HAZARDOUS MATERIAL ROUTE OPTIMIZATION USING MAMDANI FUZZY LOGIC: A DECISION SUPPORT SYSTEM BASED ON OPERATIONAL DATA

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ABSTRACT

This study aims to develop a decision support system based on Mamdani fuzzy logic for optimizing hazardous material (B3) transportation route selection that accommodates operational data uncertainty and linguistic characteristics in decision-making. A quantitative method with soft computing approach was applied to 150 B3 transportation trip data from PT Prasadha Pamunah Limbah Industri during January–June 2025 in the Jabodetabek area. Three input variables—cargo tonnage, travel distance, and order type—were integrated into 18 fuzzy rules with triangular and trapezoidal membership functions, and centroid defuzzification to produce a priority score of 0–100. Data processing used Python 3.11 with pandas, matplotlib, seaborn, and scikit-fuzzy libraries, while spatial data processing applied R 4.3 with tmaptools package and OpenStreetMap API. Model validation involved three B3 transportation experts with a minimum of ten years of experience on 30 purposively selected trip samples. Results showed risk category distributions of low, medium, and high at 54.7%, 31.3%, and 14.0%, respectively. Sensitivity analysis indicated that order type was the most dominant variable, where changing from regular to direct order increased the priority score by 30–40 points. Validation yielded a Spearman correlation of 0.879 ($p < 0.001$), classification accuracy of 83.3%, mean absolute error of 6.0 points, and a non-linear synergy effect of 10–12 points in extreme cases compared to conventional linear models. The developed model proved effective, interpretable, and ready for implementation in real-time B3 transportation management systems. The novelty lies in its ability to capture non-linear synergy effects among variables, providing more realistic risk estimation in heterogeneous Indonesian operational contexts.

Keywords: decision support system; hazardous material transportation; mamdani fuzzy logic; risk prioritization; route optimization; soft computing

INTRODUCTION

Transportation of hazardous and toxic materials (B3) represents a strategic and vital component for industrial sectors including chemicals, energy, and pharmaceuticals (Zhu & He, 2023). Despite its high economic value, this activity carries multidimensional risks that can seriously impact public safety, environmental quality, and infrastructure integrity. In Indonesia, the (Ministry of Transportation, 2023) recorded high incident rates in B3 transportation, with 38% occurring in the Jabodetabek region, indicating significant vulnerability within the logistics system. Incidents such as the chlorine leak on the Ngawi Toll Road in 2021 demonstrated systemic impacts, causing mass evacuations and substantial economic losses. Reports from (WHO, 2023) and the (ASEAN Transport Safety Report, 2023) further emphasized the urgency of this issue, with Indonesia ranking second highest in Southeast Asia for B3 transportation accidents.

The fundamental problem lies in the conventional route selection methods still dominant in Indonesia. Current practices tend to ignore risk factors beyond operational efficiency, focusing merely on distance and travel time (Y. Chen, 2021). (Zhang & Rahman, 2023) revealed that most companies still rely on drivers' subjective experience, while deterministic algorithms such as Dijkstra have limitations in processing real-time data uncertainty, including traffic dynamics and fluctuating road conditions (Yuan et al., 2022). This situation creates a crucial research gap, as the shortest route is not necessarily the safest, particularly for high-risk transportation (Janic, 2020). (Ministry of Transportation, 2023) also emphasized that weak risk analysis in route selection constitutes one of the primary causes of high incident rates.

Previous studies have attempted various approaches to address this problem. (X. Chen et al., 2020) demonstrated that fuzzy model implementation could reduce accident risks by up to 30%, while (Rahman & Kwon, 2023) successfully improved route selection accuracy to 92% using a fuzzy-AHP combination. (Amin & Zhang, 2021) developed a robust fuzzy model for hazardous material transportation network design under uncertainty. (Sun et al., 2022) and (Nguyen et al., 2023) showed that fuzzy models can comprehensively integrate various risk criteria from quantitative to qualitative data. However, these studies were predominantly conducted outside Indonesia and did not fully accommodate specific Indonesian characteristics, such as heterogeneous road infrastructure and complex local regulations (Prasetyo et al., 2020). To address these limitations, this study develops a Mamdani fuzzy logic model for B3 transportation route selection that can be practically applied in Indonesia. By integrating operational data from industrial partner PT Prasadha Pamunah Limbah Industri (PPLI) and considering local regulations, this model is expected to provide not only academic contributions but also practical solutions that can enhance B3 transportation safety and support the achievement of Sustainable Development Goals (SDGs), particularly Goal 11 (Sustainable Cities and Communities) and Goal 13 (Climate Action). The scientific merit of this paper lies in the development of an interpretable fuzzy decision support system that captures non-linear synergy effects among operational variables, which conventional linear models fail to represent. This study addresses the following research questions: (1) How to design and implement a Mamdani fuzzy logic model that accommodates data uncertainty and linguistic characteristics in B3 transportation route selection decision-making? (2) What factors are most significant in determining the safety and efficiency levels of a B3 transportation route in the Jabodetabek region? The objectives are to develop a decision support system for B3 transportation route selection based on Mamdani fuzzy logic and to validate the model through a case study using operational data from PT PPLI to identify the most influential variables affecting optimal route recommendations.

METHOD

This study employed a quantitative approach with soft computing methods based on Mamdani fuzzy logic. The research was conducted from July to December 2025 at the Transportation System Computation Laboratory, Politeknik Keselamatan Transportasi Jalan (PKTJ), Tegal, Indonesia, with operational data obtained digitally from PT PPLI in the Jabodetabek region. The data used in this study consisted of three types. First, primary data in the form of Excel files containing PT PPLI B3 transportation trips with information on date, vehicle type, order type, tonnage, travel distance, location, and load description. Second, secondary spatial data in the form of coordinate locations of destination industries, obtained through geocoding using the OpenStreetMap API (utilizing the geocode_OSM function from the tmaptools package in R 4.3). Third, risk parameter data derived from literature and consultation with logistics experts and hazardous material transportation specialists.

The fuzzy Mamdani model was designed with three input variables and one output variable. Input variables included tonnage (0–20 tons) with three categories (Light, Medium, Heavy), distance (0–100 km) with three categories (Near, Medium, Far), and order type as a discrete variable with two categories (Regular and Direct). The output variable was Priority Score ranging from 0 to 100 with three categories (Low, Medium, High). Membership functions used triangular and trapezoidal shapes based on empirical data distribution analysis and expert consultation to ensure smooth transitions between categories.

The inference system applied 18 IF-THEN rules constructed based on expert knowledge in B3 transportation. The rules used AND (minimum) and OR (maximum) operators, with centroid defuzzification method to convert fuzzy output into crisp values. Data processing and model computation were performed using Python 3.11 with pandas, matplotlib, seaborn, and scikit-fuzzy libraries. Spatial analysis and distance calculation utilized Geographic Information System (GIS) principles through R programming. Model validation was conducted using field data to ensure compatibility between simulation results and operational reality. Validation involved three B3 transportation experts with a minimum of ten years of experience, selected through purposive sampling based on professional competence and direct involvement in B3 transportation route decision-making. Thirty trip samples were selected considering extreme and moderate variations in the three main model variables. Each expert provided independent priority scores for each trip on a 0–100 scale based on professional experience without knowing the fuzzy model output to avoid confirmation bias. Validation metrics included Spearman and Pearson correlation, classification accuracy, mean absolute error, confusion matrix, and agreement rate analysis.

RESULT

Analysis of 150 B3 transportation trips from PT Prasadha Pamunah Limbah Industri during January–June 2025 in the Jabodetabek region revealed diverse operational characteristics. Cargo tonnage ranged from 0.5 to 15 tons with a mean of 6.54 tons and standard deviation of 3.82 tons. Travel distance exhibited a bimodal pattern within the range of 5–85 km with a mean of 34.12 km. Order type distribution consisted of 42% direct orders and 58% regular orders, indicating a significant proportion of emergency operations in the B3 transportation system. The fuzzy Mamdani model was designed with three input variables and one output variable. Table 1 and Table 2 present the fuzzy membership functions for input and output variables designed based on empirical data distribution and expert consultation.

Table 1.
Fuzzy Membership Functions for Input Variables

Variable	Fuzzy Set	Function	Domain	Range
Tonnage (kg)	Light	Triangle (0, 5000, 10000)	0–10000	0–1
	Medium	Triangle (8000, 12000, 16000)	8000–16000	0–1
	Heavy	Triangle (15000, 20000, 25000)	15000–25000	0–1
Distance (km)	Near	Trapezoid (0, 0, 20, 40)	0–40	0–1
	Medium	Triangle (30, 50, 70)	30–70	0–1
	Far	Trapezoid (60, 80, 100, 120)	60–120	0–1
Order Type	Regular	Discrete (0)	{0,1}	0–1
	Direct	Discrete (1)	{0,1}	0–1

Table 2.
Fuzzy Membership Functions for Output Variable

Output Variable	Fuzzy Set	Function	Domain	Range
Priority Score (0–100)	Low	Triangle (0, 20, 40)	0–40	0–1
	Medium	Triangle (30, 50, 70)	30–70	0–1
	High	Triangle (60, 80, 100)	60–100	0–1

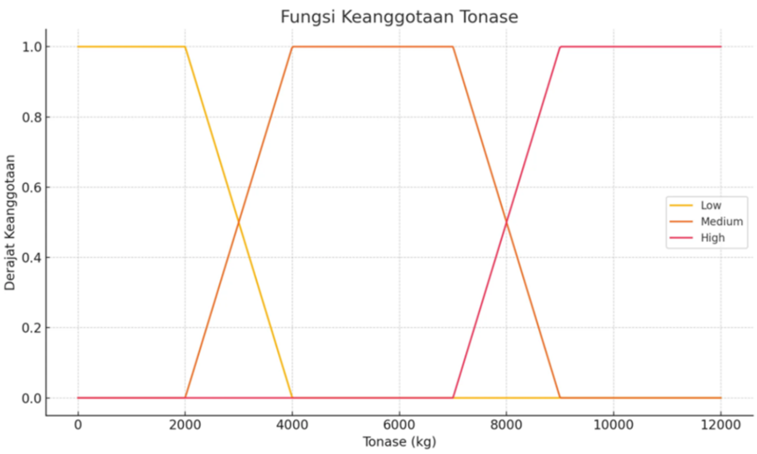
The fuzzy inference rule base was constructed based on combinations of input variables and expert knowledge in B3 transportation, as presented in Table 3. Eighteen IF-THEN rules were built to cover all possible input combinations occurring in B3 transportation operations.

Table 3.
Fuzzy Inference Rule Base

No	IF Tonnage	AND Distance	AND Order	THEN Priority
1	Light	Near	Regular	Low
2	Light	Medium	Regular	Low
3	Light	Far	Regular	Medium
4	Medium	Near	Regular	Low
5	Medium	Medium	Regular	Medium
6	Medium	Far	Regular	Medium
7	Heavy	Near	Regular	Medium
8	Heavy	Medium	Regular	Medium
9	Heavy	Far	Regular	High
10	Light	Near	Direct	Medium
11	Light	Medium	Direct	Medium
12	Light	Far	Direct	High
13	Medium	Near	Direct	Medium
14	Medium	Medium	Direct	High
15	Medium	Far	Direct	High
16	Heavy	Near	Direct	High
17	Heavy	Medium	Direct	High
18	Heavy	Far	Direct	High

(Source: Expert knowledge and PT PPLI operational data, 2025)

The inference process used AND (minimum) and OR (maximum) operators, with centroid defuzzification to produce crisp values representing the priority level of each route. Figure 1 shows the membership function for the tonnage variable illustrating smooth transitions between Light, Medium, and Heavy categories.



(Source: Processed data, 2025)

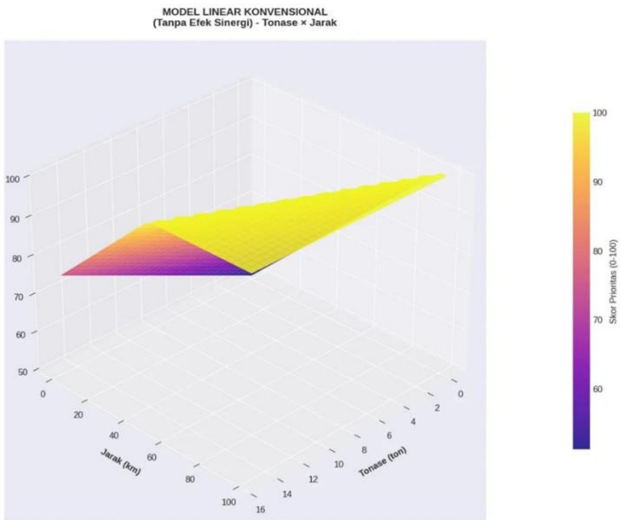
Figure 1. Fuzzy Membership Function for Tonnage Variable

Computational results for 150 trips produced the risk category distribution presented in Table 4. The Low category dominated with 82 trips (54.7%), followed by Medium with 47 trips (31.3%), and High with 21 trips (14.0%). Sensitivity analysis showed that order type was the most dominant variable affecting output, where changing from Regular to Direct increased the priority score by 30–40 points. Tonnage provided moderate influence with an increase of 15–25 points, while distance had the lowest influence with an increase of 10–15 points.

Table 4.
Distribution of Risk Categories from Model Computation

Risk Category	Number of Trips	Percentage (%)	Main Characteristics
Low	82	54.7	Regular order, medium tonnage, medium distance
Medium	47	31.3	Moderate variation in tonnage and distance
High	21	14.0	Heavy tonnage, far distance, or direct order
Total	150	100.0	

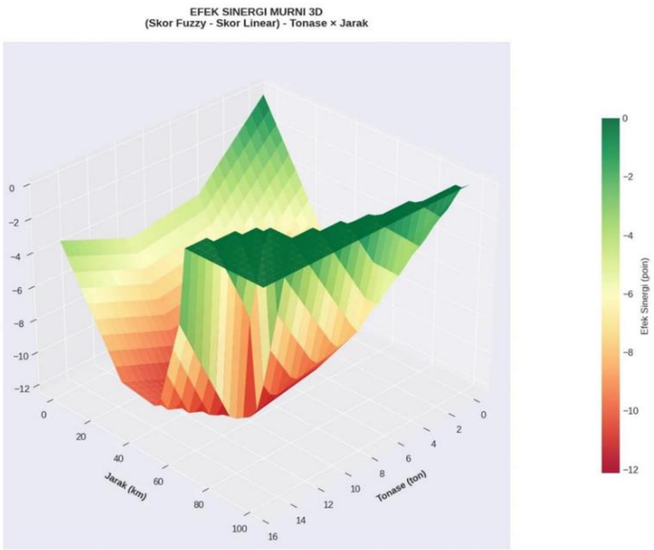
Comparative analysis between the fuzzy model and conventional linear model confirmed the existence of non-linear synergy effects that the linear approach could not represent. Figure 2 illustrates the fuzzy model response surface showing non-linear characteristics with plateau regions at low-to-medium tonnage and near-to-medium distance combinations. However, at high tonnage above 10 tons combined with far distance exceeding 60 km, a sharp priority score increase reaching 95–100 points occurred, reflecting synergy effects where risk increases exponentially rather than linearly.



(Source: Processed data, 2025)

Figure 2. 3D Visualization of Fuzzy Model with Non-Linear Synergy Effect

The synergy magnitude reached 10–12 points in critical areas, indicating that in 10–12% of extreme cases, priority decisions would differ significantly between fuzzy and linear approaches, with important practical implications for resource allocation and risk management. Figure 3 presents a comprehensive comparative analysis in four panels showing high synergy areas concentrated in the tonnage range of 10–14 tons and distance range of 75–90 km, where operational risk increases significantly and requires maximum priority.



(Source: Processed data, 2025)

Figure 3. Comparative Analysis of Fuzzy vs Linear Model with Synergy Effect Contour Map

Model validation involved three B3 transportation experts with minimum ten years of experience on 30 purposively selected trip samples. Validation results showed a Spearman correlation of 0.879 with significance $p < 0.001$, indicating a very strong relationship between model scores and expert assessments. Pearson correlation ranged from 0.927 to 0.949, confirming a very strong linear relationship. Classification accuracy reached 83.3% with mean absolute error of only 6.0 points or 6% of the full scale. Table 5 summarizes the model validation metrics confirming high validity and reliability for operational application.

Table 5.
Model Validation Metrics

Metric	Value	Interpretation
Spearman Correlation	0.879 ($p < 0.001$)	Very strong relationship with expert assessment
Pearson Correlation	0.927–0.949	Very strong linear relationship
Classification Accuracy	83.3%	25 of 30 samples correctly classified
Mean Absolute Error	6.0 points (6% scale)	Very high practical accuracy
Agreement Rate	66.7% (10-point tolerance)	Adequate for operational decisions
Average Precision	0.855	High precision for category prediction
Average Recall	0.833	Complete category detection
F1-Score	0.839	Balance between precision and recall

(Source: Expert validation results, 2025)

Confusion matrix analysis in Table 6 shows that all misclassifications occurred in adjacent categories without extreme jumps, confirming that errors were gradual and logical within the ordinal classification context. High category precision reached 1.00, ensuring no false alarms in maximum priority predictions, which is a critical advantage in B3 transportation safety contexts.

Table 6.
Confusion Matrix for Model Validation

Model Prediction \ Actual Expert	Low	Medium	High	Total
Low	8	1	0	9
Medium	1	7	1	9
High	0	1	11	12
Total	9	9	12	30

(Source: Expert validation results, 2025)

DISCUSSION

The results demonstrate that the Mamdani fuzzy model effectively integrates data uncertainty and linguistic ambiguity into an objective decision-making framework. The model produces priority scores consistent with expert assessments with computation time under one second per trip, meeting efficiency criteria for real-time implementation. Every decision can be explained through active fuzzy rule traces, providing high interpretability for dispatchers and logistics managers. This aligns with the theoretical foundation of fuzzy logic as formalized by (Dubois & Prade, 2021), who emphasized that interpretable rule-based systems are indispensable in safety-critical operational environments. Critically, the transport vehicles operating B3 cargo in the Jabodetabek region predominantly include semi-trailer and trailer configurations, which, as documented by (Budiharjo et al., 2025), are characterized by significant regulatory non-compliance in terms of load capacity and axle configuration in Indonesia. This structural non-compliance reinforces the need for an objective, data-driven priority scoring system such as the one developed in this study.

The superiority of the fuzzy Mamdani model over conventional approaches lies in its ability to process uncertain data and linguistic ambiguity. While deterministic algorithms such as Dijkstra focus solely on shortest path optimization (Yuan et al., 2022), and subjective driver experience lacks standardization (Zhang & Rahman, 2023), the fuzzy model provides an objective, repeatable, and transparent decision framework. The role of human factors in exacerbating B3 transportation risks is also documented by (Rashmi & Marisamynathan, 2023), who found through a systematic review that driver behavior—including fatigue, speeding, and inadequate hazard perception—consistently emerges as a major contributing factor in heavy freight accidents. These findings support the integration of automated decision support tools that reduce dependency on driver subjectivity in route selection. The non-linear synergy effect of 10–12 points in extreme cases represents a significant practical advantage, as linear models may underestimate priority for high-risk combinations, potentially causing delayed responses and increased safety incident risks. (Erkut & Alp, 2020) similarly demonstrated that non-linear risk propagation in hazardous material networks cannot be adequately captured through classical linear formulations, reinforcing the importance of soft computing approaches.

Compared to previous studies, (X. Chen et al., 2020) reported 30% risk reduction using fuzzy approaches, while (Rahman & Kwon, 2023) achieved 92% accuracy with fuzzy-AHP combinations. This study contributes to the literature by specifically addressing Indonesian operational contexts with heterogeneous infrastructure and local regulatory complexity. The model's interpretability through explicit rule bases distinguishes it from black-box machine learning approaches, making it more suitable for regulatory compliance and safety-critical applications. In this regard, (Liu & Zhao, 2023) showed that while deep learning models may achieve higher raw accuracy, their lack of transparency renders them less suitable for regulatory decision-making in hazardous materials logistics.

The sensitivity analysis results align with domain logic that places time urgency as the most critical factor in B3 transportation operations. The dominance of order type (30–40 point influence) reflects the operational reality that direct orders often involve emergency situations requiring immediate response, regardless of distance or tonnage. This finding supports the implementation of differentiated scheduling protocols where direct orders receive automatic priority escalation. (Mohabbati-Kalejahi & Vinel, 2021) similarly highlighted that temporal urgency parameters consistently emerge as decisive factors across diverse hazmat transportation frameworks, confirming the generalizability of this finding beyond Indonesian contexts. Furthermore, (Widyanti et al., 2025) identified that over-dimensional and overloaded (ODOL) trucks in Indonesian highways substantially increase accident probability, particularly under emergency operational conditions such as direct-order dispatching a finding that directly corroborates the heightened priority scores assigned by the fuzzy model to direct-order trips in this study.

The validation metrics confirm that the model achieves practical accuracy suitable for operational deployment. The 83.3% classification accuracy with 6.0 point MAE indicates that the model can reliably support dispatcher decisions without requiring extensive manual oversight. The high precision for the High category (1.00) is particularly important as it eliminates false alarms that could cause unnecessary resource diversion while ensuring that genuine high-risk trips are never underestimated. (Bula et al., 2019) emphasized that zero false-negative rates in high-risk trip classification are a fundamental requirement for vehicle routing systems handling hazardous materials, as missed high-risk identifications directly translate into elevated accident probabilities. In addition, (Setiono & Sabrie, 2023) argued that chain-of-responsibility frameworks in land transportation, which assign liability to all parties involved in overloading and regulation violations, require decision tools that produce defensible, traceable outputs—precisely the property demonstrated by the present fuzzy rule-based model. The integration of the fuzzy decision support system with broader freight transport modeling also warrants attention. (Akbardin et al., 2020) demonstrated that inter-zone freight transportation distribution models must account for load capacity constraints as a primary variable, a finding structurally consistent with the tonnage variable's role in the present fuzzy model. The alignment between these findings suggests that the priority scoring outputs generated by this study could be seamlessly integrated into larger-scale inter-zone freight routing frameworks. Similarly, (Castillo-Lopez & Camacho-Vallejo, 2022) developed a bi-level optimization framework for hazmat route planning with regulatory constraints, and their findings suggest that real-time priority scoring systems such as the one developed in this study can serve as effective upstream input layers for more complex vehicle routing optimization modules.

However, this study has limitations that should be acknowledged. The dependency on data from a single company over a six-month period may limit generalizability to different operational contexts. Seasonal variations and long-term trends were not captured in this dataset. Additionally, the model currently uses three primary variables, and future research could incorporate weather conditions, real-time traffic congestion, driver certification levels, and time-of-day factors to further enhance prediction accuracy.

CONCLUSION

The Mamdani fuzzy logic model developed in this study proved effective as a decision support system for B3 transportation route selection by integrating tonnage, distance, and order type variables into 18 inference rules producing a priority score of 0–100. Validation using 150 trips from PT PPLI and assessment by three experts showed a Spearman correlation of 0.879, classification accuracy of 83.3%, and mean absolute error of 6.0 points, indicating high validity and reliability for operational application. The novelty of the model lies in its ability to capture non-linear synergy effects among variables with 10–12 point deviation in extreme cases compared to conventional linear models, providing more realistic risk estimation in heterogeneous Indonesian conditions. Implementation of this model is expected to reduce manual decision variability, enhance compliance with safety regulations, and optimize vehicle and driver resource allocation in real-time B3 transportation management systems.

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