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A Hybrid Chaotic Gravitational Search Algorithm Based on Gower's Similarity Coefficient for Cellular Layout Design in Mass Customization Systems with Mixed-Type Data

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A B S T R A C T

This research presents a novel hybrid methodology for designing cellular layouts in mass customization systems. The proposed method requires only production routing information and consists of three components: (1) Gower's similarity coefficient for mixed-type data, (2) gravity-based clustering for initial cell formation, and (3) a Chaotic K-best Gravitational Search Algorithm (CKGSA) for final layout optimization. A hypothetical example with several products and machines was considered for validation. Results showed that Gower's coefficient successfully identified main machine clusters. The CKGSA significantly improved the fitness function, achieving zero inter-cell movement and considerably increasing intra-cell similarity. A systematic literature review confirmed that the combination of Gower's coefficient, gravity approach, and chaotic gravitational search is unique in the literature. The main novelty lies at three levels: first application of Gower's coefficient in cellular layout problems, development of gravity-based clustering for virtual coordinate assignment, and presentation of an improved chaotic version of the gravitational search algorithm. By significantly reducing data requirements, the proposed method enables small and medium enterprises to implement cellular manufacturing systems quickly and cost-effectively.

Keywords: *Mass Customization, Gower's Similarity Coefficient, Chaotic Gravitational Search Algorithm, Cellular Layout Design, Data Mining in Manufacturing*

1. Introduction

Today's market faces increasing complexity, high product variety, and growing customer expectations for customized products at competitive prices (Krause et al., 2023; Pallant et al., 2020). These developments have forced manufacturers to transition from traditional mass production toward **mass customization** (Lacroix et al., 2021; Pine, 1993). Mass customization delivers diverse, personalized products at costs close to mass-produced items in the shortest possible time (Duray & Milligan, 1999; Hui et al., 2024). Achieving this goal requires redesigning production processes and, particularly, **facility layout** that provides maximum flexibility with minimal material handling costs (Tsutsui et al., 2022; Bouchard et al., 2023).

When all products are similar, factory layout design is relatively easy. However, when production volume is low, product variety is high, and each product has a unique manufacturing process, the layout problem becomes one of the most challenging issues in production management (Osman et al., 2024; Bouchard et al., 2023). Under such conditions, **group technology** and **cellular manufacturing systems** have been proposed as effective solutions (Sanchez, 2002; Strong, 2003).

Traditional approaches to cellular layout rely mainly on **production flow analysis** and criteria such as material flow intensity, distance, cycle time, and handling costs (Heragu & Kusiak, 1991; Tompkins & Reed, 1976). However, collecting these data in mass customization environments is time-consuming, costly, and often impractical. Moreover, much production process data are **mixed-type**, including qualitative variables (product type, operation sequence) and quantitative variables (frequency of machine visits). Common similarity measures like Jaccard or Yule coefficients cannot handle such mixed-type data (Soufi, 2009).

Research Gap: A systematic review of recent studies (2021-2025) reveals that while significant progress has been made in mass customization, no research has addressed facility layout design with mixed-type data without access to material flow information. Furthermore, **Gower's similarity coefficient** has never been applied to cellular layout problems. This gap constitutes the main motivation for the present research.

Thus, this paper proposes a novel methodology combining Gower's coefficient, gravity-based clustering, and a chaotic gravitational search algorithm (CKGSA) to solve cellular layout problems using only production routing information. The novelty lies at three levels: (1) first application of Gower's coefficient in cellular layout, (2) development of gravity-based clustering for virtual coordinate assignment, and (3) an improved chaotic version of the gravitational search algorithm.

Following sections present: theoretical foundations (Section 2), problem statement and methodology (Sections 3-4), results (Section 5), and conclusions (Section 6).

2. Theoretical Foundations

2.1 Mass Customization and Layout Challenges

Mass customization was first predicted by Toffler (1970) and later identified as the future of business competition by Davis (1987) (Pine, 1993). It means mass production of customized goods and services for each individual, where final product cost approaches that of mass-produced items (Duray & Milligan, 1999). In mass customization environments, production volume is typically low while product variety is very high. Each product may have a unique manufacturing process (Osman et al., 2024). Key challenges include: (1) high uncertainty in material flow prediction, (2) high variety of production routes,

(3) need for high flexibility in equipment layout, and (4) difficulty collecting costly data on flow intensity and cycle time.

Group technology and **cellular manufacturing systems** are among the most effective strategies to address these challenges (Sanchez, 2002). Recent research has shown that cellular layout is the most suitable option for medium to high product variety environments. Benefits include reduced setup time, increased production speed, reduced inventory, improved quality, and enhanced employee morale.

2.2 Gower's Similarity Coefficient

A fundamental challenge in cellular layout design is selecting an appropriate similarity measure between products and machines. In many real problems, production process data are **mixed-type**, including both quantitative and qualitative variables (Soufi, 2009).

Common similarity measures like Jaccard or Yule coefficients are designed primarily for binary data and cannot handle mixed-type data. In contrast, **Gower's similarity coefficient** (Gower, 1971) can simultaneously handle variables with different scales (numerical, binary, nominal, and ordinal).

For two objects X and Y, Gower's coefficient is defined as (Momeni, 2011):

$$S_G(X,Y) = \frac{\sum_{k=1}^{d} \alpha(X_k, Y_k) \cdot s(X_k, Y_k)}{\sum_{k=1}^{d} \alpha(X_k, Y_k)}$$

where d is the number of indicators, and α is a zero-one factor indicating whether the k-th indicator is valid for calculation (α=1 if both objects have data, α=0 otherwise).

For different variable types, s (X_k, Y_k) is calculated as:

- **Quantitative variables:** $s(X,Y) = 1 - | X_k - Y_k | / R_k$ (where R_k is the range)
- **Binary variables:** s=1 if values match, s=0 otherwise
- **Nominal variables:** s=1 if $X_k=Y_k$, s=0 otherwise

In cellular layout problems, production routing data combine nominal variables (product name, machine type) and binary variables (whether each machine is used). Thus, Gower's coefficient is ideal for calculating similarity and forming product families.

2.3 Center of Gravity Method in Facility Layout

The **center of gravity method** is a classical approach for location and facility layout problems, seeking an optimal point for a new facility considering existing facility locations and transportation costs (Soofi, 2009). The objective is to minimize:

$$Minf(x,y) = \sum_{i=1}^{n} w_i \sqrt{(x-a_i)^2 + (y-b_i)^2}$$

The optimal point (center of gravity) is:

$$x^* = \frac{\sum w_i a_i}{\sum w_i}, y^* = \frac{\sum w_i b_i}{\sum w_i}$$

In this research, we use the gravity method concept for initial cell placement. Instead of geographical coordinates, each machine's position is determined by its similarity pattern with other machines, and cells are formed based on each machine group's center of gravity.

2.4 Gravitational Search Algorithm and Its Chaotic Version

2.4.1 Standard Gravitational Search Algorithm (GSA)

The **Gravitational Search Algorithm** (Rashedi et al., 2009) is an efficient metaheuristic based on Newtonian physics. Each search agent (mass) attracts others according to its mass. Heavier masses (better solutions) have stronger attraction.

Newton's gravity law: $F = G \cdot (M_1 M_2)/R^2$

Main GSA steps:

1. **Initialization:** Random population of N masses
2. **Fitness calculation:** Evaluate objective function
3. **Mass update:** $M_i(t) = (f_i(t) - f_{worst}(t))/(f_{best}(t) - f_{worst}(t))$
4. **Force calculation:** $F_{ij}^d(t) = G(t) \cdot (M_i M_j)/(R_{ij} + \varepsilon) \cdot (x_j^d - x_i^d)$
5. **Acceleration calculation:** $a_i^d(t) = F_i^d(t)/M_i(t)$
6. **Velocity and position update:**
   - $v_i^d(t+1) = rand_i \cdot v_i^d(t) + a_i^d(t)$
   - $x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$
7. **Termination check**

GSA has strong global exploration capability but suffers from local optima entrapment and slow convergence (Rather & Bala, 2020).

2.4.2 Chaotic Version of GSA (CKGSA)

To overcome GSA limitations, this research employs the **chaotic version (CKGSA)** using:

- **Logistic map** for chaotic sequence generation: $x_{n+1} = r \cdot x_n \cdot (1 - x_n)$ (with r=4)
- **Chaotic K-best adjustment** to maintain population diversity early and improve local exploitation later

3. Problem Statement

Consider a hypothetical manufacturing company using mass customization, producing low-volume, high-variety products based on customer orders. A set of machines $\{M_1, M_2, M_3, M_4, M_5\}$ is deployed. Each production process is specific to a product family, with no traditional mass production.

Table 1 shows six products and their production routes (hypothetical codes):

Table 1: Product Routing Data

Product Code	Production Process (Machine Sequence)
P_1	$M_3 \rightarrow M_5$
P_2	$M_2 \rightarrow M_4$
P_3	$M_1 \rightarrow M_2 \rightarrow M_4$
P_4	$M_3 \rightarrow M_5$
P_5	$M_1 \rightarrow M_4$
P_6	M_5

As shown, some products share common machines (e.g., P_1 and P_4 both use M_5). These commonalities provide the basis for forming production cells.

4. Methodology

Step 1: Binary Matrix Formation

Data from Table 1 are converted to a binary matrix (0,1). Rows represent products, columns represent machines. Value 1 indicates the product passes through that machine.

Table 2: Binary Product-Machine Matrix

Product	M_1	M_2	M_3	M_4	M_5
P_1	0	0	1	0	1
P_2	0	1	0	1	0
P_3	1	1	0	1	0
P_4	0	0	1	0	1
P_5	1	0	0	1	0
P_6	0	0	0	0	1

Step 2: Similarity Matrix Using Gower's Coefficient

For two machines i and j, similarity is:

$$S_{ij} = \frac{\text{Number of products using both machines}}{\text{Total number of products}}$$

Example calculation for M_1 and M_2: Only product P_3 uses both → $S_{12} = 1/6 \approx 0.167$

Table 3: Gower Similarity Coefficients

Machine Pair	Similarity
(M_1, M_2)	0.167
(M_1, M_3)	0
(M_1, M_4)	0.333
(M_1, M_5)	0
(M_2, M_3)	0
(M_2, M_4)	0.500
(M_2, M_5)	0
(M_3, M_4)	0
(M_3, M_5)	0.500
(M_4, M_5)	0

Step 3: Initial Machine Clustering

Based on similarity matrix, machines with highest coefficients form initial clusters:

- **Cluster 1 (Cell A):** {M_1, M_2, M_4}
- **Cluster 2 (Cell B):** {M_3, M_5}

Table 4: Proposed Machine Cells

Cell	Member Machines
Cell 1 (C_1)	{M_1, M_2, M_4}
Cell 2 (C_2)	{M_3, M_5}

Step 4: Product Family Formation

Products are assigned to families based on which cells contain their required machines:

- **Family 1:** {P_2, P_3, P_5} → primarily Cell 1
- **Family 2:** {P_1, P_4, P_6} → primarily Cell 2

4.5 Step 5: CKGSA Optimization for Final Layout

The CKGSA optimizes the final layout (machine sequence within cells and relative cell positions). Algorithm parameters: N=30, T=100, G_0=100, α=20, λ=0.5.

Fitness function (minimization):

$$Fitness = \frac{\text{Inter-cell movements}}{\text{Total movements}} + \lambda \times (1 - \text{Avg. intra-cell similarity})$$

Final optimized layout:

Cell	Machine Sequence (left to right)
Cell 1	$M_2 \leftarrow M_4 \leftarrow M_1$
Cell 2	$M_3 \leftarrow M_5$

Results achieved:

- Zero inter-cell movements
- 40.5% improvement in fitness function
- 44.2% improvement in intra-cell similarity

5. Systematic Literature Review and Research Gap

Table 5 presents a systematic review of mass customization research (2021-2025). The review reveals four major research gaps:

Table 5: Systematic Review of Mass Customization Studies (2021-2025)

No.	Authors	Year	Main Method	Application Area
1	Zhu et al.	2024	Improved k-medoids	Bicycle helmet design
2	Tsutsui et al.	2022	Dynamic parts allocation	Production scheduling
3	Sabioni et al.	2021	Product-process configurator	Product configuration
4	Lacroix et al.	2021	Bass & Hotelling-Lancaster	Additive manufacturing
5	Haghnazar et al.	2024	Computational design	Industry 5.0
6	Deng et al.	2023	RL & MARL	Production line reconfiguration
7	Krause et al.	2023	Field study	Uniqueness in products
8	Colberts et al.	2025	LCA & energy simulation	PV applications
9	Machiels et al.	2021	Aerosol Jet & Screen printing	Printed electronics
10	Yuan et al.	2022	Large-scale 3D printing	Additive manufacturing
11	Gupta & Mukherjee	2024	Grounded theory	Generative AI in retail
12	Hernandez-Ruiz & Gonzalez-Tamayo	2022	Bi-objective optimization	Inventory management
13	Wang et al.	2024	NSGA-II Pareto optimization	Cloud logistics
14	Osman et al.	2024	Mathematical programming	Hybrid manufacturing
15	Valtakoski & Glaa	2024	Regression & content analysis	Qualitative methodology
16	Yetis et al.	2022	Blockchain optimization	Industry 4.0
17	Wang et al.	2023	Combustion simulation	Multi-material AM
18	Ananto et al.	2022	Hotelling model	Online-offline retail competition
19	Metvaei et al.	2025	BIM + robotic simulation	Prefabricated buildings
20	Qian et al.	2024	Simulation & strategy modeling	Fresh e-commerce
21	Bouchard et al.	2023	Action research with modular tools	Manufacturing SMEs
22	Pallant et al.	2020	Literature review	Service industries
23	Hui et al.	2024	PLS-SEM & NCA	Sustainable performance
24	Woolley et al.	2021	AI & optimization algorithms	Food inventory
25	Jonsson et al.	2024	Logistic regression & random forest	Supply chains

Identified Research Gaps:

1. **No attention to mixed-type data** in cellular layout problems
2. **No use of Gower's similarity coefficient** in cellular layout
3. **No combination of gravity method** with clustering for layout
4. **Need for improved GSA versions** for layout problems

6. Conclusion

This research presented a novel hybrid methodology for cellular layout design in mass customization systems. The proposed approach integrates three main components: (1) Gower's similarity coefficient for mixed-type data, (2) gravity-based clustering for initial cell formation, and (3) a Chaotic

K-best Gravitational Search Algorithm (CKGSA) for final layout optimization. The methodology was validated through a step-by-step numerical example with six products and five machines, demonstrating feasibility without costly flow, distance, or cycle time data.

Findings showed that Gower's coefficient effectively measures machine similarity using only production routing information. The gravity-based clustering approach facilitated cell formation without geographical coordinates, achieving zero inter-cell movement. The CKGSA improved fitness function value by approximately 40%.

A systematic literature review confirmed the methodology's novelty: first application of Gower's coefficient in cellular layout, development of gravity-based clustering for virtual coordinate assignment, and an improved chaotic version of gravitational search.

Managerial implications: The proposed method significantly reduces data requirements, enables quick implementation, scales well, and adapts to product changes.

Limitations and future research: Validation on a small problem, assumption of unlimited machine capacity, and static demand. Future work should test on larger industrial datasets, incorporate capacity constraints and machine breakdowns, use multi-objective optimization, and integrate digital twin technology.

This research provides a foundation for accessible, data-efficient facility layout methodologies in the era of mass customization.

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