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# Advancing Manufacturing Efficiency: Multi-Objective Optimization in the Industry 5.0 Era

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**Abstract**—This paper explores the transition to Industry 5.0, highlighting its focus on sustainable, human-centred and resilient industrial progress. In this new era, the integration of advanced technology with human expertise is crucial, emphasising the importance of balancing efficiency, cost, quality, and sustainability. At the heart of this research is Multi-Objective Optimisation (MOO), which is used to address the complex challenges of modern manufacturing systems. We propose an innovative approach that combines mathematical modelling with swarm intelligence to tackle complex optimisation problems. A detailed Multi-Objective Mixed Integer Linear Programming (MILP) model is developed and its effectiveness is demonstrated through the application of Multi-Objective Particle Swarm Optimisation (MOPSO). The study compares the performance of MOPSO with traditional optimisation methods using synthetic data analysis. The results not only demonstrate the potential of MOPSO in modern manufacturing, but also set the stage for future research to integrate human ergonomics into the optimization framework, thereby contributing to the holistic advancement of Industry 5.0.

## I. INTRODUCTION

Industry 5.0 is a big step forward from Industry 4.0. It concentrates on sustainable, human-focused, and robust industrial progress. This shift moves the

attention from merely economic benefits to more comprehensive stakeholder principles. It integrates new technologies that support prosperity while recognizing environmental boundaries and highlighting the welfare of industrial labourers. [8]

The evolution towards Industry 5.0 represents a significant leap in manufacturing systems, moving from automated processes to intelligent systems that collaborate with human expertise. This new era emphasises the integration of human cognition and ethics into the decision-making processes of manufacturing, thereby presenting a spectrum of challenges and opportunities for improving the manufacturing framework [6].

Multi-Objective Optimisation (MOO) is a crucial tool for resolving the various conflicting objectives that arise in these complex systems. It aims to identify Pareto optimal solutions that facilitate informed and balanced decision making [4]. The importance of MOO is increasingly recognised in the fields of Industry 5.0 and supply chain management, extending its reach beyond its traditional use in operations research and engineering [7], [11].

In contrast to single-objective optimisation, MOO seeks to outline a Pareto front, presenting a set of

optimal solutions that harmonise the competing objectives [2]. The development of various algorithms, including those based on evolutionary principles, swarm intelligence and mathematical programming, is crucial to the precise articulation of the Pareto front [4], [5].

The complexity within the Industry 5.0 paradigm increases with the introduction of new objectives, including sustainability and operational efficiency. While human-machine interaction is undoubtedly an integral objective within this paradigm, the current paper will not address this aspect in its scope. Instead, this dimension is recognised as an important factor for future research efforts. The focus of this paper remains on the other critical objectives that are essential for effective optimisation strategies [3].

In essence, MOO serves as an essential tool for informed decision making amidst the complex demands that characterise Industry 5.0. This paper seeks to explore these aspects by mathematically formulating and proposing advanced algorithmic solutions to the critical MOO problems in manufacturing, and subsequently extending these solutions to supply chain management for increased efficiency [10]. The first objective of this study is to develop a comprehensive Mixed Integer Linear Programming (MILP) model for multi-objective optimization in manufacturing systems. The second objective is to evaluate the effectiveness of this model using Multi-Objective Particle Swarm Optimization (MOPSO). We recognize the importance of human factors in Industry 5.0. Therefore, our future research will integrate ergonomics to conduct more comprehensive experiments, thereby enriching the human-technology interface in manufacturing processes.

The paper is organized as follows: Section II outlines the background and motivation behind the research, detailing the objectives and the contextual framework of the study. Section III explicates the methodology, elaborating on the multi-objective optimization problem and the hybrid metaheuristic approach employed. Section IV presents the implementation details and the results obtained from the synthetic data analysis, demonstrating the applica-

tion of the methods in a computational context. The combined section V reflects on the findings of the study and discusses prospective avenues for future research, particularly the integration of human ergonomics into the optimization framework.

## II. BACKGROUND AND MOTIVATION

In this section we outline the problem, the objectives in focus, the contextual framework and the key stakeholders involved in decision making within the scope of our research.

The research addresses key objectives to improve both the efficiency and effectiveness of manufacturing processes. We focus on minimising production costs to promote economic sustainability and maximising throughput to increase productivity. A further objective is to reduce energy consumption to lower operating costs and reduce environmental impact. Quality assurance is another key objective to meet customer expectations and comply with industry standards. While the ergonomic optimisation of the human-machine interface is recognised as important, it is outside the immediate scope of this paper and will be the subject of future research. Another important consideration is the improvement of resilience to disruption, ensuring the continuity and reliability of manufacturing operations in the face of unexpected events.

The context of the problem also includes wider supply chain elements, such as

- Inventory management
- Supplier selection and management
- Distribution and logistics
- Customer service and demand forecasting

The inclusion of these supply chain components adds further objectives and constraints, increasing the complexity of the optimisation challenge. For example, the objective of minimising production costs may conflict with the pursuit of sustainable supplier practices, and efforts to maximise throughput may adversely affect transport logistics [1].

In light of these challenges, our research aims to develop a Mixed Integer Linear Programming (MILP) model to optimize key performance metrics in manufacturing, such as cost minimization and throughput maximization. Furthermore, to assess

the effectiveness of this model in the complex landscape of Industry 5.0, we employ Multi-Objective Particle Swarm Optimization (MOPSO), a method well-suited for navigating the multi-faceted objectives of modern manufacturing systems.

### III. METHODOLOGY

This section constructs a mathematical formulation for the multi-objective optimisation problem and delineates the methodological approach to its resolution. We integrate mathematical programming with heuristic methods, notably employing a hybrid metaheuristic strategy.

#### A. Multiobjective Mixed Integer Linear Programming Model

Consider a manufacturing system composed of  $n$  products,  $m$  machines,  $K$  suppliers, and  $L$  distributors, where  $i = \overline{1, n}$ ,  $j = \overline{1, m}$ ,  $k = \overline{1, K}$ , and  $l = \overline{1, L}$ .

##### 1) Decision Variables:

- $x_{ij}$ : Quantity of product  $i$  to be produced on machine  $j$ , indicating production volume.
- $y_{ik}$ : Quantity of product  $i$  to be sourced from supplier  $k$ , reflecting sourcing decisions.
- $z_{il}$ : Quantity of product  $i$  to be distributed to distributor  $l$ , representing distribution strategy.

2) *Objectives*: The objectives, subject to optimisation, are formulated as:

**Minimize Cost**  $f_1(x, y)$

$$f_1(x, y) = \sum_{i=1}^n \sum_{j=1}^m C_{ij} \cdot x_{ij} + \sum_{i=1}^n \sum_{k=1}^K S_{ik} \cdot y_{ik},$$

where  $C_{ij}$  represents the unit production cost for product  $i$  on machine  $j$ , and  $S_{ik}$  represents the unit sourcing cost for product  $i$  from supplier  $k$ .

**Maximize Throughput**  $f_2(x)$

$$f_2(x) = \sum_{i=1}^n \sum_{j=1}^m T_{ij} \cdot x_{ij},$$

with  $T_{ij}$  denoting throughput rate.

**Minimize Energy Consumption**  $f_3(x)$

$$f_3(x) = \sum_{i=1}^n \sum_{j=1}^m E_{ij} \cdot x_{ij},$$

where  $E_{ij}$  represents energy consumed by product  $i$  in machine  $j$ .

3) *Constraints*: The system is subject to the following constraints:

**Machine Capacity**

$$\sum_{i=1}^n x_{ij} \leq M_j, \quad \forall j,$$

Where  $M_j$  indicating the maximum capacity of machine  $j$ .

**Supplier Limit**

$$\sum_{i=1}^n y_{ik} \leq L_k, \quad \forall k,$$

Where  $L_k$  representing the supply limit of supplier  $k$ .

**Distribution Limit**

$$\sum_{i=1}^n z_{il} \leq D_l, \quad \forall l,$$

where  $D_l$ : is the distribution capability of distributor  $l$ .

**Production-Supply Balance**

$$\sum_{j=1}^m x_{ij} = \sum_{k=1}^K y_{ik}, \quad \forall i,$$

ensuring produced goods match sourced quantities.

**Supply-Distribution Balance**

$$\sum_{k=1}^K y_{ik} = \sum_{l=1}^L z_{il}, \quad \forall i,$$

ensuring sourced goods are fully distributed.

**Non-negativity**

$$x_{ij}, y_{ik}, z_{il} \geq 0, \quad \forall i, j, k, l,$$

The given Multiobjective Mixed Integer Linear Programming model looks into the complex workings of a manufacturing system via a reliable framework of decision variables and objectives, it's adapted from the model given by: [9]. The model covers a system that has  $n$  products,  $m$  machines,  $K$  suppliers, and  $L$  distributors. It quantifies the fundamental procedures of manufacturing activities, starting from production to distribution. The main

aims are to keep expenses low, increase productivity, and decrease energy usage, as these factors represent effective industrial practices. The process of optimization includes restrictions such as machine limitations, supplier availability, and distribution capabilities, which all contribute to the practical nature of the model. The process of optimization includes restrictions such as machine limitations, supplier availability, and distribution capabilities, which all contribute to the practical nature of the model. Such an all-encompassing method not only shows the benefits and drawbacks of operational choices but also supports Industry 5.0's pursuit of cost-effective, eco-friendly, and efficient production.

### B. Swarm Intelligence Approach

Swarm Intelligence (SI) is the paradigm of collective behaviour inspired by nature, such as flocks of birds and swarms of insects, applied to computational problems. In the field of multi-objective optimization, Particle Swarm Optimization (PSO) is adapted to Multi-Objective Particle Swarm Optimization (MOPSO), which aims to identify a set of Pareto optimal solutions representing the trade-offs of the problem.

The MOPSO algorithm has the following structure

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#### Algorithm 1: MOPSO for Multi-Objective MILP Model

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**Data:** Swarm Size  $N$ , Objectives  $f_1(x), f_2(x), f_3(x)$ , Maximum Iterations  $MaxIter$ ,  $n$  Products,  $m$  Machines,  $K$  Suppliers,  $L$  Distributors,  $H$  Operators  
**Result:** Pareto optimal solutions

- 1 **Initialise** Swarm with  $N$  particles at random positions and velocities;
- 2 **Initialise** personal best positions  $Pbest$  and global best position  $Gbest$ ;
- 3 **for**  $iter = 1$  up to  $MaxIter$  **do**
- 4     **for** each particle  $i$  in the swarm **do**
- 5         Evaluate the fitness of the particle  $i$  based on the goals  $f_1(x), f_2(x), f_3(x)$ ;
- 6         Update the personal best position  $Pbest_i$  if the current position is better;
- 7     Update the global best position  $Gbest$  based on all particles'  $Pbest$  values; **for** each particle  $i$  in the swarm **do**
- 8         Update the velocity and position of particle  $i$  according to PSO rules;
- 9     **Check constraints;**
- 10    Enforce machine, supplier and distribution constraints; Maintain production-supply and supply-distribution balance;
- 11 **Return the Pareto optimal solutions;**

---

In the algorithm 1,  $N$  represents the size of the swarm,  $f_i(x)$  are the objectives, and  $MaxIter$  is the maximum number of iterations. The algorithm uses personal and global best positions to guide the search for Pareto optimal solutions within the defined multi-objective context.

## IV. IMPLEMENTATION AND RESULTS

For the implementation, we used Python 3.10 running on a Macbook Pro 2022 machine with the Apple M1 Pro chip and 16 GB of RAM. A synthetic dataset was created to meet the operational requirements of a manufacturing company, as discussed previously. It includes various aspects of industrial operations, reflecting the complex and multi-dimensional nature of real-world scenarios. The data set has been randomly generated, taking into account the practical constraints and objectives of typical factories. This simulated data provides a basis for investigating the proposed optimisation algorithms, providing insight into their potential effectiveness in practical scenarios.

The core objective of this research is to develop and assess a numerical model designed to tackle the multi-objective optimization challenges present in production systems. Yet, efforts to scale this model to mirror the real-world proportions of a company within a computational framework, specifically utilizing the Julia language, have met with several challenges. Despite meticulous construction of the model, the computational outputs fell short of what is required for advanced analysis, underscoring the complexities involved in scaling industrial operations to realistic proportions. The instances generated within the model, based on a uniform distribution, vary from 10 to 20 products and 5 suppliers. The energy matrix for these instances ranges from 5 to 100 kWh. The parameters set for the employed metaheuristic are:

```

N = 100 # Swarm size
D = 5 # Dimensionality of the problem
MaxIter = 1000 # Maximum Iterations
w = 0.5 # Inertia weight
c1 = 1.5 # Cognitive coefficient
c2 = 1.5 # Social coefficient

```

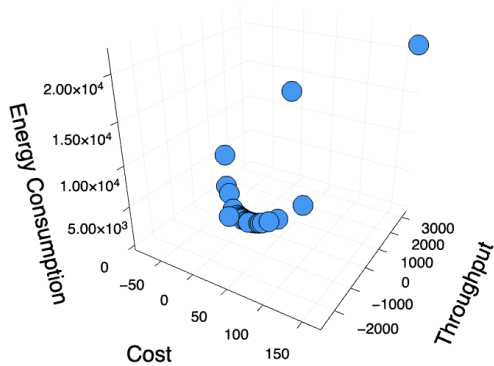


Fig. 1. Pareto front corresponding to the three first objectives.

The visualised Pareto front in Figure 1 shows solutions in the objective space of multi-objective optimisation. There are several notable observations. First, the solutions are diverse, as evidenced by the wide scatter across the three-dimensional objective space. A dense cluster near the origin on the  $f_1$  axis and in the 0-2500 range on the  $f_2$  axis suggests a plethora of solutions with analogous performance with respect to the first two objectives. In contrast, isolated data points, particularly those further out on the  $f_3$  axis, suggest outlier solutions, perhaps representing extreme trade-offs. The void in the central region of the  $f_3$  axis highlights potential trade-offs between all three objectives. Finally, the isolated dots in the upper region of the  $f_3$  axis may indicate solutions that prioritise the third objective and warrant further investigation into their practical feasibility. In essence, the Pareto front provides invaluable insight into the trade-offs inherent in the three objectives, guiding the selection of the most appropriate solution depending on the specific requirements and constraints of the problem.

A comparison has been made to evaluate the performance of the new Multi-Objective Particle Swarm Optimisation (MOPSO) technique against the well-established Non-dominated Sorting Genetic Algorithm II (NSGA-II) [5]. This evaluation is crucial in determining the relative benefits and capabilities of the innovative MOPSO method in navigating the complex optimisation landscape that

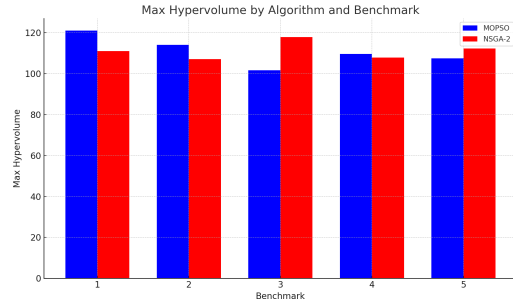


Fig. 2. Comparison between MOPSO and NSGA-II hypervolumes for 5 executions.

characterises manufacturing systems. The following sections present the results of this study and highlight the potential benefits of using MOPSO instead of traditional techniques such as NSGA-II to improve operational efficiency and decision making in the manufacturing industry.

TABLE I  
MAXIMUM HYPERVOLUME VALUES FOR MOPSO AND NSGA-2 ALGORITHMS

Benchmark	MOPSO	NSGA-2	n	m	s
1	121.021	111.063	10	2	5
2	114.090	107.147	10	3	5
3	101.706	117.840	20	2	5
4	109.714	107.866	20	3	5
5	107.559	112.296	20	5	5

The comparative performance of the MOPSO and NSGA-2 algorithms across five benchmarks is detailed in Table I and illustrated in Figure 2. From these, it is observed that the proposed MOPSO method exhibits a stronger performance in the first and second benchmarks, while NSGA-2 takes the lead in benchmarks three to five. The bar chart in the figure, with blue bars representing MOPSO and red bars for NSGA-2, visually conveys the overall effectiveness of each method across a series of twenty iterations for each of the five diverse benchmarks. This comprehensive evaluation, designed to mimic a range of industrial manufacturing scenarios, demonstrates the robustness and real-world applicability of the algorithms.

Our comparative analysis of MOPSO and NSGA-2 across varying benchmarks reveals their perfor-

mance dependency on system complexity. MOPSO excels in simpler manufacturing setups, offering higher efficiency as seen in early benchmark hypervolume values, while NSGA-2 adapts better to complex situations with its superior performance in more involved scenarios. This highlights the necessity of choosing an algorithm that aligns with the manufacturing environment's specific needs, with MOPSO favored for its quick convergence in less complex systems and NSGA-2 for its robustness in handling multifaceted, large-scale operations.

## V. CONCLUSION AND FUTURE PERSPECTIVES

In conclusion, this study presented a comprehensive analysis of the MOPSO and NSGA-2 algorithms, demonstrating their respective strengths across a series of benchmarks reflecting varied complexities within manufacturing systems. The performance evaluation, as depicted in Table I, highlighted MOPSO's proficiency in less complex scenarios and NSGA-2's robustness in more demanding environments. The selection of the optimization algorithm, therefore, should be attuned to the specific characteristics of the manufacturing system to harness the full potential of these advanced computational techniques.

In the conclusion, consider emphasizing the balance between human-centric considerations and operational efficiency as central to future developments in Industry 5.0. Acknowledge the challenges of incorporating ergonomics into multi-objective optimization (MOO) and recognize the limitations of current models when faced with the complexity of real-world applications. Mention the commitment to ongoing research to address these limitations and the need for novel algorithmic approaches that can reconcile the subjective aspects of human well-being with measurable industrial performance metrics. This approach maintains the focus on the need for industry to adapt to both human factors and technological advancements, setting the stage for future innovations in the field.

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