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ANALYSIS OF MECHANICAL PROPERTIES OF CuZn35 WITH HEAT TREATMENT USING MACHINE LEARNING & TAGUCHI OPTIMIZATION

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Abstract – Yellow brass is an alternative material for cartridge application. Heat treatment conducts on yellow brass to improve mechanical properties to fulfill the cartridge requirement. The main objective of this paper is to analyze the optimal parameters on the effect of heating temperature, holding time, and cooling medium on the tensile strength and hardness of yellow brass material as an alternative to CuZn30 replacement bullet casing material. Taguchi optimization and machine learning were carried out to evaluate several factors with a minimum number of tests using an orthogonal array experimental layout. The process parameters that will be optimized are furnace cooling media, water, and air. Annealing temperatures are 300, 400, and 500°C, and holding times are 60, 90, and 120 minutes. The results of the Taguchi method show that the parameter that has the most influence on the value of hardness and tensile strength is the heating temperature with a percent contribution of 85.8278% to hardness and 99.115% to tensile strength. On the machine learning results, the XG Boost model validation shows the MAE, RMSE, and R square values respectively 6.12; 8.23; 0.43 for the hardness response variable. The tensile strength response variable shows a value of 4.81; 7.76; and 0.49. Metrics from the validation show that a small sample using the Taguchi design can produce a good enough model to predict response.

Keywords: annealing; optimization; machine learning; Taguchi; yellow brass

1. Introduction

The cartridge is one of the modern ammunition used to be a container that wraps the projectile bullet which usually consists of gunpowder, rim, and primer. Bullet casings are very much needed in this modern era. However, the production of these cartridges still relies a lot on raw materials produced by foreign countries. The most widely used raw material for cartridge casings is Cartridge brass or CuZn30. The type of brass material that is commonly available in this country is CuZn35 or yellow brass. Yellow brass has properties that are close to Cartridge brass but still have a weakness in drawing ability because yellow brass has high hardness and strength so it has a high risk of cracking when drawing. Some of the comparable compositions in Table 1 show that the Zn content of yellow brass is higher than that of cartridge brass which shows higher tensile strength and hardness. To adjust the properties of yellow brass so that it can be shaped according to the criteria for optimal strength and minimal cracking, an annealing process is needed to reduce hardness and increase ductility.

Table 1. Comparison of the chemical composition of CuZn35 and CuZn30

Element	Content	
	CuZn30	CuZn35
Cu	68.5-71.5	64.0-68.5
Pb	Max 0.07	Max 0.15
Fe	Max 0.05	Max 0.05
Other elements	Max 0.15	-
Zn	Balance	Balance

The annealing process is a heat treatment carried out at a suitable temperature, followed by cooling at an appropriate speed. It aims to induce softness, improve the properties of cold working and relieve stresses on the specimen so that the desired structure is obtained (Istiqlaliyah and F. Rhohman, 2016). Khan *et al*., 2015 have examined the potential of brass material to be made into the cartridge, in which the results of the trial characterization of brass production (Cu-Zn 70-30) are still below the company's standard threshold. The hardness of the brass material when cold working has several 184.38 BHN which does not meet the company's standard which refers to the NATO standard SS109, which is the range of 75-90 BHN.

Due to the complexity of the parameters needed for yellow brass material to become a suitable raw material, it is necessary to have a suitable experimental design to identify process parameters in the manufacture of the material to obtain optimum hardness and tensile strength. By conducting an experimental design in the study, the optimum value can then be determined to determine the main process parameter areas that provide the best response results (Montgomery, 2001). The application of Taguchi and Machine Learning methods was applied to obtain the best response parameters and results from the experimental design. Machine learning (ML) is a branch of artificial intelligence (AI) that is concerned with the creation of models (knowledge) that can learn effectively from existing data (Kotsiantis et al., 2007). Machine learning can find out which parameters have the most influence on the response of the target.

2. Material and Method

The materials used in this research are yellow brass or CuZn35 as the material used for annealing. The yellow brass is annealed with 3 different parameters of annealing temperature, holding time, and cooling medium, the matrix of parameters is shown in Table 2.

Table 2. Research Variable Design Based on Orthogonal Matrix L_9 (3^3)

Number of experiments	Parameter process		
	Cooling Medium	Annealing Temperature	Holding Time
1	Water	300	60
2	Water	400	90
3	Water	500	120
4	Air	300	90
5	Air	400	120
6	Air	500	60
7	Furnace	300	120
8	Furnace	400	60
9	Furnace	500	90

annealing is done by using various parameters of temperature, holding time, and cooling media. The annealed material was then tested for damage with a tensile test and a hardness test to determine the response parameters in the experimental data. Next, experimental designs and modeling will be made using the Taguchi orthogonal array method and machine learning with the XGBoost, SVM, and linear regression methods. The design parameters used are shown in Table 2 with an orthogonal array matrix $L_9 3^3$. The steps applied for Taguchi optimization in this study are shown as follows:

1. Determine the quality characteristics, and what values should be optimized;
2. Determine the number of levels for the parameter design
3. Designing experimental matrices and determining data analysis procedures
4. Calculating the experimental matrix
5. Analyze the experimental results using S/N and ANOVA. analysis
6. Select the parameter level that gives optimal results
7. Make predictions at this level
8. Verify the design parameters by confirming the experiment (Koilraj *et al*., 2012)

3. Results and Discussion

The result of the Tensile Test and Hardness Test is shown in Table 3, with the calculation of mean hardness and ultimate tensile strength and signal ratio of hardness and ultimate tensile strength.

Table 3. Result data of Tensile Test and Hardness Test in variance parameter

No.	Parameter Process						
	Cooling Medium	Temperature	Holding Time	Mean Hardness	Mean UTS	SNR of Hardness	SNR of UTS
1	Water	500	60	82.8	328	38.36	50.31
2	Water	400	90	73.9	320	37.38	50.09
3	Water	300	120	71.0	316	37.03	49.98
4	Air	400	90	84.4	328	38.52	50.32
5	Air	300	120	75.5	320	37.56	50.10
6	Air	500	60	72.6	316	37.22	49.99
7	Furnace	300	120	79.5	327	38.01	50.30
8	Furnace	500	60	70.6	319	36.98	50.08
9	Furnace	400	90	67.7	315	36.61	49.98

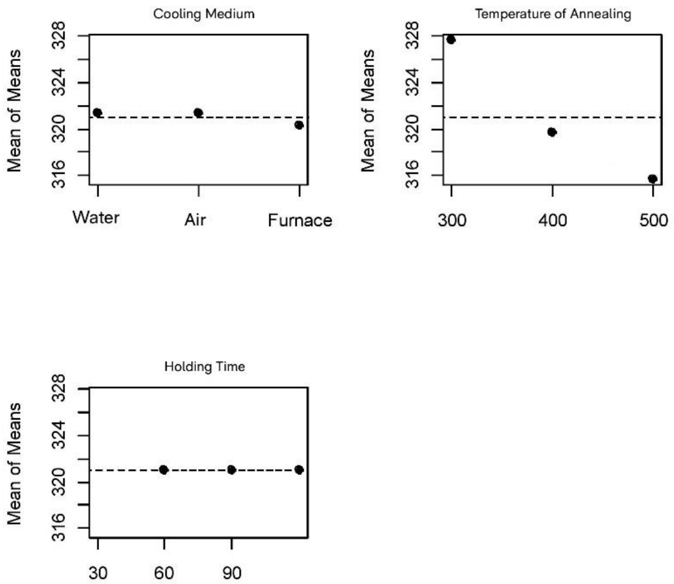

Fig. 1. Plot mean of Taguchi result for tensile strength parameters.

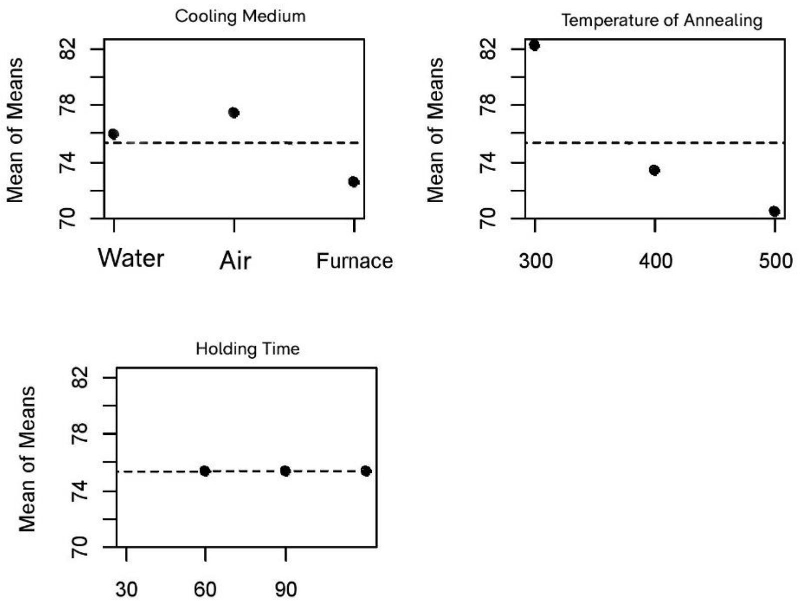

Fig. 2. Plot mean of Taguchi result for hardness parameters.

The plot mean to represent the most valuable parameter in the annealing process to get the best value of hardness and tensile strength. Figure 1 showed off the best parameter for the annealing for hardness value using an air cooling medium, 400^{o}C of temperature annealing, and 60 minutes of holding time, and figure 2 showed off the best parameter for the annealing to get tensile strength value using water cooling medium, 400^{o}C and 60 minutes of holding time. And the final calculation using the Taguchi method showed the percent of contribution and error value in Table 4 below:

Table 4. ANOVA result for hardness and tensile strength

Source	Parameters	Hardness	Tensile Strength
Highest Percent of Contribution	Temperature of annealing	85.83 %	99.69 %
Lowest Percent of Contribution	Holding Time	0 %	0 %
Prediction Value		73.87	320
	Error	0.126 %	0 %

From Table 4, it can be seen that the factor that has a significant factor on the hardness and tensile strength value is the heating temperature factor. Where the result percent of the contribution obtained is equal to 85.8278 % for hardness and 99.6944 %. The prediction value of hardness and tensile strength are 73.87 HVN and 320 MPa. The result of the prediction value of hardness and tensile strength gives a good value for yellow brass that can nearly have similar mechanical properties to cartridge brass for cartridge application. The optimal parameter has been shown for microstructures in Figure 3.

Figure 4 shows the results of grain size and boundaries on yellow brass material with air conditioning media parameters, the heating temperature of 400^{o}C, and the holding time of 60 minutes. Where the variation of these parameters, produces the optimal hardness value. In the cooling process, the cooling medium provides an opportunity for grain growth to occur during the process. The hardness value is related to grain size, where a small grain size will produce a lot of grain boundaries in the metal, where the grain boundaries act as a barrier to dislocation movement so that it can cause high hardness (Matyunin *et al*., 2019). The greater the number of grains, the smaller the grain size and a large number of grain boundaries in the specimen as a dislocation barrier, the microstructure also forms twin grain boundaries which have a function similar to that of the grain boundaries, namely as a dislocation barrier that can affect the hardness value (Shaw *et al*., 2008).

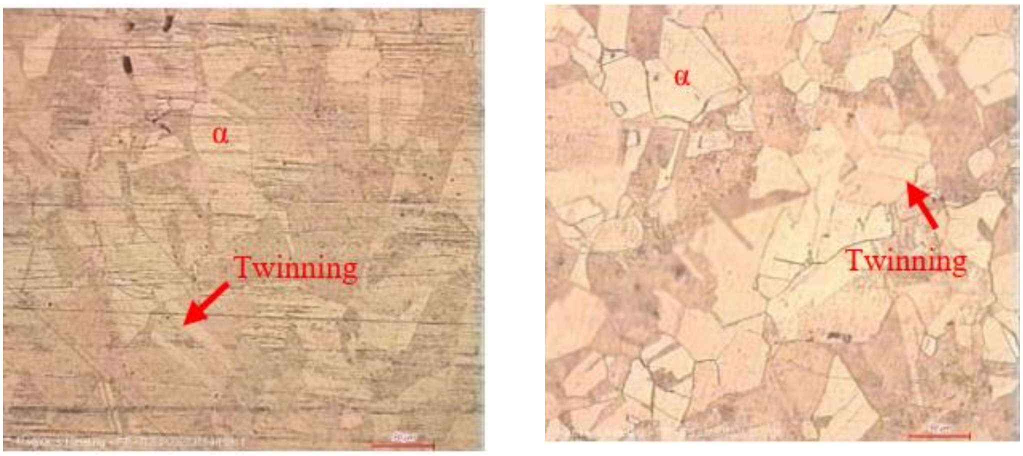

Fig. 3. Microstructure of the optimal parameter of annealed specimen.

The result of machine learning showed in Table 5 for confirming the valuable parameter that has reached in the Taguchi design experiment using XGBoost, SVM, and Linear Regression for testing the experiment data to the training data.

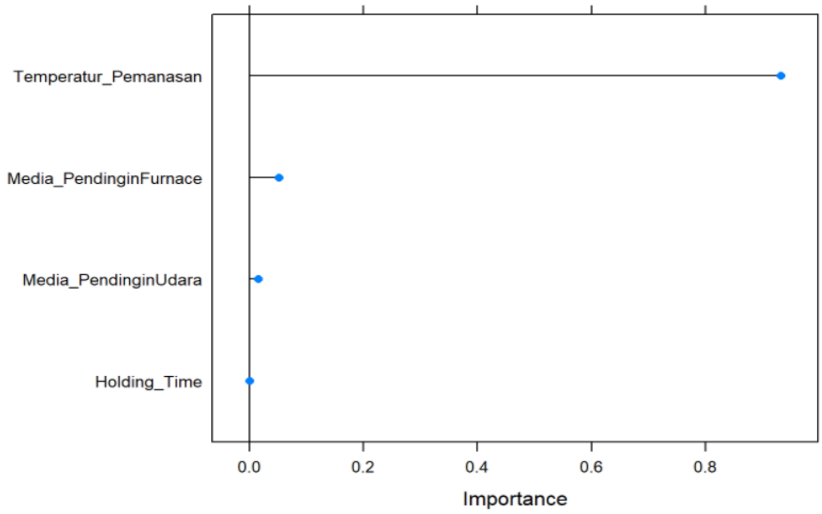

Fig. 4. Parameter influence value on tensile strength and hardness test.

Heating temperature is the most important parameter for the two response variables shown in the graph. Cooling media has little effect on the hardness response variable. The variation of holding time used does not have enough effect on the two variables.

4. Conclusion

The results of ANOVA calculations for the mean value in Taguchi show that the heating temperature has the most effect on 85.8278% on hardness and 99.115% on tensile strength. The optimal parameters obtained from the results of Taguchi's calculations are water cooling media, temperature 400 ºC, and holding time 60 minutes to obtain optimal hardness parameters, and with air cooling media parameters, temperature 400 ºC, and holding time 60 minutes to obtain optimal tensile strength parameters. optimal. The predicted optimum values for hardness and tensile strength are 73.87 and 320, respectively. And from the evaluation model, it was found that the heating temperature is the most influential variable with a scale of 0.8 compared to the cooling medium and the holding time is close to zero.

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