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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR THE PREDICTION OF QUALITY CHARACTERISTICS OF POTATO TUBERS - INNOVATOR VARIETY

Summary

The aim of the research was to create a model for prediction of tuber dry matter on the basis of underwater weight of tubers (UWW), with the use of neural modelling methods. In order to achieve the aim of the study, data from the years 2011-2017 were collected from the production fields of an individual farm located at the border of Pomeranian and West Pomeranian Voivodeships in Słupski and Sławieński districts. The subject of the research concerned potatoes of the Innovator variety, which were grown for processing purposes - production of French fries. To build a neural model, data from September sampling as well as meteorological and fertilizer data were used. A total of 82 learning cases from the fields covered by the analyses were used, which were divided into two sets. Set 1, for the construction of the neural model consisted of 75 samples. Set 2, which consisted of 7 randomly selected samples, had a validation function and did not participate in the construction of the neural model. For proper model validation, four forecast error measures were used, i.e. relative approximation error (RAE), root mean square error (RMS), mean absolute error (MAE), mean absolute percentage error (MAPE). The model MLP 8:8-12-5-1:1 (BP100,CG31b) was based on eight inputs (meteorological data, fertilization levels) and one output (dry matter of tubers under water). The analysis resulted in a forecast error of 2.81% of MAPE. Moreover, the sensitivity analysis of the neural network showed that the mean air temperature in the period from April to September (T4-9) had the greatest influence on the dry matter of tubers.
***Key words**: potato, Innovator, dry matter, neural networks, sensitivity analysis, MLP*

ZASTOSOWANIE SZTUCZNYCH SIECI NEURONOWYCH DO PREDYKCJI CECH JAKOŚCIOWYCH BULW ZIEMNIAKA ODMIANY INNOVATOR

Streszczenie

Celem pracy było wytworzenie modelu do predykcji suchej masy bulw na podstawie masy bulw pod wodą z wykorzystaniem metod modelowania neuronowego. Dla realizacji celu pracy zebrano dane pochodzące z lat 2011-2017 pochodzące z pól produkcyjnych gospodarstwa indywidualnego, zlokalizowanego przy granicy województw pomorskiego i zachodniopomorskiego w powiatach słupskim i sławieńskim. Przedmiotem badań były ziemniaki odmiany Innovator, które uprawiano na cele przetwórcze - produkcję frytek. Do budowy modelu neuronowego, wykorzystano dane pochodzące z wrześniowych próbkowań oraz dane meteorologiczne i nawozowe. Łącznie użyto 82 przypadków uczących pochodzących z pól objętych analizami, które zostały podzielone na dwa zbiory. Zbiór 1, do budowy modelu neuronowego składał się z 75 prób. Zbiór 2, który tworzyło 7 losowo wybranych prób, pełnił funkcję walidacyjną i nie uczestniczył w budowie modelu neuronowego. Dla właściwej walidacji modelu zastosowano cztery mierniki błędów prognozy, tj. globalny względny błąd aproksymacji modelu (RAE), błąd średniokwadratowy (RMS), błąd średni bezwzględny (MAE), błąd średni bezwzględny procentowy (MAPE). Wytworzony model MLP 8:8-12-5-1:1 (BP100,CG31b) bazował na ośmiu wejściach (dane meteorologiczne, poziomy nawożenia) i jednym wyjściu (sucha masa bulw pod wodą). W wyniku przeprowadzonych analiz uzyskano wynik błędu prognozy na poziomie 2.81% MAPE. Ponadto analiza wrażliwości sieci neuronowej wykazała, że największy wpływ na suchą masę bulw miała średnia temperatura powietrza w okresie od kwietnia do września (T4-9).
***Słowa kluczowe**: ziemniak, Innovator, sucha masa, sieci neuronowe, analiza wrażliwości, MLP*

1. Introduction

For several years the area of cultivation of potatoes produced in Poland for processing purposes has been increasing. Increased demand for frozen products ready for consumption results from changes in consumer preferences. The so-called "convenient food" - including French fries - is gaining popularity at the expense of limiting the consumption of potatoes in unprocessed form [8].Varieties suitable for the production of French fries differ in many parameters from edible or chips varieties. According to the data of The Research Centre for Cultivar Testing, in 2018 the National Register of Varieties included 100 varieties, of which 12 varieties were characterized as useful for the production of French fries and chips [21]. Potato producers growing potatoes for French fries usually choose foreign varieties. Many potato processing companies contract only those varieties which have passed several years of field experience and trial tests on the production line. It is important that the variety would be easy to grow and store and at the same time would provide a product that meets consumers' expectations. Varieties identified as suitable for the production of French fries must have appropriate tuber morphology and chemical composition. The requirements of external characteristics relate to shape and regularity, depth of meshes, skin thickness and diseases [4]. Important internal characteristics that ensure good product quality are: adequate dry matter and starch content, low anti-nutrient content, and low total sugars and reducing sugars [4, 11, 34, 39]. The dry matter content in tubers is a very important parameter regardless of the destination of potato use. The higher the dry matter is, the less water the tuber contains and its proper density is higher. The dry matter content largely determines the technological value of French fries: structure and brittleness of the product, oil absorption [10]. Literature sources provide different values of optimal dry matter content in French fries varieties of potato. Most often share of this parameter is in the interval of 20- 24 % of tuber weight [24, 29]. According to Lisińska [23] the use of tubers with a higher dry matter content in the process improves the crunchiness and colour of the product. French fries made from potatoes with a dry matter content of less than 20% absorb more fat during frying and are characterised by an inappropriate structure, the so-called "spongy" structure and a poorer taste [10]. The factors influencing the dry matter content of tubers under cultivation conditions are: the duration of plant growth, soil type (structure, water retention capacity, temperature), fertilization N and K (dose and type of fertilizer), meteorological conditions (temperature, precipitation, sunshine) [1, 6]. The genetic factor is also important, i.e. the variety [24]. Monitoring of dry matter content in tubers during the growing season enables skillful management of potato plantations and raw material contracting. On the basis of data on the rate of dry matter growth in tubers, farmers make decisions on the start of defoliation or excavations, and the processing company on the acceptance or rejection of raw material for processing. Current information about the dry matter content in tubers from a specific field allows for quick reorganization of deliveries to the French fries factory. Artificial neural networks are becoming an increasingly popular tool in agricultural modelling [3, 14, 16]. Their main advantages include high approximation abilities, considering many independent variables (also of a linguistic nature) and solving non-linear relationships. Artificial neural networks make it possible to forecast plant yields, both in quantitative and qualitative terms [26, 27]. The aim of this article was to obtain a simple and accurate model predicting the value of tubers' underwater weight (UWW) for Innovator variety. Having known the value of tubers underwater weight, it is easy to calculate the dry matter content in tubers. Additionally, an analysis of factors responsible for the shaping of the discussed values was attempted. The application of the sensitivity analysis of the neural network made it possible to classify by weight the factors influencing the underwater weight of tubers- and therefore the dry matter of tubers.

2. Materials and methods

The neural model for the prediction of dry matter of tubers based on the underwater weight of tubers (UWW) was built on the basis of data from production fields of the individual farm, collected in Poland in the years 2011-2017.

All the fields were located at the border of the neighbouring Pomeranian and West Pomeranian Voivodeships, i.e. in the Słupski and Sławieński districts (Fig. 1). Potatoes of the Innovator variety were grown for processing purposes - production of French fries. The area of cultivation of the mentioned cultivar and the number of fields in each year was different (Tab. 1).

Table 1. Number of fields and cultivated area of Innovator variety on the farm in the years 2011-2017
Tab. 1. Liczba pól i areał uprawy odmiany Innovator w gospodarstwie w latach 2011-2017

Year of cultivation	Number of Innovator variety fields	Area of cultivation [ha]
2011	3	208
2012	3	204
2013	3	244
2014	4	281
2015	7	295
2016	7	293,5
2017	5	344

Source: own work / Źródło: opracowanie własne

Source: own work / Źródło: opracowanie własne
Fig. 1. Research area in Słupski and Sławieński districts
Rys. 1. Obszar badań w powiatach słupskim i sławieńskim

From the first decade of July to the mid of September, at 10-14 day intervals, each year of cultivation and from all production fields, Innovator potatoes samples were collected. The main purpose of regular sampling was to determine the yield, size of tubers and dry matter content in Innovator tubers during the growth and ripening of tubers. The first sample was taken at the developmental phase after flowering, while the last sample was taken at the full maturity phase of the tubers. Data from the last sampling best visualised the final yield. A single sample consisted of tubers harvested from an area of 3 m^2, separately for each field (Fig. 2). The first sample in the first decade of July was taken from a selected place in the field (min. 15 m from the field edge) which represented average conditions for a given parcel of land. At subsequent dates, the tubers were dug in the closest neighbourhood of the sample taken at the first date. In the discussed farm, the Innovator variety was cultivated at a spacing of 90 cm. One sample of potatoes taken from a particular field at any time was grown on 25 hectares of land. Therefore, in some fields 2 or 3 samples of tubers were taken each time. Potatoes were transported to the evaluation laboratory of the processing plant's raw material, where the following were determined: tuber yield with a size greater than 28 mm, percentage share of tuber fractions 28-40 mm, 40-50 mm, above 50 mm in the total yield, length of tubers, share of internal and external defects and underwater weight of tubers (UWW - underwater weight) using the hydrostatic weight method.

Source: picture by / Źródło: fot. K. Piekutowski

Fig. 2. Innovator variety - sample of tubers with 3 m^2
Rys. 2. Odmiana Innovator - próba bulw z 3 m^2

For the construction of the neural model, which is the subject of this paper, data from the last, September samples in the years 2011-2017 were used. In total, results from 82 samples taken from the field were worked on. The collection for the construction of the neural model, called set 1, consisted of 75 samples. Collection 2, which consisted of 7 randomly selected samples, performed a validation function and did not participate in the construction of the neural model. The data used to build the neural model are shown in Table 2.

Meteorological data (average daily air temperature, daily sum of precipitation, daily sum of insolation) referring to the area and the research period were obtained from the archives of the Institute of Meteorology and Water Management - National Research Institute, synoptic station in Koszalin. The model takes into account meteorological factors collected from 1 April to x-September, i.e. the day of the last sampling in each vegetation season.

The data on fertilization and UWW values came from the database of the processing company. The total values of fertilization are the result of treatments carried out before and after planting the Innovator cultivar. In the laboratory of the processing company, the weight of tubers under water was determined for potatoes with a size of 50+ with one repeat for each sample from the field.

Determination of underwater weight of tubers (UWW-underwater weight), which is the subject of the forecast, allows for quick determination of tuber dry matter and starch content [19]. The weight of tubers under water is the primordial result of the hydrostatic weight method (according to Reiman-Parow) (Fig. 3), used by many processing companies to measure the starchy of tubers. The measurement consists of weighing potatoes in the air and submerged potatoes in water and then calculating on the basis of the obtained results of specific weight of tubers, dry matter content and starchiness. Thanks to the knowledge of the relation between the starch content and the specific weight of the potato and using Archimedes' law, it is possible to determine the starch content of the tested potatoes: this is the difference between dry matter and nonstarch components, which is 5.75% on average (Maercker constant).

Usually the values of dry matter and starch content of potatoes could be read from specially prepared Table 3.

Source: picture by / Źródło: fot. M. Piekutowska

Fig. 3. Determination of the dry matter content of potato tubers by hydrostatic weight in the COBORU SDOO in Karzniczka
Rys. 3. Oznaczanie zawartości suchej masy bulw ziemniaków metodą wagi hydrostatycznej w COBORU SDOO w Karzniczce

Table 2. Data structure in neural prediction model
Tab. 2. Struktura danych w predykcyjnym modelu neuronowym

Symbol	Unit of measure	Variable name	Scope of data
T4-9	°C	The average air temperature from April 1 to day in September in which the sample was taken	14.07- 15.31
R4-9	mm	The sum of precipitation from April 1 to day in September in which the sample was taken	288.3- 497.6
I4-9	h	The sum of insolation from April 1 to day in September in which the sample was taken	1012.5- 1371.6
N	$kg \cdot ha^{-1}$	The sum of N fertilization in the current year	147- 244
P2O5	$kg \cdot ha^{-1}$	The sum of P_2O_5 fertilization in the current year	138- 161
K2O	$kg \cdot ha^{-1}$	The sum of K_2O fertilization in the current year	210- 300
SO3	$kg \cdot ha^{-1}$	The sum of SO_3 fertilization in the current year	252- 336
MGO	$kg \cdot ha^{-1}$	The sum of MgO fertilization in the current year	60- 123
Y_UWW	g	UWW- underwater weight	327- 444

Source: own work / Źródło: opracowanie własne

Table 3. Dry matter content, specific gravity and starch content based on the underwater weight of tubers. Selected fragment of the study

Tab. 3. Zawartość suchej masy, gęstości bulw i zawartości skrobi na podstawie masy bulw pod wodą. Wybrany fragment opracowania

UWW [g]	Dry matter %	Specific gravity [g/cm^3]	Starch %
340	18,7	1,0729	12,9
345	19,0	1,0740	13,1
350	19,2	1,0752	13,4
355	19,5	1,0764	13,6
360	19,7	1,0776	13,9
365	19,9	1,0787	14,1
370	20,2	1,0799	14,3
375	20,4	1,0811	14,6
380	20,7	1,0822	14,8
385	20,9	1,0834	15,1
390	21,2	1,0846	15,3
395	21,4	1,0857	15,5
400	21,7	1,0869	15,8
405	21,9	1,0881	16,0
410	22,2	1,0892	16,3
415	22,4	1,0904	16,5
420	22,7	1,0916	16,7
425	22,9	1,0927	17,0
430	23,1	1,0939	17,2
435	23,4	1,0951	17,5
440	23,4	1,0962	17,7

Source: / Źródło: NIVAA The Netherlands Potato Consultative Institute

In processing companies, tubers' underwater weight are often used to characterize the dry matter content of the tubers and to develop specifications for the raw material, without conversion to dry matter and starch content. In view of the above, these values were taken into account when constructing the neural model.

2.1. Method of building neural model

The independent variables for the construction of the neural model have been selected in such a way as to enable the neural network to function on the basis of the input variables that are presented in Table 2.

The choice of network topology and learning method takes into account its approximation and generalization, based on their quality measures. The application of Statistica v7.1 software allowed to test networks with different architectures - linear, MLP, RBF, GRNNN. For the demonstrated neural model, the number of tested networks was 10000 using the AND tool (automatic network designer). The selection of the network was based on the best parameters determining the quality of the network.

The empirical data set was randomly divided into training, validation and test sets. The number of sets was the following: training - 53 cases, validation - 11 cases, testing - 11 cases. The division of the set was made randomly in the proportion of 70% -15% -15%, due to the number of surveyed fields.

2.2. Methodology for the evaluation of constructed neural model

Once a neural model has been constructed using the AND tool, it is evaluated on the basis of information provided by Statistica software. This are: standard deviation, mean deviation, error deviation, absolute mean deviation, deviation quotient, correlation. The best model is selected on the basis of the lowest value of the mean absolute error and the highest correlation value.

The next step is to evaluate the predictive power of the created neural models by calculating the forecast error (ex post), by comparing the data from set II with the predictive results generated from set I. These errors are calculated on the basis of data from the past, i.e. on the basis of information about forecasts that have already expired and the corresponding implementation of a dependent variable. A forecast error is the difference between the predicted of the dependent variable at time t and the forecast observed for the same period.

The validation of the created models was based on data from the years 2011-201, including 7 potato fields. These data were not taken into account when constructing neural models. The methodology described in the literature [5, 7, 9, 12, 15, 17, 32, 37] was used to assess the quality of forecasts.

– RAE – relative approximation error;

$$RAE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i)^2}} \qquad (1)$$

– RMS – root mean square error;

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad (2)$$

– MAE – mean absolute error;

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (3)$$

– MAPE – mean absolute percentage error;

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \cdot 100\% , \qquad (4)$$

where:

n – number of observations,

y_i - actual values obtained during the tests,

$\hat{y}_i$ - values determined using the model.

To better illustrate the relationship between observed and predicted tubers' underwater weight, a graphical representation is created showing mutual relations.

2.3. Sensitivity analysis of the neural network

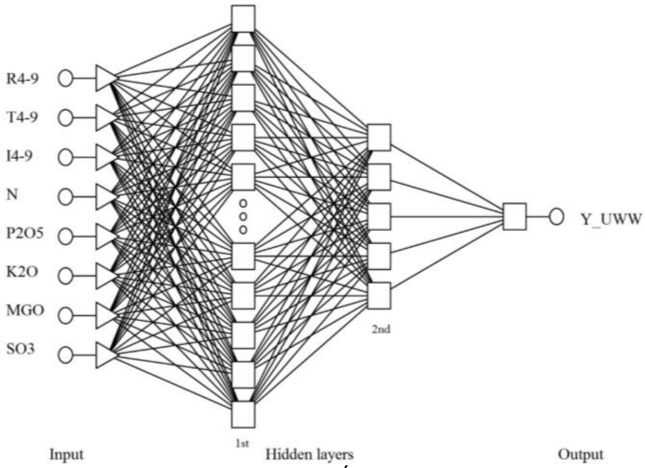
In order to check which of the examined independent features have the greatest influence on the underwater weight of tubers, a sensitive neural network analysis is carried out. When an input variable (independent feature) is removed from the model, its influence on the cumulative error of the neural network can be observed, as a result of which the significance of individual independent features is determined. There are two indicators that handle this:

– rank - shows in the numerical manner the features according to decreasing error, the rank with the value of 1 is the most important for the network,

– error quotient - is the error ratio, to the error obtained using all independent features, the larger it is, the greater the significance of a given feature. If it takes a value below 1, you can remove a given feature from the model to improve its quality, but it is not mandatory.

3. Results

The generated neural model based on the MLP network has 8 neurons at the input, 12 neurons in the first hidden layer, 5 neurons in the second hidden layer and one neuron at the output (Fig. 4). The applied method of network learning took place in two stages. In the first stage, the network was learnt by backpropagation errors with 100 epochs (BP100). In the second stage, a gradient conjugated algorithm by 31 epochs (CG31b) was used.



Source: own work / Źródło: opracowanie własne

Fig. 4. Structure of the MLP 8:8-12-5-1:1 artificial neural network

Rys. 4. Struktura sztucznej sieci neuronowej o topologii MLP 8:8-12-5-1:1

Backpropagation error is characterized by lower memory requirements than most of other algorithms, and usually achieves an acceptable level of error quicker, although achieving a precise minimum error can be time-consuming. The conjugated grading algorithm is most commonly used for MLP networks. It works significantly better than the algorithm of backpropagation error. It is recommended to use it for networks with a large number of weights and for networks with multiple output neurons [36].

Basic information on the quality and structure of the neural model is included in Table 4.

In order to determine the prediction quality, calculations were carried out of *ex post* methods, using formulas (1-4) whose results are presented in Table 5.

Table 4. The quality and structure of the neural model

Tab. 4. Struktura i wskaźniki jakościowe modelu neuronowego

Neural network structure	MLP 8:8-12-5-1:1
Learning error	0.1168
Validation error	0.0306
Test error	0.1522
Mean	374.24
Standard deviation	29.81
Average error	-0.5853
Deviation error	16.53
Mean Absolute error	13.34
Quotient deviations	0.5547
Correlation	0.8323

Source: own work / Źródło: opracowanie własne

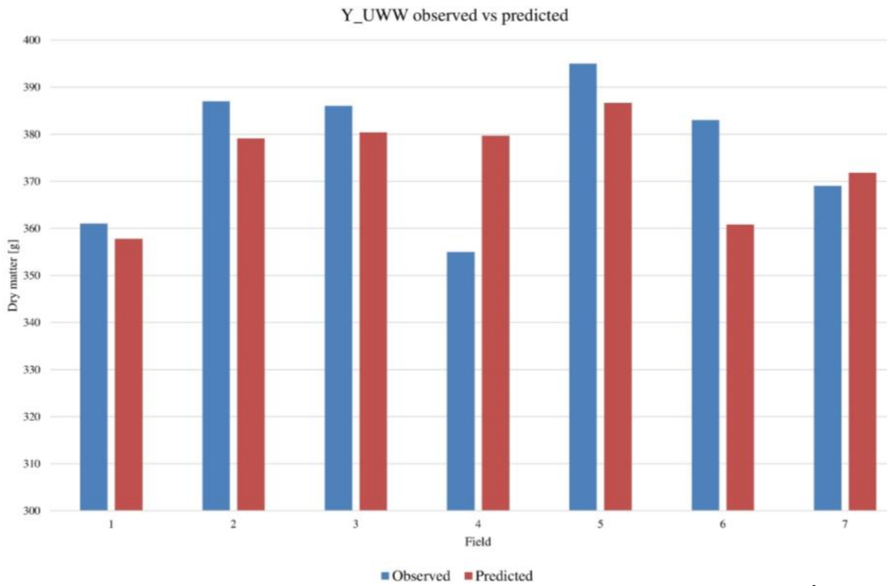
Table 5. Measures prediction *ex post* of analyzed neural model

Tab. 5. Mierniki predykcyjne ex post dla analizowanego modelu neuronowego

RAE **[-]**	***RMS*** **[-]**	***MAE*** **[t·ha^{-1}]**	***MAPE*** **[%]**
0.0286	13.54	10.68	2.86

Source: own work / Źródło: opracowanie własne

In the next step, a graphical presentation was created between the observed and predicted tubers' underwater weight of the neural model (Fig. 5).



Source: own work / Źródło: opracowanie własne

Fig. 5. Graphical presentation of observed and predicted tubers' underwater weight (Y_UWW)

Rys. 5. Graficzne przedstawianie masy bulw pod wodą (Y_UWW) rzeczywistej i prognozowanej przez model

In the last stage of calculations, a network sensitivity analysis was performed for the produced neural model. The results of this analysis are presented in Table 6.

Table 6. Sensitivity analysis of neural network
Tab. 6. Analiza wrażliwości sieci neuronowej

Variable	Quotient	Rank
R4-9	**1.4412**	**1**
T4-9	1.0844	6
I4-9	1.0377	7
N	1.1262	3
P2O5	**1.3262**	**2**
K2O	0.9988	8
MGO	1.0951	5
SO3	1.1182	4

Source: own work / Źródło: opracowanie własne

4. Discussion

Apart from the genotype, the factors influencing the accumulation of dry matter and starch in tubers are: agrotechnology and local soil and habitat conditions [18]. Many literature sources indicate high significance of meteorological conditions prevailing in a given potato vegetation season in shaping yield quality traits [2]. The results of sensitivity analysis for neural networks built on the basis of empirical data from set I partially confirm the results obtained in other studies. The mean daily temperature (T4-9) in the months 1 April - x September (date of the last sample of tubers taken from the field) is the highest rank factor in this study. The accumulation of dry matter in tubers is enhanced by warm, sunny weather at the final stage of potato vegetation [38]. The optimal temperature for potato cultivation ranges between 15-25 °C during the day and does not exceed 12 °C at night. Increased length of the day combined with high air temperatures are responsible for an increase in the content of reducing sugars in tubers. Their increased concentration in the raw material for the production of French fries leads to products with the wrong, darker colour [28]. Moreover, the potato is one of the species that also reacts to both deficiency and excess of precipitation. Excessive rainfall is not favourable for the accumulation of dry matter in tubers [30]. According to Rymuza et al. [31], in years of excessive rainfall, potatoes accumulate less dry matter and starch regardless of the location of the crop and variety (genetic factor). It is worth noting that the quality characteristics of tubers do not depend on the total annual rainfall, but more on their distribution and quantity during vegetation. The results of a six-year field study carried out by Kołodziejczyk [18] showed that the highest dry matter content in tubers was observed in the years classified as fairly moist, with moderate periods of precipitation deficiency in May and June, periodically in August, and excess in July and September. Our own study showed that the sum of precipitation in the vegetation season significantly shapes the values of UWW, however, this factor does not belong to the group of the most important factors.

Fertilization with mineral components is another independent trait with a significant influence on the explanation of UWW variability of the Innovator cultivar tubers. It is interesting that it was phosphorus that shaped the value of the forecast feature in the greatest degree. Nitrogen and potassium are the elements most frequently referred to in the literature of the subject, which show a large influence on the accumulation of dry matter in tubers [20]. The results of the sensitivity analysis confirm the significance of nitrogen, which in regard to the assigned rank loses to phosphorus. It is well known that phosphorus regulates metabolic processes in plants. Fertilization with this element in the period before tuberization phase stimulates the amount of tubers formed. However, the role of phosphorus in determining the quality characteristics of potato yield has not been clearly indicated. On the other hand, it is known that excessive nitrogen fertilisation delays the ripening of plants and a decrease in tuber yield in terms of quantity and quality. High doses of the ingredient deteriorate the colour of potato products [28]. In our own studies, the factor with the lowest influence on UWW of Innovator tubers was the amount of potassium used. However, this information is questionable with literature reports. It is known that optimal potassium fertilization brings many positive yield-forming effects. This element plays an important role in starch synthesis because it is an activator of starch synthase - the enzyme responsible for this process [13]. High doses of potassium fertilization, especially the popular potassium chloride, reduce the dry matter of tubers [33].

A properly constructed predictive model should correctly describe the analysed phenomenon [22], which means that the model should be similar to the empirical system under research. Therefore, a common problem consists in the selection of the appropriate neural network topology for a given issue, which most often takes place through the review of many variants of network topology. For predictive applications, the MLP network is the most frequently used network [12, 25]. In this work the MLP network with back-propagation error algorithm and conjugated gradient algorithm were used.

The model has been validated on the basis of field data from seven years. Four ex post error meters were used, i.e. relative approximation error (RAE), root mean square error (RMS), mean absolute error (MAE), mean absolute percentage error (MAPE). These measures were used to determine the quality of models and to determine the dry matter forecast errors of potato tubers on the basis of the underwater weight of tubers (Y_UWW).

Table 5 shows the *ex post* error values for the produced model. To the most frequently used indicators characterizing the values of prediction errors include MAPE [15, 25, 40]. The value of MAPE forecast error for the neural model based on MLP 8:8-12-5-1:1 structure was 2.86%. Having in mind the critical MAPE error rate of up to 10%, in cases which are significantly influenced by random conditions [35], the result obtained is very good.

In the last phase of calculations, the analysis of network sensitivity was performed for the neural model produced. The highest rank 1 with a quotient of 1.4412 was obtained by an independent variable in the form of average air temperature in the period from 1 April to x September (T4-9). It means that this factor has the greatest influence on the dry matter of potato tubers. Phosphorus fertilization (P_2O_5) was the second factor of rank 2 with a value of 1.3262.

Presented results of our own research show that artificial neural networks are a tool of high usefulness in forecasting the yield of Innovator cultivar in qualitative terms. Forecasts made before the planned harvest are a precious source of knowledge of the quality of the raw material and the degree of its maturity. Due to the untypical nature of some of the results obtained in the sensitivity analysis, future research ought to be extended by including a larger number of fields in the analysis, as well as testing other varieties grown for French fries purposes.

5. References

[1] Aghighi Shahverdi Kandi M., Tobeh A., Gholipoor A., Jahanbakhsh S., Hassanpanah D., Sofalian O.: Effects of different n fertilizer rate on starch percentage, soluble sugar, dry matter, yield and yield components of potato cultivars. Australian Journal of Basic and Applied Sciences, 2011, 5 (9), 1846-1851.

[2] Bombik A., Rymusza K., Markowska M., Stankiewicz C.: Variability analysis of selected quantitative characteristics in edible potato varieties. Acta Sci. Pol., Agricultura, 2007, 6 (3), 5-15.

[3] Boniecki P.: Wykorzystanie technik neuronowych w praktyce rolniczej. Journal of Research and Applications in Agricultural Engineering, 2005, 50 (2), 9-14.

[4] Carputo D., Aversano R., Frusciante L.: Breeding potato for quality traits. Acta Hort., 2005, 684, 55-64.

[5] Dar E.A., Brar A.S., Mishra S.K., Singh K.B.: Simulating response of wheat to timing and depth of irrigation water in drip irrigation system using CERES-Wheat model. F. Crop. Res., 2017, 214, 149-163.

[6] Department of Environment and Primary Industries, Australia. Potatoes: Factors affecting dry matter, 1995. Access: http://agriculture.vic.gov.au/agriculture/horticulture/vegetables/vegetables-a-z/potatoes/potatoes-factors-affecting-dry-matter.

[7] Dias H.B., Sentelhas P.C.: Evaluation of three sugarcane simulation models and their ensemble for yield estimation in commercially managed fields. F. Crop. Res., 2017, 213, 174-185.

[8] Dzwonkowski W.: Międzynarodowy rynek a eksport ziemniaków z Polski [W:] Produkcja i rynek ziemniaka. Wydawnictwo Wieś Jutra, 2012, 7-20.

[9] Emamgholizadeh S., Parsaeian M., Baradaran M.: Seed yield prediction of sesame using artificial neural network. Eur. J. Agron., 2015, 68, 89-96.

[10] Gegov Y., Pevicharova G., Nacheva E., Slavchev V.: Potato breeding lines suitable for production of frozen French fries. Bulgarian Journal of Agricultural Science, 2007, 13, 15-29.

[11] Geremew E.B., Steyn J.M., Annandale J.G.: Evaluation of growth performance and dry matter partitioning of four processing potato (*Solanum tuberosum*) cultivars. New Zealand Journal of Crop and Horticultural Science, 2007, 35, 385-393.

[12] Gonzalez-Sanchez A., Frausto-Solis J., Ojeda-Bustamante W.: Attribute selection impact on linear and nonlinear regression models for crop yield prediction. Sci. World J., 2014.

[13] Grzebisz W.: Ziemniaki. Technologia nawożenia [W:] Technologie nawożenia roślin uprawnych- fizjologia plonowania. Tom 1. Oleiste, okopowe i strączkowe. Powszechne Wydawnictwo Rolnicze i Leśne, 2012, 8, 269-323.

[14] Hardaha M.K., Chouhan S.S., Ambast S.K.: Application of artificial neural network in prediction of response of farmers' water management decisions on wheat yield. Journal of Indian water resources society, 2012, 32 (1-2), 1-2.

[15] Kantanantha N., Serban N., Griffin P.: Yield and price forecasting for stochastic crop decision planning. J. Agric. Biol. Environ. Stat., 2010, 15, 362-380.

[16] Khairunniza- Bejo S., Mustaffha S., Ismail W. I. W.: Application of artificial neural network in predicting crop yield: a review. Journal of Food Science and Engineering, 2014, 4, 1-9.

[17] Khandelwal M., Kumar D.L., Yellishetty M.: Application of soft computing to predict blast-induced ground vibration. Eng. Comput., 2011, 27, 117-125.

[18] Kołodziejczyk M.: Wpływ warunków opadowo-termicznych na skład chemiczny oraz wybrane parametry jakości bulw średnio późnych i późnych odmian ziemniaka jadalnego. Annales UMCS- Plonia, Sectio E, 2014, 69 (3), 1-10.

[19] Kumar D., Ezekiel R., Singh B., Ahmed I.: Conversion table for specific gravity, dry matter and starch content from under water weight of potatoes grown in North-Indian plains. Potato Journal, 2005, 32, 79-84.

[20] Laboski C.A.M., Kelling, K.A.: Influence of fertilizer management and soil fertility on tuber specific gravity: a review. Am. J. of Potato Res., 2007, 84, 283-290.

[21] Lenartowicz T.: Ziemniak. Lista opisowa odmian roślin rolniczych 2018 burak, ziemniak, oleiste, pastewne. Słupia Wielka, 2018.

[22] Li F., Qiao J., Han H., Yang C.: A self-organizing cascade neural network with random weights for nonlinear system modeling. Appl. Soft Comput., 2016, 42,184-193.

[23] Lisińska G.: Wartość technologiczna i jakość konsumpcyjna polskich odmian ziemniaka. Zesz. Probl. Post. Nauk. Roln., 2006, 511, 81-94.

[24] Lutomirska B.: Technologia uprawy ziemniaka przeznaczonego do przetwórstwa. Zeszyty problemowe postępów nauk rolniczych, 2008, 530, 53- 67.

[25] Niedbała G., Przybył J., Sęk T.: Prognosis of the content of sugar in the roots of sugar-beet with utilization of the regression and neural techniques. Agric. Engineering, 2007, 2, 225–234.

[26] Niedbała G., Zaborowicz M., Lenartowicz T., Kozłowski R.: Modelowanie neuronowe jako narzędzie wspomagające prognozę plonu bulw ziemniaków. W: Aktualne problemy inżynierii biosystemów. (red.) Lipiński M., Przybył J., Wydawnictwo Uniwersytetu Przyrodniczego w Poznaniu, 2015, 345-350.

[27] Niedbała G., Mioduszewska N., Mueller W., Boniecki P., Wojcieszak D., Koszela K., et al.: Use of computer image analysis methods to evaluate the quality topping sugar beets with using artificial neural networks. In: Falco, C.M., Jiang, X. (Eds.), Proc. SPIE 10033, Eighth International Conference on Digital Image Processing (ICDIP 2016), Chengdu, 2016, 100332M.

[28] NIVAA On the way to the processing industry. Opublikowane przez Nivaa- The Netherlands Potato Consultative Institute, Hollande 2002.

[29] Pshechenkov, K., Davidenkova O.: Suitability of varieties for processing in depending on growing and storage conditions. Potatoes and vegetables, 2004, 1, 22-24 (Ru).

[30] Puła J., Skowera B., 2004. Zmienność cech jakościowych bulw ziemniaka odmiany Mila uprawianego na glebie lekkiej w zależności od warunków pogodowych. Acta Agrophysica, 2004, 3(2), 359-366.

[31] Rymuza K., Radzka E., Lenartowicz T.: Wpływ warunków środowiskowych na zawartość skrobi w bulwach odmian ziemniaka średnio wczesnego. Acta Agrophysica, 2015, 22(3), 279-289.

[32] Sharma L.K., Singh T.N.: Regression-based models for the prediction of unconfined compressive strength of artificially structured soil. Eng. Comput., 2017, 34, 1-12;

[33] Simson R., Tartlan L., Nugis E., Eremeev V.: The effect of fertilizer and growing season on tuber dry matter and nitrate content in potato. Agronomy research, 2016, 14(4), 1486-1493.

[34] Singh, S.V., Marwaha R.S., Kumar D., Kumar P., Pandey S.K.: Suitability of potato varieties grown in north-eastern Indian plains for processing. Potato J, 2009, 36, 25-34.

[35] Stańko S.: Prognozowanie w agrobiznesie. Teoria i przykłady zastosowania. Wydawnictwo SGGW, Warszawa 2013.

[36] StatSoft Inc.: Statistica (data analysis software system), version 7.1. www.statsoft.com. 2005.

[37] Torkashvand A.M., Ahmadi A., Nikravesh N.L.: Prediction of kiwifruit firmness using fruit mineral nutrient concentration by artificial neural network (ANN) and multiple linear regressions (MLR). J. Integr. Agric., 2017, 16, 1634-1644.

[38] Wierzbicka A.: Wpływ odmiany, nawożenia azotem i terminu zbioru na zawartość suchej masy i skrobi w bulwach ziemniaków wczesnych. Fragm. Agron., 2012, 29(2), 134-142.

[39] Zgórska K.: Ziemniak - surowiec do produkcji żywności wygodnej i minimalnie przetworzonej. [W:] Produkcja i rynek ziemniaka. Wydawnictwo Wieś Jutra, 2012, 324-333.

[40] Zhang G.P., Patuwo E.B., Michael Y. H.: Forecasting with artificial neural networks: The state of the art. Int. J. Forecast., 1998, 14, 35-62.

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