American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Bio-Inspired Optimization of Energy-Efficient Industrial Processes

Dr. Sophie Laurent

Professor, École Centrale de Lyon, France

Abstract

Industrial energy efficiency increasingly depends on the ability to optimize complex operating decisions rather than relying exclusively on equipment replacement or isolated technological upgrades. Modern manufacturing systems involve interacting decisions concerning production sequencing, machine assignment, processing speed, transportation, preventive maintenance, peak-power demand, electricity tariffs, renewable-energy availability, product quality, and delivery performance. These problems are frequently nonlinear, combinatorial, dynamic, and computationally difficult, making conventional deterministic optimization impractical for large industrial instances. Bio-inspired optimization offers an alternative by translating mechanisms observed in biological evolution, animal populations, collective intelligence, and adaptive ecosystems into computational search strategies.

This study examines the contribution of genetic algorithms, particle swarm optimization, artificial bee colony algorithms, grey wolf optimization, evolutionary co-learning, and related hybrid metaheuristics to energy-efficient industrial-process optimization. A structured integrative review of peer-reviewed research was undertaken, with particular attention to energy-aware job-shop scheduling, flexible flow shops, variable machine speeds, transportation constraints, automated guided vehicles, batch-processing machines, and multi-objective industrial optimization. Published evidence demonstrates that bio-inspired algorithms can identify non-trivial trade-offs among energy consumption, makespan, peak demand, operating cost, and productivity in search spaces that are difficult to solve through exact optimization alone.

Genetic algorithms have been applied successfully to real-world automotive production scheduling, particle-swarm techniques have been developed for dynamic energy-efficient flow-shop scheduling, grey-wolf methods have addressed variable-speed flexible job shops, and artificial-bee-colony methods have increasingly been used for complex energy-conscious manufacturing environments. The study proposes a Bio-Inspired Industrial Energy Optimization Framework integrating digital energy measurement, process modeling, multi-objective fitness formulation, adaptive search, operational validation, and continuous learning. It argues that the principal value of bio-inspired optimization lies not in imitating nature metaphorically, but in providing computational mechanisms capable of exploring large industrial decision spaces while maintaining several competing operational objectives. Future implementation should prioritize reproducibility, constraint-aware modeling, comparison with exact and non-bio-inspired baselines, real-plant validation, uncertainty analysis, and integration with industrial energy-management systems.

Keywords: Bio-Inspired Optimization; Industrial Energy Efficiency; Genetic Algorithm; Particle Swarm Optimization; Artificial Bee Colony; Grey Wolf Optimization; Production Scheduling; Sustainable Manufacturing; Multi-Objective Optimization; Industrial Process Control

1. Introduction

Industry represents one of the most significant energy-consuming sectors of the global economy. According to the International Energy Agency's *Energy Efficiency 2025* assessment, industry accounted for nearly 40% of global final energy demand in 2024, while energy-intensive industries represented approximately three-quarters of total industrial energy demand. Industrial efficiency therefore has direct implications for operating expenditure, energy security, production competitiveness, electricity-system flexibility, and greenhouse-gas mitigation. The IEA further identifies technical efficiency, material efficiency, and process optimization as important short-term pathways for reducing energy requirements in energy-intensive production.

Traditional industrial energy-efficiency programs frequently emphasize efficient motors, improved heating systems, insulation, heat recovery, equipment replacement, and energy-management standards. These interventions remain essential, but a substantial portion of industrial energy consumption also depends on how existing equipment is operated. Machines may consume different amounts of power at different processing speeds; production tasks can sometimes be assigned to alternative machines; energy-intensive operations can be shifted away from expensive or carbon-intensive periods; unnecessary idle states can be reduced; and automated transport can be coordinated with production schedules. Industrial energy optimization is consequently becoming a decision problem as much as an equipment problem. Evidence compiled by the IEA from more than 300 industrial energy-management case studies across 40 countries indicates average energy savings of approximately 11% within the first years of systematic energy-management implementation, highlighting the practical value of monitoring, control, and optimization.

The mathematical difficulty arises because realistic industrial processes involve many interdependent decisions. Job-shop and flexible-flow-shop scheduling problems are frequently NP-hard, and their complexity increases when energy consumption, machine-speed alternatives, transportation, maintenance, time-of-use tariffs, peak-power limits, and multiple performance criteria are introduced. Salido and colleagues demonstrated this computational challenge in an energy-efficient job-shop problem in which machines could process operations at different speeds and therefore consume different amounts of energy. Their genetic algorithm solved large instances for which a commercial scheduling tool could not obtain solutions within a practical computation period.

Bio-inspired optimization addresses such problems through population-based or collective search. Genetic algorithms reproduce computational analogues of selection, crossover, and mutation. Particle swarm optimization models the information exchange and movement of a population of candidate solutions. Artificial bee colony algorithms imitate the exploration and exploitation behavior associated with foraging colonies, while grey wolf optimization abstracts hierarchical and cooperative hunting behavior. Industrial researchers have adapted these methods considerably beyond their original metaphors by adding problem-specific encodings, local search, reinforcement learning, co-evolution, adaptive operators, decomposition strategies, and hybrid optimization mechanisms. Recent studies show continued development of artificial-bee-colony, co-evolutionary, grey-wolf, and evolutionary approaches for energy-efficient manufacturing scheduling.

The research challenge is therefore no longer simply whether bio-inspired algorithms can minimize a mathematical energy function. A useful industrial solution must satisfy production constraints while balancing energy, throughput, delivery performance, quality, peak demand, equipment utilization, and sometimes carbon intensity. Küster and colleagues developed a multi-objective genetic scheduling framework applicable to an automotive production line and an automated guided vehicle, showing that meaningful energy-efficiency gains could be obtained while accepting only limited changes in production time. The present study builds upon this multi-objective perspective and develops a unified framework explaining how bio-inspired optimization can become part of practical industrial energy management rather than remaining an isolated computational experiment.

2. Objectives of the Study

2.1 Evaluation of Bio-Inspired Industrial Optimization

The first objective is to examine how established and emerging bio-inspired optimization methods can address energy-intensive industrial decisions. Particular attention is given to genetic algorithms, particle swarm optimization, artificial bee colony methods, grey wolf optimization, and multi-population evolutionary approaches.

The study evaluates these methods according to their ability to explore complex decision spaces, incorporate nonlinear constraints, handle several objectives simultaneously, and produce solutions within operationally reasonable computation periods.

2.2 Identification of Energy-Efficiency Decision Variables

The second objective is to identify where optimization can influence industrial energy performance.

The study focuses on production sequence, machine selection, processing speed, idle and standby behavior, batch formation, material transportation, peak electricity demand, time-of-use tariffs, renewable-energy availability, preventive maintenance, and production completion time.

2.3 Development of an Integrated Optimization Framework

The third objective is to construct a practical framework linking industrial energy measurement with bio-inspired optimization and operational decision-making.

The proposed framework seeks to ensure that optimization is evaluated not only according to mathematical fitness values but also through energy intensity, production performance, constraint satisfaction, robustness, computational effort, and real-process feasibility.

3. Review of Literature

3.1 Evolutionary Optimization in Energy-Aware Manufacturing

Genetic algorithms are among the most established bio-inspired methods used in industrial scheduling. Their suitability arises from their ability to represent complete production schedules as candidate chromosomes and improve them iteratively through selection, crossover, mutation, and problem-specific repair mechanisms.

May, Stahl, Taisch, and Prabhu developed a multi-objective genetic algorithm for energy-efficient job-shop scheduling in which productive and environmental objectives were evaluated simultaneously. Their work demonstrated that scheduling can be redesigned to reduce energy consumption without treating manufacturing performance as a secondary concern. The study remains an important foundation for multi-objective green production scheduling.

Salido and colleagues subsequently developed a genetic algorithm for a job-shop environment in which processing speed altered both completion time and machine energy requirements. The authors emphasized that the extended scheduling problem becomes computationally demanding for exact solution methods, while their GA generated good-quality solutions across tested instances.

.

3.2 Swarm Intelligence for Energy-Efficient Scheduling

Particle swarm optimization represents another influential family of bio-inspired algorithms. Rather than evolving candidate schedules through crossover and mutation, PSO updates candidate positions according to individual experience and information obtained from high-performing members of the search population.

Tang, Dai, Salido, and Giret developed an improved PSO algorithm for energy-efficient dynamic scheduling in flexible flow-shop environments. Their work explicitly addressed simultaneous production and energy considerations and has subsequently become a frequently referenced foundation for energy-aware flow-shop optimization.

Ding and colleagues later proposed a hybrid particle-swarm method for energy-aware flexible-flow-shop scheduling. Their model reflects the continuing development of PSO from a generic continuous optimization technique into a constraint-aware industrial scheduling approach capable of handling multi-objective manufacturing decisions.

Swarm-intelligence methods have expanded beyond PSO. Luo, Zhang, and Fan developed a grey wolf optimizer for multi-objective energy-efficient flexible job shops with variable processing speeds. Their formulation recognized that reducing machine speed may lower instantaneous power consumption but extend production duration, creating an explicit energy–time trade-off that cannot be addressed through a simplistic “slowest is most efficient” rule.

3.3 From Single-Objective Search to Industrial Multi-Objective Optimization

A major evolution in the field has been the transition from minimizing energy alone toward simultaneously optimizing several industrial outcomes.

Energy consumption cannot usually be reduced independently of processing time. Lower machine speeds may reduce power but increase makespan. Shifting production to periods with lower electricity tariffs may increase waiting time. Turning machines off during idle periods may save energy but introduce restart costs or reliability implications. Reassigning jobs can alter both energy consumption and material transportation.

Dai, Tang, Giret, and Salido incorporated transportation constraints into energy-efficient flexible job-shop optimization, demonstrating why production and internal logistics should be optimized together rather than independently. Their model linked scheduling and transportation decisions in a multi-objective framework.

Contemporary research increasingly incorporates additional objectives including carbon emissions, machine maintenance, peak demand, electricity pricing, and worker or robot constraints. This progression indicates that the principal scientific challenge is not discovering the algorithm with the most biologically interesting metaphor. It is designing search mechanisms capable of maintaining diversity across a Pareto frontier of industrially meaningful solutions from which managers can select an acceptable compromise.

4. Research Methodology

4.1 Research Design

This study adopts a structured integrative review and conceptual-framework development approach.

The manuscript does not present an invented industrial plant, fabricated sensor dataset, simulated company, or artificially generated energy-saving percentage as an empirical industrial finding. Instead, it synthesizes peer-reviewed research concerning bio-inspired optimization in manufacturing and supplements that evidence with contemporary industrial energy-efficiency data from the International Energy Agency.

The principal review period covers research from 2015 through August 2026, while earlier foundational optimization concepts are recognized where theoretically necessary.

4.2 Evidence Identification and Selection

The evidence search emphasized combinations of the terms “bio-inspired optimization,” “energy-efficient manufacturing,” “genetic algorithm energy scheduling,” “particle swarm energy-efficient flow shop,” “artificial bee colony manufacturing energy,” “grey wolf energy-efficient scheduling,” “multi-objective job shop energy,” and “industrial process optimization.”

Priority was given to peer-reviewed research that explicitly connected optimization with at least one industrial energy metric. Studies applying bio-inspired algorithms only to unrelated optimization domains were excluded from the analytical corpus.

Research was additionally evaluated according to whether it included realistic manufacturing constraints, multi-objective evaluation, industrial case studies, comparative algorithms, or explicit measurement of energy-related performance.

4.3 Analytical Framework and Validation Criteria

The evidence was categorized according to algorithmic family, industrial decision variable, energy-related objective, competing operational objective, and validation approach.

Table 1: Methodological and Evaluation Framework

Component	Study Specification
Research design	Structured integrative literature review
Main domain	Industrial energy-efficient process and production optimization
Core review period	2015–August 2026
Algorithm families	GA, PSO, ABC, GWO and evolutionary/co-evolutionary approaches
Industrial problems	Job shop, flexible job shop, flow shop, hybrid flow shop, transportation and batch processing
Energy variables	Machine energy, processing speed, idle energy, peak power, energy price and transport energy
Operational variables	Makespan, tardiness, throughput, machine utilization and logistics
Evidence preference	Peer-reviewed computational studies with industrially meaningful constraints
Original plant dataset	Not generated for this study
Primary synthesis	Algorithm–decision–objective–validation mapping
Framework output	Bio-Inspired Industrial Energy Optimization Framework

5. Analysis

5.1 Matching Bio-Inspired Algorithms to Industrial Energy Problems

The evidence shows that algorithm selection should depend on the structure of the industrial decision rather than popularity of the metaheuristic.

Genetic algorithms are particularly useful when solutions can be encoded naturally as operation sequences, machine selections, speed assignments, or combined production schedules. Their crossover and mutation operators support broad exploration of large discrete search spaces.

PSO is attractive where continuous and discrete decision variables can be represented through suitable particle encodings. Hybrid PSO variants are especially relevant when global population search requires additional local improvement to avoid premature convergence.

Artificial bee colony algorithms offer strong exploration mechanisms and are increasingly being adapted to batch-processing and complex flexible-flow-shop problems. Their modern implementations often replace generic neighborhood operators with manufacturing-specific search procedures.

Grey wolf and related swarm methods can provide effective population diversity, although their industrial usefulness depends substantially on encoding, constraint handling, and local search rather than on the original biological metaphor.

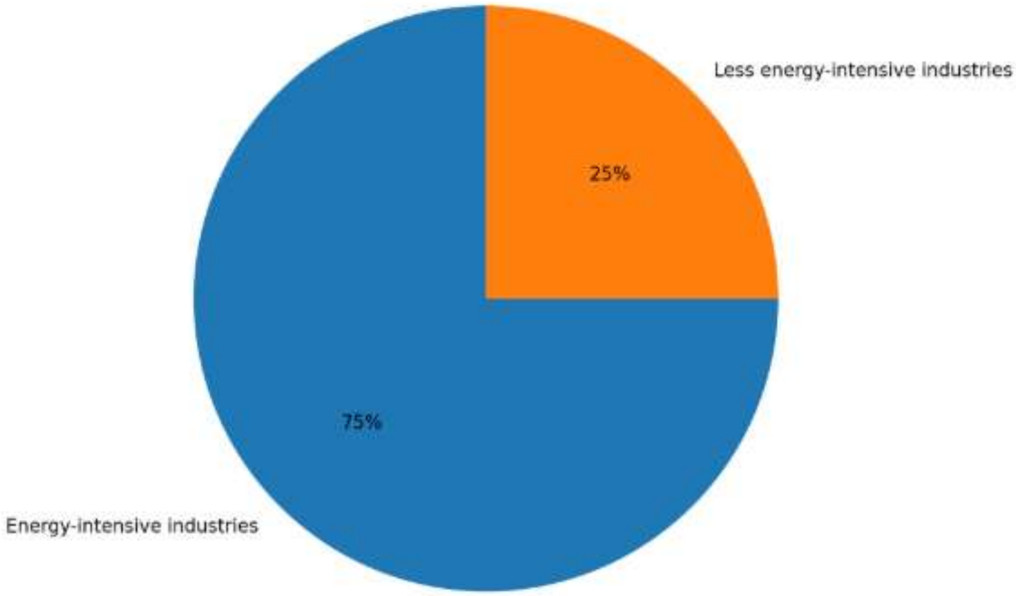
Table 2: Bio-Inspired Optimization Matrix for Industrial Energy Efficiency

Optimization Method	Biological Inspiration	Suitable Industrial Application	Energy Objective	Important Operational Trade-Off
Genetic Algorithm	Natural selection and evolution	Job-shop and production scheduling	Total energy, peak power, energy cost	Makespan and tardiness
Multi-objective GA	Evolutionary population search	Multi-criteria production planning	Energy plus carbon/cost	Throughput and delivery
Particle Swarm Optimization	Collective swarm movement	Flexible-flow-shop and dynamic scheduling	Machine and process energy	Completion time
Hybrid PSO	Collective learning + local improvement	Complex multi-stage manufacturing	Energy and peak demand	Search speed and solution diversity
Artificial Bee Colony	Collective foraging	Batch and flexible-flow-shop scheduling	Processing and idle energy	Makespan and batch utilization
Grey Wolf Optimization	Cooperative population hunting	Variable-speed flexible job shops	Energy consumption	Processing duration and quality
Co-evolutionary Algorithm	Interacting evolutionary populations	Hybrid and distributed production	Multi-stage energy minimization	Multiple conflicting objectives
Hybrid Bio-Inspired Model	Multiple biological/search mechanisms	Dynamic Industry 4.0 environments	Energy, cost and emissions	Robustness and computational complexity

5.2 Industrial Energy Demand and the Optimization Opportunity

The scale of industrial energy use provides the context for computational optimization. IEA analysis indicates that energy-intensive industrial sectors account for approximately 75% of industrial energy demand, with less energy-intensive industries representing the remaining quarter.

Figure 1: Composition of Global Industrial Energy Demand



The significance of this distribution is that modest percentage improvements within energy-intensive manufacturing can translate into substantial absolute energy savings.

However, bio-inspired optimization is not restricted to heavy industries. Less energy-intensive manufacturers often operate large numbers of electric motors, compressed-air systems, pumps, industrial robots, machine tools, refrigeration equipment, conveying systems, and flexible production lines. These facilities can provide rich optimization opportunities because operations can sometimes be rescheduled or dynamically controlled without major capital replacement.

6. Discussion

6.1 Energy Efficiency Should Be Optimized with Productivity, Not Against It

A major implication of the literature is that energy minimization alone can create technically inefficient production schedules.

Running every machine at the lowest possible speed may reduce instantaneous power but extend operating hours substantially. Excessive production shifting may reduce electricity costs but cause missed delivery deadlines. Frequent equipment shutdowns may reduce idle energy while increasing restart losses or maintenance requirements.

Küster and colleagues provide a useful industrial example because their GA framework explicitly optimized combinations of makespan, energy consumption, cost, peak shaving, alternative task modes, and multiple energy sources. Their automotive and AGV cases demonstrate that industrial optimization often involves accepting a small deterioration in one performance dimension to obtain a larger improvement in another.

A proposed algorithm should report not only total kilowatt-hours but also production quantity, completion time, tardiness, specific energy consumption, utilization, and relevant quality indicators.

6.2 Hybrid and Adaptive Algorithms Represent the Next Practical Stage

Contemporary literature increasingly moves away from isolated classical metaheuristics.

The feedback-based artificial bee colony algorithm of Wang, Tang, and Lei introduces adaptive information into bee-colony search for energy-efficient flexible-flow-shop scheduling. More recent co-evolutionary and reinforcement-learning-enhanced algorithms similarly attempt to adjust search behavior according to problem state rather than using fixed operators throughout optimization.

However, increasing algorithmic complexity also introduces an important methodological risk. A highly elaborate optimizer containing many adaptive parameters, local searches, reinforcement-learning components, and repair operators may outperform a simpler algorithm partly because it has been engineered more intensively rather than because its underlying biological mechanism is superior.

6.3 From Computational Benchmarks to Industrial Deployment

A persistent gap remains between optimization performance on benchmark problems and sustainable performance on real production systems.

Industrial deployment requires reliable sensor data, interoperable manufacturing systems, accurate energy models, cybersecurity, explainable recommendations, operator acceptance, and procedures for dealing with unforeseen events.

Salido and colleagues showed that metaheuristic search can address instances that exact scheduling tools struggle to solve within practical time limits, while Küster and colleagues demonstrated application to real industrial use cases. Nevertheless, many published optimization studies remain computational rather than operational.

7. Conclusion

Bio-inspired optimization provides a powerful computational approach for improving energy efficiency in industrial processes characterized by large, nonlinear, combinatorial, and multi-objective decision spaces.

The principal techniques examined in this study—genetic algorithms, particle swarm optimization, artificial bee colony algorithms, grey wolf optimization, and co-evolutionary approaches—have demonstrated significant applicability to job-shop scheduling, flexible manufacturing, flow shops, batch processing, machine-speed optimization, production logistics, and dynamic industrial decision-making.

The value of these methods arises from their ability to search complex spaces without requiring every relationship to possess a mathematically convenient closed-form structure.

Published research demonstrates that genetic algorithms can optimize manufacturing energy alongside production performance, that PSO can support dynamic energy-aware flow-shop scheduling, that grey-wolf optimization can address variable-speed manufacturing, and that artificial-bee-colony techniques are increasingly capable of addressing complex batch-processing and flexible-production environments.

References

1. M. A. Salido, J. Escamilla, A. Giret, and F. Barber, “A genetic algorithm for energy-efficiency in job-shop scheduling,” *The International Journal of Advanced Manufacturing Technology*, vol. 85, pp. 1303–1314, 2016, doi: 10.1007/s00170-015-7987-0.
2. G. May, B. Stahl, M. Taisch, and V. Prabhu, “Multi-objective genetic algorithm for energy-efficient job shop scheduling,” *International Journal of Production Research*, vol. 53, no. 23, pp. 7071–7089, 2015, doi: 10.1080/00207543.2015.1005248.
3. D. Tang, M. Dai, M. A. Salido, and A. Giret, “Energy-efficient dynamic scheduling for a flexible flow shop using an improved particle swarm optimization,” *Computers in Industry*, vol. 81, pp. 82–95, 2016, doi: 10.1016/j.compind.2015.10.001.
4. J. Ding, S. Schulz, L. Shen, U. Buscher, and Z. Lü, “Energy aware scheduling in flexible flow shops with hybrid particle swarm optimization,” *Computers & Operations Research*, vol. 125, Art. no. 105088, 2021, doi: 10.1016/j.cor.2020.105088.
5. S. Luo, L. Zhang, and Y. Fan, “Energy-efficient scheduling for multi-objective flexible job shops with variable processing speeds by grey wolf optimization,” *Journal of Cleaner Production*, vol. 234, pp. 1365–1384, 2019, doi: 10.1016/j.jclepro.2019.06.151.
6. M. Dai, D. Tang, A. Giret, and M. A. Salido, “Multi-objective optimization for energy-efficient flexible job shop scheduling problem with transportation constraints,” *Robotics and Computer-Integrated Manufacturing*, vol. 59, pp. 143–157, 2019, doi: 10.1016/j.rcim.2019.04.006.
7. T. Küster, P. Rayling, R. Wiersig, et al., “Multi-objective optimization of energy-efficient production schedules using genetic algorithms,” *Optimization and Engineering*, vol. 24, pp. 447–468, 2023, doi: 10.1007/s11081-021-09691-3.
8. H. Wei, S. Li, H. Quan, D. Liu, S. Rao, C. Li, and J. Hu, “Unified multi-objective genetic algorithm for energy efficient job shop scheduling,” *IEEE Access*, vol. 9, pp. 54542–54557, 2021, doi: 10.1109/ACCESS.2021.3070981.
9. J. Wang, H. Tang, and D. Lei, “A feedback-based artificial bee colony algorithm for energy-efficient flexible flow shop scheduling problem with batch processing machines,” *Applied Soft Computing*, vol. 153, Art. no. 111254, 2024, doi: 10.1016/j.asoc.2024.111254.
10. J. Wang et al., “A multi-objective dynamical artificial bee colony for energy-efficient fuzzy hybrid flow shop scheduling,” *Expert Systems with Applications*, 2025, Art. no. 125244, doi: 10.1016/j.eswa.2024.125244.
11. Y. Li, W. Huang, R. Wu, and K. Guo, “An improved artificial bee colony algorithm for solving multi-objective low-carbon flexible job shop scheduling problem,” *Applied Soft Computing*, vol. 95, Art. no. 106544, 2020, doi: 10.1016/j.asoc.2020.106544.

12. G. Gong et al., “Energy-efficient flexible job shop scheduling problem considering discrete operation sequence flexibility,” *Swarm and Evolutionary Computation*, vol. 84, Art. no. 101421, 2024, doi: 10.1016/j.swevo.2023.101421.
13. C. Liu et al., “Multi-population coevolutionary algorithm for a green multi-objective flexible job shop scheduling problem with automated guided vehicles and variable processing speed constraints,” *Swarm and Evolutionary Computation*, vol. 91, Art. no. 101774, 2024, doi: 10.1016/j.swevo.2024.101774.
14. Z. Wei, W. Liao, and L. Zhang, “Hybrid energy-efficient scheduling measures for flexible job-shop problem with variable machining speeds,” *Expert Systems with Applications*, vol. 197, Art. no. 116785, 2022, doi: 10.1016/j.eswa.2022.116785.
15. C. Wang, Y. Yao, W. Li, and X. Li, “A multi-population co-evolutionary algorithm for solving energy-efficient hybrid flow shop scheduling problem,” *Expert Systems with Applications*, vol. 297, Art. no. 129536, 2026, doi: 10.1016/j.eswa.2025.129536.
16. J. Wang, C. Wu, and Y. Peng, “Multi-objective scheduling for an energy-efficient flexible job shop problem with peak power constraint,” *Applied Soft Computing*, vol. 167, Art. no. 112330, 2024, doi: 10.1016/j.asoc.2024.112330.
17. Y. Hu, L. Zhang, Z. Zhang, Z. Li, and Q. Tang, “Matheuristic and learning-oriented multi-objective artificial bee colony algorithm for energy-aware flexible assembly job shop scheduling problem,” *Engineering Applications of Artificial Intelligence*, vol. 133, Art. no. 108634, 2024, doi: 10.1016/j.engappai.2024.108634.
18. International Energy Agency, *Energy Efficiency 2025*, Paris, France: IEA, 2025.
19. International Energy Agency, “Industrial facilities could save billions by implementing energy management,” IEA, Paris, 2025.