

INDIAN INSTITUTE OF TECHNOLOGY, KHARAGPUR DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

OPTIMISATION AND HEURISTIC METHOD LAB (IM39003)

TERM PROJECT Optimizing Bank Lending Decisions Using Metaheuristics

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Genetic Algorithm

Introduction:

Here we are using genetic algorithm for optimizing the Bank lending decisions. A Genetic Algorithm model that facilitates how banks would make an efficient decision while staying focus on the main objective of bank profit maximization.

Objective:

• To maximize the Profit.

Data:

| Data. | | | | | | | | | | |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|-------|-------|
| D | 60 | | | | | | | | | |
| K | 0.15 | | | | | | | | | |
| Loan | 10 | 25 | 4 | 11 | 18 | 3 | 17 | 15 | 9 | 10 |
| Interest | 0.021 | 0.022 | 0.021 | 0.027 | 0.025 | 0.026 | 0.023 | 0.021 | 0.028 | 0.022 |
| Rating | AAA | BB | A | AA | BBB | AAA | BB | AAA | A | A |
| Loss (λ) | 0.0002 | 0.0058 | 0.0001 | 0.0003 | 0.0024 | 0.0002 | 0.0058 | 0.0002 | 0.001 | 0.001 |

Objective Function: $Fx = \theta + \varpi - \beta - \sum_{i=0}^{n} (\lambda)$

Loan Revenue: $\vartheta = \sum_{i=0}^{n} (\text{rLL} - \lambda)$

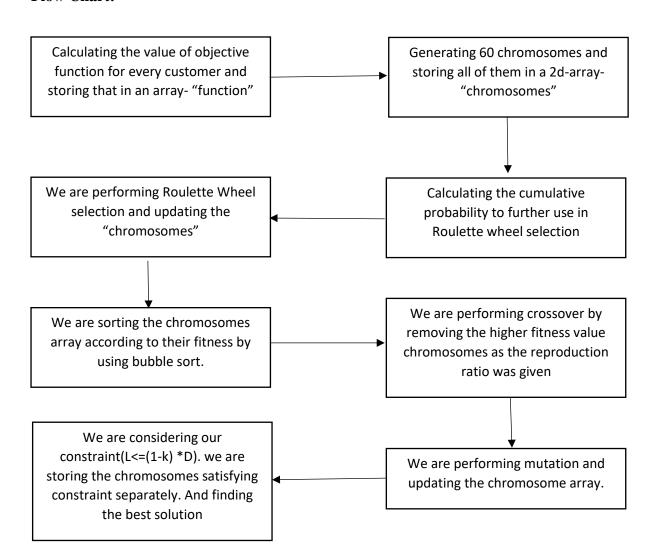
Loan Cost: $\mu = \sum_{i=0}^{n} (L\delta)$

Total transaction cost: $\varpi = \sum_{i=0}^{n} (rLT)$ **Cost of demand deposit:** $\beta = rDD$

Constraint: $L \le (1-k) *D$

| Objective | Determine a bank lending decision that maximizes the bank profit. Determine a bank lending decision that minimizes the crediting cost. |
|-------------------|---|
| Raw Fitness | $F_{x} = \vartheta +_{\varpi} - \beta - \sum_{i=0}^{n} \lambda$ |
| | - Population Size $(n) = 60$ |
| | - GA Generations $(\mathfrak{R}) = 60$ |
| | - Crossover ratio = 0.8 |
| Parameters | - Mutation ratio = 0.006 |
| | - Reproduction $ratio(n) = 0.194$ |
| | - Basic selection method is spanning the weighted roulette |
| | wheel selection |
| Stopping | -The evolution continues until: |
| Criteria | $F_{x}(t) = \Re$ where t is the time interval |

Flow Chart:



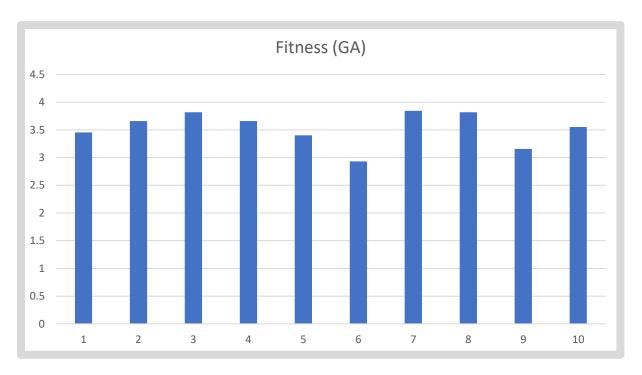
Steps:

- Step 1: Imported libraries numpy, random, math
- Step 2: Declared values for N, population_size, D, k, insti_cost, rD
- Step 3: Stored the values for loan size, loan interest rate, loss
- Step 4: Created empty arrays to store the values of loan_revenue, loan_cost, total_transaction_cost, cost_demand_deposit, function
- Step 5: Got profit value as output for every customer.
- **Step 6:** Generating **60 chromosomes** and storing them in 2d array
- **Step 7:** Calculating the cumulative probability for each chromosome and storing them in array **cum_fit**
- Step 8: Applying roulette wheel selection and updating the value of chromosomes in array.
- Step 9: Sorting array according to their fitness value (from low to high) using bubble sort
- Step 10: Applying crossover on the rest of chromosomes which do not undergo reproduction.
- Step 11: After crossover applying mutation on those chromosomes
- Step 12: Eliminating chromosomes which violates the constraint $(L \le (1-k) *D)$
- Step 13: Storing the rest of chromosomes in chromo and fitness value in fit.
- **Step 14:** Getting the maximum fitness value from **fit** and corresponding chromosome from **chromo**

Result and Inference:

Running the code for 10 times and noting the best solution and its fitness.

| Chromosomes | Fitness | Loan Size |
|-----------------------|---------|-----------|
| [0 0 1 1 0 0 1 0 1 1] | 3.4546 | 51 |
| [0 0 1 1 0 1 1 0 1 0] | 3.6602 | 44 |
| [0 0 0 1 1 1 0 0 1 1] | 3.8182 | 51 |
| [1 0 0 1 0 1 1 0 1 0] | 3.66 | 50 |
| [0 0 1 0 0 1 1 0 1 1] | 3.4038 | 43 |
| [0 0 0 0 1 1 0 1 1 0] | 2.9324 | 45 |
| [1 0 1 0 0 1 0 1 1 1] | 3.8436 | 51 |
| [0 0 0 1 1 1 0 0 1 1] | 3.8182 | 51 |
| [0 0 1 0 1 1 0 1 0 1] | 3.1572 | 50 |
| [0 0 1 0 1 1 1 0 1 0] | 3.554 | 51 |



Best solution obtained so far:

Chromosomes: [1 0 1 0 0 1 0 1 1 1]

Fitness: 3.8436

Simulated Annealing

Introduction:

Here we are using simulated annealing for optimizing the Bank lending decisions. A SA model that facilitates how banks would make an efficient decision while staying focus on the main objective of bank profit maximization.

Objective:

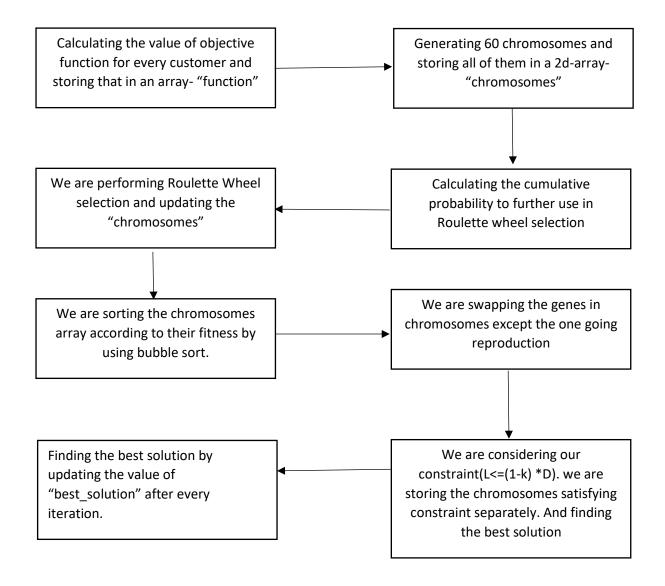
• To maximize the Profit.

Parameters:

Initial Temperature: T0 = 300

Decrease in temperature after every iteration = -5

Flow Chart:



Steps:

- Step 1: Imported libraries numpy, random, math
- Step 2: Declared values for N, population_size, D, k, insti_cost, rD
- Step 3: Stored the values for loan size, loan interest rate, loss
- Step 4: Created empty arrays to store the values of loan_revenue, loan_cost, total_transaction_cost, cost_demand_deposit, function
- Step 5: Got profit value as output for every customer.
- Step 6: Generating 60 chromosomes and storing them in 2d array
- **Step 7:** Calculating the cumulative probability for each chromosome and storing them in array **cum_fit**
- Step 8: Applying roulette wheel selection and updating the value of chromosomes in array.

Step 9: Sorting array according to their fitness value (from low to high) using bubble sort

Step 10: Declaring T0, Tf, n

Step 11: Swapping the randomly chosen bits and updating array chromosome

Step 12: Eliminating chromosomes which violates the constraint $(L \le (1-k) *D)$

Step 13: Storing the rest of chromosomes in chromo and fitness value in fitness.

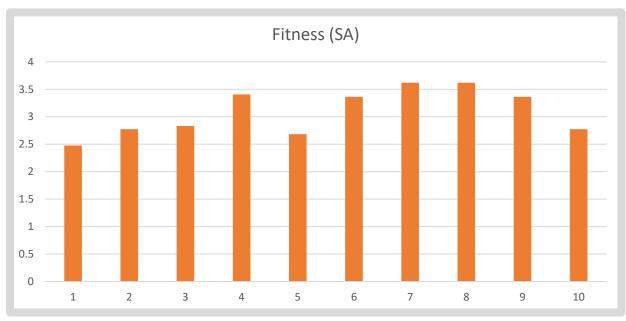
Step 14: declaring **best_solution** and applying simulated annealing and updating the value of best solution accordingly.

Step 15: Printing the value of best solution and respective chromosome.

Result and Inference:

Running the code for 10 times and noting the best solution and its fitness.

| Chromosomes | | | | | | | | | Fitness | Loan Size | | |
|-------------|---|---|---|---|---|---|---|---|---------|-----------|----|--|
| [0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1] | 2.4778 | 40 | |
| [0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0] | 2.774 | 46 | |
| [0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1] | 2.8332 | 34 | |
| [1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0] | 3.4052 | 51 | |
| [1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0] | 2.6832 | 39 | |
| [0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1] | 3.3638 | 51 | |
| [0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1] | 3.6186 | 48 | |
| [0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1] | 3.6186 | 48 | |
| [0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1] | 3.3638 | 49 | |
| [0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0] | 2.774 | 46 | |



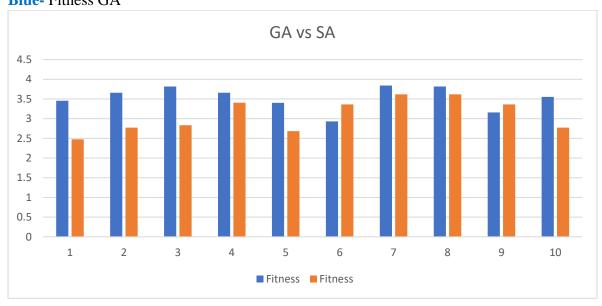
Best solution obtained so far:

Chromosomes: [0 0 0 1 0 1 0 1 1 1]

Fitness: 3.6186

Comparison:

Orange- Fitness SA Blue- Fitness GA



From here we can clearly see that *Genetic Algorithm* is giving better result than *Simulated Annealing*.

Genetic Algorithm & Simulated Annealing

Introduction:

Here we are using genetic algorithm and simulated annealing for optimizing the Bank lending decisions. A GA & SA model that facilitates how banks would make an efficient decision while staying focus on the main objective of bank profit maximization.

Objective:

• To maximize the Profit.

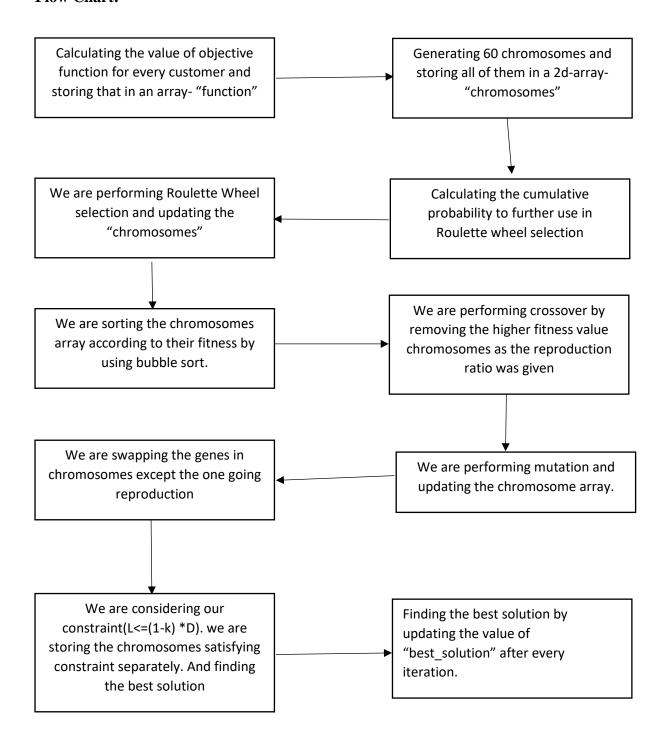
Parameters:

Initial Temperature: T0 = 300

Decrease in temperature after every iteration = -5

Crossover Probability = 0.8 Mutation Probability = 0.006 Reproduction Ratio = 0.194

Flow Chart:



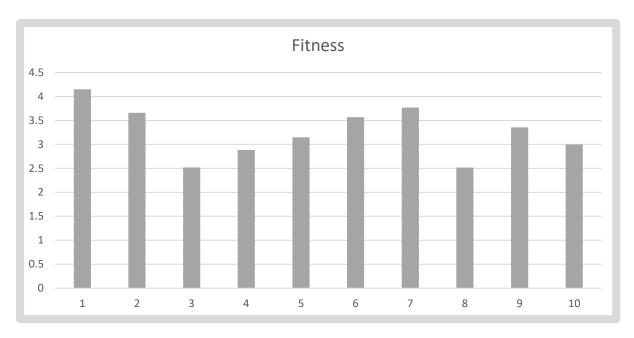
Steps:

- Step 1: Imported libraries numpy, random, math
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- Step 15: Storing the rest of chromosomes in chromo and fitness value in fitness.
- **Step 16:** declaring **best_solution** and applying simulated annealing and updating the value of best solution accordingly.
- *Step 17: Printing the value of best solution and respective chromosome.*

Result and Inference:

Running the code for 10 times and noting the best solution and its fitness.

| Chromosomes | Fitness | Loan Size |
|-----------------------|---------|-----------|
| [1 0 1 1 0 1 0 0 1 1] | 4.1494 | 47 |
| [1 0 0 1 0 1 1 0 1 0] | 3.66 | 50 |
| [0 0 1 1 0 0 1 1 0 0] | 2.5192 | 47 |
| [1 0 0 1 1 1 0 0 0 0] | 2.8828 | 42 |
| [1 0 1 0 0 0 1 0 1 1] | 3.1488 | 50 |
| [0 0 1 1 0 1 0 1 1 0] | 3.5694 | 42 |
| [0 0 1 1 1 1 0 0 1 0] | 3.769 | 45 |
| [0 1 1 1 0 0 0 0 0 1] | 2.5176 | 50 |
| [0 0 1 0 0 1 1 1 1 0] | 3.3544 | 48 |
| [1 0 1 0 0 1 1 1 0 0] | 2.999 | 49 |



Best solution obtained so far:

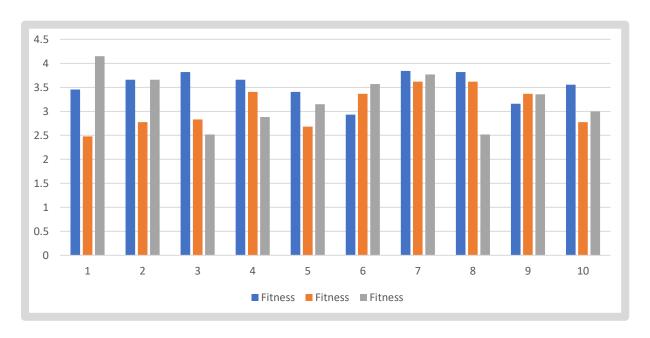
Chromosomes: [1 0 1 1 0 1 0 0 1 1]

Fitness: 4.1494

Comparison:

Orange- Fitness SA Blue- Fitness GA

Grey- Fitness GA & SA



Average fitness GA = 3.53022

Average fitness SA = 3.09122

Average fitness GA & SA = 3.25696

From here we can say using GA & SA gives better than SA but not than GA.

GA >= GA & SA >= SA