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Determination of Product Distribution Allocation in Pharmaceutical: a Case Study

Lenny Lidiawaty, Ratih Dyah Kusumastuti
Universitas Indonesia
Email: llidiawaty@gmail.com, ratih.irzan@gmail.com

ABSTRACT

Pharmaceutical distribution companies operate under tight profit margins and face increasing expectations to adopt environmentally sustainable practices. In Indonesia, companies like PT XYZ manage complex, multi-node distribution networks supplying pharmaceutical products nationwide. This complexity presents challenges in optimizing allocation decisions that address both operational efficiency and environmental sustainability. This study aims to develop a multi-objective optimization model that minimizes both total distribution costs and carbon emissions. The model is constructed using operational data from PT XYZ's enterprise resource planning (ERP) system for 2024. The optimization employs a weighted sum approach with minimum deviation to achieve an optimal trade-off between distribution cost and carbon emissions. This approach is evaluated under constraints related to warehouse capacity, transporter load limits, delivery timeliness, and product integrity. The results indicate that the model produces efficient distribution patterns, and the minimum deviation method provides a more balanced trade-off between cost and environmental impact. This outcome is especially relevant for companies seeking to align logistics performance with sustainability objectives. By integrating financial and environmental goals into a unified decision-making framework, this study provides a practical solution for pharmaceutical logistics planning. It offers strategic insights into optimizing delivery networks, selecting transport modes, and evaluating the environmental implications of distribution decisions.

KEYWORDS *Multi-objective Linear Programming, Weighted Sum Method, Cost Optimization, Transportation and Carbon Emissions*

INTRODUCTION

Effective distribution management plays a pivotal role in the pharmaceutical supply chain because it directly influences operational efficiency, service reliability, and product availability. Operations management, as defined by Stevenson (2012), is responsible for balancing supply and demand through system and process control that includes logistics, marketing, and sales. Heizer et al. (2022) emphasized that operations management includes key strategic decisions, such as facility location, inventory control, process strategy, scheduling, and quality management. These elements support the organization in achieving optimal performance. Within this context, supply chain management (SCM) emerges as a critical component of strategic operations decisions, particularly in aligning logistics functions with broader organizational goals.

More recently, the SCM framework has evolved into Sustainable Supply Chain Management (SSCM), which integrates economic, environmental, and social dimensions, known as the triple bottom line (Seuring & Müller, 2008). SSCM aims to reduce carbon emissions and promote social responsibility while maintaining profitability and competitive advantage (Hidayatno et al., 2019). It encourages green logistics practices, such as fuel-efficient routing, low-emission transport modes, and waste reduction throughout the supply chain (Shashi, 2022). Within the supply chain, distribution plays a critical role in delivering value to customers alongside procurement, production, and transportation activities (Thomas & Griffin, 1996). Cooper et al. (1997) categorized SCM into three key components: supply chain processes, management elements, and supply chain network structure. Understanding these key components is essential for designing an effective and sustainable distribution strategy within the pharmaceutical sector.

In pharmaceutical logistics, distribution activities significantly contribute to emissions and energy consumption. The World Economic Forum (2023) reported that logistics and transport generate over one-third of global CO_2 emissions, amounting to 7.7 gigatons in 2021. Bukhari et al. (2025) estimated that logistics consume approximately 20% of global energy. Meanwhile, Sadeghi et al. (2025) found that transportation accounts for approximately 63% of logistics costs. Distribution decisions that ignore sustainability often lead to excessive energy use, pollution, and dependency on fossil fuels (Pramudiawardani et al., 2020). Some pharmaceutical products require cold chain transport, resulting in even higher emissions due to refrigeration needs (Getahun et al., 2024).

Pharmaceutical distribution is complex due to product sensitivity and demand urgency. Ineffective distribution management may cause stockouts or overstocking, which disrupt healthcare services and reduce cost efficiency (Getahun et al., 2024). These challenges are particularly significant in archipelagic nations like Indonesia, where geographical complexity and infrastructure disparities often obstruct supply chain performance. In 2020, 76% of distribution facilities were concentrated in Sumatra and Java, creating unequal service access (Kementerian Kesehatan Republik Indonesia, 2020). Any delay or failure in distribution may directly affect public health outcomes (Mubarak, 2024).

The company examined in this study, PT XYZ, is one of Indonesia's largest pharmaceutical distributors. It operates 48 branches nationwide, supported by three regional distribution centers (DCs) in Jakarta, Cikarang, and Surabaya. This network enables broad market coverage but results in complex distribution allocation decisions. Each branch must be matched with the most suitable DC based on transport distance, delivery time, cost, and capacity. These variables require optimization to ensure efficiency, speed, and sustainability.

To address these decisions, previous researchers have developed various mathematical approaches. Monthatipkul (2016) applied a non-linear programming model with a load-distance method in Excel, supported by sensitivity analysis. Hua et al. (2016) used adaptive particle swarm optimization (APSO) to account for environmental variability in DC location problems. Yang et al. (2007) introduced a fuzzy chance-constrained model integrated with hybrid metaheuristics, such as tabu search and genetic algorithm, to manage uncertainty in logistics systems. Although these approaches provide important modeling tools, few integrate economic and environmental factors simultaneously.

Despite growing interest in optimization models, most existing studies remain heavily focused on cost efficiency. These models often fail to account for the uncertainties inherent in pharmaceutical distribution, particularly in developing countries with complex geographical challenges such as Indonesia. Moreover, environmental considerations such as carbon emissions, energy consumption, and transport-related pollution are frequently excluded from logistics planning. This gap highlights the urgency for research that integrates sustainability into pharmaceutical distribution models to support more resilient and environmentally responsible supply chains.

This study aims to develop an optimization model that addresses both cost efficiency and environmental sustainability. The model focuses on pharmaceutical delivery allocation from DCs to branches using a Linear Programming approach within the Multi-Objective Linear Programming (MOLP) framework. The proposed model considers real-world constraints such as transporter capacity, delivery schedules, demand variations, and multimodal logistics options. The main objective of this research is to minimize total distribution cost and reduce carbon emissions. In this way, the model supports environmentally sustainable pharmaceutical distribution practices. Practically, this model provides decision-makers with a structured tool to improve planning and meet environmental goals. Academically, it expands the scope of logistics optimization by embedding sustainability as a core objective.

RESEARCH METHOD

This study adopted a descriptive quantitative research approach aimed at optimizing the allocation of pharmaceutical product deliveries from three DCs to 48 branches operated by PT XYZ in Indonesia. The research was conducted using secondary operational data for the year 2024, which were extracted from the company's Enterprise Resource Planning (ERP) system. These data were complemented by interviews with logistics and transportation managers to validate operational assumptions. The purpose was to develop a reproducible optimization model that integrates economic efficiency and environmental sustainability in distribution planning.

The study population consisted of all delivery transactions from three DCs located in Jakarta, Cikarang, and Surabaya to 48 branches across Indonesia. This study did not apply any sampling techniques because all data from active DCs and branches were analyzed comprehensively. This approach ensured that the model accurately represented the company's entire logistics network. Data collected for the model included:

- Monthly demand volume per branch (in cubic meters)
- Annual storage capacity of each DC
- Unit freight cost (IDR/m^3) per DC-to-branch route
- Transporter capacity by mode (land, sea, air)
- Estimated distance (km) per route and mode
- Carbon emission factors per transport mode.

Emission data were sourced from the *Greenhouse Gas Reporting: Conversion Factors 2023* published by the UK Department for Business, Energy and Industrial Strategy. These factors were used to calculate the CO_2 emissions in kilograms of CO_2 equivalent (kgCO_2e) per cubic meter per kilometer. The emission calculations were adjusted based on the delivery volume and estimated distance for each DC-to-branch route. This allowed for a realistic assessment of the environmental impact of each distribution decision.

The research employed a Multi-Objective Linear Programming (MOLP) techniques implemented using the OpenSolver add-in for Microsoft Excel. This tool was selected due to its capability to handle large-scale optimization problems that are beyond the limitations of the default Excel Solver. The MOLP model was used to develop two separate single-objective models: One minimizing total logistics cost, and another that minimized total carbon emissions. These single-objective solutions served as benchmarks for calculating normalized deviation values.

To address both objectives simultaneously, a MOLP model was developed using the Weighted Sum Method. Equal weights of 50% were assigned to both cost and emission deviations. The model's objective function minimizes the total weighted deviation from the cost-optimal and emission-optimal solutions. This approach allowed decision-makers to evaluate trade-offs and select distribution plans that balanced financial performance with environmental impact.

The mathematical model comprises several key components designed to reflect real-world distribution conditions. These included a set of decision variables, parameters, objective functions, and constraints that govern the product flow from each DC to the designated branches. The decision variable represents the quantity of goods shipped from a specific DC to a branch using a particular transport mode and transporter. The model also incorporated parameters such as demand per branch, DC capacity, transportation costs, emission factors, and available transporter capacities.

Model Indices and Notation:

- $i \in I$: origin index (Distribution Center), $I = \{1,2,3\}$
- $j \in J$: index of the destination branch, $J = \{1,2,...,48\}$
- $k \in K$: index of transport modes (e.g., land, sea, air)
- $t \in T$: index for transporters

Decision Variable:

X_{ijkt}: quantity of products shipped from DC i to branch j using transport mode k and transporter t (in m³)

Parameters:

- D_j: demand at branch j (unit volume)
- S_i: capacity of DC i (unit volume)
- T_{kt}: transporter capacity of mode k and transporter t
- C_{ijkt}: unit transport cost from DC i to branch j using mode k and transporter t
- E_{jk}: carbon emission factor for branch j via mode k ($kgCO_2e/m^3/km$)
- L_{ij}: distance from DC i to branch j (km)

Objective Function 1: Minimize Total Distribution Cost:

$$Z_{Cost} = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} C_{ijkt} \,.\, X_{ijkt} \tag{1}$$

Objective Function 2: Minimize Total Emissions:

$$Z_{Emisi} = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t} X_{ijkt} \,.\, E_{ijk} \,.\, L_{ij} \tag{2}$$

Constraints:

- The total delivery to each branch must satisfy the demand:

$$\sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{t=1}^{T} X_{ijkt} = D_j \;..... \;\forall\, j \in J \tag{3}$$

- The total shipment from each DC cannot exceed capacity:

$$\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T} X_{ijkt} <= S_i \;..... \;\forall\, i \in I \tag{4}$$

- The total shipments per transporter per mode must respect capacity:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} X_{ijkt} <= T_{kt} \; \ldots.. \; \forall \; k \in K, t \in T \quad (5)$$

- Non-negativity:

$$X_{ijkt} \geq 0 \quad (6)$$

Referring to the study by Marler & Arora (2004), the weighted sum approach was one of the most widely used methods in multi-objective optimization. In this method, multiple objective functions were combined into a single aggregate objective function, where each was assigned a relative weight. In the present study, the optimal results from the two single-objective models, minimum total cost and minimum total carbon emissions, were used as reference targets in the construction of the multi-objective model. Deviations were then calculated for each criterion by comparing the actual solution with its respective optimal value. The deviations were computed using the following formulas:

$$\mathrm{Dev}_{\mathrm{Cost}} = (\mathrm{Z}_{\mathrm{cost}} / \mathrm{Z}^{*}_{\mathrm{cost}}) - 1 \quad (7)$$

$$\mathrm{Dev}_{\mathrm{Emission}} = (\mathrm{Z}_{\mathrm{emission}} / \mathrm{Z}^{*}_{\mathrm{emission}}) - 1 \quad (8)$$

where Z^{*}_{cost} and $Z^{*}_{emission}$ represent the optimal values for the single-objective model. After calculating the deviation values, the multi-objective model was constructed by combining both deviations into a single total deviation function. This was achieved by assigning specific weights to each deviation, representing a balanced preference between the two objectives. The aim of this approach is to obtain a compromise (trade-off) solution that approximates Pareto optimality.

In this study, weight values were determined using a rating method, in which the company's management independently evaluated the relative importance of each objective. Based on this assessment, equal weights of 50% were assigned to both the cost and emission criteria. The objective function of the multi-objective model is thus described as follows:

$$\text{Minimize } \mathrm{Z}_{\mathrm{deviation}} = 0.5 \times \mathrm{Dev}_{\mathrm{Cost}} + 0.5 \times \mathrm{Dev}_{\mathrm{Emission}} \quad (9)$$

This weighted sum function ensures that the selected solution achieves a reasonable balance between minimizing logistics costs and reducing carbon emissions, which is in line with the company’s operational and sustainability goals. This method is consistent with the weighted sum approach discussed by Marler & Arora (2004), which remains one of the most commonly used techniques in multi-objective optimization for engineering and operational research problems. Each criterion was normalized and incorporated into the model to reflect the balanced preferences of economic efficiency and environmental responsibility.

Sensitivity analysis involves evaluating how changes in the parameters of a linear programming (LP) model affect the optimal solution, with the aim of assessing the model’s robustness against variations in data or assumptions (Render et al., 2022). While MOLP models were typically developed under the assumption that input data such as transport tariffs (C_{ijkt}) and branch demand (D_j) were fixed and deterministic, real-world logistics systems often experienced fluctuations in cost, demand and resource availability. Sensitivity analysis assisted decision-makers in evaluating how parameter changes affected the optimal solution without necessitating complete resolution of the model. According to Render et al. (2022), such changes in MOLP models were generally classified into three main categories:

- Contribution rates-modifications to objective function coefficients,
- Technological coefficients: changes in constraint coefficients,
- Available resources: Alterations to the right-hand side values of constraints.

In this study, sensitivity analysis was performed to assess the model's robustness to real-world variability. The simulated scenarios included ±10% changes in transport costs and capacity as well as ±5% variations in demand. These tests verified the stability and practical relevance of the proposed optimization model.

RESULTS AND DISCUSSION

This section presents and discusses the outcomes of the three optimization models: cost minimization, emission minimization, and the multi-objective compromise model. These findings emphasize the importance of incorporating multiple objectives in pharmaceutical distribution planning to balance operational efficiency with environmental sustainability.

Table 1 Cost and Emission Comparison of Optimization Models

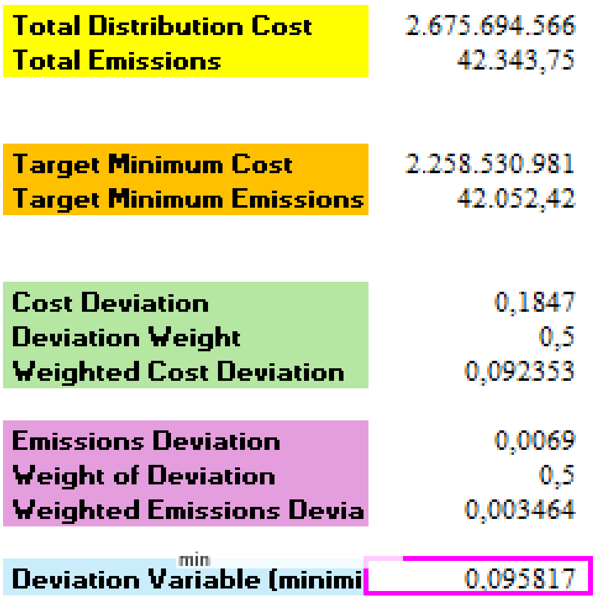
Model	Distribution Cost (IDR)	Carbon Emissions ($kgCO_2e$)
Cost Minimization	2,258,530,981	76,828.73
Emission Minimization	6,238,472,054	42,052.42
Multi-Objective Compromise	2,675,694,566	42,343.75

Single-Objective Optimization

In the cost minimization model, the total distribution cost reached IDR 2,258,530,981, which represented the most efficient financial outcome. However, the corresponding carbon emissions were relatively high at 76,828.73 $kgCO_2e$. This result demonstrates that when distribution planning prioritizes financial targets alone, the environmental impact becomes substantial. In contrast, the emission minimization model reduced total emissions to 42,052.42 $kgCO_2e$, the lowest among all models. Yet, this resulted in a significantly higher distribution cost of IDR 6,238,472,054. The result illustrated that achieving environmental goals required a trade-off with increased operational spending.

Multi-Objective Optimization

To address this trade-off, the study applied a Multi-Objective Linear Programming (MOLP) model using the weighted sum method. Equal weights (50%) were assigned to both objectives. The resulting compromise model resulted in a total cost of IDR 2,675,694,566 and emissions of 42,343.75 kgCO_2e. The deviation from the optimal cost was 0.1847 (18.47%), while the deviation for emissions was only 0.0069 (0.69%), resulting in a combined deviation value of 0.095817, as illustrated in Figure1. A total of 159 distinct transportation route combinations were used. This confirmed that the compromise model effectively minimized both deviations and produced a realistic and balanced solution.



Total Distribution Cost	2.675.694.566
Total Emissions	42.343,75
Target Minimum Cost	2.258.530.981
Target Minimum Emissions	42.052,42
Cost Deviation	0,1847
Deviation Weight	0,5
Weighted Cost Deviation	0,092353
Emissions Deviation	0,0069
Weight of Deviation	0,5
Weighted Emissions Devia	0,003464
Deviation Variable (minimi	0,095817

Figure 1 Cost and Emission Deviation Calculation in Multi-Objective Optimization

Model Comparison

The results demonstrate a significant trade-off between minimizing distribution costs and reducing carbon emissions. This trade-off was clearly reflected in the outcomes of the three models (Table 1). The cost minimization model suited organizations that strictly focused on budget constraints. The emission minimization model is aligned with firms prioritizing sustainability targets, such as carbon footprint reduction. The compromise model was the most strategic choice for balancing short-term efficiency and long-term sustainability.

Trade-Off Between Cost and Emissions

The optimization results of the three models revealed a clear trade-off between cost efficiency and environmental impact.

- The cost minimization model yielded the lowest total distribution cost (IDR 2,258,530,981), but was accompanied by the highest level of carbon emissions (76,828.73 $kgCO_2e$).
- In contrast, the emission minimization model succeeded in reducing total carbon emissions to the lowest level (42,052.42 $kgCO_2e$), but this came with a significantly higher distribution cost (IDR 6,238,472,054).
- The multi-objective model, implemented using the weighted sum method, produced a compromise solution with a moderate cost (IDR 2,675,694,566) and emission level (42,343.75 $kgCO_2e$), both of which were closer to the respective single-objective targets.

The compromise model achieved a balanced outcome between cost and emissions by preventing extreme results from single-objective models. This study demonstrated the effectiveness of multi-objective optimization in supporting decisions that address both operational efficiency and environmental goals. This approach provided a more realistic solution for pharmaceutical logistics and confirmed that a weighted optimization method could effectively manage trade-offs and support dual-target strategies.

Sensitivity Analysis

A sensitivity analysis was conducted to evaluate the robustness of the model under varying operational conditions. Four simulation scenarios were analyzed (Table 2).

Table 2 Sensitivity Analysis Results under the Cost and Demand Scenarios

Scenario	Cost (IDR)	Emissions ($kgCO_2e$)	Interpretation
Baseline	2,675,694,566	42,343.75	Baseline scenario used as a reference for comparison.
Tariff +10%	2,943,264,023	42,343.75	Costs increased by 10%, and emissions remained unchanged.
Tariff +20%	3,210,833,480	42,343.75	Substantial cost increase with no impact on emissions.
Demand -10%	2,354,529,528	37,682.58	The decrease in demand reduced both cost and emissions.
Demand +5%	2,838,350,835	44,662.90	An increase in demand raises both costs and emissions, revealing scalability constraints.

The sensitivity simulations provided several insights:

- Increases in transport tariffs directly affected distribution costs but did not affect carbon emissions, that the pricing effect was purely financial.
- Changes in branch demand volume influenced both cost and emissions. More demand led to higher metrics, whereas a drop had the opposite effect.
- The emission values remained stable even under tariff changes, indicating that the mode and route selection were resilient against pricing shifts.
- Allocation shifts demonstrated the system's sensitivity to sustainability policies (ESG-related factors). Demand fluctuations have played a key role in shaping emission patterns.
- Effective demand planning at the branch level appears to be a strategic lever for controlling both distribution costs and emissions.

These findings confirmed that the MOLP model provided actionable, balanced decision support. It enabled managers to evaluate trade-offs, supported operational agility and aligned with broader sustainability frameworks. The study also validated the practicality of integrated cost–emission optimization in the pharmaceutical logistics sector, especially in complex geographies like Indonesia.

CONCLUSION

The study demonstrates that Multi-Objective Linear Programming (MOLP) effectively optimizes pharmaceutical distribution by balancing logistics costs and carbon emissions, addressing a significant gap found in traditional single-objective models. Utilizing a weighted sum compromise method, the model harmonizes competing priorities, providing practical decision-making support. Comparative analysis of cost minimization, emission reduction, and the multi-objective compromise approaches reveals that focusing on a single goal results in trade-offs, whereas the integrated MOLP model offers a balanced, sustainable strategy that accounts for the inverse relationship between cost efficiency and environmental impact. Sensitivity analysis further shows that demand fluctuations influence costs and emissions more than transport tariffs, highlighting the need for adaptive planning and precise forecasting. For future research, incorporating stochastic variables and real-world constraints such as service-level agreements and warehouse capacities would enhance model realism. Additionally, broadening sustainability metrics to include energy consumption and environmental risks would deepen insights into green supply chain management. These improvements would bolster the model’s robustness, facilitating continuous advancements in sustainable pharmaceutical logistics and promoting more resilient, eco-friendly distribution networks.

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