

Dry Relaxation Shrinkage Prediction of Bordeaux Fiber Using a Feed Forward Neural

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Abstract—The knitted fabric suffers a deformation in its dimensions due to stretching and tension factors, transverse and longitudinal respectively, during the process in rectilinear knitting machines so it performs a dry relaxation shrinkage procedure and thermal action of prefixed to obtain stable conditions in the knitting. This paper presents a dry relaxation shrinkage prediction of Bordeaux fiber using a feed forward neural network and linear regression models. Six operational alternatives of shrinkage were predicted. A comparison of the results was performed finding neural network models with higher levels of explanation of the variability and prediction. The presence of different reposes is included. The models were obtained through a neural toolbox of Matlab and Minitab software with real data in a knitting company of Southern Guanajuato. The results allow predicting dry relaxation shrinkage of each alternative operation.

Keywords—Neural network, dry relaxation, knitting, linear regression.

I. INTRODUCTION

THE knitted fabric is formed from a single wire mesh on itself or different threads interwoven [1]. Reference [2] mentions that the most unique feature of mesh fabrics is its extensibility. This extensibility involves a deformation of the fabric and therefore a change of its original dimensions. Knit fabrics are extensible and easily deformable in width and length. Use extreme care in handling fabric at all stages whether they are stacked by hand or with machines. The fabric should rest without tension on the cutting table, which stands for unfolded accordion, and let rest 24 to 48 hours approximately before the overlap process [3]. The influence of heat on the properties of the fibers is of great importance with respect to the textile process. In almost all synthetic fibers with increasing temperature, the resistance decreases and the elongation increases, typically fiber once cooled, regains its original properties. Reference [4] indicates that exposure of the fiber to heat can cause thermal shrinkage. Knitwear deforms relatively easily, which is one of the reasons for its advantages, but otherwise there is a risk that due to its deformability may arise permanent dimensional changes of importance by use. Reference [5] mentions that when they wish to manufacture products with stable dimensions and properties 'easy care' is paramount to the manufacturer measure the shrinkage that may occur during use of the article and have test methods available. Alternative production in the

textile enterprises are subjectively determined by experts struggling to meet the design clothing specifications. This research analyzes six material flow alternatives with a specific repose time, Measurements in knitting department used as input variables to the neural network and measurements in iron steam department used as patterns to the neural network, with different reposes time. These data were also used for simple linear regression models.

In the literature there are applications of prediction using neural networks in various industrial processes such as process reengineering, continuous improvement, financial analysis, human resource planning and organizational development. Many studies [6]-[10] implied that the back propagation neural network (BNN) could efficiently resolve problems with classification and prediction. Reference [11] proposed a cost estimation model based on a fuzzy rule back propagation network, configuring the rules to estimate the cost under uncertainty. A multiple linear regression analysis is applied to analyze the rules and identify the effective rules for cost estimation. Reference [12] deals with the modeling of ring spun cotton yarn strength using a simple fuzzy expert system. The prediction accuracy of the model was found to be very encouraging. Reference [13] used the back propagation neural network (BNN) and Karhunen-Loeve (K-L) expansion method to construct a new and highly accurate grading system. Reference [14] presented a statistical modeling of the dynamic system knitting, to estimate lead times.

Artificial neural systems can be considered as simplified mathematical models of brain-like systems and they function as parallel-distributed computing networks. Artificial neural systems, or neural networks, are physical cellular systems, which can acquire, store, and utilize experimental knowledge [15]. The knowledge is in the form of stable states or mappings embedded in networks that can be recalled in response to the presentation of cues. The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. Each processing unit is characterized by an activity level (representing the state of polarization of a neuron), an output value (representing the firing rate of the neuron), a set of input connections, (representing synapses on the cell and its dendrite), a bias value (representing an internal resting level of the neuron), and a set of output connections (representing a neuron's axonal projections). Each of these aspects of the unit is represented mathematically by real numbers. Thus, each connection has an associated weight (synaptic strength) which determines the effect of the incoming input on the activation level of the unit. The weights may be positive (excitatory) or negative (inhibitory). The

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signal flow from of neuron inputs, x_j , is considered to be unidirectional as indicated by arrows, as is a neuron's output signal flow. The neuron output signal is given by [15]:

$$o = f(\langle w, x \rangle) = f(w^T x) = f\left(\sum_{j=1}^n w_j x_j\right) \quad (1)$$

where, $w = (w_1, \dots, w_n)^T \in \mathbb{R}^n$ is the weight vector. The function $f(w^T x)$ is often referred to as an activation (or transfer) function. Its domain is the set of activation values, net, of the neuron model, we thus often use this function as f (net). The variable net is defined as a scalar product of the weight and input vectors

$$net = \langle w, x \rangle = w^T x = w_1 x_1 + \dots + w_n x_n \quad (2)$$

and in the simplest case the output value o is computed as

$$o = f(net) = \begin{cases} 1 & \text{if } w^T x \geq \theta \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where, θ is called threshold-level and this type of node is called a linear threshold unit.

While fuzzy logic performs an inference mechanism under cognitive uncertainty, computational neural networks offer exciting advantages, such as learning, adaptation, fault-tolerance, parallelism and generalization [15].

II. METHODOLOGY

A case study was conducted in an enterprise of southern Guanajuato to analyze dry relaxation shrinkage for Bordeaux fiber. The research methodology is shown in Fig. 1.

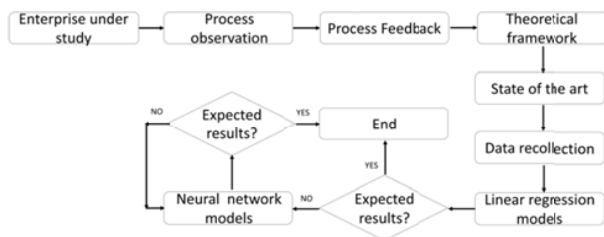


Fig. 1 Methodology research

A. Situation Analysis

After observing the process, get quality experts feedback and make the analysis of the problem. Six operational alternatives of shrinkage under study were defined (Table I).

B. Test Method

To collect data, canvases of knitting machine were taken and measured. A test method was prepared; sewing signals with small crosses were performed in the upper layer of the

canvas as indicated by Henning (1969). Eight measuring signals were conducted. Two distances of 15 cm for each direction in a square. The measurement signals are made at a distance of 7 cm from the edges (Fig. 2).

TABLE I
ALTERNATIVE ANALYSIS

Alternative	Repose Time Knitting	Manual compression	Repose time Basting	Total Repose Iron Steam
1 Without repose	0	No	0	0
2 Manual compression	0	Yes	0	0
3 Repose 24 Hr.	20 Hr.	No	4 Hr.	24 Hr.
4 Repose 56 Hr.	48 Hr.	No	8 Hr.	56 Hr.
5 Repose 65 Hr.	50 Hr.	No	15 Hr.	65 Hr.
6 Repose 77 Hr.	66 Hr.	No	11 Hr.	77 Hr.

C. Statistical Analysis Data

67 measurements were taken at each stage of the analysis. One way of testing the equality of all possible pairs of means is through Fisher and Tukey tests, where mean they do not share a letter are significantly different (Table II).

TABLE II
FISHER AND TUKEY METHOD

Alternative	N	Mean	Cluster
Without repose	67	11.7	A
Manual compression	67	11.1448	B
Repose 24 Hr.	67	11.0836	B
Repose 56 Hr.	67	10.9119	B
Repose 65 Hr.	67	10.2612	C
Repose 77 Hr.	67	10.1985	C

The Neural Network Toolbox is used to create a network. The network consists of a vector P [67, 1] like an input data and vector T [67, 1] like an output data. A feedforward network is created with two layers of 67 input elements one hundred tangsig hidden neurons, and four-output neurons purelin (Fig. 3).

Using neural network toolbox of matlab, prediction models were obtained for each alternative getting better explanation of the variability of the model and prediction. Since the linear regression models obtained using software Minitab, have very low indicators in the correlation coefficient and may not be used to estimate the fiber shrinkage (Figs. 4-9).

III. RESULTS AND VALIDATION

Using the neural network as a generalizing instrument was possible to obtain the estimate of the percentage of shrinkage for each alternative (Table III).

With these results, we can estimate the shrinkage for each component to weave in the fabric department.

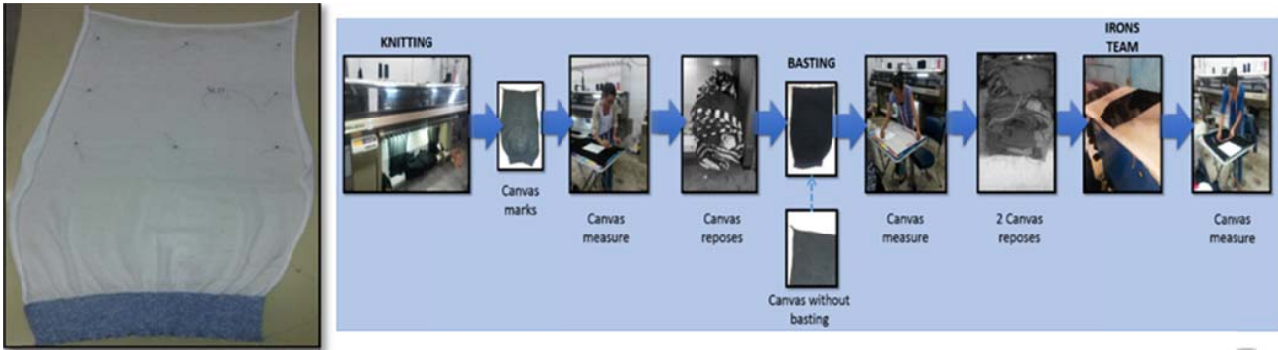


Fig. 2 Test method

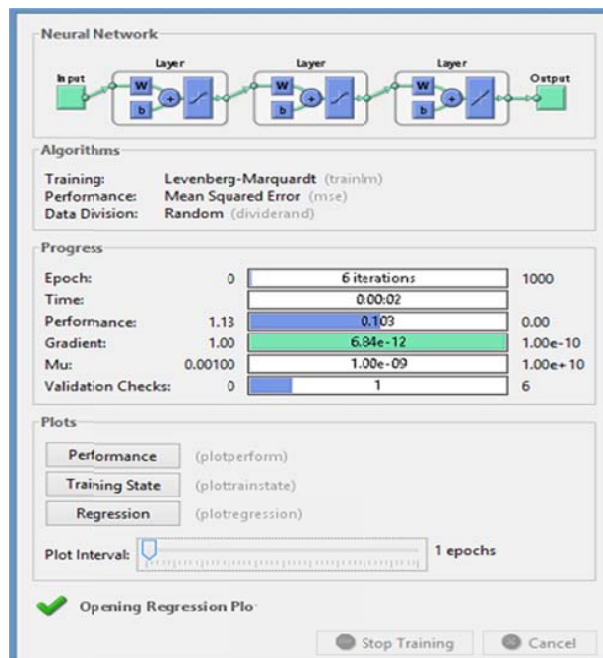


Fig. 3 Neural network feed forward

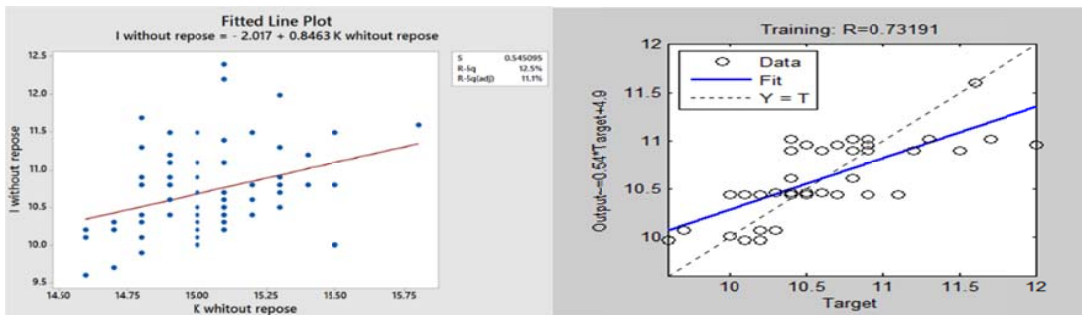


Fig. 4 Linear regression and neural network comparison for without repose alternative

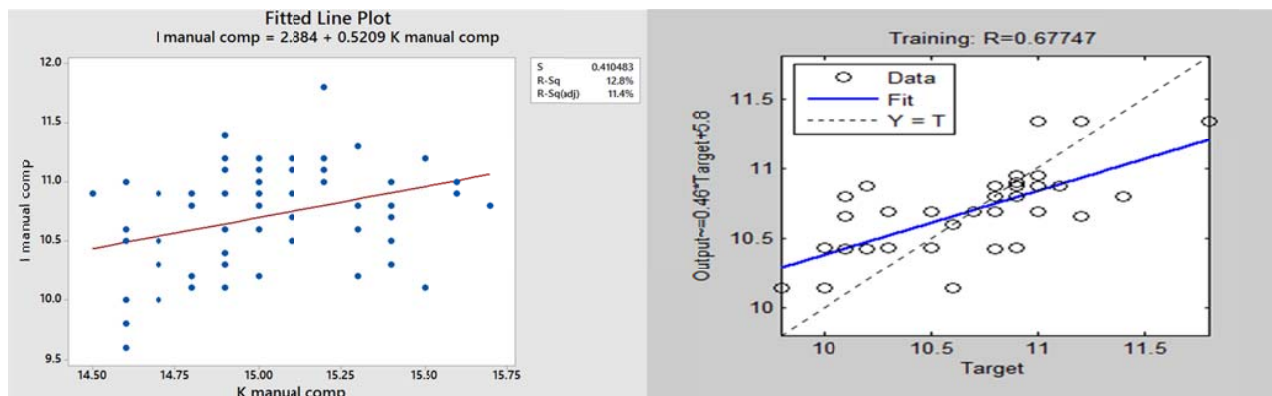


Fig. 5 Linear regression and neural network comparison for manual compression alternative

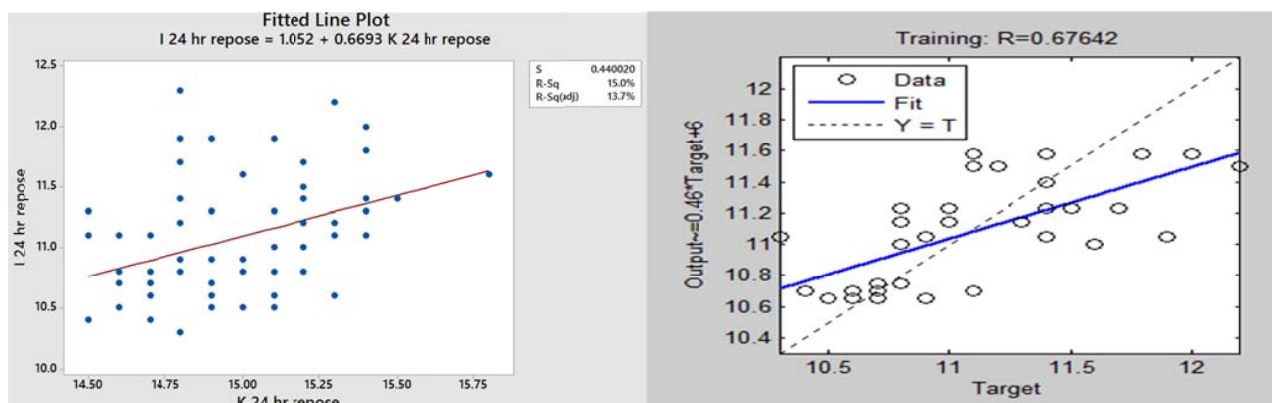


Fig. 6 Linear regression and neural network comparison for 24 hr repose alternative

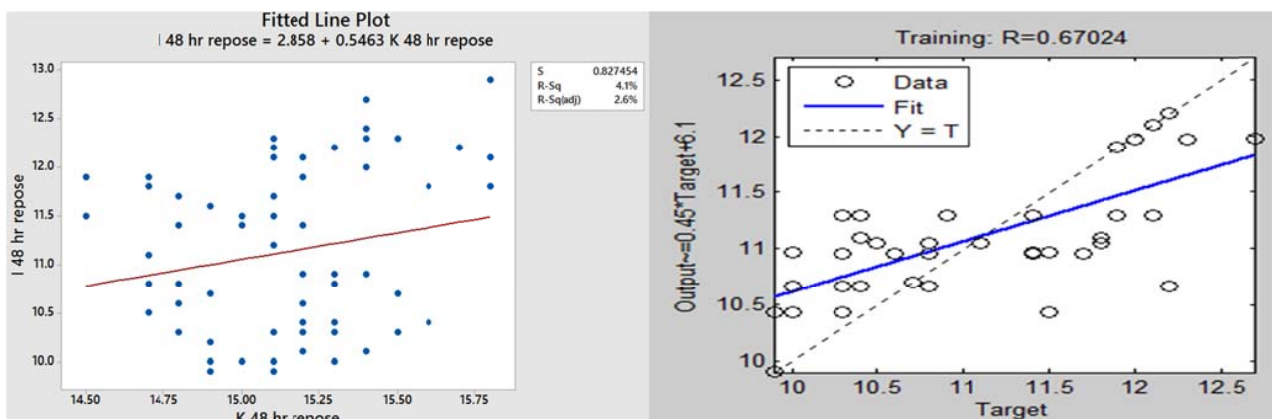


Fig. 7 Linear regression and neural network comparison for 56 hr repose alternative

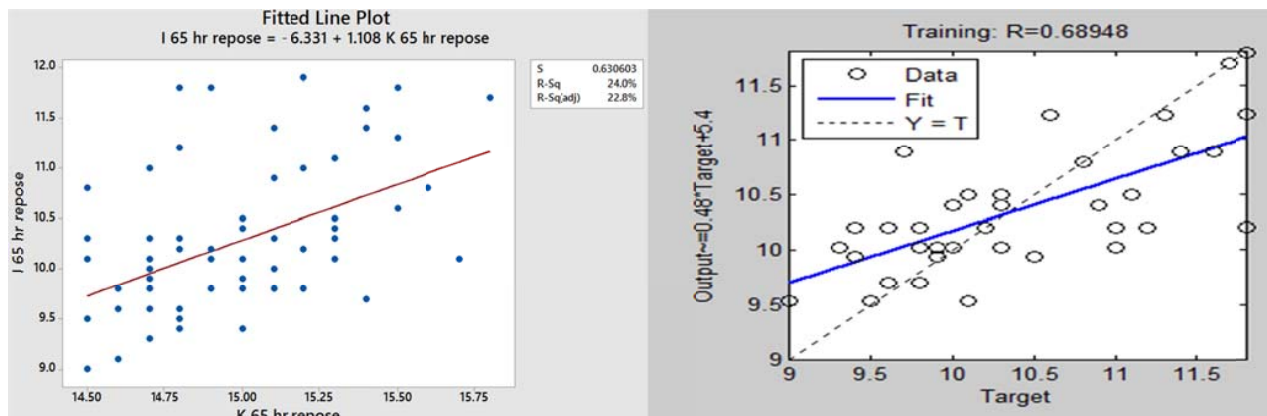


Fig. 8 Linear regression and neural network comparison for 65 hr repose alternative

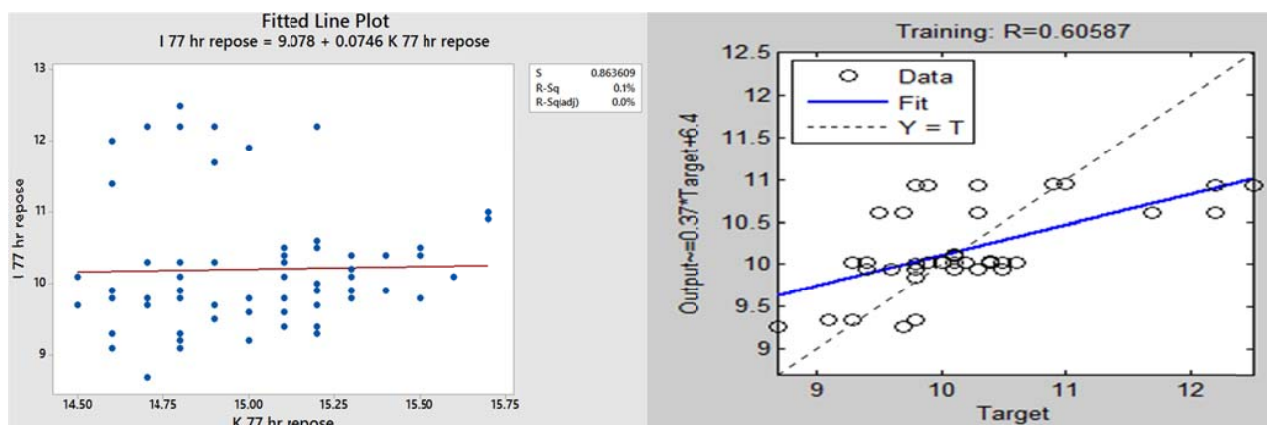


Fig. 9 Linear regression and neural network comparison for 77 hr repose alternative

TABLE III
SHRINKAGE

Alternative	Total shrinkage	Percentage shrinkage
1. Without repose	3.1940	21.4195
2. Manual compression	4.1552	27.5843
3. Repose 24 Hr.	3.9044	26.0481
4. Repose 56 Hr.	4.0238	26.5190
5. Repose 65 Hr.	4.7194	31.5218
6. Repose 77 Hr.	4.8268	32.1019

TABLE IV

VALIDATION SHRINKAGE BACK STRIPED SWEATER

#	Knitting	Iron	Shrinkage	No. rows	No. columns	Stability
1	91,5	68,5	25,13	25	19	1,3157
2	93,4	68,6	26,55	24	18	1,3333
3	93,5	68,8	26,41	22	17	1,2941
4	91,7	68,5	25,29	25	19	1,3157
5	93,4	68,6	26,55	22	17	1,2941
6	95,4	69,6	26,72	23	18	1,2777

A. Validation Knitting Enterprise

According to the observation of the results generated is considered alternative 2 as the most useful to operate in an enterprise and to comply with the design specifications. This alternative allows an agile manufacturing and stable fiber conditions. MODEL: Striped V Neck Sweater (Back). Table IV shows the corresponding measurements taken from the back striped V neck sweater. The mold has a length of 67 cm, for this reason, the canvas must have 1 to 1.5 cm of tolerance for cutting the work piece. The operator programmed the machine to weave rectilinear canvases with a length of 93.5 cm contemplating the canvas will shrink 27%, so the canvas after being subjected to steam will have a measure of 68,2 cm thereby complying with the design specification.

IV. CONCLUSIONS

In this research, linear regression and neural networks models of prediction was performed of dry relaxation shrinkage for Bordeaux fiber. A case study was performed in a textile company in southern Guanajuato. It was observed, feedback was obtained and an analysis of the problem was made. Six different operative alternatives were identified. A feed forward neural network was developed to explain the variability of the models and predict the shrinkage of each of the various alternatives. The model consists of an input P[67,1] measurements obtained in a knitting department and T[67,1] measurements obtained in an iron steam department. One model for each operational alternative was developed, determining the percentage of shrinkage respective. Validation

of the dynamic model was made through a sensitivity analysis and validation was done in the company with the V neck sweater striped pattern. The results were significant achieving compliance with the design specifications. As future work is considered, make hybrid systems incorporating fuzzy logic and neural networks.

ACKNOWLEDGMENT

This work was developed with support in part from the program for professional development of teachers (PRODEP) for the superior type, building support to the generation and innovative application of knowledge and in part from CONCYTEG under projects 14-PNPC-DPP-Q182-49. The author acknowledges the support of the National Council of Science and Technology [CONACYT] through National System of Researchers [SNI] and the support of the Secretary of Public Education [SEP] through PRODEP.

REFERENCES

- [1] Llonch, M. "La Competitividad de Los Distritos Catalanes del Género de Punto (1961-2004)". Monografias de la Revista de Historia Industrial. Publicacions de la Universitat de Barcelona, pp. 1-27, 2004.
- [2] Capdevila, X. "Regulación de la Tricotosa Rectilínea y su Influencia Sobre la Longitud de Malla", Boletín Intertex (U.P.C), vol.121, pp. 23-29, 2002.
- [3] Barretto, S. "Fabricación de Prendas en Tejido de Punto", FADU UBA. Retrieved August 13, 2014, from <http://cursos.fadu.uba.ar/apuntes/Indumentaria%20I/unidad%20practica%20n%20%201/7-%20Fabricacion%20de%20prendas%20en%20tejido%20de%20punto.pdf>.
- [4] Pocaroba, R. "Análisis de los factores que determinan la formación del pilling en tejido de punto", Tesis inédita Maestro en Ciencias, Instituto Politécnico Nacional. 2006
- [5] Henning, H. "Tipos de encogimiento de los géneros de punto de lana y su medida", Conferencias Escuela Técnica Superior de Ingenieros Industriales de Terrasa, pp. 71-86, 1969.
- [6] Lien, H. Lee, S. "A Method of Feature Selection for Textile Yarn Grading Using the Effective Distance between Clusters", Text Res J, Vol. 72, no. 10, pp. 870-878, 2002.
- [7] Pynckels, F, Kiekens, P. Sette, S. Van Langghenove, L. Impe, K. "The Use of Neural Nets to Simulate the Spinning Process". J Text Inst, vol. 88, no. 4, pp. 440-448, 1997.
- [8] Park, C. Kang, T. "Objective Rating of Seam Pucker Using Neural Networks", Text Res J, Vol. 67, no. 7, pp. 497-502, 1997.
- [9] Ludwig, L. Sapozhnikova, E. Lunin, V. Rosenstiel, W. "Error Classification and Yield Prediction of Chips in Semiconductor Industry Applications", Neur Comput App, Vol. 9, pp. 202-210, 2000.
- [10] Verikas, A. Malmqvist, K. Bergman, L. Signahl, M. "Colour Classification by Neural Networks in Graphic Arts", Neur Comput App, Vol. 7, pp. 52-64, 1998.
- [11] Fazlollahtabar, H. Mahdavi-Amiri, N. "Design of a Neuro-Fuzzy-Regression Expert System to Estimate Cost in a Flexible Jobshop Automated Manufacturing System", Int J Adv Manuf Technol, Vol. 67, pp. 1809-1823, 2013.
- [12] Majumdar, A. Ghosh, A. "Yarn Strength Modelling Using Fuzzy Expert System", Journal of Engineered Fibers and Fabrics Vol. 3, no. 4, pp. 61-68, 2008.
- [13] Hsin, L. Shyong, L. "Applications of Neural Networks for Grading Textile Yarns", Neural Comput & Applic, Vol. 13, pp. 185-192, 2004.
- [14] Baeza, R. and Cedillo, G. "Statistical Model of the Knitting System Dynamics", Proceedings of the 15th Annual International Conference on Industrial Engineering Theory, Applications and Practice. México City, 2010.
- [15] Zurada, M. "Introduction to Artificial Neural Systems", West Publishing Company, New York, 1992.