Exercise 2 Analysis

MaxCoverage:

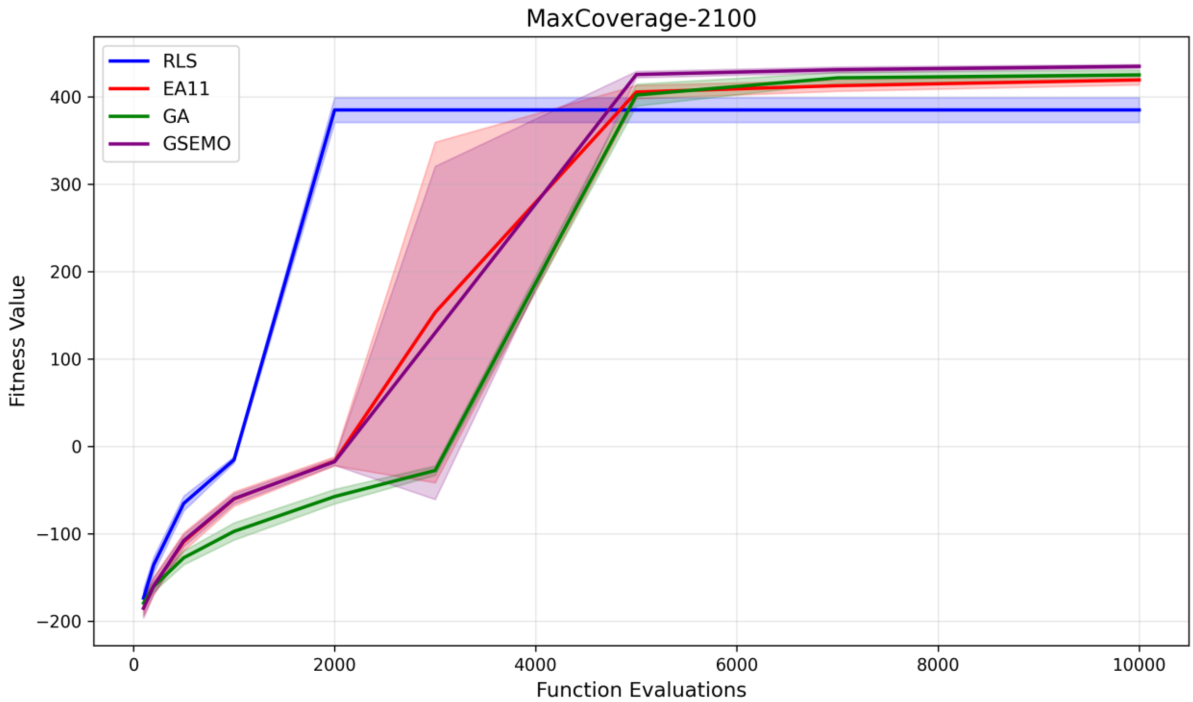

Figure 1: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxCoverage-2100

Figure 1 presents the mean and standard deviation of fitness values for RLS, (1+1) EA, GA, and GSEMO over 10,000 function evaluations on the MaxCoverage-2100 instance. RLS demonstrates the fastest initial improvement, reaching near-optimal performance within the first 2,000 evaluations; however, it quickly stagnates and fails to achieve further progress, indicating premature convergence due to its limited exploration ability. In contrast, the (1+1) EA improves more steadily and ultimately surpasses RLS, achieving higher fitness values around 420. The GA exhibits a slower start, showing higher variance early on, but gradually converges to comparable performance, benefiting from population diversity and recombination. Among all algorithms, GSEMO achieves the highest final mean fitness with reduced variance, highlighting its effectiveness in balancing exploration and exploitation through its multi-objective formulation.

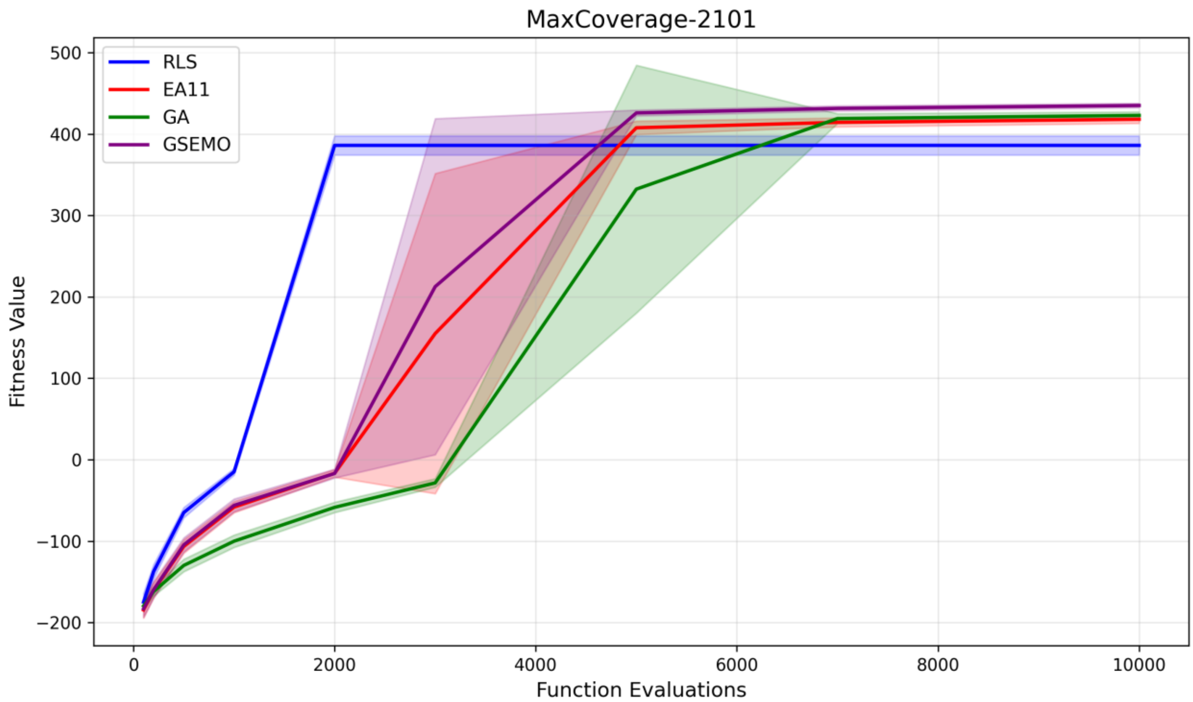

Figure 2: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxCoverage-2101

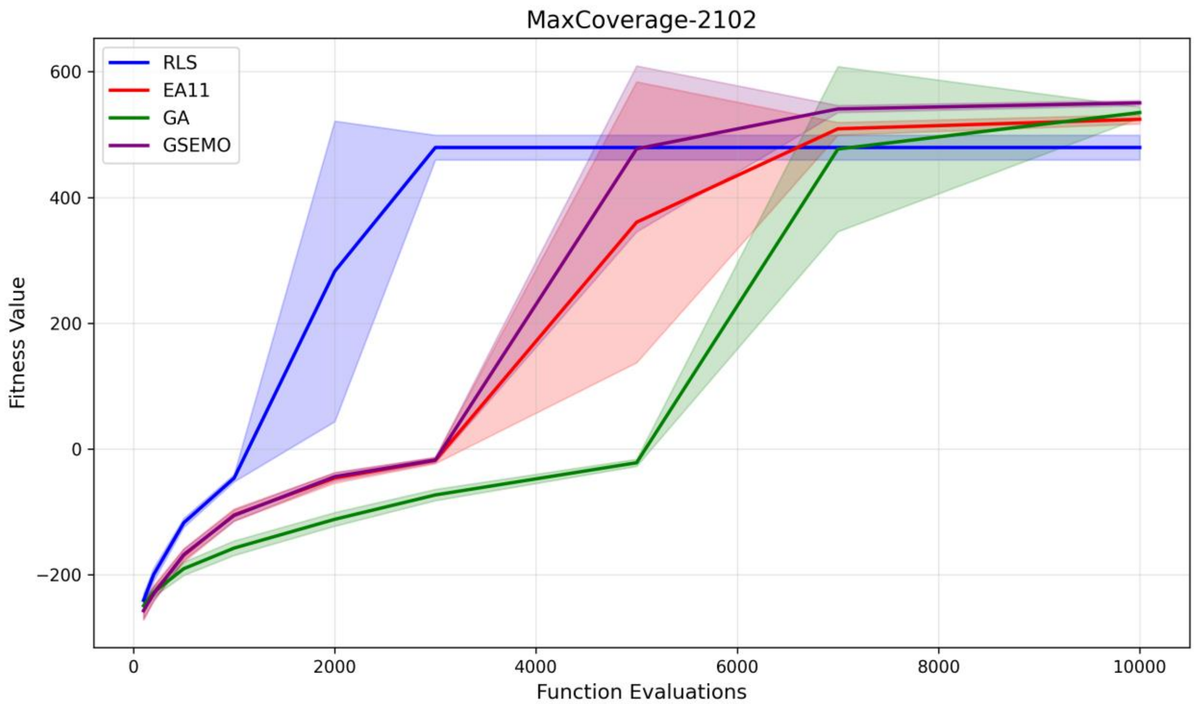

Figure 3: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxCoverage-2102

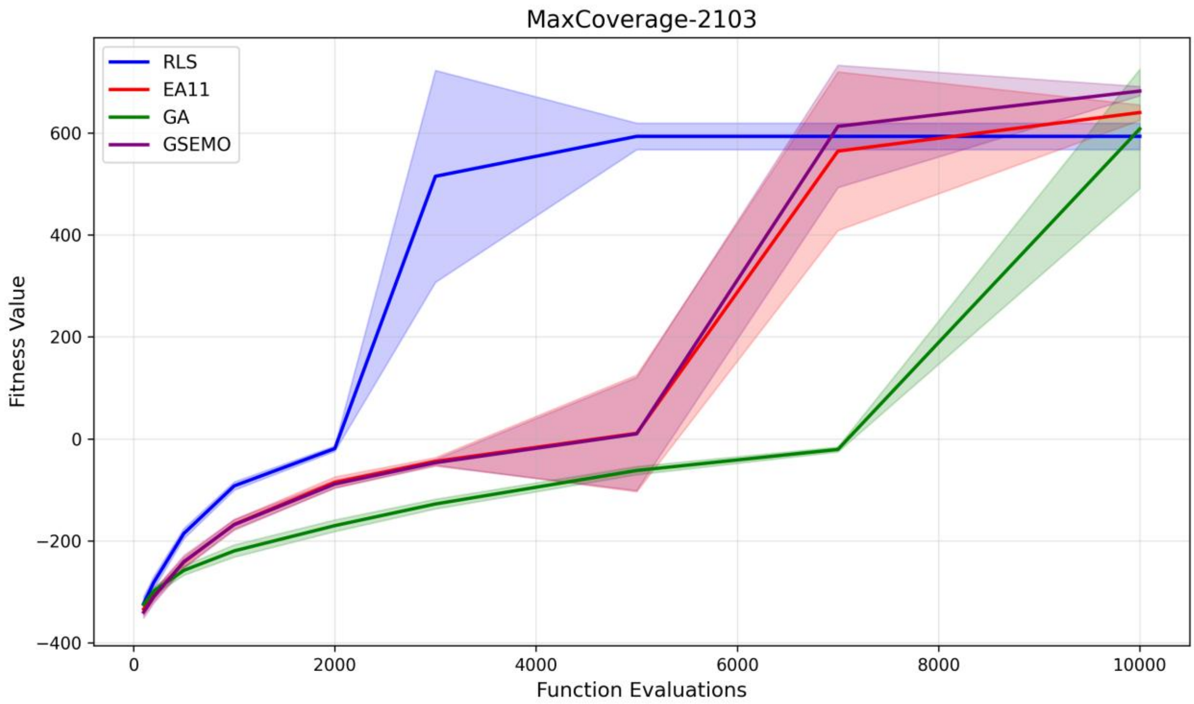

Figure 4: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxCoverage-2103

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. Overall, GSEMO provides the best trade-off performance, validating the advantage of multi-objective evolutionary optimization in submodular problems such as MaxCoverage.

MaxInfluence:

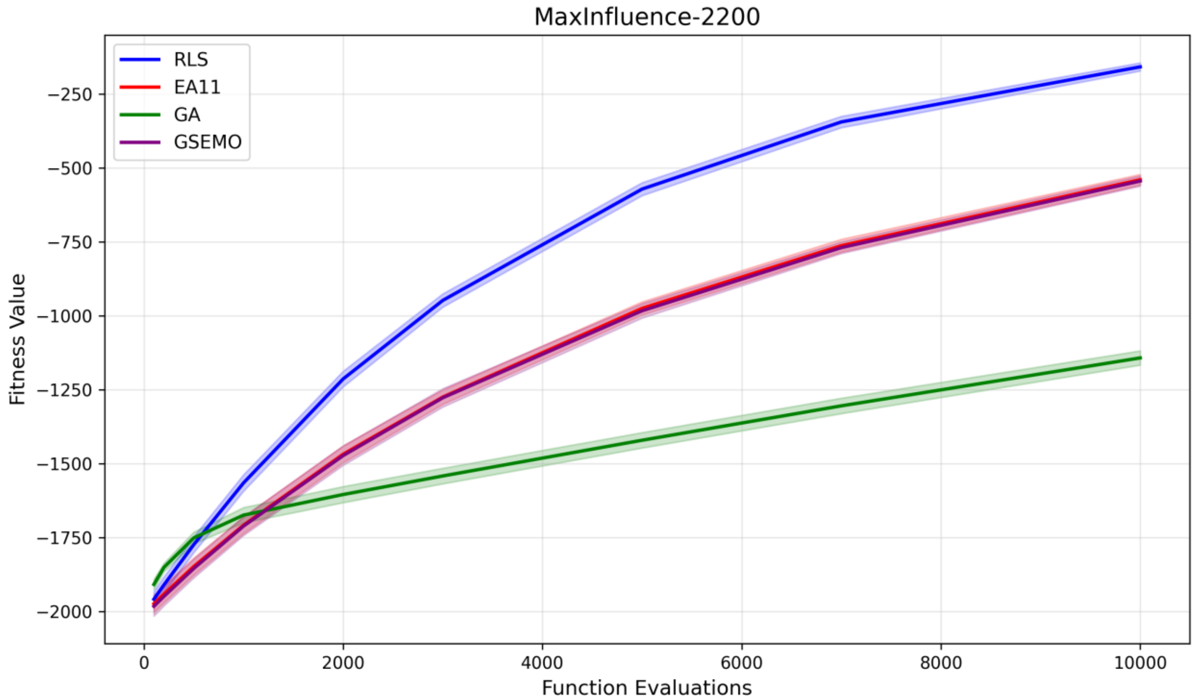

Figure 5: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxInfluence-2200

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.

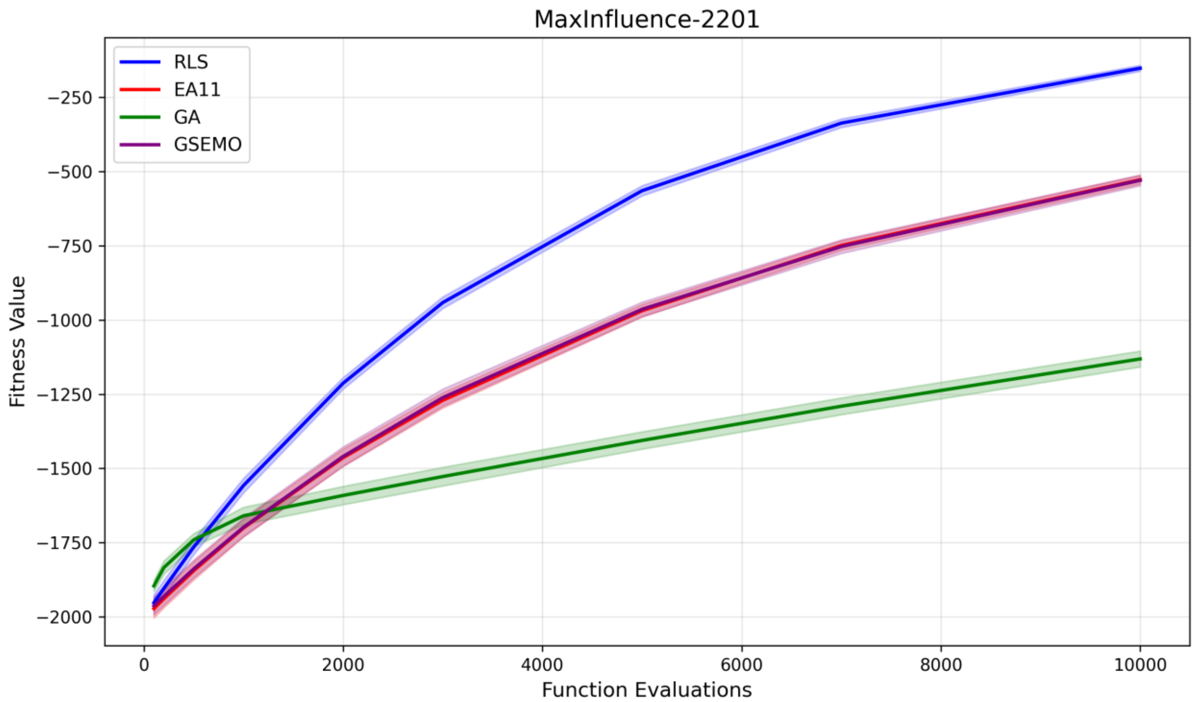

Figure 6: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxInfluence-2201

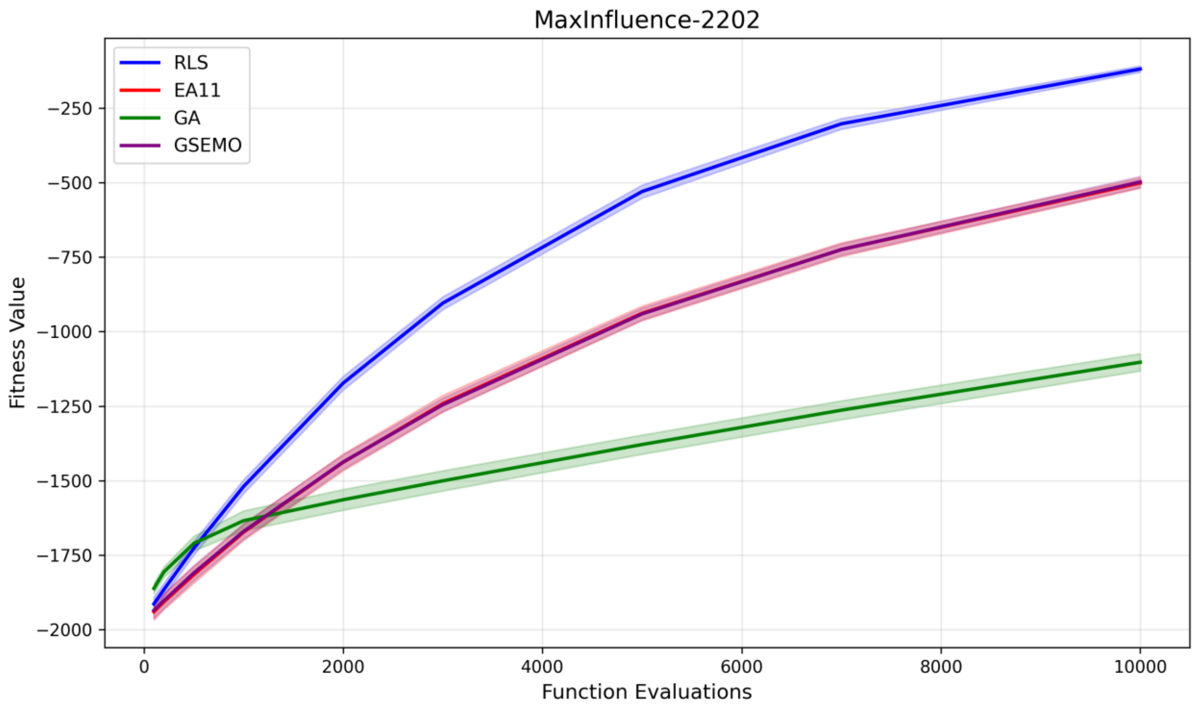

Figure 7: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxInfluence-2202

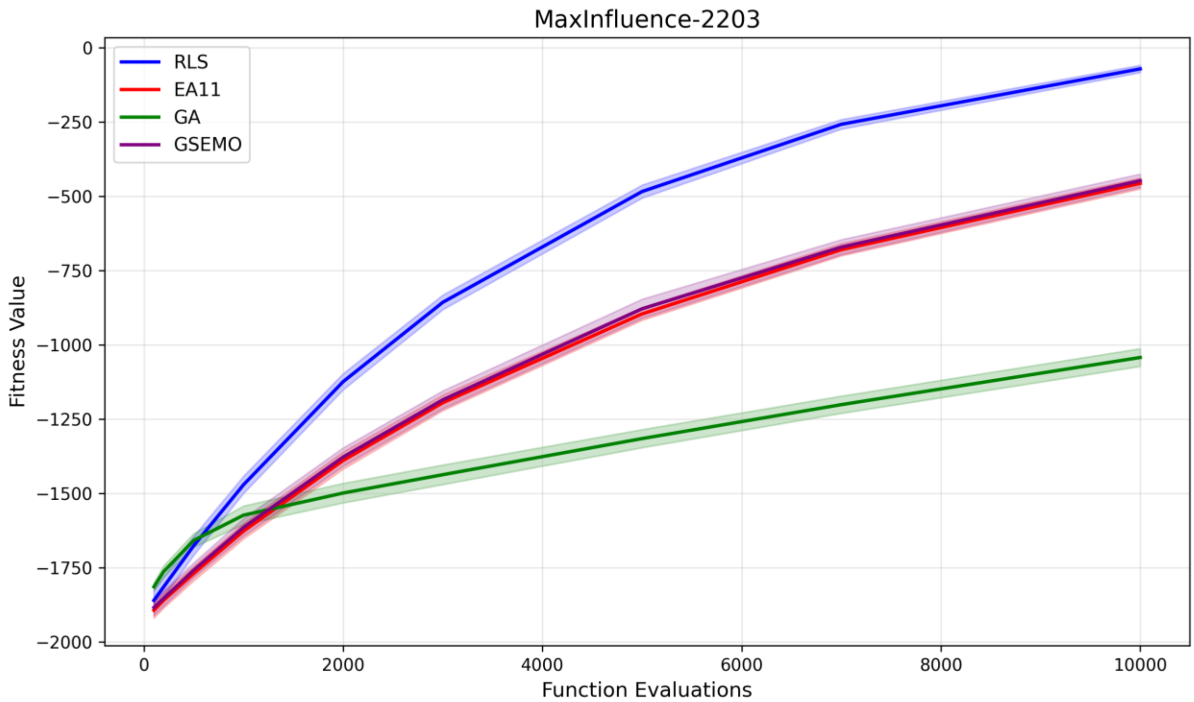

Figure 8: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on MaxInfluence-2203

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.

PackWhileTravel:

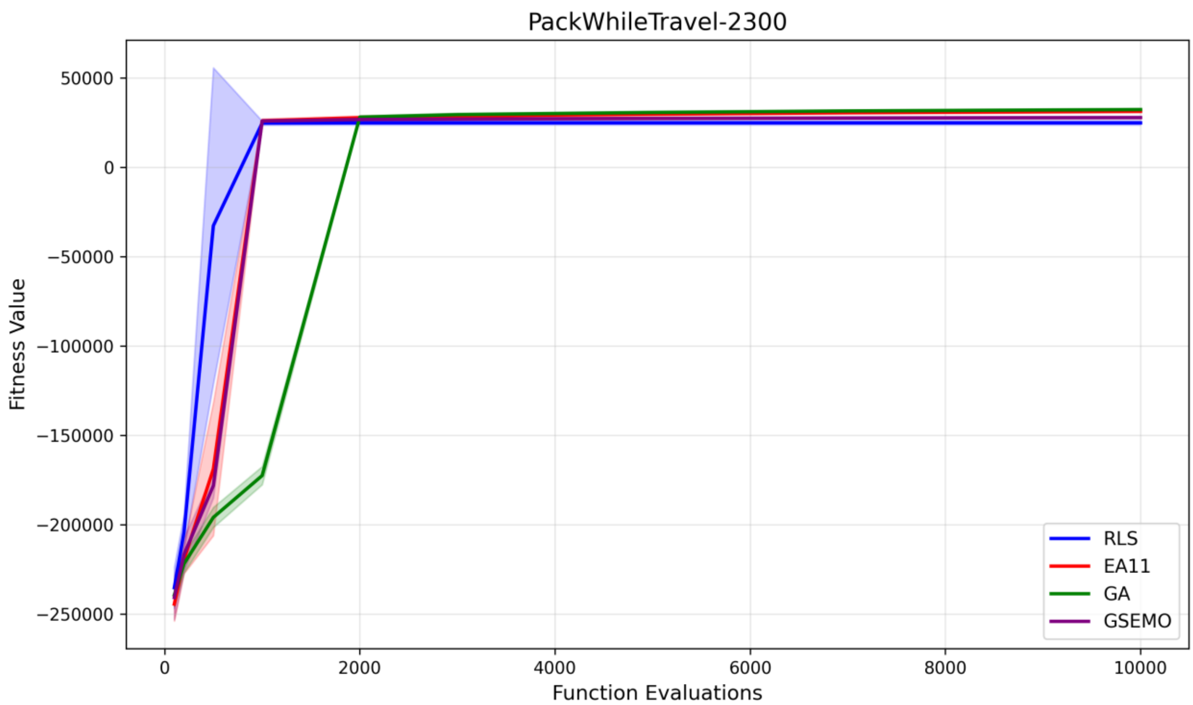

Figure 9: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on PackWhileTravel-2300

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. **GSEMO** performs almost identically to **(1+1) EA** across all evaluations, indicating that its multi-objective formulation offers no measurable improvement for this instance.

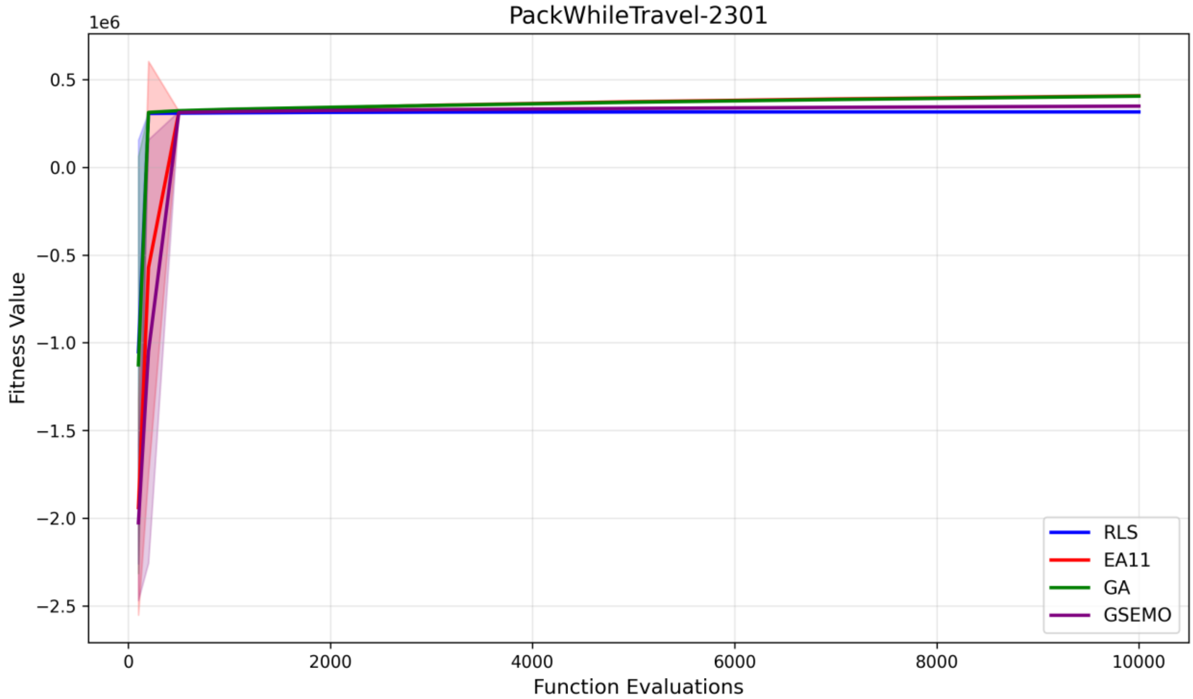

Figure 10: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on PackWhileTravel-2301

Figure 10 presents the mean and standard deviation of fitness values achieved by RLS, (1+1) EA, GA, and GSEMO on the **PackWhileTravel-2301** instance over 10,000 function evaluations. All algorithms begin with very low fitness values around -2.0×10^6 to -2.5×10^6 and experience a rapid improvement within the first 1,000 evaluations. After this early phase, the fitness values stabilize, with all algorithms converging to similar final results around 3.5×10^5. **RLS**, **(1+1) EA**, and **GA** display nearly overlapping trajectories, indicating comparable optimization performance on this instance. **GSEMO** follows the same trend and achieves an almost identical final fitness value, again suggesting that the multi-objective extension offers no additional benefit in this case. The variance is minimal across all algorithms after convergence, demonstrating consistent and stable behavior.

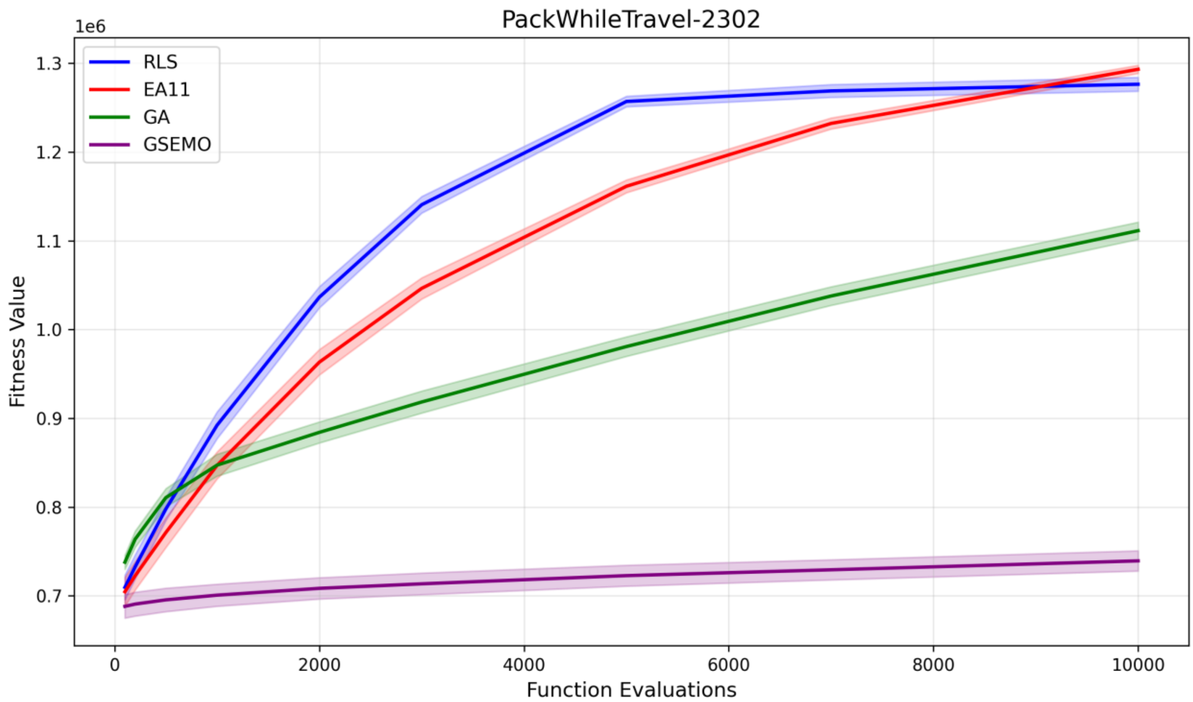

Figure 11: Performance comparison of RLS, EA (1+1), Genetic Algorithm, and GSEMO on PackWhileTravel-2302

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, GSEMO 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.

Overall, across the PackWhileTravel-2300, 2301, and 2302 instances, RLS and (1+1) EA consistently demonstrate strong and reliable performance, converging rapidly to high-quality solutions with minimal variance. GA generally achieves comparable final fitness but with slower convergence, indicating less efficient search dynamics. GSEMO, while performing similarly to (1+1) EA on simpler instances (2300 and 2301), fails to maintain competitiveness on the more complex 2302 instance, suggesting that its multi-objective formulation offers little advantage and may even hinder performance when objective trade-offs are weak or ill-defined.