Predicting Energy Balance Status of Holstein cows using Mid-Infrared Spectral data

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Introduction

Energy balance (EB) has long been considered an important indicator of cow health status (Heuer et al., 1999). Cows in negative EB (energy output exceeds energy intake) tend to have poorer reproductive performance and health (Heuer et al., 1999). However, monitoring EB and estimating breeding values require accurate and routinely available phenotypes for difficult and expensive to measure traits such as cow dry matter intake (DMI). Several methods, have been proposed to predict energy balance from routinely recorded traits (Friggens et al., 2007), including indexes such as milk fat to protein ratio. As the components of some such indexes are themselves predicted from milk, there is an accumulation of errors in the prediction process, thereby biasing downwards the correlation between true and predicted EB. Cows in negative EB mobilise body fat altering the fatty acid composition of the milk produced (Stoop et al., 2009). It has been shown that the fatty acid composition of milk can be predicted using mid infrared (MIR) spectrometry of milk (Soyeurt et al., 2006) and also that these predicted values are heritable. Being able to disentangle the different fatty acids from total fat percentage may aid in more accurately predicting EB. Better still, reducing the number of cumulated error terms by attempting to predict EB directly from MIR, may further improve the accuracy of prediction.

The objective of this study was to predict the EB status of Holstein dairy cows, directly from routinely collected milk samples using MIR data. Since MIR spectral data are available on all milk samples taken during herd-testing, the ability to monitor EB for herd management can be achieved at no extra cost. Furthermore, sufficient data will be generated on all milk recorded cows to facilitate the estimation of breeding values for EB, or to be used as early genetic predictors of animal health and fertility.

Material and methods

Data. Phenotypic data collected from the Langhill Herd of dairy cows (Scotland) between 2008 and 2010 was used to calculate energy balance. The Langhill experimental herd comprises of 2 lines of Holstein cows divergently selected for over 30 years, one selected for milk fat plus protein and the other maintained at the national average for milk fat plus protein. Cows are further split into high and low forage dietary treatments. Milking is undertaken three-times daily and yield of milk is recorded daily for each milking. Milk

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composition is recorded weekly, and DMI is recorded for 3 successive days, followed by 3 days off during lactation. Live weight is recorded automatically 3 times per day and averaged to a weekly value, and body condition score (scale 1 to 5) is recorded weekly.

Monthly between September 2008 and December 2009, milk samples from the morning (AM), mid-day (MD) and evening (PM) milking on a given day for all cows were sent to Teagasc Moorepark Dairy Production Research Centre in Ireland for analysis using a mid-infrared spectrometer (FOSS MilkoScan FT6000). The MIR spectrum represents the absorption of infrared rays through the milk sample at different wavelengths. The spectrum was stored for each milk sample.

Energy Balance. Random regression models were fitted to daily milk yield (kg), routinely recorded fat percent, protein percent, DMI, body condition score and live weight, to provide daily solutions where missing and to check existing phenotypic data. Only records from days 5 to 305 in milk were considered from parities 1 to 4. All random regression models included the fixed effects of experiment group (genetic line and feeding group), year of calving-by-season of calving, age at calving, year of record-by-month of record, a fourth order orthogonal polynomial on days post-calving and the random effect of the interaction of cow by a fourth order orthogonal polynomial on days post-calving. Relationships among cows were not accounted for and thus the random effects solutions include both the additive and permanent environmental effects of each cow. Models were fitted within parity using ASREML (Gilmour et al., 2002). Daily solutions from each random regression model were compared to the actual data collected for each trait and cow lactations were discarded from the analysis if there was poor concordance.

Two separate measures of energy status were computed for each day post-calving using the approach outlined by Emmans (1994) and the solutions from the random regression models. The measures considered were: 1) energy balance (direct_EB), a function of milk production, DMI, live weight and body condition score; and 2) body energy content (EC), a function of live weight and body condition score predicting body lipid and protein weight. These measures have previously been described in detail (Banos and Coffey, 2009). Additional to direct_EB and EC, the accumulation of body energy throughout lactation (CEE; definite integral of the EC lactation profile), deviation of daily direct_EB from the mean direct_EB within cow lactation (DEV_EB), milk fat to protein ratio (FPR) and the deviation of daily FPR from the mean FPR within cow lactation (DEV_FPR) were also computed. In total, 225 cow lactations with complete energy profiles were available for inclusion in the analysis. A total of 1,216 AM, 1,137 MD and 1,140 PM MIR readings were available. Correlations were estimated between all energy status measures and between milk composition and energy status measures.

Predictions using MIR. Partial least squares analysis (PROC PLS; SAS Institute) was used to predict direct_EB, EC, CEE and DEV_EB from the MIR. The maximum number of factors used to describe the MIR was set at 20. The optimal number of prediction factors was achieved by minimising the residuals sums of squares using one-out cross-validation. Euclidean distances for each point to the model in both the standardised measure of energy status and the predictors were examined for outliers, but none existed. Predictions were undertaken using AM, MD, and PM samples separately. In a separate series of analyses, when the range of wavelengths to be included in the model was decided on, milk yield was added to the model as a predictor.

Results and discussion

The total number of daily solutions for direct_EB, EC, CEE, DEV_EB and DEV_FPR available across parities, together with their mean values are presented in Table 1. The correlation of daily milk fat percent, daily milk protein percent and daily FPR with direct_EB was 0.05, 0.35 and -0.21 respectively; the respective correlations for EC were 0.21, 0.37 and -0.03. The correlation between daily DEV_FPR and direct_EB, EC and CEE was -0.10, 0.09 and 0.09, respectively.

Table 1: Number of cows for which energy balance was computed and mean values (standard deviation) for the four energy balance measures undertaken across parity

	Parity 1	Parity 2	Parity 3	Parity 4
Cows	85	85	44	11
direct_EB (MJ/d)	-11.4 (31.0)	-19 (35.1)	-12.8 (40.7)	-12.9 (35)
EC (MJ/d)	6456 (1192)	7211 (1195)	7698 (967)	7338 (758)
CEE (MJ/d)	761.8 (1335.8)	256.2 (1298.8)	-96.2 (1103.7)	-950.1 (693.5)
DEV_EB (MJ/d)	0 (26.1)	0 (26.6)	0 (35.7)	0 (30.2)
DEV_FPR (%)	0 (0.07)	0 (0.06)	0 (0.06)	0 (0.06)

The number of latent variables used to predict energy status varied from 8 to 18 (Table 2). Using only MIR wavelengths, predictions of direct_EB and DEV_EB (R^2 varied from 0.32 to 0.41) were superior to predictions of EC and CEE (R^2 varied from 0.20 to 0.27). Inclusion of milk yield in the prediction model increased the accuracy of prediction by 4 to 10 percentage units for direct_EB and DEV_EB; there was no impact on accuracy of predicting EC with the impact on the accuracy of predicting CEE being intermediate. Predictions of direct EB measures were always superior to predictions of indirect EB measures. The greater increase in accuracy of predicting direct_EB and DEV_EB with the inclusion of milk in the right-hand side of the equation is somewhat expected because of the part-whole relationship between milk yield and direct_EB as calculated in this study.

Although the accuracy of prediction of energy status in this study may be considered low, it must be emphasised that the components of energy status itself, may also contain error and the coefficients used to combine these traits into an overall indictor of energy status are also likely to vary across animals. Therefore, a high accuracy of prediction cannot be expected as energy status as defined herein is likely to contain considerable random noise. Furthermore, one could argue that it is not the prediction of energy balance *per se* that is important, since it itself is only used as an indictor of past and current nutritional status, but moreso the prediction of future risk of succumbing to health and fertility disorders. The results from this study show that routinely available MIR data is a better predictor of energy status, as defined in this study, than the currently recommended fat to protein ratio and its association for fertility and health should therefore also be investigated.

Table 2: Number of records used (n), variability explained (R^2) and root mean square error (RMSE(MJ)) of the cross validation, and the number of factors used for the PLS model containing only MIR predictors or MIR predictors plus milk yield across the four energy balance measures when undertaken using AM, MD, and PM samples

		Only MIR predictors			MIR predictors + milk yield		
AM	n	R^2	RMSE	Factors	R^2	RMSE	Factors
Direct_EB	1199	0.41	25	18	0.50	23	17
EC	1199	0.25	1131	17	0.25	1134	17
CEE	1199	0.27	1211	17	0.33	1158	15
DEV_ EB	1199	0.40	20	17	0.44	19	12
PM							
Direct_EB	1127	0.32	27	12	0.42	25	12
EC	1127	0.24	1129	16	0.24	1128	17
CEE	1127	0.20	1253	12	0.29	1178	8
DEV_ EB	1127	0.38	21	10	0.44	19	14
MD							
Direct_EB	1148	0.35	26	16	0.43	25	15
EC	1148	0.23	1144	16	0.22	1148	16
CEE	1148	0.25	1212	14	0.32	1158	16
DEV_ EB	1148	0.37	21	16	0.41	20	13

Conclusion

This is the first study to attempt to relate MIR data to energy status in lactating dairy cows. The predictive ability achieved using the approaches outlined in this study were greater than that sachievable using fat to protein ratio and although they may still be regarded as being relatively poor, the measures of energy status used in this study also contain error.

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