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Neural Model of the Spinning Process Dedicated to Predicting Properties of Cotton-Polyester Blended Yarns on the Basis of the Characteristics of Feeding Streams

Abstract

The subject of our research were yarns manufactured from cotton-polyester blended slivers, as well as pure cotton and polyester slivers with the use of a BD 200S rotor spinning frame. Partial models of the spinning process were developed for selected, essential yarn quality parameters, such as tenacity, irregularity of yarn's mass, hairiness, number of yarn faults (number of thin and thick places and number of neps). In order to model the variability of these parameters, the following methods were used: linear and linearised regression, non-linear multiple regression as well as ADALINE and two-layer perceptron (MLP) artificial neural networks. The best results of approximation we obtained using the MLP network. Selection of the optimum network structure was carried out for each of the parameters. A hybrid model was used to model the variability of the CV coefficient.

Key words: yarn blends, cotton, polyester-fibres, rotor spinning, yarn quality parameters, linear regression, non-linear regression, artificial neural networks.

■ Introduction

Blended yarns of cotton and cotton – polyester-fibres are the most often manufactured linear textile products. Various spinning techniques and technologies guarantee a great variability of yarns produced, whose quality is estimated on the basis of analyses of the yarn quality parameters.

The main aim of our research was to determine the influence of the percentage content of polyester-fibres in the feeding sliver and linear density of the yarn manufactured on the yarn quality parameters, as well as designing an appropriate model of the spinning process. The investigation presented herein is a continuation of our earlier works into the properties of blended yarns of cotton - polyester-fibres [2 - 5].

On the basis of the research results of investigations carried out by us, a model of the spinning process was designed with the use of artificial neural networks (ANN), which enables determine dependences, and allows to predict yarn properties on the basis of the feeding stream characteristics. A lot of publications [1, 4, 6, 14 - 19] emphasise the fact that finding solutions to research problems with the use of ANN yields better results as compared to conventional mathematical modelling, and has far more advantages than the already known techniques of statistical analysis, which

appear unsatisfactory for analysing multidimensional technical problems. This becomes particularly apparent when a difficult object cannot be precisely mathematically described, such as in the case of the spinning process.

For the first time in Poland, the authors introduced artificial neural networks to find solutions to textile technological problems [7]. The researches that have been carried out by us so far have been published in domestic as well as foreign scientific journals and presented at scientific conferences [7 - 13]. The results obtained are very promising which encourage to continue this direction of research.

■ Research plan

The yarns analysed were manufactured from cotton - polyester-fibre blended slivers of cotton - polyester-fibres and from 100% cotton & 100% polyester-fibre slivers with the use of a BD 200 S rotor spinning frame. The content of polyester-fibres in the blended slivers were 12.5%, 25%, 37.5%, 50%, 62.5%, 75% and 87.5%. The remaining part consisted of medium-length fibres that had been cotton carded (variant W1) or combed (variant W2).

Yarns with linear densities of 15, 18, 20, 25, and 30 tex were manufactured at the following parameters of the BD 200 S rotor spinning frame:

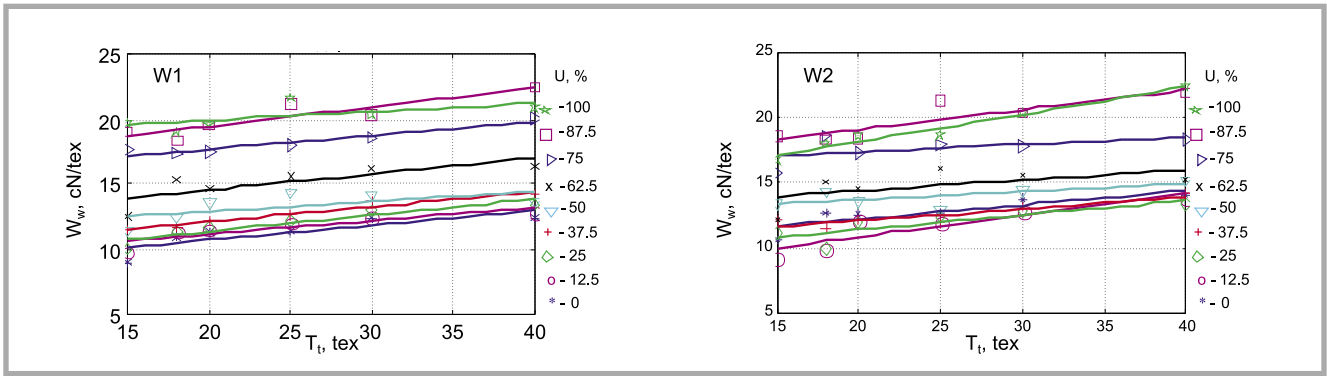


Figure 1. Dependency of the tenacity W_W on the percentage content of polyester-fibres U and the yarn's linear density T_t for the $W1$ and $W2$ variants and its approximation by linear functions.

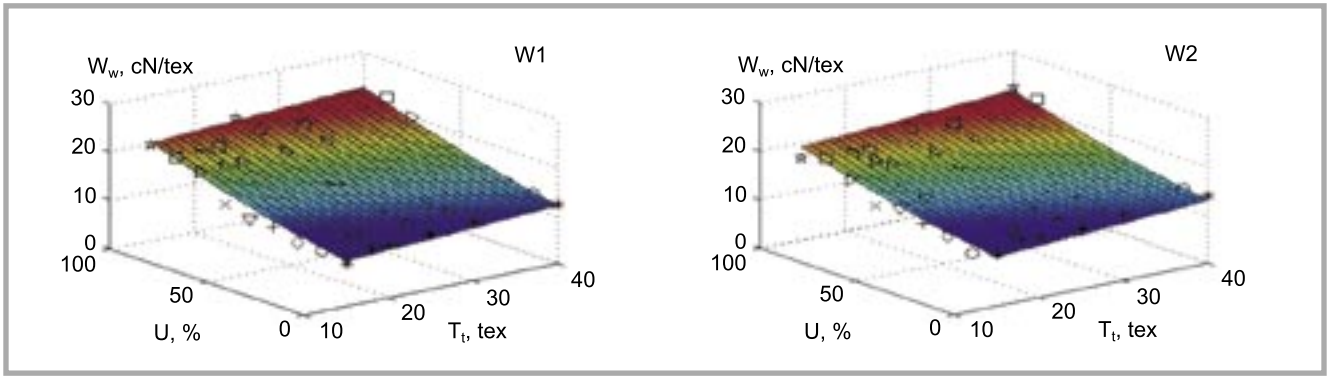


Figure 2. Modelling the dependency of the tenacity W_W on the percentage content of polyester-fibres U and yarn linear density T_t by non-linear regression equation (2) for the $W1$ and $W2$ variants.

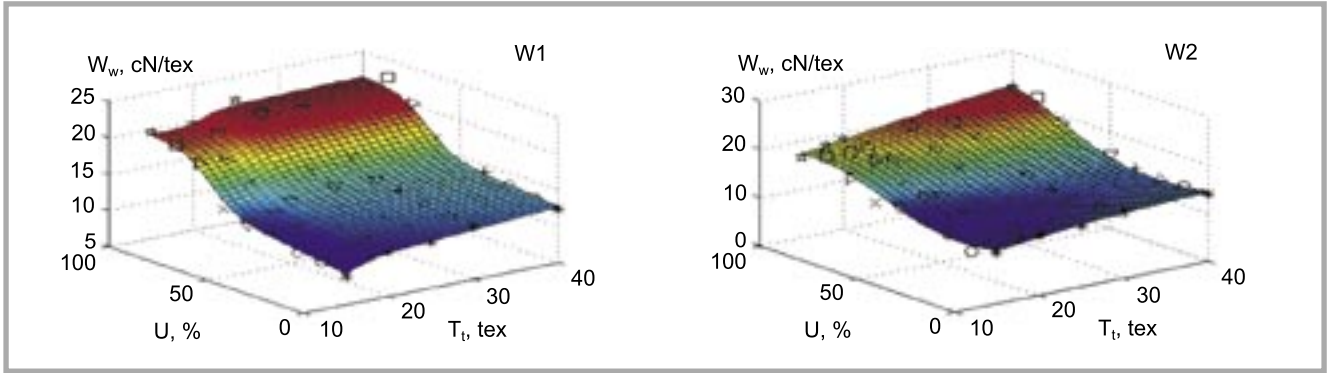


Figure 3. Approximation the dependency of tenacity W_W on the percentage content of polyester-fibres U and on the yarn's linear density T_t by MLP neural network for the $W1$ and $W2$ variants.

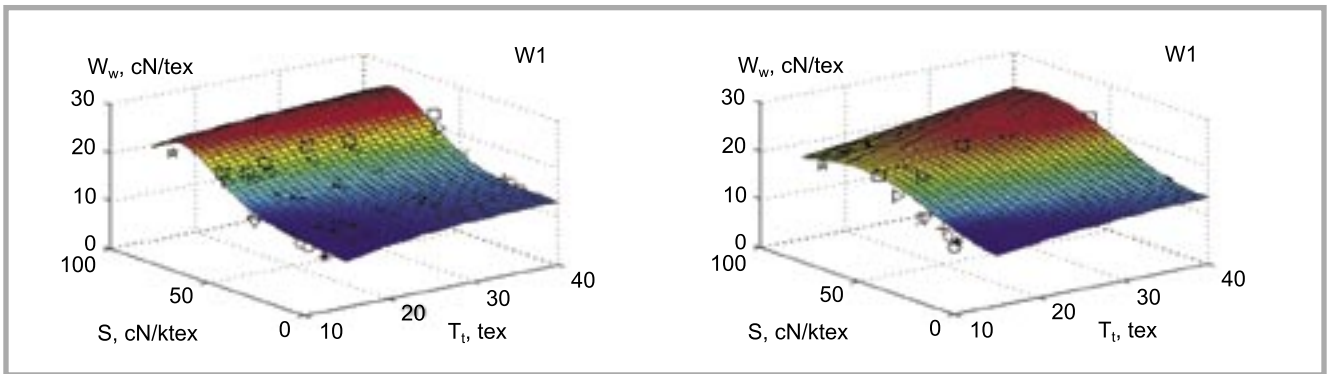


Figure 4. Approximation the dependency of tenacity W_W on the cohesion S of the feeding sliver and yarn linear density T_t by MLP neural network for the $W1$ and $W2$ variants.

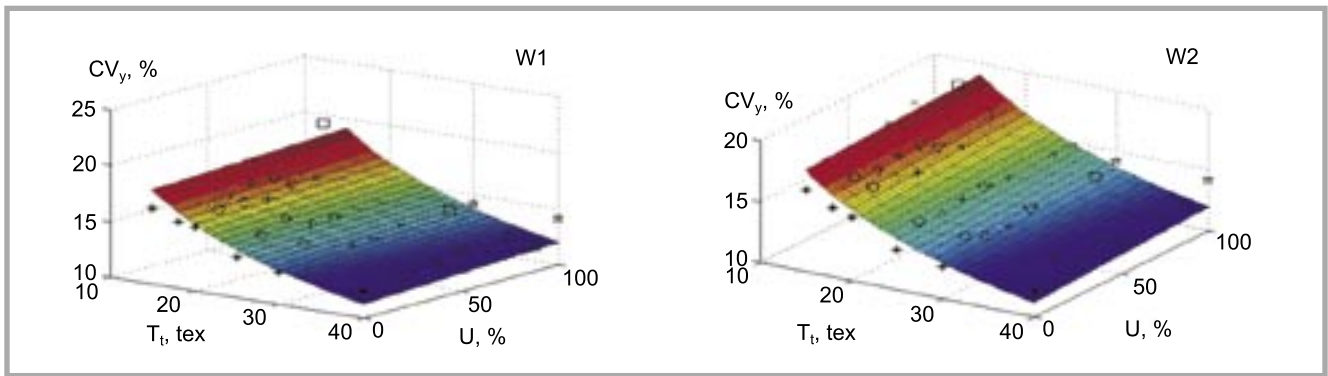


Figure 5. Dependency of the coefficient of yarns mass irregularity CV_y on the percentage content of polyester-fibres U and on the yarn's linear density T_t determined from the equation of multiple regression (6) and the Martindale formula for the W1 and W2 variants.

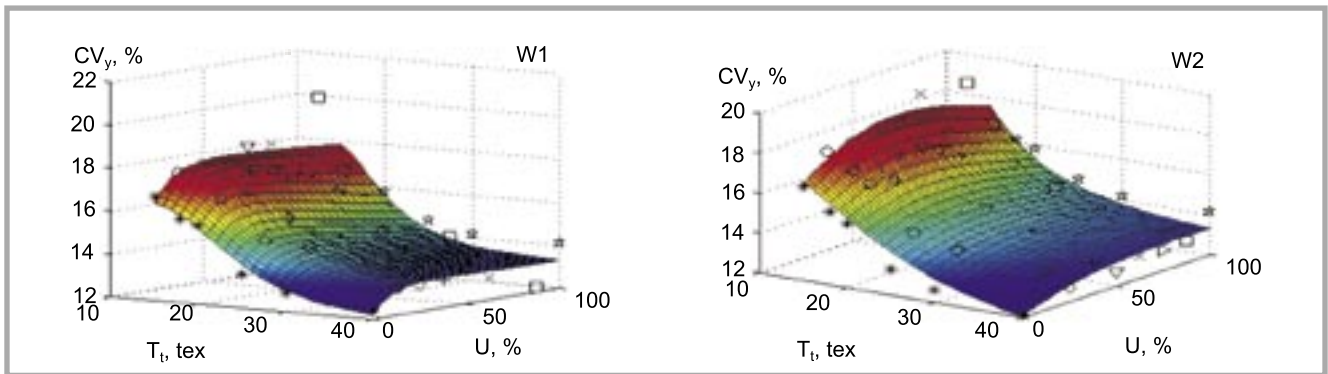


Figure 6. Approximation of the dependency of the coefficient of yarns mass irregularity CV_y on the percentage content of polyester-fibres U and yarn linear density T_t by using the MLP neural network and the Martindale formula for the W1 and W2 variants.

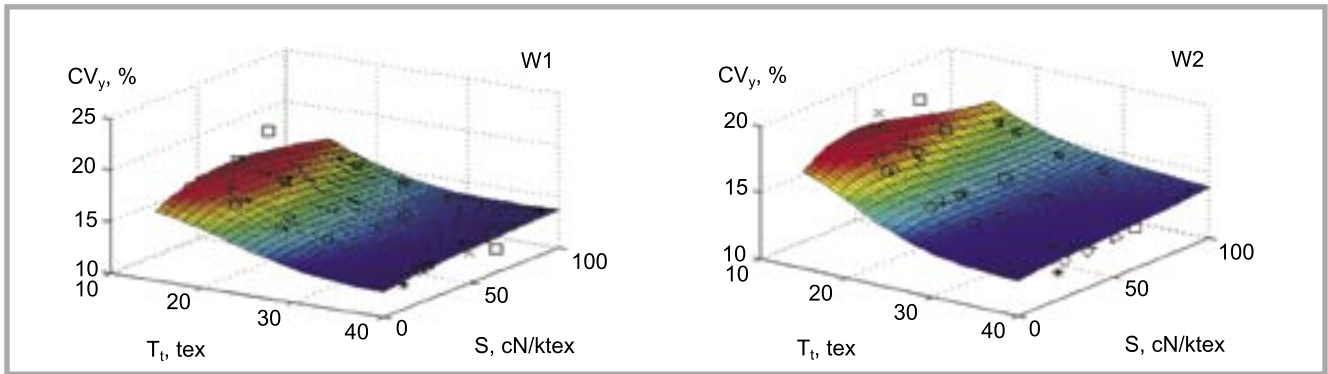


Figure 7. Approximation of the dependency of the coefficient of yarn's mass irregularity CV_y on the cohesion S of the feeding sliver and on the yarn's linear density T_t by using the MLP neural network for the W1 and W2 variants.

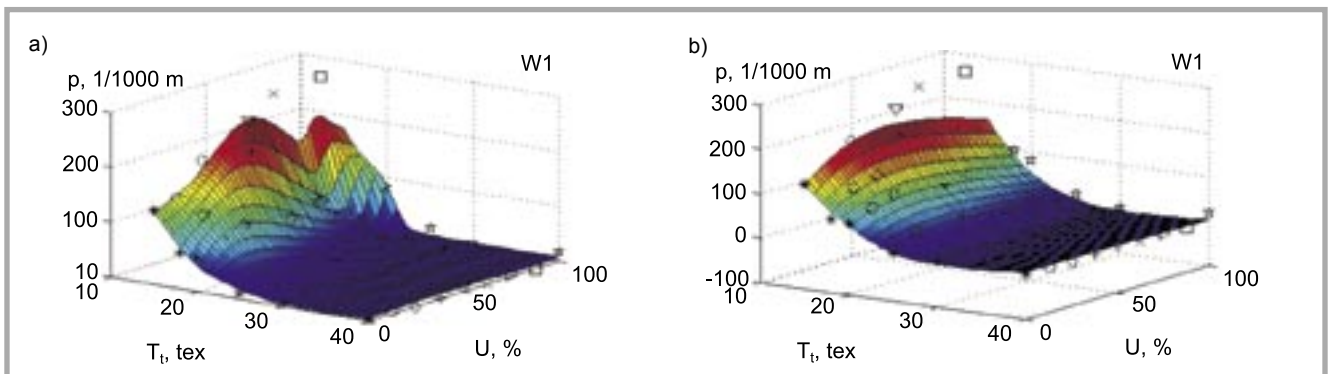


Figure 8. Dependency of the number of thin places on the percentage content of polyester fibres U and yarn linear density T_t and its approximation by MLP neural networks: a) network trained without regularisation, b) network trained with regularisation.

- rotary speed of the rotors of 50,000 r.p.m.
- rotary speed of the opening rollers of 7,000 r.p.m.

The spinning frame was fed with slivers with linear density of 4.54 ktex. In total, 108 yarn variants were manufactured.

For selected yarn parameters of essential importance, partial models of the spinning process were designed which enabled to determine the values of these parameters with dependence on the percentage content of polyester-fibres in the feeding sliver and on the linear density of the yarn manufactured. Firstly, two very significant yarn parameters: the tenacity and irregularity of mass were determined, and next the yarn hairiness and yarn faults, such as the number of thick and thin places, and the number of neps.

The influence of the feeding sliver cohesion on the yarn quality parameters was also analysed. The specific resistance or cohesion of cotton and cotton - polyester blended slivers was measured with an F 460 apparatus, from Zweigle. The cohesion of polyester and of blended slivers were significantly higher than the cohesion of cotton slivers.

■ Modelling of the yarn tenacity

The results of yarn tenacity W_W measurements for various values of the percentage content of polyester-fibres U and of the yarn linear density Tt for the W1 and W2 variants are presented in Figure 1.

Firstly, the dependency of tenacity on the yarn linear density was modelled by linear regression (1):

$$W_W = \alpha_1 Tt + \alpha_0 \quad (1)$$

where:

W_W – tenacity of yarn,

Tt – linear density of yarn,

α_1, α_0 – coefficients of regression.

The values of regression coefficients α_1, α_0 were determined by the least-squares method for both yarn variants, and for each percentage content U of polyester-fibres. The estimators of standard deviation S_W of the variable W_W , standard

deviations S_{α_1} and S_{α_0} of the coefficients determined, and the linear correlation coefficients r were also calculated. The determined values of the coefficient r , almost all of which were within the range of (0.79 – 0.98) and only for a few charts within the range of (0.54 – 0.70), confirmed the strong correlation dependency between tenacity and linear density of yarn. The average standard deviation for the approximation by the family of straight lines amounted to $S_{W1} = 0.68$ cN/tex and $S_{W2} = 0.77$ cN/tex for variants W1 and W2, respectively.

The families of straight lines (Figure 1), determined for the W1 and W2 variants, approximate the dependency of yarn tenacity on its linear density for various values of the percentage content of polyester-fibres which appear in the model as parameter. The disadvantage of these models is that they enable the calculation of yarn tenacity only for the values of parameter U , for which they were calculated. This disadvantage may be eliminated by substituting the above-mentioned models by multi-dimensional models, such as multiple regression and artificial neural networks (ANN).

The next dependencies investigated were approximated by ADALINE-type neural networks. These are single-direction networks with a linear activation function for each layer. Two-layer networks of a (2-3-1) structure were used for modelling, which means that they have two inputs, three neurons in a hidden layer, and a single neuron in the output layer. The standard deviations of determining the tenacity amounted to $S_{W1} = 1.4$ cN/tex for variant W1 and $S_{W2} = 1.6$ cN/tex for variant W2, and these values are greater when approximated by a family of straight lines. The multidimensional linear model did not secure sufficient accuracy of approximation.

On the basis of results obtained from previous research, we stated that for yarn with a linear density of 30 tex, the dependency of yarn tenacity W_W on the percentage content of polyester-fibres has a parabolic character [13]. The dependence of yarn tenacity on its linear density was

modelled by linear regression. Therefore, the dependency of yarn tenacity on the percentage content of polyester-fibres and on yarn linear density was modelled by non-linear and multiple regression of the following form:

$$W_W = b_3 U^2 + b_2 U + b_1 Tt + b_0 \quad (2)$$

where:

W_W - tenacity of yarn,

U - percentage content of polyester-fibres,

Tt - linear density of yarn

b_3, b_2, b_1, b_0 - coefficients of regression.

The values of the coefficients b_3, b_2, b_1 , and b_0 were determined by the least-square method. These values for both yarn variants and the estimators of standard deviation S_W of the variable W_W are shown in Table 1. The values of standard deviation are insignificantly smaller than those when using the ADALINE network, but are significantly greater than the average standard deviation obtained for the straight-line family. The results of approximation are presented in Figure 2.

Figure 3 presents an approximation of the dependency of yarn tenacity W_W on the percentage content of polyester-fibres U and on linear density Tt with the use of a multilayer perceptron neural network with a (2-3-1) structure which means that they have two inputs, three neurons with a sigmoidal activation function in the hidden layer and a single neuron of a linear activation function in the output layer. The estimators of standard deviation S_W of the variable S_W amounted to $S_{W1} = 0.58$ cN/tex and $S_{W1} = 0.90$ cN/tex for the variant W1 and W2, respectively. These values are much smaller than those when using the ADALINE neural network and the multiple non-linear regression. They are near to the average standard deviation obtained for the straight-line family. The best results of approximation of the dependency investigated were obtained using the MLP neural network.

The aim of our investigation was also to determine the influence of the cohesion of the feeding sliver on the quality parameters of yarn. Figure 4 presents measurement results of approximating the dependency of yarn tenacity W_W on the cohesion S of the feeding sliver, and on yarn linear density Tt with the use of

Table 1. Parameters of non-linear regression, coefficients b_3, b_2, b_1, b_0 of function (2) and standard deviations S_W of the variable W_W .

Carded cotton/PES – W1					Combed cotton/PES – W2				
b_3	b_2	b_1	b_0	S_W	b_3	b_2	b_1	b_0	S_W
3.72	6.99	0.11	7.83	1.2	3.54	5.45	0.12	8.44	1.4

a multilayer perceptron neural network with a (2-3-1) structure, which is of two inputs, three neurons with a sigmoidal activation function and a single neuron with a linear activation function in the output layer. The estimators of standard deviation S_W of the variable W_W amounted to $S_{W1} = 0.79$ cN/tex and $S_{W1} = 0.82$ cN/tex for the variants W1 and W2, respectively.

Modelling of the irregularity of yarn mass

Measurements of the coefficient of irregularity of yarn mass CV_y for different values of the percentage content of polyester-fibres U and linear densities T_t for the variants W1 and W2 were carried out with the use of an USTER Tester 3 apparatus (Figures 5 and 6).

The dependency of the coefficient of irregularity of yarn mass CV_y on its linear density has a non-linear character. It was approximated for different values of the parameter U by linearised regression equations of the form (3), [9, 10]

$$CV_y = C_0 + C_1 CV_T \quad (3)$$

Where:

C_0, C_1 – coefficients of the function,
 CV_T – theoretical value of the coefficient of irregularity of yarn mass calculated from the Martindale equation (4).

For cotton yarn it is assumed that:

$$CV_T = 106 n^{-1/2} \quad (4)$$

where:

n – average number of fibres in the yarn's cross-section:

$$n = T_{ty} / T_{tf} \quad (5)$$

where:

T_{ty} – linear density of yarn,
 T_{tf} – linear density of fibres.

For both yarn variants and each of the percentage content U of the polyester-fibres tested, the values of the coefficients C_0 and C_1 of function (3) were determined by the least-square method, after the theoretical values of the yarn mass irregularity coefficients CV_T were calculated, and before using equations (4) and (5). The estimators of the standard deviation S_{CV} of the variable CV_y , assumed as an independent variable, were also calculated, which means the measurement uncertainties of assessing the coefficient CV_y , the standard deviations S_{C0} and S_{C1} of the coefficient determination, and the

coefficient of linear correlation r between the variable CV_y and CV_T . The absolute values of the coefficient r within the range of (0.88 – 0.97) confirmed the very strong correlation dependency and the correct choice of the auxiliary variable CV_T . The average standard deviation amounted to $S_{CV1} = 0.58\%$ and $S_{CV2} = 0.50\%$ for the variants W1 and W2, respectively.

The function families determined for the variants W1 and W2 enabled the calculation of the dependency of the coefficient of irregularity of yarn mass on the linear density only for the values of the percentage content of polyester-fibres which were analysed.

The dependencies investigated were also approximated with use of multiple linear regression in the form of (6):

$$CV_y = b_1 U + b_2 CV_T \quad (6)$$

where:

CV_y – coefficient of irregularity of yarn mass,
 CV_T – theoretical value of the coefficient of irregularity of yarn mass calculated from the Martindale equation,
 U – percentage content of polyester-fibres,
 b_1 and b_2 – coefficients of multiple regression.

The values of coefficients b_1 and b_2 were determined by the least-square method. Their values for both yarn variants and the estimators of the standard deviation S_{CV} of the variable CV_y are listed in Table 2. The result of the mentioned approximation by equation (6) is shown in Figure 5.

The estimators of the standard deviation S_{CV} when using multiple regression (6) are much greater than the standard deviation obtained for the family characteristics determined from the equations of linearised regression (3). On the other hand, when using the ADALINE neural network, approximation results were obtained which were only slightly better than those for the multiple regression, which amounted to $S_{CV1} = 0.90\%$ for variant W1 and $S_{CV2} = 0.86\%$ for variant W2.

Figure 6 presents the results of modelling the coefficient of irregularity of yarn mass with dependence on the percentage content of the feeding slivers and the yarn linear density by multilayer perceptron neural networks of the structure (2-3-1) for variant W1 and (2-2-1) structure for variant W2. Similar as before, the network input signals were the percentage content of polyester-fibres U and the theoretical value of the coefficient of cotton yarn irregularity CV_T calculated from the Martindale equation, whereas the coefficient of the irregularity of yarn mass CV_y was the output signal.

Table 2. Multiple regression parameters, coefficients b_1 and b_2 of function (6) and the standard deviation S_{CV} of the variable CV_y .

Carded cotton/PES W1			Combed cotton/PES W2		
b_1	b_2	S_{CV}	b_1	b_2	S_{CV}
0.0072	1.63	1.06	0.0075	1.62	1.03

tron neural networks of the structure (2-3-1) for variant W1 and (2-2-1) structure for variant W2. Similar as before, the network input signals were the percentage content of polyester-fibres U and the theoretical value of the coefficient of cotton yarn irregularity CV_T calculated from the Martindale equation, whereas the coefficient of the irregularity of yarn mass CV_y was the output signal.

The values of the estimators of the standard deviation S_{CV} calculated, which amounted to $S_{CV1} = 0.68\%$ and $S_{CV2} = 0.64\%$ for the variants W1 and W2, respectively, are significantly smaller than those for the multiple regression and near to the average standard deviation obtained for the straight line family

Figure 7 shows the results of modelling the coefficient of irregularity of yarn mass CV_y with dependence on cohesion S of the sliver and yarn linear density T_t with the use of perceptron multilayer neural networks (MLP) of the (2-3-1) structure.

The values of the standard deviation estimators S_{CV} amounted to $S_{CV1} = 0.64\%$ and $S_{CV2} = 0.63\%$ for the variants W1 and W2, respectively.

The best approximation results of the dependencies investigated were obtained while using the MLP neural network. Therefore, in order to model the remaining parameters of the spinning process we only used artificial neural networks of the MLP type.

Selection of the optimum network structure

The selection of an appropriate network structure and suitable preparation of the learning data is extremely significant for the process of modelling functional dependencies with the use of artificial neural networks.

Similar to earlier works [13], in this case considered, the measurements, on the basis of which the learning data vectors for

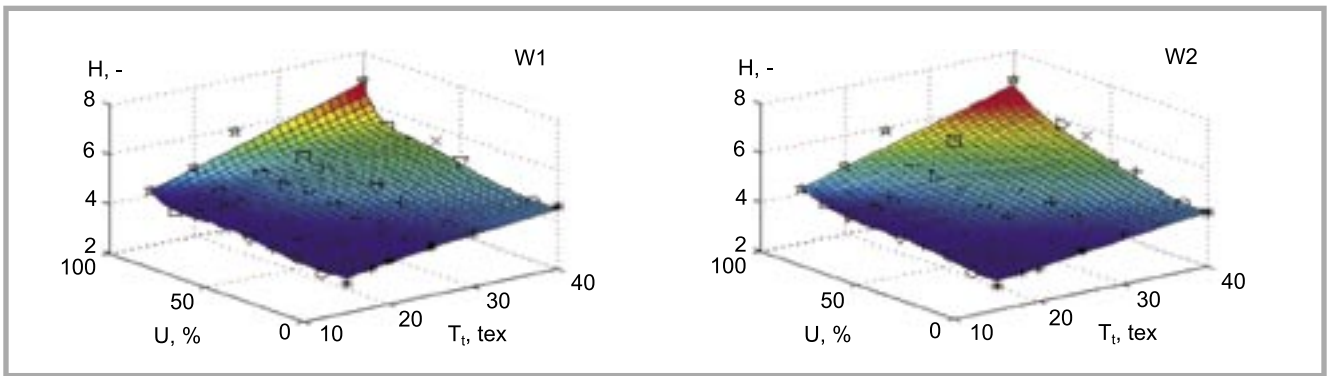


Figure 9. Dependency of yarn hairiness H on the percentage content of polyester-fibres U and yarn's linear density T_t , for the $W1$ and $W2$ variants, and its approximation by MLP neural networks of the (2-3-1) structure.

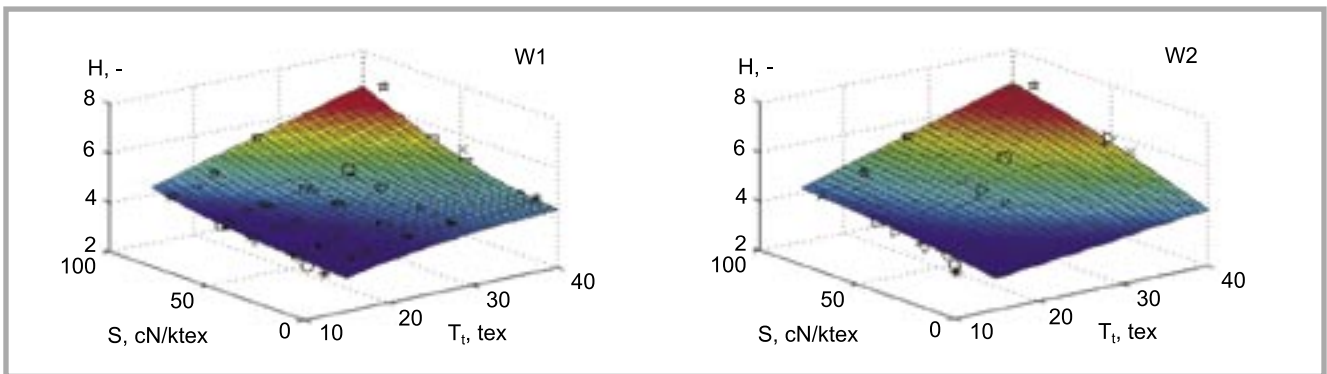


Figure 10. Dependency of yarn hairiness H on the percentage content of polyester-fibres U and yarn's linear density T_t , for the $W1$ and $W2$ variants, and its approximation by MLP neural networks of the (2-3-1) structure.

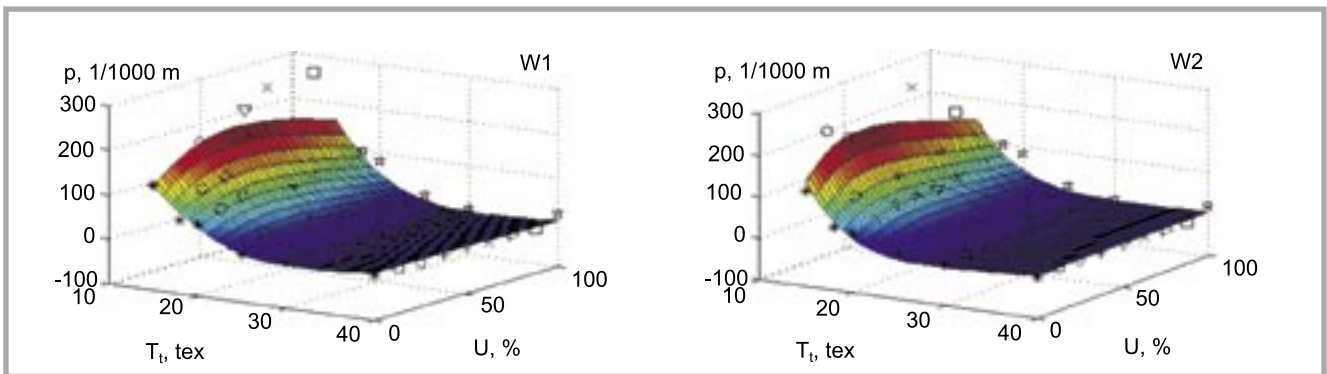


Figure 11. Dependency of the number of thin places on the percentage content of polyester-fibres U and yarn linear density T_t , for variants $W1$ and $W2$ and its approximation by MLP neural networks of the (2-3-1) structure.

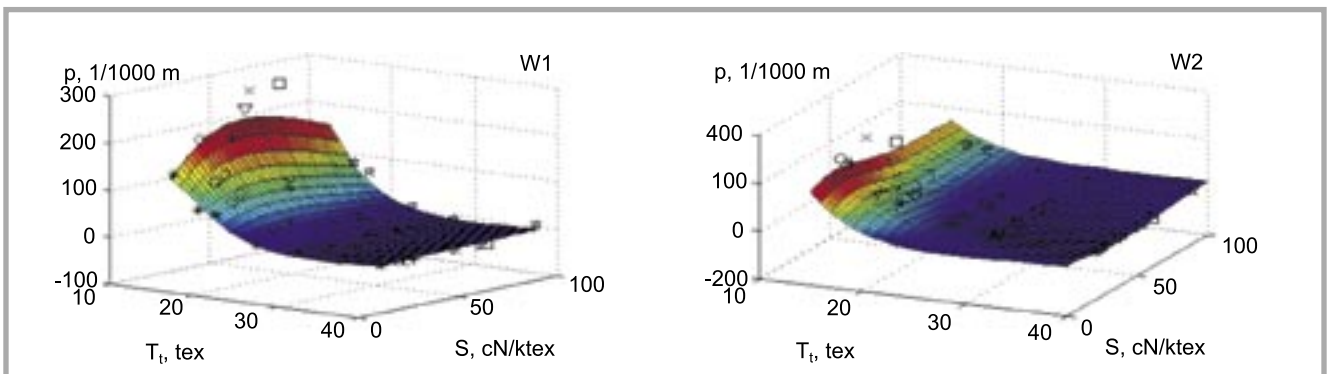


Figure 12. Dependency of the number of thin places on the cohesion S of the feeding sliver and yarn linear density T_t , for the variants $W1$ and $W2$ and its approximation by MLP neural networks of the (2-3-1) structure.

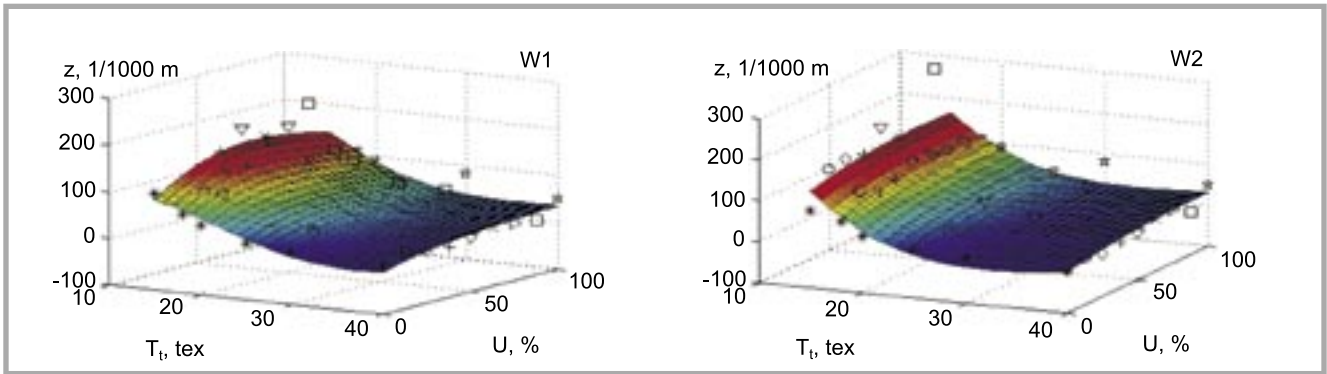


Figure 13. Dependency of the number of thick places on the percentage content of polyester-fibres U and on the yarn's linear density T_t , for variants $W1$ and $W2$ and its approximation by MLP neural networks of the (2-3-1) structure.

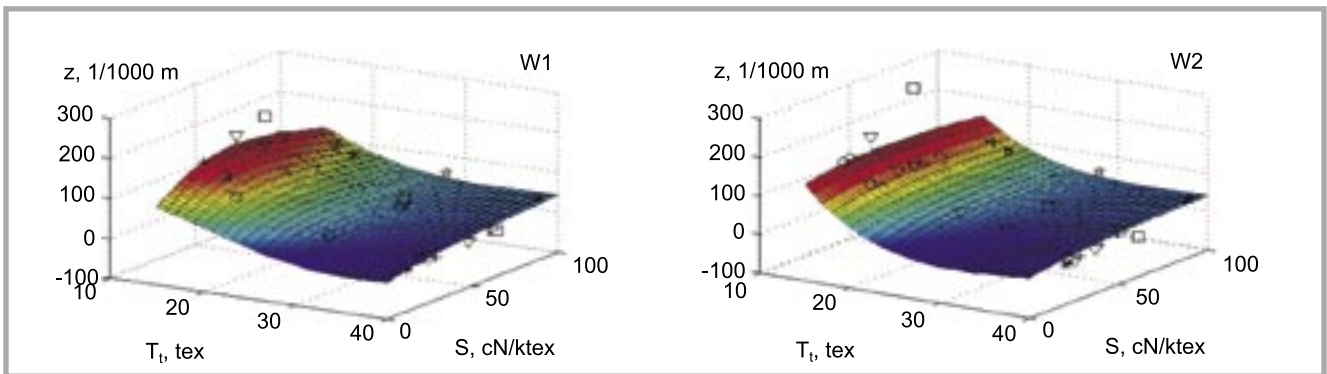


Figure 14. Dependency of the number of thick places on the cohesion S of the feeding sliver and yarn linear density T_t , for variants $W1$ and $W2$ and its approximation by MLP neural networks of the (2-3-1) structure.

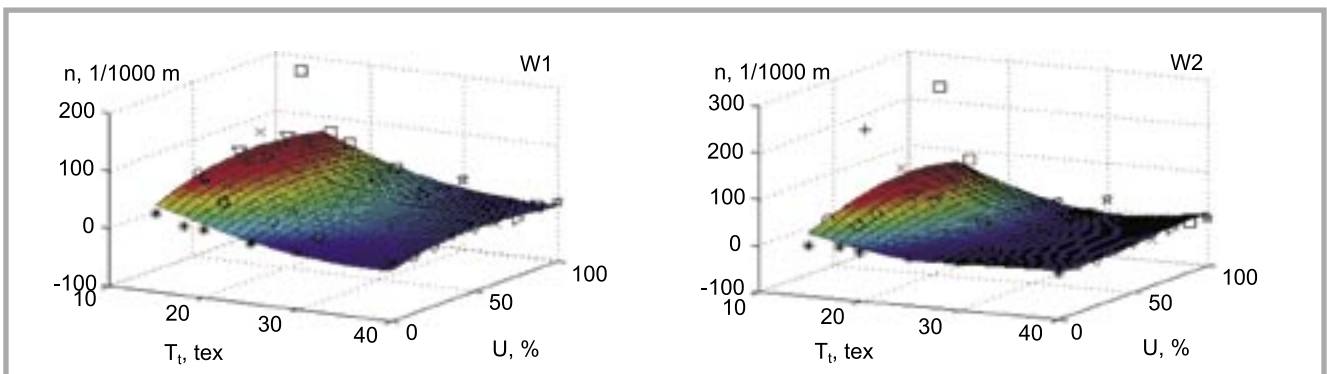


Figure 15. Dependency of the number of neps on the percentage content of polyester-fibres U and on the yarn's linear density T_t , for variants $W1$ and $W2$ and its approximation by MLP neural networks of the (2-3-1) structure.

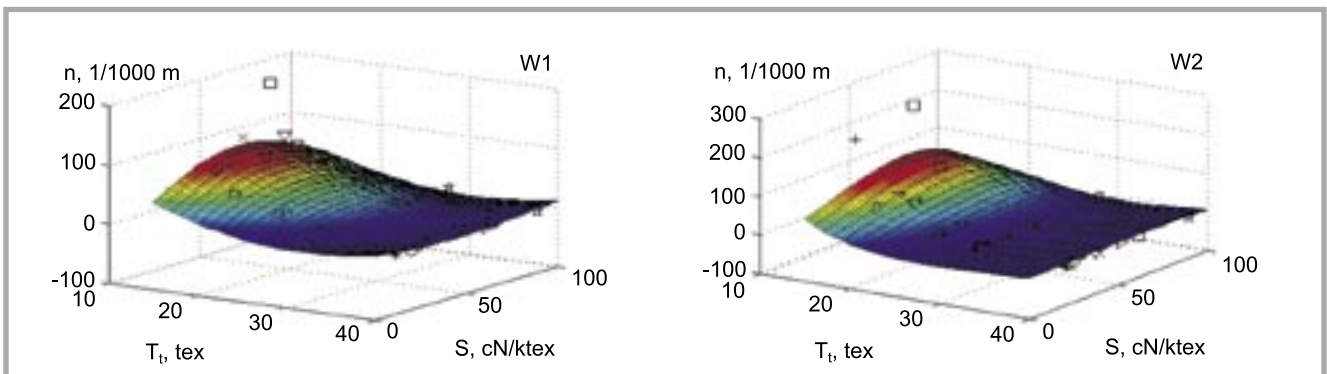


Figure 16. Dependency of the number of neps on the cohesion S of the feeding sliver and on the yarn's linear density T_t , for variants $W1$ and $W2$ and its approximation by MLP neural networks of the (2-3-1) structure.

the network are designed, were planned in such a way that the particular measuring points were evenly distributed in the measuring space. The complex problem of modelling the selected yarn properties was divided into simple modelling problems for each of the parameters independently. In order to model the selected yarn properties, single-directional, two-layer neural networks were used, with sigmoidal activation functions in the hidden layer (MLP). In the network structure marked (k-l-m), the number of network inputs (k) is determined by the number of input parameters, the number of network outputs (m) by the number of output parameters, whereas the number of neurons in the hidden layer (l) is chosen in order to secure proper modelling of the considered dependencies by the network. The number of neurons in the hidden layer was selected in such a way that it would be sufficiently great, to achieve the required accuracy of the approximation of the functional dependency model, and at the same time not so great that the network would not lost its generalisation abilities. In the case considered, for the modelling of the selected yarn parameters, the MLP networks of the (2-1-1) structure were used. The selection of an optimum number of neurons in the hidden layer (l) for each of the yarn parameters investigated was experimentally verified on the basis of the computer simulations carried out. For all the yarn parameters investigated, the structure (2-3-1) was selected as the best. The back propagation algorithm with the Levenberg-Marquardt optimisation method and the mean-square-error cost function was used.

In a few cases, in spite of the fact that MLP networks of small dimensions were used, it was not possible to avoid the effect of the modelling of measurement uncertainty or to obtain a smooth modelling function. In order to improve the generalisation properties of the network, an algorithm with Bayes automatic regularisation implemented in the Neural Network Toolbox of a MATLAB packet was used in the learning process.

Figure 8 shows an example of the dependency of the number of thin places on the percentage content of polyester-fibres U_p and on the yarn linear density T_t approximated by MLP neural networks of a (2-3-1) structure.

The chart in Figure 8.a was obtained by training the network without regu-

larisation, whereas in Figure 8.b it is with regularisation. Application of the regularisation improved the generalisation properties of the network.

■ Modelling of yarn hairiness

Figure 9 presents the results of yarn hairiness H measurements for various values of the percentage content of polyester-fibres U with dependency on the yarn linear density T_t , for the variants W1 and W2. The yarn hairiness was measured by the USTER Tester 3 apparatus.

The values calculated for the estimators of standard deviation S_H when approximated by MLP neural networks of (2-3-1) structure amounted to $S_{H1} = 0.18$ and $S_{H2} = 0.23$ for the variants W1 and W2, respectively. Modelling the dependencies investigated with use of the ADALINE network and multiple regression did not yield sufficient results.

Figure 10 presents yarn hairiness H measurement results, measured with the USTER Tester 3 apparatus and an approximation of its dependency on the cohesion S of the feeding sliver and on the yarn linear density T_t . The values obtained of the standard deviation estimators S_H and approximated by MLP networks with a (2-3-1) structure amounted to $S_{H1} = 0.20$ and $S_{H2} = 0.24$ for the variants W1 and W2, respectively.

■ Modelling of the number of yarn faults

The number of yarn faults was measured by the USTER Tester 3 apparatus

Number of thin places

Figure 11 presents the number of thin places p measured for various values of the percentage content of polyester-fibres U and yarn linear density T_t for the variants W1 and W2. The values of the estimators of standard deviation S_p and approximated by the MLP neural networks of (2-3-1) structure amounted to $S_{p1} = 34.5$ 1/1,000 m and $S_{p2} = 24.7$ 1/1,000 m for the variants W1 and W2, respectively

Figure 12 presents the number of thin places p and the approximation of its dependency on the cohesion S of the feeding sliver and on the yarn linear density T_t for the variants W1 and W2. The values of the estimators of standard deviation S_p and approximated by the MLP

neural networks of a (2-3-1) structure amounted to $S_{p1} = 33.3$ 1/1,000 m and $S_{p2} = 24.8$ 1/1,000 m for the variants W1 and W2, respectively.

Number of thick places

Figure 13 presents the number of thick places z measured for various values of the percentage content of polyester-fibres U and yarn linear density T_t for the variants W1 and W2. The values of the estimators of standard deviation S_z calculated and approximated by the MLP neural networks of a (2-3-1) structure amounted to $S_{z1} = 30.7$ 1/1,000 m and $S_{z2} = 35.1$ 1/1,000 m for the variants W1 and W2, respectively.

Figure 14 presents the number of thick places z and the approximation of its dependency on the cohesion S of the feeding sliver and yarn linear density T_t for the variants W1 and W2. The values of the estimators of standard deviation S_z approximated by MLP neural networks of a (2-3-1) structure amounted to $S_{z1} = 29.3$ 1/1,000 m, $S_{z2} = 34.5$ 1/1,000 m for the variants W1 and W2, respectively.

Number of neps

Figure 15 presents the number of neps n measured for various values of the percentage content of polyester-fibres U and yarn linear density T_t for the variants W1 and W2. The values of estimators of standard deviation S_n calculated and approximated by MLP neural networks of (2-3-1) structure amounted to $S_{n1} = 31.7$ 1/1,000 m and $S_{n2} = 40.0$ 1/1,000m for the variants W1 and W2, respectively.

Figure 16 presents the number of neps n and the approximation of its dependency on the cohesion S of the feeding sliver and on the yarn linear density T_t for the variants W1 and W2. The values of the estimators of standard deviation S_n approximated by the MLP neural networks of (2-3-1) structure amounted to $S_{n1} = 29.3$ 1/1,000 m and $S_{n2} = 34.5$ 1/1,000 m for the variants W1 and W2, respectively.

■ Summary

The results of our investigation, which concerned the properties of the fibre streams feeding a rotor spinning frame and the properties of yarns manufactured, served to build a model of the spinning

process with the use of artificial neural networks (ANN) which enables to predict optimum yarn properties on the basis of feeding stream characteristics.

Partial models of the spinning process were designed for selected, essential yarn parameters, which enable to determine the values of these parameters with dependence on the carded or combed cotton slivers used for manufacturing, the percentage content of polyester-fibres in the feeding sliver, and the linear density of the yarn manufactured.

For modelling the variability of yarn tenacity and the irregularity of the yarn mass (CV_y) the following methods were used: linear and linearised regression, non-linear multiple regression, as well as ADALINE and two-layer perceptron neural networks (MLP). The best approximation results were obtained for the MLP network. A selection of the optimum network structure was carried out.

For modelling the variability of the coefficient CV, a hybrid model was used characterised by the percentage content of polyester-fibres U_P and the theoretical value of the coefficient of cotton yarn mass irregularity CV_T calculated from the Martindale formula as the network's input signals, and the coefficient of irregularity of the yarn mass CV_y as the output signal.

The hairiness and yarn faults, such as the number of thick places, the number of thin places and the number of neps were modelled using artificial neural network of the MLP type.

For all the yarn parameters considered, partial models of the spinning process were designed which enable to determine the values of these parameters with dependence on the use of carded or combed cotton for the slivers to be obtained, the linear density of the yarn manufactured, and the cohesion of the feeding sliver. All these dependencies were modelled using artificial neural networks of the MLP type.

Conclusions

1. The dependencies investigated have a complex, non-linear character, and it is difficult to find a multi-variable function which would approximate them accurately.
2. Determining the functional dependencies of the yarn parameters inves-

tigated on each of the parameters of the spinning process independently, and next, based on these, designing a model in the form of multiple regression, occurred to be insufficiently accurate.

3. The best results of approximation were obtained while using MLP networks for all of the dependencies investigated.
4. Application of the Bayes regularisation in the learning process, significantly improved the generalising properties of the MLP networks.

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