

Optimization of Transportation Cost Using an Innovative Technique

Janardhan Mane¹, Ashok Shire^{2*}

¹ Research Supervisor, Department of Mathematics, Sanjeevane Mahavidyalaya, Chapoli – 413 513, Maharashtra, India

² Research Scholar, Department of Mathematics, Sanjeevane Mahavidyalaya, Chapoli – 413 513, Maharashtra, India

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shireashok059@gmail.com

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Abstract

Objectives: To generate an optimal or near-optimal solution while minimizing the optimality gap, thereby ensuring that the final total cost remains as close as possible to the theoretical lower bound. **Method:** This study proposes a novel Total Opportunity Cost Matrix–Standard Deviation (TOCM-SD) algorithm for generating a superior Initial Basic Feasible Solution (IBFS). The proposed method uniquely integrates opportunity cost analysis with standard deviation metrics to guide initial allocation decisions, thereby enhancing solution quality from the initial phase. The algorithm was rigorously evaluated on a diverse set of 30 balanced and unbalanced TP instances sourced from established literature. **Findings:** Comparative performance evaluation reveals that TOCM-SD secures the optimal solution in 18 of the 30 cases, translating to a 60% success rate that outperforms existing heuristic approaches. Additionally, the method severely reduces the number of iterations required to reach the final optimal solution and consistently produces lower total transportation costs. **Novelty:** The effective integration of the Total Opportunity Cost Matrix with Standard Deviation, which improves decision-making robustness during the initial phase. Enhanced refinement and accuracy metrics confirm the computational efficiency and reliability of TOCM-SD, establishing it as a highly competitive and practical alternative for transportation cost optimization.

Keywords: Total Opportunity Cost Matrix; Standard Deviation; Initial Basic Feasible Solution; Optimal solution; Transportation cost

1 Introduction

The transportation model remains a cornerstone of operations research, underpinning critical logistical decisions that balance industrial supply with consumer demand by determining the least-cost strategy for distributing homogeneous goods from multiple origins to multiple destinations. This function essential for sustaining economic equilibrium and corporate profitability in increasingly globalized markets^{(1), (2)}. As a fundamental class of linear programming problems, the transportation problem has been rigorously examined over the past several decades. Classical solution techniques, such as the North-West Corner Rule, Vogel's Approximation Method, and the Modified

Distribution Method, have established robust frameworks for solving deterministic variants^{(3), (4)}. The versatility of this mathematical structure has also enabled researchers to extend its applications to workforce scheduling, inventory control, and personnel assignment⁽⁵⁾. Despite its widespread adoption, however, the conventional transportation model relies heavily on assumptions of fixed supply capacities, known demand levels, and stable cost coefficients. Modern supply chains, in contrast, are characterized by volatility: fuel prices fluctuate, production capacities may change unexpectedly, and demand patterns frequently deviate from forecasts. More critically, the existing literature provides limited frameworks for integrating multi-objective constraints and real-time parameter adjustments within the classical linear programming structure⁽⁶⁾.

To address these operational limitations, this study proposes an enhanced transportation framework that incorporates dynamic supply–demand disruptions while preserving computational tractability. The study aims to develop a modified algorithm capable of maintaining economic balance under condition of uncertainty. It is hypothesized that the proposed approach can achieve cost savings comparable to those of classical methods while providing superior resilience. Consequently, the proposed framework is expected to serve as a more practical decision-support tool for industrial managers and other stakeholders involved in supply chain management.

2 Mathematical formulation

The transportation model determined the allocations of consignments from producing units or factories S_i where $i = 1, 2, \dots, m$ to the n number of commercial complexes D_j , $j = 1, 2, \dots, n$ in the stipulated manner by fulfilling the given constraints. The objective of this model is to carry out the transportation process at the minimum possible transportation cost. The transportation problem is a specialized form of linear programming characterized by its unique constraint structure.

$$\text{Minimize} \quad Z = \sum_{i=1}^m \sum_{j=1}^n C_{ij} X_{ij}$$

$$\text{Subjects to} \quad \sum_{j=1}^n X_{ij} = S_i, \quad S_i > 0, \quad i = 1, 2, \dots, m$$

$$\sum_{i=1}^m X_{ij} = D_j, \quad D_j > 0, \quad j = 1, 2, \dots, n$$

$$\text{Where} \quad X_{ij} \geq 0, \quad \forall i, j.$$

Table 1. Matrix of transportation.

Sources	Destinations				Supply
	1	2		n	
1	$C_{11}X_{11}$	$C_{12}X_{12}$		$C_{1n}X_{1n}$	S_1
2	$C_{21}X_{21}$	$C_{22}X_{22}$		$C_{2n}X_{2n}$	S_2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
m	$C_{m1}X_{m1}$	$C_{m2}X_{m2}$		$C_{mn}X_{mn}$	S_m
Demand	D_1	D_2		D_n	$\sum_{i=1}^m S_i = \sum_{j=1}^n D_j$

A variety of techniques have been developed to reduce transportation costs from origins to destination⁽¹⁾. A pivotal initial stage in solving a transportation problem is obtaining an initial basic feasible solution (IBFS), which typically provides a close approximation to the optimal solution while reducing the subsequent computational burden. Renfield and Vogel first formalized methods for obtaining an IBFS within the framework of linear programming⁽²⁾. Among these methods, Vogel's approximation method (VAM) stands out for its superior efficiency, whereas the least cost method and the north-west corner rule are employed contextually, depending on the structural characteristics of the problem. Amaliah et al.^{(1), (2)}, developed the Total Opportunity Cost Matrix- Minimal Total (TOCM-MT) and Bilqis Chastine Erma (BCE) methods for obtaining an initial basic feasible solution that minimizes the total transportation cost. Juman and Hoque⁽³⁾ developed a heuristic approach, referred to as the Juman-Hoque Method (JHM), which relies on columns-wise evaluation and allocates demand to the cells with the lower costs. Kargul and Sahin⁽⁴⁾ introduced the Kargul-Sahin approximation method (KSAM), an approximation technique that employs two weighted matrices to represent transportation costs, incorporating both supply and demand factors. Wireko et al.⁽⁵⁾ introduced the Maximum Range Method (MRM), which calculates the range for both rows and columns.

Karolína et al.⁽⁶⁾ applied a telematics system to potentially reduce fuel cost. Tereza et al.⁽⁷⁾ used the transportation model to potentially reduce operational cost. Acheson et al.⁽⁸⁾ developed the Demand-Based Allocation Method (DBAM), which uniquely prioritizes the smallest demand. Soomro et al.⁽⁹⁾ modified Vogel's approximation method by computing the row penalty as the difference between the two highest cost values, whereas the column penalty was determined as the difference between the two lowest cost values. Mutlu et al.⁽¹⁰⁾ selected the row or column corresponding to the higher-cost cell in the matrix and allocated the minimum of the available supply or demand to the cell with the lower cost. Nastasia et al.⁽¹¹⁾ studied water distribution in an Indonesian municipal corporation with the aim of reducing cost. Linesh et al.⁽¹²⁾ proposed the Linesh Chungath Pandey Dixit (LCPD) method, which uses the second-smallest cost as a penalty measure. Karthiyayini⁽¹³⁾ developed a methodology for optimizing the initial basic feasible solution of unbalanced transportation problems by employing standard deviations as penalty measures for both rows and columns. Esakkiammal and Murugesan⁽¹⁴⁾ compare the Zero-Suffix Method (ZSM) with two modified zero suffix methods. Islam et al.⁽¹⁵⁾ modified the least cost method for multi-objective transportation problems. Paul et al.⁽¹⁶⁾ proposed a Mean Absolute Deviation (MAD) method; Bilkour et al.⁽¹⁷⁾ integrated the TOCM approach with the Zero-Point Minimum Method, and Tiwari et al.⁽¹⁸⁾ proposed Adjusted Range Method.

2.1 Total Opportunity Cost Matrix

The Total Opportunity Cost Matrix (TOCM), introduced by Kirca and Satir⁽¹⁾, is derived through a two-step procedure (Table 1). First, the row opportunity cost matrix and the column opportunity cost matrix are constructed by subtracting the minimum cost of the respective row or column from each cell. These two intermediate matrices are then summed elementwise to obtain the Total Opportunity Cost Matrix.

3 Methodology

3.1 Total Opportunity Cost Matrix- Standard Deviation (TOCM-SD)

The integration of standard deviation into the TOCM framework addresses a limitation of purely penalty-based methods, which treat all rows and columns as equally sensitive to misallocation. By weighting the TOCM entries according to the dispersion of penalties, TOCM-SD method automatically prioritizes cells that are part of highly variable cost structures, where the risk of making a suboptimal assignment is greater. This method differs fundamentally from the existing methods. While conventional methods determine penalties directly from the given transportation matrix, the proposed method uses the Total Opportunity Cost Matrix as initial matrix for penalty determination, thereby enabling more efficient allocation of consignment.

Step 1: A balanced transportation matrix is constructed based on the specified real-world transportation problem.

If the total supply exceeds the total demand,

$$\sum_{i=1}^m S_i > \sum_{j=1}^n D_j$$

or total demand exceed the total supply

$$\sum_{i=1}^m S_i < \sum_{j=1}^n D_j$$

a fictitious production unit or purchasing centre is introduced to balance the transportation matrix. Thus, the balanced transportation problem satisfies the condition

$$\sum_{i=1}^m S_i = \sum_{j=1}^n D_j.$$

Step 2: Let the transportation problem determine the Total Opportunity Cost Matrix (TOCM), which is obtained as the sum of the Row Opportunity Cost Matrix (ROCM) and the Column Opportunity Cost Matrix (COCM). The ROCM is determined by subtracting the least cost of each row from the other entries in the respective row. Similarly, the COCM is obtained by subtracting the least cost of each column from the other entries in the respective column.

$$\begin{aligned} O_i^r &= (C_{ij}^r - \min(C_{i1}^r, C_{i2}^r, C_{i3}^r, \dots, C_{in}^r)) \\ O_i^r &= (C_{ij}^r - C_{ik}^r) \end{aligned} \quad (1)$$

Where $C_{ik}^r = \min(C_{i1}^r, C_{i2}^r, C_{i3}^r, \dots, C_{in}^r)$, $1 \leq k \leq n$.

$$\begin{aligned} O_j^c &= (C_{1j}^c - \min(C_{1j}^c, C_{2j}^c, C_{3j}^c, \dots, C_{mj}^c)) \\ O_j^c &= (C_{ij}^c - C_{lj}^c) \end{aligned} \quad (2)$$

Where $C_{lj}^c = \min(C_{1j}^c, C_{2j}^c, C_{3j}^c, \dots, C_{mj}^c)$, $1 \leq l \leq m$.

Adding equation (1) and (2), we have

$$\begin{aligned} \delta_{ij}^* &= (C_{ij}^r - C_{ik}^r) + (C_{ij}^c - C_{lj}^c) \\ \delta_{ij}^* &= O_i^r + O_j^c \end{aligned} \quad (3)$$

Step 3: The mean and standard deviation were calculated for each row after excluding the fictitious row from the analysis.

$$\mu_i = \frac{\sum_{j=1}^n C_{ij}}{n} \text{ for } i = 1, 2, \dots, n.$$

$$\sigma_i = \sqrt{\frac{\sum_{j=1}^n (C_{ij} - \mu_i)^2}{n-1}} \text{ for } i = 1, 2, \dots, m.$$

Step 4: Among the standard deviations calculated for each row, the row with the highest standard deviation is selected, as it represents the greatest dispersion of values.

$$\begin{aligned} A_f &= \max(\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_m) \\ A_f &= \max(\sigma_i) \end{aligned} \quad (4)$$

In cases where two or more standard deviations coincide, an arbitrary choice may be made among them.

Step 5: For each iteration, allocate the maximum feasible quantity to the cell with the minimum cost. This quantity is the lesser of the remaining supply and demand

$$X_{ij} = \min(S_i, D_j)$$

This allocation ensures that both supply and demand constraints are satisfied while prioritizing cost minimization.

Step 6: A row or column should be eliminated based on the satisfaction of the criteria to appropriately adjust the supply or demand. If both a row and a column simultaneously meet the elimination criteria, only one should be eliminated, rather than both.

Note: The satisfied row is excluded from the calculation of the standard deviation.

Step 7: Recompute the standard deviation for each remaining row, excluding the satisfied row from the dataset.

Step 8: Execute steps 2-7 iteratively until all supply and demand constraints are satisfied.

Step 9: Consequently, the total transportation cost (TTC) is calculated as follows.

$$TTC = \sum_{i=1}^m \sum_{j=1}^n C_{ij} X_{ij} \quad (5)$$

4 Numerical Illustration

Step 1: An unbalanced transportation matrix is typically balanced by adding a dummy row or column, as required. However, since the given matrix is already balanced (See Table 2), no such adjustment is necessary.

Step 2: Initially, the row opportunity cost matrix is computed by subtracting the minimum cost in each row from every element in that row, as specified in Equation (1). The resulting differences are then compiled to construct the reduced cost matrix.

Thereafter, the column opportunity cost matrix is derived by applying the same procedure to each column, or, equivalently, by applying Equation (2).

The, Total Opportunity Cost Matrix, denoted by δ_{ij}^* (Table 3), is obtained by adding the row opportunity cost matrix (O_i^r) and the column opportunity cost matrix (O_j^c) element-wise, according to Equation (3).

Table 2. Original numerical example (NE).

	D_1	D_2	D_3	$Supply$
S_1	4	3	4	11
S_2	10	7	5	12
S_3	8	8	3	10
S_4	5	6	6	7
$Demand$	16	10	14	

Table 3. Total Opportunity Cost Matrix.

	D_1	D_2	D_3	$Supply$
S_1	1	0	2	11
S_2	11	6	2	12
S_3	9	10	0	10
S_4	1	4	4	7
$Demand$	16	10	14	

Table 4. Allocation factor calculated.

	D_1	D_2	D_3	$Supply$	σ
S_1	1	0	2	11	1
S_2	11	6	2	12	4.50
S_3	9	10	0	10	5.50
S_4	1	4	4	7	1.73
$Demand$	16	10	14		

Step 3: Row-wise standard deviation, calculated as the root mean square deviation from the row mean, quantifies intra-row variability. Higher values indicate greater dispersion, while lower values indicate greater uniformity. The four rows have mean values of 1, 6.33, 6.33, and 3, and standard deviations of 1, 4.50, 5.50 and 1.73 respectively (Table 4).

Step 4: The maximum standard deviation σ , is designated as the allocation factor (A_f) according to Equation (4), taking a value of 5.50 for row S_3 . Given that the corresponding economic value in matrix cell C_{33} is zero, the allocation is subsequently, distributed proportionally within the feasible interval $[0, (10,14)]$, which reduces to an upper bound of 10.

Step 5: Referring to Table 5, the minimum cost cell C_{33} receive an allocation of $X_{33} = \min(10,14) = 10$ units. Consequently, the corresponding source's supply is entirely depleted, whereas the destination's demand is only partially satisfied, resulting in a remaining deficit of 4 units.

Table 5. Allocation of units.

	D_1	D_2	D_3	$Supply$	σ
S_1	1	0	2	11	1
S_2	11	6	2	12	4.50
S_3	9	10	0(10)	10	5.50
S_4	1	4	4	7	1.73
$Demand$	16	10	14		

Step-6: Reducing the row supply and column demand by the assigned flow results in a zero balance for the exhausted constraint, prompting the removal of the corresponding row or column from the transportation Table 5.

Step-7: Following the elimination of any row or column that meets the prescribed satisfaction criterion, the standard deviation is recomputed for each of the remaining rows on the left. Thus, variability is evaluated solely across the entries that do not satisfy the condition.

Step-8: Steps 2-7 are iteratively repeated until all production unit and purchasing centre constraints are satisfied.

Step-9: The total transportation cost (TTC) is 183, which is computed as the sum, over all transportation cells, of the product of the quantity of units distributed through each cell (see Table 6 and 7) and the corresponding unit transportation cost of that cell.

Table 6. Final allocation in TOCM.

	D_1	D_2	D_3	$Supply$	σ	σ'	σ''	σ'''
S_1	1(9)	0(2)	2	11	1	1	0.70	0.70
S_2	11	6(8)	2(4)	12	4.50	4.50	3.53	-
S_3	9	10	0(10)	10	5.50	-	-	-
S_4	1(7)	4	4	7	1.73	1.73	2.12	2.12
<i>Demand</i>	16	10	14					

Table 7. Final allocation in original matrix.

	D_1	D_2	D_3	$Supply$
S_1	4(9)	3(2)	4	11
S_2	10	7(8)	5(4)	12
S_3	8	8	3(10)	10
S_4	5(7)	6	6	7
<i>Demand</i>	16	10	14	

The total quantities transported from production units i to purchasing centres j are presented in the Table 7. The initial basic feasible solution is $X_{11} = 9$, $X_{12} = 2$, $X_{22} = 8$, $X_{23} = 4$, $X_{33} = 10$, $X_{41} = 7$, which the proposed method verifies as optimal. Since none of the basic variables assumes a zero value, the solution is non-degenerate. The number of units distributed using four allocation factors (A_f), computed on the basis of standard deviations, are 5.50, 4.50, 3.53, and 2.12. The corresponding initial basic feasible solutions obtained using NWCR, VAM, LCM, TDM1, RMM, CMM, TOCM-MT, MRM and TOCM- SD are 230, 187, 199, 183, 199, 187, 187, 187 and 183 respectively. As shown in Table 8, among the nine methods analysed, only TDM1 and the proposed technique achieve the optimal transportation cost 183, demonstrating identical performance and collinearity in the comparative evaluation. Moreover, both methods yield zero reform and deviation factors. Conversely, the Northwest Corner Rule and Row Minima Method exhibit the highest reform and deviation percentages, indicating relatively weaker performance.

5 Results and discussion

This section presents a rigorous comparative assessment of the cost-optimization capability of the proposed method. Its performance is benchmarked against several well-established classical techniques: the North-West Corner Rule (NWCR), Vogel's Approximation Method (VAM), Least Cost Method (LCM), Total Difference Method 1 (TDM1), Row Minima Method (RMM), Column Minima Method (CMM), Total Opportunity Cost Matrix-Minimal Total (TOCM-MT) and the Maximum Range Method (MRM). The analysis evaluates the quality of initial solutions based on total transportation cost and their proximity to the true optimal solution. The proposed approach is further assessed using three key metrics - the reforming factor, deviating factor and accuracy factor - computed via Equations (6), (7), and (8), respectively. To validate the robustness of the proposed method, a comprehensive set of numerical examples featuring varied cost structures and sourced from diverse literature is examined. As reported in Table 9, among the existing techniques, TDM1, MRM and TOCM-MT achieve optimal solutions in 12, 13, and 15 out of 30 test problems, respectively. In contrast, the proposed method attains optimal costs in 18 instances, thereby demonstrating a superior success rate relative to VAM, TDM1, TOCM-MT, and the MRM. Regarding the reforming factor, the maximum values of 44.73%, 45.52%, 58.77%, and 66.23% are recorded for the NWCR in test instances 27, 5, 9, and 30 respectively, as observed in the first column of Table 10 and Figure 1. Additionally, the second-highest reforming factor, 54.14% corresponds to the CMM as detailed in the sixth column of Table 10 and illustrated in Figure 1.

This study analyzes three types of reform factors: positive, negative and nonnegative. The positive and nonnegative factors confirm the efficacy of the proposed approach by demonstrating its capability to achieve required outcomes. Scalability is validated on large-scale problems, including an 8×9 numerical instance from a set of 30 benchmark problems. Although the exact optimal cost of 722 was not attained, the achieved cost of 760 is remarkably close to the optimum. For comparison, conventional methods, namely NWCR, VAM, LCM, TDM1, RMM, CMM, TOCM-MT and MRM produced costs of 2251, 826,

887, 844, 899, 1016, 808 and 825 respectively. These findings shows that the proposed technique effectively guides the initial basic feasible solution toward optimality. The basic variables obtained are $X_{13} = 12$, $X_{16} = 4$, $X_{25} = 10$, $X_{28} = 8$, $X_{31} = 10$, $X_{49} = 13$, $X_{56} = 8$, $X_{59} = 3$, $X_{61} = 1$, $X_{62} = 6$, $X_{63} = 3$, $X_{68} = 5$, $X_{71} = 2$, $X_{77} = 20$, $X_{82} = 15$ and $X_{84} = 8$. Since all the basic variables are non-zero, the solution is non-degenerate. Additionally, the deviating factor quantitatively captures the sensitivity and operational efficiency of the proposed technique in converging toward the optimum and is evaluated alongside the accuracy factor, which is computed using Equation (8). Table 10 reports the reform magnitudes for the 30 benchmark instances sourced from diverse origin. The highest reform magnitudes are observed for NWCR, RMM, CMM, and LCM, whose reform factor values consistently exhibit the largest deviations from zero. This indicates substantial modifications to the initial solutions and a greater potential for cost improvement.

$$R_f = \frac{IBFS - (TOCM - SD)}{IBFS} \times 100 \quad (6)$$

$$D_f = \frac{IBFS - O_c}{O_c} \times 100 \quad (7)$$

$$AC_f = \frac{\text{No. of optimal Solutions}}{\text{Total number of solutions}} \times 100 \quad (8)$$

Table 9 reports the accuracy factor, which measures the rate of achieving optimal costs. The proposed approach achieves the highest accuracy, identifying the optimum in 18 out of 30 numerical trials. The TOCM-MT ranks second, with 15 optimal solutions. TDM 1 and MRM exhibit comparable performance, achieving optimal solutions in 12 and 13 numerical instances, respectively, although both perform less effectively than the proposed approach and TOCM-MT.

Following the reform and accuracy factors, the deviating factor (D_f) evaluates a method's divergence from the optimal transportation cost, serving as a direct indicator of solution quality.

A value significantly above zero, signals a non-optimal cost that requires improvement through the Modified Distribution (MODI) or Stepping Stone methods. Conversely, a D_f close to zero indicates near-optimality, while an exact zero confirms the optimal convergence.

The five largest observed deviations are 211.77%, 142.58%, 118.06%, 97.46% and 80.94%. Four of these are associated with the NWCR, all in the first column, while the remaining deviation (118.06%) appears in the sixth column. The maximum deviation (211.77%) corresponds to the NWCR's result of 30. For this particular instance, although the true minimum cost is 722, neither the existing methods nor the proposed approach attained this value, underscoring the inherent difficulty of this numerical case. The proposed approach yields a cost of 760, which closely approximates the optimum.

For the same problem, its reform and deviating factors are numerically higher than those of other methods (see Figures 1 and 2). As reported, both factors remain strictly positive, explaining the absence of zero entries for these metrics in Table 10 and 11. In contrast, Total Opportunity Cost Matrix-Minimal Total and the Total Opportunity Cost Matrix-Standard Deviation method yield the highest number of zero deviating factors across the test problems, indicating exact convergence to the optimal solution in most instances, a trend consistently observed in Figure 2. Regarding the reform factor, NWCR, the Row Minima Method (RMM), and CMM exhibit broader ranges and higher dispersion, whereas RAM, TDM1, and VAM shows comparatively narrower reform ranges, reflecting smaller deviations from their respective initial solutions.

Table 12 compares the proposed TOCM-SD method with four established heuristics VAM, TDM1, TOCM-MT, and MRM across four large-scale problems (BSP01-BSP04). For each instance, the total transportation cost obtained by each initial solution method is reported alongside the true optimum obtained using LINGO. TOCM-SD consistently produces initial solutions with costs equal to or lower than all competing heuristic. For BSP02, it achieves a cost of 760, substantially outperforming VAM (826), TDM1 (844), TOCM-MT (808), and MRM (825), and comes within 5.3% of the LINGO optimum (722). For BSP01, TOCM-SD (2710) ties the best heuristic results (TDM1 and MRM) and falls within 1.9% of the optimum (2660). In BSP03 and BSP04, TOCM-SD yields 2750 and 2080, respectively, remaining competitive with VAM and TOCM-MT and consistently producing solutions closer to the optimal values than the other heuristics across all instances.

The results show that integrating standard deviation into the total opportunity cost framework significantly enhance the prioritization of critical allocations. This approach generates the initial basic feasible solutions that not only outperform classical methods in the majority of cases but also substantially reduce the iterative burden of reaching optimality. Moreover, the strong alignment between TOCM-SD solutions and LINGO-derived optimal solutions confirms the method's practical scalability and reliability for large-scale transportation problems.

Table 8. Analysis of initial solutions by different methods.

Sr. No.	NWCR	VAM	LCM	TDM1	RMM	CMM	TOCM-MT	MRM	TOCM-SD	Optimal	Balanced
1.	230	187	199	183	199	187	187	187	183	183	Yes
2.	1015	779	814	779	1110	779	743	781	743	743	Yes
3.	520	475	475	475	505	475	475	475	475	435	Yes
4.	540	470	435	445	470	435	435	415	435	410	Yes
5.	4285	2220	2455	2310	2290	2915	2350	2310	2420	2170	Yes
6.	64	59	69	59	74	74	61	60	59	59	Yes
7.	1815	1745	1695	1650	1925	1695	1650	1695	1650	1650	No
8.	3010	2130	2070	2130	2360	2510	2120	2070	2180	2070	Yes
9.	18800	8350	8800	7750	11050	16900	7750	7750	7750	7750	No
10.	14725	13225	14625	12925	14625	12775	12925	12475	12925	12475	No
11.	13100	9200	9800	9200	9200	10300	9200	9200	9200	9200	No
12.	8150	6000	5900	6150	6450	5850	6150	6200	5850	5600	No
13.	1500	1500	1450	1440	1450	1500	1440	1390	1440	1390	Yes
14.	640	450	470	450	500	530	440	520	440	430	Yes
15.	1950	1580	1805	1595	1580	1900	1580	1685	1580	1580	Yes
16.	3680	3520	3670	3570	3790	3460	3460	3720	3460	3460	Yes
17.	670	650	650	630	745	630	610	610	610	610	Yes
18.	975	859	894	859	1064	859	799	799	799	799	Yes
19.	10150	7790	8140	7790	11100	7790	7790	7830	7430	7430	Yes
20.	1870	1505	1705	1640	1475	1545	1685	1600	1740	1475	Yes
21.	3180	1930	2080	2020	1940	1930	2020	2040	1980	1840	Yes
22.	4160	3320	3500	3620	4120	3320	3620	3320	3620	3320	Yes
23.	1180	1020	1050	1020	1250	1110	1020	1020	1020	1020	Yes
24.	930	680	790	680	770	710	680	680	680	680	Yes
25.	1040	1040	1060	1040	1080	1040	1040	1040	1040	1040	Yes
26.	1095	711	822	711	822	1037	711	711	711	711	Yes
27.	1994	1104	1123	1102	1123	1491	1102	1102	1102	1102	Yes
28.	425	285	310	285	385	285	285	315	285	285	Yes
29.	363	290	305	290	295	295	290	295	290	290	Yes
30.	2251	826	887	844	899	1016	808	825	760	722	Yes

Table 9. Accuracy factor of different methods.

Sr. No.	Method	No. of Optimal Cost	Accuracy Factor($AC_f\%$)
1.	NWCR	1	3.33
2.	VAM	10	33.33
3.	LCM	1	3.33
4.	TDM1	12	40
5.	RMM	3	10
6.	CMM	4	13.33
7.	TOCM-MT	15	50
8.	MRM	13	43.33
9.	TOCM-SD	18	60

Table 10. Reform factor by TOCM-SD over existing methods.

Sr. No.	NWCR	VAM	LCM	TDM1	RMM	CMM	TOCM-MT	MRM	TOCM-SD	Optimal Cost
1.	20.43	2.13	8.04	0	8.04	2.13	2.13	2.13	183	183
2.	26.79	4.62	8.72	4.62	33.06	4.62	0	4.86	743	743
3.	8.65	0	0	0	5.94	0	0	0	475	435
4.	19.44	7.44	0	2.24	7.44	0	0	-4.81	435	410
5.	45.52	-9.00	1.42	-4.76	-5.67	16.98	-2.97	-4.76	2420	2170
6.	7.81	0	14.49	0	20.27	20.27	3.27	1.66	59	59
7.	9.09	5.44	2.65	0	14.28	2.65	0	2.65	1650	1650
8.	27.57	-2.34	-5.31	-2.34	7.62	13.14	-2.83	-5.31	2180	2070
9.	58.77	7.18	11.93	0	29.86	54.14	0	0	7750	7750
10.	12.22	2.26	11.62	0	11.62	-1.17	0	-3.60	12925	12475
11.	29.77	0	6.12	0	0	10.67	0	0	9200	9200
12.	28.22	2.50	0.84	4.87	9.30	0	8.94	5.64	5850	5600
13.	4.00	4.00	0.68	0	0.68	4.00	0	-3.59	1440	1390
14.	31.25	2.22	6.38	2.22	12.00	16.98	0	12.38	440	430
15.	18.97	0	12.46	0.94	0	20.25	0	6.23	1580	1580
16.	5.97	1.70	5.72	3.08	8.70	0	0	6.98	3460	3460
17.	8.95	6.15	8.27	3.17	18.12	3.17	0	0	610	610
18.	18.05	6.98	10.62	6.98	24.90	6.98	0	0	799	799
19.	26.79	4.62	8.72	4.62	33.06	4.62	4.62	5.10	7430	7430
20.	6.95	-15.61	-3.26	-6.09	-17.96	-12.62	-3.26	-9.06	1740	1475
21.	37.73	-2.59	4.80	1.98	-2.06	-2.50	1.98	2.94	1980	1840
22.	12.98	-9.03	-3.42	0	12.13	-9.03	0	0	3620	3320
23.	13.55	0	2.85	0	18.40	8.10	0	0	1020	1020
24.	26.88	0	13.92	0	11.68	4.22	0	0	680	680
25.	0	0	1.88	0	3.70	0	0	0	1040	1040
26.	35.06	0	13.50	0	13.50	31.43	0	0	711	711
27.	44.73	0.18	1.86	0	1.86	26.10	0	0	1102	1102
28.	32.94	0	8.06	0	25.97	0	0	9.52	285	285
29.	20.11	0	4.91	0	1.69	1.69	0	1.69	290	290
30.	66.23	7.99	14.31	9.95	15.46	25.19	5.94	7.87	760	722

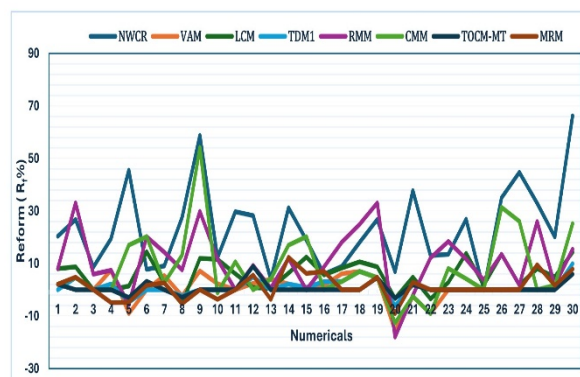

Fig 1. Reform factor across different methods.

Table 11. Deviation factor in numericals by different methods.

Sr. No.	NWCR	VAM	LCM	TDM1	RMM	CMM	TOCM-MT	MRM	TOCM-SD	Optimum Cost
1.	25.68	2.18	8.74	0	8.74	2.18	2.18	2.18	0	183
2.	36.60	4.84	9.55	4.84	49.39	4.84	0	5.11	0	743
3.	19.54	9.19	9.19	9.19	19.54	9.19	9.19	9.19	9.19	435
4.	31.70	14.63	6.09	8.53	14.63	6.09	6.09	1.21	6.09	410
5.	97.46	2.30	13.13	6.45	5.52	34.33	8.29	6.45	11.52	2170
6.	8.47	0	16.94	0	25.42	25.42	3.38	1.69	0	59
7.	10.00	5.75	2.72	0	16.66	2.72	0	2.72	0	1650
8.	45.41	2.89	0	2.89	14.00	21.25	2.41	0	5.31	2070
9.	142.58	13.54	7.74	0	42.58	118.06	0	0	0	7750
10.	18.03	6.01	17.23	3.60	17.23	2.40	3.60	0	3.60	12475
11.	42.39	0	6.52	0	0	11.95	0	0	0	9200
12.	45.53	7.14	5.35	9.82	15.17	4.46	8.03	10.71	4.46	5600
13.	7.91	7.91	4.31	3.59	4.31	7.91	3.59	0	3.59	1390
14.	48.83	4.65	9.30	4.65	16.27	23.25	0	20.93	2.32	430
15.	23.41	0	14.24	0.94	0	20.25	0	6.45	0	1580
16.	6.35	1.73	6.06	3.17	9.53	0	0	7.51	0	3460
17.	9.83	6.55	9.01	3.27	22.13	3.27	0	0	0	610
18.	22.02	7.50	11.88	7.50	33.16	7.50	0	0	0	799
19.	36.60	4.84	9.55	4.84	4.84	49.39	4.84	5.38	0	7430
20.	26.77	2.03	14.23	11.18	0	4.74	14.23	8.47	17.96	1475
21.	72.82	4.89	13.04	9.78	5.43	4.89	9.78	10.86	7.60	1840
22.	25.30	0	5.42	9.03	24.09	0	9.03	0	9.03	3320
23.	15.68	0	2.94	0	22.54	8.82	0	0	0	1020
24.	36.76	0	16.17	0	13.23	4.41	0	0	0	680
25.	0	0	1.92	0	3.84	0	0	0	0	1040
26.	54.00	0	15.61	0	15.61	45.85	0	0	0	711
27.	80.94	0.18	1.90	0	1.90	35.29	0	0	0	1102
28.	49.12	0	8.77	0	35.08	0	0	10.52	0	285
29.	25.17	0	5.17	0	1.72	1.72	0	1.72	0	290
30.	211.77	14.40	22.85	16.89	24.51	40.72	11.91	14.26	5.26	722

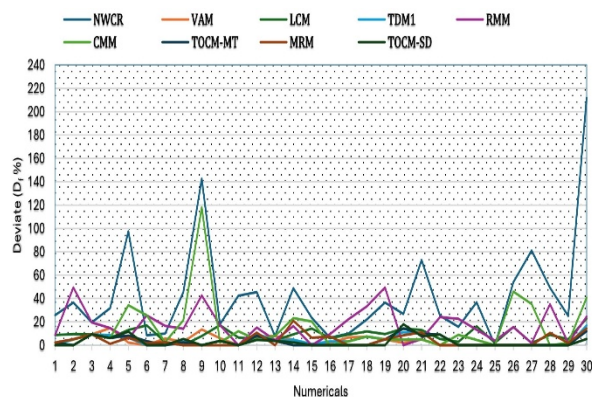
**Fig 2.** Deviation factor of different methods.

Table 12. Analysis of initial solutions for big size problems (BSP) using the existing and proposed method with LINGO software.

Sr. No.	Size	VAM	TDM1	TOCM-MT	MRM	TOCM-SD	LINGO
BSP01	11 × 12	2810	2700	2750	2710	2710	2660
BSP02	9 × 8	826	844	808	825	760	722
BSP03	12 × 11	2700	2910	2730	2780	2750	2600
BSP04	12 × 11	2080	2140	2080	2090	2080	2020

6 Conclusion

Obtaining an initial basic feasible solution (IBFS) is a fundamental step in determining the optimal solution to a transportation model. This study proposes a novel heuristic algorithm, termed TOCM-SD, for generating high-quality initial solutions with minimal computational effort. The effectiveness of the proposed method is evaluated using thirty numerical examples collected from published studies in reputed journals. The results indicate that TOCM-SD either attains the optimal initial cost or produces solutions that are very close to the optimum. The proposed algorithm demonstrates superior performance compared to classical methods, including the NWCR, LCM, VAM, TDM1, RMM and CMM as well as recently developed approaches such as TOCM-MT and MRM.

The method first constructs the total opportunity cost matrix, after which the standard deviation is computed as a penalty measure for each row to guide the allocation process toward minimum-cost cells. A comprehensive comparative analysis reveals that TOCM-SD achieves the optimal cost in 18 out of 30 test problems, outperforming TOCM-MT (15 cases), MRM and TDM1 (12 cases each), and VAM (10 cases). Moreover, the proposed method attains the highest accuracy factor of 60%, followed by TOCM-MT (50%) and both TDM1 and MRM (40%). These findings confirm the robustness and consistency of TOCM-SD in generating high-quality initial solutions. Further validation using benchmark problems (BSP01-BSP04) shows that TOCM-SD achieves the best or tied heuristic solution in three out of four cases (BSP01, BSP02, and BSP04), surpassing both classical and recent methods in several instances. Notably, for BSP02, the proposed method yields a cost of 760, which is significantly closer to the optimal value of 722 than the next-best heuristic (808). Similarly, for BSP01, the solution obtained lies within 1.9% of the optimal value. In all cases, TOCM-SD produces solutions that are closest to the LINGO optimum among the considered heuristics. The method performs reliably across both moderately sized problems (e.g., 9×8) and larger problems (e.g. 12×11), demonstrating strong scalability without requiring complex parameter tuning. By integrating standard deviation into the total opportunity cost framework, TOCM-SD enhances the prioritization of critical allocations. Consequently, it generates improved initial solutions, reduces the need for iterative refinements, and lowers overall computational effort.

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