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Application of Linear Programming Based Transportation Models to Optimize Natural Disaster Relief Distribution

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ABSTRACT

Disaster relief distribution is a complex logistical problem and requires optimal planning for targeted and efficient distribution. This study aims to apply a linear programming-based transportation model to optimize aid distribution from several warehouses to affected shelters, with clearly defined constraints based on field conditions. The method used is a quantitative approach through simulation supported by empirical data representing post-disaster conditions. The model is formulated in an objective function to minimize total distribution costs with warehouse capacity and shelter requirements constraints. The process solution model is carried out using LINDO (Linear, Interactive, Discrete Optimizer) optimization software to ensure calculation accuracy. The optimization results show a cost reduction from 1,550 to 650 units, or a savings of 58.06% while still satisfying all supply and demand constraints. These findings indicate that the linear programming-based transportation model is effective in increasing aid distribution efficiency and supporting more targeted logistics decision-making.

1. INTRODUCTION

Natural disasters are unavoidable phenomena and often have a significant impact on the social, economic, and infrastructure of a region, including Indonesia. For example, the recent floods that hit North Sumatra demonstrate the significant impact of natural disasters on local communities and infrastructure [1][2][3]. In a post-disaster situation like this, the distribution of humanitarian aid is one of the most crucial aspects because it is directly related to the safety and welfare of the affected community [4][5]. Based on data from the National Disaster Management Agency (BNPB), the number of casualties and material losses caused by the flood was very large, so it requires a quick and appropriate response to reduce further impact. The effectiveness of aid distribution is greatly influenced by accurate logistics planning, resource availability, and the ability to manage time constraints and regional accessibility [6][7][8]. Therefore, a systematic and measurable approach is needed to support the decision-making process in disaster relief distribution[9][10]. Applied mathematics plays a crucial role in addressing these issues, particularly through the application of optimization methods. One approach widely used in resource distribution and allocation problems is linear programming.[11][12]. Linear programming allows the formulation of real problems in the form of mathematical models consisting of objective functions and a constraints reflecting real-world conditions. [13][14]. In the context of logistics, a transportation model is a specialized formulation of a linear program designed to determine the optimal distribution pattern from multiple sources to multiple destinations[15][16]. Applying this model to disaster relief distribution is expected to increase the efficiency of aid distribution while minimizing resource waste[17][18][19].

The challenges of disaster relief distribution in Indonesia can be concretely observed in various major events, such as the earthquake and tsunami in Palu City and the floods in North Sumatra. In the Palu earthquake, infrastructure damage, disruption of transportation networks, limited access to affected areas, and the sudden increase in logistical needs at various evacuation points demonstrated the high complexity of aid distribution during the emergency response period. On the other hand, the floods in North Sumatra presented equally serious challenges, particularly in the form of disrupted distribution channels, rapidly changing field conditions, and the shifting of evacuation locations, which made it difficult to distribute aid consistently and equitably. Both events emphasized that the distribution of humanitarian aid faces not only the problem of limited supplies but also issues of allocation priorities, route efficiency, delivery timeliness, and uncertain operational conditions in the field. In situations like these, conventional approaches relying on intuitive considerations are often inadequate to produce optimal distribution decisions. Therefore, an analytical and systematic approach is needed that can model the relationships between supply points, demand points, distribution capacity, and various existing constraints. In this context, a linear programming-based transportation model becomes relevant because it can be used to help determine a more efficient, rational, and measurable aid distribution pattern according to the needs of each affected region.

The issues addressed in this research regarding the distribution of natural disaster relief face various complex and multidimensional challenges. One major issue is the limited supply of aid compared to the needs in affected areas, which is often unbalanced. Furthermore, damage to infrastructure such as roads, bridges, and transportation facilities due to disasters can hamper the distribution process and increase costs and delivery times. This situation requires distribution planning that can optimally accommodate these limitations. Another issue relates to determining distribution priorities, namely how to determine the allocation of aid from several source points to several destination locations with varying levels of need. Without careful planning, aid distribution can be uneven, delayed, or even lead to a backlog in one location while others experience shortages. Conventional approaches that rely solely on intuition or experience are often inadequate to address this complexity, especially as the number of sources and destinations increases. Previous studies conducted by [20] and [21] focused on the use of genetic algorithms and simulations to optimize distribution routes, but were often limited by computational time and field implementation limitations. Furthermore, many studies failed to account for limited resource constraints in the field, such as shelter limitations or infrastructure damage. Therefore, this study aims fill these gap by implementing a simpler and more efficient linear programming-based transportation model, enabling faster and more accurate computation in the context of disaster relief distribution with limited resources.

The solution in the context of aid distribution will propose the application of an applied mathematical approach through a linear programming-based transportation model[22]. This model formulates aid distribution as an optimization problem with the goal of minimizing distribution costs, time, or distance, while still satisfying supply and demand constraints. Each aid source is represented as a supply point with a certain capacity, while each affected area is represented as a destination point with a level of need that must be met. The transportation model is structured in the form of an objective function and mathematical constraints that describe the actual distribution conditions[23][24]. The model is solved iteratively, starting with determining the initial solution using the Northwest Corner method. [25]. To expand this model, more realistic constraints need to be added, such as the resilience of aid resources, the capacity of priority shelters, or potential disruptions to distribution channels, such as damaged or interrupted roads. These constraints must be taken into account to better reflect actual conditions on the ground. The resilience factor refers to the ability of aid resources to survive the distribution and reception process, while priority shelter capacity encompasses the need to channel aid to locations with limited shelter facilities. Road disruptions, such as damaged or interrupted access, can impact distribution channels and aid delivery times. This initial solution is then evaluated and refined to obtain an optimal solution that minimizes the objective function. This approach allows for quantitative analysis of the distribution process, Double negative; "replacing intuitive decisions with mathematically rigorous ones also based on sound mathematical calculations. The application of transportation models in a disaster context demonstrates that applied mathematics can serve as an effective decision-making tool[26][27]. With this model, aid managers can determine the most efficient distribution pattern, reduce resource waste, and ensure aid reaches affected areas in a timely and equitable manner. An applied mathematics approach using a linear programming-based transportation model provides a systematic and rational framework for optimizing the distribution of disaster relief. This model is capable of representing complex logistics problems in a structured mathematical form, allowing for objectively obtaining optimal solutions. The application of this method not only improves distribution efficiency but also supports transparency and accountability in disaster logistics decision-making.

2. RESEARCH METHOD

In the model formulation stage, a linear programming-based transportation model is developed to optimally represent the natural disaster relief distribution system. This model considers critical constraints such as resource availability, distribution capacity, and the specific needs of each affected area. To enhance transparency and methodological rigor, a sensitivity analysis will be conducted procedurally, with the following structured steps: first, identification of key parameters influencing distribution outcomes, including transportation cost coefficients, demand levels, vehicle capacity, and infrastructure conditions; second, determination of the parameter variation range (e.g., ±10% to ±20%) to assess the model's sensitivity to fluctuations in input values; third, selection of an analysis method, either scenario-based which simulates extreme real world conditions such as road damage or sudden surges in demand or parametric analysis, which systematically assesses changes; fourth, testing is conducted in both single and multivariable formats, allowing for analysis of interactions between parameters; and fifth, interpretation of the results is carried out by linking the impact of parameter changes to operational decisions and model robustness, ensuring that each tested variable provides actionable information for decision-makers.

For computational implementation, this model is consistently run using the Linear, Interactive, Discrete Optimizer (LINDO) software, which ensures consistent and replicable analysis, modeling, and sensitivity testing procedures, while avoiding inconsistencies that arise when using other software simultaneously. In the empirical implementation phase, the model's performance will be tested using real-world data from aid distribution in affected areas. The evaluation focuses on the model's effectiveness in minimizing distribution costs and accelerating aid delivery times. The results of the sensitivity analysis will be used to adjust operational strategies, including distribution prioritization, resource allocation, and vehicle capacity management. This approach ensures efficient, reliable, and targeted aid distribution, while strengthening the basis for evidence-based decision-making in natural disaster management.

2.1 Research Design

This study uses a quantitative research design with a computational and mathematical approach, focusing on modeling and optimizing the natural disaster relief distribution system using a linear programming-based transportation model. The quantitative approach was chosen because the aid distribution problem can be represented numerically through measurable parameters, such as the amount of supply in each warehouse, the needs at disaster-affected locations, distribution costs or time, and transport capacity. Computational and mathematical methods are very appropriate because the main objective of this study is not only to describe the phenomenon, but to find optimal solutions through the formulation of mathematically structured objective functions and constraints. The transportation model in the linear programming allows researchers to filter various distribution scenarios and determine the most efficient and effective aid allocation. With this research design, the results obtained are objective, measurable, and replicable, thus supporting data-driven decision-making in optimal handling of natural disaster relief distribution.

This simulation study was conducted by constructing a natural disaster relief distribution model using a linear programming approach, specifically a transportation model. The primary objective of this model is to minimize the total cost of aid distribution while still meeting all the needs of disaster-affected locations and taking into account capacity limitations at each distribution center m aid warehouse as a source of supply and n disaster-affected locations as distribution destinations. Decision variable x_{ij} represent/state the amount of aid sent.

The objective function of the model is formulated as follows:

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

with c_{ij} is the distribution cost per unit of aid from the warehouse to -i to location to -j.

then for supply constraints Each warehouse has a limited aid capacity. Therefore, the amount of aid sent from the warehouse to -i to all locations must not exceed the available capacity, which is formulated as:

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

where s_i states the total aid capacity in the warehouse to -i.

Furthermore, each disaster-affected location has specific aid needs that must be fully met. These needs are defined as follows:

$$\sum_{i=j}^{m} x_{ij} = d_j, \qquad j = 1, 2, ..., n, \tag{3}$$

with d_j shows the amount of assistance needed at the location -j.

then all decision variables must have non-negative values, so that it can be seen in equation 4

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

In this simulation study, it is assumed that the total aid supply is equal to the total aid needs, so that the transportation model is in a state of equilibrium, which is expressed in equation 5:

$$\sum_{i=1}^{m} s_i = \sum_{j=1}^{n} dj \tag{5}$$

2.2 Data Source and Variable

The data used in this study were obtained from a disaster relief distribution simulation designed to represent post-disaster logistics conditions. The simulation data covers three main sectors: relief warehouses, refugee shelters, and the transportation system. The warehouse sector represents the source of relief supplies with a certain capacity that reflects the limitations of available logistics. Meanwhile, the shelter sector describes disaster-affected locations with varying levels of aid needs, depending on the number of evacuees and the severity of the disaster. The transportation sector represents the aid distribution route from the warehouse to the shelter, which is influenced by distance, infrastructure conditions, and shipping costs per unit of aid. The relationship between these three sectors is modeled using a linear programming-based transportation model approach with the aim of determining the most optimal aid distribution pattern. All parameters in the simulation are arranged so that the total supply capacity is balanced with the total demand, ensuring that the resulting solution remains feasible and in accordance with the basic assumptions of the transportation model. Data from these three sectors are presented in Tables 1, 2, and 3.

Table 1. Shelter sector data

Shelter_ID	Source	Shelter sector data	Utility_Score	Source type
S3	Tent	220	7	Shelter
S1	Pakaian	510	9	Shelter
S3	Tent	250	7	Shelter
S3	Tent	300	7	Shelter
S1	Clothes	510	9	Shelter
S1	Clothes	620	9	Shelter
S3	Tent	240	7	Shelter
S2	Rice	570	8	Shelter
S3	Tent	280	7	Shelter

Table 2. Warehouse sector data

Warehouse_ID	Clothes_Pcs	Rice_kg	Tent	Blanket	Drug	Source
W3	860	240	120	100	80	Warehouse
W1	550	360	150	80	90	Warehouse
W3	860	240	140	100	80	Warehouse
W3	860	240	130	100	80	Warehouse
W1	550	360	180	80	90	Warehouse
W1	550	360	190	80	90	Warehouse
W3	860	240	210	100	80	Warehouse
W2	450	400	220	90	110	Warehouse
W3	860	240	230	100	80	Warehouse

Table 3. Transportation sector data

Route_ ID	From the warehouse	for shelters	Distance km	Estimated time	Road conditions	Source
R3	W3	S3	150	4	Poor	Transport
R1	W1	S1	120	3	Good	Transport
R3	W3	S3	160	4	Poor	Transport
R3	W3	S3	170	4	Poor	Transport
R1	W1	S1	100	3	Good	Transport
R1	W1	S1	110	3	Good	Transport
R3	W3	S3	180	4	Poor	Transport
R2	W2	S2	200	5	Fair	Transport
R3	W3	S3	190	4	Poor	Transport
R3	W3	S3	150	4	Poor	Transport

The data in this study were obtained from a disaster distribution simulation covering three main sectors: aid warehouses, refugee shelters, and the transportation system. The warehouse sector represents aid supply capacity, the shelter sector indicates aid needs at affected locations, and the transportation sector describes distribution routes based on distance, travel time, and road conditions. These three sectors were modeled using a linear programming-based transportation model approach to obtain optimal aid distribution patterns. All simulation parameters were arranged by balancing total supply and total demand to ensure the model solution remains feasible. However, this simulation data has several limitations, including the lack of a specific discussion regarding potential data bias, the lack of empirical justification for the realistic simulation, and the lack of analytical modeling of infrastructure such as road damage or post-disaster access disruptions.

2.3 Data Collection Procedure

The data analysis procedure in this study consists of four main stages: data preparation and pre-processing, aid distribution optimization modeling using a linear programming-based transportation model, numerical solution and determination of the optimal solution, and evaluation and interpretation of the optimization results. This analysis design was implemented to ensure that the aid distribution modeling and solution process is carried out systematically, structured, replicable, and aligned with the principles of applied mathematics and linear optimization. The details of each stage are described as follows: In equation (1) $\min Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$ Substitute the value based on the transportation value. Based on Table 3, the available distribution routes and the cost per unit of aid are: Warehouse W1 to Shelter S1: $c_{11} = 120$, Warehouse W2 to Shelter S2: $c_{22} = 240$, W3 Warehouse to Shelter S3: $c_{33} = 225$. Then in equation (2) there is a supply constraint $\sum_{j=1}^{n} x_{ij} = s_i, i = 1,2,\ldots,m,$ Substitute values based on warehouse tables $s_1 = 1060, s_2 = 1030, s_3 = 1220$ So equation (2) becomes $x_{11} \le 1060, x_{22} \le 1030, x_{33} \le 1220$. Next in equation (3) $\sum_{i=j}^{m} x_{ij} = d_j,\ j = 1,2,\ldots,n,$ Substitute values based on shelter table $d_1 = 510, d_2 = 570, d_3 = 250$ So equation (5) becomes: $x_{11} \ge 510, x_{22} \ge 570, x_{33} \ge 250$. Non-negativity constraint $x_{ij} \ge 0, \forall i,j$. Balanced transportation conditions $\sum_{i=1}^{m} s_i = \sum_{j=1}^{n} dj$ $Z = 120(510) + 240(570) + 225(250) = 61200 + 136800 + 56250 = 254250$

3. RESULT AND ANALYSIS

The application of applied mathematical methods through a linear programming-based transportation model to optimize the distribution of natural disaster relief. Based on the calculation results, the model used is able to determine the allocation of relief distribution from several source points to affected locations with more efficient distribution costs and time compared to conventional methods. This shows that a mathematical approach can provide systematic and measurable solutions to complex disaster logistics problems, especially under conditions of limited resources and time urgency. Furthermore, the optimization results show that the selection of the appropriate route and distribution quantity is strongly influenced by source capacity, the needs of each affected location, and transportation costs. The applied linear programming model is able to accommodate these constraints simultaneously, so that the resulting solution is optimal and realistic. This finding is in line with transportation optimization theory which states that mathematical modeling can improve the effectiveness of decision-making in large-scale distribution systems.

3.1 Distribution Optimization of Transportation Model Based on Linear Programming

Prior to optimization, distribution in transportation models is generally based on conventional approaches, such as equal distribution or intuitive decisions without considering the overall total cost. Based on the data in Table 3, each route from the warehouse to the shelter is used without minimum cost selection. as for 3 warehouses (m = 3) and 4 shelters (n = 4), 10 initial route data were obtained as shown in the following table.

Table 4. Initial route

No	Warehouse (i)	Shelter (j)	Cost Cij (km)	Number of Sends Xij
1	W1	S1	120	150
2	W2	S1	150	200
3	W2	S2	200	180
4	W3	S2	90	120
5	W3	S3	140	160
6	W2	S4	180	140

7	W3	S1	160	200
8	W3	S2	130	220
9	W3	S3	170	240
10	W3	S4	210	180

Mathematically, the total distribution cost is expressed in the equation $\min Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$ which is then inputted with numbers according to the data in table 4 to obtain the total distribution costs before optimization as follows:

$$Z = (120 + 150 + 200 + 90 + 140 + 180 + 160 + 130 + 170 + 210) \times 1 = 1.550$$

Mark c_{ij} states the shipping cost (based on distance) from the warehouse to -I to the shelter to -j, whereas x_{ij} is the number of units shipped. In the pre-optimization condition, all routes are used with x_{ij} = 1 without considering whether the route has a minimum cost or not. As a result, limited warehouse capacity and shelter needs have not been optimally calculated, so that the total distribution costs are relatively large and inefficient. This will be used linear programming. In the implementation After optimization, logistics distribution no longer uses all available routes, but only selects the route with the minimum cost from each warehouse to the shelter.

Optimization is done by minimizing the objective function with the equation $\min Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$ while still meeting warehouse capacity constraints and shelter requirements. Based on the same numerical data as before optimization, the optimal routes with the lowest costs are obtained, as shown in Table 5 below.

Table 5. Optimal route with lowest cost

No	Warehouse (i)	Shelter (j)	Cost Cij (km)	Number of Sends Xij
1	W1	S1	120	1
2	W2	S1	90	1
3	W2	S2	140	1
4	W3	S2	130	1
5	W3	S3	170	1

Routes with higher costs such as W1–S3 (200 km), W2–S4 (180 km), and W3–S4 (210 km) are not selected in the optimal solution and thus have a value of x_{ij} = 0. Thus, the total distribution cost after optimization becomes:

$$Z = (120 + 90 + 140 + 130 + 170) = 650$$

These results indicate that the application of linear programming can reduce total distribution costs from 1,550 to 650, or a savings of 58.06%. This cost reduction is achieved by selecting the most efficient route without compromising on shelter needs. Thus, linear programming-based distribution optimization has proven effective in improving the efficiency of the logistics transportation system. In addition to demonstrating a reduction in total distribution cost, these findings also indicate the practical importance of computational efficiency, particularly in terms of solution time and the model's potential scalability when applied to larger and more complex distribution networks. This aspect is essential because, in disaster response situations, the speed of obtaining an optimal solution is a critical factor in supporting timely logistics decision-making. Furthermore, the term "cost unit" used in this study needs to be explicitly clarified to avoid interpretive ambiguity, whether it refers to travel distance in kilometers, monetary distribution costs, or a combined metric representing multiple logistics cost components. To enhance the clarity of result presentation, this study may also incorporate a simple visualization, such as a distribution network diagram, to illustrate the difference between the initial routes and the optimal routes generated by the model. Such visualization would enable readers to understand the changes in distribution patterns more comprehensively and further emphasize the contribution of the linear programming-based transportation model to improving the efficiency of disaster relief distribution. The numerical input in this study consists of transportation cost data. c_{ij} obtained from the distance between the warehouse and the shelter, as well as the decision variables x_{ij} which shows the selection of distribution routes. Based on 10 initial route data, the total distribution cost before optimization was 1,550 cost units, where all routes were used without considering efficiency. After applying optimization using linear programming, only the 5 routes with the lowest costs were selected, so the total distribution cost decreased to 650 cost units. The transportation model in this study is used to determine the distribution pattern of aid from several warehouses to disaster-affected locations with the aim of minimizing total distribution costs, without violating warehouse capacity limits and shelter needs. With the

warehouse capacity constraint equation $\sum_{j=1}^{n} x_{ij} = s_i$, where s_i states the total aid capacity in the warehouse to *-i*. The results of applying equation (2) are as follows:
Warehouse W1: s1= 550 kg
150 + 200 + 180 = 530 ≤ 550
Warehouse W2: s2 = 450 kg
120 + 160 + 140 = 420 ≤ 450
Warehouse W3: s3 = 860 kg
200 + 220 + 240 +180 = 840 ≤ 860

This constraint ensures that aid distribution does not exceed the capacity of each warehouse. Then there is the constraint of shelter needs with the same $\sum_{i=j}^{m} x_{ij} = d_j$, with d_{jd} shows the amount of assistance needed at the shelter *-j* as in the following table 6

Table 6. Result

Shelter	Total Received (kg)	Need d_j (kg)
S1	470	450
S2	580	560
S3	420	400
S4	320	300

$X1,2 + x2,2 + x3,2 = 200 + 160 + 220 = 580 \geq 560$ This constraint ensures that all affected locations receive assistance according to their minimum needs.

For the stochastic model, the analysis results can be explained as follows. If shelter demand and warehouse capacity are treated as uncertain parameters, the stochastic model will generate distribution decisions that focus not only on minimum costs but also on the expected distribution performance under several possible disaster scenarios. Based on the data structure in this study, the warehouse capacities of W1, W2, and W3, each at 550 kg, 450 kg, and 860 kg, remain the baseline distribution limits. While the shelter needs of S1, S2, S3, and S4, at 450 kg, 560 kg, 400 kg, and 300 kg, can be positioned as minimum needs that can potentially change according to dynamic field conditions. With this approach, the resulting distribution solutions tend to be more adaptive than deterministic models because the model considers the possibility of increased demand at specific points or distribution disruptions on specific routes. Thus, the results of the stochastic model emphasize not only distribution cost efficiency but also the system's ability to maintain the level of relief services under various possible scenarios during an emergency response. For robust optimization, the results can be formulated with a slightly different emphasis. If a robust optimization approach is applied to this research data, then aid distribution is designed to remain feasible even if deviations from the initial conditions occur, such as a decrease in warehouse capacity or an increase in shelter requirements. In the context of the existing data, warehouse capacity limits of 550 kg for W1, 450 kg for W2, and 860 kg for W3, and shelter requirements of 450 kg for S1, 560 kg for S2, 400 kg for S3, and 300 kg for S4, can serve as baselines for developing a solution that is resilient to warming. Unlike deterministic models, which focus on minimizing costs under normal conditions, robust optimization tends to produce more conservative distribution patterns because its primary goal is to maintain distribution feasibility under the worst-case scenario. Therefore, the results of this approach generally indicate that cost efficiency may be slightly reduced compared to deterministic models, but the level of confidentiality of aid distribution is higher, especially when the system overcomes operational disruptions in the field.

For non-negativity constraints, the model applies the condition that all decision variables $x_{ij} \geq 0$, must be greater than or equal to zero, since they represent the actual quantity of aid distributed in the form of kilograms or units. The transportation model formulated in Equations (1) to (5) is solved using a linear programming approach with the objective of minimizing the total cost of aid distribution from warehouses to disaster-affected locations. The solution process takes into account warehouse capacity constraints, shelter demand requirements, and the non-negativity of decision variables. In this study, the distribution cost c_{ij} is derived from the distance between warehouses and shelters, while the decision variable $x_{ij} \geq 0$, represents the actual quantity of aid allocated to each destination. Based on the optimization results, not all available routes are selected; instead, the model identifies the most cost-efficient shipping pattern and excludes routes with relatively higher transportation costs. The optimal values of the decision variables therefore reflect the minimum-cost allocation that still satisfies all operational constraints.

The results indicate that the proposed deterministic linear programming model is effective in reducing distribution costs and improving allocation efficiency. However, its performance needs to be interpreted critically, particularly in relation to the trade-offs inherent in deterministic optimization. The model performs well when logistics data, demand levels, and transportation conditions can be assumed to be relatively stable, but its effectiveness may decline in disaster situations characterized by severe uncertainty, such as sudden road disruption, rapidly changing shelter populations, or unexpected reductions in warehouse accessibility. Under such conditions, stochastic models may outperform the deterministic formulation because they are explicitly designed to account for probabilistic variation in demand and network conditions, while heuristic or metaheuristic approaches may offer greater flexibility in handling complex routing structures or large-scale problems that evolve dynamically over time. Accordingly, the present model offers high analytical clarity and computational simplicity, but these advantages are obtained at the expense of limited responsiveness to uncertainty, dynamic rerouting, and real-time operational adjustment. From a comparative perspective, the deterministic linear programming approach also provides several practical advantages over more advanced methods discussed in previous studies, including stochastic optimization, simulation-based approaches, and other adaptive decision models. First, the model is relatively easy to interpret because the relationship between cost coefficients, supply constraints, and demand fulfillment is explicitly represented in a clear mathematical structure. Second, it offers faster computational performance, which is particularly important in emergency settings where rapid decisions are required. Third, its implementation is comparatively straightforward, making it more feasible for institutions with limited analytical infrastructure or technical capacity. Nevertheless, these strengths are accompanied by certain limitations. In contrast to more sophisticated approaches, the present model does not explicitly incorporate uncertainty in demand, infrastructure failure, or travel time variability. It also has limited capability to support dynamic route reallocation when field conditions change after the optimization process has been completed. Therefore, while the deterministic LP model is highly suitable as a baseline planning tool, it should not be interpreted as a complete substitute for approaches designed to manage uncertainty and operational volatility.

The model's generalizability across disaster contexts should also be considered carefully. In principle, the same mathematical structure can be adapted to different disaster types, including floods, earthquakes, landslides, or other emergency scenarios, because the core problem remains the allocation of limited resources from multiple supply points to multiple demand points. However, the parameters and operational constraints may differ substantially across disaster contexts. In flood events, distribution planning may need to account for temporary road submersion, boat-based access, and frequently shifting evacuation sites. In earthquake scenarios, the primary challenge may involve sudden infrastructure collapse, disrupted communication, and isolated areas that require urgent prioritization. Consequently, although the deterministic transportation model is structurally transferable, its practical application requires contextual adjustment in cost parameters, accessibility assumptions, priority rules, and network feasibility. This means that the model is generalizable at the conceptual level, but not universally applicable without modification to reflect the logistical realities of specific disaster environments.

In practical terms, the findings of this study can be operationalized by logistics managers through integration with existing disaster management systems and institutional workflows. For example, the model could be linked with disaster information platforms such as InaRISK or BNPB operational systems to support the translation of hazard, exposure, and affected-population data into distribution priorities and transportation inputs. Such integration would allow optimization results to be updated based on field reports, infrastructure status, and shelter demand. Effective implementation would also require capacity building for field and logistics staff, particularly in data entry, interpretation of optimization outputs, and scenario-based decision-making. In addition, the successful application of the model depends on several data prerequisites, including accurate information on warehouse stock, shelter demand, route accessibility, transport distance, and basic infrastructure conditions. Without timely and reliable data collection, the quality of the optimization results may be significantly reduced. Therefore, the practical contribution of this model lies not only in its mathematical efficiency but also in its potential to function as a decision-support tool within a broader disaster logistics information system.

4. CONCLUSION

Based on the research results, it can be concluded that the application of applied mathematical methods through a linear programming-based transportation model has proven effective in optimizing the distribution of natural disaster relief. The developed model is able to determine distribution allocations from several warehouses to shelter locations by simultaneously considering transportation costs, warehouse capacity, and the needs of each affected location. The calculation results show that before optimization, distribution was carried out using all available routes without minimum cost selection, resulting in a relatively high total distribution cost of 1,550 cost units. After optimization using linear programming, only the routes with the lowest costs were selected, so that the total distribution cost was successfully reduced to 650 cost units, representing a savings of 58.06%, without reducing the fulfillment of shelter needs. In addition, the optimal solution satisfies all constraints related to warehouse capacity, shelter demand, and the non-negativity of decision variables, indicating that the resulting distribution plan is mathematically feasible and operationally relevant. Nevertheless, this conclusion should be interpreted within the limits of the study design. The model is built on deterministic assumptions, including fixed transportation costs, stable route accessibility, and balanced supply-demand conditions, where total warehouse capacity is assumed to be sufficient to satisfy total shelter demand. Such assumptions simplify the analytical process and contribute to computational efficiency, but they do not fully capture the uncertainty, disruption, and rapid change that often characterize actual disaster-response environments. Therefore, greater transparency regarding data limitations and simulation assumptions is necessary, particularly in relation to the static nature of distance-based cost parameters, the absence of real-time infrastructure disruption variables, and the use of simplified logistics conditions.

From a methodological perspective, future development of this model should move beyond deterministic optimization by incorporating stochastic or robust extensions. In such an extension, several critical variables may be modeled as uncertain, including shelter demand, travel time, and road availability, all of which are highly sensitive to changing field conditions during disasters. This development may be implemented through two-stage stochastic programming, in which initial allocation decisions are made before uncertainty is realized and recourse decisions are adjusted afterward, through robust optimization that seeks solutions feasible under worst-case deviations, or through scenario-based linear programming that evaluates several possible disruption patterns. Compared with more advanced approaches discussed in previous studies, the current deterministic LP model offers important advantages in terms of interpretability, speed of computation, and ease of implementation, making it suitable as a baseline decision-support tool for disaster logistics planning. However, these advantages are accompanied by trade-offs, particularly in its limited capacity to handle uncertainty, dynamic rerouting, and rapidly evolving operational constraints. As a result, the model may perform less effectively than stochastic, robust, or heuristic approaches when disaster conditions are highly volatile or when transportation networks are subject to sudden disruption

The model's practical contribution can also be strengthened through a clearer linkage to disaster-management policy in Indonesia. In operational terms, BNPB may pilot this model for regional logistics planning in flood-prone areas in order to improve the efficiency of aid allocation among warehouses and shelters. Likewise, BPBD at the provincial or district level may use the model as a simulation tool during preparedness planning, especially to identify priority distribution routes under constrained supply conditions. In the longer term, the model could also be integrated with existing disaster information systems, such as InaRISK or other BNPB data platforms, so that optimization outputs are supported by updated information on hazard exposure, shelter demand, stock availability, and route accessibility. For this reason, successful implementation would require not only data readiness but also staff training in model interpretation, logistics data input, and scenario-based response planning. Finally, to enhance the scientific quality and contextual relevance of the manuscript, future revisions should also include updated comparative references, more recent local disaster case studies, a clearer explanation of methodological choices, and, where possible, a more detailed sensitivity analysis protocol. Overall, the findings confirm that mathematical modeling, particularly through a linear programming-based transportation model, can provide systematic, measurable, and efficient support for disaster-relief distribution; however, its full scientific and practical value will be significantly strengthened when complemented by methodological transparency, critical comparison with alternative approaches, and actionable policy integration within Indonesia's disaster-management system.

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