Management practices associated with conception rate and service rate of lactating Holstein cows in large, commercial dairy herds

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ABSTRACT

Data from lactating Holstein cows in herds that participate in a commercial progeny testing program were analyzed to explain management factors associated with herd-average conception and service rates on large commercial dairies. On-farm herd management software was used as the source of data related to production, reproduction, culling, and milk quality for 108 herds. Also, a survey regarding management, facilities, nutrition, and labor was completed on 86 farms. A total of 41 explanatory variables related to management factors and conditions that could affect conception and service rate were considered in this study. Models explaining conception and service rates were developed using a machine learning algorithm for constructing model trees. The most important explanatory variables associated with conception rate were the percentage of repeated inseminations between 4 and 17 d post-artificial insemination, stocking density in the breeding pen, length of the voluntary waiting period, days at pregnancy examination, and somatic cell score. The most important explanatory variables associated with service rate were the number of lactating cows per breeding technician, use of a resynchronization program, utilization of soakers in the holding area during the summer, and bunk space per cow in the breeding pen. The aforementioned models explained 35% and 40% of the observed variation in conception rate and service rate, respectively, and underline the association of herd-level management factors not strictly related to reproduction with herd reproductive performance.

Key words: reproductive performance, dairy cattle, management, machine learning

INTRODUCTION

Reproductive performance is influenced by many environmental and management factors, such as accuracy of estrus detection, semen handling techniques, use of synchronization or resynchronization programs, transition cow management, metabolic health, udder health, cow comfort, and lameness (Lucy, 2001; Caraviello et al., 2006).

Fertility of the service sire (Kuhn and Hutchison, 2008) and correct thawing and handling of semen affect cow fertility. Improper semen handling techniques can lead to damaged sperm membranes, reduced motility, and sperm death due to heat- and cold-shock (Foote and Parks, 1993). Caraviello et al. (2006) noted that the temperature at which semen is thawed was a significant factor affecting the proportion of cows pregnant by 150 d in milk.

Tenhagen et al. (2004) compared the economic considerations between timed AI after synchronized ovulation to AI at estrus and noted that evaluation of synchronization protocols should include reproductive performance along with the appropriate costs of treatment. When estrus detection rates are poor in herds, Ovsynch (Pursley et al., 1995) may help reproduction by increasing the service rate.

Calving-related disorders such as metritis, retained placenta, ketosis, and displaced abomasum predispose cows to reduced reproductive efficiency (Stevenson and Call, 1988; Walsh et al., 2007). Furthermore, cows consuming less dry matter during the periparturient period have delayed first ovulation and reduced fertility (Staples et al., 1990) and are predisposed to diseases that affect fertility such as metritis (Huzzey et al., 2007). Pen moves, grouping strategies, and bunk space are just a few of the factors that affect the subsequent health and performance of the transition cow (Cook and Nordlund, 2004).

Chebel et al. (2004) noted that cows with mastitis were 2.8 times more likely to experience embryonic loss than cows that did not have mastitis. Furthermore, cows with subclinical or clinical mastitis before the

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first insemination tend to require a greater number of services per conception (Barker et al., 1998; Schrick et al., 2001; Santos et al., 2004).

Environmental conditions can have a major influence on a cow's ability or tendency to exhibit signs of estrus. Overcrowding and the presence of slippery floor surfaces can restrict mounting activity (Britt et al., 1986). Furthermore, mounting activity of cows with foot problems is reduced compared with cows with good foot health (Leonard et al., 1994). Garbarino et al. (2004) found that cows classified as lame had 3.5 times greater odds of delayed cyclicity compared with cows classified as nonlame.

Although many of the aforementioned studies have focused on a few related factors that may affect reproductive performance, they tend to be limited in scope. Recently, Caraviello et al. (2006) used a machine learning algorithm to construct alternating decision trees for prediction of first-service conception rate and pregnancy status at 150 d postpartum for individual animals. Such algorithms are powerful and flexible, because they can accommodate missing data, multicollinearity, and numerous explanatory variables. Caraviello et al. (2006) focused on classification of binary outcomes (i.e., pregnant or not pregnant) and the resulting decision trees were very complex. The objective of this study was to identify factors associated with conception rate and service rate from a large number of interrelated directly and indirectly associated variables using machine learning algorithms. The objective of the machine learning algorithms was to determine the predictability of such a method when a large number of variables associated with conception and service rate were missing. This was an important objective because the data set had many missing explanatory variables.

MATERIALS AND METHODS

Data regarding production, reproduction, culling, and milk quality of lactating Holstein cows in 108 dairy herds in the Alta Genetics (Watertown, WI) Advantage progeny testing program were extracted from Dairy Comp 305 herd management software (Valley Ag Software, Tulare, CA). The herds used in this study were located in Wisconsin (40), New York (20), Minnesota (12), California (11), Michigan (4), Pennsylvania (4), Iowa (3), Idaho (3), Indiana (2), Ohio (2), South Dakota (2), Illinois (1), Maryland (1), Oregon (1), Vermont (1), and Washington (1). Herd sized ranged from 163 to 3,394 milking cows, and mean herd size was 781 milking cows. Mean conception rates for individual herds ranged from 20 to 44%, with an overall mean of 32.2%. Mean service rates ranged from 39 to 76%, with an overall mean of 56.9%. Within each herd, annual

conception rate and service rate were averaged across all successive 21-d time periods from September 1, 2006 to September 1, 2007. Conception rate was calculated as

$$\text{Conception rate} = 100 \times \frac{(\text{total no. of confirmed pregnancies})}{(\text{total no. of breedings})},$$

Furthermore, service rate was calculated as

$$\text{Service rate} = 100 \times \frac{(\text{total no. of breedings})}{(\text{total no. of cows eligible for breeding})}.$$

Cows that were eligible for breeding met the following criteria:

1. Past the voluntary waiting period (**VWP**) at the beginning of the period.
2. Nonpregnant at the beginning of the period.
3. Not marked as "do not breed" before or during the period.
4. Cow is present for >50% of the period.
5. Known outcome if inseminated before or during the period.

The VWP for a herd was defined as the number of days postpartum when 5% of cows had received their first AI. It was necessary to calculate a herd-specific VWP from the raw data, because the Dairy Comp 305 software assumes a 50-d VWP. Somatic cell score was calculated as the annual herd average from September 1, 2006 to September 1, 2007.

In addition, a survey regarding transition cow management, facilities, reproductive programs, and labor on a subset of 86 farms was completed by Alta Advantage consultants between February 1 and April 1, 2007. A total of 41 potential explanatory variables related to management factors and conditions that may affect conception rate or service rate were assessed in the survey. Preference was given to explanatory variables related to management, facilities, nutrition, and labor that could be easily and consistently measured by the Alta Advantage consultants in a 1-h walkthrough of the dairy. Furthermore, the survey used for this study was completed on only 86 of the 108 herds considered for this study because of time and labor constraints for data collection. Means, standard errors, and frequencies for explanatory variables considered in this study are provided in Table 1, and case definitions for selected explanatory variables are provided in Table 2. Because some of the continuous or categorical variables considered in this study did not apply to some herds, a

dummy variable representing “does not apply” was used when applicable. Furthermore, values that were missing or incomplete were considered as missing values in the subsequent analyses.

A regression-based decision tree was used to explain management factors associated with conception rate and service rate. The M5P algorithm (Quinlan, 1992) for building regression-based trees, as implemented in the WEKA 3.4 Data Mining Software (Witten and Frank, 2005) was used. The M5P algorithm creates a model tree that represents a combination of a decision tree (i.e., a tree diagram that is used for predicting a specific outcome in which the branches represent variables associated with the outcome) and one or more linear

regression models, for predicting a continuous outcome in 3 stages: construction, pruning, and smoothing.

As described by Quinlan (1992), construction of a model tree begins with the total set of observations designated by T . Each case is specified by the values of a fixed set of discrete and numeric attributes, as well as an associated outcome. The aim is to build a model tree that relates outcomes of the training cases to their corresponding attributes. Model trees are created by the divide-and-conquer method. The set T of training cases may be associated with a leaf node, or T may be split into subsets corresponding to the outcome of a test. This process continues and is applied to all subsets recursively.

Table 1. Census data collected from each of the 108 herds participating in the study, which represented potential explanatory variables for describing conception rate and service rate

Variable collected	Mean $\pm$ SE (frequency)
1) Voluntary waiting period	53.1 $\pm$ 9.9 d postpartum (n = 108)
2) Percentage of repeated inseminations between 4 and 17 d post-AI	8.1 $\pm$ 3.7% (n = 108)
3) Days at pregnancy examination	28 d (n = 23); ≥ 35 d (n = 85)
4) Use of natural service bulls	Yes (n = 36); no (n = 72)
5) Displaced abomasum rate ¹	5.1 $\pm$ 2.8% (n = 88)
6) Cull rate <60 d postpartum ¹	10.5 $\pm$ 3.3% (n = 107)
7) Abortion rate ¹	13.4 $\pm$ 5.1% (n = 108)
8) First test SCS	2.7 $\pm$ 0.3 (n = 108)
9) Annual SCS	2.7 $\pm$ 0.5 (n = 107)
10) First test fat:protein ratio ¹	133.2 $\pm$ 7.0% (n = 106)
11) Stillbirth rate for lactation = 1	13.1 $\pm$ 4.4% (n = 108)
12) Stillbirth rate for lactation >1	6.9 $\pm$ 2.5% (n = 108)
13) Death rate ¹	7.8 $\pm$ 4.2% (n = 107)
14) Bunk space per cow in the close-up pen	0.88 $\pm$ 0.52 m (2.9 $\pm$ 1.7 ft) (n = 81)
15) Type of housing in the close-up pen	Freestalls (n = 44); bedded pack (n = 32); freestalls with dirt lot (n = 8)
16) Stocking density in the close-up pen ¹	80.9 $\pm$ 19.5% (n = 44)
17) Bunk space per cow in the post-fresh pen	0.80 $\pm$ 0.29 m (2.63 $\pm$ 0.94 ft) (n = 76)
18) Type of housing in the post-fresh pen	Freestalls (n = 65); bedded pack (n = 10); freestalls with dirt lot (n = 8)
19) Stocking density in the post-fresh pen ¹	82.2 $\pm$ 23.3% (n = 64)
20) Housing type at time of calving	Group pens (n = 37); individual pens (n = 31); stay in close-up pen (n = 15)
21) Stall width in the breeding pen	119.3 $\pm$ 5.6 cm (47.0 $\pm$ 2.2 in) (n = 84)
22) Stall length in the breeding pen	195.7 $\pm$ 31.0 cm (77.0 $\pm$ 12.2 in) (n = 79)
23) Fans over the freestalls	Yes (n = 53); no (n = 22)
24) Fans over the feedbunk	Yes (n = 31); no (n = 44)
25) Fans in the holding area	Yes (n = 45); no (n = 30)
26) Soakers over the feedbunk	Yes (n = 50); no (n = 30)
27) Soakers in the holding area	Yes (n = 30); no (n = 50)
28) Floor surface scoring in the breeding pen	Secure, good traction (n = 57); slippery, lacks traction (n = 16)
29) Use of a resynchronization program	Yes (n = 47); no (n = 34)
30) Bunk space per cow in the breeding pen	0.54 $\pm$ 0.14 m (1.8 $\pm$ 0.5 ft) (n = 78)
31) Stocking density in the breeding pen ¹	108.8 $\pm$ 9.8% (n = 80)
32) Cows per full-time employee	70.0 $\pm$ 30.2 cows (n = 81)
33) Cows per inseminator ²	17.2 $\pm$ 8.1 cows (n = 76)
34) Cows per milking unit ¹	4.7 $\pm$ 1.6 cows per milking unit (n = 83)
35) Temperature used to thaw semen	35.0 $\pm$ 0.9°C (95.0 $\pm$ 1.6°F) (n = 64)
36) Maximum time from thaw to insemination	7.1 $\pm$ 4.2 min (n = 70)
37) Foot-trim at dry-off	Yes (n = 59); no (n = 23)
38) Foot-trim during mid-lactation (100–200 d postpartum)	Yes (n = 21); no (n = 62)
39) Foot-trim as-needed	Yes (n = 40); no (n = 42)
40) Foot-trim during early lactation (<100 d postpartum)	Yes (n = 10); no (n = 71)
41) Foot-trim during late lactation (>200 d postpartum)	Yes (n = 10); no (n = 71)

¹Case definitions provided in Table 2.

²After normalization with square root transformation.

Table 2. Case definitions for potential explanatory variables for describing conception rate and service rate

Variable ¹	Case definition
5) Displaced abomasum rate	(Total no. displaced abomasums per year)/(total no. calvings per year)
6) Cull rate <60 d postpartum	(Total no. sold cows + no. dead cows <60 d postpartum per year)/(total no. calvings per year)
7) Abortion rate	(Total no. abortions per year)/(total no. pregnancies per year)
10) First test fat:protein ratio	$100 \times [(first\ test\ fat\ percentage)/(first\ test\ protein\ percentage)]$
13) Death rate	$100 \times [(total\ no.\ dead\ cows\ per\ year)/(total\ no.\ calvings\ per\ year)]$
16) Stocking density: close-up pen	$100 \times [(average\ no.\ cows\ in\ the\ close-up\ pen)/(no.\ stalls\ in\ the\ close-up\ pen)]$
19) Stocking density: post-fresh pen	$100 \times [(average\ no.\ cows\ in\ the\ post-fresh\ pen)/(no.\ stalls\ in\ the\ post-fresh\ pen)]$
31) Stocking density: breeding pen	$100 \times [(average\ no.\ cows\ in\ the\ breeding\ pen)/(no.\ stalls\ in\ the\ breeding\ pen)]$
34) Cows per milking unit	(Maximum no. cows in the holding area at any time)/(no. milking units)

¹Numbers refer to variables in Table 1.

The first step when building the tree is to calculate the standard deviation of the outcomes of cases in T . A splitting criterion is used to determine which attribute, if any, should be used to split the portion T of the training data that reaches a particular node based on maximization of the expected error reduction. The expected error reduction, or standard deviation reduction (SDR), is calculated by

$$SDR = SD(T) - \sum_i \frac{|T_i|}{|T|} \times SD(T_i),$$

where T is the set of training cases that reach the node, and $T_1, T_2, \dots$ are the sets that result from splitting the node according to the chosen attribute. For missing values, the splitting criterion is modified, and SDR is calculated by

$$SDR = \frac{m}{|T|} \times SD(T) - \sum_{i \in \{L, R\}} \frac{|T_i|}{|T|} \times SD(T_i),$$

where m is the number of instances without missing values for the attribute, T is the set of instances that reach this node, and T_L and T_R are the sets that result from splitting on this attribute. When the splitting procedure ends, global replacement of all missing values is based on the mean/mode values of the corresponding attributes of the training examples reaching the leaves. During testing an unknown attribute value is replaced by the mean/mode value of that attribute for all training instances that reach the node, with the effect of choosing always the most populous subnode. The splitting process terminates when too few instances remain (e.g., <4) or when the class values of the instances that reach a node vary slightly; that is, when their standard deviation is only a small fraction (e.g., <5%) of the standard deviation of the original training set.

The pruning procedure uses an estimate of the expected error of T at each node. The absolute difference between the predicted value and actual value is averaged

over each of the training instances that reach the node. Because this average underestimates the expected error for unseen cases, it is multiplied by the factor $(n + v)/(n - v)$, where n is the number of training instances that reach the node and v is the number of parameters in the linear model at the node.

Finally, a smoothing process is used to compensate for discontinuities between adjacent linear models at adjacent leaves of the pruned tree. The smoothing calculation used for regression-based trees is

$$p' = \frac{np + kq}{n + k},$$

where p' is the prediction passed up to the next higher node, p is the prediction passed to this node from below, q is the value predicted by the model at this node, n is the number of training instances that reach the node below, and k is a smoothing constant (default = 15).

Performance of the M5P algorithm was assessed using 10-fold cross-validation. Because there was a total of 108 observations used in the M5P analysis, each fold consisted of roughly 10 herds. For each of 10 folds (i.e., samples drawn without replacement) of the original data, a model was constructed using cases in the remaining 9 folds and tested on cases in the 10th fold. Finally, conception rate and service rate were analyzed with a traditional linear statistical model using the GLM procedure of SAS (version 9.1.3, SAS Institute, 2008). Backward deletion was used to determine the optimal combination of explanatory variables, where "optimal" was defined as the combination with the lowest Akaike's information criterion, and all terms in the equation were significant at the $P \leq 0.05$ level.

RESULTS AND DISCUSSION

Conception Rate

The final model for describing conception rate, which was based on the largest correlation coefficient and

Figure 1. Histograms for conception rate (mean = 32.2, SD = 4.5) and service rate for 108 herds (mean = 56.9, SD = 7.6).

smallest root mean squared error from the M5P algorithm for the whole model, was as follows:

$$y_i = \mu + b_1ACC_i + b_2STOCK_i + b_3VWP_i + b_4SCS_i + b_5PGEXAM_i + b_6ABORT_i + e_i,$$

where y_i = mean conception rate within herd i ; μ = overall mean; ACC_i = accuracy, defined as the percentage of repeated inseminations between 4 and 17 d post-AI for herd i , with regression coefficient b_1 ; $STOCK_i$ = stocking density in the breeding pen for herd i , with regression coefficient b_2 ; VWP_i = length of the VWP for herd i , with regression coefficient b_3 ; SCS_i = somatic cell score for herd i , with regression coefficient b_4 ; $PGEXAM_i$ = days from insemination to pregnancy examination for herd i , with regression coefficient b_5 ; $ABORT_i$ = abortion rate for herd i , with regression coefficient b_6 , and e_i = random error.

During the pruning and smoothing process, the regression-based model tree was simplified into a single linear equation. For the model calculated by the M5P algorithm, the cross-validation coefficient of determination (R^2) was 0.25. Regression coefficients are provided in Table 3. A histogram for conception rate for the 108 herds is provided in Figure 1.

Next, the GLM procedure (SAS Institute, 2008) and backward deletion were used to predict conception rate. Interactions were ignored because the number of observations was insufficient to evaluate a large number of 2- or 3-way interactions. A total of 29 herds were removed from this analysis because of missing values for some of the predictor variables. Therefore, 79 herds were used to assess significance of the predictor variables using ANOVA type III sums of squares.

Four variables, the percentage of repeated inseminations between 4 and 17 d post-AI ($P < 0.001$), stocking density in the breeding pen ($P < 0.05$), length of the VWP ($P = 0.05$), and days from insemination to pregnancy examination ($P < 0.05$) were associated

Table 3. Regression coefficients from the M5P machine learning algorithm and ANOVA estimates based on herds with no missing data for the model describing conception rate (%)

Variable	M5P regression coefficients ¹	ANOVA ²	
		Estimates $\pm$ SE	P-value
Intercept	45.76	46.57 $\pm$ 5.47	<0.0001
Repeated inseminations between 4 and 17 d (%)	-0.37	-0.39 $\pm$ 0.11	<0.001
Stocking density in the breeding pen (%)	-0.08	-0.10 $\pm$ 0.04	0.02
Days at pregnancy examination = 28 d	-2.50	-2.15 $\pm$ 0.93	0.02
Voluntary waiting period (d)	0.09	0.09 $\pm$ 0.04	0.04
SCS (log SCS)	-1.97	-1.43 $\pm$ 0.81	0.08
Abortion rate (%)	-0.15	Not in final model	Not in final model

¹ R^2 = 0.25; root mean squared error = 3.88.

² R^2 = 0.35.

with conception rate. Somatic cell score ($P = 0.08$) also tended to be associated with conception rate. Regression coefficients, standard errors, and P -values from the linear regression analysis are provided in Table 3. Overall, the R^2 value of the linear regression model for conception rate in the 79 herds with no missing data was 0.35.

Accuracy of estrus detection, which was measured as the percentage of repeated inseminations following a cycle of 4 to 17 d post-AI, was a significant predictor of conception rate in the present study. As the percentage of inseminations during this period increased, herd average conception rate decreased.

High stocking densities in the breeding pen were also associated with reduced conception rates. Overstocking of the breeding pens is often overlooked when considering factors associated with reproductive performance. Overstocking freestall barns reduces lying time (Friend et al., 1977; Wierenga and Hopster, 1990; Fregonesi et al., 2007) and increases the frequency of aggressive interaction because of competition for stalls and resources (Fregonesi and Leaver, 2002; Fregonesi et al., 2007). In most cases, when freestalls are overstocked, bunk space is restricted simultaneously. Caraviello et al. (2006) reported that bunk space per cow was one of the most important explanatory variables affecting pregnancy status at 150 d postpartum, although it was not found to be significant in the current model.

In the present study, a longer VWP was associated with improved conception rate. Caraviello et al. (2006) found a positive relationship between length of the VWP and first-service conception rate. Foote (1978) found that cows serviced before 50 d postpartum had a lower conception rate than those serviced after a longer postpartum period. Also, cows in an Ovsynch group with VWP >76 d had a greater conception rate than cows with a VWP between 60 and 75 d (Pursley et al., 1997). In contrast, Schneider et al. (1981) observed that cows serviced very late after calving (93 ± 17 d) had lower fertility than cows serviced earlier (72 ± 18 d). The maximum VWP in the present study was 80 d postpartum, so the efficacy of a VWP greater than 80 d postpartum is subject to greater uncertainty because of extrapolation.

Herds with high SCS tended to have lower conception rates. In previous studies, cows that experienced subclinical or clinical mastitis before the first insemination required a greater number of services per conception (Barker et al., 1998; Schrick et al., 2001; Santos et al., 2004) and were 2.8 times more likely to lose their pregnancies than those not experiencing mastitis (Chebel et al., 2004). Although SCS is not equivalent to clinical mastitis, it can be used as an indicator of mastitis

because the genetic correlation between SCS and clinical mastitis is 0.72 (Rupp and Boichard, 1999).

Finally, it should be noted that herds that routinely carried out pregnancy examinations at 28 d after breeding had higher conception rates than herds that performed pregnancy examinations at ≥ 35 d after breeding ($P = 0.02$). Early in gestation, the frequency of embryonic death is high. For example, among cows diagnosed pregnant at ≤ 28 d post-AI, 10 to 16% experience embryonic loss by 56 d post-AI (Mee et al., 1994; Vasconcelos et al., 1997; Fricke et al., 1998). In addition, with 28-d pregnancy examinations, there is the potential for incorrect diagnosis. Pieterse et al. (1990) found that sensitivity and specificity of pregnancy diagnosis with ultrasound when conducted between 21 and 25 d post-AI was lower than pregnancy diagnosis conducted between 26 and 33 d post-AI. Uncertain cases may be (conservatively) labeled as pregnant so that the cows in question are not subject to resynchronization. After reexamination, these cows may not be pregnant, and these cases show up as embryonic losses (even though the cow may not have been pregnant at the time of the initial examination). In the present study, herds that had 28-d pregnancy examinations had a >2% higher average conception rate than those that carried out ≥ 35 d pregnancy examinations. A univariate analysis was conducted to determine if herds that used 28-d pregnancy examinations also had an apparent abortion risk. Abortion rate was the response variable, and days from insemination to pregnancy examination was the predictor variable. Herds that used 28-d pregnancy examinations had a 1.96% higher apparent abortion rate ($P = 0.10$). Because the effects of days at pregnancy examination and abortion rate canceled each other, we concluded that early pregnancy diagnosis was not a useful management practice for improving conception rate.

Service Rate

The final model for describing service rate, which was based on the largest correlation coefficient and lowest root mean squared error from the M5P machine learning algorithm, was as follows:

$$y_{ijk} = \mu + \text{RESY}_i + \text{SOAK}_j + b_1\text{BUNK}_{ijk} + b_2\text{CPB}_{ijk} + b_3\text{ACC}_{ijk} + e_{ijk},$$

where y_{ijk} = mean service rate within herd k ; μ = overall mean; RESY_i = fixed effect of resynchronization program (yes, no); SOAK_j = fixed effect of utilization of soakers in the holding area during summer months

Table 4. Regression coefficients from the M5P machine learning algorithm and ANOVA estimates based on herds with no missing data for the model describing service rate (%)

Variable	M5P regression coefficient ¹	ANOVA ²	
		Estimate $\pm$ SE	<i>P</i> -value
Intercept	37.7	40.7 $\pm$ 2.9	<0.0001
Repeated insemination between 4 and 17 d (%)	1.0	0.84 $\pm$ 0.19	<0.001
Cows per inseminator ³ (n)	0.14	0.003 $\pm$ 0.002	0.04
Use a resynchronization program = Yes	2.9	4.0 $\pm$ 1.5	0.009
Use soakers in the holding area = Yes	4.2	3.6 $\pm$ 1.5	0.02
Bunk space per cow in the breeding pen (cm)	3.2	2.5 $\pm$ 1.5	0.10

¹Correlation coefficient = 0.59; root mean squared error = 6.15.²R² = 0.50.³After square root transformation.

(yes, no); BUNK_{ijk} = bunk space per cow in the breeding pen for herd *k*, with regression coefficient *b*₁; CPI_{ijk} = square root of the total number of cows per inseminator for herd *k*, with regression coefficient *b*₂; AC-C_{ijk} = accuracy, defined as the percentage of repeated inseminations between 4 and 17 d post-AI for herd *k*, with regression coefficient *b*₃; and *e*_{ijk} = random error.

Once again, during the pruning and smoothing process, the model tree was simplified into a single linear regression equation. For the model created by the M5P algorithm, R² was 0.35. Regression coefficients are provided in Table 4. A histogram for service rate for the 108 herds is provided in Figure 1.

Next, the GLM procedure in SAS (SAS Institute, 2008) with backward deletion was used to predict service rate. As noted earlier, the number of observations was insufficient to test all possible interactions between predictor variables. A total of 46 herds were removed from this analysis because of missing values for some of the predictor variables. Significance of the predictor variables was evaluated using the ANOVA type III sum of squares. The R² of the linear model for service rate based on 62 herds with no missing data was 0.50. Regression coefficients, standard errors, and *P*-values from the linear model analysis are provided in Table 4. Three variables, percentage of repeated inseminations between 4 and 17 d (*P* < 0.001), utilization of a resynchronization program (*P* < 0.01), and the utilization of soakers in the holding area (*P* = 0.02) were associated with service rate.

Resynchronization programs had a beneficial effect on service rate. Least squares means service rate was 58.6 $\pm$ 1.0 for herds with a resynchronization program and 53.8 $\pm$ 1.3 for herds without a resynchronization program. Herds that used a resynchronization program in this study gave GnRH either 7 d before a pregnancy exam or on the day of pregnancy exam. A univariate analysis was used to determine if a difference existed in service rate between the 2 resynchronization methods.

There was no significant difference in the 2 resynchronization methods for the herds in this study (*P* = 0.47); however, herds that did not have a resynchronization program had lower service rates than herds that did have a resynchronization program (*P* < 0.01). Herds that rapidly achieve AI services after nonpregnant diagnoses are able to decrease the interval between AI services, thereby increasing the AI service rate (Fricke, 2002). Resynchronization programs generally utilize Ovsynch, a synchronization regimen using sequential injections of GnRH and PGF_{2α} to control ovulation for timed insemination (Pursley et al., 1995). Sterry et al. (2006) compared 2 different resynchronization strategies. One group of cows received GnRH at 26 d after timed AI (TAI) and continued the resynchronization program only if the cows were diagnosed not pregnant by ultrasonography at 33 d after TAI, whereas another group of cows began the resynchronization program only after being diagnosed not pregnant 33 d after TAI. Despite the increased service rate, delaying initiation of the resynchronization program until 33 d after TAI increased the pregnancy rate per AI in that study. Fricke et al. (2003) also found that initiation of resynchronization 19 d after first TAI service resulted in lower pregnancy rate per AI compared with initiation of resynchronization 26 or 33 d after the first TAI.

As breeding technicians in the present study gained responsibility for servicing a greater number of cows, we noted an increase in service rate. In large commercial dairy herds, a dedicated breeding technician is often responsible for the majority, if not all, of the inseminations. Because dedicated breeding technicians are able to focus on one area of management (i.e., reproductive management), they tend to service more cows compared with herds in which “everyone” is responsible for estrus detection.

Utilization of soakers in the holding area during the summer (*P* = 0.02) was associated with service rate. It is important to note that 24 of the 30 herds that

used soakers in the holding area during the summer also used fan-based cooling systems in the holding area, and this finding highlights the general importance of heat stress abatement in large herds.

Increased bunk space per cow in the breeding pen ($P = 0.10$) tended to be associated with improved service rate. Reduced access to feed may influence metabolic status, especially in early lactation (Cook and Nordlund, 2004), which may influence the onset of estrus activity. However, this finding is associative, not causal. For example, reduced bunk space also limits the number of available lock ups, which may affect compliance for the administration of estrus synchronization programs, and in most cases when bunk space is restricted, cows are also overstocked relative to stalls, resulting in reduced lying time and increased aggressive interactions due to competition for a place to rest (Fregonesi and Leaver, 2002; Fregonesi et al., 2007). Caraviello et al. (2006) reported that bunk space per cow was one of the most important explanatory variables affecting pregnancy status at 150 d postpartum.

Finally, the percentage of repeated inseminations between 4 and 17 d post-AI (i.e., accuracy of estrus detection) had a significant ($P < 0.001$) effect on service rate. As the percentage of repeated inseminations between 4 and 17 d post-AI increased by 1.0%, service rate increased by 1.0 and 0.84% for the M5P and ANOVA models, respectively. Despite the association between accuracy of estrus detection and service rate, this measure of reproductive efficiency is not a suitable method for improving service rate. First, for reproductive troubleshooting, it is impractical to recommend inseminating cows when they are not in estrus to increase service rate. Second, herds with poor accuracy of estrus detection had lower conception rates ($P < 0.001$). Furthermore, a high percentage of repeated inseminations during the period from 4 to 17 d post-AI is often the result of observing cows in visual heat (e.g., standing heat, mucus, increased activity) after a failed insemination from a synchronization program (e.g., Ovsynch, Co-Synch). Cows observed in estrus 4 to 17 d post-AI should be reinseminated. However, if a high percentage of cows are reinseminated 4 to 17 d post-AI in a herd, problems may exist in estrus detection or synchronization of ovulation. Reimers et al. (1985) suggested that many cows not in estrus on the day of their first postpartum service are actually near the middle of a normal estrous cycle. This indicates a failure in observing estrus.

CONCLUSIONS

Overall, the M5P machine learning algorithm used in the present study identified key explanatory variables

for improving herd average conception rate and service rate, and underlined the association of herd-level management factors not strictly related to reproduction with herd reproductive performance. Because of the structure of the data in this study, the M5P algorithm was not able to build and prune a decision tree; instead, the final models for conception and service rate were linear models. The ability of the M5P algorithm to accommodate missing values for potential explanatory variables did not make it any more useful than traditional linear model methods. Important environmental and management factors identified that were associated with herd conception rate and service rate performance included VWP interval, estrus detection accuracy, number of cows per inseminator, use of a resynchronization program, udder health, heat abatement, days from insemination to pregnancy examination, and stocking density in the breeding pen.

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