

IMPACT ANALYSIS OF THE CELL-CAPACITY PARAMETERS ON OPTIMAL SOLUTIONS IN A DYNAMIC CELLULAR MANUFACTURING SYSTEM (D-CMS): AN ENRICHED SENSITIVITY STUDY AND THE DETERMINATION OF PROFITABILITY THRESHOLDS

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World Journal of Advanced Research and Reviews, 2026, 32(01), 1325–1337

Publication history: Received on 06 September 2026; revised on 18 October 2026; accepted on 20 October 2026

Article DOI: <https://doi.org/10.30574/wjarr.2026.32.1.2688>

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ABSTRACT

In a dynamic cellular manufacturing system (D-CMS), the production-cell capacity, described by the two parameters LP (minimum number of machines per cell) and CL (maximum number of machines per cell), exerts a decisive influence on the optimal solutions of a mixed-integer linear programming (MILP) model aimed at minimizing the cellular load variation. Starting from two experiments gathering configurations solved by the LINGO solver (50 instances per configuration), this paper proposes an enriched sensitivity analysis of the impact of the parameters LP and CL. We show that the slack margin $\Delta = CL - LP$ is strongly correlated with the optimal value, but that this correlation crucially depends on the experimental protocol: when CL is held fixed and LP varies, the relationship becomes quasi-deterministic ($R^2 \geq 0.98$), whereas when LP and CL are randomly chosen, the coefficient of determination drops to about 0.46. We also identify the profitability thresholds S^* below which the company realizes profits (limited machine sales) and beyond which it incurs losses (massive machine sales). The results show that in-house production systematically prevails over subcontracting whenever capacity allows, and that keeping the cell slack below the threshold S^* is a necessary condition to avoid losses. These results constitute a significant deepening of the reference model previously published in Statistics, Optimization and Information Computing (see Yao K. Adrien et al., 2025), and provide industrial decision makers with operational pre-sizing rules for the cell capacity.

Keywords: Dynamic Cellular Manufacturing; Cell Capacity; MILP Programming; Sensitivity Analysis; Profitability Threshold; Exact Optimization.

1 INTRODUCTION

Cellular manufacturing systems (CMS) constitute a major application of group technology, aimed at grouping machines and parts into cells in order to reduce material handling and to improve productivity [1,2]. In a dynamic market environment, the cell layout and the unit load of each machine evolve over time, giving rise to dynamic cellular manufacturing systems (D-CMS) [3,4]. The reconfiguration of the machine park over the periods is a central issue there, both from a cost and an operational feasibility point of view [5,6]. The D-CMS literature is now abundant: Balakrishnan and Cheng [7] review its multi-period and uncertainty issues, while recent extensions integrate production planning, worker assignment or the management of cell-load variation [8-10]. In this context, production planning must simultaneously decide the composition of the cells, the assignment of the operations, and the adjustment of the machine park.

One of the central difficulties is the cellular load variation: as demand fluctuates, some cells are overloaded while others are under-utilized, generating costly imbalances and excessive intra- and inter-cellular material handling. To address this challenge, a mixed-integer linear programming (MILP) model was proposed in [11] so as to minimize the total costs (setup, operating, machine acquisition/sale, subcontracting, backorders, intra- and inter-cellular transfers) while regulating the cell load through a capacity constraint bounded by two parameters: LP (minimum cell capacity) and CL (maximum cell capacity). The model was solved to optimality with LINGO on 50 instances, with average computation times below one second.

The present article constitutes an acknowledged extension of [11]. It focuses on a question so far addressed only summarily: how do the cell-capacity parameters LP and CL influence the optimal solutions? In [11], a global correlation of 0.67 ($R^2 \approx 46\%$) between the slack margin $\Delta = CL - LP$ and the optimal value was reported, without any statistical deepening. We enrich this analysis in three ways.

First, we decompose the regression according to the experimental protocol (CL fixed and LP variable, on the one hand; LP and CL random, on the other hand), and show that the correlation changes dramatically: quasi-deterministic in the fixed case, moderate in the random case.

Second, we analytically determine a profitability threshold S^* corresponding to the value of Δ at which the net value of the objective function vanishes (loss/profit transition), and we confront it with the experimental data.

Third, we quantify the evolution of the machine purchase and sale decisions as a function of Δ , as well as the in-house production/subcontracting ratio, in order to derive operational rules for pre-sizing the cell capacity.

The paper is organized as follows: Section 2 presents a literature review and positions the contribution; Section 3 briefly recalls the MILP model and the role of LP and CL; Section 4 describes the experimental protocol (experiments 1 and 2) and the statistical methods; Section 5 presents and discusses the enriched results; Section 6 provides a managerial interpretation and recommendations; finally, Section 7 concludes and opens perspectives.

2 LITERATURE REVIEW

2.1 From cellular manufacturing systems to dynamic systems

Cell formation is a founding problem of group technology: Wemmerlöv and Hyer [12] laid its algorithmic foundations as early as 1986, aiming to identify simultaneously part families and machine groups. These works were progressively consolidated by empirical studies documenting the gains observed in industry [1], and then by taxonomic syntheses that structure the whole field [2]. Designing a CMS thus relies on grouping into cells the machines that process similar part families, so as to reduce material movements and setup times while retaining a flexibility comparable to that of a job shop. Building on these foundations, exact and heuristic approaches have since been proposed to solve the cell-formation problem, ranging from Benders' decomposition [13] to models allowing alternative process plans and replicate machines [14].

2.2 Dynamic cell reconfiguration

In a dynamic market environment, demand and product mix vary over time, making any frozen configuration obsolete. The literature has therefore introduced dynamic cellular manufacturing systems (D-CMS), in which cells are reconfigured from one period to the next. Rheault et al. [4] propose reconfigurable virtual cells suited to highly dynamic environments, while Chen [5] formalizes a mathematical program for system reconfiguration, and Balakrishnan and Cheng [6] extend the modeling to multi-period planning horizons. A comprehensive synthesis of multi-period planning and uncertainty issues is provided by Balakrishnan and Cheng [7].

2.3 Integrated models and functional alignment

Many D-CMS models now integrate production planning and worker assignment alongside cell formation. Saidi-Mehrabad and Safaei [3] combine dynamic formation with a neural approach, while Safaei et al. [8] propose a hybrid simulated annealing to solve an extended model, and Mahdavi et al. [9] integrate production planning and worker assignment within the same mathematical program.

2.4 Cell-load variation and uncertainty

The cellular load variation is identified as a central difficulty: as demand fluctuates, some cells are overloaded while others remain under-utilized, weighing both on costs and on the system balance. Delgoshaei et al. [10] thus propose a method aimed at reducing this variation in D-CMS. Moreover, the modeling of uncertainty — whether of demand or of costs — is addressed through fuzzy and stochastic approaches [15,16], which enrich the models but make the problems harder to solve and the conclusions less directly actionable.

2.5 Positioning of the contribution

The present article builds on the MILP model of [11], which already regulates the cell load by means of two capacity parameters (LP and CL). With respect to the literature reviewed above, our contribution is twofold: (i) it decomposes the effect of the capacity parameters according to the experimentation protocol, which no surveyed study does; (ii) it derives an operational profitability threshold and directly usable pre-sizing rules. The study thus provides an explicit link between the fine-grained modeling of capacities and managerial recommendations, filling a gap often emphasized in the D-CMS literature.

3 MILP MODEL AND ROLE OF THE CAPACITY PARAMETERS

3.1 Recall of the model

Let P be the set of products, M the set of machine types, C the set of cells, T the set of planning periods, and L the set of subcontractors. The model proposed in [11] involves the following decision variables: $X(p,m,m',c,c',t)$, quantity of product p processed by machine m in cell c with machine m' in cell c' at period t ; $NAJ(m,c,t)$ and $NRE(m,c,t)$, number of type- m machines added/removed in cell c at period t ; $MN(m,c,t)$, number of type- m machines present in cell c at period t ; $Y(p,l,t)$, quantity of product p subcontracted to subcontractor l at period t ; and $B(p,t)$, quantity of product p carried over (backlogged) to period t .

The objective function minimizes the total cost

$$Z = Q1 + Q2 + Q3 + Q4 + Q5 + Q6 + Q7,$$

where $Q1$ is the setup cost, $Q2$ the operating cost, $Q3$ the net machine acquisition cost ($Q3 = \sum (MCost_m \cdot NAJ_m,c,t - SalCost_m \cdot NRE_m,c,t)$), $Q4$ the subcontracting cost, $Q5$ the backorder cost, and $Q6$ and $Q7$ the intra-cellular and inter-cellular transfer costs.

Let us emphasize the economic interpretation of the sign of Z . Apart from the term $Q3$, all the components $Q1$, $Q2$, $Q4$, ..., $Q7$ are strictly positive expenses (setup, operating, subcontracting, backorder, transfers). The term $Q3$, by contrast, involves a purchase ($MCost_m \cdot NAJ_m,c,t$, expense) and a resale ($SalCost_m \cdot NRE_m,c,t$, revenue), so that it can be either positive or negative. A result $Z > 0$ therefore corresponds to the classical case where the net cost essentially stems from expenses (the machine purchases required for production exceed the sales), and this sign is then associated with a potential profit from the productive activity. Conversely, $Z < 0$ arises when the machine resale revenue $SalCost_m \cdot NRE_m,c,t$ overcompensates all the operating and acquisition costs: the optimizer then decides to divest massively from the machine park (asset sales) rather than to produce. Economically, such a solution does not correspond to a sustainable operating profit, but to an operating loss masked by asset disposal: the company sacrifices its productive capacity in order to generate cash. This is why, in the retained modeling, the negative sign of Z^* is interpreted as a loss (decapitalization of the machine park), and this imbalance lies at the heart of the analysis of the margin Δ .

3.2 Cell-capacity constraints

The two parameters under study appear in the cell-capacity constraints:

$$LP \leq \sum (m \in M) MN_m, c, t \leq CL, \quad \forall c \in C, t \in T. \quad (1)$$

Constraint (1) bounds the total number of machines present in each cell at each period between a minimum capacity LP and a maximum capacity CL . The slack margin

$$\Delta = CL - LP$$

therefore represents the magnitude of the machine-park reconfiguration allowed within a cell. The larger Δ , the further the system can move away from the number of ideal machines required to manufacture the products, which leads to massive sales of under-utilized machines and, according to the formulation of the net cost Q_3 , to negative optimal values (interpreted as losses in the retained modeling).

The machine park follows the evolution equation

$$MN_{m,c,t} = MN_{m,c,t-1} + NA_{m,c,t} - NRE_{m,c,t} \quad (2)$$

with an initial condition $MN_{m,c,0} = INT_m$.

4 EXPERIMENTAL METHODOLOGY

4.1 Protocol

We follow the protocol of [11], which generates 50 problem instances for each cell-capacity configuration, the demand being modeled by a normal law. Two experiments are considered: Experiment 1, small-scale dimension, 4 products, 2 cells, 3 machine types, 2 planning periods; Experiment 2, larger-scale dimension, 10 products, 4 cells, 3 machine types, 4 planning periods.

For each, two sub-protocols are applied: (i) CL fixed and LP variable, CL = 30, LP runs over {0, 4, 8, 12, 16, 20, 24, 28}; the margin $\Delta = CL - LP$ therefore decreases from 30 to 2 in steps of 4; (ii) LP and CL random, the pairs (LP, CL) are drawn randomly, producing configurations ranging from $\Delta = 2$ to 27 (20 configurations per experiment).

4.2 Tracked indicators

For each configuration, the following quantities averaged over the 50 instances are recorded: the optimal value Z^* , the number of acquired machines (NAJ), the number of sold machines (NRE), the in-house production (P_int), the subcontracting (P_sou), the backlog (B), and the computation times.

4.3 Statistical methods

The optimal value of the objective function is denoted Z^* ($Z^* > 0$ indicates a profit, $Z^* < 0$ a loss) and the cellular slack margin is $\Delta = CL - LP$. To study their relationship, we compute the Pearson correlation coefficient r between Δ and Z^* , then fit a simple linear regression

$$Z^* = \alpha + \beta \cdot \Delta + \varepsilon,$$

where α is the intercept, β the slope and ε the residual error term. The coefficient of determination R^2 , equal to the square of the correlation coefficient, measures the share of the variance of Z^* explained by the regression. The profitability threshold is defined as the root of the regression equation,

$$S^* = -\alpha / \beta = \{\Delta: \alpha + \beta \cdot \Delta = 0\},$$

that is, the value of Δ for which the predicted net value vanishes. Significance is judged at the $p < 0.05$ threshold.

5 RESULTS

5.1 Recall of the basic results (tables)

Tables 1 and 2 reproduce the average results of the experiments for fixed CL. We observe that as LP increases (therefore Δ decreases), the optimal value increases and eventually becomes positive from a certain threshold onward. The acquired machines increase linearly while the sold machines decrease and then stabilize at a floor value (14 in Experiment 1, 28 in Experiment 2) as soon as Δ becomes moderate. Tables 3 and 4 provide the corresponding results for the random LP/CL configurations: here again, the sign change of Z^* is observed whenever the pair (LP, CL) makes the margin Δ sufficiently small.

Table 1: Experiment 1 (4 products, 2 cells, 3 machine types, 2 periods): average optimal solutions over 50 instances, CL = 30 fixed and LP ranging from 0 to 28.

LP	CL	CL-LP	Avg. Z*	Int. prod.	Subcontr.	Backlog	Acq.	Sold
0	30	30	-228820.0	383.8	504.0	0	0	30
4	30	26	-193372.0	365.0	460.4	0	0	24
8	30	22	-140318.0	370.3	460.0	0	0	16
12	30	18	-80312.0	429.6	460.0	0	6	14
16	30	14	-21850.4	371.1	460.0	0	14	14
20	30	10	42105.9	513.3	460.0	0	22	14
24	30	6	100486.7	467.9	460.0	0	30	14
28	30	2	160602.4	471.2	460.0	0	38	14

Table 2: Experiment 2 (10 products, 4 cells, 3 machine types, 4 periods): average optimal solutions over 50 instances, CL = 30 fixed and LP ranging from 0 to 28.

LP	CL	CL-LP	Avg. Z*	Int. prod.	Subcontr.	Backlog	Acq.	Sold
0	30	30	-317126.0	3208.8	2266.9	330	0	54
4	30	26	-301381.0	2676.7	1990.0	330	0	48
8	30	22	-193026.0	2886.4	1985.4	330	0	32
12	30	18	-50737.1	3601.6	2189.4	330	12	28
16	30	14	43344.2	2851.8	1989.2	330	28	28
20	30	10	168915.7	2906.2	2034.7	330	44	28
24	30	6	345051.9	2902.0	1979.8	330	60	28
28	30	2	409299.8	2948.5	2037.4	330	76	28

Table 3: Experiment 1: random (LP, CL) configurations (20 configurations, 50 instances each).

LP	CL	Avg. Z*	Int. prod.	Subcontr.	Backlog	Acq.	Sold
10	27	-112433.0	344.1	460.0	0	2	14
12	39	-79923.8	448.3	460.0	0	6	14
12	29	-82415.5	346.2	460.0	0	6	14
13	35	-67766.1	327.8	460.0	0	8	14
14	28	-47668.6	523.3	460.0	0	10	14
15	38	-35326.9	429.0	460.0	0	12	14
15	32	-35117.5	431.4	460.0	0	12	14
16	38	-18907.1	488.6	460.0	0	14	14
17	31	-7283.2	350.6	460.0	0	16	14
18	35	12486.8	538.1	460.0	0	18	14
19	27	26081.3	472.8	460.0	0	20	14
20	29	40487.3	468.4	460.0	0	22	14
21	32	55128.5	444.6	460.0	0	24	14

22	33	68148.1	370.7	460.0	0	26	14
22	28	68188.3	366.9	460.0	0	26	14
22	40	70459.2	465.7	460.0	0	26	14
23	29	84960.3	443.6	460.0	0	28	14
24	26	99385.2	415.6	460.0	0	30	14
25	36	113075.9	367.9	460.0	0	32	14
25	40	114290.5	405.8	460.0	0	32	14

Table 4: Experiment 2: random (LP, CL) configurations (20 configurations, 50 instances each).

LP	CL	Avg. Z*	Int. prod.	Subcontr.	Backlog	Acq.	Sold
10	27	-124592.0	2887.9	2158.3	330	4	28
12	39	-76258.1	2487.7	2113.3	330	12	28
12	29	-61129.1	2983.1	2183.9	330	12	28
13	35	-44169.6	2643.1	2070.6	330	16	28
14	28	-14397.5	2538.0	2133.0	330	20	28
15	38	14391.9	2892.8	1965.6	330	24	28
15	32	2696.6	2165.6	2024.0	330	24	28
16	38	50971.8	2692.9	2150.3	330	28	28
17	31	81706.5	2756.5	2140.6	330	32	28
18	35	101642.9	2436.9	2080.2	330	36	28
19	27	133295.0	2433.4	2126.0	330	40	28
20	29	171814.0	2680.4	2166.8	330	44	28
21	32	203238.3	2751.3	2168.8	330	48	28
22	33	222287.7	2816.8	1945.7	330	52	28
22	28	225262.2	2918.8	1995.2	330	52	28
22	40	231457.2	2707.7	2157.5	330	52	28
23	29	256278.5	2505.8	2141.5	330	56	28
24	26	286771.5	2527.7	2137.4	330	60	28
25	36	343070.3	3520.7	2237.2	330	64	28
25	40	318400.6	2590.6	2155.4	330	64	28

5.2 Decomposed correlation and regression

Figure 1 presents the regression between the margin Δ and the optimal value for Experiment 1 in the fixed-CL case. The relationship is exceptionally linear: the correlation coefficient is -0.998 and the coefficient of determination reaches $R^2 = 0.996$. In other words, when CL remains fixed, the variation of the margin explains almost entirely the variation of the optimal value.

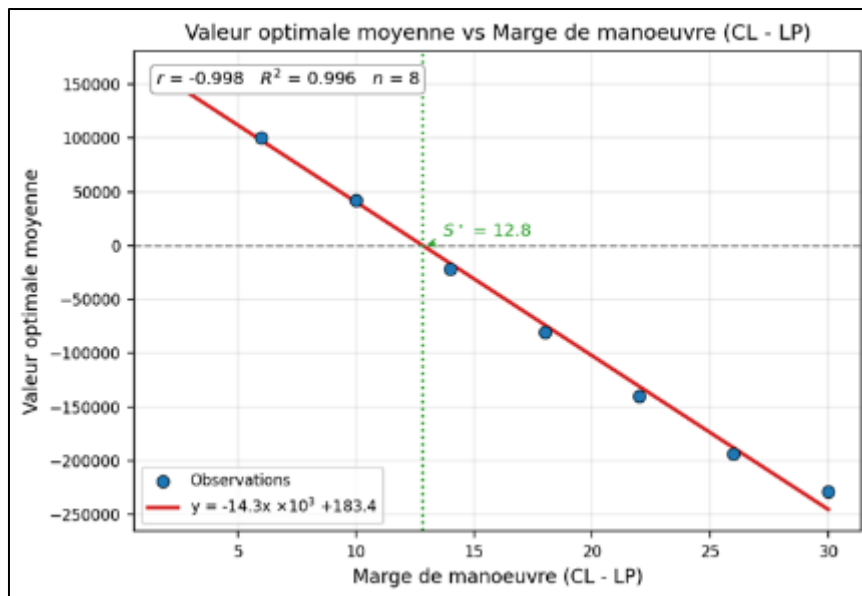


Figure 1: Regression between the slack margin CL – LP and the average optimal value, Experiment 1, fixed CL = 30. $r = -0.998$, $R^2 = 0.996$.

In the random LP/CL case (Figure 2), the correlation becomes moderate ($r = -0.68$, $R^2 = 0.46$), which corresponds exactly to the result reported in [11], where the regression had only been computed on the random configurations. This decomposition is an original contribution: it shows that, when the regression is also computed on the fixed-CL configurations (available in [11] but never statistically exploited), the relationship is in fact quasi-deterministic.

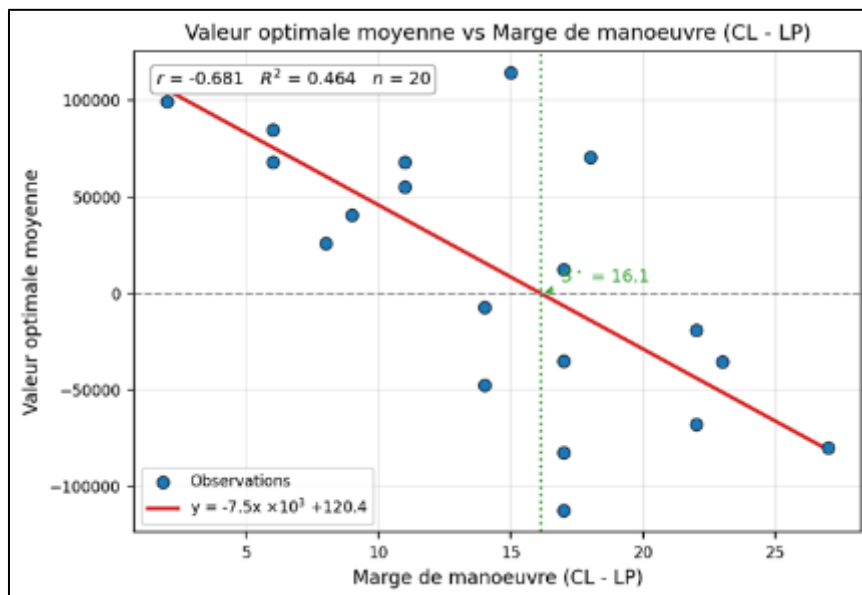


Figure 2: Regression between the slack margin and the average optimal value, Experiment 1, random LP and CL. $r = -0.68$, $R^2 = 0.46$.

The same qualitative conclusions apply to Experiment 2 (Figures 3 and 4): $R^2 = 0.982$ in the fixed-CL case vs. 0.46 in the random case. Table 5 summarizes the regression coefficients of the four configurations.

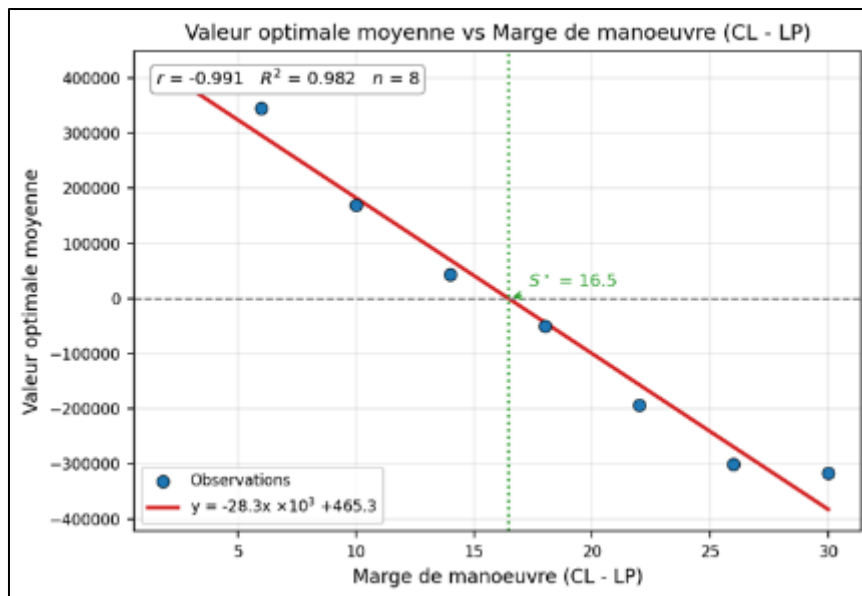


Figure 3: Regression between the slack margin and the optimal value, Experiment 2, fixed CL = 30. $r = -0.991$, $R^2 = 0.982$.

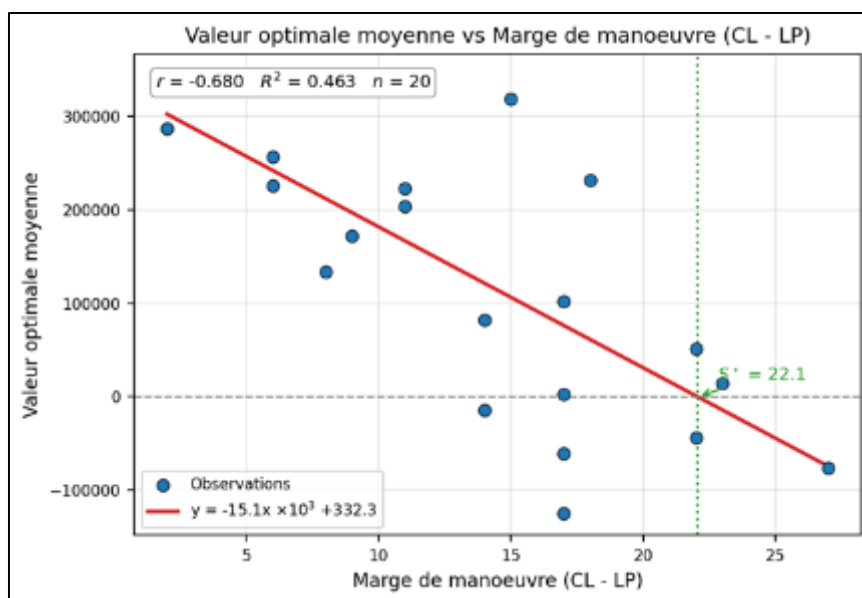


Figure 4: Regression between the slack margin and the optimal value, Experiment 2, random LP and CL. $r = -0.68$, $R^2 = 0.46$.

Table 5: Summary of the regressions of $\Delta = CL - LP$ against the optimal value Z^* . The threshold S^* is given with its 95% bootstrap confidence interval (5,000 resamples). All slope coefficients are significant ($p < 0.001$).

Protocol	r	R^2	β (slope)	Threshold S^*	95% bootstrap CI
Exp. 1, fixed CL	-0.998	0.996	-14,289	12.84	[12.32; 13.16]
Exp. 1, random	-0.68	0.46	-7,464	16.13	[13.16; 20.31]
Exp. 2, fixed CL	-0.991	0.982	-28,265	16.46	[15.54; 17.39]
Exp. 2, random	-0.68	0.46	-15,064	22.06	[18.35; 28.00]

5.3 Profitability thresholds

The profitability threshold $S^* = -\alpha/\beta$ denotes the value of Δ at which the predicted net value vanishes: below it, $Z^* > 0$ (profit); beyond it, $Z^* < 0$ (loss). The obtained values are listed in the last columns of Table 5.

Concretely, for Experiment 1 with fixed CL, the threshold is $S^* \approx 12.8$: a slack margin below about 13 machines per cell guarantees a positive net result (Figure 1). Since constraint (1) imposes $\Delta = CL - LP$, the condition $\Delta \leq S^*$ is equivalent to keeping $LP \geq CL - S^* = 30 - 12.8 \approx 17$ on a maximum capacity $CL = 30$, that is, a ratio $LP/CL \geq (CL - S^*)/CL = 17/30 \approx 57\%$. This pre-sizing rule, directly derived from the estimated threshold, advantageously replaces the qualitative recommendations whose quantitative value is not specified in the literature.

Figure 5 superimposes the random configurations of the two experiments (expressed in thousands), confirming the presence of a systematic sign change and the alignment of both experiments on a common behavioral law.

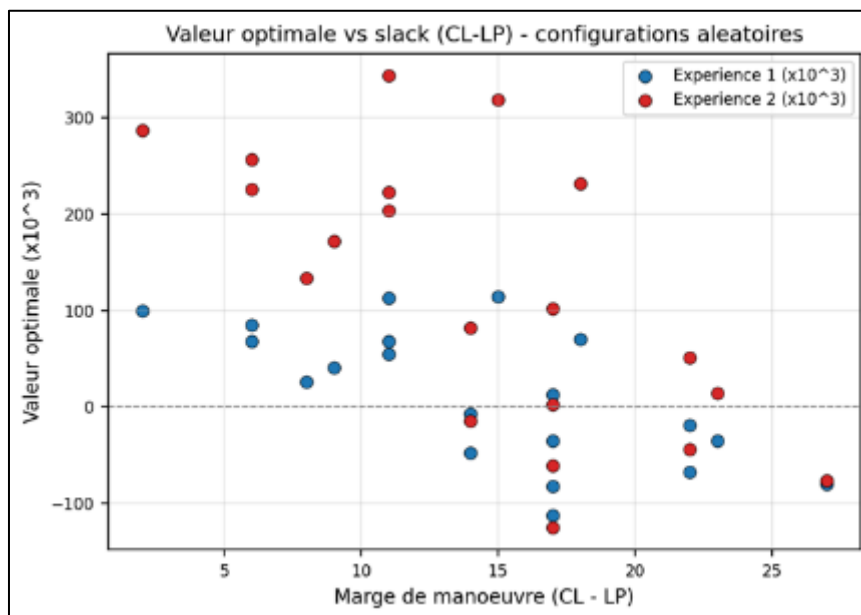


Figure 5: Optimal value (in thousands) as a function of the margin $\Delta = CL - LP$ for the random configurations of Experiments 1 and 2.

5.4 Statistical robustness of the thresholds

The precision of the threshold estimate S^* strongly depends on the protocol. In the fixed-CL case, the threshold is estimated with great precision: $S^* = 12.84$ with a 95% bootstrap confidence interval of [12.32; 13.16] for Experiment 1 and $S^* = 16.46$ with [15.54; 17.39] for Experiment 2 (Table 5). In contrast, in the random LP/CL case, the uncertainty is much wider: [13.16; 20.31] (Exp. 1) and [18.35; 28.00] (Exp. 2). This asymmetry confirms that the quasi-deterministic relationship observed at fixed CL is not an artefact: it reflects a structural and precise dependence of Z^* on Δ , which the random mixing of the two parameters blurs. It also justifies the use of a controlled protocol (fixed CL) for establishing reliable quantitative rules.

5.5 Inter-instance variability

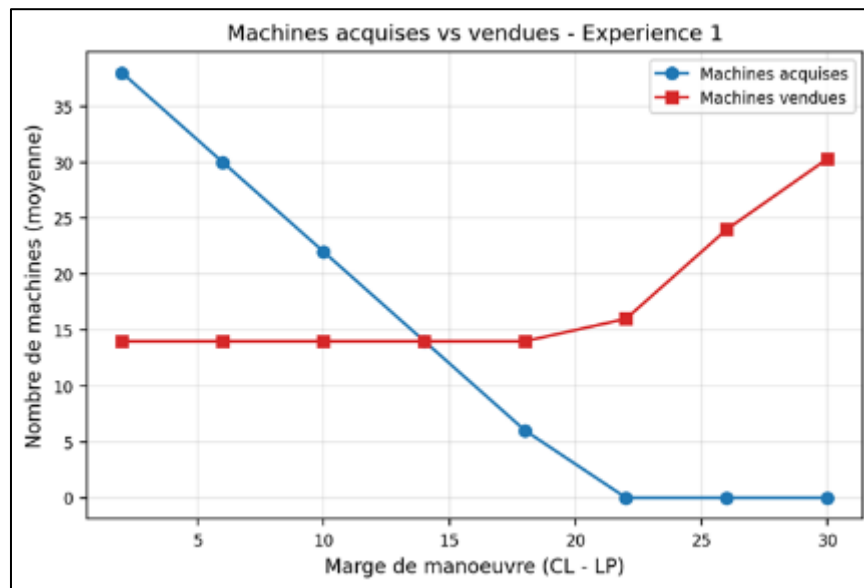
The averages reported in Table 6 are accompanied, in the reference article, by their standard deviation for two configurations of Experiment 1 at fixed $CL = 30$: $LP = 20$ ($\Delta = 10$) and $LP = 0$ ($\Delta = 30$). The standard deviation of the optimal value is small in relative terms: 1,289.6 for an average of 42,105.9 ($LP = 20$), i.e. a coefficient of variation of about 3%, and 2,636.8 for an average of -228,820 ($LP = 0$), i.e. about 1%. In-house production exhibits the same stability (coefficients of variation of 11% and 13%). These orders of magnitude indicate that the average optimal values are very stable from one instance to another, and that the conclusions drawn from the regressions rely on reliable averages rather than on isolated realizations.

Table 6: Inter-instance variability (average $\pm$ standard deviation over 50 instances) for two configurations of Experiment 1 at fixed CL = 30.

Variable	LP=20 ($\Delta=10$) — Avg.	Std. dev.	LP=0 ($\Delta=30$) — Avg.	Std. dev.
Optimal value Z^*	42,105.9	1,289.6	-228,820	2,636.8
In-house production	513.3	55.9	383.8	48.4
Subcontracting	460.0	0.0	504.0	34.1
CPU time (s)	0.56	0.05	0.65	0.11
Iterations	39.4	2.9	830.7	1,420.4

5.6 Acquired and sold machines

Figure 6 illustrates the evolution of the average numbers of acquired and sold machines for Experiment 1. When Δ is large (≥ 22), no machine is acquired and the number of sold machines is maximal; as Δ decreases, acquisitions increase linearly while sales stabilize at a constant floor value (14 for Exp. 1, 28 for Exp. 2). This behavior directly explains the sign of Z^* : sales generate a deficit (net cost Q3 negative) that the increase of acquisitions can no longer compensate at high margins.

**Figure 6: Average numbers of acquired and sold machines as a function of $\Delta = CL - LP$, Experiment 1.**

5.7 In-house production versus subcontracting

Figure 7 shows that, in Experiment 1, in-house production prevails over subcontracting when Δ is small (hence LP high), and conversely when Δ is large. We also note that the backlog is zero in Experiment 1: the demand is entirely satisfied through the combination of in-house production and subcontracting.

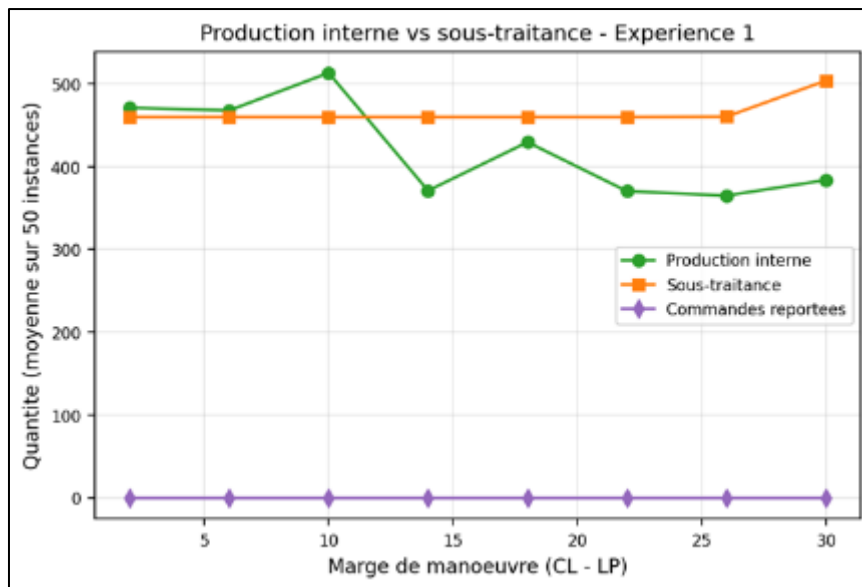


Figure 7: In-house production, subcontracting and backorders as a function of Δ — Experiment 1.

In Experiment 2, by contrast, in-house production always exceeds subcontracting, but a constant backlog of 330 units appears, indicating that the total capacity does not allow the demand to be entirely satisfied. This difference is explained by the size of the instances (10 products, 4 cells, 4 periods), which increases the capacity requirements.

6 DISCUSSION

6.1 Managerial interpretation

The results allow establishing a quantitative link between the cell-capacity policy and the economic performance. The presence of a clearly identified profitability threshold S^* provides a simple and unique operational criterion: the slack margin $\Delta = CL - LP$ must remain strictly below the threshold for the net result to be positive. Section 6.2 translates this criterion into two equivalent pre-sizing rules.

6.2 Pre-sizing rule

Rule 1 (in Δ): adjust the minimum capacity LP as a function of the maximum capacity CL so that $\Delta = CL - LP < S^*$.

Rule 2 (ratio form): define the minimum capacity by a critical capacity ratio

$$\rho^* = (CL - S^*) / CL,$$

and impose $LP \geq \rho^* \cdot CL$. Given the estimated threshold S^* , we obtain $\rho^* \approx 0.57$ (Exp. 1) and $\rho^* \approx 0.45$ (Exp. 2, $S^* = 16.5$, $CL = 30$). This rule, directly derived from the data, provides a quantifiable value that can be adjusted according to the acquisition/sale costs of the system under consideration.

These two formulations are mathematically equivalent ($LP \geq \rho^* CL \Leftrightarrow \Delta \leq S^*$), but the ratio form is more directly usable by the practitioner who often reasons in terms of capacity proportion.

6.3 Comparison between Experiments 1 and 2

Although the dimension of the instances differs strongly, both experiments exhibit the same qualitative mechanism (profitability threshold, machine acquisition/sale link with Δ). This result indicates that the model is scalable: the patterns observed at small scale are reproduced at larger scale.

Limitations

The model does not take into account machine breakdowns, maintenance, storage costs, nor the evolution of purchase/sale prices in the market. The interpretation of the sign of the objective function as loss/profit, justified in Section 3 by the balance of the net cost Q_3 , remains qualitative: the numerical value of the threshold S^* and of the critical ratio LP/CL depends on the real accounting parameters (acquisition costs $MCost_m$ and resale prices $SalCost_m$), which should be calibrated on the company data for a specific industrial application.

7 CONCLUSION

Carried out as an acknowledged extension of [11], this study provides three contributions. First, it decomposes the correlation between the cell slack margin $\Delta = CL - LP$ and the optimal value, revealing that the relationship is quasi-deterministic when CL remains fixed ($R^2 \geq 0.98$), a relationship the literature had never uncovered, having been limited to the global coefficient of 0.67 computed on the random configurations alone. Second, it introduces and computes a profitability threshold S^* allowing to discriminate profit and loss as a function of the cell capacity. Third, it provides a machine-park pre-sizing rule based on the critical ratio LP/CL .

These results offer industrial decision makers concrete levers to avoid the losses linked to an oversizing of the cell capacity. Perspectives include the integration of preventive maintenance, richer demand uncertainties, and the extension to a multi-objective framework also incorporating equity considerations between cells.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

The authors thank the co-authors of the foundational work by Yao et al. (2025) for making available the model and the experimental data.

Disclosure of conflict of interest

The author declares no conflict of interest.

REFERENCES

- [1] Wemmerlöv U, Johnson DJ. Cellular manufacturing at 46 user plants: implementation experiences and performance improvements. *Int J Prod Res.* 1997;35(1):29-49.
- [2] Selim HM, Askin RG, Vakharia AJ. Cellular manufacturing and design: a taxonomy and review. *Int J Prod Res.* 1998;36(2):185-208.
- [3] Saidi-Mehrabad M, Safaei N. A new model of dynamic cell formation by a neural approach. *Int J Adv Manuf Technol.* 2006;33(9-10):1001-9.
- [4] Rheault M, Drolet JR, Abdounour G. Physically reconfigurable virtual cells: a dynamic model for a highly dynamic environment. *Comput Ind Eng.* 1995;29(1-4):221-5.
- [5] Chen M. A mathematical programming model for system reconfiguration in a dynamic cellular manufacturing environment. *Ann Oper Res.* 1998;77:109-28.
- [6] Balakrishnan S, Cheng CH. Dynamic cellular manufacturing under multiperiod planning horizons. *J Manuf Technol Manag.* 2005;16(5):516-30.
- [7] Balakrishnan S, Cheng CH. Multi-period planning and uncertainty issues in cellular manufacturing: a review and future directions. *Eur J Oper Res.* 2007;177(1):281-309.
- [8] Safaei N, Saidi-Mehrabad M, Jabal-Ameli MS. A hybrid simulated annealing for solving an extended model of dynamic cellular manufacturing system. *Eur J Oper Res.* 2008;185(2):563-92.
- [9] Mahdavi I, Aalaei A, Paydar MM, Solimanpur M. Designing a mathematical model for dynamic cellular manufacturing systems considering production planning and worker assignment. *Comput Math Appl.* 2010;60(4):1014-25.
- [10] Delgoshaei A, Ariffin MKA, Baharudin BTHT, Leman Z. A new method for decreasing cell-load variation in dynamic cellular manufacturing systems. *Int J Ind Eng Comput.* 2016;7(1):83-110.
- [11] Yao K, Adrien, Kone Oumar, Edi K, Hilaire, Takouda P. L. Mathias. Optimizing cell load regulation capability in dynamic cell manufacturing systems. *Stat Optim Inf Comput.* 2025;14(2):611-27. doi:10.19139/soic-2310-5070-2367.
- [12] Wemmerlöv U, Hyer NL. Procedures for the part family/machine group identification problem in cellular manufacturing. *J Oper Manag.* 1986;6(2):125-47.
- [13] Heragu SS, Chen JS. Optimal solution of cellular manufacturing system design: Benders' decomposition approach. *Eur J Oper Res.* 1998;107(1):175-92.

- [14] Sofianopoulou S. Manufacturing cells design with alternative process plans and/or replicate machines. *Int J Prod Res.* 1999;37(3):707-20.
- [15] Safaei N, Saidi-Mehrabad M, Tavakkoli-Moghaddam R, Sassani F. A fuzzy programming approach for a cell formation problem with dynamic and uncertain conditions. *Fuzzy Sets Syst.* 2008;159(2):215-36.
- [16] Delgoshaei A, Ali A, Ariffin MKA, Gomes C. A multi-period scheduling of dynamic cellular manufacturing systems in the presence of cost uncertainty. *Comput Ind Eng.* 2016;100:110-32.