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Minimize shipping costs from multi-warehouse to multi-outlet with VAM and MODI

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ABSTRACT

Distribution costs are a dominant component in logistics operations, especially in multi-warehouse to multi-outlet delivery schemes involving variations in supply capacity, demand, and route costs. This study aims to minimize shipping costs by modeling the problem as a Transportation Problem (TP), generating an initial solution using Vogel's Approximation Method (VAM), and ensuring an optimal solution using the Modified Distribution Method (MODI). The case study was conducted in one planning period with input data in the form of a matrix of shipping costs per unit, supply capacity per warehouse, and demand per outlet (balanced condition). The results show that the baseline distribution cost is 4,898 (thousand IDR), while the initial VAM solution reduces the cost to 3,777 (thousand IDR). After optimality testing and improvements using MODI, the minimum cost is 3,605 (thousand IDR), with an additional improvement of 172 (thousand IDR) from the VAM solution. Compared to the baseline, the optimal solution provides savings of 1,293 (thousand IDR) or 26.40%, without violating the supply-demand constraint. These findings confirm that the VAM-MODI flow is effective as a fast, audit-friendly, and applicable end-to-end procedure for the preparation of minimum cost delivery plans in logistics companies.

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1. INTRODUCTION

Over the past five years, logistics optimization research has shifted significantly toward more adaptive and integrated distribution network design. For example, variable distribution network configurations across periods and flexible facility decisions have been modeled to address short-term demand dynamics and capacity requirements (Correia & Melo, 2022). Another study emphasized the integration of network design and operations decisions, including location decisions and order fulfillment policies in a multi-product retailer over a multi-period horizon using robust and decomposition approaches (Jiu et al., 2024). In the context of online retailing, the challenges of splitting orders and consolidating between warehouses have also been shown to increase shipping costs, necessitating an efficient allocation strategy (Y. Zhang et al., 2021).

In addition to network design, the study also demonstrates the strengthening of an integrated production-inventory-distribution optimization approach to improve service reliability and cost efficiency in multi-level supply chains (Ghasemi et al., 2024). In the industrial sector, inbound logistics optimization with MILP is used to address complex coordination needs that are usually difficult to solve manually (Baller et al., 2022). In the warehousing sector, decision-making is also moving toward space/capacity allocation based on optimization models to increase throughput and profits (Hyder & Hassini, 2025), as well as forecasting integration to improve the efficiency of order fulfillment operations (Ho et al., 2025).

Another growing trend is incorporating sustainability, emissions, and reliability into supply chain network design. A systematic review demonstrates the increasing complexity of sustainable supply chain network design and the variety of modeling approaches and algorithms involved (Madani et al., 2024). Correspondingly, multi-objective MILP models that balance costs, emissions, and reliability are also increasingly being used (Sepehri et al., 2024). In two-tier distribution, the issue of allocative justice is also a concern because the “minimum cost” decision can create a trade-off with regard to the equality of service distribution (Zehtabian, 2024). For cold chain logistics, distribution center location models also take into account product damage, time windows, refrigeration costs, and carbon emissions (Wang et al., 2024), including low carbon route optimization studies for the cold chain context (X. Zhang et al., 2024). On the methodological side, SSCND modeling is also evolving with graph learning/representation based algorithmic approaches to handle large scale (Guo et al., 2025).

While these state-of-the-art approaches are powerful for large-scale complex problems, the needs of many logistics companies at the day-to-day operational level often demand methods that are computationally lighter, transparent, easily auditable, and easily interpretable. For the tactical decision need of “how many units to ship from warehouse i to outlet j” with a minimum cost objective, the Transportation Problem (TP) remains relevant because its constraint structure is clear (supply-demand) and its solution can be executed as a delivery plan.

The combination of Vogel's Approximation Method (VAM) and Modified Distribution Method (MODI) was chosen in this study based on the need for a computationally lightweight yet systematic solution for daily multi-warehouse to multi-outlet operational decisions. VAM was chosen because it can produce an initial basic feasible solution (IBFS) that is generally more competitive than the simple corner rule, potentially reducing the number of improvement steps to the optimum (Amaliah et al., 2022). Furthermore, MODI is used as a clear potential-based (u–v) and opportunity cost optimality test, allowing for a structured and easily audited allocation improvement process for managerial decisions. Our comparative evidence shows that potential-based optimality methods like MODI can significantly reduce distribution costs with efficient iterations, while also providing a basis for method selection based on the efficiency and traceability trade-offs of solutions (Riandari & Sihotang, 2025). Theoretically, our proposed unified mathematical framework also places MODI as a dual-potential representation on the transport polytope, thus strengthening the end-to-end solution flow as a consistent procedure (Riandari, 2025). The VAM–MODI implementation has also been used in distribution case studies and has been reported to reduce costs compared to company practices, confirming its relevance for operational contexts (Adianta et al., 2024).

In TP, the quality of the initial basic feasible solution (IBFS) is important because it affects the number of iterations to the optimum. Recent research is actively developing IBFS methods that can produce initial solutions closer to the optimum. For example, the Supply Selection Method (SSM) has been compared with VAM and other IBFS methods to improve the quality of initial solutions in balanced TP (Amaliah et al., 2022). In addition, a new heuristic method for IBFS on TP is also proposed and tested on many numerical examples (Amaliah et al., 2022). In recent years, new IBFS algorithms have also been continuously introduced, such as the maximum range method which aims to produce IBFS that is increasingly close to the optimal solution (Wireko et al., 2025).

Meanwhile, the expansion of TP also occurs in parameter uncertainty/variation scenarios, for example interval TP with a heuristic approach and ILP formulation to determine the optimal cost limit (Carrabs et al., 2021). In the fuzzy/uncertainty domain, VAM modifications are also used to handle TP in uncertain environments (Pratihar et al., 2021), as well as the development of an “extended VAM” for certain fuzzy TP variants demonstrating the continued relevance of VAM as an initial solution generator (Shivani & Rani, 2024). Beyond that, research on methods for obtaining initial TP solutions is also developing through demand-based strategies (Ackora-Prah et al., 2023).

Although many previous studies have expanded the Transportation Problem (TP) into complex variants such as multi-period network redesign, stochastic demand, fuzzy TP, sustainability-oriented supply chain network design, and improved heuristics for initial basic feasible solutions these studies generally focus on methodological innovations or large-scale network complexity rather than providing a fully operational, end-to-end procedure that can be directly implemented in day to day logistics planning. Existing works rarely demonstrate a complete workflow that starts from structuring real company data into a TP model, generating a competitive initial solution using VAM, conducting potential-based optimality refinement via MODI, and finally translating the optimal allocation into an auditable delivery plan ready for managerial execution. This lack of practical, replicable, and audit-friendly end to end implementation constitutes the most obvious research gap that the present article addresses by offering a unified, transparent VAM-MODI procedure specifically tailored for real multi-warehouse to multi-outlet distribution settings.

2. RESEARCH METHOD

This study applies the Transportation Problem to minimize shipping costs from multi-warehouses to multi-outlets in one planning horizon. The input data is structured as: unit cost matrixc_{ij} (cost per unit on the warehouse-outlet route), the supply vector, the demand vector, and the company's actual distribution pattern. All data are standardized in units (units/pallets) and costs are calculated consistently according to company policy. If , the problem is balanced by adding a zero-cost dummy source/destination; disallowed routes can be modeled with a large penalty cost $ijs_i d_j x_{ij}^{aktual} \sum s_i \neq \sum d_j$.

The mathematical model follows the standard TP formulation. The solution is carried out in two stages: (1) an initial basic feasible solution is generated using VAM according to the literature, with tie-breaking based on the lowest cost and/or maximum allocation for operational stability (Amaliah et al., 2022; Shivani & Rani, 2024), (2) The solution is tested and improved to optimal using MODI (u–v method) according to potential and reduced cost procedures (Riandari & Sihotang, 2025). Stopping criteria: all reduced cost non-basic cells. Performance is evaluated through optimal cost, savings, and percentage savings; input matrix, balancing rules. Model Equation and Performance Measures$\Delta_{ij} \geq 0 Z^* \Delta Z$

$$\min Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \tag{1}$$

$$\sum_{j=1}^{n} x_{ij} = s_i, \forall i \tag{2}$$

$$\sum_{i=1}^{m} x_{ij} = d_j, \forall j \tag{3}$$

$$x_{ij} \geq 0, \forall i, j \tag{4}$$

$$Z^* = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}^* \tag{5}$$

$$\Delta Z = Z^{aktual} - Z^* \tag{6}$$

$$\%\text{Saving} = \frac{Z^{aktual} - Z^*}{Z^{aktual}} \times 100\% \tag{7}$$

3. RESULTS AND DISCUSSIONS

This section presents the results of applying the Transportation Problem model to obtain a minimum cost shipping plan from multi-warehouse to multi-outlet. To be replicable and easily verified, the results are presented in stages: (1) displaying input data (cost, supply, demand), (2) calculating baseline distribution costs as a comparison, (3) generating an initial solution using VAM and calculating its total cost, (4) conducting optimality tests and improvements using MODI until an optimal solution is obtained, and (5) summarizing the cost savings and managerial significance of the changes in allocation patterns.

Results

Stage 1. Model input data

Table 1 shows a matrix of shipping costs per unit (thousands of Rupiah/unit) for each warehouse-outlet route, along with supply and demand values. This data forms the basis for all cost calculations in the following stages. Total supply and total demand are equal, so the problem is in a balanced state.$c_{ij} = 63 + 157 + 113 = 333 = 70 + 83 + 127 + 53 = 333$

Table 1. Cost matrix (thousands of Rupiah/unit), supply, and demandc_{ij}

Source \ Destination	O1	O2	O3	O4	Supply
G1	14	16	13	11	63
G2	18	10	18	11	157
G3	5	11	15	18	113
Demand	70	83	127	53	

Stage 2. Baseline costsZ^{aktual}

For comparison, the baseline is calculated from the allocation pattern used in the same period. The total baseline cost is obtained by summing only the allocated routes.$c_{ij} \times x_{ij}(x_{ij} > 0)$

Table 2. Baseline allocation matrix (units)x_{ij}^{aktual}

Warehouse \ Outlet	O1	O2	O3	O4	Supply
G1	63	0	0	0	63
G2	7	83	67	0	157
G3	0	0	60	53	113
Demand	70	83	127	53	

Baseline cost calculation (thousands of Rp):

$G1 \rightarrow O1 = 63 \times 14 = 882$
$G2 \rightarrow O1 = 7 \times 18 = 126$
$G2 \rightarrow O2 = 83 \times 10 = 830$
$G2 \rightarrow O3 = 67 \times 18 = 1{,}206$
$G3 \rightarrow O3 = 60 \times 15 = 900$
$G3 \rightarrow O4 = 53 \times 18 = 954$

$$Z^{aktual} = 882 + 126 + 830 + 1{,}206 + 900 + 954 = 4{,}898$$

So, the baseline cost is (thousand Rp).$4{,}898$

Stage 3. Initial VAM solution and costsZ^{VAM}

After establishing the baseline, an initial basic feasible solution (IBFS) is generated using VAM. Table 3 displays the VAM allocation results that meet all supply and demand requirements. Total costs are calculated in the same manner, by summing the allocated routes.$x_{ij} c_{ij} \times x_{ij}$

Table 3. VAM results allocation matrix (units)x_{ij}^{VAM}

Warehouse \ Outlet	O1	O2	O3	O4	Supply
G1	0	0	63	0	63
G2	0	40	64	53	157
G3	70	43	0	0	113
Demand	70	83	127	53	

VAM cost calculation (thousand Rp):

$G3 \rightarrow O1 = 70 \times 5 = 350$
$G3 \rightarrow O2 = 43 \times 11 = 473$
$G2 \rightarrow O2 = 40 \times 10 = 400$
$G1 \rightarrow O3 = 63 \times 13 = 819$
$G2 \rightarrow O3 = 64 \times 18 = 1{,}152$

$G2 \rightarrow O4 = 53 \times 11 = 583$

$Z^{VAM} = 350 + 473 + 400 + 819 + 1{,}152 + 583 = 3{,}777$

So, the initial VAM solution cost is (thousand Rp).$3{,}777$

Stage 4. Test MODI optimality and optimal costZ^*

The VAM solution is then tested for optimality using MODI. If there is still a negative reduced cost in a non-basic cell, the allocation is refined through a closed loop until all. Table 4 presents the optimal allocation as a minimum-cost dispatch plan.$(\Delta_{ij} < 0)\Delta_{ij} \geq 0 x_{ij}^*$

Table 4. Optimal allocation matrix (MODI) (units)x_{ij}^*

Warehouse \ Outlet	O1	O2	O3	O4	Supply
G1	0	0	63	0	63
G2	0	83	21	53	157
G3	70	0	43	0	113
Demand	70	83	127	53	

Optimal cost calculation (thousand Rp):

$G3 \rightarrow O1 = 70 \times 5 = 350$
$G2 \rightarrow O2 = 83 \times 10 = 830$
$G1 \rightarrow O3 = 63 \times 13 = 819$
$G3 \rightarrow O3 = 43 \times 15 = 645$
$G2 \rightarrow O3 = 21 \times 18 = 378$
$G2 \rightarrow O4 = 53 \times 11 = 583$

$Z^* = 350 + 830 + 819 + 645 + 378 + 583 = 3{,}605$

So, the optimal cost is (thousand Rp).$3{,}605$

Stage 5. Summary of differences and savings

Two measures of difference are used to help the reader understand the contribution of each stage: (1) the difference in MODI improvement from VAM, and (2) savings relative to baseline.

$Z^{VAM} - Z^* = 3{,}777 - 3{,}605 = 172$

This means that MODI improved the VAM solution by 172 (thousand Rp).
$Z^{aktual} - Z^* = 4{,}898 - 3{,}605 = 1{,}293$
This means that the potential savings against the baseline is 1,293 (thousand Rp).

To ensure the accuracy of the manual calculations, this study conducted computational validation using Python. Validation was performed by recalculating the total costs for three scenarios (baseline, initial VAM solution, and optimal MODI solution), while also checking the feasibility of the solutions by matching the allocation amounts for each row (supply) and each column (demand). The Python test results are presented below to demonstrate the consistency between the manual and computational calculations.$\sum c_{ij} x_{ij}$

```python
import numpy as np

# ----------------------
# 1) Data biaya (ribu Rp/unit)
# ----------------------
C = np.array([
    [14, 16, 13, 11],  # G1 -> O1..O4
    [18, 10, 18, 11],  # G2
    [ 5, 11, 15, 18],  # G3
], dtype=float)

supply = np.array([63, 157, 113], dtype=float)
demand = np.array([70,  83, 127,  53], dtype=float)

# ----------------------
# 2) Matriks alokasi (unit)
# ----------------------
X_baseline = np.array([
    [63,  0,  0,  0],  # G1
    [ 7, 83, 67,  0],  # G2
    [ 0,  0, 60, 53],  # G3
], dtype=float)



    [70, 43,  0,  0],  # G3
], dtype=float)

X_opt = np.array([
    [ 0,  0, 63,  0],  # G1
    [ 0, 83, 21, 53],  # G2
    [70,  0, 43,  0],  # G3
], dtype=float)

def check_feasible(X, supply, demand, tol=1e-9):
    row_ok = np.all(np.abs(X.sum(axis=1) - supply) < tol)
    col_ok = np.all(np.abs(X.sum(axis=0) - demand) < tol)
    return row_ok, col_ok, X.sum(axis=1), X.sum(axis=0)

def total_cost(C, X):
    return float((C * X).sum())

for name, X in [("Baseline", X_baseline), ("VAM", X_vam), ("Optimal(MODI)", X_opt)]:
    Z = total_cost(C, X)
    row_ok, col_ok, row_sum, col_sum = check_feasible(X, supply, demand)
    print(f"\n{name}")
    print("Total cost (ribu Rp):", Z)
    print("Row sums:", row_sum, "OK:", row_ok)
    print("Col sums:", col_sum, "OK:", col_ok)

print("\nDelta VAM->Optimal:", total_cost(C, X_vam) - total_cost(C, X_opt))
print("Saving Baseline->Optimal:", total_cost(C, X_baseline) - total_cost(C, X_opt))
```

```
Baseline
Total cost (ribu Rp): 4898.0
Row sums: [ 63. 157. 113.] OK: True
Col sums: [ 70.  83. 127.  53.] OK: True

VAM
Total cost (ribu Rp): 3777.0
Row sums: [ 63. 157. 113.] OK: True
Col sums: [ 70.  83. 127.  53.] OK: True

Optimal(MODI)
Total cost (ribu Rp): 3605.0
Row sums: [ 63. 157. 113.] OK: True
Col sums: [ 70.  83. 127.  53.] OK: True

Delta VAM->Optimal: 172.0
Saving Baseline->Optimal: 1293.0
```

Figure 1. Numerical validation of allocation matrix and total cost of transportation problem model in python

Computational validation using Python shows that all allocation matrices satisfy the supply–demand constraints and produce total costs identical to manual calculations (Baseline = 4,898; VAM = 3,777; Optimal = 3,605 thousand Rp).

Discussion

The results of this study answer the main objective of the study, namely to produce a minimum-cost shipping allocation plan that meets all supply and demand. Scientifically, the cost reduction occurs because the MODI mechanism evaluates the opportunity cost in non-basic cells and directs allocation changes through a closed loop so that some flows are diverted from a combination of routes that are generally more expensive to a combination of routes that are cheaper, without violating supply and demand constraints. In other words, efficiency does not arise from "choosing the cheapest route per destination locally," but rather from the composition of allocations across routes that globally minimize total costs.

Methodologically, the relatively small difference between VAM and the optimal solution indicates that VAM is capable of generating an initial solution that is already close to optimal, so MODI requires fewer iterations to reach optimality. This is important for the operational context of logistics companies because the VAM–MODI procedure becomes easier to implement as a standard operating procedure: VAM provides a fast and feasible initial solution, while MODI provides optimality guarantees and a clear audit trail. This finding is also consistent with your study comparing initial solution methods and optimality methods (NWC tends to result in higher costs, while MODI/Stepping Stone reduces costs through systematic improvements), so the use of VAM as an initial solution generator and MODI as an optimality tester/refiner is relevant for the multi-warehouse–multi-outlet case.

From a managerial perspective, the key implication is not simply the magnitude of savings, but also the change in allocation structure: certain outlets should be supplied more from the warehouse with the most efficient cost combination, thereby reducing costs without increasing physical resources. Thus, this model provides a measurable decision-making basis for establishing shipment allocation policy for the following period.

4. CONCLUSION

The conclusion of this study confirms that the research objectives formulating a company's distribution as a Transportation Problem, generating an initial solution with Vogel's Approximation Method (VAM), optimizing it with the Modified Distribution Method (MODI) to achieve minimum cost, and measuring potential savings compared to the actual pattern can be achieved through an operational and easily replicated VAM-MODI procedure. Conceptually, the TP model ensures that all supply and demand constraints are met, while the combination of VAM as a rapid initial solution generator and MODI as an optimality tester and refiner results in a more efficient and audit-friendly delivery plan because allocation changes are determined based on traceable opportunity cost logic. This study also shows that cost efficiency does not arise from selecting the cheapest route locally per outlet, but rather from rearranging the flow composition between routes that globally minimizes total costs without violating supply-demand constraints, thus providing a strong basis for formulating delivery allocation policies in logistics companies. Development suggestions: VAM-MODI implementation should be made a routine distribution planning procedure with periodic updates to the cost matrix to ensure delivery plans are adaptive to operational changes, then validated across multiple data periods to ensure consistent savings. Furthermore, the model can be extended to more realistic variants e.g., vehicle capacity, time windows, multi-commodity, or cost/demand uncertainty and digitized in tools (e.g., spreadsheets/internal solvers) to speed up calculations, document them, and become ready to serve as standard operating procedures for decision-making. A relevant and practical extension of the current model is the incorporation of dynamic operational factors that often characterize real distribution systems, such as demand uncertainty, fluctuating transportation costs, and warehouse or vehicle capacity limitations. Future model development can adopt stochastic or interval-based formulations to accommodate uncertain demand, implement time dependent or piecewise cost functions to capture cost variability, and integrate explicit capacity constraints either through capacitated TP models or mixed-integer transport formulations so that the resulting allocation more accurately reflects real-world distribution environments. Incorporating these elements would allow the VAM-MODI framework to evolve from a deterministic minimum cost planner into a more adaptive decision-support tool capable of responding to volatility and constraints commonly faced in logistics operations.

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