

# SEAM PUCKER PREDICTION BASED ON FABRIC STRUCTURE AND MECHANICAL PROPERTIES USING FUZZY SYSTEM

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## Abstract

In this article, fuzzy system (FS) is used to predict the seam pucker. The predictions are based on fabric mechanical properties measured on the KESF system and structure properties calculated by Peirce model. Eight designed fuzzy systems in two groups enable to predict pucker seam. Inputs are fabric parameters, outputs are SS grades of warp and weft seams. Weighted Sections Method is applied on prediction of seam pucker for construction of defuzzification module. Random-search algorithm is applied on determination of raw data. Hooke-Jeeves and Yellow section algorithms are applied on determination of optimal parameters. Testing results indicate that designed fuzzy systems are effective for predicting seam pucker grades in clothing manufacturing.

**Key words:** Seam pucker, fuzzy system, prediction, fabric structure, fabric mechanical property.

## 1. Introduction

In recent years, greater attention has been paid to the influence of fabric properties on seam pucker. Many re-searches have also been working on the relationships between fabric properties and seam pucker in clothing production in order to predict seam pucker on the basis of fabric properties, especially structure and mechanical properties under low stress. Several charts and equation have also been developed for the determination of seam pucker grade, but they can only provide guidelines and cannot offer specific predictions of how the seam pucker might perform in garment manufacturing [4],[10],[11]. The FS has been successfully used in the investigations about engineering system, automatic control and predicting system. In the textile and apparel manufacturing fields, an advanced fuzzy logic has been adopted to help producing high quality goods. The intelligent sewing machine based on the neurofuzzy control algorithm has been developed to improve seam pucker and sewability [9]. The FS were applied to evaluate objective seam pucker grade [5],[9]. In this paper, the FS is used to predict seam pucker grades in garment manufacture.

## 2. Experimental

We selected 19 fabric weaves (cotton, Pe/Co, PET), all made by the 8/3 Textile, Pangrim, Viet Thang companies. We used 13 of these fabrics to train and the remaining 6 to test the FSs. Objective AATCC seam pucker grade were measured according to new method for seam pucker quantitative evaluation, described in the previous article [6]. The KESF system provides an accurate assessment of a comprehensive range of fabric properties, including tensile, shearing, bending, compression, and surface properties. Structure properties have been estimated by using the Peirce model. The measurements were taken under standard conditions. Table 1 summarizes the fabric parameters, which were used for input pattern of FSs.

**Table 1.** Fabric mechanical and structure properties for input pattern

EM1, EM2	Extension	LC1, LC2	Linearity of compression curve
LT1, LT2	Linearity of extension curve	WC1, WC2	Compression energy
WT1, WT2	Tensile energy	RC1, RC2	Compression resilience
RT1, RT2	Tensile resilience	To	Thickness under 0.5g/cm <sup>2</sup> pressure
B1, B2	Bending rigidity	Tm	Thickness under 50g/cm <sup>2</sup> pressure
2HB, 2HB2	Bending hysteresis	W	Weight of fabric 1m <sup>2</sup>
G1, G2	Shear rigidity	e	Ratio of weft extension to warp extension

2HG1, 2HG2	Shear hysteresis at 0.5° shear angle	Md	Warp density
2HG5 <sub>1</sub> , 2HG5 <sub>2</sub>	Shear hysteresis at 5° shear angle	Mn	Weft density
MIU1, MIU2	Friction coefficient	k <sub>1</sub>	Warp Cover factor
MMD1, MMD2	Mean deviation of friction coefficient	k <sub>2</sub>	Weft cover factor
SMD1, SMD2	Geometric roughness	k	Fabric cover factor

\* Suffix 1, 2 are warp and weft directions, respectively

### 3. Fuzzy systems for predicting seam pucker

A model for prediction of seam pucker according to the AATCC grades was constructed by using fuzzy logic. Inputs are 36 fabric parameters (Table 1). System's two outputs are predicting SS grades of warp and weft seams. Values of input and output variables are determined by experiments. Target pattern include values of dependent and independent variables of a fabric sample. Relationship between dependent variable and independent variables is determined based on training data, so that errors are minimal.

#### 3.1 Construction of FSs for predicting seam pucker

36 input variables are divided to 6 groups (6 variables in each group – Table 2) for FS<sub>*i*</sub> (*i* = 1, ..., 6). Outputs of the FS<sub>*i*</sub> are used as inputs of FS<sub>I</sub> and FS<sub>II</sub> systems, and outputs of them are pucker grades of warp and weft seams, respectively. This much, 8 FSs are designed.

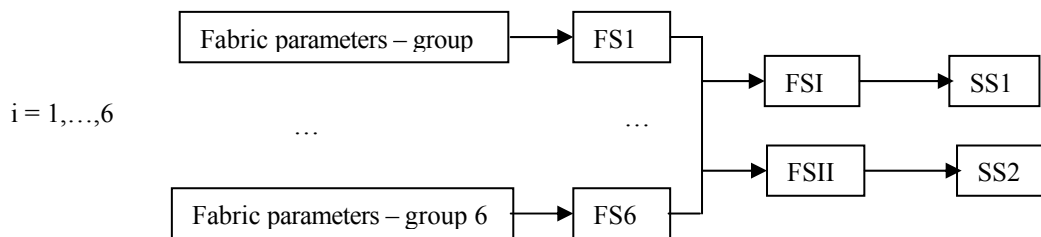


Figure 1. Schema of Fuzzy Systems for Seam Pucker Prediction

Table 2. Input variables in six groups for six FSs

FS	Variable	Value	FS	Variable	Value
1	EM1	[1.21, 6.83]	4	RT1	[32.26, 76.01]
	EM2	[2.14, 17.97]		RT2	[27.21, 73.12]
	2HG5 <sub>1</sub>	[0.52, 8.02]		RC	[41.54, 90.87]
	2HG5 <sub>2</sub>	[0.19, 8.23]		W	[6.175, 19.4]
	SMD1	[0.91, 10.53]		Md	[10.5, 143.5]
	SMD2	[1.72, 7.3]		Mn	[49.8, 89.9]
2	LT1	[0.477, 0.967]	5	2HB1	[0.0093, 0.1869]
	LT2	[0.565, 0.965]		2HB2	[0.0062, 0.2376]
	B1	[0.021, 0.55]		MIU1	[0.119, 0.187]
	B2	[0.011, 0.2659]		MIU2	[0.125, 0.187]
	LC	[0.255, 0.764]		MMD1	[0.009, 0.081]
	To	[0.146, 0.744]		MMD2	[0.0095, 0.0797]
3	WT1	[2.92, 11]	6	G1	[0.28, 2.28]
	WT2	[4.83, 29.23]		G2	[0.22, 2.37]
	α	[0.73, 5.03]		2HG1	[0.27, 4.72]
	k1	[12.55, 23.98]		2HG2	[0.11, 4.37]
	k2	[9.78, 12.46]		WC	[0.03, 0.262]
	k	[18.08, 25.73]		Tm	[0.13, 0.438]

Values of variables in a group are not so different. Learning pattern with 36 input variables, is added target pattern. Input data is inserted in text file as follows:

EM1 EM2 LT1 LT2 WT1 WT2 RT1 RT2 B1 B2 2HB1 2HB2 G1 G2 2HG1 2HG2 2HG5<sub>1</sub>  
2HG5<sub>2</sub> MIU1 MIU2 MMD1 MMD2 SMD1 SMD2 LC WC RC To Tm W  $\alpha$  Md Mn k1 k2 k

### 3.2 Fuzzification and database construction

44 fuzzy variables are designed (36 inputs, 2 outputs of FSI, FSII and 6 output variables of FSi). Linguistic value set  $T = [\text{Very\_High}, \text{High}, \text{Medium}, \text{Low}, \text{Very\_Low}]$  is using for expressing all of fuzzy variables. A fuzzy variable is determined from a **crisp** variable of system. Fuzzy state vector is described by vector  $[X_{i1}, X_{i2}, X_{i3}, X_{i4}, X_{i5}, X_{i6}, X_{i7}]$ , ( $i = 1, 2, \dots, 8$ ), every component of fuzzy variable  $X_{ij}$ ,  $j = 1, 2, \dots, 7$  is determined by parameters:

$$X_{ij} = \{x, U, T(x), M(x)\}$$

Where  $x$  is defined from fabric parameters in divided groups; Universe of discourse  $U \equiv [U_L, U_U]$  is defined from real values of crisp variables; set  $T(x)$  is defined from 5 linguistic values [Very\_Low, Low, Medium, High, Very\_High]; Membership functions  $M(x)$  enable to map the crisp variable in  $U$  into value in  $T(x)$  (linguistic values set). Values of membership functions are defined from parameters as following [2]. Initial parameters in membership functions have been obtained by considering database.

In Figure 2, five membership functions of a fuzzy variable are defined as triangular and trapezoidal functions, and are also named as five intuitive linguistic values: Very\_Low, Low, Medium, High, Very\_High; Constants are used for fuzzification of fabric parameter variables. These values have been obtained by considering experimental database.

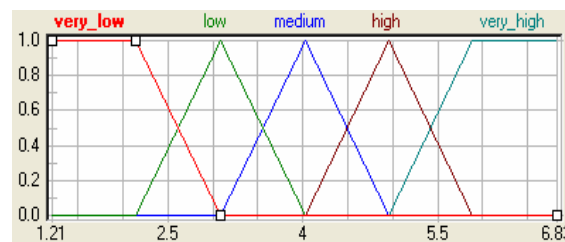


Figure 2. Fuzzification of  $X_{11}$  by membership functions of EM1

Table 3. Initial parameters of model for EM1 variable

	L	U	a	b	c	d	e
Very_Low	1.21	3.0833	1.21	1.21	2.1466	2.615	1
Low	2.1466	4.02	2.615	3.0833	3.0833	3.5516	1
Medium	3.0833	4.9566	3.5516	4.02	4.02	4.4883	1
High	4.02	5.8933	4.4883	4.9566	4.9566	5.425	1
Very_High	4.9566	6.83	5.425	5.8933	6.83	6.83	1

Table 4. Initial parameters of model for OI1 variable

	L	U	a	b	c	d	e
Very_Low	2.5916	4.2581	2.5916	2.5916	3.4248	3.8414	1
Low	3.4248	5.0913	3.8414	4.2581	4.2581	4.6747	1
Medium	4.2581	5.9245	4.6747	5.0913	5.0913	5.5079	1
High	5.0913	6.7577	5.5079	5.9245	5.9245	6.3411	1
Very_High	5.9245	7.591	6.3411	6.7577	7.591	7.591	1

\*L, U, a, b, c, d, e are initial parameters in membership functions.

For crisp input values vector with 36 components, two fuzzy sets are obtained by inference process, which are defined by two membership functions. These sets are defuzzified and two crisp values in output of system are determined. A membership degree to linguistic value is determined with a crisp value of input. True value of all of rule's suppositions is determined

by fuzzy true values of component premises. Fuzzy subset of conclusion is generated from true values of all of premises by using fuzzy implication, which is *Min* or *Product* operator. Weighted Sections Method is applied on prediction of seam pucker for construction of defuzzification module [2],[12].

Action of fuzzy model depends on parameters, which express fuzzy variables and operators. Designed fuzzy systems include 36 independent fuzzy variables (fabric parameters) and 8 dependent fuzzy variables (6 outputs of FS<sub>i</sub>, 2 outputs of FSI, FSII). A fuzzy variable X<sub>i</sub> (i = 1,...,44) is expressed by 5 linguistic values {Very\_High, High, Medium, Low, Very\_Low}. These linguistic values are represented by membership functions, are constructed by seven parameters in these membership functions. This much, we need N = 44\*5\*7 = 1540 parameters. Action of designed fuzzy model also depends on  $\gamma$  in formulas of fuzzy *conjunction* and *disjunction* operators. Therefore, we need to find out optimal values of 1548 parameters of model for minimum error.

To do this, Random-search algorithm is applied on determination of raw data for 1540 parameters [1]. Hooke-Jeeves algorithm is applied on determination of optimal parameters [8]. Yellow section algorithm is applied on determination of optimal  $\gamma$  [3]. Algorithm is finished while rate of between present comparative error and initial error smaller than  $\nu$ , and number of epoch exceeds maximal set value.

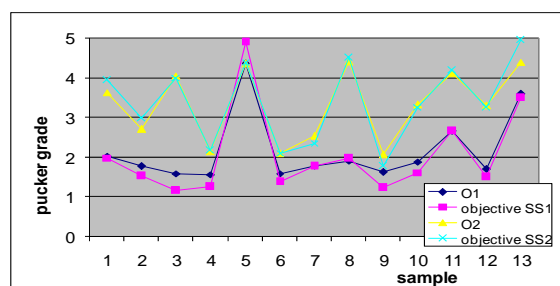
#### 4. Results and discussion

The seam pucker grade prediction program was established. The exact results of self-auto-association are shown in table 5 (13 samples). Each input pattern outputs the associated values, which are compared to the components of target pattern. The prediction method using input pattern was good.

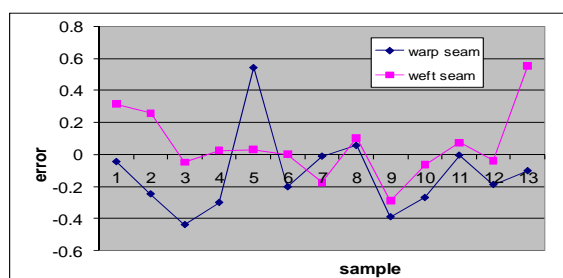
Average errors of the FSs predictive pucker grades are 0.5454 and 0.5562 for warp and weft seam, respectively while compare the outputs with objective actual pucker grades in learning set. Warp seam errors are the same as weft errors.

**Table 5.** Output patterns by self-auto-association

Sample	Outputs of FSI, FSII		Objective SS grade	
	O1	O2	Warp seam (SS1)	Weft seam (SS2)
1	2.034	3.631	1.990	3.946
2	1.774	2.720	1.528	2.978
3	1.596	4.056	1.157	4.006
4	1.566	2.152	1.266	2.177
5	4.362	4.362	4.907	4.393
6	1.591	2.106	1.389	2.107
7	1.794	2.533	1.784	2.357
8	1.917	4.402	1.974	4.505
9	1.628	2.066	1.238	1.774
10	1.887	3.333	1.618	3.266
11	2.667	4.112	2.663	4.186
12	1.701	3.297	1.514	3.258
13	3.600	4.401	3.499	4.957



**Figure 3.** Predictive and objective actual pucker grades of warp and weft seams on learning set

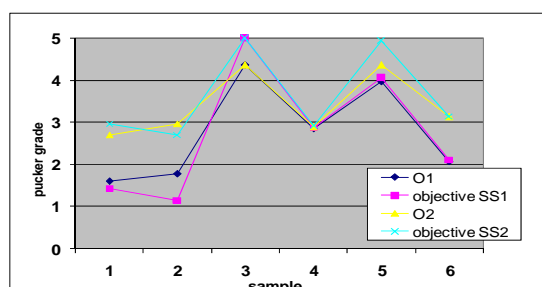


**Figure 4.** Prediction errors for different outputs on learning set

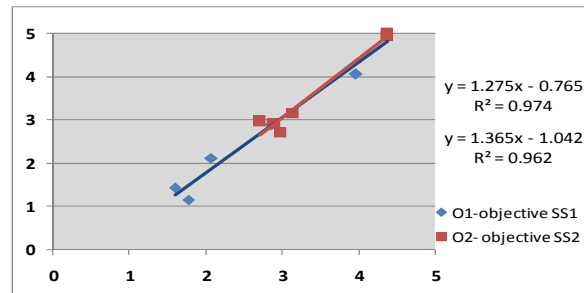
We tested 6 fabrics and seam pucker grades were evaluated objectively by the developed system for comparing the predicted seam pucker grades. The results are shown in table 6. Statistical hypothesis is tested by *Wincoxon's* test at the 95% level of significance. The method showed good correlation with actual seam pucker grades. Predictive result with maximum error is 0.624. Average errors of predictive pucker grade by the FSs are  $\pm 0.005$  and  $\pm 0.203$  for warp and weft seam, respectively while compared with objective grades in testing set.

**Table 6.** Testing results

Testing sample	Predicting grade (Outputs)		Objective SS grade	
	O1	O2	Warp seam (SS1)	Weft seam (SS2)
1	1.596	2.706	1.431	2.972
2	1.773	2.976	1.150	2.711
3	4.376	4.376	5.000	5.000
4	2.852	2.894	2.878	2.918
5	3.968	4.374	4.059	4.934
6	2.072	3.138	2.113	3.146

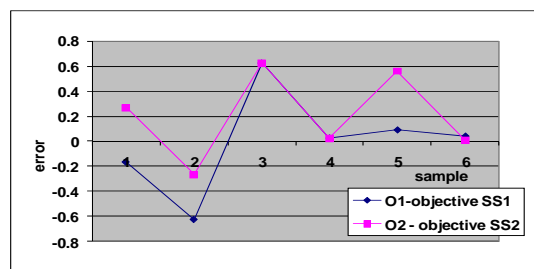


**Figure 5.** Predictive and objective pucker grades of warp and weft seams on testing set



**Figure 6.** Relationship between predictive and actual seam pucker grades on testing set

The correlation coefficients between predictive and objective actual pucker grades are about 0.974 and 0.962 for warp and weft seam, respectively. The FSs predicted pucker seams in the garment for fabrics N1, N2 and N6 with the predicted pucker grades for warp seams are below the critical value (grade 3). For fabrics where no pucker problem occurred during clothing manufacturing, the predictions by the FSs were generally higher than grade 3 (critical value). Warp seam errors with O1 output are the same as weft errors with O2 (Figure 4, 7). Errors between predictive and actual grades of N3 sample (testing set) are 0.624 for warp and weft seam, respectively. This indicates that the number of fabric samples is not large enough for the FSs to detect very clear patterns.



**Figure 7.** Prediction errors for different outputs on testing set

The results shown that the constructed FSs can predict with reasonable accuracy the pucker grades of warp and weft seams in garment manufacturing based on fabric structure and mechanical properties. Error of system was reduced after optimization process. However, errors in training and testing sets are higher than 0.5 because number of parameters is so high. The predicting results are not so good, despite the high correlation coefficients. These results may be explained because of high input variable number, predicting system is designed by two layers of fuzzy. With reduced number of input variables and increased training from a wider range of fabrics, the FSs could be expected to provide more effective seam pucker predictions.

## 5. Conclusions

Our work has demonstrated that it is possible to predict seam pucker grade in clothing manufacturing according to fabric structure and mechanical properties by using the FSs. Using this system can obtain the objective AATCC pucker grades of warp and weft seams. Good correlation between real and predictive seam pucker grades on 6 fabrics was obtained. Eight designed fuzzy systems in two groups with 36 input and 2 output variables provided an accurate prediction with all of predictions falling under the  $\pm 0.203$  error level and with the maximum error of 0.624.

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