Transition from Digital Logic to Artificial Intelligence and Fuzzy Logic Models in Logistics Decision Systems

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Abstract. Modern logistics systems require intelligent decision-making mechanisms to manage uncertainty, optimize resource allocation, and ensure timely delivery of orders. Traditional digital logic models based on Boolean functions provide a simple framework for modeling logistics decisions; however, they fail to capture the dynamic and uncertain nature of real supply chain environments. This study proposes a transition from a digital Boolean decision model to an artificial intelligence-based framework using fuzzy logic and spherical fuzzy sets. The model evaluates order urgency, resource availability, and route feasibility. Boolean decision rules are analyzed using partial derivatives to determine system sensitivity and are then extended using fuzzy logic to represent uncertainty. A spherical fuzzy optimization approach improves flexibility and adaptability. Simulation results show that the AI-based model provides smoother decision surfaces and better optimization performance compared to the digital model.

Keywords: Artificial Intelligence, Fuzzy Logic, Spherical Fuzzy Sets, Logistics Decision Systems, Supply Chain Optimization, Boolean Logic, Decision-Making Models, Route Optimization, Resource Allocation

1 Introduction

Logistics and supply chain management are fundamental elements of the modern economy. Global trade, the expansion of e-commerce platforms, and the growing demand for logistics services require decision-making systems to be more agile and intelligent. Traditional logistics models are often based on Boolean logic, where decisions are represented by only binary values (0 and 1). Although this approach is suitable for simple modeling, it cannot fully capture the uncertainty and variability present in a real-world logistics environment. In recent years, artificial intelligence and fuzzy logic have been widely used for the optimization of logistics decision-making systems. Fuzzy logic methods allow for the modeling of uncertain data in logistics systems and enable more realistic decision-making (Zadeh, 2020; Chen et al., 2021). Furthermore, in supply chain optimization, artificial intelligence methods have shown effective results in route planning, resource management, and optimization of logistics operations (Ivanov, 2021; Dolgui & Ivanov, 2022). In recent studies, spherical fuzzy sets are presented as

more advanced fuzzy models that allow the assessment of uncertainty and fluctuation factors within the same model (Ashraf et al., 2023). This approach enables the establishment of more flexible optimization mechanisms in logistic decision models. This article analyzes a logistics decision system built on a digital Boolean model and demonstrates its transition to an artificial intelligence model. The model considers three main factors: order urgency, resource availability, and route feasibility. The logistics optimization mechanism is then formed by extending the model with fuzzy and spherical fuzzy methods.
To address these challenges, a logistics decision-making model based on Boolean logic is developed and then extended using artificial intelligence and fuzzy logic techniques.

2 Methodology

A logistics company is establishing a decision-making system to optimize its supply chain. The company considers three key factors for on-time delivery of supply orders and route optimization:

1.
   a. Order urgency (x): An order can be urgent (1) or regular (0).
   b. Adequacy of available resources (y): If resources are sufficient (1), insufficient (0).
   c. Feasibility of the route (z): If the route is feasible (1), it is infeasible (0).

$$f(x, y, z) = xy \vee \bar{x}yz \vee x\bar{y}z \quad (1)$$

2. xy → The order is conducted if it is urgent and resources are sufficient.
3. $\bar{x}yz$ → Although the order is routine, resources are available and the route is favorable, it is being executed.
4. $x\bar{y}z$ → Even if the order is urgent, resources are scarce, but the route is favorable, it is executed.

This Boolean function is a supply chain decision-making model based on digital logic. Supply chain disruptions increase, delivery delays, international trade barriers, and other supply chain problems—complicate logistics operations.

$$\frac{\partial f}{\partial x} = y\bar{z} \vee z, \ \frac{\partial f}{\partial y} = x\bar{z} \vee z, \frac{\partial f}{\partial z} = y\bar{z} \vee z \quad (2)$$

Derivatives help to assess the impact of each factor entering the system:
$\partial f/\partial x = y\bar{z} \vee z$, i.e., Order urgency (x) affects order fulfillment. If the route is favorable $(z = 1)$, it does not matter whether the order is urgent or not, If the route is unfavorable $(z = 0)$, whether the order is urgent depends on resources (y).
$\partial f/\partial y = x\bar{z} \vee z$, i.e., the sufficiency of resources (y) affects the order fulfillment, if the route is favorable $(z = 1)$, whether resources are sufficient or not is irrelevant, if the route is unfavorable $(z = 0)$, the order fulfillment depends on the order's urgency (x).

$\partial f/\partial z = x \vee y$, which means that the feasibility of the route is one of the most critical factors in the order's fulfillment, If either the order is urgent ($x = 1$) or resources are sufficient ($y = 1$), the order will be executed, i.e., even if the route is unfavorable ($z = 0$). When either x or y is 1, the order can be executed.

3 Analysis of Boolean Model

The most important factor is the feasibility of the route (z). If the route is feasible (z = 1), other factors have less influence. If the route is unfavorable (z = 0), the influence of x and y on order fulfillment increases. If the order is urgent and resources are sufficient, the order can be fulfilled even if the route is unfavorable. This highlights the importance of planning alternative routes for urgent orders.

Table 1. Logistics decision model analysis.

State (x y z)	f(x, y, z)	∂f/∂x	∂f/∂y	∂f/∂z	Analysis
000	0	0	0	0	No factor influences the decision. The system is passive.
001	0	1	1	0	The route is feasible, but there are no order or resources. To change the decision, x or y must be increased.
010	0	1	0	1	Resources are available, but the route is unfavorable. The system can activate expedite or route improvement.
011	1	1	1	1	The system is active and all factors influence the decision.
100	0	0	1	1	The order is urgent, but there is a resource and routing problem. Resource augmentation and route optimization are needed.
101	1	1	1	1	Urgent orders and good routes are available. Adding resources can further strengthen the system.
110	1	1	1	1	There are order and resources, but the route is poor. Alternative route planning is essential.

111	1	1	1	1	Optimal logistics scenario: all factors are positive and the system operates at maximum efficiency.

As a result of optimizing the derivatives, the following rule can be formulated. If z=1, the order is executed. If z=0, then x=1 or y=1 must be satisfied.

$$\frac{\partial f}{\partial t} = \frac{\partial f}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial f}{\partial y}\frac{\partial y}{\partial t} + \frac{\partial f}{\partial z}\frac{\partial z}{\partial t} \tag{3}$$

$$\frac{\partial f}{\partial t} = (y\bar{z} \vee z)\frac{\partial x}{\partial t} + (x\bar{z} \vee z)\frac{\partial y}{\partial t} + (x \vee y)\frac{\partial z}{\partial t} \tag{4}$$

$$f(x, y, z) = xy \vee \bar{x}yz \vee x\bar{y}z = 00010111 \tag{5}$$

The diagram shows the Boolean partial derivatives $\partial f/\partial x$,$\partial f/\partial y$, and $\partial f/\partial z$ for all system states (x, y, z). The diagram illustrates how order urgency (x), resource availability (y), and route suitability (z) influence the decision function f(x, y, z) and highlights the most sensitive states for logistics optimization.

$$\text{Sensitivity} = \frac{\partial f}{\partial x} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial z} \tag{6}$$

3D diagram: Route planning (z) is the primary optimization factor in the logistics system; when order urgency (x) and resource availability (y) are combined, the system operates more stably, and optimization decisions are more effective when all factors are active.

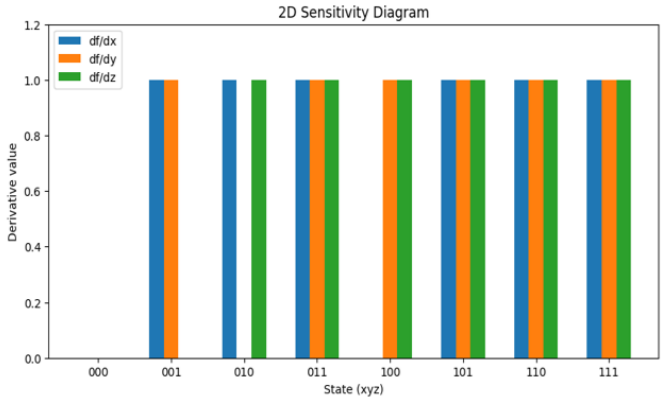


Fig. 1. 2D sensitivity diagram of the logistics decision model.

The 3D optimization sensitivity surface of the logistics decision model illustrates the combined influence of order urgency (x), resource availability (y), and route suitability (z). The height of each bar represents the total sensitivity $\partial f/\partial x + \partial f/\partial y + \partial f/\partial z$, indicating how strongly the decision function responds to changes in system factors and highlighting the most critical states for logistics optimization.

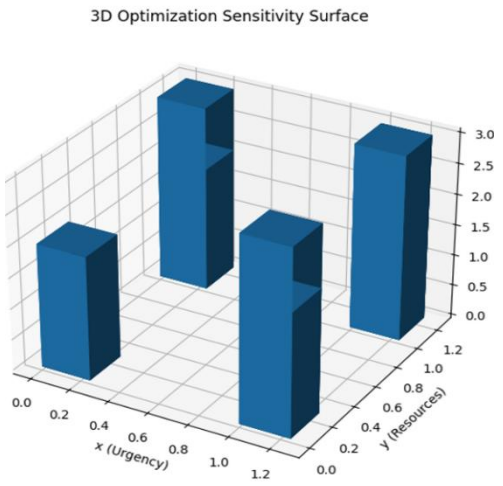


Fig. 2. 3D optimization sensitivity surface of the logistics decision model.

The given Boolean function and its time derivative have the same bit sequence:

This means that the function is equal to its derivative. In other words, the system's Boolean dynamics are structured so that changes occur according to the same logic as the function itself.

1. Static system: If $\partial f/\partial t = f\ (x, y, z)$, this indicates that the system's rate of change is determined by its own function.
2. Special case: This could mean that the system automatically reaches a steady state or self-regulates.
3. Boolean differential equation: If a Boolean function and its derivative are equal, this can be a special solution in linear Boolean differential equations.

The system responds to these changes as follows:

a) In a static system, if the variables remain constant over time ($\partial x/\partial t = 0, \partial y/\partial t = 0, \partial z/\partial t = 0$), then $\partial f/\partial t = 0$. In this case, the system is in a stable, unchanged state, and no new optimization is needed.
b) If the variables in the dynamic system change over time ($\partial x \partial t \neq 0$, etc.), then the system is operating in dynamic mode, i.e., as orders, resource status,

and routing conditions change, the decisions made by the system also change.

Table 2. Decision results of the logistics system based on Boolean variables (x, y, z).

x	y	z	Decision (f(x,y,z))
0	0	0	0 (delivery not possible)
0	0	1	0 (no resources)
0	1	0	0 (route is unfavorable)
0	1	1	1 (delivery is possible)
1	0	0	0 (no resources)
1	0	1	1 (route is available, delivery is possible)
1	1	0	1 (resource is available, delivery is possible even if the route is unfavorable)
1	1	1	1 (all conditions are met, optimal delivery)

System Behavior Analysis: If the system is in a steady state, the supply chain's state remains stable as orders and resources do not change. If changes occur (order volume increases, resources become insufficient, or the route changes), the system's decisions change in real time, A Boolean differential equation functionally defines this change and helps in the automatic optimization of the system, allowing real-world logistics decision-making processes to be simulated with simple Boolean models.

1. Boolean Function Defines Decision-Making Rules:

    - Based on the given values x (urgent order), y (resource sufficiency), and z (route feasibility), the system determines whether delivery is possible.
    - When the output of f(x,y,z) is 1, the order can be fulfilled; when it is 0, the order cannot be fulfilled.

2. Boolean Differential Equation System Behavior:

    - $\frac{\partial f}{\partial t}$ Equal to f (x, y,z) indicates that the system is stable. The system's decision-making mechanism does not change over time; that is, if the variables remain constant, the system's output also remains constant.

3. Decision-Making Can Be Simulated with Simple Boolean Models:

    - If the Boolean differential equation is equal to f (x, y,z), this means that the system operates unchanged with respect to the inputs.
    - This can indicate that the system operates under constant conditions and does not adapt to new parameters.

Interpretation: This model can simulate simple organization decision-making processes, but a more flexible model needs to be created using fuzzy logic and probability theory for real-world dynamic changes. It is more appropriate to use Fuzzy Logic and probability theory to create a more flexible model that adapts to dynamic changes in the real world.

4 Problem Statement

In the real world, organization systems do not operate with such sharp boundaries. For example:

- The order's urgency level can vary (e.g., urgency of 0.7, 0.3, etc.).
- Resource availability can vary (e.g., 0.8 resource availability).
- Route availability can be partial (e.g., 0.5 availability).

Therefore, fuzzy logic and probability theory can provide a more realistic modeling of logistics systems.

This system, built on digital logic and logical probability, can also serve as a basis for the transition to fuzzy logic.

1. Adapting the Boolean function to fuzzy logic:

    - The urgency of an order can be determined by fuzzy values such as "very urgent," "moderately urgent," and "slightly urgent," instead of binary (0 and 1).
    - Resource sufficiency can also be fuzzy: "very sufficient", "normal", "insufficient".
    - Route availability can also be fuzzy: "good", "normal", "bad".

2. Fuzzy rules for decision-making:

    - "If the order is very urgent and resources are scarce, but the route is good, then the probability of execution is 70%."
    - "If the order is less urgent and resources are abundant, but the route is bad, then the probability of execution is 50%."

3. Converting a fuzzy output into a crisp decision:

    - The system uses defuzzification methods to make the decision to accept (Y=1) or reject (Y=0) an order.

Interpretation: It is possible to build a supply chain decision-making model in the logistics ecosystem using Boolean logic, By applying logical probability, it is possible to reduce uncertainty in decision-making and make optimal route selection; by

transitioning to fuzzy logic, the system can become more adaptive and tailored to real-world conditions.

This approach presents a new method for effective decision-making in supply chain management, transportation routing, and resource optimization.

Fuzzy rules:

1. If the order is very urgent ($x \approx 1$), resources are sufficient ($y > 0.5$), and the route is favorable ($z > 0.5$), the order must be executed with an extremely high priority.
2. If the order is of medium urgency ($x \approx 0.5$) and resources are sufficient ($y > 0.7$), the order should be processed normally.
3. If the order is not urgent ($x \approx 0$), resources are insufficient ($y < 0.3$), and the route is unfavorable ($z < 0.4$), the order should be placed on hold.

These rules are modeled with fuzzy logic IF-THEN rules, resulting in a flexible decision-making system.

Output: In the fuzzy model, the probability of order fulfillment (P) is calculated as a function that varies between 0 and 1.

Variables:x - order urgency,y : sufficient resources,z - favorable route

Output:$f = 1 \rightarrow$ order accepted / executed,$f = 0 \rightarrow$ order postponed or rejected

In the AI model, we represent this as expert rules:

Rule 1: If the order is urgent and resources are sufficient, then the order should be executed.

Rule 2: If the order is urgent and the route is available, then the order should be executed.

Rule 3: If resources are sufficient and the route is favorable, then the order should be executed.

Rule 4: If only one of these conditions is met, or if none of them are met, then the order should not be executed.

Verbal expression of the AI model and its intellectual explanation: The system accepts an order if at least two of the three main factors are favorable: the order is urgent, resources are sufficient, and the route is suitable.

Formal AI model: $Decision = \begin{cases} 1, & x + y + z \geq 2 \\ 0, & otherwise \end{cases}$

Here is $x, y, z \in \{0,1\}$, i.e., the general rule of the AI model: "If there are at least 2 positive conditions, the order is fulfilled."

Table 3. Comparative analysis of the digital logic model and the AI-based decision model.

Digital Model	**AI Model (Artificial Intelligence Model)**	**Explanation**
A vector of 0s and 1s	Decision rules (IF–THEN rules)	In the digital model, the system works only with 0s and 1s. In the AI model, however, these vectors are converted into expert rules, forming the decision-making mechanism.
Logic function	Expert system model	Boolean logic functions are converted into a rule base and a knowledge base in the AI model, forming the basis of the expert system.
Formal mathematical expression	Control decision	The results obtained from the mathematical model are converted into real management decisions (e.g., order fulfillment, waiting, or priority delivery) in the AI system.

AI Model with Fuzzy Logic: When Fuzzy Logic is used in an organizational decision-making system, variables are not just 0 or 1; they are evaluated on various levels. This allows for the creation of a model that better fits real-world conditions.

Based on the fuzzy model, an optimization framework is developed to improve decision-making efficiency and system adaptability.

Optimization of the Spherical Fuzzy Model: In the organizational decision-making system, the objective of optimization is to ensure that orders are executed on time, with low cost, and via an appropriate route. In the spherical fuzzy model, this optimization is conducted based on three main parameters:μ — the strength of the positive state,θ — the degree of fluctuation and uncertainty,τ — the strength of the negative state. Condition:$0 \leq \mu^2 + \theta^2 + \tau^2 \leq 1$. This constraint ensures the model remains valid. The main objective of the model is to increase the membership rate, decrease the non-membership rate, and minimize the fluctuation level.

From a logistics perspective: the probability of order fulfillment must be high, resource shortages must be reduced, and route-related uncertainty must be minimized.

Interpretation of the optimization rules:

1. Priority execution optimization: If $\mu(x), \mu(y), \mu(z)$ is high, then the order is executed immediately. In this case, the system's optimization goal is:$max(\mu(x) + \mu(y) + \mu(z))$, i.e., the system operates with the highest efficiency when an urgent order, sufficient resources, and a favorable route are available simultaneously.
2. Optimization for urgent orders: If $\mu(x)$ and $\mu(z)$ is high, then urgent orders are switched to a fast delivery mode. Here, the optimization is to reduce time loss, strengthen priority delivery, and speed up route selection.
3. Normal Execution Optimization: If $\mu(y)$ and $\mu(z)$ is high, the system selects the normal delivery strategy. In this case, the objective is to use resources in a balanced way, use the route efficiently, and reduce additional costs.
4. Waiting and Scheduling Optimization: If $\tau(y)$ is high, i.e., the resource unavailability rate is large, the order is not executed immediately. The optimization here involves allocating buffer resources, rescheduling orders, and distributing the delivery load.
5. Uncertainty Reduction: If $\theta(x)$ or $\theta(z)$ is high, the system requires additional information. The optimization objective here is: $min\,\theta$, i.e., the system tries to reduce uncertainty before making a decision.

Overall optimization function: In the spherical fuzzy logistics model, the decision score can be expressed as follows:

$$S = w_1\mu(x) + w_2\mu(y) + w_3\mu(z) - w_4\tau(y) - w_5\theta(x,z) \tag{7}$$

where:w_1, w_2, w_3 — positive effect coefficients,w_4, w_5 — negative and uncertain effect coefficients,S — the final decision score.

Objective:$max\,S$, i.e., the system makes decisions so that positive factors increase, negative factors decrease, and uncertainty is minimized.

The optimization result from a logistics perspective: Based on this model, the following optimization strategies are derived: For route optimization, if $\mu(z)$ is low, alternative routes should be established; for resource optimization, if $\tau(y)$ is high, reserve resources and additional vehicles should be allocated; and for emergency order optimization, if $\mu(x)$ is high, a priority delivery mode should be activated. If information optimization θ is high, the system should collect more data. The spherical fuzzy optimization model ensures that decisions in the logistics system are made more flexibly and adapt to real-world conditions. This approach: prioritizes urgent orders, considers resource shortages, evaluates route suitability, and reduces uncertainty.

The 2D rule activation levels for the spherical fuzzy organization decision system are illustrated in Fig. 3. The diagram shows the activation degree of each fuzzy rule (R1–R5) derived from the system inputs. Rules R1 and R2 (Priority) exhibit the highest activation levels, indicating that urgent orders and favorable routing conditions strongly support priority delivery decisions. Rule R3 (Normal) shows moderate activation, while

Rules R4 and R5 (Wait) have lower activation levels, suggesting that delay conditions are less influential in the current system state.

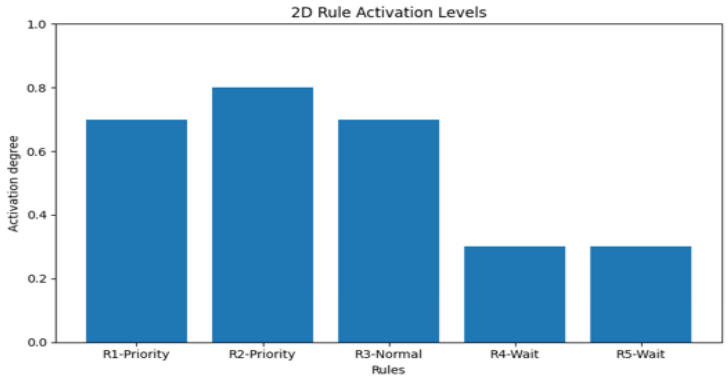


Fig. 3. 2D representation of rule activation levels in the spherical fuzzy logistics decision system.

The 3D decision surface of the spherical fuzzy logistics model is illustrated in Fig. 4. The figure shows the relationship between order urgency μ(x) and resource availability μ(y) on the system's decision score. As the membership values of urgency and resources increase, the decision score gradually rises, indicating a higher likelihood of priority or normal order execution. The AI model produces the same final decisions as the digital model but additionally provides a score for each situation, indicating the strength of the decision and the level of optimization.

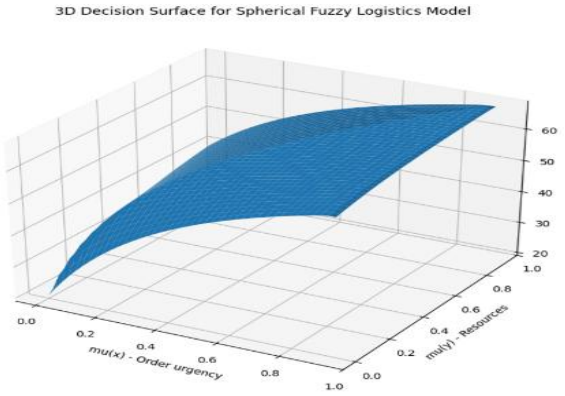


Fig. 4. 3D decision surface illustrating the relationship between input variables in the spherical fuzzy logistics model.

Thus, the model's main optimization principle is expressed as:$max(\mu), min(\theta, \tau)$, i.e., maximizing the positive state, minimizing uncertainty and negative impact. Optimization of the logistics decision model with Spherical Fuzzy Logic.

1. In the mathematical model, each factor in the spherical fuzzy set is described by three parameters: $A = \langle \mu, \theta, \tau \rangle$
   where: μ — membership degree, θ — fluctuation degree, τ — non-membership degree, and the spherical condition must be satisfied: $\mu^2 + \theta^2 + \tau^2 \leq 1$
2. Input variables for the logistics system: x — order urgency, y — resource sufficiency, z — route feasibility

Algorithm steps

Step 1: Enter the input variables: $x = \langle \mu(x), \theta(x), \tau(x) \rangle$, $y = \langle \mu(y), \theta(y), \tau(y) \rangle$, $z = \langle \mu(z), \theta(z), \tau(z) \rangle$.

Step 2: Check the spherical condition:$\mu^2 + \theta^2 + \tau^2 \leq 1$, i.e., if the condition is not met, the input is not accepted.

Step 3: Calculate the activity levels of the IF–THEN rules:R_1, R_2, R_3, R_4, R_5
Step 4: Combine the rule outcomes with the input values.

Step 5: Perform defuzzification and calculate the final score S .

Step 6: Determine the decision:$S < 40 \rightarrow$ wait,$40 \leq S < 70 \rightarrow$ normal execution,$S \geq 70 \rightarrow$ priority execution.

Step 7: Display the rule activations in the 2D diagram.

The results of the AI-based decision model for different system states are presented in Table 4.

Table 4. Comparison of digital model outputs and AI-based decision scores for different system states (x, y, z).

State (x, y, z)	Digital model	AI Decision	AI Score
(0, 0, 0)	0	0	0.00
(0, 0, 1)	0	0	0.35
(0, 1, 0)	0	0	0.30
(0, 1, 1)	1	1	0.65
(1, 0, 0)	0	0	0.35
(1, 0, 1)	1	1	0.70
(1, 1, 0)	1	1	0.65
(1, 1, 1)	1	1	1.00

The comparison between the Boolean digital model and the AI-based decision model across all system states (x, y, z) is illustrated in Fig. 5. The blue bars represent the binary output of the digital model, the orange bars show the final AI decision after threshold evaluation, and the green bars indicate the continuous AI decision score. While both models produce similar final decisions for most states, the AI model additionally provides a graded score that reflects the strength of the decision and enables improved optimization and sensitivity analysis in the decision system.

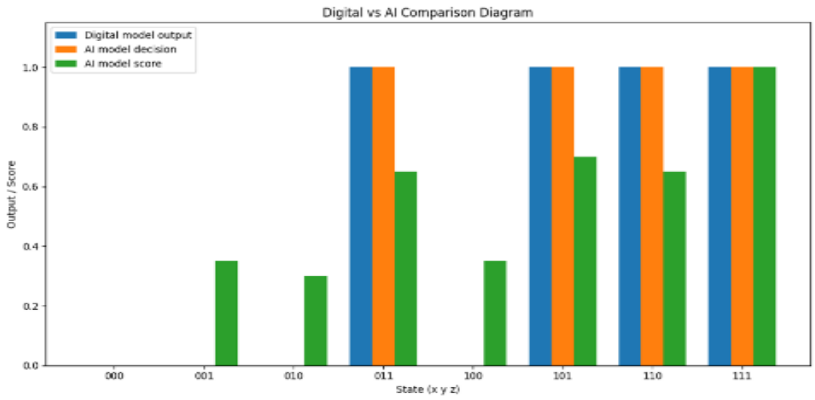


Fig. 5. Comparison of digital model outputs and AI-based decision scores across system states (x, y, z).

The comparison between the digital Boolean model and the AI-based decision model when the route suitability parameter is fixed at z = 1 is illustrated in Fig. 6. The solid surface represents the continuous response of the digital rule-based model, while the wireframe represents the AI model's weighted decision score. The axes correspond to order urgency x and resource availability y. The figure shows that the AI model provides a smoother and more adaptive decision landscape compared to the rigid structure of the digital model, enabling improved optimization and sensitivity analysis in decision-making.

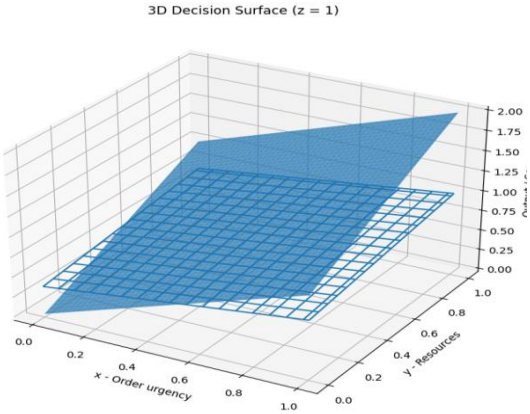


Fig. 6. 3D comparison of digital and AI-based decision models (z = 1).

The difference between the AI model decision score and the digital model surface when the route suitability parameter is fixed at z = 1 is illustrated in Fig. 7. The horizontal axis represents order urgency x, while the vertical axis represents resource availability y. The color scale indicates the optimization gap (AI score − Digital surface), highlighting regions where the AI model provides stronger or weaker responses compared to the digital model. Warm colors indicate higher AI decision scores and improved optimization, while cooler colors indicate regions where the digital model dominates. This visualization helps identify the most influential combinations of urgency and resources for decision optimization.

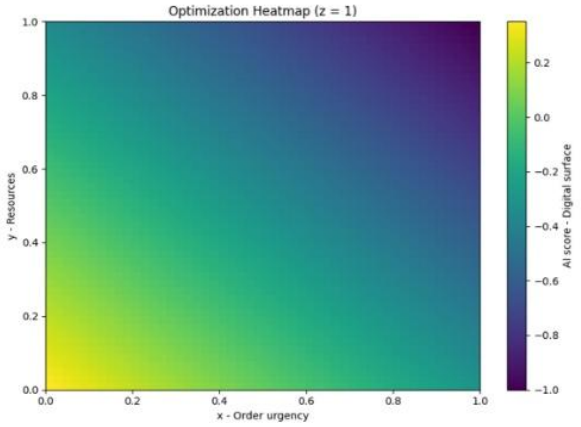


Fig. 7. Optimization heatmap of AI and digital model differences (z = 1).

However, the Boolean model has limitations in representing uncertainty and gradual changes in real-world logistics systems. Therefore, the model is extended using fuzzy logic and spherical fuzzy sets to provide a more flexible and realistic decision-making framework.

Conclusion

This study proposed a transition from a digital Boolean model to an AI-based fuzzy model for a logistics decision-making system. The analysis conducted shows that while the Boolean model can model logistics decisions in a simple and formal way, it does not fully reflect the uncertainty and variable conditions present in real-world systems. For this reason, the model has been extended with fuzzy logic and spherical fuzzy methods. The proposed model makes decisions by considering key logistics factors such as order urgency, resource availability, and route suitability. Simulation results show that the AI-based model creates a more flexible decision-making mechanism and ensures higher efficiency in optimizing logistics systems. 2D and 3D visual analyses also show that the AI model provides a smoother decision surface and higher optimization capabilities. This approach can be considered a promising method for supply chain management, transportation routing, and the development of logistics decision systems.
Conclusion

In this study, a transition from a digital Boolean decision model to an AI-based fuzzy logic model for logistics decision-making was proposed. The results show that while the Boolean model provides a simple and structured framework, it is limited in handling uncertainty and dynamic conditions. By incorporating fuzzy logic and spherical fuzzy sets, the proposed model offers a more flexible and adaptive decision-making mechanism.

The experimental and visual analysis demonstrates that the AI-based model produces smoother decision surfaces and provides additional decision scores, enabling more effective optimization and sensitivity analysis. This allows for better handling of real-world logistics scenarios involving uncertainty in order urgency, resource availability, and route feasibility.

Overall, the proposed approach enhances decision accuracy, flexibility, and optimization capability, making it suitable for applications in supply chain management, transportation systems, and intelligent logistics decision support systems.

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