Self-Organizing Systems
Assignment 1
GA, CA, and ACO
VRP and CSP
Group 18

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1 Introduction

In this assignment we examined the performance of three algorithms-**Genetic Algorithms** (GA), **Cellular Automata** (CA), and **Ant Colony Optimization** (ACO)- on two problem, one of them is that the **Vehicle Routing Problem** (VRP) and the **Cutting Stocks Problem** (CSP). Our goal is to evaluate differences in the results of each algorithms by comparing the results with their pros and cons in terms of runtime, solution quality, and convergence trends.

2 Problem Definitions

2.1 Vehicle Routing Problem (VRP)

The Vehicle Routing Problem (VRP) involves optimizing routes for vehicles to service customer demands while minimizing costs [4]. The basic vehicle routing problem (VRP) consists of a number of customers, each requiring a speci2ed weight of goods to be delivered. Vehicles dispatched from a single depot must deliver the goods required, then return to the depot. Each vehicle can carry a limited weight and may also be restricted in the total distance it can travel In our case we try to minimize the distance according to following constraints. First of all, we have 100 customers randomly located on a grid.

All routes have to begin and end at a central depot located at the coordinates (0, 0). Each customer has a randomly demand between 1 and 10 units, and the problem is defined with 5 vehicles (which have tough to define it as work days in a week), each with a maximum capacity of 20 units. To compute the distance we used the **Euclidean** distance matrix between all customers and the depot. The problem contains several constraints:

- Each customer must be visited exactly once.
- No vehicle can exceed its capacity.
- All routes must start and end at the depot.

With these constraints, we primarily aimed to minimize the total distance traveled by all the vehicles while meeting all customer demands.

2.2 Cutting Stock Problem (CSP)

The Cutting Stock Problem (CSP) focuses on minimizing material waste when cutting stock materials to meet specific customer demands [**delorme2016bin**]. In our case, we aim to minimize the total number of stock units used according to the following setup. We are provided with a fixed stock length of 100 units, and customer demands are defined as a set of n demand types, each with a required length (l_i) and quantity (q_i). The cutting patterns determine how to combine demand types within the stock length while adhering to capacity limits.

The problem contains several constraints:

- Each demand q_i must be fully satisfied.
- The sum of the lengths in a single cutting pattern cannot exceed the stock length (100 units).
- Patterns must be feasible combinations of demand lengths within the stock length.

Under these constraints, the primary objective is to minimize the total number of stock units used while meeting all customer demands.

3 Algorithms

To solve the problems, we employed three optimization algorithms:

- **Genetic Algorithms (GA)** which are inspired by natural selection by evolving the solutions through key operations such as **selection**, **crossover**, and **mutation** by improving the solution quality over **generations**.
- **Cellular Automata (CA)** simulate the evolution of a system on a grid. Each **cell** interacts with its neighbors following predefined rules, allowing optimized solutions to emerge through local interactions.
- **Ant Colony Optimization (ACO)** mimics the behavior of ants searching for food. **Pheromone**trails guide the search process, enabling a collaborative and efficient exploration of optimal solutions.

4 Experimental Setup

4.1 Datasets

The following datasets were used:

VRP: The basic Vehicle Routing Problem (VRP) involves delivering specified goods to customers using vehicles dispatched from a single depot, with each vehicle having weight and distance limits. Because of the purpose of the assignment we defined the data by following the constructions from the paper[1], we created the data randomly.

CSP: For the basic structure of the parameters for cutting stock problem we used the similar parameters that was used in the paper [3], which were, the demand lengths for the piece to be cut in the range between 500 to 1500, with corresponding demand quantities in the range from 10 to 35. With these parameters define the available material and customer requirements, guiding the optimization process to minimize the waste while meeting the demands from customers.[2]

4.2 Configurations

The experiments were configured as shown in the table 1 below:

Problem	Algorithm	Configuration Details
VRP	GA	Population size: 20, Generations: 50, Crossover rate: 0.8, Mutation rate: 0.1, Fitness function: Minimize total route distance while respecting capacity constraints.
	CA	Iterations: 50, Neighborhood size: 3, Fitness metric: Optimize routes ensuring capacity constraints and full customer coverage, Initial grid: Feasible random routes.
	ACO	Number of ants: 20, Iterations: 50, Evaporation rate: 0.5, Pheromone influence (α): 1, Distance influence (β): 5, Fitness function: Minimize total route distance.
CSP	GA	Population size: 100, Generations: 100, Mutation rate: 0.01, Fitness function: Maximize demand fulfillment while minimizing waste and penalties.
	CA	Grid size: 10×10, Iterations: 100, Mutation probability: 0.03, Reset probability: 0.05, Fitness function: Minimize waste and maintain feasible cutting patterns.
	ACO	Number of ants: 50, Iterations: 100, Evaporation rate: 0.1, Pheromone intensity: 1.0, Alpha (α): 1, Beta (β): 2, Fitness function: Maximize fulfillment while minimizing waste and penalties.

Table 1: Algorithm configurations for Vehicle Routing Problem (VRP) and Cutting Stock Problem (CSP).

5 Results and Discussion

5.1 Vehicle Routing Problem (VRP)

In this part we provided a comparison of the runtime and solution quality of algorithms applied to Vehicle Routing Problem (VRP) the runtime analysis shown in Figure 1, provides that CA had the shortest runtime, completing the task in just 0.13 seconds. This shows the CA's simpler evolutionary mechanism, which require minimal computational resources. The GA showed that a runtime of 0.88 seconds, which uses the computational effort with its iterative solution evolution through selection, crossover, and mutation. ACO had the longest runtime, completing the process in 4.76 seconds. This longer runtime illustrate that ACO's iterative pheromone-based optimization and the computational demands of balancing exploration.

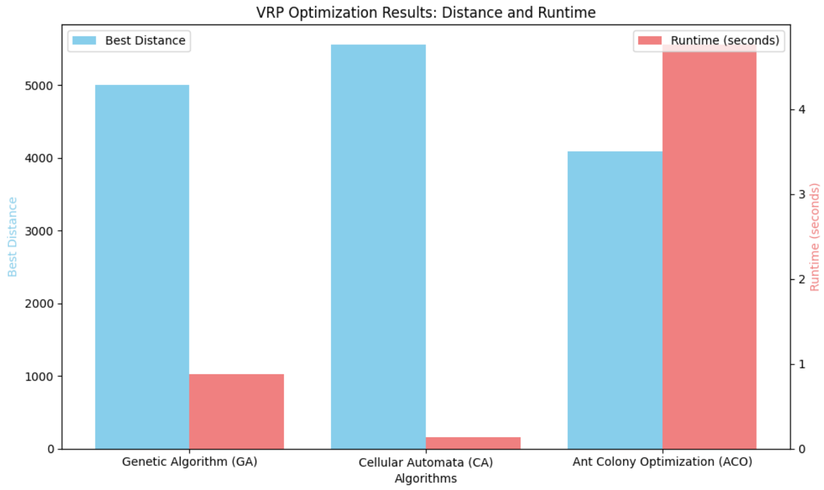

Figure 1: VRP Optimization Results

The results showed in the Table 2 highlight the trade-offs between runtime and solution quality among algorithms. CA's runtime efficiency makes it suitable for time sensitive environments, though its quality of solution, with a best distance of 5554.46, is less optimal compared to ACO. Whereas, ACO achieved the bet distance of 4092.56, offering superior solution quality but at a higher computational cost. The Genetic Algorithm provides a balanced approach, with a best distance of 4999.10 and an acceptable runtime, making it a versatile option for applications requiring a trade-off between speed and solution quality.

Algorithm	**Best Distance**	**Runtime (seconds)**
Genetic Algorithm (GA)	4999.10	0.88
Cellular Automata (CA)	5554.46	**0.13**
Ant Colony Optimization (ACO)	**4092.56**	4.76

Table 2: Updated Results for VRP Optimization Algorithms: Best Distance and Runtime.

In the figure 2, we see that ACO is the most effective algorithm in terms of achieving the optimal solution with the lowest fitness, whereas GA provides a balanced approach, gradually improving over generations but not outperforming ACO. CA converges quickly but struggles to refine the solution further, resulting in higher final fitness. This analysis underscores the importance of algorithm choice based on problem requirements, as we mentioned before that balancing computational efficiency and solution quality.

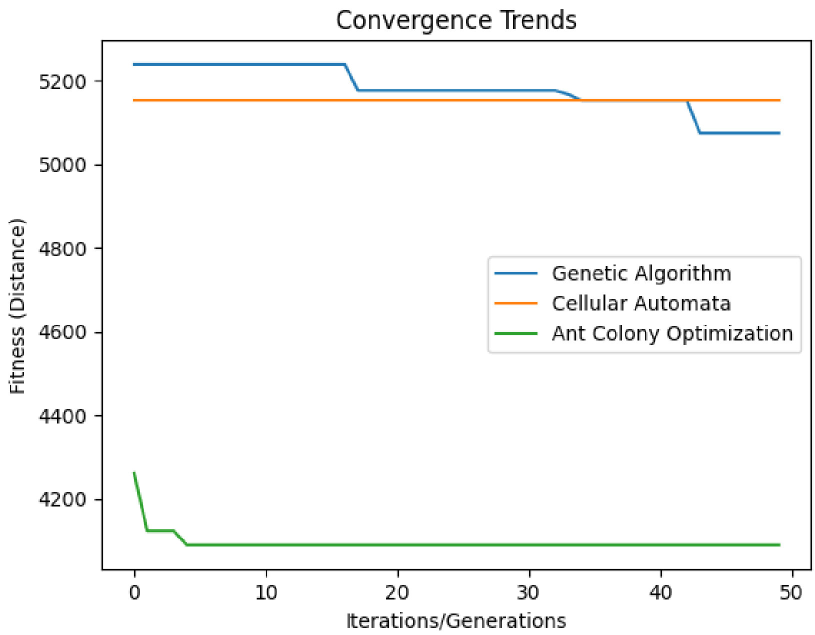

Figure 2: Convergence Trends for VRP

5.2 Cutting Stock Problem (CSP)

For the cutting stock problem, we compared the runtime and waste minimization capabilities of the algorithms. The results in Figure 4 show that Genetic Algorithm (GA) has the longest runtime at 0.96 seconds, while both Cellular Automata (CA) and Ant Colony Optimization (ACO) complete the task in significantly less time, at 0.41 and 0.60 seconds respectively. Despite the differences in runtime, all algorithms achieve the same total waste of 50 units, indicating similar performance in waste minimization. This makes CA the most time-efficient option for CSP problems, followed by ACO, while GA remains the slowest and less ideal for scenarios where runtime is critical.

From Figure 5, we observed that there is a notable differences in waste minimization and convergence behavior among the algorithms. Cellular Automata (CA) is the fastest to converge, reaching consistent waste levels early in the process. Ant Colony Optimization (ACO) demonstrates low and stable waste throughout the iterations, showcasing its effectiveness and stability. In contrast, Genetic Algorithm (GA) exhibits fluctuations in waste over iterations, indicating challenges in achieving consistent minimization. These results highlight the importance of selecting algorithms based on the specific

Algorithm	Runtime (s)	Waste
GA	0.96	50
CA	**0.41**	**50**
ACO	0.60	50

Figure 3: Comparative Results Across Alg.

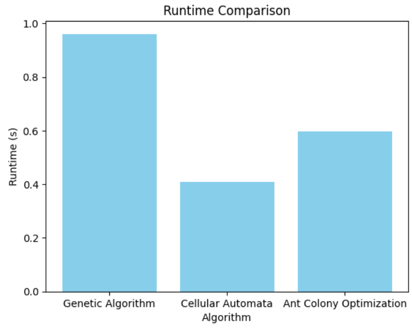

Figure 4: Runtime Comparison Across Algorithms

optimization goals, such as runtime efficiency or waste minimization, for the cutting stock problem.

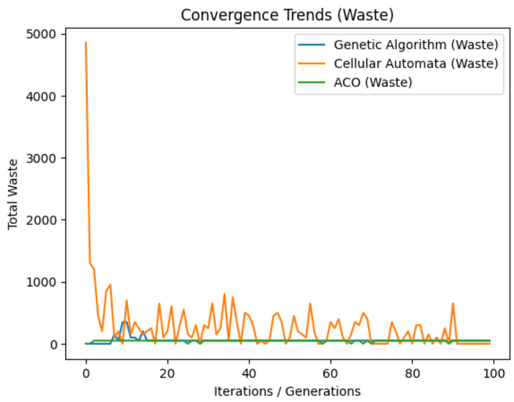

Figure 5: The Waste over the Time for the Algorithms

6 Conclusion

To summarize in the light of the information mentioned above, we can say that we evaluated the performance of Genetic Algorithms (GA), Cellular Automata (CA), and Ant Colony Optimization (ACO) on two different optimization problems, one of them is Vehicle Routing Problem (VRP), and the other one is Cutting Stocks Problem (CSP). The results showed that distinct trade-offs between the algorithms in terms of runtime, solution quality, and convergence behavior. Moreover, for the VRP, ACO consistently achieved the best solution quality by minimizing the total distance traveled, though it required a higher runtime. GA offered a balanced trade-off between runtime and solution quality, while CA demonstrated superior runtime efficiency but converged to less optimal solutions. Additionally, in the CSP, both CA and ACO proved highly effective in minimizing waste and runtime, with CA being the fastest to converge and ACO maintaining stability across iterations. GA, on the other hand, exhibited notable fluctuations and struggled to achieve consistent waste minimization, making it less reliable for this problem. These findings emphasize the importance of selecting algorithms based on the specific priorities of a problem, such as computational efficiency or solution quality.

Adding additional constraints could increase the complexity of the problem, providing more insightful comparisons of runtime differences between the algorithms. For instance, incorporating client importance in the VRP or prioritizing certain demands in the Cutting Stock Problem could yield more meaningful results.

7 Acknowledgments

This project was meant to be a group effort, but my groupmate left the group just five days before the deadline, and the group registration period was already over. As a result, I had to complete the entire project on my own.

References

[1] Barrie M Baker and M A Ayechew. "A genetic algorithm for the vehicle routing problem". In: *Computers & Operations Research* 30.5 (2003), pp. 787–800.

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