EXERCISE 3 ANALYSIS

In this exercise, a Genetic Algorithm (GA) was implemented using uniform crossover, bit-flip mutation, and a parent population of at least ten individuals. The GA was tested on the same Pseudo-Boolean benchmark problems (F1, F2, F3, F18, F23, F24, F25) under the same evaluation budget as Exercise 2, allowing direct comparison with the baseline algorithms: Random Search, Randomised Local Search (RLS), and the (1+1) Evolutionary Algorithm (EA).

Performance was evaluated using expected target value plots for each benchmark, enabling side-by-side analysis. The aim is to assess the GA's relative strengths, highlight cases where population-based search provides a clear advantage, and identify problems where simpler evolutionary methods remain equally or more effective.

F1: OneMax

OneMax is a smooth, non-deceptive problem where progress is made by flipping bits from 0 to 1 until reaching the optimum of 100. Random Search shows minimal improvement and plateaus well below the target due to its lack of refinement. Both RLS and the (1+1) EA steadily converge to the optimum, with RLS slightly faster thanks to consistent single-bit flips.

The Genetic Algorithm also reaches the optimum reliably but converges later than RLS and the (1+1) EA. On such a simple unimodal landscape, its population and crossover provide no clear advantage, though it remains stable and competitive with low variance.

Overall, mutation-based methods are most efficient for F1, but the GA performs comparably without offering additional benefits.

F2: LeadingOnes

The LeadingOnes problem evaluates solutions by counting the number of consecutive 1-bits from the start of the string, which means progress can only be made by flipping the leftmost incorrect bit. This makes the search inherently sequential and vulnerable to disruption if earlier correct bits are altered.

As in Exercise 2, Random Search performs very poorly, as the chance of sampling long prefixes of 1s is extremely low. RLS and the (1+1) EA again demonstrate strong performance, though their progress is stepwise and sometimes jagged due to the sequential dependency of the problem. RLS generally converges faster, benefiting from its strict single-bit mutation, while the (1+1) EA is occasionally slowed by multi-bit flips that undo progress.

The Genetic Algorithm also reaches the optimum but lags behind both RLS and the (1+1) EA. Its population and crossover introduce additional exploration, which is not especially helpful in a problem that rewards strict sequential improvements. Consequently, GA converges more slowly and with higher variance than the simpler algorithms.

Overall, the results confirm that for LeadingOnes, local search methods such as RLS and (1+1) EA are better suited due to their ability to exploit the structure of the problem directly. The GA remains competitive but does not provide an advantage on this sequential landscape.

F3: A Linear Function with Harmonic Weights

The F3 problem evaluates solutions by computing a weighted sum of variables, where each bit contributes additively with harmonic weights. This structure creates a smooth landscape where improvements are relatively straightforward once high-weight bits are identified and preserved.
As seen in Exercise 2, Random Search performs poorly. Although it achieves some early improvements through chance, it lacks refinement and finishes well below the global optimum, with final best-so-far values in the range of 3500–4000. This highlights the weakness of purely stochastic sampling when systematic progress is required.

Both RLS and the (1+1) EA perform strongly, consistently reaching the global optimum of ~5000. RLS tends to converge faster due to its deterministic single-bit mutations, while the (1+1) EA occasionally requires more evaluations because multi-bit flips can disrupt progress. By the end, both methods plateau reliably at the optimum with very low variance.

The Genetic Algorithm also demonstrates strong performance on F3. It steadily improves and reliably converges to the optimum, though it generally reaches it slightly later than RLS. The GA's use of crossover and a population provides no clear advantage in this linear problem, since systematic single-bit improvements already lead directly to the optimum. Nevertheless, the GA remains competitive, matching the performance of (1+1) EA and showing stable convergence across runs.

Overall, F3 confirms that for linear additive landscapes, simple local search algorithms like RLS and (1+1) EA are most efficient, while the GA achieves comparable results but without a significant benefit over these hill-climbing approaches.

F18: Low Autocorrelation Binary Sequences (LABS)

The LABS problem is a multimodal benchmark that presents a rugged and deceptive search landscape, making it far more challenging than the linear or unimodal problems seen earlier.

Progress requires coordinated multi-bit changes to reduce autocorrelation, which can easily trap algorithms in local optima.

As observed in Exercise 2, Random Search shows initial gains as early samples occasionally identify reasonable solutions, but progress quickly plateaus. By the end of the budget, RS achieves a best-so-far value of around 2.3, significantly weaker than the other algorithms. RLS demonstrates stronger early improvements by systematically applying single-bit flips, but it also stalls when further progress requires larger jumps, plateauing at roughly 3.7. The (1+1) EA performs best among the baseline methods, as its probabilistic mutation allows occasional multi-bit flips. This enables it to escape shallow local optima and continue incremental progress, reaching around 4.0 on average by the end of the run.

The Genetic Algorithm provides a competitive alternative on this rugged landscape. With its population-based search and crossover, the GA maintains diversity and is able to explore multiple regions of the search space simultaneously. This allows it to avoid premature stagnation and achieve results close to, and in some runs surpassing, the (1+1) EA. Although its convergence is slower initially, the GA continues improving steadily across the evaluation budget and reaches best-so-far values comparable to or slightly higher than the (1+1) EA in later stages. Variance across GA runs is somewhat higher, reflecting the stochastic impact of crossover, but its long-term trend confirms the benefits of population diversity in complex landscapes.

Overall, F18 highlights the strengths of algorithms capable of broader exploration. While RLS and Random Search stagnate due to limited search operators, the (1+1) EA and GA both exploit the opportunity for multi-bit improvements. The GA demonstrates that population-based methods can handle multimodality effectively, providing resilience against local optima and competitive performance on this challenging benchmark.

F23: N-Queens Problem

The N-Queens problem is a combinatorial optimisation benchmark with a rugged search space and many local optima, making incremental progress difficult.Random Search makes rapid early improvements by chance placements but quickly stagnates, finishing far from the optimum (around –650).
RLS improves efficiently at first by adjusting single queens but stalls at values of 7–8 since escaping local optima requires multi-bit moves. The (1+1) EA performs similarly early on but outperforms RLS later thanks to its occasional multi-bit flips, enabling it to reach near-optimal values of 9 with low variance, though the true optimum of 10 remains rare.

The Genetic Algorithm shows competitive results in Exercise 3. While slower to improve initially, its population and crossover mechanisms provide broader exploration, preventing premature stagnation. Over time, the GA approaches or matches the (1+1) EA's performance, with greater variance reflecting the stochastic nature of recombination.

Overall, the results confirm that RS and RLS are ineffective at finding optimal solutions, while the (1+1) EA and GA are much better suited. The EA is more consistent, but the GA demonstrates the advantage of population-based search in escaping complex local optima.

F24: Concatenated Trap

The Concatenated Trap problem is a deceptive landscape where local optima mislead search away from the global solution.

Random Search improves quickly in the earliest evaluations, as chance sampling hits partial solutions, but it stagnates around a best-so-far value of ~12, far below the optimum of 20. RLS and the (1+1) EA both exploit single-bit flips effectively within trap sub-blocks, accelerating after the first few evaluations. However, both plateau below the optimum, with the (1+1) EA achieving only a slight edge (~16.1 vs ~16.0) due to rare multi-bit flips that help escape shallow traps.

In Exercise 3, the Genetic Algorithm performs comparably to the (1+1) EA, steadily climbing and converging close to the same plateau. Its crossover and population diversity help sustain exploration, but these mechanisms do not overcome the fundamental difficulty of the trap structure, where coordinated multi-bit changes are needed. The GA shows slightly wider variance across runs, reflecting stochastic recombination, but remains competitive with the mutation-based methods.

Overall, F24 confirms that while RLS and (1+1) EA dominate RS, all three mutation-based algorithms plateau below the global optimum. The GA offers an alternative pathway with broader exploration, but like the (1+1) EA, it remains limited by the deceptive nature of the trap landscape.

F25: NK Landscapes (NKL)

NK Landscapes represent rugged, epistatic fitness surfaces with many local optima, making them strongly deceptive benchmarks.

From Exercise 2, Random Search improves quickly in the earliest evaluations, but its progress soon slows, finishing around –0.40. RLS performs worst: after brief early gains, it plateaus near –0.38, unable to escape poor local optima. The (1+1) EA performs best, climbing steadily beyond 500 evaluations and finishing around –0.31, as its occasional multi-bit flips allow it to move between basins.

With the addition of the Genetic Algorithm in Exercise 3, performance improves further. The GA starts slightly slower than RLS and the (1+1) EA, but its population diversity and crossover provide broader exploration. Over time, this allows it to escape more local traps, converging to values similar to or slightly above the (1+1) EA. The GA exhibits higher variance across runs due to stochastic recombination, but its steady upward trend demonstrates resilience in the rugged NK landscape.

Overall, F25 highlights the limitations of RS and RLS, the relative strength of the (1+1) EA, and the additional benefits of a GA. While none of the algorithms approach the global optimum within the budget, the GA shows the most consistent long-term progress by leveraging population-based search to cope with the problem's high deceptiveness.

Conclusion

These results highlight that while local search excels on structured, unimodal problems, the Genetic Algorithm demonstrates broader adaptability across diverse landscapes, reflecting the trade-off between exploration and exploitation in evolutionary computation. Random Search consistently stagnated, while RLS exploited single-bit flips effectively on smooth problems but failed on deceptive ones.

The (1+1) EA was more robust, with occasional multi-bit flips enabling it to outperform RLS, though it still plateaued on rugged functions such as NKL and Concatenated Trap. In contrast, the GA proved most versatile: on simple landscapes it matched local search methods, but on complex, multimodal problems such as LABS and N-Queens, its population diversity and crossover helped it avoid stagnation and sustain progress.

Overall, the GA showed the strongest long-term potential, confirming the advantage of population-based search in escaping local optima and tackling deceptive problem spaces.