# A NEW COMBINED APPROACH TO SOLVE THE CELL FORMATION PROBLEM WITH ALTERNATIVE ROUTINGS

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Abstract: This paper addresses the cell formation problem with alternative routings and machine capacity constraints. Given processes, machine capacities and quantities of parts to produce, the problem consists in defining the preferential routing for each part optimising the grouping of machines into manufacturing cells. The principal objective is to minimise the inter-cell traffic, while respecting machine capacity constraints. To solve this problem, we propose an integrated approach based on a multiple-objective grouping genetic algorithm for the preferential routing selection of each part (by solving an associated resource planning problem) and a heuristic for the cell formation problem.

Key words: Cellular; alternative routings; grouping genetic algorithm; multiple objectives.

## 1. INTRODUCTION

During the last years, the cell formation problem has been addressed in numerous works. A survey of approaches to the cell formation problem is given in [12]. In this paper, we focus on the cell formation problem with alternative routings and machine capacity constraints. Several routings are available for each part with a defined manufacturing process. In the same issue, different resolution methods are proposed in [1, 5, 11]. Gupta [7] proposed a two-step algorithm to solve this problem. One routing is definitely determined for each part, respecting machine capacity constraints. Next, cell formation is achieved. The drawback of this method is its sequential approach. Routing selection is performed once and the flexibility given by

[1] This project is carried out in collaboration with the Belgian Research Center for the metal-working industry (CRIF) and funded partially by the 'Région wallonne' and the 'Région flamande'.

alternative routings is not used to minimise inter-cell traffic. Nagi *et al*. [13] proposed an iterative method solving the two distinct sub-problems: cell formation, tackled with a heuristic and routing selection, addressed with the Simplex method. The use of the simplex limits the size of the considered problem. Caux *et al.* [3] proposed an approach based on simulated annealing and a branch-and-bound algorithm in order to perform routing selection and inter-cell traffic minimisation simultaneously. Each operation is performed on a given machine and each part has several possible process plans.

In this paper, we propose a new integrated approach based on a multiple objective grouping genetic algorithm (MO-GGA) to solve the routing selection problem, and an embedded heuristic to simultaneously treat the cell formation problem.

## 2. PROBLEM DESCRIPTION

The problem can be decompose in two distinct sub-problems: the grouping of operations on machines, yielding flows between the machines, and the grouping of these machines into cells to minimise the inter-cell traffic. The necessary data and hypothesis are presented hereunder. We consider a set $M = \{m_1, m_2, ..., m_m\}$ of $m$ machines in a given manufacturing system. Each machine $n$, unique and different for the resolution, is characterised by a availability parameter $d_n$. which is equal to her capacity value times her availability rate. This value must take all failures into account. We also define a set $\{p_1, p_2, ..., p_p\}$ of $p$ products. One and only one process (a sequence of $NO_k$ operations $\{o_{k1}, o_{k2}, ..., o_{k\,NOk}$) is defined for each product $k$. The major difference with earlier studies resides in the specification of this process. Each operation is not performed on one given machine but is defined as an operation type that can be accomplished on one machine type (lathe, etc.). So each operation can be performed on all machines belonging to its type. So we define a set $T = \{tm_1, tm_2, ... tm_t\}$ of $t$ machine types capable of doing all types of operations. Each machine belongs to one or several types if it is a multi-functional machine. With this hypothesis, a product has several potential routings available for a specific process. The operating time of each operation can be fixed for the considered machine type, or particularised to a specific machine. The choice of preferential routing is made by the algorithm simultaneously at the cell formation.

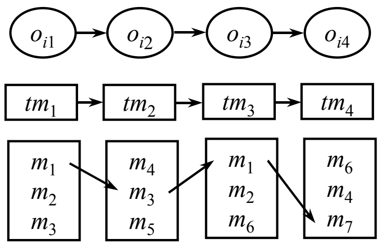


*Fig. 1.* One process corresponds to several potential routings.

This concept is illustrated in Fig. 1. A product is defined by four operations, and thus four machine types. As can be seen, a given machine $m_l$ may belong to several types (for instance $m_1$ belongs to $tm_1$ and $tm_3$. The preferential routing can be $\{m_1, m_3, m_1, m_7\}$.

The orient the grouping, we define a similarity coefficients ($SP_{kl}$), computed following Irani's method [10], between products $k$ and $l$.

To limit the difficulty of data collection, cost is taken into account through a lower utilisation limit ($LL_n$) for each machine $n$. It is a fraction of the machine availability $d_n$. The limit will be set near 100% if the machine is expensive and its use mandatory. On the other hand, this limit will be lesser than 50 % if the machine is cheap, could be doubled and must not be highly loaded to be profit-earning. A higher utilisation limit ($HL_n$) is also defined for each machine. It is used to impose some flexibility to the system. So if there is a failure on a machine, the production can be reoriented to non-fully loaded ones. If the user wants a high flexibility, he will fix $HL_n$ at a relatively low value (70% for instance). As illustrated in Fig. 2 ($U$ is the actual machine utilisation), these two limits are not considered as hard constraints, but are used in the evaluation of a proposed solution.

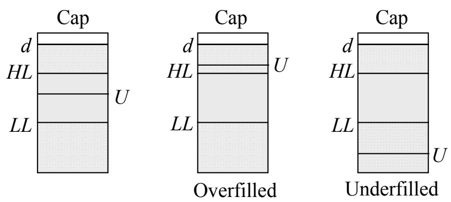


*Fig. 2.* Three case of machine utilisation in function of limit use.

## 3. MO-GGA

The genetic algorithms (GAs) are an optimisation technique inspired by the process of evolution of living organisms [9]. The basic idea is to maintain a population of chromosomes, each chromosome being the encoding (a description or genotype) of a solution (phenotype) of the problem being solved. The worth of each chromosome is measured by its fitness, which is often simply the value of the objective function of the point of the search space defined by the (decoded) chromosome. Falkenauer pointed out the weaknesses of standard GAs when applied to grouping problems, and introduced the GGA [6], which is a GA heavily modified to match the structure of grouping problems. Those are the problems where the aim is to group together members of a set (i.e. find a good partition of the set). The GGA operators (crossover, mutation and inversion) are group-oriented, in order to follow the structure of grouping problems.

Applying GAs to solve multiple-objective problems (MOP) has to deal with the twin issues of searching large and complex solution spaces and dealing with multiple, potentially conflicting objectives. The proposed approach is based on a merge of search and multicriteria decisions. Indeed, in order to come out of the MOP stated by the cost function, the authors stated for the multicriteria decision-aid method called PROMETHEE II [2]. The complete description of this method is out of the scope of this paper. It is however important to know that it computes a net flow $\phi$ which is a *kind of fitness* for each solution. This “fitness” yields a ranking, called the PROMETHEE II complete ranking, between the different solutions in the population. The relative importance of the different objectives are set *transparently* thanks to weights associated to each criterion. The used multi-objective grouping genetic algorithm (MO-GGA) is presented by Rekiek [14].

# 4. ITERATIVE SOLVING APPROACH

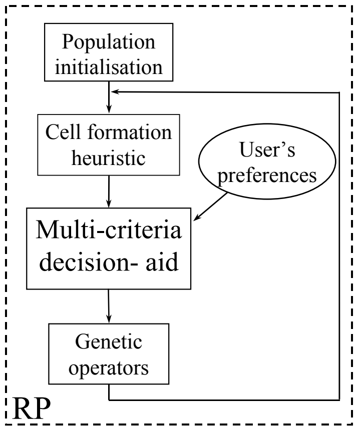


*Fig. 1.* MO-GGA with cell formation integrated heuristic.

To solve the whole problem, we use a adapted MO-GGA as shown in Fig. 1 (RP-MOGGA). The RP-MOGGA compute the allocation of operations on specific machines and the integrated cell formation heuristic add to each solution, the best grouping in cells.

A population of chromosomes (groups of operations on machines) is first initialised. All chromosomes are evaluated to compute their fitness according to several criteria: a cell formation coefficient as mentioned previously, a similarity coefficient, a multifunctional machine coefficient, a flexibility and a cost coefficients. The principal criterion to evaluate the individuals of the population is the quality of formed cell. So the cell formation heuristic (Harhalakis [8]) is applied to each chromosome, providing a grouping of machines into cells. This is an originality of the proposed approach: one of the outputs of the algorithm (the cells), resulting from a heuristic, is used to evaluate the quality of the solutions proposed by the RP-MOGGA. The best solutions are selected to be parents for the next generation of the RP-MOGGA. Genetic operators are applied, yielding a new population that is evaluated after the application of the cell formation heuristic to each individual.

# 5. ALGORITHM IMPLEMENTATION

## 5.1 Chromosome encoding and operators

The chromosome encoding and the used operators follow the classical pattern of a grouping genetic algorithm. The groups here represent machines and elements of the groups the operations.

## 5.2 Hard constraints

Two conditions are fixed for an individual to be valid. First, every operation is assigned to a accessible machine of the type required by the operation. Second, the availability of a machine cannot be overstepped.

## 5.3 Cost function

As mentioned in section 3, individuals are compared with each other thanks to the PROMETHEE II method. Five criteria are taken into consideration in the comparison of solutions: similarity between products (*RS*), use of multi-functional machines (*RM*), flexibility (RF), cost (*RC*) and cell formation coefficient (*RG*).

**Maximise the similarity coefficient :** The coefficients $SP_{kl}$ are used to compute filtered coefficients $S_{kl}$ by the parameters p (preference threshold) and q indifference threshold) as follows:

Similarity: $S_{kl} = 1$ if $p \le SP_{kl}$;
Indifference: $S_{kl} = SP_{kl}$ if $q \le SP_{kl} < p$;
Dissimilarity: $S_{kl} = 0$ if $SP_{kl} < q$.

The similarity factor *RS* is then computed as the sum of $RS_n$ coefficients, defined for each machine *n* by (1).

$$RS = \frac{1}{m}\sum_{n=1}^{m} RS_n \text{ with } RS_n = \sum_{l=1}^{p}\sum_{k=1}^{p}\left(\sum_{i=1}^{NO_l}\sum_{j=1}^{NO_k} \mathrm{S}_{\mathrm{kl}} \cdot \delta_{kin} \cdot \delta_{ljn}\right) \Bigg/ \sum_{q=1}^{NbO_n - 1} q \; ; \qquad (1)$$

$\delta_{kin} = 1$ if the operation *i* of the part *k*, $O_{ki}$, is assigned to machine *n*,
$NbO_n$ the number of operations assigned to machine *n*.

We can illustrate the principle with machine 3 performing four operations ($O_{13}$, $O_{25}$, $O_{42}$, $O_{11}$). We must compare the similarity between parts $P_1$, $P_2$ and $P_4$. Supposing that we have the following similarity coefficients: $SP_{12} = 0.68$; $SP_{14} = 0.83$; $SP_{24} = 0.23$, $S_{kl}$ ($S_{12} = 0.68$; $S_{14} = 1$; $S_{24} = 0$ ) can be computed in function of indifference ($q = 0{,}4$) and preference ($p = 0{,}8$) thresholds. The similarity coefficient $RS_3$ for machine 3 is the sum of six coefficient $S_{kl}$ between each product resulting from four operations and compared to by two ($P_1 - P_2$; $P_1 - P_4$; $P_1 - P_1$; $P_2 - P_4$; $P_2 - P_1$; $P_4 - P_1$). So we have $RS_3 = (0.68 + 1 + 1 + 0 + 0.68 + 1)/(3 + 2 + 1) = 0.727$.

**Minimise the multi-functional machine coefficient:** The problem with the similarity coefficient is that the algorithm privileges the grouping of similar operations on multi-functional machines. To minimise the flows, it is necessary to put on this machine the operations belonging to the process of a part. For this reason, we introduce the multi-functional coefficient. The parameter $MM_k$ is defined as the sum of different used machines in the chosen routing for product $k$ divided by $NO_k$ (the number of operations in the process of product $k$):

$$RM = \left( \sum_{k=1}^{p} MM_k \right) \Big/ p . \tag{2}$$

**Minimise the flexibility coefficient:** A pursued objective is to respect the target workshop flexibility. So, we penalise all overstepping of high limit ($HL_n$) fixed for each machines (section 2).

$$RF = \frac{1}{m} \sum_{n=1}^{m} \max\left\{ 0, \frac{(U_n - HL_n \times d_n)}{(d_n - HL_n \times d_n)} \right\} . \tag{3}$$

**Minimise the cost coefficient:** we must minimise the cost of the production system. So, we introduce a penalty on each machine whose the utilisation ($U_n$) is inferior to the low limit ($LL_n$):

$$RC = \frac{1}{m} \sum_{n=1}^{m} \max\left\{ 0, \frac{(LL_n \times d_n - U_n)}{LL_n \times d_n} \right\} . \tag{4}$$

**Maximise the cell formation coefficient:** This coefficient is computed after the application of a cell formation heuristic (Harhalakis' algorithm [8]), on the basis of the part flows between machines resulting from the allocation of operations on them. Once cells have been formed, the intra-cell flow ($\Phi_{\text{intra}}$) is computed and divided by the total flow between machines (Φtot).

$$RG = \Phi_{\text{intra}} / \Phi_{tot} . \tag{5}$$

## 6. RESULTS

The method has been implemented on a Windows workstation in the C++ programming language. Our case study is issued from Vivekanand [15]. It considers 12 parts and 6 machines. Some data about machine type has been completed to get all information we needed. The data used to test the method is presented in Tab. 1.

Availability of machines is expresses in minutes/week: $m_1$: 4200; $m_2$: 4260; $m_3$: 4980; $m_4$: 5400; $m_5$: 4620; $m_6$: 5340. Each part type requires up to four operations, with up to three alternative machines for performing each of them. The demand of each part is: $p_1$: 110; $p_2$: 120; $p_3$: 80; $p_4$: 150; $p_5$: 50; $p_6$: 60; $p_7$: 100; $p_8$: 50; $p_9$: 50; $p_{10}$: 90; $p_{11}$: 50; $p_{12}$: 90 units/week.

| Op | T | Op. Time | Op. Time | Op. Time | Op | T | Op. Time | Op. Time | Op. Time |
|---|---|---|---|---|---|---|---|---|---|
| $O_{1\,1}$ | 1 | $m_1$:7.68 | $m_3$:6.72 | | $O_{7\,1}$ | 3 | $m_4$:7.80 | $m_3$:6.36 | |
| $O_{1\,2}$ | 2 | $m_2$:7.80 | $m_1$:6.78 | | $O_{7\,2}$ | 2 | $m_3$:6.84 | $m_1$:6.36 | |
| $O_{1\,3}$ | 1 | $m_3$:6.72 | | | $O_{7\,3}$ | 1 | $m_2$:6.90 | $m_3$:6.66 | |
| $O_{1\,4}$ | 3 | $m_4$:6.42 | $m_5$:6.42 | | $O_{8\,1}$ | 1 | $m_3$:6.00 | $m_1$:6.36 | |
| $O_{2\,1}$ | 3 | $m_4$:7.74 | $m_5$:6.48 | | $O_{8\,2}$ | 3 | $m_4$:6.78 | $m_1$:7.44 | |
| $O_{2\,2}$ | 1 | $m_1$:7.14 | $m_4$:6.24 | | $O_{8\,3}$ | 1 | $m_5$:6.00 | $m_1$:7.26 | |
| $O_{2\,3}$ | 3 | $m_5$:6.24 | | | $O_{8\,4}$ | 2 | $m_3$:6.96 | $m_2$:7.50 | |
| $O_{3\,1}$ | 3 | $m_4$:7.62 | $m_5$:6.72 | | $O_{9\,1}$ | 2 | $m_3$:6.06 | $m_2$:7.14 | |
| $O_{3\,2}$ | 1 | $m_4$:7.44 | $m_3$:7.80 | | $O_{9\,2}$ | 3 | $m_4$:6.78 | $m_3$:7.26 | |
| $O_{4\,1}$ | 2 | $m_6$:7.14 | $m_2$:7.02 | | $O_{9\,3}$ | 1 | $m_3$:6.12 | $m_1$:6.18 | |
| $O_{4\,2}$ | 3 | $m_4$:6.90 | $m_2$:6.06 | | $O_{10\,1}$ | 3 | $m_5$:6.72 | $m_4$:6.18 | |
| $O_{4\,3}$ | 2 | $m_6$:6.54 | | | $O_{10\,2}$ | 2 | $m_5$:7.26 | $m_2$:6.06 | |
| $O_{4\,4}$ | 2 | $m_6$:6.00 | $m_2$:6.78 | $m_1$:7.62 | $O_{10\,:3}$ | 2 | $m_2$:6.90 | $m_5$:6.54 | |
| $O_{5\,1}$ | 2 | $m_3$:7.20 | $m_2$:7.32 | | $O_{10\,4}$ | 3 | $m_5$:6.54 | | |
| $O_{5\,2}$ | 1 | $m_3$:7.38 | $m_1$:7.44 | | $O_{11\,1}$ | 1 | $m_3$:7.20 | $m_1$:7.44 | |
| $O_{5\,3}$ | 3 | $m_1$:7.20 | $m_2$:6.66 | | $O_{11\,2}$ | 1 | $m_3$:7.02 | $m_1$:7.14 | |
| $O_{5\,4}$ | 1 | $m_1$:7.44 | $m_3$:7.68 | | $O_{11\,3}$ | 1 | $m_1$:7.80 | $m_3$:7.74 | $m_5$:7.44 |
| $O_{6\,1}$ | 2 | $m_6$:6.96 | $m_2$:6.90 | | $O_{12\,1}$ | 3 | $m_3$:6.54 | $m_4$:6.60 | $m_5$:6.60 |
| $O_{6\,2}$ | 2 | $m_6$:7.62 | $m_2$:7.02 | | $O_{12\,2}$ | 3 | $m_4$:7.62 | $m_5$:6.48 | |
| $O_{6\,3}$ | 2 | $m_3$:6.42 | $m_1$:6.90 | | $O_{12\,3}$ | 3 | $m_5$:7.62 | $m_4$:7.74 | |
| $O_{6\,4}$ | 2 | $m_3$:6.48 | $m_2$:6.96 | $m_6$:6.30 | | | | | |

*Tab. 1*. Operations and operating times.

The result provided are presented in Tab. 2 :

| Machine | Operations | Utilisation | Cell |
|---|---|---|---|
| 1 | $O_{1\,3}$, $O_{1\,4}$, $O_{2\,3}$, $O_{2\,3}$, $O_{7\,1}$, $O_{12\,1}$, $O_{12\,3}$, | 4185.0 | 2 |
| 2 | $O_{5\,1}$, $O_{6\,1}$, $O_{6\,3}$, $O_{6\,4}$ | 1597.2 | 3 |
| 3 | $O_{3\,1}$, $O_{3\,2}$, $O_{7\,3}$, $O_{10\,1}$, $O_{10\,2}$, $O_{10\,3}$, $O_{10\,4}$, $O_{12\,2}$ | 4871.4 | 2 |
| 4 | $O_{1\,1}$, $O_{2\,1}$, $O_{2\,2}$, $O_{4\,2}$, $O_{5\,2}$, $O_{5\,3}$, $O_{11\,1}$, $O_{11\,2}$, $O_{11\,3}$ | 5324.6 | 1 |
| 5 | $O_{5\,4}$, $O_{8\,1}$, $O_{8\,2}$, $O_{8\,3}$, $O_{8\,4}$, $O_{9\,2}$, $O_{9\,3}$ | 5362.5 | 3 |
| 6 | $O_{1\,2}$, $O_{4\,1}$, $O_{4\,3}$, $O_{4\,4}$, $O_{6\,2}$, $O_{7\,2}$, $O_{9\,1}$ | 5201.1 | 1 |

*Tab. 2*. Result of cell formation procedure.

For this solution, all criteria are evaluated. We obtain:
*RS* = 0.699 % of operations on a machine are similar in average;
*RM* = 0.569 % of different machines are used to do all the process of a product;
*RF* = 2.822 overstepping penalty are computed for the high limit;
*RC* = 0 There are no under filled machine;
*RG* = 0.711 % of the total traffic (16511.3 hours of work) is an intra-cell traffic. The inter-cell traffic is reduced to 4770.3 hours and intra-cell traffic increased to 11741 hours.

## 7. CONCLUSIONS

In this paper, we presented an original method to address the cell formation problem with alternative routings, based on a multiple-objective grouping genetic algorithm, taking several criteria into account. Considering the three most important production parameters in cell design (namely production volume, process sequences and alternative routings), the method optimises the cell formation and chooses the preferential routing of each product. In further works, the embedded cell formation heuristic will be replaced by a meta heuristic approach, to avoid being trapped in local optima during both the optimisation of the part routings and the determination of the cells.

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