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Engineering of aluminium matrix composite (AMC) reinforcement organoclay based on hotpress method using adaptive neuro-fuzzy inference system (ANFIS)

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Abstract. Aluminum Matrix Composite (AMC) reinforced organoclay is a widely used material in automotive where there is a significant increase in mechanical strength, especially if reinforced nano-sized particles. This study aims to obtain AMC with a variation of composition 1-3% wt organoclay. The method used in this research is Hotpress. Testing (characterisation) use XRD, Optical Microscope Hardness Tester. Adaptive Neuro-Fuzzy inference system (ANFIS) model can forecast density and Microhardness of AMC. The pressure used is 137.8951458634 MPa, and the temperature is varied from 490°C-600°C with a holding time of 3 hours. Testing (characterisation) is carried out using XRD, Optical Microscope, Hardness Tester, Ultrasonic testing. The results showed that the hardness increased from 15 HVN to 197 HVN. The mass density increases, and reaches optimal at a composition of 550°C with the addition of 1% by weight of organoclay, the microstructure shows AMC formed which is shown in grey and increasing hardness and density indicated by black (porosity).

Keywords: Aluminium, AMC, Hotpress, composite, metal matrix, organoclay, automotive, Adaptive neuro-fuzzy inference system, ANFIS

1. Introduction

The potential improvement in properties achievable from metal matrix composites makes them desirable materials in automotive and aerospace industries. Aluminum-based composites are gaining increased applications in the transport, aerospace, marine, oil and gas, automobile and mineral processing industries, due to their excellent strength, stiffness and wear resistance properties. This engineering has constraints in its implementation of high production costs [1]. Discontinuously reinforced metal matrix composites (MMC) have attracted extensive research in the past few decades due to their high specific stiffness, high specific strength, and high wear resistance as compared to their corresponding monolithic alloys [2].

Reinforcements in the shape of particulates generally result in isotropic mechanical properties and can be fabricated economically by conventional metallurgical techniques. With composites reinforced with silicon carbide (SiC), Aluminium oxide (Al₂O₃) and graphite. Organoclay could be a potential reinforcing component due to its availability and its major constituents such as alumina (Al₂O₃), silica (SiO₂), oxides of iron (Fe₂O₃), titanium (TiO₂), and sodium (Na₂O) [3].

The automotive and aviation industries are developing wear-resistant applications of components by looking for lighter materials that can improve fuel efficiency as evidenced by Aluminium-based composite research [4]. Aluminium based composites reinforced with micro/nano-SiC, Al₂O₃, B₄C, TiB₂, ZrO₂, SiO₂ and graphite particles, changes the microstructural characteristics that develop superior mechanical and physical properties appropriate for automotive [4]. However, the major limitation of the



use of Aluminium alloys is its soft nature, hence the need for its reinforcement with high strength-stiffness materials such as SiC, TiC, TiB₂, B₄C, Al₂O₃, and Si₃N₄ [5]. Organoclay contains reinforcing materials such as Al₂O₃, SiO₂, and Fe₂O₃ with trace presence of other materials [6] making it a potential candidate as a reinforcing agent for the production of metal matrix composite for wear applications.

The Aluminium creates an Aluminium oxide surface layer to avoid oxidative wear during the shear process. Asperity-to-asperity and wear controls that are essentially controlled by surface deformation, and surface fracture determines the level of wearability [7].

Therefore, this paper will investigate the influence of various weight fractions of Aluminium Organoclay on the mechanical properties of Al-Organoclay composites for automotive applications use Experimental Data and ANFIS model.

2. Experimental

This research uses Aluminium powder with 380 mesh particle size from Nanoshell Chemical with Organoclay (*cloisite*) as filler. The tensile and Vickers hardness tests of samples were conducted Mitutoyo microhardness tester HM-6561 by the ASTM E8/E8M-13 standards. The Metallographic examination was carried out using Olympus Digital Microscope 1600 X.

3. ANFIS (Adaptive Neuro-Fuzzy Inference System) Model for Mechanical Properties

ANFIS is a network structure in which a set of modified parameters determines the overall input-output behaviour. One of the neural network structures is the multilayer perceptrons (MLP). The ANFIS node can forecast datasets in financial time series [8].

ANFIS combines the fuzzy logic and neural network. ANFIS in its work uses a hybrid learning algorithm that combines the method of Least-Squares Estimator (LSE) and Error Back-Propagation (EBP). The use of ANFIS is done by using the membership function and works the entire network with fuzzy numbers. ANFIS Model can predict hardness, density and mechanical properties of the liquid material [9] and solid material [10].

The inputs of the proposed ANFIS are 2 (temperature, organoclay composition) and the output is 1 (Vickers Hardness). The ANFIS can determine how each of these factors impacts the index in quantitative data.

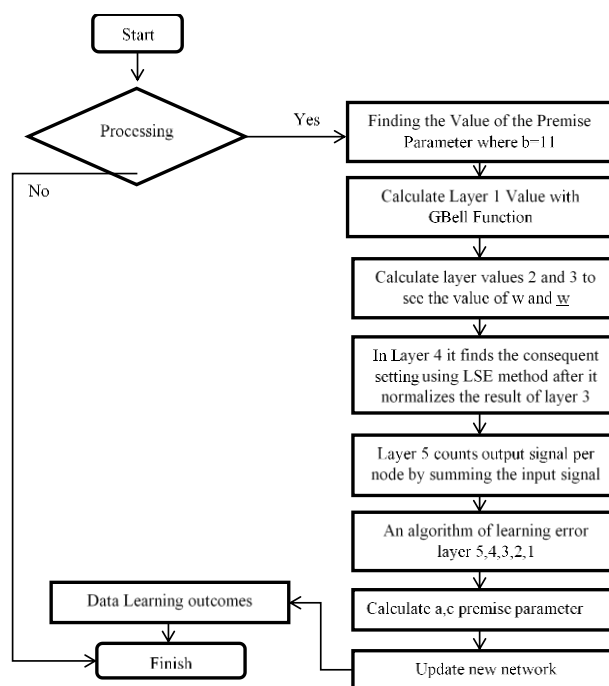


Figure 1. ANFIS flowchart.

ANFIS system process consisting of several layers as shown in Fig. 2. In the first layer of input data in each period will be fuzzification process. This process is to map the input data into the fuzzy set according to the selected classification (in this study only use two types of the fuzzy: high and low)

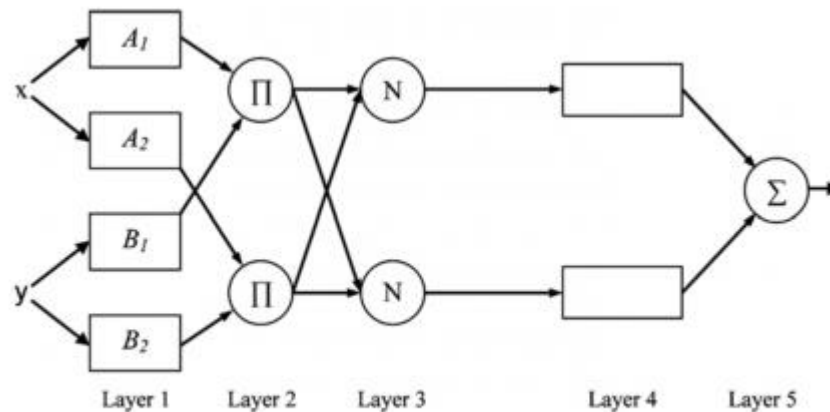


Figure 2. ANFIS block diagram.

In this process, the input will be calculated fuzzy membership function to transform the traditional set of input (crisp) to a certain degree. Membership function used is Bell type where in this membership function there are two parameters namely mean and variance, the parameter in ANFIS method called as premise parameter. In the second and third layer done inference engine process (fuzzy inference system) specified the fuzzy rule for the further calculation process. In this process, because the ANFIS system used is one input, then there is no calculation. The output node of this layer is the same as the output layer node 1. On layer three is normalised each vertex displays the degree of activation normalised. In layer four the defuzzification process performed the calculation of transforming the fuzzy results into the crisp output form. In this layer, the LSA calculation is performed to obtain following parameter values. In layer five a summary process of two outputs is performed on layer 4. In ANFIS the fuzzy system is located on layers 1, 2, 3 and 4. The fuzzy system is the hidden node determinant of the neural network system. Explanation of each layer as follows:

Layer 1:

Each adaptive node have function: $n1a = \text{Bell}(x; a1, b1, c1)$ $n2a = \text{Bell}(x; a2, b2, c2)$ where x is the input for vertices $n1a$, and $n2a$, whereas $a1, b1, c1, a2, b2, c2$ are the membership level parameters of the fuzzy set A ($=a1, a2, b1$ or $b2$) and determine the membership degree of the given x input. The bell function can approximate the membership function parameters of A :

$$\mu_A(x) = \frac{1}{1 + \left(\frac{x - ci}{2a}\right)^{2bi}} \quad (1)$$

Where $[ai, bi, ci]$ is the set of parameters. The parameters in this layer are called the parameter of the premise parameter.

Layer 2:

Each node in this layer is labeled $n3a$ and $n4a$, non-adaptive (fixed parameters) that forward results from layer 1. Because the system uses one input, there is no AND inference. Thus the output on the 2nd layer is:

$$n3a = n1a \quad (2)$$

$$n4a = n2a \quad (3)$$

Layer 3:

Each node in this layer is labeled $n5a$ and $n6a$, also non-adaptive. Each vertex displays the degree of activation normalized to the shape. $n5a = n3a / (n3a + n4a)$ $n6a = n4a / (n3a + n4a)$

Layer 4:

$$A = \begin{bmatrix} (n5a)x(n) & n5a & (n6a)x(n) & n6a \\ (n5a)x(n) & n5a & (n6a)x(n) & n6a \end{bmatrix} \quad (4)$$

Each node in this layer is an adaptive node, and in this layer, we get the matrix A , as follows: Number of matrix rows as much as the amount of input data x . In this layer sought following parameter values θ with LSE method. The equation of the LSE method is:

$$\theta = \text{inv}(A^T A) A^T \cdot y \quad (5)$$

y = Target to be achieved

$$\theta = [p1 \quad q1 \quad p2 \quad q2] \quad (6)$$

Furthermore, to calculate the output in the fourth layer is used the following equation:

$$n7a = p1 \cdot x + q1 \quad (7)$$

$$n8a = p2 \cdot x + q2 \quad (8)$$

Layer 5:

Single nodes in this layer are labeled $n9a$, which calculates all outputs as the sum of all incoming signals:

$$n9a = n7a + n8a \quad (9)$$

$$T_s(l, t) = T_g(l, t) \quad (10)$$

The value of each node is obtained by comparing the variable $n1a$ with the total variable total node.

4. Result

4.1. Mechanical properties

The results of Vickers' micro-hardness measurements on aluminium matrix surfaces and macro-Vickers hardness measurements on Al/Organoclay composite surfaces show that hotpress temperature increase decreases AMC hardness.

Table 1. Hardness vs Hotpress temperature.

% Organoclay	T Hotpress	Vickers Hardness
1%	490°C	184
2%	490°C	127
3%	490°C	197
1%	550°C	172
2%	550°C	126
3%	550°C	158
0%	600°C	127

The increase in temperature from 490°C–600°C causes a decrease in Vicker Hardness in the same composition of organoclay.

The increase in composition from 1% Wt–3% Wt causes an increase in Vicker Hardness in the same temperature condition

Table 2. Density vs Hotpress temperature.

% Organoclay	T Hotpress	Density
1%	490°C	2.50
2%	490°C	2.48
3%	490°C	2.37
1%	550°C	2.55
2%	550°C	2.53
3%	550°C	2.52
0%	600°C	2.62

The increase in temperature from 490°C–600°C causes an increase in Density in the same composition of organoclay. The increase in composition from 1% Wt–3% Wt causes a decrease in Density in the same temperature condition.

4.2. Optical Microstructure

Fig. 1 displayed the results of the metallographic examination of all the samples. The Aluminium matrix grain boundaries contain evenly distributed organoclay particles.

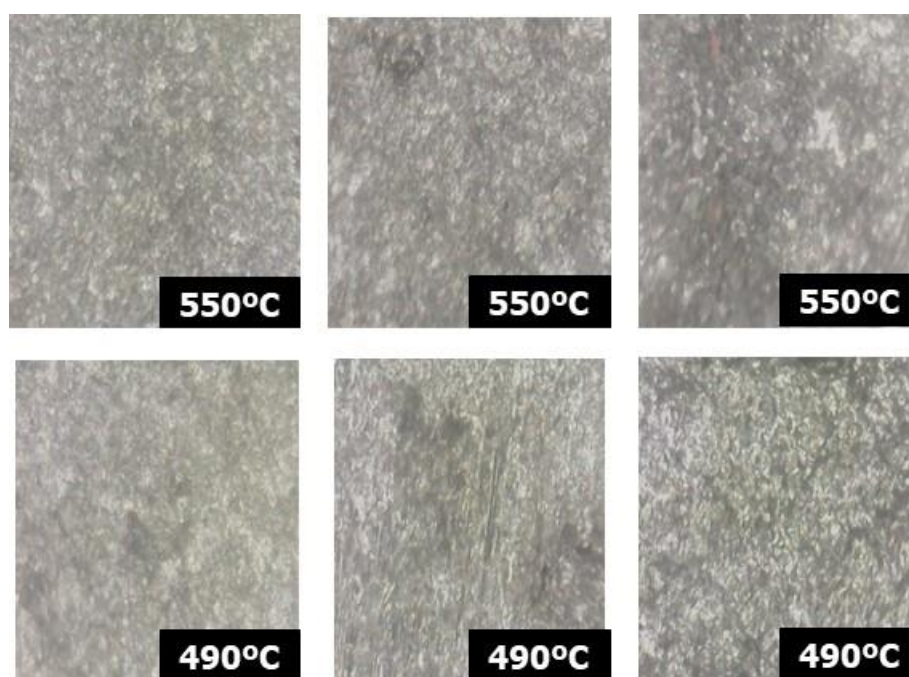


Figure 3. Optical microscope for aluminium/organoclay.

Fig. 3 AMC can be seen marked in grey and an increase in strength marked with black which indicates increasing hardness and density.

4.3. XRD characteristics

Figure of seven samples displayed the result of the wear test of the composites with various weight fractions of Organoclay particles as shown in Fig. 4. The wear rate decreases with increase in the weight fraction of the reinforcing agent (Organoclay) as compared to conventional Aluminium. Increased hardness by hard intermetallic dispersion over the Aluminium matrix, acting as a load support element causes lower wear rates observed at optimum conditions between 15-20% by weight of Organoclay.

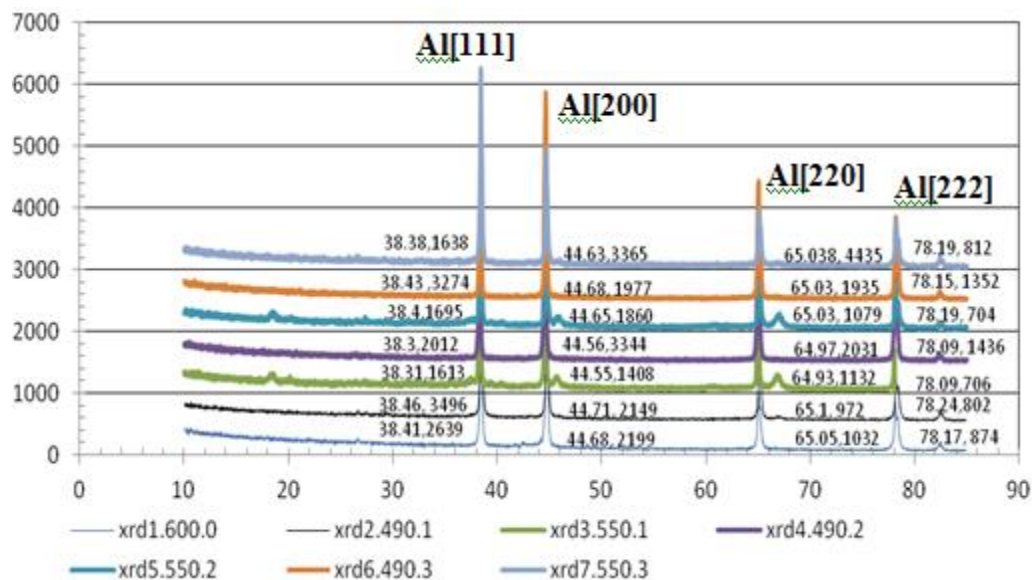


Figure 4. XRD characteristic for AMC.

5. Discussion

Data prediction process begins with import experimental data from Microsoft Excel (Fig. 5):

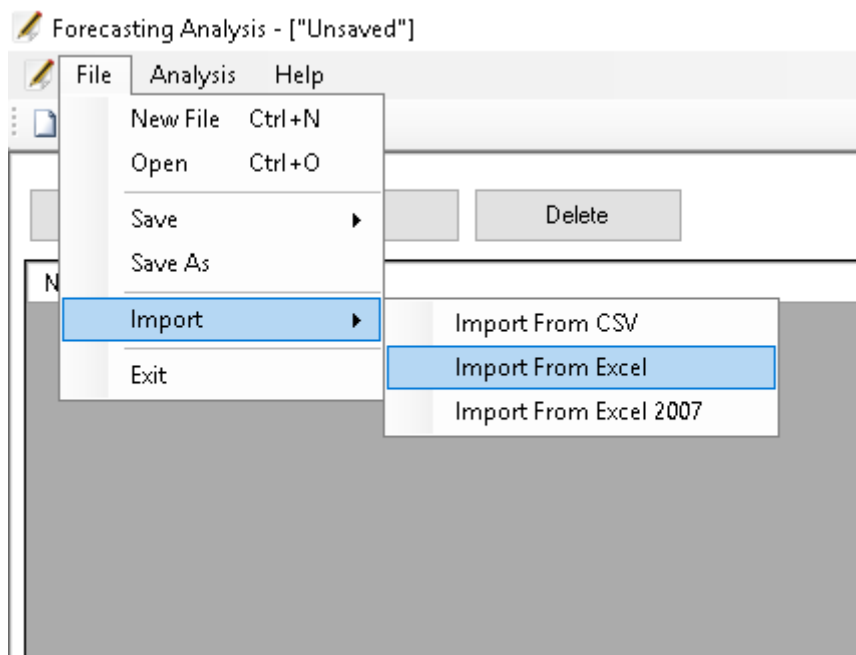


Figure 5. Import XRD data for material engineering.

Select the independent variable and the dependent variable (Fig. 6):

Figure 6. Independent and dependent variable.

Perform learning process (Fig. 7):

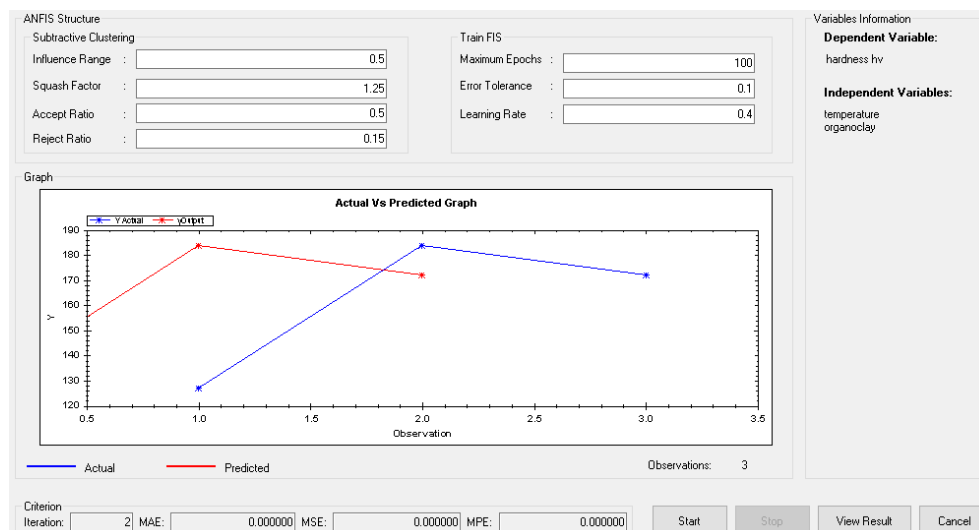
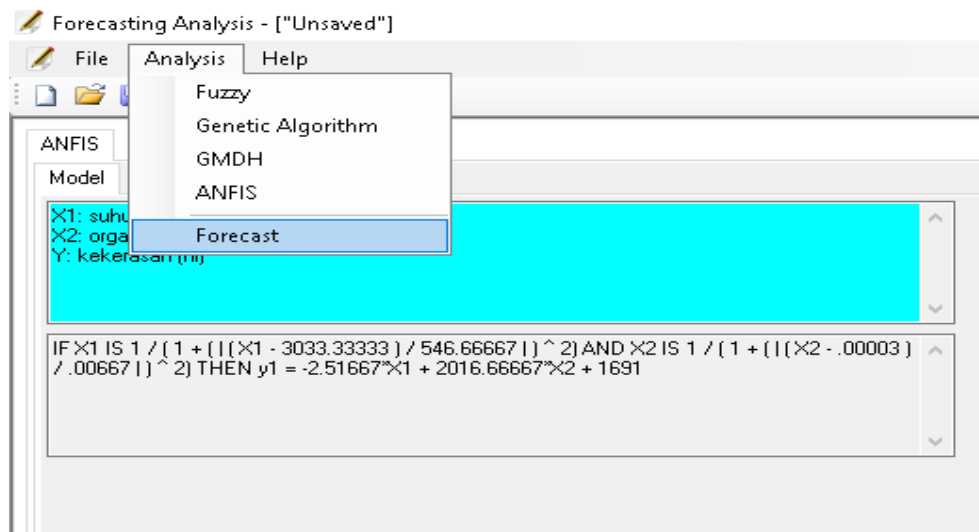


Figure 7. Learning process.

Do forecasting process (Fig. 8):

**Figure 8.** Forecasting process.

Perform data input for forecasting (Fig. 9):

ForecastedVariable													
Step	12												
	Step1	Step2	Step3	Step4	Step5	Step6	Step7	Step8	Step9	Step10	Step11	Step12	
temperature	490	500	510	520	530	540	550	560	570	580	590	600	
organoklay	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	

Figure 9. Input data for forecasting.

Data forecasting result of AMC with organoklay composition 1% (Fig. 10):

ANFIS			
Model		Forecast #10	
	temperature	organoklay	hardness hv
Step 1	490	.01	184
Step 2	500	.01	182
Step 3	510	.01	180
Step 4	520	.01	178
Step 5	530	.01	176
Step 6	540	.01	174
Step 7	550	.01	172
Step 8	560	.01	170
Step 9	570	.01	168
Step 10	580	.01	166
Step 11	590	.01	164
Step 12	600	.01	162

Figure 10. Hardness Vickers forecasting 1%Wt organoklay.

The increase in temperature from 490°C–600°C causes a decrease in Vicker Hardness in same one %wt organoclay composition condition.

Data forecasting result of AMC with organoclay composition 1% (Fig. 11):

ANFIS			
Model	Forecast #10	Forecast #11	
	temperature	organoclay	hardness hv
► Step 1	490	.02	219
Step 2	500	.02	217
Step 3	510	.02	215
Step 4	520	.02	213
Step 5	530	.02	211
Step 6	540	.02	209
Step 7	550	.02	207
Step 8	560	.02	205
Step 9	570	.02	203
Step 10	580	.02	201
Step 11	590	.02	199
Step 12	600	.02	197

Figure 11. Hardness Vickers forecasting 2%Wt organoclay.

The increase in temperature from 490°C–600°C causes a decrease in Vicker Hardness in same two %wt organoclay composition condition. Data forecasting result of AMC with organoclay composition 3% (Fig. 12):

ANFIS			
Model	Forecast #10	Forecast #11	Forecast #12
	temperature	organoclay	hardness hv
► Step 1	490	.03	254
Step 2	500	.03	252
Step 3	510	.03	250
Step 4	520	.03	248
Step 5	530	.03	246
Step 6	540	.03	244
Step 7	550	.03	242
Step 8	560	.03	240
Step 9	570	.03	238
Step 10	580	.03	236
Step 11	590	.03	234
Step 12	600	.03	232

Figure 12. Hardness Vickers forecasting 3%Wt organoclay.

The increase in temperature from 490°C–600°C causes a decrease in Vicker Hardness in same three %wt organoclay composition condition. Data forecasting result of AMC with organoclay all composition (Fig. 13):

	temperature	organoclay	hardness hv
► Step 1	490	.01	184
Step 2	490	.02	219
Step 3	490	.03	254
Step 4	500	.01	182
Step 5	500	.02	217
Step 6	500	.03	252
Step 7	510	.01	180
Step 8	510	.02	215
Step 9	510	.03	250
Step 10	520	.01	178
Step 11	520	.02	213
Step 12	520	.03	248
Step 13	530	.01	176
Step 14	530	.02	211
Step 15	530	.03	246
Step 16	540	.01	174
Step 17	540	.02	209
Step 18	540	.03	244
Step 19	550	.01	172
Step 20	550	.02	207
Step 21	550	.03	242
Step 22	560	.01	170
Step 23	560	.02	205
Step 24	560	.03	240
Step 25	570	.01	168
Step 26	570	.02	203
Step 27	570	.03	238
Step 28	580	.01	166
Step 29	580	.02	201
Step 30	580	.03	236
Step 31	590	.01	164
Step 32	590	.02	199
Step 33	590	.03	234
Step 34	600	.01	162
Step 35	600	.02	197
Step 36	600	.03	232

Figure 13. Hardness Vickers forecasting all composition organoclay.

The increase in composition from 1% Wt–3% Wt causes an increase in Vicker Hardness in the same temperature condition.

6. Conclusion

The increase in temperature from 490°C–600°C causes a decrease in Vicker Hardness in the same composition of organoclay. The increase in composition from 1% Wt–3% Wt causes an increase in Vicker Hardness in the same temperature condition. The increase in temperature from 490°C–600°C causes an increase in Density in the same composition of organoclay. The increase in composition from 1% Wt–3% Wt causes a decrease in Density in the same temperature condition.

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