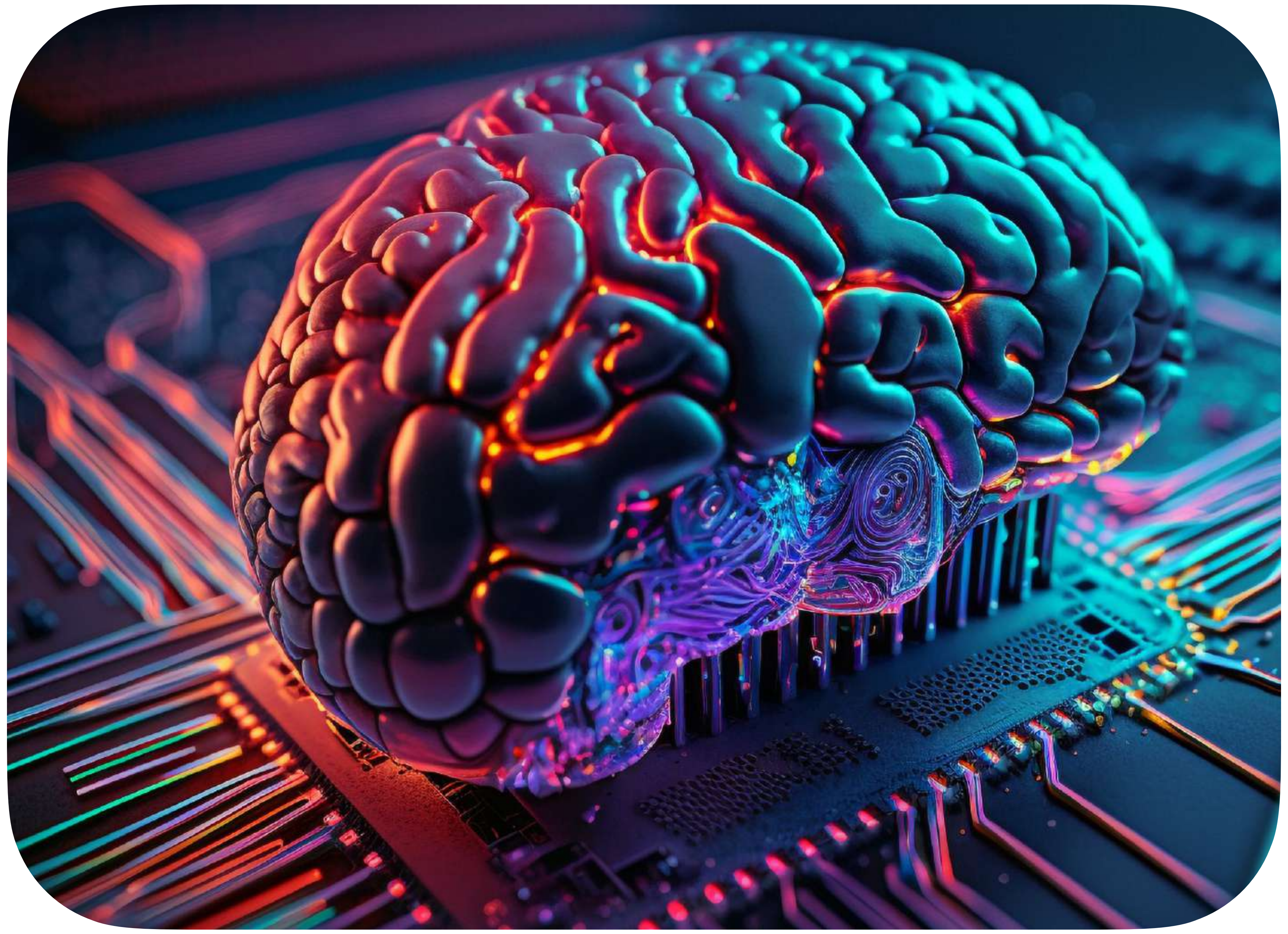
Application of AI in animal feeding and management



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Introduction

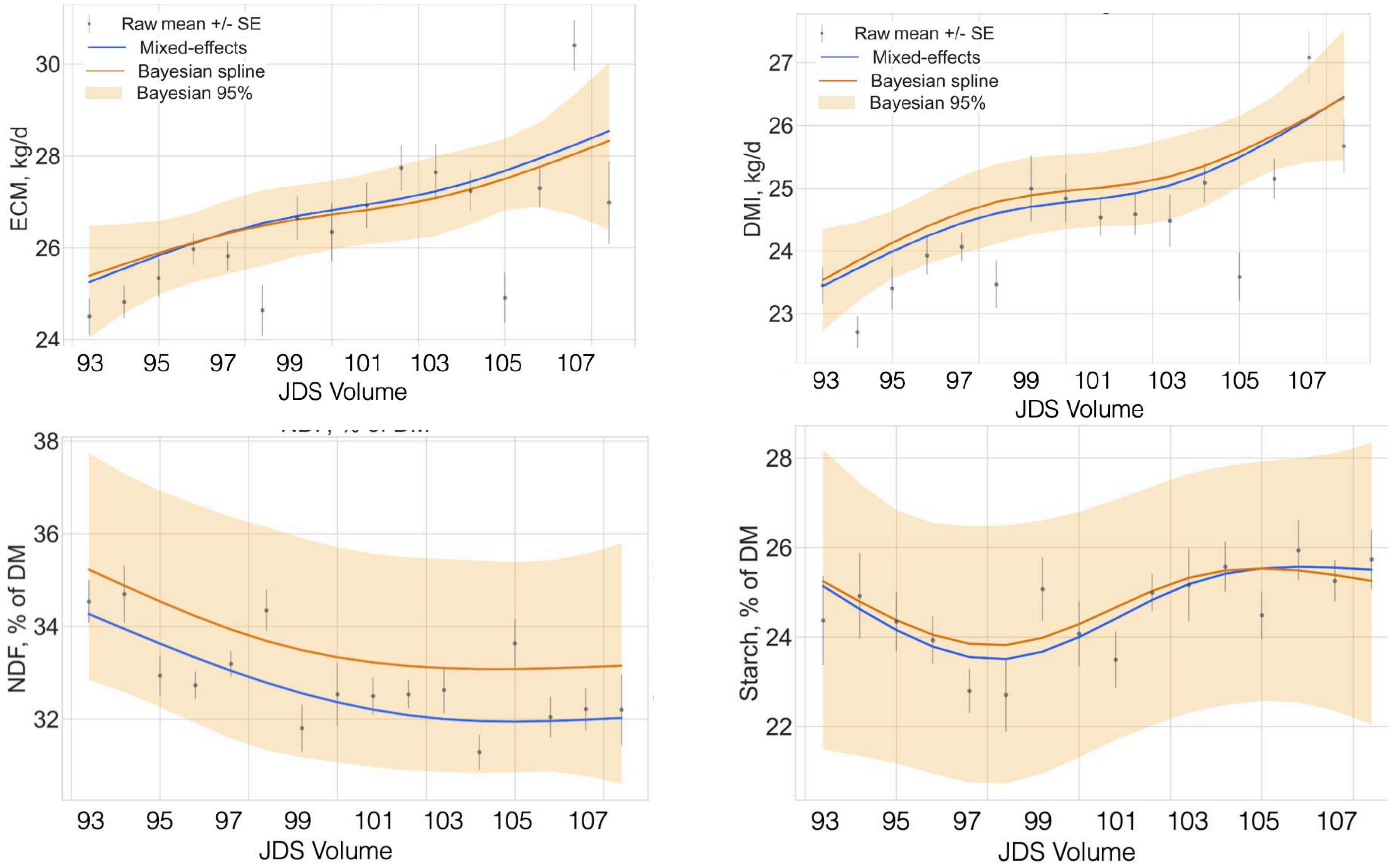
- Production, reproduction, and health of dairy cattle have continuously improved over that last decades consequence of the implementation of the knowledge that research has generated on:
  - Nutrition
  - Immunology
  - Management
  - Genetics
- However, the dairy industry is subject of strong economic 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

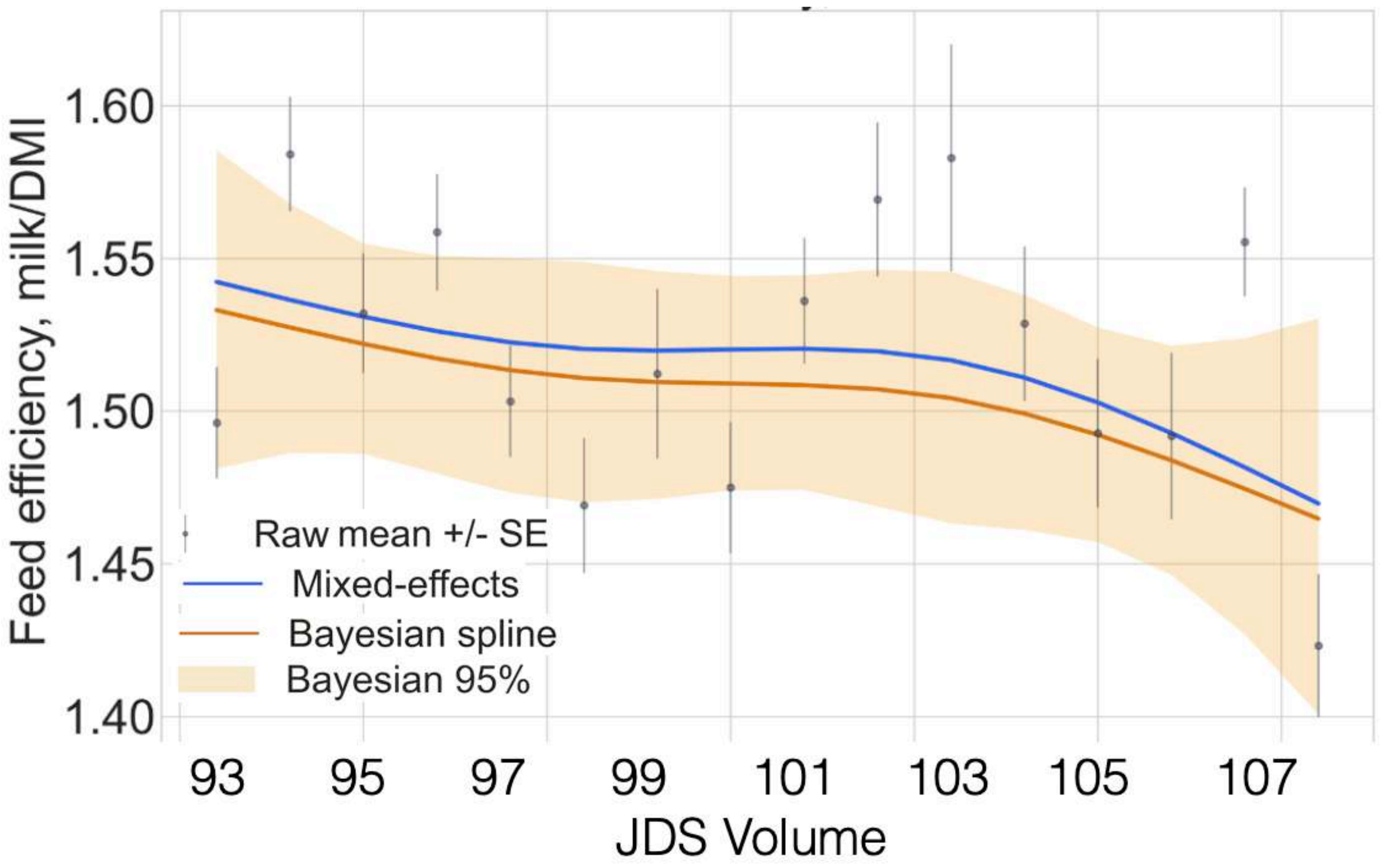
- The continuous genetic progress challenges the capacity of cows to consume all nutrients to support production and all physiological functions



Bach and Beltran (2026)

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



Bach and Beltran (2026)

State of the art

- Up until now, animal nutrition has been based on mathematical models that estimate nutritional needs for a '**reference animal**'

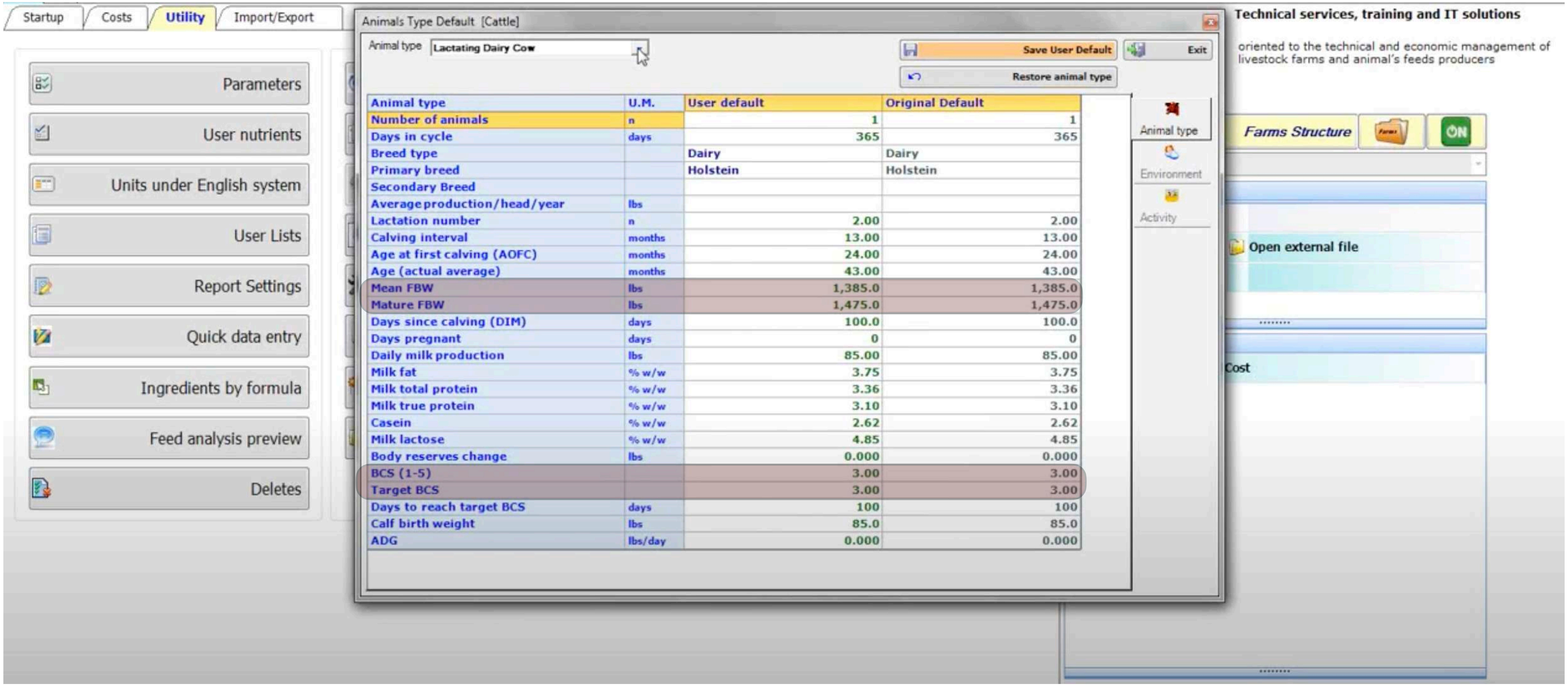
- Two main limitations:

  - 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

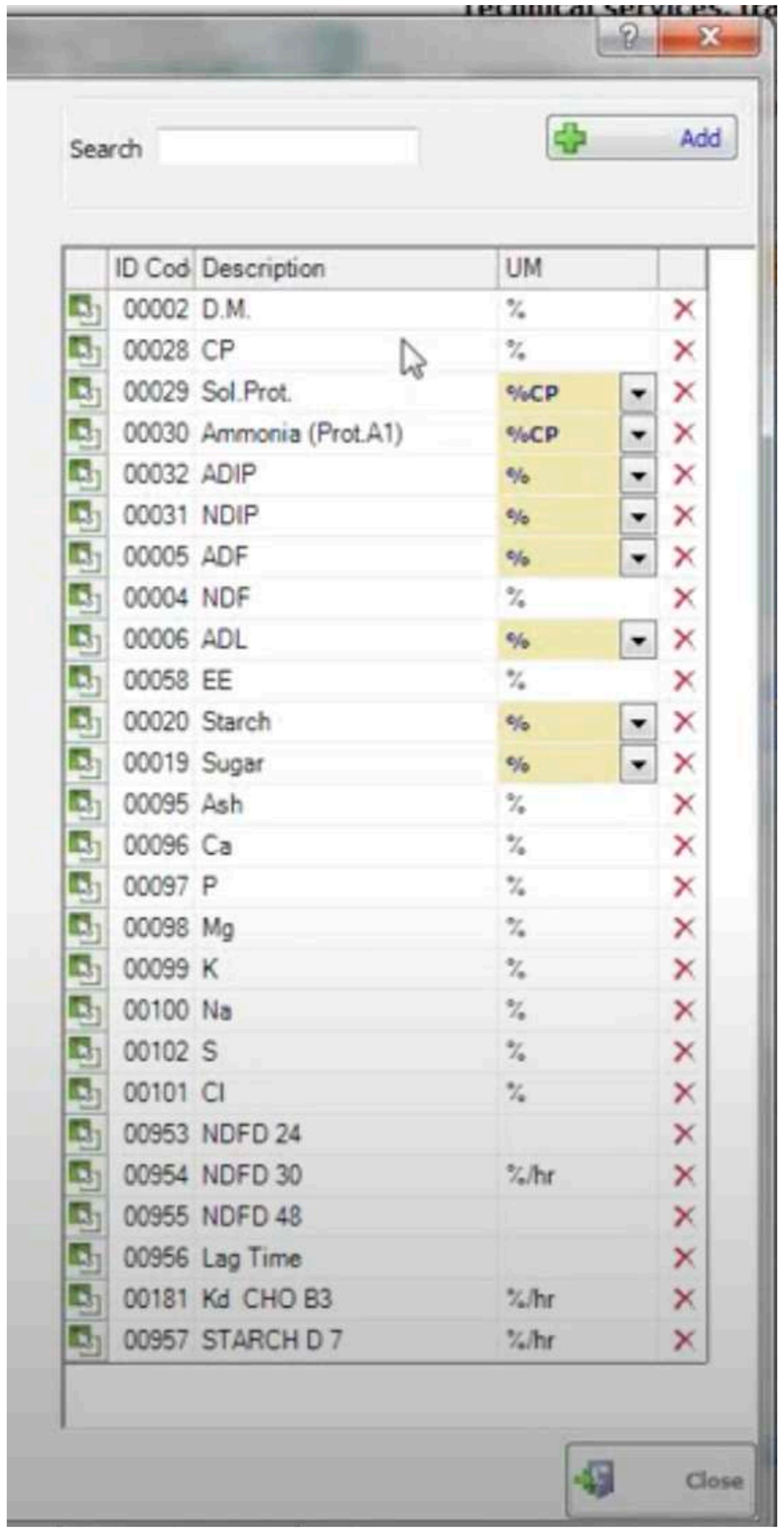
- What do we really know about the 'reference cow' when we apply models?

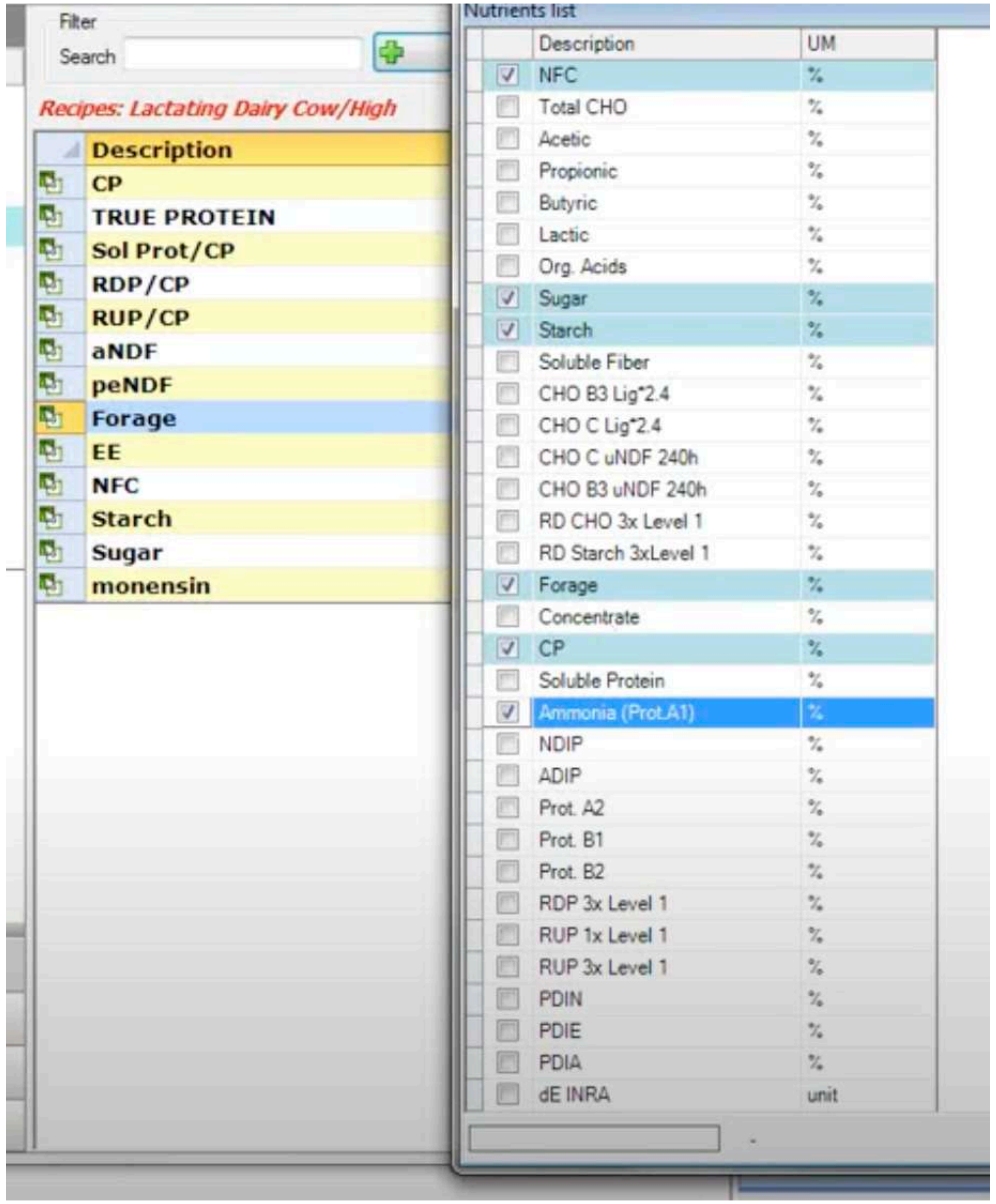


Animal type	U.M.	User default	Original Default
Number of animals	n	1	1
Days in cycle	days	365	365
Breed type		Dairy	Dairy
Primary breed		Holstein	Holstein
Secondary Breed			
Average production/head/year	lbs		
Lactation number	n	2.00	2.00
Calving interval	months	13.00	13.00
Age at first calving (AOFC)	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

State of the art

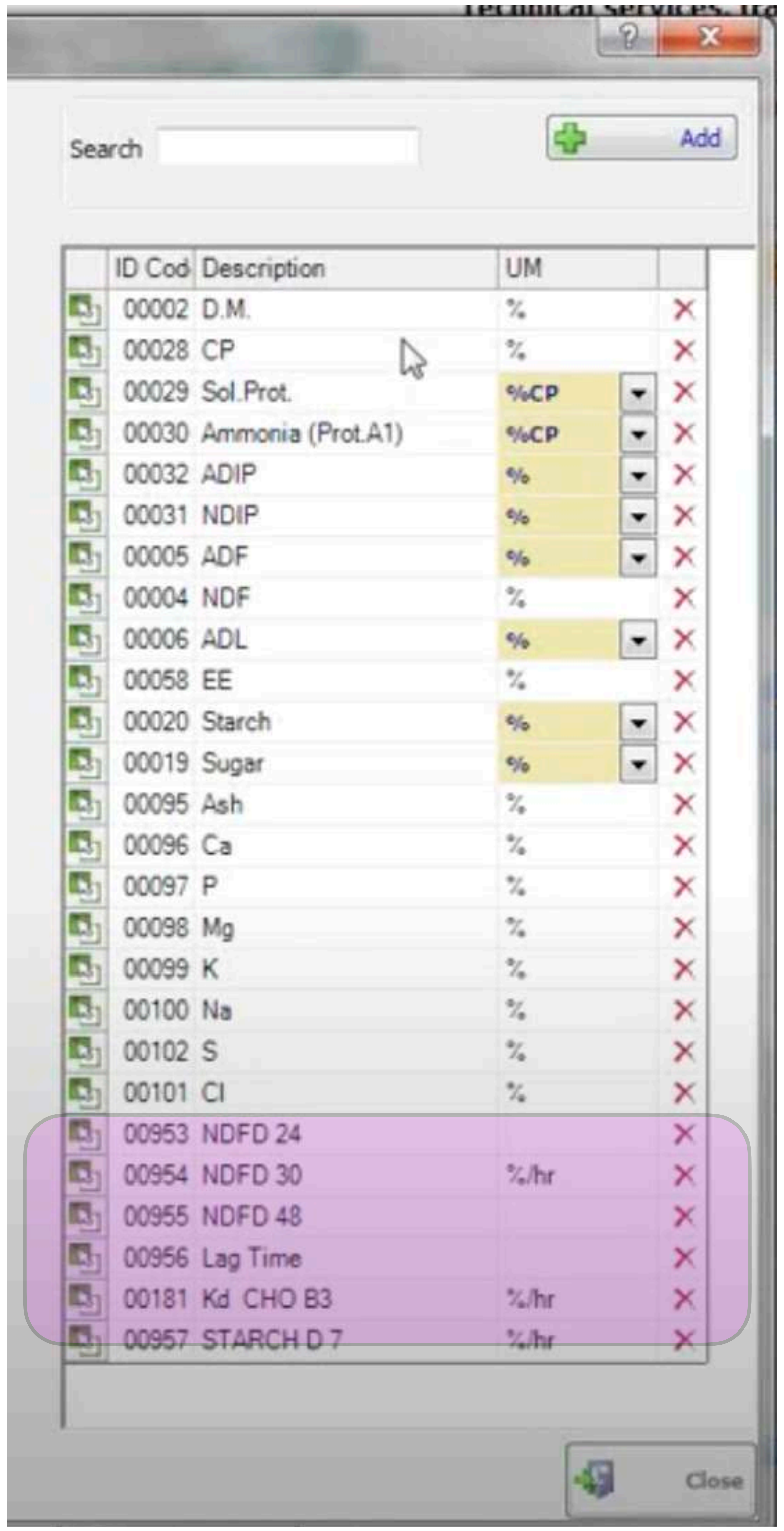
- What do we really know about the nutrients of the ingredients in a ration?

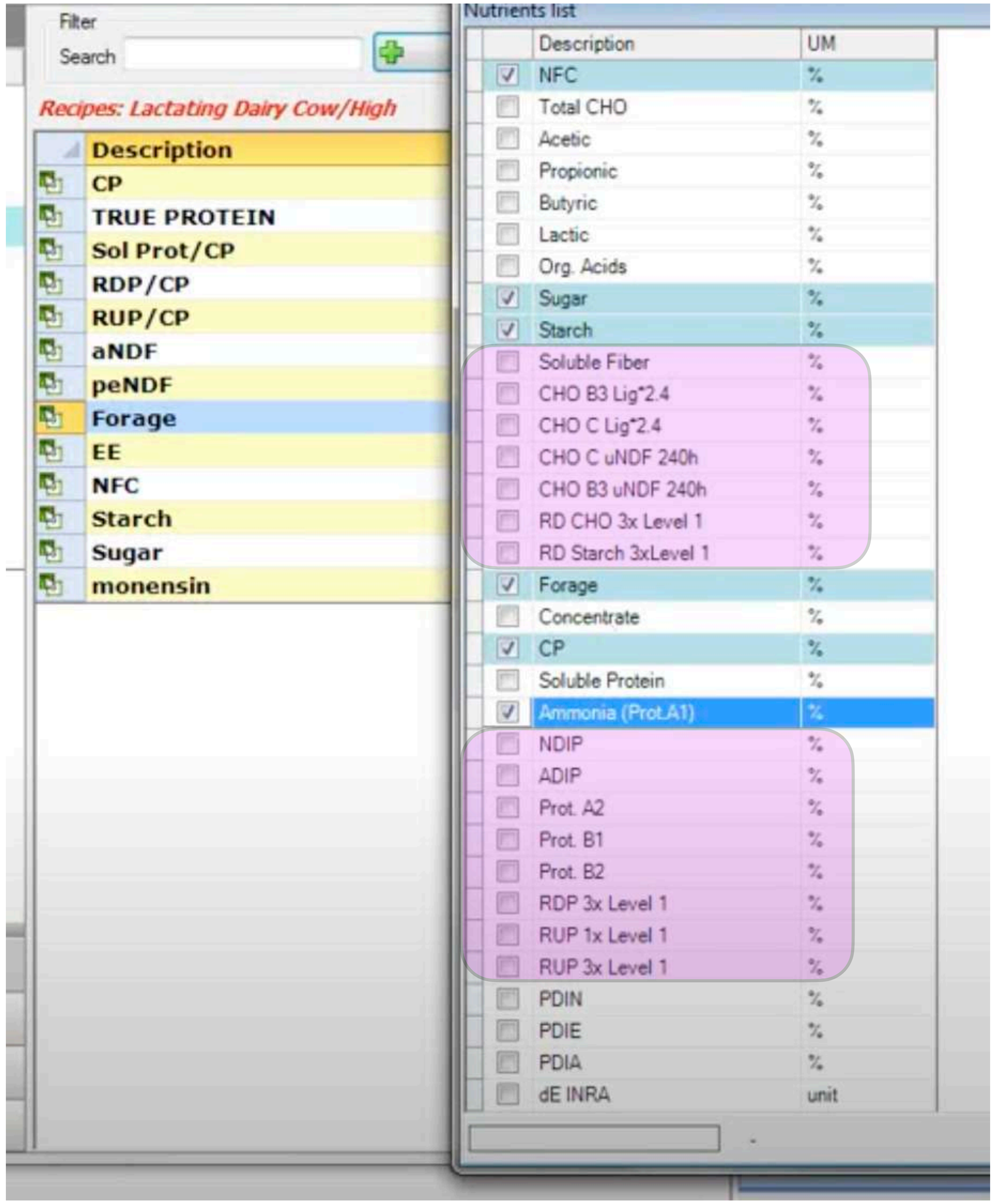




State of the art

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





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

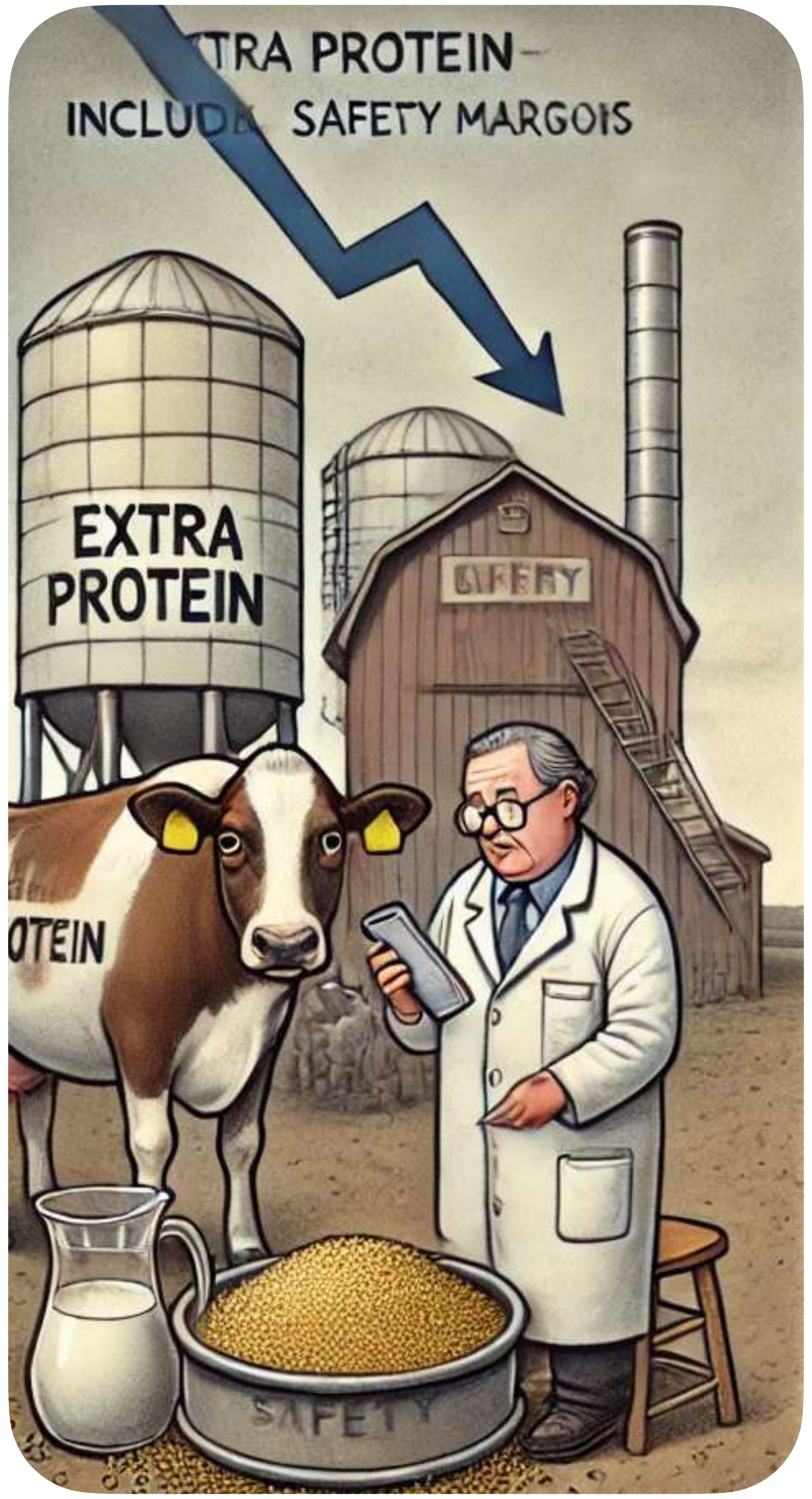
	Control		Experimental	
	Predicted	Actual	Predicted	Actual
Dry matter intake (kg)	24.6	21.6	24.6	21.2
Metabolizable energy balance (Mcal)	–3.1	–3.2	0	–1.0
Metabolizable protein (MP) balance (g)	4.8	–347.9	65.3	–311.1
NP/MP (%)	64.8	78.2	63	76.6
CP (DM %)	17.9	17.9	17.1	17.1
UIPIP (%)	40.8	39.2	38.3	36.5
Fat (%)	4.9	5.0	5.9	6.0
NDF (%)	36.6	36.6	34	34
Effective NDF (%)	21.3	21.3	21.5	21.5
NFC (%)	37.2	37.2	38.8	38.8
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

Energy allowable gain (lb/d)	Protein allowable gain (lb/d)
0.22	0.55
0.48	0.62
0.88	0.64
0.79	0.73
1.65	1.86
2.00	2.20

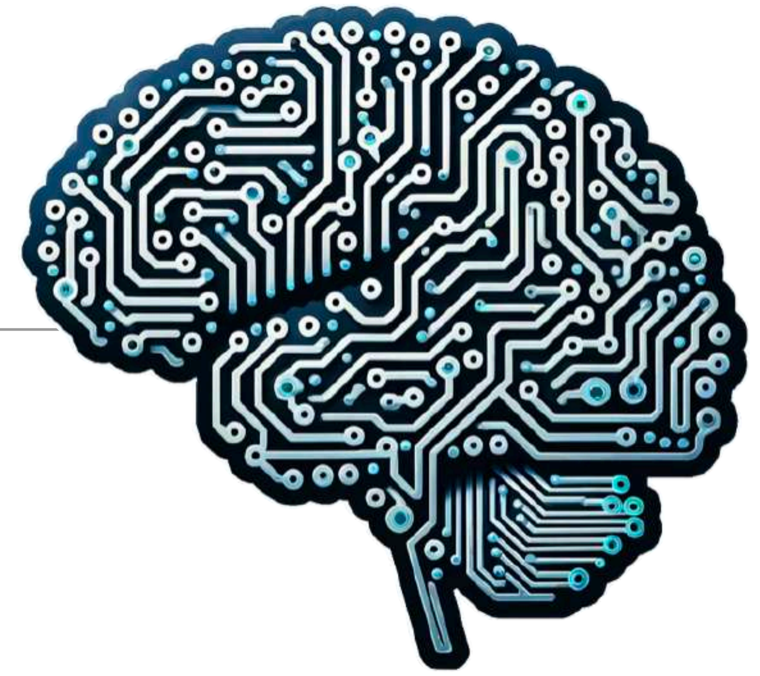
State of the art

- The uncertainty inherent in the current nutritional models (at both sides: supply and requirements) forces nutritionists to implement ‘**safety factors**’ to ensure that there 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

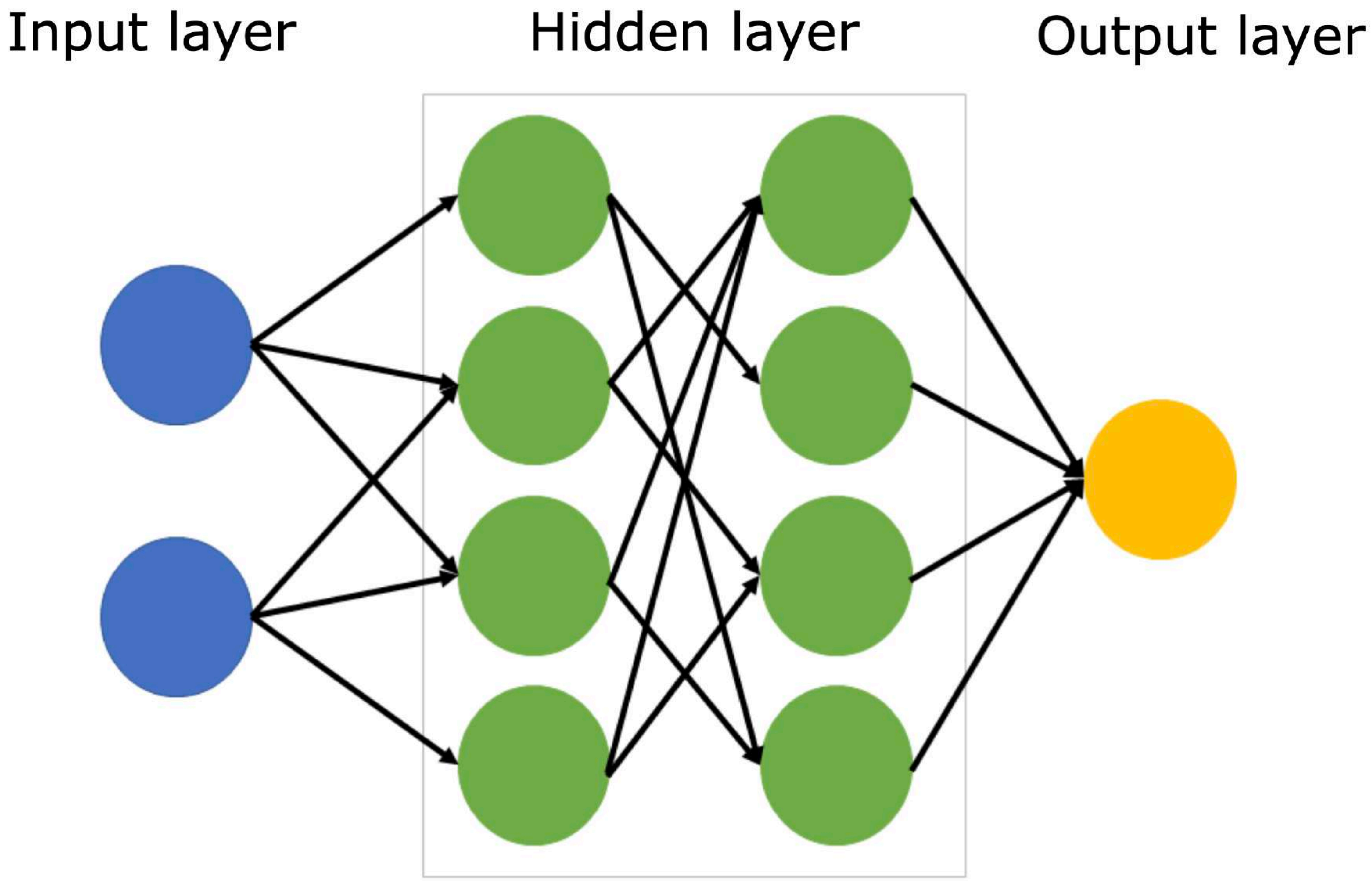


- New developments in data science, and especially, en **computacional power**, represent a major opportunity to implement AI in animal science

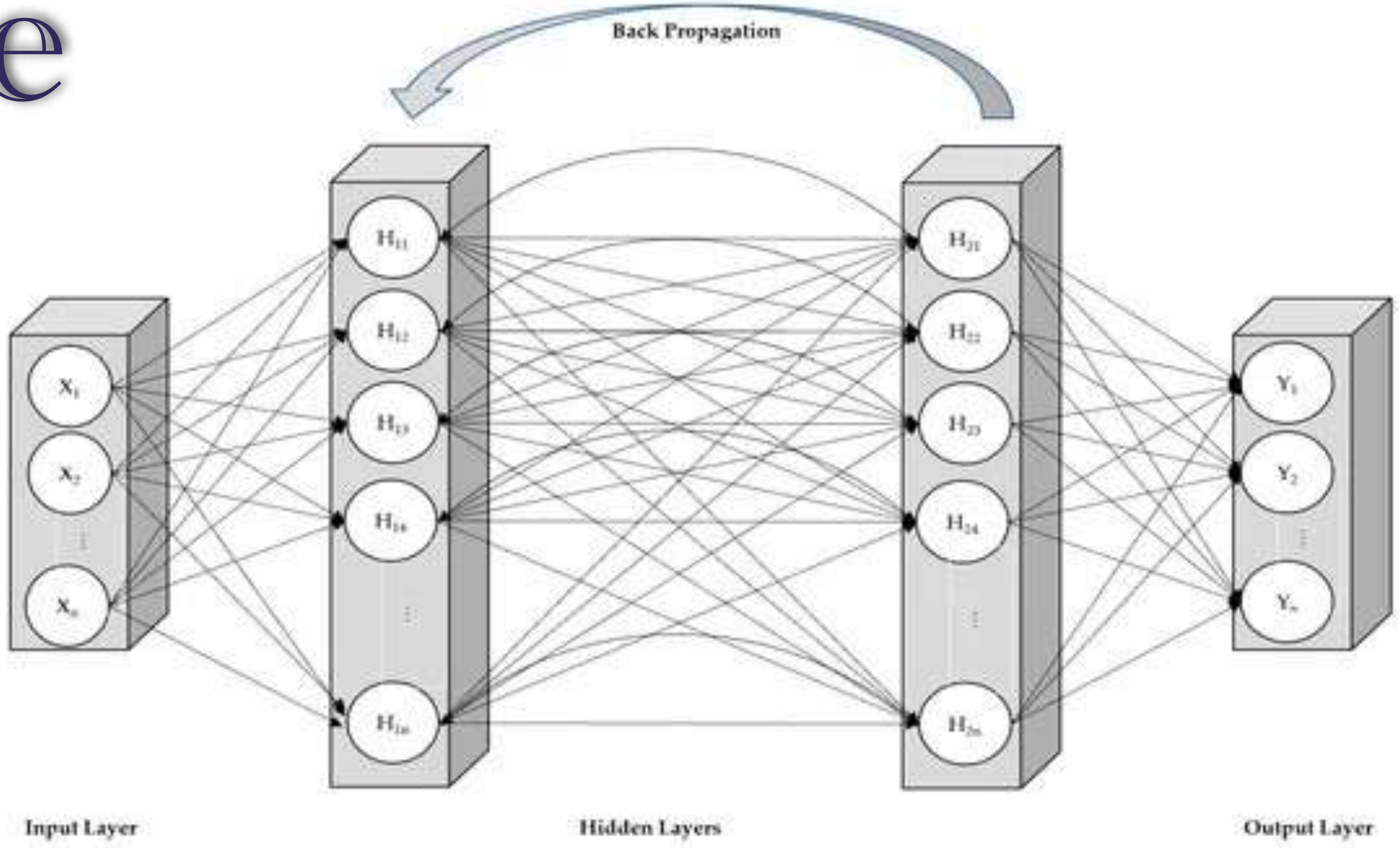
- We can, now, process large amount of data relatively fast

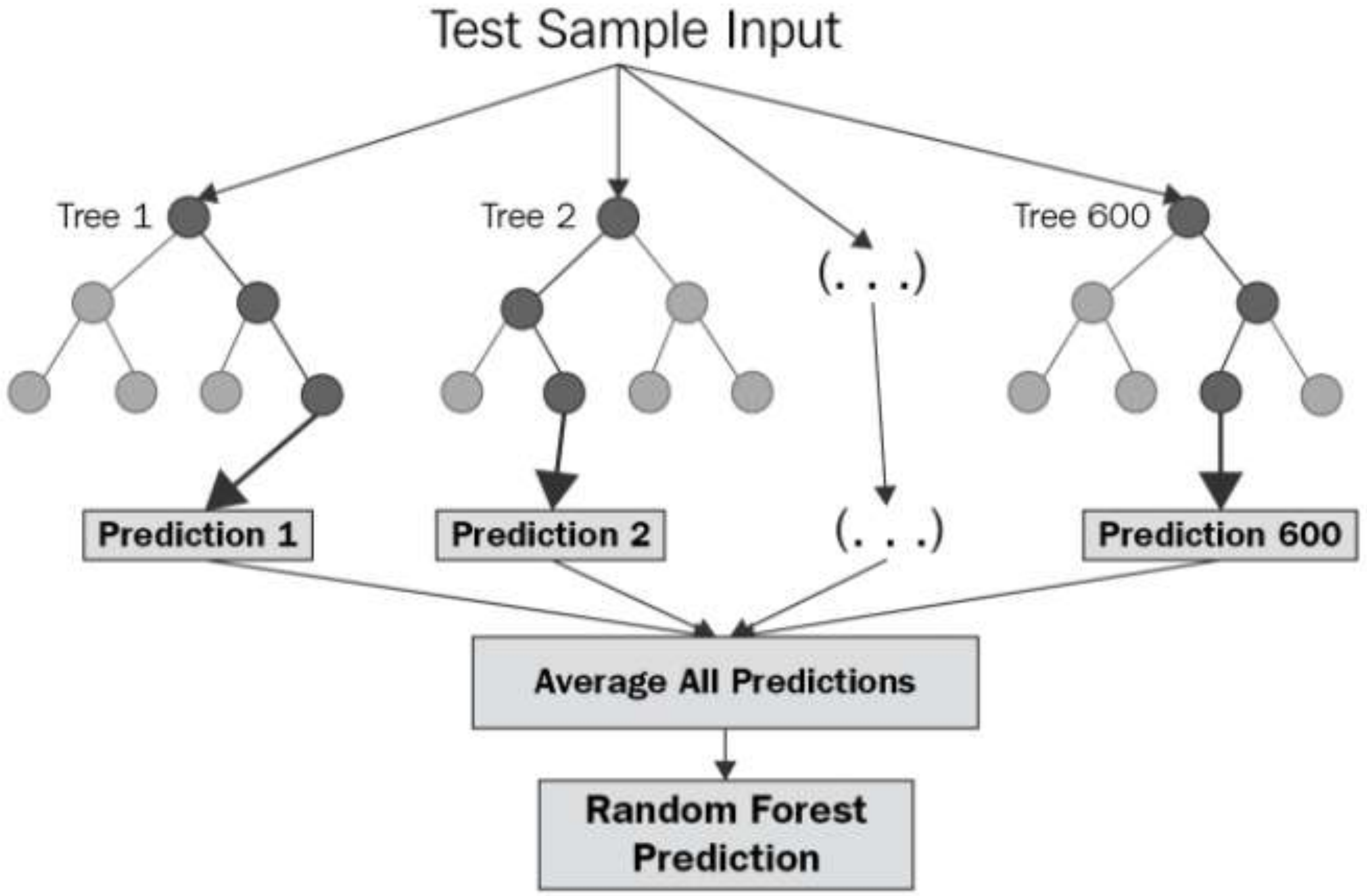
- We can implement traditional statistics, or more novel and computer intensive recursive or iterative techniques using on-farm data

Artificial Intelligence



Artificial neural networks



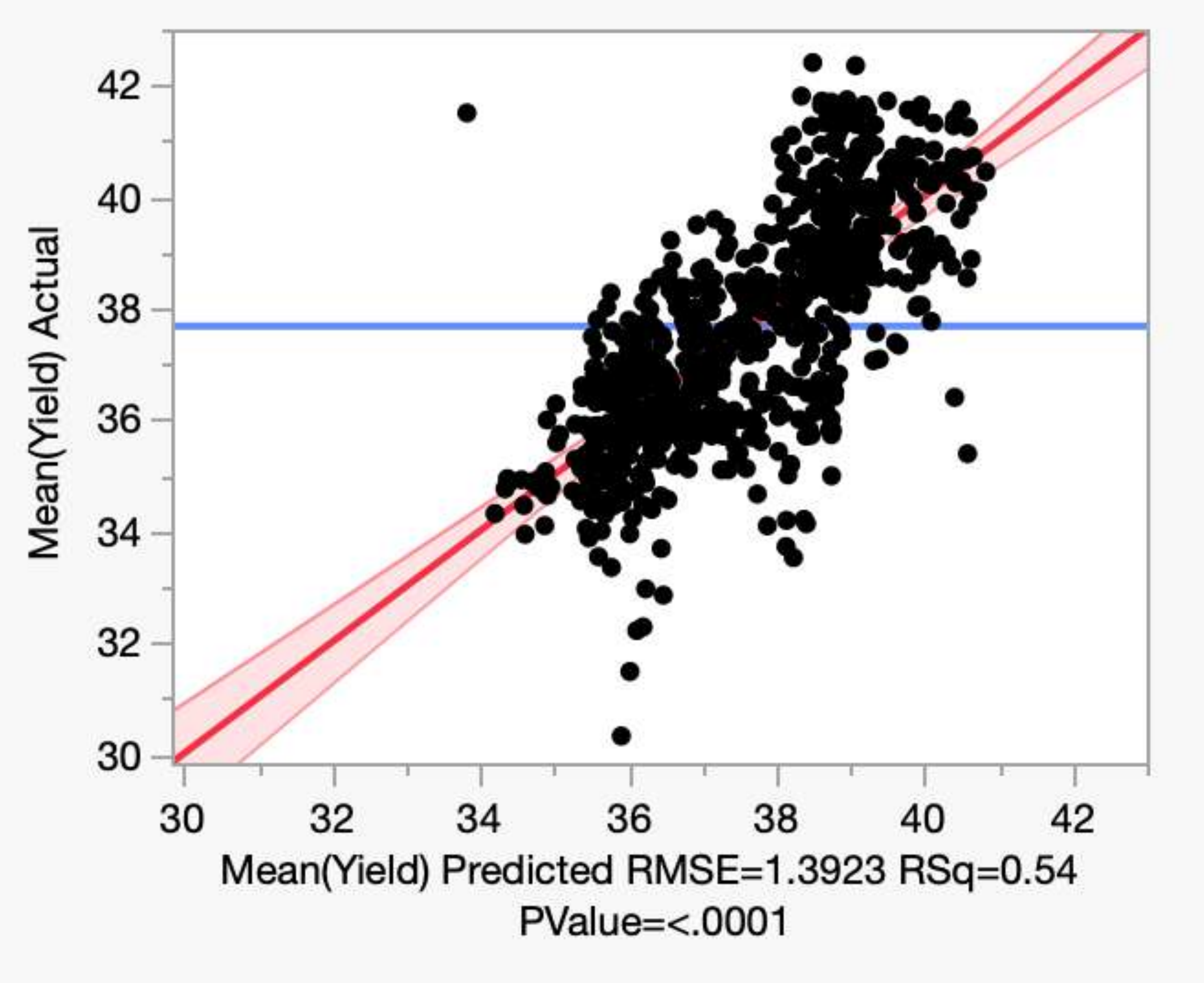


Artificial Intelligence

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

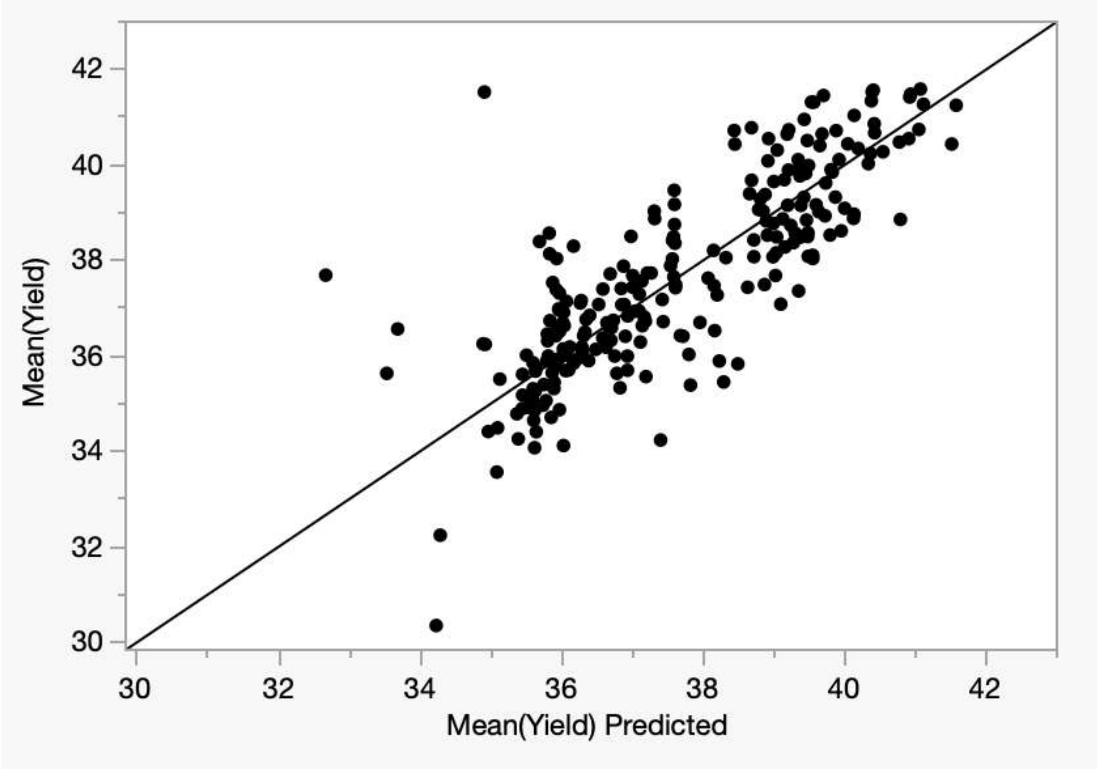
Regression

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



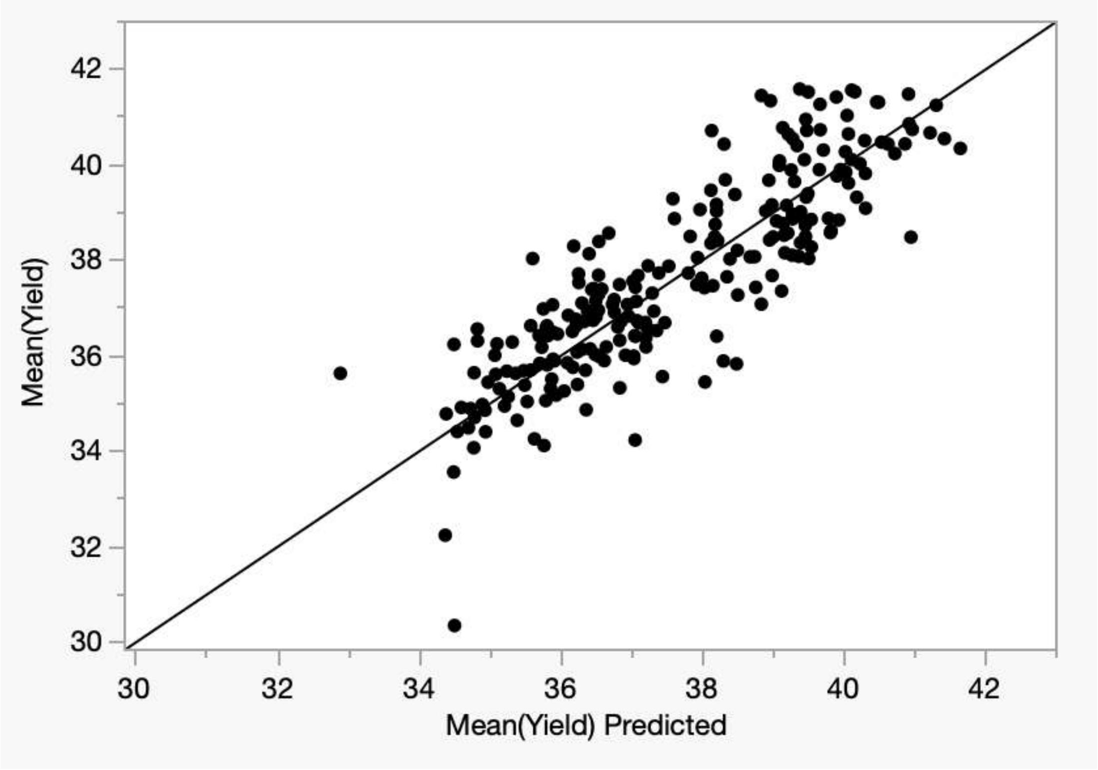
Neural (3 Neurones)

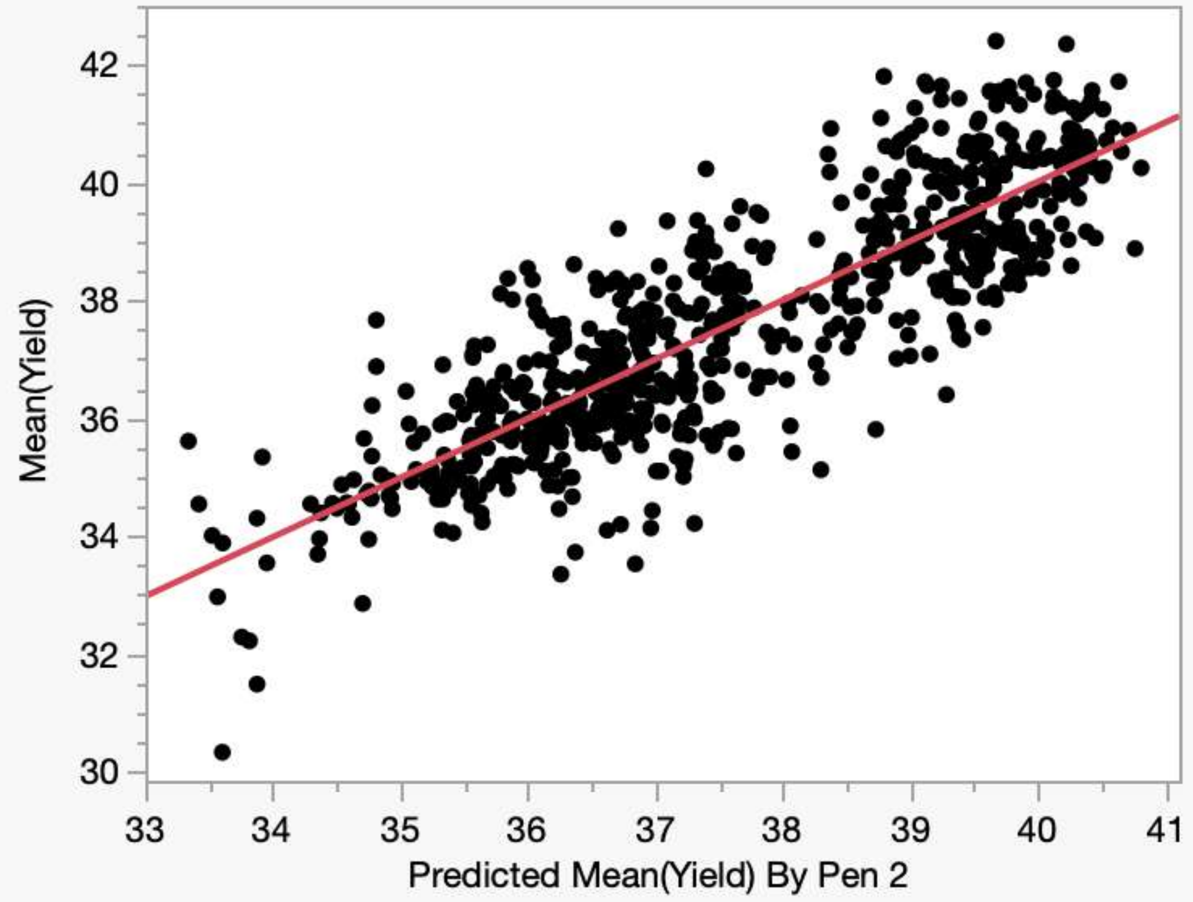
Measures	Value
RSquare	0.6498607
RASE	1.1986533
Mean Abs Dev	0.8776488
-LogLikelihood	384.03292
SSE	344.82472
Sum Freq	240



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



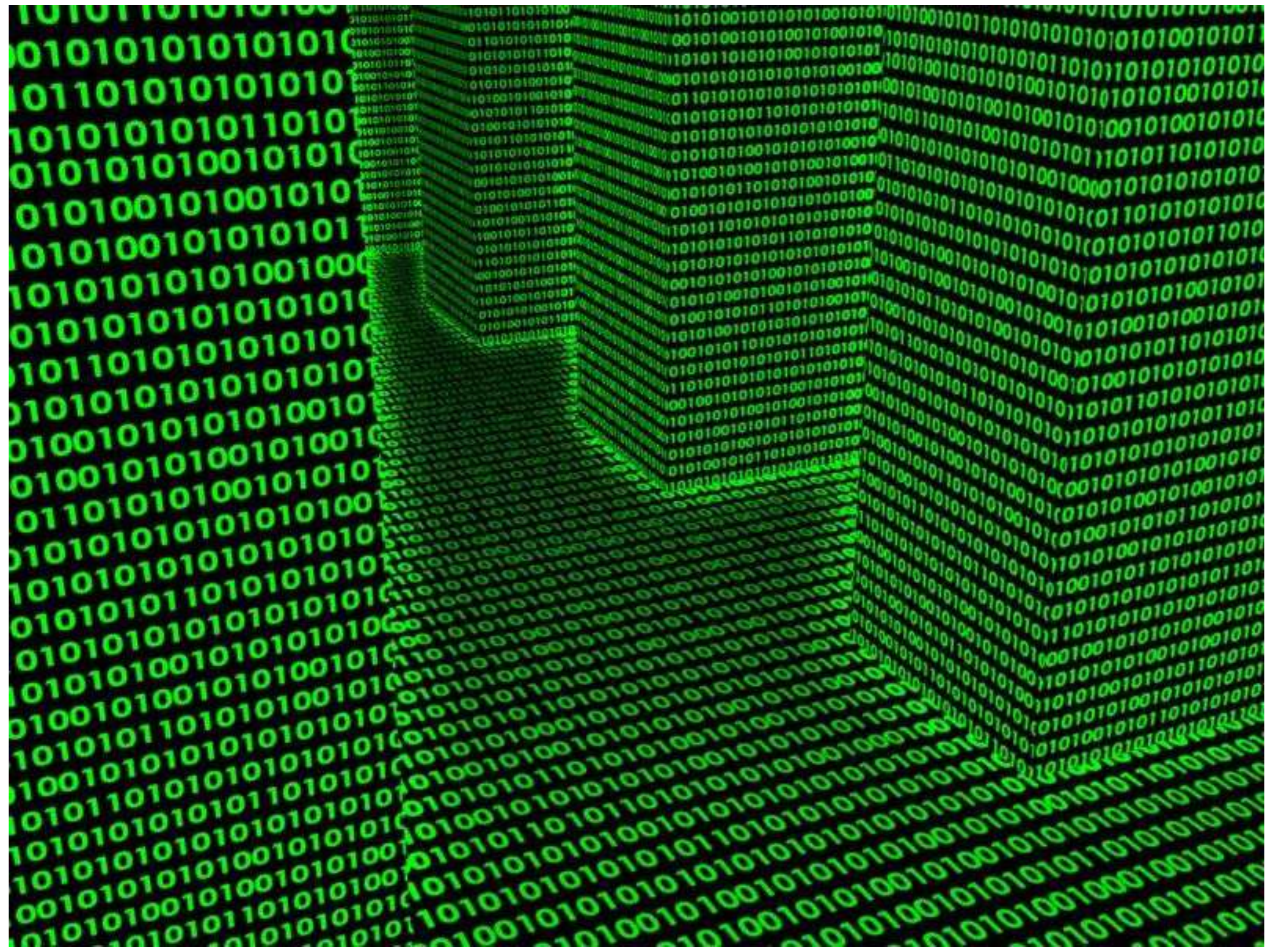


Measures	Value
RSquare	0.728672
RSquare Adj	0.728294
Root Mean Square Error	1.067468
Mean of Response	37.67431
Observations (or Sum Wgts)	480

Artificial Intelligence

Generative AI

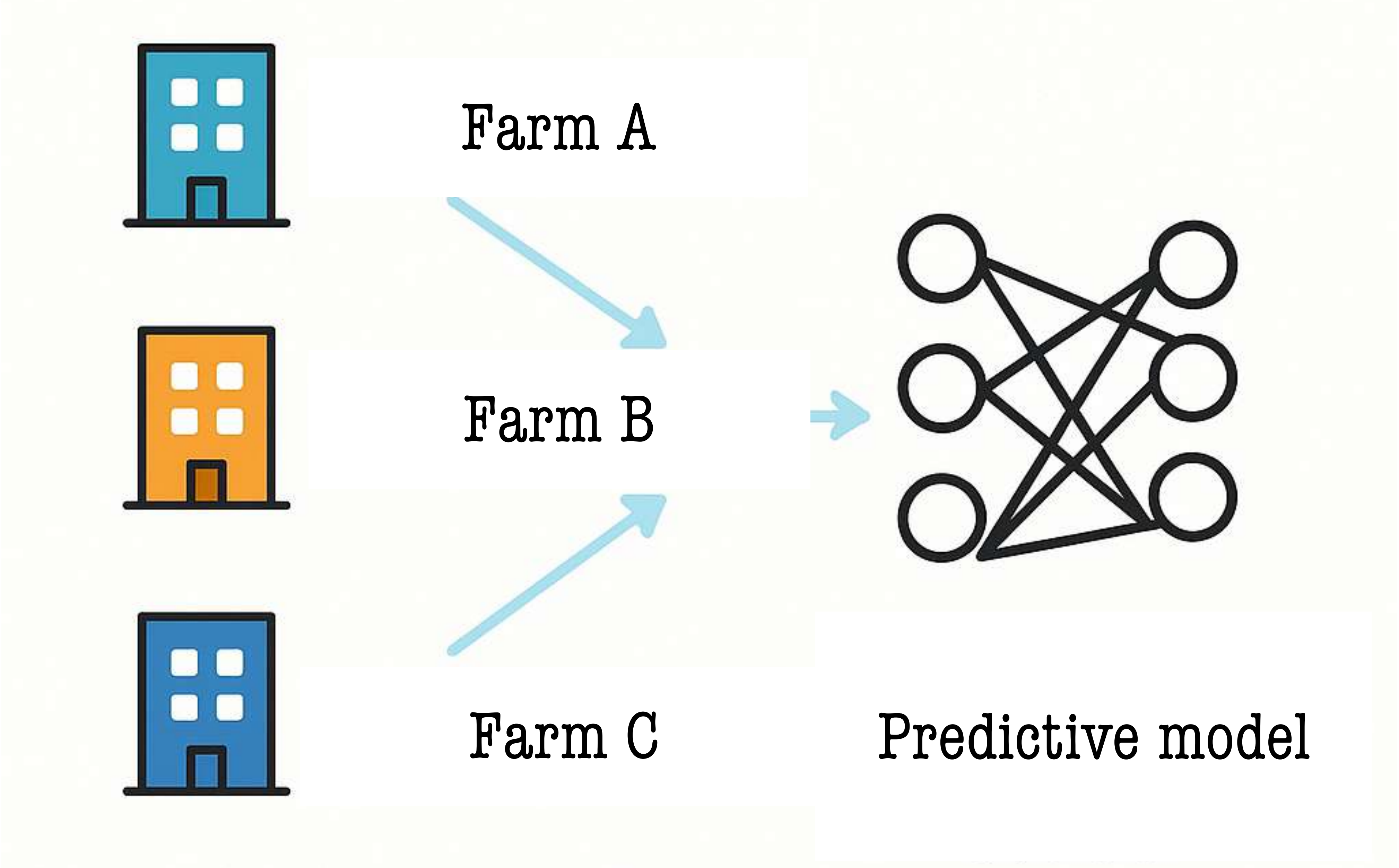
- DeepSeek: 685,000 millions of parameters
- Works with MoE (mixture-of-Experts): selects 37,000 millions of parameters depending on the ‘task’
- In animal science we work with…. 20?, 30?, 50? parameters



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



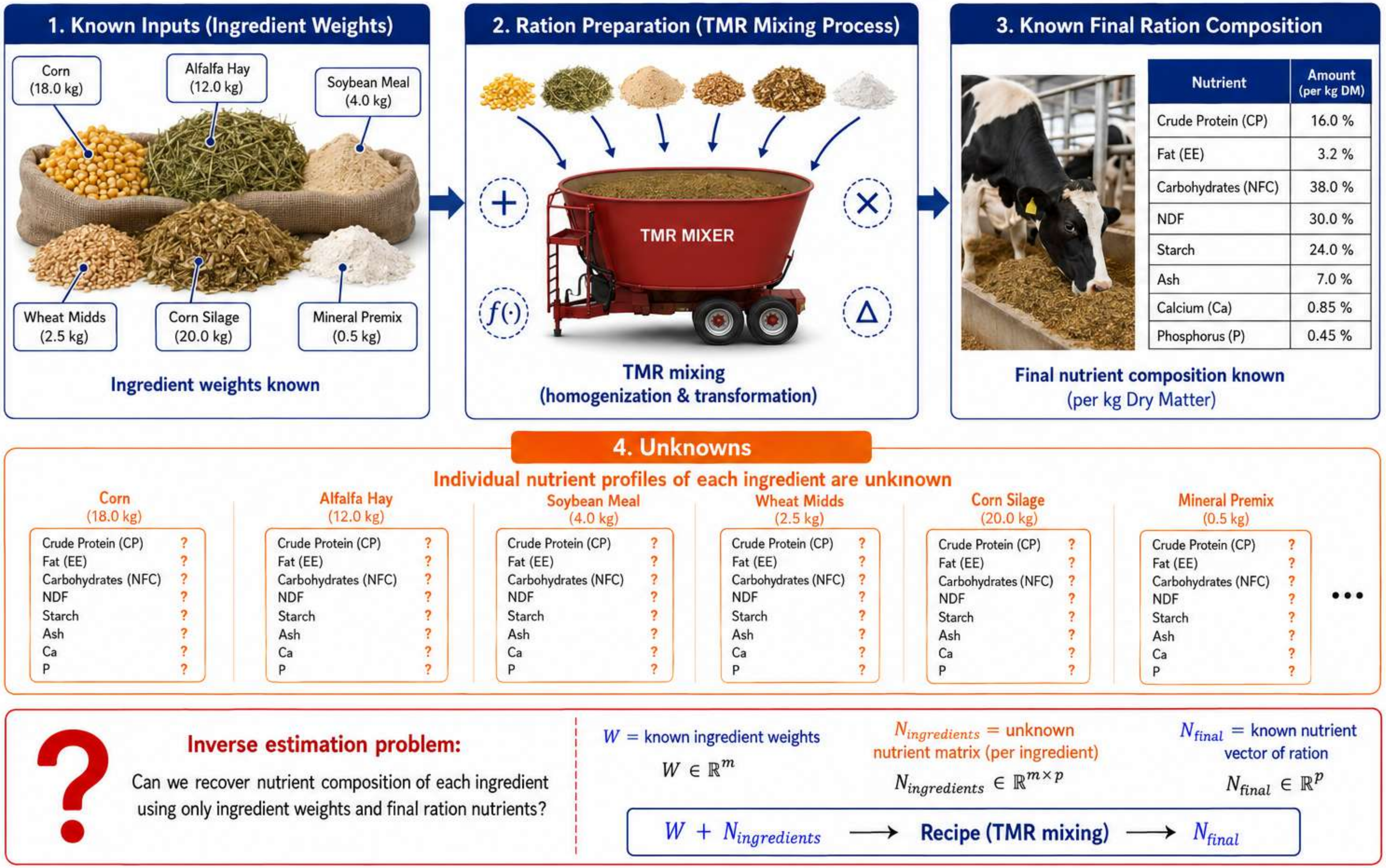
Data

- 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



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

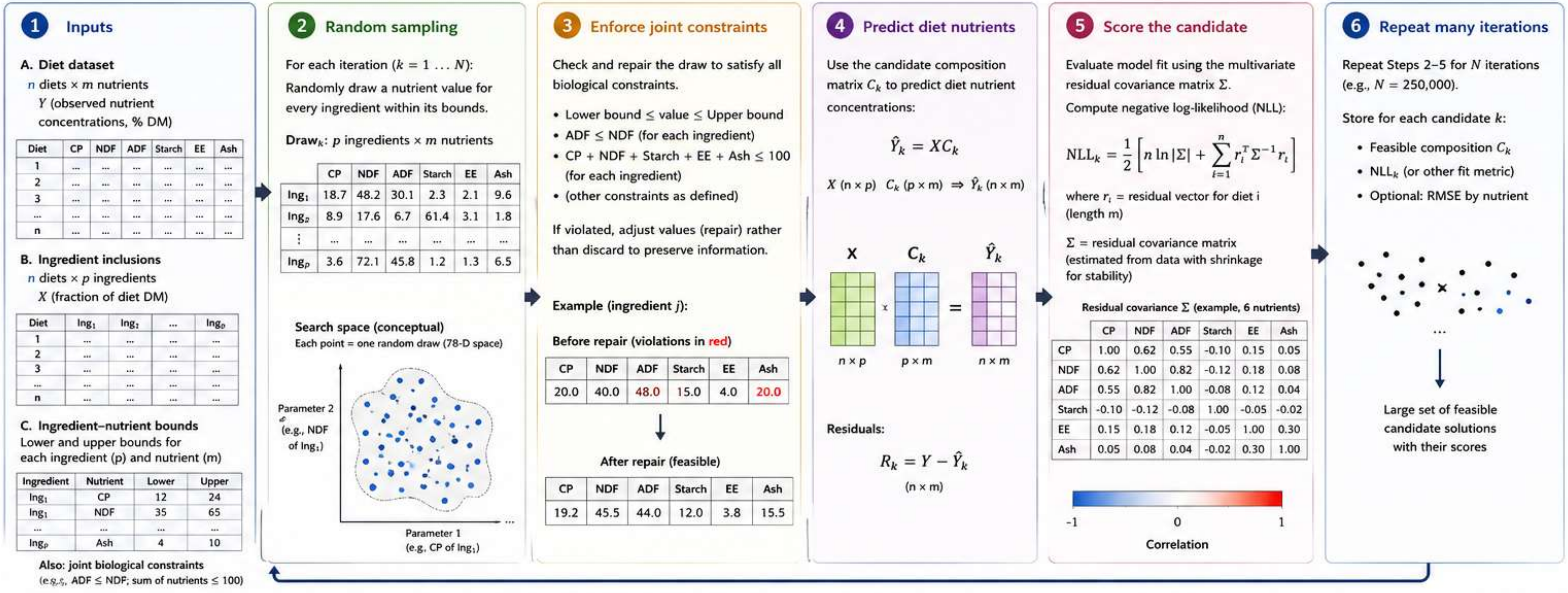
- This becomes a regression problem:

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

Artificial Intelligence

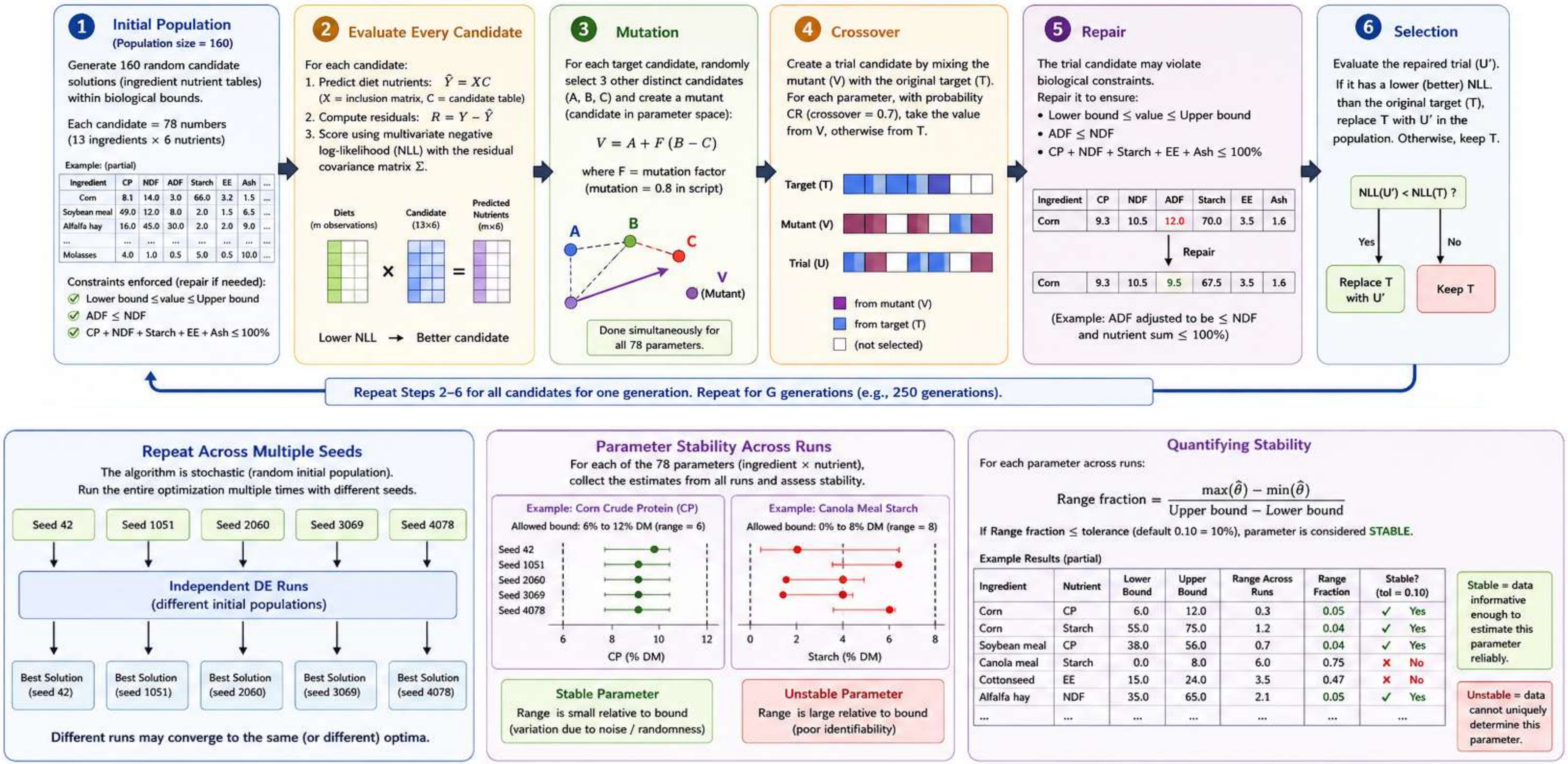
- We could try regression, but.. a more efficient approach could be:
- Constrained Montecarlo search
  - Randomly samples plausible ingredient nutrient values from biological bounds
  - Enforces constraints such as ADF ≤ NDF and CP + NDF + starch + fat + ash ≤ 100% DM, then keeps the best-fitting values

Machine Learning

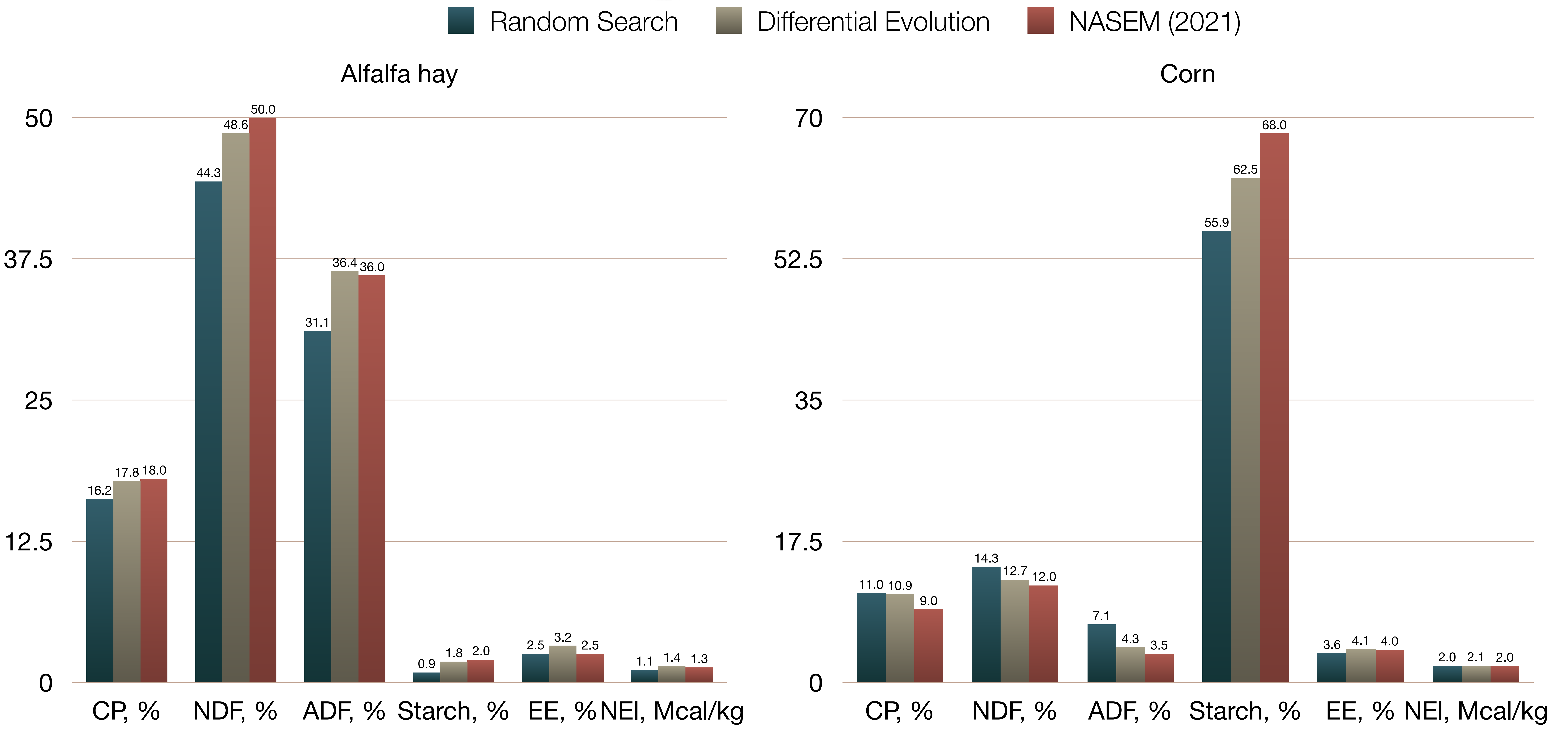


Artificial Intelligence

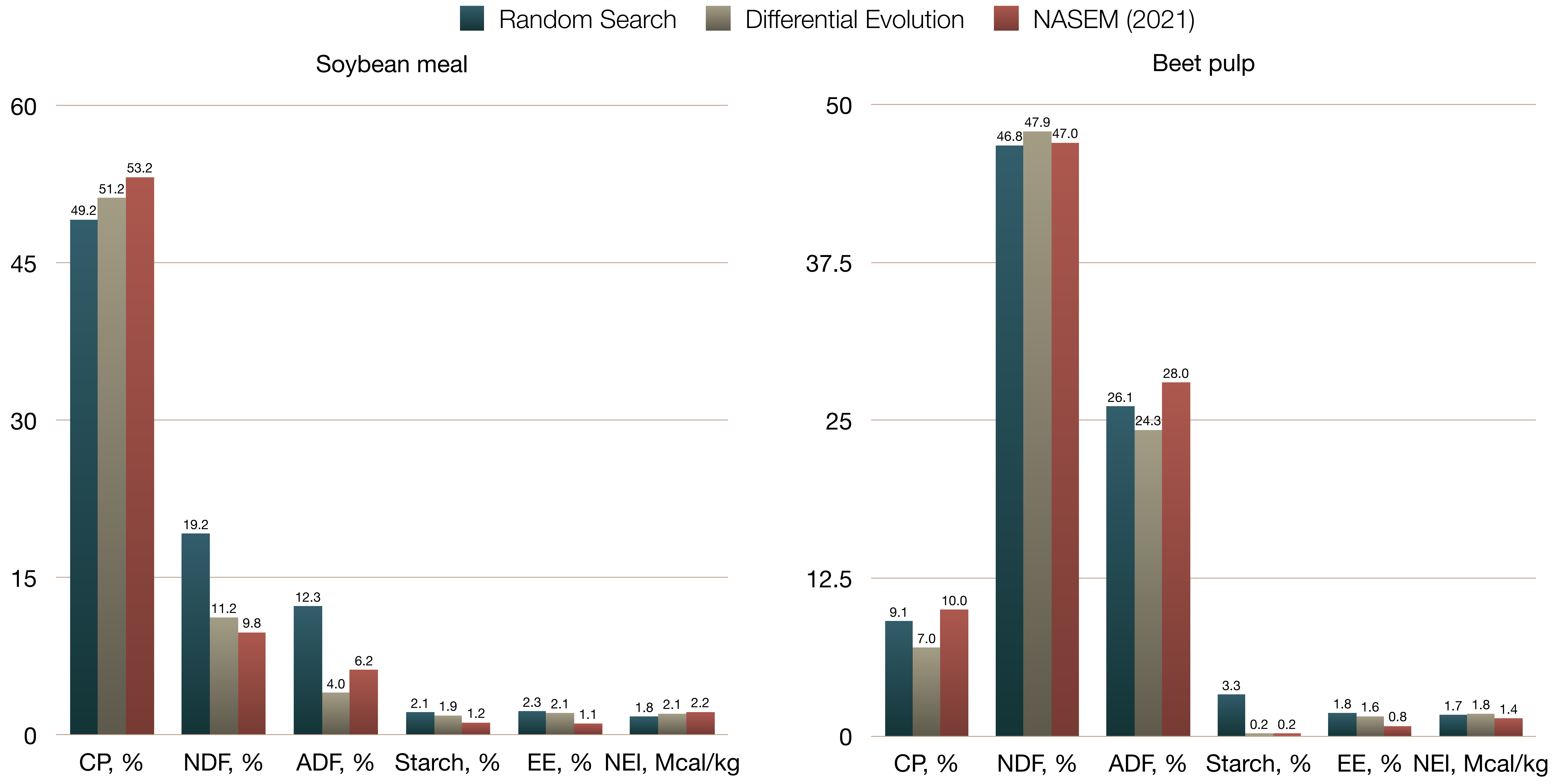
☆ Constrained differential evolution



Artificial Intelligence

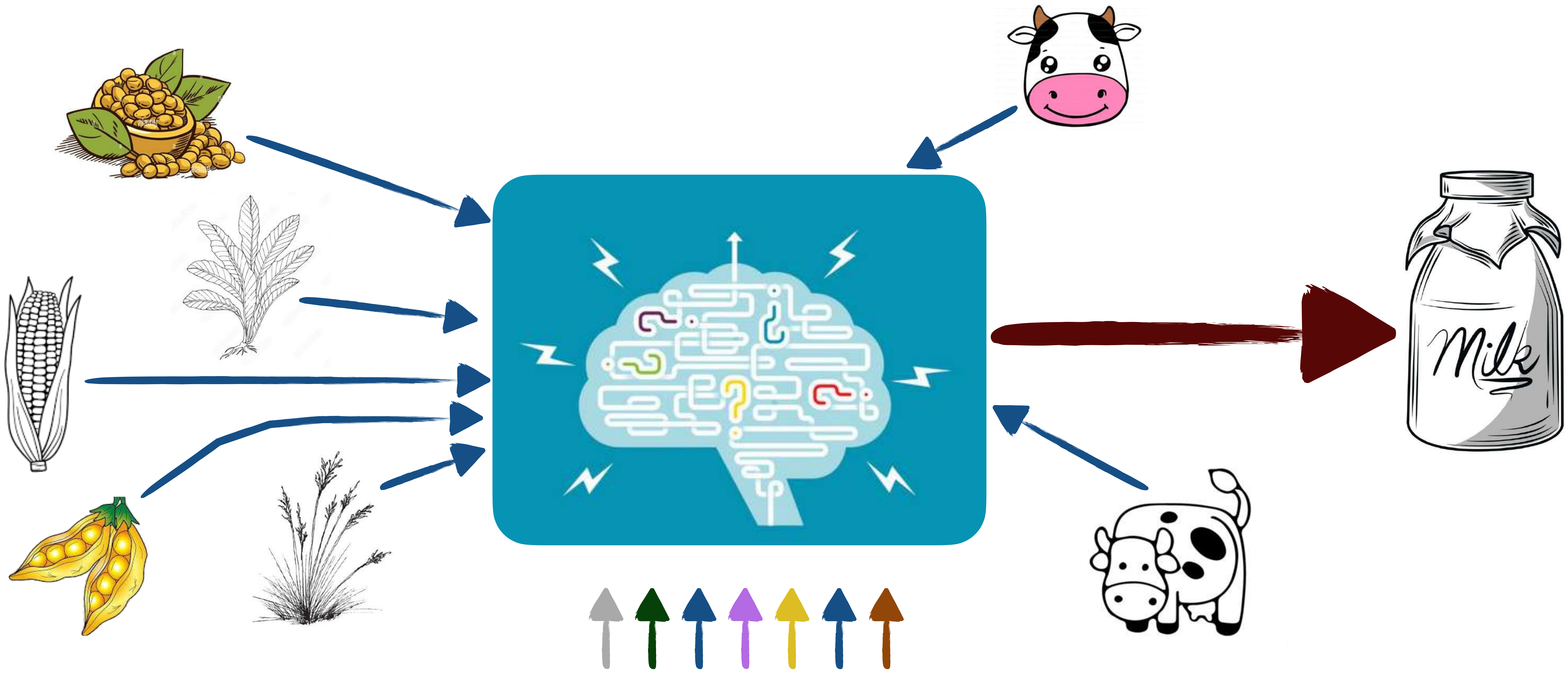


Artificial Intelligence



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

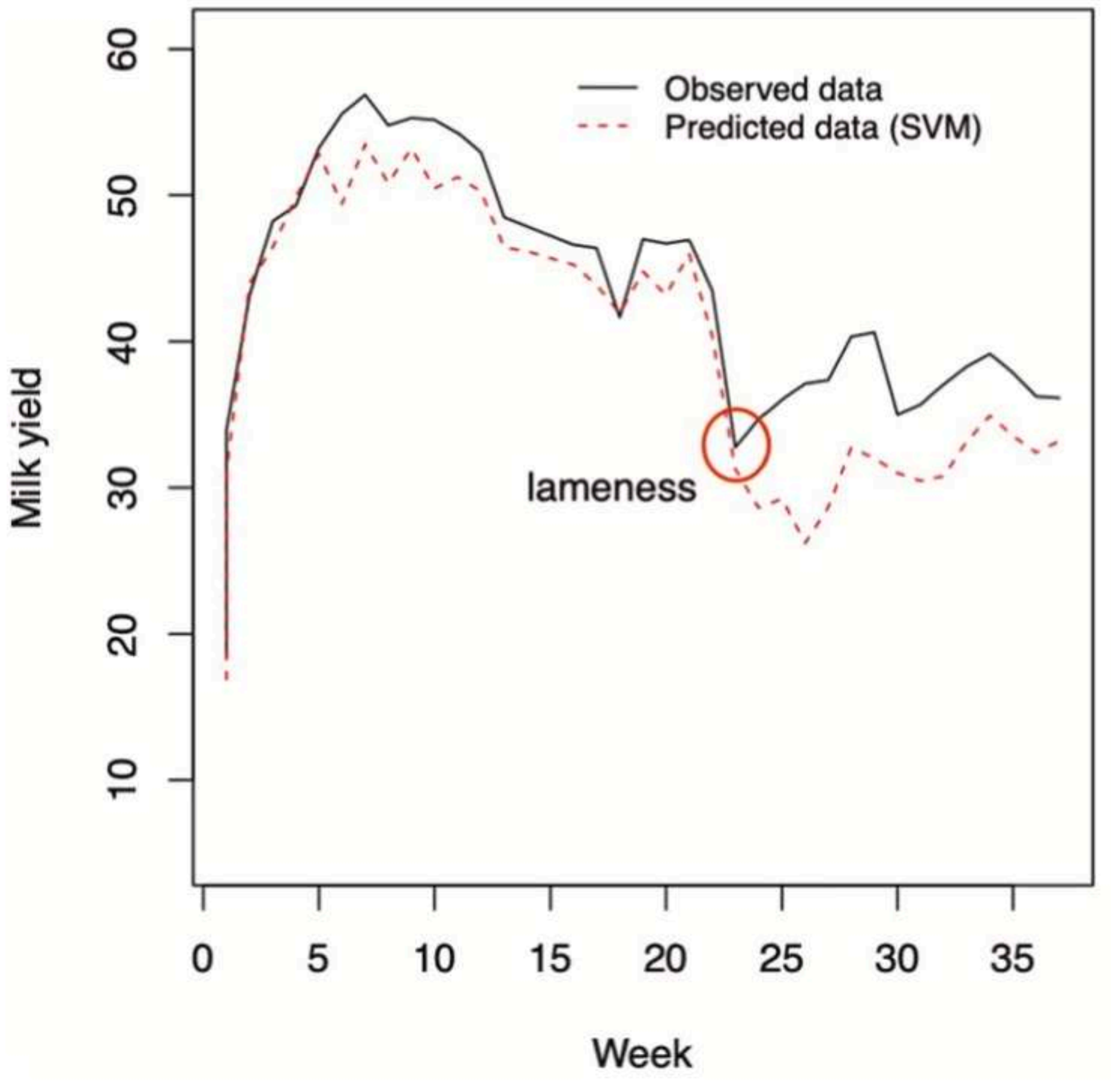
- This approach should result in more precise estimates of nutritional values of ingredients (or rations) than chemical or NIR analyses (they lack the animal response)

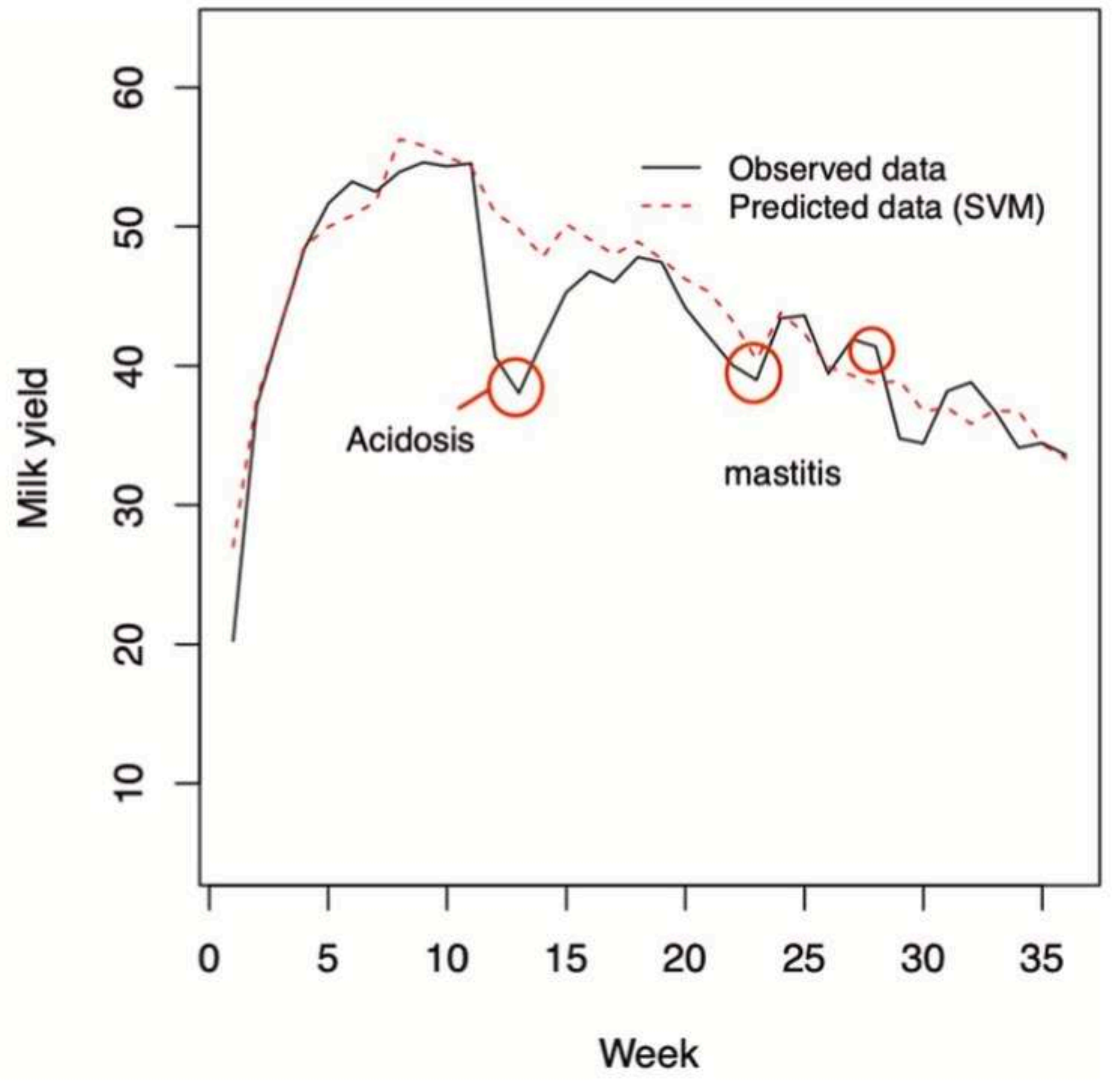
Machine Learning

- 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:

$$\textit{Milk yield}_{it} = f(\textit{ingredients}_{it}, \textit{DIM}_{it}, \textit{parity}_{i}, \mathrm{DMI}_{it}, \textit{farm}, \textit{season}\ldots) + \mathrm{error}$$

- 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

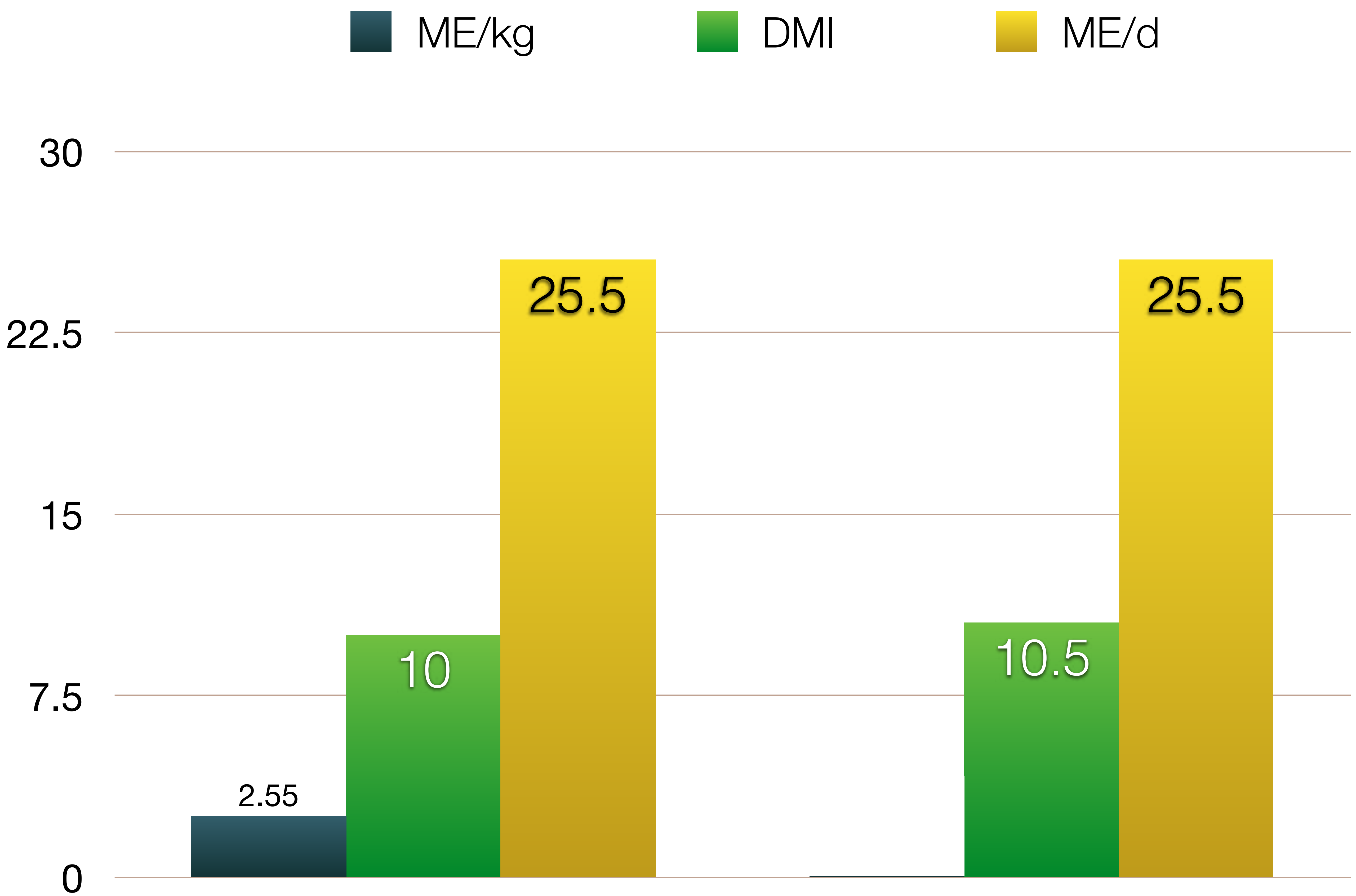
Ingredient	kg of DM/d
Alfalfa hay	2.51
Alfalfa silage	5.88
Corn	5.80
Corn silage	4.62
Barley grain	0.90
Soybean meal	2.19
Canola meal	0.97
Soybean hulls	0.96
Corn ddgs	0.22
Cottonseed whole	0.43
Beet pulp	0.85
Straw	0.30

Predicted DMI: 26.3 kg/d

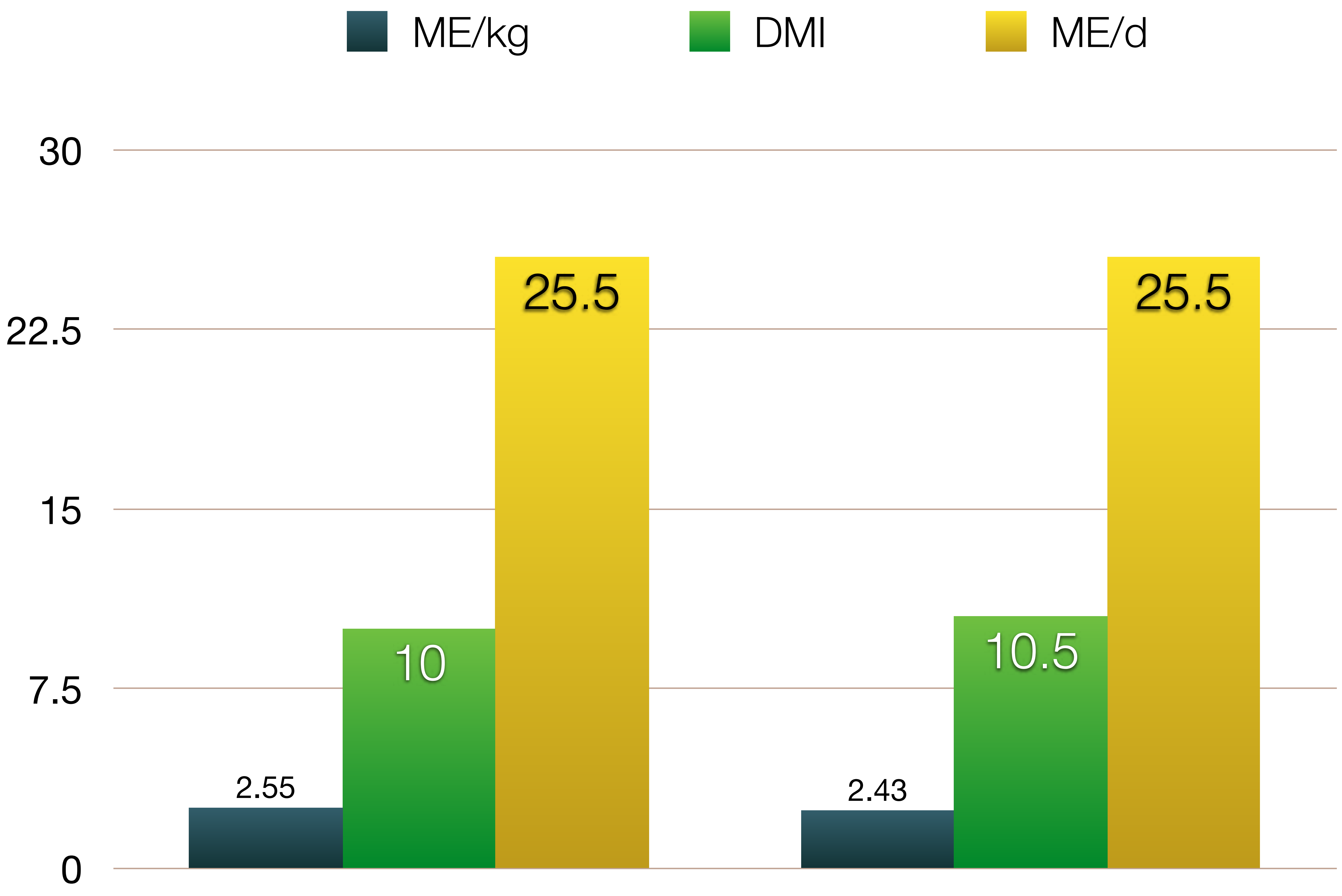
Machine Learning

- 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

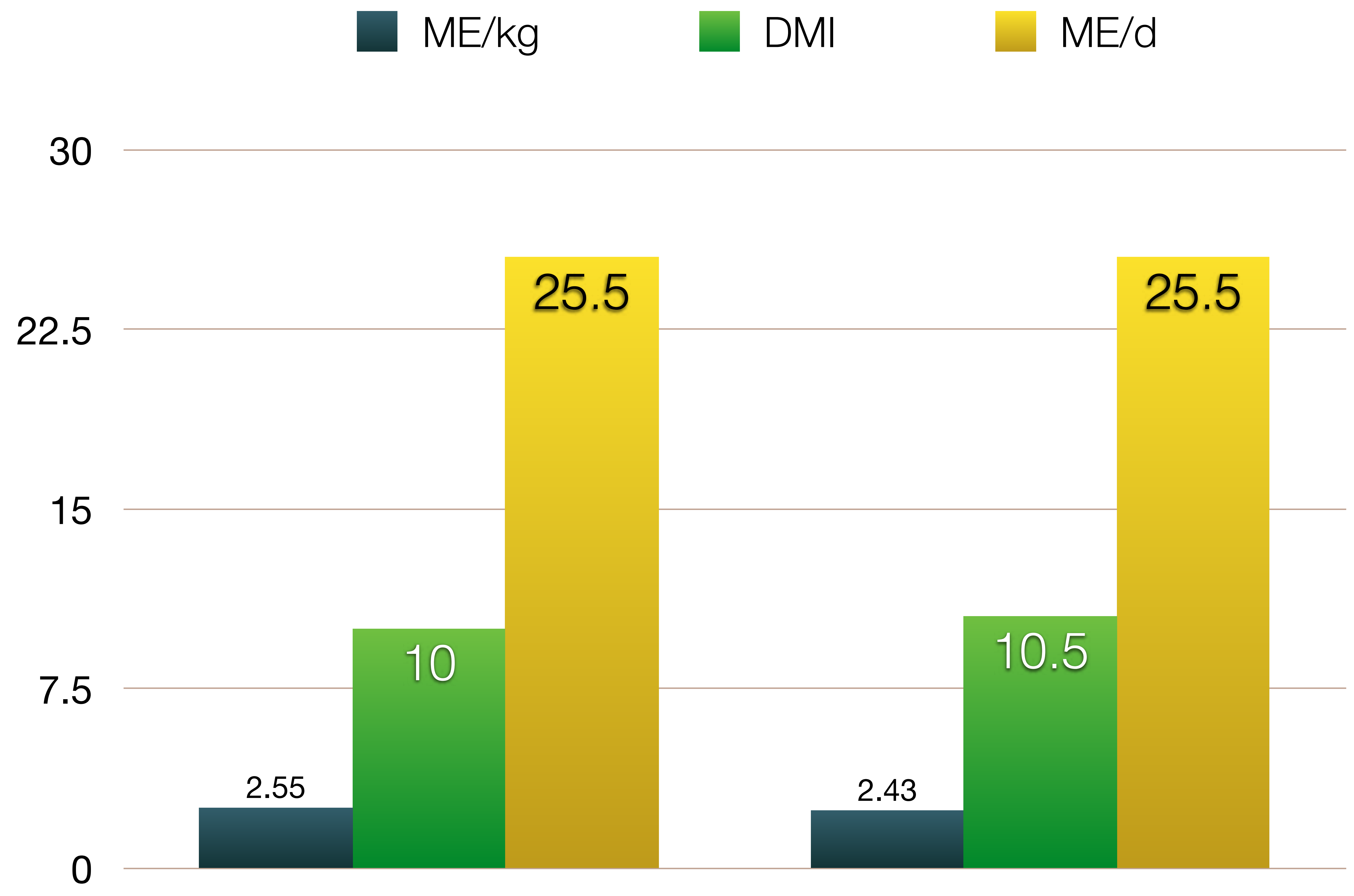


Machine Learning



Machine Learning

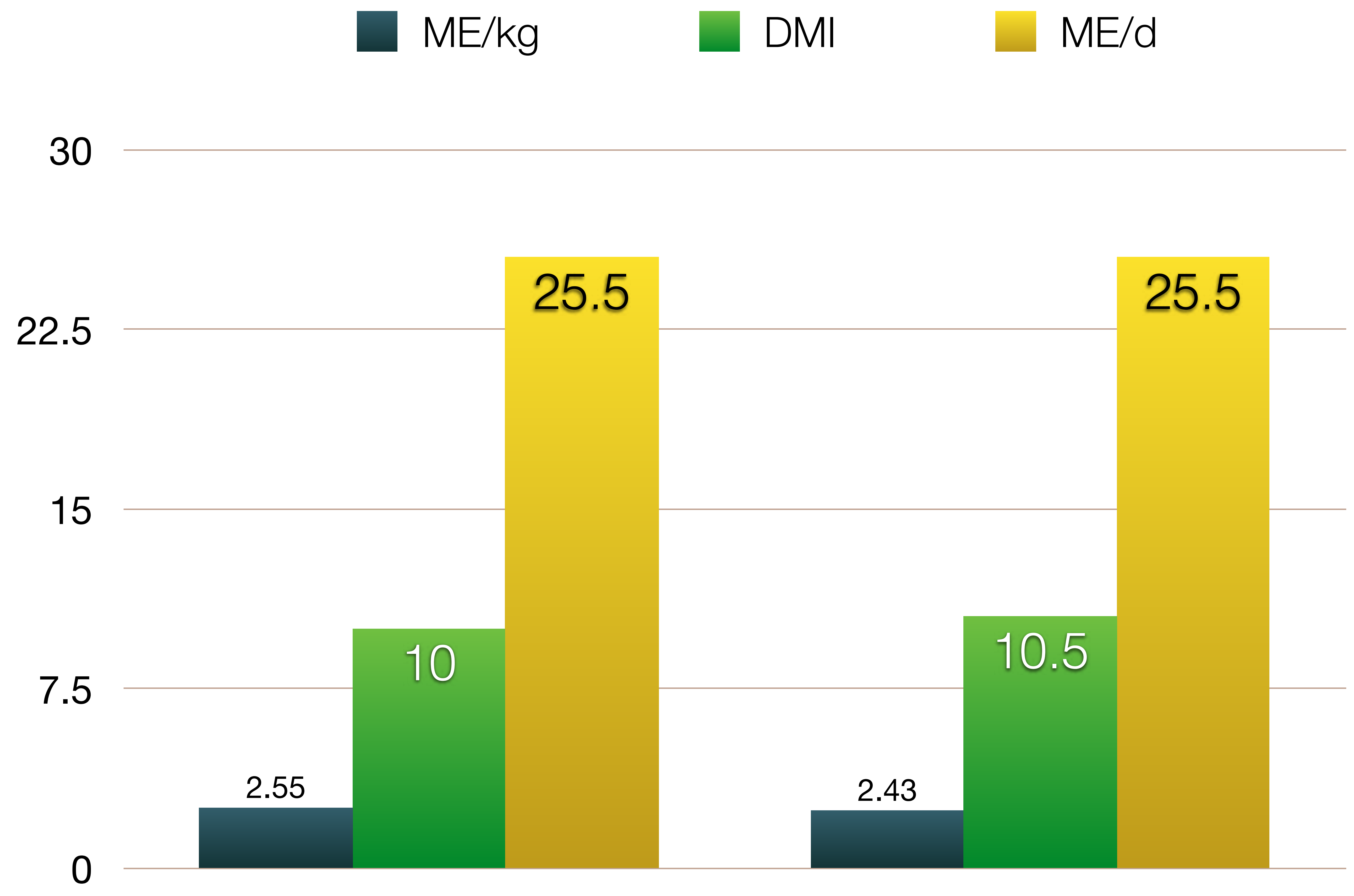
203 €/TM ~ 2.03 €/d



Machine Learning

203 €/TM ~ 2.03 €/d

190 €/TM ~ 2.0 €/d



Machine Learning

203 €/TM ~ 2.03 €/d

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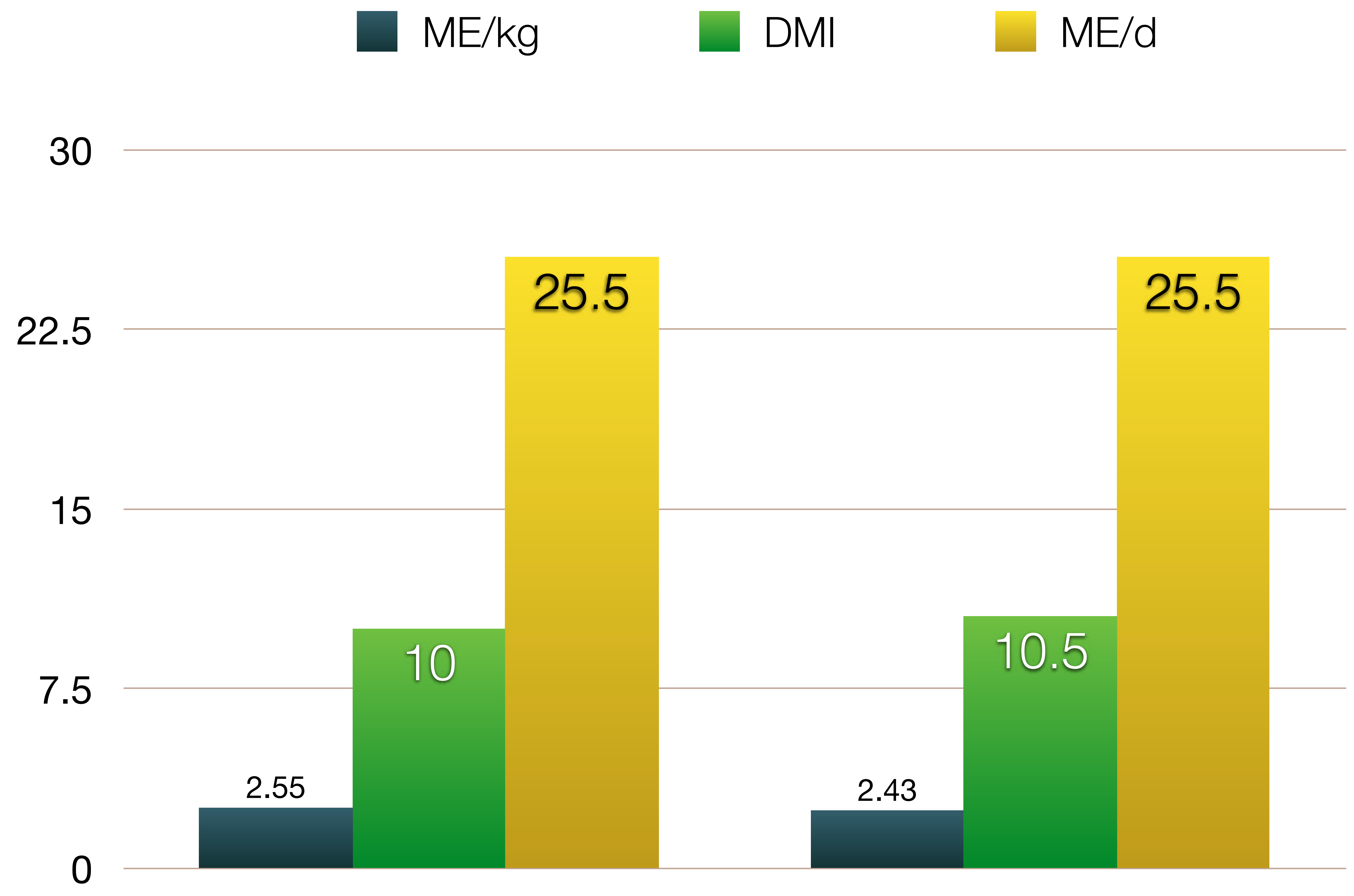


2.13 €/d

algoMilk
ALGORITHMIC DAIRYING

DAIRY

- Dashboard
- Pens
- Premixes
- Concentrates
- Rations
- Loads
- Stock
- Milk
- Environment
- Optimization
  - Grouping
  - Ration optimizer
  - Comparator
  - Animal value
  - Dry-off
- Nutritionist

COMPARATOR

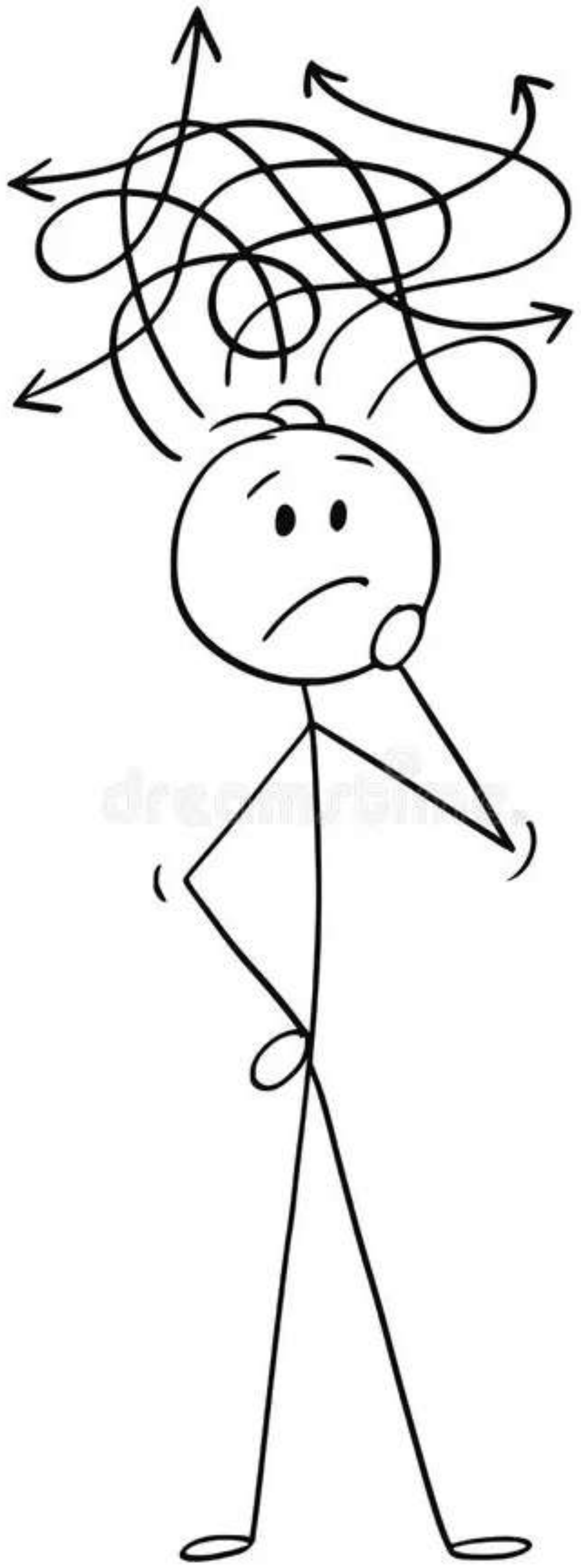
Add ration

	INTERMEDIE	*INTERMEDIE (SUGGESTED)
AS FED (KG)	59.32	58.43
DRY MATTER (KG)	27.85 (27.49)	27.62
COST DRY MATTER (TON)	314.32	304.84
COST FORMULA (€/ DAY)	8.76 (8.64)	8.42
NUMBER OF COWS	151	151
TOTAL COST (€/ DAY)	1,322 (1,305)	1,271
IOFC (€/ DAY)	1,387 (1,341)	1,417
IOFC (€/ COW)	9.19 (8.88)	9.38

Ingredient	Intermedie	*Intermedie (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
H20	1.95	2.01
Trinciato mais	24.70	24.18
Insilato Orzo	13.00	13.39
Medica ensilata	2.60	0

Nutrient	Intermedie	*Intermedie (Suggested)
DM, kg/d	27.85 (46.96)	27.62 (47.27)
CP, kg/d	4.44 (15.92)	4.41 (15.97)
NEl, 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)

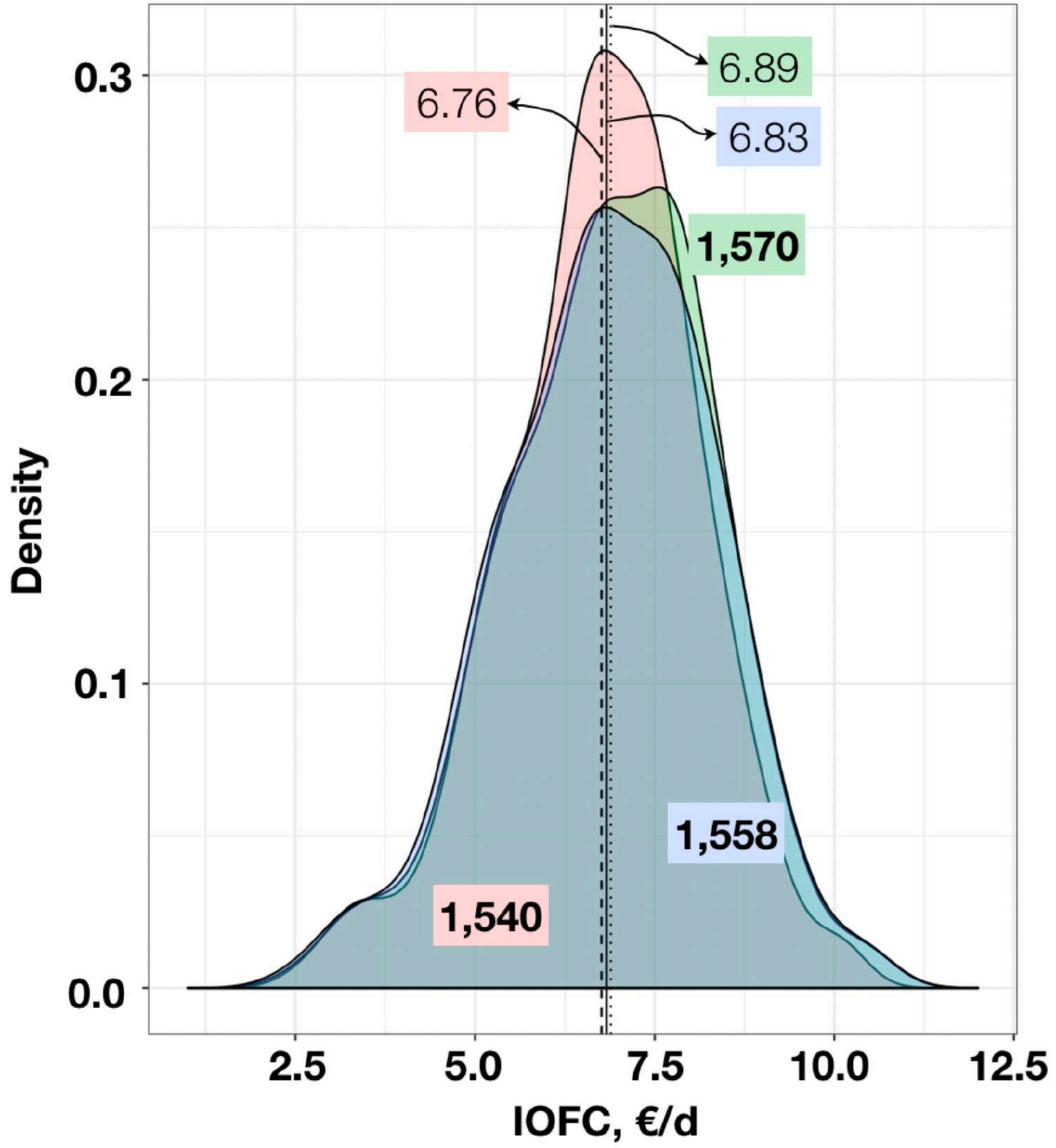
Machine Learning

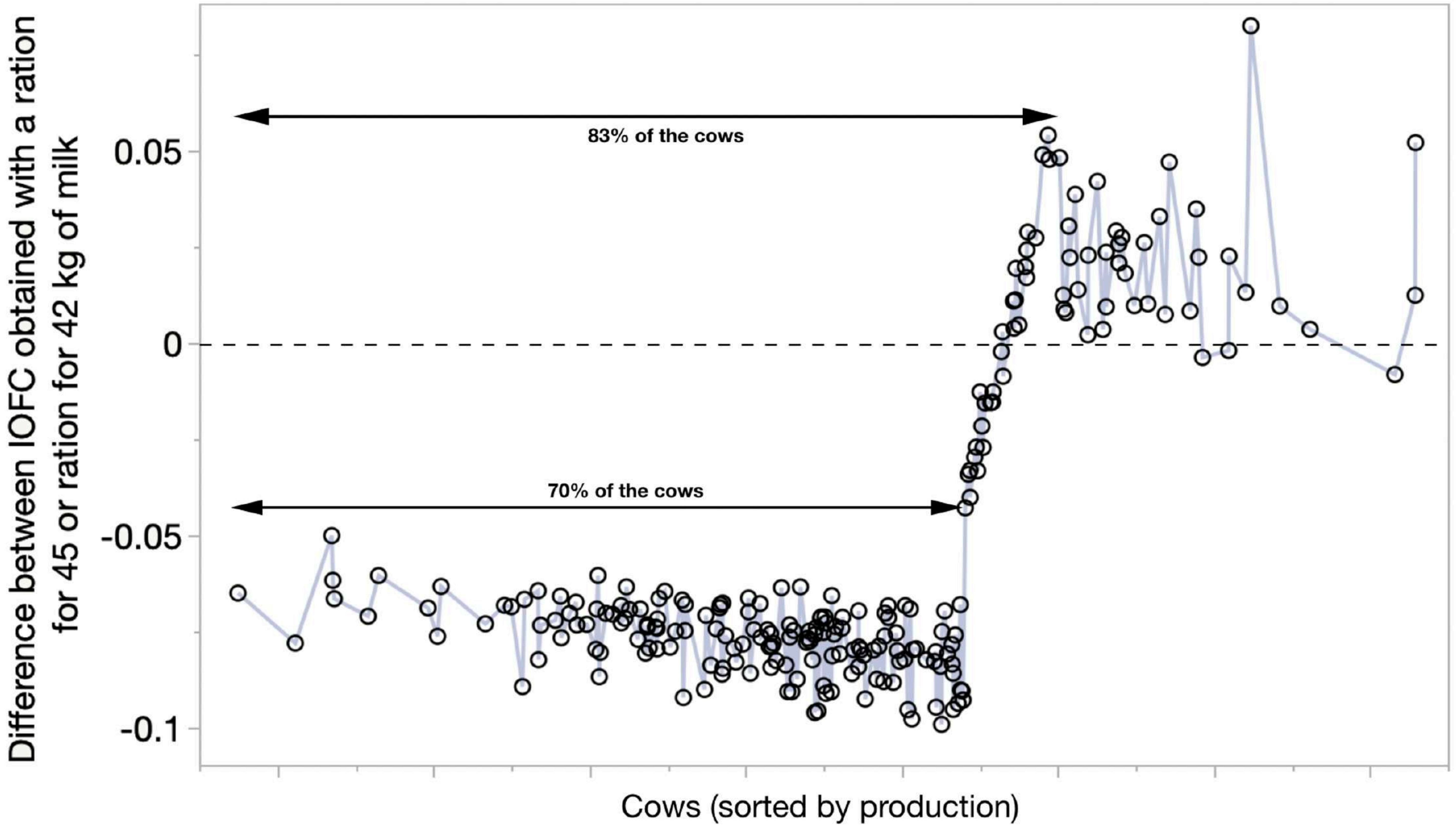


- Quite commonly, dry cows cows are split in two groups and fed 2 different rations
- But, lactating cows, are often fed a single ration (despite feeding animals that produce 15 or 70 liters)

Machine Learning

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





Bach et al. (2020)

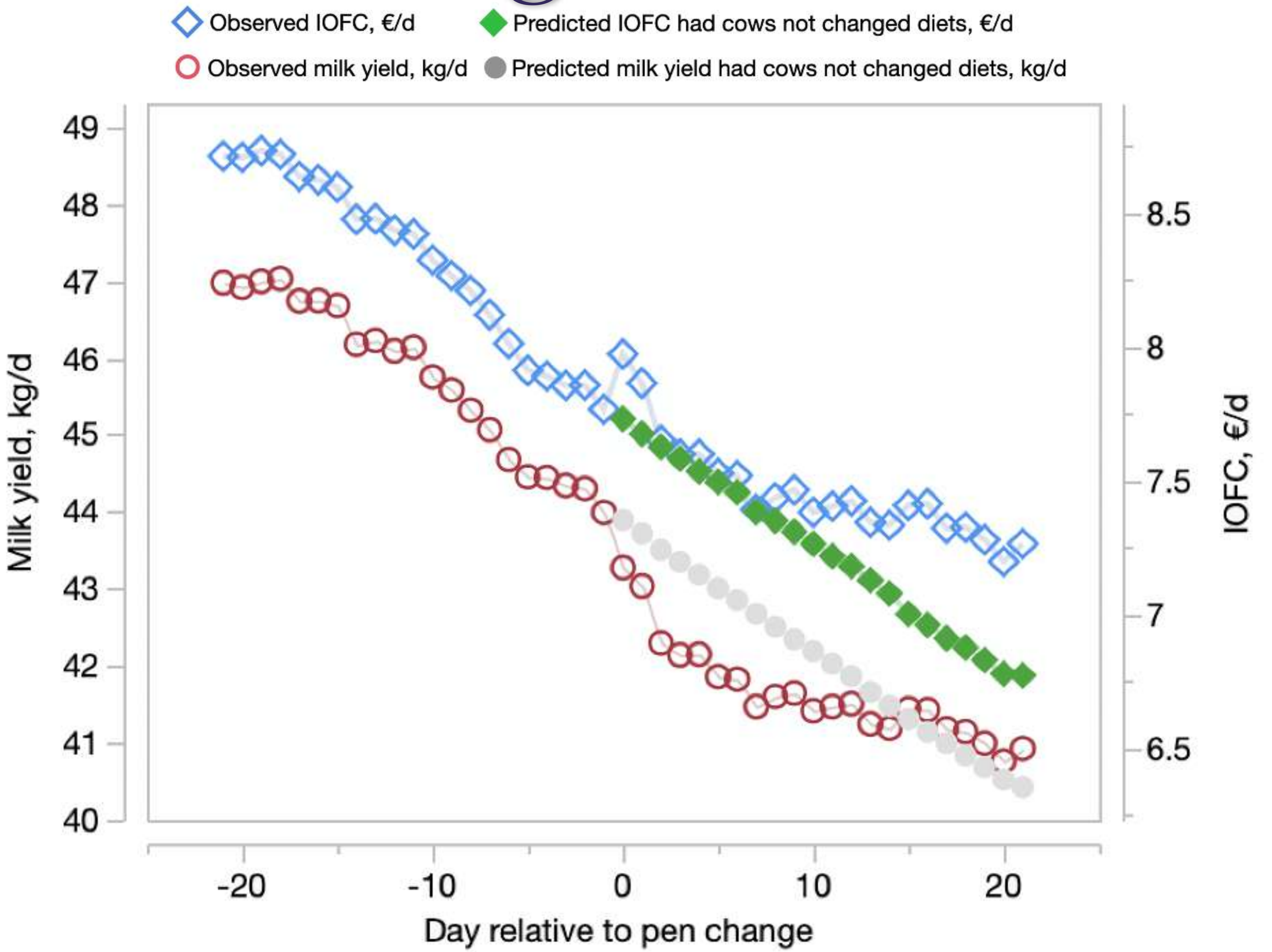
Machine Learning

	Ration		Ration		Ration		Ration	
	Initial	High	Initial	High	Initial	High	Initial	High
Cow	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

Bach (2025)

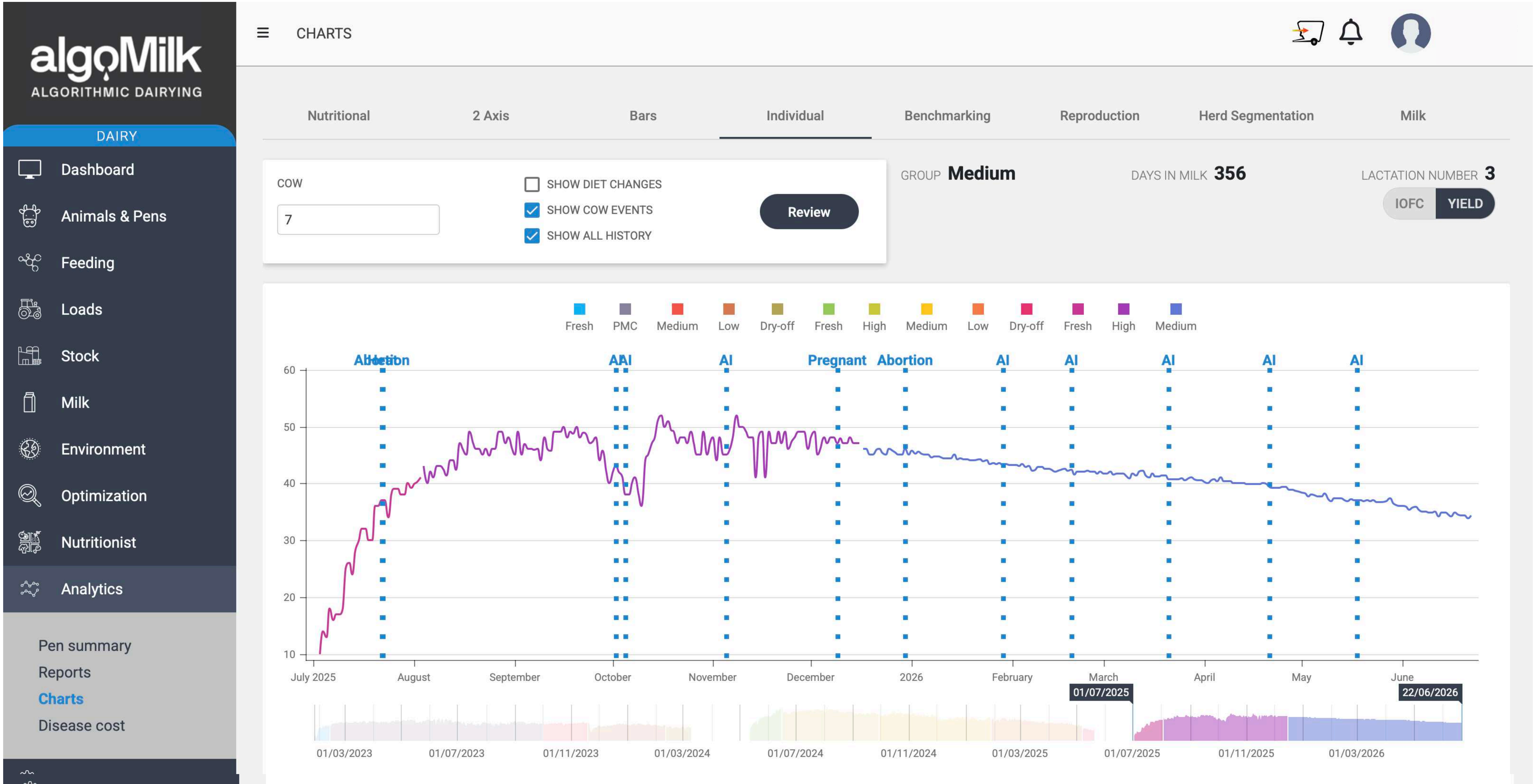
Machine Learning

High->Medium

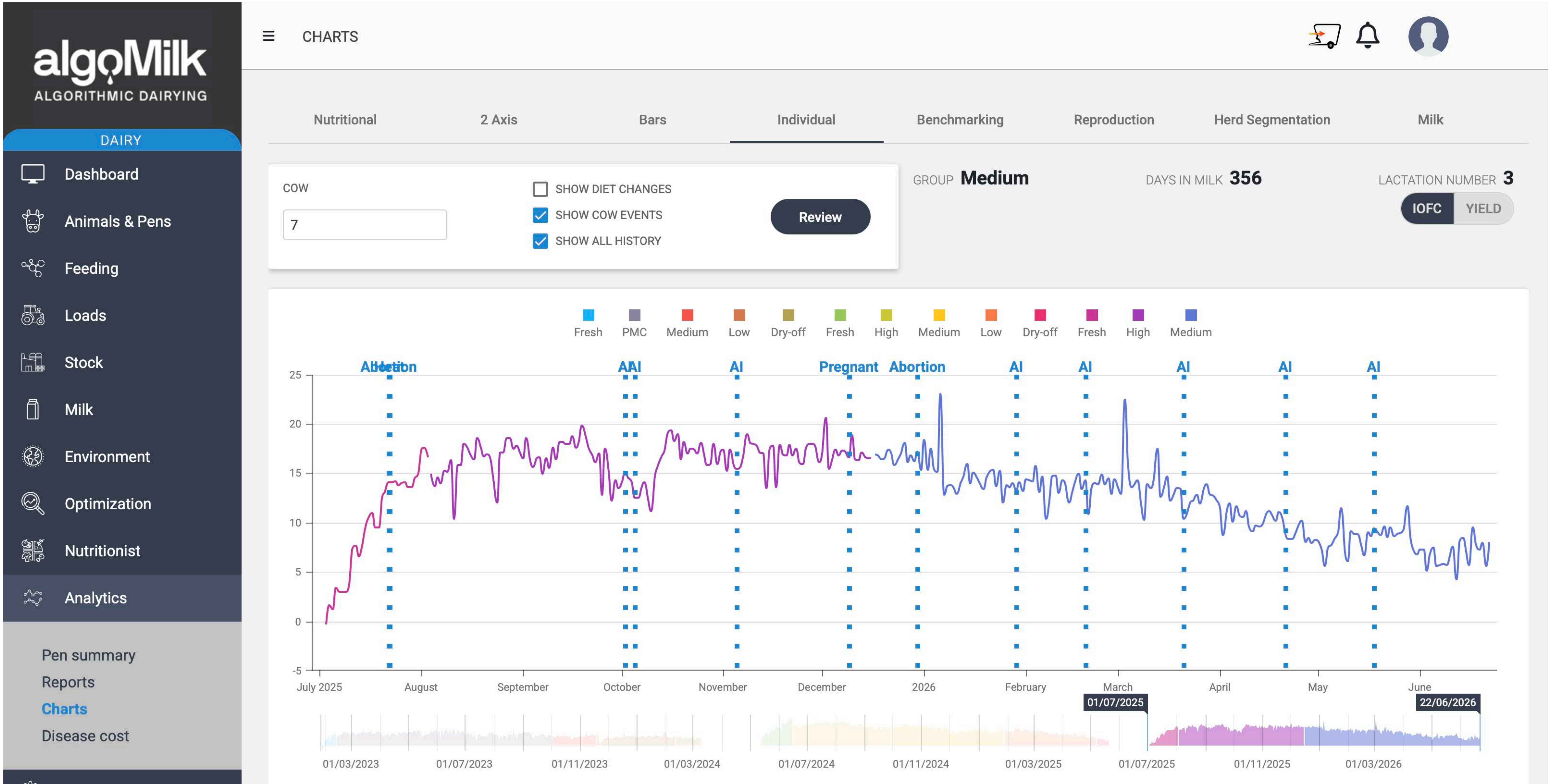


Bach (2023)

Machine Learning



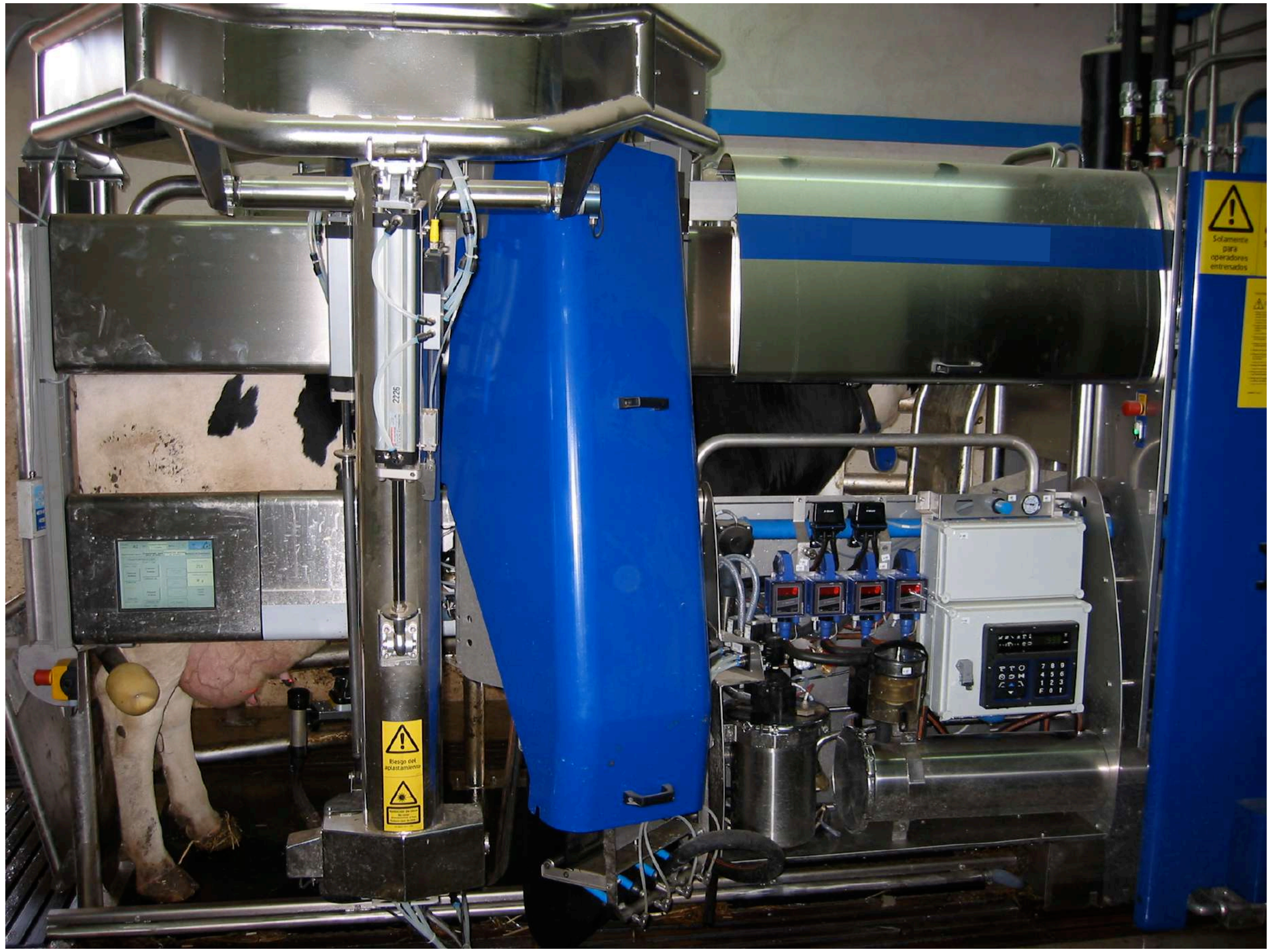
Machine Learning



Machine Learning

Machine Learning

Milking Robots/Batch milking/Feed Dispensers

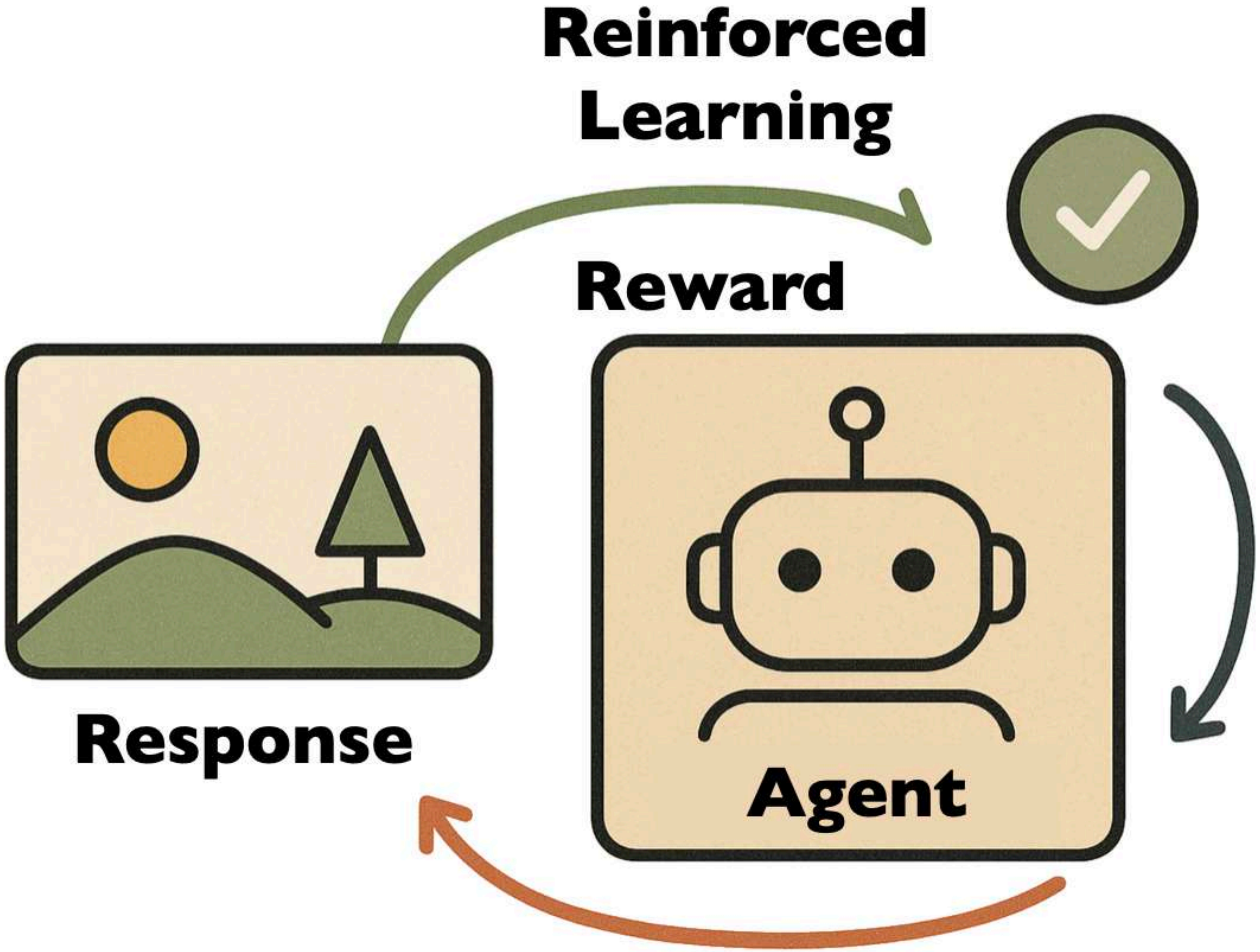


Milking Robots/Batch milking/Feed Dispensers

- 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

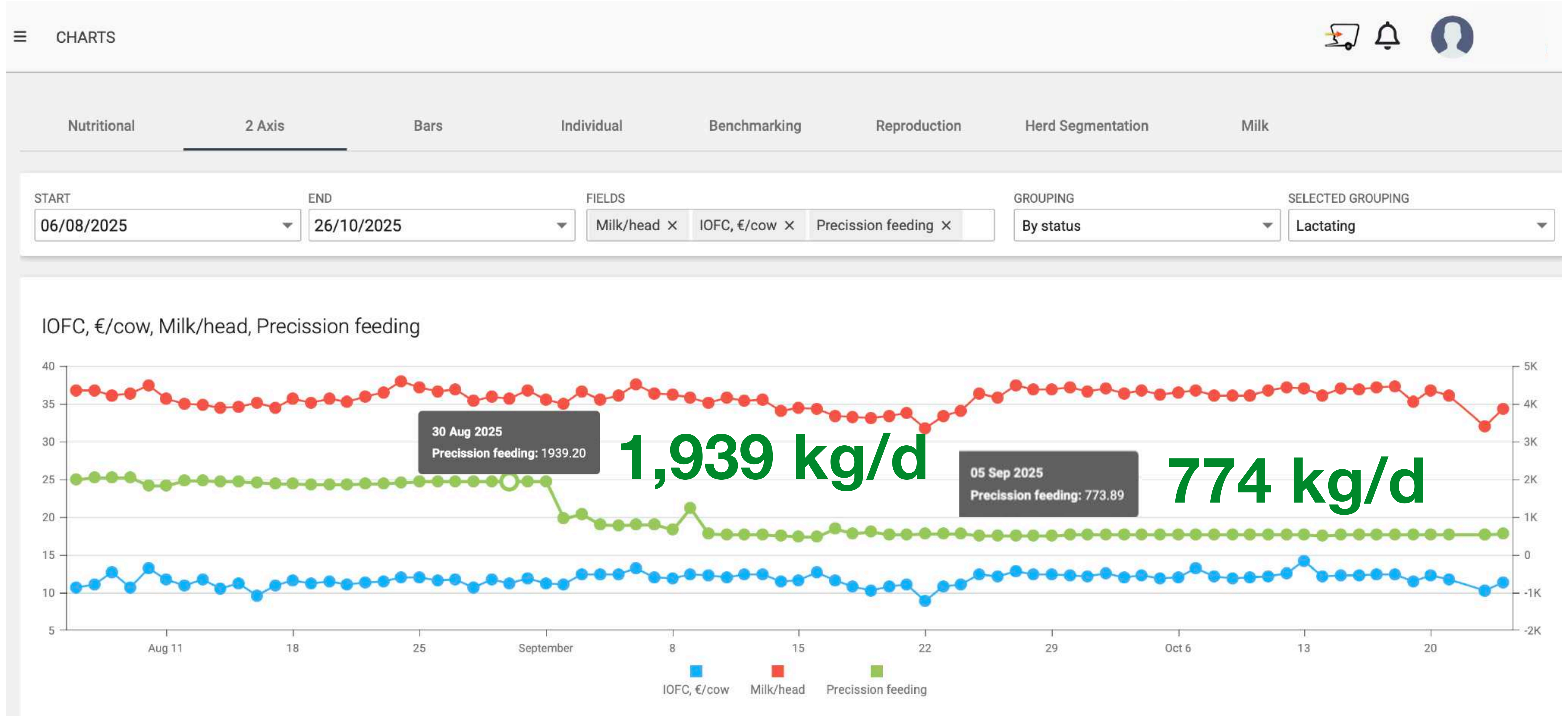
≡ PRECISION SUGGESTED

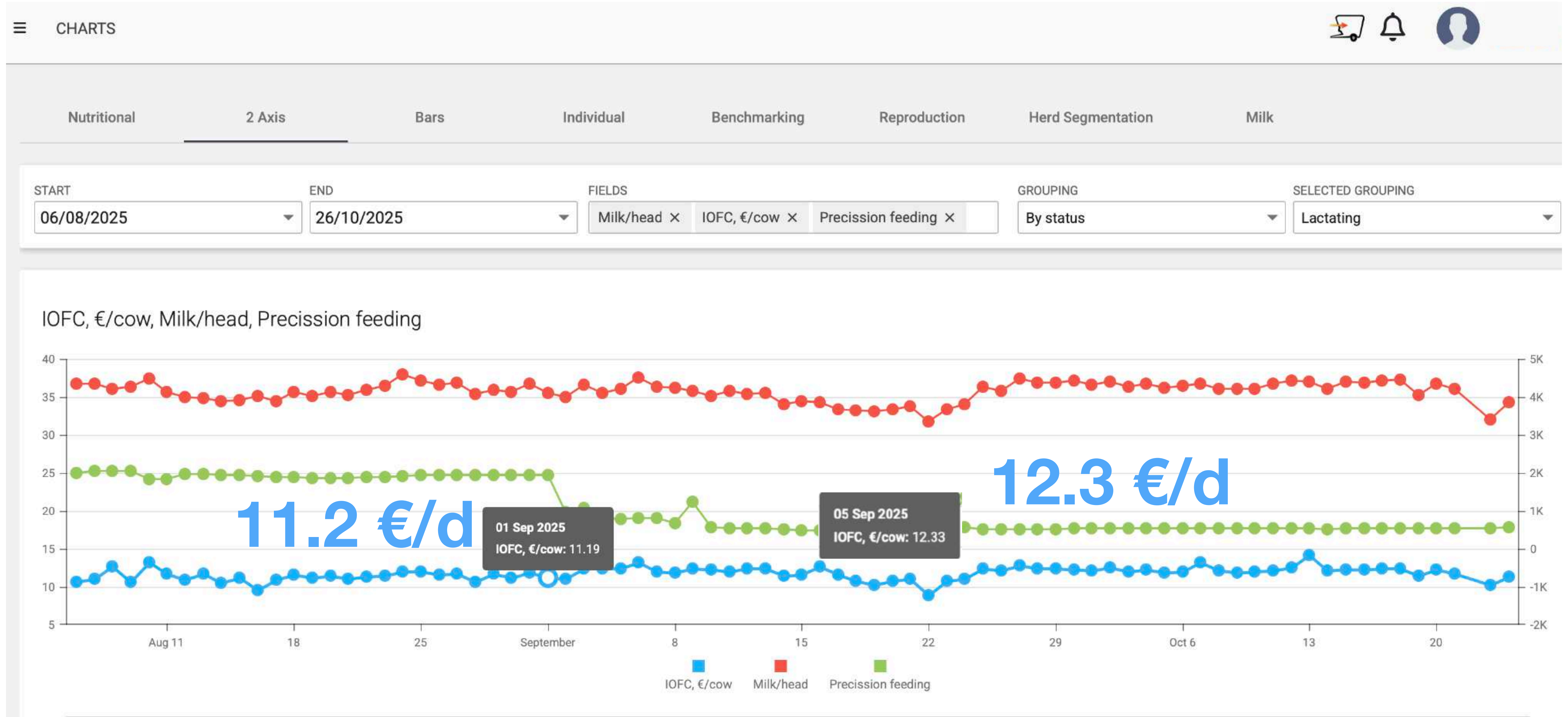
Export

Save

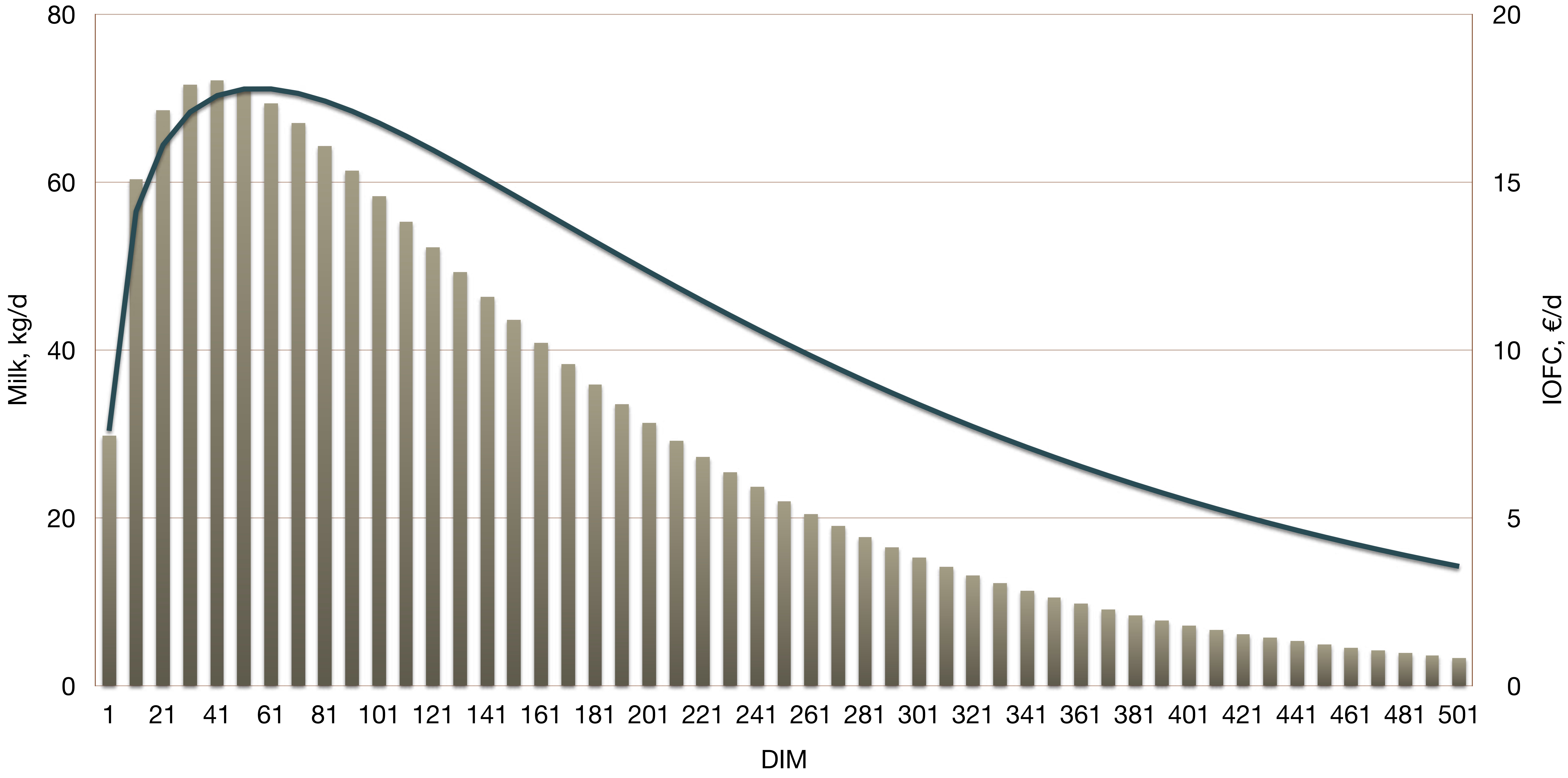
	Calculation Date	Cow	Lactation	Days in milk	Milk, kg/d	Ingredient	Quantity, kg	Suggested, kg	Difference
	23/06/2026	2012	1	512	34.93	PINSO ROBOT	1.68	0.64	-1.04
	23/06/2026	2015	2	164	49.96	PINSO ROBOT	3.3	3.05	-0.25
	23/06/2026	2017	2	93	57.2	PINSO ROBOT	2.98	2.69	-0.29
	23/06/2026	2028	1	499	25.09	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



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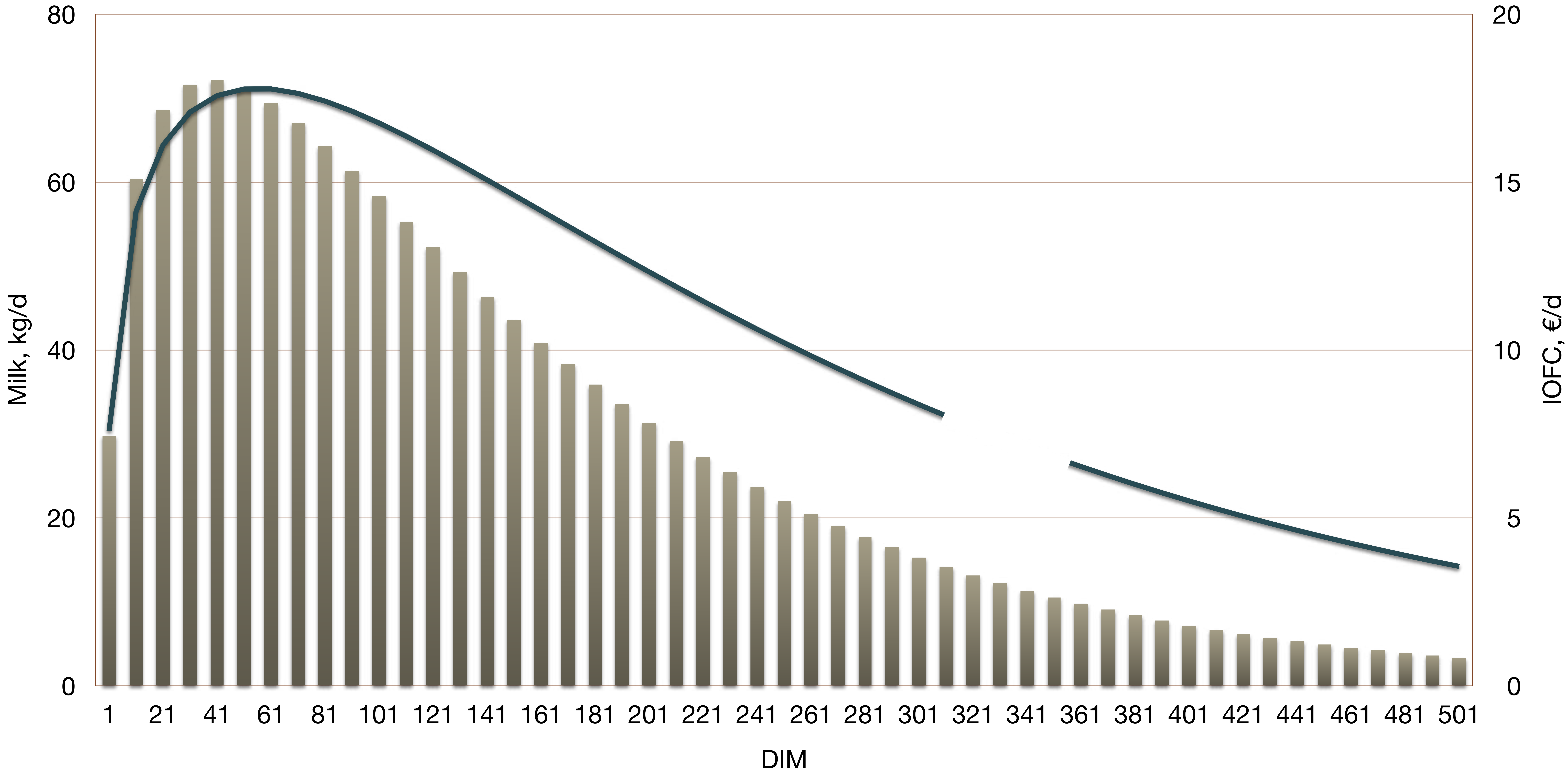

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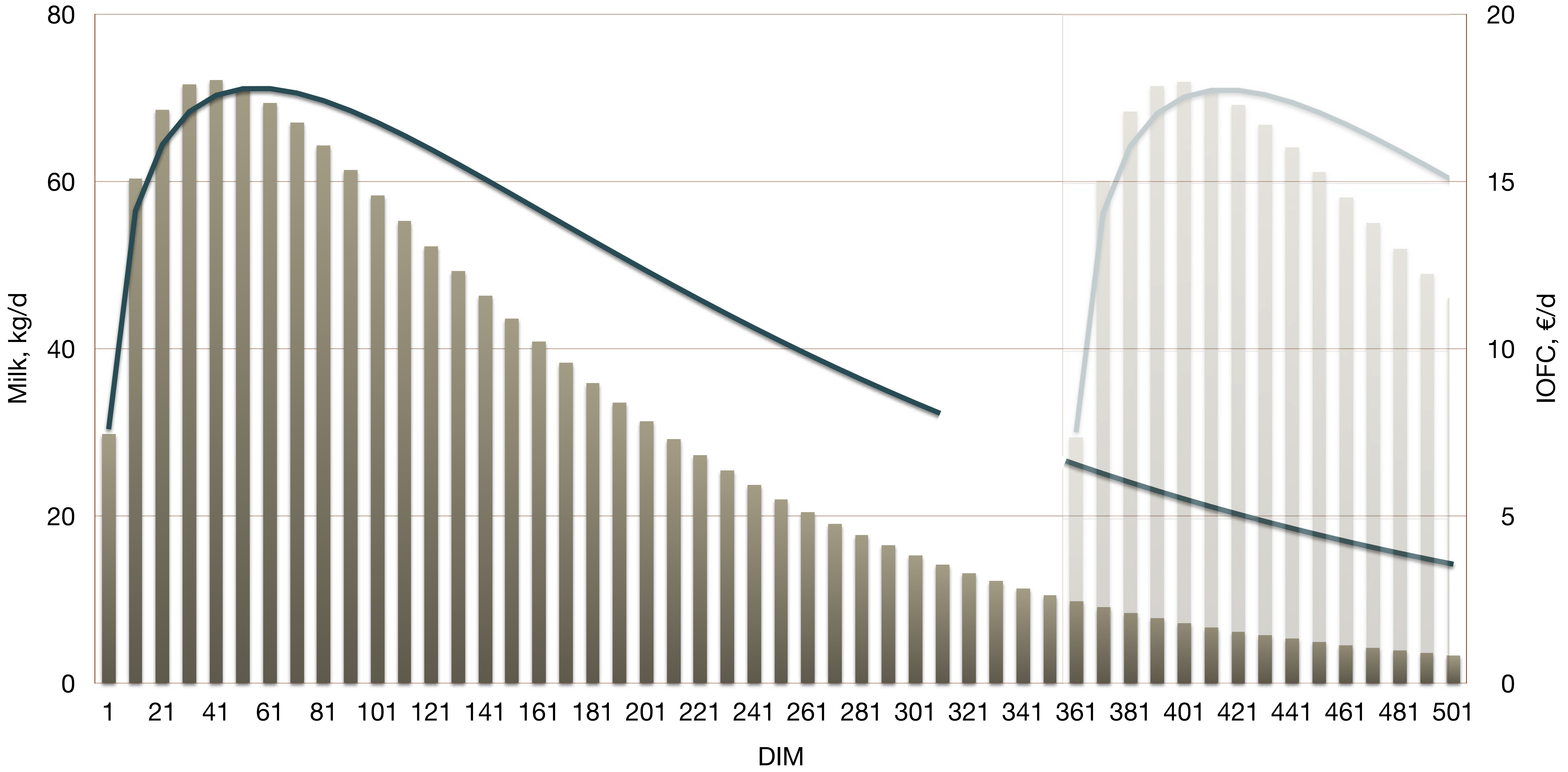

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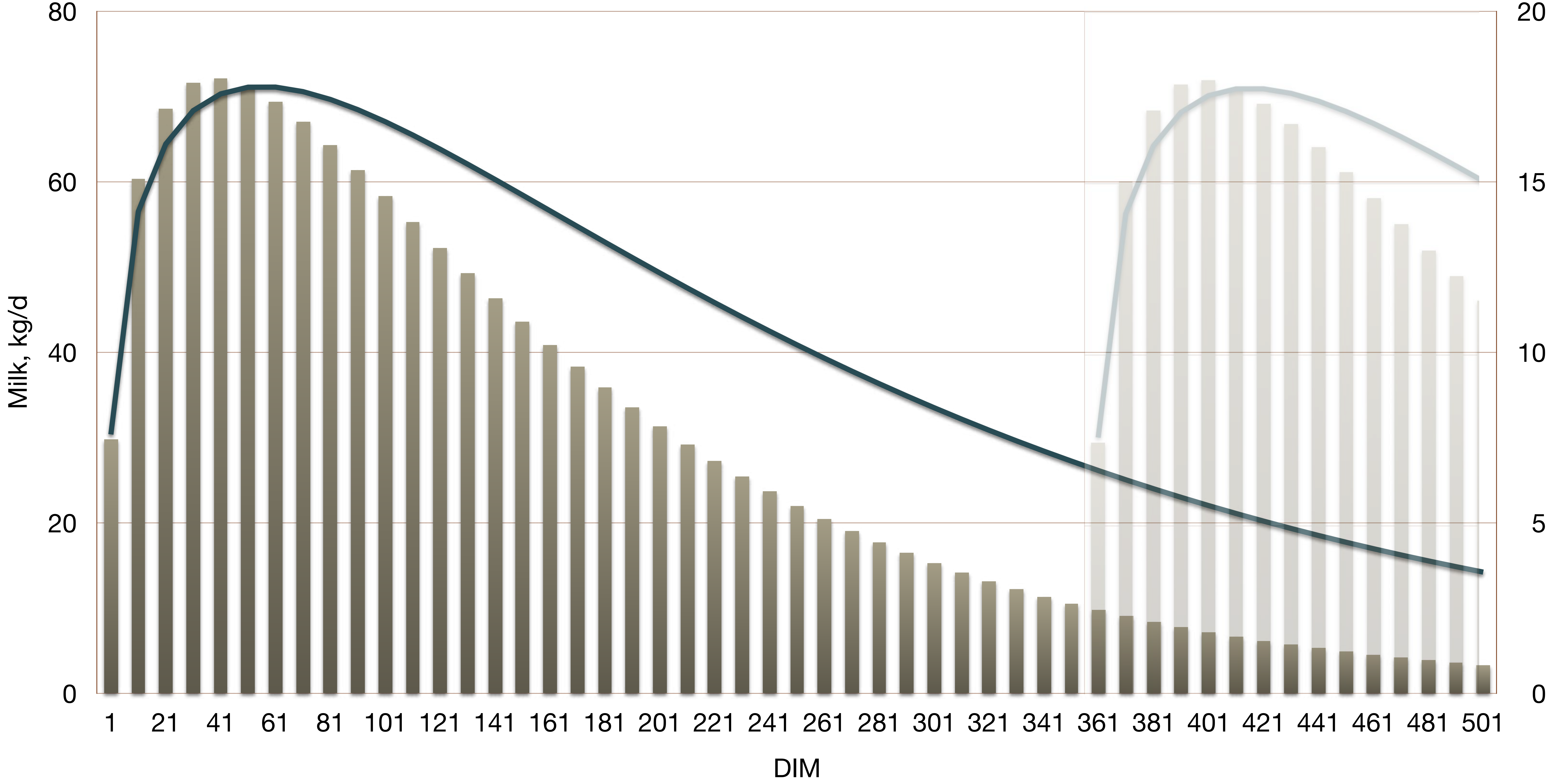

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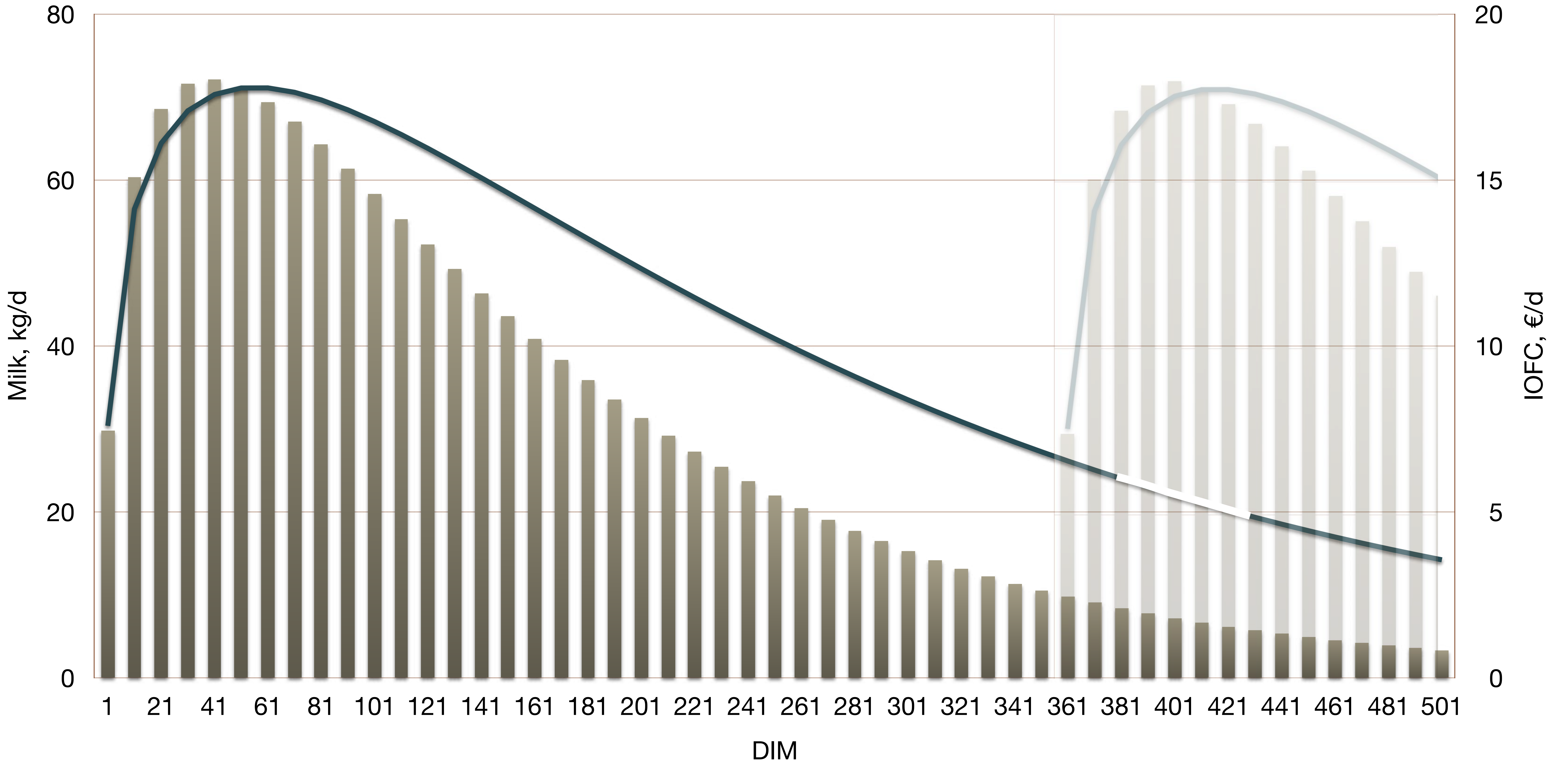

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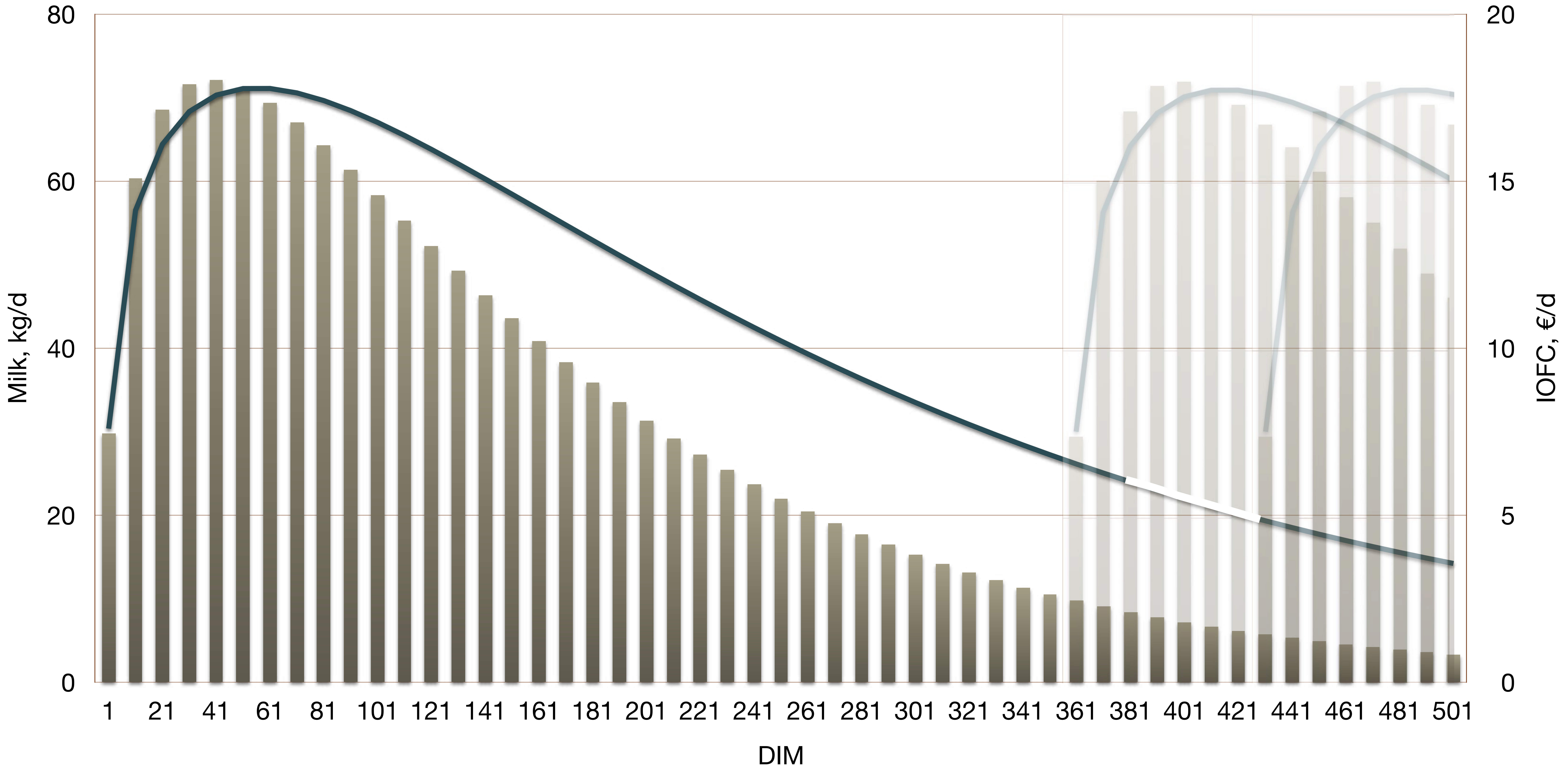

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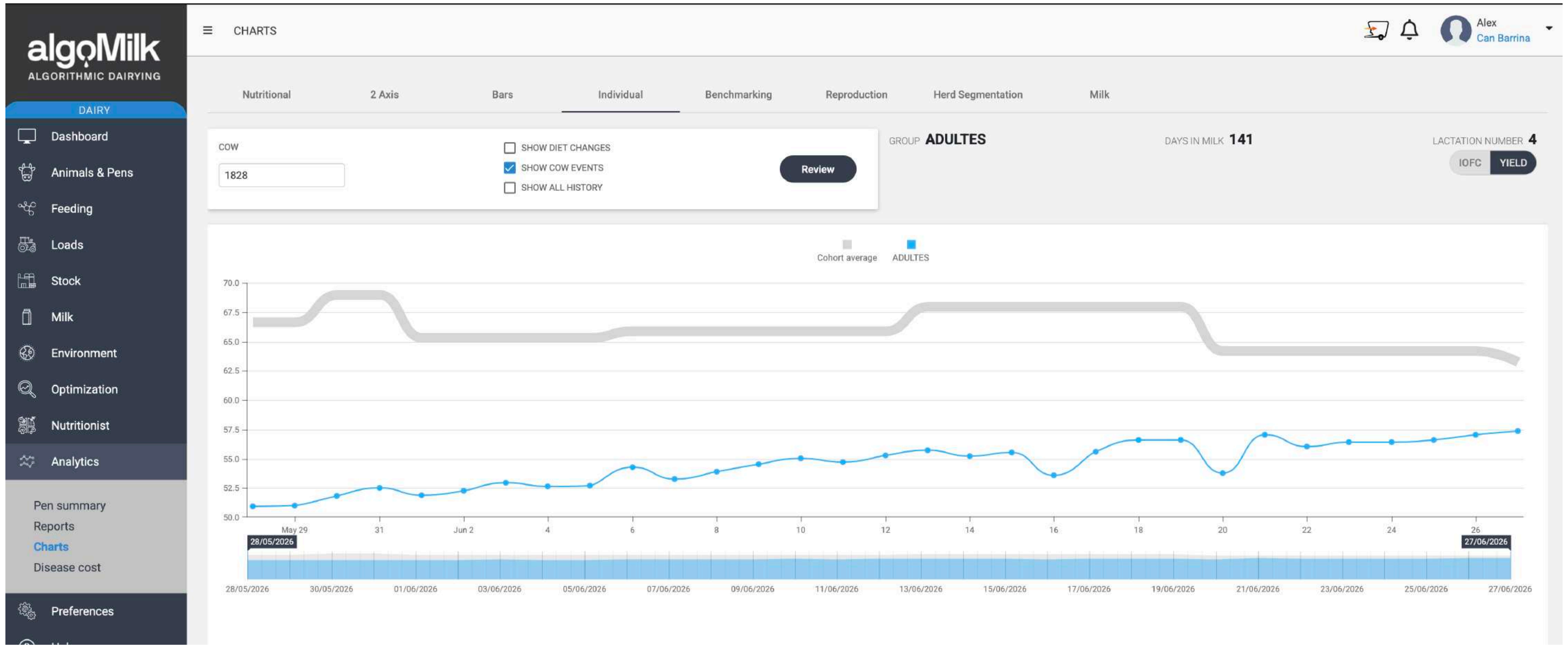

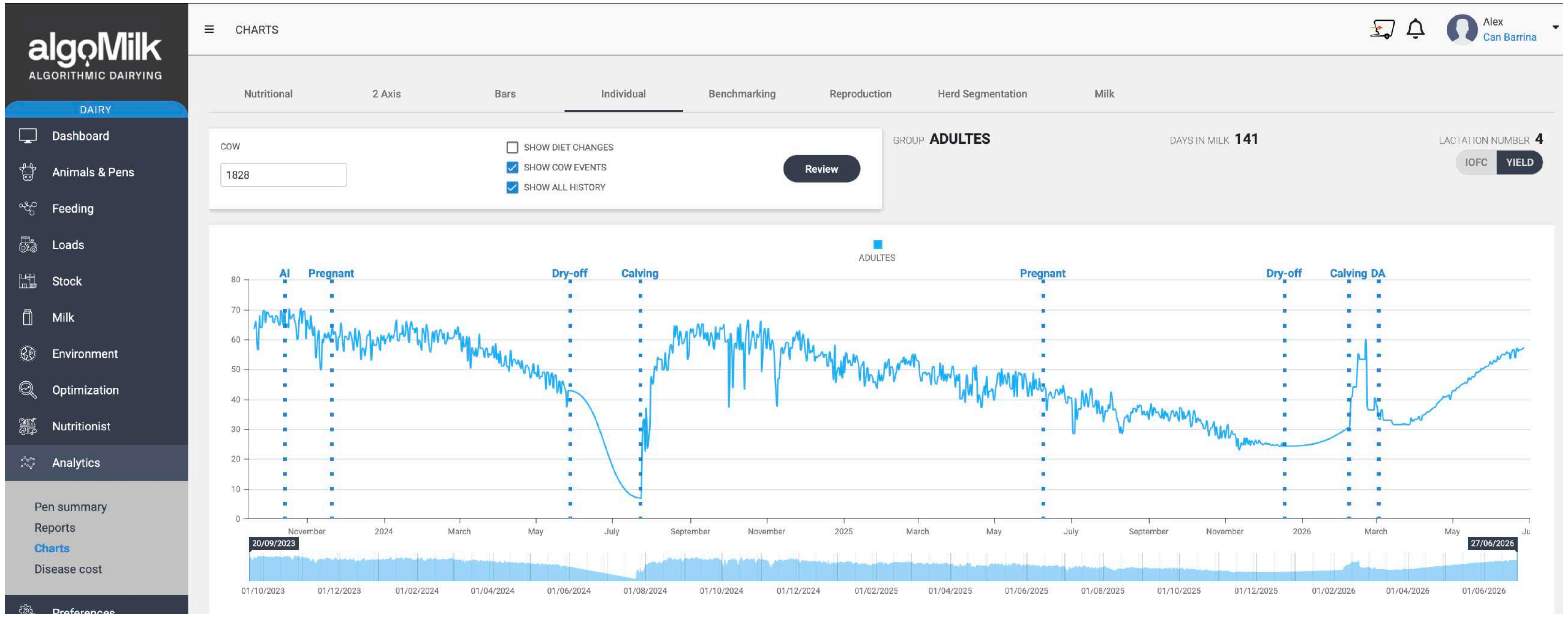

To breed or not to breed

≡ ANIMAL VALUE · JUNE 23, 2026

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

ANIMAL VALUE · JUNE 23, 2026

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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

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THANK YOU

Universitat de Lleida