Ant Colony Optimization: An Algorithm That Changed the World

ECM3428 Coursework Report
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Abstract

This report investigates the Ant Colony Optimization (ACO) algorithm and its application to the Bin Packing Problem (BPP). It discusses ACO's principles, pseudocode, complexity, limitations, and real-world applications. Results are evaluated through performance metrics, including convergence trends and scalability.

I certify that all material in this report which is not my own work has been identified. should be provided.

1 INTRODUCTION

The Ant Colony Optimization (ACO) is a metaheuristic optimisation algorithm inspired by ants' foraging behaviour [1]. It belongs to a class of derivative-free optimisers that do not require gradient calculations, making them suitable for non-differentiable or computationally expensive optimisation problems. ACO is particularly effective for solving combinatorial optimisation problems, where the objective is to find the best solution among finite possibilities.

The algorithm mimics how ants use pheromones to discover optimal paths to food sources. Initially, ants explore randomly, but as pheromone trails on shorter paths intensify, more ants are guided to follow these efficient routes. This self-reinforcing process allows ACO to identify near-optimal solutions iteratively [2].

ACO has been successfully applied to problems such as the Traveling Salesman Problem (TSP), where it finds the shortest route to visit all cities and network routing, optimising data paths in communication networks. It is also widely used in resource allocation challenges, including the Bin Packing Problem (BPP) and Cloud Resource Management[3, 4, 5].

This report investigates the application of ACO to the BPP, a classic NP-hard problem where items are assigned to bins to minimise weight differences and explores how this can be applied to real-world problems. The study explores ACO's methodology, testing, and performance metrics, including unit testing and the convergence behaviour of the models. We will also discuss the ACO's limitations and what it takes to determine what makes a successful algorithm successful in optimisation. The goal is to define criteria for a successful ACO solution and evaluate its practicality in challenging optimisation tasks.

2 APPLICATIONS

2.1 Main principles of ACO

The ACO mimics the behaviour of real ants, where artificial ants construct solutions probabilistically, guided by pheromone trails and heuristic information. A stronger a pheromone trail, represent a shorter, more successful solutions, while heuristics provide problem-specific guidance, such as distance or cost. The algorithm operates through five key steps:

- **Pheromone Initialization:** Pheromone levels are uniformly set at the start.
- **Solution Construction:** Each ant builds a solution incrementally based on probabilistic choices informed by pheromones.
- **Fitness Evaluation:** The quality of each ants path is assessed and measured.
- **Pheromone Update:** Pheromones are deposited on better solutions and evaporate over time to encourage exploration.
- **Iteration:** These steps are repeated, refining solutions over multiple cycles.

ACO balances exploration (searching broadly) and exploitation (refining known reasonable solutions), avoiding premature convergence while improving solution quality.

2.2 Provide real-world contexts

For this project, ACO is applied to the Bin Packing Problem (BPP), a classic NP-hard combinatorial optimisation problem [6]. BPP aims to assign items to bins to minimise weight differences. Although exact solutions are feasible for small instances, ACO excels in handling more extensive, more complex scenarios.

Real-world extensions of ACO in resource allocation include cloud computing and logistics. For example, in a warehouse optimisation problem, ACO can distribute 1000 items across bins, representing tasks or goods. By adjusting the different input parameters of the ACO, we can mimic many real-world problems [3].

When dealing with logistics, more specifically supply chain management, the ACO has been employed to optimise supply chain processes, such as scheduling and resource allocation, leading to more efficient operations and reduced costs. Research indicates that ACO can effectively address large-scale real-world routing problems in inbound logistics, improving planning and execution [7].

In cloud resource management ACOs can aid in the load balancing of cloud computing environments by distributing the workload more evenly across servers than traditional methods which further, enhances the performance and resource utilisation. Then in virtual machine (VM) placement, ACO can find optimal placement of VMs within data centers demonstrating significant improvements in energy efficiency. These examples show the applications that the ACO's in solving complex optimisation problems across various industries [3].

3 PSEUDOCODE

Pseudocode for ACO:

2.1 Provide Pseudocode that Describes the Algorithm

Inputs

- `ants_set`: Number of ants
- `evaporation_set`: Evaporation rate of pheromones
- `BPP_weight_set`: Type of weight distribution for items
- `num_items`: Total number of items to pack
- `bins_set`: Total number of bins available
- `iterations`: Number of iterations to perform

Steps

1. Validate the inputs to ensure all parameters are correct.
2. Initialize pheromone levels randomly for each item-bin pair.
3. Based on `BPP_weight_set`, generate the item weight distribution:
   (a) Uniform weights.
   (b) Incrementally increasing weights.
   (c) Random weights.
   (d) Exponentially distributed weights.
4. For each iteration (`1` to `iterations`):
   (a) Generate paths for all ants:
      i. For each item, assign it probabilistically to a bin using normalized pheromone levels.
      ii. Calculate fitness for each ant's path:
         - Fitness is the difference between the heaviest and lightest bins.
   (b) Identify the best path based on fitness.
   (c) Update pheromone levels:
      i. Increase pheromones on the best path, avoiding division by zero if fitness is zero.
      ii. Apply evaporation to reduce pheromone levels on all paths.
5. Record the best fitness at each iteration.
6. Display the results for the first and last generation.
7. Plot the fitness convergence over iterations.

Output

- Best, worst, and average fitness values.
- Best and worst paths taken by the ants.
- A graph of fitness over iterations.

Figure 1: Caption for the image.

4 METRICS OF ANALYSIS

To evaluate the performance of the Ant Colony Optimization (ACO) algorithm there are certain benchmarks to focus on, as achieving a perfect solution is not always feasible [8]:

1. **Solution Quality:** Compare ACO's results to known benchmarks or best-known solutions and calculate percentage deviation.
2. **Convergence Behaviour:** Analyse fitness over iterations to observe improvement trends and stability at convergence. Faster convergence is ideal but must not compromise solution quality.
3. **Stability and Robustness:** When assessing the consistency by running the algorithm with different initial conditions and parameter settings. Robust algorithms produce high-quality results consistently across varied configurations.
4. **Computational Efficiency:** Measure runtime and scalability to evaluate performance on larger problem instances. Effective algorithms maintain acceptable runtimes and quality as problem size increases.
5. **Exploration vs. Exploitation:** Ensure the algorithm balances broad search (exploration) with refining good solutions (exploitation) to avoid premature convergence. Assess solution diversity and trajectory to prevent local optima.
6. **Scalability and Applicability:** Test adaptability to various problem instances and evaluate performance on small to large scales.

Code analysis focuses on convergence trends, runtime, final fitness, and graph patterns (fluctuation, trajectory) alongside runtime and space complexity to assess performance comprehensively.

5 COMPLEXITY ANALYSIS

The time and space complexity of Ant Colony Optimization (ACO) highlights its scalability and efficiency. For n items, m bins, pants, and k iterations:

Time Complexity:

1. Path Generation: $O(n \times m \times p)$
2. Fitness Calculation: $O(n \times p)$
3. Pheromone Update: $O(n \times m)$
4. Total: $O(k \times n \times m \times p)$

Space Complexity:

1. Storing pheromone levels: $O(n \times m)$
2. Storing solutions for p ants: $O(n \times p)$
3. Total: $O(n \times (m + p))$

This analysis helps predicts resource growth with problem size, identifying computational issues the users to implement new strategies if need be such as parallelism or undertraining the upper limits of the specific code.

6 RESULTS AND EVALUATION

Many tests were conducted to evaluate the ACO algorithm and was assessed by multiple metrics of analysis as mentioned earlier as, functionality, stability and robustness, and efficiency. These include a base test, moderate test, stress test, and real-world test.

6.1 Base Test

The base test demonstrated ACO's exceptional performance in solving small-scale problems with uniform weight distributions. The algorithm achieved a perfect fitness score of 0 within 55 iterations, efficiently balancing all bins. Runtime was 0.75 seconds, with an average iteration runtime of 0.01 seconds. Time complexity O(12,000,000) and space complexity O(2,110) were manageable. The algorithm showed rapid, stable convergence and no variability in results, highlighting it's consistency and effectivess at balancing of exploration and exploitation. These results align with or exceed benchmarks, validating the algorithm's reliability for simple instances.

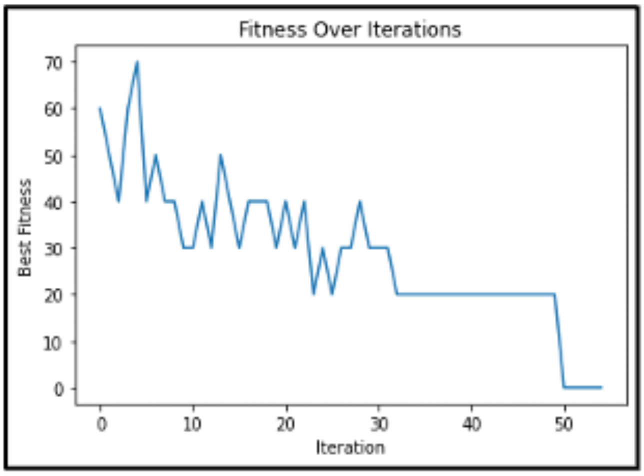

Figure 2: base results

6.2 Moderate test

For a more challenging test to see stability and ability to upscale we tested the ACO under more challenging conditions. Using an exponential weight distributions, the algorithm reduced fitness from 1577 to 99 within 120 iterations, demonstrating robust optimisation. Runtime was 5.65 seconds, with a time complexity of O(46,000,000), reflecting computational efficiency though 4x larger then base test. Convergence was steady and consistent, with no premature convergence. However, the lack of refinement techniques, such as local search, limited its ability to achieve a perfect fitness score. Compared to hybrid methods in the literature, the algorithm performed well but has potential for improvement through hybridisation or parallelism, to enhance solution quality and convergence speed.

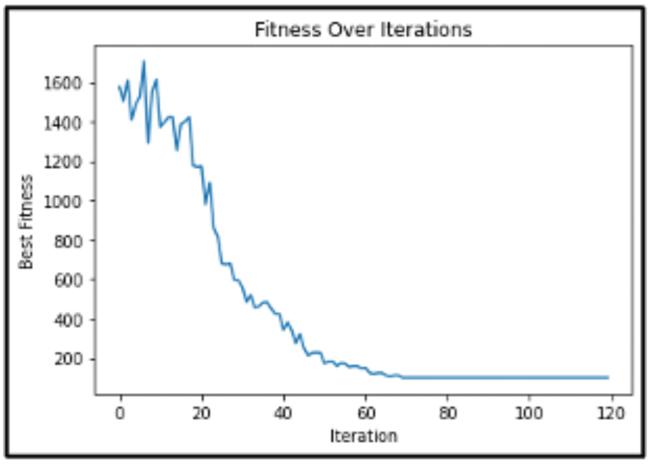

Figure 3: moderate results.

6.3 stress test

The real-world test was conducted using a random weights distribution. The algorithm achieved a fitness of 6 from 398 in 252 iterations. Runtime was 137.72 seconds, with an average iteration runtime of 0.55 seconds. The algorithm achieved near-optimal results, demonstrating strong scalability and computationall efficiency. However, the ACO proposed by J. Levine [6] hybrid methods could achieve similar results with reduced runtimes, presenting opportunities for further optimisation.

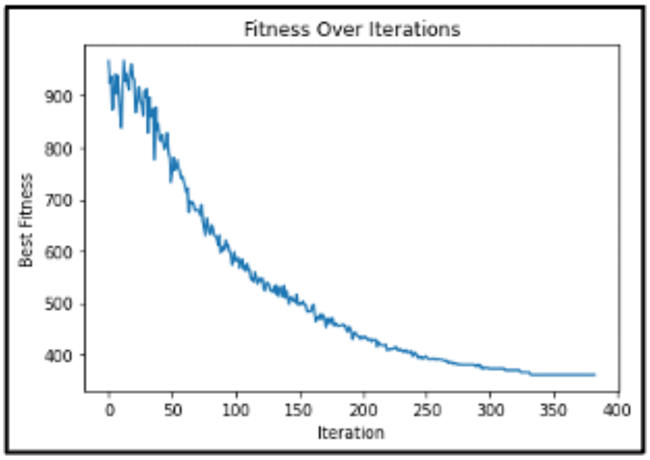

Figure 4: stress test

7 LIMITATIONS AND SOLUTIONS

7.1 General Limitations of ACO

When dealing with the ACO some limitations to have been shown is the high computational costs, particularly for large systems, leading to long execution times. Additionally, the ACO can be prone to premature convergence, where the algorithm gets trapped in a local minimum and fails to explore better solutions. Finding a good balance between exploration and exploitation of ants is crucial to address this limitation.

7.2 Code-Specific Limitations

The implemented algorithm has specific challenges. While iteration stoppers were added, the algorithm struggled before to determine an optimal stopping point dynamically. Instead, a fixed iteration count was manually as the upper length while a dyanmic for smaller problems is chosen, which might not always be optimal. Furthermore, the algorithm is highly sensitive to parameter settings, particularly the evaporation rate. Fine-tuning all these parameters often involves trial and error, especially if the code also takes a while to run.

7.3 Proposed Solutions

To overcome general limitations, parallelisation can reduce computational costs, while dynamic stopping criteria based on convergence trends can optimise execution time. Advanced pheromone update strategies, such as adaptive evaporation rates, can prevent premature convergence by maintaining a better balance between exploration and exploitation. Addionally having an automating system for fine tuning parameter setting could save time and improve consistency of the models. Adding more constraints, simulating real-life scenarios would further enhance the algorithm's practical applicability. These refinements could significantly improve ACO's efficiency and reliability.

8 CONCLUSION

The Ant Colony Optimization (ACO) algorithm effectively solves complex optimization problems like the Bin Packing Problem, demonstrating scalability, robustness, and adaptability. However, addressing computational costs, parameter sensitivity, and premature convergence is crucial for enhancing efficiency and real-world applicability in diverse scenarios.

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APPENDIX

AI-Generated Report and Comparison

I applied the Gemini 1.5 AI to generate responses for various ACO algorithm-related topics. Below is a comparison of the AI-generated content and my work.

1. ACO Principles: The AI response concisely describes key principles like artificial ants, pheromone trails, and probabilistic selection. My work offers more detailed explanations and real-world examples, making it better for in-depth understanding and practical applications. The AI content suits beginners or presentations.

2. ACO Pseudocode: The AI provides a clear, modular pseudocode suitable for general applications but lacks specific inputs or domain-specific details. My pseudocode tailors steps for the Bin Packing Problem, including fitness metrics and weight distribution, making it ideal for specific implementations. The AI version is better for general adaptability.

3. Time and Space Complexity: The AI focuses on formulas and practical applications, but struggles with mathematical depth. My analysis explores theoretical reasoning, design implications, and optimization techniques. The AI content is best for quick reference, while my work is better for understanding underlying principles.

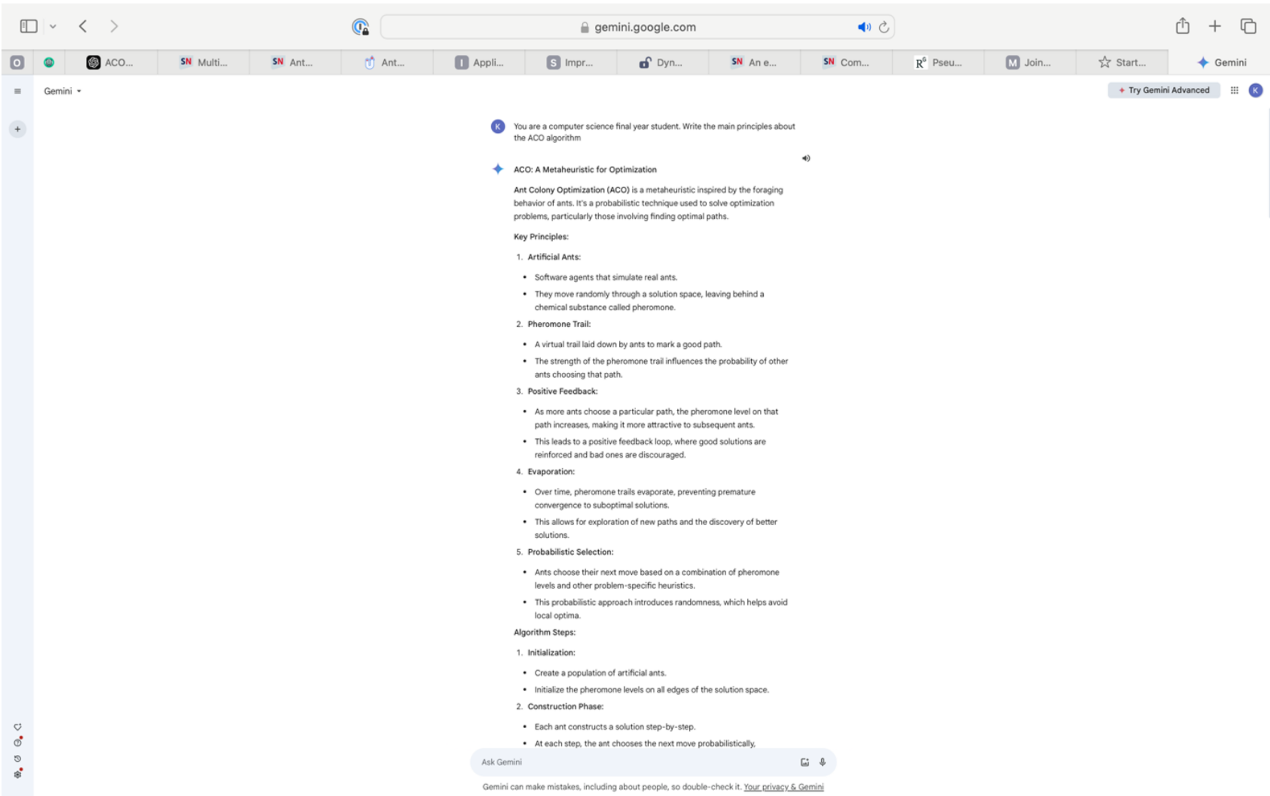
4. Limitations and Solutions: Both discuss issues like parameter sensitivity, premature convergence, and computational cost. The AI provides a concise overview and generic solutions, while my work includes practical examples and implementation challenges, making it more actionable for real-world use.

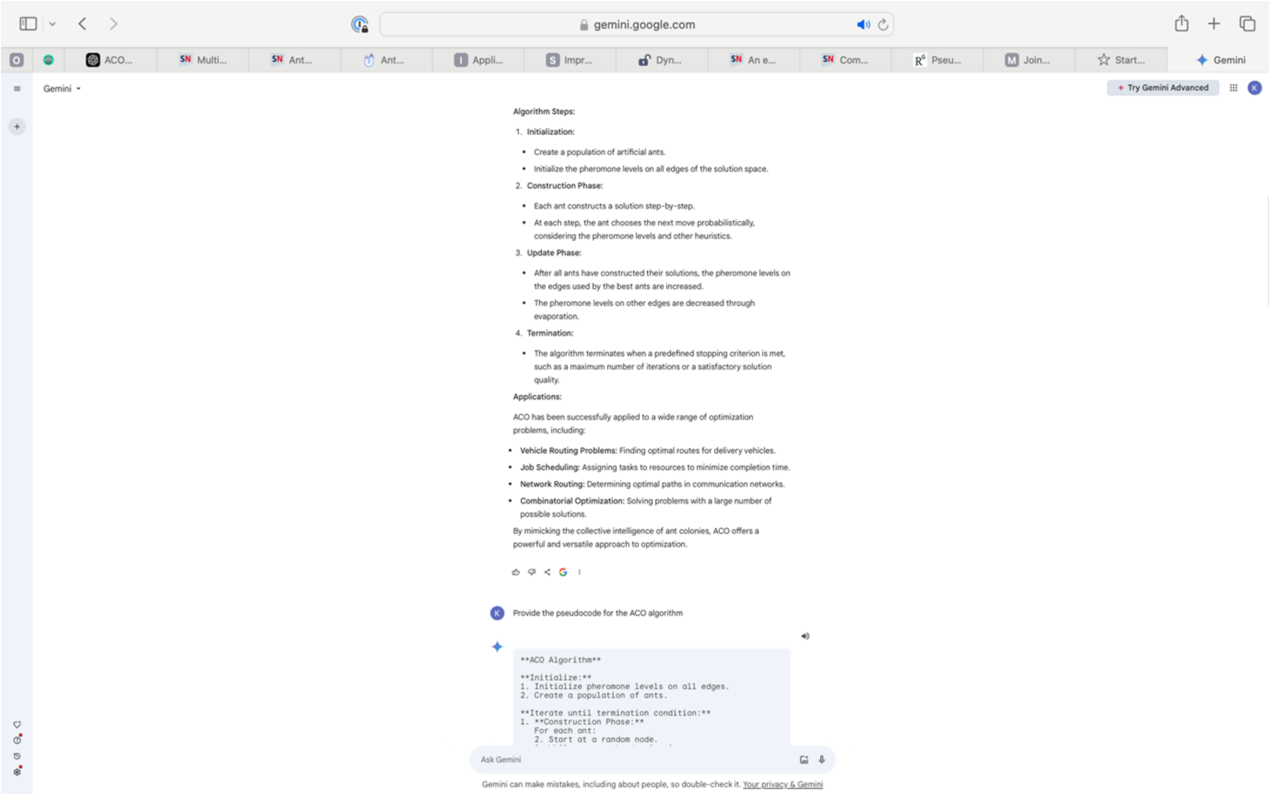
5. Real-World Applications: The AI highlights more examples but misses areas like cloud computing that I address. It provides more in theoretical insights, whereas my work focuses on more practical strategies and implementation challenges. The AI is better for a broad understanding; my work excels in practical application.

conclusion to Gen-AI

The AI-generated content is concise and best for quick reference or introductory purposes. My work offers detailed explanations, real-world examples, and practical insights, making it more suitable for researchers and practitioners implementing ACO in specific scenarios like Bin Packing or logistics.

Gen-AI Screenshots





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Algorithm Steps:

1. **Initialization:**
   - Create a population of artificial ants.
   - Initialize the pheromone levels on all edges of the solution space.
2. **Construction Phase:**
   - Each ant constructs a solution step-by-step.
   - At each step, the ant chooses the next move probabilistically, considering the pheromone levels and other heuristics.
3. **Update Phase:**
   - After all ants have constructed their solutions, the pheromone levels on the edges used by the best ants are increased.
   - The pheromone levels on other edges are decreased through evaporation.
4. **Termination:**
   - The algorithm terminates when a predefined stopping criterion is met, such as a maximum number of iterations or a satisfactory solution quality.

Applications:

ACO has been successfully applied to a wide range of optimization problems, including:

- **Vehicle Routing Problems:** Finding optimal routes for delivery vehicles.
- **Job Scheduling:** Assigning tasks to resources to minimize completion time.
- **Network Routing:** Determining optimal paths in communication networks.
- **Combinatorial Optimization:** Solving problems with a large number of possible solutions.

By mimicking the collective intelligence of ant colonies, ACO offers a powerful and versatile approach to optimization.

Provide the pseudocode for the ACO algorithm

```
**ACO Algorithm**

**Initialize:**
1. Initialize pheromone levels on all edges.
2. Create a population of ants.

**Iterate until termination condition:**
1. **Construction Phase:**
   For each ant:
   2. Start at a random node.
```

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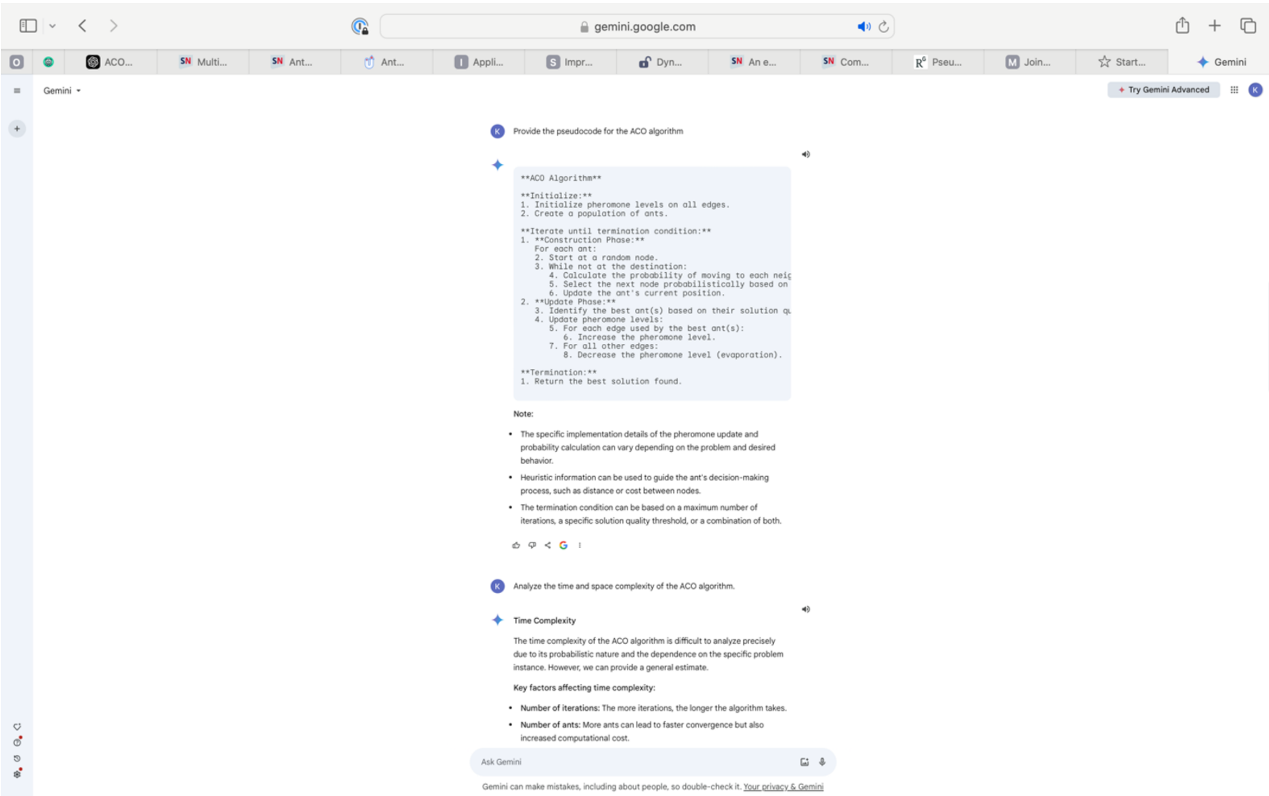

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Provide the pseudocode for the ACO algorithm

```
**ACO Algorithm**

**Initialize:**
1. Initialize pheromone levels on all edges.
2. Create a population of ants.

**Iterate until termination condition:**
1. **Construction Phase:**
   For each ant:
   2. Start at a random node.
   3. While not at the destination:
      4. Calculate the probability of moving to each neig
      5. Select the next node probabilistically based on
      6. Update the ant's current position.
2. **Update Phase:**
   3. Identify the best ant(s) based on their solution qu
   4. Update pheromone levels:
      5. For each edge used by the best ant(s):
         6. Increase the pheromone level.
      7. For all other edges:
         8. Decrease the pheromone level (evaporation).

**Termination:**
1. Return the best solution found.
```

Note:

- The specific implementation details of the pheromone update and probability calculation can vary depending on the problem and desired behavior.
- Heuristic information can be used to guide the ant's decision-making process, such as distance or cost between nodes.
- The termination condition can be based on a maximum number of iterations, a specific solution quality threshold, or a combination of both.

Analyze the time and space complexity of the ACO algorithm.

Time Complexity

The time complexity of the ACO algorithm is difficult to analyze precisely due to its probabilistic nature and the dependence on the specific problem instance. However, we can provide a general estimate.

Key factors affecting time complexity:

- **Number of iterations:** The more iterations, the longer the algorithm takes.
- **Number of ants:** More ants can lead to faster convergence but also increased computational cost.

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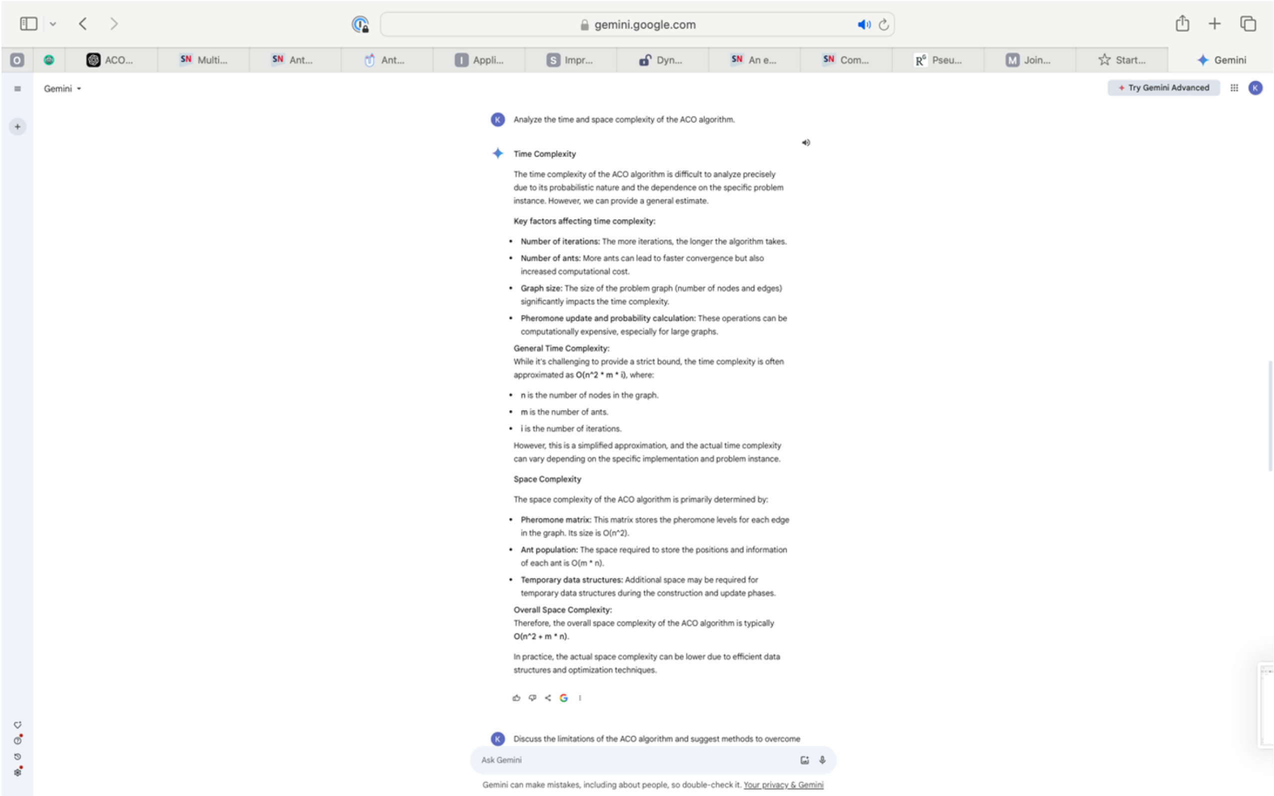
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Analyze the time and space complexity of the ACO algorithm.
Time Complexity
The time complexity of the ACO algorithm is difficult to analyze precisely due to its probabilistic nature and the dependence on the specific problem instance. However, we can provide a general estimate.
Key factors affecting time complexity:
Number of iterations: The more iterations, the longer the algorithm takes.
Number of ants: More ants can lead to faster convergence but also increased computational cost.
Graph size: The size of the problem graph (number of nodes and edges) significantly impacts the time complexity.
Pheromone update and probability calculation: These operations can be computationally expensive, especially for large graphs.
General Time Complexity:
While it's challenging to provide a strict bound, the time complexity is often approximated as O(n^2 * m * i), where:
n is the number of nodes in the graph.
m is the number of ants.
i is the number of iterations.
However, this is a simplified approximation, and the actual time complexity can vary depending on the specific implementation and problem instance.
Space Complexity
The space complexity of the ACO algorithm is primarily determined by:
Pheromone matrix: This matrix stores the pheromone levels for each edge in the graph. Its size is O(n^2).
Ant population: The space required to store the positions and information of each ant is O(m * n).
Temporary data structures: Additional space may be required for temporary data structures during the construction and update phases.
Overall Space Complexity:
Therefore, the overall space complexity of the ACO algorithm is typically O(n^2 + m * n).
In practice, the actual space complexity can be lower due to efficient data structures and optimization techniques.
Discuss the limitations of the ACO algorithm and suggest methods to overcome
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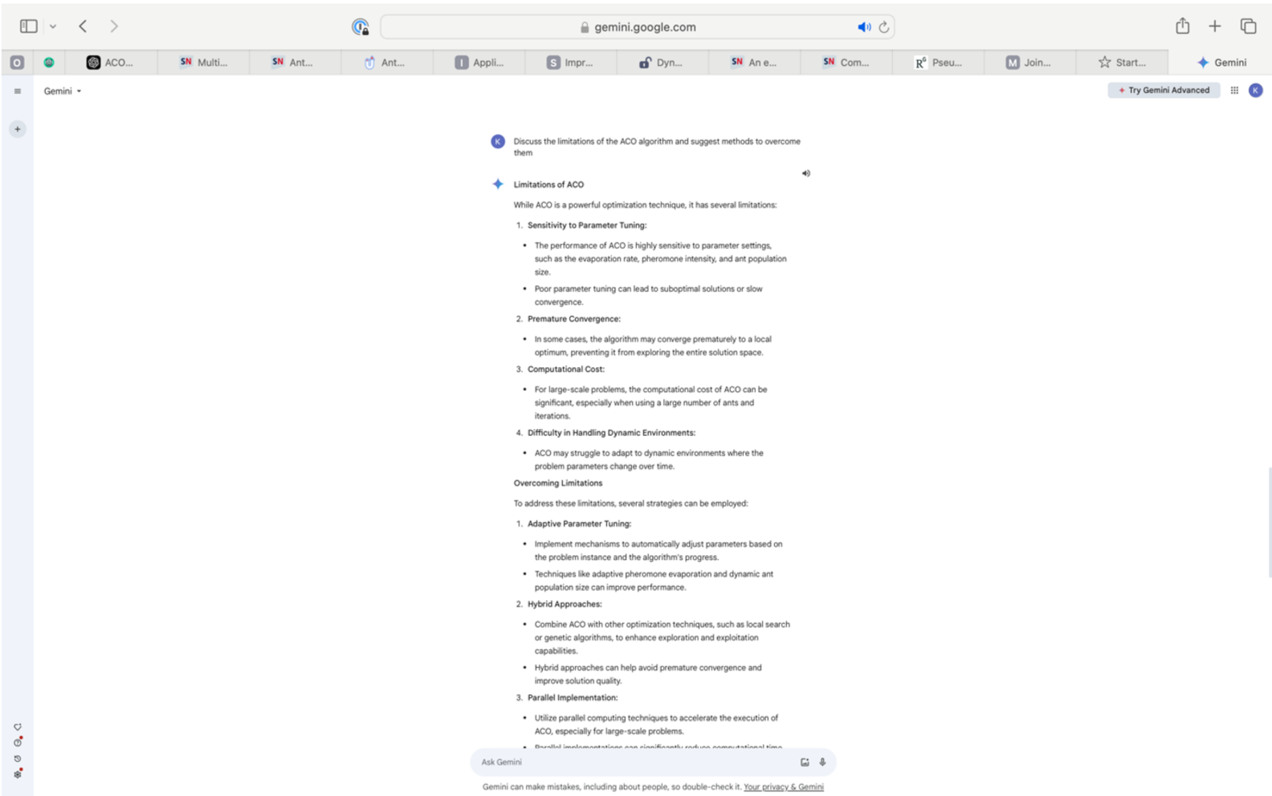
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Discuss the limitations of the ACO algorithm and suggest methods to overcome them
Limitations of ACO
While ACO is a powerful optimization technique, it has several limitations:
1. Sensitivity to Parameter Tuning:
The performance of ACO is highly sensitive to parameter settings, such as the evaporation rate, pheromone intensity, and ant population size.
Poor parameter tuning can lead to suboptimal solutions or slow convergence.
2. Premature Convergence:
In some cases, the algorithm may converge prematurely to a local optimum, preventing it from exploring the entire solution space.
3. Computational Cost:
For large-scale problems, the computational cost of ACO can be significant, especially when using a large number of ants and iterations.
4. Difficulty in Handling Dynamic Environments:
ACO may struggle to adapt to dynamic environments where the problem parameters change over time.
Overcoming Limitations
To address these limitations, several strategies can be employed:
1. Adaptive Parameter Tuning:
Implement mechanisms to automatically adjust parameters based on the problem instance and the algorithm's progress.
Techniques like adaptive pheromone evaporation and dynamic ant population size can improve performance.
2. Hybrid Approaches:
Combine ACO with other optimization techniques, such as local search or genetic algorithms, to enhance exploration and exploitation capabilities.
Hybrid approaches can help avoid premature convergence and improve solution quality.
3. Parallel Implementation:
Utilize parallel computing techniques to accelerate the execution of ACO, especially for large-scale problems.
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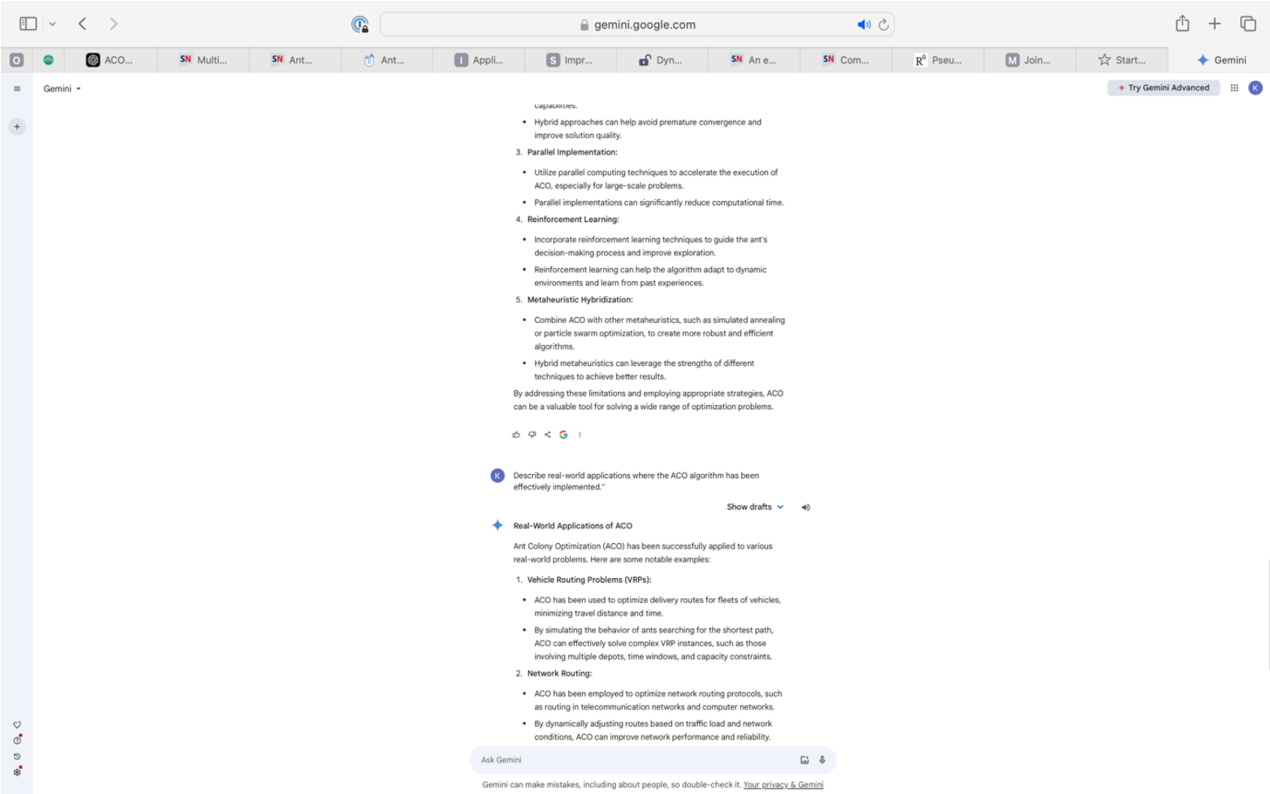

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- Hybrid approaches can help avoid premature convergence and improve solution quality.

3. **Parallel Implementation:**
   - Utilize parallel computing techniques to accelerate the execution of ACO, especially for large-scale problems.
   - Parallel implementations can significantly reduce computational time.
4. **Reinforcement Learning:**
   - Incorporate reinforcement learning techniques to guide the ant's decision-making process and improve exploration.
   - Reinforcement learning can help the algorithm adapt to dynamic environments and learn from past experiences.
5. **Metaheuristic Hybridization:**
   - Combine ACO with other metaheuristics, such as simulated annealing or particle swarm optimization, to create more robust and efficient algorithms.
   - Hybrid metaheuristics can leverage the strengths of different techniques to achieve better results.

By addressing these limitations and employing appropriate strategies, ACO can be a valuable tool for solving a wide range of optimization problems.

Describe real-world applications where the ACO algorithm has been effectively implemented."

Show drafts

Real-World Applications of ACO

Ant Colony Optimization (ACO) has been successfully applied to various real-world problems. Here are some notable examples:

1. **Vehicle Routing Problems (VRPs):**
   - ACO has been used to optimize delivery routes for fleets of vehicles, minimizing travel distance and time.
   - By simulating the behavior of ants searching for the shortest path, ACO can effectively solve complex VRP instances, such as those involving multiple depots, time windows, and capacity constraints.
2. **Network Routing:**
   - ACO has been employed to optimize network routing protocols, such as routing in telecommunication networks and computer networks.
   - By dynamically adjusting routes based on traffic load and network conditions, ACO can improve network performance and reliability.

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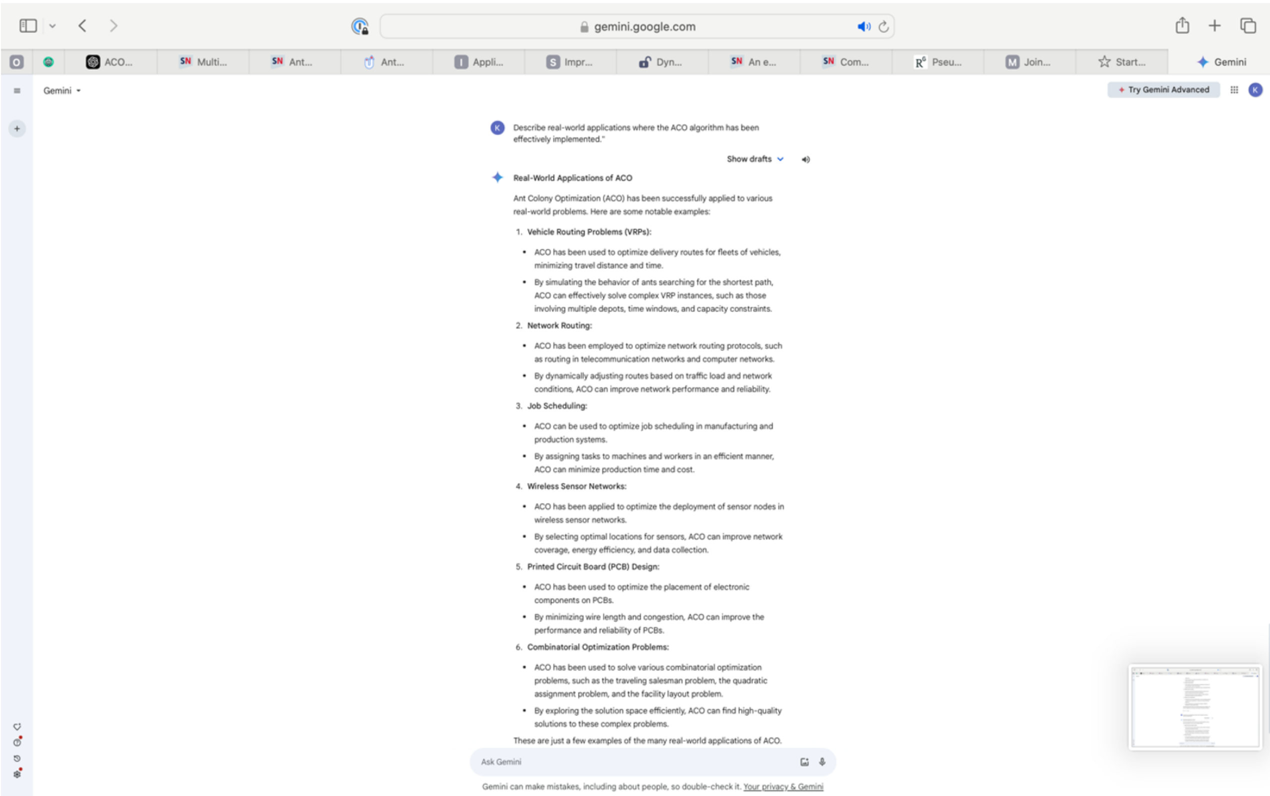

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3. **Job Scheduling:**
   - ACO can be used to optimize job scheduling in manufacturing and production systems.
   - By assigning tasks to machines and workers in an efficient manner, ACO can minimize production time and cost.
4. **Wireless Sensor Networks:**
   - ACO has been applied to optimize the deployment of sensor nodes in wireless sensor networks.
   - By selecting optimal locations for sensors, ACO can improve network coverage, energy efficiency, and data collection.
5. **Printed Circuit Board (PCB) Design:**
   - ACO has been used to optimize the placement of electronic components on PCBs.
   - By minimizing wire length and congestion, ACO can improve the performance and reliability of PCBs.
6. **Combinatorial Optimization Problems:**
   - ACO has been used to solve various combinatorial optimization problems, such as the traveling salesman problem, the quadratic assignment problem, and the facility layout problem.
   - By exploring the solution space efficiently, ACO can find high-quality solutions to these complex problems.

These are just a few examples of the many real-world applications of ACO.

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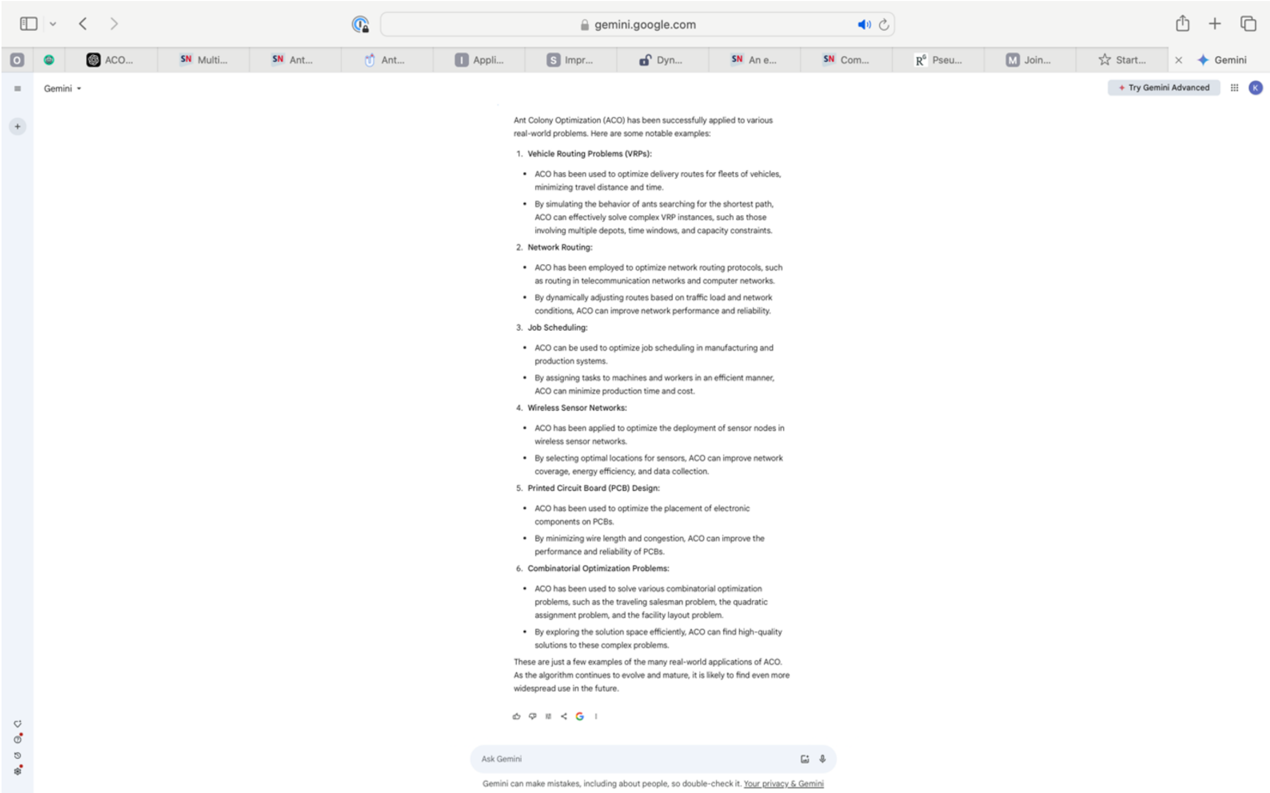
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5. Printed Circuit Board (PCB) Design:
• ACO has been used to optimize the placement of electronic components on PCBs.
• By minimizing wire length and congestion, ACO can improve the performance and reliability of PCBs.
6. Combinatorial Optimization Problems:
• ACO has been used to solve various combinatorial optimization problems, such as the traveling salesman problem, the quadratic assignment problem, and the facility layout problem.
• By exploring the solution space efficiently, ACO can find high-quality solutions to these complex problems.
These are just a few examples of the many real-world applications of ACO. As the algorithm continues to evolve and mature, it is likely to find even more widespread use in the future.
Ask Gemini
Gemini can make mistakes, including about people, so double-check it. Your privacy & Gemini

GenAI statement

Use of GenAI tools in Continuous Assessment for ECM3428 Algorithms that changed the world.

The University of Exeter is committed to the ethical and responsible use of Generative AI (GenAI) tools in teaching and learning, in line with our academic integrity policies where the direct copying of AI-generated content is included under plagiarism, misrepresentation and contract cheating under definitions and offences in TQA Manual Chapter 12.3. To support students in their use of GenAI tools as part of their assessments, we have developed a category tool that enables staff to identify where use of Gen AI is integrated, supported or prohibited in each assessment. This assessment falls under the category of **AI-supported.** This is because **the AI tools may help you gain additional understanding of the algorithm and potentially avoid spelling errors or typos.**

You can find further guidance on using GenAI critically, and how to use GenAI to enhance your learning, on Study Zone digital.

When submitting your assessment, you must include the following declaration, ticking all that apply:

AI-supported/AI-integrated use is permitted in this assessment. I acknowledge the following uses of GenAI tools in this assessment:

- ☐ *I have used GenAI tools to develop ideas.*
- ☒ *I have used GenAI tools to assist with research or gathering information.*
- ☐ *I have used GenAI tools to help me understand key theories and concepts.*
- ☐ *I have used GenAI tools to identify trends and themes as part of my data analysis.*
- ☒ *I have used GenAI tools to suggest a plan or structure for my assessment.*
- ☒ *I have used GenAI tools to give me feedback on a draft.*
- ☐ *I have used GenAI tool to generate image, figures or diagrams.*
- ☒ *I have used GenAI tools to proofread and correct grammar or spelling errors.*
- ☒ *I have used GenAI tools to generate citations or references.*
- ☐ *Other: [please specify]*
- ☐ *I have not used any GenAI tools in preparing this assessment.*
- ☐ *I declare that I have referenced use of GenAI outputs within my assessment in line with the University referencing guidelines.*

Please note: Submitting your work without an accompanying declaration, or one with no ticked boxes, will be considered a declaration that you have not used generative AI in preparing your work

If a declaration sheet cannot be uploaded as part of an assignment (i.e. at the start of an essay), students understand that by submitting their assessment, they are confirming they have followed the assessment brief and guidelines about the use of GenAI.