Niching Genetic Algorithm Experimentation

Link to Code Link to Video

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I. Introduction

Evolutionary computation techniques are widely used for solving optimization problems that contain multiple local optima. Standard Genetic Algorithms (GAs) are effective global search methods, but they often converge prematurely to a single region of the search space, losing population diversity and failing to locate multiple high-quality solutions. Many real-world optimization tasks are multimodal problems that require discovering and preserving more than one peak of the objective function. This motivates the use of niching methods, which modify the GA to maintain diverse subpopulations throughout evolution. Niching methods aim to preserve multiple subpopulations (niches) so that the algorithm can simultaneously explore and locate several optima.

The goal of this project is to apply GAs and niching GAs to multimodal optimization problems using two benchmark functions, M_1 and M_2, defined on the bounded domain $x \in [0, 1]$. Both functions are maximization tasks:

$$x^* = \arg \max_{x \in [0,1]} f(x).$$

The first function, M_1, is a multimodal sinusoidal landscape:

$$M_1(x) = \sin^6(5\pi x)$$

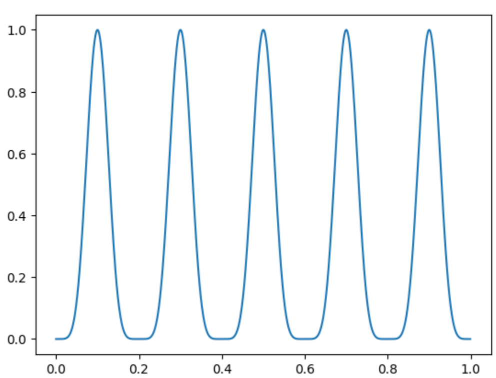

Fig. 1. Graph of $M_1(x)$

The second function, M_2, contains five asymmetric peaks of varying heights:

$$M_2(x) = e^{-2\ln(2)\left(\frac{x-0.08}{0.854}\right)^2} \cdot \left[\sin\left(5\pi \left(x^{0.75} - 0.05\right)\right)\right]^6$$

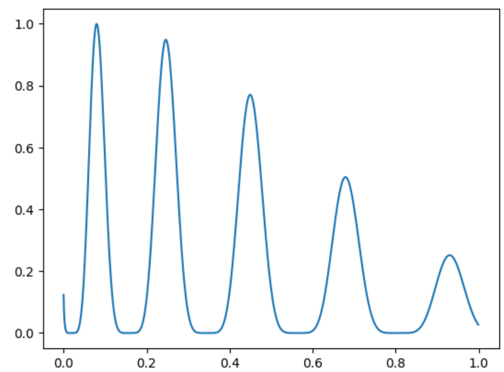

Fig. 2. Graph of $M_2(x)$

A standard GA and two niching variants—Deterministic Crowding and Parallel Hillclimbing—are applied to these functions. We analyze convergence behavior, fitness statistics, population distributions, and compare the effectiveness of the niching methods.

II. Methods

A. Standard Genetic Algorithm

The baseline GA operates on a population of N real-valued individuals $x \in [0, 1]$. Each generation includes tournament selection, simulated binary crossover (SBX) with rate p_c, Gaussian mutation with rate p_m, and elitism.

Fitness statistics collected per generation:

$$F_{\max}(t), \quad F_{\text{avg}}(t), \quad F_{\min}(t).$$

The baseline GA is expected to converge rapidly but collapse to a single peak due to loss of diversity.

B. Deterministic Crowding

Deterministic Crowding (DC) is used to preserve multiple niches within a single evolving population. Instead of global competition, offspring compete locally with their most genetically similar parent.

Procedure:

1) Select two parents via tournament selection.
2) Produce two offspring by crossover and mutation.
3) Compute phenotypic distances between offspring and parents.

4) Each offspring replaces its closest parent if it has higher fitness.

This localized replacement prevents dominant peaks from absorbing the entire population and stabilizes multiple sub-populations across the domain.

C. Parallel Hillclimbing Niching

Parallel Hillclimbing (PHC) is a multi-start strategy. Instead of maintaining niches in a single population, we run k independent GA–hillclimbing searches.

For each of the k runs:

1) Initialize a random population.
2) Run GA for several generations.
3) Apply hillclimbing for local refinement.

The output is a set of k local optima:

$$S = \{x_1^*, x_2^*, \dots, x_k^*\},$$

which naturally samples multiple peaks.

D. Experimental Setup

Experiments were conducted on M_1 and M_2 using:

$$N = 50, \quad p_c = 0.9, \quad p_m = 0.05, \quad T = 200.$$

Parallel Hillclimbing used $k = 25$ independent runs.

Metrics:

- Best, average, minimum fitness
- Number of peaks preserved
- Final distribution of solutions

III. Results

A. Baseline GA

On both benchmark functions, the baseline GA collapsed to a single peak by generation 60.

TABLE I
BASELINE GA FINAL RESULTS

Function	Best Fitness	Peaks Preserved
M_1	0.999	1 of 5
M_2	0.98	1 of 5

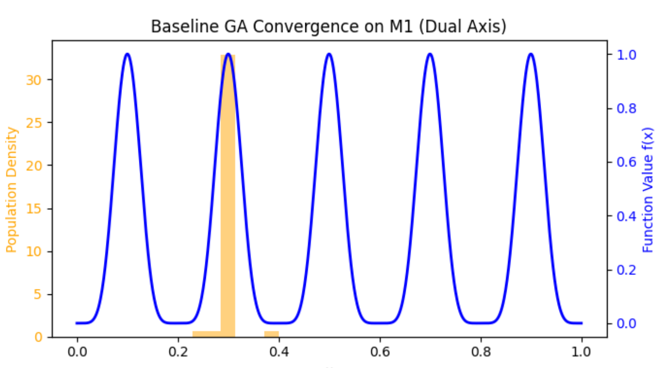

Fig. 3. GA Baseline final population solutions, converging on one of 5 possible global optima on $M_1(x)$

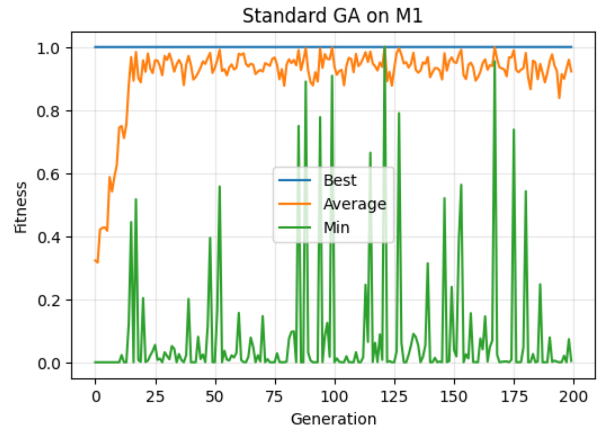

Fig. 4. Evolution of the Standard GA on the M_1 function. The best fitness quickly reaches a global maximum, but the population collapses to a single peak early, illustrating premature convergence on a multimodal landscape.

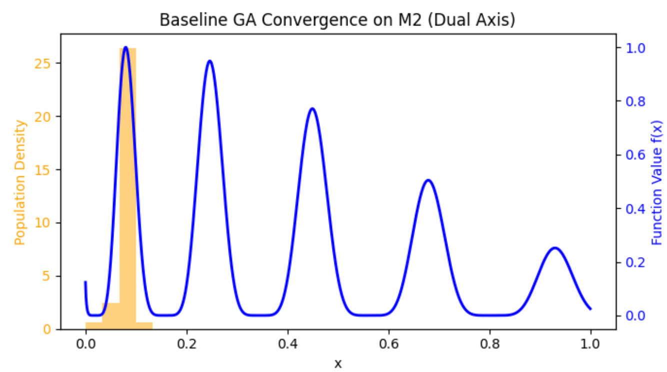

Fig. 5. GA Baseline final population solutions, converging on the global optimum on $M_2(x)$

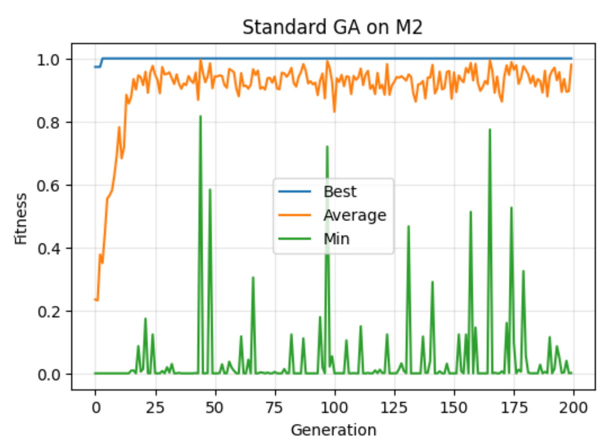

Fig. 6. Standard GA convergence on the multimodal function M_2. As with M_1, the population collapses to a single mode despite M_2's multiple peaks.

B. Deterministic Crowding

Deterministic Crowding maintained stable subpopulations across multiple modes.

TABLE II
DETERMINISTIC CROWDING FINAL RESULTS

Function	Best Fitness	Peaks Preserved
M_1	0.999	5 of 5
M_2	0.98	4 of 5

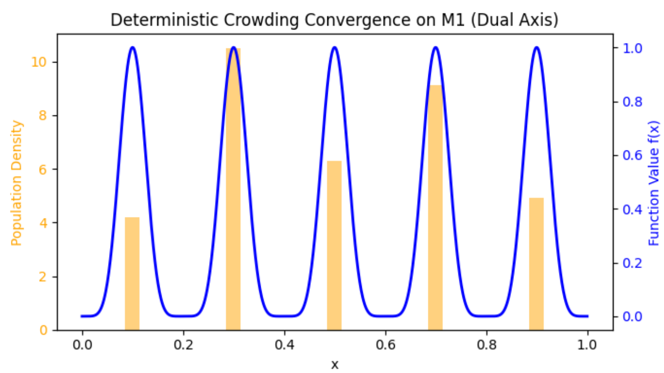

Fig. 7. Final population distribution of the Deterministic Crowding GA overlaid on the $M_1(x)$ landscape. The histogram peaks align with all five modes of the function. This confirms that multiple niches are preserved simultaneously, demonstrating effective multimodal coverage and sustained population diversity.

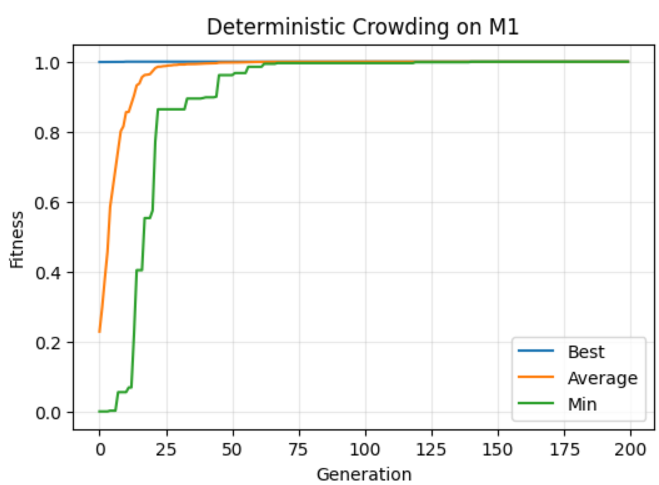

Fig. 8. Fitness evolution of the Deterministic Crowding GA on the multimodal function M_1.

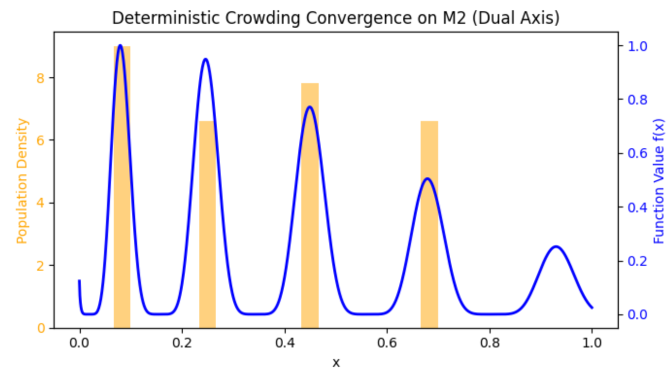

Fig. 9. Final population distribution of the Deterministic Crowding GA overlaid on the multimodal landscape M_2. Deterministic Crowding successfully maintains distinct subpopulations around several of the major peaks of M_2. The histogram bars align with four local optima despite the uneven peak heights of the function, illustrating the method's ability to preserve diversity even on more irregular landscapes.

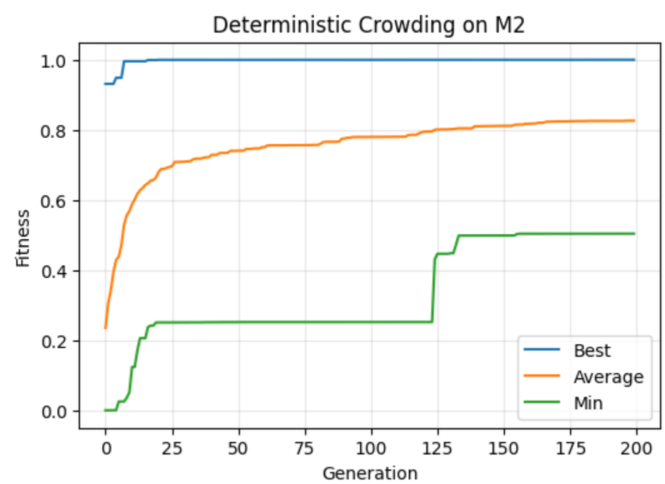

Fig. 10. Fitness evolution of the Deterministic Crowding GA on M_2. The best fitness reaches the global optimum early in the run, but the average and minimum fitness steadily improve throughout the generations. The rising minimum fitness indicates that low-performing individuals are gradually replaced within their local niches, allowing multiple peaks to remain represented in the population.

C. Parallel Hillclimbing

Parallel Hillclimbing produced diverse local optima across runs.

TABLE III
PARALLEL HILLCLIMBING FINAL RESULTS

Function	Unique Optima Found	Total Samples
M_1	5 / 5	25
M_2	2 / 5	25

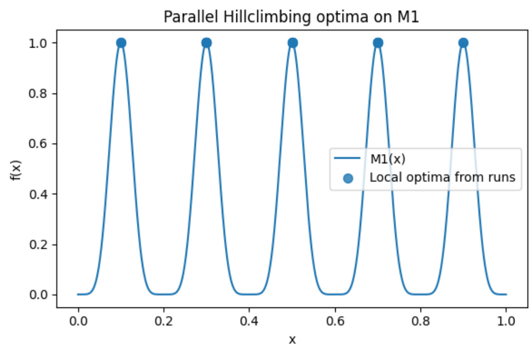

Fig. 11. Parallel Hillclimbing optima across 25 runs on M_1. Because the peaks are evenly spaced and have identical heights and basin shapes, PHC is able to recover all five local optima across the 25 runs. Each blue point corresponds to the final solution reached by a single restart.

TABLE IV
PARALLEL HILLCLIMBING PEAK COVERAGE ON M1

Peak	Center (x)	Count	Avg Fitness
1	0.10	3	1.00
2	0.30	8	1.00
3	0.50	6	1.00
4	0.70	6	1.00
5	0.90	2	1.00

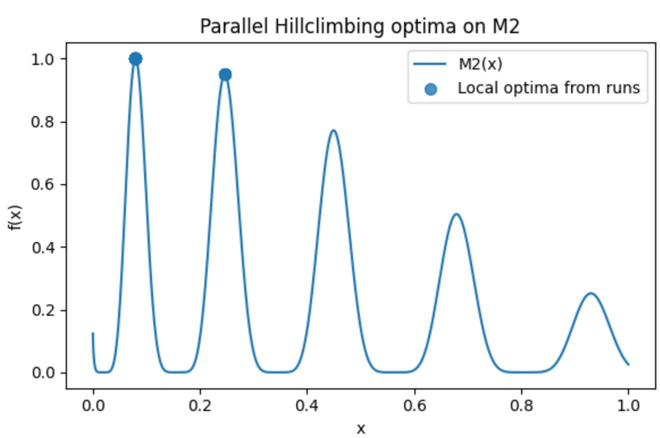

Fig. 12. Local optima obtained from 25 independent PHC runs on the multimodal function M_2. Each point represents the refined solution from a single GA–hillclimbing restart. PHC consistently locates the two dominant peaks near $x \approx 0.08$ and $x \approx 0.25$, reflecting the larger basins of attraction around these modes. Smaller and narrower peaks are not recovered.

TABLE V
PARALLEL HILLCLIMBING PEAK COVERAGE ON M2

Peak	Center (x)	Count	Avg Fitness
1	0.0797	20	1.0000
2	0.2463	5	0.9487

D. Results with Varying Crossover and Mutation Rates

See appendix for tabular result summary.

IV. EXPERIMENTAL ANALYSIS

The baseline GA converged prematurely on both multimodal landscapes. In contrast, Deterministic Crowding preserved multiple niches within a single evolving population by enforcing local competition. It excelled at maintaining stable clusters and accurately preserving all peaks in M_1.

Parallel Hillclimbing was highly effective at sampling multiple optima due to its multi-start structure. On the symmetric landscape M_1, PHC recovered all five peaks across independent runs. However, on the more irregular function M_2, Parallel Hillclimbing consistently converged to the two dominant peaks and failed to capture the smaller modes. In contrast, Deterministic Crowding maintained subpopulations around approximately four of the five peaks, providing better overall niche coverage on M_2.

Overall, both niching methods significantly outperformed the baseline GA, especially on landscapes with uneven peak heights.

V. CONCLUSION

This project implemented and compared a standard GA with two niching variants, Deterministic Crowding and Parallel Hillclimbing, on multimodal benchmark functions.

The baseline GA failed to maintain diversity and converged to a single mode. Both niching methods successfully identified multiple optima:

- Deterministic Crowding preserved multiple niches within a single population.
- Parallel Hillclimbing discovered diverse local optima across independent runs.

These findings demonstrate the importance of diversity-preserving techniques for multimodal optimization. Future work may include fitness sharing, clearing, and adaptive niching radius strategies.

REFERENCES

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[4] R. Storn and K. Price, “Differential evolution—a simple and efficient heuristic,” J. Global Optimization, 1997.

VI. Appendix

TABLE VI
Average Performance Over 10 Trials for All Methods on M_1 and M_2

Function	Method	p_c	p_m	Avg Best	Avg Avg	Avg Min	Avg Peaks	Peak Centers (sample)
M1	Standard GA	0.6	0.05	1.0	0.969832	0.162314	1.8	[0.244, 0.300]
M1	Deterministic Crowding	0.6	0.05	1.0	0.999927	0.998706	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M1	Parallel Hillclimbing	0.6	0.05	1.0	—	—	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M1	Standard GA	0.6	0.10	1.0	0.942851	0.047879	3.0	[0.784, 0.833, 0.863, 0.900, 0.957]
M1	Deterministic Crowding	0.6	0.10	1.0	0.999948	0.999251	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M1	Parallel Hillclimbing	0.6	0.10	1.0	—	—	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M1	Standard GA	0.9	0.05	1.0	0.976243	0.238608	2.2	[0.807, 0.866, 0.900]
M1	Deterministic Crowding	0.9	0.05	1.0	0.999987	0.999757	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M1	Parallel Hillclimbing	0.9	0.05	1.0	—	—	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M1	Standard GA	0.9	0.10	1.0	0.939130	0.057401	2.9	[0.700, 0.772]
M1	Deterministic Crowding	0.9	0.10	1.0	0.999988	0.999776	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M1	Parallel Hillclimbing	0.9	0.10	1.0	—	—	5.0	[0.1, 0.3, 0.5, 0.7, 0.9]
M2	Standard GA	0.6	0.05	0.994865	0.969892	0.418630	2.2	[0.043, 0.079, 0.117]
M2	Deterministic Crowding	0.6	0.05	1.0	0.787743	0.300128	4.9	[0.08, 0.247, 0.449, 0.653, 0.679, 0.931]
M2	Parallel Hillclimbing	0.6	0.05	1.0	—	—	1.7	[0.08, 0.246]
M2	Standard GA	0.6	0.10	1.0	0.939467	0.015220	3.4	[0.022, 0.079, 0.128]
M2	Deterministic Crowding	0.6	0.10	1.0	0.783998	0.320067	4.9	[0.08, 0.246, 0.449, 0.47, 0.679, 0.93]
M2	Parallel Hillclimbing	0.6	0.10	1.0	—	—	1.5	[0.08, 0.246]
M2	Standard GA	0.9	0.05	1.0	0.962319	0.210311	2.4	[0.035, 0.08, 0.123]
M2	Deterministic Crowding	0.9	0.05	1.0	0.818958	0.352074	4.6	[0.08, 0.246, 0.449, 0.679, 0.93]
M2	Parallel Hillclimbing	0.9	0.05	1.0	—	—	1.5	[0.08]
M2	Standard GA	0.9	0.10	0.994869	0.944054	0.016282	3.0	[0.000, 0.080, 0.160, 0.181]
M2	Deterministic Crowding	0.9	0.10	1.0	0.810664	0.373254	4.6	[0.08, 0.246, 0.450, 0.680]
M2	Parallel Hillclimbing	0.9	0.10	1.0	—	—	1.5	[0.08, 0.246]