Preliminary Manufacturing Cell Design in Digital Factory

G.-C. Vosniakos[1](✉), X. V. Gogouvitis[2], and E. Panos[3]

[1] School of Mechanical Engineering, National Technical University of Athens, Athens, Greece
vosniak@central.ntua.gr
[2] Safran Group, Birmingham, UK
xenofon.gogouvitis@safrangroup.com
[3] Wärtsilä, Athens, Greece

Abstract. A design methodology is presented leading from product family specifications and estimated demand to basic 3D models of the corresponding manufacturing cell. Key steps involve mapping product specifications to alternative generic process plans, then mapping processes to machine tools by comparing their capabilities to product specifications. Optimization of machine layout is carried out by a standard genetic algorithm. The method is supported by geometric libraries of simplified yet parametric machine tool models. An anemometer and wind vane production case study is presented.

Keywords: Manufacturing cell · Preliminary design · Digital factory

1 Introduction

Manufacturing Cells are small-scale systems consisting of few machines of different types producing specific part families. Manufacturing cell may be considered as a product in the wide sense. The design process includes analysis of requirements (user and technical), preliminary design, detailed design, and culminates in the commissioning and operation of the system [1]. This work focuses on the preliminary design phase, encompassing conceptual design and embodiment design. Conceptual design requires the designer to develop and compare a number of alternatives based on specific requirements and constraints. Then, the best conceptual solution is further developed at a level of detail that is enough to prove the concept. This is termed 'embodiment' and is primarily based on a mixture of general design rules and experience.

In literature, planning a manufacturing cell has been often used as synonymous to preliminary design. Due to product and manufacturing system interconnections a pertinent integrative framework is called for. Templates or modules for the production process as well as for the planning process have been proposed [2]. In configuring dynamic virtual manufacturing systems technical characteristics of machinery are matched to those required by the product according to a process plan under scheduling performance criteria [3]. Process plan mapping to product characteristics can be indirect, i.e. though an

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intermediate mapping to generic process ontologies [4]. Then, a complementary mapping from manufacturing processes to specific machines can be added. Process planning supported by actual machine capability profiles has been advocated in [5]. Changeability of process plans is also sought in matching reconfiguration of machines [6].

Product features and manufacturing capabilities can be modelled using classification tree structures and are then associated into a synthesis matrix, which is used for new products [7]. Manufacturing system design parameters and the resulting product quality were connected by a fuzzy inference system making use of process capability indices [8]. Bayesian Networks have been used to capture, yet without explicitly identifying them, interrelationships between products and machines [9].

Selection of candidate reconfigurable machines matching certain product characteristics is dealt with a NSGAII algorithm [10]. Manufacturing capability is key in designing manufacturing systems and, in particular, reconfigure them [11]. In an interactive mode, a shared data model is proposed within a virtual factory environment with heterogeneous software tools [12]. A modular factory testbed to rapidly reconFig. Manufacturing systems is presented in [13] relying on human decisions. Virtual Reality (VR) has been shown to facilitate manufacturing system design decisions through enhanced presence and immersion [14].

This paper presents a pragmatic approach to Manufacturing Cell preliminary design. Its novelty is the notion of generic process plan comprising processes specific to product geometry, size and quality and the notion of mapping from processes to specific machines. Machine layouts may be generated via genetic algorithms and visualised using parametric 3D models in conventional or VR environment.

The general framework of the approach is explained in Sect. 2. Conceptual design and embodiment design are explained in Sect. 3. Section 4 presents a case study concerning wind vanes and anemometers to illustrate the above. Section 5 summarizes conclusions and future work.

2 The Framework

The proposed framework for manufacturing cell design is shown in Fig. 1. The ultimate aim is to designate the machines comprising the cell. Manufacturing cell specifications derive directly from the product and are related to its shape, size and accuracy as well as to demand. These are the main factors that enable process selection according to Process Information Maps (PRIMA™) methodology [15].

Note that a product family may span a range of sizes, which may yield a corresponding range of complementary generic process plans. Furthermore, part size will often affect machine selection rather than process selection. Still, there might be cases where dramatic change of product size might call for process change. If both low and high demand needs to be catered for, then separate generic process plans need to be retained. However, even if product size and demand are fixed, there are alternative process plans. In any case, all alternative generic process plans correspond to a cost figure per part that may be approximately calculated according to PRIMA™. At this stage, the generic process plan or set of process plans, as necessary, yielding the lowest cost per part is selected and termed ‘best generic process plan’, see Fig. 1.

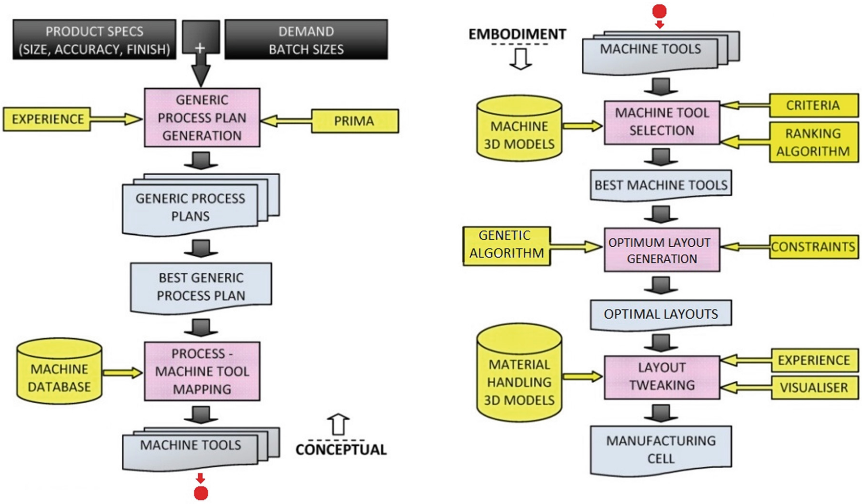


Fig. 1. Manufacturing cell preliminary design

The best generic process plan includes only types of processes and not specific machines. Yet, a manufacturing system, even at its preliminary design stage, can be described as a collection of main machines and supplementary handling equipment i.e. robots, conveyors, AGVs etc. for material handling. A detailed process plan results by instancing a generic process plan with specific machines and can even include an estimate of process duration. A database that systematically describes each machine's capabilities is required for this purpose, see Fig. 1.

The transition from generic to detailed process plans may offer a number of alternative machines per process. Machine selection delimits the border between conceptual and embodiment design. A simple selection algorithm should enumerate possibilities and rank them according to the defined criteria, e.g. acquisition, operation and maintenance cost, cost per part following an Economic Batch Quantity approach, ergonomics, familiarity of operators, similarity with other factory machines, etc.

The selected machines should be laid out in 3D space so that they can be served by operators and material handling equipment. The latter may not be selected at this stage, but pertinent requirements may be imposed in terms of estimated distance and orientation constraints between machines. Thus, a layout optimisation algorithm can be applied and the result may be visualised in a CAD or VR environment. Each layout can then be explored by virtual trials and possible tweaking.

3 Conceptual and Embodiment Design

3.1 Generic Process Plan Creation

Selecting the best manufacturing process is not obvious as the range of available processes and materials is rather large and there is a multitude of pertinent criteria, such as: part shape and dimensions, part quantity, material/process compatibility, tolerances, surface quality, process completion time, process waste (swarf, chip etc.) and recycling, equipment cost, tooling cost, environmental footprint, labor availability, supervision requirements, maintenance requirements. In our approach, we focused, in addition to the part's material, on three factors as follows.

- Geometry (G). This refers to part size: 'small' (G^{-1}), 'normal' (G^{0}), 'large' (G^{+1}).
- Quantity (Q). This refers to the expected mean batch quantity of the part, namely 'small' (Q^{-1}) for sizes up to 100, 'medium' (Q^{0}) for sizes between 100 and 1000 and 'large' (Q^{+1}) for sizes between 1000 and 10,000
- Quality (D). This refers to surface quality of the part, i.e. rough (D^{-2}), low finish (D^{-1}), medium finish (D^{0}), high finish (D^{+1}), very high finish (D^{+2}).

A combination of possible values of the above three factors is termed 'scenario'. Thus, there are in total 45 ($= 3 \times 3 \times 5$) scenarios.

3.2 Process to Machine Tool Mapping and Selection of Best Machine Tool

The choice of machine type is guided by an initial simple listing of processes against machines on which these can be implemented. Moreover, technological suitability of machines depends on the scenario (G, Q, D). For instance, part size is directly linked to machine maximum travel. Pertinent machine data is stored in a database, see Table 1, each column representing a (relational) database table.

Table 1. Main data stored in machine database (FTR: feature, Pr: process, PP: process plan)

Part	Process Plan	Phase	Machine	Capability	Process
P description	PP description	Pr description	Machine description	Machine	Pr type
Quantity	No of phases	Pr Type	Machine type	Process	FTR name 1
Initial length	Phase 1	Geom Before	Manufacturer		FTR value 1
Initial width	…	Geom After	CAD/VR model		…
Initial height	Phase m	Time	Workload		FTR name n
Initial weight	Part	Cost			FTR value n
CAD file					Phase

Cost (acquisition, setup and operation), benchmark job completion time as well as auxiliary criteria, e.g. reputation, existing experience etc.) may be considered, when more than one machines are suitable. Calculation of criteria values and ranking according to a weighted function is a simple way to determine the best alternative.

3.3 Machine Layout Generation and Optimization

Each machine is depicted as a simplified 3D model (in Solidworks™) providing its main shape and dimensions. Moreover, models are parametric allowing the user to adjust main dimensions of new equipment. Thus the models are lightweight and new machines are relatively easy to design without loss of functionality the aim being visualization in the manufacturing cell. Sample machine models are shown in Fig. 2. The layout of the machines can be decided by the user moving the machines manually until he/she is satisfied. However, it is also possible to generate automatically the machine position and orientation on an orthogonal grid. This is done by a genetic algorithm, as briefly described next.

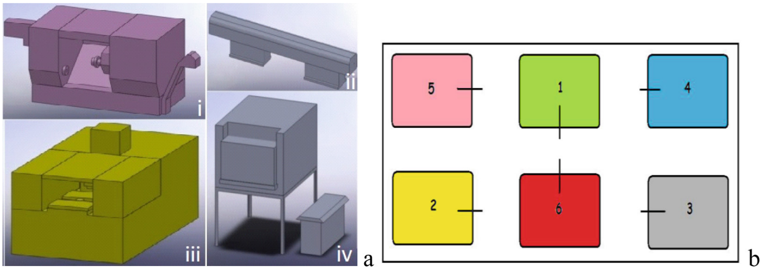


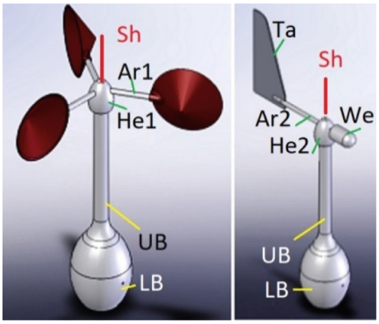
Fig. 2. (a) Sample parametrically defined machines (i) turning centre (ii) bar feeder (iii) machining centre (iv) oven (b) Position and orientation example for 6 machines

The main inputs are: N machines to be arranged on the positioning grid, the routing of each part, i.e. the sequence of machines visited by each part and the number part to be manufactured. The grid is constrained in length and width to reflect the available factory space. In the sample implementation discussed, each machine has the same footprint equal to $l * l$ space units and the floor grid size is parametrically defined by the user in multiples of l: $N(1 + n) * l$ length and $N(1 + m) * l$ width, where n and m user defined decimal numbers in the range $(-0.5, 0.5)$. The objective function to be minimized is the total length of the route of all parts concerned, weighted by the relative demand of each part (see Part: Quantity in Table 1). Thus, the GA assumes initially random positions and orientations of the ordered set of machines on which the process plan is implemented and the length of the route visiting these machines is computed, subsequently improving these positions and orientations to minimize the weighted route length for all parts manufactured in the cell. The chromosome is an array of N lines by 3 columns, the latter corresponding to X position, Y position and orientation of the respective machine. Orientation refers to the main access to the machine: it may be along the positive or negative X or positive or negative Y direction, i.e. there are 4 alternatives in total which are represented by integers 1–4. X and Y position of the machine is also represented by an integer from 1 to the maximum number of row or columns of the positioning grid. If a type of arrangement is predetermined, e.g. line, then this is handled as a constraint, i.e. solutions violating it are penalized. In the same sense a solution is penalised if orientation of a machine does not safeguard proper access, e.g. due to an adjacent wall (position on the grid border) or another machine being too close. Population size is 200, maximum number of generations is 1000 and elite count equals to 10. The GA runs in Matlab™ exploiting the inbuilt functions, e.g. 'gaoptimset' with default choices for mutation and crossover. An example corresponding to 30 parts routed through 6 machines is shown in Fig. 2(b).

Note that machine layout comes as the last step after generic process plan mapping to specific process plans and machines; no data flow backwards from layout design to process planning is intended. Materials handling systems, e.g. robots, mobile robots and conveyors are added to the layout by the user in the layout tweaking phase. Note that in case of VR visualization it is possible to superimpose 3D machine models on the actual factory environment that already contains some of the machines, see [16].

4 Case Study

The methodology presented in Sects. 2 and 3 is illustrated in a case study concerning a manufacturing system producing anemometers and wind vanes, see Fig. 3.



Part	No	G^0 d_{max} ø (mm)	G^0 l_{max} (mm)	G^{-1} scale	G^{+1} scale
Ar1	3	4.00	37.00	2/3	3/2
He1	1	20.00	25.00	3/4	7/4
Ta	1	40.00	90.00	3/4	7/4
We	1	14.00	32.00	3/4	7/4
Ar2	1	4.00	60.00	2/3	3/2
He2	1	20.00	25.00	3/4	7/4
Sh	1	4.00	139.00	2/3	3/2
LB	1	43.74	45.10	2/3	3/2
UB	1	43.74	147.50	2/3	3/2

Fig. 3. Anemometer (left) and wind vane (right) and part dimensions for sizes G^0, G^{-1}, G^{+1}

They consist of 5 and 7 different part types, three of which are shared. The original dimensions of the parts are shown as G^0 and the two variations, namely small and large, as G^{-1} and G^{+1}. All parts are made of Al alloy Al 2021 T6. Suitable processes listed in PRIMA™ to choose from range from casting and machining to blanking and drawing depending on production quantity level [15].

4.1 Process Selection Examples

Best process is selected according to the following criteria: (i) Compatibility of part's geometry with the process (ii) Compatibility of part's material with the process (iii) Cost of machine and its tooling (iv) Existing prior experience for the process and associated training requirements (v) Cost based on quantity scenarios.

For example, centrifugal casting was chosen for: Parts Sh, Ar1, Ar2, scenarios with small Q^{-1} and medium quantities Q^0 and for all quality requirements D^{-2} to D^{+2} (which are reachable when a conventional lathe is used). This choice followed the PRIMA™ process characteristics namely: convenience for cylindrical parts, compatibility with aluminium alloys, targeted at low quantities, low cost, high material utilisation (90–100%), attainment of adequate surface finish. Centrifugal casting is uniquely mapped to casting equipment. Similarly, machining was chosen for all parts but the tail (Ta). Machining in this context is synonymous to turning. Turning is uniquely mapped to lathes, yet the actual variant depends on part dimensions and production quantity. Lathes, both conventional and CNC can provide good surface finish and in case of large quantities can be combined with a bar feeder. Therefore, lathes were a valid option for all parts, all sizes G^{-1}–G^{+1}, quantities Q^{-1}–Q^{+1} and all finish specs D^{-2}–D^{+2}. The tail (Ta) was made by blanking implemented on a C-frame press for all scenarios.

4.2 Machine Layout Examples

To produce wind vanes of medium size in large quantities under low finish requirements the cell layout is shown in Fig. 4(a) consisting of two casting furnaces (for gravity casting of parts He2, We, UB, LB), two CNC lathes with bar feeders (for parts Sh, Ar2) and a C-frame mechanical press (for part Ta). To produce both anemometers and wind vanes in the same cell for large sizes in small quantities under medium finish requirements, the cell layout is shown in Fig. 4(b), consisting of a CNC lathe (for parts He1, He2, LB, UB, We), a centrifugal casting machine, a manual lathe (for parts Ar1, Ar2, Sh), a C-frame mechanical press and a CNC milling machine (for part Ta).

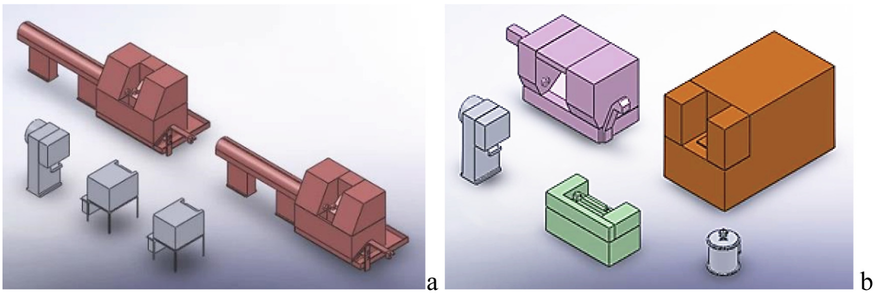


Fig. 4. Layouts for (a) vane $G^0Q^{+1}D^{-1}$ (b) anemometer and vane $G^{+1}Q^1D^0$

5 Conclusions

In conceptual design of the manufacturing cell, narrowing down the search for the best generic process plan is based on part size and accuracy as well as on production quantity which is implicitly connected to production cost. There is still ambiguity in such choice, which needs experience and intuition to solve. However, the existence of a framework within which the objects of choice are placed is most helpful. Then, mapping of generic processes plan to machine tools is based on a comparison of specific features of the machines against their counterparts of the parts to be manufactured. Such comparisons are only possible if supported by a database, whose formulation may certainly be cumbersome. In a digital factory context, this framework supports design of 'informed' cell layouts corresponding to envisaged production of part families, enabling subsequent detailed design, simulation and even a user interface for a cell monitoring digital twin. Automation aspects embedded in the methodology refer so far to automatic layout generation based on routing distance. However, in the future the most suitable generic process plan could be selected by machine learning.

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