Literature Review:
Evolutionary Algorithms for Quantum Circuit Design

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Abstract

This literature review surveys the intersection of evolutionary algorithms and quantum circuit design as of early 2026. We identify key trends, benchmark problems, active research groups, and open problems across eight sub-fields: EA-based circuit synthesis, quantum architecture search, QAOA parameter optimization, VQE ansatz design, multi-objective quantum optimization, quantum error correction, ML-based circuit design, and quality-diversity methods. A gap analysis positions our project—a fast numpy-based comparative study of six optimization methods across six quantum problems—within the broader landscape, and identifies under-explored research directions including quality-diversity optimization, transfer learning, and co-evolutionary approaches.

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1 Field Overview

The intersection of evolutionary algorithms (EAs) and quantum circuit design is experiencing a renaissance driven by the NISQ era's need for automated, hardware-aware circuit optimization. Three major trends dominate:

1. **EAs remain competitive** with reinforcement learning and generative models for small-scale circuit synthesis, with advantages in interpretability and ease of implementation.
2. **Multi-objective and noise-aware optimization** are becoming standard requirements.
3. **Hybrid approaches dominate**: pure EA or pure RL approaches are being replaced by hybrids (EA + parameter optimization, EA + noise models, GA + QAOA).

2 Key Recent Papers by Topic

2.1 EA-Based Quantum Circuit Synthesis

Paper	Venue	Year	Key Contribution
Kolle et al., "Evaluating Mutation Techniques in GA-Based QCS" [1]	GECCO	2025	Delete+swap mutations outperform others for 4–6 qubit circuits
Sunkel, Altmann, Kolle et al., "Hybrid EA Circuit Construction & Optimization" [2]	GECCO	2025	Hybrid EA+COBYLA achieves 80% depth reduction at 0.98 fidelity
"GA4QCO: GA for Quantum Circuit Optimization" [3]	arXiv	2023	GA framework for circuit optimization with Qiskit
"GASP: GA for State Preparation" [4]	Nat. Sci. Rep.	2023	GA for quantum state preparation circuits
Tandeitnik & Guerreiro, "Evolving Quantum Circuits" [5]	arXiv	2022	Island-model GA for circuit decomposition
Bhandari et al., "EA for Boolean Gates, CA, Entanglement" [6]	arXiv	2024	Mutation rate balancing for 5-qubit entangling circuits

2.2 Quantum Architecture Search (QAS)

Paper	Venue	Year	Key Contribution
"AQEA-QAS" [7]	MDPI Entropy	2025	Adaptive quantum evolutionary algorithm for QNN design
"Noise-Aware QAS Based on NSGA-II" [8]	arXiv	2026	Multi-objective noise-aware architecture search
"Hierarchical QAS" [9]	npj Quantum Inf.	2023	Hierarchical representations for modular search

Paper	Venue	Year	Key Contribution
"Balanced QNAS" [10]	Neurocomputing	2024	One-shot NAS with quantum parallelism

2.3 QAOA + Evolutionary Methods

Paper	Venue	Year	Key Contribution
"GA as Classical Optimizer for QAOA" [11]	Appl. Soft Comput.	2023	GA outperforms gradient-free optimizers for QAOA parameters
"QAOA Exponential Time for Linear Functions" [12]	GECCO	2025	Fundamental complexity limitations of QAOA
"GA-Based QAOA for Power Networks" [13]	Springer	2024	Domain-specific QAOA+GA evaluation

2.4 VQE + Evolutionary Optimization

Paper	Venue	Year	Key Contribution
"PSO for VQE (GAQPSO)" [14]	Phys. Chem. Chem. Phys.	2024	Gradient-free PSO with noise resilience for VQE
Gustafson et al., "Surrogate Optimization of VQC" [15]	PNAS	2025	Classical surrogates to accelerate VQE convergence

2.5 Multi-Objective Quantum Optimization

Paper	Venue	Year	Key Contribution
"Quantum Approximate Multi-Objective Optimization" [16]	Nat. Comp. Sci.	2025	QAOA for Pareto-optimal multi-objective solutions
"MEAS-PQC" [17]	MDPI Entropy	2023	Multi-objective EA for parameterized circuit architecture
Zorn et al., "Quality Diversity for VQC Optimization" [18]	Various	2025	CMA-MAE for quality-diversity in circuit design

2.6 Quantum Error Correction + EA

Paper	Venue	Year	Key Contribution
"Engineering QEC Codes with EA" [19]	IEEE TQE	2025	EA search for optimal stabilizer codes ($n \leq 20$ qubits)
"T-Count Optimizing GA" [20]	arXiv	2024	Up to 79% T-depth reduction via GA

2.7 ML-Based Circuit Design (Non-EA)

Paper	Venue	Year	Key Contribution
"FlowQ-Net" (GFlowNets) [21]	arXiv	2025	10–30× more compact circuits vs baselines
"AlphaTensor-Quantum" (DeepMind) [22]	Nat. Mach. Intell.	2025	RL for efficient non-Clifford gate decomposition
"Q-Fusion" (Diffusion Model) [23]	Penn State	2025	Graph-based diffusion for circuit generation
Rouillard et al., "Automated QA Design with DSL" [24]	arXiv	2025	DSL + evolutionary search rediscovers QFT, D-J, Grover

2.8 Surveys

Paper	Venue	Year
"Comprehensive Review of QCO" [25]	MDPI Quantum Reports / arXiv	2024
"QC Synthesis & Compilation Overview" [26]	arXiv	2024
"AI for Quantum Computing" [27]	Nature Communications	2025
"Review of Procedures to Evolve Quantum Algorithms" [28]	GP & Evolvable Machines	2009

3 Standard Benchmarks in the Field

Benchmark	Description	Typical Use
QFT	Quantum Fourier Transform	Circuit synthesis/compilation
Grover's Search	Unstructured database search	EA-based circuit discovery
MaxCut (via QAOA)	Combinatorial optimization on graphs	QAOA parameter optimization
State Preparation	Prepare specific target states	GA fitness via fidelity

Benchmark	Description	Typical Use
Toffoli/Fredkin Gates	Multi-qubit gate decomposition	Gate-level optimization
QASMBench	Suite of 1066 test circuits	Cross-framework benchmarking
Molecular Ground State	H_2, LiH, BeH_2 molecules	VQE ansatz optimization
Random Unitary Compilation	Arbitrary unitary matrices	Compiler optimization
Stabilizer Codes	5-qubit, Steane, Shor codes	QEC code discovery

Key metrics. State fidelity, circuit depth, gate count (total and T-count), approximation ratio, quantum volume, Hellinger fidelity, process fidelity, and hypervolume indicator (multi-objective).

4 Open Problems

The following open problems were identified across the surveyed literature:

1. **Scalability.** Most EA approaches are tested on 4–8 qubits. Classical statevector simulation becomes infeasible beyond ∼30 qubits.
2. **Continuous parameters.** Handling rotation gate parameters (R_x, R_y, R_z) within discrete evolutionary search remains an open challenge.
3. **Noise-aware optimization.** Most EAs assume ideal execution; NISQ relevance requires noise models.
4. **Standardized benchmarks.** No universally accepted benchmark suite exists for EA-based quantum circuit synthesis.
5. **Search space representation.** The optimal circuit encoding for evolutionary operators is still debated.
6. **Hardware–software co-design.** Joint optimization with hardware topology constraints is underexplored.
7. **Multi-objective trade-offs.** Richer objective spaces beyond fidelity and depth are largely unexplored.
8. **Transfer and generalization.** Evolved circuits rarely generalize across problem instances or hardware.
9. **Verification at scale.** Verifying evolved circuits becomes intractable for large qubit counts.
10. **Adaptive operators.** Self-adaptive mutation and crossover rates specifically for quantum circuit EAs are understudied.

5 Gap Analysis: This Project vs. the Literature

5.1 Project Summary

This project implements a comparative study of six optimization methods (EA, Random Search, Gradient-Based, REINFORCE, NSGA-II, MAP-Elites) for evolving quantum circuits across six benchmark problems (Grover, Flip, Inverse, Fourier, Deutsch–Jozsa, Bernstein–Vazirani) using:

- Pure numpy statevector simulation (∼μs per evaluation),
- DEAP evolutionary algorithm framework,
- 3-qubit circuits with 5 discrete gate types (I, T, H, $\text{CNOT}_\downarrow$, $\text{CNOT}_\uparrow$),

- Single-objective and multi-objective fitness (fidelity, depth, gate count),
- Quality-diversity optimization via MAP-Elites,
- Fitness caching keyed by circuit bytes.

5.2 Strengths vs. Literature

Strength	**How It Compares**
Simulation speed (∼μs/eval)	100–1000× faster than Qiskit Aer used in GA4QCO, GASP, etc.
Fitness caching	Rarely seen in published frameworks
DEAP integration	Mature, well-tested; most papers use custom implementations
Six-method comparison	EA, Random, Gradient, DL, NSGA-II, MAP-Elites compared head-to-head
Quality-diversity	MAP-Elites for algorithmic quantum circuits is nearly unexplored
Reproducibility	Deterministic seeds, 10 trials per condition, 360 total runs
No runtime Qiskit dependency	Eliminates version churn, import overhead

5.3 Gaps vs. Literature

Gap	**Severity**	**What the Literature Does**
Fixed discrete gate set only	HIGH	GA4QCO, GASP, GECCO 2025 all support parameterized rotation gates (R_x, R_y, R_z)
No noise model	HIGH	Noise-Aware QAS (2026), GA-QAOA on real hardware show noise-aware fitness is critical for NISQ
Only 3-qubit experiments	MEDIUM	Most papers test on 4–6+ qubits
Limited gate set	MEDIUM	No R_x, R_y, R_z, CZ, Toffoli gates; limits circuit expressiveness
No adaptive operators	MEDIUM	GECCO 2025 shows benefits of adaptive mutation rates
No hardware topology constraints	LOW	Compilation-aware synthesis is an emerging direction
No transfer/generalization study	LOW	DSL paper [24] shows generalizable algorithm learning

5.4 Key Positioning

The project occupies a practical niche: **a lightweight, fast, dependency-minimal framework for evolving small quantum circuits with multi-objective and quality-diversity optimization**. Most comparable to GA4QCO and GASP, but differentiated by simulation speed, DEAP integration, and the inclusion of NSGA-II and MAP-Elites. The main remaining gaps are the lack of continuous parameters, noise modelling, and larger qubit counts.

6 Emerging Topics and Niche Opportunities

6.1 Quality-Diversity for Quantum Circuits

Status: Very under-explored. Only one paper (Zorn et al. [18], CMA-MAE for VQC optimization on MaxCut/MVC/MIS/MaxClique) applies quality-diversity to quantum circuits. No work applies MAP-Elites to algorithmic quantum circuit discovery (QFT, Grover, etc.). Our project addresses this gap directly, using MAP-Elites with (depth, entanglement density) as behavioural descriptors to reveal fundamentally different circuit families for the same problem.

6.2 Noise-Aware Evolutionary Circuit Synthesis

Status: Nascent. Only one direct paper [8] applies NSGA-II with noise models, using Qiskit's noisy simulation (slow). No fast numpy-based noisy simulation for EA fitness evaluation exists. Opportunity: implement depolarizing/amplitude damping noise in numpy and show that noise-aware evolution produces more hardware-robust circuits.

6.3 Surrogate-Assisted Evolutionary Quantum Circuit Optimization

Status: Very new. Gustafson et al. [15] pioneered surrogate optimization for VQC but used gradient-based methods, not EA. No surrogate-assisted EA specifically for quantum circuit structure optimization exists.

6.4 Transfer Learning for Evolved Quantum Circuits

Status: Nearly empty. Rouillard et al. [24] showed DSL-based circuits learned on 5 qubits generalize to larger instances, but no EA-based transfer learning work exists. Open questions: can circuits evolved for 3-qubit problems seed evolution for 4–5 qubit problems? Can circuits evolved for Grover transfer to Bernstein–Vazirani?

6.5 Grammatical Evolution for Quantum Circuits

Status: Sparse but promising. A 2025 paper on grammatical evolution for Grover achieved 97.9% fidelity on IBM hardware vs 44.2% for standard Grover, with up to 93.3% depth reduction. Formalizing gate constraints as a BNF grammar could eliminate wasted evaluations on invalid circuits.

6.6 Co-Evolution for Quantum Circuits

Status: Empty. No true co-evolutionary approach to quantum circuit design exists. Co-evolving circuit structure and test cases, or co-evolving complementary circuit sub-modules, is completely unexplored.

6.7 Evolutionary Quantum Error Mitigation

Status: Nascent. One paper (IEEE 2021) uses GA for measurement error mitigation. No EA-based search for optimal error mitigation protocols (zero-noise extrapolation parameters, probabilistic error cancellation strategies) exists.

6.8 Summary of Research Whitespace

Topic	**Papers Found**	**Opportunity Level**
Quality-Diversity / MAP-Elites for QCS	1	Very High
Transfer Learning for Evolved Circuits	0	High
Co-Evolution for Quantum Circuits	0	High
Surrogate-Assisted EA for QCS	0 (direct)	High
Noise-Aware EA for QCS	1	High
Grammatical Evolution for QCS	1 (tangential)	Medium–High
Adaptive Mutation for QCS	1	Medium–High
Evolutionary Quantum Error Mitigation	1 (tangential)	Medium

Table 12: Research whitespace assessment as of February 2026.

7 Publishable Contributions

Based on the literature review and gap analysis, five concrete publication-ready research directions are identified, ranked by feasibility and novelty.

7.1 Rec. 1: Multi-Objective NSGA-II for Quantum Circuit Synthesis

Novelty: High. Status: Implemented. No published work combines DEAP's built-in NSGA-II with fast numpy statevector simulation for multi-objective quantum circuit optimization. The closest work (MEAS-PQC [17]; Noise-Aware QAS [8]) uses custom implementations or Qiskit. Our project implements this with three objectives (maximize fidelity, minimize active depth, minimize gate count) using `selNSGA2` and `eaMuPlusLambda`.

Target venues: GECCO 2026, CEC 2026, Quantum Science and Technology.

7.2 Rec. 2: Adaptive Mutation Strategies for Quantum Circuit Evolution

Novelty: Medium–High. Kolle et al. [1] evaluated fixed mutation strategies but did not study self-adaptive mutation rates or quantum-aware mutation operators. Possible extensions: gate substitution preserving unitarity, subcircuit inversion, controlled-gate promotion, 1/5 success rule adaptation, multi-armed bandit operator selection.

Target venues: GECCO 2026, IEEE Transactions on Evolutionary Computation.

7.3 Rec. 3: MAP-Elites Quality-Diversity for Circuit Repertoires

Novelty: Very High. Status: Implemented. Nobody has applied MAP-Elites to discover diverse repertoires of quantum circuits for algorithmic problems (Grover, QFT, etc.). Instead of finding one best circuit, MAP-Elites finds a map of diverse high-quality circuits indexed by structural features. Our project implements this with a 2D archive indexed by (active depth, entanglement density), achieving 79–87% coverage across problems.

Target venues: GECCO 2026, Artificial Life, Evolutionary Computation.

7.4 Rec. 4: Noise-Aware Evolutionary Synthesis with Surrogates

Novelty: Medium. Practical impact: High. Combine fast numpy noise models (depolarizing channel via Kraus operators or density matrix simulation) with surrogate-assisted evaluation (random forest or GP regression on circuit features → noisy fitness).

Target venues: Quantum Science and Technology, Physical Review A, IEEE TQE.

7.5 Rec. 5: Parameterized Gate Evolution with Hybrid EA+Local Search

Novelty: Medium. Extend the gate set with $R_x(\theta)$, $R_y(\theta)$, $R_z(\theta)$ and continuous angle parameters. EA evolves gate topology; local optimizer (L-BFGS-B or COBYLA) tunes parameters.

Target venues: GECCO 2026, J. Chemical Theory and Computation.

7.6 Rec. 6: Grammatical Evolution with Hardware Constraints

Novelty: Medium–High. Formalize existing gate preprocessing rules (CNOT adjacency, H/T cancellation) as a BNF grammar. Use grammatical evolution instead of flat integer encoding. A 2025 GE paper achieved 97.9% fidelity on real IBM hardware for 3-qubit Grover; expanding to our 6-problem benchmark suite would be a clear extension.

Target venues: GECCO 2026, Evolutionary Computation.

7.7 Summary

#	Direction	Novelty	Feasibility	Effort	Status
1	Multi-Objective NSGA-II	High	High	2–4 wk	Done
2	Adaptive Mutation	Med–High	High	3–4 wk	Future
3	MAP-Elites QD	Very High	Medium	3–5 wk	Done
4	Noise-Aware + Surrogate	Medium	Medium	4–6 wk	Future
5	Parameterized Gates Hybrid	Medium	Medium	4–6 wk	Future
6	Grammatical Evolution	Med–High	Medium	3–4 wk	Future

Table 13: Summary of publication-ready research directions.

The recommended combined paper—*"Multi-Objective and Quality-Diversity Optimization of Quantum Circuits via Statevector Simulation"*—combining Recommendations 1 and 3, has been implemented and is presented in the accompanying research paper.

8 Standout Recent Results

Several additional results merit attention:

Grammatical Evolution for Grover (2025). Evolved Grover circuits for all 8 basis states of a 3-qubit system on IBM `ibm_brisbane` achieved 97.9% fidelity vs 44.2–47.6% for standard Grover, with up to 93.3% depth reduction and 92.7% gate count reduction.

EXAQC (RIT). Neuroevolution-style search that simultaneously optimizes gate types, qubit connectivity, parameterization, and circuit depth. Achieves >90% accuracy on Iris, Wine, Seeds, and Breast Cancer benchmarks. Supports both Qiskit and PennyLane.

QuantumNAS (Wang et al., HPCA 2022). SuperCircuit approach that decouples training from search. Noise-adaptive evolutionary co-search for (circuit, qubit mapping) pairs, tested on 14 quantum computers across 12 benchmarks.

Evolutionary BP+OSD Decoding for QEC (Dec 2025). Differential evolution optimizes belief propagation weights, achieving comparable performance with 5 BP iterations vs 32 (standard) or 150 (BP with memory).

RBF Surrogate for 127-Qubit QAOA (2025). Radial basis function interpolation as an adaptive, hyperparameter-free surrogate successfully optimized 127-qubit QAOA circuits on IBM hardware.

9 Key Active Research Groups

LMU Munich (Linnhoff-Popien group). The most prolific group in the field: Kolle (mutation strategies, GECCO 2025), Altmann (hybrid EA, GECCO 2025), Zorn & Stein (quality-diversity, ICAPS 2025), Sunkel (circuit construction, GECCO 2025), Gabor (QNEAT, GECCO 2023).

MIT HAN Lab (Wang). QuantumNAS—noise-adaptive co-search.

University of KwaZulu-Natal (Rouillard, Petruccione). DSL-based algorithm design.

RIT (Kar, Krutz, Desell). EXAQC neuroevolution.

OsloMet (Bhandari, Nichele, Lind). EA for entanglement.

University of Melbourne (Creevey, Hill, Hollenberg). GASP.

10 Software Toolkits

11 Target Venues

- **GECCO 2026** (ACM Genetic and Evolutionary Computation Conference)—the premier venue; GECCO 2025 had multiple quantum circuit EA papers and dedicated quantum optimization workshops.
- **CEC 2026** (IEEE Congress on Evolutionary Computation).
- **IEEE QCE 2026** (IEEE International Conference on Quantum Computing and Engineering).
- **QIP 2026** (Quantum Information Processing).
- **Quantum Science and Technology** (IOP journal).
- **Evolutionary Computation** (MIT Press journal).
- **IEEE Transactions on Quantum Engineering**.

Tool	Description	Reference
EVOVAQ	Python toolbox for evolutionary VQC training (Qiskit)	GitHub
EXAQC	Neuroevolution for quantum circuits (Qiskit + PennyLane)	RIT
AlphaTensor-Quantum	DeepMind RL for T-count optimization	[22]
MQT Bench	∼70,000 benchmark circuits, 2–130 qubits	GitHub
Benchpress	1000+ tests for circuit compilation (up to 930 qubits)	Nat. Comp. Sci. 2025
RevLib	Reversible function/circuit benchmarks	revlib.org

Table 14: Key software toolkits for quantum circuit optimization.

Acknowledgements

Literature search and synthesis conducted in February 2026.

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