

Intelligent Inventory Control Using Fuzzy Logic

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Abstract: Inventory management under uncertainty remains a critical challenge in modern supply chains, especially for products subject to perishability, variable lead times, fluctuating demand and potential cost inflation. Traditional deterministic models often fail to capture the inherent vagueness and linguistic nature of these factors. This paper presents the design, implementation and simulation of a Mamdani-type Fuzzy Inference System (FIS) for determining optimal inventory levels. The proposed model incorporates five key input variables—Demand, Lead Time, Perishability, Probability of Price Hike and Product Cost—and produces Inventory (in days of cover) as the output. Membership functions of triangular and trapezoidal shapes were defined for each linguistic variable. A comprehensive rule base was constructed to encode expert knowledge. The system was implemented in FuzzyTech Toolbox and evaluated through surface plots, transfer characteristic plots and interactive rule evaluation. Simulation results demonstrate that the fuzzy controller produces smooth, intuitively consistent inventory recommendations that balance service level against holding and obsolescence risks. The approach offers a practical decision-support tool for inventory planners operating in uncertain environments.

Keywords: Fuzzy Logic, Inventory Control, Mamdani Inference, Perishable Goods, Supply Chain Uncertainty, Membership Functions.

1. Introduction

Effective inventory control is essential for minimizing costs while maintaining adequate service levels. Classical inventory models such as Economic Order Quantity (EOQ), continuous review (s, Q) and periodic review (R, S) systems rely on precise numerical parameters. In real-world settings, however, many parameters are imprecise: demand is expressed linguistically (“high”, “moderate”), lead times vary, products have different degrees of perishability and future price increases are probabilistic. Fuzzy set theory, introduced by Zadeh [1], provides a natural framework for handling such linguistic uncertainty.

Numerous studies have applied fuzzy logic to inventory problems [5], [9], [10], [27], [28]. Early work focused on fuzzy EOQ models with imprecise demand or cost parameters [29], [30]. More recent research has developed multi-input fuzzy controllers and periodic-review models that simultaneously consider several operational factors such as variable lead time and fuzzy demand [4], [6], [31]. Nevertheless, few models integrate the combined effects of demand intensity, replenishment lead time, product perishability,

probability of cost escalation and absolute product cost into a single decision variable—recommended inventory cover (in days). Prior work by the author examined the effect of lead time and product cost on inventory using fuzzy logic [15], providing a foundation for the present multi-factor extension.

This paper addresses that gap by designing a five-input, single-output Mamdani Fuzzy Inference System [2]. The output is expressed in days of inventory cover (0–365 days), a practically meaningful metric for planners. The remainder of the paper is organized as follows: Section 2 describes the system architecture and membership functions; Section 3 presents the rule base; Section 4 discusses simulation results and surface analyses; Section 5 concludes with limitations and future directions.

2. System Architecture and Membership Functions

2.1 Overall Structure

The proposed controller is a Mamdani-type Fuzzy Inference System [2], [7] implemented in the MATLAB Fuzzy Logic Toolbox [8]. Five crisp inputs are fuzzified, evaluated against a rule base

using the minimum (AND) operator, aggregated by the maximum (OR) operator and defuzzified by the centroid method to yield a crisp inventory recommendation. Figure 1 shows the overall project structure of the fuzzy inference system, with the five input variables connected to a single rule block that produces the Inventory output.

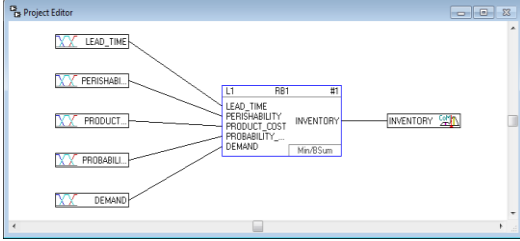


Fig. 1. Fuzzy Inference System architecture

The five input linguistic variables and the single output are defined as follows:

Demand – percentage of expected market volume. Range: 0–100 %. Unit: percentage (%). Relationship: Positive – higher demand increases the recommended inventory cover to avoid stock-outs.

Lead Time – replenishment delay from order placement to receipt. Range: 1–1000 min. Unit: minutes. Relationship: Positive – longer lead times require higher inventory to cover the waiting period.

Perishability – product shelf-life / degradation horizon. Range: 1–1000 h. Unit: hours. Relationship: Negative – highly perishable items (short shelf-life) receive lower inventory to minimise obsolescence and spoilage losses.

Probability of Hike – likelihood of a future increase in product cost. Range: 0–1 (dimensionless). Unit: probability. Relationship: Positive – higher probability of cost escalation encourages larger inventory holdings as a hedge against future price rises.

Product Cost – unit purchase cost of the item. Range: ₹2–₹100000. Unit: Indian Rupees (₹). Relationship: Moderately negative – expensive items are stocked more conservatively (lower cover) unless demand or lead-time pressure is high, in order to limit capital tied up in inventory.

Inventory (Output) – recommended inventory cover expressed as days of supply. Range: 0–365 days. Unit: days. The fuzzy inference system aggregates the five inputs through the rule base and produces a continuous recommendation that

balances service level against holding cost and obsolescence risk.

2.2 Membership Functions

All membership functions (MFs) are piecewise linear (triangular or trapezoidal) as commonly employed in fuzzy control applications [3], [7]. The linguistic terms and their approximate supports are given below.

Demand

Figure 2 shows the membership functions for Demand. Three linguistic terms: Low, Medium, High. Low decreases from 0 to approximately 35 %, Medium peaks around 45–55 % and High rises from about 60 % to 100 %.

Lead Time

Membership functions for the Lead Time are shown in figure 3. Terms: Low, Medium, High. Low is concentrated near short delays (<200 min), Medium covers the mid-range (approximately 200–600 min) and High covers long delays (>600 min).

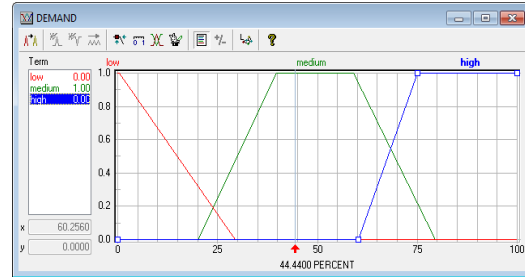


Fig. 2. Membership functions for Demand

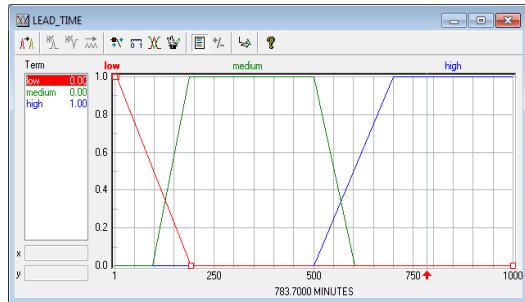


Fig. 3. Membership functions for Lead Time

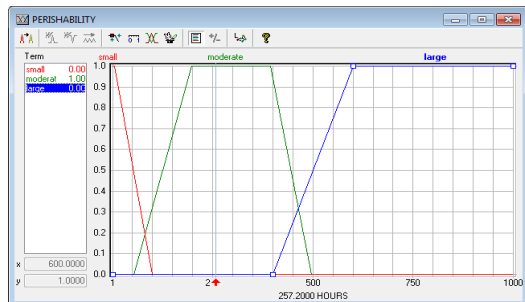


Fig. 4. Membership functions for Perishability

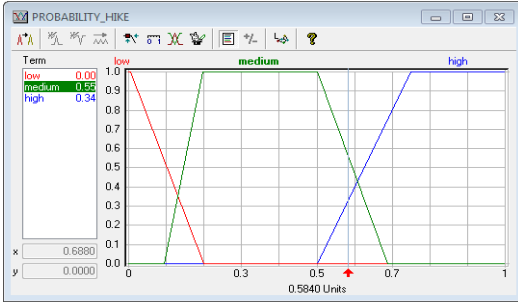


Fig. 5. Membership functions for Probability of Hike

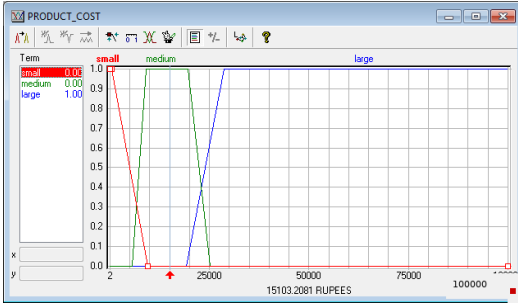


Fig. 6. Membership functions for Product Cost

Perishability

Figure 4 represents the membership functions for Perishability. Terms: Small, Moderate, Large. Small corresponds to highly perishable items (short shelf life), Moderate to intermediate shelf life and Large to relatively non-perishable products.

Probability of Hike

Figure 5 shows the membership functions for Probability of Hike. Terms: Low, Medium, High. Low covers small probabilities near zero, Medium occupies the central region and High rises toward certainty. The universe of discourse is the unit interval [0, 1].

Product Cost

Figure 6 shows the membership functions for Product Cost. Terms: Small, Medium, Large. Small covers low-cost items, Medium spans the intermediate cost band and Large covers high-value items up to ₹100 000. The large term covers expensive items that justify higher inventory investment only under strong demand or long lead times.

Inventory (Output)

Figure 7 shows the membership functions for the Inventory output. Five linguistic terms provide fine granularity: Very Low, Low, Medium, High and Very High. Very Low and Low occupy the lower end of the scale, Medium centres around the middle

range, while High and Very High extend toward the maximum of 365 days.

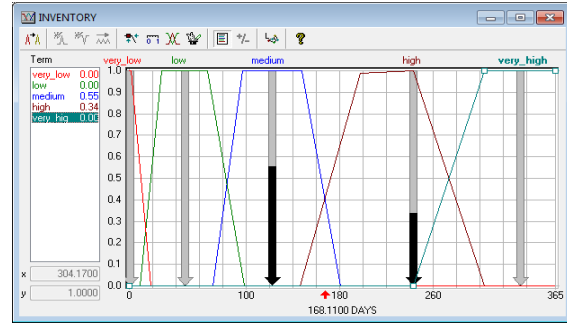


Fig. 7. Membership functions for Inventory (output)

3. Fuzzy Rule Base

A complete rule base was constructed by combining the linguistic terms of the five inputs following the classical Mamdani formulation [2]. Figure 8 shows an excerpt of the fuzzy rule base as displayed in the Rule Editor. Each rule follows the form:

IF Lead_Time is ... AND Perishability is ... AND Product_Cost is ... AND Probability_Hike is ... AND Demand is ... THEN Inventory is ...

The degree of support (DoS) for every rule is set to 1.0, indicating full confidence in the expert-derived knowledge. The inference engine uses the minimum operator for rule activation (AND) and the maximum operator for aggregation of fired rule consequents [3], [7].

#	IF	LEAD_TIME	PERISHABILITY	PRODUCT_COST	PROBABILITY_HIKE	DEMAND	THEN INVENTORY
1	low	small	small	low	low	low	21.00 low
2	low	small	small	low	medium	low	21.00 medium
3	low	small	small	low	high	low	21.00 high
4	low	small	small	medium	low	low	21.00 medium
5	low	small	small	medium	medium	low	21.00 medium
6	low	small	small	medium	high	low	21.00 high
7	low	small	small	large	low	low	21.00 medium
8	low	small	small	large	medium	low	21.00 high
9	low	small	small	large	high	low	21.00 high
10	low	small	medium	low	low	low	21.00 low
11	low	small	medium	low	medium	low	21.00 medium
12	low	small	medium	low	high	low	21.00 high
13	low	small	medium	medium	low	low	21.00 medium
14	low	small	medium	medium	medium	low	21.00 medium
15	low	small	medium	medium	high	low	21.00 high
16	low	small	medium	large	low	low	21.00 medium
17	low	small	medium	large	medium	low	21.00 high
18	low	small	medium	large	high	low	21.00 high
19	low	small	large	low	low	low	21.00 low
20	low	small	large	low	medium	low	21.00 medium
21	low	small	large	low	high	low	21.00 high
22	low	small	large	medium	low	low	21.00 medium
23	low	small	large	medium	medium	low	21.00 high
24	low	small	large	medium	high	low	21.00 high
25	low	small	large	large	low	low	21.00 medium
26	low	small	large	large	medium	low	21.00 high
27	low	small	large	large	high	low	21.00 high
28	low	moderate	small	low	low	low	21.00 low
29	low	moderate	small	low	medium	low	21.00 medium
30	low	moderate	small	low	high	low	21.00 high

Fig. 8. Excerpt of the fuzzy rule base (Rule Editor)

Illustrative rules include:

1. IF Lead_Time is low AND Perishability is small AND Product_Cost is small AND Probability_Hike is low AND Demand is low THEN Inventory is low.
2. IF Lead_Time is low AND Perishability is small AND Product_Cost is small AND Probability_Hike is high AND Demand is high THEN Inventory is high.

3. IF Lead_Time is low AND Perishability is moderate AND Product_Cost is small AND Probability_Hike is low AND Demand is high THEN Inventory is medium.

These rules encode the intuition that higher demand, longer lead times and higher probability of price increases tend to raise recommended inventory, while high perishability and high product cost tend to lower it, subject to trade-offs resolved by the fuzzy aggregation. Similar rule-based reasoning has been successfully applied in other fuzzy control domains such as battery management [16], [17] and medical dosing [11].

4. Simulation Results and Surface Analysis

The completed FIS was evaluated using the Surface Viewer and Transfer Characteristic plots of the MATLAB Fuzzy Logic Toolbox [8]. Selected two-dimensional slices of the five-dimensional input space are presented below.

4.1 Interactive Evaluation Example

For a representative operating point—Demand $\approx$ 44.4 %, Lead Time $\approx$ 784 min, Perishability $\approx$ 257 h, Probability of Hike $\approx$ 0.58, Product Cost $\approx$ ₹15 103—the system recommends approximately 168 days of inventory cover (Figure 9). To further validate the behaviour of the controller, twenty diverse input combinations spanning the operating space were evaluated. The results are summarised in Table I.

TABLE I

Simulation Results for Twenty Input Combinations

Case	Demand (%)	Lead Time (min)	Perishability (h)	Prob. of Hike	Product Cost (₹)	Inventory (days)
1	10.00	120.0	80.0	0.150	5,000	48.75
2	25.00	200.0	150.0	0.250	12,000	75.47
3	35.00	350.0	220.0	0.400	18,000	103.51
4	44.40	783.7	257.0	0.584	15,103	161.82
5	50.00	450.0	300.0	0.550	25,000	135.62
6	60.00	600.0	180.0	0.700	8,000	193.84
7	70.00	750.0	100.0	0.800	15,000	235.43
8	80.00	850.0	400.0	0.900	30,000	232.35
9	90.00	950.0	50.0	0.950	10,000	305.27
10	95.00	900.0	600.0	0.850	45,000	231.22
11	15.00	800.0	50.0	0.200	80,000	86.40
12	30.00	150.0	700.0	0.300	5,000	32.83
13	55.00	500.0	250.0	0.100	20,000	122.90
14	65.00	300.0	350.0	0.600	60,000	133.45

15	40.00	700.0	150.0	0.750	12,000	170.85
16	75.00	400.0	500.0	0.450	35,000	142.00
17	20.00	550.0	900.0	0.500	7,000	38.22
18	85.00	250.0	120.0	0.650	90,000	182.22
19	48.00	650.0	280.0	0.350	22,000	136.60
20	12.00	900.0	40.0	0.880	1,500	158.33

Case 4 corresponds to the interactive evaluation shown in Fig. 9. The remaining cases systematically explore low/high extremes of each input while keeping other variables at intermediate values, confirming that inventory rises with demand, lead time and probability of hike and falls with increasing perishability and (to a lesser extent) product cost.

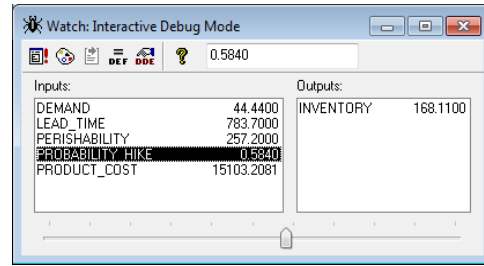


Fig. 9. Interactive rule evaluation (Watch window)

4.2 Surface Plots

Three-dimensional surface plots reveal the non-linear relationships among pairs of inputs while the remaining inputs are held at nominal values.

Perishability vs. Product Cost $\rightarrow$ Inventory (Fig. 10). Inventory is generally higher when perishability is low (long shelf life) and product cost is moderate. Extremely high perishability forces inventory downward regardless of cost.

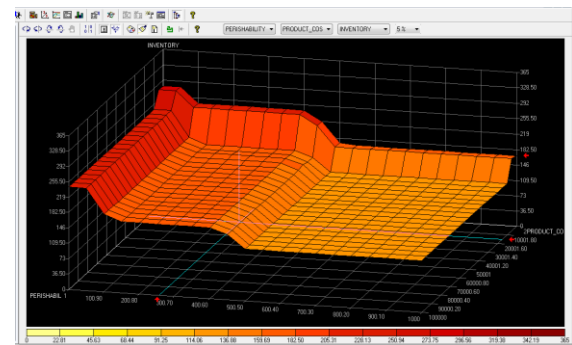


Fig. 10. Surface: Inventory vs. Perishability & Product Cost

Probability of Hike vs. Product Cost $\rightarrow$ Inventory (Fig. 11). A higher probability of future price increase encourages larger inventory holdings, especially when current product cost is not already extreme.

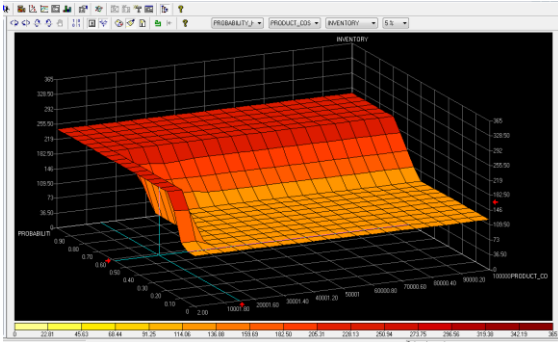


Fig. 11. Surface: Inventory vs. Probability of Hike & Product Cost

Perishability vs. Probability of Hike → Inventory (Fig. 12). The interaction shows that high perishability dominates, keeping inventory low even when the probability of a price hike is elevated.

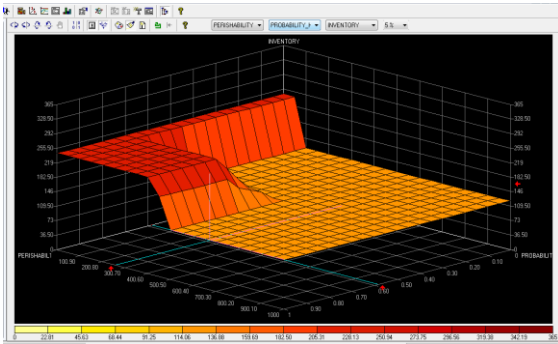


Fig. 12. Surface: Inventory vs. Perishability & Probability of Hike

Lead Time vs. Product Cost → Inventory (Fig. 13). Longer lead times increase recommended inventory, moderated by product cost. This behaviour is consistent with earlier findings on the joint influence of lead time and product cost [15].

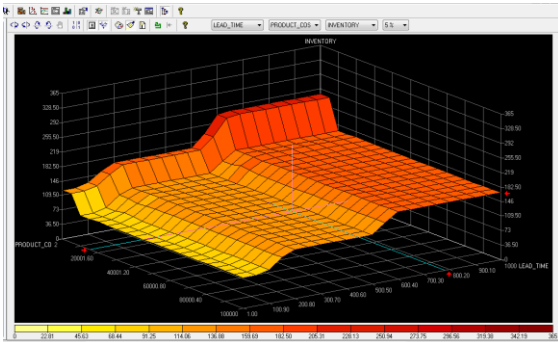


Fig. 13. Surface: Inventory vs. Lead Time & Product Cost

Lead Time vs. Probability of Hike → Inventory (Fig. 14). Both longer lead times and higher probability of cost increase push inventory upward, producing a pronounced ridge in the surface.

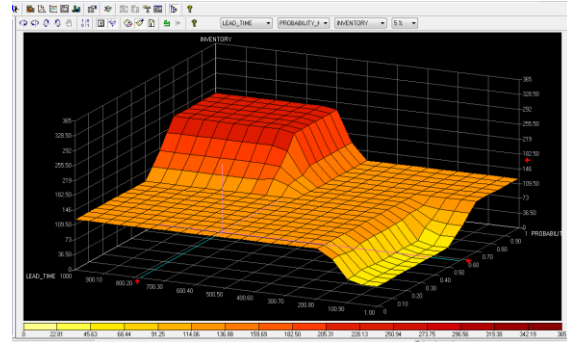


Fig. 14. Surface: Inventory vs. Lead Time & Probability of Hike

Demand vs. Probability of Hike → Inventory (Fig. 15). High demand combined with elevated probability of price hike yields the highest inventory recommendations.

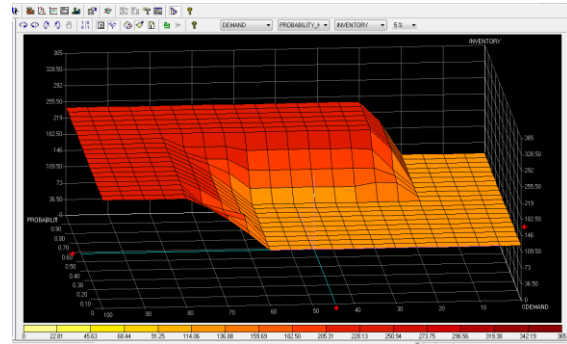


Fig. 15. Surface: Inventory vs. Demand & Probability of Hike

4.3 Transfer Characteristic Plots

Two-dimensional transfer plots further illustrate the monotonic or piecewise monotonic influence of individual variables while others are fixed. Figure 16 shows the transfer characteristic between Probability of Hike and Product Cost. Figure 17 presents the relationship between Perishability and Product Cost. Figure 18 depicts the interaction of Perishability and Probability of Hike. Collectively these plots confirm the expected directional effects: higher demand and higher probability of hike increase inventory; higher perishability decreases it.

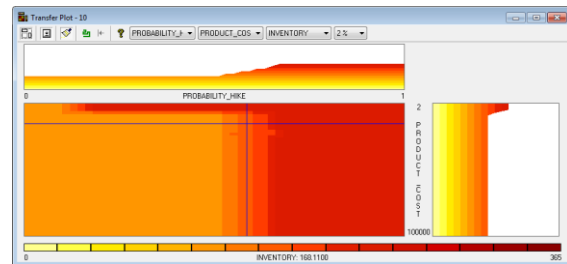


Fig. 16. Transfer plot: Probability of Hike vs. Product Cost

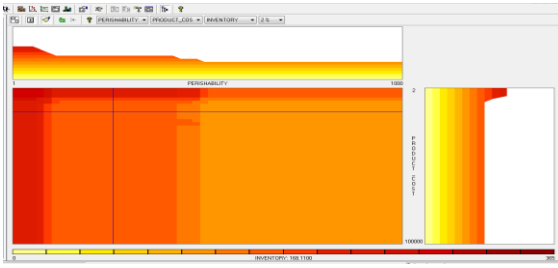


Fig. 17. Transfer plot: Perishability vs. Product Cost

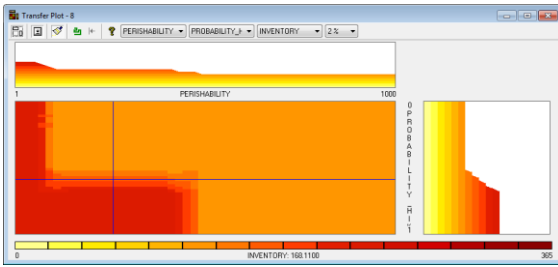


Fig. 18. Transfer plot: Perishability vs. Probability of Hike

5. Discussion

The simulation results (Table I and surface plots) demonstrate that the proposed fuzzy system produces continuous, non-linear control surfaces that respect the qualitative knowledge encoded in the rule base. Key observations include:

- Perishability exerts a strong downward pressure on inventory; highly perishable items receive low cover even under otherwise favourable conditions (Cases 12 and 17).
- Lead time and probability of price hike both act as inventory-increasing factors, consistent with risk-hedging behaviour (Cases 7, 9 and 20).
- Product cost moderates the response: expensive items are stocked more conservatively unless demand or lead-time pressure is high (Cases 11 and 18).
- Demand intensity remains the primary driver of inventory level, as expected (Cases 8–10).

Compared with classical (s, Q) or base-stock policies that require precise statistical distributions, the fuzzy controller accepts linguistic assessments that are readily available from managers and can be updated without recalculating safety factors [5], [10], [27], [31]. The smooth surfaces also avoid the abrupt policy changes that can occur with crisp threshold rules. Similar advantages of fuzzy decision-making have been observed in spectrum

allocation [13], energy systems [14] and quality-of-service control [18]. Fuzzy inventory models that incorporate learning effects or imperfect quality further demonstrate the flexibility of the approach under realistic uncertainty [29], [30].

Limitations of the present study include the reliance on expert-elicited membership functions and rules, the absence of a formal sensitivity analysis of the membership-function parameters and the lack of comparison against a classical stochastic inventory model on the same data set. These aspects constitute natural directions for future work.

6. Conclusion

A five-input Mamdani Fuzzy Inference System for inventory control has been designed, implemented and simulated. The model integrates demand intensity, replenishment lead time, product perishability, probability of future price increases and absolute product cost to recommend a continuous inventory cover measured in days. Membership functions of triangular and trapezoidal shapes, together with a comprehensive rule base, capture the essential trade-offs among service level, holding cost and obsolescence risk. Surface plots, transfer characteristics and a set of twenty diverse simulation cases confirm that the system behaves in accordance with managerial intuition and produces smooth decision surfaces suitable for practical decision support.

Future research will focus on (i) automatic tuning of membership-function parameters via genetic algorithms or neuro-fuzzy techniques, (ii) incorporation of additional inputs such as supplier reliability and storage capacity constraints and (iii) empirical validation against historical inventory and sales data from a real supply chain.

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