F24: Concatenated Trap

This analysis examines the fixed-budget plot *'F24_100D_Final'* for the Concatenated Trap problem, with the global optimum set at 20. The Concatenated Trap is a deceptive benchmark problem, as it draws algorithms toward misleading local optima that are often far from the global solution. This makes it especially valuable for comparing how Random Search (RS), Randomised Local Search (RLS), and the (1+1) Evolutionary Algorithm (EA) balance exploration and exploitation.

Given the deceptive nature of the Concatenated Trap function, the three algorithms perform reasonably well when compared to the earlier functions. The overall behaviour of solution improvement is not unlike that seen in previous graphs, but there are some distinct differences worth noting. It is evident that the RS algorithm again makes quick early gains in the first 10–20 evaluations, since random sampling often lands in sub-blocks that partially match local optima. After this initial rise, RS makes only gradual and irregular progress for the remainder of the evaluation budget, finishing at a *'best-so-far'* value of approximately 12. The inability to refine solutions explains why it stagnates far from the optimum of 20.

As expected, both the RLS and the (1+1) EA improve more gradually at first, but after ~10 evaluations, they begin to accelerate, as single-bit flips consistently improve fitness within trap sub-blocks. This leads to rapid gains, though these improvements mostly reinforce local rather than global progress. It is also evident that RLS plateaus earlier, while the (1+1) EA continues making small incremental improvements thanks to occasional multi-bit flips. Despite this, both algorithms finish closer together than previously, with (1+1) EA's final *'best-so-far'* value being approximately 16.1, which is less than 0.1 better than RLS. The small difference in results highlights the difficulty of escaping local optima in the trap landscape, even for algorithms capable of larger jumps.

A particularly interesting aspect of this plot lies in the spread of results. The (1+1) EA shows the most stable performance overall as its standard deviation is small from the beginning (1^{st}-10^{th} evaluation), narrows further during its steep growth phase (10^{th}-500^{th}), and tightens again at the plateau (~2000^{th}). This stability suggests that its mutation strategy produces broadly similar trajectories across runs, with only small stochastic differences unless rare multi-bit flips occur. Contrastingly, RLS exhibits the widest standard deviation early on (1^{st}-50^{th} evaluation), reflecting its sensitivity to the starting configuration. Depending on whether the initial solution lies closer to or further from a promising basin, progress in the first few hundred evaluations can differ significantly. Once runs settle into local optima, however, trajectories converge tightly, causing the spread to collapse at the plateau. Finally, RS initially has a similar standard deviation to the (1+1) EA; however, it retains a relatively wide spread throughout the run. This is expected, since its independent sampling continues to generate outcomes of varying quality throughout the budget.

In summary, the Concatenated Trap results show that RS again makes only shallow gains before stagnating, while RLS and (1+1) EA leverage local improvements to achieve much higher performance. However, the (1+1) EA offers only a marginal advantage, as both algorithms plateau below the global optimum. Furthermore, the standard deviation patterns highlight the unique characteristics of each algorithm as RLS begins highly unstable but converges tightly once stuck, (1+1) EA remains consistently steady, and RS remains reasonably unpredictable across the budget.