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REVIEW ARTICLE

Exploring Optimization Algorithms: A Review of Methods and Applications

Abdulrahman Abdullah Farag[1,*] **Ziad Mohammed Ali**[1] **Ahmed Mohamed Zaki**[2]
Faris H. Rizk[2] **Marwa M. Eid**[3] **EL-Sayed M. EL-Kenawy**[1]

[1] Department of Communications and Electronics, Delta Higher Institute of Engineering and Technology (DHIET), Mansoura 35111, Egypt

[2] Computer Science and Intelligent Systems Research Center, Blacksburg 24060, Virginia, USA

[3] Faculty of Artificial Intelligence, Delta University for Science and Technology, Mansoura 35111, Egypt

Emails: CH2100197@dhiet.edu.eg; CH2100056@dhiet.edu.eg; azaki@jcsis.org; farisrizk@jcsis.org; mmm@ieee.org; skenawy@ieee.org

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ABSTRACT

This review focuses on feature selection as an important parameter in tuning machine-learning models. It surveys optimization algorithms including Moth-Flame Optimization (MFO), the hybrid GA–GSA algorithm, Seagull Optimization Algorithm (SOA), Whale Optimization Algorithm (WOA), Grasshopper Optimization Algorithm (GOA), Henry Gas Solubility Optimization (HGSO), and safety-constrained Bayesian optimization. These algorithms are used in engineering design, power-system scheduling, and other application areas. The review emphasizes optimization's role in improving efficiency, reducing errors, and increasing model interpretability, and examines applications in structural engineering, additive manufacturing, and landslide-susceptibility mapping. A summary table presents the studies, methods, and key findings. The reviewed work demonstrates the adaptability and competitiveness of optimization algorithms across diverse domains and aims to guide researchers and practitioners by describing current approaches and directions for future research.

Keywords: Optimization Algorithms ▪ Metaheuristic Optimization Methods ▪ Deep Learning ▪ Optimization Applications ▪ Machine Learning Models

1. INTRODUCTION

Model optimization is an important task [1, 2, 3], and feature selection plays a major role in achieving both performance and interpretability [4]. This review is a first step toward examining a range of optimization methods and finding approaches to challenging problems across different fields. Metaheuristic methods considered include Moth-Flame Optimization (MFO), Seagull Optimization Algorithm (SOA), Whale Optimization Algorithm (WOA), Grasshopper Optimization Algorithm (GOA), Henry Gas Solubility Optimization (HGSO), and safety-constrained Bayesian optimization.

Feature selection is one of the factors that determines how well machine-learning models perform and how readily their results can be interpreted [5, 6, 7]. As demand grows for machine-learning solutions that work efficiently and are easy to understand, optimization methods become increasingly important. This review examines optimization algorithms designed to address problems specific to different application areas.

MFO has been applied to engineering design, power systems, economic load scheduling, medical imaging, nonlinear optimization, and bio-inspired computing [8, 9, 10, 11, 12].

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The hybrid GA–GSA method combines Genetic Algorithm (GA) and Gravitational Search Algorithm (GSA) approaches to address nonlinear optimization problems with multiple constraints [13, 14, 15, 16, 17, 18]. Among bio-inspired approaches, SOA models seagull behavior and has been tested on standard functions and real-world problems [19, 20, 21, 22]. WOA, inspired by bubble-net hunting, has been adapted for engineering optimization and applied in areas such as image processing, robot path planning, clustering, and classification [23, 24, 25, 26]. The review also considers GOA's flexibility in solving difficult optimization problems, safety-constrained Bayesian optimization for accelerator tuning and robotic locomotion, and applications in engineering design, structural control, additive manufacturing, and landslide-susceptibility mapping [27, 28, 29, 30].

These methods are used in practice as well as in theoretical studies. Their applications range from engineering design, power-system scheduling, and medical imaging to nonlinear optimization and bio-inspired computing. This review examines the algorithms in turn to describe their characteristics and their place in the changing field of optimization for machine learning.

2. LITERATURE REVIEW

Feature selection is instrumental in optimizing machine-learning model performance and interpretability. This review examines algorithms designed to address particular issues in different areas. It provides an in-depth look at MFO and also considers the hybrid GSA–GA approach and the bio-inspired SOA. Other topics include WOA and its applications, the Imperialist Competitive Algorithm in structural engineering, GOA across several domains, HGSO, cellular structures in additive manufacturing, and the selection of suitable tuning parameters for machine-learning algorithms. The methods are considered in terms of their applications and reported findings.

2.1 Review of Optimization Methods

The Moth–Flame Optimization (MFO) method and its principal components are examined comprehensively in [12]. MFO has been applied to optimization problems in engineering design, economic load scheduling, medical imaging, and power and energy systems. The literature discusses the number and types of applications, theoretical analyses, comparisons with other algorithms, and MFO variants and hybrids. These studies describe the current state of MFO, its limitations, and possible directions for further work. Their findings are relevant to applications in health, engineering, data mining, and optimization.

The GA–GSA hybrid algorithm in [31] is designed for nonlinear optimization with multiple constraints. GSA is used to improve initial solutions, after which genetic operators such as mutation, crossover, and selection refine candidate solutions. Benchmark problems with different objectives, constraints, and decision variables are used to evaluate the method. Comparisons with other approaches and statistical tests are reported to assess the results.

The Seagull Optimization Algorithm (SOA) in [32] is a bio-inspired computing method modeled on seagull movement and attack behavior. The behavior is represented mathematically to guide exploration of the search space. SOA was compared with nine established metaheuristics on 44 standard test functions and was also applied to seven real-world problems, including constrained problems. The reported results show its applicability to large and difficult tasks and its potential to work with refinement methods.

The Whale Optimization Algorithm (WOA) was introduced in 2016 and is based on the bubble-net hunting method described in [26]. Different variations and hybrid strategies have since been studied. The algorithm has been used by engineers for classification, robot path planning, clustering, and image processing, among other applications. Engineering optimization forms a substantial part of the reviewed work, which considers WOA's adaptations and performance across different problems.

The optimal active control of structures is considered in [33], which compares metaheuristic optimization algorithms and discusses limitations of the linear quadratic regulator (LQR). The research uses a wavelet-based LQR approach to obtain feedback solutions by combining optimization methods, including the Imperialist Competitive Algorithm and other metaheuristics. The proposed approaches do not require solving Riccati equations to account for excitation effects on the control. The study reports reduced structural responses and control-energy use, illustrating how optimization can improve active structural-control methods.

The Grasshopper Optimization Algorithm (GOA) is used in engineering design, image processing, machine learning, and power-system control [34]. The review surveys its applications, including multi-objective, binary, and chaotic settings. This broad range of uses provides a basis for assessing how GOA can be implemented to address difficult optimization problems.

Henry Gas Solubility Optimization (HGSO) is based on Henry's law, which relates the amount of gas dissolved in a substance to its properties [35]. The method was tested on 47 standard functions, the CEC'17 test set, and three real-world optimization problems. It was compared with established algorithms, including PSO, GSA, CS, GWO, and EHO, and the reported results show competitive performance. Another review compares HGSO with seven well-known algorithms and surveys its use in optimization [36].

Cellular structures made of plates, struts, or small unit cells can provide high strength-to-weight ratios, efficient energy absorption, and reduced material use. Additive manufacturing makes it possible to fabricate complex geometries layer by layer from digital data. The review in [36] covers lattice morphologies, design, and additive manufacturing of cellular structures, along with their properties, challenges, and opportunities. It identifies a need for further research into cellular-structure design, optimization, characterization, and applications, and provides context for researchers and practitioners in the field.

Choosing suitable tuning parameters is essential to the performance of machine-learning algorithms. Bayesian optimization can automate parameter selection, but unsafe settings on real-world systems can lead to failure. Safety-constrained Bayesian optimization addresses this issue by enforcing op-

Table 1. Summary of related works.

Ref.	Focus	Methodology	Key Findings
[12]	MFO	Comprehensive review	The study reviews the Moth–Flame Optimization method and its applications in medical imaging, engineering design, power systems, and economic load scheduling. It surveys MFO studies, use cases, theory, and comparisons with other algorithms, and considers variants and hybrids. It discusses the method's current status, limitations, and future research needs across health, engineering, data mining, and optimization.
[31]	GA–GSA hybrid algorithm	Nonlinear optimization with multiple constraints	The paper presents a GA–GSA hybrid method for complex nonlinear optimization with multiple constraints. Benchmark problems are used to assess the method and compare it with other approaches; statistical tests are used to evaluate the conclusions drawn from the results.
[32]	SOA	Bio-inspired computing algorithm	The Seagull Optimization Algorithm (SOA) models seagull behavior. It was tested on 44 standard functions against nine metaheuristics and applied to seven real-world business problems. The paper reports that SOA is adaptable to large problems with limited choices and can be combined with refinement methods.
[26]	WOA	Whale Optimization Algorithm	The Whale Optimization Algorithm (WOA) is inspired by bubble-net hunting. The review considers its use in image processing, robot path planning, clustering, and classification, and surveys WOA hybridizations, variants, engineering applications, and optimization performance.
[33]	Metaheuristic optimization algorithms	Active control of structures	The study compares metaheuristic methods for active structural control and addresses limitations of the linear quadratic regulator (LQR). A wavelet-based LQR combines optimization methods to find feedback solutions without solving Riccati equations; the reported results reduce structural responses and control-energy use.
[34]	GOA	Grasshopper Optimization Algorithm	The review describes the Grasshopper Optimization Algorithm (GOA) in industrial design, image processing, machine learning, and power-system control. It examines the method's flexibility and simplicity in solving difficult optimization problems.
[35]	HGSO	Henry Gas Solubility Optimization	Based on Henry's law, HGSO was tested on standard functions and real-world optimization problems. The study reports competitive performance on difficult problems and notes that the search process could be examined in greater detail.
[36]	HGSO	Henry Gas Solubility Optimization	This paper reviews Henry Gas Solubility Optimization and compares it with seven established algorithms. It reports that HGSO performs well on complex optimization problems based on the test results.
[30]	Safe Bayesian optimization	Bipedal locomotion control	Bayesian optimization is combined with hybrid zero dynamics to tune a bipedal robot controller. The approach learns controller parameters in simulation, then refines them on the Cassie robot while maintaining gait stability; experiments report smoother walking and lower steady-state tracking error.
[37]	PSO–ANN	Landslide susceptibility mapping	The hybrid PSO–ANN model is evaluated for landslide-susceptibility mapping using data from the Layleh Valley, Iran. Compared with standard ANN, the study reports greater stability. Evaluation uses the coefficient of determination (R^2), root-mean-squared error (RMSE), color intensity ratio (CER), and total order structure.

erational constraints during tuning. In robotics, a method combining Bayesian optimization with hybrid zero dynamics first tunes controller parameters in simulation, then refines them on the Cassie biped while maintaining gait stability; experiments report smoother walking and lower steady-state tracking error [30]. A related safe Bayesian optimization approach has also been evaluated for tuning particle accelerators under machine and step-size constraints [29].

The study in [37] uses a hybrid PSO–ANN model for landslide-susceptibility mapping and addresses limitations of standard ANN models, including long training times and convergence to local minima. Data from the Layleh Valley in Kermanshah, Iran, include 168,970 training samples and 42,243 test samples. Network design, weights, and PSO parameters are adjusted to improve the susceptibility maps. Input factors include slope aspect, elevation, soil type, and distance to roads. The coefficient of determination (R^2) and root-mean-squared error (RMSE) are used to assess ANN and PSO–ANN, while color intensity ratio (CER) and a total order structure are used to rank samples. Comparisons of training and validation results indicate greater stability for PSO–ANN than for the standard ANN model.

This review surveys recent optimization algorithms and their use in different fields. The literature covers metaheuristics such as MFO, GA–GSA, SOA, and WOA, alongside biological algorithms and hybrid models. Research on cellular structures in additive manufacturing addresses their design, optimization, and use, while machine-learning studies emphasize the importance of selecting suitable tuning parameters. Together, these works provide an overview of current methods and a basis for future research in feature selection and optimization.

3. UNDERSTANDING OPTIMIZATION

Optimization is important in many fields because it seeks effective solutions from a set of acceptable alternatives. The process sets objectives and selects a suitable solution under given conditions, with the aim of improving the efficiency and effectiveness of mathematical and computational models. In machine learning, reducing errors and carefully tuning algorithms are important for producing useful results. Identifying essential attributes through feature selection can improve model efficiency and interpretability. Nature-inspired algorithms, including MFO, WOA, and SOA, offer approaches to complex optimization problems.

Optimization is a versatile principle underlying many problem-solving approaches. It is a systematic mathematical and computational process for finding an optimum among available alternatives subject to parameters or constraints. Depending on the context, its objectives include improving efficiency, reducing costs, and attaining better performance. The approach is used in engineering, operations research, economics, machine learning, and logistics. Civil engineers optimize designs for resource-efficient structures, business

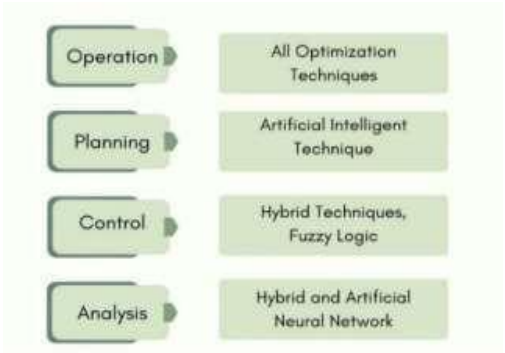


Figure 1. Optimization methods.

managers use optimization in decision-making, economists formulate models, machine-learning systems rely on optimization for training, and logistics applications use optimized route planning. Across these fields, optimization supports important decisions, effective resource allocation, and improved efficiency.

3.1 Optimization Applications

Optimization algorithms are used in many fields and influence how processes are designed and decisions are made. The Imperialist Competitive Algorithm's applications in energy design and control demonstrate the importance of optimization in structural engineering and the development of high-performing structures. Optimization also supports additive manufacturing by guiding the design and production of complex cellular structures with high strength-to-weight ratios, advancing materials science and manufacturing technology. In machine learning and data mining, optimization is used for feature selection and parameter tuning to improve predictive performance and interpretability. Particle Swarm Optimization combined with Artificial Neural Networks (PSO–ANN) and other methods has improved the accuracy of landslide-susceptibility mapping [38, 39, 40], supporting risk assessment and reduction. Safety-constrained Bayesian optimization demonstrates how system parameters can be tuned on particle accelerators and bipedal robots while maintaining operational constraints [29, 30]. These examples illustrate the flexibility of optimization techniques in addressing difficult problems. As technology progresses, optimization is likely to remain important to the development of industry.

Figure 1 shows examples of optimization methods used at different stages of an AI system. Control, research, operation, and artificial-intelligence techniques are among the approaches that can improve system performance. Methods can also improve prediction accuracy and response speed; the appropriate choice depends on the type of AI system and its performance requirements.

3.2 Optimization for Moth–Flame (MFO)

MFO is based on the behavior of moths around a flame and uses this principle to search for improved solutions. It is regarded as a metaheuristic technique applicable to many optimization tasks. The inspiration comes from moths' use of light as a guide: when more attractive lights are present, moths move toward them. MFO has been applied in power systems, medical imaging, engineering design, and economic load scheduling. In engineering design it can help use resources while meeting design requirements, and in load

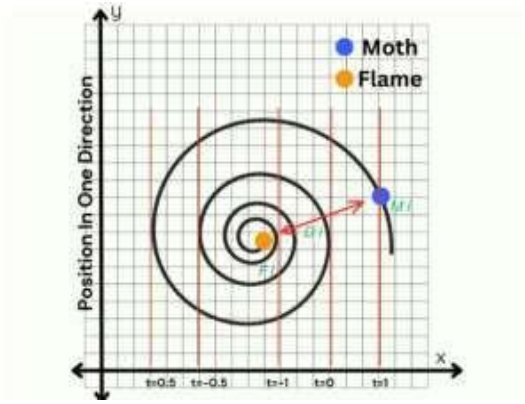


Figure 2. The way in which a butterfly moves across a grid.

scheduling it can support cost-effective energy distribution.

Figure 2 illustrates a moth moving across a grid toward a flame. The figure shows the moth and flame starting at the same point, followed by the moth's movement while the flame remains stationary. Successive time marks indicate the moth's winding path and the flame's position.

Considering MFO alongside other optimization methods makes it possible to compare their advantages and limitations and to assess whether combinations with other processes can improve performance. The literature describes the current state of MFO and identifies areas where further work may be useful. Researchers can build on the challenges and applications already reported and explore new combinations of methods. MFO is used in technical and scientific areas, and continued research can clarify its performance and identify ways to address difficult problems.

4. CONCLUSION

Optimization algorithms are used across diverse fields and influence how decisions are made and tasks are accomplished. Applications of the Imperialist Competitive Algorithm in energy design and control demonstrate the importance of optimization in developing high-performing structures. Additive manufacturing benefits from methods that guide the design and production of complex cellular structures, advancing materials science and manufacturing technology. In machine learning and data mining, optimization plays a central role in feature selection and parameter tuning, improving predictive performance and interpretability. Integrating methods such as PSO–ANN improves accuracy in earth sciences, particularly in landslide-susceptibility mapping, and supports risk assessment and reduction.

The studies reviewed here illustrate the versatility of optimization techniques for complex problems across different domains. Feature selection is an important part of optimizing machine-learning models and contributes to their performance and interpretability. The algorithms discussed, from Moth–Flame Optimization to Particle Swarm Optimization with artificial neural networks, provide insight into their strengths, applications, and comparative evaluation. This synthesis aims to guide researchers and practitioners, describe current approaches, and lay the groundwork for future developments in optimization.

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