

# Evaluation of Sewed Thread Consumption of Jean Trousers Using Neural Network and Regression Methods

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## Abstract

This paper deals with the prediction of the sewing thread consumption of jean trousers using the neural network technique. The neural network results and analysis are discussed and investigated. Indeed the findings show that neural network consumption values give better fitting of experimental results than the ones obtained using regression technique. However, compared to the experimental consumption results, theoretical ones of the sewn jean pants seem widely predictable in the desired field of interest. Among the all parameters studied, statistical analysis results also indicate that five inputs can be considered as influential ones. When classifying these five influential inputs, only three parameters are considered most significant. In fact the thread consumed to sew jean trouser samples remains influenced especially by the thread properties and needle fineness as well. Compared with the regression model, the neural network model gives a more accurate prediction and to a great extent provides the amount of sewing thread.

**Key words:** consumption, prediction, sewing, thread, neural network, regression.

## Introduction

With actual increases in sewing speeds and with the advent of both synthetic fabrics and threads, the problem of excessive thread consumption in sewing operations has become more critical and of greater interest. A reasonable estimation of potential thread sewn for the garment industry should be determined objectively not only to predict suitable thread consumed and to reduce the stocks unused, but it also allows us to use a better-quality of sewing thread for the same cost and to avoid stock rupture. However, in the general literature survey, the thread consumption problem has not been studied sufficiently for two important reasons: first because of the complexity of sewn thread evaluation, and second the high input parameters. Some works relating to thread consumption evaluation are tackled and conducted in the literature survey. Thread consumption evaluation using such techniques was measured as a function of some input parameters such as the stitch length, thread tension and its compressive modulus [1, 4 - 12, 15, 17 - 22, 25, 34 and 35]. However, the sewing thread consumption of a garment needs to be provided and predicted accurately. Several factors determine the extent of thread consumption in any sewn garment, such as the stitch length, stitch density, seam type and material thickness [16, 33]. Until now, there has been no analytical model using the neural network technique to evaluate the amount of sewn thread required to make up jean trouser garments and to predict accurately the consumed thread value. Compared with

mathematical methods (fuzzy, mathematical, geometrical, statistical, subjective, etc.) in defining, prediction and in modelling both complex and non-linear problems, the neural network method offers large levels of flexibility and remains an excellent method for predictors [2, 3, 13 - 15, 26 - 28, 32]. The purpose of this study is to determine accurately the amount of sewing thread as a function of some influential inputs. Moreover in this work, the amount needed by the type of garment was deduced by selecting the most significant parameters using statistical analysis, therefore it is focused on the evaluation and prediction of the thread consumption of jean trousers using neural network modelling. The efficiency of our model was then analysed and investigated.

## Materials and methods

### Data collection and analysis

Six different input parameters were chosen and used in the experiment to sew jean trouser specimens in order to evaluate their experimental thread consumption values. **Table 1** shows the input parameters and their corresponding levels. To regulate and adjust the sewing conditions, overall input parameters with two

regulation points were varied: the thread components expressed by the number of twisted thread ends ( $T_{ye}$ ), the needle size ( $N_s$ ), fabric thickness ( $F_{th}$ ), the mass or weight of fabric ( $W_f$ ), the stitch length ( $S_L$ ), and sewing machine type ( $S_{mt}$ ). Each level of the input parameters (1 and 2) for adjustment represents a regulation point, with 1 corresponding to the minimum, and 2 referring to the maximum, as shown in **Table 1**.

These input parameters are considered because of their probable contribution to the thread consumption value of the jean trousers. They are investigated objectively according to the factorial experimental design. Factorial designs allow for simultaneous study of the effects that several factors may have on a process. When performing an experiment, varying the levels of the factors simultaneously rather than one at a time is efficient in terms of time and cost, and also allows for the study of interactions between the factors. Interactions are the driving force in many processes. Without the use of factorial experiments, important interactions may remain undetected. Hence, in a full factorial experiment, responses are measured at all combinations of the experimental factor levels. The combinations of the

**Table 1.** Input parameters and their corresponding levels.

Input level	Twisted thread ends, $T_{ye}$	Needle size $N_s$ , Nm	Sewing machine type, $S_{mt}$	Fabric thickness $F_{th}$ , mm	Stitch length $S_L$ , mm	Weight of fabric $W_f$ , g/m <sup>2</sup>
1	2	90	Without automatic thread trimmer	0.60	2.25	268
2	3	120	Within automatic thread trimmer	0.92	2.85	417

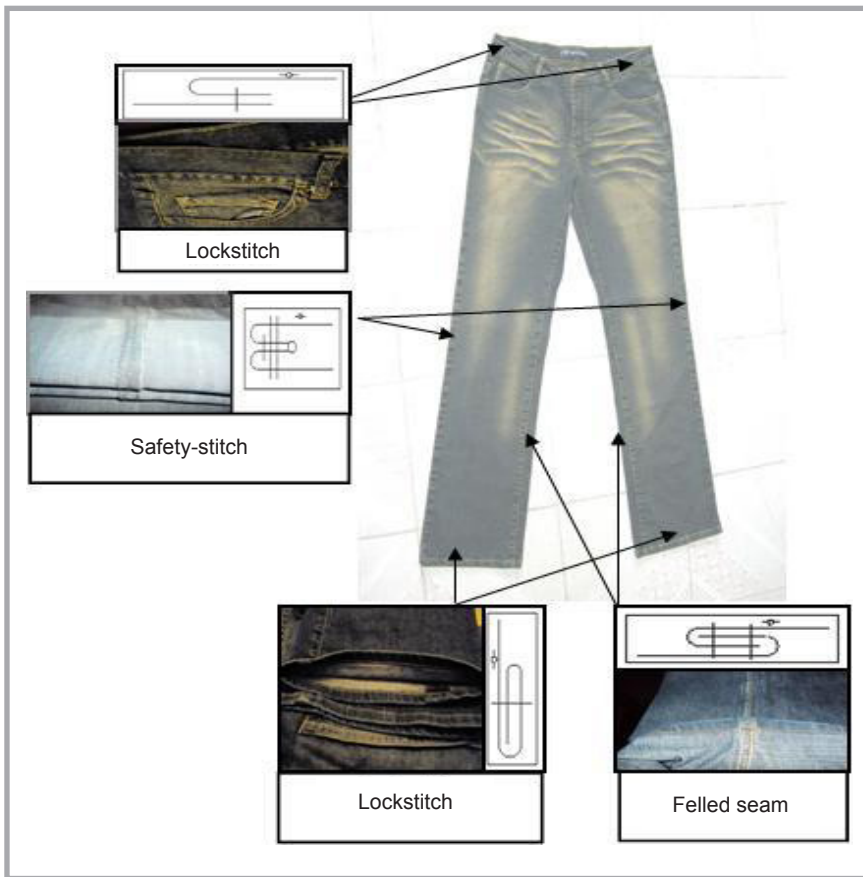


Figure 1. Different stitch types used to sew the jean trousers.

Table 2. Sewing thread consumption of trousers predicted and evaluated by the ANN model developed. ♦ $S_{TCact}$  - Represents the actual length of thread consumed during sewing of jean trouser samples, measured experimentally by unstitching. ♣  $S_{TCNN}$  - Represents the theoretical consumption of sewing thread predicted using the ANN model developed.

Test	Inputs tested within their levels						Sewing thread consumption, m	
	$S_{mt}$	$S_L$	$T_{ye}$	$N_s$	$F_{th}$	$W_f$	Experimental ♦ $S_{TCact}$ values	Theoretical ♣ $S_{TCNN}$ values
1	1	2.25	3	120	0.60	268	300	290.0
2	2	2.85			0.92	417	420	416.3
3		2.25			0.60	268	420	413.1
4	1	2.85	2	90	0.92	417	375	373.6
5	2	2.25			0.60	268	360	372.1
6	1	2.85	3	120	0.60	417	190	165.8
7	2	2.25			0.92	268	345	364.2
8	1	2.85			0.92	268	348	355.1
9	2	2.25	2	90	0.60	380	390.6	
10	1	2.85			0.92	417	250	258.3
11	2	2.25	3	120	0.92	417	200	182.6
12					0.60	268	350	346.3
13					0.92	417	210	191.4
14	1	2.85	2	90	0.92	268	330	338.3
15					0.60	417	345	340.6
16	2	2.25	3	90	0.92	268	405	405.2
17					0.60	417	310	329.5
18					0.92	417	300	297.9
19	1	2.85	2	120	0.92	268	320	289.8
20	2	2.25	3	90	0.92	268	230	232.0

factor levels represent the conditions at which responses will be measured. Each experimental condition is called a “run” and the response measurement an obser-

vation. The entire set of runs is the “design.” The number of tested samples given by the full experimental design, using Minitab 14 software, is 64 combinations

which are chosen to analyse the overall specimens. The output predicted using the neural network ( $S_{TCNN}$ ) and regression models ( $S_{TCact}$ ) is the thread length sewn, which represents the thread consumed to sew classic Jean trousers with 5 pockets. These values refer to the sewn thread lengths predicted and the actual measures of unstitch thread length values founded experimentally. As shown in Table 1, two types of jean fabrics (heavy and light) were used in the study within two different compositions: 100% Cotton and 98% Cotton + 2% Elastane. The majority of assemblies made on the jean pants were sewn with different types of stitches, for example: flat felled seam ( $2 \times 401$ ), safety stitch machine (ISO-516), overlockstitch machine (401) and lockstitch machine (301). In spite of its cross section, which is different, the appearance of this stitch, 401-401, as shown in Figure 1, can, however, be made using a JUKI DDL-8700 machine, to obtain a similar stitch. That is why we used this kind of sewing machine in our case. We will study their effect on thread consumption. All adjustment conditions are regulated to obtain good quality of assembly. Jean fabrics were seamed on JUKI DDL-8700 and MO-3316 sewing machines with two different sewing needle sizes: 111 and 83 dtex. All machine settings were the same for all trouser samples. Denim fabric layers were seamed with stitch densities of 4.5 and 3.5 stitches/cm, which were not identical to those selected by Webster et al. [34, 35].

Therefore this study is essentially carried out according to these stitches. Overall seam operations are realised within the same type of mean sewing thread count, 16.6 tex, to obtain jean trousers with 5 pockets, as shown in Figure 1. In the same Figure, all stitch kinds in some specific and basic zones are shown. In the area of the belt, belt loops and pockets, the stitches used to sew them are mentioned by lockstitch type 301 and overlockstitch type 401. Indeed this use of many more different types of stitch in Figure 1 than was explained previously is required to prevent redundant information, which makes Figure 1 and the explanation in the text complementary and not doubtful.

Sewing thread consumption values ( $S_{TC}$ ) are determined by unstitching the seam and measured according to French Standard NF G07 101. Thus after every

sewing operation of the garment, the experimental seam length was measured (see Table 2) and the thread requirement consumption of the garment obtained by adding the thread consumption of each operation  $S_{TCact}$ . Besides this, to compare theoretical and experimental results, twenty jean trouser specimens were sewn and unstitched in order to measure thread consumption at the levels prescribed by the factorial design.

### Artificial Neural Network parameters

Figure 2 shows an example of a neural network structure which is composed of three different inputs (a, b, and c) and one predictable output. To build a neural network model, some parameters should be considered. Hence the size of the hidden layers, the number of neurons in each hidden layer and the neurons in the output layer play a vital role during modelling steps.

For example, the model shown in Figure 2 is built using one hidden layer of three neurons and to test the training of network inputs. Moreover a suitable transfer function, adjusted weights and thresholds should be selected to start prediction. In fact, these neural network parameters are automatically modified during training as a function of the best accuracy of the model. The performance results of the network express the accuracy of the model, measured after training and evaluated by the error values between the actual and predicted output. Some works were conducted using the neural networks method [3, 13, 16]. To test our network model, we divided each under-design of experiments formed of 64 tests into two samples: A training sample that contains 44 random tests and a validation sample with the rest as remaining tests. In fact, our neural network is characterised by 300 iterations, for 6 inputs and one output. To build our neural model we chose one hidden layer within 4 neurons and transfer function *purelin* was selected. Hence the optimal value is obtained with four hidden neurons. The training is done and after this step the untrained data set is tested. We use the back propagation method to train the neural network and adjust weights and thresholds in the network. The training data set used in this paper consists of twenty sewn jean trouser samples. During the training step, all input parameters are fed to the network.

## Results and discussion

### Statistical and regression analysis

In order to assess the performance of the statistical (based on regression equations) and artificial neural-network models for predicting thread consumption, we investigated the experimental consumption values under applied factorial design. In fact, by classifying the contribution of each input parameter to the mean thread consumption, we analysed the factorial design using Minitab software analysis. Figure 3 shows the overall means at each level of input, represented using main effect plots. The main effect plots can be drawn for either the raw response data, the means of the output parameter for each input level, fitted values after analysing the design and predicted values for each input level. These plots are used to compare the magnitudes of all different main effects studied. A main effect occurs when the mean response changes across the input levels.

Moreover, Figure 3 also shows the variation of main input parameter effects on the mean sewing thread consumption values. According to the same figure, it is clearly noted that the needle size and type of thread used to sew jean trousers are the most influential parameters. Due to the high variation presented and saved when the input value changes from one level to another, the mean thread consumed changes enormously too. Hence we can remark also that the decrease in the size of needle (83 dtex instead of 111 dtex) caused an average decrease equal to 33.64% of the mean consumption value. According to earlier work

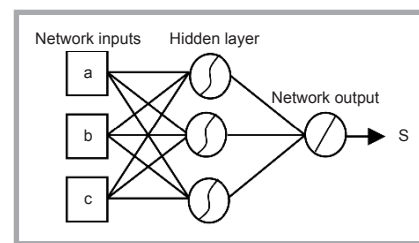


Figure 2. Example of Neural Network structure.

[15], for the highest needle size the sewing thread can cause a surplus of lengthening and a large loop of thread, which we can avoid. Thus, according to Seyam and El Sheikh's study [31], an appropriate thread for the correct needle size should be selected carefully. However, to reduce the mean value of the thread consumed, it is suitable to use sewing thread composed of two twisted threads. Furthermore increasing the number of twisted threads to sew jean trousers encourages a high consumption value. An average increase value of 21.82% was saved when the thread was composed of three twisted threads instead of two only. Thus in order to minimise sewing thread consumption, a low twisted thread number seems more recommended. By classification of the contributions of inputs, we can also remark that the weight of fabric is significant. Indeed the weight fabric parameter participates in the variation in consumption because it presents a non negligible effect when the level is modified from the lowest to the highest. Regarding the increase in the weight of fabric, the consumption value decreases by an average of 10.18%. Compared to  $N_s$ ,  $T_{ye}$  and  $W_f$ , the other input parameters can be considered as less significant due

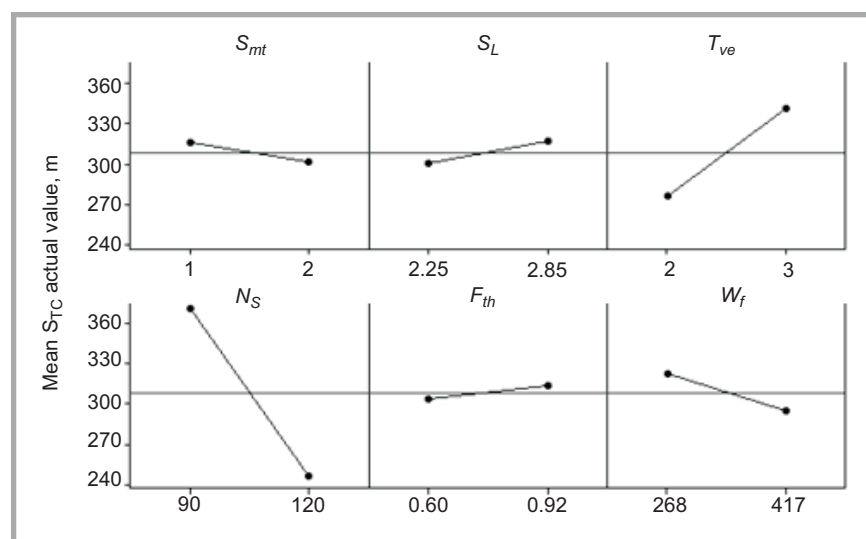


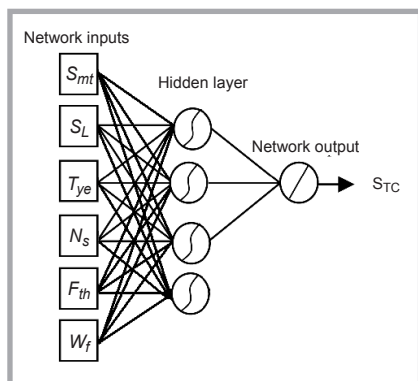
Figure 3. Main inputs effect variation for the mean value of  $S_{TC}$  given by Minitab software.

**Table 3.** Input parameters as presented by Minitab Software analysis: \*F-test - Evaluates whether the statistic observed exceeds a critical value from the distribution. If the F-statistic observed exceeds the critical value, the null hypothesis should be rejected; •T - Indicates that the parameter might be judged as significant when its p value is smaller than 0.05; °P - when the p-value of the input is less than a value of 0.05, thus this input will be kept and classified as significant. In contrast (p-value more than 0.05), the input is considered as non significant. \*SE Coef. - Standard error coefficient checks the store of standard errors of the coefficients estimated down a column in the order that they appear in the model.

Predictors	Coefficient	*SE Coef.	•T	•F	°P
Constant	581.28	50.94	11.41	-	0.000
$S_{mt}$	-21.056	7.279	-2.89	8.37	0.005
$S_L$	28.69	12.10	2.37	5.62	0.021
$T_{ye}$	65.749	7.261	9.06	82.00	0.000
$N_s$	-4.1843	0.2420	-17.29	298.88	0.000
$F_{th}$	31.41	22.69	1.38	1.92	0.172
$W_f$	-0.18499	0.04873	-3.80	14.41	0.000

to their slight contributions to the mean consumption of jean trousers. However, among the remaining inputs, fabric thickness  $F_{th}$ , seems non significant because its variation cannot affect the mean consumption value considerably. After removing the insignificant input parameter ( $F_{th}$ ), the analysis is performed once again to obtain a more significant regression equation, presented in the text as **Equation 4**. However, this part will be investigated deeply in the next works to optimise and analyse the consumption value of the sewing thread accurately. In fact, to verify the optimised regression equation and to improve our results more, other samples will be tested to validate the findings and generalise the models obtained in a large design of interest. That is why further works will help industrialists to predict and determine their consumed thread values as a function of garments. But the others two inputs, such as  $S_L$  and  $S_{mt}$ , seem influential, and as a result should be preserved and improved accurately.

Therefore to improve the analysis findings, it should be necessary to investigate the pertinence and significance of each



**Figure 4.** Artificial neural network model used.

input parameter, such as the linear regression method and analysis of variance technique. This step allows us to keep the most significant inputs only referring to the analysis of variance test. Hence regarding the analysis of variance, which represents the essential step to validate the accuracy of the model in the regression modelling method, overall input parameters predicted using factorial design analysis were investigated and given as shown in **Table 3**. Analysis of variance is a statistical test which helps the assessment of the input significance and its effects on the output studied. Based on a comparison of actual variance values of input parameters, those in the case of the same inputs are non significant [23, 24]. In fact, regarding the p-value test, each input was analysed comparing to 5%.

Nevertheless when the p-value of the input is less than a value of 0.05, this input will be kept and classified as significant [29, 30]. However, when the p-value is more than 0.05, the corresponding input should be removed because it is not significant. In this study, our equation of regression contains all factors which seem significant with a risk of 5%, except for the fabric composition parameter. Indeed when the non significance of this parameter is registered, we can understand this because it presents a p-value equal to 17.2%, which is more far than 5%. According to p-value probability, the fabric composition factor seems not sufficiently significant, with a risk of 5%, to be mistaken. Our regression analysis results show that the findings obtained, according to the factorial experimental design, are acceptable. Generally for a model with both multiple predictors and output studied ( $Y$ ), the regression equation form can be presented as shown in **Equation 1**. Due to error, which usually means 0,

**Equation 2** presents a fitted model within the output predicted, [29, 30].

$$Y = b_0 + b_1x_1 + b_2x_2 + \dots + b_kx_k + E_{rr} \quad (1)$$

$$\hat{Y} = b_0 + b_1x_1 + b_2x_2 + \dots + b_kx_k \quad (2)$$

where,  $Y$  and  $\hat{Y}$  - represent the output parameter value and predicted or fitted output, respectively,  $x$  - represents the predictors,  $b_k$  - this parameter estimates the population regression coefficients,  $E_{rr}$  - error term with normal distribution. In general, it is equal to 0.

Referring to findings given by Minitab software, the linear regression model is established as shown in **Equation 3**. For the factorial experimental design studied, the coefficient of determination  $R^2$  is equal to 0.877, which can explain that the regression model is acceptable, but it remains a function of the significance of each input parameter, as shown in **Equation 3**.

$$S_{TC} = 581 - 21.1 \times S_{mt} + 28.7 S_L + 65.7 T_{ye} - 4.18 \times N_s + 31.4 F_{th} - 0.185 W_f \quad (3)$$

Predicted  $R^2$  indicates how well the model predicts responses for new observations, whereas  $R^2$  indicates if the model fits the data tested or not. Predicted  $R^2$  prevents over fitting the model, which is, fitting the model too closely to the data in the current database set. As a result, it is not useful for predicting new data. In addition, the adjusted  $R^2$  value can be useful to validate models proposed. In fact, its value is equal to 0.845, which means it is high and can prove the effectiveness of the model of regression proposed [29, 30]. By comparison of predicted  $R^2$  and adjusted  $R^2$  values, the superiority of the first parameter may be concluded. Therefore the superiority of predicted  $R^2$  is based on its value, which is calculated within observations that are not included in the model calculation. Predicted  $R^2$  is also ranged between 0 and 1. Indeed larger values of the predicted  $R^2$  value suggest accurate models of greater predictive ability. As a result, after analysing all the input parameters' significances, the optimised regression equation can be rewritten in the following way:

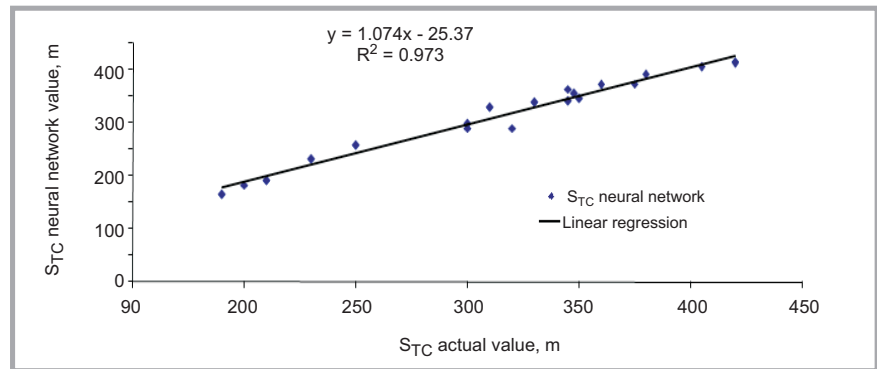
$$S_{TC} = 581 - 21.1 \times S_{mt} + 28.7 S_L + 65.7 T_{ye} - 4.18 \times N_s + 31.4 F_{th} - 0.185 W_f \quad (4)$$

#### Artificial neural network modelling method

To build our neural network model, shown in **Figure 4**, the number of hidden

layers, the number of neurons in the hidden layer, the learning rate and the number of cycles during the training were fixed. The thread components expressed by number of twisted thread ends, ( $T_{ye}$ ), the needle size ( $N_s$ ), fabric thickness ( $F_{th}$ ), the mass or weight of fabric ( $W_f$ ), the stitch length, ( $S_L$ ), and the sewing machine type, ( $S_{mt}$ ) are the input parameters of the neural network model structure. The consumption of thread to sew jean trouser samples is the output of the networks, as shown in **Figure 4**.

The data were all scaled and the hyperbolic tangent sigmoid function (tan sig) was used as the activation function for the hidden neurons. The pure linear transfer function for the output neuron is the *purelin* function. This structure is called multilayer perceptron (MLP). During the training step of the MLP, an error back propagation algorithm within the supervised technique, which is based on the error correction rule, was applied. It constitutes a feed forward back propagation network. The network that we implemented under Matlab is a perceptron that uses the back-propagation training algorithm. The network consists of six input nodes, one output neuron, and hidden neurons, which varied depending on the configuration selected. In fact the number of neurons in the hidden layer was selected according to the error and correlation coefficient R between the actual values of the sample test and those estimated by the network. It is notable that the accuracy of the results, *i.e.*, the nearness of the consumption value predicted to those for the actual thread consumption at the output, determines the performance of the network and, hence, the suitability of that particular network configuration or model. Thus the highest value of  $R^2$  is retained, indicating that the low difference between training outputs and target values is registered and a high performance successfully occurred. The result is obtained for a number of cycles equal to 300. Moreover the correlation coefficients of the neural network models are greater or comparable to those of the regression model obtained. The performance of a trained network can also be measured by the errors in the training, validation and test sets. Our results show that for the neural model obtained the regression coefficient is equal to 0.973. This high coefficient is close to 1 and explains the low mean error values between actual and predicted consumptions. Thus the neural network model de-



**Figure 5.** Post-training analysis of neural network results.

veloped seems accurate to widely predict the consumption of jean trousers. **Figure 5** shows the accuracy of the values obtained using the validation sample to test this neural network model. This is in good agreement with Jaouadi et al.'s study [16]. Regarding the good fitting of predicted values of thread consumed and the experimental unstitched lengths, we can conclude that our model helps, in our experimental design of interest, to evaluate and predict trouser consumptions.

## Conclusions

This paper aims to provide a rapid and accurate prediction method for the amount of consumed sewing thread required to make up a garment. Two modelling methodologies are used, analysed and compared in this paper: a linear regression and artificial neural networks model. The predictive power of each model is evaluated by comparing the thread consumption estimated with actual values measured after the unstitching of the garment in relation to regression coefficient  $R^2$  values. Some statistical parameters were analysed and investigated to improve the linear regression model. Findings show that the linear regression method remains insufficient to widely predict the consumption variation of jean trousers. Using the neural network technique was an accurate method to explain the consumption variation in our experimental design of interest. Comparing these techniques, it may be concluded that the neural network method widely predicts the quantity of thread required to sew jean trousers. Consequently, according to this work, the results obtained reveal that the artificial neural network approach gives the best accurate prediction, and as a result of which unused stocks can be reduced and stock rupture avoided. Besides, the results can be used

by industry to predict the amount of thread required to sew jean trouser garments and, hence, enable reliable estimation of the trouser costs and raw material required.

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## INSTITUTE OF BIOPOLYMERS AND CHEMICAL FIBRES

### LABORATORY OF ENVIRONMENTAL PROTECTION



AB 388

The Laboratory works and specialises in three fundamental fields:

- **R&D activities:** research works on new technology and techniques, particularly environmental protection; evaluation and improvement of technology used in domestic mills; development of new research and analytical methods;
- **research services** (measurements and analytical tests) in the field of environmental protection, especially monitoring the emission of pollutants;
- **seminar and training activity** concerning methods of instrumental analysis, especially the analysis of water and wastewater, chemicals used in paper production, and environmental protection in the paper-making industry.

**Since 2004 Laboratory has had the accreditation of the Polish Centre for Accreditation No. AB 551, confirming that the Laboratory meets the requirements of Standard PN-EN ISO/IEC 17025:2005.**

**Investigations in the field of environmental protection technology:**

- Research and development of waste water treatment technology, the treatment technology and abatement of gaseous emissions, and the utilisation and reuse of solid waste, Monitoring the technological progress of environmentally friendly technology in paper-making and the best available techniques (BAT), Working out and adapting analytical methods for testing the content of pollutants and trace concentrations of toxic compounds in waste water, gaseous emissions, solid waste and products of the paper-making industry, Monitoring ecological legislation at a domestic and world level, particularly in the European Union.

**A list of the analyses most frequently carried out:**

- Global water & waste water pollution factors: COD, BOD, TOC, suspended solid (TSS), tot-N, tot-P, Halogenoorganic compounds (AOX, TOX, TX, EOX, POX), Organic sulphur compounds (AOS, TS), Resin and chlororesin acids, Saturated and unsaturated fatty acids, Phenol and phenolic compounds (guaiacols, catechols, vanillin, veratrols), Tetrachlorophenol, Pentachlorophenol (PCP), Hexachlorocyclohexane (lindane), Aromatic and polyaromatic hydrocarbons, Benzene, Hexachlorobenzene, Phthalates, Polychloro-Biphenyls (PCB), Carbohydrates, Glyoxal, Glycols, Tin organic compounds.

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