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MECHANICAL PROPERTIES FORECAST IN COMPOSITES USING NEURAL NETWORKS

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Abstract: The aim of this paper is to introduce a method to forecast the mechanical properties of a composite based on its constitutive materials using a neural network. As input data, a limited number of tests to train the network are needed. From them it will be possible to make forecasts, with a less than 1% of error, the material properties. The forecasts can be done, not only inside the training range but also outside but with an unbounded error rate.

1. INTRODUCTION.

The use of technical plastics has been extensive for the last years in almost all industrial sectors. The main drawback lies in the materials price. The continual increase in price of commodities and the increase of competition pull the companies to reduce its costs dramatically to assure its competitiveness. A new stage is starting, where composites will be specifically designed for each use with the minimum cost.

Development of traditional optimization methodologies can be extremely expensive. Artificial intelligence settles a new paradigm which allows to drastically reduce new materials design costs.

Artificial Neural networks (ANN from now) allow predicting mechanical properties of the material from its composition using a reduced number of tests. These models not only have higher correlation ratios than any other, but also have the capacity to learn. This property is very important because is the responsible of the automatic error model reduction.

Later a multiobjective optimization can be done where strength, toughness and Young modulus can be simultaneously dealt. Multiobjective Genetic Algorithms like MOGA and NSGA-II can do it efficiently.

2. EXPERIMENTAL

To carry out this work first several panels of composite with different composition rates were done. Then several specimens were taken and tested. Once each composition was characterized, then a neural network was developed.

Bellow, the different parts of the experiment are described.

2.1. MATERIALS

This work used a vinyl plastisol biomaterial (PVC/DINCH) with a cellulosic filler, using as biodegradable components the plasticizer: dicarboxylate and the cellulosic filler: almond husk, or sawdust or rice husk. The chosen plasticizer for the PVC paste was a dicarboxylate named Hexamoll®DINCH. It is the nontoxic and biodegradable plasticizer H-675.

The mechanical properties tested were: Tensile ultimate stress, Modulus of Elasticity (E), strain at break, A-Shore and B-shore. The tests results can be read at [1].

The constituent rates were: 40, 50, 60 ó 80 Phr for plasticizer, 2 Phr for the stabilizer; 20, 30, 40, 50 ó 60 % of total mass for the filler. The particle granulometry of the filler was 150, 500 and 1000 µm.

The use of cellulosic fillers is justified not only for its neutrality with the environment but also for being industrial or agricultural by-products.

The material costs in Spain during the third semester of 2010 were: 90 €/t for almond husk, 94.4 €/t for rice husk, 334.33 €/t for sawdust, 2.50 €/kg and for DINCH plasticizer, 1.60 €/kg PVC resin Lacovyl PB 1172 H and 3.80 €/kg for H-675 stabilizer.

Between the range of possibilities for plasticized PVC are highly remarked the wooden like finish, which allow to substitute it. This substitution is not only beneficial for the environment but also helps to lower the costs because of its easier manufacturing, lower mass and design versatility.

Figure 1. Rice husk particles with granulometry 500 and 1000 µm seen with x10 and x80 magnification lenses.

2.2. METHOD

The ANN was modeled using commercial software: EasyNN-Plus. The models used for the soft to represent the ANN are:

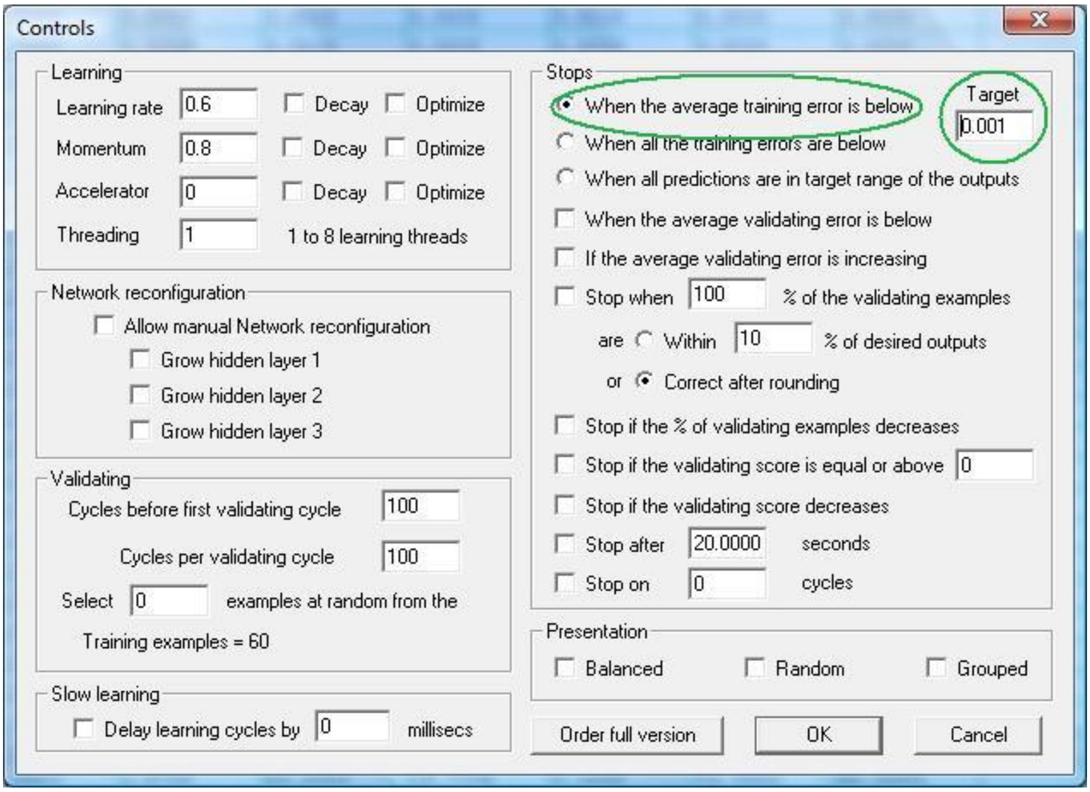
- Neuron: sigmoid or Fermi transfer function[2]. Also known as logistic function.
- Network: forwardfeed. Multilayer perceptron[3, 4].
- Training model: backpropagation [5]. The training rate and momentum rate and the number neurons and of hidden layers can be done manually or automatically.

These are the most common models in investigation and industrial studies (almost in 90% of times).

The input variables used to develop the network were: granulometry, filler percentage and plasticizer. The output variables were: strength, Young modulus, section reduction, break energy and shore A and D hardness.

Setting parameters for the ANN can be seen at figure 2.

Figure 2. Network parameters.



The model generated was made by five layers: one input, one output and three hidden layers. The number of neurons in the hidden layers was 22, 23 and 22 read from the input respectively. The total number of synapsis was 1210.

Then an individual ANN was developed per each material, obtaining similar models but suitable for each material.

3. RESULTS AND DISCUSSION.

Once the ANN was done the following results were analyses: error, relative importance of the input variables and sensibility.

3.1. MEAN ERROR OF NETWORK TRAINING

After training the ANN the mean error of the network training was about 0,0099%. This parameter is set in the soft configuration and is determined by the training. Achieving the set value is almost always possible except when the maximum gradient method fails.

The error was evaluated individually for each test point to find any anomalous point. None was found.

3.2. RELATIVE IMPORTANCE OF THE INPUT VARIABLES

In all generated ANN the three input variables: granulometry, percentage of filler and plasticizer had a significant importance, so all of them are important to describe the model.

3.3. SENSITIVITY ANALYSIS

It measures the importance of the input variables over the output ones. The sensitivity analysis is based in measuring the observed effect in any output y_k or in the error ought to the change of any input x_i. So, the more affected is the output, the more sensitivity it has with regard to the input.

There are several methods to make this analysis: error based, Jacobian matrix based, numerical sensitivity method, etc.…

The method used in this paper is one of the most extended ought to its simplicity. First the variable to analyze is fixed to its lower limit of its domain, and then the rest are put in its median. Then the studied variable is increased in small steps. Finally the change on the outputs is measured and divided by its initial (step 0) value obtaining the change percentage. All the values are added until the variable arrive to its upper limit. At this moment the overall sum gives the sensitivity value for the input.

Table1 summarizes the sensitivity analyses for all tests and inputs.

	R (MPa)	E (MPa)	A(%)	Break Energy (MJ/m^3)	Shore A	Shore D
Almond husk						
%Filler	0,0576	0,0067	0,0653	0,0928	0,0013	0,0224
Phr	0,0675	0,0766	0,0868	0,0062	0,0743	0,1195
Granulometry	0,0098	0,0015	0,0105	0,0004	0,0265	0,0117
Rice husk						
%Filler	0,0583	0,0099	0,1471	0,0791	0,0255	0,0182
Phr	0,0479	0,0904	0,0504	0,0023	0,1012	0,1091
Granulometry	0,0233	0,0071	0,0183	0,0135	0,0542	0,0204
Sawdust						
%Filler	0,0469	0,0061	0,0777	0,0484	0,0067	0,0055
Phr	0,0531	0,1164	0,0163	0,0025	0,0355	0,0488
Granulometry	0,0072	0,0027	0,0157	0,0073	0,0136	0,0108

Table 1. Sensitivity analysis

3.4. OPTIMIZATION

Once the ANN was defined, a maximization study of each separate variable was carried about.

A multivariable optimization was not considered at this work. If needed multivariable evolutionary algorithms would be needed such as: MOGA or NSGAII [6].

Table 2 summarizes the optimal material composition per each variable.

	R (MPa)	E (MPa)	A(%)	Break Energy (MJ/m3)	Shore A	Shore D
Almond husk						
	6.03	142.92	203.36	3.01	93.79	51.83
%Filler	20	42.4	20		46	52.4
Phr	40		70.4	42.8	44.4	44
Granulometry	889.5	379.5	362.5	507	889.5	1000
Price €/kg	1.598	1.175	1.684	1.607	1.118	0.995
Rice husk						
	6.1	94.6	181	3.82	86.26	44.61
%Filler	20	55.2	20		39.6	60
Phr	40		64.4	40		
Granulometry	150					413.5
Price €/kg	1.602	0.939	1.674	1.602	1.233	0.848
Sawdust						
	5.38	162.24	162.55	3.01	82.9	47.68
%Filler	20	41.2	20			42.8
Phr	40		61.6	60.4	42.1	43.4
Granulometry	150				481.5	150
Price €/kg	1.842	1.442	1.907	1.904	1.849	1.867

Table 2. Optimal compositions

4. CONCLUSIONS.

From previous results, it can be determined the influence of the input variables in the output ones, the same way as the composition to maximize each material property.

Following, for the materials and composition tested the following conclusions are shown:

1. Break strength depends on the filler percent in mass and the plasticizer in equal rate and in inversely proportional way.
2. The young modulus depends on the plasticizer in an inversely proportional way.
3. The break elongation depends on the three variables and the influence of each is determined by each material, so a general conclusion can not be done.
4. The break energy depends on the filler percent in mass and the plasticizer in equal rate and in inversely proportional way.
5. Hardness depends on the filler in straight way and the plasticizer in inversely proportional way, although when using sawdust is not so significant.
6. Maximum strength is obtained for minimum filler and plasticizer values, except when using almond husk which needs a thicker granulometry. Sawdust composites strength is 20% lower.
7. To achieve good mechanical properties using almond husk filler, more than twice thicker granulometries must be used.

8. Maximum mechanical properties will be obtained for minimum granulometry except for hardness and almond husk filler.
9. Maximum Young modulus is obtained for the minimum plasticizer, with filler percentage next to the maximum and a very fine granulometry. Except when using almond husk filler whose trend is described in the previous point. The Young modulus is significantly lower when using rice husk.
10. Maximum break elongation is obtained with next to maximum plasticizer ratios.
11. When using sawdust filler, the material costs are higher than the other materials in any case. Its mechanical characteristics are not better than the others so it is not recommended for composites manufacturing.
12. Composites with rice husk filler give the maximum break energy and strength values with minimum filler and plasticizer ratios. So it is the best option when a high toughness and strength at lower cost is needed.

5. References

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