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Assessment of goat fat depots using ultrasound technology and multiple multivariate prediction models[1]

A. M. Peres,*† L. G. Dias,* M. Joy,‡ and A. Teixeira*[2]

*Mountain Research Centre and †Laboratory of Separation and Reaction Engineering, Escola Superior Agrária, Instituto Politécnico de Bragança, Quinta de Santa Apolónia, Apartado 1172, 5301-855 Bragança, Portugal; and ‡Unidad de Tecnologia en Producción Animal, Centro de Investigación y Tecnologia Agroalimentaria de Aragón, Zaragoza, Spain

ABSTRACT: Assessment of fat depots for several goat body parts is an expensive and time-consuming task requiring a trained technician. Therefore, the establishment of models to predict fat depots based on data requiring simpler and easier procedures, such as ultrasound measurements, that could be carried out in vivo, would be a major advantage. An interesting alternative to the use of multiple linear regression models is the use of partial least squares or artificial neural network models because they allow the establishment of one model to simultaneously predict different fat depots of interest. In this work, the applicability of these models to simultaneously predict 7 goat fat depots (subcutaneous fat, intermuscular fat, total carcass fat, omental fat, kidney and pelvic fat, mesenteric fat, and total body fat) was investigated. Although satisfactory correlation and prediction results were obtained using the multiple partial least squares model (cross-verification and validation R^2 and standard prediction error values between 0.66 and 0.98 and 247 and 2,168, respectively), the best global correlation and prediction performances were achieved with the multiple radial basis function artificial neural network (verification and validation R^2 and standard prediction error values between 0.82 and 0.96 and 304 and 1,707, respectively). These 2 multiple models allowed correlating and predicting simultaneously the 7 goat fat depots based on the goat BW and on only 2 ultrasonic measures (lumbar subcutaneous fat between fifth and sixth vertebrae and the fat depth at the third sternebra). Moreover, both multiple models showed better results compared with those obtained with multiple linear regression models proposed in previous work.

Key words: artificial neural network, carcass fat composition prediction, goat, partial least squares, ultrasound technology

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INTRODUCTION

In recent years, an effort has been made to improve the prediction of body or carcass fat composition based on real-time ultrasonic data. This noninvasive technique with multivariate models provides a suitable method to accurately predict fat or muscle depots (Silva et al., 2006; Hopkins et al., 2007; Teixeira et al., 2008). Recently, multiple linear regression (**MRL**) models were proposed to estimate muscle and goat fat depots (Teixeira et al., 2008). However, some overall practical drawbacks can be pointed out: 1) one MRL model was required to estimate each carcass content; 2) in total, 5 ultrasound measurements had to be recorded, which is not practical to implement in the field; 3) some dependent or independent variables or both had to be transformed using a logarithmic scale; and 4) no data were used to validate the proposed models.

To overcome these limitations, more complex linear and nonlinear models can be applied: multiple partial least squares (**PLS2**) or multiple artificial neural networks (**ANN2**). In fact, PLS2 or ANN2 models have been successfully applied to estimate, at the same time, several dependent variables, namely, particle size distributions and ions and sugar concentrations in solution (Blanco and Peguero, 2008; Mahani et al., 2008; Dias et al., 2009).

In this work, the use of a unique model to estimate 7 goat fat depots, based on a reduced number of predictors, was evaluated. Two concepts were studied, namely, PLS2 and radial basis function (**RBF**) ANN2 models, based on 3 predictors: the goat BW and 2 ultrasound measurements, taken at the third sternebra

[1]In memory of R. Delfa.

[2]Corresponding author: teixeira@ipb.pt

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and between the fifth and sixth lumbar vertebrae. The experimental data were randomly split into 2 data sets, one used to establish the best multiple models and the other, not used during the model development, for validation purposes (Picard and Berk, 1990; Næs et al., 2002; Good and Hardin, 2003). To the best of the our knowledge, the simultaneous prediction of several goat fat depots based on in vivo ultrasound measurements and using multiple partial least squares (**PLS**) or artificial neural networks (**ANN**), has never been described in the literature.

MATERIALS AND METHODS

Animal Care and Use Committee approval was not obtained for this study because the data were obtained from an existing database (Delfa, 2004).

Animals and Experimental Procedures

The database from the experiment conducted by Delfa (2004) and published by Teixeira et al. (2008) was used. The BW and the goat fat depots weight (subcutaneous fat, intermuscular fat, mesenteric fat, omental fat, kidney and pelvic fat, total carcass fat, and total body fat) were measured on 56 adult goats. Weight of total body fat was obtained from the sum of all fat depots of the body and carcass: omental fat, mesenteric fat, kidney and pelvic fat, subcutaneous fat, and intermuscular fat. Weight of total carcass fat corresponded to the sum of subcutaneous fat, intermuscular fat, and kidney and pelvic fat depots. Only the 2 most important ultrasound measurements, according to the findings of Teixeira et al. (2008), were used for the establishment of the multiple prediction models: **US3FD** (fat depth was measured from ultrasound image taken on the third sternebra) and **UL5–6FD** (fat depth was measured from ultrasound image taken between the fifth and sixth lumbar vertebrae).

Data Analysis

The 7 goat fat depots (dependent variables) together with BW values and 2 ultrasound measurements (US3FD and UL5–6FD), used as independent variables, were employed to establish empirical PLS and ANN models. The application of these models, contrary to the MRL models, does not require the absence of multi-collinearity between the independent variables (Næs et al., 2002). All the variables (independent and dependent) were used without any mathematical treatment. The experimental fat depots data corresponding to 1.5 box-lengths beyond the upper and lower quartiles were considered outliers and were removed from the database.

PLS2 Regression Model. The multiple PLS algorithm is a linear multivariate calibration tool that can be used to estimate the 7 goat fat depots using a unique model. The PLS2 latent variables are calculated by obtaining the largest covariance between the independent (BW and 2 ultrasound measurements: US3FD and UL5–6FD) and the dependent (goat fat depots) variables. This methodology is especially suitable when the dependent variables are correlated (Blanco and Peguero, 2008). The PLS2 method handles several dependent variables by decomposing the independent and the dependent variables initial matrices into smaller matrices, corresponding to the score and loading vectors (Lozano et al., 2007; Jørgensen and Næs, 2008).

The determination of the significant PLS2 principal components (model dimensions) was made by cross-verification, using a leave-one-out methodology. A maximum number of 3 PLS2 principal components was allowed. Among them, those that minimized the least squares difference between the reference value and the measured parameter were selected. A more detailed description of PLS2 models can be found in the literature (Brereton, 2000; Lozano et al., 2007). Application of PLS2 algorithms was supported by the software package The Unscrambler 9.7 (CAMO ASA, Trondheim, Norway).

RBF-ANN2 Model. In this work a multiple neural radial-basis function network was trained using a supervised learning. These networks are very sophisticated, flexible, although complex, nonlinear modeling techniques. The RBF-ANN2 network used in this work had 3 layers (Figure 1): an input layer, a hidden layer of radial units (neurons), with exponential activation functions, and an output layer with linear units, with linear activation functions. The input layer had a maximum of 3 neurons, one for each independent variable (BW, US3FD, and UL5–6FD). The hidden layer had a variable number of hidden units, which optimal number was determined using a trial and error strategy. The output layer had a fixed number of neurons equal to the number of dependent variables studied (i.e., 7 neurons corresponding to the goat fat depots). From the RBF-ANN2 networks tested, the one that gave the best performance was retained. The networks performances were compared by computing the sum of the squared differences between the target and actual output values on each output unit. The data were processed using the commercial Statistica software (Neural Networks software, Tulsa, OK) of StatSoft Inc. (Tulsa, OK). For each network tested an automatic search for an effective subset of the specified independent variables (BW, US3FD, and UL5–6FD) was allowed.

Multiple PLS and ANN Models: Calibration and Validation. For the PLS2 and RBF-ANN2 development, the database was randomly divided to allow the validation of the models. Random data splitting was adopted because it was reported that when the observations do not form a time series, the data used for validation should be drawn at random from the entire sample (Good and Hardin, 2003). One-fourth to one-third of the entire sample data set should be set aside for validation purposes because the goodness-of-fit errors for the calibration and validation procedures

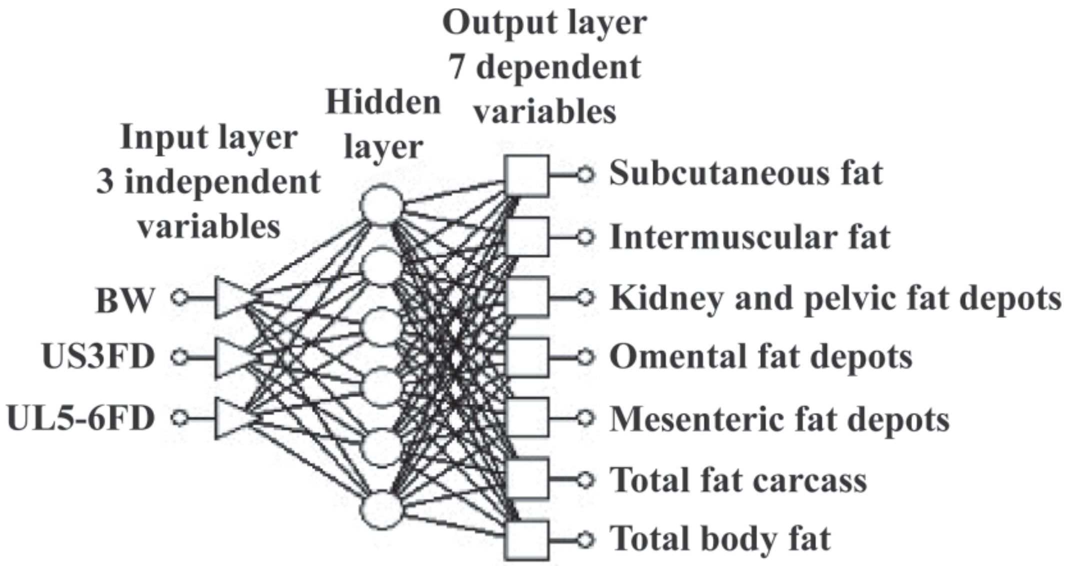

Figure 1. Diagram illustrating the structure of the RBF-ANN2 model obtained. RBF-ANN2: multiple radial basis function artificial neural network; US3FD: fat depth was measured from ultrasound image taken on the third sternebra; UL5–6FD: fat depth was measured from ultrasound image taken between the fifth and sixth lumbar vertebrae.

were based on the mean-squared sum errors (Picard and Berk, 1990; Good and Hardin, 2003). Considering the number of goats available for this study, less data were used for validation purposes. So, the experimental data were split into 2 main sets: the calibration set (44 goats corresponding to approximately 80% of the data) used for training and cross-verification or verification and, the validation set (10 goats corresponding to approximately 20% of the data).

Concerning the PLS2 model, the calibration set was used for the establishment of the regression model and for the leave-one-out cross-verification procedure. This last procedure allows the selection of a model with satisfactory regression and predictive performances. The data of the validation set, not used during the model development, were employed to evaluate the predictive capability of the PLS2 model and, so, to validate the referred model.

Regarding the RBF-ANN2 model, the calibration set was further split into 2 subsets: the training subset, constituted by approximately 80% of the calibration data, was used for training and estimating the model parameters (consisted of the data recorded for 34 goats), and the verification subset, constituted by the other 20% of the calibration data (consisting of the data recorded for 10 goats), was used to select the best network and also to verify if the model had suffered from over-fitting. This problem occurs when the network learned to model the noise but not the underlying nonlinear function that relates input to output variables. A network that shows a significant variation between training and verification mean-square errors suffers from this problem. Finally, the same validation set used for evaluating the PLS2 predictive performance was employed to evaluate the RBF-ANN2 predictive performance. The best RBF-ANN2 model was selected using sensitivity analysis technique, involving a search for an effective subset of the specified independent variables (BW, UL5–6FD, and US3FD). In this approach the sensitivity ratio for each input variable was calculated dividing the error value (representing the performance of the network if that variable was unavailable) by the baseline error (i.e., the error of the network if all variables are available). Variables with values less than 1 were removed. For network selection a series of tryouts were carried out and several RBF-ANN2 models were tested (with different number of hidden nodes). The multiple model that presented the minimum mean-squared error for the verification subset was selected.

Once the PLS2 or RBF-ANN2 model had been selected, a comparison between calibration and validation performances of the models was made, taking into account 1) the standard errors of training (**SEC**), cross-verification ($\mathbf{SEP_{CV}}$), or verification ($\mathbf{SEP_{VE}}$) and validation ($\mathbf{SEP_{VA}}$); 2) the coefficients of determination for training ($\mathbf{R^2}$), cross-verification ($\mathbf{R^2_{CV}}$), or verification ($\mathbf{R^2_{VE}}$) and validation ($\mathbf{R^2_{VA}}$); and 3) the residual predictive deviation (**RPD**). This last parameter (calculated as the relationship between the SD of the reference values of the population and the SEP_{CV} or SEP_{VE}) was also used to evaluate the predictive ability of the calibration models. It has been reported that a model with RPD values between 2 and 3 or greater than 3 possessed satisfactory or good predictive behavior, respectively (Barroco et al., 2006; Gaitán-Jurado et al., 2008; Prieto et al., 2008). It was also reported that the goodness of fit of a model that presents regression R^2 values in the range of 0.7 to 0.89 or equal to or greater than 0.9 is good or very good, respectively. Moreover, the goodness of prediction of a particular model is good if the R^2 values obtained for the validation data are greater than 0.65 (Gaitán-Jurado et al., 2008; Mandenius and Brundin, 2008).

Furthermore the PLS2 and RBF-ANN2 performances were also compared with those obtained using the MRL models proposed by Teixeira et al. (2008) to estimate each goat fat depot, using the SE values.

RESULTS AND DISCUSSION

Reference Values

The numbers of samples used, mean values, SD, as well as the range of the reference values for each fat depot analyzed used in the calibration and validation procedures of the multiple models are shown in Table 1. As can be inferred, the reference data used show increased variability for all the fat depots studied, which was required to obtain robust predictive multivariate models. The data were obtained from goats with a wide variability of BCS [varying between 1.5 and 4.5 (on a 5-point scale; Delfa et al., 1994)] and BW (57 ± 13 kg).

The exploratory descriptive analysis showed the presence of outliers for some fat depots, namely for subcutaneous fat (one outlier), intermuscular fat (2 outliers), kidney and pelvic fat depots (one outlier), total fat carcass (one outlier), and total body fat (one outlier). Two samples were identified as outliers and removed from the initial database.

Prediction Models

Characterization of the Predictive PLS2 and RBF-ANN2 Models. In PLS2 model, 3 principal components were selected for the estimation and prediction of the 7 goat fat depots, using the 3 mentioned independent variables. However, only the 2 first functions were relevant, based on the scree-plot visualization (data not shown). This model was chosen because it gave the least global standard prediction error (**SEP**) value for the 7 fat depots under study. In total, the 3 functions were able to account for 100 and 90% of the variation of the independent and the dependent variables, respectively: 88 and 83% for the first function, 10 and 3% for the second, and 2 and 4% for the third, respectively. The 3 independent variables entered, with different regression-coefficients, into all the 3 functions defined for each dependent variable in the overall PLS2 model. In general, BW was the largest contributor to the first function, and US3FD and UL5–6FD the most important independent variables for the second and third functions, respectively.

In ANN2 model, a RBF network with 3 nodes in the input layer (BW, US3FD, and UL5–6FD) and 6 nodes in the hidden layer, was selected (obtained using K-means for defining radial neuron weights; K-nearest neighbor for defining radius; and pseudo-inverse training algorithms). Twenty tryouts were performed being 50 networks, with different complexities, tested in each one. The network with the least SEP_{VE} value, which is the statistical parameter adopted to compare the performances of different types of neural networks (Gallardo et al., 2004), was retained. The results obtained for the multiple ANN regression model showed that all 3 independent variables (BW and the 2 ultrasounds measurements) presented sensitivity ratios greater than one (BW > UL5–6FD > US3FD), showing that all of them should be kept in the final multiple model.

Evaluation of the Predictive PLS2 and RBF-ANN2 Models. The performances of the PLS2 and RBF-ANN2 models were evaluated based on the SE and R^2 obtained, both for the calibration and validation steps (training, cross-verification or verification, and validation data sets). Additionally, the RPD values, calculated based on the results obtained for the cross-verification (PLS2 model) or verification (RBF-ANN2) procedures, were also used to infer about the predictive ability of the proposed multiple models.

The statistics of the PLS2 and RBF-ANN2 models used to simultaneously predict the 7 goat fat depots for the calibration (training and cross-verification or verification) and validation data sets are shown in Table 2. In this table, the SE (SEC or SEP values) and the coefficients of determination (R^2 values), as well as the residual predictive deviation (RPD values), are reported. The 2 multiple models showed, at least, good or very good fitting and prediction accuracies (for all data sets, R^2 values of PLS2 and RBF-ANN2 models were equal or greater than 0.66 or 0.81, respectively). Globally, the results obtained showed that the 2 prediction models studied provided satisfactory results based on R^2, SEC, and SEP values. Therefore, the use of 2 ultrasound measurements (US3FD and UL5–6FD) and BW values together with PLS2 or RBF-ANN2 models was an appropriate methodology to predict, at the same time, goat fat depots accurately. Nevertheless, the calibration and prediction results obtained with the RBF-ANN2 model were slightly better than those obtained with the PLS2 model. In general, greater R^2 values (between 0.81 and 0.96 and 0.66 to 0.98, for the estimation of the fat depots using RBF-ANN2 and PLS2 models, respectively), less SEC, SEP_{VE}, and SEP_{VA} values (between 298 to 1,864 g and 247 to 2,168 g, respectively) and greater RPD values (between 1.7 to 4.3 and 1.7 to 3.1, respectively) were obtained using RBF-ANN2 model. In fact, based on the RPD values obtained for the estimation of the 7 goat fat depots, the RBF-ANN2 model had good prediction capabilities (in general, RPD values greater than 3), whereas the PLS2 model only showed a satisfactory predictive performance (RPD values between 2 and 3).

The values calculated using the PLS2 and RBF-ANN2 models vs. the experimental goat fat depots for the calibration (training and cross-verification or verification) and validation data sets are presented in Figures 2 and 3. From the analysis of these figures it is clear that, although PLS2 and RBF-ANN2 models can accurately estimate and predict the fat depots the latter multiple model is slightly more accurate, showing,

Table 1. Statistics for dependent variables groups divided randomly in calibration (divided into training and cross-verification/verification data subsets) and validation data sets

Model	Item	Dependent variable, g						
		Subcutaneous	Intermuscular	Kidney and pelvic	Omental	Mesenteric	Total carcass content	Total body content
PLS2 model[1]								
Calibration set: training and cross-verification data (n = 44)	Mean	2,175	2,807	1,493	3,088	1,783	6,742	11,966
	SD	1,587	1,254	1,030	2,076	829	3,871	6,778
	Range	[114; 6,096]	[462; 5,814]	[109; 3,480]	[208; 7,724]	[439; 3,529]	[780; 14,990]	[1,572; 25,730]
Validation set (n = 10)	Mean	1,430	2,126	939	2,005	1,349	4,688	8,285
	SD	1,631	1,225	874	1,835	732	3,798	6,398
	Range	[162; 5,082]	[824; 4,354]	[159; 2,448]	[311; 5,288]	[512; 2,871]	[1,211; 11,722]	[2,445; 19,453]
RBF-ANN2 model[2]								
Calibration set: training data (n = 34)	Mean	2,110	2,771	1,499	3,061	1,813	6,648	11,881
	SD	1,483	1,286	1,020	2,044	892	3,797	6,759
	Range	[114; 6,036]	[462; 5,814]	[109; 3,284]	[208; 7,724]	[439; 3,529]	[780; 14,987]	[1,572; 25,725]
Calibration set: verification data (n = 10)	Mean	2,396	2,931	1,473	3,179	1,684	7,063	12,249
	SD	1,976	1,196	1,121	2,294	593	4,307	7,200
	Range	[694; 6,096]	[1,438; 4,914]	[409; 3,480]	[782; 5,346]	[1,133; 2,904]	[2,742; 14,425]	[4,827; 24,570]
Validation set (n = 10)	Mean	1,430	2,126	939	2,005	1,349	4,688	8,285
	SD	1,631	1,225	874	1,835	732	3,798	6,398
	Range	[162; 5,082]	[824; 4,354]	[159; 2,448]	[311; 5,288]	[512; 2,871]	[1,211; 11,722]	[2,445; 19,453]

[1]Multiple partial least squares model.
[2]Multiple radial basis function artificial neural network model.

Table 2. Statistics of the selected multiple partial least squares (PLS2) and multiple radial basis function artificial neural network (RBF-ANN2) models obtained for calibration and validation data sets

	Calibration set						
	Training data[2]		Cross-verification data[3]			Validation set[1]	
Item	SEC, g	R^2	SEP_{CV}, g	R^2_{CV}	RPD	SEP_{VA}, g	R^2_{VA}
PLS2 model							
Dependent variable							
Subcutaneous fat	576	0.86	625	0.85	2.5	678	0.91
Intermuscular fat	448	0.87	496	0.85	2.5	330	0.96
Kidney and pelvic fat depots	462	0.80	507	0.76	2.0	247	0.96
Omental fat depots	699	0.88	761	0.87	2.7	552	0.97
Mesenteric fat depots	432	0.72	490	0.66	1.7	278	0.92
Total carcass fat	1,193	0.90	1,300	0.89	3.0	968	0.97
Total body fat	1,978	0.91	2,168	0.90	3.1	1,287	0.98
	Calibration set						
	Training data[2]		Verification data[4]			Validation set[1]	
	SEC, g	R^2	SEP_{VE}, g	R^2_{VE}	RPD	SEP_{VA}, g	R^2_{VA}
RBF-ANN2 model							
Dependent variable							
Subcutaneous fat	565	0.86	551	0.93	3.6	629	0.84
Intermuscular fat	489	0.86	366	0.92	3.3	298	0.94
Kidney and pelvic fat depots	414	0.84	458	0.84	2.6	304	0.89
Omental fat depots	683	0.89	725	0.93	3.2	596	0.91
Mesenteric fat depots	386	0.81	356	0.82	1.7	310	0.84
Total carcass fat	1,175	0.90	998	0.95	4.3	937	0.93
Total body fat	1,864	0.92	1,707	0.96	4.2	1,465	0.95

[1]Statistics of validation set: R^2_{VA} = regression coefficient of determination for validation; SEP_{VA} = SE of prediction of validation.
[2]Statistics of training data set: R^2 = regression coefficient of determination for calibration; SEC = SE of calibration.
[3]Statistics of cross-verification set: R^2_{CV} = regression coefficient of determination for verification; SEP_{CV} = SE of prediction of verification; RPD = residual predictive deviation.
[4]Statistics of verification set: R^2_{VE} = regression coefficient of determination for verification; SEP_{VE} = SE of prediction of verification.

as expected, less deviation between calculated and experimental data (points are more close to the diagonal line).

Regarding the estimation of goat carcass compositions the SE values obtained in the present study, with PLS2 or RBF-ANN2 models, are less than those obtained (data not shown) using the MRL models proposed by Teixeira et al. (2008; SE values from 356 to 2,168 g against 447 to 2,367 g, respectively). Moreover, in the present study only one PLS2 or one RBF-ANN2 was established to simultaneously estimate and predict the 7 goat fat depots, against the 7 MRL models proposed by Teixeira et al. (2008). Also, the new multiple models only required the use of 2 ultrasound measurements. On the other hand, the above-mentioned MRL models were based on 3 or 4 ultrasound measurements, being in total, 5 different measurements required to estimate the 7 goat fat depots analyzed. Finally, there was no need to transform any of the independent or dependent variables, which was not the case of the MRL models reported that, in some cases, required data in logarithmic scale.

The overall results lead to the acceptance of PLS2 model and, in particular, RBF-ANN2 model as an improved and reliable methodology for standardized serial work in on-line goat carcass classification and simultaneous evaluation of the most important goat fat depots, compared with the previous reported MRL models, which only assess the different fat depots individually. In fact, one PLS2 or ANN2 model is sufficient to predict, at the same time, 7 fat depots based on a more reduced and still easily measured number of independent variables.

In conclusion, the results obtained in this work confirmed that ultrasound measurements are simple and reliable measures for goat fatness evaluation. In fact, the ultrasonic fat depth measurements at the third sternebra of the breast bone and between the fifth and sixth lumbar vertebrae in association with goat BW were efficient predictors, as reported in previous studies. The information contained in these 3 independent variables was sufficient to accurately and simultaneously predict 7 goat fat depots, using only one PLS2 or RBF-ANN2 model. In general, both multiple models were effective for goat fat depots estimation, showing, however, the RBF-ANN2 model a better predictive performance (greater RPD values). Nevertheless, the use of these models was more efficient than the MRL mod-

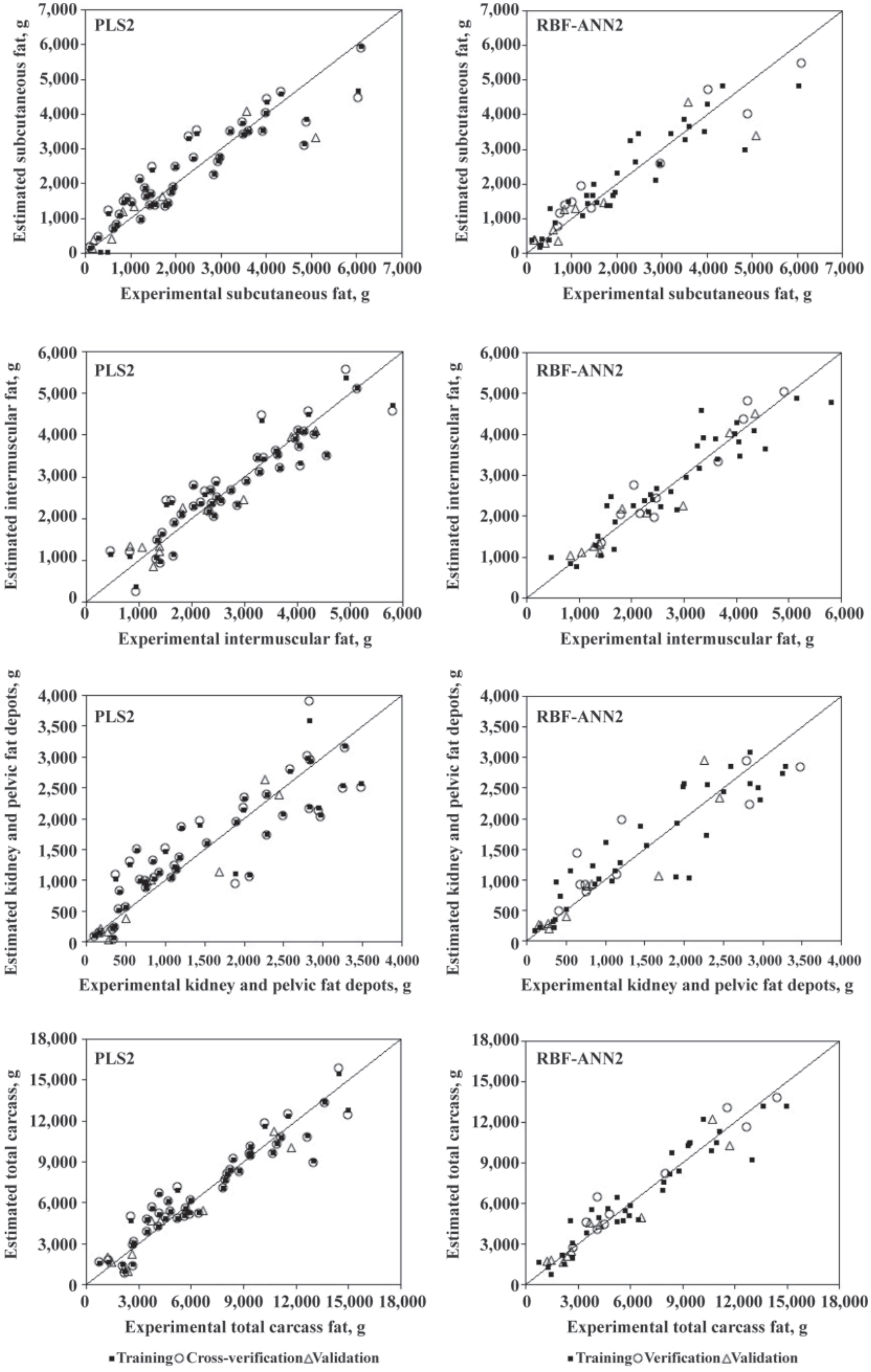

Figure 2. Estimated subcutaneous, intermuscular, kidney and pelvic fat depots, and total carcass fat depots using RBF-ANN2 and PLS2 models vs. experimental data. PLS2: multiple partial least squares; RBF-ANN2: multiple radial basis function artificial neural network.

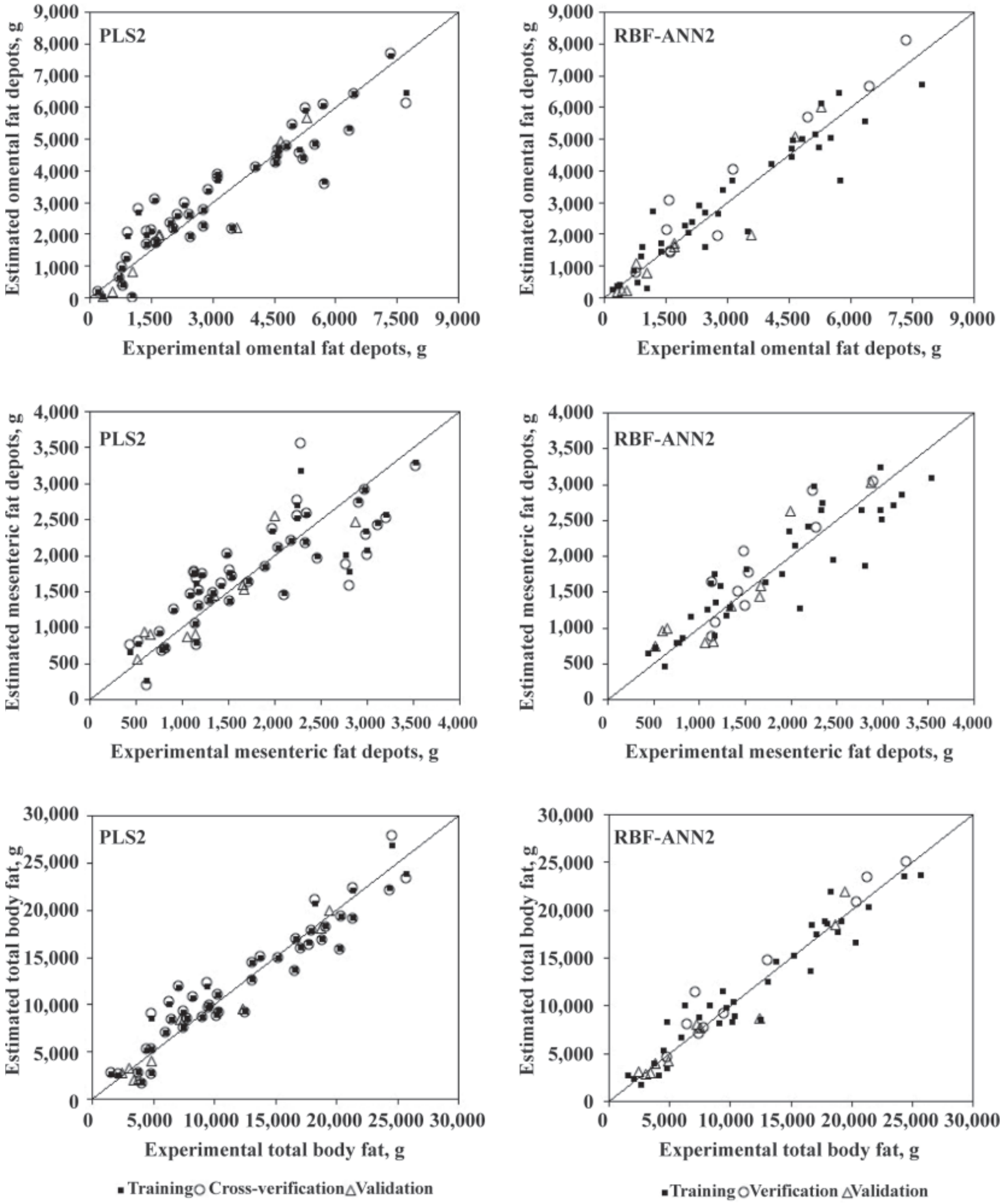

Figure 3. Estimated mesenteric and omental goat fat depots and total body fat depots using RBF-ANN2 and PLS2 models vs. experimental data. PLS2: multiple partial least squares; RBF-ANN2: multiple radial basis function artificial neural network.

els previously reported to assess the main body fat partitioning. Indeed, better results were obtained (greater determination coefficients and smaller SE), using only 1 multiple PLS or ANN model based in few ultrasound measurements, which is of major importance if it is intended to implement this methodology in the field or abattoir, where tasks must be performed quickly.

The proposed methodologies can be used as an effective practical tool to predict goat carcass and body composition. However, the prediction robustness of the proposed methodologies (RTU with PLS2 or RBF-ANN2 models) should be checked using a larger experimental database that should include goats from different breeds and with different levels of maturity. This approach would allow building a general robust and applicable model to assess goat body composition in several circumstances independent from the different factors that affect meat quality preferences.

LITERATURE CITED

Barroco, N., A. Vadell, F. Ballesteros, G. Galietta, and D. Cozzolino. 2006. Predicting intramuscular fat, moisture and Warner-Bratzler shear force in pork muscle using near infrared reflectance spectroscopy. J. Anim. Sci. 82:111–116.

Blanco, M., and A. Peguero. 2008. An expeditious method for determining particle size distribution by near infrared spectroscopy: Comparison of PLS2 and ANN models. Talanta 77:647–651.

Brereton, R. G. 2000. Introduction to multivariate calibration in analytical chemistry. Analyst (Lond.) 125:2125–2154.

Delfa, R. 2004. Los ultrasonidos como predictores del reparto del tejido adiposo y de la composición tisular de la canal en cabras adultas. PhD Diss. Zaragoza Univ., Zaragoza, Spain.

Delfa, R., A. Teixeira, C. Gonzalez, L. F. Gosalvez, and M. Tor. 1994. Relationships between body fat depots, carcass composition and body condition scores in Blanca Celtibérica goats. Options Méditerranéennes-Série Séminaires 27:109–120.

Dias, L. G., A. C. A. Veloso, D. M. Correia, O. Rocha, D. Torres, I. Rocha, L. R. Rodrigues, and A. M. Peres. 2009. UV spectrophotometry method for the monitoring of galacto-oligosaccharides production. Food Chem. 113:246–252.

Gaitán-Jurado, A. J., V. Ortiz-Somovilla, F. España-España, J. Pérez-Aparicio, and E. J. De Pedro-Sanz. 2008. Quantitative analysis of pork dry-cured sausages to quality control by NIR spectroscopy. Meat Sci. 78:391–399.

Gallardo, J., S. Alegret, and M. del Valle. 2004. A flow-injection electronic tongue based on potentiometric sensors for the determination of nitrate in the presence of chloride. Sens. Actuators B Chem. 101:72–80.

Good, P. I., and J. W. Hardin. 2003. Common Errors in Statistics (and How to Avoid Them). John Wiley and Sons Inc., Hoboken, NJ.

Hopkins, D. L., D. F. Stanley, and N. E. Ponnampalan. 2007. Relationship between real-time ultrasound and carcass measures and composition in heavy sheep. Aust. J. Exp. Agric. 47:1304–1308.

Jørgensen, K., and T. Næs. 2008. The use of LS–PLS for improved understanding, monitoring and prediction of cheese processing. Chemom. Intell. Lab. Syst. 93:11–19.

Lozano, V. A., J. M. Camiña, M. S. Boeris, and E. J. Marchevsky. 2007. Simultaneous determination of sorbic and benzoic acids in commercial juices using the PLS-2 multivariate calibration method and validation by high performance liquid chromatography. Talanta 73:282–286.

Mahani, M. K., F. Divsar, M. Chaloosi, M. G. Maragheh, A. R. Khanchi, and M. K. Rofouei. 2008. Simultaneous determination of thorium and uranyl ions by optode spectra and chemometric techniques. Sens. Actuators B Chem. 133:632–637.

Mandenius, C.-F., and A. Brundin. 2008. Bioprocess optimization using design-of-experiments methodology. Biotechnol. Prog. 24:1191–1203.

Næs, T., T. Isaksson, T. Fearn, and T. Davies. 2002. A User-Friendly Guide to Multivariate Calibration and Classification. NIR Publications, Chichester, UK.

Picard, R. R., and K. N. Berk. 1990. Data splitting. Am. Stat. 44:140–147.

Prieto, N., S. Andrés, F. J. Giráldez, A. R. Mantecón, and P. Lavín. 2008. Ability of near infrared reflectance spectroscopy (NIRS) to estimate physical parameters of adult steers (oxen) and young cattle meat samples. Meat Sci. 79:692–699.

Silva, S. R., J. J. Afonso, V. A. Santos, A. Monteiro, C. M. Guedes, J. M. T. Azevedo, and A. Dias-da-Silva. 2006. In vivo estimation of sheep carcass composition using real-time ultrasound with two probes of 5 and 7.5 MHz and image analysis. J. Anim. Sci. 84:3433–3439.

Teixeira, A., M. Joy, and R. Delfa. 2008. In vivo estimation of goat carcass composition and body fat partition by real-time ultrasonography. J. Anim. Sci. 86:2369–2376.