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A Two-stage Artifitial Neural Network Model to Predict the Shrinkage of a Polystyrene Matrix Reinforced with Silica Sand and Cement.

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Abstract

Prediction of the shrinkage for the manufacturing purposes of composite materials is not an easy task. The use of existing mathematical and statistical tools may help in solving part of the problem.On the other hand, artificial network tools are of a great importance too. In this investigation, a two-stage Artifitial neural network was used to predict the amount of shrinkage. Using an experimentally measured values of the shrinkage under different material and processing parameters to judge about the relevance of the developed model, it was found that the two-stage Artifitial neural network approach is more capable of predicting the shrinkage than the analytical models because the latter lacks consideration of the materials and processing variables.

Keywords: Shrinkage; Composite; Polystyrene; Cooling rate; Regression

1. Introduction

Shrinkage is the change in size of the product due to thermal and other contractions. Its amount is dependent upon several factors such as the type of the used material, the type of the manufacturing process and the processing parameters. Moreover, the presence of the reinforcement, its volume fraction and size also affect shrinkage phenomenon especially when dealing with composite materials. As polymer processing requires temperature, shrinkage occuring due to thermal contraction has already been studied for homopolymers [Trznadel et al, 1992, Kozlov et al, 1998] and for composites [Beloshenko et al, 2000; Krueger et al, 2003]. Beloshenko et al [2000] studied the the influence of heating temperature and extrusion ratio on the shrinkage of the isostatic polypropylene-ultra-high-molecular polyethelene (PP-UHMPE) composite system. They concluded that the higher the temperature, the higher the shrinkage value while the higher the extrusion ratio, the higher the shrinkage until a ratio of 2 is reached. It was also observed in their work that the higher the content of the UHMPE in the system, the less the shrinkage value. Other factors such as the effect of light intensity on the shrinkage strain has been studied [Silikas et al, 2000]. It was found that the decrease in shrinkage strain values observed for low intensities. In our previous work [Jalham, 1999], a well-established method of manufacturing for a polystyrene matrix reinforced with Jordanian Silica Sand and cement was reported. The work in this field continued to cover the influence of material variables such as particle size (Z) and reinforcement content (S) in addition to the process parameters such as pressure (P) and cooling rate (C) and their interaction on the compressive load capacity of the manufactured composite [Jalham, 2003]. During the conduction of the experiments a shrinkage was observed among the specimens. To be able to predict the optimum size of the product, it was decided to study the effect of these materials and processing variables on the amount of shrinkage. A rough estimate was achieved using a multiple regression model [Jalham, 2004]. Although it gave better predictions than those using the rule of mixture (analytical approach), but not satisfied enough. To come to a better prediction, it was decided to use the two-stage Artifitial neural network approach model.

2. Theory

2.1. Analytical approach:

There are various methods to obtain composite properties. For example, the mechanics of materials method, the self consistent field method, the numerical technique method, and the variational calculus method [Meyers, 1999]. The latter focuses on the upper and lower limits of the properties and does not predict those properties directly. Only when the upper and the lower bounds coincide are particular properties determined. The relations of this technique are referred to as the “rule of mixtures”. Thus a mathematical model to calculate the contraction in volume which expesses the shrinkage value can be developed as follows:

$$Vsc = Voc - \Delta Vc \quad (1)$$

Where Vsc is the volume of the composite after processing, Voc is the volume of the composite before

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processing, and ΔVc is the volume difference of the composite before and after contraction.
Formula 1 can be rewritten as :

$$\Delta Vc = Voc - Vsc \quad (2)$$

To find the relative change of volume of the sample ($\Delta Vc/ Voc$ %), formula 2 should be divided by Voc resulting in

$$\Delta Vc/ Voc = 1 - Vsc/ Voc \quad (3)$$

According to Edrees et al [1999]:

$$Vsc = (1 - \Delta V/Vo)_m (1\text{-}f)\ Voc + Voc\ f \quad (4)$$

Where f is the volume fraction of the reinforcement and (1-f) is the volume fraction of the matrix. The subscript m denotes the matrix.
Substituting formula 4 in formula 3 gives the shrinkage value as a relative change of volume of the sample:

$$\Delta Vc/ Voc = 1 - [(1 - \Delta V/Vo)_m (1\text{-}f) + f] \quad (5)$$

$\Delta Vc/ Voc$ should be measured experimentally as a function of the material and processing variables and compared to the predictions of formula 5 above.

2.2. Two-stage ANN approach:

A neural network is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data. It is so powerful because it can learn any desired input-output mapping if they have sufficient numbers of processing elements in the hidden layers. The artificial neural network used in this current work is a supervised multi-layer feedforward network trained with a standard back propagation algorithm [Kong et al, 1998]. It Computes changes to the weights in the final layer first, reuses much of the same computation to compute changes to the weight in the pre-ultimate layer, and ultimately goes back to the initial layer. Its idea is to make a large change to a particular weight if the change leads to a large reduction in the error observed at the output nodes. The three-layer network with one hidden layer that was used in this investigation is shown in figure1. The multiplayer perceptron were trained with backpropagation algorithm. The equation to update the weights in momentum learning is [Kong et al, 1998]:

$$w_{ij}(n+1)=w_{ij}(n)+\eta\delta_i(n)x_j(n)+\alpha(w_{ij}(n)-w_{ij}(n-1)) \quad (1)$$

Where w_{ij} is the weight between nodes i and j at iteration n, $\delta_i(n)$ is the local error which can be directly computed from the instantaneous error between the desired response and the system response. At the output processing elements or as a weighted sum of errors at the internal processing elements, η is step size, and α is the momentum and is set to a value between 0.1 and 0.9.

The selection of training algorithm, stopping criteria and representative training set is the most important practical aspect related to training an ANN model. The mean square error of the test set was used as the stopping criteria and to evaluate the performance of the training. The work was accomplished by using the MATLAB software facilities. Unlike other ANN approaches [Hwwu et al, 1996; Kong et al, 1998], this approach used the output of the previous training to be as input to the next one which was called in this investigation as two-stage ANN approach.

3. Methodology

To study the effect of each of the material and processing variables on the shrinkage value, three levels of each variable were considered as in [Jalham, 2003] and presented in Table 1. Three samples for each level were manufactured, because of the limited supply of the polystyrene raw material. The manufacturing of the samples was conducted according to the proposed methodology in [Jalham, 1999] and the results were presented in the form of curves that relates the relative change of volume of the sample ($\Delta Vc/ Voc$ %) values that are measured experimentally as a function of each of the material and procssing variables. The samples were prepared in the form of cylinders of a diameter of 30 mm and a height of 30 mm.

Table 1: Levels of independent variables.

Variable	Units	Level		
		1	2	3
Processing Variables				
Pressure (P)	KN	4	5	6
Cooling rate(C)	°C /min	36	18	12
Materials Variables				
Sand percentage (S)	%	5	25	50
Sand Particle Size (Z)	Micron	60	75	85

As the purpose of this paper is to discover the capability of the two-stage ANN approach to predict the behavior of the polystyrene-base composites by comparing the results of the ANN predictions and the results of predictions by the regresion approach to some of the experimental results which were not used in the training of the network. The two-stage ANN methodology starts from the training of the ANN, shown in Figure 1, through the prediction of the behavior of the polystyrene matrix composite deformed under the same conditions and ending with using the output of the previous training to be as an input to the next stage of training. This approach helps in filtrating the data int the first stage before using it in the second one.

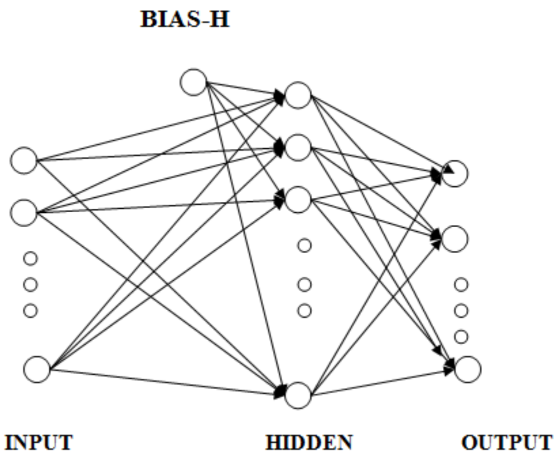

Figure1: The three–layer network with one hidden layer that was used in this investigation.

The preparation of the training data set is related to the way the output vary with inputs and availability of experimental data. If the output varies with inputs in different ways as shown in Fig2 (a & b), the training data used to generalise a model should be prepared differently. For the outputs which vary as in Fig (2b), it is necessary to optimise the training data used. To optimise the training process, Kong [Kong et al, 1998] proposed a way to select the most represantative data while in this investigation the output of the previous training were used to be as input to the next one which was called in this investigation as filtrated ANN approach.

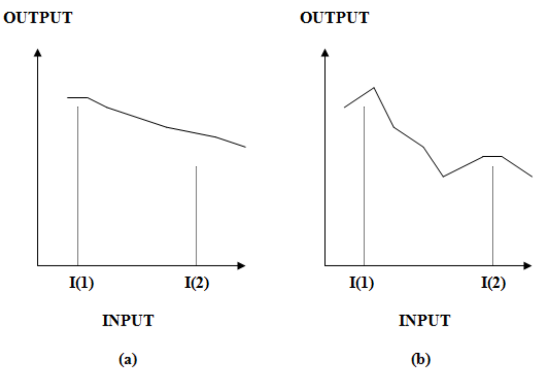

Figure 2: The different ways of output variation with the inputs.

4. Results and Discussions

The experimental results of this work are shown in figures 3-6. They show the effect of each of the materials and processing parameters and their interaction on the shrinkage value which was taken as the relative change of volume of the sample (ΔVc/ Voc %). Figure 3 shows the dependence of shrinkage value as a relative change of volume of the sample on the sand content and its interaction with the particle size of the reinforcement material. It can be observed that the higher the reinforcement content, the less the shrinkage value and for the same content of the reinforcement the higher the particle size, also the less the amount of the shrinkage. This is due to the increase of the amount of the incompressible reinforcement. A good agreement of these results with what have been repoted by Beloshenko et al [2000] was found.

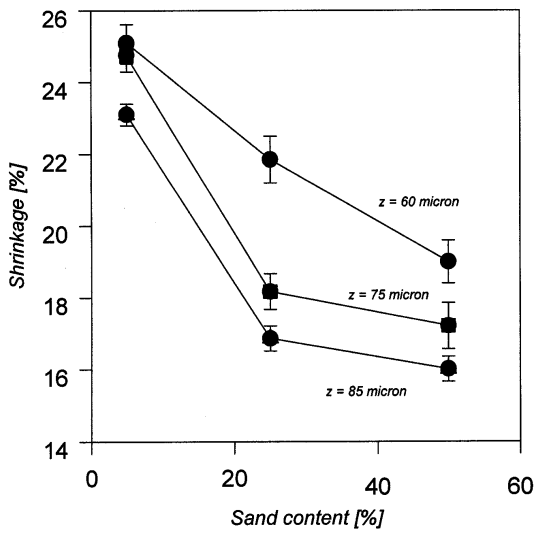

Figure 3: Dependence of the shrinkage of the samples as a relative change of volume on reinforcement content.

Figure 4 shows the dependence of shrinkage value on the pressure and its interaction with the cooling rate. It can be concluded from this figure that the higher the pressure, the higher the value of the shrinkage and for the same pressure the higher the cooling rate, the less the shrinkage. This is due to the increase of the degree of densification with the increase in the pressure during manufacturing. This is also in a good agreement with what have been repoted by Beloshenko et al [2000].

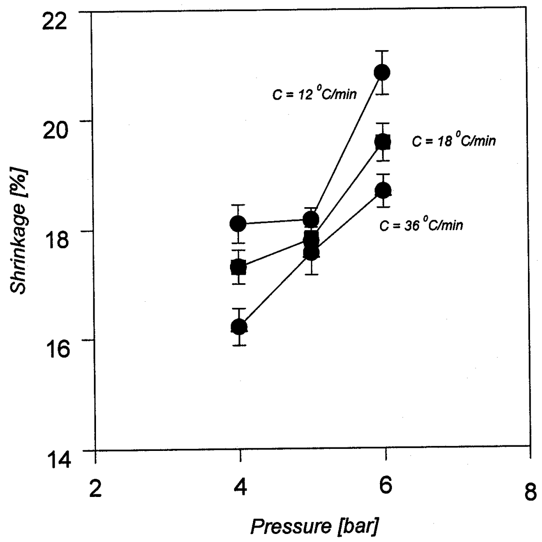

Figure 4: Dependence of the shrinkage of the samples as a relative change of volume on the pressure.

Figure 5 shows the dependence of shrinkage value on the cooling rate and its interaction with the sand content. It is clear that the higher the cooling rate, the less the value of shrinkage which is in a good agreement with the behaviour of homopolymers reported in [Trznadel et al, 1992, Kozlov et al, 1998] and for composites reported in [Beloshenko et al, 2000; Krueger et al, 2003]. This is due to the lower amount of time needed for solidification when using a high cooling rate processing.

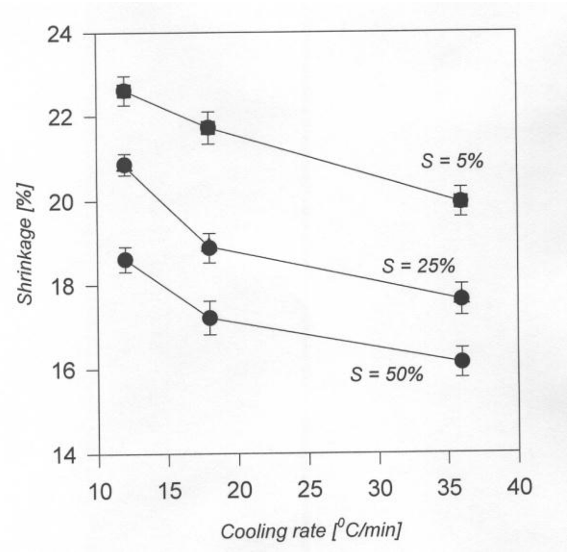

Figure 5: Dependence of the shrinkage of the samples as a relative change of volume on the cooling rate.

Figure 6 shows the dependence of shrinkage on the particle size and its interaction with the pressure vules. The figure indicates that the higher the particle size, the lower the shrinkage value although for the 85 micron particle size the 5 kN pressure shows lower shrinkage than at 5 and 6 kN. This shows that an optimum interaction of the parameters may exist when using a 5 kN pressure during processing.

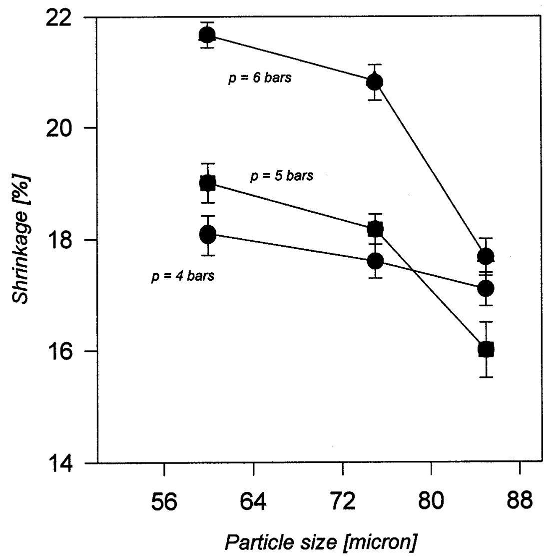

Figure 6: Dependence of the shrinkage of the samples as a relative change of volume on particle size.

It is of a great importance to find a model that may predict the value of shrinkage. This helps in reducing the number of the experiments and gives an idea about the amount of the material needed to produce an intended product. Based on the developed model above, formula 5 can be used to predict the shrinkage value. But the predictions using this formula may serve to predict the shrinkage value when the volume fraction of the reinforcement is the only variable. To be able to predict the shrinkage value when all the materials and processing values are taken into consideration, different approaches were used. In this investigation, analytical, multiple regression, and neural network approaches were of interest. MATLAB package was used as the main tool in this work. The shrinkage value was taken as the response variable and all other interactions where taken as the dependent variables.

It was decided to adopt the two-stage ANN approach because the relative error of the predicted results after the second training stage is better than after the primary stage of training and less than 5%.

A comparison between the model in formula 5, the regression model in [Jalham, 2004], and the experimental results are shown in figures 7-10. Figure 7 shows the results when the sand content is variable (S = 5, 25, 50 %) and the other variables were taken as constants with the following values: Z = 60 microns, P = 5 kN, C = 12 ^{o}C/min . The conditions for the calculations are presented under each figure. The relative change of volume of the polystyrene matrix (ΔV/Vo) was measured experimentally to be 26% and this is constant for calculation conditions. Then the value (1 - ΔV/Vo)m will be 74% and used for the calculations of formula 5 results.

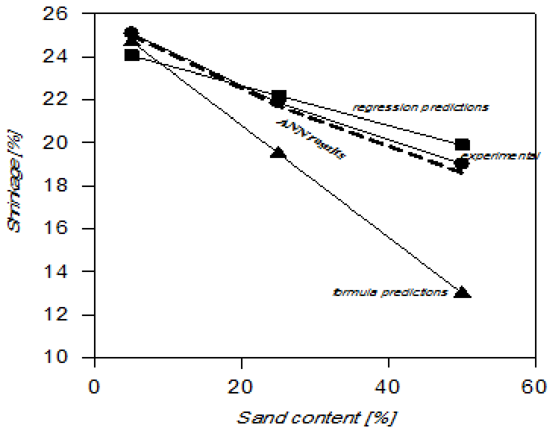

Figure 7: A comparison between the model in formula 5, the model in formula 6, and the experimental results when the sand content is variable (S = 5, 25, 50 %) and Z = 60 microns, P = 5 kN, C = 12 ^{o}C/min.

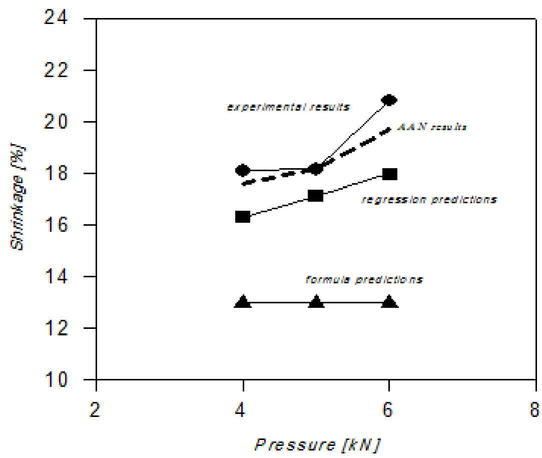

Figure 8: A comparison between the model in formula 5, the model in formula 6, and the experimental results when the pressure is variable (P = 4, 5, 6 kN) and Z = 75 microns, S = 50%, C = 12 ^{o}C/min.

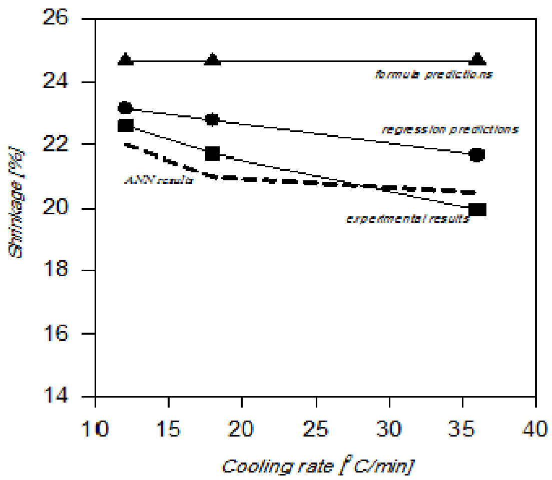

Figure 9: A comparison between the model in formula 5, the model in formula 6, and the experimental results when the cooling rate is variable (C = 12, 18, 36 C/min) and Z = 75 microns, P = 6 kN, S = 5%.

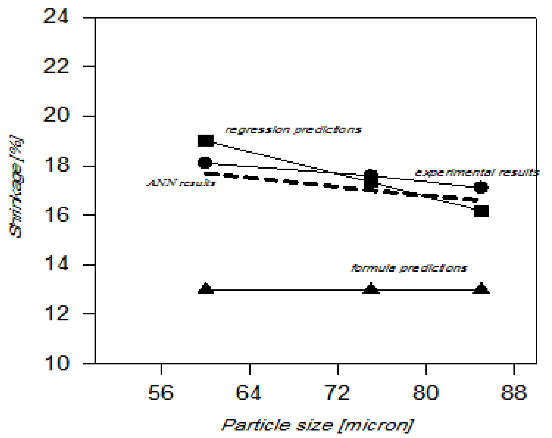

Figure 10: A comparison between the model in formula 5, the model in formula 6, and the experimental results when the particle size is variable (Z = 60, 75, 85 micron) and C = 12 C/min, P = 4 kN, S = 50%.

It is clear from these figures that the predictions using the two-stage ANN approach is better than using the multiple regression approach and better than using the analytical model developed (formula 5). This is because the model in formula 5 lacks the consideration of the conditions other than the reinforcement content.

5. Conclusions

As a result of this investigation, the following can be concluded :

- The higher the reinforcement content and the particle size, the less the shrinkage.
- The higher the pressure and the less the cooling rate, the higher the shrinkage.
- The two-stage ANN approach is better than using the multiple regression approach and better than using the analytical model.

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