Optimation of AMC’s Tensile Properties Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract. The addition of organoclay to Aluminium Matrix Composite (AMC) with heat treatment and setting process variables was able to change the microstructure affecting its mechanical properties. The method used in this study was a hot press. The pressure used was of 137.8951458634 MPa, and the temperature varies from 490-600 °C with a holding time of 3 hours. Characterization was carried out using XRD, optical microscope, hardness tester, and ultrasonic tester. The data analysis showed that the hardness increased from 126 to 197 HVN. Furthermore, the mass density also increased, and reached an optimal value with the addition of 1% wt of organoclay at a temperature of 550 °C. The microstructure exhibited that AMC was formed and increased the hardness and density. XRD results indicated that aluminium phase was successfully detected. From the results of several characterizations, it can be concluded that the optimal material has the composition by adding 1% wt of organoclay with a heating temperature of 550 °C, a pressure of 13.7859558534 MPa and a long press time of 3 hours. In this study, we construct a relationship between process variables based on experimental, computational design and use the Inference Adaptive Neuro-Fuzzy inference (ANFIS) method. Furthermore, the prediction accuracy made by the model was investigated based on the test case. The results showed that the hot press method had a relationship with the attraction properties having the same conclusion using experiments and ANFIS.

Keywords: Tensile, AMC, press method, simulation, ANFIS

1. Introduction
Aluminium Matrix Composites (AMC) is a steel substitute material that has been used in the fields of marine, automobile, and aerospace [1]. Furthermore, the mechanical properties of AMC can be improved further by varying the filler phase [2]. In general, AMC consists of two components i.e., matrix phase that is usually metals such as aluminium or alloy. Another component is reinforcement such as fibres, moustaches or particles or fillers. Aluminium is prominently used as the matrix phase because of its isotropic properties, ease of production and low cost. Practically, AMC can be strengthened with various fillers such as SiC, B4C, TiC, TiB2, TiO2, AlN, BN, and Si with various types, sizes, shapes [3]. The disadvantage of using fillers in composites is that the bonds between matrix and filler are only substituted and epoxy is usually required to bond. Increasing the weight composition of filler to strengthen AMC is able to enhance the hardness behavior but decreasing the density [4].
Organoclay is clay whose ions have been exchanged using surfactants to absorb metal ions. It is usually used as absorbents for hazardous chemicals and metals. Due to its ability to form ion bond, organoclay is used to strengthen the chemical matrix type of polymer. However, the use of organoclay to strengthen AMC is rarely reported [5]. In such purpose, optimization of filler variables is required. Optimization can determine the best condition of size, filler, and temperature by selecting systematic input values from available or allowed values [6].

Optimization of the variables which have never been studied can be done by genetic algorithms, Adaptive Neuro Fuzzy-Inference Systems (ANFIS), and multiple regression models [7]. As organoclay has never been used as amplifiers in AMC, the adaptive neural network-based fuzzy inference systems are deemed most suitable because they explore human-reasoning techniques. Fuzzy inference systems contain structured knowledge obtained from the learning process for AMC patterns that have been studied or those of experimental results. Each fuzzy describes the system's original behaviour and can be adapted to other variables. Therefore we need an experimental learning process pattern as ANFIS input to perform system optimization. [8]. Optimization using ANFIS will work well if the variables used have random properties in a population and random movement direction. Furthermore, the use of powder form can produce a composite with randomly dispersed particles [9].

In the present study, we developed aluminium matrix composite reinforced by organoclay. However, the optimization is problematic since this material has no known characteristics and mechanical properties. The commonly used regression model for aluminium composite matrix simulation can not be performed since it requires data from filler material with known characteristics. Therefore, a simulation method that can perform AMC simulations that are reinforced by random material is required. In this work, we employed Adaptive Neural Fuzzy Inference (ANFIS) models because it is suitable for random and powdery variables. The density and microhardness test performed on the composite was done to compare AMC density and microhardness of various conditions.

2. Methods

2.1. AMC fabrication and hotpress method

Organoclay was natural substance clay originated from the soil which bentonite and zeolite were modified by the addition of surfactant to change its character from hydrophilic into organophilic. The present study used Cloisite, a pre-added surfactant so it could be used directly as filler. Aluminium powder used as a nominal 30 μm AMC matrix was obtained by passing powder through a 600 mesh sieve. Aluminium powder and organoclay were mixed using alumina mortar and stirrer. The powder mixture was loaded in cylindrical moulds with a diameter of 25 mm. The powder mixture in the mould was compacted using a hotpress with a pressure of 137.8951458634 MPa. The Crucible used for hot press was in the furnace which had a maximum temperature of 1000 °C and an accuracy of temperature control (± 10 °C) using a K-type thermocouple that connected to the controller. The powder mixture in the mould was indirectly compressed die which was pressed with a hydraulic press with a pressure of 20 tons and a temperature variation of 490-600°C. Before the addition, the powder was mixed with 1%, 2%, 3% wt organoclay. The schematic diagram of these steps is shown in Figure 1.
2.2. ANFIS
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 perceptron (MLP). The ANFIS node can forecast datasets in financial time series [10]. ANFIS combines fuzzy logic and neural networks. ANFIS handles random data that combine the Least-Squares Estimator (LSE) and Back-Propagation (EBP) methods. The use of ANFIS is done by entering learning data into fuzzy logic and looking for the value with the smallest error rate. For more details about how the membership function works, see the Figure 2.

Figure 1. Schematic diagram for the making of AMC
ANFIS system process consists of several layers. In the first layer of input data in each period will be the 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).
In this process, the input was calculated fuzzy membership function to transform the traditional set of input (crisp) to a certain degree. Membership function used is the Bell-type. The membership function has two parameters namely mean and variance parameters. The parameter in the ANFIS method is called as premise parameter. In the second and third layer, inference engine process (fuzzy inference system) specified the fuzzy rule for the further calculation process. In this process, because the ANFIS system used was one input, then there was no calculation. The output node of this layer was the same as the output layer node 1. In layer three was normalized each vertex displayed the degree of activation normalized. 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 was performed to obtain the following parameter values. In layer five a summary process of two outputs was performed on layer 4. In ANFIS the fuzzy system was located on layers 1, 2, 3 and 4. The fuzzy system was the hidden node determinant of the neural network system. The schematic explanation of each layer as follows:

**Layer 1:**
Each adaptive node has 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 \( A \):

\[
\mu_A(x) = \frac{1}{1 + \left(\frac{x-c}{a} \right)^2 \cdot b^2}
\]

Where \( \{a, b, c\} \) 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 labelled \( n3a \) 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:

\[
n3a = n1a
\]
\[
n4a = n2a
\]

**Layer 3:**
Each node in this layer is labelled \( n5a \) 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:

\[
A = \begin{bmatrix}
(n_5a)x(n) & n_5a & (n_6a)x(n) & n_6a \\
(n_5a)x(n) & n_5a & (n_6a)x(n) & n_6a \\
\end{bmatrix}
\]

(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 \( \theta \) with LSE method. The equation of the LSE method is:

\[
\theta = \text{inv}(A^T A) A^T y
\]

(5)

\( y \) = Target to Be Achieved

\[
\theta = [p_1 \ q_1 \ p_2 \ q_2]
\]

(6)

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

\[
n_7a = p_1 \times x + q_1
\]

(7)

\[
n_8a = p_2 \times x + q_2
\]

(8)

Layer 5:

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

\[
n_9a = n_7a + n_8a
\]

(9)

\[
T_s (l,t) = T_g (l,t)
\]

(10)

2.3. Experimental data
AMC experimental data with organoclay reinforcement that has a variation of by weight 1% - 3% wt. Mechanical properties, namely hardness, density was used as a variable to be optimized.

2.4. Implementation of artificial neural network models
Experimental data were randomized by conducting experiments to make AMC and used as training data, test data and validation data (temperature, hardness, density). For training used the Levenberg-Marquardt feed-forward and backpropagation network how to optimize by trial and error until the smallest root-square error was obtained. After the model was trained, the code generated would be used to predict unknown targets based on the input given. The ANFIS model was developed using C # Language.

3. Results and Discussion
The composite results are expected to increase mechanical strength. In this study, organoclay was used with a percentage of 1-3% by weight. Method. The method used in the research was Hot Press. The pressure used was 137.8951458634 MPa and the temperature varied from 490-600 °C with a holding time of 3 hours. Testing (characterization) was 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 increased, and reached optimal at a composition of 550 °C with the addition of 1% by weight of organoclay, this could be simulated using ANFIS computational model.

The benefits of ANFIS include the method that helps to explore unknown particles such as the use of organoclay as an AMC amplifier. In addition, using ANFIS would be able to simulate the making of AMC reinforced by organoclay with a variety of organoclay additions and more detailed temperatures, so it is not necessary to conduct additional experiments to obtain the data with ANFIS requirements. Figure 4 displayed the results of the metallographic examination of all the samples. The Aluminium matrix grain boundaries contain evenly distributed Organoclay particles.
Based on Figure 4, it can be seen that the marking in grey and an increase in strength marking with black which indicates increasing hardness and density. Figure 5 displayed the result of the XRD of the composites with various weight fractions of organoclay particles. All samples have same peak with aluminium phase at 2-theta = 38.43°, 44.67°, 65.02°, 78.13°, and 82.33° showing miller lattices at [1 1 1], [200], [220], and [222]. This indicates that the aluminum phase was detected after a hot press was performed.
Figure 5. The XRD Characteristic of AMC.

XRD1 = AMC with hot press temperature 600°C (0% organoclay), XRD2 = AMC with hot press temperature 490°C (1% organoclay), XRD3 = AMC with hot press temperature 550°C (1% organoclay), XRD4 = AMC with hot press temperature 490°C (2% organoclay), XRD5 = AMC with hot press temperature 550°C (2% organoclay), XRD6 = AMC with hot press temperature 490°C (3% organoclay), XRD7 = AMC with hot press temperature 550°C (3% organoclay)

Figure 6. ANFIS Independent and Dependent Variable

Figure 6 shows the independent and dependent variable for providing hardness and density. Hardness and density are the dependent variables that are influenced by the independent variables of adding %wt organoclay at AMC and hot press temperature.
The data included in the ANFIS program were the data from the AMR sample XRD with a variation of 1% - 3% wt of organoclay, the data were converted into CSV format and included as a variable that would be studied for the pattern. Figure 7 describes the process of training the data using the trial and error method by looking at the smallest Mean Square Error (MSE) and Mean Prediction Error (MPE) when training MSE and MPE can be stopped by pressing the STOP button. The explanation of the variables used can be seen in Table 1. Table 1 shows an explanation of variables which using for providing hardness and density. Furthermore, Table 2 shows the % wt of organoclay, temperature affects hardness.

**Figure 7. ANFIS Learning Program**

| Variable | Description |
|----------|-------------|
| Temperature (T) | Hot press temperature of AMC. |
| Organoclay | One if the company gets an opinion regarding the doubt on-going concern, and 0 otherwise. |
| Density | Density of AMC |
| Hardness | Hardness of AMC (L = Leeb, V = Vickers, B = Britnell) |
| P | Pressure of AMC |
Table 2. Hardness vs hot press temperature

| %wt of organoclay | T hot press | 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      |

ANFIS Program also provides density value after the learning process. Table 3 shows that %wt organoclay, Temperature affects Density.

Table 3. Density vs hot press temperature

| %wt of organoclay | T hot press | 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    |

After training, and pressing the RESULT button which produces tables 2 and 3, the most optimum value of Hardness and density in the composition of adding 1% wt of organoclay at hot press temperature was 550 °C. The highest hardness was in the composition of the addition of 3% wt of organoclay at a temperature of 490 °C, but the density at that temperature was the lowest. [11]. The results showed that the hardness increased from 126 to 197 HVN. The mass density increased and reached optimum value at a composition of 550 °C with the addition of 1% wt of organoclay. This model shows a good agreement with those of experimental studies. The analysis of variance used the ANFIS method implied that all predictors were significant factors that influence the hardness and showed good predictions of the hardness and density. The model can be used to predict the tensile strength of particulate reinforced AMC.

4. Conclusion
The guidelines based on the observations from the results of the experimentation of this study, the following conclusions are inferred that ANFIS can be used to optimize and analyze the mechanical properties of AMC variables. The hardness increased from 126 to 197 HVN. The mass density increases from 2.37-2.62 gram/cm³. The optimal condition is reached at a composition of 550 °C with the addition of 1% wt of organoclay.
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Acknowledgements

The authors would like to express their sincere gratitude and appreciation to the reviewers for their constructive and valuable suggestions, in ensuring the quality of this study. Especially, the Materials Science Doctoral Program at University of Indonesia who has sponsored this study.