

# Genetic Algorithm Project Report

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Course: Artificial Intelligence and Expert Systems

Instructor: Dr. Abdi

Student: Amirhossein Eslami

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## Abstract

This project investigates the application of Genetic Algorithms (GA) to solving systems of linear and nonlinear equations with multiple variables.

The main objective is to design and implement a solver that relies solely on GA concepts, avoiding direct numerical methods.

The implemented process follows these steps:

1. Accept user-defined equations as input.
2. Generate an initial population.
3. Evaluate fitness using an error function.
4. Select parents based on fitness ranking.
5. Apply crossover and mutation operators.
6. Produce successive generations until an acceptable solution is reached.

The project is divided into three stages, addressing systems of two, three, and four variables, respectively. Special attention was given to avoiding local minima and improving convergence speed. Final results were compared with reference examples from the course materials, and several optimization strategies are proposed for future improvement.

Keywords: Genetic Algorithm, Equation Solving, Fitness Function, Crossover, Mutation

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## Chapter 1 : Solving Two-Variable Systems

The first implementation focuses on solving two-variable systems of equations.

- Input Handling: Coefficients for variables (x, y) along with constants (c1, c2) are collected from the user.
- Initial Population: Random chromosomes representing candidate solutions are generated.
- Fitness Function: Each chromosome is evaluated by computing the error of substituted values in the equations.
- Parent Selection: Chromosomes are sorted by fitness, and the top candidates are selected for reproduction.
- Crossover and Mutation:
  - \* Crossover produces new chromosomes by combining parent genes.
  - \* Mutation introduces randomness to maintain diversity and avoid premature convergence.
- GA Execution: The algorithm iteratively generates new populations until the solution converges within a predefined accuracy.
- Testing: Several test cases from lecture notes demonstrate that the GA achieved highly accurate solutions.

```
def get_equation_coefficients() -> tuple[tuple[float, float, float], tuple...:
    print("(a1 * x + b1 * y = c1):")
    a1 = float(x=input(prompt="input a1: "))
    b1 = float(x=input(prompt="input b1: "))
    c1 = float(x=input(prompt="input c1: "))

    print("\n(a2 * x + b2 * y = c2):")
    a2 = float(x=input(prompt="input a2: "))
    b2 = float(x=input(prompt="input b2: "))
    c2 = float(x=input(prompt="input c2: "))

    return (a1, b1, c1), (a2, b2, c2)
```

Figure 1-1 Genetic Algorithm Define Equation's Coefficient

```
def generate_initial_population(pop_size=100, lower_bound=-100, upper_bound=100) -> list:
    population: list = []
    for _ in range(stop/pop_size):
        x: float = random.uniform(a=lower_bound, b=upper_bound)
        y: float = random.uniform(a=lower_bound, b=upper_bound)
        chromosome: list[float] = [x, y]
        population.append(object/chromosome)
    return population
```

Figure 1-2 Generate Initial Population Function

```
def fitness(chromosome, eq1, eq2) -> Any:
    x: Any, y: Any = chromosome
    a1: Any, b1: Any, c1: Any = eq1
    a2: Any, b2: Any, c2: Any = eq2

    error1: Any = (a1*x + b1*y) - c1
    error2: Any = (a2*x + b2*y) - c2

    totalSquaredError: Any = error1**2 + error2**2

    return totalSquaredError
```

Figure 1-3 Fitness Function

```
def select_parents(population, eq1, eq2, num_parents=NUM_PARENTS_SELECTION) -> list:
    population_sorted: list = sorted(iterable/population, key=lambda chromo: fitness(chromosome=chromo, eq1=eq1, eq2=eq2))
    return population_sorted[:num_parents]
```

Figure 1-4 Parents Selection Function

```
def cross_over(parent1, parent2) -> list:
    x: Any = (parent1[0] + parent2[0])/2
    y: Any = (parent1[1] + parent2[1])/2
    return [x,y]
```

Figure 1-5 Cross Over Function

```
def mutate(chromosome, mutation_rate = MUTATION_RATE) -> Any:
    if(random.random < mutation_rate):
        chromosome[0] += random.uniform(a=MUT_MIN_BOUND, b=MUT_MAX_BOUND)

    if(random.random < mutation_rate):
        chromosome[1] += random.uniform(a=MUT_MIN_BOUND, b=MUT_MAX_BOUND)

    return chromosome
```

Figure 1-6 Mutate Function

```

def genetic_algorithm(eq1, eq2, generations=1000, pop_size=100) -> Any:
    lower: Any, upper: Any = estimate_bounds(eq1=eq1, eq2=eq2)
    population: list = generate_initial_population(pop_size=pop_size, lower_bound=lower, upper_bound=upper)

    for generation in range(stop/generations):
        population: list = sorted(iterable/population, key=lambda chromo: fitness(chromosome=chromo, eq1=eq1, eq2=eq2))
        best_fitness: Any = fitness(chromosome=population[0], eq1=eq1, eq2=eq2)

        if best_fitness < 1e-6:
            print(f"Solution found in generation {generation}")
            return population[0]

        parents: list = select_parents(population=population, eq1=eq1, eq2=eq2, num_parents=20)

        # Generate new population
        new_population: list = []
        while len(obj/new_population) < pop_size:
            parent1: Any = random.choice(seq=parents)
            parent2: Any = random.choice(seq=parents)
            child: list = crossover(parent1=parent1, parent2=parent2)
            child: list = mutate(chromosome=child)
            new_population.append(object/child)

        population: list = new_population

    print("No exact solution found. Best approximation:")
    return sorted(iterable/population, key=lambda chromo: fitness(chromosome=chromo, eq1=eq1, eq2=eq2))[0]

```

Figure 1-7 Implement Genetic Algorithm

```

eq1: tuple[float, float, float], eq2: tuple[float, ... = get_equation_coefficients()
solution: Any = genetic_algorithm(eq1=eq1, eq2=eq2)
print(f"Approximate solution: x = {solution[0]}, y = {solution[1]}")

```

Figure 1-8 Test The Algorithm

```

(a2 * x + b2 * y = c2):
input a2: 4
input b2: 4
input c2: 12
Solution found in generation 8
Approximate solution: x = 2.0002460012081356, y = 0.9998368463088123

```

Figure 1-9 The Given Input Coefficients and its Outcome

$$\begin{cases} x + 2y = 4 \\ 4x + 4y = 12 \end{cases} \Rightarrow \begin{cases} x = 2 \\ y = 1 \end{cases}$$

Figure 1-10 Comparison with Lecture Note Example

## Chapter 2 : Solving Three-Variable Systems

In this phase, the solver was extended to handle systems with three unknowns.

- Equation Parsing: A parser was implemented to convert user input strings into mathematical expressions.
- Validation: The parser was tested to ensure correctness of interpretation.
- Population Generation and Fitness Evaluation: Similar to Chapter 1, but adapted for three variables.
- Optimization Challenge: The algorithm occasionally converged to local minima. To address this, hyperparameters such as population size and mutation probability were tuned.
- Results:
  - \* With proper adjustments, the GA produced solutions close to the expected values.
  - \* However, in some cases, convergence was slower and accuracy lower compared to the two-variable case.
- Improvement: The parsing function was refined using error handling (try/catch) to avoid crashes when input length was zero.
- Verification: With the improved parser, the GA successfully solved example cases from the course materials.

```
[ 86.97729318  55.52272624 -63.15352858]
[ 89.38986747 -54.7790876   20.51801454]
[ 75.41624617  70.6048285   32.71599405]
[ 10.38029788 -59.1987186   80.97408002]
[ 57.81295752 -83.49314924  21.3168993 ]
[ 53.58523012  51.50790263  88.58781311]
[  8.9172475  -28.59502087  -3.64102061]
[  5.11679739 -94.12217514   1.81424585]]
```

Figure 2-1 Example of Initial Population Created

```
Generation 260: Fitness=0.000398 | Solution=[ 0.66666731 -4.99996553  0.75001814]
Generation 270: Fitness=0.000398 | Solution=[ 0.66666731 -4.99996553  0.75001814]
Generation 280: Fitness=0.000398 | Solution=[ 0.66666731 -4.99996553  0.75001814]

Converged at generation 282

Best Solution Found: [ 0.66666731 -4.99996553  0.75001814] | Fitness: 0.00039753
```

Figure 2-2 Example Execution after Parser Correction

$$\begin{cases} 6x - 2y + 8z = 20 \\ y + 8x \times z = -1 \\ 2z \times \frac{6}{x} + \frac{3}{2}y = 6 \end{cases} \Rightarrow \begin{cases} x = \frac{2}{3} \\ y = -5 \\ z = \frac{3}{4} \end{cases}$$

Figure 2-3 Comparison The Output with Lecture Note Example

### Chapter 3 : Solving Four-Variable Systems

The final stage scales the GA approach to four-variable systems.

- Reused Components: The equation parser and GA framework from previous chapters were adapted.
- Modifications:
  - \* Initial population generation was updated to accommodate four variables.
  - \* The fitness function and parent selection methods were extended accordingly.
- Crossover and Mutation: Two-point crossover was employed to enhance genetic diversity.
- Challenges and Debugging:
  - \* Some initial runs failed due to missing variables in the equation set.
  - \* After revising the code, the GA produced valid outputs.
- Performance:
  - \* Convergence was slower than in the previous cases due to increased complexity.
  - \* Nevertheless, the GA approximated correct solutions with reasonable accuracy.
- Validation: Testing against course-provided examples confirmed that the GA was effective, though requiring more generations to converge.

$$\left\{ \begin{array}{l} \frac{1}{15}x - 2y - 15z - \frac{4}{5}t = 3 \\ -\frac{5}{2}x - \frac{9}{4}y + 12z - t = 17 \\ -13x + \frac{3}{10}y - 6z - \frac{2}{5}t = 17 \\ \frac{1}{2}x + 2y + \frac{7}{4}z + \frac{4}{3}t = -9 \end{array} \right. \Rightarrow \left\{ \begin{array}{l} x = -\frac{3}{2} \\ y = -\frac{7}{2} \\ z = \frac{1}{3} \\ t = -\frac{11}{8} \end{array} \right.$$

Figure 3-1 Test Example from Lecture Notes

```

Generation 450: Fitness=0.071310 | Solution=[-1.50631039 -3.58116331 0.33279771 -1.20937392]
Generation 460: Fitness=0.069184 | Solution=[-1.50631039 -3.57729725 0.33279771 -1.22949652]
Generation 470: Fitness=0.063313 | Solution=[-1.50631039 -3.57140963 0.33279771 -1.22949652]
Generation 480: Fitness=0.063186 | Solution=[-1.50631039 -3.57140963 0.33279771 -1.23321487]
Generation 490: Fitness=0.063186 | Solution=[-1.50631039 -3.57140963 0.33279771 -1.23321487]

Best Solution Found: [-1.50631039 -3.56552839 0.33279771 -1.82891225] | Fitness: 0.06008997

```

Figure 3-2 Final Result for Third Example in Lecture Notes



Generation 0: Fitness=127.004842	Solution=[ 6.16553091 16.16945556 -2.15658104 -2.21036724]
Generation 10: Fitness=19.530861	Solution=[ -3.38730352 -25.48260198 0.30490369 44.36894754]
Generation 20: Fitness=17.734695	Solution=[ -3.25552233 -23.58713551 0.30490369 40.0093181 ]
Generation 30: Fitness=15.804868	Solution=[ -3.00343208 -21.396381 0.30490369 35.63696285]
Generation 40: Fitness=13.963144	Solution=[ -2.86966231 -19.34966321 0.30490369 31.22518035]
Generation 50: Fitness=12.185051	Solution=[ -2.71653881 -17.26514116 0.30490369 27.05279947]
Generation 60: Fitness=10.541389	Solution=[ -2.61584543 -15.18854255 0.30490369 22.92924996]
Generation 70: Fitness=8.915023	Solution=[ -2.39846992 -13.68131644 0.30490369 18.96829001]
Generation 80: Fitness=7.024927	Solution=[ -2.178662 -11.51478753 0.30490369 14.99521919]
Generation 90: Fitness=5.675548	Solution=[ -1.96316009 -9.96722624 0.30490369 11.68997507]
Generation 100: Fitness=4.443619	Solution=[ -1.96930911 -8.42904099 0.30490369 8.34435485]
Generation 110: Fitness=3.463299	Solution=[ -1.78012915 -7.4584595 0.30490369 6.3945639 ]
Generation 120: Fitness=2.707981	Solution=[ -1.78012915 -5.98230302 0.30490369 4.3280128 ]
Generation 130: Fitness=2.075754	Solution=[ -1.69943568 -5.86872632 0.33210244 3.46091749]
Generation 140: Fitness=1.791165	Solution=[ -1.69399958 -5.29630913 0.33210244 2.5992575 ]
Generation 150: Fitness=0.972814	Solution=[ -1.59689126 -4.61441552 0.33210244 0.84216495]
Generation 160: Fitness=0.750487	Solution=[ -1.5741883 -4.31151642 0.33210244 0.36968075]
Generation 170: Fitness=0.706840	Solution=[ -1.56917638 -4.31120867 0.33210244 0.25358975]
Generation 180: Fitness=0.637297	Solution=[ -1.56283654 -4.22204948 0.33210244 0.11303156]
Generation 190: Fitness=0.305283	Solution=[ -1.52535303 -3.85114949 0.33210244 -0.69067063]
Generation 200: Fitness=0.230173	Solution=[ -1.52535303 -3.74908846 0.33210244 -0.88105148]
Generation 210: Fitness=0.216269	Solution=[ -1.51886519 -3.74908846 0.33210244 -0.88105148]
Generation 220: Fitness=0.186251	Solution=[ -1.51886519 -3.70867263 0.33210244 -0.94337448]
Generation 230: Fitness=0.177784	Solution=[ -1.51886519 -3.6960978 0.33210244 -0.96940369]
Generation 240: Fitness=0.172078	Solution=[ -1.51682874 -3.6960978 0.33210244 -0.97938776]
Generation 250: Fitness=0.169025	Solution=[ -1.51682874 -3.68805657 0.33210244 -1.01415944]
Generation 260: Fitness=0.166817	Solution=[ -1.51598519 -3.68805657 0.33210244 -0.98607502]
Generation 270: Fitness=0.163448	Solution=[ -1.51598519 -3.6862653 0.33210244 -1.00507325]
Generation 280: Fitness=0.155574	Solution=[ -1.51598519 -3.67575464 0.33279771 -1.01539342]
Generation 290: Fitness=0.150896	Solution=[ -1.51598519 -3.66878945 0.33279771 -1.02942929]
Generation 300: Fitness=0.134583	Solution=[ -1.51316211 -3.647512 0.33279771 -1.09923119]
Generation 310: Fitness=0.121490	Solution=[ -1.51316211 -3.63394698 0.33279771 -1.09923119]
Generation 320: Fitness=0.119422	Solution=[ -1.50841471 -3.63394698 0.33279771 -1.10835896]
Generation 330: Fitness=0.113487	Solution=[ -1.50841471 -3.62511255 0.33279771 -1.11559108]
Generation 340: Fitness=0.095443	Solution=[ -1.50841471 -3.6084463 0.33279771 -1.15239723]
Generation 350: Fitness=0.094143	Solution=[ -1.50841471 -3.6084463 0.33279771 -1.16243583]
Generation 360: Fitness=0.090322	Solution=[ -1.50841471 -3.60146772 0.33279771 -1.16345611]
Generation 370: Fitness=0.085354	Solution=[ -1.50777777 -3.59753991 0.33279771 -1.176509 ]
Generation 380: Fitness=0.081243	Solution=[ -1.50777777 -3.59312712 0.33279771 -1.18984082]
Generation 390: Fitness=0.079363	Solution=[ -1.50777777 -3.58861645 0.33279771 -1.18984082]
Generation 400: Fitness=0.078794	Solution=[ -1.50777777 -3.58861645 0.33279771 -1.19162429]
Generation 410: Fitness=0.077344	Solution=[ -1.50631039 -3.58861645 0.33279771 -1.20232895]
Generation 420: Fitness=0.074585	Solution=[ -1.50631039 -3.58030492 0.33279771 -1.20232895]
Generation 430: Fitness=0.073424	Solution=[ -1.50631039 -3.58435532 0.33279771 -1.20937392]
Generation 440: Fitness=0.073424	Solution=[ -1.50631039 -3.58435532 0.33279771 -1.20937392]
Generation 450: Fitness=0.071310	Solution=[ -1.50631039 -3.58116331 0.33279771 -1.20937392]

Figure 3-3 Convergence Path Toward Final SolutionFigure 3-2

## Conclusion

This project demonstrated the feasibility of using Genetic Algorithms to solve multi-variable systems of equations without relying on direct numerical methods.

While the GA successfully solved systems of two, three, and four variables, performance issues such as local minima and slow convergence in higher-dimensional cases highlight areas for improvement.

## Future Work

- Adaptive mutation rates to reduce premature convergence.
- Hybrid approaches combining GA with classical optimization methods.
- Parallelization of population evaluation to reduce runtime.

## References

1. Course Lecture Notes
2. Problem Set Handouts
3. ChatGPT (AI Assistant)