

Review

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Review

Evolutionary Algorithms and Engineering Applications: A Comprehensive Survey of Classical Methods and Emerging Trends

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Abstract

Evolutionary algorithms (EAs) are widely used nature-inspired optimization methods capable of solving complex and high-dimensional problems across science and engineering. Foundational paradigms such as genetic algorithms, genetic programming, differential evolution, evolution strategies, and evolutionary programming have expanded into multi-objective, surrogate-assisted, hybrid, and large-scale variants, broadening their applicability to dynamic and data-driven environments. This survey provides a structured review of EAs from a domain-centric perspective, focusing on how different techniques are designed for engineering problems. Applications are examined across renewable energy, civil and structural engineering, electronics, industrial optimization, healthcare, robotics, and smart cities. We present an updated taxonomy of classical and emerging algorithms, consolidate recent application studies, and review benchmarking and reproducibility practices essential for fair evaluation. Key challenges including scalability, constraint handling, and exploration–exploitation balance are discussed alongside future directions such as EA–deep learning integration, federated optimization, and interpretable evolution. This survey offers an updated view of EAs and their engineering relevance.

Keywords: evolutionary computation; multi-objective optimization; surrogate-assisted EAs; CMA-ES; adaptive DE; memetic algorithms; GPU-accelerated EAs; medical image analysis; smart grids; evolutionary robotics

1. Introduction

Evolutionary algorithms (EAs) constitute a central paradigm in computational intelligence and soft computing, providing population-based optimization frameworks inspired by the principles of natural selection and biological evolution [1,2]. Since their inception in the 1960s and 1970s, with foundational contributions from pioneers such as John Holland, Ingo Rechenberg, and Lawrence Fogel, EAs have evolved from conceptual biological metaphors into mature optimization methodologies with strong theoretical foundations and broad applicability. Representative classes include genetic algorithms (GAs) [3–6], genetic programming (GP)[7,8], differential evolution (DE)[9,10], evolution strategies (ES)[11,12], and evolutionary programming (EP)[13]. These approaches use iterative processes of variation, selection, and inheritance to effectively explore high-dimensional, multimodal, and rugged fitness landscapes where classical optimization methods often fail[14,15]. The enduring success of EAs arises from their ability to maintain population diversity, perform global search, and adaptively balance exploration and exploitation[16,17]. Their parallel evaluation of candidate solutions provides effectiveness against local optima, noise, and non-convexity, enabling widespread adoption in engineering design optimization[18], scheduling[19], image and signal processing, bioinformatics[20], and environmental modeling[21]. Furthermore, their flexible and modular nature facilitates hybridization with learning paradigms such as neural architecture search (NAS), reinforcement learning, and

adaptive control[22]. In recent years, EA research has accelerated significantly, driven by advances in computation, availability of large-scale datasets, and integration with emerging fields such as quantum computing, AI, and big data analytics[23].

Although EAs have been widely reviewed, most prior surveys remain largely *algorithm-centric*, emphasizing taxonomies, operators, theory, and benchmark behavior. These works classify methods by their internal mechanics but provide limited insight into how different EA variants are adapted to the needs of specific engineering domains. With the rapid growth of domain-designed EA designs in areas such as energy systems, healthcare, and intelligent infrastructure, a synthesized view that links algorithmic choices to problem-driven requirements is increasingly needed.

This survey addresses that gap by offering a domain-centric synthesis of evolutionary algorithms. While covering classical EA families and modern hybrid approaches, the discussion is organized around major application domains where EAs have demonstrated significant impact. The goal is to help practitioners understand which EA variants suit particular problem characteristics, clarify how methodological developments translate to domain performance, and highlight trends emerging from real-world deployments. In addition, this survey consolidates theoretical foundations, methodological diversity, and cross-domain applications while highlighting open challenges such as scalability, convergence reliability, computational cost, and integration with large-scale and data-driven systems. The analysis underscores how EAs continue to evolve as essential tools for next-generation intelligent optimization.

2. Methodological Review Framework

This survey adopts a transparent and reproducible review protocol to ensure search completeness, consistent screening, and domain-relevant coverage.

2.1. Search Strategy

A comprehensive search was performed across IEEE Xplore, Scopus, Web of Science, ScienceDirect, and SpringerLink for the period 2015–2025. Core EA keywords included “*evolutionary algorithm*”, “*genetic algorithm*”, “*differential evolution*”, “*evolution strategies*”, “*genetic programming*”, “*memetic algorithm*”, “*surrogate-assisted evolutionary algorithm*”. To ensure methodological transparency and reproducibility, the complete Boolean search strings for all databases including explicit AND/OR structures and domain-specific filters are provided in the Supplementary Appendix (Appendix A). The initial retrieval yielded 2,183 records; after removing duplicates (412) and non-English works (76), 1,695 items remained for screening.

2.2. Screening and Selection Criteria

A total of 953 papers underwent full-text review. The refined inclusion and exclusion criteria are:

Inclusion Criteria:

- Peer-reviewed journal or conference papers (2015–2025);
- Evaluation on *two or more benchmark functions* or *one real-world engineering case*;
- Explicit description of EA components (representation, operators, selection);
- Sufficient experimental detail for replication (parameter settings, dataset/task description, and statistical reporting).

Exclusion Criteria:

- Pure swarm-intelligence studies lacking EA components;
- Works without replicable methodology (missing parameters, unclear benchmarks, incomplete metrics);
- Non-archival content (theses, non-reviewed preprints, posters, tutorials).

After applying these criteria, 312 publications formed the final corpus analyzed throughout the survey.

2.3. Classification and Taxonomy Approach

The selected works were organized using a dual-axis taxonomy comprising an *algorithmic axis* (GA, DE, ES/CMA-ES, GP, EP, hybrid EAs, and quantum-inspired EAs) and an *application axis* (healthcare, engineering design, energy systems, AI/ML, robotics, and smart cities). Figure 1 provides a unified visualization linking EA families to their dominant application domains.

Rationale Behind the Taxonomy: Different EA families possess distinct representations and search dynamics that naturally align with specific domain requirements. CMA-ES and related evolution strategies are favored in engineering and structural optimization due to their Gaussian sampling and covariance adaptation suited for high-dimensional, ill-conditioned landscapes. GAs with discrete encodings and recombination remain prevalent in routing, scheduling, and other combinatorial tasks. Differential evolution is widely applied in energy systems, control, and parameter estimation because of its simple vector-based mutation and noise resilience. Hybrid and memetic EAs dominate medical imaging and healthcare tasks, where domain heuristics, prior knowledge, and multi-objective trade-offs are critical. By integrating algorithmic and application axes, the taxonomy provides the domain-centric lens central to this survey, clarifying how methodological characteristics map onto real-world problem structures.

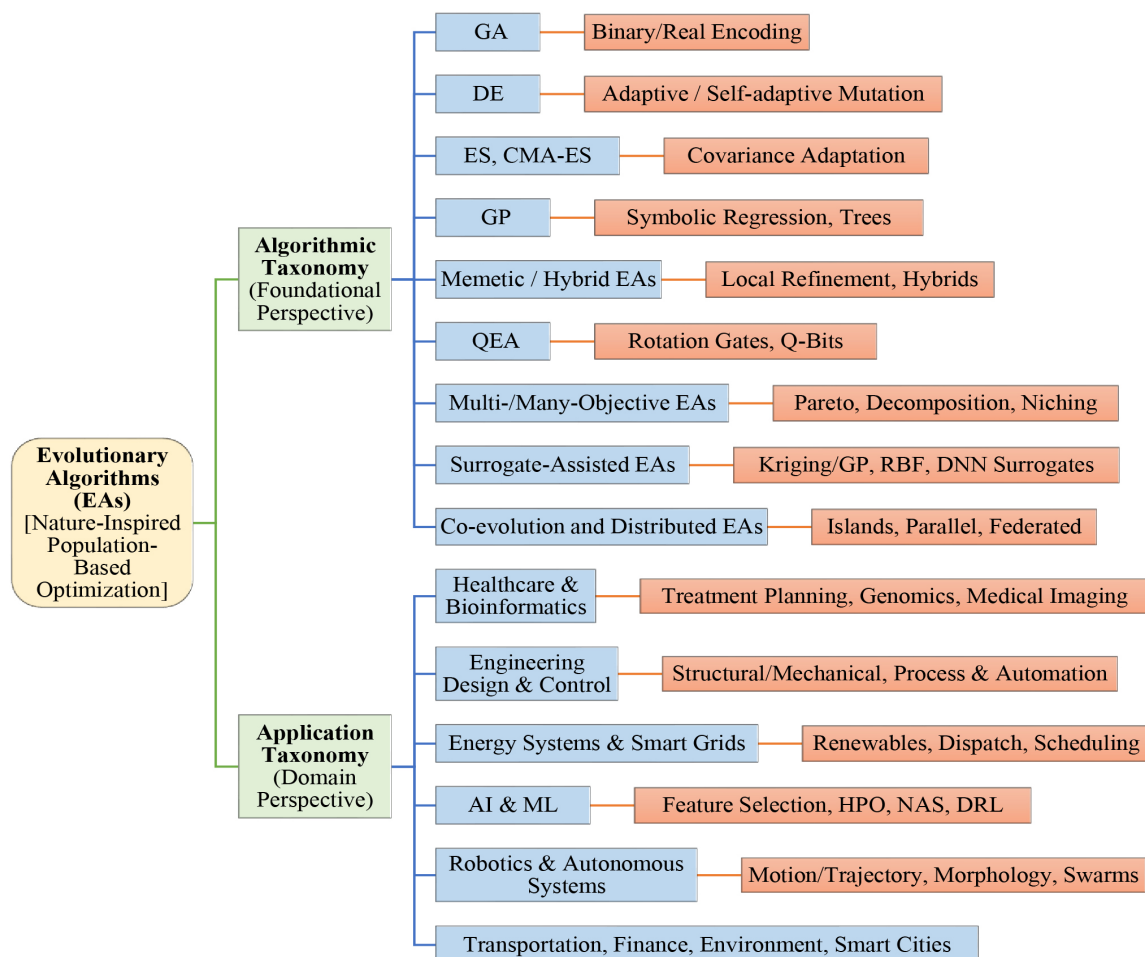


Figure 1. Taxonomy of evolutionary algorithms showing algorithmic families (left) and major application domains (right).

2.4. Study Overview

The final corpus spans one decade and covers classical, hybrid, surrogate-assisted, and quantum-inspired evolutionary algorithms.

3. Foundations of Evolutionary Algorithms

3.1. Core Mechanisms of Evolutionary Algorithms

Evolutionary algorithms are population-based stochastic optimizers driven by the principles of selection, recombination, and mutation. Although these mechanisms are standard and well documented in classical textbooks, we briefly summarize them here for completeness and refer readers to Table 1 for a compact overview of how each operator shapes exploration and exploitation. The generic evolutionary update can be written as

$$P_{t+1} = \mathcal{S}(\mathcal{M}(\mathcal{C}(P_t))), \quad (1)$$

Here \mathcal{S} , \mathcal{C} , and \mathcal{M} denote selection, crossover, and mutation, respectively. Algorithm 1 outlines the modular workflow. These components collectively enable EAs to maintain diversity, refine promising regions, and navigate rugged fitness landscapes.

Algorithm 1 Generic Evolutionary Algorithm Framework

Require: Search space Ω , fitness function $f : \Omega \rightarrow \mathbb{R}^k$, population size N , maximum generations G_{\max} , crossover rate p_c , mutation rate p_m , selection operator \mathcal{S} , crossover operator \mathcal{C} , mutation operator \mathcal{M} , replacement operator \mathcal{R}

Ensure: Best-so-far solution x^*

```

1:  $t \leftarrow 0$ 
2: Initialize population  $P^{(0)} = \{x_i^{(0)}\}_{i=1}^N$  with  $x_i^{(0)} \sim \mathcal{U}(\Omega)$ 
3: Evaluate fitness  $F^{(0)} = \{f(x_i^{(0)})\}_{i=1}^N$ 
4: Set  $x^* \leftarrow \arg \min_{x_i^{(0)} \in P^{(0)}} f(x_i^{(0)})$ 
5: repeat
6:    $t \leftarrow t + 1$ 
7:   Compute selection probabilities  $\pi^{(t-1)}$  from  $F^{(t-1)}$ 
8:    $M^{(t-1)} \leftarrow \mathcal{S}(P^{(t-1)}, \pi^{(t-1)})$ 
9:   Initialize offspring population  $O^{(t)} \leftarrow \emptyset$ 
10:  for  $i = 1$  to  $N$  step 2 do
11:    Select parents  $x_p^{(t-1)}, x_q^{(t-1)} \in M^{(t-1)}$ 
12:    Draw  $u \sim \mathcal{U}(0, 1)$ 
13:    if  $u < p_c$  then
14:       $(\tilde{x}_1^{(t)}, \tilde{x}_2^{(t)}) \leftarrow \mathcal{C}(x_p^{(t-1)}, x_q^{(t-1)})$ 
15:    else
16:       $\tilde{x}_1^{(t)} \leftarrow x_p^{(t-1)}$ ;  $\tilde{x}_2^{(t)} \leftarrow x_q^{(t-1)}$ 
17:    end if
18:    Draw  $u_1, u_2 \sim \mathcal{U}(0, 1)$ 
19:    if  $u_1 < p_m$  then
20:       $\tilde{x}_1^{(t)} \leftarrow \mathcal{M}(\tilde{x}_1^{(t)})$ 
21:    end if
22:    if  $u_2 < p_m$  then
23:       $\tilde{x}_2^{(t)} \leftarrow \mathcal{M}(\tilde{x}_2^{(t)})$ 
24:    end if
25:     $O^{(t)} \leftarrow O^{(t)} \cup \{\tilde{x}_1^{(t)}, \tilde{x}_2^{(t)}\}$ 
26:  end for
27:  Evaluate  $F_O^{(t)} = \{f(x) \mid x \in O^{(t)}\}$ 
28:   $P^{(t)} \leftarrow \mathcal{R}(P^{(t-1)}, F^{(t-1)}, O^{(t)}, F_O^{(t)})$ 
29:  Update  $x^* \leftarrow \arg \min_{x \in P^{(t)} \cup \{x^*\}} f(x)$ 
30: until  $t \geq G_{\max}$  or a convergence/fitness criterion is satisfied
31: return  $x^*$ 

```

Table 1. Relation between EA mechanisms and exploration–exploitation behavior.

Mechanism	Primary Role	Exploration	Exploitation	Control Parameter
Initialization	Provide diverse starting points	High	Low	Population size N
Selection	Prefer high-quality solutions	Low	High	Selection pressure
Crossover	Recombine traits	Moderate	Moderate	p_c
Mutation	Inject random variations	High	Low	p_m
Elitism	Preserve top individuals	Low	Very High	Elite ratio
Termination	Stop search	–	–	G_{\max}, T

3.2. Theoretical Foundations and Their Practical Implications

A theoretical understanding of evolutionary algorithms provides insight into their expected convergence behavior, stability, and search efficiency. These results not only clarify why certain EA variants behave as they do but also guide practitioners in choosing suitable operators, mutation strengths, population sizes, and hybridization strategies. Below we synthesize key theoretical concepts and highlight their practical implications.

3.2.1. Markov-Chain Convergence

Many EAs can be modeled as homogeneous Markov chains $\{X_t\}$ on a finite state space \mathcal{S} . If mutation ensures positive probability of reaching any feasible solution, the chain becomes irreducible and aperiodic, implying a stationary distribution:

$$\lim_{t \rightarrow \infty} \Pr(X_t \in S^*) = \pi(S^*) > 0, \quad (2)$$

Here S^* is the set of optimal populations [24,25].

Practical implication: algorithms with mutation operators that guarantee reachability (e.g., Gaussian noise, bit-flip mutation) avoid search stagnation and theoretically ensure long-term access to optimal regions.

3.2.2. Runtime Analysis and Drift Bounds

Runtime is often expressed as the hitting time to an optimal region:

$$\tau = \min\{t \geq 0 : X_t \in \Omega^*\}. \quad (3)$$

Drift analysis quantifies expected progress via a potential function Φ_t :

$$\mathbb{E}[\Phi_t - \Phi_{t+1}] \geq \eta \quad \text{or} \quad \mathbb{E}[\Phi_t - \Phi_{t+1}] \geq \lambda \Phi_t. \quad (4)$$

Additive drift leads to linear convergence; multiplicative drift yields logarithmic convergence.

Practical implication: algorithms that maintain diversity and proportional improvement achieve faster convergence on structured problems.

3.2.3. Landscape Properties: Discrete vs. Continuous

Discrete EAs rely on Hamming-neighborhood connectivity, whereas ES/CMA-ES use Gaussian sampling:

$$x_{t+1} \sim \mathcal{N}(m_t, \sigma_t^2 C_t), \quad (5)$$

yielding linear contraction on smooth convex landscapes [2,26].

Practical implication: CMA-ES or continuous EAs are preferable for smooth, real-valued optimization, while bit-string EAs excel on combinatorial structures.

3.2.4. Self-Adaptation and Parameter Dynamics

Adaptive rules update parameters such as mutation strength:

$$\sigma_{t+1} = \begin{cases} \alpha\sigma_t, & \text{success,} \\ \alpha^{-1/4}\sigma_t, & \text{otherwise,} \end{cases} \quad \alpha > 1. \quad (6)$$

Practical implication: success-based or learning-driven parameter control is crucial on noisy or multi-modal landscapes where static settings fail.

3.2.5. Multiobjective Optimization Guarantees

Classical MOEAs satisfy polynomial-time approximation bounds:

$$\mathbb{E}[T_\varepsilon] = \text{poly}(n, 1/\varepsilon), \quad (7)$$

with IGD and hypervolume converging under adequate diversity.

Practical implication: practitioners must ensure diversity preservation for reliable Pareto front approximation.

3.2.6. Constraint-Handling Theory

Penalty-based reformulations use:

$$F(x) = f(x) + \rho \sum_i \max\{0, g_i(x)\}, \quad (8)$$

while feasibility-based rules offer stronger guarantees under certain geometries.

Practical implication: constraint-handling should be aligned with the structure of feasible regions; feasibility-based rules often outperform penalties when constraints are tight or nonlinear.

3.2.7. No-Free-Lunch Limits

For uniform distributions over all objective functions, implying no universally superior optimizer.

$$\frac{1}{|\mathcal{F}|} \sum_f \text{Perf}_A(f) = \frac{1}{|\mathcal{F}|} \sum_f \text{Perf}_B(f), \quad (9)$$

Practical implication: this motivates the diversity of EA variants, hybridization strategies, and domain-specific adaptations discussed in subsequent sections. Designing operators, representations, and learning components to problem structure is essential for practical performance gains.

4. Types of Evolutionary Algorithms

Evolutionary algorithms constitute a broad family of population-based optimizers that differ in representation, variation operators, and selection strategies, leading to distinct performance characteristics across domains. Rather than cataloguing each method in isolation, this section adopts a domain-centric perspective: we summarize core algorithm families, highlight their strengths and limitations, and analyze where they are most suitable in engineering and scientific practice. The comparative taxonomies presented in Table 2 and Table 3 organize classical and advanced EA paradigms, respectively, linking algorithmic principles to their characteristic strengths, weaknesses, and ideal application contexts.

Table 2. Taxonomy of Classical Evolutionary Algorithms: algorithmic principles, strengths/weaknesses, and ideal application contexts.

Category	Core Principle	Representation	Application Scope	Representative Variants	Key Strengths / Weaknesses	Ideal Application Context
GA [27,28]	Survival of fittest via crossover/mutation	Binary, real, permutation	Single/multi-objective, constrained, dynamic	Canonical GA, Micro-GA, NSGA-II, NSGA-III, Quantum-GA	Strengths: flexible encoding, rich operators, great for discrete structure. Weaknesses: premature convergence, encoding sensitivity, weak on high-dim continuous spaces.	Scheduling, routing, feature selection, topology/structure design.
ES / CMA-ES [29]	Self-adaptive mutation; covariance adaptation	Real-valued vectors	Continuous, constrained, dynamic	CMA-ES, LM-CMA, MA-ES, NES, RSCMSA	Strengths: rotation-invariant search, excellent on ill-conditioned landscapes. Weaknesses: $O(d^2)$ updates, large evaluation budgets; poor direct handling of discrete variables.	Robotics, aerospace, photonics, mechatronic design, continuous optimization.
DE [30]	Differential mutation + crossover	Real-valued vectors	Continuous, dynamic, multi-objective	JADE, SHADE, L-SHADE, jDE, CoDE, SaDE	Strengths: simple and competitive on multimodal continuous spaces. Weaknesses: mutation relies on vector arithmetic \rightarrow unsuitable for permutations; stagnation risk.	Antenna design, renewable energy, controller tuning, process control.
EP [31]	Mutation-driven evolution; stochastic selection	Real-coded, Gaussian/Cauchy	Continuous, dynamic, uncertain	Fast-EP, Adaptive EP, Mixed-Mutation EP, ADM-EP	Strengths: stable under noise, conceptually simple. Weaknesses: weak recombination, slower exploitation compared to CMA-ES/DE.	Power/traffic systems, uncertain environments, signal optimization.
GP [32,33]	Evolution of symbolic expressions/programs	Tree-, graph-, grammar-based	Symbolic regression, classification, model discovery	CGP, GEP, semantic GP, multi-gene GP	Strengths: interpretable symbolic structures; rule discovery. Weaknesses: computationally expensive, bloat, unstable in high-dim continuous tasks.	Symbolic modeling, control law discovery, program synthesis, explainable ML.

Table 3. Taxonomy of Advanced Evolutionary Algorithms: multi-objective, hybrid, learning-enhanced, and quantum evolutionary paradigms.

Category	Core Principle	Representation	Application Scope	Representative Variants	Key Strengths / Weaknesses	Ideal Application Context
MOEA [34]	Pareto dominance decomposition	Real or mixed encoding	Multi-objective, constrained, large-scale	NSGA-II, NSGA-III, MOEA/D, HypE	Strengths: explicit trade-offs, strong diversity maintenance. Weaknesses: dominance weakens with many objectives; parameter sensitivity.	Engineering design, smart grids, manufacturing, resource scheduling.
MaOEA [35]	Indicator/vector-based selection > 3 objectives	Real-valued or indicator-based	Many-objective, dynamic, large-scale	MaOEA-IGD, MOEA/DD, MaOEA-R2, MaOEA	Strengths: scalable preference modeling. Weaknesses: complex reference set design; harder decision support.	Climate modeling, multi-robot coordination, multi-criteria design.
Memetic / Hybrid EAs [36,37]	EA + local search, heuristics, ML/DL models	Binary, real, hybrid	Dynamic, constrained, objective	con-GA+BDD, DE+PSO, EA+RL, EA+DNN	Strengths: strong exploitation, improved convergence speed/quality. Weaknesses: higher complexity; dependence on domain knowledge or local solvers.	Industrial automation, medical image segmentation, adaptive control, design automation.
QEA [38,39]	Qubit superposition, rotation gates	Qubit amplitudes	Combinatorial, stochastic, multi-objective	QEA, QIGA, QD-EA, quantum NSGA-II, QDistEvol	Strengths: high diversity via superposition; quantum-inspired operators. Weaknesses: simulator cost; limited scalability; hardware constraints.	Quantum circuit design, cryptography, hybrid quantum-classical pipelines.

4.1. Genetic Algorithms (GAs)

GAs are population-based metaheuristics that evolve candidate solutions via selection, crossover, and mutation. Given a search space $\mathcal{X} \subseteq \mathbb{R}^d$ and objective function $f : \mathcal{X} \rightarrow \mathbb{R}$, the population $\mathcal{P}^{(g)} = \{x^{(1)}, \dots, x^{(N)}\}$ is iteratively evaluated, varied, and updated, as summarized in Algorithm 2. GAs support binary, real-valued, permutation, and graph encodings, making them broadly applicable in discrete and combinatorial domains.

Algorithm 2 Genetic Algorithm (GA)

Require: Objective f , population size N , p_c , p_m , G_{\max}

- 1: Initialize population $\mathcal{P}^{(0)}$
 - 2: **for** $g = 0$ to G_{\max} **do**
 - 3: Select mating pool $\mathcal{M}^{(g)}$
 - 4: Apply crossover (p_c) and mutation (p_m) to form $\mathcal{O}^{(g)}$
 - 5: Evaluate offspring and perform survivor selection
 - 6: **end for**
 - 7: **return** best solution found
-

GAs perform well when meaningful building blocks can be recombined, such as in scheduling, routing, feature selection, and structured design tasks [40–47]. However, their performance typically weakens on high-dimensional continuous landscapes where operators lack directional bias and where DE or CMA-ES are more effective. Recent advances include improved encodings and automated configuration [48,49], quantum-inspired and coevolutionary variants [39,50], and hybrid GA–ML or GA–RL frameworks [43,51–54] that enhance exploration and convergence efficiency.

Comparative Analysis and Domain Suitability

Compared with DE and CMA-ES, which operate directly on continuous vectors, GAs depend on encodings and schema-based recombination, making them most suitable for discrete, combinatorial, or structured search spaces. Relative to GP, GAs are less interpretable but simpler and more computationally efficient. Overall, GAs are preferred when problem structure enables meaningful recombination of partial solutions, while continuous optimization is better handled by DE or CMA-ES.

4.2. Evolution Strategies (ES, CMA-ES)

Evolution Strategies (ES) are derivative-free optimizers designed for continuous domains, with CMA-ES being the most influential modern variant. CMA-ES adapts a multivariate Gaussian sampling distribution, and updates its mean by weighted recombination of the best μ individuals:

$$x_k^{(g)} \sim \mathcal{N}(m^{(g)}, (\sigma^{(g)})^2 C^{(g)}), \quad (10)$$

$$m^{(g+1)} = \sum_{i=1}^{\mu} w_i x_{i:\lambda}^{(g)}. \quad (11)$$

Step-size and covariance adaptation enable invariance to affine transformations and strong performance on non-separable, ill-conditioned landscapes. The core procedure is summarized in Algorithm 3. The $O(d^2)$ covariance update limits CMA-ES scalability in high dimensions, and reliable estimation requires large populations, giving high evaluation cost. Its Gaussian sampling also lacks a natural analogue in discrete or permutation spaces, making unmodified CMA-ES unsuitable for combinatorial problems. Consequently, lighter DE or PSO variants often outperform CMA-ES in low-dimensional or evaluation-constrained settings.

Algorithm 3 Covariance Matrix Adaptation ES (CMA-ES)

```

1: Initialize  $m^{(0)}, \sigma^{(0)}, C^{(0)} = I$ 
2: for  $g = 0$  to  $G_{\max}$  do
3:   Sample and evaluate  $\lambda$  offspring
4:   Select top  $\mu$  and update  $m^{(g+1)}, \sigma^{(g+1)}, C^{(g+1)}$ 
5: end for
6: return best solution

```

To reduce these issues, recent research explores reference vector-based ranking for multiobjective search [55], cooperative coevolution and landscape-aware grouping for large-scale optimization [56], noise-resilient population-size control [57], and parallel or chaotic variants [58,59]. Hybrid extensions broaden CMA-ES applications, including NAS [60], multimodal niching with PSO [61], microrobotics and trajectory planning [58,62], photonic device optimization [63,64], geophysical imaging [23,36], and wireless communication system design [65].

Comparative Analysis and Domain Suitability

Relative to GAs and DE, ES/CMA-ES provide principled step-size control and anisotropic search, making them highly effective on non-separable, ill-conditioned continuous problems. However, their quadratic update cost and reliance on continuous sampling make them less suitable for very high-dimensional or discrete tasks, where DE or GA variants tend to be more efficient. CMA-ES is therefore most appropriate when precise continuous optimization is required and sufficient evaluations are available to exploit local landscape geometry.

4.3. Differential Evolution (DE)

DE is a population-based optimizer for continuous spaces, defined by its geometry-driven mutation strategy. At generation g , each solution $x_i^{(g)}$ generates a donor vector

$$v_i^{(g)} = x_{r_1}^{(g)} + F(x_{r_2}^{(g)} - x_{r_3}^{(g)}), \quad (12)$$

followed by crossover with rate C_r to produce a trial vector, and selection retains the fitter candidate (Algorithm 4). Its simplicity, directional search via population differences, and low computational cost make DE highly effective on multimodal continuous landscapes. DE's main limitations stem from its reliance on continuous vector arithmetic making it poorly suited for categorical or combinatorial spaces without specialized encodings and its sensitivity to F and C_r , which can cause stagnation when diversity collapses. To address these issues, recent work proposes self-adaptive and collaborative DE variants for dynamic environments [66], Bayesian-assisted hybrid DE for antenna design [37], and fuzzy-logic or bidirectional DE for improved stability and search reliability [67–69]. Multiobjective and multitask extensions enhance performance on conflicting objectives [70–72], while surrogate-assisted DE accelerates expensive evaluations [73] at the cost of potential model bias. DE continues to see broad application in robotics [74], energy systems [75,76], ultrasonic sensing [77], plasma devices [78], power electronics [79], cybersecurity [80,81], scheduling [82], VANET security [83], and antenna optimization [84]. Fractional-order DE [85] further enhances exploration using historical dynamics, though at the expense of additional hyperparameters.

Algorithm 4 Differential Evolution (DE)

```

1: Initialize population  $\{x_i^{(0)}\}_{i=1}^N$ 
2: for  $g = 0$  to  $G_{\max}$  do
3:   for each  $x_i^{(g)}$  do
4:     Mutation:  $v_i^{(g)} = x_{r_1}^{(g)} + F(x_{r_2}^{(g)} - x_{r_3}^{(g)})$ 
5:     Crossover: generate  $u_i^{(g)}$  with rate  $C_r$ 
6:     Selection:  $x_i^{(g+1)} = \arg \min\{f(x_i^{(g)}), f(u_i^{(g)})\}$ 
7:   end for
8: end for
9: return best solution

```

Comparative Analysis and Domain Suitability

Compared to GAs, which naturally suit binary and permutation encodings, DE excels in continuous domains due to its directional mutation. Relative to CMA-ES, DE is cheaper per generation and easier to tune, but lacks full covariance adaptation and is more prone to stagnation. Thus, DE is most suitable for medium-scale continuous optimization, whereas GA, CMA-ES, or domain-specific MOEAs are preferable for combinatorial, highly constrained, or strongly multiobjective tasks.

4.4. Genetic Programming (GP)

GP evolves symbolic structures trees, linear expressions, and grammars to produce interpretable models, making it well suited for symbolic regression and transparent decision-making. Semantics-aware variants [86,87] improve search efficiency and reduce bloat by guiding variation with functional meaning, though GP still faces high computational cost and uncontrolled structural growth. GP has been extended to multiobjective and large-scale tasks in classification, routing, and scheduling [88–92], where hierarchical or rule-based structures are advantageous. Its performance generally weakens in high-dimensional continuous spaces, where numerical optimizers such as DE or CMA-ES converge more reliably. Federated GP [93] reduce privacy constraints by evolving local models but introduces communication and heterogeneity challenges. In software engineering, GP supports program synthesis and metamorphic relation generation [94,95], offering interpretability benefits compared to LLM-based generators but limited by semantic complexity and long-range dependencies. Overall, GP is most effective when interpretability, symbolic reasoning, or structural flexibility is required, despite scalability and representation challenges (Table 4).

Table 4. Recent advances in Genetic Programming (GP): core contributions, objectives, and outcomes.





Problem / Domain	Representation	Main Idea / Contribution	Objective(s)	Data / Benchmark
Symbolic Regression [86]  GitHub [87]  GitHub	Linear / Tree GP	Semantic encoding with mutate-and-divide propagation; counterexample-driven search with SMT verification	Error, Size, Feasibility	SR benchmarks (UCI, real-world)
High-dim Classification [88] [96]	Tree GP (MO-GP / NRS)	Multiobjective GP with feature-archive mining; rough-set detection for class overlap in unbalanced data	Accuracy, Diversity, F1/AUC	High-dimensional datasets
Dynamic Scheduling [90–92]	Linear / Grammar GP	Multitask LGP and grammar-guided LGP for interpretable, small scheduling heuristics	Makespan, Interpretability, Transferability	DFJSS / DJSS benchmarks
Routing Optimization [89,97]	GP Hyper-heuristic	α -dominance strategy with archive; knowledge transfer using auxiliary population	Effectiveness, Policy Size	UCARP and related routing tasks
Federated / Privacy-aware SR [93]  GitHub	Gene Expression	Federated GP with mean-shift aggregation and self-learning GEP for decentralized SR	Error, Privacy, Generalization	Distributed SR datasets

Table 4. Cont.

Problem / Domain	Representation	Main Idea / Contribution	Objective(s)	Data / Benchmark
Program Synthesis & Testing [94,95] 	Tree GP	Comparison of GP and LLMs on synthesis benchmarks	Success Rate, Fault Detection	PSB / Java benchmarks
Swarm Robotics [98]	Tree GP + Multi-agent Sim	GP-evolved behavior primitives enabling decentralized swarm control for shape formation	Completion Time, Generalization	DSF synthetic and real tasks
Feature Construction & FS [99,100]	Modular / Tree GP	Multi-tree modular GP for reusable features; feature removal impact for high-dimensional SR	Accuracy, Feature Reduction, Size	SRBench, regression datasets
Active, Explainable GP [101,102]	Ensemble / Survey	Pareto-guided active learning via uncertainty-diversity metrics; taxonomy of intrinsic vs post-hoc interpretability	Label Efficiency, Interpretability	SR pools / literature review






Comparative Analysis and Domain Suitability

Unlike GA, DE, or CMA-ES, which operate on fixed-length numeric encodings, GP searches over variable-length symbolic programs. This enables discovery of human-readable rules but increases computational overhead and risks bloat. For large-scale continuous optimization, DE or CMA-ES typically offer superior efficiency, whereas GP excels in domains requiring symbolic structure or interpretable models. GP therefore complements, rather than replaces, numeric evolutionary methods.

4.5. Multi-Objective and Many-Objective EAs

MOEAs extend single-objective EAs to optimize conflicting criteria such as accuracy, model size, and computational cost by generating Pareto optimal solutions [103,104]. MaOEA further scale these ideas through dominance relaxation, indicator-based selection, and decomposition strategies to remain effective in high-dimensional objective spaces. MOEAs have become increasingly important in NAS, where accuracy, efficiency, and resource constraints must be optimized jointly. Representative methods include CNN-GA [105], AE-CNN [106], AE-CNN+E2EPP [107], MOEA-PS [108], NPENAS-NP [109], EEEA-Net-C [110], CGP-NAS [111], SMCSO [112], and SPNAS [113]. These frameworks integrate Pareto-based selection, probabilistic modeling, and self-adaptive mutation to co-optimize accuracy and computational efficiency. As summarized in Table 5, EA-based NAS methods achieve competitive CIFAR-10/100 performance while significantly reducing GPU-day requirements, with models such as MOEA-PS [108] and SMCSO [112] illustrating the growing importance of MOEA/MaOEA paradigms in resource-aware architecture discovery.

Table 5. Comparison of EA-Based NAS Methods on CIFAR-10 and CIFAR-100 Datasets. A dash (–) indicates results not reported in the original paper.

Model	Year	CIFAR-10			CIFAR-100			Resorces Link
		Params (M)	Error (%)	GPU Days	Params (M)	Error (%)	GPU Days	
SMCSO [112]	2025	3.46	2.88	1.32	3.72	19.34	2.00	
SPNAS [113]	2025	6.33	1.80	1.4	6.7	12.74	1.6	
M2M-Net [114]	2024	3.79	2.44	6.0	3.83	15.23	6.0	
MOEA-PS [108]	2023	3.0	2.77	2.6	5.8	18.97	5.2	
NPENAS-NP [109]	2023	3.5	2.54	1.8	–	–	–	
CGP-NAS [111]	2023	4.04	3.70	11.5	5.9	20.63	11.28	
ESENet [115]	2023	4.53	3.56	9.0	4.53	23.65	9.0	
EEEA-Net-C [110]	2021	3.6	2.46	0.52	–	–	–	
FairNAS-A [116]	2021	–	1.80	12.0	–	12.70	12.0	
CNN-GA [105]	2020	2.9	3.22	35	4.1	20.53	40	
AE-CNN [106]	2020	2.0	3.44	27	5.4	22.40	36	
AE-CNN + E2EPP [107]	2020	4.3	5.30	7	–	–	–	
CARS [117]	2020	3.6	2.62	0.4	–	–	–	

Comparative Analysis and Domain Suitability

MOEAs and MaOEAAs provide principled mechanisms for discovering trade-offs without pre-defined weightings, making them well suited to engineering design, energy planning, and NAS. However, dominance-based methods degrade as objectives increase; hence MaOEAAs rely on reference vectors or indicator-based criteria to retain selection pressure. In practice, MOEAs are preferred when the number of objectives is small and Pareto front interpretability is important, whereas MaOEAAs are more appropriate for high-dimensional settings where user-defined preferences or performance indicators guide search.

4.6. Hybrid, Memetic, Surrogate-Assisted, Reinforcement Learning-Enhanced, and Quantum Evolutionary Algorithms

Advanced evolutionary paradigms integrate global EA search with learning, modeling, or local refinement to overcome limitations of classical EAs such as high evaluation cost, slow convergence, and weak exploitation.

4.6.1. Surrogate-Assisted Evolutionary Algorithms (SAEAs)

SAEAs couple EAs with predictive models to reduce evaluation cost in expensive optimization [118–120]. Surrogates include ANNs [121–123], BP networks [124], Gaussian Processes/Kriging [125–128], RBF models [126], SVR [129], and adaptive systems (ANFIS, BFNN) [130,131]. SAEAs follow iterative surrogate construction and EA-based search, supporting applications such as energy-efficient buildings [121,122,132], motors [124], aero-engines [131], antenna/ship design [125–127], manufacturing [123,128,130,133], and energy systems [129]. AutoSAEA [134] automates surrogate and infill selection. Despite efficiency gains, SAEAs face challenges of surrogate bias and drift in high-dimensional or noisy settings.

4.6.2. Memetic and Hybrid Evolutionary Algorithms

Memetic and hybrid EAs combine EA-based global exploration with heuristic or deterministic local search. Applications include drone-truck routing [135], vehicular offloading [136], satellite scheduling [137], berth-crane assignment [138], hybrid flow-shops [139], energy-aware job shops [140], setup-dependent scheduling [141], human-robot collaboration [142], and sustainable manufacturing [143]. They also support NAS [144], multimodal TSP [145], localization [146], polar codes [147], subpixel mapping [148], and facility layout [149]. While hybrids improve exploitation and convergence, they are sensitive to local-search design and domain heuristics.

4.6.3. Reinforcement Learning-Assisted Evolutionary Algorithms (RL-EAs)

RL-EAs adapt operators, parameters, or selection rules using learned policies [150]. Q-learning improves GA-based scheduling [151–155], while Dueling DQN aids satellite scheduling [156] and Actor-Critic supports production planning [157]. PPO stabilizes combinatorial search [158]. In DE, Q-learning and policy-gradient methods adjust mutation strategies [159–161]. RL also enhances ABC [162–167] and dynamic routing [168]. In MOEAs, RL selects objectives [169–171] or weights [172–175]. Further examples include PSO-RL [165,176], GP-RL [177], multitask MFEA-RL [178], and inverse-RL hybrids [179]. RL-EAs handle dynamic environments but incur training overhead and reward-sensitivity.

Comparative Analysis and Domain Suitability

SAEAs are most effective when evaluations are expensive (aerospace, simulation-driven design), but vulnerable to surrogate bias. **Memetic/Hybrid EAs** accelerate convergence where local refinement is meaningful (scheduling, manufacturing, NAS), though performance depends on problem-specific heuristics. **RL-EAs** excel in dynamic or heterogeneous environments (routing, resource allocation, multiagent coordination), but require extensive interactions and careful reward shaping. **QEAs** intro-

duce quantum-inspired diversity and search operators, offering potential advantages in combinatorial problems but remain limited by hardware and simulator constraints.

Overall, these paradigms complement classical GA/DE/ES by addressing evaluation cost (SAEA), exploitation (memetic/hybrid), adaptivity (RL-EA), and diversity (QEA), enabling more efficient and domain-aware search in complex real-world applications.

Table 6. Recent applications and methodological advances of Surrogate-Assisted Evolutionary Algorithms (SAEAs) in engineering and optimization domains (2020–2025).

Field	Authors / Year	Surrogate Model(s)	Objectives	Evolutionary Framework
<i>Application-oriented SAEAs</i>				
Building energy-efficient design	Bre <i>et al.</i> [121] 2020	ANN	Multi-objective	NSGA-II
	Gonçalves <i>et al.</i> [132] 2020	Adaptive surrogate	Multi-objective	NSGA-II
	Chegari <i>et al.</i> [122] 2021	ANN	Multi-objective	GA
Motor manufacturing	Li <i>et al.</i> [124] 2021	BP network	Multi-objective	MOPSO
Aero-engine compressor design	Baert <i>et al.</i> [131] 2020	BFNN	Multi-objective	Online SAEA
Antenna design	Zhang <i>et al.</i> [125] 2020	Gaussian Process	Single-objective	DE
	Yu <i>et al.</i> [126] 2020	Kriging, RBF, ANN	Single-objective	PSO, DE
Ship design	Wang <i>et al.</i> [127] 2021	Kriging	Single-objective	GA
Automobile design	Li <i>et al.</i> [130] 2022	ANFIS	Multi-objective	SSPEA
	Wang <i>et al.</i> [133] 2021	RSM, Kriging	Multi-objective	MOGA
Wing optimization	Su <i>et al.</i> [123] 2021	ANN	Multi-objective	NSGA-II
	Wansaseub <i>et al.</i> [128] 2020	Kriging	Multi-objective	Latin Hypercube + DE
Energy and power	Ma <i>et al.</i> [129] 2021	SVR	Multi-objective	NSGA-II
<i>Methodological advances in SAEAs</i>				
Cross-domain (expensive many-objective optimization)	Zhai <i>et al.</i> [133] 2023	Global + Local Kriging (composite surrogate)	Many-objective	Composite SAEA with filling sampling criterion

Table 7. RL-Assisted Evolutionary Algorithms by EA Type.

EA Type	Problem Domain	RL Role
<i>Genetic Algorithm (GA)</i>		
Q-learning [151–155]	Scheduling, team formation	Operator control, task allocation
Dueling DQN [156]	Satellite scheduling	Dual-state evaluation
Actor–Critic [157]	Steel scheduling	Adaptive trade-off learning
PPO [158]	TSP, VRP, bin packing	Stable policy optimization
<i>Differential Evolution (DE)</i>		
Variational PG [159]	Continuous SOP	Stochastic policy mutation
Policy Gradient [160]	Parameter tuning	Mutation rate control
Q-learning [161]	Trajectory design	Reward-based selection
<i>Artificial Bee Colony (ABC)</i>		
Q-learning [162,163,165–167,180]	Flow-shop, traffic	Sequence, allocation rules
DQN [168]	Vehicle routing	Route exploration
<i>MOEAs (MA, MOEA/D, NSGA-III/III)</i>		
Q-learning [172,173,175,181]	Job/flow-shop	Pareto weight tuning
DQN [169–171]	Energy, cloud	Objective adaptation
<i>Hyper-Heuristic / Ensemble</i>		
Q-learning [151,182,183]	Energy, routing	Heuristic selection
DDQN / Double Q [184]	Packing, scheduling	Reward stability

Table 7. Cont.

EA Type	Problem Domain	RL Role
<i>Other EAs</i>		
PSO (Q-learning) [165,176]	Assembly, SOP	Velocity tuning
GP (Q-learning) [177]	Team formation	Task matching
MFEA (Q-learning) [178]	Multitask	Task transfer learning
MFO (Inverse RL) [179]	SOP	Expert reward imitation

5. Applications of Evolutionary Algorithms

Evolutionary algorithms have been successfully applied across a wide range of scientific and engineering domains due to their global search capability, flexibility in handling diverse problem structures, and effectiveness in multi-objective and constraint-aware optimization. This section provides a domain-balanced overview of key application areas, focusing on healthcare, energy systems, robotics, and smart cities. Table 8 summarizes representative works across diverse fields.

Table 8. Representative works on evolutionary techniques by application area

Application Area	Examples
Engineering Design & Control [19,207]	Structural optimization, robotics, circuit design, controller tuning
Energy Systems [196,197]	Unit commitment, smart grids, renewable energy optimization
Healthcare & Bioinformatics [3,43,208–216]	Medical image segmentation, drug discovery, genomics, feature selection
Transportation & Logistics [197,199]	Vehicle routing, lane reservation, supply chain optimization
Science & Technology [12,39,217]	Quantum computing, innovation management, scientometric analysis
Neural architecture search (NAS) [37,66,205, 218,219]	Differentiable NAS, self-adaptive weights, dual-attention mechanisms, evolutionary NAS
Creative Domains [220,221]	Music composition, evolutionary art, image/video generation
Environmental Science [222–224]	Climate modeling, pollution monitoring, resource allocation
Games & Artificial Intelligence [225,226]	NPC behavior evolution, strategy games, EA+RL hybrids
Education & Social Systems	Curriculum optimization, policy design, social simulations

5.1. Healthcare and Biomedical Applications

EAs play a central role in complex clinical optimization tasks such as radiation therapy planning, where multi-objective EAs optimize beam angles, dose distributions, and organ-at-risk protection [185–188]. Advanced MOEAs incorporate clinical priors and pattern-mining strategies to improve treatment diversity and stability [189]. In genomics, GAs and DE aid in disease-gene identification and feature selection from high-dimensional datasets [190,191]. In medical image segmentation, evolutionary NAS yields efficient architectures for few-shot and domain-shift scenarios [192–195].

Limitations and Open Challenges: EAs face obstacles including high computational cost for 3D medical imaging, difficulty integrating privacy regulations (HIPAA/GDPR), and limited interpretability in clinical pipelines. Scaling evolutionary NAS to large medical datasets also remains challenging.

5.2. Energy Systems and Smart Grid Optimization

Energy systems require effective optimization under uncertainty, renewable variability, and stringent operational constraints. EAs have been widely used for unit commitment, economic dispatch, and renewable energy planning [196,197]. Differential evolution and MOEAs are widely used for optimizing photovoltaic systems, microgrids, and wind-farm layouts due to their resilience to noisy,

nonlinear objectives. Hybrid surrogate-assisted EAs further accelerate simulations for building energy design [121,122].

Limitations and Open Challenges: Dynamic, real-time grid operation demands faster convergence than classical EAs typically provide. Large-scale grid models challenge scalability, and surrogate drift may affect reliability. Future directions include hardware-aware EAs, online adaptation, and federated evolutionary control for geographically distributed systems.

5.3. Robotics, Control, and Autonomous Systems

Robotics applications use EAs for control tuning, trajectory planning, swarm coordination, and behavior synthesis. CMA-ES and DE excel in continuous control tasks such as manipulation, aerial robotics, and microrobotics [62,63]. Genetic programming and hybrid EAs evolve interpretable controllers and task policies, while evolutionary RL approaches enable adaptation in dynamic environments [151,152,158].

Limitations and Open Challenges: Real-time constraints restrict population sizes and evaluation budgets. Simulation-to-reality gaps reduce transferability, and safety-aware optimization remains underexplored. High-dimensional robotic systems necessitate more scalable, sample-efficient evolutionary controllers.

5.4. Smart Cities, Transportation, and Logistics

EAs support infrastructure planning, transportation scheduling, routing, and multi-criteria decision-making in smart cities. Applications include lane-reservation systems [198], traffic routing [168], supply-chain optimization [199], and cyber-physical coordination in IoT environments [200]. Multi-objective EAs enable trade-offs between efficiency, emissions, and congestion key factors in sustainable urban mobility.

Limitations and Open Challenges: Smart-city systems introduce dynamic, multi-agent environments where objectives evolve over time. Real-time EAs must operate under communication constraints and partial observability. Federated EAs, RL-EA hybrids, and decentralized optimization frameworks are promising future directions.

5.5. Artificial Intelligence and Machine Learning

EAs are increasingly integrated into AI pipelines for feature selection, hyperparameter tuning, and neural architecture search [201,202]. Multi-modal learning setups employ evolutionary multi-objective optimization for sensor fusion and model selection [203,204]. In secure IoT systems, post-quantum EA-blockchain frameworks enhance resilience and privacy [200]. Evolutionary NAS (ENAS) designs efficient architectures, while hybrid EA-RL and EA-gradient approaches balance accuracy and computational cost [205,206]. As shown in Figure 2, ENAS methods are generally categorized into three major evolutionary paradigms: EA, Swarm Intelligence, and Hybrid Search Strategies.

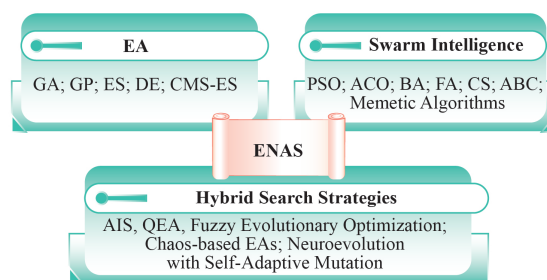


Figure 2. Categorization of ENAS frameworks into EA-based, swarm intelligence-based, and hybrid evolutionary search strategies used for neural architecture optimization.

Limitations and Open Challenges: Evolutionary NAS remains computationally expensive. Hybrid EA LLM systems introduce interpretability and consistency challenges. Distributed AI introduces synchronization and latency issues that complicate evolutionary search.

6. Challenges and Problems in Evolutionary Algorithms

EAs face persistent challenges that limit their scalability, effectiveness, and deployment in modern large-scale systems. Figure 3 summarizes the major issues and commonly adopted mitigation strategies.

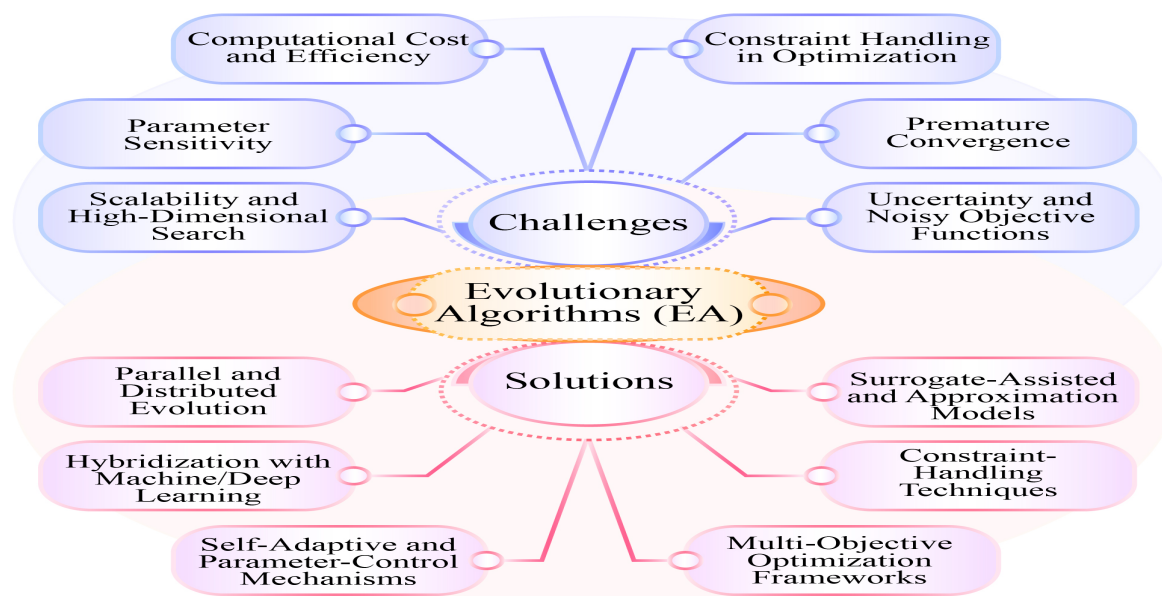


Figure 3. Challenges and corresponding solution strategies in evolutionary algorithms, illustrating key limitations such as scalability, parameter sensitivity, and computational cost along with their common mitigation approaches.

6.1. Scalability

High-dimensional problems expand the search space exponentially, requiring larger populations and stronger diversity preservation. CMA-ES suffers from $O(d^2)$ covariance updates, while L-SHADE and related DE variants scale better through self-adaptation. Modern settings such as federated or privacy-constrained optimization further strain scalability since subpopulations operate with limited coordination.

Promising Reduction Approaches: Cooperative and decomposition-based EAs offer dimensionality reduction but rely on accurate variable grouping; surrogate-assisted models reduce evaluation cost but introduce approximation bias; parallel/distributed EAs provide speedups but increase communication overhead; hardware-aware GPU-accelerated implementations help, though irregular operators limit full parallelism.

6.2. Balancing Exploration and Exploitation

Over-exploration slows convergence, whereas excessive exploitation causes premature stagnation. Static mutation or crossover rates struggle in dynamic or multimodal landscapes. RL-assisted EAs and island models provide adaptive control but require extra computation and careful design.

Promising Reduction Approaches: Self-adaptive operators, niching and clustering for diversity preservation, hybrid global local search, and RL-based operator control enhance balance, though each introduces risks such as oscillation, slower convergence, or additional training overhead.

6.3. Parameter Sensitivity and Self-Adaptation

EA performance depends heavily on mutation rates, crossover probabilities, population size, and selection pressure. Sensitivity becomes more severe in multiobjective and large-scale optimization.

Self-adaptive and AutoML-driven tuning [227] reduce manual effort but add extra meta-parameters and computational burden.

Promising Reduction Approaches: Co-evolving parameters, meta-EAs, and learning-guided control mechanisms help improve parameter adaptation, but their performance depends heavily on population size and stable reward signals.

6.4. Computational Cost and Efficiency

Population-based evaluation makes EAs expensive for simulation-based design, NAS, robotics, and multi-physics tasks. Even with GPU parallelism, evaluating thousands of candidates per generation remains a bottleneck.

Promising Reduction Approaches: Surrogate-assisted EAs reduce evaluation cost but risk search bias; weight-sharing and pruning accelerate NAS but may distort fitness ranking; quantum-inspired and probabilistic EAs improve global exploration but remain small-scale; hardware-aware EAs show promise but depend on platform-specific tuning.

6.5. Benchmarking, Reproducibility, and Comparison

Reproducibility is hindered by heterogeneous implementations, inconsistent reporting, and sensitivity to random seeds or hardware differences. Distributed and federated optimization further complicate reproducibility due to communication delays and data shifts.

Promising Reduction Approaches: Standardized benchmark suites (e.g., COCO, LSGO, NAS-Bench), open-source repositories, statistical testing with effect sizes, and emerging federated benchmarking infrastructures improve transparency but require community-wide adoption.

7. Future Research Directions and Trends

Evolutionary algorithms are entering a transformative phase driven by the dual need for *scalability* and *intelligence*. Their future trajectory is shaped by two primary drivers: (1) Hybridization with complementary computational paradigms, and (2) Integration with emerging technologies such as quantum computing, LLMs, and federated systems. These drivers are supported by three foundational pillars that must co-evolve: (1) Theoretical grounding, (2) Domain-scale real-world deployment, and (3) Interpretability and trust. Together, these elements form a convergent roadmap for next-generation evolutionary computation.

7.1. Hybrid Evolutionary Algorithms as the Central Driver

Hybrid evolutionary algorithms (HEAs) will remain the cornerstone of future EA research. The ability to combine population-based exploration with gradient-based refinement, swarm heuristics, reinforcement learning, or local search enables the creation of adaptive and problem-aware optimizers. A key future direction involves dynamic operator orchestration, where hybrid components are selected or weighted based on real-time landscape feedback. This includes RL-driven operator scheduling, adaptive switching between exploration modes, and learning-guided pruning of ineffective search branches. Such hybridization is not only algorithmic but also architectural: future EAs will behave as *self-evolving systems* that restructure their own operators and representations during the optimization process.

7.2. Integration with Emerging Technologies: The Expanding Frontier

Hybridization intersects directly with technological advances, creating several emerging pathways for EA development.

7.2.1. Quantum Computing and Quantum-inspired EAs

Quantum-inspired EAs offer richer search distributions, parallel exploration, and theoretical speedups. Beyond classical optimization, methods like QDistEvol [228] will increasingly target problems native to quantum devices, including quantum error correction, quantum control, and

circuit layout. A specific research direction is the development of quantum–classical co-evolution, where quantum subroutines evaluate fitness or generate offspring, while classical EAs guide global population dynamics.

7.2.2. Federated and Edge Evolutionary Computation

Federated and distributed environments demand optimization under privacy, communication, and heterogeneity constraints. Federated surrogate-assisted EAs [35,229] and evolutionary game-theoretic models [230–232] provide early foundations, but substantial gaps remain. Future directions include:

- **Theoretical models of communication-efficient evolution** under limited bandwidth,
- **Incentive-compatible EAs** for multi-agent and multi-owner data settings,
- **Distributed multi-objective evolution** with partial or inconsistent objective visibility.

These directions are essential for deploying EAs in smart cities, IoT ecosystems, and cyber-physical infrastructure.

7.3. Large Language Models (LLMs) as Evolutionary Meta-Controllers

LLMs are emerging as powerful agents capable of automating EA operator design, mutation generation, and adaptation logic. Frameworks such as LLaMEA [233,234] demonstrate that LLMs can synthesize new heuristics, self-correct search failures, and propose operator modifications using linguistic feedback. Figure 4 illustrates this co-evolution paradigm. Future work includes:

- **LLM-driven operator innovation:** generating new mutation/crossover families conditioned on landscape descriptors.
- **Self-reflective evolution:** EAs provide search logs, and LLMs respond with operator adjustments.
- **Hybrid symbolic–numeric search:** LLMs evolve symbolic rules while EAs refine numeric parameters.

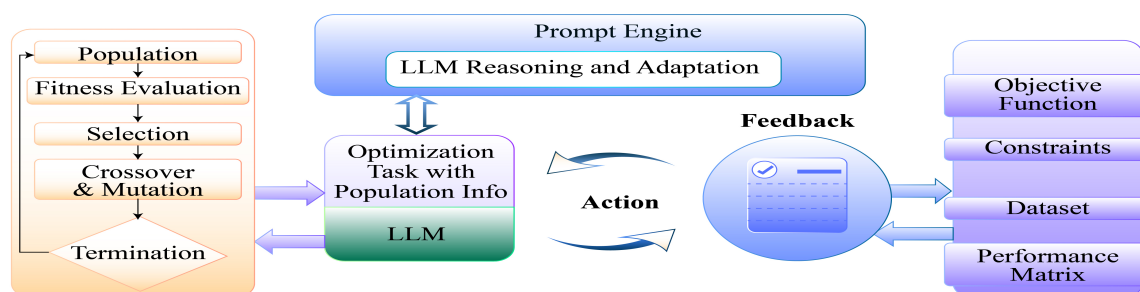


Figure 4. Conceptual workflow illustrating the integration of LLMs with EAs.

This synergy could create autonomous evolutionary frameworks capable of reconfiguring themselves without human intervention.

7.4. Real-world Applications and Societal Impact

EAs are increasingly positioned to address global challenges across climate science, energy sustainability, personalized healthcare, and resilient urban infrastructure. Unlike conventional optimizers, their multi-objective nature enables them to balance conflicting goals such as energy efficiency versus emissions, accuracy versus interpretability, or cost versus resilience. Future research should target:

- **Decarbonization and renewable energy systems:** optimizing multi-scale models for smart grids, energy storage, and demand forecasting.
- **Climate modeling and environmental resilience:** integrating uncertainty-aware EAs for long-term climate scenario simulations.
- **Precision medicine:** evolving interpretable and privacy-preserving diagnostic pipelines.

- **Real-time robotics and autonomous systems:** building fast, hardware-aware EAs for dynamic control.

These directions align EAs with major societal missions such as sustainability, healthcare equity, and global risk mitigation.

7.5. Theoretical Foundations to Support Next-Generation EAs

Despite strong empirical success, theoretical understanding lags behind algorithmic innovation. Future theory must move beyond asymptotic convergence and provide *actionable* insights for modern algorithm families. Specific future directions include:

- **Runtime and stability analysis of RL-EAs:** identifying when learned adaptation policies outperform static operators.
- **Theoretical models for federated evolution:** quantifying how communication delays, heterogeneous data, and partial participation shape convergence.
- **Landscape-aware operator theory:** linking mutation/crossover dynamics to curvature, modality, or gradient surrogate information.
- **Complexity bounds for hybrid and quantum-inspired EAs:** developing computable performance guarantees for multi-layered or quantum-driven search.

These theoretical developments are key to improving the predictability, reliability, and safety of hybrid EA systems.

7.6. Enhanced Interpretability and Trustworthiness

As EAs move into medical diagnosis, financial decision-making, defense, and public infrastructure, interpretability becomes essential. Emerging work on visualizing evolutionary trajectories, tracing operator contributions, and extracting symbolic approximations of evolved solutions marks early progress. Future directions include:

- **Causal interpretability:** understanding which operators or genetic components drive solution improvements.
- **Human-in-the-loop evolution:** enabling experts to guide search trajectories interactively.
- **Explainable multi-objective trade-offs:** visualizing preference changes and Pareto dynamics in real time.

These tools will increase trust and accountability in domains where evolution-based decisions must be auditable.

7.7. Summary of Findings

EAs are evolving into intelligent optimization frameworks that combine evolutionary search with learning, distributed computation, and quantum-inspired mechanisms. Hybridization and integration with emerging technologies form the core research engine, supported by advances in theory, interpretability, and domain-focused deployment. These developments strengthen the role of EAs as scalable, transparent, and societally impactful optimizers.

7.8. Recommendations for Practitioners and Researchers

Practitioners should exploit domain knowledge in fitness modeling, adopt hybrid and automated tuning strategies, and prefer interpretable or resource-aware designs for real-world deployment. Researchers should pursue deeper theory for adaptive and learning-driven EAs, explore quantum and federated evolutionary paradigms, and prioritize transparent, reproducible, and societally aligned EA methodologies.

8. Conclusion

Evolutionary algorithms have matured into a diverse and powerful class of optimization methods, but their effectiveness is fundamentally shaped by the interaction between algorithmic design and do-

main characteristics. This survey adopted a domain-centric perspective, synthesizing EA foundations, algorithm families, and applications across engineering, energy, healthcare, transportation, and AI. By linking representation choices, variation operators, convergence behavior, and hybridization potential to domain requirements, the survey offers a structured guide for selecting suitable EA approaches. Several overarching insights emerge. First, no single EA is universally superior performance depends on fitness landscape structure, constraints, and evaluation cost. Second, hybridization has become the dominant trend, integrating evolutionary search with machine learning, surrogate modeling, reinforcement learning, and quantum-inspired mechanisms to improve scalability and effectiveness. Third, the increasing use of EAs in safety-critical and data-sensitive environments highlights the need for stronger theoretical guarantees, transparency, and interpretability. Looking forward, EAs are poised to evolve from standalone optimizers to essential components of next-generation intelligent systems. Their strengths in handling uncertainty, multiobjective trade-offs, and distributed information make them well-suited for emerging challenges in sustainable energy, climate resilience, personalized medicine, autonomous systems, and large-scale AI. As computational infrastructures and hybrid paradigms advance, evolutionary computation will continue to play a central role in optimization-driven intelligence for complex and dynamic real-world systems.

Appendix A. Supplementary Appendix: Complete Boolean Search Strings

To support reproducibility, the complete Boolean search strings used in the literature retrieval stage are provided below. All queries were executed for the period 2015–2025.

Appendix A.1. IEEE Xplore

```
((("evolutionary algorithm" OR "genetic algorithm" OR "genetic programming" OR
"differential evolution" OR "evolution strategy" OR "memetic algorithm" OR
"surrogate-assisted evolutionary algorithm") AND ("engineering" OR "optimization" OR
"design" OR "medical" OR "energy" OR "robotics" OR "smart systems")) AND (Publication
Year: 2015-2025))
```

Appendix A.2. Scopus

```
TITLE-ABS-KEY("evolutionary algorithm" OR "genetic algorithm" OR "genetic programming"
OR "differential evolution" OR "evolution strategy" OR "memetic algorithm" OR
"surrogate-assisted evolutionary algorithm" ) AND TITLE-ABS-KEY(engineering OR medical
OR energy OR robotics OR design) AND (PUBYEAR > 2014)
```

Appendix A.3. Web of Science

```
TS = ("evolutionary algorithm" OR "genetic algorithm" OR "genetic programming" OR
"differential evolution" OR "evolution strategy" OR "memetic algorithm") AND TS =
("optimization" OR "engineering" OR "medical imaging" OR "energy system" OR "robotics"
OR "smart city")
```

Appendix A.4. SpringerLink / ScienceDirect

```
("evolutionary algorithm" OR
"genetic algorithm" OR
"differential evolution" OR
"evolution strategy" OR
"genetic programming" OR
"memetic algorithm")
AND
("engineering" OR "medical" OR "energy" OR "robotics" OR "control")
```

AND

(year: [2015 TO 2025])

References

1. R. Saborido, A. B. Ruiz, S. González-Gallardo, M. Luque, and A. Borrego, "Performance assessment of population-based multiobjective optimization algorithms using composite indicators," *IEEE Transactions on Evolutionary Computation*, 2025.
2. L. Deng and S. Liu, "Unlocking new potentials in evolutionary computation with complex network insights: A brief survey," *Archives of Computational Methods in Engineering*, pp. 1–15, 2025.
3. Z. Kuş and B. Kiraz, "Evolutionary architecture optimization for retinal vessel segmentation," *IEEE Journal of Biomedical and Health Informatics*, vol. 27, no. 12, pp. 5895–5903, 2023.
4. X. Bai, H. Jiang, C. Li, I. Ullah, M. M. A. Dabel, A. K. Bashir, Z. Wu, and S. S. Ge, "Efficient hybrid multi-population genetic algorithm for multi-uav task assignment in consumer electronics applications," *IEEE Transactions on Consumer Electronics*, vol. 71, no. 2, pp. 2395–2406, 2025.
5. J. Zhao, P. Xu, X. Wu, J. Pei, H. Fu, and Y. Li, "Power losses optimization of MMCs based on quantum genetic algorithm for HVdc transmission application," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 72, no. 4, pp. 1902–1915, 2025.
6. J.-L. Kim and E. Eor, "A genetic algorithm for solving sudoku based on multiarmed bandit selection," *IEEE Transactions on Games*, vol. 17, no. 2, pp. 429–441, 2025.
7. P. R. Criado, D. B. Rolanía, D. de la Hoz, and D. Manrique, "Estimation of distribution algorithm for grammar-guided genetic programming," *Evolutionary Computation*, vol. 32, no. 4, pp. 339–370, 2024.
8. S. Wang, Y. Mei, M. Zhang, and X. Yao, "Genetic programming with niching for uncertain capacitated arc routing problem," *IEEE Transactions on Evolutionary Computation*, vol. 26, no. 1, pp. 73–87, 2022.
9. Y. Feng, W. Sheng, Z. Wang, G. Xiao, Q. Li, L. Li, and Z. Wang, "Memetic differential evolution with adaptive niching selection and diversity-driven strategies for multimodal optimization," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 9, no. 2, pp. 1322–1339, 2025.
10. W. Qian, Y. Wu, and Z. Wang, "New wtd protocol-based fault detection filter design for interval type-2 fuzzy systems via an adaptive differential evolution algorithm," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 36, no. 10, pp. 19119–19132, 2025.
11. L. Fan, D. Yu, K. Hao Cheong, and Z. Wang, "Optimal evolution strategy for continuous strategy games on complex networks via reinforcement learning," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 36, no. 7, pp. 12827–12839, 2025.
12. W. Fang, J. He, W. Li, W. Ma, L. Zhang, X. Lan, G. Yang, J. Chen, and T. Li, "Unknown cyber threat discovery empowered by genetic evolution without prior knowledge," *IEEE Transactions on Information Forensics and Security*, vol. 20, pp. 9552–9567, 2025.
13. J.-S. Pan, P.-C. Song, S.-C. Chu, V. Snášel, and J. Watada, "Machine learning-enabled evolutionary two-stage stochastic programming," *IEEE Transactions on Emerging Topics in Computational Intelligence*, pp. 1–12, 2025.
14. G.-Y. Lin, Z.-G. Chen, C. Liu, Y. Jiang, S. Kwong, J. Zhang, and Z.-H. Zhan, "A landscape-aware differential evolution for multimodal optimization problems," *IEEE Transactions on Evolutionary Computation*, pp. 1–1, 2025.
15. X. Zhou, N. Li, L. Fan, H. Li, B. Cheng, and M. Wang, "Adaptive niching differential evolution algorithm with landscape analysis for multimodal optimization," *Information Sciences*, vol. 700, p. 121842, 2025.
16. C. Bian, Y. Zhou, M. Li, and C. Qian, "Stochastic population update can provably be helpful in multi-objective evolutionary algorithms," *Artificial Intelligence*, vol. 341, p. 104308, 2025.
17. Z. Cui, Y. Wu, T. Zhao, W. Zhang, and J. Chen, "A two-stage accelerated search strategy for large-scale multi-objective evolutionary algorithm," *Information Sciences*, vol. 686, p. 121347, 2025.
18. G. Hu, K. Song, and M. Abdel-salam, "Sub-population evolutionary particle swarm optimization with dynamic fitness-distance balance and elite reverse learning for engineering design problems," *Advances in Engineering Software*, vol. 202, p. 103866, 2025.
19. Q.-Y. Li, Q.-K. Pan, L. Wang, L. Gao, and W.-M. Li, "Dynamic cascaded flow-shop scheduling using an evolutionary greedy algorithm," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 5, pp. 1490–1501, 2025.
20. H. Manoharan and S. Edalatpanah, "Evolutionary bioinformatics with veiled biological database for health care operations," *Computers in biology and medicine*, vol. 184, p. 109418, 2025.

21. T. Goel, S. Verma, M. Tanveer, and P. Suganthan, "Alzheimer's disease diagnosis from MRI and SWI fused image using self adaptive differential evolutionary RVFL classifier," *Information Fusion*, vol. 118, p. 102917, 2025.
22. C. Wang, J. Zhao, L. Li, L. Jiao, F. Liu, X. Liu, and S. Yang, "Knowledge-aware evolutionary graph neural architecture search," *Knowledge-Based Systems*, vol. 309, p. 112810, 2025.
23. Q. Zhang, S. Yang, M. Liu, J. Liu, and L. Jiang, "A new crossover mechanism for genetic algorithms for steiner tree optimization," *IEEE Transactions on Cybernetics*, vol. 52, pp. 3147–3158, May 2022.
24. B. Doerr, M. S. Krejca, and G. Rudolph, "Runtime analysis for multi-objective evolutionary algorithms in unbounded integer spaces," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, pp. 26955–26963, 2025.
25. Y. Liang, X. Wang, H. Zhao, T. Han, Z. Wei, and Y. Li, "A covariance matrix adaptation evolution strategy variant and its engineering application," *Applied Soft Computing*, vol. 83, p. 105680, 2019.
26. X. Zhong, X. Yao, K. Qiao, D. Gong, and Y. Jin, "An indicator-based evolutionary algorithm for large-scale constrained multi-objective optimization," *IEEE Transactions on Evolutionary Computation*, pp. 1–1, 2025.
27. A. Awad, A. Hawash, and B. Abdalhaq, "A genetic algorithm (GA) and swarm-based binary decision diagram (BDD) reordering optimizer reinforced with recent operators," *IEEE Transactions on Evolutionary Computation*, vol. 27, no. 3, pp. 535–549, 2023.
28. Y. Sun, G. G. Yen, and Z. Yi, "IGD indicator-based evolutionary algorithm for many-objective optimization problems," *IEEE Transactions on Evolutionary Computation*, vol. 23, no. 2, pp. 173–187, 2019.
29. Z. He and G. G. Yen, "Many-objective evolutionary algorithm: Objective space reduction and diversity improvement," *IEEE Transactions on Evolutionary Computation*, vol. 20, no. 1, pp. 145–160, 2016.
30. Y. Xu, C. Xu, H. Zhang, L. Huang, Y. Liu, Y. Nojima, and X. Zeng, "A multi-population multi-objective evolutionary algorithm based on the contribution of decision variables to objectives for large-scale multi-/many-objective optimization," *IEEE Transactions on Cybernetics*, vol. 53, no. 11, pp. 6998–7007, 2023.
31. S. Das, R. Mallipeddi, and D. Maity, "Adaptive evolutionary programming with p-best mutation strategy," *Swarm and Evolutionary Computation*, vol. 9, pp. 58–68, 2013.
32. T. Mundhenk, M. Landajuela, R. Glatt, C. P. Santiago, B. K. Petersen, *et al.*, "Symbolic regression via deep reinforcement learning enhanced genetic programming seeding," *Advances in Neural Information Processing Systems*, vol. 34, pp. 24912–24923, 2021.
33. J. Zhong, J. Dong, W.-L. Liu, L. Feng, and J. Zhang, "Multiform genetic programming framework for symbolic regression problems," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 2, pp. 429–443, 2025.
34. Y.-R. Gu, C. Bian, M. Li, and C. Qian, "Subset selection for evolutionary multiobjective optimization," *IEEE Transactions on Evolutionary Computation*, vol. 28, no. 2, pp. 403–417, 2024.
35. J. Xu, Y. Jin, and W. Du, "A federated data-driven evolutionary algorithm for expensive multi-/many-objective optimization," *Complex & intelligent systems*, vol. 7, no. 6, pp. 3093–3109, 2021.
36. M. Hajebi and A. Hoorfar, "Multiple buried target reconstruction using a multiscale hybrid of diffraction tomography and CMA-ES optimization," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–13, 2022.
37. T.-Y. Gao, Y.-C. Jiao, Y.-X. Zhang, and L. Zhang, "A hybrid self-adaptive differential evolution algorithm with simplified bayesian local optimizer for efficient design of antennas," *IEEE Transactions on Antennas and Propagation*, vol. 73, pp. 391–404, Jan 2025.
38. R. Zhang, L. Jiao, L. Li, X. Liu, F. Liu, and S. Yang, "A quantum evolutionary learning tracker for video," *IEEE Transactions on Evolutionary Computation*, vol. 28, no. 2, pp. 418–431, 2024.
39. R. Ibarrondo, G. Gatti, and M. Sanz, "Quantum genetic algorithm with individuals in multiple registers," *IEEE Transactions on Evolutionary Computation*, vol. 28, no. 3, pp. 788–797, 2024.
40. S. Takagi, M. Sekine, T. Nakaegawa, and S.-N. Hsiao, "Optimization of rf frequencies in dual-frequency capacitively coupled plasma apparatus using genetic algorithm (ga) and plasma simulation," *IEEE Transactions on Semiconductor Manufacturing*, vol. 36, pp. 547–552, Nov 2023.
41. F. Antonello, P. Baraldi, E. Zio, and L. Serio, "A niching augmented evolutionary algorithm for the identification of functional dependencies in complex technical infrastructures from alarm data," *IEEE Systems Journal*, vol. 16, pp. 5777–5786, Dec 2022.
42. D. Aulia, R. Sarno, S. C. Hidayati, and M. Rivai, "Optimization of the electronic nose sensor array for asthma detection based on genetic algorithm," *IEEE Access*, vol. 11, pp. 74924–74935, 2023.

43. J. Wei, G. Zhu, Z. Fan, J. Liu, Y. Rong, J. Mo, W. Li, and X. Chen, "Genetic u-net: Automatically designed deep networks for retinal vessel segmentation using a genetic algorithm," *IEEE Transactions on Medical Imaging*, vol. 41, pp. 292–307, Feb 2022.
44. Y. Cao, W. Feng, Y. Quan, W. Bao, G. Dauphin, A. Ren, X. Yuan, and M. Xing, "Forest disaster detection method based on ensemble spatial–spectral genetic algorithm," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 7375–7390, 2022.
45. Y. Liu, C. Yu, X. Liang, Z. Qiu, X. Zhang, C. Lian, J. Li, J. Ji, P. Shan, X. Lyu, L. Yang, and Y. Zhao, "Genetic algorithms and machine learning enhanced laser displacement sensor point cloud augmentation for low-cost, large-scale flatness measurements," *IEEE Sensors Journal*, vol. 23, pp. 26114–26125, Nov 2023.
46. H. Chen, C. Chen, and Y. Wang, "Auto-design of multi-pass cell with small size and long optical path length using parallel multi-population genetic algorithm," *IEEE Sensors Journal*, vol. 22, pp. 6518–6527, April 2022.
47. J. Moura Fernandes, G. M. Barbosa de Oliveira, and M. Guimarães Carneiro, "Network optimization based on genetic algorithm for high-level data classification," *IEEE Latin America Transactions*, vol. 21, pp. 295–301, Feb 2023.
48. J. Jiang, Z. Sun, R. Lu, L. Pan, and Z. Peng, "Real relative encoding genetic algorithm for workflow scheduling in heterogeneous distributed computing systems," *IEEE Transactions on Parallel and Distributed Systems*, vol. 36, no. 1, pp. 1–14, 2025.
49. F. Ye, C. Doerr, H. Wang, and T. Bäck, "Automated configuration of genetic algorithms by tuning for anytime performance," *IEEE Transactions on Evolutionary Computation*, vol. 26, pp. 1526–1538, Dec 2022.
50. Y. Yu, J. Mo, Q. Deng, C. Zhou, B. Li, X. Wang, N. Yang, Q. Tang, and X. Feng, "Memristor parallel computing for a matrix-friendly genetic algorithm," *IEEE Transactions on Evolutionary Computation*, vol. 26, pp. 901–910, Oct 2022.
51. Y. Hu, J. Liu, H. Yan, and X. Guo, "Schedule disruption recovery in liner shipping service based on a reinforcement learning-enabled adaptive genetic algorithm," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, pp. 21622–21633, Dec 2024.
52. J. Ullah, H. Li, Z. Yinhui, M. Ehsan, and P. Soupios, "Enhancing reservoir characterization: Genetic algorithm-assisted correction of pore aspect ratio using cnn-lstm in petrophysical modeling," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 63, pp. 1–11, 2025.
53. J. Zhou, Q. Wu, M. Zhou, J. Wen, Y. Al-Turki, and A. Abusorrah, "LAGAM: a length-adaptive genetic algorithm with markov blanket for high-dimensional feature selection in classification," *IEEE Transactions on Cybernetics*, vol. 53, pp. 6858–6869, Nov 2023.
54. P. W. Khan and Y. C. Byun, "Optimized dissolved oxygen prediction using genetic algorithm and bagging ensemble learning for smart fish farm," *IEEE Sensors Journal*, vol. 23, pp. 15153–15164, July 2023.
55. A. Kumar, S. Das, and R. Mallipeddi, "A reference vector-based simplified covariance matrix adaptation evolution strategy for constrained global optimization," *IEEE Transactions on Cybernetics*, vol. 52, pp. 3696–3709, May 2022.
56. Y. Wu, X. Peng, H. Wang, Y. Jin, and D. Xu, "Cooperative coevolutionary CMA-ES with landscape-aware grouping in noisy environments," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 686–700, June 2023.
57. Z. Li, S. Zhang, X. Cai, Q. Zhang, X. Zhu, Z. Fan, and X. Jia, "Noisy optimization by evolution strategies with online population size learning," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, pp. 5816–5828, Sep. 2022.
58. G. Cheng, Y. Hu, W. Jing, R. An, and C. Gao, "Trajectory correction of the rocket for aerodynamic load shedding based on deep neural network and the chaotic evolution strategy with covariance matrix adaptation," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 60, pp. 844–856, Feb 2024.
59. Q. Duan, C. Shao, G. Zhou, M. Zhang, Q. Zhao, and Y. Shi, "Distributed evolution strategies with multi-level learning for large-scale black-box optimization," *IEEE Transactions on Parallel and Distributed Systems*, vol. 35, pp. 2087–2101, Nov 2024.
60. N. Sinha and K.-W. Chen, "Neural architecture search using covariance matrix adaptation evolution strategy," *Evolutionary Computation*, vol. 32, pp. 177–204, June 2024.
61. W. Luo, Y. Qiao, X. Lin, P. Xu, and M. Preuss, "Hybridizing niching, particle swarm optimization, and evolution strategy for multimodal optimization," *IEEE Transactions on Cybernetics*, vol. 52, pp. 6707–6720, July 2022.

62. Y. Liu, Z. Hou, J. Qu, X. Liu, and Q. Fan, "Optimized RRT planning with CMA-ES for autonomous navigation of magnetic microrobots in complex environments," *IEEE/ASME Transactions on Mechatronics*, vol. 29, pp. 4826–4835, Dec 2024.
63. Y. Shen, X. Zhao, Y. Zhang, Z. Zhao, Z. Jiang, C. Liang, Y. Zhou, Z. Hu, and T. Huang, "Optimization of waveguide bend loss in integrated optical gyroscope based on CMA-ES algorithm," *IEEE Sensors Journal*, vol. 25, pp. 32266–32273, Sep. 2025.
64. M. I. H. Patwary, T. Bashir, A. Iguchi, and Y. Tsuji, "Optimal design of THz NRD rat-race circuit using function expansion based topology optimization method with CMA-ES," *IEEE Photonics Journal*, vol. 16, pp. 1–12, Aug 2024.
65. T. Yin, L. Li, W. Lin, H. Hu, D. Ma, J. Liang, T. Bai, C. Pan, and Z. Han, "Joint active and passive beamforming optimization for multi-irs-assisted wireless communication systems: A covariance matrix adaptation evolution strategy," *IEEE Transactions on Vehicular Technology*, vol. 72, pp. 9281–9292, July 2023.
66. H. Qin, W. Bai, Y. Xiang, F. Liu, Y. Han, and L. Wang, "A self-adaptive collaborative differential evolution algorithm for solving energy resource management problems in smart grids," *IEEE Transactions on Evolutionary Computation*, vol. 28, pp. 1427–1441, Oct 2024.
67. J. de Jesús Rubio, "Differential evolution algorithm for fast gains learning in a high-gain controller," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 36, pp. 14201–14212, Aug 2025.
68. H. Huang, T. Li, B. Li, W. Wang, and Y. Sun, "A bidirectional differential evolution-based unknown cyberattack detection system," *IEEE Transactions on Evolutionary Computation*, vol. 29, pp. 459–473, April 2025.
69. S. X. Zhang, Y. H. Liu, X. R. Hu, L. M. Zheng, and S. Y. Zheng, "Fully informed fuzzy logic system assisted adaptive differential evolution algorithm for noisy optimization," *IEEE Transactions on Fuzzy Systems*, vol. 33, pp. 1876–1888, June 2025.
70. D. Lv, G. Xiong, X. Fu, M.-C. Wong, L.-A. Dessaint, and K. Al-Haddad, "Economic emission dispatch with stochastic renewable power and voltage source converters via reinforcement learning multi-objective differential evolution," *IEEE Transactions on Power Systems*, vol. 39, pp. 6889–6900, Nov 2024.
71. S. Wang, A. Zhou, and Y. Zhang, "Differential evolution with perturbation estimation strategy for multiobjective optimization," *Chinese Journal of Electronics*, vol. 34, pp. 871–880, May 2025.
72. Y. Hou, Y. Shen, H. Han, and J. Wang, "Many-task differential evolutionary algorithm based on bi-space similarity," *IEEE Transactions on Evolutionary Computation*, vol. 29, pp. 1215–1226, Aug 2025.
73. L. Yu, Z. Meng, and H. Zhu, "A hierarchical surrogate-assisted differential evolution with core space localization," *IEEE Transactions on Cybernetics*, vol. 55, pp. 939–952, Feb 2025.
74. S. Xie, H. Zhong, Y. Li, S. Xu, W. Liu, S. Bian, and S. Zhang, "Predictive control for an ankle rehabilitation robot using differential evolution optimization algorithm-based fuzzy narx model," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 33, pp. 1886–1895, 2025.
75. N. Priyadarshi, M. S. Bhaskar, and D. Almakhlles, "A novel hybrid whale optimization algorithm differential evolution algorithm-based maximum power point tracking employed wind energy conversion systems for water pumping applications: Practical realization," *IEEE Transactions on Industrial Electronics*, vol. 71, pp. 1641–1652, Feb 2024.
76. Y. Han, X. Zhang, J. Liu, G. Liu, and W. Yan, "Application of remote sensing technologies in monitoring and managing renewable energy sources," *IEEE Transactions on Consumer Electronics*, vol. 71, pp. 4729–4735, May 2025.
77. J. Xiong, P. Mao, and X. Li, "Enhancing ultrasonic time-of-flight estimation using adaptive differential evolution and levenberg–marquardt algorithm," *IEEE Sensors Journal*, vol. 24, pp. 1224–1232, Jan 2024.
78. F. Lan, H. Lai, Z. Guo, Z. Duan, Y. Gong, F. Xiao, and H. Gong, "Optimal design of a novel semi-elliptical bending waveguide slow wave structure via multistage collaborative deep learning and differential evolution algorithm," *IEEE Transactions on Plasma Science*, vol. 52, pp. 2991–2997, July 2024.
79. Q. Yao, J. Chen, K. Yang, J. Yao, J. Zhang, Y. Dai, W. Tang, B. Zhang, and Y. Guo, "Efficient automatic design of igbt structural parameters using differential evolution and machine learning model," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. 44, pp. 1059–1069, March 2025.
80. H. Ouyang, D. Liu, S. Li, W. Ding, and Z.-H. Zhan, "Two-stage deep feature selection method using voting differential evolution algorithm for pneumonia detection from chest x-ray images," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 9, pp. 918–932, Feb 2025.
81. Y. Zhang, X. Xu, and Y. Shi, "Construction and analysis of network cloud security situation awareness system based on dbn-de algorithm," *Journal of Cyber Security and Mobility*, vol. 13, pp. 439–459, May 2024.

82. Y. Laili, X. Wang, L. Zhang, and L. Ren, "Dsac-configured differential evolution for cloud-edge-device collaborative task scheduling," *IEEE Transactions on Industrial Informatics*, vol. 20, pp. 1753–1763, Feb 2024.
83. M. Alkhalidy, M. Bany Taha, R. Chowdhury, C. Talhi, H. Ould-Slimane, and A. Mourad, "Optimizing cp-abe decryption in urban vanets: A hybrid reinforcement learning and differential evolution approach," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 6535–6545, 2024.
84. F. Peng, X. Chen, and J. Xue, "Ai-assisted antenna optimization: Integrating evolutionary and inverse cascade neural networks with differential evolution," *IEEE Transactions on Antennas and Propagation*, vol. 73, pp. 4384–4396, July 2025.
85. K. Wang, S. Gao, M. Zhou, Z.-H. Zhan, and J. Cheng, "Fractional order differential evolution," *IEEE Transactions on Evolutionary Computation*, vol. 29, pp. 822–835, June 2025.
86. Z. Huang, Y. Mei, and J. Zhong, "Semantic linear genetic programming for symbolic regression," *IEEE Transactions on Cybernetics*, vol. 54, pp. 1321–1334, Feb 2024.
87. I. Bładek and K. Krawiec, "Counterexample-driven genetic programming for symbolic regression with formal constraints," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 1327–1339, Oct 2023.
88. Y. Zhou, N. Yang, X. Huang, J. Lee, and S. Kwong, "A novel multiobjective genetic programming approach to high-dimensional data classification," *IEEE Transactions on Cybernetics*, vol. 54, pp. 5205–5216, Sep. 2024.
89. S. Wang, Y. Mei, and M. Zhang, "A multi-objective genetic programming algorithm with α dominance and archive for uncertain capacitated arc routing problem," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 1633–1647, Dec 2023.
90. Z. Huang, Y. Mei, F. Zhang, and M. Zhang, "Multitask linear genetic programming with shared individuals and its application to dynamic job shop scheduling," *IEEE Transactions on Evolutionary Computation*, vol. 28, pp. 1546–1560, Dec 2024.
91. M. Xu, Y. Mei, F. Zhang, and M. Zhang, "Genetic programming with lexibase selection for large-scale dynamic flexible job shop scheduling," *IEEE Transactions on Evolutionary Computation*, vol. 28, pp. 1235–1249, Oct 2024.
92. Z. Huang, Y. Mei, F. Zhang, and M. Zhang, "Toward evolving dispatching rules with flow control operations by grammar-guided linear genetic programming," *IEEE Transactions on Evolutionary Computation*, vol. 29, pp. 217–231, Feb 2025.
93. J. Dong, J. Zhong, W.-N. Chen, and J. Zhang, "An efficient federated genetic programming framework for symbolic regression," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 7, pp. 858–871, June 2023.
94. J. Ayerdi, V. Terragni, G. Jahangirova, A. Arrieta, and P. Tonella, "GenMorph: automatically generating metamorphic relations via genetic programming," *IEEE Transactions on Software Engineering*, vol. 50, pp. 1888–1900, July 2024.
95. D. Sobania, J. Petke, M. Briesch, and F. Rothlauf, "A comparison of large language models and genetic programming for program synthesis," *IEEE Transactions on Evolutionary Computation*, vol. 29, pp. 1434–1448, Aug 2025.
96. W. Pei, B. Xue, L. Shang, and M. Zhang, "Detecting overlapping areas in unbalanced high-dimensional data using neighborhood rough set and genetic programming," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 1130–1144, Aug 2023.
97. M. A. Ardeh, Y. Mei, M. Zhang, and X. Yao, "Knowledge transfer genetic programming with auxiliary population for solving uncertain capacitated arc routing problem," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 311–325, April 2023.
98. Y. Qu, B. Xin, Q. Wang, M. Wang, and M. Guo, "Automated discovery of efficient behavior strategies for distributed shape formation of swarm robots by genetic programming," *IEEE Transactions on Automation Science and Engineering*, vol. 21, pp. 7599–7615, Oct 2024.
99. H. Zhang, Q. Chen, B. Xue, W. Banzhaf, and M. Zhang, "Modular multitree genetic programming for evolutionary feature construction for regression," *IEEE Transactions on Evolutionary Computation*, vol. 28, pp. 1455–1469, Oct 2024.
100. B. Al-Helali, Q. Chen, B. Xue, and M. Zhang, "Genetic programming for feature selection based on feature removal impact in high-dimensional symbolic regression," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 8, pp. 2269–2282, June 2024.
101. N. Haut, W. Banzhaf, and B. Punch, "Active learning in genetic programming: Guiding efficient data collection for symbolic regression," *IEEE Transactions on Evolutionary Computation*, vol. 29, pp. 1100–1111, Aug 2025.

102. Y. Mei, Q. Chen, A. Lensen, B. Xue, and M. Zhang, "Explainable artificial intelligence by genetic programming: A survey," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 621–641, June 2023.
103. L. Li, Q. Qiu, Z. Xiao, Q. Lin, J. Gu, and Z. Ming, "A two-stage hybrid multi-objective optimization evolutionary algorithm for computing offloading in sustainable edge computing," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 735–746, 2024.
104. Y. Xie, Q. Zhao, W. Zhou, and Z. Zhu, "Evolutionary dynamic multiobjective optimization with learning across problems," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 5, pp. 1561–1574, 2025.
105. Y. Sun, B. Xue, M. Zhang, G. G. Yen, and J. Lv, "Automatically designing CNN architectures using the genetic algorithm for image classification," *IEEE Transactions on Cybernetics*, vol. 50, no. 9, pp. 3840–3854, 2020.
106. Y. Sun, B. Xue, M. Zhang, and G. G. Yen, "Completely automated CNN architecture design based on blocks," *IEEE transactions on neural networks and learning systems*, vol. 31, no. 4, pp. 1242–1254, 2019.
107. Y. Sun, H. Wang, B. Xue, Y. Jin, G. G. Yen, and M. Zhang, "Surrogate-assisted evolutionary deep learning using an end-to-end random forest-based performance predictor," *IEEE Transactions on Evolutionary Computation*, vol. 24, no. 2, pp. 350–364, 2020.
108. Y. Xue, C. Chen, and A. Słowik, "Neural architecture search based on a multi-objective evolutionary algorithm with probability stack," *IEEE Transactions on Evolutionary Computation*, vol. 27, no. 4, pp. 778–786, 2023.
109. C. Wei, C. Niu, Y. Tang, Y. Wang, H. Hu, and J. Liang, "NPENAS: neural predictor guided evolution for neural architecture search," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 11, pp. 8441–8455, 2023.
110. C. Termritthikun, Y. Jamtsho, J. Ieamsaard, P. Muneesawang, and I. Lee, "EEEE-Net: An early exit evolutionary neural architecture search," *Engineering Applications of Artificial Intelligence*, vol. 104, p. 104397, 2021.
111. C. Garcia-Garcia, A. Morales-Reyes, and H. J. Escalante, "Continuous cartesian genetic programming based representation for multi-objective neural architecture search," *Applied Soft Computing*, vol. 147, p. 110788, 2023.
112. Y. Xue, B. Hu, and F. Neri, "A surrogate model with multiple comparisons and semi-online learning for evolutionary neural architecture search," *IEEE Transactions on Emerging Topics in Computational Intelligence*, pp. 1–13, 2025.
113. P. Jiang, Y. Xue, and F. Neri, "Score predictor-assisted evolutionary neural architecture search," *IEEE Transactions on Emerging Topics in Computational Intelligence*, pp. 1–15, 2025.
114. Z. Tan, D. Guo, J. Chen, and L. Chen, "M2M-Net: multi-objective neural architecture search using dynamic m2m population decomposition," *Neural Computing and Applications*, vol. 37, no. 27, pp. 22473–22491, 2025.
115. Z. Qiu, W. Bi, D. Xu, H. Guo, H. Ge, Y. Liang, H. P. Lee, and C. Wu, "Efficient self-learning evolutionary neural architecture search," *Applied Soft Computing*, vol. 146, p. 110671, 2023.
116. X. Chu, B. Zhang, and R. Xu, "FairNas: rethinking evaluation fairness of weight sharing neural architecture search," in *Proceedings of the IEEE/CVF International Conference on computer vision*, pp. 12239–12248, 2021.
117. C. Ying, A. Klein, E. Christiansen, E. Real, K. Murphy, and F. Hutter, "Nas-Bench-101: towards reproducible neural architecture search," in *International conference on machine learning*, pp. 7105–7114, 2020.
118. B. M. Onzo, Y. Xue, and F. Neri, "Surrogate-assisted evolutionary neural architecture search based smart-block discovery," *Expert Systems with Applications*, vol. 277, p. 127237, 2025.
119. C. He, Y. Zhang, D. Gong, and X. Ji, "A review of surrogate-assisted evolutionary algorithms for expensive optimization problems," *Expert Systems with Applications*, vol. 217, p. 119495, 2023.
120. Y. Xue, X. Zhang, F. Neri, B. Xue, and M. Zhang, "Graph neural network-based surrogate model for evolutionary neural architecture search," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 55, no. 12, pp. 9631–9644, 2025.
121. F. Bre, N. Roman, and V. D. Fachinotti, "An efficient metamodel-based method to carry out multi-objective building performance optimizations," *Energy and buildings*, vol. 206, p. 109576, 2020.
122. B. Chegari, M. Tabaa, E. Simeu, F. Moutaouakkil, and H. Medromi, "Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms," *Energy and Buildings*, vol. 239, p. 110839, 2021.
123. S. Su, W. Li, Y. Li, A. Garg, L. Gao, and Q. Zhou, "Multi-objective design optimization of battery thermal management system for electric vehicles," *Applied Thermal Engineering*, vol. 196, p. 117235, 2021.

124. Y. Li, C. Li, A. Garg, L. Gao, and W. Li, "Heat dissipation analysis and multi-objective optimization of a permanent magnet synchronous motor using surrogate-assisted method," *Case Studies in Thermal Engineering*, vol. 27, p. 101203, 2021.
125. Z. Zhang, H. C. Chen, and Q. S. Cheng, "Surrogate-assisted quasi-newton enhanced global optimization of antennas based on a heuristic hypersphere sampling," *IEEE Transactions on Antennas and Propagation*, vol. 69, no. 5, pp. 2993–2998, 2020.
126. M. Yu, X. Li, and J. Liang, "A dynamic surrogate-assisted evolutionary algorithm framework for expensive structural optimization," *Structural and Multidisciplinary Optimization*, vol. 61, no. 2, pp. 711–729, 2020.
127. J. WANG, Y. WANG, J. YI, T. HAN, P. JIANG, J. WU, Y. CHENG, and J. LIU, "Genetic optimization method of ship strong frame based on sequential surrogate model," *Chinese Journal of Ship Research*, vol. 16, no. 4, p. 44–52, 2021.
128. K. Wansaseub, S. Slesongsom, N. Panagant, N. Pholdee, and S. Bureerat, "Surrogate-assisted reliability optimisation of an aircraft wing with static and dynamic aeroelastic constraints," *International Journal of Aeronautical and Space Sciences*, vol. 21, no. 3, pp. 723–732, 2020.
129. Y. Ma, J. Wang, Y. Xiao, L. Zhou, and Z. Zhu, "Two-level surrogate-assisted transient parameters design optimization of a wound-field synchronous machine," *IEEE Transactions on Energy Conversion*, vol. 37, no. 1, pp. 737–747, 2021.
130. J. Li, Q. Zhou, H. Williams, H. Xu, and C. Du, "Cyber-physical data fusion in surrogate-assisted strength pareto evolutionary algorithm for phev energy management optimization," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 6, pp. 4107–4117, 2021.
131. L. Baert, E. Chérière, C. Sainvitu, I. Lepot, A. Nouvellon, and V. Leonardon, "Aerodynamic optimization of the low-pressure turbine module: Exploiting surrogate models in a high-dimensional design space," *Journal of turbomachinery*, vol. 142, no. 3, p. 031005, 2020.
132. D. Gonçalves, Y. Sheikhejad, M. Oliveira, and N. Martins, "One step forward toward smart city utopia: Smart building energy management based on adaptive surrogate modelling," *Energy and Buildings*, vol. 223, p. 110146, 2020.
133. N. Wang, C. Li, W. Li, X. Chen, Y. Li, and D. Qi, "Heat dissipation optimization for a serpentine liquid cooling battery thermal management system: An application of surrogate assisted approach," *Journal of Energy Storage*, vol. 40, p. 102771, 2021.
134. L. Xie, G. Li, Z. Wang, L. Cui, and M. Gong, "Surrogate-assisted evolutionary algorithm with model and infill criterion auto-configuration," *IEEE Transactions on Evolutionary Computation*, vol. 28, no. 4, pp. 1114–1126, 2024.
135. R. Zhai, Y. Mei, T. Guo, and W. Du, "A collaborative drone-truck delivery system with memetic computing optimization," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 54, pp. 3618–3630, June 2024.
136. H. Ren, K. Liu, G. Yan, Y. Li, C. Zhan, and S. Guo, "A memetic algorithm for cooperative complex task offloading in heterogeneous vehicular networks," *IEEE Transactions on Network Science and Engineering*, vol. 10, pp. 189–204, Jan 2023.
137. Y. Song, P. N. Suganthan, W. Pedrycz, R. Yan, D. Fan, and Y. Zhang, "Energy-efficient satellite range scheduling using a reinforcement learning-based memetic algorithm," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 60, pp. 4073–4087, Aug 2024.
138. L.-S. Xu, T. Huang, B.-W. Zhao, Y.-J. Gong, and J. Liu, "Continuous berth allocation and time-variant quay crane assignment: Memetic algorithm with a heuristic decoding method," *IEEE Transactions on Intelligent Transportation Systems*, vol. 26, pp. 3387–3401, March 2025.
139. H. Liu, F. Zhao, L. Wang, T. Xu, and C. Dong, "Evolutionary multitasking memetic algorithm for distributed hybrid flow-shop scheduling problem with deterioration effect," *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 1390–1404, 2025.
140. R. Li, W. Gong, L. Wang, C. Lu, and X. Zhuang, "Surprisingly popular-based adaptive memetic algorithm for energy-efficient distributed flexible job shop scheduling," *IEEE Transactions on Cybernetics*, vol. 53, pp. 8013–8023, Dec 2023.
141. F. Chen, C. Luo, W. Gong, and C. Lu, "Two-stage adaptive memetic algorithm with surprisingly popular mechanism for energy-aware distributed hybrid flow shop scheduling problem with sequence-dependent setup time," *Complex System Modeling and Simulation*, vol. 4, pp. 82–108, March 2024.
142. F. Yu, C. Lu, L. Yin, and B. Zhang, "A self-learning memetic algorithm for human-robot collaboration scheduling in energy-efficient distributed mixed fuzzy welding shop," *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 6595–6607, 2025.

143. Y. Wang, Y. Han, Y. Wang, X. Wang, Y. Liu, and K. Gao, "Reinforcement learning-assisted memetic algorithm for sustainability-oriented multiobjective distributed flow shop group scheduling," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 55, pp. 2399–2413, April 2025.
144. J. Dong, B. Hou, L. Feng, H. Tang, K. C. Tan, and Y.-S. Ong, "A cell-based fast memetic algorithm for automated convolutional neural architecture design," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, pp. 9040–9053, Nov 2023.
145. S.-J. Jian and S.-Y. Hsieh, "A niching regression adaptive memetic algorithm for multimodal optimization of the euclidean traveling salesman problem," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 1413–1426, Oct 2023.
146. Z. Wang, M. Gong, P. Li, F. Xie, and M. Zhang, "A bilevel gene-based multiobjective memetic algorithm for passive localization system deployment optimization," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 355–369, April 2023.
147. L. Liu, W. Yuan, Z. Liang, X. Ma, and Z. Zhu, "Construction of polar codes based on memetic algorithm," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 7, pp. 1539–1553, Oct 2023.
148. A. Ma, W. Zhou, M. Song, and Y. Zhong, "Multiobjective memetic spatiotemporal subpixel mapping for remote sensing imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–18, 2023.
149. L. Tang, Z. Li, and J.-K. Hao, "Solving the single-row facility layout problem by k-medoids memetic permutation group," *IEEE Transactions on Evolutionary Computation*, vol. 27, pp. 251–265, April 2023.
150. P. Li, J. Hao, H. Tang, X. Fu, Y. Zheng, and K. Tang, "Bridging evolutionary algorithms and reinforcement learning: A comprehensive survey on hybrid algorithms," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 5, pp. 1707–1728, 2025.
151. L. Cheng, Q. Tang, L. Zhang, and C. Yu, "Scheduling flexible manufacturing cell with no-idle flow-lines and job-shop via Q-learning-based genetic algorithm," *Computers & Industrial Engineering*, vol. 169, p. 108293, 2022.
152. Y. Du, J.-q. Li, X.-l. Chen, P.-y. Duan, and Q.-k. Pan, "Knowledge-based reinforcement learning and estimation of distribution algorithm for flexible job shop scheduling problem," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 7, no. 4, pp. 1036–1050, 2022.
153. F. Zhao, X. Hu, L. Wang, T. Xu, N. Zhu, and Jonrinaldi, "A reinforcement learning-driven brain storm optimisation algorithm for multi-objective energy-efficient distributed assembly no-wait flow shop scheduling problem," *International Journal of Production Research*, vol. 61, no. 9, pp. 2854–2872, 2023.
154. F. Zhao, G. Zhou, and L. Wang, "A cooperative scatter search with reinforcement learning mechanism for the distributed permutation flowshop scheduling problem with sequence-dependent setup times," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, no. 8, pp. 4899–4911, 2023.
155. J. Zheng, J. Zhong, M. Chen, and K. He, "A reinforced hybrid genetic algorithm for the traveling salesman problem," *Computers & Operations Research*, vol. 157, p. 106249, 2023.
156. Y. Song, J. Ou, P. N. Suganthan, W. Pedrycz, Q. Yang, and L. Xing, "Learning adaptive genetic algorithm for earth electromagnetic satellite scheduling," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 59, no. 6, pp. 9010–9025, 2023.
157. T. Li, Y. Meng, and L. Tang, "Scheduling of continuous annealing with a multi-objective differential evolution algorithm based on deep reinforcement learning," *IEEE Transactions on Automation Science and Engineering*, vol. 21, no. 2, pp. 1767–1780, 2023.
158. H. Liu, Z. Zong, Y. Li, and D. Jin, "NeuroCrossover: an intelligent genetic locus selection scheme for genetic algorithm using reinforcement learning," *Applied Soft Computing*, vol. 146, p. 110680, 2023.
159. H. Zhang, J. Sun, Y. Wang, J. Shi, and Z. Xu, "Variational reinforcement learning for hyper-parameter tuning of adaptive evolutionary algorithm," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 7, no. 5, pp. 1511–1526, 2022.
160. X. Liu, J. Sun, Q. Zhang, Z. Wang, and Z. Xu, "Learning to learn evolutionary algorithm: A learnable differential evolution," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 7, no. 6, pp. 1605–1620, 2023.
161. L. Peng, Z. Yuan, G. Dai, M. Wang, and Z. Tang, "Reinforcement learning-based hybrid differential evolution for global optimization of interplanetary trajectory design," *Swarm and Evolutionary Computation*, vol. 81, p. 101351, 2023.
162. F. Zhao, Z. Wang, L. Wang, T. Xu, N. Zhu, et al., "A multi-agent reinforcement learning driven artificial bee colony algorithm with the central controller," *Expert Systems with Applications*, vol. 219, p. 119672, 2023.

163. H. Li, K. Gao, P.-Y. Duan, J.-Q. Li, and L. Zhang, "An improved artificial bee colony algorithm with q-learning for solving permutation flow-shop scheduling problems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, no. 5, pp. 2684–2693, 2022.
164. F. Zhao, T. Jiang, and L. Wang, "A reinforcement learning driven cooperative meta-heuristic algorithm for energy-efficient distributed no-wait flow-shop scheduling with sequence-dependent setup time," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 7, pp. 8427–8440, 2022.
165. H. Yu, K.-Z. Gao, Z.-F. Ma, and Y.-X. Pan, "Improved meta-heuristics with Q-learning for solving distributed assembly permutation flowshop scheduling problems," *Swarm and Evolutionary Computation*, vol. 80, p. 101335, 2023.
166. J. Wang, D. Lei, and J. Cai, "An adaptive artificial bee colony with reinforcement learning for distributed three-stage assembly scheduling with maintenance," *Applied Soft Computing*, vol. 117, p. 108371, 2022.
167. Z. Lin, K. Gao, N. Wu, and P. N. Suganthan, "Scheduling eight-phase urban traffic light problems via ensemble meta-heuristics and Q-learning based local search," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 12, pp. 14415–14426, 2023.
168. B. Zhou and Z. Zhao, "An adaptive artificial bee colony algorithm enhanced by deep q-learning for milk-run vehicle scheduling problem based on supply hub," *Knowledge-based systems*, vol. 264, p. 110367, 2023.
169. Y. Tian, L. Yao, S. Shao, Y. Zhang, and X. Zhang, "Deep reinforcement learning based adaptive environmental selection for evolutionary multi-objective optimization," in *2024 IEEE congress on evolutionary computation (CEC)*, pp. 1–8, IEEE, 2024.
170. Y. Jia, Q. Yan, and H. Wang, "Q-learning driven multi-population memetic algorithm for distributed three-stage assembly hybrid flow shop scheduling with flexible preventive maintenance," *Expert Systems with Applications*, vol. 232, p. 120837, 2023.
171. Y. Zhou, Y. Ren, M. Xu, and G. Feng, "An improved NSGA-III algorithm based on deep Q-networks for cloud storage optimization of blockchain," *IEEE Transactions on Parallel and Distributed Systems*, vol. 34, no. 5, pp. 1406–1419, 2023.
172. R. Li, W. Gong, C. Lu, and L. Wang, "A learning-based memetic algorithm for energy-efficient flexible job-shop scheduling with type-2 fuzzy processing time," *IEEE Transactions on Evolutionary Computation*, vol. 27, no. 3, pp. 610–620, 2022.
173. R. Li, W. Gong, and C. Lu, "A reinforcement learning based RMOEA/D for bi-objective fuzzy flexible job shop scheduling," *Expert Systems with Applications*, vol. 203, p. 117380, 2022.
174. W. Li, S. He, X. Mao, B. Li, C. Qiu, J. Yu, F. Peng, and X. Tan, "Multi-agent evolution reinforcement learning method for machining parameters optimization based on bootstrap aggregating graph attention network simulated environment," *Journal of Manufacturing Systems*, vol. 67, pp. 424–438, 2023.
175. Y. Li, C. Liao, L. Wang, Y. Xiao, Y. Cao, and S. Guo, "A reinforcement learning-artificial bee colony algorithm for flexible job-shop scheduling problem with lot streaming," *Applied Soft Computing*, vol. 146, p. 110658, 2023.
176. W. Li, P. Liang, B. Sun, Y. Sun, and Y. Huang, "Reinforcement learning-based particle swarm optimization with neighborhood differential mutation strategy," *Swarm and Evolutionary Computation*, vol. 78, p. 101274, 2023.
177. Y. Guo, H. Wang, L. He, W. Pedrycz, P. N. Suganthan, L. Xing, and Y. Song, "A reinforcement learning-assisted genetic programming algorithm for team formation problem considering person-job matching," *Neurocomputing*, p. 130917, 2025.
178. S. Li, W. Gong, L. Wang, and Q. Gu, "Evolutionary multitasking via reinforcement learning," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 8, no. 1, pp. 762–775, 2023.
179. F. Zhao, Q. Wang, and L. Wang, "An inverse reinforcement learning framework with the Q-learning mechanism for the metaheuristic algorithm," *Knowledge-Based Systems*, vol. 265, p. 110368, 2023.
180. F. Zhao, Z. Wang, and L. Wang, "A reinforcement learning driven artificial bee colony algorithm for distributed heterogeneous no-wait flowshop scheduling problem with sequence-dependent setup times," *IEEE Transactions on Automation Science and Engineering*, vol. 20, no. 4, pp. 2305–2320, 2022.
181. P. Li, Q. Xue, Z. Zhang, J. Chen, and D. Zhou, "Multi-objective energy-efficient hybrid flow shop scheduling using Q-learning and GVNS driven NSGA-II," *Computers & operations research*, vol. 159, p. 106360, 2023.
182. L. Cheng, Q. Tang, L. Zhang, and Z. Zhang, "Multi-objective Q-learning-based hyper-heuristic with Bi-criteria selection for energy-aware mixed shop scheduling," *Swarm and Evolutionary Computation*, vol. 69, p. 100985, 2022.

183. C. Shang, L. Ma, and Y. Liu, "Green location routing problem with flexible multi-compartment for source-separated waste: A Q-learning and multi-strategy-based hyper-heuristic algorithm," *Engineering Applications of Artificial Intelligence*, vol. 121, p. 105954, 2023.
184. C. Tu, R. Bai, U. Aickelin, Y. Zhang, and H. Du, "A deep reinforcement learning hyper-heuristic with feature fusion for online packing problems," *Expert Systems with Applications*, vol. 230, p. 120568, 2023.
185. L. W. Mou, J. X. Sun, and Y. J. Cheng, "An efficient method for designing subarrayed phased arrays with all-azimuth wide beam-scanning range," *IEEE Transactions on Antennas and Propagation*, vol. 73, no. 9, pp. 6697–6706, 2025.
186. M. Gutierrez, G. Cabrera-Guerrero, and C. Lagos, "A reduced variable neighbourhood search for the beam angle optimisation problem," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 7, no. 5, pp. 1499–1510, 2023.
187. L. Si, X. Zhang, Y. Zhang, S. Yang, and Y. Tian, "An efficient sampling approach to offspring generation for evolutionary large-scale constrained multi-objective optimization," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 9, no. 3, pp. 2080–2092, 2025.
188. W. Yang, G. Zhang, Y. Liu, and Z. An, "Heat exposure assessment and comfort path recommendations for leisure jogging based on street view imagery and gps trajectories," *Sustainable Cities and Society*, vol. 119, p. 106099, 2025.
189. R. Cao, W. Chen, T. Zhang, L. Si, X. Pei, and X. Zhang, "Pattern mining-based evolutionary multi-objective algorithm for beam angle optimization in intensity-modulated radiotherapy," *Complex & Intelligent Systems*, vol. 11, p. 188, 2025.
190. B. Ye, J. Fan, L. Xue, Y. Zhuang, P. Luo, A. Jiang, J. Xie, Q. Li, X. Liang, J. Tan, *et al.*, "iMLGAM: integrated machine learning and genetic algorithm-driven multiomics analysis for pan-cancer immunotherapy response prediction," *Imeta*, vol. 4, no. 2, p. e70011, 2025.
191. P. T. Nguyen, S. G. Coetzee, I. Silacheva, and D. J. Hazelett, "Genome-wide association studies are enriched for interacting genes," *BioData Mining*, vol. 18, no. 1, p. 3, 2025.
192. F. Yasmin, Y. Xue, M. Hasan, A. Sinha, W. Ding, and H. Liu, "EvoBTseg: Evolutionary architecture search for compact and precise heterogeneous brain tumor segmentation," *IEEE Transactions on Emerging Topics in Computational Intelligence*, pp. 1–14, 2026.
193. B. Wang, W. Pei, B. Xue, and M. Zhang, "A multiobjective genetic algorithm to evolving local interpretable model-agnostic explanations for deep neural networks in image classification," *IEEE Transactions on Evolutionary Computation*, vol. 28, pp. 903–917, Aug 2024.
194. F. Yasmin, M. Hasan, S. Abdulla, M. M. Hassan, R. S. Radjabovich, A. Khader, A. Ahmed, and Y. Xue, "Optimizing brain tumor segmentation networks through evolutionary neural architecture search," in *2025 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*, pp. 1–8, 2025.
195. F. Yasmin, M. Hasan, H. Liu, A. Ali, G. Muhammad, and Y. Xue, "Resource-aware evolutionary neural architecture search for cardiac mri segmentation," in *2025 28th International Conference on Computer and Information Technology (ICCIT)*, pp. 2819–2824, 2025.
196. A. Trivedi, D. Srinivasan, K. Pal, C. Saha, and T. Reindl, "Enhanced multiobjective evolutionary algorithm based on decomposition for solving the unit commitment problem," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 6, pp. 1346–1357, 2015.
197. Z.-X. Zhang, W.-N. Chen, W. Shi, S.-W. Jeon, and J. Zhang, "An individual evolutionary game model guided by global evolutionary optimization for vehicle energy station distribution," *IEEE Transactions on Computational Social Systems*, vol. 11, no. 1, pp. 1289–1301, 2024.
198. A. Che, P. Wu, F. Chu, and M. Zhou, "Improved quantum-inspired evolutionary algorithm for large-size lane reservation," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 45, no. 12, pp. 1535–1548, 2015.
199. X. Ding and T. Liu, "A history information-guided evolutionary algorithm for the multiobjective vehicle routing problem with time windows," *IEEE Sensors Journal*, vol. 24, no. 21, pp. 35787–35800, 2024.
200. W. Ali, I. U. Din, A. Almogren, A. Altameem, and J. J. P. C. Rodrigues, "Post-quantum blockchain-based secure framework for trustworthy consumer internet of things," *IEEE Transactions on Consumer Electronics*, pp. 1–1, 2025.
201. X. Song, Y. Zhang, W. Zhang, C. He, Y. Hu, J. Wang, and D. Gong, "Evolutionary computation for feature selection in classification: A comprehensive survey of solutions, applications and challenges," *Swarm and Evolutionary Computation*, vol. 90, p. 101661, 2024.
202. Y. Xue, L. Yuan, W. Fang, M. K. Hasan, and K. Aurangzeb, "Evolutionary neural architecture search based on pre-trained surrogate model," *Applied Soft Computing*, p. 114145, 2025.

203. J. Zhang and Y.-J. Yang, "Adaptive large model building for consumer electronics data fusion via multi-modal multi-objective evolutionary algorithm," *IEEE Transactions on Consumer Electronics*, pp. 1–1, 2025.
204. F. Yasmin, Y. Xue, M. Hasan, and G. Muhammad, "EPSO-Net: A multi-objective evolutionary neural architecture search with PSO-guided mutation fusion for explainable brain tumor segmentation," *Information Fusion*, p. 104119, 2026.
205. Y. Xue, W. Tong, F. Neri, P. Chen, T. Luo, L. Zhen, and X. Wang, "Evolutionary architecture search for generative adversarial networks based on weight sharing," *IEEE transactions on evolutionary computation*, vol. 28, no. 3, pp. 653–667, 2023.
206. Y. Xue and A. Zhu, "An effective surrogate-assisted rank method for evolutionary neural architecture search," *Applied Soft Computing*, vol. 167, p. 112392, 2024.
207. Z. Xiao, Q. Qiu, L. Li, Y. Feng, Q. Lin, and Z. Ming, "An efficient service-aware virtual machine scheduling approach based on multi-objective evolutionary algorithm," *IEEE Transactions on Services Computing*, vol. 17, no. 5, pp. 2027–2040, 2024.
208. C. Rajesh, R. Sadam, and S. Kumar, "An evolutionary U-shaped network for retinal vessel segmentation using binary teaching–learning-based optimization," *Biomed. Signal Process. Control*, vol. 83, p. 104669, 2023.
209. Z. Kuş, B. Kiraz, T. K. Göksu, M. Aydın, E. Özkan, A. Vural, A. Kiraz, and B. Can, "Differential evolution-based neural architecture search for brain vessel segmentation," *Engineering Science and Technology, an International Journal*, vol. 46, p. 101502, 2023.
210. H. Li, Y. Zhang, and Q. Zuo, "Multi-objective evolutionary optimization boosted deep neural networks for few-shot medical segmentation with noisy labels," *IEEE Journal of Biomedical and Health Informatics*, vol. 29, pp. 4362–4373, June 2025.
211. J.-A. Fuentes-Tomás, E. Mezura-Montes, H.-G. Acosta-Mesa, and A. Márquez-Grajales, "Tree-based codification in neural architecture search for medical image segmentation," *IEEE Transactions on Evolutionary Computation*, vol. 28, no. 3, pp. 597–607, 2024.
212. H. Sheng, H.-L. Liu, Y. Lai, S. Zeng, and L. Chen, "Hierarchical encoding method for retinal segmentation evolutionary architecture search," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 9, no. 1, pp. 480–493, 2025.
213. W. Ying, Q. Zheng, Y. Wu, K. Yang, Z. Zhou, J. Chen, and Z. Ye, "Efficient multi-objective evolutionary neural architecture search for U-Nets with diamond atrous convolution and transformer for medical image segmentation," *Applied Soft Computing*, vol. 148, p. 110869, 2023.
214. C. Yu, Y. Wang, C. Tang, W. Feng, and J. Lv, "Eu-net: Automatic u-net neural architecture search with differential evolutionary algorithm for medical image segmentation," *Computers in Biology and Medicine*, vol. 167, p. 107579, 2023.
215. F. Yasmin, Y. Xue, M. Hasan, M. Gabbouj, M. K. Hasan, K. Aurangzeb, and G. Muhammad, "Evo-GrayNet: colon polyp detection and segmentation using evolutionary network architecture search," *IEEE Transactions on Instrumentation and Measurement*, pp. 1–14, 2025.
216. M. Hasan, F. Yasmin, H. Liu, M. M. Hassan, R. S. Radjabovich, and Y. Xue, "Automated polyp segmentation using evolutionary neural architecture search," in *2025 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*, pp. 1–7, 2025.
217. M. Coccia, S. Roshani, and M. Mosleh, "Evolution of quantum computing: Theoretical and innovation management implications for emerging quantum industry," *IEEE Transactions on Engineering Management*, vol. 71, pp. 2270–2280, 2024.
218. Y. Xue, X. Han, and Z. Wang, "Self-adaptive weight based on dual-attention for differentiable neural architecture search," *IEEE Transactions on Industrial Informatics*, vol. 20, no. 4, pp. 6394–6403, 2024.
219. Y. Xue, J. Zha, D. Pelusi, P. Chen, T. Luo, L. Zhen, Y. Wang, and M. Wahib, "Neural architecture search with progressive evaluation and subpopulation preservation," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 5, pp. 1678–1691, 2025.
220. R. De Prisco, G. Zaccagnino, and R. Zaccagnino, "Evocomposer: An evolutionary algorithm for 4-voice music compositions," *Evolutionary Computation*, vol. 28, no. 3, pp. 489–530, 2020.
221. A. Neumann, B. Alexander, and F. Neumann, "Evolutionary image transition and painting using random walks," *Evolutionary Computation*, vol. 28, no. 4, pp. 643–675, 2020.
222. F. Susanto, S. Budi, P. de Souza, U. Engelke, and J. He, "Design of environmental sensor networks using evolutionary algorithms," *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 4, pp. 575–579, 2016.
223. B. Yuan, B. Li, H. Chen, and X. Yao, "A new evolutionary algorithm with structure mutation for the maximum balanced biclique problem," *IEEE Transactions on Cybernetics*, vol. 45, no. 5, pp. 1054–1067, 2015.

224. E.-J. Cabello-Franco, D. Anton, E. Ramirez-Juidias, and F. Perea-Torres, "Optimizing water demand in citrus orchards: a novel model using evolutionary algorithms on sentinel-1 time series data," *COGENT FOOD & AGRICULTURE*, vol. 11, no. 1, 2025.
225. Q. Long, X. Tao, Y. Shi, and S. Zhang, "Evolutionary game analysis among three green-sensitive parties in green supply chains," *IEEE Transactions on Evolutionary Computation*, vol. 25, no. 3, pp. 508–523, 2021.
226. Y. Gao, J. Ning, and M. Zhang, "An evolutionary game dynamic analysis of enterprise technological innovation implementation strategy: From the perspective of green bonds," *IEEE Transactions on Engineering Management*, vol. 71, pp. 11551–11564, 2024.
227. X. Han, Y. Xue, Z. Wang, Y. Zhang, A. Muravev, and M. Gabbouj, "SaDENAS: A self-adaptive differential evolution algorithm for neural architecture search," *Swarm and Evolutionary Computation*, vol. 91, p. 101736, 2024.
228. M. A. Webster and D. E. Browne, "Engineering quantum error correction codes using evolutionary algorithms," *IEEE Transactions on Quantum Engineering*, vol. 6, pp. 1–14, 2025.
229. J. Xu, Y. Jin, W. Du, and S. Gu, "A federated data-driven evolutionary algorithm," *Knowledge-based systems*, vol. 233, p. 107532, 2021.
230. T. Chen, F. Wang, W. Hou, S. Tang, and Z. Zheng, "Dynamic incentive model for federated learning model trading via evolutionary game theory," in *ICASSP 2025 - 2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1–5, 2025.
231. Y. Chen, Y. Zhang, S. Wang, F. Wang, Y. Li, Y. Jiang, L. Chen, and B. Guo, "Dim-ds: Dynamic incentive model for data sharing in federated learning based on smart contracts and evolutionary game theory," *IEEE Internet of Things Journal*, vol. 9, no. 23, pp. 24572–24584, 2022.
232. Z. Yasser, A. Hammoud, A. Mourad, H. Otrok, Z. Dziong, and M. Guizani, "Federated learning and evolutionary game model for fog federation formation," *IEEE Internet of Things Journal*, vol. 12, no. 4, pp. 4183–4196, 2025.
233. X. Wu, S.-H. Wu, J. Wu, L. Feng, and K. C. Tan, "Evolutionary computation in the era of large language model: Survey and roadmap," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 2, pp. 534–554, 2025.
234. N. v. Stein and T. Bäck, "LLaMEA: A large language model evolutionary algorithm for automatically generating metaheuristics," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 2, pp. 331–345, 2025.

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