OPTIMIZATION OF HYBRID THERMOPLASTIC COMPOSITE PRODUCTION VIA ARTIFICIAL INTELLIGENCE APPROACH

Ercüment ÖZTÜRK, Ayfer DÖNMEZ ÇAVDAR, Tuğrul ÇAVDAR
Karadeniz Technical University, Trabzon, Turkey
Fatih MENGELOĞLU
Kahramanmaraş Sütçüimam University, Kahramanmaraş, Turkey

Abstract

Nowadays, "hybrid composites" containing multi-component additive / reinforcer instead of single matrix and single reinforcing element attract more attention in new product designs. For the hybrid composite materials to be widely used in a critical load bearing application, they must undergo extensive fatigue tests. However, this situation increases the cost as it requires extensive test programs and a long process. This study is aimed to produce the desired quality the hybrid material without a large number of productions. Particle swarm optimization (PSO), an artificial intelligence technique based on heuristic algorithm, is used to determine the best formulation in a simulation environment for the hybrid composite. This study enables finding the rates of optimum usage for hybrid composite production containing two or more additives / reinforcing materials before production and lays the groundwork for research to be carried out in the correct working ranges. As a result, it is obtained to both reduce the cost and speed up the production process with a success over than 90% by making pre-simulations using artificial intelligent optimization algorithms.

Background and Requirements

Artificial intelligence has become a widely used phenomenon in composite production. However, any study has not been found in the literature to determine the raw material additive ratios in composite production. Accordingly, a study has been conducted to determine the raw material additive ratios in hybrid thermoplastic composite production. In this study, Particle Swarm Optimization (PSO) algorithm, which is one of the Artificial Intelligence (AI) optimization algorithms, has used. With the raw material additive ratios obtained from the simulations results, new hybrid thermoplastic composites have been produced and tested. According to the test results, it has been observed that the new composites are 95.3% more successful than the previous ones (first composites which produced as control group). By this means, reducing the experimental processes, the costs, and increasing the quality in hybrid thermoplastic composite production has been ensured, and the usability of the method has been proven for the next studies.

Introduction

Composite is a mixture product consisting of at least two components (one main material (matrix) and one or more reinforcement materials). However, they have different physical, chemical and thermal properties and are insoluble in each other, to improve some properties that are not or limited in traditional materials. Consequently, the product obtained has different properties from the previous components. Besides, there is no chemical/atomic bond between the raw materials of the composite [1].

Composite production started in Mesopotamia in BC and has survived to the present. During this period, composite materials were produced and used in many different varieties in line with different purposes and needs. However, composite materials have been used in a wide range. Especially in the defense, construction, engineering, and manufacturing areas [2].

Today, composites are considered to be the only material group used in the industry that provides almost all the desired properties. Since composites are a material that has become widespread with the developing technology, R&D studies are carried out in many countries. Briefly, the most important feature that makes composites valuable is that they have a higher strength/density ratio, being more durable and lighter than other materials. Hardly, it is essential to apply a high-tech process for the composite materials to guarantee a higher quality structure and to keep the production costs at an acceptable level. Before a composite material can be used in an application, it must undergo extensive fatigue testing. However, this increases the cost as it requires extensive testing programs and a long time. Therefore, Lee et al. developed a new method using Artificial Neural Networks (ANN) architecture to predict the lifetime of high carbon, plastic and glass reinforced laminate [3].

The use of AI in composite production is becoming widespread with an increasing acceleration. Although ANN is generally used, different methods such as AI Optimization Algorithms, Machine Learning, Deep Learning, and Image Processing have also been used in recent years. Muc and Gurba, who used genetic algorithms to optimize the produced composites in terms of shape, addressed the problem of appropriate coding and correct metric selection procedures. They also discussed the components for applying Genetic Algorithm procedures with finite element analysis for layout optimization of composite structures [4].

ANN, a very common method, has been used in many research studies on composite design. Zhang et al estimated the tribological properties of short fiber composites using ANN. They estimated the wear rate and coefficient of friction for short fiber reinforced polyamide composites using multilayer feed-forward ANN. The results show that the estimated data is acceptable when compared to the actual test values [5]. Besides, in their survey study, Zhang and Friedrich discussed the estimation processes that can be performed on composite materials using ANN. They emphasized that more training data is needed for the predictive values to be acceptable in order to predict the optimum composite design and certain properties (such as fatigue life and abrasion performance). They also emphasized that obtaining general properties may be useful to reduce the number of experiments [6]. Nevertheless, Al Kadi's study can be cited as proof of the usability of AI. In his study, El Kadi showed that fiber reinforced composite materials can be used in mechanical modeling using ANN. The study showed that the use of ANN provides more accurate, if not better, predictions than those obtained by traditional methods [7]. In another study, Vassilopoulos et. al. used ANN to model the fatigue life of composite laminates. It was emphasized that only a small part of the experimental data (in the range of 40-50%) is required for all analysis procedures with this method. Therefore, they showed that the expensive and time-consuming tests required by the traditional way to construct S–N curves can be significantly reduced [8]. Hassan et al. investigated the potential of using ANNs to predict some physical properties and hardness of aluminum-copper/silicon carbide composites. It is aimed to estimate density, porosity, and hardness values, to reduce test time and cost via ANN. As a result, it has been shown that the addition of copper to the composite material has a greater effect than the addition of silicon carbide particles [9]. In addition, ANN was used to predict fatigue properties of composite materials by Al-Assadi et al [10]. However, Shabani and Mazahery stated that ANN has the capacity to eliminate the need for expensive experimental research in various manufacturing processes. They also emphasized that it is important to understand the relationships between input variables in order to interpret the data and optimize the design parameters [11].

In addition to ANN, there are also studies using machine learning and genetic algorithms. One of these studies was done by Gomes et al. In their study, Gomes et al. emphasized that anisotropic laminated composite structures are very sensitive to parameter changes, and they stated that the optimization of such structures is an important problem that needs to be addressed. In their study, they discussed the structural optimization problem of laminated composite materials by using Genetic Algorithm (GA) and neural network. They also mentioned that a parallel algorithm can be applied to solve large and real problems, as well as improvements in the GA and the training process [12].

Machine learning (ML) is seen as a promising tool for the design and discovery of new materials for a wide range of applications. In this sense, Chen and Gu summarized recent advances in composite material modeling and design applications using ML. They provided an overview of how different machine learning algorithms can be applied for the composite fabrication process. They predicted that AI will revolutionize approaches to design and optimize for next-generation materials with much higher quality and properties [13]. Besides, Vinoth and Shubhabrata used ANN and GA to design novel ultra-high molecular weight polyethylene composites with multiple reinforcements for improvement in mechanical and tribological performance [14]. In the meantime, Gu et al., in their study, proposed a new model for material design based on ML. The results show that the proposed model can accurately predict the mechanical properties of the systems. They have also shown that the model can generate new microstructural models that lead to harder and stronger materials [15].

In addition to these studies, Yang et al. used 3-D Convolutional Neural Network (CNN) to model the elastic homogenization connections of the three-dimensional-high-density composite material system. The study showed that 3-D CNN outperforms traditional approaches by up to 54%. Therefore, the deep learning approach has proven to be a good option for constructing a model with high accuracy, low computational cost, and higher learning capacity [16]. However, Gu et al used ML to predict the mechanical properties of 2-D composites and to identify high performers in terms of strength. The study also shows the effects of different parameters in the training process. Low training data showed that highly accurate predictions can be obtained even with a small number of training cycles. It was concluded that ML is a more promising tool when run with more combinations [17].

Although AI has been used in the aforementioned studies, the use of AI in the field of composite materials is still not sufficient to satisfy the requirements of industry and market. To the authors' knowledge, this is the first study to use artificial intelligence techniques for optimizing the additive ratios of hybrid composites.

Methodology and Simulation Results

Particle Swarm Optimization (PSO) is a population-based heuristic optimization algorithm created by Dr. Eberhert and Dr. Kennedy in 1995, inspired by the social behavior of bird and fish flocks [18]. Interpretively, PSO, which is a widely used method in information technologies and other disciplines today, is a technique for finding the optimum of many experimental results.

The PSO simulation is started with a large number of random solutions (particles) and the optimum result value is searched by updating the generations (possible results) in each iteration (process step). At each iteration, a solution (particle) is updated according to the optimum value. First, a particle called the 'best value' is selected in the system, and if there is a better value at the end of each iteration, it is updated as the new best value, but if not, it continues with the particle selected as the best value in the previous iteration. While continuing the operations by keeping the best value in the memory, the value to be obtained when the whole system is scanned is selected as the global best value. In this process, the best value among the particles is called 'pbest' (particle best value), and the best value globally is called 'gbest' (global best value) [19], [20].

There are also certain parameters in PSO. These are respectively; Particle number, particle size, velocity (the amount of change that can occur in a particle in each iteration), learning factors (***C1*** (according to the particle's own experience) and ***C2*** (according to the swarm experience)) and the stopping condition. Stop condition; When the maximum iteration (processing step) is reached or the fitness function reaches the desired value, the simulation is stopped [19].

In the matrix below, each row, called a particle, represents a solution. For ***n*** particles, ***n*** solutions are obtained. Particles move in research space according to two important parameters. In each iteration, first each individual's own best "***pbest***" and the best of all individuals "***gbest***" are obtained. In a PSO working with ***n*** particles, there are ***n*** "***pbest***" in each iteration, while there is only one "***gbest***". The initial value for each particle is also the "***pbest***" value when the simulation is started. In subsequent iterations, its position is updated according to the state of other particles and the current position is compared with the previous "***pbest***". If this value is a better solution than ***pbest***, it is assigned the new "***pbest***". If not, the current "***pbest***" remains [21], [22].

$$\begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1t} \\ X_{21} & X_{22} & \cdots & X_{2t} \\ \cdots & \cdots & \cdots & \cdots \\ X_{n1} & X_{n2} & \cdots & X_{nt} \end{bmatrix}_{nXt} \tag{1}$$

The fitness function for the ***i***th particle;

$$F_{fitness} = F(X_{i1}, X_{i2}, X_{i3} \dots, X_{it}) \tag{2}$$

$$F(X_{ij}) = \frac{(X_{ij} - \bar{X})^2}{n-1} \tag{3}$$

PSO simulation starts with an initial solution. Initially, each particle has a velocity and position value. Particle positions are variable values within the defined range that can be seen in 3rd formula. Particles move by adjusting their velocity according to both themselves and the swarm. The particles get closer to the optimum solution with each iteration. The velocity and position formulas of the ***n***th particle are as given in equations **(4)** and **(5)** [23]**,** [24]**.**

$$V_i^{t+1} = V_i^t + \text{C1*Unifrnd()*}(P_{best\ i}^t - X_i^t) + \text{C2*unifrnd()*}(g_{best} - X_i^t) \tag{4}$$

In this equation, ***t*** is the number of iterations. V_i^t is the velocity of ***i****th* particle in ***t****th* iteration. V_i^{t+1} is the velocity for the next iteration. ***C1*** and ***C2*** are interdependent coefficients which are social and cognitive parameters. ***Unifrnd()*** is a uniformly random distributed number between 0 and 1. After calculating the velocity, the position is calculated with the following formula [23].

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad \textbf{(5)}$$

In the simulation study, all hybrid thermoplastic composite products obtained by mixing the raw materials to be used in certain proportions were considered as particles. The system was operated by giving close values to the C1 and C2 coefficients of each particle in the population (the set of all possible composite samples). The reason why the coefficients C1 and C2 are given close to each other is to enable the particle to make a decision by advantage of the equality between its learning state and the behavioral state of the swarm.

In summary, a simulation environment is coded using the PSO algorithm. This coded system was run as described in detail above. Each composite material that is likely to be produced is considered as a particle. The best one among these particles was tried to be found and this situation continued until a desired error rate or maximum number of iterations (processing step) was reached. Reproductions were made with the production recipes (raw material additive ratios) obtained as a result of the simulations and were subjected to tensile tests. The test results were compared with previous productions and hybrid thermoplastic composites were obtained with a success rate over 95%.

The pseudo code of the PSO algorithm used in the simulation is as follows

```
For (each particle in the swarm)
          Initialize its velocity and position randomly
End;
Do
          For (each particle in the swarm)
         Evaluate Ffitness;
         If(Ffitness is better than pbest)
                  Current Ffitness is the new pbest;
         End;
         From the all the particles, choose the best pbest as gbest;
         For(each particle in the swarm)
                  Update the particle velocity according to equal (4);
                  Update the particle position according to equal (5);
         End;
While (until stopping criteria is satisfied or reached maximum number of
iteration);
```

Table I: The production recipes used in the simulations

Production Recipes Used in Simulation							
		X1*	X2	X3	X4	X5	X6
1st Recipe	X1	100	0	0	0	0	0
2nd Recipe	X2	96	4	0	0	0	0
3rd Recipe	X3	85	0	15	0	0	0
4th Recipe	X4	80	0	0	20	0	0
5th Recipe	X5	80	0	0	0	20	0
6th Recipe	X6	90	0	0	0	0	10

**X1 refers polymer matrix; X2…X6 refer compatibilizer and fillers*

In simulation studies, it has been observed that using X5 component instead of X4 component gives better results. Therefore, the X4 component was not used in subsequent productions.

Table II: Production recipes obtained from the simulation results

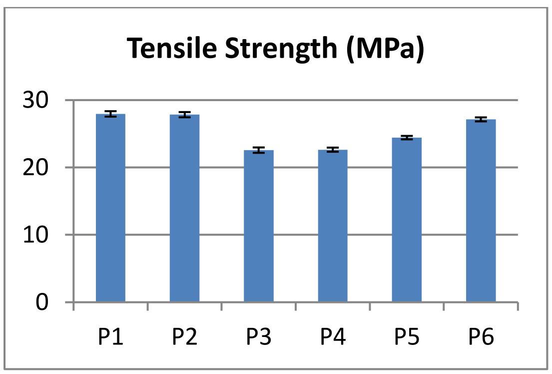
Recipes Obtained from Simulation Results						
	X1	**X2**	**X3**	**X5**	**X6**	**Total**
1st Optimum Recipe	68%	2%	7,129655%	17,13055%	5,73979%	100%
2nd Optimum Recipe	68%	2%	6,989815%	17,11157%	5,898611%	100%

The improved production recipes obtained as a result of the simulation are given in Table II. These recipes were obtained in line with the real data used in the simulation. New productions were made using these recipes. Then, tensile tests were applied on products. The results of these tests are given in Table III.

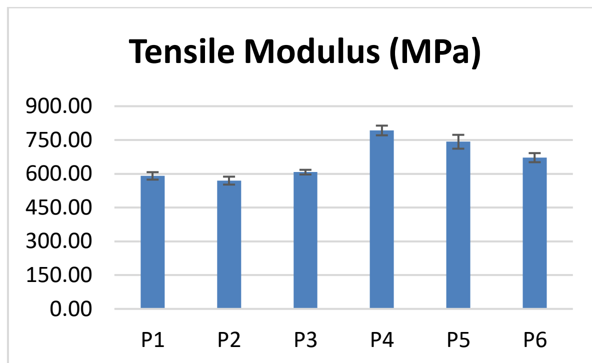
Table III: Tensile test results of the hybrid composite produced with 1 st Optimum Recipe (OR)

	Tensile Test Results		
Sample_ID	**Tensile Strength (MPa)**	**Tensile Modulus (MPa)**	**Elongation at Break (%)**
OR1	23,82	741,53	11,93
OR2	24,17	767,69	7,36

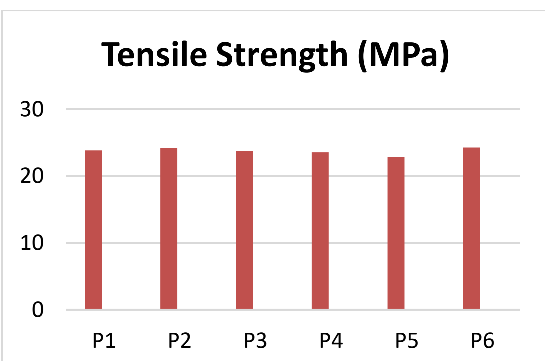
OR3	23,75	755,04	6,6
OR4	23,54	749,21	7,49
OR5	22,84	757,65	6,5
OR6	24,26	750,95	7,15
OR7	22,49	726,73	6,58
OR8	22,71	755,78	5,93
OR9	23,8	678,22	7,43
OR10	24,45	527,09	9,28



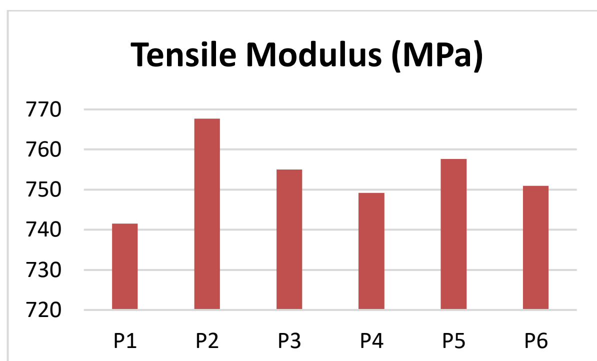
(a)



(b)



(c)



(d)

(a) and **(b)** show the test results on the first experimental productions, and **(c)** and **(d)** show the test results of the productions made with the ratios obtained as a result of the simulations. As seen in the graphs, the test results obtained are better. In addition, it should be known that the ratio of X1 (Polypropylene) in the first produced products is between 80% and 100%.

Conclusion & Future Works

The fact that raw material supply and natural resources have come to the point of consumption is an important problem throughout the world. Composite production, which is an alternative method to the solution of this problem, has become an important research and application area. However, the experimental work stages of composite production have caused enormous costs. To solve this problem, it was thought a heuristic artificial intelligence algorithm. Therefore, it is aimed to obtain optimum production recipes via PSO. With the study, it was ensured that a high-quality composite product with optimum raw material additive ratios was produced, and experimental production costs were minimized.

In all experiments and simulation studies, real values (actual production and test results) were used. In other words, virtual or predictive values were not used. This demonstrates the accuracy and usability of the proposed method. In the light of the results, the first production made with the developed recipe for high tensile properties of the samples showed that the PSO technique could be successfully used for determination of optimum additive ratios in new hybrid composite.

In the future, a hybrid method is planned to be developed via AI algorithms. With this method, more different composites will be produced. In addition, it will be tried to determine the raw material additive ratios with higher accuracy.

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