Predicting Energy Balance Using Mid Infrared Spectrometry

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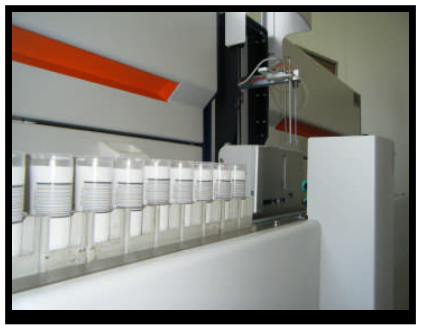
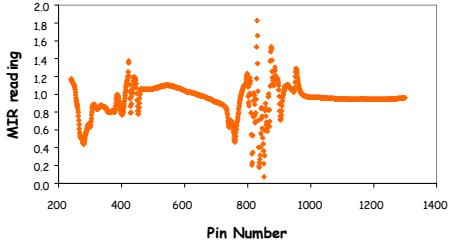
The Irish Agriculture and Food Development Authority

Introduction

- Energy balance (output – input) is a heritible indicator of fertility
- Useful for a multi-trait breeding programme
- But
  - Measurement not feasible on commercial herds
  - Little data available
- Indicators of energy balance proposed
  - Fat: protein ratio of milk

Example of energy balance prediction





Milk fat content

Milk protein content

Predicted Energy Balance

Materials and Methods

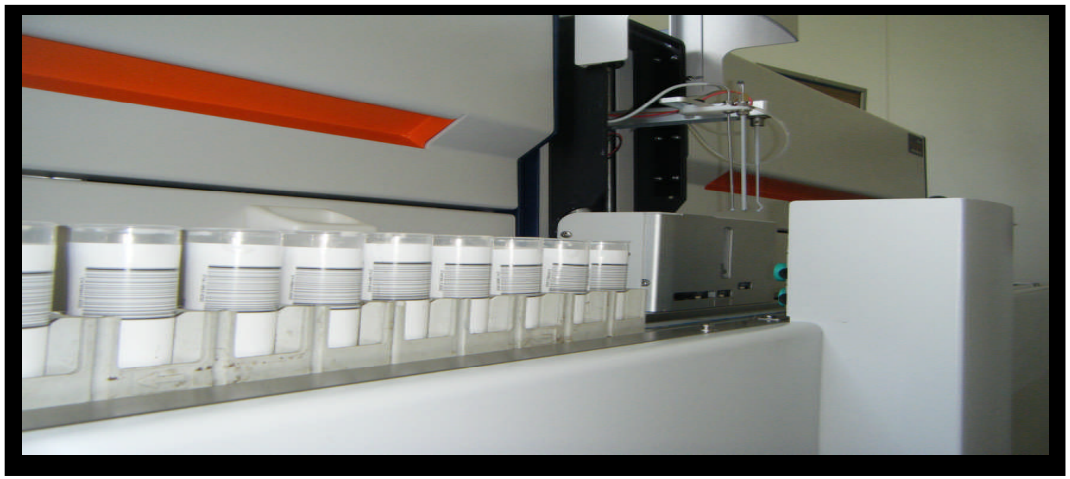
1. 2 data sets

- Langhill experimental herd (SAC, Scotland)
- Teagasc Moorepark (Ireland)
- Routinely recorded phenotypic traits
  - Milk, fat, protein, live weight, BCS, & (DMI)
- Random regressions fit to data seperately
  - Models fit within parity
  - Data retained between 1990-2011
- Energy balance (MJ/d) = inputs – outputs
  - Incl. milk, fat, protein, live weight, BCS & DMI

Materials and Methods

2. Mid infrared spectral data

- MPK samples (AM & PM) analysed weekly
- SAC samples (AM, MD & PM) analysed monthly
  - Mid 2008 – January 2011
  - Light shone through each milk sample
  - 1,060 wavelengths readings for each sample



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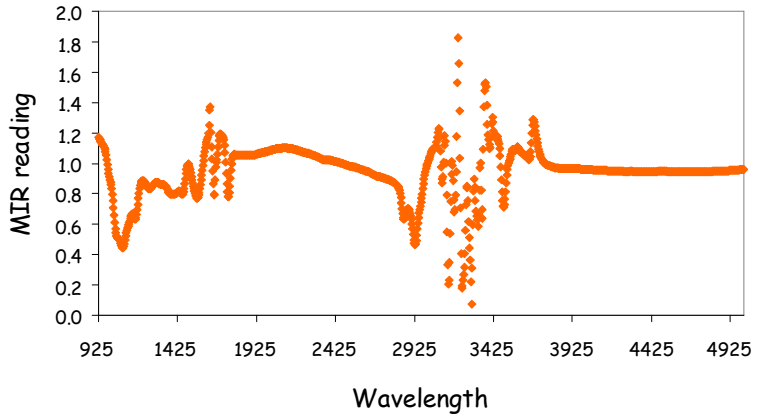


Materials and Methods

3. Prediction equations

- Partial least squares regression analysis
- Predictors: MIR spectrum and milk yield
- AM, PM & (MD) samples handled separately
- SAC samples (n ≤ 2,989)
- MPK samples (n ≤ 844)
- 3 types of analysis undertaken
  - Calibration (75%) – develop equations
  - Validation (25%) – independent test of equations

Calibration & Validation

Calibration	Validation	
1. Within Research data set		
SAC	SAC	(4 iterations)
MPK	MPK	(4 iterations)
2. Across Research data set		
SAC	MPK	
3. Pooled data sets		
SAC & MPK	SAC & MPK	

RESULTS

Within Research data set

Data Sets		Cross Val		External Validation		
Cal	Val	RMSE	R	Bias (se)	RMSE	R
SAC						
PM	PM	24	0.70	2.18(0.85)	25	0.65
AM	AM	24	0.70	1.57(0.90)	25	0.67
MD	MD	24	0.72	-2.35(0.90)	25	0.69
MPK						
PM	PM	19	0.74	3.63(1.70)	21	0.66
AM	AM	19	0.74	-1.99(1.23)	21	0.67

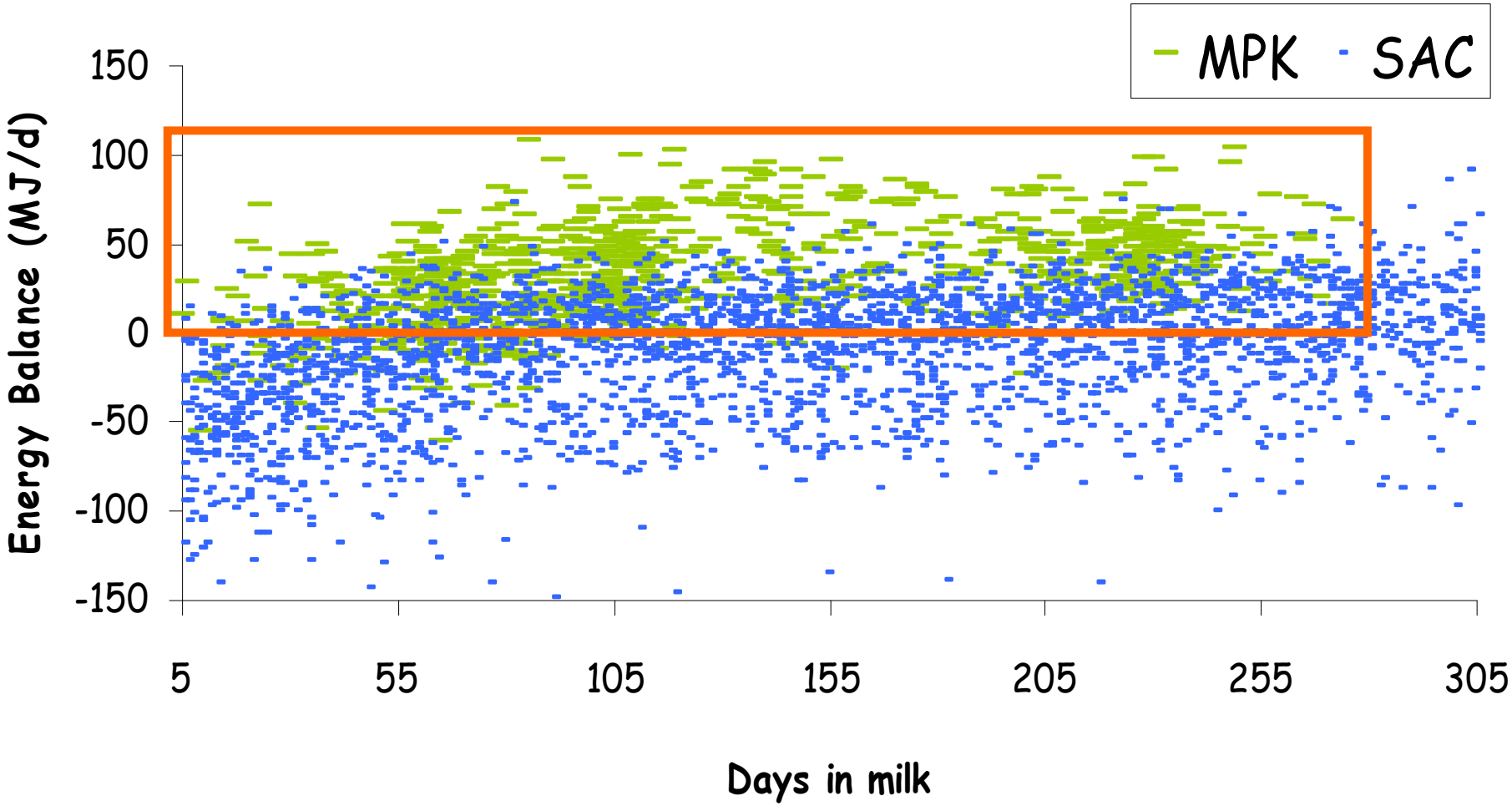
Across Research data set

Data Sets		Cross Val		External Validation		
Cal	Val	RMSE	R	b (se)	RMSE	R
SAC	MPK					
PM	PM	24	0.70	0.11(0.04)	28	0.09
AM	PM	25	0.69	0.08(0.03)	28	0.09
MD	PM	24	0.71	0.14(0.03)	28	0.15
PM	AM	24	0.70	-0.05(0.05)	28	0.03
AM	AM	25	0.69	0.00(0.04)	28	0.00
MD	AM	24	0.71	0.08(0.04)	28	0.07

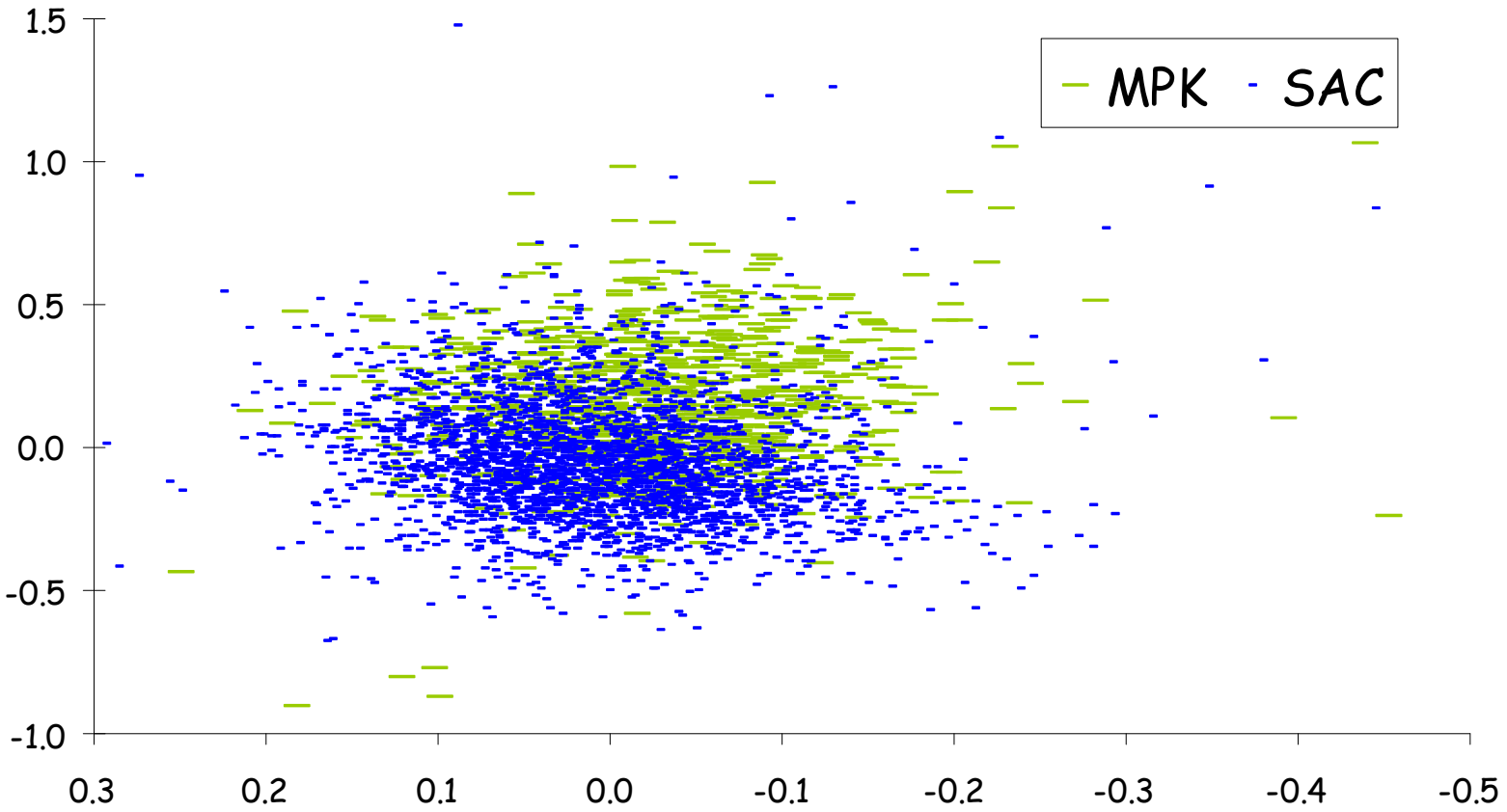
Differences

- North American vs New Zealand Holstein-Friesian
  - Milk yield, DMI, BCS, Live weight
- Feeding system
  - Total mixed ration (SAC) vs grass (MPK)
- Milking frequency

Energy Balance – SAC & MPK



PCA of spectra – SAC & MPK



Pooled Research data sets

- Cross Validation
  - RMSE = 27 MJ
  - R = 0.69
- External Validation
  - Slope = 0.98 (0.03)
  - Bias = 1.12 (0.88)
  - R = 0.69

Conclusion

- The mid-infrared spectrum is useful as an indicator of energy balance
- Not useful to predict energy balance UNLESS the variation to be predicted is represented in the calibration of equations
- Pooled data sets provides a robust equation

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http://www.robustmilk.eu

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