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# PREDICTION OF CARCASS MEAT PERCENTAGE IN YOUNG PIGS USING LINEAR REGRESSION MODELS AND ARTIFICIAL NEURAL NETWORKS*

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**Abstract**

**One of the approaches to improving performance testing of pigs is to look for mathematical solutions to increase the accuracy of calculations. This is mainly done through improvement of linear regression equations based on current data on performance tested pigs in Poland. The advances in computer technology and the improvements in mathematical analysis have made it possible to use artificial neural networks (ANNs) for prediction of carcass meat percentage in young pigs. The aim of the study was to compare the potential for live estimation of carcass meat percentage in pigs using two computational methods: linear regression equations and ANNs. The experiment used 654 gilts of six breeds, which were subjected to performance testing and slaughter analysis at the Pig Performance Testing Station (SKURTCh). The collected data were used to train ANNs to estimate carcass meat percentage in young pigs. Training was performed using the Levenberg-Marquardt algorithm. Next, meatiness estimated by ANNs was compared with the results obtained using linear modelling. It is concluded that based on the fattening and slaughter performance test results of live pigs, artificial neural networks (SSN23) are significantly more accurate in estimating carcass meat percentage in young pigs compared to the three-variable linear regression model 1. The difference in meatiness estimation between SSN23 and the four-variable linear regression model 2 was statistically non-significant in most of the breeds except Duroc and Pietrain, where the meatiness of young animals was estimated more accurately by the linear regression model.**

**Key words: pigs, performance testing of animals, carcass meat percentage, regression equations, artificial neural networks**

One of the approaches to improving performance testing of pigs is to look for mathematical solutions to increase the accuracy of calculations. This is mainly done

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through improvement (updating) of linear regression equations based on the latest data on performance tested pigs in Poland (Lisiak and Borzuta, 2014). Advances in computer technology and improvements in mathematical analysis have recently made it possible to use artificial neural networks (ANNs) for prediction of carcass meat percentage in young pigs. ANNs have been applied to solve nonlinear problems and could provide an alternative to the computational methods employed to date. Today, ANNs are widely used to solve economic, industrial or medical problems (digital image analysis). This new tool (ANNs) has had relatively little application in breeding issues. However, if the set objective states that the application of artificial neural networks will result in the classification or approximation of results, ANNs have no limitations in this regard and the use of this technique should prove satisfactory with a sufficient amount of information (Ichikawa, 2003). An example of such breeding applications of ANNs in pigs are studies by Xin (1999) and Stricklin et al. (1998), which used this technique for piglet behaviour control. Interesting results were presented by Berg et al. (1998), who concluded that advanced computer logic systems (ANNs) based on data from electromagnetic scans of pork carcasses have the capacity to improve carcass classification on the slaughter line in relation to traditional classification based on prediction assisted by linear regression equations. The analogous advantage of ANN-assisted classification over the classification based on linear regression was reported by Hervas et al. (1994) who analysed near infrared spectroscopy results for classification of Iberian pig carcasses. We do not know of any prior use of ANNs for evaluating carcasses in live animals and for predicting carcass meat percentage.

The aim of the study was to compare the potential for live estimation of carcass meat percentage in pigs using two computational methods: linear regression equations and ANNs.

## Material and methods

The experiment used 654 gilts of six breeds (Polish Large White – 161, Polish Landrace – 251, Puławska – 29, Hampshire – 12, Duroc – 99, Pietrain – 102), which were subjected to performance testing and slaughter analysis at the Pig Performance Testing Station (SKURTCh). Gilts were fattened until 100 kg of body weight. At this weight, they were subjected to live evaluation according to Eckert et al. (2014). Data were obtained on body weight (M [kg]), age (W [days]), daily gain (P [g/day]), P2 [mm] – backfat thickness behind the last rib, 3 cm off the dorsal midline, P4 [mm] – backfat thickness behind the last rib, 8 cm off the dorsal midline, and loin eye height (P4M [mm]) was measured at P4. Next, the gilts were slaughtered according to the station's procedure (Różycki and Tyra, 2010). Right half-carcasses were divided into primal cuts (ham, shoulder, neck, loin, tenderloin, belly, ribs and knuckle). These cuts were subjected to detailed dissection by isolating muscle, fat and bone tissue. The detailed dissection enabled carcass meat percentage E1 [%] to be determined using the formula:

$$E1=E2*100/(Ma+Mb+Mc+Md+Me+Mf+Mg+Mh)$$

where:

*E2* – meat weight of primal cuts,
*Ma* – weight of ham,
*Mb* – weight of shoulder,
*Mc* – weight of neck,
*Md* – weight of loin,
*Me* – weight of tenderloin,
*Mf* – weight of belly,
*Mg* – weight of ribs,
*Mh* – weight of knuckle.

Data were divided into input basic variables (P2, P4, P4M), input explanatory variables (M, P, W), input context variables ($Y_1$ – group variable based on body weight, $Y_2$ – group variable based on weight gains, $Y_3$ – group variable based on age, $Y_4$ – breed of animals) and an estimator variable (dissected carcass meat percentage (E1)).

The data were subjected to statistical analysis using Statistica and Matlab programs. The material was analysed for all the breeds together. Pearson's correlations between variables were estimated for the collected data. In the next stage, neural networks were trained. A total of 200 experiments were conducted in which:

a) The data set was randomly partitioned into three sets: a training set (70%); a validation set (15%) – used during training to check if the error increased; and a test set (15%) – used after discontinuation of training to evaluate the quality of the trained network.

b) Network training with a single hidden layer, with 3 to 14 neurons in the hidden layer with hyperbolic tangent as the activation function, and 1 neuron in the input layer with the linear activation function. Training was performed using the Levenberg-Marquardt algorithm.

After training 200 networks, errors and correlations were calculated for different network models using the training and test sets, and selection was made of 20% of the best networks with the smallest generalisation error on the test set. The mean absolute error (MAE) and the correlation (R) between prediction and the input variable value on the training and test sets were calculated.

In the first ANN training step, the input data were the basic variables from the current linear model, i.e. P2, P4, P4M. Next, the range of input data for the networks was gradually extended with explanatory variables and context variables. This produced 23 ANN models. Model SSN2 contained basic input data + explanatory variable M; Model SSN3 – basic input data + variable P; Model SSN4 – basic input data + variable W; Models SSN5 to SSN8 – different combinations of basic and explanatory variables; Model SSN9 – basic input data + context variable Y1; Models SSN10, SSN11 and SSN12 – basic input data + context variables Y2, Y3 and Y4, respectively. Models SSN13 to SSN22 – basic input data + different combinations of context variables; Model SSN23 accounted for all the variables.

Finally, the estimates of pig carcass meat percentage based on linear regression equations were compared with the results obtained using ANN-based models. The following two new regression models, developed using the current pig population as part of the project no. N N311 082240, were used for comparisons:

Model 1 had the following parameters: R=0.63, RSE=3.33, MAE=2.55
M% = –0.6039P2 – 0.1775P4 + 0.133P4M + 61.0996.

Model 2, which included breed, had the following parameters: R=0.71, RSE=3.02, MAE=2.26
for Polish Large White M% = –0.4558P2 – 0.1782P4 + 0.0473P4M + 62.6604
for Polish Landrace M% = –0.4558P2 – 0.1782P4 + 0.0473P4M + 64.1835
for Puławska M% = –0.4558P2 – 0.1782P4 + 0.0473P4M + 63.124
for Hampshire M% = –0.4558P2 – 0.1782P4 + 0.0473P4M + 61.3725
for Duroc M% = –0.4558P2 – 0.1782P4 + 0.0473P4M + 61.2038
for Pietrain M% = –0.4558P2 – 0.1782P4 + 0.0473P4M + 66.8366

where:
M% – carcass meat percentage,
P2, P4, P4M – input basic variables.

Comparative analysis was performed based on significant differences in relation to carcass meat percentage from detailed dissection (E1) using T-test for dependent variables.

## Results

In total, 654 gilts of six breeds were investigated. On the day of measurement, the animal material was characterised by a mean body weight of about 101 kg, midline (P2) and side (P4) backfat thickness of about 11 mm, and carcass meat percentage (determined based on detailed dissection) averaging 58.68%, with minimum and maximum values of 40.23% and 71.40%, respectively (Table 1).

Table 1. Means (μ), minima, maxima and standard deviation (SD) for experimental traits of all pig breeds

| Trait | N = 654 | μ | Minimum | Maximum | SD |
|---|---|---|---|---|---|
| M | Body weight (kg) | 101.43 | 95 | 118 | 2.77 |
| P | Daily gain (g/day) | 614.28 | 406 | 944 | 77.98 |
| W | Age at slaughter (days) | 167.72 | 107 | 251 | 21.33 |
| P2 | Backfat thickness at P2 (mm) | 11.83 | 6 | 24 | 3.29 |
| P4 | Backfat thickness at P4 (mm) | 11.07 | 3 | 40 | 3.19 |
| P4M | Loin eye height at P4M (mm) | 50.24 | 36 | 86 | 6.46 |
| E1 | Carcass meat percentage from detailed dissection (%) | 58.68 | 40.23 | 71.40 | 4.43 |

Table 2. Coefficients of Pearson's correlation between variables, estimated for all breeds

| | P | W | P2 | P4 | P4M | E1 |
|---|---|---|---|---|---|---|
| M | 0.015240 | 0.183239** | 0.139500** | 0.058864 | 0.129828** | –0.014247 |
| P | | –0.961264** | 0.252064** | 0.206962** | –0.080609* | –0.302438** |
| W | | | –0.222379** | –0.199768** | 0.107995** | 0.294254** |
| P2 | | | | 0.777858** | –0.213701** | –0.590319** |
| P4 | | | | | –0.289542** | –0.533694** |
| P4M | | | | | | 0.327356** |

*Significant correlation coefficient at P≤0.05; ** at P≤0.01.

Table 3. Means (μ) and minimum and maximum values of the error (MAE) and coefficient of correlation (R) for carcass meat percentage (E1) estimated by 200 artificial neural networks according to models SSN2-SSN23 using the training and test sets

| Model | TRAIN* | | | | | | TEST** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MAE | | | R | | | MAE | | | R | | |
| | μ | Min | Max | μ | Min | Max | μ | Min | Max | μ | Min | Max |
| SSN2 | 2.433 | 2.017 | 16.616 | 0.700 | –0.382 | 0.794 | 2.661 | 1.866 | 17.841 | 0.603 | –0.342 | 0.822 |
| SSN3 | 2.394 | 1.993 | 10.648 | 0.704 | –0.165 | 0.795 | 2.608 | 1.870 | 13.160 | 0.611 | –0.293 | 0.835 |
| SSN4 | 2.402 | 1.991 | 9.948 | 0.703 | –0.487 | 0.791 | 2.609 | 1.834 | 10.417 | 0.610 | –0.436 | 0.827 |
| SSN5 | 2.373 | 1.919 | 30.489 | 0.715 | –0.067 | 0.814 | 2.625 | 1.818 | 31.767 | 0.616 | –0.179 | 0.822 |
| SSN6 | 2.361 | 1.897 | 18.826 | 0.714 | –0.278 | 0.812 | 2.615 | 1.773 | 17.593 | 0.616 | –0.339 | 0.812 |
| SSN7 | 2.387 | 1.918 | 18.532 | 0.708 | –0.387 | 0.804 | 2.613 | 1.848 | 17.229 | 0.607 | –0.526 | 0.822 |
| SSN8 | 2.344 | 1.937 | 6.889 | 0.717 | –0.093 | 0.811 | 2.593 | 1.726 | 9.923 | 0.615 | –0.346 | 0.813 |
| SSN9 | 2.389 | 1.974 | 7.033 | 0.701 | –0.014 | 0.809 | 2.635 | 1.933 | 8.205 | 0.608 | –0.057 | 0.804 |
| SSN10 | 2.383 | 1.985 | 4.123 | 0.701 | 0.210 | 0.803 | 2.637 | 1.985 | 6.974 | 0.605 | –0.043 | 0.809 |
| SSN11 | 2.379 | 1.987 | 3.767 | 0.699 | 0.217 | 0.802 | 2.611 | 1.911 | 4.878 | 0.609 | 0.012 | 0.825 |
| SSN12 | 2.182 | 1.818 | 5.349 | 0.755 | 0.135 | 0.837 | 2.391 | 1.715 | 5.468 | 0.683 | 0.083 | 0.855 |
| SSN13 | 2.385 | 1.746 | 15.034 | 0.696 | 0.081 | 0.836 | 2.755 | 2.054 | 15.304 | 0.576 | 0.089 | 0.828 |
| SSN14 | 2.364 | 1.758 | 4.514 | 0.699 | 0.097 | 0.839 | 2.716 | 1.939 | 8.359 | 0.586 | –0.059 | 0.801 |
| SSN15 | 2.163 | 1.677 | 3.391 | 0.755 | 0.234 | 0.865 | 2.484 | 1.785 | 3.675 | 0.664 | 0.265 | 0.854 |
| SSN16 | 2.377 | 1.856 | 3.496 | 0.698 | 0.216 | 0.820 | 2.696 | 2.003 | 3.920 | 0.588 | 0.133 | 0.808 |
| SSN17 | 2.189 | 1.609 | 6.616 | 0.748 | 0.127 | 0.876 | 2.499 | 1.809 | 6.668 | 0.661 | 0.055 | 0.854 |
| SSN18 | 2.183 | 1.639 | 19.449 | 0.749 | 0.136 | 0.858 | 2.471 | 1.841 | 18.325 | 0.667 | 0.041 | 0.835 |
| SSN19 | 2.396 | 1.551 | 3.998 | 0.686 | –0.082 | 0.862 | 2.799 | 2.024 | 4.352 | 0.563 | –0.110 | 0.795 |
| SSN20 | 2.202 | 1.525 | 10.963 | 0.742 | –0.158 | 0.889 | 2.573 | 1.784 | 10.412 | 0.641 | –0.223 | 0.845 |
| SSN21 | 2.182 | 1.403 | 3.827 | 0.746 | 0.207 | 0.902 | 2.554 | 1.755 | 4.204 | 0.644 | 0.144 | 0.846 |
| SSN22 | 2.225 | 1.520 | 3.609 | 0.734 | 0.245 | 0.886 | 2.586 | 1.845 | 4.112 | 0.635 | 0.049 | 0.832 |
| SSN23 | 2.231 | 1.367 | 3.948 | 0.730 | 0.161 | 0.903 | 2.648 | 1.848 | 3.962 | 0.618 | 0.087 | 0.832 |

*TRAIN – training set.
**TEST – test set.

The coefficients of correlation estimated for all the breeds under study (Table 2) show that carcass meat percentage (E1) determined from detailed dissection is significantly (P≤0.01) correlated mainly with P2 and P4 backfat thickness, and to a lesser extent with loin muscle depth, and weight gain and age on the measurement day. The highest correlation coefficient was estimated between daily gain and age on the day of measurement (r = –0.9613).

Out of the SSN2–SSN23 models (Table 3) estimating carcass meat percentage (E1), the minimum absolute error for the training set was lowest for model SSN23 ($MAE_U$ =1.367), and the maximum error for this model was $MAE_U$=3.948. At the same time, model SSN23 estimated meatiness for the training set with the highest maximum accuracy of $R_U$=0.903. When analysing the errors and correlations estimated for this model on the training set, it was found that model SSN23 achieved one of the better results (minimum $MAE_T$=1.848, maximum $MAE_T$=3.962, maximum $R_T$=0.832). It was only bested by model SSN15 for which slightly lower minimum and maximum $MAE_T$ error and slightly higher minimum and maximum correlation on the test set were obtained ($MAE_{TMIN}$=1.785, $MAE_{TMAX}$=3.675, $R_{MIN}$=0.265, $R_{MAX}$=0.854, respectively).

Next, for models SSN15 and SSN23, out of the 200 networks estimating carcass meat percentage (E1) with different neuron numbers, 20% of the best networks (Top20%) were chosen according to the smallest generalisation error on the test set (Table 4). This classification was made to determine the most advantageous number of neurons per hidden layer of artificial neural networks. For these models, errors (MAE) and correlations (R) were calculated on the training and test sets. Based on the results obtained for the mean absolute error and the correlation with the input value, determined for different models and different number of neurons, it was found that increasing the number of neurons per hidden layer of each analysed model does not contribute to a considerable decrease in MAE error and to an increase in the correlation coefficient on the test set. The values of these parameters for model SSN15 ranged from $MAE_T$=2.2 (with 3 neurons) to $MAE_T$=2.1 (with 14 neurons), and the correlation was $R_T$=0.73 and $R_T$=0.74, respectively. In the case of model SSN23, the error and correlation values on the test set were $MAE_T$=2.2, $R_T$=0.72 (with 3 neurons) and $MAE_T$=2.3, $R_T$=0.69 (with 14 neurons).

Table 4. Results for 20% of the best networks of models SSN15 and SSN23 estimating carcass meat percentage (E1) with different neuron numbers in the hidden layer. Errors (MAE) and coefficients of correlation (R) estimated on the training (TRAIN) and test (TEST) sets

| No. of neurons | TRAIN | | TEST | |
|---|---|---|---|---|
| | MAE | R | MAE | R |
| | **SSN15** | | | |
| 3 | 2.238 | 0.738 | 2.183 | 0.726 |
| 14 | 2.055 | 0.788 | 2.143 | 0.740 |
| | **SSN23** | | | |
| 3 | 2.131 | 0.760 | 2.209 | 0.722 |
| 14 | 2.076 | 0.777 | 2.336 | 0.687 |

The data presented in Table 5 concerning the mean differences in estimating pig carcass meat percentage (M%) by selected models in relation to the value of this trait determined from dissection (E1) show that in model 1 it was overestimated by 0.9% ($P \leq 0.01$), 1.8% ($P \leq 0.05$) and 2.0% ($P \leq 0.01$) in PLW, Hampshire and Duroc breeds, respectively, and underestimated by –0.5% and –2.3% ($P \leq 0.01$) in PL and Pietrain breeds, respectively. In each of the analysed breeds, this parameter was estimated very accurately by model 2, and the difference of –0.0004% for most of the breeds was not significant. Model SSN23 also gave very good estimates for carcass meat percentage in the pigs of each analysed breed. Differences between the estimated and actual values were non-significant and ranged from –0.4% in Pietrain to 0.34% in Duroc.

Table 5. Mean carcass meat percentage in pigs of various breeds, estimated by selected models, as well as the mean difference in meatiness estimation using these models, in relation to E1 value from detailed dissection of the pigs

| | Breed | | | | | | Total breeds |
|---|---|---|---|---|---|---|---|
| | PLW | PL | Puławska | Hampshire | Duroc | Pietrain | |
| Meat content from dissection E1 (%) | 57.33±4.12 | 59.34±3.03 | 56.35 ±3.08 | 54.65 ±2.28 | 55.33±3.80 | 63.57±4.15 | 58.68±4.43 |
| Model 1:<br>P2 + P4 + P4M | 58.22±2.53 | 58.83±2.39 | 56.34 ±3.09 | 56.43 ±2.28 | 57.34±2.28 | 61.24±2.60 | 58.68±2.79 |
| Model 2:<br>P2 + P4 + P4M + breed | 57.33±1.92 | 59.34±1.84 | 56.36 ±2.31 | 54.65 ±1.72 | 55.33±1.78 | 63.57±1.86 | 58.68±3.17 |
| Model SSN23 | 57.39±2.10 | 59.31±2.06 | 56.51 ±2.19 | 54.81 ±0.85 | 55.67±1.92 | 63.18±1.84 | 58.68±3.10 |
| Difference | | | | | | | |
| Model 1 vs. E1 | 0.8917±3.70** | –0.4989±2.74** | –0.0087±2.11 | 1.7819±2.69* | 2.0059±2.93** | –2.3286±3.73** | 0.0008±3.44 |
| Model 2 vs. E1 | –0.0004±3.64 | –0.0004±2.63 | –0.0004±1.93 | –0.0004±2.69 | –0.0003±3.00 | –0.0003±3.57 | –0.0004±3.08 |
| Model SSN23 vs. E1 | 0.0568±3.22 | –0.031±2.41 | 0.1563±1.87 | 0.1667±2.02 | 0.3409±2.74 | –0.3905±3.34 | 0.0029±2.80 |

*Significant difference at $P \leq 0.05$; ** at $P \leq 0.01$.

To determine significant differences between the carcass meat percentage estimated with linear modelling and neural network modelling, another comparative analysis was performed using T-test for dependent variables. The results are shown in Table 6. The analysis performed for all breeds together showed no significant differences between selected models. When analysing each breed separately, it was found that for most breeds (except Puławska) there are statistically significant differences between linear models 1 and 2, and between models 1 and SSN23. No significant differences were noted between models 2 and SSN23 for PLW, PL, Puławska and Hampshire breeds. In Duroc and Pietrain, the difference between these models proved statistically significant (P≤0.01).

Table 6. Differences ± SD and significant differences (P-Value) in estimating carcass meat percentage in pigs of various breeds between (vs.) linear regression models and artificial neural networks

| | Difference (%) | SD of the difference | P-value |
|---|---|---|---|
| | **PLW** | | |
| Model 1 vs. Model 2 | 0.8920 | 0.68 | **0.0000** |
| Model 1 vs. SSN23 | 0.8348 | 1.29 | **0.0000** |
| Model 2 vs SSN23 | –0.0571 | 1.05 | 0.4939 |
| | **PL** | | |
| Model 1 vs. Model 2 | –0.4985 | 0.67 | **0.0000** |
| Model 1 vs. SSN23 | –0.4682 | 1.10 | **0.0000** |
| Model 2 vs. SSN23 | 0.0304 | 0.89 | 0.5903 |
| | **Puławska** | | |
| Model 1 vs. Model 2 | –0.0083 | 0.83 | 0.9576 |
| Model 1 vs. SSN23 | –0.1650 | 1.15 | 0.4471 |
| Model 2 vs. SSN23 | –0.1567 | 0.65 | 0.2049 |
| | **Hampshire** | | |
| Model 1 vs. Model 2 | 1.7822 | 0.74 | **0.0000** |
| Model 1 vs. SSN23 | 1.6152 | 1.49 | **0.0031** |
| Model 2 vs. SSN23 | –0.1670 | 1.06 | 0.5952 |
| | **Duroc** | | |
| Model 1 vs. Model 2 | 2.0062 | 0.60 | **0.0000** |
| Model 1 vs. SSN23 | 1.6650 | 1.12 | **0.0000** |
| Model 2 vs. SSN23 | –0.3412 | 0.88 | **0.0002** |
| | **Pietrain** | | |
| Model 1 vs. Model 2 | –2.3282 | 0.86 | **0.0000** |
| Model 1 vs. SSN23 | –1.9381 | 1.39 | **0.0000** |
| Model 2 vs. SSN23 | 0.3902 | 0.86 | **0.0000** |
| | **Total breeds** | | |
| Model 1 vs. Model 2 | 0.0012 | 1.52 | 0.9844 |
| Model 1 vs. SSN23 | –0.0021 | 1.66 | 0.9745 |
| Model 2 vs. SSN23 | –0.0032 | 0.94 | 0.9301 |

## Discussion

The present study indicates the appropriateness of using backfat thickness (P2, P4) and loin eye height (P4M) measurements as well as daily gains and age on test day as input variables for estimating carcass meat percentage in young pigs, because these variables were found to be highly significantly correlated to the carcass meat percentage determined from detailed dissection. In all the breeds changes in loin eye height, as well as changes in daily gain and age on test day, have less impact on changes in estimated trait values compared to backfat thickness measurements. The coefficients of correlation observed between P2, P4, P4M measurements and carcass meat percentage are consistent with the findings of other authors. Klimas et al. (2004), Szyndler-Nędza and Eckert (2008), and Radović et al. (2013) reported the correlation coefficients estimated between live measurements of backfat thickness and carcass meat percentage in pigs to range from r = –0.510 to r = –0.950. In the same studies, the correlations between *longissimus* muscle depth and carcass muscle content were lower and ranged from r=0.186 to r=0.523.

During the Artificial Neural Network training process, in addition to constant parameters (input and output variables), it is necessary to determine variable parameters, namely the number of hidden layers (one or more) and the number of neurons in a hidden layer. Establishing the appropriate number of neurons has an effect on the ANN training result. If the number of neurons is too small, ANNs will fail to reproduce all the nuances of a task in its structure. A large number of neurons will lead to the undesirable effect of 'learning by memorising', when the network remembers the rules instead of generalising the acquired information (Migdał-Najman and Najman, 2000; Ślipek et al., 2003). ANN training performed in the present study showed that increasing the number of neurons from 3 to 14 in a hidden network layer of each analysed model has little effect on reducing the MAE error and on increasing the correlation coefficient on the training set. The mean absolute error and the correlation coefficient on the test set for these models were also similar, regardless of the number of neurons in a hidden layer.

It is thought that any number of input variables for ANN can be used, but they should not be excessive because this increases the cost of research needed to obtain sufficient amounts of data. On the other hand, increasing the number of input variables for the networks may enable better description of the modelling process and increase ANN accuracy (Ślipek et al., 2003). In the present study, we found that individual extension of the number of input variables with explanatory and context variables (models SSN2-SSN11) had little effect on improving the estimation parameters of carcass meat percentage. The models that used a combination of context variables (SSN12-SSN22) as well as model SSN23 containing all available variables estimated this parameter with a smaller mean absolute error and with a higher coefficient of correlation. Differences in the MAE and R values on the test set between SSN12 and SSN23 models were relatively small. Therefore, for further analyses we chose one ANN model (SSN23), for which the mean absolute error (with three neurons per hidden layer) on the test set was $MAE_T$=2.2, and the correlation with the output value was $R_T$=0.72. The correlation obtained for the ANN was slightly lower than that reported by Adamczyk et al., (2005) concerning the potential use of an ANN for estimating the dressing percentage of bulls based on their growth parameters. In the cited work, artificial neural networks were trained on data from 104 bulls, based on 10 000 training cycles with 30 neurons per hidden layer, and the estimated correlation coefficient for the ANN model estimating the weight of half-carcass meat (kg) was R=0.82.

The parameters estimated in our study for model SSN23 proved better than the newly-developed linear regression model estimating E1 based on basic variables P2, P4, P4M (model 1, MAE=2.6, R=0.63). The mean absolute error (MAE) and the correlation (R) for artificial neural networks were slightly better than the MAE and R values obtained for linear model 2, which in addition to basic variables also accounted for the breed variable (MAE=2.3, R=0.71). From this it may be concluded that estimation of carcass meat percentage based on live measurements of young pigs will be more accurate if the ANN model is used. The advantage of ANN modelling over linear regression was also reported by Berg et al. (1998), who determined pork carcass composition on the slaughter line using electromagnetic scanning. The authors concluded that ANN models estimating carcass meat weight (kg), ham weight (kg) and loin weight (kg) are characterised by smaller estimation error than analogous regression equations.

In order to determine the magnitude of the difference in the estimation accuracy of carcass meat percentage (M%) between the linear regression and ANN models, the results of this parameter estimated by the above models were compared to the actual carcass meat percentage (E1) determined from detailed dissection (Table 5). Unlike the linear regression model 1 (accounting for three basic variables: P2, P4 and P4M), model 2 (accounting for four variables: P2, P4, P4M and context variable of breed: $Y_4$) as well as the artificial neural network model SSN23 were found to estimate M% with high accuracy, while the estimates did not differ significantly from the actual carcass meat percentage. In addition, comparative analysis of the estimation results of M% in different breeds between the linear regression models and the ANN model (Table 6) revealed that most of the breeds show statistically significant differences mainly between models 1 and SSN23. No significant differences were noted between the linear regression model 2 and model SSN23 except for Duroc and Pietrain. In the Duroc breed, SSN23 overestimated this parameter in relation to model 2 and the actual carcass meat percentage (E1) by 0.34%, and in the Pietrain breed SSN23 underestimated this value by 0.39%. Overall, it can be stated that the best model for estimating carcass meat percentage in Duroc and Pietrain pigs is the four-variable linear regression model 2, while in the other breeds carcass meat percentage is estimated equally well by the artificial neural network model SSN23.

Contrary to our results, Hervas et al. (1994), who classified half-carcasses from Iberian pigs based on near infrared spectroscopy of fat samples, demonstrated that the ANN model was more accurate in grouping the half-carcasses compared to the linear regression models. It should be noted, however, that the use of artificial neural networks for estimating selected traits will not always produce satisfactory results. Several studies did not yield the expected results in the form of better prediction accuracy compared to the linear regression models (Kumar, 2005; Paliwal and Kumar, 2009). This is often due to insufficient input data, limited training set, small correlation between the input data and the expected result, and also occurs when the dependent variables are skewed (SubbaNarasimha et al., 2000). Furthermore, a well-known problem associated with the back propagation algorithm is the presence of local minima in the minimised error measure function, and the networks are also prone to overfitting (Adya and Collopy, 1998).

In summing up the results of the present study, it is concluded that based on the fattening and slaughter performance test results of live pigs, artificial neural networks (SSN23) are significantly more accurate in estimating carcass meat percentage in young pigs compared to the three-variable linear regression model 1. The difference in meatiness estimation between SSN23 and the four-variable linear regression model 2 was statistically non-significant in most of the breeds except Duroc and Pietrain, where the meatiness of young animals was estimated more accurately by the linear regression model.

**References**

Adamczyk K., Molenda K., Szarek J., Skrzyński G. (2005). Prediction of bulls' slaughter value from growth data using artificial neural network. J. Centr. Europ. Agric., 6: 133–142.

Adya M., Collopy F. (1998). How effective are neural networks at forecasting and prediction? A review and evaluation. J. Forecast., l; 481–495.

Berg E.P., Engel B.A., Forrest J.C. (1998). Pork carcass composition derived from a neural network model of electromagnetic scans. J. Anim. Sci., 76: 18–22.

Eckert R., Żak G., Bereta A. (2014). Results of performance tested gilts (in Polish). Report on pig breeding in Poland. Kraków, IZ PIB XXXII: 35–48.

Hervas C., Garrido A., Lucena B., Garcia N., De Pedro E. (1994). Near infrared spectroscopy for classification of Iberian pig carcasses using an artificial neural network. J. Near Infrared Spectrosc., 2: 177–184.

Ichikawa H. (2003). Hierarchy neural networks as applied to pharmaceutical problems. Advanc. Drug Deliv. Rev., 55: 1119–1147.

Klimas R., Klimiene A., Rimkevicius S. (2004). Efficiency of breeding pigs selection according to phenotypic evaluation of meatiness. Vet. Zoot., 27: 79–86.

Kumar U.A. (2005). Comparison of neural networks and regression analysis: A new insight. Expert Syst. with Applic., 29: 424–430.

Lisiak D., Borzuta K. (2014). The influence of the SEUROP grade and weight of pig carcasses on lean meat content evaluated using regression equations from 2003 and 2011 (in Polish). Rocz. Nauk. PTZ, 10: 65–75.

Migdał-Najman K., Najman K. (2000). Neural networks, use for forecasting WIG (in Polish). Katedra Statystyki, Wydział Zarządzania, Uniwersytet Gdański, pp. 1–17. http://panda.bg.univ.gda.pl/~prezes/WWW_A_moze_sieci_neuronowe.pdf

Paliwal M., Kumar U.A. (2009). A study of academic performance of business school graduates using neural network and statistical techniques. Expert Syst. with Applic., 36: 7865–7872.

Radović Č., Petrović M., Živković B., Radojković D., Parunović N., Brkić N., Delić N. (2013). Heritability, phenotypic and genetic correlations of the growth intensity and meat yield of pigs. Biotech. Anim. Husb., 29: 75–82.

Różycki M., Tyra M. (2010). Methodology for evaluating the value of fattening and slaughter pigs carried out in the stations of performance control slaughter pigs (SKURTCh) (in Polish). Report on pig breeding in Poland. IZ PIB XXVIII: 93–117.

Stricklin W.R., de Bourcier P., Zhou J.Z., Gonyou H.W. (1998). Artificial pigs in space: using artificial intelligence and artificial life techniques to design animal housing. J. Anim. Sci., 76: 2609–2613.

SubbaNarasimha P.N., ArinzeB., Anandarajan M. (2000). The predictive accuracy of artificial neural networks and multiple regression in the case of skewed data: Exploration of some issues. Expert Syst. Applic., 19: 117–123.

Szyndler-Nędza M., Eckert R. (2008). Relationships between live measurements of backfat and longissimus dorsi thickness and fatness as well as muscularity of carcass, ham and loin of boars and gilts (in Polish). Rocz. Nauk. PTZ., 4: 103–113.

Ślipek Z., Francik S., Frączek J. (2003). Methodic aspects of creating ANN models in agrophysical research (in Polish). Acta Agrophysica, 2: 231–241.

Xin H. (1999). Assessing swine thermal comfort by image analysis of postural behaviors. J. Anim. Sci., 77: 1–9.

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