ORIGINAL PAPER

PREDICTION OF BULLS' SLAUGHTER VALUE FROM GROWTH DATA USING ARTIFICIAL NEURAL NETWORK

PRZEWIDYWANIE WARTOŚCI RZEŹNEJ BUHAJKÓW Z WYKORZYSTANIEM SZTUCZNYCH SIECI NEURONOWYCH

Krzysztof ADAMCZYK[1]*, Krzysztof MOLENDA[2], JAN SZAREK[1], Grzegorz SKRZYŃSKI[1]

[1]Department of Cattle Breeding, Agricultural University, al. Mickiewicza 24/28, 30-059 Kraków, Poland
*Corresponding author. Tel.: ++48 12 622 40 90, Fax: ++48 12 662 41 62, e-mail: rzadamcz@cyf-kr.edu.pl
[2]Department of Agricultural Mechanization, Agricultural University, ul. Balicka 104, 30-149 Kraków, Poland

Manuscript received: March 19, 2005; Reviewed: April 4, 2005; Accepted for publication: April 27, 2005

ABSTRACT

The objective of this research was to investigate the usefulness of artificial neural network (ANN) in the prediction of slaughter value of young crossbred bulls based on growth data. The studies were carried out on 104 bulls fattened from 120 days of life until the weight of 500 kg. The bulls were group fed using mainly farm feeds. After slaughter the carcasses were dissected and meat was subjected to physico-chemical and organoleptic analyses. The obtained data were used for the development of an artificial neural network model of slaughter value prediction. It was found that some slaughter value traits (hot carcass, cold half-carcass, neck and round weights, bone content in dissected elements in half-carcass, meat pH, dry-matter and protein contents in meat and meat tenderness and juiciness) can be predicted with a considerably high accuracy using the artificial neural network.

KEYWORDS: bulls; beef performance; neural networks

STRESZCZENIE

W pracy przedstawiono możliwości, jakie daje zastosowanie sztucznych sieci neuronowych do określania wartości rzeźnej buhajków mieszańców na podstawie parametrów ich wzrostu. Badaniami objęto 104 buhajki mieszańce, które opasano od 120 dnia życia do uzyskania przez nie ok. 500 kg netto. W tym czasie obowiązywał ujednolicony system żywienia grupowego w oparciu o pasze gospodarskie. Następnie zwierzęta były ubijane, ich tusze dysekowane a mięso poddawane analizom fizyko-chemicznym i organoleptycznym. Przy użyciu sztucznej sieci neuronowej określono cechy wartości rzeźnej na podstawie parametrów wzrostu buhajków. Wykazano, że szereg ważnych cech wartości rzeźnej (m.in. masa półtuszy zimnej, karkówki, mięsa udźca, udział kości w półtuszy oraz pH mięsa) mogą być określane ze stosunkowo dużą dokładnością poprzez zastosowanie sztucznej sieci neuronowej.

SŁOWA KLUCZOWE: buhajki, użytkowość mięsna, sztuczne sieci neuronowe

INTRODUCTION

Artificial neural networks (ANNs) are a calculation technique originated from the structure and function of a human brain. The basic propriety of ANNs is a possibility of less or more self-reliant investigation of the relationships between sets of inputs and corresponding sets of outputs through the determination of functional dependencies with any degree of complexity. It takes place in, so called, network self-learning process which is a gradual generalization of the information on a given phenomenon along with the investigation of particular real-time relationships among variables ([2]; [6]; [17]). ANNs perform particularly well in the detection and incorporation of non-linear relationships and can be applied to a wide variety of fields ([8]).

Many authors found a high effectiveness of ANNs application in cattle breeding. They have been used for mastitis prediction ([12]; [25]; [26]), milk, fat and protein yield prediction ([7]; [8]; [16]; [20]), estimation of somatic cell count and fat and protein content in milk ([24]), evaluation of a physiological status of cows (oestrus, calving and health status) ([11]; [19]) and analysis of in vitro embryo development ([23]). Neural network models were also developed for predicting and determination of an objective measurement of slaughter value in beef cattle using pre-slaughter information ([3]; [4]; [5]; [9]). Also, the results of the preliminary investigations carried out by Adamczyk (2002) indicated a high effectiveness of ANN in the evaluation of a slaughter value of young bulls ([1]).

The aim of the presented study was to evaluate the feasibility of predicting the slaughter value of young crossbred bulls with ANN using the data on the course of their growth.

MATERIAL AND METHODS

The investigations were carried out on 104 young bulls representing the following genetic groups: Black-and-White × Piemontese (11 bulls), Black-and-White × Hereford (11), Black-and-White × Limousine (28), Black-and-White × Aberdeen Angus (11), Black-and-White × Charolaise (10), Red-and-White × Charolaise (11), Red-and-White × Limousine (9), Red-and-White × Red Angus (8) and (Black-and-White, Polish Red, Simmental) × Salers (5).

Fattening of bulls and evaluation of their slaughter value were carried out according to the method employed in breeding value estimation at beef bulls stations in Poland ([18]). The bulls stayed at the farms where they had been born up to the age of 2-4 months. The controlled fattening from the age of 120 days was carried out at the station. The bulls were fattened until achieved 500 kg of weight, that means up to 16-18 month of life. They were kept in stanchion barns, with straw bedding and have free access to water. The same system of feeding was applied in every genetic group. The bulls were fed mainly with farm feeds supplemented with a concentrate. The share of particular feeds in total dry-matter of feed ration was following: grass silage -35% , hay -35% and concentrate -30%. The weighing of bulls were done at birth, at the day of purchase and then every each month.

At the end of fattening the bulls were slaughtered and the carcasses were subjected to the dissection according to the method used in meat industry ([13]; [14]; [15]). Seven days after slaughter the physico-chemical and organoleptic analyses were performed with the methods conventionally used in meat quality evaluation ([[21]; [22]; [27]).

The ANN used in the presented study was characterized by the following parameters: feed-forward, back-propagation training algorithm, one hidden layer (30 hidden neurons), random choice of starting values of weights ranged from –1 to 1, constant learning coefficient of: 0.2, logistic function of neuron activation, 10 000 training cycles. The choice of the ANN type was done based on the results of preliminary investigations ([1]).

The input layer of the model consisted of the nodes corresponding to the following variables: genetic group, age and body weights of a bull - in fattening period and at slaughter. The output layer (representing the variables that are being predicted) consisted of the nodes related to the following slaughter value traits: weights of hot carcass, cold half-carcass, neck, brisket, flank, best ribs, shoulder meat, fore-ribs, sirloine (T-bone) meat[1], fillet, round meat, 2nd class meat, bone content in the elements dissected from a half-carcass (BCED)[2], fat content in the elements dissected from a half-carcass (FCED)[3], meat pH, meat water-holding capacity, meat colour brilliance, contents of dry matter, fat and protein in meat, marbling, tenderness and juiciness of meat.

Data set was separated at random into training and testing data sets (the former was used to train the ANN,

[1] – m. long. dorsi extracted from sirloine (T-bone)

[2] – elements dissected from a half-carcass: neck, shoulder, sirloine (T-bone), round and hindshin

[3] – subcutaneous and intramuscular fat in the elements dissected from a half-carcass

and the latter to validate it). Sixty percent (934 records) were allocated to training, and 40% (620 records) to validation.

Because the logistic function of neuron activation in the hidden layer was chosen, the trait values were normalized between 0 and 1 prior to use with the model, according to the following formula ([10]):

$$x = x(t) = \frac{(t - t_{min})}{t_{max} - t_{min}}$$

where: t – original value of a trait, x – normalized value, t_{max}, t_{min} – maximum and minimum values of a trait, both for training and testing sets.

The final step in network activity was the denormalization of outputs through their multiplication by ($t_{max} - t_{min}$) and addition of t_{min}.

The accuracy of ANN predictions was evaluated using the coefficients of linear correlation and calculated of the differences between the actual values of traits and the corresponding ANN predictions. The classes of distribution of prediction differences together with the related percentage of predicted values were determined for each trait.

RESULTS AND DISCUSSION

The estimates of the differences and correlation coefficients between the actual values of slaughter traits and ANN predictions were the following (Tab. 1-4, Fig.1):

- for hot carcass weight: the total prediction difference varied between –12.2 and +13.0 kg and r=0.97. The particular values of differences were relatively regularly distributed within the set of prediction differences, therefore, the determination of more numerous class of predictions was difficult.
- for cold half-carcass: the total prediction difference varied between –17.6 and +14.2 kg (r=0.92) but most predicted values (87.4%) ranged from –7.9 to + 7.9 kg in relation to the actual values in the testing set (AV);
- for neck weight: the total prediction difference varied between –1.65 and +1.50 kg (r=0.88) and 84.6% of the predicted values ranged from –1.01 to +0.87 kg in relation to AV;
- for brisket weight: the total prediction difference varied between –1.32 and +2.44 kg (r=0.05) and 79.1% of the predicted values ranged from –0.56 to +0.94 kg in relation to AV;
- for flank weight: the total prediction difference varied between –2.65 and +3.13 kg (r=0.01) and 80,0% of the predicted values ranged from –1,48 to +1,40 kg in relation to AV;
- for best ribs weight: the total prediction difference varied between –1.12 to +0.98 kg (r=0.37) and 85.1% of the predicted values ranged from –0.69 to +0.77 kg in relation to AV;
- for shoulder meat weight: the total prediction difference varied between –1.31 and +0.96 kg (r=0.49) and 89.9% of the predicted values ranged from –1.07 to +0.74 kg in relation to AV;
- for fore-ribs weight: the total prediction difference varied between –2.50 and +1.45 kg (r=0.60) and 88.1% of the predicted values ranged from –0.91 to +1.06 kg in relation to AV;
- for sirloin (T-bone) meat weight: the total prediction difference varied between –0.97 and +1.21 kg (r=0.61) and 87.5% of the predicted values ranged from –0.53 to +0.55 kg in relation to AV;
- for fillet weight: the total prediction difference varied between –0.31 and +0.30 kg (r=0.60) and 83.0% of the predicted values ranged from –0.18 to +0.12 kg in relation to AV;
- for round meat weight: the total prediction difference varied between –3.49 and +3.18 kg (r=0.81) and 93.2% of the predicted values ranged from –2.15 to +1.84 kg in relation to AV;
- for 2nd class meat weight: the total prediction difference varied between –9.45 and +15.50 kg (r=0.82) and 89.7% of the predicted values ranged from –4.45 to +5.52 kg in relation to AV;
- for BCED: the total prediction difference varied between –2.08 and +1.84% (r=0.67) and most 90.7% of the predicted values ranged from –0.90 to +1.05% in relation to AV;
- for FCED: the total prediction difference varied between –1.35 and +1.74% (r=0.86) and most 92.3% of the predicted values ranged from –1.03 to +1.12% in relation to AV;
- for meat pH: the total prediction difference varied between –0.9 and +0.6 (r=0.91) and most 86.7% of the predicted values ranged from –0.4 to +0.3 in relation to AV;
- for meat water-holding capacity: the total prediction difference varied between –3.57 and +3.69 cm^2 (r=0.81) and 92.8% of the predicted values ranged from –2.11 to +2.24 cm^2 in relation to AV;
- for meat colour brilliance: the total prediction difference varied between –3.1 and +4.2% (r=0.87) and 80.1% of the predicted values ranged from –1.6 to +2.0% in relation to AV;
- for dry-matter content in meat: the total prediction

Table 1. Differences between the actual values of slaughter traits and predicted by ANN

Trait	Mean actual value in the testing set	Mean difference	Standard deviation of difference	Minimum difference	Maximum difference
Hot carcass weight (kg)	273.6	-0.70	6.67	-12.2	13.0
Cold half-carcass weight (kg)	135.0	0.60	5.45	-17.6	14.2
Neck weight (kg)	9.61	-0.06	0.68	-1.65	1.50
Brisket weight (kg)	7.19	0.02	0.62	-1.32	2.44
Flank weight (kg)	11.57	-0.15	1.16	-2.65	3.13
Best ribs weight (kg)	5.42	-0.04	0.51	-1.12	0.98
Shoulder meat weight (kg)	6.90	-0.05	0.60	-1.31	0.96
Fore-ribs weight (kg)	7.86	-0.02	0.71	-2.50	1.45
Sirloine (T-bone) meat weight (kg)	3.53	0.03	0.38	-0.97	1.21
Fillet weight (kg)	1.52	-0.05	0.12	-0.31	0.30
Round meat weight (kg)	18.93	-0.20	1.24	-3.49	3.18
2nd class meat weight (kg)	39.62	0.08	3.51	-9.45	15.50
BCED (%)	12.18	0.20	0.62	-2.08	1.84
FCED (%)	3.32	-0.02	0.67	-1.35	1.74
Meat pH	6.01	-0.10	0.25	-0.90	0.60
Meat water-holding capacity (cm^2)	7.23	0.19	1.34	-3.57	3.69
Meat colour brilliance (%)	12.9	0.40	1.47	-3.1	4.2
Dry-matter content in meat (%)	23.91	-0.09	0.74	-1.90	2.30
Fat content in meat (%)	1.47	0.13	0.64	-2.43	3.03
Protein content in meat (%)	21.24	-0.02	0.58	-1.51	2.24
Meat marbling (point)	2.0	-0.10	0.39	-1.0	2.2
Meat tenderness (point)	4.5	-0.10	0.28	-1.0	1.0
Meat juiciness (point)	4.6	-0.10	0.22	-0.7	0.8

difference varied between –1.90 and +2.30% (r=0.81) and 88.5% of the predicted values ranged from –1.05 to +1.04 kg in relation to AV;

- for fat content in meat: the total prediction difference varied between –2.43 and +3.03% (r=0.83) and 87.1% of the predicted values ranged from –0.78 to +0.85% in relation to AV;
- for protein content in meat: the total prediction difference varied between –1.51 and +2.24% (r=0.83) and 85.9% of the predicted values ranged from –0.75 to +0.74% in relation to AV;
- for meat marbling : the total prediction difference varied between –1.0 and +2.2 points (r=0.88) and 86.4% of the predicted values ranged from –0.3 to +0.6 points in relation to AV;
- for meat tenderness: the total prediction difference varied between –1.0 and +1.0 points (r=0.90) and 85.0% of the predicted values ranged from –0.4 to +0.4 kg in relation to AV;
- for meat juiciness: the total prediction difference varied between –0.7 and +0.8 points (r=0.91) and 90.7% of the predicted values ranged from –0.4 to +0.3 kg in relation to AV.

The presented results indicate that the prediction ability of ANN, characterized by the magnitude of correlation coefficient and the difference between the actual and the predicted value of a trait, was the highest for hot carcass weight and only slightly lower for many other important traits of slaughter value, such as: cold half-carcass weight, meat pH, juiciness and tenderness.

The predicted values for neck weight, round meat weight, 2nd class meat weight, FCED, meat water holding capacity, meat colour brilliance, dry-matter, fat and protein contents in meat and meat marbling were highly correlated with the actual ones (r=0.81-0.89) however, the prediction differences estimated for those traits proved to be considerable. Within this group the highest accuracies of ANN predictions were found for dry-matter and protein contents in meat.

The efficiency of ANN in the prediction of best ribs and shoulder meat weights was very poor. The prediction of flank and brisket weights appeared to be impossible but those cuts are of low culinary value.

In summary, it can be said that the differences in the ability

Table 2. Distribution of differences between the actual values of slaughter traits and predicted by ANN

Hot carcass weight		Cold half-carcass weight		Neck weight		Brisket weight	
Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)
[-12.3 ; -9.7]	9.8	[-17.7 ; -14.4]	1.6	[-1.75 ; -1.33]	3.1	[-1.42 ; -0.95]	5.3
[-9.6 ; -7.1]	9.7	[-14.3 ; -11.2]	1.0	[-1.32 ; -1.02]	4.5	[-0.94 ; -0.57]	9.8
[-7.0 ; -4.6]	8.9	[-11.1 ; -8.0]	1.8	[-1.01 ; -0.70]	11.3	[-0.56 ; -0.19]	26.8
[-4.5 ; -2.1]	16.6	[-7.9 ; -4.9]	11.1	[-0.69 ; -0.39]	14.8	[-0.18 ; 0.18]	16.3
[-2.0 ; 0.4]	12.7	[-4.8 ; -1.7]	17.9	[-0.38 ; -0.07]	15.0	[0.19 ; 0.56]	22.1
[0.5 ; 2.9]	16.0	[-1.6 ; 1.5]	19.7	[-0.06 ; 0.24]	13.5	[0.57 ; 0.94]	13.9
[3.0 ; 5.5]	6.8	[1.6 ; 4.7]	25.5	[0.25 ; 0.56]	16.1	[0.95 ; 1.31]	3.7
[5.6 ; 8.0]	6.0	[4.8 ; 7.9]	13.2	[0.57 ; 0.87]	13.9	[1.32 ; 1.69]	1.1
[8.1 ; 10.5]	5.8	[8.0 ; 11.1]	6.6	[0.88 ; 1.19]	5.6	[1.70 ; 2.07]	0.0
[10.6 ; 13.1]	7.7	[11.2 ; 14.3]	1.6	[1.20 ; 1.51]	2.1	[2.08 ; 2.45]	1.0

Flank weight		Best ribs weight		Shoulder meat weight		Fore-ribs weight	
Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)
[-2.75 ; -2.07]	3.2	[-1.22 ; -0.91]	4.0	[-1.41 ; -1.08]	3.2	[-2.60 ; -2.10]	1.0
[-2.06 ; -1.49]	8.2	[-0.90 ; -0.70]	6.0	[-1.07 ; -0.85]	9.8	[-2.09 ; -1.71]	0.0
[-1.48 ; -0.92]	17.6	[-0.69 ; -0.49]	13.2	[-0.84 ; -0.63]	12.1	[-1.70 ; -1.31]	1.3
[-0.91 ; -0.34]	18.1	[-0.48 ; -0.28]	13.7	[-0.62 ; -0.40]	9.2	[-1.30 ; -0.92]	5.5
[-0.33 ; 0.24]	14.5	[-0.27 ; -0.07]	11.6	[-0.39 ; -0.17]	4.2	[-0.91 ; -0.52]	21.1
[0.25 ; 0.82]	13.2	[-0.06 ; 0.14]	10.3	[-0.16 ; 0.05]	9.7	[-0.51 ; -0.13]	13.9
[0.83 ; 1.40]	16.6	[0.15 ; 0.35]	16.6	[0.06 ; 0.28]	16.8	[-0.12 ; 0.27]	16.6
[1.41 ; 1.97]	6.0	[0.36 ; 0.56]	9.7	[0.29 ; 0.51]	12.3	[0.28 ; 0.66]	26.3
[1.98 ; 2.55]	0.8	[0.57 ; 0.77]	10.0	[0.52 ; 0.74]	15.8	[0.67 ; 1.06]	10.2
[2.56 ; 3.14]	1.8	[0.78 ; 0.99]	4.8	[0.75 ; 0.97]	6.9	[1.07 ; 1.46]	4.2

of ANN to predict the analysed traits was considerable. However, the obtained results should be treated as one of the preliminary attempts of ANN application for the prediction of bulls' slaughter value using the growth data. For ANN to fulfill its potential in this area, continued efforts must be made. The improvement of ANN prediction ability could be achieved through: the elimination or addition of input and output variables, data preprocessing, increase of the number of hidden neurons and the number of their layers, increase of the number of ANN training cycles and change of the method of ANN training process.

The possibility of an efficient application of ANNs for the prediction of beef slaughter value was also investigated by other authors. Brethour (1994) found similar results of marbling score estimation in live bulls from ultrasound images using pattern recognition and Neural Network procedures ([3]). The comparison of sensory evaluation of meat tenderness after slaughter with the evaluation based on ultrasonic images of colour brilliance, marbling and structure of meat made by Li et al. (1999) also proved the efficiency of the models generated by means of Neural Networks in the interpretation of ultrasonic images ([9]). When evaluating the degree of cartilage ossification in the thoracic vertebrae, that could be used as a predictor of a slaughter value, Hatem and Tan (1998) successfully used ANNs in the interpretation of the relative vertebrae images ([4]). Hill et al. (2000) developed Neural Network models for predicting and classifying an objective measurement of meat tenderness using considerably numerous information including: sex, slaughter weight, hot carcass weight, meat colour brilliance, area of musculus longissimus dorsi cross-section, marbling and meat cooking method ([5]).

CONCLUSIONS

1. There is a possibility of the efficient prediction of hot carcass weight of young beef bulls from growth data using artificial neural network.

Table 3. Distribution of differences between the actual values of slaughter traits and predicted by ANN

Traits							
Sirloine (T-bone) meat weight		Fillet weight		Round meat weight		2nd class meat weight	
Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)	Classes of prediction differences (kg)	Number of predicted values (%)
[-1.07 ; -0.76]	1.8	[-0.41 ; -0.25]	2.3	[-3.59 ; -2.83]	1.9	[-9.55 ; -6.95]	3.7
[-0.75 ; -0.54]	4.4	[-0.24 ; -0.19]	6.8	[-2.82 ; -2.16]	0.5	[-6.94 ; -4.46]	4.0
[-0.53 ; -0.32]	15.3	[-0.18 ; -0.13]	21.6	[-2.15 ; -1.49]	9.2	[-4.45 ; -1.96]	18.4
[-0.31 ; -0.10]	12.3	[-0.12 ; -0.07]	18.4	[-1.48 ; -0.82]	24.5	[-1.95 ; 0.53]	25.3
[-0.09 ; 0.12]	22.3	[-0.06 ; -0.01]	13.2	[-0.81 ; -0.16]	19.0	[0.54 ; 3.03]	34.7
[0.13 ; 0.33]	21.0	[0.0 ; 0.06]	10.6	[-0.15 ; 0.51]	13.2	[3.04 ; 5.52]	11.3
[0.34 ; 0.55]	16.6	[0.07 ; 0.12]	19.2	[0.52 ; 1.18]	19.7	[5.53 ; 8.02]	0.8
[0.56 ; 0.77]	5.3	[0.13 ; 0.18]	5.6	[1.19 ; 1.84]	7.6	[8.03 ; 10.51]	0.8
[0.78 ; 0.99]	0.0	[0.19 ; 0.24]	1.5	[1.85 ; 2.51]	1.5	[10.52 ; 13.00]	0.0
[1.00 ; 1.22]	1.1	[0.25 ; 0.31]	0.8	[2.52 ; 3.19]	2.9	[13.01 ; 15.51]	1.0
Traits							
BCED		FCED		Meat pH		Meat water-holding capacity	
Classes of prediction differences (%)	Number of predicted values (%)	Classes of prediction differences (%)	Number of predicted values (%)	Classes of prediction differences	Number of predicted values (%)	Classes of prediction differences (cm^2)	Number of predicted values (%)
[-2.18 ; -1.69]	1.0	[-1.45 ; -1.04]	3.4	[-0.98 ; -0.73]	1.1	[-3.67 ; -2.84]	1.0
[-1.68 ; -1.30]	0.0	[-1.03 ; -0.73]	11.6	[-0.72 ; -0.58]	1.8	[-2.83 ; -2.12]	1.3
[-1.29 ; -0.91]	1.5	[-0.72 ; -0.42]	20.0	[-0.57 ; -0.43]	4.8	[-2.11 ; -1.39]	11.5
[-0.90 ; -0.52]	8.2	[-0.41 ; -0.11]	15.2	[-0.42 ; -0.29]	7.1	[-1.38 ; -0.66]	19.5
[-0.51 ; -0.12]	16.1	[-0.10 ; 0.20]	10.3	[-0.28 ; -0.14]	15.2	[-0.65 ; 0.06]	13.2
[-0.11 ; 0.27]	32.4	[0.21 ; 0.51]	13.4	[-0.13 ; 0.01]	24.8	[0.07 ; 0.79]	14.4
[0.28 ; 0.66]	15.3	[0.52 ; 0.81]	13.4	[0.02 ; 0.16]	26.1	[0.80 ; 1.51]	19.8
[0.67 ; 1.05]	18.7	[0.82 ; 1.12]	8.4	[0.17 ; 0.30]	13.5	[1.52 ; 2.24]	14.4
[1.06 ; 1.44]	3.2	[1.13 ; 1.43]	3.2	[0.31 ; 0.45]	3.1	[2.25 ; 2.97]	4.5
[1.45 ; 1.85]	3.5	[1.44 ; 1.75]	1.1	[0.46 ; 0.70]	2.4	[2.98 ; 3.70]	0.5

2. Some other important traits of slaughter value (cold half-carcass, neck and round meat weights, bone content in dissected elements in half-carcass, meat pH, dry matter and protein contents in meat and meat tenderness and juiciness) can also be predicted with a relatively high accuracy.
3. The artificial neural network can be treated as an interesting alternative to traditional models when examining animal production data.
4. The obtained results are encouraging but future research on optimization of neural configuration, choice of input and outputs and possible data preprocessing is necessary to increase the prediction accuracy.

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Table 4. Distribution of differences between the actual values of slaughter traits and predicted by ANN

Meat colour brilliance		Dry-matter content in meat		Fat content in meat		Protein content in meat	
Classes of prediction differences (%)	Number of predicted values (%)	Classes of prediction differences (%)	Number of predicted values (%)	Classes of prediction differences (%)	Number of predicted values (%)	Classes of prediction differences (%)	Number of predicted values (%)
[-3.2 ; -2.4]	1.5	[-2.00 ; -1.48]	1.5	[-2.53 ; -1.88]	0.8	[-1.61 ; -1.13]	1.0
[-2.3 ; -1.7]	6.6	[-1.47 ; -1.06]	4.8	[-1.87 ; -1.34]	0.2	[-1.12 ; -0.76]	5.3
[-1.6 ; -1.0]	14.8	[-1.05 ; -0.64]	21.9	[-1.33 ; -0.79]	0.6	[-0.75 ; -0.38]	23.9
[-0.9 ; -0.2]	14.0	[-0.63 ; -0.22]	20.3	[-0.78 ; -0.25]	27.9	[-0.37 ; -0.01]	21.0
[-0.1 ; 0.5]	16.3	[-0.21 ; 0.20]	13.5	[-0.24 ; 0.30]	38.9	[0.0 ; 0.37]	25.0
[0.6 ; 1.2]	14.5	[0.21 ; 0.62]	20.2	[0.31 ; 0.85]	20.3	[0.38 ; 0.74]	16.0
[1.3 ; 2.0]	20.5	[0.63 ; 1.04]	12.6	[0.86 ; 1.39]	8.4	[0.75 ; 1.12]	5.3
[2.1 ; 2.7]	6.9	[1.05 ; 1.46]	3.2	[1.40 ; 1.94]	1.3	[1.13 ; 1.49]	0.0
[2.8 ; 3.4]	1.9	[1.47 ; 1.88]	0.3	[1.95 ; 2.48]	0.3	[1.50 ; 1.87]	1.6
[3.5 ; 4.3]	2.9	[1.89 ; 2.31]	1.6	[2.49 ; 3.04]	1.3	[1.88 ; 2.25]	1.0

Meat marbling		Meat tenderness		Meat juiciness	
Classes of prediction differences (point)	Number of predicted values (%)	Classes of prediction differences (point)	Number of predicted values (%)	Classes of prediction differences (point)	Number of predicted values (%)
[-1.1 ; -0.7]	2.3	[-1.07 ; -0.78]	1.0	[-0.79 ; -0.55]	1.9
[-0.6 ; -0.4]	6.6	[-0.77 ; -0.58]	2.4	[-0.54 ; -0.40]	1.9
[-0.3 ; 0.0]	25.6	[-0.57 ; -0.38]	5.3	[-0.39 ; -0.26]	7.9
[0.1 ; 0.3]	31.0	[-0.37 ; -0.18]	17.4	[-0.25 ; -0.11]	27.9
[0.4 ; 0.6]	29.8	[-0.17 ; 0.01]	50.6	[-0.10 ; 0.03]	36.5
[0.7 ; 0.9]	3.1	[0.02 ; 0.21]	8.9	[0.04 ; 0.18]	9.2
[1.0 ; 1.2]	0.3	[0.22 ; 0.41]	8.1	[0.19 ; 0.32]	9.2
[1.3 ; 1.5]	0.3	[0.42 ; 0.61]	4.8	[0.33 ; 0.47]	4.0
[1.6 ; 1.8]	0.0	[0.62 ; 0.80]	0.0	[0.48 ; 0.61]	0.0
[1.9 ; 2.3]	1.0	[0.81 ; 1.10]	1.5	[0.62 ; 0.86]	1.5

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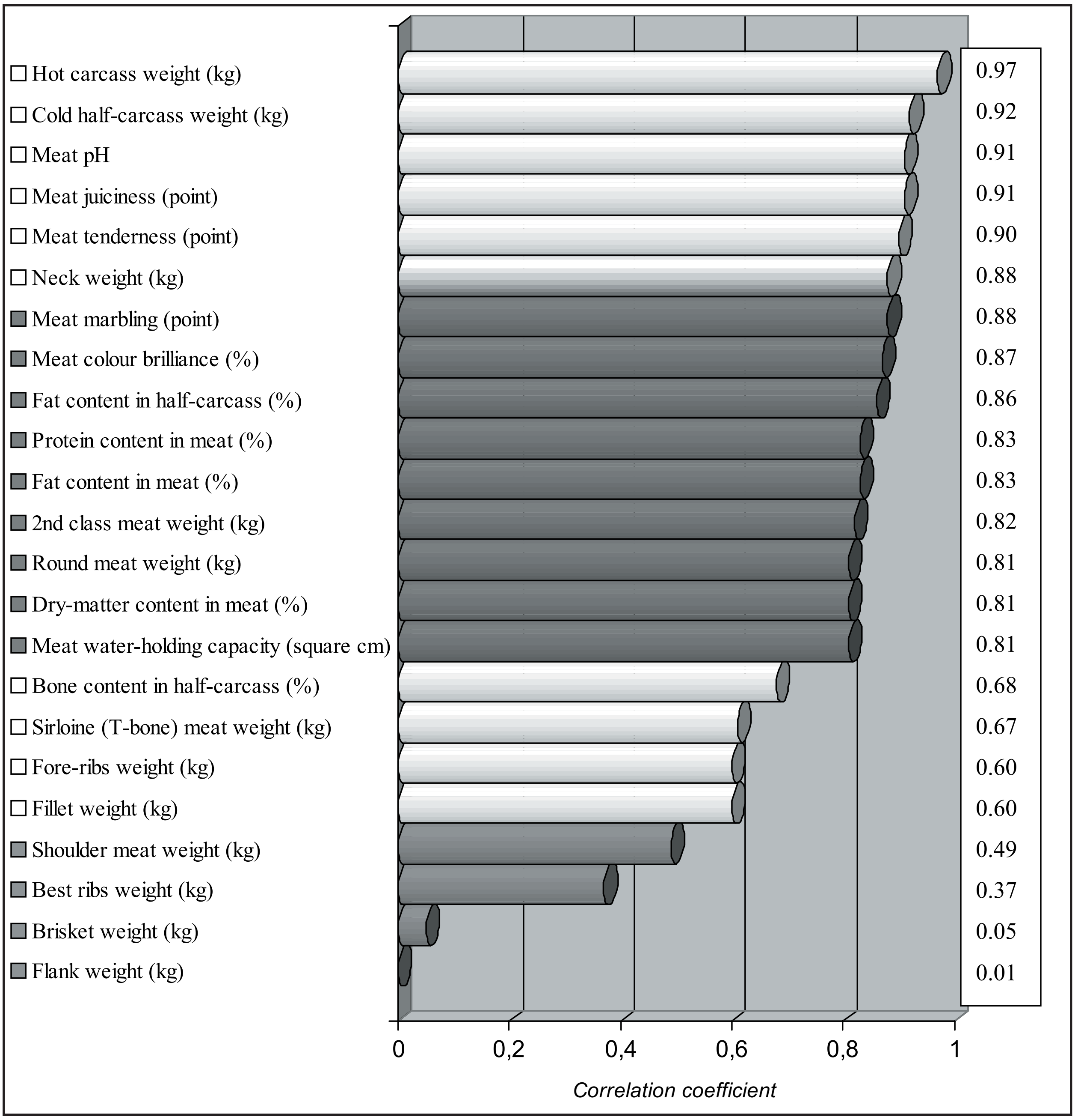

Fig. 1. Coefficients of correlation between the actual values of slaughter traits and predicted by ANN

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