COST REDUCTION OF BIODEGRADABLE COMPOSITES USING ARTIFICIAL INTELLIGENCE

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Abstract

The main cost in composites is due to the resin and plasticizer, so fillers are added to reduce cost. In the other hand they have to fulfill some mechanical requirements like strength and rigidity. This work faced this problem using a Neural Network to get the optimum composition that leads to a minimum cost fulfilling all requirements. Finally an example implementation is shown, where a plastic component weight is yet more reduced by using a Multiobjective Genetic Algorithm. As result of the method a weight reduction of 50,2% is achieved.

Keywords: *artificial, intelligence, neural, network, genetic*

1. Introduction

Composites have been extensively used during last years. Continuous increases in price of raw materials push to optimize the material costs.

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.

Later a multiobjective optimization was done where cost was optimized fulfilling strength and rigidity requirements. Multiobjective Genetic Algorithms like MOGA and NSGA-II [1] can do it efficiently.

2. Materials and Methods

This work used a vinyl plastisol biomaterial (PVC/DINCH) with 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 [2].
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 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.

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 [3]. Also known as logistic function.
- Network: forwardfeed. Multilayer perceptron [4, 5].
- Training model: backpropagation [6]. 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.

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.

As implementation example an angle bracket was analyzed. The initial design whose mass was 10,342 g. Figure 1 shows the initial design.

The FEM model was composed of the bracket angle, three flat washers and three screws. Washers and screw are made of steel. Due to the difference of elastic modulus between POM and steel, it last can be considered ideally rigid. So the part made of steel where modeled like a rigid solid and the bracket like an elastic POM. Once the model was built, a 100N load shown in the manufacturer catalogue, was applied in the single screw and while the other two were fixed in the thread. An only compression support was also applied on the basis, so the inner surface will only suffer compression stresses.

3. Results and Discussion

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

After training the ANN the mean error of the network training was about 0,0099%. 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. Then, a maximization study of each separate variable was carried about. Table 1 summarizes the optimal material composition per each variable.

Table 1. Optimal compositions.

	R (MPa)	E (MPa)	Break Energy (MJ/m^3)
Almond husk	6,03	142,92	3,1
%Filler	20	42,4	20
Phr	40	40	42,8
Granulometry	889,5	379,5	507
Price €/kg	1,598	1,175	1,607
Rice husk	6,1	94,6	3,82
%Filler	20	55,2	20
Phr	40	40	40
Granulometry	150	150	150
Price €/kg	1,602	0,939	1,602
Sawdust	5,38	162,24	3,01
%Filler	20	41,2	20
Phr	40	40	60,4
Granulometry	150	150	150
Price €/kg	1,842	1,442	1,904

As can be seen in Table 1, composites with rice husk filler give the best mechanical properties with lower cost. So this filler and composition was chosen for the studied example. Then the example multi-optimization was carried out.

The input variables for the example were individual thickness of each plane and the output where the stress and total displacement. The range per each input variable was defined and a set of points (15 in total), center distributed inside each variable domain, were generated. Then all these points where calculated generating a response surface.

Once the surface points were calculated, the optimization problem was defined as: minimize the angle mass, while de stress is lower than 55 MPa (next to yield point) and total deformation is lower than 0,5 mm.

From the calculated points, the minimization parameter and the constraints, a multiobjective genetic algorithm based on the NSGA-II algorithm estimated three candidates. Table 2 summarizes the results.

Table 2. Algorithm results.

	Total deformation (mm)	Mass (g)	Max. von mises. stress (MPa)
A	0,5	5,2	3,4
B	0,54	5,1	3,7
C	0,49	5,2	3,4

From the three candidates, the Candidate A was chosen as final design because it has more uniform thickness than C. Candidate B violated total deformation constraint. This design is 50,2% lighter than the initial one without compromising its usefulness.

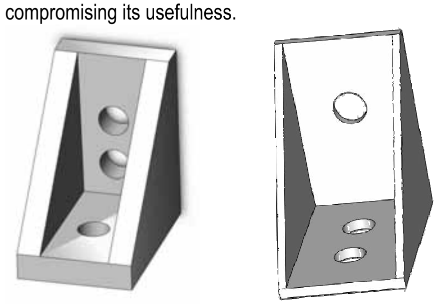

Fig. 1. Initial and final design.

4. Conclusions

It can be concluded that with the described techniques a significant cost reduction can be achieved without compromise its strength.

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