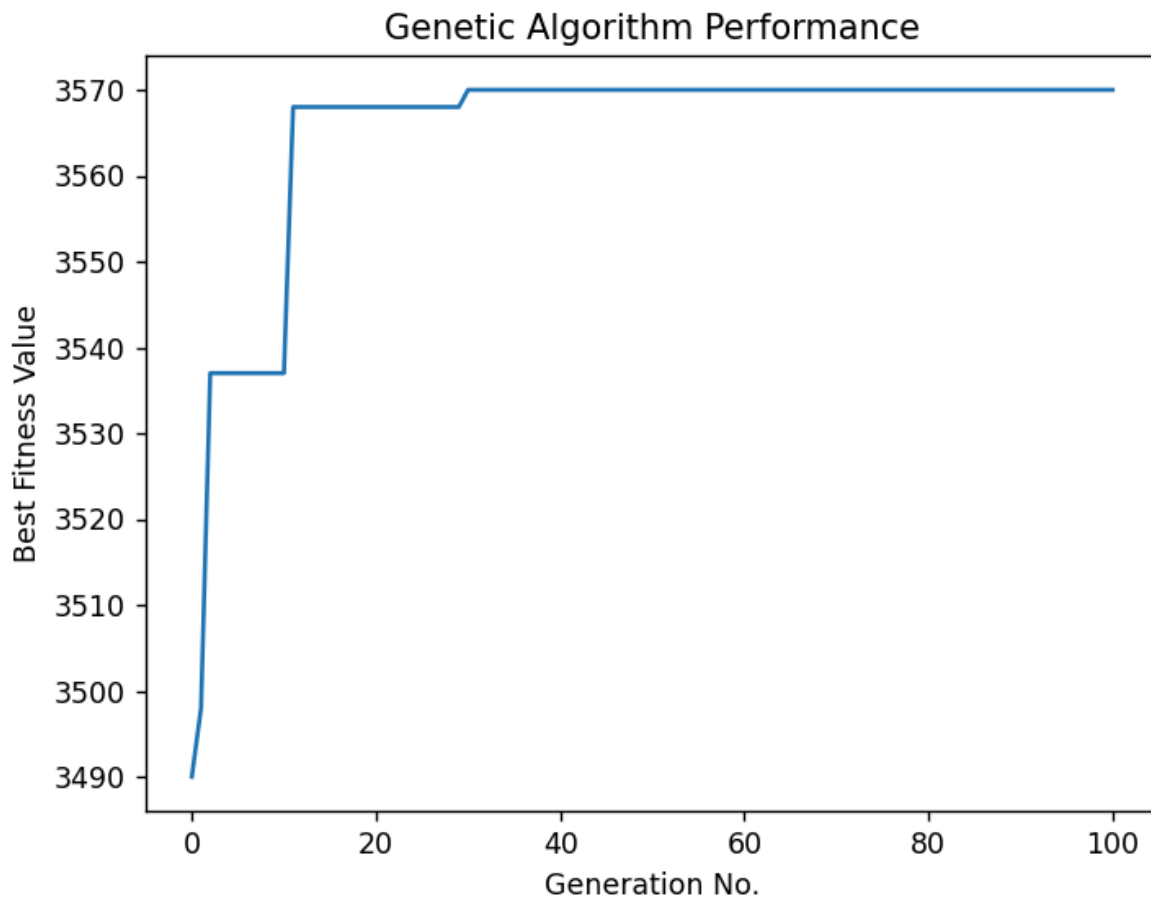
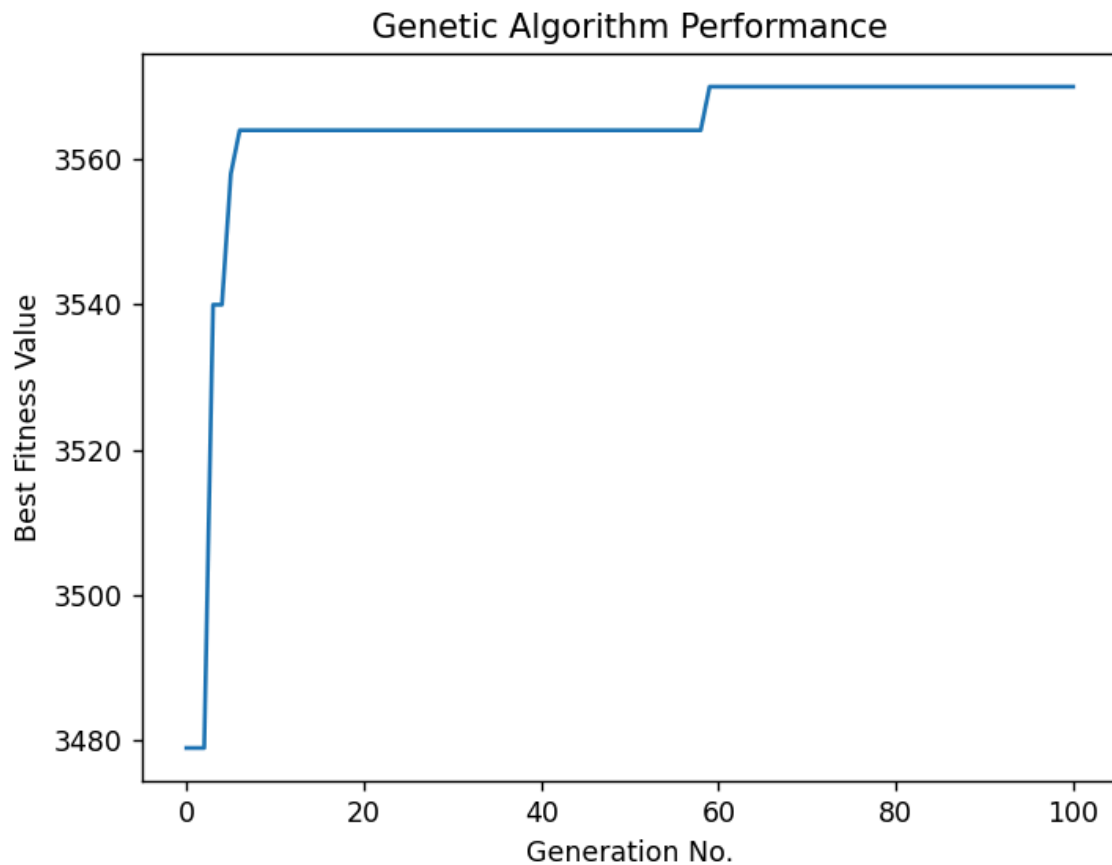


```
Running experiment: Generations=100, Population Size=50
Time and generation at which best was found: 0.00000s at Gen 0
Time and generation at which best was found: 0.00000s at Gen 1
Time and generation at which best was found: 0.00742s at Gen 10
Time and generation at which best was found: 0.02119s at Gen 29
```

[illegible]

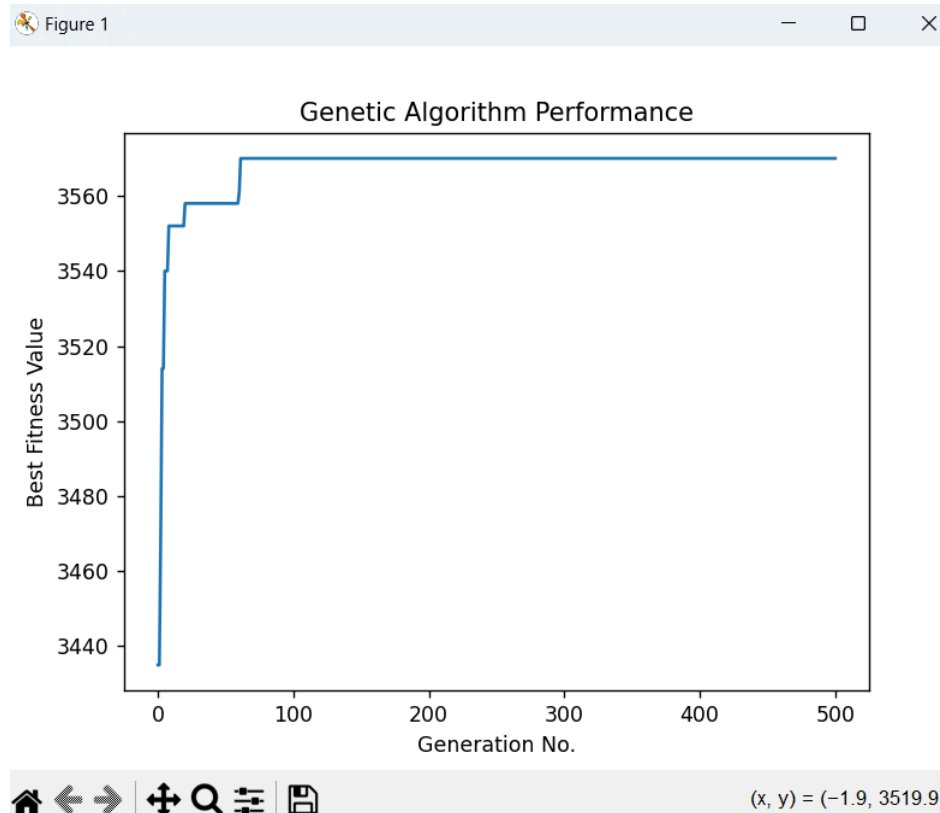
2. combinations {gen,N}: {100,100}

```
Running experiment: Generations=100, Population Size=100
Time and generation at which best was found: 0.00696s at Gen 2
Time and generation at which best was found: 0.01047s at Gen 4
Time and generation at which best was found: 0.01047s at Gen 5
Time and generation at which best was found: 0.11734s at Gen 58
```

[illegible]

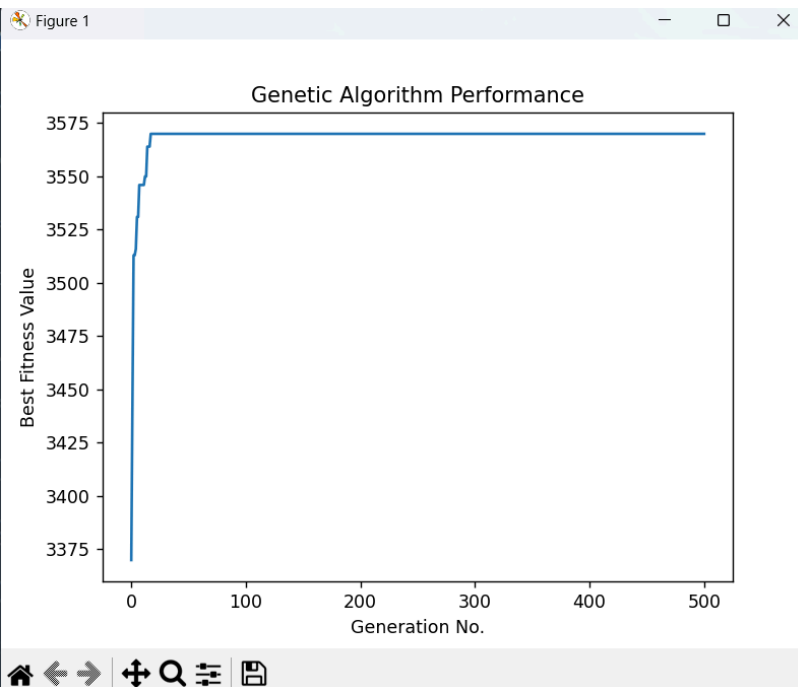
3. combinations {gen,N}: {500,50}

```
Running experiment: Generations=500, Population Size=50
Time and generation at which best was found: 0.00000s at Gen 1
Time and generation at which best was found: 0.00811s at Gen 2
Time and generation at which best was found: 0.00811s at Gen 4
Time and generation at which best was found: 0.01106s at Gen 7
Time and generation at which best was found: 0.01885s at Gen 19
Time and generation at which best was found: 0.05745s at Gen 59
Time and generation at which best was found: 0.05761s at Gen 60
```

[illegible]

4. {gen,N}: {500,100}

```
Running experiment: Generations=500, Population Size=100
Time and generation at which best was found: 0.00338s at Gen 0
Time and generation at which best was found: 0.00338s at Gen 1
Time and generation at which best was found: 0.00763s at Gen 3
Time and generation at which best was found: 0.01114s at Gen 4
Time and generation at which best was found: 0.01561s at Gen 6
Time and generation at which best was found: 0.02413s at Gen 11
Time and generation at which best was found: 0.02413s at Gen 13
Time and generation at which best was found: 0.03247s at Gen 16
```

[illegible]

Combinations

Metric	Gen=100, N=50	Gen=100, N=100	Gen=500, N=50	Gen=500, N=100
Initial fitness value and time of best solution	3490, 0.00000s at Gen 0	3479, 0.00696s at Gen 2	3435, 0.00000s at Gen 1	3370, 0.00338 at Gen 0
Best Fitness Value	3570 (1st achieved at Gen 29)	3570 (1st achieved at Gen 58)	3570 (1st achieved at Gen 59)	3570 (1st achieved at Gen 16)
Time to Best Fitness	0.02119s	0.11734s	0.05761s	0.03247s
Rate of Fitness Increase	Incremental (early stabilization)	Moderate (more steps to stabilize)	Gradual (slower but steady rise)	Rapid (faster initial improvement)
Generations for Best	Found at Gen 29	Found at Gen 58	Found at Gen 59	Found at Gen 16
Population Size Effect	Moderate fitness convergence speed	Better diversity but slower results	Slower improvement with a small pop	Faster convergence with large pop

Comparisons

Comparison	Observation
1 (Gen=100, N=50) vs 2 (Gen=100, N=100)	Larger population sizes in 2 lead to better diversity but slower convergence than in 1, as seen in delayed Gen 58 vs Gen 29.
1 (Gen=100, N=50) vs 3 (Gen=500, N=50)	Increasing generations in 3 enhances search exploration, but time to convergence is slower than 1.
1 (Gen=100, N=50) vs 4 (Gen=500, N=100)	Combining higher generations and population size in 4 leads to rapid improvement and early convergence.

2 (Gen=100, N=100) vs 3 (Gen=500, N=50)	2 converges faster than 3, suggesting larger populations compensate for fewer generations.
2 (Gen=100, N=100) vs 4 (Gen=500, N=100)	Higher generations in 4 significantly improve convergence speed compared to 2 due to more search opportunities.
3 (Gen=500, N=50) vs 4 (Gen=500, N=100)	Larger population size in 4 accelerates fitness improvements, highlighting the role of population size in larger Gen scenarios.

Conclusion/Summary:

Based on this exercise, we can clearly observe that larger populations (N=100) improve diversity and exploration but slow initial convergence, while smaller populations (N=50) converge faster but risk very early stagnation. Increasing generations (Gen=500), on the other hand, enhances search depth and solution improvement, whereas fewer generations (Gen=100) limit exploration and may result in less-than-optimal outcomes. The optimal configuration, Gen=500,N=100, balances these factors, using diversity and extended search to achieve early and consistent convergence, with the best fitness value (3570) reached at Generation 16. However, while Gen=500,N=100 stabilizes early, this may not be ideal if deeper exploration is necessary to avoid local optima, in which case Gen=500, N=50 could provide better long-term results. This highlights the trade-offs between population size, generation count, and the goals of speed, exploration, and solution quality.