Original Article

Multi-objective optimization and modeling of age hardening process using ANN, ANFIS and genetic algorithm: Results from aluminum alloy A356/cow horn particulate composite

Chidzie Chukwuemeka Nwobi-Okoye\textsuperscript{a,*}, Basil Quent Ochieze\textsuperscript{b}, Stanley Okiy\textsuperscript{c}

\textsuperscript{a} Faculty of Engineering, Anambra State University (Chukwuemeka Odumegwu Ojukwu University), Uli, Nigeria  
\textsuperscript{b} Department of Mechanical Engineering, Chukwuemeka Odumegwu Ojukwu University, Uli, Nigeria  
\textsuperscript{c} Petroleum Training Institute, Effurun, Nigeria

ABSTRACT

This study reports on the modeling and multi objective optimization of age hardening process parameters using artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). The age hardening outputs (hardness and cost) were predicted using ANN and ANFIS. ANFIS with a correlation coefficient (R) value of 0.9985 predicted the obtained hardness values better than ANN which had R value of 0.9926. For the process cost predictions, ANFIS and ANN obtained the same values of R which was 1. Later values outside the experimental data points were predicted with ANN and ANFIS. When the temperature was kept constant and other input parameters were varied, the average relative error of the predicted values for ANFIS was 0.016\% and for ANN 0.0037\%. When the temperature was varied and other input parameters kept constant, the average relative error of the hardness values predictions for ANFIS was 73.69\% and ANN was 0.2229\%. With better performance of ANN outside the experimental points, it was used as fitness function for multi objective optimization of the age hardening process parameters using genetic algorithm (GA). The results show that ANN with coarse experimental data points for learning is more effective than ANFIS in predicting process outputs in the age hardening operation of A356 alloy/CHp particulate composite. The fine experimental data requirements by ANFIS make it more expensive in modeling and multi-objective optimization of age hardening operations of A356 alloy/CHp particulate composite.

© 2019 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

* Corresponding author.
E-mails: chidoziem@yahoo.com (C.C. Nwobi-Okoye), basilquent@gmail.com (B.Q. Ochieze).
https://doi.org/10.1016/j.jmrt.2019.01.031
2238-7854\textsuperscript{©} 2019 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
1. Introduction

Age hardening requires high temperature; hence it is a high temperature process. Obtaining high temperatures for age hardening operation requires quite high amount of energy which contributes to the cost of the process. For metal matrix composites (MMCs), of which aluminum alloy (A356)/cow horn particulate (CHp) composite is a typical example, the additives to the metal matrix, for example cow horn particles, contributes to the cost of the composite and helps to harden the material. Consequently, in age hardening operations there should be a tradeoff between obtained hardness values and cost. This makes modeling age hardening operations amenable to multi-objective optimization.

Material modeling involves modeling the relationship between the input and output variables in materials processing. Optimizing process outputs requires first an establishment of the relationship between process variables and subsequent optimization of the output variable using an appropriate optimization algorithm. In modern times due to its superiorit over mathematical models, soft computing techniques such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), fuzzy logic, genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), etc. have been the tools of choice in materials modeling and optimization. The soft computing optimization algorithms classified as metaheuristics, a stochastic optimization technique, due to its numerous advantages have been the dominant optimization technique in science and engineering. This is true of genetic algorithm, a versatile metaheuristics method, which has found extensive use in solving optimization problems in manufacturing and materials engineering [1-4].

The materials science and engineering literature is replete with applications of soft computing techniques in materials modeling and optimization. Sahay et al. [1] used genetic algorithm in optimization of age hardening of aluminum alloy rods. They used an elitist nondominated sorting genetic algorithm for multiobjective optimization of industrial age-hardening operation for packed bundles of aluminum rods for energy minimization, productivity maximization, and variability reduction during age-hardening. In modern times artificial intelligence and soft computing techniques are increasingly being integrated with genetic algorithm and other metaheuristics techniques to develop optimization algorithms in materials science and engineering [5-7]. Artificial intelligence (AI) and soft computing techniques are usually more accurate [8-13]. Dey et al. [7] used computational intelligence to design novel age-hardenable aluminum alloys. In order to design the aluminum alloys based on the conflicting objectives of high strength and adequate ductility, they used a multi-objective genetic algorithm (MOGA) to search optimum solutions using the ANN models as the fitness functions. They used the MOGA to design age-hardenable aluminum alloys with superior mechanical properties at different regimes of temperature.

ANN is a very important soft computing tool in modeling of materials as stated above. Applications of ANN in materials science and engineering literature are numerous. For instance, Amirjan et al. [14] used ANN to predict the hardness and electrical conductivity of copper alloyed with Al2O3. They used four different composition of the composite comprising of different amounts of Al2O3 reinforcement at 1, 1.5, 2, 2.5 wt% and produced the composites at 5 different temperatures varying from 725 to 925 °C and 5 varying sintering time of between 15 and 180 min. The results they obtained showed that experimental electrical conductivity and hardness of specimens were in good agreement with predicted results of the ANN model, with ANN predicting the electrical conductivity at an average error of 3% and hardness with about 5%. The results equally demonstrated that ANN could be used effectively to predict the properties of metal matrix composites with ceramic reinforcement, the main subject of this present study. Hussaini et al. [15] investigated the formability of austenitic stainless steel 316 at elevated temperatures. As part of their research, they used metal forming process variables, such as distance from the center of the cup, temperature and LDR, as input to an ANN which was used to predict the thickness of drawn cup. The results from their research showed a good agreement between experimental and predicted values. Kurra et al. [16] used ANN, support vector regression (SVR) and genetic programming (GP) to develop predictive models for prediction of arithmetic mean surface roughness (Ra) and maximum peak to valley height (Rz) which were used as response variables to assess the surface roughness of incrementally formed parts in single point incremental forming (SPIF). The results they obtained showed that the developed models had satisfactory goodness of fit in predicting the surface roughness. Furthermore, they used the GP model developed for optimization of (Ra) and (Rz) using genetic algorithm. The optimum process parameters for minimum surface roughness in SPIF they obtained and validated with the experiments were found highly satisfactory results within 10% error. Ekka et al. [17] used regression analysis and ANN to predict the wear rate and coefficient of friction in three different hybrid composites (cenosphere-SiC, cenosphere-Al2O3 and SiC-Al2O3) consisting of two fillers. Their finding showed that artificial neural network is more efficient in predicting the wear rate than regression. Haghdadi et al. [18] used ANN model to estimate the high temperature flow behavior of a cast A356 aluminum alloy. The results they got indicated that the trained ANN model is a robust tool that could be used to predict the high temperature flow behavior of cast A356 aluminum alloy. Lotfi et al. [19] used ANN to predict the green shear strength of compacted samples made from iron powder. They used iron powders of three different morphologies which were mixed with three types of lubricants in different amounts to produce green compacts which were pressed uniaxially in a square floating die. A comparison of the predicted and experimental data confirmed the accuracy of their model. Shojaeefard et al. [5] used an artificial neural network (ANN) model to simulate the correlation between the Friction Stir Welding parameters and mechanical properties. Based on the excellent performance of the ANN model
it was used to predict the ultimate tensile strength and hardness of butt joint of AA7075−AA5083 as functions of weld and rotational speeds. They used a multi-objective particle swarm optimization to obtain the Pareto-optimal set. Sinha et al. [20] used multi-objective genetic algorithm based searching for designing the process schedule of Ti−Ni alloy, to achieve optimum mechanical property and shape recovery behavior. They developed an ANN to empirically describe the relationship between the processing conditions and the properties. Subsequently, they used the ANN as fitness function to a genetic algorithm for multi-objective optimization for improvement in shape recovery behavior without sacrificing the mechanical properties of the alloy. The Pareto solutions they obtained were been used as the guideline to find the process schedules, which was validated by suitable experimentation. Taghizadeh et al. [21] used an artificial neural network (ANN) model to predict the hardness drop of the water-quenched and tempered AISI 1045 steel specimens, as a function of tempering temperature and time parameters. The results of the study showed that the agreement between the predicted values of the ANN model with the experimental data was reasonably good. Vettivel et al. [22] used ANN to study the tribological behavior of sintered Cu−W composites. The ANN used the measured parameters namely the weight percentage of tungsten, sintering temperature, load and sliding distance to predict multiple material characteristics, hardness, specific wear rate, and coefficient of friction. The predicted values from the ANN agreed reasonably well with the experimental values.

In continuation, Xiang et al. [23] employed ANN to predict the fatigue property of natural rubber (NR) composites. The mechanical properties (stress at 100%, tensile strength, elongation at break) and viscoelasticity property (tan δ at 7% strain) of natural rubber composites were used inputs of ANN to predict the fatigue property (tensile fatigue life). The research results showed that the average prediction accuracy of the ANN model was 97.3%.

Furthermore, adaptive neuro-fuzzy inference system (ANFIS) models are very important artificial intelligence and soft computing technique often used in place of artificial neural networks (ANN) for modeling. Tofghi et al. [24] used ANFIS as fitness function for a particle swarm algorithm for optimization of process parameters for the production of nanoparticle-aluminum metal matrix composites. Adequate knowledge of electromagnetic stirrer (EMS) process parameters–wear relation in nanocomposite is very essential in designing products tailored to different uses and applications. Bearing this in mind, Shamspour et al. [25] applied adaptive neuro-fuzzy inference system (ANFIS) integrated with particle swarm optimization (PSO) for optimization of the parameters in EMS compocasting of nano-TiC-reinforced Al−Si alloys. They used the optimized parameters to produce semisolid cast aluminum matrix composites reinforced with nano-TiC particles. Roshan et al. [26] used ANFIS to model the mechanical properties of aluminum figures 7075. Figures produced through friction stir welding process. The process input variables were tool pin profile, tool rotary speed, welding speed, and welding axial force, while the main responses were tensile strength, yield strength, and hardness of welded zone obtained from experiment. Subsequently, the developed models were used as fitness function of simulated annealing algorithm to select optimal parameters, in which the process reaches to its desirable mechanical properties. Aydin et al. [27], used an adaptive neuro-fuzzy inference system (ANFIS) with particle swarm optimization (PSO) learning for modeling and prediction of both surface roughness and cutting zone temperature in turning of AISI304 austenitic stainless steel using multi-layer coated (TiCN + TiC + TiCN + TiN) tungsten carbide tools. The surface roughness and cutting zone temperature values predicted by the PSO-based ANFIS model were compared with the measured values derived from testing data set. Results from tests of the model showed that the predicted surface roughness and cutting zone temperature were in good agreement with measured roughness and temperature. Dewan et al. [28] used ANFIS and ANN to predict the ultimate tensile strength (UTS) of welded aluminum alloy joints produced through Friction-stir-welding (FSW). They used three critical process parameters including spindle speed (N), plunge force (Fz), and welding speed (V) as inputs to the ANFIS and ANN. When the predicted results of the ANFIS and ANN models were compared, it was found that optimized ANFIS models had better results than ANN. They therefore advocated the use of the ANFIS model for prediction of UTS of FSW joints. Krishnan and Samuel [29] modeled wire electrical discharge turning (WEDT) process using an artificial neural network with feed-forward back-propagation algorithm and using adaptive neuro-fuzzy inference system. The experimental data for training the ANFIS model was obtained using Taguchi design of experiments methodology. Since the process has two outputs—material removal rate and surface roughness, which are conflicting in nature, they used a multi-objective optimization method based on non-dominated sorting genetic algorithm-II to optimize the process. They obtained a pareto-optimal front leading to the set of optimal solutions for material removal rate and surface roughness using the ANFISGA model. They verified their results with experiments and found that it improved the performance of WEDT process. Sadrmontazi et al. [30] compared ANN, ANFIS and parametric regression models for predicting the compressive strength of EPS concrete for possible use in mix-design framework. The results they obtained showed that the ANN performed best when compared to the other two models while the parametric regression had the worst performance. Suganthi et al. [31] developed ANFIS and ANN models for the prediction of multiple quality responses in micro-EDM operations. They used
feed rate, capacitance, gap voltage, and threshold values as the input parameters and metal removal rate, surface roughness and tool wear ratio as the output parameters. The results they obtained showed that the predicted values of the responses from the ANFIS and ANN models were in good agreement with the experimental values. However, ANFIS model performed better than the ANN model. Yuan et al. [32] studied the structured and unstructured factors which affect the concrete quality. They developed ANN and ANFIS models for concrete strength prediction. The results they obtained showed that the ANN and ANFIS models predicted the concrete strength with a good degree of accuracy. In addition the ANN and ANFIS models predicted much better than the conventional regression model.

The literature surveyed above showed that in some applications, ANN models performed better than ANFIS models while in some the ANFIS model performed better than ANN. Generally, as seen in the literature, ANN and ANFIS are very good

---

Fig. 2 – SEM/EDS of the A356 alloy.

Fig. 3 – SEM/EDS of the A356 alloy with 5wt%CHp.
modeling tools for modeling, prediction and optimization of material properties for engineering and scientific applications. Also, the choice of optimization algorithm depends on the particular application and availability of efficient software tools, but genetic algorithm seems to be the dominant optimization tool.

The aim of this work is to model the hardness of metal matrix composite (MMC) produced from cow horn (CHp) and aluminum alloy (A356) metal. The hardness will be modeled using adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) and a performance comparison made between the two models. Subsequently the hardness values will be optimized using genetic algorithm optimization algorithm with either the ANN or ANFIS as the fitness function, depending on which model performed better.

2. Methodology

2.1. Experimental procedure and composite production method

2.1.1. Production of composite samples
The production process of the composite sample involves the mixing of the A356 powder and CHp reinforcement particles. The mixing was done using a 3D inversion mixer. After the mixing process, the A356 matrix/CHp ($x = 0, 5, 10, 15, 20$) composite samples were produced using spark plasma sintering. After the production of the composite, it was cut into samples as shown in Fig. 1 and the samples used for the age hardening process. For more details of the experimental procedure see Nwobi-Okoye and Ochieze [33], Ochieze [34], Ochieze et al. [35] and Basil et al. [36].

2.1.2. Thermal treatment of the samples
The thermal aging processes were done at temperatures of 150 and 350 °C. The capacity of the heat treatment furnace was 3KW. For details of this process see Nwobi-Okoye and Ochieze [33]. The microstructure of the thermally aged composites reveals the dissolution and distribution of the CHp in the metal matrix and presence of precipitates at the particles matrix interfaces with precipitation and dissolution of the CHp. The formation and presence of precipitates at the particles–matrix interfaces may be appreciated by comparing micrographs of the composite in the unheat-treated state shown in Figs. 2–6 and in the age-hardened state shown in Figs. 7–11. This precipitation increase as the wt% CHp increases in the composite.

Figs. 7–11 in the age-hardened state reveal precipitates covering the surface at the particles–matrix interfaces. This precipitation form may depend on: (i) the extra interfacial area – and hence energy – between precipitate and matrix; (ii) the possible creation of an anti-phase boundary (APB) within an ordered precipitate and (iii) the change in separation distance between dissociated dislocations due to different stacking fault energies of matrix and particles. Similar behavior of increased precipitation at interfaces has been observed in age-hardened aluminum alloy reinforced with silicon carbide particle. This is scientifically attributed to increase in dislocation density at interfaces. Scientifically, increase in dislocation density strain hardens the metal-matrix locally and provides heterogeneous nucleation sites for precipitation, thereby accelerating the aging response. Consequently, an increase in wt% of the reinforcing particles, fine grain size and distribution of these precipitates both within the grain and at grain boundaries contribute to acceleration of the aging kinetics.

Fig. 4 – SEM/EDS of the A356 alloy with 10wt%CHp.
The unreinforced alloy reveals the presence of $\alpha$-Al, Si and Mg as evidenced from the EDS spectra (see Fig. 2). From the EDS analysis of the composites material (see Figs. 3–6 and Figs. 8–11) there are indications of some possible chemical reactions between the aluminum melt and CHp which led to the release of Si, Ca and C in the composites, since the CHp consist of CaCO$_3$, SiO$_2$ as the major constituents. These constituents react with Al, Si, Mg present in the molten matrix.

Fig. 5 – SEM/EDS of the A356 alloy with 15wt%CHp.

Fig. 6 – SEM/EDS of the A356 alloy with 20wt%CHp.
alloy depending on the kinetics of reactions. These precipitations are clearly seen in Figs. 3–6 and Figs. 8–11 and confirmed by the spectra.

The various microstructures developed for the thermally age-hardened samples are shown in Figs. 7–11. The microstructure of the unreinforced A356 alloy reveals precipitation of aluminum magnesium (Al₃Mg₂), magnesium silicon (Mg₂Si), magnesium aluminum (Mg₂Al₃), and aluminum magnesium (Al₁₂Mg₁) which are Al-Mg-Si phases in α-aluminum matrix phase. The microstructures of the thermally aged
composites reveal the dissolution and distribution of the CHp in the metal matrix and presence of precipitates at the particles matrix interfaces with precipitation and dissolution of the CHp. The formation and presence of precipitates at the particles–matrix interfaces may be appreciated by comparing micrographs of the composite in the unheat-treated state (Figs. 3–6) and in the age-hardened state (Figs. 8–11). This precipitation increase as the wt% CHp increases in the composite. As shown in Figs. 8–11, the composite in the age-hardened state reveal precipitates covering the surface at the particles–matrix interfaces. This precipitation form may depend on: (i) the extra interfacial area – and hence energy – between precipitate and matrix; (ii) the possible creation of an anti-phase boundary (APB) within an ordered precipitate and (iii) the change in separation distance between dissociated dislocations due to different stacking fault energies of matrix and particles. Similar behavior of increased precipitation at interfaces was reported by Hassan et al. [37] for age-hardened aluminum alloy reinforced with silicon carbide particle. They attributed this to increase in dislocation density at interfaces. Increase in dislocation density strain hardens the metal-matrix locally and provides heterogeneous
nucleation sites for precipitation, thereby accelerating the aging response. Thus, an increase in wt% of the reinforcing particles, fine grain size and distribution of these precipitates both within the grain and at grain boundaries contribute to acceleration of the aging kinetics.

2.1.3. Determination of hardness values
The hardness test values were obtained according to the provisions of American Society for testing and materials (ASTM E18-79). A Rockwell hardness tester was used for the test. For the details of the test procedure see Nwobi-Okoye and Ochieze [33]. The variations of hardness with aging time at 150 and 350 °C are shown in Figs. 12 and 13. As shown in Fig. 12, for a given CHp% content in the composite material, the hardness increased with aging time until a certain time when the hardness peaks and starts decreasing. The same characteristics were observed in Fig. 13 at aging temperature of 350 °C. As shown in Fig. 13, the hardness increased when the aging time increased until a certain time when the peak hardness was reached and starts decreasing thereafter.

Generally, for any given aging temperature and time, the hardness increased with increase in CHp%. Although there were very few exceptions as clearly shown in Figs. 12 and 13. Also, in general for a given CHp% content of the composite, a higher age hardening temperature resulted to higher hardness values. The presence of CHp in the matrix decreased the time needed to achieve the peak hardness values as shown in Figs. 12 and 13. Increase in the aging temperature leads to a decrease in the time to obtain peak hardness values of the samples.
The added CHp particles in all experiments were generally high in the hope that their effect on hardness improvement would gradually increase with the proportion. Strength increasing mechanisms involve the increase in hardness due to grain refinement (Hall–Petch relationship), the hindering effect of the particles on dislocation motion as well as the accumulation of dislocations due to the different thermal expansion of the ceramic particles and the matrix material.

The decrease in the hardness values after the optimum point has been reached can be attributed to the over-aging of the composites. Also, the decrease in hardness values of the unhardened samples can be explained by the contribution of inter-atomic spacing due to strain hardening which arises from the fact that the inter-atomic spacing permitted a dislocation to maneuver round obstacles.

Hence, dislocations cause the hardness increase in alloy as well as residual stress increase because it acts as non-uniform nucleation sites in the interface following the heat treatment. The higher the amount of the fine grain sizes in the composite, the higher the density of the dislocation, and as a result, the higher the hardness of the composite material.

The high hardness value obtained at peak aging was due to the fine-grained structure and the dispersed precipitates in the fine-grained matrix which obstruct the easy movement of dislocations. The heat treated samples became finer grained due to the fact that the precipitates interfere with the nucleation-growth process. Thus, the precipitates enhanced nucleation by creating disorder in the incorporation of atoms into the lattice or inhibition of the surface diffusion of atoms toward growing centers and exert a detrimental effect on the crystal growth. This effect of grain refining helps improve the hardness values of the heat treated samples.

2.2. Age hardening cost determination methodology

The primary application of A356/CHp particulate composite is for production of brake drums [33–36]. Hence, we determined the age hardening cost through the following formula:

\[ \text{Agehardeningcost} = \text{heatingcost} + \text{brakedrumcompositematerialcost} \]

The brake drum composite material cost in Naira (N) is determined thus:

\[ \text{Weightofcompositebrakedrum} = 1.54 \text{ kg} \]

\[ \text{Cost/kg(A356)} = \text{N}532.80 \]

\[ \text{Cost/kg(CHp)} = \text{N}250.00 \]

The brake drum composite material cost in dollars ($) is determined thus:

\[ \$1 = \text{N}362 \]

\[ \text{Cost/kg(A356)} = \$1.47 \]

\[ \text{Cost/kg(CHp)} = \$0.69 \]

Weight \( x \) of 1% CHp in brake drum is given by:

\[ \frac{x}{1.54} \times 100 = 1 \]

\[ x = \frac{1.54}{100} = 0.0154 \text{ kg} \]

Therefore weight of 1% CHp in brake drum = 0.0154 kg.

Similarly the cost in Naira of 1% CHp in brake drum \( C_u \) is given by:

\[ C_u = 0.0154 \times 250 \]

\[ C_u = \text{N}3.85 = \$0.01 \]

To determine the heating cost we used the electricity use charge in Nigeria which is:

\[ \text{Electricityheatingcharge} = \text{N}45.24/\text{kWh} = \$0.12/\text{kWh} \]

Note: the heat treatment furnace can hold three brake drum samples produced using A356/CHp particulate composite.

Fig. 14 shows the cost model of the age hardening process in a pie chart. As shown in Fig. 14, heating time contributes most to the cost of thermal aging, while heating temperature contributes least to the age hardening cost.
3. **Soft computing techniques for modeling material properties**

Soft computing techniques consist of several computational and artificial intelligence techniques used in modeling, optimization and operations research. These techniques include but not limited to fuzzy logic, artificial neural network (ANN), adaptive neuro-fuzzy inference systems (ANFIS), expert systems etc.

3.1. **Artificial neural networks (ANNs)**

Artificial neural networks (ANN) are computational modeling tools often employed in modeling input output relationships of systems or processes where it is difficult or impossible to find mathematical models for defining such systems. ANN was inspired by the network of neurons in the brains of living organisms which enable them to act intelligently. Artificial neural networks make use of artificial neurons. Artificial neural networks (ANNs) simulate the manner of operation of natural neurons in the human body. Most ANN’s are feedforward multilayer perceptron networks. Feed forward networks use backward propagation algorithms for learning. Some learning algorithms include Levenberg–Marquardt algorithm, gradient descent algorithm, genetic algorithm or other natural optimization algorithms [38–41]. ANN consists of several nodes which represents the neurons. The input nodes represent the independent variables while the output nodes represent the dependent variables.

This study used ANN to accurately model the age hardening process of aluminum alloy A356/CHp particulate composite. Accurate prediction of the parameters of any process is critical to the quality, economics and optimal performance of the process. Once a satisfactory ANN model was developed, the model was integrated into an optimization procedure known as genetic algorithm, as its fitness function, for multi objective optimization of the age hardening process parameters. The ANN was developed with Matlab. The ANN inputs consist of temperature, percentage composition of cow horn particles and time, while the output consists of the hardness values and cost.

3.2. **The adaptive neuro-fuzzy inference system (ANFIS)**

The ANFIS is a multilayer feed-forward network consisting of nodes and directional links, which combines the learning capabilities of a neural network and reasoning capabilities of fuzzy logic [41]. According to Hosoz et al. [41] this hybrid structure of the network has the possibility of extending the prediction capabilities of ANFIS beyond ANN and fuzzy logic techniques when they are used alone. Analyzing the mapping relation between the input and output data, ANFIS can determine the optimal distribution of membership functions that would minimize the average absolute error, using either a backpropagation gradient descent algorithm alone, or in combination with a least squares method [41]. The ANFIS used in this research was developed with MATLAB.
4. Genetic algorithm

According to Piuleac et al. [42], conventional optimization methods consist of two methods: direct search methods and gradient methods. Direct search methods, such as simplex algorithm, use the objective function and constraints to search for the optimum. Gradient methods use calculus (differentiation) to obtain optimum values. Direct search methods which are considered to use brute force are slow and the gradient methods fail if the function is discontinuous or non differentiable. These deficiencies gave rise to the invention of metaheuristics which includes natural optimization algorithms. Genetic algorithm (GA) is a metaheuristics method that belongs to natural optimization algorithm. GA adopts the survival of the fittest philosophy that is central to the theory of evolution to search for the global maxima or minima of functions.
5. Results and discussion

5.1. ANN modeling and results

The feedforward backward propagation neural network model was used in this study because the application was for prediction. For the hardness prediction, the network architecture consists of three input units, one hidden layer with ten (10) hidden neurons and one output unit as shown in Fig. 15. This structure performed better than other configurations that we tested. The inputs consist of temperature, percentage composition of cow horn particles and time, while the output consists of the hardness values. The optimum network performance was reached at an epoch of 21. The epoch was set at 1000 to ensure that the network was well trained before testing and validation.

The choice of number of layers and the number of neurons are important in neural network design. According to Atuanya et al. [8] and Anderson and McNeill [43], there is no mathematical model for quantifying these network variables. A heuristic largely used by engineers and researchers was used to set the upper limit of the number of neurons in the hidden layer to be 13. Subsequently, after trial and error we chose the number of neurons to be 10 because it gave us optimum network performance. The training algorithm was Levenberg-Marquardt which performed better than others. One hundred and fifty (150) experimental inputs and responses were used for ANN training, testing and validation. Seventy percent (70%) of the data (104) were used for training, while fifteen percent (15%) each (23) were used for testing and validation respectively. The mean squared error (MSE) of the network during training, testing and validation were 0.7171, 1.5326 and 2.0147 respectively as shown in Fig. 16. The regression coefficient of the network (training, testing and validation) was 0.9926 as shown in Fig. 17. While as shown in Fig. 18, regression coefficient of the network during training, testing and validation were 0.99295, 0.98669 and 0.99273 respectively.

For the cost predictions, a network with one hidden layer and five hidden neurons was enough to predict the variations of the age hardening cost with process parameters. As in the network for hardness predictions, one hundred and
Fifty (150) experimental inputs and responses were used for ANN training, testing and validation. The training algorithm used was Levenberg–Marquardt. Seventy percent (70%) of the data (104) were used for training, while fifteen percent (15%) each (23) were used for testing and validation respectively. The mean squared error (MSE) of the network during training, testing and validation were 0.00000506045, 0.00000729572 and 0.0000086195 respectively as shown in Fig. 19. The best validation performance occurred at epoch 85 as shown in Fig. 19.

The regression coefficient of the network (training, testing and validation) was 1 as shown in Fig. 20. While as shown in Fig. 21, regression coefficient of the network during training, testing and validation were all 1.

Table 1 shows some ANN predictions of the experimental responses. Table 1 was partly used to plot Figs. 17 and 20. As shown in Figs. 17 and 20 and stated earlier, the overall regression coefficient for the network for hardness and cost prediction were 0.9926 and 1 respectively.

<table>
<thead>
<tr>
<th>S. no.</th>
<th>Temperature level (°C)</th>
<th>%wt of CHP level</th>
<th>Time (h)</th>
<th>Hardness</th>
<th>Measured</th>
<th>ANN predicted</th>
<th>Unit cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>150</td>
<td>0</td>
<td>1</td>
<td>45.60</td>
<td>46.65</td>
<td>2.399915768</td>
<td>2.399933647</td>
</tr>
<tr>
<td>2</td>
<td>150</td>
<td>0</td>
<td>2</td>
<td>48.90</td>
<td>47.89</td>
<td>2.524888144</td>
<td>2.524869658</td>
</tr>
<tr>
<td>3</td>
<td>150</td>
<td>0</td>
<td>3</td>
<td>50.10</td>
<td>49.55</td>
<td>2.649860519</td>
<td>2.649821877</td>
</tr>
<tr>
<td>4</td>
<td>150</td>
<td>0</td>
<td>4</td>
<td>50.20</td>
<td>51.36</td>
<td>2.774832895</td>
<td>2.77473558</td>
</tr>
<tr>
<td>5</td>
<td>150</td>
<td>0</td>
<td>5</td>
<td>53.21</td>
<td>53.02</td>
<td>2.899805271</td>
<td>2.899774099</td>
</tr>
<tr>
<td>6</td>
<td>150</td>
<td>0</td>
<td>6</td>
<td>55.60</td>
<td>54.35</td>
<td>3.024777646</td>
<td>3.024762112</td>
</tr>
<tr>
<td>7</td>
<td>150</td>
<td>0</td>
<td>7</td>
<td>55.79</td>
<td>55.39</td>
<td>3.149750022</td>
<td>3.149753936</td>
</tr>
<tr>
<td>8</td>
<td>150</td>
<td>0</td>
<td>8</td>
<td>56.00</td>
<td>56.27</td>
<td>3.274722398</td>
<td>3.274745885</td>
</tr>
<tr>
<td>9</td>
<td>150</td>
<td>0</td>
<td>9</td>
<td>57.10</td>
<td>57.10</td>
<td>3.399694773</td>
<td>3.399734278</td>
</tr>
<tr>
<td>10</td>
<td>150</td>
<td>0</td>
<td>10</td>
<td>57.80</td>
<td>57.91</td>
<td>3.524667149</td>
<td>3.524715435</td>
</tr>
<tr>
<td>11</td>
<td>150</td>
<td>0</td>
<td>11</td>
<td>58.10</td>
<td>58.65</td>
<td>3.649639525</td>
<td>3.649685678</td>
</tr>
<tr>
<td>12</td>
<td>150</td>
<td>0</td>
<td>12</td>
<td>58.90</td>
<td>59.19</td>
<td>3.774611901</td>
<td>3.774641327</td>
</tr>
<tr>
<td>13</td>
<td>150</td>
<td>0</td>
<td>13</td>
<td>58.89</td>
<td>59.29</td>
<td>3.899848276</td>
<td>3.899578708</td>
</tr>
<tr>
<td>14</td>
<td>150</td>
<td>0</td>
<td>14</td>
<td>59.01</td>
<td>58.60</td>
<td>4.024556652</td>
<td>4.024491445</td>
</tr>
<tr>
<td>15</td>
<td>150</td>
<td>0</td>
<td>15</td>
<td>55.78</td>
<td>56.85</td>
<td>4.149529028</td>
<td>4.149383696</td>
</tr>
<tr>
<td>16</td>
<td>150</td>
<td>5</td>
<td>1</td>
<td>50.78</td>
<td>51.29</td>
<td>2.339762177</td>
<td>2.339801476</td>
</tr>
<tr>
<td>17</td>
<td>150</td>
<td>5</td>
<td>2</td>
<td>51.07</td>
<td>52.77</td>
<td>2.464734552</td>
<td>2.464772664</td>
</tr>
<tr>
<td>18</td>
<td>150</td>
<td>5</td>
<td>3</td>
<td>55.78</td>
<td>54.49</td>
<td>2.589706928</td>
<td>2.589673338</td>
</tr>
<tr>
<td>19</td>
<td>150</td>
<td>5</td>
<td>4</td>
<td>55.78</td>
<td>55.15</td>
<td>2.714679304</td>
<td>2.714636024</td>
</tr>
<tr>
<td>20</td>
<td>150</td>
<td>5</td>
<td>5</td>
<td>57.89</td>
<td>57.64</td>
<td>2.83965168</td>
<td>2.839611644</td>
</tr>
<tr>
<td>21</td>
<td>150</td>
<td>5</td>
<td>6</td>
<td>58.90</td>
<td>59.01</td>
<td>2.964624055</td>
<td>2.964596519</td>
</tr>
<tr>
<td>22</td>
<td>150</td>
<td>5</td>
<td>7</td>
<td>60.90</td>
<td>60.28</td>
<td>3.089596431</td>
<td>3.089586971</td>
</tr>
<tr>
<td>23</td>
<td>150</td>
<td>5</td>
<td>8</td>
<td>61.30</td>
<td>61.35</td>
<td>3.214568807</td>
<td>3.21457932</td>
</tr>
<tr>
<td>24</td>
<td>150</td>
<td>5</td>
<td>9</td>
<td>62.19</td>
<td>62.15</td>
<td>3.339541182</td>
<td>3.339568884</td>
</tr>
<tr>
<td>25</td>
<td>150</td>
<td>5</td>
<td>10</td>
<td>63.00</td>
<td>62.68</td>
<td>3.464513558</td>
<td>3.464554983</td>
</tr>
<tr>
<td>26</td>
<td>150</td>
<td>5</td>
<td>11</td>
<td>63.40</td>
<td>62.83</td>
<td>3.589485394</td>
<td>3.589530393</td>
</tr>
<tr>
<td>27</td>
<td>150</td>
<td>5</td>
<td>12</td>
<td>66.70</td>
<td>62.37</td>
<td>3.714458309</td>
<td>3.71449072</td>
</tr>
<tr>
<td>28</td>
<td>150</td>
<td>5</td>
<td>13</td>
<td>60.10</td>
<td>61.04</td>
<td>3.839430685</td>
<td>3.839440705</td>
</tr>
<tr>
<td>29</td>
<td>150</td>
<td>5</td>
<td>14</td>
<td>58.90</td>
<td>58.90</td>
<td>3.964603661</td>
<td>3.96467164</td>
</tr>
<tr>
<td>30</td>
<td>150</td>
<td>5</td>
<td>15</td>
<td>56.78</td>
<td>56.73</td>
<td>4.089375436</td>
<td>4.089269775</td>
</tr>
</tbody>
</table>

Fig. 21 – ANN predictions of cost vs experimental data during training, testing and validation.
5.2. **ANFIS for age hardening prediction**

The application herein is for prediction of the obtained hardness and cost of age hardening process, and supervised learning was used. The number of epoch was set to 100 to ensure that there is sufficient number of iterations during the learning process. Fig. 22 shows the adaptive neuro-fuzzy inference system (ANFIS) for predicting the output of the age hardening process. As shown in Fig. 22, CHp%, time and temperature are the inputs to the fuzzy inference system, while the obtained hardness values or cost derived from defuzzification is the output. The membership function used for the input variables is the Gaussian function. The Gaussian membership was used because within the measured/experimental data points all the tested membership functions gave the same prediction error of approximately zero percent. However, outside the experimental data points, Gaussian membership function gave the least prediction error of 73.69% while the triangular membership function gave the highest prediction error of 79.88% when the temperature was varied. Hence Gaussian membership function was chosen. The details of predictions outside the measured/experimental data points for ANN and ANFIS models are presented in Section 5.3. The membership function for temperature drawn on the Matlab interface is shown in Fig. 23.

The ordinate of the membership function graph in Fig. 23 is the degree of membership which varies from 0 to 1. The membership functions for time and CHp (%) follow as similar pattern. The membership functions for temperature shown in Fig. 23.

---

**Fig. 22 – View of the developed fuzzy model.**

**Fig. 23 – Membership function aging temperature on the Matlab interface.**
consist of five linguistic variables namely: very low, low, average, high and very high. The membership functions for time and CHp (%) equally consist of five linguistic variables namely: very low, low, average, high and very high respectively. The output has 125 linear membership functions. The defuzzification method used was weighted average method.

After creating the input and output membership functions, the rules were established. Altogether 125 rules were created. A snippet of the rules in MATLAB interface is shown in Fig. 24. Subsequently, the data was trained to identify the parameters of Sugeno-type fuzzy inference system by using the hybrid algorithm combining the least square method and the backpropagation gradient descent method for learning and optimization. After training, the input variables from the test data set (CHp%, aging time and temperature) were presented to the trained network and the predicted output variables (hardness or cost), were compared with the experimental ones for the performance measurement. The criteria used for measuring the network performance were the correlation coefficient ($r$) and average error ($E$).

Table 2 shows the data set for the comparison of the experimental results with the predicted result from ANFIS model. Figs. 25 and 26 show the regression lines for the hardness and cost predictions respectively of the ANFIS Model. As shown in Fig. 25, the hardness predictions had a correlation coefficient of 0.9985 while the cost predictions shown in Fig. 26 had a correlation coefficient of 1.

5.3. Comparison of ANN and ANFIS predictions for values outside the experimental values

Although from Figs. 25 and 26 ANFIS predicted very well the values of experimental data points, outside the values on the experimental data points with CHP % and Time constant, ANFIS failed woefully as shown in Table 3.

As shown in Table 3, outside values on the experimental data points, ANN predictions have average relative error of 0.2229% compared to 73.6918% for ANFIS.

As Table 4 shows, when the temperature and time are on the experimental data points, and the values of CHp% is outside the experimental values ANN predictions have an average relative error of 0.0037% while ANFIS have an average relative error of 0.0160%.

The reason for the observed results is because CHp% has finer experimental data points than temperature with a much coarser experimental data point with the difference between successive experimental values being 200 °C.
The membership functions of the ANFIS outside the experimental data point for temperature did not have sufficient values to learn the variations of cost with age hardening temperature. Despite the wide temperature difference between successive temperature points in the experiment, the ANN was able to learn the variations of cost with temperature effectively.

It could be deduced from the result above that with finer experimental data points ANFIS would even outperform ANN in predictions of age hardening process outputs. But finer experimental data points mean increased cost, hence modeling with ANN is a much cheaper alternative.

Based on the facts above, ANN was chosen as the modeling tool for the multiobjective optimization of the age hardening process using genetic algorithm.
5.4. Process multi-objective optimization procedure using genetic algorithm, ANN and ANFIS

A MATLAB function which is a well trained ANN as previously described was used as the fitness function for a multi objective genetic algorithm used to carry out the optimization of the age hardening process. The upper and lower limits of the experimental variables were used as the upper and lower bounds of the optimization algorithm. The negative values of the hardness were used during the optimization because the objective of the genetic algorithm is to minimize the objective function. The optimized Pareto front achieved after 231 iterations is shown in Fig. 27. The inputs to the age hardening process corresponding to the obtained hardness and operating cost values on the optimized Pareto front are shown in Table 5. The maximum and minimum values of hardness returned by the multi objective optimization algorithm were 81.04 and 78.27 respectively, as shown in Table 5. The difference between the operating cost for the minimum and maximum hardness values on the Pareto front was $0.60.

The Pareto results show that a hardness value of 81.04 can only be obtained at a minimum cost of $2.76. Any attempt to lower the cost at a hardness value of 81.04 will result to decrease in hardness value. Similarly, a hardness value of 78.27 can only be obtained at a minimum cost of $2.16. Any attempt to increase the hardness to a higher value will lead to increase in cost. The Pareto results equally show that the CHP% contributes significantly to the lowering of cost while helping to increase hardness. That is why more than 50% of the values of the age hardening parameters on the Pareto front contains CHP% value of 20%, while others contain CHP% values of above 16%. This is equally the reason why all the hardness values on the Pareto front are above 78.27. If increase in CHP% had increased cost while increasing hardness, their would have been low values of hardness on the Pareto front. As a matter of fact, if this is the case the lowest hardness value on the Pareto front would have been 42.24 at a cost of $2.40.

Fig. 28 shows the conceptual model describing in details the NN-GA system for multi objective optimization of the age hardening process of A356/CHP particulate composite for the production of brake drums. As shown in Fig. 16, the age hardening cost data part of which is shown in Table 1 was used to train an ANN. Similarly, the hardness data obtained from the age hardening process, part of which are shown in Table 1, was used to train another ANN. A MATLAB function called NET1 and another called NET2 were created from the first and second trained ANNs respectively.

Subsequently a multi output function named multi-objective, whose outputs were age hardening cost (C) and hardness values obtained from the age hardening process, was written with MATLAB using the functions NET1 and NET2 earlier created.

Having created the multiobjective function, the characteristics of the genetic algorithm (GA) such as number of iterations, maximum optimization times, etc. were set on the GA program in MATLAB. The GA program was run using the multiobjective function as input. After running the GA program, the C and h values on the Pareto front and the corresponding values of t, temp and CHP%, were obtained as shown in Table 5.
The potential applications of the NN-GA multi-objective optimization system are numerous. For example an engineer may desire high electrical conductivity and hardness for a material by subjecting it to some treatment. But both of this may not be achieved at the same time because increasing hardness reduces conductivity. However in order to achieve the two objectives as optimally as possible requires multi-objective optimization [5]. There are several situations in which increasing the value of a desired material property results to decrease in the desired value of another property when subjected to metallurgical treatment. This is a typical case of conflicting objectives in materials engineering. In order to optimize the properties an NN-GA multi-objective algorithm may be used in such situations.

Also most times as shown in this work, to improve the properties of materials costs are incurred. The engineer always wants to minimize cost but at the same time wants materials quality to improve. Hence, the objectives are conflicting and require multi-objective optimization to achieve maximum desired quality at minimum cost.

Table 5 – Age hardening process parameters and outputs on the Pareto front.

<table>
<thead>
<tr>
<th>S. no.</th>
<th>Temperature level (°C)</th>
<th>%wt of CHp level</th>
<th>Time level (h)</th>
<th>Hardness</th>
<th>Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>179.30</td>
<td>20.00</td>
<td>3.87</td>
<td>79.70</td>
<td>2.52</td>
</tr>
<tr>
<td>2</td>
<td>176.74</td>
<td>20.00</td>
<td>5.83</td>
<td>81.04</td>
<td>2.76</td>
</tr>
<tr>
<td>3</td>
<td>317.36</td>
<td>20.00</td>
<td>1.01</td>
<td>78.27</td>
<td>2.16</td>
</tr>
<tr>
<td>4</td>
<td>317.36</td>
<td>20.00</td>
<td>1.01</td>
<td>78.27</td>
<td>2.16</td>
</tr>
<tr>
<td>5</td>
<td>324.45</td>
<td>16.88</td>
<td>1.01</td>
<td>79.63</td>
<td>2.20</td>
</tr>
<tr>
<td>6</td>
<td>177.42</td>
<td>19.96</td>
<td>4.85</td>
<td>80.66</td>
<td>2.64</td>
</tr>
<tr>
<td>7</td>
<td>178.74</td>
<td>19.99</td>
<td>4.40</td>
<td>80.94</td>
<td>2.58</td>
</tr>
<tr>
<td>8</td>
<td>178.78</td>
<td>19.99</td>
<td>4.58</td>
<td>80.46</td>
<td>2.61</td>
</tr>
<tr>
<td>9</td>
<td>323.60</td>
<td>19.99</td>
<td>1.01</td>
<td>79.02</td>
<td>2.16</td>
</tr>
<tr>
<td>10</td>
<td>180.39</td>
<td>20.00</td>
<td>4.37</td>
<td>80.24</td>
<td>2.58</td>
</tr>
<tr>
<td>11</td>
<td>176.74</td>
<td>20.00</td>
<td>5.30</td>
<td>80.94</td>
<td>2.70</td>
</tr>
<tr>
<td>12</td>
<td>176.90</td>
<td>20.00</td>
<td>5.48</td>
<td>80.99</td>
<td>2.72</td>
</tr>
<tr>
<td>13</td>
<td>177.50</td>
<td>20.00</td>
<td>5.76</td>
<td>81.02</td>
<td>2.75</td>
</tr>
<tr>
<td>14</td>
<td>179.19</td>
<td>20.00</td>
<td>4.52</td>
<td>80.40</td>
<td>2.60</td>
</tr>
<tr>
<td>15</td>
<td>176.97</td>
<td>20.00</td>
<td>5.15</td>
<td>80.87</td>
<td>2.68</td>
</tr>
<tr>
<td>16</td>
<td>176.74</td>
<td>20.00</td>
<td>5.83</td>
<td>81.04</td>
<td>2.76</td>
</tr>
<tr>
<td>17</td>
<td>177.49</td>
<td>19.99</td>
<td>4.20</td>
<td>80.11</td>
<td>2.56</td>
</tr>
<tr>
<td>18</td>
<td>324.72</td>
<td>16.44</td>
<td>1.01</td>
<td>79.67</td>
<td>2.20</td>
</tr>
</tbody>
</table>
6. Conclusions

The following conclusions could be drawn from this research:

(i) It was discovered that at aging temperature of 350 °C, the hardness increases as the aging time increases for a given percentage content of CHp% reinforcement but at a certain aging time the hardness values began to decrease. Generally, at 350 °C at a given aging time the hardness increases with increase in CHp% reinforcement, but there were few deviations.

(ii) Also, at aging temperature of 150 °C, the hardness increases as the aging time increases for a given percentage content of CHp% reinforcement but at a certain aging time the hardness values begin to decrease. At 150 °C at a given aging time the hardness increases with increase in CHp% reinforcement with some few deviations.

(iii) ANN with coarse experimental data points for learning is more effective than ANFIS in predicting process outputs in the age hardening operation of A356 alloy/CHp particulate composite.

(iv) The fine experimental data requirements by ANFIS make it more expensive in modeling and multi-objective optimization of age hardening operations of A356 alloy/CHp particulate composite.

(v) Genetic algorithm with ANN as fitness function (GA-NN system) is an excellent tool for multi-objective optimization of process parameters in age hardening process of A356 alloy/CHp particulate composite.

Conflicts of interest

The authors declare no conflicts of interest.

REFERENCES


