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NEURAL NETWORK DEVELOPMENT FOR AUTOMATIC IDENTIFICATION OF THE ENDPOINT OF DRYING BARLEY IN BULK

Summary

A thesis was proved that it is possible an automatic endpoint determination of drying barley in bulk, 1.2 meter's deep, based on a neural network, using a continuous on-line measurement of atmospheric air temperature and relative humidity, plenum air temperature and grain temperature in selected locations inside the bed - in situations in which drying air temperature and relative humidity change stochastically. The usefulness of individual input variables characterising the process as well as their influence on the quality of the obtained model were analysed. Several different topologies of the developed models were compared and the RBF type networks were selected as the best ones. The developed networks are characterised by a high, ranging from 93.3 to 99.6%, correctness of case assignment to the recognised classes in the course of the identification process and a high capability to generalise the analysed data.

WYKORZYSTANIE SZTUCZNYCH SIECI NEURONOWCYH DO AUTOMATYCZNEJ IDENTYFIKACJI ZAKOŃCZENIA NISKOTEMPERATUROWEGO SUSZENIA JĘCZMIENIA

Streszczenie

W pracy potwierdzono możliwość automatycznej identyfikacji zakończenia procesu niskotemperaturowego suszenia ziarna jęczmienia w nieruchomej warstwie o grubości 1,2 m z zastosowaniem sztucznej sieci neuronowej. Następujące wielkości były mierzone w sposób ciągły „on-line": temperatura i wilgotność względna powietrza atmosferycznego, temperatura sprężonego powietrza oraz temperatura nasion w wybranych miejscach wewnątrz komory – w sytuacji, w której temperatura powietrza suszącego i wilgotność względna zmieniały się stochastycznie. Przeanalizowano przydatność poszczególnych zmiennych wejściowych charakteryzujących proces jak również ich wpływ na jakość otrzymanego modelu. Porównano również różne topologie otrzymanych sieci. Jako najlepsze wytypowano sieci typu RBF. Znalezione sieci charakteryzowały się dużą (w granicach 93,3–99,6%), poprawnością przypisywania przypadków do rozpoznawanych klas oraz wysokiej zdolności do generalizacji analizowanych danych

1. Introduction

Based on some selected brain properties and employing only the most important principles of its activities, artificial neural networks (ANN) make it possible to solve very complex problems [4]. Their significant advantage is the ability to learn and generalise the acquired knowledge which they draw from databases provided by the user. Neural networks are characterised by inductive inference, i.e. they do not explain causes of the examined phenomena and, therefore, are employed widely in the situations when the user is in a position to identify the target and give an example how to reach it, although he/she need not be quite sure with regard to the correlations between the input factor and the obtained results [7].

Neural networks are used successfully all over the world to control and model a wide range of different processes connected with food production which are characterised by complexity, nonlinearity and a large quantity of data. They are employed, among others, in the modelling of extrusion processes, prediction of the freezing time of food products of different sizes or to control fermentation termination [3]. Neural networks are also utilised during the drying of various agricultural articles. Using ANN, Bakhshiani et al. [1] modelled the drying kinetics of tomato slices taking into consideration the temperature and drying time as well as the thickness of slices. Białobrzeski et al. [2] employed neural modelling to investigate changes of the temperature field of wheat stored in a grain silo. The RBF-type network was used to calculate the convective heat-transfer coefficient into the silo walls.

Drying of grain in bulk involves forced ventilation, by a fan, of a deep stationary bed of grain. The method utilizes the drying potential of the atmospheric air and the ventilating air is heated only in exceptional conditions when the drying potential is lacking, but even then the air is heated up only by a few degrees Celsius [5]. The heat and mass transfer in this process is not smooth, but is subjected to substantial disturbances from random fluctuations in the ambient air temperature and humidity [9]. This is probably the reason why control devices used to supervise drying cereals in bulk are not capable to identify the drying endpoint [11]. Such identification can be done manually using a grain moisture content tester. Manual supervision of drying progress, apart from being costly, depends on the operators' skill which may result in a decrease of grain quality. To solve this problem, Ryniecki et al. [8] developed an automatic determination of near-ambient barley drying in static deep beds, based on a correlation to calculate grain moisture content of the top layer, using a continuous on-line measurement of relative humidity (RH) and temperature of outlet air.

One objective of the described investigations was to develop a method of identification drying endpoint which could eliminate necessity of the difficult measurement of air RH inside a dryer. The authors intend to verify whether it is possible to build a neural network that could identify the endpoint of drying barley in bulk on the basis of the information obtained from sensors that can measure automatically and continuously atmospheric air temperature and RH, plenum air temperature and grain temperature in selected locations inside the bed in situations in which drying air temperature and RH change stochastically.

2. Material and methods

2.1. Experiments on Drying Grain in Bulk

The experimental material used for drying comprised barley grain cv. *Annabell* of 12-14% moisture content harvested in 2005 near Poznań, Poland. Barley grain was artificially wetted before the trial. For that purpose, it was sprinkled with water of specific weight and left for 24 hours in a facility in which the temperature was 8°C. After this treatment, the grain moisture content (GMC) in different trials ranged from 18 to 19.3%. The GMC determined with the assistance of the electronic moisture analyzer "Sartorius MA 30", Germany was treated as the reference (based on a precision weighing balance applying drying of 5 g sample at the temperature of 125°C to constant mass). This moisture analyzer was checked using the oven method (PN-ISO 712: 2002). The measuring accuracy of the analyzer is 0.05% w.b. (wet basis).

In order to obtain important, from the point of view of developing a neural network, information a series of six experiments was conducted. The way of carrying out these experiments has been described below. The experimental drying bin (Fig. 1) consisted of twelve segments (1), easy to disconnect, each 0.1 m high. The mass of the top segment was weighed using for this purpose an electronic balance "AXIS B 10" of Sartorius, Germany (resolution = 1 g) and the GMC during drying was calculated from the mass balance on the basis of water losses. The velocity of the air flowing through grain layers was measured at the outlet from the drying chamber using the rotameter type airflow meter (b) of the resolution 0.00022 m s^{-1} per 1 mm length of the scale (Lokkes Maskinfabrik, Denmark).

The experimental rig was equipped in a fan (2) with a control system of the engine rotational speed (3) and a heater (5) with a pulse control system of electrical power (6). Such equipment allowed precise parameter control of the air blown into the mass of grain. In order to enforce moisture desorption from grain throughout the drying period, an electronic humidistat (4b) was applied which controlled the air heater which was responsible for ensuring that the air RH blown into the grain bulk did not exceed 55%. The responsibility of the second humidistat (4a) was to switch off the fan whenever the air RH increased over the value of 96% (e.g. during periods of rainfalls).

In the course of each drying process, every 10 minutes, temperature was registered in eight and the air RH in two places of the research station. The temperature was measured with the assistance of Cu-Konstantan thermocouples (9), whereas the air RH – using a probe with a sensor that works according to the capacitive measuring principle (8) (type EE21-FT6B53/T24 of the E+E Elektronik Comp., Austria). The temperature was measured at the place where the ambient air was sucked in by fan ($T_{atm.}$), in the channel supplying the plenum air to the grain bulk (T_{IN}) and in segments of the drying chamber (T_2 – T_{12}). The RH of the atmospheric air ($RH_{atm.}$) was measured and the plenum air (RH_{IN}) was calculated based on measurements of $RH_{atm.}$, $T_{atm.}$, T_{IN} and psychrometric relationships. All thermocouples and humidity probes were connected to the computer system of data acquisition (10) and (11) (ICP-CON I-7018 of the ICP Taiwanese company) which allowed registration, visualization and archiving of measurement results. Temperature and humidity probes were calibrated before trials. After calibration, the repeatability of results and maximum differences of measurements between the applied eight temperature probes did not exceed ±0.2°C. However, due to differences between characteristics of individual sensors and their nonlinearity, the accuracy of the temperature measurements amounted to ±0.5°C.

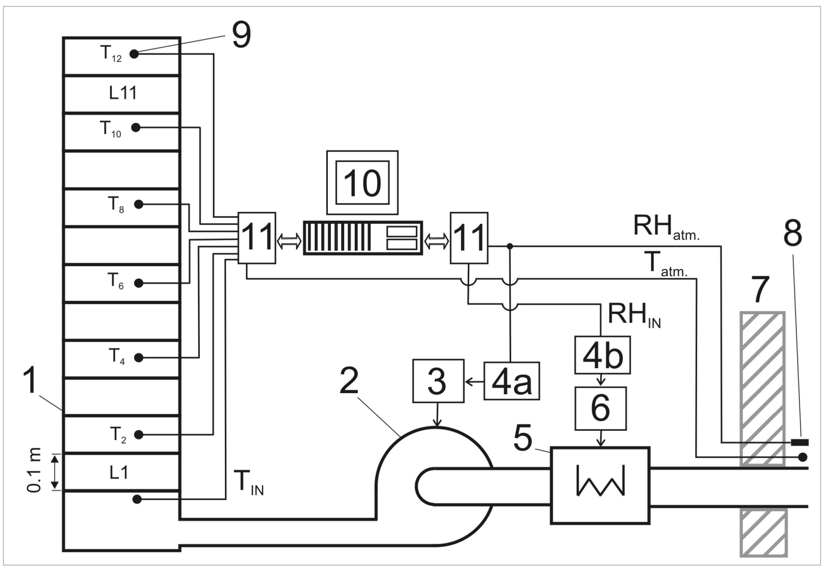


Fig. 1. Research rig: 1 – drying bin (L2 ... L12 – layers 2 – 12), 2 – fan, 3 – a control system of the engine rotational speed, 4 – humidity controller, 5 – electrical heater, 6 – a pulse control system of electrical power, 7 – wall of building, 8 – air RH probe, 9 – temperature sensors, 10 – computer PC with a data acquisition program "Vi-dry", 11 – data acquisition system's unit (Taiwanese ICP_CON I-7018)

The measurement accuracy of the air RH in the important range of 10%-96% guaranteed by the manufacturer of probes was ±2.5%. In order to improve their accuracy, probes were calibrated prior to experiments and checked after the trials in a humidistat chamber with saturated NaCl solution (reference humidity 75%). However, due to the phenomenon of the hysteresis of sensors, it was not possible to reduce the range of error below ±2%.

2.2. Methods employed to develop a neural network

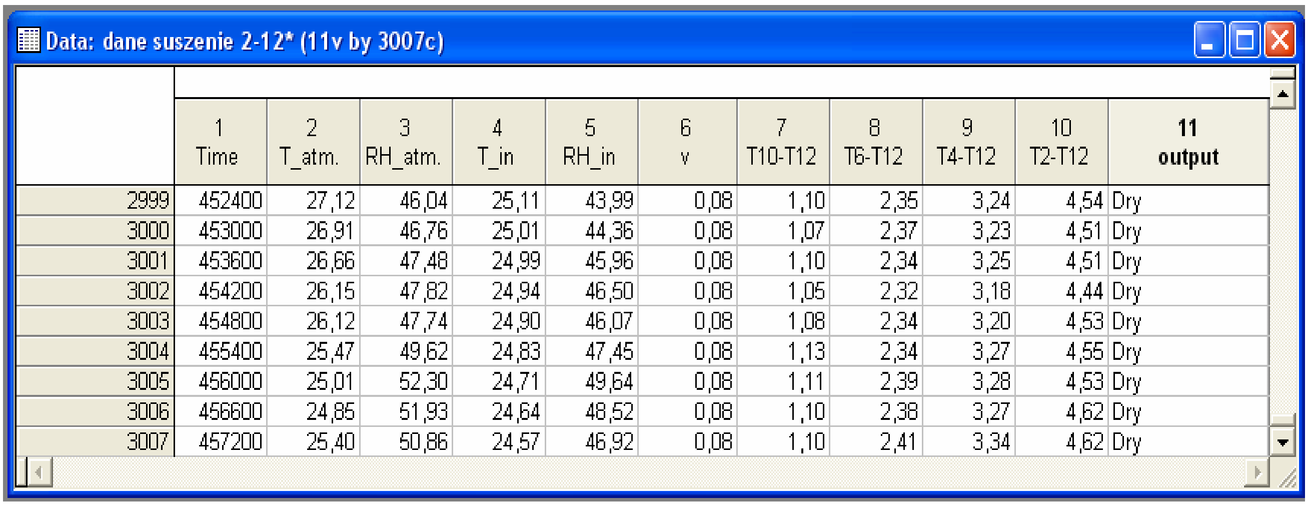
The authors used the analytical software package STATISTICA 7.1 'Neural Networks' to develop, train and test different types of neural networks. In particular, they used such modules as "Intelligent Problem Solver", "Custom Network Designer" and "Sensitivity Analysis" as well as such methods of feature selection as: "Forward stepwise selection", "Backward stepwise selection" and "Genetic algorithm". The "Intelligent Problem Solver" was used for initial network development, while the "Custom Network Designer", which allows greater interference in the parameters of the required network model, was employed for the independent selection of the network topology. The module called "Sensitivity analysis" was used for the initial analysis of the significance of input values. This analysis employs two indicators: ratio of the network error and rank. The ratio of the network error determines the impact on the network operation of the removal of individual variables (it is the ratio of the error to the error obtained using all variables). The bigger the ratio, the better and when its value is below 1, then the variable can be rejected. On the basis of the ratio the rank of a given variable is defined - where value 1 has the highest significance for the network. The following three methods were used to select features properly: "Forward stepwise selection", "Backward stepwise selection" and "Genetic algorithm". A large number of tests with different systems of input values is carried out during the operation of feature selection algorithms. For this reason, the program "Statistica – Neural Networks" uses fast learning probabilistic neural networks (PNN) or generalised regression neural networks (GRNN). During the consecutive iterations, the stepwise methods either add or remove successive variables. Genetic algorithms utilise for tracing variables such evolution mechanisms as: inheritance, crossing and mutation [6]. During the selection of features, the input system is assessed on the basis of the select error of the employed PNN and GRNN networks.

3. Model development of Neural Networks

3.1. Data files

In order to find the optimal input variables of the neural network system, two different files of training data were developed on the basis of the measurement results. The first of the files comprised temperature differences between the selected layers of grain bulk (Fig. 2). This system of variables is connected with the transfer of the drying front through the drier column. The file contains 10 (input) independent variables and one (output) dependent variable. The independent variables are of continuous type – these are measurement results, while the dependent variable is of categorical nature (it assumes two complete values to which labels were assigned: 0 – *Wet*; 1 – *Dry*). The file consists of 3007 cases. The data set was randomly divided into the following three subsets at the ratio of 2:1:1 – the training subset (1505 cases), the selection subset (751 cases) and the test subset (751 cases). The training subset is used by the Statistica 7.1 software to carry out the network model training. The next subset – selection is used to check the network quality (already during the training process). This is important to avoid network overtraining and good generalisation of knowledge. The last of the subsets – the test subset takes part in the above-mentioned processes and it is the ultimate tool which allows appropriate quality assessment of the obtained model.

The second data file comprised temperature values measured in selected layers (Fig. 3). It contains 11 independent variables and one dependent variable. The independent variables are of continuous type, while the dependent variable is of categorical nature. The file consists of 3906 cases. This data file was also divided randomly into the following three subsets: the training subset (1954 cases), the selection subset (976 cases) and the test subset (976 cases).


Data: dane suszenie 2-12* (11v by 3007c)

	1 Time	2 T_atm.	3 RH_atm.	4 T_in	5 RH_in	6 v	7 T10-T12	8 T6-T12	9 T4-T12	10 T2-T12	11 output
2999	452400	27,12	46,04	25,11	43,99	0,08	1,10	2,35	3,24	4,54	Dry
3000	453000	26,91	46,76	25,01	44,36	0,08	1,07	2,37	3,23	4,51	Dry
3001	453600	26,66	47,48	24,99	45,96	0,08	1,10	2,34	3,25	4,51	Dry
3002	454200	26,15	47,82	24,94	46,50	0,08	1,05	2,32	3,18	4,44	Dry
3003	454800	26,12	47,74	24,90	46,07	0,08	1,08	2,34	3,20	4,53	Dry
3004	455400	25,47	49,62	24,83	47,45	0,08	1,13	2,34	3,27	4,55	Dry
3005	456000	25,01	52,30	24,71	49,64	0,08	1,11	2,39	3,28	4,53	Dry
3006	456600	24,85	51,93	24,64	48,52	0,08	1,10	2,38	3,27	4,62	Dry
3007	457200	25,40	50,86	24,57	46,92	0,08	1,10	2,41	3,34	4,62	Dry

Fig. 2. Structure of the data file containing temperature differences. Variables: 1 – time from the beginning of the drying process [s]; 2 – atmospheric air temperature [°C]; 3 – atmospheric air relative humidity [%]; 4 – temperature of plenum air [°C]; 5 – relative humidity of plenum air [%]; 6 – drying air velocity [m/s]; 7, 8, 9 and 10 – temperature differences between layers in the dryer, respectively: T_{10}-T_{12}, T_6-T_{12}, T_4-T_{12}, T_2-T_{12}; 11 – output variable

Data: dane suszenie temp* (12v by 3906c)

	1 Time	2 T_atm.	3 RH_atm.	4 T_in	5 RH_in	6 v	7 T_2	8 T_4	9 T_6	10 T_10	11 T_12	12 **output**
3898	452400	27,12	46,04	25,11	43,99	0,08	24,43	23,13	22,24	20,99	19,89	Dry
3899	453000	26,91	46,76	25,01	44,36	0,08	24,43	23,15	22,29	20,99	19,92	Dry
3900	453600	26,66	47,48	24,99	45,96	0,08	24,43	23,17	22,26	21,02	19,92	Dry
3901	454200	26,15	47,82	24,94	46,50	0,08	24,43	23,17	22,31	21,04	19,99	Dry
3902	454800	26,12	47,74	24,90	46,07	0,08	24,52	23,19	22,33	21,07	19,99	Dry
3903	455400	25,47	49,62	24,83	47,45	0,08	24,54	23,26	22,33	21,12	19,99	Dry
3904	456000	25,01	52,30	24,71	49,64	0,08	24,54	23,29	22,40	21,12	20,01	Dry
3905	456600	24,85	51,93	24,64	48,52	0,08	24,66	23,31	22,42	21,14	20,04	Dry
3906	457200	25,40	50,86	24,57	46,92	0,08	24,66	23,38	22,45	21,14	20,04	Dry

Fig. 3. Data file structure containing temperature values measured in selected locations inside bulk of grain. Variables: 1 – time from the beginning of the drying process [s]; 2 – atmospheric air temperature [^{o}C]; 3 – atmospheric air relative humidity [%]; 4 – temperature of plenum air [^{o}C]; 5 – relative humidity of plenum air [%]; 6 – drying air velocity [m/s]; 7, 8, 9, 10, 11 – temperature values measured in layers 2, 4, 6, 10 and 12 of grain bulk: T_2, T_4, T_6, T_{10} and T_{12}; 12 – output variable

3,2. Data standardization

Empirical data sets are often burdened with measurement errors, noise or interference. In addition, variables of different measurement units can occur in data sets and all these factors may exert a negative impact on the operation of some ANN training algorithms. In order to avoid it, it is necessary, during the stage of initial preparation, to standardize the data, i.e. to bring all data to a non-dimensional form of a uniform range of variability (so called, pre-processing). Most frequently, scaling in relation to the minimal value (so called minimax function [7]) is applied for this purpose. It involves adjusting values fed at the input of the network to the intervals appropriate for them. Following such transformation, the smallest value of a given variable is '0' and the largest – '1', whereas the remaining values are assigned numbers between these values. One neuron in the output layer assuming values '0' and '1' for each of the classes corresponds to a two-state dependent variable.

3.3. Initial search of the network model

Intelligent Problem Solver was utilised for the initial analysis of the data. The search for an appropriate model was narrowed down to multilayer perceptrons (MLP) and radial basis function (RBF) networks. The total of 100 networks was tested of which 10 best ones were retained. In order to compare the obtained models later, the equilibrium between the error and the network diversity was preserved. All independent variables were used for the initial analysis. Five MLP and five RBF types of networks were obtained, each with 10 inputs and different number of neurons in the hidden layer. Three files characterised with diverse topology were selected (Fig. 4). They comprised:

- MLP 10-12-1 (10 neurons in the input layer, 12 neurons in the hidden layer, 1 neuron in the output layer), the network trained for 100 epochs by a back propagation algorithm followed by 14 epochs - by a conjugate gradient algorithm and, finally, a network with the smallest select error was chosen,
- RBF 10-352-1 (10 neurons in the input layer, 352 neurons in the hidden layer, 1 neuron in the output layer), the following methods were used for training: the sampling and k-nearest neighbours methods as well as pseudo-inversion (linear optimisation),
- RBF 10-522-1 (10 neurons in the input layer, 522 neurons in the hidden layer, 1 neuron in the output layer), the following methods were used for training: the sampling and k-nearest neighbours methods as well as pseudo-inversion (linear optimisation).

The lowest values of the training error and the selection error were decisive in the selection process. The most desirable feature of the ANN is its ability to generalise the acquired knowledge. The value of the selection error provides important information about knowledge generalisation; the lower this value is, the better. Increased selection error indicates the decline in the capability of the network to generalise; the trained cases were learnt 'by heart'. The test set which was not used to build the model was applied for the final test of the ANN possibilities. If the value of the test error is low, then the network should generalise new data well [11]. The obtained networks are characterised by low values of the selection and test errors.

Model Summary Report (dane suszenie 2-12)

Index	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Training/Members	Note	Inputs	Hidden(1)	Hidden(2)
5	MLP 10:10-12-1:1	0,962126	0,974700	0,966711	0,157358	0,159164	0,117819	BP100,CG14b		10	12	0
7	RBF 10:10-352-1:1	0,970764	0,965379	0,964048	0,082290	0,098332	0,075529	SS,KN,PI		10	352	0
10	RBF 10:10-522-1:1	0,979402	0,973369	0,965379	0,063239	0,071698	0,075659	SS,KN,PI		10	522	0

Fig. 4. Parameters of the best networks for the data set with temperature differences

Table 1. Results of the analysis of the variable selection for the data set with temperature differences

	Error	Time	T_atm.	RH_atm.	T_in	RH_in	v	T10-T12	T6-T12	T4-T12	T2-T12
Final	0,3658	Y	-	-	-	-	Y	Y	Y	-	Y

Table 2. Analysis results of variable selection for the data set with temperature values in selected locations inside the bulk of grain

	Error	Time	T_atm.	RH_atm.	T_in.	RH_in	v	T_2	T_4	T_6	T_10	T_12
Final	0,3485	Y	-	-	-	-	Y	Y	Y	Y	Y	Y

3.4. Decrease in the number of input data

In order to check the significance of the individual input data describing the process and limit the number in the development of the model, the sensitivity analysis was performed. After averaging the values obtained from the analyses for three models, the highest rank was obtained by the 'time' variable followed by the 'velocity' variable. On the basis of the results of the sensitivity analysis, the number of input variables was reduced. For this purpose, the following feature selection algorithms were employed: forward stepwise selection, backward stepwise selection and genetic algorithms. Each of the algorithms presented the same system of inputs. The most useful turned out to be the following variables: time, drying air velocity (v) and the following temperature differences: T_{10}-T_{12}, T_6-T_{12} and T_2-T_{12} (Tab. 1).

3.5. Proper search of the network model

The second stage of the neural network selection for the drying process prediction was the utilisation of *the custom network designer* which involved the training of the network using for this purpose the optimal input system calculated by the feature selection algorithms. Only RBF type networks were taken into account because they achieved the lowest error values in previous tests. The total of 100 networks was tested. The network selected, the best network of the RBF type of 5-352-1 topology (5 neurons in the input layer, 352 neurons in the hidden layer, 1 neuron in the output layer), was characterised by a high correctness of classification and the select error of 0.1231 and the test error of 0.1207. Another consideration taken into account was to preserve the balance between the network quality and its size. The identical procedure was employed in the case of the data set with temperature values in selected locations inside the bulk of grain. The total of 100 networks was tested of which 10 were saved. The sensitivity analyses of the obtained networks as well as the selection analyses of input variables were carried out using the same algorithms as before. In this case, the following variables were treated as the most important ones: time, drying air velocity (v) and temperatures in individual layers (Tab. 2). The results of these analyses were used to look for networks with the smaller number of inputs and then proceeding to training the network employing the optimal input system calculated by the algorithms. The total of 100 networks was tested. The network finally selected was the best network of the RBF type of 7-300-1 topology (7 neurons in the input layer, 300 neurons in the hidden layer, 1 neuron in the output layer). The values of its select and test errors were: 0.0974 and 0.1052, respectively.

4. Network model validation and discussion

Employing initially the *intelligent problem solver* and 'fine tuning' the models with the assistance of the *custom network designer*, satisfactory results were obtained (Figs. 5, 6). Small select errors (0.123131 for the first network and 0.097425 – for the second) provide the most important information for the assessment of the networks. They indicate their capability to generalise and avoid overtraining. In order to make sure that the results for the selection subset were not random, the test subset was chosen for the final selection of the model. It does not take part in the network training process and is used only once. The similar error values for the selection and test subsets indicate that the network generalises the acquired knowledge well.

The utilisation of different methods of input variable selection such as the *sensitivity analysis* or the *feature selection algorithm* aimed at the justification of the removal of the selected input variables. Identical results for all methods provide unequivocal information about their optimal selection. This made it possible to reduce significantly the number of independent variables for each of the data sets.

With regard to the classification problem, one of the important measures of the quality of the obtained model is the number of the correctly assigned cases to recognised classes. In the developed networks, this correctness remains on a high level and amounts to 99.3% for the *Wet* class and 97.3% for the *Dry* class. These values for the second network amount to 99.6% and 97.4%, respectively. When comparing the networks obtained for the first and second data sets, it can be concluded that both of them operate with similar generalisation capabilities.

5. Conclusions

1. The study confirmed the research assumption about the possibility of developing a model of an artificial neuron network for the identification of the endpoint of the low-temperature drying process in an inert barley grain 1.2 m thick. This is evident from the high correctness of the case assignment to recognised classes (ranging from 93.3-99.6%) as well as from the high capability to generalise the analysed data.

2. Using feature selection algorithms, it was possible to reduce the number of input variables: from 10 to 5 for the set of measurement results taking into consideration grain temperature differences between the selected layers of the inert grain bulk and from 11 to 7 for the set of measurement results taking into consideration grain temperature values at the selected layers of the inert grain bulk.

RBF 5-352-1

	Classification (6) (dane suszenie 2-12)	
	output.Wet.6	output.Dry.6
Total	2488,000	519,0000
Correct	2473,000	505,0000
Wrong	15,000	14,0000
Unknown	0,000	0,0000
Correct(%)	99,397	97,3025
Wrong(%)	0,603	2,6975
Unknown(%)	0,000	0,0000

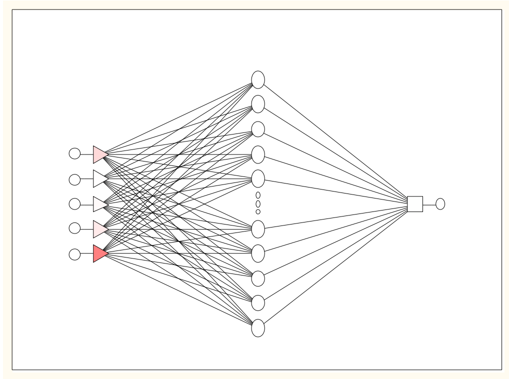


Fig. 5. Classification results for the first data set with grain temperature differences between selected layers

RBF 7-300-1

	Classification (6) (dane suszenie temp)	
	output.Wet.6	output.Dry.6
Total	3387,000	519,0000
Correct	3375,000	506,0000
Wrong	12,000	13,0000
Unknown	0,000	0,0000
Correct(%)	99,646	97,4952
Wrong(%)	0,354	2,5048
Unknown(%)	0,000	0,0000

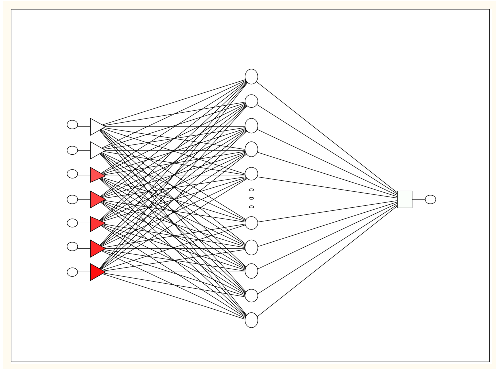


Fig. 6. Classification results for the second data set with grain temperature values in selected layers

3. The following variables: time of drying, drying air velocity and grain temperature value in all layers turned out to be the most important ones allowing the identification of the drying barley grain in bulk of 1.2 m thick.
4. Data sets containing 3906 cases, 3009 divided in three subsets: training, selection and test, are sufficient to obtain networks with satisfactory generalising values.

It is necessary to conduct further search to find the way of decreasing the number of neurons in the hidden layer of the obtained neural networks.

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