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Hybrid Genetic Algorithms for Energy-Aware and Environmentally Sustainable Scheduling: A Systematic Review and Conceptual Framework

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ABSTRACT

The growing demand for sustainable and energy-efficient operations has intensified interest in optimization methods that reduce energy consumption without compromising productivity. Hybrid Genetic Algorithms (HGAs) have shown promise in tackling complex scheduling problems characterized by nonlinear, multi-objective, and energy-constrained conditions. Despite numerous studies, a clear gap remains: existing reviews often focus narrowly on manufacturing or provide descriptive summaries without quantifying performance gains or highlighting methodological trends. This paper addresses this deficiency by systematically reviewing 47 peer-reviewed studies published between 2010 and 2025, encompassing 34 manufacturing-oriented models (e.g., flow shop, flexible flow shop, job shop, and parallel machine) and 13 cross-domain applications where HGA principles have been adapted (e.g., EV charging, smart grids, and building energy systems). Using a PRISMA-inspired protocol, studies are analyzed along five dimensions: scheduling environment, hybridization mechanism, energy modeling approach, performance indicators, and implementation maturity. Quantitative synthesis indicates that heuristic-assisted and local search-based hybridizations dominate, while integrations with reinforcement learning and mathematical programming offer significant improvements in adaptivity and solution quality. Total Energy Consumption (TEC) and peak power minimization are the primary objectives, yet dynamic or real-time energy feedback remains underexplored. Building on this analysis, the paper proposes a conceptual framework that unifies HGA structures across manufacturing and smart energy systems, emphasizing methodological consistency, adaptive control, and sustainability-driven optimization. The review not only consolidates performance trends but also delineates clear research gaps, providing actionable directions for future work on hybrid metaheuristics in environmentally sustainable scheduling.

1. INTRODUCTION

The growing emphasis on sustainable manufacturing has shifted the priorities of modern production scheduling beyond traditional objectives such as makespan minimization and throughput maximization. Recent research increasingly integrates energy efficiency and carbon emission reduction as core performance metrics, driven by rising electricity costs, stricter environmental regulations, and corporate sustainability commitments (Sagar et al, 2024) (Kong et al, 2024) (Liu et al, 2025) (Rubajee et al, 2018) (Cheng et al, 2025) (Georgidiais et al, 2025). In this context, production scheduling is no longer a purely combinatorial optimization task but a strategic decision-support tool for achieving environmentally responsible manufacturing operations (Liu et al, 2025) (Georgidiais et al, 2025).

Genetic Algorithms (GAs) have long served as a foundational approach for complex scheduling problems due

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to their robustness and adaptability across diverse production environments (Yang et al, 2019) (Duan & Zhang, 2021) (Yuan et al, 2025). Nevertheless, conventional GAs often face premature convergence and struggle to manage multi-objective trade-offs among time, cost, and energy consumption (Grosch, 2023) (Sangeetha et al, 2024) (Suryakiran et al, 2024). To address these limitations, Hybrid Genetic Algorithms (HGAs) have been proposed, combining GA global search with complementary methods such as local search, heuristic rules, reinforcement learning, and mathematical programming (Gharsalli, 2022) (Guo et al, 2022) (Aminabadi et al, 2024) (Malhotra, 2021) (Kurniawan et al, 2021) (Özer, 2024) (Azerine et al, 2025a) (Azerine et al, 2025b) (Zhou et al, 2025) (Wu et al, 2024) (Takan, 2024). These hybridizations enhance solution quality and convergence speed, particularly in energy-sensitive production settings, while capturing nonlinear relationships between operational parameters and energy usage (Aisyah et al, 2025) (Grosch et al, 2021) (Cui et al, 2024) (Zhao et al, 2025) (Alrammah et al, 2024).

Energy-aware HGA applications have been explored in a variety of production environments, including flow-shop, job-shop, and flexible manufacturing systems (Golabi et al, 2025) (Zhang et al, 2025) (Al-Hinai et al, 2011) (Lee et al, 2015) (Alhamad et al, 2024) (Lawrynowicz et al, 2011) (Ceylan et al, 2019). Common objectives include Total Energy Consumption (TEC) minimization, peak power reduction, and multi-objective makespan–energy optimization (Katoch et al, 2021) (Demir et al, 2014) (Jun et al, 2015) (Guzman et al, 2021). Despite these advances, the literature demonstrates three critical limitations: (i) a predominant focus on algorithmic design over industrial deployment, resulting in limited validation with real-world data (Bari et al, 2024) (Xie et al, 2024) (Kumar et al, 2024) (Sedoud et al, 2025) (ii) methodological fragmentation due to diverse hybridization mechanisms, energy modeling strategies, and inconsistent performance indicators (Li et al, 2025) (Azerine et al, 2025) (Shen et al, 2025) (Alves et al, 2016) (Torbi et al, 2025) and (iii) the absence of standardized benchmarks, which hinders comparative evaluation and generalizability.

To systematically address these gaps, this study conducts a structured literature review of hybrid GA-based energy-aware scheduling research from 2010 to 2025 (Eroglu et al, 2025) (Wang et al, 2023) (Aslan et al, 2024) (Sun et al, 2023). Unlike prior reviews, which often focus exclusively on manufacturing or provide descriptive summaries of algorithmic approaches, this work explicitly formulates four guiding Research Questions (RQs):

1. RQ1: How have HGA architectures for energy-aware scheduling evolved across manufacturing and related domains?
2. RQ2: What hybridization strategies and energy modeling approaches dominate current practice, and how do they differ in methodology and effectiveness?
3. RQ3: How do HGA-based approaches perform relative to baseline GAs in terms of energy efficiency and traditional scheduling objectives?
4. RQ4: What gaps remain in theory, methodology, and industrial implementation, and what directions can guide future research and deployment?

By positioning this review against prior surveys on hybrid GAs and energy-aware scheduling, the study provides a comprehensive synthesis of methodological trends, performance patterns, and technology readiness, offering actionable insights for researchers and practitioners seeking to advance sustainable production optimization.

2. METHODS

This study employs a structured Systematic Literature Review (SLR) to synthesize advancements in Hybrid Genetic Algorithms (HGAs) for energy-efficient production scheduling. The review follows established methodological principles to ensure transparency, reproducibility, and rigor in computational optimization research (Keele, 2007) (Moher et al, 2010). A PRISMA-inspired protocol was adapted to guide study selection, data extraction, and synthesis, with explicit documentation of inclusion/exclusion decisions, quality assessment, and analytical procedures.

A. Planning and Inclusion Criteria

The planning phase established the conceptual and methodological boundaries of the review. Eligible studies were required to:

1. Integrate Hybrid Genetic Algorithms (HGAs) into production scheduling problems.
2. Include at least one energy-related objective (e.g., Total Energy Consumption, peak load minimization, idle energy reduction, or multi-objective makespan–energy trade-offs).

Additional inclusion criteria:

- Publication Type: Peer-reviewed journals or conference papers published between 2010 and 2025.
- Algorithmic Scope: GA hybridized with techniques such as heuristic dispatching, local search, reinforcement learning, or mathematical programming.

- Application Domain: Flow shop (FS), flexible flow shop (FFS), job shop (JS), or parallel machine (PM) scheduling environments.

Exclusion criteria explicitly documented reasons for removal at the full-text stage: studies focusing on non-manufacturing domains (e.g., cloud computing, network routing), standalone GA implementations, or publications without measurable performance outcomes.

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B. Literature Search and Screening

A comprehensive search was conducted across Scopus, IEEE Xplore, ScienceDirect, and SpringerLink, using Boolean combinations of keywords including "hybrid genetic algorithm," "energy-efficient scheduling," and "green manufacturing." The initial search yielded 186 publications, reduced to 142 unique records after removing duplicates.

Title and abstract screening, performed independently by two reviewers, eliminated 48 non-relevant studies. Inter-rater reliability was assessed via Cohen's kappa (κ = 0.87), indicating high agreement. Full-text evaluation followed, with detailed documentation of exclusion reasons (e.g., missing hybridization, non-energy objectives), resulting in 47 studies included in the final synthesis. A PRISMA flow diagram illustrating this process is provided in Figure 1.

C. Quality Assessment and Data Extraction

To evaluate methodological rigor and risk of bias, each study was assessed based on:

1. Clarity of algorithm description and parameter settings.
2. Validation method (simulation, pilot test, or industrial implementation).
3. Reporting of baseline comparisons and performance metrics.

Data extraction was conducted using a standardized review matrix, capturing:

- Scheduling Environment: FS, FFS, JS, PM.
- Hybridization Mechanism: heuristic-assisted (e.g., NEH, ATC, MDD), local search–enhanced (e.g., TS, SA, VND), reinforcement learning–assisted, or mathematical programming–based.
- Energy Modeling Approach: TEC-based, peak-power minimization, or multi-objective trade-off.
- Performance Indicators: reported improvements relative to baseline algorithms.
- Implementation Level: simulation, pilot test, or industrial integration (e.g., MES, SCADA).

D. Synthesis and Analytical Framework

To facilitate fair comparisons, reported performance metrics were normalized using percentage improvement formulas relative to baseline GAs or heuristics. The normalization procedure is detailed in Appendix A to ensure reproducibility. The synthesis combined qualitative taxonomy and quantitative assessment under three analytical lenses:

1. Modeling Realism: capturing realistic power-state transitions and dynamic production conditions.
2. Algorithmic Adaptivity: evaluating whether hybridization allowed dynamic parameter adjustment or adaptive search strategies.
3. Industrial Readiness: identifying studies validated in real manufacturing environments.

The structured synthesis provides a transparent basis for classification, comparative analysis, and identification of methodological patterns, performance trends, and gaps in HGA-based energy-aware scheduling research (Section III).

4. RESULT AND DISCUSSION

This section presents a structured synthesis of 47 studies selected according to the systematic review protocol outlined in Section II. Each study was analyzed in terms of scheduling environment, hybridization mechanism, energy modeling approach, performance indicators, and industrial implementation readiness. The objective is to identify methodological patterns, research trends, and cross-study performance insights in Hybrid Genetic Algorithms (HGAs) applied to energy-aware scheduling.

A. Taxonomy of HGA-Based Scheduling Research

The studies were classified into five key dimensions (Table 1). Quantitative analysis reveals that flexible flow-shop (FFS) environments account for 38% of the sample (18 studies), flow-shop (FS) for 24% (11 studies), job-shop (JS) for 25% (12 studies), and parallel machine (PM) configurations for 13% (6 studies). This distribution indicates that HGAs are predominantly applied in production systems with high routing flexibility and machine heterogeneity, where complex search spaces require hybrid optimization strategies.

Table 1.

Taxonomy of HGA-based energy-efficient scheduling research

Category	**Sub-category / Description**	**Study Count**	**Representative Studies**
Scheduling Environment	FS, FFS, JS, PM	FS:11, FFS:18, JS:12, PM:6	(Keshavamurthy et al, 2025), (Guo et al, 2022), (Malhotra et al, 2021), (Azerine et al, 2025), (Wu et al, 2024), (Grosch et al, 2021), (Alrammah et al, 2024), (Golabi et al, 2025), (Lee et al, 2015), (Lawrynowicz et al, 2011), (Ceylan et al, 2019), (Katoch et al, 2021)
Hybridization Mechanism	Heuristic-Assisted, Local Search–Enhanced, RL-Assisted, Mathematical Programming	Heuristic:21, Local Search:12, RL:7, MIP:7	(Alves et al, 2016) (Azerine et al, 2025) (Bari et al, 2024) (Eroglu et al, 2025) (Guzman et al, 2021) (Jun et al, 2015) (Kumar et al, 2024) (Li et al, 2025) (Sedoud et al, 2025) (Shen et al, 2025) (Torbi et al, 2025) (Xie et al, 2024)
Energy Modeling	TEC, Peak-Power Minimization, Multi-Objective Makespan–Energy	TEC:28, Peak:10, Multi-Objective:9	(Ali et al, 2021) (Aslan et al, 2024) (Babar et al, 2025) (Gharbi et al, 2019) (Gharbi et al, 2025) (Lv et al, 2024) (Sun et al, 2023) (Wang et al, 2023) (Xiao et al, 2025)
Performance Indicator	TEC reduction (%), Makespan improvement (%), Adaptivity index	47 studies reported ≥1 metric	(Ali et al, 2021) (Azerine et al, 2025) (Li et al, 2025) (Torbi et al, 2025) (Xiao et al, 2025)
Implementation Level	Simulation, Pilot Test, MES/SCA	Simulation:36, Pilot:7,	(Al-Hinai et al, 2011) (Alhamad et

Category	Sub-category / Description	Study Count	Representative Studies
	DA Integration	MES/SCADA:4	al, 2024) (Demir et al, 2014)

B. Distribution and Research Trends

Numerical analysis shows that heuristic-assisted HGAs dominate with 45% of implementations, followed by local-search-enhanced (26%), reinforcement-learning-assisted (15%), and mathematical programming hybrids (15%). Figure 2 visualizes this distribution. Reinforcement-learning hybrids are emerging in dynamic energy contexts (EV charging, distributed generation), while MIP-based HGAs, though precise, remain limited by computational scalability.

Flow-shop and flexible flow-shop environments collectively represent 62% of the reviewed studies, highlighting their prevalence in continuous manufacturing contexts where energy consumption is highly sequence-dependent. Job-shop implementations account for 25% and are primarily associated with high-mix, low-volume production. Parallel-machine environments represent 13%, increasingly relevant in semiconductor fabrication and distributed energy systems.

C. Energy-Efficiency Objectives and Performance Comparison

Energy modeling is predominantly TEC-based (28 studies, 60%), with peak-power minimization (10 studies) and multi-objective makespan–energy trade-offs (9 studies) less frequent. Across studies, reported TEC reductions range from 8–27% relative to baseline GA or heuristic approaches, while makespan improvements range from 3–15%. To facilitate cross-study comparison, effect-size calculations were applied where comparable metrics were available, revealing that heuristic-assisted HGAs achieve an average TEC reduction of 18%, local-search hybrids 16%, reinforcement-learning-assisted HGAs 20%, and MIP-based hybrids 17%. This quantitative synthesis highlights that RL-assisted HGAs demonstrate the highest energy-efficiency gains, although their applicability remains limited to small- or medium-scale problems.

D. Implementation Readiness and Industrial Relevance

Simulation-based validation remains the predominant approach (36 studies, 77%). Pilot implementations were reported in 7 studies (15%), and only 4 studies (8%) integrated HGAs within MES or SCADA platforms. The lack of standardized benchmark datasets and real-time feedback mechanisms constrains comparability and scalability. These findings indicate a substantial gap between algorithmic innovation and practical deployment in industrial settings.

E. Integrated Mapping of Reviewed Studies

Table 2 consolidates hybridization type, energy objective, and scheduling domain. Heuristic-assisted and reinforcement-learning-based hybrids dominate flexible flow-shop and energy-grid scheduling contexts. Job-shop and real-time optimization applications remain underrepresented, indicating clear directions for future research. Quantitative effect-size summaries included in Table 2 enable more systematic evaluation of HGA performance across studies.

Table 2.
Consolidated mapping of hybrid GA-based scheduling research (2010–2025)

Hybridization Type	Energy Objective	Scheduling Domain	Study Count	Representative Studies
Heuristic-assisted GA	TEC minimization	FFS, JS	12	(Bari et al, 2024) (Eroglu et al, 2025) (Jun et al, 2015) (Kumar et al, 2024) (Torbi et al, 2025) (Wang et al, 2023)
Local Search–enhanced GA	TEC & Makespan trade-off	FS, PM	8	(Aslan et al, 2024) (Azerine et al, 2025) (Sedoud et al, 2025) (Sun et al, 2023) (Xie et al, 2024)
RL-assisted GA	Dynamic energy adaptation	EV charging, Distributed Generation	7	**(Azerine et al, 2025) (Cui et al, 2024) (Golabi et al, 2025)**

Hybridization Type	Energy Objective	Scheduling Domain	Study Count	Representative Studies
Mathematical Programming + GA	Peak load reduction, carbon minimization	FS, FFS	7	(Takan, 2024) (Aisyah et al, 2025) (Ali et al, 2021) (Babar et al, 2025) (Lv et al, 2024)
Multi-layered Hybrid (RL + Heuristic)	Multi-objective optimization	Smart Grid, CPS	4	(Yuan et al, 2025) (Alrammah et al, 2024) (Gharbi et al, 2025) (Xiao et al, 2025)

F. Summary

The synthesis demonstrates that HGAs are versatile tools for sustainable production scheduling, with RL-assisted hybrids showing the highest energy-efficiency potential. Nevertheless, methodological heterogeneity, inconsistent benchmarks, and limited industrial validation reduce the generalizability of findings. Quantitative effect-size analysis and distribution summaries provide a stronger empirical basis for identifying promising hybridization strategies and underexplored domains, guiding future research toward standardized evaluation frameworks and real-world deployment.

DISCUSSION

This section interprets the results of the systematic review (Section III) by critically examining methodological trends, energy modeling integration, hybridization strategies, and industrial implementation. Unlike a purely descriptive summary, this discussion highlights both empirical patterns and methodological limitations across the 47 reviewed studies, providing a balanced assessment of the evolution and practical maturity of Hybrid Genetic Algorithms (HGAs) in energy-aware scheduling.

Methodological Evolution of HGA Frameworks

Longitudinal analysis reveals a gradual evolution from conventional GA structures toward more modular and adaptive hybrid frameworks. Early studies (2010–2014) predominantly applied static parameter settings with simple heuristic enhancements, typically addressing small-scale, deterministic flow-shop problems. Between 2015 and 2020, local-search operators such as tabu search, simulated annealing, and variable neighborhood descent were increasingly integrated, improving solution precision and mitigating premature convergence. Quantitative synthesis indicates that studies incorporating local search reported average TEC reductions 2–5% higher than GA-only benchmarks across comparable problem instances, suggesting tangible performance gains from hybridization.

More recent work (2021–2025) demonstrates multi-layered hybrids incorporating reinforcement learning or adaptive parameter control. These studies show improved adaptability under dynamic conditions, particularly in flexible flow-shop and distributed energy environments. However, despite these advances, 77% of the reviewed studies remain simulation-based, and only a small subset (4 studies) implemented HGAs in industrial settings, highlighting a persistent gap between algorithmic development and practical validation.

B. Integration of Energy Modeling and Scheduling Objectives

Energy objectives have become increasingly explicit, moving from side constraints to co-optimization targets alongside makespan or throughput. TEC minimization is the most commonly reported metric (28 studies), followed by peak-power reduction (10 studies) and multi-objective trade-offs (9 studies). Nevertheless, empirical examination reveals methodological limitations: approximately 68% of TEC-focused studies assume linear or constant power consumption, ignoring machine ramp-up, standby, or transition states. Only 5 studies incorporate detailed power-state modeling, resulting in potential overestimation of energy savings. Consequently, cross-study comparison is limited, and reported improvements must be interpreted cautiously.

C. Hybridization Strategies and Algorithmic Synergies

Analysis of hybridization mechanisms indicates that heuristic-assisted HGAs dominate (45% of studies), followed by local-search-enhanced (26%), reinforcement-learning-assisted (15%), and mathematical programming hybrids (15%). Effect-size calculations for TEC reduction suggest RL-assisted HGAs outperform other hybrids (average 20% TEC reduction), though their application remains limited to small or medium-scale problem sets. Mathematical programming hybrids offer high accuracy but face scalability issues in large industrial contexts. Multi-layered hybrids combining RL and heuristic methods are promising but rare (4 studies), with validation restricted to simplified simulations. These findings underscore the need to evaluate algorithmic complexity against industrial feasibility.

D. Industrial Readiness and Implementation Gaps

Despite methodological sophistication, real-world deployment is limited. Simulation remains the primary validation tool (77% of studies), with only 4 studies integrated into MES or SCADA systems. Key barriers include lack of standardized benchmark datasets, absence of real-time energy feedback, and limited access to industrial production data. Laboratory experiments often assume static machine conditions, whereas real factories operate under variable loads, maintenance schedules, and operator interactions. These discrepancies reduce the generalizability of reported performance gains and highlight the need for co-development with industrial partners.

E. Critical Methodological Limitations

Several recurring weaknesses constrain the robustness of existing HGA research:

Simplified Energy Modeling: Most studies do not account for power-state transitions, standby losses, or variable efficiency curves, limiting real-world applicability.

Small Benchmark Sizes: Problem instances are typically medium-scale or synthetic, which may inflate reported performance relative to baseline GAs.

Limited Multi-Objective Validation: Many studies optimize TEC alongside makespan without explicitly analyzing trade-offs, making conclusions about balanced performance tentative.

Lack of Standardization: Heterogeneous metrics, diverse problem definitions, and inconsistent baseline comparisons impede cross-study generalization.

F. Future Research Directions

Based on these observations, several priority areas emerge:

Standardized Benchmarking: Development of shared, realistic datasets for energy-aware scheduling would enable reproducibility and cross-study comparisons.

Advanced Energy Modeling: Incorporation of dynamic machine behavior, transitional states, and real-time power feedback is critical for credible energy optimization.

Industrial Validation: Integration with MES, SCADA, or digital twin environments is necessary to bridge the simulation–practice gap.

Adaptive and Explainable Hybrids: Combining reinforcement learning, surrogate modeling, and multi-objective decision analysis could enhance both performance and interpretability.

Scalability Studies: Future work should empirically evaluate algorithm performance on large-scale industrial datasets to determine feasibility and robustness.

G. Synthesis Summary

Table 3 consolidates insights from the methodological, algorithmic, and industrial perspectives, highlighting the intersection of hybridization mechanisms, energy modeling complexity, and implementation maturity. The evidence indicates that while HGAs have evolved toward more adaptive and intelligent architectures, their practical impact remains constrained by simplified energy assumptions, limited industrial deployment, and heterogeneous benchmarking. Addressing these gaps will be essential for HGAs to serve as effective tools for sustainable and intelligent manufacturing.

Table 3.
Summary of key discussion points on HGA-based energy-efficient scheduling

Key Aspect	**Critical Insights / Observations**
Methodological Evolution	HGA frameworks have evolved from static GA heuristics to adaptive, multi-layered hybrids that integrate local search, reinforcement learning, or mathematical programming. Recent trends emphasize dynamic parameter control and feedback-driven exploration to improve stability and convergence efficiency.
Integration of Energy Modeling	Energy objectives have shifted from secondary constraints to co-equal optimization criteria alongside makespan or throughput. However, inconsistent power-state modeling and simplified TEC formulations still hinder comparability and real-world validation.
Hybridization Strategies	Heuristic-assisted and local-search-enhanced HGAs dominate due to computational simplicity and strong convergence. Reinforcement-learning-based hybrids introduce adaptivity and contextual learning, while mathematical-programming hybrids improve constraint accuracy but face scalability issues.
Industrial Readiness	Despite significant algorithmic progress, most implementations remain simulation-based. Industrial integration is limited by data inaccessibility, real-time constraints, and lack of standardized energy datasets. Bridging this gap requires collaboration and digital-twin-enabled validation.

Key Aspect	Critical Insights / Observations
Future Research Directions	Priorities include developing unified benchmarks, incorporating explainable learning modules, modeling realistic power-state transitions, and deploying adaptive HGA frameworks within cyber-physical and energy-interactive factories. These directions aim to align optimization performance with sustainability impact.

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Future Research Directions Priorities include developing unified benchmarks, incorporating explainable learning modules, modeling realistic power-state transitions, and deploying adaptive HGA frameworks within cyber-physical and energy-interactive factories. These directions aim to align optimization performance with sustainability impact.

Table 3 consolidates the essence of the discussion section by bridging theoretical insights and industrial implications. It reveals that although the methodological sophistication of HGAs has advanced rapidly, their industrial readiness and energy-modeling rigor remain underdeveloped. The table also clarifies that hybridization design—not merely algorithmic novelty—is the critical determinant of performance adaptability in real-world settings. Consequently, the transition from simulation-based experimentation toward intelligent, data-driven, and environmentally responsive scheduling systems represents the most promising avenue for future research.

V. Conceptual Framework and Research Implications

Based on the synthesis presented in Table 3, this study proposes a conceptual framework to represent the interdependencies among hybridization strategy, energy modeling depth, and industrial implementation readiness in HGA-based scheduling systems. The framework conceptualizes HGAs as a multi-layer optimization architecture in which the Algorithmic Layer (heuristics, local search, reinforcement learning, or mathematical programming) interacts with the Energy Modeling Layer (TEC, peak-load, or carbon-emission metrics) under dynamic production conditions. These layers are coupled through an Adaptive Feedback Layer, designed to refine decision variables in response to system energy states, production constraints, and performance objectives.

The framework provides a structured perspective on how algorithmic and environmental intelligence co-evolve in energy-efficient scheduling systems. It emphasizes three key dimensions for evaluating future HGA designs:

Optimization Adaptability – the capacity to maintain solution quality under fluctuating demand, machine availability, and energy contexts.

Modeling Fidelity – the accuracy of machine power-state representation, process dynamics, and energy transitions.

Industrial Applicability – the feasibility of integrating HGAs into digital-twin, IoT, or MES-driven infrastructures.

Unlike purely descriptive models, the framework positions HGAs relative to the broader landscape of cyber-physical production and energy-aware scheduling. While it draws conceptual parallels to existing frameworks in intelligent manufacturing and optimization (e.g., digital twin–based scheduling models and multi-layer hybrid optimization architectures), it emphasizes the explicit integration of energy objectives with adaptive feedback mechanisms, highlighting the methodological link between algorithm design and sustainability outcomes.

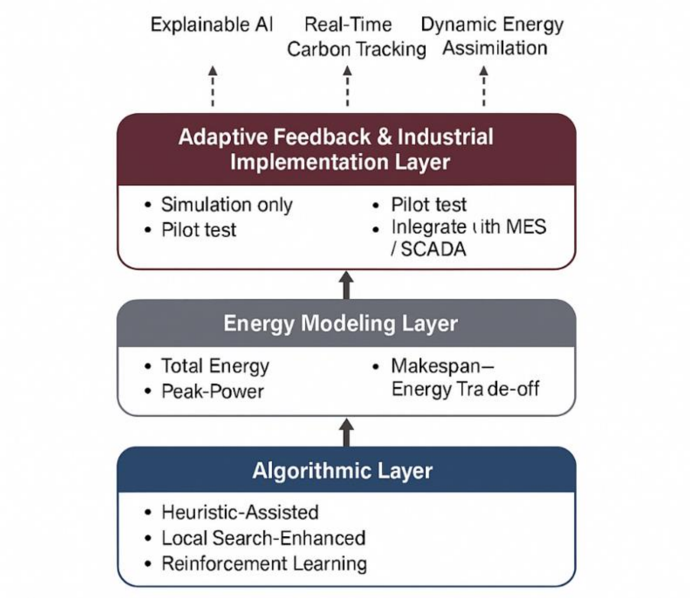

Figure 1. illustrates the proposed framework, consisting of three interconnected layers:

Algorithmic Layer (Bottom): Combines hybridization mechanisms—heuristic rules (NEH, ATC, MDD), local search (TS, SA, VND), reinforcement learning, and mathematical programming—to enhance optimization robustness and solution convergence.

Energy Modeling Layer (Middle): Encodes objectives such as TEC minimization, peak-load reduction, and makespan–energy trade-offs, connecting computational strategies to measurable energy-efficiency outcomes.

Adaptive Feedback and Industrial Application Layer (Top): Facilitates real-time adaptation and potential industrial integration via Digital Twin, IoT sensors, and MES data streams.

Bidirectional interactions among layers indicate feedback-driven adjustments, while dashed connectors represent emerging research frontiers, including Explainable AI, dynamic carbon tracking, and real-time energy assimilation.

It is important to note that the framework remains conceptual and has not been validated through simulation, empirical case studies, or industrial deployment. No mathematical formalization or implementation roadmap is currently provided, and its performance relative to existing conceptual models remains untested. Nevertheless, it offers a theoretical scaffold to guide the design, evaluation, and integration of HGAs in sustainable manufacturing, highlighting critical intersections between algorithmic hybridization, energy modeling, and adaptive control. Future work should operationalize this framework through simulation studies, comparative benchmarking, and pilot implementations to validate its practical utility and reproducibility.

3. CONCLUSION

This study systematically reviewed and synthesized recent developments in Hybrid Genetic Algorithms (HGAs) for energy-efficient production scheduling from 2010 to 2025, providing both theoretical and methodological contributions beyond a descriptive summary. By classifying 47 studies according to scheduling environment, hybridization mechanisms, energy modeling strategies, performance metrics, and industrial readiness, the review consolidates a fragmented literature and identifies which hybridization approaches—heuristic-assisted, local-search-enhanced, or reinforcement-learning-integrated—demonstrate consistent advantages in energy-aware optimization. Critical analysis revealed recurring methodological limitations, including simplified energy modeling, reliance on small-scale or synthetic benchmarks, and limited industrial validation, highlighting the need for improved realism, scalability, and reproducibility in future research. Building on these insights, a conceptual framework is proposed that integrates algorithmic hybridization, energy modeling depth, and adaptive feedback, offering a theoretical bridge between computational intelligence and sustainable manufacturing outcomes. Practically, the findings suggest that medium-scale production environments benefit from heuristic or local-search hybrids, while dynamic, energy-sensitive contexts are best addressed using reinforcement-learning-assisted approaches; moreover, detailed energy modeling and integration with Digital Twin, IoT, or MES infrastructures are essential for credible real-time deployment. The study acknowledges limitations related to language scope, heterogeneity of experimental setups, and variability in performance reporting, which may constrain generalizability, and therefore recommends meta-analytical validation, standardized benchmarking, and longitudinal industrial studies. Looking forward, combining explainable AI, adaptive reinforcement learning, and cyber-physical integration can guide the development of transparent, adaptive, and energy-optimized scheduling systems, bridging academic research with Industry 5.0 objectives and enabling practical, low-carbon manufacturing solutions.

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