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Implementation of the Fuzzy Tsukamoto method to determine the amount of beverage production

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ABSTRACT

Optimization of the amount of beverage production by applying the Fuzzy Tsukamoto Method at PT. Sariguna Primatirta Tbk. This study aims to develop a predictive model that can assist companies in determining the optimal amount of beverage production, minimizing production costs, and maximizing customer satisfaction. The research method uses a quantitative approach with a combination design of experimental methods, quantitative analysis, and model validation, including the collection of historical data on production, market demand, and raw material availability, data pre-processing, selection of input and output variables, implementation of the Fuzzy Tsukamoto algorithm, and model evaluation with Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics. The results showed that the Fuzzy Tsukamoto Method succeeded in determining the amount of beverage production with good accuracy, with an MAE of 0.25 and RMSE of 0.274 after the data was understated, proved effective in handling the uncertainty of market demand and providing optimal production recommendations based on fuzzy rules from expert knowledge. The implications of this research contribute to the scientific literature in the field of computer science and industrial management, as well as practical benefits for PT. Sariguna Primatirta Tbk in improving its production effectiveness, with the potential to be adopted by similar industries to improve operational efficiency.

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1. INTRODUCTION

In the industrial era 4.0, increasing production efficiency and effectiveness is the key to maintaining the sustainability and growth of the company (Kumar et al., 2021) (Khan et al., 2021). The Industrial Revolution 4.0 has brought fundamental transformation in the manufacturing sector through the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics. This technology enables automation of production processes, real-time data analysis, and more efficient and responsive decision-making to market changes. In the context of beverage production, the application of IoT technology enables real-time monitoring of machine conditions and production processes, which supports predictive maintenance and downtime reduction, thereby improving operational efficiency and product quality (Jagatheesaperumal et al., 2021). PT. Sariguna Primatirta, Tbk, as one of the leading beverage manufacturers in Indonesia, faces challenges in adjusting its production capacity to fluctuating market demand (Irawan et al., 2022). Therefore, this study aims to apply the Fuzzy Tsukamoto

Method in determining the optimal amount of beverage production (Nadia et al., 2020) (Bin et al., 2023).

Overcoming the challenges in managing the uncertainty and variability of market demand, Fuzzy Tsukamoto's method was chosen as a relevant approach. This method excels in handling complex and uncertain conditions by modeling a non-linear relationship between input variables, such as market demand and raw material availability, with an output variable in the form of an optimal amount of production. Unlike conventional methods that may be less flexible, Fuzzy Tsukamoto is able to generate adaptive production recommendations based on fuzzy rules integrated with expert knowledge. This is especially important in the beverage industry where fluctuations in demand are frequent and production decisions must be able to adapt quickly (Talpur et al., 2023).

The application of the Fuzzy Tsukamoto method is expected to provide a more flexible and adaptive solution to the uncertainty of market demand (Aslam et al., 2024). This research not only provides new insights in production management but also offers a framework that similar industries can adopt to improve their operational efficiency (Furstenau et al., 2020).

The purpose of this study is to develop a predictive model that can help PT. Sariguna Primatirta, Tbk in determining the optimal production quantity, minimizing production costs, and maximizing customer satisfaction (Tirkolaee et al., 2020) (Alinezhad et al., 2022). Theoretically, this study will examine the application of fuzzy logic, especially the Fuzzy Tsukamoto Method, in making production decisions based on historical data and actual market parameters (de Andrés-Sánchez, 2023) (Zrobek et al., 2020).

By applying this methodology, research is expected to contribute to the scientific literature in the field of computer science and industrial management, as well as provide practical benefits for PT. Sariguna Primatirta, Tbk in increasing the effectiveness of its production (Toorajipour et al., 2021) (Park & Lin, 2020). Another hope is that this method can be a reference for other companies in the same industry to increase their adaptive capacity to market dynamics.

Previous research applied the Fuzzy Tsukamoto method to optimize production planning in beverage companies, as a result this method can help companies determine the optimal production amount based on demand and supply (Yordanova et al., 2020). Research that uses the Fuzzy Tsukamoto method to optimize production scheduling in juice manufacturing companies, the results of this method can help companies allocate production resources more efficiently and reduce production costs (Wang et al., 2022). Research that applies the Fuzzy Tsukamoto method to optimize production planning in the dairy industry shows that this method can help companies determine the optimal amount of production by considering demand, supply, and production costs (Arshadi Khamseh, 2021). Research that uses the Fuzzy Tsukamoto method to optimize production planning in soft drink manufacturing companies, the results of this method can help companies in optimal production quantities by considering demand, supply, and production costs (Güneri & Deveci, 2023). And research that applies the Fuzzy Tsukamoto method to optimize production in beverage manufacturing companies shows that this method can help companies determine the optimal production amount by considering demand, inventory, production costs, and customer preferences (Chen et al., 2023).

Previous research on the application of Fuzzy Tsukamoto's method in production has often focused on planning optimization without considering variations in consumer preferences or specific constraints of production resources. This gap is filled by our research by developing more comprehensive and adaptive predictive models. The model considers various factors such as fluctuations in market demand, production costs, consumer preferences, and dynamic production policies, which provides a more effective approach in determining the optimal amount of production.

Some researchers focus on applying the Fuzzy Tsukamoto method to optimize production planning in the beverage, juice, food, and dairy industries, where this method is proven to help companies determine the optimal amount of production by considering factors such as demand, inventory, production costs, and customer preferences. However, there is limited research relating to the use of Fuzzy Tsukamoto's method to optimize beverage production taking into account other factors such as production resource constraints, dynamic production policies, and diverse customer preferences. Therefore, this study intends to apply Fuzzy Tsukamoto's method in determining the more optimal amount of beverage production by considering various factors such as fluctuating market demand, inventory, production costs, diverse customer preferences, production resource constraints, and dynamic production policies. The purpose of this study is to develop a comprehensive and adaptive predictive model to help PT. Sariguna Primatirta, Tbk in determining the optimal amount of beverage production, minimizing production costs, and maximizing customer satisfaction by considering various related factors.

2. RESEARCH METHOD

Research Flow

The method section in this research article will be designed to support the research objective of optimizing the amount of production at PT. Sariguna Primatirta, Tbk uses Fuzzy Tsukamoto method. A quantitative approach with a combination design of experimental methods, quantitative analysis, and model validation will be applied (Orazbayev et al., 2022).

Figure 1. Research flow

Figure 1. Explain the flow of research, starting from identifying problems, namely determining the optimal amount of production. Furthermore, needs analysis involves a literature review to understand the framework for determining the amount of beverage production, including identification of consumer trends, evaluation of previous methods. Furthermore, data collection, this research data is data on the amount of production, market demand data, and raw material availability data. This data was obtained from direct interviews at PT. Sariguna Primatirta, Tbk. Furthermore, the selection of methods The selection of Tsukamoto's fuzzy method as a solution in this study is based on the advantages of adaptability to uncertainty. Then the implementation of Tsukamoto's fuzzy method in determining the amount of beverage production includes identification of input and output variables, fuzzification of variables with corresponding membership functions (Yudhana, 2023). Furthermore, the conclusion of Fuzzy Tsukamoto's method proved successful in determining the amount of beverage production with high predictive accuracy, effective integration of expert knowledge, and adaptability to the complexity of industry dynamics, proving its superiority as a relevant and efficient approach (Mavani et al., 2021).

Data Collection

Table 1. Beverage production data

No	Day, Date	Sales	Setup	Production
1	Friday, September 1	15	16	32
2	Saturday, September 2	16	17	30
3	Sunday, September 3	14	16	26
4	Monday, 4 September	17	20	27
5	Tuesday, September 5	18	20	24
⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮
27	Rabu, 28 September	21	26	30
28	Thursday, September 29	23	20	26
30	Friday, September 30	28	30	33

Table 1. data used include historical production data, market demand data, raw material availability data, and other operational data from PT. Sariguna Primatirta, Tbk. This data is collected from company records and relevant internal data sources.

Data Processing

Data processing involves data cleansing, handling lost value, and transforming data to ensure the quality of data to be used for modeling. This process includes normalization of data and selection of relevant features based on variables and statistical significance.

Variable Selection and Model Optimization

The variables essential to the prediction model will be selected based on exploratory analysis and their significance to production output. Model optimization is carried out through the selection of the right parameters for the Fuzzy Tsukamoto Method, with the aim of increasing the accuracy and efficiency of the model.

Algorithm Implementation

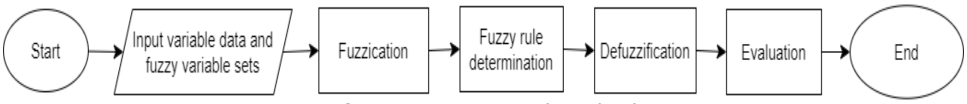

Figure 2. Generated method

In Figure 2. Explaining in the application of Fuzzy Tsukamoto's method to determine the amount of beverage production, the flow begins by identifying relevant input variables, such as market demand and raw material stock. After that, define a fuzzy set for each variable, such as low, medium, and high. Through fuzzyfication, the degree of membership of each input value is determined in a predefined fuzzy set. Fuzzy inference systems are then used to define fuzzy rules that relate input conditions to output variables, such as beverage production. These rules reflect the logic or expert knowledge of the domain. Next, aggregation of fuzzy rules and defuzzification is carried out to produce concrete values for the amount of beverage production. The output of this system is a recommendation of the amount of production that can be taken as a basis for subsequent production actions. This process creates an adaptive system that can respond to input conditions by providing optimal production recommendations according to fuzzy logic principles.

Algorithm Configuration and Model Evaluation

Algorithm configuration involves adjusting parameters such as membership functions and inference rules based on company-specific data (Lima-Junior & Carpinetti, 2020) (Gáspár et al., 2023). Model evaluation is done using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to measure model performance in predicting production numbers (Shah et al., 2021).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i-1}^{n} |y_i - \hat{y}_i| \quad (1)$$

Where n is the sum of the number of samples or observations, y_i is the actual value for the I-th observation, $\hat{y}_i$ is the predicted value for the i-th observation, $|y_i - \hat{y}_i|$ is the absolute value of the prediction error for the i-th observation (Huang et al., 2020).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}}\ \sum_{i-1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

Where n is the total number of observations, yi is the predictive value for the I-th observation, ŷi is the actual value for the 1st observation.

3. RESULTS AND DISCUSSIONS

In this section, it is explained the results of research and at the same time is given the comprehensive discussion.

Table 2. Data after normalization

Sunday	Setup	Demand	Production
First	108	116	224
Second	180	160	340
Third	150	224	374
Fourth	200	212	420

Table 2. The data used in the study was obtained from PT. Sariguna Primatirta, Tbk Tegal City Year 2023 which contains production data for 4 weeks. This data will be used for the implementation of Fuzzy Tsukamoto. The calculation of the rules of the Tsukamoto method is

carried out using the Fuzzy Tsukamoto method and using Beverage production at PT. Sariguna Primatirta, Tbk for one month, namely in September 2023 in week 4.

[R1] IF DEMAND DROPS AND SUPPLIES A LOT, THEN CLEO BEVERAGE PRODUCTION REDUCED

[R2] IF DEMAND DROPS AND SUPPLIES ARE LOW, THEN CLEO BEVERAGE PRODUCTION REDUCED

[R3] IF DEMAND GOES UP AND SUPPLIES A LOT, THEN CLEO BEVERAGE PRODUCTION ADD

[R4] IF DEMAND GOES UP AND SUPPLIES ARE FEW, THEN CLEO BEVERAGE PRODUCTION INCREASE

How many boxes of Cleo drinks must be produced, if the number of requests is 71 boxes, and the supply is 59 boxes?

There are 3 fuzzy variables that will be modeled, namely:

1. Modeling Fuzzyfication Variables
   a. Search Membership Request
      Max Request = 148
      Min Request = 46

$$\mu\text{Demand Down}(x) = \begin{cases} 0 & ; x \geq 46 \\ \left\{\frac{x-46}{148-46}\right\} & ; 46 \leq x \leq 148 \\ 1 & ; x \geq 148 \end{cases}$$

$$\mu\text{Demand Up}(x) = \begin{cases} 0 & ; x \geq 42 \\ \left\{\frac{x-46}{148-46}\right\} & ; 46 \leq x \leq 148 \\ 1 & ; x \geq 148 \end{cases}$$

$$\mu\text{Demand Down}(71) = \frac{148-71}{148-46} = \frac{77}{102} = 0{,}75$$

$$\mu\text{Demand Down}(71) = \frac{148-71}{148-46} = \frac{77}{102} = 0{,}75$$

   b. Finding Membership on Supplies
      Max Setup = 74
      Min Stock = 20

$$\mu\text{Low Stock}(x) = \begin{cases} 1 & ; x \geq 20 \\ \left\{\frac{x-20}{74-20}\right\} & ; 20 \leq x \leq 74 \\ 0 & ; x \geq 74 \end{cases}$$

$$\mu\text{Inventory Lots}(x) = \begin{cases} \left\{\frac{x-42}{74-20}\right\} & ; 20 \leq x \leq 74 \\ 1 & ; x \geq 74 \end{cases}$$

$$\mu\text{Preparation Down}(59) = \frac{74-59}{74-20} = \frac{15}{54} = 0{,}27$$

$$\mu\text{Inventory Lots}(59) = \frac{59-20}{74-20} = \frac{39}{54} = 0{,}72$$

2. Enter a membership value in the rule

[R1] IF DEMAND DROPS AND SUPPLIES A LOT OF CLEO BEVERAGE PRODUCTION REDUCED

$$\begin{aligned} \alpha\text{-predicate1} &= \min(\mu\text{Demand Down}, \mu\text{Inventory Lots}) \\ &= \min(0{,}75, 0{,}72) \\ &= 0{,}72 \end{aligned}$$

$$\mu\text{Less Production}(x) = \frac{168-x}{168-108} = 0{,}72$$

$$\begin{aligned} X1 &= \frac{168-x}{168-108} = 0{,}72 \\ &168 - x = 0{,}72 \text{ x } 60 \\ &168 - x = 43 \end{aligned}$$

$168 - 43 = x$
$125 = x$

[R2] IF DEMAND DROPS AND SUPPLIES ARE LOW, THEN CLEO BEVERAGE PRODUCTION REDUCED

a–predicate2 $= \min(\mu\text{Demand Down}, \mu\text{Inventory Lots})$
$= \min(0{,}75, 0{,}72)$
$= 0{,}72$

$\mu\text{Less Production}(x) = \frac{168 - x}{168 - 108} = 0{,}72$

X2 $= \frac{168 - x}{168 - 108} = 0{,}72$
$168 - x = 0{,}72 \text{ x } 60$
$168 - x = 43$
$168 - 43 = x$
$125 = x$

[R3] IF DEMAND GOES UP AND SUPPLIES A LOT, THEN CLEO BEVERAGE PRODUCTION ADD

a–predicate3 $= \min(\mu\text{Demand Rises}, \mu\text{Inventory Lots})$
$= \min(0{,}24, 0{,}72)$
$= 0{,}24$

$\mu\text{Less Production}(x) = \frac{168 - x}{168 - 108} = 0{,}24$

X3 $= \frac{x - 108}{60} = 0{,}24$
$x - 108 = 0{,}24 \text{ x } 60$
$x = 14 + 108$
$x = 122$

[R4] IF DEMAND GOES UP AND SUPPLIES ARE FEW, THEN CLEO BEVERAGE PRODUCTION ADD

a–predicate4 $= \min(\mu\text{Demand Rises}, \mu\text{Low Stock})$
$= \min(0{,}24, 0{,}72)$
$= 0{,}24$

$\mu\text{Less Production}(x) = \frac{168 - x}{168 - 108} = 0{,}24$

X4 $= \frac{x - 108}{60} = 0{,}24$

$x - 108 = 0{,}24 \text{ x } 60$
$x = 14 + 108$
$x = 122$

3. Defuzzyfication stage to display the results of the calculation of the predicted amount of production from demand and supply.

Find value Z

$$Z = \frac{0{,}72\text{x}125) + (0{,}72\text{x}125) + (0{,}25\text{x}122) + (0{,}25\text{x}122)}{0{,}72 + 0{,}72 + 0{,}24 + 0{,}24}$$

$$= \frac{90 + 90 + 30 + 30}{1{,}92}$$

$$= \frac{240}{1{,}92}$$

$= 125$

So the amount of cleo drink production using the Fuzzy Tsukamoto method that must be produced is 125 Cleo Drink Boxes.

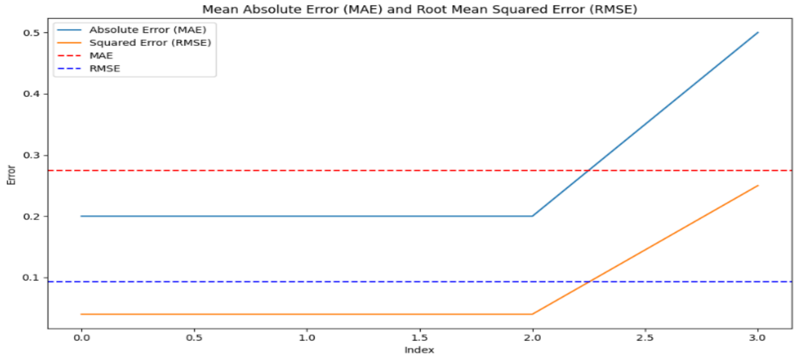

Figure 3. Mae and RMSE relief results

Figure 3. Produce an evaluation using RMSE and MAE contained in figure 3 MAE Based on the evaluation results, Fuzzy Tsukamoto's method was successful in determining the amount of beverage production at PT. Sariguna Primatirta Tbk with MAE of 0.25 and RMSE of 0.274 after the data is reduced. The MAE indicates the average predicted absolute error of 0.25 units, while the RMSE indicates that the average error in squared units is 0.274. The absolute error (MAE) and squared error (RMSE) graphs show that the prediction error is relatively small and the error distribution is close to the mean line, showing a fairly accurate prediction. Future research is recommended to test this method with more varied data and consider external factors to improve the accuracy and reliability of prediction models.

This study successfully shows that the Fuzzy Tsukamoto method is effective in determining the amount of beverage production by considering factors such as fluctuations in market demand, production costs, and consumer preferences, as evidenced by an MAE of 0.25 and an RMSE of 0.274. Compared to previous studies that only focused on optimizing production planning without taking into account consumer preferences or production constraints in detail, this study offers a more comprehensive predictive model.

The developed model not only takes into account demand and supply but also factors such as dynamic production policies and resource constraints, providing solutions that are more adaptive and suitable to real conditions. This research successfully fills a gap in the literature by providing a practical framework that can be adopted by the rest of the beverage industry to improve operational efficiency.

4. CONCLUSION

Fuzzy Tsukamoto method proved effective in determining the amount of beverage production at PT Sariguna Primatirta Tbk, with an MAE value of 0.25 and RMSE of 0.274, indicating good prediction accuracy. This model reduces the risk of overproduction and underproduction, increases operational efficiency, and production flexibility according to market demand, making a significant practical contribution to the company. For future research, it is recommended to test this method with more varied data and consider external factors such as changes in market demand and raw material availability to improve the accuracy and reliability of the model.

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