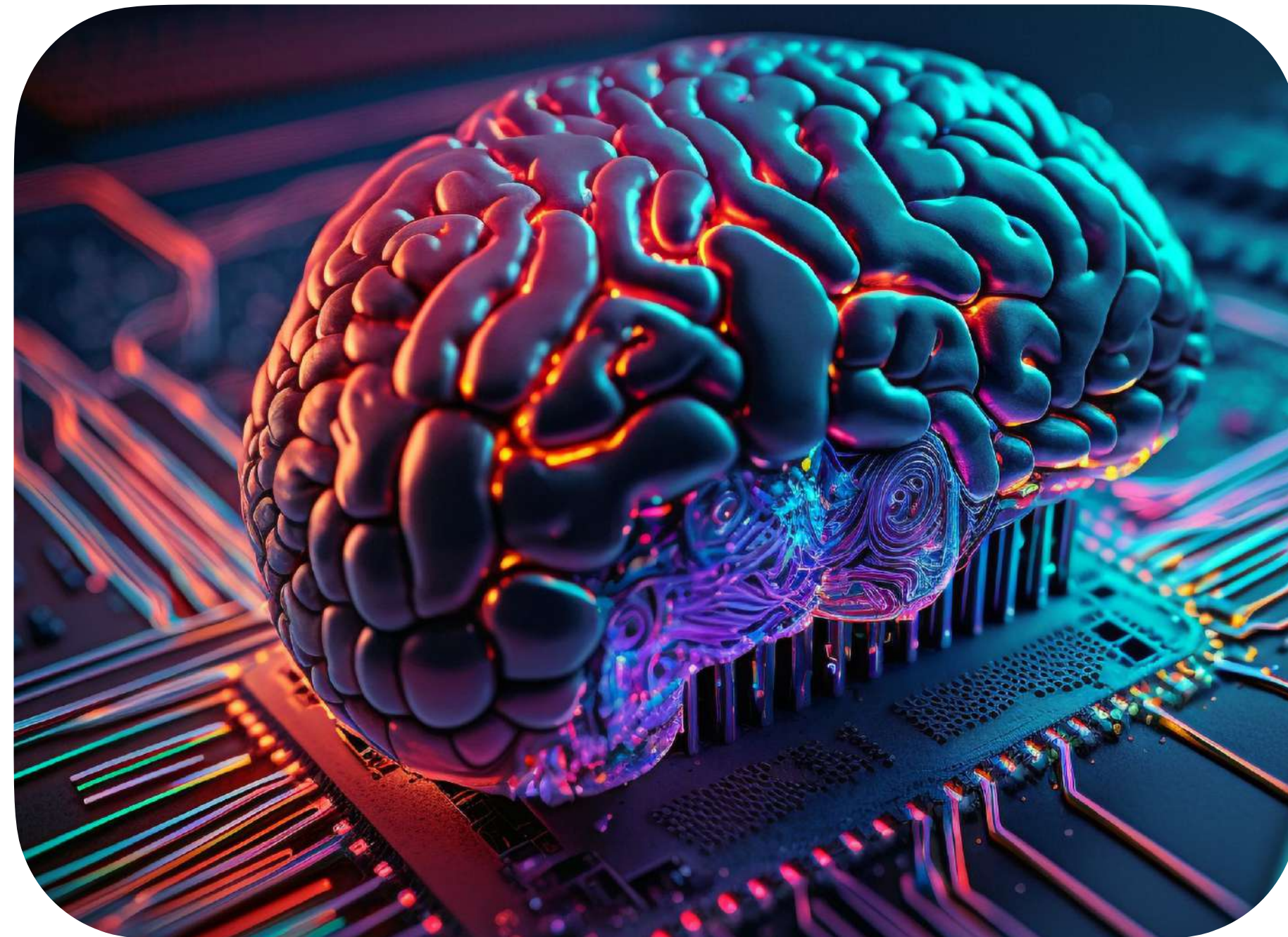


Application of AI in animal feeding and management



Alex Bach



Universitat de Lleida

Introduction

- 📌 Production, reproduction, and health of dairy cattle have continuously improved over that last decades consequence of the implementation of the knowledge that research has generated on:
 - Nutrition
 - Immunology
 - Management
 - Genetics
- 📌 However, the dairy industry is subject of strong economic tensions due to market volatility of raw materials and milk, and environmental conditions (i.e., heat waves, droughts...)

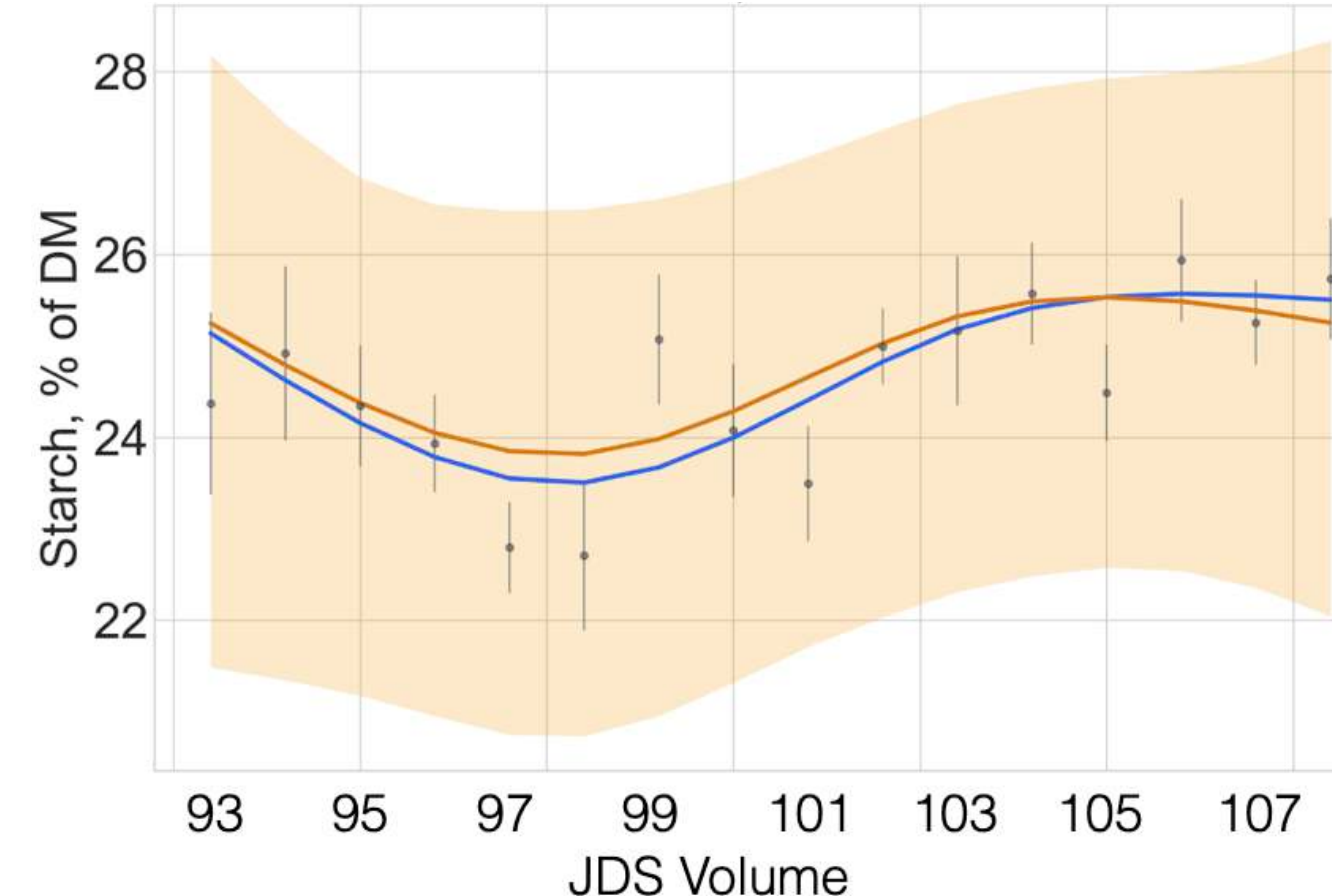
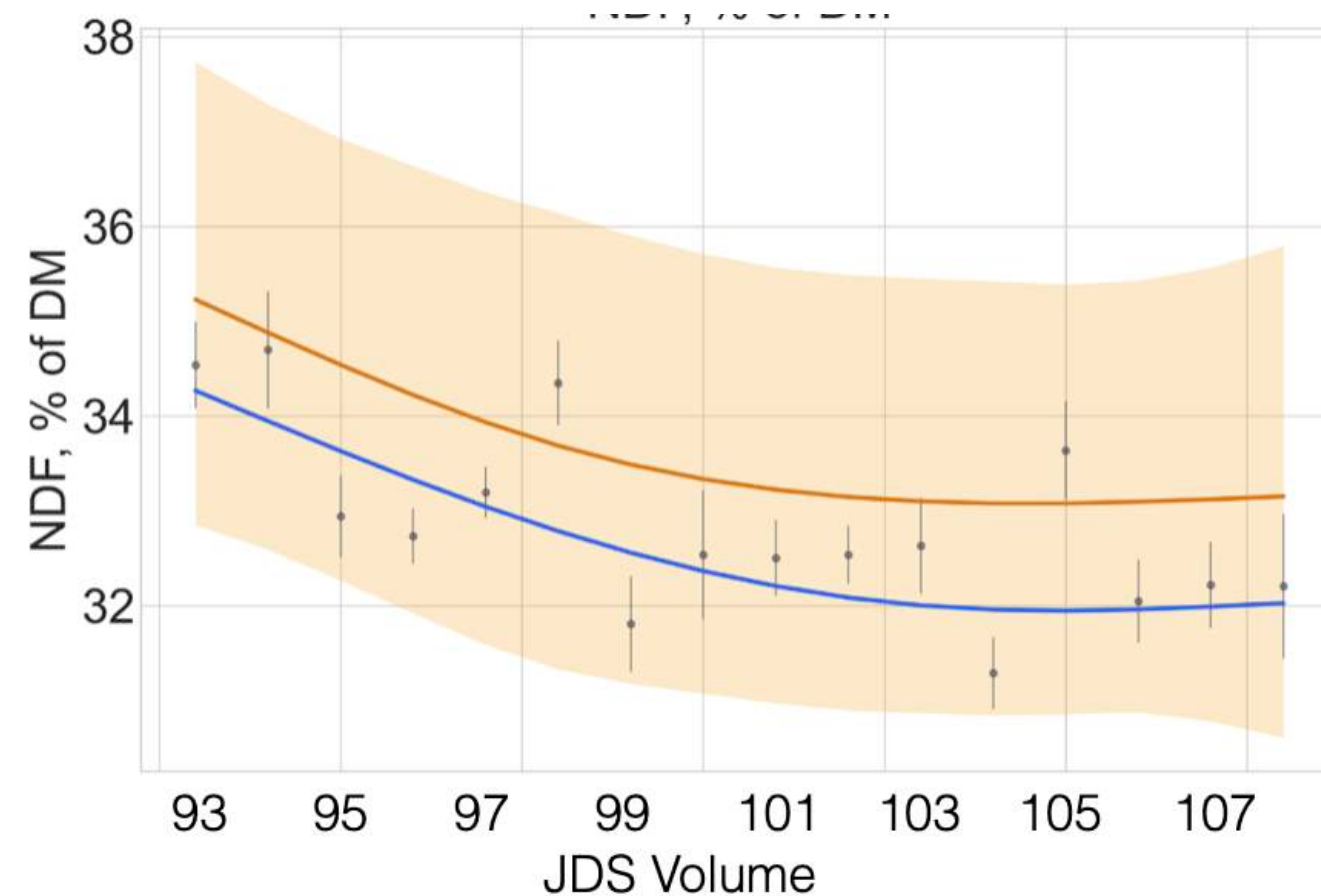
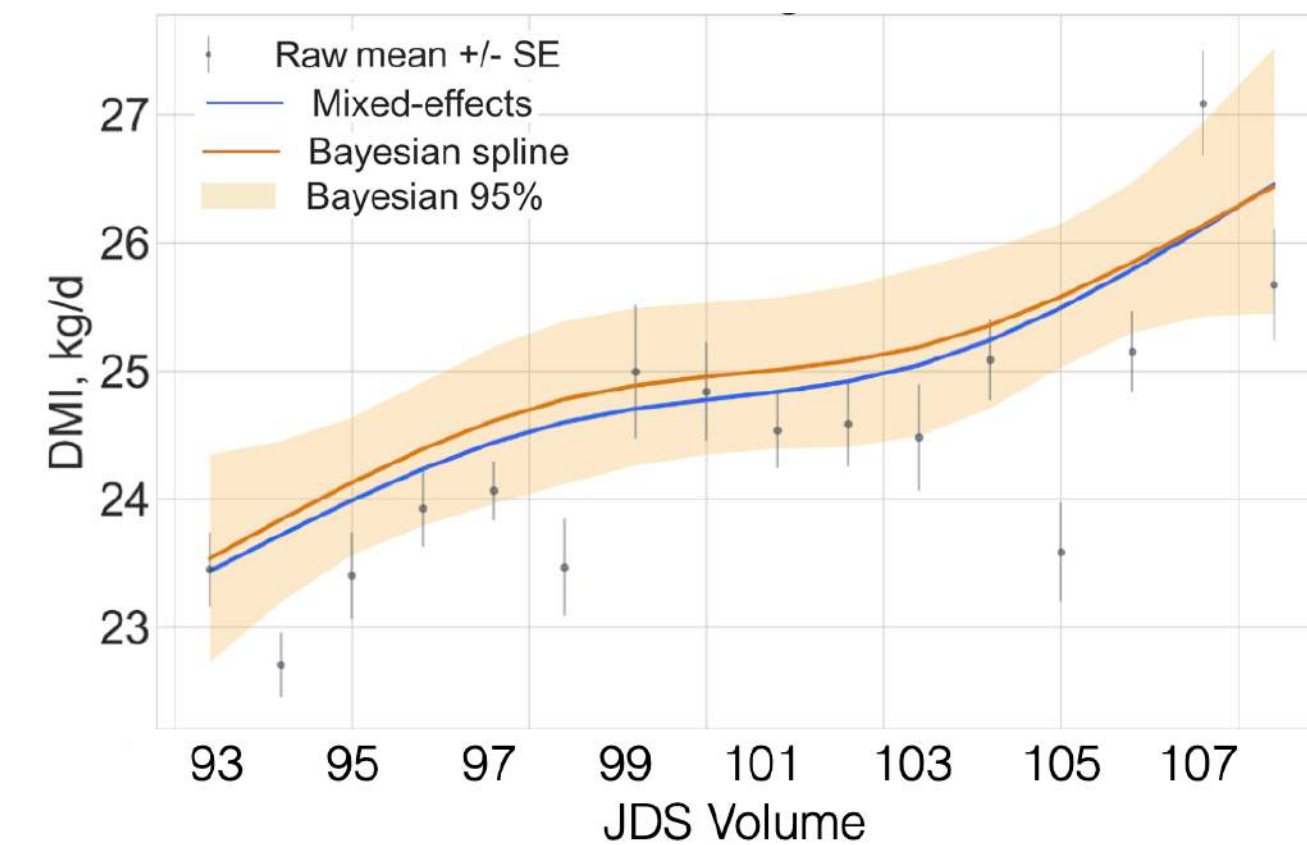
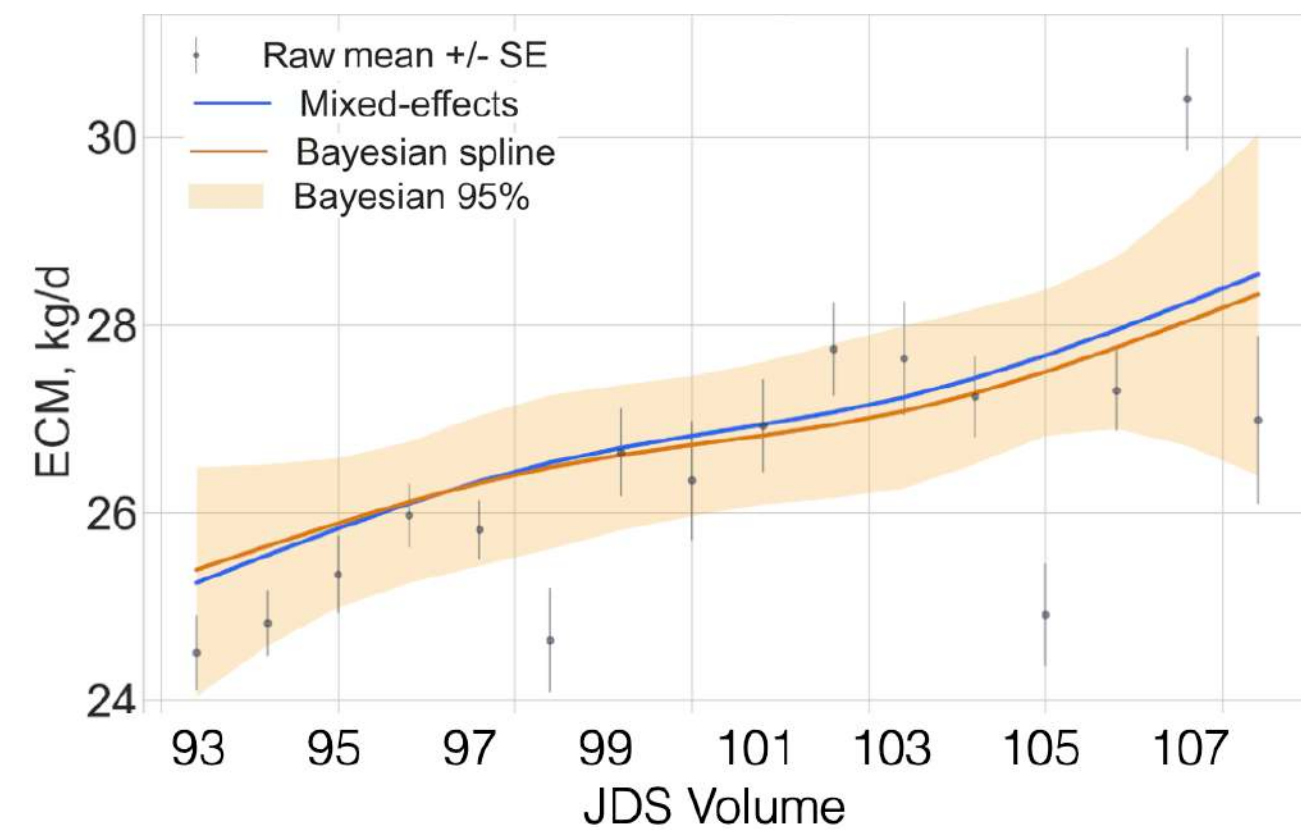
Introduction

📌 There are number of decisions that must be taken on a weekly (or daily) basis in a farm that depend on too many factors for the human mind to make the right choice:

- Intake has dropped: Do I change the ration?
- Do I buy alfalfa with 20% CP at 220€/ton
- How many cows I inseminate this week with sexed semen?
- What cows do I cull this week?
- What cows should I change to a different production pen?
- ...

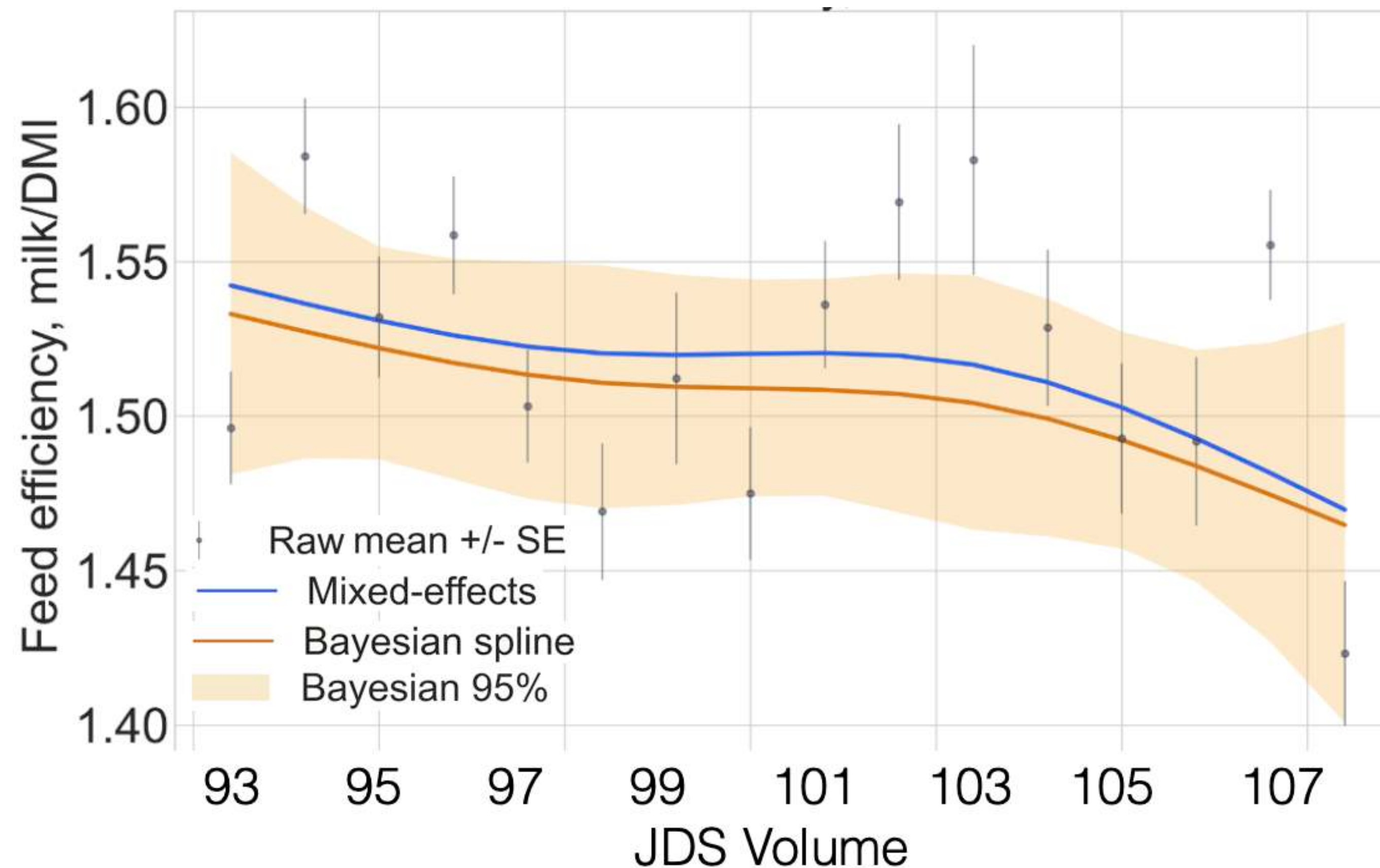
State of the art

- 📌 The continuous genetic progress challenges the capacity of cows to consume all nutrients to support production and all physiological functions



State of the art

- 📌 An increasing need to formulate ration using precise models that predict nutrient requirements as well as animal responses to specific rations are needed



State of the art

- 📌 Up until now, animal nutrition has been based on mathematical models that estimate nutritional needs for a '**reference animal**'
- 📌 Two main limitations:
 - These models, mainly factorial, estimate needs of nutrients independently (i.e., one nutrient at a time)
 - In dairy cows, there is a large degree of heterogeneity among animals within one group, which makes it difficult that the '**reference animal**' will be a good representation all cohort and thus fully optimize performance and economic results

State of the art

✿ What do we really know about the ‘reference cow’ when we apply models?

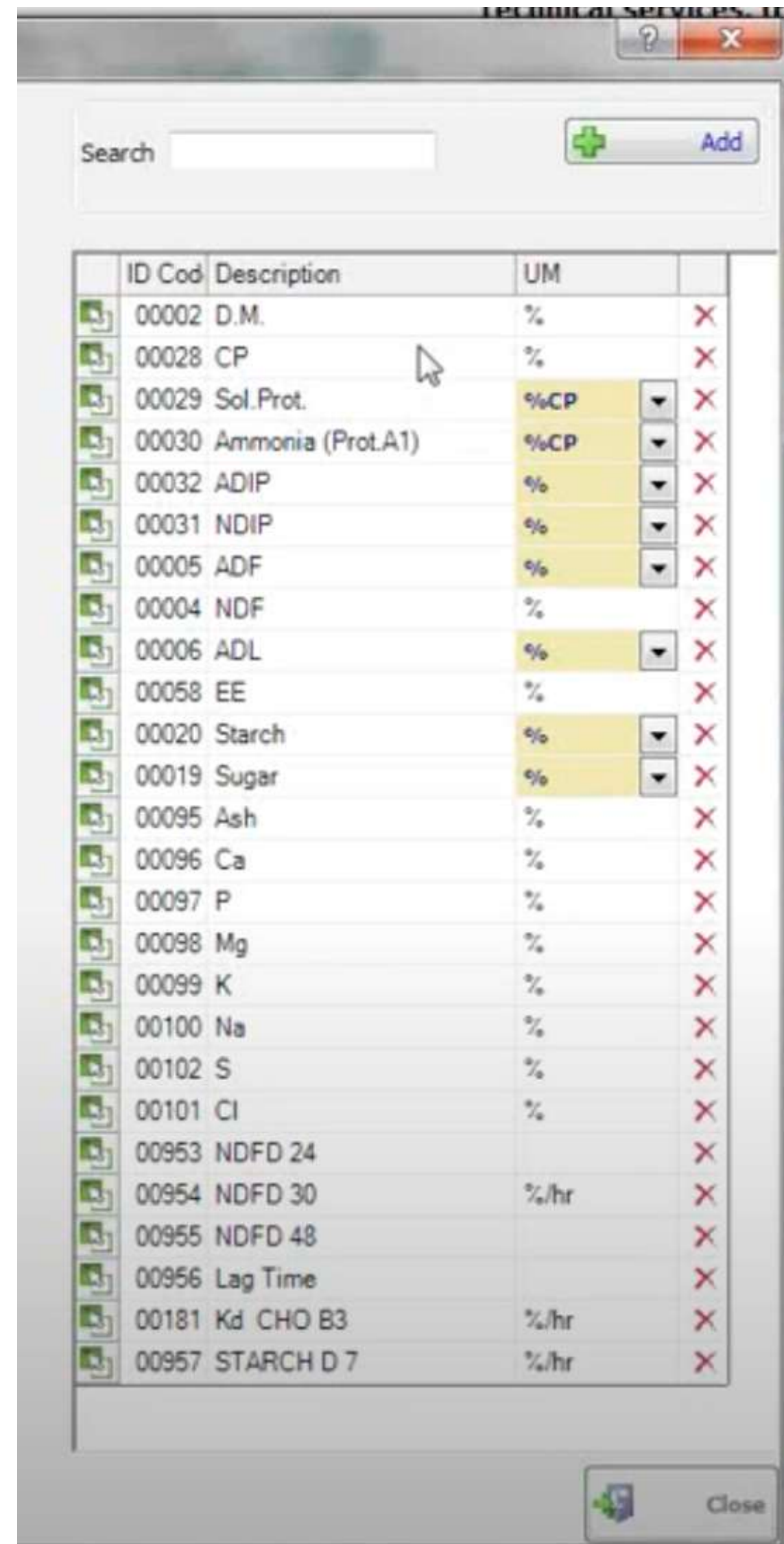
The screenshot shows a software interface with a 'Utility' tab selected. A window titled 'Animals Type Default [Cattle]' is open, displaying a table of default values for a 'Lactating Dairy Cow'. The table has four columns: 'Animal type', 'U.M.', 'User default', and 'Original Default'. The 'Animal type' is set to 'Lactating Dairy Cow'. The table lists various parameters and their default values.

Animal type	U.M.	User default	Original Default
Number of animals	n	1	1
Days in cycle	days	365	365
Breed type		Dairy	Dairy
Primary breed		Holstein	Holstein
Secondary Breed			
Average production/head/year	lbs		
Lactation number	n	2.00	2.00
Calving interval	months	13.00	13.00
Age at first calving (AOFC)	months	24.00	24.00
Age (actual average)	months	43.00	43.00
Mean FBW	lbs	1,385.0	1,385.0
Mature FBW	lbs	1,475.0	1,475.0
Days since calving (DIM)	days	100.0	100.0
Days pregnant	days	0	0
Daily milk production	lbs	85.00	85.00
Milk fat	% w/w	3.75	3.75
Milk total protein	% w/w	3.36	3.36
Milk true protein	% w/w	3.10	3.10
Casein	% w/w	2.62	2.62
Milk lactose	% w/w	4.85	4.85
Body reserves change	lbs	0.000	0.000
BCS (1-5)		3.00	3.00
Target BCS		3.00	3.00
Days to reach target BCS	days	100	100
Calf birth weight	lbs	85.0	85.0
ADG	lbs/day	0.000	0.000

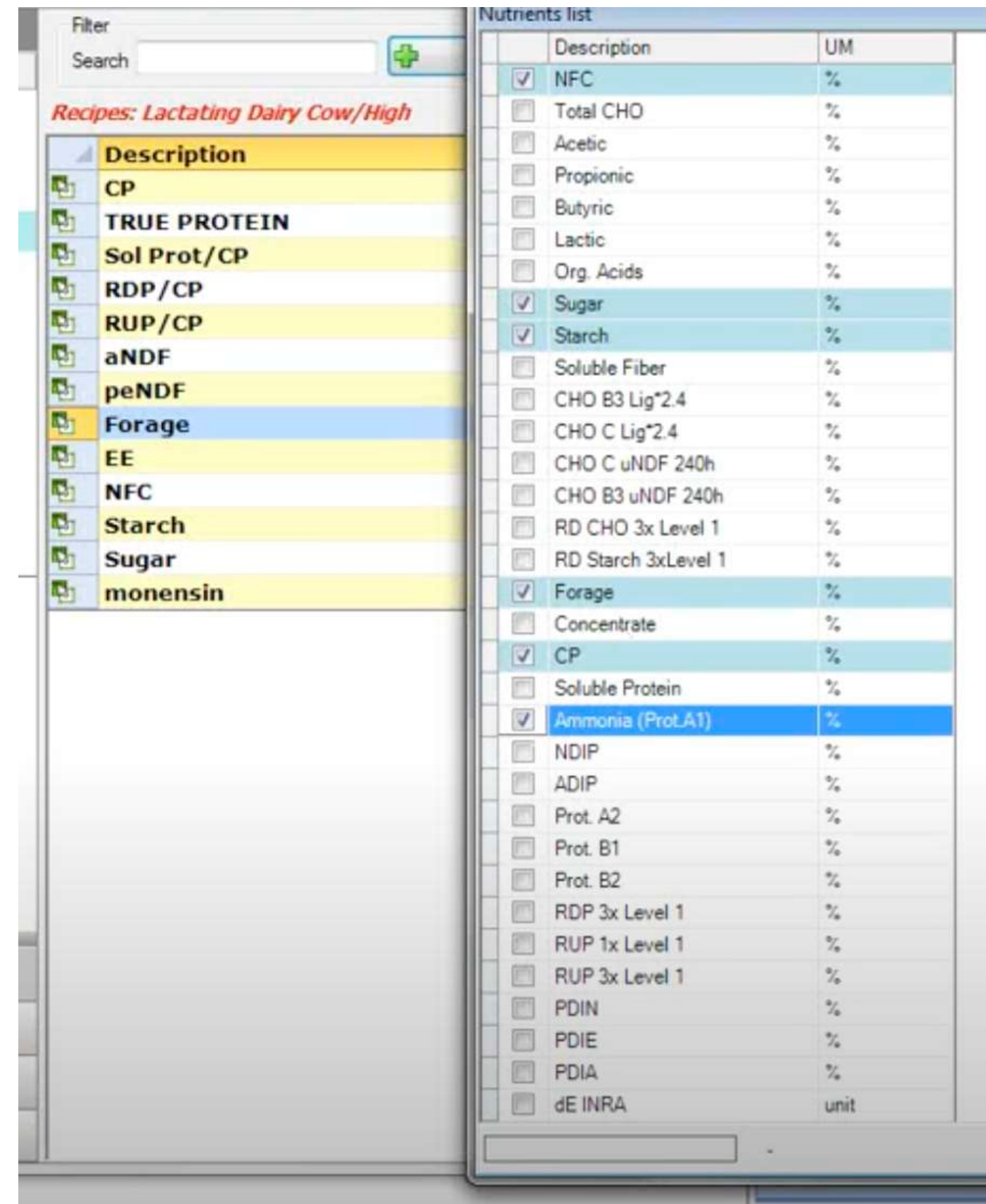
The interface also includes a sidebar with buttons for 'Parameters', 'User nutrients', 'Units under English system', 'User Lists', 'Report Settings', 'Quick data entry', 'Ingredients by formula', 'Feed analysis preview', and 'Deletes'. On the right, there is a section for 'Technical services, training and IT solutions' with a description and buttons for 'Farms Structure', 'Open external file', and 'Cost'.

State of the art

- ✿ What do we really know about the nutrients of the ingredients in a ration?



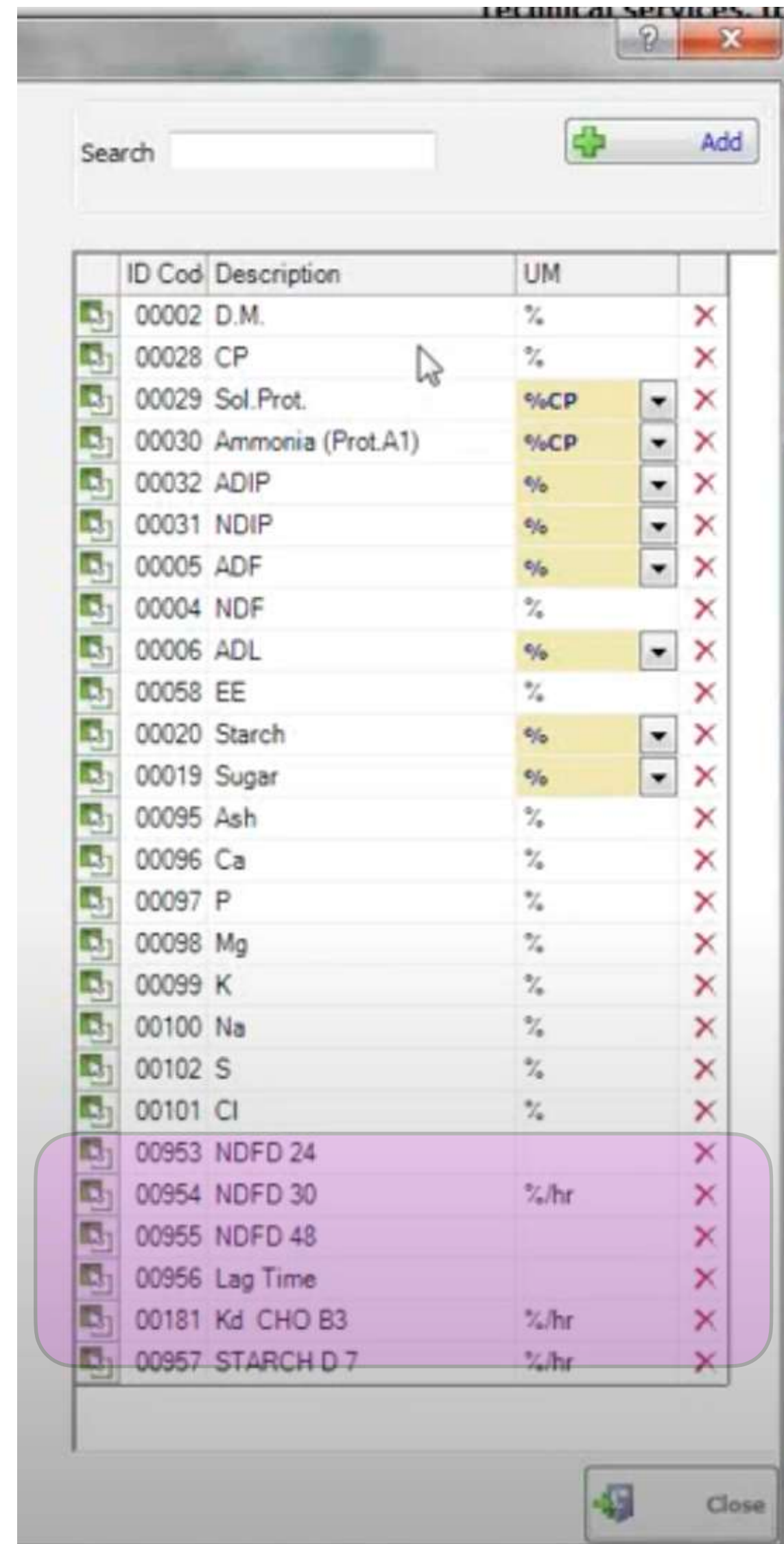
ID Cod	Description	UM	
00002	D.M.	%	X
00028	CP	%	X
00029	Sol.Prot.	%CP	X
00030	Ammonia (Prot.A1)	%CP	X
00032	ADIP	%	X
00031	NDIP	%	X
00005	ADF	%	X
00004	NDF	%	X
00006	ADL	%	X
00058	EE	%	X
00020	Starch	%	X
00019	Sugar	%	X
00095	Ash	%	X
00096	Ca	%	X
00097	P	%	X
00098	Mg	%	X
00099	K	%	X
00100	Na	%	X
00102	S	%	X
00101	Cl	%	X
00953	NDFD 24		X
00954	NDFD 30	%/hr	X
00955	NDFD 48		X
00956	Lag Time		X
00181	Kd CHO B3	%/hr	X
00957	STARCH D 7	%/hr	X



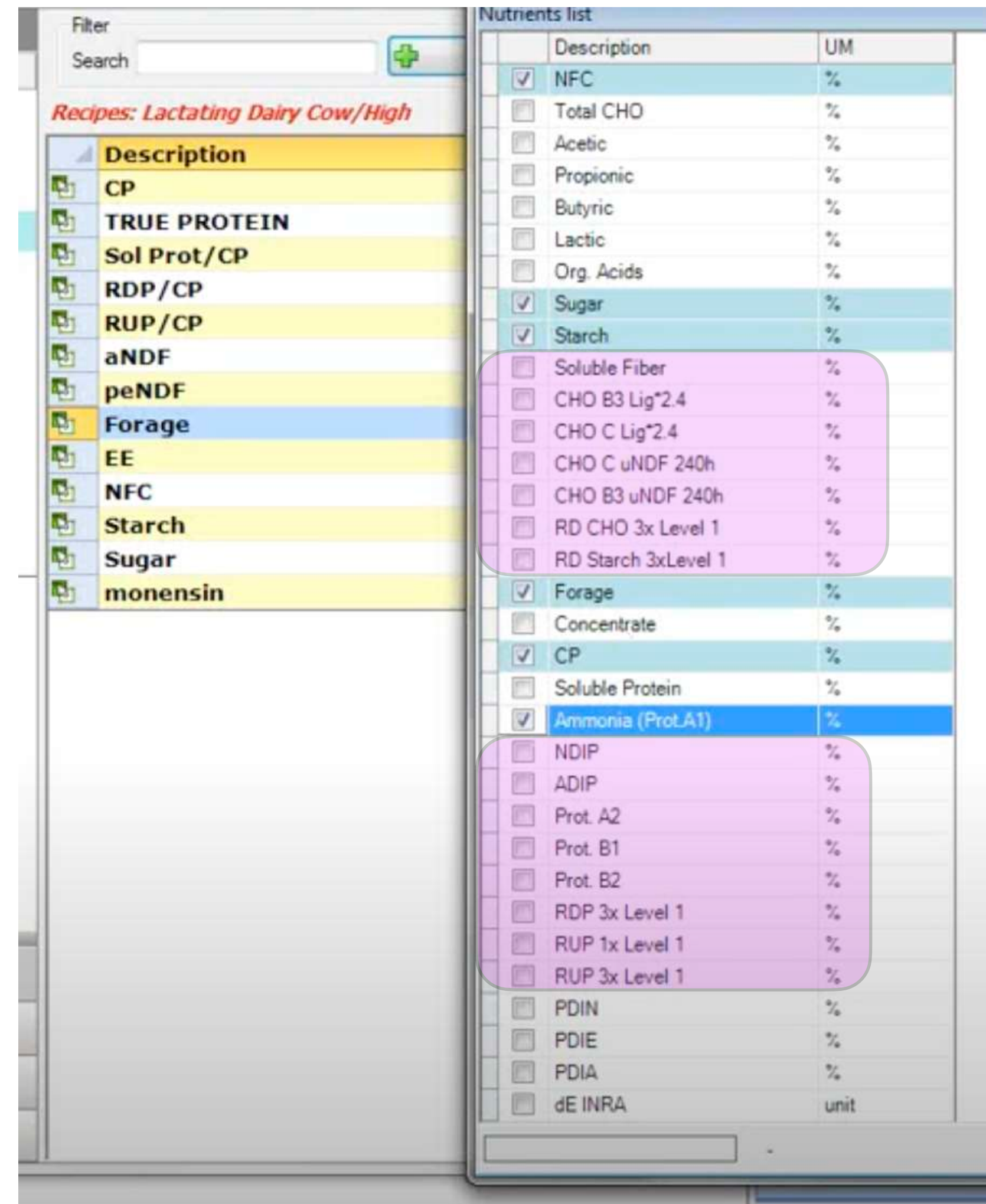
Description	UM
☒ NFC	%
☐ Total CHO	%
☐ Acetic	%
☐ Propionic	%
☐ Butyric	%
☐ Lactic	%
☐ Org. Acids	%
☒ Sugar	%
☒ Starch	%
☐ Soluble Fiber	%
☐ CHO B3 Lig*2.4	%
☐ CHO C Lig*2.4	%
☐ CHO C uNDF 240h	%
☐ CHO B3 uNDF 240h	%
☐ RD CHO 3x Level 1	%
☐ RD Starch 3xLevel 1	%
☒ Forage	%
☐ Concentrate	%
☒ CP	%
☐ Soluble Protein	%
☒ Ammonia (Prot.A1)	%
☐ NDIP	%
☐ ADIP	%
☐ Prot. A2	%
☐ Prot. B1	%
☐ Prot. B2	%
☐ RDP 3x Level 1	%
☐ RUP 1x Level 1	%
☐ RUP 3x Level 1	%
☐ PDIN	%
☐ PDIE	%
☐ PDIA	%
☐ dE INRA	unit

State of the art

- ✿ What do we really know about the nutrients of the ingredients in a ration?



ID Cod	Description	UM	
00002	D.M.	%	X
00028	CP	%	X
00029	Sol.Prot.	%CP	X
00030	Ammonia (Prot.A1)	%CP	X
00032	ADIP	%	X
00031	NDIP	%	X
00005	ADF	%	X
00004	NDF	%	X
00006	ADL	%	X
00058	EE	%	X
00020	Starch	%	X
00019	Sugar	%	X
00095	Ash	%	X
00096	Ca	%	X
00097	P	%	X
00098	Mg	%	X
00099	K	%	X
00100	Na	%	X
00102	S	%	X
00101	Cl	%	X
00953	NDFD 24		X
00954	NDFD 30	%/hr	X
00955	NDFD 48		X
00956	Lag Time		X
00181	Kd CHO B3	%/hr	X
00957	STARCH D 7	%/hr	X



Description	UM
☒ NFC	%
☐ Total CHO	%
☐ Acetic	%
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☐ Butyric	%
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☒ Sugar	%
☒ Starch	%
☐ Soluble Fiber	%
☐ CHO B3 Lig*2.4	%
☐ CHO C Lig*2.4	%
☐ CHO C uNDF 240h	%
☐ CHO B3 uNDF 240h	%
☐ RD CHO 3x Level 1	%
☐ RD Starch 3xLevel 1	%
☒ Forage	%
☐ Concentrate	%
☒ CP	%
☐ Soluble Protein	%
☒ Ammonia (Prot.A1)	%
☐ NDIP	%
☐ ADIP	%
☐ Prot. A2	%
☐ Prot. B1	%
☐ Prot. B2	%
☐ RDP 3x Level 1	%
☐ RUP 1x Level 1	%
☐ RUP 3x Level 1	%
☐ PDIN	%
☐ PDIE	%
☐ PDIA	%
☐ dE INRA	unit

State of the art

What is metabolizable protein?

★ Intake

📌 Crude protein

📌 Microbial protein

- Soluble protein (degradation rate, passage rate)

- Degradable protein (degradation rate, passage rate)

- Energy available for bacteria growth

📌 Amino acid profile of undegradable protein

📌 Protein digestibility in the intestine (passage rate)

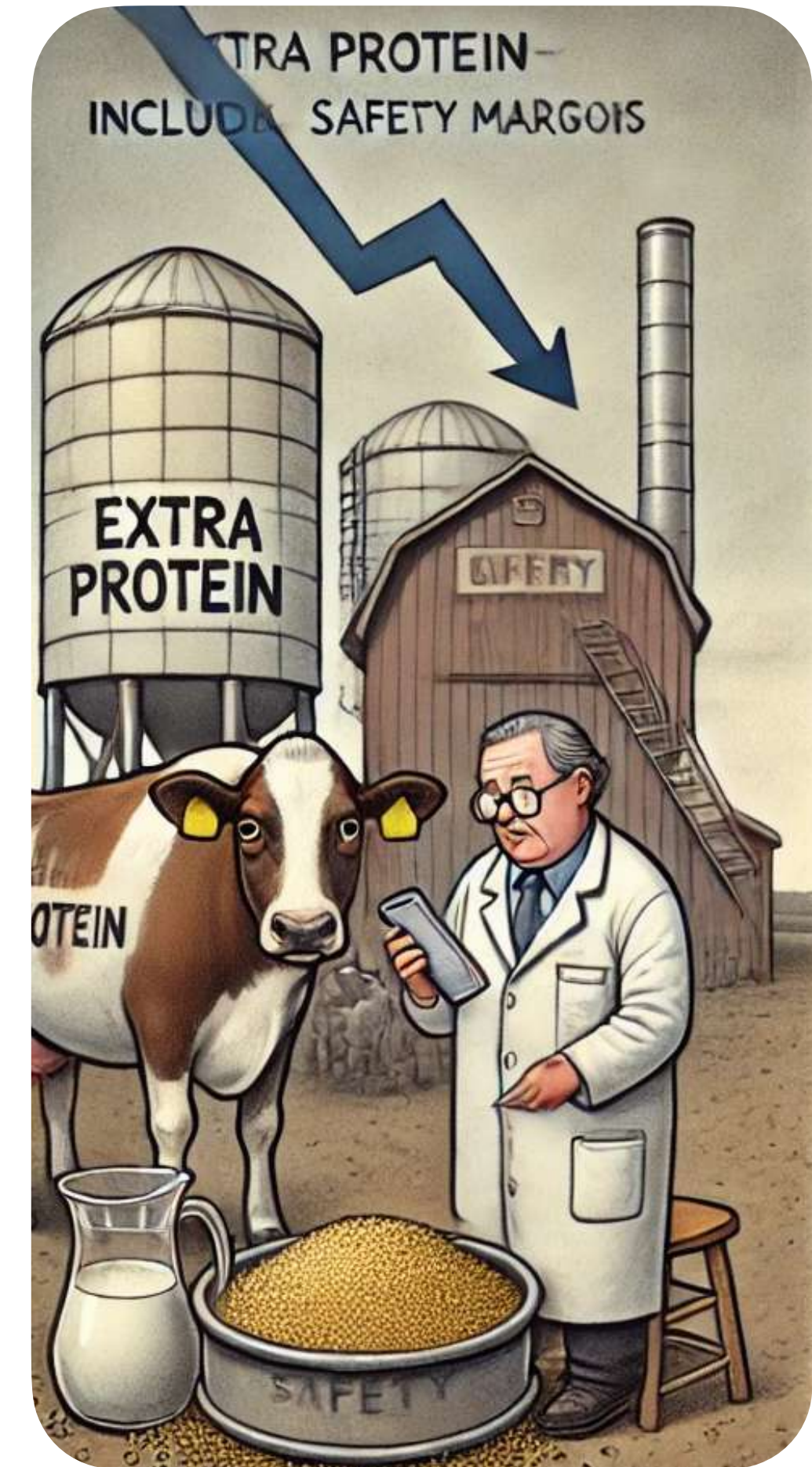
State of the art

Table 1. The CNCPS evaluation of the control and experimental diets using the predicted and actual dry matter intake values

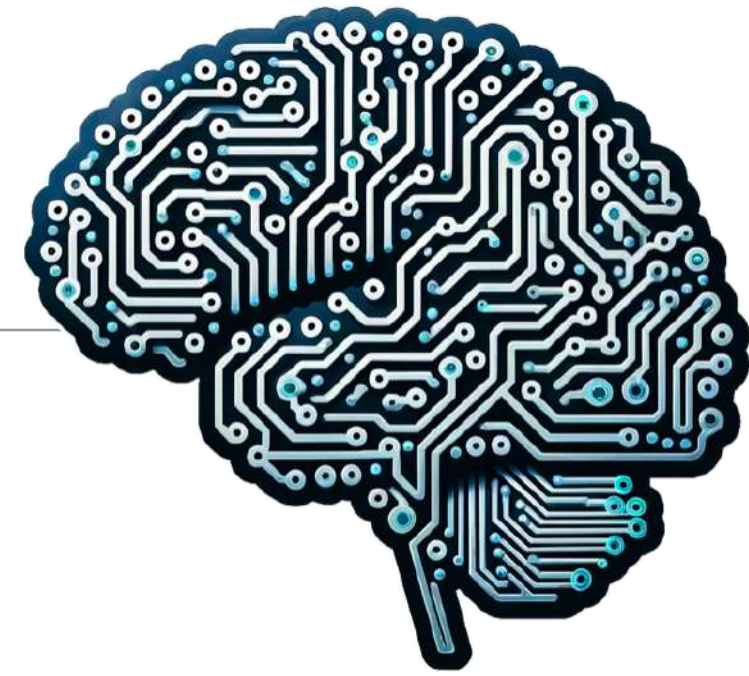
	Control		Experimental		Energy allowable gain (lb/d)	Protein allowable gain (lb/d)
	Predicted	Actual	Predicted	Actual		
Dry matter intake (kg)	24.6	21.6	24.6	21.2		
Metabolizable energy balance (Mcal)	-3.1	-3.2	0	-1.0		
Metabolizable protein (MP) balance (g)	4.8	-347.9	65.3	-311.1		
NP/MP (%)	64.8	78.2	63	76.6		
CP (DM %)	17.9	17.9	17.1	17.1		
UIPIP (%)	40.8	39.2	38.3	36.5		
Fat (%)	4.9	5.0	5.9	6.0		
NDF (%)	36.6	36.6	34	34	0.22	0.55
Effective NDF (%)	21.3	21.3	21.5	21.5	0.48	0.62
NFC (%)	37.2	37.2	38.8	38.8	0.88	0.64
					0.79	0.73
					1.65	1.86
					2.00	2.20
Rumen balance						
Peptides (% req.)	131	141	117	127		
Ammonia (% req.)	130	140	112	123		
Amino acid balance						
Met (% req.)	97	94	107	104		
Lys (% req.)	97	95	105	102		
Ile (% req.)	109	82	115	105		
Milk production (kg d ⁻¹)						
Target	45	45	45	45		
Amino acid allowed milk	42.7	35.7	48.3	46.0		
Microbial protein allowed milk	45.1	37.4	46.4	38.2		
Metabolizable energy allowed milk	42.1	42.1	45.0	44.1		

State of the art

- 📌 The uncertainty inherent in the current nutritional models (at both sides: supply and requirements) forces nutritionists to implement '**safety factors**' to ensure that there are no deficiencies that could harm productivity or health of the animal
- 📌 These safety factors have an **environmental** and **economic cost**, and in occasions (i.e., Cu) can be harmful



Artificial Intelligence



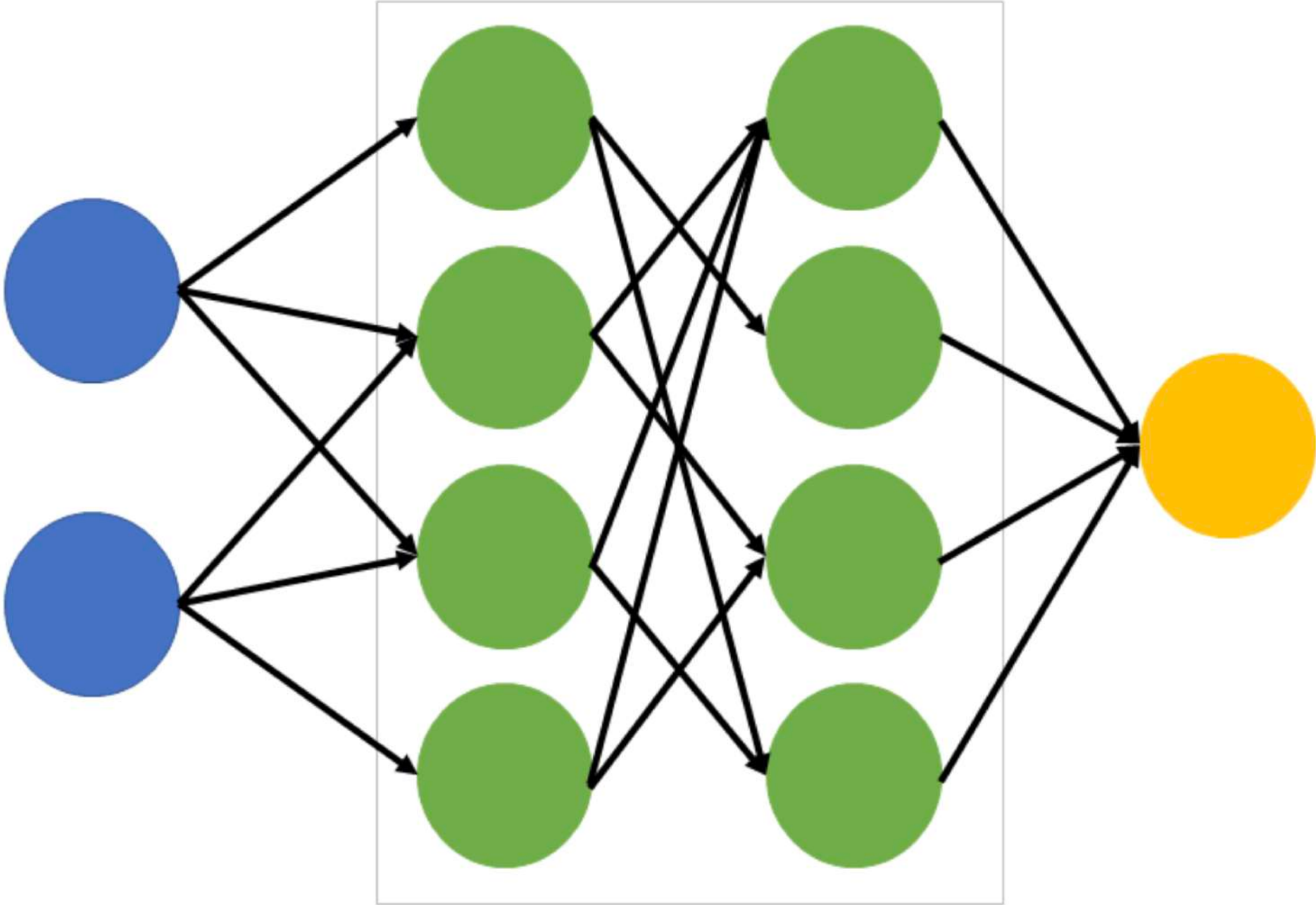
- 📌 New developments in data science, and especially, in **computational power**, represent a major opportunity to implement AI in animal science
- 📌 We can, now, process large amount of data relatively fast
- 📌 We can implement traditional statistics, or more novel and computer intensive recursive or iterative techniques using on-farm data

Artificial Intelligence

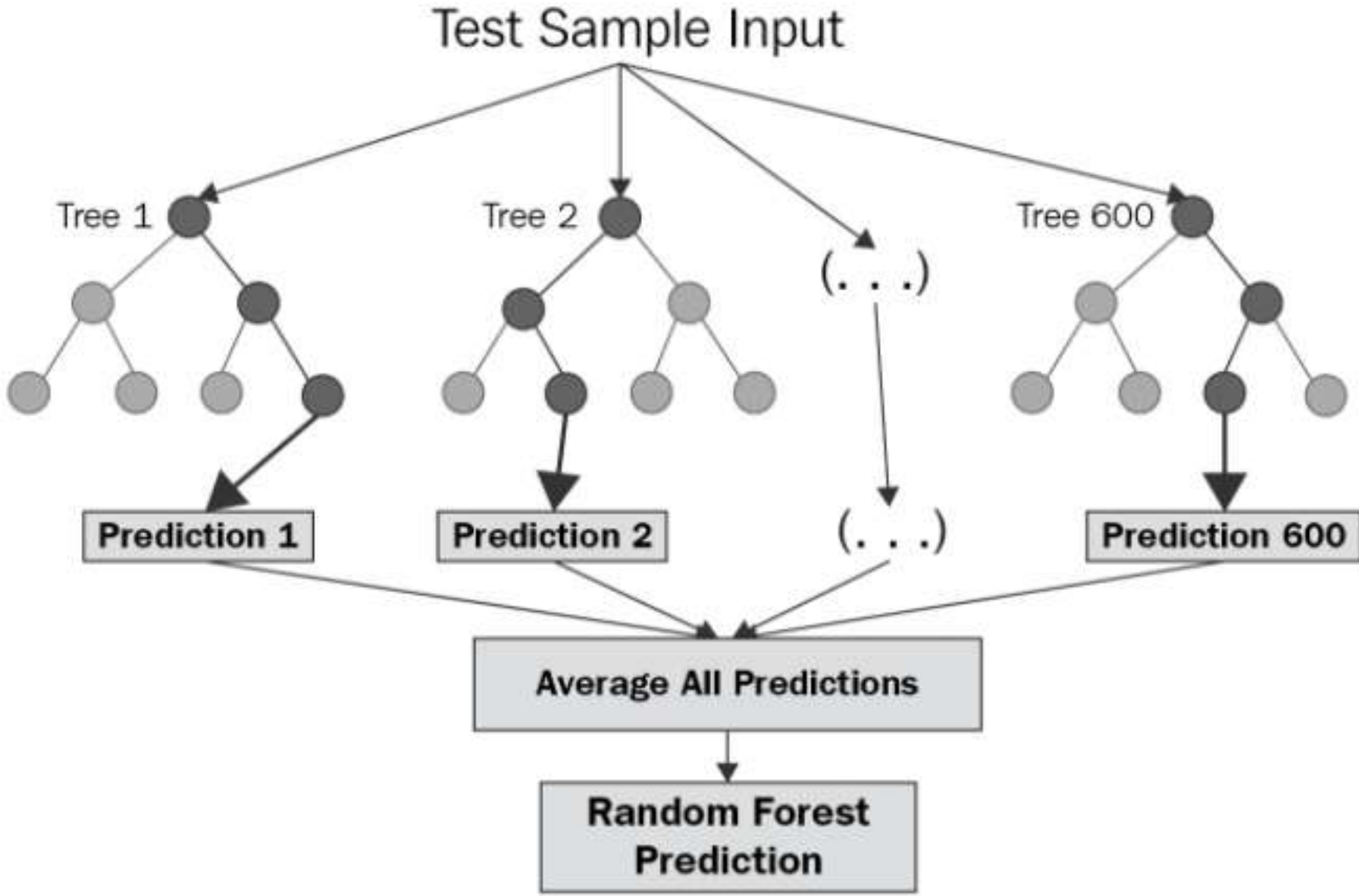
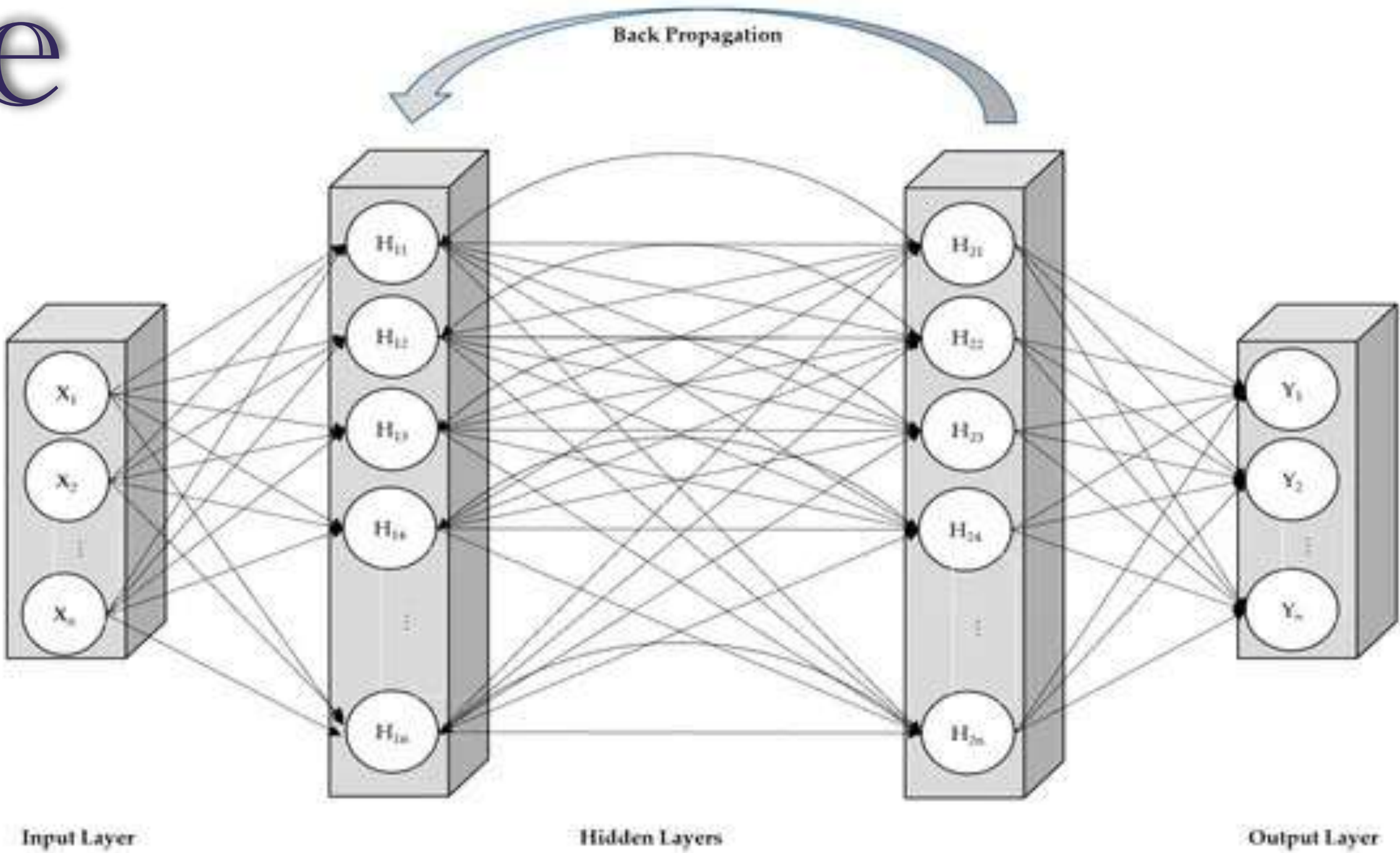
Input layer

Hidden layer

Output layer



Artificial neural networks

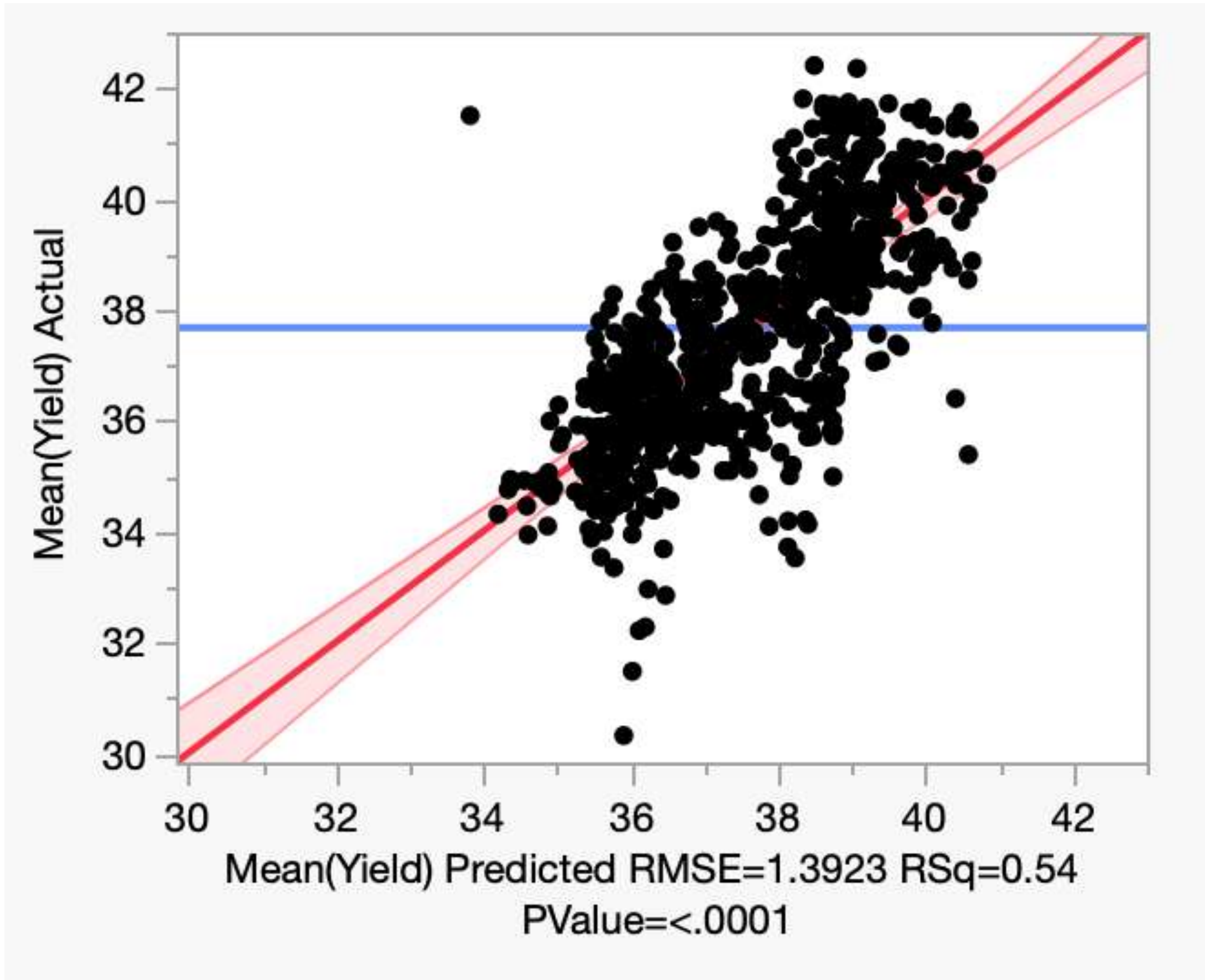


Artificial Intelligence

Milk ~ DMI, DIM, LN, CP%, NDF%, NEI

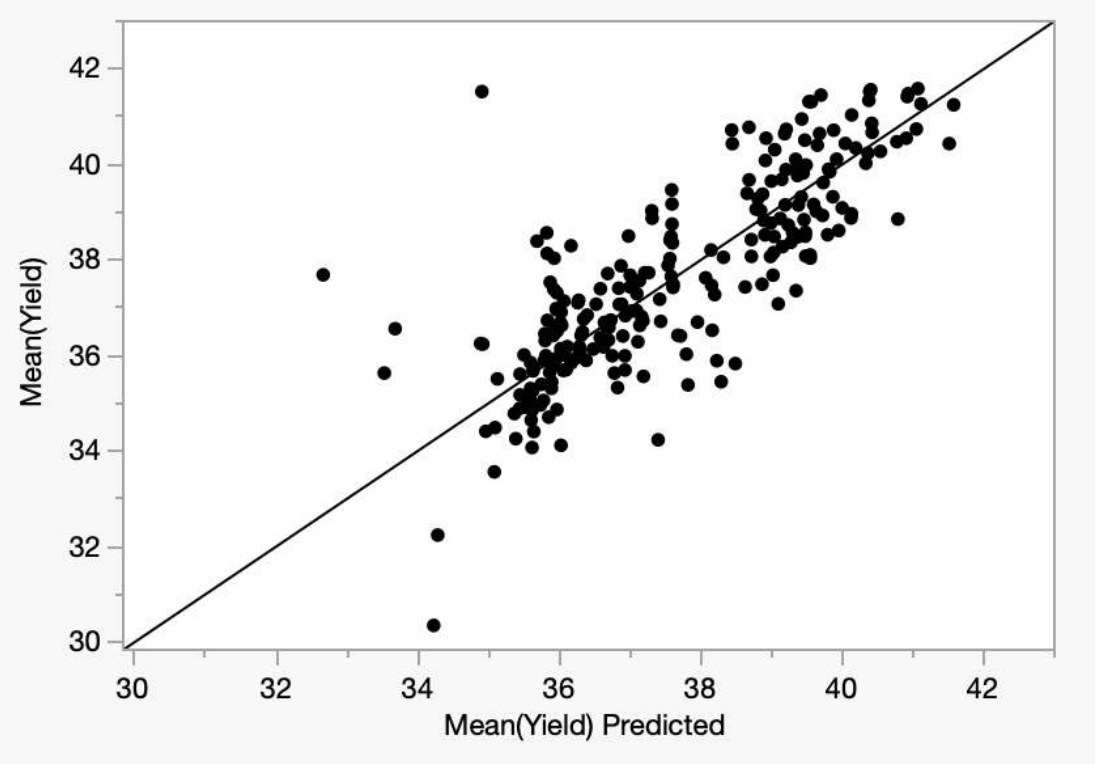
Regression

Measures	Value
RSquare	0.541616
RSquare Adj	0.537758
Root Mean Square Error	1.392322
Mean of Response	37.67431
Observations (or Sum Wgts)	720



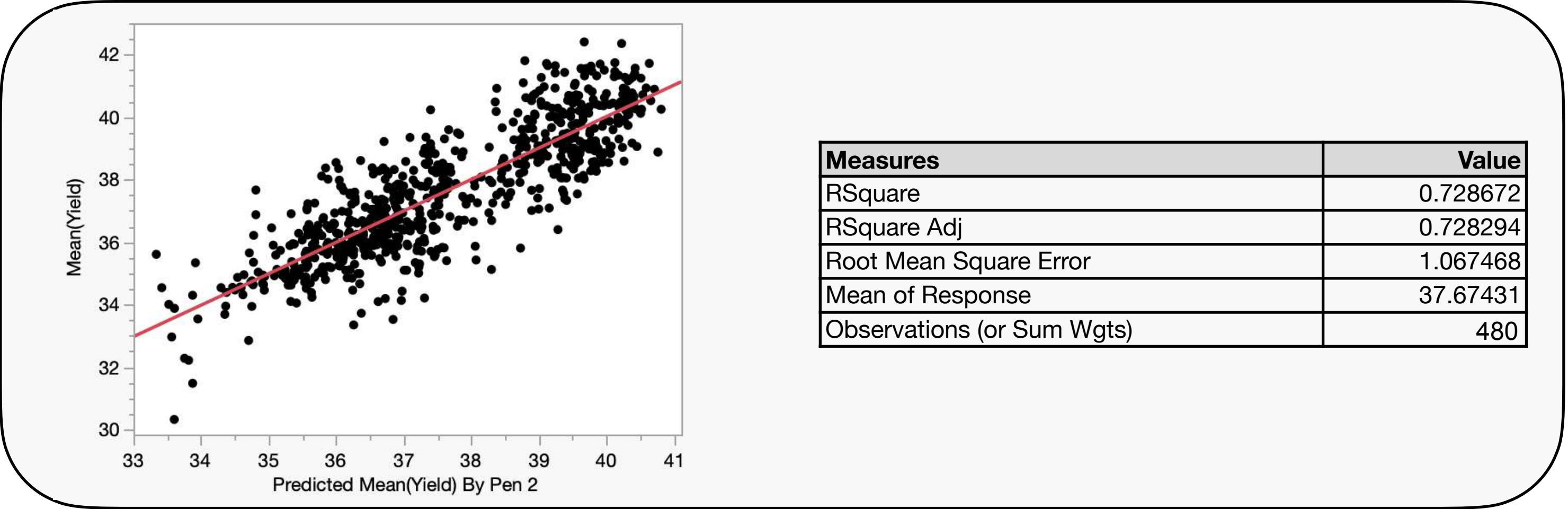
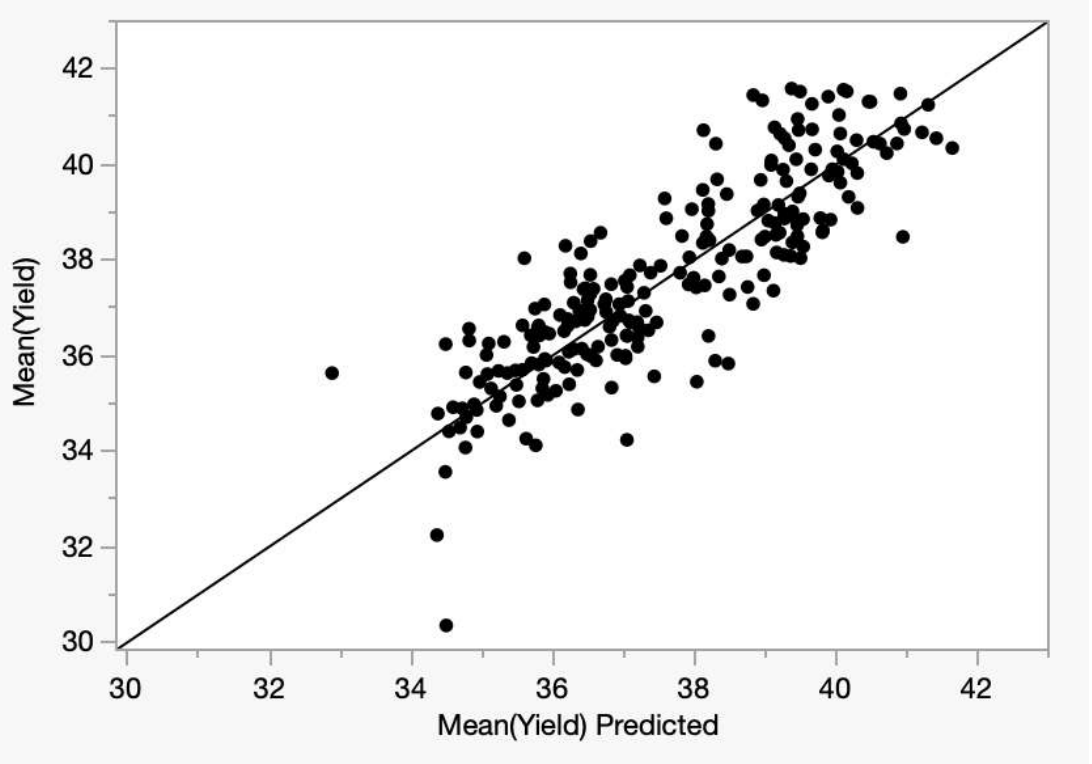
Neural (3 Neurones)

Measures	Value
RSquare	0.6498607
RASE	1.1986533
Mean Abs Dev	0.8776488
-LogLikelihood	384.03292
SSE	344.82472
Sum Freq	240



Neural (5 Neurones)

Measures	Value
RSquare	0.7354316
RASE	1.0419387
Mean Abs Dev	0.806799
-LogLikelihood	350.40519
SSE	260.55269
Sum Freq	240

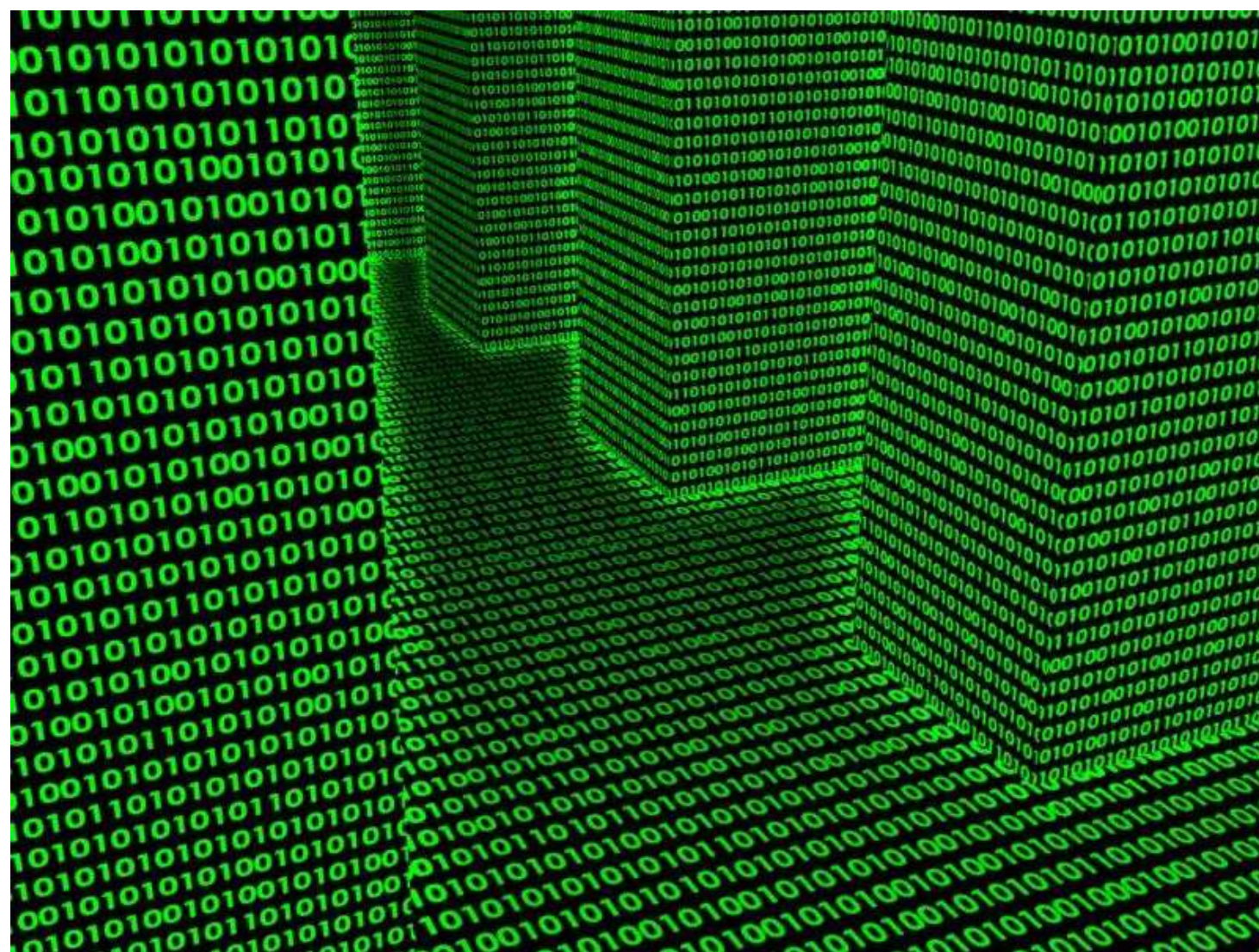


Measures	Value
RSquare	0.728672
RSquare Adj	0.728294
Root Mean Square Error	1.067468
Mean of Response	37.67431
Observations (or Sum Wgts)	480

Artificial Intelligence

Generative AI

- DeepSeek: 685,000 millions of parameters
- Works with MoE (mixture-of-Experts): selects 37,000 millions of parameters depending on the 'task'
- In animal science we work with.... 20?, 30?, 50? parameters



ChatGPT



Claude



Gemini



Meta



DeepSeek



Perplexity



Midjourney



Flux



Ideogram



Runway



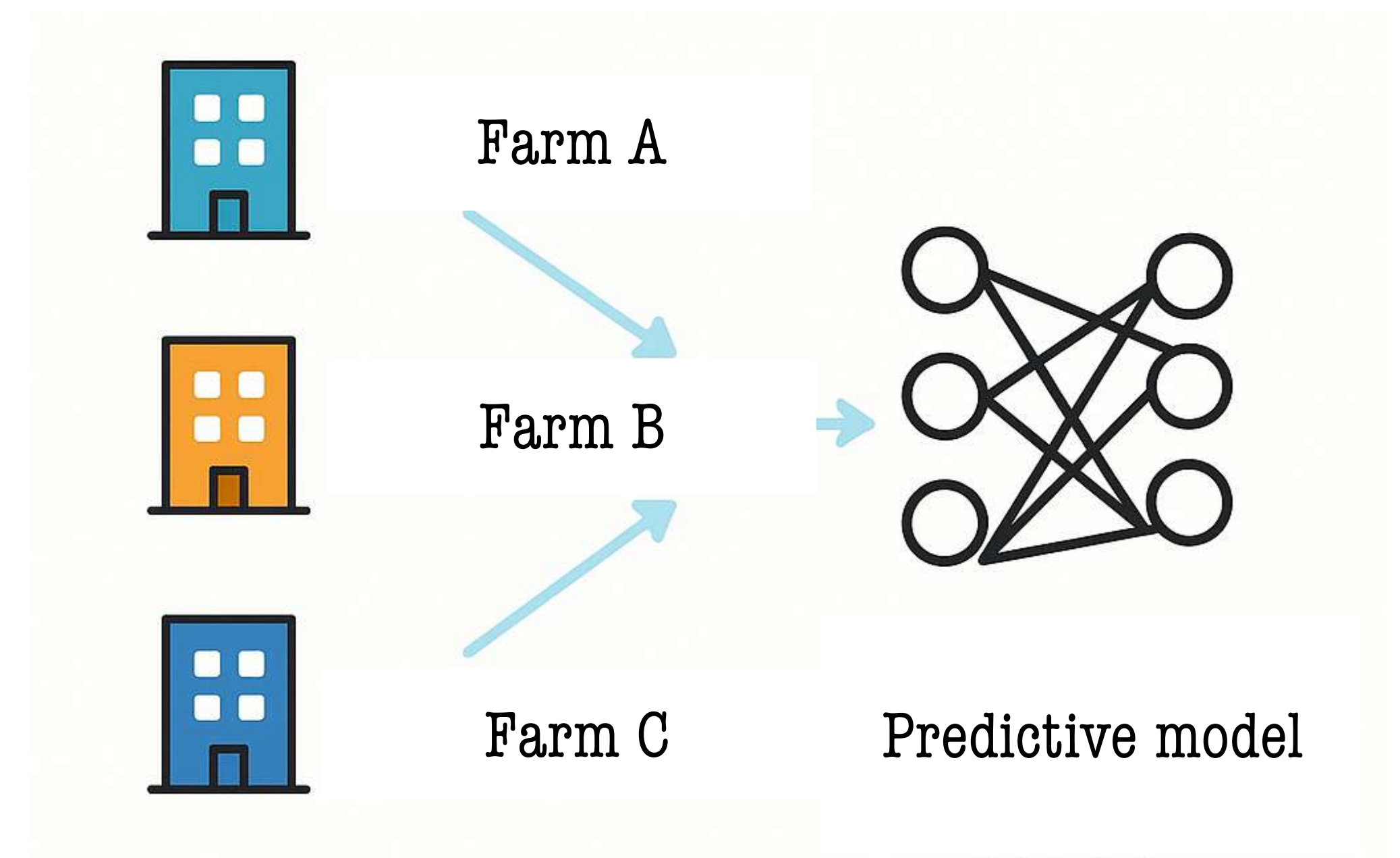
Luma



Grok

Artificial Intelligence

- 📌 Geneticists pioneered the use of ML in animal science when used genomic data to predict phenotypes (Long et al., 2007).
- 📌 In the nutrition domain, combining data from different herds is usually necessary to build a sufficiently large database to effectively run ML algorithms
- 📌 Transfer or hierarchical learning



Data

📌 Nowadays, dairy farms have a '*wealth*' of data covering most most relevant aspects of the operation:

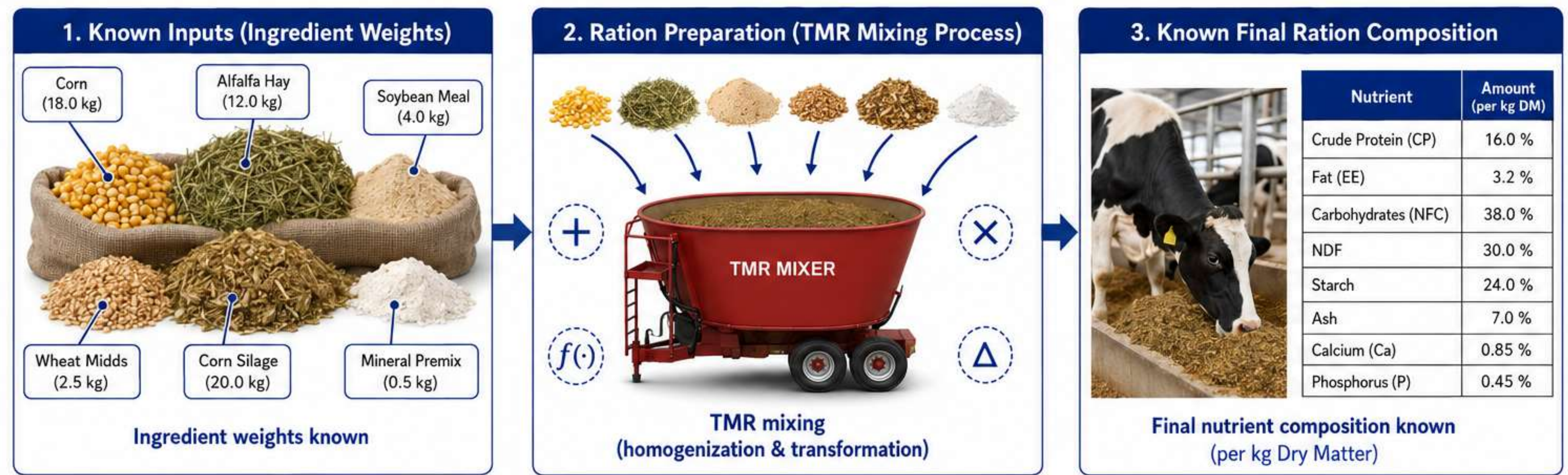
- ★ Productivity
- ★ Consumption
- ★ Prices
- ★ Health
- ★ Reproduction
- ★ Management
- ★ Genetics (genome)

Data

- Several companies are reluctant to share data across different platforms



Artificial Intelligence



4. Unknowns

Individual nutrient profiles of each ingredient are unknown

Corn (18.0 kg)	Alfalfa Hay (12.0 kg)	Soybean Meal (4.0 kg)	Wheat Midds (2.5 kg)	Corn Silage (20.0 kg)	Mineral Premix (0.5 kg)	...
Crude Protein (CP) ?	Crude Protein (CP) ?	Crude Protein (CP) ?	Crude Protein (CP) ?	Crude Protein (CP) ?	Crude Protein (CP) ?	
Fat (EE) ?	Fat (EE) ?	Fat (EE) ?	Fat (EE) ?	Fat (EE) ?	Fat (EE) ?	
Carbohydrates (NFC) ?	Carbohydrates (NFC) ?	Carbohydrates (NFC) ?	Carbohydrates (NFC) ?	Carbohydrates (NFC) ?	Carbohydrates (NFC) ?	
NDF ?	NDF ?	NDF ?	NDF ?	NDF ?	NDF ?	
Starch ?	Starch ?	Starch ?	Starch ?	Starch ?	Starch ?	
Ash ?	Ash ?	Ash ?	Ash ?	Ash ?	Ash ?	
Ca ?	Ca ?	Ca ?	Ca ?	Ca ?	Ca ?	
P ?	P ?	P ?	P ?	P ?	P ?	

Inverse estimation problem:
Can we recover nutrient composition of each ingredient using only ingredient weights and final ration nutrients?

W = known ingredient weights
 $W \in \mathbb{R}^m$

$N_{ingredients}$ = unknown nutrient matrix (per ingredient)
 $N_{ingredients} \in \mathbb{R}^{m \times p}$

N_{final} = known nutrient vector of ration
 $N_{final} \in \mathbb{R}^p$

$W + N_{ingredients}$

→ Recipe (TMR mixing) →

N_{final}

Artificial Intelligence

- ★ One can attempt to estimate one nutrient at time (similar to current nutritional models):
 - Which CP values for each ingredient best predict ration CP?
 - Which NDF values each ingredient best predict ration NDF?
- ★ We can alternatively solve:
 - Which full ingredient composition table best predicts CP, NDF, starch, ADF, ash, EE all at once?
- ★ The key is to estimate a residual covariance matrix among nutrients and scores candidate solutions using a multivariate likelihood, so correlated nutrient errors are considered jointly rather than independent RMSEs for each nutrient

Artificial Intelligence

- ★ With sufficient historical TMR and ration analyses, this becomes similar to source-separation and blind matrix factorization problems used in chemometrics and spectroscopy
- ★ For nutrient j :

$$Y_j = WX_j$$

Y_j = vector of observed nutrient concentrations across rations

W = ingredient inclusion matrix

X_j = nutrient profile of ingredients

- ★ This becomes a regression problem:

$$X_j = (W^T W)^{-1} W^T Y_j$$

Artificial Intelligence

★ We could try regression, but.. a more efficient approach could be:

★ Constrained Montecarlo search

- Randomly samples plausible ingredient nutrient values from biological bounds
- Enforces constraints such as $ADF \leq NDF$ and $CP + NDF + \text{starch} + \text{fat} + \text{ash} \leq 100\% \text{ DM}$, then keeps the best-fitting values

Machine Learning

1 Inputs

A. Diet dataset

n diets $\times$ m nutrients
 Y (observed nutrient concentrations, % DM)

Diet	CP	NDF	ADF	Starch	EE	Ash
1	...	...	...	...	...	...
2	...	...	...	...	...	...
3	...	...	...	...	...	...
...	...	...	...	...	...	...
n	...	...	...	...	...	...

B. Ingredient inclusions

n diets $\times$ p ingredients
 X (fraction of diet DM)

Diet	Ing ₁	Ing ₂	...	Ing _p
1	...	...	...	...
2	...	...	...	...
3	...	...	...	...
...	...	...	...	...
n	...	...	...	...

C. Ingredient-nutrient bounds

Lower and upper bounds for each ingredient (p) and nutrient (m)

Ingredient	Nutrient	Lower	Upper
Ing ₁	CP	12	24
Ing ₁	NDF	35	65
...	...	...	...
Ing _p	Ash	4	10

Also: joint biological constraints
(e.g., $ADF \leq NDF$; sum of nutrients ≤ 100)

2 Random sampling

For each iteration ($k = 1 \dots N$):

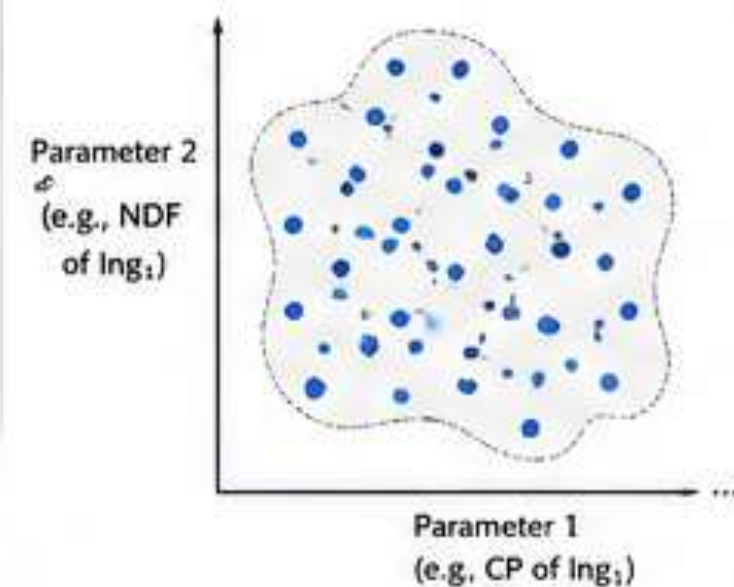
Randomly draw a nutrient value for every ingredient within its bounds.

Draw_k: p ingredients $\times$ m nutrients

	CP	NDF	ADF	Starch	EE	Ash
Ing ₁	18.7	48.2	30.1	2.3	2.1	9.6
Ing ₂	8.9	17.6	6.7	61.4	3.1	1.8
...	...	...	...	...	...	...
Ing _p	3.6	72.1	45.8	1.2	1.3	6.5

Search space (conceptual)

Each point = one random draw (78-D space)



3 Enforce joint constraints

Check and repair the draw to satisfy all biological constraints.

- Lower bound $\leq$ value $\leq$ Upper bound
- $ADF \leq NDF$ (for each ingredient)
- $CP + NDF + Starch + EE + Ash \leq 100$ (for each ingredient)
- (other constraints as defined)

If violated, adjust values (repair) rather than discard to preserve information.

Example (ingredient j):

Before repair (violations in red)

CP	NDF	ADF	Starch	EE	Ash
20.0	40.0	48.0	15.0	4.0	20.0

After repair (feasible)

CP	NDF	ADF	Starch	EE	Ash
19.2	45.5	44.0	12.0	3.8	15.5

4 Predict diet nutrients

Use the candidate composition matrix C_k to predict diet nutrient concentrations:

$$\hat{Y}_k = X C_k$$

$$X (n \times p) \quad C_k (p \times m) \Rightarrow \hat{Y}_k (n \times m)$$

$$\begin{matrix} X & C_k & \hat{Y}_k \\ n \times p & p \times m & n \times m \end{matrix}$$

Residuals:

$$R_k = Y - \hat{Y}_k$$

($n \times m$)

5 Score the candidate

Evaluate model fit using the multivariate residual covariance matrix Σ .

Compute negative log-likelihood (NLL):

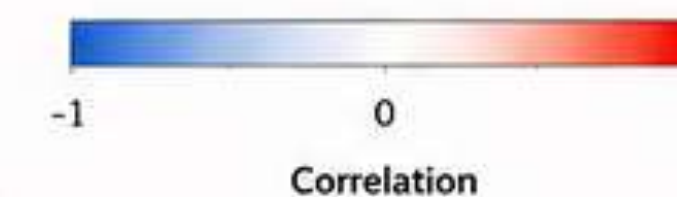
$$NLL_k = \frac{1}{2} \left[n \ln |\Sigma| + \sum_{i=1}^n r_i^T \Sigma^{-1} r_i \right]$$

where r_i = residual vector for diet i (length m)

Σ = residual covariance matrix (estimated from data with shrinkage for stability)

Residual covariance Σ (example, 6 nutrients)

	CP	NDF	ADF	Starch	EE	Ash
CP	1.00	0.62	0.55	-0.10	0.15	0.05
NDF	0.62	1.00	0.82	-0.12	0.18	0.08
ADF	0.55	0.82	1.00	-0.08	0.12	0.04
Starch	-0.10	-0.12	-0.08	1.00	-0.05	-0.02
EE	0.15	0.18	0.12	-0.05	1.00	0.30
Ash	0.05	0.08	0.04	-0.02	0.30	1.00

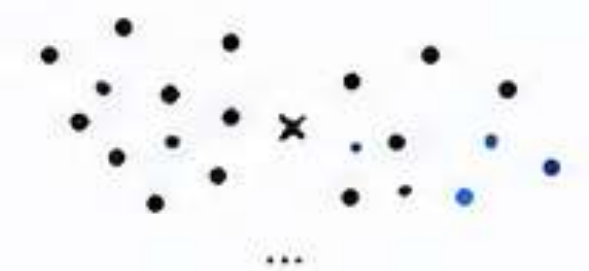


6 Repeat many iterations

Repeat Steps 2–5 for N iterations (e.g., $N = 250,000$).

Store for each candidate k :

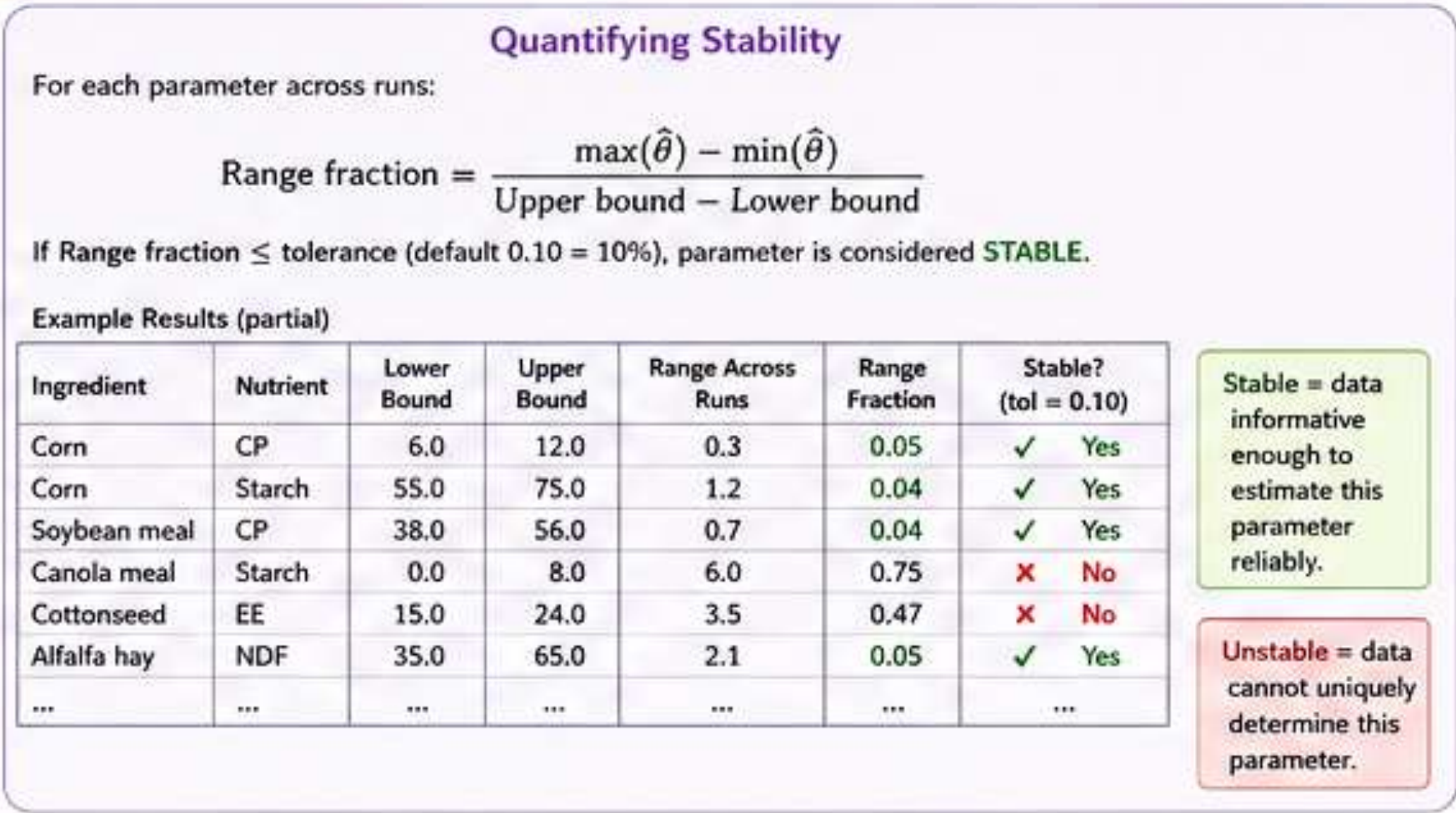
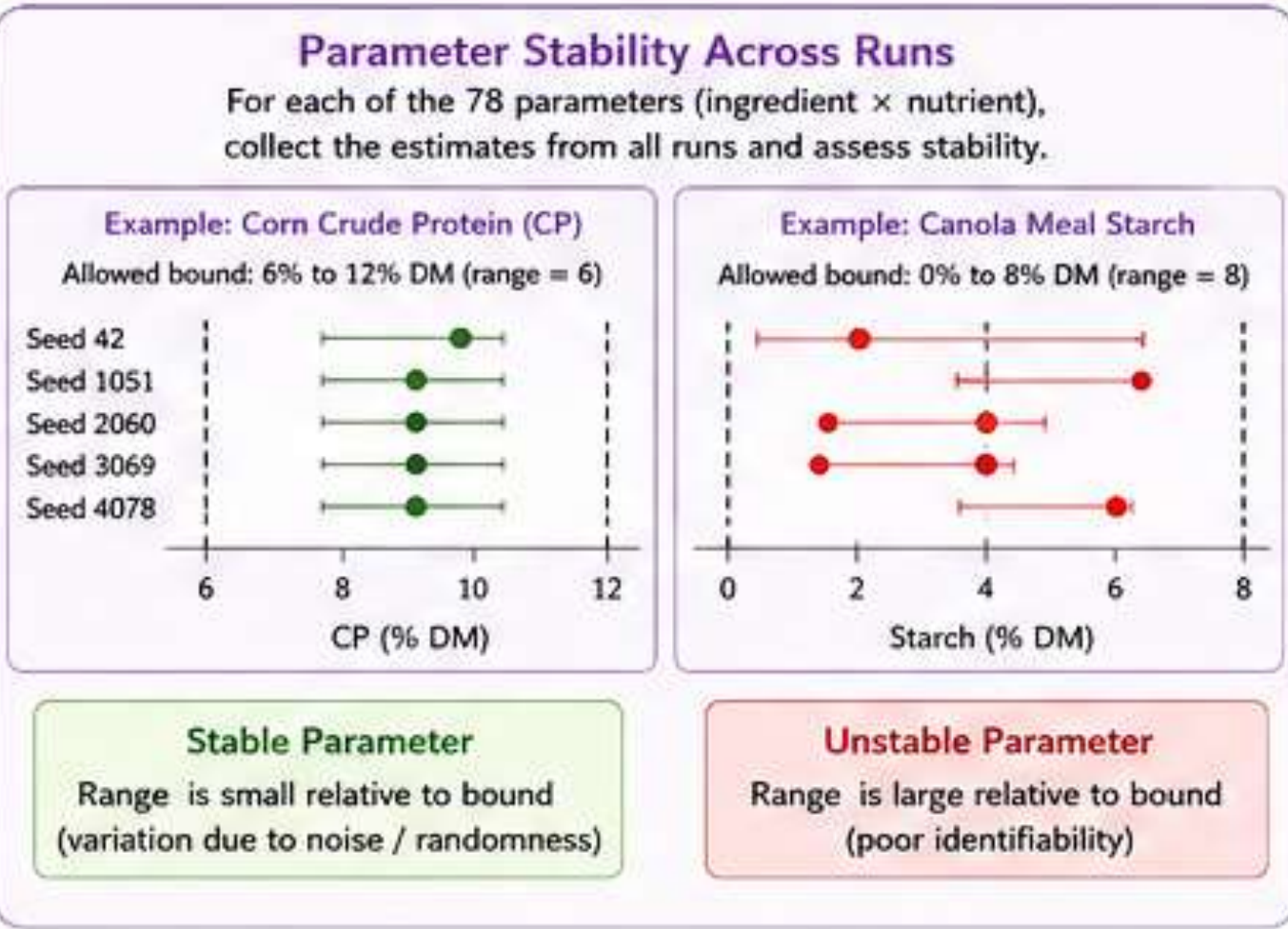
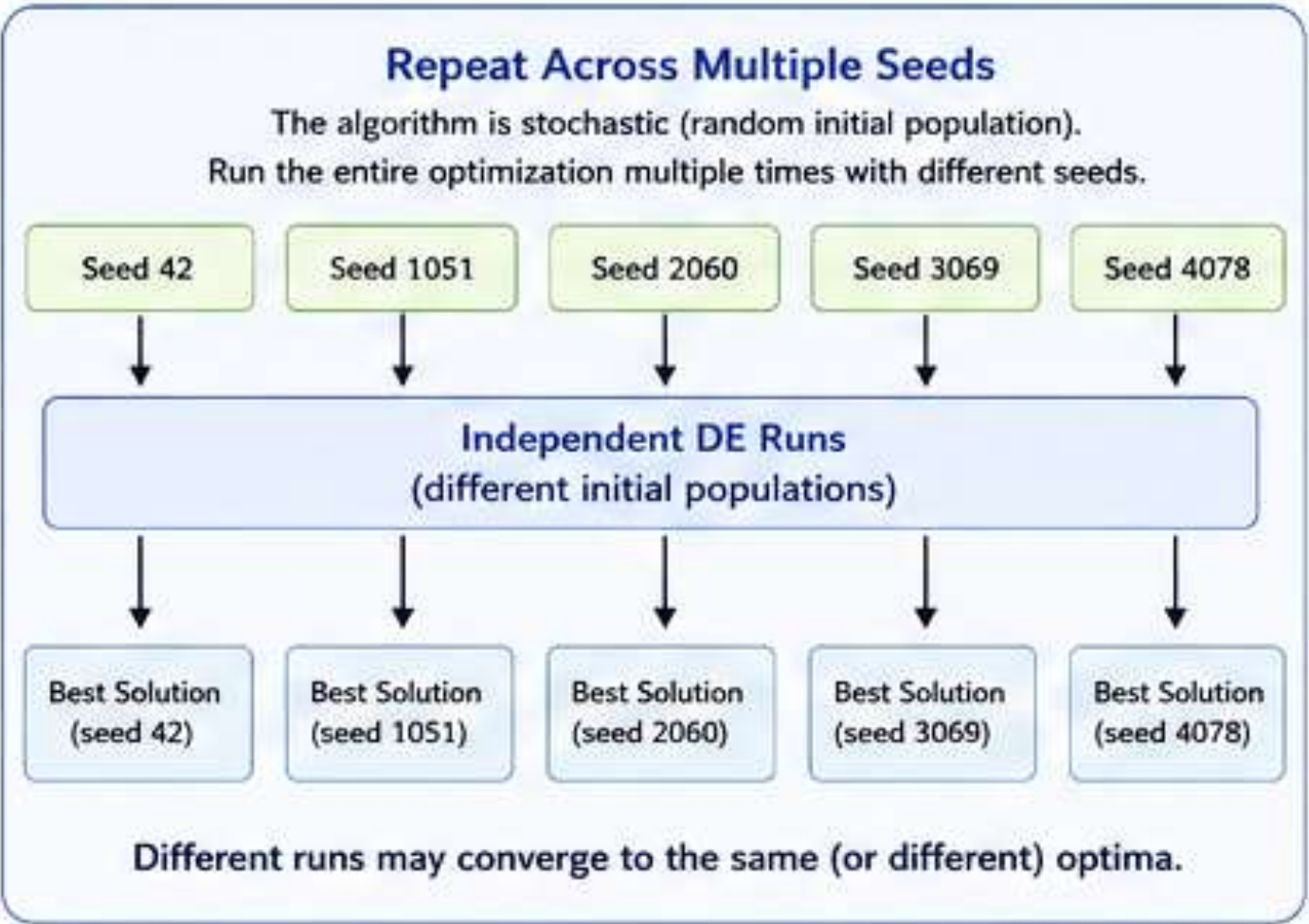
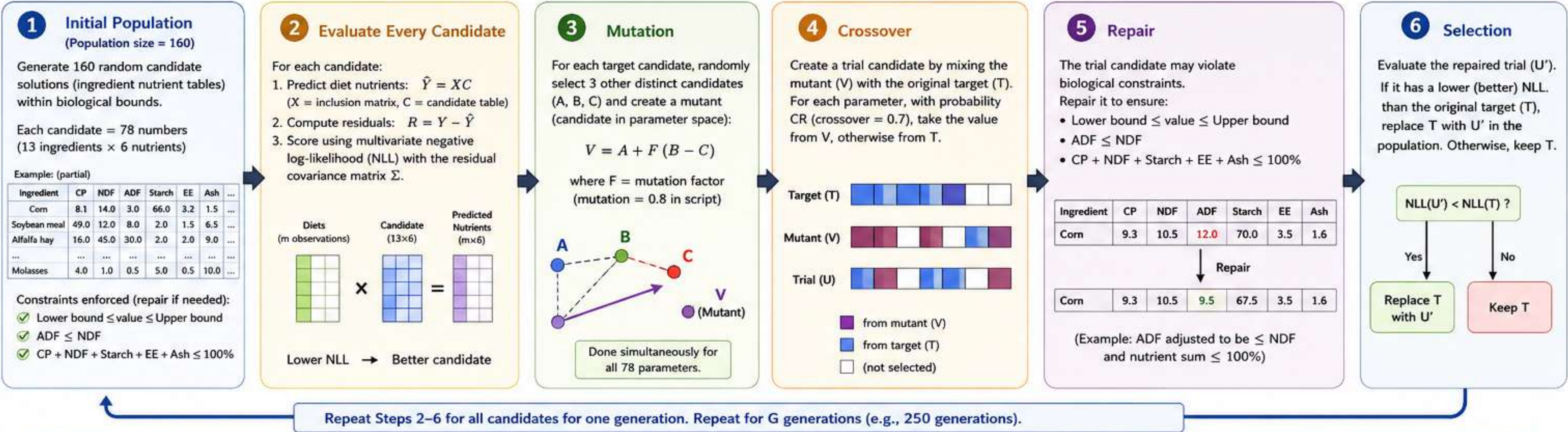
- Feasible composition C_k
- NLL_k (or other fit metric)
- Optional: RMSE by nutrient



Large set of feasible candidate solutions with their scores

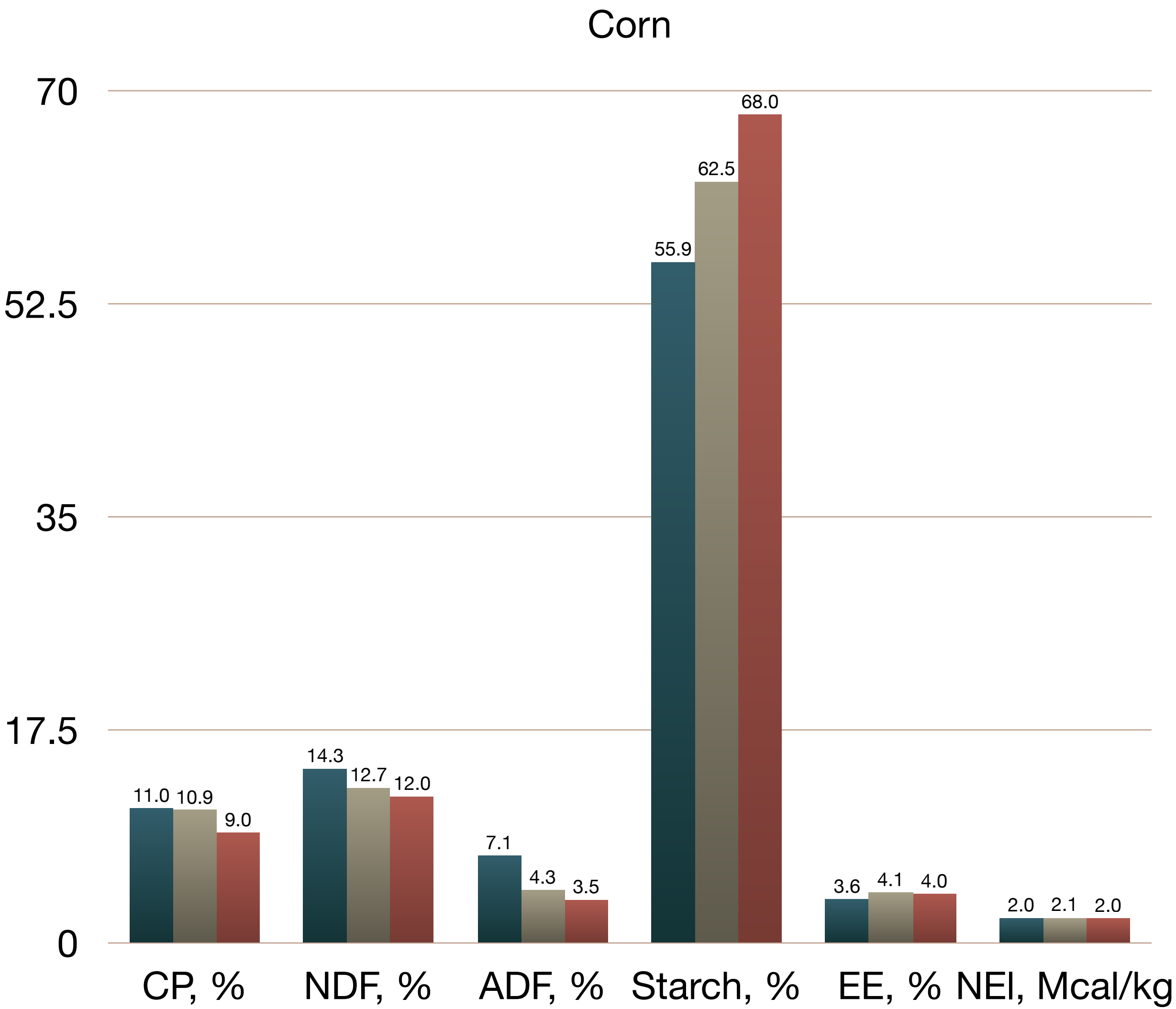
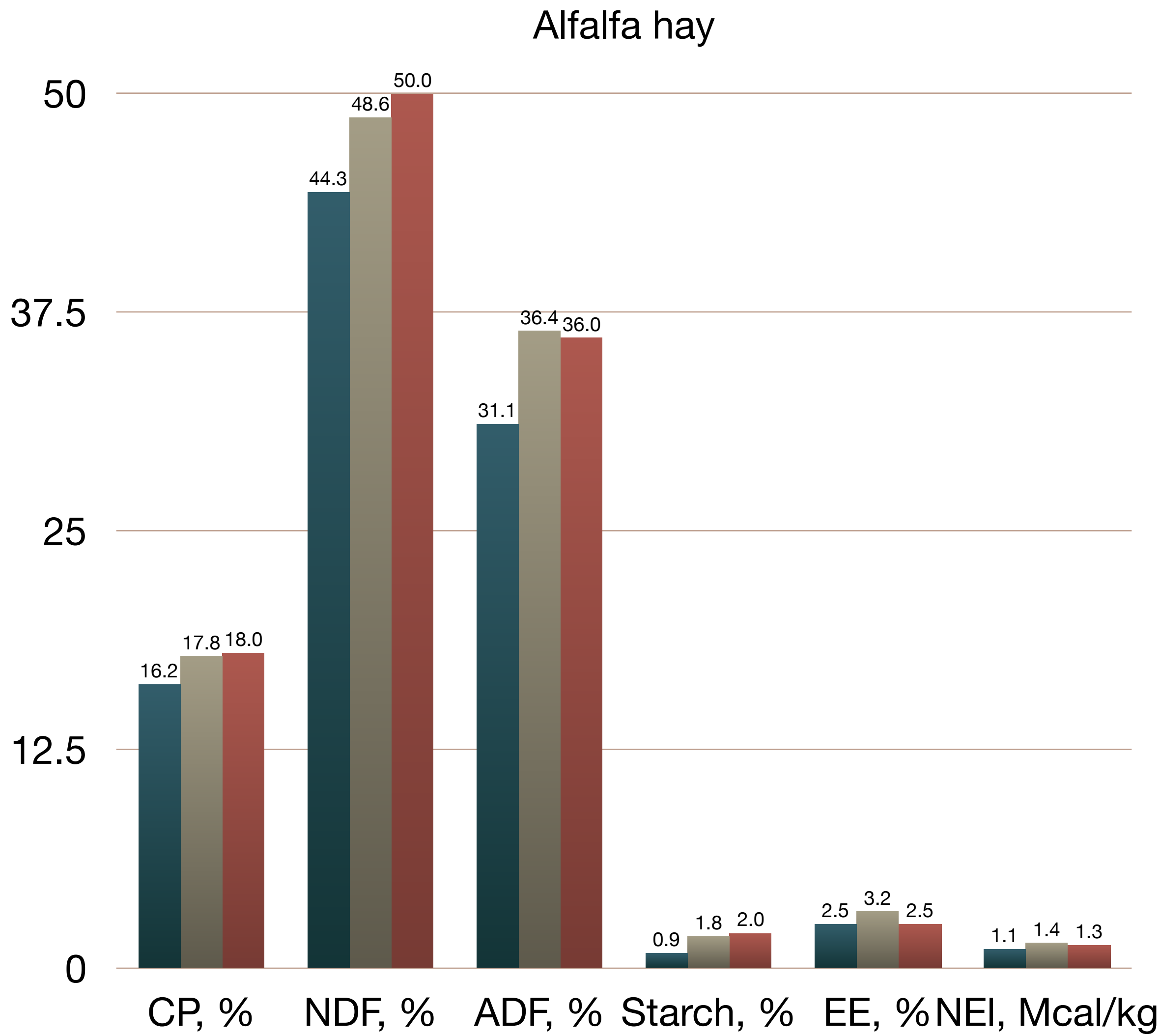
Artificial Intelligence

★ Constrained differential evolution



Artificial Intelligence

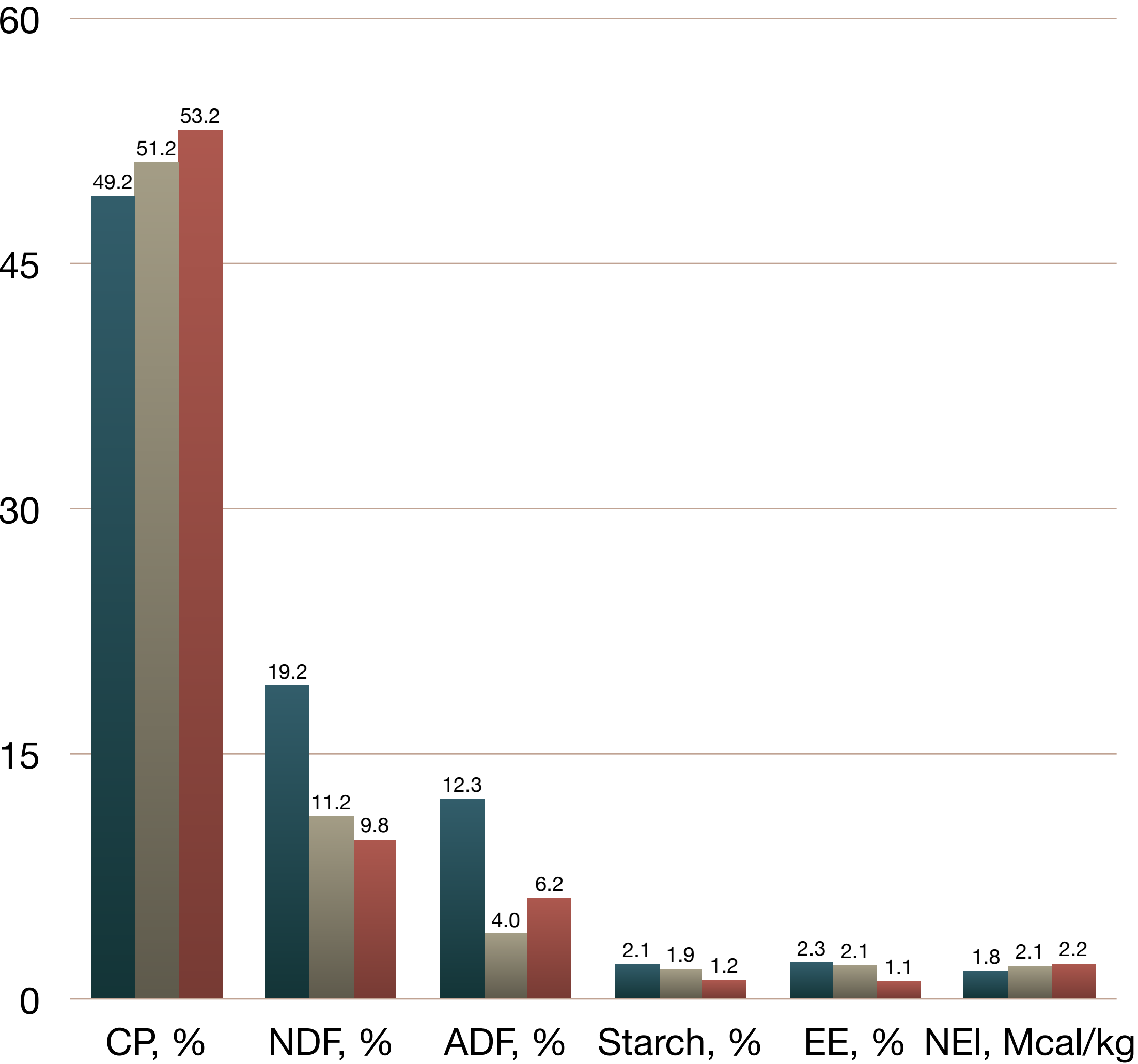
Random Search Differential Evolution NASEM (2021)



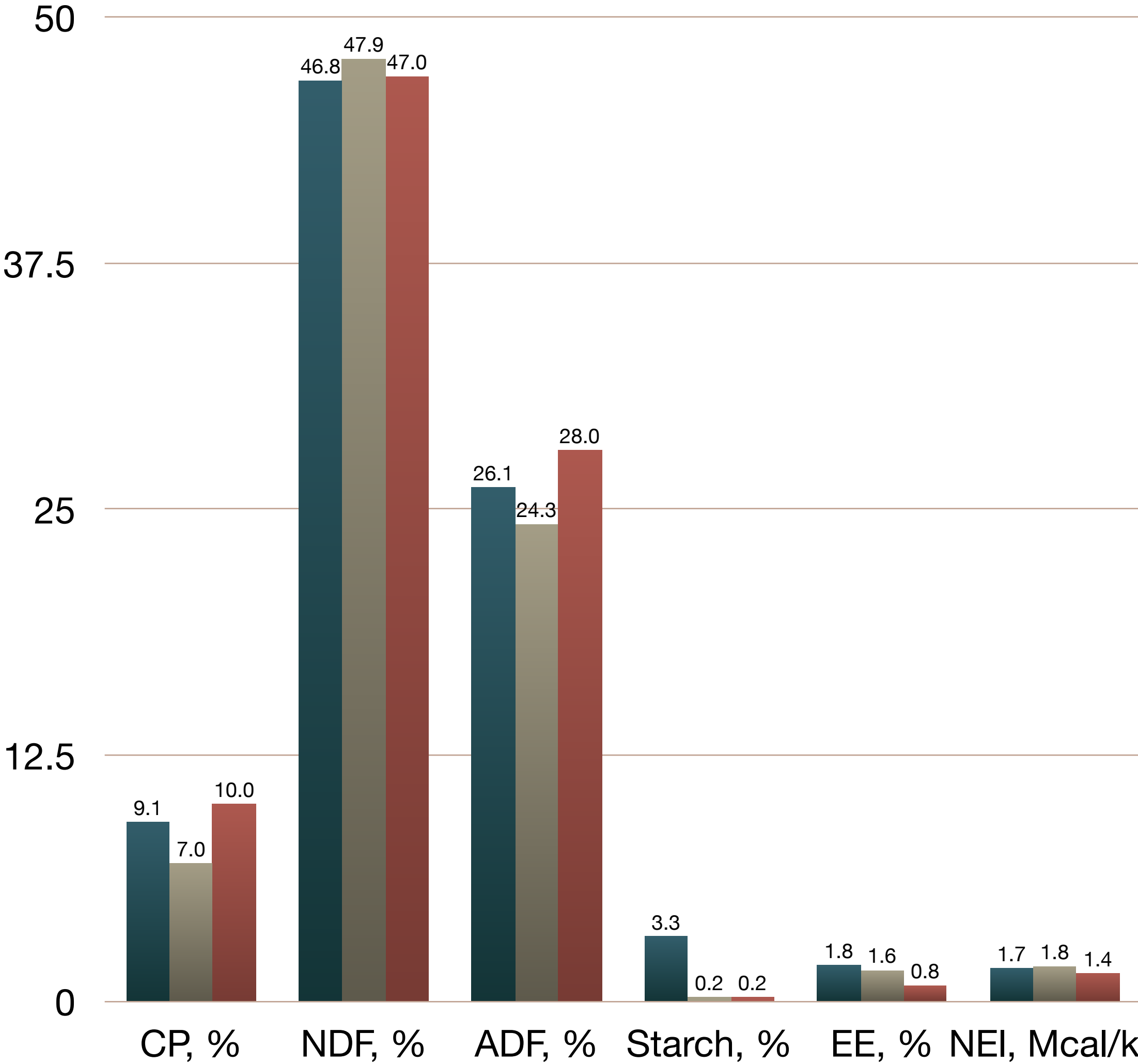
Artificial Intelligence

Random Search Differential Evolution NASEM (2021)

Soybean meal

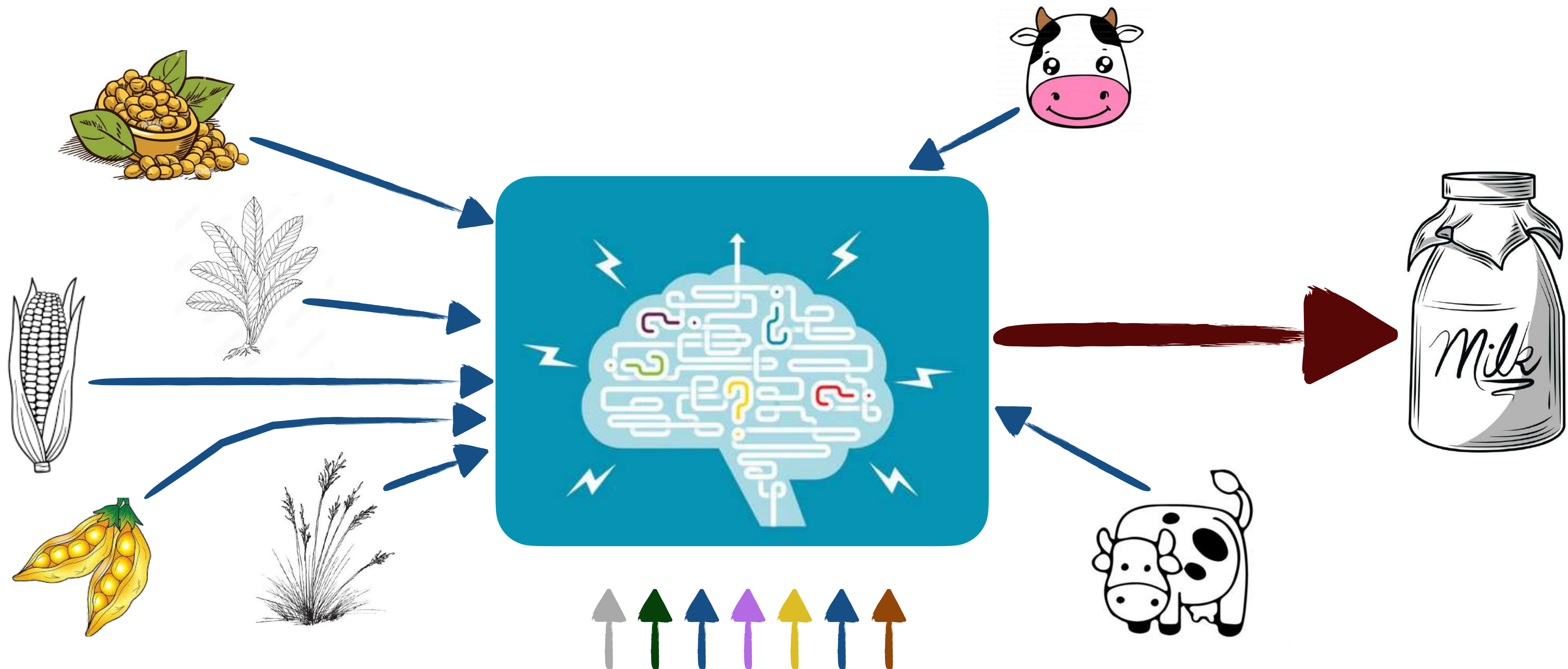


Beet pulp



Machine Learning

- ★ **New paradigm:** AI can predict the **nutritional value** of ingredients based on the **animal response**



Machine Learning

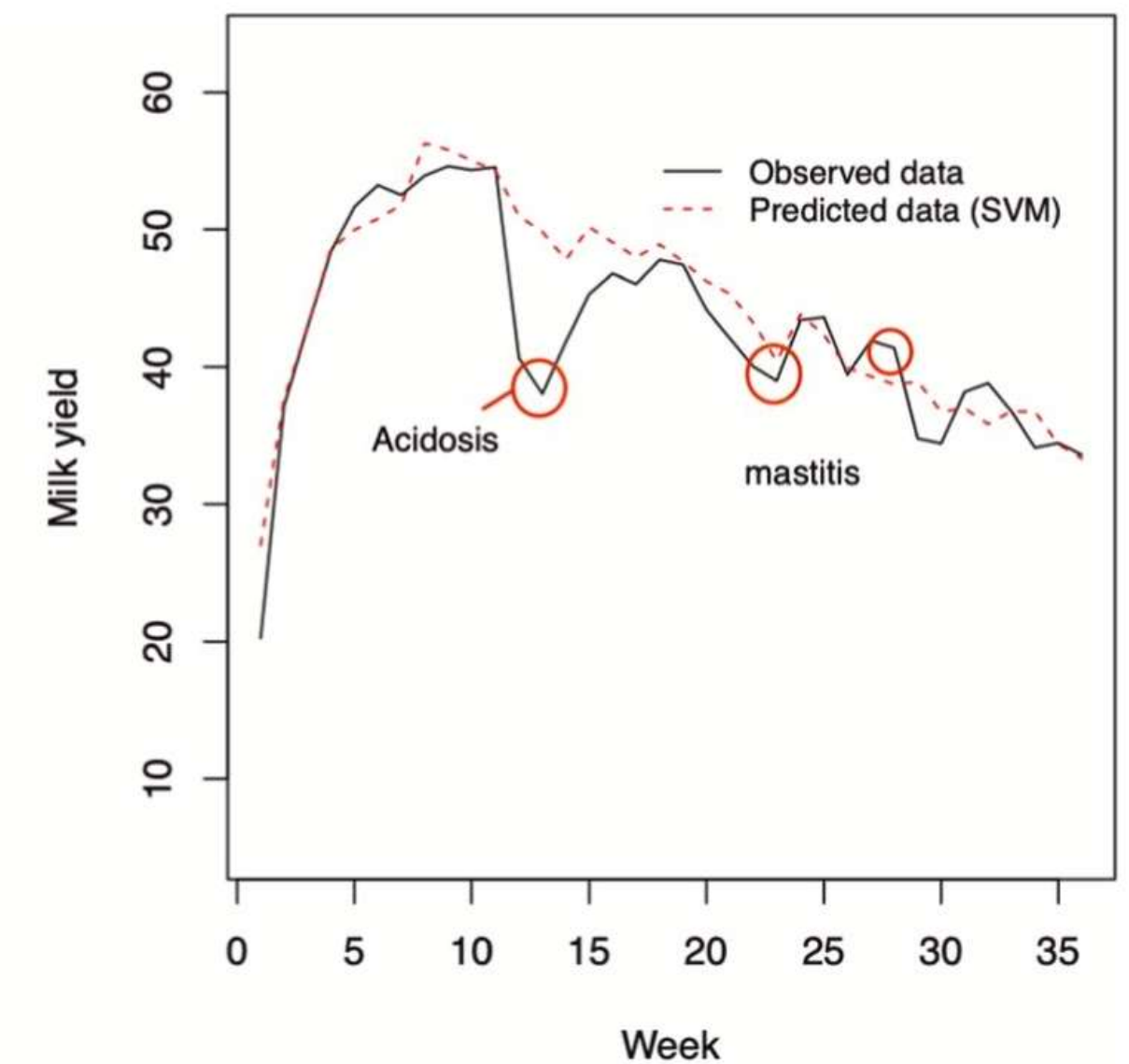
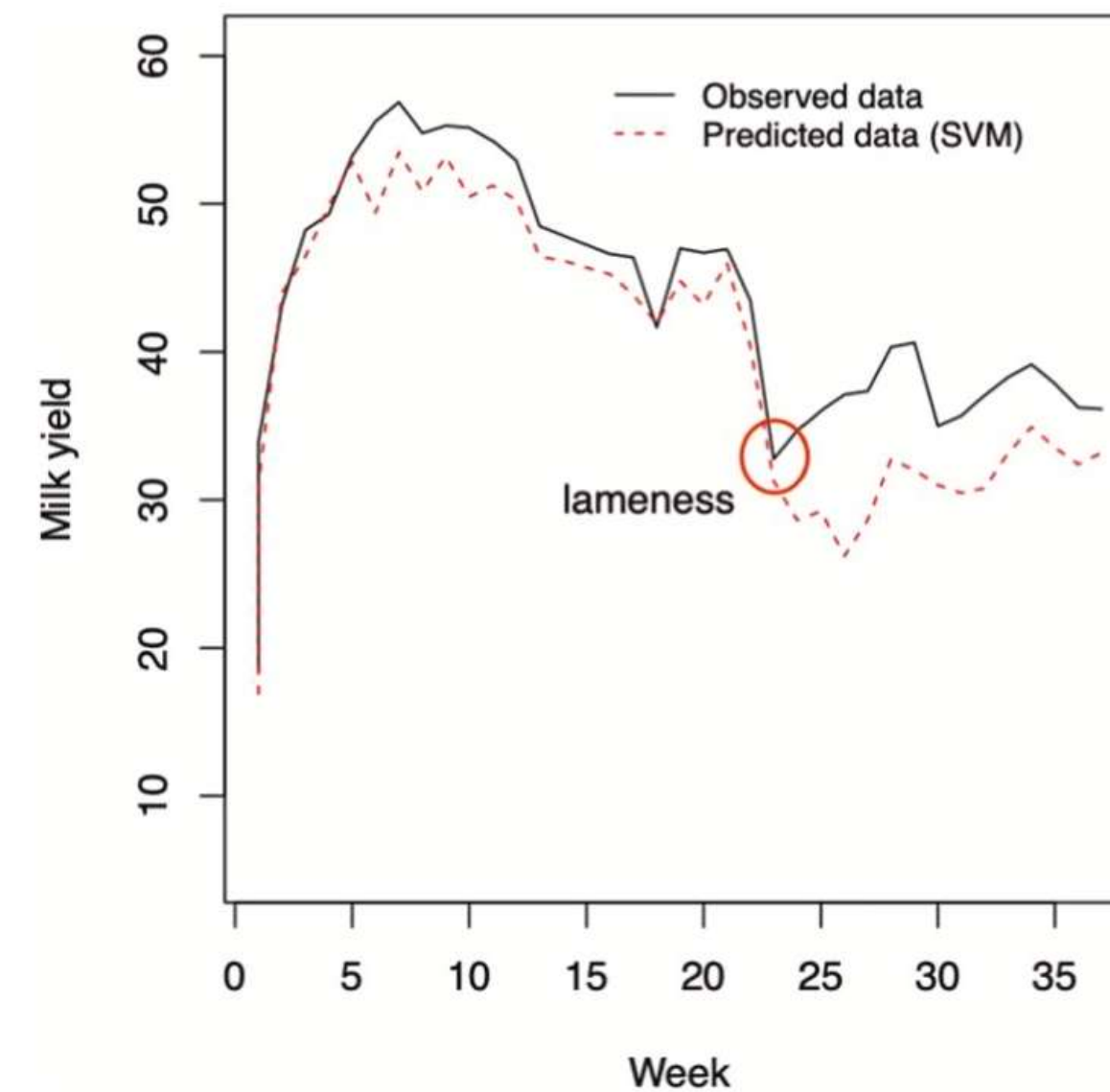
- 📌 With AI, and sufficient data, we can assess the nutritional needs of animals in a given pen and predict their response to a given combination of ingredients
- 📌 This approach should result in more precise estimates of nutritional values of ingredients (or rations) than chemical or NIR analyses (they lack the animal response)

Machine Learning

- Nguyen et al. (2020) showed the superiority of supervised ML models (support vector machine, random forest, and neural networks) in comparison with linear regression approaches to predict milk production based on **nutrients** consumed

Average error of each model for all 36 individual cows.

	Elastic regression	SVR	Random forest	Neural Network
RMSE	3.103	2.868	2.842	2.947
MAE	2.496	2.187	2.107	2.279
R^2	0.664	0.712	0.734	0.704



Machine Learning

- 📌 It can be taken further, skip the nutrients altogether
- 📌 Using daily cow-level or pen-level data:

$$\text{Milk yield}_{it} = f(\text{ingredients}_{it}, \text{DIM}_{it}, \text{parity}_i, \text{DMI}_{it}, \text{farm}, \text{season} \dots) + \text{error}$$

- 📌 The strategy is not to predict milk from nutrients, but to infer the minimum ingredient supply vector that can sustain a target production level under biological constraints
- 📌 This can be done by:
 - Generalized additive mixed models
 - Bayesian hierarchical models
 - Gradient boosting with cow/farm random effects
 - Gaussian process additive models

Machine Learning

Example rations from DE

30 kg of milk

Ingredient	kg of DM/d
Alfalfa hay	1.86
Alfalfa silage	5.76
Corn	5.12
Corn silage	4.07
Barley grain	0.41
Soybean meal	2.22
Canola meal	0.84
Soybean hulls	0.78
Corn ddgs	0.10
Cottonseed whole	0.34
Beet pulp	0.78
Straw	0.20

Predicted DMI: 22.5 kg/d

35 kg of milk

Ingredient	kg of DM/d
Alfalfa hay	2.09
Alfalfa silage	5.74
Corn	5.34
Corn silage	4.31
Barley grain	0.70
Soybean meal	2.09
Canola meal	0.83
Soybean hulls	0.93
Corn ddgs	0.26
Cottonseed whole	0.42
Beet pulp	0.77
Straw	0.24

Predicted DMI: 23.8 kg/d

40 kg of milk

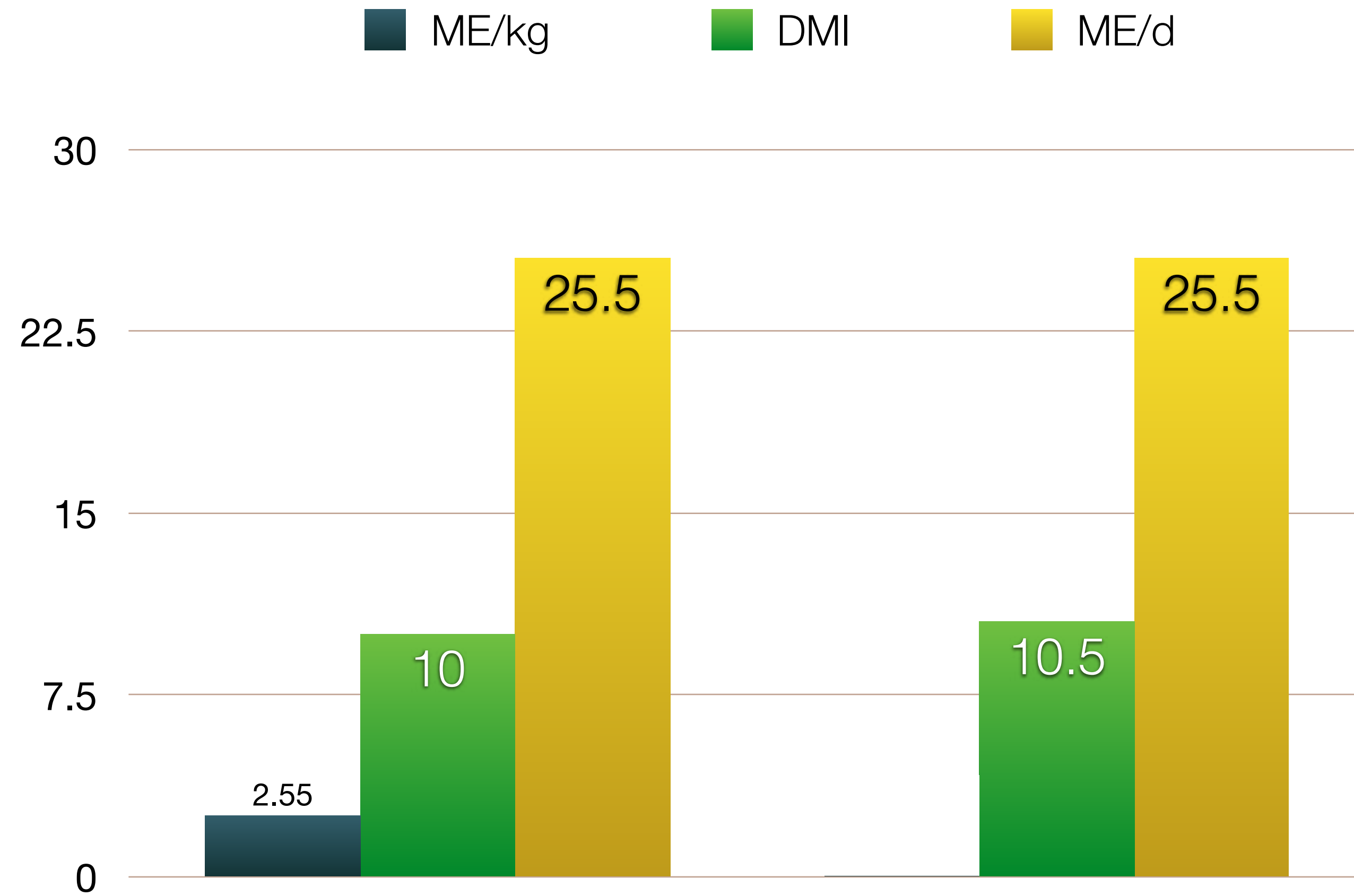
Ingredient	kg of DM/d
Alfalfa hay	2.51
Alfalfa silage	5.88
Corn	5.80
Corn silage	4.62
Barley grain	0.90
Soybean meal	2.19
Canola meal	0.97
Soybean hulls	0.96
Corn ddgs	0.22
Cottonseed whole	0.43
Beet pulp	0.85
Straw	0.30

Predicted DMI: 26.3 kg/d

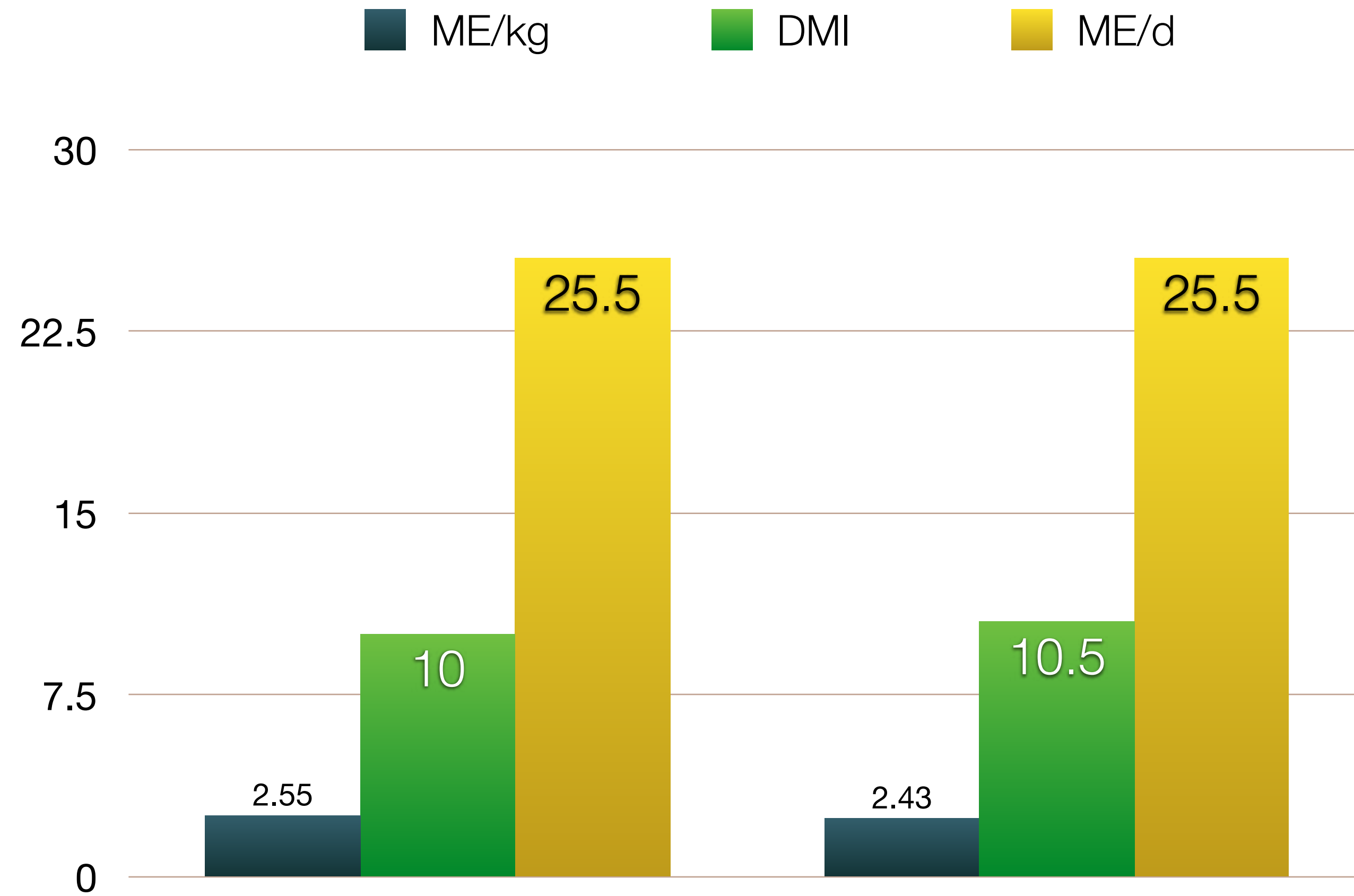
Machine Learning

- 📌 A key advantage of these new approaches is that:
 - Nutrient/ingredient needs and most important: interactions
 - Physiological status of the animals
 - Environmental conditions
 - Production/performance
 - Feed and milk prices
- 📌 Can be considered simultaneously to maximize profits, animal health...

Machine Learning

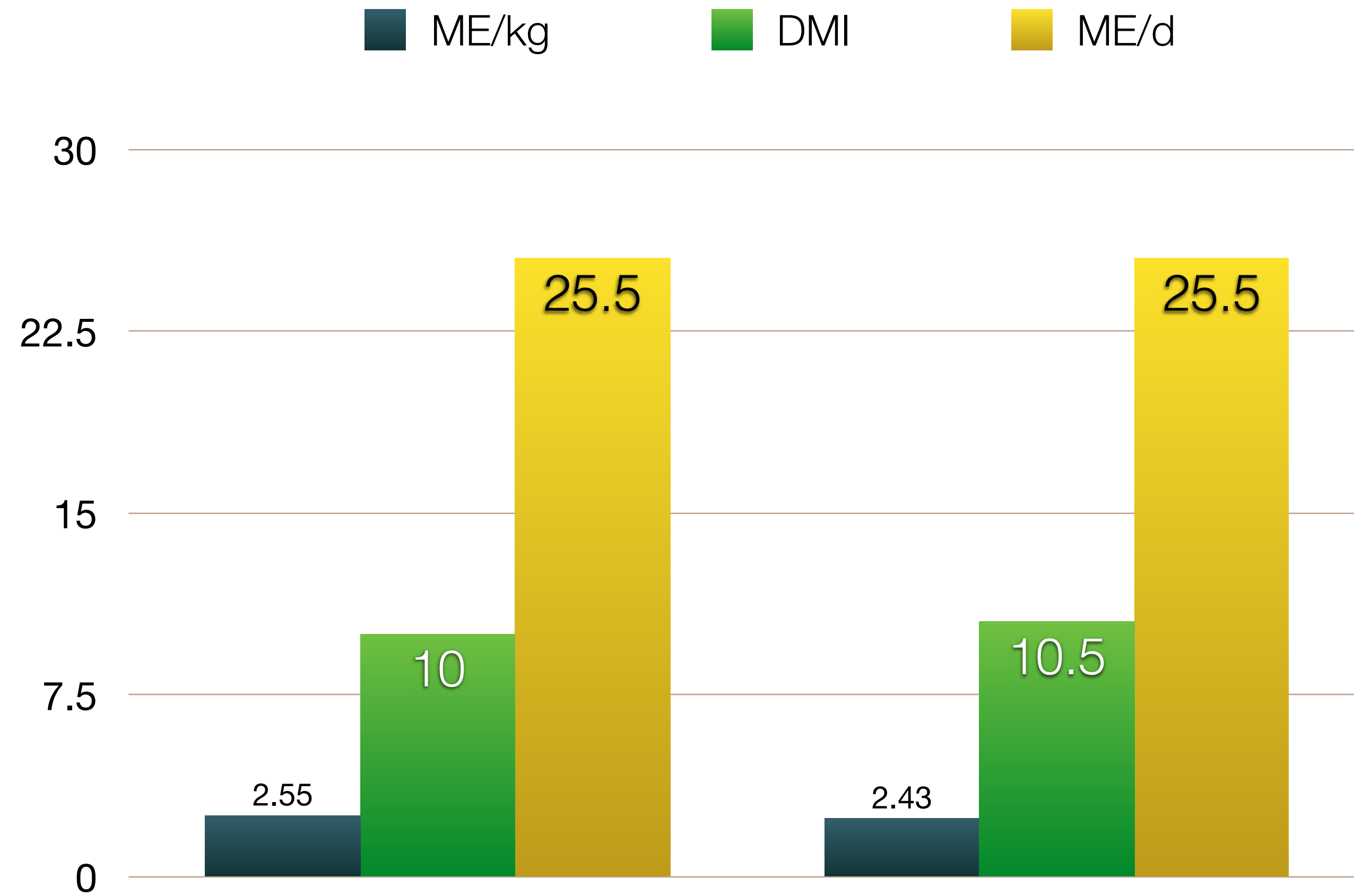


Machine Learning



Machine Learning

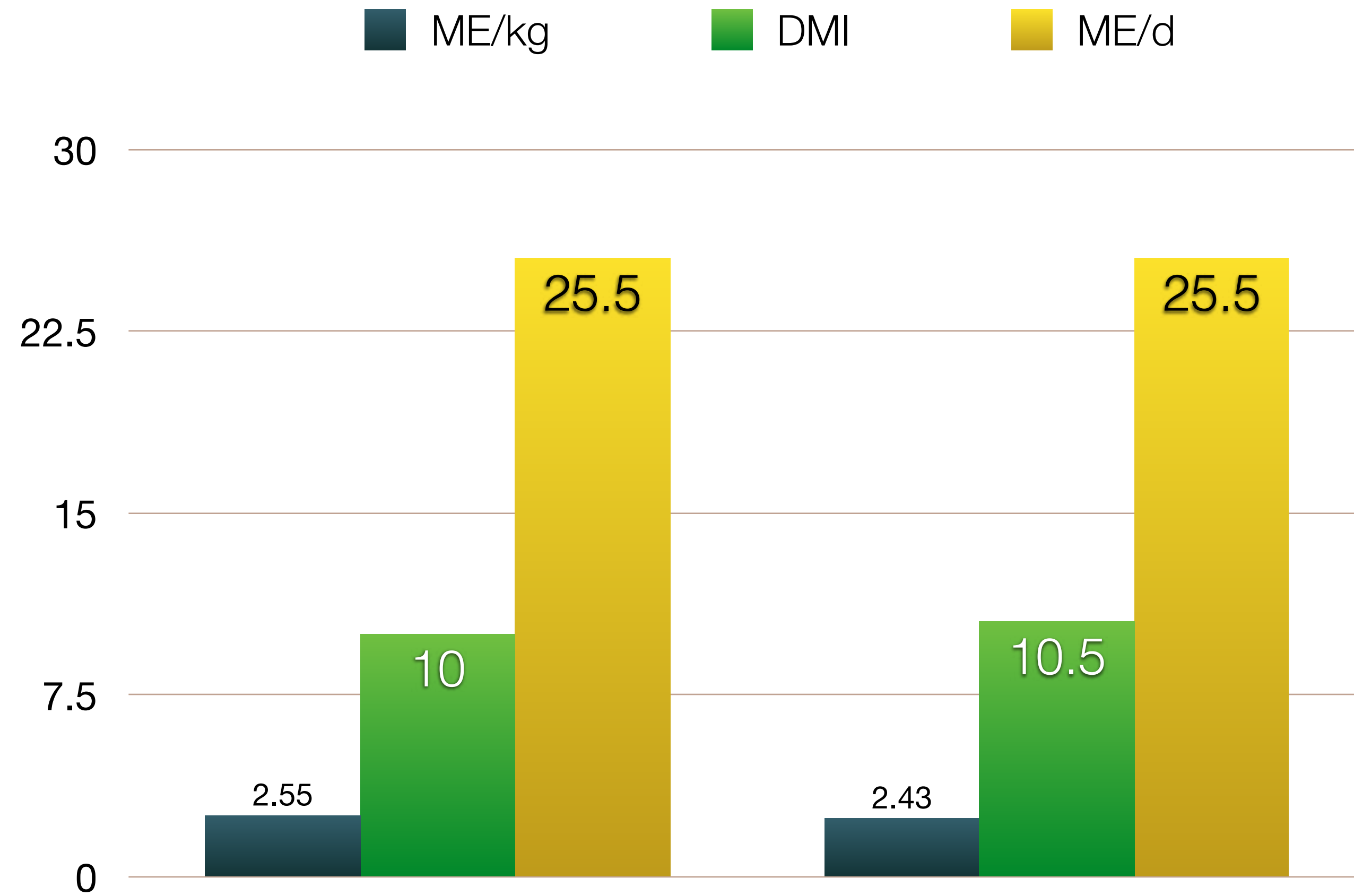
203 €/TM ~ 2.03 €/d



Machine Learning

203 €/TM ~ 2.03 €/d

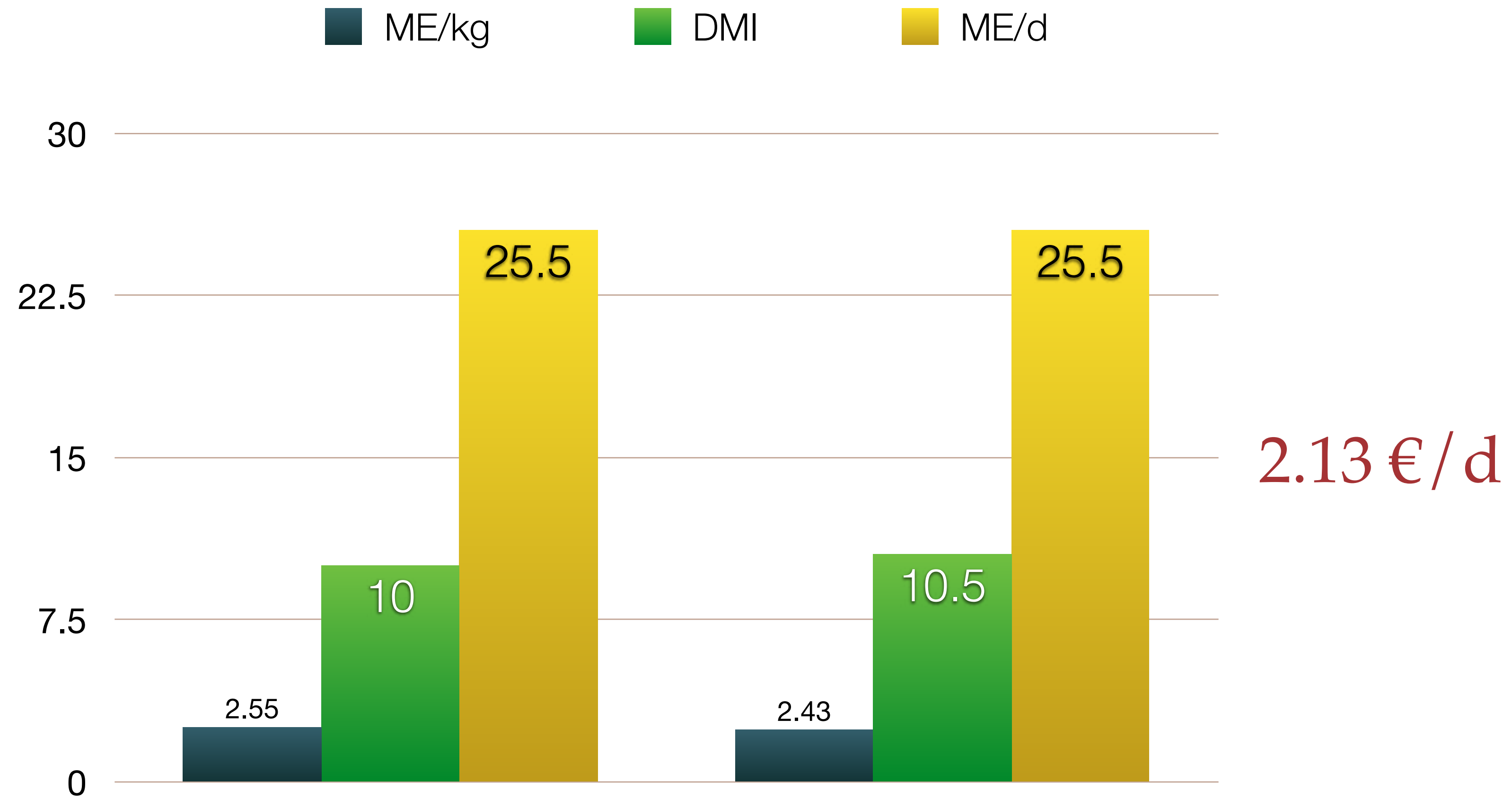
190 €/TM ~ 2.0 €/d



Machine Learning

203 €/TM ~ 2.03 €/d

190 €/TM ~ 2.0 €/d



algoMilk

ALGORITHMIC DAIRYING

DAIRY

Dashboard

Pens

Premixes

Concentrates

Rations

Loads

Stock

Milk

Environment

Optimization

Grouping

Ration optimizer

Comparator

Animal value

Dry-off

Nutritionist

COMPARATOR

Add ration

AS FED (KG)

59.32

DRY MATTER (KG)

27.85 (27.49)

COST DRY MATTER (TON)

314.32

COST FORMULA (€/ DAY)

8.76 (8.64)

NUMBER OF COWS

151

TOTAL COST (€/ DAY)

1,322 (1,305)

IOFC (€/ DAY)

1,387 (1,341)

IOFC (€/ COW)

9.19 (8.88)

INTERMEDIATE

58.43

27.62

304.84

8.42

151

1,271

1,417

9.38

*INTERMEDIATE (SUGGESTED)

58.43

27.62

304.84

8.42

151

1,271

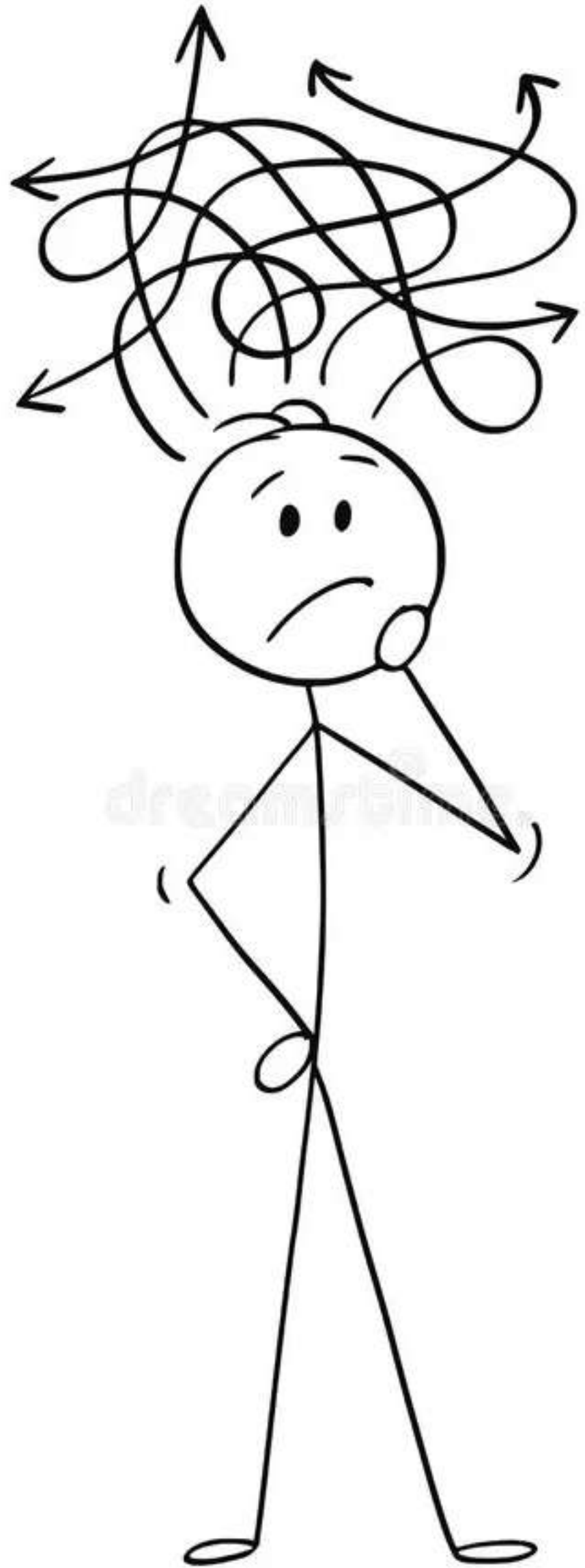
1,417

9.38

Ingredient	Intermedia	* Intermedia (Suggested)	
Medica secca	3.40	5.56	
Farina di Grain	8.20	8.01	
Mel. 34	2.10	1.89	
Mix Bal.	2.90	2.96	
Sali	0.47	0.42	
H2O	1.95	2.01	
Trinciato mais	24.70	24.18	
Insilato Orzo	13.00	13.39	
Medica ensilata	2.60	0	

Nutrient	Intermedia	* Intermedia (Suggested)
DM, kg/d	27.85 (46.96)	27.62 (47.27)
CP, kg/d	4.44 (15.92)	4.41 (15.97)
NEI, Mcal/d	45.83 (1.65)	45.20 (1.64)
NFC, kg/d	11.93 (42.84)	11.80 (42.71)
NDF, kg/d	8.80 (31.58)	8.77 (31.74)
ADF, kg/d	5.07 (18.20)	5.22 (18.91)
EE, kg/d	0.89 (3.18)	0.83 (3.01)
Ash, kg/d	1.87 (6.73)	1.87 (6.79)
Ca, kg/d	0.16 (0.59)	0.16 (0.58)
Mg, kg/d	0.06 (0.21)	0.06 (0.21)
CA Balance	11.28 (0.40)	10.72 (0.39)
Starch, %	7.68 (27.59)	7.53 (27.27)
Forage, kg/d	13.71 (49.22)	13.86 (50.18)
ME, Mcal/d	73.50 (2.64)	73.00 (2.64)

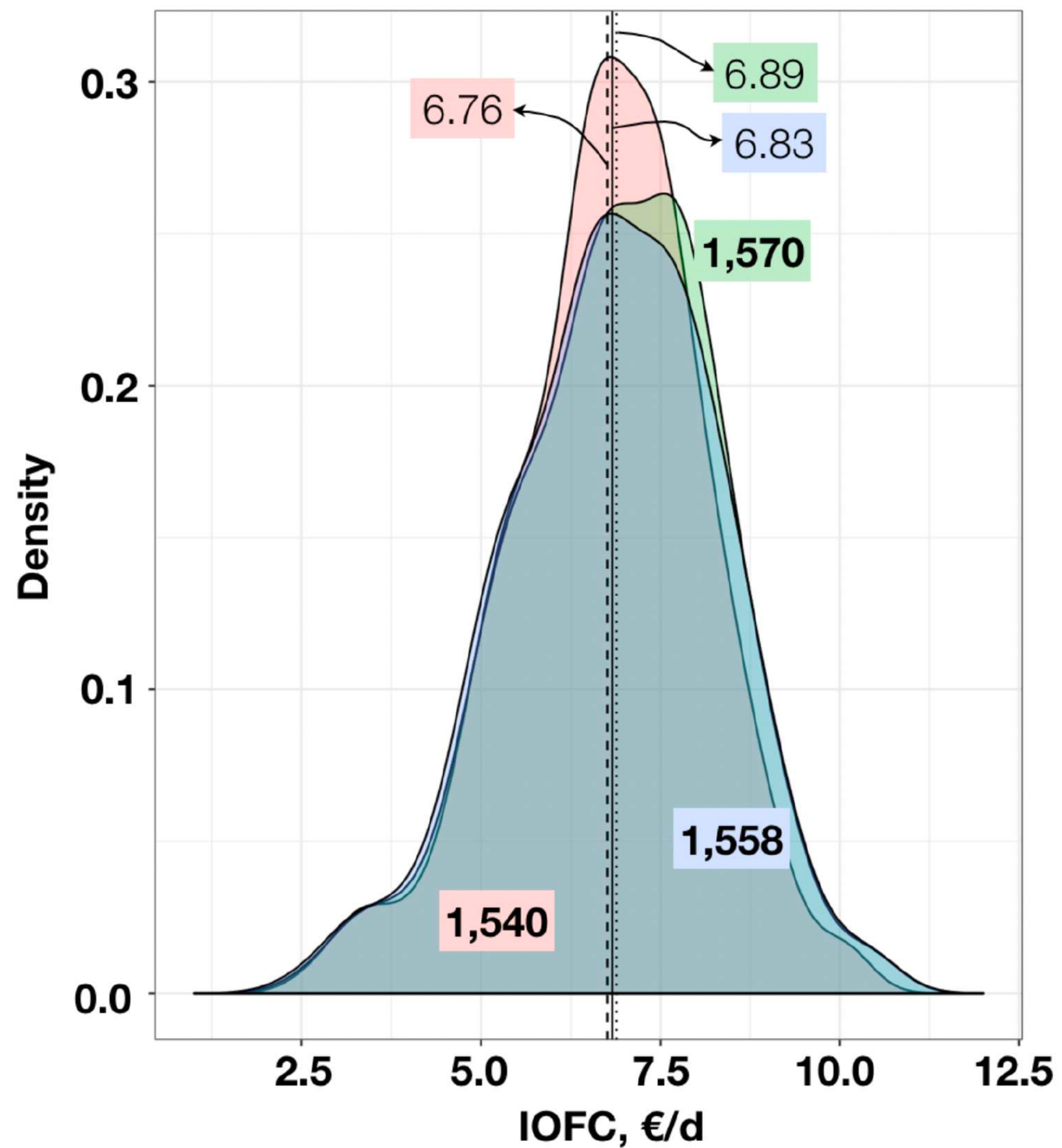
Machine Learning



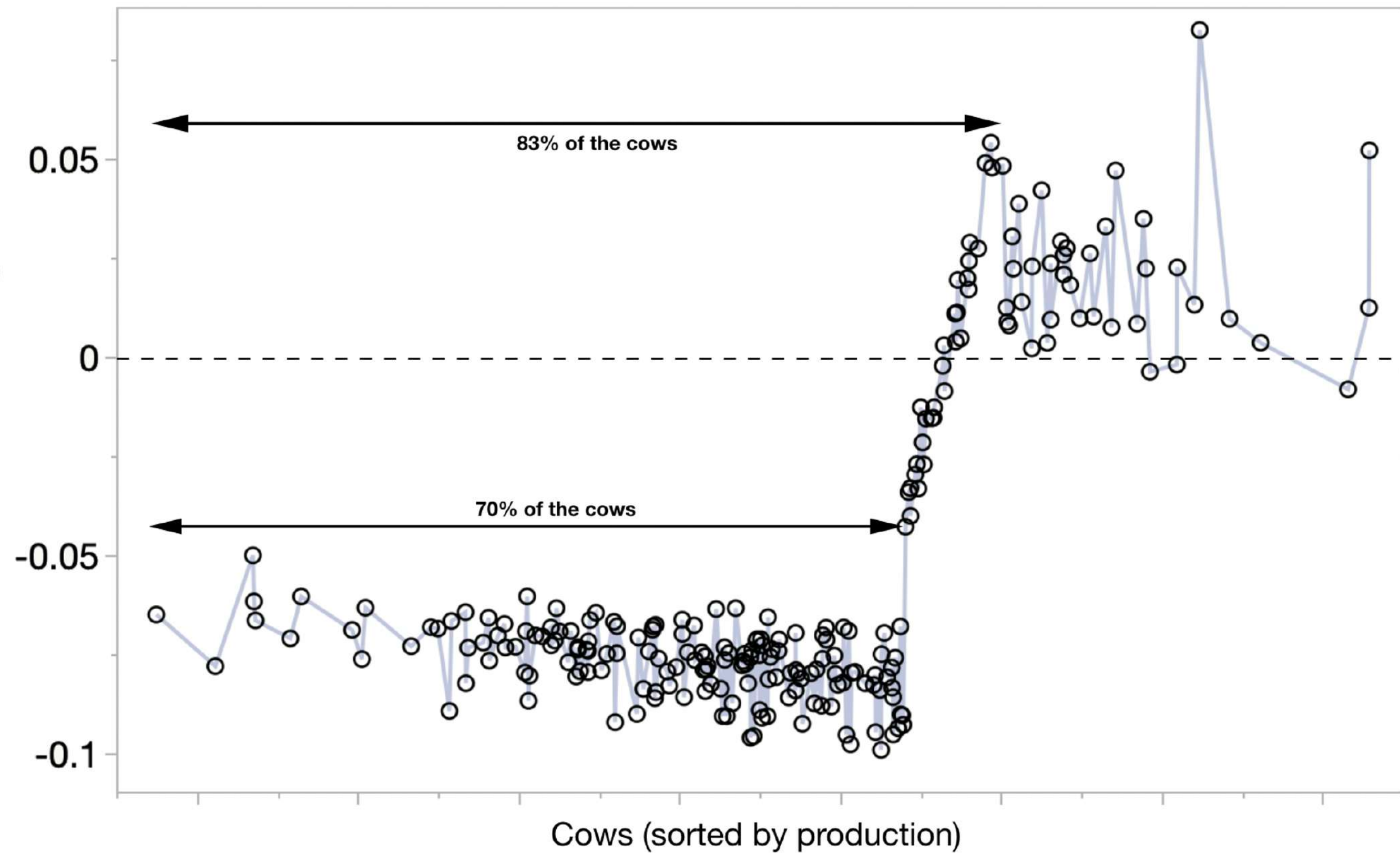
- ★ Quite commonly, dry cows are split in two groups and fed 2 different rations
- ★ But, lactating cows, are often fed a single ration (despite feeding animals that produce 15 or 70 liters)

Machine Learning

■ Ration for 35 kg ■ Ration for 42 kg ■ Ration for 45 kg



Difference between IOFC obtained with a ration
for 45 or ration for 42 kg of milk

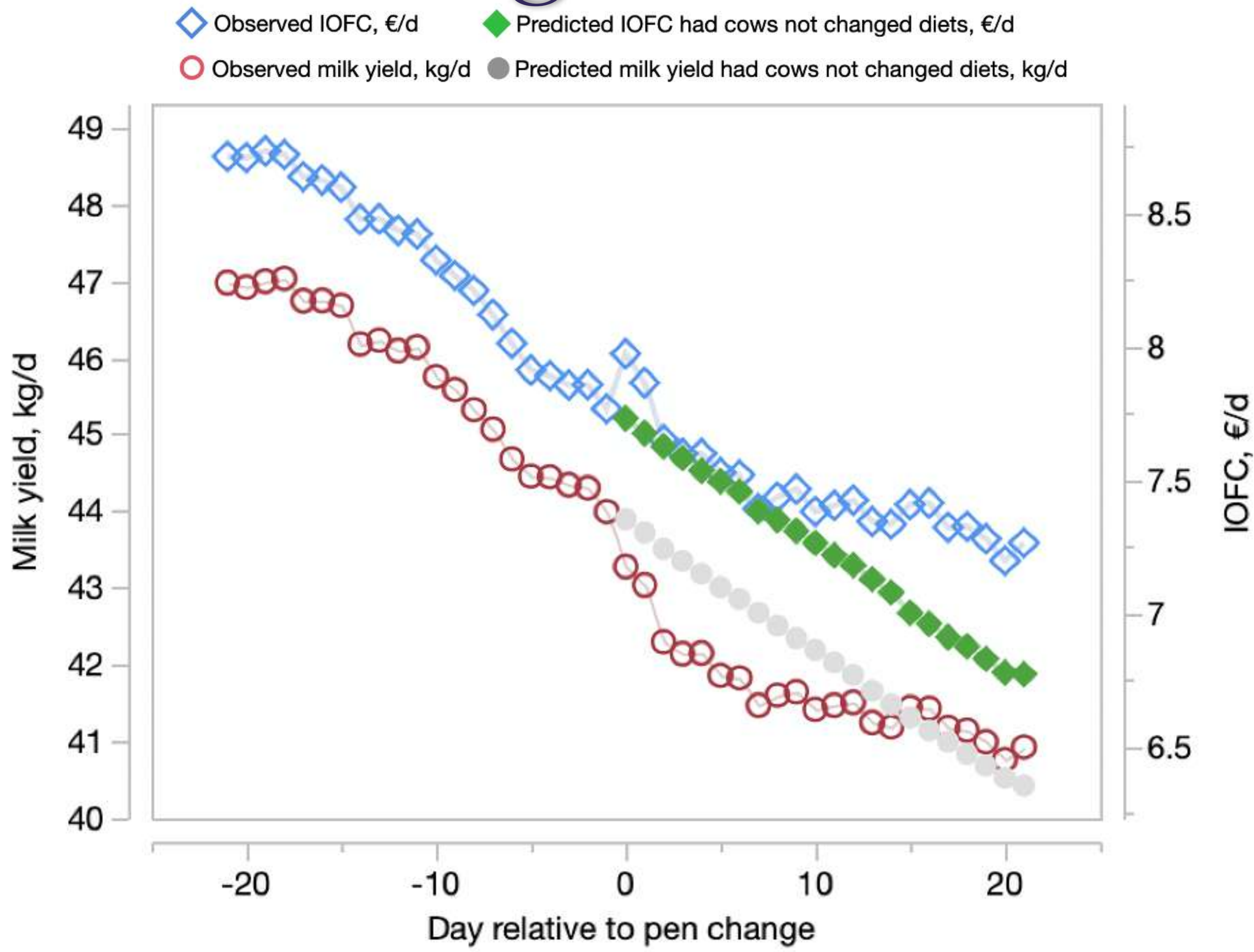


Machine Learning

Cow	Ration		Ration		Ration		Ration	
	Initial	High	Initial	High	Initial	High	Initial	High
	Milk, kg/d		Ration cost, €/T		Intake, kg/d		IOFC, €/d	
A	40	42	247	262	25.0	25.7	13.83	14.27
B	40	41.5	247	262	25.0	25.5	13.83	14.07
C	37	37.5	247	262	23.2	23.2	12.77	12.67
D	26	26	247	262	21.0	21.2	7.81	7.45
E	38	39.5	247	262	25.0	25.9	12.83	12.96
F	28	28	247	262	25.0	25.2	7.83	7.40
G	25	25	247	262	25.0	24.7	6.33	6.03
Mean	33.4	34.2	-	-	24.2	24.5	10.74	10.69

Machine Learning

High->Medium



Machine Learning

algoMilk

ALGORITHMIC DAIRYING

DAIRY

Dashboard

Animals & Pens

Feeding

Loads

Stock

Milk

Environment

Optimization

Nutritionist

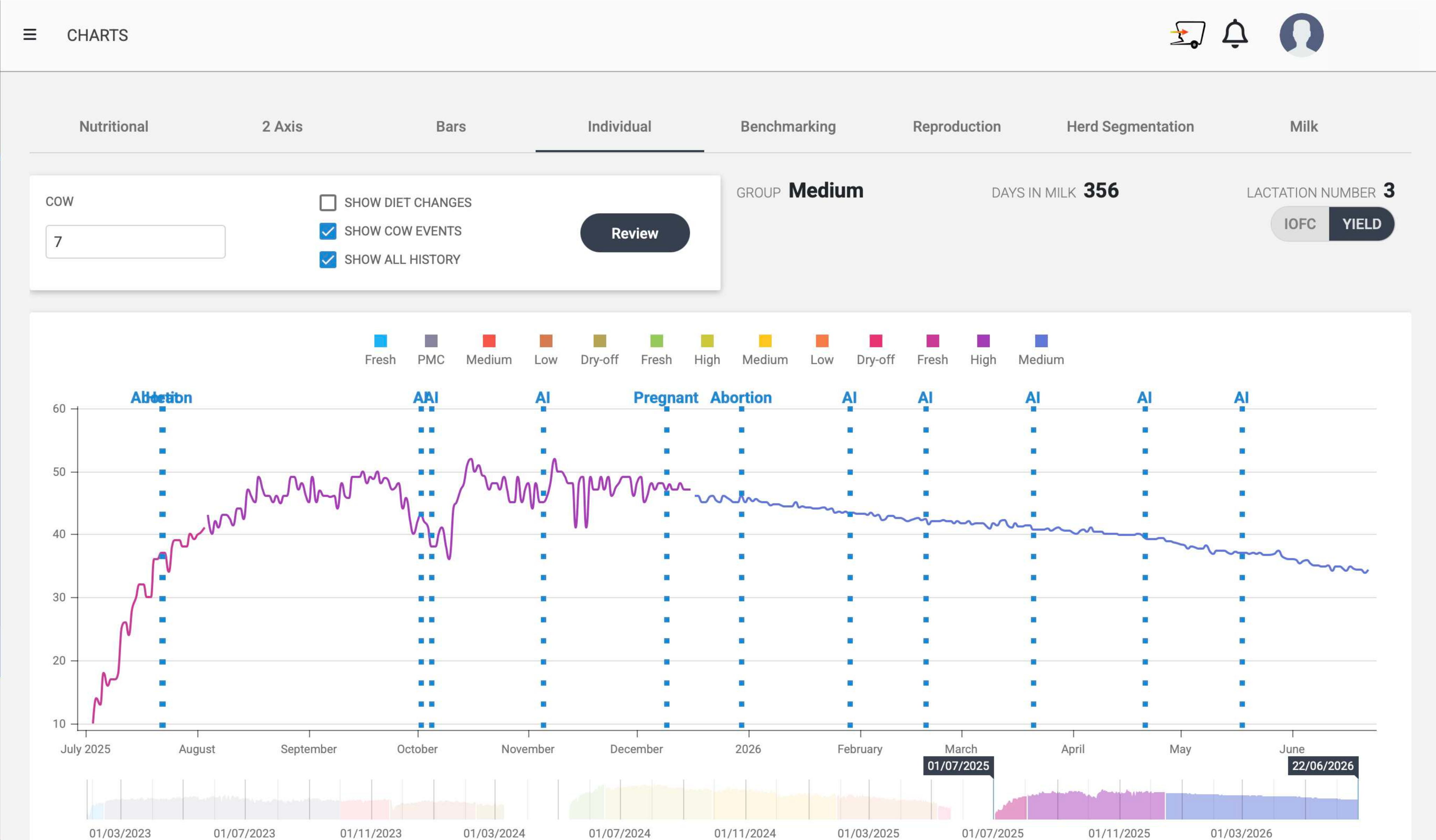
Analytics

Pen summary

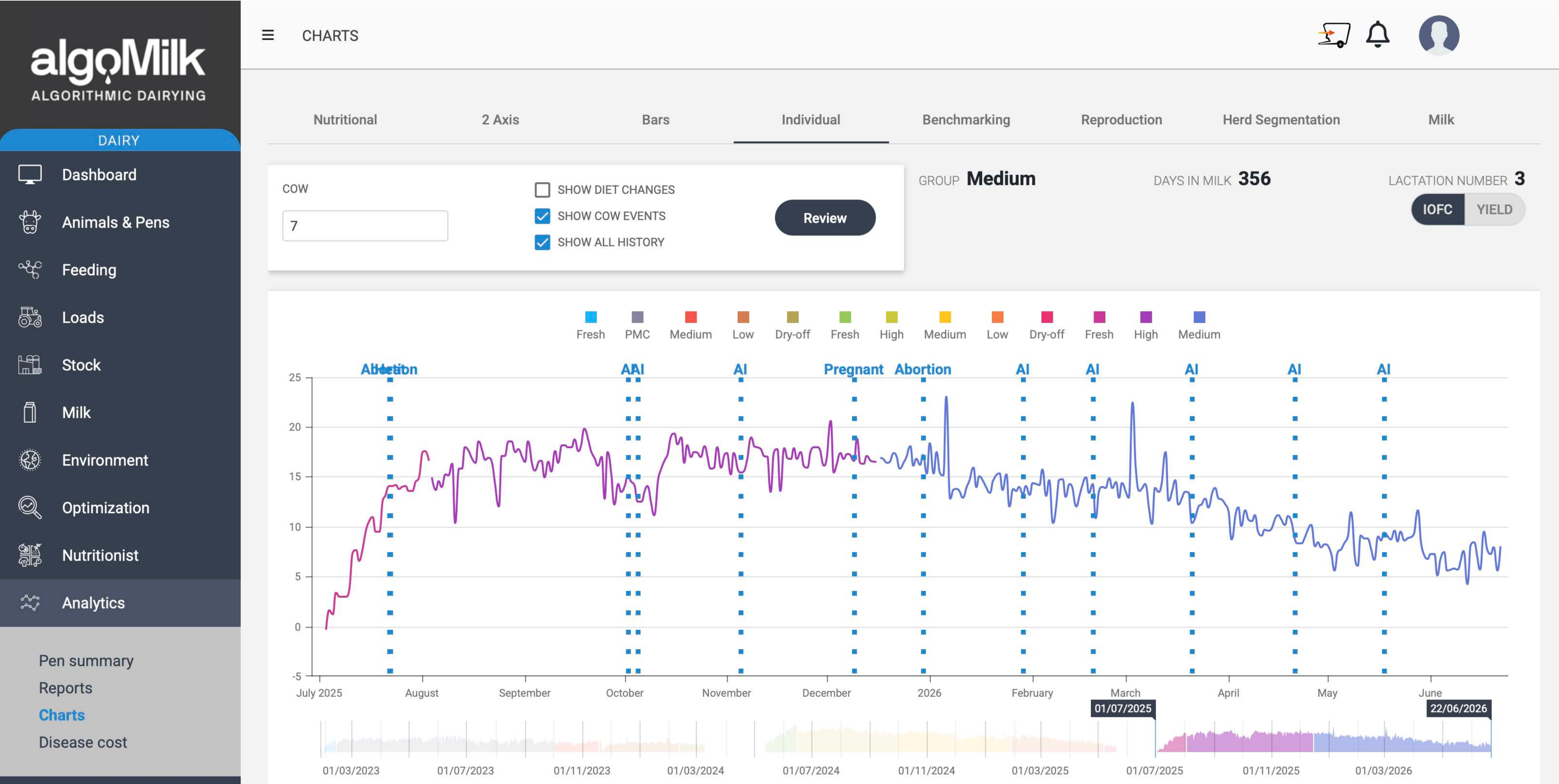
Reports

Charts

Disease cost



Machine Learning



Machine Learning



ALGORITHMIC DAIRYING

DAIRY

 Dashboard

 Animals & Pens

 Feeding

 Loads

 Stock

 Milk

 Environment

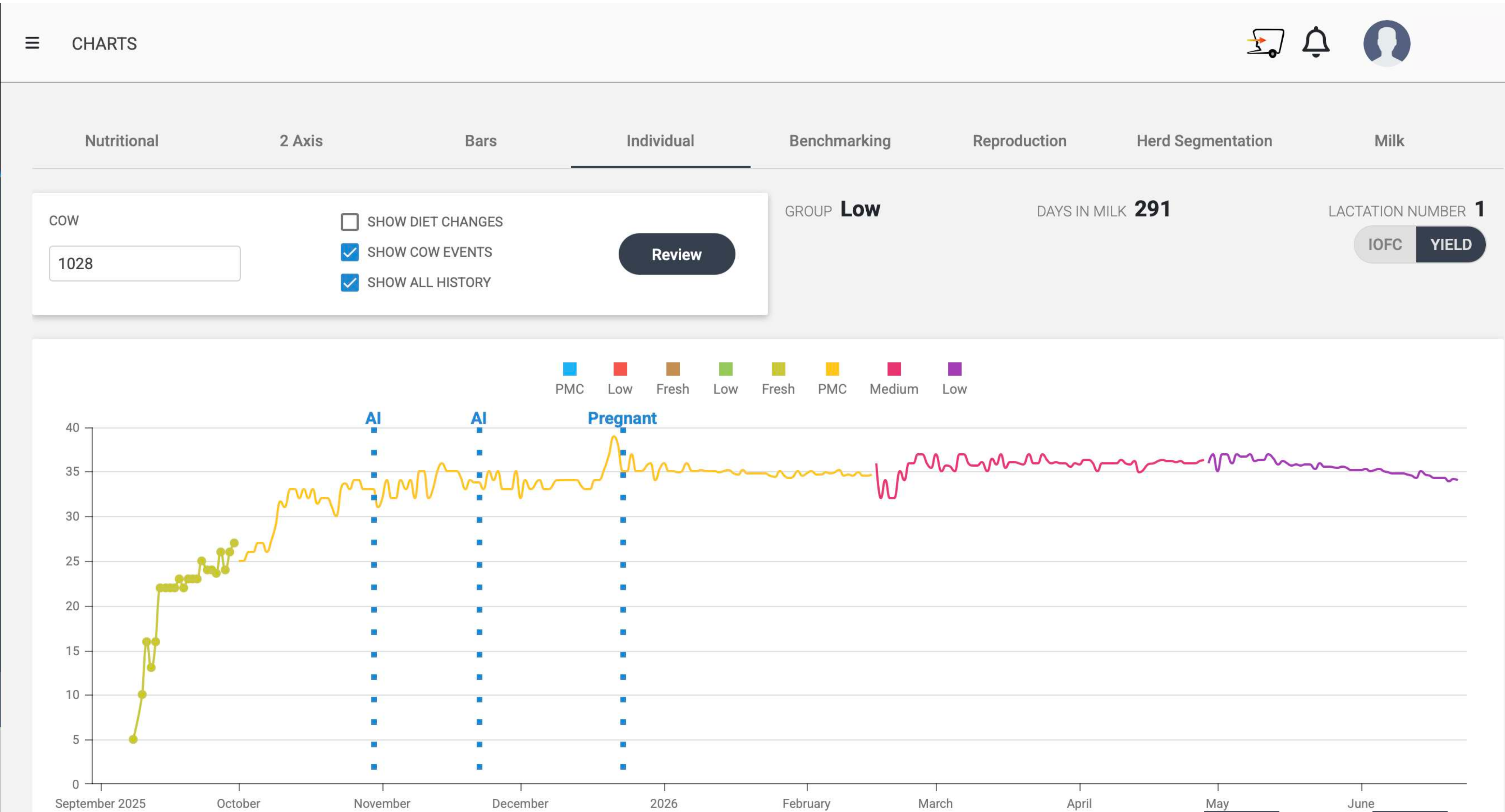
 Optimization

 Nutritionist

 Analytics

Pen summary

Reports



Machine Learning

algoMilk

ALGORITHMIC DAIRYING

DAIRY

Dashboard

Animals & Pens

Feeding

Loads

Stock

Milk

Environment

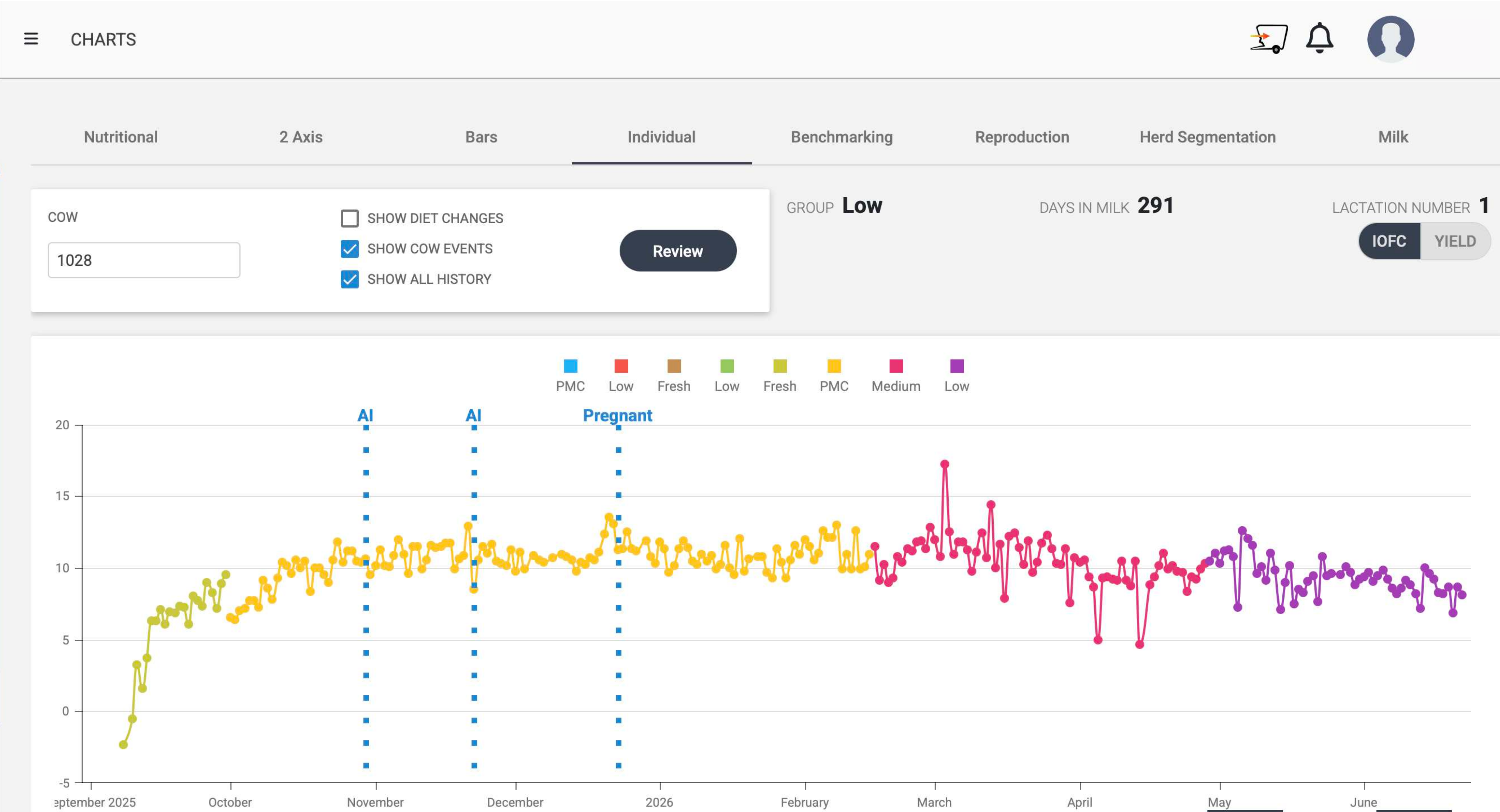
Optimization

Nutritionist

Analytics

Pen summary

Reports



PMC

Low

Fresh

Low

Fresh

PMC

Medium

Low

AI

AI

Pregnant

20

15

10

5

0

-5

september 2025

October

November

December

2026

February

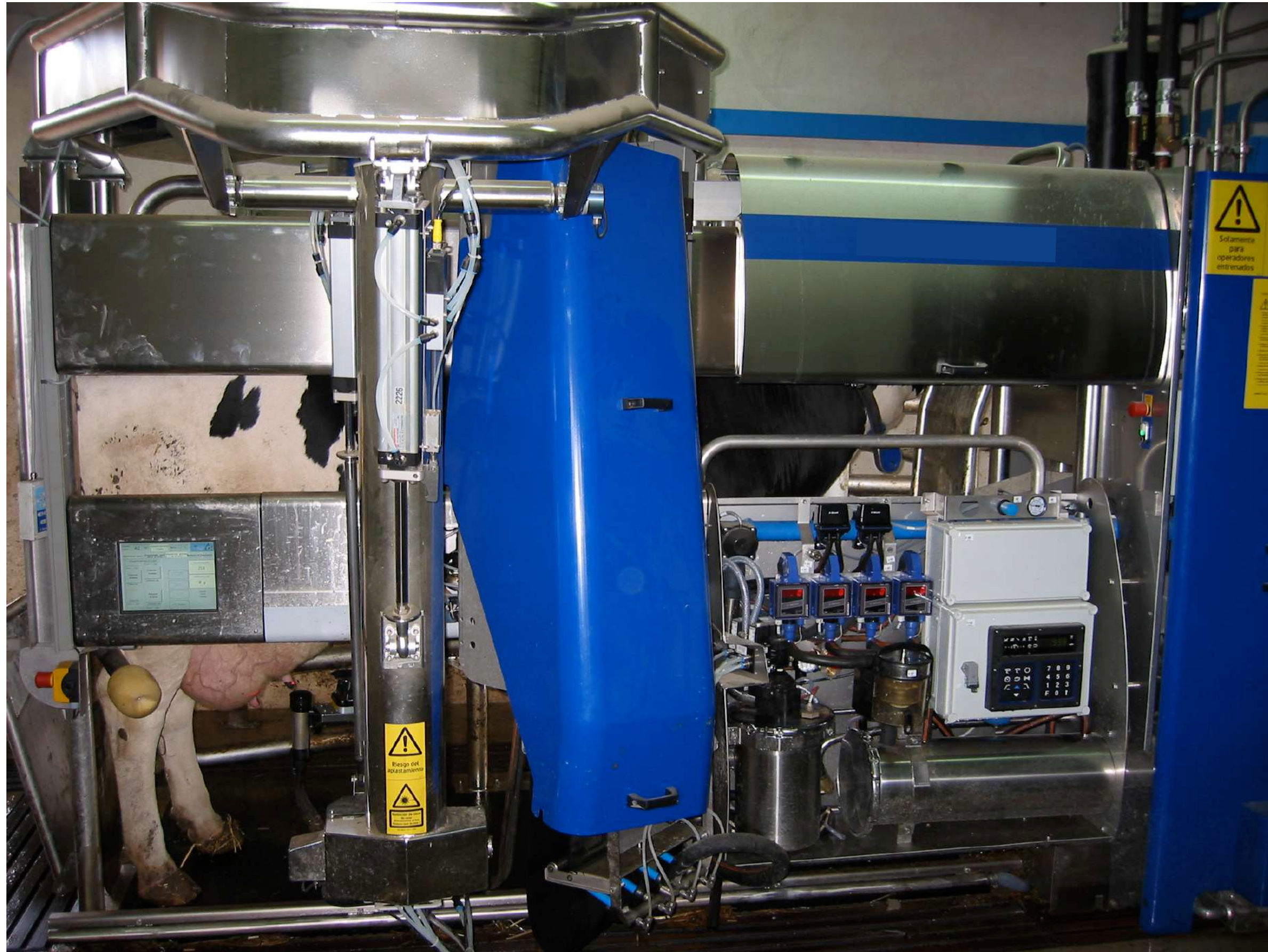
March

April

May

June

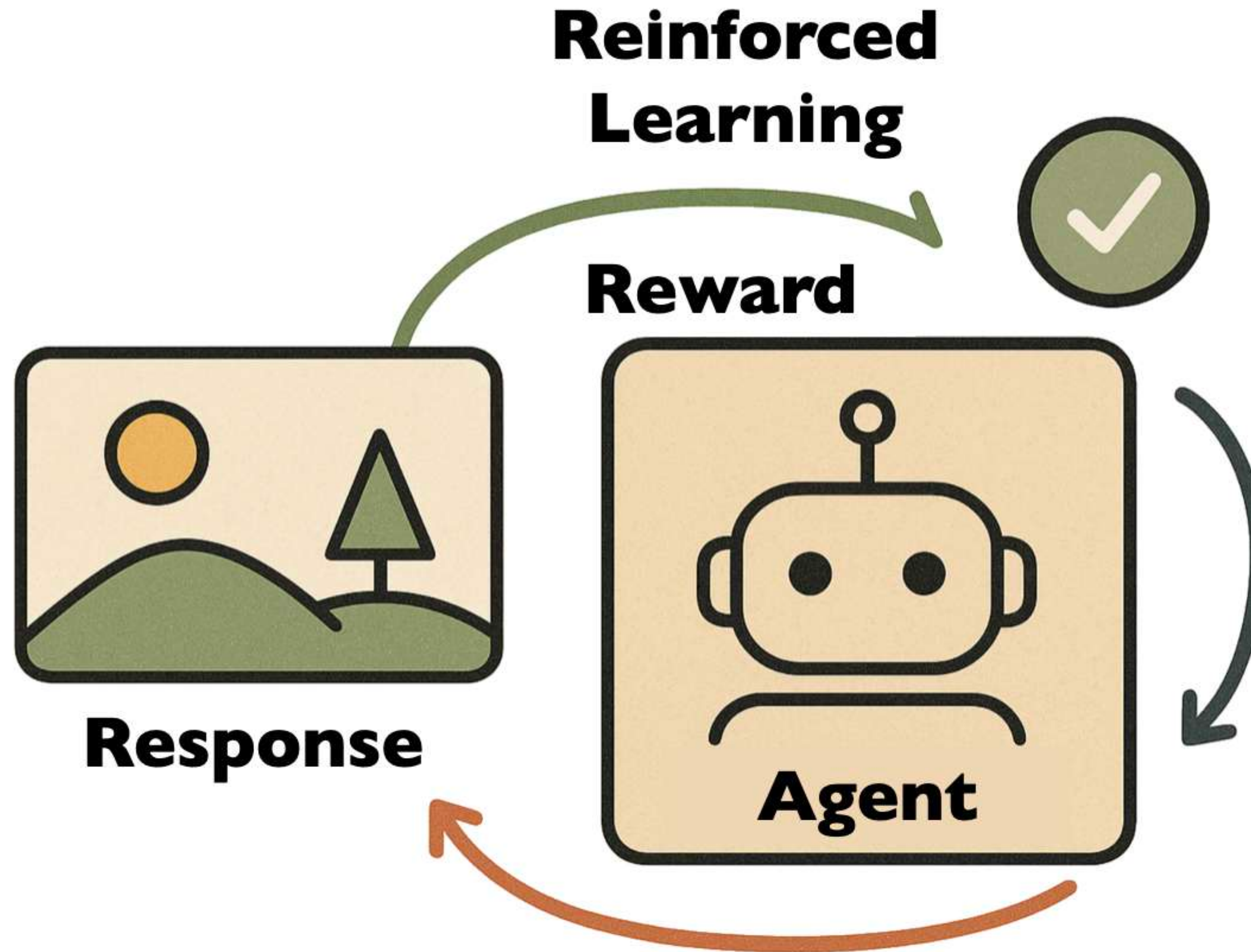
Milking Robots/Batch milking/Feed Dispensers



Milking Robots/Batch milking/Feed Dispensers

- 📌 Until now concentration supplementation is based on a fixed rules:
 - 📌 Little impact on milk production (Little et al., 2016)
 - 📌 Not all the cows respond equally to the same concentrate allowance
- 📌 Alternative approaches
 - 1) Use historical data to learn about individual animal responses using regression analyses (André et al., 2010; Morey et al., 2023; Souza et al., 2025)
 - 2) AI: Asses individual animal response to a given supplementation (investment)

Milking Robots/Batch milking/Feed Dispensers



Milking Robots/ Batch milking/Feed Dispensers



PRECISION SUGGESTED

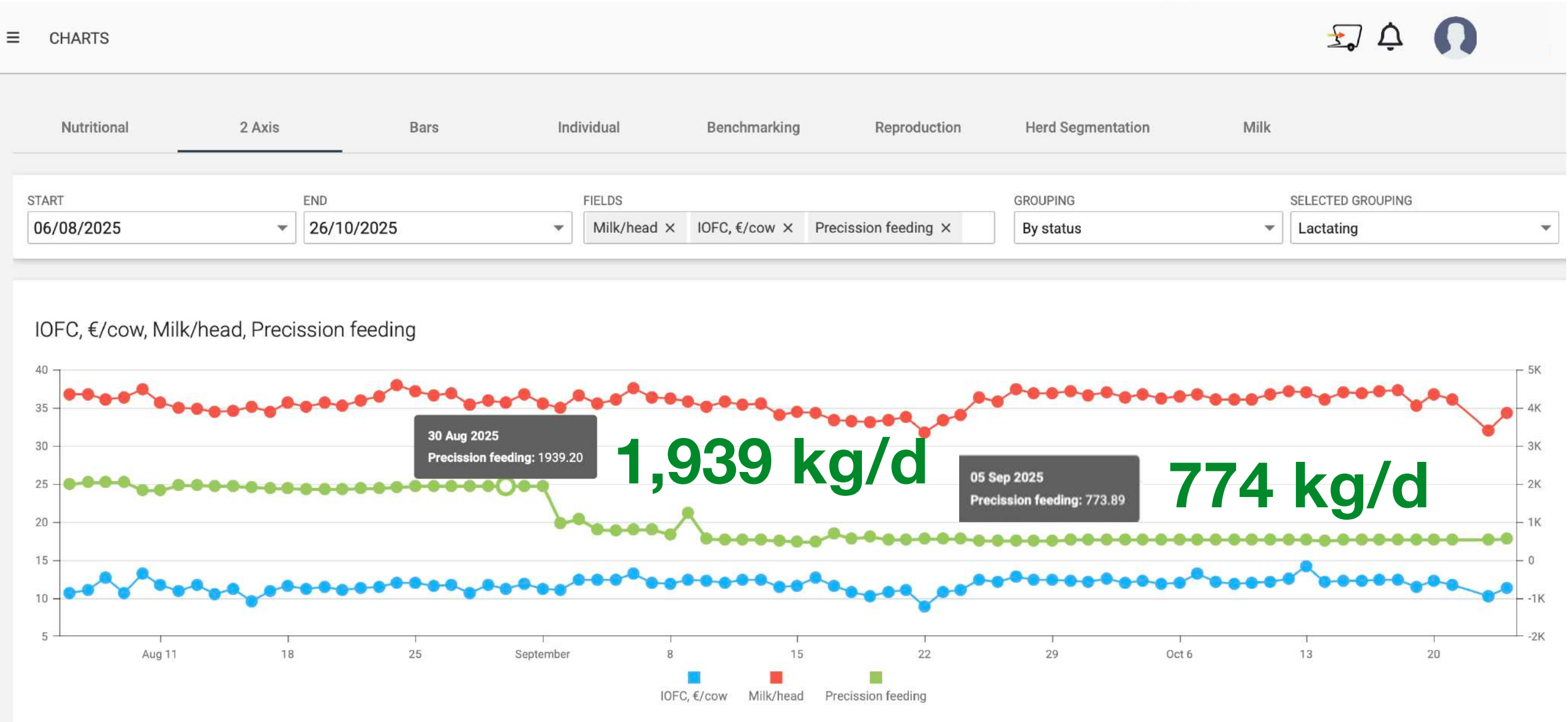


Export

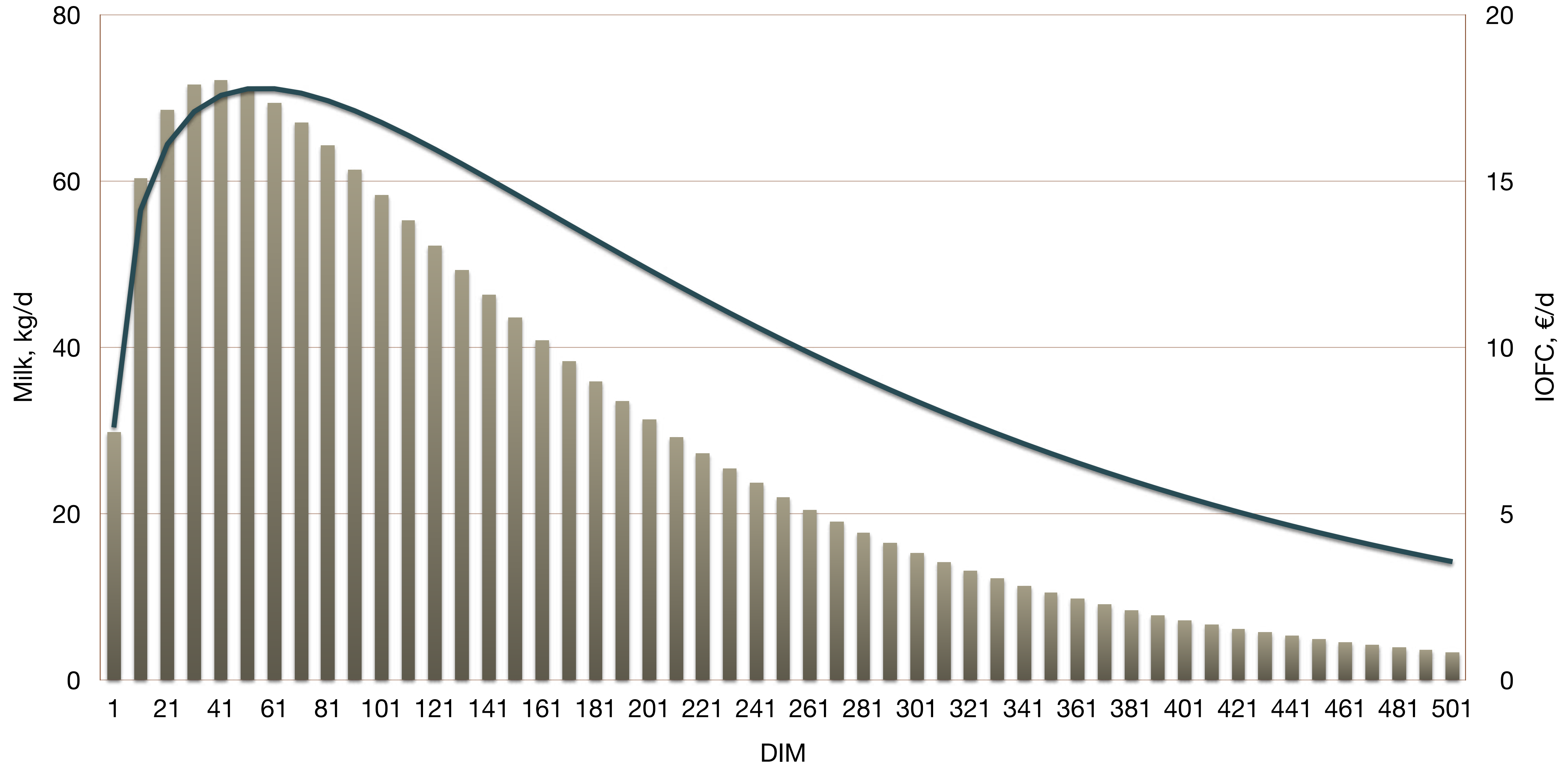
Save

	Calculation Date	Cow	Lactation	Days in milk	Milk, kg/d	Ingredient	Quantity, kg	Suggested, kg	Difference
☐	23/06/2026	2012	1	512	34.93	PINSO ROBOT	1.68	0.64	-1.04
☐	23/06/2026	2015	2	164	49.96	PINSO ROBOT	3.3	3.05	-0.25
☐	23/06/2026	2017	2	93	57.2	PINSO ROBOT	2.98	2.69	-0.29
☐	23/06/2026	2028	1	499	25.09	PINSO ROBOT	0.26	0.36	0.1
☐	23/06/2026	2032	2	19	44.7	PINSO ROBOT	2.2	2.42	0.22
☐	23/06/2026	2042	2	93	53.51	PINSO ROBOT	3.63	3.54	-0.09
☐	23/06/2026	2043	2	100	48.2	PINSO ROBOT	3.37	3.26	-0.11
☐	23/06/2026	2044	2	135	53.73	PINSO ROBOT	2.65	2.47	-0.18

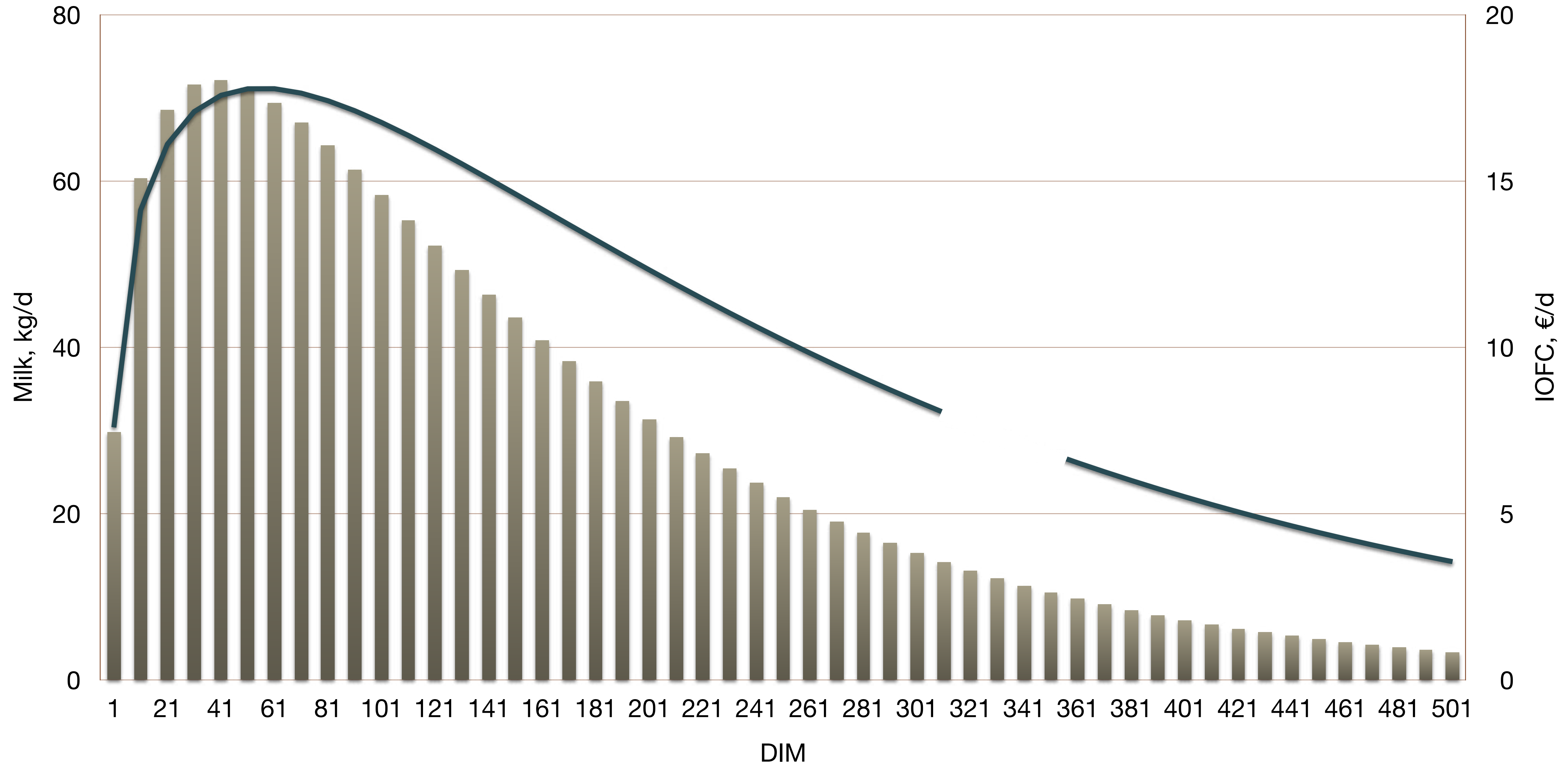
Milking Robots/ Batch milking/ Feed Dispensers



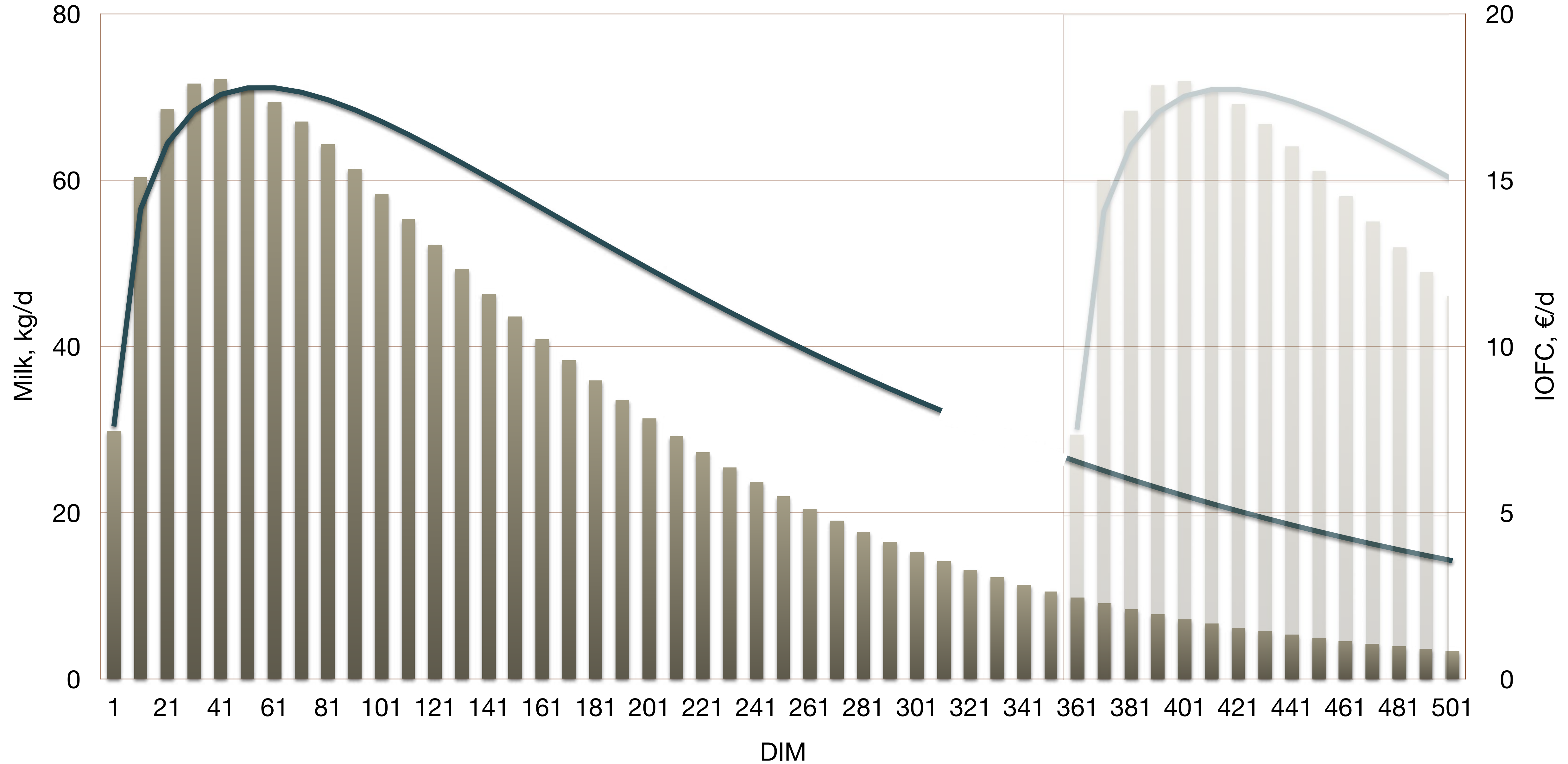
To breed or not to breed



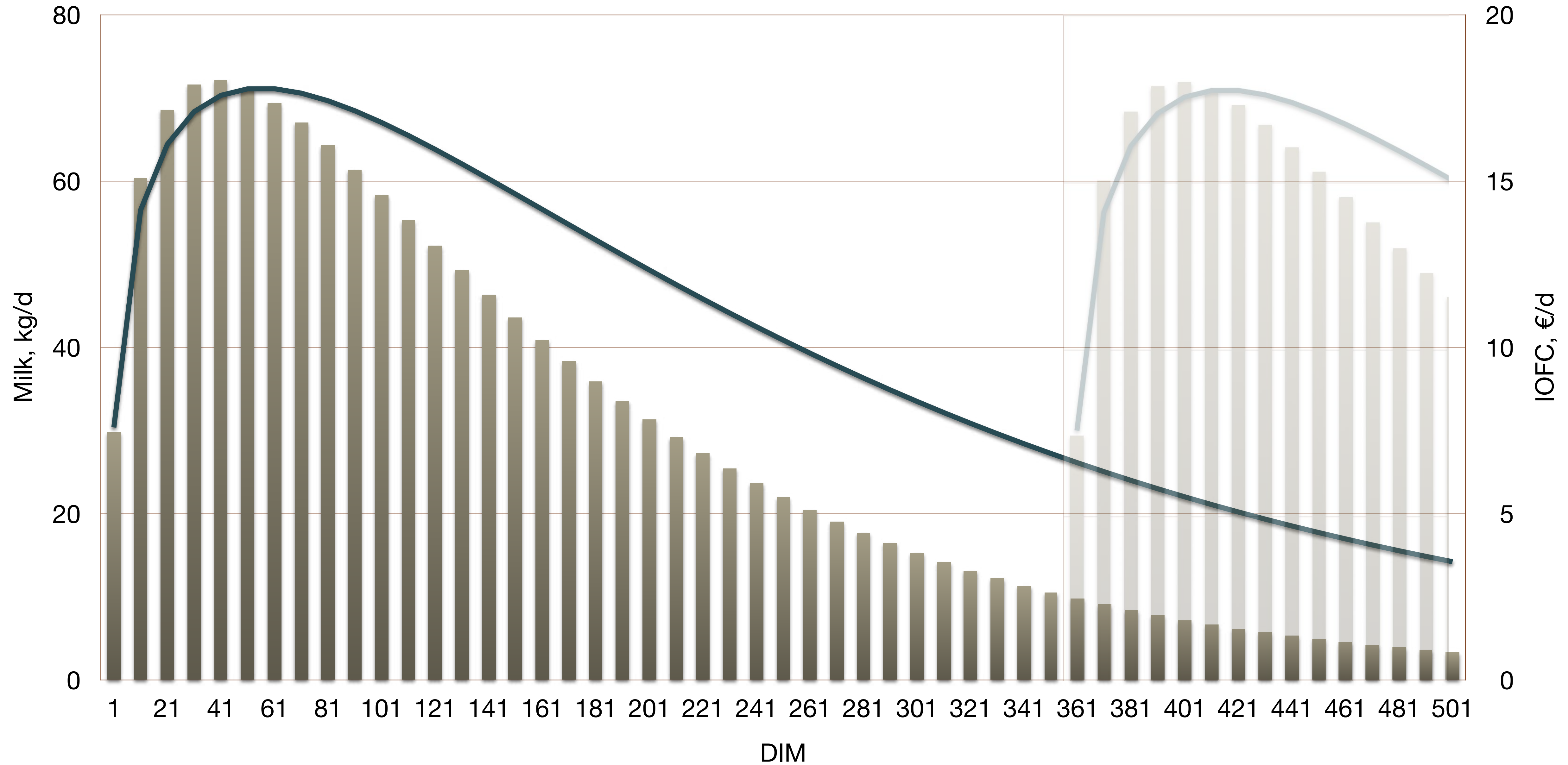
To breed or not to breed



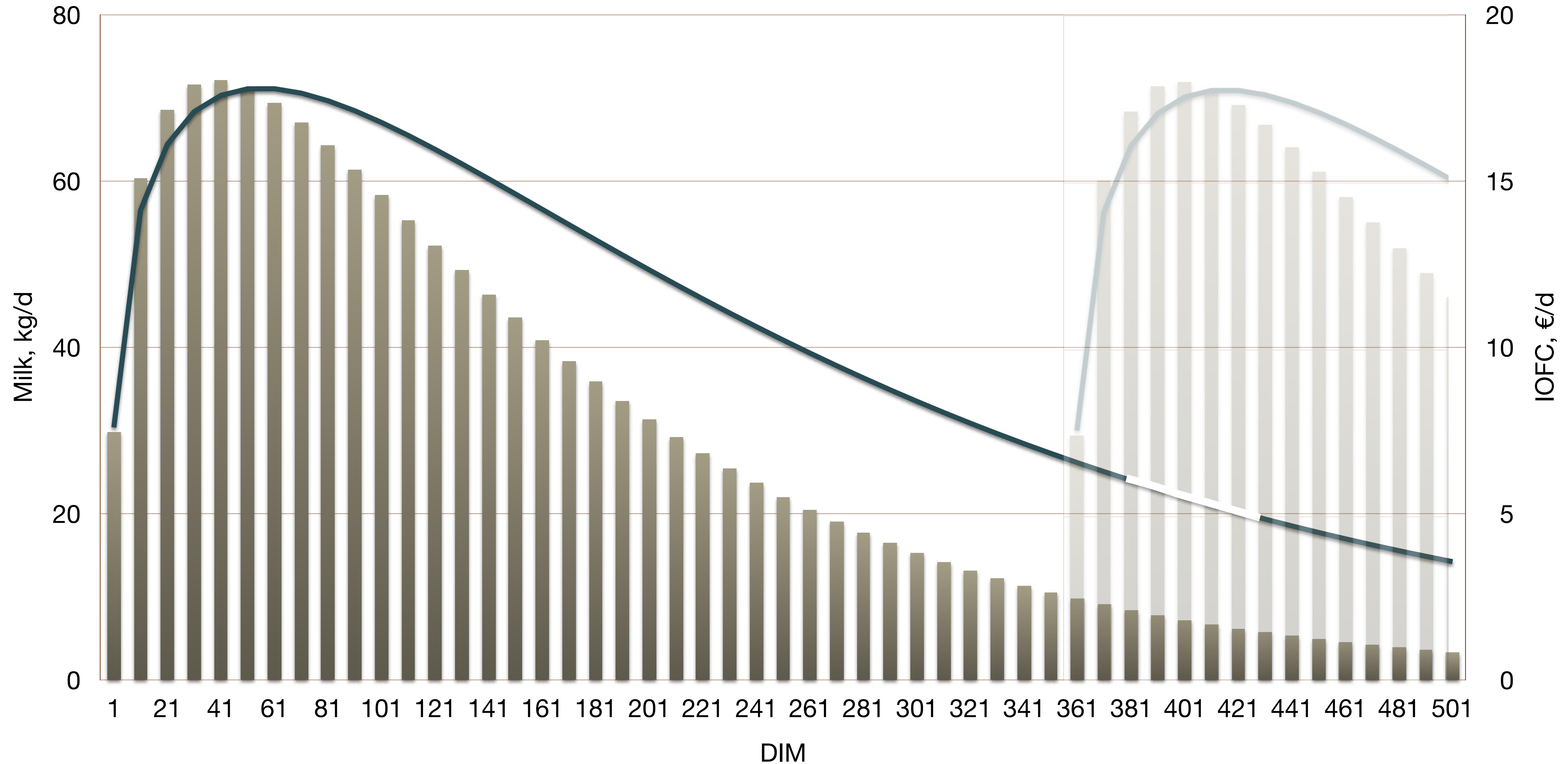
To breed or not to breed



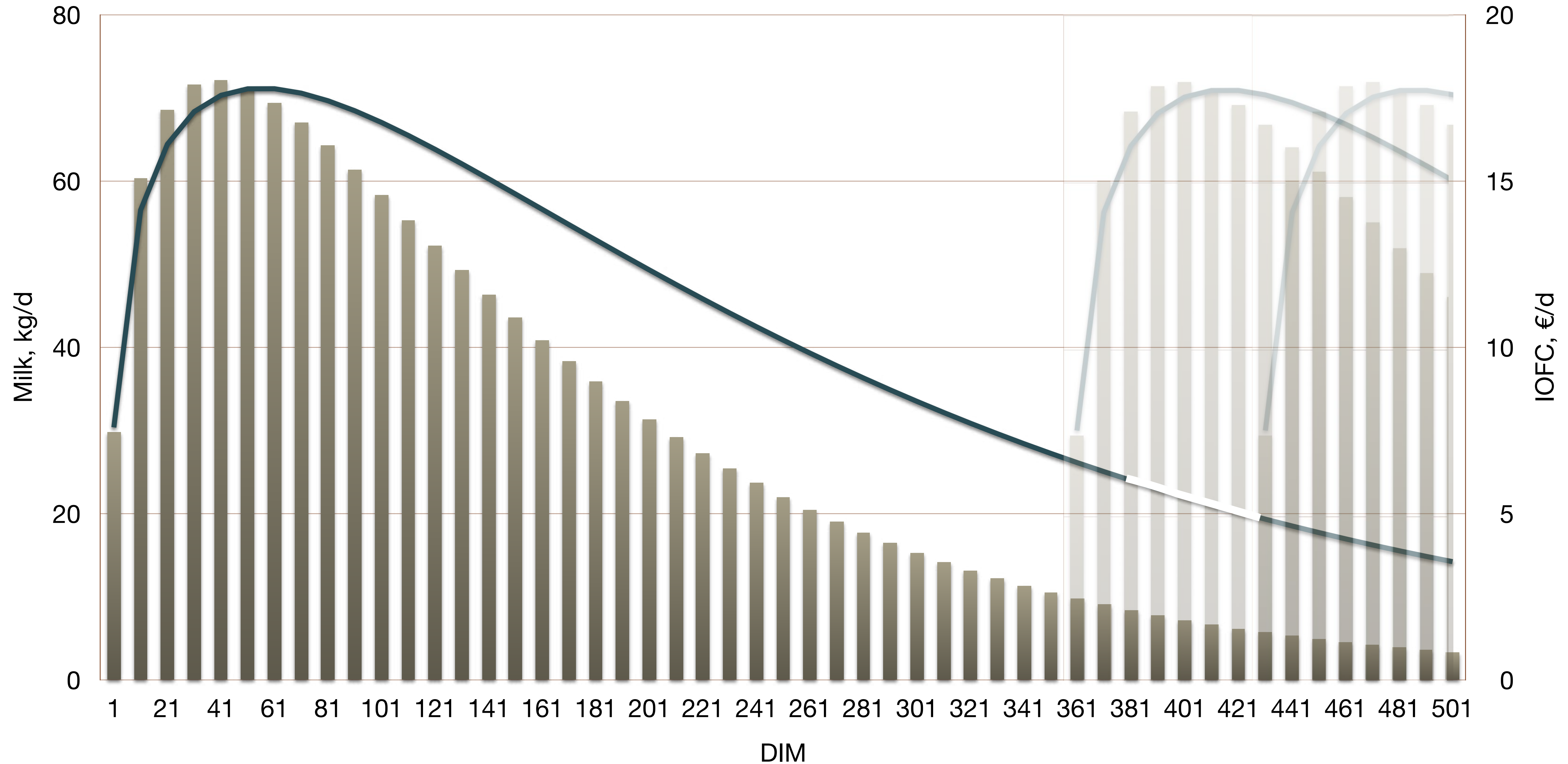
To breed or not to breed



To breed or not to breed



To breed or not to breed





To breed or not to breed



Export

Column configuration

	Cow numb...	DNB	Days in milk	Days pregnant	Current lactati...	Productive life	IOFC	IOFC (cohort)	Yield (predicted)	Yield total	Yield total (cohort)	Yield (10 d)
👁	309		264	203	4	811	13.79	15.19	834.71	41,866.90	56,622.54	50.80
👁	1687		631	216	4	1674	8.02	15.17	38.67	74,457.36	61,431.70	40.54
👁	1749		397	94	4	1677	16.56	15.19	2,262.57	80,759.50	59,813.06	54.77
👁	1805		121	0	4	575	19.97	15.16	15,477.62	29,323.14	58,708.65	60.04
👁	1821		35	0	4	755	19.93	15.18	11,695.91	35,788.69	59,662.42	60.57
👁	1828	✓	137	0	4	1073	20.10	15.17	9,365.30	49,938.60	59,522.29	55.66
👁	1887		298	181	4	1513	16.89	15.16	2,118.02	88,335.86	59,089.77	58.70
👁	1889	✓	275	0	4	1720	10.60	15.15	2,733.56	48,509.92	58,735.21	47.61
👁	1899		157	0	4	1098	19.65	15.16	12,848.43	54,602.91	59,237.34	59.45
👁	1902		359	220	4	1312	2.50	15.17	0.00	71,023.83	58,460.19	40.29
👁	1903		213	132	4	1499	20.49	15.19	4,769.26	77,495.54	60,472.27	61.60
👁	1904		155	48	4	618	23.77	15.18	11,569.29	37,996.59	60,336.53	67.38
👁	1906		330	89	4	931	9.97	15.18	2,931.25	35,020.00	57,073.63	37.98

To breed or not to breed



Export

Column configuration

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👁	1906		330	89	4	931	9.97	15.18	2,931.25	35,020.00	57,073.63	37.98

To breed or not to breed



Export

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👁	1899		157	0	4	1098	19.65	15.16	12,848.43	54,602.91	59,237.34	59.45
👁	1902		359	220	4	1312	2.50	15.17	0.00	71,023.83	58,460.19	40.29
👁	1903		213	132	4	1499	20.49	15.19	4,769.26	77,495.54	60,472.27	61.60
👁	1904		155	48	4	618	23.77	15.18	11,569.29	37,996.59	60,336.53	67.38
👁	1906		330	89	4	931	9.97	15.18	2,931.25	35,020.00	57,073.63	37.98

Summary

- ☆ The future of animal production increasingly lies in the application of **farm-specific dynamic models**, rather than relying on static or empirical models that assume all animals behave identically (a "one-size-fits-all" approach)
- ☆ The advantage of using AI is that predictions of nutritional requirements—and, in particular, animal responses—can be substantially improved for a specific herd
- ☆ One of the major limitations to economic progress in the current animal production sector stems from difficulties in exchanging data between platforms, which hinders the development and implementation of machine learning models



THANK YOU



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