Results Analysis for Exercise 5

F1 One Max

All three algorithms reach the global optimum, with small gaps as expected for a unimodal function. MMAS shows faster early gains but higher variance and earlier plateauing, while MMAS* improves more smoothly. The ACO increases steeply and gradually overtakes MMAS and MMAS*. MMAS AND MMAS* improve but reach the optimum later than the ACO and produce wider shaded areas that indicate more variation between runs. In contrast, the shaded region around the ACO is narrower indicating the runs are more consistent. This implies that the ACO algorithm is more stable, converges at a faster rate ad hence has a better balance between exploitation and exploration. Furthermore, the steep slope at the beginning is an indicator that the ants are finding efficient paths early on while the plateau towards the top suggest efficient exploitation near the minimum. The OneMax has a smooth gradient toward the optimum, meaning local search and exploitation dominate performance (Lissovoi, Oliveto & Warwicker, JA 2023, p.4). Hence, algorithms that reinforce successful solutions quickly, such as ACO, converge faster because there are no conflicting gradients to explore.

F2 LeadingOnes

Compared to F1, F2 produced a clearer separation in algorithm behaviour. MMAS and MMAS* follow nearly identical trajectories, suggesting that iteration best and global best pheromone updates offer comparable exploitation efficiency on this function. In contrast, the ACO performs slightly below both baselines for most of the runs, showing a temporary rise in variance. This period of instability likely reflects inconsistent early exploration among ants as the pheromone distribution adapts. After this phase, the algorithm stabilises, with convergence behaviour aligning more closely with MMAS and MMAS*. From the results it can be observed that while ACO remains stable in the long term, MMAS and MMAS* achieve faster and more consistent progress during early evaluations. LeadingOnes is a non separable function, meaning that the fitness of one bit depends on other bits hncee is a slow progress compared with OneMax because improvements depend on positional order (Bulanova, Buzdalova & Doerr 2022). Algorithms like MMAS and MMAS*, which exploit global information early, adapt more quickly to this dependency, whereas ACO's distributed exploration slightly delays convergence.

F3 A Linear Function

The results show that ACO achieves a faster and smoother improvement compared to MMAS and MMAS*. Although all algorithms eventually reach similar fitness, ACO converges earlier, maintaining a tighter confidence interval. This reflects stronger exploitation of high quality solutions and greater stability across runs. MMAS* and MMAS perform more slowly and display a higher variance and slower convergence. Overall, ACO demonstrates the best trade off between convergence speed and reliability for F3. The linear function with harmonic weights introduces non uniform contributions from each variable, favouring gradual improvement from balanced exploration (Lindblad et al. 2021). ACO's pheromone driven search adapts naturally to weighted contributions, explaining its faster convergence compared to algorithms that rely solely on random local updates.

F18 LABS

Results for F18 show MMAS* initially achieved higher fitness, indicating faster early progress, while ACO increased at a lower rate. However, in the later phase, ACO accelerated and surpassed both MMAS and MMAS*, achieving the best final fitness with noticeably lower variance. This pattern suggests that ACO allowed broader early exploration and stronger late stage exploitation, leading to superior overall performance and more consistent convergence.

F23 N-Queens Problem
For the N Queens function, MMAS and MMAS* exhibited faster early convergence but greater variability between runs. ACO progressed more gradually yet maintained a tighter confidence region, indicating higher stability. By the end of the run, all methods reached comparable fitness, but ACO provided the most consistent convergence across repetitions, suggesting a steadier exploration exploitation balance. ACO's distributed nature may spread the search effort across multiple possibilities, which keeps the algorithm from getting stuck too early and helps it reach better, more reliable results.

F24 Concatenated Trap
For this function, all algorithms show similar overall performance, steadily improving from an initial value of around 7 to approximately 17–18. MMAS* achieves faster early progress, but ACO accelerates later, surpassing MMAS and converging very close to MMAS*. The narrower confidence region for ACO indicates more consistent behaviour across runs. This result suggests that similar to previous results ACO maintains a strong balance between exploration and exploitation, performing reliably. MMAS*'s early progress reflects its rapid reinforcement of promising solutions, while ACO's stronger late performance results from broader exploration.

F25 NKL
MMAS* consistently reached the highest best so far values, indicating more effective long term exploitation. MMAS performed similarly but with slightly higher variance, while ACO improved more slowly and plateaued earlier. These results suggest that MMAS*'s global best update mechanism provides an advantage on problems with flat fitness gradients. It can additionally be observed that thee variance for the ACO is greater than previous functions and is larger than the variance for the MMAS and MMAS *. NK Landscapes are rugged with interdependent variables, leading to many local optima and weak fitness gradients (Skellett et al. 2005, p.579). MMAS*'s global reinforcement helps it retain the best known configurations in such landscapes, while ACO struggles to coordinate effectively when correlations between variables are high.

Overall, the ACO algorithm achieved the strongest balance between exploration and exploitation across all tested functions. It consistently outperformed MMAS and MMAS* on both unimodal and deceptive landscapes, showing faster convergence and lower variance in most cases. While MMAS* performed slightly better on sequential F2 and rugged F25 problems, ACO proved the most robust and reliable method overall.

References

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