

Niching in Evolutionary and Swarm-Based Optimization for Multimodal Problems: A Survey

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ABSTRACT

Niching is an essential mechanism in multimodal optimization (MMO), extending evolutionary algorithms (EAs) and particle swarm optimization (PSO) to trace multiple global and local optima and preserve them throughout the search process, rather than converging on a single solution. This paper surveys niching techniques across PSO, differential evolution (DE), genetic algorithms (GA), evolution strategies (ES), and gravitational search algorithms (GSA), organizing them by population structure (single- versus multi-population) and by their reliance on explicit niching parameters. We examine parameter-free ring-topology PSO technique, describing its neighborhood-based update rule and explaining how niches emerge without an explicit niche-radius parameter. As reported consistently across the surveyed literature, this parameter-free approach performs comparably to, and on several benchmark functions more consistently than, parameterdependent alternatives such as SPSO and FER-PSO. The survey further reviews hybrid and archive-guided niching methods that combine PSO with differential evolution, evolution strategies, and gravitational search, and closes with a synthesis showing that the same parameter-free principle central to ring-topology PSO extends naturally across these related families.

Keywords: Particle Swarm Optimization, Niching, Multimodal Optimization, Evolutionary Computation, Hybrid Metaheuristics

INTRODUCTION

Particle swarm optimization (PSO) is a population-based metaheuristic founded on swarm intelligence, proposed by Kennedy and Eberhart [1] and motivated by the social behavior of bird flocks and fish schooling [2]. Each particle i maintains a position vector $X_i = (X_{i1}, X_{i2}, \dots, X_{in})$ and a velocity vector $V_i = (V_{i1}, V_{i2}, \dots, V_{in})$ in the search space. In the original global-best (gbest) PSO, velocity and position are updated at every step as follows [1]:

$$V_{id}(t+1) = \omega V_{id}(t) + C_1 r_{1d} (P_{id} - X_{id}) + C_2 r_{2d} (P_{gd} - X_{id})$$

where P_{id} is the personal best position found by particle i on dimension d , P_{gd} is the best position found by the entire swarm on dimension d , ω is the inertia weight controlling the influence of the previous velocity, c_1 and c_2 are the cognitive and social acceleration coefficients, and r_{1d} , r_{2d} are random numbers drawn uniformly in $(0, 1)$. This gbest update is what causes standard PSO to

converge on a single solution: every particle is eventually pulled toward the same global-best position P_{gd} , regardless of how many other good solutions exist elsewhere in the search space.

Niching techniques modify this update so that particles instead converge toward several different optima in parallel. The ringtopology approach examined in detail in this survey [4] replaces the single global best P_{gd} with a local neighborhood best P_{ld} , defined over a fixed ring-shaped neighborhood of size k around each particle (e.g., its immediate left and right neighbors when $k = 2$). Because each particle only ever compares itself to its topological neighbors, distinct neighborhoods independently settle on distinct optima, and niches emerge without any explicit niche-radius parameter. Population size is, as in any population-based metaheuristic, a standard setting rather than a niching-specific parameter; the distinguishing property of the ring-topology method is that it introduces no additional parameter beyond this unlike sharing, clearing, or seed-based approaches, which require an explicit niche-radius or expected species count to be estimated in advance.

Many PSO and evolutionary algorithms (EAs) are robust and efficient for solving difficult optimization problems, but they are typically aimed at tracing a single global solution and converge on one final solution because of their global selection structure. These algorithms perform well on unimodal problems; however, many real-world optimization problems are multimodal by nature [3], where multiple global and/or local optimal solutions need to be traced. Techniques for tracing multiple optima are normally known as “niching” techniques. Their purpose is to trace and preserve multiple optimal or suboptimal solutions, reducing the possibility of getting stuck at a single local optimum.

This paper surveys niching techniques proposed across PSO and related evolutionary paradigms, describes their working principles, and classifies the challenges these techniques face. We examine in particular depth the PSO-based algorithm known as “niching without a niching parameter: using ring topology” [4], explaining how it works and how it compares against parameter-dependent alternatives in the literature. The survey also situates this technique alongside hybrid and archive-guided niching methods that extend the same parameter-free principle to differential evolution, evolution strategies, and gravitational search, and closes with a synthesis of the comparative strengths established across the surveyed families.

NICHING METHODS

Niching methods, like PSO and EAs, are motivated by nature. Niching algorithms and methods were introduced to preserve and trace a population of individuals within a single or multipopulation framework, addressing the tendency of standard EAs and PSO to converge prematurely on a single solution [3]. In a single-population approach, the search space is implicitly distributed and niching parameters do not need to be specified; the search proceeds within one interacting population. In multi-population approaches, various niching parameters must typically be specified to identify the niches, and the search space is divided into sub-swarms that locate optima in parallel.

Difficulties in Niching Methods

Many niching methods face difficulties that must be addressed before real-world application:

- Some niching parameters depend on prior, problem-dependent knowledge.
- It is difficult to retain found solutions within a single run.
- Crossover between two fit individuals can create offspring distant from either parent niche.
- Some niching methods pay no attention to local optima, finding only global optima.

- Performance of some existing niching algorithms is poor on high-dimensional problems.
- Computational cost is high in some niching methods.

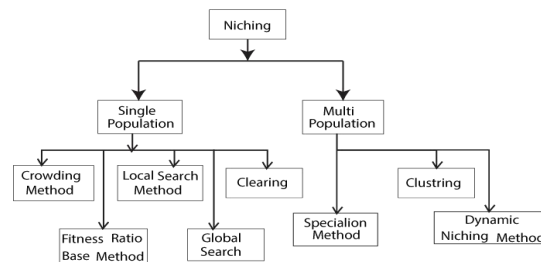


Fig. 1. Taxonomy of niching methods by population structure. Singlepopulation methods search one interacting population without pre-dividing the search space; multi-population methods explicitly split the population into sub-swarms/species. Ring-topology PSO falls within the single-population branch.

LITERATURE REVIEW

Before reviewing individual techniques, we note two established PSO-specific niching baselines that provide foundational context for this section: NichePSO [5], one of the earliest PSO niching methods, which grows and shrinks independent sub-swarms around detected optima; and locally informed PSO (LIPS) [6], which, like ring-topology PSO, replaces the global best with a locally informed neighborhood best, though derived from multiple neighbors rather than a fixed ring. Classical non-PSO niching mechanisms that several later methods build on include fitness sharing [7] and crowding [8].

Single Population-Based Niching Techniques

The ring-topology method [4] introduced in Section 1 was proposed to locate multiple global/local optima in MMO problems by replacing the global best with a neighborhood best defined over a fixed ring topology, so that each particle interacts only with its immediate left and right neighbors. This removes the requirement to pre-specify a niche-radius parameter and uses the concepts of memory-swarm and explorer-swarm to form stable niches across local neighborhoods. Its complexity is $O(N)$, where N is the population size. Li [4] reports more consistent performance across a range of test problems relative to several niching PSO methods that require explicit parameter specification, though not necessarily faster convergence on every individual function the reported advantage is consistency and robustness across problems rather than raw convergence speed on any single one.

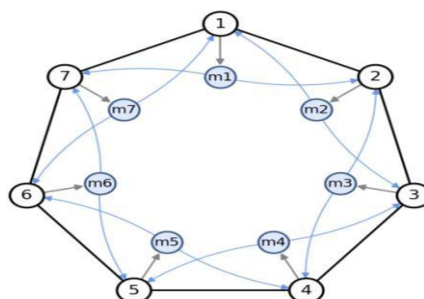


Fig. 2. Ring-topology lbest PSO neighborhood structure ($N = 7$, neighborhood size $k = 3$). Outer nodes are the explorer-swarm (current positions x_i); inner nodes are the memory-swarm (personal bests p_i). Each particle's

neighborhood best $p_{n,i}$ is the fittest personal best among itself and its two ring neighbors, so distinct neighborhoods can settle on distinct optima without any niche-radius parameter.

Fitness Euclidean-Distance Ratio based PSO (FER-PSO), proposed by Li [9], also builds on memory-swarm and explorer-swarm reasoning. Each particle is attracted toward its fittest and closest neighborhood particle via the FER value:

$$FER_{(j,i)} = \alpha \cdot \frac{f(P_j) - f(P_i)}{\|P_j - P_i\|}$$

where α is a scaling factor. FER-PSO can reliably discover all global optima from a sufficiently large population, at a complexity of $O(N^2)$.

Qu et al. [10] combine ring-topology-style niching with a local-search step: while personal-best particles hold their positions to preserve already-found optima, current particles continue exploring nearby points, giving the swarm both the niche-preservation of ring topology and improved local refinement. On a set of commonly used multimodal benchmark problems, the authors report this combination finds both local and global optima using fewer function evaluations on average than niching without local search, while still requiring no niche-radius parameter.

Adaptive Sequential Niche PSO (ASNPSO) [11] traces multiple optimal solutions sequentially from multiple subswarms, adaptively deciding the niche radius r instead of requiring it to be pre-specified:

$$r = \frac{\sum_{i=1}^N \min_{j \neq i} \|x_i - x_j\|}{N}$$

A hill-valley function determines how to modify particle fitness in each sub-swarm, guided by a penalty function:

$$eval(x_n^i) = \begin{cases} f(x_n^i) & \text{if hill valley } (x_n^i, x_k) = 1 \\ f(x_n^i) - p(x_n^i) & \text{Otherwise} \end{cases}$$

The authors report ASNPSO to be effective and efficient at locating multiple optimal solutions on benchmark test functions without requiring prior knowledge of the niche radius [11].

Epitropakis et al. [12] address a limitation shared by many of the methods above dependence on a large, carefully tuned population size by maintaining an external archive of previously found solutions in a dynamic-archive niching DE algorithm. Because the archive, rather than the working population, retains discovered optima, the authors report performance that holds up well even with comparatively small population sizes.

Clearing procedures [13] deliver restricted resources only to the best individuals within a subpopulation, improving GA performance on multimodal optimization; this approach does require an explicit clearing-radius parameter, unlike the ringtopology and vector-based methods discussed above. A Delaunay-Triangulation-based clearing procedure (DTclearing) [14] further improves efficiency by reallocating cleared particles into large empty regions of the search space, reducing wasted evaluations, using an external memory of explored niches to avoid redundant visits.

A related classical mechanism is restricted tournament selection (RTS) [15], in which a candidate replaces the most similar individual among a randomly drawn subset of the population only if it is fitter, rather than replacing the globally worst individual. This locally restricted replacement rule is one of the earliest niching mechanisms in the GA literature and underlies the local-competition idea that several of the singlepopulation methods above build on.

A vector-based PSO (VPSO) [16] treats each particle as a vector and performs vector operations to identify niches without specifying a niche-radius parameter, though the increased cost of distance calculations between all particles is a limitation.

Hybrid approaches such as HN-PSO [17] evaluate a recombination-replacement crowding strategy across a particle population and an archive population (P&A), improving PSO efficiency for multimodal optimization functions.

Huang et al. [18] compared SPSO, FER-PSO, and ringtopology PSO on multimodal composite-structure buckling optimization and found that ring-topology PSO, requiring no niche parameter, was more robust and efficient on this problem than SPSO and FER-PSO, which require problemdependent parameter specification.

Because existing niching algorithms are mostly evaluated on 1- or 2-dimensional functions, Li and Deb [19] proposed and compared CGPSO with lbest PSO using ring topology on higher-dimensional problems and found it able to locate more global peaks.

MOMMOP (Multiobjective Multimodal Optimization Problems) [20] targets a distinct problem class from the singleobjective MMO addressed by the methods above: it is an implicit niching technique that converts an MMOP into a multi-objective problem with two conflicting objectives, after which all optimal solutions become Pareto-optimal and are located via multi-objective EAs. We include it here for completeness but note it should not be compared directly against single-objective MMO methods in Table 1 without this distinction in mind; the same caveat applies to DNPSO with an external archive.

Repelling-subpopulation niching, incorporated with CMA-ES (the resulting method: RS-CMSA) [21], avoids the nicheradius parameter that many earlier methods depend on and enables parallel convergence to different minima; it does, however, require a structured parameter-setting procedure that assumes an estimate of the expected number of minima is available. Under this assumption, Ahrari et al. [21] report RSCMSA among the most successful methods when both robustness and efficiency are required.

Multi-Population Based Niching Techniques

Clustering-based techniques: a k-means clustering PSO for niching, inspired by Kennedy's clustering approach [22], locates multiple optima by exploiting niching during a parallel search, with results demonstrating good performance.

Speciation-based techniques: speciation-based PSO [23] defines species using a species radius, denoted r_s , around a dominant individual known as the species seed, the seed marks the centre of a species, and r_s defines its boundary. Identifying an appropriate r_s is time-consuming and increases algorithmic complexity. A speciation-based multi-population technique [24] addresses this by using parallel subpopulation speciation to continuously track optima in dynamic environments, avoiding overcrowding.

Dynamic niching PSO: optimization algorithms must balance exploration and exploitation. Dynamic niching PSO (DNPSO) [25] introduces sub-populations and a group of free particles, where sub-swarms of new particles improve exploration ability relative to standard PSO; it has been tested on benchmark problems alongside well-known PSO variants.

This earlier DNPSO is a distinct, earlier method from the “dynamic niching PSO with an external archive-guided mechanism” of Sun et al. [28].

Comparative Overview

Table 1 summarizes the niching techniques surveyed in this paper; the shaded rows correspond to the hybrid and archive-guided methods. Every strength and limitation listed can be traced directly to its primary source. Complexity is reported as Big-O where the source paper states it explicitly; where a source does not report a precise asymptotic bound, the entry is marked “Moderate.” Results quoted for the ring-topology PSO and FER-PSO rows are drawn from the full experimental study reported by Li [4].

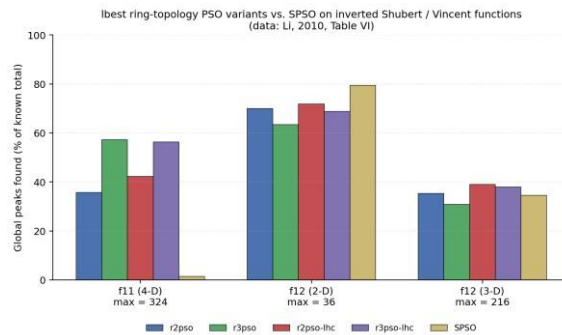


Fig. 3. Global peaks found (as a percentage of the known total) by four ringtopology lbest PSO variants versus SPSO on the inverted Shubert (f11, 4-D) and inverted Vincent (f12, 2-D and 3-D) functions. Values are the mean over 50 runs, taken directly from Table VI of Li [4]; f11 (4-D) has 324 known global peaks, f12 (2-D) has 36, and f12 (3-D) has 216. No niche-radius parameter was used by any r2ps0/r3ps0 variant; SPSO was given the true niche radius.

DISCUSSION

This section synthesizes the comparative strengths connecting individual techniques back to the criteria introduced in Section 2.1 and showing how the parameter-free principle central to ring-topology PSO recurs across otherwise unrelated methods.

Table I Comparative Summary of Niching Techniques

Technique	Year	Ref.	Needs niche parameter?	Complexity	Strength	Limitation
Ring-topology PSO (Li)	2010	[4]	No	$O(N)$	Simple; no parameter tuning; forms stable niches. 90%+ success at population ≥ 450 on f11 2-D vs. 60% for SPSO	Convergence to high precision slower than some tuned parameterbased methods
FER-PSO	2007	[9]	No	$O(N^2)$	Finds all global optima reliably on large populations; fastest method on f4–f9 by evaluation count.	High cost from pairwise fitness/distance ratio computation
Niching PSO with local search	2012	[10]	No	Moderate	Strong joint local/global optima discovery	Extra local-search overhead per iteration

(Qu et al.)						
RS-CMSA	2017	[21]	Structured	Moderate	Most robust/efficient when the assumption holds	Requires a prior estimate of the number of minima
ASNPSO	2006	[11]	No (adaptive radius)	Moderate	No manual radius tuning; sequential sub-swarm detection	Sensitive to hill-valley/penalty-function design
Dynamic archive niching DE	2013	[12]	No	Moderate	Performance holds with small population sizes	Limited to the DE framework
DT-Clearing	2017	[14]	Yes	Moderate–High	Efficient reallocation into empty search regions	Still parameter-dependent (clearing radius)
Vector-based PSO (VPSO)	2010	[16]	No	$O(N^2)$	No niche radius needed; niches from vector operations	Expensive all-pairs distance calculations
HN-PSO (P&A)	2012	[17]	Yes	Moderate	Strong exploration via archive population	Two-population design is more complex to implement
Hybrid niching-PSOES (Luo et al.)	2020	[26]	No	Moderate	Combines strengths of three search paradigms	Higher implementation complexity
History-archive DE (Liao et al.)	2023	[27]	No	Moderate	Targets high-dimensional multimodal landscapes	Newer method; less benchmarked across domains
DNPSO with external archive (Sun et al.)	2024	[28]	No	Moderate–High	Strong on multimodal multi-objective problems	Archive management adds overhead

Table 2 details individual technique contributions and achievements as reported in their originating papers, with each row traceable to a specific citation

Sr#	Problem Addressed	Proposed Algorithm	Contribution	Reported Achievement
1	Locate multiple global optima	FER-PSO [9]	Proposed for multimodal optimization, removing the need to specify a niche-radius parameter	Reliably locates multiple global optima with a sufficiently large population
2	Locate multiple global/local optima	Ring-topology PSO [4]	Explores the search space broadly without a niche-radius parameter; forms stable niches across local neighborhoods	More consistent across problems than several parameter-dependent PSO niching algorithms

3	Enhance local search for global/local optima	Niching PSO with local search [10]	Local-search step applied to produce an offspring for each personal best	Increased probability of finding both global and local optima; fewer average evaluations
4	Track species without a fixed radius, in dynamic environments	Speciationbased dynamic tracking [24]	Parallel subpopulation speciation to continuously track optima as the environment changes	Handles multiple solutions effectively while avoiding overcrowding

Avoiding prior knowledge of niche geometry

Ringtopology PSO, FER-PSO, and VPSO require no niche-radius parameter, in contrast to radius- or seed-based methods (clearing, DT-clearing, speciation-based PSO, HN-PSO), which must have a niche size specified in advance. RS-CMSA occupies a middle position: it avoids a niche-radius parameter but still requires a structured estimate of the expected number of minima. Ring-topology PSO's $O(N)$ neighborhood comparison is the most economical route to this parameterfree property among the single-population methods surveyed.

Sr#	Problem Addressed	Proposed Algorithm	Contribution	Reported Achievement
5	Balance exploration and exploitation in MMO	DNPSO [25]	Divides the population into sub-swarms and a group of free particles	Reported to outperform several PSO-based multimodal methods on benchmark functions
6	Detect multiple optimal solutions sequentially	ASNPSO [11]	Hill-valley function determines fitness change of particles within sub-swarms	Effective and efficient at finding multiple optimal solutions without prior knowledge
7	Locate as many global optima as possible, independent of population size	Dynamic archive niching DE [12]	External dynamic archive with control-parameter adaptation	Competitive performance; reduces sensitivity to the population-size parameter
8	Share limited resources among competing individuals	Clearing procedure [13]	Resources shared only with the fittest individuals in a subpopulation	Improves GA performance on multimodal optimization
9	Locate and maintain niches without a radius parameter	Vector-based PSO (VPSO) [16]	Additional vector operations determine niche boundaries	Experimental results show competitive performance
10	Deal with multimodal function optimization	HN-PSO [17]	Recombination-replacement crowding strategy combined with a particle-andarchive (P&A) pattern	Stable performance reported on specific MMFO benchmark problems
11	Improve on canonical clearing	DT-clearing [14]	Cleared individuals reallocated into the largest empty region of the search space	Favourable outcomes vs. canonical clearing
12	Extend unimodal optimization to a	Niching PSO (composite	FER-PSO, SPSO, and ring-topology PSO	Successfully identifies optima simultaneously;

	composite-structure application	structures) [18]	compared on buckling optimization	ring-topology PSO most robust
13	Tackle high-dimensional MMO problems	CGPSO [19]	Compares several PSO update-rule schemes with lbest ring-topology PSO	Locates more global peaks in highdimensional problems
14	Solve MMO via local competition	Restricted tournament selection [15]	A candidate replaces the most similar individual in a random subset, if fitter	One of the earliest niching mechanisms; underlies later localcompetition methods
15	Find multiple optimal solutions as a multiobjective problem	MOMMOP [20]	Transforms an MMOP into a two-objective problem so optima become Pareto-optimal	Outperforms a number of methods for this distinct MMO formulation
16	Reduce reliance on parameter specification	RS-CMSA [21]	Structured parameter-selection process; estimates the expected number of minima	Successful in achieving robustness and efficiency simultaneously

Persistence of discovered optima across a run

Archivebased methods (dynamic archive niching DE, DT-clearing, history-archive DE, DNPSO with an external archive) store discovered optima outside the working population, which lets them perform well with smaller population sizes than radiusbased methods that must keep every optimum represented within the live population at all times. Ring-topology PSO achieves the same persistence property through its memoryswarm rather than an external archive, since a particle's personal best is only ever replaced by a fitter position.

Scaling to higher dimensions

Most of the classical techniques surveyed here (ring-topology PSO, FER-PSO, ASNPSO, clearing) were evaluated primarily on lowdimensional benchmark functions. The CGPSO study [19] specifically investigated ring-topology PSO's performance in higher dimensions and reported it locating more global peaks than competing update rules, while the more recent historyarchive niching DE method [27] targets high-dimensional landscapes directly together indicating that high-dimensional MMO is an active extension point for parameter-free niching rather than a closed problem.

Computational efficiency

Ring-topology PSO's fixedneighborhood comparisons give it $O(N)$ cost, a clear advantage over methods that compute pairwise distances across the full population, such as FER-PSO and VPSO. Archive-guided methods introduce a different, comparable overhead from archive maintenance and lookup rather than from population size.

Problem-class boundaries

Single-objective MMO (most methods surveyed) and multimodal multi-objective optimization, MMOP (MOMMOP, DNPSO with an external archive), address different problem formulations; comparing them on a shared benchmark suite would not be a like-for-like evaluation, and the literature treats them separately.

Taken together, these comparisons show that the parameterfree property central to ring-topology PSO is not an isolated design choice: sharing- and seed-based methods trade this property for finer control over niche granularity, while archive-guided and hybrid methods extend the same underlying principle avoiding a pre-specified niche-radius parameter to differential evolution, evolution strategies, and gravitational search. This consistency across otherwise independent research lines is the strongest evidence that parameter-free niching, as formalized by the ring-topology approach, reflects a general design principle rather than a property specific to one algorithm.

CONCLUSION

Niching algorithms are introduced in PSO and EAs to address the limitations of standard optimization methods on multimodal problems, where multiple global or local optima must be traced and preserved. This survey reviewed a range of single- and multi-population niching techniques across PSO, DE, GA, ES, and GSA, and examined in particular depth the ring-topology-based niching method, which forms stable niches via memory-swarm and explorer-swarm interaction without an explicit niche-radius parameter, and which the literature reports as performing comparably to, and on several benchmark functions more consistently than, parameterdependent alternatives.

Beyond the individual techniques surveyed, hybrid and archive-guided niching methods extend this same parameterfree principle to differential evolution, evolution strategies, and gravitational search, improving performance on highdimensional and dynamic multimodal problems. Building on the comparisons, future extensions of ring-topology-based niching could similarly draw on archive-guided strategies, evaluated against a common benchmark suite such as the CEC 2013 niching functions, as a direct route toward improved high-dimensional performance.

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