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Benchmarking Metaheuristic Algorithms Against Optimization Techniques for Transportation Problem in Supply Chain Management

Felicia Lim Xin Ying[1], Suliadi Firdaus Bin Sufahani[2]*
[1,2]Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology, Universiti Tun Hussein Onn Malaysia, Muar, Malaysia
[1]felicialxy86@gmail.com, [2]suliadi@uthm.edu.my

Abstract

The optimization of transportation problems plays a significant role in supply chain management (SCM), where minimizing costs and improving efficiency are mandatory. The transition from manual methods to advanced computational approaches, such as metaheuristic algorithms, enhances decision-making and consolidates operations within SCM. Malaysia's transportation system has been confronting crucial challenges, characterized by congested roadways, limited rail connectivity and inefficient port operations, which interfere with the fluidity of goods and supply chain efficiency. This highlights the critical need for optimization techniques to enhance competitiveness and efficiency in the evolving SCM landscape. The research aims to explore the application of metaheuristic algorithms, with the Modified Distribution (MODI) method as the benchmark while employing the NorthWest Corner Method (NWCM) to obtain an initial feasible solution, to evaluate their performance in optimizing transportation problems. Metaheuristic algorithms, specifically Simulated Annealing (SA) and Particle Swarm Optimization (PSO), are implemented to explore alternative near-optimal solutions and assess the performance in terms of cost accuracy and computational efficiency. The results indicate that SA achieves a deviation of 12.92% in cost accuracy compared to the optimal MODI method, making it suitable for scenarios where precision is critical, whereas PSO which is 296.92 seconds faster, is ideal for time-sensitive applications. Finally, this study encourages future studies to explore additional algorithms, external factors and broader applications for enhanced real-world relevance and scalability to accentuate the potential of metaheuristic algorithms.

Keywords: optimization; supply chain management; MODI, simulated annealing; particle swarm optimization

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1. Introduction

Optimization of transportation problems has traditionally been reckoned on manual calculations and expert judgment to determine the most efficient routes with lowest transportation costs [1]. These methods, though effective in the past, were labor-intensive and depended heavily on years of experience, which can be cumbersome and occasionally out of date. As supply chain management (SCM) sits at the core of a business's functional divisions, it plays a critical role in balancing operational efficiency with customer satisfaction, ultimately driving profitability [2]. Therefore, modern practices and technologies that outperform conventional methods by 40-80% across key criteria are necessary to be implemented in the transportation and supply chain industry for smooth processes and efficiency enhancement [3]. However, there is limited research comparing the practical applicability of metaheuristics algorithms against optimization methods like MODI within the context of Malaysia's SCM challenges.

In recent years, metaheuristic algorithms are increasingly applied to enhance SCM optimization. [4] and [5] highlighted Simulated Annealing (SA)'s popularity due to its straightforward implementation and effective convergence properties. [6] further supported this view, illustrating that SA's global search capabilities make it a strong contender against other metaheuristic techniques like Ant Colony Optimization (ACO). Apart from that, Particle Swarm Optimization (PSO), inspired by social behavior, excels in solving large-scale transportation problem (TP), as demonstrated by [7] through novel variations balancing exploration and exploitation. These advancements emphasize the emerging methodologies in SCM optimization, highlighting TP's real-world applicability and the significance of algorithmic approaches in cost reduction and operational efficiency.

Malaysia's transportation system faces multifaceted challenges, including congested roadways, constrained rail connectivity and suboptimal port operations, all of which obstruct the flow of goods and supply chain efficiency [8]. For instance, berth delays in Port Klang due to congestion have not only elevated shipping costs but also disrupt supply chain [9]. These inefficiencies have a direct effect on Malaysian enterprises' ability to compete on the international stage by raising logistical costs and impeding timely delivery [10]. Moreover, the reliance on traditional, labor-intensive transportation management techniques further intensifies the issue, highlighting the urgent need for advanced optimization methods to enhance efficiency and adaptability in the supply chain [11].

This study aims to address these challenges by exploring both optimization and metaheuristic techniques for solving transportation problems. It focuses on determining the initial feasible solution using the NorthWest Corner Method (NWCM) and achieving the optimal solution through the Modified Distribution (MODI) method to serve as a benchmark for evaluating metaheuristic algorithms. Additionally, metaheuristic algorithms, such as Simulated Annealing (SA) and Particle Swarm Optimization (PSO), will be applied to obtain near-optimal solutions for transportation problems involving supply, demand and cost matrices. The research then compares the performance of these metaheuristic algorithms against the benchmark optimal solutions provided by MODI methods, with the goal of identifying approaches that obtain results closest to the optimal outcomes.

2. Methods

2.1 Data Collection

This research utilized two distinct supply chain datasets to investigate the optimization of costs in transportation problem. The samples of the data from the website are shown on Figure 1.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	Product ty	SKU	Price	Availability	Number of	Revenue g	Customer demographics	Stock level	Lead times	Order quai	Shipping ti	Shipping c	Shipping c	Supplier na	Location	Lead time	Productior
2	haircare	SKU0	69.80800554	55	802	8661.997	Non-binary	58	7	96	4	Carrier B	2.956572	Supplier 3	Mumbai	29	215
3	skincare	SKU1	14.84352328	95	736	7460.9	Female	53	30	37	2	Carrier A	9.716575	Supplier 3	Mumbai	23	517
4	skincare	SKU15	36.98924493	94	469	5442.087	Non-binary	9	8	69	7	Carrier B	2.42204	Supplier 1	Bangalore	14	580
5	skincare	SKU3	61.16334302	68	83	7766.836	Non-binary	23	13	59	6	Carrier C	1.729569	Supplier 5	Kolkata	24	937
6	skincare	SKU16	7.54717211	74	280	6453.798	Female	2	5	78	1	Carrier B	4.191325	Supplier 1	Bangalore	3	399
7	haircare	SKU5	1.699976014	87	147	2828.349	Non-binary	90	27	66	3	Carrier B	4.444099	Supplier 4	Bangalore	10	104
8	skincare	SKU6	4.078332863	48	65	7823.477	Male	11	15	58	8	Carrier C	3.880763	Supplier 3	Kolkata	14	314
9	cosmetics	SKU7	42.95838438	59	426	8496.104	Female	93	17	11	1	Carrier B	2.348339	Supplier 4	Bangalore	22	564
10	cosmetics	SKU8	68.71759675	78	150	7517.363	Female	5	10	15	7	Carrier C	3.404734	Supplier 4	Mumbai	13	769
11	skincare	SKU9	64.01573294	35	980	4971.146	Unknown	14	27	83	1	Carrier A	7.166645	Supplier 2	Chennai	29	963
12	skincare	SKU10	15.70779568	11	996	2330.966	Non-binary	51	13	80	2	Carrier C	8.673211	Supplier 5	Kolkata	18	830
13	skincare	SKU11	90.63545998	95	960	6099.944	Female	46	23	60	1	Carrier A	4.523943	Supplier 2	Kolkata	28	362
14	haircare	SKU12	71.21338908	41	336	2873.741	Unknown	100	30	85	4	Carrier A	1.325274	Supplier 4	Kolkata	3	563
15	skincare	SKU13	16.16039332	5	249	4052.738	Male	80	8	48	9	Carrier A	9.537283	Supplier 5	Bangalore	23	173
16	haircare	SKU70	47.91454182	90	32	7014.888	Female	10	12	22	4	Carrier B	6.315718	Supplier 1	Bangalore	22	775
17	cosmetics	SKU72	90.20442752	88	478	2633.122	Non-binary	57	29	77	9	Carrier A	6.599614	Supplier 1	Bangalore	21	152
18	haircare	SKU83	68.91124621	82	663	2411.755	Unknown	65	24	7	8	Carrier B	4.94984	Supplier 1	Bangalore	20	443
19	cosmetics	SKU17	81.46253437	82	126	2629.396	Female	45	17	85	9	Carrier C	3.585419	Supplier 1	Chennai	7	453
20	haircare	SKU18	36.44362777	23	620	9364.674	Unknown	10	10	46	8	Carrier C	4.339225	Supplier 2	Kolkata	18	374

(a)

	A	B	C	D	E	F	G	H	I	J	K	L
1	Order ID	Order Date	Origin Port	Carrier	TPT	Service Level	Ship ahead day count	Ship Late Day cou	Customer	Product ID	Plant Code	Destination Port
2	1447296447	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
3	1447158015	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
4	1447138899	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
5	1447363528	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
6	1447363981	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
7	1447351441	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
8	1447320236	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
9	1447158019	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
10	1447219341	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
11	1447398416	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
12	1447381679	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
13	1447170785	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1700106	PLANT16	PORT09
14	1447155056	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
15	1447257265	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
16	1447240989	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
17	1447257231	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
18	1447260653	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
19	1447139375	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
20	1447308590	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
21	1447191271	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1697884	PLANT16	PORT09
22	1447191284	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1699336	PLANT16	PORT09
23	1447352426	26/5/2013	PORT09	V44_3	1	CRF	3	0	V55555_53	1702652	PLANT16	PORT09

(b)

Figure 1. The sample data from (a) Fashion and beauty startup (b) Global microchip, illustrating the supply chain analysed for optimization

The mandatory dataset, focused on a Fashion and Beauty startup, includes 24 variables and 100 samples. The dataset provides insights into supply chain analysis and is accessible in Kaggle platform at https://www.kaggle.com/code/amirmotefaker/supply-chain-analysis. In this dataset, the ‘Supplier name’ refers to source, while the ‘Location’ indicates the destination. Stock levels and order quantities represent supply and demand values, respectively. The variables and descriptions are detailed in Table 1.

To ensure the validity of the research, a supplementary dataset was also incorporated. This dataset, https://www.kaggle.com/datasets/anisseezzebdi/supply-chain-logistics-problem, was provided by a global microchip producer. It contains data on 9,215 outbound orders requiring routing through a supply chain network comprising 19 warehouses, 11 origin ports and one destination port. The data is organized into seven tables, each highlighting different components of the logistics network. A summary of these tables is presented in Table 2.

Table 1. Data description of fashion and beauty startup dataset

Features	Descriptions	Data Type
Stock Level	Quantities of stock available at each origin or hub.	Numerical
Order Quantities	The number of goods requested to be shipped to each destination.	Numerical
Supplier Name	The name of suppliers associated with the transportation process.	Categorical
Location	Destinations	Categorical
Costs	Transportation costs between origins and destinations for goods.	Numerical

Table 2. Data description of global microchip dataset

Tables	Descriptions
FreightRates	All available couriers, the weight gaps for each individual lane and rates associated.
PlantPorts	The allowed links between the warehouses and shipping ports in real world.
ProductsPerPlant	All supported warehouse-product combinations.
VmiCustomers	All special cases, where warehouse is only allowed to support specific customer
WhCapacities	Warehouse capacities measured in number of orders per day.
WhCosts	The cost associated in storing the products in given warehouse measured in dollars per unit.

2.2 Data Preprocessing

The main dataset used was thoroughly examined for data quality, with no missing values, duplicate entries or outliers identified, ensuring its readiness for analysis. For the supplementary global microchip dataset, while no missing values were found, three duplicate entries were detected and removed to maintain the data integrity. Both datasets were examined for outliers using the 95th percentile as a capping threshold, and revealed no outliers.

The cleaned supplementary dataset was then updated in the 'FreightRates' variable and synchronized with the corresponding dictionary entry to ensure consistency across the data structure.

2.3. *Model Formulation*

The transportation problem (TP) focuses on efficiently moving goods from sources to destinations while meeting supply and demand constraints and it is widely applied in operations research [12]. Solving this problem involves two phases: determining the initial basic feasible solution (IBFS) and optimizing it for the best outcome [13], which in this research the two methods are NWCM and MODI respectively.

The optimal solution obtained from the TP is then serves as a benchmark to evaluate the effectiveness of metaheuristic algorithms, specifically Simulated Annealing (SA) and Particle Swarm Optimization (PSO). The mathematical formulation of general TP is as shown in Equation 1 [14]:

$$\sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}x_{ij} \quad (1)$$

Subject to Equations 2 and 3.

$$\sum_{i=1}^{m} x_{ij} = K_j,\ j = 1,2,3,\dots n \quad (2)$$

$$\sum_{j=1}^{n} x_{ij} = R_i,\ \mathrm{i} = 1,2,3,\dots \mathrm{m} \quad (3)$$

x_{ij} is the number of units transported from source i to destination j, C_{ij} is the cost per unit goods transported from source i to destination j, R_i is the total supply from all sources i, and K_j is the total demand from all destination j

2.4 Model Development

The NorthWest Corner Method provides an initial feasible solution for the TP, which is then optimized using the Modified Distribution method to minimize costs. Metaheuristic algorithms which are Simulated Annealing and Particle Swarm Optimization are later applied to explore alternative near-optimal solutions as shown in Equations 4 and 5.

Firstly, NWCM is the IBFS used as the collection of arc flows that fulfil every demand condition without providing more from any origin node than the supply available [15]. The allocation process is done based on the criteria when supply equals demand and is looped until all quantities are fully allocated.

After getting IBFS by NWCM, MODI method will be applied to obtain the optimal solution. In this step, improvement index for unallocated cells is computed and iteratively adjust allocations until no further improvements can be made (no non-negative values exist), indicating the optimal solution is reached [16].

Next, metaheuristic algorithms will be utilized to obtain near-optimal solutions for the TP. According to [5], SA algorithm can be divided into 4 steps which are described in Figure 2(a). Whereas PSO excels in two key areas: exploration and exploitation. In the exploration phase, the algorithm searches the space for promising regions, while in the exploitation phase, it fine-tunes the search to find the global optimum [17]. The pseudocode of PSO algorithm has been summarized in Figure 2(b).

$$\mathrm{V_i(t+1)} = \omega.\mathrm{V_i(t)} + \mathrm{c_1 r_1}\left(\mathrm{P_{i,best}} - \mathrm{X_i}\right) + \mathrm{c_2 r_2}\left(\mathrm{P_{g,best}} - \mathrm{X_i}\right) \quad (4)$$

$$\mathrm{X_i(t+1)} = \mathrm{X_i(t)} + \mathrm{V_i(t+1)} \quad (5)$$

V_i is the current velocity of the particle, ω is the inertia weight, $\mathrm{c1, c2}$ is the positive constants known as acceleration coefficient, $r1, r2$ is the random variables with uniform distribution between zero and one, X_i is the position of the particle at iteration $t,$ is the best position of the particle until the iteration t, and $P_{g,best}$ is the finest position of the whole swarm until the same iteration.

```
Metaheuristic Algorithm: SA
Initialize required parameters such as initial temp (T_0), end temp (T_min) and cooling coefficient
While not converged:
do
  | Generate new candidate solution (y) from neighbourhood of current solution (x)
  | Calculate change in objective function
  | If f(y) ≤ f(x) then
  |     Accept the candidate (x=y)
  | else
  | Calculate acceptance probability p(accept)=exp(-(f(y)-f(x)) / T_k)
  └Reduce temperature
Return best solution found
```

(a)

```
Metaheuristic Algorithm: PSO
Initialize required parameters such as w, c1, c2, Popsize, Maxiters, Maxrun
Initialize velocity and position of every particles
do
  | for each particle do
  |   | Evaluate Fitness value using the defined objective function
  |   | Update particle's personal best position (pBest)
  |   |_Update particle's global best position (gBest)
  | Update the inertia weight w
  | for every particle do
  |   | Update velocity with Eq. (4)
  |   |_ Update position with Eq. (5)
while the end condition is not arrived
return the gBest solution
```

(b)

Figure 2. Pseudocode of Algorithms (a) SA [19]; (b) PSO [18], detailing the algorithmic structure applied in optimization

2.5 Sensitivity Analysis

The sensitivity analysis evaluates the SA algorithm's performance by varying the initial temperature using an exponential cooling rate by Equation 6 to optimize solution quality and convergence behavior.

$$Temp_{new} = Temp_{current} \times cooling\ rate \quad (6)$$

$Temp_{new}$ is the updated (new) temperature after the current iteration, $Temp_{current}$ is the temperature at the current iteration.

This is grounded in the concept that SA is a stochastic optimization technique modelled after the annealing process in metallurgy where materials slowly cooled to achieve a well-ordered crystalline state. By employing thermodynamic principle, SA allows both uphill and downhill movements, aiming to escape local optima and find a global minimum. A high initial temperature enables broad exploration of solution spaces, including those with higher costs to avoid getting trapped in local minima while gradual cooling focused on fine-tuning the current solutions [18].

Furthermore, the model is tested on a larger dataset to assess its scalability and ensure its efficiency in real-world applications.

2.6 Comparative Analysis

In the comparative analysis phase, the effectiveness of the metaheuristic methods was evaluated against the MODI method to determine which algorithm provides solutions closest to MODI's optimal results.

Based on the analyses conducted, the findings indicate that the selected metrics: convergence rate, execution time and optimized cost demonstrated the highest significance and relevance. These metrics serve as key performance indicators, offering valuable insights for researchers addressing transportation problems within the field of SCM. The comparison focused specifically on the performance of the SA and PSO algorithms.

3. Results and Discussions

3.1 Preliminary Analysis

The descriptive statistics of Price, Stock Levels, Order Quantities and Costs have been tabulated in Table 3, providing key insights into variability and operational challenges in the supply chain. The high-cost variability (standard deviation of 258.30) stresses the importance of minimizing transportation costs, making costs reduction a primary objective in this TP.

Table 3. Descriptive statistics for variables in the supply chain dataset

	Price	Stock levels	Order quantities	Costs
Mean	49.4625	47.7700	49.2200	529.2458
Standard Deviation	31.1682	31.3694	26.7844	258.3017
Min	1.6999	0	1.0000	103.9162
Max	99.1713	100.0000	96.0000	997.4135

To further explore the relationships among these key variables, the correlation matrix was analyzed and is presented in Figure 3. The correlation matrix highlights the strength and direction of relationships between variables. The general low correlations among variables suggest the complexity of real-world supply chains influenced by external factors. Specifically, the positive correlation (0.24) between costs and lead times marks the potential for higher costs due to extended lead times, such as increased holding expenses or expedited shipping [19].

Based on Figure 4, the relationships between suppliers and their respective locations can be visualized. The plot reveals overlapping suppliers serving multiple locations, indicating opportunities for optimizing routes and costs. Suppliers with dense interconnections may benefit from logistical models to reduce complexities, making them suitable for route or cost optimization models.

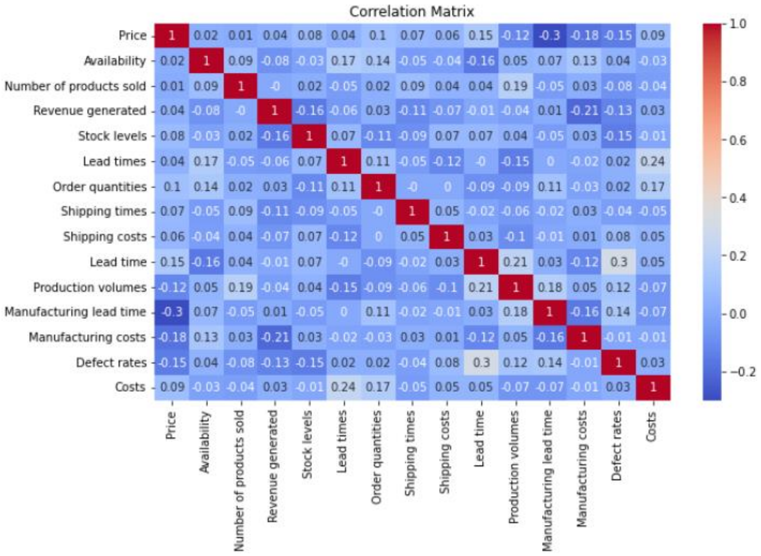


Figure 3. Correlation matrix of variables in supply chain dataset

Figure 4. The Supplier and Location Connections

3.2 The Modified Distribution (MODI) Method

The MODI method optimizes the TP, minimizing costs to an objective function value of 2,169,315.56, identical to the NWCM result. Table 4 details the allocations from suppliers to destinations, with zero denote no allocation for that particular path.

Table 4. Allocations for each route via MODI method

Route	Bangalore	Chennai	Delhi	Kolkata	Mumbai
Supplier 1	167	205	0	0	809
Supplier 2	0	904	78	206	0
Supplier 3	0	0	655	0	0
Supplier 4	0	0	0	1062	0
Supplier 5	0	0	1	0	897
Dummy	0	2	0	2	146

Supplier 1 primarily supplies Bangalore, Chennai and Mumbai, Supplier 2 distributes across Chennai, Delhi and Kolkata, while Supplier 3 focus solely on Delhi. Supplier 4 exclusively supplies 1062 units to Kolkata and Supplier 5 mainly supplies Mumbai, highlighting distinct supply patterns critical for optimizing resource allocation and transportation efficiency.

3.3 Simulated Annealing (SA)

The SA algorithm optimized the TP to a cost of 2,499,849.97, slightly higher than the MODI benchmark. The allocation matrix is tabulated in Table 5.

The algorithm utilizes a starting temperature of 1000 determined through preliminary tests which aligns with optimal convergence behaviour within acceptable runtime limits to enable broad exploration and avoid local minima [20], while the final temperature of one ensures convergence through gradual cooling. A cooling rate of 0.95 balances exploration and exploitation, reducing the risk of premature convergence [18]. These parameters are fixed for this stage, with sensitivity analysis done to oversee the temperature impact to follow in Subtopic 3.5.

Table 5. Allocations for each route via SA method

Route	Bangalore	Chennai	Delhi	Kolkata	Mumbai
Supplier 1	549.0	550.4	0	0	42.6
Supplier 2	141.1	41.3	0	670.5	169.1
Supplier 3	284.5	113.7	49.0	143.2	63.7
Supplier 4	1036.2	0	0	24.8	0
Supplier 5	199.8	301.4	193.6	104.1	99.2
Dummy	549.0	550.4	0	0	42.6

From Table 5, Supplier 4 is visualized to have allocated 1036.2 units exclusively to Bangalore, indicating significant cost advantages in this route under the SA solution. Supplier 1 prioritized Bangalore, Chennai and Mumbai with 549.0, 550.4 and 42.6 units, respectively, leaving other destinations unserved. Next, Supplier 2 supplied all destinations except Delhi, with notable allocations of 670.5 units to Kolkata and 169.1 to Mumbai. In contrast, Suppliers 3 and 5 demonstrated flexibility by distributing resources across all destinations, showcasing diverse supply strategies.

3.4 Particle Swarm Optimization (PSO)

The PSO algorithm optimized the transportation problem to a cost of 2,797,315.63, with iterative progress summarized in Table 6 and detailed resource allocations tabulated in Table 7.

Table 6. Iterations with corresponding best costs of PSO algorithm

Iterations	Best Costs	Iterations	Best Costs
Iteration 1	4,967,682.70	Iteration 33	2,249,104.72
Iteration 2	4,967,682.70	Iteration 34	2,249,104.72
Iteration 3	4,967,682.70	Iteration 35	2,169,315.56
⋮	⋮	Iteration 36	2,169,315.56
Iteration 8	4,967,682.70	⋮	⋮
Iteration 9	4,877,656.14	Iteration 99	2,169,315.56
Iteration 10	4,838,386.91	Iteration 100	2,169,315.56

Table 7. Allocations for each route via PSO method

Route	Bangalore	Chennai	Delhi	Kolkata	Mumbai
Supplier 1	0	0	0	452.6	347.9
Supplier 2	24.4	239.3	0	1018.2	36.6
Supplier 3	92.1	0	0	0	231.4
Supplier 4	95.6	0	0	701.4	0
Supplier 5	166.3	482.2	0	529.3	0
Dummy	0	0	0	452.6	347.9

PSO relies on three key parameters, inertia weight (w), cognitive constant (c1) and social constant (c2) to balance exploration and exploitation. Optimal values for these parameters, such as w=0.7, c1=2.0 and c2=2.0 ensure effective convergence towards the best solution while maintaining swarm diversity. The default values have been supported by the plot showing a constant rate from 0.6 to 0.8 illustrating the effect of inertia weight on average optimized costs in Figure 5.

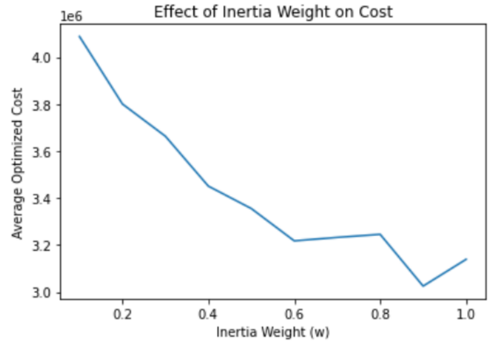
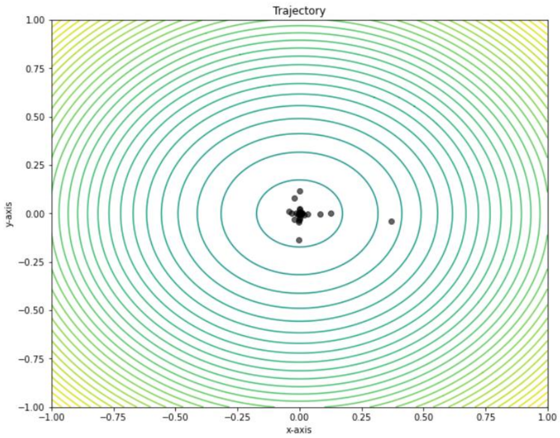


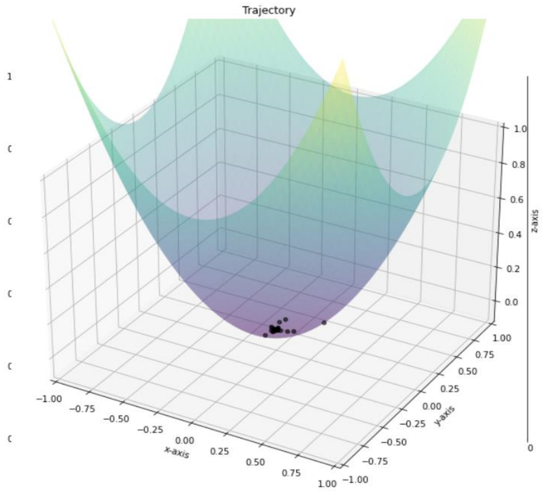
Figure 5. Line plot for effect of inertia weight on costs

With the PSO parameters set to their optimal default values, the algorithm was run for 100 iterations and the average of the best costs was calculated to ensure reliability. A sample of iterations and their corresponding best costs is shown in Table 6.

The absence of allocations to Delhi highlights potential inefficiencies due to urban constraints [21], while significant allocations to Kolkata and diverse allocation strategies across suppliers emphasize cost-driven decisions.



(a)



(b)

Figure 6. Particle Trajectory Plot (a) 2D plot; (b) 3D plot

The particle trajectory plot in Figure 6 illustrates how particles converge towards optimal solutions over time [22]. The observed convergence after Iteration 35 demonstrates the algorithm's high efficiency performance. A noticeable cluster of particles near the centre suggests that the swarm is converging towards the optimal solution showing exploitation as the particles refine their search to locate the best possible solution [18].

3.5 Sensitivity Analysis

For optimization problems, sensitivity analysis is particularly valuable for identifying the stability of optimal solutions and ensuring the model's effectiveness amid real-world uncertainties [23].

In this research, while the preliminary configuration of the SA algorithm established a reasonable basis for convergence by fixing the initial temperature and stopping criterion, sensitivity analysis systematically assessed the stability and effectiveness of the cooling strategy. Specifically, the analysis involved observing temperature reduction across iterations under a fixed exponential cooling rate [20], thereby enabling a more comprehensive evaluation of the algorithm’s convergence behavior and solution quality over the course of the optimization process, rather than relying solely on predefined starting and ending conditions.

Parameter tuning in this context was carried out by adjusting the temperature schedule within the SA algorithm. The initial temperature was set at 1000 and reduced iteratively using a constant cooling rate of 0.95, as formulated in Equation 7 for the first temperature update. The use of an exponential cooling schedule provided a more controlled and gradual reduction in temperature, which allowed for broader exploration in the early phases and more focused exploitation in the later stages of the search process [18]. This refined temperature control led to a lower final cost value, indicating improved convergence performance.

$$Temp_{new} = 1000 \times 0.95 \quad (7)$$

Iterations with the corresponding best costs for the SA algorithm with tuned parameters are summarized in Table 8. This data highlights the algorithm's iterative improvements in cost optimization, with final result of 2,449,518.79 representing a 2.01% improvement compared to the previous result (2,499,849.97) demonstrating its effectiveness in refining solutions over successive iterations.

Table 8. Iterations with corresponding best costs of SA tuned parameter

Iterations	Temperature	Best Costs
Iteration 1	950.0	2,652,926.05
Iteration 2	902.5	2,647,306.66
Iteration 3	857.4	2,647,306.66
⋮	⋮	⋮
Iteration 98	6.9	2,451,101.77
Iteration 99	6.2	2,449,518.79
Iteration 100	5.9	2,449,518.79

Throughout the study, parameter tuning was conducted exclusively for the SA algorithm, given its sensitivity to the temperature schedule, which directly influences its exploration and exploitation balance. Conversely, PSO was not subjected to parameter tuning, since this algorithm relies on particle interactions and memory of previous positions, its convergence behavior is more influenced by the global and local best solutions than by the direct control of temperature [24]. Hence, to assess PSO's performance and convergence behavior, the particle trajectory plot was performed and analyzed.

Additionally, the scalability and efficiency of the optimization model were tested using a larger dataset of 9,215 entries, compared to the original 100 entries. The results are summarized in Table 9.

Table 9. Result of the alternate larger dataset

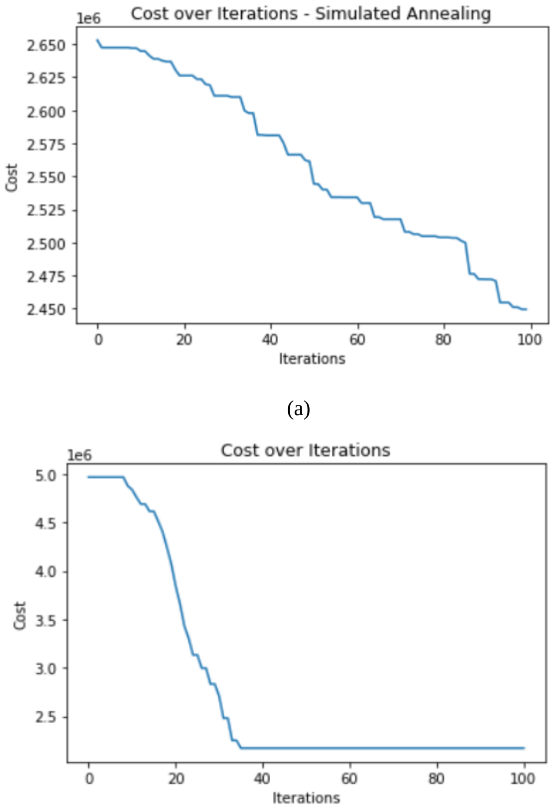
Algorithm	Simulated Annealing	Particle Swarm Optimization
Optimized Costs	5,783.13	7,134.08
Execution Time (seconds)	1,053.40	490.66

SA achieved a significantly lower optimized cost of 5,783.13 but required approximately 17 minutes to execute, demonstrating higher computational demand. With that, SA is validated to have optimized transportation costs by 28%. In contrast, PSO was faster, taking around 8 minutes but resulted in a higher cost of 7,134.08. This evaluation validates the model's effectiveness and applicability for handling larger datasets.

3.6 Comparative Analysis

This research evaluates the performance of SA and PSO based on convergence rate, solution quality and execution time. The convergence rate refers to how quickly the algorithm approaches an optimal or near-optimal solution over iterations. SA exhibits a steady and smooth cost reduction due to its gradual cooling schedule [18]. In contrary, PSO shows a sharp cost decrease between Iterations 10–30 as particles explore the solution space, followed by stabilization around Iteration 35. Rapid early-stage convergence demonstrates its efficiency in identifying optimal regions. The convergence plots are shown in Figure 7.

Next, the quality of the solution is assessed by comparing the minimized costs achieved by each algorithm. Table 10 summarizes the optimized costs and deviations from the MODI benchmark. From the table below, SA achieved a 12.92% optimized cost higher while PSO obtained a result 28.95% higher than the MODI benchmark. This result indicates that SA effectively approximates the benchmark but may settle at a near-optimal local minimum due to its probabilistic nature whereas the deviation highlights that PSO is less effective in addressing transportation problems requiring precise cost minimization.



(a)

(b)

Figure 7. Convergence plot (a) SA algorithm; (b) PSO algorithm, demonstrating algorithms' efficiency in identifying optimal regions

Table 10. Optimized costs among all three algorithms

Algorithm	Optimized Costs	Deviation from MODI
MODI	2,169,315.56	0%
Simulated Annealing (SA)	2,449,518.79	+12.92%
Particle Swarm Optimization (PSO)	2,797,315.63	+28.95%

The last metric considered is the execution time which emphasize speed without compromising solution quality. Table 11 summarizes the execution times and their differences from the MODI benchmark. From the result shown, SA completed in 70.66 seconds, making it 255.6 seconds faster than MODI while PSO required only 29.34 seconds, outperforming both MODI and SA by being 296.92 seconds faster than MODI. The significantly shorter runtime demonstrates PSO's computational efficiency due to its parallel search capabilities and straightforward update equations, despite its limitations in achieving precise cost optimization.

Table 11. Execution time among all three algorithms

Algorithm	Execution Time (seconds)	Difference from MODI
MODI	326.26	0
Simulated Annealing (SA)	70.66	-255.60 seconds
Particle Swarm Optimization (PSO)	29.34	-296.92 seconds

3.7 Overall Comparison

The overall comparison summarized the convergence rate, optimized costs and execution times of MODI, SA and PSO to evaluate their performance comprehensively. This analysis provides a balanced understanding of each algorithm's strengths and limitations, helping to identify the best choice for specific requirements. Table 12 provides a concise overview of each algorithm's performance.

The MODI, as a deterministic method, offers the most accurate solution with an optimized cost of 2,169,315.56 and an execution time of 326.26 seconds, without relying on iterative approximations, thus serving as the benchmark. SA produces a solution with a cost of 2,449,518.79, which is 12.92% higher than MODI's optimal solution but it completes in 70.66 seconds, 255.6 seconds faster than MODI. While SA's cost accuracy is slightly lower than MODI, this trade-off might be acceptable for mid-scale businesses where computational resources are limited. The algorithm maintains consistent progression until the stopping criteria are met, offering a balance between solution quality and computational efficiency. In contrast, PSO obtains a cost of 2,797,315.63, a deviation of 28.95% from MODI's solution, but it is the fastest, requiring only 29.34 seconds which is 296.92 seconds faster than MODI. Apart from that, PSO achieves a stable result by Iteration 35, showing its rapid convergence.

Table 12. Overall comparison among all three algorithms

Results	Convergence Rate	Optimized Costs		Execution Time	
		Optimized Costs	Deviation from MODI	Runtime (seconds)	Difference from MODI
MODI	Deterministic method (Does not rely on iterative approximations)	2,169,315.56	0	326.26	0
SA	Maintain consistent progression until the stopping criteria are met	2,449,518.79	+12.92%	70.66	-255.60 seconds
PSO	Achieved stable result by Iteration 35	2,797,315.63	+28.95%	29.34	-296.92 seconds

Hence, in summary, SA method will be utilised when accuracy is prioritized while use PSO when speed is more critical and slight deviations from optimality are acceptable.

3.8 Research Validation

The validity of the findings in this research is supported by both existing literature and participation in research competitions. The findings obtained in this research are aligned and well-supported by the research 'An intelligence-based hybrid PSO-SA for mobile robot path planning in warehouse' by [25] and 'Modified Particle Swarm Optimization Algorithm with Simulated Annealing Behavior and Its Numerical Verification' by [28] published in Elsevier.

In this research, SA demonstrates its capability to produce solutions with cost accuracy closely matching that of the benchmarked MODI method, deviating by 12.92% which is consistent with the characteristics outlined in the Elsevier research, where SA is praised for its good solution quality [26]. Conversely, PSO demonstrates exceptional computational efficiency which is the fastest among 3 algorithms and with 296.92 seconds faster than MODI. The remarkable speed of PSO aligns with findings from [25], where it is recognized for its fast convergence and suitability for high-dimensional optimization problems.

Beyond that, this research, titled 'Benchmarking Metaheuristic Algorithms Against Optimization Techniques for Transportation Problem in Supply Chain Management' was further validated through participation in the Research and Teaching Innovation Competition 2024 (RTIC 2024), organized by Universiti Malaysia Terengganu (UMT) and the International Creative & Innovative Idea Competition 2025 (ICIIC 2025), organized by MNNF Network. The research awarded two Gold Medals in these prestigious competitions, demonstrating its significant contribution to the field.

4. Conclusions

This study evaluates the effectiveness of different approaches in solving transportation problems, focusing on accuracy and efficiency, using the MODI method as a benchmark. The study revealed that SA outperforms PSO in terms of cost accuracy, but PSO has a faster execution time. The findings suggest that SA is more suitable when accuracy is prioritized, whereas PSO is preferred for speed, offering practical guidelines for selecting appropriate methods based on specific problem requirements. All objectives were successfully fulfilled through the results presented in Section 3.

This research contributes a comparative analysis of SA and PSO, enhancing theoretical understanding by showcasing SA's reliability in precision and PSO's adaptability in dynamic scenarios. Practically, it provides actionable insights for SMEs, helping them to choose between SA and PSO based on cost accuracy or computational speed and introduces the MODI method as a benchmark for evaluating emerging optimization approaches. In contrast to existing comparative studies, the localized emphasis on Malaysian SCM challenges addresses transportation routes and costs optimization via the utilization of real-world global microchip dataset, demonstrated the possibility of a 28% reduction in transportation costs, has emphasized the research's unique contribution. Furthermore, a comprehensive sensitivity analysis including SA temperature tuning, ensures validity and scalability, while testing on that global microchip dataset comprising over 9,000 entries demonstrates the methods' practical applicability to complex, large-scale transportation problems. This study bridges the gaps in benchmarking optimization and metaheuristic algorithms in SCM, providing actionable insights for businesses to balance cost efficiency and computational speed.

For limitations, this research is limited by the lack of access to real-world data, particularly sensitive business information related to routes and costs which restricted the use of comprehensive, real-time logistics data. Additionally, the study is based on fixed supply, demand and cost matrices, which may not reflect the dynamic and uncertain nature of real-world transportation problems. Future research could address these limitations by incorporating variability and uncertainty into the models. Furthermore, while many studies focus on individual optimization methods, there is limited research on comparing different approaches and evaluating the practicality of metaheuristic algorithms.

On top of that, several recommendations have been suggested, including future research should integrate real-world constraints such as traffic conditions, regulatory constraints and fuel price fluctuations into the models to improve their relevance. Beyond optimization capabilities, future research could also evaluate more fields for the reliability and practicality of implementing metaheuristic algorithms in transportation problem. In other respects, actionable recommendations for businesses include SMEs could implement metaheuristic algorithms to optimize transportation routes and reduce fuel costs, promote collaboration with local businesses to share transportation resources and provide employee training on the use of these optimization tools to enhance operational efficiency and drive cost-saving initiatives.

To put it in laconically, this research has provided a comprehensive analysis of the comparison between SA and PSO metaheuristic algorithm with the benchmark towards MODI method in solving transportation problems.

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