Case Study: Vehicle Routing Optimization Using Simulated Annealing

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19/07/2024

Introduction

Vehicle routing is a critical component of supply chain management, influencing both operational efficiency and cost-effectiveness. This case study explores the application of the Simulated Annealing (SA) algorithm to optimize delivery routes with the objective of minimizing total travel time. Inspired by the physical annealing process, SA starts with an initial solution and iteratively adjusts it, using a temperature parameter to accept worse solutions occasionally, thus avoiding local optima. Traditional supply chain design has predominantly focused on economic aspects, such as minimizing costs or maximizing profits. However, contemporary concerns necessitate the inclusion of environmental and social perspectives. These additional factors often complicate the problem formulation, necessitating multi-objective approaches modeled through bi-objective mixed linear programming. Given the complexity and computational burden of such problems, a meta-heuristic approach, particularly Simulated Annealing, is utilized to provide efficient solutions.

Problem Description

This study aims to optimize vehicle routing within a supply chain network to minimize total travel time for deliveries. The problem involves a fleet of vehicles starting from a central depot, delivering goods to a set of customers, and returning to the depot. The key elements of the problem include:

- A known number of customers and their locations.
- Specific demands for each customer.
- A fleet of vehicles with defined capacities.

The challenge is to determine the optimal set of routes that minimizes total travel time while meeting all customer demands.

Literature Review

Previous research has explored various aspects of supply chain design, including facility location, production levels, supplier selection, and inventory control. Recent studies have highlighted the importance of integrating environmental impacts into supply chain decisions. Simulated Annealing has shown promise in solving large, complex problems, making it a suitable candidate for vehicle routing optimization.

Methodology

The Simulated Annealing (SA) algorithm seeks to find a globally optimal solution through iterative improvements. It leverages a temperature parameter to probabilistically accept worse solutions, thus avoiding local optima and exploring a broader solution space.

Steps of the Simulated Annealing Algorithm:

1. **Initialization**: Start with an initial feasible solution, where each vehicle is assigned a preliminary route.
2. **Temperature Setup**: Set an initial temperature and define a cooling schedule.
3. **Solution Adjustment**: Iteratively adjust routes to explore nearby solutions:

- Generate a neighboring solution by swapping or adjusting routes.
- Evaluate the new solution.
- Accept the new solution if it is better.
- If the new solution is worse, accept it with a probability that decreases with temperature.

4. **Cooling**: Gradually reduce the temperature according to the cooling schedule.
5. **Termination**: Continue the process until the temperature reaches a predefined threshold or no further improvements are found.

Computational Evaluation

Small Instances:

For small-sized problems, the performance of the SA algorithm is benchmarked against the exact epsilon-constraint method. This provides a reference for evaluating the quality of solutions generated by the SA algorithm.

Large Instances:

For larger instances, the exact method is adapted by imposing a time limit for each epsilon-constraint point. The approximate efficient sets obtained from this variation are then compared with the solutions generated by the SA algorithm.

Example Implementation

Problem Statement:

The supply chain network includes multiple manufacturing sites and distribution centers. The goal is to produce and deliver four types of final products (P4 to P7), two of which are also used as intermediate materials (P4 and P5). Five potential locations are considered for facility installation.

Environmental Methodology:

The Life Cycle Assessment (LCA) methodology, using the Eco-indicator 99, is applied to model environmental impacts. This involves:

1. Inventory categorization of all relevant emissions, resource extractions, and land-use.
2. Calculation of damages to Human Health, Ecosystem Quality, and Resources.

Modeling Framework:

The SA algorithm is adapted to account for both economic and environmental objectives. The goal is to approximate the Pareto frontier, balancing profit maximization and environmental impact minimization. The algorithm incorporates:

- Multipurpose facilities that process different products using shared resources.
- Warehouses and distribution centers at pre-selected potential locations.

Solution Steps:

1. **Initial Route Setup**: An initial feasible route is generated for the fleet.
2. **Iterative Improvement**: Routes are iteratively swapped or adjusted:
    - Neighboring solutions are generated by modifying routes.

- Each solution is evaluated based on travel time and environmental impact.
- Solutions are accepted based on their evaluation and the current temperature.

3. **Cooling Schedule**: The temperature is gradually reduced, allowing the algorithm to settle into a globally optimal solution.

Results

The SA algorithm effectively balances exploration and exploitation, finding high-quality solutions for the vehicle routing problem. The ability to escape local optima results in a significant reduction in total travel time compared to traditional methods.

Conclusion

This case study demonstrates the effectiveness of the Simulated Annealing algorithm in optimizing vehicle routing. The approach not only minimizes total travel time but also incorporates environmental considerations, offering a comprehensive solution for supply chain design.

Future Research

Further studies could explore the application of the SA algorithm to multi-objective optimization problems, incorporating additional factors such as inventory levels and environmental impact. Additionally, hybrid algorithms combining SA with other optimization techniques could enhance efficiency and effectiveness.

Acknowledgments

The authors gratefully acknowledge the financial support from the Portuguese Science Foundation (FCT) under project PTDC/SEN-ENR/102869/2008. This work was partially supported by the FCT (Portuguese Foundation for Science and Technology) through PEst-0E/MAT/UI0297/2011 (CMA).