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PREDICTION OF PLASMA SURFACE MODIFICATION OF WOVEN FABRICS USING NEURAL NETWORKS

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ABSTRACT

In this paper, artificial neural networks are used to investigate the relationship between plasma processing parameters and woven surface wetting properties. In order to reduce the model complexity, a fuzzy criterion is used to select the most relevant parameters which are taken as inputs of the ANNs. The outputs are the surface water contact angle and the capillarity of woven fabrics. The use of early stopping and Bayesian regularization approaches are considered. Two different network configurations are studied. One deals with two networks each having one output layer neuron and another with a single network that gives two outputs. A comparison between these configurations and training algorithms is performed. Obtained results show that the first configuration combined with the Bayesian regularization approach is the most suitable to achieve a good generalization.

KEYWORDS

Neural networks; Fuzzy selection criterion; Modeling; Atmospheric plasma; Woven fabrics.

1. INTRODUCTION

Atmospheric plasma treatment has been widely used for textile surface modification because it offers a variety of active species for surface processing (Nasadil and Benesovsky, 2008). These active species (ions, electrons, free radicals, meta-stables, UV photons) can perform numerous surface modification processes such as surface activation, contamination removal, cross-linking and etching without affecting material bulk properties (Herbert, 2007). Surface activation consists of the introduction of new functional groups onto the treated surface in order to give it specific properties by varying its surface energy. Plasma activation is performed in gases that do not polymerize. The bombardment of the surface with the reactive plasma particles breaks covalent bonds and creates free-radicals on the treated material. These surface radicals react with the active plasma species to form various active chemical functional groups such as hydroxyl, carbonyl, carboxyl, and amine groups on the substrate surface. Such activation alters the chemical activity and characteristics of the surface. The resulting surface properties depend on the plasma gas composition. For example, oxygen and oxygen-containing plasmas lead to the grafting of polar and hydrophilic functions which increase the polarity of the fiber surface. In general, surface activation is mainly used for treating natural and man-made textile materials to raise their surface energy in order to obtain better surface characteristics such as wettability (Hossain et al., 2006; Karahan and Ozdogan, 2008), printability (Maamoun and Ghalab, 2013), dyeability (Cai and Qiu, 2008) and adhesion promotion (Leroux et al., 2009). The consequence of enhanced wetting properties are multiple and of great interest to textile manufacturing. Although plasma treatment can achieve a wide range of surface modifications, it is

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extremely difficult to understand the complex nonlinear relationship between its processing parameters and surface wetting properties. Thus, we use neural networks to construct a model since they have already been applied successfully to model various plasma-based processes (Himmel et al., 1993); (Byungwhan et al., 1994); (Huang et al., 1994); (Han et al., 1994); (Kim et al., 2001); (Allan et al., 2002); (Wang et al., 2007) as well as many other textile engineering problems (Fan et al., 1998; Chattopadhyay and Guha, 2004; Bhatacharjee et al., 2007) . Indeed, neural networks have several attractive properties which make them favorable alternatives to more traditional statistical modeling techniques. Specifically, neural networks have the ability to learn from experimental data, model complex non-linear multi-dimensional relationships without any prior assumptions about the nature of the relationships, and provide good approximations from imperfect or incomplete data (Psichogios and Ungar, 1991; Hunt et al., 1992).

However, this procedure of modeling is very complex because of the nonlinear relationship between input and output variables, the large dimensionality of the input space, the presence of redundant variables and the lack of available learning data. These factors may cause a deterioration of the generalization ability and an increase of the computational cost, thus resulting in inefficient outcomes of the model. Thus, in order to reduce the model complexity, the fuzzy sensitivity criterion developed by *Deng et al.* (2007) is considered for selecting the most relevant input variables of plasma process. This method has been successfully applied to the design of a nonwoven process and can be extended to other industrial problems in which time for obtaining learning samples is rather limited and experimental cost is often high (Deng et al., 2007). By comparison with other numerical methods, the proposed criterion was shown to be more robust and less sensitive to measured data noises and uncertainties. Furthermore, it can deal with a small number of learning data (Deng et al., 2010). These advantages provide a strong motivation to the present paper for using such method to select the most relevant plasma process parameters in order to reduce the complexity of managing data and obtain more significant and more physically interpretable results with a very limited cost. The results obtained from this fuzzy logic based method can be used to validate existing physical and chemical knowledge on the relationship between fabric structure and plasma treatment and help generate new specialized knowledge in the related field.
In this paper, a neural network approach is used for modeling the relationship between plasma processing parameters and fabric surface wetting properties. The early stopping and Bayesian regularization techniques are considered. Two different network configurations are studied. One deals with two networks each having one output layer and another with a single network combining the two outputs. A comparison between these configurations and training algorithms is done.

2. MATERIALS AND METHODS

2.1. Materials

Six different woven fabrics are used during this study. Two of them are made of viscose fibers, and the others of polyester (PET) fibers. Before air plasma treatment, the woven samples were cleaned and left in a controlled climate (20±2°C, 65±2% relative humidity (RH)) for at least 24 hours prior to all experiments. Table 1 presents the fabric features and their ranges. The numeric values 0 and 1 are used to encode the corresponding woven feature (given in parentheses). Fabric weight per unit area is measured according to the NF G 07-150 standard using an electronic weighting balance. The thickness of the fabrics is measured according to the NF G 07-153 standard at a pressure of 0.5 kPa. The yarn fineness (count) is measured by weight/length, according to the NF G 07-104 standard, and expressed in Decitex (grams per 10,000 meters). The fineness of fibers is measured according to the NF G 07-306 standard using a Vibroskop from Zweigle. The air permeability is measured by the TEXTEST Air permeability Tester (FX3300) at 196 Pa air pressure (following the NF G 07-111 standard). The surface roughness is measured by an optical profilometer (Cotec Altisurf 500) at 5 mm step size and 3x3mm^2 surface area. The porosity is calculated from the fabric's characteristics such as thickness, fabric weight and fiber material density.

Table1: Fabric features and their range

Parameter	woven1	woven2	woven3	woven4	woven5	woven6	Min	Max
Fiber nature	PET	PET	PET	PET	viscose	viscose	0 (PET)	1 (viscose)
Fabric weight (g/m^2)	160	170	200	195	180	190	160	200
Thickness (mm)	0.32	0.31	0.38	0.37	0.38	0.41	0.31	0.41
Construction	plain	plain	3/1twill	3/1twill	plain	3/1twill	0 (plain)	1(twill)
Weft density (picks/cm)	17.2	19	20	21	17	21	17.2	21
Warp density (ends/cm)	39	39.2	40	42	42	45	39.2	45
Weft count (dtex)	167	150	167	150	34	34	150	340.29
Fiber count (dtex)	1.7	0.9	1.7	0.9	1.3	1.3	0.9	1.7
Air permeability (l/m^{2}s)	54.85	19.62	103.7	49.14	786.2	673.2	19.62	786.2
Porosity (%)	63.77	60.55	61.86	62.08	68.84	69.51	60.55	69.51
Surface roughness (µm)	57.8	56.5	51.5	38.8	74.6	85.4	41.86	74.4

2.2. Plasma treatments

Plasma treatments are carried out using an atmospheric plasma machine called "Coating star" manufactured by the Ahlbrandt system (Figure 1). The following machine parameters are kept constant: frequency of 30 KHz, electrode length of 0.5m and inter-electrode distance of 1.5mm. The electrical power and treatment speed are varied respectively between 300-1000 Watts and 2-10 m/min. Plasma discharge is generated at atmospheric pressure by two electrodes and a counter-electrode both covered by a dielectric ceramic material.

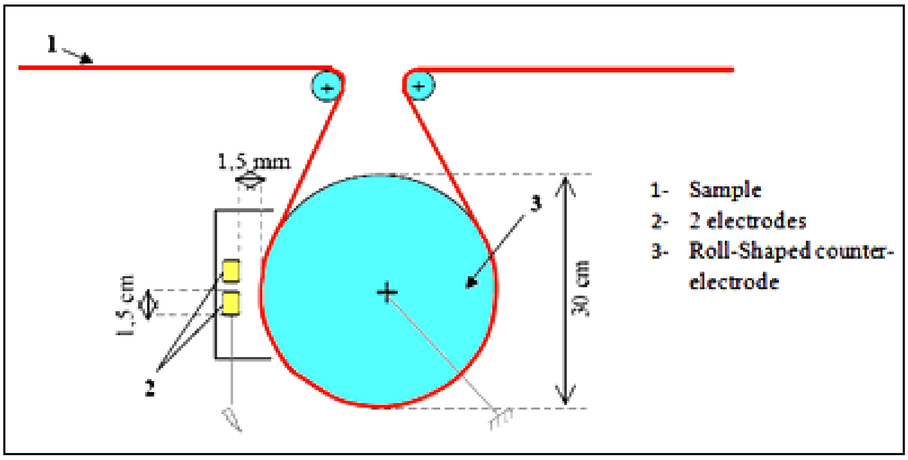


Figure 1: Atmospheric plasma treatment, using "Coating Star" system

2.3. Measurements

In order to quantify the surface treatment modification, contact angle and capillarity measurements are carried out with distilled water on a tensiometer "3S balance" from GBX. During measurements, a fabric sample of size 5cm x 3cm is connected to the tensiometer at the weighing position and progressively brought into contact with the surface of water placed in a container. On immediate contact with the water surface, a sudden increase weight is measured due to wetting forces. When the liquid is moved down to leave the fabric sample, the balance gave the values of the total weight at the end (W_t) and the weight of capillarity (W_c). These parameters are used to calculate the approximate meniscus weight (W_m) using Eq. (1).

$$\mathrm{W_m} = \mathrm{W_t} - \mathrm{W_c} \tag{1}$$

The water contact angle of woven samples can be determined from the meniscus weight using Eq. (2),

$$\mathrm{W_m} \times \mathrm{g} = \gamma_\mathrm{L} \times \cos\theta \times \mathrm{p} \tag{2}$$

Where p the sample perimeter in contact with the liquid (mm), W_m the calculated meniscus weight (g), g = 9.81m/s^2, γ_L the surface tension of the liquid (mN/m) and θ the contact angle (°).

The capillarity of woven samples are obtained from the capillarity weight values (W_c) and are expressed as a percentage (Eq. 3) of the fabric weight.

$$\text{Capillarity (\%)} = \frac{W_c \times 100}{W_s} \quad (3)$$

Where W_c the weight of water absorbed by capillarity after 2 min of contact (g) and W_s the textile sample weight.

2.4. Selection procedure of relevant input parameters

In this paper, the fuzzy logic criterion developed by *Deng et al.* (2007) is used for selecting the most relevant input parameters of plasma process. The main advantage of this method is that it can deal with a limited number of learning data points. The sensitivity criterion is formalized according to the two following principles:

- If a small variation of an input variable Δx corresponds to a large variation of the output variable Δy, THEN this input variable has a large sensitivity value *S*.
- If a large variation of an input variable Δx corresponds to a small variation of the output variable Δy, THEN this input variable has a small sensitivity value *S*.

These principles are transformed into a fuzzy model in which the input data variation Δx and the output data variation Δy are taken as two input variables and the sensitivity S as output variable. Based on this fuzzy logic sensitivity criterion, the following algorithm is proposed for selecting the most relevant variables and removing irrelevant ones.

Inputs: process input variables $X=\{x_1,\dots,x_m\}$ *and one related specific output* y_l
Output: relevant process parameters X_r*, and related sensitivity variation value* ΔS
ε *: threshold of sensitivity variation*
Initialise $X'=X$, $X_r=\{\}$, $\Delta S'_l=\{\}$
While $X' \neq \emptyset$.
Calculate the sensitivity variation of inputs in X' related to y_l *denoted* $\Delta S'_l = \{\Delta S_{1,l}, \dots, \Delta S_{k,l}, \dots, \Delta S_{size(X),l}\}$
$X_r=X_r \cup \{x_i\}$, $X'=X' \setminus \{x_i\}$ *where* $\Delta S_{i,l} > 1-\varepsilon$
$X'=X' \setminus \{x_j\}$ *where* $\Delta S_{j,l} < \varepsilon$
End

2.5. Neural network modeling

In this paper, a feed-forward neural network with two hidden layers is used for the plasma modeling. Two cases of network architecture are considered. In the first case, each output is modeled using a separate network. In the second case, a single network is used to model the two outputs. For both cases, a sigmoid transfer function was used for hidden layers and a linear transfer function was used for the output layer. This combination of activation functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy, provided that the hidden layers have enough units (Cybenko, 1989). These networks are trained with two different algorithms: the levenberg-Marquardt algorithm (*trainlm*) and the Bayesian regularization algorithm (*trainbr*). Prior to training, the available data is scaled into zero mean and unity standard deviation. After that, the entire samples are randomly divided into a training set (85 samples) and a test set (17 samples). Whenever early stopping technique is used, the initial training set is divided, in the same way, into a training set (68 samples) and a validation set (17 samples). The number of hidden neurons affects the efficiency and accuracy of learning. In order to optimize the models, the number of neurons in the hidden layers is determined using an iterative algorithm. The principle of this algorithm is to first generate a network having one neuron in each hidden layer and then add neurons one by one recurrently until some stopping criteria are reached. Since neural network is an alternate statistical method, the root mean square error (RMSE) and correlation coefficient (R) are used as performance criteria to get higher suitable models. Here, the number of hidden neurons is considered optimal when the training and test root mean square errors are both of the same order and as small as possible, and the correlation coefficients are close to 1 (Dreyfus et al., 2002). The training and test root mean square errors are calculated according to Eq. (4) and (5), respectively

$$RMSE_{Training} = \frac{1}{N_T}\sum_{i=1}^{N_T}(d_i - y_i)^2 \quad (4)$$

$$RMSE_{Test} = \frac{1}{N_t}\sum_{i=1}^{N_t}(d_i - y_i)^2 \quad (5)$$

where N_T is the number of training samples, N_t the number of test samples, d_i the desired output, and y_i the calculated output of the network. The *R* values are obtained by calculating the regression coefficients of the lines that relate network output values to their corresponding targets.

3. RESULTS AND DISCUSSIONS

In this study, 13 processing parameters and two wetting properties are collected directly from the plasma-based fabric surface modification process as shown in table 2.

Table 2: Input and output parameters

Factor	Variable name
Processing parameters	*Woven fabric features:* fiber nature (x_1); fabric weight (x_2); thickness (x_3); construction (x_4); weft density (x_5); warp density (x_6); weft count (x_7); fiber count (x_8); air permeability (x_9); porosity (x_{10}); surface roughness (x_{11}) *Plasma parameters:* electrical power (x_{12}); treatment speed (x_{13})
Properties	water contact angle (y_1); capillarity (y_2)

If we present all these 13 input parameters to the neural network, this would increase the network size, which leads to an increase of the amount of data required to estimate connection weights efficiently and decreases the processing speed. Thus, in order to reduce the size of the network, decrease the cost of data collection and improve model performance, we use the fuzzy criterion presented previously to select the relevant input variables and remove irrelevant ones. The threshold of sensitivity variation ε is set to the value 0.2. Tables 3 and 4 show the steps for identifying the inputs relevant to water contact angle and capillarity.

Table 3: Selection of relevant input variables related to water contact angle, using the fuzzy sensitivity variation criterion

	Remaining inputs	Ranked inputs by ascending ΔS	The relevant inputs	The irrelevant inputs
Step 1	All inputs, x_1 to x_{13}	x_{12}, x_{13}, x_1, x_9, x_{11}, x_8, x_6, x_{10}, x_4, x_7, x_2, x_3, x_5	x_{12}	x_5, x_3
Step 2	x_1, x_2, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}	x_{13}, x_1, x_{11}, x_9, x_8, x_7, x_4, x_{10}, x_6, x_2	x_{13}, x_1	x_2
Step 3	x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}	x_8, x_{11}, x_9, x_7, x_4, x_{10}, x_6	x_8	x_6
Step 4	x_4, x_7, x_9, x_{10}, x_{11}	x_{11}, x_9, x_4, x_7, x_{10}	x_{11}	x_{10}, x_7
Step 5	x_9, x_4	x_9, x_4	x_9	x_4

Table 4: Selection of relevant input variables related to capillarity, using the fuzzy sensitivity variation criterion

	Remaining inputs	Ranked inputs by ascending ΔS	The relevant inputs	The irrelevant inputs
Step 1	All inputs, x_1 to x_{13}	x_{12}, x_1, x_{13}, x_9, x_{11}, x_8, x_6, x_{10}, x_4, x_7, x_2, x_3, x_5	x_{12}, x_1	x_5, x_3
Step 2	x_2, x_4, x_6, x_7, x_9, x_8, x_{10}, x_{11}, x_{13}	x_{13}, x_8, x_9, x_{11}, x_7, x_4, x_6, x_{10}, x_2	x_{13}	x_2, x_{10}
Step 3	x_4, x_6, x_7, x_9, x_8, x_{11}	x_8, x_9, x_{11}, x_4, x_7, x_6	x_8, x_9	x_6, x_7
Step 4	x_{11}, x_4	x_{11}, x_4	x_{11}	x_4

According to these tables, it can be noticed that, electrical power (x_{12}), treatment speed (x_{13}), fiber nature (x_1), fiber count (x_8), air permeability (x_9) and surface roughness (x_{11}) are identified as the most relevant independent inputs for both water contact angle and capillarity. This result indicates that the modification of textile surface is not only dependent on plasma parameters, but also influenced by woven fabric features. Thus, by using the fuzzy sensitivity criterion, the number of input variables has been reduced by more than 50%. The relevant parameters selected from this criterion can be ranked in a significant order of relevancy. In fact, the earlier a given relevant parameter is identified in the selection procedure, the more relevant it is to the corresponding output property. For example, electrical power is identified as a relevant parameter at the first step of the selection procedure for both outputs. This finding highlighted the fact that this parameter is more important than the other parameters selected at subsequent steps for both water contact angle and capillarity. This ability of ranking features by their relevance is very helpful since it would enable one to evaluate the sensitivity of each selected input parameter regarding the corresponding output. This would enable in turn a better understanding on the plasma treatment process since the adjustable parameters are more concise and easier to be interpreted physically.

The relevant selected parameters are used to set up neural network models. Two cases of network configurations are studied. In the first case, two separate networks with two hidden layers and one output layer neuron are considered. The first network had an output of water contact angle and the second had an output of capillarity. The optimal architecture obtained in this case is given in Figure 2. The number of neurons in the hidden layers was 5 in both layers in the first network and 6 and 4 in the first and second layer in the second network. In the second case, a single network with two hidden layers is considered. The input layer of this network corresponds to the six selected input parameters. The output layer corresponds to the two outputs viz. water contact angle and capillarity. The optimal architecture of this network is given in Figure 3. The number of neurons in the hidden layers was 8 and 6, respectively. These networks were trained using the Levenberg-Marquardt (*trainlm*) and the Bayesian Regularization (*trainbr*) training algorithms. The performances of these networks are measured by the root mean square errors on the training and test data sets. In order to get a true unbiased indication of the network performance, a regression analysis is performed between the network response and the corresponding targets. Tables 5 and 6 give a comparison of the performances of the two configurations trained with '*trailm*' and '*trainbr*', respectively. The scatter plots of the network models in both cases are given in Figures 4 and 5 for the '*trailm*' algorithm, and in Figures 6 and 7 for the '*trainbr*' algorithm.

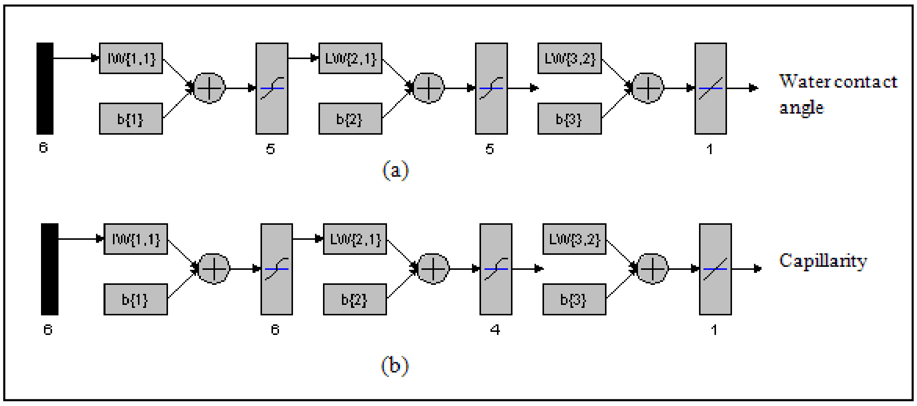


Figure 2: Network architecture for (a) water contact angle and (b) capillarity. IW(k,l) is the input weight matrix, LW(k,l) the layer weight matrix, and b(k) the bias vector

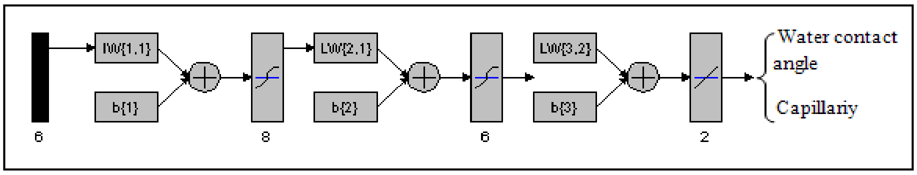


Figure 3: Network architecture for water contact angle and capillarity. IW(k,l) is the input weight matrix, LW(k,l) the layer weight matrix, and b(k) the bias vector

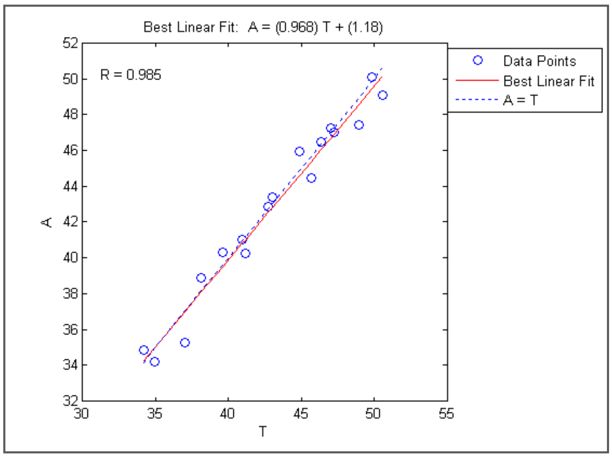
Table 5: Comparison of the two network configurations trained with Levenberg-Marquardt algorithm (*trainlm*)

Case study		Network architecture	Number of iterations	$RMSE_{Training}$	$RMSE_{Test}$	$R_{Training}$	R_{Test}
Case 1	Contact angle	6-5-5-1	25	0.734°	0.888°	0.9967	0.9848
	capillarity	6-6-4-1	105	2.08%	2.42%	0.9993	0.9993
Case 2	Contact angle	6-8-6-2	80	0.761°	1.084°	0.9965	0.9774
	capillarity			2.96%	3.47%	0.9986	0.9985

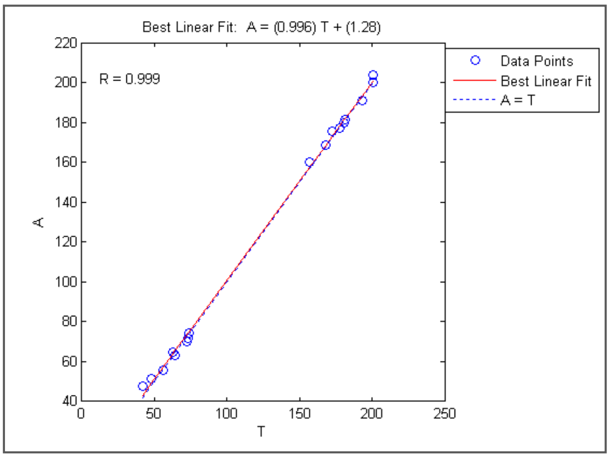
Table 6: Comparison of the two network configurations trained with Bayesian Regularization algorithm (*trainbr*)

Case study		Network architecture	Number of iterations	$RMSE_{Training}$	$RMSE_{Test}$	$R_{Training}$	R_{Test}
Case 1	Contact angle	6-5-5-1	60	0.461°	0.643°	0.9985	0.9917
	capillarity	6-6-4-1	145	0.92%	1.32%	1	0.9998
Case 2	Contact angle	6-8-6-2	120	0.569°	0.804°	0.9981	0.9876
	capillarity			1.67%	2.21%	0.9995	0.9994

It can be seen from tables 5 and 6 that the two cases give good correlation coefficients and acceptable prediction errors for both outputs, showing that their learning and generalization performances are good. This result is confirmed by Figures 4, 5, 6 and 7 which show that the network-predicted and observed test values fit closely. However, the networks models in case 1 are able to predict the water contact angle and capillarity with higher coefficients of correlation and less root mean square errors as compared with case 2. In addition, the number of hidden neurons in case 1 is less therefore the memory consumed for training is much less than in the second case. Moreover, results show that the networks trained with '*trainbr*' generalize well when tested with unseen data as compared to the networks trained with '*trailm*'. This finding can be attributed to the fact that Bayesian regularization does not require a validation data set to be separated out of the training data set. It uses all of the data. Thus, it can be concluded that the Bayesian regularization approach yields higher prediction accuracy than the early stopping technique.

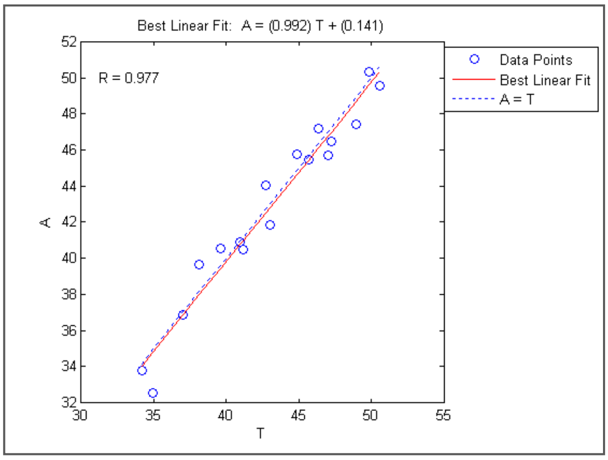


(a)

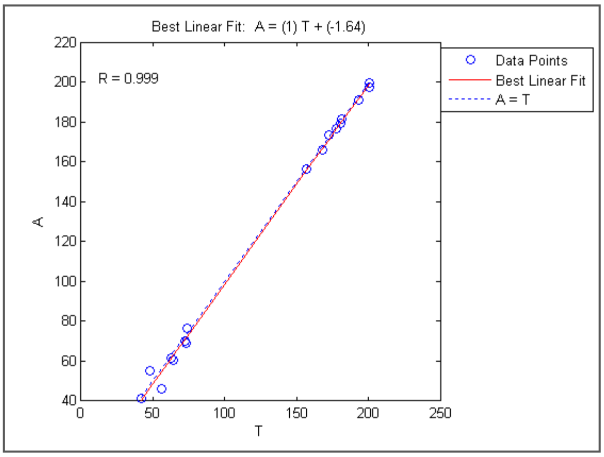


(b)

Figure 4: Correlation between output and target values of (a) water contact angle and (b) capillarity over the test set in case 1 trained with '*trainlm*'

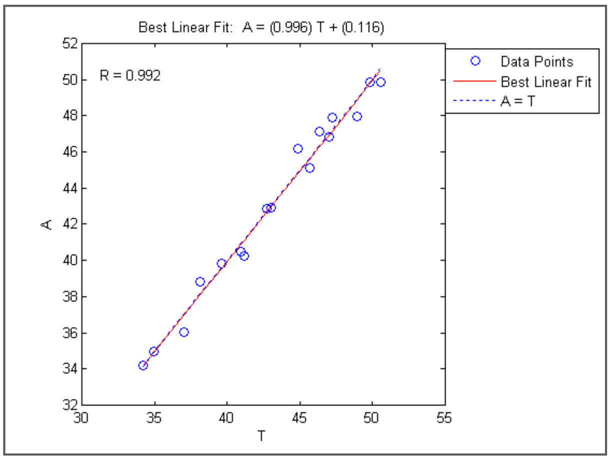


(a)

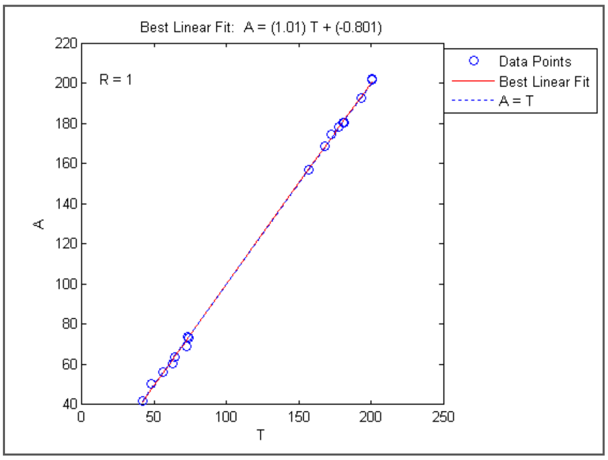


(b)

Figure 5: Correlation between output and target values of (a) water contact angle and (b) capillarity over the test set in case 2 trained with '*trainlm*'

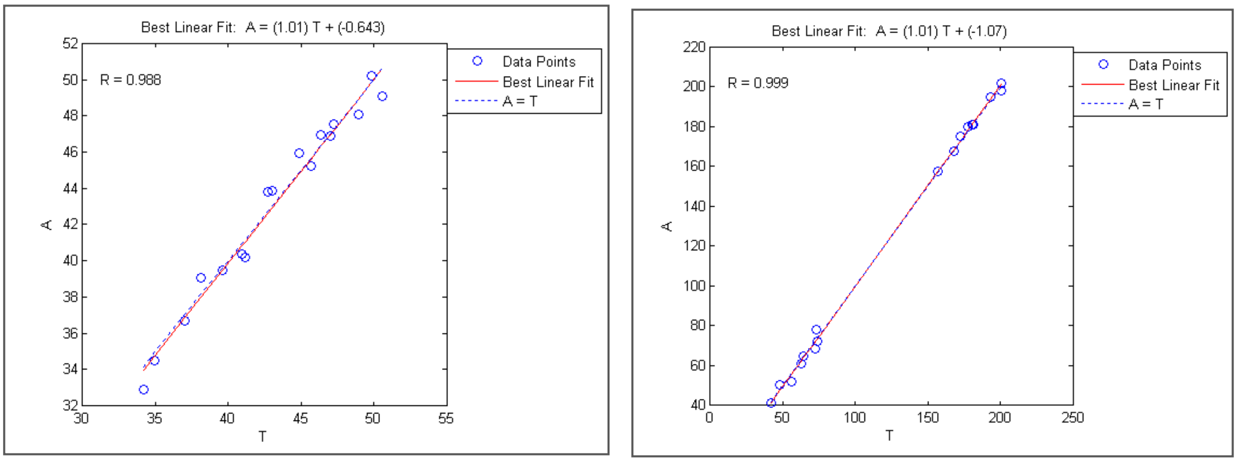


(a)



(b)

Figure 6: Correlation between output and target values of (a) water contact angle and (b) capillarity over the test set in case 1 trained with '*trainbr*'



(a) (b)

Figure 7: Correlation between output and target values of (a) water contact angle and (b) capillarity over the test set in case 2 trained with '*trainbr*'

4. CONCLUSION

In this paper, a fuzzy sensitivity criterion is used to select the most relevant parameters of plasma process which are taken as inputs of the neural net models. These models are different in the number of output neurons and learning algorithms. It was found that networks with one output layer neuron achieve better learning ability and predictive capability. Furthermore, obtained results show that the Bayesian regularization approach provides best performance on the training and test sets; however, it takes longer to converge than the early stopping. Thus, it is believed that neural networks are valuable tools to predict the water contact angle and the capillarity of woven fabrics subjected to plasma surface treatment.

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