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Application of the covariance function approach with an iterative two-stage algorithm to the estimation of parameters of a random regression test day model for dairy production traits

Joanna SZYDA

Department of Animal Genetics, Agricultural University of Wroclaw, Wrocław, Poland

Abstract. The covariance function approach with an iterative two-stage algorithm of LIU et al. (2000) was applied to estimate parameters for the Polish Black-and-White dairy population based on a sample of 338 808 test day records for milk, fat, and protein yields. A multiple trait sire model was used to estimate covariances of lactation stages. ^Athird-order Legendre polynomial was subsequently fitted to the estimated (co)vari- ances to derive (co)variances of random regression coefficients for both additive genetic and permanent environment effects. Daily and 305-day heritability estimates obtained are consistent with several studies which used both fixed and random regression test day models. Genetic correlations between any two days in milk (DIM) of the same lactation as well as genetic correlations between the same DIM of two lactations were within a biologically acceptable range. It was shown that the applied estimation procedure can utilise very large data sets and give plausible estimates of (co)variance components.

Key words: covariance function, dairy cattle, random regression model, test day data.

Introduction

Estimating (co)variance parameters of a random regression test day model for dairy production traits is computationally very challenging. Among the main reasons are: the very large number of (co)variance parameters and effects to be estimated, high correlations between parameters, and a large size of the data set needed to provide reasonable accuracy of these estimates.

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Correspondence: J. SZYDA, Department of Animal Genetics, Agricultural University of Wrocław, ul. Kożuchowska 7, 51-631 Wrocław, Poland, e-mail: szyda@karnet.ar.wroc.pl

Up to now two general approaches have been applied, these are the one-step random regression model approach and the two-step model based on covariance functions (CF). In the one-step model animal genetic and permanent environmental effects are modelled through a lactation curve function. Random regression coefficients (RRC) of the function and their (co)variance components are estimated jointly with other effects, typically using Restricted Maximum Likelihood (REML, OLORI et al. 1999) or the Gibbs sampling algorithm (JAMROZK, SCHAEFFER 1997; for a review see MISZTAL et al. 2000). The two-step approach estimates (co)variance parameters of genetic and residual effects of different lactation stages in the first step, and fits CF to the estimated (co)variance matrices to obtain (co)variances of RRC in the second step. The CF can be fitted using the generalised least square (GLS) inverse method (TIJANI et al. 1999), the expectation maximisation algorithm (MANTYSAARI 1999), modified GLS inverse (LIU et al. 2000), and weighted least squares (KIRKPATRICK et al. 1994, LIU et al. 2000). Although the one-step approach enables joint estimation of all model parameters, in practical application it is often not suitable for data sets large enough to provide accurate parameter estimates. This may result in estimates which are not biologically valid. The two-step approach enables to incorporate information from much larger data sets, and thus higher accuracy of estimates.

The objective of this study was to apply the covariance function approach with an iterative two-stage algorithm of LIU et al. (2000) to estimate (co)variance components of RRC of a random regression test day model for the first three lactations test day yields of the Polish dairy cattle population.

Material

A total of 338 808 test day records for milk, fat, and protein yields from the first three lactations were selected from the Polish Black-and-White dairy cattle popvlation. The statistical description of the data set can be found in the earlier paper by SZYDA and LIU (1999). The following selection criteria were imposed: herd-test-date (HTD) classes with at least five records, supervised monthly testing with two times milking, and calving years beginning from 1993, 1994 and 1995, respectively, for the first, second and third lactations. In the case of duplicate test day records within each of the six lactation stages defined below, one record was randomly chosen. Only complete lactations were used for estimating the parame ters. Sires with fewer than 30 daughters were excluded to achieve a better data structure. Table 1 shows the structure of the final test day data set and sire pedigree file used for parameter estimation. For each of the three lactations, 15 fixed lactation curves were fitted to data based on three calving seasons (January-March, April-August, September-December), and five classes of age at calving.

Method

Estimation of parameters on a daily basis

For the estimation of parameters of a random regression test day model, the covariance function approach with an iterative two-stage algorithm of LTU et al. (2000) was chosen. The iteration procedure is based on the iterat

Step 1

On the basis of the number of days in milk (DIM) each lactation was partitioned
into six stages: 5-50, 51-105, 106-160, 161-215, 216-259, and 260-305 DIM.
The (co)variance components for these six lactation stages were es

$$
y_{ijklmn} = \mu_{lm} + HTD_{il} + \sum_{p=1}^{5} \beta_{jlp} v_{pd} + s_{klm} + e_{ijklmn} ,
$$

 l actation l , where: y_{ijklmn} is the test day yield in the *m*-th stage of the *l*-th lactation of cow *n*, μ_{lm} is the mean for stage *m* of lactation *l*, *HTD_{il}* is the *i*-th herd-test-date effect of lactation *l*, v_{pd} is th lactation *l*, v_{pd} is the *p*-th parameter of Ali-Schaeffer function (ALI, SCHAEFFER 1987) for *d*-th DIM, β_{jlp} is the *p*-th fixed regression coefficient for lactation *l* specific to age-season class *j*, s_{klm}

In the estimation procedure fixed effects of HTD and β are estimated by ordinary least squares (stage A). Then (co)variance components of sire effects (G_s) and residual effects (R_s) are estimated via restricted maximum likelihood (stage B):

stage A
$$
y_{ijklmn} - (\hat{\mu}_{lm}^{(r-1)} + \hat{s}_{klm}^{(r-1)}) = HTD_{il}^{(r)} + \sum_{p=1}^{5} \beta_{jlp}^{(r)} v_{pd} + \varepsilon_{ijklmn}^{(r)}
$$
,

stage B
$$
y_{ijklmn} - (\hat{H}TD_{il}^{(r)} + \sum_{p=1}^{5} \hat{\beta}_{jlp}^{(r)} v_{pd}) = \mu_{lm}^{(r)} + s_{klm}^{(r)} + \xi_{ijklmn}^{(r)}
$$
,

where superscript (r) denotes an iteration round, \hat{s}_{klm} represents the estimated sire

breeding value (EBV), ε_{ijklmn} and ξ_{ijklmn} are residual effects of models in stages A
and B, respectively. Both stages are iteratively repeated until all (co)variance
components and sire EBVs converge.
Parameters of the

analyses involving a lower number of traits. In each partial analysis (co)variance parameters were estimated for 9 traits: 6 lactation stages from one lactation plus 3 stages from another lactation. Consequently, in order to map 18×18 (co)variance matrix from the full model, seven 9-trait analyses had to be performed.

Step 2

In the next step sire (G_s) and residual (R_s) (co)variances from step 1 were converted to an animal model using $G = 4G_s$ and $R = R_s - 3G_s$. As G and R refer to the lactation stages, they have to be transformed into the (co)variances of RRC using CF modelled through the third-order normalised orthogonal Legendre polynomials. For that purpose the modified weighted least squares approach (LIU et al 2000) was used. In contrast to the generalised least squares inverse approach (TIJANI et al. 1999), the weighted least squares method (KIRKPATRICK et al. 1994) incorporates information on the accuracy of parameter estimates through their sampling variances. The modification of LIU et al. (2000) comprises an iterative procedure to separate time-dependent permanent environmental effects from time-independent error effects. Derivation of (co)variances of RRC from the (co)variance estimates of the lactation stages was carried out by Maple V soft ware. modification of LIU

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effects. Derivation
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es obtained on a da
 $\sum_{i=D_{\text{min}}}^{L} \sum_{j=L}^{L}$

Estimation of parameters on a lactation basis

The (co)variance estimates obtained on a daily basis were converted to lactation based estimates using:

$$
h_{L}^{2} = \frac{\sum_{i=D_{\min}}^{L} \sum_{j=D_{\min}}^{L} \sigma_{g(i,j)}}{\sum_{i=D_{\min}}^{L} [\sum_{j=D_{\min}}^{L} (\sigma_{g(i,j)} + \sigma_{p(i,j)}) + \sigma_{e(i,i)}]} ,
$$

where, h_L^2 is the heritability referring to the lactation of L days length, D_{min} denotes the value of DIM chosen as the beginning of lactation, $\sigma_{g(i,j)}$ and $\sigma_{p(i,j)}$ are respectively genetic and permanent environmental covariances between DIM i and j, $\sigma_{e(i,i)}$ is the error variance at DIM i. Based on daily estimates, the genetic correlation $(r_{g(n,m)})$ between two lactations can be derived as follows:

$$
r_{g(n,m)} = \frac{\sum_{i_n=D_{min}}^{L} \sum_{j_m=D_{min}}^{L} \sigma_{g(i_n,j_m)}}{\sqrt{\Big[\sum_{i_n=D_{min}}^{L} \sum_{j_n=D_{min}}^{L} \sigma_{g(i_n,j_n)}\Big]\Big[\sum_{i_m=D_{min}}^{L} \sum_{j_m=D_{min}}^{L} \sigma_{g(i_m,j_m)}\Big]}}
$$

where subscripts n and m correspond to two lactations.

Results

Heritability

Daily yield heritability estimates for milk, fat, and protein, based on the (co)variances of RRC, from the first three lactations are shown in Figures 1, 2 and 3. Estimated heritabilities change during the course of lactat

Genetic correlation structure

Figures 4 and 5 show genetic correlations for daily milk and fat yields, respec-
tively, between DIM 30, DIM 150, DIM 250 and the whole course of the first lac-
tation (represented by yields at all other DIM). The three v

The middle and end stages of lactation appear to be more genetically correlated Genetic correlations for milk, fat and protein yields between the same DIM
from two lactations are presented in Figures 7, 8, and 9, respectively. All three
traits present a similar level and a general pattern of daily ge the second and the third lactation indicate that they are genetically similar.

Figure 2. Heritability estimates for daily fat yield in the 1st, 2nd, and 3rd lactations

Figure 3. Heritability estimates for daily protein yield in the Ist, 2nd, and 3rd lactations

Figure 4. Genetic correlation estimates between daily milk yields and a given DIM in the Ist lactation

Figure 5. Genetic correlation estimates between daily fat yields and a given DIM in the Ist lactation

Figure 6. Permanent environmental correlation estimates between daily milk yields and a given DIM in the Ist lactation

estimation Cows 50 096	Sires of cows 2 2 3 9	Table 1. Number of individuals and subclasses of final data set used for parameter Animals in sire pedigree file 3 2 5 5 Table 2. Heritability estimates for the 305-day lactation	Test day records 338 808	Herd-test-day subclasses 52 790	Fixed lactation curves 45
		Estimation of test day model parameters			185

Table 1. Number of individuals and subclasses of final data set used for parameter estimation

Table 2. Heritability estimates for the 305-day lactation

Estimation of test day model parameters										
on				. Number of individuals and subclasses of final data set used for p						
VS	Sires of cows	Animals in sire pedigree file	Test day records	Herd-test-day Fixed subclasses	с					
96	2 2 3 9	3 2 5 5	338 808	52 790						
		Table 2. Heritability estimates for the 305-day lactation								
	Lactation	Milk yield	Fat yield	Protein yield						
	1	0.31	0.26	0.22						
	\overline{c}	0.34	0.25	0.22						
	3	0.23	0.20	0.16						
				Table 3. Estimates of genetic correlations between 305-day lactations						
	Lactations	Milk yield	Fat yield	Protein yield						

Tabie 3. Estimates of genetic correlations between 305-day lactations

than the beginning of lactation. This is especially profound for the correlations in- volving the first lactation.

Genetic correlations calculated on the 305-day lactation basis are presented in Table 3. For milk yield the highest correlation of 0.92 is between the second and the third lactation, while for fat and protein yields betwee

Permanent environmental correlation structure

Looking at the estimates of the correlation of permanent environmental effects of milk yield of a given DIM with the rest of lactation (Figure 6) one observes that the correlations between the neighbouring DIM are as high the end stage. However, comparing to genetic correlations, the decrease in correlation for more distant DIM is faster. Figure 10 shows correlations of daily permanent environmental effects for milk yield between two lactations. Compared to

Figure 7. Genetic correlation estimates between the same DIM of two lactations for daily milk yields

Figure 8. Genetic correlation estimates between the same DIM of two lactations for daily fat yields

Figure 9. Genetic correlation estimates between the same DIM of two lactations for daily protein yields

. Permanent envir Figure 10. Permanent environmental correlation estimates between the same DIM of two lactations for daily milk yields

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daily genetic correlations (Figure 7), permanent environmental effects have much lower correlations, ranging from 0.10 between DIM 5 and DIM 50 for the first and the second lactations, to 0.35 between DIM 170 and DIM 220 for the second and third lactations.

Discussion

The estimation of parameters of a random regression model has shown to be a computationally and methodologically difficult task (STRABEL, MISZTAL 1999). The known drawbacks include low heritability estimates as obtained by MÄNTYSAARI (1999), and TIJANI et al. (1999), high heritability estimates as in JAMROZIK and SCHAEFFER (1997), POOL et al. (2000), and low or even negative genetic correlation between early and late lactation stages (JAMROZIK, SCHAEFFER 1997). The covariance function approach with an iterative two-stage algorithm of LIU et al. (2000) used in this study seems to be robust towards the structure of the data (i.e. a large number of highly correlated parameters) and the computational difficulties (i.e. a large number of records required for the accurate estimation). Originally, it has been applied to the estimation of a random regression test day model parameters for a German Holstein population. Here parameters are estimated for the population of Polish Black-and-White dairy cat tle. The values appear to follow the empirical expectations, thus giving credibility to the results obtained. Later lactations have somewhat lower heritabilities than the first one, and no evident difference in heritability was observed betwee the second and the third lactation. Among the three production traits, milk yield has the highest heritability. Compared to a one-step approach, the covariance function approach does not model each DIM as a separate trait, so that the parame ter estimates reflect averages over all DIM from the same lactation stage. Thus curves estimated in this way are likely to exhibit lower variation than curves esti mated under a one step approach. Having in mind the difficulties in obtaining accurate parameter estimates while applying a one-step approach to large data sets, it seems reasonable to reduce the number of estimated parameters by averaging over closely neighbouring DIM.

Comparison of daily estimates

Random regression model parameters for a very similar, but smaller population (the same breed and breeding region, overlapping cow birth years) were recently estimated by STRABEL and MISZTAL (1999) using a one-step animal model approach.

For these two populations no marked differences in the level of daily heritabilities is observed. However, there are some differences in the shape θ daily heritability estimates curve. The unexpected pattern found in both studies concerns highly increased heritabilities at the very early and/or the very late stage

of lactation. This is especially profound for the one-parity model of STRABEL and MISZTAL (1999). The least increase is observed in our study. A possible explanation for such results is the lack of phenotypic information necessary for an accurate estimation of (co)variances at the beginning and end of lactation. A one-parity model of STRABEL and MISZTAL (1999) utilises 96 798 test day records, their two-parity model 134 871 test day records, and our three-parity model 338 808
test day records. Moreover, the characterisation of 1 246 622 test day records from
the population available for our study indicates that there for the end part of a lactation, i.e. approximately after DIM 245 (see Figure 3 in SZYDA, LIU 1999). This is a similar stage of lactation at which we also observe an increase in daily heritability estimates. Other putative reasons for the phenomenon are constraining residual variance or properties of polynomial regression, as pointed by OLORI et al. (1999). Comparing daily estimates of

Comparing daily estimates of genetic correlations between the first and
the second lactation, our results show slightly more variation in the range of esti-
mates as in STRABEL and MISZTAL (1999), but again a very similar

Comparison of 305-day estimates

The latest 305-day lactation estimates for the Polish Black-and-White population based on the multivariate animal lactation model are available through the INTERBULL (2000). Comparison of the heritability estimated by bot model can only consider effects averaged for the whole course of lactation.

Considering genetic correlations between parities, as expected, for all three traits correlation between the first and the third parity is the lowest under lactation and test day model, and both groups of estimates are very similar. In contrast to the test day model, the lactation model estimates no large differences in correlations between the subsequent parities (i.e. $1&2, 2&3$).

In conclusion, the covariance function approach with an iterative two-stage algorithm (LIU et al. 2000) 1s an efficient method for the estimation of parameters of a random regression test day model. Among the most important advantages of this approach is its ability to utilise large data sets, which is a prerequisite for accurate estimation, especially at the beginning and end stages of lactation.

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