



Design and Development of a Decision Support System for Determining Production Quantities in the Furniture Industry Using the Tsukamoto Fuzzy Method

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Article Info :

Received:
27-09-2026
Revised:
06-10-2026
Accepted:
09-10-2026

Abstract

This study addresses the determination of production quantities in the furniture industry, where inaccurate production planning can result in excess inventory, inefficient resource utilization, or insufficient product availability. The study aimed to design a decision support system for determining production quantities at PT. XYZ using the Fuzzy Tsukamoto method. An empirical system development approach was applied using operational data on demand, production, and inventory obtained from company records for the 2024 period. The model employed three main variables, namely demand, inventory, and production, which were represented through fuzzy sets and processed using fuzzification, IF-THEN rule inference, and weighted-average defuzzification. The current-period data consisted of demand of 65 units and inventory of 55 units. The fuzzification process generated membership degrees of 0.70 and 0.30 for decreasing and increasing demand, respectively, while both low and high inventory had membership degrees of 0.50. The four fuzzy rules produced α -predicate values of 0.50, 0.50, 0.30, and 0.30, with corresponding consequent values of 55, 55, 43, and 43 units. Weighted-average defuzzification generated a mathematical output of 50.50 units, which was adopted as a production recommendation of 50 units for operational implementation. The results indicate that the developed Fuzzy Tsukamoto model can integrate demand and inventory conditions into a structured production quantity recommendation and provide an interpretable basis for production planning at PT. XYZ.

Keywords: Decision Support System, Fuzzy Tsukamoto, Furniture Industry, Production Planning, Production Quantity.



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INTRODUCTION

Increasingly intense competition characterizes the current industrial environment, compelling companies to develop production systems that are more responsive, efficient, and adaptable to changing market conditions. Production planning consequently represents a critical managerial function because decisions concerning how much to produce must reconcile market demand, available resources, inventory conditions, production capacity, and operational constraints within a limited planning horizon (Nasution & Prasetyawan, 2008). The determination of production quantity is particularly important because an inaccurate decision may generate excessive inventory, unused production capacity, material waste, or shortages that affect customer satisfaction and operational costs (Pujawan, 2015). Decision-making in such environments cannot be separated from the ability of managers to process multiple and partially uncertain factors, making systematic decision support increasingly relevant to industrial operations (Daihaini, 2001). Within the furniture industry, this challenge becomes more complex because production activities involve heterogeneous raw materials, different product specifications, variable processing requirements, and dependence on fluctuating customer orders. Recent research in the furniture sector has demonstrated that decision support systems can be employed to address production-related problems, including production scheduling, although the focus of such systems remains dependent on the specific decision context and computational method employed (Ulfia et al., 2025).

Production quantity determination is fundamentally a decision problem in which several alternatives must be evaluated against conditions that are not always represented through precise numerical relationships. Classical decision-support approaches provide structured mechanisms for

processing information and assisting managers in selecting appropriate alternatives, yet their effectiveness may be constrained when decision variables contain ambiguity, gradual transitions, or linguistic judgments (Turban et al., 2007). The use of mathematical representations for decision analysis has also demonstrated that multi-attribute problems require an appropriate mechanism for translating different criteria into a decision output that can be operationally interpreted (Azar, 2000). Fuzzy logic offers such a mechanism by representing uncertain concepts through fuzzy sets and membership functions rather than requiring every condition to be expressed as a rigid binary or deterministic value (Klir & Yuan, 1995). In this framework, linguistic expressions such as low, medium, and high can be computationally represented while preserving the gradual nature of real-world conditions, making fuzzy reasoning relevant to production decisions involving uncertain demand and resource availability (Cox, 1994). The development of fuzzy engineering further emphasizes the capacity of fuzzy systems to integrate imprecise information into computational models designed for practical engineering and managerial problems (Kosko, 1997). This characteristic provides a conceptual foundation for applying fuzzy-based decision support to production quantity determination in manufacturing environments.

In fuzzy-based decision systems, variables characterized by uncertainty or vagueness are represented through fuzzy sets in which each element possesses a crisp value associated with a particular degree of membership. The degree of membership ranges from 0 to 1, allowing a production condition to belong to different linguistic categories to varying degrees rather than being forced into a single rigid classification (Kusumadewi & Purnomo, 2004). Such representation enables decision models to accommodate gradual changes in demand, inventory, and production conditions while retaining a computational mechanism that can transform qualitative managerial reasoning into quantitative recommendations. The integration of fuzzy reasoning with computational intelligence has also expanded the capacity of decision-support systems to process nonlinear and uncertain relationships among input and output variables (Jang et al., 1997). In practical decision-making, fuzzy multi-attribute approaches demonstrate that uncertainty can be incorporated into systematic evaluation processes without eliminating the contextual information embedded in human judgment (Kusumadewi et al., 2016). These characteristics make fuzzy logic particularly relevant when production decisions cannot be derived reliably from a single deterministic relationship.

Among the available fuzzy inference approaches, the Tsukamoto method provides a structured mechanism for converting fuzzy rules into a crisp output through monotonic membership functions and weighted inference. Its computational structure is advantageous for decision-support applications because each rule produces a clearly interpretable contribution to the resulting production recommendation, allowing the relationship between operational conditions and the final decision to be traced systematically (Kusumadewi, 2003). Previous research has applied Fuzzy Tsukamoto to determine the production quantity of school chairs by incorporating demand, inventory, labor availability, and production variables, demonstrating its applicability to furniture manufacturing decisions (Bangun et al., 2023). Another study applied the method to raw-material inventory planning in the furniture industry, indicating that fuzzy inference can assist organizations in aligning material availability with anticipated production requirements under uncertain conditions (Purnomo et al., 2020). Fuzzy Tsukamoto has also been implemented in inventory prediction for an acrylic-product MSME, where the system was designed to process historical operational information and translate it into production-related predictions (Hidayatullah & Mujiyono, 2025). These studies indicate that the method has practical relevance, but they also reveal that existing applications tend to emphasize individual operational contexts rather than establishing a more integrated decision-support framework specifically focused on production quantity determination in furniture manufacturing.

The existing literature consequently leaves several conceptual and empirical issues insufficiently addressed, particularly concerning how a production-quantity decision-support system can translate multiple uncertain production conditions into an operational recommendation that remains consistent with the characteristics of furniture manufacturing. Research employing Fuzzy Associative Memory has demonstrated that fuzzy-based decision support can accommodate variables such as demand, resource availability, and production quantity, while also emphasizing adaptability to dynamic manufacturing environments (Bratadikara, 2024). However, the use of different fuzzy architectures indicates that methodological choices can substantially influence how relationships among production variables are represented and interpreted. Previous decision-support research has also established the broader role of computerized systems in structuring decision processes, yet the transition from general

decision-support concepts to a focused production-quantity model requires explicit operationalization of the variables and rules governing the production decision (Kusrini, 2007). The theoretical development of fuzzy artificial intelligence likewise confirms that fuzzy systems are particularly suitable for problems in which precise mathematical relationships are difficult to establish directly from real-world observations (Kusumadewi, 2003). A further limitation concerns the tendency of some production-oriented studies to treat prediction, inventory estimation, scheduling, and quantity determination as interchangeable objectives, even though each represents a distinct managerial decision with different input requirements and output interpretations. Addressing this distinction is important because a system designed to prioritize production schedules cannot automatically be assumed to provide an appropriate model for determining how many units should actually be produced.

The urgency of addressing this problem arises from the direct relationship between production-quantity decisions and the efficiency of material utilization, inventory management, labor allocation, production capacity, and fulfillment of customer demand. An inaccurate quantity decision can propagate through subsequent production and supply-chain activities, creating either excess stock and resource inefficiency or insufficient output and delayed order fulfillment. The furniture industry is particularly exposed to these consequences because variations in product demand must be reconciled with production processes that require material preparation, skilled labor, processing time, and finishing activities before products can be delivered. A decision-support system that explicitly models these conditions can provide a computational bridge between operational data and managerial judgment without requiring production managers to rely exclusively on subjective estimation. The research position adopted in this study is to develop a Fuzzy Tsukamoto-based decision-support model that focuses specifically on determining production quantities rather than merely predicting inventory or prioritizing production schedules. The proposed approach is intended to extend existing applications of fuzzy decision support by embedding the Tsukamoto inference mechanism within a system-oriented framework that can process relevant production variables and generate an interpretable quantity recommendation. The study therefore seeks to design and develop a decision support system for determining production quantities in the furniture industry using the Tsukamoto Fuzzy Method. Its theoretical contribution lies in strengthening the application of fuzzy decision reasoning to production-quantity determination under uncertain industrial conditions, while its methodological contribution lies in formulating an operational decision-support architecture that connects production inputs, fuzzy membership functions, inference rules, and crisp production outputs into an integrated computational process.

RESEARCH METHODS

The study constitutes empirical research based on system design and development, as the Tsukamoto Fuzzy model is developed from the operational conditions of PT. XYZ and evaluated using actual company data. This approach enables the decision support system to be designed according to the production decision requirements identified through direct observation of the production planning process rather than relying solely on conceptual simulation. System development begins by mapping the production planning process at PT. XYZ through interviews and direct observation to identify the input variables relevant to production quantity determination, consistent with the principles of decision support system development that integrate data, models, and decision-making processes (Turban et al., 2007). The collected data comprise operational information related to demand, inventory, and production parameters, which are used as the basis for constructing the fuzzy model according to the characteristics of the company's production system. The model is subsequently developed using the Tsukamoto Fuzzy Method through fuzzification, if-then rule formulation, inference, and defuzzification to generate a crisp production-quantity output, following the application of fuzzy logic in decision support systems (Kusumadewi & Purnomo, 2004). The implementation architecture connects company data inputs with membership functions and a fuzzy rule base so that the system can systematically generate production-quantity recommendations, consistent with previous applications of the Tsukamoto Fuzzy Method for production quantity determination in the furniture industry (Bangun et al., 2023).

Testing is conducted after the model and system have been implemented by using actual PT. XYZ data as test cases to ensure that each computational stage produces outputs consistent with the predefined model rules. Verification is performed by examining the accuracy of the fuzzification

process, the correct application of fuzzy rules, the calculation of α -predicate and weighted-average values, and the consistency of system outputs across different combinations of input values. Model validation is conducted by comparing the production-quantity recommendations generated by the system with the company's actual production conditions and decisions to assess the model's conformity with the observed operational characteristics. This validation procedure employs actual operational data as the basis for evaluating the application of the Tsukamoto Fuzzy Method in furniture-industry raw-material planning (Purnomo et al., 2020). System performance is evaluated based on computational accuracy, output consistency in response to changes in input values, and the difference between system-generated recommendations and actual production quantities used as reference values. This comparative evaluation is used to assess the model's capability to generate computationally consistent and operationally relevant production-quantity recommendations, following the evaluation approach applied to Tsukamoto Fuzzy-based prediction systems for inventory-related decision problems (Hidayatullah & Mujiyono, 2025).

RESULTS AND DISCUSSION

Research Data and Production Conditions

The development of the decision support system requires operational data that accurately represent the production conditions of PT. XYZ. The data used in this study were obtained from company records and documentation covering demand, production, and inventory activities during January–December 2024. These three variables were selected because they represent the main operational conditions that influence production quantity decisions in a manufacturing environment. Demand reflects the quantity of products required by the market, while inventory represents the available stock that can support the fulfillment of demand. Production represents the actual quantity manufactured by the company in each period. The integration of these variables provides the factual basis for constructing the fuzzy model and testing its ability to support production quantity decisions, consistent with the role of decision support systems in integrating operational data with computational models (Turban et al., 2007).

Production planning requires information that can describe the relationship between market requirements, available inventory, and manufacturing output. Nasution and Prasetyawan (2008) explain that production planning involves coordinating production capacity with demand and available resources, making historical operational data important for determining production decisions. The data in this study were not treated merely as descriptive records but as quantitative inputs for the subsequent fuzzification, inference, and defuzzification processes. Historical observations were also important for establishing the ranges of the fuzzy variables used in the model. This approach is consistent with computerized decision-making, in which structured operational information is transformed into a basis for decision formulation (Daihaini, 2001). The relationship among the three variables is particularly relevant in furniture manufacturing because production decisions must consider both customer requirements and stock conditions.

The collected data are presented in Table 1, which contains the demand, production, and inventory values for twelve observation periods and the values identified for the current period. The table preserves the original operational observations so that the subsequent fuzzy calculations can be traced directly to the company's recorded conditions. Demand during the twelve observation periods ranges from 54 to 97 units, while production ranges from 35 to 66 units. Inventory also shows considerable variation, with recorded values ranging from 28 to 73 units. Such variation indicates that a fixed production quantity would not adequately represent the changing operational conditions faced by the company. The use of historical demand and inventory information as a basis for production-related decisions is also consistent with previous decision-support applications in furniture manufacturing (Ulfia et al., 2025).

Table 1. Data on Demand, Inventory, and Production

No.	Month	Demand (Units)	Production (Units)	Inventory (Units)
1	Data 1	77	64	61
2	Data 2	60	55	58
3	Data 3	96	63	47

4	Data 4	97	43	54
5	Data 5	62	66	36
6	Data 6	72	46	28
7	Data 7	80	61	73
8	Data 8	54	55	36
9	Data 9	92	41	34
10	Data 10	89	51	67
11	Data 11	84	44	39
12	Data 12	55	35	70
	This Period	65	55	???

The variation shown in Table 1 demonstrates that the company's production conditions cannot be represented adequately through a single deterministic relationship between demand and production. For example, the recorded demand of 97 units in Data 4 is accompanied by production of only 43 units, whereas demand of 62 units in Data 5 is accompanied by production of 66 units. A similar difference can be observed in inventory, where Data 6 records 28 units while Data 7 records 73 units. These differences indicate that production decisions are influenced by the combined conditions of demand and inventory rather than by demand alone. Such a multi-factor decision structure is consistent with the concept of decision support, in which several relevant attributes are considered simultaneously when formulating an operational decision (Hasan, 2004).

The current-period values provide the direct inputs for the fuzzy decision process developed in this study. The recorded demand for the current period is 65 units, while the available inventory is 55 units. These values are subsequently converted from crisp numerical values into membership degrees through the fuzzification process. The selection of demand and inventory as input variables allows the system to represent gradual changes in operational conditions rather than forcing each observation into rigid categorical boundaries. Fuzzy-set theory provides a framework for representing such conditions through degrees of membership, which is particularly useful when operational categories such as low, high, decreasing, or increasing cannot be defined solely through strict binary limits (Klir & Yuan, 1995). The resulting membership values become the basis for evaluating the applicable production rules.

The data structure also establishes a direct connection between the empirical conditions of PT. XYZ and the computational stages of the proposed decision support system. The historical observations are used to establish the operational ranges of the fuzzy variables, whereas the current-period values are processed to generate the recommended production quantity. This arrangement allows the model to retain the company's actual production characteristics while providing a systematic mechanism for handling uncertainty in demand and inventory conditions. Previous applications of the Tsukamoto method have similarly used operational demand, inventory, and production-related information to support decisions involving production or inventory quantities (Bangun et al., 2023). The resulting data structure also supports subsequent verification because each fuzzy output can be traced back to the original operational inputs. This traceability is important for a decision support system intended for practical manufacturing use, where computational results need to remain interpretable to decision makers (Kusrini, 2007).

Fuzzy Set Formation and Membership Functions

The formation of fuzzy sets is the initial computational stage for transforming the operational conditions of PT. XYZ into variables that can be processed by the Tsukamoto fuzzy method. Three variables are defined in the model, namely demand, inventory, and production, with demand and inventory functioning as input variables and production functioning as the output variable. Each variable is represented by two fuzzy sets to describe gradual operational conditions rather than rigid classifications. The demand variable consists of the DECREASING and INCREASING fuzzy sets, while the inventory variable consists of LOW and HIGH fuzzy sets. The production variable consists of the DECREASING and INCREASING fuzzy sets. This configuration provides a relatively simple rule structure while retaining the ability of fuzzy logic to represent uncertainty through membership degrees (Kusumadewi & Purnomo, 2004).

The demand variable is formed from two linguistic sets, namely DECREASING and INCREASING, based on the operational range identified from the company's historical data. The

minimum boundary for demand is 50 units, whereas the maximum boundary is 100 units. The membership function for the DECREASING set is represented by a linear descending function, while the INCREASING set uses a linear ascending function. The functions are expressed in Equations (1) and (2), respectively, following the membership-function structure used in the original model. These functions assign a membership value between 0 and 1 to each demand observation according to its position within the defined range. The use of linear membership functions also facilitates computational implementation and interpretation within a Tsukamoto-based decision support system (Klir & Yuan, 1995).

$$\mu_{\text{DECREASING}}(x) = \begin{cases} 1, & x \leq 50 \\ \frac{100 - x}{100 - 50}, & 50 \leq x \leq 100 \\ 0, & x \geq 100 \end{cases} \quad (1)$$

$$\mu_{\text{INCREASING}}(x) = \begin{cases} 0, & x \leq 50 \\ \frac{x - 50}{100 - 50}, & 50 \leq x \leq 100 \\ 1, & x \geq 100 \end{cases} \quad (2)$$

The graphical representation of the demand membership functions is presented in Figure 1. The two functions form opposite linear directions, allowing a single demand value to possess different degrees of membership in the DECREASING and INCREASING sets. This characteristic is important because the model does not immediately classify demand as exclusively decreasing or increasing. Instead, the degree of membership changes continuously according to the observed demand value. Such representation is consistent with fuzzy logic, where linguistic conditions are modeled as gradual rather than mutually exclusive categories (Jang et al., 1997). The resulting demand membership degrees are subsequently used as antecedents in the fuzzy inference rules.

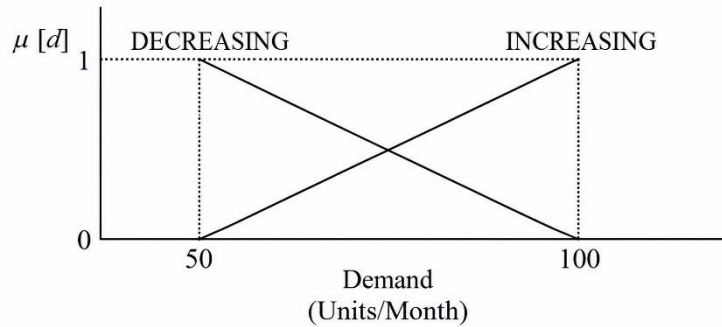


Figure 1. Membership Function of the Demand Variable

The inventory variable is constructed using the LOW and HIGH fuzzy sets, with a minimum boundary of 35 units and a maximum boundary of 75 units. The LOW set represents inventory conditions that approach the lower operational boundary, whereas the HIGH set represents conditions approaching the upper boundary. The corresponding membership functions are presented in Equations (3) and (4). Both functions use a linear form so that the degree of membership changes proportionally across the defined inventory range. This structure allows the model to accommodate intermediate inventory conditions without requiring a rigid threshold between low and high inventory. The use of fuzzy membership for inventory conditions is also relevant to production and inventory planning, where stock levels can affect the quantity that needs to be manufactured in the subsequent period (Nasution & Prasetyawan, 2008).

$$\mu_{\text{LOW}}(y) = \begin{cases} 1, & y \leq 35 \\ \frac{75 - y}{75 - 35}, & 35 \leq y \leq 75 \\ 0, & y \geq 75 \end{cases} \quad (3)$$

$$\mu_{\text{HIGH}}(y) = \begin{cases} 0, & y \leq 35 \\ \frac{y - 35}{75 - 35}, & 35 \leq y \leq 75 \\ 1, & y \geq 75 \end{cases} \quad (4)$$

The production variable functions as the output variable of the fuzzy model and is represented by the DECREASING and INCREASING fuzzy sets. Its operational range is defined between 25 and 85 units based on the production conditions identified in the company's data. The DECREASING production set uses a descending membership function, whereas the INCREASING production set uses an ascending membership function. These functions are expressed in Equations (5) and (6), providing the basis for determining the crisp consequent value associated with each activated rule. The use of monotonic output membership functions is particularly important in the Tsukamoto method because each rule produces a crisp output value according to its firing strength (Kusumadewi, 2003). The resulting output values are later combined through the weighted-average defuzzification process.

$$\mu_{\text{DECREASING}}(z) = \begin{cases} 1, & z \leq 25 \\ \frac{85 - z}{85 - 25}, & 25 \leq z \leq 85 \\ 0, & z \geq 85 \end{cases} \quad (5)$$

$$\mu_{\text{INCREASING}}(z) = \begin{cases} 0, & z \leq 25 \\ \frac{z - 25}{85 - 25}, & 25 \leq z \leq 85 \\ 1, & z \geq 85 \end{cases} \quad (6)$$

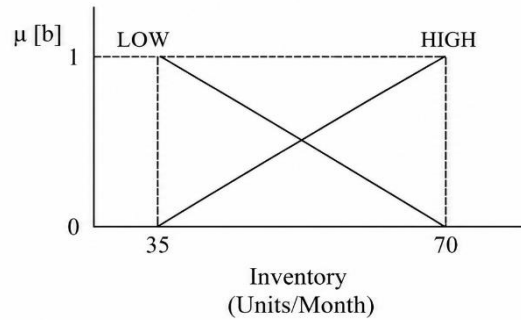


Figure 2. Membership Function of the Inventory Variable

The three sets of membership functions establish the numerical foundation for the fuzzy inference process used in determining production quantity. The demand and inventory functions convert the current-period crisp inputs into membership degrees, while the production functions convert the activated rules into corresponding crisp output values. The selected ranges of 50–100 units for demand, 35–75 units for inventory, and 25–85 units for production maintain consistency with the operational data used in the model. The overlapping nature of the paired membership functions also allows intermediate conditions to activate more than one fuzzy category simultaneously. This feature distinguishes the proposed approach from conventional deterministic classification because an operational condition can contribute to multiple rules with different strengths (Kosko, 1997). The complete production membership structure is illustrated in Figure 3 and becomes the basis for the rule inference and defuzzification stages.

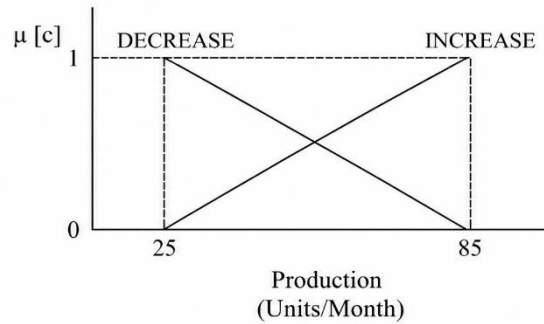


Figure 3. Membership Function of the Production Variable

Fuzzy Rule Composition and Inference Mechanism

The fuzzy rule composition stage translates the relationships among demand, inventory, and production into a set of decision rules that can be processed through the Tsukamoto inference mechanism. The rules are formulated from the two linguistic conditions of demand and the two linguistic conditions of inventory established in the previous stage. Four combinations are generated from these conditions, with demand and inventory functioning as antecedents and production functioning as the consequent. This structure enables the system to consider the simultaneous conditions of market demand and available inventory when determining the direction of production. A rule-based decision structure also provides an interpretable mechanism for connecting operational conditions with production decisions (Kusrini, 2007). The resulting rule base serves as the foundation for the calculation of each rule's firing strength.

The first rule is R1: IF demand is DECREASING AND inventory is LOW, THEN production is DECREASING. This rule represents a condition in which demand is categorized as decreasing and inventory is categorized as low. The second rule is R2: IF demand is DECREASING AND inventory is HIGH, THEN production is DECREASING. Both rules generate a DECREASING production consequent because the demand condition does not indicate an increase in market requirements. The difference between R1 and R2 lies in the inventory condition, allowing the model to distinguish between low and high stock even when the demand condition is identical. Such combinations allow multiple operational attributes to contribute simultaneously to a decision rather than relying on a single input variable (Kusumadewi & Purnomo, 2004). The two rules are included in the complete rule composition shown below.

Table 2. Fuzzy Rule Composition for Production Quantity Determination

Rule	Demand	Inventory	Production
R1	DECREASING	LOW	DECREASING
R2	DECREASING	HIGH	DECREASING
R3	INCREASING	LOW	INCREASING
R4	INCREASING	HIGH	INCREASING

The third rule is R3: IF demand is INCREASING AND inventory is LOW, THEN production is INCREASING. This rule represents a condition in which higher market requirements occur together with limited inventory, producing an inference toward increased production. The fourth rule is R4: IF demand is INCREASING AND inventory is HIGH, THEN production is INCREASING. The four rules collectively represent every combination between the two demand conditions and the two inventory conditions defined in the model. The rule structure provides a direct relationship between the membership functions and the subsequent inference calculations. A complete rule base is important because incomplete combinations could leave particular input conditions without an applicable inference path. The use of four rules also maintains a relatively simple computational structure that can be interpreted and implemented in a practical production decision-support system (Rukmana et al., 2022).

The current-period input consists of 65 units of demand and 55 units of inventory. Based on the established membership functions, the demand value has a membership degree of 0.70 in DECREASING and 0.30 in INCREASING. The inventory value has a membership degree of 0.50 in LOW and 0.50 in HIGH. These values indicate that the current demand condition has a stronger association with the DECREASING category, while the inventory condition has an equal degree of association with both categories. The simultaneous activation of multiple linguistic categories allows the system to process an intermediate operational condition rather than forcing the inputs into a single category. This characteristic is consistent with the use of fuzzy logic for decision problems involving uncertain or gradual changes in operational variables (Klir & Yuan, 1995).

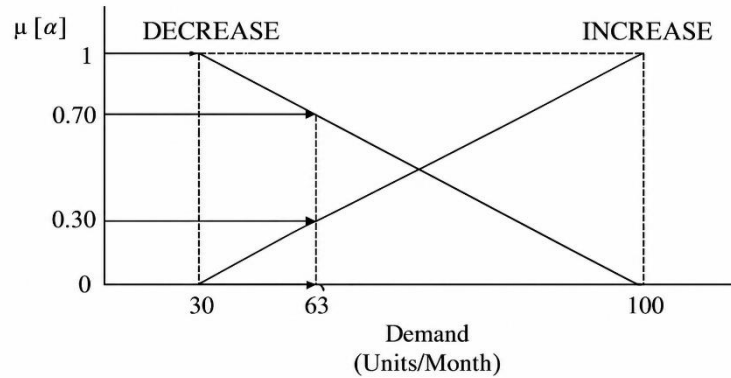


Figure 4. Membership Value of the Demand Variable

The inference process applies the MIN operator to the antecedents connected by the AND operator. For R1, the firing strength is calculated as $\alpha_1 = \min(0.70, 0.50) = 0.50$, using the DECREASING demand and LOW inventory membership values. For R2, the calculation is $\alpha_2 = \min(0.70, 0.50) = 0.50$, because the HIGH inventory membership is also 0.50. For R3, the firing strength is $\alpha_3 = \min(0.30, 0.50) = 0.30$, while R4 produces $\alpha_4 = \min(0.30, 0.50) = 0.30$. The resulting α -predicate values show that all four rules are activated, although R1 and R2 have stronger activation than R3 and R4. This calculation demonstrates how the relative membership degrees of the current demand and inventory conditions directly determine the contribution of each rule to the final production output (Bangun et al., 2023).

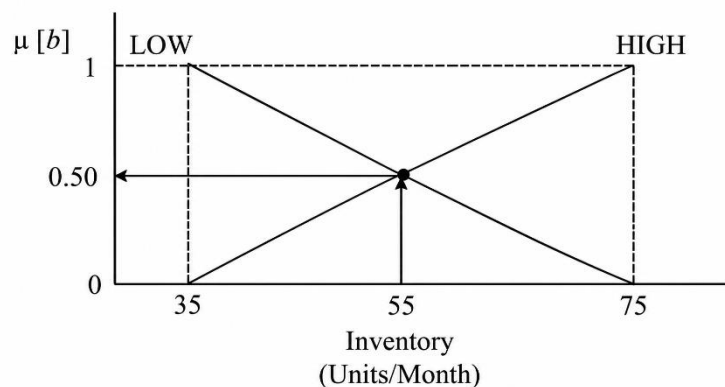


Figure 5. Membership Value of the Inventory Variable

The activated rules subsequently produce crisp consequent values based on the monotonic production membership functions defined previously. For R1 and R2, an α -predicate of 0.50 produces $c_1 = 55$ and $c_2 = 55$, respectively, while R3 and R4, with α -predicate values of 0.30, produce $c_3 = 43$ and $c_4 = 43$. The corresponding weighted contributions are $\alpha_1 c_1 = 27.50$, $\alpha_2 c_2 = 27.50$, $\alpha_3 c_3 = 12.90$, and $\alpha_4 c_4 = 12.90$. These values demonstrate that the rules associated with decreasing demand contribute more

strongly to the aggregated output than the rules associated with increasing demand. The inference results provide the numerical inputs required for the weighted-average defuzzification stage in which the activated rule outputs are combined into a single production quantity. The relationship between membership degrees, rule activation, and consequent values establishes a transparent computational pathway from the current operational data to the final production recommendation.

Production Quantity Determination and Model Evaluation

The final stage of the fuzzy Tsukamoto model is the determination of production quantity through defuzzification. At this stage, the crisp output generated by each activated rule is combined according to its firing strength. The current-period demand of 65 units and inventory of 55 units generate four activated rules with different α -predicate values. The inference results consist of $\alpha_1 = 0.50$ with $c_1 = 55$, $\alpha_2 = 0.50$ with $c_2 = 55$, $\alpha_3 = 0.30$ with $c_3 = 43$, and $\alpha_4 = 0.30$ with $c_4 = 43$. These values indicate that the rules associated with decreasing demand contribute more strongly to the aggregated production output than those associated with increasing demand. The use of weighted aggregation allows the final output to reflect the combined strength of all applicable rules rather than relying on only one rule (Kusumadewi & Purnomo, 2004).

The weighted contributions of each rule are calculated by multiplying the α -predicate by its corresponding crisp consequent value. For R1, the calculation produces $0.50 \times 55 = 27.50$, while R2 also produces $0.50 \times 55 = 27.50$. R3 produces $0.30 \times 43 = 12.90$, and R4 produces $0.30 \times 43 = 12.90$. The aggregation of these values produces a numerator of 80.80, while the sum of all α -predicate values is 1.60. The defuzzification process can be expressed using the following weighted-average equation.

$$c = \frac{\sum_{i=1}^n \alpha_i c_i}{\sum_{i=1}^n \alpha_i}$$

$$c = \frac{(0.50)(55) + (0.50)(55) + (0.30)(43) + (0.30)(43)}{0.50 + 0.50 + 0.30 + 0.30}$$

$$c = \frac{27.50 + 27.50 + 12.90 + 12.90}{1.60} = \frac{80.80}{1.60} = 50.50$$

The calculation produces a defuzzified output of 50.50 units. This value represents the mathematical output of the weighted-average procedure based on the membership degrees and rule consequents obtained from the current-period data. The result demonstrates that the fuzzy model integrates the four activated rules into a single quantitative production value rather than producing separate recommendations for each operational condition. The Tsukamoto approach is suitable for this type of calculation because each rule produces a crisp consequent that can be aggregated according to its activation strength (Cox, 1994). The resulting output provides a computational basis for determining the production quantity that should be considered by PT. XYZ.

Table 3. Defuzzification Calculation of Production Quantity

Rule	α -Predicate	Crisp Output (c)	$\alpha \times c$
R1	0.50	55	27.50
R2	0.50	55	27.50
R3	0.30	43	12.90
R4	0.30	43	12.90
Total	1.60	—	80.80

Table 3 shows that R1 and R2 have the largest contributions to the final output because their α -predicate values are higher than those of R3 and R4. The equal contribution of R1 and R2 results from the identical membership degree of 0.50 for the two inventory conditions at the current inventory value. Meanwhile, R3 and R4 contribute smaller weighted values because the INCREASING demand membership is only 0.30. The distribution of these contributions illustrates how the fuzzy system converts overlapping linguistic conditions into a quantitative production decision. Similar computational structures have been applied in fuzzy Tsukamoto-based production and inventory

decision systems to determine quantities under changing operational conditions (Purnomo et al., 2020). The result also provides an interpretable basis for evaluating whether the model output is consistent with the company's current production situation.

Based on the computational result, the model generates a defuzzified production quantity of 50.50 units, while the operational recommendation stated in the model is 50 units. The difference between the mathematical output and the stated operational quantity should be understood as a distinction between the continuous fuzzy output and the production quantity expressed in whole units. The model output itself remains 50.50 units because that value follows directly from the weighted-average calculation using the four rule outputs. The production recommendation of 50 units represents the quantity adopted in the study for operational decision-making. A whole-unit production recommendation is relevant in practical manufacturing because production quantities are implemented as discrete units rather than fractional products. The relationship between the calculated fuzzy output and the adopted production quantity provides an important point for interpreting the model's practical application.

The evaluation of the model focuses on the consistency of the computational process with the actual operational inputs of PT. XYZ. The system processes demand and inventory values through fuzzification, rule activation, consequent calculation, and weighted-average defuzzification in a sequential manner. Each stage can be traced from the original input values of 65 units of demand and 55 units of inventory to the resulting production output. This traceability supports verification of the membership calculations and the activation of the four predefined rules. Previous applications of decision support systems using fuzzy Tsukamoto have similarly emphasized the use of operational data and computational verification to support inventory and production-related decisions (Hidayatullah & Mujiyono, 2025). The resulting model provides PT. XYZ with a structured computational mechanism for translating changing demand and inventory conditions into a production quantity recommendation.

CONCLUSION

Based on the design and implementation of the decision support system at PT. XYZ, this study demonstrates that a production quantity determination model can be developed using three main variables: demand, inventory, and production. These variables represent interrelated operational conditions within the company's production planning process. The demand variable describes changes in market requirements, while the inventory variable represents the stock available during the decision-making period. The production variable functions as the output that determines the quantity to be manufactured based on the conditions of the two input variables. The three variables are represented through fuzzy sets, with DECREASING and INCREASING categories for demand and production and LOW and HIGH categories for inventory. This structure enables the system to process operational conditions through fuzzification, rule formation, inference, and defuzzification. The resulting model provides a structured and traceable decision-making mechanism based on the company's operational data.

The application of the model to the current-period conditions, with demand of 65 units and inventory of 55 units, generated membership degrees that activated four fuzzy rules. The resulting α -predicate values were 0.50 for R1 and R2 and 0.30 for R3 and R4, with consequent values of 55 and 43 units, respectively. The weighted-average calculation produced a mathematical output of 50.50 units based on the aggregation of all activated rules. This result demonstrates that the model can integrate demand and inventory conditions into a single quantitative output to support production decisions. For operational implementation in this study, the production quantity was set at 50 units as the recommendation generated by the developed model. The system provides a more structured approach to determining production quantity than relying on a single operational condition. The developed model can serve as a decision-support basis for production planning at PT. XYZ by considering changes in demand and inventory conditions simultaneously.

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