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Modeling Plasma Fabric Surface Treatment Using Fuzzy Logic and Artificial Neural Networks

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Abstract. In this paper, Artificial Neural Networks (ANNs) are used to model the effect of atmospheric air-plasma treatment on fabric surfaces with various structures. In order to reduce the complexity of the models and increase the knowledge and comprehension of the underlying process, a fuzzy sensitivity variation criterion is used to select the most relevant parameters which are taken as inputs of the reduced neural models. The model outputs are the water contact angle and the capillarity of woven fabrics, characterizing the change of fabric surfaces. The early stopping and Bayesian regularization techniques are used for improving the network's generalization capability. Two different network configurations are studied. One deals with two networks having each one output layer neuron and another with a single network combining the two outputs. Obtained results showed that the first configuration combined with the Bayesian regularization approach is the most suitable to achieve a good prediction accuracy.

Keywords: neural networks, fuzzy selection criterion, modelling, atmospheric plasma, woven fabric

1. Introduction

In recent years, atmospheric plasma treatment has gained increasing interest for application in the textile industry. This technology is an environmentally friendly alternative to conventional wet-chemical processes, since it does not require the use of water and since there is no waste production. Other advantages of it include: low cost of operation, rapid processing and high efficiency. A plasma is a partially ionized gas composed of highly excited atomic, molecular, ionic and radical species, as well as photons and electrons. These active species can enable a variety of generic surface process including surface activation by bond breaking to create reactive sites, dissociation of surface contaminants (cleaning), material volatilization and removal (etching), and deposition of conformal coatings (polymerization) [1]. In all these processes, only the topmost layer of the material are modified leaving the bulk properties unaffected. The altered surface properties are ideal for dyeing, printing, or adhesive bonding. Although enormous literature is available on plasma surface modification of textile fabrics [2-9], a systematic study on the simultaneous effects of various reaction parameters on the surface properties is still lacking. In practice, the induced plasma effects depend not only on the gas used but on a multiplicity of factors like electrical power, treatment time, substrate nature and so forth [3,4,7,10]. The relationship between these factors and surface wetting properties is very complex and non-linear. It is very difficult to characterize this relationship analytically. Thus, we use neural networks to construct a model. In fact, neural networks have numerous attractive properties for modeling complex systems such as efficient learning from experimental data, universal approximations for any arbitrary complex relation between input and output patterns, resistance to noisy or missing data, and good generalization ability [11-13]. Indeed, neural networks have recently been applied to a variety of plasma-based processes [14-17]. In this way, studies have shown that neural network models exhibit superior accuracy and predictive capabilities over traditional statistical methods and require less experimental training data [18-20].

However, developing neural network models is constrained by many factors such as the complex non-linear 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. Therefore, selecting the most relevant input variables is critical to enhance model performance and increase interpretability of the results [21,22]. In this way, the selection of process parameters allows manufacturers to adjust only a few number of the most relevant parameters in order meet the requirements. In literature, many features selection techniques have been proposed [23-25]. In our study, as the number of available

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experimental data is rather limited, we use the fuzzy sensitivity variation criterion developed by Deng et al. [26,27] to identify the most relevant fabric parameters to achieve the desired modification results by air-plasma treatment. This method has been applied successfully to the design of a non-woven process [27]. By comparison with the classical selection methods, the proposed criterion has shown to be more robust and less sensitive to measured data noises and uncertainties. Furthermore, it can deal with a very few number of learning data. These advantages proved a strong motivation to the present paper for using such method to select the most relevant plasma process parameters in order to reduce data complexity and obtain more interpretable results with a very limited cost. The results obtained from this fuzzy-based method will enable to better understand, control and optimize the plasma process in order to obtain the desired effect.

In this paper, a fuzzy sensitivity criterion is used to select the most relevant input parameters of plasma process to be used to develop neural network models for predicting fabric surface wetting properties. 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.

2. Experiments and measurements

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 are 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).

Table1. The range of woven fabric features.

Parameter	Minimum	Maximum
Fiber nature	0 (100% polyester)	1 (100% viscose)
Fabric weight (g/m^2)	160	200
Thickness (mm)	0.31	0.41
Construction	0 (plain)	1 (3/1 twill)
Weft density (picks/cm)	17.2	21
Warp density (ends/cm)	39.2	45
Weft count (dtex)	150	340.29
Fiber count (dtex)	0.9	1.7
Air permeability (l/m^2s)	19.62	786.2
Porosity (%)	60.55	69.51
Surface roughness (μm)	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 (Fig.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. During plasma treatment, woven samples are in contact with the counter-electrode, and passed through the plasma gas present between the electrodes/counter electrode gap.

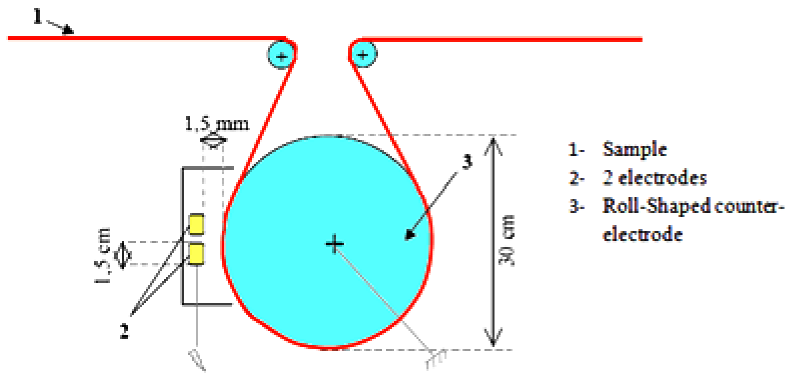

Fig. 1: Atmospheric plasma treatment, using "Coating Star" system.

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)

$$W_m = W_t - W_c \quad (1)$$

The water contact angle of woven samples can be determined from the meniscus weight using Eq. (2), since both the surface tension of liquid water and the perimeter of the contacting surface are know.

$$W_m \times g = \gamma_L \times \cos\theta \times p \quad (2)$$

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 values for the woven samples are obtained from the capillarity weight values (W_c) from wettability experiments 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.

3. Selection procedure of relevant input parameters

In this paper, the fuzzy sensitivity criterion developed by *Deng et al.* [26,27] 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. Its principle consists of calculating distances or variations between individual data samples in the input space (process parameters) and the output space (quality features), respectively. Then, fuzzy logic is used to evaluate the sensitivity variation of each input variable related to the output variable. The sensitivity for all the input variables is defined according to the two following principles:

1) 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 great sensitivity value S.

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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 [26,27].

Given a specific output variable y_l, for any pair of data sample (x_i, y_{jl}) and (x_j, y_{jl}) denoted as (i, j), the input data variation Δx_{ij} and the output data variation Δy_{ij} are calculated. The corresponding sensitivity in the data pair (i, j) related to y_l, can be obtained from this fuzzy model, i.e. $S_l(i, j) = FL(\Delta x_{ij}, \Delta y_{ij})$.

When removing x_k from the whole set of input variables, the sensitivity of the remaining input variables in the data pair (i, j) related to the output y_l can be calculated by $S_{k,l}(i, j) = FL(\Delta x_{ij}^k, \Delta y_{ij})$. The sensitivity variation of the pair (i, j) can be calculated as follows:

$$\Delta S_{k,l}(i,j) = \left| FL(\Delta x_{ij}, \Delta y_{ij}) - FL(\Delta x_{ij}^k, \Delta y_{ij}) \right| \tag{4}$$

The general sensitivity variation $\Delta S_{k,l}$ for all pairs of data samples when removing the variable x_k is defined by

$$\Delta S_{k,l} = \frac{1}{\gamma} \sum_{i=1}^{n} \sum_{j=i+1}^{n} \Delta S_{k,l}(i,j) \tag{5}$$

where $\gamma = n(n-1)/2$ the total number of data pairs.

Bigger is the value of $\Delta S_{k,l}$, more the corresponding variable x_k is relevant to the quality feature y_l.

Based on this fuzzy logic sensitivity criterion, we proposed the following algorithm for selecting the most relevant variables and removing irrelevant ones.

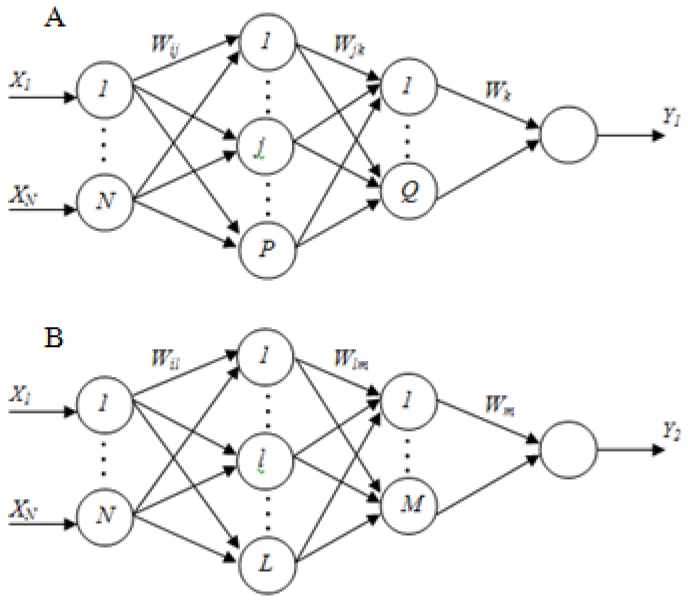
Inputs: process input variables $X=\{x_1,\ldots,x_m\}$ and one related specific output y_l
Output: relevant process parameters X_r, and related sensitivity variation value ΔS
ε : threshold of sensitivity variation

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
$\Delta S'_l = \{\Delta S_{1,l}, \ldots, \Delta S_{k,l}, \ldots, \Delta S_{size(X'),l}\}$
$X_r=X_r \cup \{x_i\}$, $X'=X' \setminus \{x_i\}$ where $\Delta S_{i,l} > 1-\varepsilon$
$X'=X' \setminus \{x_j\}$ where $\Delta S_{j,l} < \varepsilon$
End
$\Delta S = \Delta S'$

This algorithm combines both the forward and the backward search by removing the subset of the most sensitive variables and the subset of the most insensitive variables at each step. A small positive value is defined for eliminating non significant ranking order of variables. All the variables whose sensitivity variations are included between 1 and 1 are considered as the most sensitive variables. The most insensitive variables correspond to the case in which their sensitivity variations are smaller than . When this recurrent procedure is completed, we can obtain a significant and independent list of the most relevant process parameters.

4. Modeling with artificial neural networks

In this paper, feed-forward neural networks are used for the plasma modeling due to their proven high accuracy in learning nonlinear process data [14,15,18]. The network architecture includes two hidden layers. The input layer corresponds to the selected input parameters. The outputs are the water contact angle and the capillarity values. Two cases of network architecture, as shown in Figs. 2 and 3, are compared to discuss the prediction efficiency of the networks. 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.



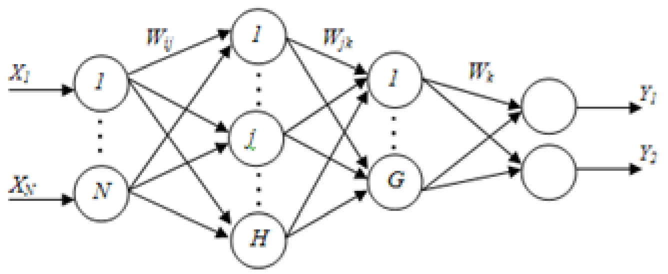
$X_1 \ldots X_N$ = input layer vector

W = weight vector

P, Q, L, M = neurons in hidden layer 1 and 2

Y_1, Y_2 = output of network 'A' and 'B' respectively

Fig.2. Network architecture of case 1.



$X_1 \ldots X_N$ = input layer vector

W = weight vector

H, G = neurons in hidden layer 1 and 2

Y_1, Y_2 = network outputs

Fig.3. Network architecture of case 2.

These networks were trained with two different algorithms: the levenberg-Marquardt algorithm (*trainlm* MATLAB training function) and the Bayesian regularization algorithm (*trainbr* MATLAB training function). The first algorithm uses an early stopping mechanism in which the error on the validation set is monitored during the training process and training is stopped when the prediction accuracy begin to decrease, whereas the second algorithm is a modification of the first one to improve the model's generalization capability. The modification consists of changing the performance function, which is normally chosen to be the sum of squares of the network errors (MSE), by adding a term that consists of mean square error of weight and biases. This performance function will cause the network to have smaller weight and biases there by forcing networks less likely to be overfit [28].

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 validation set is used to terminate training done with the training set. The testing set is kept independent and used in accuracy assessment only after training has converged.

The number of neurons in the hidden layers can significantly affect the efficiency and accuracy of learning. Thus, for optimizing the network models, the number of hidden neurons 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. This algorithm can be illustrated in the following pseudo-codes,

1. *Create an initial network with one neuron in each hidden layer* $N_{H1} = 1 \text{ and } N_{H2} = 1$.
2. *Realise 50 training iterations.*
3. *Calculate the root mean square errors* ($RMSE_{Training}, RMSE_{Test}$) *and the correlation coefficients* ($R_{Training}, R_{Test}$) *in the training and test sets.*
4. *Compare* $RMSE_{Test}$ *to* $RMSE_{Training}$ *and the correlation coefficients to 1.*

IF $\left(\frac{RMSE_{Test}}{RMSE_{Training}} < \alpha\right)$ *and* $(R_{Training} > 0.85)$ #
and $(R_{Test} > 0.85)$
Keep the predicting model with N_{H1} *and* N_{H2}
ELSEIF $N_{H1} \leq N_{H2} + 5$
Let $N_{H1} = N_{H1}$
ELSE
Let $N_{H2} = N_{H2} + 1$ *and go back to Step 2*
END IF

According to this algorithm, 50 iterations are applied at each time and some stopping criteria are used to determine when stop adding new hidden neurons**.** 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 in the same order and as small as possible, and the correlation coefficients are close to 1. The test and training root mean square errors are considered in the same order if their ratio is close to 1. Therefore, this ratio should be less than a given threshold value α to obtain good network's generalization ability. In overall, this method will help to find the optimal or at least the near-optimal number of hidden neurons since the learning algorithms used can avoid being trapped into local minima. In our application, α is set to be to 1.5. The training and test root mean square errors are calculated according to Eq. (6) and (7), respectively

$$RMSE_{Training} = \frac{1}{N_T}\sum_{i=1}^{N_T}(d_i - y_i)^2 \quad (6)$$

$$RMSE_{Test} = \frac{1}{N_t}\sum_{i=1}^{N_t}(d_i - y_i)^2 \quad (7)$$

where N_T the number of training samples is, 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. In this application, R values superior to 0.85 are considered as good matching to the targets.

5. Results and discussions

In this study, 11 fabric features and 2 plasma parameters are taken as input parameters of the plasma process. These parameters are pre-selected by experts according to their possible influence on the outputs, i.e. the water contact angle and the capillarity, as shown in Table 2.

Table 2. Input and output parameters of the plasma process.

Factor	Variables names
Plasma process parameters (inputs)	*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})
Fabric surface wetting properties (outputs)	water contact angle (y_1); capillarity (y_2)

If we take all these 13 plasma process parameters as input variables, this would increase the amount of data required to estimate the network parameters efficiently and decrease the processing speed. Thus, in order to reduce the complexity of the model and the related field data collection efforts, we use the fuzzy-based method presented forward in this paper to select the most 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 detailed steps for recursively selecting the inputs relevant to water contact angle and capillarity.

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

	Remaining inputs	Significance ranked by	Most relevant inputs	Irrelevant inputs

		ascending order ΔS		
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 input variables relevant to capillarity, using the fuzzy sensitivity variation criterion.

	Remaining inputs	Significance ranked by ascending order ΔS	Most relevant inputs	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 inputs for both water contact angle and capillarity. The only difference between them is that the orders of these two ranking lists of relevant inputs are slightly different. 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 plasma processing parameters has been reduced by more than 50%. The relevant parameters selected from this criterion can be ranked in a significant order of relevancy. For both the water contact angle and capillarity, the most important plasma process parameter is electrical power. The obtained two ranking lists are conform to general professional knowledge of experts. Therefore, it can be concluded that the fuzzy sensitivity variation criterion can effectively filter data complexity related to plasma process and provide only a better ranking results according to the process parameters relevancy. This enables in turn a better understanding on the plasma process since the adjustable parameters are more concise and easier to be interpreted physically.

The selected relevant parameters are used to set up feed-forward neural networks 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 Fig. 4. 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 Fig. 5. 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 computing the root mean square errors (RMSE) over the training and test data subsets. 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 network model predictions in both cases are given in Figs. 6 and 7 for the '*trailm*' algorithm and respectively in Figs. 8 and 9 for the '*trainbr*' algorithm.

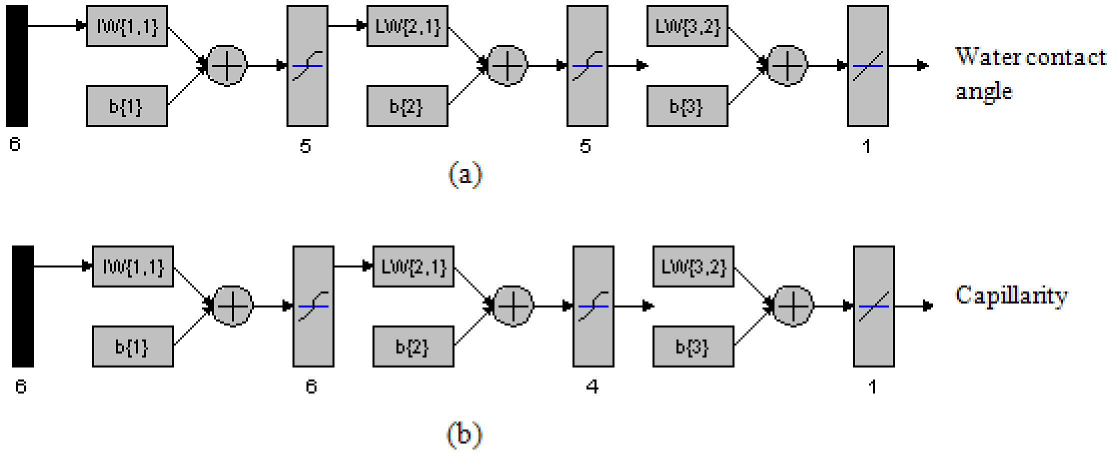


Fig.4. Network architecture for (a) water contact angle and (b) capillarity.

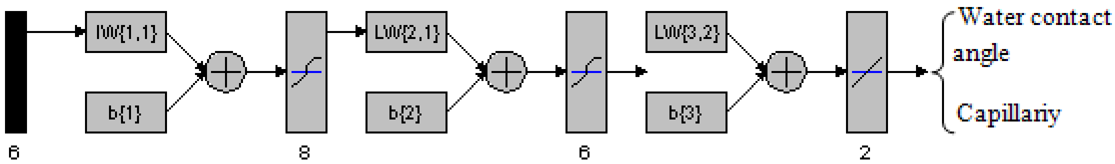


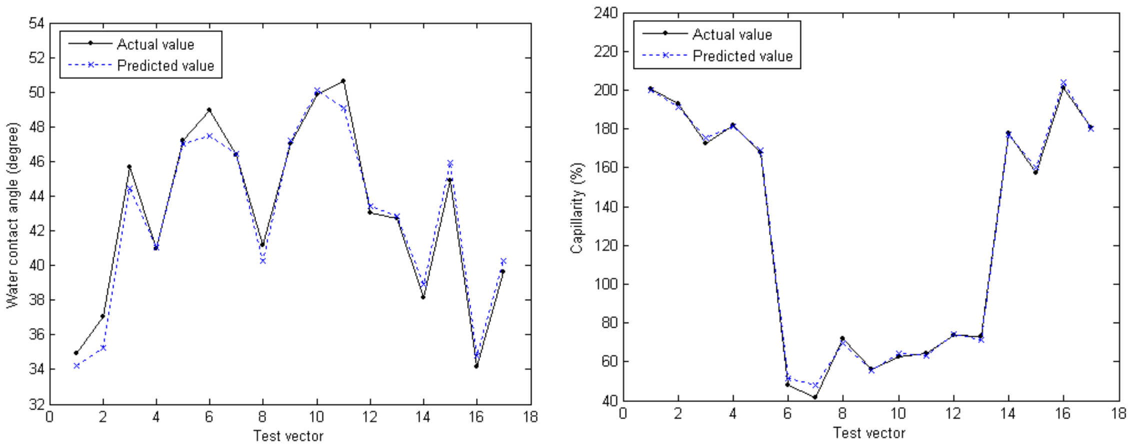
Fig.5. Network architecture for water contact angle and capillarity.

Table 5. Comparaison 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	0.9992
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

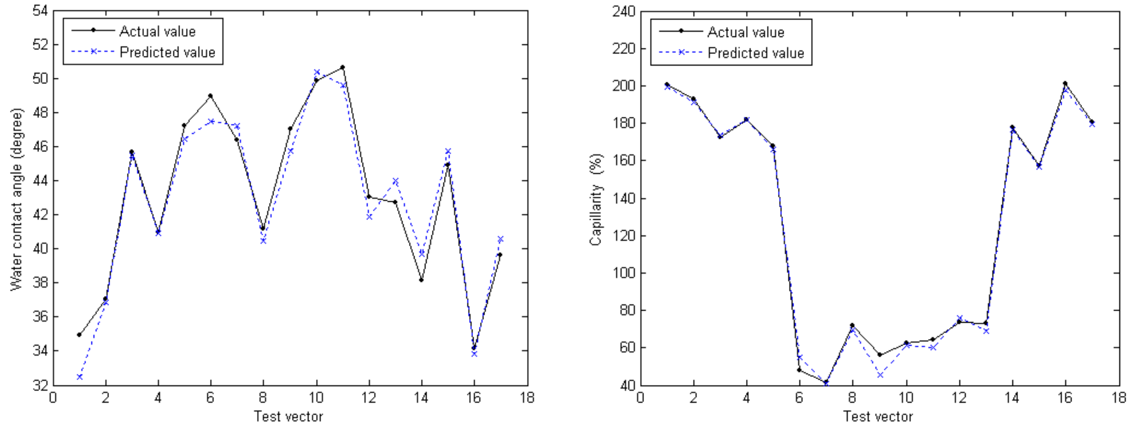
Table6. Comparaison of the two network configurations trained with Bayesian Regularization algorithm (*trainbr*).

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



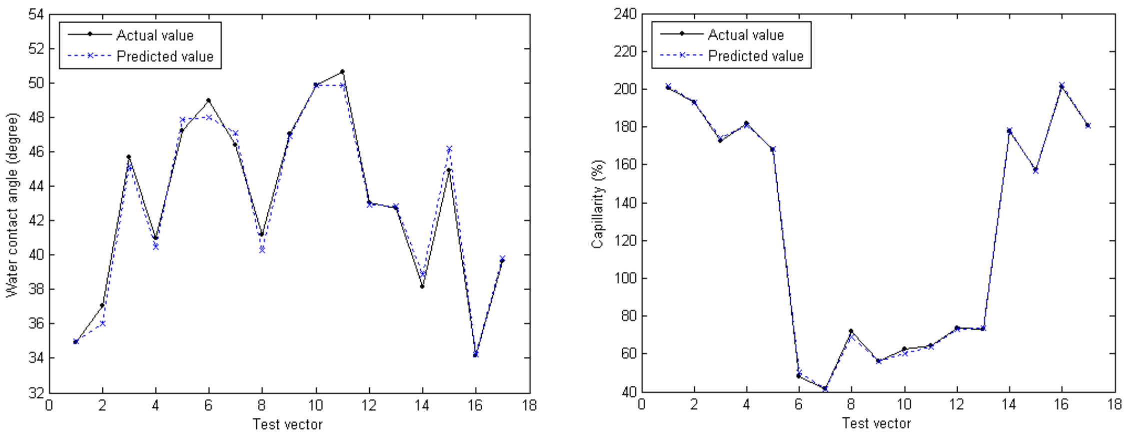
(a) (b)

Fig.6. ANN model prediction of (a) water contact angle and (b) capillarity in case 1 (*trainlm*)



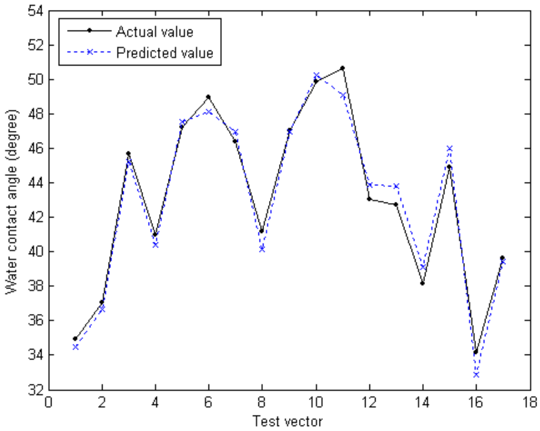
(a) (b)

Fig.7. ANN model prediction of (a) water contact angle and (b) capillarity in case 2 (*trainlm*).

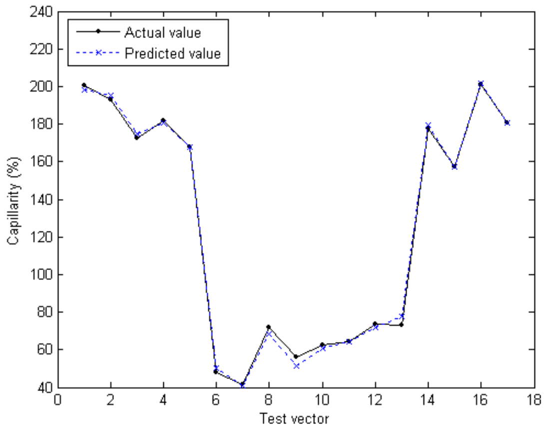


(a) (b)

Fig.8. ANN model prediction of (a) water contact angle and (b) capillarity in case 1 (*trainbr*)



(a)



(b)

Fig.9. ANN model prediction of (a) water contact angle and (b) capillarity in case 2 (*trainbr*).

It can be seen from tables 5 and 6 that the two cases give high correlation coefficients and acceptable predictions errors for both outputs, showing that their learning and generalization performances are good enough. This result is confirmed by Figs. 6, 7, 8 and 9 which show a good agreement between predicted and observed data values. 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 less much than 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*'. Thus, the Bayesian regularization approach yields higher prediction accuracy than the early stopping technique. Also, another advantage of this method is that, it does not require any separate validation data set. Also, it can be noticed that training with the '*trainbr*' algorithm takes more iterations than with the '*trainlm*' algorthim. This can be explained by the fact that the Bayesian regularization method generally takes longer to converge than early stopping. Consequently, it can be concluded that the neural network methodology is helpful towards a better understanding of the relationship between plasma processing parameters and fabric surface wetting properties

6. CONCLUSION

In this paper, a fuzzy sensitivity variation criterion was used to select the most relevant input parameters of plasma process which were used to set up feed-forward neural network models. This selection procedure would allow manufacturers to focus on the most relevant parameters in order to optimize the underlying process and minimize the number of experiments. The developed network models were different in a number of output neurons and learning algorithms. Obtained results showed that networks with one output layer neuron achieve better learning ability and predictive capability. Furthermore, it was found that the Bayesian regularization approach provides best performance on the training and test sets but, it takes longer to converge than the early stopping. Thus, it is believed that neural network models can be efficiently applied to understanding, evaluation and prediction of fabric surface modification by atmospheric air-plasma treatment.

7. References

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