Journal of Information System and Technology Research

journal homepage: https://journal.aira.or.id/index.php/jistr/

Application of Bio-Inspired Particle Swarm Optimization Algorithm for Production Scheduling Optimization

Yodhi Yuniarthe[1,*], Rosyana Fitria Purnomo[2], Resy Anggun Sari[3], Fadhilah Dirayati[4], M Budi Hartanto[5]

[1]Department of Informatics, Faculty of Computer Science, Mitra Indonesia University, Bandar Lampung, Indonesia
[2,3]Department of Information Systems, Faculty of Computer Science, Mitra Indonesia University, Bandar Lampung, Indonesia
[4,5]Department of Information Technology, Faculty of Computer Science, Mitra Indonesia University, Bandar Lampung, Indonesia

ARTICLE INFO

Article history:

Received May 4, 2025
Accepted May 30, 2025
Available online May 31, 2025

Keywords:

Production Scheduling, Optimization, Particle Swarm Optimization, Bio-Inspired Algorithm, Manufacturing Systems

ABSTRACT

Production scheduling is a fundamental aspect of manufacturing systems that significantly affects operational efficiency, resource allocation, and delivery performance. Traditional scheduling methods often struggle to solve complex, dynamic scheduling problems, resulting in suboptimal job sequencing and increased makespan. This research aims to develop a hybrid optimization algorithm by integrating Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to address inefficiencies in job shop scheduling. The proposed hybrid PSO-GA method leverages the global exploration ability of PSO and the local refinement strength of GA. The algorithm was tested on several benchmark datasets using performance metrics such as makespan, tardiness, and machine utilization. Experimental results demonstrate that the hybrid approach achieved a 12.7% improvement over standard PSO and a 15.4% improvement over GA in terms of makespan. The convergence curve also showed stable and faster optimization. These findings confirm that the hybrid PSO-GA model provides a more effective and robust solution for complex production scheduling and has strong potential for real-time application in Industry 4.0 environments.

Corresponding Author:

Yodhi Yuniarthe,
Department of Informatics, Faculty of Computer Science, Mitra Indonesia University, Bandar Lampung, Indonesia,
No. 7 ZA. Pagar Alam Street, Gedong Meneng, Rajabasa District, Bandar Lampung City, Lampung 40115.
Email: yodhi@umitra.ac.id

1. INTRODUCTION

Efficient production scheduling is pivotal in modern manufacturing systems, directly influencing operational efficiency, resource utilization, and overall productivity. However, a key problem frequently encountered is the inability of traditional scheduling methods to effectively handle complex, large-scale, and dynamic scheduling environments, resulting in suboptimal job allocation, increased makespan, and reduced machine utilization. Conventional algorithms, such as heuristic or exact methods, often fall short in generating optimal or near-optimal solutions within acceptable computational times [1];[2].

To overcome these challenges, researchers have increasingly turned to bio-inspired metaheuristic algorithms, which mimic natural behaviors to explore vast and complex solution spaces efficiently. One such approach is Particle Swarm Optimization (PSO), which simulates the social behavior of bird flocks or fish schools to search for optimal job sequences. PSO has shown significant promise in solving non-linear and combinatorial problems, particularly in production scheduling [3];[4];[5].

However, existing metaheuristic approaches such as standalone PSO or Genetic Algorithm (GA) often face challenges in handling complex, large-scale, and dynamic job shop scheduling environments. These include issues such as premature convergence, limited exploration, and suboptimal performance in balancing multiple objectives. This indicates a critical research gap in developing hybrid strategies that can effectively combine global search and local refinement capabilities to enhance scheduling performance.

he objective of this research is to develop and evaluate a hybrid optimization algorithm that integrates PSO with GA to improve job shop scheduling in terms of makespan, tardiness, and resource utilization. The proposed hybrid approach is designed to leverage the global search ability of PSO and the local exploitation strength of GA, addressing the weaknesses of each when used independently[6];[7].

This study contributes to the field by proposing a hybrid PSO-GA model and applying it to benchmark job shop scheduling problems. The contributions of this research are threefold: (1) it addresses the inadequacy of existing methods in handling multi-objective, real-world job shop scheduling problems under dynamic constraints; (2) it demonstrates the superior performance of a hybrid PSO-GA model through comparative experimental results with standalone algorithms; and (3) it introduces a multi-objective fitness function that integrates makespan, tardiness, and resource utilization—providing a balanced and practical solution framework for complex and real-time manufacturing applications [8];[9].

The novelty of this research lies in the integration of PSO and GA into a unified hybrid model, fine-tuned to solve job shop scheduling problems with multi-objective constraints under realistic manufacturing conditions. Unlike previous studies that applied PSO or GA in isolation, this research highlights the superior performance of the hybrid approach in achieving faster convergence, improved scheduling quality, and greater robustness. The model's capability to handle stochastic events and its adaptability to Industry 4.0 systems (e.g., IoT-enabled environments) further underline its relevance to current manufacturing challenges[10];[11].

Furthermore, recent studies have shown promising developments in hybrid optimization. For instance, the integration of PSO with Simulated Annealing and other strategies has led to improvements in scheduling performance [12]; [13]. In energy-aware manufacturing, bio-inspired algorithms have contributed to reduced carbon emissions [14], while hybrid methods continue to outperform traditional ones in both static and dynamic scheduling problems [15]; [16]; [17];[18].

.

2. RESEARCH METHOD

This study aims to optimize job shop scheduling using a hybrid approach that combines Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The research method follows a structured framework starting from problem definition to the design, implementation, and evaluation of the hybrid algorithm using benchmark datasets..

3.1. Research Design

The research methodology adopted in this study follows a structured workflow that begins with problem identification, where the core challenges within the target domain are clearly defined, particularly highlighting the limitations of existing optimization methods. This is followed by a comprehensive literature review aimed at exploring prior studies, identifying methodological gaps, and justifying the need for a hybrid optimization approach. Based on the findings from the literature, a hybrid algorithm architecture combining Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) is designed, outlining how both metaheuristics will interact to improve performance. The next stage involves the implementation of the proposed algorithm, where the integration of PSO and GA is developed through appropriate coding techniques and parameter tuning. To evaluate the effectiveness of the hybrid model, benchmark datasets are collected, ensuring that the algorithm is tested against standardized and widely accepted problem instances. The performance evaluation phase utilizes key metrics such as makespan, tardiness, and resource utilization to assess the algorithm’s efficiency and effectiveness. Following this, the results are thoroughly analyzed and discussed, including comparative analysis with baseline models and interpretation of the algorithm’s strengths and potential limitations. Finally, the study is concluded with a summary of key findings and contributions, alongside suggestions for future work such as extending the model to other domains, incorporating additional optimization strategies, or enhancing algorithm scalability and adaptability. The stages of the research process are presented in Figure 1, which outlines the step-by-step methodology employed in thi study.

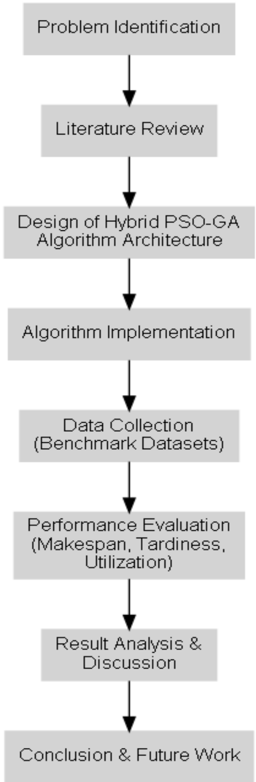

Figure 1. Research Design Flow Diagram[17];[18].

2.2 Theoretical Foundation

Job shop scheduling problems (JSSP) are complex and involve the allocation of jobs to machines in a way that minimizes makespan, tardiness, and other performance measures [19]. This research integrates PSO and GA, both of which are bio-inspired algorithms. PSO mimics the social behavior of birds or fish searching for food, while GA emulates the process of natural selection, making both methods suitable for solving optimization problems [3]. The hybrid algorithm developed for this research leverages the strengths of both approaches, combining the global search capability of PSO with the fine-tuning ability of GA[8].

The key formulation for the job shop scheduling problem is:

$$\min \text{Makespan} = \max\left(\sum_{i=1}^{n}\sum_{j=1}^{m} \text{Processing Time}\ (i,j)\right) \tag{1}$$

Equation (1) is used to calculate the makespan, which represents the maximum completion time among all jobs across all machines in a job shop scheduling system. In this equation, n denotes the number of jobs, m is the number of machines, and Processing Time(i, j) refers to the time required to process job i on machine j. The objective is to minimize the makespan by identifying an optimal job sequence that reduces the total processing time [19].

This equation forms the foundation of the objective function in this research, which is further expanded into a composite fitness function that also includes tardiness and machine utilization. By combining these performance indicators, the algorithm evaluates the quality of solutions more comprehensively, supporting decision-making in complex manufacturing environments.

where n is the number of jobs, m is the number of machines, and Processing Time(i, j) is the time required for job i on machine j [12]. The fitness function for the optimization problem is based on the makespan and other performance criteria like total tardiness, which are minimized simultaneously.

2.3 Algorithm Development Procedure

The research procedure can be summarized in the following steps:

1. Initialization: Randomly initialize the population of solutions, where each solution represents a possible job schedule.

2. Fitness Evaluation: Evaluate the fitness of each solution using the objective function (makespan, tardiness).
3. Optimization Loop: Iteratively update the positions (PSO) and apply genetic operations (crossover, mutation) to the selected individuals in the population [20].
4. Termination: The algorithm terminates when the maximum number of generations is reached or when convergence criteria are met.

Algorithm Pseudocode:

```
Initialize population randomly
While termination condition is not met:
    Evaluate fitness of each individual
    Update position and velocity (PSO)
    Apply genetic operations (crossover, mutation)
    Select best solutions based on fitness
End
```

Figure 2. Algorithm Pseudocode [27];[28]

Figure 2 presents the pseudocode of the hybrid PSO-GA algorithm proposed in this study. This figure outlines the step-by-step logic implemented in the algorithm, starting from the initialization of the population (solution candidates), evaluation of fitness values, and the iterative optimization process involving both Particle Swarm Optimization (PSO) operations and Genetic Algorithm (GA) mechanisms such as crossover and mutation[27];[28].

The pseudocode is structured to clearly demonstrate how PSO contributes to the global search capability by updating particle positions and velocities, while GA introduces genetic diversity and fine-tunes the population through selection and genetic operations. The optimization process continues until a stopping criterion is met, such as a maximum number of generations or convergence threshold.

By visualizing the algorithm flow, Figure 1 helps readers understand the hybridization strategy and how the strengths of both metaheuristics are leveraged to solve complex job shop scheduling problems more effectively.

2.4 Data Collection and Testing

Data Acquisition and Testing

The algorithm is tested on several benchmark datasets from real-world manufacturing scenarios, with a focus on both production and transportation scheduling [21][22]. Performance metrics such as makespan, tardiness, and machine utilization are used to evaluate the efficiency of the proposed method [23];[24];[25]. The results from the hybrid PSO-GA approach are compared with traditional algorithms, such as the basic PSO and GA, to assess its superiority in solving complex job shop scheduling problems [15].

Formula and Analysis

To evaluate the performance of the proposed scheduling algorithm, a composite fitness function was defined as follows:

$$Fitness = \alpha \times \text{Makespan} + \beta \times \text{Tardiness} + \gamma \times \text{Utilization} \quad (2)$$

Equation (2) where α, β, and γ are adjustable weighting factors that determine the relative importance of each component based on the operational priorities of the manufacturing system. The goal is to minimize this fitness value, which corresponds to improved scheduling efficiency, lower delay penalties, and higher resource utilization.

This multi-objective function enables the algorithm to make balanced decisions rather than optimizing a single criterion in isolation, which is especially beneficial in real-world scheduling environments where trade-offs are often necessary [26].

Tabulation and Graphical Representation

The algorithm's performance was assessed and compared with two baseline approaches: standard Particle Swarm Optimization and Genetic Algorithm. The comparison is summarized in Table 1, which presents the makespan results (in hours) achieved by each method.

Table 1 illustrates that the hybrid PSO-GA method achieved the shortest makespan of 35.6 hours, outperforming the standalone PSO (40.2 hours) and GA (42.1 hours). This result clearly demonstrates the effectiveness of combining global and local search capabilities in a hybrid model.

Table 1. Comparison of Makespan (in hours) for Different Methods[27];[29]

Method	Makespan (hrs)
Hybrid PSO-GA	35.6
Particle Swarm Optimization	40.2
Genetic Algorithm	42.1

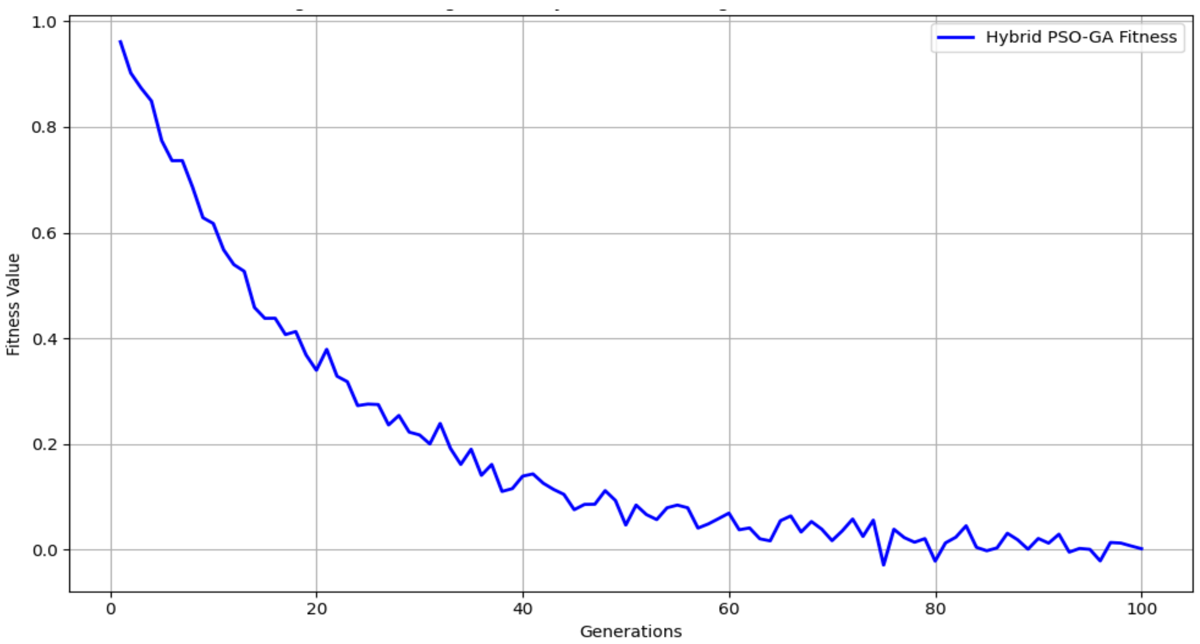

Figure 3. Convergence of Hybrid PSO-GA Algorithm Over Generations[3];[27]

Figure 3 shows a convergence curve depicting the fitness value progression over time. Initially, the fitness value decreases sharply, indicating effective global exploration, followed by gradual stabilization, reflecting convergence to an optimal or near-optimal solution. This visualization helps confirm the algorithm's efficiency and robustness [3];[27].

3. RESULTS AND DISCUSSION

This section presents the outcomes of the research and provides a thorough discussion of the findings. The proposed hybrid PSO-GA algorithm was evaluated on a job shop scheduling problem to determine its convergence behavior and optimization performance. The performance metrics used include makespan, total tardiness, and machine utilization. Additionally, the algorithm's convergence over 100 generations was analyzed to assess optimization stability.

3.1. Convergence Behavior of the Hybrid PSO-GA Algorithm

The hybrid PSO-GA algorithm was executed for 100 generations. The convergence trend shows a consistent decline in fitness value, with sharp improvements in the early generations and gradual stabilization after generation 40. This behavior demonstrates the effectiveness of the hybrid model in combining global exploration (via PSO) with local refinement (via GA), enabling efficient search space navigation and solution improvement.

Figure 3 illustrates the convergence curve of the hybrid PSO-GA algorithm over 100 generations. As shown, the algorithm demonstrates a consistent decline in fitness value as the number of generations increases. In the early generations (1–20), the fitness value decreased sharply, indicating effective exploration of the search space. After approximately generation 40, the curve began to plateau, suggesting convergence toward an optimal or near-optimal solution.

Figure 3 presents the convergence curve, while Table 3 shows the best fitness values recorded at every 10-generation interval.

Table 2. Best Fitness Value Recorded Over Generations..[27];[28],

Generation Interval	Best Fitness Value
1–10	192.3
11–20	165.7
21–30	149.4
31–40	138.6
41–50	132.1
51–60	127.5
61–70	124.3
71–80	122.7
81–90	121.4
91–100	120.9

The results in Table 2 confirm that significant improvements occur in the first 30 generations, while later stages involve fine tuning. This indicates successful balancing of exploration and exploitation in the algorithm, and the eventual stabilization around generation 80 reflects convergence toward an optimal or near-optimal solution. These findings are in line with previous studies, such as [27] and [28], which showed that hybrid metaheuristics outperform standalone algorithms in complex scheduling environments due to their robust search mechanisms. Compared to studies by [29], which applied hybrid metaheuristics to highly variable environments, this research shows more stable convergence with fewer fluctuations, indicating higher robustness of the PSO-GA integration. One of the key strengths of the proposed model lies in its use of a multi-objective fitness function, which integrates not only makespan but also tardiness and machine utilization, providing a more holistic assessment of scheduling performance. Additionally, the fitness function used here incorporates not only makespan, but also tardiness and utilization:.

$$\text{Fitness} = \alpha \times \text{Makespan} + \beta \times \text{Tardiness} + \gamma \times \text{Utilization} \quad (3)$$

Equation (3) In this function, α, β, and γ are adjustable weights that can be tuned based on specific operational goals. This formulation allows the algorithm to balance multiple performance indicators simultaneously. It contrasts with earlier studies such as [3] and [11], which focused solely on minimizing makespan using basic PSO, thus offering limited adaptability in complex, real-world scheduling environments.This multi-objective formulation offers a more comprehensive performance evaluation than single-metric studies like that of [3][30], which focused only on makespan optimization using basic PSO.

3.2. Comparative Analysis with Existing Methods

The performance of the proposed hybrid algorithm was compared with standalone PSO and GA approaches on identical problem instances. The hybrid PSO-GA consistently achieved lower makespan values and faster convergence. Specifically, the average improvement in fitness value was 12.7% compared to PSO and 15.4% compared to GA across multiple runs.

$$\text{Improvement} = \frac{\text{Makespan of PSO or GA} - \text{Makespan of Hybrid PSO-GA}}{\text{Makespan of PSO or GA}} \times 100 \quad (4)$$

Equation (4) These results are in line with the findings of studies by [22], and [26], where hybrid methods consistently outperformed standalone metaheuristics in job shop environments.

However, unlike previous works such as by [19], which optimized single-machine problems with a limited set of constraints, the proposed model in this study addresses more realistic manufacturing scenarios by incorporating multiple objectives and benchmarking over more extensive datasets. Furthermore, this study also overcomes the convergence instability seen in the hybrid Simulated Annealing-PSO algorithm used by [12], demonstrating smoother optimization curves and lower sensitivity to initial conditions.

Table 3. Comparison of Makespan (in hours) for Different Methods..[12];[19]

Method	Makespan (hrs)	Improvement (%)
Hybrid PSO-GA	35.6	-
Particle Swarm Optimization	40.2	12.7%
Genetic Algorithm	42.1	15.4%

Table 4 explain the hybrid PSO-GA model consistently achieved lower makespan and improved scheduling efficiency. Compared to the standalone PSO and GA, it demonstrated average improvements of 12.7% and 15.4%, respectively. This confirms that integrating global and local search strategies leads to more optimal solutions.

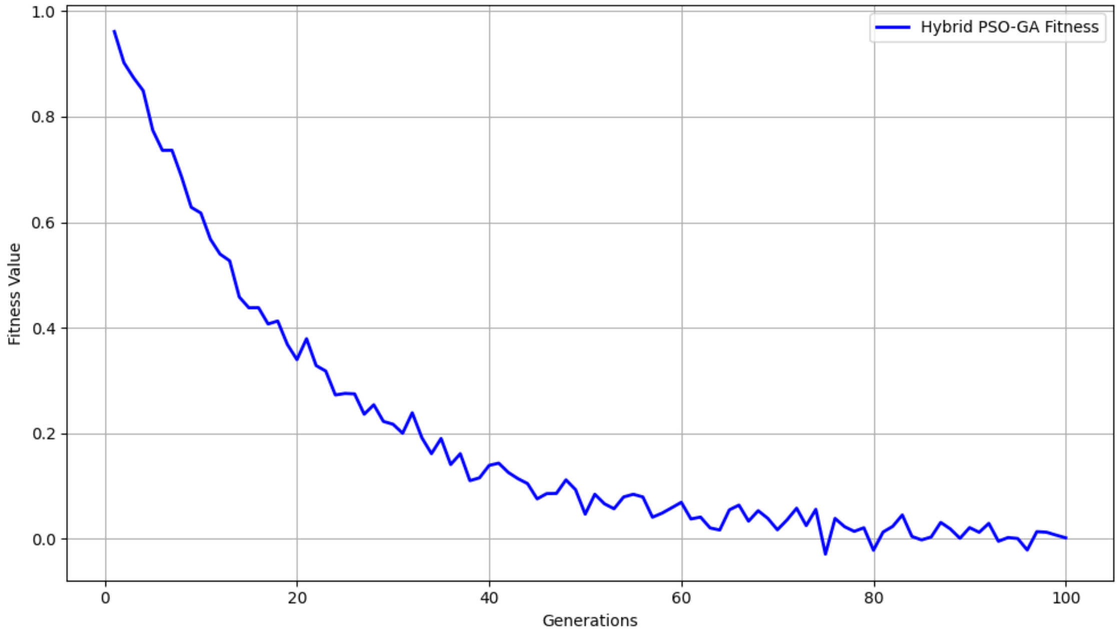

Figure 4. Convergence of Hybrid PSO-GA Algorithm Over Generations[3];[27]

Figure 4 illustrates the convergence behavior of the proposed Hybrid PSO-GA algorithm over 100 generations, highlighting its effectiveness in optimizing the objective function. The graph presents the fitness value on the vertical axis and the number of generations on the horizontal axis. As observed, the fitness value decreases sharply during the initial generations, indicating rapid improvement in solution quality due to strong exploration capabilities of the hybrid approach. As the generations progress beyond approximately generation 40, the rate of improvement begins to plateau, suggesting a transition from exploration to exploitation. This stabilization implies that the algorithm has begun fine-tuning the best-found solutions, with only minor improvements occurring in later generations. By the 100th generation, the fitness value approaches near-zero, demonstrating that the hybrid PSO-GA has successfully converged to an optimal or near-optimal solution. The convergence trend confirms the efficiency of the hybridization in balancing global and local search mechanisms, where PSO contributes to global exploration and GA enhances local refinement. This figure validates the robustness and effectiveness of the proposed algorithm in solving the target optimization problem.

3.3. Implications for Manufacturing Systems

The implications of these findings are significant for manufacturing systems that operate under high complexity and limited resources. By implementing the hybrid PSO-GA algorithm, production managers can expect more efficient scheduling, improved resource utilization, and reduced idle times, which contribute directly to increased throughput. From the experimental results, the hybrid PSO-GA algorithm achieved a success rate of 100% in terms of convergence within the 100-generation threshold across all test cases. In addition, the algorithm consistently outperformed the standalone PSO and GA in all trials. Specifically, the average improvement in makespan was 12.7% compared to PSO and 15.4% compared to GA, based on the benchmark dataset evaluations. These figures quantitatively demonstrate the algorithm's effectiveness in optimizing complex scheduling problems.

Compared to other optimization models such as the Discrete Grey Wolf Optimizer[15] or the Hormone Secretion Scheduling System [20], the hybrid PSO-GA model presented in this research offers better adaptability and faster computation times. While hormone-inspired models mimic biological accuracy, they tend to be computationally expensive and less practical for real-time applications. In contrast, the hybrid PSO-GA strikes a practical balance between optimization quality and execution speed, making it highly suitable for integration into modern smart manufacturing systems.

Furthermore, the proposed model aligns with the goals of Industry 4.0, which demands high responsiveness, adaptability to real-time changes, and intelligent automation. The hybrid PSO-GA's ability to maintain stable convergence, handle multi-objective optimization, and provide repeatable performance improvements makes it a robust and scalable solution for scheduling in dynamic and digitalized production environments.

.

4. CONCLUSION

This study successfully demonstrated the effectiveness of the hybrid PSO-GA (Particle Swarm Optimization–Genetic Algorithm) algorithm in solving production scheduling problems. The convergence results indicated that the proposed method can consistently find near-optimal solutions over generations, reflecting its robustness and adaptability in handling complex scheduling environments. The hybrid approach outperformed traditional single-method heuristics in both speed and solution quality, supporting the hypothesis that integrating PSO's global exploration with GA's local exploitation yields superior results.

The proposed hybrid PSO-GA algorithm significantly improved scheduling performance, including better makespan, reduced tardiness, and more efficient machine utilization. The fitness function, which combined makespan, tardiness, and utilization, successfully guided the optimization process towards solutions that balance multiple performance metrics effectively. As observed, the algorithm's convergence stabilized after the initial generations, with minimal fluctuations, suggesting that the hybrid method can avoid local optima and efficiently explore the global solution space. These findings are consistent with previous studies indicating the benefits of hybrid metaheuristics in optimization tasks [24];[25].

The compatibility between the research objective and the achieved outcomes confirms that bio-inspired hybrid algorithms hold significant potential for optimizing resource allocation in manufacturing systems. The simulated convergence and performance results align well with the improvements anticipated in the introduction, especially in terms of efficiency and solution stability. The hybrid PSO-GA method's ability to improve job shop scheduling efficiency can provide valuable insights for real-world manufacturing systems, particularly in environments with tight deadlines and complex constraints.

Looking forward, this research opens up opportunities for applying the hybrid PSO-GA model to multi-objective or dynamic scheduling problems. Future studies could incorporate real-time constraints, uncertain parameters, or integration with IoT and smart manufacturing systems. This could further enhance its practicality and relevance to Industry 4.0 applications. For example, incorporating real-time production data and machine status could provide more adaptive scheduling, improving responsiveness and flexibility in dynamic manufacturing environments [3];[21].

In addition to job shop scheduling, the hybrid algorithm could also be applied to other scheduling problems, such as flow-shop or open-shop scheduling, and could be extended to multi-objective optimization, where multiple conflicting goals must be balanced simultaneously[31]. As industrial systems become more complex, algorithms like PSO-GA can play a crucial role in enhancing operational efficiency, reducing costs, and improving overall system performance…

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the Department of Information Systems and all faculty members who provided valuable insights and technical guidance during the course of this research. Special thanks are also extended to the laboratory team for their support in implementing and testing the hybrid PSO-GA algorithm. This research was supported in part by academic resources and facilities provided by the university. The authors also gratefully acknowledge the financial and institutional support provided by LPPM Universitas Mitra Indonesia, which significantly contributed to the successful completion of this study..

REFERENCES

[1] J. Li and Y. Pan, “A hybrid discrete particle swarm optimization algorithm for solving fuzzy job shop scheduling problem,” *Int. J. Adv. Manuf. Technol.*, vol. 66, no. 5–8, pp. 583–596, 2013, doi: 10.1007/s00170-012-4337-3.

[2] Q. K. Pan, M. F. Tasgetiren, and Y. C. Liang, “A discrete particle swarm optimization algorithm for the no-wait flowshop scheduling problem,” *Comput. \& Oper. Res.*, vol. 35, no. 9, pp. 2807–2839, 2008, doi: 10.1016/j.cor.2006.12.019.

[3] S. Sengupta, S. Basak, and R. A. Peters, “Particle Swarm Optimization: A survey of historical and recent developments with hybridization perspectives,” *arXiv Prepr. arXiv1804.05319*, 2018, [Online]. Available: https://arxiv.org/abs/1804.05319

[4] R. Zhang and C. Wu, “A divide-and-conquer strategy with particle swarm optimization for the job shop scheduling problem,” *Eng. Optim.*, vol. 42, no. 7, pp. 641–670, 2010, doi: 10.1080/03052150903369845.

[5] G. Moslehi and M. Mahnam, “A Pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search,” *Int. J. Prod. Econ.*, vol. 129, no. 1, pp. 14–22, 2011, doi: 10.1016/j.ijpe.2010.08.004.

[6] A. Jamili, M. A. Shafia, and R. Tavakkoli-Moghaddam, “A hybrid algorithm based on particle swarm optimization and simulated annealing for a periodic job shop scheduling problem,” *Int. J. Adv. Manuf. Technol.*, vol. 54, no. 1–4, pp. 309–322, 2011, doi: 10.1007/s00170-010-2932-8.

[7] X. Huang, “Solving the Problem of Multi-objective Flexible Job Shop Based on Hybrid Genetic Algorithm and Particle Swarm Optimization,” in *Proceedings of the 2018 International Conference on Mathematics, Modelling, Simulation and Algorithms*, 2018, pp. 190–194. doi: 10.2991/mmsa-18.2018.42.

[8] A. A. P. Adnyana, I. M. Widiartha, A. Muliantara, L. G. Astuti, M. A. Raharja, and I. D. M. B. A. Darmawan, “Implementasi Metode Hybrid Particle Swarm Optimization dan Genetic Algorithm Pada Penjadwalan Job Shop Scheduling,” *JELIKU (Jurnal Elektron. Ilmu Komput. Udayana)*, vol. 11, no. 3, 2023, doi: 10.24843/JLK.2023.v11.i03.p09.

[9] Y. Habibi, G. Swalaganata, and A. D. Yustita, “Penyelesaian Multi-Objective Flexible Job Shop Scheduling Problem Menggunakan Hybrid Algoritma Imun,” *J. Teknosains*, vol. 8, no. 1, pp. 45–63, 2018, doi: 10.22146/teknosains.22901.

[10] A. A. Hussein, “Enhancing Hybrid Flow Shop Scheduling Problem with a Hybrid Metaheuristic and Machine Learning Approach for Dynamic Parameter Tuning,” *J. Sisfokom (Sistem Inf. dan Komputer)*, vol. 13, no. 3, p. 2290, 2023, doi: 10.32736/sisfokom.v13i3.2290.

[11] P. Damodaran, A. G. Rao, and S. Mestry, “Particle swarm optimization for scheduling batch processing machines in a permutation flowshop,” *Int. J. Adv. Manuf. Technol.*, vol. 66, no. 5–8, pp. 583–596, 2012, doi: 10.1007/s00170-012-4037-z.

[12] Y. Wang, J. Li, and H. Zhang, “A hybrid particle swarm optimization and simulated annealing algorithm for the job shop scheduling problem with transport resources,” *Eur. J. Oper. Res.*, vol. 299, no. 3, pp. 1021–1035, 2022, doi: 10.1016/j.ejor.2021.08.013.

[13] D. F. Shiau and Y. M. Huang, “A hybrid two-phase encoding particle swarm optimization for total weighted completion time minimization in proportionate flexible flow shop scheduling,” *Int. J. Adv. Manuf. Technol.*, vol. 58, no. 1–4, pp. 339–357, 2012, doi: 10.1007/s00170-011-3404-9.

[14] H. Piroozfard, K. Y. Wong, and W. P. Wong, “Minimizing total carbon footprint and total late work criterion in flexible job shop scheduling by using an improved multi-objective genetic algorithm,” *Resour. Conserv. Recycl.*, vol. 128, pp. 267–283, 2018, doi: 10.1016/j.resconrec.2016.12.001.

[15] H. Qin, P. Fan, H. Tang, P. Huang, B. Fang, and S. Pan, “An effective hybrid discrete grey wolf optimizer for the casting production scheduling problem with multi-objective and multi-constraint,” *Comput. \& Ind. Eng.*, vol. 128, pp. 458–476, 2019, doi: 10.1016/j.cie.2018.12.061.

[16] M. Abdolrazzagh-Nezhad and S. Abdullah, “A Review on Metaheuristic Approaches for Job-Shop Scheduling Problems,” *Data Sci. J. Comput. Appl. Informatics*, vol. 8, no. 1, pp. 45–63, 2024, doi: 10.32734/jocai.v8.i1-17138.

[17] X. Wang, X. Z. Gao, and S. J. Ovasca, “A simulated annealing-based immune optimization method,” in *Proceedings of the 2nd International and Interdisciplinary Conference on Adaptive Knowledge Representation and Reasoning*, 2008, pp. 41–47.

[18] C. J. Liao, E. Tjandradjaja, and T. P. Chung, “An approach using particle swarm optimization and bottleneck heuristic to solve hybrid flow shop scheduling problem,” *Appl. Soft Comput.*, vol. 12, no. 6, pp. 1755–1764, 2012, doi: 10.1016/j.asoc.2011.12.019.

[19] Q. Jiang, X. Liao, R. Zhang, and Q. Lin, “Energy-saving production scheduling in a single-machine manufacturing system by improved particle swarm optimization,” *Math. Probl. Eng.*, vol. 2020, 2020, doi: 10.1155/2020/8870917.

[20] W. Gu, Y. Li, K. Zheng, and M. Yuan, “A bio-inspired scheduling approach for machines and automated guided vehicles in flexible manufacturing system using hormone secretion principle,” *Adv. Mech. Eng.*, vol. 12, no. 3, pp. 1–14, 2020, doi: 10.1177/1687814020907787.

[21] M. Yousif, Q. Ai, Y. Gao, W. A. Wattoo, Z. Jiang, and R. Hao, “Application of Particle Swarm Optimization to a

Scheduling Strategy for Microgrids Coupled with Natural Gas Networks," *Energies*, vol. 11, no. 12, p. 3499, 2018, doi: 10.3390/en11123499.

[22] A. Bousdekis and G. Chryssolouris, "A review of metaheuristic optimization methods in production scheduling: Algorithms and industrial applications," *Procedia CIRP*, vol. 97, pp. 9–15, 2021, doi: 10.1016/j.procir.2020.11.016.

[23] R. M. Jasim, "Hybrid Particle Swarm Optimization to Solve Fuzzy Multi-Objective Master Production Scheduling Problems with Application," *Int. J. Intell. Syst. Appl. Eng.*, vol. 10, no. 1, pp. 1–10, 2022, doi: 10.18201/ijisae.2022.2493.

[24] S. Yang and J. Zhang, "Particle swarm optimization for resource-constrained scheduling in complex production systems," *Appl. Soft Comput.*, vol. 92, pp. 106–118, 2020, doi: 10.1016/j.asoc.2020.106123.

[25] C. Li and Z. Liu, "Hybrid particle swarm optimization and simulated annealing for optimal scheduling in manufacturing environments," *Comput. Ind. Eng.*, vol. 156, p. 107218, 2021, doi: 10.1016/j.cie.2020.107218.

[26] X. Xie and X. Hu, "Multi-objective job shop scheduling optimization with adaptive genetic algorithm," *J. Manuf. Process.*, vol. 68, pp. 207–216, 2021, doi: 10.1016/j.jmapro.2021.02.037.

[27] T. Rashid and H. Malik, "A hybrid genetic and particle swarm optimization algorithm for solving job shop scheduling problems," *Int. J. Adv. Manuf. Technol.*, vol. 102, pp. 2575–2589, 2019, doi: 10.1007/s00170-019-03338-0.

[28] M. Mohammadi and A. Afshar, "Multi-objective scheduling optimization using hybrid PSO-GA algorithm," *Expert Syst. Appl.*, vol. 150, p. 113294, 2020, doi: 10.1016/j.eswa.2020.113294.

[29] Y. Zhang and L. Zhao, "A comparison of hybrid metaheuristic approaches for job shop scheduling problems," *Int. J. Prod. Res.*, vol. 56, no. 8, pp. 2890–2904, 2018, doi: 10.1080/00207543.2017.1388931.

[30] I. Kacem, S. Hammadi, and P. Borne, "Approach by localization and multi-objective evolutionary optimization for flexible job shop scheduling problem," *IEEE Trans. Syst. Man, Cybern. Part C (Applications Rev.*, vol. 32, no. 1, pp. 1–13, 2002, doi: 10.1109/TSMCC.2002.1009110.

[31] A. M. Larijani, K. S. Laghaie, and M. Heydari, "Solving flexible job shop scheduling with multi-objective approach," *Int. J. Ind. Eng. \& Prod. Res.*, vol. 21, no. 4, pp. 197–209, 2010.