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Predicting the Bending Rigidity and Formability of Plasma-Treated Spunbond Nonwoven Fabrics Using Artificial Intelligence

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ABSTRACT

Nonwoven fabrics are used in many industries, and surface treatment by plasma can significantly change their physical and mechanical properties by changing the surface chemistry and morphology. In this paper, oxygen/argon plasma has been applied to the spunbond nonwoven fabrics to predict the obtained properties. Therefore, by using the central composite design and considering 4 independent factors including the fabric weight, fabric direction, plasma treatment duration and oxygen ratio, 51 various samples were prepared and their bending rigidity and formability were measured. SEM images showed that the surface roughness increases due to the plasma treatment. Statistical analysis revealed that all the mentioned independent factors have a significant effect on the measured parameters directly or reciprocally. Also, the use of a neural network model with two hidden layers optimized with a method according to the genetic algorithm can predict the bending rigidity and formability based on the independent factors with errors of less than 7% and 9%, respectively. The errors resulting from the surface response method for the same parameters with the same order are about 19% and 17%. The introduced method can be used as a tool to help researchers in the field of mechanical properties.

KEYWORDS
plasma treatment, neural network, NSGAII, bending rigidity, formability, spun-bond nonwoven, AI

INTRODUCTION

Polypropylene nonwoven fabric is a versatile material made from the thermoplastic polymer polypropylene. It is renowned for its durability, lightweight, breathability, moisture resistance, and cost-effectiveness, which make it a popular choice for a wide range of applications [1]. Polypropylene nonwoven fabric has numerous applications across different industries due to its unique properties. In the medical field, it is widely used to produce hospital gowns, doctor coats, scrubs, and face masks. Its ability to repel moisture and resist microorganisms makes it an ideal choice for medical apparel. Additionally, its durability and resistance to chemicals make it suitable for use as protective clothing in industrial settings [2]. A variety of items are made of PP (polypropylene) nonwoven fabrics in the consumer sector, including t-shirts, sportswear, socks, gloves, and reusable shopping bags. In the automotive industry, it is used for car interiors and insulation, taking advantage of its strength and sound absorption properties. Agriculture employs it as crop cover, while it is also used in the construction of geotextiles and furniture upholstery due to its resistance to wear and tear. Although it is not suitable for complete waterproofing, its water-resistant properties make it useful for packaging and storage containers. The non-reactive nature and absence of polar groups in PP nonwovens limit their use in certain applications such as sportswear, sanitary items, dressings, and biomaterials. To enhance their functionality and ability to absorb water, various techniques have been used to modify the surfaces of PP nonwovens [3].

Plasma treatment is one of the versatile technologies which enables the surface modification of polymeric materials without significant deterioration of their bulk properties. Plasma treatment can introduce functional groups on the surface of PP fibres. The type of functional groups depends on the nature of the gas used during plasma treatment. Etching of the surface layers is another effect of plasma treatment on polymeric fibres which affects the surface morphology and physical properties of the fabrics. The free radicals and functional groups introduced on the surface of the fibres during plasma treatment can be used for the grafting of various compounds and monomers on the textile substrates. Various studies have reported the plasma treatment and/or grafting of different compounds such as acrylic acid, chitosan, β-cyclodextrin, etc. on PP nonwoven [4-6]. Treatment of PP nonwoven with oxygen, helium or argon plasma (or their mixture) introduces oxygen-containing groups and nano-scale roughness on PP fibres, which may affect its wettability and physical properties such as tensile strength, breathability, air permeability, and low-stress mechanical properties [7-9].

Artificial intelligence is currently used in numerous fields to find the nonlinear and complex relationships between the independent and dependent parameters of engineering systems. In the textile industry, many works have been published reporting the success of using artificial intelligence to predict or optimize the physical and mechanical properties of textiles [10-19]. However, to the best of the authors' knowledge, no paper has been published regarding the prediction of bending rigidity and formability under the influence of plasma treatment. Therefore in this study, the effect of independent factors including the fabric weight, fabric direction, proportion of argon/oxygen gas in plasma, and duration of plasma treatment on the bending rigidity and formability of fabrics were studied. For this purpose, the response surface method (RSM) and neural network model (ANN) were used. These two methods have been successfully used in many researches in the textile industries [20-23]. However, the basis of RSM is based on the regression equations, while the structure of neural networks is inspired by the human brain. Moreover, a genetic algorithm-based technique was used to optimize and improve the accuracy of neural networks which will be explained later.

EXPERIMENTAL

Experimental Design

In this study, the effect of independent factors, as shown in Table 1, was investigated on the bending rigidity and formability of the polypropylene spunbond nonwoven fabrics made of the same multifilament fibres (average diameter: 22.53 µm, C.V: 8%) as the dependent factors. All samples were prepared from the Harir Baft factory, in Tehran, Iran. The direction of the fabric production on the machine was considered a 0-degree direction. The direction of 45 and 90 degrees were also considered based on that. The plasma machine was able to apply a mixture of oxygen and argon gases to the fabric. Therefore, if the ratio of the oxygen gas is P, the ratio of the argon gas is 100-P. Table 1 also shows the levels of the mentioned factors, and according to that and using the central composite design method, altogether 36 experiments were designed to be treated with plasma and measured the dependent factors.

Table 1. Characteristics of the independent factors

Factor	Unit	Level
Weight	g/m^2	12, 17, 25, 30, 35
Ratio of oxygen	%	0, 25, 50, 75, 100
Plasma duration	minute	5, 10, 15
Direction	degree	0, 45, 90

Moreover, to investigate the effect of weight and direction of the fabric without applying plasma treatment, 15 other experiments were also prepared based on the factorial design. In this way, a total of 51 experiments were accomplished, and each one was repeated three times, and the average results were considered for further analysis. Table 2 shows all the treatment runs.

Table 2. All treatments

Run No.	Time (min)	Percentage	Direction	Weight (g/m^2)
1	5	100	90	17
2	10	75	0	17
3	5	25	45	35
4	10	100	90	35
5	15	100	0	25
6	15	75	45	35
7	10	0	90	12
8	5	25	45	35
9	5	50	0	12
10	15	25	0	35

Run No.	Time (min)	Percentage	Direction	Weight (g/m^2)
11	15	0	0	17
12	10	25	90	17
13	15	0	90	30
14	15	100	45	30
15	10	0	45	25
16	15	75	45	12
17	5	50	45	30
18	10	0	45	25
19	5	0	90	25
20	10	0	0	12
21	10	75	0	17
22	10	25	0	25
23	15	0	90	35
24	15	75	90	25
25	5	75	90	30
26	5	100	45	25
27	10	25	90	17
28	10	0	0	35
29	15	75	45	12
30	5	0	0	17
31	15	50	0	30
32	5	0	0	25
33	5	100	0	35
34	5	0	0	30
35	5	100	45	12
36	10	50	90	30
37	0	0	90	12
38	0	0	0	12
39	0	0	45	12
40	0	0	90	17
41	0	0	0	17
42	0	0	45	17
43	0	0	90	25
44	0	0	0	25
45	0	0	45	25
46	0	0	90	30
47	0	0	0	30
48	0	0	45	30
49	0	0	90	35
50	0	0	0	35
51	0	0	45	35

Bending rigidity

According to BS-3356 [24], the bending length was measured using a SHIRLEY stiffness tester (model M003B, England) with a sample size of 2.5 x 20 cm. A length of fabric that bends due to its weight up to 41.5 degrees is considered as the bending length. Then, the value of bending rigidity is calculated using Equation 1 as follows:

$$B = W \times C^3 \times 9.81 \times 10^{-6} \tag{1}$$

Where W, C and B are the fabric weight in g/m^2, the bending length in mm and the bending rigidity in μN.m.

Formability

Formability, a key characteristic in fabric behaviour during garment manufacturing and wear, is influenced by various fabric properties. These include weave type, fabric density, warp and weft yarn twist, bending rigidity, and fabric tensile behaviour, particularly when subjected to small load values. Essentially, formability determines how a fabric will behave when shaped, draped, or worn, and it plays a significant role in the performance and tolerability of the fabric during the manufacturing process and in the final garment. The concept of formability is closely related to fabric handle, which encompasses a range of mechanical properties such as bending, shear stiffness, bulk compressibility, and surface frictional properties, all of which contribute to the overall feel and behaviour of the fabric. Formability is the ability of the fabric to accept a certain shape without any wrinkles. This feature is a measure of the compression that the fabric can withstand before buckling and is defined according to Equation 2 [25,26]:

$$F = B \times \frac{Ext(20_{g/cm}) - Ext(5_{g/cm})}{14.7} \tag{2}$$

Where F and Ext are the formability in mm and fabric extension in %, respectively.

Plasma treatment

PP nonwoven samples were treated using plasma equipment working at low pressure employing a radio frequency power supply (PlasmaDEJ, BasaFan, Tehran, Iran). The processing chamber was evacuated to 5.3 Pa and oxygen and argon were introduced into the chamber with an appropriate flow rate as the processing gas according to the experimental design. Plasma was generated at 150 W for the determined time. Finally, the chamber’s pressure was increased to the atmospheric pressure by entering the environment air and the plasma treated sample was used for further analyses.

Scanning electron microscopy

The surface morphology of the samples was studied using a Vega3 scanning electron microscope (Tescan, Czech Republic) after sputter coating with gold.

ANN model

By determining the relationship between a system's inputs and outputs, the neural network can predict the system output value for any input value. This model includes an input layer, one or more hidden layers, and an output layer. In each layer, there are one or more neurons that are connected to their previous and next layers through coefficients. After receiving the input values of the system in the neurons of the input layer, the final response of the system is approximated by performing mathematical operations in the hidden layer or layers and given up in the neuron of the output layer. For more information, see the reference [12,27].

Non-dominated Sorting Genetic Algorithm (NSGAII)

In the genetic algorithm, the solution to the problem must first be defined in the form of a code, called a chromosome, and each part of it is called a gene. In multi-objective optimization problems, there are sets of chromosomes called Pareto-optimal or non-dominated chromosomes. Among these solutions, there are several chromosomes where the optimization conditions are better satisfied by them and known as the Pareto-optimal front. In NSGAII, the goal is to find a set of chromosomes that has as much diversity as possible and at the same time is close to the Pareto-optimal front set. NSGAII works exactly like the genetic algorithm, except that in the evaluation of chromosomes, it only uses the tournament function by considering the concepts of the fast non-domination sorting and crowding distance [13,28]. The first one causes the solutions to be divided into different ranks, so for example the solution with rank 1 is better than rank 2, the solution with rank 2 is better than rank 3, and so on. The crowding distance shows how close a chromosome is to its neighbours. The larger this value, the greater the diversity of the chromosomes. In practice, this concept prevents the chromosomes from gathering at one or several points and spreading them in the relevant ranks. In this way, when choosing between two chromosomes, the chromosome with the better rank is selected first. If the rank of both chromosomes is the same, the chromosome with the larger crowding distance is selected [29]. Figure 1 shows the flowchart of the NSGAII algorithm.

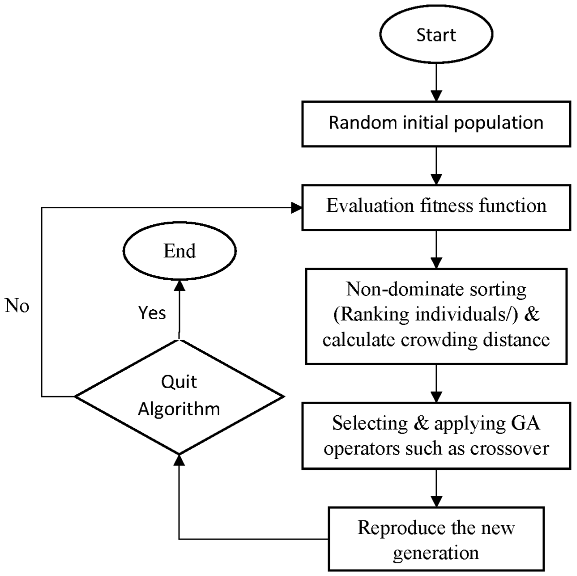


Figure 1. NSGAII algorithm

Optimizing the ANN with NSGAII

To optimize the ANN model using the genetic algorithm or NSGAII, it is necessary to convert the structure of ANN into a chromosome. In the present study, this structure includes the number of hidden layers, the number of neurons in each hidden layer, as well as the coefficients for the connection between the neurons (range between -10 to 10). Figure 2 schematically shows a chromosome that includes the mentioned items. According to the literature [14-19], in this study, it was decided to use a neural network with a maximum of two hidden layers. The number of neurons in each layer was considered up to 10 neurons. Based on this, altogether 171 coefficients are required for the connection between the neurons. As a result, the length of the created chromosome will be equal to 173 genes. If the rounded value of one of the genes #1 or #2 is between 0 and 1, the hidden layer corresponding to that gene is not considered. For example, in Figure 2, a neural network with one hidden layer with 5 neurons is considered and 31 genes are used for the coefficients. As a result, the rest of the genes have no importance. It is worth mentioning that Matlab software is used for developing the neural network and NSGAII.

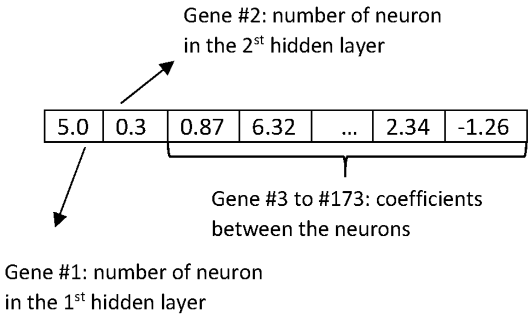
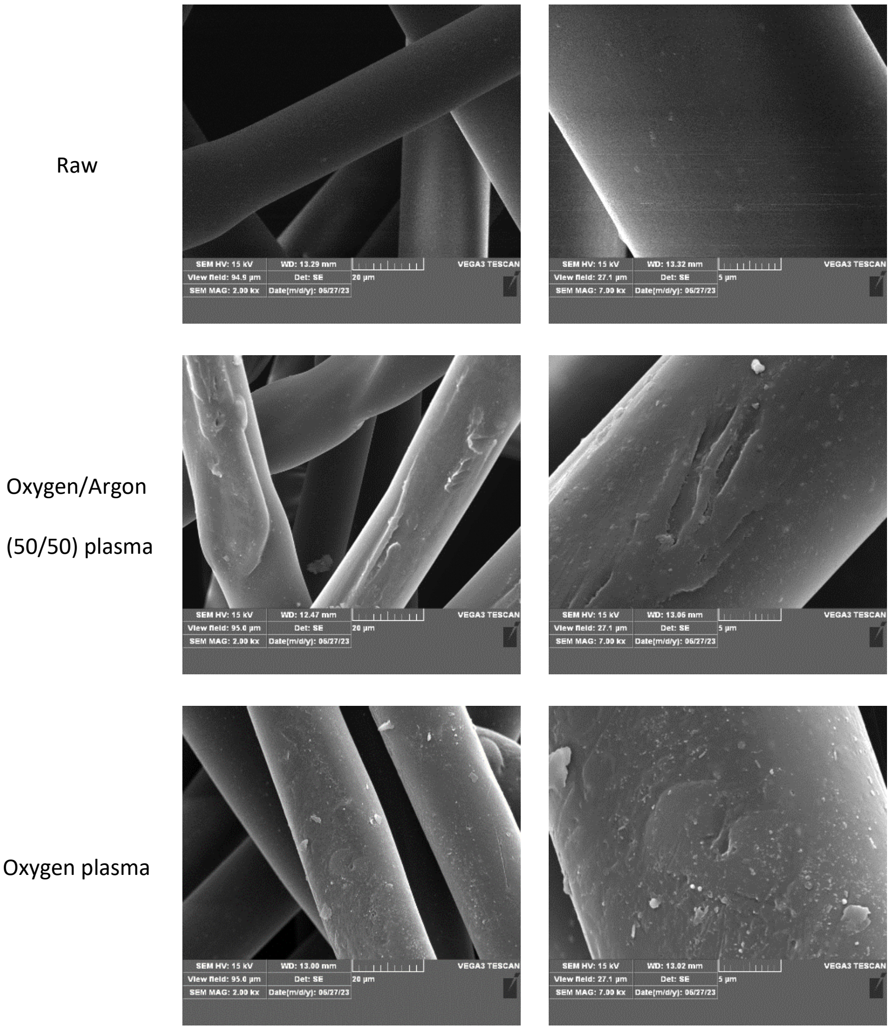


Figure 2. Chromosome containing the ANN parameters

RESULTS AND DISCUSSION

SEM results

Figure 3 shows the SEM images of raw PP nonwoven in comparison with the samples treated with oxygen, argon, and oxygen/argon (50/50%) plasma. As expected, the smooth surface of raw PP fibres was etched during the plasma treatment with both gases and their mixture. The roughness imposed by the plasma etching affects the friction coefficient of the fibres and affects their behaviour when external force is applied to the PP nonwoven fabric. Previous studies also have confirmed the introduction of oxygen-containing moieties such as hydroxyl and carbonyl groups on the surface of the PP fibres, which affects the adhesion among the fibres as well as between the fibres and coatings [6,30].



Argon plasma

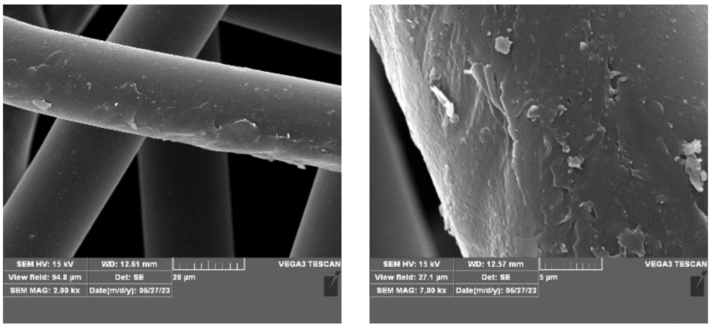


Figure 3. SEM images of raw and plasma-treated PP fibres (150 W, 15 min)

Statistical analysis

Before presenting an analysis of the obtained results, the significance of the independent variables on the dependent ones should be statistically verified. It should be mentioned that the bending rigidity and formability are the dependent factors and time, percentage, direction, weight and any combination of them are independent factors. If this meaning is proven, the analysis can be continued. The multi-way analysis of variance test (MANOVA) makes it possible to examine the simultaneous effect of several independent factors on one dependent factor in the form of the direct or reciprocal effect. At the confidence level of 90% and the P-value less than 0.1, it can be assumed that the influence of the factor under study on the dependent variable is significant. The results of MANOVA on the bending rigidity and formability are shown in Tables 3 and 4, respectively (X1=Time, X2=Percentage, X3=Direction, X4=Weight). For example, in bending rigidity (Table 3), factors X3 and X4 have a P-value less than 0.001, which is significant at a 90% confidence level. The interaction between X3 and X4 also has a p-value less than 0.001, indicating a significant effect on bending rigidity. Regarding formability (Table 4), factors X1 and X4 have a P-value less than 0.001, which is significant as well. The interactions between X2 and X4, as well as between X3 and X4, have P-values of 0.035 and 0.029, respectively, which are significant at a 90% confidence level.

As can be observed, all parameters considered in this study are statistically effective on bending rigidity and formability. Of course, some of them are not directly effective. For example, factor X2 does not directly affect both dependent factors, but its interaction with other independent factors is significant. Altogether, all of them can be used in the modelling of the dependent factors.

Table 3. MANOVA Result of the bending rigidity

Source	Sum Sq.	Df.	Mean Sq.	F	P-value
X1	125.548	1.000	125.548	2.477	0.118
X2	7.683	1.000	7.683	0.152	0.698
X3	8333.104	1.000	8333.104	164.415	0.000
X4	6953.441	4.000	1738.360	34.298	0.000

Source	Sum Sq.	Df.	Mean Sq.	F	P-value
X1.X2	169.165	1.000	169.165	3.338	0.070
X1.X3	14.385	1.000	14.385	0.284	0.595
X1.X4	480.264	4.000	120.066	2.369	0.056
X2.X3	145.163	1.000	145.163	2.864	0.093
X2.X4	174.538	4.000	43.634	0.861	0.489
X3.X4	6297.065	4.000	1574.266	31.061	0.000
Error	6588.850	130.000	50.683	-	-
Total	108497.293	152.000	-	-	-

Table 4. MANOVA Result of the formability

Source	Sum Sq.	Df.	Mean Sq.	F	P-value
X1	0.902	1.000	0.902	5.723	0.018
X2	0.001	1.000	0.001	0.008	0.931
X3	0.001	1.000	0.001	0.004	0.952
X4	5.021	4.000	1.255	7.968	0.000
X1.X2	0.321	1.000	0.321	2.036	0.156
X1.X3	0.058	1.000	0.058	0.368	0.545
X1.X4	1.167	4.000	0.292	1.851	0.123
X2.X3	0.056	1.000	0.056	0.353	0.553
X2.X4	1.682	4.000	0.421	2.669	0.035
X3.X4	1.758	4.000	0.440	2.790	0.029
Error	20.481	130.000	0.158	-	-
Total	45.851	152.000	-	-	-

Modelling

In the following, the best results in modelling the bending rigidity and formability were obtained using the quadratic regression method at a 90% confidence interval. So, the coefficients that have a P-value of less than 0.1 remain, and otherwise, they are removed from the model. The coefficients of the models and their statistical analysis for both dependent factors are presented in Tables 5 and 6. It should be mentioned that the regression modelling was accomplished using Design Expert software and the obtained equations are shown in the following (Equations 3 and 4). The weight of the nonwoven fabric (X4) is not available at any level in the market. So, it was considered as a categorical parameter and therefore the regression equation includes terms such as X4 [1], meaning the first level of the weight factor (12 g/m^2).

Table 5. ANOVA result for Regression to predict the bending rigidity

Source	Sum Sq.	Df.	Mean Sq.	F	P-value
Model	12.200	15.000	0.813	82.980	< 0.0001
X1	0.028	1.000	0.028	2.860	0.099
X3	1.930	1.000	1.930	197.050	< 0.0001
X4	8.260	4.000	2.070	210.780	< 0.0001
X2.X4	0.121	4.000	0.030	3.080	0.028
X3.X4	1.460	4.000	0.366	37.300	< 0.0001
$X3^2$	0.085	1.000	0.085	8.710	0.006
Residual	0.343	35.000	0.010	-	-
Lack of Fit	0.294	30.000	0.010	1.000	0.566
Pure Error	0.049	5.000	0.010	-	-
Cor. Total	12.540	50.000	-	-	-

Table 6. ANOVA result for Regression to predict the formability

Source	Sum Sq.	Df.	Mean Sq.	F	P-value
Model	0.320	10.000	0.032	24.620	< 0.0001
X1	0.010	1.000	0.010	7.510	0.009
X4	0.278	4.000	0.070	53.520	< 0.0001
X1.X2	0.004	1.000	0.004	2.990	0.091
X3.X4	0.017	4.000	0.004	3.220	0.022
Residual	0.052	40.000	0.001	-	-
Lack of Fit	0.046	35.000	0.001	1.030	0.549
Pure Error	0.006	5.000	0.001	-	-
Cor. Total	0.372	50.000	-	-	-

$$Bending\ rigidity = 0.674 - 0.021X1 - 0.259X3 + 0.689X4[1] + 0.104X4[2] - 0.177X4[3] - 0.253X4[4] - 0.107X2X4[1] - 0.017X2X4[2] + 0.007X2X4[3] + 0.108X2X4[4] - 0.440X3X4[1] - 0.013X3X4[2] + 0.064X3X4[3] + 0.200X3X4[4] + 0.097X3^2 \quad (3)$$

$$Formability = 0.296 + 0.005X1 - 0.092X4[1] - 0.064X4[2] - 0.009X4[3] + 0.057X4[4] - 0.012X1X2 - 0.003X3X4[1] - 0.017X3X4[2] - 0.013X3X4[3] + 0.043X3X4[4] \quad (4)$$

A closer look at Tables 5 and 6 reveals that the “Lack of Fit” for both models is not significant which means that the models are statistically acceptable. For the final evaluation of the model accuracy, the mean absolute percentage error (MAPE) is calculated over all the datasets according to Equation 5, which is equal to 17.87% and 17.73% for bending rigidity and formability, respectively.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - t_i|}{t_i} \times 100 \tag{5}$$

Where y and t are the model output and corresponding actual measured value, respectively. Although all the data have been used to obtain the regression coefficients, the obtained results do not indicate very high accuracy. Thus, the use of the ANN model (multi-perceptron network trained by backpropagation algorithm) was investigated.

In using ANN, generally, the data is divided into three groups. The first one, called the training group, is used to update the coefficients. The second one, called validation, is intended solely to control the error in the training process. It should be noted that this data group is not used for updating the coefficients. The third group called the test group, which is specifically used to evaluate the accuracy of the obtained model after the updating coefficients is accomplished. In this study, 70%, 10% and 20% of data were selected at random as the training, validation and test groups, respectively. At first, the only criterion initially set was the test group and it was tried to optimize ANN so that the maximum accuracy was achieved for predicting the test group. On this basis, the results obtained showed that although the prediction error for the test group is very small, the prediction error for the other two groups is very high. Therefore, it is not quite right to use only the MAPE of the test group as a criterion to optimize the prediction accuracy of ANN, so other groups should also be included in the evaluation. Consequently, different combinations of MAPE for all groups were examined, but the best results were obtained according to Equations 5 and 6 for the bending rigidity and formability, respectively. Therefore, the use of ANN becomes a multi-objective optimization problem. In this way, the ANN parameters should be optimized in such a way that the prediction accuracy for all three groups of training, validation and test is at the highest possible value, or in other words, MAPE close to 0 for all groups at the same time.

$$MAPE = \begin{cases} MAPE(1)_{train} \\ MAPE(2)_{validation} \\ MAPE(3)_{test} \end{cases} \tag{5}$$

$$MAPE = \begin{cases} MAPE(1)_{test} \\ MAPE(1)_{train} = MAPE(1)_{train+validation} \end{cases} \tag{6}$$

By using NSGAII, the multi-optimization of ANN parameters to achieve the lowest MAPEs was solved three times with the following setting and the best obtained Pareto-optimal front is illustrated in Figure 4. For more information about the setting parameters please refer to [31]. It must be mentioned that the other parameters of NSGAII remained based on the software default.

- Population Size: 100 chromosomes
- Number of Generations: 100
- Crossover fraction: 0.8
- Selection function: tournament with 4 chromosomes

Each point displayed in Figure 4 corresponds to a chromosome that can be selected as an ANN model. But, as it was said earlier, the ANN model is ideal and its prediction error is small for all the groups. Therefore, the chromosomes corresponding to the highlighted points, shown in Figure 4. a and 3. b, have been selected as ideal ANNs. On this basis, an ANN with two hidden layers, 4 neurons in the first hidden layer and 2 neurons in the second hidden layer, can predict the bending rigidity with MAPE of 6.5%. Also, a two-hidden layer ANN can be used to forecast the formability with MAPE of 9.1%, 4 neurons in the first hidden layer and 3 neurons in the second hidden layer.

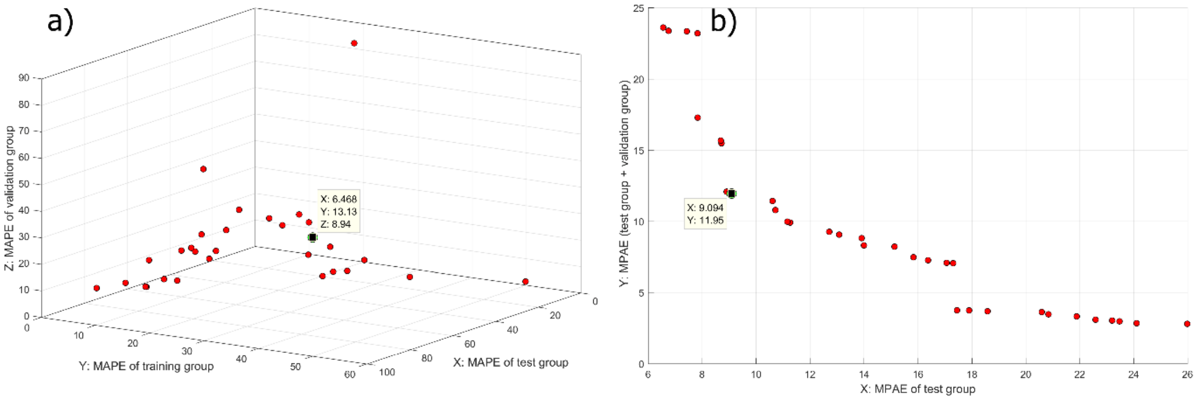


Figure 4. NSGAII output; Pareto-optimal front for (a) bending rigidity, (b) formability

Figure 5 shows the results of ANN and regression predictions for the mentioned variables. Also, to compare the accuracy of the ANN and the regression models, Table 7 is presented. To compare the accuracy of these two models, practically the results of the test group should be considered. Because two other groups have been used to determine the coefficients in ANN. it should be noted that all data (three groups) have been used to determine the regression equation. As can be seen, both in terms of bending rigidity and formability, ANN has less error and this point shows the efficiency of the neural network in predicting the bending rigidity and formability compared to the regression model. Moreover, even if the prediction accuracy is checked on all data, it is still observed that the neural network has less error than the regression model.

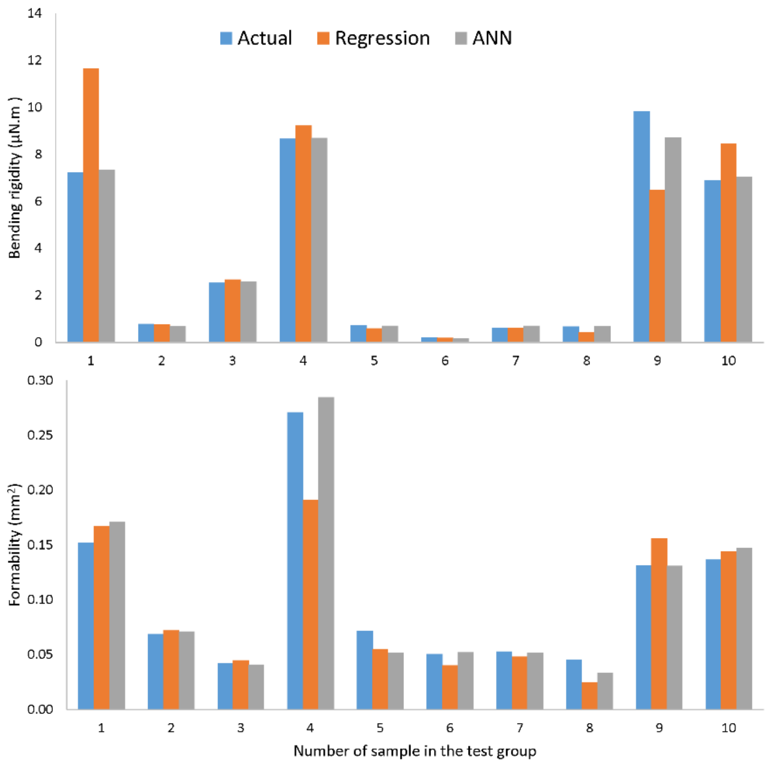


Figure 5. ANN and regression outputs, a) bending rigidity, b) formability

Table 7. MAPE for the ANN and regression models in different groups

Model	Factor	Train	validation	Test	all
ANN	Bending rigidity	13.13	8.94	6.47	11.42
	Formability	11.95		9.09	11.39
Regression	Bending rigidity	18.13	13.06	19.32	17.87
	Formability	16.53		18.02	17.73

Eventually, according to Table 7, it can be said that the ANN model can reach an error of less than 10% in predicting the values of the bending rigidity and formability while using the regression model can reach an error higher than 17% (test group).

CONCLUSION

In this study, five spunbond fabrics with different weights were selected, and then 51 experiments were designed based on the central composite design method and factors such as fabric direction, plasma treatment duration, and plasma gas ratio. Next, the bending rigidity and formability properties of the samples were measured as the dependent parameters. Statistical analysis showed that all the mentioned factors have a significant effect either directly or reciprocally on the dependent parameters. The SEM pictures demonstrated that the plasma treatment causes an increase in the surface roughness of the samples. In the next step, a regression model based on the response surface method was tried to establish a relation between the bending rigidity and formability and the aforementioned factors such as time, ratio of oxygen, plasma duration and direction. However, the accuracy of the obtained models showed that bending rigidity is associated with an error of approximately 19% and formability with an error of 17%. Therefore, to increase the accuracy of the modelling, the ANN model was used to predict each of the dependent parameters separately, and to increase its efficiency, the NSGAII method was also used. In this case, the model error was about 7% for bending rigidity and about 9% for the formability.

Author Contributions

Conceptualization – Vadood M and Haji A; methodology – Sharifi H, Vadood M and Haji A; formal analysis – Vadood M and Haji A; investigation – Sharifi H; resources – Sharifi H; writing-original draft preparation – Sharifi H, Vadood M and Haji A; writing-review and editing – Vadood M and Haji A; visualization – Vadood M; supervision – Haji A. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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