Journal of Artificial Intelligence and Data Science (JAIDA) **Vol. 1, No. 1, pp. 80-88, 2021**
Research Article

https://jaida.ikcu.edu.tr/

Modeling and Design Optimization to Determine the Mechanical Properties of a Recent Composite

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Abstract

This study proposes an appropriate optimization model for determining a new composite material's mechanical properties by neuro-regression analysis. This new composite material is obtained by combining hemp and polypropylene fibers. It was developed for the sector of upholstered furniture. First, different multiple regression models have been tried for input and output values. The $R^2_{training}$, $R^2_{testing}$, $R^2_{validation}$, and minimum, maximum values were determined for each model. Then, the stochastic optimization approach is used to predict and optimize the mechanical properties of the new biocomposite system. Finally, multiple non-linear models determine the maximum tensile strength and elongation achievable within the constraints. It is found what the optimum input parameters are needed to achieve maximum tensile strength and elongation at break values of the material and that the type of scenario and the choice of constraints for design variables are critical in the optimization problem.

Keywords: Composite material; mechanical properties; neuro-regression analysis; optimization

1. Introductıon

A composite material is made up of two materials that have distinct physical and chemical properties. When they are combined, they form a specialized material to perform a specific function, such as becoming stronger, lighter, or more resistant to electricity. One constituent is called the reinforcing phase, and the one in which it is embedded is called the matrix [1]. The matrix is reinforced with an engineered, man-made, or natural fiber, particle, or flake form reinforcing material. The matrix covers the fibers from environmental and exterior damage and transmits the load between the fibers. In turn, the fibers yield strength and stiffness to the matrix, preventing cracks and fractures.

Ciupan et al. [2] has studied the use of artificial neural networks (ANN) to predict certain mechanical properties of new composite material. The material is intended to be used to construct structural elements of upholstered furniture (chairs, armchairs, sofas) in place of wood. Ciupan and his group presented that optimizing these element's shapes using numerical simulation necessitates knowledge of the material's mechanical properties. These properties consist of tensile strength, elongation at break, Young's modulus, and Poisson's ratio. They conducted tests on the material samples and aimed to investigate how far ANN can predict the tensile strength and elongation at the break of the previously discussed composite material. Eventually, they concluded these results: In the case of elongation at break, the degree of fit between experimentally predicted output variables and those simulated using the ANN is greater than in the case of tensile strength. Throughout the recall phase, the outputs in group 2 represent the average values of the outputs used for training. For example, the simulated output (σ_M, ε_M) = (25.03, 3.13) that correlates to the input (1,0) is equivalent to the average of the outputs in the training set that correlates to the same input (1,0) and which were experimentally measured.

A study about the standard test methods for polymer matrix composite materials [3] defines the in-plane tensile properties of polymer matrix composite materials reinforced with high-modulus fibers. A mechanical testing machine grips a thin flat strip of material with a constant rectangular cross-section and monotonically loads it in tension while recording load. This test method is intended to generate tensile property data for material specifications, R&D, quality assurance, and structural design and analysis. This study used an interlaboratory testing program in which nine different laboratories tested an average of five specimens from six different materials and lay-up configurations. This study produced precision statistics for tensile strength, modulus, and failure strain. The data was all normalized concerning an average thickness. The study states that the values of Sr/X and SR/X exemplify the repeatability and the reproducibility coefficients of variation, respectively. These averages allow for a relative comparison of the tension test parameters' repeatability (within laboratory precision) and reproducibility (between laboratory precision).

Traditional modeling methods, such as response surface methodology, do not have the same advantages as neuro-regression analysis. Based on only the data, neuro-regression analysis can be used to model the behavior of complex systems [4]. On the other hand, RSM is based on model structure assumptions and requires coefficient estimation [5-9]. To maximize or minimize objective functions, stochastic optimization methods are used. Stochastic optimization is crucial in the analysis, design, and performance of modern systems [10].

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Received: 24/07/2021; Accepted: 25/08/2021

The main goal is to use Neuro-Regression steps to create optimization models for determining the mechanical properties of new composite material. In practical experiments, it is critical to estimate accurate values expressed in tensile strength and elongation. The stochastic optimization approach is used to predict and optimize the mechanical properties of a material. Multiple non-linear models are used to determine the maximum tensile strength and elongation achievable within the constraints.

2. Materials and Method

2.1. Modeling

In the modeling phase, a hybrid method is used to assess the accuracy of the predictions, which integrates the benefits of regression analysis and artificial neural networks. In this method, all of the data is divided into three sets, each containing 80%, 15%, and 5% of the total data, with the first portion used for training, the second for testing, and the third for validation. The objective of the training procedure is to minimize the error between the experimental and predicted values by adjusting the regression models and their coefficients, as shown in Table 1. The prediction results are then obtained by minimizing the effects of regression model discrepancies during the testing step. First, this procedure yields information about the prediction capacity of the candidate models. Second, the boundedness of the candidate models for prescribed values must be checked to determine whether or not the model is realistic. In this case, the maximum and minimum values of the models in the given interval for each design variable are calculated after obtaining the appropriate models in terms of $R^2_{training,}$ $R^2_{testing,}$ $R^2_{validation}$. This procedure determines whether the chosen models meet the numerous criteria required for reality [11].

The logarithm cannot be used in the modeling of this study because some of the inputs take the value of 0. Also, it is not easy to understand some variables because they have a non-linear relationship. So, the hybrid models shown in Table 2 are tried to obtain better R^2 values.

2.2. Optimization

A structure's optimization can be defined as achieving the best designs by reducing the specified single or multi-objective that corresponds to all constraints. There are two kinds of optimization techniques: traditional and nontraditional. Traditional optimization techniques, such as constrained variation and Lagrange multipliers, only apply to continuous and differentiable functions. Traditional optimization techniques cannot be used to solve engineering design problems due to their specificity. Stochastic optimization methods such as genetic algorithms (GA), particle swarm optimization (PS), and simulated annealing (SA) are advantageous in these cases. Because of the features of stochastic methods, correct solutions cannot be achieved, and using multiple methods with different phenomenological principles for the same optimization problem increases the solution's reliability [8].

This study's optimization scenarios include the following challenges: multiple non-linear objective functions, objective functions having many local extremum points, mixed-integer(discrete)- continuous nature of the design variables, non-linear constraints. To solve these optimization scenarios, Nelder-Mead Algorithm, Differential Evolution Algorithm, Simulated Annealing Algorithm, and Random Search Algorithm have been selected. For more information, please see the reference articles given in the subsections.

Table 1. *Multiple regression model types* [11]

Model Name	Nomenclature	Formula
Multiple linear	L	$a[1] + x_1 a[2] + x_2\, a[3]$
Multiple linear rational	LR	$(a[1] + x_1\, a[2] + x_2\, a[3]\ )/\ (b[1] + x_1 b[2] + x_2\, b[3]\ )$
Second order multiple nonlinear	SON	$a[1] + x_1\, a[2] + x_1^2\, a[3]+ x_2\, a[4]\ + x_1\, x_2\, a[5]+ x_2^2\, a[6]$
Second order multiple non-linear rational	SONR	$(a[1] + x_1 a[2] + x_1^2 a[3] + x_2 a[4] + x_1 x_2 a[5] + x_2^2 a[6])\ /\ b[1] + x_1 b[2] + x_1^2 b[3] + x_2 b[4] + x_1 x_2 b[5] + x_2^2 b[6])$
Third order multiple non-linear	TON	$a[1] + x_1\, a[2] + x_1^2 a[3]\ + x_1^3 a[4]+ x_2 a[5] + x_1\, x_2 a[6]+ x_1^2\, x_2 a[7] + x_2^2\, a[8] + x_1\, x_2^2\, a[9] + x_2^3\, a[10]$
First order trigonometric multiple non-linear	FOTN	$a[1] + a[2]\ Cos[x_1] + a[3]\ Cos[x_2] + a[4]\ Cos[x_3] + a[5]\ Sin[x_1] + a[6]\ Sin[x_2] + a[7]\ Sin[x_3]$

First order trigonometric multiple non-linear rational	FOTNR	$(a[1] + a[2] Cos[x_1] + a[3] Cos[x_2] + a[4] Sin[x_1] + a[5] Sin[x_2]) / (b[1] + b[2] Cos[x_1] + b[3] Cos[x_2] + b[4] Sin[x_1] + b[5] Sin[x_2])$
Second order trigonometric multiple non-linear	SOTN	$a[1] + a[2] Cos[x_1] + a[3] Cos[x_1]^2 + a[4] Cos[x_2] + a[5] Cos[x_1] Cos[x_2] + a[6] Cos[x_2]^2 + a[7] Cos[x_3] + a[8] Sin[x_1] + a[9] Cos[x_1] Sin[x_1] + a[10] Cos[x_2] Sin[x_1] + a[11] Sin[x_1]^2 + a[12] Sin[x_2] + a[13] Cos[x_1] Sin[x_2] + a[14] Cos[x_2] Sin[x_2] + a[15] Sin[x_1] Sin[x_2] + a[16] Sin[x_2]^2$
Second order trigonometric multiple non-linear rational	SOTNR	$(a[1] + a[2] Cos[x_1] + a[3] Cos[x_1]^2 + a[4] Cos[x_2] + a[5] Cos[x_1] Cos[x_2] + a[6] Cos[x_2]^2 + a[7] Sin[x_1] + a[8] Cos[x_1] Sin[x_1] + a[9] Cos[x_2] Sin[x_1] + a[10] Sin[x_1]^2 + a[11] Sin[x_2] + a[12] Cos[x_1] Sin[x_2] + a[13] Cos[x_2] Sin[x_2] + a[14] Sin[x_1] Sin[x_2] + a[15] Sin[x_2]^2) / (b[1] + b[2] Cos[x_1] + b[3] Cos[x_1]^2 + b[4] Cos[x_2] + b[5] Cos[x_1] Cos[x_2] + b[6] Cos[x_2]^2 + b[7] Sin[x_1] + b[8] Cos[x1] Sin[x_1] + b[9] Cos[x_2] Sin[x_1] + b[10] Sin[x_1]^2 + b[11] Sin[x_2] + b[12] Cos[x_1] Sin[x_2] + b[13] Cos[x_2] Sin[x_2] + b[14] Sin[x_1] Sin[x_2] + b[15] Sin[x_2]^2)$
First order logarithmic multiple nonlinear	FOLN	$a[1] + a[2] Log[x_1] + a[3] Log[x_2]$
First order logarithmic multiple non-linear rational	FOLNR	$(a[1] + a[2] Log[x_1] + a[3] Log[x_2]) / (b[1] + b[2] Log[x_1] + b[3] Log[x_2])$
Second order logarithmic multiple non-linear	SOLN	$a[1] + a[2] Log[x_1] + a[3] Log[x_1]^2 + a[4] Log[x_2] + a[5] Log[x_1] Log[x_2] + a[6] Log[x_2]^2$
Second order logarithmic multiple non-linear rational	SOLNR	$3(a[1] + a[2] Log[x_1] + a[3] Log[x_1]^2 + a[4] Log[x_2] + a[5] Log[x_1] Log[x_2] + a[6] Log[x_2]^2) / (b[1] + b[2] Log[x_1] + b[3] Log[x_1]^2 + b[4] Log[x_2] + b[5] Log[x_1] Log[x_2] + b[6] Log[x_2]^2)$

Table 2. *Hybrid models*

Model Name	**Nomenclature**	**Formula**
Hybrid	H1	$a[1] + 2 x_1 a[2] + [x_1]^2 a[3] + 2 x_2 a[4] + 2 x_1 x_2 a[5] + [x2]^2 a[6] + a[7] Cos[x_1] + a[8] Cos[x_1]^2 + a[9] Cos[x_2] + a[10] Cos[x_1] Cos[x_2] + a[11] Cos[x_2]^2$
Hybrid	H2	$a[1] + x_1 a[2] + x_1^5 a[3] + x_1^3 a[4] + 7x_2 a[5] + x_1 x_2 a[6] + x_1^4 x_2 a[7] + x_2^6 a[8] + 12 x_1 x_2^2 a[9] + x_2^5 a[10]$

2.2.1 Nelder-mead algorithm

The Nelder–Mead optimization algorithm is one of the most basic direct search methods. As a result, it is not necessary any derivative knowledge and begins with simplex to minimize the function. The iteration continues until the simplex becomes flat. This means that the function's resulting value is nearly identical at all vertices. The Nelder-Mead algorithm's iteration steps are ordering, centroid, and transformation [4].

2.2.2 Differential evolution algorithm

Differential evolution algorithm is one of the appropriate stochastic optimization methods. The differential evolution algorithm's productive parameters are population size, crossover, and scaling factor. Thus, it deals with a population of solutions rather than iterating over them. Although it does not satisfy the global optimum points for all optimization problems, the differential evolution algorithm is proposed in the literature to be robust and efficient [11].

2.2.3 Simulated annealing algorithm

The simulated annealing algorithm is another common search method that is based on the physical annealing of metal. During the melting process, the material shifts to a lower energy state and becomes tougher. Because of the algorithm's inherent structure, it is more effective at determining the global optimum. In addition, it can solve optimization problems that are continuous, mixed-integer, or discrete [12].

2.2.4 Random search algorithm

At this stage, the traditional random search algorithm employs a local optimization method from each starting point to approach a local extremum point. The proposed version of the algorithm includes some booster subroutines such as the conjugate gradient, principal axis, Levenberg Marquardt, Newton, QuasiNewton, and non-linear interior-point method in the localization of the values of all variables for the objective function. This step evaluates the fitness function with symbolic variables, and the procedure is repeated several times. [12].

2.3. Problem Definition

The appropriate model for determining the mechanical properties of new composite material is arranged by employing neuro-regression analysis.

- The design variables, where x1: Layout of the layers, x2: Angle of the tensile (°) depicted in Table 3, is the data referenced from the main study.
- 11 candidate functional constructs have been suggested to model the experimental data of new composite material have been tested for the appropriate ones in terms of $R^2_{training}$, $R^2_{testing}$, $R^2_{validation}$ values, and then boundedness of the functions is also checked.
- Using the appropriate models, two distinct optimization strategies were implemented, and four different direct search approaches were used to solve these problems.

2.4. Optimization Scenarios

Scenario 1

In this optimization problem, the objective functions define tensile strength and elongation of the material, the design variables are all supposed to be real numbers, and the search space is infinite. For this case, 1 < layout of the layers < 2 and 0 < angle of the tensile < 90. The main goal is to maximize the tensile strength and the elongation of the material. This approach can also be used to calculate the limits of the objective function.

Table 3. *Tensile strength (Mpa),σ_M and elongation at break (%), ε_M of the new composite material prepared by different layout of the layers and angle of the tensile (°)* [2]

No.	Layout of the layers	Angle of the tensile (°)	Tensile strength (Mpa), σ_M	Elongation at break (%), ε_M
1	1	0	19.90	3.01
2	1	0	19.91	3.20
3	1	0	22.00	2.65
4	1	0	23.20	3.40
5	1	0	23.50	2.74
6	1	0	24.20	3.23
7	1	0	25.40	3.35
8	1	0	26.30	3.44
9	1	45	13.50	2.58
10	1	45	14.70	2.41
11	1	45	14.75	2.63
12	1	45	15.85	3.82
13	1	45	16.60	3.65
14	1	45	17.10	2.62
15	1	45	17.30	3.44
16	1	45	17.30	3.44
17	1	45	17.30	3.44
18	1	45	17.30	3.44
19	1	45	17.30	3.44
20	1	45	17.30	3.44
21	1	45	17.30	3.44
22	1	45	17.30	3.44
23	1	45	17.30	3.44
24	2	0	12.00	2.35
25	2	0	13.30	1.68
26	2	0	13.30	1.68
27	2	0	13.30	1.68
28	2	0	13.30	1.68
29	2	0	13.30	1.68
30	2	0	13.30	1.68
31	2	45	18.50	2.30
32	2	45	20.20	3.06

33	2	45	20.20	3.06
34	2	45	20.20	3.06
35	2	45	20.20	3.06
36	2	45	20.20	3.06
37	2	45	20.20	3.06
38	2	45	20.20	3.06
39	2	45	20.20	3.06
40	2	45	20.20	3.06
41	2	45	20.20	3.06
42	2	45	20.20	3.06
43	2	45	20.20	3.06
44	2	45	20.20	3.06
45	2	90	17.40	2.88
46	2	90	19.50	3.62

Scenario 2

In addition to knowledge learned from scenario 1, a more applicable problem case must be introduced. For this reason, a new optimization problem is defined, which considers the maximization of the tensile strength and the elongation of the material. All design variables are presumed to be real numbers at the intervals: 1 < layout of the layers < 2 and 0 < angle of the tensile < 90. Moreover, to examine constructional and experimental constraints {strength, elongation} ∈ integers are appropriate.

3. Result and Discussion

In this study, 11 several regression models (Table 1) with two parameters have been tested for two outputs, and the results are listed in Table 4 and 5 in order to understand the model's capability to explain the process by estimating $R^2_{training,}$ $R^2_{testing,}$ $R^2_{validation}$ values for various regression models and the model’s functional limitation by estimating the maximum and minimum values created by the respective model.

In Table 4, the suitability of the candidate models in terms of training, testing and validation coefficients, and boundedness, the following conclusions were made: Training coefficients of all models are quite high (>0.97) while the test and validation coefficients are very low (<0 & <0.77 respectively) for L and FOTN models. In addition, the testing and validation values of the LR model are not much but low (<85 both of them), so the LR model can not provide the appropriate model too. Therefore, 11 usable model in terms of fit capabilities at the first stage falls to 8. Furthermore, as previously stated, It is anticipated to satisfy the boundedness criterion for use in model optimization. From this point of view, models SON, TON, SOTN, and H2 are also not suitable. As a result, models SONR, FOTNR, SOTNR, and H1 satisfy all the desired criteria and are also regarded as more realistic. The limitations of the models: for SONR is $-9.52x_{10}^{13}$ – $2.19x_{10}^{15}$, for FOTNR is $-3.26x_{10}^{15}$ – $1.64x_{10}^{14}$, for SOTNR is -11.76 – 26.24 and for H1 is -19.09 – 29.11. Therefore, it was concluded that the H1 model function best describes the "tensile strength" parameter.

A similar explanation can be made for Table 5: While 11 models may be suitable for training and testing coefficients for the "elongation at break," L, FOTN, FOTNR, SOTN, SOTNR, and H1 models are not available in terms of the third criterion, boundedness. Except for the three criteria given above, these five models, when it is discussed which one is more realistic, the H2 model in terms of simplicity, value range, and fit capabilities is more suitable than other models. Furthermore, alternative formulations such as LR, SON, SONR, and TON are available for use because they perform similarly.

Table 4. *Results of the Neuro-regression models for the tensile strength*

Models	$R^2_{training}$	$R^2_{testing}$	$R^2_{validation}$	Max (MPa)	Min (MPa)
L1	0.97	−0.66	0.038	19.34	17.37
LR1	0.99	0.72	0.77	18.20	13.31
SON1	0.99	0.95	0.90	22.88	1.73
SONR1	0.99	0.95	0.90	2.19×10^{15}	-9.52×10^{13}
TON1	0.99	0.95	0.90	22.88	−0.94
FOTN1	0.97	−0.73	0.094	23.15	18.37
FOTNR1	0.99	0.95	0.99	1.64×10^{14}	-3.26×10^{15}
SOTN1	0.99	0.95	0.90	22.88	−4.07
SOTNR1	0.99	0.95	0.90	26.24	−112.67
H1	0.99	0.95	0.90	26.11	−19.04
H2	0.99	0.95	0.90	22.00	1.39

Table 5. *Results of the Neuro-regression models for the elongation at break*

Models	$R^2_{training}$	$R^2_{testing}$	$R^2_{validation}$	Max (%)	Min (%)
L2	0.98	0.57	0.57	3.90	2.44
LR2	0.98	0.87	0.85	3.33	1.85
SON2	0.98	0.87	0.85	3.27	1.85
SONR2	0.98	0.87	0.85	3.54	1.85
TON2	0.99	0.87	0.85	3.36	1.85
FOTN2	0.97	-0.73	0.094	23.15	18.37
FOTNR2	0.99	0.87	0.85	3.92×10^{13}	-3.87×10^{14}
SOTN2	0.99	0.95	0.90	22.88	-4.07
SOTNR2	0.99	0.87	0.85	3.91×10^{14}	-4.05×10^{14}
H1	0.99	0.87	0.85	4.52	-0.59
H2	0.99	0.87	0.85	3.56	2.97

In Table 6, the model of "tensile strength " H1 is taken as the objective function, and the results are listed for several optimization scenarios. This table uses DE, NM, SA, and RS algorithms for each scenario, and the results are compared. For example, all algorithms determined the maximum "Tensile Strength" value for the first scenario was 26.55, while the corresponding x2 variables of "Suggested Design" values differed. This gives us four different alternative input parameter triplets to obtain the highest tensile strength. In the second scenario, the problem description is similar, but the input parameters (Layout of the layers, angle of the tensile) are forced to be integers. Using the DE and SA algorithms, the maximum tensile strength value was reduced to 1%, and the input values were $x_1 = 1$ and $x_2 = 44$.

Similarly, in Table 7, the model of "elongation at break " H2 is taken as the objective function, and the results are listed for two several optimization scenarios. This table involves the calculation based on DE, NM, SA, and RS algorithms for each scenario, and the results are compared. The maximum "Elongation at Break" value determined by all algorithms for the first scenario is 3.58, and the corresponding "Suggested Design" is the same. This gives us only one input parameter triplet to obtain the highest elongation at break. In the second scenario, the problem description is similar, but the input parameters (Layout of the layer, angle of the tensile) are forced to be integers. In this case, using the DE, NM, and SA algorithms, the maximum tensile strength was reduced to 8%, and the input values were $x_1 = 2$ and $x_2 = 75$.

Table 6. *Optimization problem results of the selected model for tensile strength*

Objective Function	Scenario No	Constraints	Optimizaiton Algorithm	Max Tensile Strength	Suggested Design
$1.898150158244077 + 1.4678873258539737\, x_1 + 0.8469133355818345[x_1]^2 + 0.05490833491406189\, x_2 + 0.10167237594192526\, x_1 x_2 - 0.0016739290005225325\, [x_2]^2 - 4.67959362010483\, Cos[x_1] + 10.99388196366126\, Cos[x_2] + 18.894432221360166\, Cos[x_1]\, Cos[x_2]$	1	$1 < x_1 < 2$, $0 < x_2 < 90$	DE NM SA RS	26.54 26.12 26.55 26.53	x_1=1.0, x_2=43.98 x_1=1.0, x_2=62.83 x_1=1.0, x_2=43.98 x_1=1.0, x_2=50.26
	2	$1 < x_1 < 2$, $0 < x_2 < 90$, $\{x_1, x_2, x_3\} \in$ Integers	DE NM SA RS	26.53 23.13 26.53 22.27	x_1=1, x_2=44 x_1=2, x_2=69 x_1=1, x_2=44 x_1=2, x_2=57

Table 7. *Optimization problem results of the selected model for elongation at break*

Objective Function	Scenario No	Constraints	Optimizaiton Algorithm	Max Elongation at Break	Suggested Design
18.56976245187751 +			DE	3.58	x_1=1.74, x_2=69.56
5.332625748774333 x_1 -	1	1 < x_1 < 2,	NM	3.58	x_1=1.74, x_2=69.56
0.6897015434525597 x_1^3-		0 < x_2 < 90	SA	3.58	x_1=1.74, x_2=69.56
0.3255438000564282 x_1^5 -			RS	3.58	x_1=1.74, x_2=69.56
0.17116361963166152 x_2 +					
0.011875685280791307 x_1 x_2 +					
0.018449736564968358 x_1^4 x_2 +		1 < x_1 < 2,	DE	3.50	x_1=2, x_2=75
0.00008170504540320082 $x_1 x_2^2$-	2	0< x_2 < 90,	NM	3.50	x_1=2, x_2=75
9.502786632380143×$10^{-10}x_2^5$-		{x_1, x_2, x_3}	SA	3.50	x_1=2, x_2=76
7.268614002730438×10^{-12} x_2^6		∈ Integers	RS	3.49	x_1=2, x_2=74

4. Conclusion

Designing optimal products from a new composite material necessitates a thorough understanding of the material's mechanical properties. Unfortunately, these properties are difficult to deduce from their constituents. Furthermore, the properties of the composite cannot be calculated using mathematical formulas from the properties of the constituents. As a result, they can only be determined experimentally using specialized machines and testing methods.

This paper aims to show the possibility of using an optimization method to determine the mechanical properties of tensile strength and elongation at break for new composite material. Results show that the optimization method is convenient to choose an appropriate model for that kind of study. So, it can provide ease of solution to these studies. Using the process variables, the optimization model is proposed to estimate the tensile strength and elongation at break. A novel model based on neuro-regression analysis methods to determine optimum mechanical properties has been introduced to eliminate this deficiency. First, a thorough investigation of non-linear multiple regression analysis was carried out, including rational forms for linear, quadratic, trigonometric, logarithmic. Second, the limitations of candidate models were validated in order to produce realistic values. Finally, several direct search methods were used, including stochastic approaches, during the optimization phase. Another indication that the choice of the objective function and constraints design variables becomes important in optimization problems. It is satisfying that the best result has been given from hybrid models rather than the standard models.

The following conclusions can be reached after the modeling of the tensile strength, σ_M, and the elongation at break, ε_M:

1) The 11 models are tried, and one appropriate model is found for two outputs. The R^2 testing and R^2 validation values of the models are at the desired level.

2) In addition, the maximum tensile strength and elongation at break values of the material were found.

3) The input parameters were found, which is needed to achieve maximum tensile strength and elongation at break values of the material.

4) The type of scenario and the choice of constraints for design variables are critical in the optimization problem.

Declaration of Interest

The author declare that there is no conflict of interest.

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APPENDIX

Nomenclature	Models
	$19.71182066869301 - 0.37026443768996825x1 - 0.017647348868625304x2$
LR1	$-51.31976284522877 + 51.31976284523468x1 + 774503.1775437717x2/-3.854604998705042 + 3.8546049987053x1 + 42541.08885662762x2$
SON1	$24.526185784658686 + 2.3350070372976797x1 - 3.9740499648135224x1^2 - 0.34202116402116317x2 + 0.2922984607984611x1x2 - 0.0020594837261504097x2^2$
SONR1	$2218.5038106203615 + 8332.47861996536x1 - 5600.060243913964x1^2 + 31088.892439939827x2 + 1847.6990367776073x1x2 - 1574.950427859876x2^2/346.81933827792716 + 44.61861835370988x1 - 175.11902955653323x1^2 + 1196.1381419252248x2 + 501.84473556335837x1x2 - 88.848501524142x2^2$
TON1	$20.94109188907611 + 4.5824368664639605x1 - 1.0712803912934319x1^2 - 1.5651055071037883x1^3 - 0.18033348484038514x2 + 0.04459740211289496x1x2 + 0.07264047537312718x1^2x2 - 0.0019446050613860057x2^2 + 0.0006617696125818712x1x2^2 - 0.000010654947332801006x2^3$
FOTN1	$9.902429779197746 + 1.3032369041527805Cos[x1] - 0.6024526244055706Cos[x2] + 11.372423196615832Sin[x1] - 1.701292858920586Sin[x2]$
FOTNR1	$-72.0344943619616 + 3086.5528215675718Cos[x1] + 68.68616422167281Cos[x2] + 330.4484534546959Sin[x1] - 834.7528817322325Sin[x2]/74.71611907347054 + 158.8667416923987Cos[x1] + 13.088655381978818Cos[x2] - 105.49720900069308Sin[x1] - 6.894967901990746Sin[x2]$
SOTN1	$3.0460545502597487 + 0.6800626431272705Cos[x1] + 5.6052888673774355Cos[x2] + 9.949815188229488Cos[x1]Cos[x2] + 6.999132839176023Sin[x1] + 0.12042831374840418Cos[x1]Sin[x1] + 3.028187782163123Cos[x2]Sin[x1] + 4.570566768978463Sin[x2] - 10.530448906883716Cos[x1]Sin[x2] - 2.375890082747342Cos[x2]Sin[x2] + 2.8328197496013865Sin[x1]Sin[x2]$
SOTNR1	$(1957.2500595090817 + 5961.234191177309Cos[x1] + 939.3962800588763Cos[x2] - 8450.710855836645Cos[x1]Cos[x2] + 987.6027093076096Sin[x1] + 3420.4660512907126Cos[x1]Sin[x1] - 699.6677723130807Cos[x2]Sin[x1] + 1375.5244699483446Sin[x2] - 1735.7546609202786Cos[x1]Sin[x2] - 7320.150314484926Cos[x2]Sin[x2] + 486.60921758147333Sin[x1]Sin[x2]) / (67.38342604363065 + 537.0007633750448Cos[x1] + 265.67098828479004Cos[x2] - 374.9260855810948Cos[x1]Cos[x2] + 236.3986433952951Sin[x1] - 286.1413334671107Cos[x1]Sin[x1] - 407.7703408734187Cos[x2]Sin[x1] + 4.457381391121794Sin[x2] + 99.66232882250745Cos[x1]Sin[x2] - 229.8443151710416Cos[x2]Sin[x2] - 78.61973683325331Sin[x1]Sin[x2])$
H1	$1.898150158244077 + 1.4678873258539737x1 + 0.8469133355818345x1^2 + 0.05490833491406189x2 + 0.10167237594192526x1x2 - 0.001673929000522532 5x2^2 - 4.67959362010483Cos[x1] + 10.99388196366126Cos[x2] + 18.894432221360166Cos[x1]Cos[x2]$
H2	$18.56976245187751 + 5.332625748774333x1 - 0.6897015434525597x1^3 - 0.3255438000564282x1^5 - 0.17116361963166152x2 + 0.011875685280791307x1x2 + 0.018449736564968358x1^4x2 + 0.000081705045403200 82x1x2^2 - 9.502786632380143 \times 10^{-10}x2^5 - 7.268614002730438 \times 10^{-12}x2^6$
L2	$19.71182066869301 - 0.37026443768996825x1 - 0.017647348868625304x2$
LR2	$-51.31976284522877 + 51.31976284523468x1 + 774503.1775437717x2/-3.854604998705042 + 3.8546049987053x1 + 42541.08885662762x2$
SON2	$24.526185784658686 + 2.3350070372976797x1 - 3.9740499648135224x1^2 - 0.34202116402116317x2 + 0.2922984607984611x1x2 - 0.0020594837261504097x2^2$
SONR2	$2218.5038106203615 + 8332.47861996536x1 - 5600.060243913964x1^2 + 31088.892439939827x2 + 1847.6990367776073x1x2 - 1574.950427859876x2^2/346.81933827792716 + 44.61861835370988x1 - 175.11902955653323x1^2 + 1196.1381419252248x2 + 501.84473556335837x1x2 - 88.848501524142x2^2$

TON2	$20.94109188907611 + 4.5824368664639605x1 - 1.0712803912934319x1^2 - 1.5651055071037883x1^3 - 0.18033348484038514x2 + 0.04459740211289496x1x2 + 0.07264047537312718x1^2x2 - 0.0019446050613860057x2^2 + 0.0006617696125818712x1x2^2 - 0.000010654947332801006x2^3$
FOTN2	$9.902429779197746 + 1.3032369041527805Cos[x1] - 0.6024526244055706Cos[x2] + 11.372423196615832Sin[x1] - 1.701292858920586Sin[x2]$
FOTNR2	$-72.0344943619616 + 3086.5528215675718Cos[x1] + 68.68616422167281Cos[x2] + 330.4484534546959Sin[x1] - 834.7528817322325Sin[x2]/74.71611907347054 + 158.8667416923987Cos[x1] + 13.088655381978818Cos[x2] - 105.49720900069308Sin[x1] - 6.894967901990746Sin[x2]$
SOTN2	$3.0460545502597487 + 0.6800626431272705Cos[x1] + 5.6052888673774355Cos[x2] + 9.949815188229488Cos[x1]Cos[x2] + 6.999132839176023Sin[x1] + 0.12042831374840418Cos[x1]Sin[x1] + 3.028187782163123Cos[x2]Sin[x1] + 4.570566768978463Sin[x2] - 10.530448906883716Cos[x1]Sin[x2] - 2.375890082747342Cos[x2]Sin[x2] + 2.8328197496013865Sin[x1]Sin[x2]$
SOTNR2	$(1957.2500595090817 + 5961.234191177309Cos[x1] + 939.3962800588763Cos[x2] - 8450.710855836645Cos[x1]Cos[x2] + 987.6027093076096Sin[x1] + 3420.4660512907126Cos[x1]Sin[x1] - 699.6677723130807Cos[x2]Sin[x1] + 1375.5244699483446Sin[x2] - 1735.7546609202786Cos[x1]Sin[x2] - 7320.150314484926Cos[x2]Sin[x2] + 486.60921758147333Sin[x1]Sin[x2])) / (67.38342604363065 + 537.0007633750448Cos[x1] + 265.67098828479004Cos[x2] - 374.9260855810948Cos[x1]Cos[x2] + 236.3986433952951Sin[x1] - 286.1413334671107Cos[x1]Sin[x1] - 407.7703408734187Cos[x2]Sin[x1] + 4.457381391121794Sin[x2] + 99.66232882250745Cos[x1]Sin[x2] - 229.8443151710416Cos[x2]Sin[x2] - 78.61973683325331Sin[x1]Sin[x2]))$