

Application of Neural Networks for Estimation of Paper Properties Based on Refined Pulp Properties

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Abstract

The main objective of the work presented was to determine the possibility of the prediction of paper properties based on refined chemical pulp properties using the neural network approach. Three main parameters related to basic refining effects were used: pulp and fibre WRV, the amount of fines and the average fibre length. These parameters were used for prediction of the following paper parameters: apparent density, breaking length and tear resistance. The classical multilayer perceptron with one hidden layer was used. The number of inputs and outputs was related to that of input and output variables. The size of the hidden layer (number of hidden neurons) was determined experimentally. The Levenberg-Marquardt algorithm was used as a training method. The available dataset was divided into two groups: 90% of experimental results were applied as training data and 10% for model verification. As a result of the trials conducted, a satisfactory level of the correlation between simulation data and experimental data was obtained. Results allow to presume that the method presented could be adapted for other papermaking pulp grades as a general control system in the industrial refining process. In such a case, the accuracy of the presented method could be even higher because of the large number of data available on-line. These data could be used as in a real-time training procedure, which would significantly improve the precision of the whole system. The lack of other effective methods of paper property prediction makes the method proposed an attractive solution to the problem presented.

Key words: pulp, paper, WRV, fibre length, fines, strength properties, neural networks, simulation.

– and the complex relationships between pulp parameters and paper properties result in a lack of universally accepted, quantitative methods of predicting final paper quality. Furthermore the quality of paper is also strongly dependent on several process parameters (*Figure 1*), which causes significant problems with obtaining reliable information about product quality in a short time. In practice, the situation could be even worse if the quality control in a paper mill is based just on a few parameters measured on-line at the dry end of a paper machine. In such a case, the other important paper properties must be tested off-line, in a laboratory, after the production process. Consequently all information related to possible variances in the product quality is obtained *post factum*, which could result in lower process efficiency due to an excessive increase in the broke due to breaks and/or an off-spec product.

All above facts support the need for an on-line measurement system which could provide early information about the general papermaking ability of pulp in terms of the prediction of the final paper properties. This would be used as an expert system for process control and to support the decision making process. The need for such a system is postulated in literature [1, 2].

Considering the fact that refining is the most important unit operation which directly influences the papermaking ability of pulp, it seems that the best location for the sampling point of the system proposed in a paper mill would be somewhere after the refining process. The main limitation related to the possibility of the prediction of paper properties based on refined pulp properties is the lack of universal mathematical descriptions of this relationship. The impact of different pulp properties on paper properties has been the subject

Introduction

Papermaking pulp represents a highly heterogeneous material of biological origin. Several different factors are used in order to characterise the papermaking applicability of chemical pulp. In general, these factors can be grouped into:

- chemical indicators (e.g. degree of cellulose polymerisation, kappa number, chemical composition)
- physical indicators (e.g. freeness, average fibre length, WRV, amount of fines).

Differences in the structure of every single fibre - even for the same pulp grade

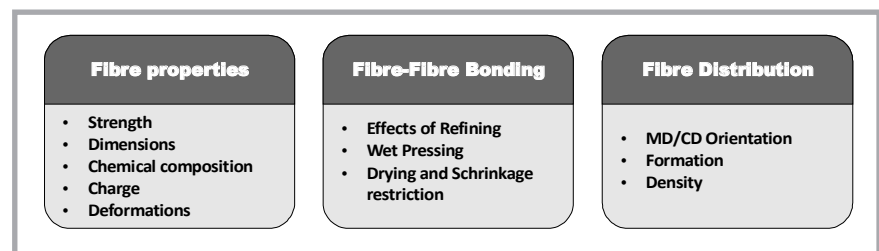


Figure 1. Most important factors affecting paper properties.

of several investigations. Among others, this topic was the field of interest of Ingmanson and Thode [3], but they did not propose any final mathematical equations. A general mathematical relationship was introduced by Page [4]:

$$\frac{1}{T} = \frac{9}{8Z} + \frac{12A \cdot \rho_f \cdot g}{P \cdot l \cdot b \cdot (RBA)}$$

where: T - tensile strength, Z - zero-span tensile strength, A - cross-sectional area of a fibre, ρ_f - density of a cell wall, g - gravity acceleration, l - fibre length, b - bond shear strength per unit bonded area, P - perimeter of the fibre cross section, and RBA is the relative bonded area of a paper.

Application of this formula under industrial conditions is problematic because of difficulties in the determination of most of the variables used in the equation. It is worth mentioning that the average fibre length is used in this equation as the one of the important factors influencing paper strength properties. Changes in the average fibre length occur mainly during the refining process and are considered as one of the main refining effects [5]. Page [6] also proved the importance of other factors related to other basic refining effects such as external and internal fibrillation and fine development. Investigations conducted by Clark [7] confirmed the significance of the average fibre length for paper strength properties. Based on results obtained, he introduced the following relationships between the average fibre length and different paper properties:

$$\begin{aligned} B_L &= K_S \times 10.5 \\ B_R &= K_P \times 11.0 \\ DFN &= K_{pz} \times 10.5 \\ T_E &= K_E \times 11.5 \\ Bu &= K_V \times 10.05 \end{aligned}$$

where: l - average fibre length, B_L - breaking length, B_R - burst strength, DFN - double fold number, T_E - tear strength, Bu - bulk, K_S , K_P , K_{pz} , K_E , K_V - coefficients.

The significant influence of the average fibre length for paper strength properties was also confirmed by Paavilainen [8]. Additionally he found that the fine fraction of chemical pulp has a lower impact on strength properties. Attempts at predicting the breaking length based on the intensity of refining were made by Olejnik [9]. The equation he obtained is very specific to one particular refining device, thus its applicability is signifi-

cantly limited. Furthermore his equation does not include any factors related to the refining effect. Interesting experiments were also done by Jahan and Rawshan [17] in which they used regression models for prediction of the effect of jute pulp addition and the beating degree on paper properties. Unfortunately their equations have been useful within a limited range and for specified pulp only. Another method was proposed by Chagaev and Zou [18] in which they introduced the so called PQI factor (pulp quality index) and FDI factor (fibre development index) based on the content ratio of fines to coarse fibres. Experimental results show that both factors could be used to monitor fibre development during mechanical pulp refining.

Currently none of the above equations is applied for the purpose of process control and decision making.

The complexity of the problem calls for further research related to alternative solutions based on algorithms used for advanced process modelling, control and optimisation. One of the promising techniques is the application of artificial neural networks (ANN). In spite of their limitations ("black box" model structure, qualitative not quantitative results), they are being applied in areas where traditional techniques (e.g. classical mathematical modeling) fail. Artificial neural networks have many advantages like a fast and elastic response (which is very important in control systems), tolerance to damage and finally an ability to learn. These features make them attractive, especially in the case of difficult engineering problems, where the performance of classical methods is not adequate.

Several examples of already working applications of ANN in the papermaking industry are known. In 1993 Kim et al. [10] published their research results about the application of a neural network system to predict the basic weight and moisture content in a pulp machine, the Kappa number in a digester, and the brightness in a bleaching plant. Gyaneshwar et al. [11] developed a neural network based model in order to achieve a desired set of opacity, tensile strength, Hercules Size Test and basis weight values for filled and sized paper. They used the CSF value, dispersed rosin size addition level, calcined clay addition level, cationic starch addition level, headbox, and pH as the input factors. There are a certain

number of successful reports related to the application of neural networks based control systems in the pulping process e.g. the continuous Kamyr digester [12] or pulp bleaching process [13]. Works related to the prediction of paper properties based on refining parameters using neural networks were also published by Ciesielski and Olejnik [14]. Scharcanski and Dodson [15] successfully carried out the simulation of the paper forming process using an artificial neural network. The model incorporated the dynamics of the forming process, including the turbulence and drainage speed.

Taking into consideration the development of the papermaking properties of any cellulose pulp, it must be mentioned that the refining process plays the most important role in this case. As a result, the aim of the work presented was to develop a predictive, neural network based model which enables the prediction of paper properties based on factors related to the most important refining effects, such as the fibre and pulp WRV, average fibre length and fine content. Similar works were done by Nieminen et al. [16], but they used data from a pilot plant paper machine and focused on the tensile index, air permeance and beta formation.

Materials and methods

Market bleached kraft softwood (pine) pulp was used in the experiments. Pulp was delivered in the form of dry sheets. Refining experiments were made using an Escher-Wyss conical refiner (Switzerland/Germany) in the semi-continuous mode. The net refining energy, rotor speed, consistency and pulp flow were used as refining control parameters. The net refining energy was varied between 0.6 to 1.8 kW, rotor speeds ranged between 600 and 1500 r.p.m., the pulp covered the 1 - 4% range, and the pulp flow 1 - 4.5 dm³/s. These conditions resulted in changes in the refining intensity (SEL), which varied from 0.95 to 4.76 J/m.

Tests of the refined pulp and laboratory paper handsheets were performed in accordance to current ISO standards. Water retention value (WRV) determinations were performed using the centrifugal method according to the SCAN-C 102 XE standard. A centrifugal force of 3000×g for 15 min was used. A Kajaani FS-200 analyser was used to measure the length-

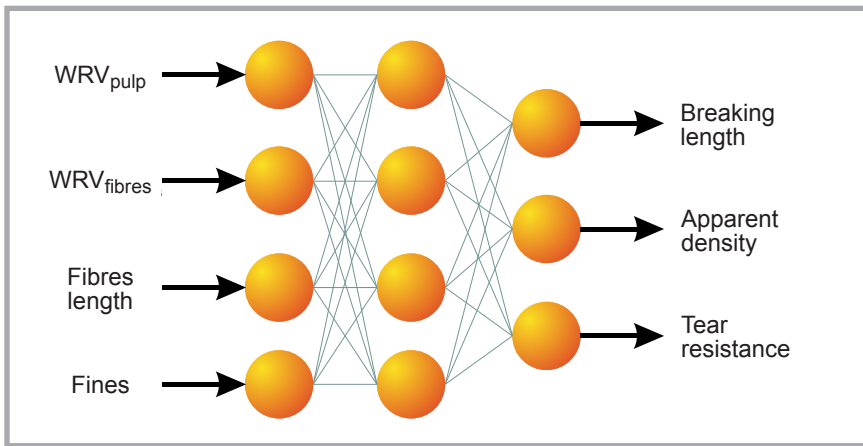


Figure 2. General structure of neural model applied.

weighted average fibre length. The entire amount of the fine fraction was determined by the gravimetric method, comparing the furnish weight before and after the screening operation. Laboratory paper sheets of 75 g/m² were formed on Rapid-Köthen apparatus (Poland) according to Standard EN ISO 5259-2:2001. Samples were then conditioned at 23 °C and 50% RH according to Standard ISO 187:1990. All the determinations of paper properties were performed according to specific ISO standards.

■ Simulations

Simulations were performed using “Matlab” with a “Neural Networks Toolbox”. A Multilayer Perceptron with one hidden layer was chosen as the structure of neural network (Figure 2). The inputs of the network were as follows: pulp WRV in %, fiber WRV in %, geometric average fibre length in mm and fines in %; outputs:

breaking length in m, apparent density in g/cm³ and tear resistance in mN. Two values of WRV (for pulp and fibres) were taken into consideration for the purpose of including of the fine WRV (value of the pulp WRV is always the result of the fibre WRV and fine WRV).

It is worth mentioning that several different pulp properties were initially taken into consideration for the purpose of attaining model input data. Among others, the following properties could be also mentioned as the most significant for final paper properties: degree of cellulose polymerisation, the kappa number, fibre coarseness and strength [19]. One of the goals of the work presented was to select the most adequate and reliable properties which could also be measured in a reasonably short time. Due to the fact that changes during the refining process were the main point of this research, only quantifiable and the most important ef-

fects related to this operation were taken into account. Scientific literature related to the impact of refining on individual fibre strengths shows that refining with low to medium energy levels has no significant influence on this parameter [20, 21], which is why the fibre strength was excluded in the present research.

The number of neurons in a hidden layer and that of training epochs were determined by the trial and error method. It should be stressed that a too small number of hidden neurons (and also training epochs) leads to a worse fit to the training data. In this case the networks work as a data filter and omits data which is poorly represented in the training set. In other words the network has a too small “memory” (in the form of weight values) to store the data. A too big number of neurons in a hidden layer causes fitting operation overload and, as a result, the ability of the neural network to interpolate declines.

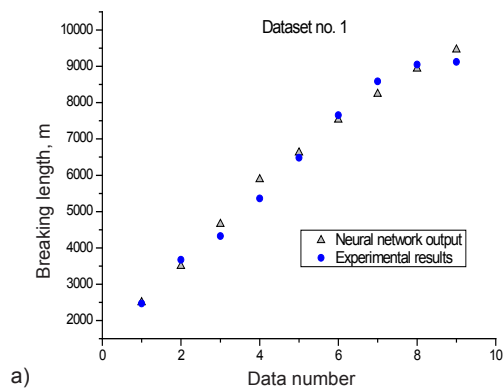
The transfer functions were set as follows: sigmoidal in the hidden layer and linear in output layer. As a training algorithm the Levenberg-Marquardt approach was chosen. Because the training procedure is an optimisation process, with initial values of the weight set randomised, there is a danger that the learning process could get “stuck” at the local minimum. To avoid this, the whole training procedure was repeated 200 times and the best results chosen by the algorithm. Because initial simulations proved the necessity of data normalisation, all data was recalculated in the range between -0.9 – 0.9. The database contained 153 vectors with 90% used to train the network and 10% just to test the model’s performance. Experimental data were grouped into 21 datasets related to individual process runs.

■ Results

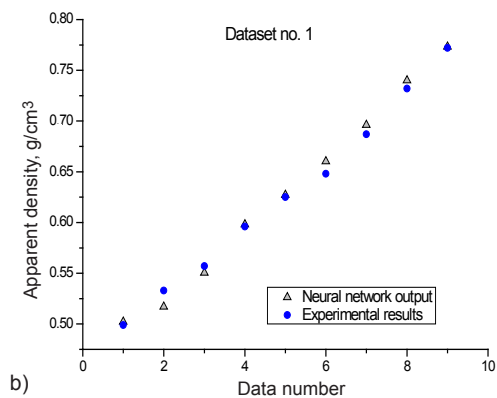
The experimentally selected number of neurons in the hidden layer was 4 and training epochs - 30. Table 1 presents correlation coefficients between the neural network’s calculation results (for all 3 outputs) and related experimental results required - both for training and testing data for different datasets for each output. Datasets 1, 9 and 21 (marked by gray shading) were chosen (randomly) for testing the neural model and were not presented to the network during the training process.

Table 1. Correlation coefficients for training and testing data.

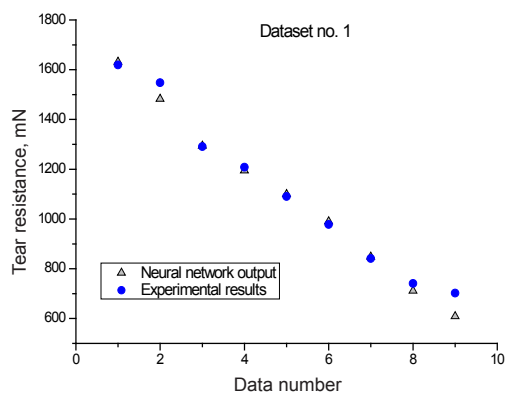
No.	R1 (Breaking length)	R2 (Apparent density)	R3 (Tear resistance)
1	0.9933	0.9971	0.9940
2	0.9860	0.9803	0.9758
3	0.9947	0.9961	0.9899
4	0.9914	0.9976	0.9912
5	0.9935	0.9852	0.9945
6	0.9921	0.9614	0.9920
7	0.9913	0.9948	0.9935
8	0.9823	0.9702	0.9842
9	0.9901	0.9853	0.9964
10	0.9987	0.9938	0.9946
11	0.9956	0.9777	0.9738
12	0.9932	0.9830	0.9867
13	0.9795	0.9942	0.9810
14	0.9959	0.9908	0.9950
15	0.9839	0.9567	0.9956
16	0.9886	0.9716	0.9820
17	0.9892	0.9689	0.9910
18	0.9905	0.9852	0.9551
19	0.9959	0.9812	0.9923
20	0.9759	0.9963	0.9844
21	0.9933	0.9964	0.9915



a)

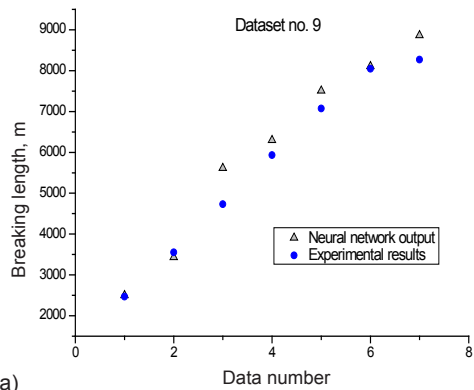


b)

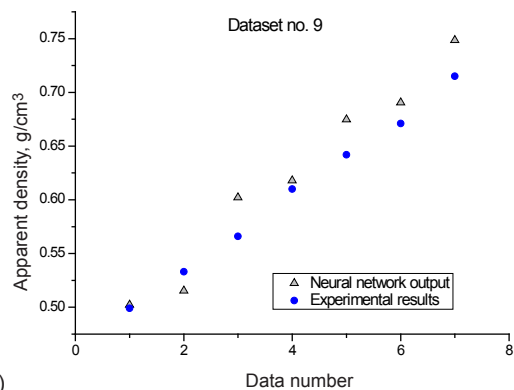


c)

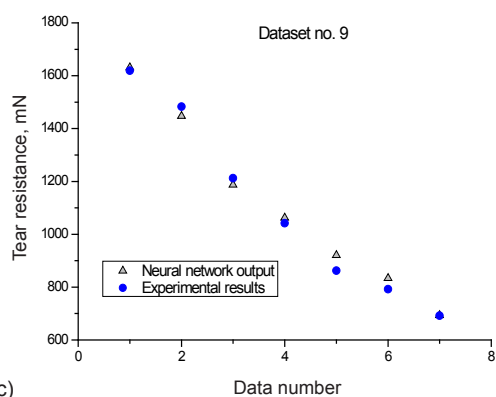
Figure 3. Neural network model results vs. experimental data for dataset no. 1; (a – breaking length, b – apparent density, c – tear resistance).



a)

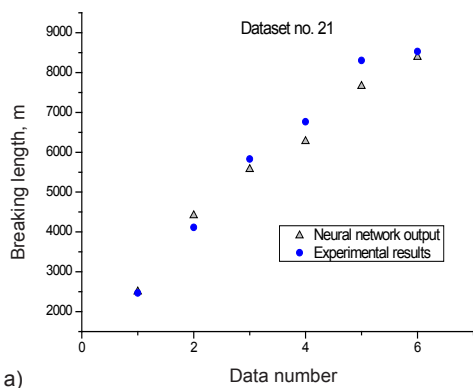


b)

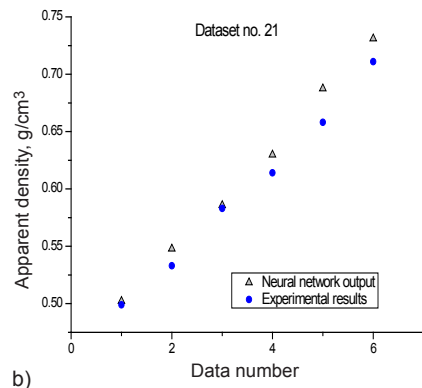


c)

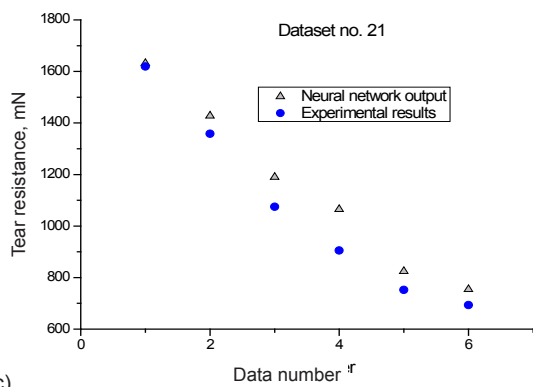
Figure 4. Neural network model results vs. experimental data for dataset no. 9; (a – breaking length, b – apparent density, c – tear resistance).



a)

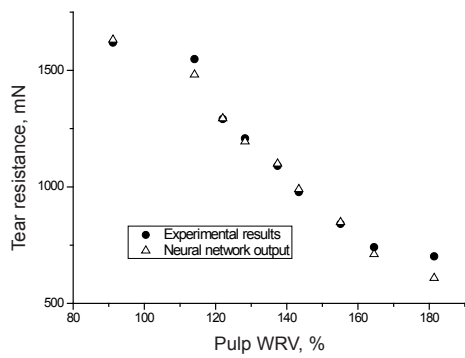


b)

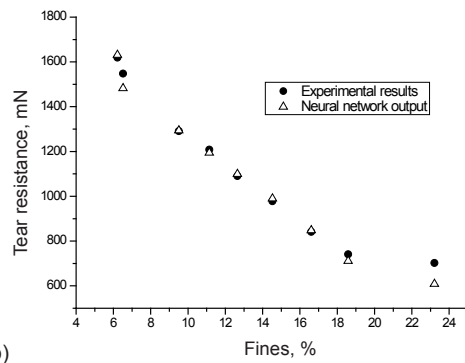


c)

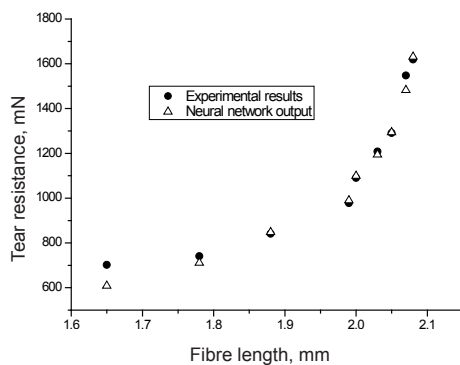
Figure 5. Neural network model results vs. experimental data for dataset no. 21; (a – breaking length, b – apparent density, c – tear resistance).



a)



b)



c)

Figure 6. Comparison of predicted and experimental values of the tear resistance vs. pulp properties used as input parameters for the ANN (a – tear resistance vs. pulp WRV, b – tear resistance vs. fine content, c – tear resistance vs. average fibre length).

In the work presented, the main difficulty was to simultaneously show the performance of the neural network for 3 outputs and 4 inputs. Finally it was decided that every output parameter would be presented in a separate figure. **Figures 3 - 5** (see pages 129) show the performance of each output for different input data sequences (4 number vectors). Each set of input sequences (one chart) is related to one process run. The results obtained indicate that the neural model described the refining process investigated with satisfactory precision for all datasets.

It is worth mentioning that the model developed is also able to correct random experimental errors (see **Figure 3**). It was found that the correlation coefficients were relatively low only in two cases (dataset no. 18 - tear resistance and dataset no. 15 – apparent density).

Potential capabilities of the method presented are confirmed by the fact that all simulations were made for data obtained from experiments conducted under various technological conditions (e.g. variable consistency, refiner load, rotational speed and pulp flow through the refining zone). It was found that none of above-mentioned technological factors had a significant, negative impact on the quality of the model's performance.

Evaluation of the magnitude of the impact for every single input parameter used in the work presented was also carried out. It must be emphasised that internal dependencies of an Artificial Neural Network are, in most cases, unknown. Furthermore relationships between the input and output parameters could differ from those determined by experiments.

Table 2 shows the comparative impact of the input parameters used on the output values. Because of the early stage of our work, the simplest and coarse method of neural model sensitivity estimation was used. The input vector was chosen randomly, the value of each input sequentially increased by 10% (only one input at the same time) and the results calculated. Results show that in the case presented, the average fibre length and amount of fines were the most important, whereas both parameters related to WRV have a minor impact. It is worth pointing out that in reality WRV usually has the most significant impact on paper strength properties, which shows the main limitation of neural network models - they

Table 2. Neural model's input sensitivity.

Input change	% of change (output response)		
	Output 1 Breaking length	Output 2 Apparent density	Output 3 Tear resistance
Pulp (WRV)	6.2	1.0	0.5
Fibre WRV	8.6	6.2	6.8
Geom. fibre length	39.5	1.9	101.2
Fines	80.5	4.5	197.3

are of the “black box” variety. The internal structure (and algorithms) has no direct connection with the mechanism of the process modelled. For the purpose of future works, the authors are going to use maps of weight values or a Kohonen neural network for neural model input sensitivity estimation. However, from a practical application point of view, the lower impact of the WRV parameter is beneficial because two other parameters: the average fibre length and amount of fines can be easily measured on-line. In practice, the large number of training data could significantly improve the precision and stability of the ANN work. On the other hand, WRV is a relatively time-consuming measurement. As a result this value is usually determined in a laboratory. The lower importance of WRV allows to presume that even if measured only sporadically, the low availability of this parameter will not significantly decrease the ANN's accuracy.

Evaluation of the accuracy of simulation in terms of the impact of every single input parameter (e.g. fibre length, fines, pulp WRV and fibre WRV) was also carried out. **Figure 6** presents the relationship between the input and output data of the model (simulation of the process). The “Tear resistance” was chosen as the output. Input data (vectors) were taken from an experimental database (data not shown during the training process). **Figure 6** presents the results for one (randomly chosen) process run. The only interconnection between the input parameters is conditioned by the mechanism of the process modelled (the experiment which delivered the input data for neural network training and evaluating).

A comparison of predicted and experimental values vs. the input parameters showed that almost the same output results were obtained in the entire experimental limits, regardless of the combination of refining parameters applied. Similar results were also obtained for two other paper properties used in the neural model.

Conclusion

A neural network model for the prediction of paper properties based on refined pulp properties using a neural network was designed, built and tested. Satisfactory results for the pulp and paper properties tested were obtained. It must be mentioned that the model presented is valid for a refining device and pulp grade, within the limits of technological parameters used during the refining process. Nevertheless it can be anticipated that the technique could be easily adapted for other refining systems and pulp grades. Further research should be undertaken in order to make the model presented more universal. Considering the industrial process, it can be also stated that the current solution could be applied as an additional paper quality control system in a paper mill.



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INSTITUTE OF BIOPOLYMERS AND CHEMICAL FIBRES

LABORATORY OF BIODEGRADATION

The Laboratory of Biodegradation operates within the structure of the Institute of Biopolymers and Chemical Fibres. It is a modern laboratory with a certificate of accreditation according to Standard PN-EN/ISO/IEC-17025: 2005 (a quality system) bestowed by the Polish Accreditation Centre (PCA). The laboratory works at a global level and can cooperate with many institutions that produce, process and investigate polymeric materials. Thanks to its modern equipment, the Laboratory of Biodegradation can maintain cooperation with Polish and foreign research centers as well as manufacturers and be helpful in assessing the biodegradability of polymeric materials and textiles.

The Laboratory of Biodegradation assesses the susceptibility of polymeric and textile materials to biological degradation caused by microorganisms occurring in the natural environment (soil, compost and water medium). The testing of biodegradation is carried out in oxygen using innovative methods like respirometric testing with the continuous reading of the CO₂ delivered. The laboratory's modern MICRO-OXYMAX RESPIROMETER is used for carrying out tests in accordance with International Standards.



The methodology of biodegradability testing has been prepared on the basis of the following standards:

- **testing in aqueous medium:** 'Determination of the ultimate aerobic biodegradability of plastic materials and textiles in an aqueous medium. A method of analysing the carbon dioxide evolved' (PN-EN ISO 14 852: 2007, and PN-EN ISO 8192: 2007)
- **testing in compost medium:** 'Determination of the degree of disintegration of plastic materials and textiles under simulated composting conditions in a laboratory-scale test. A method of determining the weight loss' (PN-EN ISO 20 200: 2007, PN-EN ISO 14 045: 2005, and PN-EN ISO 14 806: 2010)
- **testing in soil medium:** 'Determination of the degree of disintegration of plastic materials and textiles under simulated soil conditions in a laboratory-scale test. A method of determining the weight loss' (PN-EN ISO 11 266: 1997, PN-EN ISO 11 721-1: 2002, and PN-EN ISO 11 721-2: 2002).



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The following methods are applied in the assessment of biodegradation: gel chromatography (GPC), infrared spectroscopy (IR), thermogravimetric analysis (TGA) and scanning electron microscopy (SEM).

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