Evaluation of the performance measures in manufacturing cell formation

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Abstract: In this work, the Cell Formation Problem (CFP) within manufacturing systems is evaluated, seeking to optimize production processes. Accordingly, the appropriateness of the existing evaluation measures for use in dynamic manufacturing scenarios is investigated with the view of enhancing their accuracy and efficacy. The obtained findings indicate the need to reevaluate the commonly adopted evaluation measures for CFP, potentially replacing them with data-driven and context-specific approaches. A quantitative methodology is successfully used to defines parameters that quantify the quality of evaluation measures, rendering such evaluation more robust and adaptable to specific contexts. While grouping efficacy is a commonly accepted measure in this research field, it was shown to exhibit drawbacks that do not justify its widespread popularity. In response to the identified research gaps, a refined objective function is proposed for the core CFP problem. This novel function is designed to enhance solution efficiency and accuracy, ultimately contributing to improved manufacturing processes. The aforementioned findings present a significant advancement in the understanding

and application of evaluation measures in the CFP domain, offering a foundation for further research and potential enhancements in manufacturing optimization practices.

Keywords: cellular manufacturing; cell formation; performance measures; heuristic methods; grouping efficacy; multicriteria optimization.

1. Introduction

Cellular manufacturing represents a critical approach within lean manufacturing. It is also a fundamental aspect of computer-integrated manufacturing, while supporting flexible automation and enabling just-in-time production. Accordingly, it is a valuable application of group technology and a sound concept for organizing work to reduce market response times, and minimize inventories, lead times, and costs (e.g. [1-4]). The application of cellular manufacturing extends across various industries, including aerospace, defense, automotive, machining, pipe fabrication, forging, woodworking, cable manufacturing, electronics, and welding [5,6].

Therefore, addressing the challenges within cellular manufacturing – such as the Cell Formation Problem (CFP), group layout, group scheduling, and resource allocation [7] – is of interest for both practitioners and researchers. Still, the CFP remains the primary concern when designing cellular manufacturing systems. In extant research, the CFP is considered as a multi-criteria problem (e.g. [8,9]), and encompasses diverse objectives such as intercell flow, intracell workload balancing, machine duplication costs, number of bottleneck operations, number of bottleneck machines, number of bottleneck parts, workload of the busiest machine, and workload of the busiest part.

The fundamental challenge in various CFP formulations lies in adequately accommodating a 0–1 machine–part incidence matrix as input. At its core, CFP involves categorization of parts into part families and machines into machine cells. It also entails assigning the part families to suitable machine cells to maximize the reliance on intracell operations (processing a part on the machine within the corresponding cell) while minimizing the need for intercell operations (processing a part on the machine outside the corresponding cell) [10,11]. As this markedly increases the computational complexity CFP is conceptualized as an NP-hard problem.

The focus of the present study is establishing the performance measures for this CFP formulation. This research focus was motivated by the fact that, despite the core problem involving two optimization variables – number of intracell and intercell operations, respectively – all leading algorithms employ a single objective function, namely grouping efficacy. The critical question pertains to how one evaluates the quality of a heuristic solution for CFP based on a single objective criterion. Consequently, nearly all relevant work in this domain is compared based on grouping efficacy, as this measure was intuitively deemed the most suitable in literature. As this is clearly inadequate in the CFP context, the work reported here was guided by the following research question and objectives:

Research Question: How can the quality of a measure for evaluating solutions in the CFP be accurately quantified and experimentally established, leading to an improved objective function for the core CFP?

Research Objectives: The primary objective of this research is to challenge and reassess the commonly adopted measures used in evaluating solutions for the CFP. Its further goal is to quantitatively establish the parameters defining the quality of a measure within a specific context and propose a more suitable objective function for the core CFP problem.

Consequently, this paper introduces a novel, more fitting objective function for the core CFP. The contributions aim to advance the field of CFP by promoting a deeper understanding of the evaluation measures and proposing a more effective objective function to guide problem-solving approaches in this context.

The remainder of the paper is organized into six sections. Section 2 is designated for the literature review, while the research problem is delineated in Section 3, along with the key terms and notations. In Section 4, performance measures for evaluating the effectiveness of cell formation solutions are introduced, while parameters for assessing measure quality are defined and further analyzed based on this quantification in Section 5. These measures are evaluated in Section 6 through a detailed experimental assessment of solutions obtained by applying six prominent approaches for the most widely used benchmark problem instances. The article concludes in Section 7, where the study outcomes are summarized before providing recommendations for future research in this field.

2. Literature review

Although several meta-heuristic procedures for solving this core problem have been proposed over the years, only recently introduced heuristics that have yielded promising results are outlined here and are further utilized to analyze performance measures. Specifically, a simulated annealing-based meta-heuristic with variable neighborhood (SAYLL) was developed and tested by Ying et al. [1]. Diaz et al. [5] proposed a two-phase iterative method denoted as GRASP heuristic for finding lower bounds for the CFP. A hybrid meta-heuristic algorithm (GAVNS) that combines genetic algorithm with variable neighborhood search was presented by Paydar and Saidi-Mehrabad [12]. More recently, Martins et al. [13] proposed a method based on the Iterated Local Search meta-heuristic coupled with a variant of the Variable Neighborhood Descent method that uses a random ordering of neighborhoods in the local search phase (CFPAS). A grouping version of the league championship algorithm (GLCA) was developed by Noktehdan et al. in 2016 [14]. Danilovic and Ilic [15] proposed a Cell Formation Optimization algorithm (CFOPT) in 2019.

Thus far, various performance measures have been proposed, including those outlined below:

- **Grouping efficiency (*E*)**: is the first proposed performance measure for evaluating the heuristic cell formation solutions, developed by Chandrasekharan and Rajagopalan in 1986 [16].
- **Grouping efficacy (*Γ*)**: is a measure proposed in 1990, by Kumar and Chandrasekharan [17], the most used measure in literature. Authors conclude that the drawback of the previous measure, *E*, is that even a bad solution having large number of intercellular operations may have efficiency around 75%.
- **Grouping capability index (*G*):** was proposed by Hsu in 1990 (see e.g. [18,19]). This simple measure only gives importance to the number of intercellular operations.
- **Weighted grouping efficacy (*W*):** was suggested and tested on large-scale problems by Ng in 1993 [20].
- **Grouping index (*I*)**: was proposed by Nair and Narendran [21].
- **Linear performance measure (*L*)**: was initially proposed by Kattan in 2007, according to Serageldin et al. [22].
- **Second linear performance measure (*P*)**: was proposed by Serageldin et al. [22]. The drawback of this measure is that it can take negative values.
- **Second grouping efficiency measure (*S*)**: was recommended by Agrawal et al. in 2011 [23]. Authors proposed two measures and found that *S* had a better discriminating power.

- **Weighted modified grouping efficacy (*M*)**: was introduced by Al-Bashir et al. in 2018 [24]. The authors claim that this measure can be used to logically compare solutions that have the same sum of voids and exceptional elements.

In all reviewed articles pertaining to CFP algorithms, the work of Sarker [18] and Sarker and Khan [19], as well as Gonçalves and Resende [25] is cited, as these authors performed the most extensive objective function analyses and comparisons. Specifically, as a part of their investigations, Sarker [18] and Sarker and Khan [19] conducted computations on 25 machine–part incidence matrices to derive the final average-difference matrix of absolute differences among the tested performance measures based on the 0.8 weighting factor. While these authors emphasized the importance of selecting an appropriate weighting factor, they did not quantify the tested measures. As a part of their investigation, Gonçalves and Resende [25] compared grouping efficiency, and grouping efficacy and established that the latter was a more suitable performance measure due to its capability to incorporate both within-cell machine utilization and inter-cell movements, among other reasons. However, even though the authors portrayed the absence of a weighting factor as an advantage of their strategy, it is in fact a fundamental drawback when considering its practical application.

As indicated by this brief review, there exists a notable gap in extant literature concerning the selection of an objective function for optimizing and validating the results obtained by CFP algorithms, given that:

- The commonly adopted CFP goal of maximizing intracell operations and minimizing intercell operations is imprecise, allowing trivial solutions (such as grouping all machines into a single cell).
- Existing measures lack the ability to satisfy the criteria incorporating two opposite optimization variables without a weighting factor.
- Currently utilized measures that rely on a weighting factor often fail to distinguish between the two opposite optimization criteria.
- The measures utilized in CFP are not quantified.

These shortcomings have motivated the present study, which has four main objectives: (i) quantifying the existing measures for CFP evaluation, (ii) defining a weighting factor that segregates the two opposite optimization criteria, (iii) evaluating the existing measures using the proposed quantification, and (iv) introducing a novel performance measure superior to all currently available measures.

3. Definitions and notations

For clarity, the main terms related to the basic CFP are defined below.

Binary machine–part matrix: A matrix comprising of entries that take a value in the [0,1] range, indicating which machines are used to produce each part. This matrix can be represented by $A = \{a_{ij}\}$, whereby an entry a_{ij} is defined as follows:

$$a_{ij} = \begin{cases} 1, if\ \ part\ \ j\ visits\ machine\ i \\ 0, otherwise \end{cases}$$

where *i* denotes the machine index (*i*=1,…,*m*), *j* represents the part index (*j*=1,…,*n*), *m* is the number of machines, and *n* is the number of parts. A simple example of the binary machine–part matrix is given in Table 1.

Table 1 Example of binary machine–part matrix

Block: A sub-matrix of the binary machine–part matrix formed by the intersection of rows representing a machine cell and columns representing a part family [18]. In Table 1, the two sub-matrices are shaded in gray.

Void: A element with 0 appearing inside the diagonal block. In our example, the number of voids is 1.

Exception: An operation (indicated by 1s) appearing outside the diagonal blocks. In our example, the number of exceptions is 0.

3.1 Notations

m – number of machines

n – number of parts

o – total number of operations (1s) in the machine–part matrix

v – total number of zeros (0s) in the machine–part matrix, $v = m \cdot n - o$

C – number of cells

e_1 – total number of intracell operations (1s inside the diagonal blocks)

e_v – total number of voids

e_e – total number of intercell operations (exceptions)

B – block diagonal space ($B = e_1 + e_v$).

3.2 Problem formulation

The CFP objective is to group parts with similar processing requirements into part-families. This objective must strike a balance between two opposing criteria – reducing the total number of exceptions and minimizing the cell dimensions. Accordingly, the first optimization variable focuses on minimizing exceptions, while the second relates to cell dimensions. As the total number of operations within cells represents the difference between the overall number of operations and the total number of exceptions, the total number of voids is treated as the second optimization variable.

Consequently, the primary CFP objective can be defined as the minimization of both exceptions and voids. Since the decrease in the value of one variable increases the value of the other, the crucial challenge in this optimization process lies in determining the significance of the relationship between the two variables, which is vital for accurately formulating the CFP. Without a clear understanding of this relationship, the optimization results may lack clarity for managers seeking to utilize these outcomes.

Therefore, a fundamental parameter in the CFP formulation should quantify the importance of minimizing exceptions versus minimizing voids. A straightforward and intuitive parameter for this purpose is the weighting factor (q), which ranges from 0 to 1. Accordingly, a value of 0.5 represents equal importance, while 1 signifies exclusive emphasis on exceptions, and 0 indicates exclusive focus on minimizing voids. Unlike previously proposed weighting factors with unclear optimization implications, this weighting factor clearly depicts the importance of minimizing exceptions and voids.

3.3 Performance measures

It is important to emphasize that exceptions and voids unambiguously define all other variables featuring in the existing measures, as outlined below.

Grouping efficiency: $E = q \cdot \eta_1 + (1-q) \cdot \eta_2$ (1)

where η_1 –is the ratio of the number of operations inside the diagonal blocks to the total number of elements in the diagonal blocks and is thus given by: $\eta_1 = \frac{e_1}{e_1 + e_v}$,

η_2 – is the ratio of the number of voids outside the diagonal blocks to the total number of elements outside the diagonal blocks, i.e.: $\eta_2 = \frac{v - e_v}{(v - e_v) + (o - e_1)}$.

Grouping efficacy: $\Gamma = \frac{1 - \psi}{1 + \varphi}$, (2)

where ψ – is the ratio of the number of exceptional elements to the total number of operations: $\psi = e_e / o$ and φ – is the ratio of the number of voids to the total number of operations: $\varphi = e_v / o$.

Accordingly, $\Gamma = \frac{o - e_e}{o + e_v}$.

Grouping capability index: $G = 1 - e_e / o$. (3)

Weighted grouping efficacy: $W = \frac{q \cdot (o - e_e)}{q \cdot (o + e_v - e_e) + (1 - q) \cdot e_e}$. (4)

Grouping index: $I = \frac{B - q \cdot e_v + (1 - q) \cdot (e_e - A)}{B + q \cdot e_v + (1 - q) \cdot (e_e - A)}$, (5)

where A is a correction factor, whereby $A = 0$ for $e_e \leq B$, and $A = e_e - B$ for $e_e > B$.

Linear performance measure: $L = 1 - \frac{1}{2} \cdot \left(\frac{e_e}{o} + \frac{e_v}{v} \right)$. (6)

Second linear performance measure: $P = 1 - \frac{e_e + 0.5 \cdot e_v}{o}$. (7)

Second grouping efficiency measure: $S = 1 - k \cdot \left(\frac{q \cdot e_e + (1 - q) \cdot e_v}{C} \right) \cdot \frac{1}{\sqrt{m \cdot n}}$, (8)

where k is a scaling factor frequently set to2.

Weighted modified grouping efficacy:

$M = \frac{1}{2} \left(\frac{e_1 + e_e - e_v}{e_1 + 2 \cdot e_e} \right) + \frac{1}{2} \left(\frac{e_1 - e_e + e_v}{e_1 + 2 \cdot e_e} \right)$, or simply $M = \frac{e_1}{e_1 + 2 \cdot e_e}$. (9)

4. Measure quantification

To effectively compare measures when applied to the same problem, the criteria by which one measure outperforms another need to be precisely defined. Accordingly, parameters that quantify the quality of measures in the CFP context are established below.

First, given the presence of two optimization variables in CFP, a measure should incorporate a weighting factor. Although weighted sum approaches are often constrained in multi-objective optimization, achieving a balance between two variables is manageable. However, the relationship between these variables is not clearly defined in the existing weighting factors. Moreover, users of the optimization procedure should be able to define the impact of optimization variables on the final solution. To meet these requirements, a simple representation of the weighting factor $q \in [0,1]$ is required, such as $O = q \cdot x_1 + (1-q) \cdot x_2$, where O is the objective function and x_1 and x_2 are the optimization variables. This approach helps users understand the impact of individual variables on the objective value. Furthermore, it's crucial that these optimization variables also need to be clearly defined with respect to exception and void minimization, allowing users to unambiguously determine their relative importance in their specific context.

The objective function boundaries also require precise definition, particularly in the CFP, given that its objective function can be expressed in terms of density, which is a relative quantity that takes bounded and predetermined values. This characteristic is invaluable for heuristics but is rare in most combinatorial problems. In each iteration, the objective function is calculated and compared with the previous values. As heuristics necessitate significant number of iterations, algorithm efficiency directly depends on the objective function characteristics. The first significant advantage of bounded objective functions is the possibility to check the distance between the current solution and the optimum. Another, perhaps more important, advantage is that bounded objective functions enable simple pre-processing, which reduces the size of the processed instance. Feasible space is reduced accordingly and after that any other procedure could be proceeded on such reduced instance. The evaluation in [15] and their findings confirmed the significant impact of reduction on efficacy in all tested instances. It is also important to note that in the CFP all output values are integers, allowing the feasible solution set to be markedly reduced.

Lastly, as the discrimination power plays a crucial role in evaluation it should be considered when assessing a measure's effectiveness.

In the upcoming sub-sections, these key parameters will be quantified for the nine measures presented earlier. While this quantification may appear as a basic mathematical analysis of the optimization problem, it is well-suited to the specific characteristics of the core CFP problem, where the simplicity of quantifying parameters using elementary operations offers a distinct advantage.

4.1 Weighting factor

Some studies have misconstrued the purpose of the weighting factor, incorrectly assuming it's primarily for enhancing measure quality. The primary role of a q is to allow users to prioritize specific aspects during the optimization process. Among the nine measures discussed previously, only *E, W*, *I*, and *S* incorporate a weighting factor, as outlined below.

- *E* provides the simplest and most distinct impact of the q on variables (density of operations within diagonal blocks and the density of voids), allowing users to define optimization variables from their perspective and establish clear priorities.
- *W* was designed as an attempt to introduce q into the commonly used grouping efficacy measure. However, as a clear separation of concerns is lacking, Equation (4) can be rewritten as $W = \dfrac{q \cdot e_1}{q \cdot B + (1-q) \cdot e_e}$, indicating that the total number of operations within diagonal blocks is related to q, but the inverse relationship involves both q and $(1 - q)$, making it less straightforward.
- *I* introduces a more intricate relationship between optimization variables and the q.
- Like *E*, *S* exhibits a simple and distinctly separated the impact of the q on each variable. It has an advantage over *E* as its optimization variables encompass voids and exceptions.

In the discussion that follows, to allow objective comparison of measures that have weighting factors with those that do not, q=0.5 is adopted, signifying that both variables are given equal priority in the optimization process.

4.2 Void-exception relation

When optimizing two variables, understanding their influence on the measure's value is crucial. If this relationship is unclear, the consumer of the optimization won't know if the obtained result is superior to another result. In such cases, quantifying the quality of the obtained result becomes challenging. While measures *Γ*, *G*, *W*, *L*, *P*, *S*, and *M* establish a clear and straightforward relationship between the impacts of voids and exceptions, *E* and *I* lack such clarity.

To quantify the relationship between voids and exceptions, we examine the scenario where the current objective value remains constant when e_e is changed by Δe_e and e_v is changed by Δe_v .

For ***Γ***:

$$\mathit{\Gamma} = \frac{o - e_e}{o + e_v} = \frac{e_1}{o + e_v} = \frac{e_1 + \Delta e_1}{o + e_v + \Delta e_v}$$

$$\Rightarrow \quad e_1(o + e_v) + \Delta e_1(o + e_v) = e_1(o + e_v) + e_1 \Delta e_v$$

$\Rightarrow \quad \frac{\Delta e_1}{\Delta e_v} = \frac{e_1}{o + e_v} \quad \Rightarrow \quad \frac{\Delta(o - e_e)}{\Delta e_v} = -\frac{\Delta e_e}{\Delta e_v}$ since $\Delta o = 0$ and the sign of the exception change is opposite to the void change.

Finally, $\frac{\Delta e_e}{\Delta e_v} = -\frac{e_1}{o + e_v} = -\Gamma$.

Therefore, two different partitions are characterized by the same measure value if and only if the ratio of the changes is equal to the measure itself. This simple relationship correlates the impact of exceptions and voids with the measure. It implies that the impact of variables is almost equal for the near-optimal solutions, and that the impact of exceptions increases as the solution quality decreases. Therefore, this measure does not provide clear insight into the impact of optimization variables.

G is solely dependent on exceptions, making it suitable only in rare instances where exceptions are the sole concern to the user.

W is equivalent to *Γ* when q=0.5, due to which the same conclusions apply (other q values are discussed later).

For ***L***, the exception-void ratio is equal to o/v as shown below:

$$\frac{\Delta e_e}{\Delta e_v} = -\frac{o}{v}.$$

For ***P***:

$$P = 1 - \frac{e_e + 0.5 \cdot e_v}{o}$$

$$\Rightarrow \quad e_e + \Delta e_e + 0.5(e_v + \Delta e_v) = e_e + 0.5 e_v$$

$$\Rightarrow \quad \Delta e_e + 0.5 \Delta e_v = 0 \quad \Rightarrow \frac{\Delta e_e}{\Delta e_v} = -0.5 \, .$$

Therefore, for an equal measure value, the change in the number of voids should be twice the change in exceptions.

M depends on exceptions only, due to which the conclusions related to *G* apply.

S considers the number of cells as parameters, which are functions of voids and exceptions. Consequently, the number of voids and the number of exceptions cannot be isolated on different sides of the fraction.

On the other hand, measures *E* and *I* imply no direct relationship between voids and exceptions.

E consists of two factors: the density of operations inside blocks and the density of zeros outside blocks. As the size of blocks is influenced by the distribution of voids and exceptions, establishing their impact is difficult.

I provides two different definitions for the link between *B* and e_e (however, the second case is extremely rare):

$A = 0$ for $e_e \le B$, and $A = e_e - B$ for $e_e > B$.

For $A = 0$ and $q = 0.5$:

$$I = \frac{o + 0.5 \cdot e_v - 0.5 \cdot e_e}{o + 1.5 \cdot e_v - 0.5 \cdot e_e} \, .$$

A sufficient condition for *I* to have value 1 is absence of voids in conjunction with the optional number of exceptions. This directly implies a poor discrimination power of this measure.

In conclusion, *L* and *P* maintain a constant ratio of the impact of voids and exceptions, making these measures convenient for weighting factor implementation. *Γ* and *W* ($q = 0.5$) are suitable when the impact of optimization variables needs to be adjusted based on the quality measure itself. *G* and *M* are applicable in rare scenarios where only the number of exceptions is of interest. Finally, *E*, *I*, and *S* make it difficult to extract simple conditions for the optimization environment.

4.3 Boundaries

In an ideal scenario without any restrictions on measure boundaries, the best measure would be given by $O = q \cdot e_e + (1-q) \cdot e_v$. However, this objective function is unbounded. Consequently, researchers opted to work with densities of exceptions and voids, leading to variations in measures primarily based on how density is defined.

- Measures *Γ, G, W*, and *P* are normalized by the total number of operations (*o*) and their values are bound within the [0, 1] range.
- In *L*, exceptions are normalized by *o*, while voids are normalized by their total number of voids (*v*). *L* is also bounded within the [0, 1] range.
- Measure *S* is normalized by $\frac{C\sqrt{m \cdot n}}{k}$ and is also bounded within the [0, 1] range.
- Conversely, both *S* and *P* are unbounded and can have negative values.

4.4 Discrimination power

A measure's ability to distinguish between solutions is closely tied to its treatment of voids and exceptions. As a result, that measure is not necessarily superior to another that does not make such distinction. The difference could stem from varying priorities in the void-exception relation for each measure. For a fair comparison of measures, it's essential to account for the impact of different void-exception relations on evaluating discrimination power.

This evaluation may involve calculating the two-dimensional (void, exception) distribution for each measure and using statistical measures derived from this distribution to quantify discrimination power. However, this method can be impractical for some measures.

Alternatively, discrimination power of different measures can be evaluated experimentally. In this case, the validity of the results relies on the test instances covering a wide range of problem classes. The evaluation presented in this paper is based on a well-known list of instances that meet these criteria.

5. Experimental comparison of the discrimination power of the key performance measures

In conventional experimental evaluations of heuristic procedures, algorithms are tested on specific instances, and their performance is compared based on the objective function values and execution time. Sensitivity analysis is often used to ascertain how the results vary across different test instances. However, the experimental evaluation conducted as a part of the present study takes a different approach, where by the test instances are characterized by three parameters: the number of cells, the number of exceptions, and the number of voids. These parameters allow us to analytically calculate all tested objective functions. The conclusions drawn from this evaluation yield a measure ranking that is valid only for the specific set of parameters applied. As such, sensitivity analysis does not need to be performed to validate these conclusions.

When adopting this strategy, the challenge lies in generalizing this evaluation to represent various types of real-life incidence matrices, encompassing sparse, normal, and dense operations, a wide range of optimal values, as well as outliers, singletons, and residuals. To achieve this objective, we defined a set of parameter triplets derived from the results of well-known CFP heuristics applied to a reference set of 34 test instances. This approach resulted in an absolute ranking of the tested measures, applicable to all reference results published in the literature. Consequently, the obtained findings do not require sensitivity analysis.

Before presenting further details of our experimental evaluation, it is vital to delineate the procedure selection criteria. The selection may seem inappropriate as we compared only very good solutions for each instance, which might not effectively represent the solution space. However, including solutions of lower quality would complicate the presentation without substantially enhancing the understanding of the assumptions outlined in this paper. Moreover, the focus here is on comparing measures, while utilizing the results of these algorithms when applied to the specified instances to populate the table with relevant data. This data is then used to draw conclusions regarding the advantages and drawbacks of the tested measures.

The reference set of 34 test instances can be accessed via http://mauricio.resende.info/data/cell-formation/. Notably, instances denoted as No. 1 and No. 1a, although considered the same source by some authors, are distinct. It's essential to explain why we selected these 34 test instances dating back to before the year 2000. Despite their age, these instances remain authoritative today due to providing comparisons with the best-published results and representing the most challenging instances for the observed problem.

As shown in Table 2, we utilized approaches SAYLL, GRASP, GAVNS, CFPAS, GLCA, and CFOPT, all of which were recently developed and share the same objective of maximizing grouping efficacy (Γ).

Table 2 Referent methods sourced from literature

The obtained results (as well as those published in the referenced papers) are presented in Table 3, where absence of data for certain instances indicates that the algorithms were not tested on those instances by the authors of the relevant work. For the weighted functions, we assume $q = 0.5$. The input variables (o), output variables C, e_v and e_e (highlighted in gray to emphasize variables from which all other data is analytically derived), as well as parameters v, e_1, and B calculated from previous columns, are presented first, while the subsequent columns contain measure values calculated from corresponding variables and parameters. W is excluded as it yields identical results to Γ when $q = 0.5$. The first three rows provide the average and minimal values for the column, along with the count of entries above the column average.

To highlight specific properties, different labels are used:

- Non-optimal solutions with a value of 1 are labelled with [a].
- Minimum values are labelled with [b].
- Negative values are labelled with [c].
- The entire S column is labelled with [d] as it represents the only unbounded measure.
- Equal values for different partitions are labelled with [e].
- The entire instance No. 22 is labelled with [f], being the only instance where all measure values are 1.
- Values exceeding the average for the observed column are labelled with [g], enabling direct visual comparison of measure value deviations. For instance, for instances 1 and 2, measure Γ has all but one value above the average, while measure L has values spread around the average for the same instances. Since we only considered the best results for all instances, measures with better discrimination power have fewer entries above the average.

Table 3 Comparison of key performance measures using the most widely used six approaches (q=0.5)

5.1 Weighting factor as a tuning parameter

The weighting factor was proposed as a tuning parameter by several authors, who usually recommend lower values for high-dimensional problems, thereby attributing greater significance to the density of zeros outside the diagonal blocks [18]. To assess the validity of this perspective, we computed grouping efficiency for five high-dimensional instances using three q values (0.3, 0.5, and 0.7), as presented in Table 4.

Table 4 Grouping efficiency values for five high-dimensional instances

Observations indicate that the values of E increase with lower q values, resulting in greater disparities between E and Γ (ranging from 0.1263 in No. 33 to 0.4168 in No. 31). Moreover, solutions featuring a greater number of exceptions and fewer voids tend to yield better grouping efficiency. For instance, in No. 30, the highest result of E=0.9419 (q=0.3) is achieved with e_v=11 and e_e=40, followed by the result of E=0.9335 with e_v=15 and e_e=38, and the least favorable result of E=0.8960 with e_v=41 and e_e=27.

However, irrespective of the chosen q value, the range of E values is significantly narrower compared to the range of Γ values. Consequently, the measure's quality for the examined instances is not affected by q.

6. Discussion of results

The value of Γ ranges from 0.42963 (instance No. 18) to 1 (instance No. 22). As outlined in the preceding section, Γ is more responsive to alterations in the number of voids than to shifts in the number of exceptional elements. Instances No. 21 and No. 30 underscore this characteristic.

Measure E falls within the range [0,1] and displays the second largest number of entries above the average, indicating relatively lower discriminating power. Its value remains high even with a considerable number of exceptional elements in solutions (observed in instances No. 9, 14, 15, 16, 17, 18, 19, 21, 25, 26, 27, 28, 29, 30, 31), often surpassing Γ by more than 0.3 in certain instances.

Measure G is non-negative and solely considers the number of exceptional elements, being insensitive to voids within diagonal blocks. Consequently, a smaller number of exceptions results in a higher value of G. Calculations across all test instances show that G ranges from 0.52252 to 1. However, its main drawback stems from the potential to attain a value of 1 even if a perfect block diagonal form is not achieved (as seen in instances No. 1a, 10, 11), leading to higher values than those obtained when applying Γ.

Measure I also adheres to non-negativity and displays the lowest number of entries above the average. However, its discrimination power is compromised as this measure can take the value of 1 even when a perfect block diagonal form is not achieved (as was the case in instances No. 1, 5 and 8).

Measure L, falling within the [0,1] range, exhibits the second-lowest number of entries above the average. Considering that the measure with the lowest number of entries is the unusable measure I, it can be reasonably deduced that L boasts the best discrimination power among the tested measures.

Measure P was unable to effectively classify solutions in several instances (No. 3, 4, 21, 30, and 31), rendering its discrimination power unacceptable.

Measure S has the inappropriate flexibility to take negative values in certain instances (e.g., No. 9, 28).

Measure M can attain the value of 1 even when a perfect block diagonal form is not achieved (instances No. 1a, 10, and 11).

In sum, except for L, all tested measures exhibit some of the previously discussed drawbacks. Its advantages are further confirmed by the findings reported in Table 5,where the eight measures (W is excluded as it yields identical results to Γ when q = 0.5) are compared in terms of the void-exception relation (VER), dependencies (VE; where 've' denotes that the measure depends on both voids and exceptions, 'v' denotes only voids dependence, while the dash is used in all other cases), boundaries (BND), number of entries above average (AAVG), 1I and NEG (denoting the existence of 1 as the value of the non-optimal solution and the occurrence of negative values, respectively), and SEP (which indicates if the measure struggles to classify solutions that are effectively classified by other measures). The favorable entries are shaded in gray, reinforcing the superiority of L with respect to all attributes.

Table 5 Summarized comparison results

The conclusions drawn from this research are crucial considerations when devising a new optimization algorithm for the CFP. Specifically, although Γ is commonly considered the optimal measure for CFP, the findings presented in this work confirm that it suffers from several notable drawbacks (uncertainty in the impact of optimization variables on the final solution in particular), limiting its practical utility. The condition where different partitions yield the same measure value only if the ratio of changes equals the measure implies variable impact alterations during the optimization process. This uncertainty in the impact of optimization variables on the final solution prohibits the creation of a generic measure with a weighting factor, as evidenced by the unsuccessful attempt with *W*.

Conversely, despite the absence of a weighting factor, *L* possesses commendable qualities, as the impact ratio of optimization variables, represented by o/v, essentially mirrors the density of operations and is readily known in advance.

Given these insights, a potential generic measure incorporating a weighting factor could be formulated as follows:

$$L = 1 - \frac{1}{2} \cdot \left(q \frac{e_e}{o} + (1-q) \frac{e_v}{v} \right), \quad q \in [0,1] .$$

This measure encapsulates all desirable features of the linear performance measure while integrating a clearly defined weight function. The user can seamlessly implement any desired relationship between the significance of voids and exceptions. For instance, for equal impact, the weighting factor should align with the operations density as shown below:

$$\frac{q}{o} = \frac{1-q}{v} \Rightarrow q = \frac{o}{o+v} .$$

It's important to note that while the proposed measure is a compelling example, it may not represent the ultimate solution. It serves as a demonstration of how prior research can be leveraged to craft a robust, hybrid measure.

7. Conclusion

This paper provides an evaluation of the existing performance measures for the core cell formation problem (CFP). The idea of questioning commonly used measures for core CFP solutions arose since the favorite measure, grouping efficacy, has some obvious shortcomings. Its main drawback is the inadequate treatment of the two optimization variables in single criterion optimization procedures.

The first step in the process of comparing relevant measures from literature was to quantify the rules for measure quality. These rules were stated, and measures theoretically compared according to them. It was concluded that the best way to compare the discrimination power of measures is experimental evaluation, since a suitable test population was available. The aim of the experimental evaluation was to visualize important parameters that classify the advantages and disadvantages of the measures regarding the discriminations power. Conclusions were summarized accordingly.

The achievements of this research can be succinctly summarized numerically based on the results presented in Table 5. The binary variable values in columns 1I, NEG, and SEP play a pivotal role in distinguishing between useful and ambiguous objective functions. If any of these columns indicate 'true,' the corresponding measure is deemed unsuitable. Consequently, out of the nine measures tested, five are found unsuitable for application in CFP. Furthermore, the number of entries above average, used as a criterion to quantify discrimination power, underscores the superiority of measures *I* (83) and *L* (91) in this regard. Lastly, in addition to the clear criteria from columns VE and BND, column VER represents a fundamental criterion, as stated in Section 4.2, revealing how the optimization variables influence the objective function's value. For instance, a value of $-\frac{e_1}{o+e_v}$ for *Γ* is not easily interpretable by a manager when deciding to implement the CFP algorithm. On the contrary, the value of -o/v for *L* clearly reinforces the constancy of the ratio as a function of exceptions and voids. Therefore, the primary research conclusion highlights the evident drawbacks of the measure implicitly considered as the best in CFP optimization. Additionally, a new hybrid measure has been proposed, meeting all the criteria of a good measure.

The main contributions of this research are summarized below:

1. Critique of Commonly Adopted Measures
2. Quantification of Measure Quality
3. Development of a New Objective Function

In the context of this research, understanding the managerial aspect is crucial for its practical implementation and implications within a manufacturing setting. The findings of this study have significant managerial implications for decision-makers and practitioners in the manufacturing domain:

1. **Evaluation Measure Selection**: Managers can use the insights from this research to make informed decisions regarding the selection of appropriate evaluation measures for assessing their manufacturing processes. By understanding the limitations and advantages of various measures, they can choose those that align best with their specific objectives and operational environment.
2. **Resource Allocation for Optimization**: The proposed refined objective function can guide managers in allocating resources effectively within the manufacturing system. Optimizing the allocation of machines and manpower based on this function can lead to improved operational efficiency, reduced costs, and enhanced productivity.
3. **Dynamic Problem Handling**: Acknowledging the dynamic nature of the CFP is vital for managers. They need to adapt quickly to changes in part requirements, machine capacities, and other parameters. The study's emphasis on dynamic problem-solving can guide managers in creating agile production systems.
4. **Strategic Manufacturing Optimization**: The research provides a foundation for developing strategic plans to optimize manufacturing processes. Managers can integrate the proposed objective function into their strategic decision-making processes, enabling them to align manufacturing objectives with broader organizational goals more effectively.
5. **Investment and Technology Decisions**: Insights from the research can guide managers in making decisions related to investments in technology and automation. Understanding the most suitable objective function can guide the allocation of resources toward technology that aligns with the manufacturing process's optimization goals.

By incorporating the findings and recommendations presented here into their decision-making processes, managers can enhance their ability to optimize manufacturing processes, adapt to dynamic challenges, and drive overall operational excellence in their organizations.Prior to commencing the optimization process, managers should delineate priorities regarding the significance of minimizing extensions versus minimizing cell sizes, thereby establishing the weight coefficient. Next, they need to apply the proposed algorithm based on an objective function aligned with the measure criteria outlined in this paper.

Based on the work reported here, several directions can be proposed for future research in this domain, which should focus on (1) further development of performance measures; (2) detailed analytical comparison of measures; and (3) introduction of weighting factors with precise rules that define the values of these factors.

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Table captions

Table 1 Example of binary machine–part matrix

Table 2 Referent methods sourced from literature

Table 3 Comparison of key performance measures using the most widely used six approaches (q=0.5)

Table 4 Grouping efficiency values for five high-dimensional instances

Table 5 Summarized comparison results

Table 1 Example of binary machine–part matrix

Machine	Part				
	p1	p2	p3	p4	p5
m1	1	1	0	0	0
m2	1	1	0	0	0
m3	0	0	1	1	1
m4	0	0	1	1	1
m5	0	0	0	1	1

Table 2 Referent methods sourced from literature

No.	**Method**	**Algorithm**	**Source**
1	SAYLL	Simulated annealing with variable neighborhood	[1]
2	GRASP	GRASP heuristic	[5]
3	GAVNS	Genetic with variable neighborhood	[12]
4	CFPAS	Hybrid VN Descent	[13]
5	GLCA	League Championship	[14]
6	CFOPT	Hybrid heuristic	[15]

Table 3 Comparison of key performance measures using the most widely used six approaches (*q*=0.5)

	Alg.	*C*	*O*	e_v	e_e	*v*	e_1	*B*	*Γ*	*E*	*G*	*I*	*L*	*P*	*S*	*M*
avg									0.66659	0.87952	0.75740	0.87540	0.85034	0.68498	0.65483	0.63256
min									0.42963	0.71717	0.52252	0.73134	0.71974	0.41441	0.77878	0.35366
above average									100	113	94	83	91	100	136	93
1	GRASP	2	16	3	2	19	14	17	0.73684[g]	0.85621	0.87500[g]	0.84615	0.85855[g]	0.78125[g]	0.57742[d]	0.77778[g]
	CFPAS CFOPT	3	16	0	4	19	12	12	0.75000[g]	0.91304[g]	0.75000	1.00000[a]	0.87500[g]	0.75000[g]	0.77463[d]	0.60000
1a	SAYLL GAVNS GLCA CFOPT	2	14	3	0	21	14	17	0.82353[g]	0.91176[g]	1.00000[a]	0.83784	0.92857[g]	0.89286[g]	0.74645[d]	1.00000[a]
2	SAYLL GAVNS CFPAS GLCA CFOPT	2	20	3	4	15	16	19	0.69565[g]	0.79605	0.80000[g]	0.86667	0.80000	0.72500[g]	0.40839[d]	0.66667[g]
	GRASP	2	20	4	5	15	15	19	0.62500	0.73849	0.75000	0.82979	0.74167	0.65000	0.23936[d]	0.60000

3	SAYLL GRASP	2	46	3	7	44	39	42	0.79592[g]	0.89137[g]	0.84783[g]	0.93617[g]	0.88982[g]	0.81522[e]	0.47295[d]	0.73585[g]
	GAVNS CFPAS GLCA CFOPT	3	46	1	8	44	38	39	0.80851[g]	0.90875[g]	0.82609[g]	0.97701[g]	0.90168[g]	0.81522[e]	0.68377[d]	0.70370[g]
4	SAYLL GRASP GLCA	2	22	4	2	26	20	24	0.76923[g]	0.87500	0.90909[g]	0.85185	0.87762[g]	0.81818[e]	0.56699[d]	0.83333[g]
	GAVNS CFPAS CFOPT	3	22	2	3	26	19	21	0.79167[g]	0.89683[g]	0.86364[g]	0.91489[g]	0.89336[g]	0.81818[e]	0.75944[d]	0.76000[g]
5	SAYLL GAVNS CFPAS GLCA CFOPT	5	23	0	9	54	14	14	0.60870	0.92857[g]	0.60870	1.00000[a]	0.80435	0.60870	0.79487[d]	0.43750
	GRASP	3	23	9	6	54	17	26	0.53125	0.76810	0.73913	0.73134[b]	0.78623	0.54348	0.43020[d]	0.58621
6	SAYLL GAVNS CFPAS GLCA CFOPT	4	21	3	4	56	17	20	0.70833[g]	0.88991[g]	0.80952[g]	0.87234	0.87798[g]	0.73810[g]	0.80057[d]	0.68000[g]
	GRASP	3	21	6	2	56	19	25	0.70370[g]	0.86077	0.90476[g]	0.79310	0.89881[g]	0.76190[g]	0.69611[d]	0.82609[g]
7	SAYLL GAVNS CFPAS GLCA CFOPT	4	35	1	10	61	25	26	0.69444[g]	0.90934[g]	0.71429	0.96825[g]	0.84895	0.70000[g]	0.71933[d]	0.55556
	GRASP	3	35	6	7	61	28	34	0.68293[g]	0.85531	0.80000[g]	0.85185	0.85082[g]	0.71429[g]	0.55773[d]	0.66667[g]
8	SAYLL GRASP GAVNS CFPAS GLCA CFOPT	3	61	0	9	99	52	52	0.85246[g]	0.95833[g]	0.85246[g]	1.00000[a]	0.92623[g]	0.85246[g]	0.76283[d]	0.74286[g]
9	SAYLL GRASP GAVNS CFPAS GLCA CFOPT	2	91	18	27	69	64	82	0.58716	0.71717[b]	0.70330	0.82775	0.72121	0.60440	-0.77878[c]	0.54237
10	SAYLL GAVNS CFPAS GLCA CFOPT	5	24	4	3	76	21	25	0.75000[g]	0.90000[g]	0.87500[g]	0.85965	0.91118[g]	0.79167[g]	0.86000[d]	0.77778[g]
	GRASP	3	24	10	0	76	24	34	0.70588[g]	0.85294	1.00000[a]	0.74359	0.93421[g]	0.79167[g]	0.66667[d]	1.00000[a]
11	SAYLL GRASP	3	46	4	0	104	46	50	0.92000[g]	0.96000[g]	1.00000[a]	0.92308[g]	0.98077[g]	0.95652[g]	0.89113[d]	1.00000[a]

	GAVNS CFPAS GLCA CFOPT															
12	SAYLL	6	58	10	9	264	49	59	0.72059[g]	0.89814[g]	0.84483[g]	0.85401	0.90347[g]	0.75862[g]	0.82353[d]	0.73134[g]
	GRASP	5	58	15	7	264	51	66	0.69863[g]	0.87269	0.87931[g]	0.80519	0.91125[g]	0.75000[g]	0.75480[d]	0.78462[g]
	GAVNS CFPAS CFOPT	7	58	8	9	264	49	57	0.74242[g]	0.91284[g]	0.84483[g]	0.87786[g]	0.90726[g]	0.77586[g]	0.86466[d]	0.73134[g]
	GLCA	7	58	10	8	264	50	60	0.73529[g]	0.90140[g]	0.86207[g]	0.85507	0.91210[g]	0.77586[g]	0.85670[d]	0.75758[g]
13	SAYLL GLCA	6	61	10	10	275	51	61	0.71831[g]	0.89985[g]	0.83607[g]	0.85915	0.89985[g]	0.75410[g]	0.81815[d]	0.71831[g]
	GRASP	5	61	14	9	275	52	66	0.69333[g]	0.87727	0.85246[g]	0.81935	0.90077[g]	0.73770[g]	0.74905[d]	0.74286[g]
	GAVNS CFPAS CFOPT	7	61	9	10	275	51	60	0.72857[g]	0.90688[g]	0.83607[g]	0.87050	0.90167[g]	0.76230[g]	0.85192[d]	0.71831[g]
14	SAYLL GAVNS CFPAS GLCA	10	85	5	37	283	48	53	0.53333	0.89410[g]	0.56471	0.93243[g]	0.77352	0.53529	0.78106[d]	0.39344
	GRASP	6	85	16	33	283	52	68	0.51485	0.82735	0.61176	0.82703	0.77761	0.51765	0.57428[d]	0.44068
	CFOPT	8	85	6	36	283	49	55	0.53846	0.88795[g]	0.57647	0.92105[g]	0.77763	0.54118	0.72632[d]	0.40496
15	SAYLL	7	116	13	27	364	89	102	0.68992[g]	0.90056[g]	0.76724[g]	0.89344[g]	0.86576[g]	0.71121[g]	0.73918[d]	0.62238
	GRASP	4	116	27	19	364	97	124	0.67832[g]	0.86444	0.83621[g]	0.81633	0.88102[g]	0.71983[g]	0.47510[d]	0.71852[g]
	GAVNS CFPAS CFOPT	6	116	17	23	364	93	110	0.69925[g]	0.89165[g]	0.80172[g]	0.86923	0.87751[g]	0.72845[g]	0.69571[d]	0.66906[g]
16	SAYLL	8	126	27	38	562	88	115	0.57516	0.84945	0.69841	0.81695	0.82518	0.59127	0.69024[d]	0.53659
	GRASP	6	126	35	35	562	91	126	0.56522	0.82997	0.72222	0.78261	0.82997	0.58333	0.55521[d]	0.56522
	GAVNS	8	126	26	38	562	88	114	0.57895	0.85286	0.69841	0.82192	0.82607	0.59524	0.69500[d]	0.53659
	CFPAS	8	126	31	35	562	91	122	0.57962	0.84203	0.72222	0.80000	0.83353	0.59921	0.68547[d]	0.56522
	GLCA	8	126	27	38	562	88	115	0.57516	0.84945	0.69841	0.81695	0.82518	0.59127	0.69024[d]	0.53659
	CFOPT	9	126	17	43	306	83	100	0.58042	0.85024	0.65873	0.86923	0.80159	0.59127	0.67925[d]	0.49112
17	SAYLL GAVNS CFPAS GLCA CFOPT	9	88	9	32	344	56	65	0.57732	0.88717[g]	0.63636	0.89474[g]	0.80510	0.58523	0.78082[d]	0.46667
	GRASP	6	88	24	27	344	61	85	0.54464	0.81992	0.69318	0.78281	0.81171	0.55682	0.59104[d]	0.53043
18	SAYLL GLCA	5	111	34	48	289	63	97	0.43448	0.74553	0.56757	0.75362	0.72496	0.41441[b]	0.18000[d]	0.39623
	GRASP	5	111	24	53	289	58	82	0.42963[b]	0.77033	0.52252[b]	0.80083	0.71974[b]	0.41441[b]	0.23000[d]	0.35366[b]
	GAVNS	6	111	28	51	289	60	88	0.43165	0.75918	0.54054	0.78039	0.72183	0.41441[b]	0.34167[d]	0.37037
	CFPAS CFOPT	7	111	30	49	289	62	92	0.43972	0.75741	0.55856	0.77186	0.72738	0.42342	0.43571[d]	0.38750
19	SAYLL GAVNS CFPAS	7	113	11	50	347	63	74	0.50806	0.86091	0.55752	0.89474[g]	0.76291	0.50885	0.59369[d]	0.38650

	GLCA CFOPT															
	GRASP	5	113	28	43	347	70	98	0.49645	0.79775	0.61947	0.79026	0.76939	0.49558	0.33792[d]	0.44872
20	SAYLL GAVNS GLCA	5	136	30	6	564	130	160	0.78313[g]	0.90069[g]	0.95588[g]	0.83146	0.95135[g]	0.84559[g]	0.72787[d]	0.91549[g]
	GRASP	4	136	41	1	564	135	176	0.76271[g]	0.88257[g]	0.99265[g]	0.79188	0.95998[g]	0.84191[g]	0.60314[d]	0.98540[g]
	CFPAS CFOPT	6	136	25	9	564	127	152	0.78882[g]	0.90955[g]	0.93382[g]	0.85207	0.94475[g]	0.84191[g]	0.78582[d]	0.87586[g]
21	SAYLL GAVNS GLCA	5	153	45	38	547	115	160	0.58081	0.82419	0.75163	0.77667	0.83468	0.60458[e]	0.37258[d]	0.60209
	CFPAS CFOPT	6	153	33	44	547	109	142	0.58602	0.84438	0.71242	0.81717	0.82604	0.60458[e]	0.51495[d]	0.55330
22	SAYLL GRASP GAVNS CFPAS GLCA CFOPT	7	131	0	0	829	131	131	1.00000[f]	1.00000[f]	1.00000[f]	1.00000[f]	1.00000[f]	1.00000[f]	1.00000[f]	1.00000[f]
23	SAYLL GRASP GAVNS CFPAS GLCA CFOPT	7	130	11	10	830	120	131	0.85106[g]	0.95198[g]	0.92308[g]	0.92226[g]	0.95491[g]	0.88077[g]	0.90318[d]	0.85714[g]
24	SAYLL GRASP GAVNS CFPAS GLCA CFOPT	7	131	20	20	829	111	131	0.73510[g]	0.91160[g]	0.84733[g]	0.86755	0.91160[g]	0.77099[g]	0.81557[d]	0.73510[g]
25	SAYLL GAVNS CFPAS GLCA CFOPT	11	131	21	50	829	81	102	0.53289	0.86792	0.61832	0.84727	0.79649	0.53817	0.79168[d]	0.44751
	GRASP	10	131	21	52	829	79	100	0.51974	0.86477	0.60305	0.84615	0.78886	0.52290	0.76439[d]	0.43169
26	SAYLL GAVNS CFPAS CFOPT	12	131	12	61	829	70	82	0.48951	0.89209[g]	0.53435	0.89873[g]	0.75994	0.48855	0.80366[d]	0.36458
	GRASP	10	131	21	59	829	72	93	0.47368	0.85307	0.54962	0.84211	0.76214	0.46947	0.74180[d]	0.37895
27	SAYLL GAVNS CFOPT	12	130	16	61	790	69	85	0.47260	0.86936	0.53077	0.87045	0.75526	0.46923	0.78845[d]	0.36126
	GRASP	10	130	24	61	790	69	93	0.44805	0.83409	0.53077	0.82288	0.75019	0.43846	0.71976[d]	0.36126
	CFPAS	11	130	17	62	790	68	85	0.46259	0.86287	0.52308	0.86345	0.75078	0.45769	0.76322[d]	0.35417
28	SAYLL	5	219	82	54	510	165	247	0.54817	0.77799	0.75342	0.73968	0.79632	0.56621	-0.00741[c]	0.60440

	GAVNS CFPAS GLCA CFOPT															
	GRASP	4	219	71	66	510	153	224	0.52759	0.77617	0.69863	0.75726	0.77971	0.53653	-0.26852[c]	0.53684
29	SAYLL	10	211	58	84	1077	127	185	0.47212	0.80517	0.60190	0.77344	0.77402	0.46445	0.60433[d]	0.43051
	GRASP		211	43	94	1077	117	160	0.46063	0.82396	0.55450	0.81182	0.75729	0.45261	0.57585[d]	0.38361
	GAVNS		211	57	87	1077	124	181	0.46269	0.80325	0.58768	0.77470	0.76738	0.45261	0.42680[d]	0.41611
	CFPAS		211	44	90	1077	121	165	0.47451	0.82660	0.57346	0.81034	0.76630	0.46919	0.58514[d]	0.40199
	CFOPT	12	211	21	100	1077	111	132	0.47845	0.87720	0.52607	0.89091[g]	0.75328	0.47630	0.71904[d]	0.35691
30	SAYLL GAVNS CFOPT	14	128	11	40	1102	88	99	0.63309	0.92676[g]	0.68750	0.91165[g]	0.83876	0.64453	0.89613[d]	0.52381
	GRASP	10	128	41	27	1102	101	142	0.59763	0.84323	0.78906[g]	0.76705	0.87593[g]	0.62891	0.80611[d]	0.65161[g]
	CFPAS GLCA	14	128	15	38	1102	90	105	0.62937	0.91168[g]	0.70313	0.88593[g]	0.84476	0.64453[e]	0.89206[d]	0.54217
31	SAYLL GAVNS CFPAS	14	167	14	75	1333	92	106	0.50829	0.90706[g]	0.55090	0.90698[g]	0.77020	0.50898	0.83586[d]	0.38017
	CFOPT	15	167	12	76	1333	91	103	0.50838	0.91455[g]	0.54491	0.91837[g]	0.76795	0.50898[e]	0.84852[d]	0.37449
32	SAYLL	18	302	52	133	2398	169	221	0.47740	0.85553	0.55960	0.83413	0.76896	0.47351	0.80220[d]	0.38851
	GRASP	11	302	79	127	2398	175	254	0.45932	0.81853	0.57947	0.77871	0.77326	0.44868	0.63959[d]	0.40793
	GAVNS	10	302	71	128	2398	174	245	0.46649	0.82903	0.57616	0.79390	0.77328	0.45861	0.61702[d]	0.40465
	CFPAS	14	302	59	129	2398	173	232	0.47922	0.84671	0.57285	0.81902	0.77412	0.47517	0.74157[d]	0.40139
	CFOPT	16	302	48	133	2398	169	217	0.48286	0.86262	0.55960	0.84390	0.76979	0.48013	0.78229[d]	0.38851
33	SAYLL GRASP GAVNS CFPAS CFOPT	10	420	37	36	3580	384	421	0.84026[g]	0.95103[g]	0.91429[g]	0.91913[g]	0.95198[g]	0.87024[g]	0.88458[d]	0.84211[g]

Table 4 Grouping efficiency values for five high-dimensional instances

No.	Approach	e_v	e_e	Γ	E $(q = 0.3)$	E $(q = 0.5)$	E $(q = 0.7)$
29	SAYLL	58	84	0.4721	0.8526	0.8052	0.7577
	GRASP	43	94	0.4606	0.8610	0.8240	0.7869
	GAVNS	57	87	0.4627	0.8505	0.8032	0.7560
	CFPAS	44	90	0.4745	0.8639	0.8266	0.7893
	CFOPT	21	100	0.4784	0.8917	0.8772	0.8627
30	SAYLL	11	40	0.6331	0.9419	0.9268	0.9116
	GRASP	41	27	0.5976	0.8960	0.8432	0.7904
	GAVNS	11	40	0.6331	0.9419	0.9268	0.9116
	CFPAS	15	38	0.6294	0.9335	0.9117	0.8899
	GLCA	15	38	0.6294	0.9335	0.9117	0.8899
	CFOPT	11	40	0.6331	0.9419	0.9268	0.9116
31	SAYLL	14	75	0.5083	0.9227	0.9071	0.8914
	GAVNS	14	75	0.5083	0.9227	0.9071	0.8914
	CFPAS	14	75	0.5083	0.9227	0.9071	0.8914
	CFOPT	12	76	0.5084	0.9270	0.9145	0.9021
32	SAYLL	52	133	0.4774	0.8919	0.8555	0.8192
	GRASP	79	127	0.4593	0.8703	0.8185	0.7667
	GAVNS	71	128	0.4665	0.8766	0.8290	0.7815
	CFPAS	59	129	0.4792	0.8871	0.8467	0.8063
	CFOPT	48	133	0.4829	0.8961	0.8626	0.8291
33	SAYLL	37	36	0.8403	0.9666	0.9510	0.9355
	GRASP	37	36	0.8403	0.9666	0.9510	0.9355
	GAVNS	37	36	0.8403	0.9666	0.9510	0.9355
	CFPAS	37	36	0.8403	0.9666	0.9510	0.9355
	CFOPT	37	36	0.8403	0.9666	0.9510	0.9355

Table 5 Summarized comparison results

	VER	VE	BND	AAVG	1I	NEG	SEP
Γ	Γ	ve	[0,1]	100	no	no	no
E	-	ve	[0,1]	113	no	no	no
G	voids	v	[0,1]	94	yes	no	no
I	-	-	[0,1]	83	yes	no	no
L	-o/v	ve	[0,1]	91	no	no	no
P	-0.5	ve	[0,1]	100	no	no	yes
S	-	ve	-	136	no	yes	no
M	voids	v	[0,1]	93	yes	no	no

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