Optimizing Sales Assignments: A Case Study Using the Hungarian Method

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Abstract

Efficient assignment of sales personnel to geographic territories is a critical operational challenge in sales force management. In sales territory assignments, which involve aligning sales territories with sales personnel, optimization models have evolved to handle combinatorial complexities and multiple conflicting objectives. This has often involved incorporating local managerial knowledge to enhance model-derived solutions (Zoltners & Sinha, 2005). The complexity of these assignments, amplified by considerations like travel time, road networks, and disruptions, has made the Hungarian method a viable tool for facilitating efficient and effective territory design. This study applies the Hungarian Method to optimize the allocation of five employees based in Kakinada, Rajahmundry, Visakhapatnam, Vijayawada, and Bhimavaram to six sales territories—Amalapuram, Yanam, Tadepalligudem, Peddapuram, Ramachandrapuram, and Annavaram—while minimizing total travel distance. To address the unbalanced nature of this problem (5 employees versus 6 destinations), a dummy employee was introduced, completing the 6×6 cost matrix. Standard row and column reductions were performed, followed by iterative zero-covering and adjustment procedures until an optimal assignment was achieved. The final allocation matched each real employee to a territory, with the dummy absorbing the unassigned destination (Yanam), resulting in a minimal total distance of **349 km**. This demonstrates the efficacy of the Hungarian Method in delivering optimal, one-to-one assignments even under unbalanced conditions. The methodology and findings provide a practical framework for territory optimization in field sales operations.

- **Keywords:** Assignment problem, Hungarian algorithm, Unbalanced assignment, Distance minimization, Row and column reduction

Introduction

The Hungarian algorithm, formalized by Harold Kuhn in 1955 and later refined by James Munkres, is a celebrated combinatorial optimization method that solves the classic assignment problem in polynomial time. It guarantees a minimum-cost matching between two equal-size sets—commonly agents and tasks—either using matrix reduction or bipartite graph matching techniques. In practical business scenarios like sales territory allocation, the number of salesmen (agents) and sales territories (tasks) often differ, resulting in an unbalanced assignment problem. Since the Hungarian algorithm requires a square cost matrix, analysts introduce dummy rows or columns—filled with zero cost entries—to balance the matrix before applying the algorithm. This strategy preserves the mathematical integrity of the optimization, ensuring that unused agents or territories do not contribute to the total cost.

This article explores an insightful case study involving the assignment of salesmen to sales territories, where travel distance between each salesman and territory serves as the cost metric. When the counts of salesmen and territories do not match, dummy entries are used to square off the matrix, enabling the algorithm to determine assignments that minimize total travel distance. This approach not only streamlines logistical efficiency, but also balances workload and resource distribution across the sales team. The case study demonstrates how organizations can optimize territory coverage, reduce operational costs, and improve strategic alignment between sales staff and their local territories.

In our case, we balanced the original 5×6 distance matrix by introducing a **dummy sixth employee** with zero-cost assignments. This enabled application of the Hungarian process to derive an optimal match between the five real employees and five of the six territories, leaving the dummy assigned to one territory. The result was a **minimal total travel distance of 349 km**, showcasing the method's robustness even under unbalanced conditions.

Literature review

1. Foundations and Theoretical Development

- The assignment problem involves assigning n agents to n tasks with minimum total cost, and by extension maximizing total profit, in a bipartite graph ([PMC article])(PMC).
- Harold W. Kuhn (1955) introduced the Hungarian Method, drawing from earlier Hungarian mathematicians like Kőnig and Egerváry; Munkres (1957) refined it, establishing its polynomial time complexity and practical viability (PMC).

- The method was originally O(n4n^4), but later improvements by Edmonds–Karp and Tomizawa reduced complexity to O(n3n^3), with further optimizations for sparse graphs achieving $O(m\,n + n^2 \log n)$ or even $O(m\sqrt{n}\log(nC))$ under integer weight bounds (Wikipedia).

2. Algorithm Mechanics & Implementation Insights

- The Hungarian Method proceeds through iterative row and column reductions, followed by covering zeros, adjusting uncovered entries, and constructing a perfect matching via augmenting paths in the reduced-cost graph—ensuring an optimal assignment is achieved (CP Algorithms).
- It is particularly effective on a square cost matrix, but can handle unbalanced cases by introducing dummy rows or columns with zero cost to square the matrix.

3. Extensions, Variants & Performance Enhancements

- For sparse cost matrices, especially in large-scale or constrained contexts like crowdsourcing, the sHungarian algorithm (a variation of Hungarian) uses sparse storage and row compression, reducing runtime to $O(n\,k)$ (where k is the number of non-zero entries) while maintaining solution quality (SpringerOpen).
- Academic efforts have produced exact or near-exact heuristic variants, including faster implementations of limited-capacity generalized assignment and dynamic assignment algorithms, markedly lowering runtime versus standard Hungarian for incremental changes or large problem sets (arXiv, ResearchGate).
- A distributed version of Hungarian was proposed for multi-robot coordination, enabling parallel, decentralized assignment with preserved optimality using local computation and communication protocols (arXiv).

4. Comparative Analyses and Alternatives

- Alternative algorithms like the auction algorithm, FlowAssign, or linear programming formulations (branch-and-bound, simplex-based solvers) are sometimes competitive, especially for highly unbalanced or large-scale cases—but the Hungarian algorithm typically remains the standard benchmark for quality and efficiency in balanced assignment settings (ar5iv).
- A small-scale academic study showed that a customized heuristic method can produce comparable results to Hungarian but with reduced computational time, making it appealing

for constrained environments where ease and speed matter more than theoretical optimality (SCIRP).

5. Applications in Real-World and Specialized Domains

- Personnel scheduling: Staff-to-task or teacher-to-subject assignments have leveraged the Hungarian algorithm to yield transparent and optimal results outperforming commercial solvers like LINGO (SCIRP).
- Spatio-temporal crowdsourcing: Task assignment problems with geographical/time constraints have adopted the sHungarian variant for scaling efficiency while minimizing travel cost (SpringerOpen).
- Robotics & sensor networks: The Hungarian algorithm features in distributed multi-robot orchestration and sensor-target matching systems, achieving globally optimal assignments in decentralized frameworks (arXiv).
- Generalized assignment: Cases like limited-capacity assignment are solvable via reduced O(n3)O(n^3) or O(n4)O(n^4) Hungarian adaptations when constraints are encoded appropriately (arXiv).

6. Strengths and Limitations

Strengths:

- Guaranteed optimality for square or properly padded assignment matrices.
- Strong theoretical foundation, derived from primal-dual and bipartite matching theory.
- Adaptable to distributed, sparse, or multi-agent systems, and to variations like spatio-temporal or generalized assignments.
- Polynomial-time performance, efficient for moderate nn.

Limitations:

- Computational bottleneck for large dense matrices due to O(n3)O(n^3) scaling, though mitigated by sparse or incremental variants.
- Memory constraints in extremely large problems, particularly unbalanced ones requiring matrix padding.
- Less suited to highly dynamic or weighted, capacity-constrained scheduling unless extended or combined with other heuristics or decomposition techniques (SpringerOpen, Wikipedia).

Statement of problem

This study is mainly focused on application of real world problem faced by the Company in Kakinada, sales department for optimizing their resources in allotment of sales persons to markets. The salesman-sales territory problem, in short, uses assignment technique to find the suitable sales person to the compatible sales market based on the distance between the origin city to destination city. This problem briefs the complexity faced by the organisation (sales dept.) to allot the right person to right location. Hence, it minimises the time of traveling by the sales person and also reduces the overall cost of achieving the tasks assigned to them.

Objectives

- Ensures methodological correctness when number of tasks exceeds number of agents, as described in operation research literature
- Follows the algorithmic protocol for cost minimization in assignment problems
- Confirms practical effectiveness of the method and aligns with theoretical expectations for optimal matching.

Research Methodology and Materials

1. Study Design

This study employs a case-study design, focusing on a specific unbalanced assignment scenario involving five sales employees across Andhra Pradesh and six target territories. This method is particularly suited to provide deep insights in small-N research contexts, as it allows detailed examination of the conditions and mechanics underlying assignment optimization.

2. Data and Materials

- Origins (Employees): O_1 (Kakinada), O_2 (Rajahmundry), O_3 (Visakhapatnam), O_4 (Vijayawada), O_5 (Bhimavaram).
- Destinations (Territories): D_1 (Amalapuram), D_2 (Yanam), D_3 (Tadepalligudem), D_4 (Peddapuram), D_5 (Ramachandrapuram), D_6 (Annavaram).
- Cost Matrix: Initial 5×6 matrix recording travel distances from each origin to each destination. A sixth dummy row (O_6) filled with zero costs was added to balance the matrix to a 6×6 square form, essential for Hungarian method application in unbalanced problems ([turn0search12]).

3. Preprocessing

- Matrix Balancing: A dummy row represents an artificial employee to accommodate the extra destination, ensuring a square cost matrix. This is a standard approach to unbalanced assignment as described in literature.
- Zero-cost Representation: Dummy entries set to zero allow the algorithm to assign unassigned tasks without distorting cost minimization.

4. Application of the Hungarian Algorithm

The methodology followed classical Hungarian method steps:

Step1: Row Reduction: Subtract the minimum value of each row from all elements of that row, ensuring at least one zero per row.

Step2: Column Reduction: Subtract the minimum value of each column from all elements in that column, ensuring at least one zero per column.

Step3: Zero-Covering and Assignment: Apply zero-marking and elimination rules to tentatively assign zero-cost cells:

- Rows or columns with exactly one zero receive a tentative assignment and competing zeros in the same column or row are crossed out.

Step4: Minimum-Line Covering: Draw the minimum number of horizontal or vertical lines to cover all zeros. If the number equals the matrix dimension (6 in this case), the current zeros define the optimal assignment. If fewer, proceed to adjustment.

Step5: Adjustment of Uncovered Cells: Identify the smallest value not covered by any line, subtract it from all uncovered cells, and add it to each cell at intersections of covering lines. Repeat zero-covering and line-cover checks until optimality is reached. This continues until one zero per row and column can be assigned.

5. Final Assignment and Validation

After convergence, each real employee (O_1–O_5) was assigned a unique destination (D_4, D_5, D_6, D_3, D_1 respectively), with the dummy row absorbing D_2. This yielded a total minimum travel distance of 349 km. The assignment was validated by confirming that all rows and columns had exactly one zero-marked assignment, consistent with Hungarian optimality criteria.

DATA ANALYSIS

The study contains 5 employees from different origins: Kakinada, Rajahmundry, Visakhapatnam, Vijayawada, Bhimavaram.

Sales territories to be allotted, (Destinations): Amalapuram, Yanam, Tadepalligudem, peddapuram, Ramachandrapuram, Annavaram.

	D1	D2	D3	D4	D5	D6
O1	63	52	46	20	33	52
O2	65	72	16	42	44	80
O3	214	182	258	153	184	108
O4	185	213	112	196	190	234
O5	65	96	32	142	94	158

Here Origins are 5 and destinations are 6, means it is an Unbalanced Assignment problem. When Number of Columns and Number of Rows are equal, the problem is balanced problem, and when not, it is called an unbalanced problem.

- In unbalanced problem, when it occurs, and there are more rows than columns, simply add a dummy column .
- If the number columns exceed than the rows, simply add a dummy row.
- Since the dummy task or person is non-existent, we enter zeros in its row or column as the cost or time estimate.

	D1	D2	D3	D4	D5	D6
O1	63	52	46	20	33	52
O2	65	72	16	42	44	80
O3	214	182	258	153	184	108
O4	185	213	112	196	190	234
O5	65	96	32	142	94	158
O6	0	0	0	0	0	0

STEP1:

Subtract the Minimum of each row of the effectiveness matrix,from all the elements of the respective rows.

Modified matrix after ROW REDUCTION,

	D1	D2	D3	D4	D5	D6
O1	43	32	26	0	13	32
O2	49	56	0	26	28	64
O3	106	74	150	45	76	0
O4	73	101	0	84	78	122
O5	33	64	0	110	62	126
O6	0	0	0	0	0	0

STEP2:

Further, modify the resulting matrix by subtracting the minimum element of each column from all the elements of the respective columns.

Modified Matrix after COLUMN REDUCTION,

	D1	D2	D3	D4	D5	D6
O1	43	32	26	0	13	32
O2	49	56	0	26	28	64
O3	106	74	150	45	76	0
O4	73	101	0	84	78	122
O5	33	64	0	110	62	126
O6	0	0	0	0	0	0

STEP3:

Now test whether it is possible to make an assignment using only Zeros. If it is possible, the assignment must be optimal.

A)Starting with Row1 in the matrix, examine the rows one by one until a row containing. exactly single zero element is found. Then an experimental assignment [] is marked to that cell. Now cross all other zeros in the column in which the assignment has been made. This eliminates the possibility of making further assignment in that column.

B)When the set of Rows has been completely examined, an identical procedure is applied successively to columns starting with column1, examine all columns until a column containing exactly one zero is found. Then make an experimental assignment in that position and cross other zeros in the row in which the assignment has been made.

	C1	C2	C3	C4	C5	C6
R1	43	32	26	0	13	32
R2	49	56	0	26	28	64
R3	106	74	150	45	76	0
R4	73	101	0(X)	84	78	122
R5	33	64	0(X)	110	62	126
R6	0	0(X)	0(X)	0(X)	0(X)	0(X)

Since, R4 And R5 are not yet assigned so use Hungarian Method

Hungarian Method

STEP4:

Once we complete the Step3, follow the following procedure

Then draw the Minimum number of horizontal and vertical lines to cover all the zeros in the resulting matrix. Let the min number of lines be ‘N’. now there may be two possibilities’

i) If N=n, the number of rows(columns) of given matrix, then an optimal assignment can be made. So make the zero assignment to get the required solution.

ii) If N>n, then proceed to next step.

A Rule to DrawMinimum Number of Lines

1. Tick(√) rows that do not have any marked zero

2. Tick(√) columns having marked zeros or otherwise in ticked rows 3, tick(√) rows having marked zeros in ticked columns

4. Repeat 2 and 3 until the chain of ticking is complete

5. Draw lines through all unticked rows and ticked columns. Repeat the procedure till all the rows are assigned

	C1	C2	C3(√)	C4	C5	C6
R1	43	32	26	0	13	32
R2(√)	49	56	0	26	28	64
R3	106	74	150	45	76	0
R4(√)	73	101	0(X)	84	78	122
R5(√)	33	64	0(X)	110	62	126
R6	0	0(X)	0(X)	0(X)	0(X)	0(X)

Drawn lines on R2, R4, R5, C3

STEP5:

Determine the smallest element in the matrix, not covered by the 'N' lines, subtract this minimum element from all uncovered elements and add the same element at the intersection of horizontal and vertical lines. Thus, the second modified matrix is obtained.

Again repeat Step 3 and 4 until minimum number of lines become equal to the number of Rows(Columns) of the given matrix, N=n

In this case, smallest number in the uncovered region is '26' Apply it in the matrix.

	C1	C2	C3	C4	C5	C6
R1	43	32	26	0	13	32
R2	23	30	0	0	2	38
R3	106	74	26	45	76	0
R4	47	75	0	58	52	96

R5	7	38	0	84	36	100
R6	0	0	26	0	0	0

STEP6:

1. To make Zero Assignment, Examine the row successively until a row – wise exactly single zero is found
2. Repeat the assignment problem procedure to make the above matrix assigned.
3. Repeat the above step successfully until one of the following situation arise:

i) If no unmarked zero is left, then the process ends, or

ii) if there lie more than one of the unmarked zeros in any column or row, then mark [] one of the unmarked zeros arbitrarily and mark a cross (X) in the cells of remaining zeros in its row and column. Repeat the process until no unmarked zero is left in the matrix.

4. Thus exactly one marked '[]' zero in each row and each column of the matrix is obtained. The assignment corresponding to these marked zero will give the optimal assignment.

	C1	C2	C3(√)	C4	C5	C6
R1	43	32	26	0	13	32
R2(√)	23	30	0	0(X)	2	38
R3	106	74	26	45	76	0
R4(√)	47	75	0(X)	58	52	96
R5(√)	7	38	0(X)	84	36	100
R6	0	0(X)	26	0(X)	0(X)	0(X)

Least value in the uncovered area is '7' insert the value in the intersection cells and subtract the value from the uncovered cell values.

	C1	C2	C3	C4(√)	C5	C6
R1(√)	43	32	7	0	13	32
R2(√)	23	30	7	0(X)	2	38

R3	~~106~~	~~74~~	~~7~~	~~45~~	~~76~~	~~0~~
R4	~~40~~	~~68~~	~~0~~	~~51~~	~~45~~	~~89~~
R5	~~0~~	~~31~~	~~0(X)~~	~~77~~	~~29~~	~~93~~
R6	~~0(X)~~	~~0~~	~~7~~	~~0(X)~~	~~0(X)~~	~~0(X)~~

Least value in the uncovered area is '2'. Insert the value in the intersection cells and subtract the value from the uncovered cell values.

	C1	C2	C3	C4	C5	C6
R1	41	30	5	0	11	30
R2	21	28	5	0	0	36
R3	106	74	7	2	76	0
R4	40	68	0	2	45	89
R5	0	31	0	2	29	93
R6	0	0	7	2	0	0

All the rows are assigned with the values, so the problem got its optimal solution. Employee1 Destination4

Employee2----- Destination5

Employee3----- Destination6

Employee4----- Destination3

Employee5------ Destination1

Dummy ---------- Destination2

Total Distance

E1D4

20K

m

E2---D5 -- 44Km

E3---D6 -- 108Km

E4---D3 -- 112Km

E5---D1 -- 65Km

Dummy---D2 ---0Km

Total Optimal Distance=20+44+108+112+65=349Km

Findings and analysis

1. Handling of Unbalanced Assignment
   - You effectively managed the mismatch between 5 employees and 6 destinations by introducing a dummy row (O_6) filled with zeros. This ensured a square 6×6 cost matrix, enabling the Hungarian Method to operate correctly and deliver an optimal solution.
2. Cost Minimization via Row & Column Reduction
   - As per the Hungarian algorithm, the matrix underwent systematic row reduction (subtracting the least value in each row) and column reduction (subtracting the least in each column), ensuring each row and column contained at least one zero cost element—a core step in the optimization process (BrainKart).
3. Zero-Covering and Adjustment Logic
   - The assignment progressed using zero-covering techniques, in which the algorithm identified rows or columns with a single zero, made tentative assignments, and eliminated competing zeros. When the minimum number of covering lines exceeded the dimension, cost adjustments (subtracting the smallest uncovered value and updating intersecting entries) were performed iteratively until convergence was achieved (BrainKart, universalteacherpublications.com).
4. Optimal Assignment & Distance Sum
   - Final results paired each of the five real employees to one territory, while Yanam (D2) remained assigned to the dummy—representing an unserved destination. The total minimized travel distance amounted to 349 km, indicating a globally optimal solution for the given cost matrix.
5. Algorithmic Guarantees
   - The Hungarian Method guarantees an optimal assignment for balanced matrices and, by extension, for unbalanced problems after appropriate padding with dummy rows or columns (Wikipedia).

6. Practical Implications

- Assigning real employees to actual territories while the dummy handles the extra destination means one territory remains unserved. This is acceptable in mathematical terms, but alerts management to reconsider staffing or territory importance—especially if Yanam is a priority zone.

Suggestions

1. IncludeWeightedCostsBeyondDistance:
   Integrate additional factors such as sales potential, employee skill, or expected revenue per territory into the cost matrix. If aiming to *maximize* benefit instead of minimizing cost, convert benefit values into costs by taking opportunity loss (subtracting each from the maximum) before applying the Hungarian algorithm—a standard transformation for maximization tasks (universalteacherpublications.com, Reddit).
2. SensitivityAnalysisforRobustness
   Explore how changes in cost estimates (e.g., traffic delays or distance inaccuracies) could alter assignment outcomes by performing sensitivity analysis. This builds confidence in the solution and prepares for real-world variability.

Handling Unassigned Territories

3. AddressUnservedDestinations:
   The dummy row assignment to Yanam indicates it remains unassigned by real employees. Reevaluate the importance and sales potential of this territory. If it holds strategic value, consider adjusting staffing or reallocating resources.
4. Priority-BasedConstraints:
   Use differentiated assignment costs to prioritize some territories over others—assign a penalty or bonus weight to ensure high-priority zones are served, while leaving low-priority ones unassigned if needed.

Operational and Strategic Recommendations

5. DynamicAssignmentforTemporality:
   For operations across multiple periods, incorporate time-sensitive factors like seasonal

demand or regional fluctuations. Re-run the optimized assignment periodically to adapt resources dynamically.

6. ScalabilitywithModernVariants:
   For larger problems or high-dimensional cost matrices, consider sparse or distributed Hungarian algorithm variants such as "sHungarian" or GPU-accelerated versions to improve scalability (BrainKart, india free notes.com).

Implementation Best Practices

7. EnsureAccuracyinCostMatrixConstruction:
   Verify each cost entry with reliable data—GPS-based travel distances or time-tracking—so that results reflect practical reality effectively.
8. DocumentZero-CoveringSteps:
   For transparency and reproducibility, maintain detailed records of each zero-covering and adjustment iteration. This aligns with standard Hungarian Method procedures (Wikipedia, Reddit).
9. ExploreAlternativeMatchingMethods(WhenNeeded):
   While Hungarian Method is optimal for balanced and padding-adjusted problems, strong alternatives like min-cost max-flow or linear programming approaches may outperform in cases with extensive constraints or large unbalanced margins (Reddit).

Conclusion

This study demonstrated the effective use of the Hungarian Method to optimize the assignment of five sales representatives to six territories—a typical unbalanced assignment problem. By correctly introducing a dummy employee to create a square 6×6 cost matrix and executing classical Hungarian steps (row- and column-reductions, zero-covering, and iterative adjustments), the analysis yielded an optimal total travel distance of 349 km. Such results align with the algorithm's theoretical performance guarantees established by Kuhn (1955) and Munkres (1957) (journal-aprie.com, ieomsociety.org).

Key findings from the assignment include:

- Optimal Matching, where each real employee was best paired with a specific territory ($O_1 \to D_4$, $O_2 \to D_5$, $O_3 \to D_6$, $O_4 \to D_3$, $O_5 \to D_1$), and the dummy row absorbed the surplus territory (D_2).

- Unserved Territory: Yanam remained unmatched by real staff, highlighting an area for strategic reassessment.
- Resource Efficiency: The minimized travel distance reflects efficient territory coverage, blending operational precision with methodological transparency.

Future Work

- Incorporate Additional Metrics: Future research could build on this foundation by incorporating multi-factor costs, including sales potential, skill alignment, and revenue forecasts.
- Explore Advanced Variants: For larger or more complex scenarios, employing sparse, distributed, or incremental Hungarian algorithms may enhance practicality and scalability.
- Dynamic Reassignment: In fast-paced field environments, real-time updates and adaptive assignments—perhaps assisted by machine learning—could improve responsiveness to changing conditions.

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