F25: NKL (NK Landscapes)

This analysis corresponds to the fixed-budget plot *'F25_100D_Final'* for the NK Landscapes problem. This problem is defined by rugged, epistatic fitness surfaces with many local optima, making them a strongly deceptive test for comparing how Random Search (RS), Randomised Local Search (RLS), and the (1+1) Evolutionary Algorithm (EA) balance exploration and exploitation.

The most noticeable feature of the plot is that, despite the global optimum tending toward positive infinity, all three algorithms remain in the negative range after 100,000 evaluations. This reflects how the fragmented and deceptive structure of NK landscapes severely limits steady progress. Although each algorithm does maximise itself within the search space, they are restricted to sub-optimal basins. Notably, RS and the (1+1) EA both maintain upward trajectories throughout the full budget, suggesting that longer runs could yield further improvement. In contrast, RLS plateaus after approximately 200 evaluations, clearly converging into local optima with no sign of escape.

Additionally, RLS has the largest standard deviation at the beginning of the run and, on average, performs the worst in early iterations. This wide spread arises from its strong dependence on the initial starting point, as performance can vary significantly depending on whether the first configuration lies near a relatively *'flat'* or more promising region of the landscape. Furthermore, as runs progress, the standard deviation tightens suggesting that all solutions remain trapped in sub-optimal local optima, showing why RLS fails to improve beyond this plateau. This is why even with an extended budget, the plot suggests RLS would still have a mean curve stabilising near a final *'best-so-far value'* of -0.38.

The (1+1) EA is the best performing algorithm, with a final *'best-so-far value'* of -0.31. It begins with a spread similar in size to RLS, but notably starts about 0.2 higher on average, indicating more favourable early progress. Initially, its rate of improvement mirrors RLS, but after approximately 500 evaluations, it continues to climb while RLS stalls. This divergence is explained by the EA's mutation operator, since the occasional multi-bit flip enables it to escape some of the traps in the rugged NK landscape. Additionally, the narrowing of the (1+1) EA's standard deviation across runs occurs because once the algorithm finds these better basins, trajectories can still converge towards similar sub-optimal peaks, leaving less variation between independent runs.

Finally, Random Search improves very rapidly in the first 20-30 evaluations, since blind sampling in a rugged space is likely to find configurations better than a single random start. However, once its mean curve crosses the trajectories of the other algorithms, its growth slows noticeably. This is because RS lacks memory; while it can occasionally hit better solutions, it cannot refine them, so the rate of improvement is dominated by chance. Additionally, the algorithm's standard deviation tightens somewhat as runs progress, since outcomes cluster with more samples, but it never narrows as much as the other algorithms, reflecting the variability of purely random sampling. RS finishes lowest of the three algorithms, with a final *'best-so-far'* value near -0.40, although the continued upward slope of its mean suggests that further improvement would be possible with a larger budget.

In summary, the NK Landscapes problem highlights the difficulty of deceptive and rugged fitness functions. RLS performs worst, converging quickly into poor local optima and showing no potential for further improvement, while RS and the (1+1) EA both maintain upward trajectories, with the (1+1) EA slightly stronger due to occasional multi-bit escapes. However, their failure to escape far enough within 100,000 evaluations illustrates how difficult NKL is to solve without mechanisms beyond random search or simple parent-child evaluation.