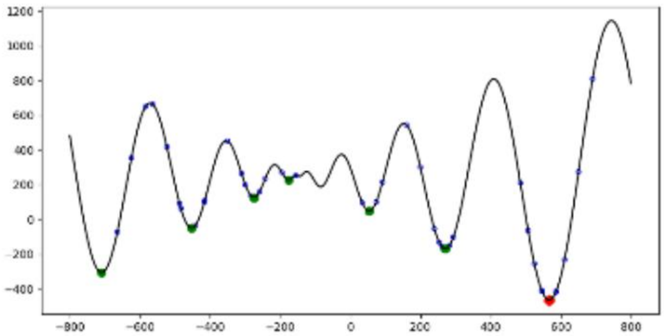
Documentation – AI Optimization Algorithms

Task 1 – Hill Climbing on the New Schwefel Function (1D, 2D, 3D)

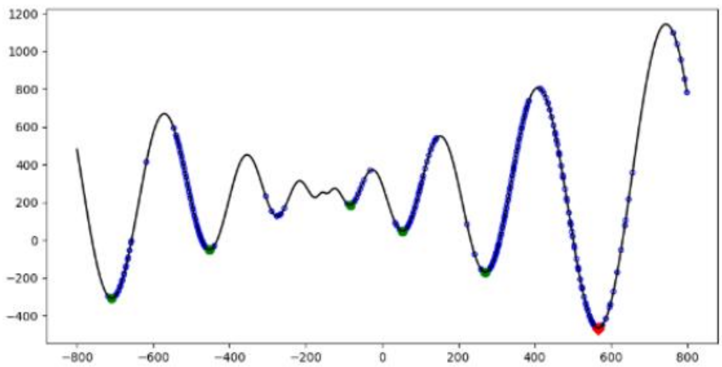
- **Goal**: Find the global minimum of the New Schwefel function.
- **Domain**: -800 < x < 800 (1D).
- Algorithm starts at a random point and iteratively moves in steps d toward lower function values.
- On the plots:
  - Blue circles = steps of the algorithm
  - Green dots = local minima
  - Red diamonds = final solution



Bonus – Stochastic Hill Climbing

Finding the global minimum of the New Schwefel function (1D) using Stochastic Hill Climbing.

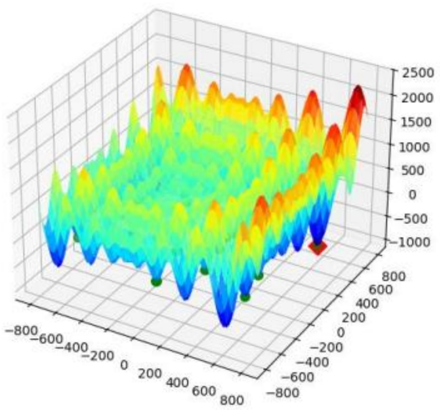
The difference compared to the classical hill climbing algorithm is the possibility to occasionally jump randomly to a new point, which helps to avoid being trapped in a local minimum.



Bonus – Extension to 2D and 3D

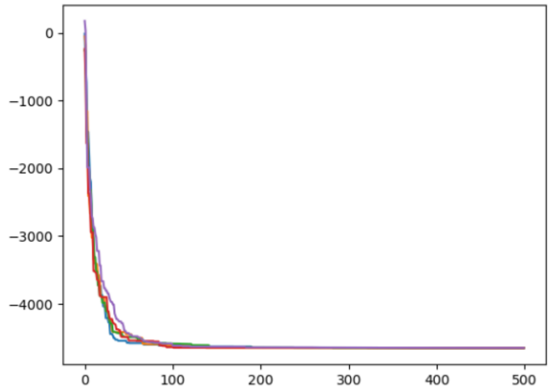
Extending the original task from searching the minimum of a 1D function to 2D and 3D functions.

- Domain: -512 < x < 512
- The code searches for the global minimum in two-dimensional and three-dimensional space with adaptive step reduction.
- In the 2D case, the function is visualized in a 3D surface plot where local minima are marked with green dots and the global minimum with a red diamond.
- Search in 2D is performed in 4 directions (up, down, left, right), while in 3D it is performed in 6 directions (forward, backward, up, down, left, right).



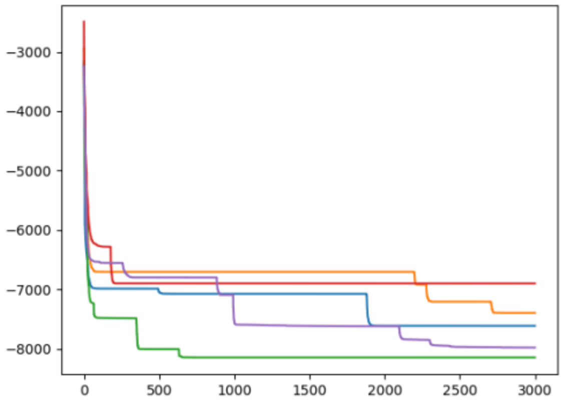
Task 2 – Genetic Algorithm for Function Optimization

- **Goal**: Find the global minimum of the New Schwefel function with 10 variables.
- **Setup**: 5 runs, 500 generations, 100 individuals.
- **Selection**: elitist (top 20) + tournament (80).
- **Crossover**: one-point.
- **Mutation**: probability 0.1.
- Convergence occurs mostly in the first 100 generations.
- **Best fitness**: -4648, -4650, -4650, -4649, -4649.
- In 2 out of 5 runs, the global minimum was reached.



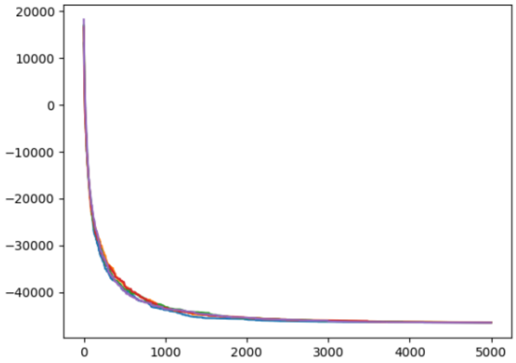
Bonus A – Eggholder function (10D)

- 5 runs, 3000 generations, 500 individuals.
- Mixed selection: elitist, tournament, random.
- Multi-point crossover and group crossover used.
- Stronger mutations applied to subgroups.
- Best fitness: -7612, -7394, -8145, -6899, -7978.
- Result: very hard to solve; one run came close to the global minimum.



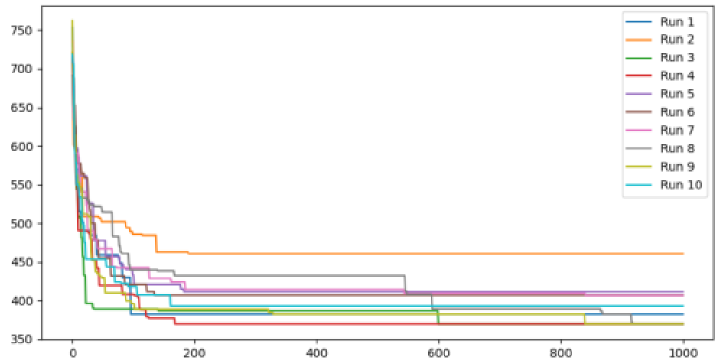
Bonus B – New Schwefel function (100D)

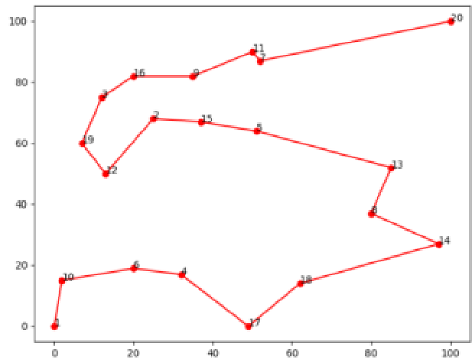
- 5 runs, 5000 generations, 400 individuals.
- Elitist, tournament, and random selection.
- One-point crossover, varying mutation intensities.
- Converged in first 1000 generations.
- Best fitness: -46436, -46385, -46396, -46412, -46436.
- Did not reach the exact global minimum but got very close.



Task 3 – Genetic Algorithm for Path Planning (TSP-like)

- **Goal**: Find the shortest path through 20 points in the plane.
- **Setup**: 10 runs.
- **Selection**: elitist (8%), tournament (82%), random (10%).
- **Crossover**: copy fragment from one parent + fill remaining from the other (preserves permutation).
- **Mutation**: swap mutation with probability 0.05.
- **Best fitness values**: 382, 460, 369, 369, 410, 406, 406, 369, 369, 392.
- The GA found the optimal solution in ~40% of runs, and near-optimal in most others.





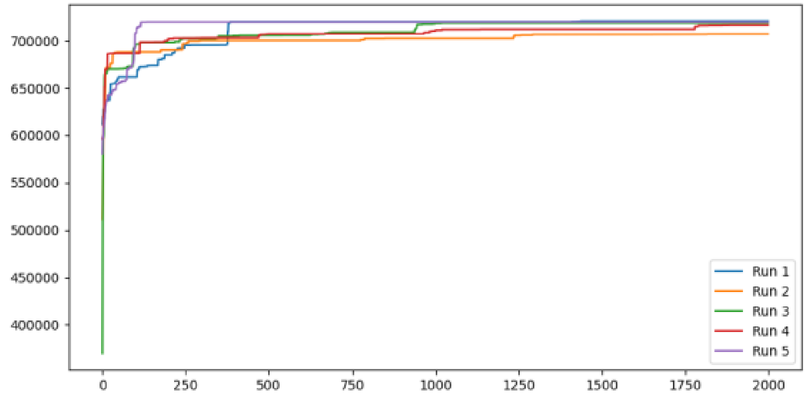
Task 4 – Genetic Algorithm for Investment Allocation

- **Goal**: Distribute investments into 5 financial products under constraints.
- Compared penalty methods:
  - **Death penalty**: strictly excludes invalid solutions, but slows down learning and risks local minima.
  - **Step penalty**: softer, allows optimization but still restrictive.

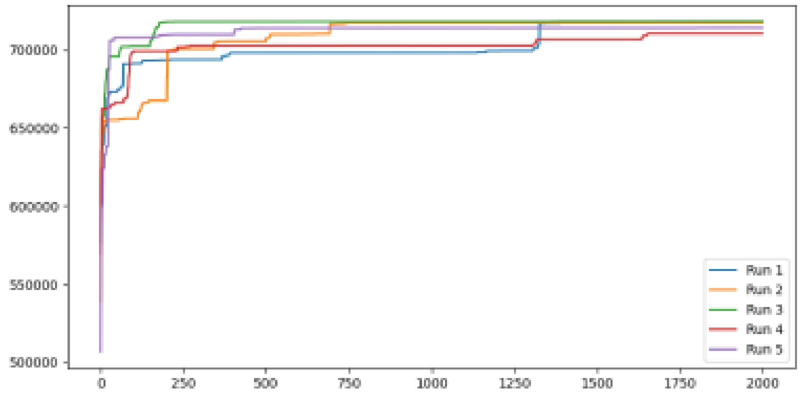
- ○ **Proportional penalty**: best performance; allows weak solutions but gradually improves them → smoother, faster convergence.

Results:

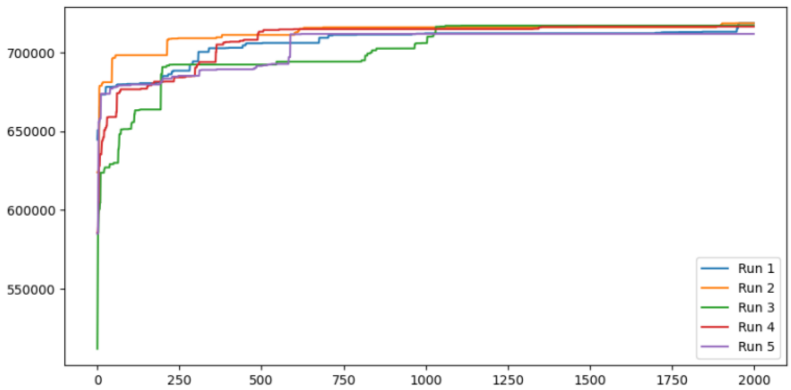
- Best *death penalty*: 720787.56 (good but stuck in local optimum).



- Best *proportional penalty*: 718172.00 (closest to optimal, reasonable variable distribution).



- Best *step penalty*: 718825 (slightly worse distribution, still close).



- None reached the exact global minimum, but proportional penalty gave the best convergence.

Conclusion

- Hill climbing works for low-dimensional functions, but stochastic variant and dimensional extensions help avoid local minima.
- Genetic algorithms are effective for multi-dimensional optimization, though very complex functions (like Eggholder) remain challenging.
- GA proved successful in path planning (TSP-like) and in investment allocation, with proportional penalties yielding the best results.