Genetic Algorithm Parameters Analysis

This document presents a detailed analysis of the various parameters used in the Genetic Algorithm for optimizing circuit configurations. The goal is to determine the optimal settings for each parameter to ensure efficient and effective performance of the algorithm.

Introduction

Genetic Algorithms (GAs) are powerful optimization tools inspired by the principles of natural selection and genetics. The performance of GAs is highly dependent on the proper tuning of their parameters. This analysis focuses on two main categories of parameters:
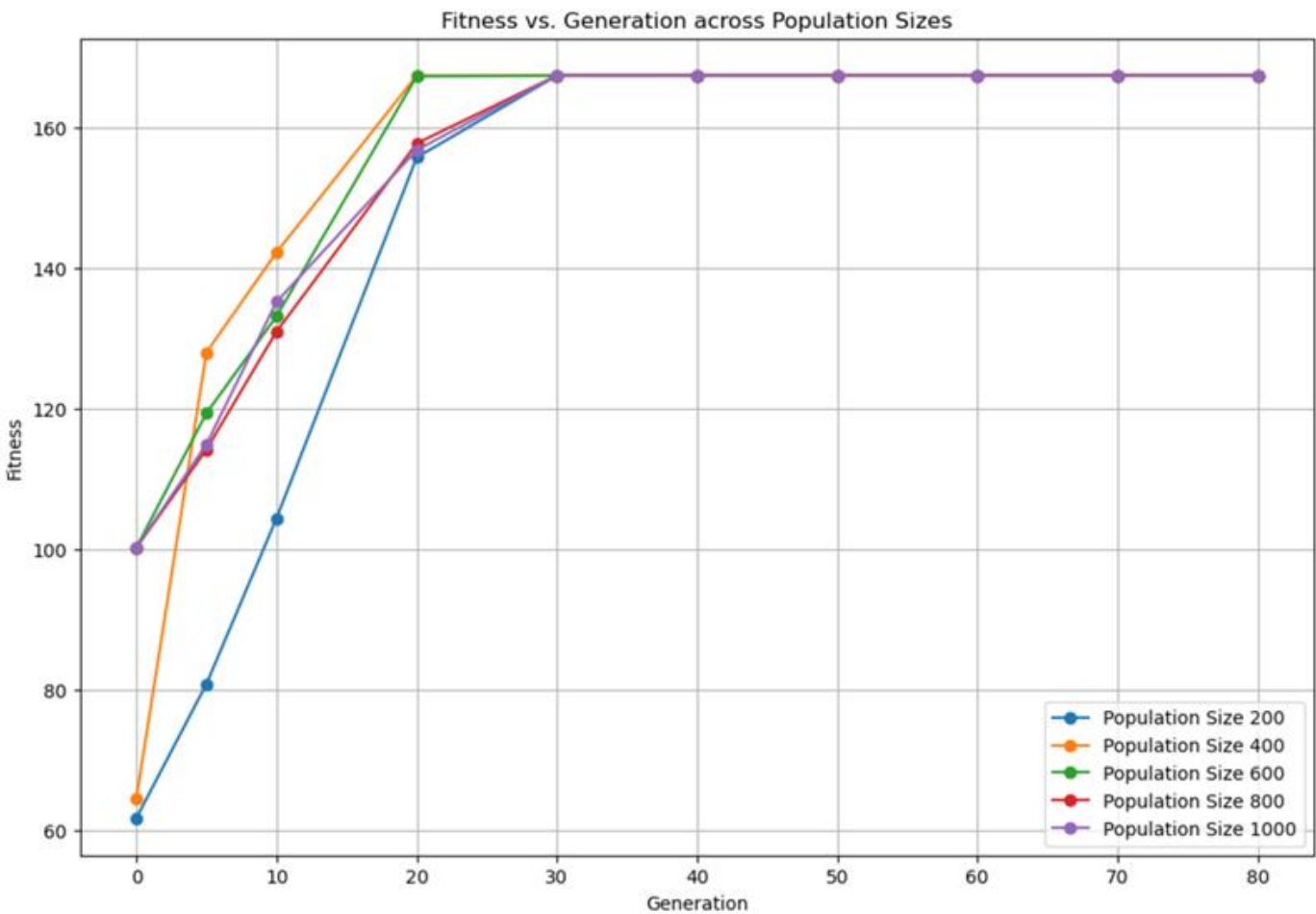
- Algorithm Parameters
- Circuit Parameters

Algorithm Parameters Analysis

Population Size

Population size determines the number of individuals in each generation. A larger population size increases the genetic diversity but also requires more computational resources.

Analysis Results

- Population sizes of 600, 800, and 1000 start with relatively high initial fitness values, indicating that they quickly find high-quality solutions.

- The fitness values increase rapidly in the early generations.

- A population size of 400 shows the fastest increase in fitness, reaching 167.378 by generation 20.

- All population sizes eventually stabilize at a fitness value of 167.378, demonstrating effective convergence of the algorithm.

Parameter Choice

A population size of 400 is optimal as it balances computational cost and convergence speed effectively.

Tournament Size

Tournament size determines the number of individuals randomly selected from the population for each tournament. The winner of each tournament, being the individual with the highest fitness, is selected to be a parent for the next generation.

Analysis Results

Fitness vs. Generation across Tournament Sizes
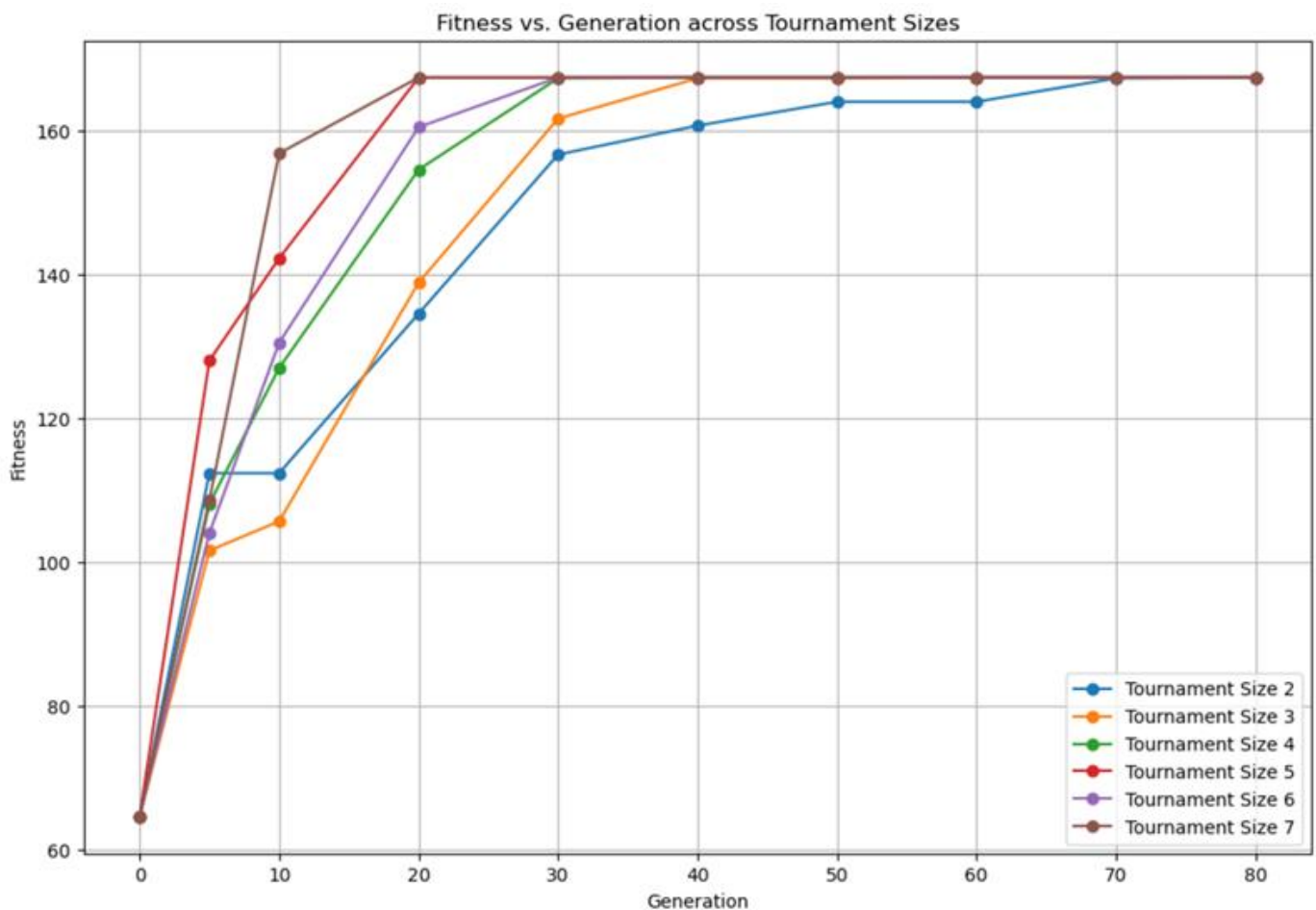
- All tournament sizes show a rapid increase in fitness within the first 10 generations.

- Tournament Size 5 reaches the highest fitness value (around 165) by generation 20 and remains stable.

- Sizes 6 and 7 also achieve high fitness values but are slightly lower than Tournament Size 5.

Parameter Choice

Choosing a tournament size of 5 ensures that the genetic algorithm efficiently explores the solution space and quickly converges to high-quality solutions, making it suitable for most optimization problems.

Crossover Rate

The crossover rate is a probability value (usually between 0 and 1) that dictates the likelihood of applying the crossover operation to generate new offspring from two parent individuals. It helps control the genetic diversity in the population by mixing genes from different parents.

Analysis Results

Fitness vs. Generation across Crossover Rates
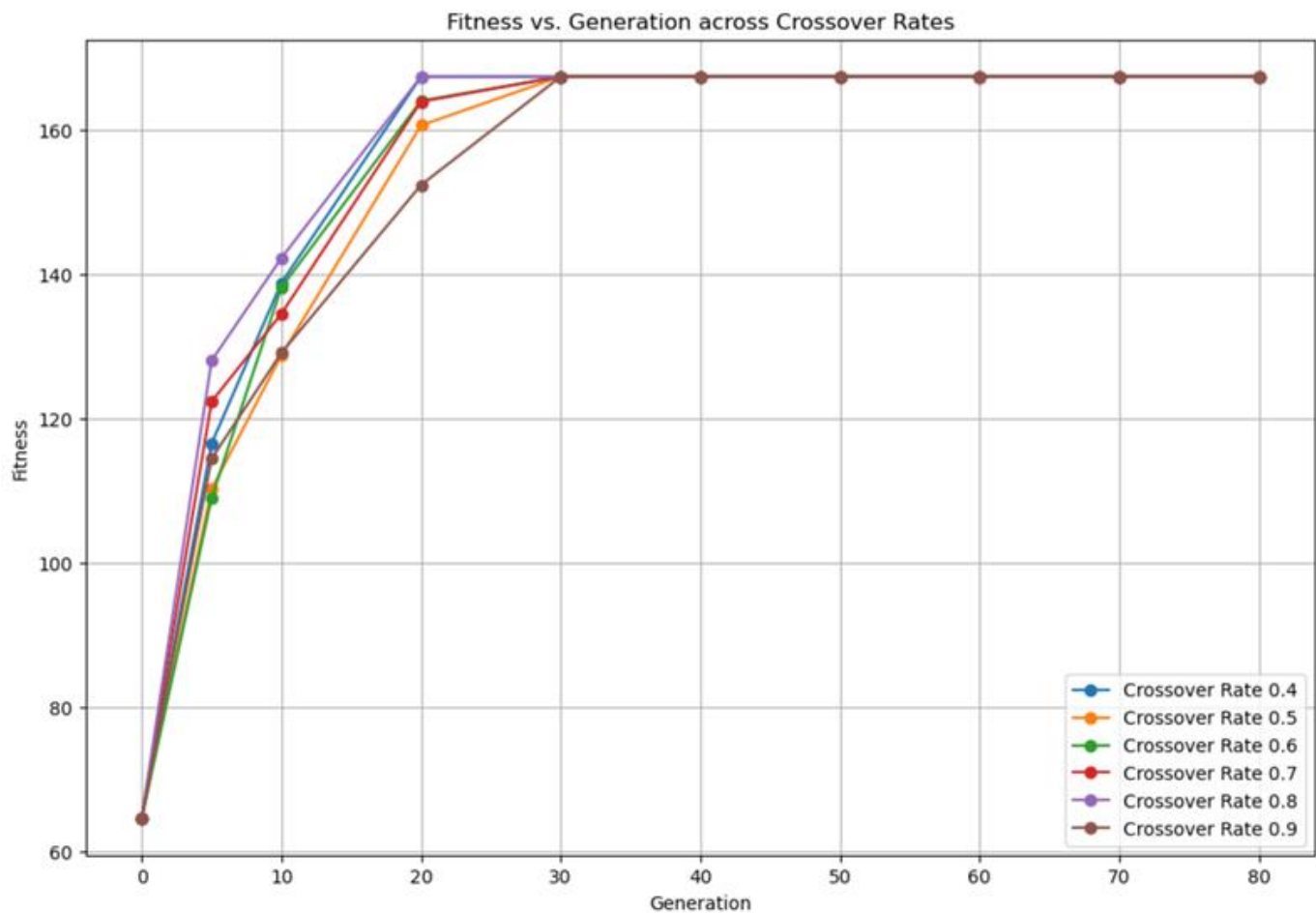
- Crossover rates of 0.7 and 0.8 demonstrate the fastest convergence, achieving the maximum fitness value the quickest.

- All crossover rates eventually reach the same maximum fitness value, indicating robustness across different rates.
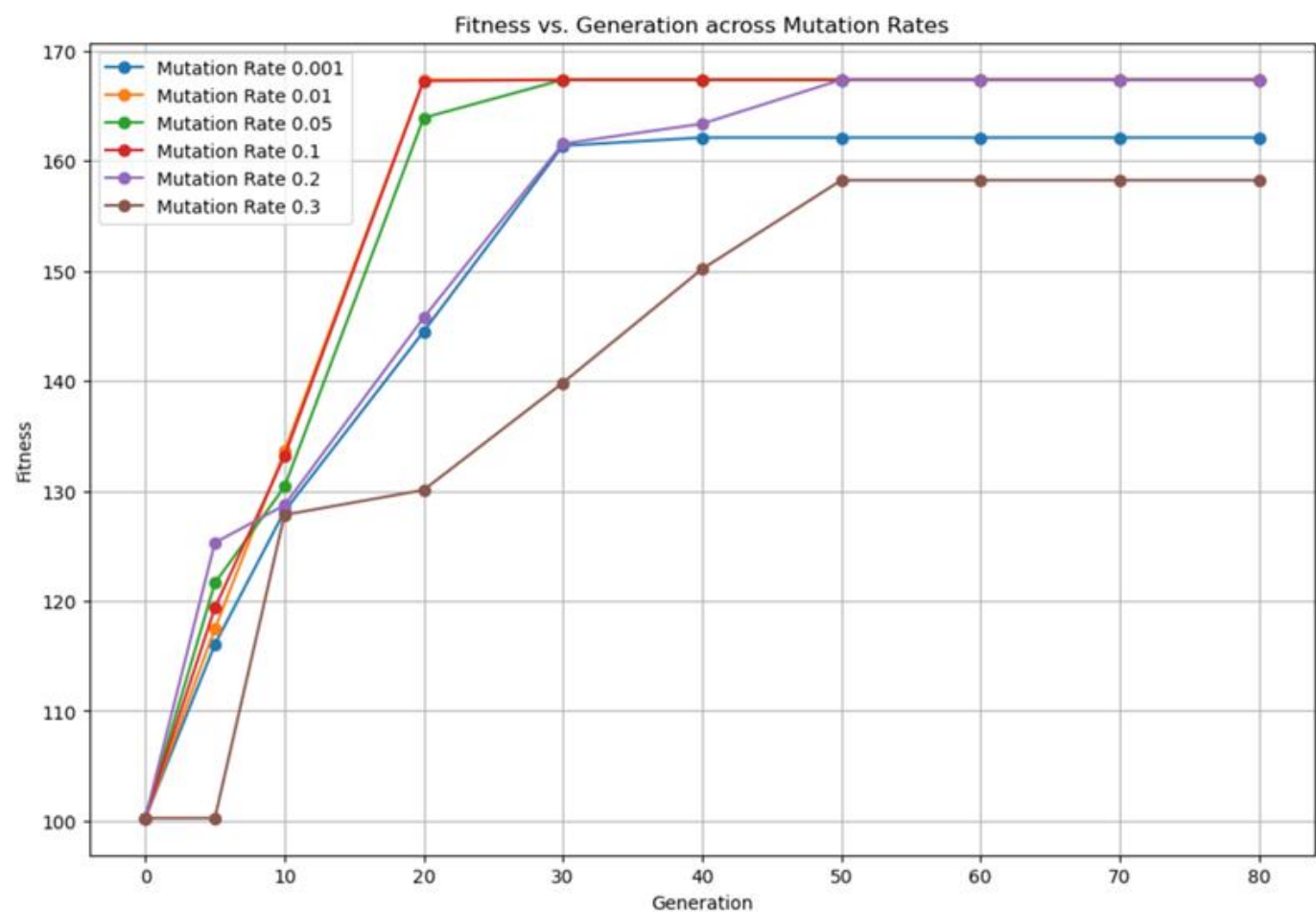
Parameter Choice

For future runs, consider using a crossover rate of 0.8 to achieve the fastest improvement and robust performance.

Mutation Rate

Mutation rate is a crucial parameter in genetic algorithms, representing the probability of randomly altering genes in an individual's genome. It helps maintain genetic diversity within the population, preventing premature convergence to local optima and enabling the exploration of the solution space.

Analysis Results

Fitness vs. Generation across Mutation Rates

- Lower mutation rates (0.01, 0.05, and 0.1) demonstrate quicker convergence and higher final fitness values compared to higher mutation rates (0.2 and 0.3).

- Mutation rate 0.01 shows the fastest and most stable improvement.

Parameter Choice

Use a mutation rate of 0.01 to achieve rapid convergence and robust performance.

Elite Percentage

The elitePercentage parameter in a genetic algorithm controls the elitism strategy. This strategy directly preserves the best-performing individuals from the current generation into the next generation without any mutation or crossover. This ensures that the top-quality genes are passed on, enhancing the algorithm's efficiency and stability.

Analysis Results

Fitness vs. Generation across elitePercentage
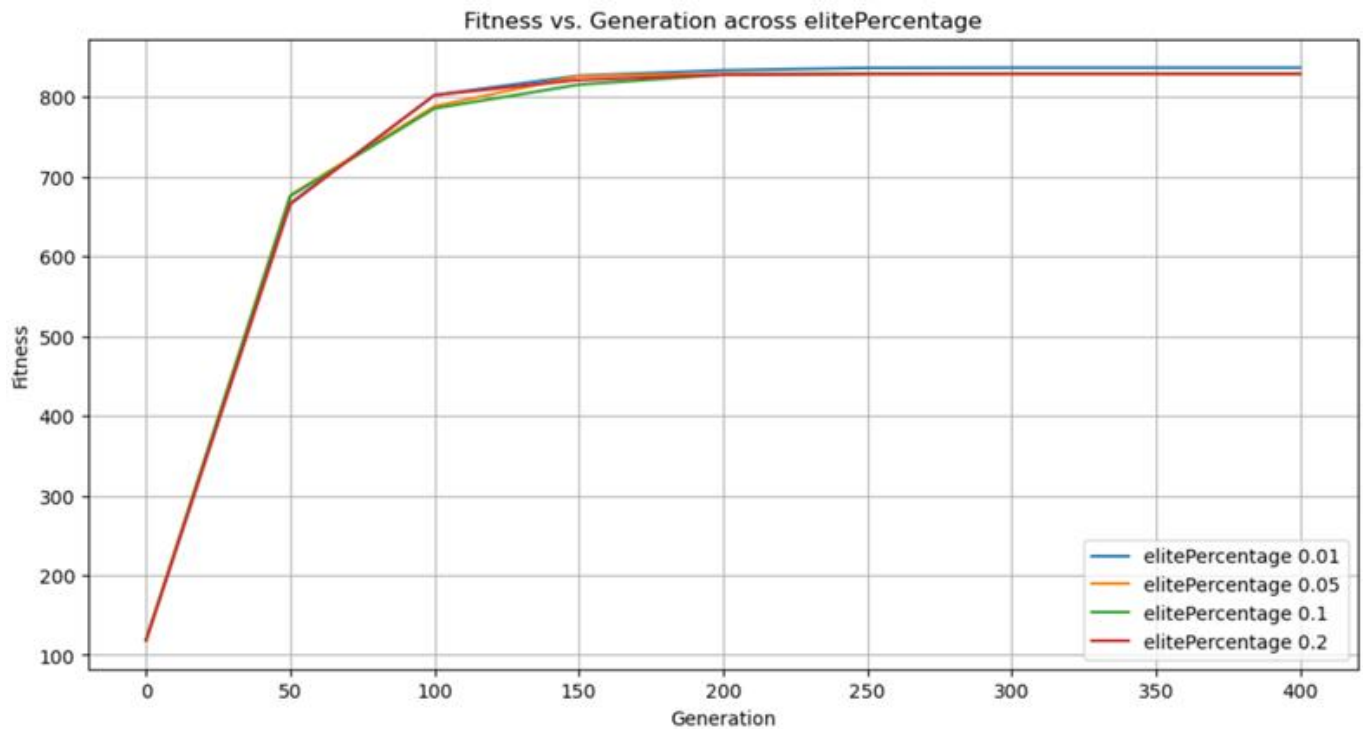
- elitePercentage values of 0.01 show the highest fitness values consistently, reaching a fitness of 836.835 by generation 250.
- elitePercentage values of 0.05, 0.1, and 0.2 show slower fitness increases, with all stabilizing around 829.175 by generation 250.

Parameter Choice

0.01 ensures rapid convergence to high fitness values while maintaining the robustness of the genetic algorithm.

Circuit Parameters Analysis

Number of Units

The number of units in the circuit configuration can significantly affect performance metrics like elapsed time, performance, recovery, and grade.

Analysis Results

Num Units	Elapsed Time (s)	Performance	Recovery	Grade	Final Circuit Configuration
4	1.35789	110.25	0.150332	0.965671	2 1 1 2 4 0 0 0 3 3 0 2 5
6	2.45652	232.583	0.280938	0.977566	1 6 5 5 5 2 3 0 5 1 5 2 4 5 2 7 0 0 2
8	4.5209	341.632	0.37187	0.989275	4 7 7 1 7 0 3 0 3 6 0 1 4 0 3 5 0 3 2 0 3 9 8 0 0
10	6.82153	437.72	0.471582	0.990517	0 8 1 6 2 7 0 10 8 8 8 1 4 8 1 9 8 0 11 8 1 3 2 8 1 2 2 7 8 1 5

Visualization
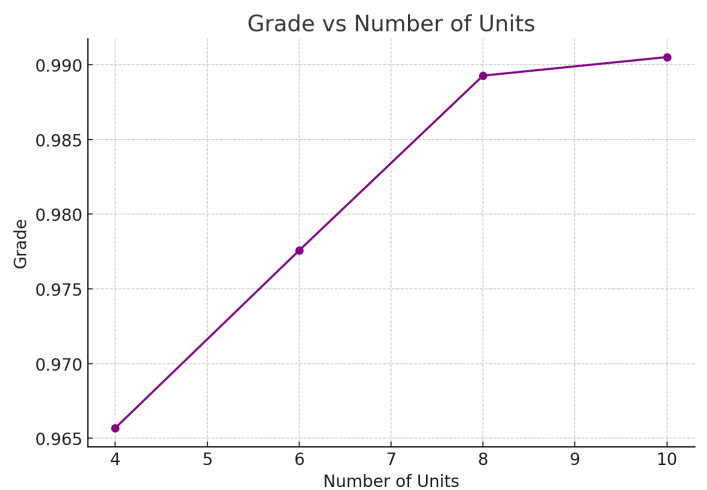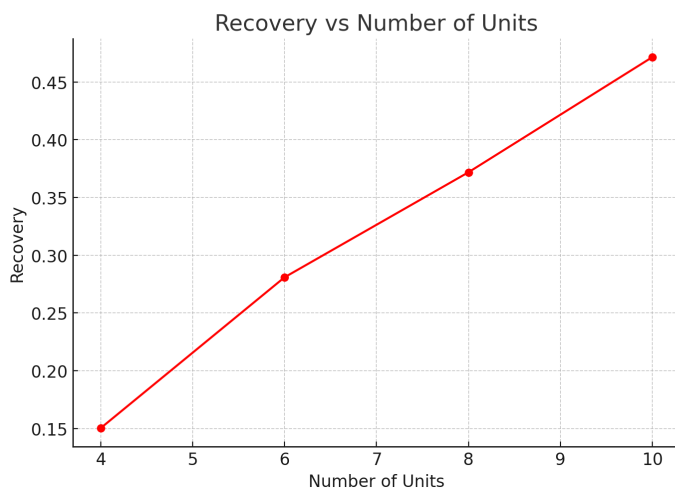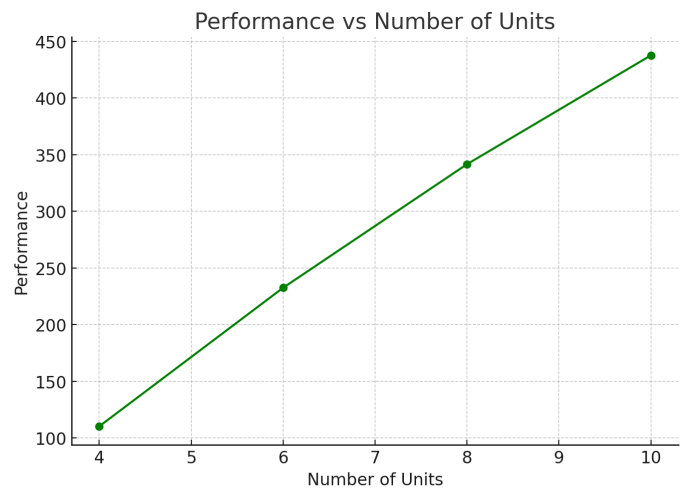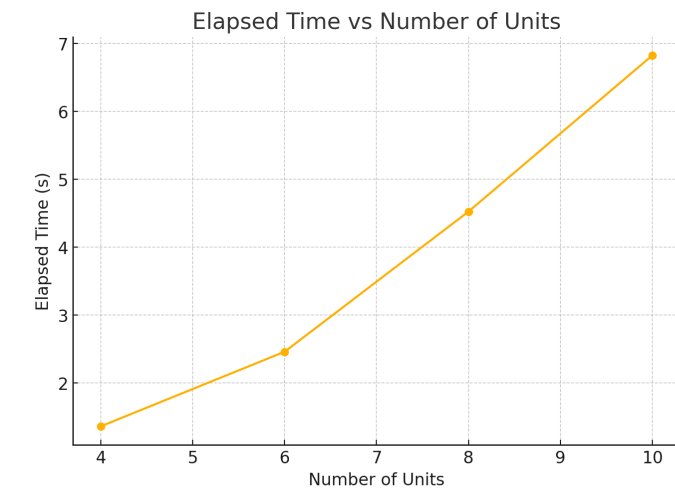
Trends

- **Elapsed Time**: Increases almost linearly with the number of units, reflecting increased complexity and processing time.

- **Performance**: Improves significantly with an increasing number of units, indicating better processing capabilities and efficiency.

- **Recovery**: Increases with the number of units, suggesting improved system capacity to recover from errors or faults.

- **Grade**: Slight improvement with the number of units, indicating overall better performance and efficiency in larger configurations.

Purity of Input Feed (Gerardium:Waste Feed Ratio)

The purity of the input feed, represented as the ratio of gerardium feed to waste feed, can significantly affect performance metrics like elapsed time, performance, recovery, and grade.

Analysis Results

Gerardium:Waste Feed	Elapsed Time (s)	Performance	Recovery	Grade	Final Circuit Configuration
10:90	6.64633	437.72	0.471582	0.990517	5 7 1 6 2 3 5 10 7 7 2 7 1 7 1 0 7 1 8 7 1 9 2 2 3 7 1 4 7 5 11
20:80	6.44538	862.07	0.494251	0.983232	8 3 6 9 3 6 4 5 3 6 10 5 2 3 6 11 10 3 3 5 2 8 3 2 0 5 2 7 3 6 1
30:70	6.97441	1320.43	0.498122	0.984718	7 2 2 8 2 8 9 10 10 3 10 2 0 2 8 1 3 8 11 2 0 4 2 0 6 2 3 7 2 8 5
40:60	6.51499	1838.62	0.522236	0.984274	5 10 10 7 0 5 6 0 5 11 10 0 5 0 3 9 0 3 8 0 5 2 10 0 3 0 3 4 0 3 1
50:50	6.95478	2369.51	0.534505	0.985107	7 10 8 4 8 4 6 8 4 1 10 8 0 10 3 7 8 0 9 8 4 11 8 0 5 10 10 3 8 0 2
60:40	6.10315	3029.69	0.652294	0.970762	6 10 8 3 9 8 4 10 8 1 10 8 2 9 8 5 9 6 7 10 9 0 9 6 11 10 9 6 10 10 8
70:30	5.96057	4044.07	0.758418	0.969211	5 10 5 3 10 5 0 10 5 1 10 5 8 10 5 2 10 4 4 5 5 7 5 2 11 10 5 9 10 5 6
80:20	5.83807	5417.92	0.816378	0.97778	2 10 2 1 10 2 6 10 3 3 10 2 7 2 5 11 10 2 8 10 2 4 10 2 5 10 2 9 10 2 0
90:10	5.46021	7134.92	0.902775	0.984013	7 10 7 5 10 2 9 10 7 3 10 7 0 10 7 8 10 7 4 10 10 2 10 10 6 10 7 1 10 5 11

Visualization

Impact of Gerardium:Waste Feed Ratio on Circuit Performance Metrics
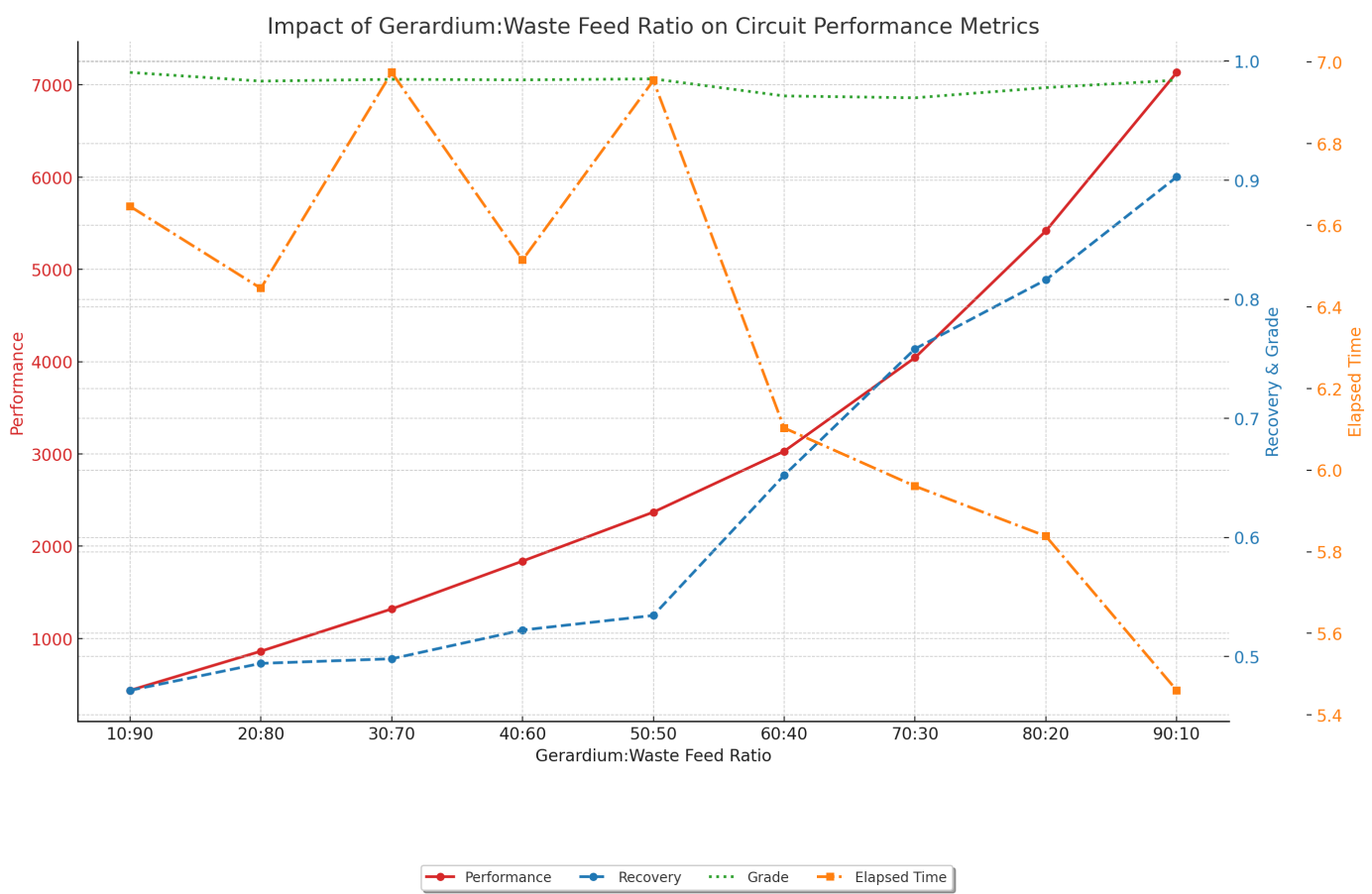
Trends

- **Performance** (red line, circles) shows a significant increase as the proportion of gerardium feed increases.
- **Recovery** (blue line, dashed) improves with higher gerardium feed, indicating better extraction efficiency.

- **Grade** (green line, dotted) remains relatively stable with slight fluctuations.
- **Elapsed Time** (orange line, squares) shows a decreasing trend, suggesting improved computational efficiency with higher purity feeds.

# Price Ratio of Gerardium to Waste Disposal

The economic parameters, specifically the reward for gerardium and the penalties for waste disposal, significantly affect the performance metrics of the circuit. This analysis examines how changes in these economic parameters impact the optimum circuit configuration, performance, recovery, and grade.

Analysis Results

Default reward and penalty is 100 and -750.

Reward/Penalty Coefficient	Num Units	Elapsed Time (s)	Performance	Recovery	Grade	Final Circuit Configuration
Reward of £100 * 5 per kg	5	1.99066	167.379	0.202835	0.977224	3 1 4 6 2 2 4 5 1 1 1 4 0 1 1 3
Reward of £100 * 5 per kg	10	6.86852	437.72	0.471582	0.990517	1 6 9 8 6 9 2 6 9 4 10 6 6 6 9 0 3 6 9 3 3 5 6 1 11 6 9 7 3 5 1
Reward of £100 * 10 per kg	5	2.08692	167.379	0.202835	0.977224	2 3 4 6 5 3 3 3 4 0 1 1 4 3 3 2
Reward of £100 * 10 per kg	10	6.76027	437.72	0.471582	0.990517	0 7 5 3 7 0 11 7 5 1 7 5 9 7 5 2 6 8 0 10 7 7 6 6 8 6 7 5 7 5 4
Penalty of £750 * 5 per kg	5	1.94702	167.379	0.202835	0.977224	1 5 4 4 4 3 2 4 3 6 4 4 1 0 0 3
Penalty of £750 * 5 per kg	10	6.7229	437.72	0.471582	0.990517	7 6 9 1 6 9 4 5 6 9 6 9 8 6 9 3 10 6 6 5 5 2 6 9 0 6 7 11 5 2 7
Penalty of £750 * 10 per kg	5	1.87025	162.125	0.196688	0.977106	0 3 4 4 5 3 3 3 0 6 1 1 0 3 0 2
Penalty of £750 * 10 per kg	10	7.42508	437.72	0.471582	0.990517	2 9 2 11 9 8 7 9 8 1 6 9 8 9 8 0 9 8 4 10 9 9 9 8 5 6 3 2 6 6 3

Visualization
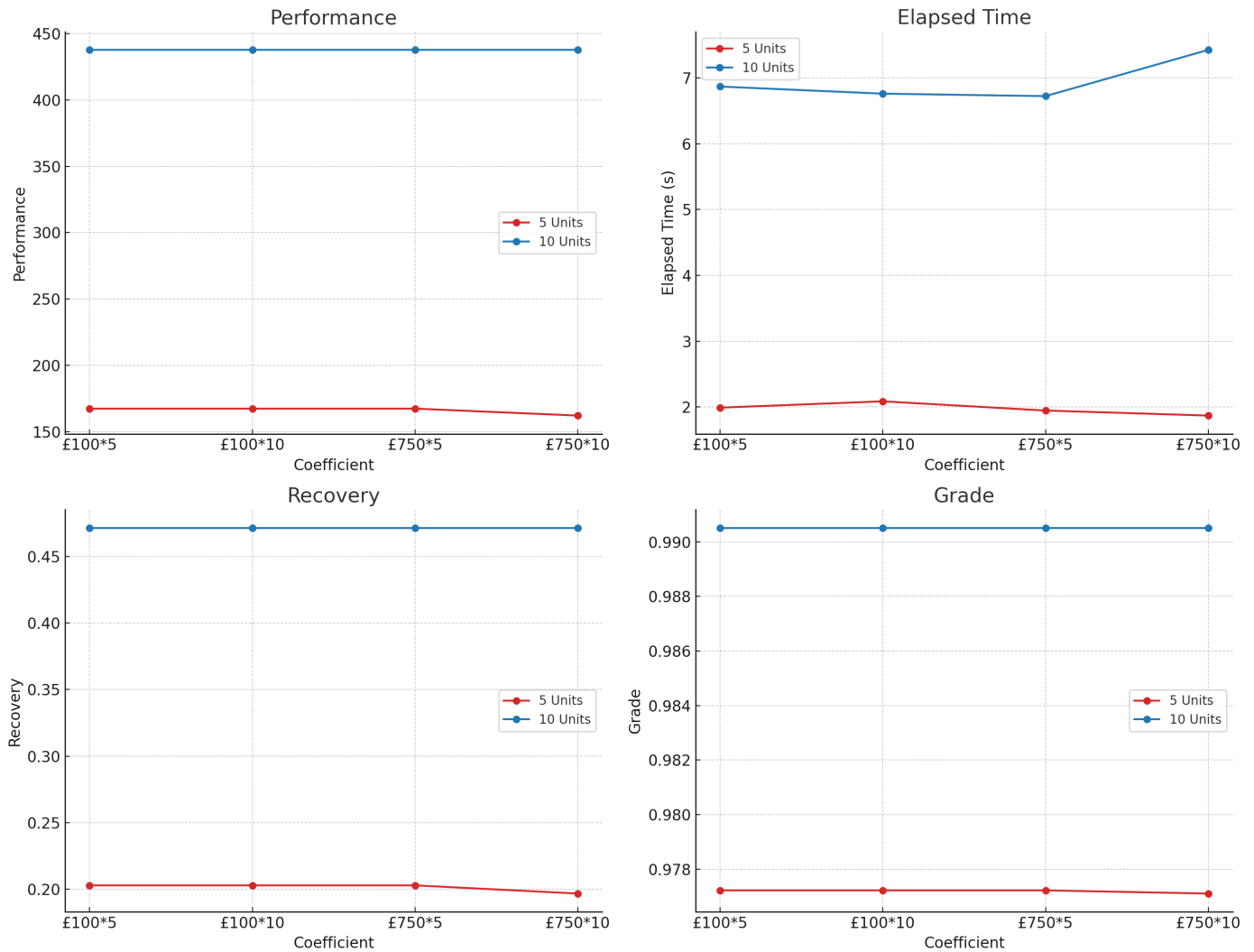
The visualizations above show the impact of different economic parameters on the circuit performance metrics for configurations with 5 and 10 units:

- **Performance**: Remains constant at 167.379 for lower penalty coefficients but drops to 162.125 when the penalty increases significantly. For 10 units, the performance remains stable at 437.72 across all economic parameters.

- **Elapsed Time**: Shows slight variations but generally increases with higher penalties. For 5 units, elapsed time decreases slightly with increased reward but rises with higher penalties.

- **Recovery**: Remains relatively constant for both 5 and 10 units, indicating that recovery is less sensitive to changes in economic coefficients.

- **Grade**: Remains stable for both 5 and 10 units, showing minimal fluctuation.

Recommendations

- **Optimize for Higher Units**: Configurations with more units (10 units) are less sensitive to economic parameter changes, maintaining stable performance and grade.

- **Penalty Management**: When penalties for waste disposal are high, consider optimizing circuit configurations to minimize waste, as higher penalties can negatively impact performance.

- **Reward Adjustments**: Increasing rewards has minimal impact on performance and recovery, suggesting that optimizing for penalties might be more critical in achieving better economic outcomes.