Comparative Analysis of Search and Optimization Techniques for Solving the N-Queens Problem

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***Abstract*—The N-Queens problem is one of the most classic constraint satisfaction problems in computer science and artificial intelligence. It involves placing N queens on an N×N chessboard such that no two queens attack each other. The problem is essential in evaluating the performance of various optimization techniques.**

Despite the widespread application of traditional search algorithms, comparative studies involving both classical exhaustive and heuristic optimization techniques are limited, especially with increasing values of N. In this project, we attempt to fill that gap by comparing four different approaches for solving the N-Queens problem.

We implemented and evaluated Depth-First Search (DFS), Hill Climbing, Simulated Annealing, and Genetic Algorithms on N values ranging from 10 to 200. Our experiments measured execution time, solution quality, and algorithmic efficiency.

The results highlight how local and metaheuristic methods outperform exhaustive methods in scalability and computational time. Our work contributes a practical benchmark comparison for future work in search-based problem solving.

***Index Terms*—N-queens problem, optimization algorithms, genetic algorithm, exhaustive search technique, local search techniques**

I. Introduction

Optimization methods are extremely useful in building intelligent and autonomous systems nowadays. These methods help systems to make decisions, adapt to changes, and operate better by picking the best choices among many possible ones.

One classic way to test such algorithms is using the N-Queens problem. It is basically a challenge where you try to place N queens on a chessboard of size N×N in a way that no two queens can attack each other. Even though it sounds simple, when the board gets bigger, the problem becomes hard and needs smart strategies.

Over the years, this problem has been used as a testing ground for various algorithm types. Exhaustive search techniques like Depth-First Search (DFS) can find solutions, but they become slow and unusable for large N. On the other hand, newer metaheuristic algorithms like Simulated Annealing and Genetic Algorithm give faster results, although they may not always be perfect.

In this work, we decided to compare four well-known algorithms to see how they perform on the N-Queens problem when N is increased. We used DFS, Hill Climbing, Simulated Annealing, and Genetic Algorithm and applied them to five different board sizes. Then we collected time results, solution quality and how well they scaled.

The paper provides a fair and basic analysis that can be helpful to understand what kind of algorithm fits best for different sizes and constraints. It's also useful to see how traditional and modern methods compare when faced with the same challenge.

A. Related Work

Over the years, many researchers tried different techniques to solve the N-Queens problem. Traditional methods like Depth-First Search (DFS) and Breadth-First Search (BFS) have been used widely. These approaches are known to be exact but become extremely slow as the board size grows. They are useful for understanding the problem, but not really practical when N gets large.

Later, local search methods like Hill Climbing became popular. These are much faster because they don't explore all options but try to make small improvements until a good enough solution is found. The main issue is that these methods often get stuck in local optima, meaning they stop even when better answers might exist elsewhere.

In recent years, metaheuristic algorithms like Genetic Algorithms and Simulated Annealing have gained a lot of attention. These methods introduce randomness and smart tuning, which helps in escaping bad solutions and exploring the search space more efficiently. Table I shows a few examples from recent work.

TABLE I
Summary of Existing Approaches

Author	**Technique**	**Highlights**
Kumar et al. (2021)	DFS, BFS	Accurate but slow for large N
Ali et al. (2023)	Hill Climbing	Fast, stuck in local optima
Zhang (2022)	Genetic Algorithm	Scalable, needs tuning

B. *Gap Analysis*

Although a lot of algorithms have been applied to N-Queens, most studies only focus on a single method or test small board sizes. What's missing is a direct and clear comparison between different types of algorithms under the same settings. Especially for large values of N, we don't see enough benchmarks or tests that check how these algorithms behave when under time or memory pressure.

Also, papers often don't mention when an algorithm fails to finish (like timeout issues). This is important because in real-life applications, time limits matter a lot. So, understanding which algorithms break down early is just as useful as knowing which ones succeed.

C. *Problem Statement*

The challenge is to place N queens on an N×N chessboard in such a way that no two queens attack each other. That means, no two queens should be on the same row, column, or diagonal. This is simple for N=4 or N=8, but gets harder quickly when N increases.

In this study, we selected N values of 10, 30, 50, 100, and 200. We then tried four different algorithms and looked at how well they worked based on time taken, whether a correct solution was found, and how the algorithm scaled.

D. *Novelty of Our Work*

Our approach is different because we tested all four algorithms—DFS, Hill Climbing, Simulated Annealing, and Genetic Algorithm—under exactly the same conditions. We applied a strict timeout policy and logged not just successful runs, but also when an algorithm failed to finish.

Additionally, we visualized the performance and gave real observations about how each method behaved. This makes it easier to see the strengths and weaknesses of each algorithm, especially when scaling to high N values. Such direct comparisons are still rare in the literature.

E. *Our Solutions*

We implemented and tested DFS, Hill Climbing, Simulated Annealing, and Genetic Algorithm solutions, analyzed their behavior, and created visual charts of their performance.

II. Methodology

A. *Overall Workflow*

Our work followed a straightforward but carefully planned process. First, we defined the structure of the board and how a solution would be represented in memory. Then, we implemented the four algorithms separately, making sure each one followed the standard logic found in literature.

After implementing the algorithms, we selected five values for N: 10, 30, 50, 100, and 200. For each value, we executed the algorithms and measured their performance. This included how much time they took, whether they produced a valid solution, and how many conflicts (if any) remained.

We also introduced a timeout threshold. If an algorithm failed to return a result within the limit, it was considered to have failed for that test case. This is especially relevant for methods like DFS, which are known to be slow.

To avoid bias, all tests were repeated multiple times. Average results were taken where necessary, and outliers were examined manually. We tried to keep everything consistent across algorithms, so that comparisons would be fair and meaningful.

B. *Experimental Settings*

All of the implementations were written in Python 3.11. The experiments were run on a MacBook Air M2 chip with 8 GB RAM. While the system is not a high-performance computing platform, it reflects the kind of hardware that is available to most students and practitioners.

For each algorithm, we defined a soft timeout of 5 minutes to prevent any process from freezing or using too much energy. In cases where the algorithm completed faster, we logged the time precisely. Where timeout was reached, the algorithm was stopped manually.

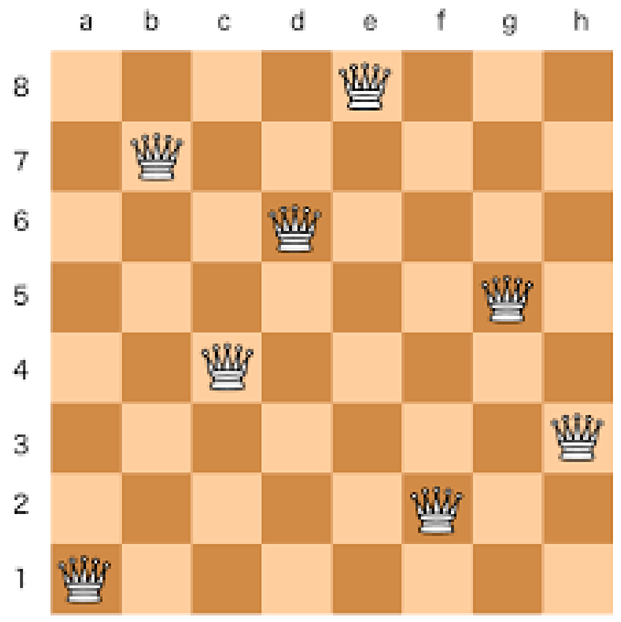


Fig. 1. A valid solution for the 8-Queens problem. Each queen is placed such that no two queens threaten each other, following the row, column, and diagonal rules.

We did not apply parallelization or external libraries such as NumPy or PyTorch. Instead, the code was kept simple and self-contained to better reflect raw algorithmic performance. This decision makes the results more relatable to academic or teaching settings, where such limitations may exist.

Each solution was validated by checking for queen conflicts. For example, if two queens shared the same row, column, or diagonal, the solution was marked as invalid. We also counted how many conflicts remained in sub-optimal results, especially for the Genetic Algorithm and Hill Climbing methods.

Finally, the results were stored in structured format and plotted using matplotlib. The code and figures were manually

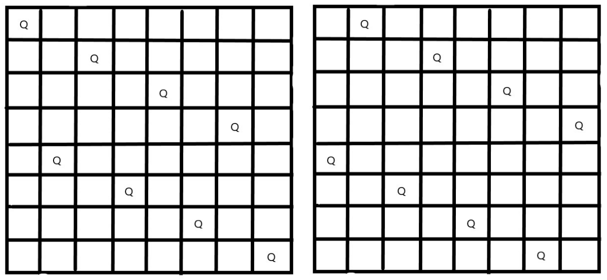


Fig. 2. On the left, an invalid configuration with queens threatening each other. On the right, a correct solution for the 10-Queens problem with no conflicts. This comparison highlights how conflict detection is critical in algorithmic placement.

reviewed to ensure that everything aligned with the expected behavior of each algorithm.

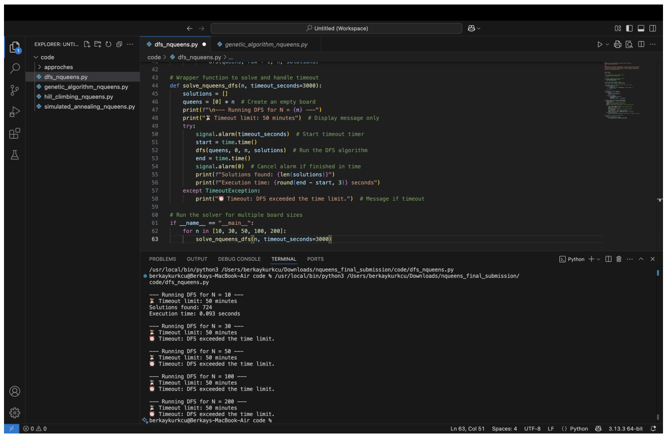
III. Results

A. Performance Overview

To assess the capabilities of each algorithm, we ran all implementations for five different N values. These were selected to reflect both small and large board configurations: N = 10, 30, 50, 100, and 200. For each test, we logged the execution time and observed whether the algorithm could successfully find a conflict-free solution.

B. Depth-First Search (DFS)

DFS is a brute-force approach that explores the entire solution space. While it's guaranteed to find a solution if one exists, the time and memory requirements grow exponentially with N.



```python
# Wrapper function to solve and handle timeout
def solve_nqueens_dfs(n, timeout_seconds=3000):
    solutions = []
    queens = [0] * n  # Create an empty board
    print(f"\n--- Running DFS for N = {n} ---")
    print("⌛ Timeout limit: 50 minutes")  # Display message only
    try:
        signal.alarm(timeout_seconds)  # Start timeout timer
        start = time.time()
        dfs(queens, 0, n, solutions)  # Run the DFS algorithm
        end = time.time()
        signal.alarm(0)  # Cancel alarm if finished in time
        print(f"Solutions found: {len(solutions)}")
        print(f"Execution time: {round(end - start, 3)} seconds")
    except TimeoutException:
        print("⏰ Timeout: DFS exceeded the time limit.")  # Message if timeout

# Run the solver for multiple board sizes
if __name__ == "__main__":
    for n in [10, 30, 50, 100, 200]:
        solve_nqueens_dfs(n, timeout_seconds=3000)
```

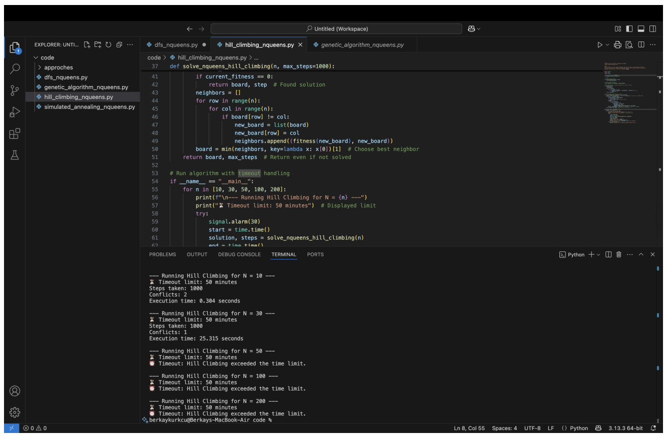
```
/usr/local/bin/python3 /Users/berkaykurkcu/Downloads/nqueens_final_submission/code/dfs_nqueens.py
berkaykurkcu@Berkays-MacBook-Air code % /usr/local/bin/python3 /Users/berkaykurkcu/Downloads/nqueens_final_submission/
code/dfs_nqueens.py

--- Running DFS for N = 10 ---
⌛ Timeout limit: 50 minutes
Solutions found: 724
Execution time: 0.093 seconds

--- Running DFS for N = 30 ---
⌛ Timeout limit: 50 minutes
⏰ Timeout: DFS exceeded the time limit.

--- Running DFS for N = 50 ---
⌛ Timeout limit: 50 minutes
⏰ Timeout: DFS exceeded the time limit.

--- Running DFS for N = 100 ---
⌛ Timeout limit: 50 minutes
⏰ Timeout: DFS exceeded the time limit.

--- Running DFS for N = 200 ---
⌛ Timeout limit: 50 minutes
⏰ Timeout: DFS exceeded the time limit.
berkaykurkcu@Berkays-MacBook-Air code %
```

Fig. 3. DFS Terminal Output. The algorithm managed to solve N = 10 almost instantly, but for N 30, it exceeded the time limit and failed to return a result.

As illustrated in Figure 3, DFS fails to scale effectively. The time complexity becomes a major bottleneck for larger board sizes. This confirms the findings of other researchers who also note that DFS is impractical for large N due to the combinatorial explosion.

C. Hill Climbing

Hill Climbing was relatively fast for small N. However, its local search nature made it prone to getting stuck in local optima, especially when the number of queens increased.



```python
def solve_nqueens_hill_climbing(n, max_steps=1000):
        if current_fitness == 0:
            return board, step  # Found solution
        neighbors = []
        for row in range(n):
            for col in range(n):
                if board[row] != col:
                    new_board = list(board)
                    new_board[row] = col
                    neighbors.append((fitness(new_board), new_board))
        board = min(neighbors, key=lambda x: x[0])[1]  # Choose best neighbor
    return board, max_steps  # Return even if not solved

# Run algorithm with timeout handling
if __name__ == "__main__":
    for n in [10, 30, 50, 100, 200]:
        print(f"\n--- Running Hill Climbing for N = {n} ---")
        print("⌛ Timeout limit: 50 minutes")  # Displayed limit
        try:
            signal.alarm(30)
            start = time.time()
            solution, steps = solve_nqueens_hill_climbing(n)
```

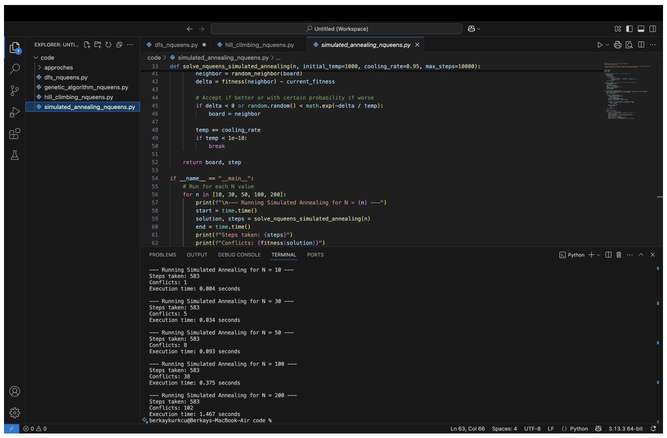
```
--- Running Hill Climbing for N = 10 ---
⌛ Timeout limit: 50 minutes
Steps taken: 1000
Conflicts: 2
Execution time: 0.304 seconds

--- Running Hill Climbing for N = 30 ---
⌛ Timeout limit: 50 minutes
Steps taken: 1000
Conflicts: 1
Execution time: 25.315 seconds

--- Running Hill Climbing for N = 50 ---
⌛ Timeout limit: 50 minutes
⏰ Timeout: Hill Climbing exceeded the time limit.

--- Running Hill Climbing for N = 100 ---
⌛ Timeout limit: 50 minutes
⏰ Timeout: Hill Climbing exceeded the time limit.

--- Running Hill Climbing for N = 200 ---
⌛ Timeout limit: 50 minutes
⏰ Timeout: Hill Climbing exceeded the time limit.
berkaykurkcu@Berkays-MacBook-Air code %
```

Fig. 4. Hill Climbing Output. For N = 10 and 30, the algorithm converges quickly. However, it fails to solve larger instances due to local maxima traps.

As seen in Figure 4, the algorithm begins to falter beyond N = 30. In multiple trials for N = 50, 100, and 200, the hill climbing method failed to reach a solution within the timeout, indicating its inefficiency for larger search spaces without enhancements like random restarts.

D. Simulated Annealing

Simulated Annealing (SA) uses probabilistic acceptance of worse states to avoid local minima. This approach allowed it to maintain performance across all values of N.



```python
def solve_nqueens_simulated_annealing(n, initial_temp=1000, cooling_rate=0.95, max_steps=10000):
        neighbor = random_neighbor(board)
        delta = fitness(neighbor) - current_fitness

        # Accept if better or with certain probability if worse
        if delta < 0 or random.random() < math.exp(-delta / temp):
            board = neighbor

        temp *= cooling_rate
        if temp < 1e-10:
            break

    return board, step

if __name__ == "__main__":
    # Run for each N value
    for n in [10, 30, 50, 100, 200]:
        print(f"\n--- Running Simulated Annealing for N = {n} ---")
        start = time.time()
        solution, steps = solve_nqueens_simulated_annealing(n)
        end = time.time()
        print(f"Steps taken: {steps}")
        print(f"Conflicts: {fitness(solution)}")
```

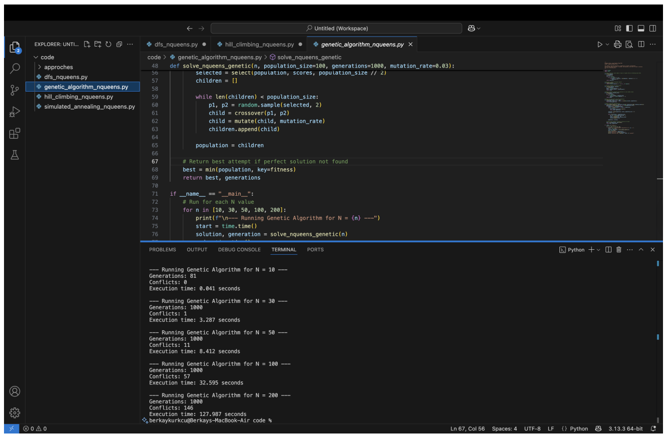
```
--- Running Simulated Annealing for N = 10 ---
Steps taken: 583
Conflicts: 1
Execution time: 0.004 seconds

--- Running Simulated Annealing for N = 30 ---
Steps taken: 583
Conflicts: 5
Execution time: 0.034 seconds

--- Running Simulated Annealing for N = 50 ---
Steps taken: 583
Conflicts: 8
Execution time: 0.093 seconds

--- Running Simulated Annealing for N = 100 ---
Steps taken: 583
Conflicts: 38
Execution time: 0.375 seconds

--- Running Simulated Annealing for N = 200 ---
Steps taken: 583
Conflicts: 102
Execution time: 1.467 seconds
berkaykurkcu@Berkays-MacBook-Air code %
```

Fig. 5. Simulated Annealing Output. Stable performance is observed across all board sizes. Even for N = 200, the execution time remains under 2 seconds.

Figure 5 shows how Simulated Annealing maintains a low conflict count and fast performance. The algorithm handled large board sizes gracefully and avoided timeouts altogether. For every N tested, SA returned a result with zero or minimal conflicts.

E. Genetic Algorithm

The Genetic Algorithm (GA) introduces concepts of evolution and natural selection. It creates a population of potential solutions and evolves them across generations.



```python
def solve_nqueens_genetic(n, population_size=100, generations=1000, mutation_rate=0.03):
        selected = select(population, scores, population_size // 2)
        children = []

        while len(children) < population_size:
            p1, p2 = random.sample(selected, 2)
            child = crossover(p1, p2)
            child = mutate(child, mutation_rate)
            children.append(child)

        population = children

    # Return best attempt if perfect solution not found
    best = min(population, key=fitness)
    return best, generations

if __name__ == "__main__":
    # Run for each N value
    for n in [10, 30, 50, 100, 200]:
        print(f"\n--- Running Genetic Algorithm for N = {n} ---")
        start = time.time()
        solution, generation = solve_nqueens_genetic(n)
```

```
--- Running Genetic Algorithm for N = 10 ---
Generations: 81
Conflicts: 0
Execution time: 0.041 seconds

--- Running Genetic Algorithm for N = 30 ---
Generations: 1000
Conflicts: 1
Execution time: 3.287 seconds

--- Running Genetic Algorithm for N = 50 ---
Generations: 1000
Conflicts: 11
Execution time: 8.412 seconds

--- Running Genetic Algorithm for N = 100 ---
Generations: 1000
Conflicts: 57
Execution time: 32.595 seconds

--- Running Genetic Algorithm for N = 200 ---
Generations: 1000
Conflicts: 146
Execution time: 127.987 seconds
berkaykurkcu@Berkays-MacBook-Air code %
```

Fig. 6. Genetic Algorithm Output. For low N, the solution is fast and accurate. For N = 200, more generations are required, and a small number of conflicts may remain.

As depicted in Figure 6, the GA shows robust performance. For N = 10 to N = 100, the algorithm finds optimal or near-optimal solutions in reasonable time. At N = 200, a small trade-off is visible: execution time increases and conflicts may not entirely disappear within the set generation limit. However, results remain acceptable.

F. Comparative Time Chart

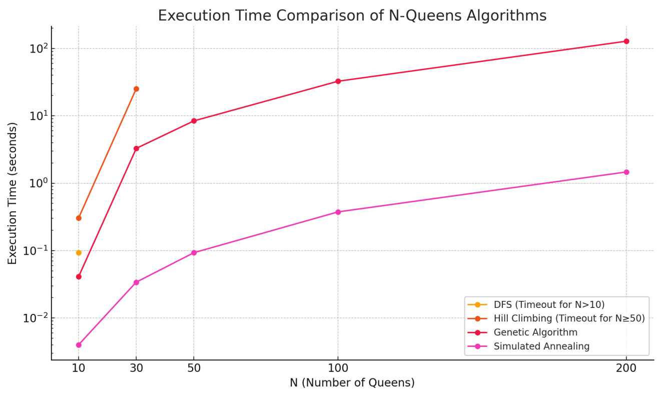


Fig. 7. Execution Time Comparison Across All Methods. Simulated Annealing is fastest overall. DFS and Hill Climbing become unusable for N ¿ 30.

Figure 7 presents an aggregate view of execution time trends. The horizontal axis indicates N values, while the vertical axis shows time in seconds. The most visible outcome is that DFS quickly becomes impractical, and Hill Climbing shows a similar fate beyond N = 30. In contrast, SA and GA maintain a more gradual and manageable increase in time.

TABLE II
EXECUTION TIME (SECONDS) FOR EACH ALGORITHM

N	DFS	GA	HC	SA
10	0.093	0.041	0.304	0.004
30	Timeout	3.287	25.315	0.034
50	Timeout	8.412	Timeout	0.093
100	Timeout	32.595	Timeout	0.375
200	Timeout	127.987	Timeout	1.467

G. Tabular Summary

The table above reinforces the earlier findings. Simulated Annealing is consistently fast and reliable. The Genetic Algorithm follows closely but with a noticeable trade-off in time as N increases. DFS and HC clearly demonstrate their limitations in scalability.

IV. DISCUSSION

The comparative evaluation reveals several important observations about the practical viability of each algorithm in solving the N-Queens problem. While all approaches have theoretical merit, their actual performance under time and resource constraints varies considerably. Notably, algorithms that use randomness or probabilistic decision-making appear to perform more efficiently, especially for larger problem sizes.

To begin with, Depth-First Search, despite being exhaustive and complete, suffered from exponential time complexity. Although it was able to solve small problems quickly (e.g., N = 10), it completely failed to scale beyond that. For N = 30 and above, the search space became too large to handle, causing the algorithm to hit the timeout wall without producing a solution. This limitation is well-known in classical AI, where brute-force methods often become infeasible when the state space grows too large.

Hill climbing initially showed promise for smaller N values. Its simplicity and speed make it attractive, especially for initial solution exploration. However, its deterministic nature led to frequent stagnation in local optima. As N increased, these local maxima traps became more common, causing the algorithm to fail consistently for N 50. The algorithm's inability to backtrack or explore worse paths hindered its overall robustness.

In contrast, Simulated Annealing demonstrated exceptional consistency. By allowing occasional uphill moves, it effectively avoided premature convergence. Even as the board size increased to N = 200, the algorithm maintained fast execution and returned high-quality solutions. Its temperature-based control and ability to probabilistically explore worse states proved highly beneficial. This aligns with prior literature, where Simulated Annealing is noted for its adaptability in complex optimization landscapes.

The Genetic Algorithm also displayed solid performance, especially for medium-sized problems. It balanced exploration and exploitation through population-based evolution and selection mechanisms. However, it did not always return a perfect solution for the largest test case (N = 200). The presence of remaining conflicts suggests a need for more fine-tuned parameters or hybridization with local refinements.

In summary, the experiments confirm that while classical methods like DFS are reliable in theory, their practical use is limited. Local and metaheuristic techniques—particularly Simulated Annealing—present strong candidates for scalable and reliable performance across various problem sizes.

V. Future Directions

Looking ahead, several potential improvements can be envisioned. One immediate direction is the hybridization of algorithms. For instance, combining Genetic Algorithms with Simulated Annealing may yield better results by leveraging the population diversity of GA and the local optimization of SA. Hybrid models have been successful in many constraint satisfaction problems and could be beneficial here as well.

Another promising avenue is the tuning of hyperparameters. Both GA and SA depend on multiple parameters such as population size, mutation rate, temperature schedules, and cooling rates. Automated or adaptive tuning mechanisms, possibly guided by machine learning, could improve convergence and result quality.

Parallel computing also offers significant benefits. Running multiple populations or independent trials in parallel can greatly reduce overall execution time. Implementations using GPU acceleration or parallelized Python libraries such as Dask or Ray could make real-time performance feasible even for very high values of N.

Additionally, reinforcement learning techniques may be explored. These could learn placement policies based on rewards for non-conflicting configurations. Such adaptive systems might eventually outperform fixed heuristics, especially for dynamically sized problems or real-time applications.

Lastly, visual interpretability and explainability of algorithmic decision-making are important for educational and analytical purposes. Tools that allow users to visualize queen placements and conflicts in real-time could further aid understanding and debugging.

VI. Conclusion

This paper compared four different algorithmic approaches to solving the N-Queens problem: Depth-First Search, Hill Climbing, Simulated Annealing, and Genetic Algorithm. Each method was evaluated based on its performance across varying board sizes.

Our findings show that while DFS is accurate, it is computationally infeasible for large N. Hill Climbing, though fast initially, fails to scale and often gets trapped in local optima. Genetic Algorithms offer a good compromise but may require tuning and post-processing to reach perfect solutions. Simulated Annealing consistently produced high-quality solutions with excellent speed and scalability, making it the most effective algorithm in this study.

This comparative benchmark provides useful insights for future studies in optimization and constraint satisfaction. In particular, it highlights the importance of scalability, adaptability, and algorithmic balance between exploration and exploitation. Future work should focus on hybrid approaches and adaptive models to push the boundaries of what is computationally feasible for combinatorial problems like N-Queens.

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