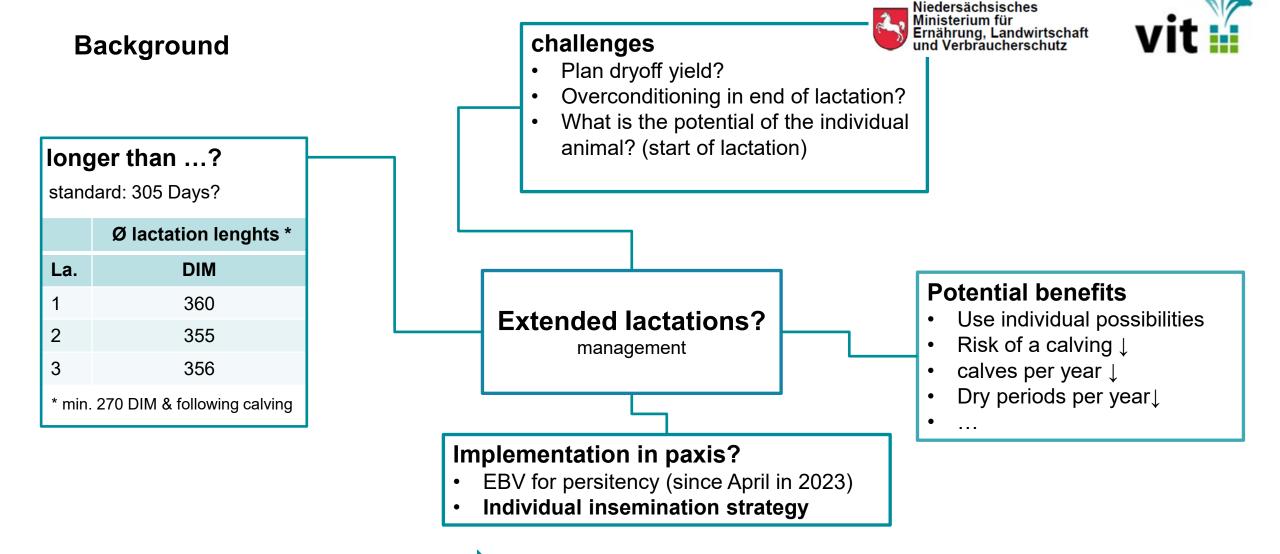


Optimize the individual insemination strategy in extended lactations of dairy cattle using a neural net to predict phenotypic lactation curves

75th EAAP Annual Meeting, Florence, Italy - 1/5 September 2024

L. Polman, J. Wabbersen, J. Braunleder, S. Schierenbeck, R. Reents *IT Solutions for Animal Production* (vit)



A) Estimate phenotypic lactation curve at start of lactation

B) Calculate back when to start with insemination

→ dryoff yield, planed time for dry period

03.09.2024

Individual insemination strategy





- Use neural net with 3x per year training to predict daily lactation curves with all new information
 - Training with 3.1 Mio. full lactation curves from 2017 onwards (use milk-kg)
 - Include approx 290.000 lactations > 400 DIM

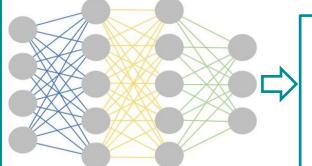
Input parameters

- lactation number
- breed
- age at calving
- season at calving
- previous calving interval
- mean herd-test-day (from RRTDM for milk traits)
- mean milk yield on farm in differnet periods during lactation in last year
 - arround DIM 150 (120 bis 180)
 - arround DIM 305 (275 bis 335)
- timestamp of last (=succsessfull) insemination in lactation
 - test different possible future timestamps while prediction
- test-day-records of previous lactations
- first test-day-records of actual lactation

Training

on completed lactations

official test-day-records from milk recording system



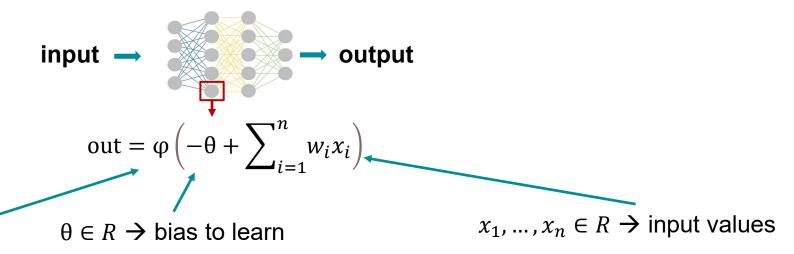
Output: prediction

- all informations available at time of prediction
- allow missing values
- daily



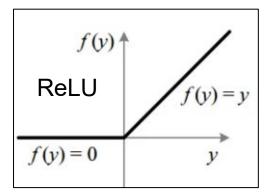






Activation function

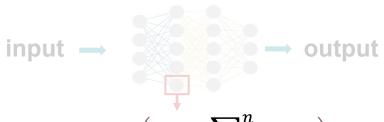
- ReLU Rectified Linear Unit (hidden layers)
- Linear (output layer)



https://databasecamp.de/ki/relu

How an artificial neuron works





n = number of weeks m = N training cases

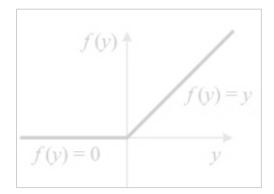
 $out = \varphi\left(-\theta + \sum_{i=1}^{n} w_i x_i\right)$

 $\theta \in R \rightarrow \text{bias to learn}$

 $x_1, \dots, x_n \in R \rightarrow \text{input values}$

Activation function

- ReLU Rectified Linear Unit (hidden layers)
- Linear (output layer)



https://databasecamp.de/ki/relu

$w_1, \dots, w_n \in R \rightarrow \text{parameter/weights to learn}$

$$J(\boldsymbol{w}) = \frac{1}{m} \sum_{i=1}^{m} L(\widehat{\boldsymbol{y}}^{(i)}, \boldsymbol{y}^{(i)})$$

input prediction orginal output x_1, \dots, x_n $\widehat{y}_1, \dots, \widehat{y}_n$ y_1, \dots, y_n

minimize squared Euclidean distance

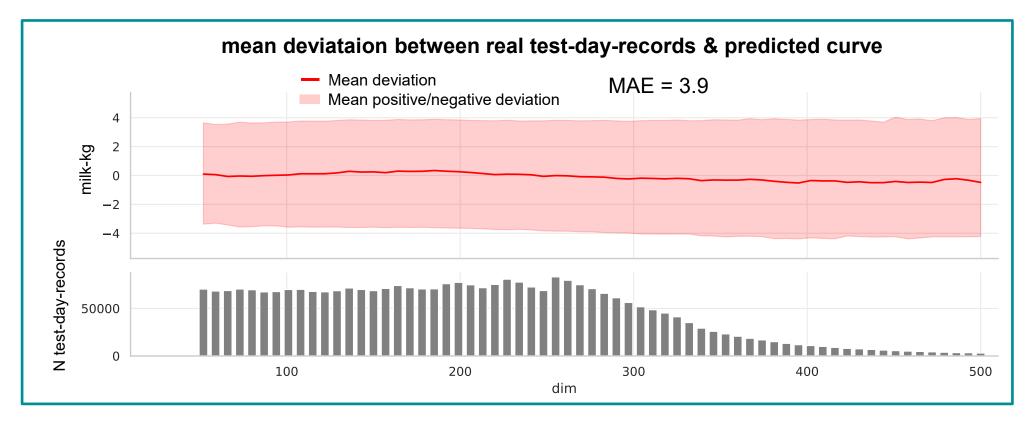
iteratively

gradient descent method to find local minimum of cost fuction *J*

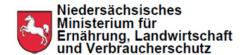
Results



- "validation" scenario:
 - training & prediction simulated for April 2021
 - compare prediction with real shown lactation curves
 - Consider that the predicted curve is smoothed and the test-day-records curve fluctuates!



Discussion & Conclusion





- the use of a neural network to predict extended lactation curves works in general
 - Our results need to be contextualized within the work of other groups (Innes et al., 2023)
- Areas of application
 - optimized insemination
 - plausibilization of test-day-records
 - management (feeding, general farm strategy, ...)
 - ...
- missing input values are permitted (best use of available inputs) → useful in practice
- future improvements are probably still possible
 - integration of additional parameters
 - many possible adjustment options in training/structure of the neural network
 - alternatives to neural networks? (random forests, k-nearest neighbors algorithm (KNN), gradient boosting, ...)
 - increasing number of data sets with long lactations that can be trained on



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