

OPTIMIZATION OF COBOTS AND OPERATORS ASSIGNMENT IN CELLULAR MANUFACTURING SYSTEMS: A MATHEMATICAL MODEL AND HEURISTIC APPROACH

S M SALEEMUDDIN¹, Sanjeev Reddy K HUDGIKAR²

This study presents a mathematical model and a heuristic method for optimizing the assignment of cobots and operators in a cellular manufacturing system. The mathematical model incorporates decision variables for cobot and operator assignments, an objective function to minimize the total cost, and constraints to ensure compatibility and resource limitations. The heuristic method, based on a greedy algorithm, iteratively assigns cobots and operators to cells based on cost considerations, while respecting compatibility and resource constraints. Although the heuristic does not guarantee an optimal solution, it provides a practical approach for solving larger-scale problems efficiently. The proposed model and heuristic method offer insights and tools for improving the efficiency and cost-effectiveness of cellular manufacturing systems utilizing cobots and operators.

Keywords: Cobots, Operators, Cellular manufacturing system, Optimization, Mathematical model, Heuristic method

1. Introduction

Cellular manufacturing systems have gained significant attention in modern manufacturing industries due to their ability to improve efficiency, productivity, and flexibility. In such systems, the allocation of resources, specifically cobots (collaborative robots) and human operators plays a crucial role in achieving optimal performance. The effective assignment of cobots and operators to different cells within the manufacturing system can result in reduced costs, improved productivity, and enhanced overall system performance.

The assignment problem involves determining which cells should be assigned cobots, operators, or both, based on various factors such as task compatibility, resource availability, and cost considerations. This problem can be formulated as a mathematical model, where decision variables represent the assignment of cobots and operators, and an objective function aims to minimize the total cost. However, solving this model for large-scale systems can be computationally intensive and time-consuming. To address the challenges of optimizing cobot and

¹ Research Scholar, Dept of ME, VTU, Belagavi, Karnataka, India, e-mail: saleem324@gmail.com

² Professor, Dept of ME, Sharnbasva University, Kalaburgi, Karnataka, India.

operator assignments in cellular manufacturing systems, heuristic methods provide efficient and practical approaches. Heuristics, such as greedy algorithms, offer approximate solutions by iteratively making locally optimal decisions. These methods can significantly reduce computational complexity while still providing satisfactory results.

In this study, we propose a mathematical model that considers the assignment of cobots and operators in cellular manufacturing systems. The model aims to minimize the total cost associated with cobot usage and operator employment. Additionally, compatibility constraints between cells and resources, as well as limitations on the number of cobots and operators per cell are incorporated to ensure feasible and practical solutions.

To solve the assignment problem efficiently, we employ a heuristic method based on a greedy algorithm. This approach iteratively assigns cobots and operators to cells, considering their compatibility and cost factors, while respecting resource limitations. Although the heuristic method may not guarantee an optimal solution, it provides a practical and time-efficient approach for solving larger-scale problems. By optimizing the allocation of cobots and operators in cellular manufacturing systems, this research aims to enhance system performance, reduce costs, and improve overall efficiency. The proposed mathematical model and heuristic method contribute to the body of knowledge in the field of cellular manufacturing systems, providing insights and tools for decision-makers to optimize resource allocation and achieve improved manufacturing outcomes.

2. Literature Review

The utilization of cobots in manufacturing has gained significant attention in recent years due to their ability to collaborate with human operators, increasing productivity and safety in various tasks. Several studies have focused on the benefits of integrating cobots into cellular manufacturing systems. For example, A proposed a method for optimizing the assignment of cobots and operators to minimize the total makespan in a multi-product manufacturing environment. Their results demonstrated improved system efficiency and reduced production time [20].

Moreover, the assignment of human operators in cellular manufacturing systems is a crucial aspect that affects productivity, skill utilization, and human-robot collaboration. Research has been conducted to explore operator assignment strategies and their impact on system performance and developed a mixed-integer linear programming model to assign operators in a cellular manufacturing system, considering skill requirements, workload balancing, and operator cross-training. The results indicated increased system flexibility and reduced labor costs [18].

In addition to mathematical models, heuristic methods have gained attention as practical approaches to solving large-scale problems. Greedy algorithms, genetic algorithms, and simulated annealing are among the commonly used heuristic methods. These methods offer faster computation times and can provide reasonably good solutions, although they may not guarantee optimality [26].

Several researchers have focused on the integration of cobots into cellular manufacturing systems. They have examined the benefits of cobots in terms of increased productivity, flexibility, and safety. Cobots, with their ability to collaborate with human operators, have been shown to enhance task allocation and workload balancing, leading to improved overall system performance[19].

Furthermore, the consideration of human factors and ergonomics in cobot and operator assignment has emerged as an important research area. Studies have investigated factors such as worker comfort, fatigue, and skill requirements when assigning tasks to cobots and operators. By optimizing the allocation of tasks based on ergonomic considerations, researchers aim to create healthier and more productive work environments [23].

It offers a comprehensive exploration of CMS, focusing on the critical aspects of design, planning, and control. Notably, the book delves into various optimization techniques, including the application of greedy algorithms. These algorithms play a pivotal role in the process of machine-part grouping and layout design within CMS, allowing manufacturers to optimize resource allocation and improve production efficiency. A. Kusiak's work provides both theoretical foundations and practical insights, making it an indispensable resource for researchers and practitioners in manufacturing [1].

The author presents an integrated approach to Cellular Manufacturing Systems (CMS). It builds upon the foundational concepts of CMS and focuses on practical applications. A key highlight is the emphasis on optimization techniques, including greedy algorithms, which are essential for enhancing the overall productivity and efficiency of CMS. The book provides valuable insights into how these algorithms can be effectively implemented to optimize manufacturing processes. It targets a wide audience, from engineers and researchers to manufacturing professionals seeking to improve their production systems [2].

In this influential paper provides a comprehensive review of Cellular Manufacturing Systems (CMS). It serves as a foundational work in the field, offering readers a deep understanding of CMS principles and benefits. Importantly, the paper discusses the role of heuristic algorithms, including greedy approaches, in solving optimization problems associated with CMS. By highlighting the significance of CMS and the heuristic algorithms used to address complex manufacturing challenges, this paper laid the groundwork for subsequent research in the field [6].

This paper presents a novel algorithm designed specifically for the machine-cell formation problem, a critical aspect of CMS. Machine-cell formation involves the efficient grouping of parts and machines into cells to streamline production. The paper outlines how their innovative greedy algorithm effectively addresses this challenge, showcasing its practical applicability and potential for optimizing manufacturing processes [7].

The author explains an extensive overview of Cellular Manufacturing Systems. It covers various components of CMS and explores the algorithms and heuristics used for their design and optimization. Notably, the paper discusses the role of greedy algorithms among other approaches, shedding light on their relevance and effectiveness in shaping efficient CMS. This survey paper serves as a valuable reference for researchers and practitioners seeking to gain a comprehensive understanding of CMS and its optimization techniques [14].

2. This review article, authored by S. Sarin and R. K. Gupta and published in 2006, places specific emphasis on the machine-part grouping problem within Cellular Manufacturing Systems. It discusses various algorithms, including greedy approaches, used to create efficient machine cells. The paper provides insights into the challenges and solutions related to machine-part grouping, making it a valuable resource for researchers and practitioners in the field of CMS [15].

This paper provides a comprehensive review of different algorithms and techniques for machine-part grouping and cell formation within Cellular Manufacturing Systems. It places a strong emphasis on the application of greedy algorithms in this context. Additionally, the paper discusses future research directions, offering valuable insights for researchers aiming to advance the field of CMS optimization [8].

In this review paper explores the multi-objective optimization approaches applied to cell formation within Cellular Manufacturing Systems. It addresses the use of greedy algorithms and other techniques to tackle conflicting objectives. The paper offers a comprehensive overview of multi-objective optimization in CMS, making it a valuable resource for researchers interested in optimizing CMS with multiple conflicting goals [11].

This presents a comparative study of genetic algorithms and greedy algorithms in the context of machine-part cell formation within Cellular Manufacturing Systems. It evaluates the strengths and weaknesses of both approaches, providing valuable insights for researchers and practitioners aiming to choose the most suitable algorithm for their specific CMS optimization needs [22].

This paper explores various machine-part grouping problems encountered in Cellular Manufacturing Systems. It examines how greedy algorithms and other optimization techniques can be applied to address these challenges. The paper serves as a valuable resource for researchers, offering in-depth insights into the

complexities of machine-part grouping and the algorithms that can be employed to optimize this aspect of CMS [9].

This paper provides a comprehensive overview of various aspects of cellular manufacturing systems, including cell formation using different algorithms, such as greedy, genetic algorithms, and mathematical programming techniques [12].

In this paper focuses on genetic algorithms, it discusses the use of greedy algorithms as a benchmark for comparison. It highlights the strengths and weaknesses of greedy approaches in cell formation problems [16].

This paper reviews various algorithms, including greedy heuristics, for cell formation in group technology. It assesses their performance and provides insights into when and how greedy algorithms can be effective [3].

This study presents a greedy algorithm for solving the machine layout problem in cellular manufacturing systems. It discusses the algorithm's performance and compares it with other heuristic approaches [10].

In this paper work focuses on refining a specific greedy heuristic for the machine layout problem, providing insights into optimization techniques [4].

This paper introduces an enhanced version of a greedy algorithm for the machine layout problem, demonstrating the potential for improving the efficiency of these algorithms [5].

In this study primarily employs genetic algorithms, it discusses the integration of greedy algorithms into a hybrid approach for optimizing cellular manufacturing systems [25].

This paper addresses the machine layout problem with a focus on considering various aisle designs, using a greedy algorithm as the optimization approach [13]

Objective

To minimize the total cost associated with the allocation of cobots and operators to cells while ensuring compatibility between the assigned resources and resource limitations.

In simpler terms, the goal is to find the best possible assignment of cobots and operators to different cells within the manufacturing system in a way that reduces costs and improves overall efficiency and productivity. This involves considering factors such as the cost of using cobots and employing operators, their compatibility with specific tasks in each cell, and the maximum number of resources that can be assigned to each cell without exceeding capacity constraints. The mathematical model and heuristic approach are designed to achieve this objective by providing a systematic and practical way to make these assignments

in a manner that optimizes the manufacturing system's performance while minimizing costs.

Novelty:

The proposed model and approach for optimizing the assignment of cobots and operators in cellular manufacturing systems offer several points of novelty and innovation:

Integration of Cobots and Operators: The model integrates the assignment of both cobots and human operators, which is a novel approach. Many existing studies often focus on cobots or operators individually, but this model considers their joint assignment, reflecting the reality of modern manufacturing systems where collaboration between humans and cobots is crucial.

Mathematical Model with Compatibility: The inclusion of compatibility matrices (a_{ij} and b_{ik}) in the mathematical model to ensure that assigned cobots and operators are compatible with the tasks in each cell is a novel feature. This ensures that the assignments are not only cost-effective but also operationally feasible.

3. Greedy Algorithm Overview:

Methodology:

1. Initialize assignments and total costs:

Initialize matrices to keep track of cobots and operators assigned to cells:
 cobots_assigned: Matrix of shape (n_cells, n_cobots) to track cobot assignments.

 operators_assigned: Matrix of shape (n_cells, n_operators) to track operator assignments.

Initialize arrays to keep track of total costs:

 total_cost_cobots: Array of shape (n_cells,) to store the total cost of cobots in each cell.

 total_cost_operators: Array of shape (n_cells,) to store the total cost of operators in each cell

2. Greedy assignment:

For each cell (from 1 to n_cells): Iterate through cobots and assign cobots to the cell based on the following condition.

 Check if there are no operators assigned to the cell.

 Check if the maximum allowed cobots per cell is not exceeded.

Update the assignment and total cost of cobots for the cell.

Iterate through operators and assign operators to the cell based on the following conditions:

Check if there are no cobots assigned to the cell.

Check if the maximum allowed operators per cell is not exceeded.

Update the assignment and total cost of operators for the cell.

Print results:

For each cell:

Print the assigned cobots and operators for the cell.

Print the total cost of cobots and operators for the cell.

Calculate and print the overall total cost:

Sum the total costs of cobots and operators for all cells to get the overall total cost.

4. Develop a mathematical model

Here's a mathematical model that incorporates cobots (collaborative robots) and operators in a cellular manufacturing system:

Decision Variables:

x_{ij} : Binary variable indicating whether cobot_j is assigned to cell_i

$$\begin{aligned} x_{ij} &= 1 \\ &= 0 \text{ otherwise} \end{aligned}$$

y_{ik} : Binary variable indicating whether operator_k is assigned to cell_i

$$\begin{aligned} y_{ik} &= 1 \\ &= 0 \text{ otherwise} \end{aligned}$$

Objective Function: The objective is to minimize the total cost, which includes the cost of using cobots and the cost of employing operators. The objective function can be defined as follows:

$$\text{Minimize Cost} = \sum_{i=1}^n \sum_{j=1}^m c_{ij} * x_{ij} + \sum_{i=1}^n \sum_{k=1}^p w_{ik} * y_{ik}$$

where:

n: Total number of cells in the manufacturing system.

m: Total number of cobots available.

p : Total number of operators available.

c_{ij} : Cost of using cobot $_j$ in cell $_i$.

w_{ik} : Cost of employing operator $_k$ in cell $_i$.

Constraints:

Each cell should have either a cobot or an operator assigned to it (or both):

$$\sum_{j=1}^m x_{ij} + \sum_{k=1}^p y_{ik} \geq 1 \text{ for all } i = 1 \text{ to } n$$

Cobots and operators should be assigned to compatible cells (where they can perform their tasks):

$$a_{ij} * x_{ij} \leq 1, \forall i = 1 \text{ to } n, j = 1 \text{ to } m,$$

$$b_{ik} * y_{ik} \leq 1, \forall i = 1 \text{ to } n, k = 1 \text{ to } p,$$

Where:

a_{ij} = Compatibility matrix indicating whether cobot $_j$ can perform tasks in cell $_i$.

b_{ik} : Compatibility matrix indicating whether operator $_k$ can perform tasks in cell $_i$.

The number of cobots and operators assigned should not exceed the available resources:

$$\sum_{j=1}^m x_{ij} \leq u_i, \forall i = 1 \text{ to } n, \text{ (cobots in each cell should be less than or equal to the available cobots)}$$

$$\sum_{k=1}^p y_{ik} \leq v_i, \forall i = 1 \text{ to } n, \text{ (operators in each cell should be less than or equal to the available operators)}$$

Binary constraints on decision variables: $x_{ij}, y_{ik} = \{0, 1\}, \forall i, j, k$.

In this model, the decision variables x_{ij} and y_{ik} determine the assignment of cobots and operators to cells. The objective function aims to minimize the total cost, which considers the costs associated with using cobots and employing operators. The constraints ensure that each cell has at least one cobot or operator (or both) assigned, the compatibility between cobots/operators and cells, and that the number of assigned cobots/operators does not exceed the available resources.

5. Description of the Mathematical Model for Cobots and Operators Assignment in Cellular Manufacturing Systems:

The mathematical model proposed for the optimization of cobots and operators assignment in cellular manufacturing systems aims to minimize the total cost while considering compatibility and resource constraints. The model is designed to provide an efficient and cost-effective allocation of cobots and operators to various cells in the manufacturing system.

The model involves decision variables, an objective function, and several constraints. The decision variables include binary variables (x_{ij} and y_{ik}) that indicate whether a specific cobot or operator is assigned to a particular cell or not. The objective function seeks to minimize the total cost, which is calculated by summing the costs associated with cobots and operators across all cells. The costs are determined based on the assignment of cobots and operators to cells.

The constraints ensure that each cell has at least one cobot or operator (or both) assigned to it. This constraint guarantees that every cell can perform its tasks effectively. Additionally, the model incorporates compatibility matrices (A_{ij} and B_{ik}) to ensure that cobots and operators are assigned to cells where they can perform their tasks optimally. Compatibility matrices indicate the compatibility between cobots/operators and cells.

The model also includes constraints on the number of cobots and operators assigned to each cell, ensuring that the assigned numbers do not exceed the available resources. These constraints reflect the capacity limitations of the manufacturing system and help maintain a balanced assignment of cobots and operators across cells. Lastly, the model includes binary constraints on the decision variables, indicating that cobots and operators can only be assigned to a cell ($x_{ij}, y_{ik} = 1$) or not assigned ($x_{ij}, y_{ik} = 0$). By formulating the cobots and operators assignment problem into a mathematical model, the proposed approach provides a systematic and quantifiable framework for optimizing the allocation of resources in cellular manufacturing systems. The model can be solved using various optimization techniques such as linear programming or heuristic algorithms, enabling decision-makers to efficiently allocate cobots and operators, minimize costs, and improve the overall performance of the manufacturing system.

Input

In the analysis presented, a comparison between the Greedy Algorithm and PSO (Particle Swarm Optimization) has been conducted to address resource allocation problems in three distinct case studies. The primary focus of this comparison has been on evaluating the total costs incurred by both algorithms across these cases.

The comparison reveals a consistent pattern wherein the Greedy Algorithm consistently yields lower total costs when contrasted with the results obtained

from PSO in all three case studies. This outcome suggests that, for the specific problem instances examined, the Greedy Algorithm excels in cost minimization. However, it is crucial to acknowledge that the selection of an optimization algorithm is not a one-size-fits-all decision. Several factors come into play when making this choice, including the complexity of the problem at hand, available computational resources, and the particular optimization objectives pursued. To enhance the depth of this analysis, it is recommended to augment the comparison with supplementary information. This could encompass insights into the computational time consumed by each algorithm, any pertinent constraints or limitations incorporated into the models, and an exploration of the conditions under which one algorithm demonstrates superiority over the other. Furthermore, to bolster the validity of the observed cost differences, conducting a statistical analysis would be advantageous. Such an analysis could establish whether the discrepancies in costs between the two algorithms are statistically significant, thereby providing a more robust basis for the comparative evaluation.

Inputs: For Industry Problem.

M/P	1	2	3	4	5	6	7
1	0	1	0	1	0	0	1
2	0	0	1	0	1	0	0
3	1	1	0	1	0	0	1
4	1	0	1	0	0	1	0
5	0	0	1	1	1	1	0

Case study 2. (Waghodekar and Sahu, 1984)

M/P	1	2	3	4	5	6	7	8	9
1	1	0	0	1	0	0	1	0	0
2	0	0	0	0	0	1	0	1	1
3	0	1	1	0	1	0	0	0	0
4	0	0	0	0	0	1	0	1	1
5	0	1	1	0	1	0	0	0	0
6	1	0	0	1	0	0	1	0	0
7	1	0	0	1	0	0	1	0	0

Case study 3. (Boctor.F.F, 1991)

M/P	1	2	3	4	5	6	7	8	9	10	11
1	0	0	1	0	0	0	1	0	0	0	1
2	1	1	0	0	0	1	0	0	1	0	0
3	1	1	0	0	0	1	0	0	1	0	0
4	0	0	0	1	1	0	0	1	0	1	0

5	0	0	1	0	0	0	1	0	0	0	1
6	0	0	1	0	0	0	1	0	0	0	1
7	0	0	0	1	1	0	0	1	0	1	0

Output

Taking one real time problem from XYZ Company at Hyderabad, India and two case studies

		Greedy algorithm Total cost	PSO Total cost
Industry Problem 1:	5x7	\$59	\$65
Case study2	7x9	\$57	\$75
Case study3	7x11	\$72	\$90

For Industry Problem: Assigning of Cobots and Operators to the respective cells.

	Cell 1		Cell2	
Industry Problem 1:	Cobots	Operators	Cobots	Operators
	1	2	1	1

Greedy Algorithm Elapsed Time: 0.0009999275207519531 seconds

PSO Elapsed Time: 1.4548585414886475 seconds

For Case Study 2: (Waghodekar and Sahu, 1984)

	Cell 1		Cell2		Cell3	
Case Study 2	Cobots	Operators	Cobots	Operators	Cobots	Operators
	1	2	1	1	2	1

For Case Study 3: (Boctor.F.F, 1991)

	Cell 1		Cell2		Cell3	
Case Study 1	Cobots	Operators	Cobots	Operators	Cobots	Operators
	1	2	1	1	2	1

Summary

In summary, based on the provided Cobot Assignment and Operator Assignment matrices, along with the respective costs for cobots and operators, the following results were obtained:

Considering only the cobots, the cost for the objective function was determined to be **75** units.

Considering only the operators, the cost for the objective function was found to be **49** units.

Considering the cobots and operators, the cost for the objective function was calculated to be **59** units.

These results reflect the total cost incurred based on the assigned cobots and operators in the cellular manufacturing system. The specific costs are determined by the assignment decisions made according to the compatibility, resource constraints, and costs associated with the cobots and operators in each cell. By analyzing the objective function costs, decision-makers can gain insights into the efficiency and cost-effectiveness of different assignment scenarios, which can inform resource planning, optimization strategies, and decision-making processes to enhance the performance of the cellular manufacturing system.

6. Conclusion

In the quest for cost reduction and efficient resource allocation within cellular manufacturing systems, our research has yielded valuable insights and demonstrated the prowess of the Greedy Algorithm. Across a series of case studies, we consistently witnessed the Greedy Algorithm's ability to minimize total costs, making it a compelling choice for manufacturers seeking to optimize their operations economically. Case Study 1, with a total cost of **\$59** compared to PSO's **\$60**, showcased the algorithm's cost-efficiency. Furthermore, the scalability of the Greedy Algorithm became evident in Case Study 2, where it efficiently handled a larger problem size (**7x9**), and in Case Study 3, addressing a highly complex problem (**7x11**). Its adaptability positions it as a versatile tool for resource allocation, capable of catering to various industry-specific constraints and demands.

Our comparative analysis with Particle Swarm Optimization (PSO) provided valuable insights into the strengths and trade-offs of each approach. While PSO demonstrated its proficiency in addressing complex optimization challenges, it often incurred higher costs and required more computational time than the Greedy Algorithm. The Greedy Algorithm's practical applicability, simplicity, and computational efficiency emerged as standout features. Moreover, our case studies illuminated the potential for manufacturers to benefit from the Greedy Algorithm's adaptability and cost-effectiveness in real-world manufacturing scenarios. In conclusion, the choice between the Greedy Algorithm and PSO hinges on the specific needs of the problem, with the Greedy Algorithm proving to be a powerful ally in achieving cost reduction and resource optimization within cellular manufacturing systems while maintaining practicality and computational efficiency.

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