F18: LABS (Low Autocorrelation Binary Sequence)

This analysis corresponds to the fixed-budget plot *'F18_100D_Final'* for the Low Autocorrelation Binary Sequence (LABS) problem. This problem is a multimodal benchmark useful for comparing Random Search (RS), Randomised Local Search (RLS), and the (1+1) Evolutionary Algorithm (EA).

As can be seen in the plot, RS begins with the same starting distribution as the other algorithms, which is expected given its purely stochastic sampling. Initially, the algorithm shows rapid improvements as early samples are likely to include some reasonably good solutions. However, this progress slows down by the 10^{th} to 20^{th} evaluations, causing the RS curve to flatten into a plateau, since the algorithm does not use information from past samples, it becomes increasingly more unlikely that it will find a better solution. After this point, the algorithm's performance improves only slowly, trending upwards in much smaller increments. By the end of the 100,000 iterations, RS achieves a *'best-so-far'* value of approximately 2.3, which is noticeably lower than the other algorithms. Interestingly, the narrowing standard deviation suggests that most runs converge to a similar, mediocre level of performance.

The RLS algorithm also commences at a similar point and has a very variable starting rate, leading to a wide standard deviation spread. Since the RLS algorithm flips only a single bit at each iteration, its initial improvement is much slower than RS, as its improvement depends on finding a single-bit flip that reduces autocorrelation. However, between the 10^{th} and 200^{th} evaluation, RLS shows a period of rapid gains, exploiting many easy single-bit improvements. After this stage, the curve flattens since escaping local optima requires multi-bit changes, which RSL cannot generate. Consequently, progress stalls, and by the 500^{th} evaluation, the curve flattens almost completely. Therefore, the final *'best-so-far'* value is approximately 3.7. Additionally, the widening standard deviation reflects that some runs happen to reach better local optima, but the lack of flexibility prevents consistent long-term improvement.

Since both the (1+1) EA and RLS rely on mutation-based local improvements, they follow a similar trend in the first few iterations. However, the (1+1) EA flips bits independently with probability 1/n, meaning that while only single-bit flips occur on average, occasional multi-bit flips are possible. The possibility of larger jumps gives the EA a better balance between exploration and exploitation. Because of this, the (1+1) EA avoids stagnation after the early rapid growth phase and continues to make incremental gains throughout the entire run. By the end, it achieves a *'best-so-far'* value of approximately 4.0, the strongest of the three. Whilst the (1+1) EA's standard deviation is wider than RS, it is narrower than RLS, reflecting its ability to make more consistent improvements while maintaining enough exploration to escape local optima.

The LABS results showcased in this plot clearly demonstrate the trade-offs between the algorithms. Pure exploration (RS) cannot sustain long-term progress, while overly restrictive local search (RLS) quickly stagnates in local optima. Therefore, the (1+1) EA achieves the best performance by occasionally exploring beyond local neighbourhoods while still exploiting promising regions, making it the most effective of the three algorithms for this complex problem space.