Journal of Manufacturing Systems 26 (2007) 147–160

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Technical paper

Sequential process planning: A hybrid optimal macro-level approach

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A R T I C L E I N F O

Article history:
Received 20 July 2007
Received in revised form
15 November 2007
Accepted 3 March 2008

A B S T R A C T

Increased global competition and unpredictable market changes are challenges facing manufacturing enterprises. Changes of part design and engineering specifications trigger frequent and costly changes in process plans, setups, and machinery. The paradigm shift in manufacturing systems and their increased changeability also require corresponding responsiveness in support functions; process planning is a key logical enabler that should be further developed to cope with changes encountered at the system level and to support new manufacturing paradigms and continuously evolving products. Retrieval-based planning, predicated on rigid predefined boundaries of part families, does not satisfactorily support this changeable manufacturing environment. On the other hand, pure generative planning is not yet a reality. Therefore, a sequential hybrid approach at the macro level is proposed where, initially, the part family's master plan is retrieved, followed by application of modeling tools and solution algorithms to arrive at the plans of the new parts, whose features could exceed its respective original family boundaries. Two distinct generative methods, namely reconfigurable process planning and process replanning, are presented and compared. A genuine reconfiguration of process plans to optimize the scope, extent, and cost of reconfiguration is achieved using a 0–1 integer programming model. Also, because the problem is combinatorial in nature, a random-based evolutionary simulated annealing algorithm has been tailored for replanning. The developed methods are, conceptually and computationally, analyzed and validated using an industrial case study.

1. Introduction

Mass customization and agile manufacturing are paradigms that have emerged recently to address the new challenges of the 21st century of highly customized and varying products. Products are continuously evolving beyond the boundaries of their original part families. At the design level, product variety and new product introductions for a dedicated manufacturing system are not usually considered. A flexible manufacturing system (FMS) overcomes this challenge by having all of the needed functionality built in a priori; however, this results in high initial capital investment as well as relatively lower utilization. To stay competitive, increasingly responsive manufacturing systems and their enablers are beginning to emerge [1]. Reconfigurability is an engineering technology that makes it possible to react quickly and efficiently to market changes [2]. A reconfigurable manufacturing system (RMS) is 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 process technology. Modularity, integrability, customization, convertibility, and diagnosability are its distinct characteristics [3]. When these characteristics are embedded in the system design, a high degree of reconfigurability is achieved [4]. This 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 [5]. Reconfigurability aims at achieving more competitiveness by exploiting new technology and supporting business paradigms [1]. RMS is gradually becoming a reality and is being deployed by many mid to large-volume manufacturers [6]. Reconfiguration could be achieved at the system or machine levels, and it may be classified as soft (logical) or hard (physical) in nature [1]. 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.

This paper describes a hybrid planning methodology, where retrieval of master or existing plans initially takes place followed by generative processing by means of algorithmic and optimization methods. A review is presented of process planning methods, especially those that would support changeable manufacturing systems

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0278-6125/$ – see front matter
doi:10.1016/j.jmsy.2008.03.003

Notations

Reconfigurable process planning notations (Section 5.1):

- x_i — x_i is a 0–1 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 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}.
- 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 — $C = [ci, j]$ is the precedence penalty matrix.
- S — $S = [si, j]$ is the work piece refixturing time matrix.
- Os — $Os = \{Os_i\}$ is the work piece refixturing time matrix for original features (i.e. not to include the new feature) after subtracting the missing features.
- Tr — $Tr = \{Tr_i\}$ is the 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 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 tool change time vector for original features-not including the new feature to-be-inserted.

Simulated annealing notations (Section 5.2):

- P — Precedence constraint matrix, where every row 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_o.
- B — B is 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 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 — $\Delta E = \text{ObjFn}(N) - \text{ObjFn}(B)$.

at large as well as continuously evolvable part families. The proposed sequential process planning methodology is described, and the knowledge retrieval and manipulation portion of it is detailed, followed by description of the generative mathematical programming portion. The overall developed methodology, the two developed models, and their algorithms are examined and discussed. An industrial test case of a family of single-cylinder engine front covers was employed for verification and also to illustrate the application of the presented methodology.

2. Previous work

Process planning has two distinct levels, macro level and micro level [7]. 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 used optimization criteria 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 determined through rule-based knowledge that was acquired from machining practices [8]. 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 are based on the traveling salesperson (TSP) problem formulation (an example is Lin and Wang [9]). Koulamas [10] 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.

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 [11] discussed research, development, and deployment of concepts and technologies to develop variant process planning systems for RMS. Bley and Zenner [12] 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 product 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, which are solved using either nontraditional optimization methods or heuristics. Kiritsis and Porchet [13] 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. Joo, Park, and Cho [14] proposed a conceptual framework for the adaptive and dynamic process planning system that can rapidly and dynamically generate the needed process plans based on shop floor status.

There is a dearth of literature that offers generative process planning solutions for RMS. Xu, Tang, and Cheng [15] presented a clustering method for multipart 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, and the mathematical model and algorithm of the pattern recognition for recognizing the similar suboperation group within the entire part family was