# Advanced and Classical Selection Methods in Genetic Algorithms: A Comprehensive Comparative Analysis

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***Abstract*—Selection mechanisms critically influence the convergence behavior and solution quality of Genetic Algorithms (GAs). This study presents a rigorous empirical comparison of six selection methods: three classical methods—Random Selection, Roulette Wheel Selection (RWS), and Tournament Selection (TS)—and three adaptive methods: Fitness-Distance Balance (FDB), Dynamic FDB (dFDB), and Functional Weight-based Selection (FW). Experiments were conducted across 23 classical benchmark functions (F1–F23) and 10 CEC2019 functions (cec01–cec10), with each configuration executed 30 times using consistent GA parameters. Performance was assessed using Best, Mean, Median, and Standard Deviation, with statistical significance determined by the Wilcoxon rank-sum test ($\alpha = 0.05$). The results reveal that TS consistently achieved the best or statistically equivalent performance in 30 out of 33 functions, outperforming both classical and adaptive alternatives. Notably, RWS showed surprising competitiveness, outperforming adaptive methods such as FDB and dFDB in several scenarios. While dFDB and FW improved over static FDB, they failed to consistently outperform TS. These findings confirm TS as a robust default choice for diverse optimization landscapes and provide new empirical evidence regarding the limited practical advantage of current adaptive strategies within GAs. This study contributes the first controlled GA-based evaluation of adaptive selection mechanisms on both classical and CEC2019 benchmarks, offering insights for practitioners designing efficient evolutionary systems. Limitations related to fixed GA settings, function diversity, and adaptive method complexity are acknowledged, and future work is suggested to explore hybrid and problem-aware selection strategies.***

***Keywords*—Genetic algorithm; selection mechanisms; FDB; tournament; roulette wheel; evolutionary computation; optimization**

## I. Introduction

Genetic Algorithms (GAs) represent a foundational technique in evolutionary computation, widely applied for solving complex optimization tasks by emulating the processes of natural selection and evolution [1]. A key determinant of GA performance is the selection operator, which mediates the trade-off between exploration of the solution space and exploitation of high-quality individuals [2]. Over time, a diverse range of selection methods has been developed—from traditional approaches like Roulette Wheel and Tournament Selection [2], [3], to more advanced, adaptive techniques such as the FDB family, including FDB, dFDB, and FW methods [4], [5]. These adaptive methods dynamically adjust selection pressure based on population distribution and fitness, potentially improving convergence and mitigating premature stagnation.

While considerable attention has been given to modifying GA components—including crossover, mutation, and population structure—relatively few studies have systematically compared selection strategies across a broad spectrum of problem types. Notably, distance-aware selection mechanisms have gained popularity in other metaheuristics, including LSHADE [6], Whale Optimization Algorithm (WOA) [7], and Stochastic Fractal Search (SFS) [8], demonstrating promising outcomes. However, their effectiveness within the traditional GA framework remains underexplored. Moreover, although GAs have been successfully applied in various fields, from photovoltaic modeling [9] to power system optimization [10], the optimal choice of selection strategy under consistent algorithmic settings is still an open question.

This study addresses this gap by systematically evaluating six selection methods—three classical and three adaptive—within a canonical GA setup. The goal is to empirically assess their comparative performance across diverse benchmarks and derive practical recommendations for researchers and practitioners. The primary contributions of this work are:

- Comprehensive Comparison of Selection Strategies: This work presents one of the first integrated empirical comparisons between classical GA selection methods (Random, Roulette Wheel Selection, Tournament Selection) and adaptive FDB-based methods (FDB, dFDB, FW), under a unified experimental setup.
- Diverse and Challenging Benchmarking: The evaluation spans 23 classical benchmark functions and 10 CEC2019 functions, encompassing unimodal, multi-

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modal, composite, and high-dimensional landscapes.

- Robust Statistical Validation: In addition to standard performance metrics (Best, Mean, Median, Standard Deviation), the study employs the Wilcoxon rank-sum test to rigorously assess the statistical significance of observed differences between selection strategies.
- In-Depth Literature Integration: The study synthesizes and contextualizes prior research on both classical and modern selection approaches, clarifying existing gaps.
- Actionable Insights for Practitioners: By holding all other GA components constant and varying only the selection mechanism, the study isolates its effect on performance, demonstrating that selection alone can significantly impact results.

The remainder of this study is organized as follows: Section II reviews classical and advanced selection methods. Section III describes the proposed methodology. Section IV presents experimental results and statistical analysis. Section V discusses key findings and their implications. Section VI concludes the study and outlines future research directions.

## II. LITERATURE REVIEW

This section briefly reviews key developments in selection methods, beginning with classical techniques, followed by recent adaptive strategies based on the FDB framework.

### A. Classical Selection Methods

Classical selection strategies in GAs primarily include proportional selections such as RWS and ranking-based methods, including TS. While simple and computationally efficient, RWS is highly sensitive to skewed fitness distributions; a small number of very fit individuals can dominate the mating pool, increasing the risk of premature convergence [2]. TS, in contrast, applies controlled selection pressure and has been widely adopted for its robustness, but it does not inherently incorporate population diversity or spatial distribution of solutions. As noted by Shukla et al. [11], while tournament size can modulate pressure, classical methods generally ignore diversity, which can hinder their performance on multi-modal or complex landscapes.

In response to these limitations, enhancements have been proposed. For example, Cuevas et al. [12] introduced a Golden Section Selection inspired by the golden ratio, which outperformed traditional schemes on selected benchmarks by improving solution quality by approximately 15–20%. Likewise, Oladimeji et al. [13] demonstrated performance gains in the Mayfly Algorithm by replacing random selection with RWS.

Table I summarizes key studies on classical selection methods.

TABLE I. SUMMARY OF CLASSICAL SELECTION METHOD STUDIES

| Reference | Focus | Methodology | Results |
|---|---|---|---|
| Goldberg & Deb (1991) [2] | Comparative analysis of selection schemes | Modeling and simulations | Tournament-based methods exert stronger selection pressure |
| Julstrom (1999)[3] | Rank-based vs. TS equivalence | Analytical probability-based analysis | TS preferred due to simplicity and consistent pressure |
| Zhang & Kim (2001)[14] | Selection methods for layout optimization | Experiments on machine layout problems | TS and ranking selection outperformed others |
| Zhong et al. (2005) [15] | RWS vs. TS on benchmark functions | Benchmark tests with fixed settings | TS converged faster than RWS |
| Mashohor et al. (2005) [16] | Selection for industrial inspection | Evaluation of PCB inspection system | Elitist selection gave the best results |
| Shukla et al. (2015) [11] | Review of selection techniques | Conceptual and experimental analysis | TS incurred lower overhead for similar results |
| Yadav et al. (2017) [17] | Multiple selection schemes | Conceptual and partial experiments | TS and elitism yielded faster convergence |
| Cuevas et al. (2018) [12] | Golden section vs. traditional methods | Benchmark optimization | Golden-section improved quality by ∼15–20% |
| Oladimeji et al. (2024)[13] | RWS in Mayfly algorithm | Benchmarked on face/iris datasets | RWS improved accuracy and reduced error |

### B. Advanced Selection Methods (FDB Family)

To address the limitations of classical selection strategies, the FDB family introduces a mechanism for maintaining population diversity by jointly considering an individual's fitness and its spatial distance from the best-performing solution. The original FDB method, introduced by Kahraman et al. in 2019 [4], assigns each individual a composite score that combines normalized fitness and distance values. The general FDB scoring equation is:

$$\text{Score}_i = \delta \cdot \text{normF}_i + (1 - \delta) \cdot \text{normD}_i \qquad (1)$$

where, normF and normD are the normalized fitness and distance scores, respectively, and $\delta \in [0, 1]$ is a weight controlling the trade-off between exploitation and exploration.

Multiple variants of FDB have since been developed. One notable extension is Fitness-Distance Balance with Functional Weights (FW), proposed by Tao et al. in 2021 [5]. Rather than using a fixed weighting parameter, FW introduces a stochastic weighting scheme where $\delta$ is sampled from a probability distribution (e.g., Gaussian or Cauchy) during each generation.

Another enhancement is Dynamic Fitness-Distance Balance (dFDB), introduced by Kahraman et al. [8], which varies the weight $\delta$ over time according to a predefined schedule. Typically, dFDB starts with greater emphasis on diversity (higher distance weight) and gradually shifts toward fitness-based exploitation as the search progresses.

Table II summarizes key contributions utilizing the FDB family of methods.

**Research Gap:** While classical selection strategies such as RWS and TS have been extensively evaluated on standard benchmark functions, their effectiveness on large-scale or highly complex optimization problems remains insufficiently studied. Conversely, adaptive methods—including FDB, dFDB, and FW—have demonstrated strong potential in modern metaheuristics, but their systematic integration into and evaluation within traditional GAs is still lacking.

TABLE II. SUMMARY OF FDB-BASED SELECTION METHODS

| Reference | Focus of Study | Methodology | Key Findings |
|---|---|---|---|
| Kahraman et al. (2019)[4] | Introduction of FDB | Applied in various meta-heuristics (90 benchmarks) | FDB improved diversity and solution quality |
| Tao et al. (2021)[5] | FW for dynamic balance | Integration into spherical search algorithm | FW outperformed traditional methods |
| Tan et al. (2022) [18] | Chaotic FDB-based selection | Hybrid wind-driven optimization with FDB | Enhanced accuracy and faster convergence |
| Battal & Guvenc (2022) [6] | FDB-integrated LSHADE | Energy hub management | Superior performance in energy optimization |
| Hou et al. (2024) [7] | Adaptive FDB in WOA | Modified WOA with FDB component | Increased accuracy and faster convergence |
| Kahraman et al. (2024) [19] | dFDB for SFS | Applied to SFS and photovoltaic optimization | dFDB provided superior robustness |
| Kahraman et al. (2023)[19] | dFDB for GBO | Incorporated dFDB into GBO | Improved exploration and balanced search |
| Mashaqbeh & Mjlae (2025) [20] | FDB-enhanced Jaya | Cloud task scheduling | Reduced makespan by up to 38.98% |

TABLE III. CONFIGURATION AND PARAMETERS USED FOR ALL EXPERIMENTS

| Parameter | Value |
|---|---|
| Population Size | 75 |
| Generations | 3000 |
| Encoding | Real-valued vector |
| Benchmark Functions | CEC2019 and Classical (F1–F23) |
| Dimensions | 10 (CEC2019); varies (F1–F23) |
| Crossover Type | Blend crossover (BLX-0.5) |
| Crossover Rate | 0.7 |
| Mutation Type | Uniform mutation |
| Mutation Rate | 0.3 (per individual) |
| Runs | 30 |
| Statistical Test | Wilcoxon Rank-Sum Test ($\alpha = 0.05$) |
| Performance Metrics | Best, Mean, Median, Std |
| Random | Uniformly random |
| RWS | Proportional to fitness |
| TS | TS size $= 3$ |
| FDB | Static weight $\delta = 0.5$ |
| dFDB | $\delta$ decreases every frequency $= 10$ |
| FW | Gaussian sampling for dynamic $\delta$ |

This study bridges this gap through a unified and controlled comparison across both traditional and CEC2019 benchmark sets.

## III. METHODOLOGY

This study employed a standardized GA implemented in MATLAB to ensure a consistent experimental framework across all comparisons. The only varying component was the selection method, while all other algorithmic elements were held constant. Table III summarizes the GA configuration and selection method parameters used throughout the experiments.

The GA evolved with a population of 75 individuals over 3000 generations. Each individual was encoded as a real-valued vector, with bounds and dimensions determined by the benchmark function. For reproduction, blend crossover (with a rate of 0.7 and gamma in the range $[-0.5, 1.5]$) and uniform mutation (applied with a 0.3 probability per individual) were used.

Six selection strategies were tested:

- Random: No selection pressure; individuals were randomly chosen.
- RWS: Proportional selection based on normalized fitness.
- TS: A tournament of size 3 selects the best among randomly sampled candidates.
- FDB: Applies a composite score based on static weight $\delta = 0.5$ combining normalized fitness and distance to the current best.
- dFDB: The weight $\delta$ decreases linearly from 0.6 to 0.0 over the total number of generations to balance exploration and exploitation dynamically.
- FW: Uses a stochastic weight $\delta \sim \mathcal{N}(0.5, 0.1)$ resampled each generation, providing adaptive selection pressure.

The benchmark consisted of two test suites:

- F1–F23: Classical benchmark functions covering unimodal, multimodal, and hybrid categories.
- CEC2019 (cec01–cec10): Designed to challenge optimization strategies through transformed, rotated, and composite problem landscapes, implemented at 10 dimensions.

For each function and selection method pair, 30 independent runs were executed. Performance was evaluated based on the Best, Mean, Median, and Std of the final fitness values. Additionally, the Wilcoxon rank-sum test was applied to assess statistical significance between each method and TS, which served as a robust baseline due to its proven performance in preliminary evaluations.

## IV. RESULTS

This section presents a comprehensive evaluation of the six selection methods across two benchmark suites: the classical functions F1–F23 and the CEC2019 test functions (cec01–cec10). The evaluation is based on multiple statistical indicators (Best, Mean, Std, Median) and supported by Wilcoxon rank-sum tests for statistical significance. Convergence curves and boxplots are included to visualize the performance dynamics and distributional patterns.

### A. *Performance on CEC2019 Benchmark Functions (cec01–cec10)*

The CEC2019 benchmark suite includes complex, composition-based, and real-world inspired optimization problems characterized by large search spaces, deceptive landscapes, and challenging global minima. Table IV presents the performance metrics, and Table V reports the Wilcoxon test results against TS.

TABLE IV. Results on CEC2019 (Best, Mean, Median, Std over 30 Runs)

| Fun | Measure | FDB | dFDB | Random | RWS | TS | FW |
|---|---|---|---|---|---|---|---|
| cec01 | Best | 48.4E+6 | 10.3E+6 | 41.4E+6 | 923.6E+3 | **155.6E+3** | 843.1E+3 |
| | Mean | 978.7E+6 | 125.6E+6 | 1.7E+9 | 4.2E+6 | **1.5E+6** | 4.8E+6 |
| | Median | 606.6E+6 | 106.5E+6 | 534.0E+6 | 3.1E+6 | **1.2E+6** | 3.6E+6 |
| | Std | 906.8E+6 | 89.9E+6 | 2.3E+9 | 3.6E+6 | **1.1E+6** | 3.6E+6 |
| cec02 | Best | 21.3E+0 | 17.5E+0 | 49.7E+0 | 17.3E+0 | **17.3E+0** | 17.3E+0 |
| | Mean | 56.5E+0 | 17.8E+0 | 124.7E+0 | 17.3E+0 | **17.3E+0** | 17.3E+0 |
| | Median | 51.8E+0 | 17.8E+0 | 107.9E+0 | 17.3E+0 | **17.3E+0** | 17.3E+0 |
| | Std | 19.6E+0 | 240.9E-3 | 51.2E+0 | 1.2E-3 | **246.0E-6** | 1.1E-3 |
| cec03 | Best | 12.7E+0 | 12.7E+0 | 12.7E+0 | 12.7E+0 | **12.7E+0** | 12.7E+0 |
| | Mean | 12.7E+0 | 12.7E+0 | 12.7E+0 | 12.7E+0 | **12.7E+0** | 12.7E+0 |
| | Median | 12.7E+0 | 12.7E+0 | 12.7E+0 | 12.7E+0 | **12.7E+0** | 12.7E+0 |
| | Std | 582.2E-6 | 348.9E-6 | 1.6E-3 | 154.5E-9 | **51.7E-9** | 194.3E-9 |
| cec04 | Best | 2.5E+3 | 86.7E+0 | 21.0E+3 | 11.1E+0 | **5.0E+0** | 17.1E+0 |
| | Mean | 5.7E+3 | 956.7E+0 | 59.9E+3 | 43.7E+0 | **46.5E+0** | 61.9E+0 |
| | Median | 5.6E+3 | 617.4E+0 | 57.0E+3 | 38.6E+0 | **44.3E+0** | 45.4E+0 |
| | Std | 1.9E+3 | 949.3E+0 | 32.4E+3 | 18.6E+0 | **24.2E+0** | 38.6E+0 |
| cec05 | Best | 2.1E+0 | 1.2E+0 | 3.9E+0 | 1.0E+0 | **1.0E+0** | 1.1E+0 |
| | Mean | 2.7E+0 | 2.1E+0 | 9.9E+0 | 1.2E+0 | **1.0E+0** | 1.3E+0 |
| | Median | 2.7E+0 | 2.1E+0 | 9.4E+0 | 1.2E+0 | **1.0E+0** | 1.2E+0 |
| | Std | 324.5E-3 | 384.1E-3 | 3.7E+0 | 170.9E-3 | **19.3E-3** | 172.1E-3 |
| cec06 | Best | 11.1E+0 | 7.3E+0 | 11.7E+0 | 2.4E+0 | **1.8E+0** | 2.3E+0 |
| | Mean | 14.2E+0 | 9.4E+0 | 14.5E+0 | 3.3E+0 | **4.5E+0** | 3.4E+0 |
| | Median | 14.1E+0 | 9.5E+0 | 14.6E+0 | 3.3E+0 | **4.7E+0** | 3.2E+0 |
| | Std | 1.7E+0 | 1.1E+0 | 1.3E+0 | 625.7E-3 | **1.2E+0** | 649.3E-3 |
| cec07 | Best | 1.1E+3 | 275.0E+0 | 1.2E+3 | 20.9E+0 | **-61.8E+0** | -272.2E+0 |
| | Mean | 1.8E+3 | 709.1E+0 | 2.0E+3 | 241.1E+0 | **231.7E+0** | 159.4E+0 |
| | Median | 1.7E+3 | 698.9E+0 | 2.0E+3 | 231.3E+0 | **217.5E+0** | 121.2E+0 |
| | Std | 422.5E+0 | 275.0E+0 | 311.7E+0 | 151.0E+0 | **143.5E+0** | 165.8E+0 |
| cec08 | Best | 6.9E+0 | 5.0E+0 | 6.6E+0 | 4.7E+0 | **1.2E+0** | 3.6E+0 |
| | Mean | 8.2E+0 | 7.1E+0 | 8.0E+0 | 5.6E+0 | **4.0E+0** | 5.2E+0 |
| | Median | 8.2E+0 | 7.1E+0 | 8.1E+0 | 5.7E+0 | **4.1E+0** | 5.4E+0 |
| | Std | 635.2E-3 | 1.0E+0 | 454.7E-3 | 453.5E-3 | **1.1E+0** | 681.5E-3 |
| cec09 | Best | 137.3E+0 | 6.1E+0 | 1.8E+3 | 2.6E+0 | **2.5E+0** | 2.6E+0 |
| | Mean | 928.0E+0 | 193.9E+0 | 7.2E+3 | 3.1E+0 | **2.9E+0** | 3.1E+0 |
| | Median | 947.6E+0 | 159.3E+0 | 6.0E+3 | 3.1E+0 | **2.9E+0** | 3.1E+0 |
| | Std | 328.3E+0 | 191.3E+0 | 4.3E+3 | 278.4E-3 | **210.9E-3** | 240.6E-3 |
| cec10 | Best | 20.5E+0 | 20.2E+0 | 20.6E+0 | 2.0E+0 | **3.4E+0** | 20.0E+0 |
| | Mean | 20.9E+0 | 20.4E+0 | 21.0E+0 | 19.4E+0 | **19.5E+0** | 20.0E+0 |
| | Median | 20.9E+0 | 20.5E+0 | 21.0E+0 | 20.0E+0 | **20.0E+0** | 20.0E+0 |
| | Std | 219.2E-3 | 149.6E-3 | 152.8E-3 | 3.3E+0 | **3.0E+0** | 1.3E-3 |

As with the classical functions, TS maintained its dominance in this suite. It achieved the best or second-best fitness values on nearly all functions, with low variance and high reliability. FW again emerged as the closest competitor, achieving statistically indistinguishable performance on some functions (e.g., cec04, cec06, cec08) with $p$-values above the 0.05 threshold. RWS showed a more variable pattern: it was competitive on some easier CEC functions (e.g., cec02, cec05), but less reliable on harder ones such as cec01 and cec07.

The adaptive FDB and dFDB methods exhibited lower performance overall. While dFDB improved upon static FDB, especially on functions like cec05 and cec09, both methods lagged significantly behind TS, FW, and RWS. Their higher standard deviations and poorer best values indicate instability and insufficient convergence, particularly under fixed computational budgets.

Convergence curves (Fig. 1) highlight the rapid and stable convergence of TS and FW, in contrast to the delayed and irregular behavior of the adaptive methods. Boxplots (Fig. 2) for cec01–cec10 further illustrate these trends.

### *B. Performance on Classical Benchmark Functions (F1–F23)*

The classical suite includes a variety of unimodal, multimodal, hybrid, and composition functions. Table VI,VII and

TABLE V. WILCOXON RANK-SUM TEST ($p$-VALUES) FOR CEC2019 VS. TOURNAMENT

| Func. | TS vs RWS | TS vs FDB | TS vs dFDB | TS vs Rand. | TS vs FW |
|---|---|---|---|---|---|
| cec01 | 2.00E-06 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 5.60E-07 (S) |
| cec02 | 1.09E-10 (S) | 3.02E-11 (S) | 3.01E-11 (S) | 3.02E-11 (S) | 5.48E-11 (S) |
| cec03 | 7.04E-07 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 8.84E-07 (S) |
| cec04 | 8.65E-01 (NS) | 3.02E-11 (S) | 3.34E-11 (S) | 3.02E-11 (S) | 2.01E-01 (NS) |
| cec05 | 6.12E-10 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 4.98E-11 (S) |
| cec06 | 1.34E-05 (S) | 3.02E-11 (S) | 3.34E-11 (S) | 3.02E-11 (S) | 2.43E-05 (S) |
| cec07 | 8.30E-01 (NS) | 3.02E-11 (S) | 1.70E-09 (S) | 3.02E-11 (S) | 3.27E-02 (S) |
| cec08 | 1.16E-07 (S) | 3.02E-11 (S) | 1.61E-10 (S) | 3.02E-11 (S) | 2.43E-05 (S) |
| cec09 | 4.71E-04 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 1.17E-03 (S) |
| cec10 | 9.93E-02 (NS) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 2.71E-02 (S) |

S = Significant; NS = Not Significant ($\alpha = 0.05$)

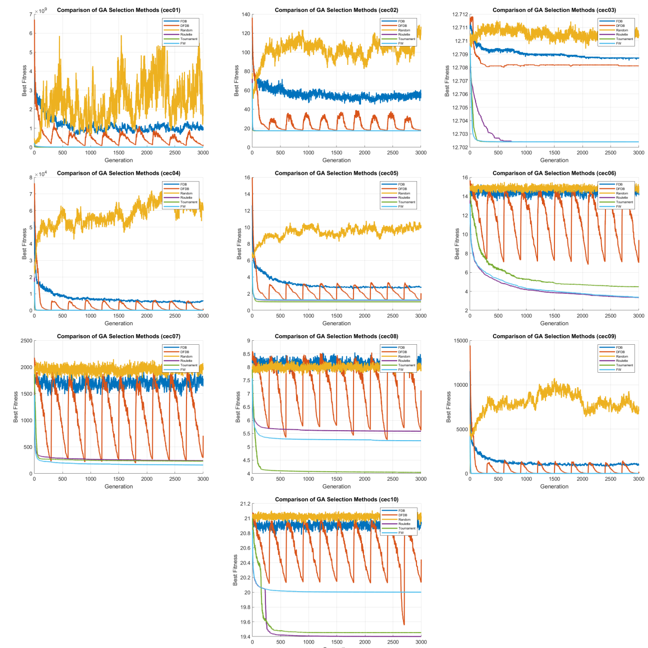

Fig. 1. Convergence curves of selection methods in the optimization of the CEC2019 suite.

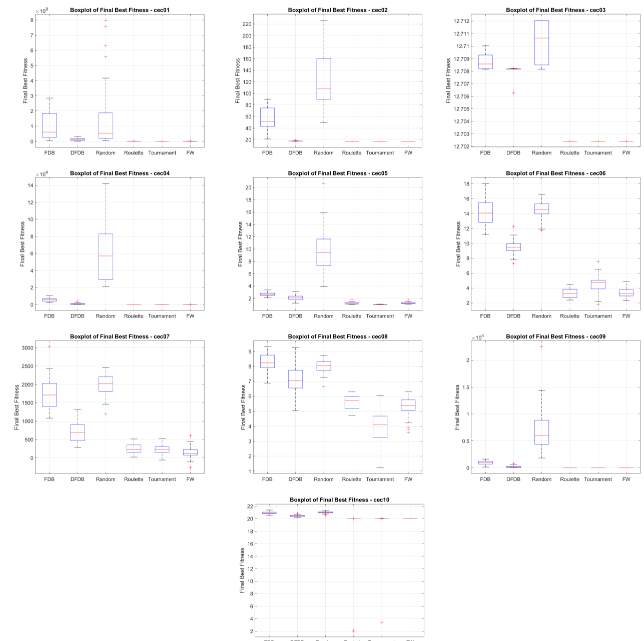

Fig. 2. Boxplot obtained from selection methods on CEC2019 suite.

VIII summarizes the best, mean, and standard deviation of the final fitness values for each function over 30 independent runs.

Across the majority of functions, the TS technique achieved the most consistent performance. This was particularly evident in unimodal functions such as F1 (Sphere) and F6 (Step), where TS achieved optimal solutions in all runs with negligible variance. Notably, FW closely followed TS in most cases, often achieving statistically indistinguishable performance as confirmed by Wilcoxon tests ($p > 0.05$ in many functions such as F8 and F10).

RWS, while simpler and non-adaptive, exhibited mixed performances. It outperformed both adaptive methods (FDB and dFDB) on a significant subset of functions, particularly on F1–F7. The static FDB method consistently yielded the weakest results across both unimodal and multimodal functions, indicating convergence stagnation and poor exploitation. The dynamic variant, dFDB, demonstrated improvements over its static counterpart in some multi-modal problems (e.g., F13, F20), but remained inferior to TS, FW, and RWS in the majority of scenarios.

Statistical analysis (Table VIII) supports these findings. TS significantly outperformed all other methods ($p < 0.05$) on the vast majority of functions. FW was the only method that frequently achieved statistically similar results to TS. Visual inspection of convergence curves (Fig. 3) and boxplots (Fig. 4) corroborates the numerical results.

### C. Statistical Summary and General Observations

A cross-suite statistical perspective reveals the following insights:

TABLE VI. RESULTS ON F1–F12 (BEST, MEAN, MEDIAN, STD)

| Fun | Measure | FDB | dFDB | Random | RWS | TS | FW |
|---|---|---|---|---|---|---|---|
| F1 | Best | 3.86E+03 | 3.65E+02 | 2.98E+04 | 1.22E+00 | **3.56E-04** | 1.36E+00 |
| | Mean | 7.37E+03 | 1.25E+03 | 5.27E+04 | 2.56E+00 | **5.27E-03** | 2.73E+00 |
| | Median | 6.82E+03 | 1.23E+03 | 5.03E+04 | 2.65E+00 | **5.08E-03** | 2.73E+00 |
| | Std | 1.99E+03 | 6.12E+02 | 9.83E+03 | 6.84E-01 | **3.56E-03** | 7.11E-01 |
| F2 | Best | 4.19E+03 | 4.43E+00 | 4.25E+03 | 4.12E-01 | **2.23E-03** | 5.01E-01 |
| | Mean | 2.34E+16 | 9.53E+00 | 5.17E+12 | 5.86E-01 | **1.30E-02** | 6.29E-01 |
| | Median | 5.35E+10 | 9.37E+00 | 1.06E+09 | 5.84E-01 | **1.31E-02** | 6.20E-01 |
| | Std | 1.21E+17 | 2.04E+00 | 2.03E+13 | 8.16E-02 | **7.62E-03** | 7.47E-02 |

TABLE VII. RESULTS ON F13–F23 (BEST, MEAN, MEDIAN, STD)

| Fun | Measure | FDB | dFDB | Random | RWS | TS | FW |
|---|---|---|---|---|---|---|---|
| F13 | Best | 4.84E+07 | 3.90E+04 | 1.26E+08 | 4.37E-02 | **5.91E-06** | 6.22E-02 |
| | Mean | 1.53E+08 | 1.81E+06 | 6.24E+08 | 9.02E-02 | **3.83E-03** | 1.15E-01 |
| | Median | 1.36E+08 | 7.68E+05 | 6.26E+08 | 8.71E-02 | **2.63E-04** | 1.17E-01 |
| | Std | 6.69E+07 | 2.83E+06 | 2.18E+08 | 3.10E-02 | **5.26E-03** | 2.94E-02 |

TABLE VIII. WILCOXON RANK-SUM TEST ($p$-VALUES) FOR F1–F23 VS. TOURNAMENT

| Fun | TS vs RWS | TS vs FDB | TS vs dFDB | TS vs Rand. | TS vs FW |
|---|---|---|---|---|---|
| F1 | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F2 | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F3 | 6.70E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 9.92E-11 (S) |
| F4 | 4.08E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F5 | 3.56E-04 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 7.66E-05 (S) |
| F6 | 2.70E-03 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 5.20E-10 (S) |
| F7 | 4.71E-04 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 2.62E-03 (S) |
| F8 | 4.73E-01 (NS) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 7.51E-01 (NS) |
| F9 | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F10 | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F11 | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F12 | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F13 | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) |
| F14 | 1.90E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 1.90E-11 (S) |
| F15 | 3.18E-04 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 4.94E-05 (S) |
| F16 | 7.88E-12 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 7.88E-12 (S) |
| F17 | 2.26E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 2.50E-11 (S) |
| F18 | 2.99E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 2.99E-11 (S) |
| F19 | 2.57E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 2.57E-11 (S) |
| F20 | 6.05E-07 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.52E-07 (S) |
| F21 | 5.96E-05 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 6.75E-05 (S) |
| F22 | 4.21E-04 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 7.68E-04 (S) |
| F23 | 8.18E-07 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 3.02E-11 (S) | 9.03E-08 (S) |

S = Significant; NS = Not Significant ($\alpha = 0.05$)

- TS consistently achieved top results across both benchmarks, confirming its robustness and effectiveness in both simple and complex landscapes.
- FW, although relatively simple, showed strong performance. It was statistically equivalent to TS in many cases and could serve as a viable alternative, particularly in problems where slightly more exploration is desirable.
- RWS performed better than expected. It surpassed both adaptive methods in many tests and was statistically competitive with TS on select functions.
- dFDB improved upon the static variant but remained inconsistent. It showed promise in maintaining diversity but lacked the convergence efficiency of TS and FW.
- Static FDB and Random Selection were the least effective. They struggled with both exploitation and stability, particularly in high-dimensional and multimodal functions.

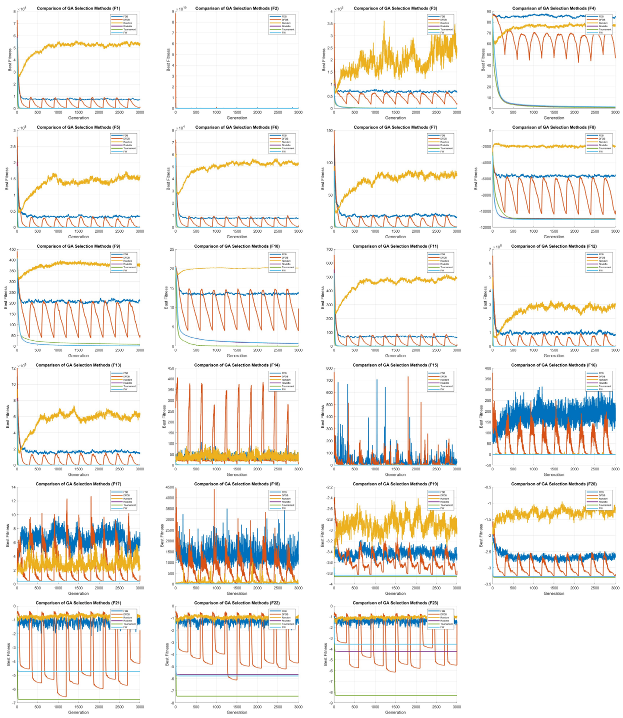

Fig. 3. Convergence curves of selection methods in the optimization of functions F1 to F23.

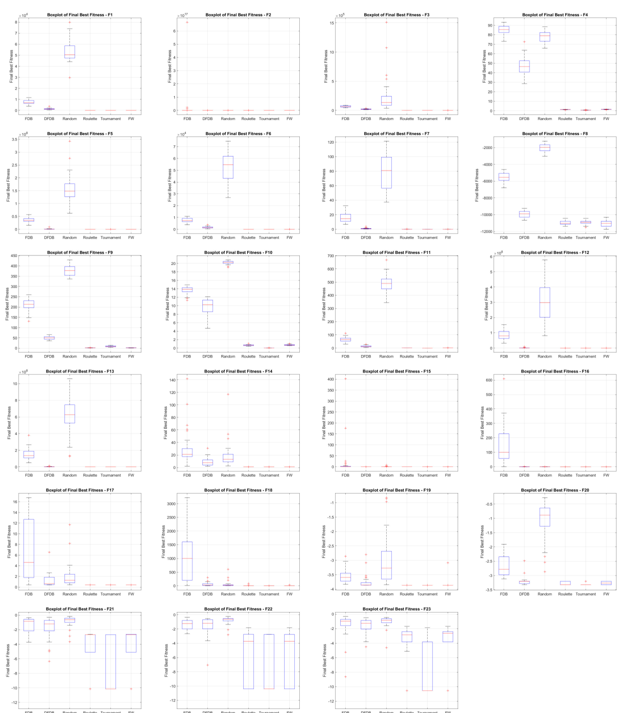

Fig. 4. Boxplot diagram obtained from selection methods on functions F1 to F23.

## V. Discussion

### A. Robustness and Efficiency of Tournament Selection

The TS consistently emerged as the most effective method across both benchmark suites. These results can be attributed to TS's balanced exploitation-exploration tradeoff, particularly with the moderate tournament size ($k = 3$) used in this study. The deterministic pressure of TS ensures that fitter individuals are consistently favored, facilitating rapid convergence in unimodal and smooth landscapes (e.g., F1, F6, cec02), while still preserving diversity enough to maintain effectiveness in multimodal problems.

### B. Competitiveness of Functional Weight-Based Selection

FW Selection demonstrated competitive performance—often statistically indistinguishable from TS on both classical and CEC functions. The method introduces probabilistic selection that is biased by fitness scores but retains stochasticity to avoid premature convergence. This allows FW to maintain a broader exploration radius compared to TS, which can be advantageous in deceptive or rugged landscapes.

### C. Re-Evaluating Roulette Wheel Selection

RWS, despite its simplicity and non-adaptive nature, demonstrated surprisingly strong performance on several classical functions, particularly unimodal and moderately multimodal ones (e.g., F1–F5, F10). This challenges the common assumption that adaptive strategies always outperform classical ones. However, RWS also exhibited more variability on highly multimodal or deceptive landscapes.

### D. Random Selection as a Baseline

As expected, Random Selection performed poorly across all benchmarks, reinforcing the necessity of selection pressure in evolutionary search [21], [22], [23], [24], [25], [26], [27], [28], [29], [30]. Interestingly, Random outperformed static FDB in a few instances (e.g., F18, F19), highlighting that without appropriate tuning, even diversity-focused selection may lead to inefficient search.

### E. Limitations of FDB and dFDB

The FDB selection techniques, particularly the static variant, were consistently outperformed by other methods [31], [32], [33], [34], [35], [36], [37], [38], [39]. The static FDB struggled to converge effectively, often yielding large standard deviations and poor mean fitness values. This was evident in functions such as F2, F5, F12, and cec01. The likely cause is the fixed weighting between fitness and diversity: while diversity helps in early search stages, excessive emphasis on it can hinder convergence in later stages. The dFDB showed partial improvement but still lagged behind in most scenarios.

### F. Implications for Algorithm Design

The comparative results suggest that classical methods such as TS and RWS, despite their simplicity, remain highly effective across diverse problem domains [40], [41], [42]. The findings also imply that hybrid strategies, such as switching from exploration-heavy to exploitation-heavy selection over time, may outperform static or single-strategy methods.

## VI. Conclusion

This study has presented a rigorous comparative evaluation of six selection strategies in GAs, encompassing classical strategies (TS and RWS), adaptive mechanisms (FW, FDB, and dFDB), and a baseline random strategy. Across 33 benchmark functions—including the classical F1–F23 suite and the CEC2019 set—the TS method demonstrated superior robustness, achieving the best or statistically comparable results in the majority of cases. FW method emerged as a strong alternative, often yielding statistically indistinguishable performance with the added benefit of enhanced exploration through adaptive weight control.

Interestingly, RWS, despite its non-adaptive nature, outperformed the adaptive FDB and dFDB methods on a substantial number of functions, highlighting its retained competitiveness in structured problem landscapes. In contrast, the FDB-based strategies underperformed in both convergence and consistency, suggesting the need for better tuning or hybridization. Random Selection illustrated the essential role of selection pressure in evolutionary search.

### A. Limitations of the Study

Despite its comprehensive scope, all evaluations were conducted under fixed population sizes and generations, which may constrain generalizability. Furthermore, the benchmark functions used do not fully reflect the stochasticity and complexity of real-world applications. The implementations of FDB and dFDB used fixed parameter schedules, which might not be optimal across all problem types.

### B. Future Work

The findings suggest several promising directions: development of hybrid selection strategies combining the strengths of TS with diversity mechanisms; integration of adaptive scheduling or self-regulating parameters; and exploring the interplay between selection methods and other GA components such as crossover operators and mutation schemes.

## Data Availability

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

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