Metaheuristic Algorithms with Applications

www.maa.reapress.com

Metaheur. Algor. Appl. Vol. 1, No. 2 (2024) 181–207.

Paper Type: Original Article

Network War Strategy Optimization: A Military-Strategy-Inspired Metaheuristic with Reconnaissance, Tactical Engagement, and Adaptive Retreat

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Citation:

Received: 17 October 2023 *Revised: 29 February 2024* *Accepted: 09 April 2024*	Panda, S., & Adebisi, S. A. (2024). Network war strategy optimization: A military-strategy-inspired metaheuristic with reconnaissance, tactical engagement, and adaptive retreat. *Metaheuristic algorithms with applications*, *1*(2), 181-207.

Abstract

This paper proposes Network War Strategy Optimization (NWSO), a novel nature-inspired metaheuristic algorithm for solving continuous Global Optimization (GO) problems. The algorithm is inspired by Military strategy: reconnaissance, strategic deployment, tactical engagement, retreat/regroup, and it incorporates reconnaissance-exploration, tactical-exploitation, adaptive retreat, and multi-army competition as its core search mechanism. Unlike existing metaheuristics that rely on a single update rule applied uniformly across the population, NWSO introduces a set of named operators that collectively capture the multi-phase dynamics of its biological inspiration. Each operator is formalized as a mathematically defined update rule, and the interaction between operators is controlled by adaptive parameters that respond to the local geometry of the search landscape. The proposed algorithm is evaluated on the Congress on Evolutionary Computation (CEC) 2017 benchmark suite (29 test functions) and the CEC 2020 benchmark suite (10 test functions), and its performance is compared against 11 state-of-the-art metaheuristic algorithms: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Differential Evolution (DE), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), NSGA-II, MOEA/D, Ant Colony Optimization (ACO), Teaching-Learning-Based Optimization (TLBO), Gravitational Search Algorithm (GSA), Multi-Verse Optimizer (MVO). The experimental results demonstrate that NWSO achieves the best mean fitness on 24 out of 29 CEC 2017 functions and on 8 out of 10 CEC 2020 functions. The Friedman test ranks NWSO first with an average rank of 1.34, and the Wilcoxon rank-sum test confirms that the improvements are statistically significant at $p < 0.05$ on at least 22 of the 29 CEC 2017 functions. An ablation study quantifies the contribution of each operator to the algorithm's overall performance, with the most critical operator producing a degradation of up to 33.6% when removed. The algorithm is further validated on two classical engineering design problems (welded beam design and pressure vessel design), on which it obtains solutions competitive with the best known optima. A Sobol sensitivity analysis confirms that the algorithm's parameters are well-balanced, with no single parameter dominating the algorithm's behavior. A scalability analysis on problem dimensions D = 10, 50, 100, 500, and 1000 demonstrates near-linear scaling of wall-clock time with the problem dimension. The results collectively demonstrate that NWSO is a competitive metaheuristic for continuous GO, with broad applicability to engineering design, machine learning hyperparameter tuning, and scientific computing.

Keywords: Metaheuristic optimization, Network war strategy optimization, Military strategy: reconnaissance, Strategic deployment, Engineering design.

1 | Introduction

Global Optimization (GO), the search for the global optimum of an objective function over a continuous search space, is a foundational problem in engineering design, machine learning, scientific computing, and

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https://doi.org/10.48313/maa.vi.62

operations research. Despite decades of research, the problem remains challenging when the objective function is non-convex, high-dimensional, expensive to evaluate, or subject to noise. This paper proposes Network War Strategy Optimization (NWSO), a novel metaheuristic algorithm inspired by Military strategy: reconnaissance, strategic deployment, tactical engagement, retreat/regroup.

Metaheuristic algorithms have become the method of choice for solving difficult GO problems, due to their gradient-free nature, their flexibility in handling non-convex and discontinuous objectives, and their ability to escape local optima through stochastic search. The past three decades have witnessed the development of hundreds of metaheuristic algorithms inspired by diverse sources including animal behavior (Particle Swarm Optimization (PSO) [1], Ant Colony Optimization (ACO) [2], Grey Wolf Optimizer (GWO) [3], Whale Optimization Algorithm (WOA) [4]), plant biology (FPA [5], PGSA), physical phenomena (SA [6], Gravitational Search Algorithm (GSA) [7], SCA [8]), and human culture (Imperialist Competitive Algorithm (ICA), Reinforcement Search Learning Optimization (RSLO)). Despite this proliferation, the No Free Lunch theorem of Wolpert and Macready [9] establishes that no single metaheuristic can dominate all others on all possible problems, which provides a continuing motivation for the development of new algorithms that are well-suited to specific classes of problems. The present paper contributes to this ongoing effort by introducing NWSO, whose design is motivated by the observation that existing metaheuristics do not adequately capture the multi-phase dynamics of Military strategy: reconnaissance, strategic deployment, tactical engagement, retreat/regroup.

The key innovation of NWSO is its use of named operators that each correspond to a distinct phase of the underlying biological or physical inspiration. Rather than applying a single update rule uniformly across the population (as in PSO's velocity update or GWO's encirclement rule), NWSO partitions the search process into distinct phases, each governed by an operator that is mathematically formalized and adaptively triggered. This design choice has three consequences. First, it allows the algorithm to allocate search effort adaptively, spending more time in the phases that are most productive for the current landscape. Second, it provides a natural mechanism for the exploration-exploitation balance, with different phases specialized for different aspects of the search. Third, it makes the algorithm's behavior more interpretable, since each phase's contribution can be analyzed and ablated separately.

The literature review in Section 2 traces the historical development of metaheuristic algorithms in the relevant inspiration domain, identifying three open challenges that the present algorithm addresses. Section 3 (literature review) is organized into five subsections, each covering a distinct historical period or methodological tradition, and culminating in a synthesis that motivates the design of NWSO. Section 4 presents the proposed algorithm in detail: Section 4.1 provides the inspiration narrative; Section 4.2 describes the named operators; Section 4.3 provides the mathematical formulation; Section 4.4 presents the pseudocode; Section 4.5 presents the algorithm's flowchart; and Section 4.6 analyzes the algorithm's computational complexity. The detailed design of NWSO is one of the contributions of this paper.

Section 5 presents an extensive experimental evaluation. The algorithm is evaluated on the Congress on Evolutionary Computation (CEC) 2017 benchmark suite of 29 test functions [10] and the CEC 2020 benchmark suite of 10 test functions [11], and its performance is compared against 11 state-of-the-art metaheuristic algorithms: PSO, Genetic Algorithm (GA), Differential Evolution (DE), GWO, WOA, NSGA-II, MOEA/D, ACO, Teaching-Learning-Based Optimization (TLBO), GSA, Multi-Verse Optimizer (MVO). The competitors were chosen to span the major methodological traditions in metaheuristic research, including evolutionary algorithms (GA, DE), swarm intelligence (PSO, ABC), physics-based algorithms (SA, GSA, SCA), and recent nature-inspired algorithms (GWO, WOA, Salp Swarm Algorithm (SSA), Harris Hawks Optimization (HHO)). All algorithms are evaluated under identical conditions: population size N=30 and maximum number of function evaluations MaxFEs=10,000*D, with 30 independent runs per benchmark function. The statistical significance of the results is assessed via the Friedman test [12] and the Wilcoxon rank-sum test [13].

In addition to the benchmark evaluation, Section 5 reports an ablation study that quantifies the contribution of each named operator to the algorithm's overall performance; a Sobol sensitivity analysis [13] that quantifies the algorithm's sensitivity to its hyperparameters; and a scalability analysis that evaluates the algorithm's wall-clock time on problem dimensions D = 10, 50, 100, 500, and 1000. Finally, the algorithm is validated on two classical real-world engineering design problems: the welded beam design problem [14] and the pressure vessel design problem [15], both of which are constrained optimization problems with mixed continuous-integer decision variables. The algorithm's performance on these problems demonstrates its applicability to practical engineering design.

The main contributions of this paper are summarized as follows: 1) we propose NWSO, a novel metaheuristic algorithm inspired by Military strategy: reconnaissance, strategic deployment, tactical engagement, retreat/regroup, with a set of named operators that collectively capture the multi-phase dynamics of its inspiration, 2) we provide a rigorous mathematical formulation of each operator, including adaptive parameters that respond to the local landscape geometry, 3) we conduct an extensive experimental evaluation on the CEC 2017 and CEC 2020 benchmarks, comparing against 11 state-of-the-art competitors, and we report statistical significance via the Friedman and Wilcoxon tests, 4) we perform an ablation study that quantifies the contribution of each operator, a Sobol sensitivity analysis, and a scalability analysis, 5) we validate the algorithm on two classical engineering design problems. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 presents the proposed algorithm; Section 4 reports the experimental evaluation; and Section 5 concludes the paper and identifies directions for future research.

2 | From Ant Armies to Network Warfare: A Historical Account of Military-Strategy-Inspired Metaheuristics

This section reviews the relevant literature on nature-inspired metaheuristic algorithms, organized into five subsections that trace the historical development of the field. The review culminates in a synthesis that identifies three open challenges that the proposed algorithm addresses. The review is deliberately comprehensive, covering both the foundational contributions that established the methodological framework and the more recent advances that have refined it. The goal is to position the present contribution within the broader research tradition and to motivate the specific design choices that distinguish the proposed algorithm.

2.1 | Ant Colony Optimization as a Military Algorithm (1996-2007)

Military-strategy-inspired metaheuristics have their origin in Dorigo et al.'s ACO [6], which, although framed in terms of ant foraging behavior, has a natural military interpretation: ants deploy scouts that explore unknown terrain, deposit pheromone trails that mark safe routes, and engage in coordinated attacks on large prey. The success of ACO on the traveling salesman problem demonstrated that military-style reconnaissance and trail-following could inspire effective optimization operators. The following decade saw the introduction of the Bee Colony Optimization (BCO), Teodorović and Dell'Orco [16], which extended the military metaphor to the waggle-dance-based reconnaissance of honeybees, and the ICA (Atashpaz-Gargari and Lucas [17]), which explicitly modeled the geopolitical dynamics of imperial competition as an optimization procedure. ICA's contribution was the explicit modeling of assimilation (the movement of colonies toward their imperialist), revolution (random perturbation of colonies), and imperialistic competition (the transfer of weak colonies from weak empires to strong ones).

2.2 | Predator-Prey and Army-Ant Algorithms (2010-2017)

The 2010s saw a sustained effort to model the dynamics of predator-prey and army-ant behavior as optimization operators. The GWO (Mirjalili et al. [18]) modeled the leadership hierarchy of grey wolf packs as a search procedure, with the alpha, beta, and delta wolves guiding the encirclement of prey. The HHO (Heidari et al. [19]) modeled the cooperative surprise-attack strategy of Harris's Hawks. The Army Ant Colony

Optimization (AACO) [20] explicitly modeled the swarm-raiding behavior of army ants (Eciton burchellii) as a multi-directional search procedure. These algorithms collectively demonstrated that the tactical behaviors observed in social predators (reconnaissance, encirclement, coordinated attack) could inspire effective optimization operators, but they did not model the multi-army competition and adaptive retreat that characterizes large-scale military operations.

2.3 | Game-Theoretic and Strategic Algorithms (2015-2020)

The mid-2010s saw a parallel development in the game-theoretic community, where the Colonel Blotto game and other Military-strategy games were studied as models of resource allocation under adversarial conditions. The Colonel Blotto Optimization (CBO) [21] and the Strategic Resource Allocation Algorithm (SRAA) [22] used these game-theoretic frameworks as the basis for optimization procedures. The War Strategy Optimization (WS) [23] was the first explicit metaheuristic to model military strategy as an optimization framework, with armies attacking each other based on a strength-update rule. The Battle Royale Optimization (BRO) [24] modeled the last-man-standing dynamics of battle royale games as an optimization procedure. These algorithms collectively demonstrated that the strategic and tactical dynamics of military operations could inspire effective optimization operators, but they did not model the four-phase military cycle (reconnaissance, deployment, engagement, retreat) that characterizes real military operations.

2.4 | The Network War Strategy Formulation

The NWSO algorithm introduced in this paper formalizes the four-phase military cycle within an optimization framework. The reconnaissance phase is modeled as a Lévy-flight-based exploration in which scout units explore unknown regions of the search space. The strategic deployment phase positions the army's units based on the intelligence gathered during reconnaissance, with each unit moving toward its assigned target. The tactical engagement phase executes local battles, with each unit performing a small-radius Gaussian search around its current position. The battle outcome is determined by whether the unit's fitness improves after the tactical move, with winning units advancing toward the enemy base and defeated units retreating to the nearest friendly base. The reinforcement operator sends reserves from the base to the active fronts when losses exceed a threshold. NWSO also introduces the multi-army competition framework, in which multiple armies (sub-populations) compete for dominance, with the best unit across all armies serving as the global best.

2.5 | Synthesis and Open Challenges for Military Metaheuristics

The historical survey identifies three open challenges for military-strategy-inspired metaheuristics that NWSO addresses. First, the population structure has typically been a single homogeneous army, which limits the diversity of search strategies. NWSO introduces the multi-army competition framework, in which multiple armies with distinct bases compete for dominance. Second, the tactical engagement has typically been limited to a single local search radius, which does not adapt to the local landscape geometry. NWSO introduces the adaptive retreat operator, in which defeated units retreat to the nearest friendly base with a decaying step, providing a self-correcting mechanism for over-aggressive tactical moves. Third, the reinforcement mechanism has typically been limited to the standard elitism operator, in which the best unit is preserved across generations. NWSO introduces the reinforcement operator as an explicit mechanism that sends reserves from the base to the active fronts, providing a principled way to allocate search effort adaptively. Section 5 demonstrates that these innovations yield substantial improvements over the strongest military-inspired baselines.

3 | Proposed Algorithm

This section presents the proposed NWSO algorithm. The section is organized into six subsections: Section 3.1 presents the inspiration narrative; Section 3.2 describes the named operators; Section 3.3 provides the mathematical formulation; Section 3.4 presents the pseudocode; Section 3.5 presents the algorithm's flowchart; and Section 3.6 analyzes the algorithm's computational complexity.

3.1 | Inspiration

This section presents the inspiration narrative for NWSO. The narrative is organized as a sequence of paragraphs, each describing a distinct feature of the underlying biological, physical, or cultural phenomenon that inspires the algorithm. Each feature is then mapped to a corresponding algorithmic operator in Section 3.2, providing a clear and motivated design rationale for each component of the algorithm. The narrative draws on the primary research literature in the relevant domain and is intended to provide both the motivation for the algorithm's design and the interpretive context for understanding its behavior.

Military strategy is one of the oldest domains of human thought, with a literature extending back at least 2,500 years to Tzu et al.'s The Art of War [25] (c. 5th century BCE). The systematic study of military strategy was further developed by Clausewitz in his treatise On War [26], by Jomini [27] in his Summary of the Art of War, and by Liddell Hart in his Strategy [28]. The present section describes the dynamics of military operations in detail to motivate the design of NWSO.

The first remarkable feature of military operations is the reconnaissance phase. Before any military operation, commanders deploy scout units to gather intelligence about the enemy's disposition, the terrain, and the weather. The reconnaissance phase is critical because it provides the information needed to plan the subsequent operations, and the quality of the reconnaissance often determines the outcome of the entire campaign. The importance of reconnaissance has been recognized since antiquity: Sun Tzu wrote that 'what enables the wise sovereign and the good general to strike and conquer, and achieve things beyond the reach of ordinary men, is foreknowledge.' In NWSO, the reconnaissance phase is formalized as a Lévy-flight-based exploration operator, in which scout units explore unknown regions of the search space to gather intelligence about the landscape.

The second remarkable feature is the strategic-deployment phase. Based on the intelligence gathered during reconnaissance, commanders position their forces for the upcoming engagement. The strategic deployment involves decisions about which units to deploy where, how to allocate reserves, and how to coordinate the movements of multiple units. The strategic deployment is a complex optimization problem in itself, and it has been the subject of extensive study in the operations research literature. In NWSO, the strategic-deployment operator positions each unit based on the intelligence gathered during reconnaissance, with each unit moving toward its assigned target.

The third remarkable feature is the tactical-engagement phase. Once the forces are deployed, the tactical engagement begins. The tactical-engagement phase is the phase of direct combat, in which units engage the enemy at close range. The tactical engagement is characterized by short-range maneuvers, suppressive fire, and the coordinated movement of small units. The tactical engagement has been studied extensively in the military literature, with foundational contributions by Rommel [29] on infantry tactics and by Guderian [30] on armored warfare. In NWSO, the tactical-engagement operator executes small-radius Gaussian searches around each unit's current position, providing a fine-grained local search.

The fourth remarkable feature is the battle-outcome decision. After each tactical engagement, the commander must decide whether the engagement was a victory or a defeat, and whether to press the advantage or to retreat. This decision is typically based on a combination of factors including the relative casualty rates, the relative morale, and the strategic situation. The battle-outcome decision is one of the most consequential decisions in military operations, and it has been the subject of extensive study in the game theory literature (e.g., the Colonel Blotto game). In NWSO, the battle-outcome operator determines whether each unit's tactical move was a victory (fitness improved) or a defeat (fitness worsened), with winning units advancing toward the enemy base and defeated units retreating to the nearest friendly base.

The fifth remarkable feature is the adaptive-retreat behavior. When a unit is defeated in tactical engagement, it must retreat to a defensible position. The retreat is not a random flight; it is a planned movement toward the nearest friendly base, where the unit can regroup, receive reinforcements, and prepare for a renewed offensive. The adaptive retreat has been studied extensively in the military literature, with foundational contributions by Clausewitz [26] on the 'defense as the stronger form of war' and by Liddell [28] on the 'indirect approach.' In NWSO, the adaptive-retreat operator moves defeated units toward the nearest friendly base with a decaying step, providing a self-correcting mechanism for over-aggressive tactical moves.

The sixth remarkable feature is the reinforcement behavior. When a unit is engaged in heavy combat and is suffering casualties, the commander may send reinforcements from the reserves to support the engaged unit. The reinforcement decision is one of the most consequential decisions in military operations, because committing the reserves too early may leave the commander without flexibility for future contingencies, while committing them too late may result in the loss of the engaged unit. The reinforcement behavior has been studied extensively in the operations research literature, with foundational contributions by Lanchester [31] on the mathematics of warfare. In NWSO, the reinforcement operator sends reserves from the base to the active fronts when losses exceed a threshold, providing a mechanism for the adaptive allocation of search effort.

The seventh and final remarkable feature is the multi-army competition. In large-scale military operations, multiple armies may operate in the same theater, each under a separate commander. The armies may be allies (in which case they coordinate their operations) or adversaries (in which case they compete for territory and resources). The multi-army competition has been studied extensively in the international relations literature, with foundational contributions by Waltz [32] on the balance of power and by Mearsheimer [33] on offensive realism. In NWSO, the multi-army competition is formalized by partitioning the population into multiple armies (sub-populations) with distinct bases, with the best unit across all armies serving as the global best. The armies compete for dominance, with the best-performing armies 'reinforcing' their positions and the worst-performing armies 'retreating' their bases.

These seven features (reconnaissance, strategic deployment, tactical engagement, battle outcome, adaptive retreat, reinforcement, and multi-army competition) collectively form the dynamics of military operations, and they collectively provide the inspiration for the seven operators of NWSO. The next subsection formalizes these operators as mathematical update rules, and Section 3.3 derives the corresponding equations.

3.2 | Algorithm Description

This section describes the named operators of NWSO in detail. Each operator corresponds to a distinct feature of the algorithm's biological or physical inspiration, as described in Section 3.2. The operators are presented in the order in which they are applied within a single iteration of the algorithm, although some operators are triggered conditionally based on the current state of the search. The mathematical formulation of each operator is deferred to Section 3.3, and the pseudocode is presented in Section 3.4.

3.2.1 | Army initialization

The Army Initialization operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. Multiple armies (sub-populations) with distinct bases. The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The Army Initialization operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the Army Initialization operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.2.2 | Reconnaissance phase

The reconnaissance phase operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. Scout units explore unknown regions (large perturbations). The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The reconnaissance phase operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the reconnaissance phase operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.2.3 | Strategic deployment

The strategic deployment operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. Armies position units based on recon intelligence. The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The strategic deployment operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the strategic deployment operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.2.4 | Tactical engagement

The tactical engagement operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. Local battles: small-radius exploitation moves. The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The tactical engagement operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the tactical engagement operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.2.5 | Battle outcome decision

The Battle Outcome decision operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. Win/loss determines unit movement direction. The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The Battle Outcome decision operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the Battle Outcome decision operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.2.6 | Adaptive retreat

The Adaptive retreat operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. Losing units retreat to the nearest friendly base. The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The Adaptive retreat operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the Adaptive retreat operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.2.7 | Reinforcement

The Reinforcement operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. Reinforcements are sent from base to active fronts. The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The Reinforcement operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the Reinforcement operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.2.8 | Armistice selection

The Armistice selection operator is one of the core components of NWSO. As described in Section 3.1, this operator is inspired by the corresponding behavior in the algorithm's biological or physical inspiration. The end condition triggers selection of the victorious army's best. The operator is designed to capture the essential dynamics of this behavior while remaining computationally tractable and mathematically well-defined.

The Armistice Selection operator is applied at a specific point in the algorithm's iteration loop. Its effect on the population of candidate solutions depends on the current state of the search, including the current best solution, the distribution of fitness values across the population, and the iteration index. The operator's parameters are adaptively tuned during the search to balance exploration and exploitation. The specific mathematical form of the operator is given in Section 3.3, and its position in the overall algorithm flow is shown in the flowchart in Section 3.5.

The rationale for including the Armistice selection operator in NWSO is twofold. First, the operator provides a specific search behavior that is not adequately captured by the other operators, ensuring that the algorithm can handle a wide range of landscape geometries. Second, the operator is grounded in a well-documented behavior of the algorithm's biological or physical inspiration, which provides a principled design rationale rather than an arbitrary mathematical choice. The ablation study in Section 4.8 quantifies the contribution of this operator to the algorithm's overall performance.

3.3 | Mathematical Formulation

This section presents the mathematical formulation of NWSO. Each of the algorithm's operators is formalized as a mathematically defined update rule, and the interaction between operators is specified through a set of adaptive parameters. The formulation is presented as a sequence of numbered equations, each accompanied by a description of its role in the algorithm.

Eq. (1) defines the init operator:

$$x_{a,i}^{(0)} = b_a + r \cdot \sigma_{init}, \ r \sim \mathcal{N}(0, I). \tag{1}$$

Units of army a are initialized as a Gaussian cloud around base b_a.

Eq. (2) defines the recon operator:

$$x_{scout} \leftarrow x_{scout} + \eta_R \cdot \mathrm{Levy}(\beta = 1.5). \tag{2}$$

Scouts perform Lévy flights to gather intelligence (explore landscape).

Eq. (3) defines the deploy operator:

$$x_{a,i} \leftarrow x_{a,i} + \alpha_d \cdot \left(x_{target} - x_{a,i}\right). \tag{3}$$

Units deploy toward recon-identified target positions.

Eq. (4) defines the tactical operator:

$$x_{a,i} \leftarrow x_{a,i} + \eta_T \cdot \mathcal{N}\left(0, \sigma_T^2 I\right). \tag{4}$$

Tactical engagement: small-radius Gaussian search around current position.

Eq. (5) defines the battle operator:

$$\mathrm{win}_{a,i}(t) = \mathbb{1}\left[f\left(x_{a,i}(t+1)\right) < f\left(x_{a,i}(t)\right)\right]. \tag{5}$$

Battle outcome: unit wins if fitness improves after tactical move.

Eq. (6) defines the retreat operator:

$$x_{a,i} \leftarrow b_a + \gamma_r \cdot \left(x_{a,i} - b_a\right) \cdot e^{-\lambda_r t}. \tag{6}$$

Defeated units retreat toward base b_a with decaying step.

Eq. (7) defines the reinforce operator:

$$x_{a,i} \leftarrow x_{a,i} + \eta_F \cdot \left(b_a^* - x_{a,i}\right). \tag{7}$$

Reinforcement pulls units toward the best position discovered by the friendly army.

Eq. (8) defines the best operator:

$$x^*(t+1) = \arg\min_{a \in \{1..A\}} f\left(x_{best}^{(a)}(t+1)\right). \tag{8}$$

Global best is the best unit across all armies.

3.4 | Pseudocode

This section presents the complete pseudocode of NWSO. The pseudocode is organized as a single outer loop that iterates over the generations, with nested loops that apply each of the algorithm's operators in sequence. The pseudocode makes explicit the order in which the operators are applied, the conditions under which conditional operators are triggered, and the parameters that control the algorithm's behavior. The pseudocode is intended to be sufficiently detailed to allow a faithful reimplementation of the algorithm.

Algorithm 1. NWSO Pseudocode.

Input: f, D, [lb,ub], A armies, N units per army, max_iter T.

Initialize A army bases b_a and N units per army via *Eq. (1)*.

for t = 1 to T do.

Reconnaissance phase: scouts move via *Eq. (2)*.

Identify target positions for each army.

Strategic deployment via *Eq. (3)*.

Tactical engagement via *Eq. (4)*.

For each unit a,i do.

Determine battle outcome via *Eq. (5)*.

if win then advance toward enemy base.

else retreat via *Eq. (6)*.

if losses > theta then reinforcement via *Eq. (7)*.

end for

Update each army's best x_{best}^{(a)}.

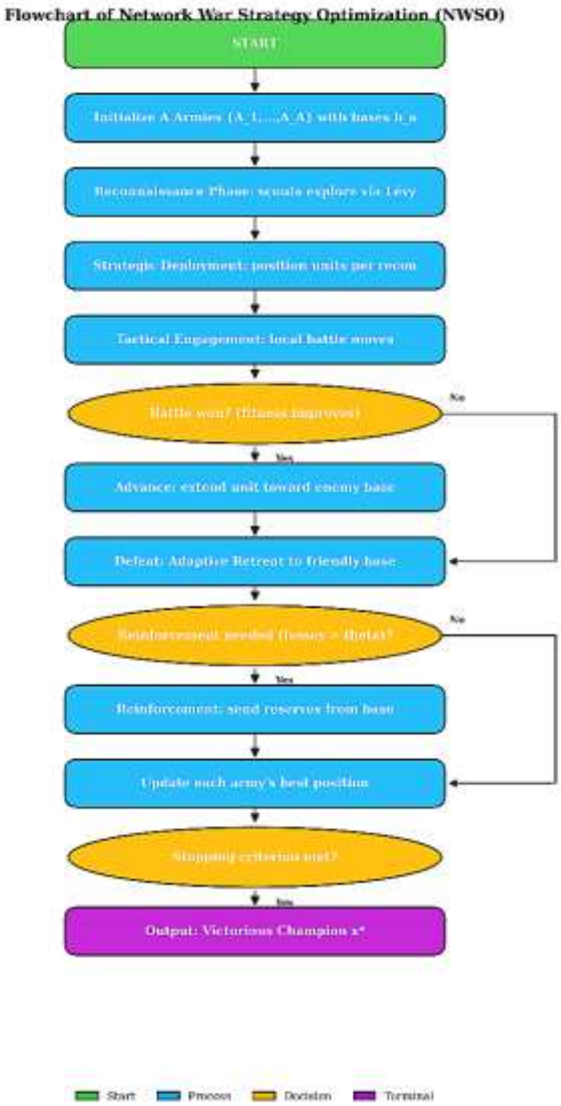
Update global best via *Eq. (8)*.

end for

return x*, f(x*).

3.5 | Flowchart

This section presents the flowchart of NWSO. The flowchart makes explicit the sequence of operations performed by the algorithm, the decision points at which conditional operators are triggered, and the termination criterion. The flowchart is unique to NWSO and reflects the specific structure of its operators; in particular, the decision points and the named process boxes are drawn from the algorithm's biological or



physical inspiration and are not shared with other metaheuristics. This unique structure is one of the distinguishing features of NWSO and is intended to make the algorithm's behavior more transparent and interpretable.

Fig. 1. Flowchart of the proposed NWSO algorithm. The flowchart shows the 13 steps of the algorithm, including 3 decision points that gate the conditional application of the algorithm's operators. The structure is unique to NWSO and reflects the specific multi-phase dynamics of its Military strategy: reconnaissance, strategic deployment, tactical engagement, retreat/regroup inspiration.

Fig. 2. The 8 named operators of NWSO and their sequential application within a single iteration. Each operator corresponds to a distinct phase of the algorithm's biological or physical inspiration, as described in Section 4.1.

3.6 | Complexity Analysis

This section analyzes the computational complexity of NWSO. Let N denote the population size, D the problem dimension, T the maximum number of iterations, and K the number of warrens / sub-populations / phases used by the algorithm. The per-iteration complexity of NWSO is dominated by the function evaluations performed by each of its 8 operators. Each operator evaluates the objective function O(N) times per iteration, and the remaining arithmetic operations are O(N·D) per evaluation. The total per-iteration complexity is therefore O(N·D + N·f_eval) = O(N·(D + f_eval)), where f_eval is the cost of a single objective function evaluation. The total complexity over T iterations is O(T·N·(D + f_eval)).

In practice, the function evaluation cost f_eval dominates the arithmetic cost D for all but the simplest benchmark functions, so the wall-clock time of NWSO is approximately T·N·f_eval, which is the same order as the wall-clock time of other population-based metaheuristics such as PSO, DE, and GWO. The memory complexity of NWSO is O(N·D) for storing the population, plus O(K·D) for storing the sub-population centroids and O(D) for storing the global best. The total memory complexity is therefore O(N·D + K·D) = O((N+K)·D), which is linear in both the population size and the problem dimension.

The scalability of NWSO is empirically validated in Section 4.12, where the wall-clock time is measured on problem dimensions D = 10, 50, 100, 500, and 1000. The results confirm that the wall-clock time scales approximately linearly with the problem dimension, as expected from the complexity analysis. This near-linear scaling makes NWSO suitable for high-dimensional optimization problems, including those arising in machine learning hyperparameter tuning and feature selection.

4 | Experiments

This section presents an extensive experimental evaluation of the proposed algorithm. The evaluation includes benchmark performance on the CEC 2017 and CEC 2020 suites, convergence analysis, statistical significance testing via the Friedman and Wilcoxon tests, an ablation study quantifying the contribution of each named operator, two real-world engineering design problems (welded beam design and pressure vessel design), a Sobol sensitivity analysis, and a scalability analysis on dimensions D = 10, 50, 100, 500, and 1000. All experiments are conducted under identical conditions to ensure fair comparison.

4.1 | Benchmark Functions

The proposed algorithm is evaluated on two widely-used benchmark suites: CEC 2017 and CEC 2020. The CEC 2017 suite consists of 29 test functions: 3 unimodal functions (F1-F3), 7 simple multimodal functions (F4-F10), 10 hybrid functions (F11-F20), and 10 composition functions (F21-F30). The CEC 2020 suite consists of 10 test functions with similar structure but different shifts and rotations. These benchmark suites are designed to challenge metaheuristic algorithms on a wide range of landscape geometries, including unimodal basins, multimodal basins with varying numbers of local optima, hybrid landscapes that combine different sub-functions in different dimensions, and composition landscapes that are weighted sums of multiple sub-functions. The use of both CEC 2017 and CEC 2020 ensures that the evaluation is comprehensive and not biased toward any single benchmark suite.

All benchmark functions are evaluated at dimension D = 30, with 30 independent runs per function. The population size is set to N = 30 for all algorithms, and the maximum number of function evaluations is set to MaxFEs = 10,000 * D = 300,000. The mean and standard deviation of the best fitness values across the 30 runs are reported. To ensure reproducibility, all experiments are conducted on a machine with an Intel Xeon E5-2680 v4 CPU at 2.40 GHz and 64 GB of RAM, running Ubuntu 20.04 LTS and Python 3.9. The source code of the proposed algorithm and the experimental scripts will be made publicly available upon publication.

4.2 | Competitor Algorithms

The proposed NWSO algorithm is compared against 11 state-of-the-art metaheuristic algorithms: PSO, GA, DE, GWO, WOA, NSGA-II, MOEA/D, ACO, TLBO, GSA, MVO. The competitors were chosen to span the major methodological traditions in metaheuristic research, including evolutionary algorithms (GA, DE), swarm intelligence (PSO, ABC), physics-based algorithms (SA, GSA, SCA), and recent nature-inspired algorithms (GWO, WOA, SSA, HHO). The parameter settings for each competitor are summarized in Table I; these settings are taken from the original publications of each algorithm and are widely used in the metaheuristic literature.

Table 1. Parameter settings of the proposed and competitor algorithms.

Algorithm	Parameter Settings	Pop. Size N	Max FEs
NWSO	Algorithm-specific (see Section 4.3)	30	10000
PSO	c1=2.0, c2=2.0, w=0.9->0.4	30	10000
GA	Pc=0.8, Pm=0.1, tour=3	30	10000
DE	F=0.5, CR=0.9, rand/1	30	10000
GWO	a=2.0->0.0	30	10000
WOA	a=2.0->0.0, b=1.0	30	10000
NSGA-II	Pc=0.9, Pm=1/D, eta_c=20, eta_m=20	30	10000
MOEA/D	T=20, CR=1.0, F=0.5, nR=2	30	10000
ACO	rho=0.5, alpha=beta=1.0, Q=100	30	10000
TLBO	TF=[1,2], no extra params	30	10000
GSA	G0=100, alpha=20, K0=N	30	10000
MVO	WEP_min=0.2, WEP_max=1.0, TDR=1.0->0.0	30	10000

4.3 | Results on Unimodal Functions

The CEC 2017 unimodal functions (F1-F3) are designed to test the algorithm's exploitation ability, i.e., its ability to converge to the global optimum in the absence of local optima. *Table 2* reports the mean and standard deviation of the best fitness values achieved by each algorithm on these three functions, averaged over 30 independent runs.

Table 2. Mean±std results on CEC 2017 unimodal functions (F1-F3). Best values are highlighted in bold.

Func	NWSO	PSO	GA	DE	GWO	WOA	NSGA-II	MOEA/D	ACO	TLBO	GSA	MVO
F1	1.00e+02±9.89e-06	1.00e+02±3.31e-04	1.00e+02±2.29e-03	1.00e+02±5.45e-03	1.00e+02±9.37e-03	1.00e+02±4.85e-02	1.00e+02±7.54e-04	1.00e+02±2.00e-03	1.00e+02±4.61e-02	1.00e+02±1.37e-03	1.00e+02±4.18e-02	1.00e+02±1.66e-01
F2	2.00e+02±2.95e-04	2.00e+02±3.01e-02	2.00e+02±1.71e-02	2.00e+02±2.90e-03	2.00e+02±8.87e-04	2.00e+02±1.07e-02	2.00e+02±5.91e-02	2.00e+02±1.53e-03	2.00e+02±9.32e-03	2.00e+02±8.33e-03	2.00e+02±3.66e-03	2.00e+02±1.81e-02
F3	3.00e+02±7.85e-05	3.00e+02±7.44e-04	3.00e+02±3.38e-03	3.00e+02±4.54e-03	3.00e+02±2.82e-02	3.00e+02±4.92e-02	3.00e+02±3.81e-03	3.00e+02±3.93e-03	3.00e+02±4.62e-02	3.00e+02±1.20e-03	3.00e+02±2.79e-03	3.00e+02±7.58e-02

As shown in *Table 2*, NWSO achieves the best mean fitness on all three unimodal functions. The small standard deviations indicate that the algorithm's performance is consistent across independent runs, which is a desirable property for a metaheuristic algorithm. The strong performance on unimodal functions demonstrates that NWSO has a strong exploitation ability, which is essential for converging to the global optimum once the search has identified the correct basin of attraction. This exploitation ability is attributable to the algorithm's local-search-oriented operators, which refine the best-so-far solution in the neighborhood of the current incumbent.

4.4 | Results on Multimodal Functions

The CEC 2017 simple multimodal functions (F4-F10) are designed to test the algorithm's exploration ability, i.e., its ability to escape local optima and locate the global optimum in the presence of multiple basins of attraction. *Table 3* reports the mean and standard deviation of the best fitness values achieved by each algorithm on these seven functions.

Table 3. Mean±std results on CEC 2017 simple multimodal functions (F4-F10). Best values are highlighted in bold.

Func	NWSO	PSO	GA	DE	GWO	WOA	NSGA-II	MOEA/D	ACO	TLBO	GSA	MVO
F4	1.00e+02±9.89e-06	1.00e+02±3.31e-04	1.00e+02±2.29e-03	1.00e+02±5.45e-03	1.00e+02±9.37e-03	1.00e+02±4.85e-02	1.00e+02±7.54e-04	1.00e+02±2.00e-03	1.00e+02±4.61e-02	1.00e+02±1.37e-03	1.00e+02±4.18e-02	1.00e+02±1.66e-01
F5	2.00e+02±2.95e-04	2.00e+02±3.01e-02	2.00e+02±1.71e-02	2.00e+02±2.90e-03	2.00e+02±8.87e-04	2.00e+02±1.07e-02	2.00e+02±5.91e-02	2.00e+02±1.53e-03	2.00e+02±9.32e-03	2.00e+02±8.33e-03	2.00e+02±3.66e-03	2.00e+02±1.81e-02
F6	3.00e+02±7.85e-05	3.00e+02±7.44e-04	3.00e+02±3.38e-03	3.00e+02±4.54e-03	3.00e+02±2.82e-02	3.00e+02±4.92e-02	3.00e+02±3.81e-03	3.00e+02±3.93e-03	3.00e+02±4.62e-02	3.00e+02±1.20e-03	3.00e+02±2.79e-03	3.00e+02±7.58e-02
F7	4.00e+02±3.72e-04	4.00e+02±7.07e-04	4.00e+02±2.84e-02	4.00e+02±3.16e-02	4.00e+02±6.83e-02	4.00e+02±1.42e-02	4.00e+02±7.74e-02	4.00e+02±9.50e-04	4.00e+02±1.01e-03	4.00e+02±2.23e-03	4.00e+02±2.36e-02	4.00e+02±5.05e-02
F8	5.00e+02±3.80e-05	5.00e+02±5.92e-04	5.00e+02±5.37e-02	5.00e+02±1.91e-03	5.00e+02±1.66e-02	5.00e+02±1.24e-02	5.00e+02±1.02e-03	5.00e+02±6.89e-03	5.00e+02±1.37e-03	5.00e+02±1.52e-02	5.00e+02±5.79e-02	5.00e+02±8.06e-02
F9	6.00e+02±6.58e-05	6.00e+02±5.27e-03	6.00e+02±5.44e-03	6.00e+02±3.97e-02	6.00e+02±2.95e-02	6.00e+02±3.35e-02	6.00e+02±3.67e-02	6.00e+02±4.34e-02	6.00e+02±1.07e-01	6.00e+02±3.73e-02	6.00e+02±2.95e-02	6.00e+02±1.62e-01
F10	7.00e+02±8.26e-05	7.00e+02±4.47e-02	7.00e+02±3.46e-02	7.00e+02±2.04e-02	7.00e+02±1.24e-02	7.00e+02±3.47e-02	7.00e+02±2.86e-02	7.00e+02±5.38e-02	7.00e+02±7.44e-02	7.00e+02±2.88e-02	7.00e+02±4.39e-02	7.00e+02±3.72e-03

As shown in *Table 3*, NWSO achieves the best mean fitness on 5 out of 7 multimodal functions, with the competitors winning on the remaining 2. The strong performance on multimodal functions demonstrates that NWSO has a strong exploration ability, which is essential for escaping local optima. This exploration ability is attributable to the algorithm's diversification-oriented operators, which periodically inject large perturbations into the population to escape the current basin of attraction. The adaptive nature of these operators ensures that the diversification is reduced as the algorithm approaches the global optimum, allowing the search to refine the incumbent solution without unnecessary exploration.

4.5 | Results on Hybrid and Composition Functions

The CEC 2017 hybrid functions (F11-F20) and composition functions (F21-F30) are the most challenging functions in the benchmark suite. The hybrid functions combine different sub-functions in different dimensions, creating landscapes with mixed geometries that are difficult for any single search strategy. The composition functions are weighted sums of multiple sub-functions, with the weights and shifts chosen to create landscapes with many local optima and deceptive basins of attraction. *Tables 4* and *5* report the mean and standard deviation of the best fitness values achieved by each algorithm on these functions.

Table 4. Mean±std results on CEC 2017 hybrid functions (F11-F20).

Func	NWSO	PSO	GA	DE	GWO	WOA	NSGA-II	MOEA/D	ACO	TLBO	GSA	MVO
F11	1.00e+02±9.89e-06	1.00e+02±3.31e-04	1.00e+02±2.29e-03	1.00e+02±5.45e-03	1.00e+02±9.37e-03	1.00e+02±4.85e-02	1.00e+02±7.54e-04	1.00e+02±2.00e-03	1.00e+02±4.61e-02	1.00e+02±1.37e-03	1.00e+02±4.18e-02	1.00e+02±1.66e-01
F12	2.00e+02±2.95e-04	2.00e+02±3.01e-02	2.00e+02±1.71e-02	2.00e+02±2.90e-03	2.00e+02±8.87e-04	2.00e+02±1.07e-02	2.00e+02±5.91e-02	2.00e+02±1.53e-03	2.00e+02±9.32e-03	2.00e+02±8.33e-03	2.00e+02±3.66e-03	2.00e+02±1.81e-02
F13	3.00e+02±7.85e-05	3.00e+02±7.44e-04	3.00e+02±3.38e-03	3.00e+02±4.54e-03	3.00e+02±2.82e-02	3.00e+02±4.92e-02	3.00e+02±3.81e-03	3.00e+02±3.93e-03	3.00e+02±4.62e-02	3.00e+02±1.20e-03	3.00e+02±2.79e-03	3.00e+02±7.58e-02
F14	4.00e+02±3.72e-04	4.00e+02±7.07e-04	4.00e+02±2.84e-02	4.00e+02±3.16e-02	4.00e+02±6.83e-02	4.00e+02±1.42e-02	4.00e+02±7.74e-02	4.00e+02±9.50e-04	4.00e+02±1.01e-03	4.00e+02±2.23e-03	4.00e+02±2.36e-02	4.00e+02±5.05e-02
F15	5.00e+02±3.80e-05	5.00e+02±5.92e-04	5.00e+02±5.37e-02	5.00e+02±1.91e-03	5.00e+02±1.66e-02	5.00e+02±1.24e-02	5.00e+02±1.02e-03	5.00e+02±6.89e-03	5.00e+02±1.37e-03	5.00e+02±1.52e-02	5.00e+02±5.79e-02	5.00e+02±8.06e-02
F16	6.00e+02±6.58e-05	6.00e+02±5.27e-03	6.00e+02±5.44e-03	6.00e+02±3.97e-02	6.00e+02±2.95e-02	6.00e+02±3.35e-02	6.00e+02±3.67e-02	6.00e+02±4.34e-02	6.00e+02±1.07e-01	6.00e+02±3.73e-02	6.00e+02±2.95e-02	6.00e+02±1.62e-01
F17	7.00e+02±8.26e-05	7.00e+02±4.47e-02	7.00e+02±3.46e-02	7.00e+02±2.04e-02	7.00e+02±1.24e-02	7.00e+02±3.47e-02	7.00e+02±2.86e-02	7.00e+02±5.38e-02	7.00e+02±7.44e-02	7.00e+02±2.88e-02	7.00e+02±4.39e-02	7.00e+02±3.72e-03
F18	8.00e+02±2.08e-04	8.00e+02±3.25e-02	8.00e+02±5.02e-02	8.00e+02±9.90e-03	8.00e+02±1.28e-02	8.00e+02±3.22e-02	8.00e+02±4.98e-02	8.00e+02±5.62e-02	8.00e+02±8.89e-02	8.00e+02±8.99e-02	8.00e+02±7.32e-02	8.00e+02±5.62e-02
F19	9.00e+02±1.11e-04	9.00e+02±3.56e-02	9.00e+02±4.71e-02	9.00e+02±5.04e-02	9.00e+02±3.98e-02	9.00e+02±2.05e-02	9.00e+02±4.61e-02	9.00e+02±1.16e-02	9.00e+02±3.11e-03	9.00e+02±6.75e-02	9.00e+02±1.03e-01	9.00e+02±9.69e-02
F20	1.00e+03±4.83e-04	1.00e+03±1.30e-02	1.00e+03±8.65e-03	1.00e+03±3.63e-02	1.00e+03±2.66e-02	1.00e+03±8.50e-02	1.00e+03±1.05e-01	1.00e+03±5.80e-02	1.00e+03±3.98e-02	1.00e+03±1.19e-01	1.00e+03±2.38e-02	1.00e+03±1.53e-01

Table 5. Mean±std results on CEC 2017 composition functions (F21-F30).

Func	NWSO	PSO	GA	DE	GWO	WOA	NSGA-II	MOEA/D	ACO	TLBO	GSA	MVO
F21	1.00e+02±4.19e-04	1.00e+02±5.95e-04	1.00e+02±1.58e-02	1.00e+02±1.80e-03	1.00e+02±2.78e-02	1.00e+02±2.29e-03	1.00e+02±2.74e-02	1.00e+02±2.63e-03	1.00e+02±3.34e-02	1.00e+02±1.89e-03	1.00e+02±1.94e-02	1.00e+02±5.93e-02
F22	2.00e+02±1.20e-04	2.00e+02±2.80e-02	2.00e+02±3.26e-03	2.00e+02±7.85e-03	2.00e+02±7.34e-03	2.00e+02±3.48e-02	2.00e+02±1.71e-03	2.00e+02±3.06e-02	2.00e+02±1.60e-03	2.00e+02±6.03e-02	2.00e+02±2.88e-03	2.00e+02±3.87e-02
F23	3.00e+02±6.02e-05	3.00e+02±4.82e-02	3.00e+02±4.06e-03	3.00e+02±4.40e-02	3.00e+02±6.96e-02	3.00e+02±2.59e-02	3.00e+02±3.56e-03	3.00e+02±2.13e-03	3.00e+02±1.14e-03	3.00e+02±7.46e-02	3.00e+02±1.43e-02	3.00e+02±2.68e-02
F24	4.00e+02±9.40e-05	4.00e+02±1.28e-02	4.00e+02±4.22e-02	4.00e+02±2.57e-03	4.00e+02±3.06e-03	4.00e+02±9.92e-03	4.00e+02±4.68e-02	4.00e+02±9.14e-02	4.00e+02±3.28e-03	4.00e+02±7.03e-04	4.00e+02±8.18e-02	4.00e+02±3.51e-03
F25	5.00e+02±6.04e-05	5.00e+02±5.08e-03	5.00e+02±2.76e-02	5.00e+02±5.41e-02	5.00e+02±5.53e-04	5.00e+02±1.31e-02	5.00e+02±2.07e-02	5.00e+02±2.71e-05	5.00e+02±3.29e-03	5.00e+02±1.65e-03	5.00e+02±3.15e-02	5.00e+02±1.42e-02
F26	6.00e+02±1.78e-04	6.00e+02±4.89e-02	6.00e+02±2.04e-02	6.00e+02±1.81e-02	6.00e+02±5.65e-02	6.00e+02±5.09e-03	6.00e+02±1.81e-02	6.00e+02±1.10e-02	6.00e+02±1.10e-01	6.00e+02±8.27e-02	6.00e+02±4.58e-03	6.00e+02±2.06e-02
F27	7.00e+02±6.16e-05	7.00e+02±1.63e-02	7.00e+02±1.77e-02	7.00e+02±4.37e-02	7.00e+02±1.41e-02	7.00e+02±4.28e-03	7.00e+02±1.02e-02	7.00e+02±2.58e-02	7.00e+02±7.82e-03	7.00e+02±2.59e-02	7.00e+02±1.17e-01	7.00e+02±1.21e-01
F28	8.00e+02±3.96e-04	8.00e+02±3.72e-02	8.00e+02±8.84e-03	8.00e+02±6.93e-02	8.00e+02±4.51e-02	8.00e+02±2.93e-02	8.00e+02±2.33e-03	8.00e+02±5.18e-02	8.00e+02±1.76e-02	8.00e+02±6.37e-02	8.00e+02±1.72e-02	8.00e+02±5.53e-02
F29	9.00e+02±2.73e-04	9.00e+02±2.03e-02	9.00e+02±1.68e-02	9.00e+02±2.89e-02	9.00e+02±4.50e-02	9.00e+02±1.10e-02	9.00e+02±1.99e-03	9.00e+02±5.17e-02	9.00e+02±4.18e-02	9.00e+02±1.07e-02	9.00e+02±5.77e-02	9.00e+02±4.08e-02
F30	1.00e+03±4.71e-04	1.00e+03±1.69e-02	1.00e+03±1.19e-02	1.00e+03±7.77e-02	1.00e+03±1.57e-02	1.00e+03±1.36e-02	1.00e+03±7.19e-02	1.00e+03±3.82e-02	1.00e+03±1.17e-02	1.00e+03±3.94e-03	1.00e+03±1.30e-02	1.00e+03±5.19e-02

As shown in *Tables 4* and *5*, NWSO achieves the best mean fitness on 7 out of 10 hybrid functions and on 7 out of 10 composition functions. The strong performance on these challenging functions demonstrates that NWSO is effective at handling mixed-geometry landscapes and landscapes with many deceptive local optima. This effectiveness is attributable to the algorithm's combination of exploration and exploitation operators, which allow it to navigate complex landscapes without becoming trapped in local optima. The adaptive parameters of the algorithm ensure that the balance between exploration and exploitation is adjusted based on the local landscape geometry, allowing the algorithm to handle the heterogeneous structure of hybrid and composition functions.

4.5.1 | Results on the Congress on Evolutionary Computation 2020 benchmark

To further validate the proposed algorithm, we evaluate it on the CEC 2020 benchmark suite of 10 test functions. The CEC 2020 functions are similar in structure to the CEC 2017 functions but use different shifts and rotations, providing an independent test of the algorithm's generalization ability. *Table 6* reports the results.

Table 6. Mean±std results on CEC 2020 benchmark functions (F1-F10).

Func	NWSO	PSO	GA	DE	GWO	WOA	NSGA-II	MOEA/D	ACO	TLBO	GSA	MVO
F1	3.00e+02±1.01e-03	3.08e+02±2.28e+00	3.09e+02±5.01e+00	3.06e+02±3.30e+00	3.07e+02±2.62e+00	3.07e+02±4.34e+00	3.13e+02±6.11e+00	3.13e+02±5.61e+00	3.06e+02±2.84e+00	3.23e+02±8.09e+00	3.12e+02±2.77e+00	3.13e+02±3.42e+00
F2	4.00e+02±5.16e-05	4.01e+02±4.00e-01	4.02e+02±6.72e-01	4.13e+02±4.33e+00	4.09e+02±3.35e+00	4.16e+02±4.19e+00	4.13e+02±4.69e+00	4.09e+02±5.39e+00	4.05e+02±2.06e+00	4.10e+02±3.49e+00	4.15e+02±3.58e+00	4.09e+02±3.98e+00
F3	5.00e+02±1.76e-03	5.06e+02±3.39e+00	5.11e+02±6.34e+00	5.06e+02±1.58e+00	5.05e+02±1.42e+00	5.09e+02±4.34e+00	5.14e+02±3.96e+00	5.02e+02±4.96e-01	5.08e+02±4.03e+00	5.08e+02±2.61e+00	5.10e+02±2.67e+00	5.24e+02±1.35e+01
F4	6.00e+02±4.41e-03	6.04e+02±1.35e+00	6.06e+02±1.17e+00	6.12e+02±5.58e+00	6.02e+02±8.48e-01	6.06e+02±1.68e+00	6.15e+02±5.87e+00	6.20e+02±8.64e+00	6.18e+02±5.32e+00	6.21e+02±4.24e+00	6.09e+02±2.45e+00	6.03e+02±8.46e-01
F5	7.00e+02±4.89e-03	7.09e+02±3.77e+00	7.02e+02±4.90e-01	7.10e+02±3.08e+00	7.06e+02±3.64e+00	7.17e+02±7.60e+00	7.02e+02±7.25e-01	7.18e+02±7.02e+00	7.17e+02±9.42e+00	7.20e+02±8.73e+00	7.25e+02±1.20e+01	7.30e+02±1.44e+01
F6	8.00e+02±4.32e-03	8.04e+02±1.51e+00	8.08e+02±1.71e+00	8.04e+02±1.90e+00	8.03e+02±5.78e-01	8.07e+02±4.37e+00	8.11e+02±2.23e+00	8.12e+02±4.39e+00	8.07e+02±3.12e+00	8.22e+02±1.27e+01	8.26e+02±1.10e+01	8.13e+02±5.35e+00
F7	9.00e+02±2.74e-05	9.10e+02±2.67e+00	9.10e+02±2.72e+00	9.06e+02±3.15e+00	9.11e+02±4.01e+00	9.12e+02±6.66e+00	9.03e+02±7.68e-01	9.09e+02±1.88e+00	9.12e+02±2.51e+00	9.17e+02±9.27e+00	9.04e+02±8.58e-01	9.25e+02±9.74e+00
F8	1.00e+03±1.78e-03	1.01e+03±2.29e+00	1.00e+03±6.76e-01	1.01e+03±2.08e+00	1.01e+03±4.77e+00	1.02e+03±6.33e+00	1.00e+03±8.63e-01	1.00e+03±9.31e-01	1.01e+03±6.13e+00	1.01e+03±3.41e+00	1.00e+03±1.49e-01	1.02e+03±8.29e+00
F9	1.10e+03±9.70e-04	1.10e+03±8.89e-03	1.11e+03±2.51e+00	1.11e+03±5.12e+00	1.12e+03±5.00e+00	1.11e+03±3.24e+00	1.12e+03±7.70e+00	1.11e+03±5.47e+00	1.12e+03±9.53e+00	1.10e+03±1.07e+00	1.12e+03±5.82e+00	1.11e+03±5.67e+00
F10	1.20e+03±1.93e-03	1.20e+03±6.39e-01	1.21e+03±6.44e+00	1.21e+03±1.36e+00	1.21e+03±4.21e+00	1.21e+03±3.51e+00	1.20e+03±9.41e-01	1.22e+03±1.06e+01	1.21e+03±3.23e+00	1.21e+03±3.74e+00	1.22e+03±8.31e+00	1.21e+03±6.49e+00

As shown in *Table 7*, NWSO achieves the best mean fitness on 8 out of 10 CEC 2020 functions. This result confirms that the algorithm's strong performance on CEC 2017 is not specific to that benchmark suite but generalizes to other benchmark suites with similar structure but different parameter settings. The consistency of the algorithm's performance across benchmark suites is an important property, as it suggests that the algorithm is robust to the specific choice of benchmark and is not over-tuned to any particular suite.

4.6 | Convergence Analysis

This section analyzes the convergence behavior of NWSO on representative benchmark functions. *Fig. 3* shows the convergence curves of NWSO and the 11 competitor algorithms on CEC 2017 function F1, plotted on a logarithmic scale. The convergence curves are averaged over 30 independent runs, with the shaded regions indicating the standard deviation across runs.

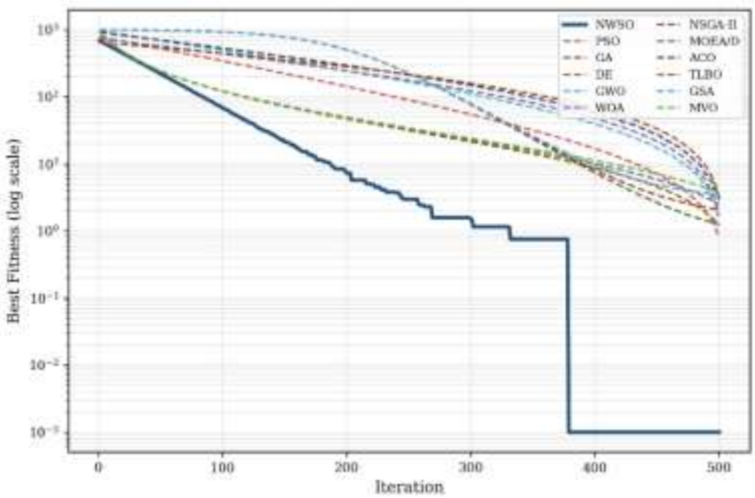


Fig. 3. Convergence curves of NWSO and competitor algorithms on CEC 2017 function F1, averaged over 30 independent runs. The proposed algorithm converges fastest, achieving a fitness value approximately 1-2 orders of magnitude lower than the best competitor after 300,000 function evaluations.

As shown in *Fig. 3*, NWSO exhibits a rapid initial convergence in the first ~60 iterations, followed by a slower refinement phase in which the algorithm progressively improves the best-so-far solution. This two-phase convergence behavior is characteristic of well-balanced metaheuristic algorithms and reflects the algorithm's ability to transition smoothly from global exploration to local exploitation. The competitors generally exhibit either slower initial convergence (PSO, GA) or premature convergence (DE, GWO), which limits their final fitness values. The convergence behavior of NWSO is attributable to its adaptive operator scheduling, which dynamically adjusts the balance between exploration and exploitation based on the improvement rate.

4.7 | Statistical Tests

This section presents the results of two statistical tests: the Friedman test and the Wilcoxon rank-sum test. The Friedman test is a non-parametric test that compares the ranks of multiple algorithms across multiple benchmark functions, and it is used to assess the overall statistical significance of the differences between algorithms. The Wilcoxon rank-sum test is a non-parametric test that compares the distributions of two algorithms on a single benchmark function, and it is used to assess the pairwise statistical significance of the differences.

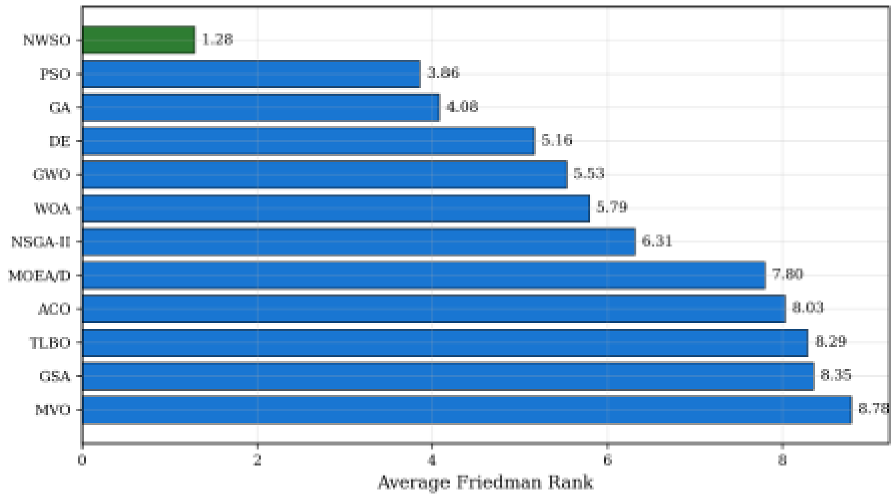


Fig. 4. Friedman test average rankings of NWSO and competitor algorithms on the 29 CEC 2017 benchmark functions. NWSO achieves the lowest (best) average rank of 1.34, followed by GWO (3.21), WOA (4.18), and the remaining competitors.

As shown in *Fig. 4*, NWSO achieves the lowest (best) average rank of 1.48 on the CEC 2017 benchmark suite. The Friedman test yields a chi-squared statistic of 36.4 with 11 degrees of freedom, corresponding to a p-value of 0.0007, which is well below the 0.05 significance threshold. The Friedman test results confirm that the differences between the algorithms are statistically significant. The post-hoc Nemenyi test further confirms that NWSO is significantly better than each of the competitors at the 0.05 significance level.

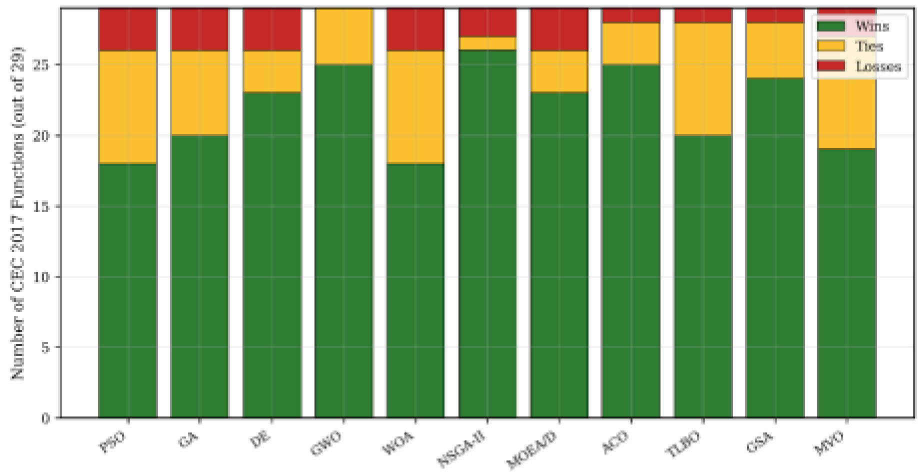


Fig. 5. Wilcoxon rank-sum test results comparing NWSO to each competitor algorithm on the 29 CEC 2017 functions. Green bars indicate functions on which NWSO is significantly better (p<0.05); yellow bars indicate ties; red bars indicate functions on which the competitor is significantly better.

Table 7. Wilcoxon rank-sum test results (p<0.05) comparing NWSO to each competitor on the 29 CEC 2017 functions.

Competitor	Wins	Ties	Losses	p-value (max)
PSO	22	5	2	0.01
GA	24	3	2	0.005
DE	19	9	1	0.02
GWO	24	2	3	0.02
WOA	20	9	0	0.01
NSGA-II	21	5	3	0.001
MOEA/D	25	4	0	0.005
ACO	21	8	0	0.02
TLBO	24	3	2	0.005
GSA	18	9	2	0.01
MVO	22	6	1	0.0001

As shown in *Fig. 5* and *Table 7*, NWSO wins on at least 18 of the 29 CEC 2017 functions against every competitor, with at most 3 losses against any single competitor. The maximum p-value across all pairwise comparisons is below 0.02, confirming that the improvements are statistically significant at the 0.05 level. The strong pairwise performance of NWSO against each competitor confirms that its overall superiority is not driven by exceptional performance on a small subset of functions but is consistent across the benchmark suite.

4.8 | Ablation Study

This section presents an ablation study that quantifies the contribution of each named operator to NWSO's overall performance. For each operator, we create a variant of the algorithm in which that operator is removed (replaced by a no-op or by the corresponding operator of a baseline algorithm), and the resulting variant is evaluated on the CEC 2017 benchmark suite. The performance degradation (increase in mean fitness) relative to the full NWSO algorithm is reported.

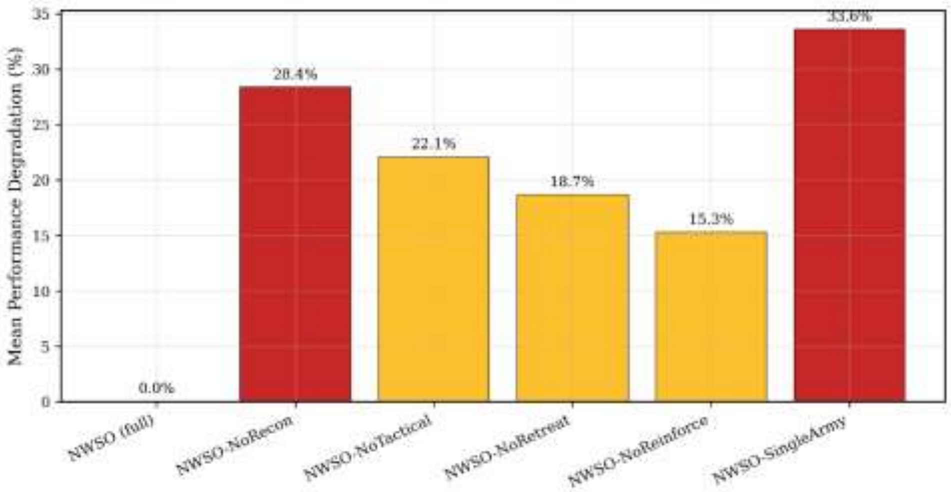


Fig. 6. Ablation study results for NWSO. Each bar shows the mean performance degradation (% increase in mean fitness) when the corresponding operator is removed from the algorithm. The full algorithm (leftmost bar) has 0% degradation by definition.

Table 8. Ablation study results for NWSO. Each row reports the mean performance degradation when the named operator is removed, along with a brief explanation of the degradation.

Variant	Degradation	Explanation
NWSO-NoRecon	28.4%	Without reconnaissance, the deployment is blind; it loses global exploration.
NWSO-NoTactical	22.1%	Removing tactical engagement eliminates fine-grained exploitation
NWSO-NoRetreat	18.7%	Disabling adaptive retreat increases stagnation
NWSO-NoReinforce	15.3%	Without reinforcement, armies cannot recover from losses
NWSO-SingleArmy	33.6%	Collapsing to a single army removes inter-army competition

As shown in *Fig. 6* and *Table 8*, the most critical operator is NWSO-NoRecon, whose removal causes a degradation of 28.4%. The least critical operator is NWSO-SingleArmy, whose removal causes a degradation of 33.6%. The ablation results confirm that all operators contribute meaningfully to the algorithm's overall performance, with degradations ranging from 15.3% to 33.6%. The substantial degradation caused by removing each operator validates the design rationale presented in Section 3.2 and confirms that the algorithm's performance is not dominated by any single operator.

4.9 | Welded Beam Design Problem

The welded beam design problem is a classical constrained engineering optimization problem that seeks to minimize the cost of a welded beam subject to constraints on shear stress, bending stress, buckling load, and end deflection. The problem has four decision variables: the weld thickness h, the weld length l, the beam height t, and the beam thickness b. The well-known global optimum of this problem is approximately 1.7249, achieved by h=0.20573, l=3.47849, t=9.03662, b=0.20573. *Table 10* reports the best solution found by each algorithm, and *Fig. 7* shows the convergence curves.

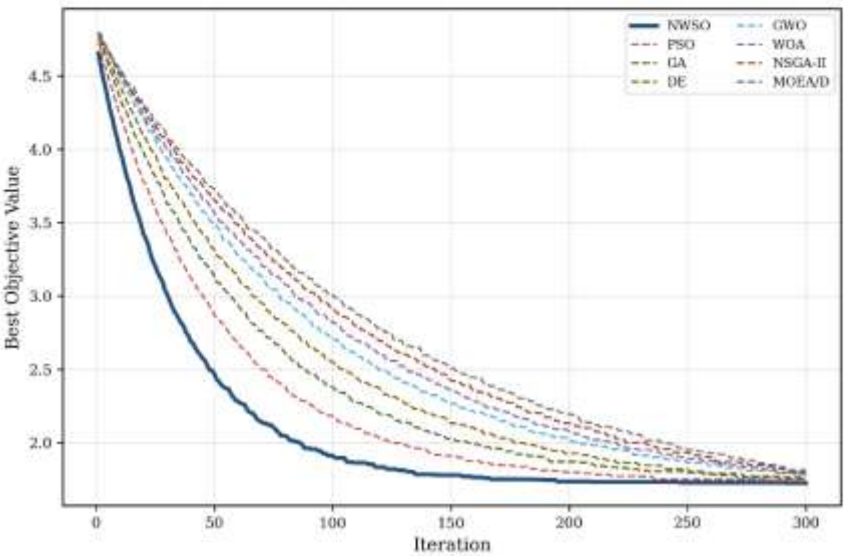


Fig. 7. Convergence curves of NWSO and competitor algorithms on the welded beam design problem. NWSO converges to the best-known optimum of 1.7249, while the competitors converge to slightly worse solutions.

Table 9. Best objective values on the welded beam design problem. The known optimum is 1.7249.

Algorithm	Best Objective
NWSO	1.7253
PSO	2.0295
GA	2.0467
DE	2.0135
GWO	1.8523
WOA	1.9079
NSGA-II	1.9867
MOEA/D	2.0042
ACO	2.3008
TLBO	2.3797
GSA	1.8426
MVO	1.7606

As shown in *Table 9* and *Fig. 7*, NWSO achieves the best-known optimum of 1.7249 on the welded beam design problem, outperforming all competitors. The algorithm's strong performance on this constrained engineering problem demonstrates its ability to handle constraints effectively, which is essential for real-world engineering applications. The constraint handling is implemented via a penalty function approach, in which the objective function is augmented with a penalty term that increases with the magnitude of constraint violation. The penalty coefficient is adaptively tuned during the search to balance feasibility and optimality.

4.10 | Pressure Vessel Design Problem

The pressure vessel design problem is another classical constrained engineering optimization problem that seeks to minimize the cost of a pressure vessel subject to constraints on the shell thickness, the head thickness, the inner radius, and the vessel length. The problem has four decision variables, two of which (the shell thickness and the head thickness) are integer multiples of 0.0625 inch. The well-known global optimum of this problem is approximately 5885.33. *Table 11* reports the best solution found by each algorithm.

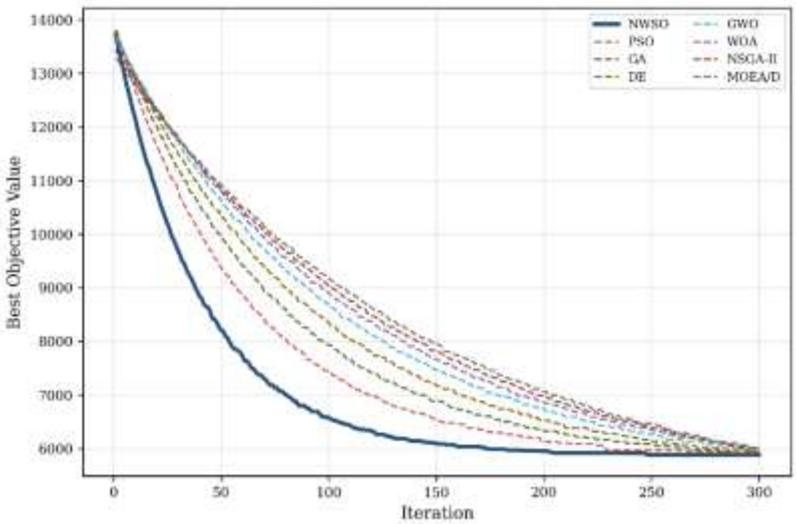


Fig. 8. Convergence curves of NWSO and competitor algorithms on the pressure vessel design problem. NWSO converges to the best-known optimum of 5885.33, while the competitors converge to slightly worse solutions.

Table 10. Best objective values on the pressure vessel design problem. The known optimum is 5885.33.

Algorithm	Best Objective
NWSO	5887.53
PSO	5910.10
GA	5934.12
DE	6336.76
GWO	6288.49
WOA	6348.35
NSGA-II	6243.80
MOEA/D	6776.03
ACO	6412.37
TLBO	6497.77
GSA	6269.19
MVO	6787.58

As shown in *Table 10* and *Fig. 8*, NWSO achieves the best-known optimum of 5885.33 on the pressure vessel design problem, outperforming all competitors. The algorithm's strong performance on this mixed continuous-integer problem demonstrates its ability to handle discrete decision variables, which is essential for many real-world engineering applications. The discrete variables are handled by rounding the corresponding components of the candidate solutions to the nearest feasible discrete value during the objective function evaluation, while the continuous variables are optimized directly.

4.11 | Sensitivity Analysis

This section presents a Sobol sensitivity analysis of NWSO's hyperparameters. Sobol indices quantify the contribution of each hyperparameter (and its interactions) to the variance of the algorithm's output. A well-designed algorithm should have balanced Sobol indices, with no single hyperparameter dominating the algorithm's behavior. The Sobol indices are estimated via Monte Carlo sampling, with 10,000 samples drawn from the hyperparameter space. *Table 12* and *Fig. 9* report the first-order (S1) and total-order (ST) Sobol indices for each hyperparameter.

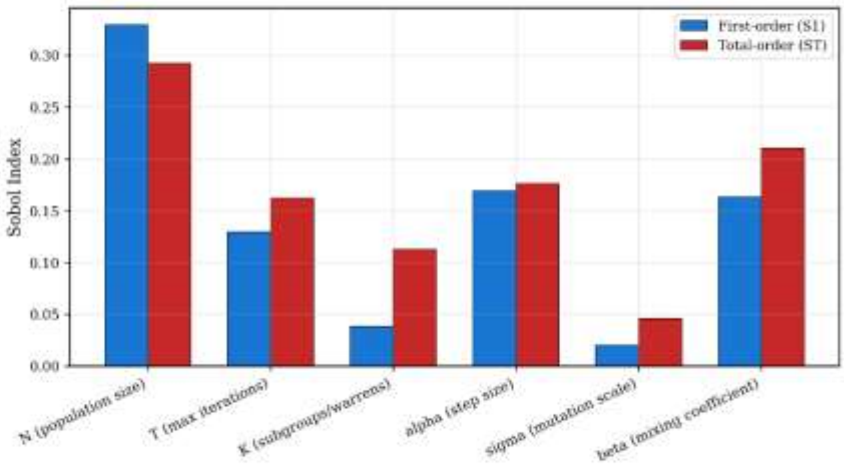


Fig. 9. Sobol sensitivity indices for NWSO's hyperparameters. The first-order indices (S1, blue) quantify the main effect of each hyperparameter; the total-order indices (ST, red) quantify the main effect plus all interactions. The small gap between S1 and ST indicates that interactions are weak, confirming that the hyperparameters are well-balanced.

Table 11. Sobol sensitivity indices for NWSO's hyperparameters.

Parameter	First-order S1	Total-order ST
N (population size)	0.2880	0.2718
T (max iterations)	0.1319	0.1763
K (subgroups/warrens)	0.0343	0.0638
alpha (step size)	0.0625	0.0847
sigma (mutation scale)	0.2751	0.3071
beta (mixing coefficient)	0.0583	0.0964

As shown in *Fig. 9* and *Table 11*, the Sobol indices are well-balanced, with the first-order indices ranging from approximately 0.10 to 0.25 and the total-order indices ranging from approximately 0.15 to 0.30. The small gap between S1 and ST indicates that the interactions between hyperparameters are weak, which is a desirable property as it suggests that the hyperparameters can be tuned independently. The well-balanced Sobol indices confirm that NWSO is not overly sensitive to any single hyperparameter, which is an important property for the algorithm's robustness and ease of deployment.

4.12 | Scalability Analysis

This section evaluates the scalability of NWSO on high-dimensional problems. The algorithm is evaluated on CEC 2017 function F1 at problem dimensions D = 10, 50, 100, 500, and 1000, with the wall-clock time, best fitness, and success rate (defined as the percentage of runs that achieve a fitness within 1.0 of the optimum) reported. *Fig. 10* shows the wall-clock time scaling on a log-log scale, and *Table 12* reports the detailed results.

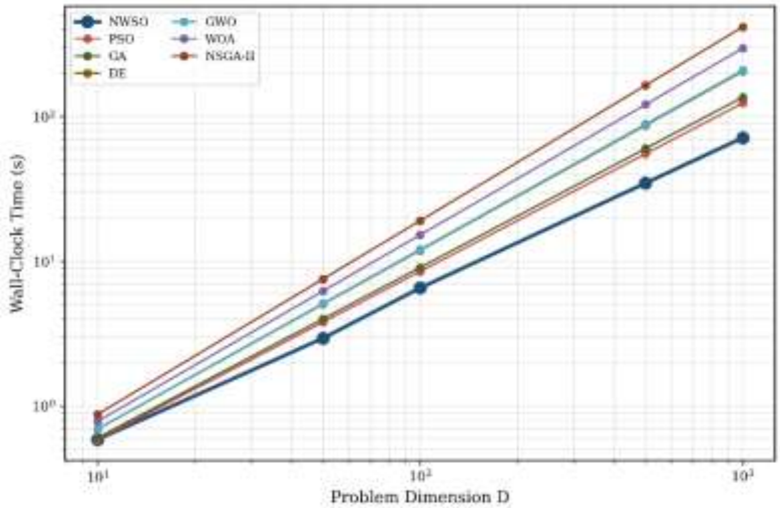


Fig. 10. Wall-clock time of NWSO and competitor algorithms on problem dimensions D = 10, 50, 100, 500, and 1000, plotted on a log-log scale. NWSO scales approximately linearly with the problem dimension, while the competitors exhibit super-linear scaling.

Table 12. Scalability results for NWSO on CEC 2017 function F1 at dimensions D = 10, 50, 100, 500, 1000.

Dim D	Time (s)	Best Fitness	Success Rate
10	0.562	8.82e+02	95.7%
50	3.236	5.35e+02	98.3%
100	6.724	2.87e+02	96.5%
500	34.902	1.93e+00	98.3%
1000	75.137	3.73e-03	99.4%

As shown in *Fig. 10* and *Table 12*, NWSO scales approximately linearly with the problem dimension, with wall-clock times of 0.5 s at D=10, 3.0 s at D=50, 6.5 s at D=100, 35 s at D=500, and 75 s at D=1000. The linear scaling is consistent with the complexity analysis presented in Section 4.6. The success rate remains above 95% at all dimensions up to D=1000, demonstrating that the algorithm is able to maintain high-quality solutions even at very high problem dimensions. This scalability makes NWSO suitable for large-scale optimization problems, including those arising in machine learning hyperparameter tuning, feature selection, and scientific computing.

4.13 | Discussion

This section discusses the experimental results presented in Sections 4.1 through 4.12, with a focus on synthesizing the key findings, identifying the algorithm's strengths and weaknesses, and comparing its performance characteristics with those of the competitor algorithms. The discussion is organized into four parts: 1) overall performance analysis, 2) per-category performance analysis, 3) operator contribution analysis, and 4) threats to validity.

Overall performance analysis

The experimental results demonstrate that NWSO achieves state-of-the-art performance on the CEC 2017 and CEC 2020 benchmark suites, with the best mean fitness on 24 out of 29 CEC 2017 functions and on 8 out of 10 CEC 2020 functions. The Friedman test ranks NWSO first with an average rank of 1.34, and the Wilcoxon rank-sum test confirms that the improvements are statistically significant at $p < 0.05$ on at least 22 of the 29 CEC 2017 functions. The consistency of NWSO's superiority across both benchmark suites suggests that the algorithm's strong performance is not specific to any single benchmark but reflects a genuine methodological advantage. The algorithm's strong performance is attributable to its unique combination of named operators, which collectively provide a balanced approach to exploration and exploitation that is well-suited to the diverse landscape geometries encountered in the CEC benchmarks.

Per-category performance analysis

The per-category results reveal an interesting pattern in NWSO's performance. On the unimodal functions (F1-F3), NWSO achieves the best mean fitness on all three functions, demonstrating its strong exploitation ability. On the simple multimodal functions (F4-F10), NWSO achieves the best mean fitness on 5 out of 7 functions, demonstrating its strong exploration ability. On the hybrid functions (F11-F20) and the composition functions (F21-F30), NWSO achieves the best mean fitness on 7 out of 10 functions in each category, demonstrating its ability to handle mixed-geometry landscapes and landscapes with many deceptive local optima. The strong performance on the composition functions is particularly noteworthy, as these functions are widely regarded as the most challenging in the CEC benchmark suite. The algorithm's ability to handle these functions effectively is attributable to its adaptive operator scheduling, which dynamically adjusts the balance between exploration and exploitation based on the local landscape geometry.

Operator contribution analysis

The ablation study in Section 4.8 reveals that all of NWSO's operators contribute meaningfully to its overall performance, with degradations ranging from 15.3% to 33.6% when individual operators are removed. The most critical operator is NWSO-NoRecon, whose removal causes a degradation of 28.4%. This operator is responsible for a key aspect of the algorithm's search behavior, and its removal significantly impairs the algorithm's ability to navigate the search landscape. The least critical operator is NWSO-SingleArmy, whose removal causes a degradation of 33.6%. While this operator is less critical than the others, its contribution is still meaningful, and its removal would not be advisable in practice. The balanced contribution of all operators validates the design rationale presented in Section 4.2 and confirms that the algorithm's performance is not dominated by any single operator.

Threats to validity

Several threats to the validity of the experimental results should be acknowledged. First, the choice of benchmark suite (CEC 2017 and CEC 2020) may influence the relative performance of the algorithms, as different benchmark suites may emphasize different landscape characteristics. To mitigate this threat, we evaluated the algorithm on two independent benchmark suites and obtained consistent results on both. Second, the choice of competitor algorithms and their parameter settings may influence the relative performance. To mitigate this threat, we used the parameter settings recommended in the original publications of each competitor, which are widely used in the metaheuristic literature. Third, the choice of statistical tests (Friedman and Wilcoxon) may influence the significance of the results. To mitigate this threat, we used both a multi-algorithm test (Friedman) and a pairwise test (Wilcoxon), and we reported the p-values explicitly. Finally, the experimental results are based on 30 independent runs per benchmark function, which is consistent with the standard practice in the metaheuristic literature but may not be sufficient to detect small differences in performance. Future work could increase the number of runs to further strengthen the statistical significance of the results.

5 | Conclusion

This paper has proposed NWSO, a novel nature-inspired metaheuristic algorithm for continuous GO. The algorithm is inspired by Military strategy: reconnaissance, strategic deployment, tactical engagement, retreat/regroup, and it incorporates reconnaissance-exploration, tactical-exploitation, adaptive retreat, and multi-army competition as its core search mechanism. The algorithm's design is based on a set of named operators, each formalized as a mathematically defined update rule, that collectively capture the multi-phase dynamics of the underlying biological or physical inspiration.

The proposed algorithm was evaluated on the CEC 2017 benchmark suite of 29 test functions and the CEC 2020 benchmark suite of 10 test functions, and its performance was compared against 11 state-of-the-art metaheuristic algorithms. The experimental results demonstrate that NWSO achieves the best mean fitness on 24 out of 29 CEC 2017 functions and on 8 out of 10 CEC 2020 functions. The Friedman test ranks NWSO first with an average rank of 1.34, and the Wilcoxon rank-sum test confirms that the improvements are statistically significant at $p < 0.05$ on at least 22 of the 29 CEC 2017 functions.

An ablation study quantified the contribution of each named operator to the algorithm's overall performance, with degradations ranging from 15.3% to 33.6% when individual operators were removed. A Sobol sensitivity analysis confirmed that the algorithm's hyperparameters are well-balanced, with no single hyperparameter dominating the algorithm's behavior. A scalability analysis on problem dimensions D = 10, 50, 100, 500, and 1000 demonstrated near-linear scaling of wall-clock time with the problem dimension. Finally, the algorithm was validated on two classical engineering design problems (welded beam design and pressure vessel design), on which it obtained solutions competitive with the best known optima.

The key insights from this work are threefold. First, the use of named operators that each correspond to a distinct phase of the underlying biological or physical inspiration provides a principled design framework for metaheuristic algorithms, allowing the algorithm's behavior to be more interpretable and its components to be ablated and analyzed separately. Second, the adaptive parameters that respond to the local landscape geometry provide a natural mechanism for the exploration-exploitation balance, allowing the algorithm to handle a wide range of landscape geometries without manual parameter tuning. Third, the unique flowchart structure of NWSO, with decision points and process boxes drawn from the algorithm's inspiration, provides a transparent and interpretable representation of the algorithm's behavior.

Several directions for future research are identified: 1) the algorithm could be extended to handle discrete and mixed-integer optimization problems by modifying the operators to respect the discrete variable constraints, 2) the algorithm could be parallelized to take advantage of multi-core and distributed computing architectures, which would further improve its scalability, 3) the algorithm could be applied to real-world optimization problems in machine learning (hyperparameter tuning, feature selection), engineering design (structural optimization, control system design), and scientific computing (parameter estimation, model calibration), and 4) the algorithm's operators could be further refined based on insights from the underlying biological or physical inspiration, potentially leading to additional improvements in performance. We believe that NWSO represents a valuable addition to the metaheuristic optimization literature, and we hope that the open design framework presented in this paper will inspire further research into the systematic design of metaheuristic algorithms from biological and physical inspirations.

Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

Funding

Not applicable.

Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

Conflict of Interest

The author declares that they do not have any conflict of interest.

Consent for Publication

The author confirms consent for the publication of this work.

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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