ASSESSING THE QUALITY OF NEURAL MODELS USING A MODEL OF FLOW CHARACTERISTICS OF FABRICS AS AN EXAMPLE

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Abstract

In this article, a method for assessing the quality of now-widespread neuron models is presented. Attention has been paid to the significance of analysing individual input quantities in the model constructed. Then, the parameters which are quantitative measures of the neural model's quality have to be specified. The need for structural verification of the network is stressed, which is the basis for stating that the neural model obtained has been well matched with the investigation results. The assessment of the neural model's quality has been shown, using a model of the flow characteristics of fabrics as an example.

Key words:

Impact air-permeability, neural model, woven fabrics, verification

Introduction

Neural networks are a group of numerical algorithms that can be used in the approximation of a function, classification and grouping of data, as well as for solving special optimisation problems. Neural networks as numerical algorithms of a specific structure are capable of processing information. Calculations are performed in the graph structure, whose points are individually parametrised non-linear functions. Networks can approximate any complex and complicated mappings, and the structure accepted can be fitted by means of experimental data. The user does not need to know or assume in advance the existence of any form of relationship occurring in the model sought, or even know whether any relationships occur at all. Therefore, neural networks are now frequently used for approximation, including the textile industry.

Neural networks and a hybrid neural model, for example, served the authors [12,19] to determine such parameters of rotor yarns as mean force and the coefficient of variation in mass of cotton yarn in relation to the linear mass of the fibre and the rotational speed of the rotor.
A neural network was also used to find the dependence of the pressure drop on the fabric as a function of its structural parameters and the parameters of the flowing fluid [3]. At the same time, attention was paid to the phenomenon of fibre swelling during the flow of water through the product (in particular, this phenomenon concerned rayon fibres).
A neural network taught by means of an algorithm of backward propagation of errors was used to identify defects in fabrics [4], [5]. White fabric was adopted as a standard. On the other hand, fabric whose surface showed oily stains, holes, and the missing of threads of the weft or the are missing was adopted as a defective fabric. The product surface is scanned by means of a digital camera and the picture is transferred to a computer, where the image is processed.

Considering the advantages of artificial neural networks, they have been used to describe flow properties of fabrics for the pulse increase in pressure.

The impact permeability of fabrics and its measurement

The static permeability of air is a characteristic property of products placed as porous membranes across the region of air movement. The air flow is of a steady character, while the values of the quantities being measured do not change during a single measurement.

Dynamic permeability is understood as a property of a flat textile product describing differences in the behaviour of the product measurement area during steady and transient air throughflows [7]. Studies on the dynamic permeability of fabrics are usually carried out in two stages [11]. The first stage consists in establishing the static flow-characteristics of a textile product specimen, i.e. the relationship between the pressure difference p_s on both sides of the product as a function of the air volume flux. During the second stage, its dynamic characteristics are determined. This relationship is obtained on a dynamic measurement stand [10]. The product is mounted on the upper base of a cylinder-shaped measuring device. Inside the cylinder there is a piston. As a testing signal for the assessment of flow properties of textile products, a jump change in the volume of the area under the specimen is used, as a result of which a transient air flow is forced through the membrane. The movement of the piston is the technical realisation of a unit jump – one of the many possible dynamic actions – which causes a pulsed increase in pressure on the product specimen under study. Due to the impact character of the piston's movement, the notion of the impact air permeability has been introduced. The following time courses are recorded on the stand: *p(t)* – the pressure pulse, *x(t)* – the piston movement; *h(t)* – the specimen deflection.

The measure of the impact permeability of textile products is an index of the form:

$$IP = \frac{1}{n}\sum_{i=1}^{n}\frac{\max\limits_{t\geq 0}\ p_i(t)}{\max\limits_{t\geq 0}\ p_i(t) + \max\limits_{t\geq 0}\ p'_i(t)} - 0,5 \,, \tag{1}$$

where: *i=1,2,...,n* – the number of measurement repetitions.

The value of the *IP* index is determined on the basis of the calculated hypothetical pressure pulse $p_i'(t)$ [18] and the measured real pulse $p_i(t)$, which occurs on the fabric specimen studied.
The index defined by formula (1) is constructed in such a way that it can assume positive and negative values. This index assumes values from within the interval *(-0,5;0,5)*. Negative values of the *IP* index show that less air will flow through the fabric under dynamic conditions than in static conditions. The pores in the fabric subjected to dynamic investigations may not have time to open up. The negative value of the *IP* index means that more pores in the fabric will open up during transient air flows. As a result, a greater amount of the air will flow through a porous product than under steady flow conditions. Zero values of the index suggest that the difference in the pressure on both sides of the textile product specimen is the same under both dynamic and static conditions.

Studies on the impact permeability of fabrics have been carried out basing on experiment-designing methods [2], [6]. These methods have been used to find a mathematical model of the object of study such as fabrics [16]. At the first stage of the designed experiment, a qualitative mathematical model of the object under study is made. Thus, input and output, constant quantities and disturbances must be determined. The second stage consists in selecting a design, which defines the method of determination of measuring points in the area of input quantities. In the case of textile objects, it is recommended that a steady-system design is used [8], [16], since most textile objects manifest limited controllability [9]. At the third stage, the values of output quantities are measured at the points determined by the design. The selection of measuring points according to the steady-system design is made on the basis of the criterion determined for a specific case. Such a design can be called a user's design. Most often it does not use any conventional criterion such as orthogonality or rotatability. At the fourth stage, the obtained dependence of the output quantities on the input quantities at those measuring points which are not indicated by the design selected are verified [8], [9].

A neural model of the flow properties of fabric

Making use of methods of designing the experiments, the flow properties of fabrics of diversified structural parameters were studied (Table 1). The zero values of the twist given in Table 1 were obtained for flat filaments. This concerns the warp threads of fabrics such as 12, 14, 15, 17 and the weft threads of fabrics such as 13, 14, 17. The zero values of the twist and weft crimp of fabrics 12 and 15 were obtained for yarns made of microfibres.
The set of input quantities of a qualitative model includes the following structural parameters of fabrics: thickness $Gr \in [0.27;\ 0,76]$mm, number of threads of the warp $Lo \in [22;\ 82]$units./cm and the weft $Lw \in [18;\ 40]$units./cm, linear mass of the warp $Mlo \in [9.6;\ 57.3]$tex, of the weft $Mlw \in [8.5;\ 58.3]$tex, twist of the warp threads $So \in [0;\ 378]$twist./m, weft $Sw \in [0;\ 378]$twist./m and weft take-up $Ww \in [0.0;\ 13.0]$%.

The selection of elements of the set of input quantities was based on an analysis of sensitivity [15] and the preliminary assessment of the effect of the individual parameters on the value of the *IP* permeability index defined by formula (1). This index is an output quantity of the qualitative mathematical model. The set of constant quantities includes relative air humidity (66%), temperature (22ºC) and the surface of the specimen studied (100.29cm^2). The group of disturbances includes electromagnetic disturbances, pressure, and those structural parameters not otherwise mentioned. Based on the investigations, the mean values of the *IP* impact permeability indices of the products were determined (Table 1).
The value of *IP* index determined for the 18th fabric differs from the others; this fabric characterised low air permeability in static conditions. Nevertheless, the parameters of fabric assigned as the 18th are within the domain of determinacy of the model.

Table 1. Structural parameters of fabrics and the calculated values of the *IP* indices

Woven fabric denotation	Gr	Lo	Lw	Mlo	Mlw	So	Sw	Ww	IP
-	mm	units/cm	units/cm	tex	tex	twist/m	twist/m	%	-
1	0.72	35	19	43	54.3	153	131	6.7	0.0233
2	0.62	22	33	26.4	40.9	214	167	11.6	0.0131
3	0.36	38	35	29.3	20.3	206	195	0.3	0.0151
4	0.74	35	19	52.0	49.6	154	139	5.5	0.0359
5	0.42	43	24	24.9	26.3	378	378	6.5	0.0268
6	0.75	35	21	44.6	44.6	254	230	4.0	0.0487
7	0.75	35	18	51.0	53.7	149	121	8.0	0.0411
8	0.69	36	23	50.7	47.1	271	262	2.9	0.0380
9	0.67	38	22	50.0	48.5	269	277	4.5	-0.0377
10	0.66	27	23	57.3	58.3	228	228	7.1	-0.0540
11	0.75	56	25	41.1	38.7	278	278	1.5	-0.0592
12	0.48	82	30	9.6	25.5	0	0	0.0	-0.0135
13	0.38	45	32	20.6	19.4	215	0	3.1	-0.0197
14	0.28	48	26	19.7	8.5	0	0	0.3	-0.0941
15	0.27	44	35	12.2	18.5	0	0	0.0	-0.0677
16	0.65	27	25	48.9	50.3	271	258	7.1	-0.0467
17	0.67	49	40	26.6	24.4	0	0	13.0	-0.0719
18	0.33	45	33	19.4	35.1	244	172	12.4	-0.2330

where: Gr – fabric thickness, Lo – number of warp threads, Mlo – linear mass of warp, Mlw – linear mass of weft, So – twist of warp threads, Sw – twist of weft threads, Ww – weft take-up, IP – index according to equation (1).
Remark: The same abbreviations are valid for the next tables.

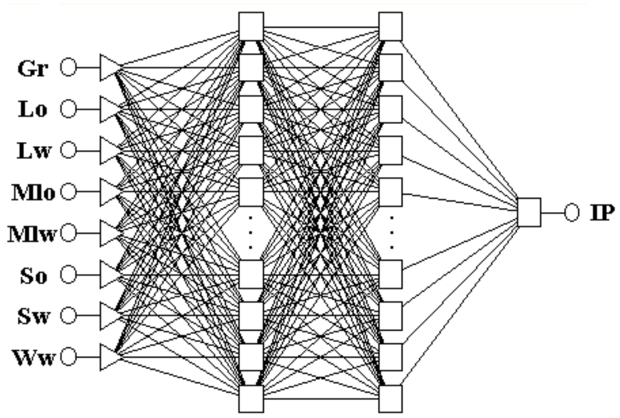

Figure 1. Neural model of flow properties of fabrics

To find a qualitative mathematical model, the so-called function of the object of studies, a multi-layer perceptron was used [15]. Multi-layers perceptrons belong to one-way networks, and are characterised by stable behaviour. There are no connections inside the layers in them. They can be interpreted as models of the input-output type, where weights and threshold values are their parameters. The values of the weights are ascribed to individual inputs. The threshold values define the strength of excitation needed to cause ignition. The process of teaching a neural network is a method of controlling the weight of the neurons' connections. It is equivalent to matching the parameters of the model represented by the network to the available teaching data. The neural network was built by means of the Automatic Network Designer, an option offered by the Statistica Neural Networks PL program. A multi-layer perceptron with two hidden layers of the form *8:8-13-13-1:1* (Figure 1) was obtained. Each layer of the hidden networks has thirteen neurons.

The Automatic Network Designer generated a neural model by using an algorithm of the back propagation error at the beginning of the teaching process. The network was taught for a hundred iterations. Next, an algorithm of conjugate gradient descent was used. In this case, the teaching of the network lasted for thirteen iterations. The final form of the network was obtained in the thirteenth iteration.

Assessment of neural models

The analysis of the neural network input's sensitivity

It has been suggested that the first step in assesssing the model obtained in the form of an artificial neural network should be to analyse the sensitivity of the input of a neural network [14]. It offers an insight into the usefulness of the individual input variables. It indicates which variables which can be neglected without causing any loss in the network's quality, as well as those key variables which can never be omitted. However, care must be taken while drawing conclusions. The analysis of sensitivity shows the loss that is incurred by rejecting a concrete variable. However, due to the relationship between the variables, such an index calculated independently for each variable may not reflect the real situation. Such inter-related variables may prove to be useful when used together. In the sensitivity analysis, a certain amount of data is rejected. Therefore, an increase in the network's errors should be anticipated.

The quotient β of the error obtained during the start-up of the network for a set of data without one variable and an error obtained with a set of variables is assumed to be the basic measure of network sensitivity. The quotient β indicates how many times the error of the network increases following the removal of variable data. The greater the error after the removal of the variable in relation to the original error, the more sensitive the network is to the lack of this variable. Thus, if $\beta \leq 1$, then the removal of a variable does not have any effect on the quality of the network, and even improves the quality of the network. After carrying out the sensitivity analysis for all the variables, the variables can be ranked in respect of importance. The ranks indicate the order of the variables according to the magnitude of the quotient (the first one is the most important).

Parameters of quality of the models

The next step in assessing the neural model's quality is the decision of whether to accept the model obtained on the basis of the qualitative parameters.

The first parameter is the quotient of standard deviations ρ_w in the errors and data for the validation subset. The quotient is used to evaluate the quality of validation; the anticipated mean error of the prediction is equal to the standard deviation calculated for the output value in the teaching (validation) set. The quotient shows whether the attempt to build a regressive model has been successful. If it assumes a value greater than or equal to unity, it means that the model realised by the network does not give any better results than the model which always gives the same predicted signal at the output, which is simply the mean of the output values observed earlier. The value of this quotient smaller than unity testifies that the system output obtained by means of the network is better at estimation. The smaller the value, the better the guess of the model at unknown output values. If the network builds a model that will not make any mistakes whatsoever, the quotient will reach zero. (Of course, the latter case is purely hypothetical, although it could happen if the process being modelled is deterministic, and the network manages to discover its real model.)

Another parameter is the error for the validation subset ε_w obtained while teaching the network. This error is subject to minimisation during the course of teaching the network (at least for the teaching subset). This is expressed by the sum of the squared differences between the set values and the values obtained at the outputs of each output neuron. This is a standard function of the error used in the course of teaching neural networks, which is efficient in the majority of regressive problems.

Still another parameter of quality is the quotient of standard deviations ρ_y of the prediction errors and data of the set of output quantity values; for neural networks operating effectively, the mean value of prediction errors for the known cases should be expected to be close to zero. This also means that the

standard deviation of prediction errors will be definitely smaller than the standard deviation for the specimen value. Otherwise, the prediction results will not be better than those that can simply be obtained by guessing. For this reason, the quotient for networks predicting data effectively (that is, which is capable of generalisation) should be considerably smaller than unity [13]. It is assumed [1], [14], that if $\rho_y \leq 0.1$, then the neural model has been well matched to the investigation results. A coefficient value greater than 0.7 disqualifies the model created by the network.
The last parameter is the standard correlation coefficient R_P (R-Pearson's) between the calculated and the real output values. The value of the coefficient should be close or equal to unity, which means that the prediction is ideally correlated with the current output values; however, that does not mean that the prediction is ideal. In practice, the correlation coefficient is a good index of network quality.

The structural verification of models

The last step in assessing the quality of the neural model and, at the same time, the last important stage of the designed experiment, is the verification of the model obtained. It is suggested that structural verification be performed [8], [9], [17]. When using this criterion for a neural model, the set of measuring points should be expanded to include the features of the verification object, whose parameters are within this model's domain of determinacy. Then, the process of teaching the network of the originally proposed structure should be employed, and afterwards, the quality of the neural model should be checked by means of quality parameters.
The positive result of the verification carried out means that the neural model approximating the dependence of the output quantity on the input ones is well matched to the measurement results. This model is capable of making predictions, confirmed by the good network quality parameters which are obtained.

Assessment of the model of fabric flow properties

According to the method of assessment of the neural model quality, the sensitivity of the individual inputs of the neural network of the model of fabric flow properties was analysed first. The results obtained are presented in Table 2.

Table 2. Results of the sensitivity analysis (network *8:8-13-13-1:1*)

Inputs	**Gr**	**Lo**	**Lw**	**Mlo**	**Mlw**	**So**	**Sw**	**Ww**
Quotient β	3.2153	1.7608	1.7834	3.4470	3.7335	2.8409	3.0166	2.4495
Ranks	3	8	7	2	1	5	4	6

The above table contains quotients β of the error obtained on the network start-up for a set of data without one variable, and the error obtained for a set of data with all the variables and the ranks related to them. All the values obtained of the quotients β are greater than unity, which testifies to the fact that input quantities (the structural parameters of fabrics) have a significant effect on the value of the *IP* index.

For an artificial neural network of the form *8:8-13-13-1:1*, the following quality parameters have been obtained: the quotient of error standard deviations and the data for the validation subset ρ_w=0.200828, the error for the validation subset ε_w=0.017796, the quotient of standard deviations of prediction errors and data of the set of the standard deviations of the prediction errors and the data of the set of the output quantity values ρ_y=0.3576, and the R-Pearson standard correlation coefficient R_P=0.9373.
The standard deviation quotients ρ_w and ρ_y are considerably smaller than unity. The value of the quotient ρ_y is smaller than 0.7. thus we can state that the neural model obtained was well matched to the investigation results. Moreover, the error ε_w obtained for the validation subset was small. The R-Pearson standard correlation coefficient demonstrates that the values of the impact permeability indices as calculated by means of the network are linearly well correlated with the values obtained in the experiment.

For making the structural verification, two fabrics were used: *W1* and *W2* of the structural parameters and values of the impact permeability index listed in Table 3.
The parameters of the fabrics selected are within the domain of determinacy of the form:
$[0.27; 0,76] \times [22; 82] \times [18; 40] \times [9.6; 57.3] \times [8.5; 58.3] \times [0; 378] \times [0; 378] \times [0.0; 13.0] \subset \Re^8$ of the neural model being built.

Table 3. Structural parameters of the fabrics used for verification and the calculated values of the IP indices

Woven fabric denotation	Gr	Lo	Lw	Mlo	Mlw	So	Sw	Ww	IP
-	**mm**	**units/cm**	**units/cm**	**tex**	**tex**	**twist/m**	**twist/m**	**%**	**-**
W1	0.76	36	23	50.4	47.2	270	250	3.7	0.0438
W2	0.41	43	24	25.1	25.7	290	200	5.9	-0.0562

Using the Statistica Neural Networks PL program, the authors tested a perceptron network of the form *8:8-13-13-1:1* for the values of input quantities expanded to include the structural parameters of the fabric *W1* (verification 1), and then *W2* (verification 2).
After a new network was obtained (the network of an unchanged structure, *8:8-13-13-1:1*), the sensitivity of the individual input quantities was analysed. The effects of the analysis are presented in Tables 4 and 5. It results that all the input quantities of the neural model are significant (using the verifying fabrics *W1* and *W2* in both cases).

Table 4. Sensitivity analysis results (network *8:8-13-13-1:1*) – verification 1

W1	Gr	Lo	Lw	Mlo	Mlw	So	Sw	Ww
Quotient β	2.1216	1.0806	1.1628	1.8079	1.5966	1.2246	1.1038	1.6216
Ranks	1	8	6	2	4	5	7	3

Table 5. Sensitivity analysis results (network *8:8-13-13-1:1*) – verification 2

W2	Gr	Lo	Lw	Mlo	Mlw	So	Sw	Ww
Quotient β	3.1303	1.4918	1.2907	1.3231	1.2274	2.9368	1.6392	3.2634
Ranks	2	5	7	6	8	3	4	1

The following quality parameters were obtained for the neural model using successive verifying fabrics:
W1: ρ_w=0.455561, ε_w=0.101282, ρ_y=0.4970, R_P=0.9083, where the network was obtained using an algorithm of backward propagation of errors (teaching the network for 100 iterations) and an algorithm of conjugate gradient descent, after which the best network in respect to the error on the validation set was selected; it was obtained in the 22nd iteration.
W2: ρ_w=0.576569, ε_w=0.091166, ρ_y=0.3421, R_P=0.9402, where the network was obtained using an algorithm of backward propagation of errors (teaching the network for 100 iterations) and an algorithm of conjugate gradient descent, after which the best network in respect to the error on the validation set was selected; it was obtained in the 24th iteration.
In connection with the positive result obtained for the analysis of sensitivity of the input quantities expanded to include successively the parameters of the verifying fabrics and the good quality parameters of the neural model during verification, it can be concluded that the structural verification yielded a positive result.
In conclusion, the constructed neural model of fabric flow properties offers a good description of the effect of the structural parameters of the flat textile products under study on the value of the impact permeability index of these products.

Conclusions

- Neural models are an important tool for the mathematical description of the phenomena analysed. They solve the tasks of optimising non-linear problems, and are used for the approximation of functions.
- The method of assessment of neural models' quality using the analysis of sensitivity of the individual input quantities, the assessment by means of quality indices, and finally, the structural verification of the network obtained, allows us to state that the neural model obtained was well matched to the investigation results.
- The positive result of the neural network assessment testifies to the fact that the network is capable of generalisation. Thus, the neural model has an ability to approximate the outputs corresponding to these points in the space of inputs that do not belong to the training set.

References:

1. *Ballou J.W., Roetling J.A., High Speed Tensile Testing of Fibres, Textile Research Journal, 1958, Vol. 28, No 8, pp. 631-646.*
2. *Box, G.E.P., Draper, N.R., Empirical Model-Building and Response Surfaces, Wiley, New York 1987.*
3. *Brasquet C., Le Cloirec P., Pressure Drop Through Textile Fabrics – Experimental Data Modelling Using Classical Models and Neural Networks, Chemical Engineering Science, 2000, Vol. 55, No. 15, pp. 2767-2778.*
4. *Chung-Feng J.K., Ching-Jeng L., A Back-Propagation Neural Network for Recognizing Fabric Defects, Textile Research Journal, 2003, Vol. 73, No. 2, pp. 147-151.*
5. *Chung-Feng J.K., Ching-Jeng L., Cheng-Chih T., Using a Neural Network to Identify Fabric Defects in Dynamic Cloth Inspection, Textile Research Journal, 2003, Vol. 73, No. 3, pp. 238-244.*
6. *Deming, S.N., Morgan, S.L., Experimental Design: A Chemometric Approach, Elsevier Sc. Pub. B.V., Amsterdam, 1993.*
7. *Gniotek K., Dynamic Permeability of Textiles, Fibres & Textiles in Eastern Europe, 1996, Vol. 4, No. 2, pp. 54-55.*
8. *Gniotek, K., Modelling and Measurement of Textile Objects for Experiment Design, Fibres & Textiles in Eastern Europe (ISI), 2002, No. 10, pp. 52-57.*
9. *Gniotek, K., Controllability of Object Measured for the Need of Experiment Design, XVII IMEKO World Congress, Metrology in the 3rd Millenium, pp. 1922-1925, Dubrovnik, Croatia, 2003.*
10. *Gniotek K., Tokarska M., Pomiary udarowej przepuszczalności powietrza płaskich wyrobów włókienniczych (in Polish), materiały V Szkoły – Konferencji Metrologia Wspomagana Komputerowo, SOWA Sp. z o.o., Tom 3, ss. 235-240, Rynia k/Warszawy, 2001.*
11. *Gniotek, K., Tokarski, P., New Methods of Assessing Static and Dynamic Flow Characteristic of Textiles, Textile Research Journal, 2000, Vol. 70, No. 1, pp. 53-58.*
12. *Jackowska-Strumiłło L., Jackowski T., Chylewska B., Cyniak D., Application of Hybrid Neural Model to Determination of Selected Yarn Parameters, Fibres & Textiles in Eastern Europe, 1998, Vol. 6, No. 4, pp. 27-32.*
13. *Statistica Neural Networks PL. Poradnik użytkownika (in Polish), StatSoft Polska, 2001.*
14. *Statistica Neural Networks PL. Przewodnik problemowy (in Polish), StatSoft Polska, 2001.*
15. *Tadeusiewicz R., Sieci neuronowe (in Polish), Akademicka Oficyna Wydawnicza RM, Warszawa 1993.*
16. *Tokarska, M., Application of Experiment Design Method to Fabric Impact Air-Permeability Research, proceedings of 6th International Conference of Faculty of Engineering and Marketing of Textile, Technical University, Lodz, Poland, 2003.*
17. *Tokarska M., Neural Model of the Permeability Features of Woven Fabrics, Textile Research Journal, 2004, Vol. 74, No. 12, pp. 1045-1048.*
18. *Tokarska M, Model of Pressure Drop on Woven Fabric, proceedings of 8th Conference of Faculty of Engineering and Marketing of Textile, Technical University, Lodz, Poland, 2005.*
19. *Jackowska-Strumiłło L., Jackowski T., Cyniak D., Czekalski J., Neural Model of the Spinning Process for Predicting Selected Properties of Flax/Cotton Yarn Blends, Fibres & Textiles in Eastern Europe, 2004, Vol. 12, No. 4, pp. 17-21.*

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