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Cell design and multi-period machine loading in cellular reconfigurable manufacturing systems with alternative routing

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This paper deals with the design and loading of Cellular Reconfigurable Manufacturing Systems in the presence of alternative routing and multiple time periods. These systems consist of multiple reconfigurable machining cells, each of which has Reconfigurable Machine Tools and Computer Numerical Control (CNC) machines. Each reconfigurable machine has a library of feasible auxiliary machine modules for achieving particular operational capabilities, while each CNC machine has an automatic tool changer and a tool magazine of a limited capacity. The proposed approach consists of two phases: the machine cell design phase which involves the grouping of machines into machine cells, and the cell loading phase that determines the routing mix and the tool and module allocation. In this paper, the cell design problem is modelled as an Integer Linear Programming formulation, considering the multiple process plans of each part type as if they were separate part types. Once the manufacturing cells are formed, a Mixed Integer Linear Programming model is developed for the cell loading problem, considering multi-period demands for the part types, and minimising transportation and holding costs while keeping the machine and cell utilisations in each period, and the system utilisation across periods, approximately balanced. An illustrative problem and experimental results are presented.

Keywords: cellular manufacture; reconfigurable manufacturing systems; mixed integer linear programming; cell formation; machine loading

1. Introduction

Given the current turbulent and uncertain manufacturing environment, some critical requirements for a manufacturing system are essential for survival. Short lead times, more variants, low and fluctuating volumes and low prices are some of the general features of next generation manufacturing systems (Molina et al. 2005). Strategies designed to meet these requirements lead to different types of manufacturing system, such as Dedicated Manufacturing Systems (DMS), Cellular Manufacturing Systems (CMS) or Flexible Manufacturing Systems (FMS). DMS provide profitable and cost-effective production in a stable market but are unable to operate effectively in the present dynamic market scenario. CMS aim at achieving production efficiency when there are a variety of part types that can be grouped into part families. FMS use expensive CNC machines with fixed hardware and software to produce a variety of parts, but the implementation of these systems has not been very successful, with abrupt market fluctuations because of the lower throughput, high cost or complex design. An emerging paradigm in the manufacturing environment defines the Reconfigurable Manufacturing System (RMS) concept and the Reconfigurable Machine Tool (RMT) technology.

In contrast to conventional CNCs, which are general-purpose machines, RMTs are designed for a specific, customised range of operation requirements and may be cost-effectively converted when the requirements change (Landers, Min, and Koren 2001). An RMT is designed with an adjustable and modular structure that enables either machine scalability or machine convertibility, using some basic and auxiliary machine modules (Koren 2010, 211–218). When the auxiliary modules are changed, different operations can be performed on the new machine configuration. In response to the market changes, new Modular Reconfigurable Machine (MRM) tools have been developed (Padayachee and Bright 2012). In an MRM, the modularity and flexibility of the machine is achieved by adding and removing the modules, selected from precompiled modules and concatenated by means of a series of standardised mechanical interfaces, thus permitting a variety of combinations in which modules could be joined (Majija, Mpofu, and Modungwa 2013). RMTs and MRMs are generally used as part of an RMS.

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An RMS is

> a manufacturing system designed at the outset for rapid changes in structure, as well as in hardware and software components in order to quickly adjust production capacity and functionality within a part family in response to sudden changes in market or in regulatory requirements. (Koren et al. 1999)

These manufacturing systems are configured to produce a family of different part types that share some similarities (Xiaobo, Jiancai, and Zhenbi 2000). Time reduction for introducing new products to the market, together with high quality and low cost, is key for enterprise survival in the current environment. The manufacturing system must be able to yield different batch sizes from different product types, using the exact capacity and functionality required in each case.

A CMS is based on the group technology principle of grouping similar parts into part families. In this type of manufacturing system, machines are grouped into cells, where each cell is dedicated to process one or more part families. There are numerous papers in the literature dealing with CMS, especially studying methods for cell formation based on graph theory (e.g. Askin and Chiu 1990), clustering (e.g. Chandrasekharan and Rajagopalan 1987), mathematical programming (e.g. Defersha and Chen 2006), metaheuristics (e.g. Farahani and Hosseini 2011; Ying, Lin, and Lu 2011), neural networks (e.g. Ateme-Nguema and Dao 2009; Sengupta, Ghosh, and Dan 2011), etc. There are also some review papers on this topic (e.g. Selim, Askin, and Vakharia 1998; Ghosh et al. 2014).

A CMS helps in reducing work-in-process, set-up time, manufacturing lead-time and material handling, and improves productivity (Wemmerlöv and Johnson 1997). However, a CMS lacks flexibility and, thus, cannot respond to some requirements such as dynamic part mix and demand variation. The integration of modular machines within a CMS can help to reduce the level of performance deterioration, including some degree of adaptability.

This paper is related to the cell design and loading problem in the presence of alternative routing and multiple time periods within a cellular manufacturing system containing RMT and CNC machines. Alternative routing arises when there are multiple process plans for each part type, giving rise to the generalised group technology (GGT) concept (Kusiak 1987). An Integer Linear Programming (ILP) model for cell design and a new Mixed-Integer Linear Programming (MILP) model for multi-period cell loading have been developed in that framework, including as basic objectives the minimisation of total intercellular transportation and holding costs, and workload imbalances, and considering production limitations on tools and modules.

Several methods have been proposed for cell design and loading with alternative routing as part of the GGT literature. Many authors have developed methods for grouping parts into families or machines into cells but considering only one of the alternative process plans (Logendran, Ramakrishna, and Sriskandarajah 1994; Sofianopoulou 1999). This approach makes only partial use of the flexibility provided by the multiplicity of process plans. Some studies have imposed machine capacity constraints (Choobineh 1988; Kang and Wemmerlöv 1993), without considering the workload distribution. Some researchers (Kumar and Shanker 2000; Swarnkar and Tiwari 2004) have addressed the loading problem using a bi-criteria approach (minimising system imbalance and maximising the throughput), but not taking into account alternative routing.

Methods in the literature specifically aimed at cell formation using reconfigurable machines can be found in Pattanaik, Jain, and Mehta (2007) and Pattanaik and Kumar (2010). In these works, a methodology is presented to design machine cells with modular machines using characteristics of reconfigurable manufacturing. The methodology is based on the clustering approaches used in group technology, grouping machines into cells but without dealing with the loading problem.

Xing et al. (2009) developed an artificial neural network to solve the cell formation problem in a Cellular Reconfigurable Manufacturing Systems (CRMS), which is defined as a set of reconfigurable manufacturing cells (RMCs) with the following advantages, compared to traditional manufacturing cells: machines are logically, instead of physically, organised in an RMC, the RMC is changeable during a production plan horizon, and machines can be shared by different RMCs. This paper is focused on the cell formation problem.

Eguia et al. (2013) also centred their studies on CRMS but considering a new approach to simultaneously solve the cell formation and the scheduling of part families for the effective working of a CRMS. The approach consists of an MILP model to represent both problems simultaneously with the objective of minimising production costs and the development of a tabu search algorithm for solving large instances.

To the best of our knowledge, only one research (Yu et al. 2012) is in regard to part grouping and loading in CRMS. These authors considered multiple cells, each of which has CNC machines with tool limitations, and presented an MILP model to solve both problems at the same time with the objective of minimising the maximum workload assigned to machines. The methodology to be presented in this paper extends the formulation of Yu et al. (2012) considering: multiple process plans for each part type, RMT with a library of auxiliary modules, multi-period demands for the part types, transportation and holding costs as the main objective function, and balancing workloads as the secondary objective.

This paper is organised as follows. In the next section, the cell design problem for CRMS with alternative process plans for each part type is described in detail, together with its mathematical formulation and methods from the literature that can be used to solve the problem. In Section 3, the multiple period loading problem for CRMS is presented and formulated. In Section 4, numerical results from a case study are reported. The last section summarises and concludes.

2. Reconfigurable manufacturing cells design

A CRMS consists of multiple RMCs, each of which has RMT and/or CNC machines, a set-up station, and an automatic material handling and storage system. Each CNC machine within an RMC has an automatic tool changer and a tool magazine with limited capacity. The automatic tool changer gives flexibility to the CNC machine so that it can perform various types of operation without requiring a great effort in switching from one operation to another. Each RMT within an RMC has a library of basic and auxiliary modules. The basic modules are structural in nature (such as base, columns, slideways and tables) and auxiliary modules are kinematical or motion-giving (such as spindles, tool changers, etc.). A particular combination of different basic and auxiliary modules provides a particular set of operational capabilities to the RMT. Figure 1 shows a schematic description of a CRMS with two different RMCs.

The RMC design problem involves the grouping of machines (RMT and CNC machines) into machine cells using the information on the sequence of operations for the different process plans of each part type. For conventional manufacturing cell design problems, two alternatives are considered in the literature: either the alternative process plans are treated as if they were separate part types, or aggregate part types are built from the alternative process plans of each part type.

In the first case, the problem transforms itself into a conventional (i.e. without alternative routing) cell formation problem, except that instead of grouping machines and part types, what must be grouped are machines and process plans. The objective is to find clusters of machines and process plans so that the maximum number of operations of each process plan family can be performed within the cell. Most cell formation methods from the literature use as input data the information on the sequence of operations for each process plan, and then generate a binary machine/process plan incidence matrix. Some of these methods assume that the number of cells to be formed is given. Also, some methods have the possibility of imposing a limit on the number of machines per cell. Most of these methods assume that there is only one machine of each type.

Alternatively, when a binary machine/process plan incidence matrix is given, the multiple process plans of each part type can be aggregated in order to form virtual part types. One way is to form a non-binary machine/virtual part type incidence matrix with the average use of each machine per each unit part type and then apply a fuzzy clustering technique.

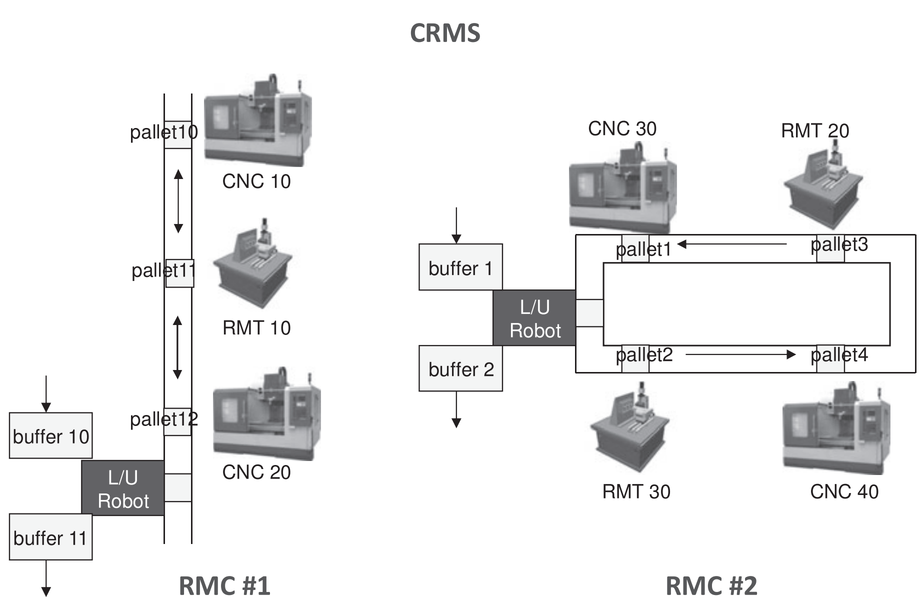

Figure 1. RMC and CRMS: schematic description.

Different mathematical formulations for the cell formation problem have been proposed in the literature to solve the problem optimally. Some of these formulations consider indirect measures, such as similarity, bond energy, ranking etc., to obtain a block diagonal form from the part-machine incidence matrix using a sequential approach (Kusiak 1987; Srinivasan, Narendran, and Mahadevan 1990). In such approaches, the machine groups and part families formed are such that the number of exceptional elements and voids is minimised. But in a manufacturing situation, the costs of voids and exceptional elements may vary, indicating that their importance might be considered explicitly.

In this paper, an ILP model for the simultaneous grouping of machines and alternative process plans is developed using the alternative process plans as if they were separate part types. The problem transforms itself into a standard cell formation problem (i.e. without alternative routing), except that it is machines and process plans that must be grouped instead of machines and part types. This formulation is based on the nonlinear mathematical model proposed by Adil, Rajamani, and Strong (1993) and the ILP model proposed by Boctor (1991).

The notation used in the ILP model to solve the simultaneous cell formation problem with alternative routing is the following:

2.1 *Indexes and input data*

- Part types: $i = 1, \ldots, N$
- Process plans of each part type: $r = 1, \ldots, PP_i$ (PP_i is the number of process plans of part type i)
- CNC machines (set NM) and RMT (set RM): $k = 1, \ldots, M$
- Cells: $c = 1, \ldots, C$ (C is the maximum number of cells to be formed)
- a_{kir}: machine/process plan binary incidence matrix (=1 if machine type k is required for any operation of the r-th process plan of part type i, and 0 otherwise)
- q: weighting parameter that measures the importance of voids versus exceptional elements ($0 \le q \le 1$)

2.2 *Decision variables of cell formation*

- $X_{kc} = 1$ if machine type k is assigned to cell c
- $Y_{irc} = 1$ if r-th process plan of part type i is assigned to cell c
- $E_{kirc} = 1$ (exceptional element) if r-th process plan of part type i requires a machine type k outside of the cell c to which that process plan is assigned
- $H_{kirc} = 1$ (void) if r-th process plan of part type i does not require a machine type k inside of the cell c to which that process plan is assigned

The cell formation problem that identifies machine groups and process plan families simultaneously can be formulated as the following ILP model.

$$[P1] \quad \text{Minimise} \quad q \cdot \sum_c \sum_k \sum_{r=1}^{r=PP_i} \sum_i H_{kirc} + (1-q) \cdot \sum_c \sum_k \sum_{r=1}^{PP_i} \sum_i E_{kirc} \tag{1}$$

subject to

$$\sum_c Y_{irc} = 1 \quad \forall i, \forall r \tag{2}$$

$$\sum_c X_{kc} = 1 \quad \forall k \tag{3}$$

$$\sum_i PP_i \cdot X_{kc} - \sum_{r=1}^{r=PP_i} \sum_i a_{kir} Y_{irc} + \sum_{r=1}^{r=PP_i} \sum_i a_{kir} E_{kirc} \ge 0 \quad \forall k, \forall c \tag{4}$$

$$\sum_i PP_i \cdot (1 - X_{kc}) - \sum_{r=1}^{r=PP_i} \sum_i (1 - a_{kir}) Y_{irc} + \sum_{r=1}^{r=PP_i} \sum_i (1 - a_{kir}) H_{kirc} \ge 0 \quad \forall k, \forall c \tag{5}$$

$$\sum_i PP_i \cdot \sum_k X_{kc} \geq \sum_{r=1}^{r=PP_i} \sum_i Y_{irc} \quad \forall c \tag{6}$$

$$M \cdot \sum_{r=1}^{r=PP_i} \sum_i Y_{irc} \geq \sum_k X_{kc} \quad \forall c \tag{7}$$

$$X_{kc}, Y_{irc},\ E_{kirc}, H_{kirc} \in \{0,1\}\ \forall k = 1,\ldots,M; \forall i = 1,\ldots,N; \forall r = 1,\ldots,PP_i; \quad \forall c = 1,\ldots,C \tag{8}$$

The objective function (1) minimises the weighted sum of intracellular voids and intercellular movements. Constraints (2) ensure that each machine is allocated to a cell. Similarly, constraints (3) guarantee that each process plan is assigned to a cell. Constraints (4) indicate that if a machine type k is not assigned to cell c (X_{kc} = 0), the number of times that machine type k is required to complete parts in the process plans assigned to cell c, i.e. the corresponding number of exceptional elements ($\sum_{r=1}^{r=PP_i} \sum_i a_{kir} E_{kirc}$), must be greater than or equal to the number of operations requiring that machine in all the process plans assigned to cell c ($\sum_{r=1}^{r=PP_i} \sum_i a_{kir} Y_{irc}$). Similarly, constraints (5) imply that if a machine type k is assigned to cell c (X_{kc} = 1), the number of times that machine type k is not required in any of the process plans assigned to cell c, i.e. the corresponding number of voids $\left(\sum_{r=1}^{r=PP_i} \sum_i (1 - a_{kir}) H_{kirc}\right)$, must be greater than or equal to the number of process plans assigned to the cell c that do not use that machine type $\left(\sum_{r=1}^{r=PP_i} \sum_i (1 - a_{kir}) Y_{irc}\right)$. Finally, constraints (6) and (7) are added to guarantee that if any machine type is assigned to a cell c then at least one process plan must be assigned to this cell, and vice versa. Binary restrictions on the variables are imposed by constraints (8). The value of C is an upper bound on the number of cells to be formed.

If the machine/process plan binary incidence matrix is small, the above model can be optimally solved using appropriate optimisation software. But for the efficient solution of larger problems, heuristics approaches are needed. There are a number of heuristic techniques to solve the standard cell formation problem efficiently. Some of the solution methods try to rearrange the binary machine/part incidence matrix (a_{kir}) in order to bring the non-zero elements around the diagonal. There are also clustering techniques that identify clusters of either parts or machines. A third group of methods use graph decomposition techniques to find the manufacturing cells. Also, several multi-step or iterative *ad hoc* heuristics have been proposed in the literature. Finally, other methods to solve the manufacturing cell formation problem efficiently include metaheuristics: Tabu Search, Simulated Annealing or Genetic Algorithms.

In this paper, in addition to solving the model optimally, and for the sake of comparison, some existing cell formation heuristics and metaheuristics from the literature have also been applied, namely ZODIAC (Chandrasekharan and Rajagopalan 1987), GRAFICS (Srinivasan and Narendran 1991), MST (Srinivasan 1994), Simulated Annealing (Boctor 1991; Chen, Cotruvo, and Baek 1995), Tabu Search (Sun, Kim, and Batta 1995) and Self-Organising Neural Network – SONN (Lozano et al. 1998). MST is a greedy heuristic which can handle cell size constraints while the other two heuristics (ZODIAC and GRAFICS) are two commonly used, non-hierarchical clustering approaches for manufacturing cell formation. In these heuristics the information about the binary machine/process plan incidence matrix (a_{kir}) is used for grouping machines into cells, maximising the sum of similarity coefficients between every two machines in a cell (with similarity measured according to the number of process plans which use both machines). Process plans are then assigned to the cell in which the majority of its operations are performed. Simulated Annealing and Tabu Search are two well-known metaheuristics applied to solve a large number of combinatorial problems, and, in particular, they have been used to solve the cell formation problem. Both methods start with an initial feasible solution and repeatedly generate neighbouring solutions. Both methods differ in the mechanism required to generate the neighbourhood and to select the new solution. Finally, in SONN a fuzzy aggregate part-machine incidence matrix is computed using Equation (9). The assignment of process plans to machine cells is performed using the same criterion as in the previous heuristics.

$$\tilde{a}_{ki} = \frac{\sum_r a_{kir}}{PP_i} \tag{9}$$

3. Multi-period cell loading problem

Once the cell design problem has been solved, the resulting cells can be physically implemented and the cell loading planned. The cell loading consists of determining the routing mix, and the tool and module allocation, i.e. which quantity of each part type is to be assigned to each alternative route in each time period and how many auxiliary modules and tools of each available type are to be assigned to each RMT and CNC machine in each period. To do this an MILP model, formulated below, is proposed. The basic objectives of this phase are to minimise total intercellular transportation and holding costs of parts, as well as to balance machine and cell utilisations.

Let us introduce additional notation to be used in the cell loading problem.

3.1 *Indexes and basic input data*

- Time periods: $t = 1, \ldots, T$ (T is the planning horizon)
- D_i^t: demand for part type i in period t
- Tool types (set TT) and auxiliary module types (set AM): $z = 1, \ldots, Z$
- s_{zk}: number of tool slots required by tool type z in CNC machine k
- TMC_k: tool magazine capacity of CNC machine k ($k \in NM$)
- MNA_k: maximum number of auxiliary modules for RMT k ($k \in RM$)
- TC_z^t: number of available units of tool type z ($z \in TT$) in period t
- TA_z^t: number of available units of auxiliary module type z ($z \in AM$) in period t
- TL_z: tool life of tool type z ($z \in TT$)
- AL_z: average life of auxiliary module type z ($z \in AM$)
- $d_{ijrz} = 1$ if j-th operation of r-th process plan of part type i requires tool type z, and 0 otherwise
- p_{ijrk}: processing time of j-th operation of r-th process plan of part type i at machine k
- H_k^t: maximum workload available for machine k in period t
- α: maximum inter-cell utilisation imbalance
- β: maximum intra-cell utilisation imbalance
- γ: maximum inter-period utilisation imbalance
- CM: unit intercellular transportation cost
- CH^t: unit holding cost in period t

3.2 *Additional input data from cell design*

- n_{ir}: number of inter-cell movements along route r of part type i (obtained from phase 1 X_{kc} and a_{irk})
- $b_{kc} = 1$ if machine type k belongs to cell c (obtained from phase 1 X_{kc})
- q_c: number of machines in cell c (obtained from phase 1 X_{kc})

3.3 *Decision variables of cell loading*

- x_{ir}^t: quantity of part type i to be assigned to route r in period t
- I_i^t: inventory of part type i at the end of period t
- ε_{zk}^t: number of tools of type z ($z \in TT$) assigned to CNC machine k ($k \in NM$) in period t and number of auxiliary modules of type z ($z \in AM$) assigned to RMT k ($k \in RM$) in period t
- u_k^t: workload of machine k in period t
- w_c^t: total workload of machines in cell c in period t

The cell loading problem can be formulated as the following MILP model.

$$[P2] \quad \text{Minimise} \quad CM\sum_t\sum_i\sum_r n_{ir}x_{ir}^t + \sum_t\sum_i CH^t I_i^t \quad \text{subject to} \tag{10}$$

$$I_i^t = \sum_{t'=1}^{t'=t}\sum_r x_{ir}^{t'} - \sum_{t'=1}^{t'=t} D_i^{t'} \quad \forall i, \forall t \tag{11}$$

$$I_i^T = 0 \quad \forall i \tag{12}$$

$$\sum_{z \in TT} s_{zk}\varepsilon_{zk}^t \le TMC_k \quad \forall k \in NM, \forall t \tag{13}$$

$$\sum_{z \in AM} \varepsilon_{zk}^t \le MNA_k \quad \forall k \in RM, \forall t \tag{14}$$

$$\sum_{k \in M} \varepsilon_{zk}^t \le TC_z^t \quad \forall z \in TT, \forall t \tag{15}$$

$$\sum_{k \in RM} \varepsilon_{zk}^t \le TA_z^t \quad \forall z \in AM, \forall t \tag{16}$$

$$\sum_i \sum_j \sum_r d_{ijrz} p_{ijrk} x_{ir}^t \le TL_z \varepsilon_{zk}^t \quad \forall z \in TT, \forall\, k \in NM, \forall t \tag{17}$$

$$\sum_i \sum_j \sum_r d_{ijrz} p_{ijrk} x_{ir}^t \le AL_z \varepsilon_{zk}^t \quad \forall z \in AM, \forall\, k \in RM, \forall t \tag{18}$$

$$\sum_i \sum_j \sum_r \sum_z d_{ijrz} p_{ijrk} x_{ir}^t = u_k^t \quad \forall k, \forall t \tag{19}$$

$$w_c^t = \sum_k b_{kc} u_k^t \quad \forall c, \forall t \tag{20}$$

$$u_k^t \le H_k^t \quad \forall k, \forall t \tag{21}$$

$$(1-\alpha)\frac{\sum_c w_c^t}{C} \le w_c^t \le (1+\alpha)\frac{\sum_c w_c^t}{C} \quad \forall c, \forall t \tag{22}$$

$$(1-\beta)\sum_c \frac{w_c^t}{q_c} b_{kc} \le u_k^t \le (1+\beta)\sum_c \frac{w_c^t}{q_c} b_{kc} \quad \forall k, \forall t \tag{23}$$

$$(1-\gamma)\frac{\sum_t \sum_c w_c^t}{T \cdot C} \le \frac{\sum_c w_c^t}{C} \le (1+\gamma)\frac{\sum_t \sum_c w_c^t}{T \cdot C} \quad \forall t \tag{24}$$

$$x_{ir}^t, I_i^t, u_k^t, w_c^t \ge 0, \ \varepsilon_{zk}^t \in Z^+ \quad \forall i, r, t, k, c, z \tag{25}$$

The objective function (10) minimises total costs, including both intercellular transportation costs and inventory holding costs. Constraints (11) compute inventories at the end of each period and impose that the part demand of each period must be satisfied. Constraints (12) impose a zero inventory at the end of the planning horizon for all part types. The limitations on the tool magazine capacity of each CNC machine and the physical limitations on the number of auxiliary modules that can be attached to each RMT are represented by constraints (13) and (14), respectively. Constraints (15) and (16) impose the limitations on the number of available tools and auxiliary modules. Constraints (17) and (18) imply that for each tool type (respectively, auxiliary module types) the total life corresponding to the number of tools (respectively, auxiliary modules) assigned to each machine should be larger than or equal to the corresponding workloads for that tool type (respectively, auxiliary module types) on that machine. Constraints (19) compute the workload of each machine in each period while constraints (20) compute the workload of each cell in each period as the sum of the workloads of machines assigned to the cell. Constraints (21) correspond to the maximum workload allowed for each machine. Workload balancing in each period is considered through constraints (22), (23) and (24), which bound for each period, the deviation of each cell workload, of each machine workload and of the system workload with respect to their average values. Constraints (25) declare that all variables are continuous except for the integer variables ${\varepsilon_{zk}}^t$.

The above model is different from other approaches in that not only does it consider the total costs as the main objective function but also balancing the workload as the secondary objective function. The latter objective requires that all machines in the same cell be approximately equally loaded, that the average utilisation of the machines in each cell be approximately the same for all the cells in each period, and that the average system utilisation for each period be similar. This objective helps prevent bottlenecks and thus increases throughput. Also this model includes RMT and auxiliary modules as part of the CRMS, considering limitations on the number of modules per machine and on the total number of module copies of each auxiliary module type.

An MILP formulation is a natural approach to this problem. The number of integer variables depends on the degree of tool and module commonality between operations and in any case cannot exceed the number of machine types times the number of tool types. Constraints (13)–(16) are multi-knapsack, which implies that the problem may not be easily solved in the worst case. Although in the illustration presented in the next section, given its moderate size, the model has been solved optimally, more efficient solution strategies (e.g. metaheuristic approaches) may have to be developed for larger sized problems.

4. Illustration

This section considers a manufacturing system involving 14 machines (of which 11 are CNC machines, numbered 1–11, and 3 RMT, numbered 12–14) and 10 part types. Table 1 shows the sequence of operations of the alternative process plans of each part type. Note that there are a total of 23 alternative routes (ranging from 1 to 6 operations per route) using 6 tool types (numbered 1–6) and 3 auxiliary module types (numbered 7–9).

From Table 1, the machine/process plan incidence matrix is generated using only the first attribute (i.e. machine type) of each operation. Table 2 shows the corresponding binary machine/process plan incidence matrix (a_{kir}).

The cell design model [$P1$] has been solved optimally using the linear programming software LINGO® v.9 on a 3.3 GHz Intel® Core(TM) i5-2400 CPU. Table 3 shows the machine cells and associated process plan families obtained by the optimisation software for different values of the weighting parameter q from 0 to 1 (in steps of 0.1) and a maximum number of 6 cells (C). According to these results, the minimum number of intracellular voids obtained is 6 and occurs when $q = 1$ and the 14 machines are grouped into the maximum number of 6 cells while the minimum number of exceptional elements is 0 corresponding to $q = 0$ and 3 cells formed. For intermediate values of the weighting parameter q, the number of cells, voids and exceptional elements vary between the above limits. In this illustration, choosing a value for the relative weight of voids and exceptional elements $q = 0.1$ is reasonable due to the resulting cell sizes (between 3 and 4 machines per cell) and the number of formed cells (4 cells).

Table 1. Routing data.

Part type	Route	Operation sequence (machine, processing time, tool/module)					
i	r	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$
1	1–1	(6, 5, 2)	(5, 12, 3)	(6, 7, 5)			
	1–2	(4, 8, 1)	(13, 6, 9)	(3, 5, 6)	(4, 5, 1)	(13, 6, 9)	
	1–3	(3, 10, 6)	(13, 5, 8)	(3, 10, 2)	(13, 8, 9)	(4, 4, 2)	
2	2–1	(14, 6, 8)	(1, 5, 3)	(8, 4, 5)	(14, 5, 7)	(8, 5, 5)	(1, 5, 1)
	2–2	(8, 3, 1)	(2, 9, 4)	(8, 5, 6)	(1, 10, 3)		
3	3–1	(6, 2, 3)	(7, 8, 5)	(6, 3, 5)			
	3–2	(10, 9, 1)	(12, 7, 9)	(10, 9, 3)			
	3–3	(9, 8, 2)	(12, 4, 9)	(9, 6, 6)	(13, 4, 8)	(10, 4, 6)	(12, 5, 7)
4	4–1	(10, 7, 6)	(9, 10, 6)	(10, 6, 1)			
	4–2	(7, 7, 1)	(6, 4, 2)	(11, 12, 4)	(7, 9, 4)	(6, 5, 3)	(5, 8, 5)
5	5–1	(11, 4, 4)	(5, 6, 6)	(11, 4, 6)			
	5–2	(6, 4, 2)	(5, 4, 5)	(7, 4, 1)	(6, 4, 5)	(7, 5, 5)	
6	6–1	(11, 3, 4)	(7, 6, 4)				
	6–2	(5, 8, 6)	(6, 7, 3)				
7	7–1	(6, 4, 2)	(7, 3, 4)	(5, 5, 6)	(6, 6, 3)	(7, 3, 5)	(11, 5, 4)
	7–2	(6, 5, 5)	(5, 4, 5)				
	7–3	(4, 7, 4)	(3, 8, 2)	(13, 5, 8)	(4, 6, 1)		
8	8–1	(10, 7, 3)					
	8–2	(3, 6, 3)					
9	9–1	(4, 6, 2)	(3, 6, 6)	(13, 5, 9)			
	9–2	(2, 4, 1)	(8, 3, 6)	(2, 6, 5)			
10	10–1	(4, 5, 4)	(3, 5, 6)	(10, 5, 1)	(4, 7, 2)	(3, 5, 3)	
	10–2	(14, 10, 7)					

Table 2. Machine/process plan incidence matrix.

	Part-process plan (*i–r*)																						
Machine type (k)	1–1	1–2	1–3	2–1	2–2	3–1	3–2	3–3	4–1	4–2	5–1	5–2	6–1	6–2	7–1	7–2	7–3	8–1	8–2	9–1	9–2	10–1	10–2
1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
3	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0
4	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0
5	1	0	0	0	0	0	0	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0
6	1	0	0	0	0	1	0	0	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0
7	0	0	0	0	0	1	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0
8	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
9	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0
11	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0
14	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 3. Optimal cell design solutions (machine groups and process plan families).

	Cells							
q	I	II	III	IV	V	VI	Voids	Except.
0.0	(5, 6, 7, 11) (1–1; 3–1; 4–2; 5–1; 5–2; 6–1; 6–2; 7–1; 7–2)	(1, 2, 8, 14) (2–1; 2–2; 9–2; 10–2)	(3, 4, 9, 10, 12, 13) (1–2; 1–3; 3–2; 3–3; 4–1; 7–3; 8–1; 8–2; 9–1; 10–1)				55	0
0.1	(5, 6, 7, 11) (1–1; 3–1; 4–2; 5–1; 5–2; 6–1; 6–2; 7–1; 7–2)	(1, 2, 8, 14) (2–1; 2–2; 9–2; 10–2)	(3, 4, 13) (1–2; 1–3; 7–3; 8–2; 9–1; 10–1)	(9, 10, 12) (3–2; 3–3; 4–1; 8–1)			27	2
0.2; 0.3	(5, 6, 7, 11) (1–1; 3–1; 4–2; 5–1; 5–2; 6–1; 6–2; 7–1; 7–2)	(1, 2, 8) (2–1; 2–2; 9–2)	(3, 4, 13) (1–2; 1–3; 7–3; 8–2; 9–1; 10–1)	(9, 10, 12) (3–2; 3–3; 4–1; 8–1)	(14) (10–2)		22	3
0.4	(5, 6, 7) (1–1; 3–1; 4–2; 5–2; 6–2; 7–1; 7–2)	(1, 2, 8) (2–1; 2–2; 9–2)	(3, 4, 13) (1–2; 1–3; 7–3; 8–2; 9–1; 10–1)	(9, 10, 12) (3–2; 3–3; 4–1; 8–1)	(14) (10–2)	(11) (5–1; 6–1)	13	7
0.5	(5, 6, 7) (1–1; 3–1; 4–2; 5–2; 6–2; 7–1; 7–2)	(1, 2, 8) (2–1; 2–2; 9–2)	(3, 4, 13) (1–2; 1–3; 7–3; 9–1; 10–1)	(9, 10, 12) (3–2; 3–3; 4–1)	(14) (8–1; 8–2; 10–2)	(11) (5–1; 6–1)	11	9
0.6	(5, 6, 7) (1–1; 3–1; 4–2; 5–2; 6–2; 7–1; 7–2)	(1, 2, 8) (2–2; 9–2)	(3, 4, 13) (1–2; 1–3; 7–3; 9–1; 10–1)	(9, 10, 12) (3–2; 3–3; 4–1)	(14) (2–1; 8–1; 8–2; 10–2)	(11) (5–1; 6–1)	10	10
0.7; 0.8; 0.9; 1	(5, 6) (1–1; 3–1; 4–2; 5–1; 5–2; 6–2; 7–1; 7–2)	(2, 8) (2–2; 9–2)	(3, 4, 13) (1–2; 1–3; 7–3; 9–1)	(7, 9, 11, 12) (6–1)	(1, 14) (2–1; 10–2)	(10) (3–2; 3–3; 4–1; 8–1; 8–2; 10–1)	6	17

Table 4. Cell design solutions from heuristic methods (machine groups and process plan families).

Cell design method	I	II	III	IV	V	VI	Voids	Except.
MST; GRAFICS; SA-Boctor; SA-Chen; TS-Sun; SONN	(5, 6, 7, 11)	(1, 2, 8, 14)	(3, 4, 13)	(9, 10, 12)			27	2
	(1–1; 3–1; 4–2; 5–1; 5–2; 6–1; 6–2; 7–1; 7–2)	(2–1; 2–2; 9–2; 10–2)	(1–2; 1–3; 7–3; 8–2; 9–1; 10–1)	(3–2; 3–3; 4–1; 8–1)				
Zodiac	(5, 6)	(1, 2, 8, 14)	(3, 4, 13)	(9, 10, 12)	(7)	(11)	14	10
	(1–1; 4–2; 5–2; 6–2; 7–1; 7–2)	(2–1; 2–2; 9–2; 10–2)	(1–2; 1–3; 7–3; 8–2; 9–1; 10–1)	(3–2; 3–3; 4–1; 8–1)	(3–1; 6–1)	(5–1)		

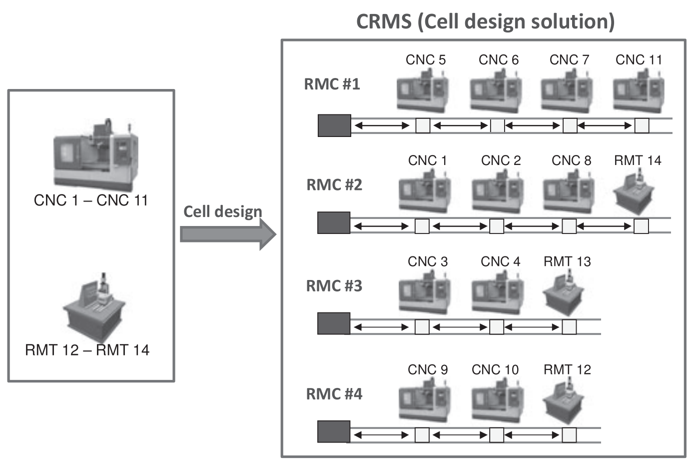

Figure 2. Visual representation of the cell design solution.

Table 5. Demand scenario for cell loading.

	Part type									
	1	2	3	4	5	6	7	8	9	10
Demand for period 1	–	18	15	8	9	–	16	12	18	–
Demand for period 2	10	18	18	8	10	8	–	–	–	12
Demand for period 3	12	18	–	–	–	12	18	8	15	14
Demand for period 4	–	10	16	12	8	–	–	15	12	10

As mentioned in Section 2, three *ad hoc heuristics* (MST, ZODIAC and GRAFICS), three metaheuristics (SA-Boctor, SA-Chen and TS-Sun) and a fuzzy neural network (SONN) have also been applied to solve this cell design problem. In order to be able to compare these methods with the optimal ILP model results, a cell size limit has not been considered and the same objective function has been used. The comparison has been carried out for a value of $q = 0.1$. The three *ad hoc* heuristics do not need the number of cells to be fixed a priori and process plans are assigned to the cell in which the impact on the objective function is lowest. For the other four methods, a maximum number of $C = 4$ cells has been established. The cell design results for these seven heuristic methods are shown in Table 4. Note that 6 of the methods have also obtained the optimal solution, while ZODIAC has grouped the 14 machines into 6 cells. Note that, in the optimal four-cell configuration, many part types (e.g. 1, 3, 4, 7, 8, 9 and 10) have process plans that are assigned to different cells, thus increasing the flexibility for the cell loading phase. Let us assume that the four-cell solution that appears in both Tables 3 and 4 is selected. This CRMS configuration is shown in Figure 2.

Table 6. Additional data.

Tool slots per tool type ($\forall z \in TT$, $\forall k \in NM$)	s_{zk}	1
Tool magazine capacity ($\forall k \in NM$)	TMC_k	3
Number of auxiliary modules ($\forall k \in RM$)	MNA_k	2
Number of available tool copies ($\forall z \in TT$)	TC_z^t	6
Number of available module copies ($\forall z \in AM$)	TA_z^t	2
Tool life ($\forall z \in TT$)	TL_z	120
Auxiliary module life ($\forall z \in AM$)	AL_z	120
Maximum workload for machine ($\forall k \in NM$, $\forall t$)	H_k^t	240
Maximum inter-cell imbalance	α	0.30
Maximum intra-cell imbalance	β	0.60
Maximum inter-period system utilisation imbalance	γ	0.30
Unit intercellular transportation cost	CM	1
Unit holding cost $\forall t$	CH^t	0.1

Table 7. Optimal cell loading solution: production plan (x_{ir}^t).

Part-process plan		Production plan		
(i–r)	x_{ir}^1	x_{ir}^2	x_{ir}^3	x_{ir}^4
1–1		0.646	4.865	
1–2		1.478	3.750	
1–3		11.261	0.000	
2–1	3.486	0.000	0.000	0.000
2–2	16.997	18.126	15.494	9.897
3–1	9.599	12.360		7.065
3–2	3.358	3.506		2.525
3–3	2.043	2.134		1.427
4–1	7.613	7.950		4.177
4–2	0.387	0.050		0.800
5–1	9.000	5.775		3.707
5–2	0.000	4.225		4.293
6–1		0.000	12.000	
6–2		8.000	0.000	
7–1	5.841		0.811	
7–2	10.159		17.189	
7–3	0.000		0.000	
8–1	0.000		0.000	0.000
8–2	12.000		8.770	14.230
9–1	18.000		15.000	12.000
9–2	0.000		0.000	0.000
10–1		0.000	0.000	0.000
10–2		12.000	12.000	10.000

The cell loading model [$P2$] has been solved for the optimal four-cell solution. In order to analyse the performance of the proposed approach in a dynamic environment four time periods have been considered, with production requirements shown in Tables 5 and 6.

The MILP model [$P2$] has been solved using the linear programming software LINGO® v.9 on a 3.3 GHz Intel® Core(TM) i5-2400 CPU, taking 7 s. Tables 7–10 show the optimal solution computed, which has an objective function value of 17.53 (representing total intercellular transportation and inventory holding costs). Solving the problem imposing additional integrality constraints on the x_{ir}^t variables took longer than 8 min and gave an optimal objective function value of 20.71, i.e. an 18.1% gap. Note that the rounding errors for not imposing integrality constraints on the x_{ir}^t variables are less important the higher the values of the demands.

Note that although part types 2, 3, 4 and 5 have similar production requirements in periods 1 and 2, their corresponding production plan varies completely for each period. Thus, although the proposed CRMS uses the same cell configuration for the whole planning horizon, the flexibility provided by the possibility of selecting different process plans allows meeting dynamic production requirements with high system performance.

Table 8. Optimal cell loading solution: inventories (I_i^t).

Part type (i)	I_i^1	I_i^2	I_i^3	I_i^4
1		3.385	0	
2	2.483	2.609	0.103	0
3	0	0		0
4	0	0		0
5	0	0		0
6		0	0	
7	0		0	
8	0		0.770	0
9	0		0	0
10		2.000	0	0

Table 9. Optimal cell loading solution: workloads (u_k^t; w_c^t).

Cell (c)	Machine (k)	u_k^1	u_k^2	u_k^3	u_k^4
I	3	180	232.61	161.367	157.383
	4	108	64.259	138.75	72
	13	98.173	172.665	127.541	65.71
	Total (w_c^t)	386.173	469.534	427.658	295.093
II	9	104.732	109.378	96.623	61.758
	10	167.571	175.005	154.597	105.461
	12	41.893	43.751	38.649	30.521
	Total (w_c^t)	314.196	328.135	289.869	197.739
III	5	126.941	123.702	131.189	45.81
	6	160.69	159.797	152.432	76.866
	7	118.041	137.696	76.865	107.951
	11	105.857	46.799	40.054	39.25
	Total (w_c^t)	511.53	467.994	400.541	269.877
IV	1	204.832	181.257	154.937	98.974
	2	152.971	163.131	139.443	89.077
	8	167.352	145.005	123.949	79.179
	14	58.351	120	120	100
	Total (w_c^t)	583.507	609.393	538.329	367.23
Average	403.55	448.851	468.764	414.099	282.485

The problem has also been solved assuming that for each part type only one of the alternative routes can be used along the whole planning horizon. That approach is quite common in the literature. The criterion that has been used for selecting the route is the minimisation of total intercellular transportation and inventory holding costs in the loading phase. That means adding to model [$P2$] some binary variables δ_{ir} (=1 if route r of part type i is selected, 0 otherwise) and the following constraints, which may also use the upper bounds of the total quantity of each part type to be produced:

$$\sum_r \delta_{ir} \leq 1 \quad \forall i \tag{26}$$

$$\sum_t x_{ir}^t \leq \delta_{ir} \cdot \sum_t D_i^t \quad \forall i, \forall r \tag{27}$$

For this single-route variant, the optimal objective function value that results is 103.68 (104.31 if the values of the variables x_{ir}^t are forced to be integer). Note how, by allowing more than one route per part type, using the same resources (CNC and RMT, tools and auxiliary modules) and balancing the workloads, costs have been greatly reduced due to flexibility. Actually, most of the potential flexibility associated with the existence of alternative routing is lost if, as many approaches do, only one of the alternative routes of each part type is selected in the cell design phase.

Finally, the problem has also been solved using all routes but forcing the selection of just one route per part type in each period, i.e. all alternative routes are available for the cell loading phase, but in each time period only one route per

Table 10. Optimal cell loading solution: number of tools, modules and tool magazine slots used.

Tool type ($z \in$ TT)	$\sum_k \varepsilon_{zk}{}^1$	$\sum_k \varepsilon_{zk}{}^2$	$\sum_k \varepsilon_{zk}{}^3$	$\sum_k \varepsilon_{zk}{}^4$
1	4	4	3	3
2	3	4	3	3
3	5	5	6	4
4	4	4	4	3
5	4	3	3	3
6	6	6	5	6
Module type ($z \in$ AM)	$\sum_k \varepsilon_{zk}{}^1$	$\sum_k \varepsilon_{zk}{}^2$	$\sum_k \varepsilon_{zk}{}^3$	$\sum_k \varepsilon_{zk}{}^4$
7	2	2	2	2
8	2	1	1	1
9	2	2	2	2
CNC machine ($k \in$ NM)	$\sum_z s_{zk}\varepsilon_{zk}{}^1$	$\sum_z s_{zk}\varepsilon_{zk}{}^2$	$\sum_z s_{zk}\varepsilon_{zk}{}^3$	$\sum_z s_{zk}\varepsilon_{zk}{}^4$
1	3	2	2	1
2	2	2	2	1
3	2	2	2	2
4	1	2	2	1
5	2	3	3	2
6	3	3	3	3
7	3	3	2	3
8	3	2	2	2
9	2	2	2	2
10	3	3	3	3
11	2	2	1	2
Reconf. Mach. Tool ($k \in$ RM)	$\sum_z s_{zk}\varepsilon_{zk}{}^1$	$\sum_z s_{zk}\varepsilon_{zk}{}^2$	$\sum_z s_{zk}\varepsilon_{zk}{}^3$	$\sum_z s_{zk}\varepsilon_{zk}{}^4$
12	2	2	2	2
13	2	2	2	2
14	2	1	1	1

Table 11. Optimal cell loading solution: comparison with other approaches.

	Without integrality constraints on $x_{ir}{}^t$		With integrality constraints on $x_{ir}{}^t$	
	Objective function	CPU time (hh:mm:ss)	Objective function	CPU time (hh:mm:ss)
Proposed approach	17.527	0:00:07	20.712	0:08:47
Single-route selection	103.677	0:00:03	104.310	0:00:10
Multiple-route, single assignment per period	100.643	0:00:38	100.911	5:36:51

part type can be selected. In this case, not all the flexibility is lost. This variant involves adding to model [$P2$] some binary variables $\delta_{ir}{}^t$ (=1 if route r of part type i is selected in period t, 0 otherwise) and constraints similar to (26)–(27) for each period. The optimal objective function value obtained is 100.64 (100.91 if the values of the variables $x_{ir}{}^t$ are forced to be integer). Table 11 summarises these results.

5. Conclusions

This study has considered the cell design and multi-period loading problem for CRMS with CNC machines and RMT, taking into account the presence of alternative process plans for each part type. Alternative routing is recognised as an effective means of coping with the loss of flexibility inherent to dedicated machines in CMS. The methodology proposed in this paper has handled both problems sequentially; first solving the cell design once and for all, and then carrying out cell loading for each planning horizon using the solution from the cell design step.

For cell design, an ILP model has been presented that minimises a weighted linear combination of intercellular movements and intracellular voids. This model has been solved optimally, with some heuristic methods from the group technology/cellular manufacturing literature, on an illustrative example. In some of the heuristic methods, process plans are treated as if they were separate part types, and families of process plans and associated machine cells are formed. In one of these methods (namely, SONN), however, the different process plans of each part type are used to form aggregate part types and to group machines using these aggregate part types.

For multi-period cell loading, an MILP model for assigning parts to the alternative routes is proposed, minimising total intercellular transportation and inventory holding costs while keeping intracellular, intercellular and inter-period utilisation approximately balanced. Constraints on tool magazine capacity, number of auxiliary modules per RMT, number of tool and auxiliary modules available, tool and module life restrictions and finite machine capacity are imposed.

The proposed approach has been applied to a small sample for the purpose of illustration and has confirmed that cell design and cell loading for CRMS, considering the specific production features of CNC machines and RMT, can be handled as sequential problems, which can therefore be solved separately. As for the cell design phase, apart from solving the proposed model optimally, some existing cell formation methods have been applied, provided that they do not exclude the subsequent use of any route. As for the cell loading phase, it has been modelled as an MILP aiming at two objectives (i.e. inter-cell flow and workload balancing), allowing in each period the selection of more than one route for each part type in order to take maximum advantage of the existing flexibility.

The machine loading solution obtained using the proposed approach could be validated through simulation, which represents a topic for further research. Thus, by simulating the system configuration, part routing and workloads computed, the system performance for the multiple period production plan may be assessed. Moreover, considering random machine failures and disturbances would also allow studying the robustness of the proposed solution.

Finally, in this paper the solution approach is based on exact methods. However, computing an optimal solution for this type of MILP may become impractical for large sized problems due to the excessive computation time required. This means that for larger problems a metaheuristic solution algorithm would have to be developed. Such an approximate solution approach can be validated by comparing the known optimal solutions with the smaller sized problems. This is also a topic for further research.

Disclosure statement

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