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# Artificial Neural Network and Fuzzy Logic Based Techniques for Numerical Modeling and Prediction of Aluminum-5%Magnesium Alloy Doped with REM Neodymium

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## Abstract

In this study, the mechanical properties of aluminum-5%magnesium doped with rare earth metal neodymium were evaluated. Fuzzy logic (FL) and artificial neural network (ANN) were used to model the mechanical properties of aluminum-5%magnesium (0 - 0.9 wt%) neodymium. The single input (SI) to the fuzzy logic and artificial neural network models was the percentage weight of neodymium, while the multiple outputs (MO) were average grain size, ultimate tensile strength, yield strength elongation and hardness. The fuzzy logic-based model showed more accurate prediction than the artificial neutral network-based model in terms of the correlation coefficient values (R).

## Keywords

Al-5%Mg Alloy, Neodymium, Artificial Neural Network, Fuzzy Logic, Average Grain Size and Mechanical Properties

## 1. Introduction

5xxx series aluminum alloy is generally used in transport and construction industries such as railway, airspace, automobile, field ship and welded structural parts because of its high strength to weight ratio, reasonable corrosion resistance, excellent welding properties, high fracture toughness, and super elasticity [1] [2]. Improvement of the performance of 5xxx aluminum alloy is required in order to broaden its application.

Generally, the alloy cannot be strengthened by heat treatment. Its main strengthening effect comes from strain hardening and solution strengthening [3]. One effective way to improve the mechanical properties of 5xxx aluminum alloys is solution strengthening using micro-alloying. Alloying with rare earth elements such as cerium (Ce), lanthanum (La), ytterbium (Yb), scandium (Sc), strontium (Sr), scandium (Sc), samarium (Sm) and erbium (Er) have been shown to improve the mechanical properties of 5xxx aluminum alloys. For example, Zhang *et al.* [4] indicated that the addition of cerium and lanthanum below 0.3 wt% and 0.2 wt% respectively, obviously increased the strength and ductility of Al-3 wt%Mg alloy, addition of rare earth metal above 0.3 wt% was harmful to the microstructure of the alloy. Song *et al.* [5] reported that the addition of 1% wt ytterbium improved the mechanical properties of Al-5 wt%Mg alloy. Wang *et al.* [6] reported that the addition of scandium to Al-10Mg alloy improved the mechanical properties of the alloy due to grain refinement. Zhou *et al.* [7] reported that the addition of scandium up to 0.6% increased the tensile and yielded strength of Al-5%Mg alloy though it severely degraded the ductility of the alloy.

For some rare earth metals, such as neodymium, terbium, dysprosium promethium, gadolinium, holmium and thulium, previous research contains few reports of their effects on the mechanical properties of Aluminum magnesium alloys. Previous study on the effect of neodymium on the mechanical properties of near-eutectic aluminum silicon alloy, indicated that the addition of Nd below 0.3wt% to Al-12Si alloys refined the morphology of the $\alpha$ (Al) and Si phases which resulted in improved mechanical properties [8]. However, the effects of neodymium as a micro-alloying element on the structure and properties of Al-Mg alloys have not been studied. Hence, this study focused on investigating the role of neodymium addition in improving the structure and mechanical properties of aluminum-magnesium alloy.

Recently modeling methods such as fuzzy logic (FL) and artificial neural networks (ANN) systems have been used by many researchers for predicting the mechanical properties of engineering materials. Fuzzy logic is a very vital artificial intelligence and soft computing tool used in modeling engineering materials. Applications of fuzzy logic in the prediction and modeling of the mechanical properties of engineering materials are numerous. For instance, Anukwonke *et al.* [9] achieved extensive research on the use of Fuzzy logic for the prediction of ultimate tensile strength, yield strength, hardness, elongation and impact strength of Al-5%Mg-doped with nickel. Barzani *et al.* [10] used a fuzzy logic model to predict the surface roughness of Al-Si-Cu-Fe die-casting alloy doped with strontium, bismuth and antimony; the predicted machining performance surface had an error factor of 5.4%. Rahman *et al.* [11] studied the influence of steel fibers on mechanical properties such as compressive strength, flexural strength and post-peak deformation of steel-fiber reinforced concrete using a fuzzy model the predicted mechanical properties had an error factor of 7.5%. Chibueze *et al.* [12] successfully predicted the impact strength, flexural strength, hardness of sponge gourd and luffer fiber reinforced epoxy composite using a fuzzy logic model. Gence *et al.* [13] developed a rule-based fuzzy logic model for predicting compressive strengths and elasticity modulus of strength of concrete containing haematite. From the reviewed literature on modeling and predicting using FL the experimental data and predicted values were well matched, highlighting the success of applying FLs in modeling and prediction of mechanical properties of engineering materials.

Additionally, the artificial neural network (ANN) model is a very important soft computing tool frequently used in place of fuzzy logic for modeling. Deng *et al.* [14] used the ANN model to predict the tensile strength and hardness of Cu-Al alloys produced using the powder metallurgy method. ANN was applied to determine the composition of Cu-Al alloys for achieving a particular tensile strength and hardness level. Khalai *et al.* [15] used ANN to understand the effect of chemical composition (carbon equivalent) parameters on the ultimate tensile strength of the API X70 steels after thermo-mechanical treatment. Mahalle *et al.* [16] used ANN to develop predictive models for prediction of strain hardening exponent, ultimate strength, yield strength, strain and elongation of Inconel 718 alloy. Singh *et al.* [17] used ANN to predict % elongation, tensile strength, yield strength, strain hardening exponent and strength coefficient for the extra deep drawn (EDD) quality steel in blue brittle region. Parvizi *et al.* [18] used an artificial neural network (ANN) to predict the tensile strength and hardness of porous NiTi shape memory alloy. Shabani and Mazahery [19] used an ANN model to simulate the correlation between the morphology, distribution of secondary dendrite arm spacing (SDAS) and the eutectic Si fibers and mechanical properties such as tensile strength, hardness and ductility. Sterjovski *et al.* [20] studied impact toughness, hardness, hot ductility and hot strength of micro-alloyed steels using ANN. From the reviewed literature on modeling with ANN, the actual experimental and predicted values were well matched, highlighting the success of applying ANNs in predicting mechanical properties.

Significantly, the literature contains few studies on modeling and prediction of the mechanical properties of 5xxx aluminum alloys. This study investigates the use of fuzzy logic and artificial neural network systems for the prediction of mechanical properties of Al-5%Mg based on experimental data. The fuzzy logic models are compared with artificial neural networks (ANN) created for the same data. Such a model would notably reduce further experimental work and save cost in the design of 5xxx aluminum magnesium alloys.

## 2. Materials and Method

Pure aluminum wire (99.9% pure), magnesium powder (98.9% pure) and neodymium powder (98.5% pure) were materials used for producing the alloys with a nominal composition of Al-5%Mg-xNd (x = 0, 0.1, 0.3, 0.5, 0.7 and 0.9). The melting was done in a 10 kg medium crucible furnace [1] [9]. A reference alloy, named Al-5%Mg had no Nd addition, whereas Al-5%Mg-0.1%Nd, Al-5%Mg-0.3%Nd, Al-5%Mg-0.5%Nd, Al-5%Mg-0.7%Nd and Al-5%Mg-0.9%Nd were modified with neodymium (Nd) additions of 0.1%, 0.3%, 0.5%, 0.7% and 0.9%, respectively. The optical metallurgical microscope (model: L2003A) and Phenom ProX type scanning electron microscope were used to analyze the microstructures of the alloy. Image J software was used to evaluate the average grain size. The tensile tests were carried out using an Instron universal tester (Model: 3367) with a cross-head speed of 50 mm/min. The hardness tests were measured using Phase II 900-355 digital motorized Brinell hardness tester machine with a 2.5 mm diameter ball indenter and with a minimum force of 62.5N.

## 3. Results and Discussion

### 3.1. Mechanical Properties of the Studied Alloy

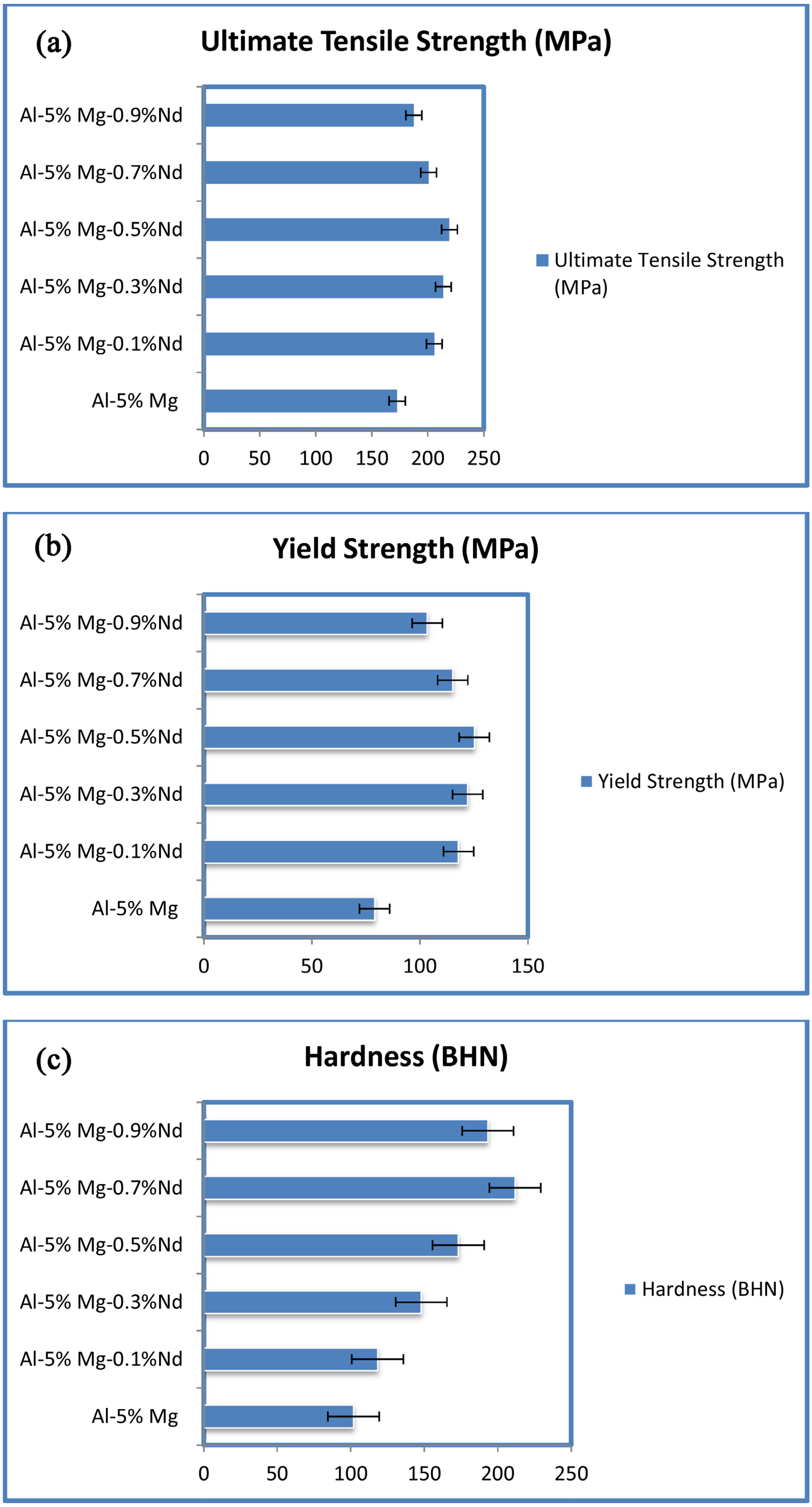
As shown in **Table 1** and **Figures 1(a)-(d)**, although neodymium was added in trace amounts, the tensile strength, yield strength, hardness and elongation of Al-5%Mg alloy had a remarkable improvement when rare earth metal neodymium was added. With the increase of neodymium content, the tensile strength, yield strength, hardness and elongation values initially increased. The tensile and yield strength reached the highest values when the content of neodymium was 0.5 wt%, hardness reached the top value when the content of Nd was 0.7 wt%, elongation reached the highest value when the content of neodymium was 0.3 wt%. The tensile strength increased from 172.74 to 219.35 MPa, the yield strength increased from 79.09 to 125.26 MPa, the hardness increased from 101.92 to 211.76 HBN, the elongation increased from 10.27% to 13.04%, and after that, further increase in Nd addition, the tensile strength, yield strength, hardness and elongation decreased. The reasons for the improvement in the strength of Al-5%Mg were reduced grain size, fine-scale uniformly distributed $\beta$ ($Al_3Mg_2$) intermetallic and solid solution strengthening processes.

### 3.2. Average Grain Size

From **Figure 2**, it was revealed that with increase in neodymium, the average grain size decreased first from 73.66 μm to 45.6 μm and reached the lowest value when neodymium was 0.5 wt%. Further increase in concentration, deteriorated

**Table 1.** Average grain size and mechanical properties of the studied alloy.

| Alloy composition | Ultimate tensile strength (MPa) | Yield strength (MPa) | Hardness (BHN) | Elongation (%) | Average grain size (micron) |
|---|---|---|---|---|---|
| Al-5%Mg | 172.74 | 79.09 | 101.92 | 10.27 | 73.66 |
| Al-5%Mg-0.1%Nd | 205.85 | 117.89 | 118.23 | 11.57 | 67.9 |
| Al-5%Mg-0.3%Nd | 213.88 | 122.11 | 148.01 | 13.04 | 56.92 |
| Al-5%Mg-0.5%Nd | 219.35 | 125.26 | 173.18 | 12.38 | 45.6 |
| Al-5%Mg-0.7%Nd | 200.82 | 115.26 | 211.76 | 11.09 | 51.53 |
| Al-5%Mg-0.9%Nd | 187.51 | 103.42 | 193.22 | 8.42 | 106.95 |


(a)
Ultimate Tensile Strength (MPa)
Al-5% Mg-0.9%Nd
Al-5% Mg-0.7%Nd
Al-5% Mg-0.5%Nd
Al-5% Mg-0.3%Nd
Al-5% Mg-0.1%Nd
Al-5% Mg
0 50 100 150 200 250
Ultimate Tensile Strength (MPa)
(b)
Yield Strength (MPa)
Al-5% Mg-0.9%Nd
Al-5% Mg-0.7%Nd
Al-5% Mg-0.5%Nd
Al-5% Mg-0.3%Nd
Al-5% Mg-0.1%Nd
Al-5% Mg
0 50 100 150
Yield Strength (MPa)
(c)
Hardness (BHN)
Al-5% Mg-0.9%Nd
Al-5% Mg-0.7%Nd
Al-5% Mg-0.5%Nd
Al-5% Mg-0.3%Nd
Al-5% Mg-0.1%Nd
Al-5% Mg
0 50 100 150 200 250
Hardness (BHN)

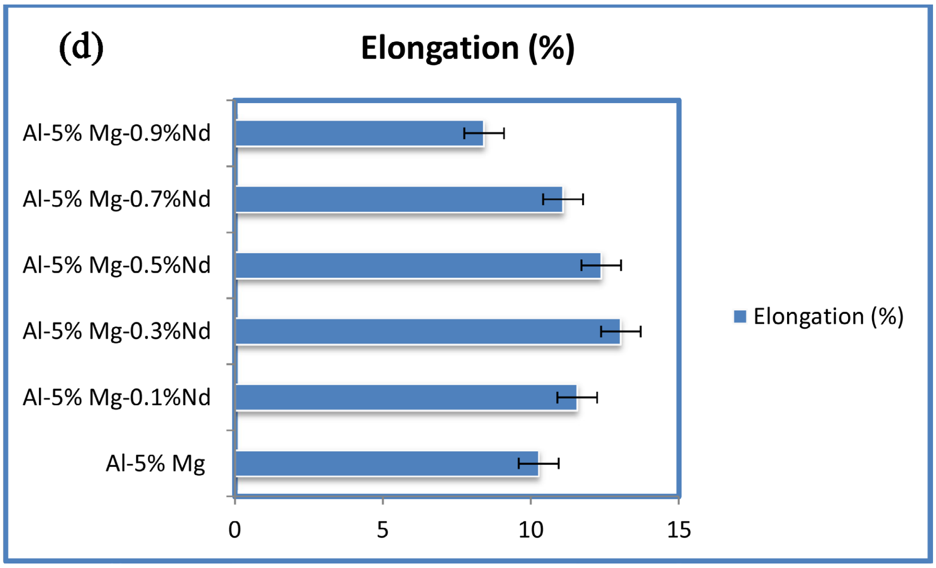



**Figure 1.** (a) Effect of Nd contents on the ultimate tensile strength of Al-5%Mg alloy; (b) Effect of Nd contents on the yield strength of Al-5%Mg alloy; (c) Effect of Nd contents on the hardness of Al-5%Mg alloy; (d) Effect of Nd contents on the elongation of Al-5%Mg alloy.

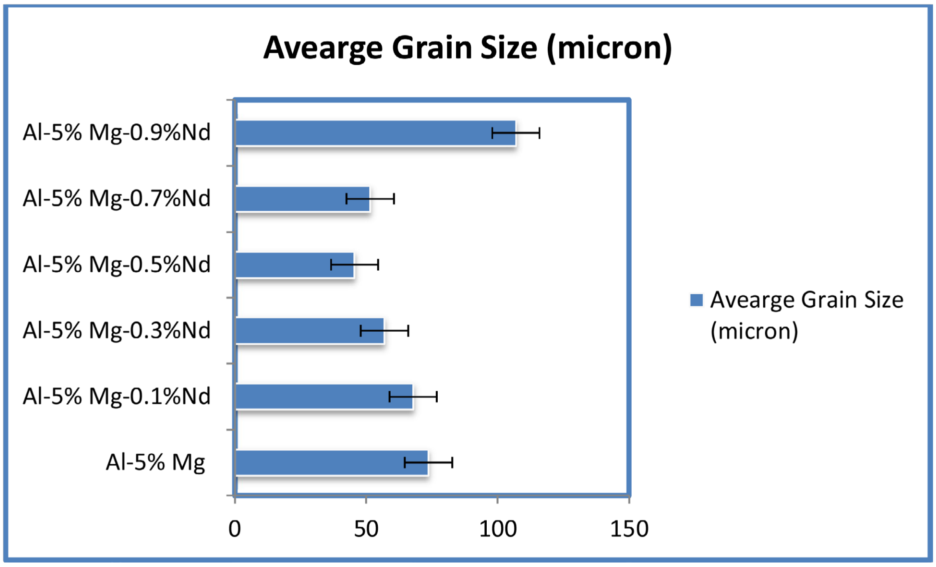



**Figure 2.** Effect of Nd contents on the average grain size of Al-5%Mg alloy.

the grain refining efficiency. Undoubtedly, the idea behind the decrease in the grain size was attributed to the grain refinement and modification of the globular morphology of $\beta$ ($Al_3Mg_2$) intermetallic compound. The additives increased the number of solidification sites for heterogeneous nucleation of the primary aluminum phase which led to increase in grain boundary area per unit volume and a decreased in the intraparticle distance [21].

### 3.2. Optical Microstructure

Figure 3(a) shows the micrograph of the Al-5wt%Mg alloy. The microstructure comprises mainly of $\alpha$-phase and $\beta$-phase, this is in agreement with Al-Mg phase

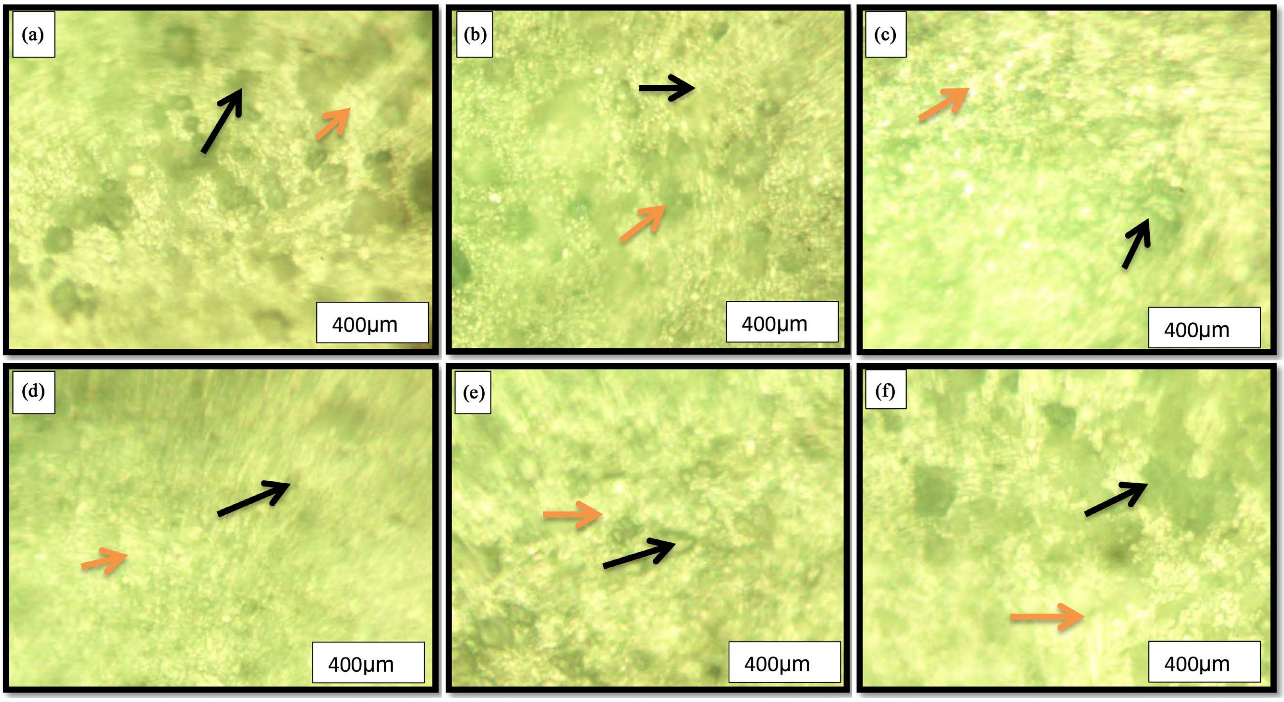



**Figure 3.** Optical micrograph, (a) Al-5%Mg, (b) Al-5%Mg-0.1%Nd, (c) Al-5%Mg-0.3%Nd, (d) Al-5%Mg-0.5%Nd, (e) Al-5%Mg-0.7%Nd and (f) Al-5%Mg-0.9%Nd.

diagram [22]. The alpha phase is the region where magnesium formed a solid solution with the aluminum matrix while the beta phase is the intermetallic compound ($Al_3Mg_2$). The intermetallic phase compound existed in globular morphology separated from the solid solution by the grain boundary.

Figures 3(b)-(f) show the microstructure of Aluminum-5 wt% magnesium alloy doped with (0.1, 0.3, 0.5, 0.7, 0.9, and 1.0) wt% neodymium. From the micrographs, micro-alloying reduced the globular morphology of the $\beta$-intermetallic phase; this resulted in a reduction of grain size. Optimum grain refinement was obtained when neodymium of 0.5 wt%, a further increase in concentration resulted in the formation of chains of globular $\beta$-intermetallic phase which lessened the mechanical properties of the alloy. Neodymium addition neither forms any independent phase nor creates any new phase with the Al-5%Mg alloy system. This is in agreement with the Al-Nd phase diagram [23].

Figure 4(a) shows the SEM micrograph of Al-5%Mg alloy. It was revealed that the structure consists of $\alpha$-phase and $\beta$ phase. The $\alpha$-phase is the region where Al formed solid-solution with the magnesium matrix while $\beta$ phase is the intermetallic compound. Figure 4(b) shows the SEM of Al-5%Mg + 0.5%Nd. It was observed that the microstructure of the alloy revealed the $\alpha$-phase surrounded by a fine $\beta$ phase. The addition of neodymium to Al-5%Mg alloy led to solid solution strengthening and modification of globular intermetallic, which resulted in increase ultimate tensile strength of the alloy. Figure 4(c) shows the SEM of Al-5%Mg + 0.7%Nd. It was observed addition of neodymium above 0.5% to Al-%5Mg alloy created inactive particles detrimental to the strength. Also, with the

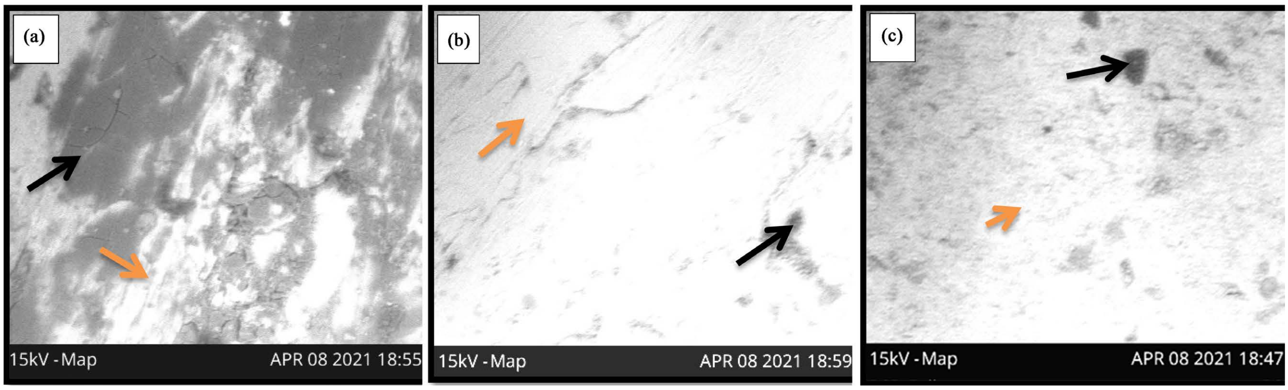



**Figure 4.** SEM micrograph, (a) Al-5%Mg, (b) Al-5%Mg-0.5%Nd, (c) Al-5%Mg-0.9%Nd.

help of image analysis software Image J, the 3D surface plot was obtained as revealed in **Figures 5(a)-(f)**, this 3D surface plot graphically shows the intensity values of the microstructural analysis. The pink colour shows the distribution of $\beta$ ($Al_3Mg_2$) in the $\alpha$ phase (green and yellow coloration).

## 4. Modeling

In this study, fuzzy logic and artificial neutral network-model were utilized to predict the effect of rare earth neodymium (Nd) on the structure and mechanical properties of Al-5%Mg *i.e.*, average grain size, tensile strength, yield strength, hardness and percentage elongation.

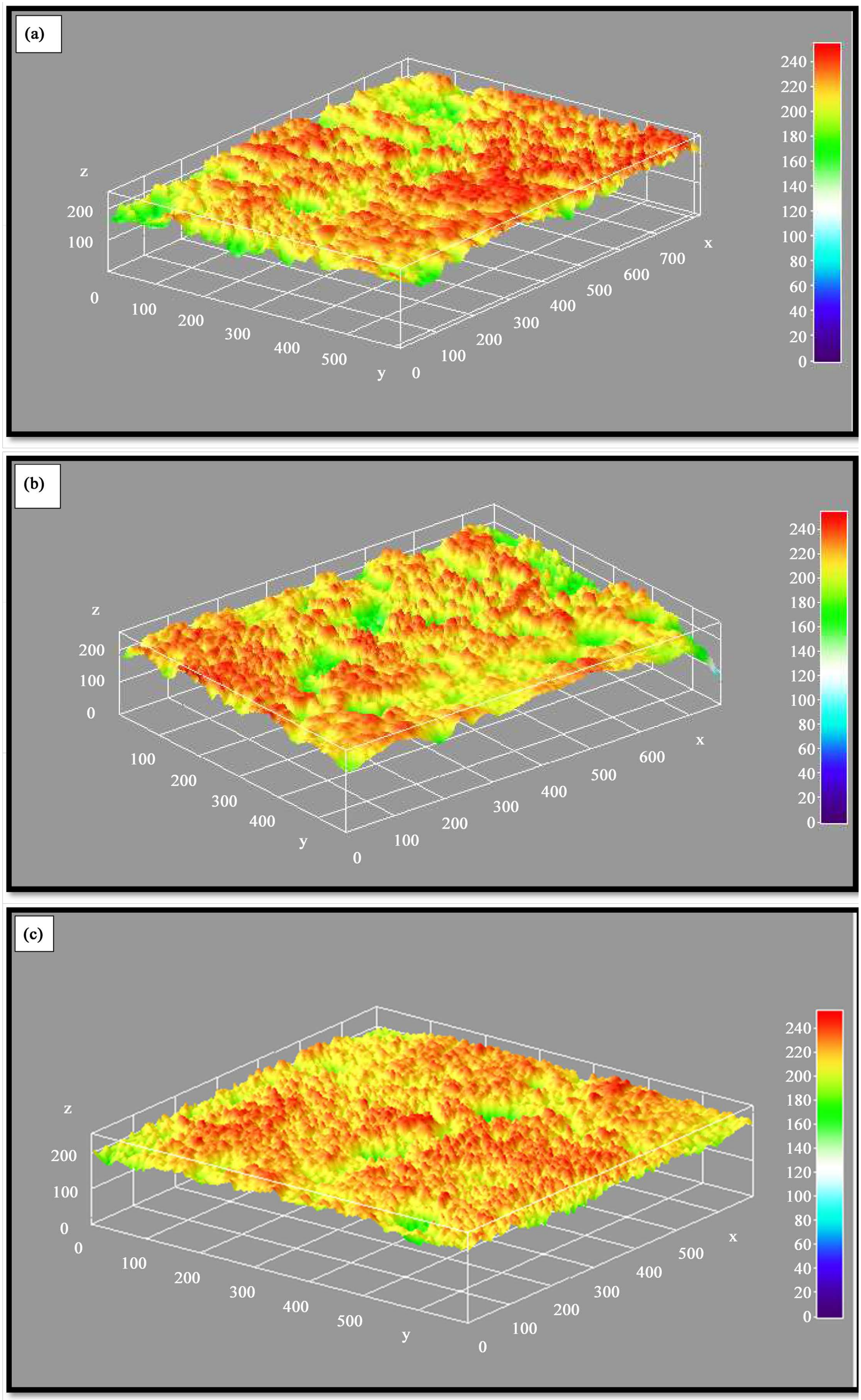
### 4.1. Fuzzy Logic Modeling

The Fuzzy Logic model contains three components: fuzzification, fuzzy inference system, and defuzzification. The fuzzifier maps crisp numbers into fuzzy variables, rule bases are a collection of IF-THEN statements. It maps input fuzzy variables into output fuzzy variables. Defuzzification maps output fuzzy variables into crisp quantity. **Figure 6** shows the workflow of fuzzy logic simulation. The model takes in the amount of neodymium as a single input variable, which is transformed into a fuzzy plane. Base rules are written which determine the study's outputs based on the centroid method, and the Mamdani method is used for defuzzification.

As shown in **Figure 7**, micro-alloying with neodymium represented the input variable to the fuzzy inference system, while the average grain size, yield strength, tensile strength, elongation and hardness derived from defuzzification were the output variables.

**Figure 8** depicts the membership function for the micro-alloying using neodymium. The membership function contained ten linguistic variables namely: mo1, mo2, mo3, mo4, mo5, mo6, mo7, mo8, mo9, mo10.

Six (6) fuzzy logic models were utilized in the prediction the modeling. Model I contained seventeen (17) linguistic variables for the output (average grain size) as shown in **Figure 9**, model 2 contained thirty-five (35) linguistics for the output (hardness) as shown in **Figure 10**, model 3 contained eighteen (18) linguistic


(a)
z
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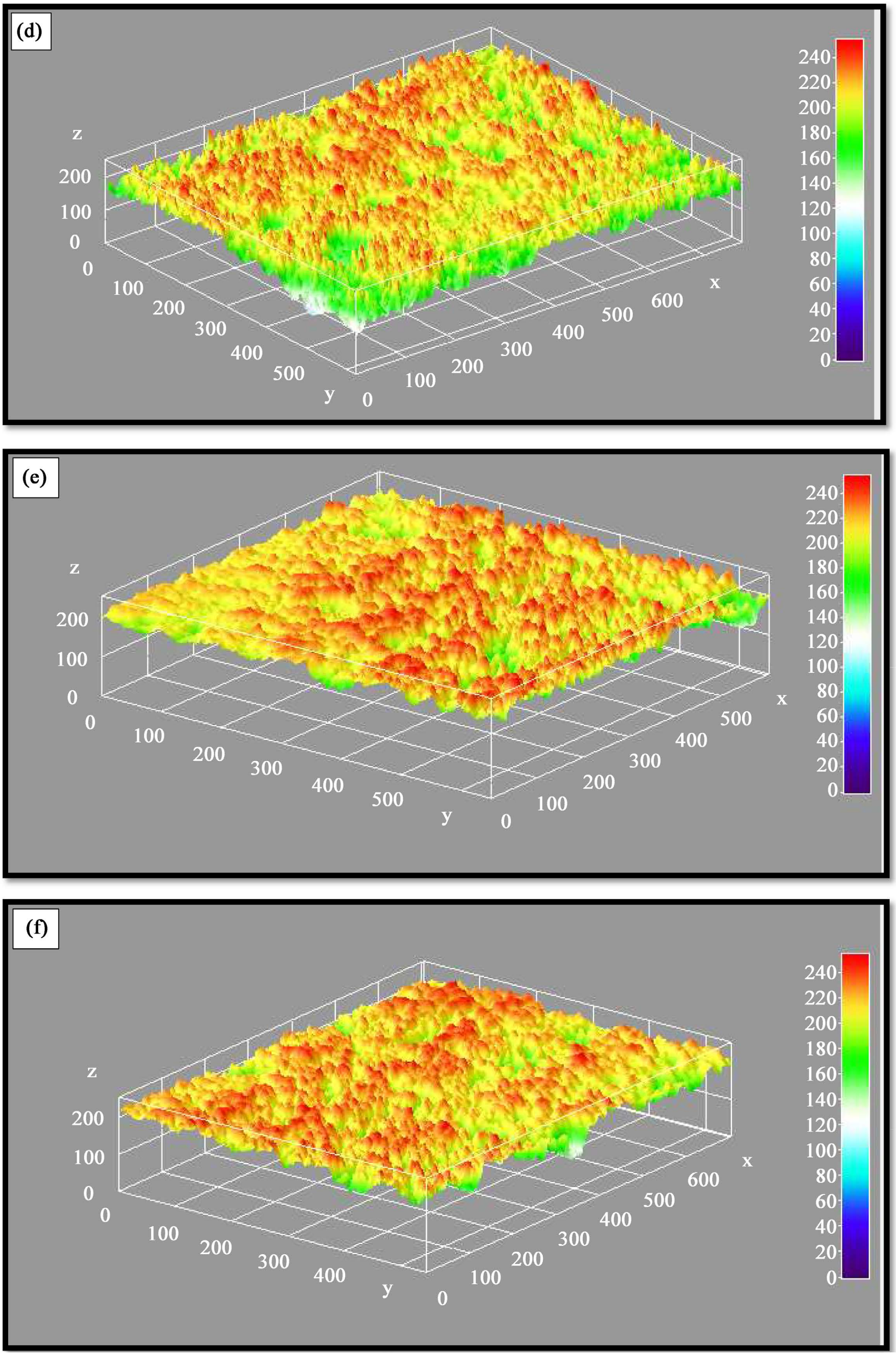


**Figure 5.** Surface plot (3D view) of microstructure. (a) Al-5%Mg, (b) Al-5%Mg-0.1%Nd, (c) Al-5%Mg-0.3%Nd, (d) Al-5%Mg-0.5%Nd, (e) Al-5%Mg-0.7%Nd and (f) Al-5%Mg-0.9%Nd.

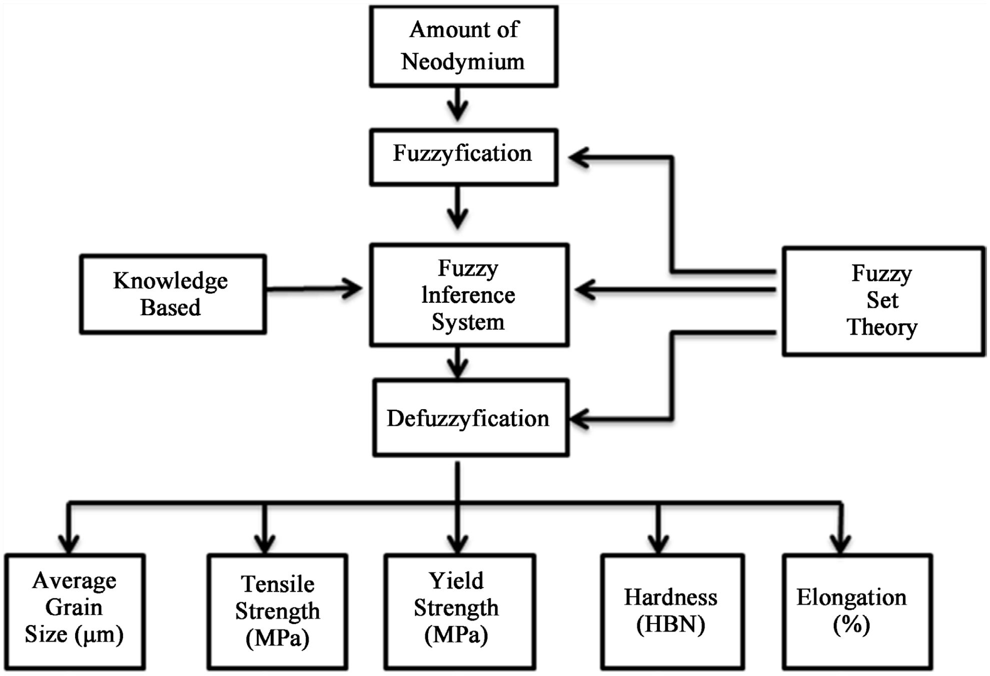


Figure 6. Workflow of fuzzy logic-based simulation.

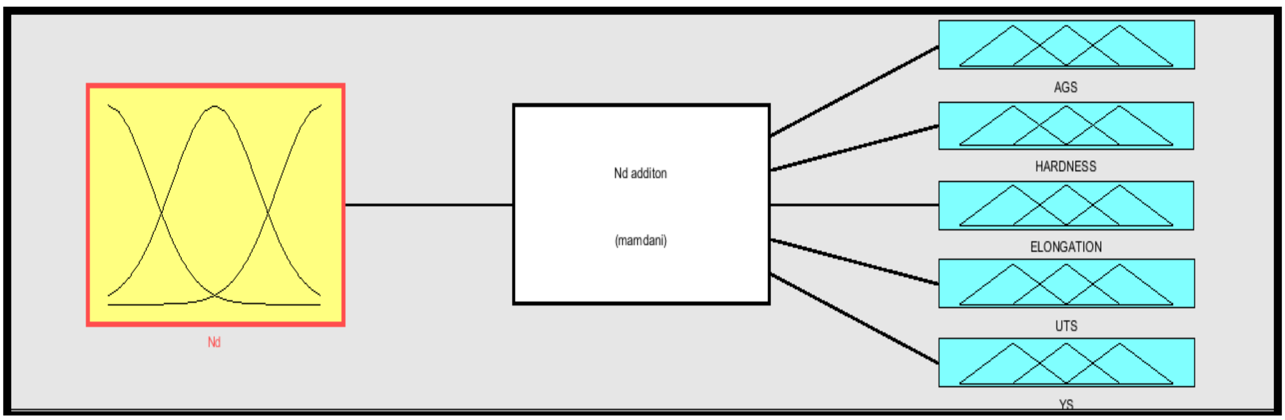


Figure 7. Fuzzy inference system for micro-alloying of Al-5%Mg using Nd.

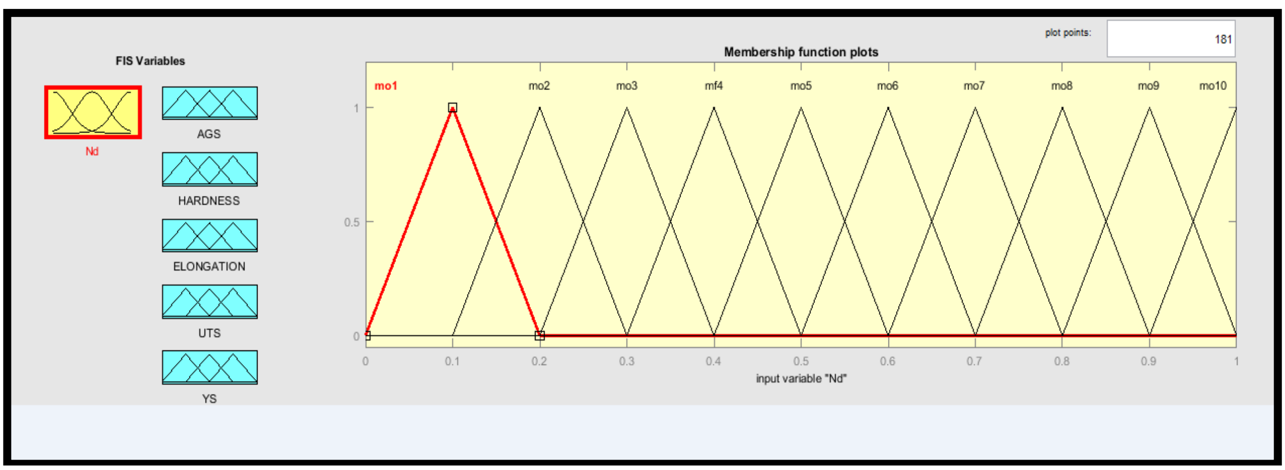


Figure 8. Membership function.

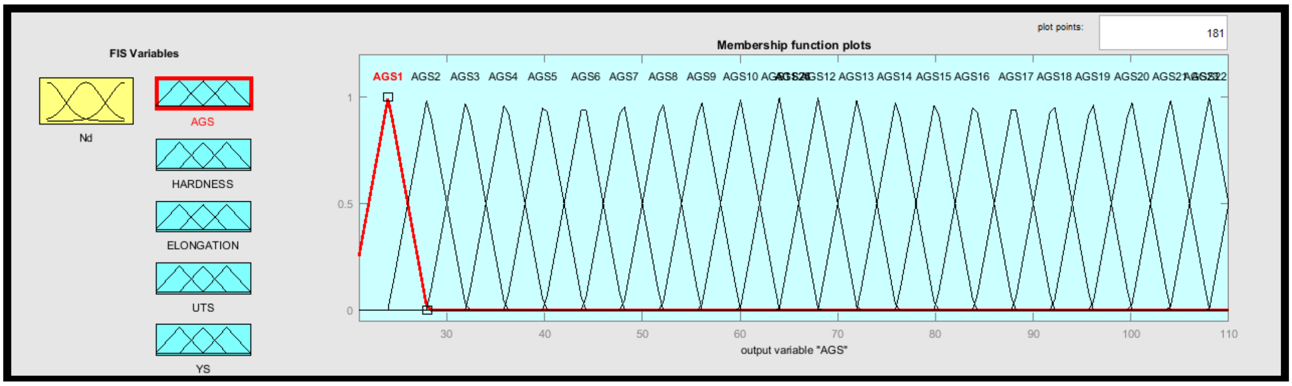


Figure 9. Membership function for average grain size.

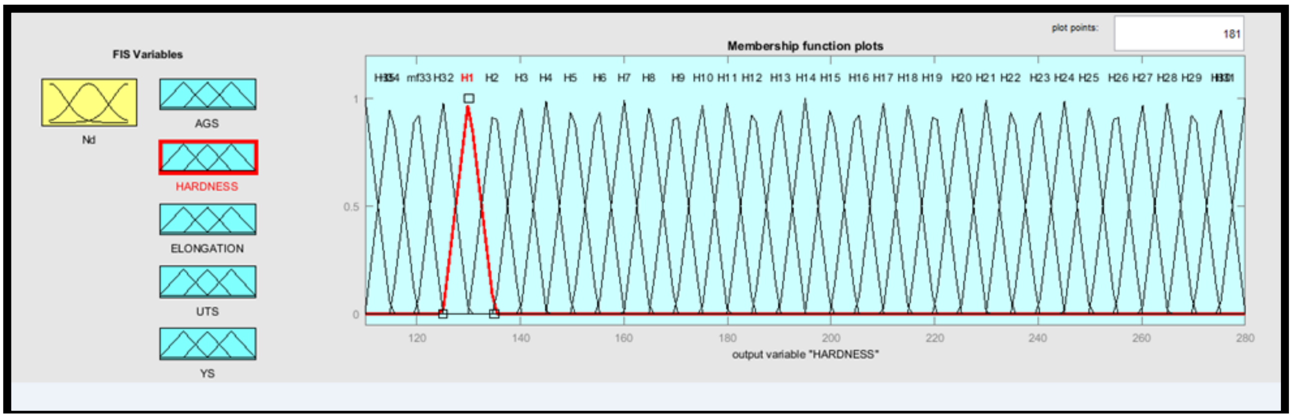


Figure 10. Membership function for hardness.

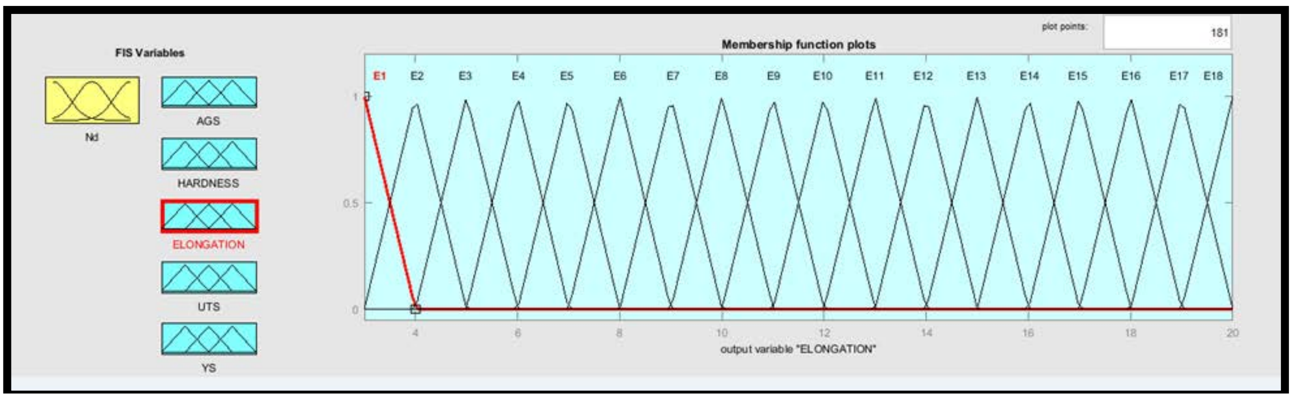


Figure 11. Membership function for Elongation.

variables for % elongation as shown in Figure 11, model 4 contained sixteen (16) variables for tensile strength as shown in Figure 12 and model 5 contained sixteen (16) variables for yield strength as shown in Figure 13.

From Table 2 and Figures 14(a)-(e) Fuzzy logic prediction for Al-5%Mg (0.1% - 1%) Nd gave correlation coefficient (R) of 0.9996 for average grain size, ultimate tensile strength with correlation coefficient (R) of 0.9995, yield strength with correlation coefficient (R) of 0.9831, elongation with correlation coefficient (R) of 0.9958 and hardness with correlation coefficient (R) of 0.9978. The correlation coefficients

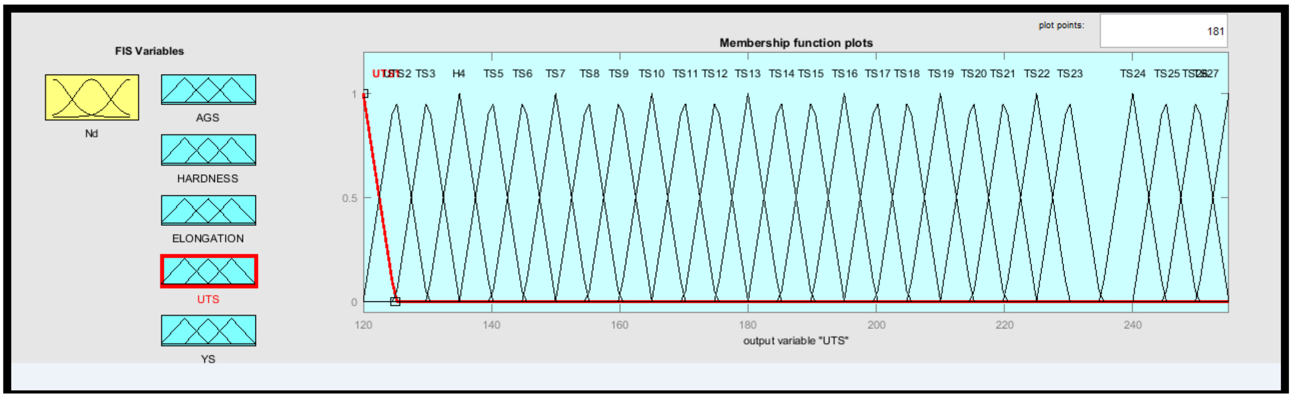


**Figure 12.** Membership function for ultimate tensile strength.

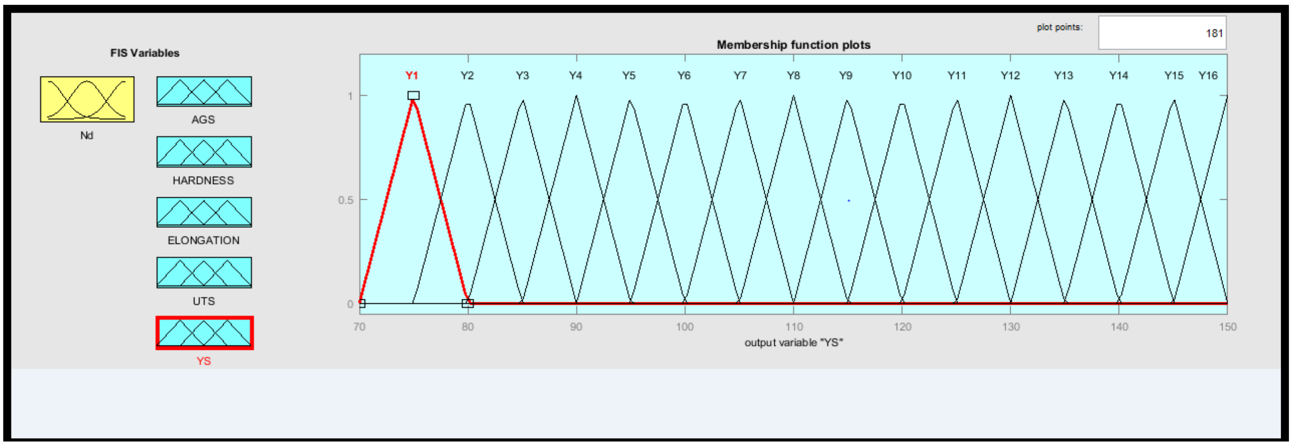


**Figure 13.** Membership function for yield strength.

**Table 2.** Actual and fuzzy logic predicted average grain size and mechanical properties of Al-5%Mg alloy modified with Nd.

| %wt of Nd | Actual AGS (μm) | Predicted AGS (μm) | Actual UTS (MPa) | Predicted UTS (MPa) | Actual YS (MPa) | Predicted YS (MPa) | Actual %E | Predicted %E | Actual hardness (BHN) | Predicted hardness (BHN) |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 67.9 | 68 | 205.85 | 205 | 117.89 | 120 | 11.57 | 12 | 118.23 | 120 |
| 0.3 | 56.92 | 56 | 213.88 | 215 | 122.11 | 120 | 14.04 | 14 | 148.01 | 145 |
| 0.5 | 45.59 | 44 | 219.35 | 220 | 125.26 | 125 | 17.71 | 18 | 173.18 | 170 |
| 0.7 | 51.53 | 52 | 200.82 | 200 | 115.26 | 115 | 12.52 | 13 | 211.76 | 210 |
| 0.9 | 106.95 | 108 | 187.51 | 185 | 103.42 | 105 | 8.42 | 8 | 193.22 | 195 |
| Correlation coefficient | 0.9996 | | 0.9995 | | 0.9831 | | 0.9958 | | 0.9978 | |

of actual experimental data and predicted data for average grain size, ultimate tensile strength, yield strength and hardness were above 0.9, thus the result demonstrated agreement between the experimental values and fuzzy model [24].

### 4.2. Artificial Neural Network (ANN)

The ANN used in this study consists of input, hidden and output layers as shown in Figure 15 input layer consist of one neuron representing the input variable (wt% of neodymium), each of the ten (10) hidden layers, while number of nodes in output layers consist of five neurons of each of the experimental data: average grain size, ultimate tensile testing, yield strength, elongation and hardness. For the simulation of artificial neural network, sixty –five percent (65) of the experimental data were used for training while twenty-five percent (25) were used for validation.

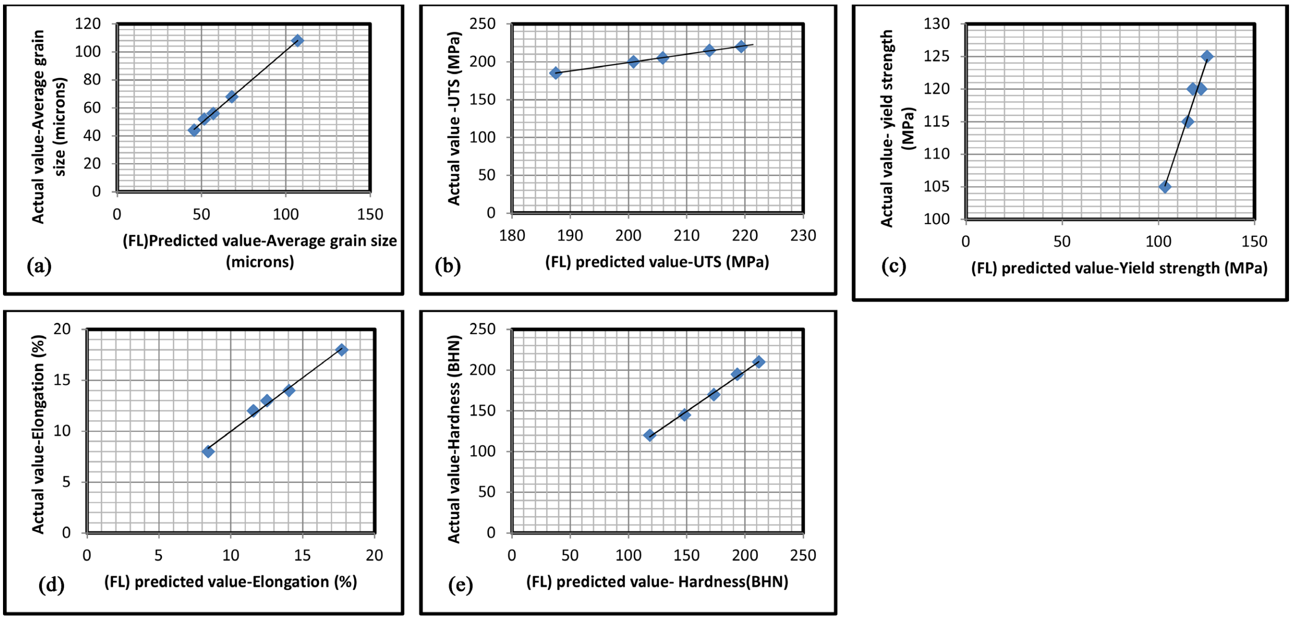


Figure 14. Correlation coefficient between the experimental & predicted values for testing data of (a) average grain size (b) ultimate strength, (c) yield strength (d) % elongation, (e) hardness.

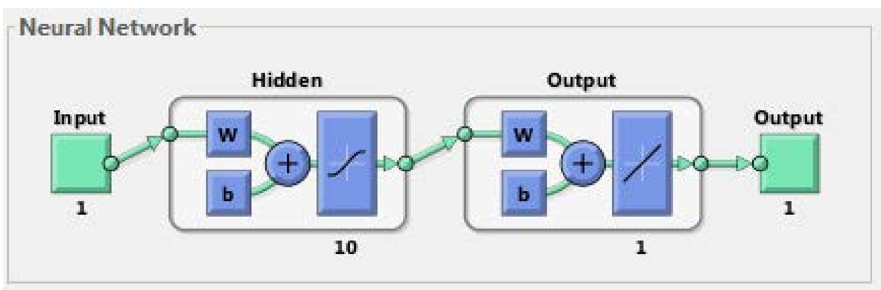


Figure 15. Schematic diagram of the ANN model for prediction of properties of magnesium alloys. Schematic of a single-hidden-layer neural network: one (1)-input, ten (10) hidden neurons and five (5) output layers.

From Figures 16(a)-(e) and Table 3, artificial neural network simulation for Al-5%Mg (0.1% - 1%) Nd gave correlation coefficient (R) of 0.9161 for average grain size, ultimate tensile strength with correlation coefficient (R) of 0.9459, yield strength with correlation coefficient (R) of 0.9570, elongation with correlation coefficient (R) of 0.9951 and hardness with correlation coefficient (R) of 0.97186. The correlation coefficients of actual experimental data and predicted data for average grain size, ultimate tensile strength, yield strength and hardness

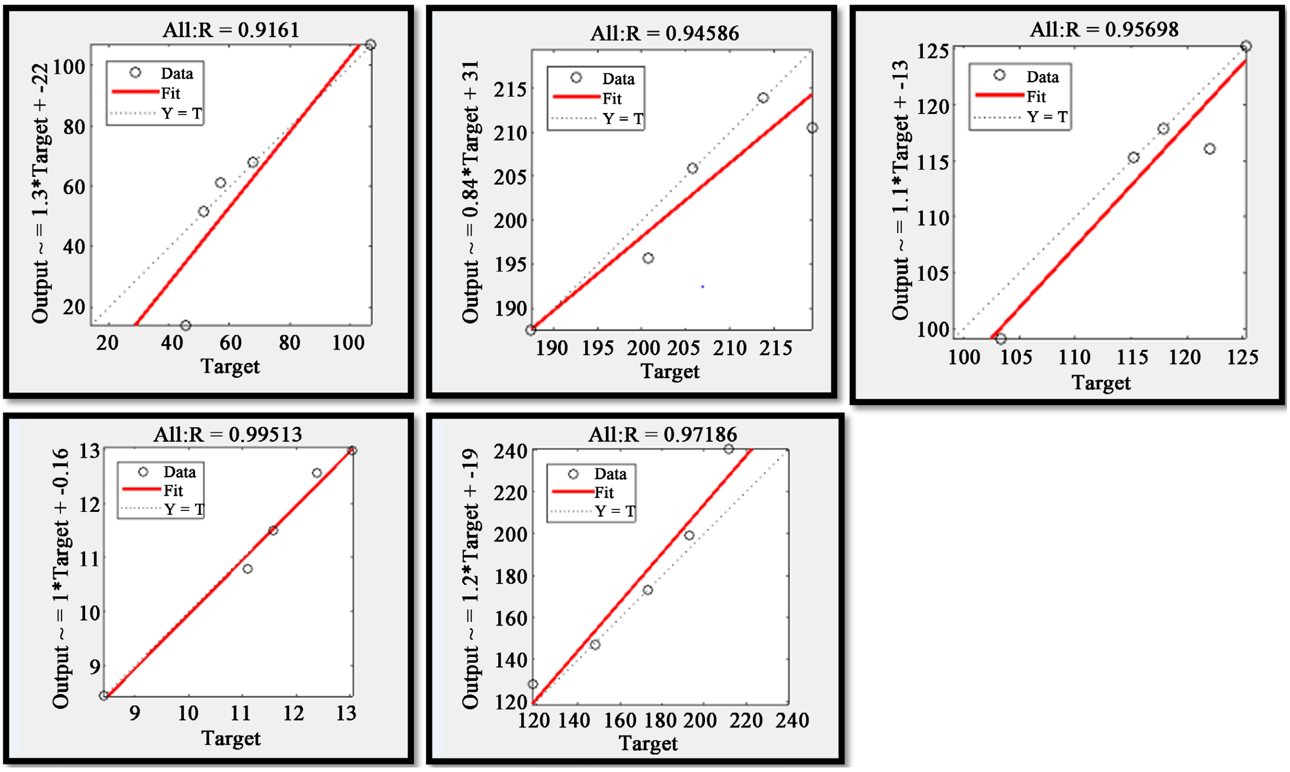


**Figure 16.** Correlation coefficient (ANN). (a) Average grain size, (b) Ultimate tensile strength, (c) Yield strength, (d) Elongation and (e) Hardness.

**Table 3.** Actual and artificial neural network predicted, average grain size and mechanical properties of Al-5%Mg alloy modified with Nd.

| %wt of Nd | Actual AGS (μm) | Predicted AGS (μm) | Actual UTS (MPa) | Predicted UTS (MPa) | Actual YS (MPa) | Predicted YS (MPa) | Actual %E | Predicted %E | Actual hardness (BHN) | Predicted hardness (BHN) |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 67.9 | 67.90 | 205.85 | 205.85 | 117.89 | 117.89 | 11.57 | 11.50 | 118.23 | 128.21 |
| 0.3 | 56.92 | 61.19 | 213.88 | 213.88 | 122.11 | 116.11 | 14.04 | 12.99 | 148.01 | 147.13 |
| 0.5 | 45.59 | 13.94 | 219.35 | 210.47 | 125.26 | 125.26 | 17.71 | 12.57 | 173.18 | 173.18 |
| 0.7 | 51.53 | 51.53 | 200.82 | 195.82 | 115.26 | 115.26 | 12.52 | 10.78 | 211.76 | 240.32 |
| 0.9 | 106.95 | 106.95 | 187.51 | 187.51 | 103.42 | 99.06 | 8.42 | 8.43 | 193.22 | 198.96 |
| Correlation coefficient | 0.9161 | | 0.9459 | | 0.9570 | | 0.9951 | | 0.9719 | |

were above 0.9, thus the result demonstrated agreement between the experimental values and ANN model [24].

### 4.3. Comparison of ANN and FL Predictions

Generally, Fl is more applicable in interpreting uncertainties connected with data. On the other hand the ANN is a nonlinear based technique. In order to compare the accuracy of the predicted numerical values of ANN and FL, the correlation coefficient R values obtained for both models were compared. From **Figure 14** and

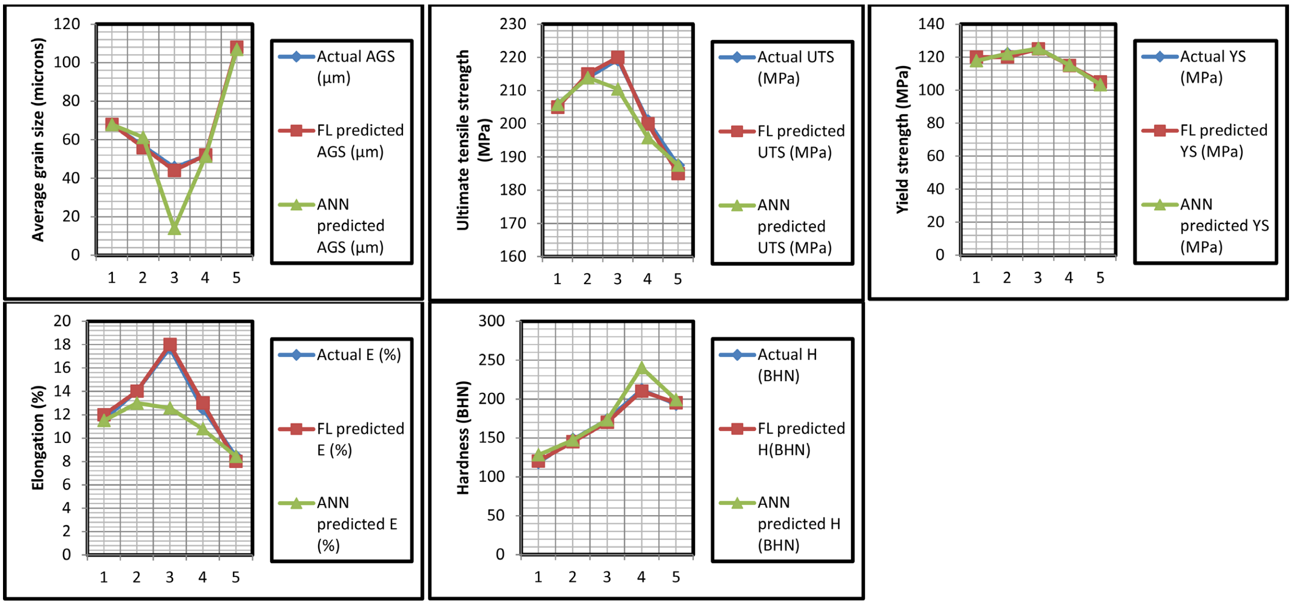


**Figure 17.** Comparison of ANN and FL predictions.

**Figure 16** and **Figure 17** show the average correlation coefficient values obtained for ANN and FL based models were 0.9572 and 0.9952 respectively. The correlation coefficient values of ANN and FL had a strong positive relationship. It was observed that FL based model predictions fit the line of perfect prediction more than ANN based model thus the experimental values were estimated FL efficiently. The higher accuracy of prediction by Fl can be linked to fact for complex problem analysis, ANN needs large data for accurate interpretation while FL based model does not [25].

## 5. Conclusions

Modeling and prediction of mechanical properties of aluminum-5% magnesium (0 - 0.9 wt%) neodymium using artificial neural network and fuzzy Logic approaches, the following conclusions can be summarized as follows:

- Trace addition of Nd below 0.5 wt% greatly improved the tensile strength, yield strength and elongation of Al-5 wt% alloy, mainly through grain refinement: morphological changes in detrimental shape of $\beta$-$Al_3Mg_2$ intermetallic compounds and reduction of $\alpha$-Al grain size. Also, minor addition of Nd below 0.6 wt%, generally improved the hardness of Al-5 wt% alloy.
- The Fuzzy model predicted the average grain size for Al-5%Mg (0.1% - 1%)Ni with a correlation coefficient (R) of 0.9996 for average grain size, ultimate tensile strength with a correlation coefficient (R) of 0.9988, yield strength with a correlation coefficient (R) of 0.9914, elongation with correlation coefficient (R) of 0.9972 and hardness with correlation coefficient (R) of 0.9978.
- Artificial neural network predicted gave a correlation coefficient (R) of 0.9161 for average grain size, ultimate tensile strength with a correlation coefficient (R) of 0.9459, yield strength with a correlation coefficient (R) of 0.9570, elonga-

tion with a correlation coefficient (R) of 0.9951 and hardness with a correlation coefficient (R) of 0.97186.


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## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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## Abbreviations

UTS: Ultimate tensile strength
AGS: Average grain size
YS: Yield strength
ANN: Artificial neural network
FL: Fuzzy logic