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A Review of Usage Metaheuristic Algorithms in Brain-Computer Interface

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Abstract

Brain–Computer Interface (BCI) systems translate neural activity into machine-interpretable commands, enabling direct communication between the brain and external devices. However, Electroencephalography (EEG) and Functional Near-Infrared Spectroscopy (FNIRS) signals used in BCIs are inherently noisy, non-stationary, and high-dimensional, making manual feature engineering and model tuning highly inefficient. Metaheuristic optimization algorithms, inspired by natural or social behaviors, have emerged as powerful tools for automating these processes. This review provides a comprehensive overview of how metaheuristics such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), and Grey Wolf Optimizer (GWO) have been applied in EEG and FNIRS-based BCIs for channel selection, feature extraction, and classifier tuning. It also discusses the rise of hybrid EEG–FNIRS systems and the integration of metaheuristics with deep learning, Reinforcement Learning (RL), and transfer learning frameworks to enhance adaptability and cross-session generalization. A dedicated case study highlights the Trees Social Relationship (TSR) algorithm, a novel ecology-inspired metaheuristic that balances cooperation and competition among solutions. TSR demonstrates strong potential for feature selection, neural network optimization, and adaptive BCI calibration, outperforming traditional algorithms in convergence speed and stability. Collectively, the review identifies key trends from 2020 to 2025, including hybrid and multi-objective metaheuristics, real-time adaptation, and explainable optimization frameworks. The study concludes that metaheuristics are not merely auxiliary tools but foundational elements in building intelligent, robust, and self-adaptive BCI systems capable of real-world operation.

Keywords: Brain–computer interface, Electroencephalography, Functional near-infrared spectroscopy, Metaheuristic optimization, Feature selection.

1 | Introduction

Over the past few decades, the vision of creating a direct link between the human brain and computational systems has evolved from science fiction into a rapidly advancing scientific discipline known as Brain–Computer Interface (BCI). The fundamental goal of a BCI is to decode neural activity and translate it into

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control commands for external devices, bypassing conventional neuromuscular pathways. This allows individuals to interact with their environment solely through thought. BCIs have profound implications for medical rehabilitation, assistive communication, neuroprosthetics, and cognitive enhancement. Beyond clinical use, BCIs are being explored in gaming, education, mental health monitoring, and human–machine interaction, marking a new era in how humans and machines communicate [1].

A modern BCI system typically consists of several processing stages: signal acquisition, preprocessing, feature extraction, feature selection, classification, and feedback generation. The first step involves capturing brain activity through neuroimaging or electrophysiological methods. Depending on the application, BCIs can be invasive (e.g., electrocorticography, intracortical electrodes) or non-invasive (e.g., Electroencephalography (EEG), Magnetoencephalography (MEG), or Functional Near-Infrared Spectroscopy (FNIRS)). While invasive BCIs offer high precision, they are associated with surgical risks and ethical constraints. Consequently, non-invasive BCIs have gained more widespread attention due to their safety, lower cost, and ease of use [2].

1.1 | Electroencephalography and Functional Near-Infrared Spectroscopy as Non-Invasive Modalities

Among non-invasive modalities, EEG and FNIRS are two of the most popular and complementary techniques. EEG records the brain's electrical activity using scalp electrodes, providing a millisecond-level temporal resolution. This makes it ideal for capturing fast neural oscillations and event-related potentials associated with motor, sensory, or cognitive events. However, EEG suffers from limited spatial resolution and is highly sensitive to artifacts from muscle movement, eye blinks, and environmental noise [3]. In contrast, FNIRS measures hemodynamic changes in the cerebral cortex by tracking Oxygenated (HbO) and Deoxygenated Hemoglobin (HbR) concentrations using near-infrared light. It provides better spatial localization than EEG and is relatively immune to electrical noise. The trade-off is that FNIRS has poor temporal resolution and a delay of several seconds due to the hemodynamic response. Despite this limitation, FNIRS is valuable for understanding cortical activation patterns during cognitive tasks [4].

When used together, EEG and FNIRS form a hybrid BCI system that captures both rapid electrical activity and slower hemodynamic changes, offering a more comprehensive view of brain dynamics. Such fusion enables improved classification accuracy, greater robustness to noise, and richer physiological interpretation. For example, EEG may detect an immediate motor intention, while FNIRS confirms sustained cortical activation related to that intention. Hybrid BCIs have been shown to enhance control reliability, making them promising for neurorehabilitation and mental-state monitoring applications [5].

1.2 | Challenges in Current Brain–Computer Interface Systems

Despite significant progress, several obstacles hinder the practical deployment of BCIs. The first challenge lies in the non-stationary and noisy nature of neural signals. Artifacts from muscle activity, respiration, and motion often contaminate EEG and FNIRS signals. Moreover, neural patterns vary across sessions, subjects, and even within the same individual due to fatigue or attention shifts. This variability leads to poor generalization of models trained on one dataset when applied to new conditions [6], [7].

Another challenge is the high dimensionality of brain data. A typical EEG system may record signals from 32 to 128 channels, each sampled at hundreds of hertz. Similarly, FNIRS sensors may collect multiple wavelength readings per channel. These large datasets contain redundant and irrelevant information, making feature extraction and selection critical. Selecting optimal feature and parameter subsets is nontrivial because exhaustive search is computationally infeasible. Consequently, manual or heuristic tuning often leads to suboptimal results [7]. A further limitation concerns calibration and adaptation. Traditional BCIs require each user to undergo a lengthy calibration phase to collect labeled data and train a classifier. This process is time-consuming and uncomfortable, particularly for patients. Moreover, models degrade over time as brain dynamics evolve, requiring periodic recalibration. An ideal BCI should minimize calibration time and adapt dynamically to new sessions or users without performance loss. Lastly, real-time operation is a key requirement for practical BCIs. Algorithms must process data quickly to provide instantaneous feedback, especially in closed-loop control systems such as neuroprosthetics or robotic arms. Achieving high accuracy while maintaining low latency and computational efficiency remains a delicate balance [8].

1.3 | The Role of Optimization in Brain–Computer Interfaces

Optimization is the backbone of every machine learning and signal processing pipeline. In BCI, optimization problems take many forms: selecting filter parameters, determining the best feature subsets, adjusting classifier weights, and fine-tuning deep network architectures. Each stage requires decisions that affect performance, yet the search space is vast, nonlinear, and multidimensional. Traditional optimization techniques such as gradient descent, grid search, or convex optimization are often unsuitable for BCI problems because the underlying objective functions are non-differentiable, stochastic, and multimodal. Additionally, many BCI-related objectives, such as maximizing accuracy while minimizing the number of selected channels, are inherently multi-objective and discrete, further complicating the optimization process.

This is where metaheuristic algorithms come into play. Metaheuristics are general-purpose optimization strategies inspired by natural and social phenomena such as evolution, swarm behavior, or physical laws. They do not rely on gradient information, making them ideal for complex, black-box optimization problems. Metaheuristics strike a balance between exploration (searching broadly across the solution space) and exploitation (refining promising areas), enabling them to escape local minima and find near-optimal solutions efficiently [8].

1.4 | Metaheuristics: Concepts and Motivation

The term metaheuristic derives from the Greek words meta (beyond) and heuriskein (to find). These algorithms provide high-level strategies that guide lower-level heuristics to explore solution spaces intelligently. Over the years, metaheuristics have been classified into several categories:

I. Evolutionary Algorithms (EAs): these include Genetic Algorithms (GA), Differential Evolution (DE), and evolutionary strategies, which mimic natural selection and genetics.

II. Swarm Intelligence (SI): algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and the Grey Wolf Optimizer (GWO) simulate collective behaviors observed in animals.

III. Physics-based methods include Simulated Annealing (SA) and the Gravitational Search Algorithm (GSA), which model physical processes.

IV. Human or social-based algorithms: newer algorithms such as Teaching–Learning-Based Optimization (TLBO) or the Trees Social Relationship (TSR) algorithm draw inspiration from human or ecological interactions.

In BCI research, these algorithms are primarily used for feature selection, parameter optimization, and classifier tuning. For instance, GA may evolve feature subsets that yield higher classification accuracy, while PSO may optimize neural network hyperparameters for EEG classification. The combination of exploration and adaptability makes metaheuristics particularly powerful for EEG and FNIRS data, where the signal space is complex and dynamic [9].

1.5 | Why Metaheuristics Fit the Brain–Computer Interface Domain

Several inherent characteristics of BCI problems make them ideally suited for metaheuristic optimization:

I. High dimensionality: EEG and FNIRS signals produce vast feature spaces. Metaheuristics can efficiently search these spaces without exhaustive evaluation.

II. Nonlinearity: the relationship between neural features and cognitive states is nonlinear and often unknown. Metaheuristics do not require explicit mathematical models, allowing flexible adaptation.

III. Noise and uncertainty: metaheuristics tolerate noisy objective evaluations, making them robust against imperfect training data.

IV. Hybrid objective functions: BCI tasks often involve trade-offs, such as maximizing accuracy while minimizing latency or the number of electrodes. Multi-objective metaheuristics (like NSGA-II or SPEA-II) can handle such scenarios effectively.

V. Adaptation over time: the stochastic nature of metaheuristics enables online adaptation, an attractive feature for real-time BCI applications in which brain states evolve.

Because of these strengths, metaheuristics have been successfully used to enhance EEG- and FNIRS-based BCIs across diverse applications, including Motor Imagery (MI) classification, emotion recognition, mental workload estimation, and speech MI decoding [2], [10].

1.6 | Typical Applications in Brain–Computer Interface Research

In recent literature, metaheuristic algorithms have found roles in almost every stage of BCI processing:

Feature selection and channel reduction

Selecting a subset of relevant channels or features can drastically reduce computational cost and improve generalization. Algorithms like GA, PSO, and GWO have been used to identify optimal EEG channels for MI and mental workload tasks. In FNIRS, metaheuristics help identify wavelength–region combinations that maximize discriminative power.

Classifier parameter tuning

Many classifiers, including Support Vector Machines (SVMs), K-Nearest Neighbors (KNNs), and Deep Neural Networks (DNNs), require parameter tuning. PSO and DE have been applied to optimize hyperparameters, such as kernel coefficients and network learning rates, resulting in significant gains in classification accuracy.

Hybrid optimization

Recent works combine metaheuristics with machine learning and deep learning techniques. For example, hybrid CNN–GWO or ABC–PSO models simultaneously optimize feature extraction and classification, resulting in end-to-end adaptive systems. These methods outperform manually tuned models in most cases.

Transfer learning and adaptation.

Some studies explore using metaheuristics to guide domain adaptation across subjects or sessions. This approach minimizes calibration time by transferring knowledge while maintaining accuracy. Although still emerging, it holds promise for practical, real-world BCI deployment.

Model compression and deployment

For portable or edge-implemented BCIs, minimizing computational load is vital. Metaheuristics can prune neural networks or compress model architectures without significant performance degradation, supporting real-time usability [11–13].

1.7 | Recent Developments and the Trees' Social Relationship Algorithm

While classical metaheuristics like GA, PSO, and ACO have dominated for years, researchers continue to develop newer algorithms with improved convergence and diversity handling. One such innovation is the TSR algorithm, introduced in recent years. TSR draws inspiration from how trees interact in an ecosystem, sharing resources through interconnected root systems and competing for sunlight. This natural balance of cooperation and competition allows TSR to adapt its exploration–exploitation trade-off dynamically.

In TSR, each candidate solution is represented as a “tree” that exchanges information with its neighbors, reflecting mutual growth relationships. The algorithm uses nutrient-sharing (akin to information sharing) to encourage promising solutions and competitive exclusion to eliminate poor ones. This design allows TSR to maintain population diversity while focusing search around high-potential regions. Early experiments show that TSR performs competitively with, or better than, established methods for optimizing continuous and discrete problems, making it a promising candidate for BCI applications.

In the BCI context, TSR could optimize multi-objective problems such as maximizing classification accuracy while minimizing latency and electrode count. It may also be used to tune hyperparameters of deep learning architectures or select hybrid EEG–FNIRS feature subsets. Unlike some metaheuristics that tend to converge prematurely, TSR's ecosystem-inspired interactions make it resilient against stagnation [14–16].

1.8 | The Need for a Comprehensive Review

Despite the rapid adoption of metaheuristics in BCI research, most studies focus on a single algorithm or application. A unified perspective on how these algorithms compare across modalities (EEG, FNIRS, hybrid), tasks (MI, emotion, speech), and objectives (feature selection, adaptation) is lacking. Moreover, new algorithms such as TSR and hybrid approaches integrating metaheuristics with Reinforcement Learning (RL) remain underexplored.

Therefore, a systematic review is necessary to consolidate existing knowledge, highlight recent advancements, and identify open research gaps. Such a review can help the research community better understand how metaheuristics contribute to improved feature efficiency, reduced calibration error, and better generalization. Furthermore, it can inspire future exploration into combining optimization strategies with adaptive learning, self-supervised modeling, and explainable AI frameworks [7], [17].

1.9 | Scope and Objectives of This Review

This review provides a comprehensive overview of the use of metaheuristic algorithms in brain–computer interfaces, focusing on both EEG and hybrid EEG–FNIRS modalities. The objectives are as follows:

I. Summarize existing metaheuristic approaches applied to BCI signal processing and classification.

II. Discuss how these algorithms improve performance, particularly in feature selection, parameter optimization, and cross-domain adaptation.

III. Compare traditional algorithms (GA, PSO, DE, ACO, GWO) with emerging methods like TSR.

IV. Highlight recent trends from 2020 to 2025, including hybrid deep–metaheuristic architectures and multi-objective optimization.

V. Identify challenges and future directions, such as online adaptation, real-time deployment, and integration with reinforcement or transfer learning.

By analyzing these aspects, the review aims to bridge the gap between classical optimization theory and its modern applications in BCI. It also seeks to position metaheuristic algorithms not just as auxiliary tools but as foundational components driving the next generation of adaptive, intelligent, and interpretable BCI systems [7], [18].

2 | Related Work

Over the past two decades, the use of metaheuristic algorithms in BCI research has transitioned from experimental novelty to a cornerstone methodology for optimizing signal processing, feature extraction, and classification pipelines. The concept of applying population-based optimization to brain signals arose from the realization that EEG and FNIRS data are inherently high-dimensional, non-stationary, and nonlinear. Traditional deterministic or gradient-based optimization methods often fail to handle these complexities. Consequently, metaheuristics inspired by natural and collective intelligence emerged as ideal candidates for searching large, noisy parameter spaces [7].

2.1 | Early Developments in Metaheuristic-Based Brain–Computer Interfaces

The earliest applications of metaheuristics in BCI date back to the late 2000s, primarily involving GA for channel selection and parameter tuning in EEG-based MI classification. These pioneering studies demonstrated that GA could effectively identify a reduced subset of electrodes while maintaining classification accuracy comparable to or superior to that of full-channel configurations. This early success validated the potential of evolutionary optimization for EEG signal analysis [19].

During the 2010s, as computational resources improved, PSO became widely adopted in feature extraction and classifier parameter optimization. PSO's ability to handle continuous search spaces made it particularly suitable for tuning hyperparameters of machine learning classifiers, such as SVM and Artificial Neural Networks (ANNs). Researchers observed that PSO not only achieved faster convergence than GA but also produced smoother optimization landscapes, leading to more stable classification results. At the same time, DE and ACO began to attract attention. DE was favored for its robustness against noisy objective functions, an essential trait given the EEG's variability. ACO, originally developed for discrete optimization problems, was adapted for selecting optimal feature subsets and spatial filters. Collectively, these early studies demonstrated that metaheuristics could significantly outperform random or exhaustive search methods, paving the way for more sophisticated applications. However, until around 2018, most implementations were relatively narrow in scope, focusing on static datasets, single subjects, or offline analyses. The last five years have seen a paradigm shift: researchers now employ metaheuristics for real-time BCIs, cross-subject generalization, and multimodal integration, reflecting a broader and more ambitious view of optimization in brain-signal processing [19].

2.2 | Feature Selection and Channel Optimization

Feature selection remains one of the most popular applications of metaheuristics in BCI research. EEG and FNIRS signals are typically characterized by a large number of features extracted from time, frequency, and time–frequency domains. However, not all features contribute equally to classification; redundant or noisy features can degrade performance and increase computational complexity. Metaheuristics address this by intelligently exploring feature subsets to maximize classification accuracy while minimizing redundancy [11].

2.2.1 | Electroencephalography-based feature selection

EEG algorithm, inspired by the foraging behavior of bees. ABC has demonstrated excellent performance in reducing feature dimensionality for emotion recognition using EEG signals. By dynamically balancing exploration (scout bees searching for new solutions) and exploitation (employed bees refining known solutions), ABC yields compact feature sets that generalize well across participants.

2.2.2 | Functional near-infrared spectroscopy-based feature selection

In FNIRS-based BCIs, metaheuristics have been applied to select optimal features from HbO and HbR signals. Since FNIRS signals are slower and less noisy than EEG, feature extraction often involves statistical descriptors such as mean, slope, skewness, and kurtosis. In recent work, PSO and GWO have been employed to identify the most discriminative FNIRS features during mental arithmetic and MI tasks. These algorithms improved classification performance by over 5–10% relative to manual feature selection, highlighting their adaptability across modalities [11].

A particularly impactful study applied seven different metaheuristic optimizers, including PSO, the Firefly Algorithm (FA), the Bat Algorithm (BA), and GWO, to the same FNIRS dataset. Results showed that all algorithms improved accuracy, but GWO achieved the best performance and the fastest convergence. This study established GWO as a robust choice for hemodynamic feature selection [11].

2.2.3 | Hybrid electroencephalography–functional near-infrared spectroscopy feature selection

Hybrid BCIs that combine EEG and FNIRS data introduce new challenges, as the feature space becomes exponentially larger. Metaheuristics are increasingly used to handle this complexity. Researchers have proposed multi-objective optimization frameworks in which one objective maximizes classification accuracy, and another minimizes feature count. Hybrid variants, such as the Enhanced Whale Optimization Algorithm (E-WOA), have demonstrated exceptional performance in selecting complementary EEG and FNIRS features, outperforming classical optimizers by nearly 4% in accuracy. The success of metaheuristics in feature selection underscores their importance as general-purpose tools for balancing accuracy and computational efficiency, especially in hybrid systems with high feature redundancy [11].

2.3 | Classifier Tuning and Model Optimization

While feature selection has dominated earlier studies, recent research has shifted toward tuning classifiers and learning architectures using metaheuristics. In traditional BCI pipelines, classifier parameters, such as kernel type, regularization coefficient, and learning rate, significantly affect performance. Manual tuning is inefficient and may overlook optimal configurations; hence, population-based optimization has become a standard solution.

2.3.1 | Tuning classical machine learning models

SVMs are among the most common classifiers in BCI systems. Metaheuristics such as PSO and GA have been widely used to tune their hyperparameters (e.g., the penalty parameter C and the kernel parameter γ). Studies have shown that optimized SVMs consistently outperform default configurations, particularly in noisy or imbalanced EEG datasets. DE has also been employed to optimize both SVM and KNN classifiers, resulting in smoother convergence and greater stability.

Random Forests and Extreme Learning Machines (ELMs) have similarly benefited from metaheuristic-based parameter tuning. For instance, GWO has been used to optimize the number of hidden neurons in ELMs, improving classification accuracy without increasing computational load [20].

2.3.2 | Optimizing neural network architectures

As deep learning gained prominence in BCI research, metaheuristics emerged as a new tool for optimizing deep network architectures. Algorithms such as GA, PSO, and ABC have been used to select the number of layers, neurons, activation functions, and learning rates. The results indicate that metaheuristic-tuned networks outperform manually designed ones in both accuracy and generalization.

For example, hybrid CNN architectures optimized with an ABC–GWO strategy have achieved state-of-the-art accuracy in EEG emotion recognition. The metaheuristic component ensures that the network architecture dynamically adapts to signal complexity, avoiding overfitting and redundant computations [20].

2.3.3 | Deep reinforcement and adaptive models

More recently, metaheuristics have been combined with RL and adaptive algorithms to improve real-time adaptability. RL aims to train agents that adapt to user feedback or reward signals, but the performance of such models depends heavily on hyperparameters. Metaheuristics can optimize these parameters, ensuring that RL-based BCIs learn efficiently. This integration creates closed-loop systems that self-adjust during operation, marking a step toward autonomous BCIs [20].

2.4 | Hybrid Electroencephalography–Functional Near-Infrared Spectroscopy and Multimodal Optimization

Hybrid EEG–FNIRS systems have become a focal point of BCI research due to their potential to combine the speed of EEG with the spatial detail of FNIRS. However, integrating these modalities poses challenges:

synchronizing signals, aligning features, and balancing information across modalities. Metaheuristics offer elegant solutions to these problems.

Recent hybrid studies have used multi-objective optimizers such as NSGA-II and SPEA-II to select optimal feature sets from EEG and FNIRS signals jointly. These algorithms generate Pareto-optimal fronts that represent trade-offs between conflicting objectives, such as accuracy and feature count. For example, hybrid feature optimization using PSO and DE has been shown to improve both robustness and interpretability, which are critical for clinical applications [20].

Additionally, some works combine metaheuristics with transfer learning, using optimization to align feature spaces across subjects. This reduces calibration time and increases generalization, one of the most persistent challenges in BCI. Such hybrid frameworks suggest that optimization will be key to achieving plug-and-play BCIs that adapt across users and sessions [20].

2.5 | Emerging Algorithms and Bio-Inspired Innovations

The past five years have witnessed an explosion of new metaheuristic algorithms inspired by ecology, social structures, and evolutionary processes. While traditional methods such as GA, PSO, and ACO remain dominant, newer algorithms offer novel mechanisms for balancing exploration and exploitation [20].

2.5.1 | Whale, Moth, and Cuckoo search algorithms

Bio-inspired algorithms such as the Whale Optimization Algorithm (WOA), Moth Flame Optimization (MFO), and Cuckoo Search (CS) have been successfully applied to BCI feature optimization. WOA, modeled on the bubble-net hunting strategy of humpback whales, has been particularly effective in selecting features for emotion recognition and MI classification. Its adaptive encircling mechanism allows it to converge rapidly without losing population diversity.

MFO and CS, although less common in BCI, have shown potential for EEG feature ranking and hybrid feature fusion tasks. Their ability to navigate large search spaces with low parameter sensitivity makes them suitable candidates for multimodal fusion problems [20].

2.5.2 | The tree's social relationship algorithm

A major addition to the metaheuristic family is the TSR algorithm. Unlike swarm-based or evolutionary methods, TSR is modeled after the ecological interactions among trees in a forest, including cooperation (nutrient sharing) and competition (for sunlight). Each solution is treated as a "tree" that exchanges resources with others based on proximity and fitness.

TSR's hybrid mechanism allows it to maintain population diversity longer than many traditional algorithms, avoiding premature convergence. Its adaptability to both discrete and continuous optimization tasks makes it particularly promising for EEG–FNIRS systems, which involve mixed-domain data. Initial experiments outside the BCI (e.g., image segmentation and process optimization) indicate that TSR outperforms classical algorithms such as PSO and DE in terms of convergence rate and solution stability. Translating these benefits to BCI could lead to more efficient feature selection, hyperparameter tuning, and adaptive model training [20].

2.5.3 | Hybrid and ensemble metaheuristics

An emerging trend is the fusion of multiple metaheuristic algorithms to create hybrid optimizers. For instance, combining GWO with PSO or ABC with DE has produced robust results in EEG feature selection. These ensemble strategies exploit the strengths of individual algorithms while compensating for their weaknesses. Hybrid metaheuristics are especially useful for non-convex optimization landscapes where single algorithms struggle.

In BCI, hybrid approaches are being explored for emotion recognition, cognitive workload assessment, and speech MI. For example, an ABC–GWO hybrid was shown to improve CNN-based emotion recognition accuracy by nearly 10% compared to traditional deep networks. These results suggest that multi-strategy optimization could become a dominant approach in future BCI systems [20].

2.6 | Comparative Analyses and Benchmarks

Several studies have compared the performance of multiple metaheuristics on standard EEG or FNIRS datasets. Results generally reveal that no single algorithm universally outperforms others; performance often depends on data characteristics and problem formulation. However, some patterns emerge:

I. GWO and its variants tend to perform best in feature selection due to their adaptive balance of exploration and exploitation.

II. PSO excels in continuous parameter tuning but is prone to premature convergence without diversity control.

III. GA performs well in discrete search spaces but can be computationally intensive.

IV. Newer methods like WOA, Firefly, and TSR show promise but require further benchmarking.

V. Benchmarking efforts remain fragmented, as different studies use different datasets, preprocessing methods, and classifiers. The lack of standardized evaluation protocols remains an open issue in assessing algorithmic superiority objectively [1].

2.7 | Challenges and Research Gaps

Despite substantial progress, several challenges persist in applying metaheuristics to BCI:

I. Computational efficiency: Most metaheuristics are iterative and require numerous fitness evaluations. This can be prohibitive for real-time BCIs unless parallelized or simplified.

II. Parameter sensitivity: many algorithms depend on parameters (e.g., the inertia weight in PSO and the crossover rate in GA). Improper tuning may lead to poor convergence.

III. Cross-subject generalization: most studies optimize models for a single user or session. Metaheuristics for transfer learning and cross-subject adaptation remain underexplored.

IV. Hybrid BCI complexity: as hybrid EEG–FNIRS systems generate enormous feature spaces, optimization becomes computationally demanding. Multi-objective and distributed metaheuristics may help, but are still in their infancy.

V. Interpretability: while metaheuristics can effectively select features, understanding why those features are optimal from a neurophysiological perspective remains challenging. Integrating explainable AI with optimization could address this gap [20].

2.8 | Summary of the Research Landscape

Overall, the literature demonstrates a clear trajectory: from using simple GA-based feature selection in early EEG studies to employing sophisticated hybrid metaheuristics for multimodal deep learning optimization. The timeline of this evolution aligns with advances in computational power and the growing emphasis on adaptive, real-time BCI systems.

Recent years (2020–2025) have introduced three key trends:

I. Integration of deep learning and metaheuristics: using metaheuristics to optimize deep architectures like CNNs and RNNs for EEG classification.

II. Hybrid and multi-objective optimization: applying advanced algorithms such as NSGA-II, E-WOA, and TSR to handle multimodal and multi-criteria tasks.

III. Toward real-time adaptive BCIs: leveraging metaheuristic optimization within RL or continual learning frameworks for on-the-fly adaptation.

Collectively, these trends illustrate a shift from offline experimentation to adaptive, explainable, and efficient BCI systems driven by optimization intelligence.

3 | Common Metaheuristic Algorithms

Metaheuristic algorithms have become a central tool in optimizing BCI systems due to their ability to handle nonlinear, stochastic, and high-dimensional optimization problems. Unlike deterministic or gradient-based approaches, metaheuristics do not require analytical gradients or convexity assumptions, making them highly suitable for complex domains such as EEG and FNIRS signal processing. These algorithms explore vast search spaces through adaptive, population-based mechanisms inspired by biological evolution, animal swarming, or social and physical phenomena [9].

In the context of BCI, metaheuristics are primarily employed for three key purposes: feature selection, classifier parameter tuning, and channel optimization. Each of these tasks presents a distinct optimization landscape, some continuous, some discrete, and many multimodal, necessitating algorithms that can efficiently balance exploration (global search) and exploitation (local refinement). Among the numerous techniques developed over the years, five have emerged as foundational in BCI research: GA, PSO, DE, ACO, and GWO. These algorithms represent diverse philosophies of search behavior, each offering unique advantages and limitations depending on the specific task and signal modality.

The following subsections present an overview of these common metaheuristic algorithms, their working principles, and their relevance to BCI optimization [9], [12].

3.1 | Genetic Algorithm

The GA is one of the earliest and most widely adopted metaheuristics. Introduced by John Holland in the 1970s, GA is inspired by the principles of natural evolution, selection, crossover, and mutation. A GA begins with a population of candidate solutions, often represented as binary strings (chromosomes). Each chromosome encodes a potential solution to the optimization problem, and its quality is assessed using a fitness function that reflects the objective to be optimized, such as maximizing classification accuracy or minimizing error.

3.1.1 | mechanism and workflow

GA operates through iterative cycles known as generations. In each generation, the algorithm selects fitter individuals using selection strategies such as roulette wheel, tournament, or rank selection. These selected individuals undergo crossover, exchanging parts of their chromosomes to generate new offspring, followed by mutation, which introduces small random variations. This process mimics genetic evolution, gradually driving the population toward fitter solutions.

A standard GA follows these steps:

I. Initialization–randomly generate a population of candidate solutions.

II. Evaluation–compute the fitness of each individual using an objective function.

III. Selection–choose individuals based on fitness.

IV. Crossover and mutation–create new individuals by recombination and random alteration.

V. Replacement–form a new population for the next generation.

VI. Termination–repeat until convergence or a stopping criterion is met.

3.1.2 | Applications in brain–computer interface

GA has been widely applied to feature selection for EEG-based MI and emotion recognition tasks. In MI classification, GA can identify optimal subsets of frequency-domain or spatial features derived from techniques like Common Spatial Pattern (CSP) analysis. Studies show that GA-selected features achieve higher accuracy with fewer channels than using all features.

In parameter tuning, GA has been employed to optimize hyperparameters for classifiers such as SVM and KNN, where traditional grid search methods are computationally expensive. For example, GA can evolve the penalty parameter (C) and kernel width (γ) of SVMs to maximize classification performance. GA's discrete representation also makes it ideal for selecting electrode combinations in multi-channel EEG systems, reducing computational cost while maintaining robust decoding performance.

Despite its versatility, GA's major drawbacks include relatively slow convergence and the risk of premature stagnation if diversity is not maintained. However, hybrid GA variants, such as GA combined with PSO or fuzzy logic, have mitigated these limitations, achieving faster, more stable results in BCI applications.

3.2 | Particle Swarm Optimization

PSO, introduced by Kennedy and Eberhart in 1995, draws inspiration from the collective behavior of birds flocking or fish schooling. Unlike GA, which relies on evolutionary operators, PSO is a population-based search that updates candidate solutions (particles) based on their positions and velocities in the search space.

3.2.1 | mechanism and workflow

Each particle in the swarm represents a potential solution characterized by a position vector (its current candidate solution) and a velocity vector (its direction of movement). The particles move through the search space influenced by:

I. Their personal best position (pBest) is the best solution found by that particle so far.

II. The global best position (gBest) is the best solution found by the entire swarm.

At each iteration, a particle updates its velocity and position using the following equations:

$$v_i(t+1) = w \cdot v_i(t) + c_1 r_1 \big(pBest_i - x_i(t)\big) + c_2 r_2 \big(gBest - x_i(t)\big),$$
$$x_i(t+1) = x_i(t) + v_i(t+1),$$

Where w is the inertia weight controlling exploration, c_1 and c_2 are acceleration coefficients for cognitive and social influence, and r_1 and r_2 are random factors introducing stochasticity [21].

3.2.2 | Applications in brain–computer interface

PSO's simplicity and continuous search capability have made it a favorite for optimizing real-valued parameters in EEG and FNIRS systems. In EEG feature extraction, PSO has been used to optimize spatial filters in CSP-based frameworks, improving discrimination between MI classes. Similarly, PSO has tuned time–frequency window sizes in wavelet-based features for emotion recognition tasks.

Another common use of PSO is in classifier optimization. For instance, PSO can automatically determine neural network weights or SVM kernel parameters. In adaptive BCIs, PSO has also been used to adjust feedback parameters, thereby enhancing user training efficiency dynamically.

PSO's convergence speed and ability to exploit global knowledge make it efficient for large-scale optimization problems. However, its tendency to converge prematurely toward local minima in highly multimodal landscapes can be problematic. To counter this, variants such as Quantum-Behaved PSO (QPSO) and Chaotic PSO have been introduced to enhance diversity and escape local traps, showing improved robustness in EEG optimization tasks [18].

3.3 | Differential Evolution

DE, developed by Storn and Price in 1997, is another evolutionary algorithm that excels in continuous optimization. It combines the concepts of mutation, crossover, and selection like GA, but operates on real-valued vectors, making it suitable for tuning continuous parameters.

3.3.1| mechanism and workflow

In DE, each candidate solution (vector) generates a mutant vector by adding the weighted difference between two population vectors to a third vector. A crossover operation mixes the mutant with the original vector to form a trial vector. The selection step compares the trial vector with the original and retains the one with better fitness. The mutation process is expressed as:

$$v_i = x_{r1} + F(x_{r2} - x_{r3}),$$

Where x_{r1}, x_{r2}, and x_{r3} are distinct randomly selected individuals, and F is a scaling factor controlling the amplification of differential variations.

3.3.2|Applications in brain–computer interface

DE's strength lies in its simplicity and its ability to handle noisy fitness landscapes, which are common in EEG and FNIRS signals. It has been successfully applied to optimize feature-extraction parameters, such as spectral frequency bands, and to tune classifier weights in multi-layer perceptron and convolutional network architectures.

In MI classification, DE has been used to optimize parameters in adaptive filter banks, enhancing the separability of left–right MI tasks. DE's balance between exploration and exploitation makes it a reliable alternative to PSO for continuous optimization problems, particularly when the objective function is rugged or contains plateaus.

Moreover, DE's population-based design allows it to integrate naturally into multi-objective frameworks, enabling optimization across accuracy, latency, and energy consumption. Hybrid models combining DE with RL have also been explored, where DE optimizes RL hyperparameters to improve the adaptability of real-time BCIs.

3.4|Ant Colony Optimization

ACO, proposed by Dorigo in 1992, is inspired by the foraging behavior of ants. When searching for food, ants deposit pheromones on paths, guiding other ants toward promising routes. Over time, shorter and more efficient paths accumulate more pheromone, reinforcing optimal routes.

3.4.1| mechanism and workflow

In ACO, artificial ants construct candidate solutions step by step, guided by a pheromone matrix representing learned desirability. The probability of choosing a specific component depends on the pheromone level (indicating prior success) and heuristic information (problem-specific cues). After each iteration, pheromone levels are updated, evaporating over time to prevent stagnation and to concentrate on better solutions.

ACO is particularly effective for combinatorial optimization, where solutions can be represented as paths or sequences, such as selecting subsets of EEG channels or features.

3.4.2|Applications in brain–computer interface

In BCI research, ACO has been widely applied to channel selection and discrete feature optimization. For instance, in EEG MI studies, ACO identifies optimal electrode subsets that maximize classification accuracy while minimizing computational cost. This is especially important in portable BCIs, where fewer electrodes are desirable for usability and comfort.

ACO has also been integrated with feature selection wrappers, where the pheromone trail corresponds to the discriminative power of selected features. Compared to GA, ACO tends to converge faster and produce more stable feature subsets. Its main limitation lies in tuning its pheromone evaporation and reinforcement rates, which can significantly affect convergence speed. To address this, adaptive ACO variants dynamically adjust their parameters based on population diversity, thereby achieving improved performance on EEG emotion recognition and workload estimation tasks [12].

3.5 | Grey Wolf Optimizer

The GWO, introduced by Mirjalili in 2014, is a relatively recent addition to the family of SI algorithms. It models the leadership hierarchy and hunting strategies of grey wolves in nature. Wolves live in packs structured into four roles: alpha, beta, delta, and omega, each contributing differently to decision-making and movement within the search space.

3.5.1 | mechanism and workflow

GWO simulates the process of encircling, hunting, and attacking prey:

I. The alpha wolf represents the best solution, the beta and delta wolves represent the next best, and the omega wolves follow.

II. Wolves update their positions based on the locations of alpha, beta, and delta, thus balancing exploration and exploitation.

III. The equation governs the encircling behavior:

$$X(t+1) = X_p(t) - A \cdot D,$$

where D, A, and C are coefficient vectors controlling step size and direction.

As iterations progress, A decreases linearly, shifting the search from exploration to exploitation, ensuring convergence toward the best solution [18], [19].

3.5.2 | Applications in brain–computer interface

GWO has gained remarkable popularity in EEG and FNIRS optimization due to its strong convergence and parameter-free nature. It has been used to select EEG channels, tune CNN architectures, and optimize feature subsets for hybrid EEG–FNIRS BCIs.

In emotion recognition tasks, hybrid ABC–GWO models have achieved near-perfect accuracy by combining GWO's exploitation efficiency with ABC's exploration. GWO's adaptability has also made it effective in multimodal fusion, where it can balance the influence of EEG and FNIRS features.

Compared to earlier algorithms, GWO consistently demonstrates faster convergence and better accuracy in high-dimensional feature spaces. However, like other swarm methods, it may suffer from reduced diversity in later iterations. To mitigate this, enhanced variants such as Chaotic GWO, Modified Grey Wolf Optimizer (MGWO), and Hybrid GWO–PSO have been proposed, yielding superior robustness and generalization in EEG classification [12].

3.6 | Comparative Discussion

The algorithms discussed above each embody unique mechanisms for exploring and exploiting the search space. Their relative effectiveness in BCI optimization depends on the problem type, objective function, and data characteristics.

I. GA is best suited for discrete problems, such as feature or channel selection, but can be computationally intensive.

II. PSO excels at continuous optimization, achieving fast convergence, but requires careful control to avoid premature stagnation.

III. DE offers robustness against noise and is well-suited for tuning continuous parameters.

IV. ACO performs exceptionally in combinatorial and discrete optimization but can be sensitive to parameter settings.

V. GWO provides a well-balanced trade-off between simplicity and effectiveness, often outperforming others in EEG feature selection and hybrid optimization.

These algorithms are often embedded in wrapper-based frameworks, where the fitness function evaluates classification accuracy using a learning model such as an SVM or a CNN. This approach ensures that selected features or tuned parameters directly improve predictive performance. While this can be computationally expensive, it provides the highest relevance to the final BCI task [12].

3.7 | Toward Hybrid and Adaptive Metaheuristics

Recent trends indicate increasing interest in hybrid metaheuristics, in which two or more algorithms are combined to leverage their complementary strengths. For example:

I. GA–PSO hybrids use GA's genetic diversity with PSO's rapid convergence.

II. ABC–GWO and DE–ACO hybrids combine exploration and exploitation more effectively than any single algorithm.

III. Newer bio-inspired methods, such as the TSR algorithm, integrate ecological cooperation and competition, further enhancing search diversity.

These hybrid methods have shown superior results in EEG emotion recognition, speech imagery decoding, and MI classification. The ongoing evolution of metaheuristics from simple swarm models to ecologically inspired ecosystems signals a shift toward self-adaptive optimization frameworks, capable of dynamically adjusting search strategies based on feedback from BCI data.

4 | Applications in Electroencephalography/Functional Near-Infrared Spectroscopy Brain–Computer Interface

Metaheuristic algorithms have become indispensable tools for developing efficient and accurate BCI systems. Their flexible, model-free optimization strategies allow researchers to tackle complex problems in EEG and FNIRS signal analysis, where conventional deterministic or gradient-based approaches often fail. In particular, metaheuristics are used to optimize three major aspects of BCI pipelines: channel and feature selection, classifier tuning, and multimodal integration in hybrid EEG–FNIRS systems.

Each of these tasks poses distinct challenges. EEG data are typically high-dimensional, comprising hundreds of time–frequency features across multiple electrodes, whereas FNIRS signals are slower and contain hemodynamic noise and drift. Both modalities are prone to inter-subject variability and session-to-session nonstationarity. Metaheuristic algorithms address these challenges by efficiently searching large, nonlinear solution spaces, often achieving better performance and generalization than manual or brute-force methods.

The following subsections describe how metaheuristics have been applied across key areas of EEG- and FNIRS-based BCIs [3].

4.1 | Channel and Feature Selection

One of the earliest and most persistent problems in EEG and FNIRS analysis is the curse of dimensionality. The brain's electrical and hemodynamic signals are distributed across multiple regions, yet only a subset contributes meaningful information for a given cognitive or motor task. Using all available channels or features not only increases computation time but also risks overfitting, especially when training data are limited. Thus, selecting the most informative channels and features is a critical step toward building efficient and interpretable BCIs.

4.1.1 | Electroencephalography channel optimization

In EEG-based systems, electrode configuration plays a vital role in decoding performance. However, many electrodes record redundant or noisy information, making it unnecessary to use the full array in real-time applications. Metaheuristic algorithms such as PSO, GA, and GWO have been widely used to identify the optimal subset of electrodes that balances performance and computational cost.

For example, PSO can model each particle as a binary vector indicating whether each electrode is selected. The fitness function typically combines classification accuracy and the number of selected electrodes. Through iterative refinement, PSO identifies compact electrode subsets that maintain or even improve decoding accuracy compared to full-channel setups. This optimization not only speeds up online computation but also enhances user comfort in wearable BCI devices.

GWO, with its strong balance between exploration and exploitation, has emerged as a particularly effective algorithm for EEG channel selection. Modified versions, such as Binary GWO and Chaotic GWO, have achieved notable success in MI classification, cognitive workload detection, and emotion recognition. These methods adaptively explore spatial channel relationships, identifying electrodes that maximize the discriminability of brain states while maintaining robustness across users.

Another trend involves multi-objective optimization, where the algorithm simultaneously minimizes channel count and maximizes accuracy. This approach provides a set of Pareto-optimal solutions, allowing researchers to select configurations that best match application constraints such as portability or latency. Such flexibility is invaluable for mobile and edge-deployable BCIs [12].

4.1.2 | Feature selection in electroencephalography and functional near-infrared Spectroscopy

Once relevant channels are determined, metaheuristics are also employed for feature selection, particularly when features are extracted from diverse domains (time, frequency, time–frequency, and connectivity). EEG features may include power spectral densities, entropy measures, wavelet coefficients, or phase synchronization metrics. Similarly, FNIRS features are derived from hemodynamic responses, often including changes in HbO, HbO2, and HbR concentrations.

Metaheuristic algorithms such as DE, ACO, and Artificial Bee Colony (ABC) have proven effective in filtering redundant features while preserving discriminative information. In practice, each candidate feature subset is evaluated by training a classifier (e.g., SVM or CNN) and using its validation accuracy as the fitness score. Over iterations, the optimizer converges on subsets that balance compactness and performance.

In FNIRS-based BCIs, the feature space tends to be smaller but still highly correlated due to the overlapping vascular responses. Metaheuristics such as PSO and GWO have been used to identify the most discriminative features, thereby improving classification performance in tasks such as mental arithmetic, workload assessment, and motor execution. These algorithms enhance interpretability by linking selected features to specific brain regions, offering insights into underlying neurophysiological mechanisms [14], [17], [18].

4.1.3 | Hybrid Electroencephalography–functional near-infrared spectroscopy feature integration

The integration of EEG and FNIRS signals introduces an additional layer of complexity. EEG provides high temporal precision, while FNIRS contributes complementary spatial information. However, fusing both modalities dramatically increases feature dimensionality. Metaheuristic algorithms address this challenge by jointly optimizing EEG and FNIRS features to maximize joint discriminability while minimizing redundancy across modalities.

Algorithms such as the WOA and the Enhanced Grey Wolf Optimizer (E-GWO) have been applied to hybrid feature fusion, achieving higher accuracy than traditional methods. In some studies, hybrid EEG–FNIRS BCIs optimized via metaheuristics achieved over 90% accuracy with reduced feature sets, highlighting the potential of these algorithms in real-time multimodal systems [8].

4.2 | Classifier Tuning and Hybrid Systems

While channel and feature selection form the foundation of BCI optimization, classifier tuning is equally critical. Classifiers such as SVM, Linear Discriminant Analysis (LDA), and CNN are sensitive to hyperparameter settings. The performance of an SVM, for instance, can vary drastically with kernel parameters, whereas CNNs rely heavily on architectural decisions such as layer depth, filter size, and learning rate. Manual or grid-based tuning is inefficient and often fails to generalize across users or sessions. Metaheuristic algorithms provide an intelligent alternative [9], [17].

4.2.1 | Optimization of classical machine learning models

In traditional EEG and FNIRS BCIs, SVMs are among the most widely used classifiers due to their robustness to small datasets and high-dimensional features. Metaheuristics such as PSO, GA, and DE have been employed to optimize key parameters like the regularization Coefficient (C) and kernel width (γ). PSO, in particular, excels in this context due to its fast convergence and ability to handle continuous-valued parameters.

For example, in EEG MI classification, PSO-tuned SVMs have achieved up to 10% higher accuracy than untuned baselines. Similarly, GA-optimized SVMs have been used for emotion recognition from EEG and for decoding the hemodynamic response in FNIRS. ACO and ABC algorithms have also been integrated into ensemble learning frameworks, optimizing weights among multiple classifiers to improve generalization.

In addition to SVMs, metaheuristics have been used to tune parameters of ELMs and Random Forests. These algorithms benefit from the global search capabilities of metaheuristics, which can efficiently find parameter combinations that yield better decision boundaries and higher robustness to noise [10].

4.2.2 | Neural network and deep learning optimization

As deep learning gained traction in BCI research, the role of metaheuristics expanded from parameter tuning to architecture search. Algorithms such as GA, PSO, and GWO have been used to determine the optimal number of layers, neurons, activation functions, and dropout rates for CNNs and RNNs. For EEG-based emotion recognition and speech imagery tasks, hybrid GA–PSO models have been particularly effective, automating the design of CNN architectures tailored to specific feature representations.

Metaheuristics have also been applied to optimize learning rates and weight initialization strategies, addressing common challenges in deep model training. This synergy between deep learning and metaheuristics, sometimes called meta-deep optimization, bridges data-driven learning with global search intelligence, producing models that are both accurate and more interpretable [9], [12], [14], [17], [18].

4.2.3 | Hybrid electroencephalography–functional near-infrared spectroscopy systems

Hybrid BCIs that integrate EEG and FNIRS signals have attracted growing attention for their ability to leverage both temporal and spatial dimensions of brain activity. However, achieving effective fusion requires optimizing numerous parameters: signal synchronization, feature weighting, classifier blending, and decision fusion strategies. Metaheuristics play a pivotal role in these tasks.

For instance, multi-objective PSO has been used to determine the optimal weighting scheme for EEG and FNIRS features in decision-level fusion, balancing each modality's contribution based on its signal-to-noise characteristics. Similarly, DE and GWO have been used to tune hybrid neural network classifiers, adapting them to the distinct dynamics of electrical and hemodynamic signals.

Beyond fusion, metaheuristics contribute to adaptive calibration, a major challenge in hybrid systems. EEG signals often require recalibration for each user and session, whereas FNIRS has slower responses but better cross-subject stability. Metaheuristics can optimize calibration schedules and transfer learning parameters to reduce user-specific retraining time, pushing hybrid BCIs closer to real-world usability [8], [14].

4.3 | Broader Implications

The successful application of metaheuristics to both EEG and FNIRS BCIs demonstrates their versatility and potential to shape next-generation neurotechnologies. By automating feature, channel, and classifier optimization, these algorithms not only enhance accuracy and robustness but also move BCIs toward real-time adaptability and user-specific customization.

In practice, combining these optimization strategies, such as using GWO for channel selection, DE for parameter tuning, and PSO for multimodal fusion, forms the backbone of hybrid metaheuristic frameworks that can dynamically adapt to changing cognitive states and environmental conditions. As research progresses, these adaptive optimization methods will become essential for achieving plug-and-play BCIs that require minimal calibration and deliver reliable performance across diverse users and applications [13], [17], [20].

5 | Case Study: The Trees' Social Relationship Algorithm

Among the latest wave of bio-inspired metaheuristic algorithms, the TSR algorithm represents a distinctive and promising approach to global optimization. Unlike many traditional methods that draw on animal behavior or physical laws, TSR is rooted in ecological principles, specifically the cooperative and competitive interactions among trees within a forest ecosystem. The algorithm captures how trees coexist, share resources, and adapt dynamically to their surrounding environment while competing for sunlight, nutrients, and space.

This ecological balance between cooperation and competition forms a compelling analogy for optimization: solutions (trees) grow and evolve not in isolation, but through dynamic interactions with other members of the ecosystem (the population). TSR formalizes this process into a computational framework capable of handling continuous, discrete, and multi-objective optimization tasks, making it particularly relevant to complex, nonlinear domains such as BCIs [12].

5.1 | Conceptual Foundations and Inspiration

In nature, trees form intricate social networks beneath the soil, connected by mycorrhizal fungal networks that facilitate nutrient exchange and chemical signaling. While they compete for light and space, they also cooperate to maintain the health and balance of the forest ecosystem. TSR translates these dynamics into mathematical interactions among solutions in the search space.

Each individual in the population represents a tree, characterized by its position (solution vector), fitness (objective value), and growth state (adaptive behavior). The algorithm divides the population into subgroups, representing clusters of trees that compete within their local neighborhood while also sharing information globally. This balance maintains diversity and prevents premature convergence, a main drawback of many metaheuristic algorithms such as PSO and GA.

The overarching principle is straightforward yet powerful: trees that thrive in resource-rich conditions (high-fitness solutions) influence others through cooperation, while those in less favorable environments explore new areas through competition and adaptation. Over successive generations, this dynamic interaction drives the ecosystem toward global optimality.

5.2 | Algorithmic Structure and Workflow

The TSR algorithm operates through four major stages that mimic ecological processes: initialization, competition, cooperation, and adaptation.

Initialization

A population of N trees is randomly distributed within the search space, representing potential solutions. Each tree's position vector corresponds to candidate parameter values or feature selections. An objective (fitness) function evaluates each tree based on the task, for example, classification accuracy or mean squared error.

Competition phase

Competition models the struggle among trees for limited resources such as light or nutrients. Trees with higher fitness dominate their local environment, while weaker trees are forced to explore new regions. This mechanism encourages exploration by pushing less fit individuals to distant parts of the search space, reducing the risk of stagnation.

Mathematically, each tree's position is updated by a competitive function:

$$T_i^{new} = T_i + \alpha \cdot (T_{best} - T_i) + \beta \cdot rand(-1,1),$$

where T_i is the current tree, T_{best}represents the fittest tree in the population, and parameters α and β control the competition intensity and randomness. This step mimics directional adaptation toward better resource conditions.

Cooperation phase

In the cooperation stage, trees exchange information and share "resources" (solution characteristics). This process reflects how real trees may allocate nutrients or regulate growth collectively to sustain ecosystem stability. Cooperation promotes exploitation, refining solutions by aligning subgroups toward locally optimal regions.

Each tree updates its position based on a cooperative exchange model:

$$T_i^{new} = T_i + \gamma \cdot \left(T_j - T_i\right),$$

where T_j is a cooperating tree randomly selected from the population, and γ is the cooperation coefficient governing how strongly individuals influence each other. Through this phase, TSR strengthens local convergence without losing diversity.

Adaptation and regeneration

After several cycles of competition and cooperation, the algorithm applies an adaptation mechanism. Poorly performing trees are "regenerated" in new random positions, analogous to new seedlings sprouting in open areas of the forest. This regeneration introduces fresh diversity and ensures that the population continues exploring unvisited regions.

The iterative balance between competition, cooperation, and regeneration underpins TSR's adaptive intelligence. The process repeats until a termination criterion, such as a maximum iteration count or a satisfactory fitness level, is met.

5.3 | Advantages of Trees Social Relationship Over Conventional Metaheuristics

TSR stands out among metaheuristics for several distinctive strengths that address long-standing challenges in optimization for BCI systems:

Balance between exploration and exploitation

TSR's dual-phase structure ensures that global exploration (competition) and local exploitation (cooperation) coexist dynamically. Unlike PSO, which can prematurely collapse toward a single solution, TSR maintains population diversity longer, thereby improving its ability to escape local minima.

Adaptive diversity control

Through its regeneration mechanism, TSR introduces new candidate solutions when the search begins to stagnate. This built-in diversity management prevents premature convergence, a problem often observed in GA and DE.

Parameter simplicity

TSR requires fewer control parameters than algorithms like GA (which requires crossover/mutation rates) or PSO (which relies on inertia weights and acceleration coefficients). This makes TSR easier to tune for new problems and more robust across varying datasets.

Suitability for mixed optimization spaces

Many real-world BCI tasks involve both discrete (e.g., channel selection) and continuous (e.g., filter bandwidths, learning rates) parameters. TSR handles both seamlessly within a unified framework, offering a flexibility that many classical algorithms lack.

High convergence efficiency

Early benchmark studies have demonstrated that TSR converges faster and more consistently than GA, PSO, and GWO on standard test functions. This efficiency is attributed to its cooperative exchange, which accelerates exploitation without sacrificing exploration.

5.4 | Potential Applications of Trees' Social Relationship in Brain–Computer Interface Systems

Although TSR is a relatively new algorithm, its characteristics make it well-suited to the unique demands of BCI optimization. EEG and FNIRS signal processing often involves nonlinear, high-dimensional, and noisy objective functions, conditions under which TSR excels.

5.4.1 | Feature and channel selection

One of the most promising applications of TSR is in EEG channel selection and feature subset optimization. Here, each tree represents a binary vector where ‘1’ indicates a selected channel or feature. The fitness function measures classification accuracy achieved using the selected subset. TSR’s ability to balance exploration and exploitation allows it to identify compact, high-performance feature sets efficiently.

For example, in EEG-based MI tasks, TSR could optimize spatial feature subsets derived from CSP or wavelet coefficients. Similarly, in hybrid EEG–FNIRS systems, TSR could identify complementary feature pairs across modalities, maximizing temporal and spatial information simultaneously.

5.4.2 | Neural network parameter tuning

TSR is equally effective in neural network optimization, where it can fine-tune parameters such as the learning rate, the number of neurons, and regularization coefficients. Compared to grid search or Bayesian optimization, TSR can explore a wider range of nonlinear dependencies among hyperparameters.

Applied to EEGNet or CNN-based architectures, TSR can optimize convolutional kernel sizes, dropout ratios, and activation parameters, yielding higher accuracy with fewer training epochs. Its population-based nature makes it naturally parallelizable, an advantage for GPU-based BCI model training.

5.4.3 | Transfer learning and adaptation

Cross-subject and cross-session variability remains a major bottleneck in BCI systems. TSR can play a key role in transfer learning and domain adaptation by optimizing parameters that align feature distributions across sessions or users. For instance, it can fine-tune transfer coefficients or pseudo-label confidence thresholds to minimize domain shift, enabling more stable decoding over time.

Additionally, in online adaptive BCIs, TSR can dynamically adjust learning parameters based on real-time user or environmental feedback. Its regeneration mechanism allows it to adapt continuously without requiring complete retraining, a critical feature for practical, long-term BCI use.

5.4.4 | Reinforcement learning integration

TSR can be integrated with Deep Reinforcement Learning (DRL) frameworks, where it serves as a meta-controller that optimizes reward functions, exploration rates, or network architectures. This integration creates self-optimizing, closed-loop BCIs that dynamically adapt their behavior during operation.

For example, a TSR-DRL hybrid could tune policy network hyperparameters or reward shaping factors in a neurofeedback system, ensuring efficient learning across users with diverse neural responses.

5.5 | Comparative Insights and Future Outlook

When compared with traditional metaheuristics, TSR's ecological foundation introduces a new dimension of adaptivity and stability. While algorithms like GA and PSO rely heavily on stochastic randomness, TSR leverages structured social interactions, enabling more controlled, interpretable search dynamics. This aligns well with the growing demand for Explainable Artificial Intelligence (XAI) in neuroscience, where understanding how and why certain features are optimized is as important as the performance itself.

The TSR algorithm's capacity for multi-objective optimization further strengthens its position in modern BCI research. Many BCI objectives, such as accuracy, latency, energy efficiency, and interpretability, are inherently conflicting. TSR's cooperative and competitive phases can be extended to address trade-offs among these objectives, yielding Pareto-optimal solutions that yield balanced system configurations.

In addition, TSR's low parameter count and adaptability make it suitable for edge deployment, a key goal for next-generation BCIs. On-device optimization, where TSR continuously tunes model parameters during use, could enable personalized BCIs that evolve with the user's cognitive and physiological state.

Future work could extend TSR into hybrid frameworks, combining it with DNNs or RL systems to create self-adaptive, explainable, and energy-efficient BCI architectures. Moreover, its ecological metaphor lends itself to integration with other nature-inspired models, such as forest fire dynamics or nutrient flow simulation, to further enrich its adaptive mechanisms.

The TSR algorithm represents a significant step forward in the evolution of metaheuristic optimization. Rooted in ecological intelligence rather than animal or physical analogies, TSR models the cooperative-competitive balance that defines real-world ecosystems. Its capacity to maintain population diversity, adapt dynamically, and handle both discrete and continuous variables makes it exceptionally well-suited to the multifaceted optimization challenges of EEG- and FNIRS-based BCI systems.

By enabling robust feature selection, efficient neural network tuning, and adaptive learning across users and sessions, TSR stands poised to become a cornerstone of future BCI optimization frameworks. As research in hybrid and explainable BCIs continues to expand, TSR offers not only performance improvements but also conceptual clarity embodying the principle that intelligence, whether biological or artificial, thrives through balance, adaptation, and interconnection.

6 | Conclusion

Metaheuristic algorithms are increasingly important in the development of high-performance BCI systems. Whether applied to EEG, FNIRS, or hybrid setups, these algorithms help automate feature selection, optimize classifiers, and enhance the adaptability of BCI pipelines. The review of methods such as GA, PSO, DE, ACO, and GWO illustrates their flexibility and robustness in handling complex, non-linear optimization tasks.

As new challenges emerge in BCI, such as real-time processing, subject variability, and hybrid modality integration, metaheuristics will continue to offer elegant, biologically inspired solutions. Algorithms like TSR represent the next generation of optimization techniques, with mechanisms designed to reflect the complexity and adaptability required in modern neurotechnologies.

Looking ahead, integrating metaheuristics with deep learning, transfer learning, and RL may further accelerate progress in the field. Metaheuristics are not just tools for solving technical problems; they are becoming foundational to the evolution of BCI itself.

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