LIVE WEIGHT PREDICTION AND GENETIC PARAMETER ESTIMATION USING TYPE TRAITS FOR ITALIAN HOLSTEIN COWS

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Importance live weight (1)

• Tool for herd management and monitoring animals
• Used for calculating energy balance for a feeding ration
• Size of animals is related to animal maintenance costs, feed efficiency and gas emission

• Feed efficiency and gas emission
  • Quantity of milk produced per quantity of dry matter intake
  • By improving feed efficiency ➔ environmental impact is reduced
Importance live weight (2)

• Different viewpoints, common interest:
  • Farmer interest: Efficiency
  • Consumer interest: Environmental impact

• Most farmers would not care about gas emission:
  • Invisible so not noticed
  • No ‘visible’ cost (i.e. no bills)
  • However make them aware that they paid the feed that was converted into gas

• Most consumers would not care about efficiency:
  • However efficiency impacts on consumer prices
Live weight data

- Routine availability required
- However: No routine collection
- Solution: Estimate live weight from existing routine data
  - Age at type scoring
  - Type scoring
State of the art

- Several countries have developed live weight prediction using type traits

- ANAFI and the University of Padova in 1997 have developed live weight prediction equations, using a small dataset with individual weight measurements and 2 routine type traits: Stature and Chest width (Cassandro et al., 1997)

- ANAFI has derived new prediction equations, using more and more recent weights and adding more type traits
Objectives

• Set-up phenotypic and genetic prediction equations for live weight using type traits
  • Estimate genetic parameters for live weight
  • Estimate selection indices for live weight

• Use of live weight for other purposes:
  1. **Functional index** → IES (Indice Economico Salute) → New Anafi EBV (August 2016)
  2. Feed efficiency
    • Predicted feed efficiency (short term)
    • Predicted feed efficiency including DGV estimates based on individual measurements (long term)
  3. Greenhouse gas/Methane emission
    • Predicted CH₄ emission (short term)
    • Predicted CH₄ emission including DGV estimates based on individual measurements (long term)
Material and Methods

- 36 farms with in total 6,895 individual weights from 3,256 cows in different parities
- Weighing through milking robots
- Period 2013-2015
- Average live weight: 642,45 kg ± 87,30
- Range 400,00 – 957,00 kg
Editing

- Only first parity cows retained → 862 cows in 30 herds
  - Stage of lactation max 12 months
  - Cow age 22-41 months
  - Max days between individual live weight and type scoring ± 24 d

- Simple statistics

<table>
<thead>
<tr>
<th>Traits</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured weight (kg)</td>
<td>595,16</td>
<td>73,16</td>
<td>400</td>
<td>837</td>
</tr>
<tr>
<td>Lactation stage (days)</td>
<td>141,57</td>
<td>78,35</td>
<td>10</td>
<td>365</td>
</tr>
<tr>
<td>Age at type scoring (months)</td>
<td>30,45</td>
<td>4,31</td>
<td>22</td>
<td>41</td>
</tr>
</tbody>
</table>
Phenotypic prediction of live weight: Model definition

Stepwise regression has been applied and various models have been tested

1. \[ Y = HYM + MC + SL + \text{other predictors} \]
2. \[ Y - (HYM + MC + SL) = \text{other predictors} \]

- \(Y\): measured weight
- \(HYM\): herd-year-months of weighing
- \(MC\): month of calving
- \(SL\): stage of lactation
- Other predictors:
  - Age of cow at scoring
  - Stature, chest width, body depth, rump width, BCS (when available)
Phenotypic prediction of live weight: Model selection

<table>
<thead>
<tr>
<th>Linear terms</th>
<th>Quadratic terms</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1</strong> Age, Stature, Rump width</td>
<td>Chest width, BCS</td>
<td><strong>0.78819</strong></td>
</tr>
<tr>
<td><strong>2</strong> Stature, Rump width</td>
<td>Age, Chest width, BCS</td>
<td><strong>0.78819</strong></td>
</tr>
<tr>
<td><strong>3</strong> Age, Stature, Rump width</td>
<td>Age, Chest width, BCS</td>
<td><strong>0.78825</strong></td>
</tr>
<tr>
<td><strong>4</strong> Age, Stature, Body depth, Rump width</td>
<td>Chest width, BCS</td>
<td><strong>0.79120</strong></td>
</tr>
<tr>
<td><strong>5</strong> Age, Stature, Rump width</td>
<td>Chest width, Body depth, BCS</td>
<td><strong>0.79155</strong></td>
</tr>
<tr>
<td><strong>6</strong> Age, Stature, Body depth</td>
<td>Chest width, BCS</td>
<td><strong>0.79025</strong></td>
</tr>
<tr>
<td><strong>7</strong> Age, Stature</td>
<td>Chest width, Body depth, BCS</td>
<td><strong>0.79057</strong></td>
</tr>
<tr>
<td><strong>8</strong> Age, Stature, Chest width, Body depth, BCS</td>
<td>Stature, Chest width, Body depth, BCS</td>
<td><strong>0.79354</strong></td>
</tr>
<tr>
<td><strong>9</strong> Age, Stature, Chest width, Body depth, Rump width, BCS</td>
<td><strong>0.79141</strong></td>
<td></td>
</tr>
<tr>
<td><strong>10</strong> Age, Stature, Chest width, Body depth, Rump width</td>
<td><strong>0.74594</strong></td>
<td></td>
</tr>
</tbody>
</table>
Validation model

- Final data-set randomly splitted
  - 70% reference set
  - 30% validation set
  - Done twice
- In validation sets correlations between measured weight and predicted weight have been estimated and ranged between 0.62-0.70
## Validation set statistics

<table>
<thead>
<tr>
<th>Trait</th>
<th>Mean±SD</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured weight</td>
<td>598.24 ± 73.00</td>
<td>427 – 821</td>
</tr>
<tr>
<td>Predicted weight</td>
<td>598.29 ± 46.45</td>
<td>453 – 742</td>
</tr>
<tr>
<td>Stature (1-50)</td>
<td>31.31 ± 6.20</td>
<td>9 – 48</td>
</tr>
<tr>
<td>Chest width (1-50)</td>
<td>28.48 ± 5.00</td>
<td>15 – 43</td>
</tr>
<tr>
<td>Rump width (1-50)</td>
<td>26.49 ± 5.28</td>
<td>10 – 41</td>
</tr>
<tr>
<td>Body depth (1-50)</td>
<td>30.95 ± 4.39</td>
<td>16 – 47</td>
</tr>
<tr>
<td>BCS (1-5)</td>
<td>3.02 ± 0.48</td>
<td>2 – 4.5</td>
</tr>
</tbody>
</table>
Phenotypic trend within 1st lactation
Phenotypic trend by age
Phenotypic type traits and live weight trends across years
Phenotypic milk yield and live weight trends across years
EBV for live weight (1)

- Traits: 1) Live weight 2) Stature 3) Chest width 4) Body depth 5) Rump width 6) BCS
- BCS not always available, therefore estimated 2 formulas: with and without BCS
- EBV: vector of EBVs, G: genetic covariance vector/matrix, C: predictors
- Example with 4 predictors:

\[
\begin{align*}
EBV_{LW} &= G_{LW,C}G_{CC}^{-1}EBV_C \\
&= \begin{bmatrix} \sigma_{A12} & \sigma_{A13} & \sigma_{A14} & \sigma_{A15} \end{bmatrix} \begin{bmatrix} \sigma_{A22} & \sigma_{A23} & \sigma_{A24} & \sigma_{A25} \\
\sigma_{A32} & \sigma_{A33} & \sigma_{A34} & \sigma_{A35} \\
\sigma_{A42} & \sigma_{A43} & \sigma_{A44} & \sigma_{A45} \\
\sigma_{A52} & \sigma_{A53} & \sigma_{A54} & \sigma_{A55} \end{bmatrix}^{-1} \begin{bmatrix} EBV_2 \\
EBV_3 \\
EBV_4 \\
EBV_5 \end{bmatrix}
\end{align*}
\]
EBV for live weight (2)

- EBV is a composite index based on single traits and accounting for covariances
- Can also be used for foreign animals (MACE indices)
- Same approach can be used for DGVs and GEBVs
From live weight towards efficiency

- Metabolic weight = Live weight^{0.75}
- Metabolic weight is proportional to maintenance needs
- Feed efficiency = Milk/Dry matter intake
- Dry matter intake was derived using information of:
  - Fat corrected milk yield and fat yield
  - Metabolic weight
- Chase and Sniffen (1985)
Phenotypic feed efficiency trend

![Graph showing phenotypic feed efficiency trend from 1998 to 2013. The graph compares Dry matter intake, Milk production, and Feed efficiency over the years. The trend shows an increase in Feed efficiency and a slight increase in Milk production, while Dry matter intake remains relatively stable.](image-url)
Feed efficiency versus total merit index for young and proven bulls
Final remarks

• We’re on our way to establish routine evaluation for:
  • Feed efficiency
  • Gas emission

• We aim at EBV, DGV and GEBV

• Current selection goal already improves feed efficiency and gas emission, but extra attention can increase genetic gain

• Indices will be included in total merit index

• Questions?