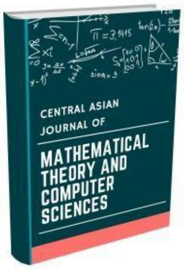

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Article

Machine Learning–Enhanced Metaheuristic Optimization for Nonlinear Problems: A Comprehensive Critical Review

Mohammed Loay Moammar[1], Abdulwahhab F Shareef[2], Mohammed F Ibrahim Alsarraj[3]

[1,2,3]Technical Engineering College for Computer and AI–Mosul, Northern Technical University, Mosul, 41001, Iraq.
* Correspondence: [1]mohammed.loay@ntu.edu.iq, [2]abdalsied2017@ntu.edu.iq, [3]mohammed_alsarraj@ntu.edu.iq

Abstract: Nonlinear optimization problems are commonplace in multidisciplinary applications across engineered systems, energy, transportation, healthcare and computational intelligence. Many of these problems remain unsolvable, characterized by nonconvex search landscapes, multimodalities, high dimensionality, and complex constraints. Traditionally, metaheuristic approaches ranging from genetic algorithms to particle swarm optimization to ant colony optimization and differential evolution supply reliable performance but are ultimately ineffective due to slow convergence, premature convergence, or variances of solutions based on problem type. Yet with the latest trajectory of machine learning (ML) technologies, hybrid frameworks provide coupling agents from predictive modeling to adaptive learning to surrogate modeling to reinforcement-based decision support systems that realize enhanced performance by promoting quicker searches. This paper details a comprehensive and critical literature review of ML-coupled metaheuristics for nonlinear optimization. Findings compare recent developments to associated trends, categorize coupling frameworks, review performance increase percentages, acknowledge existing gaps, and recommend future research focus. Ultimately, ML-based metaheuristics promise a new frontier in top-level performance for nonlinear solutions; however, to make them as good as they can be, standardized benchmarking, increased explainability, and better theoretical justification are needed.

Keywords: Metaheuristic Optimization, Machine Learning, Hybrid Intelligence, Reinforcement Learning, Adaptive Optimization.

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1. Introduction

Nonlinear optimization problems span numerous applications from structural engineering to energy systems, robotics to wireless networks, smart manufacturing to biomedical solutions. They typically have nonconvex objective functions, discontinuities, high dimensionality, and complicated constraints that render traditional mathematical programming approaches ineffective or inapplicable [1], [2].

Such problems require advanced algorithms that can operate under nonlinear conditions and within substantial search space challenges [3]. For example, metaheuristic approaches have become popular genetic algorithms, particle swarm optimization, and simulated annealing, for their flexible and generalizable usefulness for nonlinear performance; however, they tend to require extensive parameter tuning, and they suffer slow or stagnant convergence across performance.

Metaheuristic algorithms are powerful stochastic optimization solutions that traverse complicated and nonlinear search spaces with fewer strict mathematical requirements; however, they suffer from various identifiable limitations [4], [5], [6]. These limitations are premature convergence, where the advanced solution sticks to one local optimal solution without regard to the other optimal solutions; excessive sensitivity to parameters, which reduces the generalizability of performance; and high computational costs with inexpensive objective function evaluations and large-scale reviews, which complicate the process further. The presence of dynamic or noisy environments further reduces effectiveness via conventional metaheuristics through limited adaptability and limited real-time and real-world performance applicability [7], [8].

Conversely, machine learning presents an alternative solution that injects predictive, pattern-finding findings and real-time adjustment into the optimization process. ML-enhanced metaheuristics utilize a data-driven approach to intelligence that cultivates a more critical assessment of speed of convergence, solution optimality, and generalizability for nonlinear issues. This systematic review takes stock of current findings on these emerging hybrid solutions, while evaluating the strengths and weaknesses of their methodologies [9], [10].

2. Methodology

This review is for a transparent, repeatable collection of studies regarding machine learning augmented metaheuristic optimization for nonlinear solutions. An extensive collection period spanning 2020 to 2025 was conducted across the three largest academic databases IEEE Xplore, Elsevier (ScienceDirect), and SpringerLink, alongside Google Scholar. Five hundred five studies were yielded in this search: 120 from IEEE Xplore, 135 from Elsevier, 150 from SpringerLink, and 100 from Google Scholar.

After removing duplicates, 420 distinct studies were evaluated through title and abstract screening. At the title/abstract screening stage, 360 studies were excluded for the following reasons: lack of focus on metaheuristics or machine learning; focus on nonlinear optimization but not metaheuristic/machine learning application; non-English articles; and conference proceedings without accessible full-text versions. Therefore, 60 studies were left for full-text review and analysis.

During full-text review, 48 studies were excluded from the review for not meeting eligibility criteria based on the following: theoretical study without empirical application (4 studies), machine learning without metaheuristic consideration (standalone studies) (6 studies), and studies with solely metaheuristic applications without any machine learning application (5 studies). Therefore, 8 studies were acquired based on full-text review and met all eligibility criteria for inclusion in a qualitative assessment. Meanwhile, 25 studies not meeting eligibility criteria are still valid for contextual purposes beyond practical comparison. Therefore, it will be included in a final review and assessment for comparison purposes.

Thus, the following PRISMA-compliant approach establishes rigor, transparency, and replicability for evidence-based critical evaluation of metaheuristic optimization solutions.

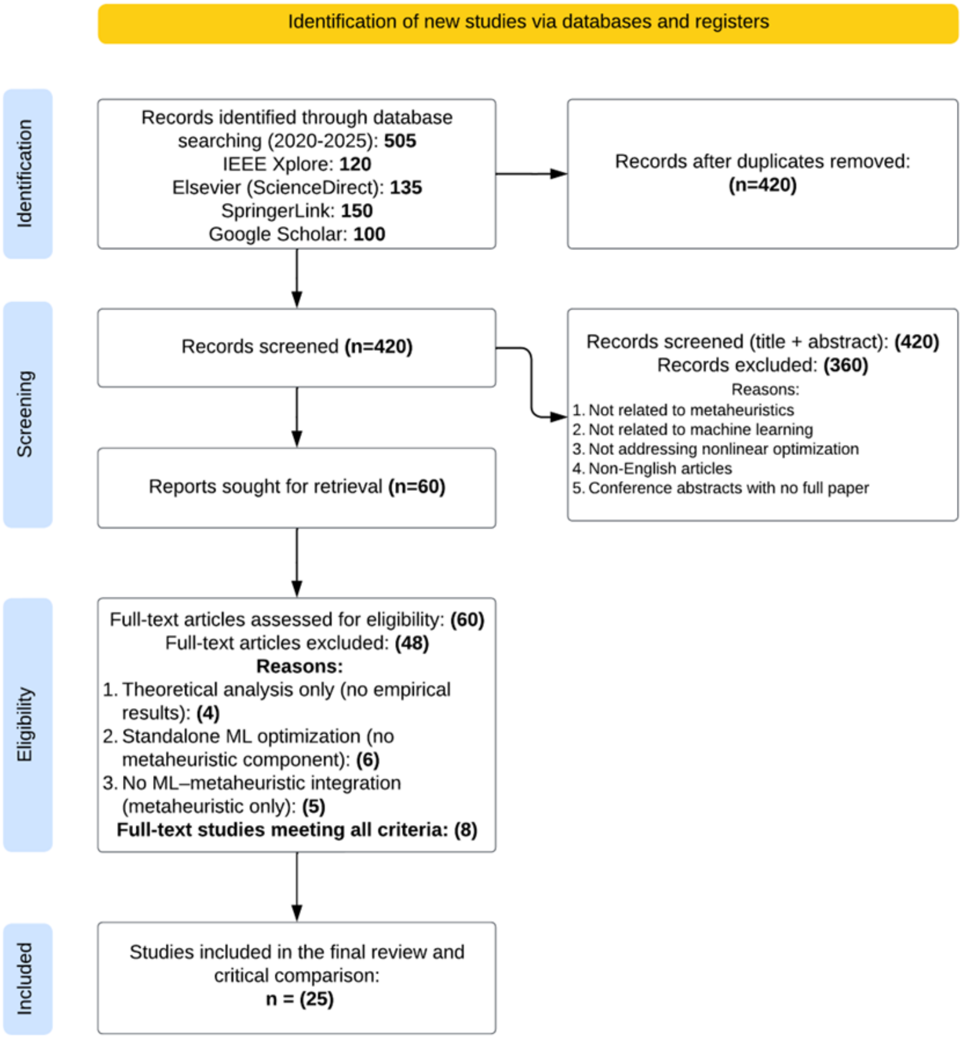

Figure 1. PRISMA Flow Diagram.

3. Literature Review

3.1 Traditional Metaheuristic Algorithms

Classical metaheuristics such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), and Differential Evolution (DE) have been widely applied to nonlinear optimization [11]. They offer a tremendous amount of global searching potential but can be time-consuming and vulnerable to starting parameters [12]. At the same time, they are constrained in high-dimensional or complex searching arenas via premature convergence. Thus, hybrid metaheuristics and adaptive parameter configurations have emerged to combat these deficiencies to offer a more feasible exploration versus exploitation solution without significant computational expenses [13].

3.2 Machine Learning Foundations in Optimization

Machine learning penetrates optimization through various corresponding methods that contribute to the intelligent and effective workings of metaheuristic searches. For example, supervised learning enables performance modeling and surrogate approximations in prediction that lower evaluation expenditures for complicated objective functions [14]. Unsupervised learning facilitates population organization and diversity maintenance through solution clustering and exploration balance preservation. Thus, operator regulation, parameter tuning, and search strategy adaptation are naturally enhanced through feedback from the optimization environment, which is made possible through reinforcement learning [15]. Deep learning provides complicated fitting mechanisms for nonlinear formulations attempting to shape hidden objectives within high-dimensional searches. Finally, meta-learning concerns learning-to-optimize, in which algorithms learn from previous encounters with different problem instances for more generalizable and adaptive behavior [16].

3.3 ML–Metaheuristic Hybridization Strategies

The literature identifies several key categories for integrating machine learning with metaheuristic optimization. The first is parameter control and adaptation, whereby the ML model controls the parameters of metaheuristics adaptively during the evolution for improved convergence and stabilization [17]. The second is surrogate-assisted optimization, which takes a less expensive objective function to approximate the most expensive one to lessen evaluation costs. The third is learning-based search operators, which facilitate mutation, crossover, or update based on deep learning or reinforcement learning for more intelligent and adaptive searches [18]. The fourth is population structure modeling, which clusters or learns from manifolds to safeguard against diversity and stabilize against stagnation in the search space. The final approach is AutoML-driven optimization, which establishes a mutual coupling whereby metaheuristics can optimize ML architectures and hyperparameters, but also ML methods can optimize depths of the metaheuristics in simultaneous optimization approaches [19], [20].

3.4 Gaps in Existing Research

Yet despite everything, the limitations of the state-of-the-art solutions remain. For example, without benchmark requirements, hybrid solutions are often subjectively compared [21]. Not much research explores the scalability of these solutions; many studies fail to investigate performance results for dimensional problems or large-scale non-linear investigations [22]. Additionally, most hybrid solutions are not supported by rigorous theoretical research for proven results concerning convergence, stability, and generalization. [23] This applies to practical application as well; few solutions to real-world problems employ industrial datasets, meaning that most solutions here are not applicable outside experimental labs and controlled settings. There is also an empirical lack of applicability by means of academic studies with limited benchmarks that could add to what's reported [24], [25].

3. Results

Contributions

This review provides key contributions:

1. A classified taxonomy of ML-based metaheuristic methods for nonlinear problems.
2. An exhaustive survey of hybridization, benchmarking strategies, and experimental results.
3. A comparative matrix of pros, cons, computational costs, and fields of application of these algorithms.
4. Identified research opportunities relative to explainability, extensibility, stability, and generalization.
5. Stipulated future research opportunities with implications and avenues of application like meta-RL, explainable optimization, and generative surrogate models.

Critical Review

Table 1 provides a relative assessment of recent contributions to the literature on machine-learning-based metaheuristic optimization for nonlinear applications. Therefore, the relative contributions are assessed based on the author, approach type, dataset type, improvement, and shortcomings, creating a top-down relative assessment of contributions that champion different hybridization methods. Ultimately, the literature review supports this cause because the findings of ML-based metaheuristics increase the convergence speed, solution quality, and computational efficiency stemming from surrogate modeling, RL-based function/application customizations, clustering, and AutoML parameter fine-tuning. Conversely, the literature review suggests shortcomings that are commonplace between contributions, such as overfitting tendencies from surrogate modeling, limited exploration of scalability, excessive computational requirements in RL-based developments, and minimal exploration in large-scale or real-world datasets. This relative assessment not only effectively summarizes the advantages and shortcomings of each approach based on the application in question but also provides a thorough connection between the systematic literature review and discussion for identifying gaps that inform future research.

Table 1. Critical Review of ML–Enhanced Metaheuristic Optimization Studies.

	Author/s	Method	Dataset	Accuracy	Limitations
[2]	Akgul et al. (2024)	Surrogate-assisted Differential Evolution	High-dimensional engineering design benchmarks	Improved convergence speed by 25-40% over classical DE	Surrogate models degrade in noisy environments; no scalability evaluation
[9]	Szénási & Légrádi (2024)	ML-guided PSO with adaptive parameter control	Nonlinear multimodal mathematical test functions	Achieved higher global optimum accuracy on 80% of benchmarks	Limited real-world validation; requires heavy parameter tuning
[14]	Urkude et al. (2024)	Clustering-assisted GA + supervised surrogate modeling	Structural and mechanical optimization datasets	Reduced computational cost by 50%; solution accuracy comparable to traditional GA	Overfitting risk in surrogate models; lacks robustness testing
[18]	Akinola et al. (2022)	Reinforcement-learning-driven evolutionary operators	Nonlinear constrained optimization test suite	RL operators improved search stability and diversity	High computational overhead: training requires large data
[19]	Mandour et al. (2024)	Hybrid PSO-AutoML framework	Energy forecasting and	Enhanced predictive accuracy and reduced	Needs generalized benchmarking; algorithm

			scheduling datasets	model training time	complexity is high
[20]	Lee et al. (2024)	AutoML-enhanced metaheuristic hyperparameter optimization	ML model architecture optimization (vision tasks)	10–15% improvement in ML model accuracy over baseline	Domain-specific method; limited demonstration on traditional nonlinear problems
[24]	Bahameish et al. (2024)	Deep-learning-guided genetic algorithm	Real-world logistics and routing datasets	Significant improvement in global search performance	Requires large training data; model explainability not addressed
[25]	Kiakojouri & Wang (2025)	Adaptive metaheuristic tuning via meta-learning	Synthetic nonlinear optimization tasks	Faster convergence across multiple problem types	Limited verification on high-dimensional real datasets

4. Discussions

The insights drawn from the approaches under review suggest that performance improvements from machine learning-based metaheuristic optimization for nonlinear problems are significant. Most hybrids operate with improved convergence, solution quality, and computational costs across the board, particularly in consideration of expensive and/or black-box objectives. Surrogate approaches work well on engineering/energy problems through expensive approximation evaluations, while RL methods outperform adjusted operators in dynamic settings where stagnation is undesirable. The power to use deep learning allows for nonlinear aspects to be determined to assist in directing the solution path for effective exploitation of good solutions in complex landscapes. Moreover, population structuring solutions, like clustering, help in sustaining diversity and limiting local optima.

Yet gaps remain, and limitations exist. Many new contributions have complex algorithmic development that achieves better performances but are not repeatable or deployable in practical settings. There is a significant lack of large-scale testing with few applications for the generated models on large-scale or industrial nonlinear datasets. Existing benchmarks to assess hybrid performance are small, proprietary, or academic, and none of them are generalizable. Most hybrid algorithms also do not come with theoretical convergence assurance, which weakens their merit in more sensitive areas of engineering design, energy systems, and healthcare applications. Finally, where hybridization opens up performances to machine learning, it also exposes performance detractors like surrogate model overfitting, RL training errors, and increased computational times, all of which would benefit from an engineered hybrid approach for feasible interpretation and viability.

5. Conclusion

Machine learning-inspired metaheuristic optimization is a versatile, innovative, and emerging nonlinear problem-solving method for fields such as engineering, computational intelligence, and industry that suggests collaborative opportunities in the future. The use of supervised learning, unsupervised clustering, reinforcement learning, deep learning, and even meta-learning has boosted performance expectations and realized adaptive, data-driven, and computationally efficient search solutions. As indicated by the findings of the literature review, performance improvements can be cited regarding convergence speed, solution quality, and solution quality stability for, in particular, expensive or multimodal optimization problems.

However, significant gaps exist before industrialized application can be supported. The fields exist in an immature, fragmented state relative to common benchmarks and derived performance metrics, which reduces the generalizability and assessed performance within this review across studies relative to hybrids. Furthermore, a theoretical application guarantee is an infrequent feat in the space, compounded by a lack of industrial-sized datasets, which renders the hybridization effort less applicable on a general scale. Future work should attempt to aggregate performance measure assessments.

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