ENHANCED FUZZY LOGIC-BASED APPROACH TO INVENTORY MANAGEMENT CONSIDERING SPARE PART LIFETIME AND LEAD TIME UNCERTAINTY

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ABSTRACT: Effective management of spare parts inventory is essential for maintaining uninterrupted industrial operations. Traditional systems often struggle to adapt to the dynamic uncertainties of machine health and lead times, which can result in inadequate inventory levels and increased downtime. This research introduces a novel integration of fuzzy logic control to improve inventory management by addressing these uncertainties. The study focuses on spare part management in a wood substitute manufacturing case involving the refiner process, utilizing a min-max inventory strategy in conjunction with a fuzzy inference system that evaluates machine health and lead times. Various fuzzy numbers, including triangular, trapezoidal, pentagonal, and hexagonal, are employed to model these uncertainties, leading to reduced holding and stock costs compared to conventional approaches. The results show that the total cost under the fuzzy inventory control policy is approximately three times lower and substantially less than that of the non-fuzzy policy, as confirmed by 95% confidence intervals that are clearly distinct. However, the analysis reveals no significant difference among the fuzzy numbers, indicating flexibility in selection based on specific application needs. Overall, this work underscores the potential of fuzzy logic control to optimize spare part inventory management in industrial contexts.

KEYWORDS: *Spare Part; Inventory; Fuzzy; Machine Health; Lead Time*

1.0 INTRODUCTION

Efficient management of spare parts inventory is critical for ensuring uninterrupted operations in various industrial environments. Traditional inventory management systems often find it challenging to respond to the dynamic and uncertain nature of machine health status and lead times, resulting in suboptimal inventory levels and increased downtime. To address these challenges, the integration of fuzzy logic control presents a promising strategy to enhance spare part inventory management by incorporating the inherent uncertainty and imprecision associated with machine health status and lead times. Machine health status is a critical factor influencing the demand for spare parts. As machines operate, their health status can deteriorate over time due to factors such as wear and tear, aging components, or environmental conditions. A decline in machine health can heighten the likelihood of component failures or malfunctions, leading to increased demand for spare parts necessary for repairs and maintenance activities.

This research focuses on a case study of a manufacturing company producing medium-density fiberboard (MDF) in Thailand. The continuous production process of MDF is illustrated in Figure 1.

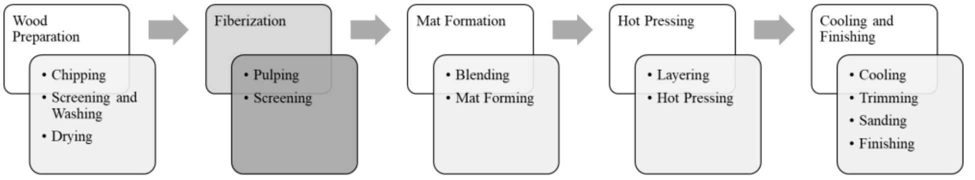


Figure 1: Operation process chart of medium-density fiberboard.

Our study focused on the pulping process, where the refiner plays a crucial role. The segments of the refiner, as depicted in Figure 2, are spare parts. Currently, inventory management follows the min-max inventory policy. The minimum inventory level (Min) serves as a reorder point, triggered when the total inventory, comprising on-hand and in-transit stock, falls below the Min threshold. At this point, the order quantity (Q) is adjusted to reach the maximum inventory level (Max). The Q value can be determined either as the difference between Max and Min or calculated using the economic order quantity formula. Consequently, the maximum inventory level (Max) is the sum of the minimum level (Min) and the order quantity (Q). Figure 3 illustrates the inventory control process for these spare parts. The primary drawback of the current inventory management system is its failure to account for the stochastic nature of machine conditions and spare part lead times. This limitation can result in overstocking or understocking, leading to increased inventory management costs.

Figure 2: Refiner segments of defibrator.

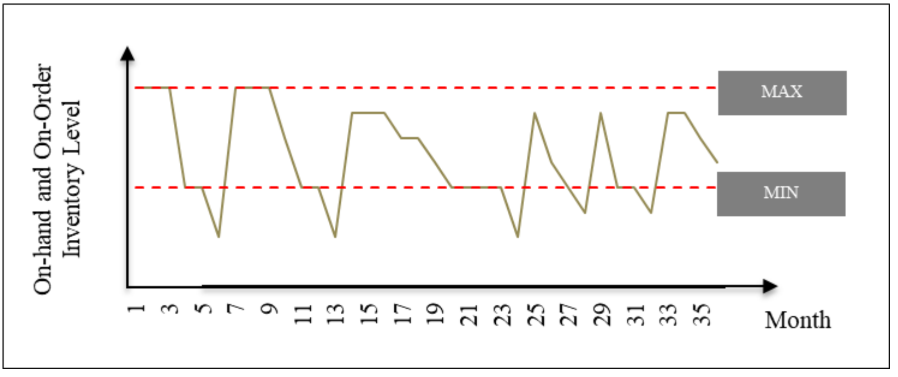


Figure 3: Refiner segments inventory level by month.

The objective of this research is to propose a spare parts inventory system using fuzzy logic control to address the uncertainties associated with machine health and spare part lead times. The existing approach for determining order quantity based on a fixed maximum may not be ideal. By modeling the uncertainties in machine health indicators and lead time forecasts, the system seeks to optimize inventory levels. Integrating fuzzy logic assessments into the replenishment decision-making process can enhance inventory management efficiency, improve resilience to uncertainty, and reduce overall inventory costs.

A fuzzy inference system is employed to establish relationships between input and output variables within a system. In this context, precise inputs are transformed into fuzzy inputs through a fuzzification interface. Following fuzzification, a rule base is created. The combination of the rule base and database forms the knowledge base. Defuzzification is then applied to convert the fuzzy values back into actual output values. Fuzzy inference systems are utilized in various fields, including management and manufacturing contexts [1–5]. Fuzzy control has emerged as a promising method for addressing the complexities inherent in probabilistic inventory models, particularly when dealing with uncertainties. Hsieh [6] proposed a fuzzy inventory model tailored for the computer mouse industry, which accounts for uncertainties in demand and lead time while focusing on order quantities, reorder points, and safety stock. The study's results indicate that utilizing trapezoidal fuzzy numbers can minimize total annual inventory and safety stock costs. Similarly, De and Rawat [7] developed exponential fuzzy numbers to address uncertainties related to demand and lead time, concentrating on order quantities and safety stock. Their findings demonstrate that using exponential fuzzy numbers facilitates sensitivity analysis of optimized parameters in response to variations in service levels. Aengchuan and Phruksaphanrat [8] applied fuzzy logic to determine order quantities and reorder points in the wood-based furniture industry, considering uncertainties in both demand and supply. Their results reveal that the proposed fuzzy inventory system (FIS) can achieve lower costs compared to traditional

FIS lot-sizing methods. Uthayakumar and Karuppasamy [9] developed a fuzzy inventory model for lot sizing in the healthcare sector by incorporating demand variables, storage costs, order costs, and order quantities. Their research suggests that using triangular fuzzy numbers results in a total cost slightly higher than that of a crisp model. Jamegh et al. [10] created a fuzzy logic system for determining safety stocks in the dairy processing industry while considering factors such as demand, raw material availability, end-of-stock, and safety stock. Their findings indicate that implementing trapezoidal fuzzy numbers positively affects the reduction of safety stock levels. However, in terms of fuzzy inventory, researchers are increasingly interested not only in inventory management parameters but also in related issues. These include active steering control systems [11], hard turning [12], machine deterioration [13, 14], carbon emissions [15–17], defective items [18], financial issues [19], and transportation scheduling [20], among others.

Based on the aforementioned literature, although significant advancements have clearly been made in inventory management within fuzzy environments, the application to spare part inventory systems, particularly those incorporating condition-based maintenance strategies, remains largely unexamined. This study addresses this research gap by proposing a novel inventory control framework that utilizes fuzzy logic modeling alongside machine health monitoring. By using machine health status as a determinant of spare part demand and accounting for variability in order lead times, the proposed system introduces a more responsive and adaptive inventory strategy.

This research contributes to the development of robust and adaptive inventory systems capable of tackling the challenges posed by uncertainties in machine health status and order lead times. Unlike traditional models that operate under deterministic assumptions, our approach employs fuzzy logic control to manage and model the ambiguity common in real-world industrial operations, thus enhancing decision-making under uncertainty. This integration not only strengthens the connection between predictive maintenance and inventory planning but also promotes greater operational resilience and cost efficiency. The framework adds to the growing body of research in FISs by providing a practical and empirically validated model adaptable to continuous production environments. Through a real-world case study involving the MDF industry, this study aims to demonstrate both the theoretical contributions and practical implications of this enhanced fuzzy logic-based inventory system for industrial practitioners and researchers alike.

2. RESEARCH METHOD

This study introduces a novel fuzzy logic-based inventory management framework aimed at addressing uncertainties in spare part lifetime and lead time, particularly in continuous manufacturing environments. In contrast to traditional systems that depend on fixed reorder points and simplistic assumptions about uncertainty, this approach integrates the entire modeling, inference, and evaluation process. The research begins with the formulation of real-world problems and advances through fuzzy system development, rule-based inference using a Mamdani fuzzy inference system, and uncertainty modeling via Monte Carlo simulation, culminating in a cost-based performance evaluation. Major features include the utilization of machine health indicators and stochastic lead times as fuzzy input variables, representing a condition-based inventory strategy that is seldom considered in conventional models. In addition, the study employs four types of fuzzy numbers, namely, triangular, trapezoidal, pentagonal, and hexagonal, to represent uncertainty in the output variable flexibly, allowing for a detailed comparison of their performance. By integrating these elements, the proposed framework provides a comprehensive and adaptable decision-support system that enhances inventory control under uncertainty, ultimately contributing to more resilient and cost-efficient industrial operations.

This section outlines the methodology used for developing, testing, and evaluating the FIS for managing spare part inventory. Figure 4 illustrates the research framework. The first step involved identifying the problem to be addressed. A case study of the manufacturing process at a company producing MDF in Thailand was conducted to define the objectives, scope, and various requirements. Next, the FIS was developed, followed by a numerical experiment for evaluation. Finally, the results are summarized and discussed.

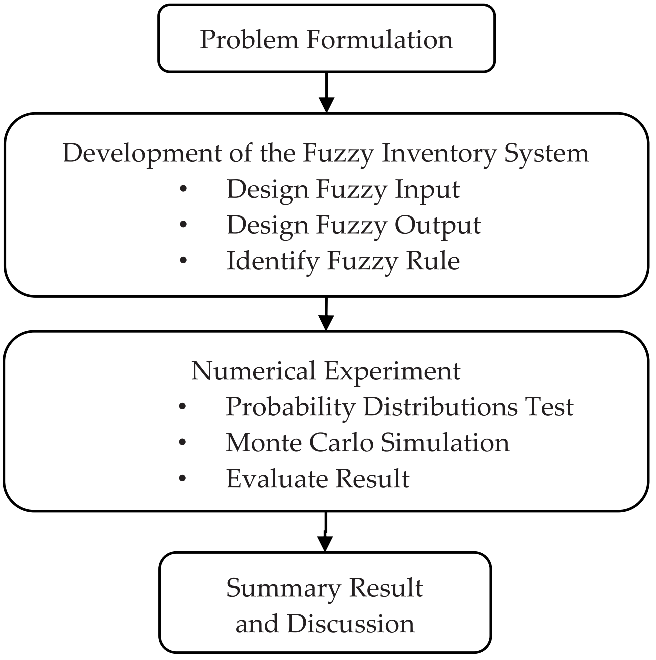


Figure 4: Research method.

2.1 Development of the FIS

The development of the FIS consisted of three core components: fuzzy inputs, fuzzy outputs, and fuzzy rules. The system included two fuzzy input variables: spare part lifetime and order lead time, both represented by triangular membership functions derived from historical data and observations. A single fuzzy output variable, the maximum quantity, was defined using various types of fuzzy numbers, including triangular, trapezoidal, pentagonal, and hexagonal.

A fuzzy set is characterized by a membership function that assigns values ranging from [0, 1] to elements within a domain, space, or universe of discourse X. In this context, a fuzzy set $\tilde{A}$ in the universe X is represented by a set of pairs as follows:

$$\tilde{A} = \{x, \mu_A(x); x \in X\} \tag{1}$$

where $\mu_A: X \in \rightarrow [0,1]$ is a mapping known as the degree of membership function of the fuzzy set A and $\mu_A(x)$ is known as the membership value of $x \in X$ in the fuzzy set $\tilde{A}$. These membership grades are typically expressed as real numbers within the range of [0,1]. A fuzzy number $\tilde{A}$, defined as a fuzzy set on the real line R, must satisfy the following conditions:

i. $\mu_{\tilde{A}}(x_0)$ is piecewise continuous.
ii. There exists at least one $x \in X$ with $\mu_{\tilde{A}}(x_0) = 1$.
iii. $\tilde{A}$ must be normal and convex.

In this study, four fuzzy sets are investigated; 1) triangular fuzzy set, 2) trapezoidal fuzzy set, 3) pentagonal fuzzy set, and 4) hexagonal fuzzy set. Further details on these fuzzy sets can be found in Chakraborty et al. [14] and Pathinathan and Ponnivalavan [21]. Subsequently, a fuzzy rule base consisting of nine rules was constructed using the Mamdani fuzzy inference approach. These rules establish relationships between input levels (low, medium, and high) and output levels (low, medium, and high). The max-min compositional operation in fuzzy reasoning produces fuzzy outputs. These outputs can be expressed as

$$\mu_Q(y) = \left(\mu_{D_1}(x_1) \cap \mu_{LT_1}(x_2)\right) \cup .. \left(\mu_{D_n}(x_1) \cap \mu_{LT_n}(x_2)\right) \tag{2}$$

where ∩ signifies the minimum operation and ∪ signifies the maximum operation. D_i, LT_i, and Q_i are fuzzy subsets defined by the corresponding membership functions. Afterward, to translate the fuzzy outputs into precise values, the center-of-gravity method was applied for defuzzification. This method is used to transform the fuzzy inference output into a non-fuzzy value, as expressed by

$$y = \frac{\sum y(\mu_Q(y))}{\sum \mu_Q(y)} \tag{3}$$

2.2 Numerical Experiment Design

A Monte Carlo simulation was performed to model the range of outcomes while considering uncertainties in demand, lifetime, and lead time based on 36 months of historical inventory data from the refiner segment. A statistical analysis was conducted to assign appropriate probability distributions to the input variables; the analysis validated through a chi-square test. Utilizing random parameters based on their respective distributions, the simulation was performed for 30 runs. Inventory costs were analyzed with respect to ordering costs, which include expenses related to placing and receiving orders, and holding costs, which encompass storage expenses and opportunity costs, with an annual interest rate of 1.5%. A cost analysis was conducted by varying parameters such as spare part lifetime and lead time, calculating inventory costs with different fuzzy numbers, and comparing average monthly inventory costs. The assumptions, notations, and equations for the analysis are provided as follows. *Assumption*:

i. The demand for refiner segments of the defibrator is uncertain and depends on the machine's health status.
ii. Order lead time is unpredictable but can be estimated using available data and expert knowledge.
iii. Shortages are not allowed.

Notation:

O: Ordering cost per order
K: Number of orders per year
H: Holding cost per unit
Q_h: Holding quantity per year
C: Unit price
I: Interest rate

The inventory cost, including ordering cost, holding cost, spare part cost, and total cost are expressed via the following Equations (4)–(6), respectively.

$$\text{Ordering cost} = KO \tag{4}$$
$$\text{Holding cost} = (H+IC)Q_h \tag{5}$$
$$\text{Total cost} = KO + (H+IC)Q_h \tag{6}$$

Finally, the overall inventory management costs that include ordering, holding, and stock costs were computed. These results were further assessed through a 95% confidence interval analysis to compare the effectiveness of various inventory control policies.

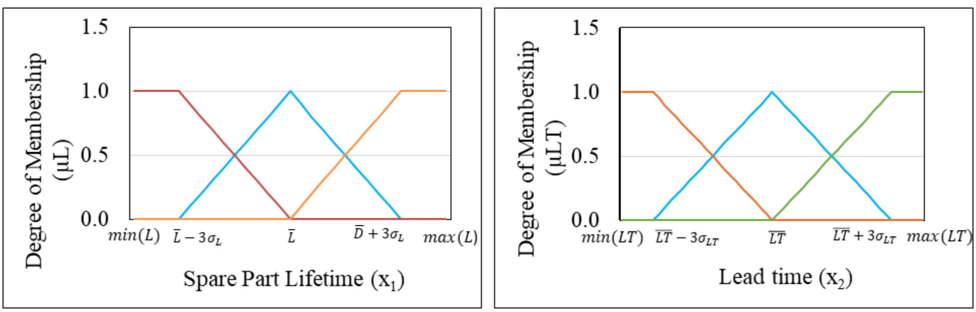
3. RESULTS AND DISCUSSION

3.1 FIS Model

The proposed FIS model consists of three components: fuzzy inputs, fuzzy outputs, and fuzzy rules. The two fuzzy input variables are spare part lifetime and order lead time, and the output variable is the maximum quantity. These variables are expressed using linguistic terms.

3.1.1 Fuzzy Inputs

The fuzzy inputs include spare part lifetime and order lead time, described by the membership functions μ_L and μ_{LT}, respectively. Fuzzy lifetime and lead time were established based on observations and historical data analysis. Each is categorized into three linguistic values of low, medium, and high, as illustrated in Figure 5. The input parameters were shaped by a normal distribution that that captures the uncertainty concerning spare part lifetime and lead time. The universe of discourse for the spare part lifetime is defined over the interval [min(L), max(L)], where min(L) and max(L) denote the minimum and maximum observed lifetimes, respectively. Membership functions for the lifetime are defined by the parameters ($\min(L)$, $\bar{L} - 3\sigma_L$, $\bar{L}$, $\bar{L} + 3\sigma_L$, $\max(L)$), as shown in Figure 5(a). Likewise, the universe of discourse for the lead time input space is defined within the interval [$\min(LT)$, $\max(LT)$], where $\min(LT)$ and $\max(LT)$ denote the minimum and maximum observed lead times, respectively. Membership functions for lead time are determined by these parameters ($\min(LT)$, $\overline{LT} - 3\sigma_{LT}$, $\overline{LT}$, $\overline{LT} + 3\sigma_{LT}$, $\max(LT)$), as shown in Figure 5(b).



(a) (b)

Figure 5: Input membership functions: (a) spare part lifetime MFs and b) lead time MFs.

3.1.2 Fuzzy Outputs

Traditional min-max inventory models rely on a fixed maximum quantity value. However, in practice, uncertainties in demand and lead time render fixed values unsuitable, particularly given the irregularities in demand patterns. To address this, a fuzzy output is proposed, namely, the fuzzy maximum quantity, which is defined by membership functions denoted as μ_Q . This fuzzy maximum quantity is categorized into three linguistic values: low, medium, and high. The range for the maximum quantity output is established within the interval [min(Q), max(Q)], where max(Q) signifies the highest observed quantity in current practices, whereas min(Q) targets minimizing the total inventory cost. In addition, we aim to illustrate various types of fuzzy numbers to provide decision-makers with a plethora of options.

Therefore, classical triangular and trapezoidal fuzzy numbers were used in this research, alongside pentagonal and hexagonal fuzzy numbers, which offer additional capacity to convey uncertain knowledge and formulate responses. Figure 6 illustrates the various types of fuzzy numbers utilized in this study. Four types of fuzzy numbers were employed to model the output variable within the fuzzy inference system, as depicted in Figure 6. The triangular fuzzy number (Figure 6a) is straightforward and intuitive, typically used in early model development and suitable when uncertainty is centered around a peak value, exhibiting symmetric or asymmetric spreads. The trapezoidal fuzzy number (Figure 6b) represents range-based uncertainty, where multiple values carry equal likelihood, thus providing enhanced flexibility for cases in which the output may fall within a defined interval.

The pentagonal fuzzy number (Figure 6c) offers higher resolution than the previous types and is effective when modeling more complex uncertainty distributions, particularly when the data indicates numerous transitions in membership levels. Finally, the hexagonal fuzzy number (Figure 6d) provides the greatest granularity and adaptability among all four, making it ideal for capturing highly nuanced or irregular uncertainty patterns in systems that exhibit complex or unpredictable behaviors.

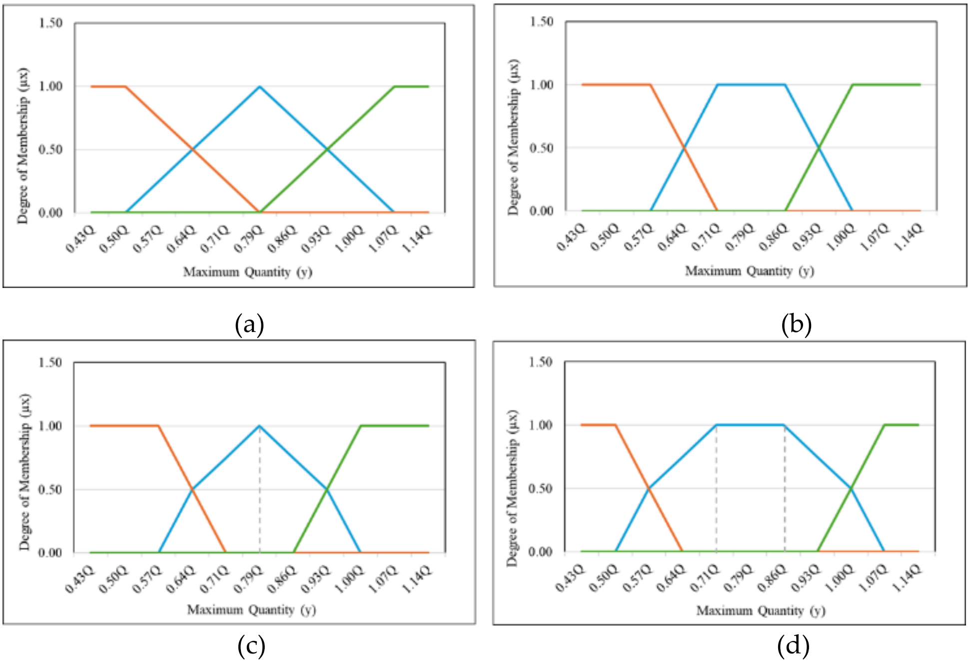


Figure 6 Different types of output membership functions: (a) triangular fuzzy numbers, b) trapezoidal fuzzy numbers, c) pentagonal fuzzy numbers, and d) hexagonal fuzzy numbers.

3.1.3 Fuzzy Rules

The fuzzy inference approach of the proposed system is of the Mandani type. The relationships among spare part lifetime (x_1), lead time (x_2), and maximum quantity (y) are described by the following rules:

R1: IF x_1 is low AND x_2 is low THEN y is medium ELSE
R2: IF x_1 is low AND x_2 is medium THEN y is high ELSE
R3: IF x_1 is low AND x_2 is high THEN y is high ELSE
R4: IF x_1 is medium AND x_2 is low THEN y is medium ELSE
R5: IF x_1 is medium AND x_2 is medium THEN y is medium ELSE
R6: IF x_1 is medium AND x_2 is high THEN y is high ELSE
R7: IF x_1 is high AND x_2 is low THEN y is low ELSE
R8: IF x_1 is high AND x_2 is medium THEN y is low ELSE
R9: IF x_1 is high AND x_2 is high THEN y is medium

3.2 Numerical Experiment

A case study examining historical inventory data over 36 months of refiner segments was conducted to manage spare part inventory using the min-max inventory methodology. A comprehensive cost analysis was performed utilizing a Monte Carlo simulation, a statistical technique designed to model and analyze the behavior of complex systems and processes. This method encompasses the generation of numerous random samples or scenarios to explore a range of possible outcomes and to estimate the probabilities linked to various results. As part of this process, a probability distribution was assigned to each input variable, including demand, spare part lifetime, and lead time, to reflect their associated uncertainties. Following this, thorough analyses of the input data distributions were performed, and hypotheses regarding the probability distributions were evaluated using the chi-square goodness-of-fit test. The results of the input data fitting distributions are summarized as follows. The annual demand follows a binomial distribution, expressed as $b(1.00, 0.67)$. The spare part lifetime is characterized by a uniform distribution, denoted as $U(31,64)$. In addition, the lead time conforms to a normal distribution, represented as $N(4.089,1.765)$.

Next, input parameters such as demand, spare part lifetime, and lead times were randomly generated using Minitab statistical software, corresponding with their specified distributions over 30 runs. The total cost of inventory management, encompassing ordering, holding, and stock costs, was calculated for each run. A 95% confidence interval analysis for the mean total inventory management cost was then conducted using statistical software. Figure 7 illustrates the interval plot of total inventory management costs by inventory control policy, comparing non-fuzzy and fuzzy inventory control using triangular, trapezoidal, pentagonal, and hexagonal fuzzy numbers. The results show that the total inventory management cost under the fuzzy inventory control policy is significantly lower than that of the non-fuzzy policy. However, no significant difference exists among the various fuzzy numbers.

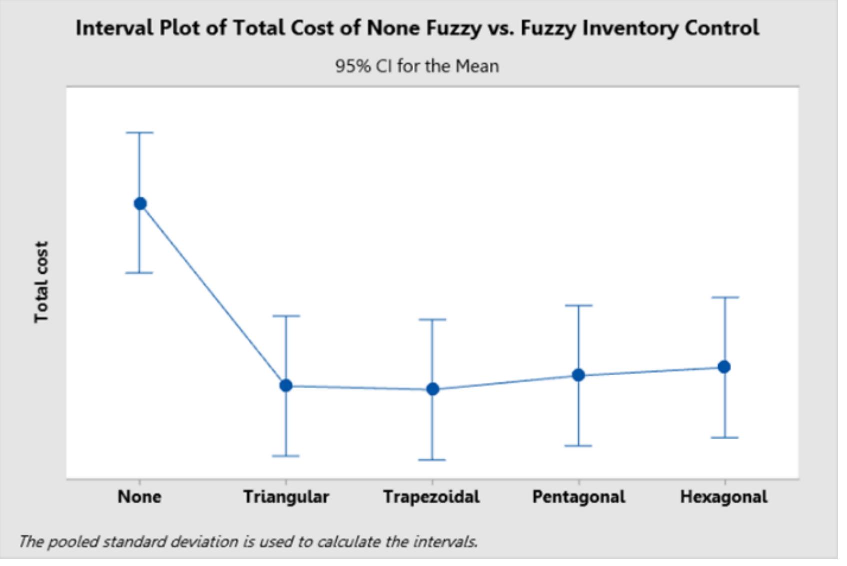


Figure 7: Interval plot of total inventory management cost by inventory control policy.

This study highlights the advantages of incorporating fuzzy logic control into spare part inventory management, demonstrating its effectiveness compared to traditional methods such as the min-max inventory approach. One significant finding of our research is that uncertainties related to spare part lifetime and lead time play a critical role in determining maximum inventory levels within the fuzzy logic framework. The results indicate that fuzzy control outperforms non-fuzzy control systems, primarily due to its ability to minimize overall inventory management costs. In a spare part inventory system designed with fuzzy logic, the maximum inventory level can be adjusted based on both the health status of machines and the unpredictability of lead times. This adaptability facilitates a more efficient inventory management strategy, helping to maintain optimal inventory levels and prevent shortages. Our findings are consistent with these conclusions, particularly in managing uncertainties, even though our research expands the application by integrating machine health into the model. In addition, Aengchuan and Phruksaphanrat [8] demonstrated the advantages of fuzzy control in the wood-based furniture industry, reporting lower costs compared to conventional lot-sizing. Their domain is similar to our MDF manufacturing context, which reinforces the external validity of our findings.

However, unlike their approach, we tested a broader set of fuzzy numbers, including pentagonal and hexagonal forms, providing additional flexibility in representing uncertainty. Despite this, the results from these different forms of fuzzy representation showed minimal differences. This consistency can be attributed to several key factors. First, each type of fuzzy number is structurally designed to handle uncertainty, suggesting that switching between these forms generally yields insignificant deviations in results. This outcome may be influenced by the characteristics of the case study problem, where the input variables, specifically lifetime and lead times, do not exhibit extreme fluctuations. Consequently, no particular type of fuzzy number demonstrates a significant advantage over others in this context. Second, when the underlying data distribution is uniform across the various fuzzy representations, using different types of fuzzy numbers is likely to result in similar outcomes, provided they are applied within the same analytical framework. Finally, the adaptability of fuzzy numbers plays a crucial role here; changes in representation from triangular to trapezoidal fuzzy numbers typically produce only marginal changes in calculations, leading to slight fluctuations in final outcomes. This inherent flexibility is fundamental to the reliability of fuzzy number methodologies in managing uncertain data.

Therefore, the minor differences among fuzzy numbers in our results align with the findings of Chakraborty et al. [14], who noted that hexagonal fuzzy numbers offer more granularity without significantly affecting overall output in stable systems. In our case, the limited variability in the input data distributions (e.g., uniform lifetime and normally distributed lead time) likely contributed to the minimal impact of fuzzy number selection. From a practical standpoint, this implies that decision-makers may choose simpler fuzzy forms, such as triangular or trapezoidal numbers, without compromising accuracy, particularly in environments with moderate data variability. By contrast, industries with more volatile systems might benefit from more complex shapes, such as hexagonal fuzzy numbers, for enhanced precision.

7. CONCLUSION

This study demonstrated the potential of integrating fuzzy logic control into spare part inventory management, specifically for a wood substitute manufacturing company. By addressing uncertainties related to machine health status and lead times, the proposed fuzzy inventory system exhibits significant advantages over traditional methods such as the min-max inventory approach. Incorporating various fuzzy numbers (triangular, trapezoidal, pentagonal, and hexagonal) into the model provides a more adaptive strategy for dealing with uncertainties, resulting in reduced inventory management costs.

Although other fuzzy numbers showed improvements over non-fuzzy approaches, our study found that the differences between them were not statistically significant, suggesting that the choice of fuzzy numbers may be tailored based on specific application needs.

Overall, this research highlights the effectiveness of using fuzzy logic control to manage spare part inventories in industrial settings, offering a practical and robust solution for reducing uncertainties and enhancing decision-making processes. This approach equips industrial practitioners with valuable tools to achieve cost-efficiency while streamlining supply chains, ultimately leading to improved operational reliability and reduced downtime. The findings pave the way for future research into the broader applications of fuzzy logic in inventory and supply chain management.

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AUTHOR CONTRIBUTIONS

Dollaya Buakum: Conceptualization, Methodology, Data Curation, Validation, Writing – Original Draft Preparation; Nikorn Sirivongpaisal: Conceptualization, Methodology, Data Curation, Validation, Writing – Reviewing and Editing; Chukree Daesa, Runchana Sinthavalai, Sivasit Wittayasilp, Sirirat Suwatcharachaitiwong, Sirirat Pungchompoo, and Aree Teeraparbseree: Conceptualization, Methodology, Data Curation, Validation.

CONFLICTS OF INTEREST

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission and declare no conflict of interest regarding the manuscript.

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