THE SET-UP OF A LABORATORY TYPE COATING/LAMINATING UNIT AND THE OPTIMISATION OF LAMINATION PROCESS OF DENIM FABRICS

Ayşe Genç[1], Mehmet Yüceeer[2], Nihan Karakaplan[2] and Cem Güneşoğlu[3]

[1]Çalık Denim R & D Centre, The 1st Organized Industrial Zone, Malatya, Turkey
[2]İnönü University, Chemical Engineering Department, Malatya, Turkey
[3]Gaziantep University, Textile Engineering Department, Gaziantep, Turkey
Ayse.KorkmazGenc@calikdenim.com

Abstract: *Lamination process is a finishing process applied to bring functionality, physical modification and change at appearance by combining two separate materials (fabric, polymer film layer or membrane). The process increased its popularity at denim industry especially in fabric-fabric lamination form in the last decade. Despite its market interest, lamination has setbacks in R&D studies for optimization to enhance the product performance due to large numbers of parameters and difficulties in producing samples. In this study, an adaptive laboratory type coating/laminating unit was developed as the first time in textile industry and the lamination of denim-denim fabric process has been optimized through statistical analysis and modelling studies by artificial neural network (ANN) and least-square support vector (LS-SVM) machine.*

Keywords: *Lamination, optimization, artificial neural network, least-square support vector machine.*

1 INTRODUCTION

Coating is a process in which a polymeric layer is applied directly to one or both surfaces of the fabric, on the other hand lamination is defined as finishing process applied to bring functionality, physical modification and change at appearance by combining two separate materials. Conventional laminated textiles normally consist of one or more textile substrates that are combined using a prepared polymer film or membrane by using adhesives or by using heat and pressure [1]. Lamination found increased interest in denim market, especially in fabric-fabric lamination form by adhesive usage. It is clear that adhesive amount (weight) in the process strongly affect laminated product various properties; also it is a matter of cost. In many cases, producers use adhesive amount as recommended by the supplier, however it is needed to examine to determine the optimum adhesive amount for high volume of production. However, experimental study on fabric lamination is limited since there is large number of parameters to examine and the lamination machinery works with whole fabric width which results large amount of sample and adhesive consumption. Best to our knowledge, there is no laboratory type lamination machine available. In this study, we developed an adaptive laboratory type coating/laminating machine with lower than 40 cm working width which has two separate fabric roll feeding, powder scattering head (for particle loadings), hot-melt adhesive tank and adhesive feeding units. The roller pins are adaptive to change the feeding positions, material type and adhesive feeding face also it is possible to control material and adhesive feeding speeds. The scheme and actual view of the laboratory machine is given in Figure 1.

In this study, denim-denim fabric lamination is conducted by the mentioned machine; various properties are measured and lamination process parameters are optimized through statistical analysis (ANOVA and Design Expert) to find the most suitable adhesive weight for industrial scale applications and modelling studies (ANN and LS-SVM) to assess the predictability of the results and to decide if this study can be applied for industrial scale works as proposed.

2 EXPERIMENTAL

2.1 Materials

100% cotton, denim fabric samples used at lamination were supplied by Çalık Denim, Malatya, Turkey. The constructional details of the samples are given in Table 1. The lamination adhesive was polyurethane based (HB Fuller, USA) reactive hot-melt adhesive with low curing temperature and adhesive weight was varied as 25, 50, 75 and 100 g/m^2 at the trials and 30 m/min fabric feeding speed.

Table 1 Sample details

Sample code	Weave type	Fabric sett [thread/cm]	Yarn count (Warp x Weft)	Weight [g/m^2]
D1	3/1 Z twill	47 x 25	Ne 24/1 x Ne 30/1	342
D2	3/1 Z twill	42 x 26	Ne 20/1 x Ne 18/1	355

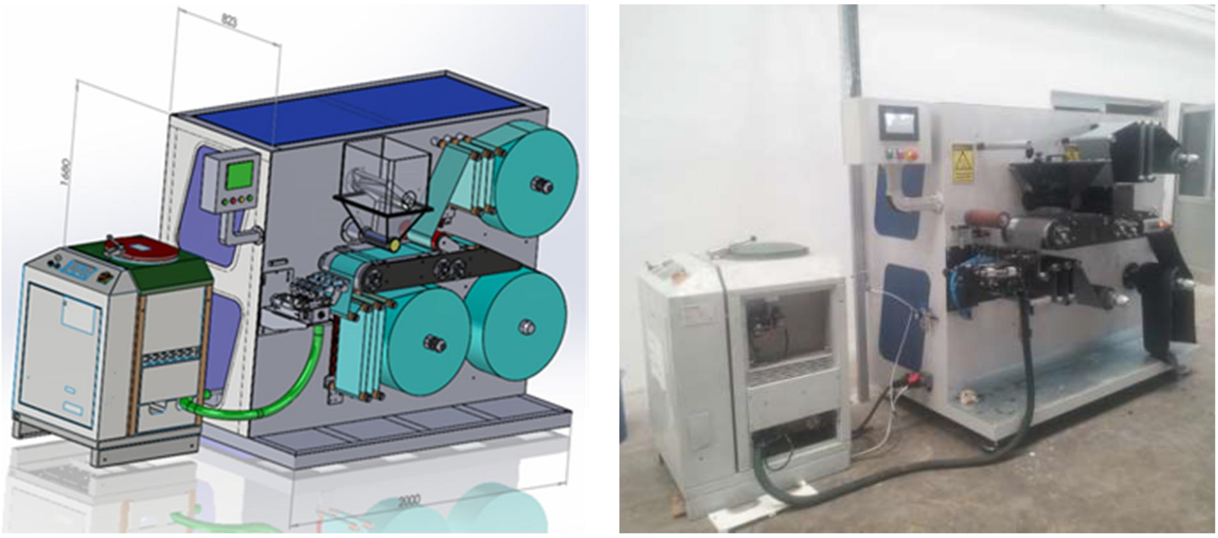

Figure 1 General view of developed coating / laminating machinery

2.2 Methods

After the laminations, the samples were rinsed, dried and tensile strength (ASTM D 5034), tearing strength (ASTM D1424), delamination strength (ASTM D 2724-07), air permeability (ISO 9237), water resistance (ISO 20811) and water vapor permeability (ISO 11092) measurements at the standard laboratory conditions were conducted. All the measurements were repeated for five times and results were recorded as data for optimization studies. All data were subjected to statistical analysis with ANOVA to find out the contribution importance and proposed model strength between adhesive weight and measured property and the optimization study was then applied first with Design Expert V.10. The study is also validated through ANN and LS-SVM modelling as mentioned before.

A typical ANN has feed forward architecture and consists of three or more layers of neurons: one input layer, one output layer and one or more hidden layers (Figure 2). Each of the layers has a set of connections, with a corresponding scalar weight, between itself and each neuron of preceding layer. When the weight of a particular neuron is updated, it is said that neuron is learning and ANN is training. In a feed forward back-propagation ANN, the input data (x_i) is passed to the neurons in input layer as signal. The data is weighted in hidden layers (y_i) by associated weights in each interconnection through non-linear transfer function. The sum of weighted inputs is converted to outputs (z_i) through activation function [2].

On the other hand, support vector model (SVM) is a machine learning technique which is based on the statistical learning theory and structural risk minimization principle. The SVM uses a based quadratic programming optimization to identify model parameters, while avoiding local minima and have an advantage over other regression methods.

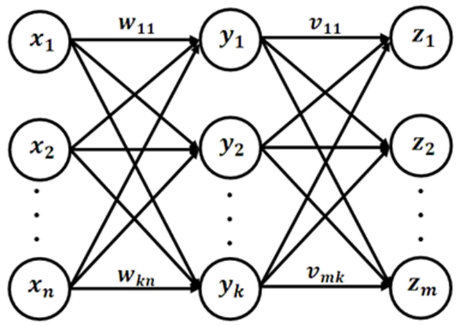

Figure 2 ANN architecture

A modified version of SVM, called the least square support vector model (LS-SVM) results in a set of linear equations instead of quadratic optimization problem [3]. A general LS-SVM architecture is as also given in Figure 3. Detailed information is given elsewhere [4-6].

In the modeling studies, adhesive weights and denim sample mechanical parameters (sett value, yarn count and weight) were selected as input and output was limited to delamination strength, air permeability and water vapour permeability parameters of laminated samples. The random 65% of the measured values were used for the training and the rest for the test. In the course of training of ANN, which was based on Levenberg–Marquardt method [7], the number of neurons in the layers, training accuracy and number of iterations were determined by using trial and error method; thus the optimum number of neurons obtained in the layers were determined as 9. For the development of the models, Neural Network Toolbox, LS-SVM Lab v1.7 and MATLAB 7.0 were used.

$$\text{Input layer}\begin{cases} x_i \\ x_{i+1} \\ x_{i+2} \end{cases} \rightarrow\rightarrow\rightarrow \boxed{\begin{array}{c}\text{Training LS-SVM with} \\ \text{optimized } \gamma \text{ and } \delta^2\end{array}} \rightarrow y$$

Figure 3 LS-SVM architecture

Table 2 Measurement results of the samples

Property	Sample Code					
	D1	*D2*	*D1-D2 (25)**	*D1-D2 (50)**	*D1-D2 (75)**	*D1-D2 (100)**
Tensile strength [kgf]	64 (warp) 24 (weft)	67 (warp) 26 (weft)	110 (warp) 59 (weft)	102 (warp) 64 (weft)	110 (warp) 64 (weft)	112 (warp) 69 (weft)
Tearing strength [kgf]	3197 (warp) 1892 (weft)	4567 (warp) 2610 (weft)	6263 (warp) 3262 (weft)	4893 (warp) 3131 (weft)	4175 (warp) 2871 (weft)	3653 (warp) 2022 (weft)
Delamination strength [kgf]	-	-	5.56	11.67	> 20	> 20
Air permeability [mm/s]	139.08	455.65	88.85	49.83	15.20	3.95
Water resistance [mbar]	13.13	6.77	17.10	19.60	19.76	23.20
Water vapour permeability [g/m^2/day]	1061.18	956.74	929.66	776.45	570.82	193.35

*The number in brackets is the adhesive weight used to laminate D1 and D2.

The model performances were then assessed by evaluating the scatter between the experimental and predicted results via statistical parameters, that is correlation coefficient (*R*), mean absolute percentage error (*MAPE* %), and root mean square error (*RMSE*). The statistical values were determined as follows:

$$\mathrm{R} = \frac{\sum_{i=1}^{N}(\mathbf{x_i} - \bar{\mathbf{x}})\,(\mathbf{y_i} - \bar{\mathbf{y}})}{\sqrt{\sum_{i=1}^{N}(\mathbf{x_i} - \bar{\mathbf{x}})^2}\,\sqrt{\sum_{i=1}^{N}(\mathbf{y_i} - \bar{\mathbf{y}})^2}} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}} \tag{2}$$

$$\mathrm{MAPE}\ (\%) = \frac{1}{N}\sum_{i=1}^{N}\left(\left|\frac{y_i - x_i}{x_i}\right|\right)\cdot 100 \tag{3}$$

where, x_i is an observed value, y_i is a simulated value, N is the number of data points, $\bar{x}$ is the mean value of observations, and $\bar{y}$ is the mean value of simulations. A higher value of the *R* and smaller values of *MAPE* and *RMSE* would indicate a better performance of the model.

3 RESULTS AND DISCUSSION

The averages of the measurements are given in Table 2. CV values [%] of the measurements were lower than 10% in all cases. Table 2 showed that increase in adhesive weight resulted trends in the properties.

The ANOVA tables are given in Table 3-10. The proposed models are given at the bottom of ANOVA tables.

Table 3 ANOVA table for tensile strength in warp direction

Source	Sum of Squares	F value	Probability > F
Model	2420.53	15.10	0.0076
A	1922.00	23.97	0.0045
A^2	498.53	6.22	0.0549
Residue	400.84		

Tensile strength (warp direction): 68.971 + 1.21 A - 7.075x10^{-3} A^2 (A: adhesive weight), Adjusted R^2: 0.8011, Standard deviation: 8.95

Table 4 ANOVA table for tensile strength in weft direction

Source	Sum of Squares	F value	Probability > F
Model	2447.03	848.97	< 0.0001
A	0.12	0.13	0.7375
A^2	498.53	518.88	< 0.0001
A^3	128.44	133.69	
Residue	3.84		

Tensile strength (weft direction): 25.137 + 2.054 A - 0.0343A^2 + 1.813x10^{-4} A^3 (A: adhesive weight), Adjusted R^2: 0.9973, Standard deviation: 0.98

Table 5 ANOVA table for tearing strength in weft direction

Source	Sum of Squares	F value	Probability > F
Model	5.196xE6	14.97	0.0122
A	2.104xE6	18.18	0.0130
A^2	2.964xE6	25.61	0.0072
A^3	1.731xE6	14.96	
Residue	4.629xE5		

Tearing strength (warp direction): 3929.637 + 157.51A - 3.703 A^2 + 0.02105 A^3 (A: adhesive weight), Adjusted R^2: 0.8568, Standard deviation: 340.20

Table 6 ANOVA table for tearing strength in warp direction

Source	Sum of Squares	F value	Probability > F
Model	1.908xE6	62.35	0.0003
A	94902.72	6.20	0.0551
A^2	1.813xE5	118.49	0.0001
Residue	76522.48		

Tearing strength (weft direction): 2296.163 + 39.764 A - 0.427 A^2 (A: adhesive weight), Adjusted R^2: 0.9460, Standard deviation: 123.71

Table 7 ANOVA table for delamination strength

Source	Sum of Squares	F value	Probability > F
Model	503.72	107.81	< 0.0001
A	495.50	212.09	< 0.0001
A^2	8.22	3.52	0.1195
Residue	11.68		

Delamination strength: -0.37371 - 0.30071 A - 9.08455 A^2
(A: adhesive weight), Adjusted R^2: 0.9683,
Standard deviation: 1.53

Table 8 ANOVA table for air permeability

Source	Sum of Squares	F value	Probability > F
Model	1.056xE5	86.21	0.0001
A	86393.09	141.00	< 0.0001
A^2	19251.07	31.42	0.0025
Residue	3063.49		

Air permeability: 287.39987 - 7.16737 A + 0.043962 A^2
(A: adhesive weight), Adjusted R^2: 0.9605,
Standard deviation: 24.75

Table 9 ANOVA table for water resistance

Source	Sum of Squares	F value	Probability > F
Model	185.23	64.54	0.0003
A	172.15	119.97	0.0001
A^2	13.07	9.11	0.0295
Residue	7.18		

Water resistance: 10.35763 + 0.23827 A - 1.14562 A^2
(A: adhesive weight), Adjusted R^2: 0.9478,
Standard deviation: 1.20

Table 10 ANOVA table for water vapour permeability

Source	Sum of Squares	F value	Probability > F
Model	7.955xE5	288.84	< 0.0001
A	7.395xE5	536.99	< 0.0001
A^2	56037.73	40.69	0.0014
Residue	6885.43		

Water vapour permeability: 1008.9712 - 0.60702 A - 0.075005 A^2
(A: adhesive weight), Adjusted R^2: 0.9880,
Standard deviation: 37.11

"The probability > F" value as recorded as input for optimization with Design Expert when it is smaller than 0.005.

Design Expert model was run to consider the highest possible property value with lowest adhesive weight as mentioned before and the result is as given in Table 11. According to Table 11, we concluded that the lowest hot melt adhesive weight in the selected denim fabrics lamination must be 37 g/m^2 to receive the highest possible property values.

The screening performances of the models are given in Table 12. The results showed that the ANN model produced *MAPE* values lower than that of the LS-SVM and *R* values were higher than 0.9 in all of the outputs. The ANN model exhibited better performance in predicting laminated fabric properties but overall evaluation demonstrated that the study performed at the laboratory scale coating/laminating machine could be predicted through the ANN or the LS-SVM modellings; thus it is concluded that the machinery meets industrial requirements of controlling and predicting concerns.

4 CONCLUSIONS

In this study, a laboratory type coating/laminating machine was developed as the first time in textile industry and the lamination of denim-denim fabric process has been optimized through statistical analysis and modelling studies by artificial neural network (ANN) and least-square support vector (LS-SVM) machine. We obtained the minimum adhesive weight to be used in the process when considering highest property values of laminated fabrics and the ANN and LS-SVM modelling study revealed that the findings were predictable and reliable. Thus we concluded that findings obtained by using the mentioned machine are applicable for industrial studies.

ACKNOWLEDGEMENT: *This study is supported by TUBITAK under 1505 program with the contract No. 5140065.*

Table 11 Design Expert optimization

Run #	Tensile strength (weft)	Tensile strength (warp)	Tearing strength (weft)	Tearing strength (warp)	Delamination strength	Air permeability	Water vapour permeability	Adhesive weight [g/m^2]
1	100.933	63.4802	5745.19	3185.71	8.29737	60.0566	881.98	37.30
2	101.23	63.5188	5740.43	3186.91	8.34617	59.6796	881.028	37.45
3	100.838	63.4394	5750.07	3184.43	8.24663	60.4527	882.966	37.14

Table 12 Statistical parameters of the models

Output	Training set				Test set		
	Model	RMSE	MAPE [%]	R	RMSE	MAPE [%]	R
Air permeability	ANN	3.053×10^{-6}	7.96×10^{-6}	1.0000	3.7384	4.3420	0.9939
	LS–SVM	24.4744	29.07271	0.9585	29.4573	34.3360	0.9872
Water vapour permeability	ANN	1.50×10^{-9}	2.68×10^{-10}	1.0000	66.5430	3.1370	0.9804
	LS–SVM	28.0534	4.8537	0.9951	33.5706	6.0109	0.9954
Delamination strength	ANN	8.147×10^{-6}	1.33×10^{-7}	1.0000	361.316	2.989	0.9821
	LS–SVM	38.5502	0.8133	0.9998	784.960	14.512	0.8990

5 REFERENCES

1. Singha K.: A Review on coating & lamination in textile: Processes and applications, American Journal of Polymer Science 2(3), 2012, pp. 39-49, doi: 10.5923/j.ajps.20120203.04
2. Atasoy I., Yuceer M., Ulker E.O., Berber R.: Neural network based control of the acrylonitrile polymerization process, Chemical Engineering & Technology 30(11), 2007, pp. 1525-1531, DOI: 10.1002/ceat.200700225
3. Vishesh S., Manu S., Vivek A., Sumit K.S., Ashwani K.S., Vyshnav L.: Data mining and analytics: A proactive model, International Journal of Advanced Research in Computer and Communication Engineering 6(2), 2017, pp. 524-526, DOI 10.17148/IJARCCE.2017.62117
4. Vapnik V.: Statistical learning theory, John Wiley, NY, USA, 1998, ISBN-13: 978-0471030034
5. Suykens J.A.K., Vandewalle J.: Least squares support vector machines classifiers, Neural Network Letter 9(3), 1999, pp. 293-300, DOI https://doi.org/10.1023/A:1018628609742
6. Li C., Zhu X., Cao G., Suı Sh., Hu M.: Identification of the Hammerstein model of a PEMFC stack based on least squares support vector machines, Journal of Power Sources 175(1), 2008, pp. 303-316, https://doi.org/10.1016/j.jpowsour.2007.09.049
7. Iqbal J., Iqbal A., Arif M.: Levenberg–Marquardt method for solving systems of absolute value equations, Journal of Computational and Applied Mathematics 282, 2015, pp. 134-138, https://doi.org/10.1016/j.cam.2014.11.062