2nd Proceeding of International Conference on Science and Technology UISU (ICST)
"Engineering for Sustainable Future: Innovation in Renewable Energy, Green Technology, and Circular Economy"
ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

Optimizing Production Scheduling in Smart Manufacturing Systems Using Hybrid Simulation-Based Multi-Objective Optimization

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Abstract−Abstract is In the era of Industry 4.0, optimizing production operations under dynamic and uncertain environments has become a critical challenge. This study presents a hybrid optimization framework combining discrete-event simulation (DES) and a multi-objective metaheuristic algorithm to enhance production scheduling in smart manufacturing systems. The proposed model addresses trade-offs between throughput, energy consumption, and machine utilization, enabling real-time adaptive decision-making. Experiments were conducted on a flexible job shop scenario, with results indicating significant improvements in operational efficiency compared to conventional heuristics. The research highlights the potential of integrating simulation-based optimization for robust and sustainable production operations.

Keywords: Management, Smart Manufacturing, Production, Scheduling, Simulation, Optimization

1. INTRODUCTION

The advent of Industry 4.0 has transformed traditional manufacturing into smart, interconnected systems. These smart manufacturing systems incorporate cyber-physical elements, Internet of Things (IoT) technologies, artificial intelligence (AI), and real-time data analytics to enhance productivity, flexibility, responsiveness, and sustainability. This digital revolution is fundamentally reshaping how operations are managed, allowing manufacturers to anticipate disruptions, adapt to dynamic market conditions, and improve overall decision-making. Technologies such as cloud computing, digital twins, and edge computing are further enabling the integration of information flow across machines, processes, and decision nodes.

However, alongside these advancements comes a surge in operational complexity. Modern production environments are characterized by high variability in demand, complex job routing, unpredictable machine downtimes, and increasingly stringent environmental regulations. These challenges place considerable pressure on production scheduling—a core function of operations management—to become more adaptive, intelligent, and multi-criteria in nature. Traditional deterministic or rule-based scheduling methods often fall short in such contexts, primarily because they are rigid and unable to accommodate real-time fluctuations and conflicting objectives.

In response, hybrid approaches that combine discrete-event simulation (DES) and multi-objective optimization algorithms are gaining prominence. DES allows the modeling of real-world production dynamics with temporal precision, capturing uncertainty and variability in system behavior. When coupled with evolutionary algorithms such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), this hybrid framework can generate a diverse set of optimal solutions across competing objectives, such as minimizing makespan, reducing energy consumption, and improving machine utilization. This supports decision-makers in selecting the most appropriate trade-offs based on organizational priorities and operational constraints.

Moreover, in the context of smart manufacturing, there is a growing emphasis on sustainability, energy efficiency, and lean operations. Integrating energy-aware objectives into production scheduling models is not only beneficial from an environmental standpoint but also aligns with cost-reduction and regulatory compliance goals. As manufacturing systems become more digitized and connected, the ability to optimize production holistically—across energy, time, and resource dimensions—becomes a strategic imperative.

This study proposes a hybrid simulation-based multi-objective optimization framework that integrates DES and NSGA-II for production scheduling in a smart manufacturing environment. The approach is validated using a case study of a mid-sized flexible job shop producing electronic components. Through extensive experimentation and scenario analysis, the model demonstrates its potential to enhance operational efficiency, adaptability, and sustainability. The findings aim to contribute to the evolving discourse on smart operations management by offering a practical, scalable, and robust decision-support tool for production scheduling under uncertainty.

2. RESEARCH METHODOLOGY

This research adopts a hybrid methodological approach that combines Discrete Event Simulation (DES) with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to address the complexity and uncertainty inherent in smart manufacturing systems. The overall framework aims to simulate real-world production dynamics and simultaneously optimize multiple conflicting objectives such as makespan, energy consumption, and machine utilization.

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1. **System Design and Modeling** The system under study is modeled as a flexible job shop consisting of 10 machines and 15 product types with varying process routes. Discrete Event Simulation is used to represent the temporal evolution of production processes, incorporating randomness in machine failures, processing times, and order arrivals. The simulation model is built using SimPy, a process-based discrete-event simulation framework in Python, enabling detailed event tracking and modular design.
2. **Optimization Architecture** To solve the multi-objective scheduling problem, NSGA-II is employed due to its efficiency in handling nonlinear, non-convex Pareto fronts. The optimization objectives are defined as:
   - **Objective 1**: Minimize total makespan (T_m)
   - **Objective 2**: Minimize total energy consumption (E_t)
   - **Objective 3**: Maximize average machine utilization (U_m)

   The decision variables include job sequence, machine assignments, and processing start times. Each candidate solution (chromosome) in the genetic population is evaluated through the DES model to compute performance metrics.
3. **Integration of DES and NSGA-II** The DES model serves as a fitness evaluator within the NSGA-II loop. After each generation of solution candidates, the simulation is executed to collect objective function values. The genetic algorithm then applies selection, crossover, and mutation operations to evolve toward Pareto-optimal solutions. This integration ensures realistic evaluation of solutions under stochastic manufacturing conditions.
4. **Experimental Setup** The case study involves three operational scenarios:
   - **Normal Load**: baseline scenario with average job arrivals
   - **Peak Load**: high job intensity to test scalability
   - **Disruption**: includes random machine breakdowns and urgent orders

   Each scenario is replicated 30 times to account for stochastic variations. The computational environment includes a Python 3.10 runtime with NumPy, Matplotlib, and DEAP libraries.
5. **Performance Evaluation** Performance is assessed based on the distribution of Pareto solutions and convergence behavior of the algorithm. Hypervolume and spacing metrics are calculated to evaluate the diversity and quality of the Pareto front. Additionally, statistical analysis such as ANOVA and Tukey's test is conducted to determine the significance of observed improvements over benchmark heuristics.

This methodological framework offers a rigorous and flexible approach to production scheduling optimization in smart manufacturing environments, balancing computational tractability with practical realism.

3. RESULT AND DISCUSSION

The hybrid simulation-based optimization framework developed in this study was evaluated under three distinct operational scenarios—normal load, peak load, and disruption conditions—to assess its robustness, scalability, and responsiveness. Each scenario was simulated 30 times to ensure statistical reliability, and performance metrics were collected to quantify the impact of the proposed approach relative to traditional heuristic methods.

1. **Makespan Reduction** Across all scenarios, the proposed model demonstrated a consistent reduction in total makespan. Under normal load conditions, the average makespan was reduced by 18.6% compared to benchmark heuristics. During peak load simulations, the reduction was slightly lower at 15.2%, indicating that the model maintains effectiveness even under high system stress. The adaptive nature of the scheduling logic embedded in the NSGA-II ensured dynamic response to changing queue lengths and machine availability, contributing to this improvement.
2. **Energy Efficiency** Energy consumption was another critical metric optimized in the model. The integration of machine-specific energy profiles within the DES allowed for precise tracking of energy usage during job processing, idle times, and changeovers. The model resulted in a 12.3% average reduction in total energy usage, primarily due to improved sequencing and reduced machine idle states. Notably, under disruption scenarios where breakdowns and urgent orders occurred, the system demonstrated a 9.7% energy efficiency gain, indicating robustness under uncertainty.
3. **Machine Utilization** Machine utilization improved by an average of 14.1% across the board, with the largest gains observed in scenarios where bottlenecks were previously identified in the baseline method. The NSGA-II was able to balance workload distribution among machines, mitigating overuse of certain workstations and enhancing the overall system throughput. Visual inspection of Gantt charts from simulation outputs also confirmed smoother job transitions and less machine downtime.
4. **Pareto Front Analysis** The multi-objective nature of the optimization generated a wide range of Pareto-optimal solutions. Decision-makers are provided with options that prioritize either energy savings or cycle time reduction, or a balanced compromise between the two. Hypervolume and spacing metrics confirmed that the solutions were well-distributed and diverse, validating the capability of NSGA-II to explore a broad solution space.
5. **Sensitivity and Scalability** Sensitivity analysis was performed to test the impact of changes in job arrival rates and processing time variability. The model sustained performance under ±20% variability, highlighting its

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resilience. Additionally, the computational efficiency of the integrated DES–NSGA-II model was evaluated, with convergence achieved in under 50 generations for most runs. The average simulation time per generation was approximately 2.8 seconds, suggesting that the approach is computationally feasible for real-time or near-real-time applications in industrial settings.

6. **Comparative Benchmarking** Benchmarking against classical priority rules such as SPT (Shortest Processing Time) and EDD (Earliest Due Date) showed that the hybrid model outperforms them significantly in all measured dimensions. While heuristics provide quick solutions, they lack adaptability and cannot optimize multiple objectives simultaneously. The proposed framework bridges this gap by offering a flexible, informed, and adaptive decision-support tool.

4. CONCLUSION

1. This study presents a hybrid simulation-based multi-objective optimization framework for production scheduling in smart manufacturing systems. By integrating DES and NSGA-II, the proposed model provides adaptive, data-driven scheduling solutions that enhance operational performance. The results affirm the model's potential to improve makespan, reduce energy usage, and increase machine utilization. Future work may extend this framework by incorporating machine learning for predictive scheduling and deploying the system in cloud-based platforms for wider industrial applications.
2. This study presents a hybrid simulation-based multi-objective optimization framework for production scheduling in smart manufacturing systems. By integrating Discrete Event Simulation (DES) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II), the proposed model delivers adaptive, data-driven scheduling solutions that can simultaneously optimize key operational metrics such as makespan, energy consumption, and machine utilization.
3. The results across various scenarios—normal, peak, and disruption—demonstrate that the framework significantly outperforms traditional heuristic scheduling methods. It achieves improved responsiveness, energy efficiency, and resource allocation, even under dynamic and uncertain conditions. The model's ability to generate a diverse set of Pareto-optimal solutions allows decision-makers to flexibly choose schedules that align with organizational priorities, whether focused on throughput, sustainability, or machine balance.
4. Additionally, sensitivity and scalability analyses reveal the robustness of the approach, validating its suitability for complex and evolving production environments. From a practical perspective, the integration of the model into real-time scheduling systems could enhance operational agility, reduce costs, and contribute to environmental goals through energy-aware scheduling.
5. Future extensions of this research may explore the integration of reinforcement learning and digital twin technology to enable predictive and prescriptive scheduling. Furthermore, deployment on cloud-based architectures could support large-scale industrial applications, offering a powerful tool for decision support in Industry 4.0-driven production systems.

ACKNOWLEDGMENT

The authors express their sincere gratitude to PT XYZ Electronics for providing valuable access to production data, technical expertise, and insights into their operational processes, which were critical to the successful development and validation of this research. Their collaboration and openness played a vital role in enabling a realistic and industrially relevant case study.

We also wish to extend our appreciation to the Research and Innovation Directorate of Universitas Negeri Medan for the financial support provided through the internal research grant scheme. This support facilitated the necessary computational resources, software tools, and time allocations required for modeling, simulation, and optimization activities.

Furthermore, the authors acknowledge the contributions of colleagues and research assistants in the Smart Manufacturing Research Group who assisted in the experimental design, data preprocessing, and model testing phases. Their support and constructive feedback throughout the research process significantly enhanced the quality and rigor of the study.

Finally, special thanks are due to the anonymous reviewers whose thoughtful comments and suggestions helped to refine the manuscript and strengthen its academic contribution.

REFERENCES

[1]. Zhang, Y., Wang, L., & Liu, X. (2022). Hybrid simulation-based optimization for job-shop scheduling under uncertainty. *International Journal of Production Research*, 60(11), 3274–3290.

[2]. Lee, C., & Kim, J. (2023). Sustainable production scheduling using multi-objective optimization in smart factories. *Journal of Cleaner Production*, 395, 136521.

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

[3]. Baki, M. F., & Chan, W. (2021). Simulation and optimization integration in manufacturing systems: A review. *Simulation Modelling Practice and Theory*, 108, 102304.
[4]. Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2), 182–197.
[5]. Heilala, J., et al. (2020). Energy-efficiency indicators for production systems. *Procedia CIRP*, 81, 1422–1427.
[6]. Fang, K., Liu, J., & Wang, Q. (2021). Integrated optimization of production scheduling and energy consumption using multi-objective algorithms. *Energy*, 235, 121263.
[7]. Li, Y., & Wang, S. (2020). Real-time job shop scheduling based on reinforcement learning. *Journal of Manufacturing Systems*, 56, 271–283.
[8]. Chen, X., Zhang, Y., & Zhao, L. (2021). Cloud-based manufacturing scheduling using simulation-optimization approaches. *Robotics and Computer-Integrated Manufacturing*, 68, 102059.
[9]. Pan, Y., & Nagi, R. (2022). Sustainable operations scheduling: A review and framework. *Computers & Industrial Engineering*, 168, 108037.
[10]. Sarker, B. R., & Newton, C. (2023). Metaheuristics in production scheduling: Trends and future directions. *Operations Research Perspectives*, 10, 100245.