APPLICATION OF A MULTITRAIT ANIMAL MODEL TO PREDICT NEXT TEST-DAY MILK PRODUCTION

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ABSTRACT

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Effects of six seasons of calving, three herd production levels, and three lactations on test-day milk yield were studied using test-day records from Holstein cows. Lactation curves were estimated within each herd level-lactation-season subclass by fitting a regression model with a sixth degree polynomial to days in milk least square means. Significant ($P < .001$) season differences were detected with summer calving season depressing peak test-day milk production, total lactation yield and time to attain peak test-day production. First lactation cows had typical lower peaks and were more persistent than later lactation cows. Curves shifted upwards with herd production level with narrower differences at the end of lactation.

After assessing effects of the above factors; lactation data consisting of 171,922 test-day milk records for first lactation Holstein cows tested in 600 Michigan herds from 1988 to 1992 were divided into ten stages of lactation. Each stage was a 30-day days in milk (DIM) interval. With ten stages treated as separate traits, a multiple trait animal model was used to estimated the phenotypic variances and covariances among these traits within three herd production levels.

The model for each trait contained fixed effects of season of calving by DIM, season of test by temperature-humidity index and age at calving, and random additive genetic effects. Phenotypic (co)variances between traits were used to predict next test-day milk yield deviations for individual cows. Test-day milk deviations were predicted using either 1, 2 or 3 previous test-day deviations for a cow.

Biases in predicting test-day deviations averaged near zero when 3 previous test-day deviations were used. Biases were greatest when using only 1 previous test-day deviation. For the low herd production level, overall population mean biases were -.311, -.132 and -.005 kg when using either 1, 2 or 3 previous test deviations respectively. The corresponding root mean square errors did not differ much (3.32, 3.12, and 3.19, respectively). The traits or days in milk intervals predicted most accurately were between 120-270 days. Biases and root mean square errors were similar for medium and high production herd groups.

DEDICATION

This work is dedicated to my wonderful sister Rosemany Ngwerume who passed away on April 24, 1994, just before my final exam.

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1. INTRODUCTION

Dairy managers need to accurately evaluate milk production responses resulting from management changes or the implementation of new technologies to determine if they are cost effective. Evaluating production responses is critical to maintain long-run profitability. Because comparison with control groups is often not possible on farms, this task is difficult. In addition there may be periods when no specific changes or multiple management changes are made, that require monitoring production trends in order to effectively evaluate general management and herd health status. Without control groups, producers are forced to assess production change of the entire herd or a group of cows from period to period. This is difficult because cows in a herd or group contributing to a day's production vary as cows freshen or dry off between periods being assessed. In addition, a cow's test-day yield is influenced by systematic environmental effects such as season of calving, season of test and herd, and physiological factors such as stage of lactation, age and number of days open. Importantly, stage of lactation, season of test and days open change between periods for each cow. A within herd standardization of test-day yields for all these effects allows comparison between periods and between individual cows within a herd. Making these adjustments is useful for management and selection purposes. In the Netherlands, for example, test-day yields of cows recorded prior to 250 days in milk are standardized for age and season of calving and stage of lactation. The standardized tests are averaged to give a herd index which is used as a management guide by producers (Wilmink, 1987).

A cow's performance can be llustrated by the following general model for the phenotypic expression of a quantitative trait:

$$\mathbf{P_{ij} = \mu + G_i + PE_i + TE_{ij}}$$

where P_{ij} is the jth test-day record of the ith animal.

μ is a test-day constant level of performance for a group of animals which can be thought of as the average value that a group in a population have in common including the average level of management for the group. The term μ would, therefore, represent major identifiable fixed environmental effects that affect a cow's test-day record such as herd, management level, age of the animal at calving, the year and the season of calving, days in milk after calving and season of test. Since some fixed effects would change throughout a cow's lactation, μ might be different for each test-day record of an individual cow.

G_i is the sum of the genetic values which includes both additive and non-additive genetic effects. An additive genetic effect is the effect of a single allele at one locus on the expression of the trait of interest. The sum total of these additive genetic effects from all loci give the additive genetic value (A) of an individual. A random sample half of the alleles will be transmitted to progeny of that animal. The non-additive genetic effects include dominance and epistasis. Dominance genetic effects are caused by the combination of a pair of alleles at one locus. Dominance genetic effects are not transmitted to progeny from one parent, but arise due to the particular combination of alleles received from both parents. The dominance genetic value of an animal is the sum total of all dominance genetic effects over all loci. Epistatic genetic effects are the result of interactions among additive and dominance effects. Epistatic genetic effects are commonly assumed to be non-significant in genetic evaluation problems and measurement of such effects is difficult.

PE_i is the sum of effects of environmental factors which permanently influence the performance of animal i, i.e. influence all subsequent observations made on an individual. For example, the feeding regime used to raise dairy heifers, if extreme (poor feeding or excessive energy), can influence mammary development, hence becoming a permanent environmental effect influencing all lactations. If a cow is preferentially treated during all her lactations, then preferential treatment can be a permanent environmental effect.

TE_{ij} is the sum of random environmental effects which affect the jth record of animal i and thus are temporary. A temporary environmental effect may influence one or more observations on the individual but is not repeated for every observation. Whether or not an individual receives a particularly favorable or unfavorable influence is assumed to be by chance for each observation.

The underlying assumptions for the above model are:

i. P_{ij} is random and normally distributed

ii. the expected value of P_i is μ

iii. expected value of G_i, PE_i and TE_{ij} is zero

iv. the covariances among G_i, PE_i and TE_{ij} are zero

Since G_i and PE_i repeat in every record, then the sum of the permanent effects, termed real producing ability (RPA) of an animal, can be denoted as follows:

$$\mathbf{RPA_i = G_i + PE_i}$$

Further test-day producing ability (TDPA) of an animal can then defined as:

$$\mathbf{TDPA_i = RPA_i + TE_{ij}}$$

To monitor herd or individual cow performance, attention needs to be paid to TE_{ij} which can increase or decrease. Dairy producers would be interested in improving TE_{ij} through management changes. A method to predict TE_{ij} for comparison to actual test-day performance of individual cows which is the focus of this study would be desirable. This would allow producers to determine if cows performed better than expected on a test-day as a result of management. Use of animal models has been a breakthrough in that both G_i and PE_i (RPA) for an individual animal can be estimated and results in more accurate estimation of fixed effects. The RPA has been computed for total lactation yields. Estimation of TDPA of a cow has not been done because of lack of methods to predict TE_{ij}.

Daily milk yields can provide a useful measure of a herd's current performance and as an indication of management and disease problems. Producers, veterinarians and feed consultants make numerous decisions based upon weekly or monthly changes in daily milk averages within a herd. Such comparisons are often used to evaluate new management practices, feed changes, or feed additives. However, comparison of changes in average daily milk based upon milk tank comparisons does not account for addition of fresh or removal of dry and antibiotic treated cows, changes in stage of lactation or seasonal differences between periods of measurement.

Often, subgroups such as the high producer strings are of interest, requiring individual milk weights. Changes in monthly test-day daily milk averages provided by Michigan DHIA and a number of other DHIA organizations do not account for changes in stage of lactation and normal seasonal trends which, jointly, can result in more than a 10% change in daily milk production for a cow over a 30-day period. As a result, comparison of daily milk averages are crude, potentially, resulting in inaccurate assessment of management changes and health status of herds. Methods are necessary to adjust daily milk weights for test-day comparison.

Currently, several methods are being used to account for stage of lactation by adjusting milk to 150 days in milk (McCraw and Butcher, 1976; Steuernagel, 1988; Nordlund, 1987). Steuernagel also adjusts for age and parity. However, season of calving, which also influences production peak and rate of decline was only considered by (McCraw and Butcher, 1976). Herd production level may also influence rate of lactation decline.

Summarizing test-day records into a single measure, lactation yield, as is common practice has some deficiencies. Adjustments of a 305-day cumulative value for systematic environmental effects such as herd, season and age of calving can be done but it would be difficult to adjust for systematic effects specific to each individual test day making up the 305 day record. Such factors include the effects of temperature, relative humidity, pregnancy, use of bST and disease. It would require accurate start and stop times for disease, use of bST, etc., to get accurate test interval estimates of milk production from which to compute 305-day production.

Many methods have been developed to predict total lactation yield or 305 day milk yield. For monitoring management changes one method has been to compare projected 305 day Mature Equivalent (ME) values from one test day to the next test-day (Galligan and Ferguson, 1991; Eicker et al., 1993). This accounts for age, season of calving and herd level but it is difficult to quantify change in 305 ME values to change in daily milk. Prediction of short production periods, such as to the next test-day, would likely be more accurate compared to predicting longer periods as is done in projecting 305-day records. Further, prediction of test-day production or the next test-day production in lieu of predicting 305-day yield would be more useful in monitoring cow and herd production change resulting from changes in management such as ration modification or use of bST.

The problem of accurately comparing daily milk production has resulted in requests by a number of feed consultants and veterinarians for a better system to monitor production changes in dairy herds. A useful system would predict production for the next test day while accounting for physiological changes in each cow and season of test or change in the environment. The predicted values could then be compared to the actual values for that test day to determine if there is a significant change in production. When predicting unobserved test-day records, it is desirable to make maximum use of the predictability of the lactation curve and to minimize the error of prediction from a sample of daily records.

2. Objectives

2.1 Lactation Curves (Study one)

The objectives of this study were 1) to assess the effect of six seasons, three herd production levels and parity on the shape of lactation curves, 2) to derive factors that can be used to estimate herd mean production at 150 days postpartum.

2.2 Predicting Test-day Milk Production (Study 2)

The objectives of this study were to 1) estimate phenotypic, additive genetic and residual (co)variances of test-day milk production for ten 30-d days in milk intervals treated as separate traits; 2) predict next test-day milk production deviations using deviations from the previous 1, 2, or 3 tests (traits).

3. Review of Literature.

3.1 Introduction

Milk production is influenced by a number of non-genetic factors. When attempts are made to estimate the genetic value of an animal, the effects of some of these factors have to be removed. Adjusting records for known causes of variation is a must in making accurate culling and selection decisions.

The non-genetic or environmental factors affecting milk yield are documented in numerous investigations reported in the literature. Problems of estimating a number of these effects, their magnitude and mutual interrelations have been thoroughly investigated. Some of the environmental factors that affect milk production will be reviewed in this section. A review on the advantages of modelling test-day production vs 305-day lactation yield is also given.

3.2 Environmental factors affecting a cow's production

3.2.1 Effect of Cow's Age

Age at calving of a cow is one of the main factors affecting milk, protein and fat yields in dairy cattle. Yield increases with age at a decreasing rate and reaches a maximum at maturity. Yield then decreases as cows become still older. Auran (1973) reported that age explains about 20-40 % of the total variation in milk production. Influence of month of calving on production records is also well established. So, in Canada, an age-month adjusted record is known as a Breed Class Average (BCA) and in the United States the adjusted records are known as

Mature Equivalents (ME). In a review, Freeman (1971) reported the history and basic problems both of estimating age effects and their practical application as adjustment factors. Unbiased estimates of age effects require simultaneous consideration of herd, year, season of calving, age and cow effects together with their interactions (Daniel, 1981, 1982a).

Several workers showed that the influence of age at calving on monthly test-day yields decreased with advancing lactation, accounting for about 41% to 50% of total variation of first monthly test to about 2% to 5% for the last three test-days (Auran, 1973; Dannel, 1981). Ronningen (1967) showed 5.7% of the variation in maximum daily yield in first lactation was due to age at calving.

Dannel (1981) studied the effects of age at calving on both total lactation production and individual test-day yields of milk and fat percentages. Lactation milk yields increased with increasing age at calving for the Swedish Red and White (SRB) and Swedish Friesian (SLB) dairy breeds. Effects of age at calving on 305 day milk production and test-day milk production of SRB breed reported by Danell (1981) are in Table 1. Younger cows (20 to 25 months) gave 150-200 kg more for each month of age while older cows (26 to 33 months) had a smaller (only 25-33 kg) increase in yield with increasing age. There is a trend of 50 kg / month in the interval between 24 and 33 months of age. Although test-day fat percentages were also affected by age at calving, the effects were far less than milk yield. Younger calving cows had lower fat % values than those calving older. Effects of age of the cow on a test-day have been studied (Ng-Kwai-Hang et al., 1984; Stanton et al., 1992). Ng-Kwai-hang et al. (1984) indicated that milk production increased markedly between two and five years of age and then increased at a slower rate between five and six years of age. Percentage of fat in milk increased linearly between two and five years followed by a drop between five and six years. Stanton et al. (1992) used a test day model to study the effects of age on test-day production and concluded that age at calving would account for more variation in test-day production than age on test-day.

Effects of age on milk production has also been examined in terms of lactation number or parity. Wood (1967) showed the effect of parity on the lactation curve parameter. The constant **a** representing average daily production on a log scale was 3.53, 3.72, 3.97, 3.86 for first, second, third and fourth or greater parities respectively. The increase may result from successive parities promoting udder development and from a cow's physiological development in general.

Parity differences have been shown in terms of persistence, with first lactation cows being more persistent than later lactations. Keown et al. (1986) reported similar persistence of fat % and protein %. Wiggans and Van Vleck (1979) reported parity to have little effect on projection factors for protein yield.

Table 1. Average constant estimates and SE for the effects of age at calving on lactation yield and test-day yields of milk in kg for Swedish Red and White dairy breed.

AGE	305-d	1	2	3	4	5	6	7	8	9	10
20-21	-530.3	-2.14	-2.15	-2.05	-1.77	-1.66	-1.78	-1.48	-1.49	-1.26	-1.05
22-23	-249.5	-1.09	-1.02	-.0.94	-0.95	-0.79	-0.73	-0.65	-0.61	-0.63	-0.58
24-25	-108.6	-0.41	-0.43	-0.42	-0.39	-0.34	-0.27	-0.31	-0.33	-0.36	-0.34
26-27	-14.2	0.07	0.01	-0.04	-0.05	-0.08	-0.05	-0.11	-0.13	-0.12	-0.07
28-29	76.3	0.37	0.34	0.30	0.23	0.20	0.18	0.12	0.21	0.26	0.29
30-31	188.2	0.74	0.76	0.63	0.61	0.55	0.57	0.53	0.57	0.56	0.55
32-33	287.3	1.08	1.12	1.07	1.02	0.94	0.93	0.88	0.84	0.73	0.59
34-35	350.7	1.37	1.38	1.43	1.30	1.18	1.15	1.01	0.94	0.81	0.61

Source: Dannel (1981).

3.2.2 Season of Calving

The effect of season or month of calving exerts a considerable influence on the cow's milk production. The relationship of yield with month of calving is caused in part by the seasonal variations in feeding and care. The quality and quantity of feed or pasture seems to be of particular importance. In countries where the grazing system is short and cows are housed and fed indoors for most of the year, the highest lactation is given by cows calving during the autumn and early winter (Danell, 1982a).

Auran (1973) used test-day records to study the influence of month of calving on individual test-days. The effects of monthly and cumulative yield showed that month of calving was not as important as age at calving. Month of calving accounted for about 1.8% of the total variation in the first test-day and about 7.8% in the seventh and eighth test-days. Thus, contrary to the age effects, the effect of month of calving is largest towards the end of lactation. At the early stage of lactation, body reserves can supply part of the energy requirements and the production may therefore be less influenced by month of calving. Danell (1981) also reported findings similar to those found by Auran in using test-day records from Swedish dairy herds. When calving occurred in September for example, the yield was below average in the first month but above average in the last month of lactation. This suggested an interaction between month of calving and stage of lactation which makes the shape of the lactation curve dependent upon month of calving. Miller et al. (1967) ranked this interaction as the second most important source of variability in developing factors for monthly records. Effect of month of calving can vary in different years, herds, regions, although the general pattern seems to be the same overall (Auran, 1973; Dannel, 1981).

In addition to test-day milk yield, milk components are influenced by season of calving. Fat% showed seasonal variation which was the reverse of the effect on test-day milk yield. The month with the highest milk yield had the lowest fat test results (Danell, 1981; Schultz et al., 1990). Schultz et al. (1990) showed that test-day fat and protein percent were highest for cows calving from April through August and lowest for cow calving from September through March.

Month of test also affects test-day production (Sysrtad, 1965; Dannel, 1981;

Ng-Kwai-Hang et al., 1984). Lindgren et al. (1980) did a comprehensive study on the effect of non-genetic factors on monthly protein records of individual cows. Month of test was significant for all stages of lactation. During the period 2-9 months after calving, 6-8% of the variation in protein content was attributed to month of test. During the first month only 2 % was due to month of test, partly a result of larger overall variation in protein content during that period. Lindgren et al. (1980) concluded that a cow's production is less affected by month of testing immediately after calving than later in the lactation. Protein % showed steady increasing values during winter and decreasing values during summer a similar trend observed on Norwegian data by Sysrtad (1965, 1977). The low values in summer could be due to change in feed as cows generally were put out to pasture during summer, leading to an unfavorable balance between energy and protein in the diet.

3.2.3 Stage of Lactation

This is one of the several factors that change during lactation of a cow. Parity, age at calving, season of calving are fixed for a given lactation. Effects of stage of lactation are well documented. In general, daily milk yield increases to a peak a few weeks (30 to 90 days) after calving and then gradually declines to dry off. The graph of daily milk production against time (usually for 305 days) post calving is a lactation curve. Methods which characterize lactation curves allow for statistical comparison of milk production for the entire lactation and avoid restriction to the linear phase post-peak. This would include the critical first months of lactation in nutritional or physiological experiments. Knowledge of the lactation curve shape in dairy cattle is important because the pattern of how a cow produces milk over time could determine her biological and economical efficiency for purposes of feeding and selection. The shape of a lactation curve could be incorporated into the process of extending lactations. Sire and cow genetic ranking can be based on extended lactation records. An evaluation of sires could use the parameters derived from lactations of daughters. For a herd, three major uses of lactation curves would be i) to compare herd values to reference values, ii) to compare animals within herd, and iii) to monitor production after a management change.

3.2.3.1 Mathematical functions for describing lactation curves

Since the 1920's there has been considerable interest in mathematical description and analysis of the lactation curve in dairy cattle. Mathematical functions described below have been used to depict the shape of the lactation. Usefulness of these parameters has however been limited because of systematic divergence from typical lactation curves. Wood (1967) noted that the gamma curve approximated the lactation curve for milk yield. Wood's equation of the form

$$\mathbf{y_n = an^b e^{-cn}}$$

is the non-linear form of the incomplete gamma function and $\mathbf{y_n}$ is production on day **n**, **a** is the scaling factor and **b** and **c** are coefficients that define shape of the lactation curve before and after peak, respectively. Woods equation implicitly assumes more variable production at the peak than at extremes of the curve thus requiring a logarithmic transformation of the gamma curve to achieve homogenous variances. A group of cows usually have higher variance of production around the first two months than around eight months. Kellogg et al. (1977) suggested that other than random variation contributing to this comparison of variance two factors also cause such variation; i) cows have different lactation curves so individuals following different curves will differ much more at the second than the eight month and ii) the actual days post-partum for the second record of monthly production can range from about 35 to 70 days in milk for a group of cows. Therefore, early production records reflect a time period when production is changing more rapidly. Kellogg et al., (1977) suggested that techniques of intrinsically non-linear regression would fulfil the assumption of equal variance throughout a lactation. Using data from 4 lactations of 36 cows, Kellogg and coworkers (1977) found variances of deviation from the estimated curves were approximately equal after the first month of lactation thus supporting the use of non-linear equation of the untransformed Wood's (1967) equation using techniques of intrinsically non-linear regression.

Cobby and LeDu (1978) compared 3 regression methods to estimate parameters of the incomplete gamma function. Analysis of the residuals indicated that each method tended to overpredict actual data during early and late lactation. As such, reparameterization of the incomplete gamma function was proposed. They reported a 14% reduction in residual mean square when using non-linear techniques as opposed to linear regression on the logarithm transformed equation.

Using the incomplete gamma function, Congleton and Everett (1980) predicted daily and cumulative yield to 305 days post-calving and compared predictions to actual 305 day records. They found that fitting the log transformed incomplete gamma function by linear regression to monthly observations of daily milk gave a prediction with a bias of -15.1 kg and a root mean square of 183.4 kg in predicting 305 day cumulative milk.

Grossman et al. (1986) modified Wood's equation by multiplication with sine and cosine coefficients to account for other seasonal effects other than season of calving. The following equation was used

$$y_n = an^b e^{-cn}[1 - u \sin(x) + v \cos(x)]$$

where **a, b, c, u** and **v** are coefficients to be estimated, **n** is the day of lactation and **x** is the day of year computed as radians. The log transformation of the above equation was used in the form of a multiple regression model. Grossman and Koops (1988) proposed yet another lactation curve model, the multiphasic function which considers milk yield resulting from several phases of lactation. The multiphasic function has the form:

$$y_t = \sum a_i b_i [1 - \tanh^2(b_i(t - c_i))]$$

where;

y_t	=	milk yield at time t (t = days in milk)
n	=	number of phases
a_i	=	half asymptotic total yield for phase i
b_i	=	rate of yield relative to a_i (per day for phase i)

c_i = time of yield in days for phase i

The multiphasic model was fit to 17,607 complete lactation records from the Dutch Friesland Black and White in the Netherlands by Grossman and Koops (1988). The authors observed that the optimal model was the diphasic function (n=2) for which six parameters must be estimated. The diphasic function proved to be superior to the incomplete gamma function (Wood, 1967) in terms of less correlated residuals. For example, it was observed that the incomplete gamma function tended to over-predict milk yield from 30 through 110 days, underpredict from 130 to 230 days and again overpredict throughout the end of lactation. Residuals were also highly correlated and ranged from -.91 to .37 with a standard deviation of .37.

Since lactation curves represent amount of milk or milk components produced on each days in milk (DIM), they have also been estimated by solving for the least square estimates for DIM. Seasonal effects on production and reproduction influence both the amount of milk produced per day and duration of lactation. Therefore solving for DIM solutions requires accounting for variation due to season. Keown et al. (1986) estimated lactation curves for six seasons of freshening within 5 production groups and three lactation groups by solving for least square estimates for DIM. Curves were formed by adding an overall mean to season-stage of lactation subclasses. A similar approach was later used by Schultz et al. (1990) who estimated lactation curves for three parity groups and three breeds. In this study, lactation curves were smoothed by medians of five and repeated means of pairs. In estimating lactation curves by solving for the DIM least square estimates, Stanton and coworkers (1992) used a test-day model that included test-day effects to solve for DIM solutions.

3.2.4 Effect of Gestation

The relationship between reproductive efficiency and production has been reported in many investigations. As early as 1955, Carman attributed the negative correlation between lactation and reproductive efficiency to the depressing influence of high production on fertility. Lee et al. (1961) however assumed that this negative correlation was caused by the inhibitory action of gestation on production. Milk yield is depressed by gestation towards the end of lactation as demonstrated in many investigations reviewed by Gustafson (1972 cited by Auran, 1974). The influence of placental homornes was considered to be responsible. Reece (1958) explained this relationship with the theory that progesterone inhibits the stimulatory effect of estrogen on secretion of pituitary lactogen during lactation.

The variables that have been used to study the influence of gestation on production include calving interval (CI), days open (DO), days carried calf (DCC) and days dry (DD). Calving interval can however, be divided into two periods, DO and the gestation period with most of the variation in CI determined by the variation in DO.

Lactation yield increases as days open increases. The study done by Weller et al. (1985), defined length of period affecting annualized milk as:

[(Total Lactation yield)/CI] * 365.

He found maximum milk yield was at 75 to 91 days open for heifers and at 61 to 75 days open for cows. Influences of present lactation DO and previous lactation DO were examined simultaneously by Funk et al. (1987). As present DO increased from 20 to 300 days, lactation yields for FCM, milk, and milk fat increased approximately 1250, 1350 and 45 kg respectively. As previous DO increased from 20 to 300 days, lactation yields for FCM, milk and milk fat increased approximately 625, 650, and 25 kg. A study on Israeli cows (Bar-Anan and Soller, 1979) indicated that longer days open in previous lactation also increased lactation yield. These findings confirm the reports by previous authors (Auran, 1974; Oltenacu et al., 1980; Schaeffer & Henderson, 1972;). However, first lactation cows are less affected by days open than later parity yields (Auran, 1974).

A few researchers have studied the influence of DCC on lactation performance. The yield falls off about 100 days after conception amounting to 3-5 kg per day as the interval from conception to calving increases (Dannel, 1981). Keown and Everett (1986) studied the effects of days carried calf (DCC) on 305 day actual milk, fat and protein yield by lactation. In this study, maximum loss of lactation yield in first lactation cows was 510 kg milk, 15.2 kg fat, and 17.1 kg protein which occurred at 221 to 230 DCC. Milk, fat and protein yields in 305 d decreased continually from less than 41 DCC through 221-230 DCC after which the trend reversed for all three traits. Reasons for this reversal is however unknown. In the same study, estimates for second and third lactations were more similar than estimates for first lactation cows. The effect of DCC is more significant for milk than fat or protein for all lactations. Fat and protein are more persistent than milk and maybe less influenced by these factors than milk yield.

Funk et al. (1987) reported that cows dry 60 to 90 days gave the most milk the following lactation. Schaeffer and Henderson (1972) also indicated effects of days dry on subsequent production with dry periods of about 60 days resulting in the greatest subsequent production. Days dry have a larger impact on second lactation cows compared with later lactations (Wilton et al., 1967).

Heritability for DO is less than 10%, with most estimates close to zero. Therefore, adjustment of milk records for days open (DO) has been suggested since 305 day milk yields increase as number of DO increases (Schaeffer, Everett & Henderson, 1973). For adequate adjustment in milk records for DO or DCC breeding dates must be reported accurately. However, losses of information from missing breeding dates are normally very large. This is probably the major reason why adjustments of lactations for DO or DCC have not been incorporated into many genetic evaluation systems. One scheme that currently includes DCC is the Northeast Multiple Trait AI summary (Everett and Schmitz, 1993).

3.2.5 Heat Stress

It is apparent that performance, well being and health of the animal are influenced by biometeorological factors. The most important climatological factors are heat stress during the hot season and the wind chill factor during the cold winter. Buffington et al. (1981) defined heat stress as any combination of environmental parameters producing conditions that are higher than the temperature range of the animal's neutral zone. The survival and performance of an animal during heat stress periods depends on several weather factors especially temperature and humidity (Linvill and Pardue, 1992).

Heat stress increases the length of the estrus cycle, shortens the period of estrus, reduces conception, and increases embryo mortality with a corresponding decrease in fertility and placental malfunction. Further, fetal growth is retarded, gestation period is lengthened and calves show a corresponding lower birth mass as well as decreased ability to survive (Brody et al., 1948; Fuquay et al., 1979; Thatcher et al., 1974). Heat stress results in decreased feed intake, particularly roughage intake. Decreases in roughage intake maybe responsible for the decrease in the percentage butterfat in milk (Dupreeze et al., 1990). In a study by Roussel et al. (1969), milk production and nonfat milk solids were significantly decreased by thermal stress.

Due to vulnerability of dairy cows to heat stress caused by hot, humid weather, dairy cows can benefit from the micro-climate modifications to improve their comfort zone and performance. Appropriate facilities to protect cattle from climatic extremes are of cardinal importance for optimal performance. Protection includes location of the farm, shade, modification of dairy facilities, direct wetting of cattle by sprinkling combined with other supplemental cooling designs such as air fans (Dupreez et al., 1990). These practices ensure evaporative cooling which is ideal for protection against heat stress (Harn, 1981). Thatcher et al. (1974) studied milk production and breeding efficiency under climatically controlled conditions. Cows in air conditioned facilities produced 10% to 40% more FCM than cows in facilities that were not air conditioned. Studies by Romen et al. (1977) revealed that cows placed under shade to remove solar radiational heating produced more milk and have higher conception rates than unshaded cows. Ngwerume et al. (1991) looked at the effect of curtain walled freestall housing on milk production during summer in Michigan. Results suggested that using curtain walls that can be rolled up during summer to allow more air movement in the barn, alleviated milk decline due to heat stress.

3.2.6 Herd and Herd Level

For lactation milk yield, Van Vleck and Henderson (1961a) estimated that the variation due to herd accounted for 35% of the total variation. The influence of herd on milk production is mostly due to management within a given herd. Herd management includes such aspects as calf raising methods, age at first calving practices, feeding practices and herd health program to mention a few aspects. Auran (1973) studied the effects of herd on monthly test-day milk production. It was found that herd effects accounted for approximately 25-45% of the total sums of squares in monthly test-day yield and 30 to 42% in cumulative milk yield. The easiest way to remove herd effects of cows is to compare individuals within herds. Auran (1973) also looked at the influence of herd production level by analyzing three herd average levels. Herd level accounted for

5-23% of the total sums of squares in test-day yield with 74 to 89% of the herd effects in the first eight test-day yields and about 11 to 36% in the ninth and tenth. Wiggans (1980) reported that herd average was most important is early lactation for projecting lactation records since it provided a reference point for sample day production and accounted for the subsequent higher production in higher producing herds.

3.2.7 Bovine Somatotropin

A significant increase in milk, fat and protein yields due to treatment of cows with bovine somatotropin (bST) has been documented. Increases in milk yield to bST have been variable with increases in lactation yield between 15 to 20 % (Burton et al., 1987) and the increase being dose dependent (Thomas et al., 1991). Despite the controversy surrounding the use of bST commercially, it was finally approved for commercial use in the United States. Based on research over several lactations, Burton et al., (1987), recommended that bST be initiated when the cow is in positive energy balance and pregnant, i.e. 90 to 120 d of lactation. Due to its approval there is increasing concern about its potential effects on milk records and consequently sire and cow evaluations. Potentially, how then can bST be handled using the current mathematical models for genetic evaluations. Additional challenges would occur in the case of ignorance of the real status of the cows treated or not treated which would arise due to poor reporting (Colleau, 1989). The results of a simulation study conducted by Colleau (1989) indicated that the reduction in genetic gains was 1-10%. When bST was allocated to the best cows, large biases of up to 30% in the evaluations were observed. To accurately model lactation records from bST treatments, information such as dosage administered, dates individual cows began and ceased receiving bST and time when it was administered will be needed along with good statistical models.

3.3 Modelling Test-day Production vs Modelling 305-day Production

The above section has attempted to give a brief overview of some of the environmental factors that influence a cow's production record. In this section, the advantages and disadvantages of modelling 305-day milk production and the possibility of modelling actual test-day milk production will be discussed.

3.3.1 Analyzing 305-day yield

Genetic evaluation of dairy sires has been based, for many years, on the analysis of 305 day (305-d) lactation yields. The basis of 305-d yield is a set of test-day yields taken at approximately 30 day intervals. This standard length allows records to be compared without concern for the length of the production period. However, one difficulty is that a cow must have the opportunity to complete 305 days in milk before this measure of her productive ability exists. For cows that are sold or die, this information not available (Wiggans and Van Vleck, 1979) meaning that the 305-d yield must be estimated. In many cases 305-d lactation yields are estimated from lactations that are in progress. There are several advantages of extending records to 305-d production. The prediction of total lactation is important for early estimates of breeding values and individual cow performance which aid in management decisions. As a result, producers are able to identify low producing cows earlier and make culling decisions sooner. Prediction of 305-d records for lactations in progress and culled cows provides data from more daughters for evaluating dairy sires (Congleton and Everett, 1980; Wilmink, 1987; Wiggans and Van Vleck, 1979; Danell, 1982b). Danell (1982b) pointed out that extending part lactations to 305-d offers the potential of shortening the generation interval. Also, it is possible to reduce breeding program costs by culling progeny tested bulls with low breeding values for milk up to a half year earlier than when using completed 305-d lactations (Henderson and Van Vleck, 1961c, 1961d). However, the accuracy of extending records to a 305-day yield will depend on the number of test-days involved and the method used to project these test-day records.

Many researchers have developed factors for extending records in progress to a complete 305-d lactation. Examples include single regression of the remaining part of the record on the last known test-day yield; multiple regression of the unknown part on known test-day yields; and use of functions describing the lactation (Van Vleck and Henderson, 1961b, Miller et al., 1971, 1972; Keown and Van Vleck, 1973; Auran, 1976; Schaeffer et al., 1977; Wiggans and Van Vleck, 1979; Congleton and Everett, 1980; Wilmink, 1987). In general, the last known test-day yield provides the most information about yield in the remaining lactation.

3.3.1.1 USDA projection factors

The projection procedure currently used by USDA is based on the yield for the number of days the cow actually milked, plus an estimate for the remainder of the 305-day lactation derived from the last available sample-day yield. For records of 155 d or less, the ME herd average for cows calving in the same herd 1 to 2 years prior to the record's last sample day is incorporated into the computed projection factors. The use of ME herd average was reported by Wiggans and Van Vleck (1979) to increase the accuracy of the projection by providing information on the normal yield level of the herd. Separate factors have been developed for 4 seasons of freshening, two lactation groups (first and second or later), three U.S. regions, and five breeds. The four calving seasons are 1) December through February, 2) March through May, 3) June through August and 4) September through November. The projection procedure for milk or fat is as follows:

$$\hat{Y}_{305} = Y_{DIM} + (\hat{Y}_D)\,(305 - DIM)$$

where

$\hat{Y}_{305}$ is projected 305-day yield, Y_{DIM} is yield for the partial record, $\hat{Y}_D$

is estimated average daily yield for the remainder of the lactation and **(305 - DIM)** is days remaining.

For records with greater than 155 days:

$$\hat{Y}_D = [\alpha_s + \beta_s(DIM)](Y_s) + \alpha_F + \beta_F(DIM)$$

where α is an intercept, s is sample day , β is a slope, Y_s is sample-day yield, F is the DIM factor. For records with 155 days in milk or less estimated average daily milk yield is as follows:

$$\hat{Y}_D = [\alpha_s + \beta_s(DIM)](Y_s) + [\alpha_H + \beta_H(DIM)](Y_H)$$

where Y_H is actual herd-average yield.

3.3.2 Analyzing test-day records

Prediction of 305-d production is not without error (Schaeffer and Burnside, 1976). There is still a quest to improve methods for extending part lactations to 305-d production. Recently, Trus and Buttazzoni (1990) proposed a method that describes the lactation curve as a series of correlated traits. This model predicts the residuals for each trait that can be added to the expected values to estimate a missing test-day record which can then be summed with other test-day yields to give lactation yield. This method is currently being used in Italy.

As mentioned in the above section, major emphasis is placed on standardized lactation production when selecting dairy cattle. Summarizing test-day records into a single measure is a common practice. However, adjusting this cumulative record for environmental effects such as herd, season and age of calving eliminates the possibility of adjusting for those effects peculiar to individual test-day records. With 305-d yields such effects which are test-day specific are assumed to be random and to average out over the lactation. These effects may be quite different from the average effects for the lactation, hence they may not average out (Meyer et al., 1989; Stanton et al., 1992). Meyer et al. (1989) reported low heritabilities for milk (.17), fat (.15), and protein (.13) yields. These low values were partly attributed to short-term environmental variation affecting daily performance which could not be accurately accounted for by modelling lactation totals.

Modelling individual test-day records for both genetic evaluations and management purposes might eliminate some of the problems of extending records to 305-day yield, as well as the problems associated with accurately modelling 305-day yields. When modelling individual test-day records, a linear model that is assumed to explain test-day records is important. This model shall be referred to as a "Test-day Model". By definition, a test-day (TD) model is a method of evaluating daily production of milk, fat, protein and somatic cell count considering effects for each test-day in place of one set of fixed effects over the 305-day lactation. A TD model would need to incorporate the general shape of the lactation curve (Schaeffer et al., 1977; Trus and Buttazzoni, 1990; Stanton et al. 1992) and accurately account for the test-day environmental effects affecting all cows on the same test-day and along with effects specific to each particular cow such as days carried calf, days open and disease. Analyzing test-day records may provide a valuable tool for herd management as well as genetic evaluations. In terms of management, dairy producers are interested in accurate evaluation of their feeding and management practices so their best programs can be repeated (Everret and Schmitz, 1993). On the other hand, geneticists desire accurate estimates of these environmental effects and management programs so that they can be eliminated or properly adjusted when evaluating animals for breeding purposes. Research which looks at the prediction of future test-day records and adjustments for test-day effects will be beneficial.

Few studies utilizing TD models are reported in literature. Meyer et al., (1989) used a TD model to compute genetic parameters using test-day records of first lactation cows. In this study, test-day records were split into 30-day intervals and yield in each interval was analyzed separately by either using a model with herd-year-season (HYS) subclasses or a model with herd-test-day effects (HTD). Fitting HTD effects which accounted for the environmental effects specific to the day of test reduced residual variances as compared to fitting HYS. The proportion of total sums of squares for milk yield explained by HTD ranged from 36% to 86% for three regions. Ptak and Schaeffer (1992) used a test-day model for genetic evaluation of 576 sires. The breeding values for the same sires were also estimated using 305-day lactation yield. The rank correlations between the two methods ranged from .889 to .96. Although these results do not suggest which method is better, at least the results show that using a test-day model ranks the animals differently. However, Ptak and Schaeffer showed that when using HTD effects in the model, residual variances were greatly reduced as compared to adjusting for HYS effects only. Further research using simulated records is needed.

Everett and Schmitz (1993) developed a herd test-day model which corrects for the effects of age on test-day, days carried calf, days in milk, month of calving and herd test-day milk within each herd. In this model an auto-correlation structure was assumed for the residual (co)variance matrix structure. The advantages of the test-model developed by Everett and Schmitz (1993) over the conventional 305-d production models is that it permits age, month of calving and DIM effects to vary by herd and includes a herd-testday effect that adjusts for differing effects of sampling dates. Since this is a fixed effect model, the residuals are summed for cows and used for genetic evaluations.

3.3.2.1 Predicting next test-day production

In North Carolina, McCraw and Butcher (1976) estimated lactation curves that can be used to determine expected production of lactating cows based on breed, age, month of calving and stage of lactation. A fifth degree polynomial was used to construct lactation curves within breed-age-season subclasses. A dramatic seasonal influence was observed. Cows calving in summer months peaked at a much lower level of production and had flatter lactation curves. However, in the North Carolina system, herd production level is not considered.

Nordlund (1987) developed a method to adjust test-day milk to a 150 days in milk value to assess management effects from month to month. The value was termed Adjusted Corrected Milk (ACM) with the formula as below:

ACM = (.0432*lbs milk) +(16.23*(lbs milk*%fat/100)) + (((ADIM-150) *.0029)*lbs milk)

where

ADIM is average days in milk, .29% is the average decline rate per day and FCM = (.432*lbs milk) + (16.23 * lbs fat).

Nordlund's formula however ignores season of calving which has a significant influence on milk production and assumes a fixed percentage of first lactation cows. The ACM assumes a constant slope for the whole lactation curve which is not correct.

In Minnesota, Steurnergal (1988) developed a formula for management level milk (MLM) which can be used to monitor production and to determine management changes from the previous month. MLM was derived by adjusting milk, fat %, and protein % production for lactation number and stage of lactation for each cow. Using MLM factors, cow values are adjusted to 150 days in milk and a second lactation base. However, MLM might not give a good indication of management changes since season of calving is not considered.

Stanton and Jones (1993) used a simplified version of Everett and Schmitz (1993) test-day model for developing standard lactation curves for projecting test-day records in New York dairy herds. In this method, if an animal does not have a previous record, the predicted current test-day milk will be the standard curve value. In the case of cows with previous test-day records;

future test-day production = previous test-day production +
(solution for future test-day minus solution for previous test-day).

Using this procedure to project lactations, the mean differences between predicted and actual test-day values for milk yield, fat % and protein % averaged approximately .158 lb, .004% and .006% and root mean squares of 11.65 lbs, .69% and .25% respectively. In this study, incorporating previous test-day information appeared to be more accurate than just using reference curves alone to project lactations.

Better methods to predict test-day production and to monitor daily production are still needed.

Advantages of modelling actual test records using test-day models can be summarized as follows:

i. Methods to project records to 305-day yield will not be necessary.

ii. If cows are grouped according to production on a test-day, such grouping, if known, can be included in the models describing test-day records.

iii. For genetic purposes, cows can be evaluated as long as they have at least one test-day measurement.

i.v. The use of BST, if recorded, can be accounted for as an effect on a specific test-day.

v. Comparison of performance of cows within herd based on test-day will be more accurate as animals will be compared on the same test-day and as such would have experienced the same environment.

vi. Using a TD model would account for variable amounts of information from different lactations.

vii. TD models permit estimates of fixed effects to vary across herds, stages of lactation.

viii. Differing effects of sampling date can be considered.

ix. A test-day model has the potential to reduce residual variances which may lead to better genetic estimates.

The disadvantages of using test-day yields would be: the need to adjust for days in milk; the need to store all of the individual test-day yields on a cow; the computation of genetic evaluations may take more time due to the increased number of observations (test-day yields) and more complex statistical models that might be used for test-day yields.

3.4 Animal Models.

Statistical models applied to data obtained from animals attempt to describe biological processes and effects quantitatively. The goal is to fit a practical model that describes the biological situation as closely as possible. By describing all the factors that may influence the observation on an individual, the researcher will likely develop a good ideal model.

Henderson (1988) notes that an animal model can take many different forms depending on the number of measurements per animal, the objectives of the study and whether genetic relationships exist among the animals in the data. As such, an animal model can account for repeated records, multiple traits, non additive genetic effects, litter effects and in addition, a number of environmental effects.

An additive genetic model is an integral part of the mixed linear models assumed for virtually all animal breeding applications of best linear unbiased prediction (BLUP). The general form of mixed linear models with one random factor is as follows

$$\mathbf{y} = \mathbf{X}\boldsymbol{b} + \mathbf{Z}\mathbf{u} + \mathbf{e} \qquad [1]$$

where $\mathbf{y}$ = N x 1 vector of observations,

$\boldsymbol{b}$ = p x 1 vector of fixed effects associated with y,

$\mathbf{u}$ = q x 1 vector of random effects associated with y,

$\mathbf{X}$ & $\mathbf{Z}$ = known incidence matrices of order N x p and N x q respectively that relate elements of b and u to elements of y and

$\mathbf{e}$ = an N x 1 vector of residual effects with

$$\mathbf{E(y) = X}\boldsymbol{b}\mathbf{, E(u) = 0 \text{ and } E(e) = 0} \text{ and}$$

$$\mathbf{V}\begin{bmatrix} y \\ u \\ e \end{bmatrix} = \begin{bmatrix} ZGZ'+R & ZG & R \\ GZ' & G & 0 \\ 0 & 0 & R \end{bmatrix}$$

The elements of u can contain additive genetic effects, non additive genetic effects, maternal effects and permanent environmental effects. The mixed model equations for the BLUE of the estimable functions of b and for BLUP of u are therefore:

$$\begin{bmatrix} X'R^{-1}X & X'R^{-1}Z \\ Z'R^{-1}X & Z'R^{-1}Z+G^{-1} \end{bmatrix} \begin{bmatrix} \hat{b} \\ \hat{u} \end{bmatrix} = \begin{bmatrix} X'R^{-1}y \\ Z'R^{-1}y \end{bmatrix}$$

All multitrait linear models are special cases of the above general linear model. Suppose there are t traits, one random factor and observations are ordered within traits then:

$$\begin{aligned} y' &= (y_1', y_2', \ldots, y_t') \\ u' &= (u_1', u_2', \ldots, u_t') \\ e' &= (e_1', e_2', \ldots, e_t') \end{aligned}$$

$$V(u) = V \begin{bmatrix} u_1 \\ u_2 \\ \cdot \\ \cdot \\ \cdot \\ u_t \end{bmatrix} = G = \begin{bmatrix} g_{11}I & g_{12}I & \cdots & g_{1t}I \\ g_{12}I & g_{22}I & \cdots & g_{2t}I \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ g_{1t}I & g_{2t}I & \cdots & g_{tt}I \end{bmatrix} = I * G_0$$

$$G_0 = \begin{bmatrix} g_{11} & g_{12} & \cdot\;\cdot\;\cdot & g_{1t} \\ g_{12} & g_{22} & \cdot\;\cdot\;\cdot & g_{2t} \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ g_{1t} & g_{2t} & \cdot\;\cdot\;\cdot & g_{tt} \end{bmatrix}$$

This model assumes no relationships are considered. Therefore, the numerator relationship matrix $\mathbf{A} = \mathbf{I}$. The model also assumes the genetic covariance between traits for the random variable $\mathbf{u}$ is not zero. Similarly the residual (co)variance matrix is as follows:

$$V(e) = \mathbf{R} = \begin{bmatrix} r_{11}\mathbf{I} & r_{12}\mathbf{I} & \cdot\;\cdot\;\cdot & r_{1t}\mathbf{I} \\ r_{12}\mathbf{I} & r_{22}\mathbf{I} & \cdot\;\cdot\;\cdot & r_{2t}\mathbf{I} \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ r_{1t}\mathbf{I} & r_{2t}\mathbf{I} & \cdot\;\cdot\;\cdot & r_{tt}\mathbf{I} \end{bmatrix} = \mathbf{I} * \mathbf{R}_0$$

A common feature of all animal models, although they take the above form, is the use of the additive genetic relationship matrix (**A**). Diagonal elements of A assuming no epistasis, equal $1+F_i$ where F_i is a coefficient of inbreeding for animal i. When multiplied by the additive genetic variance ($\sigma_a 2$), $A\sigma_a 2$ describes the variance-covariance structure among additive genetic (breeding) values of animals. From the above general mixed linear model, the mixed model for the multiple trait individual animal model are as follows (Schaeffer, 1984, Meyer, 1985).

$$\begin{bmatrix} X'R^{-1}X & X'R^{-1}Z \\ Z'R^{-1}X & Z'R^{-1}Z+A^{-1} * G_0^{-1} \end{bmatrix} \begin{bmatrix} \hat{b} \\ \hat{a} \end{bmatrix} = \begin{bmatrix} X'R^{-1}Y \\ Z'R^{-1}Y \end{bmatrix} \qquad [4]$$

with

$$V(a) = V \begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ \cdot \\ a_t \end{bmatrix} = \begin{bmatrix} g_{11}A & g_{12}A & \cdots & g_{1t}A \\ g_{12}A & g_{22}A & \cdots & g_{2t}A \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ \cdot & \cdot & & \\ g_{1t}A & g_{2t}A & \cdots & g_{tt}A \end{bmatrix} = A * G_0$$

where **A** is the numerator relationship matrix among animals.

The additive genetic animal models have become accepted as the models of choice for the genetic evaluation of animals by utilizing BLUP. Fitting the additive genetic effect for each animal allows males and females to be evaluated simultaneously taking into account all relationships between animals. Then, genetic values of animals without records such as sires or dams, are predicted by augmenting the mixed model equations with function of the inverse of the relationship matrix.

3.4.1 Advantages of multiple trait analysis.

Multitrait models are useful to improve the accuracy of genetic evaluations, especially of lowly heritable traits and to account for selection effects. While univariate analysis assumes that all correlations between traits are zero, joint analyses of correlated traits utilizes all traits to obtain estimates for each trait and is therefore likely to yield more accurate results. Multitrait analysis (MTA) improves accuracy of parameter estimates by reducing or eliminating bias due to selection. Usually in animal breeding, one or more traits have undergone selection. For example in sequential selection, observations on one trait are used for selection and the selected group of animals is then measured for subsequent traits. As such, evaluation of the second trait by single trait analysis is potentially biased by selection on the first trait.

Pollack et al. (1984) and Walter and Mao (1985) examined the ability of MTA to reduce or eliminate bias due to either sequential selection or selection on correlated traits. Results indicated that in both cases bias in the single trait evaluation was eliminated by MTA. Schaeffer (1984) also noted the increase in accuracy of genetic evaluations by MTA as demonstrated by the reduction in variance of prediction errors (PEV). The ability of MTA to reduce PEV depends on error and genetic correlations used for the analysis.

A second advantage of MTA is that it allows every animal to be evaluated for all traits without actually being observed for all traits (Schaeffer, 1984). This is due to non-zero genetic and residual covariances among traits that are incorporated into the analysis. The correlation between errors for the different traits has a direct effect on the contribution from an observation on a trait (Schaeffer, 1984). As the absolute value of the correlation increases, the weight on observations from other traits also increases. As such, multiple trait evaluations can be greatly different from single trait evaluations due to correlations among traits.

A third advantage of MTA is the estimation of variance and covariance when different variables are observed on different experimental units and the same linear model is not possible for both traits. Usually components of variances are estimated between traits measured on the same individual when the same linear model is assumed for each trait. For example, the genetic covariance between milk and fat production in dairy cattle is obtained from measurement of both milk and fat on each cow and the covariances is estimated using the sum of the crossproduct of the two traits. Sometimes, however, crossproducts of the traits do not exist. Yearling weight, for example, is measured on male and female offspring in beef cattle, thus requiring a different model for each offspring.

Schaeffer et al. (1978) demonstrated a procedure for estimation of covariance components when sums of crossproducts between the traits do not exist.

3.4.2 Disadvantages of Multiple trait Analysis.

The major limitations of MTA is the increased number of equations to be solved. Costs could be greater because of the time needed to construct and solve a large set of equations iteratively. The complexity of multiple trait models increases rapidly beyond two traits. Convergence might be slow as the number of traits increases. A cost-benefit justification for multiple trait models would be dependent on the particular model and whether shortcuts can be applied to calculations.

4. Assessing the effects of herd production level, lactation number and season of freshening on shape of lactation curves for test-day milk, energy corrected milk, and milk components.

4.1 ABSTRACT

Test-day records of 150,000 Holstein cows from Michigan herds tested between January 1989 and December 1991 were used to estimate lactation curves for milk, energy corrected milk (ECM), fat% and protein% in milk. Lactation curves were estimated for three parity groups; first, second and third or later lactation within six seasons of calving and three herd production levels resulting in 54 curves for each trait. A fixed classification model considering days in milk (DIM), age at calving, herd, and season of calving was used. Estimated least square means for days in milk (DIM) were smoothed by a regression model using a six degree polynomial.

Differences due to season of calving were significant ($P< .001$) for all traits. Peak test-day milk production was depressed by summer calving seasons with production being lowest for the July-August calving season. Total lactation yield was depressed for cows calving in summer seasons. For each lactation, November-February were the best months for calving to maximize total 305 day milk production.

Time to peak milk production differed with herd production level. Cows in high production herds tended to peak later compared to low production herds. For first lactation cows, days to peak milk production after calving was 58, 61, and 67 for low, medium and high production herds respectively. Peak production increased with herd production level reflecting good management in high production herds.

The standard lactation curves produced by fitting a sixth degree polynomial were used to derive factors for adjusting test-day production to 150 days in milk postpartum. The base group used was second lactation cows calving during November-December. Adjusting test-day milk for season of calving, lactation and days-in-milk provides dairy producers with test-day milk averages that can be used to monitor production changes in a herd from test day to test day.

4.2 INTRODUCTION

Dairy producers enrolled in production recording schemes are aware of the benefits of monitoring herd and individual cow performance. Dairy production is enhanced by identifying the downward trends in performance and taking corrective action to alleviate any decline in performance. Evaluating response to altered herd management or new technology is critical not only in the short term but for maintaining long run profitability.

Production can be monitored in different ways e.g., rolling herd average, daily production, or production per day of life. Unless such indicators are adjusted for environmental and animal variables, they might not be very accurate in the diagnosis of herd performance.

Nordlund (1987) developed adjusted fat corrected milk (ACM) to account for lactation shape and use to monitor production from month to month to evaluate management changes. The ACM is a crude adjustment for days in milk. It adjusts test-day FCM to 150 days in milk. The formula for computing ACM is:

ACM = (.0432 x lbs milk) +(16.23 x (lbs milk x %fat/100)) + (((ADIM-150) x .0029) x lbs milk)

where

ADIM is average days in milk,

.29% is the average decline rate per day

and FCM is (.432 x lbs milk) + (16.23 x lbs fat).

Nordlund's formula, ignores season of calving and assumes a constant decline rate for lactation which is not correct. Since variation due to season of calving is not adjusted, estimated changes in management may be in error possibly resulting in incorrect management decisions.

Steurnergal (1988) developed a formula for management level milk (MLM) which also is used to monitor production changes from the previous months. MLM is computed by adjusting milk, fat%, and protein% production for lactation number and stage of lactation for each cow and computing a herd average. The base group is second lactation at 150 days in milk. MLM is an improvement over Nordlund's crude estimate but also ignores variation due to season of freshening.

Lactation curves describe the effect of days in milk and with proper use can be used to evaluate a herd, to evaluate subgroups within a herd and to monitor performance changes. Lactation curves generally have two features. The first one is that curves for different production levels are parallel and secondly younger cows are more persistent than older cows. The curve for a mature cow generally declines linearly until advanced pregnancy causes a sharper decline

(Kellogg et al., 1977).

Several mathematical functions have been used to describe lactation curves. Wood (1967) approximated the lactation curve for milk yield with an incomplete gamma function with three parameters; **a** associated with the average daily production, and **b** and **c** being coefficients that define the shape of the lactation curve pre and post peak, respectively. Grossman et al. (1986) modified Wood's equation by multiplying with sine and cosine coefficients to account for seasonal effects other than season of calving. In 1988, Grossman and Koops proposed another lactation curve model, a multiphasic function which considers milk yield resulting from several phases of lactation.

Lactation curves have been estimated by solving for the least square estimates for DIM (Keown et al., 1986; Stanton et al., 1992; Shultz et al., 1990). Seasonal effects on production and reproduction influence both the amount of milk produced per day and duration of lactation. Therefore, variation due to season must be adjusted when solving for DIM solutions. McCraw and Butcher (1976) estimated lactation curves that can be used to determine expected production of lactating cows based on breed, age (<36 and ≥ 36 months), month of calving and stage of lactation. A fifth degree polynomial was fitted to the DIM means to construct lactation curves within breed-age-season-subclasses. A dramatic seasonal influence was observed. Cows calving in summer months peaked at a much lower level of production and had flatter lactation curves. This study did not consider herd production level.

Keown et al. (1986) estimated lactation curves by solving for least square estimates for DIM by six seasons of freshening within five herd production groups and for three lactation groups. Curves were formed by adding an overall mean to season-stage subclasses. A similar approach was later used by Schultz et al. (1990) who estimated lactation curves for three parity groups and three breeds. In this study lactation curves were smoothed by medians of five and repeated means of pairs. Stanton and Jones (1993) used a model that included herd test-day effects to solve for DIM solutions for milk, fat and protein for three lactation groups, three herd production levels and two seasons of calving. Currently such lactation curves are being utilized in North-Eastern dairy herds to project future test-day production.

The effect of season or month of calving exerts a considerable influence on a cow's milk production. The relationship of yield with month of calving is caused in part by the seasonal variations in feeding and environmental factors such as heat stress. The quality and quantity of feed or pasture is important for some countries. In countries where the grazing season is short and cows are housed indoors for most of the year, the highest lactation yield is produced by cows calving during autumn and early winter (Danell, 1981). Wunder & McGilliard (1971), using dairy records from Michigan Dairy Herd Improvement Association (DHIA), reported that for second or later lactations cows, yield was more for January to April calvings and less for May to October calvings.

Since season of calving is an important source of variation in test-day production, it is important to include it in the derivation of projection factors that either project test-day records to 305-day production or predict individual test-day records.

Herd and herd production level also have a tremendous influence on the performance of dairy cows. The effect of herd on production is mainly due to management which varies from herd to herd. Wiggans (1980) reported on the importance of considering herd production level when extending lactation records.

The objective of this study was to compute lactation curves for cows calving in different herd production levels, parities and seasons. The curves will be used to compute 150-d days in milk adjustment factors that can be used to standardize test-day milk averages for individual herds to second lactation at 150 days in milk.

4.3 MATERIALS AND METHODS

4.3.1 Data

Test-day records of milk, fat % and protein % of 150,000 holstein cows in 1,800 Michigan Dairy Herds tested from January 1989 to December 1991 were used in this analysis. Data were supplied by Michigan DHIA. The following criteria were used for screening records:

i. Age at calving was restricted to 18-36 months for first lactation cows, 30-48 months for second lactation cows and greater than 42 months for third and greater parities.

ii. Records of herds involved in bST research herds were dropped.

iii. First test-day record of a cow's lactation must be less than 60 days in milk otherwise the cow was dropped from the data set.

iv. Lactation must be greater than 180 days in milk.

Tests beyond 305 days were dropped. The decision of restricting the lactation length to 305 days was based on the fact that test-day records past 305 days in lactation were scarce and therefore, the lactation curves may not be adequately smoothed after 305 days in milk.

After editing, ECM was computed for each test-day to give an indication of the energy value of milk. The following formula was used (Tyrell and Reid, 1965):

$$\text{ECM} = .72 \times (\text{Protein\%} \times \text{milk lbs}/100) + 12.95\ (\text{fat\%} \times \text{milk lbs}/100) + .327 \times \text{milk lbs.}$$

Preliminary analysis showed the significant ($P < .001$) effects of herd production level, season of test and parity on test-day milk production. Therefore, test-day records were grouped by herd production level (HPL) and six seasons of calving. Season of calving was defined by two month intervals with January and February being the first class and November-December being the sixth class. Three HPL were defined according to the 1990 annual ME milk herd averages. The year 1990 was chosen based on the fact that it was the middle year of the data set. The HPL groups were low (<7,718 kg ME milk average), medium (7,718-9,535 kg ME milk average) and high (>9,535 kg ME milk average). Number of records and means for the three HPL are shown in Table 1.

4.3.2 Model

To estimate DIM solution, the following mixed linear model was used for the univariate analysis of test-day milk yield, ECM yield, fat or protein percentage.

y_{ijklm} = $\mu + H_i + YR_j + DIM_k + b_1(AGE) + b_2(AGE^2) + C_{(i)l} + e_{ijklm}$

where

y_{ijklm} = TD milk, ECM, fat % or protein %;

H_i = Herd, 1,2,..., N;

YR_j = Year of Calving, 1988-1991;

DIM_k = Days in milk, 1,2,...,299;

Age_{ijklm} = Age at calving as a covariate with b_1 and b_2 being the linear and quadratic age coefficients, respectively;

$C_{(i)l}$ = random cow effect with C distributed as $N(0, I\sigma_c^2)$;

e_{ijlkmn} = random residual with e distributed as $N(0, I\sigma_e^2)$.

The Statistical Analysis System (SAS) was used for analyzing the data. Analysis was done within each HPL-Parity-Season subclass giving a total of 54 estimated lactation curves. Within each of the 54 subsets, days in milk (DIM) was divided into one day interval classes starting from day 7 to 305. The single day class interval was used to estimate daily solutions for DIM.

Herd-year and random cow effects were absorbed. An overall mean was added to DIM solutions to form the DIM least square estimates. The DIM means were smoothed by fitting a sixth degree polynomial. The predicted DIM values from the polynomial equation were used as the standard lactation curve

Table 1. **Number of test-day records (N) and mean for test-day milk, ECM, fat and protein for three lactation groups in three herd production levels (HPL)**

HPL			Mean		
	N	Milk (kg)	ECM (kg)	Fat %	Protein %
Low : (<7,718 kg Annual ME average)					
Lactation 1	130,405	19.81	20.83	3.81	3.30
Lactation 2	96,171	22.50	23.78	3.83	3.33
Lactation 3+	211,408	23.73	24.96	3.81	3.29
Medium : (7,718-9535 kg Annual ME average)					
Lactation 1	529,563	24.17	25.23	3.76	3.28
Lactation 2	367,119	27.44	28.76	3.78	3.31
Lactation 3+	644,707	28.81	30.09	3.77	3.26
High : (> 9,535 kg Annual ME average)					
Lactation 1	270,783	28.27	29.28	3.72	3.24
Lactation 2	189,481	32.47	33.69	3.73	3.26
Lactation 3+	307,458	34.16	35.32	3.72	3.20

values for the production traits.

4.4 RESULTS AND DISCUSSION

A sixth degree polynomial was fit to DIM solutions to estimate lactation curves for test-day milk, ECM yield and fat and protein percentage. The R-square values ranged from .90 to .9958% for milk and ECM and ranged from .60 to .98 for fat and protein percentage.

4.4.1 Season of freshening.

Table 2 shows the days in milk for peak milk production for the 54 milk lactation curves that were estimated. Day of peak milk varied with season of freshening, lactation number and HPL. Peak milk production seemed to occur early for summer calvings (May-August). Figures 1, 2, and 3 show seasonal milk curves and demonstrate the variation in time of peak and production due to season of freshening for second lactation cows calving in low, medium and high production herds. Depression of daily milk production and the days to peak as well as amount of peak milk produced for cows calving in summer months is, in part, due to heat and humidity (Figure 4). This trend was also observed by Keown et al. (1986). Figure 4 demonstrates some indication of simultaneous changes in slopes influenced by season of year for cows in various stages of lactation.

Table 2. Day of peak milk production for the different season of calving groups by herd production level.

	HERD PRODUCTION LEVEL		
SEASON of CALVING	**< 7,718 kg**	**7,718-9,535 kg**	**> 9,535 kg**
	Days	**Days**	**Days**
Lactation 1			
Jan-Feb	58	61	67
Mar-Apr	49	57	63
May-Jun	44	53	58
Jul-Aug	43	53	62
Sep-Oct	51	59	67
Nov-Dec	51	60	67
Lactation 2			
Jan-Feb	42	48	49
Mar-Apr	39	45	49
May-Jun	35	41	46
Jul-Aug	36	37	48
Sep-Oct	37	42	47
Nov-Dec	39	43	47
Lactation 3+			
Jan-Feb	43	48	49
Mar-Apr	41	47	51
May-Jun	39	47	52
Jul-Aug	39	47	52
Sep-Oct	39	46	52
Nov-Dec	53	35	51

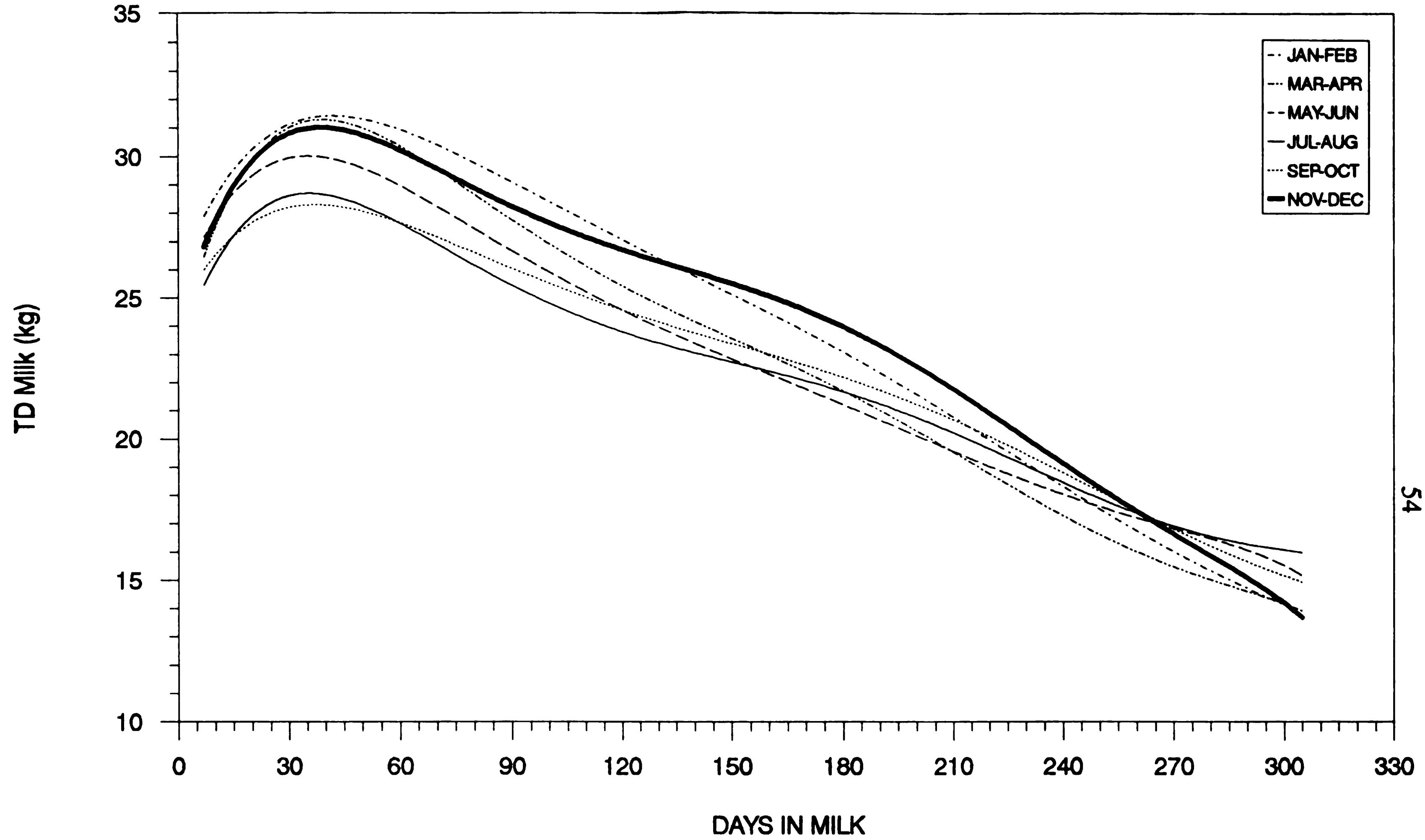

Figure 1. Test day milk season curves for second lactation cows in low producing herds

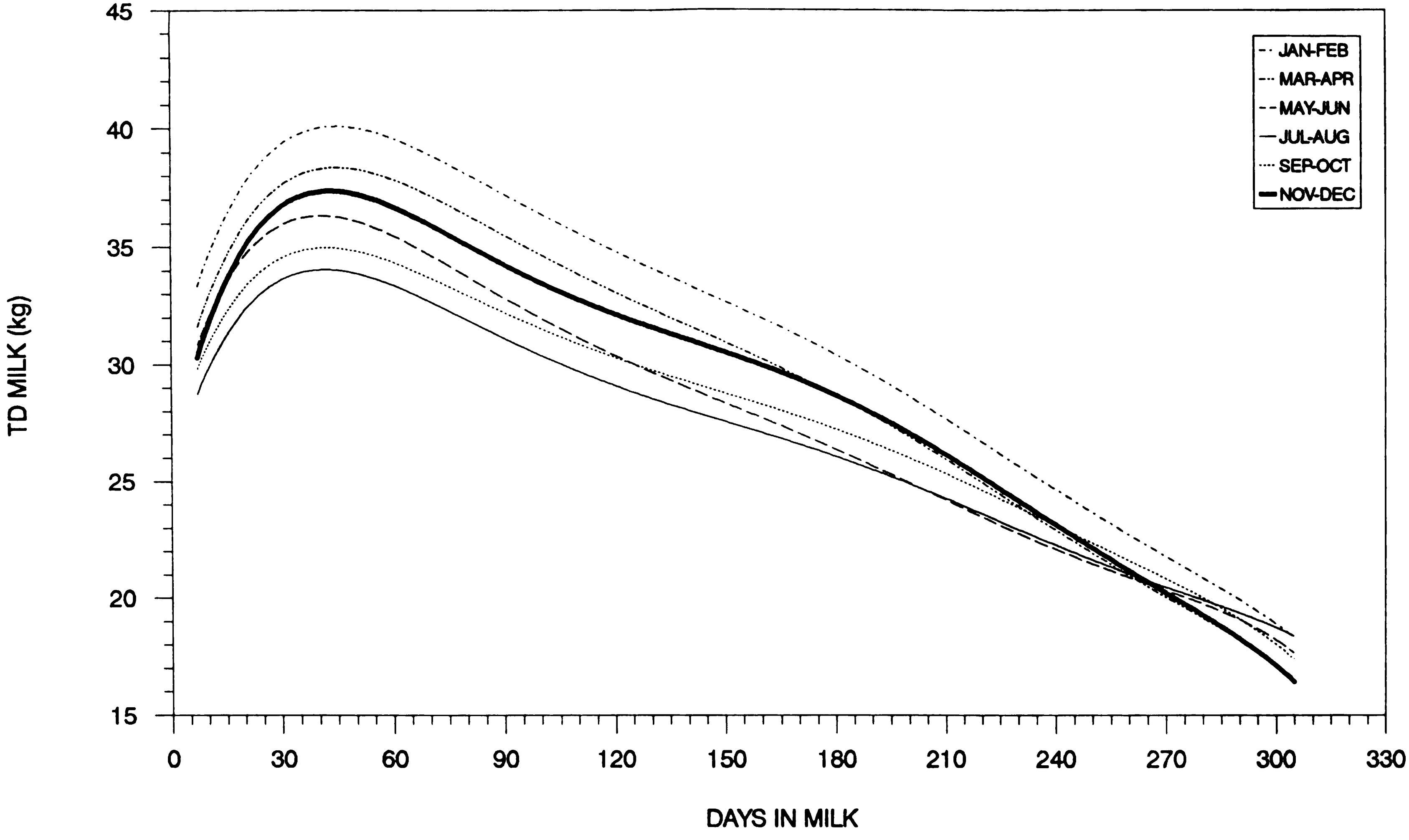

Figure 2. Test-day milk season curves for second lactation cows in medium producing herds

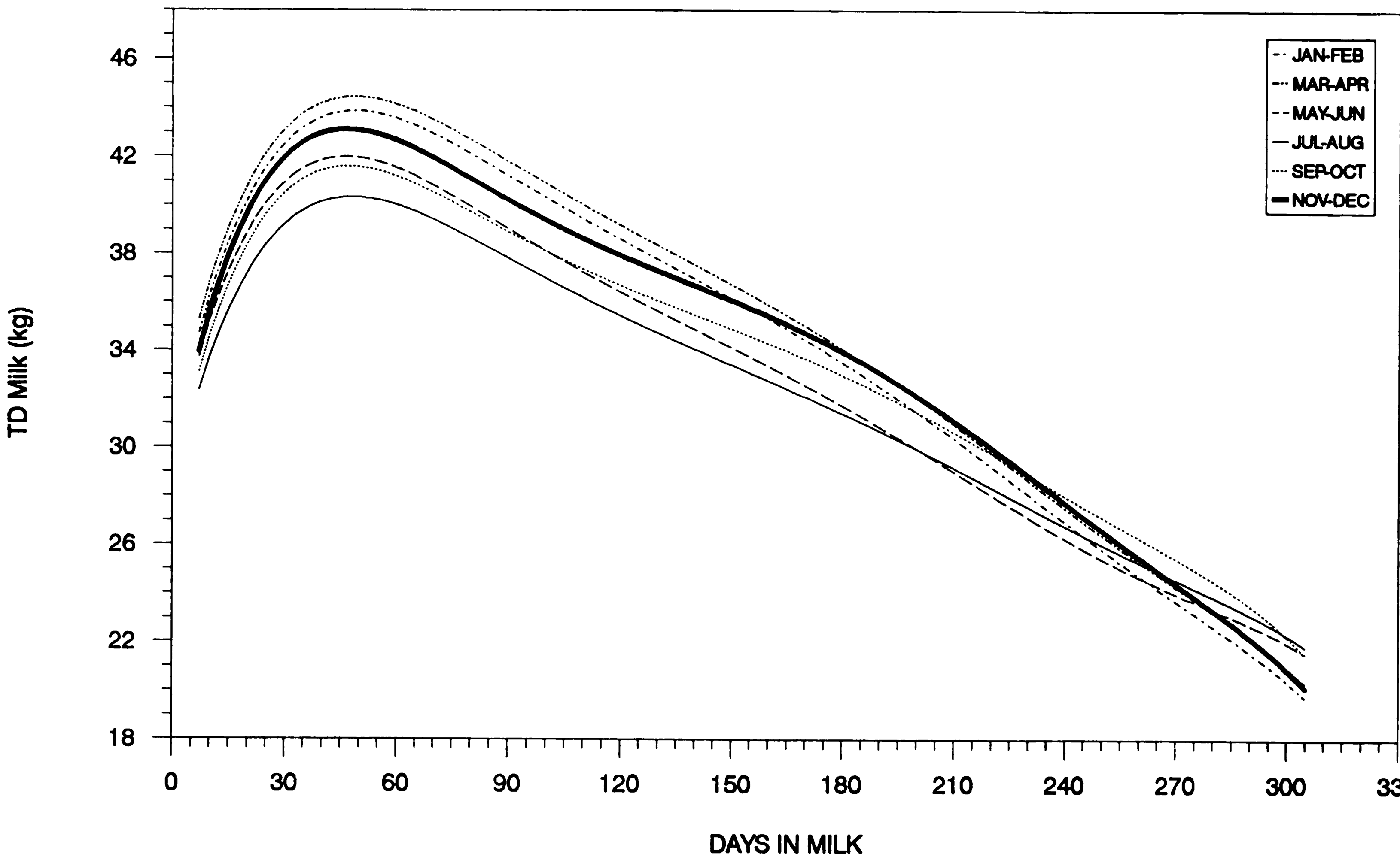

Figure 3. Test-day milk season curves for second lactation cows in high producing herds

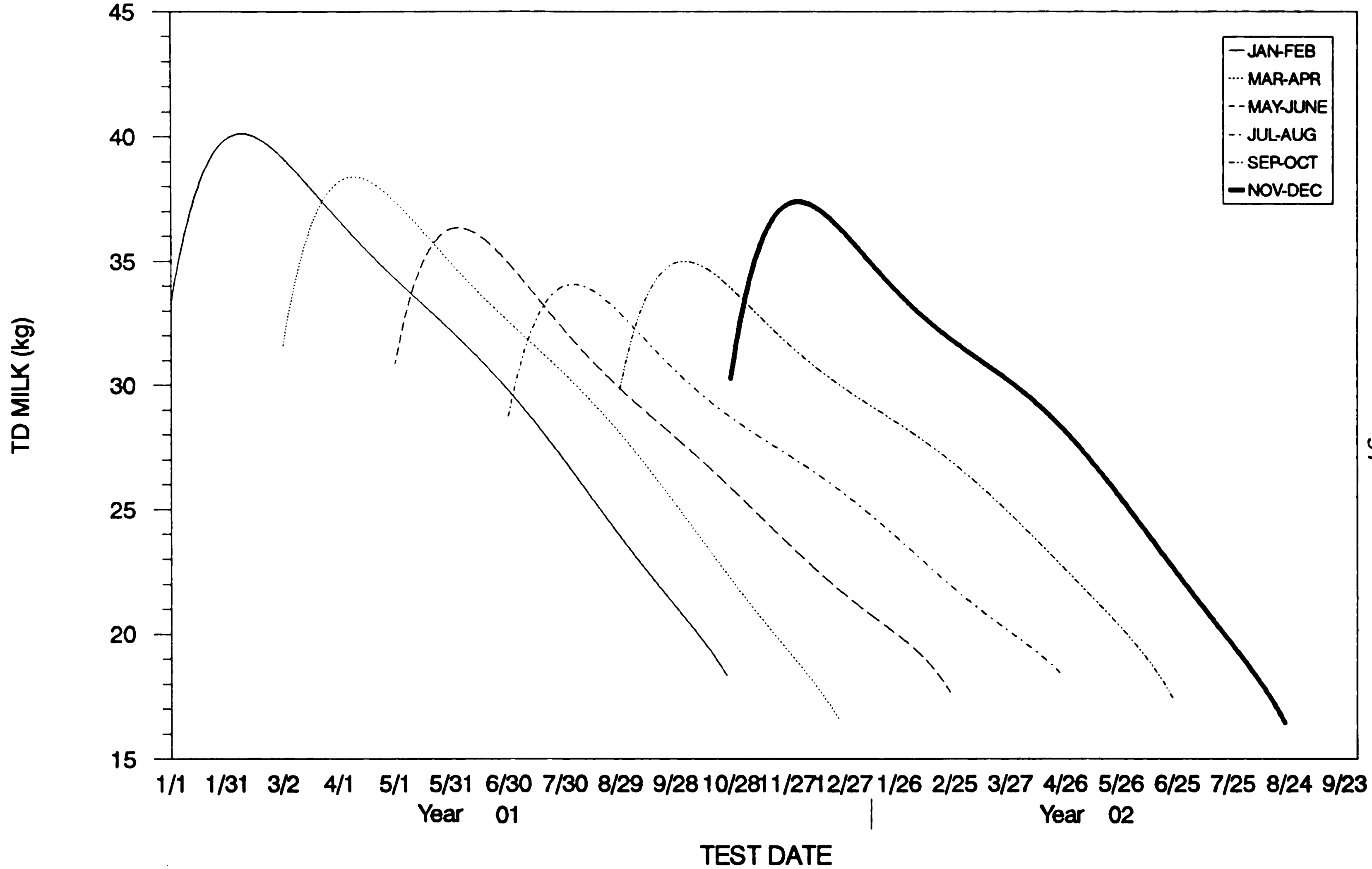

Figure 4. Test-day milk season curves for second lactation cows in medium producing herds for two years (01 and 02)

For example, the decline in production increases between 6/30 and 8/29 for cows calving in January-February, March-April and May-June. This increase in decline might be more consistent if calving groups were based on one month, not two month groupings. Tables 3, 4 and 5 contain peak values for the four traits by herd level and season of calving for lactations 1, 2 and 3 or greater, respectively.

Figures 5, 6 and 7 show the differences in season curves for ECM, protein percent and fat percent, respectively for second lactation cows in medium producing herds. Both protein and fat percent dropped from calving to a nadir 30 to 60 days postpartum. There is also a clearly defined low production point for both fat and protein percentage later in lactation (about 120 to 180 days postpartum) for cows calving in fall, winter and early spring (Figures 6 and 7). Fat% peaked at the beginning of lactation while protein peaked either at the beginning or end of lactation. Fall and winter seasons tended to promote higher protein peaks in these herds. For example, peak protein % was 3.67% for November-December calvings and 3.51% for the July-August (Figure 6) and for low producing herds, peak protein % for January-February calvings was 3.76% vs 3.49% in July-August (Table 4). For second lactation cows in all herd production levels, summer calvings depressed protein % in early lactation. Again low production in summer could be due to heat stress that results in decreased feed and reduced roughage intake. However, later into lactation, cows calving in summer months had higher protein levels (Figure 6). For example, at about 150 days postpartum, protein percentage averaged 3.375 % for July-August calvings

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Table 3. Predicted Peak Test-Day Production for First Lactation cows for different seasons of calving by herd production level (HPL)

	PEAK			
Season	**Milk (kg)**	**ECM(kg)**	**Fat %**	**Protein %**
HPL < 7,718 kg				
Jan-Feb	24.32	24.82	4.44	3.72
Mar-Apr	24.39	24.63	4.23	3.61
May-Jun	22.92	23.09	4.11	3.60
Jul-Aug	22.39	22.70	4.25	3.38
Sep-Oct	23.07	23.94	4.26	3.52
Nov-Dec	24.19	25.13	4.38	3.60
HPL 7,718-9,535 kg				
Jan-Feb	29.16	29.64	4.53	3.68
Mar-Apr	28.74	28.71	4.34	3.59
May-Jun	27.88	27.70	4.14	3.55
Jul-Aug	26.69	26.93	4.15	3.44
Sep-Oct	27.43	28.28	4.34	3.49
Nov-Dec	28.76	29.62	4.51	3.62
HPL > 9,535 kg				
Jan-Feb	33.58	33.70	4.63	3.61
Mar-Apr	33.06	32.78	4.38	3.55
May-Jun	32.02	31.68	4.29	3.49
Jul-Aug	30.58	30.71	4.25	3.39
Sep-Oct	31.86	32.55	4.53	3.47
Nov-Dec	32.78	33.34	4.66	3.58

Table 4. **Predicted Peak Test-Day Production for Second Lactation cows for different seasons of calving by herd production level (HPL)**

	PEAK			
Season	**Milk (kg)**	**ECM (kg)**	**Fat %**	**Protein %**
HPL < 7,718 kg				
Jan-Feb	31.44	33.44	4.54	3.76
Mar-Apr	31.31	32.46	4.39	3.74
May-Jun	30.03	31.18	4.20	3.59
Jul-Aug	28.71	29.46	5.09	3.49
Sep-Oct	28.31	30.18	4.41	3.63
Nov-Dec	31.03	33.28	4.56	3.72
HPL 7,718-9,535 kg				
Jan-Feb	40.11	41.54	4.52	3.60
Mar-Apr	38.38	39.90	4.57	3.65
May-Jun	36.34	37.06	4.20	3.60
Jul-Aug	34.06	34.66	4.23	3.51
Sep-Oct	34.98	36.71	4.37	3.51
Nov-Dec	37.38	39.38	4.66	3.67
HPL > 9,535 kg				
Jan-Feb	43.86	45.13	4.75	3.66
Mar-Apr	44.43	45.50	4.73	3.55
May-Jun	41.97	41.97	4.32	3.52
Jul-Aug	40.33	40.60	4.24	3.46
Sep-Oct	41.58	43.00	4.56	3.57
Nov-Dec	43.10	44.65	4.72	3.65

Table 5. Predicted Peak Test-Day Production for Third and later Lactation cows for different seasons of calving by herd production level (HPL)

	PEAK			
Season	**Milk (kg)**	**ECM(kg)**	**Fat %**	**Protein %**
HPL < 7,718 kg				
Jan-Feb	33.61	35.59	4.70	3.71
Mar-Apr	33.58	35.06	4.59	3.66
May-Jun	31.61	32.89	4.35	3.58
Jul-Aug	30.13	31.03	4.30	3.52
Sep-Oct	31.01	33.08	4.49	3.62
Nov-Dec	33.35	35.84	4.66	3.69
HPL 7,718-9,535 kg				
Jan-Feb	40.06	41.76	4.76	3.67
Mar-Apr	39.42	40.72	4.69	3.62
May-Jun	37.32	38.00	4.44	3.53
Jul-Aug	35.78	36.45	4.40	3.50
Sep-Oct	37.49	39.38	4.67	3.60
Nov-Dec	41.63	41.63	4.84	3.68
HPL > 9,535 kg				
Jan-Feb	44.13	44.96	4.61	3.56
Mar-Apr	45.94	46.44	4.63	3.53
May-Jun	43.66	43.60	4.58	3.47
Jul-Aug	42.19	42.57	4.41	3.51
Sep-Oct	42.88	44.86	4.91	3.70
Nov-Dec	46.65	47.94	4.81	3.54

and 3.2% per day for November-December season of freshening for second lactation cows in medium producing herds. Animals calving in July-August would be lactating in December and January at 150 DIM, obviously during cooler months. Fat % also showed a similar pattern (Figure 7). In Table 4 for low producing herds, July-August season of calving had the highest peak fat % production. Peaks for fat% tend to occur at the beginning of lactation (Figure 7) while protein peaks tend to occur at the end of lactation (Figure 6). Higher peaks are associated with greater lactation mean percentages.

Milk and ECM curves for three seasons, March-April, July-August and November-December are shown in Figure 8. For all three calving seasons milk production trailed behind ECM production although both traits followed a similar trend. Peaks for ECM were greater than milk. Lactation curves for all four traits are shown on Figure 9 for November-December month of freshening for second lactation cows in medium herd production level. This gives a visual comparison between milk, ECM and, fat and protein percentages.

The relationship of yield with month of calving is influenced by the seasonal variations in feeding and heat stress. To determine the best season for calving in terms of total lactation for milk production for the Michigan herds, the DIM values were summed to 305-day value and a ratio for each season of calving to July-August season was computed. The ratios show the benefit of winter calving (Table 6). Our findings agree with others (Dannel, 1981; Keown et al., 1986; Stanton et al., 1992) that highest lactation production is given by cows

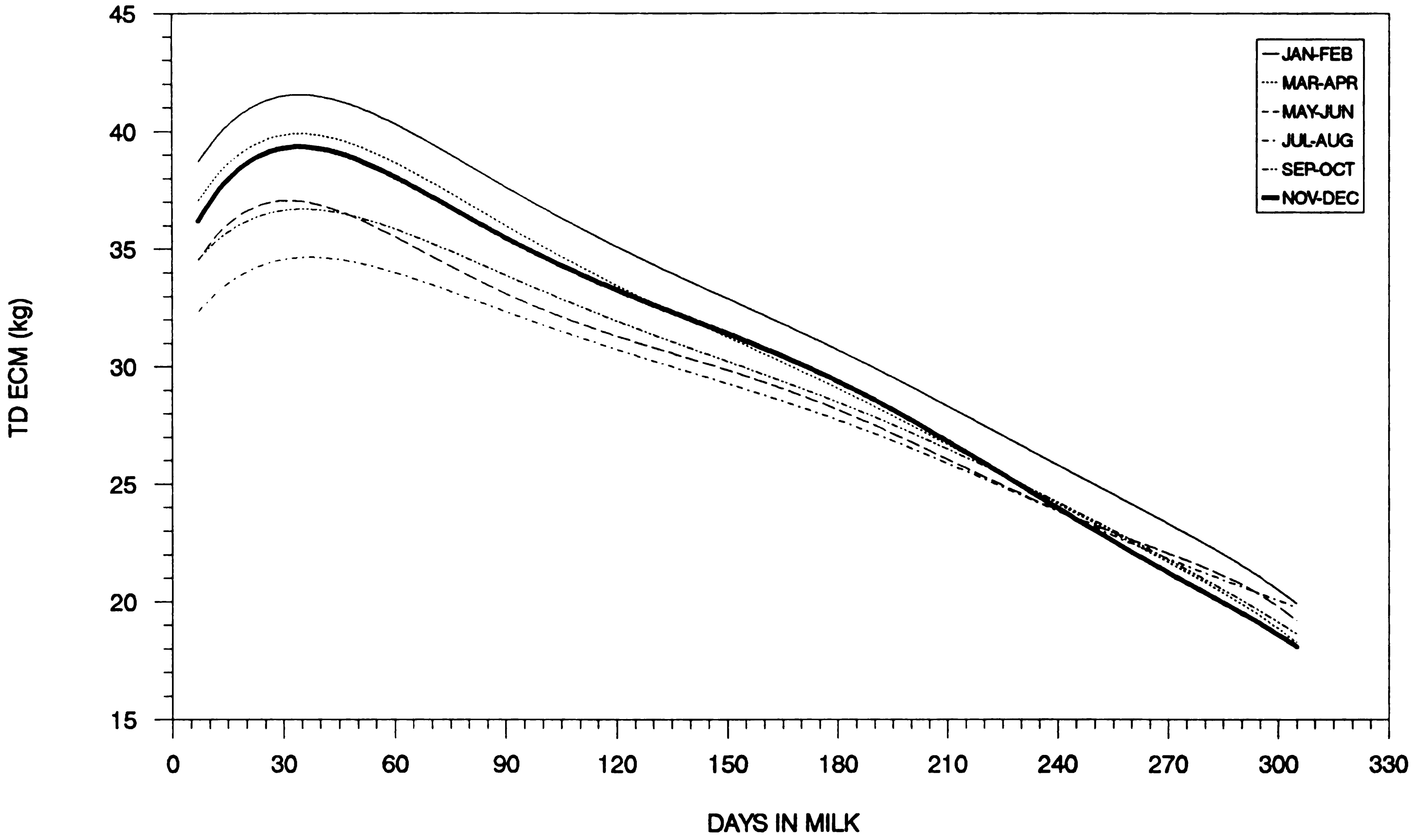

Figure 5. Test-day ECM season curves for second lactation cows in medium producing herds

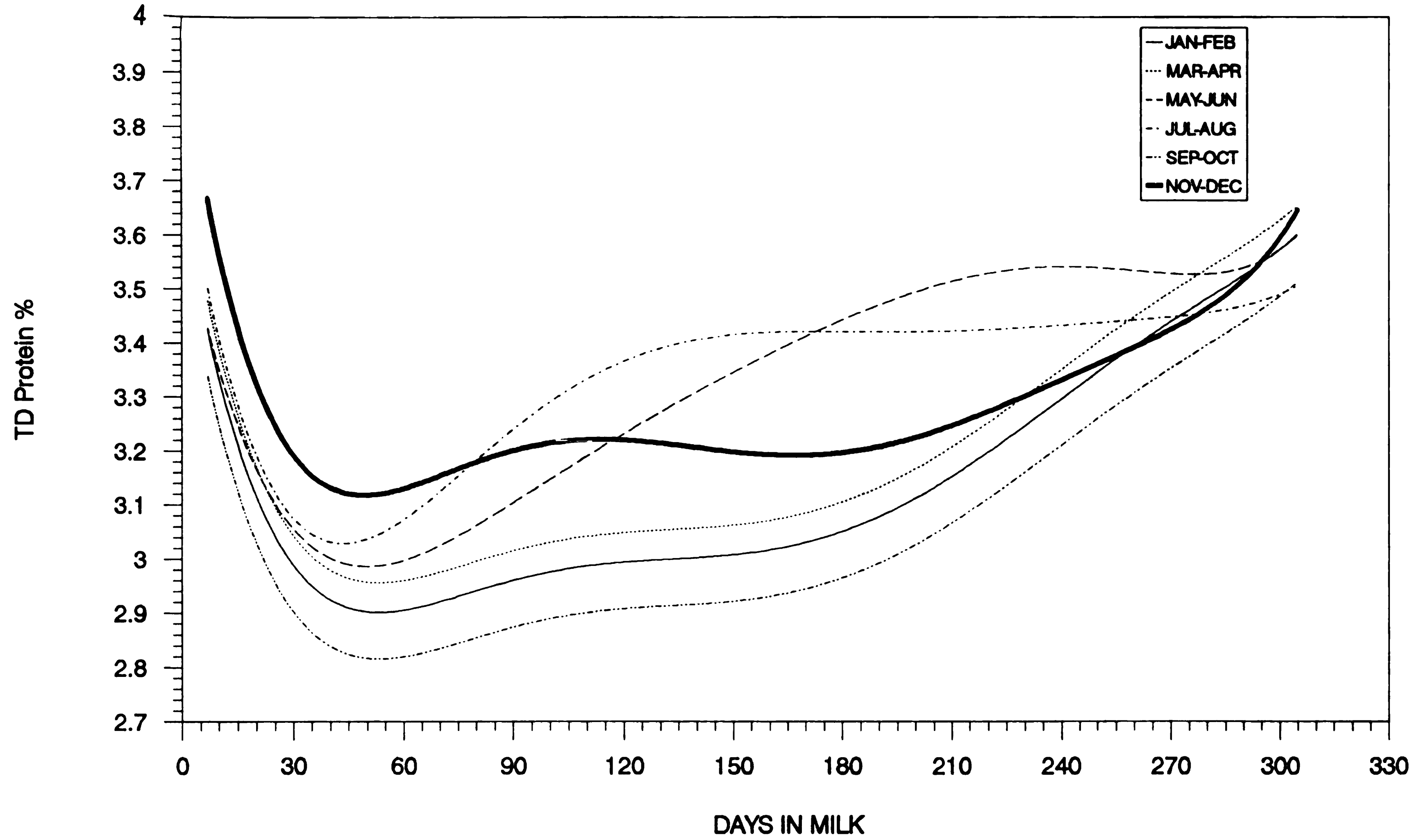

Figure 6. Test-day protein % season curves for second lactation cows in medium producing herds

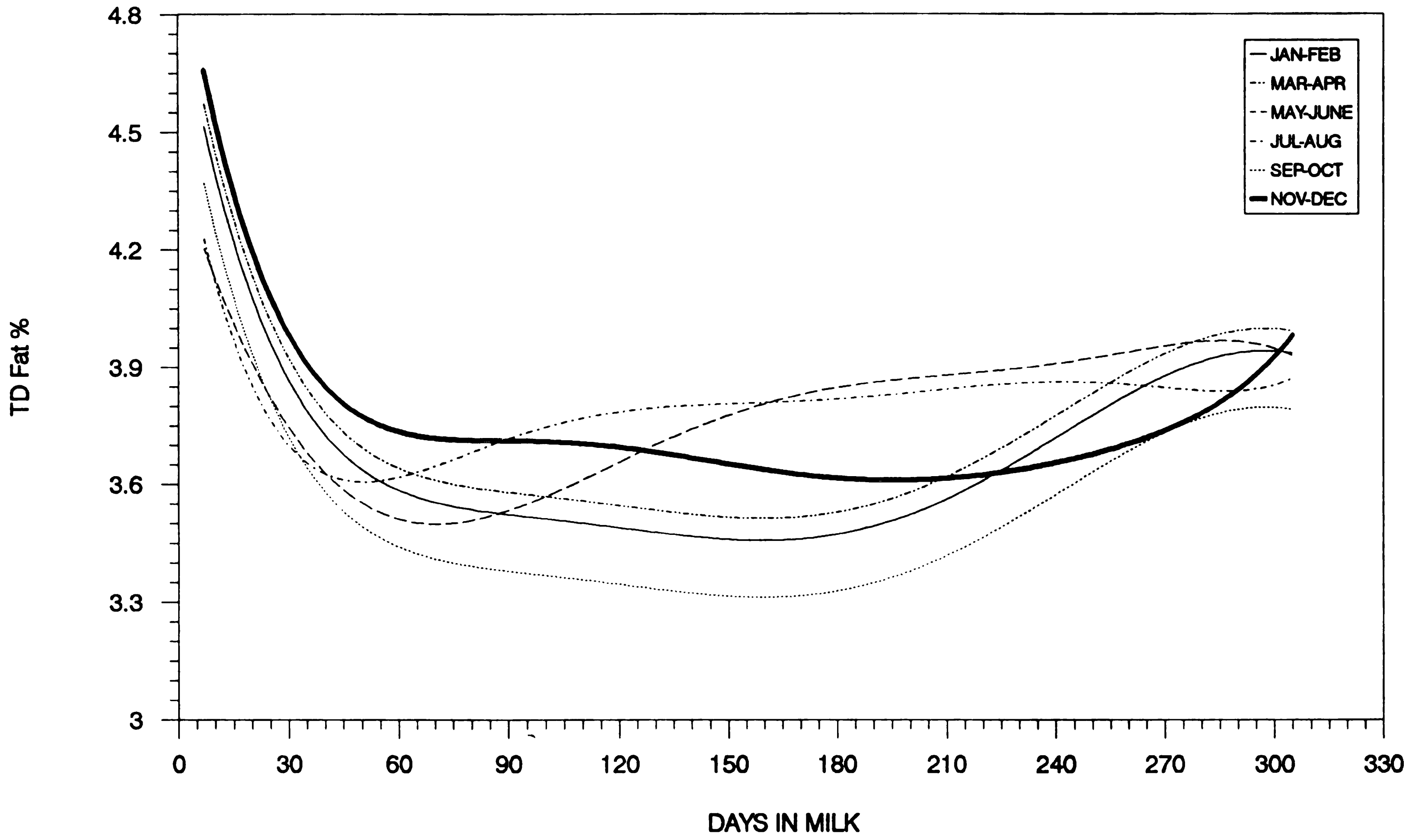

Figure 7. Test-day fat % season curves for second lactation cows in medium producing herds

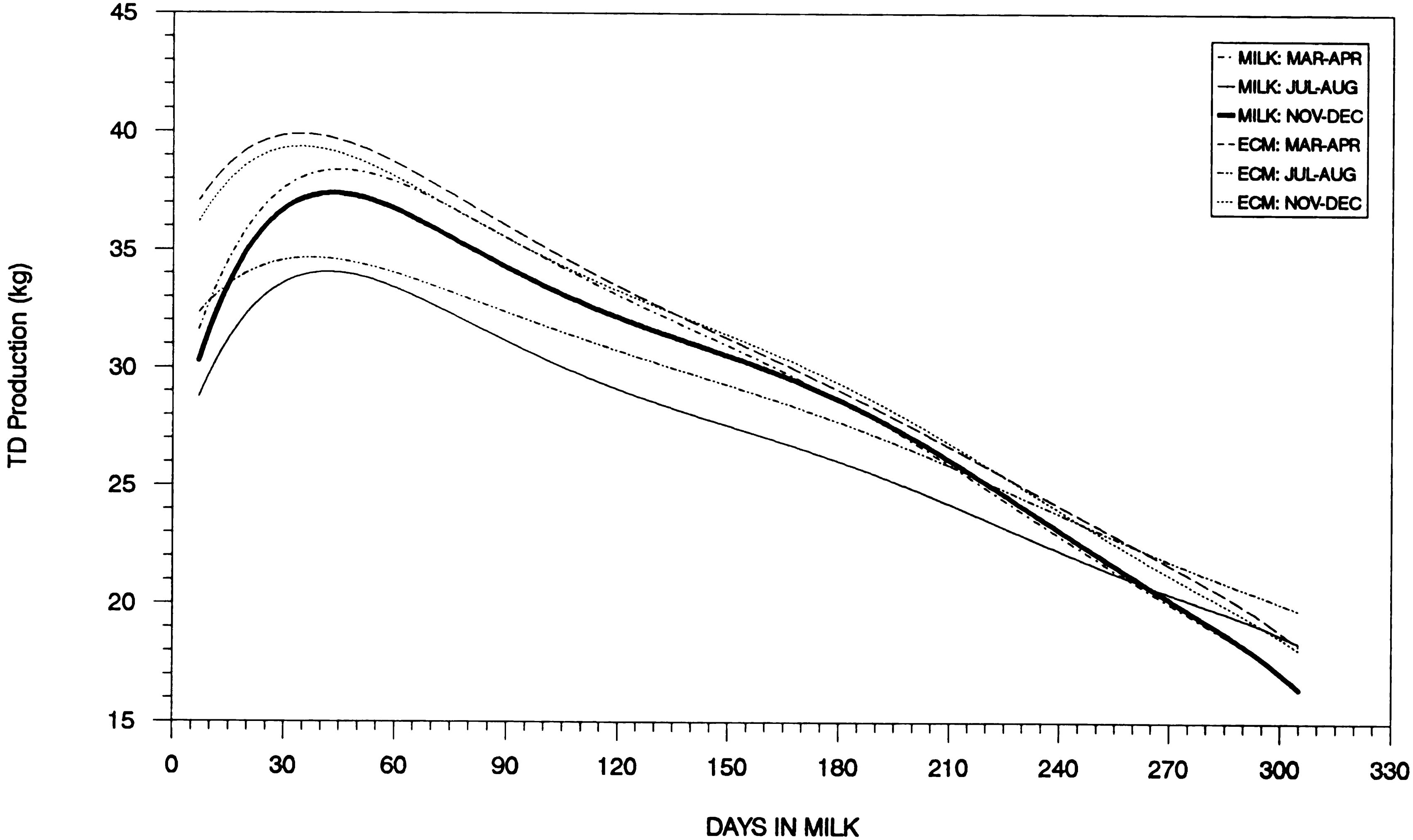

Figure 8. Test-day milk and ECM production for second lactation cows calving in MAR-APR, JUL-AUG or NOV-DEC in medium producing herds

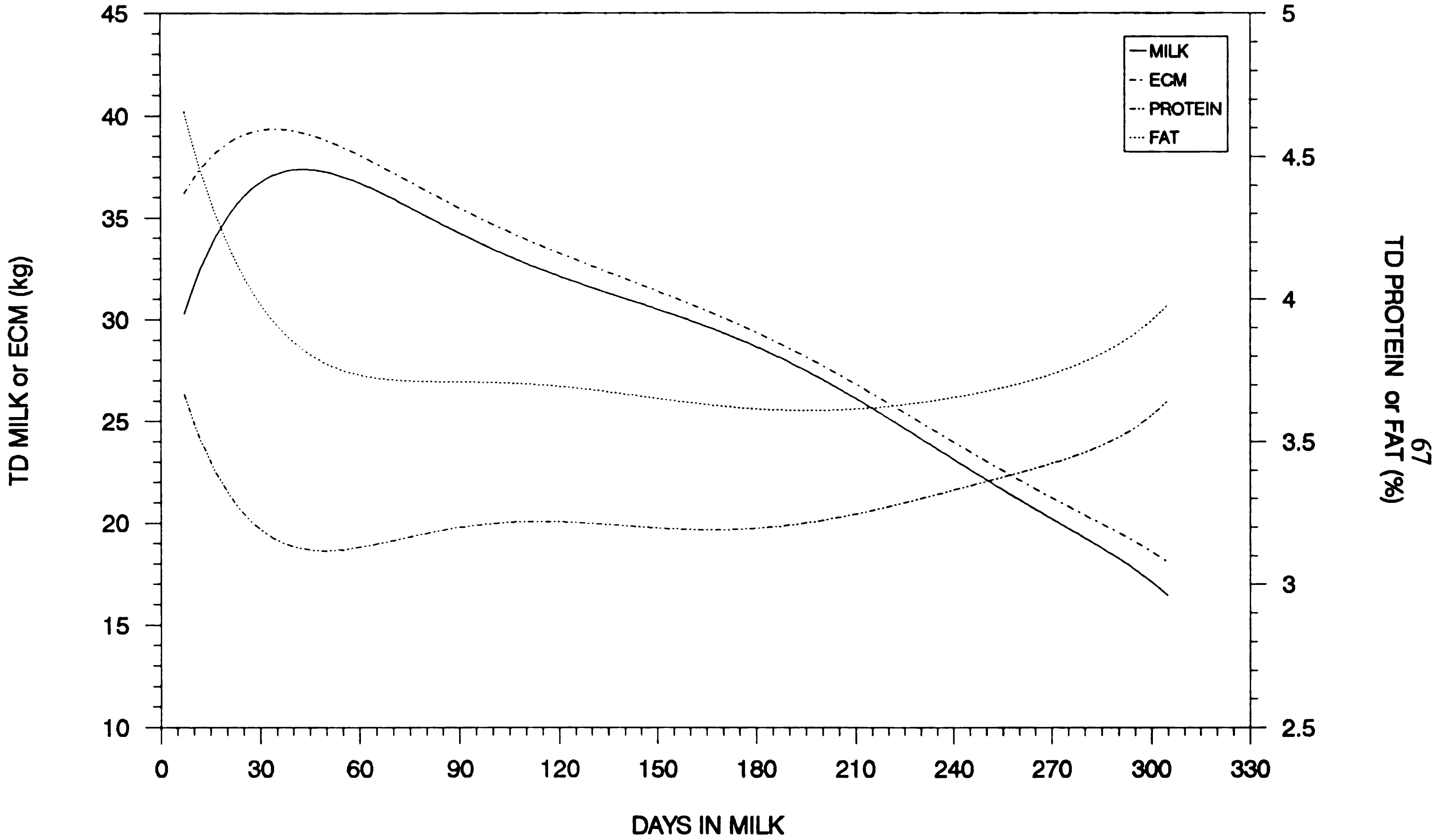

Figure 9. Test-day milk, ECM, fat % and protein % curves for second lactation cows calving in NOV-DEV in medium producing herds

Table 6. **Ratio of lactation production for calving seasons to July-August calving season by lactation number, season of freshening and Herd Production Level**

Season	Herd Production Level		
	<7,718 kg	7,718-9535 kg	> 9,535 kg
		RATIO	
Lactation 1			
Jan-Feb	1.024	1.042	1.050
Mar-Apr	1.008	1.014	1.031
May-Jun	.991	1.007	1.020
Jul-Aug	1.000	1.000	1.000
Sep-Oct	1.035	1.027	1.047
Nov-Dec	1.042	1.049	1.050
Lactation 2			
Jan-Feb	1.069	1.156	1.056
Mar-Apr	1.025	1.091	1.074
May-June	1.015	1.031	1.020
Jul-Aug	1.000	1.000	1.000
Sep-Oct	1.010	1.033	1.042
Nov-Dec	1.075	1.075	1.055
Lactation 3+			
Jan-Feb	1.092	1.096	1.030
Mar-Apr	1.057	1.053	1.051
May-Jun	1.020	1.021	1.017
Jul-Aug	1.000	1.000	1.000
Sep-Oct	1.046	1.080	1.019
Nov-Dec	1.110	1.144	1.017

calving during the autumn and early winter. For first and third or later lactations, November-December season was the best season for freshening to maximize total milk production. Similarly, for the second lactation cows in low producing herds November-December was also a good season but January-February was the best for the medium and high producing herds. Wunder and McGilliard (1971) used data from Michigan to study the influence of season on milk production. In this study of second and later lactations, January to April calvings resulted in greater production than May to October season of calving.

4.4.2 Herd Production Level

Time of peak milk production increased with herd production level within lactation group as shown on Table 2. First lactation cows in low producing herds calving in NOV-DEC peaked earlier (51 days postpartum) when compared to first lactation cows in high producing herds (67 days postpartum). The same was observed for the other lactation groups. Since cows peak higher in high producing herds, it may take them longer to peak. On the other hand, if feed intake is not adequate in low producing herds, peaks may occur earlier as body reserves are used up more rapidly.

Tables 3, 4 and 5 show the actual peak production for all the traits examined by herd level and season of calving for lactation 1, 2 and 3+, respectively. Peak milk and ECM production increased with herd level as expected. For example, for third or later lactations, peak milk production was 33.35, 41.63 and 46.65 for low, medium and high producing herds, respectively, for the November-December season of calving. For protein and fat % it was difficult to discern a trend for all three herd production levels for the three lactation groups. Lack of a defined trend could be due to the fact that the herd production levels were based on milk ME average. For example, peak fat % increased with herd production level; 4.56, 4.66 and 4.72 % for second lactation cows calving in November-December in low, medium and high production herds respectively. However, for July-August season of calving, peak fat % was 5.09, 4.23 and 4.24 % for low, medium and high producing herds respectively. Such results indicate the significant interaction between herd management and season of calving for component percentages. However, some drop in component percentages is likely resulting from increases in production since they are antagonistic.

Figure 10 demonstrates milk lactation curves within the three herd levels for first and second lactation cows calving in November-December. As expected, curves shift upwards from low to high production levels. The curves are closer at the end of lactation than at peak indicating the interaction between herd level and days in milk. Figures 11 and 12 demonstrate that fat and protein curves follow similar patterns across herd levels, but percentages decrease with increase in herd production level.

4.4.3 Lactation number

When examining the period of peak across lactations, first lactation cows tended to peak latest and second lactation cows peaked earliest for milk and ECM (Figures 13 and 14). Lactation curves for milk and ECM were flatter for first

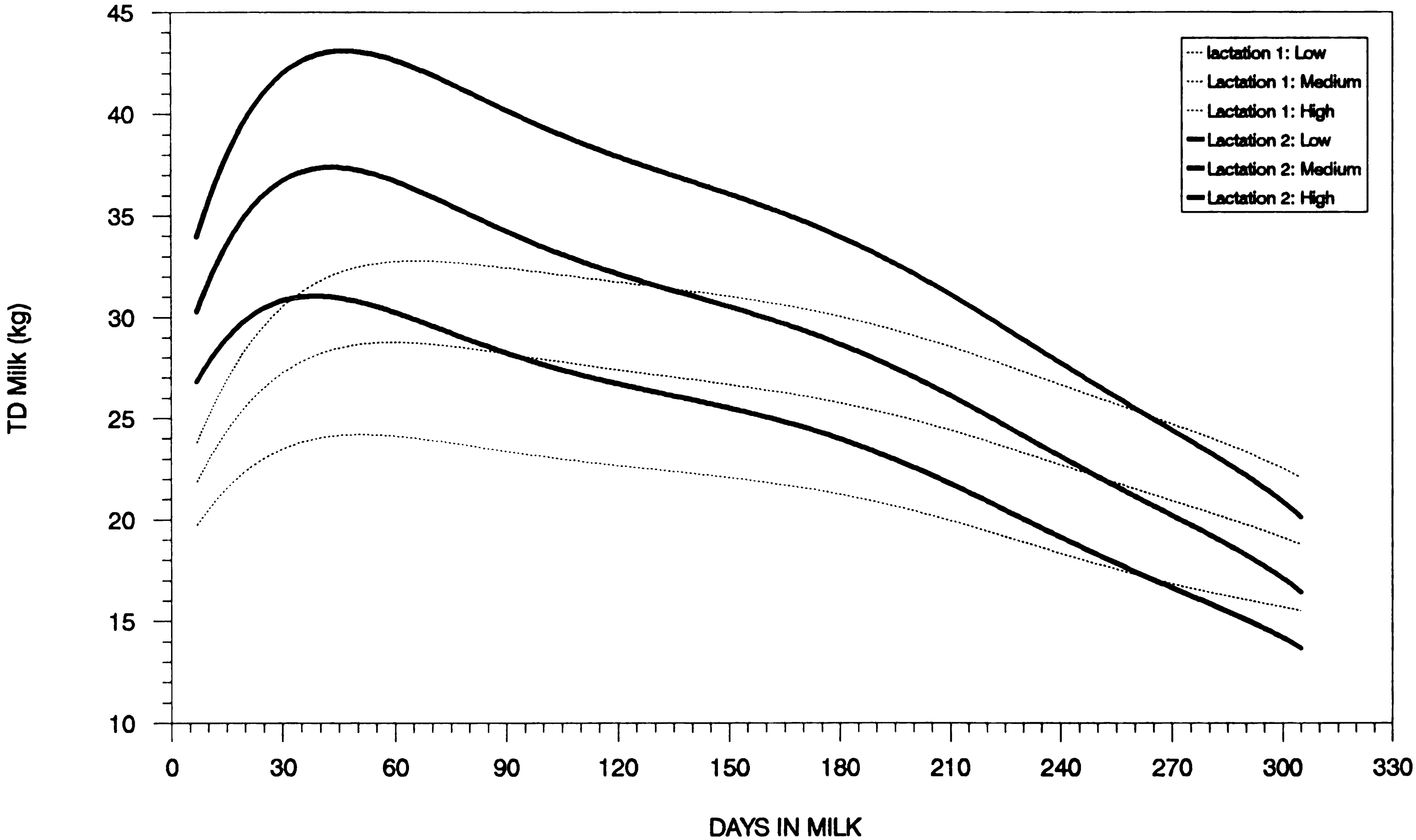

Figure 10. Test-day milk curves for first and second lactation cows calving in NOV-DEC in low, medium and high producing herds

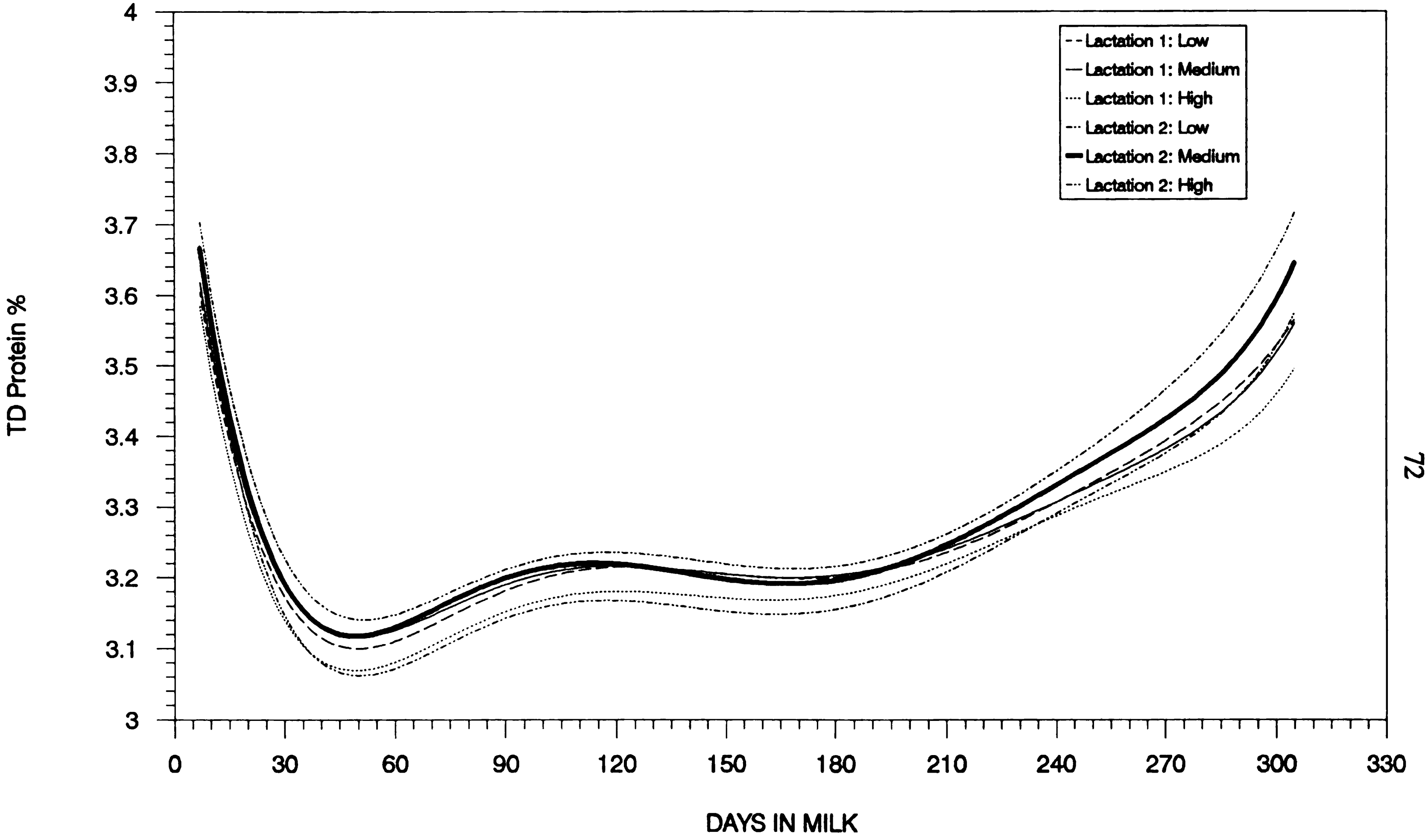

Figure 11. Test-day protein % curves for first and second lactation cows calving in NOV-DEC in low, medium or high producing herds

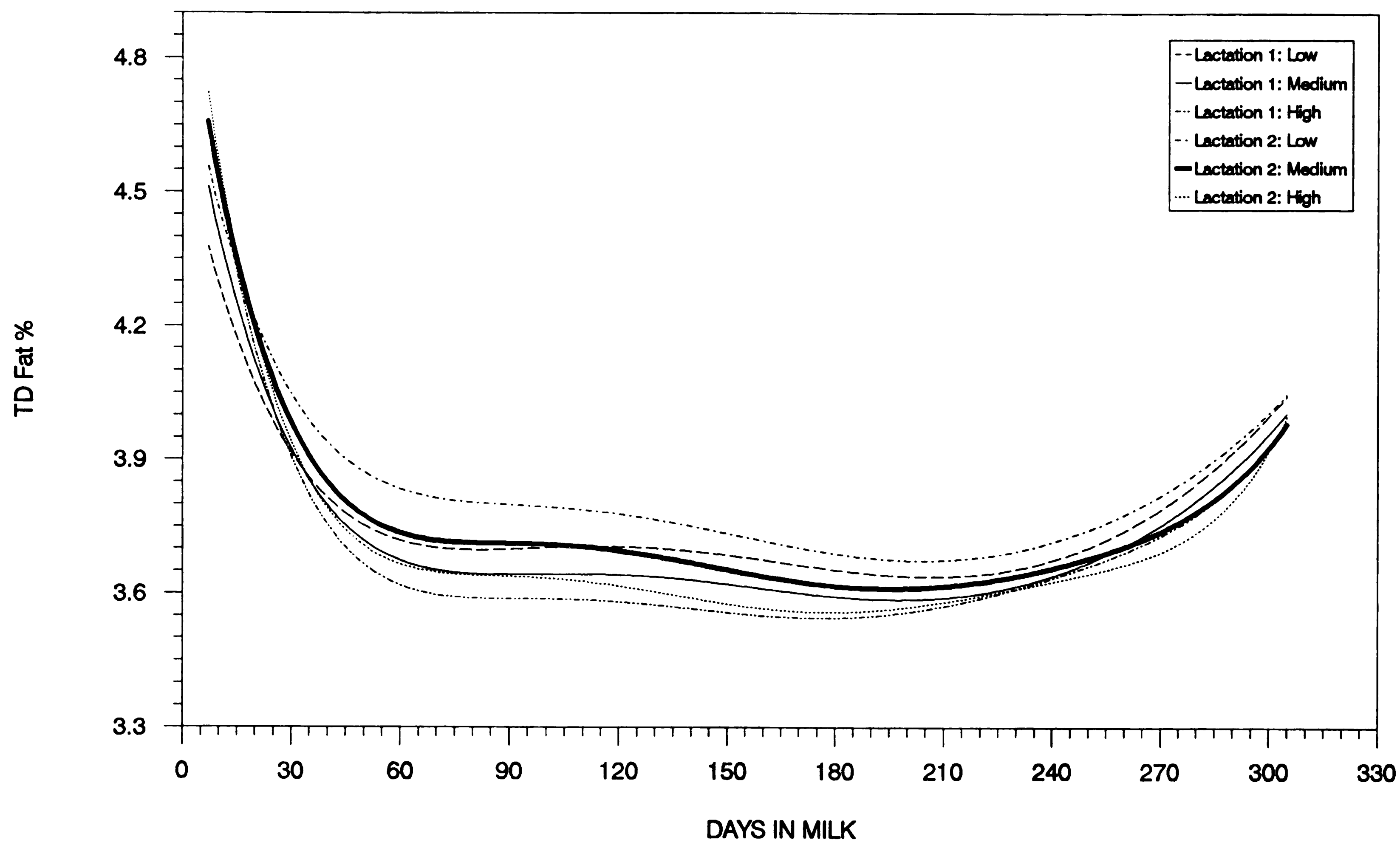

Figure 12. Test-day fat % curves for first and second lactation cows calving in NOV-DEC in medium producing herds

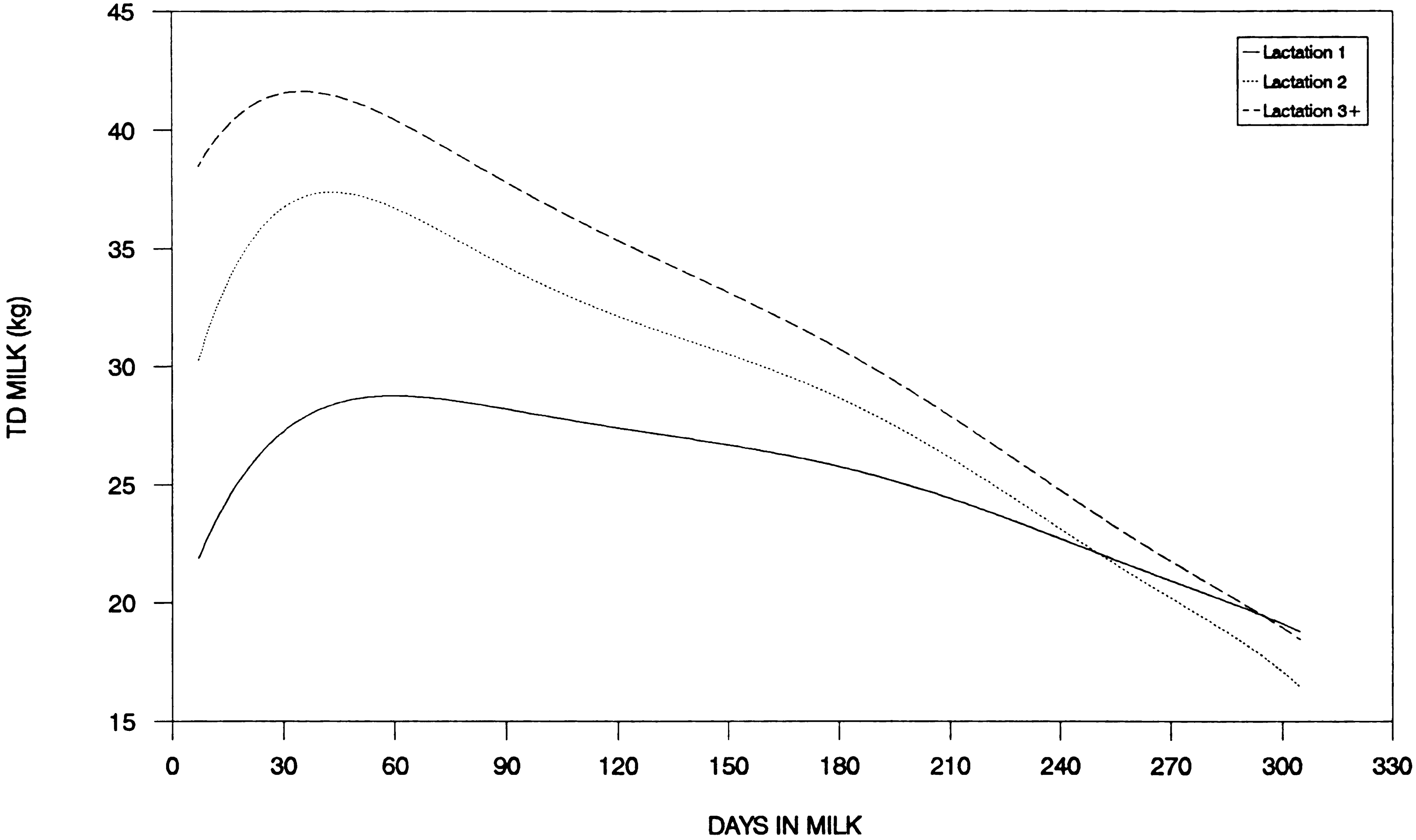

Figure 13. Test-day milk curves for first, second and third or later lactation cows calving in NOV-DEC in medium producing herds

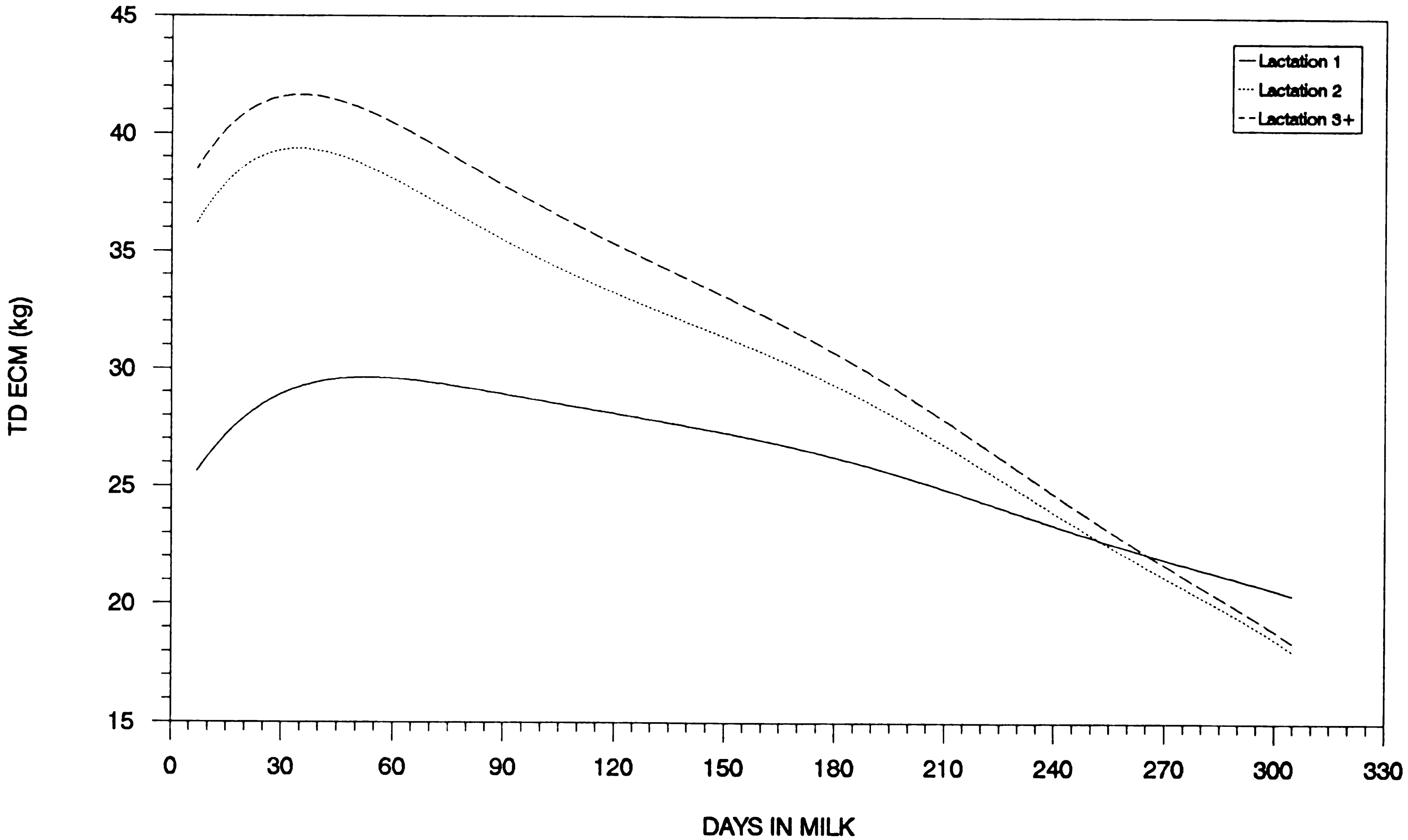

Figure 14. Test-day ECM curves for first, second and third or later lactation cows calving in NOV-DEC in medium producing herds

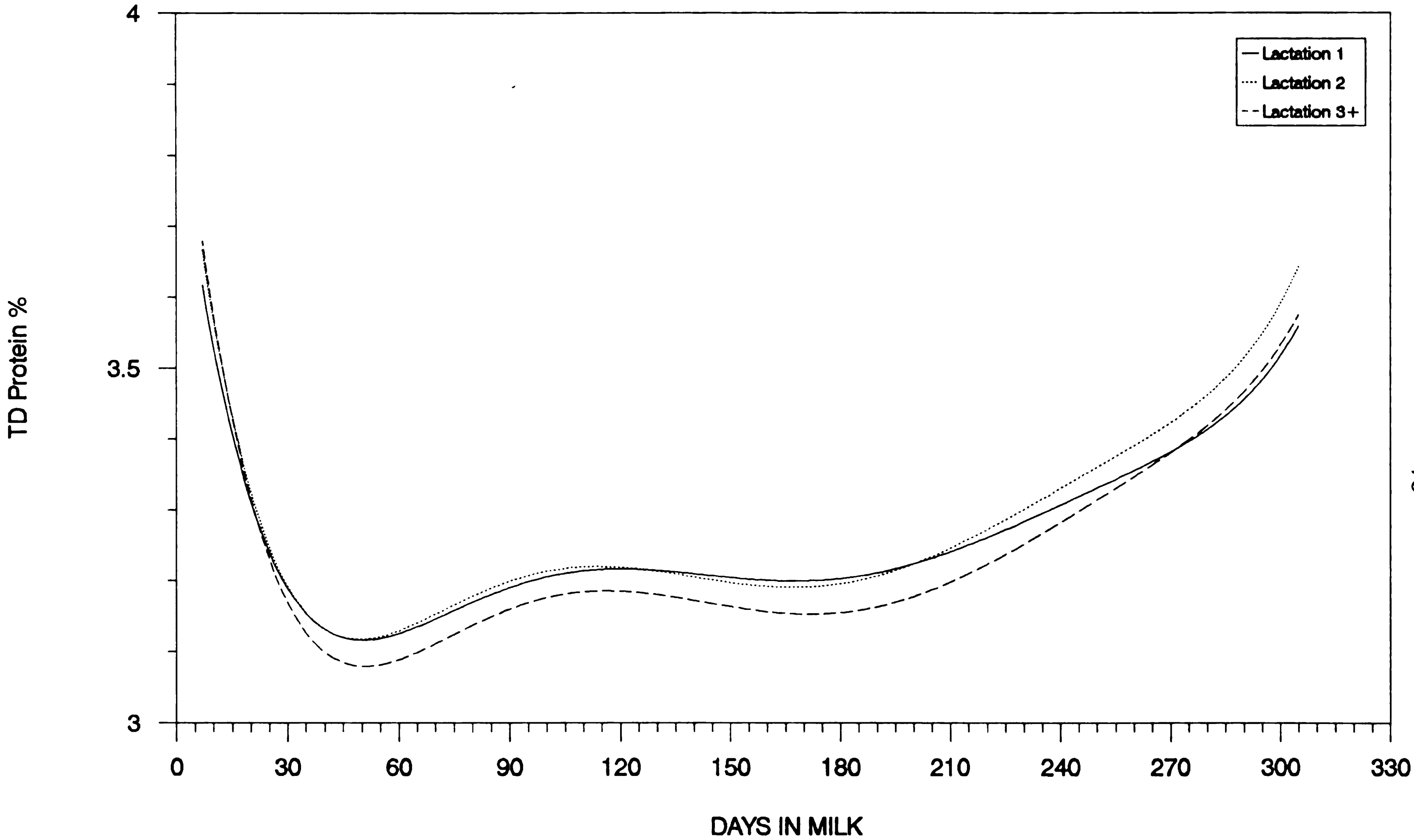

Figure 15. Test-day protein % curves for first, second and third or later lactation cows calving in NOV-DEC in medium producing herds

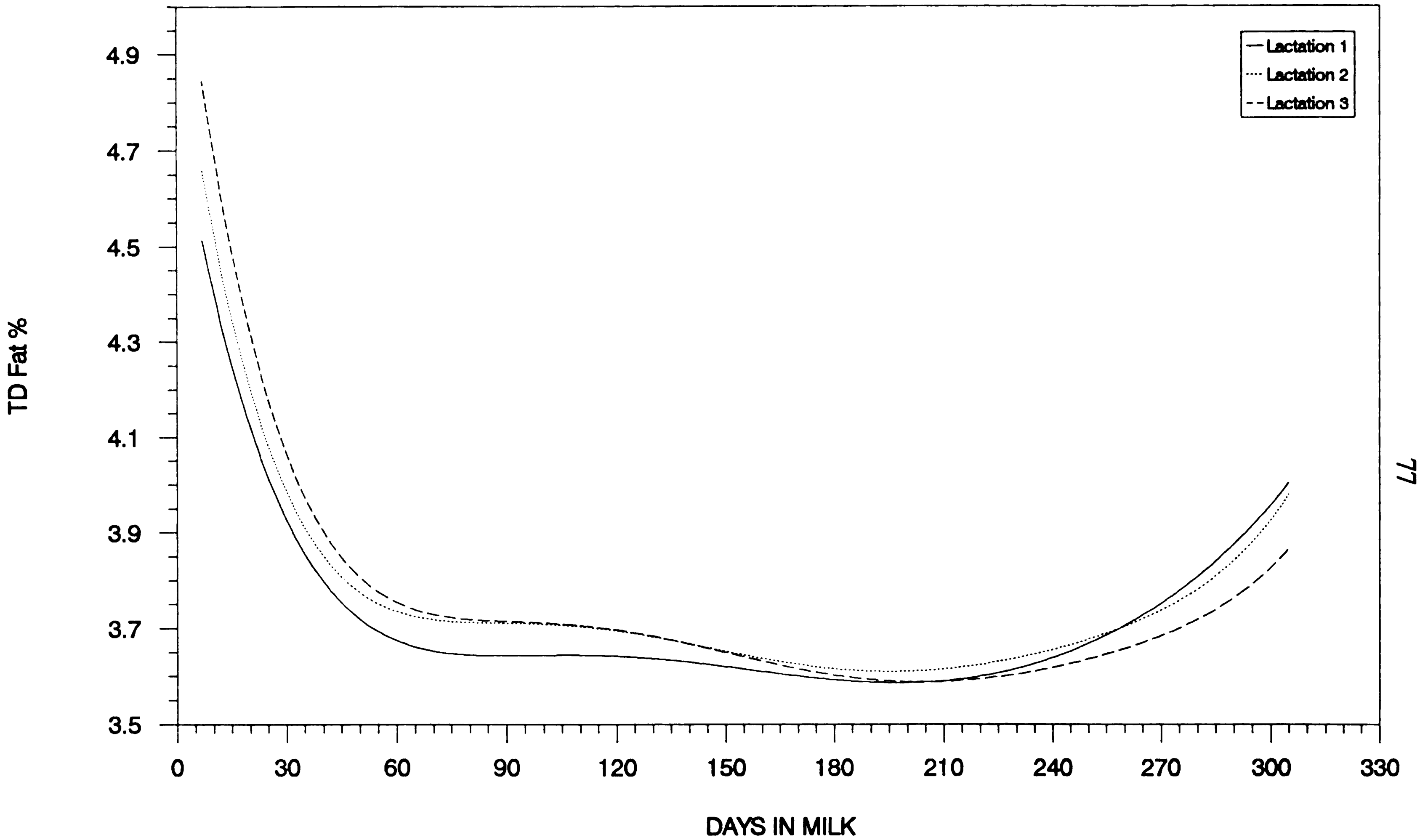

Figure 16. Test-day fat % curves for first, second and third or later lactation cows calving in NOV-DEC in medium producing herds.

lactation cows, demonstrating their high persistency. This results in first lactation cows producing more at the end of lactation than second and third or later lactation cow. Protein % is lower for third or later lactations (Figure 15) while fat % is lower for first lactation (Figure 16).

4.4.4 Adjusting milk to 150 DIM

For management purposes, dairy producers want to assess their herd's production from month to month. In order to do this using daily milk, test-day production has to be adjusted for stage of lactation, season of calving and lactation number and then standardized to a common base with a mean computed for daily milk which can be monitored from month to month. Reference lactation curves are a useful tool for this purpose. Some DHI organizations in the US adjust test-day milk to a 150 day DIM value and compute a herd mean for this adjusted daily milk value. As mentioned above, Steurnegal (1988) and Nordlund (1987) developed methods to adjust test-day production to 150 days in milk. However, their methods do not consider season of freshening and herd production level.

Factors to adjust records to 150 days in milk were developed from the standard curves computed in this study. Sixth degree polynomial regressions for the 54 curves are in Appendix I. The second lactation group calving in NOV-DEC was chosen as the base group. An example of how to use these factors to adjust a cow's record to the base group at 150 days in milk is illustrated below.

4.4.4.1 Illustration of how to compute factors to adjust test day production to 150 DIM standardized to second lactation cows calving in November-December.

Cow Amanda is in Parity 1 at 47 days in milk and calved in April in a herd with an annual ME average > 9,535 kg milk.

Let her test-day (TD) yield = 30.50 kg.

Adjusting her Record to 150 DIM as if she was in her 2nd lactation and calved in November-December (base group).

Adjusted 150 day production = (TD yield) x Factor

Factor = 36.08 / Standard DIM Yield for Amanda's lactation class. (36.08 is from Table 7)

From Appendix I, Table 9.

Standard yield at 47 DIM = $20.096926 + 0.579507(D) - 0.009521(D^2) + 0.000073851(D^3) - 0.000000307(D^4) + 6.541044E\text{-}10(D^5) - 5.59630E\text{-}13(D^6)$

= 32.61 kg where D = 47 days in milk

Factor = 36.08/32.61
= 1.106

Adjusted 150 day production = 30.50 x 1.106 = 33.75 kg

Table 7 shows the standard 150 DIM test-day means for second lactation cows calving in November-December for all three herd production levels.

Table 7. **Standard lactation test-day values for 150 days in milk for second lactation cows calving in November-December used as base for standardized 150 days in milk within three herd production levels.**

Trait	**Herd Production Level**		
	< 7,718 kg	**7,718-9,535 kg**	**>9,535**
Milk (kg)	25.51	30.52	36.08
ECM (kg)	26.56	31.41	36.67
Fat %	3.73	3.65	3.58
Protein %	3.22	3.20	3.15

4.5 CONCLUSIONS

Lactation curves were estimated by fitting a 6th degree polynomial to least square means for three lactation groups, three herd production levels and six seasons of freshening. The R-square values ranged from .90 to .9958 for milk and ECM and ranged from .60 to .99 for protein and fat %.

Season of calving had a significant effect on the shape of lactation curves. Calving in summer months depressed both time to reach peak milk production and peak production. For components, a nadir was reached earlier by cows calving in July-August compared to other calving seasons. November-December seemed to be the best season for calving for the Michigan Dairy herds in terms of total lactation yield for milk. July-August season had the lowest total lactation production for milk. The low production for summer calvers is probably due, in part, to the depressing effects of heat stress.

Milk and ECM lactation curves did not coincide. Milk tended to trail behind ECM although following the same shape or trend. Peak milk and ECM production coincided with the nadir in protein and fat %.

First lactation cows had lower peaks and flatter, more persistent lactation curves compared to second and third or later lactation cows. For protein and fat %, third lactation cows exhibited low values when compared to first and second lactation cows, which were similar in component percentages.

Milk and ECM curves shifted upward with herd production level group. However, less differences for milk and ECM and were at the end of lactation than at peak for the three herd production groups. Protein and fat % differed little with increased production levels. Small differences could be due to the fact that herd production levels were based on ME milk herd average. Breaking these levels by fat or protein production would enhance the observed differences for components. This study supports the need to develop separate adjustment factors for parity, herd production levels and season of calving to account for these environmental and physiological factors that influence daily milk yields.

5. Application of a multitrait animal model to predict next test-day milk production.

5.1 ABSTRACT

Lactation data consisting of 171,922 test-day milk records for first lactation Holstein cows tested in 600 Michigan herds from 1988 to 1992 were divided into ten stages of lactation. Each stage was a 30-day days in milk interval (DIM). With stages treated as ten separate traits, a multiple trait animal model (MTA) was used to estimated the phenotypic variances and covariances among these traits within three herd production levels. The model for each trait contained fixed effects of season of calving by DIM, season of test by temperature-humidity index and age at calving, and random additive genetic effects. Phenotypic (co)variances between traits were used to predict next test-day milk yield deviations for individual cows from standardized lactation curve values. This method was evaluated using 50 randomly selected herds within each herd production level. Test-day milk deviations were predicted using either 1, 2 or 3 previous test-day deviations for a cow. Predicted test-day production was the sum of the predicted deviation and the expected standard lactation curve value.

Biases in predicting test-day deviations averaged near zero for the overall population of 50 herds and within herd-testdays when 3 previous test-day deviations were used. Biases were greatest when using only 1 previous test-day deviation. For the low herd production level, overall population mean biases were -.311, -.132 and -.005 kg when using either 1, 2 or 3 previous test deviations respectively. The corresponding root mean square errors did not differ much (3.32, 3.12, and 3.19, respectively). The traits or days in milk intervals predicted

most accurately were between 120-270 days. Biases and root mean square errors were similar for medium and high production herd groups.

Same predictions were made using slopes of standard lactation curves and the previous test-day weight. These predictions resulted in larger mean biases with greater root mean square errors. For low producing herds, the overall mean bias was .487 kg with a root mean square error of 3.87 kg when using a slope from a curve estimated from season of calving by DIM solutions using an animal model. The bias was even larger (1.13 kg) with predictions from the slope of a standard curve which was fit by a sixth degree polynomial model and ignored additive genetic effects. Results were similar for the medium and high herd production levels.

5.2 INTRODUCTION

Dairy managers need to accurately evaluate milk production responses resulting from management changes or the implementation of new technologies to determine if they are cost effective. This is critical to maintaining long-run profitability, but because comparison with control groups is often not possible on farms, this task is difficult. In addition, there may be periods when no specific changes or multiple management changes are made, that require monitoring production trends in order to effectively evaluate general management and herd health status. Without control groups, producers are forced to assess production change of the entire herd or a group of cows from period to period. This is difficult because cows in a herd or group contributing to a day's production vary as cows freshen or dry off between periods being assessed. In addition, a cow's test-day yield is influenced by systematic environmental effects such as season of calving, season of test and herd, and physiological factors such as stage of lactation, age and number of days open. Importantly, stage of lactation, season of test and days open change between periods for each cow. A within herd standardization of test-day yields for all these effects allows comparison between periods and between individual cows within a herd. Making these adjustments is useful for management and selection purposes.

Currently, several methods are being used to account for stage of lactation by adjusting daily milk to 150 days in milk (McCraw and Butcher, 1976; Steuernagel, 1988; Nordlund, 1987). Steuernagel also adjusts for age and parity. Only McCraw and Butcher (1976) included season of calving, which influences production peak and rate of decline. None included herd production level which may also influence rate of lactation decline.

Summarizing test-day records into a single measure, lactation yield, as is common practice has some deficiencies. Adjustments to a 305-day cumulative value for systematic environmental effects such as herd, season and age of calving can be done but it would be difficult to adjust for systematic effects specific to individual test days making up the 305 day record. Such factors include the effects of temperature, relative humidity, pregnancy, use of bST and disease. It would require accurate start and stop times for disease, use of bST, etc., to get accurate test interval estimates of milk production from which to compute 305-day production.

The problem of accurately comparing daily milk production has resulted in requests by feed consultants and veterinarians for a better system to monitor production changes in dairy herds. A useful system would predict production for the next test day while accounting for physiological changes in each cow and season of test or change in the environment. The predicted values could then be compared to the actual values for that test day to determine if there is a significant change in production.

When predicting unobserved test-day records, it is desirable to make maximum use of the predictability of the lactation curve and to minimize the error of prediction from a sample of daily records. Many mathematical models have been proposed to model lactation production (Wood, 1967; Grossman and Koops, 1988, Deboer et al., 1989, Weigel et al., 1992). Stanton et al. (1992) used standard lactation curves derived from a test-day model that considers herd level, age at calving, days in milk, season of calving and herd-testday to predict next test-day production from the slope and previous test-day weight. Trus and Buttazzoni (1990) proposed a multitrait model that can be used to estimate missing test-day weights to compute total lactation production. Their approach subdivided lactation into ten 30-day periods, treating each period as a trait. For the purpose of computing total lactation, they used the (co)variances between traits to compute values for missing test-days (traits). Estimation of a missing last test-day in a lactation was a unique case in their method in which only prior tests are used to estimate the missing last test. This method provides the basis to estimate next test-day production at any point in the lactation using (co)variances from prior observed individual test yields. There are several advantages to using multitrait models. The major advantage being simultaneous consideration of more than one trait to obtain the phenotypic, additive or residual relationships between the traits.

The objective of this study was to use phenotypic (co)variances computed between ten 30-d stages of lactation classes to predict phenotypic production deviations for individual cows for the next test day using either 1, 2 or 3 previous test-day deviations.

5.3 MATERIALS AND METHODS

5.3.1 Data

Data were 171,922 test-day milk records of first lactation Holstein cows calving in 600 Michigan herds and tested between 1988 and 1992. Herds with less than 80 cows were not used. Cows with completed 305 d lactations were used with test-day (TD) yields greater than 305 days in milk (DIM) excluded. Lactation records were deleted if first reported test-day had greater than 60 DIM or age at calving was different from 18 to 36 months. Records with highly improbable TD yield were deleted. Herds were grouped into three herd production levels based on 1990 annual ME milk herd averages as defined in section 4.3. A summary of the number of observations and means for TD milk yield are given in Appendix II, Table 1.

Weather data was obtained from the Michigan State University Climatology Center and merged with test-day data. The weather data included hourly observations of dry bulb and dew point temperature.

5.3.2 Model

To determine the fixed effects of season of calving, age and temperature-humidity index on test-day milk yield, a single trait animal model was run within each of three herd production levels. Six, two-month season of calving classes were defined as January-February ,..., November-December. Classes of days in milk were formed by 3-day intervals up to day 150 and then 5-day intervals up to 305 days in milk. Nine classes for age at calving in months were defined as 18-20; 21-22; 23-24; 25-26; 27-28; 29-30; 31-32; 33-34; and 35-36. Three seasons of test were defined as December to April; May to August and September to November. Temperature-humidity index (THI) (Standards, American Society of Agriculture Engineers, 1991) was computed from the following formula:

$$THI = 41.2 + t_{db} + .36 \times t_{dp}$$

where: t_{db} = mean daily dry bulb temperature (°C)

t_{dp} = mean daily dew point temperature (°C)

Mean daily temperatures were averages of 24 hourly measurements. THI provides a reasonable measure of the combined effects of humidity and air temperature. Seven classes of THI were defined as : < 30, 30-40, >40-50, >50-65, >65-70, >70-75 and >75. Preliminary analysis showed that previous day THI had more influence on test-day yield than THI for the day of test. Therefore, THI was lagged by one day. The single trait animal model used was:

$$y_{ijklmnp} = \mu + HYR_i + SDIM_j + SOTTHI_k + AGE_l + a_m + p_n + e_{ijklmnp} \qquad [1]$$

where

$y_{ijklmnp}$	=	the pth test-day milk record for a cow in HYR i;
HYR_i	=	the ith herd-year subclass;
$SDIM_j$	=	the jth season of calving by days in milk subclass for a cow on the pth test-day with j = 1,2,...,468;
$SOTTHI_k$	=	the kth season of test by THI subclass for a cow on the pth test-day with k = 1,2,...,20;
AGE_l	=	lth age at calving for a cow with l = 1,2,...,9;
a_m	=	random additive genetic effects pertaining to cows, sires and dams, with **a** as $N(\mathbf{0}, \mathbf{A}\sigma_a^2)$;
p_m	=	random permanent environmental effects for each cow with **p** as $N(\mathbf{0}, \mathbf{I}\sigma_p^2)$ and
$e_{ijklmnp}$	=	random residual effects with **e** as $N(\mathbf{0}, \mathbf{I}\sigma_e^2)$

5.3.2.1 Estimating (co)variances between test intervals

DHIA test-day records making up a cow's lactation where classified into ten 30-day days in milk intervals. Test-day yields within each interval were treated as separate traits. A second model, a multitrait animal model, was used to estimate the (co)variance between the ten intervals. This second model included the fixed effects used in the single trait model [1]. Ten traits were defined but they could not be analyzed simultaneously. Simultaneous analysis of more than two traits in multitrait models could not be run because the number of equations to solve increased and convergence was not be reached. Since, the objective was to predict any test-day using information from 3 or less previous tests, traits were grouped into groups of four as shown below.

	TRAIT									
TRAIT	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	x	x	x	x						
2		x	x	x	x					
3			x	x	x	x				
4				x	x	x	x			
5					x	x	x	x		
6						x	x	x	x	
7							x	x	x	x

Then, (co)variances for each set of four trait combinations were computed two traits at a time. For example, in the first set, the 2 trait combinations were trait 1 and 2, trait 1 and 3, and trait 1 and 4. The sampling variance of trait 1 was estimated by averaging the three variances. Fixed effect classes (days in milk, season of test and THI) differed for the ten traits of a cow since these effects were test-day specific.

The multitrait model was:

$$\mathbf{y} = \mathbf{X}b + \mathbf{Z}\alpha + \mathbf{e} \qquad [2]$$

where

$$\mathbf{y} = \begin{bmatrix} y_i \\ y_j \end{bmatrix}$$ is a vector of test-day milk records on traits i and j;

$$b = \begin{bmatrix} b_i \\ \beta_j \end{bmatrix}$$ is a vector of constants for traits i and j;

$$\mathbf{X} = \begin{bmatrix} X_i & 0 \\ 0 & X_j \end{bmatrix}$$ is a design matrix corresponding to fixed effects of traits i and j;

$$\alpha = \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix}$$ is a random vector of additive genetic effects for traits i and j;

$$\mathbf{Z} = \begin{bmatrix} Z_i & 0 \\ 0 & Z_j \end{bmatrix}$$ is a design matrix corresponding to the random additive effects of traits i and j and

$$\mathbf{e} = \begin{bmatrix} e_i \\ e_j \end{bmatrix}$$ is a random vector of residuals for traits i and j.

vectors a and e were from multivariate normal distributions with expected values

$E(y) = Xb$, $E(a) = 0$ $E(e) = 0$ and

$$G = V\begin{bmatrix} a_i \\ a_j \end{bmatrix} = \begin{bmatrix} Ag_{11} & Ag_{12} \\ Ag_{12} & Ag_{22} \end{bmatrix} = A * G_o$$

A is the numerator relationship matrix among animals. The relationships considered were based on sires and dams. Inbreeding was not considered. Similarly

$$R = V\begin{bmatrix} e_i \\ e_j \end{bmatrix} = \begin{bmatrix} Ir_{ii} & Ir_{ij} \\ Ir_{ij} & Ir_{jj} \end{bmatrix} = I * R_o$$

The mixed model equations for the multiple trait individual animal models are:

$$\begin{bmatrix} X'R^{-1}X & X'R^{-1}Z \\ Z'R^{-1}X & Z'R^{-1}Z + A^{-1} * G^{-1} \end{bmatrix} \begin{bmatrix} \hat{\beta} \\ \hat{\alpha} \end{bmatrix} = \begin{bmatrix} X'R^{-1}y \\ Z'R^{-1}y \end{bmatrix}$$

The above models were solved by a Derivative-Free Restricted Maximum Likelihood (DFREML) algorithm (Meyer, 1989b). The DFREML procedure relies on the repeated use of Gaussian elimination in conjunction with sparse matrix techniques to evaluate the log likelihood function (L) using a convergence criterion of 10^{-8}. Number of iterations to reach convergence varied from 100 to 300.

5.3.2.2 Predicting next test-day production

From the solutions of the above equations, the population parameter estimates **R** and **b** are used for prediction of test-day production of a cow using the following procedure:

First compute:

$$\mathbf{e_0} = \mathbf{y_0} - \mathbf{E(y_o)} = y_o\text{-}Xb$$

where

e_o is a vector of 1,2, 3 observed deviations for previous test-day yields of a cow.

y_o is a vector of 1, 2 or 3 previous TD milk yields (traits) of a cow.

$\mathbf{E(y_o)}$ or Xb is the expected yield for the previous 1, 2 or 3 traits for an average cow in a cow's herd subgroup class.

Let e_p be a vector of unknown or predicted deviations for the next test-day and y_p be the predicted TD milk yield. So previous or observed phenotypic deviations were defined as the difference between the expected standardized TD yield (Xb) and the previous observed TD milk yield (y_o). The expected standard TD yield for each test-day of a cow is the sum of her class solutions for season of calving by DIM, age at calving and season of test by THI, plus a herd deviation. So Xb is a within herd subclass average. The herd deviation is a five year herd average computed as the mean of individual cow TD milk yields minus solutions from the three fixed effects (season of calving by DIM; age at calving and season of test by

THI). The addition of this deviation to Xb makes Xb specific for a herd as the deviation accounts for the difference between a herd's production level and the average production for the herd production level group of the herd. As a result,

$E\ (y_o - Xb) = 0$ and

$E\ (y_p - Xb) = e_p = 0$ for the average of all cows in a herd on a test-day, i.e., the expected average of previous and predicted deviations for cows in a herd is zero.

If average e_p varies from zero, this suggests a change has occurred, possibly a management change which has influenced the production of cows in the herd.

Henderson (1988) demonstrated the following procedure to predict missing residuals:

$$e_p = R'_{op} R_{oo}^{-1} e_o \qquad [3]$$

where $\mathbf{R}_{op}$ = submatrix of the residual (co)variance matrix (R) corresponding to intervals with missing observations

$\mathbf{R}_{oo}$ = submatrix of R corresponding to observed records

This method can be used to predict the deviation ($\mathbf{e}_p$) for the next test day from one, two or three previous observed test-day records. Since the goal was to estimate phenotypic deviations, the phenotypic (co)variances are used. An unobserved test-day record was therefore predicted as:

$$\hat{y}_p = X\hat{b} + \hat{e}_p \qquad [4]$$

In practice the test-day yield being predicted would be today's yield or a recent yield so that the one day lagged THI is available and the actual yield for the test-day is known.

Figure 1 illustrates 3 previous deviations (traits 1-3) for a cow in a herd and the comparison of the predicted TD milk yield (trait 4) with the actual test-day yield.

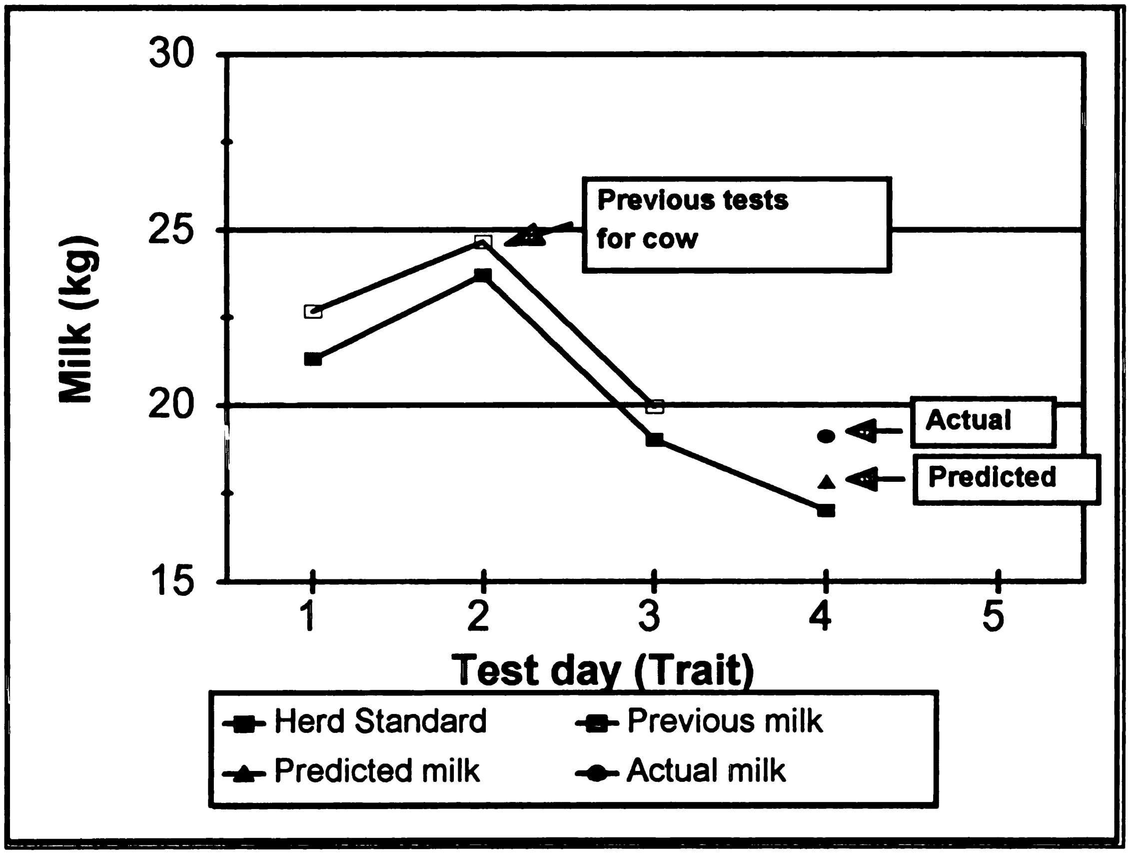

Figure 1. Predicting test-day milk production from previous test-day deviations.

To test this method of prediction, prediction biases were computed for cows in 50 randomly selected herds within each herd production level using the five year data set. Biases for each cow were computed as observed deviation minus predicted deviation:

$$\mathbf{bias} = \mathbf{e_o - e_p} \qquad [5]$$

Root means square errors (RMSE) of the prediction were approximated as the standard deviation of the mean biases (Stanton et al., 1992). Mean biases and RMSE were computed 1) across herds, DIM intervals (traits) and Herd-TD, 2) within herd across all cows and traits; 3) within herd test-days and 4) within each trait across herds. Since the objective of the study is to assess how well this method predicts the herd's current test-day average, the within Herd-TD biases will be critical to evaluate.

5.3.2.3 Prediction of next test-day using lactation curve slopes

TD production was also predicted in a more traditional way using the slope of standard lactation curves. First, the slope was computed between the previous and current test-day by dividing by the standard TD milk (from a standard curve) for the current DIM of a particular cow by the standard milk for the previous test-day DIM of the cow. Standard curves represented six seasons of calving and three herd production levels. The previous TD production was then multiplied by the slope to predict the current TD record.

In this study, standard curves were computed from the method discussed previously in section 4.3.2 and from the single trait animal model in section 5.3.2.

5.4 RESULTS AND DISCUSSION

5.4.1 Age at calving

Figure 2 shows the effect of age at calving on milk production for the three herd production levels. The solutions are shown in Appendix II, Table 2. In all cases, age effects on milk tended to increase with increasing age at calving. However, the age solutions for the low herd production level were much smaller as compared to those of the medium and high production levels. This shows the need to develop separate age adjustment factors for different production levels. Everett and Schmitz (1993) showed that within herd age effects were different from global population age effects. He developed a TD model that will compute intra-herd age effects.

5.4.2 Season of test by temperature-humidity index

Appendix II, Table 3 shows the temperature and the THI ranges for the twelve months of the year averaged over five years. Figures 3, 4 and 5 demonstrate the influence of season of test-THI on test-day milk for low, medium and high production herd levels, respectively. For the December to April season, drop in milk production was highest for THI class 6 and 7 (>65-70 and > 70-75) For May-August, the threshold THI was 70. Beyond a THI of 70, TD milk production started to decline. However, the same THI class tended to be more favorable in high producing herds for September-November test-season as seen by the increase from .01 to 2.5 kg/day. This season class had few test-days with THI above 70. Classes in the extremes for each season of test had fewer observations.

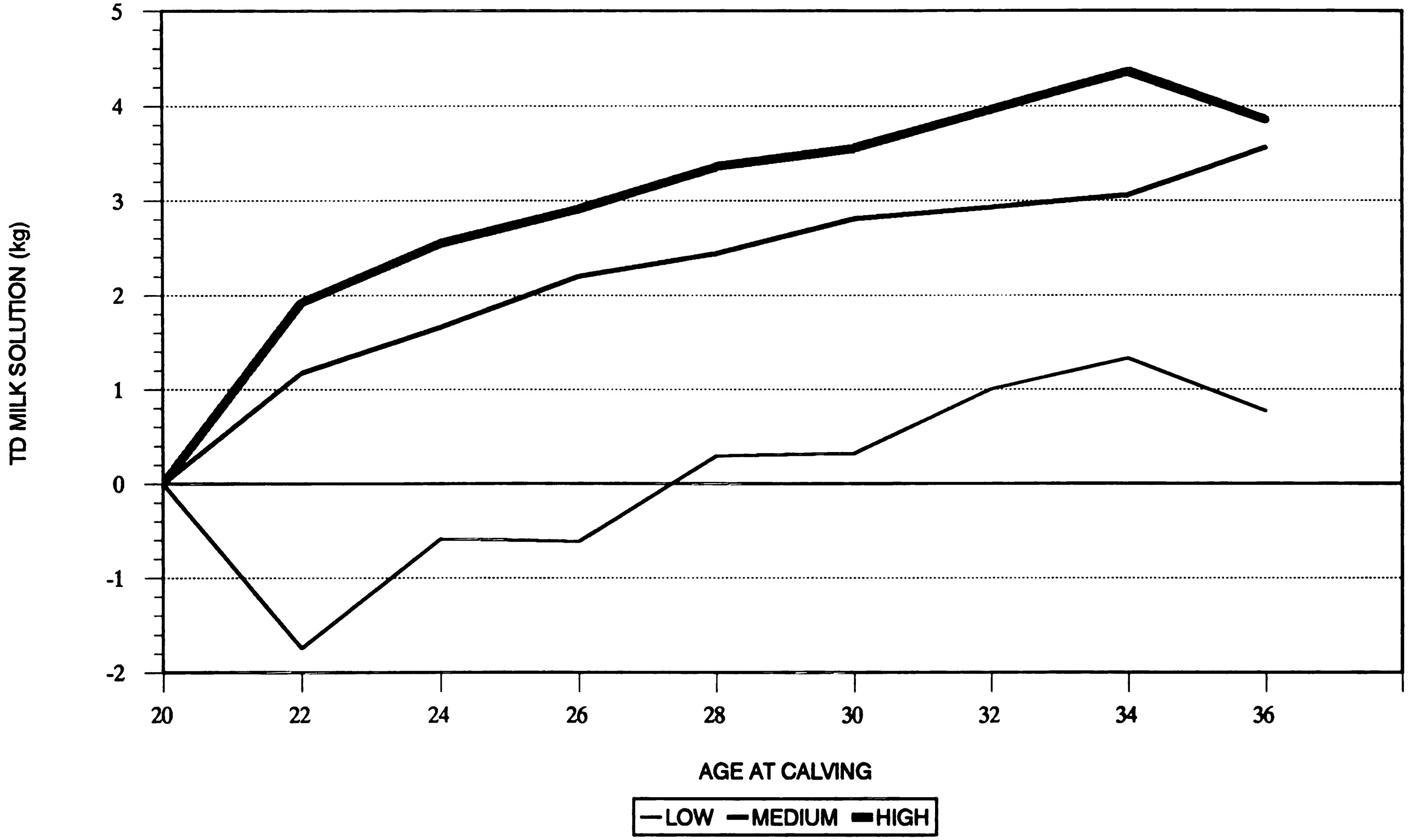

Figure 2. Effect of age at calving on test-day milk production of first lactation cows in low, medium and high production herds

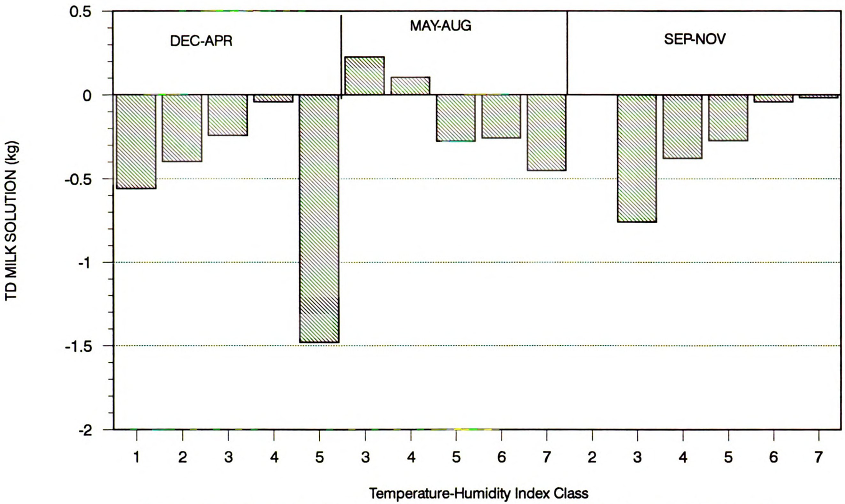

Figure 3. Effect of temperature-humidity index within season of test on milk production of first lactation cows in low producing herds

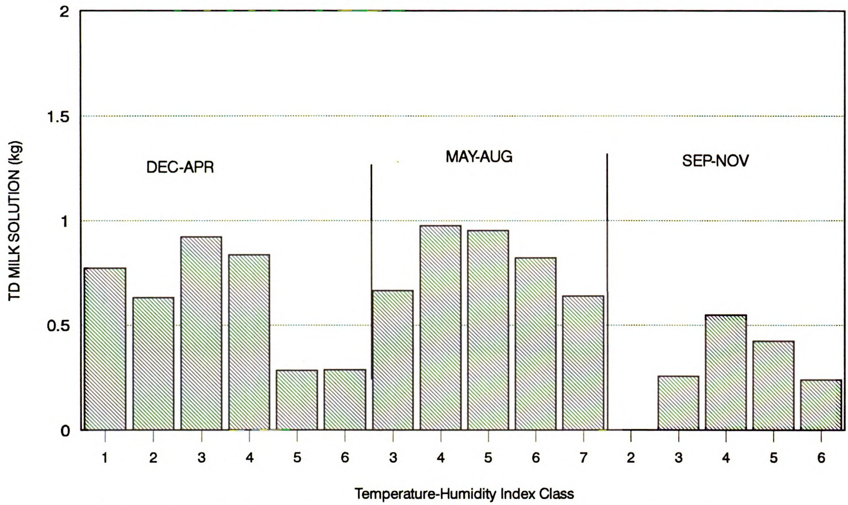

Figure 4. Effect of temperature-humidity index within season of test on milk production of first lactation cows in medium producing herds

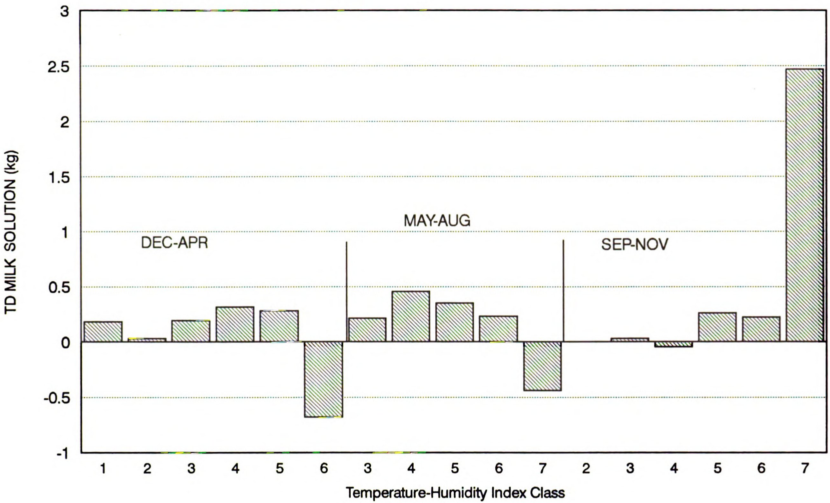

Figure 5. Effect of temperature-humidity index within season of test on milk production of first lactation cows in high producing herds

5.4.3 Phenotypic and Residual correlation among DIM interval traits

Table 1 shows the phenotypic variances, covariances and correlations among the DIM interval traits for TD records from cows in low producing herds. Phenotypic variances tended to be higher for the first two tests and tended to increase towards the end of lactation. Phenotypic covariances were higher for adjacent traits and decreased for traits further apart. Phenotypic correlations followed a similar trend. For example, the phenotypic correlation between traits one and two was .60 and .51 between traits one and four. The estimated correlations were, however, lower than the correlations reported by Trus and Buttazzoni (1990). The differences could be due to different models used. Trus and Buttazoni (1990) used a fixed effect model which ignored the random effects. Highest correlations for adjacent traits were observed after peak production or 90 DIM (traits 4 to 8).

Residual (co)variances and correlations are shown in Table 2 for the low herd production level. Residual correlations tended to be lower for early lactation and slightly increased in magnitude for later tests. The magnitude of the residual correlations were similar to those obtained by Trus and Buttazoni (1990). Residual covariances tended to be lower for traits further apart. This probably suggests there will not be much gain in predictions using traits that are far apart as the strength of their correlations is weaker.

Table 1: Phenotypic variances (diagonal), covariances (above diagonal) and correlations (below diagonal) among TD milk weights in ten 30-day days in milk intervals for first lactation cows in low producing herds.

	TRAIT									
TRAIT	1	2	3	4	5	6	7	8	9	10
1	**22.86**	13.02	10.54	11.66						
2	.60	**20.54**	12.33	11.32	10.8					
3	.50	.62	**19.25**	12.28	11.03	10.24				
4	.51	.58	.64	**19.71**	12.71	12.70	10.45			
5		.55	.58	.67	**18.74**	12.72	11.84	10.58		
6			.56	.67	.68	**19.28**	16.18	14.33	10.20	
7				.58	.63	.74	**19.06**	13.70	11.88	10.87
8					.59	.70	.72	**18.49**	15.74	12.19
9						.59	.68	.75	**18.57**	12.25
10							.57	.65	.69	**19.75**

Table 2. Residual variances (diagonal), covariances (above diagonal) and correlations (below diagonal) among TD milk weights in ten 30-day days in milk intervals for first lactation cows in low producing herds.

	TRAIT									
TRAIT	1	2	3	4	5	6	7	8	9	10
1	**16.97**	5.94	9.37	5.93						
2	.41	**16.38**	10.10	8.32	7.78					
3	.52	.59	**15.98**	9.11	8.67	7.65				
4	.39	.50	.65	**14.29**	9.47	9.46	7.32			
5		.52	.56	.71	**12.02**	8.72	5.15	5.92		
6			.48	.71	.69	**15.22**	9.81	8.24	7.82	
7				.53	.44	.64	**14.12**	7.59	9.60	6.64
8					.45	.69	.59	**12.58**	9.39	5.46
9						.62	.63	.65	**14.46**	10.33
10							.57	.46	.69	**15.21**

Table 3. **Phenotypic variances (diagonal), covariances (above diagonal) and correlations (below diagonal) among TD milk weights in ten 30-day days in milk intervals for first lactation cows in medium producing herds.**

	TRAIT									
TRAIT	1	2	3	4	5	6	7	8	9	10
1	**24.27**	13.97	11.23	10.70						
2	.58	**24.63**	14.04	12.17	16.71					
3	.49	.64	**21.80**	14.37	14.03	12.16				
4	.45	.57	.67	**23.61**	16.31	22.37	13.16			
5		.59	.62	.69	**22.90**	14.76	13.76	12.08		
6			.58	.74	.70	**22.23**	15.46	13.78	12.39	
7				.61	.64	.71	**20.89**	14.71	13.84	12.45
8					.58	.66	.70	**21.34**	15.23	15.30
9						.59	.65	.71	**21.73**	16.02
10							.56	.64	.70	**24.97**

Table 4. **Residual variances (diagonal), covariances (above diagonal) and correlations (below diagonal) among TD milk weights in ten 30-day days in milk intervals for first lactation cows in medium producing herds.**

	TRAIT									
TRAIT	1	2	3	4	5	6	7	8	9	10
1	**19.21**	5.76	5.42	4.38						
2	.37	**18.31**	12.09	5.71	11.25					
3	.33	.65	**13.90**	9.12	7.61	5.98				
4	.30	.38	.59	**15.51**	11.22	15.61	5.28			
5		.54	.59	.79	**14.94**	6.62	6.35	7.72		
6			.41	.69	.52	**15.37**	6.40	8.96	8.32	
7				.39	.46	.52	**15.92**	9.98	10.36	9.22
8					.48	.57	.61	**16.30**	11.23	7.85
9						.50	.59	.64	**16.30**	12.90
10							.56	.50	.67	**19.76**

Table 5. **Phenotypic variances (diagonal), covariances (above diagonal) and correlations (below diagonal) among TD milk weights in ten 30-day days in milk intervals for first lactation cows in high producing herds.**

	TRAIT									
TRAIT	1	2	3	4	5	6	7	8	9	10
1	**24.26**	14.23	11.70	9.45						
2	.57	**26.27**	16.31	13.79	12.66					
3	.48	.64	**23.78**	15.58	14.58	13.18				
4	.40	.56	.66	**23.41**	16.25	14.41	14.66			
5		.51	.61	.68	**24.22**	17.05	16.30	14.95		
6			.55	.63	.69	**24.71**	17.59	16.68	18.13	
7				.59	.65	.71	**25.20**	18.13	17.02	15.98
8					.60	.67	.72	**25.11**	18.95	18.24
9						.61	.66	.73	**25.84**	19.53
10							.58	.66	.73	**29.88**

Table 6. **Residual variance (diagonal), covariances (above diagonal) and correlations (below diagonal) among TD milk weights in ten 30-day days in milk intervals for first lactation cows in high producing herds.**

	TRAIT									
TRAIT	1	2	3	4	5	6	7	8	9	10
1	**21.99**	11.47	8.15	7.40						
2	.53	**21.72**	11.12	10.88	9.04					
3	.40	.55	**19.37**	10.28	10.64	9.40				
4	.36	.51	.56	**19.10**	12.45	9.75	7.64			
5		.43	.54	.62	**19.55**	11.72	10.30	10.66		
6			.48	.53	.62	**18.83**	11.83	10.94	10.91	
7				.45	.56	.63	**18.62**	13.15	11.86	10.30
8					.54	.57	.66	**19.84**	13.34	12.16
9						.54	.58	.66	**20.06**	12.03
10							.49	.57	.62	**22.58**

Although phenotypic and residual variances tended to be higher for medium and high producing herds (Tables 3, 4, 5, and 6), the correlations were of the same magnitude and followed a similar trend as those estimated for low producing herds. For all herd production levels, highest residual correlations between adjacent residuals tended to occur at the center of lactation.

5.4.4 Predicting current test-day milk using one, two or three previous TD records

5.4.4.1 Low Producing Herds

Table 7 shows the mean biases from five years of data from the 50 herds in the low production level when deviations were predicted from either one, two or three previous test deviations. Overall means reflect the average bias for cows across all herds for 5 years, 1988-1992. Herd means reflect average bias for cows within herds across all years and Herd-TD reflects averages within herd-testday. Root mean squares errors are averages for within Herd and within Herd-TD.

Using only the previous test to predict the current TD deviation was less accurate than using two or three previous tests (Table 7). Mean biases were smaller when three previous tests were used and largest when only one previous test. Overall population bias was reduced by about 96% when three previous TD deviations were used instead of using only two tests. Within HERD-TD biases averaged -.352 kg, -.210 kg, and -.037 kg when predicting from one two or three tests, respectively. The negative signs show that there was a tendency of the method to overestimate the deviations. Although the bias was improved by using more information to predict, the RMSE from using either one, two or three previous tests did not differ much. So the variance of prediction within Herd-TD deviations was similar when using one, two or three previous tests. As expected the variance is less for within Herd-TD than within Herd or for the overall population. The expectation is that the average bias for a herd on a test-day is zero. This is because Xb was adjusted for average production of the herd over time. Therefore, herd average e_p and e_o on test day are expected to be zero with a difference between the two or bias of zero. However, the expected deviation of individual cows would depend on their performance in a herd. If previous deviations of each cow were adjusted to average zero, their e_p would have an expectation of zero. This likely would reduce RMSE for within Herd-TD.

Within trait biases and RMSE are also shown on Table 7. Trait 7 to 9 (181-270 DIM) were predicted more accurately than other parts of the lactation curve. Prediction of early and peak production which occurred at 60-90 DIM was least accurate as reflected by bias and RMSE. This is probably because in early lactation the correlation among the DIM intervals were lower than after peak. Variation in physiological events in early lactation likely contributes to lower correlations.

Appendix II, Tables 4, 5 and 6 show the minimum, maximum, mean and SD of the observed and predicted test-day deviations when using either one, two or three previous tests for low producing herds.

Tables 8 and 9 show the prediction biases obtained by using the slope of standard curves estimated by an animal model and a multiple regression model

Table 7. **Mean biases and root mean square errors (RMSE) for predicting current test-day deviations from either 1, 2, or 3 previous test-day deviations for first lactation cows in low producing herds**

		Number of previous records used to predict.					
		1		2		3	
		BIAS	RMSE	BIAS	RMSE	BIAS	RMSE
OVERALL[1]		-.311	3.32	-.132	3.12	-.005	3.19
HERD[2]		-.310	3.12	-.159	2.91	-.074	3.02
HERD-TD[3]		-.352	2.40	-.210	2.31	-.037	2.38
TRAIT (DIM)[4]							
1	<30	-	-	-	-	-	-
2	30-60	- 2.08	3.92	-	-	-	-
3	61-90	-.059	3.41	-.661	3.38	-	-
4	91-120	-.186	3.42	-.132	3.30	-.879	3.54
5	121-150	-.096	3.04	-.081	2.97	-.055	2.91
6	151-180	-.242	2.81	-.189	2.82	-.186	2.79
7	181-210	-.038	3.21	-.041	3.15	-.037	3.20
8	211-240	-.033	3.28	-.048	3.16	-.051	3.14
9	241-270	-.083	3.09	-.086	3.06	-.014	3.53
10	270-305	-.220	3.08	-.170	3.08	.189	3.04

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds.
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday.
[4]Population bias and RMSE for cows within each trait.

Table 8. **Biases along with Mean and SD of actual and predicted test-day milk yields predicted from the previous test-day record of first lactation cows in 50 low producing herds over five years using a slope of a standard lactation curve estimated by a model that considers additive genetic effects.**

		ACTUAL TD MILK (kg)		PREDICTED MILK (kg)		BIAS	
		Mean	**SD**	**Mean**	**SD**	**MEAN**	**RMSE**
OVERALL[1]		21.22	5.22	21.70	5.67	.487	3.87
HERD[2]		21.46	4.58	21.95	5.13	.489	3.70
HERD TD[3]		21.43	3.49	21.98	2.83	.549	2.85
TRAIT	(DIM)[4]						
2	30-60	24.15	5.18	27.55	7.15	-3.41	5.65
3	61-90	24.09	5.03	24.00	5.21	-.086	3.86
4	91-120	23.15	4.92	23.32	4.88	.177	3.74
5	121-150	22.28	4.54	22.35	4.74	.071	3.40
6	151-180	21.38	4.28	21.65	4.43	.266	3.09
7	181-210	20.72	4.48	20.71	4.15	-.017	3.38
8	211-240	19.55	4.34	19.68	4.22	.128	3.54
9	241-270	18.50	4.50	18.57	4.11	.065	3.20
10	271-305	17.18	4.74	17.56	4.34	.373	3.04

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds.
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday.
[4]Population bias and RMSE for cows within each trait.

Table 9. **Biases along with Mean and SD of actual and predicted test-day milk yields predicted from the previous test-day records of first lactation cows in 50 low producing herds over five years using a slope of a standard lactation curve fit estimated by a regression model that did not include additive genetic effects.**

		ACTUAL TD MILK (kg)		PREDICTED MILK (kg)		BIAS	
		MEAN	SD	MEAN	SD	MEAN	RMSE
OVERALL[1]		20.99	5.06	22.12	5.28	1.13	3.56
HERD[2]		21.20	4.43	22.34	4.64	1.15	3.36
HERD-TD[3]		21.12	3.37	22.30	3.63	1.18	2.65
TRAIT (DIM)[4]							
2	30-60	22.77	3.84	23.73	4.56	.959	3.71
3	61-90	24.10	5.04	25.56	5.53	1.460	3.96
4	91-120	23.15	4.93	24.84	5.23	1.693	3.92
5	121-150	22.28	4.54	23.44	5.02	1.168	3.55
6	151-180	21.38	4.26	22.31	4.56	.928	3.17
7	181-210	20.72	4.49	21.32	4.27	.600	3.45
8	211-240	19.55	4.34	20.63	4.47	1.074	3.73
9	241-270	18.50	4.50	19.43	4.31	.931	3.27
10	271-305	17.15	4.66	18.37	4.45	1.226	3.12

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday
[4]Population bias and RMSE for cows within each trait

that did not consider animal relationships. The results show that smaller biases are obtained by using standard lactation curves from an additive genetic animal model (Table 8) suggesting that considering the additive genetic effects provides more precise estimates for the fixed effects. When mean biases where compared to the prediction from the multitrait animal model (MTA) (Table 7), the results show that the MTA is a more accurate method. The one advantage of this MTA method is that a cow's previous performance on 1, 2 or 3 separate test-days is used to predict current test-day performance and this performance can be adjusted for effects specific to each test-day such as temperature-humidity index.

5.4.4.2 Medium Producing Herds

Table 10 shows the mean biases and the RMSE for prediction done in medium producing herds using the MTA method. Again for this group using three previous TD deviations resulted in lower biases. However, RMSE were larger when using three previous tests versus one or two previous tests. The RMSE were larger than in low producing herds.

When looking at individual traits, traits 3 through 6 (61-180 DIM) had the lowest mean bias and RMSE. Trait seven (181-210 DIM) was poorly predicted, and had the highest RMSE when 3 previous traits were used. The reason for such poor prediction for trait seven is unknown. However, one can speculate that the poor prediction is due to the phenotypic (co)variances used for prediction of this trait. The increased RMSE of trait seven is contributing to the increase in RMSE for the overall population, Herd and Herd-TD. Potentially, the RMSE would be in line with values for the low herd production group if trait seven had a RMSE similar to other traits. The bias for trait ten (270-305 DIM) was also higher. The magnitude of the observed and predicted deviations from using one, two or three previous tests are shown in Appendix II (Tables 7, 8 and 9).

Results from predictions of test-day deviations using slopes from standard curves are shown in Tables 11 and 12. Results were similar to those from the low herd production group. Using a slope from lactation curves estimated from an animal model was more accurate than slope estimated from a model ignoring additive genetic effects. The MTA method was most accurate but the RMSE resulting from using three previous deviations was larger than values from the two slope methods.

5.4.4.3 High Producing Herds

Tables 13, 14 and 15 show the results of the prediction for high producing herds. In this group, the trend was similar to the other two groups. There was a tendency for the MTA method to slightly overestimate the actual production or deviations. The poorest method again was predicting from a slope resulting from a model that ignores additive genetic effects. Appendix II, Tables 10, 11, and 12 contain the magnitude of the observed and predicted deviations from using one, two, or three previous tests.

Few results have been reported on the use of a MTA approach to predict test-day production. Trus and Buttazzoni used the same method to predict missing TD records, but their model was a fixed effect model and also included

Table 10. **Mean biases and root mean square errors (RMSE) for predicting current test-day deviations from using either 1, 2, or 3 previous test-day deviations for first lactation cows in 50 medium producing herds over five years.**

		Number of previous records used to predict. 1		2		3	
		BIAS	RMSE	BIAS	RMSE	BIAS	RMSE
OVERALL[1]		-.052	3.48	-.049	3.40	-.039	5.53
HERD[2]		-.067	3.34	-.056	3.32	.012	5.52
HERD-TD[3]		.089	2.23	-.075	2.24	-.032	3.30
TRAIT (DIM)[4]							
1	<30	-	-	-	-	-	-
2	30-60	.053	3.95	-	-	-	-
3	61-90	.001	3.51	-.004	3.49	-	-
4	91-120	.019	3.35	..030	3.26	.032	3.28
5	121-150	.034	3.28	-.048	3.15	.074	3.36
6	151-180	-.062	3.32	.028	3.84	.036	3.87
7	181-210	.684	3.36	.669	3.22	.743	11.94
8	211-240	-.328	3.31	-.187	3.08	-.169	3.07
9	241-270	.107	3.25	.085	-.067	-.036	3.08
10	270-305	-.869	3.82	-.746	-.086	-.883	3.77

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday
[4]Population bias and RMSE for cows within each trait

Table 11. **Biases along with Mean and SD of actual and predicted test-day milk yields predicted from the previous test-day record of first lactation cows in medium producing herds using a slope of a standard lactation curve estimated by a model that considers additive genetic effects.**

		ACTUAL TD MILK (kg)		PREDICTED MILK (kg)		BIAS	
		MEAN	SD	MEAN	SD	MEAN	RMSE
OVERALL[1]		25.21	5.68	25.31	5.52	.106	3.80
HERD[2]		25.05	5.08	25.17	4.98	.120	3.65
HERD-TD[3]		25.03	3.47	25.17	3.37	.165	2.47
TRAIT (DIM)[4]							
2	30-60	27.85	5.19	27.31	5.94	-.538	4.95
3	61-90	28.07	5.14	28.00	5.25	-.070	3.89
4	91-120	27.54	5.15	26.64	5.15	.017	3.59
5	121-150	26.64	5.15	26.71	4.97	.071	3.46
6	151-180	25.57	4.95	25.76	4.95	.192	3.50
7	181-210	24.68	5.04	24.18	4.76	-.498	3.48
8	211-240	23.69	4.96	24.28	5.00	.594	3.58
9	241-270	22.42	4.99	22.53	4.71	.108	3.39
10	271-305	20.42	5.40	21.50	4.95	1.080	3.86

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday
[4]Population bias and RMSE for cows within each trait

Table 12. **Biases along with Mean and SD of actual and predicted test-day milk yield predicted from the previous test-day records of first lactation cows in medium producing herds using a slope of a standard lactation curve estimated by a regression model that did not include additive genetic effects.**

		ACTUAL TD MILK (kg)		PREDICTED MILK (kg)		BIAS	
		MEAN	SD	MEAN	SD	MEAN	RMSE
OVERALL[1]		24.91	5.66	26.41	5.85	1.51	3.72
HERD[2]		24.74	5.04	26.24	5.23	1.50	3.56
HERD TD[3]		24.73	3.46	26.29	3.65	1.56	2.45
TRAIT (DIM)[4]							
2	30-60	27.88	4.77	29.72	6.33	1.840	5.14
3	61-90	28.06	5.14	30.31	5.70	2.248	4.10
4	91-120	27.54	5.15	29.45	5.44	1.912	3.76
5	121-150	26.64	5.15	28.22	5.30	1.582	3.58
6	151-180	25.56	4.99	26.85	5.21	1.287	3.62
7	181-210	24.68	5.04	25.60	3.50	.922	3.50
8	211-240	23.69	4.95	24.64	3.55	.957	3.55
9	241-270	22.42	4.99	23.60	3.49	1.177	3.49
10	271-305	20.42	5.40	22.36	3.75	1.948	3.75

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday
[4]Population bias and RMSE for cows within each trait

DCC. They found that adjacent residuals tended to do a better job of predicting missing observations. The method, however, also tended to overpredict total production as seen in this study. Deviation of 90-100 kg from observed total lactation yields were reported. Herd production level was not considered.

Stanton et al. (1992) projected test-day records using standard lactation curves and a previous record. This is similar to the approach in this study using slopes. In their study, a TD record was predicted by a adding the difference in pounds between the current and previous DIM solutions of the standard curve to the previous TD record of a cow. For the cows with no previous record the TD record was estimated by the lactation curve. In their study the mean bias was .158 lbs and the standard deviation of the bias averaged 11.65 lbs. Again, the prediction were not done within herd production level. Applying the method to all herds might be misleading as the method might be less precise for certain herd production levels.

Everett and Schmitz (1993) developed a method that projects management level milk within a herd. However, Everett considered herd-testday effects and DCC. Fixed effects are unique within herds. In our study global fixed effect solutions are used for individual herd. If individual herd solutions can be used, the MTA method might be more precise.

Table 13 **Mean biases and root mean square errors (RMSE) for predicting current test-day deviations from either 1, 2, or 3 previous test-day deviations for first lactation cows in 50 high production herds**

	Number of previous records used to predict					
	1		2		3	
	BIAS	**RMSE**	**BIAS**	**RMSE**	**BIAS**	**RMSE**
OVERALL1	.029	3.71	.042	3.48	-.050	3.44
HERD[2]	-.053	3.51	-.027	3.29	-.008	3.25
HERD-TD[3]	-.145	2.13	-.114	2.03	-.108	2.06
TRAIT (DIM)[4]						
1 <30	-	-	-	-	-	-
2 30-60	.033	4.40	-	-	-	
3 61-90	.002	3.67	.032	3.65	-	
4 91-120	-.008	3.76	-.004	3.66	.010	3.66
5 121-150	-.019	3.67	-.010	3.50	-.007	3.49
6 151-180	.021	3.64	-.025	3.45	-.027	3.43
7 181-210	.032	3.45	-.046	3.30	-.049	3.26
8 211-240	.115	3.52	-.124	3.36	-.128	3.35
9 241-270	.162	3.41	-.181	3.25	-.189	3.22
10 270-305	-.018	3.77	-.060	3.67	-.047	3.66

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds.
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday.
[4]Population bias and RMSE for cows within each trait.

Table 14. Biases along with Mean and SD of actual and predicted test-day milk yields predicted from the previous test-day record of first lactation cows in 50 high producing herds over five years using a slope of a standard lactation curve estimated by a model that considers additive genetic effects.

		ACTUAL TD MILK (kg)		PREDICTED MILK (kg)		BIAS (kg)	
		MEAN	SD	MEAN	SD	MEAN	RMSE
OVERALL[1]		29.15	6.26	29.14	6.04	.006	4.04
HERD[2]		8.67	5.68	28.78	5.53	.112	3.80
HERD-TD[3]		28.39	3.65	28.53	3.49	.138	2.28
TRAIT	(DIM)[4]						
2	30-60	31.56	5.73	30.52	6.22	-1.047	5.29
3	61-90	32.24	5.40	32.09	5.82	-.151	4.24
4	91-120	31.70	5.50	31.75	5.31	.056	4.05
5	121-150	30.83	5.55	30.95	5.34	.122	3.95
6	151-180	29.71	4.60	29.84	5.34	.125	3.88
7	181-210	28.63	5.60	28.77	5.41	.144	3.65
8	211-240	27.61	5.71	27.69	5.41	.080	3.54
9	241-270	26.09	5.69	26.24	5.44	.142	3.53
10	271-305	23.94	6.19	24.42	5.32	.479	3.78

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday
[4]Population bias and RMSE for cows within each trait

Table 15. Biases along with Mean and SD of actual and predicted test-day milk yield predicted from the previous test-day records of first lactation cows in 50 high producing herds over five years using a slope of a standard lactation curve fit estimated by a regression model that did not include additive genetic effects.

		ACTUAL TD MILK (kg)		PREDICTED MILK (kg)		BIAS (kg)	
		MEAN	SD	MEAN	SD	MEAN	RMSE
OVERALL[1]		29.04	6.19	30.83	6.44	1.79	4.03
HERD[2]		28.53	5.60	30.35	5.89	1.82	3.78
HERD-TD[3]		28.25	3.62	30.17	3.81	1.91	2.34
TRAIT (DIM)[4]							
2	30-60	32.04	5.17	32.73	6.52	.687	4.78
6	31-90	32.24	5.39	34.89	6.33	2.655	4.55
4	91-120	31.70	5.50	34.20	5.74	2.509	4.23
5	121-150	30.83	5.55	32.75	5.70	1.923	4.12
6	151-180	29.71	5.60	31.23	5.63	1.518	3.99
7	181-210	28.63	5.60	29.86	5.63	1.227	3.74
8	211-240	27.61	5.71	28.67	5.61	1.060	3.61
9	241-270	26.09	5.69	27.58	5.71	1.489	3.62
10	271-305	23.95	6.09	26.04	5.60	2.089	3.93

[1]Population mean and RMSE
[2]Biases are averages of biases for 50 herds and RMSE are averages of RMSE for 50 herds
[3]Biases are averages of biases within Herd-Testday and RMSE are averages of RMSE within Herd-Testday
[4]Population bias and RMSE for cows within each trait

5.5 CONCLUSIONS

Lactation test-day milk yields were classified into ten traits based on 30-day DIM intervals. A multitrait animal model was used to estimate the (co)variances among these traits. A procedure of Henderson (1988) for estimating residuals for missing records was used to estimate the phenotypic deviations for next test-day yield of cows using either one, two or three previous tests. Using three previous tests was most accurate with one test being the least accurate in predicting next test-day deviation. Thus more information used to predict the current test, the better the prediction.

The study included the fixed effect of THI to accurately account for the temperature-humidity influence on test-day production.

Traditional methods that predict next test-day yields from slopes were less accurate than the MTA approach. The study showed that an animal model probably gives better estimates of the fixed effects thereby estimating lactation curves more accurately. Biases from predictions using a slope from curves estimated with models that ignore additive genetic effects were much larger as compared to slopes from curves estimated by an animal model.

6. SUMMARY

This research assessed the influence of herd production level, season of calving, age at calving, season of test and temperature-humidity index on test-day milk production of first lactation cows.

The first study revealed the influence of season of calving, herd production level and parity on lactation curve shapes. Lactation curves were estimated as least square means for days in milk (DIM) fit with a sixth degree polynomial for six seasons of calving within three lactation groups and three herd production levels resulting in 54 curves. Lactation curves for cows calving in the summer season classes showed lower peaks as compared to other seasons. The time to peak was also reduced for cows calving in summer. November-December was the best season for calving in the Michigan dairy herds to maximize total lactation yield for milk. For milk fat and protein percentages, a nadir was reached earlier by cows calving in July-August as compared to other calving seasons.

First lactation cows were more persistent, peaked later and had flatter curves as compared to second, third or later lactations. Cows in high producing herds peaked higher than those in lower herd production levels.

From this study it is obvious that when extending part lactations, different factors are needed for different seasons of calving, herd production levels and lactation groups. The results of the first study helped in the design of the second study in which the objective was to use a multitrait animal model (MTA) method to predict next test-day milk using either 1, 2 or 3 previous test-day

records. The uniqueness of this approach was the use of MTA and the inclusion of a test-day's temperature-humidity index in the model.

Age at calving effects on test-day milk differed for the three herd production levels. Test-day milk production tended to increase with increasing age at calving. Effects were much smaller for lower production herds than for medium and high production herds.

The interaction between season of test and temperature-humidity index was significant. For the December to April season of test, THI above 65-70 causes a decrease in milk yields. For the May to August season, the threshold occurred beyond 70.

The MTA method of predicting test-day production was compared to prediction using slopes computed from two methods. The MTA method was superior in the three herd production levels. With the MTA, using three previous tests to predict current test-day was more accurate than including one or two previous tests.

Of the two methods used to compute slopes, the method that used an animal model gave more precise estimates of the fixed effects and less bias in predicting test-day production.

The MTA method can be recommended because it:

1. allows for inclusion of effects specific to a test-day, i.e., temperature humidity index;

2 allows the inclusion of effects specific to a cow on a test-day, i.e.,

bST and pregnancy status;

3. accounts for additive genetic effects in the estimate of fixed effects and

4. Allows for the inclusion of more information on a cow, i.e., more than one previous test.

From the MTA model, average TD deviations for a cow could be used for culling. With this model, genetic parameters of the different parts of the lactation curve are also obtained. However, results from selecting for a specific stage of lactation are not known.

The MTA model gives the potential to use estimated individual cow additive genetic effects and permanent environmental effects. If these are computed, a more accurate comparison of individual cows for culling purposes will be possible.

In the future, it is recommended to assess the inclusion of reproductive parameters such as days carried calf and days open as they may improve predictions. Days carried calf (DCC) depresses milk production from about 240 days until the end of lactation (Everett and Schmitz, 1993). Therefore its inclusion in the MTA method may improve the accuracy of prediction of test-day records at the end of lactation. In addition, adjusting previous observed test-day deviations on individual cows to average zero would result in an expectation for their predicted test-day deviation (e_p) of zero. This adjusts for cow's ability within herd. This would likely result in lower RMSE for within Herd-TD.

7. APPENDICES

APPENDIX I

Days in milk polynomial regression coefficients for milk, ECM, fat % and protein %

MILK (kg) : HERD MEAVG < 17000 lbs

PARITY 1

JAN-FEB	$18.560200 + 0.269777(D) - 0.004552(D^2) + 0.000035725(D^3) - 0.000000156(D^4) + 3.59363E\text{-}10(D^5) - 3.36825E\text{-}13(D^6)$
MAR-APR	$17.450885 + 0.367398(D) - 0.006773(D^2) + 0.000054021(D^3) - 0.000000223(D^4) + 4.605589E\text{-}10(D^5) - 3.76038E\text{-}13(D^6)$
MAY-JUNE	$18.904490 + 0.233895(D) - 0.004697(D^2) + 0.000040285(D^3) - 0.000000181(D^4) + 4.141675E\text{-}10(D^5) - 3.83373E\text{-}13(D^6)$
JUL-AUG	$17.721787 + 0.282919(D) - 0.005987(D^2) + 0.000054770(D^3) - 0.000000254(D^4) + 5.805767E\text{-}10(D^5) - 5.22181E\text{-}13(D^6)$
SEP-OCT	$18.562957 + 0.239017(D) - 0.004512(D^2) + 0.000038046(D^3) - 0.000000165(D^4) + 3.507899E\text{-}10(D^5) - 3.507899E\text{-}10(D^6)$
NOV-DEC	$17.504233 + 0.364484(D) - 0.007211(D^2) + 0.000065637(D^3) - 0.000000308(D^4) + 7.114372E\text{-}10(D^5) - 6.37785E\text{-}13(D^6)$

PARITY 2

JAN-FEB	$25.844901 + 0.337320(D) - 0.006915(D^2) + 0.000059100(D^3) - 0.000000265(D^4) + 5.937625E\text{-}10(D^5) - 5.20445E\text{-}13(D^6)$
MAR-APR	$23.387810 + 0.511912(D) - 0.011282(D^2) + 0.000104(D^3) - 0.000000487(D^4) + 1.1351165E\text{-}9(D^5) - 1.0349E\text{-}12(D^6)$
MAY-JUNE	$25.146559 + 0.340777(D) - 0.007935(D^2) + 0.000073650(D^3) - 0.000000353(D^4) + 8.447547E\text{-}10(D^5) - 7.99941E\text{-}13(D^6)$
JUL-AUG	$23.164802 + 0.387234(D) - 0.009074(D^2) + 0.000085296(D^3) - 0.000000399(D^4) + 9.066441E\text{-}10(D^5) - 7.96913E\text{-}13(D^6)$
SEP-OCT	$24.492228 + 0.252813(D) - 0.005579(D^2) + 0.000048794(D^3) - 0.000000214(D^4) + 4.5641E\text{-}10(D^5) - 3.73672E\text{-}13(D^6)$
NOV-DEC	$24.032090 + 0.465577(D) - 0.010667(D^2) + 0.000103(D^3) - 0.000000508(D^4) + 1.2162248E\text{-}9(D^5) - 1.1328E\text{-}12(D^6)$

PARITY 3 +

JAN-FEB	$26.436420 + 0.422200(D) - 0.008536(D^2) + 0.000073439(D^3) - 0.000000333(D^4) + 7.57916E\text{-}10(D^5) - 6.78889E\text{-}13(D^6)$
MAR-APR	$25.285906 + 0.512543(D) - 0.010804(D^2) + 0.000095008(D^3) - 0.000000432(D^4) + 9.747421E\text{-}10(D^5) - 8.6045E\text{-}13(D^6)$
MAY-JUNE	$26.626050 + 0.309845(D) - 0.006347(D^2) + 0.000050694(D^3) - 0.000000212(D^4) + 4.516075E\text{-}10(D^5) - 3.85783E\text{-}13(D^6)$
JUL-AUG	$24.197644 + 0.381015(D) - 0.008205(D^2) + 0.000070968(D^3) - 0.000000310(D^4) + 6.671917E\text{-}10(D^5) - 5.58441E\text{-}13(D^6)$
SEP-OCT	$25.392358 + .364694(D) - .0077984(D^2) + 0.000071081(D^3) - 0.000000322(D^4) + 7.194993E\text{-}10(D^5) - 6.34615E\text{-}13(D^6)$
NOV-DEC	$26.055479 + 0.469600(D) - 0.010392(D^2) + 0.000097264(D^3) - 0.000000465(D^4) + 1.091656E\text{-}9(D^5) - 1.0003E\text{-}12(D^6)$

ECM (kg) : HERD MEAVG < 17000 lbs

PARITY 1

JAN-FEB	$22.778425 + 0.089846(D) - 0.001189(D^2) + 0.000004421(D^3) - 5.995033E\text{-}9(D^4) + 6.409924E\text{-}12(D^5) - 1.6825E\text{-}14(D^6)$
MAR-APR	$20.869979 + 0.219564(D) - 0.004216(D^2) + 0.000030821(D^3) - 0.000000105(D^4) + 1.576549E\text{-}10(D^5) -7.07552E\text{-}14(D^6)$
MAY-JUNE	$21.939104 + 0.097631(D) - 0.002692(D^2) + 0.000027439(D^3) - 0.000000137(D^4) + 3.303809E\text{-}10(D^5) -3.13183E\text{-}13(D^6)$
JUL-AUG	$20.578665 + 0.136040(D) - 0.003016(D^2) + 0.000028524(D^3) - 0.000000136(D^4) + 3.141009E\text{-}10(D^5) - 2.83706E\text{-}13(D^6)$
SEP-OCT	$21.836948 + 21.836948(D) - 0.001985(D^2) + 0.000014767(D^3) - 5.361006E\text{-}8(D^4) + 8.428101E\text{-}11(D^5) - 3.90564E\text{-}14(D^6)$
NOV-DEC	$21.306508 + 0.235099(D) - 0.005102(D^2) + 0.000048994(D^3) - 0.000000241(D^4) + 5.754831E\text{-}10(D^5) - 5.28509E\text{-}13(D^6)$

PARITY 2

JAN-FEB	$31.749282 + 0.138430(D) - 0.003495(D^2) + 0.000028190 (D^3) - 0.000000117(D^4) + 2.387195E\text{-}10(D^5) - 1.89162E\text{-}13(D^6)$
MAR-APR	$28.780355 + 0.288612(D) - 0.007235(D^2) + 0.000064922 (D^3) - 0.000000285(D^4) + 6.003695E\text{-}10(D^5) - 4.83283E\text{-}13(D_6)$
MAY-JUNE	$29.653278 + 0.158289(D) - 0.005086(D^2) + 0.000053593(D^3) - 0.000000278(D^4) + 6.965777E\text{-}10(D^5) - 6.76923E\text{-}13(D^6)$
JUL-AUG	$26.962741 + 0.205377(D) - 0.005462(D^2) + 0.000053788(D^3) - 0.000000260(D^4)+ 6.047019E\text{-}10(D^5) - 5.37239E\text{-}13(D^6)$
SEP-OCT	$29.909067 + 0.033320(D) - 0.001108(D^2) + 0.000005790(D^3) - 2.198208E\text{-}9(D^4) + 6.62357E\text{-}11(D^5) -1.352005E\text{-}13(D^6)$
NOV-DEC	$30.203679 + 0.260937(D) - 0.007177(D^2) + 0.000073567(D^3) - 0.000000374(D^4) + 9.170771E\text{-}10(D^5) - 8.6724E\text{-}13(D^6)$

PARITY 3+

JAN-FEB	$33.355291 + 0.180195(D) - 0.004551(D^2) + 0.000039300(D^3) - 0.000000178(D^4) + 4.092341E\text{-}10(D^5) - 3.73547E\text{-}13(D^6)$
MAR-APR	$31.636575 + 0.268640(D) - 0.006649(D^2) + 0.000056770(D^3) - 0.000000236(D^4) + 4.62487E\text{-}10(D^5) - 3.35336E\text{-}13(D^6)$
MAY-JUNE	$31.804189 + 0.112939(D) - 0.003564(D2) + 0.000033631(D3) - 0.000000161(D^4) + 3.760605E\text{-}10(D^5) - 3.43528E\text{-}13(D^6)$
JULA-AUG	$29.265988 + 0.135925(D) - 0.003265(D_2) + 0.000025970(D^3) - 0.000000102(D^4) + 1.858697E\text{-}10(D^5) - 1.18834E\text{-}13(D^6)$
SEP-OCT	$31.230555 + 0.150220(D) - 0.003773(D^2) + 0.000030782(D^3) - 0.000000124(D^4) + 2.354011E\text{-}10(D^5) - 1.6851E\text{-}13(D^6)$
NOV-DEC	$33.157787 + 0.228729(D) - 0.006236(D^2) + 0.000060718(D^3) - 0.000000297(D^4) + 7.035286E\text{-}10(D^5) - 6.45467E\text{-}13(D^6)$

FAT % : HERD MEAVG < 17000 IBS

PARITY 1

JAN-FEB	$4.784496 - 0.055509(D) + 0.001034(D^2) - 0.000009586(D^3) + 4.5541405E\text{-}8(D^4) - .04835E\text{-}10(D^5) + 9.277578E\text{-}14(D^6)$
MAR-APR	$4.502008 - 0.042651(D) + 0.000741(D^2) - 0.000006887(D^3) + 3.559429E\text{-}8(D^4) - 9.23435E\text{-}11(D^5) + 9.29375E\text{-}14(D^6)$
MAY-JUNE	$4.317131 - 0.032555(D) + 0.000399(D2) - 0.000001800(D^3) + 2.926803E\text{-}9(D^4) - 6.149101E\text{-}13(D^5) + 4.0475E\text{-}15(D^6)$
JUL-AUG	$4.288202 - 0.039832(D) + 0.000804(D^2) - 0.000007243(D^3) + 3.3630682E\text{-}8(D^4) - 7.83487E\text{-}11(D^5) + 7.234014E\text{-}14(D^6)$
SEP-OCT	$4.481086 - 0.036164(D) + 0.000658(D^2) - 0.000005766(D^3) + 2.6759001E\text{-}8(D^4) - 6.35356E\text{-}11(D^5) + 6.081416E\text{-}14(D^6)$
NOV-DEC	$4.608210 - 0.036717(D) + 0.000568(D^2) - 0.000004271(D^3) + 1.6411957E\text{-}8(D^4) - 3.11611E\text{-}11(D^5) + 2.383076E\text{-}14(D^6)$

PARITY 2

JAN-FEB	$4.813068 - 0.042862(D) + 0.000728(D^2) - 0.000006510(D^3) + 3.0592965E\text{-}8(D^4) - 7.0106E\text{-}11(D^5) + 6.184371E\text{-}14(D^6)$
MAR-APR	$4.697708 - 0.050211(D) + 0.000947(D^2) - 0.000009585(D^3) + 5.2652065E\text{-}8(D^4) - 1.43253E\text{-}10(D^5) + 1.503961E\text{-}13(D^6)$
MAY-JUNE	$4.409835 - 0.032147(D) + 0.000408(D^2) - 0.000001924(D^3) + 2.9527505E\text{-}9(D^4) - 2.982046E\text{-}12(D^5) + 9.17493E\text{-}15(D^6)$
JUL-AUG	$5.330250 - 0.039104(D) + 0.000781(D^2) - 0.000006843(D^3) + 3.0232551E\text{-}8(D^4) - 6.59472E\text{-}11(D^5) + 5.636696E14(D^6)$
SEP-OCT	$4.680708 - 0.043469(D) + 0.000815(D^2) - 0.000007357(D^3) + 3.4788688E\text{-}8(D^4) - 8.34476E\text{-}11(D^5) + 8.019642E\text{-}14(D^6)$
NOV-DEC	$4.816938 - 0.041601(D) + 0.000678(D^2) - 0.000005522(D^3) + 2.330944E\text{-}8(D^4) - 4.9039E\text{-}11(D^5) + 4.133813E\text{-}14(D^6)$

PARITY 3+

JAN-FEB	$5.026725 - 0.051873(D) + 0.000828(D^2) - 0.000006765(D^3) + 2.8350699E\text{-}8(D^4) - 5.63272E\text{-}11(D^5) + 4.094646E\text{-}14(D^6)$
MAR-APR	$4.912596 - 0.052036(D) + 0.000919(D^2) - 0.000009007(D^3) + 4.8784292E\text{-}8(D^4) - 1.32045E\text{-}10(D^5) + 1.38406E\text{-}13(D^6)$
MAY-JUNE	$4.570462 - 0.033351(D) + 0.000356(D^2) - 0.000001014(D^3) + 2.908021E\text{-}9(D^4) - 1.951924E\text{-}11(D^5) + 2.63086E\text{-}14(D^6)$
JUL-AUG	$4.601333 - 0.050159(D) + 0.000994(D^2) - 0.000009010(D^3) + 4.1751907E\text{-}8(D^4) - 9.63258E\text{-}11(D^5) + 8.765212E\text{-}14(D^6)$
SEP-OCT	$4.733951 - 0.039764(D) + 0.000712(D^2) - 0.000006386(D^3) + 3.0067753E\text{-}8(D^4) - 7.15439E\text{-}11(D^5) + 6.799363E\text{-}14(D^6)$
NOV-DEC	$4.950589 - 0.045784(D) + 0.000745(D^2) - 0.000006223(D^3) + 2.7294989E\text{-}8(D^4) - 6.02727E\text{-}11(D^5) + 5.346951E\text{-}14(D^6)$

PROTEIN % : HERD MEAVG < 17000 lbs

PARITY 1

JAN-FEB	$3.774972 - 0.039997(D) + 0.000814(D^2) - 0.000007698(D^3) + 3.7076092E\text{-}8(D^4) - 8.73484E\text{-}11(D^5) + 8.01896E\text{-}14(D^6)$
MAR-APR	$3.667156 - 0.035792(D) + 0.000702(D^2) - 0.000006492(D^3) + 3.1723416E\text{-}8(D^4) - 7.71211E\text{-}11(D^5) + 7.304939E\text{-}14(D^6)$
MAY-JUNE	$3.628918 - 0.036179(D) + 0.000717(D^2) - 0.000006492(D^3) + 3.1834166E\text{-}8(D^4) - 8.06405E\text{-}11(D^5) + 8.185511E\text{-}14(D^6)$
JUL-AUG	$3.658257 - 0.035970(D) + 0.000726(D^2) - 0.000006089(D^3) + 2.5414815E\text{-}8(D^4) - 5.25126E\text{-}11(D^5) + 4.305274E\text{-}14(D^6)$
SEP-OCT	$3.771255 - 0.042912(D) + 0.000971(D^2) - 0.000009618(D^3) + 4.7727755E\text{-}8(D^4) - 1.16649E\text{-}10(D^5) + 1.120757E\text{-}13(D^6)$
NOV-DEC	$3.866311 - 0.043213(D) + 0.000886(D^2) - 0.000008334(D^3) + 3.9721986E\text{-}8(D^4) - 9.33081E\text{-}11(D^5) + 8.624617E\text{-}14(D^6)$

PARITY 2

JAN-FEB	$3.826484 - 0.041780(D) + 0.000843(D^2) - 0.000007924(D^3) + 3.7753091E\text{-}8(D^4) - 8.73349E\text{-}11(D^5) + 7.808622E\text{-}14(D^6)$
MAR-APR	$3.812229 - 0.045555(D) + 0.000971(D^2) - 0.000009868(D^3) + 5.2179011E\text{-}8(D^4) - 1.35517E\text{-}10(D^5) + 1.361626E\text{-}13(D^6)$
MAY-JUNE	$3.702129 - 0.036803(D) + 0.000703(D^2) - 0.000006153(D^3) + 2.9250283E\text{-}8(D^4) - 7.21558E\text{-}11(D^5) + 7.161339E\text{-}14(D^6)$
JUL-AUG	$3.730167 - 0.041252(D) + 0.000844(D^2) - 0.000007325(D^3) + 3.184039E\text{-}8(D^4) - 6.84506E\text{-}11(D^5) + 5.809646E\text{-}14(D^6)$
SEP-OCT	$3.927049 - 0.050756(D) + 0.001173(D^2) - 0.000011815(D^3) + 5.9034526E\text{-}8(D^4) - 1.44026E\text{-}10(D^5) + 1.372719E\text{-}13(D^6)$
NOV-DEC	$3.991473 - 0.047426(D) + 0.000971(D^2) - 0.000009222(D^3) + 4.4540327E\text{-}8(D^4) - 1.06108E\text{-}10(D^5) + 9.958419E\text{-}14(D^6)$

PARITY 3 +

JAN-FEB	$3.849888 - 0.045030(D) + 0.000904(D^2) - 0.000008496(D^3) + 4.0573591E\text{-}8(D^4) - 9.43379E\text{-}11(D^5) + 8.498215E\text{-}14(D^6)$
MAR-APR	$3.790675 - 0.045921(D) + 0.000933(D^2) - 0.00000903(D^3) + 4.5624122E\text{-}8(D^4) - 1.13527E\text{-}10(D^5) + 1.094378E\text{-}13(D^6)$
MAY-JUNE	$3.737808 - 0.042533(D) + 0.000812(D^2) - 0.000007105(D^3) + 3.3458358E\text{-}8(D^4) - 8.13045E\text{-}11(D^5) + 7.942724E\text{-}14(D^6)$
JUL-AUG	$3.808120 - 0.048198(D) + 0.000993(D^2) - 0.000008753(D^3) + 3.8777254E\text{-}8(D^4) - 8.52576E\text{-}11(D^5) + 7.429068E\text{-}14(D^6)$
SEP-OCT	$3.944287 - 0.054921(D) + 0.001265(D^2) - 0.000012824(D^3) + 6.4768845E\text{-}8(D^4) - 1.60038E\text{-}10(D^5) + 1.545867E\text{-}13(D^6)$
NOV-DEC	$3.995065 - 0.051168(D) + 0.001054(D^2) - 0.000010057(D^3) + 4.8716057E\text{-}8(D^4) - 1.16248E\text{-}10(D^5) + 1.09039E\text{-}13(D^6)$

MILK (kg): HERD MEAVG 17000-21000 lbs.

PARITY 1

JAN-FEB:	$19.570864 + 0.450577(D) - 0.007895(D^2) + 0.000066832(D^3) - 0.000000309(D^4) + 7.302981E\text{-}10(D^5) - 6.91163E\text{-}13(D^6)$
MAR-APR	$18.778936 \quad 0.475830(D) - 0.008179(D^2) + 0.000064390(D^3) - 0.000000269(D^4) + 5.719319E\text{-}10(D^5) + 5.719319E\text{-}10(D^6)$
MAY-JUNE	$19.687441 + 0.417827(D) - 0.007634(D^2) + 0.000063429(D^3) - 0.000000278(D^4) + 6.219799E\text{-}10(D^5) - 5.5889E\text{-}13(D^6)$
JUL-AUG	$19.042971 + 0.403748(D) - 0.007742(D^2) + 0.000068342(D^3) - 0.000000313(D^4) + 7.131615E\text{-}10(D^5) - 6.43836E\text{-}13(D^6)$
SEP-OCT	$19.142833 + 0.409074(D) - 0.007500(D^2) + 0.000065416(D^3) - 0.000000302(D^4) + 7.017259E\text{-}10(D^5) - 6.53759E\text{-}13(D^6)$
NOV-DEC	$18.925611 + 0.477691(D) -0.008625(D^2) + 0.000074139(D^3) - 0.000000336(D^4) + 7.594587E\text{-}10(D^5) - 6.77215E\text{-}13(D^6)$

PARITY 2

JAN-FEB	$29.608509 + 0.613426(D) - 0.012519(D^2) + 0.000112(D^3) + 0.000000519(D^4) + 1.2016537E\text{-}9(D^5) - 1.09708E\text{-}12(D^6)$
MAR-APR	$27.875609 + 0.613426(D) - 0.012519(D^2) + 0.000112(D^3) - 0.000000519(D^4) + 1.2016537E\text{-}9(D^5) - 1.09708E\text{-}12(D^6)$
MAY-JUNE	$27.508181 + 0.557217(D) - 0.012090(D^2) + 0.000111(D3) - 0.000000531(D4) + 1.2702873E\text{-}9(D5) - 1.20118E\text{-}12(D6)$
JUL-AUG	$25.603216 + 0.521804(D) - 0.011116(D^2) + 0.000101(D^3) - 0.000000469(D^4) + 1.0830154E\text{-}9(D^5) - 9.83891E\text{-}13(D^6)$
SEP-OCT	$26.779859 + 0.504980(D) - 0.010762(D^2) + 0.000098220(D^3) - 0.000000462(D^4) + 1.0792343E\text{-}9(D^5) - 9.9734E\text{-}13(D^6)$
NOV-DEC	$26.139598 + 0.685363(D) - 0.014624(D^2) + 0.000136(D^3) - 0.000000649(D^4) + 1.5264198E\text{-}9(D^5) - 1.40865E\text{-}12(D^6)$

PARITY 3+

JAN-FEB	$29.107826 + 0.588819(D) - 0.011060(D^2) + 0.000090951(D^3) - 0.000000396(D^4) + 8.633663E\text{-}10(D^5) - 7.42822E\text{-}13(D^6)$
MAR-APR	$26.748951 + 0.713787(D) - 0.013943(D^2) + 0.000119(D^3) - 0.000000534(D^4) + 1.197178E\text{-}9 (D^5) - 1.0561E\text{-}12(D^6)$
MAY-JUNE	$28.152215 + 0.491875(D) - 0.009019(D^2) + 0.000069662(D^3) - 0.000000285(D^4) + 5.937944E\text{-}10(D^5) - 4.94134E\text{-}13(D^6)$
JUL-AUG	$25.768233 + 0.556589(D) - 0.010716(D^2) + 0.000088702(D^3) - 0.000000382(D^4) + 8.262542E\text{-}10(D^5) - 7.07023E\text{-}13(D^6)$
SEP-OCT	$26.682172 + 0.615445(D) - 0.012252(D^2) + 0.000106(D^4) - 0.000000479(D^4) + 1.0748333E\text{-}9(D^5) - 9.55233E\text{-}13(D^6)$
NOV-DEC	$26.055479 + 0.469600(D) - 0.010392(D^2) + 0.000097264(D^3) - 0.000000465(D^4) + 1.091656E\text{-}9(D^5) - 1.0003E\text{-}12(D^6)$

ECM(kg): HERD MEAVG 17000-21000 lbs.

PARITY 1

JAN-FEB	$24.368318 + 0.264980(D) - 0.004822(D^2) + 0.000041142(D^3) - 0.000000196(D^4) + 4.893202E\text{-}10(D^5) - 4.93094E\text{-}13(D^6)$
MAR-APR	$23.044177 + 0.272255(D) - 0.004427(D^2) + 0.000029041(D^3) - 8.810769E\text{-}8(D^4) + 1.066412E\text{-}10(D^5) -1.9894E\text{-}14(D^6)$
MAY-JUNE	$22.944299 + 0.275609(D) - 0.005665(D^2) + 0.000051847(D^3) - 0.000000243(D^4) + 5.639921E\text{-}10(D^4) - 5.16291E\text{-}13(D^5)$
JUL-AUG	$22.476565 + 0.226208(D) - 0.004279(D^2) + 0.000038470(D^3) - 0.000000181(D^4) + 4.20192E\text{-}10(D^5) - 3.84745E\text{-}13(D^6)$
SEP-OCT	$23.254221 + 0.230834(D) - 0.003909(D^2) - 0.003909(D^3) - 0.000000136(D^4) + 2.99993E\text{-}10(D^5) - 2.67745E\text{-}13(D^6)$
NOV-DEC	$23.737637 + 0.307443(D) - 0.005840(D^2) + 0.000051519(D^3) - 0.000000240(D^4) + 5.561407E\text{-}10(D^5) - 5.05068E\text{-}13(D^6)$

PARITY 2

JAN-FEB	$36.649567 + 0.346071(D) - 0.008074(D^2) + 0.000073312(D^3) - 0.000000344(D^4) + 8.050983E\text{-}10(D^5) - 7.46363E\text{-}13(D^6)$
MAR-APR	$35.007667 + 0.346071(D) - 0.008074(D^2) + 0.000073312(D^3) - 0.000000344(D^4) + 8.050983E\text{-}10(D^5) - 7.46363E\text{-}13(D^6)$
MAY-JUNE	$32.397490 + 0.366211(D) - 0.009535(D^2) + 0.000097395(D^3) - 0.000000499(D^4) + 1.2510525E\text{-}9(D^5) - 1.22084E\text{-}12(D^6)$
JUL-AUG	$30.809021 + 0.257043(D) - 0.005747(D^2) + 0.000051692(D^3) - 0.000000239(D^4) + 5.458405E\text{-}10(D^5) - 4.85765E\text{-}13(D^6)$
SEP-OCT	$33.078773 + 0.250317(D) - 0.005679(D^2) + 0.000049772(D^3) - 0.000000225(D^4) + 5.03196E\text{-}10(D^5) - 4.45235E\text{-}13(D^6)$
NOV-DEC	$33.859664 + 0.393754(D) - 0.009415(D^2) + 0.000089466(D^3) - 0.000000431(D^4) + 1.0180521E\text{-}9(D^5) - 9.37552E\text{-}13(D^6)$

PARITY 3+

JAN-FEB	$37.344581 + 0.291597(D) - 0.006244(D) + 0.000050187(D^3) - 0.000000211(D^4) + 4.460289E\text{-}10(D^5) - 3.73083E\text{-}13(D^6)$
MAR-APR	$34.432751 + 0.410362(D) - 0.008816(D^2) + 0.000072977(D^3) - 0.000000303(D^4) + 6.061931E\text{-}10(D^5) - 4.58365E\text{-}13(D^6)$
MAY-JUNE	$34.440378 + 0.243759 (D) - 0.005462(D^2) + 0.000046818(D^3) - 0.000000210(D^4) + 4.705644E\text{-}10(D^5) - 4.12732E\text{-}13(D^6)$
JUL-AUG	$31.793790 + 0.268499(D) - 0.005166(D^2) + 0.000039866(D^3) - 0.000000163(D^4) + 0.000000163(D^5) - 2.66805E\text{-}13(D^6)$
SEP-0CT	$34.110845 + 0.330998(D) - 0.006918(D^2) + 0.000057513(D^3) - 0.000000247(D^4) + 5.255278E\text{-}10(D^5) - 4.38899E\text{-}13(D^6)$
NOV-DEC	$33.157787 + 0.228729(D) - 0.006236(D^2) + 0.000060718(D^3) - 0.000000297(D^4) + 7.035286E\text{-}10(D^5) - 6.45467E\text{-}13(D^6)$

FAT %: HERD MEAVG 17000-21000 lbs.

PARITY 1

JAN-FEB	$4.865069 - 0.054502(D) + 0.000919(D^2) - 0.000007790(D^3) + 3.4210148E\text{-}8(D^4) - 7.27908E\text{-}11(D^5) + 5.906713E\text{-}14(D^6)$
MAR-APR	$4.688932 - 0.056106(D) + 0.001049(D^2) - 0.000010165(D^3) + 5.309201E\text{-}8(D^4) - 1.38205E\text{-}10(D^5) + 1.399669E\text{-}13(D^6)$
MAY-JUNE	$4.358283 - 0.034853(D) + 0.000441(D^2) - 0.000002252(D^3) + 5.1411914E\text{-}9(D^4) - 4.08351E\text{-}12(D^5) - 6.49727E\text{-}16(D^6)$
JUL-AUG	$4.433903 - 0.046924(D) + 0.000913(D^2) - 0.000008126(D^3) + 3.7393747E\text{-}8(D^4) - 8.61623E\text{-}11(D^5) + 7.85637E\text{-}14(D^6)$
SEP-OCT	$4.629036 - 0.046485(D) + 0.000875(D^2) - 0.000008075(D^3) + 3.9366684E\text{-}8(D^4) - 9.70948E\text{-}11(D^5) + 9.535162E\text{-}14(D^6)$
NOV-DEC	$4.810550 - 0.047449(D) + 0.000756(D^2) - 0.000005984(D^3) + 2.4808443E\text{-}8(D^4) - 5.17695E\text{-}11(D^5) - 5.17695E\text{-}11(D^6)$

PARITY 2

JAN-FEB	$4.848686 - 0.053428(D) + 0.000885(D^2) - 0.000007509(D^3) + 3.3168572E\text{-}8(D^4) - 7.11653E\text{-}11(D^5) + 5.824799E\text{-}14(D^6)$
MAR-APR	$4.905476 - 0.053428(D) + 0.000885(D^2) - 0.000007509(D^3) + 3.3168572E\text{-}8(D^4) - 7.11653E\text{-}11(D^5) + 5.824799E\text{-}14(D^6)$
MAY-JUNE	$4.403694 - 0.030721(D) + 0.000315(D^2) - 0.000000616(D^3) + 5.389522E\text{-}9(D^4) - 2.800368E\text{-}11(D^5) + 2.800368E\text{-}11(D^6)$
JUL-AUG	$4.544226 - 0.052091(D) + 0.001051(D^2) - 0.000009757(D^3) + 4.6629501E\text{-}8(D^4) - 1.1127E\text{-}10(D^5) + 1.048623E\text{-}13(D^6)$
SEP-OCT	$4.751836 - 0.047514(D) + 0.000875(D^2) - 0.000007912(D^3) + 3.7599509E\text{-}8(D^4) - 9.0256E\text{-}11(D^5) + 8.635875E\text{-}14(D^6)$
NOV-DEC	$5.016570 - 0.057863(D) + 0.001013(D^2) - 0.000008875(D^3) + 4.0728639E\text{-}8(D^4) - 9.40255E\text{-}11(D^5) + 8.679679E\text{-}14(D^6)$

PARITY 3+

JAN-FEB	$5.129514 - 0.058935(D) + 0.000960(D^2) - 0.000008079(D^3) + 3.5735068E\text{-}8(D^4) - 7.77436E\text{-}11(D^5) + 6.542564E\text{-}14(D^6)$
MAR-APR	$5.060528 - 0.059377(D) + 0.001017(D^2) - 0.000009409(D^3) + 4.8112013E\text{-}8(D^4) - 1.24633E\text{-}10(D^5) + 1.267446E\text{-}13(D^6)$
MAY-JUNE	$4.706764 - 0.041113(D) + 0.000496(D^2) - 0.000002298(D^3) + 2.8754276E\text{-}9(D^4) - 7.367225E\text{-}12(D^5) + 1.69265E\text{-}14(D^6)$
JUL-AUG	$4.737814 - 0.055419(D) + 0.001048(D^2) - 0.000009326(D^3) + 4.2994143E\text{-}8(D^4) - 9.93091E\text{-}11(D^5) + 9.0874E\text{-}14(D^6)$
SEP-OCT	$5.000339 - 0.053354(D) + 0.000912(D^2) - 0.000007837(D^3) + 3.5837512E\text{-}8(D^4) - 8.3669E\text{-}11(D^5) + 7.856924E\text{-}14(D^6)$
NOV-DEC	$4.950589 - 0.045784(D) + 0.000745(D^2) - 0.000006223(D^3) + 2.7294989E\text{-}8(D^4) - 6.02727E\text{-}11(D^5) + 5.346951E\text{-}14(D^6)$

PROTEIN %: HERD MEAVG 17000-21000 lbs

PARITY 1

JAN-FEB	$3.697221 - 0.035694(D) + 0.000708(D^2) - 0.000006522(D^3) + 3.0863348E\text{-}8(D^4) - 7.20023E\text{-}11(D^5) + 6.58618E\text{-}14(D^6)$
MAR-APR	$3.633067 - 0.036662(D) + 0.000756(D^2) - 0.000007191(D^3) + 3.5562501E\text{-}8(D^4) - 8.68749E\text{-}11(D^5) + 8.249526E\text{-}14(D^6)$
MAY-JUNE	$3.574368 - 0.033355(D) + 0.000673(D^2) - 0.000006179(D^3) + 3.0464081E\text{-}8(D^4) - 7.71046E\text{-}11(D^5) + 7.788858E\text{-}14(D^6)$
JUL-AUG	$3.626643 - 0.035694(D) + 0.000713(D^2) - 0.000005921(D^3) + 2.4518771E\text{-}8(D^4) - 5.04122E\text{-}11(D^5) + 4.126954E\text{-}14(D^6)$
SEP-OCT	$3.755259 - 0.044309(D) + 0.001024(D^2) - 0.000010199(D^3) + 5.0363839E\text{-}8(D^4) - 1.21759E\text{-}10(D^5) - 1.21759E\text{-}10(D^6)$
NOV-DEC	$3.879384 - 0.043248(D) + 0.000896(D^2) - 0.000008576(D^3) + 4.1714884E\text{-}8(D^4) - 1.00137E\text{-}10(D^5) + 9.457497E\text{-}14(D^6)$

PARIYT 2

JAN-FEB	$3.681860 - 0.042476(D) - 0.042476(D^2) - 0.000008020(D^3) + 3.8508055E\text{-}8(D^4) - 9.04778E\text{-}11(D^5) + 8.275931E\text{-}14(D^6)$
MAR-APR	$3.736440 - 0.042476(D) + 0.000853(D^2) - 0.000008020(D^3) + 3.8508055E\text{-}8(D^4) - 9.04778E\text{-}11(D^5) + 8.275931E\text{-}14(D^6)$
MAY-JUNE	$3.643926 - 0.035317(D) + 0.000678(D^2) - 0.000005950(D^3) + 2.8334702E\text{-}8(D^4) - 7.00354E\text{-}11(D^5) + 6.969587E\text{-}14(D^6)$
JUL-AUG	$3.769015 - 0.044202(D) + 0.000913(D^2) - 0.000008046(D^3) + 3.5739404E\text{-}8(D^4) - 7.91489E\text{-}11(D^5) + 6.975244E\text{-}14(D^6)$
SEP-OCT	$3.840897 - 0.048185(D) + 0.001130(D2) - 0.000011468(D3) + 5.7653164E\text{-}8(D^4) - 1.41543E\text{-}10(D5) + 1.358236E\text{-}13(D6)$
NOV-DEC	$3.961791 - 0.048829(D) + 0.001033(D) - 0.000010077(D^3) + 4.9795866E\text{-}8(D^4) - 1.21001E\text{-}10(D^5) + 1.153619E\text{-}13(D^6)$

PARITY 3+

JAN-FEB	$3.805760 - 0.042599(D) + 0.000836(D^2) - 0.000007685(D^3) + 3.6042632E\text{-}8(D^4) - 8.2537E\text{-}11(D^5) + 7.338162E\text{-}14(D^6)$
MAR-APR	$3.783588 - 0.047434(D) + 0.000974(D^2) - 0.000009436(D^3) + 4.7546296E\text{-}8(D4) - 1.18156E\text{-}10(D5) + 1.140423E\text{-}13(D6)$
MAY-JUNE	$3.699887 - 0.040907(D) + 0.000780(D^2) - 0.000006807(D^3) + 3.1991988E\text{-}8(D^4) - 7.76842E\text{-}11(D^5) + 7.588073E\text{-}14(D^6)$
JUL-AUG	$3.791871 - 0.047954(D) + 0.000982(D^2) - 0.000008602(D^3) + 3.7949447E\text{-}8(D^4) - 8.34002E\text{-}11(D^5) + 7.294862E\text{-}14(D^6)$
SEP-OCT	$3.928558 - 0.055463(D) + 0.001275(D^2) - 0.000012834(D^3) + 6.4228333E\text{-}8(D^4) - 1.57193E\text{-}10(D^5) + 1.504522E\text{-}13(D^6)$
NOV-DEC	$3.995065 - 0.051168(D) + 0.001054(D^2) - 0.000010057(D^3) + 4.8716057E\text{-}8(D^4) - 1.16248E\text{-}10(D^5) + 1.09039E\text{-}13(D^6)$

MILK (kg): HERD MEAVG > 21000 lbs.

PARITY 1

JAN-FEB	$20.891444 + 0.550796(D) - 0.009002(D^2) + 0.000072003(D^3) - 0.000000316(D^4) + 7.114211E\text{-}10(D^5) - 6.4471E\text{-}13(D^6)$
MAR-APR	$20.096926 + 0.579507(D) - 0.009521(D^2) + 0.000073851(D^3) - 0.000000307(D^4) + 6.541044E\text{-}10(D^5) - 5.5963E\text{-}13(D^6)$
MAY-JUNE	$19.964633 + 0.589884(D) - 0.010657(D^2) + 0.000091094(D^3) - 0.000000413(D^4) + 9.523384E\text{-}10(D^5) - 8.77709E\text{-}13(D^6)$
JUL-AUG	$19.391712 + 0.522564(D) - 0.009081(D^2) + 0.000075194(D^3) - 0.000000328(D^4) + 7.227282E\text{-}10(D^5) - 6.35738E\text{-}13(D^6)$
SEP-OCT	$20.546637 + 0.509218(D) - 0.008689(D^2) + 0.000072230(D^3) - 0.000000319(D^4) + 7.118654E\text{-}10(D^5) - 6.34228E\text{-}13(D^6)$
NOV-DEC	$20.208420 + 0.580625(D) - 0.010198(D^2) + 0.000087644(D^3) - 0.000000401(D^4) + 9.216724E\text{-}10(D^5) - 8.38377E\text{-}13E\text{-}13(D^6)$

PARITY 2

JAN-FEB	$30.123020 + 0.752666(D) - 0.014650(D^2) + 0.000128(D^3) - 0.000000589(D^4) + 1.3597525E\text{-}9(D^5) - 1.23986E\text{-}12(D^6)$
MAR-APR	$30.699820 + 0.752666(D^2) - 0.014650(D^3) + 0.000128(D^3) - 0.000000589(D^4) + 1.3597525E\text{-}9(D^5) - 1.23986E\text{-}12(D^5)$
MAY-JUNE	$29.374789 + 0.719253(D) - 0.014470(D^2) + 0.000129(D^3) - 0.000000602(D^4) + 1.4088117E\text{-}9(D^5) - 1.29956E\text{-}12(D^6)$
JUL-AUG	$28.315268 + 0.663607(D) - 0.012935(D^2) + 0.000112(D^3) - 0.000000508(D^4) + 1.1582771E\text{-}9(D^5) - 1.04837E\text{-}12(D^6)$
SEP-OCT	$28.600983 + 0.74145(D) - 0.015026(D^2) + 0.000136(D^3) - 0.000000641(D^4) + 1.5091129E\text{-}9(D^5) -1.40639E\text{-}12(D^6)$
NOV-DEC	$29.051251 + 0.806921(D) - 0.016444(D^2) + 0.000149(D^3) - 0.000000702(D^4) + 1.6368485E\text{-}9(D^5) - 1.49943E\text{-}12(D^6)$

PARITY 3+

JAN-FEB	$30.395120 + 0.752666(D) - 0.014650(D^2) + 0.000128(D^3) - 0.000000589(D^4) + 1.3597525E\text{-}9(D^5) - 1.23986E\text{-}12(D^6)$
MAR-APR	$29.655188 + 0.858392(D) - 0.016048(D^2) + 0.000134(D^3) - 0.000000596(D^4) + 1.3244586E\text{-}9(D^5) - 1.1601E\text{-}12(D^6)$
MAY-JUNE	$28.820848 + 0.758732(D) - 0.013831(D^2) + 0.000115(D^3) - 0.000000513(D^4) + 1.1750844E\text{-}9(D^5) - 1.07907E\text{-}12(D^6)$
JUL-AUG	$28.285681 + 0.700089(D) - 0.012384(D^2) + 0.000096632(D^3) - 0.000000396(D^4) + 8.108496E\text{-}10(D^5) - 6.53259E\text{-}13(D^6)$
SEP-OCT	$27.231419 + 0.815996(D) - 0.015149(D^2) + 0.000127(D^3) - 0.000000556(D^4) + 1.2283832E\text{-}9(D^5) -1.07962E\text{-}12(D^6)$
NOV-DEC	$30.163300 + 0.874279(D) - 0.016558(D^2) + 0.000142(D^3) - 0.000000635(D^4) + 1.4191664E\text{-}9(D^5) - 1.25222E\text{-}12(D^6)$

ECM(kg): HERD MEAVG > 21000 lbs.

PARITY 1

JAN-FEB	$26.411556 + 0.322023(D) - 0.005190(D^2) + 0.000039782(D^3) - 0.000000172(D^4) + 3.983705E\text{-}10(D^5) - 3.80856E\text{-}13(D^6)$
MAR-APR	$24.745699 + 0.351677(D) - 0.005331(D^2) + 0.000033975(D^3) - 0.000000101(D^4) + 1.180932E\text{-}10(D^5) - 1.799E\text{-}14(D^6)$
MAY-JUNE	$24.074561 + 0.400496(D) - 0.007740(D^2) - 0.007740(D^3) - 0.000000325(D^4) + 7.50956E\text{-}10(D^5) - 6.84651E\text{-}13(D^6)$
JUL-AUG	$23.429072 + 0.322281(D) - 0.005475(D^2) + 0.000045917(D^3) - 0.000000205(D^4) + 4.630985E\text{-}10(D^5) - 4.15997E\text{-}13(D^6)$
SEP-OCT	$25.831184 + 0.270486(D) - 0.004080(D^2) + 0.000029800(D^3) - 0.000000117(D^4) + 2.321344E\text{-}10(D^5) - 1.83353E\text{-}13(D^6)$
NOV-DEC	$26.225464 + 0.338744(D) - 0.006027(D^2) + 0.000051653(D^3) - 0.000000237(D^4) + 5.473163E\text{-}10(D^5) - 4.97381E\text{-}13(D^6)$

PARITY 2

JAN-FEB	$39.134899 + 0.384859(D) - 0.008270(D^2) + 0.000071772(D^3) - 0.000000328(D^4) + 7.551739E\text{-}10(D^5) - 6.92746E\text{-}13(D^6)$
MAR-APR	$39.504099 + 0.384859(D) - 0.008270(D^2) + 0.000071772(D^3) - 0.000000328(D^4) + 7.551739E\text{-}10(D^5) -6.92746E\text{-}13(D^6)$
MAY-JUNE	$35.643039 + 0.426981(D) - 0.009839(D^2) + 0.000094589(D^3) - 0.000000464(D^4) + 1.1164824E\text{-}9(D^5) - 1.04168E\text{-}12(D^6)$
JUL-AUG	$34.266410 + 0.351199(D) - 0.006752(D^2) + 0.000056336(D^3) - 0.000000252(D^4) + 5.723355E\text{-}10(D^5) - 5.145E\text{-}13(D^6)$
SEP-OCT	$36.252342 + 0.418084(D) - 0.008869(D^2) + 0.000079302(D^3) - 0.000000370(D^4) + 8.647921E\text{-}10(D^5) -7.98219E\text{-}13(D^6)$
NOV-DEC	$38.291747 + 0.421432(D) - 0.009401(D^2) + 0.000085067(D^3) - 0.000000394(D^4) + 8.955862E\text{-}10(D^5) - 7.94357E\text{-}13(D^6)$

PARITY 3+

JAN-FEB	$38.965899 + 0.384859(D) - 0.008270(D^2) + 0.000071772(D^3) - 0.000000328(D^4) + 7.551739E\text{-}10(D^5) - 6.92746E\text{-}13(D^6)$
MAR-APR	$37.821224 + 0.521771(D) - 0.010640(D^2) + 0.000088128(D^3) - 0.000000371(D^4) + 7.613819E\text{-}10(D^5) - 5.97131E\text{-}13(D^6)$
MAY-JUNE	$36.298880 + 0.432068(D) - 0.008884(D^2) + 0.000079436(D^3) - 0.000000379(D^4) + 9.085786E\text{-}10(D^5) - 8.57625E\text{-}13(D^6)$
JUL-AUG	$35.001319 + 0.368056(D) - 0.006051(D^2) + 0.000040885(D^3) - 0.000000143(D^4) + 2.380641E\text{-}10(D^5) - 1.36593E\text{-}13(D^6)$
SEP-OCT	$36.416400 + 0.469138(D) - 0.008927(D^2) + 0.000071718(D^3) - 0.000000303(D^4) + 6.424692E\text{-}10(D^5) - 5.39581E\text{-}13(D^6)$
NOV-DEC	$40.302362 + 0.460849(D) - 0.009411(D^2) + 0.000079160(D^3) - 0.000000347(D^4) + 7.574721E\text{-}10(D^5) - 6.49208E\text{-}13(D^6)$

FAT % : HERD MEAVG > 21000 lbs.

PARITY 1

JAN-FEB	$5.048945 - 0.067368(D) + 0.001179(D^2) - 0.000010363(D^3) + 4.7264329E\text{-}8\ (D^4) -1.05468E\text{-}10\ (D^5) + 9.100925E\text{-}14(D^6)$
MAR-APR	$4.746303 - 0.060394(D) + 0.001136\ (D^2) - 0.000011111(D^3) + 5.8306157E\text{-}8(D^4) - 1.52009E\text{-}10\ (D^5) + 1.539698E\text{-}13\ (D^6)$
MAY-JUNE	$4.602926 - 0.049267(D) + 0.000781(D^2) - 0.000006103(D^3) + 2.6888897E\text{-}8(D^4) -6.3316E\text{-}11(D^5)\ \ 6.139711E\text{-}14\ (D^6)$
JUL-AUG	$4.565005 - 0.050892(D) + 0.000933(D^2) - 0.000008085(D^3) + 3.6734433E\text{-}8(D^4) - 8.42399E\text{-}11(D^5) + 7.690035E\text{-}14(D^6)$
SEP-OCT	$4.900238 - 0.060757(D) + 0.001109\ (D^2) - 0.000009966(D^3) + 4.7055883E\text{-}8\ (D^4) - 1.11824E\text{-}10\ (D^5) + 1.055021E\text{-}13(D^6)$
NOV-DEC	$5.057261 - 0.063961(D) + 0.001105(D^2) - 0.000009622(D^3) + 4.4345716E\text{-}8(D^4) - 1.0323E\text{-}10(D^5) + 9.609434E\text{-}14(D^6)$

PARITY 2

JAN-FEB	$5.183988 - 0.070509(D) + 0.001256(D^2) - 0.000011261(D^3) + 5.2484906E\text{-}8(D^4) - 1.20317E\text{-}10(D^5) - 1.20317E\text{-}10(D^6)$
MAR-APR	$5.162458 - 0.070509(D) + 0.001256(D^2) - 0.000011261(D^3) + 5.2484906E\text{-}8(D^4) - 1.20317E\text{-}10(D^5) + 1.072484E\text{-}13(D^6)$
MAY-JUNE	$3.622237 - 0.037410(D) + 0.000746(D^2) - 0.000006876(D^3) + 3.3999209E\text{-}8(D^4) - 8.59603E\text{-}11(D^5) + 8.649698E\text{-}14(D^6)$
JUL-AUG	$4.580025 - 0.055538(D) + 0.001110(D^2) - 0.000010357(D^3) + 4.9789683E\text{-}8(D^4) - 1.19289E\text{-}10(D^5)\ \ 1.12721E\text{-}13(D^6)$
SEP-OCT	$4.911130 - 0.056032(D) + 0.000987(D^2) - 0.000008633(D^3) + 3.9946431E\text{-}8(D4) - 9.37468E\text{-}11(D5) + 8.804132E\text{-}14(D6)$
NOV-DEC	$5.147496 - 0.068979(D) + 0.001258(D2) - 0.000011559(D3) + 5.5999201E\text{-}8(D^4) - 1.36547E\text{-}10(D^5) + 1.324887E\text{-}13(D^6)$

PARITY 3+

JAN-FEB	$5.050068 - 0.070509(D) + 0.001256(D^2) - 0.000011261(D^3)\ \ 5.2484906E\text{-}8(D^4) - 1.20317E\text{-}10(D^5) + 1.072484E\text{-}13(D^6)$
MAR-APR	$5.003657 - 0.060413(D) + 0.001010(D^2) - 0.000009137(D^3) + 4.6053712E\text{-}8(D^4) - 1.18552E\text{-}10(D^5) + 1.205131E\text{-}13(D^6)$
MAY-JUNE	$4.963884 - 0.060390\ (D) + 0.000910(D^2) - 0.000006558(D^3) + 2.5219758E\text{-}8(D^4) -5.\ 02575E\text{-}11(D^5) + 4.10649E\text{-}14\ (D^6)$
JUL-AUG	$4.775133 - 0.058955(D) + 0.001118(D^2) - 0.000010127(D^3) + 4.7686933E\text{-}8(D^4) - 1.12529E\text{-}10(D^5) + 1.051363E\text{-}13(D^6)$
SEP-OCT	$5.300176 + -0.062925(D) + 0.001061(D^2) - 0.000008991(D^3) + 4.0485695E\text{-}8(D^4) - 9.28613E\text{-}11(D^5) + 8.559221E\text{-}14(D^6)$
NOV-DEC	$5.279307 - 0.075968(D) + 0.001311(D^2) - 0.000011440(D^3) + 5.2584515E\text{-}8(D^4) - 1.21606E\text{-}10(D^5) + 1.119567E - 13(D^6)$

PROTEIN %: HERD MEAVG > 21000 lbs.

PARITY 1

JAN-FEB	$3.649535 - 0.034359 (D) + 0.000660 (D^2) - 0.000005902(D^3) + 2.7231262E\text{-}8(D^4) - 6.21586E\text{-}11(D^5) + 5.574643E\text{-}14(D^6)$
MAR-APR	$3.593252 - 0.034961(D) + 0.000707(D^2) - 0.000006549(D^3) + 3.1485496E\text{-}8(D^4) - 7.48975E\text{-}11(D^5) + 6.941994E\text{-}14(D^6)$
MAY-JUNE	$3.551865 - 0.033444(D) + 0.000678(D^2) - 0.000006238(D^3) + 3.0653883E\text{-}8(D^4) - 7.70039E\text{-}11(D^5) + 7.70981E\text{-}14(D^6)$
JUL-AUG	$3.609378 - 0.035384(D) + 0.000693(D^2) - 0.000005741(D^3) + 2.40419E\text{-}8(D^4) - 5.05605E\text{-}11(D^5) + 4.273525E\text{-}14(D^6)$
SEP-OCT	$3.730886 - 0.044397(D) + 0.001022(D^2) - 0.000010212(D^3) + 5.0725878E\text{-}8(D^4) - 1.23419E\text{-}10(D^5) + 1.176079E\text{-}13(D^6)$
NOV-DEC	$3.858075 - 0.045363(D) + 0.000952(D^2) - 0.000009197(D^3) + 4.5149176E\text{-}8(D^4) - 1.09212E\text{-}10(D^5) + 1.036456E\text{-}13(D^6)$

PARITY 2

JAN-FEB	$3.782083 - 0.041012(D) + 0.000800(D^2) - 0.000007319(D^3) + 3.4337185E\text{-}8(D^4) - 7.89735E\text{-}11(D^5) + 7.069964E\text{-}14(D6)$
MAR-APR	$3.669063 - 0.041012(D) + 0.000800(D^2) - 0.000007319(D^3) + 3.4337185E\text{-}8(D^4) - 7.89735E\text{-}11(D^5) + 7.069964E\text{-}14(D^6)$
MAY-JUNE	$3.622237 - 0.037410(D) + 0.000746(D^2) - 0.00000687(D^3) + 3.3999209E\text{-}8 (D^4) - 8.59603E\text{-}11(D^5) + 8.649698E\text{-}14(D^6)$
JUL-AUG	$3.690833 - 0.040241(D) + 0.000807(D^2) - 0.000006903(D^3) + 2.9861118E\text{-}8(D^4) - 6.4751E\text{-}11(D^5) + 5.629547E\text{-}14(D^6)$
SEP-OCT	$3.894535 - 0.053992(D) + 0.001236(D^2) - 0.000012413(D^3) + 6.1972593E\text{-}8(D^4) - 1.51244E\text{-}10(D^5) + 1.442741E\text{-}13(D^6)$
NOV-DEC	$3.960364 - 0.051064(D) + 0.001065(D^2) - 0.000010295(D^3) + 5.0610572E\text{-}8(D^4) - 1.22588E\text{-}10(D^5) + 1.165573E\text{-}13(D^6)$

PARITY 3+

JAN-FEB	$3.675863 - 0.041012(D) + 0.000800(D^2) - 0.000007319(D^3) + 3.4337185E\text{-}8(D^4) - 7.89735E\text{-}11(D^5) + 7.069964E\text{-}14(D^6)$
MAR-APR	$3.735807 - 0.044797(D) + 0.000895(D^2) - 0.000008416(D^3) + 4.1216223E\text{-}8(D^4) - 9.97323E\text{-}11(D^5) + 9.381195E\text{-}14(D^6)$
MAY-JUNE	$3.638324 - 0.039455(D) + 0.000759(D^2) - 0.000006791(D^3) + 3.2742988E\text{-}8(D^4) - 8.12292E\text{-}11(D^5) + 8.06713E\text{-}14(D^6)$
JUL-AUG	$3.807478 - 0.048837(D) + 0.000992(D^2) - 0.000008749(D^3) + 3.9217572E\text{-}8(D^4) - 8.80461E\text{-}11(D^5) + 7.8901E\text{-}14(D^6)$
SEP-OCT	$4.037144 - 0.057251(D) + 0.001285(D^2) - 0.000012752(D^3) + 6.3168634E\text{-}8(D^4) - 1.53349E\text{-}10(D^5) + 1.457874E\text{-}13(D^6)$
NOV-DEC	$3.859189 - 0.052438(D) + 0.001095(D^2) - 0.000010621(D^3) + 5.2192046E\text{-}8(D^4) - 1.26054E\text{-}10(D^5) + 1.193026E\text{-}13 (D^6)$

APPENDIX II.

Table II. 1. Number of records, cows, sires and dams, Mean and SD for test-day milk yield by herd production level.

	HERD PRODUCTION LEVEL		
	LOW	MEDIUM	HIGH
Number of herds	200	200	200
Number of records	20,420	58,760	92,742
Number of cows	4,866	12,494	19,921
Number of Sires	635	1,159	1,298
Number of Dams	1,841	4,674	7,960
Mean TD milk (kg)	21.29	25.01	28.94
SD TD milk (kg)	5.34	5.69	6.26

Table II. 2. Age at calving solutions (SOL) and SE for test-day milk production of first lactation cows by herd production level

	HERD PRODUCTION LEVEL					
	LOW		MEDIUM		HIGH	
AGE (months)	SOL.	SE	SOL.	SE	SOL.	SE
18-20	.000	.000	.000	.000	.000	.00
21-22	-1.74	2.81	1.17	1.15	1.917	.66
23-24	-.590	2.81	1.658	1.12	2.543	.63
25-26	-.617	2.80	2.195	1.13	2.912	.63
27-28	.288	2.80	2.439	1.13	3.362	.63
29-30	.320	2.80	2.807	1.13	3.553	.62
31-32	1.00	2.81	2.926	1.13	3.961	.66
32-34	1.33	2.82	3.057	1.15	4.360	.66
35-36	.77	2.82	3.560	1.16	3.849	.68

Table II. 3. **N, min, max, mean for daily dry bulb and dew point temperature and temperature humidity index for a five year period, 1988-1992 from five weather stations in Michigan.**

	DRY BULB TEMP (^{0} C)				DEW POINT TEMP (^{0} C)			THI		
MONTH	N	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN
JAN	1,046	-21.66	10.43	-3.66	-26.78	9.21	-7.30	10.30	54.63	34.91
FEB	969	-19.91	9.05	-4.43	-27.15	3.47	-8.68	11.54	51.44	33.65
MAR	1,054	-18.61	19.44	.032	-27.34	15.28	-5.02	12.74	65.68	39.43
APR	1,045	-6.81	25.49	6.92	-13.10	17.87	.40	29.68	71.77	48.27
MAY	1,075	1.02	27.22	13.78	-7.31	22.11	6.23	40.13	75.60	57.19
JUNE	1,025	5.86	29.56	18.50	-1.02	20.83	11.19	48.47	78.09	63.75
JULY	1,075	9.84	31.80	30.87	.23	22.94	14.66	53.88	79.39	67.39
AUG	1,081	9.93	31.04	20.02	.53	23.98	14.74	53.25	80.86	66.55
SEP	1,015	.56	27.89	15.38	-3.77	21.67	10.50	41.76	76.28	60.39
OCT	1,048	-1.69	22.71	8.80	-8.89	18.36	3.86	37.03	70.03	51.40
NOV	1,029	-10.37	17.85	3.07	-14.26	15.02	-0.88	26.10	63.21	43.95
DEC	1,059	-22.71	11.54	-3.33	-28.17	9.18	-6.99	8.57	55.82	35.35

Table II. 4. **Min, Max , Mean and SD of observed deviations and predicted deviations using deviations from the previous test-day record of first lactation cows in low producing herds**

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT (DIM)		MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-16.59	13.71	-.383	4.67	-6.93	14.26	-1.70	2.99
3	61-90	-15.38	13.72	-.289	4.48	-9.96	8.23	-.230	2.80
4	91-120	-18.39	15.71	-.370	4.43	-9.81	8.74	-.185	2.86
5	121-150	-13.69	14.10	-.335	4.13	-11.85	10.13	-.238	2.86
6	151-180	-12.16	12.18	-.469	3.89	-9.29	9.58	-.227	2.81
7	181-210	-15.13	12.76	-.356	4.06	-10.22	10.22	-.393	3.26
8	210-240	-12.49	14.32	-.289	4.06	-10.88	9.17	-.256	2.91
9	241-270	-12.20	13.93	-.163	4.25	-10.64	12.20	-.245	3.45
10	271-305	-14.32	15.80	-.330	4.58	-8.05	9.19	-.108	2.80

Table II. 5. Min, Max , Mean and SD of observed deviations and predicted deviations using deviations from the two previous test-day records of first lactation cows in low producing herds

TRAIT (DIM)		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
		MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-	-	-	-	-	-	-	-
3	61-90	-15.38	13.71	-.289	4.48	-9.57	9.15	-.372	2.91
4	91-120	-18.38	15.71	-0.37	4.43	-10.86	9.75	-.239	3.06
5	121-150	-13.69	14.11	-.335	4.13	-11.03	10.91	-.254	3.03
6	151-180	-12.16	12.18	-.469	3.90	-10.91	10.35	-.280	3.11
7	181-210	-15.13	12.76	-.356	4.05	-10.67	12.76	-.356	3.31
8	210-240	-12.49	14.32	-.289	4.06	-10.54	14.32	-.337	2.85
9	241-270	-12.20	13.93	-.163	4.25	-14.32	9.75	-.249	3.44
10	271-305	-14.32	12.02	-.330	3.45	-7.67	9.37	-.160	2.73

Table II. 6. **MIN, MAX, Mean and SD of observed deviations and predicted deviations using deviations from three previous test-day records of first lactation cows in low producing herds**

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT (DIM)		MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-
4	91-120	-18.39	15.71	-.370	4.43	-10.18	10.63	-.508	3.19
5	121-150	-13.69	14.11	-.335	4.13	-12.08	10.42	-.280	3.11
6	151-180	-12.16	12.18	-.469	3.89	-11.22	10.33	-.282	3.13
7	181-210	-15.14	12.75	-.356	4.05	-10.26	10.36	-.393	3.33
8	210-240	-12.49	14.32	-.288	4.06	-10.76	8.99	-.339	2.89
9	241-270	-12.19	13.93	-.163	4.25	-15.74	14.19	-.178	3.96
10	271-305	-14.32	15.80	-.330	4.59	-7.76	9.46	-.189	2.79

Table II. 7. Min, Max, Mean and SD of observed deviations and predicted deviations using deviations from the previous test-day record of first lactation cows in medium producing herds

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT	(DIM)	MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-16.85	22.29	-.094	4.75	-10.96	20.79	-.041	2.79
3	61-90	-20.71	20.88	-.053	4.65	- 9.60	12.70	-.054	2.71
4	91-120	-16.90	24.78	-.016	4.67	-13.65	13.76	-.035	3.06
5	121-150	-20.53	25.35	.023	4.72	-11.68	17.12	-.011	3.22
6	151-180	-17.90	19.16	-.047	4.62	-13.23	16.34	.015	3.04
7	181-210	-16.15	22.90	.651	4.78	-12.45	13.34	-.032	3.22
8	210-240	-24.89	24.19	.129	4.67	-11.37	16.13	.458	3.37
9	241-270	-18.70	23.04	.200	4.73	-17.76	17.26	.092	3.33
10	271-305	-17.75	19.21	-.721	5.32	-13.78	16.98	.147	3.49

Table II. 8. **Min, Max, Mean and SD of observed deviations and predicted deviations using deviations from the two previous test-day records of first lactation cows in medium producing herds**

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT		MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-	-	-	-	-	-	-	-
3	61-90	-20.72	20.88	-.053	4.65	-9.67	12.56	-.057	2.82
4	91-120	-16.91	24.79	-.016	4.67	-13.15	12.99	-.046	3.16
5	121-150	-20.53	25.35	.023	4.72	-14.96	16.80	-.025	3.51
6	151-180	-17.90	19.16	-.047	4.63	-15.84	23.30	-.017	4.41
7	181-210	-16.15	22.91	.651	4.78	-10.72	15.05	-.018	3.41
8	210-240	-24.89	24.19	.129	4.67	-10.50	13.85	.316	3.42
9	241-270	-18.70	23.04	.200	4.73	-14.46	17.20	.267	3.54
10	271-305	-15.97	19.19	-.721	5.32	-15.97	19.19	.143	3.73

Table II. 9. **Min, Max, Mean and SD of observed deviations and predicted deviations using deviations from three previous test-day records of first lactation cows in medium producing herds**

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT	(DIM)	MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-	-	-	-	-	-	-	-
3	61-90	-	-	-	-	-	-	-	-
4	91-120	-16.90	24.79	-.016	4.67	-13.11	13.02	-.048	3.17
5	121-150	-20.52	25.35	.023	4.72	-14.09	16.40	-.051	3.85
6	151-180	-17.90	19.16	-.047	4.63	-15.16	23.51	-.011	4.39
7	181-210	-16.15	22.91	-.094	4.78	-70.78	62.63	-.094	12.68
8	210-240	-24.89	24.19	.129	4.67	-10.88	14.08	.298	3.44
9	241-270	-18.70	23.04	.200	4.73	-14.57	17.43	.236	3.55
10	271-305	-19.14	19.14	.236	3.55	-15.89	19.14	.161	3.73

Table II. 10. Min, Max , Mean and SD of observed deviations and predicted deviations using deviations from the previous test-day record of first lactation cows in high producing herds

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT	(DIM)	MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-25.77	38.03	-.103	5.35	-11.78	12.64	-.137	3.06
3	61-90	-23.42	29.22	-.062	4.93	-16.00	23.61	-.064	3.32
4	91-120	-16.74	37.82	-.048	5.05	-15.34	19.15	-.041	3.24
5	121-150	-17.92	29.95	-.053	5.08	-11.63	26.28	-.033	3.51
6	151-180	-19.59	27.11	-.016	5.10	-12.61	27.11	-.037	3.57
7	181-210	-19.68	34.65	.020	5.09	-13.92	19.26	-.011	3.63
8	210-240	-18.36	40.30	.127	5.18	-11.49	20.22	.012	2.97
9	241-270	-14.82	27.23	.256	5.22	-14.83	30.43	.096	3.91
10	271-305	-20.69	24.72	.113	5.76	-11.21	20.58	.195	3.95

Table II. 11. Min, Max , Mean and SD of observed deviations and predicted deviations using deviations from the two previous test-day records of first lactation cows in high producing herds

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT	(DIM)	MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-	-	-	-	-	-	-	-
3	61-90	-23.42	29.22	-.062	4.93	-14.20	20.38	-.001	3.42
4	91-120	-16.74	37.82	-.048	5.05	-14.70	16.33	-.095	3.48
5	121-150	-17.92	29.95	-.053	5.08	-14.43	21.61	-.053	3.63
6	151-180	-19.59	27.11	-.016	5.10	-13.30	16.52	-.042	3.78
7	181-210	-19.68	34.65	.020	5.09	-11.52	17.57	-.026	3.84
8	210-240	-18.36	40.30	.127	5.18	-11.08	15.96	.127	3.18
9	241-270	-14.82	27.23	.256	5.22	-13.05	23.80	.076	4.04
10	271-305	-20.69	24.72	.113	5.76	-12.34	20.00	.173	4.15

Table II. 12. Min, Max, Mean and SD of observed deviations and predicted deviations using deviations from three previous test-day records of first lactation cows in high producing herds

		OBSERVED DEVIATIONS				PREDICTED DEVIATIONS			
TRAIT	(DIM)	MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD
2	30-60	-	-	-	-	-	-	-	-
3	61-90	-	-	-	-	-	-	-	-
4	91-120	-16.74	37.82	-.048	5.05	-14.64	16.19	-.059	3.37
5	121-150	-17.92	29.95	-.053	5.08	-14.69	21.29	-.046	3.66
6	151-180	-19.59	27.11	-.016	5.10	-13.42	15.53	-.043	3.79
7	181-210	-19.68	34.65	.020	5.09	-11.92	16.76	-.028	3.89
8	210-240	-18.36	40.30	.127	5.18	- 9.93	15.67	.001	3.19
9	241-270	-14.82	27.23	.256	5.22	-12.31	23.07	.068	4.08
10	271-305	-20.69	24.72	.113	5.76	-12.08	18.07	.161	4.17

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