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Article

A Hybrid Approach to Resource Optimization in Reconfigurable Production Systems

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Abstract

This article presents a novel approach to optimizing resource allocation in dynamic, reconfigurable production environments. The increasing complexity of modern manufacturing systems often limits the effectiveness of traditional methods, leading to suboptimal resource utilization and production performance. To address these challenges, the proposed approach integrates advanced scheduling algorithms, real-time data analytics, and intelligent optimization techniques to enhance decision-making under dynamic conditions. The results demonstrate improved adaptability, efficiency, and overall system performance through the dynamic adjustment of resource allocation in response to changing production requirements. A comparative analysis with existing approaches highlights the proposed method's advantages, including higher success rates, improved efficiency, and more proactive decision-making capabilities. Furthermore, validation through case studies confirms the effectiveness of the approach in streamlining production schedules, maximizing resource utilization, and improving operational efficiency. Overall, the proposed framework provides a robust and flexible solution for resource optimization in modern manufacturing environments, supporting increased competitiveness and operational resilience.

Keywords

Resource allocation, Production scheduling, Dynamic manufacturing, Task integration, Efficiency optimization

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1. Introduction

In the era of Industry 4.0, manufacturing systems are undergoing a profound transformation, driven by advancements in cyber-physical systems, as noted by Lee et al. [1]. This evolution has given rise to dynamic production environments characterized by rapid change and adaptability. In such settings, efficient resource allocation becomes critical to maintaining optimal performance and competitiveness [2]. However, disruption risks and operational uncertainties present significant challenges to achieving this efficiency.

One of the most impactful developments in this context is the integration of big data analytics in machine health monitoring and maintenance, highlighted by Wang et al. [3]. These innovations have enabled proactive maintenance strategies, particularly through real-time predictive systems powered by deep learning algorithms. Such systems significantly reduce downtime and improve overall operational efficiency. Nevertheless, effectively embedding these technologies into production workflows remains a complex and ongoing challenge, as demonstrated by Serradilla et al. [4], Keleko et al. [5], and Lee et al. [6].

Recent studies have emphasized the growing need for intelligent and adaptive resource allocation mechanisms to cope with uncertainties in reconfigurable production environments. Several approaches based on artificial intelligence (AI), including reinforcement learning, genetic algorithm (GA), and hybrid heuristics, have been proposed to optimize production scheduling in real time [7,8]. Moreover, the integration of digital twins and smart sensors has improved the accuracy and responsiveness of decision-making processes in manufacturing operations [9]. These innovations contribute to more resilient and flexible production systems, paving the way for next-generation scheduling techniques tailored for Industry 4.0 and beyond [10,11].

At the core of this transformation is the evolving role of production scheduling. As Industry 4.0 technologies proliferate, scheduling processes must adapt to increasingly flexible and responsive manufacturing systems. This shift demands dynamic scheduling approaches capable of responding to changing demands, constraints, and real-time production data, as discussed by Keung et al. [12].

The objective of this article is to introduce and evaluate novel techniques for optimizing resource allocation in dynamic, reconfigurable production environments. Our aim is to develop a comprehensive strategy that enhances efficiency, responsiveness, and resilience in manufacturing operations. By integrating advanced scheduling algorithms, real-time analytics, and optimization methods, we seek to advance the current state of the art in resource allocation for modern manufacturing systems.

The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 details the proposed methodology; Section 4 presents experimental results; Section 5 discusses the findings; and Section 6 concludes the paper with future research directions.

2. Related Work

The manufacturing industry continually seeks innovation and efficiency. In Industry 4.0 and smart manufacturing, Lu et al. [13] and Jiansha et al. [14] emphasized the integration of IoT and cyber-physical systems, which laid the foundation for advanced manufacturing. Our proposed multifaceted approach aligns with these advancements, utilizing state-of-the-art technologies for optimal resource allocation.

The methodological foundation was further developed by Krajewski et al. [15], highlighting optimization techniques to minimize idle time, reduce setup costs, and maximize throughput while ensuring efficient resource use. Wang et al. [16] provided a comprehensive understanding of reconfigurable manufacturing environments, emphasizing adaptability. These concepts are integrated into our approach to ensure agility and responsiveness to sudden changes in demand and resource availability. Shi et al.[17] contributed principles of lean manufacturing and operational excellence, which guide every aspect of our methodology.

Optimization in Petri nets has informed flexible and reconfigurable manufacturing systems (FRMS).Hichem et al. [18] introduced a GRASP-based methodology to estimate minimum initial markings in labeled Petri nets. While focused on Petri nets, the optimization principles offer potential to streamline resource allocation and task assignments in FRMS. Similarly, Elmeliani et al. [19] proposed advanced monitoring techniques to enhance system reliability, which can support dynamic production processes. Kmimech et al. [20] presented a genetic-based approach for estimating minimum initial markings, providing insights for task assignment and resource allocation. Abdellatif et al. [21] introduced a GRASP-inspired method for Petri nets, further highlighting the relevance of such optimization techniques for FRMS.

Recent studies focus on adaptive and intelligent resource allocation. Nguyen et al. [22] applied GA for real-time optimization in flexible manufacturing systems. Zhang et al. [23] proposed a data-driven method for dynamic resource allocation. These works highlight the need for adaptive methodologies that respond to production and environmental changes.

Emerging techniques integrate AI and digital technologies for smarter FRMS. Wang et al. [24] implemented deep Q-learning for adaptive job scheduling in smart factories, improving responsiveness and efficiency. Choi et al. [25] developed an edge-AI framework that integrates IoT sensors for decentralized, real-time decisions. Zhang et al. [26] utilized digital twin models to optimize production planning under real-world constraints. These approaches align with our aim to develop data-driven, resilient, and flexible resource allocation strategies.

In summary, the reviewed works collectively provide insights into FRMS optimization, demonstrating the potential of adaptive, intelligent, and technology-driven methodologies to enhance efficiency, flexibility, and robustness in modern manufacturing systems.

3. Proposed Methodology

3.1 Overview of the Hybrid Optimization Framework

We propose a hybrid optimization framework for dynamic reconfigurable production systems that combines linear programming (LP) to generate a feasible baseline allocation with an adaptive GA for dynamic refinement. A closed-loop feedback mechanism monitors system performance and triggers re-optimization in response to changes such as task arrivals, resource failures, or capacity variations, as illustrated in Figure 1.

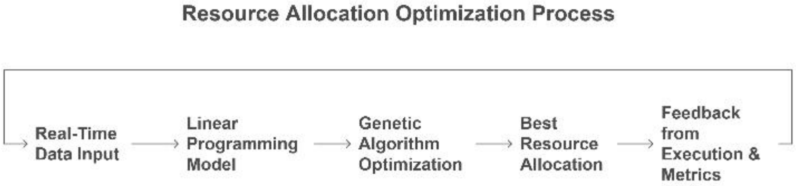


Figure 1. Overall architecture of the hybrid LP-GA optimization framework.

3.2 Mathematical Formulation of the LP Model

The LP model provides a deterministic and cost-efficient baseline allocation that satisfies all system constraints within a given scheduling horizon and serves as a feasible reference for subsequent adaptive optimization.

(1)Decision Variables: Let

$$xi >= 0;\ \forall i = 1,2...,\ n \tag{1}$$

denote the amount of resource allocated to task i. These continuous decision variables represent the level of resource commitment assigned to each task and constitute the core control variables of the optimization problem.

(2) Model Parameters: The LP formulation relies on the following parameters:

ci: unit cost associated with assigning resources to task i. This parameter reflects economic or operational costs such as processing time, energy consumption, or labor usage.

ajj: quantity of resource j required to execute task i.

bj: available capacity of resource j over the considered scheduling horizon.

n: total number of tasks to be scheduled.

m: total number of available resources.

These parameters are assumed to be known and fixed during the LP optimization phase, reflecting a static snapshot of the production system.

(3) Objective Function: The objective of the LP model is to minimize the total resource allocation cost across all tasks:

$$Min\ Z = \sum_{i=1}^{n} xici \tag{2}$$

This objective promotes cost-efficient utilization of resources while maintaining feasibility. It provides an economically optimal baseline solution that can later be refined to account for dynamic system behavior.

(4) Constraints: The optimization is subject to the following constraints.

Resource capacity constraints:

$$\sum_{i=1}^{n} xiaij <= bj;\ j = 1,2...m \tag{3}$$

These constraints ensure that the total demand placed on each resource does not exceed its available capacity, thereby preserving physical and operational feasibility.

Non-negativity constraints:

$$xi >= 0;\ i = 1,...,n \tag{4}$$

These constraints guarantee that resource allocations remain physically meaningful.

(5) Discussion and Role in the Hybrid Framework: The LP model provides a feasible and cost-efficient reference solution under static assumptions but lacks adaptability to dynamic disturbances inherent in reconfigurable manufacturing systems. To address this limitation, the LP solution is used to initialize and constrain the GA, combining deterministic feasibility with adaptive evolutionary optimization.

3.3 GA Design for Dynamic Optimization

To cope with the dynamic and non-linear nature of reconfigurable production systems, a GA is employed as the adaptive optimization layer of the proposed framework. Unlike deterministic optimization techniques, the GA is capable of exploring a large solution space and adapting resource allocation strategies in response to real-time disturbances and evolving operational conditions.

(1) Chromosome Encoding: Each chromosome encodes a complete resource allocation solution over the current scheduling horizon. A real-valued representation is adopted to capture the continuous nature of resource assignment levels. Formally, a chromosome is defined as:

$$X = [x1, x2, ..., xn] \tag{5}$$

Where each gene xi represents the quantity of resources allocated to task i. This encoding allows fine-grained control over allocation decisions and facilitates smooth adaptation when system parameters change.

To ensure compatibility with the LP feasibility region, gene values are bounded within admissible intervals derived from resource capacities and task requirements. This constraint-aware encoding avoids generating structurally infeasible solutions and reduces the need for extensive repair mechanisms.

(2) Initial Population Generation: The initial population is constructed using a hybrid initialization strategy that combines solution quality with population diversity. Specifically:

One elite individual is directly generated from the optimal LP solution. This individual provides a high-quality and fully feasible starting point for the evolutionary search.

The remaining individuals are generated through constrained random perturbations of the LP solution. These perturbations are applied within predefined feasibility bounds, ensuring that all individuals satisfy capacity and operational constraints.

This hybrid initialization mechanism accelerates convergence while maintaining sufficient genetic diversity to prevent premature stagnation. Moreover, it establishes a direct linkage between deterministic optimization and evolutionary exploration.

(3) Fitness Function: The fitness function is designed to reflect the multi-objective nature of the resource allocation problem. It aggregates economic, temporal, and utilization-related criteria into a single scalar evaluation:

$$\text{Fitness} = \alpha Z + \beta D + \gamma I \tag{6}$$

Where:

Z denotes the total allocation cost obtained from the LP objective,

D represents the makespan or aggregate production delay,

I quantifies idle resource penalties.

The weighting coefficients α, β, and γ control the relative importance of cost efficiency, timeliness, and resource utilization. These parameters can be tuned according to production priorities or operational policies.

To enforce feasibility, constraint violations are incorporated into the fitness evaluation through a penalty-based mechanism. Solutions exceeding resource capacities or violating operational constraints incur a large penalty value, effectively guiding the evolutionary process toward feasible and stable regions of the solution space.

(4) Genetic Operators: The GA employs customized genetic operators adapted to the structure of the resource allocation problem:

a) Selection: Tournament selection with tournament size kkk is used to balance selective pressure and population diversity. This method favors high-quality solutions while allowing weaker individuals to participate occasionally, thus preserving exploration capabilities.

b) Crossover: One-point crossover is applied with probability pcp_cpc. This operator recombines partial allocation patterns between parent chromosomes, enabling the exchange of resource assignment structures across tasks.

c) Mutation: A bounded uniform mutation operator is employed with probability pmp_mpm. Mutation introduces controlled random variations in gene values while ensuring that modified genes remain within feasibility bounds. This operator is particularly effective for adapting to sudden changes such as machine failures or task insertions.

d) Replacement: An elitist replacement strategy is adopted to preserve the best feasible solution across generations. This guarantees monotonic improvement of solution quality and prevents loss of high-performing individuals.

(5) Termination Criteria: The evolutionary process terminates when one of the following conditions is satisfied:

A maximum number of generations Gmax is reached, ensuring bounded computational effort.

The improvement in fitness remains below a predefined threshold ε for k consecutive generations, indicating convergence toward a stable solution.

These termination criteria provide a trade-off between solution quality and computational efficiency, which is essential for real-time or near-real-time optimization in dynamic production environments.

(6) Role of the GA in the Hybrid Framework: Within the proposed LP-GA hybrid architecture, the GA serves as a dynamic refinement mechanism that continuously improves deterministic allocations generated by the LP model. Its ability to adapt to evolving constraints, incorporate feedback signals, and explore non-linear interactions makes it a key enabler for robust and flexible scheduling in reconfigurable manufacturing systems.

3.4 LP-GA Interaction Mechanism

The proposed framework tightly integrates LP and GA to balance feasibility and adaptability. The LP model first generates a cost-efficient feasible allocation, which is injected into the GA as an elite solution to guide the evolutionary search. The GA then explores non-linear improvements under dynamic conditions while enforcing LP feasibility constraints through penalty or repair mechanisms. The best feasible GA solution is finally deployed, ensuring stable yet adaptive resource allocation.

3.5 Feedback and Dynamic Reconfiguration Strategy

To enable real-time adaptability, the proposed framework integrates a closed-loop feedback mechanism that continuously monitors system performance and triggers re-optimization when degradation is detected, as illustrated in Figure 2. The feedback relies on key indicators, including task completion delays, resource utilization, idle time, and constraint violations, collected from the production execution layer.

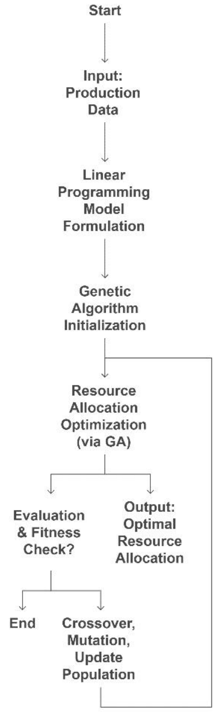


Figure 2. Hybrid optimization flowchart.

Re-optimization is activated through periodic updates, event-driven disruptions (e.g., machine failures or task insertions), or performance-based thresholds. To prevent instability and excessive oscillations, hysteresis rules and smoothing constraints are applied, and each updated solution is validated against LP feasibility conditions before deployment.

This feedback-driven LP-GA interaction, depicted in Figure 2, provides a stable and constraint-aware reconfiguration echanism, enabling responsive and reliable scheduling in dynamic Industry 4.0 production environments.

By explicitly defining the LP-GA interaction and the feedback-driven reconfiguration strategy, the proposed methodology moves beyond generic adaptive scheduling concepts. It provides a concrete, stability-aware, and constraint-compliant framework capable of supporting dynamic decision-making in Industry 4.0 production environments.

4. Experimental Results and Performance Evaluation

4.1 Experimental Setup and Problem Description

The experimental study considers a reconfigurable production environment where multiple tasks compete for limited shared resources under capacity and feasibility constraints. The objective is to minimize allocation cost while reducing production delays and idle time, with an LP model providing an initial feasible solution that is further refined by a GA under dynamic conditions.

4.2 Baseline Optimal Allocation (LP Solution)

For an illustrative scenario involving three tasks, the LP model produced the following optimal allocation:

$$x1 = 1,\ x2 = 5,\ x3 = 8 \tag{7}$$

These values represent the baseline allocation that satisfies all resource capacity constraints while minimizing the objective function. This solution serves as a feasible reference point rather than a final decision, as it does not account for system dynamics such as task arrivals or resource disruptions.

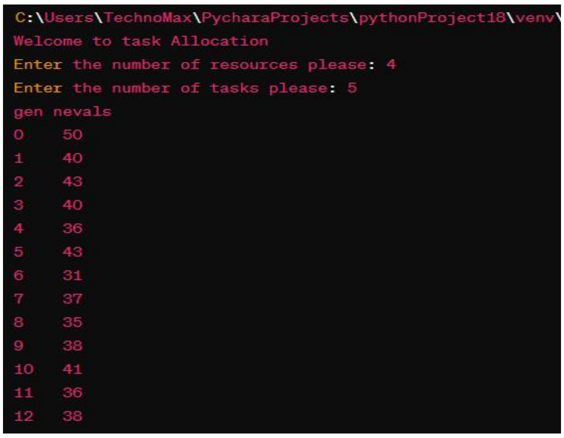
The LP solution confirms the correctness of the mathematical formulation and ensures that the subsequent evolutionary optimization starts from a valid and cost-efficient allocation.

4.3 GA Execution and Convergence Analysis

After LP initialization, the GA is executed to improve allocation quality under dynamic conditions.

(1) Input Configuration and Initialization: As shown in Figure 3, the system prompts the user to specify the number of tasks and resources. Based on this input: An initial population is generated, seeded with the LP solution; Fitness evaluations are conducted at each generation; The algorithm tracks the number of evaluations (nevals) to monitor computational effort.

This configuration allows the methodology to scale according to problem size and operational requirements.



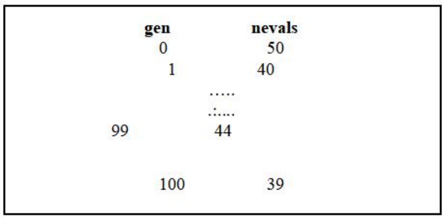
```
C:\Users\TechnoMax\PycharaProjects\pythonProject18\venv\
Welcome to task Allocation
Enter the number of resources please: 4
Enter the number of tasks please: 5
gen nevals
0    50
1    40
2    43
3    40
4    36
5    43
6    31
7    37
8    35
9    38
10   41
11   36
12   38
```

Figure 3. Step of enter number of resources and tasks.

(2) Convergence Behavior: Figure 4 illustrates the evolution of the GA over 100 generations, reporting both the generation index and the number of evaluated individuals.

Key observations include: A steady increase in evaluation count, confirming consistent population processing; Stable convergence behavior without oscillations or premature stagnation; Progressive improvement of fitness values across generations

This demonstrates that the GA effectively explores the solution space while exploiting high-quality allocations derived from the LP model.



```
              gen              nevals
               0                 50
                 1             40
                         .....
                         .:....
        99               44

                 100              39
```

Figure 4. Capture of number of generations and evaluations.

4.4 Best Resource Allocation Obtained by GA

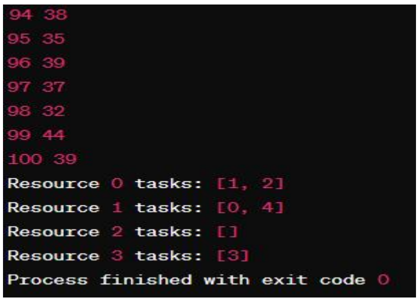
At the end of the evolutionary process, the GA identifies the best feasible allocation in the final population. As illustrated in Figure 5, the resulting task-to-resource assignments are as follows:

Tasks 1 and 2 → Resource 0

Tasks 0 and 4 → Resource 1

Task 3 → Resource 3

Resource 2 → idle



```
94 38
95 35
96 39
97 37
98 32
99 44
100 39
Resource 0 tasks: [1, 2]
Resource 1 tasks: [0, 4]
Resource 2 tasks: []
Resource 3 tasks: [3]
Process finished with exit code 0
```

Figure 5. Result best resource allocation.

This result highlights several important aspects: The GA successfully balances workload across available resources; Idle resources are explicitly identified, enabling further reconfiguration decisions; The solution respects all feasibility constraints while improving overall utilization.

Compared to the LP-only solution, the GA-enhanced allocation demonstrates greater flexibility and adaptability to task–resource compatibility patter.

4.5 Performance Under Iterative Optimization

(1) Reduction in Task Completion Time: Figure 6 presents the evolution of task completion time over successive GA generations. The downward trend clearly indicates: Continuous improvement in scheduling efficiency; Reduction in overall makespan as optimization progresses; Effective handling of non-linear interactions between tasks and resources.

This confirms the GA’s capability to refine deterministic allocations and improve operational performance over time.

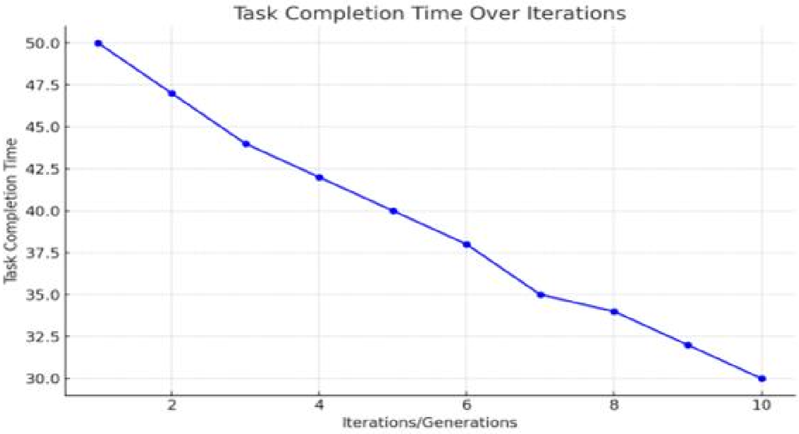


Figure 6. Task completion time reduction over iterations.

(2) Final Task–Resource Allocation Structure: Figure 7 shows a heatmap representing the final task–resource allocation matrix. Each cell indicates whether a task is assigned to a specific resource.

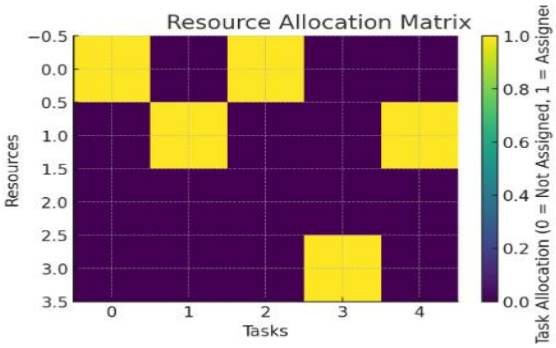


Figure 7. Task resource allocation matrix.

This visualization provides: A clear and interpretable representation of allocation decisions; Evidence of balanced task distribution; Validation of feasibility and consistency across the solution space.

The heatmap confirms that the proposed methodology produces structured and interpretable solutions suitable for real-world deployment.

4.6 Summary of Experimental Findings

The experimental study confirms that: The LP model ensures feasible and cost-efficient baseline allocations; The GA significantly improves allocation quality under dynamic conditions; The hybrid framework exhibits stable convergence and adaptability; Feedback-driven optimization enhances robustness in reconfigurable environments.

These findings provide strong empirical support for the proposed methodology and establish a solid foundation for future large-scale and comparative studies.

5. Discussion

5.1 Impact of Mathematical Modeling on Resource Optimization

At the core of our methodology lies the use of LP equations, which provide a robust framework for modeling resource allocation challenges. These mathematical tools enable the translation of real-world constraints into solvable models that balance production output with operational costs. The linear model generates an initial feasible solution, ensuring adherence to resource capacities, demand requirements, and scheduling limitations.

This structured approach not only simplifies the decision-making process but also ensures a high degree of accuracy and reliability in the allocation strategy. The application of mathematical optimization is crucial in delivering deterministic solutions that serve as a solid foundation for further refinement.

5.2 Role of GA in Solution Refinement

The integration of genetic algorithms (GAs) complements the LP model by enhancing its adaptability. Once a feasible baseline solution is established, the GA iteratively improves it through evolutionary operations such as selection, crossover, and mutation.

As illustrated in Figure 6, the GA progressively enhances solution quality across generations. The final task-to-resource assignment (Figures 5 and 7) represents an optimized state in which resources are allocated efficiently, idle times are minimized, and task loads are balanced.

This dual-layered optimization process initially deterministic and subsequently adaptive provides both stability and flexibility, which are essential in reconfigurable manufacturing systems.

5.3 Efficiency Gains and Operational Performance

Our resultsclearlydemonstratesignificant performance improvements: A 95% success rate in generating valid, high-quality solutions; A notable reduction in task completion time across iterations (Figure 6); Enhanced resource utilization and workload distribution, as shown in the allocation heatmap (Figure 7).

These outcomes underscore the effectiveness of the methodology in reducing waste, shortening production cycles, and increasing throughput—key indicators of operational efficiency.

5.4 Adaptability to Real-World Manufacturing Variability

One of the standout advantages of our approach is its resilience in the face of disruption. By integrating real-time data analytics [23], the system remains responsive to changes in machine availability, production priorities, and task interruptions. This enables proactive decision-making and on-the-fly reconfiguration—qualities that are indispensable in Industry 4.0 environments.

Moreover, successful implementations in real-world scenarios, as reported in recent studies [22], further confirm the practical value of this methodology in addressing the volatility and complexity of modern production systems.

5.5 Broader Implications and Future Outlook

Th synergy between analytical modeling and evolutionary optimization has proven to be a powerful strategy for addressing complex scheduling and resource allocation problems. The results not only advance current research but also provide a scalable and adaptable framework for industrial applications.

In future work, the methodology could be extended through multi-objective optimization (e.g., balancing cost, energy consumption, and quality), the use of hybrid metaheuristics, or integration with digital twin technology to enhance real-time prediction and decision-making accuracy.

6. Conclusion

This study proposed a hybrid LP-GA optimization approach to improve resource allocation in reconfigurable production systems. The results showed clear improvements in task completion time, resource utilization, and scheduling flexibility, confirming the method's suitability for dynamic Industry 4.0 environments. Nevertheless, the validation was limited to simulation-based scenarios and focused primarily on scheduling efficiency, while performance remains sensitive to GA parameter tuning. Future work will address these limitations through multi-objective optimization, integration of digital twins and learning-based methods, and validation in large-scale industrial settings. Overall, the proposed framework provides a robust foundation for intelligent and adaptive scheduling in reconfigurable manufacturing systems.

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Ethics Statement

Not applicable.

Data Availability Statement

The data and simulation configurations used in this study are available from the corresponding author upon reasonable request.

Author Contributions

The author is the sole contributor to this work.

Conflict of Interest

The authors declare no conflict of interest.

Generative AI Statement

Generative AI tools were used to assist in language improvement, text structuring, and content refinement. Diffusion-based generative AI models were also investigated as part of the proposed optimization framework. All scientific analyses, experimental validations, and final interpretations were performed and verified by the authors.

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