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A Fuzzy Criterion for Selecting Relevant Process Parameters for the Development of Nonwoven Products

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Abstract. In this paper, we present a new fuzzy selection criterion which takes into account both the sensitivity of measured data and human knowledge concerning the relations between process parameters and quality features of nonwoven product. This selection criterion permits to rank the process parameters of the related nonwoven production line and take the most relevant ones as input variables of the model for designing new nonwovens products. Compared with the classical selection criteria, the proposed method is more robust and less sensitive to proximities of measurement and uncertainties. This method has been validated using real data collected from a nonwoven process and a predefined questionnaire filled by experts.

Keywords: relevant parameter selection, fuzzy logic, human knowledge, OWA, nonwoven materials

1. Introduction

Nonwoven products are fibrous materials characterized by a large range of interesting properties. Due to various application fields and good performance/production cost ratio, the number of end-uses designed with nonwoven materials has significantly grown in the last decades. Face to international competition on the textile market, nonwoven materials should be developed to satisfy more and more demanding and complex specifications and increasing requirements for international standards in different application fields. In the same time, nonwoven product designers are strongly involved in cost reduction projects and apply the basics of value analysis during the development of these manufacturing products. [1]

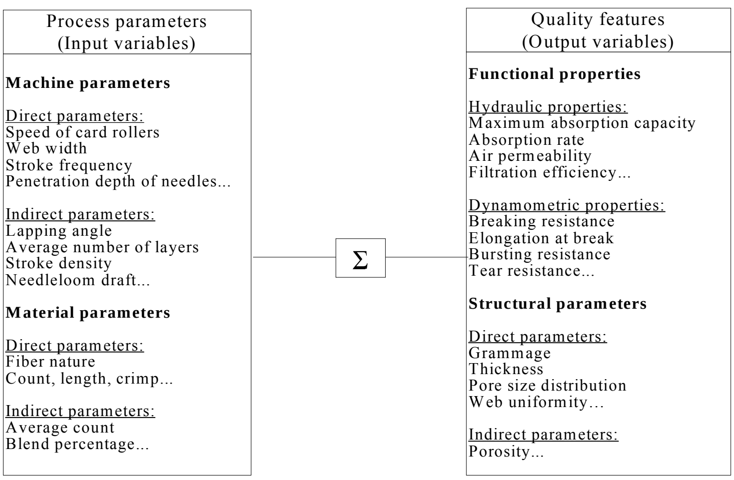

Fig. 1: Modelling relationship between process parameters and quality features for nonwoven products

Consequently, great attention has been paid to model the relationship between process parameters (machine parameters, raw material parameters, and environment parameters) and quality features (functional properties, structural parameters). After the definition of their global structure (single/multilayer complex

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structure, feature of each layer…), new nonwoven products can be perfected and produced by adjusting process parameters according to the related model. In this paper, we suppose that the environment of the quality features is constant and acceptable for production. Under this condition, machine and material parameters are taken as input variables; structural parameters and functional properties as output variables respectively. The input parameters can be divided into two categories: direct parameter and indirect parameter. Direct process parameters are obtained from direct measurements with sensors while indirect process parameters can be calculated from direct parameters according to some known physical laws. In other words, indirect parameter can be considered as mathematical combination of several direct parameters. The corresponding model is illustrated in Fig.1.

However, this procedure of modelling is rather complex for the following reasons: 1) the relationship between input and output variables is usually nonlinear; 2) the number of process parameters is too large and there often exists interdependencies between them; 3) the quantity of available learning data is often very small; 4) the learning data are coming from an uncertain environment. In this condition, there is a strong need for modelling with a small set of relevant process parameters in order to reduce the complexity and decrease the number of trials.

In this paper, we present a fuzzy selection method integrating both the qualitative human knowledge of experts and the quantitative measured data. Compared with classical selection criteria, it is more robust, less sensitive to proximities existing in measured data and easier to be interpreted physically. Using this criterion, we can effectively classify input variables by ranking and then select the most significant variables. After the presentation of the general selection procedure in the second section, the third section shows how we can explore and aggregate the human knowledge related to process/product relation. The fourth section exposes a method for integrating the human knowledge into the selection procedure. This procedure is illustrated using an example coming from the nonwoven industry. The results are finally discussed and some prospects are proposed.

2. Selection procedure of relevant variables

In the existing literature, most of the methods for variable selection have been carried out in the frame of supervised data classification, i.e. the objective of selection is to improve the classification accuracy or class label predictive accuracy of data samples [2]. Several well-known methods are the decision-tree method [3], the nearest-neighbor method [4], the mutual information measure based method [5] and the hyperbox generation based method [6], information-theoretical connectionist network model for removing both irrelevant and redundant variables [7] and wrapper model, which evaluates alternative subsets of variables by running some induction algorithm on the learning data and using the estimated accuracy of the resulting classifier as its metric [8]. There also exist some works on unsupervised variable selection using conditional Gaussian networks [2] and data clustering techniques [9].

In practice, the performance of these data based variable selection methods is strongly related to the quality and the quantity of data samples and the criterion defined, which may vary from task to task. These methods are not efficient to solve variable selection problems in some industrial processes. In these processes, limited by the cost and the time of measurement, the quantity of data is often too small to constitute a correct distribution for obtaining significant classification results. Moreover, the physical knowledge of experienced operators and experts on processes and products is not well exploited. In this case, the class separability based criteria for variable selection should be replaced by variable sensitivity based criteria such as gradient descent. Also, if possible, human physical knowledge on the problem and measured numerical data should be used in a complementary way in order to improve the criterion of selection and to cross-validate the results obtained from these two information sources.

In our previous work, a classical selection criterion has been proposed to rank the nonwoven process parameters by linearly combining the human knowledge conformity criterion and the sensitivity of measured data [10]. In practice, when the values of a selection criterion for two variables are very close, they are generally considered as having the same level of relevancy and the order between them is not significant. Contrarily, for two variables having a big difference in values of selection criterion, their order should be significant. According to this principle, classical selection criteria are too sensitive and mask real physical significance in related results. In this section, we propose a fuzzy logic based linguistic criterion. With this criterion, we can effectively filter data proximities related to measurement and obtain only significant orders in the corresponding results. This criterion is expressed as $F=f(H,S)$, in which the first element H represents the human knowledge on nonwoven processes and products and the second element S the sensitivity of measured data defined according to the following two assumptions:

1) IF a small variation of an input variable Δx corresponds to a large variation of the output variable Δy, THEN the sensitivity value S is big.

2) IF a large variation of an input variable Δx corresponds to a small variation of the output variable Δy, THEN the sensitivity value S is small.

These assumptions can be transformed into fuzzy rules for building a fuzzy model in which Δx and Δy are taken as two input variables and S as output variable. This fuzzy model includes an interface of fuzzification, a base of fuzzy rules, an inference mechanism and an interface of defuzzification. After the fuzzification procedure, each of the two input variables is transformed into a fuzzy variable with three fuzzy values*: big, medium small*, corresponding to membership functions *trampf(x,[-0.5,-0.1,0.1,0.5])*, *trimf(x,[0.1,0.5,0.9])* and *trampf(x,[0.5,0.9,1,1.1,1.5])* between [0,1]. The output variable S is transformed into a fuzzy variable with five fuzzy values: *Very Small (VS), Small (S), Medium (M), Big (B), Very Big (VB)*, corresponding to membership functions *trampf(x,[-0.5,-0.1,0.1,0.5])*, *trimf(x,[0.1,0.3,0.5])*, *trimf(x,[0.3,0.5,0.7])*, *trimf(x,[0.5,0.7,0.9])* and *trampf(x,[0.7,0.9,1.1,1.3])* between [0,1].

We define the following fuzzy rules in Table 1 according to the human experience of experts:

Table1. Fuzzy rules for the data sensitivity

S		Δy small	Δy medium	Δy big
Δx	small	small	big	very big
	medium	small	medium	big
	big	very small	small	medium

Given fixed values of Δx and Δy, we can calculate the corresponding numerical value of sensitivity S from these fuzzy rules. Then, we denote $S = FL(\Delta x, \Delta y)$. The Mamdani method [11] has been used for defuzzification. When removing x_k from the whole set of input variables, the corresponding sensitivity variation can be calculated as follows.

Let m be the number of process parameters (input variables) assumed to be influent on one specific quality feature (output variable). Denote $X_s = (x_{s1}, x_{s2}, \ldots, x_{sk}, \ldots, x_{sm})^T$ the data of all the process parameters and $Y_s = (y_1, y_2, \ldots, y_l, \ldots, y_n)^T$ the data of quality features that correspond to the sample s ($s \in \{1, \ldots, z\}$). It is to be noticed that the pre-selection of the input variables is assumed by the experts according to their experience, voluntary allowing possible interdependencies between variables. These dependencies are considered during our selection procedure. All the measured data on these z samples have been normalized to be on the interval of [0, 1] in order to eliminate the scale effects. For two different samples i and j (one pair), their variations related to all process parameters and one specific quality feature yl, denoted as Δx_{ij} and Δy_{ij} respectively, can be calculated by

$$\Delta x_{ij}^k = \sqrt{\sum_{\substack{p \in \{1,\ldots,m\} \\ p \neq k}} \left(x_{ip} - x_{jp}\right)^2} \tag{1}$$

By assigning $\Delta x := \Delta x_{ij}$ and $\Delta y := \Delta y_{ij}$, we can obtain from the previous fuzzy model the sensitivity value $FL(\Delta x_{ij}, \Delta y_{ij})$, corresponding to all the process parameters and the pair of samples (i, j). In the same way, we can also obtain $FL(\Delta x_{ij}^k, \Delta y_{ij})$, corresponding to all the process parameters except x_k and the pair of samples (i, j).

The sensitivity variation of the pair *(i,j)* when removing x_k, denoted as can be calculated as follows.

$$\Delta S_{ij}^k = FL(\Delta x_{ij}, \Delta y_{ij}) - FL(\Delta x_{ij}^k, \Delta y_{ij}) \tag{2}$$

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

$$\Delta S_k = \frac{1}{\gamma}\sum_{i=1}^{n}\sum_{j=i+1}^{n} S_{ij}^{k,l} \quad (3)$$

Bigger is the value of ΔS_k, more the corresponding input variable x_k is relevant to the quality feature y_l.

The objective of our criterion is to select the most relevant independent process parameters, so the redundant and related inputs would be removed by following backward algorithm:

Input: process parameters $X = \{x_1, ..., x_k, ..., x_m\}$ and one related specific quality feature y_l
Output: relevant process parameters X_r and related sensitivity variation value ΔS

Initialize $X'=X$, $X_r=\{\}$, $\Delta S'=\{\}$
while $size(X') > \tau$
calculate the sensitivity variation of inputs in X' *related to* y_l *denoted* $\Delta S'=\{\Delta S_1, ..., \Delta S_k, ..., \Delta S_{size(x)}\}$
$X_r=X_r+\{x_i\}$ $X'=X'-\{x_i\}$ *where* $\Delta S_i=max(\Delta S')$
$X'=X'-\{x_j\}$ *where* $\Delta S_j=min(\Delta S')$
end
$\Delta S=\Delta S'$

First, we identify the most relevant process parameter with highest sensitivity variation, and eliminate the smallest one. After they are removed, a new step for calculating the sensitivity variation with decreased number of inputs is generated using our fuzzy criterion. This process can be repeated until the predefined threshold τ is reached. At each step, the remaining unidentified dependent inputs related to the identified inputs will be dropped down in the sensitivity variation ranking list and be removed in the next steps. Thus, we can obtain a significant and independent list X_r of relevant process parameters.

In this case, the procedure of input selection is finally completed and a collection of relevant process parameters is selected for the modelling procedure.

3. Aggregation of human knowledge

The objective of the aggregation procedure of human knowledge is to clarify uncertainties and dissimilarities according to expert's level and confidence. The human knowledge from k^{th} process parameter on l^{th} quality feature is colleted from a predefined questionnaire filled by nonwoven experts on process/product relations in Table 2. For simplicity, we consider at a time that only one process parameter has influence on each quality feature. Also, we consider that experts have different levels of expertise and that their knowledge is generally incomplete and uncertain.

Table 2. Questionnaire representing the knowledge of the expert v ($v\in\{1,\ldots,h\}$) related to the influence of a process parameter on a product structure

expert's knowledge	Degree of confidence	Expert's Level
I_1…	C_1…	E_1…
I_v…	C_v…	E_v…
I_h…	C_h…	E_h…

In Table 2, I_v corresponds to the knowledge expressed by the expert v using the linguistic terms *very positive (VP)*, *positive (P)*, *null (0)*, *negative (N)*, and *very negative (VN)* representing the type of influence of the process parameter on the product structure respectively. C_v represents the degree of confidence of the expert v on his own knowledge using the linguistic terms: *little certain (LC)* and *certain (C)*. E_v represents the expert's level estimated by the panel's leader using the linguistic terms: *high, medium, and, low*. I_v, C_v and E_v are subjective expressions of the knowledge. Our procedure for aggregating the expert's knowledge is sequenced by 3 steps:

Step1: calculation of the dissimilarities between expert's knowledge

In practice, it usually exists dissimilarities between expert's knowledge on relations between process parameters and quality features because their professional background and personal sensitivity are quite different. Therefore, at this step, we define a distance criterion for estimating the dissimilarity of knowledge between different experts.

Firstly, we transform the knowledge into a fuzzy variable defined by five triangular membership functions *{VP, P, 0, N, VN}* as shown in Fig.2. Each triangular membership function, denoted as *trimf(x,[*a_t,b_t,c_t*]) (*$t\in[1,5]$*)*, represents one type of influence of process parameters on quality features.

If we remove the v^{th} expert's knowledge, we denote U_{t_v} as the number of remaining experts voting for t^{th} type of influence and R_{t_v} as the corresponding percent of vote for t^{th} type of influence, calculated by $R_{t_v}=\frac{U_{t_v}}{h-1}\times 100\%$. The area corresponding to R_{t_v} percent of the t^{th} type of influence, denoted as A_{t_v}, is calculated according to $A_{t_v}=\frac{R_{t_v}}{2}\left(c_t-a_t\right)$ and illustrated in Fig.3.

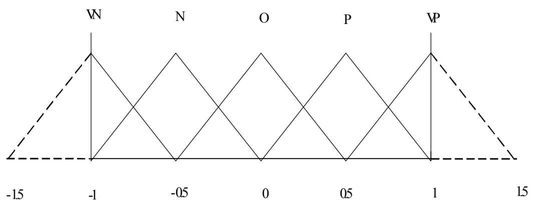

Fig. 2: Fuzzy variable representing the knowledge

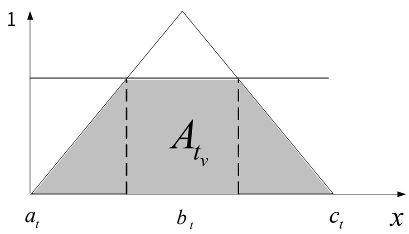

Fig. 3: illustrated A_{t_v}

Denote C_v as the centre of gravity of the voting region *trimf(x,[*a_v,b_v,c_v*])* by v^{th} expert. Also, we denote $C_v^{'}$ as the centre of gravity of the voting region by the other experts except v. The distance d_v is calculated between these two centres of gravity using the following equation

$$d_v=\left|C_v-C_v^{'}\right|=\left|b_v-\frac{\sum_t^5 b_t R_{t_v}}{\sum_t^5 R_{t_v}}\right| \quad (4)$$

The resulting distance is then transformed into linguistic value from *{small*, *medium*, *big}*. These linguistic values correspond to the uniform triangular membership functions *trimf(x,[-1,0,1])*, *trimf(x,[0,1,2])* and *trimf(x,[1,2,3])* between [0,2].

Larger the distance d_v is, more dissimilarity between v^{th} expert's knowledge is related to the other experts.

Step 2: optimization of the knowledge's weight

At this step, fuzzy logic is used to determine the weights of knowledge according to the calculated distances, expert's professional levels and degrees of confidence. Firstly, we consider that the weights of knowledge for different experts are fuzzy values with triangular membership functions *{very small(VS), small(S), medium(m), big(B), very big(VB)* correspond to triangular membership functions *trimf(x,[-0.25,0,0.25])*, *trimf(x,[0,0.25,0.5])* , *trimf(x,[0.5,0.75,1])* and *trimf(x,[0.75,1,1.25])* between [0,1].

The weight w_v corresponding to the v^{th} knowledge *(*$v\in\{1,\ldots,h\}$*)* can be estimated using a set of fuzzy rules obtained according to the following principles:

1) if the level of an expert is high and his/her confidence on the knowledge is high and the distance of his/her knowledge is close to that of the other experts, then the corresponding weight should be enhanced and the related knowledge can be considered as a very important information in the aggregated final result.

2) If the level of an expert is low and his/her confidence on the knowledge is low and the distance of his/her knowledge is far away from that of the other experts, then this knowledge should be removed. These two extreme principles and other observation lead to the construction of the 18 fuzzy rules shown in Table 3.

Table 3. Fuzzy rules for estimating knowledge's weight

The bigger is w_v, the more reliable the v^{th} knowledge is and the more important information this expert can provide. These rules have been validated by professional experts on nonwoven process.

W_k		E_k High level			E_k Medium level			E_k low level		
C_k	Certain	Very Big	Big	Medium	Big	Medium	Small	Medium	Small	Small
	Little certain	Big	Medium	Small	Medium	Small	Small	Small	Very Small	Null
		Small	Medium	Big	Small	Medium	Big	Small	Medium	Big
		D_k			D_k			D_k		

<u>Step 3: aggregating the knowledge using OWA</u>

At this step, the entire expert's knowledge is aggregated using OWA operator [12]. The new weights w'_v are then calculated: $w'_v = w_v/sw$ *with* $sw = \sum_{v=1}^{h} w_v$ $(v \in [1,h])$. The type of influence *'VP', 'P', '0', 'N'* and *'VN'* are then replaced by numerical values B=[1,0.5,0,-0.5,-1]'. Thus, the aggregating value of expert's knowledge, denoted $H_{k,l}$ is estimated by flowing equation

$$H_{k,l} = \left\| W^T \cdot B \right\| = \left| 1 \times w_1 + 0.5 \times w_2 + 0 \times w_3 + (-0.5) \times w_4 + (-0.5) \times w_5 \right| \text{ with } W=[w'_v;\ v \in [1,h]]$$

According to this procedure, $H_{k,l}=1$ corresponds to the most important influence of k^{th} process parameter related to l^{th} quality feature; and a small value of $H_{k,l}$ is considered as non important influence.

4. Combination between human knowledge and numerical sensitivity

In this session, fuzzy logic is used for obtaining a more robust ranking criterion combining two elements $S_{k,l}$ and $H_{k,l}$ according to the fuzzy rules shown in Table 4.

Table 4 Fuzzy rules for combining data sensitivity and human knowledge

$F_{k,l}$		and if $H_{k,l}$ is small	medium	big
if $S_{k,l}$ is	small	small	medium	medium
	medium	small	medium	medium
	big	medium	medium	big

These fuzzy rules permit to build a fuzzy model in which $S_{k,l}$ and $H_{k,l}$ are taken as two input variables and $F_{k,l}$ as output variable. After the fuzzification procedure, each of them is transformed into a fuzzy variable with three fuzzy values: *big, medium and small*. The Mamdani method [10] is used for calculating the output value from input values.

We consider that the output variable $F_{k,l}$ varies in the range of [0,1]. More the value of $F_{k,l}$ is close to 1, more the corresponding variable x_k is relevant. In general cases, the membership functions of $S_{k,l}$ can be denoted as *Triangle*(e_1,e_1,f_1), *Triangle*(e_1,f_1,g_1) and *Triangle*(f_1,g_1,g_1). the membership functions of $H_{k,l}$ can be denoted as *Triangle*(e_2,e_2,f_2), *Triangle*(e_2,f_2,g_2) and *Triangle*(f_2,g_2,g_2). The corresponding parameters e_1, f_1, g_1 and e_2, f_2, g_2 are defined by $e_1 = \min_k \{S_{k,l}\}$, $g_1 = \max_k \{S_{k,l}\}$ and $f_1 = \frac{e_1 + g_1}{2}$; $e_2 = \min_k \{H_{k,l}\}$, $g_1 = \max_k \{H_{k,l}\}$ and $f_2 = \frac{e_2 + g_2}{2}$.

5. Analysis of the results for a nonwoven process

In this part, we validate our fuzzy criterion using a series of 23 sets of data provided by a nonwoven process dedicated to liquid absorption. Each set of data corresponds to a nonwoven product generated by experimentation.

First, we propose to study the quality feature/process parameters relations for a nonwoven product which is manufactured by a drylaid needlepunched process. We focus on six direct process parameters and three indirect process parameters related to the cross-lapper and needle-loom. These parameters are firstly pre-selected by nonwoven experts according to their possible influence on quality feature 'porosity', which is one of the main critical structural parameter related to super-absorbent properties. The nonwoven direct process parameters are: '$x_{1:}$ take-off apron speed of cross-lapper', '$x_{2:}$ delivery apron speed of the cross-lapper', '$x_{3:}$ production speed', '$x_{4:}$ stroke frequency', and '$x_{5:}$ penetration depth of needles', and the indirect parameters are: '$x_{6:}$ needleloom draft', '$x_{7:}$ number of layers' and '$x_{8:}$ stroke density'. We predefined a selection threshold at 50% of the total amount of inputs in the final selected list ($\tau = 4$). The steps for identifying the relevant inputs are presented in Table 5.

Table 5 Identification of relevant inputs using the fuzzy selection criterion (without human knowledge)

	Remaining inputs	Significance ranked by ascending S	Identified input	Eliminated inputs
Step 1	All inputs , x_1 to x_8	$x_7, x_5, x_2, x_6, x_1, x_3, x_8, x_4$	x_7	x_4
Step 2	$x_5, x_2, x_6, x_1, x_3, x_8$	$x_5, x_6, x_8, x_3, x_2, x_1$	x_5	x_1
Step 3	x_6, x_8, x_3, x_2	x_6, x_8, x_3, x_2	x_6	x_2
Step 4	x_8, x_3	x_8, x_3	x_8	x_3

Using the fuzzy selection procedure, we identify the '$x_{7:}$ number of layers', '$x_{5:}$ penetration depth of needles', '$x_{6:}$ needleloom draft' and '$x_{8:}$ stroke density' as the most relevant independent process parameters.

Secondly, we continue the procedure by combining obtained results and the human knowledge collected from a predefined questionnaire on process/product relations filled by experts.

Table 6 Identification of relevant inputs using human knowledge

			Influence on "porosity"										
			Expert 1		Expert 2		Expert 3		Expert 4		Expert 5		OWA Relevancy factor
			High Level		High Level		Low level		Medium Level		Medium level		
			distance	weight	distance	weight	distance	weight	distance	weight	distance	weight	
Process parameters	Direct parameters	Penetration depth of needles	0.3907	0.6471	0.2500	0.8270	0.2500	0.4276	0.3907	0.6471	0.2500	0.6776	0.6629
	Indirects parameters	Number of layers	1.0000	0.7500	0.2499	0.4277	0.2499	0.4277	1.0000	0.5000	1.4996	0.2177	0.4443
		Needleloom draft	0.8423	0.7538	0.9999	0.5001	0.3317	0.2354	0.2503	0.6776	0.2503	0.4276	0.4071
		Stroke density	1.0000	0.5000	0.4473	0.6356	0.8317	0.3023	0.4473	0.6356	0.8317	0.5523	0.2698

The corresponding results obtained after the aggregation procedure of the human knowledge is illustrated in Table 6. Finally, we combine the data sensitivity and human knowledge. All theses results are compared to classical criterion and are presented in Table 7.

Table 7 Comparison between different selection methods

Process parameters	Fuzzy Sensitivity Variation (FSV)		Human Knowledge (HK)		Fuzzy combining sensitivity variation and human knowledge (FSVHK)		Classical criterion (CC)	
	value	rank	value	rank	value	rank	rank	rank
Penetration depth of needles	-0.0076	2	0.6629	1	0.5500	1	0.5992	3
Number of layers	0.0171	1	0.4443	2	0.4990	2	0.2500	4
Needleloom draft	-0.0016	3	0.4071	3	0.4640	3	0.9659	1
Stroke density	-0.0602	4	0.2698	4	0.2680	4	0.6111	2

In Table 7, we can notice that 'penetration depth of needles' rise to the first rank in FSVHK (rank 1) compared with FSV (rank 2). The result of FSVHK is more conform to expert's knowledge than that of FSV because it deals with more complete information on the relation between process parameters and quality features (Fig.4). We can also notice that the 'number of layers' input variable is selected as a relevant process parameter (rank 2) with FSVHK compared with that of CC This result is due to fuzzy capability of taking into account significant data variation trend (Fig.5) and filter useless variation (non variation) (rank 4).The 'needleloom draft' appears to be relevant with the CC (rank 2). Contrarily, the FSVHK shows that this variable is less relevant comparable to the other three relevant parameters (rank 4). This result shows that FSVHK is more robust and less sensitive to the data measured in a very small range (proximity) (Fig.6).

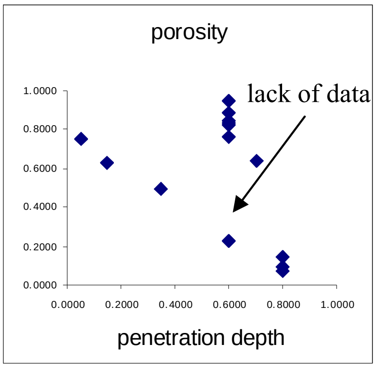

Fig. 4: relationship from the collection data between 'penetration of needles' and 'porosity'

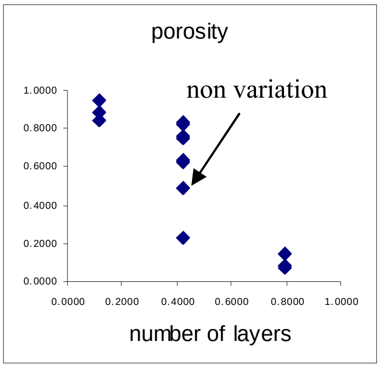

Fig. 5: relationship from the collection data between 'average number of layer' and 'porosity'

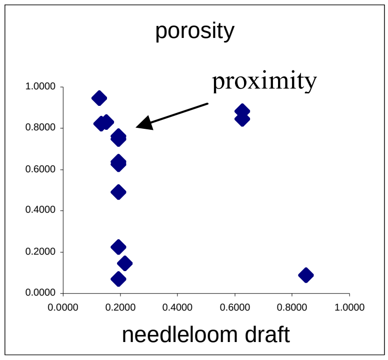

Fig. 6: relationship from the collection data between 'needleloom draft' and 'porosity'

After the validation of experts, 'penetration depth of needles' , 'number of layers' and 'needleloom draft' are influences which are more important than 'stroke density' on 'porosity'. This result appears in the fuzzy criterion thank to the robust of the fuzzy selection criteria. We can also notice that the fuzzy criterion can filter data complexity related to manufacturing process and can provide only a better ranking result according to the process parameters relevancy.

6. Conclusion

In this paper, we present a fuzzy criterion for selecting relevant process parameters from a nonwoven process. This criterion permit to combine data sensitivity is considered to be more relevant to specific manufacturing processes, and human knowledge, is considered to be more relevant to general professional knowledge of experts and operators. The selection of process parameters allows producers to adjust only a few numbers of the most relevant parameters in order to meet the requirements of customers on product quality. Compared with the other numerical selection criteria, this fuzzy selection criterion can lead to more robust, more significant and more physically interpretable results. Another advantage is that the proposed selection criterion can deal with a very few number of learning data. Then, it can be effectively applied to industrial selection problems in which production time for obtaining learning samples is rather limited and experimentation cost is often high. This method has been successfully applied to the design of a nonwoven process and can also be extended to other industrial problems.

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