A COMPREHENSIVE REVIEW OF THE REPTILE SEARCH ALGORITHM: PRINCIPLES, APPLICATIONS, AND FUTURE DIRECTIONS

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DOI: 10.17973/MMSJ.2025_06_2025049

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Metaheuristic optimization methods are extensively employed to address complex real-world problems, but problems like premature convergence and poor search persist. Reptile Search Algorithm (RSA) is a new nature-inspired optimization method founded on the cooperative hunting strategy of crocodiles. This review offers an in-depth examination of RSA, examining its theoretical roots, mathematical modelling, and relative performance compared to established methods such as PSO, GWO, and WOA. The novel encircling and hunting mechanisms of the algorithm provide a balance between exploration and exploitation, increasing global search efficiency. Performance tests on benchmark problems and engineering problems prove RSA's strength, flexibility, and performance in multimodal and high-dimensional problems. In real-world applications, RSA has been effectively applied to machine learning, engineering design, and industrial optimization. RSA indicates promising outcomes but parameter tuning and hybridization with other techniques remain challenging. Future work should target adaptive methods, parallel execution, and domain-specific optimization to make it more applicable in various areas.

KEYWORDS

Reptile Search Algorithm (RSA), Optimization algorithms, Metaheuristics, RSA variants, Encircling and Hunting Mechanisms, Evolutionary Computation, Swarm Intelligence.

1 INTRODUCTION

Optimization is an elemental part of addressing high-dimensional, nonlinear, or multimodal functions-based complex problems in science and engineering. Optimization using traditional gradient-based methods tends to fail when dealing with non-differentiable or discontinuous problems because they use local derivative information [Wolpert 1997]. Metaheuristic algorithms, on the other hand, provide more stable solutions by integrating exploration (global search) and exploitation (local refinement) strategies. These algorithms are able to generate nearly optimal solutions with reduced computational work, which makes them extremely useful in a wide range of fields like artificial intelligence, medicine, and mechanical engineering [Blum 2003].

Among all the different metaheuristic strategies, bio-inspired algorithms have attracted considerable interest since they can mimic problem-solving behaviors from nature. For example, Particle Swarm Optimization (PSO) is based on the social dynamics of flocks of birds [Gad 2022], Ant Colony Optimization (ACO) on pheromone-based ant foraging [Rahman Lingkon 2024], Grey Wolf Optimizer (GWO) on hierarchical hunting strategies [Mirjalili 2014], and Krill Herd Algorithm (KHA) on krill swarm herding behaviors [Gandomi 2012]. Although these algorithms have produced successful outcomes in numerous applications, issues like premature convergence, inadequate exploration-exploitation trade-off, and low convergence rates have necessitated the development of better models.

The Reptile Search Algorithm (RSA) put forward by Laith Abualigah et al. in 2022 [Abualigah 2022] is an example of one such development motivated by crocodile hunting strategies. RSA presents two separate operational stages—encircling (exploration) and hunting (exploitation)—which emulate the strategic and cooperative predatory action of reptiles. Encircling includes surrounding the prey, whereas the hunting stage focuses on energy-effective group attacks via high walking and belly walking mechanisms. This two-phase mechanism aims to break the limitations of previous algorithms by enhancing convergence rate and solution quality and achieving a balance between diversification and intensification.

Notwithstanding the recent success of RSA and continuous improvements with hybrid methods like Quantum RSA, Lévy Flight-improved RSA, and hybrids with other optimization methods [Almotairi 2022a; Huang 2022], its relative performance in comparison to traditional methods is still inadequately studied. Furthermore, the literature presently lacks a comprehensive critical review that systematically evaluates the strengths, limitations, and prospects of RSA in real-time and adaptive contexts. Hence, this research seeks to fill this void by analyzing RSA against PSO, ACO, GWO, and KHA, with a focus on hybridization methods and determining future trends for enhancement. The aim is to present a thorough understanding of the position of RSA in contemporary optimization applications and provide insight into how it can be optimized further for real-world implementation.

2 MECHANICS AND MATHEMATICAL FORMULATION OF THE REPTILE SEARCH ALGORITHM (RSA)

The Reptile Search Algorithm (RSA) models the hunting strategies of crocodiles, which involve encircling prey, coordinated attacks, and cooperative movements [Abualigah 2022]. RSA follows a population-based search approach, iteratively refining solutions to optimize a given objective function. The algorithm consists of two primary phases: exploration and exploitation, each governed by distinct mathematical models.

2.1 *Initialization of RSA*

RSA begins by randomly initializing a population of candidate solutions. Each solution represents a potential answer to the optimization problem, similar to how a group of crocodiles searches for prey. The solutions are generated within predefined search space limits, ensuring diversity in the initial population. The initial positions of the candidate solutions are defined as:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,n} \end{bmatrix} \tag{1}$$

where: X represents the population of N candidate solutions, Each row corresponds to an individual solution in the search space, $X_{i,j}$ represents the j th variable of the i th candidate solution, n is the dimensionality of the optimization problem. Each solution is initialized using:

$$x_{i,j} = LB + rand \times (UB - LB) \tag{2}$$

Where: UB and LB are the upper and lower bounds of the search space, $rand$ is a random number between 0 and 1.

2.2 *Exploration Phase (Encircling the Prey)*

Exploration ensures that the search covers a diverse set of solutions. In RSA, crocodiles initially encircle their prey before attacking, which is mathematically represented using high walking and belly walking strategies. These movements help distribute candidate solutions across the search space, preventing premature convergence.

In high walking strategy, crocodiles raise their bodies and move cautiously toward prey, maintaining a broad search radius. Mathematically, this is expressed as:

$$X_{i,j}(t+1) = Best_j(t) \times (-\eta_{i,j}(t) \times \beta - R_{i,j}(t) \times rand) \tag{3}$$

Where: $Best_j(t)$ is the best-obtained solution at iteration t, $\eta_{i,j}(t)$ is the hunting operator affecting search movement, β is a parameter controlling search accuracy, $R_{i,j}(t)$ reduces the search area over time, $rand$ introduces randomness to maintain diversity.

In belly walking strategy, crocodiles remain closer to the ground, reducing their movement range. This ensures a more localized search within promising regions. The mathematical representation is

$$X_{i,j}(t+1) = Best_j(t) \times X_{r1,j} \times ES(t) \times rand \tag{4}$$

Where: $X_{r1,j}$ is a randomly chosen solution influencing search direction, $ES(t)$ (Evolutionary Sense) is a probability factor adjusting movement magnitude. These exploration strategies allow RSA to efficiently cover the search space, preventing stagnation in local optima.

2.3 *Exploitation Phase (Hunting the Prey)*

Once the best regions are identified, RSA shifts from exploration to exploitation, where crocodiles hunt using coordination and cooperation. These mechanisms refine the solutions, improving convergence toward the global optimum. In hunting and coordination phase, crocodiles coordinate their movements to converge toward the optimal prey location. This is mathematically expressed as:

$$X_{i,j}(t+1) = Best_j(t) \times P_{i,j}(t) \times rand \tag{5}$$

Where: $P_{i,j}(t)$ represents the percentage difference between the best solution and the current solution. $rand$ introduces controlled randomness to avoid premature convergence.

Crocodiles cooperate in groups, attacking prey together to ensure a successful hunt. This phase is modelled as:

$$X_{i,j}(t+1) = Best_j(t) - \eta_{i,j}(t) \times \in - R_{i,j}(t) \times rand \tag{6}$$

Where: $\in$ is a small perturbation factor preventing excessive exploitation, $R_{i,j}(t)$ ensures convergence by gradually reducing movement range. These exploitation mechanisms allow RSA to fine-tune solutions and improve convergence accuracy.

2.4 *Transition Between Exploration and Exploitation*

RSA dynamically switches between exploration (encircling phase) and exploitation (hunting phase) based on iteration progress. The algorithm divides the total iterations T into four phases: High Walking (Exploration): $t \le \frac{T}{4}$, Belly Walking (Exploration): $\frac{T}{4} < t \le \frac{T}{2}$, Hunting Coordination (Exploitation): $\frac{T}{2} < t \le \frac{3T}{4}$, Hunting Cooperation (Exploitation): $t > \frac{3T}{4}$

This adaptive mechanism allows RSA to balance global search (exploration) and local refinement (exploitation), ensuring better optimization performance.

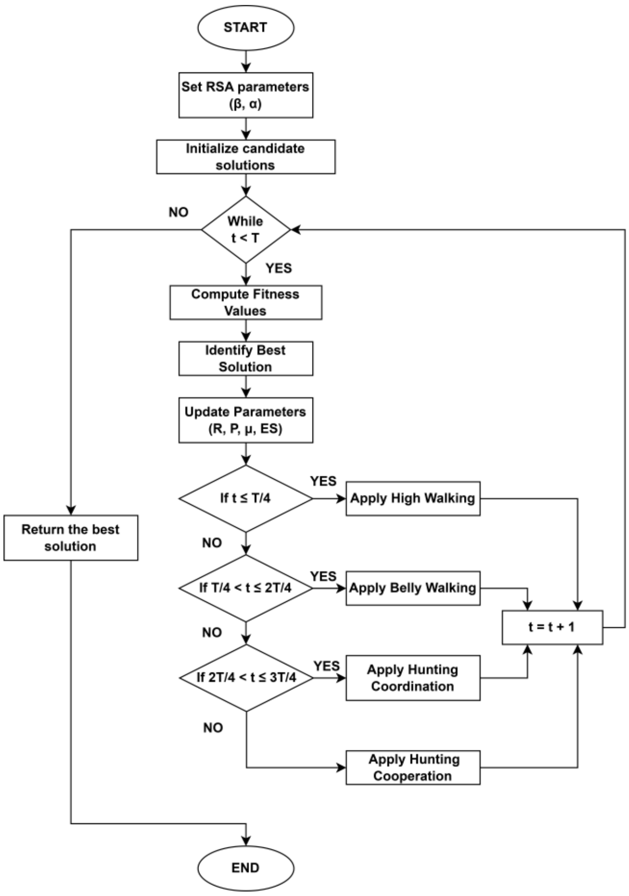

Figure 1 RSA Flowchart

2.5 *Termination Condition*

RSA continues searching until it reaches one of the following stopping criteria: 1. Maximum Iterations Reached: The algorithm stops after a predefined number of iterations T. 2. Convergence Criterion Met: If the difference between the best and worst solutions falls below a threshold. 3. No Significant Improvement: If the best solution remains unchanged for a set number of iterations.

2.6 *Summary of RSA Mechanics*

Initialization: Generate a population of candidate solutions. Exploration: Crocodiles encircle prey using high walking and belly walking. Exploitation: Crocodiles hunt using coordination and cooperation. Adaptive Transition: RSA dynamically shifts between exploration and exploitation. Termination: The algorithm stops based on a stopping criterion. These mechanics allow RSA to efficiently explore search spaces while refining optimal solutions, making it a competitive optimization algorithm. Fig.1 shows the working algorithm flowchart for RSA [Abualigah 2022].

3 RSA COMPARED TO OTHER OPTIMIZATION ALGORITHMS

3.1 *Comparison with Well-Known Algorithms Such as PSO, GWO, WOA, ALO, and KHA*

Metaheuristic algorithms are broadly applied in the solution of hard optimization issues. The Reptile Search Algorithm (RSA) is one newly proposed bio-inspired optimization strategy with better performances compared to those algorithms in various applications. As an assessment to understand its potency, RSA is contrasted against prominent metaheuristic algorithms like Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO), and Krill Herd Algorithm (KHA) [Mirjalili 2015]. From the comparison shown in Tab. 1, it is clear that RSA offers a more organized and cooperative style of hunting behavior with increased convergence rates and flexibility in various scenarios of optimization. [Mehta 2023]

3.2 *Advantages of RSA*

RSA combines biological approaches of crocodile movement and is thus a very adaptive and effective optimization algorithm.

One of the most significant attributes of any optimization algorithm is having a balance between exploration and exploitation [Wolpert 1997]. The balance between exploration and exploitation is provided by the Reptile Search Algorithm (RSA) using two primary methods: encircling, which supports global search, and hunting, which provides greater local search. In contrast to PSO, GWO, and WOA, which are based on random movement or inertia-based updates, RSA can actually oscillate between an exploration-exploitation high-walking strategy and a hunting strategy efficiently. This dynamical adaptation allows RSA to realize a consistent and continuous improvement in optimization performance [Hachemi 2023].

Algorithm	Inspiration	Exploration and Exploitation Mechanism	Strengths	Limitations
PSO	Swarm behavior of birds and fish	Position update based on velocity and personal/global best	Fast convergence in continuous problems	Prone to local optima
GWO	Leadership hierarchy of grey wolves	Alpha, beta, and delta wolves guide the search	Good balance between exploration and exploitation	Struggles with high-dimensional problems
WOA	Bubble-net hunting of whales	Spiral updating position around prey	Strong convergence	May stagnate in local optima
ALO	Random movement of antlions trapping prey	Roulette wheel selection for search intensification	Efficient search mechanism	Slow convergence in large-scale problems
KHA	Movement of krill swarms	Random and directed movement influenced by density	Robust performance in multimodal functions	High computational cost
RSA	Crocodile hunting behavior	Encircling, hunting coordination and cooperation	Strong adaptability, reduced local optima trapping	Requires parameter tuning

Table 1. Comparison of various nature inspired algorithms

Most optimization algorithms, such as Particle Swarm Optimization (PSO) and Ant Lion Optimizer (ALO), tend to be trapped in local optima, which restricts their ability to solve intricate problems [Brahmarapu 2023]. The Reptile Search Algorithm (RSA) addresses this issue by virtue of its hunting coordination and cooperation mechanism, where candidate solutions cooperate and dynamically modify their search directions, thus minimizing the likelihood of premature convergence [Faramarzi 2020]. Furthermore, hybrid RSA models have also proved to improve even more in addressing global optimization issues, improving performance and solution quality [Maashi 2023].

The RSA has been found to be very efficient in solving a broad variety of real-world optimization problems in many fields. In engineering design, it has been used to optimize structures, and in medical image processing, it has been found efficient in MRI segmentation [Abualigah 2023]. RSA has also been used in renewable energy systems for optimal power allocation and in machine learning for hyperparameter tuning of neural networks [Hachemi 2023]. Relative to other algorithms such as the Krill Herd Algorithm (KHA) and Ant Lion Optimizer (ALO), RSA's adaptability across discrete, continuous, and big-scale problems makes it a next-gen optimization technique with tremendous potential.

The RSA attains a good balance between exploration and exploitation through crocodile-hunting-inspired dynamic behavioral modeling. It successfully escapes local optima using cooperative search strategies and exhibits better adaptability on a range of complex optimization problems. RSA has been successfully applied in engineering design, medical imaging, energy systems, and machine learning.

3.3 RSA Limitations

While the Reptile Search Algorithm (RSA) has numerous advantages, there are also some limitations that need to be researched and developed. One of the most important of these challenges is the possibility of premature convergence under certain conditions [Sasmal 2024]. Though RSA optimally trades off exploration and exploitation, it can still end up at a suboptimal solution, especially in extremely complex multimodal search spaces where the Whale Optimization Algorithm (WOA) or Grey Wolf Optimizer (GWO) can outperform it [Zheng 2023]. Another drawback of RSA is its reliance on parameter tuning to work best. The critical parameters including the hunting coefficient η, encircling factor β, and randomness factor R need to be properly adjusted in order to get the best outcome [Reddy 2023]. Adaptive RSA variants were suggested to cope with this shortcoming, yet more work remains to be carried out to advance self-tuning mechanisms that facilitate the robustness and efficiency of the algorithm.

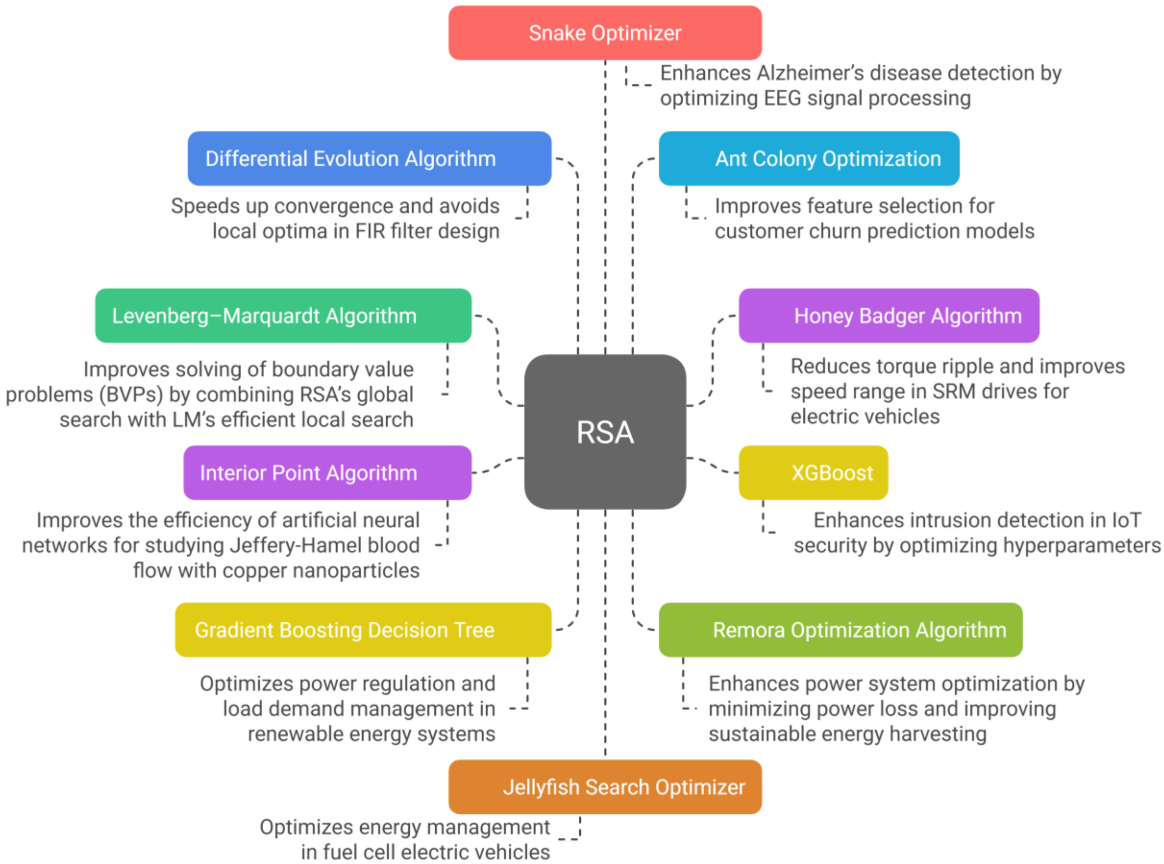

Figure 2. RSA Hybridization and Advantages of Hybridization

4 RSA VARIANTS, ENHANCEMENTS, AND APPLICATIONS ACROSS DIVERSE FIELDS

The RSA has been extensively used to solve optimization problems because of its flexibility and effectiveness. Its performance has been further improved through different enhanced versions and hybrid models that integrate RSA with other optimization methods to tap their combined strengths. A variation of such innovation is the Improved Reptile Search Algorithm (IRSA) that brings into play a mutation technique (MT) and mean transition mechanism in order to keep exploration and exploitation in check and hence proves fruitful in constrained industrial engineering issues [Sonia 2023]. The Hybrid Reptile Search Algorithm (HRSA) merges RSA with Remora Optimization Algorithm (ROA) in order to strengthen it for optimization-related tasks and cluster analysis [Almotairi 2022a].

Another important advancement is the Reptile Search Algorithm with Lévy Flight and Interactive Crossover (LICRSA), which improves convergence precision and iteration efficiency, suitable for engineering optimization issues. The Modified Reptile Search Algorithm (MRSA) involves adaptive chaotic reverse learning and elite alternative aggregation, which is helpful in numerical optimization and robot path planning [Li 2022]. Furthermore, the Quantum Mutation Reptile Search Algorithm (QMRSA) utilizes a quantum mutation search mechanism to optimize performance, and its applications include global optimization and data clustering [Almodfer 2022].

Other developments are the Multi-Learning-Based Reptile Search Algorithm (MLBRSA), which combines Q-learning, competitive learning, and adaptive learning to enhance decision-making, especially for software requirement prioritization [Kailasam 2023]. The Levy Flight-Based Reptile Search Algorithm (L-RSANM) incorporates the Nelder-Mead simplex search to enhance exploitation, making it efficient for power system optimization, such as automatic voltage regulator (AVR) and power system stabilizer (PSS) design. Improved Reptile Search Algorithm by Salp Swarm Algorithm

(RSA-SSA) has been proposed for improving image segmentation performance, especially in medical image processing [Abualigah 2023].

In addition, the Binary Reptile Search Algorithm (BRSA) has been hybridized with LASSO regression for feature selection, which is of significant importance in COVID-19 microarray gene selection [Ervural 2023]. Finally, the Opposition-Based Learning Reptile Search Algorithm with Cauchy Mutation (OBL-RSACM) enhances population diversity and convergence rate, which is useful in photovoltaic model parameter estimation. These varied improvements and hybrid models illustrate the versatility and increasing potential of RSA in solving complex optimization problems in different fields. Fig. 2 shows the advantages of the hybridizations of RSA with other algorithms [Sonia 2023] [Almotairi 2022a] [Almodfer 2022].

4.1 Engineering and Industrial Optimization

Structural design optimization is an important field of engineering where computational methods have a major contribution to making efficient and cost-saving designs. RSA has been widely applied in structural design optimization to optimize weight, strength, and stability [Almotairi 2022b]. One of the most significant uses is in natural frequency constraints, where RSA optimizes the design to maximize vibration performance and material efficiency. Using RSA, engineers are able to effectively balance cost and performance constraints in structural systems [Hassani, 2024].

RSA has shown remarkable improvement in tuning power system and wind turbine PID controllers. RSA optimizes the proportional-integral-derivative (PID) parameters to provide a faster response time, less overshoot, and improved stability for dynamic systems. Research has compared RSA with other traditional tuning approaches and found it to be more efficient in solving complex multi-modal search spaces [Izci 2022].

In smart grids, distributed generation (DG) location is an essential consideration in making energy efficient. RSA helps optimize DG locations while minimizing power loss and improving voltage stability. Furthermore, RSA helps in optimal energy storage system sizing and placement for enhancing power grid resilience.

Major Field of Application	Specific Application	Algorithm Used
Healthcare and Biomedical Engineering	EEG Signal Processing for Brain-Computer Interface (BCI)	RSA + PR-RSA
	Alzheimer’s Disease Detection	RSA + Snake Optimizer
	Parkinson’s Disease Detection	RSA + LSTM
Power Systems and Renewable Energy	Load Frequency Control	RSA + HBA (Honey Badger Algorithm)
	Renewable Energy Optimization	RSA + ROA (Remora Optimization Algorithm)
	Photovoltaic (PV) Optimization	Modified RSA
	Power Grid Voltage Stability	RSA
Cybersecurity and Cryptography	IoT Intrusion Detection	RSA + XGBoost
	Cryptographic Key Optimization	Modified RSA
Industrial and Control Systems	Electric Furnace Temperature Regulation	RSA
	Cloud Task Scheduling	RSA
Machine Learning and Data Science	Feature Selection for Customer Churn Prediction	RSA + ACO (Ant Colony Optimization)
	Sentiment Analysis	RSA + Deep Learning
Image Processing and Computer Vision	Copy-Move Image Forgery Detection	RSA + Deep Transfer Learning
Robotics and Automation	Mobile Robot Navigation	RSA
Wireless Communication and IoT	IoT-Based Node Localization	RSA + LLE (Locally Linear Embedding)
	Wireless Sensor Networks (WSN) Routing	Chaos RSA (CRSA)

Table 2. Summary of Application of RSA and its variants

4.2 Computer Vision and Image Processing

RSA has been utilized in medical image segmentation applications like brain MRI segmentation and breast cancer detection. Utilizing RSA, researchers can improve segmentation accuracy for improved disease diagnosis. The algorithm chooses the optimal features and fine-tunes the segmentation boundaries [Emam 2023].

In image processing, RSA is used to improve image deblurring through optimal restoration filter parameter tuning. This enhances the quality of blurred images due to motion or defocusing, and RSA is thus an effective tool for image deblurring [Dutta 2023].

RSA is used in noisy sonar image segmentation too, in which it is helpful in identifying objects underwater. With its strength to resist noise and optimize parameters in segmentation, RSA is helpful in marine defense and exploration processes [Rajput 2022].

4.3 Machine Learning and Data Science

RSA is critical in machine learning as it optimizes feature selection, resulting in improved classification accuracy. By eliminating irrelevant features, RSA improves the performance of classifiers like support vector machines (SVM) and deep learning models [Abualigah 2023].

Sentiment analysis is facilitated by RSA through feature reduction and hyperparameter tuning. By combining RSA with fuzzy rough set models, sentiment classification has improved accuracy at lower computational complexity [Chaudhry 2023].

RSA facilitates the tuning of hyperparameters for deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs). RSA boosts training efficiency and avoids overfitting, which results in enhanced model generalization [Chavan 2025].

4.4 5.4 Renewable Energy and Smart Grids

RSA is utilized for the optimization of photovoltaic (PV) systems for the maximum output in renewable energy systems. The algorithm provides real-time tracking of the Maximum Power Point (MPP) with a change in environment, hence ensuring better energy efficiency [Navarro 2023].

RSA is used in load frequency control in hybrid power systems to maintain system stability and frequency regulation. RSA keeps frequency deviations to a minimum by dynamically adjusting the control parameters, improving power quality in multi-source energy supplies.

4.5 Medical and Biomedical Applications

RSA has been used in medical diagnosis for diseases like COVID-19 and Alzheimer's. Through optimal feature selection and classification models, RSA improves accuracy of medical imaging and predictive medical models [Manohar 2024].

RSA helps train neural network-based medical prediction models by optimizing their weights and biases. This results in better accuracy in disease prediction, and hence RSA becomes an essential tool in healthcare analytics.
The RSA has undergone different advanced and hybrid models to enhance its performance to solve intricate optimization issues. Advancements like IRSA, HRSA, and QMRSA utilize sophisticated methods like quantum mutation, Lévy flight, and adaptive learning to solve engineering, image processing, and data clustering problems efficaciously. RSA finds extensive use in structural design, power systems, medical image segmentation, and machine learning for applications such as feature selection and hyperparameter optimization. RSA also finds use in renewable energy optimization and smart grid usage by optimizing energy efficiency and system stability. RSA's versatility in general makes it useful in various fields. Tab. 2 shows various applications of Hybrid variants of RSA.

5 RSA CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Reptile Search Algorithm (RSA) has attracted much attention due to its high efficiency in handling complicated optimization issues. Nevertheless, with growing problem sizes and real-time tasks requiring quicker responses, RSA is encountered with numerous challenges. The main limitations of RSA are discussed in this section, along with proposed directions for future research to improve its functionality.

5.1 Large-Scale Optimization Problems

The Reptile Search Algorithm (RSA) has been utilised successfully across a number of engineering and machine learning problems, showcasing its performance and efficiency. Its performance usually degrades when addressing huge-scale problems. In high-dimensional search spaces, RSA is at risk of premature convergence and slow exploration, restricting its optimization ability. One of the primary issues is that classical RSA can have difficulty achieving a good exploration-exploitation trade-off in large search spaces and thus perform worse on complex problems. Furthermore, as problem complexity increases, the computational cost of RSA increases dramatically, which raises efficiency issues [Abu-Hashem 2024].

To tackle these issues, researchers have put forward numerous solutions to boost RSA's efficiency on large-scale optimization. One of them is the creation of multi-objective RSA variants that can deal with large-scale, multi-constraint optimization problems more efficiently. Another solution, which has great potential, is integrating RSA with distributed and parallel computing systems so that it can handle large datasets more efficiently and perform better in scalability. These efforts are looking forward to extending RSA's usability to more challenging real-world problems without compromising its optimization effectiveness.

5.2 Computational Complexity Reduction

One of the major challenges of the Reptile Search Algorithm (RSA) is its computational complexity, especially when used in real-world engineering applications. Because RSA is an iterative algorithm, it consumes a lot of computation time, which makes it less practical for time-critical applications. Moreover, high-dimensional problems tend to have slower convergence rates, which further restricts RSA's applicability in complex optimization problems.
To overcome these challenges, various solutions have been proposed by researchers to improve the efficiency of RSA. One such solution is the implementation of adaptive mechanisms that dynamically change the trade-off between exploration and exploitation during run-time, enhancing search performance. Another useful approach is the hybridization of RSA with surrogate modeling methods like Kriging and Gaussian Process Regression, which reduce the number of function calls and decrease computational costs. In addition, reinforcement learning-based approaches have also been investigated for adaptively shaping RSA's search behavior to enable it to better optimize complicated issues. These new developments are made to make RSA more computationally efficient and also more applicable in a wider range of engineering and optimization problems.

5.3 Hybridization with Deep Learning Models

With the increasing need for artificial intelligence-based optimization, the Reptile Search Algorithm (RSA) has been combined with deep learning models for applications like hyperparameter tuning and feature selection. RSA, however, has some limitations when used in deep learning. One of the significant drawbacks is that typical RSA does not naturally support gradient-based learning, which limits its efficiency in optimizing deep learning models. Also, when used in large neural networks, RSA is computationally expensive, which makes it less feasible for computationally intensive applications.
To overcome these challenges, researchers have attempted various hybrid solutions to make RSA more effective in deep learning. One such solution is to combine RSA with models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers to enhance optimization performance. Another solution is applying RSA for Neural Architecture Search (NAS), which is used to automate the process of designing deep learning models, making it more efficient and less labor-intensive. In addition, RSA has been combined with Generative Adversarial Networks (GANs) for enabling data augmentation and model performance optimization. Such developments are focused on enhancing RSA's flexibility in deep learning applications while increasing computational efficiency and scalability.

5.4 RSA for Real-Time Applications Such as Autonomous Systems and Robotics

The Reptile Search Algorithm (RSA) has been proven effective in real-time use, but its computation needs and response time need enhancement to suit rigid performance specifications. A main limitation is that RSA's iterative mechanism may not match the real-time specifications required by applications like robotics and autonomous vehicle navigation. Also, it is a main limitation that RSA's adoption into dynamically and constantly varying environments is not easy, reducing its practical value in actual contexts.

To resolve these issues, various solutions have been suggested by researchers to improve RSA's real-time performance. One such solution is creating lightweight variants of RSA specifically tailored for quick decision-making with quicker response times. Another potential solution is combining RSA with reinforcement learning methods to facilitate adaptive path planning in autonomous robots, making them more efficient at navigating complex environments. Furthermore, RSA has been integrated with Simulated Annealing (SA) as a process to obtain the process of rapid convergence, thus rendering RSA more preferable for real-time optimization applications. These developments aim at enhancing RSA's flexibility and speed in real-time applications while keeping its optimization quality intact.

5.5 Adaptive Parameter Tuning for RSA Using AI-Based Strategies

One of the major limitations of the Reptile Search Algorithm (RSA) is its sensitivity to manual parameter tuning, which impacts its versatility in various problem domains. RSA's performance is greatly influenced by parameters like step size and exploration factor, which need to be set optimally by an expert. This makes it difficult to use RSA efficiently for a broad range of optimization problems without significant fine-tuning.

In order to surpass this limitation, there have been some proposed solutions for improving RSA's flexibility. One of them is using AI-based adaptive parameter adjustment methods like Bayesian Optimization and Reinforcement Learning to adapt RSA hyperparameters in real-time. Another efficient solution is using self-adaptive methods where RSA parameters adapt dynamically depending on the problem's complexity to be solved. Furthermore, the creation of genetic algorithm-based variants of RSA has been investigated to automatically evolve the best parameter settings without much human intervention. These efforts seek to improve RSA's usability and flexibility on a wide range of optimization problems as well as its overall performance.

The Reptile Search Algorithm has proven to be extremely efficient in solving optimization problems in numerous domains. Nevertheless, its usage in large-scale, real-time, and AI-based environments needs further improvements. Future studies must emphasize the integration of RSA with enhanced computational methods, optimizing RSA for real-time uses, and incorporating adaptive learning techniques to improve its efficiency.

6 CONCLUSION

Reptile Search Algorithm (RSA) has proved to be a potent bio-inspired optimization method with excellent performance in addressing challenging, high-dimensional, and multimodal optimization problems. Drawn from the inspiration of crocodile hunting tactics, RSA balances exploration and exploitation by leveraging its distinctive encircling, hunting coordination, and cooperation methods. Comparison studies against renowned metaheuristic methods like PSO, GWO, and ALO emphasize RSA's flexibility, reliability, and efficacy in a wide range of applications such as engineering, machine learning, medical imaging, and renewable energy systems.

Despite its encouraging performance, RSA is subject to parameter adjustment, premature convergence in some situations, and high computational complexity for large-scale issues. Future research must aim to create adaptive parameter adjustment mechanisms, hybrid models incorporating deep learning, and real-time implementations to boost RSA's effectiveness. The ever-evolving nature of the algorithm through hybridization and modification strategies suggests its capacity to emerge as a top optimization tool for the solution of real-world problems.

ACKNOWLEDGMENTS

This article was co-funded by the European Union under the REFRESH – Research Excellence For Region Sustainability and High-tech Industries project number CZ.10.03.01/00/22_003/0000048 via the Operational Programme Just Transition and has been done in connection with project Students Grant Competition SP2025/062 “Specific research on progressive and sustainable production technologies” financed by the Ministry of Education, Youth and Sports and Faculty of Mechanical Engineering VŠB-TUO.

REFERENCES

[Abualigah 2022] Abualigah, L., et al. Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer. Expert Systems with Applications, 2022, 191, 9574174. https://doi.org/10.1016/j.eswa.2021.116158

[Abualigah 2023] Abualigah, L., et al. Improved Reptile Search Algorithm by Salp Swarm Algorithm for Medical Image Segmentation. Journal of Bionic Engineering, 2023, 20, 4, pp 1766–1790. https://doi.org/10.1007/s42235-023-00332-2

[Abu-Hashem 2025] Abu-Hashem, M. A., et al. Integrated Local Search Technique With Reptile Search Algorithm for Solving Large-Scale Bound Constrained Global Optimization Problems. Optimal Control Applications and Methods, 2025, Vol.46, pp 775-788. https://doi.org/10.1002/oca.3230

[Almodfer 2022] Almodfer, R., et al. Reptile Search Algorithm for Global Optimization and Data Clustering. Human-Centric Computing and Information Sciences, 2022, Vol.12, No.30, pp 1-20. https://doi.org/10.22967/HCIS.2022.12.030

[Almotairi 2022a] Almotairi, K. H., and Abualigah, L. Hybrid Reptile Search Algorithm and Remora Optimization Algorithm for Optimization Tasks and Data Clustering. Symmetry, 2022, Vol.14, No.3, 458. https://doi.org/10.3390/sym14030458

[Almotairi 2022b] Almotairi, K. H., & Abualigah, L. Improved reptile search algorithm with novel mean transition mechanism for constrained industrial engineering problems. Neural Computing and Applications, 2022, Vol.34, No.20, pp 17257–17277. https://doi.org/10.1007/s00521-022-07369-0

[Blum 2003] Blum, C., and Roli, A. Metaheuristics in combinatorial optimization. ACM Computing Surveys, 2003, Vol.35, No.3, pp 268–308. https://doi.org/10.1145/937503.937505

[Brahmarapu 2023] Brahmarapu, S. V. H. H., and Badar, A. Q. H. Comparative Study of Optimization Techniques and Fuzzy Logic Controller for Load Frequency Control in Hybrid Power System. 2023 IEEE 3rd International Conference on Sustainable Energy and Future Electric Transportation, SeFet 2023, pp 1-6. https://doi.org/10.1109/SeFeT57834.2023.10245520

[Chaudhry 2023] Chaudhry, R., and Rishiwal, V. An Efficient Task Allocation with Fuzzy Reptile Search Algorithm for Disaster Management in urban and rural area. Sustainable Computing: Informatics and Systems, 2023, Vol.39, 100893. https://doi.org/10.1016/j.suscom.2023.100893

[Chavan 2025] Chavan, V. D., and Yalagi, P. C. K. Network Intrusion Detection System Using Reptile Search with Whale Optimization Algorithm and Multi Head Attention Long Short Term-Memory in IoT. International Journal of Intelligent Engineering and Systems, 2025, Vol.18, No.1, 171–183. https://doi.org/10.22266/ijies2025.0229.14

[Dutta 2023] Dutta, T., et al. Automatic Clustering of Hyperspectral Images Using Quantum Reptile Search Algorithm. Smart Innovation, Systems and Technologies, 2023, Vol.358, pp 653-664. https://doi.org/10.1007/978-981-99-3416-4_52

[Emam 2023] Emam, M. M., et al. A modified reptile search algorithm for global optimization and image segmentation: Case study brain MRI images. Computers in Biology and Medicine, 2023, Vol.152, 106404. https://doi.org/10.1016/j.compbiomed.2022.106404

[Ervural 2023] Ervural, B., and Hakli, H. A binary reptile search algorithm based on transfer functions with a new stochastic repair method for 0–1 knapsack problems. Computers and Industrial Engineering, 2023, Vol.178, 109080. https://doi.org/10.1016/j.cie.2023.109080

[Faramarzi 2020] Faramarzi, A., et al. Equilibrium optimizer: A novel optimization algorithm. Knowledge-Based Systems, 2020, Vol.191, 105190. https://doi.org/10.1016/j.knosys.2019.105190

[Gad 2022] Gad, A. G. Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review. Archives of Computational Methods in Engineering, 2022, Vol.29, No.5, pp 2531–2561. https://doi.org/10.1007/s11831-021-09694-4

[Gandomi 2012] Gandomi, A. H., et al. Krill herd: A new bio-inspired optimization algorithm. Communications in Nonlinear Science and Numerical Simulation, 2012, Vol.17, No.12, pp 4831–4845. https://doi.org/10.1016/j.cnsns.2012.05.010

[Hachemi 2023] Hachemi, A. T., et al. Modified reptile search algorithm for optimal integration of renewable energy sources in distribution networks. Energy Science and Engineering, 2023, Vol.11, No.12, pp 4635–4665. https://doi.org/10.1002/ese3.1605

[Hassani 2024] Hassani, S., et al. Enhanced damage detection for noisy input signals using improved reptile search algorithm and data analytics techniques. Computers and Structures, 2024, Vol.296, 107293. https://doi.org/10.1016/j.compstruc.2024.107293

[Huang 2022] Huang, L., et al. An Improved Reptile Search Algorithm Based on Lévy Flight and Interactive Crossover Strategy to Engineering Application. Mathematics, 2022, Vol.10, No.13, 2329. https://doi.org/10.3390/math10132329

[Izci 2022] Izci, D., et al. PID Controller Design for DFIG-based Wind Turbine via Reptile Search Algorithm. IEEE Global Energy Conference, GEC, 2022, pp 154–158. https://doi.org/10.1109/GEC55014.2022.9986617.

[Kailasam 2023] Kailasam, J. K., et al. MLBRSA: Multi-Learning-Based Reptile Search Algorithm for Global Optimization and Software Requirement Prioritization Problems. Biomimetics, 2023, Vol.8, No.8, 615. https://doi.org/10.3390/biomimetics8080615

[Li 2022] Li, Y., et al. Detecting Starch-Head and Mildewed Fruit in Dried Hami Jujubes Using Visible/Near-Infrared Spectroscopy Combined with MRSA-SVM and Oversampling. Foods, 2022, Vol.11, No.16, 2431. https://doi.org/10.3390/foods11162431

[Maashi 2023] Maashi, M., et al. Modeling of Reptile Search Algorithm with Deep Learning Approach for Copy Move Image Forgery Detection. IEEE Access, 2023, Vol.11, pp 87297–87304. https://doi.org/10.1109/ACCESS.2023.3304237

[Manohar 2024] Manohar, B., et al. A hybridized LSTM-ANN-RSA based deep learning models for prediction of COVID-19 cases in Eastern European countries. Expert Systems with Applications, 2024, Vol.256, 124977. https://doi.org/10.1016/j.eswa.2024.124977

[Mehta 2023] Mehta, P., et al. A novel generalized normal distribution optimizer with elite oppositional based learning for optimization of mechanical engineering problems. Materialpruefung/Materials Testing, 2023, Vol.65, No.2, pp 210–223. https://doi.org/10.1515/mt-2020-0091.10.1515/mt-2020-0091

[Mirjalili 2015] Mirjalili, S. The Ant Lion Optimizer. Advances in Engineering Software, 2015, Vol.83, pp 80–98. https://doi.org/10.1016/j.advengsoft.2015.01.010

[Mirjalili 2014] Mirjalili, S., et al. Grey Wolf Optimizer. Advances in Engineering Software, 2014, Vol.69, pp 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007

[Navarro 2023] Navarro, M. A., et al. An analysis on the performance of metaheuristic algorithms for the estimation of parameters in solar cell models. Energy Conversion and Management, 2023, Vol.276, 116523. https://doi.org/10.1016/j.enconman.2022.116523

[Rahman 2024] Rahman Lingkon, Md. L., and Ahmmed, Md. S. Application of an improved ant colony optimization algorithm of hybrid strategies using scheduling for patient management in hospitals. Heliyon, 2024, Vol.10, No.22, e40134. https://doi.org/10.1016/j.heliyon.2024.e40134

[Rajput 2022] Rajput, S., at al. Noisy Sonar Image Segmentation using Reptile Search Algorithm. Proceedings of the 2022 International Conference on Connected Systems and Intelligence, CSI 2022, pp 1-10. https://doi.org/10.1109/CSI54720.2022.9923950

[Reddy 2023] Reddy, S. V. K., and Murthy, J. K. Secure Cluster based Routing Using Multiobjective Trust Centric Reptile Search Algorithm for WSN. International Journal of Intelligent Engineering and Systems, 2023, Vol.16, No.2, pp 526-535. https://doi.org/10.22266/ijies2023.0430.43

[Sasmal 2024] Sasmal, B., et al. Reptile Search Algorithm: Theory, Variants, Applications, and Performance Evaluation. Archives of Computational Methods in Engineering, 2024, Vol.31, No.1, pp 521–549. https://doi.org/10.1007/s11831-023-09990-1

[Sonia 2023] Sonia, C., and Tamilselvi, S. A novel power conversion structure for grid-connected photovoltaic applications based on MLI and LeBlanc transformer using IRSA technique. Energy and Environment, 2023, Vol.0, No.0. https://doi.org/10.1177/0958305X231210994

[Wolpert 1997] Wolpert, D. H., and Macready, W. G. No free lunch theorems for optimization. IEEE Transactions on Evolutionary Computation, 1997, Vol.1, No.1, pp 67–82. https://doi.org/10.1109/4235.585893

[Zheng 2023] Zheng, Y., et al. An improved reptile search algorithm based on mathematical optimization accelerator and elementary functions. Journal of Intelligent and Fuzzy Systems, 2023, Vol.45, No.3, pp 4179–4208. https://doi.org/10.3233/JIFS-223210

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