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Defining the damaging process of cereal grains on the basis of artificial neural network

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A b s t r a c t. The objective of the research consisted in the development of a model allowing to forecast the damage attributable to wheat grains under the impact of multiple dynamic loads. Laboratory research which provided the model basis was effected for two types of grain stress: through random unsupported impacts inflicted on grains by a rotating arm, and - in a second experiment - loading the grains on support. In the course of the research, the following variables were altered: energy, number of impacts and water-content in grains. Two models were developed, relying on feed-forward three-layer artificial neural networks (ANN). One of the networks provided th e model of the phenomena occurring in the course of unsupported impacts to grains, while the other reflected the impacts on supported grains. In the model of loads effected on unsupported grains, the network had the following features: 14 neurons in the first layer, 9 neurons in the second and 1 neuron in the third layer. In the case of supported grain impacts, the network was as follows: 7 neurons in the first and second layers, and one neuron in the third . The obtained models were verified by comparing the precision level of ANN with the existing empirical models. The comparative analysis of the relative error terms obtained, showed that the values of error obtained for regression analysis were higher than the values obtained for ANN.

K e y w o r d s: grain damage, multiple dynamic loads, artificial neural network

INTRODUCTION

In the majority of mechanical processes related to harvesting and the post-harvest processing of cereal grains, multiple dynamic loads predominate, inflicted on individual grains. The existing research [4,8,17] has shown that inflicted impacts result in significant quality deterioration of the harvested material, whether earmarked for sowing or consumption. This fact is the consequence of impact-inflicted external and internal damage to grain - the extent of which depends both on the energy and number of impacts. It has also been found that the water-content of impact-absorbing grains influenced the character and volume of emerging deformations and damage [1,5,15]. It may be assumed that the process of deformation occurring in effect of multiple impacts bears a similarity to the process of fatigue in construction materials. The assessment of fatigue resistance of the studied grain can be used in the evaluation of the susceptibility of particular varieties to mechanical harvesting.

The research on deformation and damage sensitivity of grains relies on multiple impacts inflicted on individual grains. The results of such experiments are - in the majority of cases - statistically processed in order to define certain regularities occurring between the load conditions inflicted on grain and the volume of deformation occurring as a result of accumulated load energy [3,7,9,13]. The question arises: to what extent is it possible to develop a model simulating the course of the studied process on the basis of computer technology? Such a model would allow the time of the experiment to be shortened significantly and would eliminate the need for lengthy and troublesome research. One of the tools that can be used to develop a model for forecasting the value and number of deformities occurring in grain subjected to multiple impacts, consists in the application of artificial neural networks (ANN).

ANNs are composed of many simple elements operating in parallel [11,21]. These elements are inspired by biological nervous systems. The network function is determined largely by the connections between elements (neurons). A single neuron with N inputs is shown in Fig. 1. Here the individual inputs X_j, weighted by elements W_j, are summed to form the weighted inputs to the transfer function F. The neuron has a bias B (ANN with biases can represent relationships between inputs and outputs more easily than networks without biases) and an output Y.

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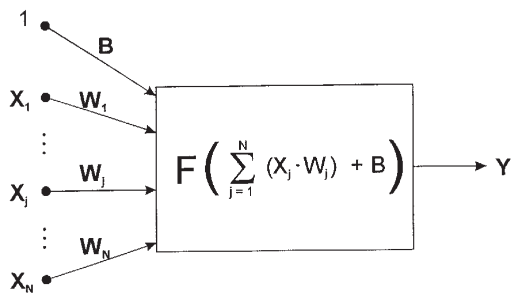

Fig. 1. Scheme of an artificial neurone.

Due to their advantages, they have been used with increasing frequency in agricultural technology [2,16,19,21]. Feed-forward multi-layer ANNs can be used as universal approximators. Therefore, the objective of the present study consisted in the development of a feed-forward artificial neural network, the architecture of which would ensure maximum precision in the definition of the deformities of loaded grains. The Neural Network Toolbox of MATLAB was used to build the ANN models.

MATERIALS AND METHODS

The research was carried out on the Roma variety of wheat grain. Grains were loaded onto specially constructed benches. One of them was used to effect dynamic loads without support (Fig. 2); while the other one served to study supported dynamic loads (Fig. 3). The first stand was constructed with a rotating arm and electromagnetic movable keeper [13,14]. The second stand (Fig. 3) was built with a rotating disc with 100 holes with grain and a beater ram operated by a crank level mechanism. Every movement of the beater was combined with a motion of the rotary disc which provided a single grain to be beaten [7]. The water-content of the loaded grains in these particular samples was at an interval of 14 - 26%. On each bench, samples consisting of one hundred grain units were loaded in one experimental episode. The number of impacts was increased starting from one up to a hundred. At every tenth impact, the deformities were identified through X-ray analysis of each grain unit, according to the method developed at the Institute of Agrophysics, Polish Academy of Sciences, in Lublin [10]. The above method allows one to ascertain the so called "Position Indicator of Deformities" (W) correlated to the sprouting capacity of the damaged grain [10,12,20]. As a result of laboratory research, values for W were found for various levels of exogenous variables. In the bench used to study the unsupported impacts, the following independent variables were identified: water-content in grains, number of impacts. In the bench used to study supported impacts, the exogenous variables were defined as: the impacts energy

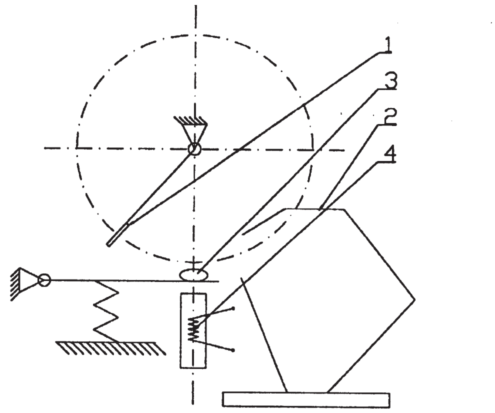

Fig. 2. Rotor stand for multiple dynamic loads: 1 - hitting plate, 2 - gauge, 3 - grain, 4 - electromagnet.

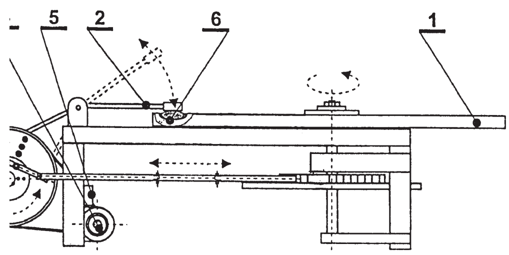

Fig. 3. Ram stand for multiple dynamic loads: 1 - rotating disc, 2 - beater ram, 3 - crank lever mechanism, 4 - motor, 5 - grain, 6 - spring latch mechanism.

(change in the mass of loading weight), water-content in grains [12], and number of impacts.

Since the deformation processes in the case of loading the supported and unsupported grains are significantly different, two ANNs were developed. The following assumptions were adopted:

- the network modelling the sequence of unsupported impacts has two inputs (water-content in grains, and the number of impacts);
- the network modelling the sequence of supported impacts has three inputs (impact energy, water-content in grains, and the number of impacts);
- each network is a three-layered feed-forward net with one initial neuron (the deformation indicator is the initial variable);
- neurons positioned in particular layers are not connected while neurons in neighbouring layers are cross-connected unit to unit;
- neurons in the first and second layers display the sigmoid transfer function while the neuron belonging to the third (initial) layer displays a linear transfer function.

The experimental data were divided randomly into the sets of learning, testing, and verifying patterns for each network.

The learning process of neural network was implemented on the basis of modified error back-propagation algorithm [11,21]. It was created by generalizing the Widrow - Hoff learning rule to multiple layer networks. The back-propagation training algorithm is an iterative gradient algorithm designed to minimise the mean square error between the actual outputs and desired outputs. In order to intensify the efficiency of learning, the adaptive learning rate [11] and momentum [11,21] were applied. The momentum allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Without momentum, a network may get stuck in a shallow local minimum. With momentum, a network can slide through such a minimum and find the global minimum. Adding the adaptive learning rate to back-propagation algorithm can decrease training time.

We have no precise relationship definitions allowing us to define the number of neurons in the first and the second neuron layers. That is why the numbers of neurons in these layers were defined on the basis of a series of computer simulations effected for various architectures of neural networks. In successive simulations, the numbers of neurons were altered in the input layer and the hidden layer. In the network with two input gates, the number of neurons was altered within the interval 2 -16, in the first layer, and 1 -17 neurons, in the second layer. In the case of three input gates network, the intervals were respectively: 3-17 and 1-17 neurons. In the third layers of each network, a single neuron was adopted, according to the experimental assumptions. Next, each network was subjected to multiple learning processes. After the termination of learning, those networks were identified which reflected the modelled phenomena best.

The best network has been chosen based on the value of the adopted measure of the network working error (mBw) for the data from the testing data sets. This measure was calculated from the formula [6]:

$$mBw = |aveBw| + sdBw \tag{1}$$

where: mBw - a measure of the network working error (%); Bw - relative error (%); aveBw - arithmetic mean of Bw (%); sdBw - standard deviation of Bw (%).

The obtained ANN models were verified through comparative study in relation to function notation received through the multiple linear and exponential regression analysis. The following equations were analysed:

– in the case of linear regression:

2 input gates: $Y=a \cdot X_1+b \cdot X_2+c,$ (2)

3 input gates: $Y= a \cdot X_1+b \cdot X_2+c \cdot X_3+d,$ (3)

– and in the case of exponential regression, respectively:

2 input gates: $Y=d + \exp (c+a \cdot X_1^2+b \cdot X_2),$ (4)

3 input gates: $Y= e + \exp (d+a \cdot X_1^3+b \cdot X_2^2+c \cdot X_3).$ (5)

RESULTS AND DISCUSSION

As a result of the testing process, the optimum architectures were obtained. The optimum ones were selected on the basis of minimum processing error terms, in relation to the studied conditions of grain loading. Testing modes were applied to test the neural networks. These modes were not shown in the network learning process. Such conditions allowed the checking of the network generalisation capacity. The following architectures were selected as optimum (minimal value of mBw):

– in relation to double-input network (modelling the unsupported loading):
  14 neurons, in the first layer,
  9 neurons, in the second layer,
  1 neuron, in the third layer;
– for the network with three input gates (modelling the supported loading):
  7 neurons, in the first layer,
  7 neurons, in the second layer,
  1 neuron, in the output layer.

As an outcome of regression analysis, the equation coefficients were obtained.

The values of regression coefficients for the cases where significant regression was found were presented in Table 1 (unsupported impacts) and in Table 2 (supported impacts). In the case of the model with two inputs, no significant exponential regression was found.

The comparison of relative error terms obtained (for sets containing the testing and verifying data) showed that the error values received in regression analysis were greater

T a b l e 1. Mean relative errors in unsupported grain loading obtained by regression analysis, and on the basis of Artificial Neural Networks (ANN)

Type of regression	Regression coefficients	Data set	Mean relative error for regression analysis (%)	Mean relative error for ANN (%)
Linear	a = -0.78 b = 11.85 c = 0.76	Test 1 Test 2 Verify 1 Verify 2	$49 \cdot 10^3$ $154 \cdot 10^3$ $168 \cdot 10^3$ $220 \cdot 10^3$	$47 \cdot 10^3$ $36 \cdot 10^3$ $61 \cdot 10^3$ $78 \cdot 10^3$

T a b l e 2. Mean relative errors in unsupported grain loading obtained by regression analysis, and on the basis of Artificial Neural Networks (ANN)

Type of regression	Regression coefficients	Data set	Mean relative error for regression analysis (%)	Mean relative error for ANN (%)
Linear	a = 0.53	Test 1	$35\cdot10^3$	$4.7\cdot10^3$
	b = 11.25	Test 2	$121\cdot10^3$	$39\cdot10^3$
	c = 10.64	Verify 1	$41\cdot10^3$	$4.6\cdot10^3$
	c = -3.98	Verify 2	$80\cdot10^3$	$9.8\cdot10^3$
Exponential	a = 0.012	Test 1	$38\cdot10^3$	$4.7\cdot10^3$
	b = 0.41	Test 2	$117\cdot10^3$	$39\cdot10^3$
	c = 0.39	Verify 1	$40.5\cdot10^3$	$4.6\cdot10^3$
	d = - 2.9	Verify 2	$79.7\cdot10^3$	$9.8\cdot10^3$
	e = -20.32			

than the corresponding values obtained for ANN. In unsupported loading, the values of mean error term of linear regression were 1.1 to 4.3 times greater compared to the neural network (Table 1). Whereas, in the case of supported loading, the values of mean relative errors in linear regression were 3.1 to 9.1 greater, and in the case of exponential regression 3 to 8.8 times greater compared to ANN (Table 2).

The above comparison shows that the models developed on the basis of ANNs allowed us to obtain a higher precision of process representation. Thus, ANNs are a more useful tool in research on the deformation and damage rate of grain, compared to the previously used statistical methods of results processing. In view of the growing possibilities of computer technology, the artificial neural networks can be used successfully in forecasting the deformity and damage to loaded grains.

CONCLUSIONS

1. Models developed on the basis of artificial neural networks (ANN) carry a much lower error, compared to models obtained through regression analysis. This means that ANNs reflect the studied phenomenon with much higher precision.

2. Obtaining such highly precise representation of grain deformations under multiple loading was possible only as a result of repeated ANN learning processes for the widely changing neurone numbers in the first and the second layers.

3. In spite of the similarity of the phenomena studied, the ANN architectures obtained differ considerably. In the process of unsupported grain loading, the neural network had the following numbers of neurones: 14 neurones in the first layer, 9 neurones in the second layer, and one neurone in the third layer. In the case of supported grain loading, the network was as follows: 7 neurones in the first and second layers, with a single neurone in the third layer.

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