© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723370

Optimization Of Fuel Inventory Management at a Retail Petrol Pump Using Linear Programming

HRIDAY DAS
PES University, Bengaluru, India

Abstract- Background: Retail fuel stations must balance stock availability with the cost of carrying fuel inventory. Methods: This study uses a 61-day daily inventory register (1 June–31 July 2026) for Motor Spirit (MS) and High-Speed Diesel (HSD) at a selected retail petrol pump. A two-stage approach was used: a data-quality audit followed by two independent Linear Programming (LP) models. Each model minimizes holding cost subject to daily inventory balance, a safety-stock floor, an assumed tank-capacity ceiling, and non-negative replenishment. Safety stock was set at twice average monthly demand and rounded upward to the nearest 10 L. The LPs were solved with scipy.optimize.linprog using HiGHS and independently validated for 122 fuel-day rows. Results: The audit identified 19 negative-inventory observations (15.6% of 122 rows) and only two deliveries per fuel during the study period. Total demand was 33,362 L for MS and 31,033 L for HSD. Historical combined holding cost was Rs. 23,794.86, compared with Rs. 6,074.13 under the LP benchmark, a model-based potential reduction of Rs. 17,720.74 (74.47%). Historical stockout days fell from 15 to zero and average combined inventory from 6,251.19 L to 1,637.62 L. All 122 optimized rows satisfied the model constraints, and all nine sensitivity scenarios remained feasible. Conclusion: The LP provides a transparent benchmark for demand-linked replenishment, but the reported savings are not a guaranteed operational forecast. Supplier lead time, minimum order quantity, delivery schedules, ordering cost, verified tank capacity, and longer demand histories are required for an implementable procurement model.

Keywords— Fuel inventory management; Linear programming; retail petrol pump; safety stock; holding-cost minimization; replenishment optimization.

I. INTRODUCTION

Inventory management seeks to maintain sufficient stock to meet demand while controlling the resources tied up in inventory. Retail petrol stations face this problem in a particularly visible form because Motor Spirit (MS) and High Speed Diesel (HSD) are sold continuously, replenishment generally arrives in bulk, and storage is bounded by tank capacity. Excess inventory increases capital tied up in stock, while inadequate inventory can create stockout risk and disrupt service.

Operations Research provides mathematical methods for converting these competing requirements into explicit decision models. Linear Programming (LP) is especially useful when the objective and operational constraints can be represented by linear relationships. Inventory models based on mathematical programming have been applied to safety-stock decisions, replenishment, petroleum distribution, and broader supply-chain planning [1]–[5], [10]–[13].

The present study examines a selected retail petrol pump using a daily register covering 1 June to 31 July 2026. The study is deliberately transparent about the quality of the underlying records. The source data contain negative inventory observations, an unexplained month-boundary discontinuity, a discrepancy between daily-register and dashboard demand totals, and a demand series with only two distinct values per fuel-month. Rather than silently correcting these issues, the study audits and reports them before optimization.

The research question is whether a demand-driven replenishment policy can maintain a defined safety-stock floor and assumed tank-capacity ceiling while reducing holding cost relative to the historical bulk-delivery pattern. The contribution is an auditable, day-indexed LP benchmark for two fuels at a single retail outlet, together with independent constraint validation and sensitivity analysis.

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723370

II. RELATED WORK AND RESEARCH GAP

Inventory optimization literature provides several relevant foundations. Safety-stock determination has been addressed through optimization and simulation-based approaches, emphasizing the trade-off between service protection and inventory cost [1], [11]. Classical lot-sizing and dynamic inventory models establish the role of replenishment timing and inventory carryover in cost minimization [7], [13]. More recent work has used mixed-integer programming for inventory and supply-chain decisions where operational constraints such as ordering structure, capacity, or discrete decisions matter [4], [8], [12].

Petroleum-specific studies also demonstrate the value of mathematical optimization. Benantar, Ouafi, and Boukachour developed a petrol-station replenishment formulation [2], while Nwanya examined petroleum-product reorder-point and order-quantity policies from an inventory-cost perspective [10]. Fatima and Tufail applied LP in an oil-refinery context [5]. These studies show that petroleum inventory and distribution decisions can be formalized quantitatively, but the decision scale and operational assumptions differ from a single-station, two-fuel daily inventory problem.

The present study therefore focuses on a narrower but highly transparent setting: two independent LPs based directly on a retail station's daily register, with explicit day-by-day inventory balance, safety-stock and capacity constraints, and an independent validation step. The study also treats data quality as part of the analytical process. This combination is intended as a benchmark rather than as a claim that the model already represents the station's complete procurement process.

The main research gap addressed is consequently methodological and operational: a simple LP can be made auditable at the individual-station level, but its managerial interpretation must remain bounded by the quality of the input data and by the absence of supplier-side constraints. The study makes those boundaries explicit rather than presenting an idealized solution as a guaranteed field outcome.

III. METHODOLOGY

A. Research Design and Data

The study uses a quantitative, analytical case-study design with two stages. Stage 1 audits the daily inventory register for missing values, duplicate Date+Fuel combinations, negative demand or receipt values, arithmetic reconciliation, negative inventory, demand reconciliation, and month-boundary continuity. Stage 2 formulates and solves separate LP models for MS and HSD, validates the optimized trajectories, and performs one-at-a-time sensitivity analysis.

The observation period contains 61 days and two fuel types, giving 122 fuel-day records. Each record contains Date, Fuel Type, Opening Stock, Receipt, Meter Sales/Demand, and Closing Stock. A parallel Tank Sales field was identical to Meter Sales for all 122 rows, so it did not provide an independent second demand measure.

The first-day opening inventory used to initialize the LP was 5,000 L for MS and 8,000 L for HSD. The historical negative inventory values were preserved in the audit and historical comparison but were not recursively fed into the LP. The LP instead propagates its own inventory state from the verified positive day-one opening balance.

B. Data-Quality Audit

Audit item	Finding	Treatment
Missing values	0 of 122 rows	No imputation required
Duplicate Date+Fuel records	0	No duplicates
Negative demand/receipts	0	No correction required
Arithmetic balance	122/122 rows reconciled	Opening + Receipt − Demand = Closing
Negative inventory	19 rows; 4 episodes	Retained and disclosed

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723370

Dashboard vs. daily-register demand	1.8%–2.3% gap	Traceable daily-register totals used
June/July stock discontinuity	Present for both fuels	Flagged; not used in LP recursion
Demand variation	Only two values per fuel-month	Disclosed as provenance limitation

TABLE I. DATA-QUALITY AUDIT SUMMARY

C. LP Formulation
For each fuel, let t = 1,…,61 denote the study day. The decision variables are x_t, the replenishment received on day t in litres, and I_t, the closing inventory at the end of day t. The observed daily Meter Sales value is D_t. Safety stock SS_t and capacity CAP_t vary by month, while the holding-cost rate h is constant within each fuel.

The objective minimizes accumulated holding cost:

$$\textit{Minimize}\ \ Z = \Sigma(t=1 \text{ to } T)\ h\ I\_t$$

The inventory balance is:

$$I\_t = I\_(t-1) + x\_t - D\_t, \quad t = 1,\dots,T$$

The constraints are:

$$I\_t \geq SS\_t;\ I\_t \leq CAP\_t;\ x\_t \geq 0, \text{ for all } t$$

The day-one opening inventory I_0 is fixed at the observed positive opening stock. MS and HSD are solved independently because the source model contains no shared storage, joint procurement, or common decision variable between the two fuels.

The LP was solved with scipy.optimize.linprog using the HiGHS dual-simplex implementation. Each fuel has 122 decision variables: 61 replenishment variables and 61 closing-inventory variables. Because holding cost is the only objective term and replenishment is unconstrained above zero, the mathematical optimum is to reduce excess starting inventory and, when feasible, replenish close to the safety-stock floor. This daily-replenishment behavior is a direct consequence of the stated model rather than a heuristic assumption.

D. Safety Stock, Capacity, and Holding Cost

Fuel	Month	Safety stock (L)	Capacity (L)	Holding cost (Rs./L/day)
MS	June 2026	900	11,000	0.0315
MS	July 2026	1,290	11,440	0.0315
HSD	June 2026	910	17,600	0.0296
HSD	July 2026	1,130	17,600	0.0296

TABLE II. OPTIMIZATION PARAMETERS

Safety stock was calculated as CEILING(2 × average daily demand, 10). This is explicitly a research assumption because the source data do not contain supplier lead time, service-level targets, or the statistical inputs required for a formal probabilistic safety-stock calculation. Tank capacity is also an assumption because verified physical specifications were unavailable. For HSD, the source workbook contained inconsistent figures of 17,600 L and 7,821 L for the same physical tank; 17,600 L was retained consistently because it was the more defensible documented value. Holding-cost rates of Rs. 0.0315/L/day for MS and Rs. 0.0296/L/day for HSD were carried from the source workbook; their underlying 12% annual capital-carrying assumption was not independently verifiable.

E. Historical-Cost Treatment and Validation
For historical holding cost, negative closing inventories were clipped to zero because negative

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723370

physical inventory has no economically meaningful holding cost. The negative observations themselves were retained for the stockout count and data-quality discussion. The optimized solution was independently checked row by row against the balance equation, safety-stock floor, capacity ceiling, and non-negativity of replenishment.

Validation check	Rows	Pass	Fail
Balance equation	122	122	0
Safety-stock floor	122	122	0
Tank-capacity ceiling	122	122	0
Non-negative replenishment	122	122	0
Sensitivity runs (MS/HSD/combined)	27	27	0

TABLE III. LP VALIDATION SUMMARY

F. Sensitivity Analysis

Nine sensitivity scenarios were independently re-solved: demand at −10% and +10%; safety stock at −20% and +20%; and holding cost at −10% and +10%, each with the base case retained. The three parameter families therefore produced 27 independent solver outputs across MS, HSD, and the combined result. No scenario produced an infeasible model or a constraint violation.

IV. RESULTS

A. Demand and Historical Inventory Pattern

Fuel	Month	Total demand (L)	Average/day (L)	Maximum/day (L)	Std. dev. (L)
MS	June 2026	13,500	450.00	560	67.47
MS	July 2026	19,862	640.71	752	66.72
HSD	June 2026	13,620	454.00	564	67.47
HSD	July 2026	17,413	561.71	673	66.72

TABLE IV. DEMAND STATISTICS

Total demand over the study period was 33,362 L for MS and 31,033 L for HSD. Average daily demand increased from June to July for both fuels. The historical register contained only two deliveries per fuel across the entire 61-day horizon, producing a bulk-delivery sawtooth pattern and four negative-inventory episodes: MS on 12–16 June and 9–11 July, and HSD on 18–21 June and 7–13 July.

B. Overall Optimization Results

Metric	Historical / Actual	LP optimized / Model-based
MS demand (L)	33,362	33,362
HSD demand (L)	31,033	31,033
Combined holding cost (Rs.)	23,794.86	6,074.13
Holding-cost reduction	—	Rs. 17,720.74 (74.47%)
Stockout days	15	0
Average combined inventory (L)	6,251.19	1,637.62

TABLE V. OVERALL HISTORICAL VS. LP-OPTIMIZED RESULTS

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723370

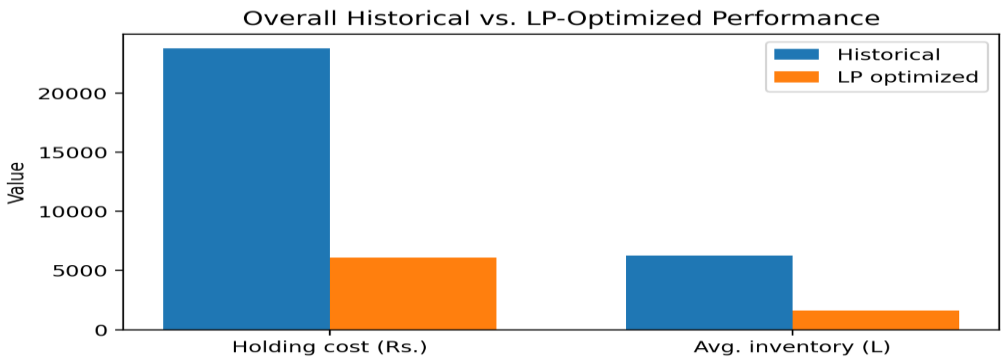

Fig. 1. Overall historical versus LP-optimized performance.

C. Monthly Results

Fuel / Month	Demand (L)	Actual / LP receipts (L)	Actual / LP HC (Rs.)	Reduction
MS / June	13,500	16,000 / 9,400	5,879.16 / 1,398.60	76.21%
MS / July	19,862	16,000 / 20,252	5,740.75 / 1,259.69	78.06%
HSD / June	13,620	8,000 / 6,530	3,322.24 / 2,378.95	28.39%
HSD / July	17,413	24,000 / 17,633	8,852.71 / 1,036.89	88.29%

TABLE VI. MONTHLY HISTORICAL VS. LP-OPTIMIZED RESULTS

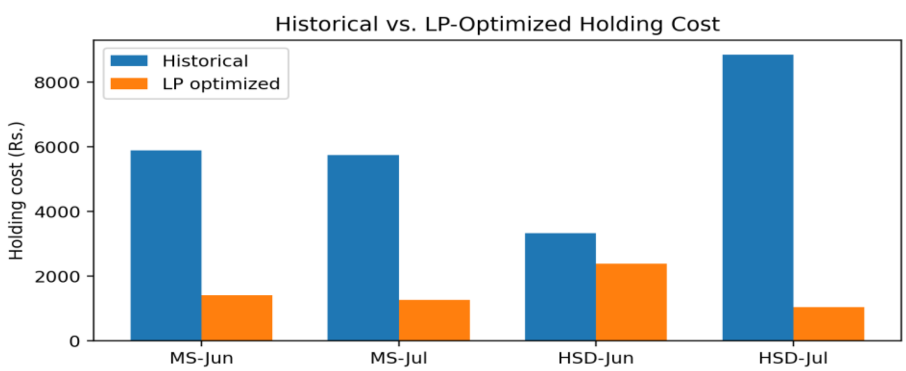

Fig. 2. Historical versus LP-optimized holding cost by fuel and month.

D. Sensitivity Results

Scenario	Parameter change	Combined optimal HC (Rs.)	Change from base
Demand −10%	Demand	6,321.47	+4.07%
Base demand	—	6,074.12	Base
Demand +10%	Demand	5,875.96	−3.26%
Safety stock −20%	Safety stock	5,416.35	−10.83%
Base safety stock	—	6,074.12	Base
Safety stock +20%	Safety stock	6,735.52	+10.89%
Holding cost −10%	Holding cost	5,466.71	−10.00%

Base holding cost	—	6,074.12	Base
Holding cost +10%	Holding cost	6,681.54	+10.00%

TABLE VII. NINE-SCENARIO SENSITIVITY ANALYSIS

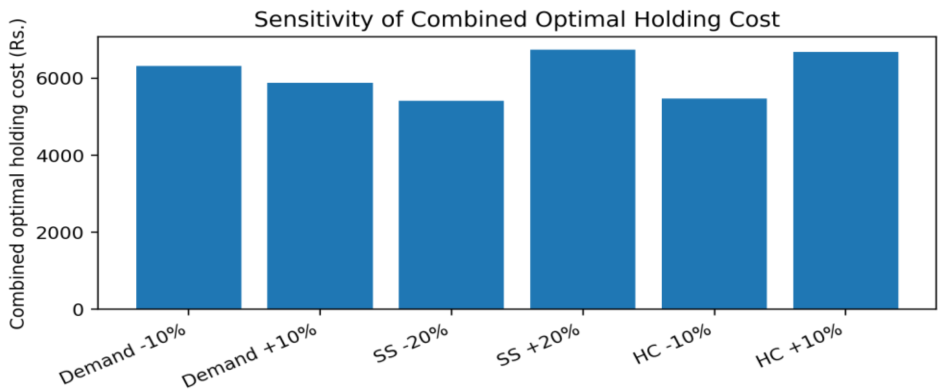

Fig. 3. Sensitivity of combined optimal holding cost.

V. DISCUSSION

The optimization result is consistent with the structure of the objective function. Since the model assigns a positive holding cost to every litre held and contains no ordering cost or delivery-frequency penalty, the solver has an incentive to keep inventory as close as possible to the safety-stock floor while still meeting demand. The resulting 74.47% reduction in holding cost is therefore best interpreted as the difference between the historical bulk-delivery trajectory and an idealized lower-inventory benchmark.

The largest monthly percentage reduction occurs for HSD in July (88.29%). The source data show that this month contained the longest negative-inventory episode and was followed by a 24,000-L historical receipt, creating a high average inventory level relative to the 1,130-L assumed safety stock. The LP instead distributes replenishment closer to daily demand, reducing the time that fuel remains above the modeled protection level.

The sensitivity results highlight the importance of the safety-stock assumption. A 20% decrease in safety stock reduces combined optimal holding cost by 10.83%, while a 20% increase raises it by 10.89%. This is expected because safety stock directly determines the inventory floor in a holding-cost-only objective. Consequently, the safety-stock assumption should not be interpreted as a verified operational policy; it is the principal parameter that should be recalibrated when service-level and lead-time data become available.

Holding-cost-rate sensitivity behaves differently. A ±10% change in the rate produces an almost exactly proportional ±10% change in the objective while leaving the underlying replenishment trajectory unchanged. The rate is therefore a scaling parameter in this model rather than a structural decision parameter.

The result also illustrates why a simple LP should not be confused with a complete procurement model. In real fuel replenishment, minimum delivery quantities, supplier schedules, lead times, truck capacity, and fixed ordering costs can make daily replenishment impossible or uneconomic. Mixed-integer and petroleum-distribution models in the literature explicitly address some of these discrete and network constraints [2], [4], [8], [12]. The present LP should therefore be used as a transparent benchmark from which a more operational model can be developed.

Finally, the data-quality audit materially affects interpretation. The 19 negative-inventory rows, the 1.8%–2.3% dashboard reconciliation gap, the June/July stock discontinuity, and the two-value-per-month demand pattern limit the strength of any claim about general operational performance. The study's main methodological value is consequently the combination of optimization and disclosure: the model remains reproducible because assumptions and unresolved data issues are explicitly identified.

VI. MANAGERIAL IMPLICATIONS

- Use the LP solution as a benchmark for evaluating the current bulk-delivery policy rather than as a ready-to-execute order schedule.
- Improve daily inventory measurement and delivery recording, preferably through fixed-time dip-chart readings or automated tank-gauge data.
- Verify physical tank capacities before imposing capacity constraints in an operational model.
- Collect supplier lead times, minimum order quantities, truck or delivery capacities, delivery-day restrictions, and fixed ordering costs.
- Re-estimate safety stock using verified lead-time and service-level information instead of the current 2× average-demand research rule.
- Once supplier-side data are available, extend the LP to a MILP or periodic-review model that can represent discrete delivery decisions and ordering costs.

VII. LIMITATIONS AND FUTURE RESEARCH

The study has a 61-day observation window, which limits inference about seasonality and longer-term demand. The historical baseline contains 19 negative-inventory observations and unresolved reconciliation issues. Verified tank capacities are unavailable, and HSD capacity required selecting one of two inconsistent source values. Supplier lead time, minimum order quantity, delivery frequency, delivery schedule, and ordering cost are absent, forcing the LP to assume same-day replenishment with unrestricted non-negative order quantities. The demand series also takes only two distinct values per fuel-month, which is disclosed as a provenance limitation.

Future work should extend the dataset to at least a full year, incorporate verified supplier and tank parameters, and reformulate the problem as a MILP or periodic-review model where appropriate. Stochastic or robust optimization could address demand uncertainty, while simulation could test the policy under more realistic demand and delivery conditions. Real-time tank-gauge data and demand forecasting could support a rolling-horizon optimization system, and the single-station model could eventually be extended to a multi-station petroleum distribution network.

VIII. CONCLUSION

This study developed two independent Linear Programming models for MS and HSD inventory management at a selected retail petrol pump using a 61-day daily inventory register. The models minimized holding cost subject to daily inventory balance, an assumed safety-stock floor, an assumed tank-capacity ceiling, and non-negative replenishment. The complete base solution was independently validated across 122 optimized fuel-day rows, with zero violations of the balance equation, safety-stock, capacity, or replenishment constraints.

Under the stated assumptions, the LP benchmark reduced combined holding cost from Rs. 23,794.86 to Rs. 6,074.13, a model-based potential reduction of Rs. 17,720.74 (74.47%). Historical stockout days fell from 15 to zero and average combined inventory from 6,251.19 L to 1,637.62 L. All nine sensitivity scenarios remained feasible, with safety stock showing the strongest modeled effect on the objective.

These figures should not be presented as guaranteed real-world savings. The current LP is intentionally an idealized benchmark because supplier lead time, minimum order quantity, delivery schedules, ordering costs, and verified tank capacities are not available in the source data. The study's practical contribution is therefore the transparent structure of the benchmark and the identification of the additional operational data required to convert it into a realistic procurement decision-support model.

REFERENCES

[1] B. Amirjabbari and N. Bhuiyan, "Determining supply chain safety stock level and location," *Journal of Industrial Engineering and*

Management, vol. 7, no. 1, pp. 42–71, 2014. Journal of Industrial Engineering and Management

[2] A. Benantar, R. Ouafi, and J. Boukachour, "A petrol station replenishment problem: New variant and formulation," *Logistics Research*, vol. 9, Art. no. 6, 2016. Springer

[3] S. E. Dınçer and E. Ekin, "Solution approach with linear programming to spare parts inventory management problems in aviation sector," *Journal of Life Economics*, vol. 4, no. 2, pp. 77–102, 2017. Journal of Life Economics

[4] S. N. Emenike, A. Ioannou, and G. Falcone, "An integrated mixed integer linear programming model for resilient and sustainable natural gas supply chain," *Energy Sources, Part B: Economics, Planning, and Policy*, vol. 17, no. 1, Art. no. 2118901, 2022. Taylor & Francis

[5] A. Fatima and M. Tufail, "Improving productivity through linear programming: A case of oil refinery industry," *SAE Technical Paper 2020-01-5128*, 2020. SAE International

[6] Gurtu, "Optimization of inventory holding cost due to price, weight, and volume of items," *Journal of Risk and Financial Management*, vol. 14, no. 2, Art. no. 65, 2021. MDPI

[7] F. W. Harris, "How many parts to make at once," *Operations Research*, vol. 38, no. 6, pp. 947–950, 1990. INFORMS

[8] A. H. I. Lee and H. Kang, "A mixed 0-1 integer programming for inventory model: A case study of TFT-LCD manufacturing company in Taiwan," *Kybernetes*, vol. 37, no. 1, pp. 66–82, 2008. Emerald

[9] Y. Liu, D. Kalaitzi, M. Wang, and C. Papanagnou, "A machine learning approach to inventory stockout prediction," *Journal of Digital Economy*, vol. 4, pp. 144–155, 2025. ScienceDirect

[10] S. C. Nwanya, "Inventory cost framework for managing the petroleum product reorder point and order quantity policies," *Cogent Business & Management*, vol. 6, no. 1, Art. no. 1558475, 2019.

[11] M. Schmidt, W. Hartmann, and P. Nyhuis, "Simulation based comparison of safety-stock calculation methods," *CIRP Annals*, vol. 61, no. 1, pp. 403–406, 2012. ScienceDirect

[12] J. J. Vicente, "Optimizing supply chain inventory: A mixed integer linear programming approach," *Systems*, vol. 13, no. 1, Art. no. 33, 2025. MDPI

[13] H. M. Wagner and T. M. Whitin, "Dynamic version of the economic lot size model," *Management Science*, vol. 5, no. 1, pp. 89–96, 1958. INFORMS