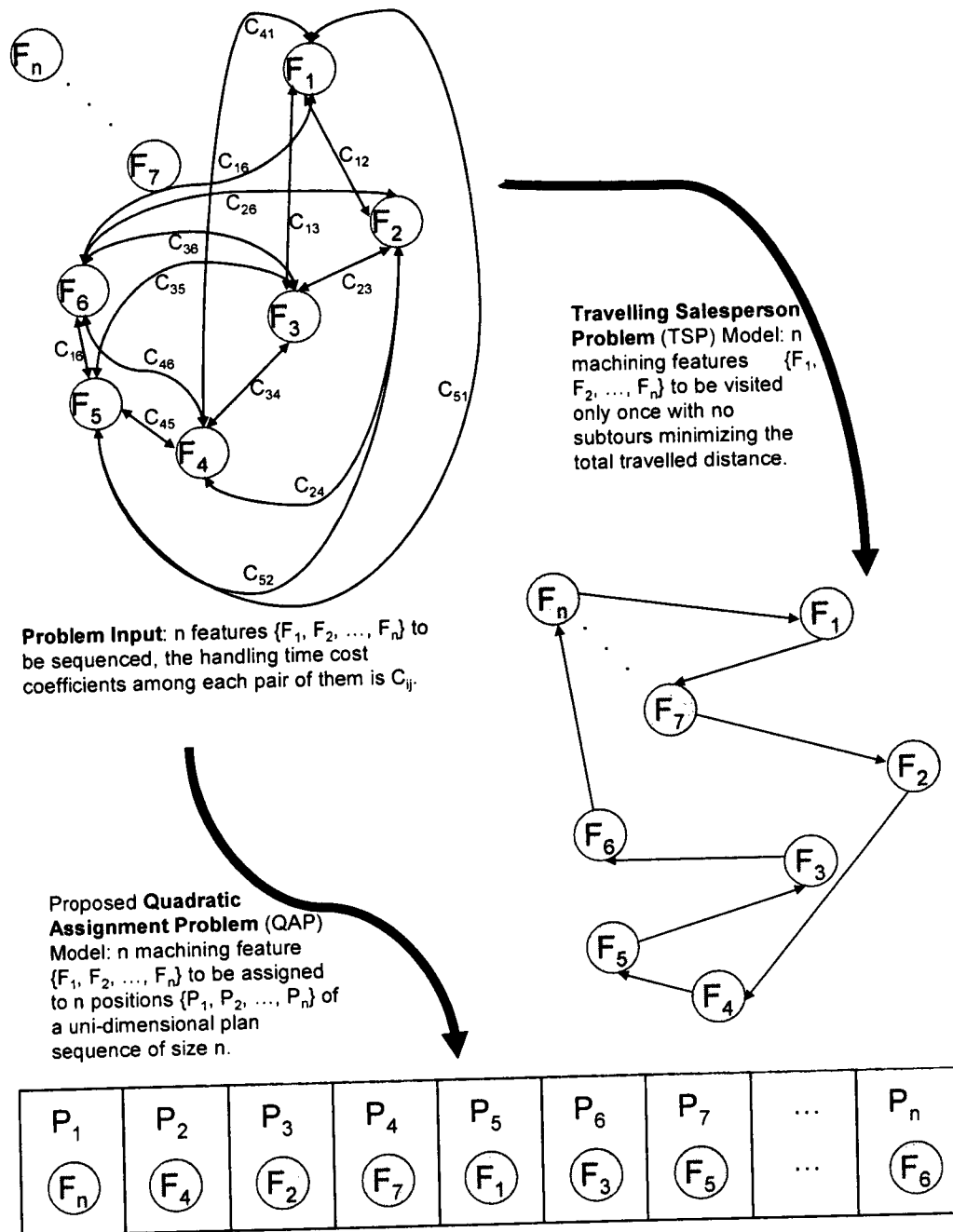


Figure (5.2) Conceptual comparison of the classical TSP model with the proposed QAP-based model

The RPP model was applied to the same Handspike benchmark problem formulated and solved using Xpress-MP solver and modeling language. The original plan sequence for the composite part is $\{A_r, G, C, A_f, E, D, F\}$. Upon solving the RPP model, feature B was inserted at position 3 in the process plan sequence. The new reconfigured sequence is $\{A_r, G, B, C, A_f, E, D, F\}$ (Azab and ElMaraghy 2007). The corresponding value of the

objective function is 14 time units compared with 11 time units obtained by the QAP-based proposed method. It is also evident by looking at the plan sequences obtained by both methods, shown in Table 5.4 that the RPP method results in partial reconfiguration of the original plan sequence of the composite part, whereas the QAP-based re-planning method re-shuffles the original composite plan sequence since it re-plans the processes from scratch. The RPP solution limits the changes to the original process sequence/plan by locally reconfiguring it. This reduces the potentially costly efforts on the shop floor for changing set-ups or fixtures and associated ripple effects.

Table (5.4) Comparing RPP against QAP-based Re-planning

Method	Solutions	Objective function value
RPP	Composite: {A _r , G, C, A _f , E, D, F} New: {A _r , G, B , C, A _f , E, D, F}	7 time units 14 time units
QAP-based Re-planning	Composite: {A _r , G, C, A _f , F, E, D} New: {A _r , C, B, E, F, D, G, A_f }	7 time units 11 time units

In essence, the two models approach the process sequencing/planning variation problem differently, one by locally re-configuring it (RPP) and the other by re-planning it (QAP-based). Both approaches have their advantages and applications.

5.5 A Combinatorial Optimization Problem

The problem in hand constitutes a combinatorial optimization problem which is proven to be NP-complete (Garey and Johnson (1979), Irani *et al.* (1995), Reddy *et al.* (1999)). The acronym NP is for “Non-deterministic Polynomial”. An NP-complete problem is a computational problem that is as hard as any reasonable problem (Papadimitriou and Steiglitz 1982). Examples of NP-complete problems are the layout problem, Knapsack problem, integer-linear programming in general, etc. The practical significance of an NP-complete problem lies exactly in the widespread belief that such problems are inherently intractable from the computational point of view; that they are not susceptible to efficient algorithmic solution; and that any algorithm that correctly solves an NP-complete problem will require in worst case an exponential amount of time,

and hence will be impractical for all but very small instances (Papadimitriou and Steiglitz 1982).

The distinction between exponential functions and polynomials becomes clear since polynomials grow more slowly than exponential functions. So polynomial algorithms with growth rate n^k (even when k is large) are more efficient in comparison with exponentially growing algorithms. A problem is said to be difficult if it can be proved that any algorithm, which will solve every instance of the problem is an exponential algorithm. Such problems do exist, but they are rather obscure. A problem for which no polynomial algorithm is known is called an intractable problem. If there is a polynomial algorithm to solve a problem, one can claim it is easy to solve. It requires some sophisticated mathematical techniques to show that the complexity of any algorithm conceivable for the problem cannot be bounded above by a polynomial. Such techniques are being discovered by computer scientists with the advent of latest developments in computational complexity theory.

The introduction of the concept of NP-completeness is important in this field. When a problem is shown to be NP-complete, this does not mean that it is unsolvable, but it can be claimed that instances of the problem can be solved and that a general solution is not available. The following are the possible solution trends: The first trend is using a non-polynomial time algorithm. The time complexity functions reflect the worst-case behavior of the algorithms. An exponential time algorithm may perform well on average-case inputs. An example of such algorithms is the well-known simplex algorithm used to solve the linear programming problem. In the worst case the algorithm may require an exponential time, but practice shows that the algorithm performs with a low order polynomial on average inputs. As for the second trend, heuristics, approximate algorithms can be used to settle at a good or near-optimal solution. Most optimization methods fall in this category. The non-linear QAP as well as the linearized model could still be applied to solve large instances of the problem; however, termination criterion should be pre-specified. Evolutionary methods, strategic meta-heuristics, etc., could also

be used to obtain approximate sub-optimal solutions. A random based search heuristic is proposed in Section 5.5 to solve large instances of the Process Re-Planning problem.

5.6 Non-Traditional Optimization

The objective, as mentioned earlier, is to sequence a global set of machining operations of a given part, subject to a number of precedence constraints, in order to minimize the total idle time spent mainly in repositioning the work piece or fixture and tool changes. This problem has already been proven to be NP-hard as explained in Section 5.4. Hence, a new search heuristic based on Simulated Annealing (SA) has been developed. SA is a hill-climbing search method suitable for solving combinatorial problems as well as continuous problems with multi-modal objective functions (Vidal 1993). A search heuristic based on SA is tailored towards the problem at hand. The notation used is as follows:

P	Precedence constraint matrix, where every represents a precedence relationship between a pair of two features/operations. Each row is composed of two features/operations IDs representing a predecessor successor relationship.
T	$T = [t_{ij}]$ is an $m \times m$ symmetric handling time matrix.
t	t is the annealing temperature; initial annealing temperature is t_0 .
B	Search current point.
N	New search point after applying the SA operator, where a move is randomly chosen to one of the neighboring solutions.
S_{max}	Outer loop count.
S	Outer loop counter.
z	Inner loop count; it decreases by α , where $0 < \alpha < 1$. For the first loop it is starts with a value z_{max} .
j	Inner loop counter.

BestSoFar A variable to store the best search point visited so far.

ObjFn Value of the objective function for a given sequence.

ΔE $\Delta E = \text{ObjFn}(N) - \text{ObjFn}(B)$.

1. **Read problem input:**
 px2 precedence constraint matrix (P).
 mxm handling time matrix (t).
2. **Set initial search parameters (Temperature/Inner loop count):**
 Set $t \leftarrow t_0$; set $z \leftarrow z_{\max}$.
3. **Randomly generate initial search point B (also current search point) using a function to generate a random permutation of size m; also store the B in BestSoFar, which is storage for the best search point visited so far:**
 Set $B \leftarrow \text{randperm}(m)$; set $\text{BestSoFar} \leftarrow B$.
4. **Initialize outer loop counter:**
 Set $S \leftarrow 1$.
5. **Initialize inner loop counter:**
 Set $j \leftarrow 1$.
6. **Create a new search point , i.e. sequence (N):**
 Randomly choose a move to one of the neighbor solutions of the current search point B.
7. **Check feasibility of N:**
 If N $\begin{cases} \text{feasible} & \text{jump to step 10} \\ \text{infeasible} & \text{proceed to next step} \end{cases}$.
8. **Make another move:**
 Randomly choose a move to a neighbor solution; increment a counter i.
 If N is infeasible & $i \leq 10$ goto step 7; ifelse B is feasible jump to step 10; else proceed to next step.
9. **Validate N against precedence constraints:**
 A tailored repair mechanism specifically designed for the problem in hand is used.
10. **Calculate energy differential:**
 Set $\Delta E \leftarrow \text{ObjFn}(N) - \text{ObjFn}(B)$, where ObjFn is the objective function value of a sequence.
11. **Decide acceptance of new sequence N:**
 Accept all new sequences that are of better quality and, following an exponential random distribution, some that are of less quality.
 If $\Delta E < 0$ or $\text{rand} \leq e^{-(\Delta E/T)}$ set $B \leftarrow N$. If B is of better quality than BestSoFar, set $\text{BestSoFar} \leftarrow B$.
12. **Repeat for current temperature:**
 Set $j \leftarrow j+1$; if $j < z\alpha$, goto step 6.
13. **Lower the SA temperature & increment outer loop counter:**
 Set $t \leftarrow \alpha t$; $z = \alpha z$; $0 < \alpha < 1$; set $S \leftarrow S+1$.
14. **Apply a mutation operator:**
 Set $B \leftarrow \text{Shuffle}(B)$.
15. **Check termination criteria:**
 If no progress is made for z loops terminate; i.e. if $S \leq S_{\max}$ goto step 5, otherwise the algorithm terminates.

Figure (5.3) Proposed search algorithm for sequencing m features with p precedence constraints.

The proposed algorithm is detailed in Figure 5.3; it is comprised of two nested loops, an outer loop (steps 4-15 of proposed algorithm given in Figure 5.3) where the annealing temperature (t) decreases and an inner one, which iterates a number of loops that decrease with t (steps 5-12). In the inner loop new moves to neighboring solutions are accepted if they are of better quality to allow for hill climbing as demonstrated by step 11; lower quality solutions are also accepted with an exponential probability distribution. An algorithm is developed to validate the generated relaxed sequences against the precedence constraints and, then as needed, repair them if no valid feasible solutions are generated after a certain number of moves. The reason behind this validation process is that the solution space before the application of the constraints is factorial in size; it is also believed that the size of this part of the solution space is exponential in nature, which renders the search infeasible after applying the constraints. Therefore, it would be inefficient to wait until a feasible solution is generated randomly since the probability of its generation was shown to be poorly low. Also a Genetic Algorithms mutation operator is applied at the end of each outer loop to increase the chances of exploring more parts of the feasible solution space (step 14). The best solution found is always stored and updated. Generation of the objective function cost matrices for the different configurations of a given part was automated using an algorithm that exploited the symmetry property of the objective function matrices.

5.7 Summary

A novel mathematical model has been developed for process planning in changeable and reconfigurable manufacturing at a macro-level. Global optimum process plans are obtained by re-planning from scratch, when highly optimized process plans are required for economies of scale of mass production and the new mass customization manufacturing paradigms. The new process planning model compares favorably with the TSP model. Since the Re-Planning problem is combinatorial in nature, a random-based evolutionary Simulated Annealing algorithm has also been tailored to solve large instance problems.

6. APPLICATION IN METAL-CUTTING

This chapter is dedicated to present the main case study of this dissertation, where a family of front engine cover parts is machined on a Vertical Reconfigurable Machining Center. The proposed methodology was applied, where both generative Reconfigurable Process Planning (RPP) and Process Re-Planning models and methods were exploited and compared. The chapter concludes with a discussion of the obtained results.

6.1 Case Study Description

An engine front cover family of parts is used in this chapter. The two developed process planning methodologies were employed and compared in terms of their performance and merits. The cover belongs to an aluminum single-cylinder, air-cooled engine with overhead valves. Two variants of the front cover are given: an original existing one, which is currently being machined on the shop floor and a new instance with new and missing features. The original instance could also be the family's composite part in a typical retrieval planning argument. The aluminum front covers are die cast to the near net shape; finish machining is required for precision features and the tapped holes. Chamfered Cores are used where possible in the casting process to eliminate drilling for several tapped and clearance holes.

6.2 Setup Information

A three axis horizontal RMT would be used, hence three setups are required to produce the part in order to access the features on the front and back faces (-Z, +Z) and the side face (+X). The part is located on specific cast datum points to machine the features on the back face (+Z). Hence, machined datum points are generated and used to machine features on the front face. In each fixture, the part is placed on three pins (datum points A as shown in Figure 6.1). The two dowel holes of the part are inserted in two pins to restraint the planner three degrees of freedom (datum points Y as shown in Figure 6.1). These two pins are of varying cross section; one is circular while the other is diamond. Finally, two clamps ensure that the part does not get lifted off the setup. The ratio of the time required to position the work piece on a different fixture (composed mainly of

unloading the work piece, cleaning the setup, and loading the work piece) to the tool change time is assumed 2:1 based on practical experience. Note that it is assumed that the time required to reposition the work piece does not include that for tool changeover if required.

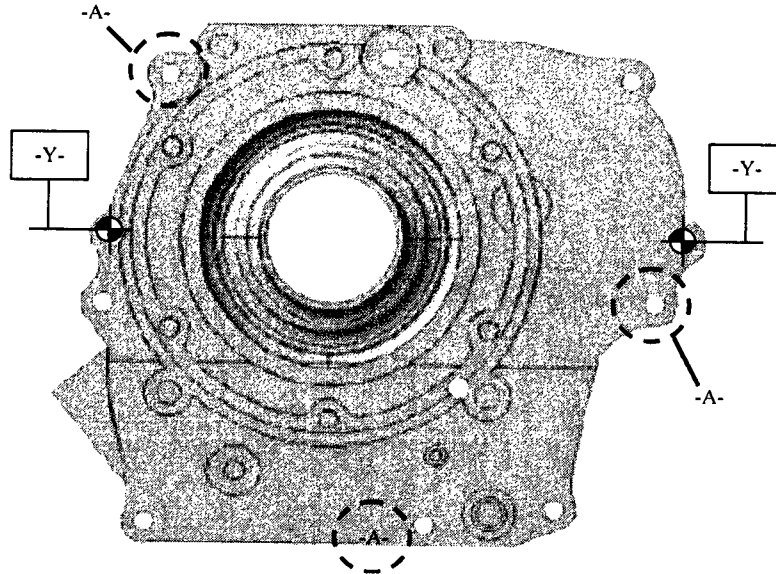


Figure (6.1) The fixturing scheme adopted for the single cylinder engine front cover part family.

6.3 Precedence Information

The precedence constraints applied in this case study are: 1) the features accessibility; 2) the logical sequence of operations; 3) the dimensional and geometrical precedence constraints are considered; 4) the non-destructive constraints; 5) the precedence due to machined setup datum points; and 6) good machining practices.

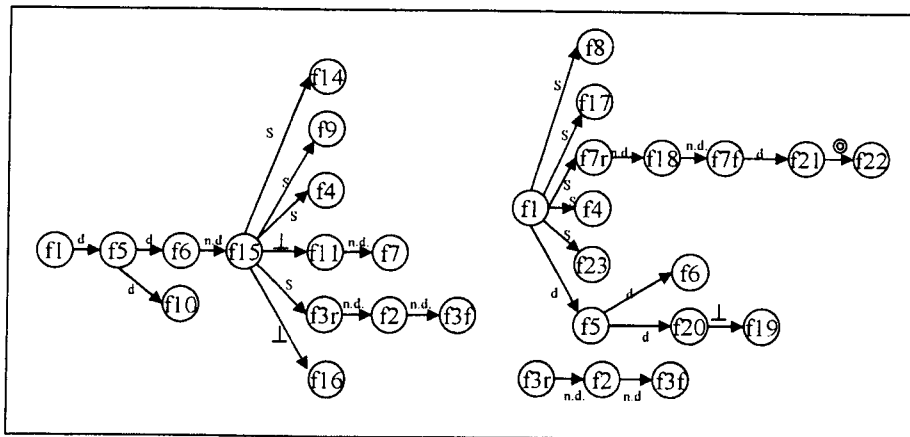


Figure (6.2) Feature precedence graph (FPG) of the original composite and the new single cylinder engine front cover

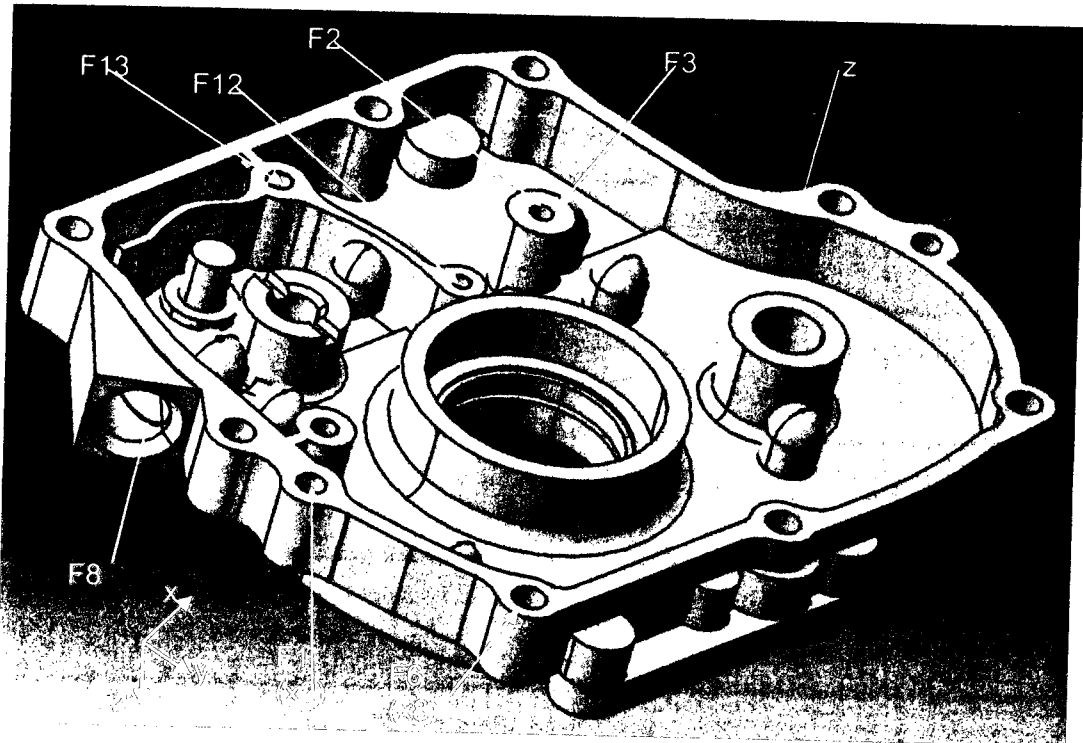


Figure (6.3) Composite part of the engine front covers family.

The Features Precedence Graphs (FPGs) for both the composite and the new part are shown in Figure 6.2, which can be easily translated to an OPG using the operations information given in Tables 6.1 and 6.2. The type of precedence is shown on the FPG by having the arrows carrying a symbol denoting its type. Precedence due to fixture or setup datum points is indicated by an 's'; n.d. for non-destruction constraints as explained in section 2; d for dimensional precedence and if it was GD&T, the appropriate GD&T symbol is then used. Some feature labels in the FPG were suffixed by r or f to indicate when necessary; for some specific features both roughing and finishing operations are required when these roughing and finishing nodes for the same feature are separated by some other features due to non-destruction precedence constraints. For example f2 is a precision through hole, while f3 is flat smooth surface perpendicular to f2. In this case a rough milling of f3 has to take place before f2 can be drilled. At the same time, finish milling cannot take place except after f2 is done, otherwise burrs due to the drilling operation would destroy the surface finish of f3. The machining alternative employed is given in Table 6.3 by considering a possible Tool Access Direction (TAD) combination.

Some dimensions, as well as GD&T constraints, dictate that some operations be performed using the same setup. If an alternative violates any of these conditions, a penalty cost is incurred to represent the extra time and effort required to achieve the desired tolerances.

Table (6.1) Features, operations, tools, and TAD for engine front cover composite part

Features			Operations		Tools		TADs	# of Features
ID	Function	Description	ID	Description	ID	Description		
F1	Locate cover onto the cylinder block	8mm precision dowel holes, through holes	OP1	Drilling	T1	Step drill Ø7mm	Z	2
			OP2	Boring	T2	Bore Ø7.5mm		
			OP3	Finish boring	T3	Bore Ø8mm		
F2	Governor mechanism seating bore	Precision bore, through hole	OP4	Drilling	T4	Drill Ø7mm	Z, -Z	1
			OP5	Boring	T2	Bore Ø7.5mm		
			OP6	Finish boring	T3	Bore Ø8mm		
F3	Governor mechanism mounting face	Flat, smooth surface perpendicular to bore f2	OP7	Rough milling	T5	End mill	Z	1
			OP8	Finish milling	T6	Face mill		
F4	Seating face for external device	Boss with cast blind hole	OP9	Finish milling	T6	Face mill	-Z	1
F5	Crankshaft bearing pocket	Stepped through hole. Concentricity critical	OP10	Rough boring	T7	Special rough boring tool	Z	1
			OP11	Semi-finish boring	T8	Special semi-finish boring tool		
			OP12	Finish boring	T9	Special finish boring tool		
F6	Cylinder block mounting holes	8 clearance holes on part profile	OP13	Drilling	T4	Drill Ø7mm	Z, -Z	8
F7	Seating face for external device	Flat, smooth surface	OP14	Milling	T5	End mill	-Z	1
F8	Oil plug	Tapped hole for oil plug, through hole	OP15	Drill's spot face	T10	Spot face and tap drill	X	1
			OP16	Tapping	T11	M20-1.5 tap		
F9	External device mounting holes	4 tapped blind holes	OP17	Tapping	T12	M10-1.5 tap	-Z	4
F10	Cam shaft seating bore	Precision bore, blind	OP18	Rough boring	T13	Bore Ø16.25mm	Z	1
			OP19	Semi-finish boring	T14	Bore Ø17.25mm		
			OP20	Finish boring	T15	Bore Ø18mm		
F11	External device mounting holes	6 holes for bosses	OP21	Drilling	T1	Step drill Ø7mm	-Z	6
			OP22	Tapping	T16	Special 9/32 (inch) tap		
F12	Sensor mounting hole	Blind hole	OP23	Drilling	T1	Step drill Ø7mm	Z	1

Table (6.2) Features, operations, tools, and TAD for engine front cover composite part (continued).

Features			Operations		Tools		TADs	# of Features
ID	Function	Description	ID	Description	ID	Description		
f13	Sensor mounting hole	Blind hole	OP24	Drilling	T1	Step drill Ø7mm	Z	1
f14	External device mounting holes	Boss with internal blind hole	OP25	Finish milling	T6	Face mill	-Z	1
F15	Gasket sealing surface	Smooth, flat surface. Datum -z-	OP26	Finish milling	T6	Face mill	Z	1
F16	External component mounting feature	Step hole	OP27	Drilling	T4	Drill Ø7mm	-Z	1
			OP28	Boring	T2	Bore Ø7.5mm		
			OP29	Finish boring	T3	Bore Ø8mm		
			OP30	Drilling	T17	Special drill Ø4.5mm		

6.4 Part Family

In this section, details of two parts of the engine front cover part family are given: a hypothetical composite part and a new variant belonging to the family.

6.4.1 Composite Part

The part shown in both Figures 6 and 1A is assumed to be the family's composite part. 3D views are used to represent the front cover for compactness, while front and back views are shown in Appendix A. Important dimensioning and geometric tolerance specifications and annotations relevant to the applied precedence constraints are specified on the rear and front 3D views. Details of each feature, its corresponding operations, tools, and TAD are shown in Tables 6.1 and 6.2. The objective function matrix can be easily constructed using the tooling and TAD information.

Table (6.3). Employed TAD alternative for engine front cover composite part

Features															
f1	F2	f3	f4	f5	f6	f7	f8	f9	f10	f11	f12	f13	f14	f15	f16
Z	-Z	Z	-Z	Z	Z	-Z	X	-Z	Z	-Z	Z	Z	-Z	Z	-Z

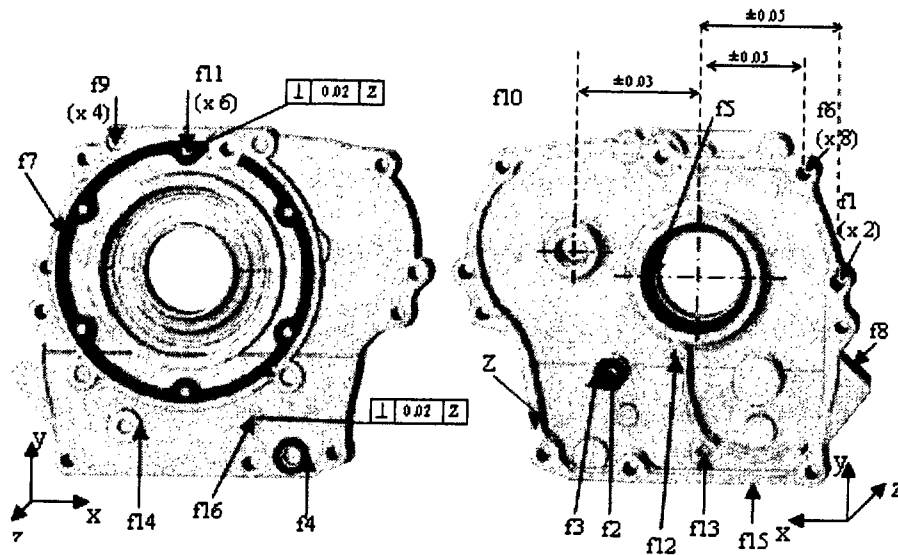


Figure (6.4) Engine front cover composite part (front and back views).

6.4.2 New Member Part

A new member of the front cover extended family, illustrated in Figure 7, is introduced. It contains eight features in common with the existing composite part (highlighted in black in both Figures A1 and A2 in Appendix A), but it also has seven new features, which do not exist in the original part family's composite part. Details of the features are shown in Tables 6.5 and 6.6. The machining alternative employed is given in Table 6.4 by considering a possible TAD combination.

Table (6.4) Employed TAD alternative for the new variant of engine front covers

Features														
f1	f2	f3	f4	f5	f6	f7	F8	F17	f18	f19	F20	F21	F22	F23
Z	-Z	Z	-Z	Z	-Z	-Z	X	X	-Z	-Z	Z	-Z	-Z	-Z

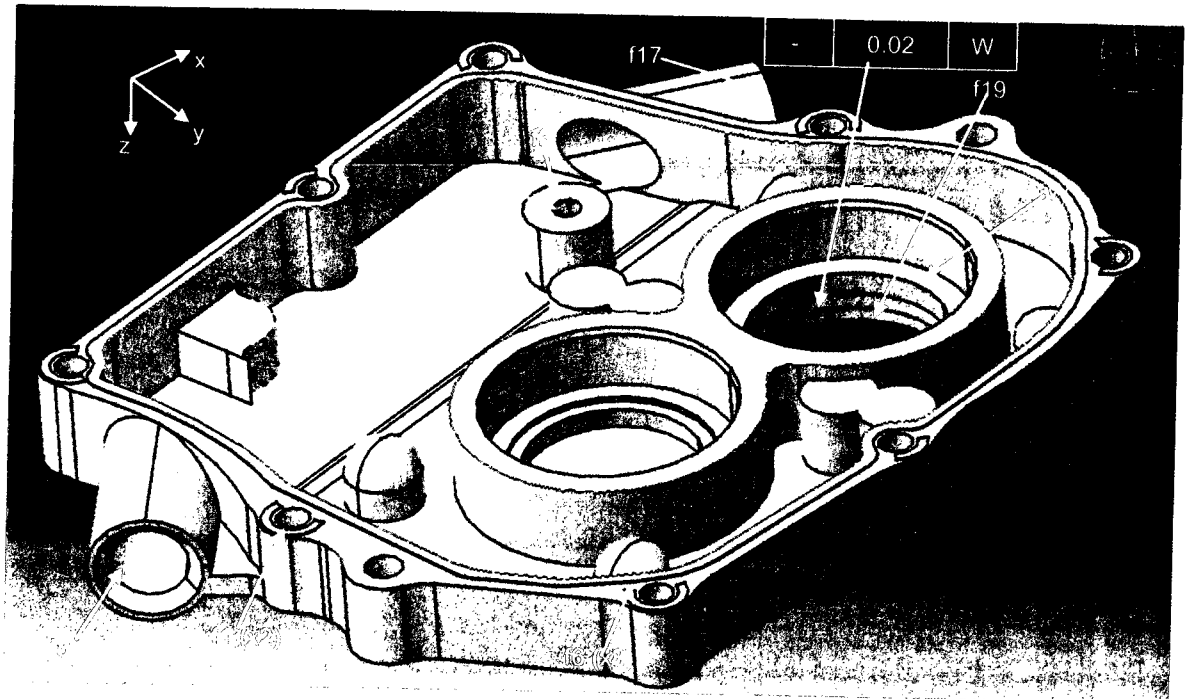


Figure (6.5) Engine new front cover variant.

Table (6.5) Features, operations, tools, and TAD for a new variant of engine front covers.

Features			Operations		Tools		TADs	# of Features
ID	Function	Description	ID	Description	ID	Description		
F1	Locate cover onto the cylinder block	8mm precision dowel holes, through holes	OP1	Drilling	T1	Step Drill Ø7mm	z	2
			OP2	Boring	T2	Bore Ø7.5mm		
			OP3	Finish boring	T3	Bore Ø8mm		
F2	Governor mechanism seating bore	Precision bore, through hole	OP4	Drilling	T4	Drill Ø7mm	Z, -Z	1
			OP5	Boring	T2	Bore Ø7.5mm		
			OP6	Finish boring	T3	Bore Ø8mm		
f3	Governor mechanism mounting face	Flat, smooth surface perpendicular to bore f2	OP7	Rough milling	T5	End mill	Z	1
			OP8	Finish milling	T6	Face mill		
F4	Seating face for external device	Boss with cast blind hole	OP9	Finish milling	T6	Face mill	-Z	1
F5	Camshaft bearing pocket	Stepped blind hole	OP10	Rough boring	T18	Step drill Ø49mm	Z	1
			OP11	Semi-finish boring	T19	Bore Ø51mm		
			OP12	Finish boring	T20	Bore Ø52mm		
F6	Cylinder block mounting holes	8 clearance holes on part profile	OP13	Drilling	T4	Drill Ø7mm	Z, -Z	8

Table (6.6) Features, operations, tools, and TAD for a new variant of engine front covers
(continued).

Features			Operations		Tools		TADs	# of Features
ID	Function	Description	ID	Description	ID	Description		
F7	Seating face for external device	Flat, smooth surface	OP14'	Rough milling	T5	End mill	-Z	1
			OP15'	Finish milling	T21	Face mill b		
F8	Oil plug	Tapped hole for oil plug, through hole	OP16'	Ext./int. surface finishing	T10	Spot face and tap drill	X‡	1
			OP17'	Tapping	T22	M18-1.5 tap		
F17	Oil plug	Tapped hole for oil plug, through hole	OP31	Ext./internal surface finishing	T10	Spot face and tap drill	X‡	1
			OP32	Tapping	T22	M18-1.5 tap		
F18	External device mounting holes	8 tapped blind holes	OP33	Tapping	T23	Tap drill Ø7mm	-Z	18
F19	Crankshaft hole	21.5mm hole	OP34	Rough boring	T24	Bore Ø19mm	Z, -Z	1
			OP35	Semi finish boring	T25	Bore Ø20.5mm		
			OP36	Finish boring	T26	Bore Ø21.5mm		
F20	Crankshaft bearing pocket	52mm pocket	OP37	Rough boring	T18	Step drill Ø49mm	Z	1
			OP38	Semi finish boring	T19	Bore Ø51mm		
			OP39	Finish boring	T20	Bore Ø52mm		
F21	Sensor mounting bore	16mm bore	OP40	Boring	T27	Bore Ø14mm	-Z	1
			OP41	Boring	T28	Bore Ø16mm		
			OP42	Groove	T29	Special bore Ø5mm		
			OP43	Finish milling	T21	Face mill b		
F22	Sensor mounting hole	7mm hole	OP44	Drilling	T4	Drill Ø7mm	-Z	1
F23	Governor mechanism	Flat, smooth surface	OP45	Milling	T5	End mill	-Z	1

[‡] f8 & f17 TAD is different; however reconfiguring the RMT, adding a 4th axis, eliminated this distinction.

6.5 Reconfigurable Machining Resources

The original three-axis horizontal configuration of the RMT is not sufficient for producing the new part; an extra dedicated setup or two special angle head tools would be required to machine feature f17, for example. Hence, the machine tool would have to be reconfigured by adding an appropriate rotational axis of motion to the spindle or table, i.e., the RMT transforms into a 4-axis horizontal machining center.

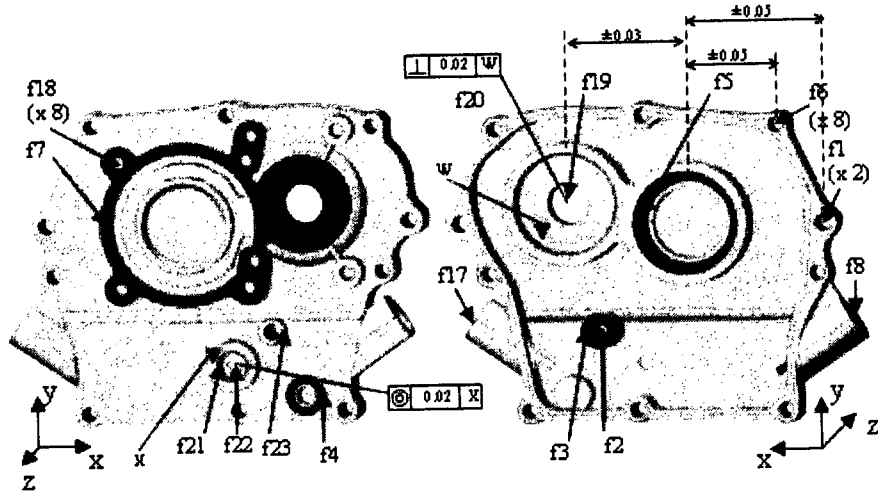


Figure (6.6) Engine new front cover variant (front and back views).

6.6. Results

6.6.1 Reconfigurable Process Planning (RPP) Results

The master macro-process plan for the composite engine cover, originally solved using a Genetic Algorithms toolbox developed by Azab (2003), is retrieved. The obtained features sequence is {f13, f12, f1, f5, f6, f15, f3r, f10, f8, f4, f14, f2, f16, f11, f9, f7, f3f}. The common features {f1, f5, f6, f3r, f8, f4, f2, f7, f3f} are extracted from this solution by subtracting those that are not found in the new part. Now, that the initial features sequence is obtained, the RPP procedure is applied to find the optimum insertion position for features f17- f23 respectively. Seven iterations were performed to optimally insert the seven new features as shown in Table 6.7.

Table (6.7) Results for the seven RPP iterations

#1	{f1, f5, f6, f3r, f17, f8, f4, f2, f7r, f7f, f3f}
#2	{f1, f5, f6, f3r, f17, f8, f4, f2, f7r, f18, f7f, f3f}
#3	{f1, f5, f19, f6, f3r, f17, f8, f4, f2, f7r, f18, f7f, f3f}
#4	{f1, f5, f20, f19, f6, f3r, f17, f8, f4, f2, f7r, f18, f7f, f3f}
#5	{f1, f5, f20, f19, f6, f3r, f17, f8, f4, f2, f7r, f18, f7f, f21, f3f}
#6	{f1, f5, f20, f19, f6, f3r, f17, f8, f4, f2, f7r, f18, f7f, f21, f22, f3f}
#7	{f1, f5, f20, f19, f6, f23, f3r, f17, f8, f4, f2, f7r, f18, f7f, f21, f22, f3f}

The obtained solution and its corresponding objective function value for the obtained reconfigured part are shown in Table 6.8. Formulation details for the first and second iterations are given, for demonstration purposes, in Appendices A.

Table (6.8) Final RPP Solution & Corresponding Objective Function Value

Solution	Objective function value
{f1, f5, f20, f19, f6, f23, f3r, f17, f8, f4, f2, f7r, f18, f7f, f21, f22, f3f}	21 time units

The Plan Reconfiguration Index (RI_{Plan}) reported a value of 90%, indicating that the master plan was significantly reconfigured, i.e., the obtained best plan sequence for the new part was significantly different as a result of planning reconfiguration of the original composite plan for the part family's master part.

6.6.2 Process Re-planning Results

Ten SA runs were performed for each engine front cover, the composite as well as the new member of the front cover family. The near optimal operation sequences are given in Tables 6.9 and 6.10. For the composite part, the mean and standard deviation of the objective function values are 21.1 and 1.2 time units respectively. The mean and standard deviation for the new cover are 20.7 and 3.3 time units respectively.

Table (6.9) Planning runs results for the engine front covers original composite part

#	Plan Sequences	Objective Function Value (Time Units)
1 st Run	1 5 6 15 3 12 13 8 10 16 2 11 7 3f 4 14 9	22
2 nd Run	1 5 15 6 3 11 16 7 9 2 4 14 10 3f 13 12 8	20
3 rd Run	1 12 13 5 6 15 10 3 11 2 16 8 3f 7 4 9 14	21
4 th Run	8 1 5 6 13 12 15 3 11 4 9 14 7 2 16 3f 10	20
5 th Run	1 5 12 6 15 13 3 16 2 11 4 9 14 7 10 3f 8	21
6 th Run	13 12 1 5 8 6 15 3 16 2 11 7 9 3f 10 4 14	22
7 th Run	1 13 5 12 6 10 15 3 11 4 14 2 16 9 7 8 3f	19
8 th Run	1 13 5 6 12 15 10 3 2 3f 14 4 11 8 7 16 9	23
9 th Run	12 1 5 6 15 3 10 8 11 16 7 2 9 3f 13 4 14	22
10 th Run	13 12 1 5 6 15 3 10 11 14 16 2 3f 7 4 9 8	21
	Mean	21.1
	Standard Deviation	1.2

† Solution in bold face is the best one obtained.

For the front cover composite part, it can be concluded from the small difference in magnitude (2.1 time units) between the best objective function values obtained and the averages, as well as the small values of the standard deviation that the results obtained were consistent. In many cases, more than one solution is obtained with an identical value of the objective function. The search algorithm parameters were tested to arrive at the best working ranges. Figure 8 demonstrates the output and convergence for one of the runs.

Table (6.10) Re-Planning runs results for the engine front covers new variant

#	Plan Sequences	Objective Function Value (Time Units)
1 st Run	1 5 20 3 4 7 18 7f 6 2 23 21 3f 19 22 17 8	17
2 nd Run	1 5 20 3 7 2 17 3f 18 7f 19 21 22 6 23 8 4	23
3 rd Run	1 5 17 20 3 7 19 18 2 7f 8 23 21 22 6 3f 4	23
4 th Run	1 5 20 3 19 23 7 2 4 17 18 3f 7f 21 8 6 22	23
5 th Run	1 7 5 20 3 23 4 19 18 7f 21 2 22 6 17 3f 8	24
6 th Run	1 7 23 3 5 20 4 18 7f 21 17 8 6 19 2 22 3f	21
7 th Run [‡]	1 5 20 3 7 23 2 3f 4 6 19 18 7f 21 22 17 8	15
8 th Run	1 3 7 23 18 4 7f 21 5 20 17 19 8 22 2 3f 6	24
9 th Run	1 5 3 20 2 7 18 19 23 3f 7f 21 4 17 8 22 6	20
10 th Run	3 1 5 20 7 18 23 4 7f 19 21 22 2 3f 6 17 8	17
Mean		20.7
Standard Deviation		3.3

[‡] Solution in bold face is the best one obtained.

Since re-planning was carried out from scratch, the plans obtained using the Process Re-Planning method were significantly different than the original composite plans and hence, a high value of 128% of RI_{Plan} was reported, i.e. 1.28 more tool changes and work piece repositioning were reported in the new plan than the original existing or composite ones. The Design Reconfiguration Index RI_{Design} reported a high value of 60% (in the design space the new part's design is quite significantly distant from the original one); therefore, it was anticipated that in the process planning space the globally highly optimized plans obtained by Re-Planning would be quite distant from the original existing or master plans and hence, from the localized RPP plans which would be closer to the old plans ($RI_{Plan}=90\%$ for RPP). The quality of the new plans obtained by Re-

Planning showed a slight improvement in terms of the value of the handling time objective criteria, over their RPP counterpart when considering the mean obtained for the preformed 10 runs. However, the difference is quite significant between the RPP solution and the best solution obtained by Re-Planning, which showed about 25% improvement over the RPP counterpart. This is expected since the Re-Planning approach solves the whole global sequencing problem, while the RPP algorithm limits reconfiguration to a subset of the total solution space. This is an advantage in agile manufacturing environments where product customization, changes, and evolution occur frequently as it reduces the changes to be made on the shop floor to execute the new process plans. The RPP methodology offers a quick, feasible and optimal solution albeit not necessarily the exact global optimum.

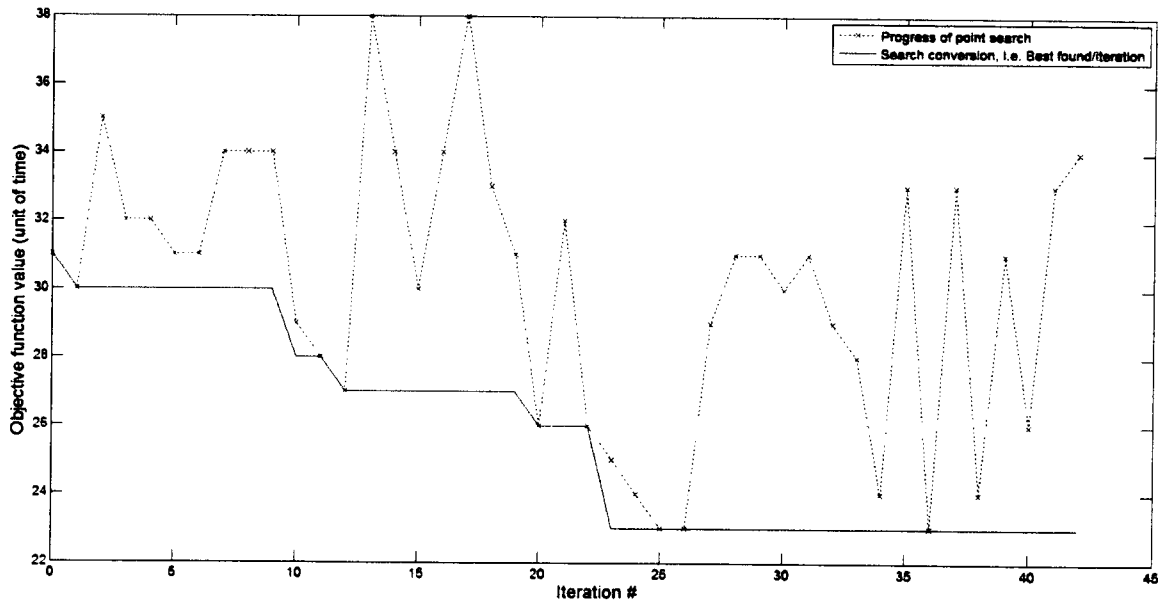


Figure (6.7) Conversion curve for one of 10 SA runs performed for the new engine front cover.

6.7 Summary

An industrial case study of a family of single cylinder front engine covers is used for illustration and verification. Both generative Reconfigurable Process Planning (RPP) and Process Re-Planning are used to alter the current existing plans and arrive at the new ones

for the new part with its newly introduced features. The computational behavior and advantages of the proposed models are discussed, analyzed and compared with classical models.

7. APPLICATION AND VERIFICATION IN INSPECTION AND ASSEMBLY

In this chapter, the developed methodology, mathematical models and solution methods are being implemented in different domains of application than metal cutting and machining manufacturing (Azab *et al.* 2008). The primary purpose is to test and validate the conceptual soundness of the proposed methods in both assembly and inspection planning. The sequential hybrid process planning methodology, along with the Reconfigurable Process Planning (RPP) generative model, is used in assembly planning. The problem was also solved using Process Re-Planning by solving the proposed linearized Quadratic Assignment Problem (QAP) model. QAP-based planning was tested and verified in the field of inspection planning, where both the original nonlinear and the linearized models were solved. Application of the RPP and the QAP planning schemes for assembly and inspection planning are discussed in Sections 7.1 and 7.4 respectively; case studies in the fields of assembly and inspection planning are presented in sections 7.2 and 7.5 respectively. A thorough analysis and comparison of the proposed methods are presented in section 7.3. Section 7.6 concludes and summarizes the main issues in this chapter.

7.1 Reconfigurable Assembly Planning

Assembly planning is an important production planning activity in the product development cycle. It specifies assembly operations to combine components or sub-assemblies together to form the finished product. The main objective, as discussed earlier in Section 2.6, is to organize a proper assembly sequence in which the components can be grouped or fixed together to construct a final product in minimal assembly time and, hence, with minimal cost. In case of planning single task assembly operations, where one assembly head is used at a time, the objective becomes to minimize the transient changeover time between consecutive assembly operations.

7.1.1 Assumptions & Notations

The assumptions made in this model are as follows:

1. The considered precedence constraints include:
 - Logical sequence of operations.
 - Geometric Dimensioning & Tolerancing (GD&T) constraints.
2. Sequencing is carried out on the assembly operations level.
3. Operation, tooling and fixtures selection was done in advance.
4. Setup, and tool information required for each operation was specified and given in advance

The notations used are as follows:

- n denotes the problem size and it is the total number of decision variables and it could also be interpreted as the total number of assembly operations including the new operations to-be-inserted.
- $C=[c_{i,j}]$ is the $n \times n$ precedence penalty matrix. A row would be assigned to each possible insertion position. For each row, a relatively large value would be assigned if the precedence between the operation to be inserted and each operation of the original sequence, at a time, is violated.
- $S=[s_{i,j}]$ is the $n \times n$ work piece repositioning time matrix. A row would be assigned to each possible insertion position. For each row, the time required to reposition the work piece on the given fixtures (setups) in order to be able to switch between each pair of the successive operations of the new possible permutation, i.e after the insertion of the new operation to be..
- $O_s=\{O_{s_i}\}$ is the $1 \times n$ old work piece repositioning time vector, which is a vector of the time required to reposition the work piece on the given fixtures (setups) in order to be able to switch between pairs of successive operations of the original sequence (i.e. not to include the new operation) after subtracting the missing operations.

- $Tr = \{Tr_i\}$ is the $1 \times n$ right tool change time vector (i.e. the tool change between the new to-be-inserted operation and every operation in the old sequence from the right side).
- $Tl = \{Tl_i\}$ is the $1 \times n$ left tool change time vector (i.e. the tool change between the new to-be-inserted operation and every operation in the old sequence from the left side).
- $Ot = \{Ot_i\}$ is the $1 \times n$ old tool change time vector, which is a vector of the tool change time in order to be able to switch between pairs of successive operations of the original sequence after subtracting the missing operations, i.e. not including the new operation to-be-inserted.

The decision variables are:

x_i is a 0-1 integer variable, where i runs from 1 to n . Its value is 1 if new operation is inserted at position i ; 0 otherwise. The position i takes the value 1 when the new operation is inserted right before the first feature of the original array of operations and takes the value n when it is positioned right after the last feature of the original array, i.e. feature f_{n-1} .

7.1.2 Formulation

Two criteria are considered: 1) time for repositioning the assembly in-process on different fixtures, and 2) time for tools changeover in case of robotic assembly. The objective is to minimize the handling time. The time spent for rapid tool traverse between consecutive operations is ignored due to its relatively minor contribution. Also the time required for transportation of the assembly in-process between different assembly workstations as well as that spent to adjust the assembly setups and tool change are also ignored since these detailed parameters are not determined at this macro-level. The objective function is given by equation 7.1.

$$\min. \sum_{i=1}^n \sum_{j=1}^{n-1} C_{i,j} .x_i + \sum_{i=1}^n \left(\sum_{k=1}^{n-1} S_{i,k} \right) .x_i - \sum_{i=1}^n O_{S_i} .x_i + \sum_{i=1}^n (Tr_i + Tl_i) .x_i - \sum_{i=1}^n O_{t_i} .x_i \quad (7.1)$$

The first term represents the penalty for violating precedence constraints. The second term represents the cost of repositioning the assembly in-process on the different fixtures (i.e. setup cost as commonly referred to in the literature). The first summation of $S_{i,k}$ over k represents the setup cost associated with a new sequence, i.e. the setup cost between every pair of preceding features in this permutation.

The terms Tr_i and Tl_i with their summation over i from 1 to n depict the tool change cost. They account for the new precedence cost due to the insertion of the new assembly operation between two existing operations in the original sequence- one to the right (Tr_i) and one to the left (Tl_i). Finally, the O_{S_i} and O_{t_i} terms represent the handling time change incurred due to changing the original precedence between the two operations in the original sequence after subtracting the missing features that are separated by inserting the new operation, and hence, the old setup and tool change time are subtracted.

The constraints system of the RPP model is advantageously simple and is represented by:

$$\sum_{i=1}^{n+1} x_i = 1 \quad (7.2)$$

This constraint prevents a operation from being inserted more than once at any position.

7.2 Assembly Planning of a Family of a Household Product

7.2.1 Case Study Description

The assembly process of a family of a household product is the subject of this section. Two different variants of a small kitchen appliance (a kettle) were considered.

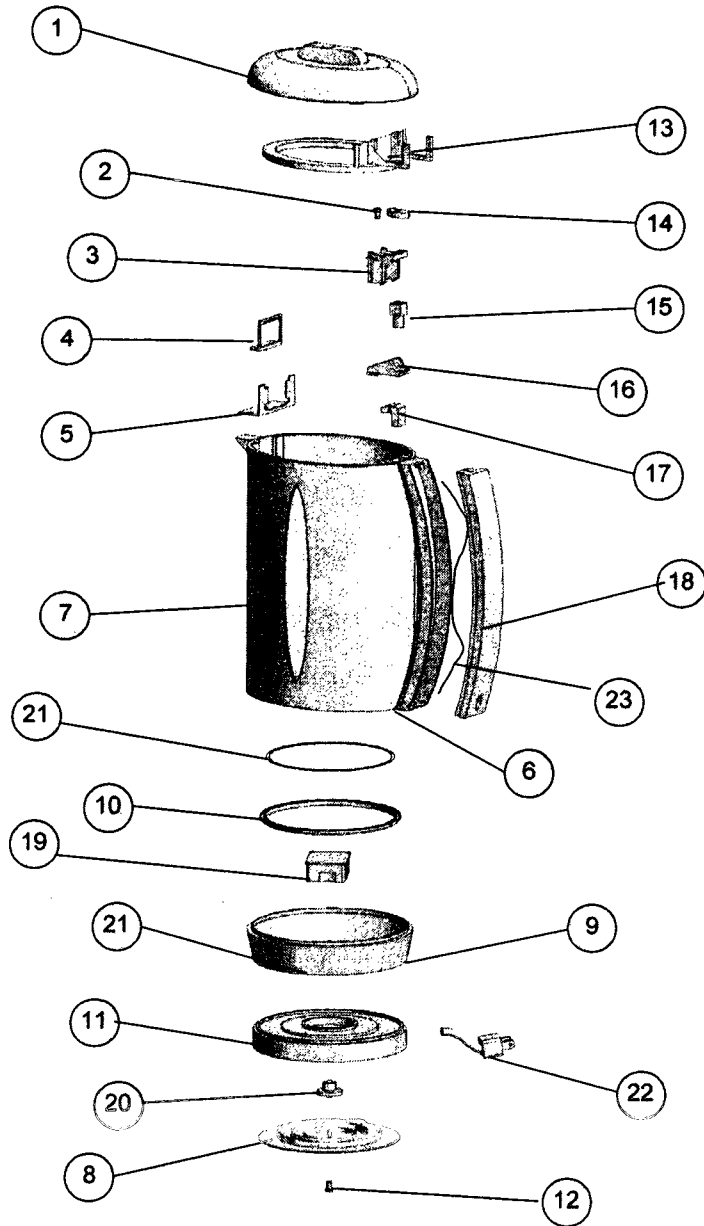


Figure (7.1) Electric kettle family original Assembly Design exploded CAD model.

Table (7.1) Electric kettle original assembly operations details.

Operation ID	Description of Assembly Operations	Setup Used (Assembly Direction)
1	Put main body (Part #6)	Vertical, Upright
2	Fix water indicator (Part #7)	Vertical, Upright
3	Fix lead wire (Part #23)	Vertical, Upright
4	Insert lens cover (Part #17)	Vertical, Upright
5	Insert steam switch (Part #16)	Vertical, Upright
6	Insert steam tube (Part #15)	Vertical, Upright
7	Insert steam separator (Part #3)	Vertical, Upright
8	Fix screw (Part #2)	Vertical, Upright
9	Insert switch cover (Part #14)	Vertical, Upright
10	Fix filter frame (Part #5)	Vertical, Upright
11	Insert filter (Part #4)	Vertical, Upright
12	Fix handle (Part #18)	Vertical, Upright
13	Fix lid cover (Part #13)	Vertical, Upright
14	Fix lid (Part #1)	Vertical, Upright
15	Put body lower (Part #9)	Body lower Setup
16	Insert controller (Part #19)	Body lower Setup
17	Insert heating plate (Part #10)	Body lower Setup
18	Insert heating O'Ring (Part #21)	Body lower Setup
19	Assemble body lower subassembly with main body	Vertical, Upside down
20	Assembly power base upper (Part #11)	Vertical, Upside down
21	Fix power cord (Part #22)	Vertical, Upside down
22	Insert adaptor (Part #20)	Vertical, Upside down
23	Assemble power base lower (Part #8)	Vertical, Upside down
24	Screw power base subassembly to the main body (Part #12)	Vertical, Upside down

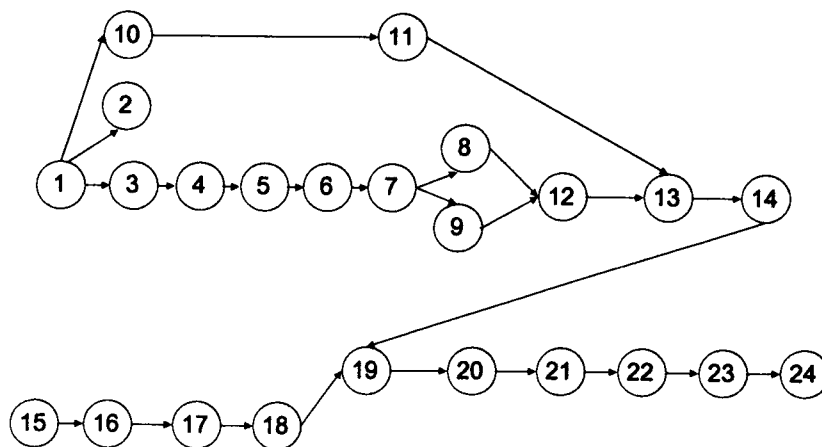


Figure (7.2) Original Electric kettle FPG.

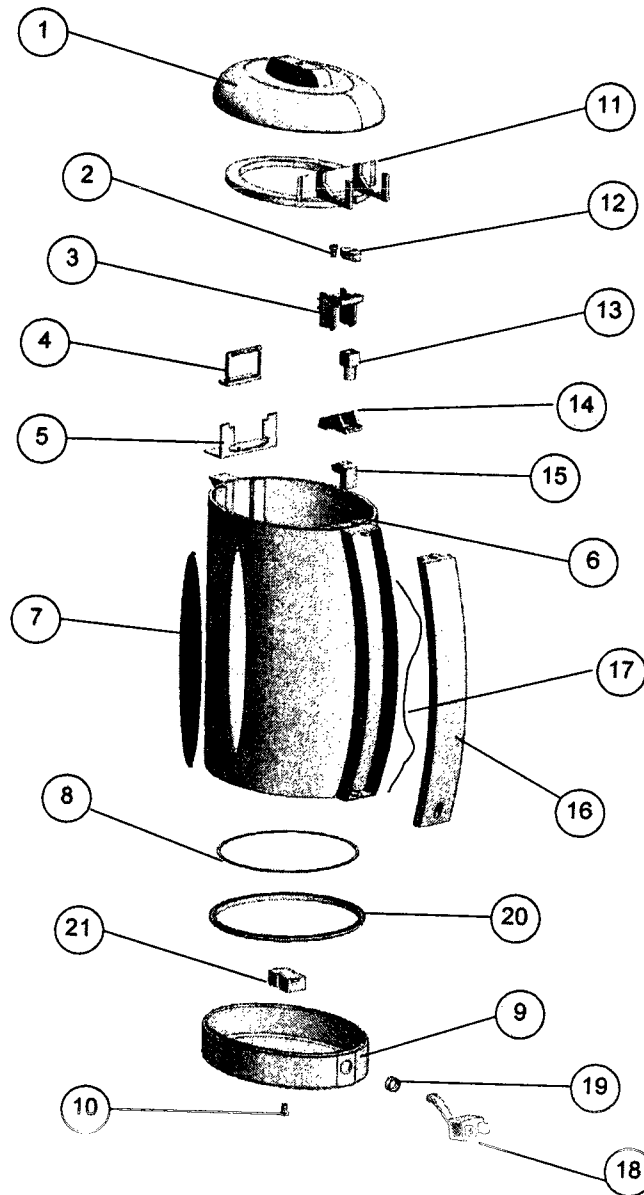


Figure (7.3) Electric kettle new variant exploded CAD.

The original product design is shown in Figure 7.1. Design For Assembly (DFA) analysis was performed to enhance the assemblability of the product. A modified product design was introduced as shown in Figure 7.3. The part count in the new variant kettle was reduced from 24 to 22. The components of the Power Base Lower subassembly were all combined in the newly designed Body Lower part # 9 in the new variant kettle. All details related to the assembly operation are given in Tables 7.1 and 7.2. Three different setups are needed for the new design compared to two for the original design. Two setups are used for the main body in two opposite assembly directions (one position where the

kettle would be upright and another where it would be upside down), and a third setup to assemble the Body Lower subassembly. Manual assembly of the two variants is assumed; hence, the tool change time is ignored. Operations Precedence Graphs (OPGs) for both kettle family variants are given in Figures 7.2 and 7.4.

Table (7.2) Electric kettle new variant assembly operations details.

Operation ID	Description	Setup Used
1	Put main body (Part #6)	Vertical, Upright
2	Fix water indicator (Part #7)	Vertical, Upright
3	Fix lead wire (Part #23)	Vertical, Upright
4	Insert lens cover (Part #17)	Vertical, Upright
5	Insert steam switch (Part #16)	Vertical, Upright
6	Insert steam tube (Part #15)	Vertical, Upright
7	Insert steam separator (Part #3)	Vertical, Upright
8	Fix screw (Part #2)	Vertical, Upright
9	Insert switch cover (Part #14)	Vertical, Upright
10	Fix filter frame (Part #5)	Vertical, Upright
11	Insert filter (Part #4)	Vertical, Upright
12	Fix handle (Part #18)	Vertical, Upright
13	Fix lid cover (Part #13)	Vertical, Upright
14	Fix lid (Part #1)	Vertical, Upright
15	Put body lower (Part #9)	Body lower Setup
16	Insert controller (Part #21)	Body lower Setup
17	Insert heating plate (Part #20)	Body lower Setup
18	Insert heating O'Ring (Part #8)	Body lower Setup
19	Assemble body lower subassembly with main body	Vertical, Upside down
24	Screw body lower subassembly to main body (Part #10)	Vertical, Upside down
25	Insert bushing (Part #19)	Body lower Setup
26	Fix power cord (Part #18)	Body lower Setup

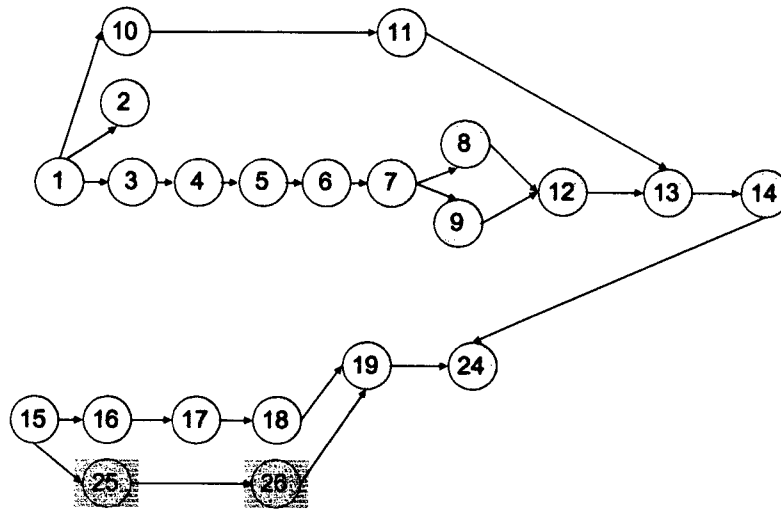


Figure (7.4) New FPG showing new operations for the new electric kettle variant (Highlighted in red).

7.2.2 Reconfigurable Assembly Planning Results

Two iterations were carried out to insert the new two operations. In Tables 7.3- 7.5, precedence cost, setup and tool change formulation matrices and vectors for the second iteration are given respectively. As mentioned earlier, tool change is neglected since manual assembly is used. Hence, all tool change vectors are zero vectors. Setup change time is assumed to take an arbitrary unit time. Precedence penalties of a 1000 unit time are assumed.

The given plan for the original variant of the Electric Kettle is {15, 16, 17, 18, 1, 10, 11, 2, 3, 4, 5, 6, 7, 9, 8, 12, 13, 14, 19, 20, 21, 22, 23, 24}. Missing assembly operations for the new kettle (variant 2) were subtracted resulting in the following sequence {15, 16, 17, 18, 1, 10, 11, 3, 4, 5, 6, 7, 9, 8, 12, 13, 14, 2, 19, 24}. Results of each iterative step of the RPP solution method are given in Table 7.6, where the new inserted sequence is highlighted in bold face. The value of the objective function is 2 time units corresponding to 2 acts of repositioning the assembly in-process on different fixtures. It should be noted that each act of repositioning is assumed to take an arbitrary time period of one unit time in this case study, since only repositioning of the work piece is considered. Manual operation is performed and hence, the handling time objective function tool change

the modified one exhibited different logical precedence relationships; hence in spite of them being technically identical they are considered different entities at the operations macro-planning level.

Table (7.5) Work piece repositioning time matrix C for the second iteration.

0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0
0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0
0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0
0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1

Table (7.6) New part plan detailed results

Iteration 1:	{15, 16, 17, 18, 1, 10, 11, 3, 4, 5, 6, 7, 9, 8, 12, 13, 14, 2, 19, 24}
Iteration 2:	{15, 16, 17, 25 , 18, 1, 10, 11, 3, 4, 5, 6, 7, 9, 8, 12, 13, 14, 2, 19, 24}
Final Sequence:	{15, 16, 17, 25, 18, 26 , 1, 10, 11, 3, 4, 5, 6, 7, 9, 8, 12, 13, 14, 2, 19, 24}

7.2.3 Assembly Re-Planning Results

The same problem was solved by the Process Planning method from scratch, where linearized QAP mathematical programming was utilized. The problem formulation is given by equations 7.3-7.10. The handling time matrix is shown in Table 7.7. The GAMS algebraic modeling language and CPLEX Mixed Integer Programming (MIP) solver were used.

Table (7.7) Handling time matrix T for electric kettle new variant.

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	0

$$\min. \sum_{i=1}^{22} \sum_{j=1}^{22} T_{i,j} \sum_{k=1}^{21} q_{i,j,k} \quad (7.3)$$

Subject to:

$$\sum_{k=1}^{22} y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, 22\} \quad (7.4)$$

$$\sum_{k=1}^{22} y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, 22\} \quad (7.5)$$

$$y_{i,k} + y_{j,k+1} - 2q_{i,j,k} \geq 0 \quad \forall i, j, k \in \{1, 2, \dots, 22\} \quad (7.6)$$

$$y_{i,k} + y_{j,k+1} - q_{i,j,k} \leq 0 \quad \forall i, j, k \in \{1, 2, \dots, 22\} \quad (7.7)$$

Equations 7.4-7.7 are feasibility constraints.

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{10,k} \quad \forall l \in \{1,2,\dots,22\} \quad (7.8)$$

...

$$\sum_{k=1}^l y_{19,k} \geq \sum_{k=1}^l y_{24,k} \quad \forall l \in \{1,2,\dots,22\} \quad (7.9)$$

Equations 7.8-7.9 provide a sample of the precedence constraints given by Figure 7.4. For example, equation 7.8 represents the first precedence constraint (1→10); equation 7.9 represents the last precedence constraint (19→24). The rest of the precedence constraints {(10→11), (11→13), (1→2), (1→3), (3→4), (4→5), (5→6), (6→7), (7→9), (7→8), (9→12), (8→12), (12→13), (13→14), (15→16), (16→17), (17→18), (18→19), (15→25), (25→26), (26→19)} could be easily expressed mathematically in the same way.

$$y_{i,k}, q_{i,j,k} = (0,1) \quad \forall i,j,k \in \{1,2,\dots,22\} \quad (7.10)$$

The problem was modeled using the GAMS algebraic modeling language and solved using the Mixed Integer Programming (MIP) CPLEX solver. This is an instance of a large problem size; thus, a termination criterion of a 1000 second solution time was specified. The optimality of the obtained solution is not guaranteed, i.e. sub- or near-optimal solutions may be obtained. The values of the following decision variables ($y_{1,1}$, $y_{2,19}$, $y_{3,9}$, $y_{4,10}$, $y_{5,11}$, $y_{6,13}$, $y_{7,14}$, $y_{8,16}$, $y_{9,15}$, $y_{10,2}$, $y_{11,12}$, $y_{12,17}$, $y_{13,18}$, $y_{14,20}$, $y_{15,3}$, $y_{16,6}$, $y_{17,7}$, $y_{18,8}$, $y_{19,21}$, $y_{20,22}$, $y_{21,4}$, $y_{22,5}$) were equal to one; the rest were zeros, i.e., the obtained plan sequence is **{1, 10, 15, 25, 26, 16, 17, 18, 3, 4, 5, 11, 6, 7, 9, 8, 12, 13, 2, 4, 9, 8, 12, 13, 2, 4, 19, 24}**. The values of the following auxiliary decision variables ($q_{1,10,1}$, $q_{2,14,19}$, $q_{3,4,9}$, $q_{4,5,10}$, $q_{5,11,11}$, $q_{6,7,13}$, $q_{7,9,14}$, $q_{8,12,16}$, $q_{9,8,15}$, $q_{10,15,2}$, $q_{11,6,12}$, $q_{12,13,17}$, $q_{13,2,18}$, $q_{14,19,20}$, $q_{15,21,3}$, $q_{16,17,6}$, $q_{17,18,7}$, $q_{18,3,8}$, $q_{19,20,21}$, $q_{25,26,4}$, $q_{26,16,5}$) were equal to one; the rest were zeros. Note that the values of the auxiliary variables are consistent with those of the main decision variables. An auxiliary variable $q_{i,j,k}$ denotes that operation j is preceded by operation i , where the order of operation i is k . Also note that $q_{24,*,*}$ is all zeros since

operation 24 was sequenced as the last operation. The obtained value of the objective function is 3 time units. The sub-optimal solution obtained by the linearized QAP mathematical programming method is clearly quite distant from the exact optimal solution; it is even in this case of an inferior quality compared to that obtained by Assembly Re-Planning in section 7.2.1. This demonstrates the strength and advantage of using the RPP method for problems with relatively minor input product design changes expressed by RI_{Design} (10%). It could be concluded that for problems with low input product design change, both the localized RPP and the global solution methods (QAP-based or non-traditional optimizers) are quite close (see Figure 7.5).

It is quite important to note that the design changes for this case study are measured using the given available assembly operations information, which reflect the enhancements achieved by using the DFA method. As for the Process Planning Reconfiguration Index (RI_{Plan}), zero value was reported for the RPP method, which signifies that no changes would be incurred in setups and fixtures due to reconfiguring the process plan/sequence. The RI_{Plan} for this case study accounts for the fixture changes only since the tool change component is absent for manual assembly. Therefore, it could be noted that the amount of reconfiguration (RI_{Plan}) of the process plans produced by the RPP method is proportional to the amount of change at the product design level measured by RI_{Design} .

7.3 Comparison Between Re-Configurable Planning and Re-Planning

The problem of determining the most appropriate planning methods is a function of two independent planning factors on two different levels: product design level and manufacturing system one. It is beneficial at this point before proceeding any further to summarize the distinctive differences between the different proposed generative planning solution methods. As shown in Figure 7.5, Reconfigurable Process Planning (RPP) offers, by design, localized optimal plans, which minimize the distance in the process planning domain between the original existing or master plans and the resulting new

plans and, hence, minimizes the reconfiguration effort. The exact optimal Linearized Quadratic Assignment Problem (QAP) mathematical programming method provides the exact optimal solution; however, limitations on problem sizes that could be solved for optimality exist. Finally, approximate algorithms and heuristics, which include either non-traditional optimization such as the SA-based heuristic, or QAP mathematical programming with a termination criterion, provide near- or sub-optimal plans. The SA generally takes less computation run time than the QAP mathematical programming.

The first factor in selecting one of these planning methods is related to the input of the process planning problem, which is the extent of change and evolution of the design of the product being considered. The second factor is related to the manufacturing system capacity and the required volume of production where the extent and cost of change in process plans, set ups, and fixtures may or may not be justified.

On the product level, the proposed Design Reconfiguration Index (RI_{Design}) offers a systematic method of evaluation and quantification of the extent of changes that took place on the design level, which is an input to the problem at hand by definition. This metric captures the design changes that would impact, and be translated into, logical changes on the process planning level. ElMaraghy *et al.* (2008) provided a more thorough and in-depth analysis and methods to express the changes and evolution that products and part families exhibit based on Cladistics. The purpose of the introduced design reconfiguration index is to quantify the distance between the new variant and its existing/composite counterpart in the design features space (see Figure 7.5).

The larger this distance is the higher the value of RI_{Design} and vice versa. As shown in Figure 7.5, the distance in the design space is quite indicative of the corresponding distance in the process planning solution space. Hence, for lower values of RI_{Design} , it would be expected that the global optimum would lie in the proximity of the original existing solution in the process planning domain. Therefore, the localized RPP solution would most likely yield satisfactory results. Moreover, for large size instances of the problem, the RPP is capable of providing exact optimal solutions, albeit not global,

because of its advantageous polynomial computational time complexity. As for the exact QAP mathematical programming method, it is clearly limited to planning problems of limited size, yet it provides exact global optimal solutions. Finally, for the approximate algorithms, the near optimal solutions obtained in this case could produce even inferior quality solutions in comparison with the localized RPP plans. However, it is important to note that this is not the general case. This argument was validated and proven by the results obtained in the Kitchen Household Product Family case study, where the quality of the Reconfigurable Assembly Planning solutions was better than the near optimal ones obtained by the approximate QAP mathematical programming method. Note that the RI_{Design} was only 10% for this problem.

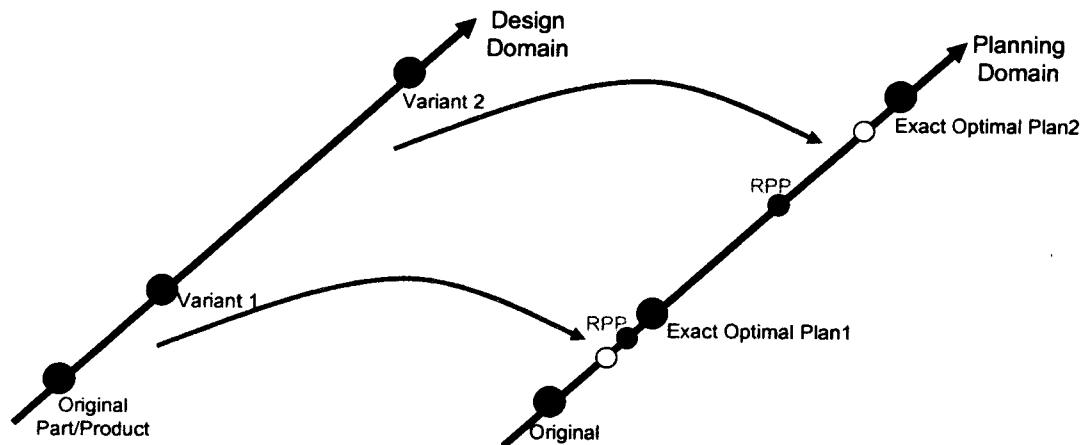


Figure (7.5) Change in the Product Design Domain Versus that in the Process Planning One.

For higher RI_{Design} values, which means larger distance between the two variants in the features/operations space and hence in the planning one as well, the situation is the opposite. Approximate algorithms would most probably yield solutions of more superior quality than those obtained by the localized RPP method in terms of the handling time objective criteria. But, the question then becomes how large the volume of production in question, which would lead us to the second factor in selecting the appropriate solution method.

On the manufacturing system level, the targeted volume of production also influences as well the selection of the solution method. For example, for the previous higher RI_{Design} case study of the Front Engine Cover Part Family in Chapter Six, the approximate algorithms would most likely yield more optimized solutions in terms of the objective criteria; however, this does not necessarily mean that applying these better handling time plans is what is best considering the whole situation, where production volume is believed to be a critical contributing factor. For lower-volume job shops and batch production, the localized RPP method could most likely be a better choice, since the localized optimal plans would be immediately translated into less reconfiguration and change on the shop floor. Less reconfiguration effort for all the downstream activities would occur, such as production scheduling, setup changes, labor training, ramp-up, quality, etc. Conversely, for larger volumes of production such as dedicated flow lines and high capacity RMS, global highly optimized plans would be a must since the running cost components are likely to be of greater impact than the initial fixed ones. Therefore, the approximated algorithms and heuristics, and the exact optimal QAP methods if applicable, would be preferred.

7.4 Quadratic Assignment Problem (QAP) Inspection Planning

With the growing competition in the global market, pursuing high product quality is a major concern in the manufacturing industry. To assure desired quality requirements, conducting massive inspections has become an important task in modern quality control. The coordinate measuring machine has been recognized as a powerful tool for dimensional and geometric tolerance inspection in the manufacturing industry (Hwang *et al.* 2004). In this section, the application of the QAP process planning model in inspection planning is demonstrated.

The objective in inspection planning is to sequence a global set of inspection tasks for a given part and inspection sensors in order to minimize the total changeover time to switch between successive inspection operations. This changeover time is mainly time spared in sensor changes, repositioning of the work piece, probe orientation changes and finally the total rapid traverse time traveled by the probe (Mohib *et al.* 2008).

The Quadratic Assignment Problem (QAP) is the problem of assigning a set of n objects to another set of n objects in order to minimize the sum of the costs associated with pairs of assignment (Erdogan and Tansel 2007). In inspection planning it is required to assign n objects, which are the inspection features of the part to be inspected to n positions, in one-dimensional space representing the order of inspection tasks/features.

The assumptions made, in this model, are summarized as follows:

Sequencing is carried out on the inspection features level. An inspection feature is the feature on which a tolerance item is specified. A tolerance item is a dimensional or geometric tolerance.

Based on industrial practice, the average time to change part setup is 13 minutes; the time required to change probe orientation is 3 minutes (Hwang *et al.* 2004). The rapid traverse time to switch between two successive operations is evaluated by dividing the travel distance by the probe traveling speed (Mohib *et al.* 2008).

To create a feasible measurement plan, precedence constraints and common practice rules must be respected. According to GD&T, certain geometric tolerances, such as concentricity and parallelism, require that datum features be measured before the features that use them as a reference (Hwang *et al.* 2004).

7.4.1 Notation

The problem size, defined as the total number of decision variables, is denoted as m . It could also be interpreted as the total number of inspection features.

The handling time matrix, which is an $m \times m$ symmetric, is denoted by $T=[t_{ij}]$; it represents the time taken to change sensors, part and probe orientation, as well as that taken by the probe to rapid traverse between consecutive inspection operations. Tactile sensing only is considered; hence, sensor changes are not included.

7.4.2 Decision variables

The decision variable $y_{i,k}$ is a 0-1 integer variables, where both i and k runs from 1 to n . The value of the decision variable is 1 if the feature i is positioned in location k ; otherwise it is zero.

7.4.3 Objective function formulation

Three different criteria are considered: 1) time required for repositioning of the work piece being inspected, 2) time required to change the probe orientation, and finally 3) time spared by the probe traveling from one feature to the other. The objective is to minimize the idle time, where no value adding takes place. Therefore, the objective function is:

$$\min. \sum_{i=1}^m \sum_{j=1}^m T_{i,j} \sum_{k=1}^{m-1} y_{i,k} \square y_{j,k+1} \quad (7.11)$$

7.4.4 Constraints Formulation

The constraints of the QAP-based model are:

$$\sum_{k=1}^m y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, m\} \quad (7.12)$$

Constraint 2 ensures that an inspection feature is only assigned once.

$$\sum_{i=1}^m y_{i,k} = 1 \quad \forall k \in \{1, 2, \dots, m\} \quad (7.13)$$

Constraint 3 ensures that no more than one inspection feature is assigned to position k .

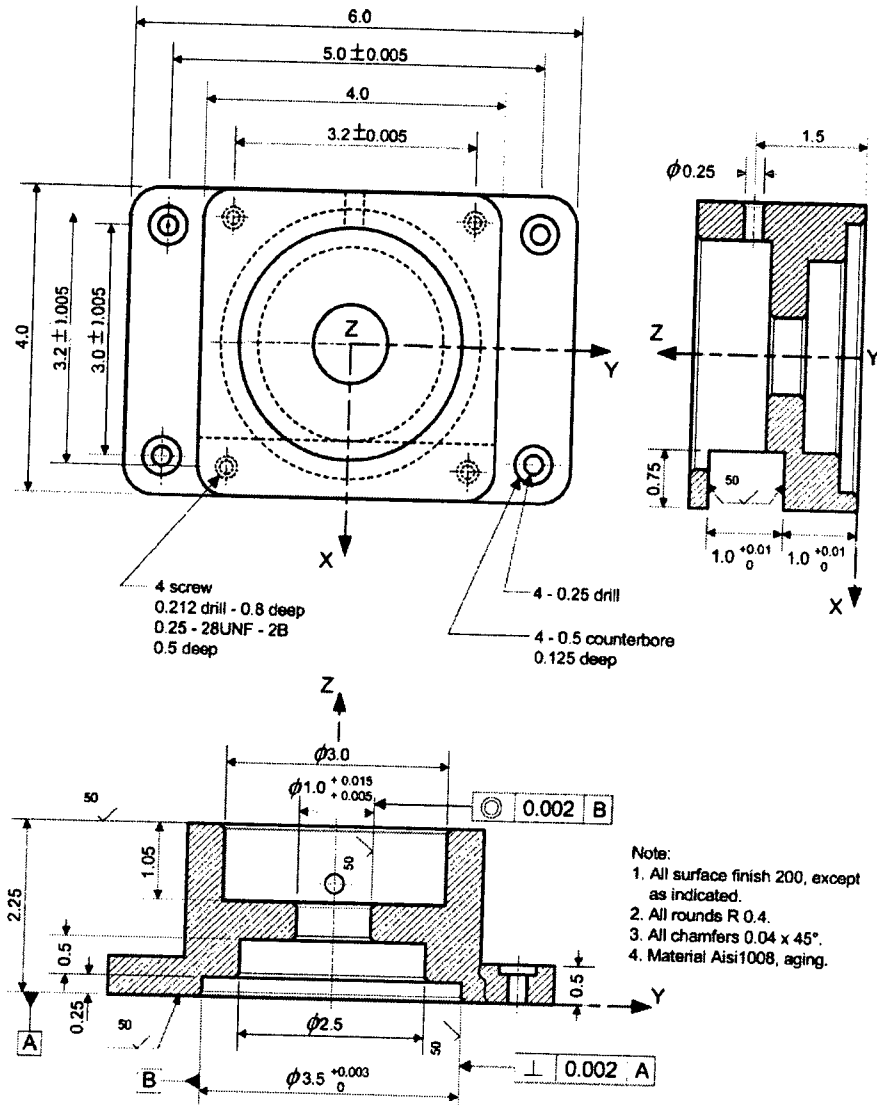
$$\sum_{k=1}^l y_{i,k} \geq \sum_{k=1}^l y_{j,k} \quad \forall l \in \{1, 2, \dots, m\} \quad (7.14)$$

For a pair of machining features i and j , this precedence constraint ($i \rightarrow j$) mandates that inspection feature i be measured prior to measuring feature j . The decision variable $y_{i,k}$ would be equal to one when inspection feature i is measured at position k . For that to take place, the inspection features i and j , y_{i,k_1} and y_{j,k_2} would equal one when the index k_1 is less than the index k_2 . Hence, the summation of $x_{i,k}$ over k must always be greater than or equal that of $y_{j,k}$ over k . The summation would run n times, where each time it stops at a different value; it starts with 1 and ends at n . Therefore, for every precedence constraint, a set of n inequalities represented by equation 7.14 have to be defined.

$$y_{i,k} = (0,1) \quad \forall i,k \in \{1,2,\dots,m\} \quad (7.15)$$

7.5 Inspection Planning of a Machine Spindle Cover

This section is based on a case study presented by Hwang *et al.* (2004). The part is a spindle cover of a machine tool; the blue prints defining the part's dimensioning and GD&T, and the part's features are shown in Figures 7.6 and 7.7 respectively. All dimensions in the drawings are in inch. Only inspection feature defined in Table 7.8 are considered; the rest of the features require a special probe to measure the distance between two threaded features.



After performing accessibility analysis, the features accessibility information is used to derive the required part setup and probe orientation (Hwang *et al.* 2004). Only one part setup is necessary for inspecting all of the CMM measurement items, where the part is positioned in a vertical upside position, i.e. part orientation $-Z$ is facing the probe's axis. As for the necessary probe orientations, probe orientations $-Z$ and $-X$ are required. The inspection features are measured in orientations $-Z$ and $-X$.

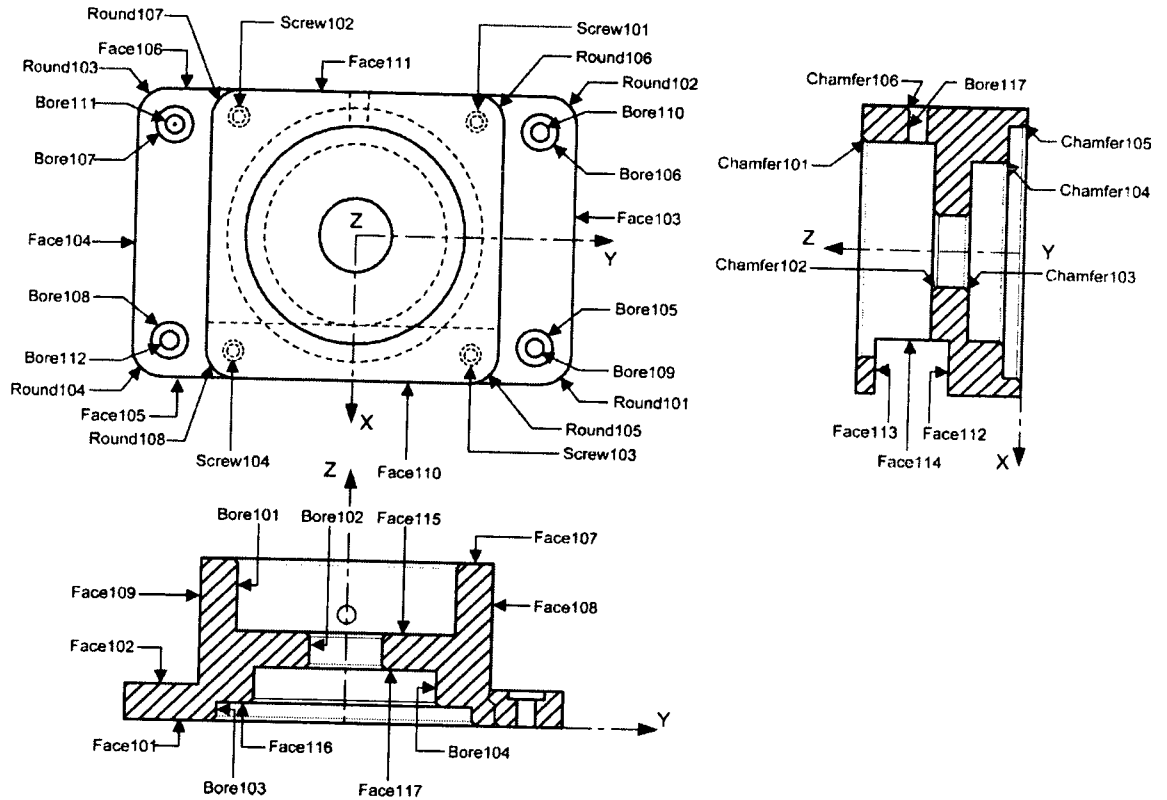


Figure (7.7) Spindle cover inspection features.

Table (7.8) Inspection features data.

Feature ID	Inspection Feature	Feature Type	Part Orientation	Probe Access Direction
1	Face101	Planar	Vertical Upside down (-Z)	-Z
2	Face112	Planar	Vertical Upside down (-Z)	-X
3	Face113	Planar	Vertical Upside down (-Z)	-X
4	Bore102	Cylindrical	Vertical Upside down (-Z)	-Z
5	Bore103	Cylindrical	Vertical Upside down (-Z)	-Z
6	Bore109	Cylindrical	Vertical Upside down (-Z)	-Z
7	Bore110	Cylindrical	Vertical Upside down (-Z)	-Z
8	Bore111	Cylindrical	Vertical Upside down (-Z)	-Z
9	Bore112	Cylindrical	Vertical Upside down (-Z)	-Z

Several GD&T constraints exist. Face101 is a primary datum. The primary datum GD&T constraint would be expressed as follows: (Face101→{*}), which means feature Face101 precedes all other features as illustrated in the FPG given by Figure 7.8 (note Face and Bore were abbreviated as F and B respectively in Figure 7.8). Bore103 and

Bore102 are datum features for features Bore109, Bore110, Bore111 and Bore112; i.e. (Bore103→{Bore109, Bore110, Bore111, Bore112}), (Bore102→{Bore109, Bore110, Bore111, Bore112}).

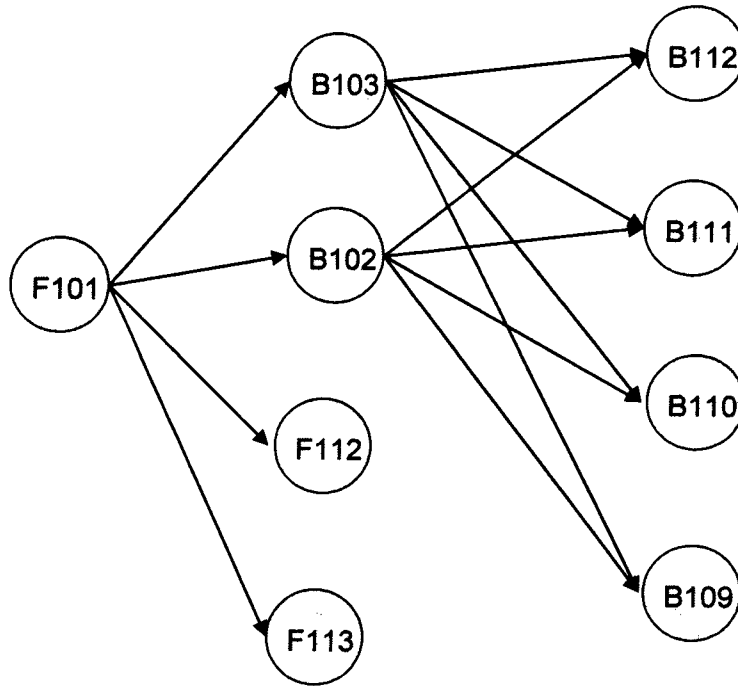


Figure (7.8) Feature precedence graph for Spindle Cover part.

Table (7.9) Symmetric rapid traverse time matrix.

	Face101	Face112	Face113	Bore102	Bore103	Bore109	Bore110	Bore111	Bore112
Face101	-	3.000	4.000	0.950	0.125	2.916	2.916	2.916	2.916
Face112		-	1.000	3.825	3.125	4.000	6.000	6.000	4.000
Face113			-	4.825	4.125	5.000	7.000	7.000	5.000
Bore102				-	0.825	3.741	3.741	3.741	3.741
Bore103					-	3.041	3.041	3.041	3.041
Bore109						-	3.000	5.831	5.000
Bore110							-	5.000	5.831
Bore111								-	3.000
Bore112									-

Table (7.10) Symmetric probe orientation change-time matrix.

	Face101	Face112	Face113	Bore102	Bore103	Bore109	Bore110	Bore111	Bore112
Face101	-	3.000	3.000	0.000	0.000	0.000	0.000	0.000	0.000
Face112		-	0.000	3.000	3.000	3.000	3.000	3.000	3.000
Face113			-	3.000	3.000	3.000	3.000	3.000	3.000
Bore102				-	0.000	0.000	0.000	0.000	0.000
Bore103					-	0.000	0.000	0.000	0.000
Bore109						-	0.000	0.000	0.000
Bore110							-	0.000	0.000
Bore111								-	0.000
Bore112									-

The Total handling time matrix C is shown in Table 7.11. As explained earlier, part setup time, probe orientation change time and probe rapid traverse time sum up to the total changeover time. Since only one part setup is used to inspect the Spindle Cover, the summation of the rapid traverse time matrix (given by Table 7.9) and the probe orientation change matrix (given by Table 7.10) result in the handling time matrix. Since all matrices are symmetric, only the upper triangular part of each matrix is shown for illustration.

Table (7.11) Symmetric handling time matrix T.

	Face101	Face112	Face113	Bore102	Bore103	Bore109	Bore110	Bore111	Bore112
Face101	-	6.000	7.000	0.950	0.125	2.916	2.916	2.916	2.916
Face112		-	1.000	6.825	6.125	7.000	9.000	9.000	7.000
Face113			-	7.825	7.125	8.000	10.000	10.000	8.000
Bore102				-	0.825	3.741	3.741	3.741	3.741
Bore103					-	3.041	3.041	3.041	3.041
Bore109						-	3.000	5.831	5.000
Bore110							-	5.000	5.831
Bore111								-	3.000
Bore112									-

The QAP-based formulation is given by equations 7.16-7.35. Sample constraints and the objective function are also expanded in Appendix B to clearly demonstrate the model constraint equations and inequalities.

$$\min. \sum_{i=1}^9 \sum_{j=1}^9 T_{i,j} \sum_{k=1}^8 y_{i,k} \square y_{j,k+1} \quad (7.16)$$

Subject To:

$$\sum_{k=1}^9 y_{i,k} = 1 \quad \forall i \in \{1, 2, \dots, 9\} \quad (7.17)$$

$$\sum_{i=1}^9 y_{i,k} = 1 \quad \forall k \in \{1, 2, \dots, 9\} \quad (7.18)$$

For GD&T datum relationship (Face101 \rightarrow {*}), a set of precedence constraints represented by equations 7.19-7.26 express mathematically this dimensional relationship. Note, that according to Table 7.7, inspection feature Face101's ID is 1.

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{2,k} \quad \forall l \in \{1, 2, \dots, 9\} \quad (7.19)$$

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{3,k} \quad \forall l \in \{1, 2, \dots, 9\} \quad (7.20)$$

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{4,k} \quad \forall l \in \{1, 2, \dots, 9\} \quad (7.21)$$

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{5,k} \quad \forall l \in \{1, 2, \dots, 9\} \quad (7.22)$$

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{6,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.23)$$

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{7,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.24)$$

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{8,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.25)$$

$$\sum_{k=1}^l y_{1,k} \geq \sum_{k=1}^l y_{9,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.26)$$

For GD&T datum relationship (Bore103→{Bore109, Bore110, Bore111, Bore112}), a set of precedence constraints represented by equations 7.27-7.30 express mathematically this dimensional relationship. Note, that according to table 7.7, inspection feature Bore103's ID is 5, while those of Bore109, Bore110, Bore111 and Bore112 are 6, 7, 8 and 9 respectively.

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{6,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.27)$$

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{7,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.28)$$

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{8,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.29)$$

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{9,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.30)$$

For GD&T datum relationship (Bore102→{Bore109, Bore110, Bore111, Bore112}), a set of precedence constraints represented by equations 7.31-7.34 expresses

mathematically this dimensional relationship. Note, that according to Table 7.1, inspection feature Bore102's ID is 4, while those of Bore109, Bore110, Bore111 and Bore112 are 6, 7, 8 and 9 respectively.

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{6,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.31)$$

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{7,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.32)$$

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{8,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.33)$$

$$\sum_{k=1}^l y_{5,k} \geq \sum_{k=1}^l y_{9,k} \quad \forall l \in \{1,2,\dots,9\} \quad (7.34)$$

$$y_{i,k} = (0,1) \quad \forall i,k \in \{1,2,\dots,9\} \quad (7.35)$$

The QAP inspection planning model was solved using the GAMS algebraic modeling language and the Mixed Integer Non-Linear Programming (MINLP) SBB solver. SBB is a new GAMS solver developed for Mixed Integer Nonlinear Programming (MINLP) models. It is based on a combination of the standard Branch and Bound (B&B) method known from Mixed Integer Linear Programming and some of the standard Nonlinear Programming (NLP) solvers already supported by GAMS.

Solving the non-linear QAP yielded the following near optimal solution {Face101, Bore102, Bore103, Bore112, Bore111, Bore110, Bore109, Face112, Face113}, where the values of the following decision variables ($y_{1,1}$, $y_{2,8}$, $y_{3,9}$, $y_{4,2}$, $y_{5,3}$, $y_{6,7}$, $y_{7,6}$, $y_{8,5}$, $y_{9,4}$) were equal to one and the rest was zeros. The obtained sub-optimal corresponding objective function value is 23.8 minutes. The linearized QAP model was also formulated and solved to arrive at the exact optimal solution {Face101, Bore103, Bore102, Bore112, Bore111, Bore110, Bore109, Face112, Face113}. The corresponding value of the

objective function was slightly improved to 23.7 minutes. This shows part of the argument presented in section 7.3, where it was explained that approximate non-linear methods would yield near optimal solutions, whereas exact optimal methods such as the linearized QAP mathematical programming yields exact optimal plans. The difference between the exact and approximate solution is very minor, but for larger problem instances this difference would be more significant. The solutions obtained are consistent with those obtained by (Hwang *et al.* 2004) using an approximate Neural Network and a greedy algorithm.

7.6 Summary

In conclusion, the developed sequential process planning approach was tested and validated in domains of applications other than metal cutting. It was demonstrated how the developed abstract concepts and mathematical models could be applied in both assembly and inspection planning. An assembly case study of a family of kitchenware products were used to verify the generative Reconfigurable Process Planning (RPP) method, whereas a benchmark problem of a spindle cover inspection was used to demonstrate the applicability of the Quadratic Assignment Problem (QAP) method. The results obtained were thoroughly discussed and analyzed in both sections 7.3 and 7.5. The strength of the proposed approach was demonstrated through the logical reconfiguration that takes place on the process plans side, where missing and new operations and features were being elegantly subtracted and inserted respectively. It was demonstrated how only logical changes on the part and product levels result in changes on the planning level. Optimal reconfiguration of the original existing plans has taken place with the minimum possible effort in order to minimize: 1) the extent of changes on the shop floor of all downstream activities, 2) labor training on the new plans and finally 3) any possible errors due to their introduction.

8. DISCUSSION & CONCLUSION

8.1 Discussion

Globalization, unpredictable markets, increased products customization and the quest for competitive advantages are but a few of the many challenges manufacturing enterprises are increasingly facing now and in the future. Frequent changes in products, production technologies and manufacturing systems are evident today along with their significant implementation cost. This trend is on the rise in view of the paradigm shifts witnessed in manufacturing systems and their increased flexibility, agility and changeability to cope with the evolution of both parts and product families. Change is inevitable and it requires corresponding responsiveness in manufacturing support functions, both at the physical level, by providing modular and reconfigurable machinery and control systems, and at the logical level, through novel planning and re-planning at the process and production planning and control levels to achieve cost-effective adaptability.

An optimal macro-level process plan can easily become less optimal in such changeable production environment; hence, the importance of adapting to the changes and producing alternate optimal operations sequences for the changed parts becomes obvious. A novel sequential hybrid process planning methodology has been developed. Semi-generative planning, which is variant in nature yet capable of generating process plans for parts with features beyond those present in the current part family can best meet these challenges. Conceptually, the master process plan of the part family's composite part is retrieved; then generative modeling tools and algorithms are applied to arrive at the new process plan for the new part, whose definition does not necessarily lie entirely within the original boundary of its respective part family. Design changes on the part level that would be translated into logical changes on the planning level are considered. Data structures and graphs, which represent the declarative knowledge and precedence relationships between features/operations, are manipulated. The macro-level process plan is formulated as a sequence of operations corresponding to a set of features in the part. Under this proposed sequential, hybrid semi-generative notion, two distinct methods are

presented and compared in this work: localized Reconfigurable Process Planning (RPP) and globally highly optimized Process Re-Planning. Both methods support evolving part families, which are becoming a reality, due to the current challenges of unpredictable customer-centered markets and emergence of new reconfigurable and changeable manufacturing equipment and agile business paradigms. For RPP, genuine reconfiguration of the master process plan of the part family's composite part is carried out iteratively to arrive at the new process plan of the new part. A novel semi-generative mathematical model for macro-level based plan reconfiguration has been presented. The RPP advantageously provides a polynomial computational time complexity compared with its NP-hard classical counterparts. Matlab scripts have been developed to automate the tedious, time consuming and error prone formulation steps and procedures per iteration. Two reconfiguration indices on the part and the plan levels have been developed to help choose the appropriate methods of planning and evaluate the extent of reconfiguration and change of the resulting new plans. As for Process Re-Planning, a planning method suitable for the generation of highly optimized process plans from scratch of new parts/products has been developed. A novel adaptation of the Quadratic Assignment Problem (QAP) mathematical model has been developed for process planning. The new formulation overcomes the limitations, conceptual flaws and complexity of its classical Traveling Salesperson Problem (TSP) counterpart. The TSP model outputs a cyclic tour solution with no start or end, unlike the required sequence. This means that the optimized problem becomes slightly different than the original problem in question, with one more route or cost component compared to the original problem. The newly developed QAP formulation assigns the different operations or features of a plan their positions in a one-dimensional array or sequence. For the first time, the precedence constraint, which is a corner stone of the process planning problem, is modeled. Sub-tour elimination constraints are overcome. As the Re-Planning problem exhibits combinatorial characteristics, a random-based evolutionary Simulated Annealing algorithm heuristic has been developed to obtain optimal or near-optimal operation sequences for large instance-size problems. A process plan validation scheme is developed and used to maintain the specified precedence relationships.

The developed process planning methods were applied to an industrial example of a single-cylinder family of engine front covers defined by a composite cover and a corresponding master process plan. A new macro-level process plan was generated for a new cover, the features of which differ (new, missing and modified) significantly from those that exist in the original family. The manufacturing system machines and setups had to be reconfigured accordingly to be capable of producing the new features in the introduced front cover. The solution quality of the obtained results from both RPP and Re-Planning methods are quite close in terms of the objective function value when considering the statistical mean of the ten different runs of the random-based Re-Planning method. However, this is not the case when considering the best solutions obtained; the best Re-Planning solution showed about 25% improvement over its RPP counterpart. The Re-planning method produces highly optimized global-optimal process plans. This is expected since the Re-Planning approach solves the sequencing problem globally, while the proposed RPP algorithm has the advantage of limiting reconfiguration to a subset of the total solution space to minimize the extent of change. Table 4 summarizes the main characteristics, pros and cons and significant differences between those two methods.

Table (8.1) Comparison of the two proposed process planning approaches

Criteria	Process Planning by Reconfiguration	Process Re-planning
Step 1: Retrieval portion	√	√
Step 2: Generative portion	Minimal	Substantial
Quality of Solution	Localized exact optimal solutions	Global, highly optimized, near-optimal solutions
Plan Reconfiguration Index (RI_{Plan})	Low values indicating minimally changed plans, i.e. close to original plan	High values indicating significantly changed plans
Computational Complexity (Cost)	Lower <u>polynomial</u> computational cost	Higher factorial <u>NP-Complete</u> computational cost

The RPP iterative mathematical scheme scales better than the Re-Planning scheme with a polynomial complexity compared with the NP-hard classical Re-planning schemes. The RPP methodology offers a quick, feasible, and localized optimal solution, albeit not the exact global optimum. This, though an obvious limitation, could prove to be an important advantage for relatively low volume batch production and in agile manufacturing environments, where products evolve and are customized frequently or when engineering changes are numerous, which is presently typical in almost all manufacturing settings during the product/process development phases. The localized optimal solutions, obtained by the RPP method, minimize the extent of reconfiguration and the impact on the related shop floor activities and hence, would incur less costs, cause less disruptions and minimize effort by all the downstream plant floor activities; that in turn would decrease the time required to introduce new products to the market, i.e., less opportunity cost. This would also be translated into minimal time and cost required for the training of labor on the new plans and hence, less mistakes that would affect quality. The Plan Reconfiguration Index (RI_{plan}) shows, as expected, that the amount of reconfiguration demonstrated by the new process plans obtained by the Re-Planning method is more than that produced when using RPP.

The process planning effort, whether by employing RPP or Re-Planning, is normally done off-line. However, as concluded, the time savings and improved efficiency and solution quality can greatly benefit from the developed fast and computationally efficient algorithms in order to address the increasingly more frequent introductions of design modifications during product development and due to the high uncertainty and turbulence of today's markets. The RPP method is advantageously solved in linear time; it provides much smaller polynomial solution space and fairly complicated mathematical model with low number of constraints; hence, it is computationally more tractable. The introduced Process Re-Planning QAP-based scheme is combinatorial in nature; hence, an evolutionary simulated annealing heuristic was developed that practically takes negligible time per run on a Pentium 4 with 2 MB/2 GB memory hierarchy. Multiple runs are possible to arrive at alternate solutions efficiently. Moreover, converting the code

deployed on Matlab (an interpreter) into an executable could further reduce the algorithm execution time.

The presented methodologies readily support evolving parts and products families as well as manufacturing systems and account for changes in parts' features beyond the scope of their original respective product families. The developed methods and models are generic and general, since they operate at a high level of granularity (Macro-Planning). Hence, they are applicable to reconfiguring process plans in different domains, e.g. metal removal, additive manufacturing, assembly, robots task planning, etc. This has been demonstrated for both assembly and inspection planning.

The models introduced could not only serve well outside the field of industrial engineering but even outside the engineering discipline altogether. The developed methods are applicable in other fields of science and engineering where classical optimal sequencing problems exist.

8.2 Conclusions

Changeable Manufacturing Systems represent a natural evolution of previous manufacturing systems. Future changeable Reconfigurable Manufacturing Systems (RMS) support economy of scope and also –to a great extent- economy of scale by providing the exact capacity and functionality required when it is required. This thesis addresses a new problem that arises due to the increased changes in products and hence, in systems and the need to manage these changes cost effectively and with least disruption of downstream production activities and their associated high cost. It proposes novel solutions for the need to frequently plan and re-plan manufacturing processes. At the outset, a new Sequential Semi-Generative methodology to solve the classical problem of process planning is developed to support both evolvable parts, the geometry of which does not strictly lie within the borders of their respective original families, as well as new changeable manufacturing systems technologies. Under this proposed hybrid sequential notion, the following conclusions could be made about the developed generative process planning schemes:

1. One of the main contributions is the development of new mathematical model for solving the classical problem of process planning, at a macro-level, through reconfiguration. In this thesis, the planning was conceptually changed from an act of sequencing to one of insertion and reconfiguration for certain design changes and for certain low volume of production settings. The proposed methods enrich the science of manufacturing systems on both a theoretical and practical levels by providing methods and models for an important logical enabler to support state of the art manufacturing technology. The proposed treatment is essential for the realization of Changeable/Reconfigurable manufacturing, yet not limited to this particular paradigm, since frequent product changes are experiences in almost all types of manufacturing.
2. Reconfigurable Process Planning (RPP) is a novel mathematical programming model to reconfigure macro-level process plans. It supports evolvable part families, which are becoming a reality, due to the current challenges of unpredictable customer-centered markets and emergence of new reconfigurable and changeable manufacturing equipment and agile business paradigms.
3. The presented RPP model is compared with the classical Traveling Salesperson Problem (TSP) model. The RPP model provides much smaller solution space and less complicated number of constraints than its TSP counterpart; hence, it is computationally more tractable.
4. A Quadratic Assignment Problem (QAP) formulation, which is a new 0-1 integer mathematical model based on a novel adaptation of the classical formulation, has been developed for process planning. It presents a mathematical formulation of the precedence constraints for the first time in the literature. The conceptual flaws in the classical TSP model were corrected in the proposed model. It also overcomes the complexity of the sub-tour elimination constraints in the TSP formulation. Solving it, near optimal plans;

- as for the linearized QAP model, it provides absolute exact global optimal results.
5. Reconfiguration indices have been proposed to measure the extent of change on the product design and process planning levels. RI_{Design} was proven useful in the selection of the appropriate method of planning. RI_{Plan} evaluates the impact of the process plans changes on downstream shop floor activities; and helps choose among alternate sequences with substantially similar total cost by opting for the one that causes the least changes on the shop floor, which saves other indirect costs such as those related to errors and quality issues due to changes.
 6. Reconfigurable Process Planning (RPP) offers localized optimal plans, which minimize the distance in the process planning domain between the original/existing or master plans and the resulting new ones, and hence minimizes the reconfiguration effort. The amount of reconfiguration (RI_{Plan}) of the process plans produced by the RPP method is proportional to the amount of change at the product design level measured by RI_{Design} .
 7. Linearized exact optimal Quadratic Assignment Problem (QAP) mathematical programming provides the exact optimal solution; however, limitations of problem size that could be solved for optimality exist. Finally, approximate algorithms and heuristics, which are either non-traditional optimization such as the SA-based heuristic or QAP mathematical programming applying a termination criterion, provide near- or sub-optimal plans; practically SA takes less computational run time than QAP mathematical programming.
 8. One of the main benefits of the proposed methods is to reduce the time and cost required to generate a process plan. The overall proposed methodology is more advantageous than existing methods such as the so-called non-linear process planning or pre-planning scenarios, where alternate process plans are developed and provided ahead of time in anticipation of future changes. In addition to the obvious cost and computational burden that is avoided by the developed approach, future changes in products and technology cannot be

fully predicted; hence, the usefulness of pre-planned alternatives is diminished. Furthermore, pre-planned processes would likely become obsolete as manufacturing resources and technologies are changed. The presented process planning methods can improve the efficiency of process planning activities and can help “manage changes” on the shop floor by introducing an important changeability enabler in the field of process planning. The planner would have the option of choosing to completely change the process plans using highly optimized globally optimal re-planning or to employ localized optimal reconfiguration, depending on anticipated production volume, product variability and market stability.

9. The problem of determining the most appropriate planning method is function of two independent planning factors on two different levels: the product design level and the manufacturing system operation level. The first factor in the selection of one of these planning methods is related to the input of the process planning problem, which represents the extent of change and evolution of the considered product design variants. The second factor is related to the manufacturing system capacity and the required volume of production where the extent and cost of change in process plans, setups, and fixtures may or may not be economically justified. The following guidelines have been developed for selecting the most appropriate method of process planning:

- a. On the product level, RI_{Design} offers a systematic method of evaluation and quantification of the extent of change of changes that took place at the design level, which is an input to the planning problem definition. This metric captures the design changes that would impact and be translated into logical changes on the process planning level; it quantifies the distance between the new variant and its existing/composite counterpart in the design features space. This distance in the design space is indicative of resultant distances in the process planning solution space. Low values of RI_{Design} indicate that the global optimum would lie in the proximity of the original existing

solution in the process planning space. Therefore, the localized RPP solution would be the recommended choice over the approximate algorithms. For high RI_{Design} values, which mean larger distance in both the features and planning spaces, the case is reversed. The exact/approximate algorithms would be recommended to process re-plan from scratch.

- b. On the manufacturing system level, the production volume also affects the selection of the solution method. For low-volume job shops and batch production, the localized RPP method would be a better choice, since the localized optimal plans would directly be translated into less change and less additional cost on the shop floor. Conversely, for large volumes of production such as dedicated flow lines and RMS, global and highly optimized plans would be a must since the running cost components are of significant importance. Therefore, the approximated algorithms and heuristics, and the exact optimal QAP methods if applicable, would be preferred.
10. Three industrial case studies in metal cutting, assembly and inspection were used for testing and application. The developed methods were also illustrated using a hypothetical benchmark problem. In metal cutting, planning the machining operations for a family of aluminum engine front covers were carried out using both RPP and Process Re-Planning. The applicability and soundness of the newly developed process planning concepts, models, and methods was demonstrated through assembly and inspection planning for a household product family and machine tool spare part respectively. Consistent results were obtained for the reconfigured assembly plan of the Kitchenware kettle. As for the inspection of the Spindle Cover part, consistent results to those reported in the work of Hwang *et al.* (2004) were obtained, which provides useful verification.

8.3 Significance

1. This dissertation addresses a new problem that arises due to the increased changes in products and systems and the need to manage these changes cost effectively and with the least disruption of the production activities and their associated high cost.
2. A New “Changeability Enabler”, namely the “Reconfigurable Process Planning (RPP) was developed.
3. A New Hybrid Sequential Semi-Generative Methodology to solve the problem of macro-level process planning. Two generative methods, RPP and Process Re-Planning were proposed and novel mathematical programming models were developed to satisfy the need to frequently and efficiently plan and re-plan manufacturing processes were developed.
4. A novel 0-1 RPP integer mathematical programming model for reconfiguring process plans was formulated and applied, for the first time, to the process planning/sequencing problem. Reconfiguration of precedence graphs to optimize the scope and cost of process plans reconfiguration is achieved by inserting/removing features/operations iteratively in the string representation of their precedence graphs.
5. A novel adaptation of the Quadratic Assignment Problem (QAP) has been developed for process planning; it overcomes the complexity and conceptual and mathematical flaws in the existing models in the literature; it models for the first time the precedence constraint, which is a fundamental corner stone of the process planning problem.
6. Two changeability metrics at the Design and Process Planning levels, namely the Design Reconfiguration Index RI_{Design} and the Plan Reconfiguration Index RI_{Plan} have been introduced. RI_{Design} is a similarity metric that measures the extent of changes at the product design level, which is the primary input to the process planning problem. On the other hand, RI_{Plan} is a novel performance index in the field of process planning, which is used to evaluate macro-level process plans; it measures the extent and cost of reconfiguration. Hence, RI_{Plan} can help in

distinguishing between two alternate process plans with close value of the handling time objective by opting for the one that would cause the least changes on the shop floor, i.e. the one with lower RI_{Plan} value.

7. The proposed RPP mathematical model scales better with the problem size compared with the classical process planning techniques based on the Traveling Salesperson Problem (TSP) model. The RPP model has an advantageous polynomial computational time complexity function.
8. The proposed models and methods improve the efficiency of process planning activities and would be easy to integrate with existing pre- and post-planning CAD/CAM applications and tools. The proposed Sequential Process Planning methodology, at large, can help “manage changes” on the shop floor by introducing an important changeability enabler in the field of process planning. It also has the potential for making significant cost savings in implementing the frequent changes in products.

8.4 Future Work

The following issues are suggested for further research and investigation as extensions of the developed research:

Clustering is important in process planning; clustering of processes (aggregation) is needed to perform line balance for multi-stage processing; it is also important to ensure that design requirements, such as grouping of certain operations on the same fixture or relative to a certain datum to ensure cost effective fulfillment of the specified tolerances, are met. In this work, clustering is implied by the employed objective function, where tool changes and repositioning of the work piece are minimized. However, this may also be addressed at a different level since the considered problem, in principle, is primarily a sequencing problem. Clustering could be applied a priori or a posteriori as a revision tool that would help ensure that all design specified functionality and requirements are met.

For Reconfigurable Process Planning (RPP), the order of insertion of the new features to be considered in the generative process of the new process plan is amongst one of the critical factors to arrive at a global optimal plan. However, it is important to point out that the aim of the current RPP generative method in this work is to obtain localized reconfigured process plans, where the extent of reconfiguration of the new process plan is minimized. A new process planning approach is currently being explored to obtain highly refined global solutions using RPP when high volume of production is required. A meta-heuristic would be used where the problem knowledge would be exploited to strategically guide the search within the problem's combinatorial solution space. The choice of the tool, on the outset, that would portray the backbone of the heuristic, can potentially address a lot of issues, such as the order of insertion.

The first step in the proposed sequential process planning methodology involves identifying the family of parts/products closest to the new variant and retrieving its master plan and manipulating the corresponding declarative data. Such choice depends on the measure of similarity between the two sets of features in old and new variant, which is a challenging problem that could be subject of future research.

It has been demonstrated that the proposed process planning approach is practical and easy to implement and apply. It can be readily integrated with upstream and downstream applications, through standard CAD/CAM data inputs and outputs, for both pre-processing of data prior to macro-level planning and further detailing of individual processes through micro-planning to determine thorough process parameters such as cutting speed, feed rate, depth of cut, etc., in a metal removal application.

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APPENDIX A: RECONFIGURABLE PROCESS PLANNING (RPP) FORMULATION

This appendix is provided to give detailed formulations of the RPP model for the Front Engine Cover Case Study. The penalty cost, setup cost, tool change time matrices and vectors of the first two iterations were given as an example.

A.1 Iteration 1

Table (A.1) Penalty cost matrix

1000	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Table (A.2) Setup cost matrix

2	0	2	2	2	2	0	0	2
2	2	2	2	2	2	0	0	2
0	2	2	2	2	2	0	0	2
0	2	2	2	2	2	0	0	2
0	2	2	2	0	2	0	0	2
0	2	2	2	0	2	0	0	2
0	2	2	2	2	2	2	0	2
0	2	2	2	2	0	2	2	2
0	2	2	2	2	0	0	2	2
0	2	2	2	2	0	0	2	2

Table (A.3) Old setup cost vector

0	0	2	2	2	2	0	0	2	0
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Table (A.4) Old tool change time vector

0	1	1	1	1	1	1	1	1	0
---	---	---	---	---	---	---	---	---	---

Table (A.5) Right tool change time vector

0 1 1 1 1 0 1 1 1 1

Table (A.6) Left tool change time vector

1 1 1 1 0 1 1 1 1 0

A.2 Iteration 2

Table (A.7) Penalty cost matrix

0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	1000	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1000	0
0	0	0	0	0	0	0	0	0	1000	0

Table (A.8) Setup cost matrix

2	0	2	2	2	0	2	0	0	0	2
2	2	2	2	2	0	2	0	0	0	2
0	2	0	2	2	0	2	0	0	0	2
0	2	0	2	2	0	2	0	0	0	2
0	2	2	2	2	0	2	0	0	0	2
0	2	2	2	2	2	2	0	0	0	2
0	2	2	2	0	2	0	0	0	0	2
0	2	2	2	0	2	0	0	0	0	2
0	2	2	2	0	2	0	0	0	0	2
0	2	2	2	0	2	0	0	0	0	2
0	2	2	2	0	2	0	0	0	0	2
0	2	2	2	0	2	0	0	0	0	2
0	2	2	2	0	2	0	0	0	2	2

Table (A.9) Old setup cost vector

0 0 2 2 2 0 2 0 0 0 2 0

Table (A.10) Old tool change time vector

0 1 1 1 1 0 1 1 1 1 1 0

Table (A.11) Right tooling change cost vector

1 1 1 1 1 1 1 1 1 1 1 0

Table (A.12) Left tooling change cost vector

0 1 1 1 1 1 1 1 1 1 1 1

APPENDIX B: QUADRATIC ASSIGNMENT PROBLEM (QAP) FORMULATIONS

This appendix is provided to give detailed formulations of the QAP model for the Handspike benchmark. Part of the mathematical model for the composite part solved in chapter five is expanded. In order to better demonstrate the mathematical equations that were concisely represented by the notation used in the previous sections, an example of each type of constraint as well as part of the objective function is expanded. Since each constraint equation represents a set of equations or inequalities, the following notation “Constraint a(b)” is used to number the constraint equations and inequalities, where b represents the equation (inequality) number in the set of equations (inequalities) representing the a constraint equation, as shown in chapter five.

B.1 Objective Function Formulation

$$\begin{aligned} \text{Min. } Z = & (x_{1,1}x_{2,2} + x_{1,2}x_{2,3} + x_{1,3}x_{2,4} + x_{1,4}x_{2,5} + x_{1,5}x_{2,6} + x_{1,6}x_{2,7}) + 4(x_{1,1}x_{3,2} + x_{1,2}x_{3,3} \\ & + x_{1,3}x_{3,4} + x_{1,4}x_{3,5} + x_{1,5}x_{3,6} + x_{1,6}x_{3,7}) + 4(x_{1,1}x_{4,2} + x_{1,2}x_{4,3} + x_{1,3}x_{4,4} + x_{1,4}x_{4,5} + x_{1,5}x_{4,6} + \\ & x_{1,6}x_{4,7}) + 4(x_{1,1}x_{5,2} + x_{1,2}x_{5,3} + x_{1,3}x_{5,4} + x_{1,4}x_{5,5} + x_{1,5}x_{5,6} + x_{1,6}x_{5,7}) + (x_{1,1}x_{6,2} + x_{1,2}x_{6,3} + \\ & x_{1,3}x_{6,4} + x_{1,4}x_{6,5} + x_{1,5}x_{6,6} + x_{1,6}x_{6,7}) + (x_{1,1}x_{7,2} + x_{1,2}x_{7,3} + x_{1,3}x_{7,4} + x_{1,4}x_{7,5} + x_{1,5}x_{7,6} + \\ & x_{1,6}x_{7,7}) + x_{2,1}x_{1,2} + \dots + x_{3,1}x_{1,2} + \dots + x_{4,1}x_{1,2} + \dots + x_{5,1}x_{1,2} + \dots + x_{6,1}x_{1,2} + \dots + x_{7,1}x_{1,2} + \dots \\ & x_{7,6}x_{6,7} \end{aligned}$$

B.2 Sample of the Feasibility Constraints

Constraint 1(1):

$$x_{1,1} + x_{1,2} + x_{1,3} + x_{1,4} + x_{1,5} + x_{1,6} + x_{1,7} = 1$$

...

Constraint 1(7):

$$x_{7,1} + x_{7,2} + x_{7,3} + x_{7,4} + x_{7,5} + x_{7,6} + x_{7,7} = 1 ;$$

Constraint 2(1):

$$x_{1,1} + x_{2,1} + x_{3,1} + x_{4,1} + x_{5,1} + x_{6,1} + x_{7,1} = 1 ;$$

...

Constraint 2(7):

$$x_{1,7} + x_{2,7} + x_{3,7} + x_{4,7} + x_{5,7} + x_{6,7} + x_{7,7} = 1 ;$$

B.3 Sample of the Precedence Constraints

The following constraints represent the first precedence constraint between A_r and D , i.e. i indices 1 and 3.

Constraint 3(1):

$$x_{1,1} - x_{3,1} \geq 0$$

Constraint 3(2):

$$x_{1,1} + x_{1,2} - x_{3,1} - x_{3,2} \geq 0$$

Constraint 3(3):

$$x_{1,1} + x_{1,2} + x_{1,3} - x_{3,1} - x_{3,2} - x_{3,3} \geq 0$$

Constraint 3(4):

$$x_{1,1} + x_{1,2} + x_{1,3} + x_{1,4} - x_{3,1} - x_{3,2} - x_{3,3} - x_{3,4} \geq 0$$

Constraint 3(5):

$$x_{1,1} + x_{1,2} + x_{1,3} + x_{1,4} + x_{1,5} - x_{3,1} - x_{3,2} - x_{3,3} - x_{3,4} - x_{3,5} \geq 0$$

Constraint 3(6):

$$x_{1,1} + x_{1,2} + x_{1,3} + x_{1,4} + x_{1,5} + x_{1,6} - x_{3,1} - x_{3,2} - x_{3,3} - x_{3,4} - x_{3,5} - x_{3,6} \geq 0$$

Constraint 3(7):

$$x_{1,1} + x_{1,2} + x_{1,3} + x_{1,4} + x_{1,5} + x_{1,6} + x_{1,7} - x_{3,1} - x_{3,2} - x_{3,3} - x_{3,4} - x_{3,5} - x_{3,6} - x_{3,7} \geq 0$$

$$x_{i,k} \in \{0,1\}, \forall i, k \in \{1, 2, \dots, 7\}$$

VITA AUCTORIS

Ahmed Azab received his B.Sc. and M.Sc. degrees from Cairo University, Egypt in Mechanical Engineering with an Industrial Engineering focus. He is currently a doctoral candidate at University of Windsor, Canada in the department of Industrial & Manufacturing Systems Engineering. He is also employed by the Intelligent Manufacturing Systems (IMS) Centre as a research engineer. He is an elected research affiliate of the International Academy of Production Engineering (CIRP), which is a world leading organization in production engineering research and is at the forefront of design, optimization, control and management of processes, machines and systems. For his paper, coauthored with his advisor Prof. Hoda ElMaraghy, presented in the CIRP General Assembly in Dresden Germany, Mr. Azab is one of three finalists for the prestigious Taylor medal- an annual CIRP award (given since year 1958) named after the famous industrial engineering scientist Frederick W. Taylor in recognition of young scientists of outstanding merits in the field, who demonstrated excellence in researching production engineering problems. Beside process planning, his research interests also span Operations Research, Nontraditional Optimization, Manufacturing Systems, Control theory, Robotics and Assembly. Mr. Azab has a total of four years of industrial experience in the field of CAD/CAM/CAE. A list of his up-to-date publications are given below:

Contributions to Books:

- Azab, A., Elmaraghy, H. and Samy, S., 2008, "Reconfiguring Process Plans: A New Approach to Minimize Change," Changeable and Reconfigurable Manufacturing Systems, H. ElMaraghy, Springer (In progress).
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- Azab, A., Badrous, S., ElMaraghy, H., 2008, "Comparative Analysis of Assembly Planning Approaches," 2nd CIRP International Conference on Assembly Technologies and Systems (CATS), Toronto, Canada, In progress.
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- Azab, A. and ElMaraghy, H., 2008, "Combined Clustering & Sequencing for Assembly Planning," Design working group at the 58th CIRP General Assembly, Manchester, UK.
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