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Innovation in Four-Dimensional Transportation: A Hybrid Algorithm Based on Ant Colony and Particle Swarm Optimization

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Abstract

Adjusting four-dimensional transportation (4DT) is a difficult problem in logistics systems, which involves time, location, transportation modes, and cargo types. To come up with a solution to this problem, this work introduces a new breeding algorithm that combines Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), which would allow the exploration exploitability mechanism to search for optimal solutions. Existing data sets, which encapsulate real transportation problems, were replicated and utilized to implement the proposed algorithm in Python with results smoothed using a moving average method to alleviate noise. Moreover, Taguchi's technique was the performance of the algorithm was further improved, which was used for parameter tuning. The experimental results proved the superiority of the proposed algorithm over conventional methods that provided a 7.52% cost reduction compared to ACO and a 3.3% enhancement against PSO as it succeeded in increasing the effectiveness of logistics optimization. This work presents a step towards model-based systems engineering of more complex transportation systems, and recommends merging machine learning techniques in the future to obtain superior performance predictions in changing environments.

Keyword:

Metaheuristic Algorithms, Four-Dimensional Transportation Optimization, Ant Colony Optimization, Particle Swarm Optimization, Logistics and Supply Chain Optimization.

1. Introduction

With the current age of globalization, logistics and transportation systems are becoming increasingly complex due to the need for efficiency, cost-effectiveness, and sustainability. The four-dimensional transportation problem (4DTP), in which supply chain operations are optimized through coordination across time, location, transportation modes, and product types, has been a significant challenge for researchers (Sinuany-Stern, 2021). As logistics involve a high degree of dynamism, advanced optimisation methods are needed to improve processes and decrease costs, which traditional methods have failed to provide. A significant solution carried out in application of metaheuristic algorithms like Genetic Algorithms (GA) and Ant Colony Optimization (ACO) has been a great support, however, these methods have their own limitations like slow convergence, stagnation to local optima, and adjusting to real-time constraints. To overcome these limitations, this study presents a new hybrid algorithm combining ACO and Particle Swarm Optimization (PSO) to find an appropriate trade-off between exploration and exploitation in complex transportation problems (Gupta & Arora, 2021).

The hybrid algorithm is engaged with the exploratory ability of PSO and exploitative ability of ACO to optimize four-dimensional logistics operation. In contrast to traditional approaches, this one realizes a complementarity between the global search capabilities and refinement of the solution which results in lowered computational overhead and better transport performance. The study uses a robust experimental setup with Python-based simulation models and real-world-inspired datasets to assess the impact of an algorithm's performance. Our results show that the hybrid method outperforms standalone ACO and PSO in terms of transportation costs, computational efficiency, and solution stability.

1.1. Research Importance

In world transportation systems, the four-dimensional transportation (4DT) problem is one of the most complex problems in modern logistics systems, whose distribution processes have interleaved space, time, modes of transportation, and types of products, which brings difficulties in planning and reducing operational costs. The vast growth of logistics services and global e-commerce puts even more pressure on the development of models that can be used to optimize and design transportation operations under time restrictions, demand dynamics, product diversities, and multimodal facilities.

This is especially the case in areas like global supply chain management, smart logistics, as well as the delivery of perishable items (food and pharmaceutical products), where ineffective transportation results in high costs, delayed delivery, and environmental deterioration. Traditional models based on single algorithms like ACO and PSO have issues like slow convergence towards the optimal solution or getting stuck in local solutions, failing to reach better performance. We require a comprehensive integrated solution to solve these matters and ultimately bring measurable value for planning correctness and transport efficiency. This work addresses how to do this by means of a new hybrid algorithm that integrates ACO and PSO to jointly accomplish the optimization of resource utilization and operational costs.

1.2. Research objectives

The objective of this research is to find an optimal solution for the four-dimensional transportation problem as a hybrid algorithm based on ACO and PSO balancing exploration-exploitation which ensures better computational efficiency and reduction in operating cost. It also aims to evaluate how well the algorithm performs on realistic data (inspired by real transportation problems) to find and optimize where need the parameter tuning using Taguchi method allows developing solutions to be more stable and accurate.

This research is in the following categories. The first section provides an introduction to the Four-Dimensional Transportation Problem (4DTP) and its importance. Section 2 discusses related work, focusing on traditional and heuristic methods. The mathematical model is described in Section 3, which is followed by Section 4 that outlines the methodology and the invention of the hybrid algorithm between ACO and PSO. In Section 5, the results that are achieved by the proposed algorithms are presented. Section 6 offers a discussion analyzing the algorithm’s performance vis-a-vis standard practices, and interpreting the influence of different variables on outputs. Concluding remarks and future recommendations in section 7. And finally, the references cited in the study.

2. Literature Review

With the development of logistics operations, recently over the past decades the research of multi-dimensional transportation problems has gained considerable attention. Abu Kila et al. (2021) implemented a case study on multi-dimensional transportation problems for graphical representation of the complexity in shipping between nodes (Abo-

Kila et al., 2021). Similarly, Revathi et al. (2021) focused on multi-level time-dependent 4DT problems with uncertainty and discussed the difficulties of dynamic logistical settings (Revathi et al., 2021). Jana et al. 2019 further elaborate on these challenges (Halder Jana et al., 2019). Four Dimensional Fixed-Charge (FC) multi-component transportation problems (MITPs) under various constraints were studied by Halder Jana et al. (2019) incorporating budget limitations and space constraints for perishable goods (Halder Jana et al., 2019).

Related Studies to Metaheuristic algorithms applied to Transportation Problems, Zhang et al. (2014) showed these algorithms can promote optimization efficiency whereas Younis et al. (2018), an improved evolutionary algorithm for multi-objective transportation problems (Younis et al., 2018; Zhang et al., 2014). To address this sustainability concern Samanta et al. (2024) in a related work, Gupta et al. (2021) explore the minimization of carbon emissions in 4DT models under uncertainty, with a focus on balancing cost efficiency and environmental considerations (Gupta & Arora, 2021; Samanta et al., 2024). Additionally, Shao et al. (2023) valid to highlight the role of multimodal transport optimization under carbon regulations in the development of sustainable transport (Shao et al., 2023).

Over the years, metaheuristic algorithms have been employed to solve optimization problems in several studies. Chen et al. (2015) utilized PSO for combinatorial optimization problems, including the vehicle routing problem, validating its efficacy in dynamic transport situations (CHEN et al., 2015). Zouari et al. (2018) proposed a hybrid Ant Colony Optimization algorithm to solve the strongly connected knapsack problem, demonstrating the benefits of hybridization to solve complex optimization problems (Zouari et al., 2018). On the one hand genetic algorithms have been used to optimize important systems, which is emphasized in the research, where genetic algorithms helped improve device performance by improving their reliability and reducing operational and maintenance costs using genetic algorithms (Kamel & Mahdi, 2024).

In terms of maritime transportation, Adhi et al. In (2023), hybrid PSO was utilized for improving inventory routing of bulk products transportation, thereby showcasing the adaptability of hybrid methods in logistics (A Adhi, 2023). Similarly, Juntama et al. (2020) introduced a distributed heterogeneous hybrid optimization algorithm for 4D air traffic management and verified its applicability in real-time adaptive path planning (Juntama et al., 2020).

Moreover, studies like Ritzinger et al. (2016) have covered hybrid methods for vehicle routing under uncertainty, demonstrating their flexibility with respect to real-life logistics scenarios (Ritzinger et al., 2016). Chen et al. (2020) proposed a hybrid method based on Gray Wolf Optimization (GWO) and Tabu Search algorithm for effectively solving discrete combinatorial optimization problems with time constraints to prove that hybrid techniques usually outperform independent methods (Chen et al., 2020). It is well known that metaheuristic hybridization helps to mitigate early convergence and improves the quality of the solution. Xhafa et al. (2009) further pointed out that the integration of several metaheuristics enables us to use their complementarity to cope with algorithmic deficiencies of single metaheuristics (Xhafa et al., 2009). Kalathil & Elias (2016) showcased hybrid methods as effective in addressing local optima challenges, whereas Lau et al. (2007) confirmed this strong applicability of ANOVA as well for large combinatorial problems (Kalathil & Elias, 2016; Lau et al., 2007). However, Shirdel et al. (2024) proposed a hybrid algorithm of genetic Algorithm (GA) and Ant Colony Optimization for four-dimensional transportation problems, exploiting the genetic diversity and the intensive search mechanism of the ant algorithm, it provides greatly improved the efficiency of the solution and the solution cost (Shirdel et al., 2024).

What's New:

Unlike the above-mentioned methods, this research presents a hybrid ACO-PSO framework to mitigate several drawbacks in the existing literature.

- Exploration-Exploitation Balance: This hybrid approach counteracts premature convergence as it synergizes the robust exploratory strength of PSO with the effective exploitative behavior of ACO, leading to a more efficient candidate solution honing.
- Computational Efficiency: The hybrid method is significantly more computationally efficient than the stand-alone ACO or PSO while preserving solution quality.
- Cost Optimization: The proposed algorithm demonstrates better cost efficiency compared to classic methods, proving to be an applicable solution in real-life logistic implementations.

This study is novel in that it was the first study to address the four-dimensional transportation challenge through the implementation of an ACO-PSO hybrid metaheuristic algorithm.

3. Mathematical model and problem statement

3.1. Problem Statement

The Four-Dimensional Transportation Problem (4DTP) is one of the most complicated logistical problems, where optimization should be executed through four dimensions simultaneously: original place of sources, destination markets, product categories, and transportation modes. Conventional transportation issues tend to optimize for minimization objectives like cost or distance only, while 4DTP introduces new complexities such as dynamic constraints, time-variability in stochastic demand and multimodal dependability in routing. This issue is particularly relevant in real life applications such as in global supply chains, smart logistics and large-scale e-commerce networks, where efficient models are needed to address multi-tier distribution, storage constraints and time-varying transport costs (Baidya, 2022; Revathi et al., 2021).

This inherent complexity prevents conventional single-objective models from being applied and requires the creation of hybrid optimization techniques combining the efficiency of heuristics with the validity offered by mathematical modeling. The need to cope with these challenges then calls for innovative computational frameworks that can deal to high-dimensional data structures while maximizing cost, time, and resource allocation. In this study, we propose a new generation of hybridized solution framework with better exploration and exploitation in metaheuristic algorithms, which combines positive aspects of ACO and PSO to achieve better solution accuracy and convergence speed. Using a sophisticated mathematical formulation, this study generalizes classical transport models to include multidimensional objective functions and multidimensional constraints, combining advanced optimization theory with industrial contexts.

3.2. Mathematical Model

In order to establish a solid mathematical formulation for the Four-Dimensional Transportation Problem (4DTP), this research proposes a multi-objective optimization framework which combines various transportation constraints and cost-minimization approaches. The mathematical model aims to minimize the overall logistics cost (C), the distance time (S), and the efficiency of the network (N), indicating that these targets are quite practical according to the real distribution network (Bakhayt, 2016; El-Shorbagy et al., 2020; Halder Jana et al., 2019).

$$Min.C = \sum_{c=1}^{d}\sum_{b=1}^{m}\sum_{a=1}^{p}\sum_{d=1}^{n} G_{cbad} * F_{cbad} \tag{1}$$

Where:

G_{cbad}: Cost to transport a single unit of product (a) from the warehouse (c) to the market (b) using the transport modality (d).

F_{cbad}: Amount of good (a) shipped from store (c) to market (b) using the transport type (d).

$$\sum_{c=1}^{d}\sum_{a=1}^{p}\sum_{d=1}^{n} F_{cbad} = f_b, \forall b \in [1, m] \tag{2}$$

Where (f_b) reflects the total demand for market b.

$$\sum_{b=1}^{m} \sum_{a=1}^{p} \sum_{d=1}^{n} F_{cbad} = e_w, \forall w \in [1, d] \tag{3}$$

Where (e_w) is the amount available in the warehouse w.

$$\sum_{c=1}^{d} \sum_{b=1}^{m} \sum_{d=1}^{n} F_{cbad} = E_h, \forall h \in [1, p] \tag{4}$$

Where (E_h) are the amount needed for market b form product h.

$$\sum_{c=1}^{d}\sum_{b=1}^{m}\sum_{a=1}^{p} F_{cbad} = L_k, \forall k \in [1, n] \tag{5}$$

Where (L_k) represents the allocated capacity for the transport modality k.

$$\sum_{c=1}^{d} m(c) = \sum_{b=1}^{m} d(b) = \sum_{d=1}^{n} p(d) \tag{6}$$

$$F_{cbad} \geq 0, \forall c, b, a, d \tag{7}$$

The model can also be extended to other use cases by adding different objectives (multi-objective functions) like minimizing total transportation time and travel distance, using the variables (S_{cbad}) and (N_{cbad}), respectively.

$$Min.S = \sum_{c=1}^{d}\sum_{b=1}^{m}\sum_{a=1}^{p}\sum_{d=1}^{n} S_{cbad} * F_{cbad} \tag{8}$$

$$Min.N = \sum_{c=1}^{d}\sum_{b=1}^{m}\sum_{a=1}^{p}\sum_{d=1}^{n} N_{cbad} * F_{cbad} \tag{9}$$

The goal of this problem is to minimize transportation costs by optimizing resources, as seen in Equation (1). Equation (2) ensures that there is enough demand for the amount transported and Equation (3) constrains the amount transported to avoid overcapacity of the warehouse. Equation (4) links the volumes transported to the specific product demands, and Equation (5) regulates the transport modalities by bounding the shipments to the available capacity. While Equation (6) preserves overall balance in the transportation variables, Equation (7) incorporates non-negativity conditions. Next, by minimizing time and distance, Equations (8) and (9) reflect the food logistics service quality and decrease the operational cost. Such solutions provide integrated and efficient results compared to existing approaches that such a simple model very well captures in the context of the current transportation hub/route problem.

The abstract synthesizes a decision-making model that provides a unified framework for multi-objective transportation optimization, allowing for flexibility and incorporation into active logistics and supply chain problems.

4. Method

The experimental methodology undertaken in this study aims to measure the performance of newly developed a hybrid metaheuristic approach based on Ant Colony Optimization and Particle Swarm Optimization. It aims to improve the optimization ability of four-dimensional transportation (4DT) by combining ACO with strong exploration and PSO with fast convergence and exploitation mechanism. Implemented on simulated transportation scenarios to replicate real-world logistical constraints, the hybrid algorithm provides a systematic and rigorous evaluation. Its methodology results an optimal combination of transportation cost, execution time, and stability by coupling adaptive mechanisms that facilitate dynamic collaboration between ACO's pheromone-based search mechanism and PSO's velocity-based optimization.

4.1. Encoding the 4DT problem Solution

A vital component of our hybrid approach is how solution representation is done. In this structure, each candidate solution is represented as a multi-dimensional matrix which encodes the delivery of products from warehouses to markets using specific transport modes. It is given as (Equation 10):

$$X = [W_i, M_j, P_k, T_q] \tag{10}$$

where:

W_i: Warehouse index, denoting the supply locations.

M_j: Market index, that means the destinations.

P_k: Product index, the product transported.

T_q: Transport mode index, indicating the method of transport.

Therefore, every transportation decision can be stored in this multi-dimensional structure while making sure that all the logistical constraints are satisfied.

4.2. Bounds and Cost Evaluation

The proposed Algorithm adopts a constraint-penalty mechanism to ensure the feasibility of transportation solutions. The solution is penalized for any violations of the pre-defined constraints using the following equation (Equation 11):

$$F(X) = C(X) + \lambda \sum_{violations} Pv \tag{11}$$

where:

C(X): Total transportation cost.

Pv: The penalty term for violating the constraints.

λ : A penalty weight term that adjusts dynamically.

Such a formulation is better able to discourage infeasible solutions and direct the search when it comes to finding valid and lower-cost transportation plans.

4.3. *Work Flow of Hybrid ACO-PSO Algorithm*

Utilizing ACO for wide search and PSO for fine-tuning, the hybrid algorithm effectively converges towards the minimum transportation costs. Algorithm 1 show pseudo-code which describes execution of the algorithm:

```
Initialize transportation solution matrix X = [W, M, P, T]

Initialize pheromone trails (ACO) and velocity parameters (PSO)

Define cost function considering transportation costs and penalties

FOR each iteration:

  FOR each ant:

    Construct a transportation plan based on pheromone levels

    Evaluate cost and feasibility

    Update pheromone values using:

      τ_{ij} = (1 - ρ)  τ_{ij} + Δτ_{ij}

    Where:

      ρ = pheromone evaporation rate

      Δτ_{ij} = pheromone reinforcement for high-performing solutions

  FOR each particle:

    Compute fitness based on total cost

    Update velocity and position using:

      V_{new} = ω  V_{old} + C1  rand()  (pBest - X) + C2  rand()  (gBest - X)

    Adjust transportation assignments based on velocity changes

  Hybridization:

    - If ACO discovers an improved solution, increase pheromone intensity.

    - If PSO identifies a local refinement, adjust velocity parameters.
```

Check termination criteria (max iterations or solution convergence)

Return optimized transportation plan.

Algorithm 1: Pseudo-code for execution of proposed algorithm.

This enables a tunable balance between simultaneous exploration and exploitation. The next variables have been used in the structured pseudo-code of the hybrid ACO - PSO (ant colony optimization - particle swarm optimization) algorithm and is defined for the first time in this research:

- V_{new}: Adjusted Velocity of a Particle (PSO), the adjusted particle movement speed in a PSO search space.
- V_{old}: Previous Particle Velocity (PSO), velocity of the previous iteration before updates.
- C1: A coefficient, indicating the influence of the particle's own best solution (pBest).
- C2: The cognitive (swarm) component to the weight assigned to the globally best solution, gBest, found by the swarm.
- rand(): Randomization Factor: a uniformly distributed random number in the interval [0,1], used in PSO movements to introduce stochastic behavior.
- pBest : Personal Best Position, the best solution that a given particle has achieved so far.
- gBest: The best solution found by the entire swarm at a given iteration (Global Best Position).
- ω : Inertia Weight, it regulates the impact of the previous velocity on the new velocity which is a balance between exploration and exploitation.

4.4. *Choosing the Best Solution*

The best solution is decided based on that after applying the ACO-PSO hybrid optimization.

- Transportation Cost Optimization: The solution with the lowest transportation cost is selected.

- Constraint Satisfaction: Violation of feasibility constraints produces penalty adjustments in solutions.

- Stability of Execution Time: The algorithm adopts a perspective across time and selects stable and consistent solutions.

4.5. Parameter Tuning and Experimental Setup

Taguchi's Design of Experiments (DoE) was employed to tune the parameters of ACO-PSO. The best option values are shown in Table 1.

Table 1: Optimal Parameter Selection for ACO-PSO.

Parameter	Tested Levels	Optimal Value
Ant Count (ACO)	[50, 100, 150]	100
Pheromone Evaporation Rate	[0.1, 0.3, 0.5]	0.3
Inertia Weight (PSO)	[0.4, 0.6, 0.8]	0.6
Cognitive Coefficient C1	[1.0, 1.5, 2.0]	1.5
Social Coefficient C2	[1.5, 2.0, 2.5]	2.0

The values were chosen after multiple experimental runs which gave sufficient coverage for the search space, as well as the computation performance.

4.6. The Solution Approach

The hybrid algorithm model in this paper proposes an optimal balance between the exploration structure of new solutions and the exploitation structure of optimal solutions by integrating ACO and PSO. Following an iterative and incremental method, in the early stages, ACO is used to discover optimum transport ways based upon the pheromone revise measure that allows building up efficient starting cures. This is followed by updating the particle velocity and position to the best solutions found using PSO, which improves the solution significantly, allowing them to converge and preventing them from settling for local optima.

The individual solutions are evaluated against a multi-objective cost function that includes both direct transportation costs, and efficiency of resource utilization and stability of solutions over time. The best cost is calculated through Equation 12.

$$C_{total} = \sum_{i=1}^{n}(C_{transport,i} + C_{resource,i} + C_{stability,i}) \quad (12)$$

Where :

$C_{transport,i}$: Transportation cost for each route

$C_{resource,i}$: Representation of the effectiveness of resource use.

$C_{stability,i}$: Assesses the stability of the solution based on demand and route variance.

In ACO, the pheromone update rule is given by Equation 13 to reinforce the good solutions:

$$T_{cb} = (1 - p) * T_{cb} + \Delta T_{cb} \quad (13)$$

where ρ is the pheromone evaporation rate, and ΔT_{cb} is proportional to the quality of the explored solution. The velocities of the particles in the PSO are updated according to Equation 14:

$$V_{new} = \omega * V_{old} + C1 * rand(.) * (pBest - X) + C2 * rand(.) * (gBest - X) \quad (14)$$

The definitions of the variables of Equation 14 are explained in detail in paragraph 4.3 above, which can be referred to understand the symbols and criteria used in the mathematical formulation of the model. By considering both the collaborative search mechanism of ACO and the heuristic searching of PSO, the hybrid algorithm can effectively reduce transportation costs by 7.52% and improve performance by up to 3.3%, confirming the efficiency of solutions as well as ensuring accurate, precise and stable results for four-dimensional transportation systems.

4.7. Data Preparation and Algorithm Testing

This study created a four-dimensional simulation dataset based on realistic four-dimensional transportation problems which is developed to assess the performance of the proposed algorithm accurately. The input for the data was based on benchmarks taken from current logistic systems but was generated to investigate the actual road users and the challenges that companies face in running their multi-dimensional transport operation. Also, the data set contains several warehouses and distribution centers, each of them with a given storage capacity, which guarantees that there are reasonable limits similar to the reality of logistics scenarios.

Diverse datasets were generated with variations in routes, transportation, and distribution constraints to evaluate the solution(s) proposed to minimize the cost and improve the performance of the logistics systems. The nature of the benchmark dataset allows us to simulate complex transportation scenarios, thus the performances of the proposed algorithm were compared with other traditional methods, such as ACO and PSO. It makes sure that the evaluation actually determines an operating environment thus allowing more realistic operation of an evaluation, validating the results, and thus validating the solution provided is an action that works.

5. Results

In order to evaluate the performance of proposed hybrid ACO-PSO, experiments were conducted on structured dataset that mimics real-life transportation (4DT) systems. This dataset covers various constraints, such as transportation costs, warehouse capacities, product demands, and vehicle types, providing a complete environment for evaluation. Evaluation was carried out in three different phases:

1. Baseline transport costs: The baseline cost of transport was calculated based on the sum of the transport cost associated with sending each product from a warehouse to a market adjusted for the type of vehicle used (i.e., a large truck costs 20% more but carries 40% more products)

2. Implementation of hybrid algorithm: The dataset has been executed on ACO-PSO hybrid to optimize exploration transportation cost and solution stability.

3. Benchmarking stands-alone ACO and PSO implementations for comparative performance analysis of the proposed hybrid algorithm.

5.1. Dataset and Problem Configuration

Full transportation cost matrix, warehouse capacity and market demand in Table 2.

Table 2: Problem Data for Four-Dimensional Transportation Optimization.

Product	Warehouse 1			Warehouse 2			Available Quantities
	Market 1	Market 2	Market 3	Market 1	Market 2	Market 3	
P1	4	3	2	1	3	4	250, 200
P2	2	5	1	2	2	2	230, 250
P3	3	2	3	4	3	4	200, 180
Market Demand P1, P2, P3	200, 350, 120	130, 140, 100	90, 70, 150	-	-	-	-

In a four-dimensional transportation problem (4DT), this table (Table 2) shows the transportation cost matrix and available product quantities. It shows the unit transportation cost of three products (P1, P2, and P3) from two warehouses (Warehouse 1 and Warehouse 2) to three markets (Market 1, Market 2, and Market 3).

- These first three columns denote the unit transportation cost from Warehouse 1 to each market.
- Subsequent three columns indicate unit transportation cost from Warehouse 2 to each market.
- Last column represents total quantity of each product available across warehouses
- The last row states the market demands, with the needed amounts in P1, P2, and P3 for every market.

By accurately representing the initial, destination that need to be traversed, as well as the corresponding supply and demand, researcher can analyze data to make the correct logistics decisions that maintain supply and demand balance and minimizes costs, supported by the proposed ACO-PSO hybrid algorithm.

5.2. Implementation of the Proposed Algorithm

The hybrid ACO-PSO algorithm was applied to the dataset resulting in its optimal transportation assignments and total transportation costs as shown in Table 3.

Table 3: Transportation Plan Optimized with Hybrid ACO-PSO Algorithm.

Product	Warehouse	Truck Type	Market	Quantity Delivered	Cost ($)
P1	2	Small hauler	1	200	200
P2	1	Small hauler	1	350	700
P3	1	Small hauler	1	120	360
P1	1	Small hauler	2	130	390
P2	2	Small hauler	2	140	280
P3	1	Small hauler	2	100	200
P1	1	Small hauler	3	90	180
P2	1	Small hauler	3	70	70

P3	1	Small hauler	3	150	450
Total Transportation Cost					2,830 $

Comparison:

- Hybrid ACO-PSO outperformed the conventional approaches with respect to cost.
- Cost Savings from Warehouses and Hauler type Efficiency.

5.3. Comparison with Ant Colony Optimization (ACO)

In order to determine the influence of hybridization, ACO algorithm was solved separately (Table 4).

Table 4: Cost evaluation with respect to ACO.

Product	Warehouse	Truck Type	Market	Quantity Delivered	Cost ($)
P1	2	Large hauler	1	200	240
P2	1	Small hauler	1	350	700
P3	1	Small hauler	1	120	360
P1	2	Small hauler	2	130	390
P2	2	Small hauler	2	140	280
P3	2	Small hauler	2	100	300
P1	1	Small	3	90	180

		hauler			
P2	1	Small hauler	3	70	70
P3	1	Large hauler	3	150	540
Total Transportation Cost					3,060

Comparison:

- Although the ACO algorithm was effective in terms of quality, it incurred higher costs when compared to the hybrid ACO-PSO method.
- In some cases, total expenditure increased due to large truck allocations.
- Hybridization minus an additional 7.52% cost reduction for comparison to standalone ACO.

5.4. Benchmarking Against Particle Swarm Optimization (PSO)

Additionally, a standalone PSO algorithm was run, and results are shown in Table 5.

Table 5: Cost Analysis of Standalone PSO.

Product	Warehouse	Truck Type	Market	Quantity Delivered	Cost ($)
P1	2	Large Truck	1	200	240
P2	1	Small Truck	1	350	700
P3	1	Small Truck	1	120	360
P1	1	Small Truck	2	130	390

P2	2	Large Truck	2	140	336
P3	1	Small Truck	2	100	200
P1	1	Small Truck	3	90	180
P2	1	Small Truck	3	70	70
P3	1	Small Truck	3	150	450
Total Transportation Cost					2,926

Comparison:

- PSO provided good cost minimization capabilities, yet it was still higher than the hybrid.
- Hybridization alone gave you another 3.3% cheaper than a standalone PSO.

5.5. Performance analysis and experimental comparison

In order to facilitate precise assessment of the performance of the suggested hybrid algorithm, it was systematically established to examine its efficiency and efficacy along with Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), conventional algorithms widely utilized for the optimization of Four-Dimensional Transportation (4DT). The comparison included analysed strengths and weaknesses of each algorithm, namely ACO is good in searching for various paths but it suffers from slow convergence to the optimal answer and additional PSO offers fast convergence but it gets trapped from local opts offers a suboptimal response.

Python programming language was used for all the experiments, building a full-fledged simulation model to mimic a typical 4DT logistics environment. Synthetic datasets were created according to transport models developed from real, complex logistics operations while adding constraints for transport, product demand, and costs of operations.

As a metric for the best diagnosis accuracy and least result variance, the Taguchi approach was used to optimize the parameters for the model algorithms.

Key metrics including solution accuracy, convergence speed, and transportation cost reduction were used to evaluate the performance of each algorithm. The outcomes showed that the proposed hybrid algorithm resulted in 7.52% lower cost than ACO and 3.3% lower cost than PSO, thus proving to be efficient in optimizing logistic operations. Table 6 compared the proposed hybrid algorithm to conventional algorithms.

Table 6: Comparative analysis of the algorithm's performance.

Metric	ACO	PSO	Hybrid Algorithm (ACO-PSO)
Average Transportation Cost ($)	3,060	2,926	2,830
Convergence Speed (Iterations)	150	100	90
Solution Stability	Medium	Low	High
Optimal Solution Accuracy	87%	90%	95%

All values in the table have been obtained through computational experiments on a Python environment using advanced computational libraries (NumPy, Pandas, Matplotlib). The same data was used for the proposed hybrid algorithm and traditional methods. The proposed approach shows great promise for solving the four-dimensional transportation problem where the dynamics of the logistics environment have high complexity, therefore, the hybrid algorithm is a dependable and effective method.

6. Discussion

Comparative analysis confirms the hybrid ACO-PSO algorithm outperforming:

- Efficiency: The least cost of transport (2,830 $).
- Computational Stability: More consistent solution across iterations.
- Exploration vs. Exploitation Balance: Improved over individual ACO and PSO limitations

Main Results:

- ACO is well global exploration but suffers premature convergence.
- PSO fine-tunes solutions but exploration in solution space is less diverse.
- Hybridization achieves cost-effectiveness through the dynamic balance of exploration (ACO) and exploitation (PSO).

So, this study gives good contribution for hybrid metaheuristics to solve 4DT problems.

7. Conclusions and Recommendations

The aim of this research is to develop a hybrid algorithm that solves the challenges of optimizing four-dimensional transportation operations specifically by a combined method of ACO and PSO. The new approach allows a good balance between exploitation and exploration, leading to better transport efficacy and lower operational cost as the results showed. The performance of logistics system was improved by using the hybrid algorithm by reducing the transportation cost by 7.52% and 3.3% compared to ACO and PSO respectively.

Through descriptive results , it also shows how the Taguchi method works, enhanced the parameter tuning, and accordingly leads to a more stable solution with a lesser volatility in performance, hence a lower number of iterations to get an optimal solution. Convergence speed information obtained by experimental results shows that the combination of ACO and PSO can achieve faster convergence without losing the quality of the solution, and will help dynamic transportation systems to achieve better logistics planning and decision-making processes. Overall, considering these outcomes, the hybrid algorithm seems to be an efficient and practical method for optimizing complex transportation systems which can be implemented in several applications such as supply chain management, logistics planning, and intelligent transportation optimization. Such techniques lie at the heart of advanced AI research, opening up faster transportation operations in more complex operating environments.

Depending on the obtained results, the project could be extended by applying machine learning methods to enhance the models' predictive performance, enabling the algorithm to switch to dynamic estimations of the input parameters with respect to both demand and resource availability. The algorithm is suggested to be extended to more complex realistic scenarios with multimodal transportation systems and to evaluate the algorithm performance under actual operation conditions.

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