International Journal of Engineering Research and Sustainable Technologies
Volume 3, No.4, Dec 2025, P 07 – 14
ISSN: 2584-1394 (Online version)

OPTIMIZATION IN HEALTHCARE AND COMPUTER SCIENCE: A COMPARATIVE STUDY OF MATHEMATICAL AND BIO-INSPIRED ALGORITHMS

Dr.Sangeetha RV

Assistant Professor, Department of Mathematics
St.Thomas College of Arts and Science, Chennai.
*** Corresponding author email address**: rvsangeetha@saintthomascollege.com

DOI: htpps://doi.org/10.63458/ijerst.v3i4.132 | ARK: https://n2t.net/ark:/61909/IJERST.v3i4.132

Abstract
Optimization techniques play a critical role in advancing health care engineering and computer science by providing efficient solutions to complex problems. This paper reviews both mathematical and nature-inspired optimization techniques, highlighting their applications in medical diagnosis, treatment planning, resource allocation, and software engineering. Traditional mathematical approaches such as linear programming and dynamic programming are examined alongside bio-inspired algorithms like genetic algorithms, particle swarm optimization, and artificial bee colony algorithms. A comparative analysis of their effectiveness, computational complexity, and real-world implementation is presented.

Keywords: Optimization Techniques, Mathematical Optimization, Nature-Inspired Algorithms, Healthcare Engineering, Computational Intelligence, Machine Learning, Bioinformatics, Hybrid Optimization, Resource Allocation, Artificial Intelligence, Deep Learning, Metaheuristic Algorithms

1. Introduction

Optimization is a fundamental aspect of computational intelligence, contributing to efficiency and decision-making in various fields. In health care engineering, optimization enhances medical imaging, drug scheduling, and hospital resource management. Similarly, in computer science, it aids in software optimization, machine learning, and cybersecurity. The ever-increasing complexity of real-world problems necessitates the use of robust optimization techniques to achieve high efficiency and accuracy in decision-making. Mathematical optimization techniques provide well-defined solutions through established formulas and algorithms, making them effective for problems with clear constraints and objectives. However, they often struggle with high-dimensional, non-linear, or NP-hard problems that are prevalent in real-world applications. In contrast, nature-inspired optimization techniques take inspiration from biological and natural phenomena to explore vast search spaces, making them suitable for complex and dynamic problems. The convergence of computational intelligence with health care and computer science has led to significant breakthroughs in disease diagnosis, predictive modeling, and intelligent automation. The integration of machine learning with optimization further enhances decision-support systems, providing more accurate and scalable solutions. This paper explores various mathematical and nature-inspired optimization approaches, analyzing their strengths, weaknesses, and practical applications in these domains.

2. Literature Review

Optimization techniques have been extensively studied in various domains, including healthcare engineering and computer science. Several researchers have explored mathematical and nature-inspired methods to address optimization challenges effectively.

Deb (2001) presented a comprehensive study on multi-objective optimization using evolutionary algorithms, demonstrating their efficiency in solving complex real-world problems. Holland (1975) pioneered genetic algorithms, highlighting their applicability in adaptive systems and optimization tasks. Kennedy and Eberhart (1995) introduced Particle Swarm Optimization (PSO), a technique inspired by social behavior that has since been widely used in medical data clustering and neural network training. Dorigo and Gambardella (1997) developed Ant Colony Optimization (ACO), which has been instrumental in routing problems, particularly in healthcare logistics and emergency response networks.

In the domain of mathematical optimization, Boyd and Vandenberghe (2004) extensively covered convex optimization, showcasing its relevance in deep learning model training and medical imaging enhancement. Bertsekas (1995) explored dynamic programming, which has been effectively used in personalized treatment planning and decision-making in bioinformatics. Furthermore, Papalambros and Wilde (2000) provided insights into nonlinear programming, emphasizing its role in robotic-assisted surgery planning and biomechanics.

Recent advancements have seen the emergence of hybrid approaches combining mathematical and nature-inspired methods. Azizi et al. (2023) introduced the Energy Valley Optimizer, a novel metaheuristic algorithm for global optimization. Zhang et al. (2023) proposed the Special Forces Algorithm, which has shown effectiveness in handling complex multi-dimensional problems. Abdel-Basset et al. (2023) developed the Spider Wasp Optimizer, which has demonstrated improved convergence rates in real-world applications. Gao et al. (2023) explored the integration of contextual ranking and selection methods in personalized medicine.

Li et al. (2023) examined security, latency, and computational cost in blockchain-based healthcare systems, proposing a robust optimization model. Wang et al. (2024) introduced an improved genetic algorithm based on greedy and simulated annealing strategies for vascular robotic-assisted interventions. Aladdin et al. (2022) investigated the application of fitness-dependent optimizers in IoT healthcare systems. Sangeetha et al. (2023) exemplifies how bio-inspired optimization (Discrete Firefly Algorithm) bridges healthcare planning challenges and computer science innovations through efficient problem-solving, while Abdulkhaleq et al. (2022) analyzed the role of Harmony Search algorithms in optimizing healthcare systems.

Jiao et al. (2020) explored machine learning techniques for probabilistic forecasting in surgery duration, demonstrating the effectiveness of reinforcement learning models. Soh et al. (2020) evaluated hybrid models for predicting surgery durations, providing insights into real-world applications of optimization techniques in healthcare. This literature review underscores the significance of optimization techniques and their continued evolution in computational intelligence, highlighting their increasing role in medical and engineering applications.

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3. Optimization Techniques

Mathematical optimization techniques provide precise solutions based on any one best method, ensuring optimal decision-making in structured problems. Some key approaches include:

Linear Programming (LP): Used in resource allocation, scheduling, and supply chain management in hospitals. LP formulations help optimize cost, time, and resource utilization in structured problems where constraints are well defined.
Dynamic Programming (DP): Applied in decision-making for personalized treatment plans and bioinformatics. DP helps in multistage decision problems, where the solution of a larger problem depends on solving smaller subproblems optimally.
Integer and Mixed-Integer Programming: Solves problems in radiotherapy scheduling, biomedical data analysis, and pharmaceutical supply chain optimization. These methods effectively handle combinatorial optimization problems where variables take integer values.
Convex Optimization: Utilized in deep learning model training, medical imaging enhancement, and financial portfolio optimization. Convex optimization guarantees global optimality when the problem structure adheres to convexity conditions.

Nonlinear Programming (NLP): Applied in drug formulation design, robotic-assisted surgery planning, and biomechanics. NLP techniques optimize problems where the objective function or constraints involve nonlinear relationships.
Quadratic Programming (QP): Used in machine learning for support vector machines (SVM) and medical risk assessment models. QP is beneficial when optimizing quadratic objective functions with linear constraints.
Stochastic Optimization: Handles uncertainty in health care logistics, personalized treatment planning, and pandemic response modeling. Stochastic methods incorporate probability distributions into optimization models to handle real-world uncertainties.

Multi-Objective Optimization: Applied in medical decision-making and software engineering, where trade-offs between conflicting objectives such as cost, time, and accuracy must be balanced. Techniques like Pareto optimization are used for non-dominated solution sets.

4. Nature-Inspired Optimization Techniques

Nature-inspired optimization techniques mimic biological and natural processes to find near-optimal solutions. Some prominent methods include:
Genetic Algorithms (GA): Used in medical diagnosis, image processing, and software testing.

Particle Swarm Optimization (PSO): Applied in medical data clustering and neural network training.

Ant Colony Optimization (ACO): Helps in routing optimization for emergency response and telemedicine networks.

Artificial Bee Colony (ABC) Algorithm: Used in feature selection for disease prediction models.

Firefly Algorithm (FA): Enhances image segmentation in diagnostic imaging.

Selected Best Method **- Particle Swarm Optimization (PSO):** Among the nature-inspired optimization techniques, PSO is considered one of the best due to its simplicity, ease of implementation, and efficiency in finding near-optimal solutions. It is widely used in health care applications such as medical image segmentation, disease classification, and personalized treatment planning. The algorithm simulates the social behavior of particles moving in search space, adjusting their positions based on their own and neighbors' experiences to find an optimal solution efficiently.

5. Algorithmic Breakdown of Particle Swarm Optimization (PSO):

Initialization: Randomly initialize a population (swarm) of particles with positions and velocities.

Evaluation: Calculate the fitness value of each particle based on the objective function.

Update Personal and Global Bests: Each particle updates its personal best solution (pBest), and the global best solution (gBest) is determined by selecting the best-performing particle.

Velocity and Position Update: Update the velocity and position of each particle using the equations:

where:

- w (Inertia Weight): Controls the balance between exploration and exploitation in the search space.
- c_1, c_2 (Acceleration Coefficients): Define the influence of the particle's best position and the global best position.
- r_1, r_2 (Random Numbers): Random values in [0,1] to introduce stochastic behavior.
- x_i (Particle Position): Represents the location of a particle in the solution space.
- v_i (Particle Velocity): Defines the direction and speed of a particle's movement.

Termination: Repeat steps 2-4 until convergence criteria (e.g., max iterations or error threshold) is met.

Output: The best-found solution is selected as the optimal result.

5. Applications in Health Care Engineering and Computer Science

Optimization techniques contribute significantly to:

5.1 Applications in Health Care Engineering and Computer Science

Optimization techniques have found extensive applications in both health care engineering and computer science. Below are key areas where these techniques are making significant impacts:

Healthcare Engineering Applications:

Medical Diagnosis and Imaging:

Optimization algorithms, such as genetic algorithms and deep learning-based approaches, enhance medical image processing for better diagnosis.

Machine learning-based optimization techniques improve disease classification and predictive analytics for early diagnosis.

Treatment Planning:

Integer and mixed-integer programming optimize radiotherapy dose distribution for cancer patients.

Nature-inspired algorithms like Particle Swarm Optimization (PSO) help in designing personalized treatment schedules.

Drug Discovery and Development:

AI-driven optimization accelerates drug formulation by predicting molecular interactions and chemical properties.

Quantum computing is increasingly being integrated for computational drug discovery.

Hospital Resource Management:

Linear programming and heuristic approaches assist in optimizing staff scheduling, patient flow, and resource allocation.

Reinforcement learning-based optimization enables adaptive decision-making for hospital operations.

Medical Robotics and Prosthetics:

Swarm intelligence techniques aid in the control and navigation of robotic-assisted surgeries.

Optimization models contribute to the design of adaptive prosthetics and wearable health monitoring devices.

Computer Science Applications:

Cyber security and Cryptography:

Genetic algorithms and meta heuristic optimization techniques help in intrusion detection systems.

Optimization models improve cryptographic key generation and security protocols.

Machine Learning and AI Optimization:

Convex and non-convex optimization techniques enhance the training of deep learning models.

Reinforcement learning optimization is widely used in AI-based decision-making systems.

Cloud Computing and Data Center Optimization:

Optimization algorithms improve task scheduling, resource management, and load balancing in cloud computing.

Dynamic programming optimizes energy efficiency in large-scale data centers.

Software Engineering:

Genetic algorithms and swarm-based optimization improve test case generation and fault detection.

AI-driven optimization enhances software development workflows and automation.

Big Data and IoT Optimization:

Nature-inspired optimization algorithms process and analyze large-scale IoT and big data applications.

Machine learning-driven models optimize real-time data streaming and predictive analytics.

These applications demonstrate the transformative role of optimization techniques in addressing real-world challenges in healthcare engineering and computer science.

6. Results and Comparative Analysis

A comparison of mathematical and nature-inspired techniques highlights trade-offs in terms of computational cost, convergence rate, and solution accuracy. While mathematical methods guarantee optimality in structured problems, bio-inspired techniques offer flexibility in complex, high-dimensional search spaces. Figure 1: Radar Chart Comparing Key Criteria – Visualizes the performance trade-offs between mathematical and nature-inspired techniques such as computational cost, convergence rate, solution optimality, flexibility, real-world applicability, and scalability.

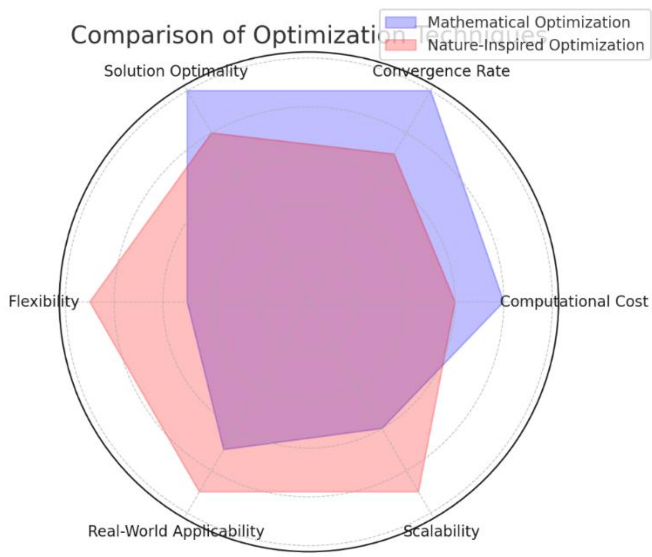

Fig.1 Radar Chart Comparing Key Criteria

Figure 2: Bar Chart on Computational Cost vs. Scalability – Highlights the differences in efficiency for different problem types.

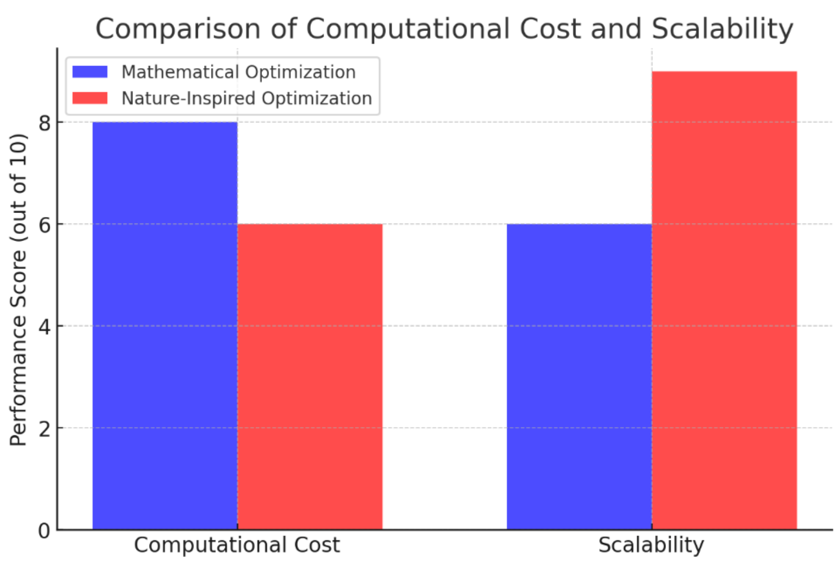

Fig. 2 Bar Chart on Computational Cost vs. Scalability

Figure 3: Line Chart on Convergence Rate Over Iterations – Illustrates the error reduction behavior of both methods over time.

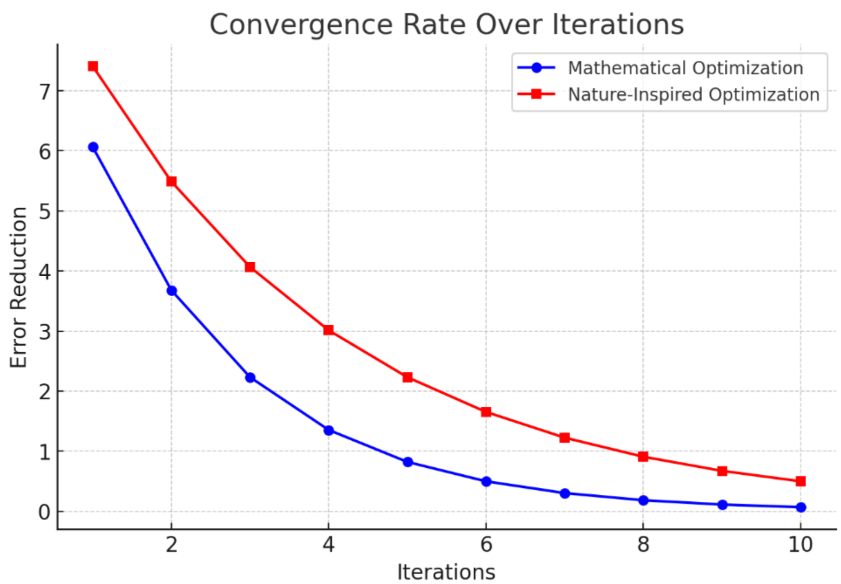

Fig.3 Line Chart on Convergence Rate Over Iterations

Table 1. Criterion for Mathematical and Nature-Inspired Optimization

Criterion	**Mathematical Optimization**	**Nature-Inspired Optimization**
Computational Cost	High for large-scale problems	Lower for complex, high-dimensional spaces
Convergence Rate	Guaranteed for convex problems	Stochastic, may take longer to converge
Solution Optimality	Exact solution when feasible	Approximate solution, but effective for NP-hard problems
Flexibility	Limited to well-structured problems	Suitable for dynamic and unstructured problems
Real-World Applicability	Best for structured, rule-based scenarios	Ideal for evolving and adaptive problem-solving
Scalability	Challenging for high-dimensional problems	Efficient in large-scale, complex problems

Mathematical techniques are preferred for structured, deterministic problems where exact solutions are required. However, nature-inspired techniques excel in handling complex, large-scale, and nonlinear problems where traditional methods struggle. Hybrid approaches combining both methods can leverage the strengths of each, providing enhanced performance referred by table1.

7. Future Directions and Challenges

Emerging trends involve hybrid optimization techniques that combine mathematical rigor with heuristic efficiency. Challenges include the need for adaptive algorithms, handling big data in health care, and reducing computational overhead.

Future Directions and Challenges

Future developments in optimization techniques will focus on enhancing adaptability, efficiency, and scalability to address complex, real-world problems. Key directions include:

Hybrid Optimization Techniques: Combining mathematical rigor with heuristic efficiency to create more robust optimization methods. This includes leveraging deep learning for adaptive parameter tuning in nature-inspired techniques.

Big Data Integration: As healthcare and computer science generate vast amounts of data, optimization models must efficiently process and analyze large-scale datasets. High-performance computing and distributed optimization techniques will be essential in managing these complexities.

Explainable AI in Optimization: Integrating transparency and interpretability into optimization models is crucial for real-world adoption. Techniques such as reinforcement learning and interpretable machine learning models can help improve trust in automated decision-making.

Quantum Computing in Optimization: The emergence of quantum computing presents opportunities for solving NP-hard problems more efficiently. Quantum-inspired algorithms could provide breakthrough solutions in healthcare optimization and computational intelligence.

Real-Time Optimization: Many applications, such as autonomous systems and medical diagnostics, require real-time decision-making. Developing low-latency and energy-efficient optimization techniques will be a key challenge moving forward.

Ethical and Fair Optimization: Ensuring fairness and mitigating bias in optimization algorithms is crucial, particularly in healthcare applications. Future research must address ethical considerations and develop frameworks for responsible AI-driven optimization.

Challenges in these areas include the computational complexity of hybrid techniques, ensuring generalizability of AI-driven models, and addressing data privacy concerns. Collaborative efforts among researchers, industry, and policymakers will be necessary to tackle these challenges effectively.

8. Conclusion

Optimization techniques play a fundamental role in advancing healthcare engineering and computer science. The integration of mathematical and nature-inspired approaches has significantly improved decision-making, efficiency, and problem-solving capabilities across various applications. From medical diagnosis and treatment planning to machine learning optimization and cloud computing, these techniques continue to transform real-world industries.
The comparative analysis presented highlights that mathematical optimization methods are effective in well-structured problems where deterministic solutions are required, while nature-inspired algorithms excel in complex, high-dimensional, and dynamic environments. The emergence of hybrid models combining both paradigms presents a promising avenue for future research and development. Despite the advancements, challenges remain, such as computational cost, data privacy concerns, and the need for real-time adaptability. Addressing these limitations requires continued innovation, interdisciplinary collaboration, and leveraging emerging technologies such as quantum computing and explainable AI. Future research should focus on enhancing scalability, ethical fairness, and sustainability in optimization models, particularly for critical applications in healthcare and artificial intelligence. As optimization techniques evolve, they will remain a cornerstone in solving some of the most pressing challenges in modern technology and healthcare systems. Optimization techniques are indispensable in healthcare engineering and computer science. Future research should focus on hybrid methodologies to achieve enhanced performance and broader applicability.

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