Prediction of 100-d and 305-d Milk Yields in a Multibreed Dairy Herd in Thailand Using Monthly Test-Day Records[1/]

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Abstract

The ability of eight procedures to predict 100-d and 305-d milk yields using monthly test-day records was tested using 28,452 daily yields from 88 cows in a multibreed dairy herd provided by the Sakon Nakhon Agricultural Research and Training Center. The eight procedures were: test interval method, gamma function, mixed log linear, and second, third, fourth, fifth, and sixth degree polynomial models. The breed groups represented in the multibreed herd were HF, 1/2HF 1/2RS, and 3/4HF 1/4RS. Prediction of 100-d and 305-d milk yields by the eight procedures were compared with actual 100-d and 305-d milk yields within breed group x lactation number x calving age and breed group x lactation number x calving season subclasses. Least squares means of individual cow differences predicted and actual 100-d and 305-d milk yields were computed for each subclass. Number of significant least square means of differences and ranking of models within and across subclasses for 100-d and 305-d were used to evaluate the predictive ability of the eight procedures. The highest-ranking model for 100-d was model 4 (third degree polynomial) and for 305-d was model 3 (second degree polynomial). However, no procedure was uniformly better across all subclasses. Thus, perhaps several models might be needed for a genetic evaluation of the animals in this multibreed population. If computational simplicity were the primary goal, then perhaps a single model (model 3) might suffice. However, the results of this study apply only to the data set and the multibreed population used here. To obtain results of national relevance, this study needs to be repeated with a larger multibreed population that more accurately represents the Thai multibreed population.

Key words: dairy cattle, milk yield, test-day yield, prediction, multibreed

Introduction

Recording of milk yields is essential for genetic improvement and herd management in dairy cattle. Under increasing pressure to reduce cost, numerous milk-testing schemes have been developed in many countries. One of the most widely used is monthly recording. In Thailand, monthly test-day records are used to compute cumulative productions of milk and fat to 100-d and 305-d for dairy genetic evaluation purposes. The Dairy Promotion Organization (DPO), and probable other organizations in Thailand, compute *monthly* milk yields using a *single* test-day milk yield sample, and then, these monthly estimates are used to compute the accumulated 100-d and 305-d milk yields. This procedure is *not* appropriate for individual animals because it will, in

[1/] This research was supported by the Florida Agricultural Experiment Station and a grant from the Thailand Research Fund under the Royal Golden Jubilee Project, and approved for publication as Journal Series No.R-08065.
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most cases, either overestimate or underestimate accumulated milk yields. Notice that this procedure is different from the test-interval method (Sargent *et al.*, 1968; Norman *et al.*, 1999), which computes total milk yields of *intervals* between two consecutive test days using the average milk yield of these *two* test-days.

Although the test-interval method is the most widely used procedure to compute cumulative milk production traits, prediction of these milk traits could potentially be improved by using a linear or a nonlinear function. Koonawootrittriron *et al.* (2001) showed that the second degree polynomial was the best out of seven models to predict daily and 305-d milk yields and the sixth degree polynomial model was the best for the prediction of 100-d milk yield within breed group x lactation number x calving age and breed group x lactation number x calving season subclasses in a Holstein Friesian-Red Sindhi herd in the Northeast of Thailand, when using all daily lactation records.

Milk recording organizations in Thailand sample milk production traits on a monthly basis. These are the records used for genetic animal evaluation in dairy cattle. Thus, milk prediction models need to be revalidated under a test-day sampling strategy, and then compared to the test-interval method for their ability to predict 100-d and 305-d milk production yields under Thai conditions.

Thus, the objectives of this study were to assess the predictive ability of the test-interval method and of seven models (gamma, mixed log linear, second to sixth degree polynomial models) to predict 100-d and 305-d milk yields based on monthly test-day records relative to the actual 100-d and 305-d milk yields of individual cows within breed group x lactation number x calving age and breed group x lactation number x calving season subclasses.

Materials and Methods

Animals, Management, and records

This study used the same data set as Koonawootrittriron *et al.* (2001). Thus, only a reduced description of it will be given here. Daily lactation yields (28,452, 5 to 305 d) from 75 Holstein Friesian (HF), 8 ½ HF ½ Red Sindhi (RS), and 5 ¾ HF ¼ RS dams were collected at the Sakon Nakhon Agricultural Research and Training Center (SARTC) between 1997 and 1999.

Cows were assigned to three breed groups according to their breed composition (HF, 1/2HF 1/2RS, and 3/4HF 1/4RS). Animals of all breed compositions were milked twice a day, and raised under the same nutritional (grass and concentrate plus minerals) and management conditions. Cows were artificially inseminated up to three times, and if not pregnant at 60 d after last insemination, they were placed with a clean up bull. Pregnant cows were dried off two months prior to calving.

Lactation number was classified as first, second, third, and fourth and later lactations. Calving seasons were defined as winter (November to February), summer (March to June), and rainy (July to October). Two calving ages per lactation were defined. This resulted in eight lactation x calving age subclasses: 1) calving age less than 30 months x lactation 1, 2) calving age equal to or greater than 30 months x lactation 1, 3) calving age less than 44 months x lactation 2, 4) calving age equal to or greater than 44 months x lactation 2, 5) calving age less than 60 months x lactation 3, 6) calving age equal to or greater than 60 months for the third lactation, and 7) calving age greater than 60 months x lactation 4 and greater.

Models and Data Analysis

To accomplish the objectives of this research lactation records from the SARTC data set had to be sampled according to the current milk sampling procedure used in Thailand. Monthly sampling of milk production traits is the prevalent system in Thailand. Because of colostrum, sampling usually begins 5 d postpartum. Thus, daily milk yields from the SARTC data set were sampled on days 5, 35, 65, 95, 125, 155, 185, 215, 245, 275, and 305 of each lactation. These 11 measurements per lactation were used as monthly test-day records to assess the predictive ability of the test-interval method (TIM) and the seven prediction equations to predict 100-d and 305-d milk yields used by Koonawootrittriron *et al.* (2001).

Firstly, the 11 monthly test-day records were used to predict individual cow lactation daily milk yields (5 to 305d) within breed group x lactation x calving age and breed group x lactation x calving season subclasses using the test-interval method and the seven prediction equations. Secondly, accumulated 100-d and 305-d milk yields for individual lactations were computed using these eight prediction procedures. The predicted values for 100-d and 305-d milk yields from each procedure were deviated from their corresponding actual 100-d and 305-d milk yields. Least squares means of 100-d and 305-d milk yield deviations (predicted minus actual milk yields) for the test-interval method and the seven prediction procedures were obtained separately for each set of breed group x lactation x calving season and breed group x lactation x calving age subclasses. The statistical model used was:

$$d_{ijk} = \mu + subclass_i + model_j + e_{ijk}$$

where

d_{ijk}	=	difference between predicted and actual milk production of cow k at 100-d or at 305-d of lactation, within subclass i and model j,
μ	=	overall mean,
$subclass_i$	=	i^{th} breed group x lactation x calving season or breed group x lactation x calving age,
$model_j$	=	j^{th} prediction model and,
e_{ijkl}	=	residual.

All effects in the model were assumed to be fixed, except for the residual term that was assumed to be independent, identically distributed with mean zero and a common variance. T-statistics were then used to test if the predicted and actual 100-d and 305-d milk yields differed significantly.

For completeness, the prediction equations used to compute accumulated milk yields at 100 d and 305 d are briefly described below. For further details on prediction models 1 to 7, see Koonawootrittriron *et al.* (2001).

1) Test-interval method:

$$TMY = (P_1 \times D_1) + \sum_{i=2}^{k}[(\frac{P_i + P_{i-1}}{2}) \times D_i] + (P_{k+1} \times D_{k+1}) \qquad [1]$$

where TMY is total milk yield, P_1 is the milk yield of the first test-day record, D_1 is interval between five days after calving and the first record, P_i is the milk yield on test-day i (i = 2,…, k), D_i is the interval between test-record record i – 1 and i (i = 2,…, k), P_{k+1} is the milk yield on the last test-day before drying off, and D_{k+1} is the interval between the last test-day and the day a cow was dried off (Sargent et al., 1968).

2) Prediction model 1: Gamma function (Wood, 1967):

$$y_t = at^b e^{-ct} \qquad [2]$$

where y_t is the milk yield on day *t* in each subclass, ***a*** is the initial yield of lactation, ***b*** represents the increasing slope, and ***c*** represents the decreasing slope. Computations were done using the natural logarithm of equation 1, i.e.,

$$\ln y_t = \ln a + b \ln t - ct + \varepsilon_t$$

where ε_t is the residual. Thus, the predicted yield on day t was, $y_t = \exp(\ln y_t)$.

3) Prediction model 2: mixed log second-degree polynomial (Ali and Schaeffer, 1987),

$$y_t = b_0 + b_1\gamma_t + b_2\gamma_t^2 + b_3 w_t + b_4 w_t^2 + e_t \qquad [3]$$

where y_t = milk yield on day t, $\gamma_t = t/305$, $w_t = \ln(305/t)$, t = days since calving or days in milk, b_0, b_1, b_2, b_3, and b_4 are regression coefficients, and e_t is the residual.

4) Prediction models 3, 4, 5, 6, and 7: second, third, fourth, fifth, and sixth polynomial regression models,

$$\text{Model 3: } y_t = b_0 + b_1 t + b_2 t^2 + e_t \qquad [4]$$

$$\text{Model 4: } y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + e_t \qquad [5]$$

$$\text{Model 5: } y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + e_t \qquad [6]$$

$$\text{Model 6: } y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + e_t \qquad [7]$$

$$\text{Model 7: } y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + b_6 t^6 + e_t \qquad [8]$$

where y_t = milk yield on day t, t = days since calving, b_0, b_1, b_2, b_3, b_4, b_5 and b_6 are regression coefficients, and e_t is the residual.

Program PROC REG of the SAS statistical system (SAS, 1990) was used to compute the regression coefficients in models 1 through 7 and to obtain the predicted daily milk yields (5 to 305 d) for all models.

Accumulated (100 d and 305 d) individual cow actual and predicted milk yields, and predicted (test-interval method, models 1 to7) minus actual accumulated milk yield deviations were computed using the general SAS program (SAS, 1990). Least squares means of accumulated milk yield deviations per subclass were obtained using the LSMEANS statement of PROC GLM (SAS, 1990). T-tests were used to assess the significance of the accumulated deviations per model within and across subclasses.

Results and Discussion

Predicted 100-d milk yields by eight procedures relative to actual yields

Calving age subclasses. Least squares means of 100-d milk yield deviations (predicted minus actual milk yields) of the test-interval method and seven prediction models by breed group x lactation x calving age subclasses are presented in Table 1. Models 2, 4, 5, 6, and 7 had nonsignificant 100-d milk yield deviations (predicted minus actual milk yield ($P > 0.05$) for all subclasses. The test-interval method (TIM) had two, and model 1 had three significant differences of LS means for 100-d milk yield deviations (at least $P < 0.05$). Model 3 had four significant differences (at least $P < 0.05$). Among the models with nonsignificant deviations, two tiers can be distinguished: models 4 and 5 (mean absolute deviation = 6.3 kg), and models 2, 6, and 7 (mean absolute deviation of about 8.6 kg). Thus, models 4 and 5 appear to be good choices for 100-d milk predictions. However, because it is simpler than model 5, model 4 (third degree polynomial) should be the model of choice. Notice that this choice of model for 100-d milk yields using 11 test-day records here differed from the best model found (model 7) when using all daily records by Koonawootrittriron *et al.* (2001). The number of test-days considered (and probably the test-day values themselves) would likely affect 100-d predictions, and the model that will have the smallest deviations from actual 100-d milk yields.

Table 1. Least squares means of 100-d milk yield deviations (predicted minus actual milk yields) of the test-interval method and seven prediction models by breed group x lactation x calving age subclasses

Breed group[1/]	Lactation number	Calving age	No. of lactations	Actual Yield (kg)	TIM[2/]	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
HF	1	< 30 mo	8	1,061.5	-52.4	-121.8	119.4	-12.7	-2.4	-4.2	-3.9	-8.9
HF	1	≥ 30 mo	10	1,210.9	-42.3*	-46.7**	-6.6	-62.4**	-32.6	-15.8	-13.2	-13.5
HF	2	< 44 mo	19	1,072.3	-41.1	-12.3	7.7	-18.0	-8.7	-12.5	-8.9	-6.0
HF	2	≥ 44 mo	24	1,394.8	-50.4*	-41.5	-46.9	-57.9**	-33.3	-14.7	-13.8	-13.1
HF	3	< 60 mo	6	1,214.7	-12.8	68.0	59.5	11.3	10.5	12.6	16.4	16.7
HF	3	≥ 60 mo	3	1,401.4	33.7	56.6	107.4	32.0	66.1	70.9	77.3	66.5
HF	≥ 4	all ages	18	1,261.3	-7.2	-31.0	20.1	26.2	34.1	52.6	56.2	56.2
1/2HF 1/2RS	1	≥ 30 mo	4	900.7	85.1	108.7*	-19.7	-16.2	-5.1	-9.2	-12.4	-12.0
1/2HF 1/2RS	2	< 44 mo	3	1,228.8	-42.2	36.5	36.6	-4.0	-15.8	23.0	39.9	40.6
1/2HF 1/2RS	2	≥ 44 mo	3	1,125.1	-4.6	-100.4	146.7	-6.9	-0.3	20.8	19.5	19.4
1/2HF 1/2RS	3	< 60 mo	3	1,481.4	-9.1	92.9**	27.5	-1.7	8.2	23.3	19.9	23.3
3/4HF 1/4RS	1	< 30 mo	2	1,415.9	-47.4	-33.6	-2.2	-114.3**	-60.0	-4.3	-8.4	-6.8
3/4HF 1/4RS	1	≥ 30 mo	3	1,417.0	-5.8	1.3	11.2	-61.8*	-22.1	18.8	19.6	18.7
All	All	All	106	1,234.3	-27.2*	-17.7	8.4	-22.1	-6.3	6.3	8.6	8.7

[1/] HF = Holstein Friesian, RS = Red Sindhi
[2/] Test-interval method
[3/] Model 1: $y_t = at^b e^{-ct}$ Model 2: $y_t = b_0 + b_1\gamma_t + b_2\gamma_t^2 + b_3 w_t + b_4 w_t^2 + e_t$
Model 3: $y_t = b_0 + b_1 t + b_2 t^2 + e_t$ Model 4: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + e_t$
Model 5: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + e_t$ Model 6: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + e_t$
Model 7: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + b_6 t^6 + e_t$
Where y_t is milk yield at day in lactation t, t = days in lactation, γ_t = t/305, w_t = ln(305/t)
* significant (P < 0.05) for Ho: LSMEAN=0, ** highly significant (P < 0.01) for Ho: LSMEAN=0.

Calving season subclasses. Table 2 shows LS means of 100-d milk yield deviations of the TIM and seven prediction models by breed group x lactation x calving season subclasses. Results for calving season subclasses were similar to those of calving age subclasses. Models 4 through 7 had nonsignificant 100-d milk yield deviations (P > 0.05) for all breed group x lactation x calving season subclasses. Least squares means of predicted minus actual 100-d milk yields from TIM and model 2 were significantly different (P < 0.05) for two out of twenty calving season subclasses. Model 3 had three significant differences (P < 0.01). The least accurate model was model 1; it had four significant differences (at least P < 0.05). As it happened with calving age subclasses, the model of choice overall was model 4 (third degree polynomial).

All procedures (the test-interval method and the seven prediction models) had LS means of 100-d milk yield deviations that varied in value and level of significance of the two sets of subclasses above (calving age and calving season). This variability suggests that there was no uniformly better model across all subclasses in this data set. However, an overall ranking across calving age and calving season subclasses can be constructed using 1) the number of significant subclasses found per procedure, and 2) the level of significance of the overall LS mean of the predicted minus the actual 100-d milk yields. The resulting ranking (first to last) was: 1) model 4 (third degree polynomial), 2) model 5 (fourth degree polynomial), 3) model 6 (fifth degree polynomial), 4) model 7 (six degree polynomial), 5) model 2 (mixed log second degree polynomial), 6) TIM (the test-interval method), 7) model 3 (second degree polynomial), and 8) model 1 (gamma function).

Table 2. Least squares means of 100-d milk yield deviations (predicted minus actual milk yields) of the test-interval method and seven prediction procedures by breed group x lactation x calving season subclasses

Breed group[1/]	Lactation number	Calving season[2/]	No. of lactations	Actual yield (kg)	TIM[3/]	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
HF	1	Winter	9	1,237.9	-59.9*	-116.3**	6.5	-82.9**	-50.5	-33.3	-27.5	-27.6
HF	1	Summer	3	1,216.3	-11.6	-47.1	165.6*	39.7	67.7	69.1	67.6	68.0
HF	1	Rainy	16	968.6	-44.8	-42.2	5.7	-16.6	-15.6	-16.5	-19.8	-27.1
HF	2	Winter	13	1,354.1	-74.5*	-81.2**	-3.7	-97.5**	-58.0	-38.2	-36.7	-32.4
HF	2	Summer	7	1,430.2	-10.6	-46.5	-133.6	-47.6	-33.9	-20.1	-16.3	-18.3
HF	2	Rainy	23	1,140.6	-41.3	6.5	0.1	-5.7	1.1	2.2	4.0	5.2
HF	3	Summer	2	1,664.6	17.0	35.4	-104.5	5.6	56.2	61.1	73.3	57.7
HF	3	Rainy	7	1,166.2	-1.4	72.4	63.4	21.8	21.3	23.7	26.3	26.4
HF	$\geq$ 4	Winter	9	1,306.5	-4.1	-89.0	4.8	66.3	90.7	98.6	95.3	95.8
HF	$\geq$ 4	Summer	4	1,226.3	-28.5	-63.1	34.6	8.2	20.0	4.0	4.8	4.6
HF	$\geq$ 4	Rainy	5	1,208.0	4.3	99.1	36.1	-31.6	-24.5	8.8	26.7	26.5
1/2HF 1/2RS	1	Winter	3	898.6	117.9	142.2*	-26.5	-27.7	-11.2	-8.5	-14.9	-14.4
1/2HF 1/2RS	1	Rainy	1	906.8	-13.2	28.2	0.8	18.5	13.0	-11.4	-4.8	-4.5
1/2HF 1/2RS	2	Winter	2	1,242.6	-10.0	-115.7	120.3*	-4.7	-15.7	9.6	21.3	22.9
1/2HF 1/2RS	2	Summer	1	1,090.1	-10.9	-191.3	47.0	20.2	26.9	48.5	47.0	46.8
1/2HF 1/2RS	2	Rainy	3	1,162.2	-36.5	-183.9*	20.8	-14.5	-14.6	21.1	29.5	29.1
1/2HF 1/2RS	3	Winter	2	1,563.8	-1.4	99.0**	19.3	13.4	12.0	24.5	19.1	20.5
1/2HF 1/2RS	3	Summer	1	1,316.5	-24.6	80.7	44.1	-32.0	0.7	21.1	21.5	29.1
3/4HF 1/4RS	1	Winter	4	1,520.6	-12.0	4.7	13.1	-76.4**	-24.3	20.8	19.2	18.7
3/4HF 1/4RS	1	Summer	1	1,000.4	-64.2	-81.9	-23.1	-108.5	-89.2	-35.6	-34.9	-32.2
All	All	All	106	1,234.3	-27.2*	17.7	8.4	-22.1	-6.3	6.3	8.6	8.7

[1/] HF = Holstein Friesian, RS = Red Sindhi

[2/] Winter = November – February, Summer = March – June, Rainy = July – October

[3/] Test-interval method

[4/] Model 1: $y_t = at^b e^{-ct}$

Model 2: $y_t = b_0 + b_1\gamma_t + b_2\gamma_t^2 + b_3 w_t + b_4 w_t^2 + e_t$

Model 3: $y_t = b_0 + b_1 t + b_2 t^2 + e_t$

Model 4: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + e_t$

Model 5: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + e_t$

Model 6: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + e_t$

Model 7: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + b_6 t^6 + e_t$

Where y_t is milk yield at day in lactation t, t = days in lactation, $\gamma_t = t/305$, $w_t = \ln(305/t)$

* significant (P < 0.05) for Ho: LSMEAN=0, ** highly significant (P < 0.01) for Ho: LSMEAN=0.

This ranking indicated that the ability of TIM to predict individual cow 100-d milk yields was intermediate compared to that of the seven prediction models. In addition, the overall LS mean of the predicted minus actual 100-d milk yield for TIM was the only significant value (P < 0.05). These results indicate that the TIM is not as accurate as any of the other seven procedures to predict individual cow 100-d milk yield using monthly test-day records.

The ranking of 100-d milk yield predictive ability of models 1 through 7 using monthly test-day records (4, 5, 6, 7, 2, 3, 1) was similar to the ranking of the same models using all daily lactation records (7, 5, 6, 2, 4, 3, 1; Koonawootrittriron *et al.*, 2001). Only two procedures changed their ranking: model 4 ranked first, and model 7 ranked fourth here, and their corresponding rankings when using all daily records were fourth and first, respectively. These changes in ranking were solely due to the use of different numbers of daily records for the prediction of lactation curves. Probably a different set of monthly test-day would also have produced a different ranking.

If a single lactation model were to be chosen for 100-d milk yield genetic evaluations, a third degree polynomial (model 4) would probably be an appropriate model for both calving age and calving season subclasses in this population. However, if a more accurate accountability of 100-d milk yield per cow within calving age and(or) calving season subclasses were desired, perhaps a *set* of lactation models rather than a single model would be required for the genetic evaluation system.

Predicted 305-d milk yields by eight procedures relative to actual yields

Calving age subclasses. Least squares means of individual cow 305-d milk yield deviations using TIM and the seven prediction models within breed group x lactation x calving age subclasses are presented in Table 3.

Table 3. Least squares means of 305-d milk yield deviations (predicted minus actual milk yields) for the test-interval method and seven prediction models by breed group x lactation x calving age subclasses

Breed group[1/]	Lactation number	Calving age	No. of lactations	Actual Yield (kg)	TIM[2/]	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
HF	1	< 30 mo	8	2,356.9	-24.9	4.3	-9.4	48.3	53.2	43.5	43.0	-11.5
HF	1	≥ 30 mo	10	2,723.6	-36.5	6.4	-4.2	-35.4	-18.4	-9.8	-2.2	10.0
HF	2	< 44 mo	19	2,827.1	-53.7	-56.3	5.8	-7.8	5.6	-6.4	-13.8	33.1
HF	2	≥ 44 mo	24	3,442.6	-75.2*	-69.0*	-21.4	-42.1	-32.3	-30.6	-28.0	-70.6*
HF	3	< 60 mo	6	3,292.9	-3.4	13.1	31.7	25.6	37.6	29.5	51.3	-68.2
HF	3	≥ 60 mo	3	3,398.6	-33.9	-46.8	-21.6	-43.8	-5.2	-16.1	62.7	54.6
HF	≥ 4	all ages	18	2,700.4	-12.6	38.3	92.5	77.0	83.7	88.3	95.5	121.5
1/2HF 1/2RS	1	≥ 30 mo	4	2,014.2	112.0*	1.17	21.8	31.6	38.5	32.4	24.6	34.7
1/2HF 1/2RS	2	< 44 mo	3	2,566.6	5.0	70.1	94.7*	63.2	63.2	37.1	64.6	139.6**
1/2HF 1/2RS	2	≥ 44 mo	3	2,137.2	-14.1	6.6	29.9	15.5	17.8	32.2	27.6	26.3
1/2HF 1/2RS	3	< 60 mo	3	2,755.7	-14.3	42.9	43.7	21.7	25.8	34.1	44.0	77.1
3/4HF 1/4RS	1	< 30 mo	2	3,579.0	-28.7	0.4	26.2	-35.3	-6.6	21.2	-0.8	-131.5*
3/4HF 1/4RS	1	≥ 30 mo	3	3,478.2	-106.0*	135.8**	-79.1	-104.3	-93.9	-65.3	-59.7	-138.5**
All	All	All	106	2,915.2	-34.4*	-19.0	15.8	3.1	13.9	13.2	18.2	7.4

[1/] HF = Holstein Friesian, RS = Red Sindhi
[2/] Test-interval method
[3/] Model 1: $y_t = at^b e^{-ct}$ Model 2: $y_t = b_0 + b_1\gamma_t + b_2\gamma_t^2 + b_3 w_t + b_4 w_t^2 + e_t$
Model 3: $y_t = b_0 + b_1 t + b_2 t^2 + e_t$ Model 4: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + e_t$
Model 5: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + e_t$ Model 6: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + e_t$
Model 7: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + b_6 t^6 + e_t$
Where y_t is milk yield at day in lactation t, t = days in lactation, $\gamma_t = t/305$, $w_t = \ln(305/t)$
* significant (P < 0.05) for Ho: LSMEAN=0, ** highly significant (P < 0.01) for Ho: LSMEAN=0.

Four prediction models (models 3, 4, 5, and 6) had nonsignificant LS means of 305-d milk yield deviations for all calving age subclasses. The TIM and the other 3 models had at least one significantly different subclass (at least P < 0.05). Model 2 had one, model 1 had two, the TIM had three, and model 7 had four significantly different subclasses.

Calving season subclasses. Table 4 shows the LS means of individual cow 305-d milk yield deviations (predicted minus actual milk yields) for TIM and the seven prediction models within breed group x lactation x calving season subclasses. The pattern of calving season subclasses with statistically significant LS means of individual cow 305-d deviations was quite similar to the one found for calving age subclasses. Models 3 through 6 showed no significant differences, models 1 and 2 had only one significant difference ($P < 0.05$), the TIM had two subclasses with significant differences ($P < 0.05$), and model 7 had five significantly different subclasses (at least $P < 0.05$).

Table 4. Least squares means of 305-d milk yield deviations (predicted minus actual milk yields) for the test-interval method and seven prediction procedures by breed group x lactation x calving season subclasses

Breed group[1/]	Lactation number	Calving season[2/]	No. of lactations	Actual yield (kg)	TIM[3/]	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
HF	1	Winter	9	2674.9	-12.7	3.2	-7.0	-35.7	-23.2	-13.3	-6.1	-18.5
HF	1	Summer	3	2678.8	-24.9	85.0	151.9	122.7	158.0	134.3	152.0	242.3*
HF	1	Rainy	16	2330.2	-62.4	-31.0	-84.9	-2.3	-4.0	-5.5	-13.2	-92.0
HF	2	Winter	13	3161.0	-98.3	-102.3	-31.1	-58.3	-42.0	-39.1	-31.8	-55.1
HF	2	Summer	7	3206.9	11.8	9.6	63.5	38.5	51.8	50.6	50.1	-72.2
HF	2	Rainy	23	3165.0	-70.8*	-63.6*	-19.3	-29.2	-21.0	-30.5	-37.8	6.7
HF	3	Summer	2	3705.8	-37.9	-56.1	-25.7	-58.7	-4.3	-18.7	99.2	-0.4
HF	3	Rainy	7	3220.2	-6.6	7.2	25.2	19.9	31.3	23.7	42.5	-34.9
HF	≥ 4	Winter	9	2630.1	0.5	110.7	147.7	141.1	148.2	144.7	150.2	168.3*
HF	≥ 4	Summer	4	2955.0	-22.7	-58.8	1.5	-12.8	0.5	7.3	13.0	43.4
HF	≥ 4	Rainy	5	2623.5	-28.1	-14.4	66.1	33.6	35.2	51.5	63.0	99.7
1/2HF 1/2RS	1	Winter	3	1752.2	112.0*	-14.8	-13.6	-2.4	3.0	7.1	-4.4	-34.6
1/2HF 1/2RS	1	Rainy	1	2800.1	111.7	112.3	128.0	133.3	144.8	108.3	111.3	242.5
1/2HF 1/2RS	2	Winter	2	2618.0	-3.6	88.1	146.4*	102.6	107.0	126.2	128.0	189.7**
1/2HF 1/2RS	2	Summer	1	1921.6	16.1	89.2	118.0	101.3	100.7	117.3	110.6	110.1
1/2HF 1/2RS	2	Rainy	3	2318.0	-12.0	-11.7	-12.3	-23.5	-23.9	-53.9	-30.0	2.7
1/2HF 1/2RS	3	Winter	2	2956.5	25.6	43.0	36.8	31.9	34.3	39.8	48.7	86.0**
1/2HF 1/2RS	3	Summer	1	2354.1	-8.2	42.7	57.4	1.3	8.9	22.6	34.7	-60.6
3/4HF 1/4RS	1	Winter	4	3661.7	-79.9	-94.7	-41.1	-78.4	-57.5	-32.9	-35.4	-110.1*
3/4HF 1/4RS	1	Summer	1	2946.0	-55.8	-57.8	-20.6	-69.7	-64.6	-22.1	-39.0	-83.2
All	All	All	106	2915.2	-34.4*	-19.0	15.8	3.1	13.9	13.2	18.2	7.4

[1/] HF = Holstein Friesian, RS = Red Sindhi
[2/] Winter = November – February, Summer = March – June, Rainy = July – October
[3/] Test-interval method
[4/] Model 1: $y_t = at^b e^{-ct}$ Model 2: $y_t = b_0 + b_1\gamma_t + b_2\gamma_t^2 + b_3 w_t + b_4 w_t^2 + e_t$
Model 3: $y_t = b_0 + b_1 t + b_2 t^2 + e_t$ Model 4: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + e_t$
Model 5: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + e_t$ Model 6: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + e_t$
Model 7: $y_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5 + b_6 t^6 + e_t$
Where y_t is milk yield at day in lactation t, t = days in lactation, $\gamma_t = t/305$, $w_t = \ln(305/t)$
* significant ($P < 0.05$) for Ho: LSMEAN=0, ** highly significant ($P < 0.01$) for Ho: LSMEAN=0.

The overall ranking of 305-d milk yield predictive abilities of these procedures, based on the number of nonsignificant differences and their overall LS means of the 305-d milk yield deviations in calving age and calving season subclasses, was (first to last): 1) model 3 (second degree polynomial), 2) model 5 (fourth degree polynomial), 3) model 4 (third degree polynomial), 4) model 6 (fifth degree polynomial), 5) model 2 (mixed log second degree polynomial, 6) model 1 (gamma function), 7) TIM (the test-interval method), and 8) model 7 (sixth degree polynomial).

As with 100-d milk yields, the ability of TIM to predict 305-d milk yields ranked close to the bottom among the eight prediction procedures. Also, the TIM procedure was the only one to produce overall significant differences (predicted minus actual) for 100-d and 305-d ($P < 0.05$). These results suggest that using TIM to predict either 100-d or 305-d milk yields from monthly test-day records would probably produce biased predicted milk yields, which in turn, may bias genetic predictions for these traits.

The ranking of the seven prediction models for 305-d milk yields here (3, 5, 4, 6, 2, 1, 7) was very similar to that obtained using all daily milk yields (3, 2, 5, 4, 7, 6, 1; Koonawootrittriron *et al.*, 2001). Again, only two models changed ranking. Models 2 was fifth and model 7 was the bottom model here, whereas model 2 shared the top spot with model 3, and model 7 was fifth for the all daily records case. Thus, models 2 (mixed log second degree polynomial) and model 7 (sixth degree polynomial) appeared to be more sensitive to the number of daily records used to predict daily lactation yields. Considering both sampling strategies (all daily records and monthly test-day records), model 3 (second degree polynomial) could be considered the most appropriate model to predict individual cow 305-d milk yields for this data set. The simplicity and computational ease of model 3 (quadratic equation), makes it ideal for large-scale computations such as those in national genetic evaluations. Thus, model 3 could be used instead of TIM for the computation of 305-d milk yields in national genetic evaluations in Thailand. Before a final decision is reached in this regard, however, this study needs to be repeated with a larger multibreed population that is more representative of the actual national Thai cattle population.

Random regression models (Schaeffer and Dekkers, 1994; Jamrozik *et al.*, 1997; Jamrozik and Schaffer, 1997) are currently a popular alternative to the classical total production for genetic evaluation of dairy cattle. Should random regression models be applied to the multibreed Thai dairy cattle population in the future, model 3 could be the equation used in both the fixed and in the random portion of a random regression model using monthly test-day yields. However, because there was no uniformly best model for all calving age and calving season subclasses in this HF-RS multibreed herd, a more accurate genetic evaluation system may need to consider several lactation prediction equations for the various breed group x lactation number x calving age and on breed group x lactation number x calving season subclasses. Using a large number of lactation prediction models, however, may unduly increase the complexity of a genetic evaluation system, particularly in a multibreed population. Thus, as an approximation, only a small number of lactation prediction equations could be defined (e.g., 3 or 4), which may be appropriate to predict individual cow lactation daily yields (and accumulated milk yields) with sufficient accuracy within calving age or calving season subclasses.

The current Thai cattle population has more than 10 different breeds *Bos indicus* and *Bos taurus* represented both in purebred and in crossbred form. The population is largely unstructured and has a large number of crossbreds composed of up to seven breeds. The only attempt to develop a large-scale sire evaluation began in 1996 through a collaboration between Kasetsart University and the Dairy Promotion Organization of Thailand (DPO, 1996). The procedure used was a unibreed best linear unbiased prediction, and the model was a single-trait (100-d and 305-d milk and fat yield) animal model (Henderson, 1973; Quaas and Pollak, 1980). Considering the amount of available dairy data and the complexity of the Thai multibreed population, a potential research work could consider accumulated yields and a multibreed model that uses model 4 for 100-d and model 3 for 305-d accumulated milk and fat yields. This next piece of research will help revalidate the daily milk yield models used here, and it will determine their usefulness in a larger, more complex, multibreed population.

Conclusions

The ability of the test-interval method and seven prediction models to predict 100-d and 305-d milk yields using monthly test-day records of cows in a multibreed Holstein Friesian-Red Sindhi herd of SARTC varied by breed group x lactation number x calving age and breed group x lactation number x calving season subclasses.

None of the eight prediction procedures was uniformly better across all subclasses for either 100 d or 305 d milk yields. In addition, the eight procedures ranked differently for 100-d and 305-d accumulated milk yields. The most appropriate model for 100-d milk yield predictions was model 4 (third degree polynomial), whereas for 305-d, model 3 (second degree polynomial) was the best performer. It should be stressed however, that these results apply strictly to this multibreed population and this data set. To obtain broader conclusions applicable nationally, a substantially larger multibreed data set that captures the diversity of breeds and crossbred groups of the Thai cattle population will be needed. However, this study provides a good indication of the types of lactation prediction models that might be applicable under Thai conditions.

Because the performance of the eight models here differed across calving age and calving season subclasses, several lactation prediction models might be needed for a national Thai genetic evaluation. This aspect also needs to be revisited with a large national Thai multibreed data set, with the purpose of finding a model, or a set of models, that is computationally simple, and gives reasonably accurate genetic predictions.

Acknowledgements

The authors are thankful for the financial support from the Thailand Research Fund under the Royal Golden Jubilee Project. The authors are grateful to the staff of the Sakon Nakhon Agricultural Research and Training Center for making their data set available for this research. The authors thank T. A. Olson, J. Rosales, and C. E. White for reviewing the manuscript.

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