PREDICTING RESIDUAL BAGGING BEND HEIGHT OF KNITTED FABRIC USING FUZZY MODELLING AND NEURAL NETWORKS

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Abstract:

In this research, fuzzy modelling and neural network methods were used and compared to predict the residual bagging bend height of knitting fabric samples. Studies undertaken to minimize the bagging phenomenon vary significantly with the test conditions including the experimental field of interest, the input parameters and the applied method. Hence, we attempt to formulate a theoretical model of predicting bagging behaviour in our experimental design of interest. By analysing the bend height of overall bagging samples, this paper provides an effective neural network model to evaluate and predict the residual bagging bend height of the knitting specimens after test. It also provides the impact of each input parameter in our experimental field of interest to simulate this phenomenon after use. Moreover, the contribution of these influential input parameters was analysed and discussed. Nevertheless, our results show that residual bagging height decreases when yarn contains elastane filament, Spandex©. This finding is in agreement with Mirostawa et al. [11] that with an increase of the elastane content in fabric, permanent bagging decreases, whereas elastic bagging increases. According to the analytical results obtained, the neural network model gives a more accurate prediction than the fuzzy one.

Key words:

Fuzzy logic analysis , neural network, bagging bend height, knitting fabric, elastane filament, residual deformation

Introduction

Knitting fabrics are widely used thanks to their ability to conform to shapes and their improved drape ability. Because of good flexibility of knitting technology, more knitted structures have been developed for technical applications in recent years [1]. However, the bagging phenomenon, called sometimes poaching, remains a handicap of woven and knitted fabrics during and after use. This, which often occurs on the level of the knees of trousers and the elbows of shirts, can be cancelled only by pressing or sharpening. Thus, a permanent lengthening of the fabric, localised at 1%, causes a poaching, thus obliging the user to pass by again his clothing [19]. Bagging properties are defined as: the residual strength, residual extensibility, residual height and residual bagging shape [11, 13, 17] of knitted and woven fabrics. It is characterised by a more or less reversible deformation of the fabrics caused by a carried mechanical distension. Several techniques were used to analyse bagging, such as multi-axial cyclic deformation [11], the method which is inspired by standard ASTM D 4032, and the hollow roll panel of relieving [21] which evaluates the resistance capacity of bagging samples.

The literature suggests that many studies are conducted to predict and analyse the bagging bend phenomenon. Gurnewald and Zoll [23] have studied the mechanism of fabric poaching. Yokura et al. [4] used the volume of the formed pocket as an index of poaching tendency and proposed a system to envisage an objective evaluation of fabric. Zhang et al. [24, 25, 18] applied several cycles to fabric samples and after five cycles of load, in order to study the mechanism of fabric poaching, the volume of the formed pocket and the resistance of samples after cyclic test. Uçar [5] used a similar mechanism to study the poaching of knitting fabrics. By analysing the deformation of fabrics at the elbows and knees, a new developed apparatus was established by Kisiliak [10]. Zhang and Yeung [16, 19] developed a method in order to predict and evaluate the properties of fabric bagging using image processing.

In this work, we investigate the impact of the input parameters on predicting residual bagging bend height. In addition, the results from a neural network model and from a fuzzy analysis ones are compared to determine which technique is more accurate in predicting the residual bagging bend height behaviour.

Fuzzy logic technique

Several studies [3, 6-8] are conducted using a fuzzy approach in order to simulate, predict and evaluate textile structure properties. In fact, several advantages make fuzzy logic theory among the tools of forecast which are most used by researchers. Altinoz [3] suggests that fuzzy logic is an enabling technology that can be used to capture expertise and compute using linguistic rules for supplier selection. 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 fuzzified 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 [7]. 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, Gaussian, Gaussian combination and trapezoidal membership functions were used to evaluate and predict bagging quantitatively. Figure 1 shows the tested membership functions of ‘Course count’ input parameter in our present study.

The overall rules elaborated in order to evaluate and predict the residual named ‘permanent bagging bend height’ are shown in Table 2.

According to Cheng [15], using the neural network technique gives a more accurate prediction result and shows a higher

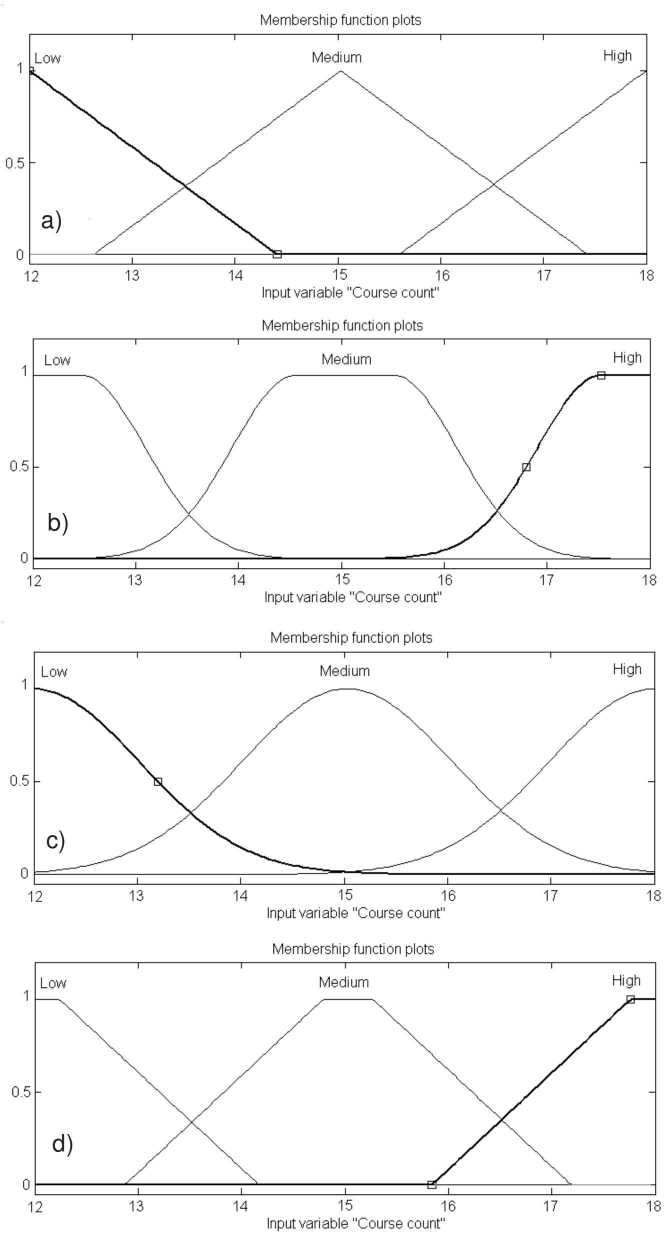

Figure 1. Example of Triangular (a), Gaussian (b), Gaussian combination (c) and Trapezoidal (d) membership function of 'Course count' input parameter.

accuracy than regression analysis. In addition, Toshio [14] suggests that to evaluate and simulate objectively wrinkled fabrics, a trained neural network model was successfully implemented. The neural network technique is usually used as a method for prediction and automatic inspection [14, 16]. As with the fuzzy method, the neural network presents some steps to apply. In general, define the input, the hidden and the output layer (Figure 2). The number of the used layers is function of hierarchical neural network performance. Then, it is necessary to impose the transfer function and adjustable weights (synapse weight) of the layers. After a training procedure, the next step consists of determining the optimal values of the outputs within minimal error ones. Therefore, after some learning cycles, the effectiveness of the neural network model was tested by calculating values using unknown data.

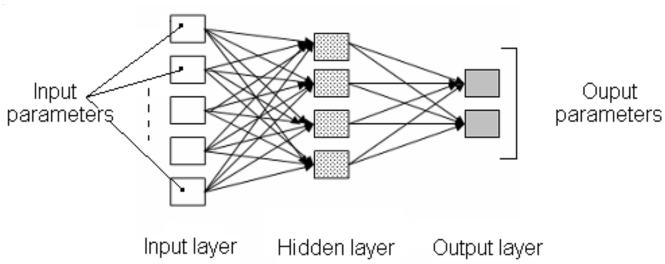

Figure 2. Hierarchical neural network structure.

Table 2. Fuzzy rules of residual bagging bend height Neural Network technique.

Rule n°
• If (Binding is high) and (Gauge is low) and (Course count is medium) and (type of yarn is high) then (Bagging is medium) (1) • If (Binding is high) and (Gauge is low) and (Course count is low) and (type yarn is high) then (Bagging is low) (1) • If (Binding is high) and (Gauge is low) and (Course count is medium) and (type yarn is high) then (Bagging is low) (1) • If (Binding is low) and (Gauge is low) and (Course count is high) and (type yarn is low) then (Bagging is low) (1) • If (Binding is high) and (Gauge is low) and (Course count is low) and (type yarn is low) then (Bagging is high) (1) • If (Binding is low) and (Gauge is low) and (Course count is medium) and (type yarn is low) then (Bagging is high) (1) • If (Binding is high) and (Gauge is high) and (Course count is low) and (type yarn is low) then (Bagging is medium) (1) • If (Binding is low) and (Gauge is high) and (Course count is medium) and (type yarn is low) then (Bagging is low) (1)
(1): Represents the weight applied to each rule. In general, the specific weights range from 0 to 1 under the weight setting.

Our hierarchical neural network is a simple artificial neuron which has n inputs. Those represent the output of other neurons which are connected to the current hierarchical neural net. These input parameters are balanced by synapse weights Wi (real). In our case, the permanent bagging bend height represents the only output parameter (Y). All these balanced inputs (e1....en) will be summed up to obtain activation. If this activation exceeds a random number, threshold, then output of the transfer function is transmitted to the neuron of the next layer. Finally, the hierarchical neural network is assigned (Figure 3).

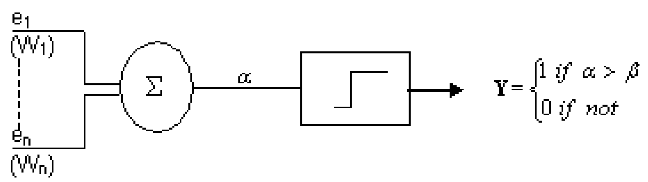

Figure 3. Tested neural network model.

Experimental

We used the input parameters within the levels shown in Table 3. Each parameter has different levels which define the experimental field of interest. Table 3 shows also the fixed adjustments used to produce the knitted pocket samples and their correspondent levels.

The assembled acrylic yarn (yarn count 66.67 g/m) was produced on the ring spun mill. After twisting each acrylic single yarn, the elastane filament, type Spandex(c), was added with the twisted structure which represents the first kind of yarn within elastane (level 1). But, the second tested sample of twisted yarn is without filament (level 0). We note that the overall

Table 3. Levels of the overall tested samples input parameters.

Levels	Rectilinear knitting machine input parameters			Yarn input parameter
	Course count	Gauge (mm)	Binding	Type of yarn (66.67 tex)
0	12	5	Jersey	Without elastane
1	14	7	1x1 rib	Within elastane
2	16	-	-	-
3	18	-	-	-

specimens are first twisted using a Volkmann twist mill type VTS-07. Figure 4 shows the assembled yarn structure (two twisted yarns and Spandex(c) filament). Two kinds of the twisted yarns were analysed to determine their contributions to the permanent bagging height geometry.

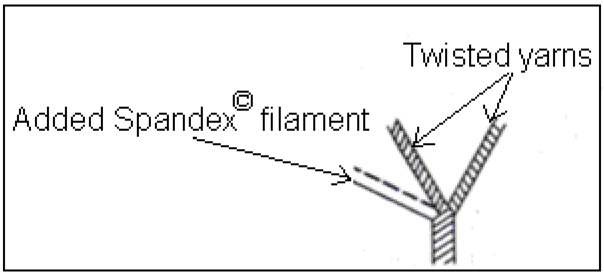

Figure 4. Assembled yarn (two twisted yarns + Spandex(c) filament).

Four input parameters were used and analysed to evaluate their impacts on the residual bagging bend of the knitted samples. In order to investigate objectively these input parameters, we choose a Tagauchi experimental design. We denote by 0, the lowest level and by 1, the highest level in the case of only two levels. However, in the case of more than two levels, we used 2, 3, 4, etc. These designations were used to analyse suitably the results. The knitting machine, the manual rectilinear machine type MORRETTO, is equipped with some points of adjustment: 'Gauge', 'Course count' and 'Binding'.

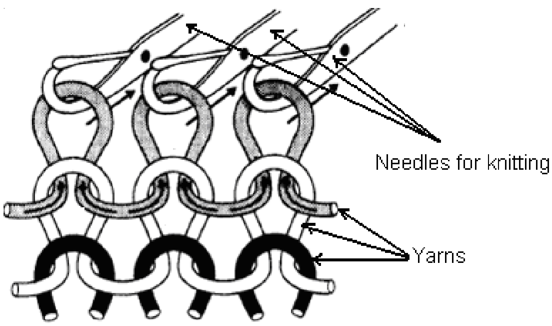

Figure 5. Jersey structure.

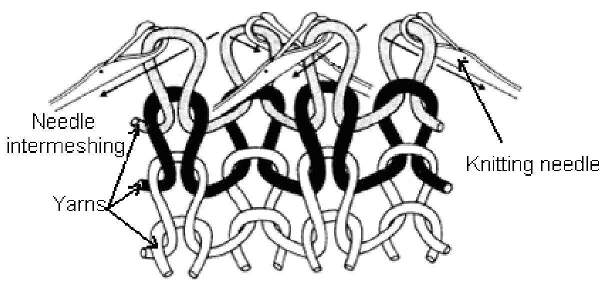

Figure 6. 1x1 rib structure

The appearance of each specimen of jersey knitted structure and 1x1 rib fabric one is shown in Figure 5 and Figure 6 respectively.

Twenty-four samples were prepared and analysed according to Tagauchi experimental design. Referring to Figure 7, each knitting sample is tested using force (300cN) which causes multidirectional deformations to all the knitting fabrics tested. The width of the sample is a function of the rate of lengthening previously saved in both column and range directions. However, the length of each knitted fabric sample is 100 mm. The test procedure is resumed in two steps. Moreover, after five hours of duration of the applied probe, the remnant deformations in two perpendicular planes (column direction and arranged direction) were measured. But these measures should be taken after relaxation time (30 minutes) and the applied force was removed.

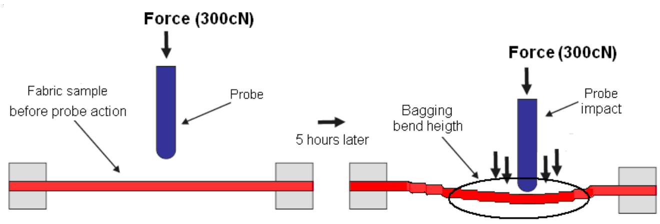

Figure 7. Residual bagging height structure after applied force (300 cN) for 5 hours.

During our experimental tests, we considered processing conditions suggested by AFNOR standard NF G00-003 [22]. Hence, a temperature of 20°C ± 2°C and a relative humidity of 65% ± 2% were maintained. Before testing, the overall samples should be relaxed twenty-four hours in the standard atmosphere previously mentioned. After conditioning the specimens, overall samples are investigated using experimental and theoretical methods such as fuzzy logic and neural network ones.

In our work, fuzzy logic and neural network methods are conducted and compared to determine the best one in bagging bend height prediction. The first part of our work consists in fuzzy modelling. In this part, triangular, Gaussian, Gaussian combination and trapezoidal membership functions were used to evaluate and predict bagging quantitatively. Referring to our earlier study [6], for fuzzy modelling, we used the Fuzzy Logic Toolbox of MATLAB software, version 7.0.1. The possible fuzzy rules of bagging shape behaviour, as mentioned in Table 1 are obtained by using our previous experimental database. Then, these rules are trained for our fuzzy model using each fuzzy membership previously involved. According to our earlier study [6], Figure 8 shows the basic structure of the fuzzy logic model, which includes fuzzification, fuzzy inference, fuzzy rule base and defuzzification.

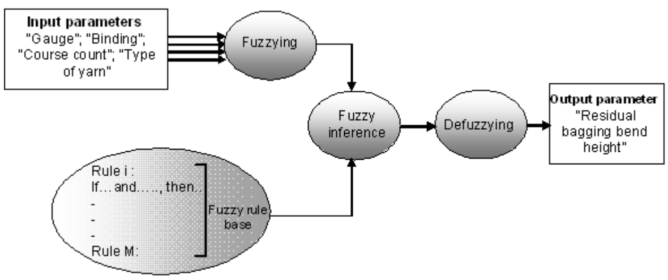

Figure 8. Basic structure of fuzzy logic model.

However, the aim of the second part consists of predicting the permanent bagging bend height using the neural network technique. We used the back-propagation algorithm to compare the desired output and the neural network one. As suggested by Prabal [12], among the various kinds of learning algorithms for the neural network, back-propagation is the best.

Results and discussion

Fuzzy modelling

In the present work we applied both fuzzy modelling and neural network theory. Table 4 shows the overall tested bagging bend samples and the variation between experimental (actual) values and theoretical (predicted) values of the bagging bend height which are expressed by the error value. The bagging bend height of tested knitting fabric is investigated using fuzzy theory system. To validate results, it is usually better to compare the theoretical output values and the experimental ones, which here shows that the fuzzy model is relatively well verified with our tested database particularly when using a triangular membership function.

Figures 9-12 show the regression model evolutions of the bagging bend height behaviour using the fuzzy logic method as a function of the experimental results. Hence, these figures show also the theoretical regression using the triangular, Gaussian, Gaussian combination and trapezoidal membership functions. After comparing the results given by the regression analysis model and those obtained using our fuzzy model, we remark that the regression coefficient ranges from 0.684 (case of Gaussian shaped) to 0.821 (case of triangular membership). Figure 9 presents the highest value of the regression coefficient value using the fuzzy modelling technique.

Referring to Majumdar's results [9], it was found that the triangular membership function for each input gives the best prediction accuracy. According to our earlier work [6] among these tested membership functions mentioned above, the simplest is the triangular one because it is formed with straight lines.

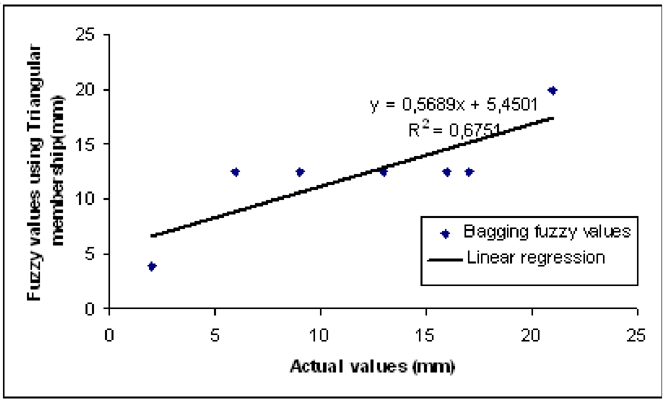

Figure 9. Relationship between actual values and fuzzy predicted ones of residual bagging bend height evolution using Triangular membership function.

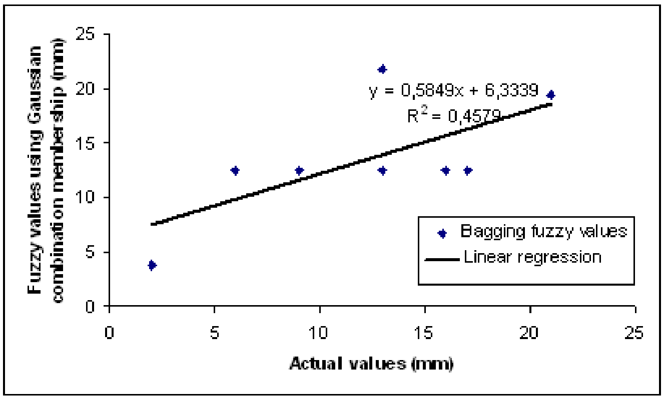

Figure 10. Relationship between actual values and fuzzy predicted ones of residual bagging bend height bagging evolution using Gaussian combination function.

But the biggest error was obtained in the case of Gaussian combination membership function because there the lowest regression coefficient (R2=0.4579) was obtained. The highest regression coefficient value, R=0.821, proves that the residual bagging bend height can be relatively well predicted using fuzzy modelling.

Table 4. Residual bagging bend height predicted and evaluated using Fuzzy Modelling and Neural Networks methods.

N° sample	Binding	Gauge	Course Count	Type of Yarn	Actual values, A_v (mm)	Theoretical values (mm)					Errors between actual values and values with Neural and Fuzzy theory (mm)				
						Neural Networks theory values, NN_v (mm)	Fuzzy theory values using different memberships (mm)				NN_v-A_v	FT_v-A_v	FG_v-A_v	FGC_v-A_v	FTr_v-A_v
							Triangular, FT_v	Gaussian, FG_v	Gaussian combination, FGC_v	Trapezoidal, FTr_v					
1	1	5	14	1	16	16	12.5	12.5	12.5	12.5	0	-3.5	-3.5	-3.5	-3.5
2	1	5	12	1	9	8.975	12.5	12.5	12.5	12.5	-0.025	-3.5	-3.5	-3.5	-3.5
3	1	5	16	1	6	6	12.5	12.5	12.5	12.5	0	-6.5	-6.5	-6.5	-6.5
4	0	5	18	0	13	13	12.5	21.7	21.7	21.7	0	-0.5	8.7	8.7	8.7
5	1	5	12	0	17	17	12.5	12.5	12.5	12.5	0	-4.5	-4.5	-4.5	-4.5
6	0	5	16	0	21	21	21.2	21.3	21.4	21.3	0	-1.1	-1.2	-1.6	-1.4
7	1	7	12	0	13	10.986	12.5	12.5	12.5	12.5	-2.014	-0.5	-0.5	-0.5	-0.5
8	0	7	14	0	2	3.055	17	17	20	21.2	1.055	1.88	1.74	1.81	1.77

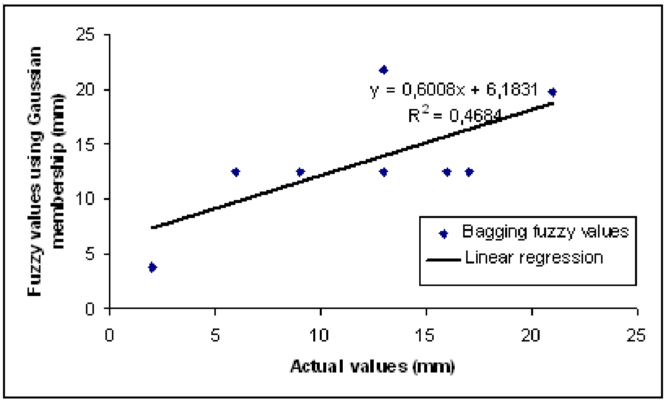

Figure 11. Relationship between actual values and fuzzy predicted ones of residual bagging bend height bagging evolution using Gaussian membership function.

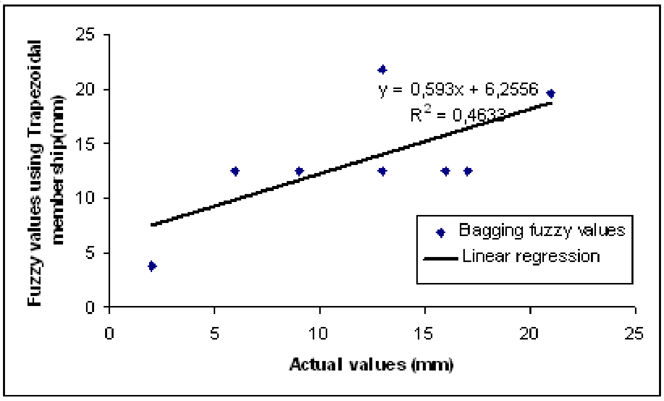

Figure 12. Relationship between actual values and fuzzy predicted ones of residual bagging height bagging evolution using Trapezoidal membership function.

Learning neural networks

To analyse the results obtained with the neural network technique, we use the transfer function which can be the combination of two transfer functions such as 'tansig' and 'poslin'. We note that the minimal mean squared error, MSE, value is carried out for a value of a number of hidden layers is between 20 and 44; the good result corresponds to 40 hidden neurons. In addition, the best prediction results of testing sets were found after 2000 iterations. Thus, for our application and

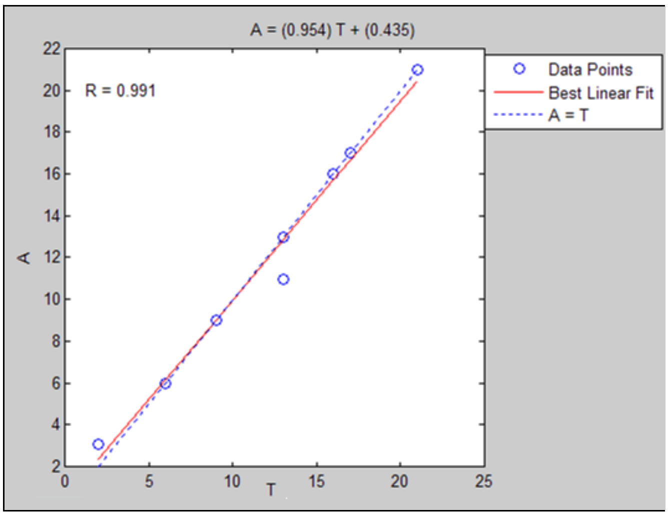

Figure 13. Residual bagging bend height theoretical model evolution using neural network theory.

after the tests carried out, it seems possible to obtain a low average quadratic error value.

Therefore, Figure 13 shows the regression model of neural network results as a function of the experimental ones. As shown in Figure 13, the coefficient of determination value for neural network method is 0.99 meaning a better prediction.

However, the correlation coefficients, R, between actual and predicted residual bagging bend height using fuzzy method range from 0.676 to 0.821. Indeed, we saved the relatively higher correlation coefficients, R=0.684, R=0.821 R=0.676 and R=0.68 of Gaussian, triangular, Gaussian combination and trapezoidal shaped membership functions respectively. Comparing these values to neural network one, it may be concluded that the results given from the neural network are generally consistent. Hence, we conclude that the trend and the values obtained from neural network show a better prediction performance [12]. Our findings agree with Yeung [12] that traditional methods are limited to evaluating bagging appearance by single parameters such as height, which cannot represent the abundant information given by the appearance of a bagged fabric [17].

Conclusion

We have predicted the residual bagging bend height of two different knitted fabrics using two theoretical methods: fuzzy modelling and neural networks. Our findings show that the prediction performance is best for the neural network model. Indeed, the results also show that the change of fuzzy membership function affects the prediction accuracy of the residual bagging bend height. Besides, our findings agree with the Majumdar's findings [9] that the triangular membership function for each input gives the best prediction accuracy. Compared to experimental results, it may be concluded that, overall, theoretical models using fuzzy technique are marked by relatively acceptable correlation coefficients especially using triangular membership function.

As suggested by Yeung [16], traditional methods are limited to evaluating bagging appearance by single parameters such as height, which cannot represent the abundant information given by the appearance of a bagged fabric. In addition, compared with the experimental results, the theoretical model can be used to predict permanent bagging height of knitted fabrics. In fact, we have concluded that the error values between analytical and experimental results within and without elastomeric yarns show the effectiveness of the fuzzy forecast model. Nevertheless, the results show that residual bagging height decreases when yarn contains elastane filament. This finding is basically in agreement with Mirostawa et al. [11] in that with an increase of the elastane content in fabric, permanent bagging decreases, whereas elastic bagging increases.

Compared to the fuzzy model, the neural network one gives accurate results. In contrast, the correlation coefficient obtained by the fuzzy technique using different membership functions is relatively lower (ranging from 0.676 to 0.821) than that given by the neural network model (R=0.99). Thanks to the neural network technique, we could make possible the forecast of the value of the remnant bagging bend arrow reached exactly on the sample center.

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