ARTICLE IN PRESS



J. Dairy Sci. 99:1–10 http://dx.doi.org/10.3168/jds.2015-10153 © American Dairy Science Association[®], 2016.

Customized recommendations for production management clusters of North American automatic milking systems

Marlène Tremblay,*¹ Justin P. Hess,* Brock M. Christenson,* Kolby K. McIntyre,* Ben Smink,† Arjen J. van der Kamp,‡ Lisanne G. de Jong,‡ and Dörte Döpfer*

*Department of Medical Sciences, Food Animal Production Medicine Section, School of Veterinary Medicine, University of Wisconsin-Madison, 2015 Linden Drive, Madison 53706

†Lely North America, 775 250th Avenue, Pella, IA 50219

Lely International N.V., Cornelis van der Lelylaan 1, 3147 PB, Maassluis, the Netherlands

ABSTRACT

Automatic milking systems (AMS) are implemented in a variety of situations and environments. Consequently, there is a need to characterize individual farming practices and regional challenges to streamline management advice and objectives for producers. Benchmarking is often used in the dairy industry to compare farms by computing percentile ranks of the production values of groups of farms. Grouping for conventional benchmarking is commonly limited to the use of a few factors such as farms' geographic region or breed of cattle. We hypothesized that herds' production data and management information could be clustered in a meaningful way using cluster analysis and that this clustering approach would yield better peer groups of farms than benchmarking methods based on criteria such as country, region, breed, or breed and region. By applying mixed latent-class model-based cluster analysis to 529 North American AMS dairy farms with respect to 18 significant risk factors, 6 clusters were identified. Each cluster (i.e., peer group) represented unique management styles, challenges, and production patterns. When compared with peer groups based on criteria similar to the conventional benchmarking standards, the 6 clusters better predicted milk produced (kilograms) per robot per day. Each cluster represented a unique management and production pattern that requires specialized advice. For example, cluster 1 farms were those that recently installed AMS robots, whereas cluster 3 farms (the most northern farms) fed high amounts of concentrates through the robot to compensate for low-energy feed in the bunk. In addition to general recommendations for farms within a cluster, individual farms can generate their own specific goals by comparing themselves to farms within their cluster.

This is very comparable to benchmarking but adds the specific characteristics of the peer group, resulting in better farm management advice. The improvement that cluster analysis allows for is characterized by the multivariable approach and the fact that comparisons between production units can be accomplished within a cluster and between clusters as a choice.

Key words: cluster analysis, automatic milking system, benchmarking, recommendation, production management

INTRODUCTION

Automatic milking systems (AMS) are increasing in popularity and number around the world (de Koning, 2010). As systems become more advanced under constraints of well-being, technical improvements, and economic feasibility, the variety in dairy management systems increases—from organic grazing to standard herds, from tie stalls to AMS, and from small family farms to large freestall herds. Even with the best technology in place, it is necessary to know one's strengths and weaknesses to make continuous improvements and set appropriate management and production goals. The dairy industry is similar to other production systems in which benchmarking is used to compare herds and motivate producers to set goals for their farm (Khade and Metlen, 1996; Boda, 2006; von Keyserlingk et al., 2012), but it is important for benchmarking to be based on the correct comparison group given the wide variety in the dairy industry.

Many dairy record systems, benchmarking programs, and benchmarking results have been published in non-peer-reviewed publications that enable producers to compare themselves with others and monitor their production progress. Benchmarking uses percentile ranks of the production values of groups of farms to compare farms within peer groups. However, grouping for conventional benchmarking is commonly limited to the use of a few factors such as farms' geographic region

Received July 22, 2015.

Accepted March 17, 2016.

¹Corresponding author: mtremblay@wisc.edu

TREMBLAY ET AL.

or breed of cattle. For example, the USDA's National Agricultural Statistics Service (NASS) summarizes yearly production by region or by herd size (USDA NASS, 2014). Similarly, the DHI's executive analysis "Udder Health Monitor" report compares a herd's SCC with that of herds of a similar size broken down into 3 groups: 1-199, 200-999, and >999 cows (Dairy Records) Management Systems, 2014). In addition, DHI's "Herd Management Comparison" report uses breed averages (Holstein or Jersey) by region and the industry's standard goals (Dairy Records Management Systems, 2014). More advanced programs, such as DairyMetrics, can be used to select smaller comparison groups but with the additional restriction items being limited to data found in DHI reports such as SCC and milking frequency (Dairy Records Management Systems, 2012). Specific to AMS, the social network "Benchmark" (Lely Industries N.V., Maassluis, the Netherlands) allows farmers to compare performance variables to that of others in their social network or from selecting others in the same region or with the same farm size. However, these benchmarking methods rely on personal judgment to create peer groups, and the restrictions used (e.g., country, breed, region, or breed and region) do not account for the wide range of systems and conditions in today's dairy industry.

In contrast to the previously mentioned methods, cluster analysis is used to make groups of similar observations that can be based on many different variables (Borcard et al., 2011). Brotzman et al. (2015) used 16 performance values to cluster large Wisconsin dairies into 6 groups that were then characterized into best, good, and poor performance. In a similar industry, the dairy goat farming systems in Italy was successfully characterized into 3 major groups separated into 5 clusters using a cluster analysis of a variety of performance, facility, and management data (Usai et al., 2006). Clusters define neighbors not necessarily as geographic neighbors but neighbors in "similarity of farm characteristics."

Given the wide range in conditions in the dairy industry, to make comparison groups, many factors that significantly affect a herd's production ability need to be assessed simultaneously. In Brotzman et al. (2015), many other limiting factors exist, although herd size was limited to those with at least 200 cows and some environmental variation was limited by only examining Midwestern US dairy herds. In addition, many factors unique to AMS that might affect production are not included in these aforementioned benchmarking and clustering methods. For example, traffic type and the number of robots per pen have been shown to significantly affect milk production in AMS farms (Tremblay et al., 2016). Also, some criteria, such as milking frequency (2 or 3 times per day), do not apply to AMS because cows in an AMS are free to regulate their milking frequency individually. In addition, most benchmarking tools are based on data collected via DHI databases, which is based on measurements taken only once every 3 to 4 wk. Automatic milking systems or parlor systems and sensor technology provides an opportunity to use results collected on a daily basis.

There is a need to compare AMS farms based on relevant variables in an unbiased fashion, which is not currently being provided for these specialized farms. The goals of this study were to characterize farming patterns of AMS herds to prioritize and customize advice for producers regarding their farm management. We hypothesized that herds' production data and management information could be grouped into meaningful multivariable clusters and that this clustering approach would produce better peer groups than conventional benchmarking methods that create peer groups based on criteria such as country, region, breed, or breed and region alone. The specific aim was to perform a cluster analysis of hundreds of North American AMS dairy farms with respect to significant risk factors identified by a generalized mixed linear model. Identifying a farm's nearest neighbor in terms of production patterns and management limitations would allow advice to be tailored to these modern specialized producers.

MATERIALS AND METHODS

A total of 529 North American dairy farms with Lely Astronaut AMS (Lely Industries N.V., Maassluis, the Netherlands) had weekly data collections for 4 yr (2011–2014), which produced 54,065 observations. A previous study found 20 variables from this data set to be significantly associated with changes in milk production (kg) using a generalized linear mixed regression model (Tremblay et al., 2016).

Of the 20 available variables, 5 were categorical variables. The numbers of farms per categorical variable levels and variable explanations are detailed in Table 1. Traffic type (i.e., how cows move through the pen among the AMS, freestalls, and feed fence) can be free or forced. With free cow traffic, cows decide when to enter the AMS, whereas with forced cow traffic, the producer creates one-way traffic toward the AMS. The variable Traffic_Type was coded as "free" or "forced." The Robots_per_Pen variable represented the number of robots per pen of cows. By default, this variable also represents the number of cows in a pen and the pen's physical dimensions. By design, each pen will have about 60 cows per robot. For example, Robots_per_Pen of "1" is designed with 1 robot in a pen of about 60 cows and Robots_per_Pen of "2" is Download English Version:

https://daneshyari.com/en/article/10973664

Download Persian Version:

https://daneshyari.com/article/10973664

Daneshyari.com