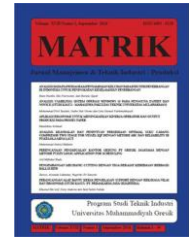




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Journal homepage: <http://www.journal.umg.ac.id/index.php/matriks>



Natural Rubber Inventory System Using the EPQ and Fuzzy EPQ Models with Sensitivity Analysis

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ARTICLE INFORMATION

doi: 10.350587/Matrik
v27i1.12379

Article History :

Article Submission
August 2, 2026

Reviewer Revisions
September 13, 2026

Publish
September 30, 2026

ABSTRACT

Uncertainty in natural rubber production due to deterioration factors poses a serious challenge to the sustainability of rubber plantations. The EPQ (Economic Production Quantity) inventory model is suitable for this production environment, while the Fuzzy EPQ model accommodates parameter uncertainty. Meanwhile, sensitivity analysis is employed to examine how changes in parameters affect decision variables. The results of the Fuzzy EPQ study on sources S1 and S2 indicate that neither the fuzzy centroid nor the fuzzy alpha-cut significantly affects the EPQ. The opposite is true for source S3. Meanwhile, the sensitivity analysis results show that changes in the production setup cost parameter affect the optimal production size, Q^* , as well as the total inventory cost, $TC(Q^*)$.

Keywords :

EPQ, Fuzzy EPQ, Persediaan,
Karet alam, Analisis sensitivitas



1. Introduction

Uncertainty in natural rubber production is a complex problem caused by environmental, technical, economic, social, and policy factors. Production instability not only reduces crop productivity but also affects farmers' incomes, the sustainability of the rubber industry, and the economic stability of rubber-producing regions. Therefore, a comprehensive management strategy is needed. This includes using appropriate technologies, improving farmers' skills and knowledge, providing government policy support, and adapting to climate change to ensure stable and sustainable natural rubber production in the future [1][2].

Uncertainty in natural rubber production caused by deterioration is a serious issue that affects the sustainability of rubber plantations. Deterioration occurs not only in the rubber trees but also in the land, tapping system, and the quality of the harvested rubber. Factors such as tree age, overexploitation, climate change, poor maintenance, and disease are the main causes of deterioration. The impacts are wide-ranging, from lower productivity and product quality to economic losses and environmental damage. Therefore, sustainable plantation management, appropriate cultivation practices, and supportive government policies are needed to reduce the risk of deterioration and ensure that natural rubber production remains stable and competitive. [3][4].

The Economic Order Quantity (EOQ) model is a fundamental method in inventory management aimed at determining the optimal order quantity to minimize total inventory costs. Although it is simple and easy to apply, EOQ has various limitations due to the assumption that inventory arrives all at once, and it does not consider the step-by-step production process. The EOQ model becomes less relevant in modern industrial conditions that involve continuous internal production. [5][6]. Therefore, an Economic Production Quantity (EPQ) model is needed. This model more realistically depicts production conditions by considering the production and consumption

rates simultaneously. Thus, EPQ becomes a more effective alternative in inventory management for manufacturing companies.

The Periodic Order Quantity (POQ) model is an inventory control method that determines the order quantity based on the needs during a specific period. This model provides ease in scheduling orders and is quite flexible to changes in periodic demand. However, POQ has various weaknesses, especially because it does not consider the stepwise production process, production rate, and the simultaneous relationship between production and consumption of goods [7][8]. As a result, this model is less suitable for application in modern manufacturing industries that use continuous production systems.

Therefore, a more realistic EPQ model is needed, one that can accurately depict actual production conditions by considering both production levels and demand levels simultaneously. Thus, EPQ becomes a more effective alternative for inventory control in manufacturing companies [9][10].

Fuzzy EPQ is an extension of the EPQ method that accommodates uncertainty in inventory parameters, such as demand, holding costs, setup costs, and production rates. In this method, parameters that cannot be precisely determined are represented using fuzzy numbers, allowing the model to depict more dynamic real-world conditions. Thus, Fuzzy EPQ produces more flexible production policies and supports more realistic inventory decision-making compared to conventional EPQ, especially in uncertain conditions [11].

Sensitivity analysis is a method to evaluate how changes in input parameters (such as holding costs, setup costs, and demand levels) affect total inventory costs and the optimal production lot size. This helps managers identify the most critical variables in the manufacturing system. Sensitivity is tested by increasing or decreasing the value of certain parameters (for example, $\pm 10\%$, $\pm 20\%$, or $\pm 50\%$) to observe their impact on the decision variables in the EPQ model, [12][13].

Based on the background presented above, the research problems can be formulated as follows: (1) How can the natural rubber inventory model be developed using the deterministic EPQ method? (2) How can the natural rubber inventory model be extended using the Fuzzy EPQ method to accommodate parameter uncertainty? (3) What are the differences between the EPQ and Fuzzy EPQ methods in determining the optimal production quantity and total inventory cost? (4) How sensitive is the Fuzzy EPQ model to changes in its parameters?

Based on these research problems, the objectives of this study are: (1) to develop a natural rubber inventory model using the deterministic EPQ method; (2) to develop a natural rubber inventory model using the Fuzzy EPQ approach to accommodate parameter uncertainty; (3) to compare the results of the EPQ and Fuzzy EPQ methods in determining the optimal production quantity and total inventory cost; and (4) to analyze the sensitivity of the Fuzzy EPQ model to changes in its parameters.

2. Research Methods

The research method consists of the classical EPQ method, the Fuzzy EPQ method, and sensitivity analysis. In the classical EPQ method, data were collected on production setup cost (S), holding cost (H), annual natural rubber demand (D), natural rubber production rate (P), and the correction factor $(1 - d/p)$. The economic production quantity (Q) was then calculated. After determining the economic production quantity using the EPQ method, the total inventory cost (TC) was calculated [9].

The same parameter values were applied in the Fuzzy EPQ method, except that the production setup cost (S) was represented by a triangular fuzzy number. The triangular fuzzy setup cost consists of S_U , S_M , and S_L , where U, M, and L represent the upper, medium, and lower values, respectively. These three fuzzy values were then defuzzified using the centroid and α -cut methods. The defuzzified setup cost,

together with the other parameters, was used to calculate the economic production quantity (Q). The total inventory cost (TC) was calculated after the economic production quantity was obtained. [11].

An addition/subtraction of $\pm 10\%$, $\pm 20\%$, $\pm 30\%$ is applied to SU, SM, and SL to determine the impact of changes in the economic production size as well as the impact on the total inventory cost [12].

$$Q^* = \sqrt{\frac{2SD}{H(1-\frac{d}{p})}} \quad (1)$$

$$TC = \frac{SD}{Q} + \frac{QH}{2} \left(1 - \frac{d}{p}\right) \quad (2)$$

$$S = \frac{S_1 + S_2 + S_3}{3} \quad (3)$$

$$S = \frac{((SL + \alpha(SM - SL)) + ((SU - \alpha(SU - SM)))}{2} \quad (4)$$

Description

Q^* = Economic production quantity

S = Production setup cost

D = Annual natural rubber demand

d = Monthly natural rubber demand

p = Monthly natural rubber production rate

H = Holding cost

$(1 - \frac{d}{p})$ = Correction factor

TC = Total inventory cost

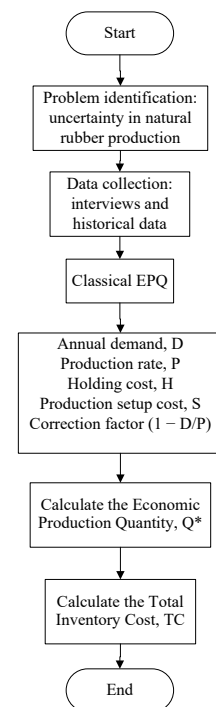


Figure 1. Research Procedure

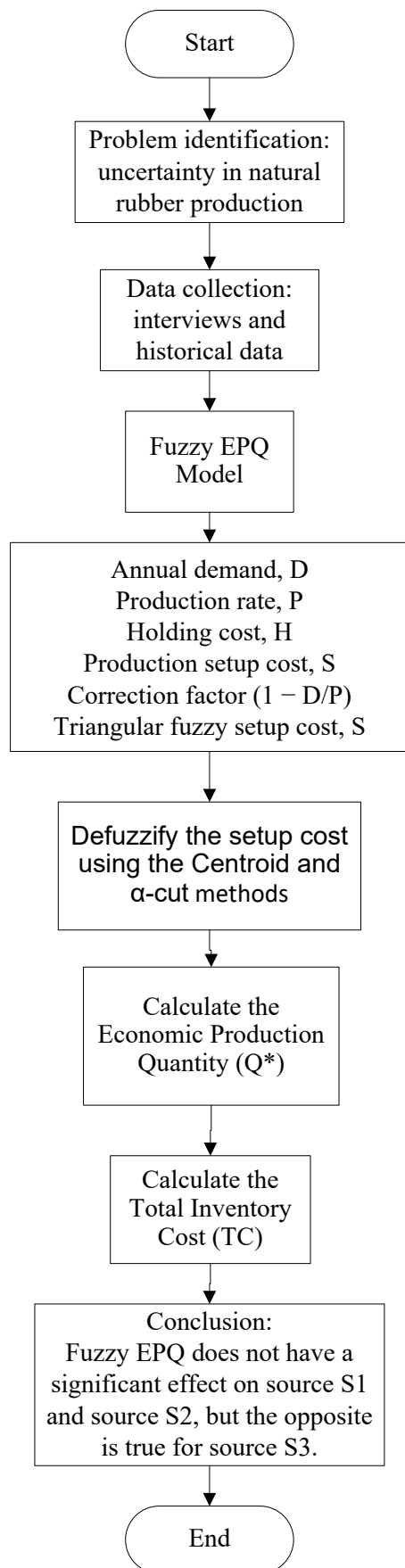


Figure 1. Research Procedure (Continued)

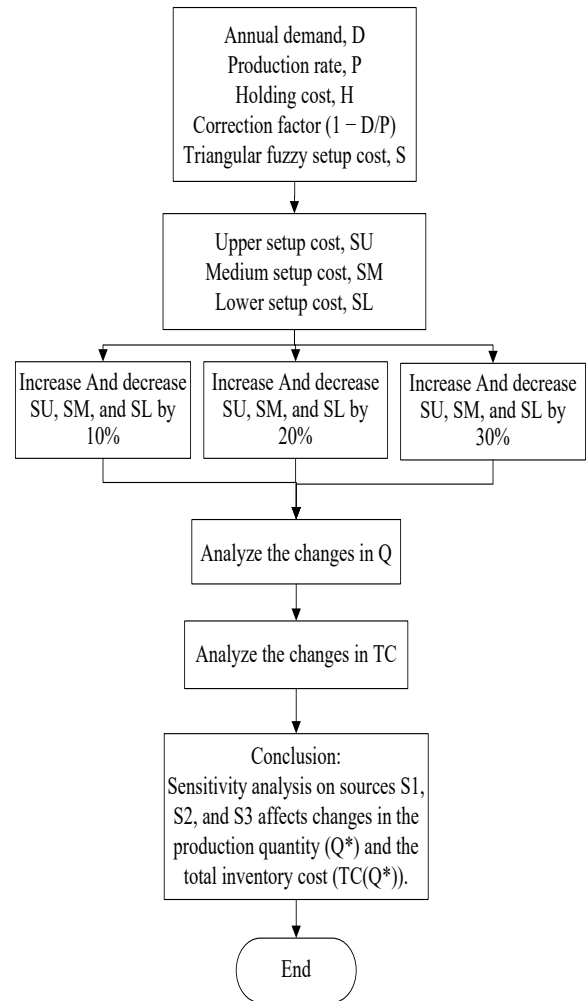


Figure 1. Research Procedure (Continued)

3. Results and Discussions

This research found a difference between the results of the Classical Economic Production Quantity (EPQ) and the Fuzzy EPQ, both for the optimal production quantity (Q^*) and the total cost ($TC(Q^*)$). This difference is evident, especially when the Fuzzy model uses the Centroid and Alpha-Cut defuzzification methods. In essence, if you incorporate parameter uncertainty into the inventory model, the decisions regarding the optimal production quantity and its cost can change.

$S1=SL$ = Lowest production setup cost value
 $S2 = SM$ = Medium production setup cost value
 $S3 = SU$ = Highest production setup cost value
 S = Defuzzified production setup cost value
 $\alpha = 0,5$

Table 1. EPQ S1 for DA.1, DB.1, DC.1

H	S	D	P	(1-d/p)
672,18	2000000	31377	312059	0,899

Table 1. EPQ S1 for DA.1, DB.1, DC.1
Continued

H(1-d/p)	2SD	Q*	TC
605	125508000000	14408	8710956

Table 2. EPQ S2 for DA.2, DB.2, DC.2

H	S	D	P	(1-d/p)
672,18	2000000	237694	604763	0,607

Table 2. EPQ S2 for DA.2, DB.2, DC.2
Continued

H(1-d/p)	2SD	Q*	TC
407,99	950776000000	48274	19695252

Table 3. EPQ S3 for DA.3, DB.3, DC.3

H	S	D	P	(1-d/p)
672,175	2000000	163446	340689	0,520

Tabel 3. EPQ S3 for DA.3, DB.3, DC.3
Continued

H(1-d/p)	2SD	Q*	TC
349,698	653784000000	43238	15120419

Table 4. Defuzzification Results for Row 1, S1
Defuzzification

Centroid	Alpha-Cut
1966667	1975000

Table 5. The results of the Sensitivity Analysis of the Upper Production Setup Cost for the First Row, S1

SU=2800000	Q	TC
SU+0,3=	3640000	19437,54
SU+0,2=	3360000	18674,98
SU+0,1=	3080000	17879,94
SU-0,1=	2520000	16173,01
SU-0,2=	2240000	15248,06
SU-0,3=	1960000	14263,25

Table 6. The results of the Sensitivity Analysis of the Medium Production Setup Cost for the First Row, S1

SM=2000000	Q	TC
SM+0,3=	2600000	16427,72
SM+0,2=	2400000	15783,24
SM+0,1=	2200000	15111,3
SM-0,1=	1800000	13668,69
SM-0,2=	1600000	12886,96
SM-0,3=	1400000	12054,65

Table 7. The results of the Sensitivity Analysis of the Lower Production Setup Cost for the First Row, S1

SL=110000	Q	TC
SL+0,3=	1430000	12183,12
SL+0,2=	1320000	11705,17
SL+0,1=	1210000	11206,84
SL-0,1=	990000	10136,97
SL-0,2=	880000	9557,228
SL-0,3=	770000	8939,968

Table 8. Defuzzification Result for the Second Row, S2

Defuzzifikasi	
Centroid	Alfa-Cut
1966667	1975000

Table 9. The results of the Sensitivity Analysis of the Upper Production Setup Cost for the Second Row, S2

SU=2800000	Q	TC
SU+0,3=	3640000	10297,28
SU+0,2=	3360000	9893,303
SU+0,1=	3080000	9472,117
SU-0,1=	2520000	8567,852
SU-0,2=	2240000	8077,848

SU-0,3= 1960000 7556,135 123311779,4

Table 10. The results of the Sensitivity Analysis of Medium Production Setup Cost for the Second Row, S2

	SM=2000000	Q	TC
SM+0,3=	2600000	8702,787	142024478,4
SM+0,2=	2400000	8361,367	136452705,1
SM+0,1=	2200000	8005,4	130643518,8
SM-0,1=	1800000	7241,157	118171509,1
SM-0,2=	1600000	6827,028	111413167,2
SM-0,3=	1400000	6386,1	104217475

Table.11. The results of the Sensitivity Analysis of the Lower Production Setup Cost for the Second Row, S2

	SL=1100000	Q	TC
SL+0,3=	1430000	6454,16	105328172,2
SL+0,2=	1320000	6200,956	101196034,5
SL+0,1=	1210000	5936,963	96887826,66
SL-0,1=	990000	5370,185	87638336,67
SL-0,2=	880000	5063,059	82626216,2
SL-0,3=	770000	4736,058	77289748,05

Table 12. Defuzzification Result for the Third Row, S3

Defuzzification	
Centroid	Alpha Cut
1636667	1727500

Table 13. Sensitivity Analysis Results of the Upper Production Setup Cost for the Third Row, S3

	SU=2800000	Q	TC
SU+0,3=	3640000	9223	129011820
SU+0,2=	3360000	8861	123950547
SU+0,1=	3080000	8484	118673614
SU-0,1=	2520000	7674	107344323
SU-0,2=	2240000	7235	101205198

SU-0,3= 1960000 6768 94668794

Table 14. The results of the Sensitivity Analysis of the Medium Production Setup Cost for the Third Row, S3

	SM=2000000	Q	TC
SM+0,3=	2600000	7795	109034889
SM+0,2=	2400000	7489	104757332
SM+0,1=	2200000	7170	100297510
SM-0,1=	1800000	6486	90722511
SM-0,2=	1600000	6115	85534004
SM-0,3=	1400000	5720	80009734

Table 15. The results of the Sensitivity Analysis of the Lower Production Setup Cost for the Third Row, S3

	SU=1100000	Q	TC
SL+0,3=	1430000	5781	80862438
SL+0,2=	1320000	5554	77690117
SL+0,1=	1210000	5318	74382624
SL-0,1=	990000	4810	67281615
SL-0,2=	880000	4535	63433715
SL-0,3=	770000	4242	59336807

Table 16. The results of the Classical EPQ

Source	Q*	TC(Q*)
S1	14.408	8.710.956
S2	48.274	19.695.252
S3	43.238	7.562.750

Table 17. The results of the Fuzzy EPQ

Fuzzy EPQ			
Q*	TC(Q*)	Q*	TC(Q*)
Centroid	Centroid	Alpha-Cut	Alpha-Cut
14.287	8.638.059	14.318	8.656.341
47.870	19.530.435	47.972	19.571.769
39.114	13.678.199	40.185	14.052.637

In source S1, the Classical EPQ produced an optimal quantity of 14,408 units with a cost of Rp8,710,956. After running the Fuzzy EPQ Centroid, Q^* decreased to 14,287 units, which is about 0.84% or a difference of 121 units. The cost also decreased to Rp8,638,059, saving Rp72,897, also about 0.84%. So, in S1, introducing uncertainty doesn't significantly change the production decision. The production difference is less than 1%, so the Classical EPQ solution is stable and not vulnerable if the parameters are fuzzy.

Meanwhile, in source S2, Classical EPQ produces the largest optimal output, 48,274 units, and a cost of Rp19,695,252. The characteristics of the parameters (demand, production, setup/holding costs, etc.) make the lot size large. Fuzzy EPQ Centroid reduces Q^* to 47,870 units, a difference of 404 units (0.84%). Costs also decrease to Rp19,530,435, saving Rp164,817 (0.84%). The pattern is similar to S1, where Fuzzy EPQ corrects the decision of Classical EPQ, but the correction is small, so the representative fuzzy parameter value in S2 is not far from the deterministic value.

Meanwhile, the results from source S3 are really different from S1 and S2. With Classical EPQ, Q^* is at 43,238 units, and the total cost is Rp7,562,750. But when using Fuzzy EPQ that is Centroid, Q^* decreased quite significantly, down to 39,114 units. The difference is 4,124 units, or about 9.54%. The percentage decrease in Q^* in S3 is much larger than in S1 and S2, which is only about 0.84%. In S3, it's almost 10%. This means that the decision on how much to produce in S3 is really more sensitive to parameter uncertainty. But the most striking thing is the total cost. Even though Q^* decreased, instead of being cheaper, the total cost skyrocketed that is from Rp7,562,750 to Rp13,678,199. So, the cost increased by about Rp6,115,449, or nearly 81%. Using the Alpha-Cut method, Q^* became 40,185 units, approximately 3,053 units lower than the Classical EPQ, equivalent to a decrease of about 7.06%. But the total cost remained higher, at Rp14,052,637. That means an increase of Rp6,489,887 or about 85.8% compared to Classical EPQ. Interestingly, in S3, it is very clear that a decrease in Q^* or optimal production does not automatically lead to a decrease in total costs.

A previous study introduced a new sustainable EPQ model that incorporates environmental factors and considers the variability of defective products, reworkable products, and scrap items under stockout conditions. The main objective is to minimize total costs and greenhouse gas emissions. This model is applied to real-world problems, and extensive sensitivity analysis is conducted to evaluate its behavior under various conditions. The main findings show that a 50% reduction in emission costs through investment in green technology can lower total costs by 9.457%, increase production volume by 11.719%, and reduce the maximum stockout quantity by 2.031%. [14][15].

In addition, another study discusses the limitations of the classic EPQ model, which assumes all products are perfect, and proposes an extended EPQ model to address defective production. The proposed model considers scenarios where defective products are classified based on uniform and normal distributions, and can be repaired, of low quality, or scrapped. This model integrates the processes of repairing, inspecting, and reworking defective products into the EPQ framework, with the aim of determining the optimal production quantity. [16][17].

Additionally, another study focuses on the development of a multi-item EPQ strategy in a 'grey' environment and space constraints, assuming that demand cannot be predicted with certainty. The goal is to optimize the cycle time and total cost of the multi-item EPQ inventory model. To achieve this, the paper uses Lagrangian coefficients to solve the constrained optimization problem and applies the gray relational analysis approach and gray data in developing the EPQ inventory model. The results are compared with analyses using 'crisp' and 'fuzzy' data, showing that 'crisp' data outperforms the other two types of data in terms of cycle time and cost across all problem scales, while 'grey' data performs better than 'fuzzy' data. [18][19].

Another study expands the classic EPQ model by integrating regular Preventive Maintenance (PM) activities in the process manufacturing industry. The aim is to address the limitations of the traditional EPQ model, which does not consider PM and defective production processes, making it inapplicable in real-world situations. [20][21].

The studies reviewed above show that many inventory models have been developed as extensions of the classical EPQ model. This is because the classical EPQ model has limitations, as it assumes that all parameters, such as demand rate, holding cost, setup cost, and production rate, are known with certainty. In practice, however, this assumption is rarely valid because these parameters are often affected by uncertainty resulting from demand fluctuations, changes in raw material prices, and variations in operating conditions.

To address these limitations, an uncertainty method is used so that inventory decisions become more flexible and realistic. The uncertainty model used here, which differs from several previous studies, is the fuzzy model on EPQ [14][22].

The results show that the total inventory cost using Fuzzy EPQ is lower than EPQ. It indicates that the application of fuzzy logic provides a more efficient solution under conditions of uncertainty. Conversely, if the total cost is slightly higher, this condition can be interpreted as additional costs arising from the presence of a buffer to anticipate the risk of demand uncertainty or operational costs [23][24].

Next, a sensitivity analysis is conducted to determine the impact of parameter changes on the model's calculation results. The parameter tested here is the production setup cost. The results of the sensitivity analysis show that changes in each parameter have different levels of impact on the optimal production quantity and total inventory cost [25][26].

If demand increases, the optimal production quantity tends to rise, so the company must produce in larger quantities to meet market needs. Conversely, if storage costs increase, the optimal production quantity will decrease because the company tries to reduce the amount of inventory held to lower storage costs. Meanwhile, an increase in setup costs generally causes the optimal production quantity to rise so that the setup frequency can be reduced [27].

The managerial implications of this research clearly show that production decisions and resource selection cannot solely rely on the Classical EPQ. The deterministic model assumes that all parameters, from demand, setup costs, storage costs, to production levels, are certain. But in reality, it's not always like that. For S1 and S2, the difference in results between the deterministic and fuzzy models is

quite small. It means that both sources are quite stable despite the uncertainty. But, in source, S3 is a different story. In source S3, the difference in total cost is really significant. So, decision-makers must be extra cautious with the uncertainty in the S3 parameters. If the company is pursuing the lowest total cost amidst uncertainty, S1 becomes an attractive option. Because it provides the lowest TC in both the Centroid and Alpha-Cut methods. Moreover, the difference in results between Centroid and Alpha-Cut in S1 is very small, so the S1 solution is considered quite robust against defuzzification methods. On the other hand, S3 cannot be taken arbitrarily. Classical EPQ initially seems the cheapest, but once everything is modelled fuzzy, that advantage disappears immediately. This is a sign that there are hidden cost risks that are not visible in the deterministic model.

Sensitivity analysis of production setup costs (SU) is conducted to determine how much changes in setup costs affect the optimal production quantity (Q^*) and total cost $TC(Q^*)$ for each source, namely S1, S2, and S3. The setup costs are varied by $\pm 10\%$, $\pm 20\%$, and $\pm 30\%$ from the base SU value of Rp2,800,000. This analysis is important because setup costs are one of the main parameters in the EPQ model. Changes in setup costs can influence decisions regarding production lot sizes. The higher the cost incurred each time the production process begins, the greater the tendency for the company to increase the production quantity in one cycle, thereby reducing the setup frequency. Conversely, when setup costs decrease, production in smaller lots becomes more feasible. The analysis results show that in S1, S2, and S3 there is a consistent pattern, namely that an increase in SU causes an increase in Q^* and $TC(Q^*)$, while a decrease in SU causes a decrease in Q^* and $TC(Q^*)$.

4. Conclusion and Recommendations

There are three findings that emerge from this comparison. First, Fuzzy EPQ produces a lower Q^* than Classical EPQ in all sources. The decrease is small in S1 and S2, but in S3, the difference is much larger. Secondly, in S1 and S2, fuzzification only slightly reduces the total cost. This shows that the deterministic solution of these two sources is already quite strong, although the fuzzy approach can still adjust to

the presence of uncertainty. Third, S3 has a different story. Fuzzy EPQ does reduce the optimal production quantity by 7–10%, but in return, the total cost increases drastically, by about 81–86%. This condition indicates that S3 is much more sensitive to uncertainty than the other two sources. Centroid also consistently produces Q^* and $TC(Q^*)$ that are slightly lower than Alpha-Cut. However, the difference in S1 and S2 is very slight, so the choice of defuzzification method does not really change the decision. In S3, the gap becomes larger. This means that the higher the uncertainty, the more the influence of the defuzzification method is felt on the final result.

So, this research clearly proves that Fuzzy EPQ is not just a mathematical addition to Classical EPQ. This method can show how stable and sensitive production decisions are to parameter uncertainty. The most interesting part is that the position of S3 changed drastically: it was the most economical according to the Classical EPQ, but that cost advantage disappeared once uncertainty was included. This emphasises the importance of incorporating uncertainty into production and inventory decision-making. Suggestion for the future, this research can be continued by adding fuzzy to other parameters besides the production setup cost parameter.

The results of the sensitivity analysis indicate that the production setup cost (SU) has a positive effect on the optimal production quantity and total cost in the cases S1, S2 and S3. An increase in SU causes an increase in Q and TC and a decrease in SU causes a decrease in Q and TC. When SU increases by 30%, we get a Q of 19,437.54 units for S1, 10,297.28 units for S2 and 9,223 units for S3. Meanwhile, the respective total costs (TC) are Rp11,751,722, Rp168,045,629, and Rp129,011,820.

The results show that an increase in setup costs leads the system to larger production lot sizes in an effort to reduce the number of setups. However, increasing the lot size does not eliminate the effect of increasing the setup costs on total costs. Therefore, setup cost can be regarded as a critical parameter in both the EPQ and Fuzzy EPQ models. Besides having the potential to reduce the overall costs, the ability to control

the setup costs provides companies some flexibility to operate with decreased production lot sizes. The sensitivity analysis results emphasize the necessity of accounting for the cost uncertainty in inventory decision making especially for the factors that cause large changes to Q and TC.

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