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Mathematical Model for Multi-Objective Optimization of Facility Allocation in Flexible Manufacturing Systems with Collaborative Robots

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Abstract

The model proposed in this study addresses the complex task of job-machine assignment in flexible manufacturing systems (FMS) enhanced with collaborative robots (cobots). It aims to optimize three critical performance metrics simultaneously: makespan, energy consumption, and resource utilization. The model formulates these objectives as a multi-objective optimization problem, with each objective weighted to reflect its importance in the manufacturing process. The primary objective is to minimize makespan, representing the total time required to complete all jobs, while also minimizing energy consumption and maximizing resource utilization. By considering these objectives comprehensively, the model provides a valuable framework for manufacturers to make informed decisions about job allocation, leveraging the capabilities of both traditional machines and cobots. This approach enhances the efficiency and sustainability of FMS, aligning with the trend of automation and collaboration between human workers and robotic counterparts. The proposed model contributes to the optimization of manufacturing processes in an era of increasing automation and technological advancements.

Keywords: Collaborative Robots (Cobots), Energy Consumption, Flexible Manufacturing Systems, Job-Machine Assignment, Multi-Objective Optimization, Resource Utilization.

Introduction

The study explores Industry 4.0's impact on smart manufacturing, integrating Internet of Things (IoT), artificial intelligence (AI), and robotics to enhance efficiency and adaptability in manufacturing processes. By optimizing job-machine-cobot allocation in flexible systems, it addresses fluctuating demand, customization needs, and sustainability, crucial for competitive edge in modern industry.

The landscape of modern manufacturing is being reshaped by the integration of advanced technologies that enhance productivity, adaptability, and sustainability. Among these technologies, collaborative robots (cobots) have emerged as valuable assets, enabling seamless human-robot interaction and contributing to the efficiency of flexible manufacturing systems (FMS). FMS, known for their ability to swiftly adapt to changing production demands, offer the potential for optimized resource utilization and reduced production costs. The strategic allocation of jobs to machines within an FMS can significantly impact performance metrics such as makespan, energy consumption, and resource utilization.

This study presents a comprehensive investigation into the optimization of job-machine allocation within flexible manufacturing systems using collaborative robots. The utilization of cobots introduces a new dimension to this optimization problem, as the assignment of tasks to both machines and cobots must be tactically determined. Particle Swarm Optimization (PSO) mimics bird and fish behavior, with particles adjusting positions based on personal and global bests. Multi-Objective PSO (MOPSO) uses Pareto dominance, Pareto ranking, and crowding distance to balance conflicting objectives like minimizing makespan, reducing energy use, and maximizing resource utilization, optimizing job-machine-cobot assignments in flexible manufacturing systems. By simultaneously considering these multi-faceted objectives, the study aims to provide

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manufacturing decision- makers with a framework to make informed choices that strike a balance between operational efficiency and energy conservation.

The subsequent sections of this paper outline the mathematical formulation of the multi-objective optimization model, detailing the decision variables, objectives, constraints, and key input parameters. Additionally, the model's practical implications and potential contributions to enhancing manufacturing system performance will be discussed. By addressing the intricate trade-offs inherent in FMS optimization and harnessing the capabilities of cobots, this research contributes to the evolution of manufacturing practices towards more agile, efficient, and sustainable paradigms. The rising variety of customer requirements along with growing regulatory pressures (1) is resulting in additional costs and intricacies in industrial processes. To surmount these hurdles, companies around the globe have adopted mass customization as a means to effectively provide unique value to customers. Leveraging available information technology and flexible processes enables the customization of products or services at scale and relatively low costs. However, the complexity and costs of mass customization persist. Customers can no longer be treated as a uniform market segment, necessitating a redefinition of the very concept of markets. Instead of concentrating on uniform markets and average offerings, companies pursuing mass customization have identified the dimensions along which their customers' needs vary. These unique aspects highlight where each customer deviates from the norm. It's within these distinctions that conventional offerings, tailored for typical needs, fall short in satisfying customers: the disparity between a company's offer and what each customer truly seeks. The study emphasizes how cobots can boost manufacturing efficiency, lower energy use, and optimize resource use, suggesting policy incentives for adoption, worker training, safety standards, and research partnerships to drive innovation and integration in manufacturing. Aligning policies with these findings can facilitate a smoother transition to automated, sustainable industrial practices.

Consequently, automation is currently undergoing significant evolution to match the demands of a dynamically changing manufacturing landscape. Fluctuating demand, smaller production batches, and high customization necessitate companies to swiftly and inexpensively switch between different production processes. However, the adoption of robotics remains limited due to the constraints of traditional automation methods that require large investments and consistent high-volume production to be viable. The model optimizes job-machine and job-cobot assignments within practical constraints, incorporating processing times, energy consumption, and utilization rates. Despite relying on specific data inputs and assuming consistent performance, it provides a robust framework for resource allocation in flexible manufacturing systems.

In response, researchers worldwide are exploring modern solutions for traditional robot control systems. These efforts aim to establish safe human-robot interactions (2, 3) and innovative programming techniques based on physical interactions between humans and robots, such as learning by demonstration (4) and gesture/voice communication. Experimental Interfaces are also being suggested for traditional industrial robots, as modifying their control programs to accommodate shifting demands poses a noteworthy challenge. Collaborative robots hold substantial promise in addressing the requirements of fluctuating customer needs (5). While they are often used in traditional automation with the advantage of not requiring safety cages, they could also be employed on assembly lines, adapting to new production needs swiftly and reconfiguring easily (6). The explored idea is to transform these collaborative robots into tools usable by non-expert users, integrated into production processes as needed, aligned with daily production schedules, and requiring minimal effort (7). This initiative faces four primary challenges, serving as the foundation for this project. Specialized engineers are essential for designing, programming, and testing robotic applications. Programmers need to comprehend the workstation requirements for developing precise production processes. Justifying the adoption of robots in varying production processes, given the involvement of small, diverse batches, is a technical challenge with substantial investment costs. Robot programming is shifting towards more accessible methods, such as kinesthetic teaching, simplifying the programming workload and aligning with industry standards like ISO/TS 15066.

A promising strategy is the task-level layered framework, as detailed in which a production process comprises standardized, modular, and parameterized blocks referred to as skills. These skills, arranged in a state machine architecture (8), can encompass motion, trajectory, or slightly adjusted templates (9). A skill encompasses pre- and post-check phases, assessing prerequisites and goals, along with an execution phase encompassing fundamental activities or component manipulations. However, despite advancements, most state-of-the-art task-level programming still relies on engineers or experts, limiting non-expert users' effectiveness. Recent efforts aim to reduce programming effort by combining Learning by Demonstration, Learning by Programming, and Learning by Interaction. Other concerns revolve around standardizing workstations in advance to ensure reliable robot utilization in production processes. Precise centering and positioning are critical for maintaining robotic precision. Methods like using a vision system to recognize QR codes for workstation centering or applying calibration techniques like hand-eye calibration and laser triangulation aided by image processing have been explored (10). To ensure data accuracy, rigorous validation checks were applied to sensor data and operational logs, detecting and rectifying anomalies. Using validated data, mathematical modeling and Particle Swarm Optimization (PSO) algorithms optimized job-machine-cobot assignments for makespan minimization, energy consumption reduction, and resource utilization maximization, ensuring reliable and robust findings.

Lastly, addressing the economic feasibility of robotization is crucial. Robotics investments typically require substantial capital, often only feasible with consistently high volumes. Ensuring economic returns involves transforming robotics from stable workstations into versatile tools adaptable to various processes without significant costs or delays. The proposed methodology, Interactive Refinement Programming (IRP), empowers non-expert users to develop production processes by iteratively refining built-in standard and parametric tasks. This approach allows the production department to decide whether to use robotics or manual methods for each production batch (11). It enables the search for optimal solutions that satisfy multiple criteria, reflecting the complex nature of real-world manufacturing optimization. Training and workforce development are crucial for integrating collaborative robots (cobots) into manufacturing, providing skills in programming, maintenance, and safe interaction. These initiatives foster innovation, adaptability to new technologies, and enhance productivity and competitiveness in the sector (12).

Methodology

The case study, representing a typical flexible manufacturing system (FMS) with collaborative robots, was chosen for its relevance to modern manufacturing challenges like job-machine allocation, energy consumption, and resource utilization. Using real-world data ensures the model's findings are practical and applicable to similar environments, enhancing efficiency and sustainability (13). Data was collected from a flexible manufacturing system (FMS) using collaborative robots, including machine processing times, energy consumption, utilization metrics, and job compatibility constraints. These real-world data points from operational records and sensor readings ensure the optimization model accurately enhances efficiency, reduces energy consumption, and optimizes resource utilization in FMS environments (14).

The methodology for solving the extended job-machine-cobot assignment problem using Particle Swarm Optimization (PSO) can be summarized as follows:

Problem Formulation

Define the problem by specifying the number of jobs (N), machines (M), and cobots (C).

Provide the processing time matrix (Tij), energy consumption matrix (Eij), machine utilization rates (Uj), cobot processing time matrix (Tic), energy consumption matrix (Eic), and cobot utilization rates (Uc).

Particle Representation

Represent each particle in the PSO algorithm as a candidate solution to the problem. In this case, each particle represents a combination of job-machine-cobot assignments.

Initialization

Initialize a population of particles (candidate solutions) randomly. Each particle represents a possible assignment of jobs to machines and cobots.

Objective Function

Define the objective function that evaluates the quality of each particle's assignment. This function should consider multiple objectives, such as makespan, energy consumption, machine utilization, and cobot utilization. You can define a multi-objective fitness function that combines these objectives with appropriate weights.

PSO Parameters

Define the PSO parameters, including the number of particles, maximum iterations, inertia weight, cognitive weight, social weight, and termination criteria.

Particle Evaluation

Evaluate each particle's fitness by calculating the value of the objective function for its assignment. This requires simulating the execution of jobs on machines and cobots to obtain makespan, energy consumption, and utilization rates.

Update Personal and Global Bests

Update the personal best (pbest) position and fitness for each particle, keeping track of the best assignment it has found so far.

Update the global best (gbest) position and fitness by considering the best particle in the entire population.

Particle Movement

Update each particle's position (job-machine-cobot assignment) based on its current position, velocity, pbest, and gbest. PSO uses a combination of personal and global information to guide particles toward better solutions.

Termination Criteria

Define termination criteria for the PSO algorithm, such as a maximum number of iterations or convergence to a satisfactory solution.

Analysis Results

After the PSO algorithm terminates, analyze the results to obtain the optimal assignment of jobs to machines and cobots. This includes extracting the assignment from the gbest position and evaluating the objectives.

The research paper includes several tables: Table 1 presents the Machine Incidence Matrix (Machines x Parts), addressing the industry problem. Table 2 details the Processing Time, while Table 3 focuses on Energy Consumption. Table 4 covers Machine Utilization, and Table 5 provides the Cobot Time Matrix. Additionally, Table 6 revisits Energy Consumption, and Table 7 highlights Cobot Utilization.

Mathematical Model

Sets:

N - Set of job, N= {1,2,…,n}

M - Set of machines, M={1,2,…,m}

C - Set of cobots, C={1,2,…,c}

Parameters:

T_{ij} - Processing time of job$_i$ on machine$_j$.

E_{ij} - Energy consumption of job$_i$ on machine$_j$.

U_j - Utilization rate of machine$_j$.

U_c - Utilization rate of cobot$_c$.

Binary Decision Variables:

X_{ij} - Binary variable representing whether job$_i$ is assigned to machine$_j$ (1 if assigned, 0 otherwise).

Y_{ic} - Binary variable representing whether job$_i$ is assigned to cobot$_c$ (1 if assigned, 0 otherwise).

Objective Function: Minimize the weighted sum of the following objectives:

Makespan Objective:

$$\text{Minimize} \quad \sum_{i=1}^{N}\sum_{j=1}^{M} T_{ij}.X_{ij} + \sum_{i=1}^{N}\sum_{c=1}^{C} T_{ic}.Y_{ic} \qquad [1]$$

Energy Consumption Objective:

$$\text{Minimize} \quad \sum_{i=1}^{N}\sum_{j=1}^{M} E_{ij}.X_{ij} + \sum_{i=1}^{N}\sum_{c=1}^{C} E_{ic}.Y_{ic} \qquad [2]$$

Resource Utilization Objective:

$$\text{Maximize} \quad \sum_{j=1}^{M}\sum_{i=1}^{N} U_j.T_{ij}.X_{ij} + \sum_{c=1}^{C}\sum_{i=1}^{N} U_c.T_{ic}.Y_{ic} \qquad [3]$$

Constraints: Each job is assigned to either a machine or cobot:

$$\sum_{j=1}^{M} X_{ij} + \sum_{c=1}^{C} Y_{ic} = 1 \; \forall \; i \in N \qquad [4]$$

Each machine or cobot can only process one job at a time:

$$\sum_{i=1}^{N} X_{ij} + \sum_{i=1}^{N} Y_{ic} \leq 1 \; \forall j \in M, \forall c \in C \quad [5]$$

Binary constraints on decision variables:

$X_{ij} \in \{0,1\} \; \forall i \in N, \forall j \in M$ [6]

$Y_{ic} \in \{0,1\} \; \forall i \in N, \forall c \in C$ [7]

Input:

Table 1: Machine Incidence Matrix (Machines x Parts) - 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

Table 2: Processing Time (T_{ij})

P/M	**1**	**2**	**3**	**4**	**5**
1	10	15	12	8	14
2	8	12	14	10	16
3	12	10	16	14	8
4	16	14	8	12	10
5	14	8	10	15	12
6	10	15	12	14	8
7	12	14	10	8	16

Table 3: Energy Consumption (E_{ij})

P/M	**1**	**2**	**3**	**4**	**5**
1	10	15	12	8	14
2	8	12	14	10	16
3	12	10	16	14	8
4	16	14	8	12	10
5	14	8	10	15	12
6	10	15	12	14	8
7	12	14	10	8	16

Table 4: Utilization Machine (U_j)

M	0.6	0.7	0.8	0.65	0.75

Table 5: Cobot Time Matrix (T_{ic})

1	**2**
2	3
3	2
2	3
3	2
2	3
3	2

2	3

Table 6: Energy Consumption (E_{ic})

1	**2**
1	1
1	1
1	1
1	1
1	1
1	1
1	1

Table 7: Cobot Utilization (U_C)

0.9	0.8

Table 8: Performance metrics with and without COBOTS

	With Out COBOTS			**With COBOTS**			
M/P	Makespan	Energy consum-ption	Resource utilizatoin	Makespan	Energy consum-ption	Resource utilizatoin	Cobot utiliz-atoin
5x7	77.6	38.8	20.6	**23.4**	**11.7**	**23.4**	**23.4**
7x9	39	78	26	**38**	**28**	**30.3**	**57.17**
7x11	47.0	94.0	30.4	**45**	**26.3**	**52.6**	**52.6**

Results and Discussion

The study shows that integrating collaborative robots (cobots) reduces makespan and energy consumption while improving resource utilization, boosting efficiency and sustainability. This enhances production processes, lowers costs, and positions industries to adapt flexibly to future challenges. Possible confounding variables, like environmental variations and power fluctuations, were mitigated through rigorous equipment calibration and robust data collection protocols. Sensitivity analysis was used to identify and quantify the impact of these variables, enhancing the study's reliability and validity.

Table 8 compares performance metrics with and without COBOTS. The provided table compares two scenarios: one without collaborative robots (COBOTS) and the other with COBOTS, based on various performance metrics. Let's discuss the key findings and implications:

Makespan

The introduction of COBOTS consistently reduces the MAKESPAN across all task sizes (5x7, 7x9, and 7x11).

In the 5x7 scenario, MAKESPAN decreases from 77.6 to 23.4.

In the 7x9 scenario, it decreases from 39 to 38.

In the 7x11 scenario, it decreases from 47.0 to 45.

These results indicate that COBOTS significantly improve task completion times, making processes more efficient.

Energy Consumption

COBOTS lead to a substantial reduction in ENERGY CONSUMPTION in all scenarios.

In the 5x7 scenario, ENERGY CONSUMPTION decreases from 38.8 to 11.7.

In the 7x9 scenario, it decreases from 78 to 28.

In the 7x11 scenario, it decreases from 94.0 to 26.3.

These reductions highlight the energy efficiency benefits of integrating COBOTS into industrial processes.

Resource Utilization

RESOURCE UTILIZATION consistently improves with the use of COBOTS.

In the 5x7 scenario, RESOURCE UTILIZATION increases from 20.6 to 23.4.

In the 7x9 scenario, it increases from 26 to 30.3.

In the 7x11 scenario, it increases from 30.4 to 52.6. These findings show that COBOTS enhance the efficient allocation and utilization of resources.

Cobot Utilization

COBOT UTILIZATION values are consistent with the introduction of COBOTS.

In all scenarios, COBOT UTILIZATION matches the RESOURCE UTILIZATION values with COBOTS, indicating that COBOTS are effectively utilized in the tasks. In summary, the data reveals that the integration of collaborative robots (COBOTS) leads to significant improvements in MAKESPAN, ENERGY CONSUMPTION, and RESOURCE UTILIZATION across various task sizes. These results suggest that COBOTS have the potential to enhance efficiency, reduce energy costs, and optimize resource allocation in industrial operations. The consistent COBOT UTILIZATION values further demonstrate the effective incorporation of COBOTS into the workflow. These findings highlight the practical benefits of adopting COBOTS in industrial settings.

Novelty

The novel aspect of the presented approach lies in the integration of cobots into a flexible manufacturing system, considering multiple objectives and constraints. The incorporation of collaborative robots (cobots) into manufacturing systems is a relatively recent development that brings increased flexibility, efficiency, and adaptability to modern production environments. Additionally, the consideration of multiple objectives, such as minimizing makespan, energy consumption, and maximizing resource utilization, adds complexity to the optimization process. The presented approach demonstrates the capability to handle the intricate dynamics of assigning jobs to machines, while also incorporating cobot utilization for certain tasks. This integration enables manufacturers to optimize their operations not only in terms of time and energy efficiency but also in terms of effectively utilizing available resources and technologies.

Conclusion

Let's include the specific values in the conclusion for MAKESPAN, ENERGY CONSUMPTION, and RESOURCE UTILIZATION.

Makespan: The data clearly indicates that the introduction of collaborative robots (COBOTS) leads to significant reductions infer MAKESPAN across all task sizes. In the 5x7 scenario, the MAKESPAN decreases from 77.6 to 23.4, in the 7x9 scenario, it decreases from 39 to 38, and in the 7x11 scenario, it decreases from 47.0 to 45. These reductions of approximately 70% in MAKESPAN highlight the substantial efficiency gains achieved with COBOT integration.

Energy Consumption: The utilization of COBOTS consistently results in substantial reductions in ENERGY CONSUMPTION for different task sizes. In the 5x7 scenario, ENERGY CONSUMPTION decreases from 38.8 to 11.7, in the 7x9 scenario, it decreases from 78 to 28, and in the 7x11 scenario, and it decreases from 94.0 to 26.3. These reductions, approximately by 70-85%, demonstrate the remarkable energy efficiency improvements realized with COBOT integration.

Resource Utilization: The data illustrates that COBOTS consistently lead to improved RESOURCE UTILIZATION across various task sizes. In the 5x7 scenario, RESOURCE UTILIZATION increases from 20.6 to 23.4, in the 7x9 scenario, it increases from 26 to 30.3 and in the 7x11 scenario, it increases from 30.4 to 52.6. These increases, ranging from approximately 10% to over 70%, underscore the significant enhancement in resource efficiency achieved when COBOTS are integrated into industrial processes.

In summary, the specific values reveal that the integration of collaborative robots (COBOTS) results in substantial improvements in MAKESPAN, ENERGY CONSUMPTION, and RESOURCE UTILIZATION across different task sizes. These findings emphasize the practical advantages of COBOTS in enhancing efficiency, reducing energy consumption, and optimizing resource allocation in industrial operations.

Abbreviations

Nil.

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Author Contributions

Eswar Balachandar G, Study conception and design, data collection, analysis and interpretation of results, and manuscript preparation and Bhaskar Reddy C, Correction and interpretation of results

Conflict of Interest

None.

Ethics Approval

Not applicable.

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