MODEL OF ACTUAL CONTACT AREA OF RYE AND WHEAT GRAINS WITH FLAT SURFACE

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Abstract. The objective of the research presented was to create a mode determining the relationship between the actual contact area of cereal grains, pressure force and humidity, with the application of artificial neural networks (ANN). As an additional factor describing the grain material, the unit contact area of grain with a flat surface, for a specified pressure force and humidity, was considered. The analysis results proved that the unit contact area determined for the pressure force $N_j = 100$ N and water content $W = 15$ kg·kg^{-1} dry mass should be assumed as a variable characterising the grain material. It was found that the phenomenon studied is best modelled by the three-layer ANN with: three neurons in the first hidden layer, eight neurons in the second hidden layer and one neuron in the output layer.

Keywords: artificial neural networks, contact surface, grains.

Introduction

In many cases, it is necessary to determine the contact area. This can be the case of correct estimation of contact stresses during grain compression tests and the internal friction force. The size of such area is also of particular importance while studying the pressure of grain mass on a tank bottom and walls. According to the research made so far, friction occurring at the contact point between the grain plant material and flat surface depends mainly on the pressure force and contact surface area, and thus on the stresses present at the contact surface. However, only in a few research projects of the friction phenomenon the contact area was taken into consideration.

The contact area can be defined as follows (Fig. 1):

- **nominal contact area** – formed by the outline of the area occupied by a grain;
- **actual contact area** – area of the immediate contact of objects. In case of a grain mass, it is a sum of all unit micro-contact areas. It constitutes just a fraction of the nominal contact area.
- **unit contact area** – actual contact area determined for a single grain.

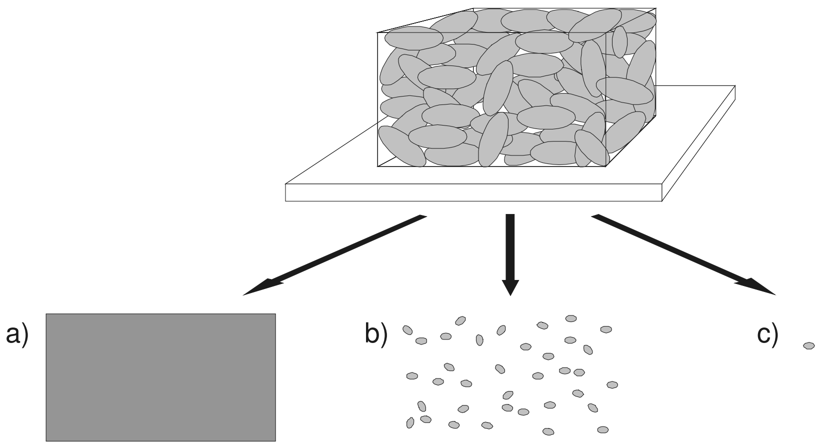

Fig.1. **Contact area types**: a – nominal; b – actual; c – unit

Rare studies of the actual contact area were focused mainly on single grains, and thus on the single contact area. That made it difficult to apply the results obtained in practice. So far, no model of plant grain structure has been created and neither has the relationship between the elementary and actual contact area of such materials been established [1]. Therefore, in addition to the examination of individual grains, it is necessary to study the grains in mass. That should allow a better representation of the actual conditions, in which the phenomena occurring in contact with the structural material are most frequently involved in the layer of grains. The results of such studies may contribute to higher accuracy of calculations of various types of structures of tanks, conveyors, silos, handling equipment etc. This is particularly important nowadays, when a broad range of modern structural materials available requires careful selection.

The objective of the research presented was to create a model determining the relationship between the actual contact area of cereal grains, pressure force and humidity, with the application of artificial neural networks (ANN). As an additional factor describing the grain material, the unit contact area of grain with a flat surface, for a specified pressure force and humidity, was considered. The unit contact area was considered as the material constant, characterising seeds in terms of their ease of increasing the actual contact area under the pressure applied. The working hypothesis can be, therefore, presented as follows:

$$S_m = f\,(N_m,\ W,\ S_j) \tag{1}$$

where S_m – actual contact area of the grain mass, mm^2;
S_j – unit contact area determined for a specified grain pressure and humidity, mm^2;
N_m – pressure force exerted on the grain mass, N;
W – water content in the grains, kg·kg^{-1} dry mass.

Artificial neural networks, one of the modern modelling methods, allow developing different models that are more accurate than the regression models [1; 2; 5-8].

Materials and methods

The experiments were carried out on the grains of two types of cereals: *Roma* wheat and *Dańkowskie Złote* rye.

For each of the species, both the unit and actual contact areas were determined. While determining the actual contact area for grain mass, the material being analysed was loaded with seven force values from 80 N to 440 N, and each specie was tested at six water content levels – from 10 to 35 kg·kg^{-1} dry mass. The unit contact area was determined for two water content values 10 and 15 kg·kg^{-1}dry mass, subjecting the grains to seven force values (from 40 N do 220 N). The experiment set up is shown in Fig. 2.

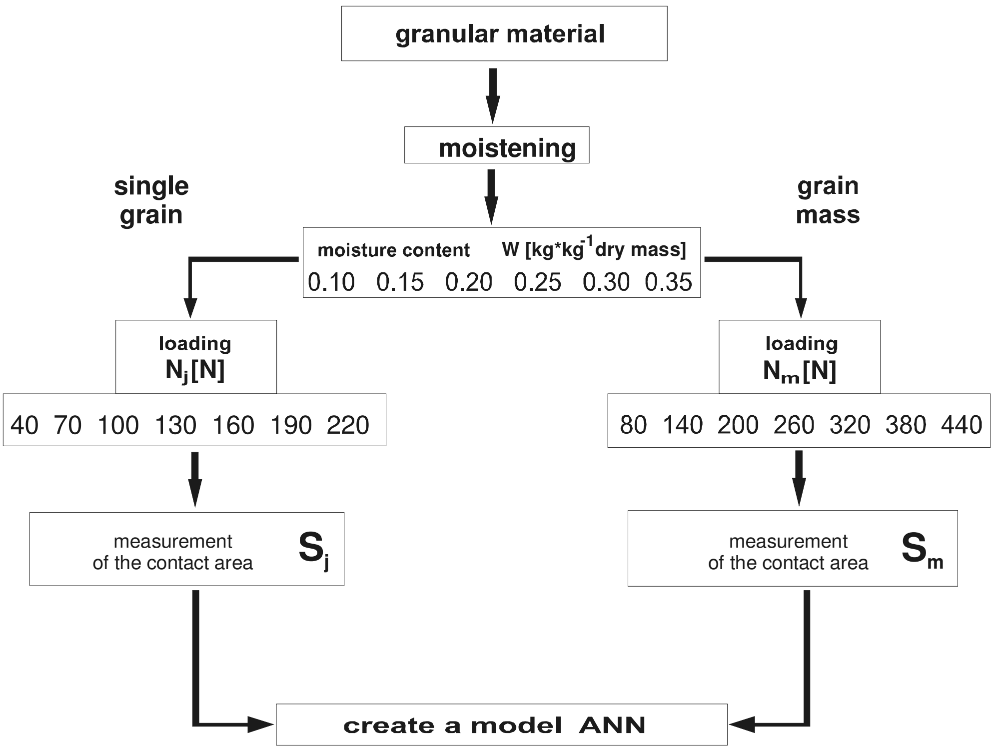

Fig. 2. **Experiment diagram**

The measurements were carried out according to the method proposed by Frączek [3; 4]. It is based on the acquisition of the contact area image obtained in a special test rig. The nominal contact area was 70 x 120 mm.

Using the MultiScan software, with the binarisation and application of proper morphologic filters, series of dark images were obtained which represent the area of seeds contacting the flat surface. Measuring that area was reduced to counting points forming the specific area. The result obtained was expressed in square millimetres or percentage of grey area in relation to the total area of the analysed surface.

Artificial Neural Networks were applied to create the model. The first stage of creating the neural model required determining for which pressure force and water content, the measured value of the unit contact area S_i characterises the grain material best. To this end, neural models were created taking into consideration the output variables: pressure force N_m, water content W and values S_j (determined for seven different pressure force values N_j and two water content values W – 14 input variables were obtained). For the best models, i.e., those characterised by minimal training error value, the sensitivity analysis was performed, which allowed elimination of the least significant variable S_j. The entire process was repeated several times with a reduced number of inputs to the neural network.

As a result of 13 iterations performed, the value of the unit contact area S_j was established (determined for the selected values of the pressure force and water content), which was applied in the second stage of the neural model creation, according to the working hypothesis (1). An output variable for the model being created was the actual contact area S_m. Various architectures of three-layer Perceptron type artificial neural networks were studied. Those networks have 3 neurons in the input layer (3 input variables) and 1 neuron in the output layer (1 output variable). The number of neurons in the hidden layer was changed from 2 to 8, to find the best ANN architecture.

To create neural models, the Statistica Sieci Neuronowe – Automatic Designer software was used. Each time, 100 various neural networks were created, out of which 10 best ones were saved for further analyses. In order to complete the training process of the networks, the data obtained in the laboratory tests were randomly divided into the training, test and validation sets, in proportion 70:15:15. The best model was selected based on the value of the relative error measure MBw for the test and validation sets. The MBw measure is a sum of: absolute valued of mean relative percentage error and standard deviation of that error [2].

Results and discussion

The results of the analyses carried out at the first stage of the neural model creation indicated that as the variable describing the grain material, the unit area of contact should be assumed, determined for the pressure force $N_j = 100$ N and water content $W = 15$ kg·kg^{-1} dry mass. That variable was denoted $S_{j\ 100\text{-}15}$. This ensures the highest accuracy of the model (minimum error). Therefore, as the variables for neural networks created at the second stage of tests, it was assumed as follows:

- N_m – pressure force exerted on the grain mass, N
- W – water content in the grains, kg·kg^{-1} dry mass
- $S_{j\ 100\text{-}15}$ – unit contact area which best describes the grain material – determined for the pressure force N_j =100N and water content values $W = 15$ kg·kg^{-1} dry mass, mm^2

10 neural models were developed and, as a result of the analysis performed, it was found that the phenomenon studied is best described by a three-layer ANN with:

- three neurons in the input layer;
- eight neurons in the hidden layer;
- one neuron in the output layer.

Marked sn8, the network was characterised with the smallest error for the validation set and one of the smallest errors for the training set (Figure 3). The value of the relative error measure MBw, for the validation set was 21.4 %, and for the training set 7.7 %. The value of the mean relative error for the training set was – 0.3 %, and for the validation set – 7.5%. However, for the data from the test set, which was not used while creating the model (training the neural network), the mean relative error was – 6.3 %. ,

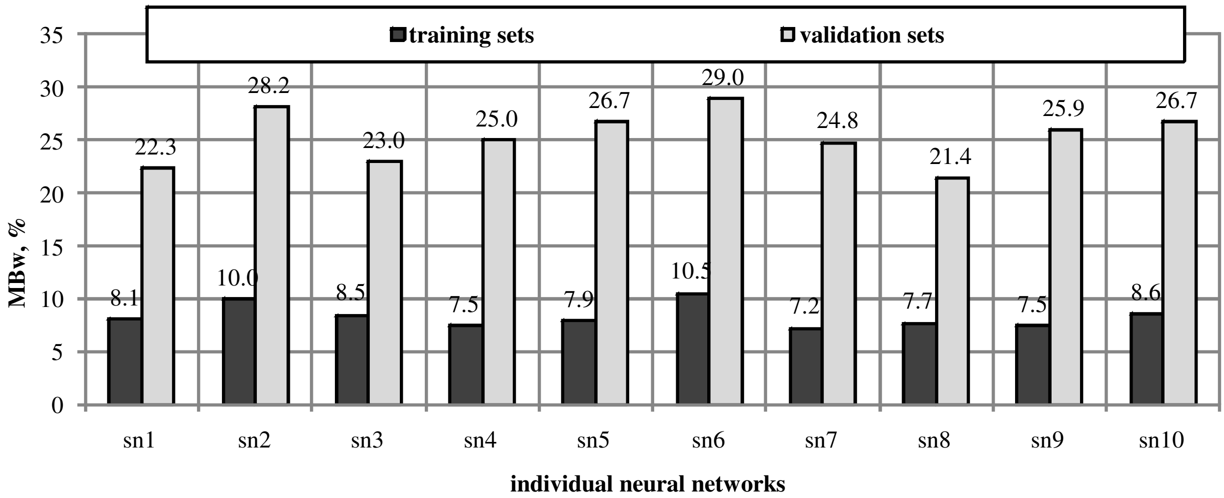

Fig. 3. **Values of the relative error measure MBw for individual neural networks**

Fig. 4 presents the results of simulation of the contact area S_m depending on the water content and pressure force, separately for each of the tested cereals, *Roma* wheat and *Dańkowskie Złote* rye. In both cases, a marked increase of the contact area was observed along with the increase of the values of the factors stimulating it.

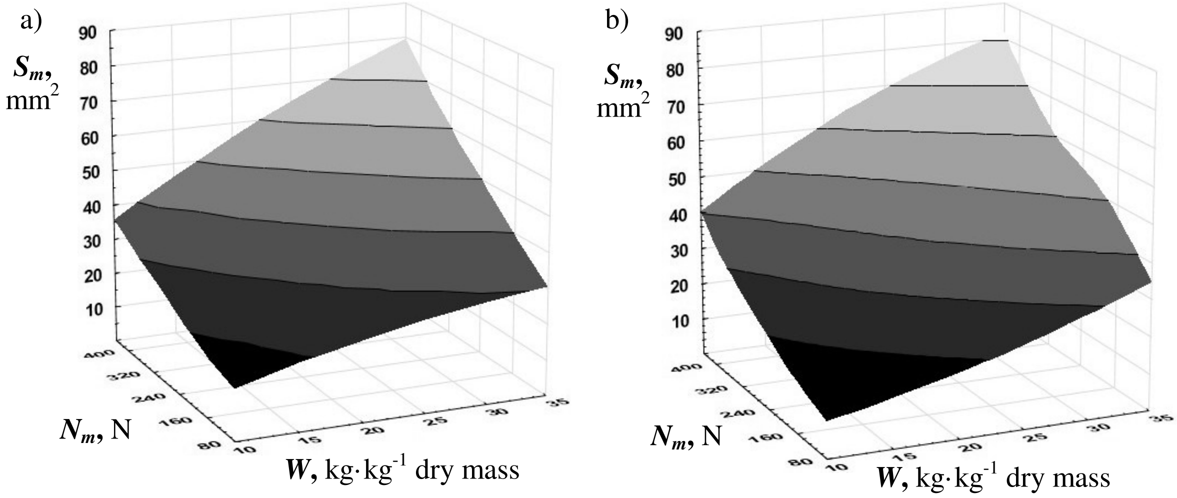

Fig. 4. **Simulation results with the sn8 neural network:**
a – *Roma* wheat; b – *Dańkowskie Złote* rye

Conclusions

1. The analysis results proved that the unit contact area determined for the pressure force $N_j = 100$ N and water content $W = 15$ kg·kg^{-1} dry mass should be assumed as a variable characterising the grain material.
2. It was found that the phenomenon studied is best modelled by the three-layer ANN with: three neurons in the first hidden layer, eight neurons in the second hidden layer and one neuron in the output layer.
3. The studies carried out proved that increasing the load causes faster gain of the unit contact area of the grains, comparing to the actual area. This is probably due to the fact that in the first loading phase, dislocation of individual grains occurs and, then elastic and plastic deformations occur at the contact point between individual grains.
4. Statistically significant effect of the water content and pressure on the value of the contact areas measured was found.

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