Intelligent Techniques for Modeling the Relationships between Sensory Attributes and Instrumental Measurements of Knitted Fabrics

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ABSTRACT
The present investigation provides a promising tool for engineering industrial products design. In fact, two soft computing approaches, namely artificial neural network (ANN) and fuzzy inference system (FIS), have been applied to model the relationship between sensory properties and instrumental measurements of knitted fabrics. The prediction performance of these models was evaluated using the root mean square error (RMSE). The obtained results show the models' ability to predict tactile sensory attributes from the measured surface and compression properties. These neural and fuzzy models may help textile industrialists to satisfy the specific needs of consumers.

Keywords: Prediction, sensory analysis, instrumental evaluation, intelligent techniques, fuzzy logic, neural network.

INTRODUCTION
Consumer preference for textile products is largely determined by sensory characteristics. Tactile feeling is one of the most important sensory characteristics. The sensory evaluation method, widely used in the food-processing and cosmetic industry, has been adapted to textile products [1, 2, 3, 4] to characterize the tactile feeling as a consumer evaluation.

However, sensory evaluation is time-consuming and expensive. Therefore, reliable and practical methods are needed to accurately predict sensory tactile attributes, at least in the product development and quality control stages. Several methods have been developed for measuring the tactile feeling of fabrics according to their physical mechanical, thermal and surface properties. In 1970, Kawabata and his co-workers, in Japan, developed a KES-FB system [5, 6, 7] for fabric hand evaluation. This system measured fabric properties, namely tensile and shearing, bending, compression, and surface properties at low stress, simulating the forces encountered when handling a fabric. In 1990, several scientists in Australia built another instrument system called the FAST system [8]. This instrument was basically a simplified version of the Japanese KES-FB system. In order to reduce the time needed to evaluate the fabric properties through the Kawabata KES-FB system, an alternative device based on the fabric extraction technique has been provided by Pan, et al. [9, 10].

Attempts have been made to relate instrumental measurements to the consumer's perceptions. Several investigators have used statistics and multivariate analysis, such as multiple factor analysis MFA and principal component analysis PCA [11, 12, 13], for selecting the relevant instrumental and sensory properties and analyzing the sensory data. Furthermore, a wide range of statistical or empirical methods have been proposed for modeling the relationship between instrumental measurements and sensory properties. In particular, PCA [14, 15], Weber-Fechner's law [16, 17] and Steven's power law [17, 18] have usually been applied. Although classical computing techniques were relatively easy to interpret and analyze sensory data, some limitations related to the non-linear relations in sensory domain had been reported [12].

Currently, new methods based on intelligent techniques (fuzzy logic, neural networks...) are used to treat a great number of textile applications [19, 20]. These methods have shown many advantages in characterizing some complex concepts related to sensory and instrumental evaluation of tactile properties. Several investigators have performed fuzzy logic systems to analyze the evaluation of sensory comfort [19]. Zeng et al. have used the fuzzy logic technique for modeling the relationship between the production parameters and the physical features of fabrics [21]. Hui et al. have developed a neural network to predict the consumer's sensory data from the fabric properties [22]. El-Ghezal Jeguirim et al. have applied fuzzy logic and neural network models to predict the sensory properties from process and structure parameters of knitted fabrics [23].

However, these intelligent techniques have been not used for the modeling of the relationship between the sensory attributes and instrumental characteristics. In this paper, the neural network and fuzzy logic-based models were developed to predict the sensory attributes, evaluated by a trained panel, of knitted fabrics from instrumental measurements of compression, thickness and surface properties.

MATERIALS AND METHODS

Materials

Fifteen Jersey industrially-produced knitted fabrics were studied in the present investigation.
Details of knitting parameters, i.e., the material (100% cotton and Cotton/Elastane), the count of yarns (25 tex and 20 tex) and the English gauge of the knitting machine (24 and 28), were given in our previous work [13].

In order to evaluate finished fabrics having the same properties as those traded in the market; the bleached or dyed fabrics were processed with finishes that are traditionally used by the textile industrialists. Fabrics were treated by boiling and through the following finishing stages:

- Enzymatic bio-polishing: this treatment was carried out in order to prevent pill formation caused by the friction on the woven and knitted fabric surface,
- Softening: this finish was used to confer fabrics a softer feeling,
- Calendaring: consisted of treating fabrics with pressurized rollers.

Instrumental Evaluation of Surface and Compression Properties

The physical properties of knitted fabrics were evaluated by the KES-F system developed by Kawabata and his co-workers [5, 6, 7]. This instrument measured the low stress mechanical and surface properties, such as fabric extension, shear, bending, compression, surface friction and roughness. In fact, wide ranges of statistical or multivariate analysis have been proposed for exploring the sensory/instrumental relationship. The obtained results have revealed that the compression, thickness and surface properties significantly correlated with the sensory data [14, 18]. In the present study, eight properties were measured under standard conditions, including compression, thickness and surface properties of the knitted fabrics. The measured parameters are shown in *Table I*.

TABLE I. Fabrics mechanical parameters measured on KES-F.

	Parameter	*Symbol*	*Description*	*Unit*
KES-FB3	Compression and Thickness	LC	Linearity of pressure-thickness curve	-
		WC	Compressional energy	gf.cm/cm^2
		RC	Compressional resilience	%
		T_0	Thickness at 50Pa	mm
		T_M	Thickness at 5000Pa	mm
KES-FB4	Surface	MIU	Coefficient of friction	-
		MMD	Frictional roughness	-
		SMD	Geometrical roughness	µm

In the case of fabrics and especially knitted fabrics, anisotropy had to be taken into consideration with each surface parameter P having two values, representing the wale and course directions of the fabric, noted respectively P-W and P-C.

Sensory Evaluation

In this study, the sensory analysis method, particularly the quantitative descriptive analysis (QDA) [24] method, was used. The analysis was performed by a trained sensory panel composed of seven persons (2 men, 5 women, aged from 30 to 50). They have been trained to describe the different kinds of textile products according to the ISO Standard [2, 25].

In part of the training, the assessors were focused on the development of a descriptive language to be used as a basis for scoring the products. To further support the language development, reference materials were identified to anchor the scoring scale [13, 26-28]. After several sessions of vocabulary development, the trained assessors agreed on a list of attributes and an evaluation procedure. In order to indicate the relative intensity for each attribute, a 0–10 linear nonstructured scale was selected.

The presentation order was random for each assessor with a maximum of six fabrics per session [2, 4, 29]. In order to control the panel performance, the individual and global repeatability of the panel were evaluated. Furthermore, the pertinence of the attributes had been checked using a two-way analysis of variance ANOVA and Principal Component Analysis PCA [13]. Hence, eleven pertinent attributes (*Table II*) were used to describe the quantitative tactile properties of the different types of knitted fabrics.

TABLE II. List of pertinent attributes.

Bipolar attributes	*Surface attributes*	*Handle attributes*
Thin-thick	Hairy	Falling
Light-heavy	Soft	Crumple –like
Supple-rigid	Sticky	Responsive
	Slippery	Elastic

Evaluation Conditions

Before instrumental and sensory evaluation, the samples were precut into 20 cm x 20 cm squares and relaxed using the relaxlab according to the French standards [30]. The tests were performed in a standard atmosphere (20±2 °C and 65±5 % RH) [31]. The fabrics were preconditioned for 24 hours before evaluation.

Artificial Neural Network

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model 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 available in the literature [32]. Among these algorithms, multilayer perceptron (MLP) had been successfully applied. A typical multi-layer 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. 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 minimised 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, developed by Rumelhart et al. [33], 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.

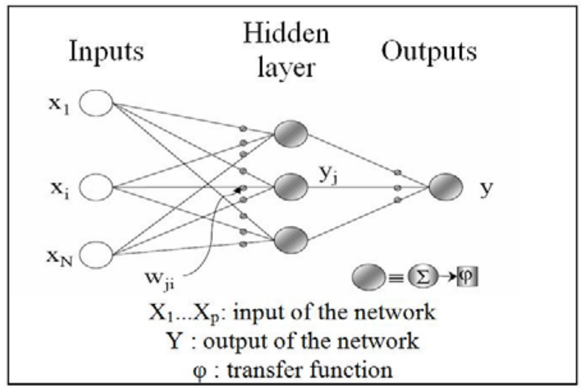

FIGURE 1. A multilayer artificial neural network.

Fuzzy Interference System

The foundation of fuzzy logic, which is an extension of crisp logic, was first proposed by Zadeh [34]. The theoretical aspects of fuzzy logic and fuzzy arithmetic have been explained in many standard textbooks [35]. In crisp logic, such as binary logic, variables are true or false, black or white, 1 or 0. In fuzzy logic, a fuzzy set contains elements with only partial membership ranging from 0 to 1 to define the uncertainty of classes that do not have clearly defined boundaries. For each input and output variable of a fuzzy inference system (FIS), the fuzzy sets are created by dividing the universe of discourse into a number of sub-regions, named in linguistic terms (high, medium, low etc.). If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs as $A=\{x, \mu A(x) \mid x \in X\}$ where $\mu A(x)$ is the membership function of x in A.

Once the fuzzy sets are chosen, a membership function for each set is created. A membership function is a typical curve that converts the input from 0 to 1, indicating how the input belongs to a fuzzy set. This step is known as “fuzzification”.

Membership function can have various forms, such as triangle, trapezoid, sigmoid and Gaussian.

The linguistic terms are then used to establish fuzzy rules. Fuzzy rules provide quantitative reasoning that relates input fuzzy sets with output fuzzy sets. A fuzzy rule base consists of a number of fuzzy if-then rules. For example, in the case of two inputs and a single output fuzzy system, it could be expressed as follows:

> If x is Ai and y is Bi, then z is Ci
> where x, y and z are variables
> representing two inputs and one output;
> Ai, Bi and Ci, the linguistic values of x,
> y and z respectively.

The rule base contains linguistic rules that are provided by experts. It is also possible to extract rules from numerical data. Once the rules have been established, the FIS can be viewed as a system that maps an input vector to an output vector.

The output of each rule is also a fuzzy set. Output fuzzy sets are then aggregated into a single fuzzy set. This step is known as "aggregation". Finally, the resulting set is resolved to a single output number by "defuzzification".

RESULTS AND DISCUSSION

Correlation between Sensory Attributes and Instrumental Properties

In order to reach acceptable performances of the models, fuzzy and neural techniques were used to model correlation between highly-related sensory and instrumental properties. In fact, sensory attributes were predicted from the instrumental parameters having a strong correlation (with an absolute value of correlation coefficient greater than or equal to 0.50 up to 0.91).

TABLE III. Correlation coefficients between sensory and mechanical properties.

	MIU-C	*MMD-C*	*SMD-C*	*MIU-W*	*MMD-W*	*SMD-W*	*LC*	*EC*	*T0*	*TM*	*RC*
Falling	-0.50	-0.91	0.70	-0.65	0.35	-0.86	-0.18	0.07	0.02	-0.60	-0.70
Thin-thick	0.46	0.79	-0.56	0.69	-0.38	0.75	0.23	-0.14	-0.07	0.75	0.77
Light-heavy	0.25	0.77	-0.59	0.67	-0.35	0.74	0.36	-0.06	-0.14	0.75	0.76
Supple-rigid	0.49	0.91	-0.72	0.61	-0.30	0.87	0.22	-0.17	0.08	0.55	0.69
Sticky	0.11	0.12	-0.25	0.00	-0.01	0.36	-0.02	0.12	0.27	-0.19	-0.06
Slippery	-0.44	-0.75	0.66	-0.62	0.38	-0.79	-0.43	-0.05	0.06	-0.44	-0.61
Soft	-0.55	-0.91	0.76	-0.50	0.26	-0.83	-0.05	0.14	-0.09	-0.32	-0.48
Hairy	-0.48	-0.59	0.62	-0.29	-0.03	-0.47	0.28	0.50	-0.31	-0.04	-0.13
Elastic	0.46	0.85	-0.71	0.75	-0.55	0.89	0.47	0.04	-0.27	0.48	0.80
Responsive	0.23	0.57	-0.32	0.65	-0.55	0.55	0.45	0.07	-0.49	0.71	0.81
Crumple –like	0.44	0.70	-0.55	0.31	-0.20	0.70	-0.21	-0.25	0.22	0.27	0.41

The Principal Component Analysis was used to establish the correlations between the instrumental measurements of compression, the surface characteristics and the sensory properties perceived by the trained panel. In *Table III*, the rank correlation coefficients for the tactile characteristics are reported. High correlation coefficients, implying a strong relationship between the instrumental measures of tactile characteristics and sensory properties, are highlighted.

Table III shows that only frictional and geometrical roughness in the courses direction (MMD-C and SMD-C) were used to predict the hairy attributes. It is also noted that the linearity of the pressure-thickness curve (LC), the compression energy (EC) and the thickness at 50Pa (T0) present a non-significant correlation with all the sensory attributes [13]. Thus, these instrumental properties were not selected for the following modeling study. However, the geometrical and frictional roughness, the compression resilience and the thickness at 5000 Pa were considered as the important instrumental properties in modeling the sensory attributes of knitted fabrics.

Data Analysis

From the correlation results (*Table III*), one sensory attribute (*sticky*) and three instrumental properties, namely LC, EC and T0, have been excluded from the input/output data of modeling study.

Table IV shows the values' range (minimum and maximum) of the remaining instrumental parameters and sensory attributes of fifteen samples. The standard deviations of experimental values are also given in *Table IV*.

TABLE IV. Values range of instrumental and sensory parameters.

Inputs	*MAX*	*MIN*	*Standard deviation*
MIU-C	2.5	2.2	0.10
MMD-C	2.6	1.2	0.39
SMD-C	1.5	1.1	0.12
MIU-W	2.2	2.0	0.06
MMD-W	3.2	1.1	0.80
SMD-W	2.8	1.2	0.52
TM	1.1	0.8	0.07
RC	0.7	0.5	0.06

Outputs	*MAX*	*MIN*	*Standard deviation*
Falling	7.3	2.9	3.3
Thin-thick	3.9	2.7	2.3
Light-heavy	4.2	3.0	2.4
Supple-rigid	4.9	2.5	2.9
Slippery	6.2	5.3	3.4
Soft	6.9	5.0	3.6
Hairy	1.1	0.6	0.8
Elastic	4.5	0.3	1
Responsive	1.5	0.3	0.8
Crumple –like	7.2	3.1	4.3

PREDICTING THE SENSORY ATTRIBUTES FROM MECHANICAL PROPERTIES

Neural Network Modeling

Optimization of Neural Model Parameters

The optimization of learning parameters, namely the number of hidden layers and the number of neurons in each hidden layer, mainly influenced the predicted performance of the ANN model.

In this investigation, only one hidden layer was used, as a single hidden layer has shown sufficient power for any degree of accuracy in most applications [20, 23, 36]. Consequently, only the number of hidden neurons became critical. In this case, the optimal hidden neurons number was optimized by the trial and error method. The network was trained using a different number of neurons in the hidden layer from 1 to 10 sequentially. It was found sufficient to use 3 neurons in the hidden layer. This neurons number provided the best predicted performance in terms of the mean square error MSE.

$$MSE = \frac{1}{N}\sum_{1}^{N} e^{2} \quad (1)$$

where N: data number, e: prediction error e = Y-T, where T: the real attribute score and Y: the estimated attribute score.

In general, it is known that when the network is too much trained, the network memorizes the training set and does not generalize well. The training holds the key to an accurate solution, so the criterion to stop training must be very well described. The cross validating stopping rule was used for ending training in this research. When the error in the cross validation increased, the training was stopped since the point of best generalization was reached.

Thus, the data set was divided into training, cross validation and test sets at random. From the fifteen samples, we used 9 (60%) samples as training set, 3 samples (20%) as cross validation set and 3 samples (20%) for testing the prediction performance of model.

The data were scaled to fall between -1 and + 1. The sigmoid and the linear transfer functions were used as an activation function for the hidden neurons and the output neuron, respectively.

Predicted Performances of Neural Models

The predicted performance of the neural models was evaluated separately in the training data, validation data and testing data. The neural models' performances were evaluated according to the root mean square error (RMSE). The RMSE was defined as the square root of MSE, obtained as shown previously in Eq. (1).

The predicted performances' results of the neural models revealed that the neural models had a good performance in predicting the sensory attributes from the instrumental properties (*Figure 2*). In fact, it was observed that the obtained RMSE values were considerably lower than the mean variations of the experimental values expressed by standard deviation values.

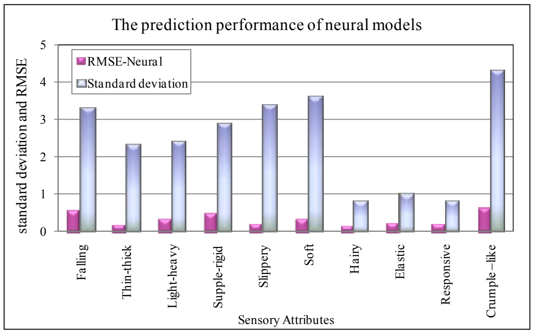

FIGURE 2. The prediction performances of neural models.

Fuzzy Logic Modeling

Input Space Reduction

In this investigation, eight instrumental properties were taken as input data in the prediction models. The eleven sensory relevant attributes were used as output data. However, in the fuzzy modeling procedures, the number of these input variables was still too large with respect to the learning data (fifteen samples). Hence, the Principal Component Analysis (PCA) was applied to reduce the number of the input variables [37]. The PCA performed a linear transformation of an input variable vector for representing all original data in a lower-dimensional space with minimal information lost. In our case, the two first components, representing the original variable vector in the direction of its two first largest eigenvectors of the variable covariance matrix, were taken as input data. The main steps adopted in this work in order to predict the sensory attributes from the fabrication parameters are shown in *Figure 3*.

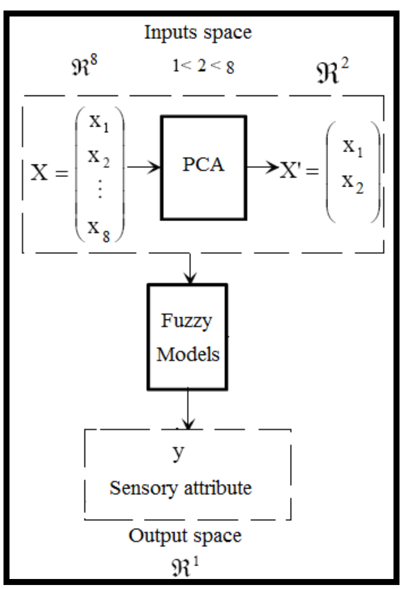

FIGURE 3. General depiction of the fuzzy proposed models.

Optimization of Fuzzy Model Parameters

In our investigation, a fuzzy variable was built for each sensory attribute. The various steps of the fuzzy modeling procedure were proposed as follows:

- *Step 1:* Fuzzification of inputs variables: The input data of fuzzy systems were converted to three fuzzy subsets: small (S), medium (M) and big (B). The trapezoidal membership functions were adapted (*Figure 4*).
- *Step 2:* Fuzzification of outputs variables: Each output variable was partitioned into five fuzzy subsets: very small (VS), small (S), medium (M), big (B) and very big (VB) (*Figure 4*).
- *Step 3*: Fuzzy rules generation: The fuzzy rules were extracted from the fabric samples of a learning base. The rules extraction was adjusted for each attribute in order to take into account different situations. The fuzzy systems evaluation was generated relating to the learning data. In this way, we effectively resolved the conflicts between the different rules and then decreased the information lost by selecting only the most influential rules. Then, the all input/output data were used for validating the effectiveness of the model.
- *Step 4*: Aggregation and defuzzification of outputs: The Mamdani method [38] was used for calculating the output inferred by a set of fuzzy rules. Mamdani fuzzy inference method was the most commonly applied fuzzy methodology. Under the Mamdani method, there was a fuzzy set for each output variable that needs defuzzification. The centroid method was applied for defuzzification.

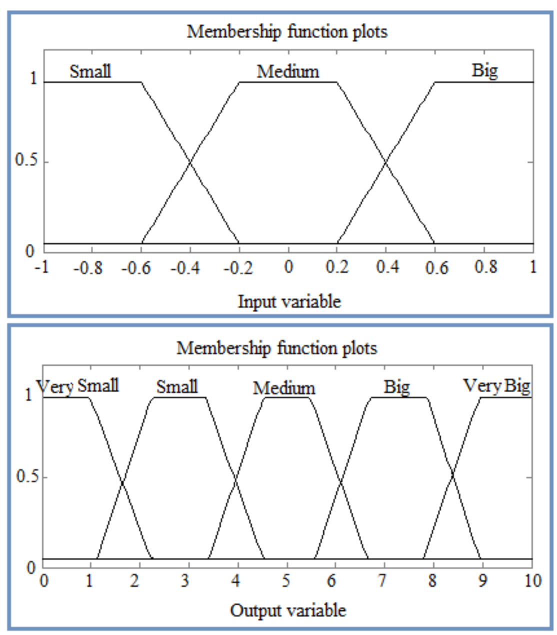

FIGURE 4. Membership functions of input and output variables.

For example, the obtained rules of the *falling* attribute model are shown in *Figure 5*. It was observed that for the input variables equal to -3.5 and -0.8 respectively, the two rules (Rules 2 and 3) were active and the corresponding output data was equal to 3.3.

<u>Prediction Performances of Fuzzy Models</u>

Figure 6 represents the comparison between the root mean square error (RMSE) of fuzzy models and the mean variations of the experimental values expressed by standard deviation values. The statistical performance criteria values exhibited the successful ability of the fuzzy models to predict the sensory attributes from instrumental properties. In fact, the obtained RMSE values were significantly lower than the standard deviation values.

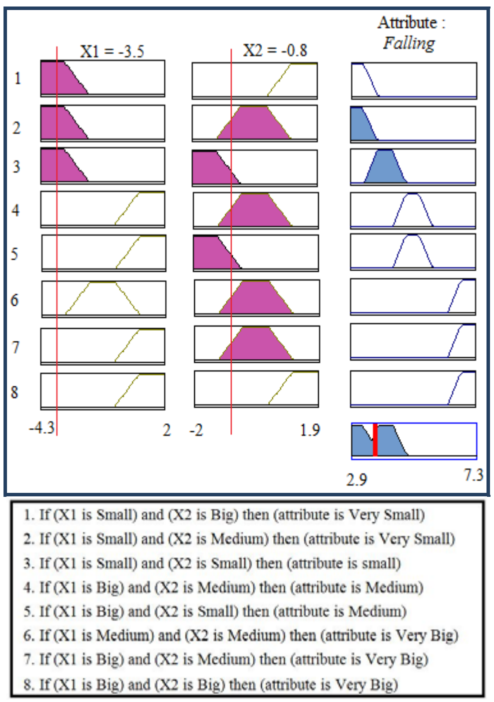

FIGURE 5. Fuzzy model rules of *falling* attribute.

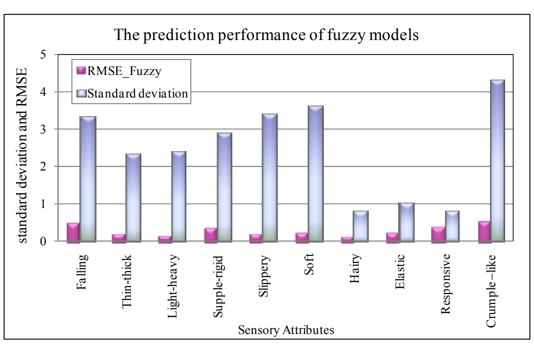

FIGURE 6. The prediction performances of fuzzy models.

<u>Comparison of the Predicted Performance of Neural and Fuzzy Models</u>

The fuzzy and neural models were compared in terms of predicted performance by representing the root mean square error RMSE (*Table V* and *Figure 7*). It is noted that the neural and fuzzy models presented a similar predicted performance. The statistical criterion RMSE values were slightly lower for fuzzy models compared to those of neural models for all attributes except the *responsive* attributes' case. However, the 'black box' problem associated with neural networks could hinder the widespread adoption of this method. In fact, the fuzzy techniques have an advantage over the neural ones, since the linguistic fuzzy rules can be interpreted. Thus, it was possible to observe how the fuzzy model performed its computations.

TABLE V. Fuzzy and neural models prediction performances.

Attributes	*Neural models*	*Fuzzy models*
Falling	0.55	0.49
Thin-thick	0.17	0.18
Light-heavy	0.33	0.14
Supple-rigid	0.47	0.34
Slippery	0.2	0.18
Soft	0.31	0.22
Hairy	0.14	0.12
Elastic	0.21	0.22
Responsive	0.19	0.38
Crumple –like	0.64	0.53

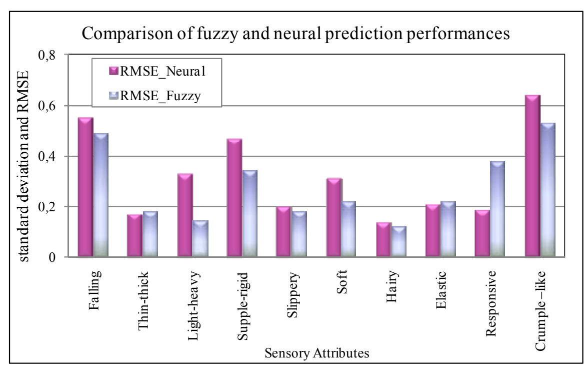

FIGURE 7. Comparison of fuzzy and neural models prediction performances.

CONCLUSIONS

In order to face the competitive environment, textile companies are interested in designing and producing new industrial products adapted to the consumers' preferences and demands.

In this paper, the fuzzy and neural models were developed to predict the tactile sensory attributes of knitted fabrics from instrumental parameters. In order to evaluate the performances of the proposed models, the statistical criterion, namely the root mean square error (RMSE), was estimated.

The obtained results revealed that the neural networks and fuzzy logic provided an alternative approach for predicting the tactile sensory attributes from the instrumental parameters of knitted fabrics. In fact, the RMSE values were considerably lower than the mean variations of the experimental values. The predicted performances of the neural and fuzzy models were also compared according to the root mean square error RMSE. Both techniques were a promising tool for the design of engineering industrial products, in order to satisfy the specific needs of consumers. In addition, the minimal number of experiments or learning data and the short cycles of product design and product development were sufficient.

However, the fuzzy models' performances were slightly better than the neural models. In addition, the "black box" problem associated with neural networks could hinder the widespread adoption of this method. In fact, the fuzzy techniques have two advantages over the neural ones. The fuzzy models permitted the results' interpretation and the integration of the linguistic sensory attributes.

Moreover, several investigations revealed that better results could be obtained when these techniques were used in combination [14]. Hence, this work used the combination of the neural and fuzzy approaches. In fact, we were interested in extending the development of a model based on the neuro-fuzzy methodology. In fact, this approach combined the self-learning ability of the neural networks and the human-like reasoning style of fuzzy systems. Neuro-fuzzy models could provide a way to link sensory attributes with mechanical properties or processes' parameters of fabrics.

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