Abstract: The quality and performance of composite-based materials are functions of their mechanical properties. Hence, a scientific basis is needed for the determination of the feasible combination of process parameters that will bring about excellent mechanical properties. This study examines the potential of artificial neural network (ANN) for the prediction of mechanical properties, namely density and hardness of graphene nanoplatelet (GNP)/polylactic acid (PLA) nanocomposite developed under various operating conditions of spark plasma sintering (SPS) technique. A back-propagation having a 2-12-2 architecture and Levenberg–Marquardt algorithm was developed to predict the mechanical performance in terms of density and hardness property of GNP/PLA nanocomposites. The predictions of the modelled results were compared with those of the experimental value obtained. The model gave a low root-mean-squared error and performed well with the correlation coefficient (R) for both outputs; density (0.95497) and hardness (0.9832) found to be close to 1. The results of the predicted data were discovered to be very consistent with the values obtained from the actual experimental test result, hence showing the reliability of the model.

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PUBLIC INTEREST STATEMENT
The novel spark plasma sintering (SPS) technique over the years has often been engaged in the development of metal and ceramic composites, while only a few research has considered SPS technique in the development of polymer composite and nanocomposite. SPS has numerous merits such as the possibility of high densification of greater than 99%, low porosity, and fast sintering time compared with conventional techniques. This study is targeted at contributing to an enhanced understanding of artificial neural network in predicting the mechanical performance of spark plasma sintered graphene nanoplatelet/polylactic acid nanocomposite which finds its application in automobile, aerospace, and electronics. The density and hardness properties were predicted via the back-propagation having a 2-12-2 architecture and Levenberg–Marquardt algorithm. The predictions of the modelled results were compared with those of the experimental value obtained. The results of the predicted data were found to be very consistent with the values obtained from the actual experimental test result, hence showing the reliability of the model.
from the actual experimental test result. Thus, our study confirmed the efficiency of a well-trained ANN system in estimating the density and hardness property of SPSed GNP/PLA nanocomposites. Hence, the ANN technique is a reliable decision-making tool capable of reducing the excessive cost incurred in experimental characterisation for newly developed polymer composites. This will serve as a decision-making tool for manufacturing industries where SPS techniques will be employed for processing GNP/PLA polymer nanocomposite.

**Subjects:** Composites; Materials Processing; Polymers & Plastics; Nanoscience & Nanotechnology

**Keywords:** ANN; density; hardness; SPS; PLA; GNP

1. **Introduction**

Polyactic acid (PLA) has received much consideration as a result of its renewable origin, thereby promoting environmental sustainability. Its increasing rate of production is on the premise of industrial demand for durable bioplastic – a suitable replacement for fossil fuel-based plastics in performance and processing characteristics. This application is targeted at the field of electronics, automotive, etc. (Murariu et al., 2015). However, the slow crystallization remains a major deterrent to full acceptance of PLA in technical applications compared to other thermoplastics of fossil origin. Hence, there is a need for a new PLA grade that will outperform the existing ones. The extension of PLA in technical applications such as electrical appliances and automotive parts is subjected to the modification and enhancement in crystallinity of PLA. This has created a need to improve PLA properties such as thermal resistance, mechanical, degradation, and barrier properties. According to Gui, Lu, and Cheng (2013), a high cooling rate characterised by the injection moulding technique is said to be responsible for the production of amorphous PLA. This gives rise to the production of a PLA material with a lower heat distortion temperature and reduced mechanical properties. Hence, the production of highly crystalline PLA remains a major focus for researchers and industrialist. Among several means of increasing the usability of PLA in several applications, one is by developing a composite. The composite material, according to Rajak, Pagar, Menezes, and Linul (2019), is an amalgamation of a base material known as a matrix or a binder and a filler material (reinforcement). The filler material can be in the form of fragments, particles, fibers, or natural or synthetic whiskers (Barbero, 2017; Tsai, 2018). The inclusion of these fillers in polymers results in composite material with enhanced and superior properties when compared to properties possessed by individual material (Rajak, Pagar, Kumar, & Pruncu, 2019). Composite materials can be classified based on the type of constituent engaged in its preparation. It can be based on matrix phase, which gives rise to the polymer matrix composite, ceramic matrix composite, and metal matrix composite. With respect to reinforcement, it can be sectioned into fiber-reinforced, particle-reinforced, and sheet-moulding composites. Also, it could be based on the scale which comprises the nanocomposite and biocomposite (Rajak et al., 2019, 2019). Furthermore, to achieve excellent properties of these composites, the method of preparation of these composite materials is highly important. A comparative investigation of techniques was performed by Jebawi, Sixou, Seguela, Vigier, and Chervin (2006). They observed a significant increase in crystallinity for sintered samples when compared with the compression-moulded ones. This is said to be accompanied by a nearly twofold increase in young modulus. A greater continuity of stiff crystalline phase was observed for sintered material when compared with the one that was compression moulded. The method of sintering is seen to be beneficial in incorporating a large amount of minerals or metallic fillers at a larger amount than that allowed in melt processing. Hence, the production technique of SPS as a novel approach could provide the possibility of enhancing the crystallisation properties of PLA towards a better performing or improved PLA and its nanocomposites.
SPS technique could serve as an alternative and unique processing technique other than the conventional melt-compression and injection moulding technique used in the fabrication of polymer composite. In SPS, effectively welded powder particles are obtained at a sintering temperature close to the onset of the melting range, which is proven from mechanical properties (Jebawi et al., 2006). According to German (2010), sintering is regarded as a thermal treatment for bonding particles into a coherent, predominantly solid structure via mass transport events that often occur on the atomic scale. The bonding leads to improved strength and lower system energy. Spark plasma sintering (SPS) process is a rapid sintering method, which is characterised by a homogeneous distribution of heating over the entire volume of the powder compact on a macroscopic scale. More importantly, the heating power is directed at the exact location in the micro-scale where energy is required for the sintering process. This results in a favourable sintering behaviour, reduced grain growth, and suppressed powder decomposition (Suárez et al., 2013).

Graphene is a single layer of sp² carbon atoms arranged in a honeycomb structure and having an outstanding mechanical and very high surface area (Kim., 2012). Graphene nanoplatelet (GNP) is made up of few stacked graphene layers, possessing oxygen-having functional groups along the edges (Pinto, Martins, Moreira, Mendes, & Magalhaes, 2013). GNPs, novel nanofillers, have single or multiple graphitic planes, exceptional properties in terms of their mechanical strength, and chemical stability. Aside from its cost-effectiveness, its high specific surface area promotes effective stress transfer at the composite interface and provides higher reinforcement compared to carbon nanotubes (Lahiri et al., 2012; Potts, Dreyer, Bielawski, & Ruoff., 2011).

According to Rajak et al. (2019), nanocomposite is a novel material obtained by combining two or more distinctive materials at the nanoscale. This study is predicated on the necessity to explore a novel composite manufacturing technique which is non-conventional towards achieving a composite material that will be pores free, biodegradable, and environmentally sustainable as a composite material for a variety of applications including automobile.

1.1. Artificial neural network

Artificial neural network (ANN) is a class of mathematical modelling useful for efficient exploring and analysing the interaction between large sets of inputs and outputs. It has its extensive application in material processing (Jain, Mao, & Mohiuddin., 1996). ANN has presented a strong framework for modelling nonlinear systems for decades, particularly those that are chemically arranged (Altarazi, Ammouri, & Hijazi, 2018; Hinton, 1992). The most desired merit of ANN is its capacity to model complex, nonlinear, multidimensional function connections without any previous assumption about the nature of the relationship (Akhtar, Ozdemir, Tayfur, & Akkol, 2003; Zhang, Barkoula, Kocsis, & Friedrich., 2003). It helps to better understand highly uncertain systems and assist in the probable prediction of their future responses, thereby making it a relevant tool in the material research field. It has been used in many fields of research among which are development of material structures, regression, optimization, modelling of processes, etc. (Jayabal, Rajamuneeswaran, Ramprasath, & Balaji, 2013; Kashyap & Datta, 2015; Shen, Wang, & Li, 2007; Xu, Zhang, & Zhang, 2015).

ANN is proficient in the structure–property analysis of polymers based on a limited number of measurement results (Jiang, Gyurova, Schlarb, Friedrich, & Zhang, 2008; Zhang et al., 2003). The engagement of intelligent computational system helps to reduce the routine experimental characterisation in new polymer composite development (El Kadi, 2006; Jiang, Zhang, & Friedrich, 2007; Zhang & Friedrich, 2003). This process is engaged in solving the time-consuming challenge, which often arises via finding optimum filler composition to determine the best mechanical and physical properties in polymer composites. In a brief, ANN prediction technique is a mean of reducing large-scale laboratory measurement.

The operations of ANN have its origin from the workings of the human nervous systems. It acquires knowledge like the human brain in a learning process and stores this knowledge via the
interneuron connection known as synaptic weight. The ANN structure majorly divided into three segments: input layer, hidden layer, and output layer (Mahdavi Jafari, Soroushian, & Khayati, 2017). The structure in an ANN can be represented as Equation (1).

\[ \text{Nin} \rightarrow [N1 – N2 – \ldots – Nh]h \rightarrow \text{Nout} \]  

(1)

where

\( \text{Nin} \) and \( \text{Nout} \) denote the number of input and output variables, respectively; \( N_1, N_2, \) and \( Nh \) are the numbers of the neurons in each hidden layer, and \( h \) is the number of hidden layers.

ANN comprises of the nodes (neurons) organised in layers, weighted links between the nodes and activation function (Altarazi et al., 2018).

ANN has been employed to forecast in manufacturing processes’ resulting material properties using input features of material compositions and processes’ operational parameters. This method has been used in several articles to answer composite-related problem such as interrelationship between various variables in a manufacturing process to the life cycle prediction of the composite (Vineela, Dave, & Chaganti, 2018). The structure of the network can be adjusted to enhance the performance of the network (Pradeep, Srinavan, & Himavathi, 2012). ANNs have been explored to predict many properties which include the dynamic mechanical, wear, and fatigue properties of polymer composites (Zhang & Friedrich, 2003). It has also been found to be very precise with a wide variation of stress and temperature compared to those of explicit nonlinear viscoelastic constitutive model (Al-Haik, Hussaini, & Garmestani, 2006).

It is able to estimate outputs nonlinear functions of the inputs so that the generalized model can be built over the available data (Zhang & Friedrich, 2003). The activation functions were in charge of delivering the outputs when provided with a weighted sum of input neurons. The weighted sum of the inputs plus a bias makes up the output of a neuron. The weight remains a major determining function in neural network. The multiplicative parameter, which is associated with each interconnected node–node, is known as weight (Altarazi et al., 2018).

A better approximate desired function is obtained by iteratively training the network with some sample data and weight modification (Cheung & Cannons, 2002). The training process involves reducing the sum of square error between actual and predicted outputs, using the available training data, by continuous adjustment and finally determining the weights connecting neurons in adjacent layer (Sha & Edwards, 2007). Hence, the evaluation of the network performance is done by a different data set aside the training set.

The mean squared error (MSE) and regression (R) are major parameters used to assess the efficient performance of neural network in predicting desired properties or output. The MSE is the average squared difference between the predicted values and experimental data. The lower value gives better fitness. The lower this value, the better the fitness. The ideal value is zero, which indicate no error. The regression (R) measures the correlation between the predicted and the experimental values. An ideal value of 1 indicates a close relationship, while zero (0) indicates a random relationship (Khanam et al., 2016).

1.2. Recent studies on graphene-reinforced nanocomposite

Batakliev et al. (2019) worked on the nanoindentation analysis of 3D-printed poly (lactic acid)-based composites reinforced with graphene and multiwall carbon nanotube. Best nano mechanical properties were observed at 6 wt.% addition of GNP or Multi-wall carbon nanotubes (MWCNT). Formation of aggregates was observed at 9 and 12 wt.% of the mono-filled nanocomposites. At these concentrations (9 and 12 wt.%), a worst dispersion of the carbon nanofiller and lower hardness and elasticity were observed. Yang et al. (2019) provided a better understanding of the
crystallisation characteristic of PLA. In this study, graphene (GN) content ranging from 0 to 2.0 wt. % and PLA were solution blended and then compression moulded at 190°C and 10 MPa. The non-isothermal crystallisation kinetics indicated that GN played an active part as a nucleating agent for PLA. The graphene content and cooling rate serve as a key factor for non-isothermal melt crystallisation process. Kim et al. (2019) in their study fabricated an electrically conducting and mechanically reinforced PLA composite by incorporating graphene (GNPs). Improvement was observed in the mechanical properties such as tensile strength and strain even at a low GNP concentration of 2 wt.%. The electrical conductivity was also enhanced. Mansour, Tsongas, and Tzetzis (2019) conducted a study on the mechanical and dynamic properties of 3D-printed PLA reinforced with graphene. The properties of 3D-printed PLA nanocomposite containing 10 wt.% graphene show improved modulus, strength, and hardness of the nanocomposite. A similar study was also performed by Prashantha and Roger (2017) where the multifunctional properties of 3D-printed poly (lactic acid)/graphene nanocomposite were examined by fused deposition modelling. Graphene inclusion was seen to have enhanced the properties of the nanocomposite.

1.3. Studies on ANN predictions and optimisation of polymer-based composites

The ANN has been confirmed by various studies as a useful mathematical tool in polymer-based composite. A few of their findings and proofs are presented in this article.

Bayraktar, Uzun, Çakıröglu, and Guldas (2017) worked on the 3D-printed plastic parts and predicted the mechanical properties using ANNs. The samples were produced using PLA. The experiment was conducted based on varied melt temperature, thickness values, and raster pattern orientation. The tensile strength of the samples is influenced by the melt temperature, layer thickness, and raster pattern orientation. The best-performing model has \( R^2 \) values of 0.999199 and 0.999997 for test and training, respectively, with criss-cross raster pattern. The prediction and optimisation of the tensile strength, ductility, and density properties of polyvinyl chloride (PVC) composite under different weight percentages of virgin PVC, CaCO\(_3\), plasticizers, and recycled PVC using ANN were conducted by Altarazi et al. (2018). The result proved the efficiency of ANN modelling in determining the optimal weight percentage of the different PVC composite constituents so as to achieve the required composite property. The strength of both experimental procedure and ANN mathematical modelling was also explored in a study by Vineela et al. (2018) on the ultimate tensile strength of short fibre composite made of glass fibre, carbon fibre, and epoxy resin. The volume fraction of the carbon short fibres is the input variable, and six neurons used in the hidden layer and the ultimate tensile strength are the outputs. Eight data sets were used in all; four data sets were used as input variable, two for validation and two data sets for testing. The training set has a correlation coefficient \( R \) of 0.99, whereas the overall \( R \)-value is 0.49. The unavailability of sufficient data is said to be responsible for the wide disparity in both \( R \)-values. The prediction made by the ANN model was compared with the regression model. The prediction made by ANN is more accurate as compared with the regression model. The major limitation with the ANN model is that it requires more data sets (more experiments). The introduction of the noise of 2000 random values into the signal, which serves as an input into the ANN, resulted in correlation coefficient \( R \) of approximately 1 for all the data sets. The best performance value sets mean square error converges is 325,957 at epoch 18 out of 24. Khanam et al. (2016) studied the mechanical and thermal properties of graphene/Linear-low density polyethylene (LLDPE) nanocomposites via optimisation and prediction using ANN. LLDPE was reinforced with 1, 2, 4, 6, 8, and 10 wt.% weight grade C (GNP). The processing was done using a screw extruder of different speed. The optimisation of the thermal and mechanical properties was done under various applied process conditions using the ANN. The results of the ANN model further affirm ANN as a tool to predict the material properties before manufacturing and to save money, time, and effort. Further application of ANN on the polymer can be found in a study by Burgaz, Yazici, Kapusuz, Alisir, and Ozcan (2014) to predict the effect of clay composition and temperature on the thermal stability, crystallinity, and thermos mechanical properties of poly (ethylene oxide)/clay nanocomposite. The feed-forward back was selected as the algorithm. The ANN results confirm that the thermal stability of Polyethylene oxide (PEO) nanocomposite increases with decreased enthalpy of melting.
and relative crystallinity, and there exists a directly proportional relationship between the modulus (stiffness) and thermal stability. This further confirms ANN as a useful mathematical tool in the thermal analysis of polymer/clay nanocomposites. The simulated data agree well with the experimental data. A comparative study using both ANN and multi-linear regression (MLR) found ANN to give a better prediction of compressive strength. ANN has a correlation coefficient $R^2$ of 0.97, while MLR has 0.81. This is found in a study of compressive strength of VARTM-processed polymer composite by Seyhan, Tayfur, Karakurt, and Tanoglu (2005). The three-layer feed-forward ANN used consists of three input neurons, one output neuron, and two hidden neurons. The amount of thermoplastic binders, initial fibre preform thickness prior to VARTM process, and composite fibre volume fraction are the input variables, while the compressive strength is the output variable considered in this study. Hence, it can be concluded that ANN was a useful tool for the characterisation of the effect of some critical material parameters on the properties of polymer composite, most especially with sufficient amount of experimental data. The back-propagation neural network with 3-5-1 architecture was used in the prediction of the abrasive wear properties of unfilled and graphite-filled carbon fibre-reinforced epoxy composite under various testing conditions. The Levenberg–Marquardt (LM) proves superior among the various network-performing algorithms evaluated. A well-optimised and trained neural network with LM training algorithm was employed for the prediction of the wear rate as a function of filler content, normal load, and sliding distance (Rao, Varadarajan, & Rajendra, 2014). The predicted data are perfectly consistent when compared with the experimental result. Prasad, Gowda, and Velmurugan (2014) predicted the microhardness, tensile, and three-point bending test properties of coir fiber-reinforced composite using ANN. The predicted values were observed to match up with the experimental values in their early study.

1.4. Artificial neural network prediction on SPS-fabricated composite

Mahdavi Jafari et al. (2017) performed hardness optimization for Al6061-MWCNT nanocomposite prepared by mechanical alloying using ANNs and genetic algorithm (GA). The choice ANN architecture 6-18-1 gave the optimal structure of the model, with 1.52% mean absolute error and $R^2 = 0.987$. The optimal hardness 87.5 Micro-Vicker (MV) is obtained via the combined effect of input parameters of sintering temperature 346°C, sintering time 0.33 h, compact pressure 284.82 MPa, milling time 19.66 h, and vial speed 310.5 rpm at 0.53 wt.% carbon nanotube (CNT). The comparison of the predicted values with the experimental data revealed that the GA–ANN model is a powerful method to find the optimal conditions for preparing Al6061-MWCNT.

Furthermore, the GA and particle swarm optimization techniques were used with integrated ANN to optimize the SPS process parameters of nanostructured nickel–titanium copper-shape memory alloys (NiTiCu-SMAs) (Velmurugan & Senthilkumar, 2019). This is to achieve better mechanical property. The NiTiCu elements with different particle size were consolidated in within these parameters: temperature of 700–900°C, pressure of 20–40 MPa, and soaking time of 5 min. The sintered products were subjected to mechanical analysis such as density and microhardness. The reduction in particle size and increase in temperature and pressure are identified as factors contributing to the enhancement of density and microhardness. This study will contribute to the body of knowledge by providing information on the efficiency of ANN in predicting the mechanical property of graphene-reinforced PLA composite. Many works have been reported on the prediction of the mechanical properties of nanocomposites using the response surface methodology, GA, Taguchi method, and factorial-based models (Mahdavi Jafari et al., 2017). However, the use of ANN prediction technique for SPSed polymer composite sample has not been reported in any available literature. When compared to other predictive techniques, ANN has the ability to study the hidden relationship among the data without imposing any barrier on the input variables. The back-propagation algorithm of the ANN assists in minimising the prediction error. Hence, the model can be improved via iteration. It also captures the nonlinear and complex relationship between the input variables and converts it into the specified output. This work will assist the manufacturing industries on the use of the ANN technique for the prediction of material properties prior to composite development and manufacturing. It serves as a quick, cost-saving, and reliable decision-making tool in the development of nanocomposites.
in experimental decision to identify the interaction of a combination of parameters on the thermal and mechanical properties of GNP-reinforced PLA composite products during manufacturing.

2. Methodology
The physical experiment consists of the material selection, composite preparation, and characterization as explained in the following subsections.

2.1. Material selection
Commercially available PLA in powder form, having a maximum particle size of 180 µm size, mesh size of 80, and purity of 99%, is the matrix material selected for fabrication of nanocomposite samples. The PLA powder was supplied by Micro Powder, Inc., New York. GNP, having an average size diameter of 5 µm, surface area of 50–80 m²/g, and average thickness of 15 nm, is used as reinforcement for fabrication of the nanocomposites.

2.2. Preparation of GNP/PLA nanocomposite
The GNP/PLA nanocomposites were produced under various conditions of SPS technique (Figure 1). The temperature parameters used in processing the nanocomposite range from 120°C to 160°C, while the pressure range is 20–30 MPa. This is consistent with the operating conditions of SPS, where the powder is consolidated at a temperature lower than their melting point (Cavaliere, 2019). The percentage weight proportion of PLA and GNP for 95:5 PLA, respectively, was mixed in a tubular mixer to achieve homogeneity for 6 h, which is then poured into a graphite die. This is to achieve a 30-mm-diameter and 10-mm-thick GNP/PLA nanocomposite. The theoretical density of the nanocomposite is obtained using Equation (1), which serves as a basis to calculate the relative density of the developed nanocomposite under the process conditions.

\[
\text{Theoretical density} = 100 \left( \frac{\% \text{ GNP}}{\text{Density of GNP}} + \frac{\% \text{ PLA}}{\text{Density of PLA}} \right)
\]

The samples were produced by sintering using the SPS machine (model HHPD-25, FCT GmbH, Germany). More details of the experiment are available in our previous work (Adesina et al., 2011).
Graphite sheet was utilized to avert the immediate contact of the powder with the die and the punches. And also makes the ejection of the sintered product easier. The composites were sintered at varied conditions of temperature and pressure, under vacuum. Graphite contaminations on the surface of the sintered product were sandblasted.

### 2.3. Characterisation
The compactness of the sintered materials is known via the measurement of density. The compact samples were weighed both samples in air and in water using the principle of Archimedes to calculate the relative densities of the sintered samples. This is calculated with respect to the theoretical density of the admixed powders. The mechanical properties were carried out under ASTM standard E 384-16 using the microhardness tester (Future Tech FM-700) with test force 100 gf and a holding time of 15 s (Figure 2). Five indentations were made on individual samples and the mean value reported. The variation in the microhardness and density with response to sintering processing conditions is reported in Table 1.

### 2.4. Numerical experiment
The Response surface methodology (RSM) was employed for the combination of the process parameters, namely temperature and pressure, with two experimental responses, namely density and hardness. The data set combined with the aid of RSM was used to train the ANN toolbox of MATLAB 2018a environment using the LM algorithm. The training was done to find the best configuration for the ANN model, i.e. the number of neurons and hidden layers while assigning weights and biases to the network nodes. A number of different configurations were tried, and the root-mean-square error was compared, before settling for the network with the least MSE. From Figure 3, the developed network comprises two input layers and two output layers with two hidden layers comprising 10 and 2 neurons, respectively. The process of training is an iterative process which is subjected to changes in the weights and biases until the desired target is met. The algorithm employed for the training is presented as follows:

```matlab
net=newff(minmax(p),(Altarazi et al., 2018; Kim., 2012),{'tansig','purelin'},'trainlm');
net.trainParam.show = 5;
net.trainParam.epochs = 300;
net.trainParam.goal = 1e-5;
[net,tr]=train(net,p,t);
```

Figure 2. Performance goal plot.
for \(i=1:2\)

\[
\text{figure}(i) \\
[m(i),b(i),r(i)]=
\text{postreg}(a(i,:),t(i,:));
\]

end;

\[a=	ext{sim}(\text{net},p)\]

3. Results and discussion

The process parameters used as an input into the ANN as well as the corresponding output target as determined by the RSM two-factor combination in our previous work (Adesina et al., 2019) are presented in Table 1. The factors are the temperature and pressure values, while the response is the density and hardness values.

### Table 1. Experimental design and actual response results of density and hardness

| Runs | Temperature (°C) | Pressure (MPa) | Density (g/cm³) | Relative density (%) | Hardness (HV) |
|------|------------------|----------------|-----------------|----------------------|---------------|
| 1    | 160.00           | 30.00          | 1.288           | 99.2                | 265.00        |
| 2    | 135.00           | 30.00          | 1.282           | 98.7                | 243.31        |
| 3    | 129.82           | 25.00          | 1.276           | 98.2                | 230.76        |
| 4    | 147.50           | 17.93          | 1.283           | 98.8                | 249.55        |
| 5    | 135.00           | 20.00          | 1.278           | 98.4                | 235.94        |
| 6    | 147.50           | 25.00          | 1.284           | 98.8                | 251.61        |
| 7    | 147.50           | 32.07          | 1.287           | 99.1                | 255.16        |
| 8    | 147.50           | 25.00          | 1.284           | 98.8                | 251.61        |
| 9    | 147.50           | 25.00          | 1.284           | 98.8                | 251.61        |
| 10   | 147.50           | 25.00          | 1.284           | 98.8                | 251.61        |
| 11   | 165.18           | 25.00          | 1.288           | 99.1                | 264.44        |
| 12   | 147.50           | 25.00          | 1.284           | 98.8                | 251.61        |
| 13   | 160.00           | 20.00          | 1.285           | 98.9                | 257.42        |

Figure 3. The training plot.

```matlab
for i=1:2
    figure(i)
    [m(i),b(i),r(i)]=postreg(a(i,:),t(i,:));
end;
a=sim(net,p)
r
```
From Table 1, the process parameters, namely temperature and pressure, are taken as input into the ANN, while density and hardness are taken as the output target. This was iteratively trained using the back-propagation and the LM algorithm. The performance goal and the training plot are shown in Figures 2 and 3. The essence of the performance and the training plot is to ensure that the right weights and biases are assigned to the nodes of the network. The performance goal plot which represents the suitability or otherwise of the trained network is said to be met when the training line cuts across the goal horizontal line as shown in Figure 4. This indicates that the ANN has been adequately trained and correlated the input data for predictive purpose. The process is iterative, and the network architecture can be adjusted until the performance goal is met. The value of the MSE for the 153 iterations was 0.0005. The MSE is a network performance function, which measures the performance of the network according to the mean of squared errors. The negligible value of the MSE indicates the high degree of correlation among input variables and a tendency for good predictive purpose.

From Figure 3, the solid line represents the best-fit linear regression line between the outputs and targets. The correlation coefficient $R$ is 1 when there is an exact linear relationship between the output and the target and zero when there is no relationship between the output and the target. The training correlation coefficient $R$ for the training plot is 0.99995, which indicates a linear relationship between the output and target.

From Figure 4, the values of the gradient and the training gain Mu was found to be 0.013833 and 0.001, respectively. The small values of the gradient and the training gain indicate that the difference between the output and target is negligible. The error reduces after more epochs of training but might start to increase on the validation data set as the network starts overfitting the training data. The training stops after 153 iterations, and the best performance is taken from the epoch with the lowest validation error, which is zero (Figure 4).

Figures 5 and 6 show the regression plots which compare the output of the network to the expected targets. The process of network validation produced the regression plots that are used as a basis of comparison for the network output and the expected target. The correlation coefficients for the two regression plots were 0.95497 and 0.9832 for the density and hardness, respectively. These two values are close to 1 which implies the development of a good model with correlative and predictive ability. The regression plots show a high degree of agreement between the data points and the line of best fit for the network output and the expected target. The second regression plot for the hardness shows greater agreement.
correlative and predictive ability as indicated by the closeness of the correlation coefficient $R$ to 1 (0.9832) as opposed to the first regression plot for density (0.95497). This implies that the performance of the network improves upon fine-tuning the network through iterative training and adjustments of weights and biases. The predictive line equation for density and hardness property, which are the output neurons, are expressed as Equations (1) and (2), respectively.

$$y = (0.91)T + (0.11)$$

(3)
The results obtained from the experimental and the predicted responses using ANN are presented in Table 2.

The validation of the developed network was performed using random (arbitrary) values within the range of the input parameters for the temperature and pressure. Some random values of the temperature and pressure within the range of the experimental input parameters were arbitrarily selected and given as input into the developed network (Table 3). The response from the network in terms of the density and hardness was observed to fall within the range of the actual and predicted values of the density and hardness by interpolation. This confirms that the developed network is adequately trained for correlative and predictive purposes.

The root-mean-square value for the actual values \( (A_{r.m.s}) \) is expressed by Equation (4).

\[
A_{r.m.s} = \sqrt{\frac{\sum_{i=1}^{n}(\text{Actual})^2}{n}}
\]  

The root-mean-square error for the actual and the predicted value \( (E_{r.m.s}) \) is given by Equation (5).

\[
E_{r.m.s} = \sqrt{\frac{\sum_{i=1}^{n}(\text{Actual} - \text{Predicted})^2}{n}}
\]  

The ratio of the two values given in Equation (6) gives the average classification error that determines the degree of agreement between the actual and the predicted values.

\[
E_c = \frac{E_{r.m.s}}{A_{r.m.s}}
\]  

From the mathematical calculation, the r.m.s value of the density obtained is 4.6281, the r.m.s error is 0.001423, while the average classification error of density is 0.00031. The r.m.s value of hardness is 902.949, the r.m.s error of hardness is 20.6147, and the average classification error of hardness is 0.0228.

### Table 2. Actual and predicted values of density and hardness

| Runs | Actual values | ANN Predicted values |
|------|---------------|-----------------------|
|      | Density (g/cm\(^3\)) | Hardness (HV) | Density (g/cm\(^3\)) | Hardness (HV) |
| 1.   | 1.288         | 265.00               | 1.289         | 264.95       |
| 2.   | 1.282         | 243.31               | 1.282         | 242.25       |
| 3.   | 1.276         | 230.76               | 1.278         | 234.69       |
| 4.   | 1.283         | 249.55               | 1.281         | 246.70       |
| 5.   | 1.278         | 235.94               | 1.278         | 236.53       |
| 6.   | 1.284         | 251.61               | 1.284         | 250.74       |
| 7.   | 1.287         | 251.16               | 1.286         | 254.79       |
| 8.   | 1.284         | 251.61               | 1.284         | 250.74       |
| 9.   | 1.284         | 251.61               | 1.284         | 250.74       |
| 10.  | 1.284         | 251.61               | 1.284         | 250.74       |
| 11.  | 1.288         | 264.44               | 1.289         | 266.79       |
| 12.  | 1.284         | 251.61               | 1.284         | 250.74       |
| 13.  | 1.285         | 257.42               | 1.286         | 259.23       |
Considering the average classification error of density (0.00031) and that of hardness (0.0228), the values are small and negligible, thus indicating a high degree of agreement between the actual and predicted values of density and hardness. This also points to the fact that the developed model is adequately trained and suitable for the predictive purpose. Furthermore, the mathematical model developed for the prediction of density shows greater precision in its predictive ability when compared to the model for hardness. This is evidenced in the magnitude of the r.m.s error and average classification error for density and for hardness which was 0.001423 and 20.6147 as well as 0.00031 and 0.0228, respectively. The lower the r.m.s error, the higher the precision of the developed model and vice versa.

The actual and predicted values of the density and hardness were presented in Figures 7 and 8, respectively. The similarity in the data sets and plot pattern indicates the closeness of the predicted values to the actual values. This also indicates the high efficiency of the developed neural network for correlative and predictive purpose.

### Table 3. The validation of the developed network using random experimental values

| Runs | Temperature (°C) | Pressure (MPa) | Density (g/cm³) | Hardness (HV) |
|------|------------------|----------------|----------------|--------------|
| 1    | 140.00           | 31.50          | 1.273          | 261.50       |
| 2    | 130.00           | 28.00          | 1.280          | 244.08       |
| 3    | 120.00           | 26.00          | 1.271          | 232.45       |
| 4    | 150.00           | 18.00          | 1.289          | 248.03       |
| 5    | 159.00           | 22.00          | 1.292          | 236.74       |
| 6    | 155.00           | 24.00          | 1.289          | 251.99       |
| 7    | 145.00           | 23.00          | 1.288          | 253.89       |
| 8    | 133.00           | 24.00          | 1.286          | 252.47       |
| 9    | 147.00           | 21.00          | 1.281          | 250.79       |
| 10   | 160.00           | 26.00          | 1.280          | 251.77       |
| 11   | 125.00           | 20.00          | 1.287          | 265.35       |
| 12   | 148.00           | 22.00          | 1.290          | 252.01       |
| 13   | 158.00           | 23.50          | 1.285          | 258.30       |

Figure 7. Actual and predicted values of density.
4. Conclusion

This study has proven the competence of the ANN technique for the simulation of the mechanical properties of GNP/PLA nanocomposite. The neural network 2-12-2 (2 input neurons, 12 hidden neurons in two hidden layers, and 2 output neurons) is trained using LM training algorithm, based on its superior performance over other algorithms. The prediction of the density and the hardness properties was made by a well-trained neural network based on the processing parameter of the SPS technique as input parameters. The predictions can be said to be perfectly acceptable since it gave a higher degree of consistency with the experimental test results, thus confirming conclusively that the developed model is highly suitable for the predictive purpose. This work finds application in the manufacturing industries prior to the development of polymer composites and for the prediction of its mechanical properties. The quality of the developed nanocomposites is a direct function of its mechanical properties. Hence, good product development of satisfactory service and functional requirements could be promoted via ANN prediction. Furthermore, with the increasing dynamics of manufacturing and emerging materials such as nanocomposites, the use of a scientific approach such as ANN will complement the manufacturer’s experience in the design prediction, mechanical property prediction, and selection processes in the evolution of GNP-reinforced PLA nanocomposite. In addition, the application of the ANN technique in the prediction of mechanical properties will assist in quick, cost-effective, and reliable decision-making. Finally, this work will serve as a good compass for researchers on the continuous implementation of ANN in several industrial sectors such as automotive, aerospace, electronics, and communication, thereby enhancing process monitoring and control systems of the industry.

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