



Adding value to test-day data by using modified best prediction method

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Abstract

Computation of lactation yields from test-day data has lost much of its importance for genetic evaluations as the use of test-day models is currently quite widespread. In the other hand its interest for intra-farm management is increasing as a base for advanced management tools. The first and principal aim of this study was to develop a method which takes into account advantages and disadvantages of existing methods, and to test its potential to provide useful management tools to dairy farmers. A test-day model with modifications to able daily run and management tools was developed. Because of its similarities with best prediction, the method developed here was called modified best prediction. The second objective was to compare the accuracy of this new method with best prediction and test interval methods. Modified best prediction showed good results for predicting daily yields and was slightly better than best prediction for lactation yields prediction. Management tools obtained with modified best prediction are explained.

Keywords: Lactation yields computation, modified best prediction, test-day model, management tools.

1.0 Introduction

Milk performance recording and computing of lactation yields from test-day yield data had historically two main purposes: intra herd management and genetic evaluation. The last one is often the main reason to do milk recording, however the desire of assessing precisely phenotypic performances of dairy cows was at the origin of milk recording. As the use of test-day models is currently quite widespread, lactation yields computation for genetic evaluations has lost much of its importance. At the same time, its interest for intra-farm management has increased because farms are getting larger and economic sustainability is more and more difficult to achieve.

The official method recommended by ICAR (2009) to compute lactation yields is the test interval method (**TIM**). This method connects test-day data using linear interpolation between them. Over the years, alternative methods for computing cumulated productions were developed and approved by ICAR. These methods are interpolation using standard lactation curves (Wilmink, 1987), multiple trait prediction (**MTP**, Schaeffer and Jamrozik, 1996) and best prediction (**BP**; VanRaden, 1997). MTP combines, using a Bayesian method, the a priori knowledge on standard lactation curve and the observed data. BP combines recorded yields into a lactation record using selection index procedures, therefore it has best linear prediction properties. BP is more accurate than TIM but less accurate than simultaneously equations as provided by BLUP (Pool and Meuwissen, 1999).

Furthermore, several authors have shown the potential for calculating cumulated production with test-day models (**TDM**). Pool and Meuwissen (1999), Mayeres *et al.* (2004), and Vasconcelos *et al.* (2004) reported the ability of a TDM to predict daily and lactation yields. Mayeres *et al.* (2004), Koivula *et al.* (2007), and Caccamo *et al.* (2008) showed the interest of using a TDM to bring useful management tools to dairy farmers. However full, population wide TDM require important computations resources. They are therefore performed on schedules, e.g., three times a year for the INTERBULL international genetic evaluations. This reduces their direct usefulness as farmers need lactation yields and other management results a few days after milk recording.

The aim of this study was first to develop a new method which takes into account advantages and disadvantages of existing methods, is applicable on the field, and brings useful management tools. The

second objective was to test the ability of this new method to describe and predict daily and lactation yields.

2.0 Materials and Methods

2.1 Data

Data available in this study were 21, 839,073 test-day data (milk, fat, protein, and somatic cell count) coming from milk recording in Walloon region of Belgium and collected between January 1980 and March 2010. These data included all lactations and all dairy breeds, including dual purpose breeds. Pedigree and lactation data were also provided.

Additional data consisting in daily individual milk yields were collected in 8 herds. After editing, 132,607 daily production records, from 562 lactations, 312 cows and 4 herds were kept.

2.2 Model

Because of its similarities with BP, the method developed here was called modified-BP (**mBP**). However, some elements of others methods have been included.

The mBP method has the following properties:

multiple-trait computation (milk, fat and protein yields, somatic cell score);

(co)variances are supposed to be known and constant;

standard lactation curves account for general pattern of lactation curve within breed and age at calving classes, year of production within herd, season of production within herd, herd deviation from general pattern of lactation curve, and genetic value of the cow.

The main differences between mBP and BP are the definition of the standard lactation curves and the inclusion of individual genetic value. In order to minimize bias, components of standard lactation curves specific to the herd are computed jointly with random individual effect. Components of standard lactation curves obtained using the whole population (i.e. genetic values and general pattern of lactation within breed, age at calving and parity) are not recomputed each time but extracted from databases. If a cow moves from one herd to another during its lactation, standard lactation curves components specific to the herd are changed at the time of transfer. The inclusion of genetic effects is important for predicting daily yields when lactation is in progress if a cow is genetically more or less persistent than population average.

Among possible implementations of this method, we choose to use a multi-trait multi-lactation random regression TDM that allowed direct joint estimation of fixed and random effects. Data were pre-corrected for population level effects in order to make possible a daily run at herd level. Therefore, mBP could be located between BP and population-wide TDM with BLUP properties integrating ideas about distributed computing and sequential solving (Gengler *et al.*, 2000). Classical fixed herd \times test-day effect was replaced by three herd effects to enable herd-management prediction following Mayeres *et al.* (2004). These three effects are a fixed herd \times test year effect, a fixed herd \times test month \times period of 5 years effect, and a random herd \times test day effect. These three herd effects reflect evolution of herd management level, corrected for lactation stage, age at calving, parity, and genetics.

The global model could be written as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Tt} + \mathbf{Wh} + \mathbf{Zp} + \mathbf{Za} + \mathbf{e}$$

Where:

- \mathbf{y} is the vector of observations (milk, fat and protein yields, somatic cell score);

- $\boldsymbol{\beta}$ is the vector of fixed effects:

- class of 5 DIM \times class of breed \times class of age at calving (data are pre-corrected for this effect),
- herd \times test year,
- herd \times test month \times 5 year period;

- t is the vector of random herd x test-day effect;
- h is the vector of herd x year of calving random regression coefficients;
- p is the vector of permanent environmental random regression coefficients;
- a is the vector of genetic additive random regression coefficients (data are pre-corrected for this effect);
- e is the vector of residuals;
- X, T, W and Z are incidence matrices assigning observations to effects.

Herd x year of calving random regression effect was not used for somatic cell score modelling.

Finally a variant of this method was tested. This variant contains integration of expectations of constant animal effects to observed average values using a Bayesian prediction approach. The Bayesian method is similar to the MTP method, only avoiding expectations about lactation shape curves. This approach was called **mBPb**. Using this variant, the expected value of the residuals in a given lactation for a given animal was forced to be zero. The reason for the development of this alternative method was that with standard mBP, expected value of the residuals is only zero by herd. The consequence is that predicted curves could not reflect the observed records of extreme cows compared to the average animal in this herd.

(Co)variances estimations were obtained from REML and Gibbs sampling (Misztal, 2009).

2.3 Validation

In order to validate mBP, adjustment quality and prediction ability were studied. Adjustment quality is the difference between observed records used for solving the model and predicted values for these test-days. Prediction ability is the ability of the model to predict values of the following test-day. mBP and mBPb were run for 400 herds. Data of last available test-day were set to zero. All records needed for running mBP and mBPb were used to assess the adjustment quality of the model; and daily predictions for the last available test-day were used to assess the prediction ability of the model. Mean error, mean square error and correlations were computed for these two parameters.

Lactation yields prediction was also estimated. To match as much as possible to the reality, official test-day records were simulated, using actual daily production and respecting the schedule of conditions and the characteristics of the Walloon situation:

- each herd had the probability of 87 percent to be simulated in a A4 test plan and 13 percent to be simulated in a A6 plan;
- time between two tests was between 22 and 37 days (A4) or between 38 and 53 days (A6). To make test interval longer, each test-day had also 1 percent of probability to be cancelled;
- corresponding to the current practice, tests were not done in July for A4 plan;
- first test of the lactation had to be performed after the fourth day in milk.

A total of 200 simulations were done. Using these simulated test-day data, mBP, mBPb, BP and TIM lactations yields were computed and compared to the real ones. When real daily milk yields were missing, predictions for these days were not taken into account for mBP, mBPb, BP and TIM lactation yields calculation. For each method, mean, standard deviation, relative bias and correlation with actual lactation yields were computed on overall data set, by parity, and by test plan.

BP method was official best prediction program downloaded on AIPL website. To allow comparison with mBP, data were pre-corrected for parity x age at calving x breed, and standard lactation curves accounted for herd x season of calving.

Lactation yields prediction when lactation is in progress was also studied. The method was similar but only 25 simulations were done. For each simulation, 11 data sets were created: the first one contained only first test-day records; the second one contained only first and second test-day records, and so on. Each 305-d lactation yields prediction was compared to the real one for each data set.

3.0 Results and discussion

3.1 Lactation curve modelling and herd means

As described before mBP is a method to compute daily and lactation yields, but it also can compute management tools such as evolution of herd effects, peak yield and persistency. This method can be run daily herd by herd, and farmers can receive results a few days after milk recording. Figure 1 shows milk yields modelled with mBP method from an ended lactation. Prediction of entire lactation with four test-day records is shown on Figure 2. The inclusion of genetic effects in lactation curve allows to take into account genetic persistency of a cow, in addition to average persistency of the herd (explained by herd x year of calving effect) and of the breed (explained by class of 5 DIM x class of breed x class of age at calving effect).

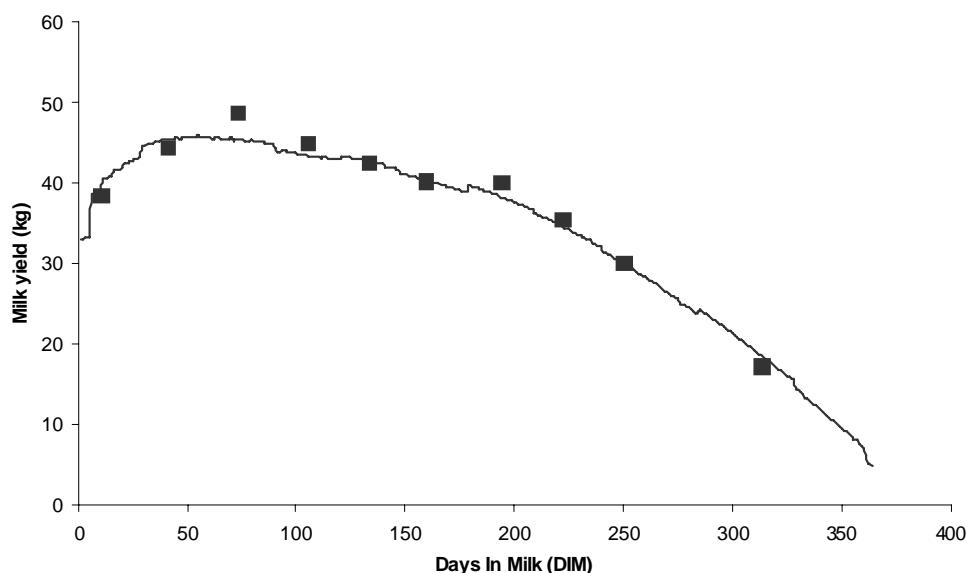


Figure 1. Illustration of the modelling of a lactation by modified-best prediction (mBP) method. (■ test day record; —mBP modelling).

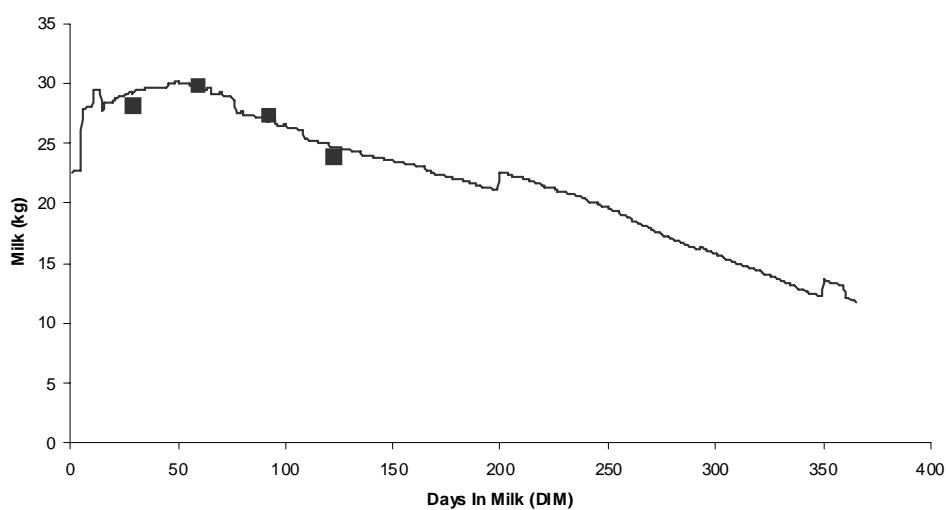


Figure 2. Prediction of the entire lactation with four test day records by modified-best prediction (mBP) method. (■ test day record; — mBP modelling).

As in Mayeres *et al.* (2004) a modification of classical fixed herd x test-date effect was done in order to predict herd effects for each day of the lactation. Figure 3 shows evolution of these three effects for a particular herd. Herd x test year effect shows a regular decrease of management level over the years. Herd x test month x period of 5 years effect shows seasonal variation of management level inside years. And herd x test-day effect includes the part of the herd variation that is not explained by the two previous effects. Sum of these three effects shows the general evolution of herd management, which is decreasing in this particular herd. General decrease can be explained by an extension of farrowing practices and seasonal variation by period of grazing or seasonal feeding. But if these variations can not be explained, results indicate management problems that need to be identified and solved. These herd management level indicators are corrected for lactation stage, breed, age at calving, and genetic, so interpretation of these values is more accurate than interpretation of raw yields. Similarly to Kovalova *et al.* (2007), values of random herd x test day effect reflects difference between predicted and observed values for herd management. No thresholds to detect management problems have been tested so far. Herd x calving year random regression could also be plotted as done by Caccamo *et al.* (2008).

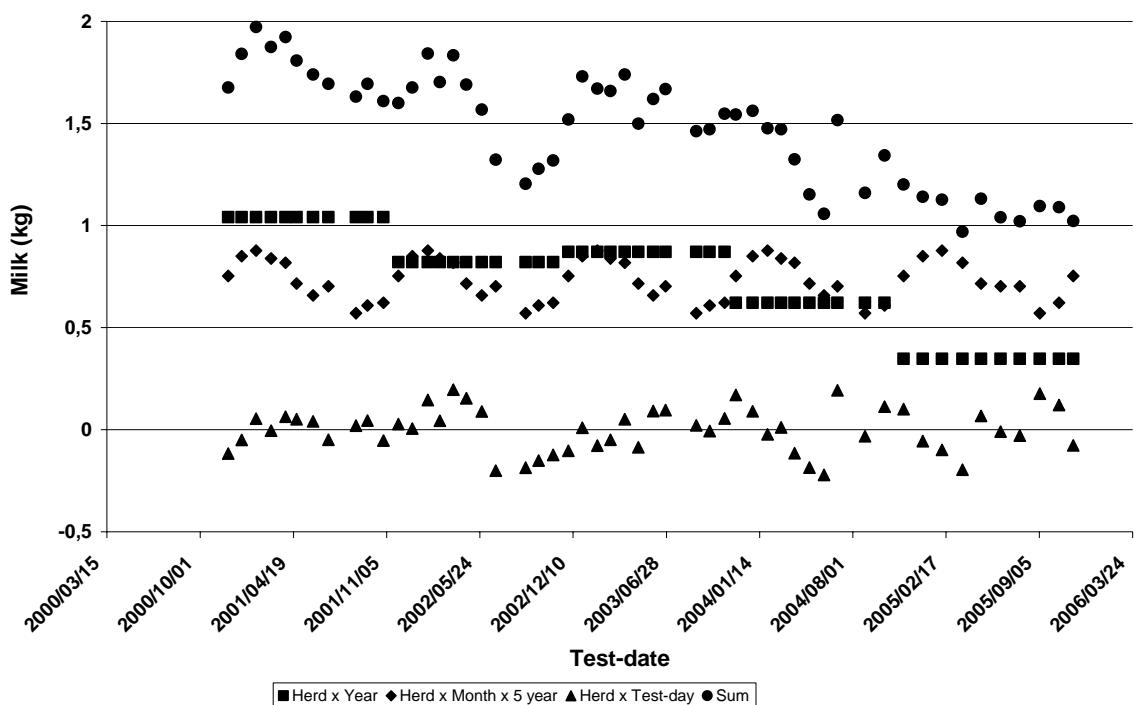


Figure 3. Evolution of herd solutions for a particular herd.

3.2 Validation

Adjustment quality was analyzed for mBP and mBPb methods. Table 1 shows results for parity one. Results were similar for other parities. Adjustment quality is the difference between available records and predicted values for these test-days. As shown in Table 1 mean error is null, mean square error is small and correlations are high, ranging from 0.85 for somatic cell score to 0.95 for milk yields. The two methods showed similar results. Prediction ability is shown in Table 2 for first parity. Prediction ability is the ability to predict values of the following test-day. The mBPb method was inferior to mBP in its ability to predict yields of following test-day. This result was not unexpected as in mBPb the prediction is centred on the already observed values for a given cow. Further results given in Table 3 will show that this issue disappears when more test-days become available.

Table 1. Adjustment quality for mBP and mBPb methods in first parity.

Trait	N	mBP			mBPb		
		ME ¹	MSE ²	Corr. ³	ME ¹	MSE ²	Corr. ³
Milk (kg)	651,266	0.00	4.28	0.95	0.00	4.17	0.95
Fat (kg)	651,266	0.00	0.01	0.92	0.00	0.01	0.92
Protein (kg)	651,266	0.00	0.01	0.93	0.00	0.01	0.94
SCS	556,791	0.00	0.70	0.85	0.00	0.68	0.85

¹ ME: mean error.² MSE: mean square error.³ Corr.: correlation between observation and prediction.*Table 2. Prediction ability for mBP and mBPb methods in first parity.*

Trait	N	mBP			mBPb		
		ME ¹	MSE ²	Corr. ³	ME ¹	MSE ²	Corr. ³
Milk (kg)	7,368	-0.09	12.37	.87	-1.73	29.47	.75
Fat (kg)	7,368	0.00	0.03	.83	-0.06	0.06	.69
Protein (kg)	7,368	0.01	0.01	.85	-0.07	0.03	.72
SCS	6,233	0.00	1.70	.57	-0.22	2.31	.49

¹ ME: mean error² MSE: mean square error³ Corr.: correlation between observation and prediction

Simulation of fictive test-day yields was done with real daily milk yields in order to maximize situations that can be present in reality. Lactations yields were computed using 5 methods: real yields, mBP, mBPb, BP, and TIM. For each method, mean and standard deviation were reported. Relative bias and correlation with real productions were also computed. For lactation yields description (when lactation is finished), analyse was done per parity and per data collecting plan. For lactation yields prediction (when lactation is in progress), analyse was done by number of available tests. Table 3 shows that mBP method was the best method even if differences were quite small. BP had higher relative bias for first parity. Additional study has to be made to see if it can be explained by production level. After 3 tests, lactation yields were predicted with high precision: relative bias was smaller than 1 percent and correlations were higher than .90 with mBP and mBPb methods. With BP, this level of precision was reached after 5 available tests.

4.0 Conclusions

The new proposed method called mBP is a daily and lactation yields computation method based on TDM that can bring management tools such as evolution of management level, peak yield and persistency. This method can be run daily herd by herd, and farmers can receive results a few days after milk recording. Validation showed that mBP was better than mBPb, that was developed to solve issues with extreme cows, and BP but differences were small. Possible management tools can be directly deduced from results that are potentially very useful tools to dairy farmers.

Table 3. Lactation yields prediction when lactation is terminated (description) and when lactation is in progress (prediction) for 4 methods: mBP, mBPb, BP, and TIM, compared with real lactation yields.

N	305-d lactation yields																		
	Real		mBP				mBPb				BESTPRED				TIM				
	Mean	std	Mean	std	r.bias ¹	Corr. ²	Mean	std	r.bias ¹	Corr. ²	Mean	std	r.bias ¹	Corr. ²	Mean	std	r.bias ¹	Corr. ²	
DESCRIPTION																			
all																			
by parity	80200	7230	1930	7227	1917	-0.04	0.991	7235	1949	0.07	0.990	7077	1927	-2.12	0.985	7254	1951	0.33	0.990
lact=1	26600	6361	1352	6361	1364	0.00	0.985	6369	1383	0.13	0.985	6012	1200	-5.49	0.979	6376	1382	0.24	0.984
lact=2	17600	7348	1853	7356	1849	0.11	0.990	7363	1880	0.20	0.990	7217	1775	-1.78	0.987	7385	1883	0.50	0.990
lact=3	15600	7986	2182	7962	2176	-0.30	0.991	7974	2217	-0.15	0.991	7946	2177	-0.50	0.991	8000	2205	0.18	0.990
lact=4	10000	8036	1999	8029	1970	-0.09	0.990	8050	2000	0.17	0.989	8045	1993	0.11	0.989	8086	2004	0.62	0.988
lact=5	4800	8157	1877	8128	1823	-0.36	0.986	8148	1878	-0.11	0.987	8137	1865	-0.25	0.988	8176	1890	0.23	0.987
lact=6 +	5600	6643	1730	6677	1673	0.51	0.988	6644	1717	0.02	0.988	6631	1673	-0.18	0.987	6655	1718	0.18	0.988
by data collection plan																			
A4	69774	7230	1930	7229	1917	-0.01	0.991	7236	1948	0.08	0.991	7080	1928	-2.07	0.986	7253	1950	0.32	0.991
A6	10426	7230	1930	7213	1912	-0.24	0.988	7225	1955	-0.07	0.987	7054	1924	-2.43	0.982	7256	1958	0.36	0.987
PREDICTION																			
number of available tests																			
1	3179	7716	1833	7489	1670	-2.94	0.907	7373	2343	-4.45	0.811	7731	1954	0.19	0.838	-	-	-	-
2	5638	7556	1889	7449	1800	-1.42	0.934	7466	2308	-1.19	0.884	7786	2030	3.04	0.896	-	-	-	-
3	6271	7473	1861	7436	1852	-0.50	0.948	7509	2216	0.48	0.920	7653	1989	2.41	0.923	-	-	-	-
4	6695	7292	1867	7272	1877	-0.27	0.960	7345	2136	0.73	0.943	7368	1962	1.04	0.942	-	-	-	-
5	7603	7117	1904	7101	1910	-0.22	0.974	7160	2085	0.60	0.966	7114	1976	-0.04	0.962	-	-	-	-
6	7211	7272	1878	7248	1863	-0.33	0.979	7299	1989	0.37	0.975	7213	1919	-0.81	0.968	-	-	-	-
7	6842	7462	1958	7438	1936	-0.32	0.985	7482	2033	0.27	0.983	7376	1989	-1.15	0.977	-	-	-	-
8	6066	7602	1908	7566	1882	-0.47	0.988	7595	1947	-0.09	0.987	7484	1919	-1.55	0.981	-	-	-	-
9	5267	7745	2082	7720	2067	-0.32	0.992	7742	2122	-0.04	0.991	7610	2114	-1.74	0.986	-	-	-	-
10	3701	7639	2024	7613	2006	-0.34	0.992	7626	2042	-0.17	0.992	7455	2024	-2.41	0.987	-	-	-	-
11	2656	7816	2110	7786	2083	-0.38	0.993	7803	2116	-0.17	0.992	7624	2135	-2.46	0.988	-	-	-	-

¹Relative bias (%) = (mean - real mean)*100 / real mean

²Correlations between real and predicted lactation yields

5.0 Acknowledgments

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