AN INTEGRATED APPROACH FOR THE DESIGN OF PLANT LAYOUT AND MATERIAL FLOWS

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Abstract

Cellular Manufacturing is a successful application of Group Technology concepts: we want to group parts into families having similar characteristics and identify dedicated set of machines (cells) to process the different families while minimizing the number of parts that need to be processed by machines placed in different cells (Inter-Cell Flow). The proposed approach consists on iteratively running an algorithm for the cell formation. At each iteration, (*i*) we run a simulation for the cell configuration obtained in the optimization phase, (*ii*) we measure a set of performance indicators, and, (*iii*) on the ground of a suitably designed feedback indicator, we re-define similarity coefficients for the cell formation. Both in the optimization and feedback phases, techniques based on a greedy-like approach and Simulated Annealing are introduced. Simulation experiments are performed varying demand scenarios and material flow management rules. Encouraging results are presented and discussed.

Keywords: Group Technology, Optimization, Simulation

1 INTRODUCTION

Group Technology concepts were introduced by Mitrofanov (1959) with the goal of identifying similar attributes of objects (*parts*) to be produced. One of the most successful application of these concepts is the so called *Cellular Manufacturing*: we want to group parts into *families* with similar characteristics and identify dedicated set of machines (*cells*) to process the different families [1, 2]. So doing, the objective is to minimize the number of parts that need to be processed by machines that are placed in different cells (from now on *Inter-Cell Flow*, or ICF). According to Selim, Askin and Vakharia [3], this approach represents an hybrid between Job Shop and Flow Shop production system. Referring to Askin and Standridge [4] a manufacturing designer through these concepts aims at obtaining "the advantages of flow line systems in environments previously ruled by job shop procedures". Unfortunately, considering Inter Cell Flow as a unique indicator in the cell formation phase, may result in a very poor layout from the point of view of other more "productivity-related" indicators (such as, WIP, Mean Flow Time etc.) Hereafter we propose a novel integrated approach aiming at supporting the design phase of a *cellular* layout of a manufacturing production plant taking into account traditional indicators such as Flow time, WIP, production rate and number of tardy parts.

Recent advances in meta-heuristics have encouraged the creation of approaches and tools that integrates simulation and optimization techniques [5].

Figure 1 illustrates our integrated optimization/simulation approach. The basic procedure consists of the iterative execution of a standard cell formation algorithm relying on the definition of machine-pair similarity coefficients and on clustering techniques. At each iteration we consider similarity coefficients modified on the ground of some performance indicator (feedback indicator) obtained from the analysis of a simulation run. The output of this first phase (optimization phase) is a possible plant layout. In the successive iterations, we may improve the layout in terms of other indicators. In a second phase (simulation phase), simulations are performed varying demand scenarios, and, more importantly, adopting different Machine Queue Priority (Material Flow Management) rules. We investigate two different approaches for the optimization phase: a greedy-like algorithm and an algorithm based on Simulated Annealing (SA). Also in the feedback phase we test two different methods, namely, a *deterministic* method and a method based on SA.

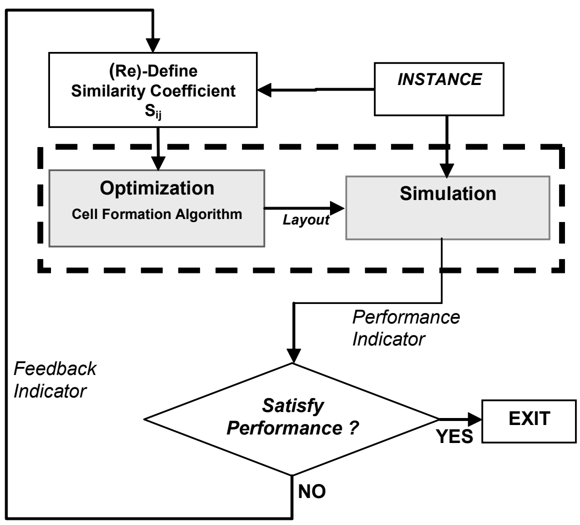


Figure 1: Integrated Optimization/Simulation Approach

The remainder of this paper is organized as follows: we first present the main features of the optimization phase and the similarity coefficient method and how we use feedback indicators to obtain modified similarity coefficients for the next iteration of the layout optimization phase. We then describe the simulation phase in Section 3 including the automatic generation of the model. Section 4 is devoted to the description of the experiments and Section 5 to computational results. Conclusions follow.

2 OPTIMIZATION PHASE: THE CELL FORMATION PROBLEM

In this section we focus on the layout design phase. This is *the* typical application of the Group Technology concepts consisting of determining the (disjoint) sets of machines called *cells*. In our study we make use of standard methods of the Group Technology literature but in a new framework where the input of an optimization problem accounts for the results of a simulation run.

Similarity coefficients are well known instruments for the cell formation problem. A similarity coefficient s_{jh} measures the degree of "similarity" between two machines j and h, *given* the set P of parts to be produced together with their *part-cycles*. The basic idea of this approach is to reduce the family formation problem to a special graph partitioning (clustering) problem in the following way:

1. Define the undirected complete graph $G = (M, E)$, where M is the set of machines, E is the set of all the possible machine pairs jh, and edge jh has weight equal to the similarity coefficient s_{jh}.

2. Solve the clustering problem on G: it consists of determining k disjoint and non-empty sets (i.e., cells) of nodes (i.e., machines) such that the total weight of edges with endpoints in different sets is minimized. This is also equivalent to maximize the sum of similarity coefficients corresponding to machine pairs belonging to the same set. As the computational complexity is concerned, such a problem is NP-Hard.

The above procedure makes it convenient to place very similar machines in the same cell or poorly similar machines in different cells.

A large number of similarity coefficients has been proposed in the group technology literature, see for instance Yong [6] for a review. In our study we make use of known similarity coefficients that are reported in Table 1, where:

- a is the number of parts visiting both machine j and h;
- b [and c] is the number of parts visiting j [h] but not h [j];
- d is the number of parts visiting nor h and j.

Notice that these similarity coefficients ranges in the interval [0,1].

Table 1: Two similarity coefficients

Coefficient name	s_{jh}	*Range*
Jaccard	$\frac{a}{a+b+c}$	0-1
Simple Matching	$\frac{a+d}{a+b+c+d}$	0-1

In our integrated approach, the clustering problem is solved by using a simple *greedy*-like algorithm (see [7]), and by a SA-based algorithm which is described in the following paragraph.

2.1 Simulated Annealing algorithm for the cell formation phase

In the optimization phase we exploit the application of SA techniques in order to overcome the disadvantages related to local search methods. The SA approach has been introduced in 1983 by Kirkpatrick, Gelatt and Vecchi [8] and well adapted to many combinatorial optimization problems and, in particular, to manufacturing systems layout design (see Souilah [9]). SA technique is based on statistical mechanic concepts concerning the solid annealing process which takes into account stochastic relations concerning the behavior of a system in thermal equilibrium.

In our implementation, we make use of two indicators: the main performance indicator for a given layout configuration is ICF. We also make use of another indicator, namely, the *Intra-Cell Flow* for cell k that is the number of parts exchanged between machines placed *in* cell k.

Starting from a feasible layout S_0 -generated, for instance, with the greedy-like approach -we consider moving a machine from one cell to another. Let $c(h)$ be the cell where machine h is located and identify a pair of machines j and h, placed in different cells and corresponding to a largest coefficient s_{jh}, i.e.:

$$s_{ij} = \max\{s_{rt} : c(r) \neq c(t)\} \qquad (1)$$

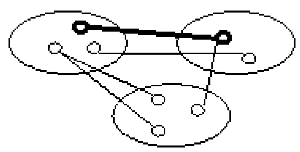
(see figure 2). In order to decide what machine is moved, we compute the intra-cell value corresponding to cell $c(h)$ after moving machine j to this cell, and the intra-cell value corresponding to cell $c(j)$ after moving machine h to this cell. In conclusion we move the machine to the cell corresponding to the larger intra-cell flow increment. We refer to this new layout as S'. The modified solution S' is accepted on the ground of the ICF values coming from the output of two simulation runs for these two layout configurations. Using the Metropolis rule [8,9]:

- Let ICF_0 be the inter-cell value corresponding to S_0
- Let ICF' be the inter-cell value corresponding to S'
- Let $\Delta = ICF' - ICF_0$

If $\Delta < 0$ then the layout is updated to S' else S' is accepted with a probability

$$p = e^{-\frac{\Delta}{T}} \qquad (2)$$

where the *temperature* T is a parameter which, starting from an initial value T_0, decreases as the algorithm



proceeds.

Figure 2: Arc with maximum similarity coefficient value, for a generic layout configuration *S*.

The SA parameters setting included in our optimization module is presented in the following. The initial temperature T_0 is set to 50°. In SA, for a fixed value of the temperature, several solutions (accepted or not) are generated. This number is a parameter called *epoch length N*. In our approach augmenting the N value turns out to be not particularly effective, therefore in most experiments N equals few units. The selected decreasing function of the parameter T is a commonly used [8] geometric function:

$$T_n = rT_{n-1} \tag{3}$$

where r represents the *cooling ratio* which is set to 0.8. Then the algorithm *stopping criterion* is represented by a freezing temperature, equal to T_{freezing} = 10° so that when $T < T_{\text{freezing}}$ then the algorithm stops.

2.2 Similarity coefficient modification for the feedback phase

In the proposed approach, we exploit the results of simulation experiments as a *feedback* for possible re-design of the cells layout (see Figure 1). To do this we developed similarity coefficients formulas that take into account the indications that we may derive from the last simulation runs.

The similarity coefficient modification has been implemented in two different way, (*i*) deterministic and (*ii*) SA-based. The first one impacts on a similarity coefficient formula with an additional normalized contribution in the ratio. The second one impacts in the formula in terms of a substitution of an element in the ratio coming from a SA procedure. The comparisons between the performance related to the two modification strategies will be illustrated in Section 5.

As (*i*) the deterministic approach is concerned, we tested the following modification of the Jaccard coefficient (see Table 1):

$$\bar{s}_{jh} = \frac{a+e}{a+b+c+e} \tag{4}$$

with the usual meaning for *a*, *b*, *c*, *d*. Parameter *e* is (directly or inversely, depending on the particular indicator) proportional to *one* selected performance indicator. Simulation experiments show that, for this purpose, it is not effective to consider more than one indicator. Notice that, $\bar{s}_{jh}$ still ranges in the interval [0,1].

With reference to the SA-based similarity coefficient modification, we illustrate hereafter the basic idea with reference to the Jaccard formula. After a simulation run, we measure a generic indicator; for instance the number of parts exchanged between two machines (IMF) and denote it by *e* (after a suitable normalization). We then compute the modified similarity coefficient

$$\bar{s}'_{jh} = \frac{e}{e+b+c} \tag{5}$$

i.e., the new element *e* replaces *a* in the similarity coefficient. In the successive optimization phase, we are using this new coefficient with a certain probability. To this purpose we define

$$\Delta = s_{jh} - \bar{s}'_{jh} \tag{6}$$

If $\Delta < 0$ we accept the new coefficient. Otherwise we accept it with a probability equal to (2). Machine-similarity matrix is modified accordingly. The meaning of these operations consists of enriching the information contained in the similarity coefficient with the feedback derived from a simulation run (see Figure 1). In this particular example (where Jaccard coefficient and IMF are used), we modify (increase) the similarity coefficient value when simulation indicates a larger amount of parts exchanged between two machines.

The settings for temperature *T* remain similar to those illustrated in Section 2.1.

As regards the indicators used as a feedback, we identify two main categories:

Machine-related indicators: possible machine-related performance indicators are utilization ratio, size of waiting parts' queue, parts' average waiting time. In our experiments, we focus our attention on ICF (inter-cell flow, i.e., the number of parts visiting machines more than one cell.)

Part-related indicators: we measure as a simulation output the following indicators for each part type: WIP (Average, Max, Min), Flow time (Average, Max, Min), Number of Tardy Parts (Average, Total, Max, Min).

ICF is particularly important since it depends on the parts' cycles but also on the demand volume for those parts. Traditional formulas (reported in Table 1) does not consider the effect of the demand volume. In our work, similarity coefficient have been re-designed for taking into account this important issue.

3 SIMULATION PHASE

3.1 Automatic Generation of the Simulation Model

Once the optimization phase has been completed, a new layout is available for the testing phase. For this purpose we developed a special tool for *automatically* generating the simulation model of the layout obtained by the last optimization phase. Automatic generation of the simulation model has been helpful to speed up the experimental phase and hence for testing our layout design tool prototype.

We used the simulation environment provided by Arena, (Rockwell) whose features enables implementing the automatic model generation tool in Visual Basic® for Application. The main function of this tool consists of a user interface (*userform*) that makes it possible for the user to modify demand levels, machine queues priority rules, parts' due dates, number of cells, and, also, number of machines and parts.

All the variables are automatically loaded once the userform has been compiled. Figure 3 shows the user interface mask and the graphic of a simulation model.

4 EXPERIMENTAL DESIGN PHASE

Test phase has been performed on several instances generated varying a number of parameters denoted as *factors*. These are set to different values (*levels*) in different instances. Adopting a DOE-like approach, we only performed a significant subset of all the experiments resulting from combining all the possible factors' levels.

We compared the performance of three different settings: in the first one, we use the greedy-like approach for the optimization phase and the deterministic modification of the similarity coefficients in the feedback phase. The second setting adopts the greedy-like approach for the optimization and the SA-based feedback phase. Finally, in the third setting a SA-based approach is used both for the optimization and the feedback phase.

4.1 Factor levels

The varying parameters (factors) and the different levels for each parameter are in order:

Instance: characterized by the following input data, *for each part*: part cycles (the sequence of machines visited by one part), daily demand, due date, processing times at visited machines, travel times, layout, *feedback* performance indicators.

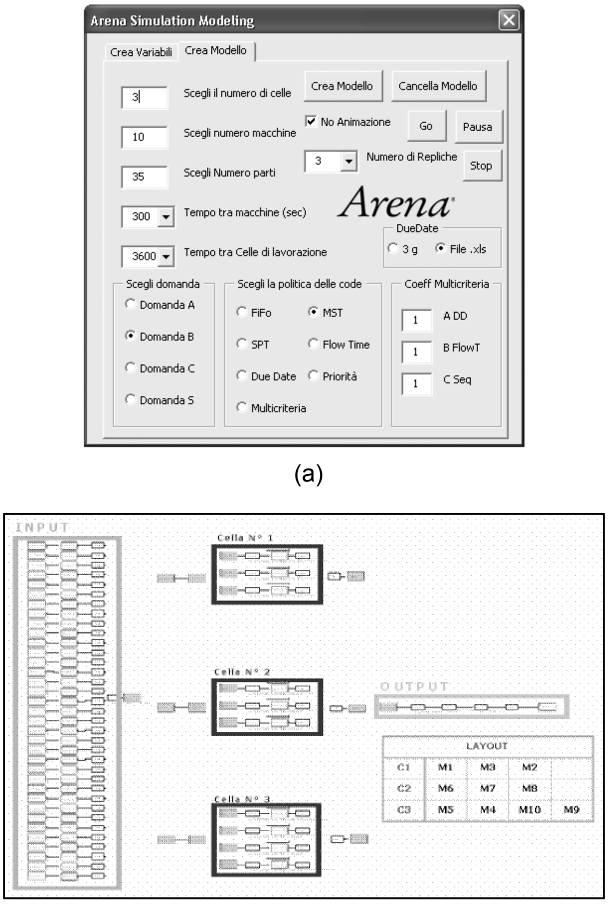
Queue priority rules: FIFO, Shortest Processing Time (SPT), Minimum Slack Time (MST), MC (a linear combination of different criteria).

Similarity coefficients: Jaccard, Simple Matching (see Table 1), Russel and Rao, Sokal and Sneath 2 (see [6]).

Indicators: Inter-Machine flows (IFM), Mean Flow Time, Max Flow Time, Number of Tardy Parts (LST).

Demand levels: Demand Level B (medium congestion), Demand Level C (high congestion).

The experiments have been performed as follows. The selected instances have three levels in the number of part types and machines. More in particular the size of the first instance is 35 part types and 10 machines (35/10), the second 50 part types and 15 machines (50/15), the third 70 part types and 20 machines (70/20). The last instance has been tested only by the SA-approach.



(a)

(b)

Figure 3: Simulation "userform" (a) and graphic of a simulation model with 3 cells (b)

5 COMPUTATIONAL RESULTS

For the sake of clarity, the computational results presented hereafter relates to a meaningful subset of performance indicators for each layout configuration. In particular we consider:

- Inter-Cell Flow (ICF),
- Parts' Mean Flow Time (PMFT)
- Number of Tardy Parts (LST)
- Average Number of Parts in Queue (ANPQ)
- Average Waiting Time in Queue (AWTQ)

As pointed out at the beginning of Section 4, we report the results for three different settings:

1. Greedy-like: greedy-like approach for the optimization phase and deterministic modification in the feedback phase.
2. SA-feedback: greedy-like for the optimization and the SA-based feedback phase.
3. SA: a SA-based approach is used both for the optimization and the feedback phase.

Tables 2 and 3 show the results obtained for an instance size of 35 part types and 10 machines. This instance has been tested for a medium demand level, i.e. demand level B (see Table 2) and for an high demand level, i.e. demand level C (see Table 3). The results concerning the SA-feedback setting, have been obtained using a Simple Matching similarity coefficient, MST as Machine Queue Priority rule and LST as feedback indicator. For the SA setting, the *Jaccard* similarity coefficient, the FIFO Machine Queue Priority rule and the IFM as the feedback indicator have been used.

Table 2: Comparisons Instance 35/10 - Demand level B

Indicator	*Units*	*Greedy-like*	*SA feedback*	*SA*
ICF	# of parts	314303	307224	89394
PMFT	days	0.851	0.849	0.843
LST	%	5.19	4.83	4.74
ANPQ	# of parts	49.38	49.38	59.91
AWTQ	days	0.260	0.260	0.299

Table 3: Comparisons Instance 35/10 - Demand level C

Indicator	*Units*	*Greedy-like*	*SA feedback*	*SA*
ICF	# of parts	329816	322294	136017
PMFT	days	1.23	1.18	1.17
LST	%	10.61	9.71	9.92
ANPQ	# of parts	83.59	79.30	88.10
AWTQ	days	0.451	0.434	0.462

As one may expect, since the feedback indicator (IFM) is directly related to the performance we want to improve, ICF dramatically decreases adopting the SA setting (see Table 2). For higher demand level (Demand Level C) the system becomes more congested and we observe a moderate performance improvement in terms of LST, ANPQ, AWTQ in the experiments corresponding to the SA- feedback setting (see Table 3). However the best performance in terms ICF and PMFT persists when SA is adopted also in the optimization phase.

The best results, independently on the used approach, are always obtained within the third iterations of the optimization-simulation process. For the 35/10 instance, the number of cells obtained using the different approaches are 3, 3, 2, respectively for the greedy-like, SA feedback, and SA. The layout with two cells is partly responsible of the decreased ICF values obtained in the experiments with the SA setting.

Tables 4 and 5 summarizes the simulation outputs for an instance size of 50 part types and 15 machines. We may observe that the best performance is obtained with the SA-feedback setting. In particular, these results are produced using a Simple Matching similarity coefficient, a FIFO Machine Queue Priority rule and IFM as feedback indicator. The SA setting provides better results than the greedy-like setting; it has been performed selecting the Jaccard formula as similarity coefficient, FIFO as Machine Queue Priority and IFM as feedback indicator. Also in these experiments it is confirmed the positive impact of IFM as feedback indicator on ICF and PMFT. This trend, as expected, persists in each of the two demand levels scenarios, i.e. B e C.

For the 50/15 instance, the number of cells obtained using the different approaches are 5, 2, 3, respectively for the greedy-like, SA feedback, and SA. The layout with two cells is partly responsible of the decreased ICF values obtained in the experiments with the SA-feedback setting.

Table 4: Comparisons Instance 50/15 - Demand level B

Indicator	*Units*	*Greedy-like*	*SA feedback*	*SA*
ICF	# of parts	380741	71488	160302
PMFT	days	2.18	2.12	2.14
LST	%	34.48	33.52	33.84
ANPQ	# of parts	155.97	161.46	159.94
AWTQ	days	0.431	0.449	0.445

Table 5: Comparisons Instance 50/15 - Demand level C

Indicator	*Units*	*Greedy-like*	*SA feedback*	*SA*
ICF	# of parts	400062	76187	168570
PMFT	days	3.87	3.80	3.82
LST	%	46.71	45.71	45.81
ANPQ	# of parts	310.88	316.01	314.15
AWTQ	days	0.782	0.795	0.789

Tables 2, 3, 4, 5 highlight the good performance of SA-approach in terms of ICF with a dramatic reduction which ranges between 58% and 71% in the scenarios with medium demand congestion while respecting, more or less, stable levels of other indicators. We point out that, for a moderate number of part types, the SA provides a substantial ICF reduction if used in the optimization phase. When the number of part types becomes larger the best performance corresponds to using SA in the feedback phase only. We notice also that PMFT is lower for the settings using SA. Furthermore it is noticeable the effect of IFM as feedback indicator used together with FIFO as Machine Queue Priority rule.

6 CONCLUSIONS

We adopt an integrated optimization/simulation approach in order to design the layout of a cellular manufacturing system. The novelty of this approach, which is based on the definition of machine-pair similarity coefficients and clustering techniques, consists of iteratively re-defining the similarity coefficients on the ground of the results of a simulation run. The introduction of an information feedback in the cells formation problem show to be very effective in the optimization-simulation process.

Good results in terms of inter-cell material flows are obtained especially when the integrated approach involves the exploitation of SA-based techniques in the information feedback procedure as well as in the optimization phase.

Future research should consider the following issues:

- design of new mechanisms for embedding simulation results feedback into the optimization phase rather than similarity coefficients,
- application of the integrated optimization-simulation procedure to different hard combinatorial problems.

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