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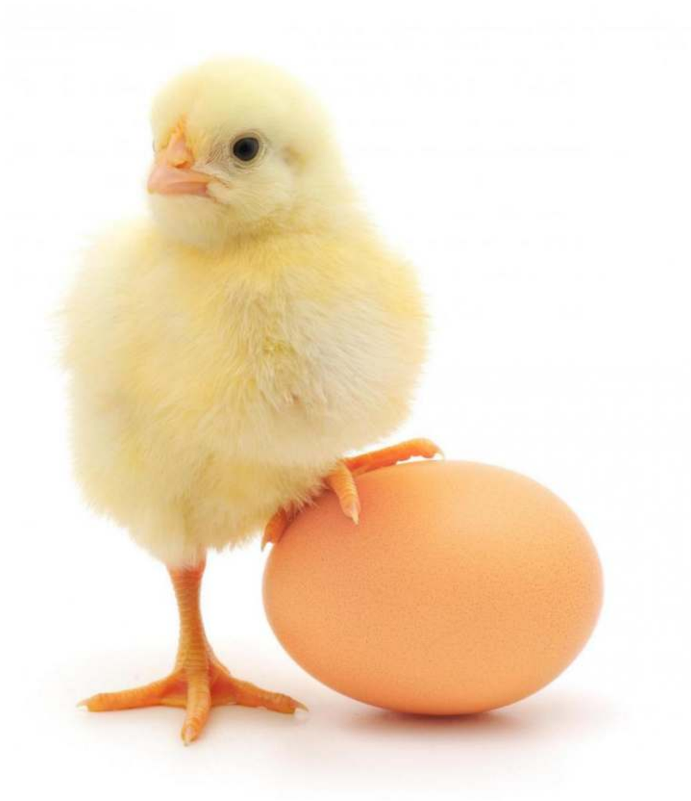

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Estimating and Predicting Feed Conversion in Broiler Chickens by Modeling Covariance Structure

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Abstract: Modeling covariance structure was used to estimate and to predict feed conversion in broiler chickens from one experiment under repeated-measures design. Eight treatments that consisted in a combination of four strains (Arbor Acres, Ag Ross 308, Cobb and RX) and two sexes were evaluated at six ages (7, 14, 21, 28, 35 and 42 d) in two blocks with three replicates *per* block. Feed conversion was subjected to a mixed model, MIXED procedure in SAS® software, where was modeled covariance structure using ten types. Also, it was obtained a correlogram and analyses of variance for each structure. Means±standard errors were estimated and polynomial trends were assessed using linear, second- and third-order to predict the trait over ages. First-Order Autoregressive Moving-Average was chosen the best covariance structure that is extremely important to obtain more accuracy of estimate (from 1.048 at 7 days to 1.703 at 42 days for Cobb) and predicted (from 1.061 at 7 days to 1.577 at 42 days for Cobb) means on feed conversion, which is better predicted when linear effect is used because it presented very closely both estimate and predicted means at all ages, except at 14 days. Modeling covariance structure allowed us to choose the best model to estimate and to predict feed conversion, opening the windows to understand a little more about its trend over ages and also to purpose nutrition managements that may be adopted to maximize growth and to minimize total cost of poultry production.

Key words: Growth parameter, mixed model, poultry science, repeated-measures

Introduction

Feed intake and its efficient utilization is one of the major concerns in poultry as feed cost is one of the highest components of total cost of production. Feed alone may contribute from 60 to 70% to the total cost of production in broiler chickens (FAO, 2006). Better utilization of feed and avoiding unnecessary feed wastage could be the leading factors in minimizing total cost of poultry production.

Accurate prediction of growth patterns, such as feed conversion and related co (variances) across age is crucial for broiler producers. Taking into account bioeconomic models, broiler growers can make better management decisions in monitoring and controlling growth, especially in estimating daily nutrient requirements at different ages (Hancock *et al.*, 1995; Gous, 1998).

Feed conversion is an index that associates both feed intake and gain weight these are routinely evaluated weekly on the same experimental units in broiler chicken performance experiments, which are carried out up to 42 d of age. Indeed this type of experiment is under repeated-measures design.

Reasons to carry out experiments under repeated-measures design are:

(1) The suspect that treatment effects over time are changed,
(2) They provide adjusted conditions for control of accessory factors that may influence the response,
(3) They improve, in general, the accuracy of estimated contrasts, which are associated to differences between means from response at different times (Gill, 1986; Reiczigel, 1999).

Responses from points close in time are usually more highly correlated with each other points than responses from points far-apart in time under repeated-measures design (Littell *et al.*, 1996). An immediate consequence to ignore the presence this correlation is the apparent significant difference between means of treatments are exaggerated and the sensitivity of tests for interaction is seriously reduced. When the correlation of errors is ignored, the inferences may be or may not be distorted, depending on degree of homogeneity of covariance from data at different times (Gill, 1986; Crowder and Hand, 1990).

The correlation among measurements within-subjects factor across time can be fitted with a special covariance structure, which usually assumes independent errors. Fitting an appropriated covariance structure is essential for inferences on means may be correct and valid. More details about covariance structures may be found in SAS (1999).

Repeated-measures design has been usually employed in experiments in the medical area (Paterson, 2001), in the animal science (Allen *et al.*, 1983; Simianer, 1986), in the human area (Gomez, 2006; Hildebrandt *et al.*, 2006) and in the statistical methodologies (Liang and Zeger, 1986; Berkovits *et al.*, 2000). Specifically in the poultry science, the papers, which employ this methodology, are poor (Heier *et al.*, 1999; Choy *et al.*, 2002; Rosário *et al.*, 2005).

The aim of the current study was to determine the best model to estimate and to predict feed conversion in broiler chickens by modeling covariance structure.

Materials and Methods

Animals and experimental conditions: It was carried out one experiment, where 1920 young chickens (960 males and 960 females) from four broiler strains (Arbor Acres, Ag Ross 308, Cobb, and RX) were used to measure feed intake and gain weight weekly, across six weeks. The three first strains are commercial and the last one is an experimental strain.

The care of the birds met the guidelines of the Canadian Council on Animal Care (1993). Birds were housed in floor pen (2.20×1.80 m^2) with 6 pens *per* treatment and 40 young chickens *per* pen. Four types of feed were available, containing the metabolizable energy levels (MJ/kg) and the crude protein (g/kg), respectively: 0-7 d: 12.34 and 225; 8-14 d: 12.76 and 215; 15-35 d: 13.18 and 192; 36-42 d: 13.18 and 190. Feed and water were available *ad libitum* during the entire experimental period.

Feed conversion was calculated for each pen as following: [feed intake (kg)/gain weight (kg)]. All assumptions of the F-test were verified and confirmed in descriptive statistic analyses in SAS® software.

Statistical analyses: Treatments consisted in a combination of four strains and two sexes in a whole of eight treatments, which were measured at six ages (7, 14, 21, 28, 35, and 42 d). The experimental design was defined as balanced complete blocks (two blocks and three replicates *per* block) with eight treatments assigned randomly and six ages of measurements. Each experimental unit or subject (pen) had 40 birds.

The statistical model used was:

$$Y_{ijklm} = \mu + \beta_l + \alpha_i + \lambda_j + (\alpha\lambda)_{ij} + d_{ijkl} + \tau_m + (\alpha\tau)_{im} + (\lambda\tau)_{jm} + (\alpha\lambda\tau)_{ijm} + e_{ijklm}$$

where,

$i = 1,\ldots, 4$; $j = 1, 2$; $k = 1, 2, 3$; $l = 1, 2$; $m = 1,\ldots, 6$;

Y_{ijlkm} is the observation in i^{th} strain and j^{th} sex in l^{th} block and k^{th} replicate in m^{th} age;

μ is the model constant;

β_l is the effect of the block l^{th};

α_i is the effect of the strain i^{th};

λ_j is the effect of the sex j^{th};

$(\alpha\lambda)_{ij}$ is the interaction between strain and sex;

d_{ijkl} is the random effect associated with l^{th} block and k^{th} replicate, in i^{th} strain and j^{th} sex, assuming $d_{ijkl} \sim N(0, G\sigma^2_d)$, where $G\sigma^2_d$ is the covariance matrix between-subject (pen) assuming independent errors;

τ_m is the effect of the age m^{th};

$(\alpha\tau)_{im}$ is the interaction between strain and age;

$(\lambda\tau)_{jm}$ is the interaction between sex and age;

$(\alpha\lambda\tau)_{ijm}$ is the interaction between strain and sex and age;

e_{ijklm} is the random error associated with l^{th} block and k^{th} replicate, in i^{th} strain, j^{th} sex and m^{th} age, with $e_{ijklm} \sim N(0, R\sigma^2_e)$, where $R\sigma^2_e$ is covariance matrix within-subject (pen) that was modeled, assuming dependent errors.

Ten covariance structures were used to model e_{ijklm}: Variance Components, Compound Symmetric, First-Order Autoregressive, First-Order Autoregressive with random effect for pen, Toeplitz, Unstructured, Heterogeneous First-Order Autoregressive, Heterogeneous First-Order Autoregressive with random effect for pen, Heterogeneous Compound Symmetric and First-Order Autoregressive Moving-Average, according to SAS (1999), where may be found more details about each structure.

Feed conversion was subjected to a mixed model, MIXED procedure in SAS® software (Littell *et al.*, 1996), using the approaches presented by Littell *et al.* (1998; 2000). For all analyses, we assumed $p<0.05$.

Akaike's Information Criterion (AIC) (Akaike, 1974) and Schwarz's Bayesian Criterion (SBC) or Bayesian Information Criterion (BIC) (Schwarz, 1978) were used to indicate relative goodness-of-test and may be used to compare models with the same fixed effects but different covariance structures. Formulae for their computation are: $AIC = -2\log L(\hat{\theta}) + 2k$, where $L(\hat{\theta})$ is the maximized likelihood function and k is the number of free parameters in the model and BIC = $-2\ln L(\hat{\theta}) + k\ln(n)$, where n in the number of observations, equivalently, the sample size; k is the number of free parameters to be estimated and $L(\hat{\theta})$ is the maximized value of the likelihood function for the estimated model. The smallest value for both criteria indicates the best fit.

One correlogram (Cressie, 1991), assuming Toeplitz as the reference type and analyses of variance were obtained for each tested covariance structure. We preferred Toeplitz because it is the most general structure and it exploits existence of trends in (co) variances over time, characteristics that Unstructured does not present.

To choose the best covariance structure, we took into account jointly AIC and BIC Criteria, the correlogram and a covariance model, which provides a good fit to the Toeplitz estimates and had a small number of parameters as assumed by Littell *et al.* (2000).

Table 1: Comparison of ten covariance structures using Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC)

Structure name	$(i,j)^{th}$ element	Estimated parameters	AIC[1]	BIC[1]
Variance Components	$\sigma^2_k 1(i = j)$ and i corresponds to k^{th} effect	1	-875.0	-873.2
Compound Symmetric	$\sigma^2_1 \pm \sigma^2 1\ (i = j)$	2	-912.2	-908.5
First-Order Autoregressive	$\sigma^2\ \rho^{[i=j]}$	2	-925.8	-922.1
First-Order Autoregressive with random effect for pen	$\sigma^2\ \rho^{[i=j]}$ with random effect for pen	3	-925.7	-920.1
Toeplitz	$\sigma_{[i-j]+1}$	6	-920.3	-909.1
Unstructured	σ_{ij}	21	-1084.4	-1045.1
Heterogeneous First-Order Autoregressive	$\sigma_i\sigma_j\rho^{[i-j]}$	7	-1088.1	-1075.0
Heterogeneous First-Order Autoregressive with random effect for pen	$\sigma_i\sigma_j\rho^{[i-j]}$ with random effect for pen	8	-1095.7	-1080.7
Heterogeneous Compound Symmetric	$\sigma_i\sigma_j[\rho 1(i \neq j)+1(i = j)$	7	-1065.9	-1052.8
First-Order Autoregressive Moving-Average	$\sigma^2[\gamma\rho^{[i-j]-1} 1(i \neq j)+1(i = j)$	3	-926.1	-920.5

[1]the smallest is better

Table 2: Values of probability for F-tests for fixed effects for ten covariance structures

Structure name	Strain (St)	Sex (Se)	St×Se	Age (A)	St×A	Se×A	St×Se×A
Variance Components	<0.0001	<0.0001	0.1640	<0.0001	0.0041	0.7973	0.9252
Compound Symmetric	<0.0001	<0.0001	0.5647	<0.0001	<0.0001	0.6282	0.7070
First-Order Autoregressive	0.0001	<0.0001	0.6416	<0.0001	0.0016	0.8830	0.7194
First-Order Autoregressive with random effect for pen	0.0001	<0.0001	0.6532	<0.0001	0.0005	0.8364	0.6967
Toeplitz	0.0002	<0.0001	0.6664	<0.0001	0.0003	0.8314	0.6725
Unstructured	<0.0001	<0.0001	0.5647	<0.0001	<0.0001	0.6702	0.5252
Heterogeneous First-Order Autoregressive	<0.0001	<0.0001	0.5821	<0.0001	<0.0001	0.7348	0.5321
Heterogeneous First-Order Autoregressive with random effect for pen	<0.0001	<0.0001	0.5254	<0.0001	<0.0001	0.6419	0.3931
Heterogeneous Compound Symmetric	<0.0001	<0.0001	0.6245	<0.0001	<0.0001	0.4465	0.3536
First-Order Autoregressive Moving-Average	0.0002	<0.0001	0.6697	<0.0001	0.0003	0.8385	0.6630

We estimated means±standard errors and we modeled polynomial trends over time based on linear, second- and third-order on interactions between strain×age and sex×age using the MIXED procedure in SAS® software using the best chosen covariance structure. Both estimated ± standard errors and predicted ± standard errors means were plotted in a graph for comparisons.

Results and Discussion

Choosing the covariance structure: AIC and BIC values for ten covariance structures are presented in Table 1. It was found that Heterogeneous First-Order Autoregressive with random effect for pen and Variance Components had the smallest and the largest values both AIC and BIC, indicating the best and the worst covariance structure, respectively. From all tested covariance structures, there were only two that disagreed in relation to the rank (from the smallest to the largest value) between AIC and BIC values, they were: Unstructured and Heterogeneous Compound Symmetric.

Usually the agreement between these criteria will not always be evidenced on the choice of best model, because they penalize the models differently, where BIC is more severe for the number of estimated parameters than AIC. Since our objective is parsimonious modeling of the covariance structure, we relied more on the BIC than the AIC. This fact may explain the discrepancy between values from these criteria on all tested covariance structures verified in Table 1. Our results were according to Littell *et al.* (2000), who found disagreement between AIC and SBC values in a pharmaceutical study. In contrast, Heier *et al.* (1999), studying mortality and Marek's disease in Norwegian and imported White Leghorns, found agreement between AIC and SBC.

Fig. 1 contains the correlogram, which is a graphical device for assessing correlation structure, showing basically the correlation function. It could be seen that the best adjustment with Toeplitz structure occurred with First-Order Autoregressive Moving-Average. Although Heterogeneous First-Order Autoregressive with random effect for pen had the smallest AIC and BIC criteria it did not show suitable adjustment with Toeplitz, presenting the second worst adjustment, only inferior than Variance Components. The addition of random effect for pen both Heterogeneous First-Order Autoregressive and First-Order Autoregressive lead these covariance structures plus Variance Components to present the worst agreement with Toeplitz.

Correlogram has been plotted by Littell *et al.* (1998; 2000), who empathized its importance to help them to choose the best covariance structure to model data set from repeated-measures design. We are according to

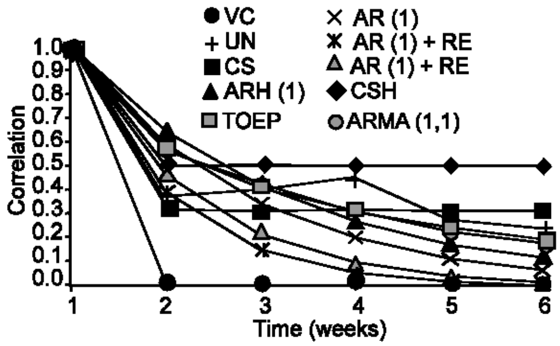

Fig. 1: Correlogram for each covariance structure, VC: Variance Components, CS: Compound Symmetric, AR(1): First-Order Autoregressive, AR(1)+RE: First-Order Autoregressive with random effect for pen, TOEP: Toeplitz, UN: Unstructured, ARH (1): Heterogeneous First-Order Autoregressive, ARH (1)+RE: Heterogeneous First-Order Autoregressive with random effect for pen, CSH: Heterogeneous Compound Symmetric, ARMA (1,1): First-Order Autoregressive Moving-Average

those authors, because in our study the correlogram also helped us to take this decision.

The addition of random effect for pen did not result in better models in our study. It was a surprise for us because usually this addition leaves to better results when between-subject variation is modeled together with within-subject variation, as verified by Littell *et al.* (1998;2000). We believed that the within-subject variation was more important than the between-subject variation to define the best covariance since the data set presented homogeneity of variance, which might have minimized the between-subject (pen) in our study.

Table 2 contains values of probability of F tests for fixed effects (strain, sex, age and their interactions) for each tested covariance structure. The probabilities values did not differ for all covariance structures for only sex and age effects ($p<0.0001$). For strain effect significances were similar ($p< 0.0002$). For sex x age effect was found discrepancy between covariance structures, where Compound Symmetric, Unstructured, Heterogeneous First-Order Autoregressive, Heterogeneous First-Order Autoregressive and Heterogeneous First-Order Autoregressive with random effect for pen presented the smallest probability ($p<0.0001$) and the others presented probabilities from $p = 0.0003$ (Toeplitz and First-Order Autoregressive Moving-Average) to $p = 0.0041$ (Variance Components). For interactions between strain×age, sex × age and strain×sex×age no significances were evidenced for all covariance structures.

When we analyze data sets no modeling covariance structure, it is assumed the Variance Components structure and from our results it was verified that it would not be suitable to this objective, leading us to erroneous conclusions. We demonstrated that depending on the covariance structure assumed to analyze the data set, the significances may be or may not be distorted, leaving to wrong or no accurate conclusions (Table 2).

As related by Vonesh and Chinchilli (1997) when the analysis of variance from data set under repeated-measures design is obtained, three hypothesis tests on fixed effects are made: 1st: there is no difference between treatments (coincidence of profile hypothesis), 2nd: there is no difference between ages (constancy hypothesis) and 3rd: there is no interaction between fixed effects (parallelism of profile hypothesis). In current study we found parallelism of profile hypothesis only for interactions between strains×sex, sex×age and strain×sex×age, which means to say that these effects have constancy trends over ages. All the others fixed effects were significant from Table 2.

Based on the information from Table 1 and 2, Fig. 1 and our assumptions, we concluded that First-Order Autoregressive Moving-Average (only 3 estimated parameters: *rho* = 0.7511, *gamma* = 0.5699 and residual = 0.001187) was the best choice of covariance structure to model feed conversion. This structure was also chosen by Lorenzo Bermejo *et al.* (2003), who compared linear and nonlinear functions and covariance structures to estimate feed intake pattern in growing pigs and by Pala and Savas (2006), who studied relationships between daily, morning, evening and peak yield and persistency in Turkish Saanen goats.

Modeling covariance structure from repeated-measures data has been reported in several studies. Heier *et al.* (1999) found that Unstructured was the best approach to model the cumulative mortality by Marek's disease in chickens. Mansour *et al.* (1985;1991) assessed conformation traits using First-Order Autoregressive structure in Holstein cows. Littell *et al.* (1998) defined the best covariance structure to investigate effects of several supplemental sources of dietary magnesium on urinary magnesium excretion in lambs as First-Order Autoregressive plus random pen effect.

Estimating and predicting means over time: In Fig. 2 are presented estimated means±standard errors for interaction between strain×age and sex×age (no significant) modeled with First-Order Autoregressive Moving-Average structure. Comparing them it was verified that there was differentiated trend between strains within each age and between ages within each strain, where at least one strain differed from the others at 7, 14 and 42 days, being Cobb showed the best mean. From 21 to 35 days Cobb was also the best, but it was equal to Arbor Acres and Ag Ross 308. Between ages a same strain differed between all them. Sexes

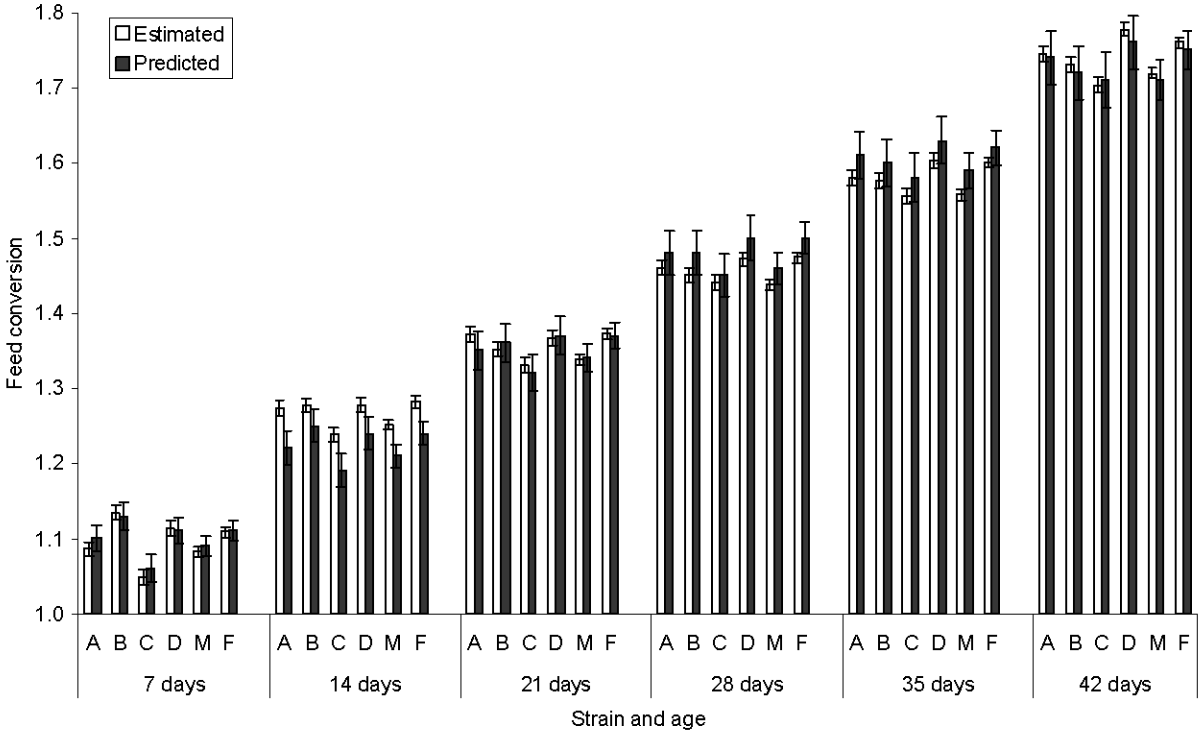

Fig. 2: Interactions between strain×age and sex×age modeled with First-Order Autoregressive Moving-Average covariance structure: estimated means±standard errors in columns and predicted means±standard errors on linear effect in points, A: Arbor Acres, B: Ag Ross 308, C: Cobb, D: RX; M: male, F: female

differed among them within and between ages, where males were better than females. Our results are according to Rosário *et al.* (2005) and indicated us that selection pressure on our experimental strain (RX), which is still in development and presented the largest mean at 42 days, should be more intensive if the aim will be to improve its feed conversion compared with each other commercial strains.

Also, in Fig. 2 are presented predicted means±standard errors for interaction between strain×age and sex×age (no significant) accommodating the covariance through First-Order Autoregressive Moving-Average structure in polynomial trends. Previous analyses showed that only linear effect was significant for interaction between strain x age ($p = 0.0003$). Second- and third-order effect did not present any significance. Then, we concluded that linear effect would be the best model to explain the data set. We could observe that the adjustment between estimated and predicted means, within each interaction, was extremely strong at all ages, except at 14 days. This fact convinced us that the choice of the covariance structure to model the data set was accurate, because the intervals of the estimated and predicted means were overlapped.

Van Buggenhout *et al.* (2004) investigated the validity of the assumption of linearity in an adaptive modeling approach in terms of prediction accuracy, which was compared with the dynamic growth response of broilers using a time-variant parameter estimation procedure and they concluded that last one was slightly better modeled assuming non-linear dynamics in a short time window. Our results were disaccording to those authors because showed that feed conversion was modeled better employing a linear model, since at all ages, except at 14 days, the estimated and predicted means showed the strongest adjustment among them. However, Lorenzo Bermejo *et al.* (2003) found that for selection on early feed intake linear-segmented, logistic and Richards's functions resulted in the most usable estimates up to 120 days in pigs that lead us to believe that the employment of linear effect must be correct.

Below are presented the coefficients (±standard errors) of fitted linear equations within each interaction:

(The FC is feed conversion and A is age)

Arbor Acres:	FC = 0.9664 (±0.01453)+0.01843 (±0.000512) A
Ag Ross 308:	FC = 1.0101 (±0.01453)+0.01681 (±0.000512) A
Cobb:	FC = 0.9317 (±0.01453)+0.01843 (±0.000512) A
RX:	FC = 0.9783 (±0.01453)+0.01871 (±0.000512) A
Male:	FC = 0.9843 (±0.01034)+0.01829 (±0.000365) A
Female:	FC = 0.9600 (±0.01034)+0.01786 (±0.000365) A

Regarding strains, we could observe that the smallest angular coefficient was found for Ag Ross 308, but from 7 to 21 days Cobb presented the smallest ($p<0.05$) predicted mean and from 28 to 42 days this strains plus Arbor Acres and Ag Ross 308 were better than RX. Sexes no differed among them.

Several works have been carried out to predict growth parameters (Parks, 1982; Emmans, 1995; Wang and Zuidhof, 2004; Cangar *et al.*, 2006; Orheruata *et al.*, 2006). Growth models have also been used to determine optimum feeding regimen. Models have been developed to show the relationship between feed intake and gain weight. Aerts *et al.* (2003a;b) calculated daily feed supply on the basis of a model-based control algorithm, which was able to grow the birds according to different target trajectories, as closely as possible, ranging from restricted to compensatory growth.

Because each strain responsed differently over ages on feed conversion, our results may be applied in the practice for poultry to estimate daily nutrient requirements, basically energy and protein, at different ages in bioeconomic models as proposed by Gous *et al.* (1999;2002), maximizing gain weight and minimizing feed intake. Indeed this relationship has been always looked for broiler producers.

Finally, modeling covariance structure allowed us to choose the best model to estimate and to predict feed conversion, opening the windows to understand a little more about its trend over ages and also to purpose nutrition managements that may be adopted to maximize growth and to minimize total cost of poultry production.

References

Aerts, J.M., M. Lippens, G. De Groote, J. Buyse, E. Decuypere, E. Vranken and D. Berckmans, 2003a. Recursive prediction of broiler growth response to feed intake by using a time-variant parameter estimation method. Poult. Sci., 82: 40-49.

Aerts, J.M., S. Van Buggnhout, E. Vranken, M. Lippens, J. Buyse, E. Decuypere and D. Berckmans, 2003b. Active control of the growth trajectory of broiler chickens based on online animal responses. Poult. Sci., 82: 1853-1862.

Akaike, H., 1974. A new look at the statistical model identification. IEEE Transaction on Automatic Control, 19: 716-723.

Allen, O.B., J.H. Burton and J.D. Holt, 1983. Analysis of repeated measurements from animal experiments using polynomial regression. J. Anim. Sci., 57: 765-770.

Berkovits, I., G.R. Hancock and J. Nevitt, 2000. Bootstrap resampling approaches for repeated measure designs: relative robustness to sphericity and normality violations. Educ. Psychol. Meas., 60: 877-892.

Canadian Council on Animal Care, 1993. Guide to the Use of Experimental Animals (Ottawa: CCAC).

Cangar, Ö., J.M. Aerts, E. Vranken and D. Berckmans, 2006. End-weight prediction in broiler growth. Br. Poult. Sci., 47: 330-335.

Choy, Y.H., J.S. Brinks and R.M. Bourdon, 2002. Repeated-measure animal models to estimate genetic components of mature weight, hip height and body condition score. J. Anim. Sci., 80: 2071-2077.

Cressie, N.A.C., 1991. Statistics for Spatial Data (New York: Wiley).

Crowder, M.J. and D.J. Hand, 1990. Analysis of repeated measures (New York: Chapman and Hall).

Emmans, G.C., 1995. Problems in modelling the growth of poultry. World's. Poult. Sci. J., 51: 77-89.

Food and Agriculture Organization of thee United Nations-FAO, 2006. <http://www.fao.org> (28 Oct. 2006).

Gill, J.L., 1986. Design and analysis of experiments in the animal and medical sciences, vol. 1 (Ames: The Yowa State University Press).

Gomez, R., 2006. Gender invariance of the five-factor model of personality among adolescents: A mean and covariance structure analysis approach. Pers. Indiv. Differ., 41: 755-765.

Gous, R.M., 1998. Making progress in the nutrition of broilers. Poult. Sci., 77: 111-117.

Gous, R.M., E.T. Moran Jr., H.R. Stilborn, G.D. Bradford and G.C. Emmans, 1999. Evaluation of the parameters needed to describe the overall growth, the chemical growth and the growth of feathers and breast muscles of broilers. Poult. Sci., 78: 812-821.

Gous, R.M., E.T. Moran Jr., H.R. Stilborn, G.D. Bradford and G.C. Emmans, 2002. Modeling energy and amino acid requirements in order to optimise the feeding of commercial broilers. Simpósio Internacional ACAV-Embrapa sobre Nutrição de Aves. Concórdia, pp: 82-94.

Hancock, C.E., G.D. Bradford, G.C. Emmans and R.M. Gous, 1995. The evaluation of the growth parameters of six strains of commercial broiler chickens. Br. Poult. Sci., 36: 247-264.

Heier, B.T., J. Jarp, M.I. Kaldhusdal, G. Schaller and I.B. Forus, 1999. A longitudinal field study of mortality and Marek's disease in Norwegian and imported White Leghorns. Prev. Vet. Med., 40: 207-219. 395.

Hildebrandt, T., J. Langenbucher, S. Carr, P. Sanjuan and S. Park, 2006. Predicting intentions for long-term anabolic-androgenic steroid use among men: A covariance structure model. Psychol. Addict. Behav., 20: 234-240.

Liang, K.Y. and S.L. Zeger, 1986. Longitudinal data-analysis using generalized linear-models. Biometrika, 73: 13-22. 397.

Littell, R.C., P.R. Henry and C.B. Ammerman, 1998. Statistical analysis of repeated measures data using SAS procedures. J. Anim. Sci., 76: 1216-1231.

Littell, R.C., G.A. Milliken, W.W. Stroup and R.D. Wolfinger, 1996. SAS® system for mixed models (Cary: SAS Institute Inc.).

Littell, R.C., J. Pendergast and R. Natarajan, 2000. Modelling covariance structure in the analysis of repeated measures data. Stat. Med., 19: 1793-1819.

Lorenzo Bermejo, J., R. Roehe, G. Rave and E. Kalm, 2003. Comparison of linear and nonlinear functions and covariance structures to estimate feed intake pattern in growing pigs. Livest. Prod. Sci., 82: 15-26.

Mansour, H., E.L. Jensen and L.P. Johnson, 1991. Analysis of covariance structure of repeated measurements in Holstein conformation traits. J. Dairy Sci., 74: 2757-2766.

Mansour, H., E.V. Nordheim and J.J. Rutledge, 1985. Maximum likelihood estimation of variance components in repeated measures design assuming autoregressive errors. Biometrics, 41: 287-294.

Orheruata, A.M., S.E. Vaikosen, G. Alufohia and G.O. Okagbare, 2006. Modeling growth response of broiler chicken to feed consumption using linear data based model structure. I. J. Poult. Sci., 5: 453-456.

Pala, A. and T. Savas, 2006. Relationships between daily, morning, evening and peak yield and persistency in Turkish Saanen goats. Anim. Sci. J., 77: 532-537.

Parks, J.R., 1982. A Theory of Feeding and Growth of Animals (Berlin: Springer-Verlag).

Paterson, S., 2001. Use of repeated measure linear modeling to analyze longitudinal data from experimental parasite infections. J. Parasitol., 87: 969-971.

Reiczigel, J., 1999. Analysis of experimental data with repeated measurements. Biometrics, 55: 1059-1063.

Rosário, M.F., M.A.N. Silva, V.J.M. Savino, A.A.D. Coelho and M.C. Moraes, 2005. Evaluation performance of the broiler chicken genotypes through repeated measures. Braz. J. Anim. Sci., 34: 2253-2264 (Suppl. 5). (in Portuguese).

SAS Institute, 1999. SAS/STAT User's Guide Version 8.2 (Cary: SAS Institute Inc.).

Schwarz, G., 1978. Estimating the dimension of a model. Ann. Stat., 6: 461-464.

Simianer, H., 1986. A general approach to the use of multiple traits with repeated measurements in estimation of breeding values. Livest. Prod. Sci.,15: 315-324.

Van Buggenhout, S., J.M. Aerts, E. Vranken and D. Berckmans, 2004. Non-linear modelling of broiler growth using a time-variant parameter estimation method. Transactions of the American Society of Agricultural Engineers, 47: 1757-1764.

Vonesh, E.F. and V.M. Chinchilli, 1997. Linear and nonlinear models for the analysis of repeated measurements (New York: M. Dekker).

Wang, Z. and M.J. Zuidhof, 2004. Estimation of growth parameters using a nonlinear mixed Gompertz model. Poult. Sci., 83: 847-852.