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Modeling milk urea of Walloon dairy cows in management perspectives

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ABSTRACT

The aim of this study was to develop an adapted random regression test-day model for milk urea (MU) and to study the possibility of using predictions and solutions given by the model for management purposes. Data included 607,416 MU test-day records of first-lactation cows from 632 dairy herds in the Walloon Region of Belgium. Several advanced features were used. First, to detect the herd influence, the classical herd × test-day effect was split into 3 new effects: a fixed herd × year effect, a fixed herd × month-period effect, and a random herd test-day effect. A fixed time period regression was added in the model to take into account the yearly oscillations of MU on a population scale. Moreover, first autoregressive processes were introduced and allowed us to consider the link between successive test-day records. The variance component estimation indicated that large variance was associated with the random herd × test-day effect (48% of the total variance), suggesting the strong influence of herd management on the MU level. The heritability estimate was 0.13. By comparing observed and predicted MU levels at both the individual and herd levels, target ranges for MU concentrations were defined to take into account features of each cow and each herd. At the cow level, an MU record was considered as deviant if it was <200 or >400 mg/L (target range used in the field) and if the prediction error was >50 mg/L (indicating a significant deviation from the expected level). Approximately 7.5% of the MU records collected between June 2007 and May 2008 were beyond these thresholds. This combination allowed for the detection of potentially suspicious cows. At the herd level, the expected MU level was considered as the sum of the solutions for specific herd effects. A herd was considered as deviant from its target range when the prediction error was greater than the standard deviation of MU averaged by herd test day. Results showed that 6.7% of the herd test-day MU levels between June 2007 and May 2008 were considered deviant. These deviations seemed to occur more often during the grazing period. Although theoretical considerations developed in this study should be validated in the field, this research showed the potential use of a test-day model for analyzing functional traits to advise dairy farmers.
Key words: milk urea, test-day model, autoregression, target range

INTRODUCTION

Dairy farmers need management tools for decision making (e.g., about culling or feeding). Therefore, the use of milk records should be more than simple reporting of yield performance or to provide data for the estimation of breeding values. For several years, the Walloon Breeding Association, in collaboration with Gembloux Agricultural University, has undertaken research and development to increase the usefulness of milk recording data for management purposes (e.g., by adapting the lactation yield computation method; Mayeres et al., 2004). This research could be extended to include functional traits such as milk urea (**MU**), which is routinely measured by milk recording organizations, and eventually could provide valuable feeding management feedback to dairy farmers.

Urea is the major contributor to the NPN fraction of milk and represents 5 to 6% of the total nitrogen in milk. Milk urea nitrogen is primarily derived from BUN because urea equilibrates with water in the body. This equilibrium explains the high correlation between MUN and BUN concentrations (Depeters and Ferguson, 1992). Blood urea nitrogen derives from at least 2 sources: the liver detoxification of ammonia diffused from the rumen and the catabolism of AA in the liver (Depeters and Ferguson, 1992). Thereby, MU concentration could reflect protein metabolism in the cow and could be related to the diet.

Several researchers have studied the links between MU concentrations and nutritional or environmental

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factors at the herd and individual levels. These studies have shown that MU is related mostly to the dietary CP (Broderick and Clayton, 1997; Hojman et al., 2004; Nousiainen et al., 2004) or to the surplus of nitrogen that is available in the rumen for microbial growth compared with the available energy (RDP balance, or OEB in the Dutch and Belgian standard; Hof et al., 1997; Schepers and Meijer, 1998; Frand et al., 2003). Moreover, MU concentrations are related to individual production traits, such as test-day production of milk, fat, or protein. Several studies have also associated MU with environmental effects, such as season, month of calving, parity group, or stage of lactation (Broderick and Clayton, 1997; Godden et al., 2001; Rajala-Schultz and Saville, 2003).

Generally, MU is thought of as an indicator that provides feedback on feeding management for dairy producers. Because of its large variability within cows, which is not accurately accounted for in most studies, the authors instead recommend using MU information at the herd level. For instance, Jonker et al. (2002) showed that providing average herd MUN values to farmers resulted in better feed management and in a change in MUN toward the target value. In France especially, the milk recording organization in the Pas-De-Calais Region has proposed an MU-based diagnostic tool for breeders (Juan, 2004). Given the MU level of the herd and the number of cows that are in the target range for MU (200 to 400 mg/L), the technician gives advice to breeders on a better energy:protein ratio in the ration (Juan, 2004). Use of MU as a tool to evaluate dairy herd feeding is usually based on phenotypic values, generally the herd average MU from a bulk sample. However, as reported in several previous studies, MUN shows large variability within cows (Wood et al., 2003; Mitchell et al., 2005; Miglior et al., 2007). Moreover, several studies have shown the possibility of using solutions or predictions from a test-day model for production or SCC traits to advise dairy farmers (Van Bebber et al., 1999; Koivula et al., 2007).

Using the modeling of MU concentrations, we had the long-term objective for this project of bringing feed management tools to dairy farmers. Toward this general objective, the approach in this study was to define a range of target MU concentrations for each cow and for each herd according to its own specificity. The specific objectives of this paper were 1) to formulate a random regression test-day model for Walloon first-lactation cows adapted to the specificities of MU that would permit the herd effects to be brought out; 2) to estimate the (co)variance components and heritabilities for this trait; 3) to study the potentialities of this approach for defining individual and herd thresholds for desirable MU concentrations.

MATERIALS AND METHODS

Data

Data used in this study were MU test-day concentrations measured by mid-infrared spectrometry during milk recording in the Walloon Region of Belgium and were collected between January 2003 and May 2008. In contrast to most previous studies, MU values were preferred to MUN values for modeling: because Walloon dairy farmers currently receive urea information expressed as MU concentration (mg/L of milk), the same standard should be maintained for future practical implications. Moreover MU and MUN express basically the same trait: MUN (mg/dL) = MU/21.4 (mg/L). In this study, only first-lactation cows were used, to limit the amount of data but to keep records related to similar cows from a physiological point of view. In fact, the authors associated levels of MU with the parity group effect (Broderick and Clayton, 1997; Godden et al., 2001). Herd inclusion criteria included a minimum of 4 yr of records and at least 5 first-lactation cow records for each test day. These conditions were aimed to obtain a sufficient amount of data by classes of fixed effects to have a reliable estimation of solutions for fixed effects related to herds. Records from 632 selected herds were thus retained; 1,528 herds were rejected for failing to pass the inclusion test. Descriptions of the global data set and the data set used for the estimation of variance components are given in Table 1. The complete data set included 607,416 test-day records from 72,468 first-parity Holstein cows. Pedigree data were extracted from the database used for the official Walloon genetic evaluations, and the pedigree file contained 231,083 animals.

The pedigree was limited to animals born after 1980 for estimation of the variance components and of the parameters for first-order autoregressive processes. Moreover, test-day records were required to have been collected between 5 and 365 DIM and before June 2007. This time restriction was applied because records between June 2007 and May 2008 would be used afterward to illustrate the definition of individual and herd thresholds. The data subset for estimation of the variance components represented 422,753 observations.

Model

The model used was based on a model described previously by Mayeres et al. (2004) and was used for modeling milk, fat, and protein yields. As explained by Mayeres et al. (2004), replacing the classical herd × test date fixed effect by the sum of 3 herd effects [a fixed herd × test year, a fixed herd × test month-period, and

Table 1. Descriptive statistics of the complete edited data set and of the data set used for estimation of variance components

Item	Data set for the variance components estimation	Complete data set
Milk urea (MU) records (n)	422,753	607,416
Mean ± SD of MU (mg/L)	246.6 ± 106.6	255.1 ± 105.9
CV of MU (%)	43	42
Cows with records (n)	128,789	231,083
Animals in the pedigree (n)	57,035	72,468
Sires in the pedigree (n)	7,875	23,029

a random herd × test-day (**HTD**) effect] increased the usefulness of the model to predict production records for each potential test day without producing reranking of animals for milk, fat, and protein yields (Mayeres et al., 2004). The sum of the herd × test month-period and the herd × test year effects was then considered as the expected production of the herd for a given test day corrected for nonherd effects (Mayeres et al., 2004). That model was chosen as a basis because it produced encouraging results for production traits and because it is currently used in the new application of milk recording in the Walloon Region.

Additional adaptations of the model were done by considering specificities of MU based on the evidence of the phenotypic periodic trend across time and the link between successive (herd) test dates. First, yearly oscillations of MU around a quadratic trend at the population scale were observed in a preliminary study. Grossman et al. (1986) suggested the use of a time period regression including sine and cosine terms to take into account this kind of seasonal variation. Therefore, a random population test-day effect and a fixed time period regression were added to the model.

Second, a first-order autoregressive process was added for both the random population test-day effect and the random HTD effect. This process was described by Wade and Quaas (1993) and allowed for covariance among effects. For instance, a fortuitous (e.g., diet-related) event in a given herd for a given test day would affect the average MU concentrations in this herd for the current test day, but also for the next test day.

The following single-trait random regression test-day model was then defined:

$$\mathbf{y} = \mathbf{Rr} + \mathbf{X\beta} + \mathbf{Ww} + \mathbf{Hh} + \mathbf{Q}(\mathbf{Cc} + \mathbf{Zp} + \mathbf{Za}) + \mathbf{e}, \quad [1]$$

where $\mathbf{y}$ is the vector of test-day MU; $\mathbf{r}$ is the vector of periodic regression coefficients (i = 1 to 4) for the corresponding incidence matrix $\mathbf{R}$, with the definition of each column i as $R_1 = n$, $R_2 = n^2$, $R_3 = \sin(n_r)$, and $R_4 = \cos(n_r)$, where n is the number of days since January 1, 2003, divided by 365.25 (to take into account the periodicity of approximately 1 yr) and n_r is n, computed as radians; $\boldsymbol{\beta}$ is the vector of fixed effects, which were herd × test year, herd × test month period, and DIM class × breed × age at calving. The herd × month period effect was defined within a herd as months in a 5-yr period; $\mathbf{w}$ is the vector of random population test-day effects, assumed to follow a first autoregressive process across time; $\mathbf{h}$ is the vector of the random HTD effect, assumed to follow a first autoregressive process; $\mathbf{c}$ is the vector of herd × time period of calving random regression coefficients; $\mathbf{p}$ is the vector of permanent environmental random regression coefficients; $\mathbf{a}$ is the vector of additive genetic random regression coefficients; $\mathbf{e}$ is the vector of random residuals; $\mathbf{X}$, $\mathbf{W}$, $\mathbf{H}$ are incidence matrices assigning observations to effects; and $\mathbf{Q}$ is the covariate matrix of second-order Legendre polynomials linking observations to incidence matrixes $\mathbf{C}$, $\mathbf{Z}$, defined in a way that $\mathbf{QC}$ and $\mathbf{QZ}$ assigned observations to random regression effects. Options other than Legendre polynomials exist as the basis for the random component of the regression (e.g., splines). However, as a quite standard way of describing random effects, Legendre polynomials were used so as not to add more complexity in the model.

The expectations and covariance structure for random effects were as follows: $E(\mathbf{y}) = \mathbf{Rr} + \mathbf{X\beta}$; $E(\mathbf{w}) = 0$; $E(\mathbf{h}) = 0$; $E(\mathbf{c}) = 0$; $E(\mathbf{p}) = 0$; $E(\mathbf{a}) = 0$; $E(\mathbf{e}) = 0$; and $V\left(\mathbf{w}\right) = \mathbf{S_w}\sigma^2_{t_w}$; $V\left(\mathbf{h}\right) = \mathbf{S_h}\sigma^2_{t_h}$; $V\left(\mathbf{c}\right) = \mathbf{I}\sigma^2_c$; $V\left(\mathbf{p}\right) = \mathbf{I}\sigma^2_p$; $V\left(\mathbf{a}\right) = \mathbf{A}\sigma^2_a$; $V\left(\mathbf{e}\right) = \mathbf{I}\sigma^2_e$, where

$$\mathbf{S_w} = \begin{bmatrix} 1 & \rho_w^{t_2-t_1} & \rho_w^{t_3-t_1} & \dots & \rho_w^{t_n-t_1} \\ \rho_w^{t_2-t_1} & 1 & \rho_w^{t_3-t_2} & \dots & \rho_w^{t_n-t_2} \\ \rho_w^{t_3-t_1} & \rho_w^{t_3-t_2} & 1 & \dots & \rho_w^{t_n-t_3} \\ \dots & \dots & \dots & \dots & \dots \\ \rho_w^{t_n-t_1} & \rho_w^{t_n-t_2} & \rho_w^{t_n-t_3} & \dots & 1 \end{bmatrix};$$

$$\mathbf{S_h} = \begin{bmatrix} 1 & \rho_h^{t_2-t_1} & \rho_h^{t_3-t_1} & \cdots & \rho_h^{t_n-t_1} \\ \rho_h^{t_2-t_1} & 1 & \rho_h^{t_3-t_2} & \cdots & \rho_h^{t_n-t_2} \\ \rho_h^{t_3-t_1} & \rho_h^{t_3-t_2} & 1 & \cdots & \rho_h^{t_n-t_3} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \rho_h^{t_n-t_1} & \rho_h^{t_n-t_2} & \rho_h^{t_n-t_3} & \cdots & 1 \end{bmatrix};$$

where t_k are the consecutively available test-day periods, within a herd for the HTD effect (or in the whole population for the population test-day effect), arranged in ascending order from lowest (t_1) to highest (t_n); ρ_h is the HTD effect autocorrelation coefficient; $\sigma^2_{t_w}$ is the population test-day effect variance component; $\sigma^2_{t_h}$ is the HTD effect variance component; ρ_w is the population test-day effect autocorrelation coefficient; $\mathbf{I}$ is the identity matrix; σ^2_c is the herd × period of calving variance component; σ^2_p is the permanent environmental variance component; $\mathbf{A}$ is the additive relationship matrix; σ^2_a is the additive genetic variance component; and σ^2_e is the residual variance component. Random effects of the model were assumed to be normally distributed.

Definition of the Correlation Coefficients ρ_w and ρ_h

As defined by Wade and Quaas, (1993), a first-order autoregressive process implies that only 1 parameter besides the variance is needed: ρ, which can be considered to be the estimated correlation between the current and the previous value of the process. These parameters for the population test day and the HTD effects were set up based on data from January 1, 2003, to May 31, 2007. The correlation between average MU concentrations for 2 successive population test days was computed and was assumed to be the ρ_w. For the HTD effect, ρ_h was defined as a function of the number of days between the current and the previous HTD. Actually, in contrast to the population test-day effect for which successive levels were generally separated by only 1 d, the number of days between successive HTD levels could vary between 23 and 64 d, depending on the milk recording scheme (A4, which is the monthly recording of 2 daily milkings, or A6, which is the recording of 2 daily milkings every 6 wk) and on the month (no recording usually happened in July for the A4 scheme). This function was set up as follows. First, correlations between averaged MU observed values for 2 successive HTD were computed according to the number of days between the studied HTD. Only correlations estimated on more than 99 HTD pairs were used for the second step to avoid artifacts caused by the lack of information. Second, a logarithmic regression function of these correlations on the number of days between 2 successive recordings was fitted; observed correlations were weighted by the number of observations. Finally, the logarithmic regression function was included in the algorithm as presented by Wade and Quaas (1993) for defining the (co)variance matrix for the effect that followed a first-order autoregressive structure. For this implementation, negative correlations between successive HTD were set to zero and correlations up to 1 were set to 1.

Variances Components and Heritabilities

Variance components were estimated using the data subset defined previously. Matrices $\mathbf{S_h}$ and $\mathbf{S_w}$ were established and the estimation of (co)variances was done by average information-REML (Misztal, 2007), which was slightly modified to permit the use of (co)variance matrices externally defined for the HTD and population test-day effects.

The average daily heritability was computed as the ratio of genetic variance to total variance for each DIM from 5 to 305 d, and was averaged across the entire lactation. The average proportions of variance caused by each effect as well as the repeatability (calculated as the ratio between the sum of genetic and permanent environmental effects to the total variance) were also computed with the same method.

Definition of Individual and Herd Thresholds

As described above, 2 modifications were introduced into the program BLUPF90 (Misztal, 2007). The first one allowed inclusion of (co)variance matrices externally defined for the autoregressive processes, and the second one provided empirical Bayesian predictors of future records based on estimated fixed and random effects.

Model [1] was solved in a first step for data from January 2003 until June 2007, in a second step for data until July 2007, and so on for data from each month until May 2008. The solutions of the last months were then analyzed (first for June 2007, then for July 2007, and so on until May 2008). This approach allowed us to study the evolution of the MU target range and the number of records deviating from the defined thresholds month by month through 1 yr. This corresponded to a simulated real-life situation as if this methodology were being applied in the field. Indeed the long-term objective of this research was to advise farmers on the feeding of their cows based on indicators such as MU provided by the milk recording data. This feedback would be sent monthly to dairy farmers after each milk recording. Therefore, it would imply running the analysis every month. Prediction errors (**PE** = prediction − observation), standard deviations of the PE, and correlations between observed and predicted MU values were estimated.

The definitions of individual and herd target MU ranges were then investigated. First, the basic approach for exploiting the results given by test-day models such as those by Van Bebber et al. (1999) and Koivula et al. (2007) was investigated: a cow or a herd record was considered suspicious if it deviated from its expected value. Those suspicious records could reflect management or feeding problems. Records that were much higher or much lower than the usual levels of the cow or the herd were then detected, for example, if the ration had been changed with the inclusion of a new silage and had dramatically increased the MU herd level. Therefore, this approach implied the definition of expected MU levels at both the cow and herd levels.

At the cow level, the expected individual MU concentration was defined as the empirical Bayesian prediction given by the model, that is, the sum of the solutions of model [1] for all effects except the residual. At the herd level, for each test day within each herd, the observed HTD MU level was defined as the sum of the solutions of model [1] for herd × test year, herd × test month-period, and HTD effects. The expected HTD MU level was computed as the sum of the solutions given by model [1] for herd × test year and herd × test month-period fixed effects plus the expected value for the HTD effect, computed as the solution of the model for the HTD effect of the previous HTD multiplied by the corresponding ρ_h.

For both the individual and herd levels, thresholds to consider a record as suspicious or deviant (indicating a likely feeding problem) were defined after testing different options. At the cow level, a record was considered deviant when the absolute PE was greater than 50 mg/L; this value represented a 20% PE on the global mean of MU since January 2003, which was 255.1 mg/L. This threshold (**THRC1**) was arbitrarily chosen by considering that a 20% error was more likely to reflect a deviant record because of a likely feeding problem than because of the lack of precision of the model. At the herd level, the option retained (**THRH**) considered a herd as deviant from the target range when the PE was higher than the "natural variation at the herd level," considered as the standard deviation of the MU concentrations averaged by HTD.

Second, we studied the possibility of using a fixed field threshold (**THRC2**) at the cow level. This field threshold considered a record as deviant when the observed MU concentration was out of the range of 200 to 400 mg/L. This range is used in the field in Belgium and the north of France, according to Deswysen et al. (1997) and Juan (2004). However, target ranges given by the scientific and the practical literature varied. Kohn et al. (2002) recommended the 180 to 250 range as target values. Recommendations from the practical literature were more abundant: 215 to 340 (Adam, 2005), 175 to 300 (De Brabander et al., 1999), and 200 to 400 (Deswysen et al., 1997; Juan, 2004). This last range was chosen for this study and was discussed afterward. Finally, we investigated the definition of a threshold at the cow level (**THRCC**) as a mixture of both the THRC1 and THRC2.

RESULTS AND DISCUSSION

Data

The mean and standard deviation of MU records from the complete data set was 255.1 ± 105.9 mg/L (Table 1). The coefficient of variation was 42%. Several authors have reported average MU values in the same range but with lower coefficients of variation, from 15 to 33% (adapted from Mitchell et al., 2005; Stoop et al., 2007; König et al., 2008). The large variation found in this study could be explained by different feeding systems among Walloon herds, namely, the supplementation of grass-based feeding during the summer months or the type of forage used during the winter season (grass silage, maize silage, or beet pulp; Frand et al., 2003). Moreover, Figure 1 shows the average test-day MU in the population across years and suggests a seasonal trend within year, which covered all herds beyond their specificities. Milk urea seemed to be the highest during summer months, especially in August, and the lowest during the month of February. The same trend with higher MU during the summer months (July to September) has been reported by several authors (Godden et al., 2001; Rajala-Schultz and Saville, 2003; Wattiaux et al., 2005). This fluctuation could reflect the grazing period and the access of cows to fresh pasture, which typically contains highly degradable protein and has a high protein-to-energy ratio (Soriano et al., 2001). Moreover, this seasonal effect varied from year to year; the MU level increased slightly across years. For instance, the monthly mean for MU concentration was 185 mg/L for February 2003 and increased to 271 mg/L for February 2008. Wattiaux et al. (2005) also found variation across years. They suggested that interpreting monthly MUN averages may be not reliable unless adjustments have been made to standardize values for

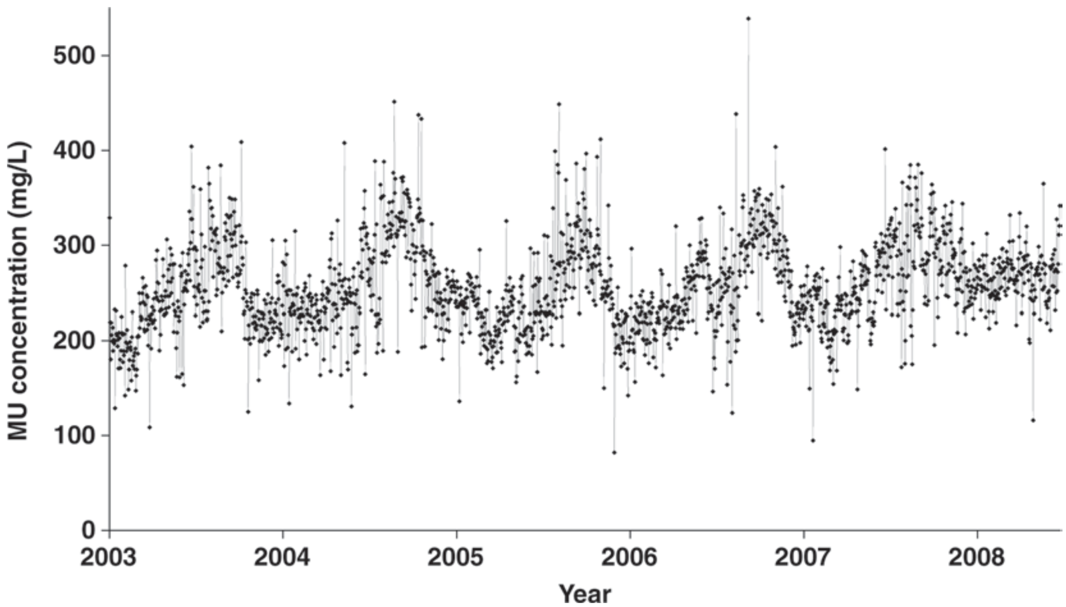

Figure 1. Trend (daily means) in milk urea (MU) concentrations for first-lactation cows across time from January 2003 to May 2008.

certain sources of variation. Thus, this explained the inclusion in the model of a time period regression at the population level.

The trend in concentrations of MU across DIM is given in Figure 2. The curve for MU seemed to be a mirror image of the milk yield. The average MU at calving was close to 285 mg/L; it then decreased to 225 mg/L at approximately 30 to 40 DIM and finally rose slightly until 280 DIM to the same level as the one at calving. A similar trend was observed by Miglior et al. (2007) and Wood et al. (2003). As discussed by Wood et al. (2003), this trend may be due to the physiological changes and the evolution of the metabolic demands of milk production across DIM. However Godden et al. (2001) and Wattiaux et al. (2005) reported that the MU trend across a lactation was similar to the lactation curve. This pattern of change in MU might be observed when MUN data are summarized on a 30-d interval basis (Wattiaux et al., 2005).

Autoregressive Processes

Based on the observed correlation between MU averages for successive population test days, ρ_w was fixed at 0.58. Figure 3 shows the evolution of observed correlations between averaged MU values for 2 successive HTD and the number of days between the recordings. The correlations varied from 0.63 at 25 d between recordings to 0.27 at 64 d between recordings. These correlations were moderate but indicated that an event in a given herd for a given test day affecting the MU level would have an impact on the average MU in the same herd but would be observed for the next test day. Logically, with increased intervals, and therefore more days between recordings, the correlation between successive recordings decreased. Correlations predicted by the logarithmic regression are also indicated in Figure 3. The ρ_h was then defined as a function of the number of days between successive recordings within the same herd (nb_{days}):

$$\rho_h = 1.20165 - 0.19984 \times \ln(nb_{days}).$$

Predicted correlations with the logarithmic regression function higher than 1 for the low number of days were due to the lack of observed correlations for those numbers of days, and the "extrapolation" to lower intervals produced these values.

Variances Components and Heritabilities

The pattern of variance components across the first lactation for MU concentration is shown in Figure 4. Total variance was explained mainly by the HTD effect: the average proportion of variance caused by the HTD effect was 48%. This indicates that the management and the herd environment were important factors explaining the variability in MU concentrations. Wood et al. (2003) also observed a highly significant HTD effect on MUN, and Stoop et al. (2007) found that the proportion of the global variance attributable to the HTD effect was 58%. The repeatability was 0.22,

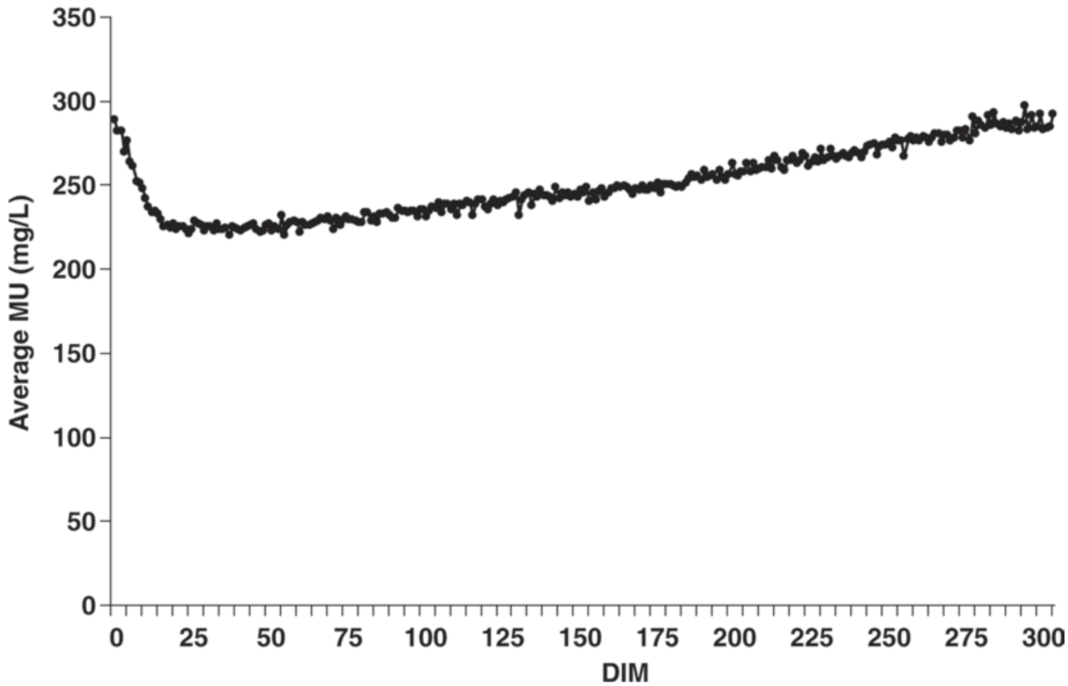

Figure 2. Trend (daily means) in milk urea (MU) concentrations for first-lactation cows across DIM.

indicating that the individual cow variability was low in comparison with the herd variability. These results have large implications for the development of feeding management tools based on modeling MU; the herd effects influenced the MU values more than did the individual cow features.

As reported previously by Miglior et al. (2007), the permanent environmental variance was higher at the beginning and end of the lactation. The genetic variance was higher at the end of the lactation. Except for the first 30 DIM, the genetic variance was higher than the permanent environmental variance. Average

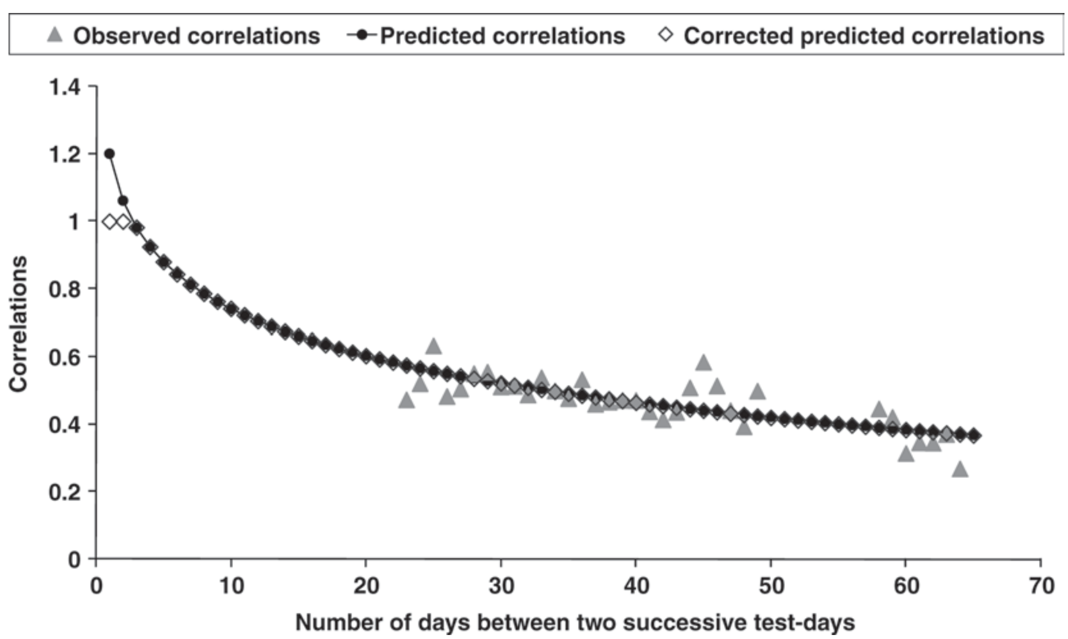

Figure 3. Observed correlations and predicted correlations (with a logarithmic regression) between solutions for successive herd × test-day effects computed with model [1] according to the number of days between the 2 successive recordings within the same herd.

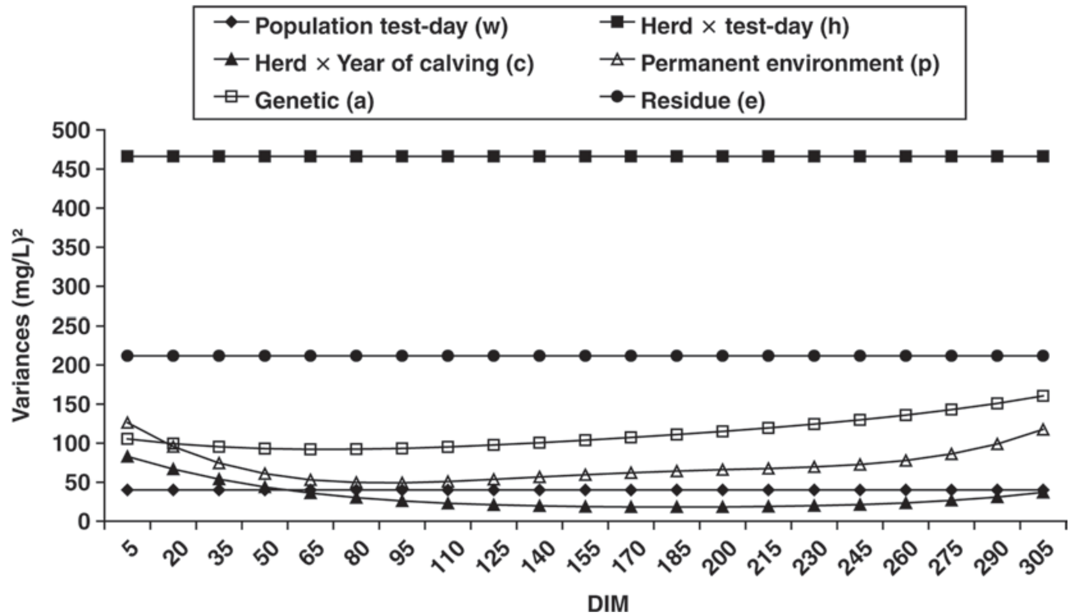

Figure 4. Variance components by DIM.

daily heritability was 0.13. Heritability estimates for MU concentrations in the first lactation were variable and ranged from 0.13 to 0.44 (Wood et al., 2003; Stoop et al., 2007; König et al., 2008). These differences were probably due to the models applied (using the HTD effect as a fixed or random effect) or to the heritability computation method (including the HTD effect or not in the denominator, or computing heritability on 305-d production). If the heritability was estimated as the ratio between genetic variance and the sum of genetic, permanent environmental, and residual variances as shown in Stoop et al. (2007), the value was higher: 0.29.

The heritability estimate found in this study was low but could permit animal selection based on MU. However, as discussed by Wood et al. (2003), the direct economic importance of MU from a genetic point of view is unclear. These authors indicated that the most promising use of MU could be as a tool for indirect selection for fitness traits such as fertility. Beyond these considerations, this study investigated an alternative use for modeling MU and used breeding values for this trait as a part of a more global tool for management purposes.

Predictions Estimation and Target Range at the Individual Cow Level

Solutions and predictions were then computed as described previously for records between June 2007 and May 2008. The correlation between individual expected and observed MU levels for the data between June 2007 and May 2008 (115,925 records) was 0.92. The average PE was near zero (−0.02 mg/L), indicating that underestimated records were likely balanced by overestimated records. Moreover, the standard deviation of PE was 38 mg/L and the average absolute PE was 29 mg/L. However, these values were largely influenced by "extreme PE": Figure 5 indicates the distribution of individual PE. Minimum and maximum PE were, respectively, −273 and 400 mg/L. The results showed that 16% of the records were predicted with an absolute error greater than 50 mg/L. This threshold represented 20% PE on the global mean of MU since January 2003, which was 255.1 mg/L. These records were not linked to early DIM in the lactation, particular months, or particular herds. However, they could indicate that these records were influenced by a particular event that was not taken into account by the model, and they could represent deviant records.

According to Deswysen et al. (1997) and Juan (2004), the optimal range for MU used in the field in Belgium and the north of France is from 200 to 400 mg/L. The second threshold tested at the individual level was then defined around these values. Table 2 indicates the frequency of deviant and nondeviant records in the data set according to both thresholds. Approximately 16.5% of the records were considered deviant for the first threshold (PE <50 mg/L) and 27.2% were considered deviant for the second threshold (200 ≤ MU ≤ 400 mg/L). The high standard deviation for MU records considered deviant with both THRC1 and THRC2 (181

Table 2. Comparison of the percentage and the mean and standard deviation of milk urea (MU) for individual records considered as deviant or not according to the threshold 1 (THRC1), which considered a record as deviant when the prediction error (PE) was higher than 50 mg/L, and according to the threshold 2 (THRC2), which considered a record as deviant when the observed MU concentration was lower than 200 mg/L or higher than 400 mg/L

	THRC2 (200 ≤ MU ≤ 400 mg/L)	
THRC1 (PE <50 mg/L)	Deviant	Nondeviant
Deviant	7.4%; 273 ± 181 mg/L	9.1%; 299 ± 59 mg/L
Nondeviant	19.8%; 236 ± 142 mg/L	63.7%; 286 ± 53 mg/L

mg/L) indicated that this class contained extreme MU records. It should also be noted that 60% of the observations considered nondeviant with both thresholds ranged between 234 and 338 mg/L. The definition of an individual target range for MU concentrations or a threshold at the cow level could be a mixture of both approaches. Indeed THRC1 could allow for detection of cows for which the MU concentration changed significantly from its expected value because of physiological processes at the early stage of lactation. For instance, MU was associated with energy balance in multiparous high-yielding Holstein cows (Reist et al., 2002). Moreover, this threshold takes into account the unavoidable variation of MU linked to the season or the stage of lactation. Aside from these considerations, some farmers or advisers currently use THRC2, although it does not take into account seasonal or genetic variations. Combining both thresholds gave 7.4% deviant records. This percentage was lower but could focus on records truly suspicious and avoid attracting attention to records that deviated from their expected value but that stayed in an acceptable MU range (deviant for THRC1 and nondeviant for THRC2), or on records that were up to 400 mg/L but were due to the season (deviant for THRC2 and nondeviant for THRC1). Table 3 indicates the percentage of deviant records by month according to THRCC. Generally, no recording happened in July for herds in the A4 milk recording scheme; the low number of records in Table 3 was due to herds being in the A6 scheme. The proportion of deviant cows did not differ greatly across time: from 5.22% in July to 8.57% in November.

Target Range at the Herd Level

As mentioned previously, MU concentrations varied among herds and across time. This demonstrates the interest in defining a target MU range for each herd by taking into account its own specificities and removing individual cow influences. A given herd at a given test day was considered suspicious or deviant when the absolute difference between the observed and expected HTD MU levels was higher than the “natural variation at the herd level,” considered as the standard deviation of the MU concentrations averaged by HTD and equal to 89.23 mg/L. This threshold (THRH) was fixed after testing different options and seemed to be the most sensitive.

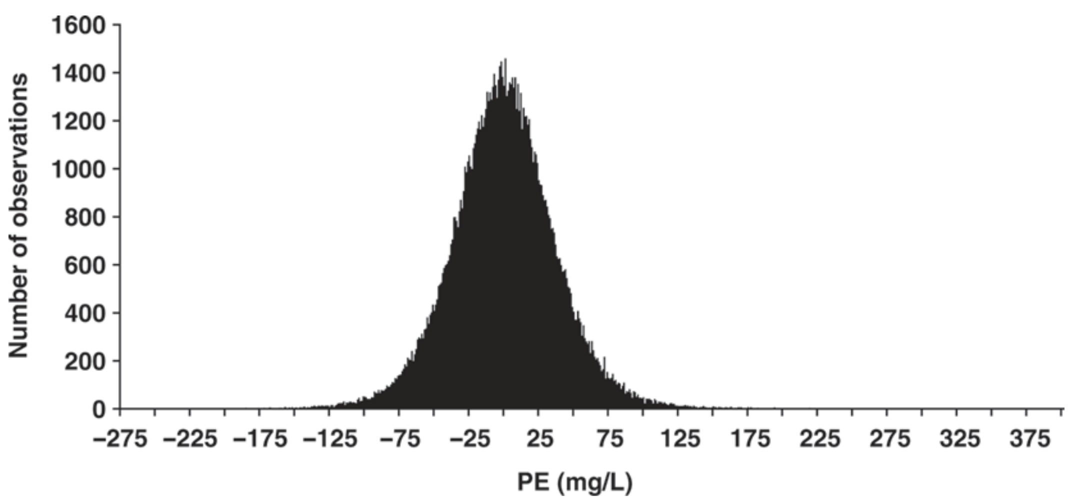

Figure 5. Distribution of prediction error (PE) of records between June 2007 and May 2008.

Table 3. Number of individual deviant records or herd × test-day deviant records based on the threshold at the cow level (THRCC) and the herd level (THRH)

Month	Records (n)	Deviant cows based on THRCC (%)	Controlled herds (n)	Deviant herds based on THRH (%)
June 2007	10,052	8.09	491	0.41
July 2007	1,993	5.22	94	5.32
August 2007	9,690	7.74	507	9.86
September 2007	9,480	8.61	484	12.19
October 2007	10,294	7.72	494	10.32
November 2007	10,423	7.55	493	8.52
December 2007	10,396	7.62	483	6.63
January 2008	10,839	7.40	497	2.21
February 2008	10,413	5.49	469	2.56
March 2008	10,445	6.71	478	1.88
April 2008	11,048	6.86	495	5.86
May 2008	10,392	8.57	474	8.86

Figure 6 shows the evolution of the expected and observed HTD MU levels for a particular herd chosen in our database between June 2007 and May 2008. The record for March was found to be deviant. The curve clearly indicated an increase in the MU level during that month and could indicate a nonpunctual feeding event. It could, for instance, be explained by the degradation of the silages or the exhaustion of some forage reserves, which may have disturbed the feeding balance. These events could occur at the end of the winter season on Walloon dairy farms.

When THRH was applied to the data set, 6.7% of the HTD were found to be deviant. Of the 541 herds studied, 241 included at least 1 deviant HTD. Table 3 indicates the percentage of deviant herds according to month for the period between June 2007 and May 2008. This proportion varied between 0.04% for June and 12.19% for September. The greatest proportion of deviant cows occurred during the end of summer and the beginning of fall, and the lowest proportion occurred, for example, during the indoor months. Indeed, fine-tuning the ration during the grazing period is

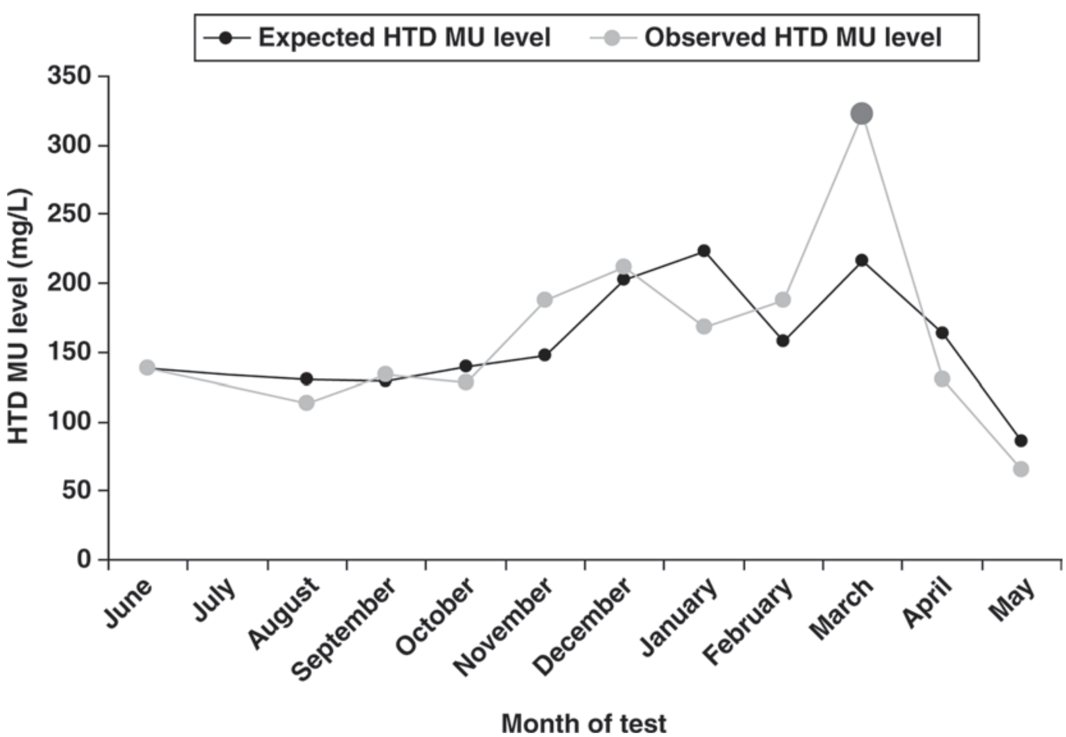

Figure 6. Evolution of the expected herd × test-day (HTD) milk urea (MU) level and the observed HTD MU level in a given herd. Deviant HTD record is indicated in dark gray.

more difficult for farmers than doing so during the stall months. Moreover, the new crop maize silage included in the ration in the fall could be a reason for the high herd deviant percentage. This assumption is supported by Hojman et al. (2004), who studied the relationship between groups of rations fed to milking cows and test-day mean herd MUN concentrations. They found a significant relationship for the feed group "summer crop harvested as silage," which included maize and sorghum. Furthermore, the association between MU and season could be confounded by the stage of lactation and a nutritional effect (Godden et al., 2001). In Belgium, milk tends to be better paid in the fall and winter months than in summer. Therefore, dairy farmers tend to group calving around October. The higher number of deviant herds at that time of the year could also be due to a large proportion of cows in the early stage of lactation in those herds. The pattern of change in the first few weeks after calving is complex and may reflect the changing metabolism of the cow (Wattiaux et al., 2005).

Moreover, environmental considerations could be added in our approach, and an environmental fixed threshold at the herd level should be considered and combined with the threshold based on the expected level. Indeed, given the potential for nitrogen pollution of dairy production and the expected link between MU and nitrogen excretion and utilization efficiency in dairy cattle (Jonker et al., 1998), this issue must be studied and included in any future feeding advice.

The most integrating approach should be to combine fixed thresholds and thresholds based on the expected MU concentration at both the cow and herd levels. Therefore, dairy farmers could be alerted when the HTD level is considered deviant and then be identified which cows are not in the desired range of the MU level.

CONCLUSIONS

Because of its relationships with protein metabolism in the dairy cow, MU is a valuable indicator of feeding management for farmers. Milk urea target values used in the field are generally fixed and are defined as between 200 and 400 mg/L. However, these thresholds do not take into account specificities of the cow. For instance, a cow could be beyond this range because of its genetics or its stage of lactation. This study combined this approach with the use of solutions given by a test-day model to develop more specific indicators.

Results showed the potential of using test-day models for longitudinal functional traits (in this case MU) to advise dairy farmers. Nevertheless, theoretical considerations given in this study should be validated in the field. In addition to considering simplification of the model, the modeling effort should be extended to all parities and herds. Moreover, the fixed thresholds indicated should be validated. Protein percentage is also an indicator of the protein supply in the feed and should be considered at the same time as MU in any future decision-making tools. Other traits could also reflect the protein metabolism (e.g., protein-to-fat ratio or lactose-to-fat ratio). In addition, implications in terms of nitrogen excretion of animals were not considered in this study. Furthermore, a validation in the field using feeding data should be achieved. Finally, opportunities for implementing this approach routinely for decision making should be taken into account.

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