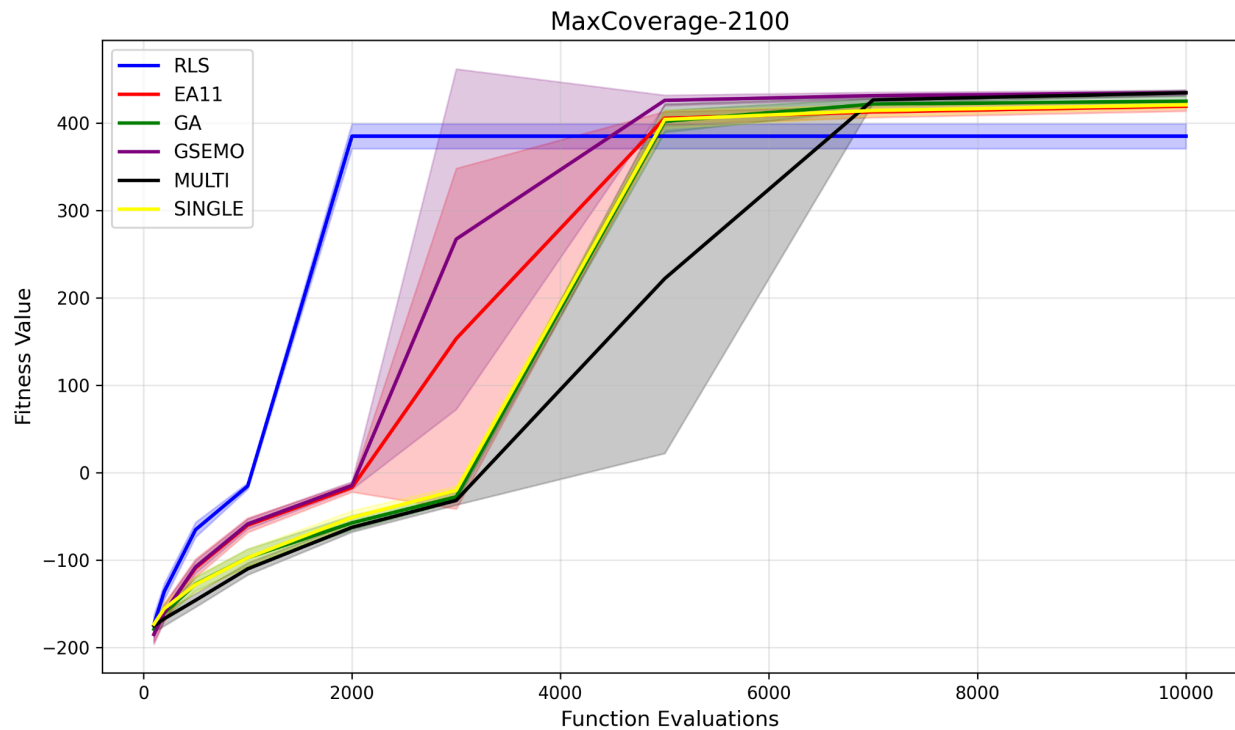# Exercise 3 Analysis

MaxCoverage:

Figure 1. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2100

Figure 1 presents the mean and standard deviation of fitness values for RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions over 10,000 function evaluations on the MaxCoverage-2100 instance. RLS again demonstrates the greatest initial fitness improvement, reaching near-optimal performance within the first 2,000 fitness evaluations. However, this initial convergence stagnates throughout the rest of the graph and ultimately performs comparatively worse than the other algorithms. On the contrary, the (1 + 1) EA improves more gradually outperforms that of RLS, achieving higher fitness values at around 4,500 fitness evaluations. The GA exhibits a slower start, showing higher variance early on, but gradually converges to comparable performance, benefiting from population diversity and recombination. Despite this, GSEMO achieves the greatest final mean fitness with reduced variance, indicating strong convergence and effective balancing of exploration and exploitation.

When comparing the single-objective and multi-objective functions, an extremely clear disparity in quality can be identified. Initially both functions perform identically with minimal

variance from the mean, until after approximately 3,000 fitness evaluations at which point the single-objective function significantly outperforms that of the multi-objective function. This difference in quality can largely be attributed to the fact that the provided single-fitness graph does not effectively capture the trade-offs considered within the multi-objective formulation, with the Pareto-front being invisible within a single-fitness projection. While the single-objective function attempts to optimise one scalar fitness value, the multi-objective function attempts to generate a diverse Pareto-front that balances competing objectives, in this case cost against fitness. Through this, its apparent underperformance in the graph reflects its more complex objective rather than genuine inefficiency.
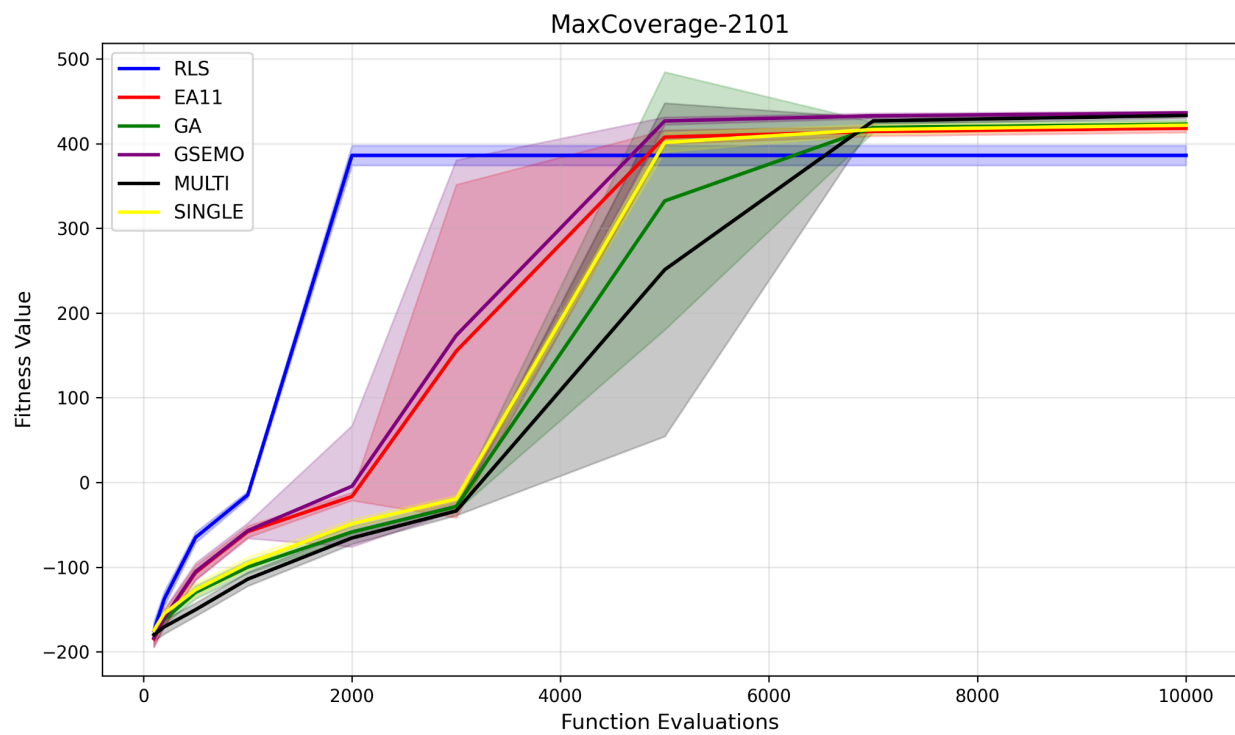

Figure 2. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2101
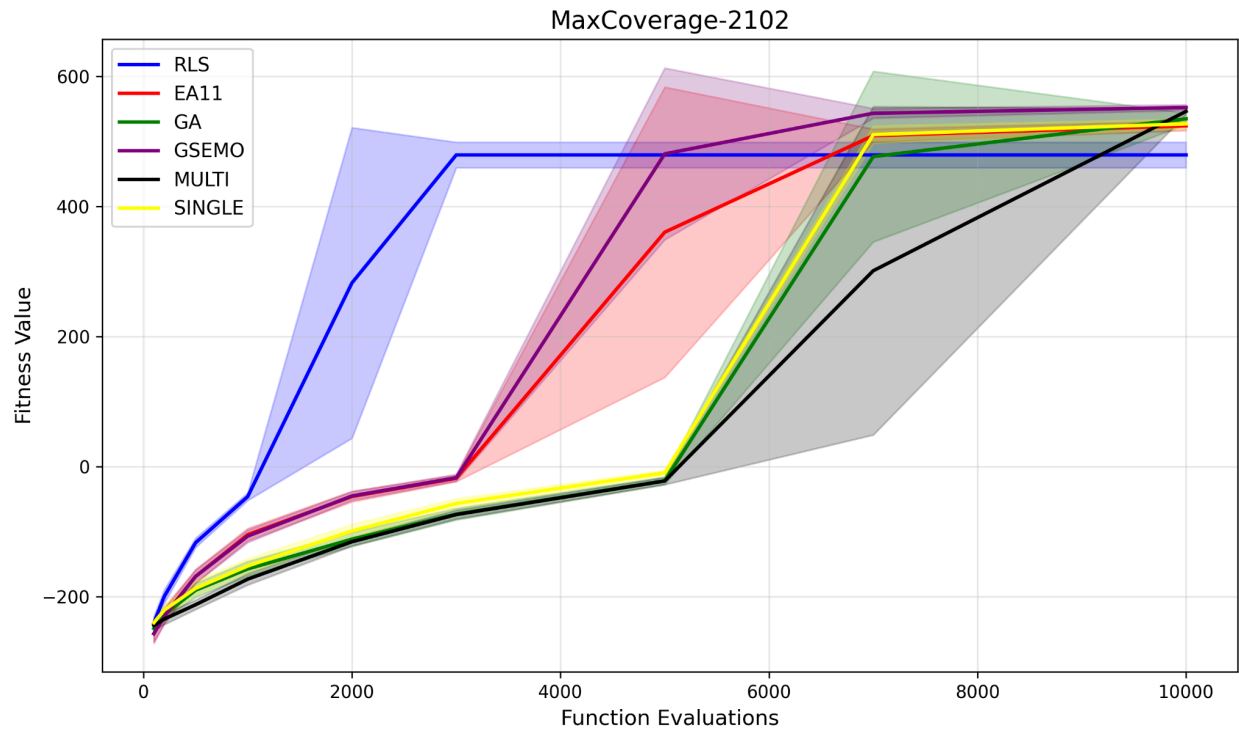
Figure 3. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2102
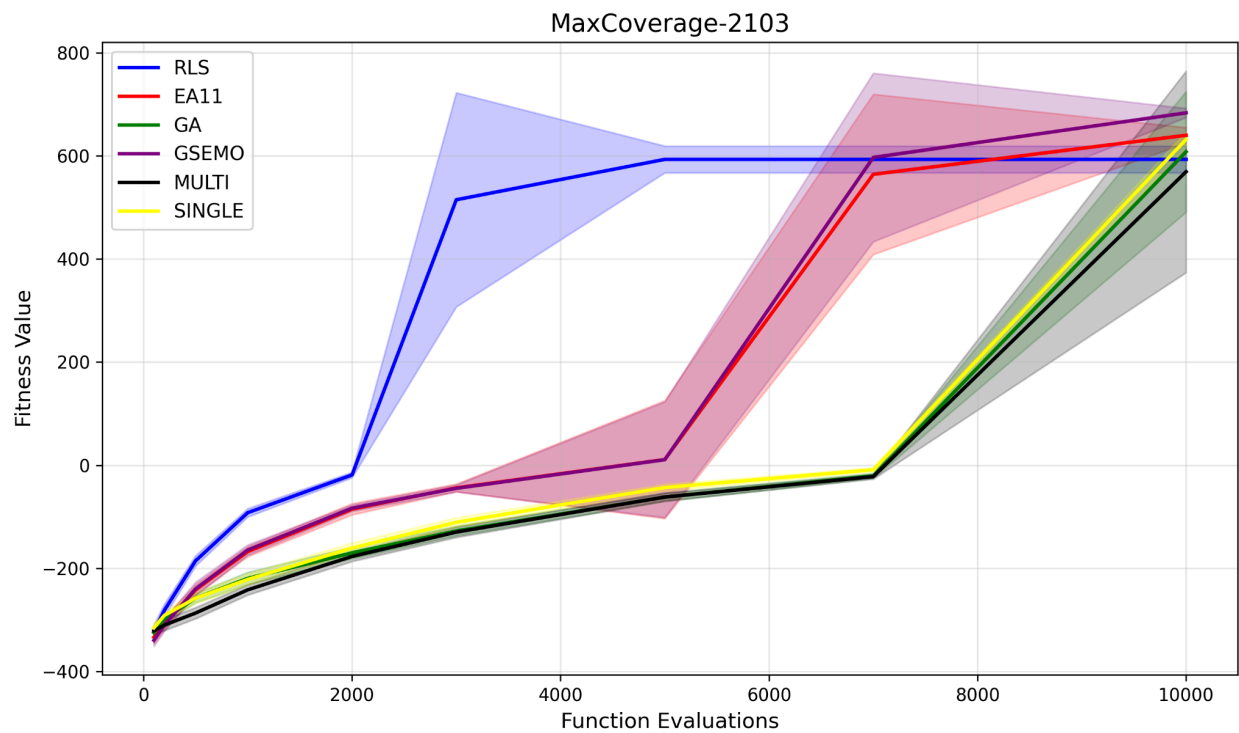

Figure 4. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2103

Figures 2, 3, and 4 all support the claims from figure one leading to the conclusion that while single-objective methods like RLS, (1+1) EA, and the single objective GA, can efficiently find reasonable solutions, the population-based and multi-objective nature of GSEMO enables more robust convergence towards superior solutions. Through this observation of clear dominance in relation to GSEMO against the single-objective formulation and multi-objective formulation, it can be identified that the two very clearly struggled to maintain a meaningfully diverse population. Looking deeper, it can be understood that the GSEMO collected a set of non-dominated solutions throughout every generation, whereas the other functions did not and only cleansed the population of dominated solutions at the end of the program's execution. Overall, GSEMO provides the best tradeoff performance, validating the advantage of multi-objective evolutionary optimization in submodular problems such as MaxCoverage.
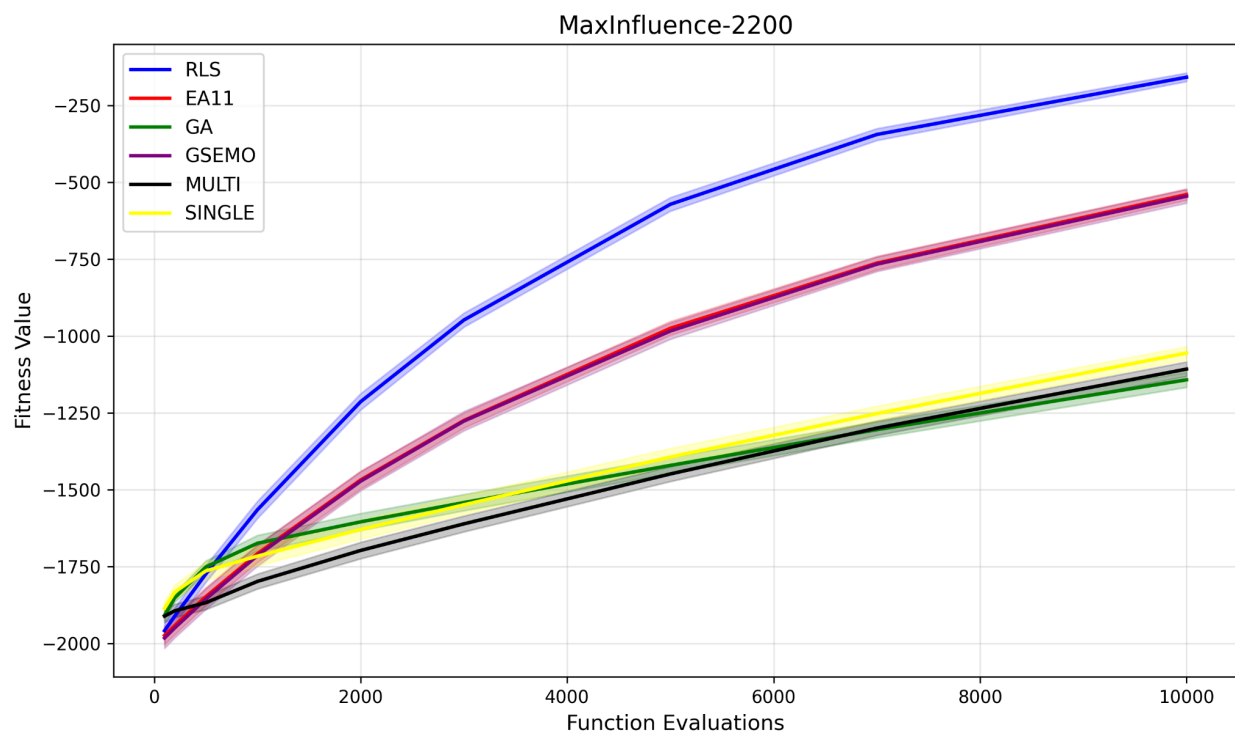
MaxInfluence:

Figure 5. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2200

Figure 5 shows the mean and standard deviation of fitness values achieved by RLS, (1+1) EA, GA, and GSEMO on the MaxInfluence-2200 instance over 10,000 function evaluations. In this case, all algorithms start from a low initial fitness value near -2000 and show gradual improvement over time. RLS and the exhibits the steepest increase, consistently achieving the

best performance across the evaluation budget, with low variance indicating stable convergence. The (1+1) EA and GSEMO follow almost identical trajectories, suggesting that in this instance, the multi-objective formulation of GSEMO provides little to no advantage over the single-objective (1+1) EA. Both algorithms improve steadily but remain consistently below RLS. In contrast, the GA performs considerably worse, showing slow progress and stabilizing at much lower fitness values around -1400, indicating poor adaptation or ineffective population dynamics for this problem type.

Within *Figure 5*, both the multi-objective formulation and single-objective formulation perform suboptimally when compared to RLS, (1+1) EA, and GSEMO. It is worth noting, however, that these two algorithms perform identically to the GA, indicating similarly poor stablisation and convergence.
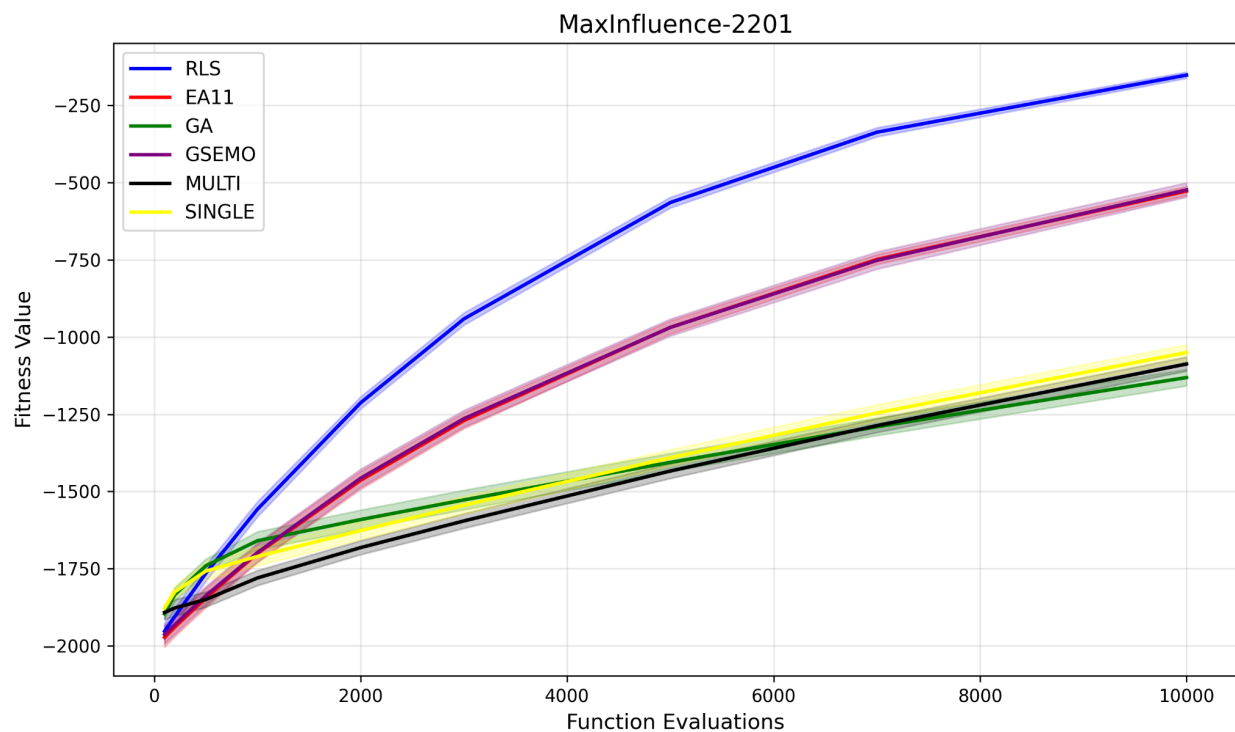

Figure 6. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2201
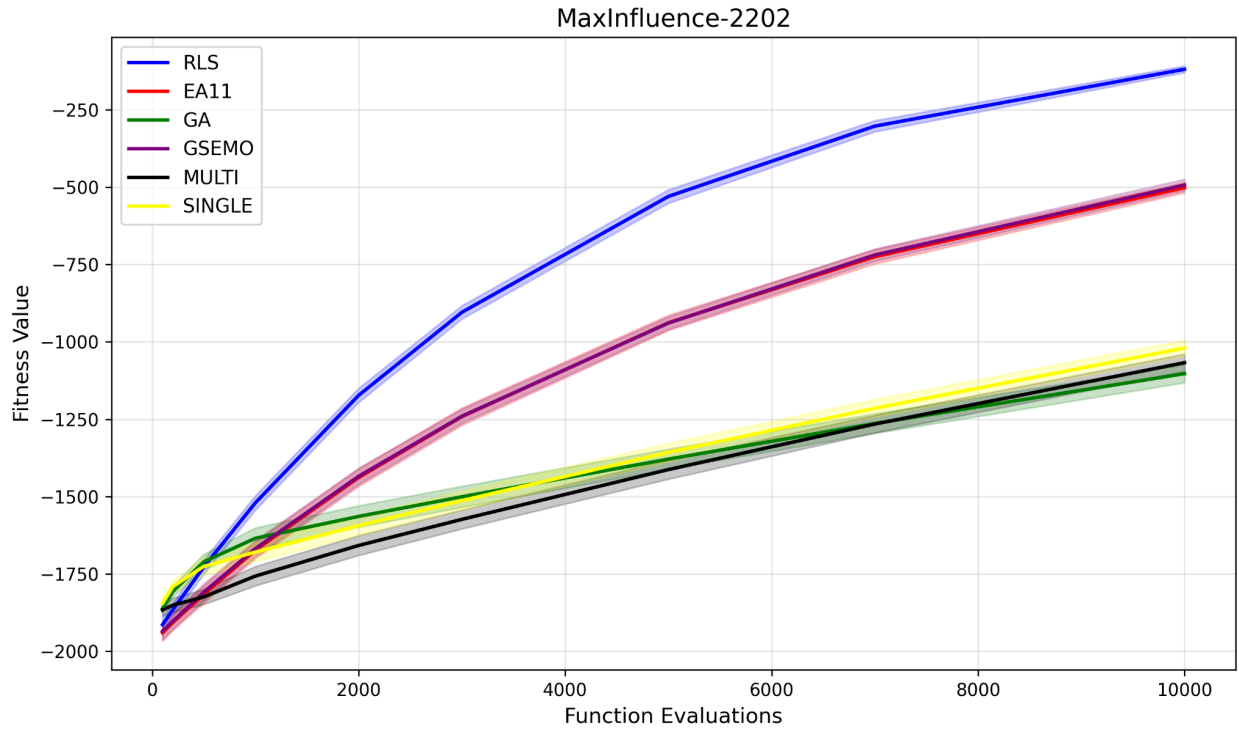
Figure 7. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2202
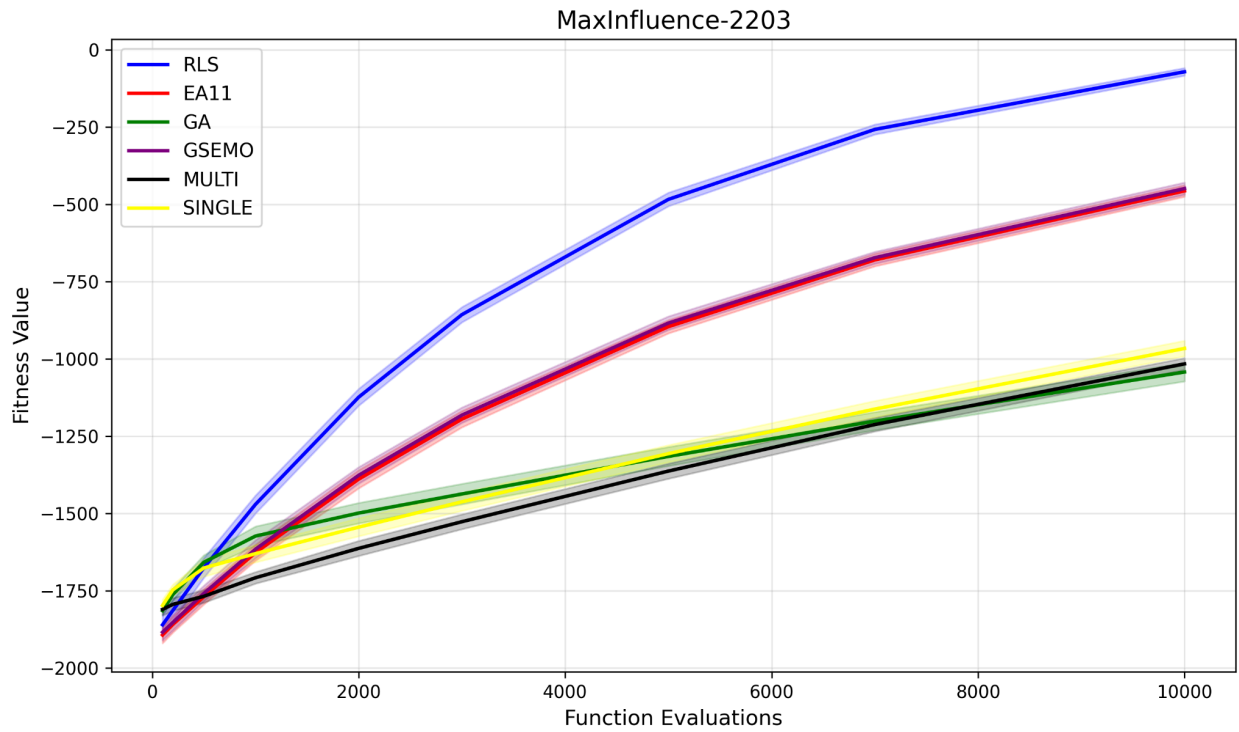

Figure 8. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2203

Overall, RLS clearly outperforms the other algorithms on MaxInfluence-2200, while the similarity between (1+1) EA and GSEMO suggests that the added complexity of multi-objective optimization does not yield benefits for this instance, likely due to a weaker trade-off structure between the objectives.

In addition, the small bit flips present in mutation-based operations for evolutionary algorithms are likely to experience deception within these problem environments. As these evolutionary algorithms produce solutions with minimal incremental modifications, progress towards a more efficient solution stagnates heavily.
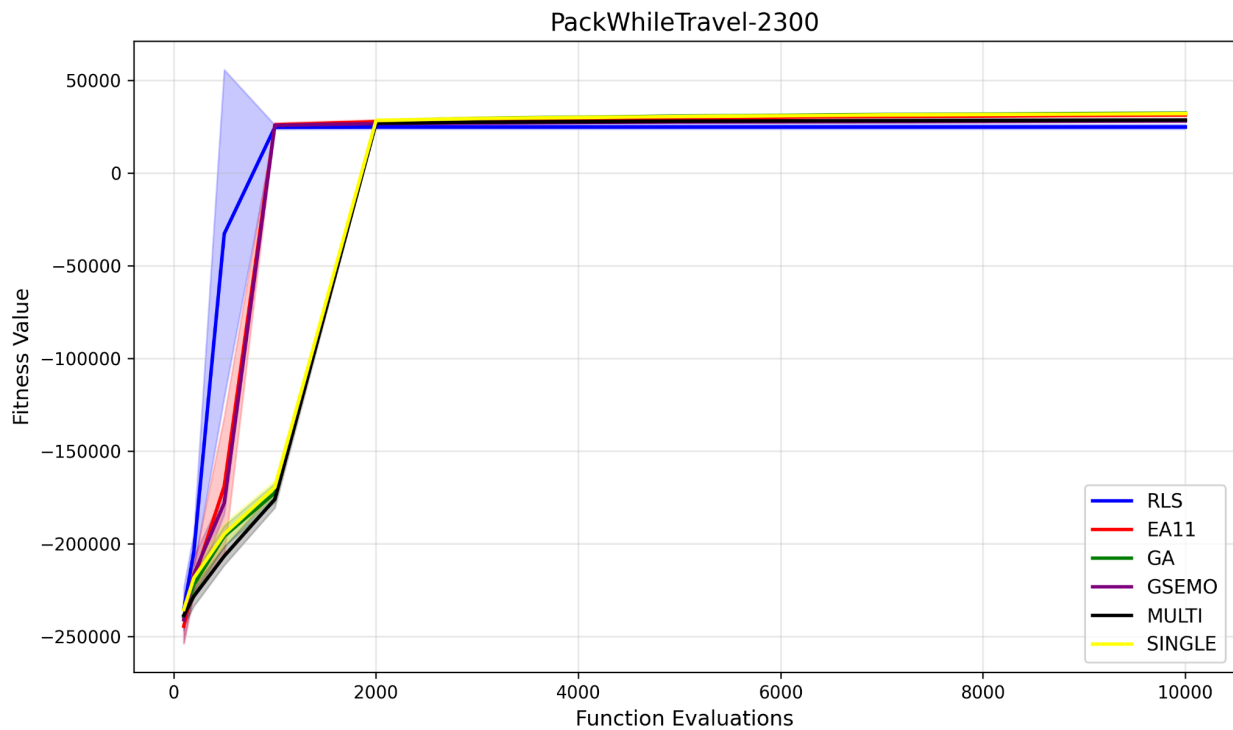

PackWhileTravel:

Figure 9. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2300

Figure 9 presents the mean and standard deviation of fitness values achieved by RLS, (1+1) EA, GA, and GSEMO on the PackWhileTravel-2300 instance over 10,000 function evaluations. All algorithms begin with very low fitness values around -250,000 and show rapid improvement in the early stages. RLS and (1+1) EA achieve the fastest convergence, reaching near-optimal fitness within the first 1,000 evaluations and maintaining stable performance afterward. RLS

exhibits slightly higher variance early on but quickly stabilizes. GA lags behind during the initial phase, showing slower progress and requiring significantly more evaluations to reach comparable performance, though it eventually converges near the same fitness level. The same occurs with the single-objective function and multi-objective function, taking significantly longer to produce any meaningful quality solutions. GSEMO performs almost identically to (1+1) EA across all evaluations, indicating that its multi-objective formulation offers no measurable improvement for this instance.
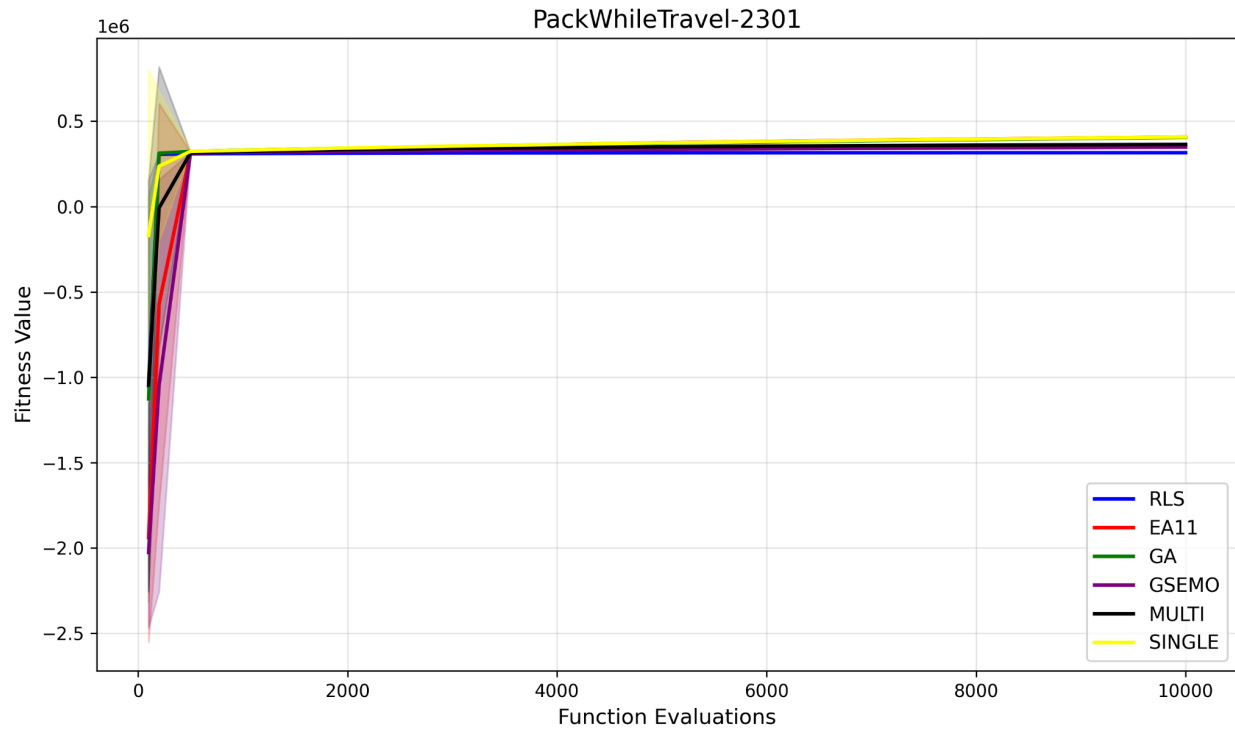

Figure 10. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2301
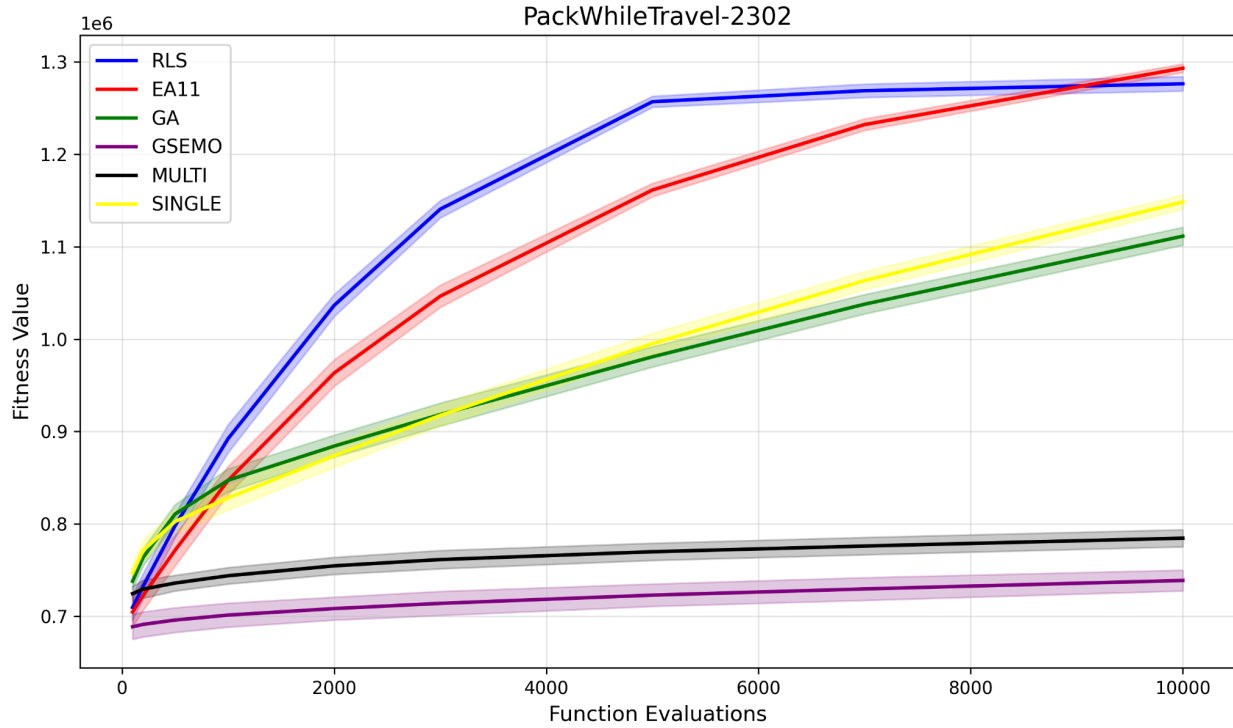
Figure 11. Performance comparison of RLS, EA (1+1), Genetic Algorithm, GSEMO, Single-Objective function and Multi-Objective functions on MaxCoverage-2302

Figure 11 presents the mean and standard deviation of fitness values achieved by RLS, (1+1) EA, GA, and GSEMO on the PackWhileTravel-2302 instance over 10,000 function evaluations.
In this instance, there are clear differences in performance. RLS and (1+1) EA both exhibit strong and steady improvement, with RLS initially leading but (1+1) EA slightly surpassing it by the end of the run, indicating robust convergence. GA shows slower but continuous progress, achieving moderately high fitness values but remaining below the top performers. In contrast, the GSEMO and multi-objective formulation performs substantially worse, displaying minimal improvement throughout and plateauing at much lower fitness values. This suggests that for the PackWhileTravel-2302 instance, simpler single-objective evolutionary methods are far more effective, and the multi-objective formulation used by GSEMO fails to capture meaningful trade-offs or guide the search efficiently. This notion can be supported through the significant difference in performance observed through the inclusion of the single-objective function, with this function performing identically to the GA.