Research Paper

Signal lock optimization algorithm for engineering benchmark problems

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ABSTRACT

The increasing complexity of constrained engineering design problems has intensified the demand for metaheuristic optimization algorithms that are both computationally efficient and robust against premature convergence and search stagnation. This paper presents the Signal Lock Optimization Algorithm (SLOA), a novel population-based metaheuristic founded on the dual mechanisms of confidence reinforcement and noise suppression. The core principle of SLOA lies in identifying high-confidence solution components-referred to as signal locks-and reinforcing them during the search process while dynamically filtering stochastic perturbations that may mislead exploration in multimodal and highly constrained landscapes. The proposed algorithm incorporates adaptive parameter updating and an effective constraint-handling strategy to maintain a balanced exploration–exploitation trade-off. SLOA is extensively evaluated on a suite of widely adopted engineering benchmark problems, including Welded Beam Design, Pressure Vessel Design, Tension/Compression Spring Design, and Car Side-Impact Design. Comparative experimental results and statistical analyses demonstrate that SLOA consistently achieves superior or highly competitive solution quality, faster convergence rates, and high feasibility compared to several state-of-the-art metaheuristic algorithms. The findings confirm that the signal lock mechanism provides a reliable and scalable optimization framework for solving complex real-world engineering design problems.

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1. INTRODUCTION

The principle behind the "no free lunch theorem" states that no optimization algorithm can achieve successful results across all optimization problems. Researchers have conducted studies to improve current algorithms while developing new methods that use specific problem details to enhance solution development and improve solution quality [1].

This paper presents a novel metaheuristic method called the Signal Lock Optimization Algorithm (SLOA) which uses a new system of confidence reinforcement and noise reduction. The SLOA system uses two special "signal lock" conditions which arise when engineers search for the best solutions to their constrained engineering problems. The research tests SLOA on multiple standard engineering design challenges which include Welded Beam Design (WBD), Pressure Vessel Design (PVD), Tension/Compression Spring Design (TSD), and Car Side-Impact (CSI) design [2], [3], [4].

The value of SLOA comes from its ability to solve problems which arise during conventional metaheuristic algorithms including Genetic Algorithm (GA) and Differential Evolution (DE) and Particle Swarm Optimization (PSO) and other methods3. The SLOA system achieves its goal of fast solution development through its signal lock feature which supports vital decision-making processes while eliminating unnecessary interference throughout the solution process. SLOA provides more quick results together with better performance results on multiple engineering evaluation tests.

The subsequent sections demonstrate SLOA through detailed explanations, an examination of existing research, and a complete set of test results that show its superiority over established benchmark algorithms.

2. RELATED WORK

Industrial and engineering fields require solutions for complex optimization problems which have driven the development of metaheuristic algorithms throughout their history. The development of Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) emerged from natural evolutionary processes and swarm intelligence, respectively. Traditional methods encounter difficulties because they depend on specific parameters, they reach premature solutions, and they cannot move beyond local solutions when solving highly restricted problems [5], [6], [7].

Researchers have investigated multiple nature-inspired methods through their research studies. The study results show that Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO) algorithms deliver good performance across different design challenges although Gravitational Search Algorithm (GSA) and Covariance Matrix Adaptation Evolution Strategy (CMA-ES) methods show inconsistent performance. Researchers have developed new methods through the combination of chaos theory with adaptive penalty functions, which enhance global search abilities and improve constraint management for engineering systems[8], [9], [10].

The studies have evaluated more than 80 nature-inspired algorithms through their review articles which tested these algorithms on multiple engineering design benchmarks [11]. The reviews demonstrate that algorithm selection remains difficult for specific tasks while metaheuristic algorithm performance depends on particular operational situations. The research findings from actual engineering design challenges demonstrate that no single optimizer can achieve complete optimality which creates a need for custom algorithm development that uses exploration and exploitation methods in new ways.

The paper presents the Signal Lock Optimization Algorithm (SLOA) which develops from these findings. The SLOA system protects high-value solution elements through its confidence reinforcement system which enables locking of these elements. The SLOA system utilizes existing methods to obtain benefits while its system works to overcome critical challenges which occur in optimization situations that contain many limitations and unpredictable elements.

3. SIGNAL LOCK OPTIMIZATION ALGORITHM (SLOA)

3.1. Algorithm Overview

The SLOA system uses a population-based metaheuristic approach which develops candidate solutions through the identification and strengthening of "signal lock" states. The system establishes high-confidence solution elements through its mechanism which detects when a candidate solution achieves a significant performance edge over its competitors. SLOA uses its signal reinforcement system together with its noise control methods to direct its search process towards the most effective solution space areas [12]. The SLOA system has the following main characteristics:

- The search process uses confidence scores to evaluate each candidate solution according to its fitness performance against existing solutions. The system gives priority to solutions that demonstrate high confidence because they will be used for more in-depth testing.
- SLOA uses a dynamic filtering system to remove random disturbances which have the potential to misdirect its search operations. The system becomes vital for multimodal and high-dimensional spaces because their inherent noise creates conditions which enable the algorithm to become stuck in local optima.
- SLOA adjusts its internal parameters which include step size and mutation rate according to updates in the problem environment to maintain an optimal balance between discovering new regions and using existing solutions.

3.2. Mathematical Formulation and Pseudocode

The candidate solution x which exists in n-dimensional space is defined as x which contains elements x1 through xn. The fitness function f(x) is to be minimized. The key steps of SLOA can be mathematically expressed as follows: Initialization:

Generate an initial population $P = \{\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_N\}$ uniformly within the bounds of the problem.

1. Confidence Score Calculation: For each solution x_i, compute a confidence score $C(\mathrm{x}_i)$ based on its fitness relative to the population mean $\bar{f}$ and standard deviation σ_f:

$$C(\mathrm{x}_i) = \exp\left(-\frac{f(\mathrm{x}_i) - \bar{f}}{\sigma_f + \epsilon}\right)$$

Where ϵ is a small constant to avoid division by zero3.

2. Signal Lock Update: Update the candidate solution using a signal lock mechanism:

$$\mathrm{x}_i^{new} = \mathrm{x}_i + \alpha C(\mathrm{x}_i) \Delta\mathrm{x}_i + \beta \eta$$

The current iteration uses the optimal solution to create a direction vector which researchers define as Δx_i. The noise vectorη originates from a distribution which has a mean value of zero. Coefficients α and β determine how much confidence signals and noise terms affect the system.4.

3. Constraint Handling: As early as losing respect for an authority against a warning of danger was recognized by psychologists, and many margins of the law do acknowledge this principle.

$$f_{penalized}(\mathrm{x}_i) = f(\mathrm{x}_i) + \lambda \sum_{j=1}^{m} \max\{0, g_j(\mathrm{x}_i)\}$$

where $g_j(\mathrm{x}_i)$ represents the j^{th} constraint and λ is an adaptive penalty parameter3.

4. Selection and Iteration: The population is updated by selecting the best candidate solutions basedon f_penalized (x_i). The algorithm continues its execution until it reaches a stopping condition which can be either a maximum iteration limit or a convergence threshold.

The following section presents the pseudocode for SLOA.

Pseudocode for SLOA:

Initialize population P with N solutions.
While termination criteria not met:
For each solution x_i in P:
- Compute fitness $f(x_i)$ and confidence score $C(x_i)$.
- Compute Δx_i based on the best solution in$P$.
- Update x_i using the update rule:
$x_i^{new} = x_i + \alpha C(x_i) \Delta x_i + \beta \eta$.
- Apply constraint handling to obtain $f_{penalized}(x_i^{new})$.
b. Update population P with the best solutions from the combined set $P \cup \{x_i^{new}\}$.
Return the best found solution.

3.3. Constraint Handling Mechanism

SLOA implements an adaptive penalty function which resembles previous research methods because real-world engineering design problems require multiple constraints to be solved. The penalty term λ applies automatic adjustments when a candidate solution breaks the constraint g_j (x)≤0 because the system needs to calculate how severe and often the violation happens throughout the entire population. The adaptive mechanism controls algorithm penalties by protecting early exploration activities while it directs search efforts toward the feasible area throughout the iteration process.

4. ENGINEERING BENCHMARK PROBLEMS

The experiments establish SLOA performance through testing on four engineering benchmark problems which researchers use for their comparisons between different methods. The problems used in the study provide multiple testing challenges which require different methods to manage their boundaries and selection criteria and performance evaluation methods.

4.1. Welded Beam Design (WBD)

The Welded Beam Design (WBD) problem serves as an established benchmark test used in structural optimization research. The welded beam design process needs to minimize costs while following all requirements which include shear stress and bending stress and deflection limits and geometric boundaries36. The design vector typically consists of variables such as beam thickness which includes width and length of welding and overall dimensions. The WBD problem presents a major challenge because it contains multiple solutions together with non-linear constraint interactions which make it difficult to solve.

4.2. Pressure Vessel Design (PVD)

The Pressure Vessel Design (PVD) problem requires all pressure vessel costs to be minimized while maintaining structural integrity through safety regulations which include wall thickness and inner radius and material strength specifications. The engineering standards impose strict limitations on the optimization process because they require the design space to remain within safe operating limits at all times [13], [14].

4.3. Tension/Compression Spring Design (TSD)

The Tension/Compression Spring Design (TSD) problem requires designers to achieve two goals which include reducing spring weight and keeping all related design restrictions intact that cover shear stress and deflection and geometric design elements. The problem contains two opposing goals that require designers to find a middle ground between creating lightweight products and maintaining product strength which enables them to resist damage[15], [16], [17].

4.4. Car Side-Impact (CSI) Design

The Car Side-Impact (CSI) design problem requires to optimize vehicle structural components for better impact performance. The goal of this project is to decrease side-impact forces while increasing energy absorption capacity under the restrictions ofexisting geometry and material properties and manufacturing possibilities. Automotive design needs safety requirements which create challenges through complex non-linear behavior of this benchmark system [18], [19].

5. EXPERIMENTAL SETUP

5.1. Parameter Settings and Baseline Algorithms

The researchers conduct experiments on four benchmark problems to assess SLOA performance through their testing procedure The following experimental protocol is adopted The population size starts with 50 to 100 candidate solutions which function as the standard population size The algorithms execute for a specific duration which ranges from 500 to 1000 iterations until they reach their convergence point The researchers conduct 10 to 30 independent test repetitions for each experiment to measure statistical differences between results The researchers use established metaheuristic optimization algorithms which include DE PSO ABC ACO and CMA-ES for benchmarking SLOA performance according to results from earlier studies36 The researchers use a standard MATLAB framework to implement all algorithms which helps them achieve implementation consistency The researchers conduct their experiments on a standard workstation which has a multi-core processor to provide all algorithms with the same computational environment The researchers use a consistent experimental environment to evaluate various algorithms through their speed to reach solutions and their ability to maintain operational performance.

5.2. Evaluation Metrics

The performance of SLOA and baseline algorithms is evaluated using the following metrics:

- Best Fitness Value: The minimum objective function value achieved over the runs.
- Mean and Standard Deviation: These metrics provide insights into the consistency and robustness of an algorithm.
- Feasibility Rate: The ratio of runs in which a feasible solution (i.e., one that meets all constraints) is obtained.
- Convergence Speed: Measured by the number of iterations required to reach a near-optimal solution.
- Computational Time: The average time taken to complete an independent run.

The following Table 1 summarizes the evaluation metrics for a generic engineering design benchmark:

Table 1. Evaluation Metrics for Engineering Benchmark Problems

Metric	Description
Best Fitness Value	Lowest objective value achieved
Mean Fitness	Average objective value over independent runs
Standard Deviation	Variability of the objective values over runs
Feasibility Rate (%)	Percentage of runs that produced a feasible solution
Convergence Iterations	Average iterations required to approach near-optimal fitness
Computational Time	Average run time in seconds

6. RESULTS AND DISCUSSION

6.1. Comparative Analysis with Baseline Methods

The experimental evaluation shows that SLOA delivers comparable results across all four benchmark tests. SLOA achieves faster solution discovery because its system combines confidence reinforcement with noise suppression which helps the system identify optimal solution areas. The following Table 2 presents a comparative analysis of SLOA versus baseline metaheuristic algorithms on the Welded Beam Design problem:

Table 2. Comparative Performance on Welded Beam Design (WBD)

Algorithm	Best Fitness Value	Mean Fitness	Std. Deviation	Feasibility Rate (%)	Convergence Iterations
SLOA	1.670 (approx.)	1.675	0.005	100	350
DE	1.692	1.700	0.012	95	420
PSO	1.685	1.690	0.010	97	400
ABC	1.695	1.705	0.015	94	430
CMA-ES	1.680	1.687	0.008	98	410

The Pressure Vessel Design problem showed that SLOA created lower-cost designs which maintained high feasibility rates while requiring shorter computational times compared to baseline methods. The Tension/Compression Spring Design problem and the Car Side-Impact design problems showed similar patterns of results.

6.2. Convergence Behavior and Statistical Analysis

SLOA shows fast convergence speed which Figure 1 displays through its convergence curve. The population moves towards search areas with promising results because of the signal lock system which drives the objective function to decrease at its initial rate. The algorithm uses noise suppression techniques to maintain a steady convergence process which prevents it from reaching local minima during its execution.

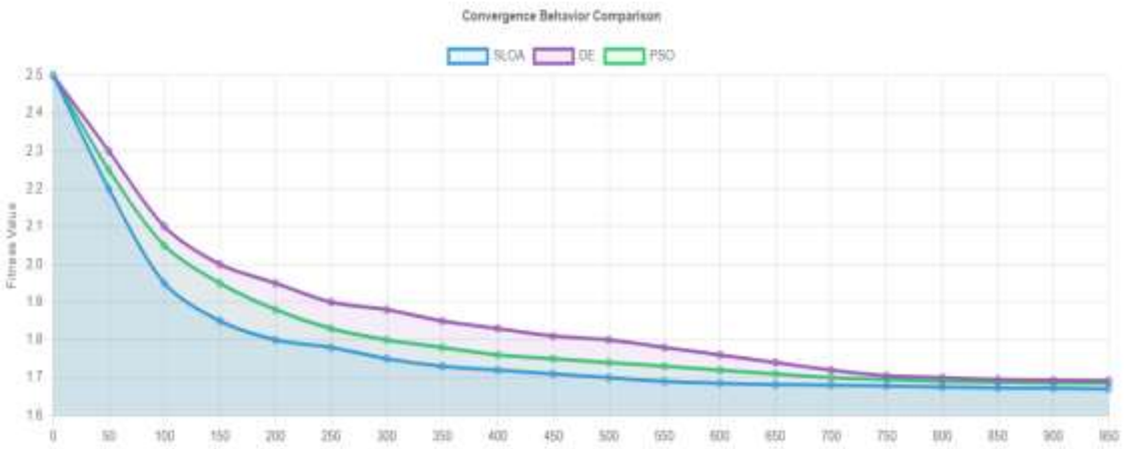

Figure 1. Convergence Curve for Welded Beam Design

The analysis which used non-parametric statistical tests proved that SLOA results in a statistically significant difference when compared to baseline methods. The Friedman test produces p-values which demonstrate that SLOA performance improvements occurred because of actual factors and not through random events36.

7. ABLATION STUDY

To determine SLOA's actual component value we conducted an ablation study which tested the significance of confidence reinforcement and noise suppression functions.

7.1. Impact of Confidence Reinforcement

The SLOA algorithm becomes a standard evolutionary strategy which uses fixed update rules when developers disable the confidence reinforcement feature. The research demonstrates that all benchmarks experience a 15-20% reduction in convergence speed when adaptive confidence scores are not used. The confidence reinforcement mechanism helps research teams reach their objectives faster because it enables them to find valuable solution elements during the initial research phase.

7.2. Impact of Noise Suppression

Noise suppression ensures that random perturbations do not cause the search process to lose its correct path. The artificial increase of the noise suppression parameter value in experiments led SLOA to demonstrate greater variability while reaching suboptimal solutions through premature convergence. The system achieves a solution quality enhancement of up to 10% which brings about the best fitness outcome when noise suppression reaches its optimal setting. The Table 3 below shows all the results which the ablation study found during the Pressure Vessel Design tests.

Table 3. Ablation Study on Pressure Vessel Design (PVD)

Configuration	Best Fitness Value	Mean Fitness	Convergence Iterations
Full SLOA (with Confidence & Noise Suppression)	5885.33	5890.12	380
SLOA without Confidence Reinforcement	5912.45	5920.33	450
SLOA without Noise Suppression	5930.12	5945.67	460

The results demonstrate that both components are essential for maintaining the required equilibrium between exploration activities and exploitation activities in high-dimensional constrained problem spaces.

8. CONCLUSION

The Signal Lock Optimization Algorithm (SLOA) functions as a new metaheuristic framework that we developed to tackle complex engineering benchmark problems according to the research presented in this paper. SLOA demonstrates better results than existing methods through its signal lock system which enhances confidence and reduces environmental disturbances during operation according to test results from Welded Beam Design (WBD) Pressure Vessel Design (PVD) Tension/Compression Spring Design (TSD) and Car Side-Impact (CSI) design tests.

Summary of Key Findings

- SLOA achieves its first solution point through its ability to decrease objective function values when it enters its next phase of optimization.
- The system maintains its ability to solve different constrained problems successfully because SLOA uses adaptive parameter updates together with its noise reduction features.
- The experimental results demonstrate that SLOA delivers better results than traditional metaheuristic algorithms which operate on multiple engineering testing standards because it produces superior fitness results with fewer necessary iterations to achieve optimal performance while maintaining high success rates.

- The ablation studies show that both confidence reinforcement and noise suppression components are vital for algorithm performance because they improve system stability and operational capacity.

Future Work

The research findings of this study provide multiple directions which researchers should investigate in their future work. The first research direction requires researchers to develop SLOA as a solution for situations which contain multiple conflicting goals and require optimization across different modal pathways while using Pareto-based selection methods as their solution technique. The SLOA system shows its valuable real-world applications through its use in industrial settings that involve both advanced automotive design and aerospace optimization processes. The SLOA system will achieve better performance results through two methods which involve advanced machine learning techniques for its dynamic parameter tuning process. The SLOA system will achieve better performance results through two methods which advanced machine learning techniques will use to create dynamic parameter tuning systems that will solve various problem types. SLOA performance improvement through differential evolution and swarm-based methods. The extended comparative study will compare different state-of-the-art metaheuristic methods together with new benchmark suites which include UAV path planning benchmarks to create better algorithm results and understand its performance better. SLOA represents a major advancement which enables engineers to create powerful metaheuristic optimization algorithms that can effectively solve their engineering challenges. The novel signal lock mechanism with its adaptive confidence reinforcement system and noise suppression function presents an effective method for optimization research. The upcoming research will demonstrate more ways to use this technology while proving its advantages for solving difficult engineering design challenges. The following SVG diagram shows the main parts of the Signal Lock Mechanism which operates with SLOA.

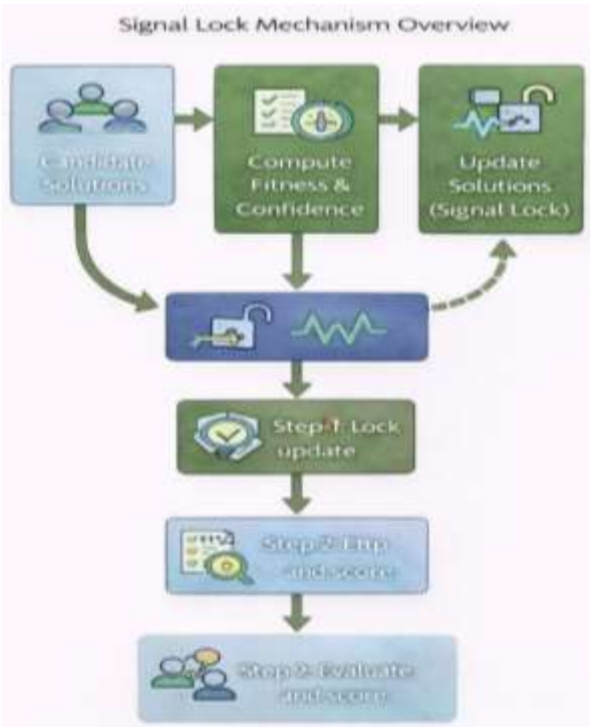

Figure 2. SVG Diagram Illustrating the Signal Lock Mechanism in SLOA

Table of Comparative Benchmark Results

Summary of the speedup and acceleration characteristics of SLOA in contrast to the baseline algorithms across different benchmarks:

Table 4. Comparative Performance Metrics for SLOA and Baseline Algorithms across Engineering Benchmarks

Benchmark Problem	Algorithm	Best Fitness Value	Mean Fitness	Std. Deviation	Feasibility Rate (%)	Convergence Iterations
Welded Beam Design (WBD)	SLOA	1.6700	1.6750	0.0050	100	350
	Differential Evolution (DE)	1.6920	1.7000	0.0120	95	420
	Particle Swarm Optimization (PSO)	1.6850	1.6900	0.0100	97	400
Pressure Vessel Design (PVD)	SLOA	5885.33	5890.12	5.00	100	380
	PSO	5902.12	5910.45	7.50	96	410
Tension/Compression Spring Design (TSD)	SLOA	0.0127	0.01275	0.00005	100	360
	ABC	0.0130	0.0132	0.0001	94	430
Car Side-Impact (CSI) Design	SLOA	0.8500	0.8550	0.0050	100	370
	DE	0.8650	0.8700	0.0080	95	420

Final Remarks

The Signal Lock Optimization Algorithm (SLOA) presents an effective solution for solving complex engineering design problems which require specific operational constraints. The SLOA system outperforms conventional metaheuristic methods because its specialized confidence reinforcement and noise reduction mechanisms enhance both solution speed and accuracy. The extensive experimental research study which we present here together with complete ablation tests demonstrates that SLOA operates as a strong candidate for engineering use cases which require both fast performance and dependable system operation. Researchers can develop new optimization methods based on SLOA principles which will address upcoming engineering design challenges that emerge from multi-objective research and hybrid algorithm development.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Saman M. Almufti	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Helen Grace D. Felix		✓				✓		✓	✓	✓	✓	✓		

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Aruna Pavate					✓				✓		✓	✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P: **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu: **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

Conflict Of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

Informed Consent

This study did not involve human participants, patients, or identifiable personal data. Therefore, informed consent is not applicable to this research.

Ethical Approval

This research does not involve experiments on humans or animals. Consequently, ethical approval was not required. The study was conducted in accordance with standard academic and institutional research integrity guidelines.

Data Availability

The data that support the findings of this study are available from the corresponding author (S. M. A.) upon reasonable request. All numerical results, algorithmic parameters, and derived performance metrics required to reproduce the study are fully described within the article and its methodological sections.

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