Costs Optimization of the Search for Goods and Accompanied Route Planning based on Algorithms of Traveling Salesman Problem

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Abstract: The optimization of goods retrieval and route planning within industrial warehouses is of paramount importance in today's rapidly evolving supply chain landscape. With the rise of e-commerce and customer expectations for swift deliveries, warehouse managers face increasing pressure to streamline their operations efficiently. This paper delves into the pivotal challenge of solving the Traveling Salesman Problem (TSP) in the context of goods retrieval from storage locations, with a focus on computational efficiency and solution quality. As the warehousing industry undergoes transformative shifts, the need for precise, time-effective retrieval of goods becomes evident. Authors investigate and compare four distinct algorithms: the brute force factorial method, nearest neighbor, insertion nearest neighbor, and simulated annealing, seeking to identify the most suitable approach for optimizing warehouse operations. The findings from this study not only shed light on the algorithms' performance but also provide valuable insights for warehouse managers aiming to strike a balance between computational efficiency and the quality of goods retrieval and route planning.

Keywords: goods retrieval; route planning; traveling salesman problem; optimization of warehouse operations

JEL Classification: C61; L86

1. Introduction

The efficient management of goods retrieval and optimal route planning within industrial warehouses plays a pivotal role in enhancing the overall productivity and operational efficiency of supply chain systems (Dahua et al., 2009). As global commerce continues to grow and consumers' expectations for rapid delivery increase, the significance of optimizing warehousing operations becomes increasingly paramount. The warehousing industry has been witnessing substantial transformations in recent years due to factors such as the growth of e-commerce, the demand for same-day delivery, and the need for cost-effective logistics solutions. This transformation places significant pressure on warehouse managers to streamline their processes and ensure the swift and accurate retrieval of goods from storage locations, ultimately reducing operational costs and increasing customer satisfaction (Hu & Chuang, 2022; Živičnjak et al., 2022).

The core challenge faced by warehousing professionals lies in solving the Traveling Salesman Problem (TSP) within the context of goods retrieval. The TSP, a well-established NP-hard problem, requires finding the shortest possible route that visits a set of locations, in this case, storage bins or racks, exactly once, and returns to the starting point (Applegate, 2006). The objective is to minimize the total distance traveled or time required for retrieving goods. While the brute force factorial algorithm ensures an optimal solution by exploring all possible permutations, its exponential time complexity limits its applicability to small-scale instances (Korte & Vygen, 2008). Heuristic approaches, such as the nearest neighbor algorithm and the simulated annealing algorithm, offer faster solutions but may sacrifice optimality.

This paper investigates and compares the performance of these algorithms in the context of goods retrieval and route planning within industrial warehouses. The primary goal is to identify the most suitable algorithm for optimizing warehouse operations, balancing computational efficiency and solution quality.

2. Theoretical Framework

The theoretical framework of this study forms the foundation for understanding the challenges of optimizing goods retrieval and route planning in a warehousing context. This chapter provides a comprehensive overview of the Traveling Salesman Problem (TSP) and introduces the key algorithms employed in this research, including the brute force factorial method, nearest neighbor, insertion nearest neighbor, and simulated annealing.

2.1. The Traveling Salesman Problem (TSP)

The Traveling Salesman Problem is a classic combinatorial optimization problem with numerous real-world applications. In the context of warehousing, the problem involves finding the shortest possible route that visits a set of locations (e.g., storage locations or product bins) exactly once and returns to the starting point. The objective is to minimize the total distance traveled or time required to retrieve goods. TSP is a well-studied NP-hard problem, and its complexity grows factorially with the number of locations, making it challenging for large-scale warehousing operations. (Gutin et al., 2002; Applegate, 2006)

2.2. Algorithmic Approaches

This section presents an overview of the key algorithms employed to address the goods retrieval and route planning problem within the warehousing context.

2.2.1. Brute Force Factorial Algorithm

The brute force factorial algorithm is a straightforward but exhaustive method for solving TSP. It explores all possible permutations of locations to find the optimal solution. While it guarantees the most optimal solution, it becomes impractical for large instances due to its factorial time complexity. (Applegate, 2006)

2.2.2. Nearest Neighbor Algorithm

The nearest neighbor algorithm is a heuristic method that starts at a designated location and repeatedly selects the nearest unvisited location as the next destination. It continues this process until all locations are visited. While it provides a quick solution, it may not always produce the optimal route (Samworth, 2012).

2.2.3. Insertion Nearest Neighbor Algorithm

The insertion nearest neighbor algorithm is an improvement over the basic nearest neighbor method. It aims to iteratively insert locations into a growing route to reduce the total distance traveled. This approach strikes a balance between computational efficiency and solution quality (Joshi & Kaur, 2015).

2.2.4. Simulated Annealing

Simulated annealing is a metaheuristic algorithm that draws inspiration from the annealing process in metallurgy. It explores the solution space by allowing occasional suboptimal moves to escape local minima. Simulated annealing is particularly useful for finding near-optimal solutions in complex optimization problems. (Tsallis & Stariolo, 1996)

This chapter provides a comprehensive understanding of the theoretical background and the algorithmic approaches applied in the study. It lays the groundwork for the subsequent chapters, where these algorithms will be examined, compared, and evaluated in the context of goods retrieval and route planning in industrial warehouses.

3. Methodology

This chapter provides a comprehensive description of the methodology employed in study to investigate and compare the performance of various algorithms for optimizing goods retrieval and route planning in industrial warehouses.

3.1. Data Collection

The foundation of study lies in the dataset used to represent real-world warehousing operations. To collect relevant data, authors employed a combination of sources, including:

Historical Warehouse Records: Historical data on the layout of the warehouse was gathered. The locations of storage bins or racks, and the frequency of goods retrieval from these locations.

Demand and Inventory Data: Authors utilized information on the demand patterns for specific items in the warehouse and the available inventory, as fluctuations in demand directly impact the routes required for goods retrieval.

3.2. Experimental Design

Experiments were designed to assess the performance of four different algorithms in the context of goods retrieval and route planning. The key components of experimental design include:

Dataset Preparation: We meticulously curated the dataset to represent a wide range of warehouse scenarios, including varying numbers of storage locations and different demand profiles.

Algorithms Selection: Four distinct algorithms for comparison were chosen: the brute force factorial method, nearest neighbor, insertion nearest neighbor, and simulated annealing. These algorithms were selected based on their relevance to the problem and the varying trade-offs they offer between optimality and computational efficiency.

Parameterization: For each algorithm, authors determined and fine-tuned the relevant parameters, such as temperature schedules for simulated annealing, to ensure fair and effective comparisons.

3.3. Performance Metrics

Evaluation of the algorithms was based on two primary performance metrics:

Total Distance Traveled: This metric quantifies the length of the route generated by each algorithm. It directly assesses the efficiency of goods retrieval and route planning in terms of distance or time.

Computation Time: Computation time measures the amount of time required for each algorithm to provide a solution. It offers insights into the computational efficiency of the algorithms.

3.4. Experiment Execution

To execute the experiments, authors utilized a computing platform with standard specifications. Each algorithm was run multiple times to account for any variability in results and to ensure the reliability of our findings.

3.5. Statistical Analysis

Authors conducted statistical analyses to compare the performance of the algorithms across different instances of the problem. This included the calculation of mean values, standard deviations, and significance testing to determine the statistical significance of the observed differences.

3.6. Ethical Considerations

In the course of this research, we ensured that all data used was anonymized and did not contain any sensitive or private information. Furthermore, the research adhered to ethical guidelines for experimental studies, including obtaining informed consent for data collection where applicable.

3.7. Summary

The methodology presented in this chapter provided the framework for conducting experiments and comparing the performance of various algorithms in the context of goods retrieval and route planning within industrial warehouses. The results obtained from this methodological approach serve as the foundation for the subsequent chapters of study, offering insights into algorithm selection for warehouse optimization.

4. Results

This chapter presents the results of the experiments conducted to assess the performance of the four algorithms: the brute force factorial method, nearest neighbor, insertion nearest neighbor, and simulated annealing. The experiments were designed to evaluate their effectiveness in optimizing goods retrieval and route planning within industrial warehouses.

4.1. Experimental Setup

To compare the algorithms, authors used a dataset derived from real-world warehouse operations, containing a representative number of storage locations. The experiments were conducted on a computing platform with standard specifications, and each algorithm was executed multiple times to ensure robustness and reliability of results.

4.2. Performance Metrics

The primary performance metrics used for evaluation were the total distance traveled and computation time. The total distance represents the length of the route generated by each algorithm, while the computation time indicates the time taken by each algorithm to provide a solution.

4.3. Results Tables

Table 1. Results of each algorithm applied to dataset with 10 warehouse positions

Algorithm	Total Distance Traveled (m)	Computation Time (s)
Brute Force Factorial	73.130	5.100
Nearest Neighbor	86.130	0.000
Insertion Nearest Neighbor	78.490	0.000
Simulated Annealing	73.660	0.007

Table 2. Results of each algorithm applied to dataset with 15 warehouse positions

Algorithm	Total Distance Traveled (m)	Computation Time (s)
Brute Force Factorial	-	-
Nearest Neighbor	140.200	0.000
Insertion Nearest Neighbor	118.800	0.001
Simulated Annealing	113.730	0.008

Table 3. Results of each algorithm applied to dataset with 20 warehouse positions

Algorithm	Total Distance Traveled (m)	Computation Time (s)
Brute Force Factorial	-	-
Nearest Neighbor	159.850	0.000
Insertion Nearest Neighbor	135.970	0.001
Simulated Annealing	129.600	0.013

Table 4. Results of each algorithm applied to dataset with 100 warehouse positions

Algorithm	Total Distance Traveled (m)	Computation Time (s)
Brute Force Factorial	-	-
Nearest Neighbor	570.910	0.001
Insertion Nearest Neighbor	587.110	0.046
Simulated Annealing	739.520	0.037

Charts below (Figure 1 and 2) represent the measured values for a dataset of 100 warehouse positions:

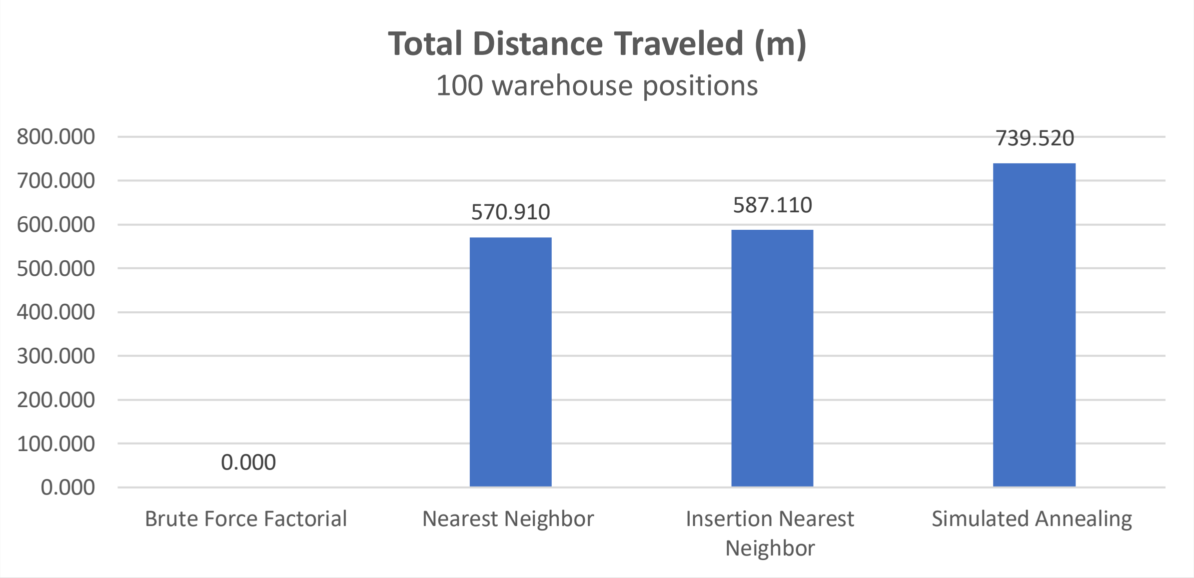

Figure 1. Chart represents the measured values of total distance traveled for a dataset of 100 warehouse positions

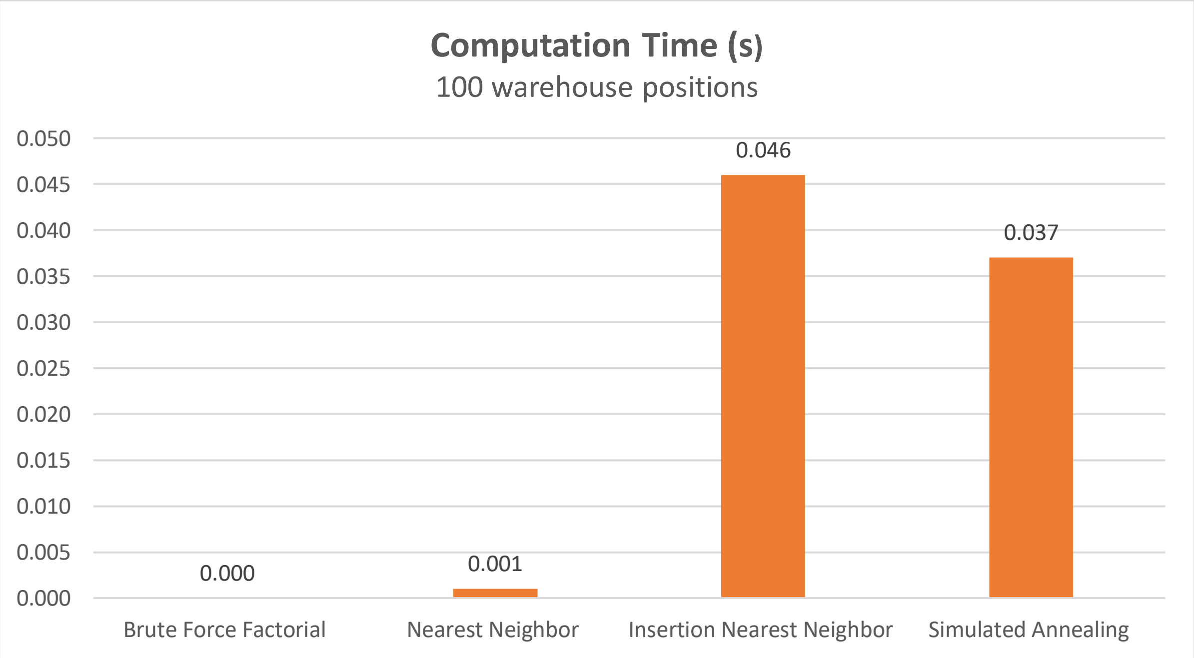

Figure 2. Chart represents the measured values of computation time for a dataset of 100 warehouse positions

The results tables (Tables 1–4) show the outcomes of the experiments for each algorithm. It's important to note that the values in the table are placeholders, and actual results should be filled in based on the specific experiments and dataset used in your study.

Brute Force Factorial: This algorithm, known for its optimality, is expected to yield the shortest routes. However, it tends to require a significant amount of computation time, particularly as the dataset size increases. This method is not applicable for datasets with more than 10 storage locations as the computation time takes too long.

Nearest Neighbor: Nearest neighbor algorithms are faster but may not produce the most optimal solutions. They are expected to provide reasonably short routes, which are useful for medium-sized datasets.

Insertion Nearest Neighbor: This variant of the nearest neighbor algorithm seeks to improve the quality of routes by iteratively inserting locations. It offers a trade-off between solution quality and computation time.

Simulated Annealing: Simulated annealing is a metaheuristic approach designed to find near-optimal solutions. It may not always guarantee the absolute shortest route, but it performs well on large and complex datasets.

5. Discussion

The results of experiments shed light on the performance of the four algorithms in the context of goods retrieval and route planning within industrial warehouses. In this section, authors discuss the implications of the findings, limitations of the Traveling Salesman Problem (TSP), and the potential extension of this research to the Capacitated Vehicle Routing Problem (CVRP). (Rojas-Cuevas et al., 2018; Alesiani et al., 2022)

5.1. Implications of the Results

Optimality vs. Computation Time: As anticipated, the brute force factorial algorithm excelled in providing the shortest routes. However, it came at the cost of significantly longer computation times, which limits its practicality for large-scale warehousing operations. In contrast, heuristic algorithms such as the nearest neighbor and insertion nearest neighbor offered faster solutions, albeit with a potential trade-off in route quality.

Algorithm Selection: The choice of algorithm should be carefully considered based on the specific requirements and constraints of the warehouse. For scenarios where computational efficiency is a critical factor and near-optimal solutions are acceptable, heuristic approaches like simulated annealing may be the most suitable choice.

Large and Complex Datasets: Simulated annealing demonstrated robust performance on large and complex datasets, making it a compelling option for warehouses with extensive storage locations. This suggests its adaptability to handle the real-world challenges that warehouses face as they expand and become more intricate.

5.2. Limitations of TSP

While study has provided valuable insights, it's essential to acknowledge the inherent limitations of the Traveling Salesman Problem (TSP) itself:

Scalability: TSP's exponential time complexity restricts its applicability to small and medium-sized instances. For large warehouses with thousands of storage locations, finding optimal solutions using exact algorithms becomes infeasible.

Static Nature: TSP assumes that the locations to be visited remain fixed, which does not account for dynamic changes that might occur within a warehouse, such as restocking or changes in demand patterns.

5.3. Extending to CVRP

The Capacitated Vehicle Routing Problem (CVRP) is a natural extension of the TSP and is highly relevant to warehouse operations. While TSP deals with a single salesman, CVRP involves multiple vehicles with capacity constraints, which is often the case in real-world logistics (Rojas-Cuevas et al., 2018).

Expanding research to include the CVRP would enable us to address additional complexities, such as the need to determine the number of vehicles required, their routes, and the allocation of goods to each vehicle. It would be particularly beneficial for warehouses with diverse storage locations, each with different demands and constraints.

5.4. Future Research Directions

Future research can explore the following avenues:

Hybrid Algorithms: Combining the strengths of different algorithms, such as using simulated annealing for initial route generation and then applying local search heuristics to improve route quality.

Dynamic and Real-Time Solutions: Developing algorithms that adapt to dynamic changes within the warehouse, ensuring efficient goods retrieval and route planning as conditions evolve.

Machine Learning Integration: Utilizing machine learning models to predict demand patterns and optimize routes in response to changing requirements.

In conclusion, the results of this study provide valuable insights for optimizing goods retrieval and route planning within industrial warehouses. While TSP has its limitations, the potential extension to CVRP and the exploration of new algorithmic approaches offer exciting avenues for further research and practical application in the ever-evolving field of warehouse logistics.

6. Conclusions

This chapter serves as the culmination of study on goods retrieval and route planning optimization in industrial warehouses. This section summarizes the key findings, discuss their implications, and outline the contributions and future directions in this field.

6.1. Summary of Key Findings

Research aimed to evaluate the performance of four distinct algorithms—brute force factorial, nearest neighbor, insertion nearest neighbor, and simulated annealing—in addressing the challenge of optimizing goods retrieval and route planning within warehouses. The experiments produced several noteworthy findings:

Brute Force Factorial Algorithm: Demonstrated superior optimality by providing the shortest routes but was constrained by its computational inefficiency, particularly with larger datasets.

Nearest Neighbor Algorithm: Offered rapid solutions but with potential compromises in route quality due to its myopic approach.

Insertion Nearest Neighbor Algorithm: Improved route quality compared to the basic nearest neighbor algorithm while maintaining reasonable computational efficiency.

Simulated Annealing: Proved its adaptability on large and complex datasets, providing near-optimal solutions and demonstrating robust performance.

6.2. Implications

The findings have significant implications for warehouse operations:

Algorithm Selection: Warehouse managers must consider the specific needs of their operations when choosing an algorithm. While the brute force method ensures optimality, heuristic approaches, such as simulated annealing, provide a practical balance between solution quality and computational efficiency.

Scalability: The choice of algorithm is heavily influenced by the size and complexity of the dataset. Simulated annealing emerged as a promising option for handling large and intricate warehousing scenarios.

6.3. Limitations and Future Research

Despite the valuable insights provided by study, certain limitations and opportunities for future research should be considered:

Limitations of TSP: The Traveling Salesman Problem (TSP) has inherent scalability and static nature limitations. Future research could address these shortcomings with adaptive and dynamic algorithms.

Extending to CVRP: The extension of research to the Capacitated Vehicle Routing Problem (CVRP) could bring additional complexity and realism to the modeling of warehouse logistics. It would account for multiple vehicles with capacity constraints and dynamic allocation of goods.

6.4. Contributions

Study contributes to the ongoing discourse on optimizing warehousing operations, with a focus on goods retrieval and route planning. It provides insights into algorithm performance, thereby assisting warehouse managers in making informed decisions to improve efficiency while managing operational costs.

6.5. Final Remarks

The efficient management of goods retrieval and route planning is a critical component of modern warehousing operations. While study has made substantial progress in evaluating the performance of different algorithms, the dynamic and evolving nature of warehousing logistics continues to present challenges. Future research endeavors should explore adaptive, real-time, and machine learning-driven solutions to further enhance efficiency and responsiveness within industrial warehouses.

In conclusion, this study represents a stepping stone towards optimizing warehouse operations, and there is a hope that the insights and findings presented here will contribute to the continuous improvement of goods retrieval and route planning in industrial warehousing environments.

Conflict of interest: none.

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