Fitting and Predicting Dairy Lactation Curves based on Test-Day Records

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Outline

Introduction

Background / Motivation

- **Precision Nutrition**: Diet adjustments based on the real needs of each animal, optimizing feed use and reducing waste.
- **Strategic Genetic Selection**: Aiding in the identification of animals with superior productive potential to accelerate genetic gain within the herd.
- **Proactive Health Monitoring**: Using the expected curve as a baseline to detect deviations that may signal health problems early on.
- **Economic Planning**: Enabling more accurate forecasting of milk production, costs, and profits to support strategic financial decisions.
- **Traditional models**: rigid forms and systematic bias.
- **Modern Data-Driven Models**: Feature dependency and extensive inputs.

Lactation Curve

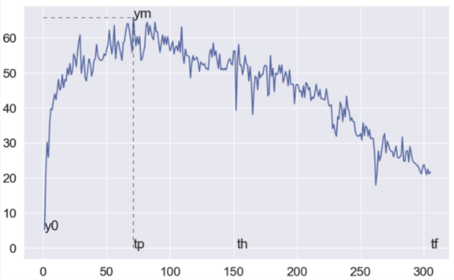


Figure: Lactation curve.

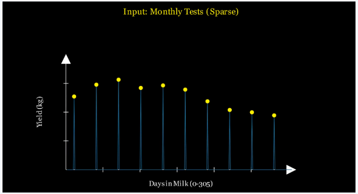
Objectives

Goal: Develop and evaluate a novel data-driven lactation model designed as a deep learning autoencoder architecture that reconstructs complete 305-day lactation curves using incomplete or sparse test-day records.

Background / Motivation

- **RQ1**: What is the models' overall effectiveness in lactation curve reconstruction when utilizing only sparse test-day data points and parity information?
- **RQ2**: How does the proposed model perform with fewer training examples through data ablation to simulate data-scarce scenarios?
- **RQ3**: Are benchmark predictions useful features for improving autoencoder performance beyond raw test-day samples?
- **RQ4**: How do models perform across different test-day sampling frequencies ranging from 5 to 60-day intervals?
- **RQ5**: How well do models extrapolate a complete curve from minimal, sequential data collected during early lactation?

Lactation Curve



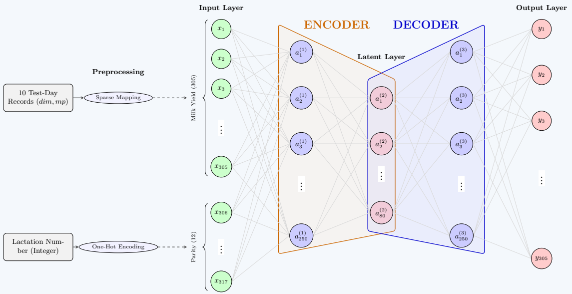
Deep Learning Autoencoder Model

The core of our approach is a deep learning autoencoder, specifically designed to learn a compressed, meaningful representation of the lactation curve.

Autoenconder model

- **Encoder - Feature compression**: It compresses the sparse 317-dimensional input (305 milk yields + 12 parity features) into a low-dimensional, 80-neuron latent representation, capturing the most fundamental and consistent underlying patterns of lactation.
- **Decoder: Curve Reconstruction**: The decoder component utilizes the 80-neuron compressed latent code to reconstruct the complete, dense 305-day lactation curve. The reconstructed output is a full prediction of daily milk yield, even for days without recorded test data.

Lactation Curve



Hyperparameters

Table: Hyperparameter Search Space and Optimal Values for the Autoencoder Model

Hyperparameter	Search Space / Values	Optimal Value
Number of hidden layers	Integer: 1 to 3	1
Neurons per hidden layer	Integer: 150 to 350	250
Latent (bottleneck) units	Integer: 20 to 80	80
Activation function	Choice: 'tanh', 'relu', or 'selu'	tanh
Dropout rate	Choice: 0.1, 0.4, or 0.6	0.1
Learning rate	Choice: 0.001 or 0.0001	0.0001
Batch size	Choice: 16, 32, 64, 128, or 256	64

Methodology

❶ Data

- 7,766 raw lactation records.
- 2,855 unique, high-quality lactations curves for analysis and model training.

❷ Baseline Models

- Ali & Schaeffer.
- Dijkstra.
- Milkbot.
- Wilmink.
- Wood.

❸ Metrics and Evaluation

- 5-Fold Cross-Validation.
- Metrics: Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE).

Parameters for all five benchmark models were estimated using the non-linear least-squares method.

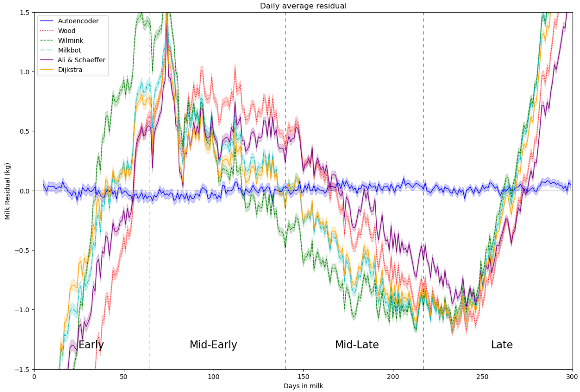
RQ1: What are the models' overall effectiveness in lactation curve reconstruction?

Model	R^2		RMSE		MAE	
	Mean	Δ %	Mean	Δ %	Mean	Δ %
Autoencoder	**0.74 ± 0.01**	-	**4.8 ± 0.07**	-	**3.2 ± 0.04**	-
Ali & Schaeffer	0.27 ± 0.07	-63.5	5.9 ± 0.07	22.9	3.9 ± 0.04	21.9
Dijkstra	0.64 ± 0.02	-13.5	5.5 ± 0.06	14.6	3.8 ± 0.05	18.7
Milkbot	0.60 ± 0.02	-18.9	5.7 ± 0.06	18.8	3.9 ± 0.05	21.9
Wilmink	0.66 ± 0.02	-10.8	5.4 ± 0.08	12.5	3.8 ± 0.06	18.7
Wood	0.67 ± 0.02	-9.5	5.4 ± 0.08	12.5	3.7 ± 0.06	15.6

The autoencoder achieved a statistically significant improvement in lactation curve reconstruction compared to all five conventional benchmark models.

Results and Discussion

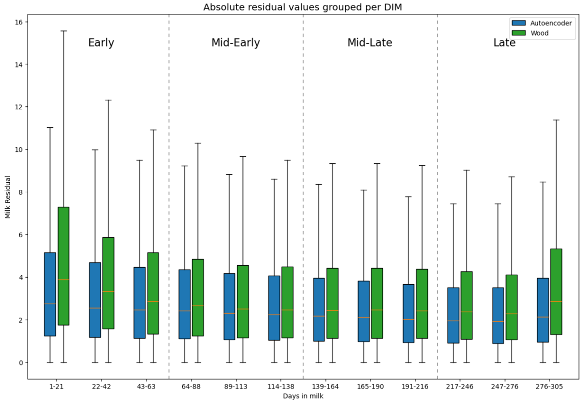
RQ1: What are the models' overall effectiveness in lactation curve reconstruction?



Unbiased Autoencoder: In contrast, the autoencoder's average residual (blue line) remains tightly centered on zero across the entire lactation, demonstrating it is a reliable and unbiased predictor.

Results and Discussion

RQ1: What are the models' overall effectiveness in lactation curve reconstruction?



Unbiased Autoencoder: In contrast, the autoencoder's average residual (blue line) remains tightly centered on zero across the entire lactation, demonstrating it is a reliable and unbiased predictor.

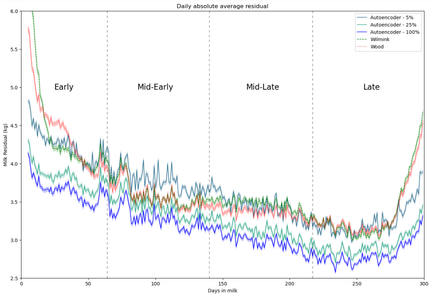
Results and Discussion

RQ2: How does the proposed model perform with lacking training examples (Data Ablation)?

Data Ablation effects

Model	R^2		RMSE		MAE	
	Mean	Δ %	Mean	Δ %	Mean	Δ %
AE - 100%	0.74 ± 0.01	-	4.8 ± 0.07	-	3.2 ± 0.04	-
AE - 75%	0.74 ± 0.01	-	4.8 ± 0.06	-	3.2 ± 0.04	-
AE - 50%	0.74 ± 0.01	-	4.9 ± 0.06	2.1	3.2 ± 0.04	-
AE - 25%	0.73 ± 0.01	-1.4	5.0 ± 0.06	4.2	3.3 ± 0.04	3.1
AE - 10%	0.71 ± 0.01	-4.1	5.1 ± 0.06	6.2	3.5 ± 0.04	9.4
AE - 5%	**0.69 ± 0.01**	**-6.8**	**5.3 ± 0.06**	**10.4**	**3.7 ± 0.04**	**15.6**
AE - 2.5%	0.66 ± 0.02	-10.8	5.5 ± 0.08	14.6	3.9 ± 0.06	21.9
Wood	**0.67 ± 0.02**	**-9.5**	**5.4 ± 0.08**	**12.5**	**3.7 ± 0.06**	**15.6**
Wilmink	0.66 ± 0.02	-10.8	5.4 ± 0.08	12.5	3.8 ± 0.06	18.7

Key Observations



Reduced Training Data: Even with a smaller training set, achieving results statistically equivalent to the Wood model when trained on only 5% of the original dataset.

Results and Discussion

RQ3: Are benchmark predictions useful features for improving autoencoder performance beyond raw test-day samples?

Model	R^2		RMSE		MAE	
	Mean	Δ %	Mean	Δ %	Mean	Δ %
Autoencoder	0.741 ± 0.012	-	4.83 ± 0.064	-	3.18 ± 0.037	-
AE W/ All	0.733 ± 0.011	-1.080	4.90 ± 0.042	1.449	3.25 ± 0.021	2.201
AE W/ Ali & Schaeffer	0.739 ± 0.012	-0.270	4.84 ± 0.065	0.207	3.20 ± 0.042	0.629
AE W/ Milkbot	0.740 ± 0.012	-0.135	4.84 ± 0.067	0.207	3.19 ± 0.047	0.314
AE W/ Wilmink	0.740 ± 0.012	-0.135	4.84 ± 0.066	0.207	3.19 ± 0.034	0.314
AE W/ Wood	0.739 ± 0.011	-0.270	4.84 ± 0.063	0.207	3.20 ± 0.030	0.629

There was no statistically significant improvement in lactation curve reconstruction.

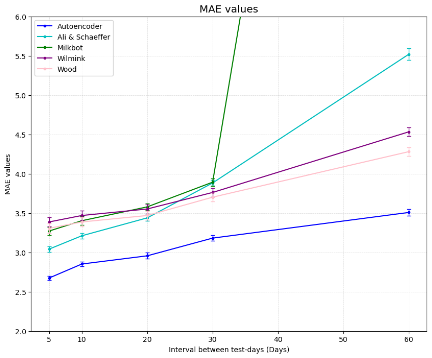
Results and Discussion

RQ4: How do models perform across different test-day sampling frequencies ranging from 5 to 60-day intervals?

Multiple FI sampling test day

		Metrics					
		R^2		RMSE		MAE	
Interval	Model	Mean	Δ %	Mean	Δ %	Mean	Δ %
5 days	**Autoencoder**	**0.81 ± 0.009**	-	**4.2 ± 0.04**	-	**2.7 ± 0.03**	-
	Ali & Schaeffer	0.75 ± 0.011	-7.4	4.6 ± 0.06	9.5	3.0 ± 0.03	11.1
	Dijkstra	0.73 ± 0.013	-9.9	4.9 ± 0.07	16.7	3.3 ± 0.05	22.2
	Milkbot	0.73 ± 0.013	-9.9	4.9 ± 0.07	16.7	3.3 ± 0.05	22.2
	Wilmink	0.72 ± 0.014	-11.1	5.0 ± 0.08	19.0	3.4 ± 0.06	25.9
	Wood	0.73 ± 0.014	-9.9	4.9 ± 0.08	16.7	3.3 ± 0.06	22.2
10 days	**Autoencoder**	**0.78 ± 0.010**	-	**4.4 ± 0.05**	-	**2.9 ± 0.03**	-
	Ali & Schaeffer	0.68 ± 0.019	-12.8	4.9 ± 0.07	11.4	3.2 ± 0.04	10.3
	Dijkstra	0.71 ± 0.014	-9.0	5.0 ± 0.07	13.6	3.4 ± 0.05	17.2
	Milkbot	0.70 ± 0.013	-10.3	5.0 ± 0.07	13.6	3.4 ± 0.05	17.2
	Wilmink	0.70 ± 0.014	-10.3	5.1 ± 0.08	15.9	3.5 ± 0.06	20.7
	Wood	0.72 ± 0.014	-7.7	5.0 ± 0.08	13.6	3.4 ± 0.06	17.2
15 days	**Autoencoder**	**0.77 ± 0.011**	-	**4.6 ± 0.06**	-	**3.0 ± 0.04**	-
	Ali & Schaeffer	0.48 ± 0.041	-37.7	5.3 ± 0.08	15.2	3.4 ± 0.04	13.3
	Dijkstra	0.69 ± 0.014	-10.4	5.1 ± 0.06	10.9	3.5 ± 0.05	16.7
	Milkbot	0.66 ± 0.014	-14.3	5.3 ± 0.06	15.2	3.6 ± 0.04	20.0
	Wilmink	0.69 ± 0.016	-10.4	5.2 ± 0.08	13.0	3.6 ± 0.06	20.0
	Wood	0.70 ± 0.015	-9.1	5.1 ± 0.08	10.9	3.5 ± 0.06	16.7
30 days	**Autoencoder**	**0.74 ± 0.012**	-	**4.8 ± 0.07**	-	**3.2 ± 0.04**	-
	Ali & Schaeffer	0.27 ± 0.069	-63.5	5.9 ± 0.07	22.9	3.9 ± 0.04	21.9
	Dijkstra	0.64 ± 0.015	-13.5	5.5 ± 0.06	14.6	3.8 ± 0.05	18.8
	Milkbot	0.60 ± 0.016	-18.9	5.7 ± 0.06	18.8	3.9 ± 0.05	21.9
	Wilmink	0.66 ± 0.017	-10.8	5.4 ± 0.08	12.5	3.8 ± 0.06	18.8
	Wood	0.67 ± 0.016	-9.5	5.4 ± 0.08	12.5	3.7 ± 0.06	15.6
60 days	**Autoencoder**	**0.70 ± 0.014**	-	**5.2 ± 0.08**	-	**3.5 ± 0.04**	-
	Ali & Schaeffer	-3.45 ± 0.264	-592.9	8.9 ± 0.16	71.2	5.5 ± 0.07	57.1
	Dijkstra	0.47 ± 0.022	-32.9	6.5 ± 0.07	25.0	4.6 ± 0.05	31.4
	Milkbot	-7.59 ± 0.288	-1184.3	27.8 ± 0.08	434.6	18.8 ± 0.06	437.1
	Wilmink	0.47 ± 0.024	-32.9	6.5 ± 0.07	25.0	4.5 ± 0.06	28.6
	Wood	0.57 ± 0.020	-18.6	6.1 ± 0.08	17.3	4.3 ± 0.05	22.9

Prediction Task



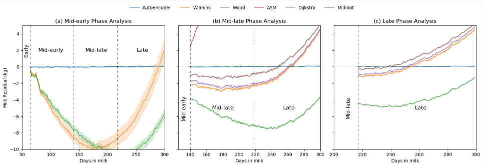
Results and Discussion

RQ5: How well do models extrapolate a complete curve from minimal, sequential data collected during early lactation?

Multiple FI sampling test day

Model	Mid-early		Mid-late		Late	
	Mean	Δ %	Mean	Δ %	Mean	Δ %
Autoencoder	**5.1 ± 0.07**	**-**	**5.1 ± 0.07**	**-**	**5.2 ± 0.06**	**-**
Ali & Schaeffer	-	-	84.9 ± 1.37	1,565	50.7 ± 0.56	875.0
Dijkstra	-	-	11.3 ± 0.30	122	10.0 ± 0.23	92.3
Milkbot	-	-	10.3 ± 0.23	102	9.3 ± 0.19	78.8
Wilmink	26.1 ± 0.78	412	18.1 ± 0.40	255	14.9 ± 0.29	186.5
Wood	16.7 ± 0.30	227	13.3 ± 0.20	161	11.2 ± 0.16	115.4

Daily herd average residuals



Conclusions

The model's flexibility, stemming from over 100,000 trainable parameters compared to 3 to 5 in traditional models, allows it to capture complex, non-linear dynamics from the data. Its architecture enables it to learn a holistic, generative representation of a lactation curve.

- **Accurate**: Significantly lower prediction error than standard models.
- **Unbiased**: Eliminates the systematic average residual error patterns of traditional methods.
- **Robust**: Maintains high performance with sparse training data and infrequent sampling.
- **Practical**: Utilizes only commonly available data, making it suitable for direct application on dairy farms.

Thank You

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