IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received July 14, 2020, accepted August 4, 2020, date of publication August 21, 2020, date of current version September 17, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3018505

A Hybrid GRASP Algorithm for an Integrated Production Planning and a Group Layout Design in a Dynamic Cellular Manufacturing System

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ABSTRACT Demand fluctuations influence the configuration of manufacturing workshops. Integration of optimal production planning via the replenishment organization, can significantly reduce the excessive ++reconfigurations number in each period and, thereafter, the global managing costs. In this article, we discuss the joint machines Group layout design (GLD) and lot-sizing problem (LSP) in a dynamic cellular manufacturing system (DCMS). We propose a novel multi-period model to determine the best cell formation, necessary configurations over each period, and optimal production and inventory policy that minimizes intra and inter-cell material handling, holding costs, and multitasks machines relocation. We propose a novel mixed-integer programming (MIP) associated model which is then solved by using the commercial software Optimizer CPLEX. Additionally, we present a hybrid greedy randomized adaptive search procedure (GRASP) enhanced with a path relinking procedure (PR) to solve the problem. Computational results on several benchmarks and randomly generated instances show the effectiveness and the relevance of the proposed approach and highlight the integration value.

INDEX TERMS Group layout design, DCMS, lot-sizing, GRASP.

I. INTRODUCTION

Recognizing that many factors must be considered in choosing how to layout a facility, a suitable facility layout planning is necessary to enhance efficiency and flexibility in any manufacturing environment. Today, the factories are aware that opting for a layout type has a significant impact on the firm's ability to compete in the market and its long-term success. Also, owing to increasing pressure from customers for shorter product life cycles, developing flexibility becomes necessary to many companies. The strategy of adopting one fixed layout without considering demand changes causes additional manufacturing costs and increases jobs tardiness. The models that integrate customer order changes are known as the Dynamic Cellular Manufacturing System (DCMS).

The associate editor coordinating the review of this manuscript and approving it for publication was Sun-Yuan Hsieh.

Cellular manufacturing (CM) is a well-known manufacturing technology that helps companies to improve manufacturing flexibility and productivity by the maximum use of available resources. CM is a powerful tool for increasing production and flexibility. In such a system, we group similar machines in the same machine cells, and products or parts having similar routing and processing in the same part or product families. Cellular Manufacturing Systems (CMS) are dedicated to meet the requirements of modern industries working in highly unstable environments (Kumar *et al.* [1], Rensi *et al.* [2], Delgoshaei *et al.* [3], Bortolini *et al.* [4], Negahban and Smith [5]).

CM concept is used in many companies today to enhance flexibility, reduce set up, handling, and inventory costs, and optimize the factories' layout. The objective is to group a set of problems; thus, allowing us to find a single solution to them, which leads companies to save money, and efforts.

CMS consists of four decisional cycles (Kia *et al.* [6]) as follows:

- First decision: It consists of the cell formation problem that aims to design and form cells according to the parts production quantities or demand, and routings. The idea is to group parts according to their processing similarities and machines into machine cells.
- Second decision: It tackles the group layout design (GLD) that aims to lay grouped machines within cells and ensures a better intra-cell layout, then to arrange the formed cells in relation to one another.
- Third decision: it concerns group scheduling problem eyeing to determine the order of the jobs processing. The objective is to find the sequence of jobs that minimize or maximize a given scheduling criterion.
- Fourth decision: It focuses on the resource allocation problem. The problem raises when limited resources among a system should be optimized to meet the production objectives.

Except for some few attempts, extant research deals with these four decisions separately. In this study, we consider the first and second decisions integrated with Lot-Sizing Problem (LSP) decisions. The considered LSP consists of determining a production planning of an N items set (multi-products) for a planning horizon with T periods that minimizes the reconfiguration and managing costs. Its use aims to evaluate the impact of inventory and production planning on cellular manufacturing design and reconfiguration.

The LSP has been widely investigated in prior studies. For instance, several mathematical programming models on LSP have been proposed (Bushuev *et al.* [7], Wörbelauer *et al.* [8]. Zouadi *et al.* [9], Zouadi *et al.* [10]). Apart some papers in the literature, layout and lot-sizing have always been studied separately although integrating both decisions could minimize the managing costs significantly. The two problems have always been treated separately. Guoqing *et al.* [11] introduce a new integrated strategy that combines storage location assignment with a capacitated lot-sizing problem. The authors developed a dynamic mixed integer programming for the joint problem. Also, Rafiee *et al.* [12] propose a mathematical model for integrated cell formation and inventory decisions. However, the authors did not consider production planning and Group layout reconfigurations jointly in a DCMS, nor did they take into account their mutual impacts.

Based on the above discussion, we develop in this research a novel mathematical programming model to joint machines Group layout design (GLD) and lot-sizing problem (LSP) in a DCMS. This model is an extension of Kia *et al.* [6] model to the case of lot-sizing with novel constraints. The model aims to find a dynamic cell formation plan, and a production planning that minimize costs. Since machines Group layout design and lot-sizing problem are NP-Hard. Computational complexities are therefore burdensome. To solve the problem in an acceptable time especially for large instances, we adapt a Greedy randomized adaptive search procedure algorithm (GRASP) embedded with a Path Relinking (PR) procedure.

The remainder of the paper is organized as follows. State of art is provided in section 2. The problem statement and the mathematical model are expanded in Section 3. Then, the developed metaheuristic is explained in Section 4 and the results are discussed in Section 5. Finally, this article concludes with its main contributions and its future research avenues.

II. STATE OF THE ART

CM has received much attention in the two last dedicates. Indeed, many researchers have contributed to the literature by solving different variations of this problem. In 2009, Bulgak *et al.* [13] presented a comprehensive model for the design of CMS. The model features the presence of alternate process routings, operation sequence, duplicate machines, machine capacity, and lot splitting. Three years later, Mahdavi *et al.* [14] formulated a new mathematical model to minimize the exceptional elements and number of voids in cells. The objective is to ensure higher performance and optimize cell utilization. In the same year, Egilmez *et al.* [15] developed a non-linear mathematical model for the stochastic CMS. The problem is detected in both machine and labor-intensive cells, where operation times are probabilistic in addition to uncertain customer demand. Mahdavi *et al.* [16] proposed an integrated mathematical model considering cell formation and layout simultaneously. The goal of the model is to group similar parts and corresponding different machines in the same cells. Machines sequence in each cell and cell's positions are specified in the system. Kia *et al.* [17] also presented a mixed-integer programming model for multi-floor layout design of CMS in a dynamic environment. A novel aspect of this model is to jointly determine the cell formation (CF) and group layout design (GLD) as the interrelated decisions involved in the design of a CMS to achieve an optimal (or near-optimal) design solution for a multi-floor factory in a rolling planning horizon. In 2017, Raoofpanah *et al.* [18] proposed a novel mathematical model considering environmental issues. They investigated the effect of green parameters on optimality. In the same year, Feng *et al.* [19] present a comprehensive linear model that is developed for the integrated cell formation, and worker assignment problem to determine the optimal allocation of machines, parts, and workers. Specific characteristics of this model include the simultaneous consideration of production planning, the coexistence of alternative process routings, a lot splitting, workload balancing between cells, and worker over-assignment to multiple cells.

In our study, we consider a group layout design with lot-sizing problem and an inventory management policy in a DCMS. For an updated state of the art on LSP, readers are referred to Brahimi *et al.* [20]. In the literature, there is a dearth of research dealing with these decisions simultaneously. Safaei *et al.* [21] presented an integrated mathematical model of the multi-period cell formation and production planning in DCMS. Also, in 2016, Aalaei and Davoudpour [22] proposed a new dynamic CM model in supply chain design considering labor assignment. They considered multiple plan locations, multi markets allocations with production planning, and various part mix. During the same year, Sakhaii *et al.* [23] propose a robust optimization approach for an integrated dynamic cellular manufacturing system, and production planning with unreliable machines. They aim to minimize costs related to machines, workers, production, and parts movements. In parallel, Aghajani *et al.* [24] proposed a mathematical programming model for CMS controlled by Kanban with rework consideration. One year after, Paydar *et al.* [25] tackled the dynamic virtual cellular manufacturing with the supplier selection option. They proposed a hybrid metaheuristic algorithm to solve the problem. In sum, it seems that none of these studies considers the production planning and the inventory policy impact on the DCMS layout and reconfiguration. Accordingly, this research aims to cover this gap.

Many resolution approaches were developed to solve the CMS to optimality. Wu *et al.* [26] proposed a genetic algorithm for integrating cell formation with machine layout and scheduling. Pillai and Subbarao [27] developed a genetic algorithm-based solution procedure for forming part families and machine cells, which can handle all the changes in demands and product mixes without any relocations. After that, Safaei *et al.* [21] presented an efficient hybrid metaheuristic based on Mean-Field Annealing (MFA) and simulated annealing (SA) for solving an extended version of the DCMS. The objective is to minimize the sum of the machine's fixed and variable costs, inter- and intra-cell material handling, and reconfiguration costs. Also, Tavakkoli-Moghaddam *et al.* [28] design a scatter search method for a novel multi-criteria group scheduling problem in a CMS. The detailed results confirm the efficiency and effectiveness of the proposed algorithm to provide good solutions, especially for medium and large-sized problems. Afterwards, Rezaeian *et al.* [29] proposed a new nonlinear programming model in a dynamic environment. Furthermore, a novel hybrid approach based on the genetic algorithm and artificial neural network is proposed to solve the presented model. Subsequently, Deep *et al.* [30] proposed a genetic algorithm to design a CMS for a dynamic part population considering multiple processing routes. In the same year, Ulutas and Islier [31] proposed a clonal selection-based algorithm to solve the real-life dynamic facility layout problem. Recently, Prakash *et al.* [32] analyzed the prioritization of barriers influencing the improvement in the effectiveness of the manufacturing system. They developed an integrated fuzzy-based multi-criteria decision-making (F-MCDM) framework to assist management of the case company in the selection of the most effective manufacturing system. Also, Imran *et al.* [33] used simulation integrated with a hybrid genetic algorithm to solve the CMSs to minimize work in process. In this study, a hybrid GRASP is proposed with a path relinking algorithm to solve the problem due to its efficiency and its ability to solve NP-hard combinatorial problems.

In summary, the main contributions of this article are the following. Firstly, we propose a novel integrated model with main decision variables for the group layout design integrated with a lot-sizing problem in a DCMS. Secondly, we suggest a hybrid GRASP embedded within a path relinking algorithm to solve the problem. Finally, we prove through an extensive numerical analysis the significant difference obtained by generating layout in DCMS with or without considering the inventory and production policy, and we highlight by the end the value of the integration.

III. PROBLEM STATEMENT AND MODEL FORMULATION

A. PROBLEM ASSUMPTIONS

The studied problem integrates lot-sizing problem with an extended dynamic group layout design, which are both NP-hard problems (Logendran *et al.* [34], Chen [35], Sahni and Gonzales [36]). To formulate this problem, several assumptions have been considered:

- To reconfigure the cells over each period of the planning horizon, there is no need to modify buildings. Physical barriers do not exist between cells.
- The formed cells have an equal area in a multi-row layout of facilities concept. Also, the number of cells to form and locations are given in advance. However, the shape of the cells is not specified. It is flexible with a maximum and a minimum limit.
- Each product demand is deterministic and known over the planning horizon T.
- Each product follows all operations prescribed in the route sheet of parts. An operation could be divided between several machines. For each product, processing times of each machine are known over the planning horizon T.
- Each machine has a constant set up cost, which is considered over each period if the machine is used. Also, each machine type has a known operation cost depending on its functionality. In addition, machines have a replacement cost that occurred by moving a machine from a cell to another one. Replacement cost exactly matches both installation and uninstallation costs which are equal.
- All machines could process more than one operation, so they can be used for several purposes without having extra-costs.
- No capacity constraint is assumed for the machine's productivity.
- Set up, and holding costs are fixed and known in advance, and no inventory capacity is considered in the model.
- We consider, in this model, a multiperiod finite planning horizon, multi-products, and multitask machines.

B. NOTATIONS AND DECISION VARIABLES

1) SETS

P	$= \{1, 2, \ldots, P\}$ part types index
K(p)	$= \{1, 2, \ldots, Kp\}$ parts operations indices

M = {1, 2, ..., M} Machines types index
C = {1, 2, ..., C} Cells index
L = {1, 2, ..., L} Locations index
T = {1, 2, ..., T} Time periods index

2) MODEL PARAMETERS

- ES_p : Inter-cell material unitary handling cost per part p per unit of distance
- AS_p : Intra-cell material unitary handling cost per part p per unit of distance
- θ_m : Replacement cost for a machine m
- h_p : Holding cost per part p.
- D_{pt} : Demand for part type p in period t
- B_U : Upper possible cell size limit
- B_L : Lower possible cell size limit
- t_{kpm} : Processing time of operation k on machine m per part p
- $d_{ll'}$: Distance between two locations l and l'
- β_m : Variable cost of machine type m for each unit time
- a_{kpm} : 1 if operation k of part p can be processed on machine type m, 0 otherwise.

3) DECISION VARIABLES

- X_{kpmlt} : Number of parts of type p produced by operation k on machine type m located in location l in period t
- ∂_{pt} : Binary variable indicating the occurrence of the production of part type p in period t.
- I_{pt} : Inventory level of parts of type p in period t.
- F_{mlct} : 1 if one unit of machine type m is in location l and assigned to cell c in period t, 0 otherwise
- $Z_{kpmlm'l't}$: Number of parts of type p produced by operation k on machine type m located in location l and moved to the machine m′ located in location l′ in period t

C. MIP MODEL

The study aims to provide companies with a layout configuration model that minimizes the handling and configuration costs. Several studies in the literature propose models that could be used by companies to reconfigure their layout. However, these models do not consider demand volatility and its impact on reducing cost. In our study, the model proposed by Kia *et al.* [6] is extended to integrate the lot-sizing decision and inventory management policy according to the demand changes. Our study aims to have a better understanding of the inventory impact, and demand fluctuation on the layout reconfiguration costs. The developed CMS model is now formulated as non-linear mixed-integer programming:

$$\textbf{Min} \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{l}^{L}\sum_{m'}^{M}\sum_{l'\neq l}^{L}\sum_{p}^{P}\sum_{kp}^{Kp} F_{mlct} \times F_{m'l'ct} \times Z_{kpmlm'l't} \times d_{ll'} \times AS_p \times \partial_{pt} \quad (1.1)$$

$$+ \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{c'\neq c}^{C}\sum_{m}^{M}\sum_{l}^{L}\sum_{m'}^{M}\sum_{l'\neq l}^{L}\sum_{p}^{P}\sum_{kp}^{Kp} F_{mlct} \times F_{m'l'c't} \times Z_{kpmlm'l't} \times d_{ll'} \times ES_p \times \partial_{pt} \quad (1.2)$$

$$+ \frac{1}{2}\sum_{c}^{C}\sum_{l}^{L}\sum_{m}^{M}\theta_m \times F_{mlc,t=1} + \frac{1}{2}\sum_{t=1}^{T}\sum_{l}^{L}\sum_{m}^{M}\theta_m \times \left|\sum_{c}^{C} F_{mlct} - \sum_{c}^{C} F_{mlc,t+1}\right| \quad (1.3)$$

$$+ \sum_{t=1}^{T}\sum_{p}^{P}\sum_{kp}^{Kp}\sum_{m}^{M}\sum_{l}^{L} \beta_m \times t_{kpm} \times X_{kpmlt} \times \partial_{pt} \quad (1.4)$$

$$+ \sum_{t=1}^{T}\sum_{p}^{P} h_p \times I_{p,t} \quad (1.5)$$

$$\textbf{S.t.}\ I_{p,t} = I_{p,t-1} + \left(\sum\nolimits_{m=1}^{M}\sum\nolimits_{l}^{L} X_{k=k_p,pmlt}\right) - D_{pt} \quad \forall p \in P,\ \forall t \in T \quad (2)$$

$$\sum\nolimits_{m=1}^{M}\sum\nolimits_{l}^{L} X_{k=1,pmlt} \leq M \times \partial_{pt} \quad \forall p \in P,\ \forall t \in T \quad (3)$$

$$X_{kpmlt} \leq M \times a_{kpm} \quad \forall k \in Kp,\ \forall p \in P,\ \forall m \in M,\ \forall l \in L,\ \forall t \in T \quad (4)$$

$$\mathrm{X_{kpmlt}} = \sum\nolimits_{m'}^{M}\sum\nolimits_{l'}^{L} \mathrm{Z_{kpmlm'l't}} \quad \forall \mathrm{k} \in \mathrm{Kp},\ \forall \mathrm{p} \in \mathrm{P},\ \forall \mathrm{m} \in \mathrm{M},\ \forall \mathrm{l} \in \mathrm{L},\ \forall \mathrm{t} \in \mathrm{T} \quad (5)$$

$$X_{kpm'l't} = \sum\nolimits_{m}^{M}\sum\nolimits_{l}^{\prime L} Z_{k-1pmlm'l't} \quad \forall k \in Kp,\ \forall p \in P,\ \forall m' \in M,\ \forall l' \in L,\ \forall t \in T \quad (6)$$

$$\sum\nolimits_{m}^{M}\sum\nolimits_{l}^{L} F_{mlct} \geq B_U \quad \forall c \in C,\ \forall t \in T \quad (7)$$

$$\sum\nolimits_{m}^{M}\sum\nolimits_{l}^{L} F_{mlct} \leq B_L \quad \forall c \in C,\ \forall t \in T \quad (8)$$

$$\sum\nolimits_{m}^{M}\sum\nolimits_{c}^{C} F_{mlct} = 1 \quad \forall l \in L,\ \forall t \in T \quad (9)$$

$$F_{mlct}, S_{mt} \in \{0, 1\} \quad \forall m \in M,\ \forall c \in C,\ \forall l \in L,\ \forall t \in T \quad (10)$$

$$X_{kpmlt}, Z_{kpmlm'l't}, I_{p,t} \geq 0 \quad and\ integer \quad \forall k \in Kp,\ \forall p \in P,\ \forall m \in M,\ \forall l \in L,\ \forall t \in T \quad (11)$$

The objective function (1) minimizes the sum of Inter and Intra material handling cost, replacement, machines use, set up, and holding costs over the planning horizon. Constraint (2) is the inventory flow conservation equation. Constraint (3) guarantee the cancellation of produced quantities for periods without set up costs. Constraints (4) guarantee the cancellation of produced quantities if the machine is not used or if the machine could not process the parts. Constraints (5) and (6) are material flow conservation equations between machines. Constraints (7) and (8) define the cell size limit. Constraint (9) implies that each machine is in a location l. Constraint (10) and (11) set the binary and non-negative decision values.

D. MODEL LINEARIZATION

The proposed model is a nonlinear mixed-integer programming (MIP) model. A linearization procedure is applied to convert it into a linearized MIP. The aim is to linearize equations (1.1), (1.2), and (1.3). Equations (1.1) and (1.2) are quite similar. We adapt the linearization procedure proposed by Kia *et al.* [6]. Thus, two decision variables $H_{kpmlm'l'ct}$ and $H_{kpmlm'l'cc't}$ are introduced as follows:

$$F_{mlct} \times F_{m'l'ct} \times Z_{kpmlm'l't} \times \partial_{pt} = H_{kpmlm'l'ct} \quad (12)$$

$$F_{mlct} \times F_{m'l'c't} \times Z_{kpmlm'l't} \times \partial_{pt} = H_{kpmlm'l'cc't} \quad (13)$$

The introduction of these two variables implies the addition of the following two constraints (14 and 15) to the model:

$$\begin{aligned} H_{kpmlm'l'ct} &= Z_{kpmlm'l't} - M(3 - F_{mlct} - F_{m'l'ct} - \partial_{pt}) \\ &\quad \forall k \in Kp,\ \forall p \in P,\ \forall m, m' \in M, \\ &\quad \forall c \in C,\ \forall l, l' \in L,\ \forall t \in T \quad (14) \end{aligned}$$

$$\begin{aligned} H_{kpmlm'l'cc't} &= Z_{kpmlm'l't} - M(3 - F_{m'l'c't} - F_{m'l'ct} - \partial_{pt}) \\ &\quad \forall k \in Kp,\ \forall p \in P,\ \forall m, m' \in M, \\ &\quad \forall c, c' \in C,\ \forall l, l' \in L,\ \forall t \in T \quad (15) \end{aligned}$$

Concerning the equation (1.3), we adopt the procedure proposed by many studies in the literature like Ahkioon *et al.* [13] and Kia *et al.* [6]. Two decision variables (NO_{mlt}, NO_{mlt}) are proposed to rewrite the absolute term as follows:

$$|\sum_{c}^{C} F_{mlct} - \sum_{c}^{C} F_{mlc,t+1}| = NO_{mlt} + NO_{mlt} \quad (16)$$

The following constraint should be added to the model:

$$\begin{aligned} &\sum_{c}^{C} F_{mlct} - \sum_{c}^{C} F_{mlc,t+1} = NO_{mlt} - NO_{mlt} \\ &\qquad \forall k \in Kp,\ \forall p \in P,\ \forall m \in M,\ \forall l \in L,\ \forall t \in T \quad (17) \end{aligned}$$

This updated model with the added linearized terms was used to find solutions using the commercial software CPLEX. Our results are given in section 5. The quality of the solutions depends mainly on the size of the instances. For large instances, a hybrid approach based on GRASP is proposed to find near-optimal solutions.

IV. HYBRID GRASP ALGORITHM

To provide approximate resolution approaches to the problem, we adapt the Greedy Randomized Adaptative Search Procedure (GRASP) for generating good quality solutions in a moderate computational time. Moreover, a local search procedure is provided based on the path relinking algorithm to ensure the search intensification performance.

The GRASP was introduced first by Feo and Resende (1989) [37] to solve a set covering problem. Then, many adaptations of this metaheuristic were used to solve hard optimization problems. The GRASP is based on two stages. The first stage is the randomized solution construction to ensure the search diversification effectiveness, and the second stage is the local improvement phase that aims to intensify the

Algorithm 1 Pseudo-Code of the GRASP Metaheuristic

```
procedure GRASP(Max Iterations, starting solution)
Read Input();
 for k = 1, . . . , Max Iterations do
    Solution ← Greedy Randomized Construction
    (starting solution);
      if Solution is not feasible then
      Solution ← Repair(Solution);
      endif;
    Solution ← Local Search based on path relinking
    (Solution);
    Update Solution (Solution,Best Solution);
 end;
return Best Solution;
End GRASP.
```

search procedure and to reach local optima. For more surveys on GRASP, readers are referred to Feo and Resende [38], Pitsoulis and Resende [39], Zouadi *et al.* [9] and Resende and Ribeiro [40]. Algorithm 1 presents the general scheme of a GRASP with path relinking procedure.

A. SOLUTION ENCODING

Solution encoding is an essential feature for the effectiveness of the proposed hybrid GRASP algorithm implementation. The encoding architecture affects convergence and time execution of the algorithm and facilitates local improvement strategy based on the path relinking procedure. In this article, we propose an encoding based on a vector that consists of three ingredients.

The first ingredient is the matrix $[\text{Lot} - \text{S}]_t$, which represents the binary decision variables of the production occurrence of the part type p over a period t. While creating this vector, the first period should be equal to one if the demand is positive in order to have feasible solutions. Figure 1 corresponds to an example of this lot-sizing decision encoding. The example shows that part type 1 will be manufactured in period t; however, part type 2 will not be manufactured.

$$\begin{bmatrix} [\text{Lot} - \text{S}]_t & p = 1 & p = 2 & \ldots & p = P \\ \partial_{pt} & 1 & 0 & \ldots & 1 \end{bmatrix}$$

FIGURE 1. Binary lot-sizing decision Matrix in a period *t*.

The second element, called $[M\_L]_t$, is related to the assignment of the required machines to the locations over a period respecting the requirement of constraint 9. Figure 2 gives an example of a matrix $[M\_L]_t$. We assume that the number of machines is equal to the number of locations, thus, all machines should be assigned to a location, which implies that the sum of values of each line is equal to one.

The last ingredient is dedicated to a matrix $[L\_C]_t$ representing the assignment of the location to cells over a time period. Figure 3 illustrates an example of $[L\_C]_t$ matrix.

$$\begin{bmatrix} [\mathrm{M\_L}]_t & L=1 & L=2 & \dots & L=L \\ m=1 & 1 & 0 & \dots & 0 \\ m=2 & 0 & 0 & \dots & 1 \\ \dots & \dots & \dots. & \dots & \dots \\ m=M & 0 & 1 & \dots & 0 \end{bmatrix}$$

FIGURE 2. **$[M\_L]_t$ Matrix in a period *t*.**

This generated matrix should respect constraints 7 and 8 defining the size of the cells.

$$\begin{bmatrix} [L\_C]_t & c=1 & c=2 & \dots & c=C \\ L=1 & 0 & 1 & \dots & 0 \\ L=2 & 1 & 0 & \dots & 0 \\ \dots & \dots & \dots. & \dots & \dots \\ L=L & 0 & 0 & \dots & 1 \end{bmatrix}$$

FIGURE 3. **$[L\_C]_t$ Matrix in a period *t*.**

The solution encoding is thus composed of three elements that constitute the solution presentation scheme in period t. However, the general solution presentation over the planning horizon is formulated and described in Figure 4, where the three terms of the solution presentation over one period are generated over the planning horizon.

$$[[Lot - S]_t, [M\_L]_t, [L\_C]_t]$$

FIGURE 4. **General solution encoding.**

B. RANDOMIZED CONSTRUCTION

The implementation of the proposed hybrid GRASP algorithm relies on several restarts. At each restart, a randomly generated solution is formed using the previous solution scheme composed of three ingredients, then, it is used as a starting solution (seed) to run the algorithm. The generation of the first starting solution follows the hierarchical approach of the encoding. We start by randomly generating the lot-sizing decision matrix [Lot − S], then the $[\mathrm{M} - \mathrm{L}]_t$ matrix and finally the $[\mathrm{L} - \mathrm{C}]_t$ matrix.

The GRASP is based at each iteration on a randomly generated solution, which is used as a starting solution for the algorithm. Then, a randomization procedure is proposed to randomize this solution. The randomized procedure consists of randomizing the three vectors of the solution presentation $\left[[\mathrm{Lot} - \mathrm{S}]_t, [\mathrm{M\_L}]_t, [\mathrm{L\_C}]_t\right]$ at each period sequentially. Randomizing the vector $[\mathrm{Lot} - \mathrm{S}]_t$ consists of choosing periods with a positive manufacturing decision of parts type p having ∂_{pt} equal to 1. Then, we determine the next period s with positive manufacturing decision of the part type p. The randomization of the first solution consists of choosing a random period to produce product p between t and t + s instead of the period s. The procedure is applied in each period where the part type p has a positive production decision which will allow randomizing all periods with positive manufacturing decision.

To randomize $[\mathrm{M\_L}]_t$ et $[\mathrm{L\_C}]_t$, we sweep all the matrix lines over each period. The randomization procedure consists of exchanging the location of a set of machines with other machines. The choice of the machine and the set of machines to exchange between location is made randomly. The same procedure is adapted to randomize the matrix $[\mathrm{L\_C}]_t$ by considering the location as machines and cells as locations.

Finally, at each iteration of the GRASP algorithm, generated randomized solution decisions are used to calculate the fitness based on the proposed objective function of the proposed mathematical model. This corresponds to integrate the randomized solutions binary decisions in the mathematical model as decision variables and to solve the model by CPLEX at each iteration. The solution returned by CPLEX defines the optimal manufacturing quantities, dynamic machines, location assignment, and dynamic cells formation over the planning horizon according to the binary decision of the solution resulting from the randomization phase.

Regarding the algorithm stopping criterion, once a given number of iterations without improvement is performed compared to the best-found solution, the algorithm stops the randomization phase and generates randomly a new restart. The number of restarts and non-improvement iterations related to the randomization phase are the main two parameters impacting the convergence of the hybrid GRASP algorithm. These parameters are tuned based on a statistical design of experiments procedure to ensure the quality of the generated solutions. More details about the tuning procedure are given in the next section.

C. LOCAL SEARCH WITH PATH RELINKING

The proposed GRASP is enhanced with a path-relinking procedure, which is a local search aiming to intensify the research and making significant improvements in terms of solution quality. It was first introduced by Glover [41], [42] to explore connections with the best solutions found by tabu search or scatter search. Many applications could be found on integrating the GRASP with Path relinking and on stating its relevance on the GRASP in term of solution quality and computational time (Zouadi *et al.* [9]). An example of this technique's mechanism is shown in Figure 5.

In this implementation, the proposed Path relinking procedure explores the trajectory that links the best solution found and the randomized solution obtained at each iteration of the GRASP procedure. The relinking procedure consists of finding a set of solutions over each movement, eying to form the path between elite solutions that could enhance the search significantly. In this study, the relinking procedure consists of linking the best solution found with the obtained randomized solution. In each move, the link of the two solutions generates new solutions in the path which are tested using the objective function of the mathematical model. If a new solution is better than the randomized one, the new solution replaces the randomized one. The procedure is turned on until a stopping criterion.

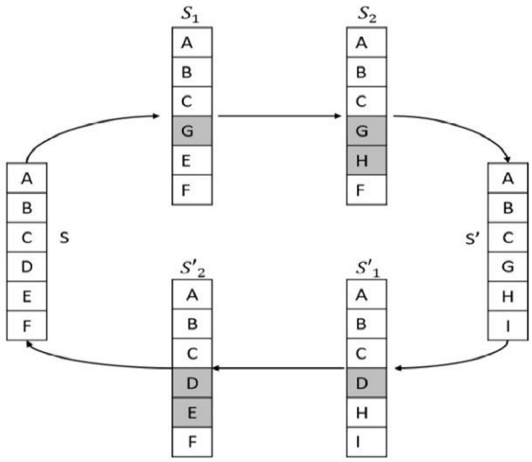


FIGURE 5. Path relinking moves.

The relinking moves follow the hierarchical architecture of the solution presentation composed of three vectors. At each iteration, a set of movements is performed to convert the randomized solution to be as the best solution found. At each move, we obtain a new solution that is tested using the objective function of the model. If the solution is better than the best solution found, the new founded solution replaces the best solution until a stopping criterion. The movements on the obtained solution are performed firstly on the vector $[\mathrm{Lot}-\mathrm{S}]_t$, then the vector $[\mathrm{M\_L}]_t$, and finally the vector $[\mathrm{L\_C}]_t$.

The stopping criterion used in the path relinking procedure implementation is based on the non-improvement iterations compared to the best solution found. The best value adopted in this implementation was tuned and determined through a statistical design of experiments procedure described in section V.

V. NUMERICAL EXPERIMENTS

We summarize in this section the numerical experiments performed on the proposed model and the developed algorithm. The obtained results from the resolution approaches will be compared following three different instances classifications:

According to the number of periods of the planning horizon

According to the type of demand

Integration value of the lot-sizing and group layout design in DCMS

Many tests have been realized to tune the GRASP parameters based on a statistical design of experiments procedure. The number of restarts is the first parameter to tune, then the number of iterations without improvement related to the randomization phase and finally the non-improvement number of iteration of the path relinking local search. These parameters are listed in Table 1.

After a large number of runs, differents values of these parameters were considered and tested. Then, The best values of these three pameters were selected $(\lambda; \kappa; \Psi) = (300; 25; 15)$. The number of restarts (λ) that offers the best tradeoff between computational time and solution quality is set at 300 for each restart. For the parameter related to the number of iterations without improvement, it is fixed at 25 for the randomized phase of the hybrid GRASP algorithm (κ), and 15 for the path reliniking procedure (Ψ).

TABLE 1. Parameters of the Hybrid GRASP.

λ:	Number of restarts of Hybrid GRASP
κ:	Number of iterations without improvement for randomization
Ψ:	Number of iterations without improvement for Path relinking

To show the performance and the features of the proposed model and the proposed approach, we use randomly generated instances based on the literature. Further details regarding the examples used to generate these random instances are provided in Kia *et al.* [6] and Zouadi *et al.* [9]. The instances are generated using different values based on literature examples (see Table 2). The total number of the generated instances is up to 1920. The tests are performed by Cplex Version 12.9 with an Intel core i7, 2.4 GHZ, and 8-GB RAM.

TABLE 2. Parameters used to generate the instances.

Parameters	Values			
Planning horizon	2, 3, 4, 6, 8, 12			
Part types Number	4, 8, 16,32			
Number of machines	5	10	20	40
Number of cells	2	3	4	5
Upper cell size limit	2	3	4	5
Lower cell size limit	3	5	10	10
Type of demand	stationary, linearly increasing, linearly decreasing, seasonal with peak in the middel, seasonal with valley in the middel.			
Holding cost	0,5 – 1			
Set up cost	100 – 200			

A. GROUPED ACCORDING TO THE NUMBER OF PERIODS OF THE PLANNING HORIZON

In the following, we provide a performance analysis of the proposed hybrid GRASP with path relinking compared to Cplex. However, when Cplex could not prove optimality, we compare with the best-found solution. The tested instances have a planning horizon up to 20 periods to analyze the performance of the proposed approach on large instances.The gap used to assess the deviation of the proposed hybrid GRASP comparing to Cplex is calculated using equation (18).

$$\mathrm{Gap} = \frac{\mathrm{CPLEX} - \mathrm{Hybrid\ GRASP}}{\mathrm{Cplex}} \tag{18}$$

For table 3, the first column represents the number of periods in the planning horizon. Columns 2, and 3 respectively show the average solution obtained by Cplex, and the average computational time. The last three columns respectively give the average solution of the hybrid GRASP, its average computational time and the gap between Cplex and the hybrid GRASP.

TABLE 3. Hybrid GRASP with path relinking results.

Period	Cplex		Hybrid GRASP with PR		
	AS	AT (s)	AS	AT (s)	GAP
2	34670	7123	34980	267	-0,89%
3	51134	19134	51767	602	-1,22%
4	62783	54139	63646	1504	-1,36%
6*	94956	90345	96334	2980	-1,43%
8*	119568	112657	121079	3345	-1,25%
12*	167496	193094	170456	5968	-1,74%

Results show that when we increase the planning horizon, the complexity of the problem becomes higher, and the results of the hybrid GRASP are −1,31% of average over the 1920 tested instances. Table 4 shows the gap matrix between Cplex and the hybrid GRASP following the planning horizon and the number of parts type.

TABLE 4. Gap between hybrid GRASP and Cplex following Planning horizon and part type number.

Planning horizon	Part type Number			
	4	8	16*	32*
2	0%	-0,33%	-1,49%	-1,72%
3	-0,26%	-0,58%	-1,75%	-2,29%
4	-0,41%	-0,85%	-1,81%	-2,35%
6*	-0,58%	-0,89%	-1,88%	-2,37%
8*	-0,72%	-0,92%	-1,65%	-1,70%
12*	-1,28%	-1,23%	-1,97%	-2,49%

According to Table 4, the gap becomes more important when the number of periods in the planning horizon or the part type number increase. However, for small instances, the hybrid GRASP solutions reach optimality in a reasonable computational time.

B. GROUPED ACCORDING TO THE TYPE OF DEMAND

We now group the results according to the type of demand. We propose five types of demands shapes following Teunter *et al.* [43] (Stationary, Positive trend, Negative trend, Seasonal with a peak and valley in the middle). Each type of demand, is composed of 384 instances. The aim is to assess the problem performance under several demand functions.

In table 5, the first column shows the used type of demand. The second column gives the Cplex average solution of the instances with similar demand type, while the last column presents the average solution of the hybrid GRASP.

TABLE 5. Gap between hybrid GRASP and Cplex following the type of demand.

Type f demand	Cplex	Hybrid GRASP	GAP
Stationary	99493	100389	-0,90%
Positive Trend	112390	113758	-1,22%
Negative Trend	108982	110430	-1,33%
Seasonal (Peak in middle)	104045	105948	-1,83%
Seasonal (Valley in middle)	105697	107737	-1,93%

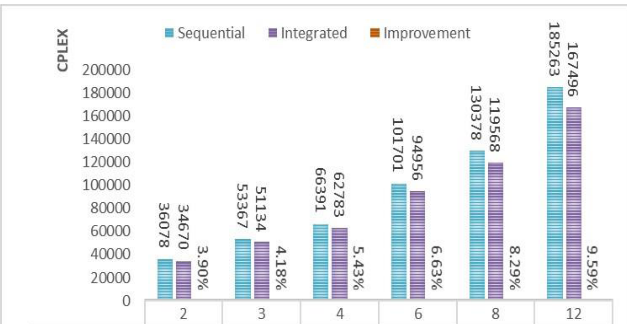
This analysis shows that the gap provided by the hybrid GRASP in comparison with the Cplex is lower when the demand is stationary, with positive and negative trend. In the meanwhile, the gap gets higher when we test on the two seasonal types of demands (Peak and valley in the middle).

C. INTEGRATION VALUE OF THE LOT-SIZING AND GROUP LAYOUT DESIGN IN DCMS

In the following, we show the impact of the lot-sizing integration with group layout design in DCMS and how it influences the nature of the problem. Therefore, we firstly test a sequential version of the problem on all the instances. This sequential version starts by solving the lot-sizing problem and uses its outputs as inputs to solve the group layout problem. After testing the sequential version, we test the integrated problem of group layout design and lot-sizing.

As explained before, the reconfiguration of cells (GLD) is induced by the fluctuations in demands in DCMS. The aim is to assess the integration value of GLD and lot-sizing, and how it will lead to minimize the managing costs in DCMS.

The graph presented in Figure 6 gives the number of periods according to the objective function of the model. The graph shows that on the instances with a longer planning horizon, the gap between sequential and integrated resolution becomes more important, which is explained by the economy of scale performed by the integrated model. The integration of the problems gives an average of (6,34%) over the 1920 instances, which represents essential savings and benefits for companies using DCMS. The coordination between planning and cells configuration allows us to have a beneficial policy that will contribute to minimize set up, configuration, and inventory costs.



	2	3	4	6	8	12
Sequential	36078	53367	66391	101701	130378	185263
Integrated	34670	51134	62783	94956	119568	167496
Improvement	3.90%	4.18%	5.43%	6.63%	8.29%	9.59%

FIGURE 6. Value of integration.

VI. CONCLUSIONS AND PERSPECTIVES

In this study, we developed an integrated model that provides a better understanding of the impact of the inventory decisions on a group layout problem in a DCMS. Our contribution consists of emphasizing the extent to which production planning impacts the group layout problem decisions in DCMS. Besides, the paper proposes a new mathematical model and an extended hybrid GRASP to solve the problem in a reasonable computational time. Results state the relevance of our approach in terms of solution quality and execution time and show that the value of integration reaches 6,34%. These findings constitute a basic assumptions for further research that could integrate carbon emission impact or would consider multi-objective functions while solving the group layout problem in DCMS.

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