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ANN AND FUZZY TECHNIQUES FOR MODELING THE RESIDUAL BAGGING BEHAVIORS OF DENIM FABRICS AS FUNCTION OF FRICTIONAL PROPERTIES

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ABSTRACT

This paper deals with the evaluation and prediction of the residual bagging behaviors of denim fabric specimens. It also provides the impact of each frictional input parameter in our experimental field of interest to simulate the bagging phenomenon after several denim clothing uses. Hence, we attempt to formulate theoretical models of predicting bagging behaviors. Therefore, two soft computing approaches, artificial neural network (ANN) and the fuzzy inference system (FIS), have been applied and compared. The prediction accuracy and performance of these models was evaluated using the correlation coefficient (R), the root mean square error (*RMSE*) and the mean relative absolute error (*MRAE*).
The obtained results show the models' ability to predict the bagging behaviors of denim fabrics from the frictional parameters. Therefore, according to the analytical findings, the comparison of the modeling technique prediction performances shows that fuzzy models give a more accurate result than the neural network models.

KEYWORDS

Bagging behaviors; Denim fabric; Frictional inputs; Fuzzy logic; Neural network.

1. INTRODUCTION

Bagging is the residual part which remains after several multidirectional requests, such as in the knees, elbow and hand zones. The literature suggests that many studies are conducted to predict and analyze the bagging bend phenomenon based on the yarn and fabric properties (Abghari et al., 2001; Amirbayat and Namiranian, 2006a, 2006b; Dostar et al. 2010; Karimian et al. 2013; Gazzah et al. 2014a). However, no more works were conducted to evaluate and modeling the bagging behaviors basing on the frictional inputs related to yarns and fabrics.
Modeling of the bagging behaviors by deciphering the relationship between both the yarn and fabric properties can be considered as a fruitful field in textile research. In fact, it seems important from the industrial and user's viewpoint, because it affects the appearance quality of the garments. To predict the bagging properties Zhang et al. (Zhang et al. 2000a, 2000b, 2000c) studied the viscoelastic behavior of fibres during the bagging of wool woven fabrics using a mathematical model based on of rheological mechanisms. The prediction accuracy of these mathematical models is not very encouraging due to the assumptions or simplifications used while building these models.
Statistical regression modeling techniquesare alsoused by many researchers to predict the bagging behaviors of knitted and woven fabrics (Zhang et al., 1997; Hassani and Zadeh, 2012; Gazzah et al., 2014b, 2015b).
Some intelligent techniques such as fuzzy logic and neural network approaches are used in large textile applications, due to their flexibility and accuracy of modeling complex textile phenomena. Besides, two different metaheuristic techniques (Ant Colony Optimization approach and Genetic Algorithm) were also applied to optimize the bagging behaviors (Gazzah et al., 2015 a). Frictional inputs, as well as those related to yarn and fabric structures are investigated to analyze their significances on the regression models relative to bagging properties. Also, to evaluate fabric bagging behaviors, Young et

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al. (2002), used the neural network to modeling fabric bagging when evaluating the subjective perception data of the bagging appearance which can be predicted from the images of the bagged fabrics. Jaouachi (Jaouachi et al., 2010; Jaouachi, 2013) has successfully used the fuzzy modeling to study and predict only the residual bagging bend height of knitted fabric which is not sufficient to characterize the bagging appearance. Until now, there is no sufficiently information to evaluate and predict the contribution of the yarn and fabric friction parameters on the residual bagging behavior. In this paper, the neural network and fuzzy logic-based models are compared and discussed to predict the residual bagging behaviors, expressed by residual bagging height, residual bagging volume, bagging recovery and the kinetic velocity, of denim fabrics as function of the studied frictional parameters.

2. METHODS AND MATERIALS

2.1. Data base

Twenty nine twill 3/1 denim fabric samples were industrially produced, investigated and studied in the present work. The details of yarn parameters related to the studied specimens were given by Table 1. First, to measure yarn-to-yarn friction, weft yarns composed the bagged fabrics, developed instrument, Simulator Abrader Tester are used (Jaouachi et al., 2011b). The number of abrasion cycles and the residual mechanical properties reflect the friction between yarns and rigidity rate. Before the yarn breakages, the number of abrasion cycles was saved and then, the yarn shear rigidity was measured using a dynamometer tester type Lloyd. The average abrasion cycle values of each yarn sample correspond to 50 tests.

Table 1: Details of yarn samples

Fabric Id.	Linear density (tex)		Twist (T/m)		Breaking strength (N)		Elongation at break (%)		Rigidity (N/m)		Abrasion (cycles)	
	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft
1	80	38	413	458	9.78	5.99	8.04	5.84	521	554	1250	1756
2	100	47	467	342	11.42	5.78	7.05	5.18	365	635	2000	1820
3	80	80	413	431	9.78	9.74	8.04	6.73	521	1369	1250	1750
4	80	47	413	342	9.78	5.78	8.04	5.18	521	635	1250	1820
5	88	70	526	622	7.86	5.99	6.45	5.81	517	1546	1850	1242
6	88	70	526	622	7.86	5.99	6.45	5.81	517	942	1850	1642
7	84	52	460	324	7.98	5.73	6.37	5.75	549	1935	1330	700
8	84	50	569	434	7.98	6.28	6.37	6.72	549	1769	1360	750
9	60	47	674	342	9.47	5.78	6.31	5.18	432	635	1600	1820
10	70	56	621	641	9.06	9.45	5.17	6.34	652	672	1420	1820
11	80	47	413	565	9.78	6.39	8.04	10.11	521	623	1250	2000
12	80	60	413	453	9.78	7.2	8.04	10.9	521	1167	1250	1430
13	80	60	413	324	9.78	8.08	8.04	5.49	521	1683	1250	750
14	80	67	413	317	9.78	5.62	8.04	4.39	521	1957	1250	700
15	80	47	413	824	9.78	6.39	8.04	10.11	521	623	1250	2000
16	80	47	413	342	9.78	5.78	8.04	5.18	521	635	1250	1820
17	80	60	413	324	9.78	6.98	8.04	4.39	521	1810	1250	1600
18	80	36	413	541	9.78	3.82	8.04	4.35	521	713	1250	1970
19	80	60	413	324	9.78	6.98	8.04	4.39	521	1810	1250	830
20	80	36	413	715	9.78	4.44	8.04	5.81	521	623	1250	2000

21	70	36	621	715	9.06	4.44	5.17	5.81	652	623	1420	2000
22	88	67	526	647	7.86	6.28	6.45	6.49	517	721	1710	1542
23	88	42	526	626	7.86	6.68	6.45	6.31	517	643	1710	1843
24	80	80	413	547	9.78	9.54	8.04	11.36	521	761	1250	2000
25	80	36	413	715	9.78	4.44	8.04	5.81	521	623	1250	2000
26	80	47	413	741	9.78	6.28	8.04	7.58	521	647	1250	1820
27	60	36	674	715	9.47	4.44	6.31	5.81	432	623	1600	2000
28	80	36	413	635	9.78	5.88	8.04	8.49	521	947	1250	1750
29	80	36	413	635	9.78	5.88	8.04	8.49	521	947	1250	1750

Second, to objectively measure and calculate the frictional forces generated by the conformator (a hemispherical ball) to the surface of denim samples, the shear and the tensile properties, the Kawabata Evaluation System KES- FB4 (Kawabata & Niwa, 1991) was used. Even though, to simulate the impact of friction caused by the conformator to fabric during bagging test, the frictional coefficient (MIU) parameter values were calculated. The KES- FB4 system is equipped by a hand feeling finger touch system to measure and evaluate the MIU frictional property of tested fabrics.

Table 2 shows the principal fabric characteristics investigated such as composition, weft density (Wt_D), and the mechanical properties measured using the Kawabata evaluation system for fabrics. These parameters are measured to evaluate the friction contribution on the recovery kinetic velocity of bagged samples.

Table 2: Main details of the denim fabric samples

Fabric Id	Composition	Mass (g/m^2)	W_D^a (cm^{-1})	MIU_{Wp}^b (-)	MIU_{Wt}^c (-)	G_{Wt}^d (N/m. radian)	G_{Wp}^d (N/m. radian)	EM^e (%)	LT^f (-)
1	95%CC$^{\alpha}$+5% Elast$^{\beta}$ (RG+78dtex)	352	22	0.163	0.186	1.64	4.03	0.864	1.41
2	100% CC	391	24	0.171	0.198	1.18	3.42	0.924	1.86
3	100% CC	438	21	0.163	0.184	1.18	3.42	0.924	2.45
4	100% CC	311	22	0.147	0.15	4.75	4.98	0.863	6.18
5	100% CC	316	17	0.164	0.133	8.89	10.39	0.805	7.12
6	100% CC	371	23	0.181	0.145	7.78	33.66	0.564	6.58
7	100% CC	342	16	0.178	0.145	7.018	5.54	0.801	5.31
8	100% CC	323	17	0.166	0.133	7.97	3.73	0.869	6.25
9	100% CC	288	22	0.192	0.136	7.53	7.49	0.788	6.63
10	100% CC	299	22	0.17	0.170	4.10	20.96	0.675	3.21
11	95%CC+5% Elast (RG+78dtex)	328	18	0.188	0.182	1.83	18.98	0.708	1.39
12	71%CP$^{\eta}$+24%PES$^{\sigma}$+5% Elast	410	20	0.194	0.188	2.18	19.11	0.61	5.17
13	100% CP(♠OE)	394	20	0.186	0.174	5.14	8.98	0.735	3.23
14	100% CC (OE)	341	19	0.172	0.180	7.72	8.27	0.817	3.39
15	95%CC+5% Elast (♣RG+78dtex)	372	18	0.181	0.181	5.91	18.01	0.606	1.77
16	100% CC	368	22	0.186	0.176	5.73	22.3	0.596	2.27
17	100% CC	390	20	0.16	0.166	4.64	4.03	0.864	3.39
18	95% TENCEL + 5% Elast	359	17	0.192	0.183	4.70	21.62	0.695	2.74
19	100% CC	387	22	0.192	0.188	2.72	22.25	0.638	2.28

20	71%CP+24%PES+5% Elast	341	19,5	0.2	0.189	2.33	24.33	0.617	1.93
21	71%CP+24%PES+5% Elast	328	22	0.171	0.188	1.62	6.03	0.852	1.10
22	95%CC+5% Elast (RG+78dtex)	445	17	0.139	0.192	2.37	29.13	0.584	2.03
23	95%CC+5% Elast (RG+78dtex)	416	20	0.175	0.189	2.07	14.13	0.725	2.00
24	71%CP+24%PES+5% Elast	430	20	0.189	0.196	1.83	34.62	0.569	1.43
25	71%CP+24%PES+5% Elast	334	21	0.183	0.185	2.35	20.33	0.61	2.48
26	71%CP+24%PES+5% Elast	223	21	0.201	0.181	2.34	32.87	0.512	1.59
27	71%CP+24%PES+5% Elast	243	20	0.17	0.184	2.26	18.98	0.75	2.1
28	95%CC+5% Elast (RG+78dtex)	356	20	0.186	0.187	1.04	10.81	0.733	1.02
29	95%CC+5% Elast (RG+78dtex)	342	22	0.191	0.194	2.33	31.84	0.621	2.54

Note: $^{\alpha}$CC : carded cotton, $^{\beta}$Elast : elastane, $^{\eta}$CP: Combed cotton, $^{\sigma}$PES: polyester, $W_D{}^{a}$: the weft density, $MIU_{Wp}{}^{b}$: the frictional coefficient in the warp direction of the fabric, , $MIU_{Wt}{}^{c}$: the frictional coefficient in the weft direction of the fabric, $G_{Wt}{}^{d}$: the shear rigidity in the weft direction of the fabric, $G_{Wp}{}^{d}$: the shear rigidity in the warp direction of the fabric, EM^{e}: the fabric elongation at 500 gf/cm in the weft direction of the fabric, LT^{f}: the linearity of stress/elongation curve tested in the weft direction of the fabric, (-): without unit, ♦OE: means Open End spun yarn, ♣RG: means Ring spun yarn.

For the bagging test, all specimens are conditioned during 24 hours on the experimental laboratory conditions to be relaxed. Moreover, the size of each specimen prepared to bagging test is 100mm x 50mm. According to the French Standard NF G 07-213 (Afnor, 2001), bagging tester type *Sodemat* was used to measure residual bagging height R_{bh_t}each 5 minutes. Therefore, the bagging recovery ($\mathrm{B_{rec}}$) values were measured as function of different relaxation times (see Equation 1).

$$\mathrm{B_{rec}}(mm) = R_{bh_{t+1}} - R_{bh_t} \quad (1)$$

Where:

- R_{bh_t}: Residual bagging height value at “t” time expressed in millimetre.
- $R_{bh_{t+1}}$: Residual bagging height value at “t+1” time expressed in millimetre.

Similarly, to evaluate the recovery velocity variation during relaxation time, the values of the bagging height were investigated and saved each five minutes. The kinetic velocity value,traducing the bagging ability of fabric to return to the initial position, of the residual bagging height $\mathrm{KV_{bh}}$ is calculated using the Equation 2.

$$\mathrm{KV_{bh}} = \frac{\mathrm{bh_0 - bh_t}}{\mathrm{t}} \quad (2)$$

Where:

- bh_0: The initial bagging height value when the applied conformator is removed.
- bh_t: The residual bagging height value after the applied relaxation time.
- t: The time after which the residual bagging measured to express the denim fabrics recovery value.

The bagging testand the experimental conditions are described in Jaouachi’s work (Jaouachi, 2013). Hence, each woven fabric sample should be maintained under hemispherical ball during 5 hours. The applied steel ball, called either conformator, load was deduced by using preliminary elongation test during 48h under 300 cN regarding the *Sodemat* manufacturer’s instructions.

To evaluate the residual bagging volume of denim samples, image analysis process was adopted and included capturing digitized images of bagged zones. Then, image processing of the captured images, transforming digitized values to recognize residual bagging volume, R_{bv}.

During image processing, overall suitable parameter values such as the magnification value, the position, the brightness, and the angle of the light source, are adjusted and then kept constant to obtain comparative images and results. After bagging test, the studied samples are captured using a digital camera. So, the obtained images are transferred into gray level (ranged from 0, referred to black colour to 255 referred to white colour) images which refer to a two dimensional light intensity function. The gray level distribution presented the 3D bagging volume appearance. Using *mesh* function on Matlab software, the images in 3D are obtained by conversion of those previously presented in 2D into gray scale level and returned into double precision. An uneven distribution of intensity in the image was occurred due to both the 3D deformation and the fabric texture’s colour. These intensity distribution values stilled function of the fabric variation profile which modified the gray level over a certain spatial distance. Each sample was repeated 9 times to obtain mean residual bagging volume values. Indeed, Table 3 shows the different parameters characterizing residual bagging behaviour (R_{bh}, R_{bv}, $KV_{bh}$and B_{rec}) relative to the different tested denim fabric samples.

Table 3: Bagging behaviour parameters of denim fabric samples.

Fabric Id	R_{bv}(mm^3)	R_{bh}(mm)	B_{rec}(%)	KV_{bh}(10^{-6} m/s)
1	4150	10.2	32	9.02
2	2500	10.1	32.66	9.66
3	5500	10.8	28	10.53
4	6750	12.78	14.8	12.19
5	9250	14	6.66	13.03
6	7450	13.1	12.66	12.79
7	7874	13	13.33	12.88
8	8243	13.5	10	12.22
9	8100	13	13.33	12.36
10	4500	11	26.66	10.47
11	4282	11	26.66	10.43
12	5464	12	20	12.06
13	4610	11.5	23.33	10.5
14	5406	12	20	11.68
15	5312	11.5	23.33	11.25
16	4549	11	26.66	11.07
17	6100	11	26.66	11.01
18	5560	11.1	26	10.83
19	4056	10.75	28.33	11.21
20	2430	10.02	33.2	10.85
21	3525	10.34	31.06	10.51
22	2338	10.03	33.13	10.37
23	3585	10	33.33	10.28
24	3050	10.03	33.13	9.56
25	3361	10.17	32.2	10.01
26	3642	10.4	30.66	10.19
27	3800	10.5	30	10.51
28	3711	10.64	29.06	10.31
29	4130	10.94	27.06	10.99

In our work, fuzzy logic and neural network methods are conducted and compared to determine the best one in bagging behaviours prediction.

2.2. Artificial Neural Network

An artificial neural network (ANN), usually called neural network (NN), is a mathematical or computational model that tries to simulate the structure and functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation.

Neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. There were many different ANN structures and learning algorithms. Among these algorithms, multilayers perception (MLP) had been successfully applied. A typical multi-layers neural network with a single hidden layer is shown in Figure 1. Each neuron received a signal from the neurons from the previous layer and these signals were multiplied by separate synaptic weights. The weighted inputs were then summed up and passed through a transfer function, which converted the output to a fixed range of values.

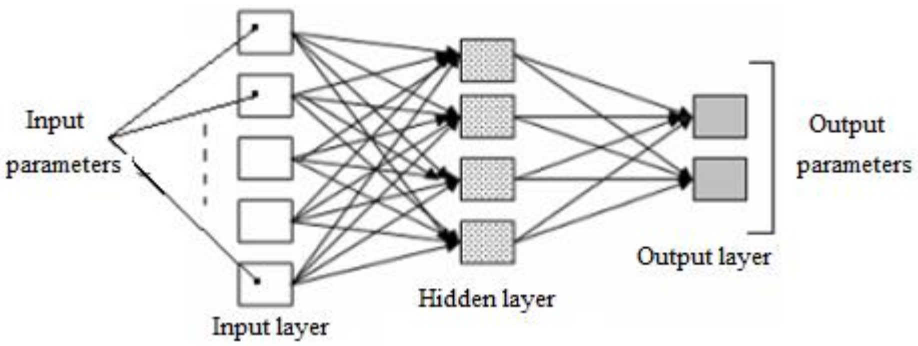


Figure 1: An example of multilayer artificial neural network

The output of the transfer function was then transmitted to the neurons of the next layer. This process continued and finally the output was produced at the output node. Predicted output was then compared with the desired output and an error signal was generated. The error signal was then minimized in iterative steps by adjusting the synaptic weights using a suitable training algorithm. Among the various kinds of algorithms for training neural network, back propagation algorithm, was the most widely used one. Network weights were adapted iteratively until some appropriate stopping criteria were met and the best weight vector that corresponds to the best generalization was achieved.

2.3. Fuzzy logic method

A fuzzy logic theory system works on many types of vague data, but the originator must specify the relations between them using a rule database. The rules start in parallel to accumulate the presumptions in favour or not of such or such solution. A fuzzy set contains elements with only partial membership ranging from 0 to 1 to define uncertainty for classes that do not have clearly defined boundaries. Usually, the fuzzy logic method is based on four essential steps. First, fuzzification consists to convert the feature values of input and output parameters. Second, design of the fuzzy rules to implement the model for prediction. Third, the fuzzyfied values are then inferred to provide decisions by the inference engine with the support of the fuzzy rule base. Finally selection by defuzzification converts fuzzy sets into a crisp value (Cox, 1995). There are five built-in methods supported: centroid (used on our study), bisector, medium-maximum (the average of the maximum value of the output set), high-maximum and low-maximum. In our work, “Triangular”, “Sigmoidal”, “Gaussian”, “S-shaped built”, “Z-shaped built” and “Trapezoidal” membership functions were used to evaluate and predict bagging behaviors quantitatively.

3. RESULTS AND DISCUSSION

3.1. Predicting the residual bagging behaviors using the Artificial Neural Network (ANN)

In this paper, neural network algorithm is used for the bagging modeling due to the high accuracy of this system in learning nonlinear process data. The denim fabric samples are divided into a training set (20 samples) and a test one (9 samples). The validation set is used to achieve training done with the training set. According to a developed algorithm using the MATLAB software, less than 500 iterations were applied at each time. Moreover, some stopping criteria are used to determine when we stop adding new hidden neurons. Since neural network is an alternate statistical method, the root mean square error (RMSE), the relative mean absolute error (RMAE) and correlation coefficient (R) are used as performance criteria to carry out the best 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. When the correlation coefficient values are close to 1.That means a good relationship between actual and predicted values were saved.

The training and test root mean square errors are calculated according to Equations 3 and 4 respectively.

$$RMSE_{Training} = \sqrt{\frac{1}{N_T}\sum_{i=1}^{N_T}(d_i - y_i)^2} \tag{3}$$

$$RMSE_{Test} = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(d_i - y_i)^2} \tag{4}$$

The training and test relative mean absolute error are calculated according to Equations 5 and 6, respectively.

$$MRAE_{Training} = \frac{1}{N_T}\sum_{i=1}^{N_T}\frac{|d_i - y_i|}{d_i} * 100 \tag{5}$$

$$MRAE_{Test} = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{|d_i - y_i|}{d_i} * 100 \tag{6}$$

Where:

N_T : is the number of training samples,

N_t : is the number of test samples,

d_i: is the desired outputvalue,

y_i:is the calculated neural output (predicted value).

The R values are obtained by calculating the regression coefficients of the lines that relate network outputvalues to their corresponding targets. In this application, *R* values superior to 0.85 are considered as good (AbdJelil et al., 2013).Table 4 shows the *RMSE*, *MRAE*, and the correlation coefficient R of training and test samples given by the neural network.

Table 4 : Performance evaluation of the neural network models

	Outputs (bagging behaviors)			
	R_{bh}	R_{bv}	B_{rec}	KV_{bh}
$RMSE_{Training}$	0.39	786.09	2.605	0.495
$RMSE_{Test}$	0.499	617.23	3.326	0.439
$MRAE_{Training}$	0.14%	0.61%	0.38%	0.173%
$MRAE_{Test}$	0.42%	1.06%	1.22%	0.285%
$R_{Training}$	0.927	0.885	0.927	0.8504
R_{Test}	0.928	0.977	0.928	0.906

According to Table 4, the neural network models give high and acceptable coefficient values for both training ant test samples. In fact, the correlation coefficients are ranged from 0.85 to 0.977 which are close to 1 for all outputs. As shown in Figures 2 and 3 there are good agreements between predicted and observed data values. Thus, our findings seem improved widely. Moreover, the prediction errors for all outputs showed that their learning and generalization performances are good enough. The MRAE values are ranged between 0.14% and 1.22% which are considered low (El ghazel et al., 2011). Consequently, it may be concluded that the neural network methodology is helpful towards a better understanding of the relationship between the frictional parameters and the bagging properties of denim fabric samples.

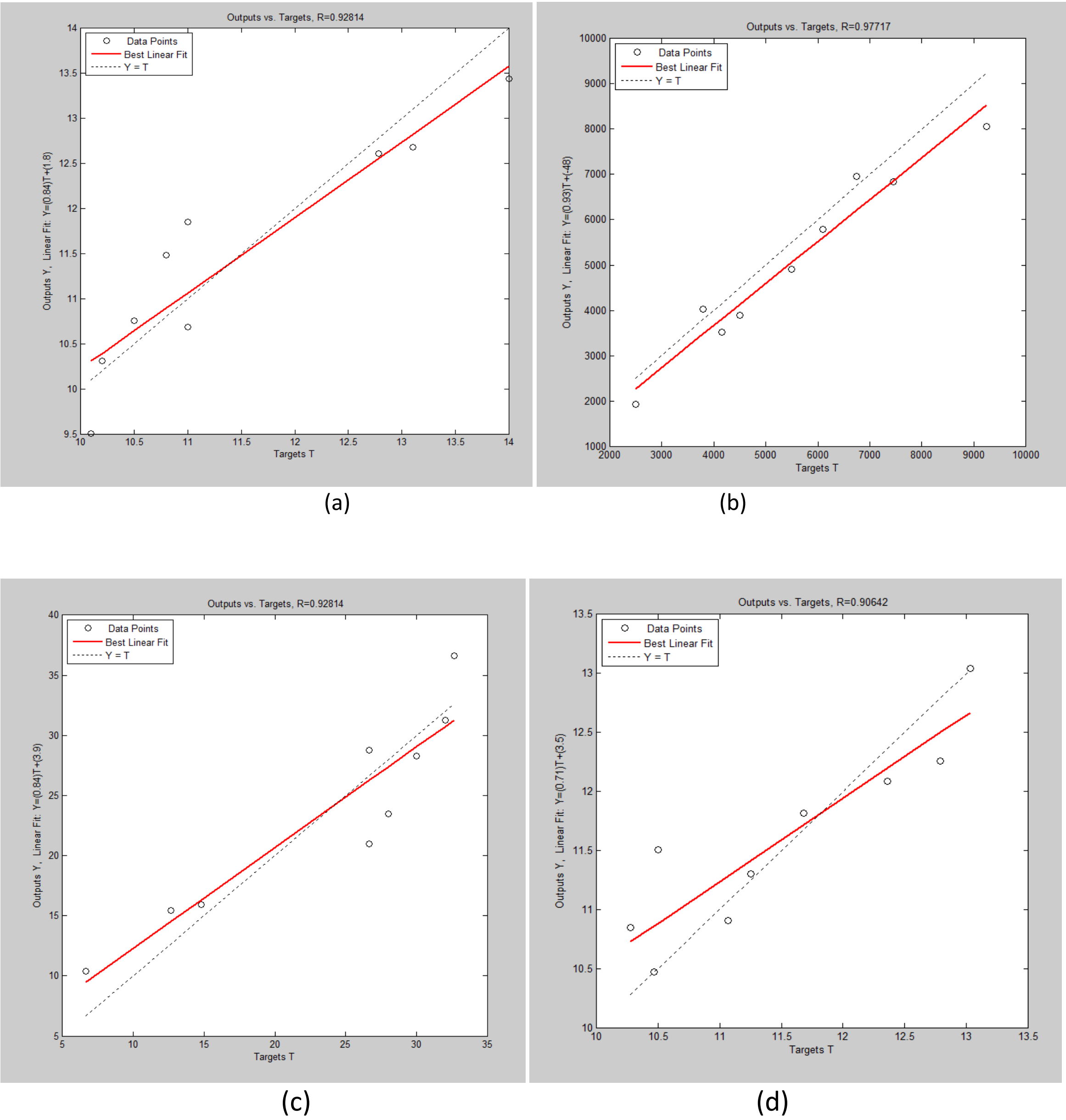


Figure 2: Artificial Neural Network prediction of (a) the residual bagging height, (b) the residual bagging volume, (c) the bagging recovery and (d) the kinetic velocity for the test denim fabric samples

3.2. Predicting the residual bagging behaviors using the fuzzy logic theory

All input and output values are converted to three fuzzy subsets: low, medium and high. Different membership functions are adapted for each bagging characteristic.In fuzzy inference, the Mamdani method was used for calculating the output inferredby a set of fuzzy rules (Mamdani and Assilian, 1975).

The residual bagging height, R_{bh}

Four different membership functions ("Triangular", "Trapezoidal", "Gaussian" and "G-bell shape") are chosen and applied as shown in Figure 3. Among these membership functions, the "Triangular" and "Trapezoidal" membership functions are more required for good fuzzy inference systems (Jaouachi et al., 2010). Indeed, these functions offer more details and are considered as the simplest membership functions because they are formed using straight lines. Although, the"Gaussian" membership functions and "Generalized bell" membership functions achieve smoothness, they are unable to specify asymmetric membership functions, which are important in certain applications.

ure 3: Different membership functions applied for R_{bh} property parameter

The overall rules used, shown in Table 5 are fixed and then developed in order to investigate the best to fit experimental values in our specific design of interest. Otherwise, Table 5 shows the selected fuzzy rules using our input and output parameters. Hence, using the membership functions relative to each fuzzy input. It may be concluded that it has significant effect on the R_{bh} value. Regarding our experimental data base, it can be concluded, also, that the variation of the input levels affects considerably the fuzzyfied R_{bh} value.

Table 5. Fuzzy model rules of R_{bh}

Rule Nb.	Rules
1	If (Mass is medium) and (Wt_D is high) and (MIU is medium) and (Wt_{Rig} is medium) and (Ab_{cycles} is high) then (R_{bh} is medium)
2	If (Mass is high) and (Wt_D is high) and (MIU is low) (Wt_{Rig} is low) and(Ab_{cycles} is high)then (R_{bh} is high)
3	If (Mass is high) and (Wt_D is medium) and (MIU is medium) and (Wt_{Rig} is medium) and (Ab_{cycles} is high) then (R_{bh} is medium)
4	If (Mass is high) and (Wt_D is medium) and (MIU is high) and (Wt_{Rig} is low) and (Ab_{cycles} is low) then (R_{bh} is low)
	If (Mass is medium) and ($Wt_D$is high) and (MIU is high) and (Wt_{Rig} is low) and (Ab_{cycles} is low) then (R_{bh} is low)
6	If (Mass is medium) and (Wt_D is low) and (MIU is low) and (Wt_{Rig} is high) and (Ab_{cycles} is high) then (R_{bh} is high)
7	If (Mass is high) and (Wt_D is medium) and (MIU is medium) and (Wt_{Rig} is high) and (Ab_{cycles} is high) then (R_{bh} is medium)
8	If (Mass is high) and (Wt_D is low) and (MIU is high) and ($Wt_{Rig}$is low) and (Ab_{cycles} is medium) then (R_{bh} is low)
9	If (Wt_D is low) then (R_{bh} is high)
10	If (Wt_D is high) then (R_{bh} is low)
11	If (Wt_D is high) and (MIU is low) then (R_{bh} is high)
12	If (MIU is high) then (R_{bh} is low)
13	If (Wt_{Rig} is high) then (R_{bh} is high)
14	If (Wt_{Rig} is low) then (R_{bh} is low)

The findings reveal that theresidual bagging height depends accurately on the frictional parameters of the denim fabrics such as yarn-to-yarn frictions, yarn-to-metal friction (expressed by weft density, Wt_D, weft rigidity, Wt_{Rig} and abrasion cycles, Ab_{cycles}) and metal-to-fabric frictions (expressed by mean frictional coefficient, MIU).Hence, it can be concluded that the yarn-to-yarn friction and the metal- to-fabric friction caused by the contact of conformator to the fabric surface remained influential inputs which affect accurately on the residual bagging height.

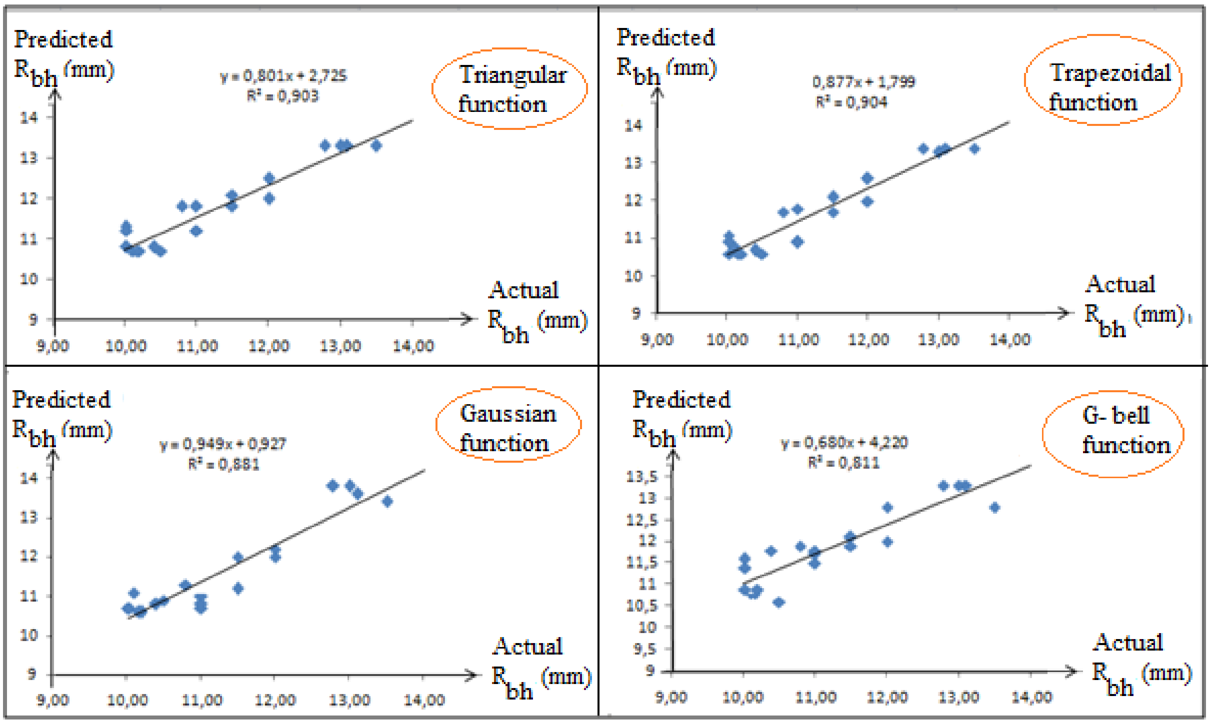


Figure 4: Linear regression evolution between predicted and actual residual bagging height values using fuzzy logic models

The regression models (see Figure 4) present good regressioncoefficient values, which improvetheeffectiveness of the developed fuzzy models. In fact,thecoefficient of regression R^2 is ranged from 0.811 (using "Generalized bell-shaped" membership function) to 0.904 (using "Trapezoidal" membership function). Thus, we can deduce that the R_{bh}seemspredictable sufficiently in our experimental designof interest. Besides, compared to theexperimental results, our theoretical findingsgivemore accurate prediction of the residual bagging height R_{bh}.

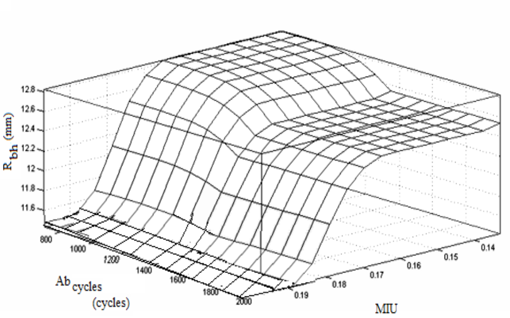
Moreover, the root mean square error (RMSE), the relative mean absolute error (RMAE) and the correlation coefficient (R) are used as performance criteria to get higher suitable models (see Table 6) which can be applied further.

Table 6: Performance evaluation of the different fuzzy logic models relative to R_{bh}

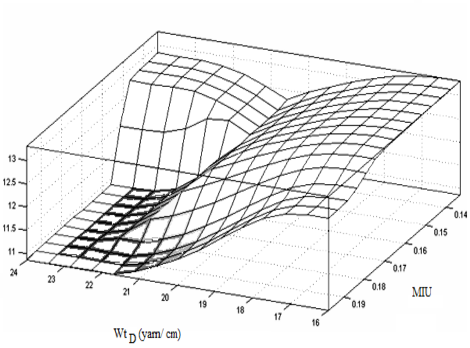
Performance evaluation parameters	Fuzzy membership functions			
	« Triangular »	« Trapezoidal »	« Gaussian »	« G – bell »
RMSE	0,61	0,55	0,54	0,81
MRAE	0,47	0.11	0,41	0,64
R	0,95	0,95	0,94	0,9

Regarding these findings, as shown in Table 4, and comparing the error values obtained using different membership functions, it may be concluded that the "Trapezoidal" function presents the lowest mean error values within highest correlation coefficient ones. As a consequence, applying the "Trapezoidal" function, the prediction of the residual bagging height can be considered fruitful and accurate in our applied design of interest.

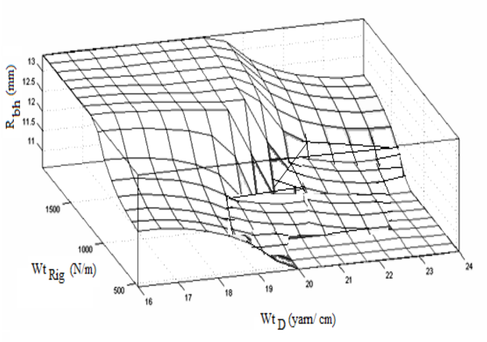
Figure 5 shows the relationship among the effect of the frictional input parameters on the residual bagging height. From Figures 5a and 5b, it is noted that, as the MIU increases, there is concomitant decrease of the R_{bh}. The Wt_D, also, exhibits similar influence on the residual bagging height (see figures 5b and 5c). However there is an acceptable relationship between the weft rigidity values and the R_{bh} property because they increase together when the weft yarn density decreases (figure 5c). This influence becomes negligible when the weft yarn rigidity is more than 1500 N/m.



(a)



(b)



(c)

Figure 5: Residual bagging height evolution as a function of studied frictional inputs:(a) as function of MIU and Ab_{cycles}, (b) as function of MIU and Wt_D (c) as function of Wt_{Rig} and Wt_D

The residual bagging volume, R_{bv}

Among the fuzzy membership functions, four specific ones only (“Sigmoidal shaped built-in”, “Z-shaped built-in”, “S-shaped built-in” and “G-bell shape”)are, hence, applied due to their effectiveness to modeling the residual bagging volume. For the “Sigmoidal” membership function, it is either open left or right. Indeed, asymmetric and closed membership functions can be synthesized using two sigmoidal functions, so in addition to the basic “*sigmf*”, we also have the difference between two “Sigmoidal” membership functions, *“dsigmf”,* and the product of two sigmoidal functions *“psigmf”.* However, polynomial functions based curves account for several of the membership functions in the toolbox. Three related membership functions are the Z, S, and Pi curves, all named because of their shapes to predict widely the volume of bagged denim samples. The function *“zmf”* is the asymmetrical polynomial curve open to the left. But, *“smf”* is the mirror-image function that opens to the right, and *“pmf”* is zero on both extremes with a rise in the middle (see Figure 6).

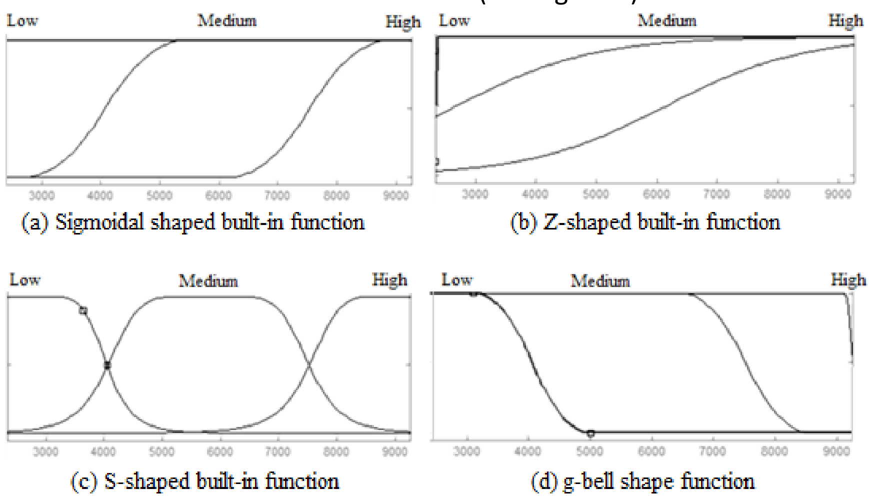


Figure 6: Different membership functions applied to modeling the residual bagging volume

The overall rules used, as shown in Table 5, are fixed and developed in order to investigate the best fitting experimental values in the specific field of interest.

Table 7 shows the building of fuzzy rules using our input and output parameters which are applied to construct the best fuzzy models of R_{bv} property. Regarding our experimental database, it can be concluded that the variation of the fuzzyfied input values affects the R_{bv}property considerably.

Table 7. Fuzzy model rules of R_{bv}

Rule No.	Rules
1	If (Mass is low) and (Wt_D is medium) and (MIU is medium) and (Wt_{Rig} is medium) and (Ab_{cycles} is low) then (R_{bv} is medium)
2	If (Mass is low) and (Wt_D is medium) and (MIU is medium) and (Wt_{Rig} is medium) and (Ab_{cycles} is high) then (R_{bv} is medium)
3	If (Mass is high) and (Wt_D is high) and (MIU is low) and (Wt_{Rig} is low) and (Ab_{cycles} is high) then (R_{bv} is high)
4	If (Mass is high) and (Wt_D is medium) and (MIU is medium) and (Wt_{Rig} is high) and (Ab_{cycles} is medium) then ($R_{bv}$is high)
5	If (Mass is low) and (Wt_D is high) and (MIU is high) and (Wt_{Rig} is low) and (Ab_{cycles} is high) then ($R_{bv}$is low)
6	If (Mass is medium) and (Wt_D is medium) and (MIU is high) and ($Wt_{Rig}$is low) and (Ab_{cycles} is low) then (R_{bv} is low)
7	If (Mass is high) and (Wt_D is low) and (MIU is high) and (Wt_{Rig} is low) and (Ab_{cycles} is medium) then (R_{bv} is low)
8	If (Mass is medium) and (Wt_D is low) and (MIU is low) and (Wt_{Rig} is high) and (Ab_{cycles} is high) then (R_{bv} is high)
9	If (Mass is medium) and (Wt_D is high) and (MIU is medium) and (Wt_{Rig} is medium) and (Ab_{cycles} is high) then (R_{bv} is medium)
10	If (Mass is medium) and (Wt_D is high) and (MIU is medium) and (Wt_{Rig} is low) and (Ab_{cycles} is high) then (R_{bv} is low)
11	If (Mass is medium) and (Wt_D is high) and (MIU is high) and (Wt_{Rig} is low) and (Ab_{cycles} is low) then (R_{bv} is medium)
12	If (Mass is medium) and (Wt_D is low) and (MIU is low) and (Wt_{Rig} is high) and (Ab_{cycles} is medium) then (R_{bv} is high)
13	If (Mass is medium) and (Wt_D is low) and (MIU is low) and (Wt_{Rig} is high) and (Ab_{cycles} is high) then (R_{bv} is high)
14	If (Mass is high) and (Wt_D is medium) and (MIU is high) and (Wt_{Rig} is low) and (Ab_{cycles} is low) then (R_{bv} is medium)

To investigate the performance of the fuzzy logic models predicting the residual bagging volume, the theoretical (predicted) values of the R_{bv} were compared to the exprimental (actual) values ones as shown in Figure 7.

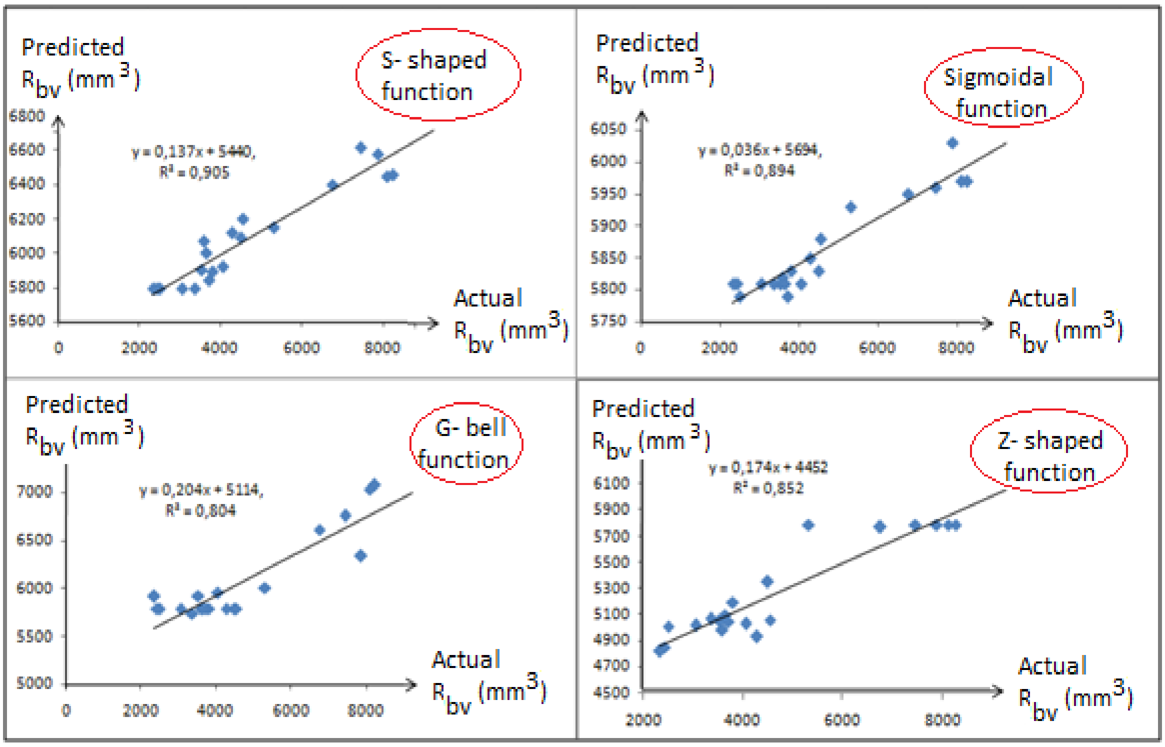


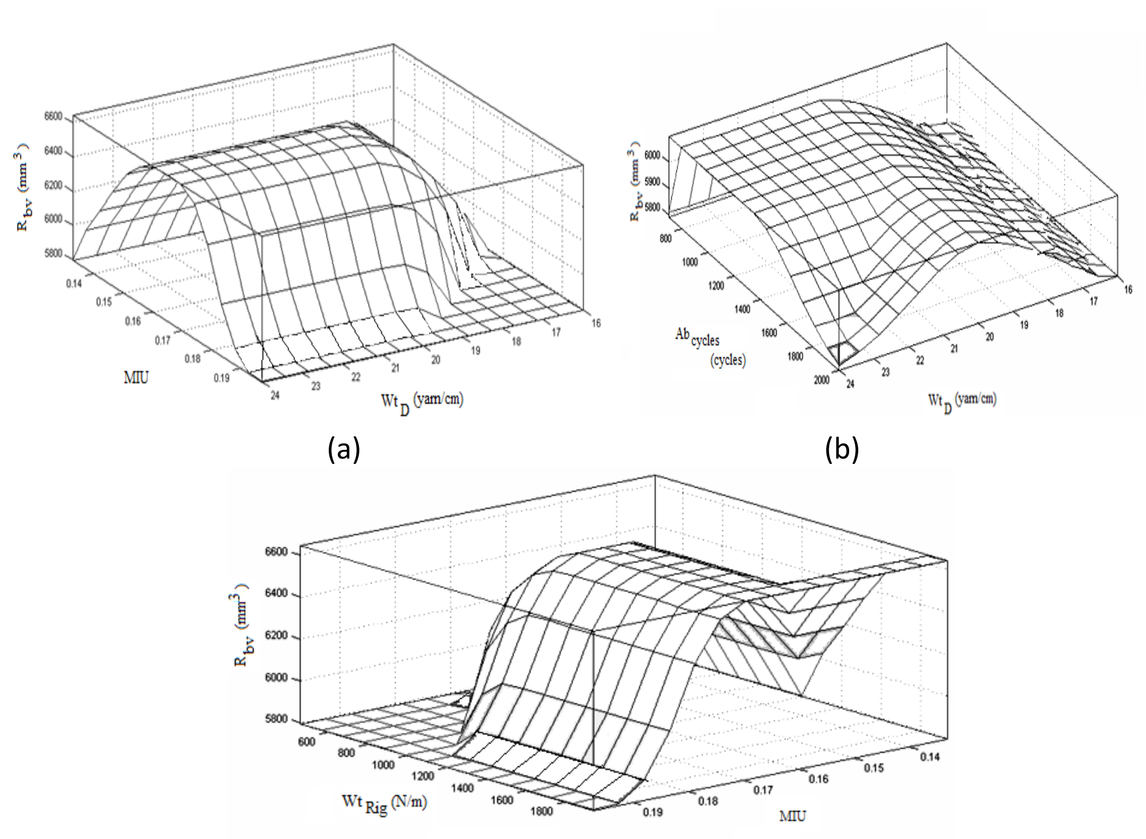
Figure 7: Linear regression evolution between predicted and actual residual bagging volume values using fuzzy logic

Moreover, the root mean square error ($RMSE$), the relative mean absolute error ($RMAE$) and correlation coefficient (R) are used as performance criteria to get higher suitable models (see Table 8).

Table 8. Performance evaluation of the different fuzzy logic models analysing the R_{bv}

Performance evaluation parameters	Fuzzy membership functions			
	« Smf »	« Sigm »	« G- bell »	« Zmf »
RMSE	2178	2198	2080	1692
MRAE	0.34	0.35	0.31	0.29
R	0.95	0.94	0.90	0.92

Regarding the obtained results, the mean relative absolute error values (MRAE) are ranged between 0.29% and 0.35% which can be considered low and significant (El Ghazel et al., 2011). Also, the correlation coefficient R is very close to 1 (between 0.9 and 0.95) for the tested fuzzy membership functions. However, by comparing the results to studied fuzzy membership functions, the S- shaped function gives the best correlation coefficient value. Hence, using this function, it may be possible to predict the residual bagging volume accurately as function of the studied frictional parameters. Consequently, the modeling of this bagging characteristic seems fruitful using the fuzzy logic theory.



(a) (b)

(c)

Figure 8: Residual bagging volume evolution as a function of studied frictional inputs:(a) as function of MIU and Wt_D, (b) as function of Ab_{cycles} and Wt_D, (c) as function of MIU and Wt_{Rig}

The effect of overall studied parameters on the residual bagging volume is shown in Figure 8. We remarked that the weft yarn density and the MIU are the most important and influential frictional parameters. In Figures 8a and 8b, it is shown that the residual bagging volume decreases when the weft density increases more than 18 yarns per centimeter. However, the effect becomes not significant under this value. Figure 8c shows that the weft rigidity and the residual bagging volume are correlated positively. In fact, this bagging property increases with the increase of the weft rigidity, then becomes stable 1500N/m, exactly as the behavior of the residual bagging height.

The bagging recovery, B_{rec}

For the modeling of the bagging recovery, four different fuzzy membership functions were chosen and applied (“Triangular”, “Trapezoidal”, “Gaussian” and “G-bell shape”), due to their significant results in our cases.

Figure 9 shows the evolution within the relationships between the actual and the predicted bagging recovery values using these mentioned membership functions.

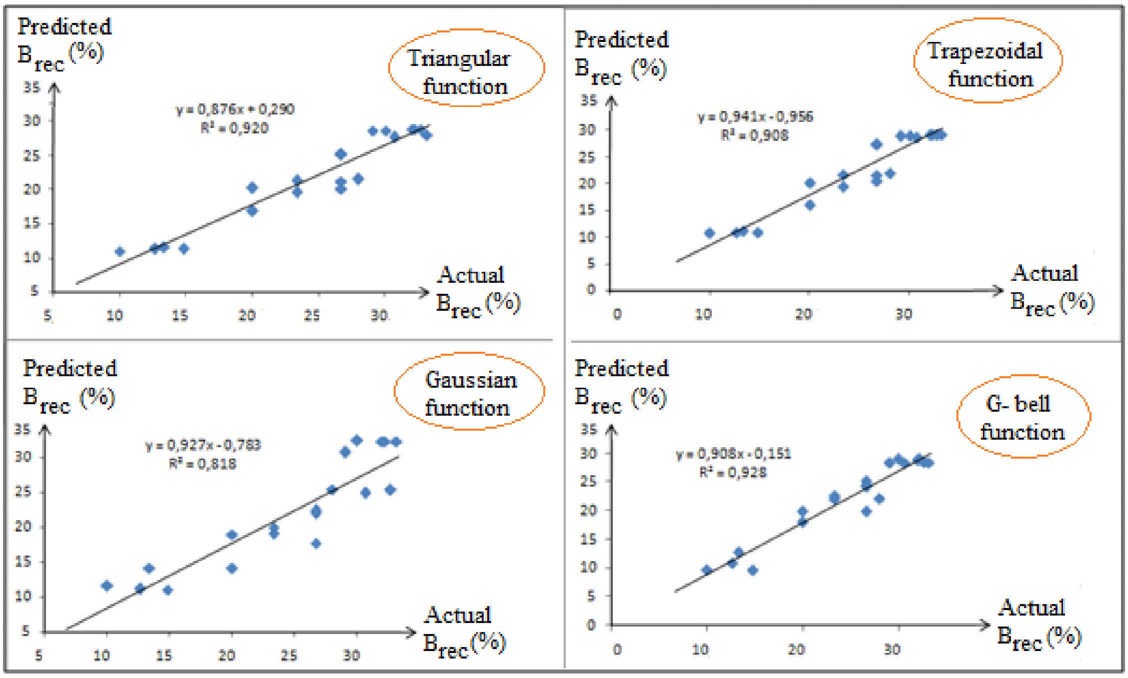


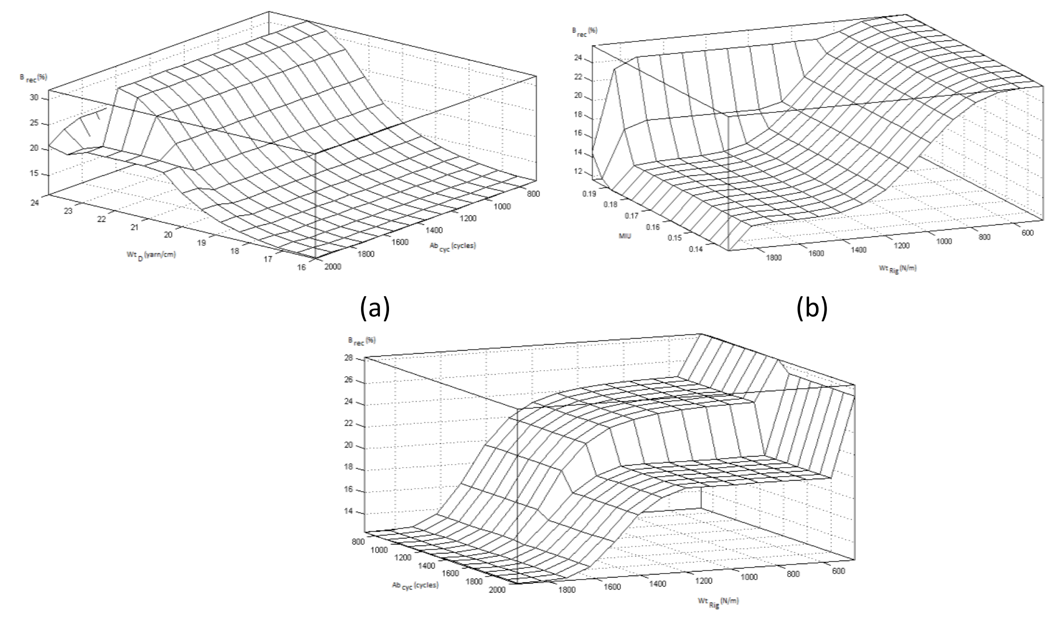
Figure 9: Linear regression evolution between predicted and actual bagging recovery values using fuzzy logic

The root mean square error (RMSE), the relative mean absolute error (RMAE) and correlation coefficient (R) are used to investigate and discuss objectively the effectiveness of the developed fuzzy models (see Table 9).

Table 9. Performance evaluation of the different fuzzy logic models to predict the B_{rec} values

Performance evaluation parameters	Fuzzy membership functions			
	« Triangular »	« Trapezoidal »	« Gaussian »	« G- bell »
RMSE	3.41	3.21	4.04	3.06
MRAE	0.11	0.11	0.13	0.10
R	0.95	0.95	0.90	0.96

By analyzing the range value of MRAE parameter (from 0.10% to 0.13%), we remark that the predicted B_{rec} values seem significant and can explain the accuracy of fuzzy theory method. In addition, the R values are ranged from 0.90 to 0.96 which seem very close to 1.Otherwise, the applied fuzzy functions can help to understand the B_{rec} behavior variation in the specific design of interest. However, among this applied fuzzy models, the “Generalized- bell” one remained the suitable function to fit experimental B_{rec} values (see table 9). It is very important to note that, using the “Generalized- bell” function to predict the behavior of the residual bagging recovery, it helps to understand the evolution of this bagging property as function of tested frictional inputs as shown in Figure 10.Indeed,high relationships between frictional inputs (especially MIU, Wt_D and Wt_{Rig}) and the bagging recovery were, hence, found and saved.



(a) (b)

(c)

Figure 10: Bagging recovery evolution as a function of studied frictional inputs:(a) as function of Ab_{cycles} and Wt_D, (b) as function of MIU and Wt_{Rig}, (c)as function ofWt_{Rig} and Ab_{cycles}.

The obtained results show clearly that when the MIU increases, the application of conformator on the surface of fabric is higher and helps to increase the bagging recovery (see Figure 10b). This result is in good agreement with the Zhang's study results (Zhang et al., 1997). As a consequence, frictional input parameter, MIU, remained affecting enormously the residual bagging behavior and the appearanceof denim fabrics. The weft density is an input parameter which seems influent on the yarn friction resistance because, higher the density of the fabric is, lower the yarns can slide and move. Besides, Figures 10a shows that the increase of the weft yarn density encourages the increase of the yarn-to-yarn friction resistance and as a consequence, the rigidity value increases too. Moreover, the increase of the weft yarn density helps the bagging phenomenon to appear and ameliorates the fabric appearance. So, the frictional input parameters present positive effects to optimize the bagging recovery and minimize the shape of bagged zones in the garment especially after relaxation time and stress removing.

According to results shown in Figures 10b and 10c, there is a high relationship between the weft yarn rigidity and the bagging recovery. In fact, when the rigidity parameter increases, the bagging recovery property decreases which encourages predicting the bagging recovery property in our experimental design of interest. The residual bagging recovery decreases with the increase of weft yarn rigidity. In fact, more we have a high rigidity, more frictional resistance appears which causes the decrease of the bagging recovery. This result seems in good agreement with the Hossein and Sanaz's study finding (2012) applied to knitted fabrics. Indeed, the fabric rigidity seems prevent the deformation resistance during the bagging test and cause the increase of residual bagging height. So, the decrease of the bagging recovery can be accured due to the rigidity of denim fabrics after bagging stress remove.

The kinetic velocity of the residual bagging height,KV_{bh}

For the modeling of kinetic velocity relative to bagging height property, we applied three fuzzy membership functions ("Gaussian", "Sigmoidal shaped built-in" and "S-shaped built-in"). These functions are selected as the best ones which can give good theoretical results to predict the KV_{bh} property.

Figure 11 shows the relationships between the actual and the predicted kinetic velocity values using these fuzzy membership functions mentioned previously.

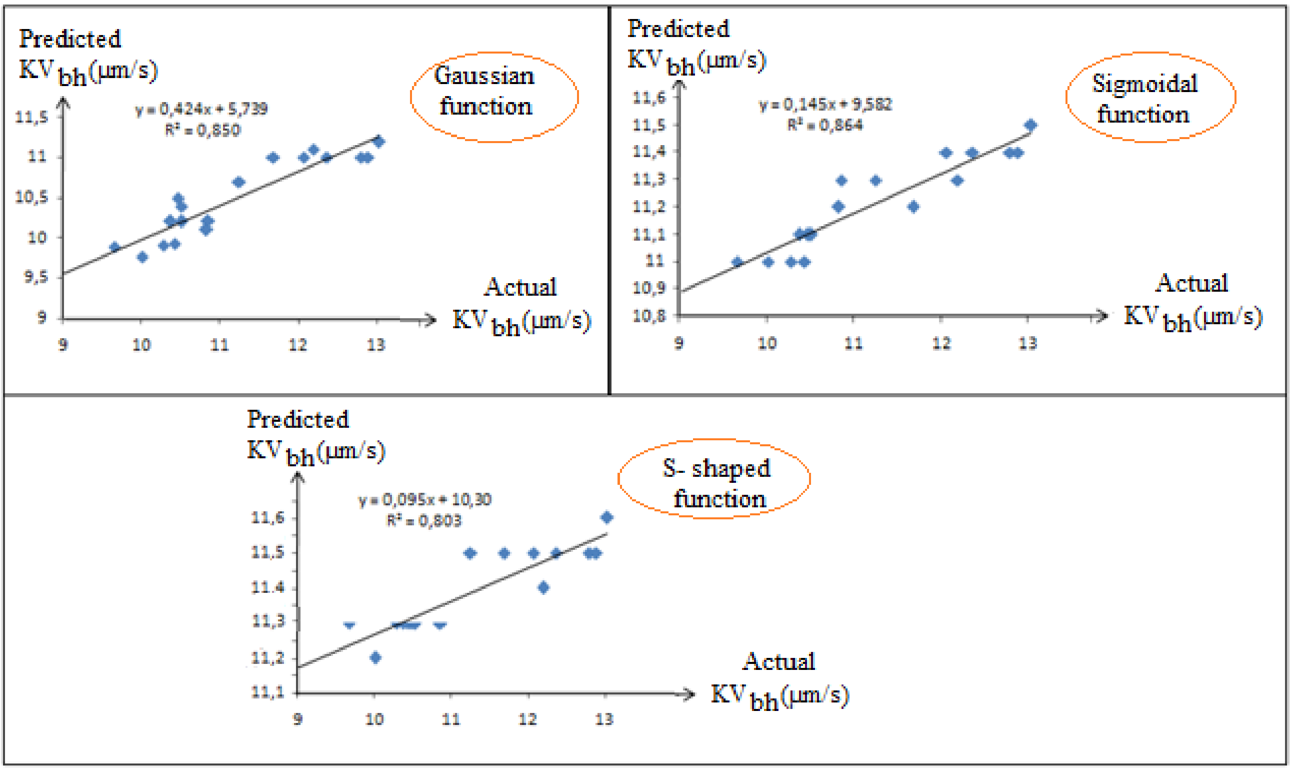


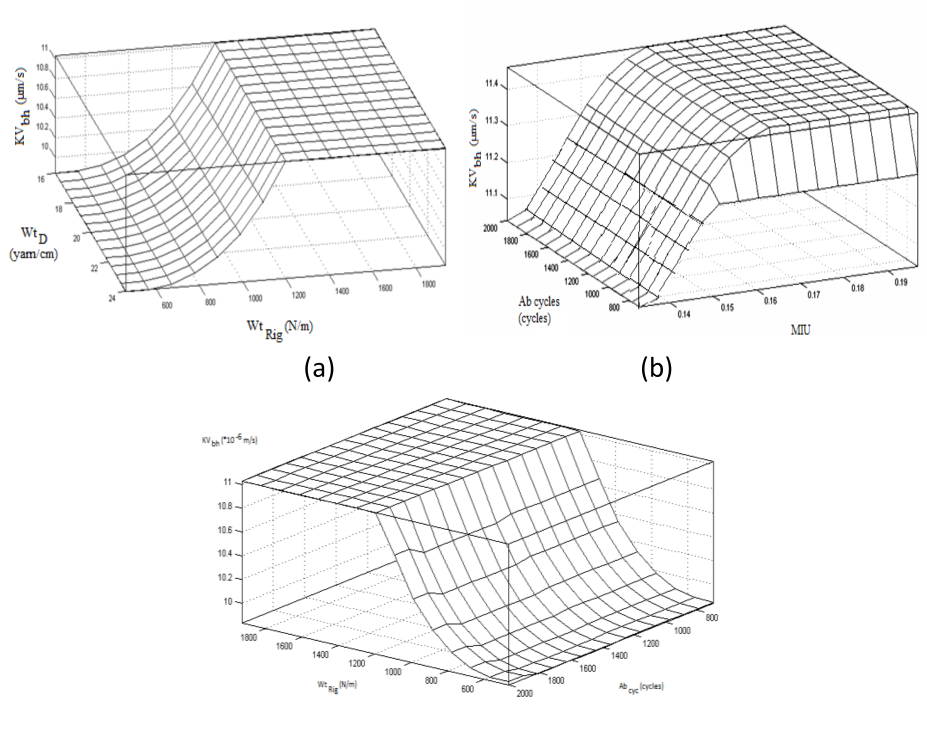
Figure 11: Linear regression evolutions between predicted and actual kinetic velocity values using studied fuzzy membership functions

The root mean square error (*RMSE*), the relative mean absolute error (*RMAE*) and correlation coefficient (*R*) are used as performance criteria to select significant fuzzy models (see Table 10).

Table 10. Performance evaluation of the different fuzzy logic models of the KV_{bh} property

Performance evaluation parameters	Fuzzy membership functions		
	Gaussian	Sigmoidal	S- shaped
RMSE	0.97	0.91	0.95
MRAE	0.65	0.7	0.78
R	0.92	0.93	0.89

Regarding the findings, the mean relative absolute error values (MRAE) are ranged from 0.65% to 0.78% which can be considered acceptable and significant. Besides, the correlation coefficient, R, seems close to 1 (between 0.89 and 0.93) for these fuzzy membership functions. However, among overall studied fuzzy functions, the ”Sigmoidal” function gives the highest correlation coefficient value within acceptable error. The relative fuzzy model can be considered useful in the prediction of the kinetic velocity as function of the used frictional parameters.



(a) (b)

(c)

Figure 12: The kinetic velocity of bagging height evolution as a function of studied frictional inputs:(a) as function of Wt_{Rig} and Wt_D, (b) as function of MIU and Ab_{cycles},(c)as function ofWt_{Rig}andAb_{cycles},

Figure 12 shows the frictional input parameters have the same effect on the kinetic velocity and on the residual bagging height.

Comparison between fuzzy and neural prediction performance

The prediction performances of neural and fuzzy models are compared according to the Mean relative absolute error (MRAE) and the correlation coefficient (R) as shown in Table 11.

Table 11. Summary of prediction results of neural and fuzzy models

Residual bagging behaviors	Neural models		Fuzzy models	
	MRAE	R	MRAE	R
R_{bh}	0,14	0,92	0,11	0,95
R_{bv}	0,61	0,88	0,34	0,95
B_{rec}	0,38	0,92	0,1	0,96
KV_{bh}	0,17	0,85	0,7	0,93

Basing on the results obtained, it is revealed that the fuzzy models are slightly powerful than the neural models. The performance criteria are better for fuzzy models compared to those for neural models for all properties excepting the *RMAE* of the kinetic velocity. Applying the best fuzzy function in each residual bagging property, there is a more significance of fuzzyfied values than those saved using neural network technique. These findings can help industrial and researchers to predict widely the bagging ability of tested denim samples in our experimental design of interest. Moreover, basing on the obtained results, it seems possible to prevent, evaluate and optimize the denim fabric bagging properties as function of frictional inputs. Neural network method can be also useful to modeling the bagging behaviors. But it remained not sufficiently compared to fuzzy theory technique.

Regarding all summarized results in Table 11, the performance indicators used, reflect the effectiveness of the fuzzy method to predict the bagging behaviors of denim fabric samples as function of frictional inputs.

4. CONCLUSION

This study is interesting for denim consumers and industrial applications during long and repetitive uses. Undoubtedly, the denim garments remained the largely used and consumed, hence, this particularity proves the necessity to study it in order to evaluate the bagging phenomenon which occurs as function of number of uses. Although it is fashionable to have bagging, the denim fabric remains, in contrast with the worsted ones, the most popular fabric to produce garments. Moreover, regarding this characteristic, the large uses and the acceptable value of denim fabrics, their aesthetic appearance behaviour due to bagging phenomenon can be analyzed accurately because compared to worsted fabrics, they have a high value and the repetitive tests to investigate widely bagged zones can fall the industrial. The paper has practical implications in the clothing appearance and other textile industry, especially in the weaving process when friction forms (yarn-to-yarn, yarn- to- metal frictions) and stresses are drastic. This can help to understand why residual bagging behaviour remained after garment uses due to the internal stress and excessive extensions. Regarding the selected influential inputs and outputs relative to bagging behaviors, there are some practical implications that have an impact on the industrial and researchers to study objectively the occurrence of this aesthetic phenomenon. Indeed, this study discusses the significance of the overall inputs; their contributions on the denim fabric bagged zones aims to prevent their ability to appear after uses. Moreover, the results obtained regarding the fabric mechanical properties can be useful to fabric and garment producers, designers and consumers in specifying and categorizing denim fabric products, insuring more denim cloth use and controlling fabric value. For applications where the subjective view of the consumer is of primary importance, the KES-FB system yields data that can be used for evaluating fabric properties objectively and prejudge the consumer satisfaction in view point of the bagging ability. Therefore, this study shows that by measuring shear, tensile and frictional parameters of KES- FB, it may be possible to evaluate bagging properties. However, it highlights the importance and the significance of some inputs considered influential or the contrast (non significant) for other researches.

In this paper, we have predicted the residual bagging behaviors (residual bagging height, residual bagging volume, bagging recovery and the kinetic velocity) of denim fabric samples using two theoretical methods: fuzzy logic theory and neural networks. Our findings showed that the prediction performance is high for the fuzzy models. Indeed, the results show, also, that the change of fuzzy membership function affects enormously the prediction accuracy of the residual bagging characteristics. Compared to experimental results, it may be concluded that overall theoretical models using fuzzy technique are marked by relatively good and significant correlation coefficients. However, for the residual bagging height, and using the “Trapezoidal” membership function, best result is found. For the kinetic velocity, the residual bagging volume and for the bagging recovery, the “Sigmoidal” function, the “S- shaped” and the “Generalized - bell” membership function seem the best ones respectively to explain the behaviors of the bagged denim samples widely. In addition, compared with the experimental results, the theoretical models seem suitable and can be used to predict residual bagging behaviors of denim fabrics accurately. However, the fuzzy technique remained the best applied method to evaluate studied bagging behaviors. Indeed, we have concluded either, that the error values (RMSE and MRAE) between theoretical and experimental results traduce the effectiveness of both the fuzzy and the neural models to predict and evaluate bagging behaviors.

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