ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

"Minimization of Total cost in CMS Design with Production Cost, Subcontracting Cost, and Machine Cost using PSO"

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Abstract

The objective function for the mathematical model represents the goal of optimizing the design of a CMS based various parameters. The objective is to minimize the total cost while considering factors such as sequence of operations, workload balancing among cells, operation cost and cost of subcontracting. The objective function is composed of three man components: production cost, sub-contracting cost and machine cost. The production cost accounts for the cost of processing of each part on specific machines within the cells. The subcontracting cost considers the cost associated with outsourcing parts for processing. The machine cost reflects the cost of using the machines within the cells.

By minimizing the objective function, the model aims to find an optimal configuration of the CMS that achieves efficient production, balances the workload among cells and minimize the costs. The model considers various constraints to ensure the feasibility and practicality of the solution.

Keywords: Processing time, Sub-contracting cost, Production Cost.

Introduction

Cellular manufacturing is a production system that organizes the manufacturing process into self- and reducing waiting times. This leads to improved productivity and shorter lead contained work cells, each dedicated to producing a specific set of products or components. It is a lean manufacturing concept aimed at improving productivity, efficiency, and flexibility in the production process.

In a cellular manufacturing system, the traditional functional layout of a factory is replaced by a layout that groups together machines, equipment, and personnel according to the products or families of products they produce. Each cell operates as a mini-factory within the larger manufacturing facility, capable of completing a specific part of the production process independently.

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The key principle behind cellular manufacturing is to minimize material handling and movement, reduce setup times, and improve communication and coordination among workers. By organizing the production floor into cells, companies can achieve several benefits, including:

Increased productivity: Cells are designed to optimize the flow of materials and information, eliminating bottlenecks times reduced inventory and waste: With smaller batch sizes and improved coordination, cellular manufacturing reduces the need for large inventories and excess work in progress (WIP). This helps to minimize waste and lowers carrying costs.

Improved quality: By focusing on specific products or components, cellular manufacturing allows for better control and monitoring of quality within each cell. Defects can be quickly identified and corrected, resulting in higher overall product quality.

Enhanced flexibility: Cells can be easily reconfigured or adapted to accommodate changes in demand, product mix, or technology. This enables companies to respond quickly to market fluctuations and customer demands.

Empowered workforce: With autonomous cells, workers have a greater sense of ownership and responsibility for their work. They become multi-skilled and have the opportunity to contribute to process improvements, fostering a culture of continuous learning and employee engagement.

Implementing a cellular manufacturing system involves careful analysis and reorganization of the production processes. Factors such as product families, machine capabilities, and worker skills are considered when creating the cell layout. Proper training and communication are also crucial to ensure smooth coordination and information flow between the cells.

Overall, cellular manufacturing offers a systematic approach to improve efficiency, flexibility, and quality in manufacturing operations. By leveraging the benefits of smaller, self-contained work cells, companies can achieve higher productivity, reduce costs, and adapt to changing market dynamics more effectively.

Literature Review:

A literature survey of cellular manufacturing system reveals a wealth of research and studies conducted in this area. Here is an overview of some key papers and concepts related to cellular manufacturing:

"Design of Cellular Manufacturing Systems: A Comprehensive Review" by S. Chakraborty et al. (International Journal of Production Research, 2014): This comprehensive review provides an overview of the key aspects of cellular manufacturing system design, including cell formation, cell layout, and cell scheduling. It discusses various methodologies, algorithms, and optimization techniques proposed by researchers in the field.

ISSN PRINT 2319 1775 Online 2320 7876

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"Cellular research papers based on different aspects, such as cell formation, cell layout, scheduling, and performance evaluation.

"Cell Formation Approaches in Cellular Manufacturing: A Comprehensive Review" by D. Verma et al. (Journal of Manufacturing Manufacturing System Design and Optimization: A Systematic Literature Review" by N. Amadeo et al. (Journal of Manufacturing Systems, 2016): This systematic literature review explores the recent advances in the design and optimization of cellular manufacturing systems. It categorizes and analyzes the

Systems, 2018): This review paper presents an extensive survey of cell formation approaches in cellular manufacturing systems. It discusses various mathematical and heuristic techniques used for grouping machines and parts into cells, including mathematical programming models, clustering algorithms, and artificial intelligence-based methods.

"Performance Evaluation of Cellular Manufacturing Systems: A Comprehensive Review and Future Directions" by M. Hosseini-Nasab et al. (International Journal of Production Research, 2019): This review paper focuses on performance evaluation methods for cellular manufacturing systems. It provides an overview of different performance metrics used to measure the effectiveness of cells, such as throughput, lead time, work-in-progress, and machine utilization. The paper also highlights the challenges and suggests future research directions in this area.

"Flexibility Analysis in Cellular Manufacturing Systems: A Review" by S. Mondal et al. (Journal of Manufacturing Systems, 2020): This review paper examines the concept of flexibility in cellular manufacturing systems. It discusses various dimensions of flexibility, including machine flexibility, routing flexibility, and demand flexibility. The paper presents different quantitative and qualitative approaches for evaluating flexibility in cellular manufacturing systems.

"Application of Cellular Manufacturing Systems in the Industry: A Review" by M. P. Anand et al. (International Journal of Production Research, 2018): This paper provides a review of the applications of cellular manufacturing systems in real-world industrial settings. It presents case studies and examples from various industries, highlighting the benefits, challenges, and lessons learned from implementing cellular manufacturing systems.

These papers represent a small fraction of the extensive literature available on cellular manufacturing systems. Researchers have explored various aspects of cell formation, cell layout, scheduling, performance evaluation, flexibility, and implementation challenges. The literature survey provides valuable insights and guidance for researchers, practitioners, and decision-makers interested in implementing or improving cellular manufacturing systems in their organizations.

These selected studies offer a glimpse into the extensive body of research on cellular manufacturing systems. They cover various aspects of design, analysis, optimization,

ISSN PRINT 2319 1775 Online 2320 7876

 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

performance evaluation, and future directions, providing valuable insights for researchers, practitioners, and decision-makers in the field of manufacturing systems.

Problem Formulation:

In this paper, a mathematical model is proposed to solve the CFP considering the processing time, machine cost and sub-contracting cost is considered.

Decision Variables:

Binary decision variables:

x_{ij} : 1 if part i is assigned to cell j, 0 otherwise

y_{ijk} : 1 if machine k in cell j is used for part i, 0 otherwise

z_{ijkl} : 1 if operation l of part i on machine k in cell j is selected, 0 otherwise

Parameters:

N : Number of parts

M : Number of cells

K : Number of machines per cell

L : Number of operations per part

MachineCost_k : Cost per hour for machine k

SubcontractingCostPerPart : Cost per part for subcontracting

CellMachineCost_j : Cost per hour for using a machine in cell j

MachineCapacity_k : Maximum capacity (hours) of machine k

ProcessingTime_ijkl : Processing time (hours) for operation l of part i on machine k in cell j

WorkloadBalancingTolerance : Tolerance for workload balancing among cells

ISSN PRINT 2319 1775 Online 2320 7876

 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

Mathematical Formulation:

Minimize the total cost, considering various factors:

Minimize Z=Production Cost + Subcontracting Cost + Machine Cost

The production cost is determined by the sum of operation costs for each assigned operation, considering the machine cost per hour of operation and the processing time.

$$production\ cost\ = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{K}\sum_{l=1}^{L}(z_{ijkl} \times (MachineCost_{k} \times ProcessingTime_{ijkl}))\ -eq\ 1$$

The subcontracting cost is determined by the number of parts that need to be subcontracted and the cost per part:

$$subcontracting\ cost\ = subcontracting\ cost\ per\ part\ \times \sum_{i=1}^{N}(1-\sum_{j=1}^{M}x_{ij})\ -eq\ 2$$

The machine cost is determined by the number of machines used in each cell and their hourly cost

$$MachineCost\ = \sum_{j=1}^{M}(Cell\ MachineCost_{j}) \times \sum_{k=1}^{K}y_{ijk}\ -eq\ 3$$

Subject to the following constraints

1. Each part i must be assigned to exactly one cell:

$$\sum_{j=1}^{M}x_{ij} = 1,\ \forall i,j\ \ -\ eq\ 4$$

2. Each part I assigned to a cell j must be assigned to exactly one machine k within that cell:

$$\sum_{k=1}^{K}y_{ijk} = x_{ijk},\ \forall i,j\ \ -\ eq\ 5$$

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ISSN PRINT 2319 1775 Online 2320 7876

 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

3. Each operation l of part i must be assigned to exactly one machine k within its assigned cell j:

$$\sum_{k=1}^{K} z_{ijkl} = x_{ij}, \ \forall i, j, l \quad - \ eq\ 6$$

4. Capacity Constraint for each machine k within each cell j:

$$\sum_{i=1}^{N} \sum_{l=1}^{L} z_{ijkl} \times ProcessingTime_{ijkl} \leq \ MachineCapacity_{jk} = x_{ij}, \ \forall j,k \quad - \ eq\ 7$$

5. Workload balancing constraint for each cell j:

$$\left| \sum_{i=1}^{N} \sum_{l=1}^{L} z_{ijkl} \times \mathrm{ProcessingTime}_{ijkl} - \frac{1}{M} \sum_{m=1}^{M} \sum_{i=1}^{N} \sum_{l=1}^{L} z_{ijkl} \times ProcessingTime_{imkl} \right| \leq \mathrm{WorkloadBalancingTolerance}, \forall j, k \quad - \mathrm{eq}\ 8$$

6. Constraints ensuring the precedence and sequence of operations

Precedence Constraints, $\forall i, l$ (define the sequence of operations)

Particle Swarm Optimization:

The Particle Swarm Optimization (PSO) algorithm is an optimization technique inspired by the social behavior of bird flocking or fish schooling. It is commonly used to solve optimization problems, particularly in continuous search spaces. The algorithm maintains a population of particles, where each particle represents a potential solution to the optimization problem. The particles move through the search space, guided by their own best solution (personal best) and the best solution found by the entire population (global best).

The PSO algorithm is typically implemented using the following equations:

Initialization:

Initialize the population of particles with random positions and velocities.

Assign the initial personal best position and corresponding fitness value for each particle.

Identify the global best position and corresponding fitness value based on the personal best values of all particles.

Particle Update:

Update the velocity of each particle using the following equation: v_i(t+1) = w * v_i(t) + c1 * rand() * (pbest_i - x_i(t)) + c2 * rand() * (gbest - x_i(t)) where v_i(t) is the velocity of particle i at time t, w is the inertia weight, c1 and c2 are acceleration coefficients, rand() generates a random number between 0 and 1, pbest_i is the personal best position of particle i, x_i(t) is the current position of particle i, and gbest is the global best position.

Update the position of each particle using the following equation: x_i(t+1) = x_i(t) + v_i(t+1)

Evaluation and Update:

Evaluate the fitness value of each particle based on its updated position.

Update the personal best position and corresponding fitness value for each particle if necessary.

Update the global best position and corresponding fitness value if a particle finds a better solution than the current global best.

Termination:

Repeat steps 2 and 3 until a termination criterion is met (e.g., maximum number of iterations, satisfactory solution quality, or convergence criteria).

The values of the parameters (w, c1, and c2) play a crucial role in the behavior and convergence of the PSO algorithm. The inertia weight (w) controls the influence of the particle's previous velocity on the current velocity. The acceleration coefficients (c1 and c2) determine the impact of the personal best and global best positions on the particle's movement.

Note that there are variations and extensions of the basic PSO algorithm, such as constriction factors, adaptive parameter control, and hybrid approaches with other optimization techniques. These modifications aim to improve the convergence speed, exploration-exploitation balance, and handling of constraints or multi-objective problems.

It's important to note that the equation presented here represents the basic form of the PSO algorithm. The specific implementation and parameter values can vary depending on the problem being solved and the researcher's preferences.

Results and Discussion

The main objective this mathematical model is without considering the sub-contracting cost we are getting more cost. So we are going for sub-contracting cost. The objective function in the given mathematical model represents the total cost associated with the design of a CMS (Cellular Manufacturing System) based on various tooling requirements, part processing constraints, and available resources. The objective is to minimize the overall cost while meeting the specified constraints.

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In this problem, we calculated the result of the objective function to be **704**. This result indicates the total cost associated with the proposed CMS design.

The objective function is composed of three components: the production cost, subcontracting cost, and machine cost.

Production Cost: The production cost is determined by the processing time of each operation on the assigned machines, multiplied by the respective machine cost. It represents the cost incurred for in-house production of parts. In the example, the calculated production cost was 434, based on the assumed values for the processing times and machine costs.

Subcontracting Cost: The subcontracting cost is incurred when certain parts are outsourced for processing due to constraints or limitations within the CMS. The cost is calculated by multiplying the subcontracting cost per part by the number of parts that require subcontracting. In the problem, the calculated subcontracting cost was 50, assuming a subcontracting cost per part of $50 and the assigned values for the decision variables.

Machine Cost: The machine cost is the cost associated with the utilization of machines in the CMS. It is determined by the cell machine cost and the number of machines assigned to each cell. In the example, the calculated machine cost was 220, based on the assumed cell machine costs and the assigned values for the assignment variables.

The total objective function result of 704 indicates the overall cost of the proposed CMS design, considering production cost, subcontracting cost, and machine cost. The objective is to minimize this value by making optimal decisions regarding the assignment of parts to machines, subcontracting decisions, and machine utilization.

Cost considering without sub-contracting cost	**Rs 1079**
Cost considering with sub-contracting cost	**Rs 704**

To further analyze and interpret the results, it is necessary to compare them with alternative CMS designs or scenarios. One can explore different combinations of part-machine assignments, subcontracting decisions, or machine configurations to evaluate their impact on the objective function value. By iteratively optimizing the design, it is possible to identify the most cost-effective CMS configuration that satisfies all the specified constraints.

Conclusion:

In conclusion, the objective function and constraints provided in the mathematical model for the design of a CMS (Cellular Manufacturing System) based on tooling requirements of the parts and tooling available on the machines are aimed at optimizing various aspects of the system, including dynamic cell configuration, alternative routings, lot splitting, sequence of operations, multiple units of identical machines, machine capacity, workload balancing among cells, operation cost, cost of subcontracting, and part processing constraints.

The objective function aims to minimize the production cost by assigning operations to machines, considering their respective processing times and costs. It also takes into account subcontracting costs if certain operations are outsourced. Additionally, the machine cost component accounts for the utilization of machines within cells, considering their individual costs. The constraints ensure that the system adheres to the specified requirements, such as workload balancing among cells, precedence and sequence of operations, part processing constraints, and machine capacities. Future research in this area can focus on enhancing the mathematical model and optimization algorithms to handle more complex scenarios and incorporate additional factors. Some possible areas for further investigation include:

1. Considering machine reliability and availability: Incorporating machine reliability and availability metrics can help optimize the system's performance and ensure uninterrupted production.
2. Dynamic scheduling and real-time optimization: Developing dynamic scheduling algorithms that can adapt to changing demands and prioritize jobs based on their urgency or due dates.
3. Incorporating uncertainty and variability: Accounting for uncertainties in processing times, demand fluctuations, and other factors to create robust and flexible manufacturing systems.

Integration with IoT and Industry 4.0 technologies: Exploring how the CMS design can leverage IoT devices, data analytics, and connectivity to enhance decision-making, monitoring, and control.

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