Modelling metabolic efficiency
Do we need to understand the biological meaning of residual feed intake breeding values?

M.H. Lidauer[1], T. Andersen[2], U.S. Nielsen[2], E.A. Mäntysaari[1]*, G.P. Aamand[3]

[1]Natural Resources Institute Finland (Luke), Jokioinen, Finland
[2]SEGES Innovation P/S, Aarhus N, Denmark
[3]Nordic Cattle Genetic Evaluation, Aarhus N, Denmark

Residual feed intake (RFI)

- Models by its definition (intake – expected intake) the metabolic efficiency in a broad sense that captures variation due to:

  - ability to digesting feed
  - ability to have low energy loss through CH_4 exhalation
  - ability to utilize metabolizable energy for the different energy pathways

- intake: usually measurements for dry matter intake

- expected intake: through modelling of intake requirements for energy sinks (usually by partial regression analyses)

Residual feed intake for Nordic Total Merit Index

- Implemented into Nordic Total Merit in 2020

- Since then, more data is added (CFIT data)

- Along this we have recognized:
  - Partial regression coefficients may vary significantly across time and parities
  - For both CFIT data and research farm data

Aim of the study

Attempt to understand metabolic efficiency

Objective

Study different modelling approaches

Data from 4 herds with CFIT feed intake

Means of daily observations

	First parity	Later parities
N	18,221	28,588
DMI	21.3	24.5
MBW	95.0	103.3
ECM	28.9	37.1
MY	22.0	28.5
FY	1.3	1.7
PY	1.0	1.2

- 46,822 weekly records
- 1st to 6th parity
- 1,211 Jersey cows with records
- Years: 2019, 2020, 2021

DMI = dry matter intake [kg]
MBW = metabolic body weight [$kg^{0.75}$]
ECM = energy corrected milk [kg]

MY = milk yield [kg]
FY = fat yield [kg]
PY = protein yield [kg]

A: **Currently used RFI model** (RFI_partial_regressions)

First step:

  a) partial regression analyses of dry matter intake (DMI)

$$DMI = c_1 \times A + c_2 \times A^2 + LP + LYS + HYS + \gamma_1 \times ECM + \gamma_2 \times MBW + \gamma_3 \times \Delta BW + rfi$$
  where
  - partial regressions nested within LP classes
  - A = calving age
  - LP = lactation month x parity classes
  - LYS = lactation x year x season
  - HYS = herd x year x season

  b) raw rfi values adjusted for heterogeneous variance

  c) RFI observation = rfi* + estimates for LYS and HYS

A: **Currently used RFI model** (RFI_partial_regressions)

Second step:

estimating breeding values by a repeatability animal model:

$$RFI = LYS + HYS + pe + a + e$$

where

- LYS = lactation x year x season
- HYS = herd x year x season
- pe = random permanent environmental effect
- a = random additive genetic effect
- e = random residual

B: Regression on requirements (RFI_reg_on_requirement)

- Same as approach A but step 1 model was modified:

$$DMI = c_1 \times A + c_2 \times A^2 + LP + LYS + HYS + \varphi \times eDMI + rfi$$

regression on expected dry matter intake (eDMI) instead of partial regressions

- eDMI: firstly calculating energy requirements (ER) in mega joule (MJ):

$$ER\ [MJ/day] = 4.81 \times ECM + 0.603 \times MBW - 27.6 \times BW\_Loss + 38.3 \times BW\_Gain$$

(based on Agnew et al., 2003)

and subsequently:

$$eDMI = ER \times average\ of\ [DMI\ kg\ /\ (MJ/day)]$$

C: **Requirements RFI** (RFI_requirements)

- Same as approach A but the raw rfi observations in step 1 were calculated as:

  rfi = DMI − eDMI

D: **Regression on expected feed intake** (ReFI)

- A different approach where feed intake is regressed on expected feed intake

- Covariables for expected feed intake are calculated using energy requirement estimates from dairy cow nutrition studies

- Allows to model metabolic efficiency from a biological perspective

D: **Regression on expected feed intake** (ReFI)

- DMI was modelled by a random regression model:

$$DMI = \beta \times eDMI + \eta \times eDMI + \psi \times eDMI + \alpha \times eDMI + \varepsilon$$

with fixed regression coefficients
β nested within herd × year × parity classes

and random regression coefficients
η nested within herd × year × month classes
ψ nested within animal permanent environmental effect
α nested within additive genetic animal effect

Results

- Variance components for different approaches

- Genetic correlations between metabolic efficiency and yield traits
  (multivariate analyses of first parity yield deviations)

- Quick look on phenotype means of 10% genetically superior cows
  (cows selected alternatively based on the 4 different sets of EBV)

Results: Estimates of regression coefficients

Covariables	RFI_partial_regressions			RFI_regression_on _requirement	ReFI
	ECM	MBW	ΔBW	eDMI	eDMI
Coefficient	γ_1	γ_2	γ_3	φ	β
First parity estimates	0.31	0.159	-0.28	0.46	1.04
Later parities estimates	0.18	0.196	-0.24	0.32	1.01
Biological expectation	0.49	0.062	3.91	1.00	1.00

Results: Heritability and genetic correlations with yield traits

Approach	h^2	Genetic correlations to:		
		Milk yield	Fat yield	Protein yield
RFI_partial_regressions	0.14	0.47	0.17	0.31
RFI_regression_on_requirement	0.16	0.43	0.24	0.30
RFI_requirement	0.10	-0.01	-0.20	-0.16
ReFI	0.10	0.02	-0.28	-0.10

positive correlation: unfavourable
negative correlation: favourable

Results: Phenotypic means of superior cows

10% best cows based on the EBV by different approaches

Approach		DMI	MBW	ECM	MY	FY	PY	FCE
All cows		21.2	94.9	28.7	21.8	1.30	0.946	**1.35**
10% best cows	RFI_partial_regressions	18.6	94.7	26.3	18.8	1.22	0.860	**1.41**
	RFI_regression_on_requirement	18.4	92.8	25.3	18.3	1.17	0.833	**1.38**
	RFI_requirement	19.9	93.1	29.1	21.5	1.34	0.966	**1.46**
	ReFI	19.8	93.9	29.8	22.0	1.37	0.982	**1.51**

DMI = dry matter intake [kg]
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ECM = energy corrected milk [kg]

MY = milk yield [kg]
FY = fat yield [kg]
PY = protein yield [kg]

FCE = ECM/DMI

Conclusions

- Currently used RFI model favours cows with low production

- ReFI (regression on expected feed intake) favours cows with high production and high efficiency

- Poor performance of the RFI model was due to the inability of the RFI model to properly estimate the partial regression coefficients for the energy sinks

Thank you!