Approaches for Developing and Implementing Precision Feeding Programs to Maximize Feed Efficiency

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ABSTRACT

Nutritional management of dairy cattle is of importance to the industry due to its influence on production performance and association with large expenses for producers. Current ration formulation may be improved by predicting feeding recommendations for individual animals, rather than groups of animals, through precision feeding. Automated feeding systems (AFS) designed to deliver individual rations must include response-based models that utilize individual cow production data to make feed recommendations. These models require large data sets of individual cow responses to a variety of nutritional interventions. As a result, an experiment was designed to collect individual response data from 24 Holstein cows fed supplemental top dresses. After analyses, dry matter intake (DMI), milk yield (MY), milk fat yield, milk protein yield, feed efficiency, and activity were significantly affected by top dress ($P < 0.001$). These results suggest opportunity to use precision feeding to implement economically optimal ration recommendations designed to increase dairy cow production. Therefore, a second experiment was conducted in order to develop and test two algorithms that targeted individualized feeding to increase feed efficiency. Milk protein percentage ($P = 0.008$) and feed efficiency ($P < 0.001$) were significantly affected by a 3-way interaction between top dress, algorithm, and week. These results highlight the opportunity for precision feeding to increase the efficiency of individual dairy cows. Although the control group resulted in greater income over feed costs than either of the developed algorithm

feeding strategies, algorithm refinement and modification may result in more efficient feeding recommendations that are economically viable.

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GENERAL AUDIENCE ABSTRACT

Nutritional management of cattle is crucial to the dairy industry. The feeding of dairy cattle is the largest expense for producers and directly influences cow production. In particular, precision feeding of dairy cattle may have the ability to lower costs for farmers and increase the productivity of dairy cows. Currently, cattle are fed in group configurations, where cows with similar nutrient requirements are offered the same diet. However, individually feeding dairy cows utilizing precision technologies may have the ability to increase the production performance of cattle. Utilizing precision feeding to individually feed dairy cattle requires automated feeding systems (AFS) designed to decrease the additional labor associated with feeding animals as individuals. However, algorithms designed to predict individual animal nutrient requirements are lacking for use in AFS. As a result, large data sets of individual cow responses to varying diets are necessary to train algorithms designed to predict unique ration formulations for individual animals. Two experiments were developed to collect individual animal production responses that were used to develop two response-based algorithms capable of influencing feed efficiency of individual cows. The results from these experiments highlight the potential for precision feeding of dairy cattle to influence individual animal feed efficiencies and milk production. Future improvements in algorithm development and training are necessary in order for these feeding strategies to be economically worth the investment of AFS on commercial dairy farms.

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CHAPTER 1: INTRODUCTION

Nutritional management of cattle is of crucial importance to the dairy industry. The feeding of dairy cattle is the largest expense for producers and influences the production of dairy cows. Lowering costs associated with feeding cattle and improving the production performance of cows on-farm is of interest to help advance the dairy industry. Currently, most cattle are fed as groups of similar animals that are offered the same ration. However, individualized precision feeding may result in increased feed efficiencies of individual animals and decreased feed costs on-farm. However, many challenges have slowed the adoption of on-farm precision feeding in the dairy industry.

Individualized feeding of dairy cattle drastically increases on-farm labor if automated systems to handle the physical feeding and data integration are not implemented. However, these tangible and technological systems present significant initial investments for farmers. Precision technologies that are automated to reduce on-farm labor must also be compatible with current housing configurations for cattle on individual farms. The type and amount of feed that can be delivered through automated feeding systems (AFS) also differ and are evaluated in Chapter 2. Automated feeding systems inclusive of precision technologies consist of many options and implementing these systems on-farm will depend on the housing configurations and goals of specific dairy operations.

In order for AFS to individually feed dairy cattle on-farm, predictions of ration recommendations for specific animals are needed. The models necessary to derive individual animal feed recommendations must be based on individual production responses of dairy cattle. However, minimal data sets consisting of individual animal responses to various feedstuffs currently exist. Chapter 3 details an experiment focused on obtaining individual animal responses from cattle fed four top dress treatment options that were added to a total mixed ration (TMR). The base TMR was fed to all cows and only a supplemental top dress was used in an attempt to recognize individual animal differences. Precision feeding only a portion of an animal's daily ration, in the form of a supplement, is likely the most effective feeding intervention when treating cattle as individual animals. Feeding entire dietary rations through automated systems would likely result in mechanical issues with feed delivery, increased eating time for cows in individual feeding stations, and greater initial investments to install larger feeding systems.

After individual animal responses have been recorded, models must be developed in order to analyze individual animal differences to various feedstuffs and make predictions for precision ration formulation. Previous research on the effectiveness of models designed to individually feed dairy cattle is limited due to the lack of individual animal response data. Chapter 4 explores the development of two algorithms aimed at maximizing individual animal feed efficiencies. The algorithms developed were based on the individual production performance data obtained in Chapter 3. Precision feeding models must be response-based and able to update in real-time to make improved ration recommendations on a short-term basis. These models should also include various outputs depending on the interests of specific producers.

The current work focuses on reviewing multiple types and uses of physical precision technologies designed to automatically feed dairy cattle (Chapter 2). The results from previous research studies utilizing AFS are discussed (Chapter 2). The basis for analytical model development and information storage and integration is also considered (Chapter 2). An experiment designed to collect individual animal production responses and to characterize these differences is then reported (Chapter 3). Finally, a second experiment focused on developing two algorithms to individually feed dairy cattle is discussed and an economic analysis of conventional dairy feeding techniques vs. individualized feeding strategies is included (Chapter 4).

CHAPTER 2: LITERATURE REVIEW: PRECISION TECHNOLOGIES FOR INDIVIDUALIZED FEEDING OF DAIRY CATTLE

This chapter will be submitted to the Journal of Dairy Science as: T. P. Price, K. M. Daniels, and R. R. White. Graduate Student Literature Review: Precision technologies for individualized feeding of dairy cattle.

Abstract

Dairy cattle feeding is an essential component of the industry due to its economic relevance and influence on cow production performance. Precision feeding of dairy cows has increased in popularity and aims to maximize cattle production and decrease farm costs. Therefore, the objective of this review is to characterize advancements, opportunities, and gaps in our existing knowledge of individualized, precision feeding. Increasing profit for dairy farms may be possible by refining current ration recommendations that are targeted for groups of animals by developing individualized feeding recommendations aimed at maximizing feed efficiency. In order for individualized feeding to be practical on-farm, automated feeding systems (AFS) are necessary to offset the increased on-farm labor associated with feeding individual animals. Multiple precision technologies are a part of AFS and are highlighted. Many existing AFS are also reviewed and their limitations are evaluated. On-farm, AFS must be compatible with the housing system(s) and the types and quantities of feed available at specific dairy operations. In order to supply AFS with the ability to make real-time feeding recommendations for individual animals, models based on individual animal responses must be developed to increase cattle productivity. Individualized models must be response-based, contain a system for individualized data storage and integration, and be capable of estimating individual animal feed intake in order to make accurate feeding predictions on-farm. Areas of future research and developments in precision feeding are also explored.

Keywords: dairy cow, automated feeding, individualized

Introduction

Dairy cattle nutritional management and feeding is a critical component of dairy operations due to its economic impacts and is important for farmers on a global scale. In 2017, the USDA estimated that total monthly feed costs, per cwt of milk sold, were $10.50 (USDA). The 2017 Census of Agriculture also reported that feed was the largest expense for dairy producers in the United States, totaling $14.9 billion, and accounting for roughly 45% of production expenses (USDA NASS Census of Agriculture). Improvements in our nutritional management strategies for feeding dairy cattle may enable reductions in feed costs for farmers and increased dairy production worldwide.

Focusing on improving productivity of cows, such as feed efficiency and milk yield (MY), may result in greater income for farmers while helping to lower feed costs. In order to improve productivity of dairy cattle from a nutritional standpoint while minimizing feed costs, it is most logical to begin with refining ration recommendations to increase feed efficiencies. Improving current feeding recommendations may have the ability to increase productivity of cattle on-farm. The 2001 National Research Council (NRC) "Nutrient Requirements of Dairy Cattle" formulates rations based on estimates that encompass dry matter intake (DMI), energy requirements and digestible energy (DE) of feeds, fat digestion and absorption, carbohydrate requirements, protein and amino acid requirements, and vitamin and mineral recommendations for feeding groups of cattle in similar life stages and with similar requirements (National Research Council, 2001). As such, the current version of the NRC makes recommendations for groups of cattle, rather than for individual animals. When feeding animals in groups on-farm, all animals are fed to the average of the group, and therefore, 50% of the animals are overfed and 50% are underfed. While this type of feeding may require less intensive labor on farms, overfed cattle are likely consuming costly feed they do not need, and underfed cattle are likely not reaching their individual production maximums or earning the maximum profit for farmers.

It has been shown that cows respond as individuals and hold unique genetic merit for many production parameters in the short-term including DMI, MY, milk fat percentage, milk fat yield, milk protein percentage, milk protein yield, feed efficiency, and activity (Chapter 3). As a result, individualized precision feeding may help to increase overall production of dairy cattle. However, precision feeding and traditional group feeding require entirely different feeding and management approaches that have been investigated, but rarely reviewed. First, automation of feeding systems is necessary to feed cows individually on-farm. The current NRC does not provide individual animal feeding recommendations, and therefore, new models for individualized feeding need to be developed in order to appropriately estimate accurate individual animal requirements that are more precise than recommendations for feeding groups of animals. These models must be based on large data sets of production responses from individual animals. However, large data sets that include individual animal production responses are scarce and additional research is needed to obtain this information for use in model development. Developed models then require on-farm testing to evaluate actual animal production performance and to establish if the models need to be modified.

Automated feeding systems (AFS) are increasing in popularity and allow for decreased labor associated with precision feeding on-farm (Wierenga and Hopster, 1991). The objective of this review is to characterize advancements, opportunities, and gaps in our existing knowledge of precision feeding. First, automated technologies that can be implemented on-farm to deliver individual rations to unique animals will be detailed. Next, model development to predict individual cow feed requirements will be discussed. Lastly, gaps in our current knowledge of precision feeding of dairy cattle and areas of future research will be explored.

Automated Precision Technologies for Individualized Feeding

Automated feeding systems include many precision technologies in order to feed dairy cattle as individuals. Because there is a wide range of AFS, they should be compared in terms of several important practical considerations. These considerations include compatibility with housing systems, quantity of feed handled daily, number of animals fed per unit, and types of feedstuffs that can be handled by the AFS. These practical limitations of AFS dictate usability, expected on-farm productivity responses, and likely return on investment.

Suitability of an AFS is dictated largely by housing system. There are multiple housing styles that can make up dairy operations, and single farms often incorporate multiple housing styles. Housing styles include individual housing (e.g., sick pens, tie stalls, etc.), indoor group housing (e.g., bedded packs, free stalls, etc.), and outdoor group housing (e.g., pastures, dry lots, etc.), among others (Bewley et al., 2017). Each of these housing styles differ in terms of their requirements for AFS. For example, in free stall systems, an AFS must allow individualized feeding within a group pen. This requires the AFS to identify individual animals (typically based on RFID technology) (Trevarthen and Michael, 2008; Singh et al., 2014), exclude access to the feeder to allow only the targeted individual to consume feed, dispense a custom amount and type of feedstuff(s), and clear any unconsumed refusals. For AFS in outdoor settings, the system might additionally be required to resist extreme weather conditions and stand-alone from other farm resources (e.g., grain hoppers, silos, etc.).

Different AFS are also defined by their daily feed handling capacity and suitability for different feed types. In previous studies, AFS have been used to feed the concentrate component of a ration (Wierenga and Hopster, 1991) or to feed an entire ration (Belle et al., 2012). In most systems feeding only a portion of the total ration, the AFS is self-contained and includes a feed storage area. For AFS designed to feed the entire or majority of a ration, they are either connected to the existing feed storage and mixing infrastructure on farms (e.g., stationary mixers, rail-mounted feed wagons, feed bunkers, silos, etc.) (Oberschätzl-Kopp et al., 2016) or require manual loading of a pre-mixed ration daily. Automated feeding systems that require manual loading of feed daily have higher labor requirements, but are also more flexible in terms of the types of feedstuffs that can be fed. For example, Oberschätzl-Kopp et al. (2016) used a rail-guided wagon as the basis of an AFS to feed group housed cattle and was able to feed a partially mixed ration (PMR) through the system. Collectively, the housing system suitability, feed handling capacity, and type of feedstuffs capable of being delivered by an AFS dictate the number of cows that can be fed by each unit per d. Although this seems trivial, the number of units needed to feed a group of animals, the amount of feed fed through the units, and the resultant changes in productivity are the major drivers that determine whether the system will prove profitable. As seen with the adoption of robotic milking systems, we can expect that the base price of labor and the expected annual inflation of labor costs will also have a major impact on whether adopting an AFS is a profitable decision (Pezzuolo et al., 2016). Because of the major differences in the possible applications of AFS and their net result on farm management and cow productivity, systems designed for feeding different types and amounts of feed should be considered separately because of their very different objectives.

General Precision Technologies that make up AFS

It is estimated that feeding in a conventional group system accounts for approximately 25% of total, on-farm labor expenses daily (Grothmann et al., 2010). There are many types of automated feed delivery technologies, including rail-guided wagons, conveyor belts, and self-propelled robots (Grothmann et al., 2010). Comparisons between these automated feed delivery technologies are detailed in Figure 0-1. Although discussed as separate systems, these different technologies can be used together within AFS to provide the most suitable combination of individual technology attributes to enhance system efficiency. For example, a robot could be used to load rail-guided wagons or conveyor belts. Similarly, a conveyor belt can be used to load wagons or a robotic feeder. Due to the individual nature of farm design and feeding system requirements, considering these technologies as possible parts of a larger AFS is likely appropriate.

In addition to functioning to deliver feed, AFS can also be used to limit the amount of feed an animal can consume (Wierenga and Hopster, 1991) and can be designed to provide more frequent deliveries of feedstuffs than conventional, manual methods (Belle et al., 2012). These changes in feed delivery frequency and quantity may benefit farm profitability. In a survey carried out on 18 farms in Switzerland, Germany, Denmark, and the Netherlands in 2008, farms with AFS dispensed fresh feed 7.2 times per d, on average, and fed up to 10 different dietary components (Grothmann et al., 2010). Increasing the feeding frequency for dairy cattle is known to increase DMI, milk production, and milk components (Campbell and Merilan, 1961). Farm managers also stated that animals fed by AFS seemed less stressed due to more frequent feedings and lower-ranked cows were able to consume more feed (Grothmann et al., 2010). From these survey results and other assessments of AFS, it is clear that appropriately applied AFS have the potential to individually feed animals on commercial farms to enable more individualized ration formulation, to improve the health and well-being of cattle, and to decrease labor associated with feeding. To better evaluate the evidence for each of these claims, AFS will be discussed based on their intended purpose.

Automated Concentrate Distributors for Individual Cows in Group Housing

Automated concentrate feeding stations can be utilized to feed individual cows in group housing configurations. These feeding systems are especially useful for supplementing a specific amount of concentrate to individual cows that are all fed a standard total mixed ration (TMR) as a group. For example, the Lely Cosmix (Lely; Maassluis, The Netherlands) is available to producers and ensures each cow receives a specified amount of concentrates daily, especially if some cows do not consume all of their concentrates in an automatic milking system (AMS). Automated concentrate feeding systems generally consist of a few feeding stalls in a group pen, like the Lely Cosmix or a milking parlor (or robot), equipped to feed small quantities of concentrates during milking. These feeding stations, whether in the home pen or the parlor, are equipped with technology (e.g., RFID, Bluetooth, etc.) able to recognize and identify when an individual enters the feeding stall. The feeding system then dispenses a pre-calculated amount of concentrate feed based on the cow's individual, daily allotment.

A major consideration for the use of individual concentrate feeding systems is how much concentrate to allocate to each individual. Various feeding strategies are utilized on-farm that differ in the amount of concentrates fed to specific animals and when these feeds are delivered (Wierenga and Hopster, 1991). Feeding smaller, but more frequent, concentrates have been shown to positively affect productivity of cows through increased DMI, MY, and milk components (Shabi et al., 1999). In a study performed by D'incà et al. (2017), offering concentrate feeds through an automated feeder to a group of dairy cattle fed a TMR resulted in higher intakes and shorter rumination periods. This precision feeding strategy also resulted in higher MY, but lower milk fat percentage, and depressed total tract neutral detergent fiber digestibility (D’incà et al., 2017). Automated concentrate distributor systems have also been shown to reduce the lying time of many cows due to the small number of physical feeding stations available (Wierenga and Hopster, 1991). Low-ranking cows, in particular, often have to stand and wait long periods of time before they are able to access the feeding stations (Wierenga and Hopster, 1991). Therefore, competition at the feeding stations may negatively influence animal welfare, and more research needs to be conducted to determine the appropriate stocking density of cattle to concentrate feeding stations.

Automated Forage Distributors for Individual Cows in Group Housing

Automated forage distributors are similar to automated concentrate distributors, but are capable of handling larger feedstuffs. However, only limited research utilizing automated forage feeders exists. Additionally, there are no known commercial, automated forage feeder technologies available. Forage feedstuffs require larger precision technologies (e.g., rail-guided wagons, conveyor belts, robots, etc.) to transport these materials that are often more expensive to install on-farm. Ipema et al. (1988) conducted a study of an automated forage distributor that was capable of dispensing two feed ingredients or a mixture of feedstuffs into eight feeding stations designed to individually feed a group of 20 cows ad libitum. Conveyor belts weighed and transported individual feedstuffs to a rail-mounted wagon (Figure 0-1) responsible for transporting the custom feed to a particular feed bunk that a cow had accessed (Ipema et al., 1988). Dairy cattle fed through this automated forage feeding system had higher feed intakes that resulted in greater MY, milk fat, and milk protein yields than cows fed by a conventional feeding system (Ipema et al., 1988). However, it was also found that only five cows could be fed by a single feeding station due to the long feeding times of cattle each day (Mihina et al., 1992). As a result, individualized feeding of forage is successful in increasing dairy cow performance, but a large number of feeding stations and greater maintenance requirements may be necessary due to the more robust technologies required to handle the larger feed volume of forages.

Automated TMR Distributors for Cattle in Group Housing

Feeding TMR to dairy cattle has become increasingly popular due to the ability to provide feed to cattle that is complete and nutritionally balanced (Schingoethe, 2017). Automated TMR feeding stations in group housing is an efficient way to deliver TMR to groups of cattle with reduced, on-farm labor and more frequent feedings (Belle et al., 2012). For example, the DairyFeed C 8000 (GEA Innovations; Columbia, MD) is available commercially and is designed to handle feedstuffs of any consistency and rations of any size. Commercially available AFS, similar to the DairyFeed C 8000, would be practical investments for large farms looking to feed entire rations to cows individually. Typically, conventional feeding systems deliver TMR to cows only once or twice each day and require significant time contributions from farm workers (Pezzuolo et al., 2016). More frequent feedings of TMR by automated systems have been shown to decrease feed sorting and improve access to feed for all cows in a herd (DeVries et al., 2005). Increased feeding frequencies have also shown increases in cow visits to feeding stations (Oostra et al., 2005) and greater consumption of feed throughout the day (Mäntysaari et al., 2006). However, this change in feeding pattern also results in increased restlessness and decreased lying behavior of cattle (Mäntysaari et al., 2006). Ideally, the welfare and comfort of cattle would not be affected by feeding strategy and biological consequences may occur if rest requirements are not met, as lying helps to stimulate rumination and prevent ruminal acidosis (Temple et al., 2016).

In addition to animal productivity benefits, automated TMR systems have been shown to reduce the cost of TMR preparation and distribution (Pezzuolo et al., 2016). Energy costs for daily feeding are lower for farms utilizing an AFS compared to operating a conventional mixing wagon (Oberschätzl et al., 2015). Automated TMR feeding systems show promise to feed groups of cows in an efficient manner, while decreasing costs for farmers and offering more frequent delivery of feedstuffs. However, utilizing completely automated TMR distributors to feed individual animals may not be practical on-farm, because automated systems are likely unable to dispense such large quantities of feedstuffs in individual bunks. Individualized, custom supplements may be a more practical use of individualized, AFS. Although, recent advancements in precision technology, such as the DairyFeed C 8000, may be more capable of handling the types of feedstuffs and quantities of total rations.

Automated Feeding Systems as a part of Automatic Milking Systems

Automated feeding systems are commonly associated with AMS. Cattle utilizing an automated feeding and milking system need to access the feed bunks and automatic milker without assistance from farmers (Devir et al., 1996). Therefore, feeding systems are a crucial part of AMS because they provide incentives to motivate cows to move around the milking area (Kerrisk, 2009). Automated concentrate feeders are often offered in automatic milking stalls to help entice cows to access the automatic milker, such as seen in the commercially available Pearson In Parlor Feed System (Pearson International LLC; Athy County Kildare, Ireland) and Lely Astronaut (Lely; Maassluis, The Netherlands). These feeders are typically designed to recognize cow identification and programmed to offer specific concentrate types and quantities depending on an animal’s daily recommendation for concentrates, as seen with the GEA DairyRobot R9500 Robotic Milking System (GEA Innovations; Columbia, MD). However, the feeding area outside the milking stalls of these integrated systems can also be utilized to feed the majority of the cows’ ration automatically, in the form of forage or TMR, in order to reduce on-farm labor (Kerrisk, 2009). Automated milk data can also be utilized in real-time and in conjunction with feed intake data to make quick and frequent management decisions that enable maximum cow performance (Devir et al., 1996). This type of individualized cow data can be used to manage dairy operations at the individual cow level in order to enhance productivity of outputs of interest, such as feed efficiency, MY, and specific milk components.

One problem with automated concentrate feeding in AMS is the varying amounts of concentrates a cow can consume while in the milking station. Inconsistent milking frequencies and differences in the speed of milking affect the amount of time a cow spends in the milking station each day (Kerrisk, 2009). Increasing the amount of concentrates fed to cattle increases energy intake, and therefore, increases MY (Lawrence et al., 2015). However, if cows do not access or spend enough time in the automatic milker daily, they will under-consume their allotment of concentrates and productivity will be sacrificed. Therefore, feeding concentrates in AMS alone may be inefficient and automated feeders outside of the milking stall may be necessary for cows to access any concentrate feeds they were unable to consume in the milking station (Kerrisk, 2009). In a study by Melin et al. (2005) that focused on individual cow feeding responses in two-cow traffic situations in AMS, milking frequency had significant effects on feeding patterns. Therefore, cows with different milking frequencies require different feeding strategies to ensure their nutritional requirements are met daily; feeding all cows in a group the same is not the most logical way to enhance herd production. Perhaps more importantly, the random variation in feeding patterns between the cows in this study was caused by individual differences between animals (Melin et al., 2005). Therefore, managing cows on an individual basis has potential for making better nutritional predictions to influence individual production parameters. Individual cows elicit different responses when encountering the same situation, and therefore, management decisions made on a group level, rather than on an individual basis, are inefficient. Automatic milking systems allow cows to be fed automatically and individually, and therefore, individual feeding rates and type of feed to best improve production need to be determined. Research has shown that individual cows hold unique genetic merit and respond differently to a variety of supplemental feeds (Chapter 3). This type of feeding requires new model development and training from large data sets of individual cow responses that are limited ("Model Development to Predict Individualized Feed Requirements" section below).

Individualized, Concentrate Supplementation for Pasture-Based Dairy Cows

Global interest for grazing dairy cattle on pasture has increased due to the decrease in cost of milk production associated with greater utilization of pasture as a major feed source (Dillon et al., 2008). However, seasonal and locational differences in pasture availability and varying nutrient content of pastures result in the need for additional feed sources to supplement dairy cow diets (Chapman et al., 2014). Supplementing pasture-based cows with concentrate feedstuffs is a common management practice to overcome low or poor quality pasture supplies (Holmes and Roche, 2007). Similar to concentrate feeders for cattle in indoor housing (discussed above), concentrate feeders for cows consuming pasture may be automated to feed a specific amount of concentrates to a group of cattle or individualized to supplement specific animals with varying amounts and types of feedstuffs. Individualized concentrate feeders would also be automated and able to record daily intake of individual animals. Supplementing individual cows on pasture with concentrate feeds has been shown to increase DMI and MY of individual animals (Hills et al., 2015). Hills et al. (2015) exemplifies the improvement individualized feeding can have on many production parameters on-farm. A study carried out by Garcia et al. in 2007 revealed that feeding concentrates to grazing cows based on individual cow requirements, rather than fixed-rate allocation of concentrates to the entire herd, showed a 2.9% increase in MY, an 11.1% increase in milk fat yield, and a 7.0% increase in milk solids (García et al., 2007). It has been shown that variation in intake among individual animals is high when cows are fed in group configurations on a restricted basis, such as low pasture availability, and that high producing cows increase their consumption of the least restricted feed, such as a supplemental concentrate, in order to compensate for their higher nutrient requirements (García et al., 2000; García and Holmes, 2005). Therefore, on-farm labor and cattle productivity may be optimized by feeding concentrates to herds on pasture at an individual level, rather than feeding to the average of the herd on a group basis. Like other automated systems, individual intake results can be combined with daily milk data in order to make specific and individualized nutritional interventions in real-time.

Model Development to Predict Individualized Feed Requirements

With multiple precision feeding technologies available for use in AFS for almost any housing configuration on-farm, relevant automated feeding algorithms are needed to increase feed efficiencies of individual cows to ensure investment in the infrastructure is worthwhile. Specifically, precision feeding systems need to positively influence output productivity, while not affecting the metabolic health of cattle. For example, Pino et al. (2018) fed eight Holstein heifers either isoenergetic precision diets or traditional ad-libitum diets. Rumen pH was lower for cows fed ad-libitum and ad-libitum diets also resulted in faster rates of passage, increased digestion rates, and shorter retention time in the rumen. However, precision feeding showed improved feed efficiency compared to ad-libitum feeding strategies (Pino et al., 2018). These results highlight the need for improvements in precision ration formulation to continue to improve feed efficiency, while not altering feed passage and digestion rates.

In order to make individualized, precision feeding economically worthwhile for farmers globally, the increases in cow productivity need to be significant. Maximum cow productivity from a nutritional management standpoint requires accurate, predicted requirements that are specific to each animal and her responses. Algorithms designed to make these nutritional predictions will likely require automated sensing of other parameters related to performance to be effective. Fortunately, many farms currently collect various forms of data on their herd including body weight (BW), MY, milk components, and activity. Leveraging this automatically collected and recorded data may facilitate development of more accurate models. However, this information is rarely utilized in the short-term to make better nutritional management decisions to influence individual animal productivity. In order to adjust and fine-tune current nutritional requirements for dairy cattle to an individual basis, new models need to be created that are trained by large sets of individual cow data and responses.

Existing models used for formulating rations for dairy cattle are ill equipped for use with precision ration formulation. Existing models, like the NRC, use animal type, physiological status, BW, body condition, environmental and management descriptions, DMI, and energy and nutrient supply from rations as inputs (National Research Council, 2001). These models were derived from data based on averages from groups of animals. They predict energy, nutrient, vitamin, and mineral requirements associated with the targeted (inputted) levels of production (National Research Council, 2001). In order to be used more efficiently within precision ration formulation systems, models need to be based on individual animal data to account for animal differences and should seek to predict responses, rather than requirements. Precision models should include specific inputs from each animal, such as individual animal DMI, production performance, and activity. These precision models have the opportunity to inform management to optimize productivity by accounting for individual animal inputs.

In addition to these differences from existing models, models for individualized feeding of dairy cattle should contain several consistent characteristics, regardless of the AFS implemented on-farm. These characteristics include training of individual models with specific animals to achieve response-based models, individual animal on-farm data storage and integration, and estimating the DMI of individual animals for AFS that do not record refusals of entire rations. Each of these attributes are discussed below.

Analytical Development of Response-Based Models

One major limitation of nutrient requirement systems, such as the NRC, is their focus on predicting required amounts of nutrients needed to achieve a given level of performance. Maximizing production is often different than optimizing production efficiency (Liebe and White, 2019). Experimental designs in research facilitate evaluation of how a group of animals responds to dietary intervention, not how individual animals respond (Liebe and White, 2019). For example, the linear and logit models utilized by Liebe and White (2019) could make predictions for various management decisions for a group of animals, but could not account for differences between animals. As discussed previously, individual cows offer unique responses (Chapter 3). As a result, response-based nutrition models are needed to enhance dairy feeding, but most current response data is focused on groups of cattle, rather than individual animals (Liebe and White, 2019). For research to attempt development of response-based models, large data sets of individual cow production responses are necessary. Research will then be needed to test how different model development approaches can be used to obtain effective feeding recommendations, given a targeted level of performance. A large part of producing efficient models will require referencing stored data on individual animals in order to make the most informed feeding recommendations in real-time.

Individual Animal Data Storage and Integration

To combine all of the individualized data that precision technology has to offer to make better, real-time nutritional decisions, computerized information systems are needed to store and analyze this data on-farm. These information systems will also be necessary on-farm when developing unique models after on-site training periods are employed. These systems are designed to automate the interpretation of various forms of information and assist farmers in complex decision-making (Pietersma et al., 1998). The automation of predicting what to feed individual animals in real-time will enable AFS to operate more effectively with precise recommendations. Accessible storage of heterogeneous forms of data on-farm is crucial for data integration and precision feeding predictions (Schuetz et al., 2018). These computerized systems manage and control activities that are part of a cycle consisting of decision-making, implementation, and assessment where decisions are made, an action occurs, and performance feedback is considered (Pietersma et al., 1998). This feedback system will enable response-based models to self-update and continue to improve the recommended requirements for individual cows on a daily basis. However, AFS need to ensure diet recommendations and feeding are within acceptable nutrient limits to protect against negative, long-term health effects. Therefore, the feedback segment of AFS should be confined by upper and lower limits for individual feedstuffs to ensure proper forage to concentrate ratios are sustained. The development of automated, computerized systems to handle this data for farmers will simplify and improve nutritional management decisions on-farm.

More advanced models need to be developed to accurately predict nutrient requirements for individual dairy cows. However, most of the data available to base these models come from publications that report average response data from groups of animals. As a result, collections of individual animal data sets need to be reported in order to enable derivation of more appropriate models that focus on precision feeding of individual animals. Therefore, a major reason for the limited, individual precision models is caused by the lack of individual animal data sets.

Estimating DMI of Individual Animals

Feed intake of individual animals needs to be predicted because most feeding systems on-farm are not capable of recording refusal values or do not feed and measure the total intake of an animal's diet. Accurately predicting voluntary feed intake of dairy cattle is crucial to accurate formulation of rations (Halachmi et al., 2004). Dry matter intake is also an integral part of calculating feed efficiency and for informing AFS on what individual animals should be offered at any given time (Halachmi et al., 2004). If total DMI is not recorded by AFS, modeling can be used in order to predict DMI of individual animals. However, AFS equipped with the ability to record offered feed and feed refusals offer more precise intake results for individual animals.

Actual feed intake of individual cows in commercial operations is often unknown because individualized AFS capable of recording this information are rarely implemented on commercial farms to feed entire rations (Kamphuis et al., 2017). Van der Waaij et al. (2016) predicted individual cow intake utilizing a test data set driven by machine learning. Derivation data was used to train an artificial neural network that was based on biological neural networks efficient for use with highly dimensional and nonlinear relationships (Van der Waaij et al., 2016). These networks are used as universal function approximators, but they require large amounts of data to train these settings since no pre-assumptions are made. The developed model was able to predict individual cow intake with precision of 7.7% based on cow number, concentrate, MY, parity, weight, rumination, lactation day, fat percent, protein percent, outdoor temperature, and outdoor humidity (Van der Waaij et al., 2016). This model was useful in determining intake of specific cows on-farm when individual intake was not recorded by AFS. After training this model with a test database, it may be able to be applied to new cows to accurately predict their feed intakes.

In another study by Kamphuis et al. (2017), three modeling approaches were assessed on their ability to predict feed intake of individual cows. The first model applied an existing formula to estimate energy requirement utilizing parity, BW, fat corrected milk, and protein corrected milk and assumed this requirement to be equal to energy intake (Kamphuis et al., 2017). The second model utilized mixed linear regression and contained the same variables as the first model, with and without weather data. The third model applied a machine learning technique of boosted regression tree, with the same variable utilized in the above models, with and without weather data (Kamphuis et al., 2017). Boosted regression tree is a nonlinear predictive method that segments the predictor space using binary splits into smaller regions that contain similar training observations (Kamphuis et al., 2017). After validation between estimated and actual feed intakes, the second model had very high correlations (0.91) between actual and estimated intakes (Kamphuis et al., 2017). Model one had a much lower correlation (0.46) and the third model had an intermediate correlation (0.73) (Kamphuis et al., 2017). However, when validated with new, independent data, the accuracy of all three models decreased. More modern, boosted regression tree models were associated with lower correlations, but proved to be more robust to sets of data that were independent from the training data. Therefore, boosted regression tree models may be especially valuable in commercial dairy farms due to their ability to deal with incomplete data sets (Kamphuis et al., 2017).

In general, nonlinear models seem to be the best predictors of individual cow DMI. Utilizing machine learning to train precision models capable of predicting DMI shows promise when multiple, individual animal parameters are assigned as inputs. Boosted regression tree models also allow for errors or missing values from data sets that are likely to occur on-farm. Accurate DMI predictions are needed for precision ration formulation and feed efficiency calculations. However, additional research in this area is needed to better understand how durable these types of models are across cattle with varying characteristics.

The Gap in Knowledge

Precision feeding of dairy cattle through automated systems shows promise to increase feed efficiency and MY of individual animals, while decreasing on-farm labor and feed expenses. However, the models needed to drive these systems have not been created and perfected. Data on individual animal responses to dietary interventions are needed to develop and test appropriate models that best predict the nutrient requirements of individual animals and recommend the most ideal diet composition and quantity for specific cows.

Precision models designed to individually feed dairy cattle should be derived to accommodate current AFS utilized in research scenarios and on precision farms that integrate AFS software. Data warehouses and computerized systems will be crucial in order to house future feed prediction models, individual animal responses from AFS, and sensor-based data also collected on farms. These systems will need to be capable of integrating all forms of this information, on an individual animal basis, in order to make the most accurate predictions possible in real-time. Improving the automated control systems for technological processes of feeding, milking, and service based on precision technologies is the key to precision advancement in dairy farming (Shevchenko et al., 2013).

Future research should focus on recording individualized feeding and response data from many cows and using this data to test various model forms on output responses of individual animals. After successful models have been established to predict diet recommendations for individual cows, these feeding strategies should be tested through AFS to determine the ease of daily feeding on commercial farms. Finally, these models should be modified to be compatible with the various AFS options available to producers.

Conclusions

Individually feeding dairy cattle through precision technologies has the ability to increase profit for producers and lower feed costs on-farm. In order to increase the production performance of individual dairy cows, individualized feeding of custom rations aimed at maximizing feed efficiency is worth investigating. However, models designed to make individualized feeding recommendations need to be developed and implemented in AFS in order to reduce labor requirements on-farm. Research obtaining large data sets on individual cow responses is needed to develop these precision models. Precision feeding has the ability to influence many aspects of the dairy industry, as a whole.

Acknowledgments

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Figures

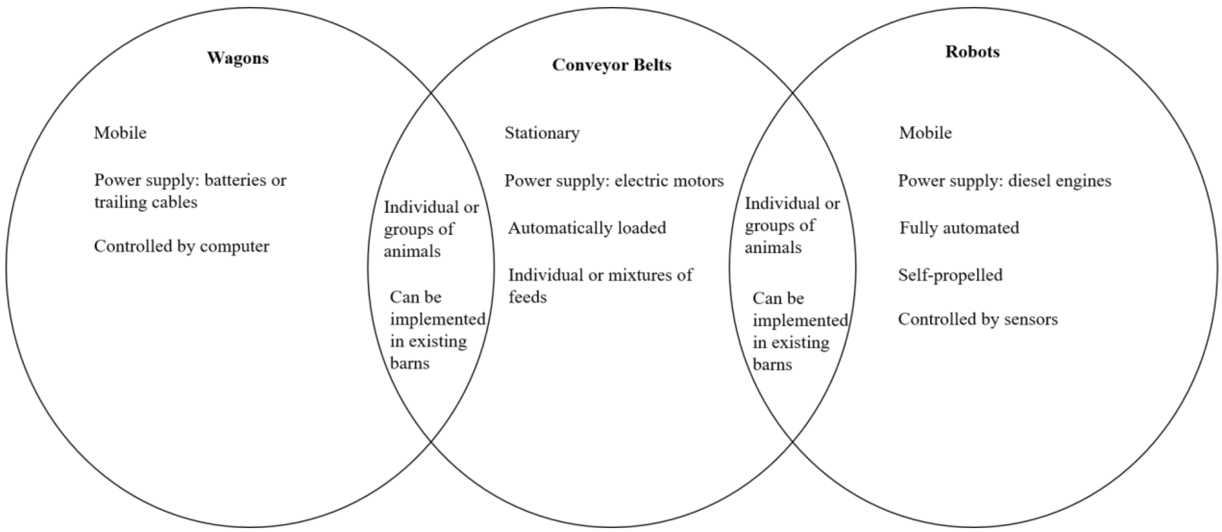

Figure 0-1. Comparisons of precision technologies powering individualized feeding.

CHAPTER 3: SHORT-TERM ADAPTATION OF DAIRY CATTLE PRODUCTION PARAMETERS TO INDIVIDUALIZED CHANGES IN DIETARY TOP DRESS

This chapter will be submitted to the Journal of Dairy Science as: T. P. Price, D. M. Liebe, K. M. Daniels, and R. R. White. Short-term adaptation of dairy cattle production parameters to individualized changes in dietary top dress.

Abstract

Automated feeding is of primary interest to support individualized, precision dairy production and to increase feed efficiency of dairy cattle. Automated feeding systems (AFS) are unique because they target individual animals and can deliver interventions on a rapid time-scale. Because such systems focus on individual animals and more immediate intervention/response intervals than traditional feeding practices, new datasets of individual cow responses to dietary interventions are likely needed to develop algorithms to supplement decision-making for AFS. The objective of this study was to determine immediate and short-term effects of changes in diet composition on production parameters of dairy cattle fed varying amounts of supplemental top dresses. A 4 x 4 replicated Latin square was used to evaluate the responses of 24 Holstein cows fed either no top dress (TMR Only) or increasing amounts of: corn grain (CG), soybean meal (SBM), or chopped mixed grass hay (GH) top dressed on a total mixed ration (TMR) over four 9-d periods. Throughout each period, treatment diets were top dressed at incrementally increasing rates to provide 0% to 20% of calculated net energy of lactation (NEL) intake of the ration to be supplied by the top dress. Production performance responses for dry matter intake (DMI), milk yield (MY), milk fat percentage and yield, milk protein percentage and yield, feed efficiency, and activity to top dress intake were analyzed for each 9-d period. All variables were analyzed using a mixed-effect model and two different time ranges were analyzed separately. Samples collected from d3 and 4 and from d7 and 8 of each period were averaged and used to reflect "immediate" vs "short-term" responses to top dress. Immediate and short-term DMI ($P < 0.001$), MY ($P < 0.001$), milk fat yield ($P < 0.001$), milk protein yield ($P < 0.001$), feed efficiency ($P < 0.001$; $P = 0.026$) and cow activity ($P = 0.021$; $P < 0.001$) were significantly affected by top dress. Short-term milk fat percentage was significantly affected by top dress ($P = 0.004$), but treatment differences were not detected in the immediate response time-frame (P = 0.239). These results suggest opportunity to use individualized feeding strategies to adjust dietary composition in the short-term to target economically optimal formulations without sacrificing production or to increase production performance of individual animals. However, more data sets need to be generated to reach this goal.

Keywords: short-term, precision feeding, individualized

Introduction

Precision dairy feeding systems may have the ability to maximize individual cow feed efficiency and milk yield (MY) while decreasing labor expenses. Precision feeding systems may be automated for efficiency of on-farm labor and individualized in order to feed each cow a unique supplement. This approach to individualized feeding has the opportunity to maximize each cow's feed efficiency, MY, and milk components of interest based on the unique genetic merit of individual animals. Also, many dairy farmers currently collect multiple forms of data on their individual cows daily (Borchers and Bewley, 2015). However, these data are rarely compiled and utilized to make real-time improvements in individual cow performance. The various information many dairy farmers already collect could be utilized in advanced algorithms, as part of a precision feeding system, to maximize feed efficiency and production. Through automated, individualized, and data-based feeding approaches, precision feeding technologies may allow greater opportunity to more precisely and more automatically tailor dietary supplements to individual animals. However, we lack data to quantify this potential benefit and to define appropriate and necessary decision-making algorithms.

The transition to precision nutritional management is slow and there is limited expansion of automated and individualized dairy cow feeding technologies. The slow introduction of precision technologies to commercial dairy farms may be influenced by many factors (Russell and Bewley, 2013). Automated feeding systems (AFS) are costly and require time and labor to install on-farm. Additionally, each cow on the dairy operation must be trained to operate the new system. These training periods require increases in time and labor for farmers and may potentially sacrifice milk production while the cows become accustomed to the system. Dairy farmers also feel that the increases in milk production or feed efficiency from precision systems may not outweigh the initial investment costs (Russell and Bewley, 2013). In addition to these challenges, and perhaps most importantly, developing accurate dairy precision feeding systems is a slow process due to the lack of available data on individual dairy cows that is necessary to inform algorithms about what types of feeding strategies should be implemented when using automated feeders for individual animals. However, if collections of data are generated and integrated, and appropriate algorithms are derived from these data, increases in feed efficiencies and MY may provide additional profit for farmers. Favorable outcomes may outweigh initial investment costs and labor expenses associated with automated feeding technologies.

Automated feeding systems may have difficulty handling and dispensing large quantities of feed in the form of a total mixed ration (TMR). Therefore, feeding only a small portion of the diet by an automated system in the form of a supplement is likely the most cost effective and efficient method of automated feeding for dairy cattle operations. This is effectively the same approach that in-parlor feeding systems and automatic milking systems (AMS) utilize, but these systems do not generally supplement feeds to cater to animals' unique nutrient requirements. Instead, most existing in-parlor feeding systems and AMS feed cows a common concentrate as part of a partially mixed ration (PMR), as opposed to a TMR. In PMR feeding systems, palatable concentrates are fed separately from forages that are typically fed out of feed bunks. Concentrates, on the other hand, are either fed in the milking parlor, in the AMS, or at some other designated location besides the forage feed bunk.

Provision of individualized concentrate supplementation raises questions such as: what should the supplement composition consist of, and when, if at all, should the supplement composition or quantity of supplement offered be changed? Allen (2000) summarized that specific physical and chemical characteristics of diets can affect dry matter intake (DMI) in the short-term and discussed dietary ingredients that are appropriate for diet formulation. Al-Suwaiegh et al. (2002) reported that corn and sorghum distillers' grains fed at 15% of a TMR (DM basis), had no effect on DMI or efficiency of milk production. However, these research studies, like the majority of the current literature, are not focused on individual animals or the unique differences between animals in order to maximize feed efficiency.

Determination of individualized concentrate composition to precisely match nutrient requirements and maximize feed efficiency poses challenges. For instance, it is currently unknown what to include in the concentrate, how much concentrate to feed, and how frequently concentrate composition and/or quantity must be adjusted to maximize individual cow feed efficiency. Therefore, new types of experimentation and data collection are required to enable development of decision support tools and automated feeding algorithms. The objective of this experiment was to determine immediate and short-term responses of changes in diet composition on feed efficiency, MY, and milk components in dairy cattle fed increasing amounts of supplemental top dresses. Individualized cow data that are collected from this experiment can then be used to derive automated, individualized feeding algorithms in an attempt to assign unique top dress types and quantities to cows that will maximize their specific production parameters.

Materials and Methods

Animals, Housing, and Diets

All procedures involving animals were approved by the Institutional Animal Care and Use Committee of Virginia Tech (protocol # 18-002). This experiment was conducted from February 4th, 2019 to March 26th, 2019 (inclusive of the adaptation and experimental periods).

Twenty-four Holstein dairy cows (12 primiparous and 12 multiparous; 597 ± 59 kg of body weight (BW); and 204 ± 23 days in milk (DIM) at the beginning of the experiment) were randomly assigned to one of four treatment groups in a replicated 4 x 4 Latin square design (Figure 1-1). Cows were housed in a 24-stall pen within a free stall barn and fed once daily (1300 h) using a Calan gate system (American Calan Inc.; Northwood, NH). Cows were allowed a 14-d adaptation period before beginning the experiment wherein they were trained to locate their assigned Calan door; this period also allowed ample time for social group reconstruction (von Keyserlingk et al., 2008). In later sections, data collected from each cow during this period will be referred to as "initial performance". A 36-d experimental period followed the adaptation period and consisted of four 9-d treatment periods. During each period, cows were assigned to one of four top dress treatments: corn grain (CG), soybean meal (SBM), chopped mixed grass hay (GH), or no top dress (TMR Only). Figure 1-1 details the overall experimental design of this study. A common TMR was fed as the base for all diets which, on a dry-matter basis, was composed mainly of corn silage, corn grain, brewers grain, and soybean hulls (Table 1-1). The formulated composition of the common TMR fed to all treatment groups is detailed in Table 1-1. The quantity of material top dressed daily varied across each 9-d period and is summarized in Table 1-2. On d0, 1, and 2 of each period, top dress was gradually increased in quantity to target providing 0%, 5%, and 10% of each cow's predicted dietary net energy of lactation (NEL) intake, respectively. On d3 and 4, top dress quantity was targeted to provide 10% of each cow's dietary NEL intake. On d5 and 6, top dress quantity provided 15% and 20%, respectively, of each cow's predicted dietary NEL intake. The top dress inclusion rate was retained at 20% of each cow's predicted dietary NEL intake on d7 and 8 (Table 1-2). As each period progressed and increasing amounts of top dress were provided, correspondingly less TMR was offered. Cows on the TMR Only treatment were fed TMR ad libitum. Over each 9-d treatment period, treatment diets were formulated to be isoenergetic in concentration. The quantity of feed offered daily to each cow was calculated based on their individual nutrient requirements, estimated from their performance over the previous day. The amount of feed offered daily was adjusted to target approximately 2 to 5 kg (as-fed basis) in daily refusals for each animal; this ensured ad libitum feeding without excess waste. Because cows were allowed to eat to satiety, total daily energy intake may have varied.

Feeding Procedure

Daily refusal sampling and feeding began at 1300 h. During daily feeding, all cows were first moved to the far side of their pen and blocked from accessing any of the feed bunks while refusal sampling and feeding took place each day. This prevented cows from continuing to eat from their assigned bunk and potentially affecting refusal weights. Preventing all cows from accessing their Calan gates during feeding also kept the cows from consuming any TMR before the top dress treatments had been added and thoroughly mixed. This strategy also prevented cow aggression towards one another in attempts to reach the first few feed bunks where fresh feed was deposited. Free stalls and water were still available during this time and the entire refusal sampling and feeding procedure lasted, on average, 2.5 h each day. All cows were taken to the parlor for their afternoon milking while daily refusal sampling and feeding occurred, and returned to their pen at approximately 1400 h daily. All cows then had access to fresh feed in their individual feed bunk shortly after the afternoon milking when the daily feeding procedure was finished at approximately 1530 h.

A Calan data ranger (American Calan Inc.; Northwood, NH) was used to vacuum and remove refusals from each feed bunk. The Calan data ranger weighed the refusal amounts from each bunk and individual refusal weights for each cow were recorded daily. The refusals from all feed bunks were then emptied from the Calan data ranger and approximately 454 kg of TMR from a stationary mixer was dispensed into the Calan data ranger. The target amount of TMR for each cow was then dispensed into each feed bunk using the Calan data ranger. The TMR was dispensed within approximately 2.5 kg (as-fed basis) in either direction of the target TMR amount, and the exact amount of TMR added to each bunk was recorded and used in the statistical analyses.

Supplemental top dresses for each cow were weighed into buckets by-hand on a digital platform scale (Defender 5000 XtremeW, model T51XW; Ohaus Corp.; Parsippany, NJ). The scale used for top dress measurement is calibrated bi-annually, has a minimum capacity of 0.40 kg, has a maximum capacity of 100.00 kg, and measures in 0.02 kg units. Top dresses were measured within 0.09 kg (as-fed basis) of the target top dress amount for each animal and then added on top of the TMR in each designated feed bunk. The supplemental top dresses were then thoroughly mixed by-hand in order to incorporate all of the top dress into the top third of TMR in each feed bunk.

Milking Procedure

All cows were milked twice daily, approximately every 12 h, in a double 12 De Laval parallel parlor (Dairymen Specialties, Inc.; Harrisonburg, VA). This parlor is equipped with an inline AfiMilk MPC Milk Meter (Afimilk Ltd; Kibbutz Afikim, Israel) for monitoring individual cow MY, and an AfiLab Milk Analyzer (Afimilk Ltd; Kibbutz Afikim, Israel) for inline individual cow milk composition analysis. Milk yield and composition (e.g., milk fat, milk protein) data were collected on each cow twice daily as the cow's radio-frequency identification (RFID) tag was read by the system. This information was stored in AfiFarm dairy farm management software (Afimilk Ltd; Kibbutz Afikim, Israel). Milk lactose data were also collected by the AfiLab Milk Analyzer, but the returned data were not biologically plausible (i.e., milk lactose percentages of ~2.3% when we expected ~4.8% milk lactose) and were therefore discarded. Additionally, monthly milk samples were also collected and measured at regular milkings during the experimental period and representative samples were analyzed for milk fat and protein percentages in a commercial laboratory (Table 1-5).

Each lactating cow was also equipped with a pedometer on one hind leg with embedded RFID technology (AfiAct II Leg Tag; Afimilk Ltd; Kibbutz Afikim, Israel). These monitors recorded the number of steps taken daily by each cow; these data were then compiled and reported in 12 h periods (at each milking). After milking, cows exited the parlor through an exit alley containing a walk-over BW scale and RFID reader (AfiWeigh; Afimilk Ltd; Kibbutz Afikim, Israel). Individual cow BW were recorded twice daily in association with milking, and these data were fed into the AfiFarm dairy farm management software.

Sample Collection and Analysis

Fresh samples of TMR and GH were collected daily. However, because only one load each of CG and SBM (Big Spring Mill Inc.; Elliston, VA) were utilized throughout the entire experiment, these feeds were sampled only once at the beginning of the experiment, after delivery to the farm. When sufficient sized samples of orts were available, refusal samples were collected daily using the quartering method (ServiTech Laboratories). For all samples of fresh feed and orts, approximately 500 g (as-fed basis) of each sample was collected. All samples were then frozen at -20°C until nutrient analysis.

Before analysis, individual cow refusal samples were pooled within each cow over 9-d periods. The daily, fresh TMR and GH samples were also pooled over 9-d periods, as these feedstuffs likely differed in chemical composition throughout each period. Therefore, one pooled refusal sample for each cow, one pooled TMR sample, and one pooled GH sample were analyzed for each period. However, the CG and SBM top dress samples were not pooled and only a single sample of each was analyzed over the course of the experiment.

Samples were analyzed for dry matter (DM), crude protein (CP), neutral detergent fiber (NDF), acid detergent fiber (ADF), ash, ether extract (EE), starch, and acid detergent lignin (ADL). Prior to analyses of chemical composition, all samples were dried to constant weight in a 55°C forced-air oven (Thermo Scientific Heratherm Advanced Protocol Ovens, Model 51028115; Fisher Scientific; Waltham, MA) for 24 h and ground with a Model 4 Wiley mill (A. H. Thomas Scientific; Swedesboro, NJ) to pass through a 1-mm screen. Crude protein was calculated as nitrogen (N) x 6.25 after quantification of total N by combustion analysis (Vario El Cube CN analyzer; Elementar Americas Inc.; Mount Laurel, NJ). An Ankom200 fiber analyzer (Ankom Technology; Macedon, NY) with the addition of heat stable α-amylase and sodium sulfite was used to determine NDF concentrations. Feed ADF content was assessed using the Ankom200 fiber analyzer (Ankom Technology; Macedon, NY) according to manufacturer specifications. Ash concentrations were determined after heating samples for 8 h in a muffle furnace at 500°C. Ether extract was analyzed by using the Ankom XT10 with petroleum ether according to manufacturer recommendations. Starch concentrations were determined using the acetate buffer method with α-amylase from *Bacillus licheniformis* (FAA; Ankom Technology; Macedon, NY) and amyloglucosidase from *Aspergillus niger* (E-AMGDF; Megazyme International; Wicklow, Ireland). Feed ADL was assayed for by utilizing ADF residues that were agitated for 3 h in 72% sulfuric acid on a rocking platform (Flask Dancer; Boekel Scientific; Feasterville-Trevose, PA). The chemical composition of individual feedstuffs, including TMR, CG, SBM, and GH, are shown in Table 1-3.

After analyses, the reported CP content of the CG is unrealistically high. To better understand if this CP content was truly representative of what animals consumed, we back-calculated the CP content of the feed using the analyzed diet samples and the analyzed refusal samples. In each instance, we found similar (<2% unit difference) results in the estimated CP content of this top dress. Based on this exercise, it appears that the CG fed to cattle in this experiment was likely contaminated with a higher protein ingredient. As such, the results should not be taken to reflect responses associated with top dressed CG alone and should be assumed to represent top dressing with a CG, protein commodity mixture.

Statistical Analysis

Outcomes of interest included: DMI, MY, milk fat percentage, milk fat yield, milk protein percentage, milk protein yield, feed efficiency, and activity. Because of the short and dynamic nature of the sampling periods, two time ranges were analyzed separately. Samples collected from d3 and 4 of each period were averaged and used to reflect "immediate" adaptation to the alternative top dress strategies. Samples collected from d7 and 8 of each period were also averaged and used to reflect "short-term" responses to changes in top dress supplementation. All variables were analyzed in R version 3.5.2 (R Core Team, 2018) using a mixed-effect model with fixed effects for top dress and random effects for animal, period, and square. Individual cow performance data collected during the 14-d adaption period were averaged by cow and resultant values (DMI, MY, milk fat percentage, milk fat yield, milk protein percentage, milk protein yield, feed efficiency, and activity) were used as covariates in statistical models. Tukey's Honest Significant Differences were used for mean separation. Significant differences between treatments were declared at $P <$ 0.05 and tendencies were declared at $P < 0.10$.

Results and Discussion

Dry Matter Intake Responses

Immediate and short-term DMI responses were significantly affected by top dress type (P < 0.001; Table 1-4). It is not surprising that top dress type affected DMI, as the top dresses differed in factors well-acknowledged to influence DMI. These factors include NDF, starch, particle size, and palatability. Animals consuming diets with top dressed GH consumed significantly less feed than cows on SMB, CG, or TMR Only diets immediately and in the short-term (Table **1-4**). The depression in intake associated with GH could be attributed to the higher NDF content and lower starch concentration of this top dress when compared to CG and SBM (Table 1-3). However, our compositional analysis of GH seems to indicate an unlikely high starch content (Table 1-3). We assume this is an analytical or computational error. High NDF concentrations have previously been shown to downregulate feed intake; Mertens (1987) suggested that NDF can be used to predict DMI of dairy cows due to the positive correlation between NDF and the bulking density of feeds. Lower-starch diets have also been shown to decrease DMI in Holstein cows (Oba and Allen, 2003). Additionally, the GH had larger particle size than any other treatment that likely resulted in lower palatability. Larger particle size has been shown to decrease DMI of lactating dairy cows, as well (Kononoff et al., 2003). Ingestion of long fiber is well-linked with gut fill and reduced feed intake (White et al., 2017).

It is also likely that palatability affected the immediate responses of cows to the different top dress treatments. Immediate DMI of cows consuming CG was significantly higher than the DMI of cows consuming TMR Only diets (24.7 vs. 23.1 kg/d DM basis; Table 1-4). Previous studies have identified CG as a highly palatable feedstuff for lactating dairy cows (Loosli and Warner, 1958); the increased DMI of the CG treatment in the immediate response time-frame is likely associated with the high palatability of CG. In the longer-term, feedback mechanisms have been identified that link higher starch diets with depressed intakes (Allen et al., 2009). Starch is highly digestible and associated with rumen fermentation that increases propionate as a proportion of VFA absorbed. Satiety signals that end meal consumption in dairy cattle are likely caused by propionate, as propionate concentration in the liver is drastically increased during meal consumption and then rapidly metabolized (Allen et al., 2009). This rapid metabolism may have a suppressive effect on feed intake, likely by stimulating oxidation of acetyl-CoA in the liver (Kennedy and Allen, 2019). If present, this intake inhibition was likely already occurring by the short-term sampling range, especially since the concentration of CG in the experimental diets would be highest during this time, as the higher-starch CG treatment was no longer different from the SBM or TMR Only treatments (23.4 vs 23.1 and 22.1 kg/d DM basis, respectively; Table 1-4).

Feed intake of cows on the SBM diet did not differ from the TMR Only diet in either the immediate or short-term response time-frames. This was somewhat unexpected because CP intake is commonly linked with increased DMI (Kalscheur et al., 1999) and it was hypothesized that cows consuming SBM diets would have higher intakes than cows on TMR Only diets due to the high CP concentration of the SBM top dress. However, it is possible that the composition of the basal TMR Only diet was already high enough in CP and that the additional provision associated with SBM intake did not result in altered intake regulation. The TMR Only diet is the sole feed fed to lactating cows at this dairy operation and is therefore likely not limiting in CP concentration. The formulated TMR contained 11.7% metabolizable protein (MP) balance and 53 g rumen degradable protein (RDP) balance (DM basis). Similarly, Imaizumi et al. (2010) reported that the addition of soybean and cottonseed meal did not significantly affect DMI, compared to a control diet with 15.9% CP and 10.8% MP (DM basis). Therefore, the TMR Only diet was likely sufficient in protein concentrations and DMI was not affected by the addition of SBM in the current study.

It is worth noting that the random effect of animal was significant for DMI in both the immediate and the short-term response periods ($P < 0.001$; $P = 0.005$; Table 1-4). Although animal effects can represent a number of factors, including those directly associated with individual animal differences, they can also be easily confounded with other less clear influences. In this case, the significance of animal effects is of interest because it highlights specific differences among animals that were repeatable across top dress types. Although not surprising because we expect animal genetic merit to play a major role in governing feed intake regulation (Buttchereit et al., 2011), this significant difference among individuals across treatments is a challenge for individual animal feeding algorithms. If such algorithms are developed, the persistent differences among individuals suggest that model training or learning should occur at the individual animal level. This implies that data collected and presented in the literature on groups of animals may have minimal use in developing precision feeding algorithms that capitalize on individual variation.

With a 2.5 h daily holding period where all 24 cows only had access to 12 lying stalls and no feed, lying and feeding behaviors may have been negatively affected. When there are more cows than laying stalls in a pen, lower-ranked cows spend less time lying down (Metz, 1985). In a study performed by Metz (1985), preventing lying behavior for 3 h resulted in increased lying behavior for the subsequent 3 h. However, MY was not affected by lying deprivation (Cooper et al., 2007). In contrast, withholding feed for 3 h resulted in decreased lying time for 1 h after the deprivation, as hunger dominated the need to rest (Metz, 1985). When both lying behavior and feed were withheld for 3 h, lying had priority over eating and lying times were similar to those during ad libitum feeding (Metz, 1985). Therefore, in the current experiment with a 2.5 h holding period, the housing and feeding procedure may have affected lying times and decreased DMI of cows, especially of lower-ranked individuals. Shortening the daily holding period by utilizing more efficient feeding methods and eliminating any competition at the free stalls may help decrease these negative effects on cow behavior.

Milk Yield

Milk yield was significantly affected by top dress type in the immediate and short-term response periods ($P < 0.001$; Table 1-4). In both response periods, animals consuming CG and SBM treatments had significantly greater MY than cows consuming GH or TMR Only treatments (34.2 and 35.4 vs 31.6 and 31.4 kg/d DM basis, respectively). In the field of nutrition, convention in experimental design dictates that we focus on grouped animal responses and look at differences in responses after adaptation to diets; however, when attempting to derive models for optimizing individual animal efficiency, there may be variation in the short-term that can be exploited. The increased MY of animals on the SBM diet, in particular, supports this idea because animals had elevated MY without elevated DMI. Although this short-term increase in productivity may be minor on the annual scale of daily production, future studies focusing on the within-animal repeatability of these types of temporal responses to feed alteration could reveal repeatable patterns and support a cyclic feeding strategy or one with a number of short-term interventions designed to create “bumps” in productivity on a weekly or semi-monthly basis.

Immediate and short-term MY were also significantly affected by initial performance ($P < 0.001$; Table 1-4); The MY of individual cows throughout the experimental period were similar to their yield values prior to the experiment. For example, the highest producing animals before the experiment continued to produce the most milk throughout the experiment across all treatment options. These responses were expected because of previous knowledge about individual animal genetic merit (Visscher and Goddard, 1995). The significance of initial responses suggests that individual cow genetics play an important role in governing MY. Given the moderate heritability of MY traits (Visscher and Goddard, 1995), it is not surprising that animals' MY prior to the experiment significantly affected their MY throughout the experiment. The significance of period on immediate and short-term MY responses ($P = 0.019$; $P = 0.006$; Table 1-4) is consistent with the expected lactation curve for these animals (Grossman et al., 1986). At the start of the trial, cows averaged 204 DIM and produced an average of 33.8 kg of milk daily. By period four, average milk production had decreased to 32.5 kg per d due to increased DIM.

Milk Fat Percentage and Yield

During the immediate response period, milk fat percentage was not affected by top dress ($P = 0.239$; Table 1-4), period ($P = 0.998$; Table 1-4) or animal ($P = 0.186$; Table 1-4), but was significantly related to initial milk fat percentage ($P < 0.001$; Table 1-4). The lack of significant treatment effects on milk fat percentage in the immediate term could be due to the time associated with regulating milk fat synthesis or may be associated with the limited nutritional differences induced by the top dresses. Regulation of milk fat synthesis is associated with both digestive processes and tissue metabolism (Bauman and Griinari, 2001). De novo fatty acid synthesis is inhibited by specific fatty acid intermediates that are produced in the mammary gland and milk fat synthesis is limited by hydrolysis and biohydrogenation of lipids in the rumen (Bauman and Griinari, 2001). The machinery regulating milk fat synthesis may not have responded to the dietary shifts of experimental treatments by d3 or 4 of each period. It has also been shown that diets depressing milk fat synthesis included large amounts of readily digestible carbohydrates and reduced amounts of fibrous composition (Davis et al., 1964). This suggests that our experimental diets may have been within acceptable nutritive composition ranges that did not result in negative effects on milk fat synthesis in the immediate term due to the lower concentrations of energy coming from top dress during this time. However, the limited effect of animal and period on milk fat percentage was unexpected, as animal genetic merit (Abdallah and McDaniel, 2000) and stage of lactation (Stoop et al., 2009) are known to typically influence milk fat percentages. It is possible that the individual animal effect was entirely explained by the significant initial performance effect and no additional individual animal variation in milk fat percentage could be partitioned into the animal term of the model. Finally, it is also possible that the short-term nature of the study did not capture a long-enough snapshot of the lactation curve to demonstrate the expected differences between periods.

In the short-term, milk fat percentage was significantly affected by treatment (P = 0.004; Table 1-4) and initial performance (P < 0.001; Table 1-4). Diets top dressed with CG resulted in milk fat percentages similar to GH and SBM top dressed diets, and were lower than milk fat percentages produced on the TMR Only treatment (Table 1-4). Milk fat depression is typically associated with readily digestible carbohydrates and lower amounts of fiber that impedes normal rumen function (Davis et al., 1964). The increased carbohydrate concentration and decreased fiber content of the experimental CG diet associated with the highest level of CG feeding was sufficient to induce changes in milk fat percentage. The consistency of the effect of initial performance on short-term milk fat percentage suggests that individual animal differences in performance are likely to outweigh treatment-induced differences, providing further evidence for the need to develop databases on individual animal observations to enable precise and accurate feeding algorithms for individuals, rather than groups of animals.

There was a trend for an effect of period on short-term milk fat percentage responses (P = 0.074; Table 1-4), but no significant effect of animal (P = 0.976; Table 1-4). The tendency for a period effect observed for milk fat percentages in the short-term is more sensible than the lack of an effect observed in the immediate response period. Milk fat percentages are expected to change with energy balance throughout the lactation curve (Buttchereit et al., 2011). As discussed with the immediate term milk fat percentage responses, the variation in milk fat percent associated with animal may have also been better captured by the continuous, initial milk fat percentage term, rather than the discrete, random animal term. The difference between the immediate treatment effects on milk fat percentage and the short-term effects suggest that the time delay in regulating milk fat synthesis may be important to consider when designing strategies to capitalize on short-term responses of individual cows. Although MY responses may be more immediate, influencing economically important factors like milk fat may require longer data collection periods for algorithm development and testing.

As expected, immediate and short-term milk fat yield results mirrored the MY and milk fat percentage responses (Table 1-4). Top dress significantly affected milk fat yield in the immediate and short-term response periods (P < 0.001; Table 1-4). In the immediate time-frame, cows consuming the TMR Only and GH treatment diets had reduced milk fat yields compared to the groups supplemented with CG and SBM. This shift in milk fat yield was consistent with the elevated MY of those treatment groups. During the short-term response period, animals supplemented with GH had lower milk fat yields than animals consuming any other treatment diet (Table 1-4). Again, this response was consistent with the depressed MY of cows consuming supplemental GH. Cows receiving TMR Only diets had reduced MY, but this was counterbalanced by the elevated milk fat percentage of this group, resulting in no difference in milk fat yield compared to the CG and SBM treatment groups.

Milk Protein Percentage and Yield

Milk protein percentage was not affected by top dress in the immediate or short-term response periods (P > 0.767; Table 1-4). The limited effect of treatment on milk protein percentage was not expected. The treatments were not designed to be isonitrogenous, and therefore, it was expected that higher protein consumption would drive elevated milk protein synthesis (Kalscheur et al., 1999; Huhtanen and Hristov, 2009). Certainly, the elevated MY responses, on the SBM diet in particular, highlighted that animals were sensitive to this treatment. However, this sensitivity did not confer changes in milk protein percentage. The lack of significant changes in milk protein percentage likely suggests animals were already receiving adequate MP supplies to facilitate peak milk protein synthesis.

Milk protein percentage was significantly affected by initial milk protein percentage in the immediate response time-frame (P = 0.016; Table 1-4) and tended to be affected in the short-term response period (P = 0.084; Table 1-4). An additional significant effect for the discrete, random animal term was observed in the immediate response time-frame (P = 0.023; Table 1-4), but not in the short-term response period (P = 0.383; Table 1-4). The relationship between initial milk protein percentages and the milk protein percentages observed throughout the experiment highlights individual animal differences in milk protein synthesis and the consistency of those differences across dietary interventions. The change in the significance of the animal term between the immediate and the short-term response periods may reflect some latency of unique individuals to respond to dietary interventions. Another reason for this change in significance between the two time-frames may be due to the greater concentrations of energy in the diets provided by the various top dresses throughout the short-term response period.

Milk protein yield was affected by top dress (P < 0 .001; Table 1-4), initial milk protein yield (P < 0.001; Table 1-4), and animal (P < 0.001; Table 1-4), but not by period (P > 0.134; Table 1-4), during both the immediate and the short-term response time-frames. The supplemental SBM treatment resulted in greater milk protein yield compared to the other top dress treatments during both periods. This elevated milk protein yield was likely due to the elevated MY of cows consuming the supplemental SBM top dress. Feeding additional MP is a primary driver of elevated

MY (Sutton, 1989). Diets supplemented with degradable protein have been shown to increase MY, but they do not consistently improve milk protein concentration (Thomas, 1984). Additionally, the effects of initial milk protein yield and animal are more examples that suggest individualized feeding has the ability to improve milk protein yield beyond typical group housing diets, due to the unique genetics of specific cows.

Feed Efficiency

Top dress significantly affected immediate and short-term feed efficiency ($P < 0.001$; $P = 0.026$; Table 1-4). In the immediate response time-frame, feed efficiency was highest for cows consuming GH and SBM diets; however, no statistical differences exist between CG and TMR Only diets or CG and SBM diets (Table 1-4). The increase in feed efficiency of cows consuming supplemental SBM agrees with previous literature that shows that high protein supplements commonly increase feed efficiency (Neal et al., 2014). In the short-term response period, feed efficiency was highest for cows consuming GH diets and there were no statistical differences in feed efficiency between CG, SBM, or TMR Only treatments (Table 1-4). Cows consuming GH diets may appear more efficient on supplemental GH due to the recorded decrease in DMI. In the short-term, cows are able to support elevated MY despite low DMI, as they can leverage body reserves. However, if this strategy was employed long-term, decreases in MY would likely be expected to more adequately reflect intake levels. Cows would also be expected to lose BW and body condition with depressed DMI while maintaining production levels. As a result, feedstuffs that depress intake in the short-term may not be suitable for use in individualized feeding systems that target maximizing feed efficiency, due to their potential for decreases in MY and BW loss.

Immediate feed efficiency was also affected by initial performance and animal ($P < 0.001$; Table 1-4). These results suggest that there are short-term variations in individual cow feed efficiencies that can be used to maximize feed efficiency, and therefore, profit from dairy cattle on commercial farms. However, we are unsure of longer-term responses to this type of intervention, and the repeatability of these responses across a full lactation curve is still unknown. The responses shown in this study are the result of instantaneous responses to feeding high quality top dresses. In the longer-term, we may want to consider leveraging for lower quality feeds that are likely associated with lower costs, but also possible long-term health concerns. Finding an achievable balance between these strategies, and indeed assessing whether they are even worthwhile from an economic standpoint, is warranted.

Activity

Immediate and short-term cow activity was significantly affected by top dress (P = 0.021; P < 0.001; Table 1-4). In the immediate time-frame, cows consuming GH took significantly more steps than cows on the SBM treatment. In the short-term response period, cows consuming GH diets were more active and took significantly more steps than cows on any other treatment (Table 1-4). These results suggest that cows consuming supplemental GH diets were unsatisfied with the feed they were offered and likely traveled to other feed bunks frequently in an attempt to access more desirable feedstuffs. These animals may have been agitated due to the lower palatability of GH in their ration and likely spent more time searching for alternative feed options. Feeding staff also observed this behavior and reported cows on supplemental GH diets attempting to steal from other feed bunks. Consequently, cows consuming GH diets likely had higher maintenance requirements, and therefore, less available energy for milk production. Feedstuffs with low palatability may be poor supplement choices for individualized feeding systems because they increase activity levels, increase maintenance requirements, and decrease MY.

Immediate and short-term activity levels were significantly affected by initial performance ($P < 0.001$; Table 1-4) and a tendency for an animal effect in the immediate response time-frame exists ($P = 0.076$; Table 1-4). Like other initial performance and animal effects, these results display the appropriateness of individualized, nutritional treatment of dairy cattle. Cattle behave as individuals, even in their activity level. Immediate activity was significantly affected by period ($P = 0.039$; Table 1-4), and therefore, distance a cow travels is likely related to DIM. Cow activity does not necessarily map directly to changes in production parameters in the immediate or short-term response periods, but more closely relates to changes in intake.

Conclusions

Dairy cattle behave as individuals in regard to many production parameters. As a result, individualized feeding, rather than group feeding, may increase feed efficiency of cattle on-farm. However, more studies are needed in order to increase the available data of production responses to individual cow feeding strategies. This collection of data can then be used in order to develop algorithms capable of predicting custom supplements for individual animals. These algorithms would be based on individual cow data that many commercial dairy farmers already collect, but rarely utilize to make predictions to enhance milk production and feed efficiency. Although expensive to implement, automated precision feeding systems may have the potential to continuously improve dairy cow production parameters by supplementing common diets with individualized and custom feed mixes predicted by precision algorithms.

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Tables

Table 1-1. Formulated composition of the common total mixed ration (TMR) fed to all treatment groups[1]

Ingredient	kg, DM basis	kg, as-fed basis
Corn silage, brown midrib	7.727	22.205
Alfalfa hay	0.682	0.779
Brewers grain	2.568	8.560
Corn grain, dry, ground	3.409	3.874
Cottonseed, whole, with lint	1.364	1.482
Milk cow concentrate	7.885	8.735
Corn grain, dry, ground	2.272	2.581
Soybean hulls, ground	1.729	1.900
Canola meal	1.271	1.410
Amino plus[a]	1.240	1.410
Palmit 80[b]	0.271	0.273
Blood meal, dried	0.245	0.273
Sodium bicarbonate	0.158	0.159
Limestone, ground	0.158	0.159
Potassium carbonate	0.136	0.136
Salt, white	0.090	0.091
Volclay 90[c]	0.054	0.057
Molasses, cane	0.041	0.057
OmniGen-AF[d]	0.054	0.057
Potassium magnesium sulfate	0.027	0.027
MHA, dry[e]	0.024	0.024
Calcium phosphate, mono-dical	0.022	0.023
Mepron[f]	0.018	0.018
Diamond XPC[g]	0.013	0.014
Selenium yeast, 0.06%	0.012	0.014
Ultrasorb[h]	0.011	0.012
Clarifly[i]	0.010	0.010
Biotin[j]	0.009	0.009
Zinpro 5[k]	0.007	0.008
Trace mineral blend	0.006	0.006
Vitamin A, D, E blend	0.004	0.004
Vitamin E premix, 60%	0.002	0.002
Rumensin 90[l]	0.001	0.001
TOTAL	23.639	45.637

[1]TMR formulated to provide 61.7 mCal metabolizable energy (ME) per d; 2,750 g of metabolizable protein (MP) per d; 39.0 kg of ME allowable milk per d; and 39.0 kg of MP allowable milk per d.
[a]Rumen protected soybean meal; Ag Processing, Inc; Omaha, NE.
[b]Vegetable palm oil; rumen bypass fat; ADM Animal Nutrition; Quincy, IL.

[c]Granular sodium bentonite; binder and digestive aid; American Colloid Company; Hoffman Estates, IL.
[d]Immune support supplement; microbial ingredients, vitamins, and aluminosilicates; Phibro Animal Health Corporation; Teaneck, NJ.
[e]Granular formulation of ALIMET; 84% methionine activity and 100% absorbed; NOVUS; Saint Charles, Missouri.
[f]Rumen protected DL-methionine; RP Nutrients, Inc; East Troy, WI.
[g]Saccharomyces cerevisiae fermentation product; Diamond V; Cedar Rapids, Iowa.
[h]Mycotoxin deactivator; Micron Bio-Systems Ltd.; Buena Vista, VA.
[i]Diflubenzuron feed-through fly control; Central Garden and Pet Company-Central Life Sciences; Schaumburg, IL.
[j]2,200 mg Biotin/kg
[k]Trace mineral concentrate containing 30,688.51 ppm manganese, 5,370.57 ppm copper, 306.30 ppm iron, 75,187.97 ppm zinc, 613.32 ppm iodine, and 1,687.43 ppm cobalt (DM basis); Zinpro Performance Minerals; Eden Prairie, Minnesota.
[l]Monensin sodium energy supplement for increased milk production efficiency; Elanco Animal Health; Greenfield, IN.

Table 1-2. Feedstuff inclusion rates in experimental treatment diets of a total mixed ration (TMR) with and without the addition of corn grain (CG), soybean meal (SBM), or grass hay (GH) (% of dietary net energy of lactation (NEL) intake)

	Feedstuffs			
Treatments[1]	TMR	Corn Grain (CG)	Soybean Meal (SBM)	Grass Hay (GH)
Day 3/4: Immediate				
TMR Only	100	0	0	0
CG	90	10	0	0
SBM	90	0	10	0
GH	90	0	0	10
Day 7/8: Short-term				
TMR Only	100	0	0	0
CG	80	20	0	0
SBM	80	0	20	0
GH	80	0	0	20

[1]Treatments: TMR Only = TMR with no top dress; CG = TMR with corn grain top dress; SBM = TMR with soybean meal top dress; GH = TMR with mixed grass hay top dress.

Table 1-3. Chemical composition of total mixed ration (TMR), corn grain (CG), soybean meal (SBM), and grass hay (GH) feedstuffs (%, DM basis)

Item	TMR	Corn Grain (CG)	Soybean Meal (SBM)	Grass Hay (GH)
DM	46.7	84.3	81.6	92.8
CP	15.1	21.2[a]	51.7	6.80
NDF	39.7	13.4	9.80	73.8
ADF	22.1	3.70	4.60	44.3
Ash	6.10	4.30	10.1	7.20
Ether Extract	4.70	0.00	1.60	2.30
Starch	19.3	51.8	3.70	20.5[b]
ADL	2.40	0.60	0.40	5.40

[a]Suspected to be higher than typical values due to contamination during storage.
[b]Suspected to be higher than typical values due to analytical or computational error.

Table 1-4. Mean production performance responses of 24 cows in a replicated Latin square design consuming experimental treatment diets of a total mixed ration (TMR) with and without the addition of corn grain (CG), soybean meal (SBM), or grass hay (GH)

Response Variable (DM basis)	Days	Treatments[1] TMR Only	CG	SBM	GH	SEM	P-values Top Dress	Initial Performance	Period	Animal
DMI, kg/d	3/4	23.1[b]	24.7[c]	23.6[bc]	20.1[a]	0.510	<0.001	<0.001	0.579	<0.001
	7/8	22.1[b]	23.4[b]	23.1[b]	16.4[a]	0.770	<0.001	0.002	0.583	0.005
Milk yield, kg/d	3/4	31.4[a]	34.2[b]	35.4[b]	31.6[a]	0.950	<0.001	<0.001	0.019	0.012
	7/8	33.0[a]	35.8[b]	36.3[b]	30.8[a]	0.990	<0.001	<0.001	0.006	0.050
Milk fat, %	3/4	4.64	4.63	4.54	4.61	0.039	0.239	<0.001	0.998	0.186
	7/8	4.68[b]	4.42[a]	4.61[ab]	4.53[ab]	0.064	0.004	<0.001	0.074	0.976
Milk fat yield, kg/d	3/4	1.46[a]	1.58[b]	1.61[b]	1.46[a]	0.043	<0.001	<0.001	0.164	0.011
	7/8	1.55[b]	1.56[b]	1.67[b]	1.40[a]	0.048	<0.001	<0.001	0.014	0.586
Milk protein, %	3/4	2.92	2.91	2.91	2.89	0.047	0.964	0.016	0.656	0.023
	7/8	2.95	2.95	2.96	3.01	0.061	0.767	0.084	0.241	0.383
Milk protein yield, kg/d	3/4	0.922[a]	0.991[ab]	1.03[b]	0.915[a]	0.033	<0.001	<0.001	0.134	<0.001
	7/8	0.973[ab]	1.05[bc]	1.08[c]	0.930[a]	0.032	<0.001	<0.001	0.147	<0.001
Feed efficiency, kg milk/kg feed	3/4	1.37[a]	1.39[ab]	1.49[bc]	1.58[c]	0.039	<0.001	<0.001	0.607	<0.001
	7/8	1.56[a]	1.56[a]	1.58[a]	2.28[b]	0.20	0.026	0.129	0.681	0.886
Activity, steps/h	3/4	96.4[ab]	91.3[ab]	85.8[a]	99.2[b]	4.40	0.021	<0.001	0.039	0.076
	7/8	101[a]	92.1[a]	92.4[a]	123[b]	4.00	<0.001	<0.001	0.765	0.625

[1]Treatments: TMR Only = TMR with no top dress; CG = TMR with corn grain top dress; SBM = TMR with soybean meal top dress; GH = TMR with mixed grass hay top dress.
[a-c]Means within a row with different superscripts differ significantly from one another ($P < 0.05$).

Figures

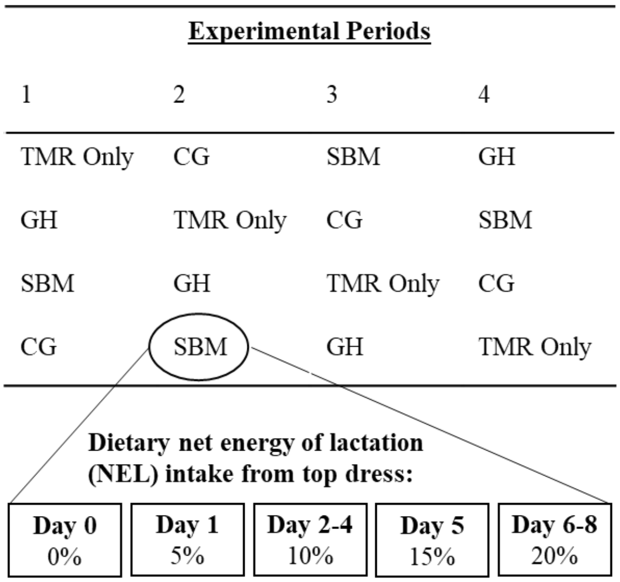

Figure 1-1. The experimental design consisted of four periods that were 9-d in length. During each period, six cows were randomly assigned to one of four treatment options. Experimental treatments included: TMR Only = TMR with no top dress, CG = TMR with corn grain top dress, SBM = TMR with soybean meal top dress, and GH = TMR with mixed grass hay top dress. A replicated 4 x 4 Latin square was implemented and each group of six cows was fed a different experimental treatment diet over the four periods. Cows were fed increasing amounts of dietary net energy of lactation (NEL) intake from top dress over each period, as shown in the rectangles above.

Supplementary Materials

Table 1-5. Individual cow milk yield (MY), milk fat percentage, and milk protein percentage from monthly analyses (organized by cow ID)

Cow ID	Lactation #	Calving Date	DIM	Analysis Date	MY, kg/d	Milk Fat, %	Milk Protein, %
5096	4	9/8/2018	164	2/18/2019	40.6	6.6	3.4
5096	4	9/8/2018	192	3/18/2019	32.9	5.2	3.6
5175	4	7/15/2018	219	2/18/2019	34.7	4.3	3.6
5175	4	7/15/2018	247	3/18/2019	36.9	4	3.5
5225	4	8/21/2018	182	2/18/2019	36.6	5.3	3.7
5225	4	8/21/2018	210	3/18/2019	41.2	4.9	3.6
5293	3	8/4/2018	199	2/18/2019	33.6	4.6	3.6
5293	3	8/4/2018	227	3/18/2019	27.5	4.3	3.6
5294	3	6/27/2018	237	2/18/2019	30.2	5.5	3.3
5294	3	6/27/2018	265	3/18/2019	30.5	4.3	3.4
5320	3	8/22/2018	181	2/18/2019	40.6	3.8	3.6
5320	3	8/22/2018	209	3/18/2019	34.7	4.1	3.3
5333	3	7/5/2018	229	2/18/2019	29.5	4.6	3.8
5333	3	7/5/2018	257	3/18/2019	25.3	4.2	3.4
5421	2	8/25/2018	178	2/18/2019	41.2	4.9	3.2
5421	2	8/25/2018	206	3/18/2019	36.4	4.1	3.2
5459	2	7/7/2018	255	3/18/2019	18.6	5.4	3.8
5463	2	6/27/2018	237	2/18/2019	26.8	6.1	3.6
5463	2	6/27/2018	265	3/18/2019	29.5	5.9	3.8
5476	2	7/30/2018	204	2/18/2019	44.4	3.8	3.4
5476	2	7/30/2018	232	3/18/2019	38.1	3.6	3.4
5479	2	8/14/2018	189	2/18/2019	44.2	5.1	3
5479	2	8/14/2018	217	3/18/2019	44.1	4.3	3.1
5555	1	7/30/2018	204	2/18/2019	34.6	4	3.3
5555	1	7/30/2018	232	3/18/2019	35.2	3.9	3.1
5558	1	7/4/2018	230	2/18/2019	30.2	5.2	3.9
5558	1	7/4/2018	258	3/18/2019	28.1	5.2	3.8
5563	1	7/30/2018	204	2/18/2019	38.6	5.6	3.1
5563	1	7/30/2018	232	3/18/2019	35.5	4	3.2
5568	1	7/4/2018	230	2/18/2019	35.3	5.4	3.4
5568	1	7/4/2018	258	3/18/2019	33.1	5.1	3.5
5578	1	7/25/2018	209	2/18/2019	22.8	5.8	3.8
5578	1	7/25/2018	237	3/18/2019	21.0	5.8	3.8
5580	1	8/13/2018	190	2/18/2019	32.7	4.3	3.4
5580	1	8/13/2018	218	3/18/2019	30.9	4.4	3.2
5585	1	8/23/2018	180	2/18/2019	34.5	3.7	3.1
5585	1	8/23/2018	208	3/18/2019	31.2	3.8	2.5
5587	1	9/16/2018	156	2/18/2019	25.9	4.9	3.7
5587	1	9/16/2018	184	3/18/2019	28.6	5	3.7

5601	1	6/29/2018	235	2/18/2019	42.7	4	3.4
5601	1	6/29/2018	263	3/18/2019	43.6	4.2	3.3
5603	1	7/25/2018	209	2/18/2019	37.5	4.3	2.8
5603	1	7/25/2018	237	3/18/2019	34.5	3.9	3
5611	1	7/27/2018	207	2/18/2019	30.0	4.8	3.5
5611	1	7/27/2018	235	3/18/2019	28.6	4.1	3.5
5617	1	7/24/2018	210	2/18/2019	32.3	4.9	3.5
5617	1	7/24/2018	238	3/18/2019	29.4	5.4	3.2

CHAPTER 4: ALGORITHM DEVELOPMENT FOR INDIVIDUALIZED PRECISION FEEDING OF SUPPLEMENTAL TOP DRESSES TO MAXIMIZE FEED EFFICIENCY OF DAIRY CATTLE

This chapter will be submitted to the Journal of Dairy Science as: T. P. Price, D. M. Liebe, K. M. Daniels, and R. R. White. Algorithm development for individualized precision feeding of supplemental top dresses to maximize feed efficiency of dairy cattle.

Abstract

Individualized, precision feeding of dairy cattle may have the ability to increase feed efficiency and farm profitability. Targeting individual cows, rather than groups of animals, is likely an effective approach for maximizing production parameters. However, algorithms designed to make feeding recommendations for specific animals based on individualized data are scarce. The objective of this study was to develop and test two algorithms designed to improve feed efficiency of individual cows by supplementing diets with varying types and quantities of top dresses. An economic analysis was performed to compare feed costs and milk income between the algorithm feeding strategies and conventional feeding. Twenty-four Holstein dairy cows were assigned to one of three treatment groups: control group (n = 8) fed a common total mixed ration (TMR) ad libitum, algorithm 1 (n = 8) which utilized a mixed-model approach with feed efficiency as the response variable; or algorithm 2 (n = 8) which grouped cows based on top dress response efficiency structure to assign individualized top dress supplementation. Both algorithms were trained over a 36-d training period immediately prior to the 35-d algorithm testing period in this experiment. Production responses for dry matter intake (DMI), milk yield (MY), milk fat percentage and yield, milk protein percentage and yield, feed efficiency, and activity were analyzed using a mixed-effect model with fixed effects for feeding algorithm, top dress, week, and their 2- and 3-way interactions. Milk protein percentage ($P = 0.008$) and feed efficiency ($P < 0.001$) were affected by a 3-way interaction between top dress, algorithm, and week. Initial performance affected MY ($P < 0.001$), milk fat percentage and yield ($P < 0.001$), milk protein percentage ($P = 0.025$), milk protein yield ($P < 0.001$), feed efficiency ($P = 0.022$), and activity ($P = 0.029$). Results highlight the individual differences between cows and the need for individualized, precision feeding strategies. However, the algorithms developed in this experiment were not successful at maximizing production performance, economically. Algorithm 1 cows were the most efficient, but resulted in lower income over feed costs than the control group. Algorithm 2 cows were the least efficient and resulted in the highest feed costs. Algorithm refinement and training modifications are needed to maximize production through individualized feeding utilizing economically optimal ration formulation.

Keywords: dairy cow, model development, precision feeding

Introduction

Innovative dairy farm technologies have increased operation productivity, decreased costs per cow, and contributed tremendously to the financial success of farmers (El-Osta and Morehart, 2000). From a global study performed in 2013, approximately 69% of dairy producers reported use of precision dairy technologies on farms (e.g., pedometers to monitor activity, collars to monitor rumination, sensors in the milking parlor to measure milk yield (MY) and conductivity of milk, etc.) (Borchers and Bewley, 2015). Of the producers that utilized precision technologies, MY, cow activity, and mastitis were most commonly monitored with precision management technologies (Borchers and Bewley, 2015). However, many dairy farmers feel that there is unused functionality in their precision management systems (Eastwood et al., 2016). Many farmers collect a variety of data on individual cows; however, these data are rarely compiled and integrated to make informed decisions on how to more accurately feed or manage individual cows in order to increase feed efficiency or MY. Precision feeding systems may have the ability to maximize feed efficiency, and ultimately MY. However, most current precision feeding systems do not treat cows as individuals, but rather focus on diet and ingredient recommendations for groups of animals with similar characteristics (e.g., bred heifers, high milk producing cows, low milk producing cows, dry cows, etc.) (Zanton and Heinrichs, 2008).

Individually feeding cows is common in research studies. However, it is not a typical industry practice because it is costly and labor-intensive. Utilizing and compiling as many forms of information on individual cows in order to make informed predictions of how to best feed cows as individuals is an approach likely to increase profitability of entire dairy herds. Precision nutrition models have been shown to be capable of improving the performance of dairy farms by meeting nutritional requirements more effectively (Wang et al., 2000). Precision nutrition models have also been shown to be capable of affecting dairy parameters, including positive increases in predicted MY (White and Capper, 2014). Similar modeling approaches could also be utilized to make feeding recommendations for individual cows, based on precision parameters many farmers already collect.

Feeding cows on-farm as individuals would be costly to implement, and automated feeding systems (AFS) that are likely necessary to reduce labor costs would require substantial upfront investment. However, if improvements in feed efficiency are drastic enough, the increases in producers' profits may far outweigh the technology's cost. Feeding custom, individualized supplements to dairy cattle, in addition to a total mixed ration (TMR), may be an economical way to improve feed efficiencies while minimizing labor costs. Each cow could be fed a common TMR and supplemented with custom feedstuff(s) through individualized feeding. Therefore, the objective of this experiment was to develop and test two algorithms designed to characterize the supplement type and quantity that should be fed to maximize individual cow feed efficiency. An economic analysis that compares feed costs and income from milk production for each algorithm and the control group is also included to evaluate the economic practicality of individualized feeding utilizing the developed algorithms.

Materials and Methods

Animals, Diets, and Housing

All procedures involving animals were approved by the Institutional Animal Care and Use Committee of Virginia Tech (protocol # 18-002). This experiment was conducted from March 27th, 2019 to April 30th, 2019.

Twenty-four Holstein dairy cows (12 primiparous and 12 multiparous; 710 ± 88 kg of body weight (BW); and 241 ± 23 days in milk (DIM) at the beginning of the study) were housed in a

24-stall pen within a free stall barn and fed once daily (1300 h) using a Calan gate system (American Calan Inc.; Northwood, NH). Each cow was randomly assigned to one of three treatment groups. The control group was managed according to normal farm practices and was fed a TMR ad libitum without top dress, as described below. The other two treatment groups represented different precision feeding approaches. The groups differed in the algorithm used to assign top dress types and quantities to individual cows. Both algorithms were trained from data obtained from a 36-d training period, presented as a separate experiment (Chapter 3). The independent training period occurred immediately prior to the 35-d experimental testing period which was used to generate the results presented in the present work. During the 36-d training period, cows were exposed to all diet options including: TMR (control), TMR plus corn grain (CG), TMR plus soybean meal (SBM), or TMR plus mixed grass hay (GH) in a 4 x 4 replicated Latin square design. The quantity of material top dressed varied across each period over a gradual increase to target providing 0% to 20% of predicted dietary net energy of lactation (NEL) intake (Chapter 3). The algorithms utilized during this experimental testing period (described in detail below) queried this training data to develop individualized animal feeding recommendations based on the goal of maximizing individual cow feed efficiency. The experimental design of both the training and testing periods are detailed in Figure 2-1. One cow was removed from the experiment on d17 due to abortion. Analyses included the data on this cow until she was removed from the experiment.

During this experimental testing period, the four top dress treatment options included: CG, SBM, GH, or no top dress (control). A common TMR was fed as the base of all diets and was composed of mainly corn silage, corn grain, brewers grain, and soybean hulls (Table 2-1). The formulated composition of the common TMR fed to all treatment groups is detailed in Table 2-1.

Each cow was fed ad libitum and the quantity of feed offered daily to each cow was calculated based on their individual nutrient requirements, estimated from their performance over the previous day. The amount of feed offered daily was adjusted to target approximately 2 to 5 kg (as-fed basis) in daily refusals for each animal; this ensured ad libitum feeding without excess waste. Both algorithms were updated weekly in an attempt to make improved feeding recommendations to increase individual cow feed efficiency.

Algorithm Development

Algorithm 1. Eight of the 24 cows were randomly assigned to this mixed-model feeding approach that provided individual feeding recommendations. Data on dry matter intake (DMI), MY, milk components, activity, and BW collected daily were paired with the treatment feeding schedule information to generate a dataset that matched feed quantity and composition offered on the previous day with MY and composition data from the current day, following the logic that what we fed a cow yesterday is likely to impact her milk production and composition today. The response variable for all models used in this algorithm was feed efficiency (MY / feed intake) expressed as a percent of the individual animal's maximum feed efficiency. A unique model was derived for each top dress type to describe how the remotely sensed data interacted with that top dress type to impact feed efficiency as a percent of maximum efficiency (FPM). Models followed the general structure:

$$FPMij = \mu + \alpha + \beta l + \alpha\beta l + \epsilon ij$$

Where $FPMij$ is the feed efficiency of the ith cow on the jth day as a percent of that individual cow's maximum feed efficiency, μ is the overall mean, αij is the effect of intake of top dress of cow i on day j, βl is a vector of l parameters including: animal, DIM, MY, milk fat (%), milk protein (%), blood in milk (%), daily activity (steps), and gynecological status, $\alpha ij\beta l$ is the interaction between treatment of cow i on day j and the individual explanatory variables l, and ϵij is the error term for the measurement taken on cow i on day j. Variables were removed for non-significance using a stepwise, backward elimination procedure. Non-significant main effects involved in significant interactions were retained even if $P > 0.10$. Once a model was derived where all variables were either significant ($P < 0.05$), tending toward significance ($P < 0.10$), or involved in significant interactions, the model was considered final. Models were re-derived weekly and a unique model was developed for each top dress type. Final models by week and top dress type are reported in Formulated composition of the common total mixed ration (TMR) fed to all treatment groups[1]

Ingredient	kg, DM basis	kg, as-fed basis
Corn silage, brown midrib	7.727	22.205
Alfalfa hay	0.682	0.779
Brewers grain	2.568	8.560
Corn grain, dry, ground	3.409	3.874
Cottonseed, whole, with lint	1.364	1.482
Milk cow concentrate	7.885	8.735
Corn grain, dry, ground	2.272	2.581
Soybean hulls, ground	1.729	1.900
Canola meal	1.271	1.410
Amino plus[a]	1.240	1.410
Palmit 80[b]	0.271	0.273
Blood meal, dried	0.245	0.273
Sodium bicarbonate	0.158	0.159
Limestone, ground	0.158	0.159
Potassium carbonate	0.136	0.136
Salt, white	0.090	0.091
Volclay 90[c]	0.054	0.057
Molasses, cane	0.041	0.057
OmniGen-AF[d]	0.054	0.057
Potassium magnesium sulfate	0.027	0.027
MHA, dry[e]	0.024	0.024
Calcium phosphate, mono-dical	0.022	0.023
Mepron[f]	0.018	0.018
Diamond XPC[g]	0.013	0.014
Selenium yeast, 0.06%	0.012	0.014
Ultrasorb[h]	0.011	0.012
Clarifly[i]	0.010	0.010

Biotin[j]	0.009	0.009
Zinpro 5[k]	0.007	0.008
Trace mineral blend	0.006	0.006
Vitamin A, D, E blend	0.004	0.004
Vitamin E premix, 60%	0.002	0.002
Rumensin 90[l]	0.001	0.001
TOTAL	23.639	45.637

[1]TMR formulated to provide 61.7 mCal metabolizable energy (ME) per d; 2,750 g of metabolizable protein (MP) per d; 39.0 kg of ME allowable milk per d; and 39.0 kg of MP allowable milk per d.

[a]Rumen protected soybean meal; Ag Processing, Inc; Omaha, NE.

[b]Vegetable palm oil; rumen bypass fat; ADM Animal Nutrition; Quincy, IL.

[c]Granular sodium bentonite; binder and digestive aid; American Colloid Company; Hoffman Estates, IL.

[d]Immune support supplement; microbial ingredients, vitamins, and aluminosilicates; Phibro Animal Health Corporation; Teaneck, NJ.

[e]Granular formulation of ALIMET; 84% methionine activity and 100% absorbed; NOVUS; Saint Charles, Missouri.

[f]Rumen protected DL-methionine; RP Nutrients, Inc; East Troy, WI.

[g]Saccharomyces cerevisiae fermentation product; Diamond V; Cedar Rapids, Iowa.

[h]Mycotoxin deactivator; Micron Bio-Systems Ltd.; Buena Vista, VA.

[i]Diflubenzuron feed-through fly control; Central Garden and Pet Company-Central Life Sciences; Schaumburg, IL.

[j]2,200 mg Biotin/kg

[k]Trace mineral concentrate containing 30,688.51 ppm manganese, 5,370.57 ppm copper, 306.30 ppm iron, 75,187.97 ppm zinc, 613.32 ppm iodine, and 1,687.43 ppm cobalt (DM basis); Zinpro Performance Minerals; Eden Prairie, Minnesota.

[l]Monensin sodium energy supplement for increased milk production efficiency; Elanco Animal Health; Greenfield, IN.

Table *2-2* and the patterns of significance are discussed in the Results and Discussion section.

Once derived, the models were used to predict FPM for each cow based on their production records from the previous week and assuming they would be fed 0%, 5%, 10%, 15%, or 20% of their predicted NEL intake from each top dress. The resulting prediction matrix was reduced to obtain the maximum predicted FPM for each individual cow. The top dress type and level that produced the highest predicted FPM for each animal were used as the feeding strategy for that cow for the subsequent week.

Algorithm 2. Eight cows were also randomly assigned to the second algorithm aimed to differentiate cows by feed composition efficiency response structure in terms of feed to milk ratio (FtM). The FtM was calculated as feed intake per unit MY, where lower FtM was considered more efficient. Data were standardized to the percentage of maximum FtM for each individual cow over the entire experimental period. Principal component analysis (PCA) was employed to discern clusters of similar cows and make feed recommendations based on the resulting FtM. Each FtM record was calculated using the previous day's feeding record and the current day's MY. We did not assume any relationship *a priori* between the records from different days of a given cow's diet. The aim of PCA is to reduce a dataset's dimensionality to better summarize important variables. In this research, separate PCA were done for each top dress, but using all cows' data. The first two dimensions of PCA were used with each of the four top dresses, because variance was sufficiently reduced with a diminishing reduction in variance with additional dimensions. The proportion of variance explained by each axis is typically plotted in a scree plot, which depicts each eigenvector of the covariance matrix divided by the sum of diagonal values in the covariance matrix. Correlations between each day's weight in the linear combination of variables used for each dimension in the PCA were recorded (Table 2-3). Based on the correlations between principal components and FtM responses by d, all responses had an influence on principal component 1, while d1 and 4 had the greatest correlations with component 2. Therefore, d1 and 4 appeared to be the greatest differentiator between cows' FtM responses. The use of only two dimensions also allowed for visual evaluation of clustering in the behavior of each cow's efficiency on each top dress. An example plot of PCA run on all cows fed the GH top dress is shown in Figure 2-2.

After performing PCA on each top dress using all 24 cows' FtM records, *k*-means clustering was employed to systematically group cows based on their responses. K-means clustering aims to group data points into *k* groups such that the within-group mean distance is minimized. The resulting centroids, or centers of each cluster, create boundaries in space where any given point inside that boundary is closer to one centroid than all others. Diagrams of their boundaries are called Voronoi diagrams and can be used to classify out-of-sample observations by nearest centroid or cluster. Different values for *k* were explored from two to eight, with the optimal number of clusters being that which reduced the within-group sum of squared (WGSS) distances the most, while keeping the total number of groups relatively low. Optimizing groups in *k*-means is typically done by finding the "elbow" in the plot of WGSS by cluster number, where the drop in WGSS levels off and additional groups only provide minimal distance reductions. For TMR, CG, SBM, and GH, the chosen numbers of groups to sufficiently partition cow feeding patterns were four, two, three, and four, respectively. An example PCA plot with groups annotated is shown for the GH top dress in Figure 2-3. With each cow grouped by each top dress, the mean FtM values for each group were assigned to all cows in a given group, resulting in each cow having 4 assigned FtM values, one for each top dress. Cows were then assigned a top dress based on which of their four assigned groups had the lowest mean group FtM.

TMR. Eight of the 24 cows were randomly assigned to the TMR treatment. These animals were fed solely TMR ad libitum, with no additional top dress for the duration of the experiment (Table 2-1). This treatment acted as the control and offered a baseline for comparing algorithms 1 and 2. This treatment also represents a typical dairy feeding operation without individualized intervention to attempt improving feed efficiency.

Feeding Procedure

The feeding regime over this experimental testing period was the same for the preceding experiment utilized for algorithm training (Chapter 3). Briefly, refusal sampling and feeding began daily at 1300 h and lasted, on average, 2.5 h. All cows were allowed to freely consume their custom rations shortly after their afternoon milking which occurred at 1400 h. First, daily refusal samples were obtained using the quartering method (ServiTech Laboratories). The Calan data ranger (American Calan Inc.; Northwood, NH) was used to remove and weigh refusals from each bunk and to dispense the target amount of TMR into each bunk. The TMR was dispensed within approximately 2.5 kg (as-fed basis) in either direction of the target TMR amount for each cow. The specified supplemental top dress for each cow was weighed by-hand on a digital platform scale (Defender 5000 XtremeW, model T51XW; Ohaus Corp.; Parsippany, NJ). The top dresses were measured within 0.09 kg (as-fed basis) of the target top dress amount for each animal and then added on top of the TMR in the designated feed bunk. The top dresses were thoroughly mixed by-hand in order to incorporate all of the top dress into the top third of TMR in each Calan bunk.

Milking Procedure

The milking procedure over this experimental testing period was also the same as in the preceding training experiment (Chapter 3). In summary, all cows were milked twice daily, approximately every 12 h at 1300 h and 0100 h, in a double 12 De Laval parallel parlor (Dairymen

Specialties, Inc.; Harrisonburg, VA). This parlor is equipped with an inline AfiMilk MPC Milk Meter (Afimilk Ltd; Kibbutz Afikim, Israel) for monitoring individual cow MY, and an AfiLab Milk Analyzer (Afimilk Ltd; Kibbutz Afikim, Israel) for inline individual cow milk composition analysis (e.g., milk fat, milk protein). Milk lactose data were also collected by the AfiLab Milk Analyzer, but the returned data were not biologically plausible (i.e., milk lactose percentages of ~2.3% when we expected ~4.8% milk lactose) and were therefore excluded. Each cow was also equipped with a pedometer on one hind leg with embedded radio-frequency identification (RFID) technology (AfiAct II Leg Tag; Afimilk Ltd; Kibbutz Afikim, Israel). These monitors recorded the number of steps taken daily for each cow. Data obtained from the pedometers were reported in 12 h periods to match each milking. After milking, the cows exited the parlor through an exit alley containing a walk-over BW scale and RFID reader (AfiWeigh; Afimilk Ltd; Kibbutz Afikim, Israel). Individual cow BW were recorded twice daily in association with milking and these data were auto-compiled into the AfiFarm dairy farm management software (Afimilk Ltd; Kibbutz Afikim, Israel).

Sample Collection and Analysis

Samples of TMR and GH were collected daily and composited into 7-d samples that corresponded to the 7-d periods between algorithm updates. Because only one load each of CG and SBM (Big Spring Mill Inc.; Elliston, VA) were utilized throughout the entire experiment, these feeds were sampled only once after delivery to the farm. When sufficient orts were available (~500 g, as-fed basis), refusal samples were collected daily before feeding using the quartering method (ServiTech Laboratories). All samples were frozen at -20°C until analyses. Before analyses, individual cow refusal samples were thawed, pooled within each cow over 7-d periods, and subsequently processed in the same manner as previously described in the training period (Chapter

3). In short, all samples were ground with a Model 4 Wiley mill to pass through a 1-mm screen (A. H. Thomas Scientific; Swedesboro, NJ) and analyzed for dry matter (DM) (AOAC International, method 934.01), crude protein (CP) (AOAC International, method 968.06), neutral detergent fiber (NDF) (AOAC International, method 2002.04), acid detergent fiber (ADF) (AOAC International, method 973.18), ash (AOAC International, method 942.05), ether extract (EE) (AOAC International, method 920.39), starch (AOAC International, method 920.40), and acid detergent lignin (ADL) (AOAC International, method 973.18). The chemical composition of individual feedstuffs, including TMR, CG, SBM, and GH, are shown in Table 2-4. The CP content of the CG is unrealistically high. To better understand if this CP content was truly representative of what animals were consuming, we back-calculated the CP content of the feed using the analyzed diet samples and the analyzed refusal samples. In each instance, we found similar (<2% unit difference) results in the estimated CP content of this top dress. Based on this exercise, it appears that the CG fed in this experiment was likely contaminated with a higher protein ingredient. As such, the results should not be taken to reflect responses associated with top dressed CG alone and should be assumed to represent top dressing with a CG, protein commodity mixture.

Statistical Analyses

Outcomes of interest included: DMI, MY, milk fat percentage, milk fat yield, milk protein percentage, milk protein yield, feed efficiency, and activity. All variables were analyzed in R version 3.5.2 (R Core Team, 2018) using a mixed-effect model with fixed effects for feeding algorithm, top dress, week, and the 2- and 3-way interactions among these variables. An effect for the initial level of the response variable (from the adaptation to the training period) was also included. Random effects were included for animal, period, and square. Comparisons across treatments during the testing period and targeted contrasts back to the control TMR were used for mean separation. Least square means (LSM) were calculated and separation of means was based on contrasts between the treatment groups (algorithm by top dress type) and the control group, within or across weeks (as appropriate given the significance of the various interactions involving time). Significant differences between treatments were declared at $P < 0.05$.

Results and Discussion

Efficacy of Algorithms

Dry Matter Intake Responses. Dry matter intake was significantly affected by week (P = 0.022; Table 2-5). Significance values and LSM are included in Table 2-5. Overall, the DIM of the cows increased over the experimental period. As lactation progresses and DIM of cattle increases, DMI typically declines after an initial spike post calving (Martin and Sauvant, 2007). The cows utilized for this experiment were 241 DIM at the beginning of the study and were well past the initial DMI spike after calving. However, DMI increased over the experimental period. Figure 2-4 shows DMI responses by algorithm type and top dress used, by week. The five week experimental period may not have been long enough to capture the expected decline in DMI as stage of lactation advanced.

Unexpectedly, DMI in the experimental period was not affected by top dress as it was in the training period (Chapter 3). This may suggest that using algorithms to select efficient feedstuff combinations for individual animals resulted in selection of feedstuffs that did not dramatically change DMI. Therefore, both algorithms may have identified efficiency benefits associated with maintaining DMI. This is encouraging because feedstuffs that depress DMI may increase feed efficiency in the short-term, but will likely lead to excessive mobilization of body reserves and eventual decreases in feed efficiency long-term. For example, during the training period, cows receiving GH diets had reduced feed intake and increased efficiency. The reduced feed intake on the GH diet was likely caused by the higher NDF content and larger particle size of this top dress (Mertens, 1987; Kononoff et al., 2003). The lower energy density of GH suggests we would expect impaired productivity if fed long-term. In the first week of algorithm deployment, GH was a common choice for top-dresses; however, as algorithms were retrained each week, selection changed, likely reflecting the selection of more durable efficiency improvements. This suggests that the proposed approach to training and updating algorithms on short-term data may be sufficient to overcome some challenges associated with short-term responses, such as unintended long-term consequences associated with reductions in DMI due to palatability or individual animal differences.

Milk Yield. Milk yield was affected by initial performance ($P < 0.001$; Table 2-5) and significance values and LSM are included in Table 2-5. The initial performance effect highlights persistency of differences between animals and suggests that MY of cows throughout the experiment was similar to their specific yield values before the experiment. This result suggests that the developed algorithms were not capable of increasing the MY of individual animals above their unique production levels.

It was also expected that as week, and therefore DIM, increased, MY would decrease. Figure 2-5 shows MY responses by algorithm type and top dress used, by week. A typical lactation curve is characterized by a steady decline in MY towards the end of lactation (Kadhim et al., 2004). However, the algorithms and supplemental top dresses may have masked the expected week effect and decrease in MY as DIM increased throughout the study. Therefore, the developed algorithms may have had a positive effect on slowing MY decline as lactation progressed. Alternatively, the 35-d experimental period may not have been long enough to capture the expected decline in milk production. The absence of top dress and week effects may also be caused by the algorithmic selection for feed efficiency, rather than MY. Future research on refined algorithm development is needed to influence MY through individualized feeding techniques. In particular, differences in the objective of algorithms should be tested. By selecting for feed efficiency, we possibly generated more modest responses in both MY and DMI than if we were to select for either individually or use another multi-objective response criteria selecting for both simultaneously without forcing a linear relationship (as is done in MY/DMI).

Milk Fat Percentage and Yield. Milk fat percentage and yield were affected by initial performance ($P < 0.001$; Table 2-5) and significance values and LSM are included in Table 2-5. Like MY, milk fat percentages of individual animals throughout the experimental period were similar to milk fat percentage values from the beginning of the study. This result shows the individuality of cows. This individuality could suggest that individualized feeding approaches are necessary and can help better match individual animal requirements with supplies or could suggest that individual performance is governed by genetic and environmental factors more than it is by feeding interventions, meaning that individualized feeding may be unnecessary. Our results perhaps suggest the latter because milk fat percentage was not significantly influenced by the algorithms developed in this experiment or the top dresses assigned to individual animals by these algorithms. Additional research is necessary to determine if genetic and environmental factors can be affected by individualized feeding approaches. Figure 2-6 shows milk fat percentage responses by algorithm type and top dress used, by week.

As expected, milk fat yield results mirrored the MY and milk fat percentage responses. Initial performance significantly affected milk fat yield ($P < 0.001$; Table 2-5), and like the MY results suggest, individual animals maintain their specific level of production throughout lactation. The two algorithms tested in this experiment were not effective at overpowering these individual animal production levels. However, the developed algorithms seem to be successful at preventing declines in total MY, and therefore milk fat yield, as DIM increases (Kadhim et al., 2004). Longer training periods before algorithm development or different modeling techniques may prove to be able to further increase milk fat yields. Figure 2-7 shows milk fat yield by algorithm type and top dress used, by week.

Top dress and week did not significantly affect milk fat percentage or yield. The lack of significant top dress effects suggests that the experimental treatment diets were within normal carbohydrate and fiber ranges because it is commonly seen that milk fat is decreased by diets high in readily digestible carbohydrates and low fiber content (Davis et al., 1964). It was also expected that week would affect milk fat percentage and yield in the current study, because previous studies have shown decreases in milk fat as lactation progresses (Stoop et al., 2009). Similar to the training period, the length of the experimental period of this study may not have been long enough to capture these expected differences over the lactation curve.

Milk Protein Percentage and Yield. Milk protein percentage was significantly affected by a 3-way interaction between top dress, algorithm, and week (P = 0.008; Table 2-5) and by initial performance (P = 0.025; Table 2-5). Milk protein yield was significantly affected by week (P = 0.007; Table 2-5) and initial performance (P < 0.001; Table 2-5), as well. Significance values and LSM are included in Table 2-5.

Milk protein percentage was affected by a 3-way interaction between top dress, algorithm, and week (P = 0.008; Table 2-5) and Figure 2-8 shows milk protein percentage responses by algorithm type and top dress used, by week. This result suggests that individualized, precision feeding through top dressing has the ability to influence the protein percentage of milk. It was expected that top dressing with higher protein feeds would increase milk protein synthesis

(Kalscheur et al., 1999; Huhtanen and Hristov, 2009). Based on pre-planned contrasts, cows fed TMR predicted by algorithm 2 in week three (P = 0.034), SBM predicted by algorithm 1 in week three (P = 0.002), and TMR predicted by algorithm 1 in week four (P = 0.021), resulted in significantly higher milk protein percentages when compared to cows fed ad libitum TMR. Cows fed GH predicted by algorithm 2 in week three (P = 0.046) and CG predicted by algorithm 2 in week five (P = 0.002) resulted in significantly lower milk protein percentages. As a result, CG and GH may not be effective top dresses for use under algorithm 2 because of their decline in milk protein percentage (Figure 2-8). Individualized algorithms need to be developed with consideration of the available feedstuffs on-farm and be developed to prevent decreases in MY or components, while selecting for feed efficiency. Implementing multi-objective response criteria for selection of several parameters of interest may be worth investigation through future research.

It was also expected that DIM, and therefore week, would cause milk protein percentage to increase as lactation progressed (Friggens et al., 2008). However, milk protein percentage generally decreased over the experimental period (Figure 2-8). Current algorithms may have contributed to the unexpected decrease in milk protein percentage by making poor assignments of individual animals to specific top dress types and quantities. Alternatively, the base TMR may have been deficient in metabolizable protein (MP). However, this is unlikely because the base TMR used in this experiment is the sole feed fed on this particular dairy operation and was formulated to provide 2,750 g MP per d (Table 2-1) which is an acceptable MP content for large breed cattle producing at this level (Herdt, 2014).

Initial performance also had a significant effect on milk protein percentage (P = 0.025; Table 2-5) and suggests unique production thresholds exist between individual animals. These results may highlight the ability of individualized feeding with updated algorithm techniques to affect the protein percentage of milk or may suggest individual differences between cows cannot be influenced through dietary interventions. However, future research focused on fine-tuning the development and training of algorithms and their training periods may increase milk protein percentage of individual animals.

Milk protein yield was affected by week (P = 0 .007; Table 2-5) and initial performance (P < 0.001; Table 2-5). Figure 2-9 shows milk protein yield responses by algorithm type and top dress used, by week. In the current study, milk protein yield decreased throughout the experiment (Figure 2-9). The expected decrease in milk protein yield was associated with time, and the effect of week is consistent with stage of lactation (Friggens et al., 2008). Initial milk protein yields for individual animals at the beginning of the experiment were similar to their milk protein yields throughout the experiment. Therefore, milk protein yield is likely linked with the genetic and environmental factors that the current algorithms were not able to dictate. The algorithms utilized in this experiment were able to increase milk protein percentage, but not milk protein yield. However, altering these algorithms or utilizing different selection criteria may have a greater influence on milk protein yield through individualized feeding.

Feed Efficiency. As expected, feed efficiency was affected by many factors, and a 3-way interaction between top dress, algorithm, and week exists (P < 0.001; Table 2-5). Feed efficiency was also affected by initial performance (P = 0.022; Table 2-5). Feed efficiency significance values and LSM are included in Table 2-5 and Figure 2-10 shows feed efficiency responses by algorithm type and top dress used, by week.

The 3-way interaction between top dress, algorithm, and week (P < 0.001; Table 2-5) suggests that individualized feeding of top dress supplements has the ability to affect feed efficiency of dairy cattle. Based on pre-planned contrasts, cows fed SBM from algorithm 2 predictions in week four of the experimental period showed significantly decreased feed efficiencies when compared to cows fed TMR ad libitum (P = 0.039). However, cows fed TMR diets assigned by algorithm 2 resulted in the highest feed efficiencies (Table 2-5). The developed algorithms were capable of influencing feed efficiency, but refined models and algorithm training may reflect higher efficiencies of all supplemental interventions when compared to cows fed solely TMR. As a part of this interaction, feed efficiency was also affected by week; it was expected that feed efficiency would decrease as lactation progressed (St-Pierre et al., 2008), and in general, feed efficiency decreased over the experimental period, but this decrease was not uniform across all top dresses (Figure 2-10). Unexpectedly, cows fed TMR ad libitum experienced numerical increases in feed efficiency (Figure 2-10). As a result, the length of the experimental period may not have been long enough to capture the expected decrease in efficiency of the control group. This interaction suggests that the developed algorithms are capable of influencing feed efficiency by supplementing individual animals with various top dresses. However, more efficient algorithms need to be developed in order to maximize their influence on individual efficiencies.

Activity. Cow activity was affected by initial performance (P = 0.029; Table 2-5). Activity significance values and LSM are included in Table 2-5 and Figure 2-11 shows activity responses by algorithm type and top dress used, by week. Individual cows took roughly the same number of steps throughout the experiment as they did before the experiment; this suggests that cows act as individuals, even in their activity levels. Previous research has found that less active cows produce less milk (Reader et al., 2011). Therefore, it is important that individualized feeding does not alter the activity levels of cattle. We did not expect to see a top dress, algorithm, or week effect on activity level. The lack of significant effects on activity level suggests that individualized feeding techniques with the developed algorithms in this experiment did not alter typical activity behavior of dairy cattle.

Economic Analysis of Algorithm Outcomes

The two developed algorithms resulted in minimal statistical differences in animal performance compared to the TMR control group that represents conventional feeding strategies (Table 2-5). However, the costs associated with feeding according to each algorithms' specifications, and the return on milk from each algorithm should be evaluated to determine if any practical benefits from algorithm utilization exist that are not shown by the analyses above. Each of the experimental algorithms and the TMR control group predicted feeding recommendations for eight cows. The following analyses will be based on total costs and returns from feeding all eight cows in each group due to the differences in particular feedstuffs offered to individual cows in the algorithm feeding groups.

First, the costs associated with feeding the eight cows by each algorithm were investigated. The TMR control group consumed 13,052 kg (as-fed basis) of TMR throughout the 35-d experimental period. The cost associated with feeding eight cows TMR ad libitum was $1,722.86 over the 35-d experimental period or $49.22 per d. Algorithm 1 cows consumed, in total, 9,480 kg (as-fed basis) of TMR, 373 kg (as-fed basis) of CG, 555 kg (as-fed basis) of SBM, and 418 kg (as-fed basis) of GH. As a result, utilizing algorithm 1 to feed eight cows cost $1,650.32 over the 35-d period or $47.15 per d. Algorithm 2 utilized 12,498 kg (as-fed basis) of TMR, 366 kg (as-fed basis) of CG, 442 kg (as-fed basis) of SBM, and 140 kg (as-fed basis) of GH to feed eight cows over the entire experimental period. Algorithm 2 resulted in $2,084.89 of feed expenses to feed eight cows over the 35-d experimental period, or $59.57 per d. The TMR control group fed eight cows for numerically less than either algorithm developed in this experiment. However, it was less expensive to feed cattle utilizing algorithm 1 than with algorithm 2.

Secondly, the total amount of milk produced by the eight cows fed under each feeding strategy was evaluated. Cows fed TMR ad libitum produced 8,327 kg of milk over the experimental period, while cows fed by algorithm 1 produced only 7,812 kg of milk over the 35-d period. The eight cows fed by algorithm 2 produced 8,276 kg of milk. The TMR control cows and the algorithm 2 cows produced similar amounts of milk over the experimental period. However, algorithm 2 feeding strategy had the highest feed costs. Then, utilizing 2020 milk prices of $0.40 per kg, the revenue from milk between the feeding strategies was compared. The revenue from the TMR control cows' production over the experimental period was $3,304.42 or $94.41 per d. Algorithm 1 revenue from the eight cows fed by this strategy was $3,100.05 or $88.57 per d. The eight cows fed by algorithm 2 were associated with $3,284.18 in revenue from milk over the experimental period, or $93.83 per d.

Feed expenses and milk revenues were then compared between algorithmic feeding strategies. The TMR control group resulted in the maximum profit for producers of $1,581.56 over the experimental period or $45.19 per d when feed expenses were subtracted from milk revenue income. Algorithm 1 left farmers with $1,449.47 over the 35-d period or $41.42 per d after feed costs were subtracted from milk income. Algorithm 2 is responsible for even less profit for producers totaling $1,199.29 over the experimental period or $34.27 per d. As a result, TMR ad libitum feeding is the cheapest option for producers when compared to the two algorithms developed in this experiment. While algorithm 1 cows were the most efficient, feed costs associated with this feeding strategy were also higher than TMR feeding. Algorithm 2 resulted in higher MY than algorithm 1, but did not result in greater production than ad libitum TMR feeding.

Overall, neither algorithm was economically successful at influencing individual production parameters of dairy cattle when compared to a conventional TMR feeding regime. However, this study revealed many individual animal differences and may suggest potential for effective algorithm development to individually feed cattle to increase dairy production through economically viable feeding recommendations.

Relevance for Future Work

Individualized feeding through the use of precision algorithms shows promise to affect feed efficiency of cattle on-farm. However, additional research is necessary to determine if genetic and environmental MY and component differences between cattle, as shown by many initial performance effects, can be affected by individualized feeding approaches. Algorithm modifications are necessary to influence production parameters of interest through economical ration development. In particular, differences in the objective of algorithms should be tested and extensive research focused on the development of algorithms capable of targeting specific production parameters that may be of interest for various dairy operations is needed. Future collection of individual cow response data to a multitude of top dress feedstuffs is also necessary to inform modeling exercises that include economic analyses to lower feed costs. Algorithms also need to be developed to be capable of feeding a wide variety of top dresses because commodity types and costs vary by location. Short-term algorithm training was utilized in this experiment because longer-term training techniques would extend further into lactation, reducing the amount of time individualized feeding could occur. Future research on the minimal training period length required to create efficient algorithms is also warranted to ensure maximum on-farm response to individualized feeding.

Conclusions

Individualized feeding of dairy cattle utilizing the algorithms developed in this experiment affected feed efficiency and milk protein percentage of animals. Individual animal differences for many production parameters were also detected and were not affected by the developed feeding strategies. As a result, future research investigating the genetic and environmental factors between animals, to determine if individualized feeding is capable of influencing these effects, is needed. However, the two developed algorithms in this experiment resulted in minimal statistical differences in animal performance when compared to cows fed TMR ad libitum. Neither developed algorithm is currently practical for use on-farm from an economic standpoint; feeding TMR ad libitum is more cost effective when compared with returns from milk. As a result, future research on more refined model development and training is needed to develop individualized feeding algorithms capable of influencing production parameters of interest through economical ration recommendations.

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Tables

Table 2-1. Formulated composition of the common total mixed ration (TMR) fed to all treatment groups[1]

Ingredient	kg, DM basis	kg, as-fed basis
Corn silage, brown midrib	7.727	22.205
Alfalfa hay	0.682	0.779
Brewers grain	2.568	8.560
Corn grain, dry, ground	3.409	3.874
Cottonseed, whole, with lint	1.364	1.482
Milk cow concentrate	7.885	8.735
Corn grain, dry, ground	2.272	2.581
Soybean hulls, ground	1.729	1.900
Canola meal	1.271	1.410
Amino plus[a]	1.240	1.410
Palmit 80[b]	0.271	0.273
Blood meal, dried	0.245	0.273
Sodium bicarbonate	0.158	0.159
Limestone, ground	0.158	0.159
Potassium carbonate	0.136	0.136
Salt, white	0.090	0.091
Volclay 90[c]	0.054	0.057
Molasses, cane	0.041	0.057
OmniGen-AF[d]	0.054	0.057
Potassium magnesium sulfate	0.027	0.027
MHA, dry[e]	0.024	0.024
Calcium phosphate, mono-dical	0.022	0.023
Mepron[f]	0.018	0.018
Diamond XPC[g]	0.013	0.014
Selenium yeast, 0.06%	0.012	0.014
Ultrasorb[h]	0.011	0.012
Clarifly[i]	0.010	0.010
Biotin[j]	0.009	0.009
Zinpro 5[k]	0.007	0.008
Trace mineral blend	0.006	0.006
Vitamin A, D, E blend	0.004	0.004
Vitamin E premix, 60%	0.002	0.002
Rumensin 90[l]	0.001	0.001
TOTAL	23.639	45.637

[1]TMR formulated to provide 61.7 mCal metabolizable energy (ME) per d; 2,750 g of metabolizable protein (MP) per d; 39.0 kg of ME allowable milk per d; and 39.0 kg of MP allowable milk per d.
[a]Rumen protected soybean meal; Ag Processing, Inc; Omaha, NE.
[b]Vegetable palm oil; rumen bypass fat; ADM Animal Nutrition; Quincy, IL.

[c]Granular sodium bentonite; binder and digestive aid; American Colloid Company; Hoffman Estates, IL.
[d]Immune support supplement; microbial ingredients, vitamins, and aluminosilicates; Phibro Animal Health Corporation; Teaneck, NJ.
[e]Granular formulation of ALIMET; 84% methionine activity and 100% absorbed; NOVUS; Saint Charles, Missouri.
[f]Rumen protected DL-methionine; RP Nutrients, Inc; East Troy, WI.
[g]Saccharomyces cerevisiae fermentation product; Diamond V; Cedar Rapids, Iowa.
[h]Mycotoxin deactivator; Micron Bio-Systems Ltd.; Buena Vista, VA.
[i]Diflubenzuron feed-through fly control; Central Garden and Pet Company-Central Life Sciences; Schaumburg, IL.
[j]2,200 mg Biotin/kg
[k]Trace mineral concentrate containing 30,688.51 ppm manganese, 5,370.57 ppm copper, 306.30 ppm iron, 75,187.97 ppm zinc, 613.32 ppm iodine, and 1,687.43 ppm cobalt (DM basis); Zinpro Performance Minerals; Eden Prairie, Minnesota.
[l]Monensin sodium energy supplement for increased milk production efficiency; Elanco Animal Health; Greenfield, IN.

Table 2-2. Weekly variables included in algorithm 1 models for each treatment

Week	Treatments[1]	Variables included in model[2]
1	TMR Only	TMR * DIM + TMR * MY + Gynecological Status + Animal ID
	CG	CG * Animal ID + CG * MY + CG * Gynecological Status
	SBM	SBM * Animal ID + MY
	GH	GH * Animal ID + GH * Milk Protein + Milk Fat + Activity + GH * Gynecological Status
2	TMR Only	TMR + Milk Protein + Milk Lactose + TMR * Milk Fat + TMR * Blood + TMR * DIM + TMR * MY + Animal ID
	CG	Animal ID * CG + CG * DIM + CG * MY + CG * Gynecological Status
	SBM	TMR * Animal ID + SBM * Animal ID + Animal ID
	GH	TMR + GH * Animal ID + Gynecological Status
3	TMR Only	TMR + Blood + TMR * DIM + TMR * MY
	CG	TMR + CG * Animal ID + CG * DIM + CG * MY + CG * Gynecological Status
	SBM	TMR * Animal ID + SBM * Animal ID
	GH	TMR + GH * Animal ID + Gynecological Status
4	TMR Only	TMR * Animal ID + Milk Lactose + TMR * Blood + MY
	CG	TMR * Animal ID + CG * Animal ID + Milk Fat + CG * DIM + CG * Activity + CG * Gynecological Status
	SBM	TMR * Animal ID + SBM + Milk Fat + DIM + MY
	GH	TMR + Animal ID + GH * Animal ID + GH * Gynecological Status
5	TMR Only	TMR * Animal ID + Milk Protein + Milk Lactose + TMR * Blood + TMR * MY
	CG	TMR * Animal ID + CG * Animal ID + CG * DIM + CG * Activity + CG * Gynecological Status
	SBM	TMR * Animal ID + SBM * Animal ID + Milk Fat + DIM + MY
	GH	TMR + GH * Animal ID + Milk Fat + DIM + GH * Gynecological Status

[1]Treatments: TMR Only = TMR with no top dress; CG = TMR with corn grain top dress; SBM = TMR with soybean meal top dress; GH = TMR with mixed grass hay top dress.
[2]Lactose variables recorded from AfiLab Milk Analyzer were retained in models, regardless of calibration errors.

Table 2-3. Correlations between the feed to milk ratio (FtM) on each day of feeding and principal components 1 and 2 (PC1 & PC2) for each of the experimental treatment diets fed over d0 to 7

	TMR		Corn Grain		Soybean Meal		Grass Hay	
Day	PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2
0	0.80	-0.06	0.90	0.28	-0.77	-0.14	0.76	-0.15
1	0.72	-0.60	0.86	0.21	-0.54	0.81	0.62	0.72
2	0.81	0.54	0.92	-0.01	-0.93	0.13	0.84	-0.20
3	0.78	0.51	0.87	0.31	-0.87	0.14	0.81	-0.40
4	0.90	0.13	0.86	-0.41	-0.90	-0.21	0.78	-0.33
5	0.88	-0.02	0.86	0.06	-0.86	-0.12	0.73	-0.23
6	0.87	-0.32	0.85	-0.38	-0.80	-0.40	0.76	0.13
7	0.83	-0.24	0.91	0.01	-0.73	-0.17	0.84	0.14

Table 2-4. Chemical composition of total mixed ration (TMR), corn grain (CG), soybean meal (SBM), and grass hay (GH) feedstuffs (%, DM basis)

Item	TMR	Corn Grain (CG)	Soybean Meal (SBM)	Grass Hay (GH)
DM	46.7	84.3	81.6	92.8
CP	15.1	21.2[a]	51.7	6.80
NDF	39.7	13.4	9.80	73.8
ADF	22.1	3.70	4.60	44.3
Ash	6.10	4.30	10.1	7.20
Ether Extract	4.70	0.00	1.60	2.30
Starch	19.3	51.8	3.70	20.5[b]
ADL	2.40	0.60	0.40	5.40

[a]Suspected to be higher than typical values due to contamination during storage.
[b]Suspected to be higher than typical values due to analytical or computational error.

Table 2-5. Mean production performance of cows fed utilizing one of two algorithms or fed a common total mixed ration (TMR)[1]

Response Variable (DM basis)	Treatments[2,3]				P-values							
	TMR	CG	SBM	GH	Top Dress	Algorithm	Week	Initial Performance	Top Dress x algorithm	Top Dress x Week	Algorithm x Week	Top Dress x Algorithm x Week
DMI, kg/d					0.075	0.292	0.022	0.134	0.672	0.2122	0.419	0.067
Algorithm 1	N/A	N/A	21.2 ± 1.78	19.7 ± 1.63								
Algorithm 2	21.3 ± 1.86	24.3 ± 1.88	25.5 ± 1.71	22.0 ± 1.73								
TMR Control	23.4 ± 1.43	N/A	N/A	N/A								
MY, kg/d					0.299	0.441	0.276	<0.001	0.482	0.356	0.192	0.399
Algorithm 1	N/A	N/A	30.8 ± 1.41	30.0 ± 1.15								
Algorithm 2	32.5 ± 1.55	34.2 ± 1.55	30.5 ± 1.29	31.9 ± 1.39								
TMR Control	33.0 ± 1.00	N/A	N/A	N/A								
Milk Fat, %					0.309	0.137	0.403	<0.001	0.296	0.131	0.096	0.543

Algorithm 1	N/A	N/A	4.42 ± 0.119	4.63 ± 0.084								
Algorithm 2	4.62 ± 0.132	4.38 ± 0.126	4.58 ± 0.099	4.43 ± 0.117								
TMR Control	4.42 ± 0.066	N/A	N/A	N/A								
Milk Fat Yield, kg/d					0.142	0.669	0.1500	<0.001	0.456	0.433	0.628	0.957
Algorithm 1	N/A	N/A	1.37 ± 0.061	1.37 ± 0.043								
Algorithm 2	1.43 ± 0.066	1.56 ± 0.062	1.35 ± 0.048	1.43 ± 0.057								
TMR Control	1.46 ± 0.030	N/A	N/A	N/A								
Milk Protein, %					0.067	0.238	<0.001	0.025	0.281	0.606	0.238	0.008
Algorithm 1	N/A	N/A	2.89 ± 0.075	2.85 ± 0.058								
Algorithm 2	2.89 ± 0.082	2.73 ± 0.087	3.00 ± 0.067	2.89 ± 0.073								

TMR Control	2.80 ± 0.048	N/A	N/A	N/A								
Milk Protein Yield, kg/d					0.700	0.552	0.007	<0.001	0.650	0.662	0.876	0.162
Algorithm 1	N/A	N/A	0.899 ± 0.052	0.837 ± 0.040								
Algorithm 2	0.951 ± 0.056	0.959 ± 0.057	0.891 ± 0.046	0.923 ± 0.051								
TMR Control	0.929 ± 0.034	N/A	N/A	N/A								
Feed Efficiency, kg milk/kg feed					0.043	0.632	0.002	0.022	0.251	0.028	0.089	<0.001
Algorithm 1	N/A	N/A	1.46 ± 0.119	1.56 ± 0.112								
Algorithm 2	1.64 ± 0.120	1.42 ± 0.121	1.32 ± 0.114	1.45 ± 0.115								
TMR Control	1.45 ± 0.111	N/A	N/A	N/A								

Activity, steps/h					0.238	0.422	0.435	0.029	0.810	0.949	0.809	0.511
Algorithm 1	N/A	N/A	101 ± 7.09	104 ± 6.14								
Algorithm 2	92.5 ± 7.53	96.2 ± 7.50	90.2 ± 6.57	101 ± 6.83								
TMR Control	103 ± 5.34	N/A	N/A	N/A								

[1]Least squares means ± SEM are shown for each response variable.
[2]Treatments: TMR = TMR with no top dress; CG = TMR with corn grain top dress; SBM = TMR with soybean meal top dress; GH = TMR with mixed grass hay top dress.
[3]N/A = no cows assigned to top dress.

Figures

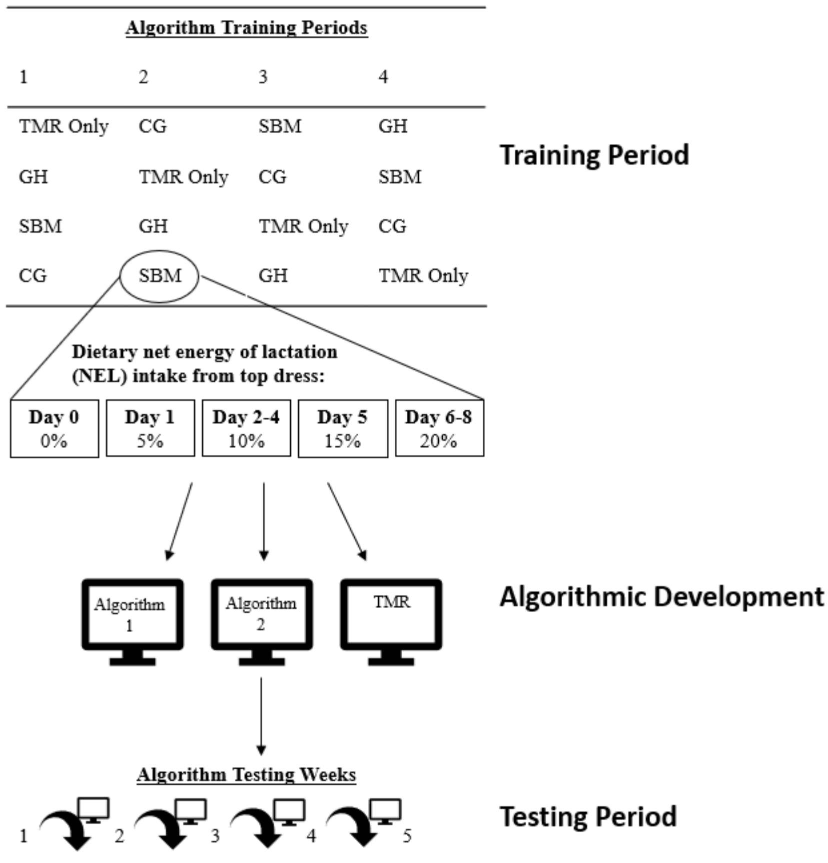

Figure 2-1. The experimental design consisted of a training period, an algorithmic development period, and a testing period. The training period consisted of four periods that were 9-d in length and is reported in Chapter 3. During each training period, six cows were randomly assigned to one of four top dress treatment options: TMR Only = TMR with no top dress, CG = TMR with corn grain top dress, SBM = TMR with soybean meal top dress, or GH = TMR with mixed grass hay top dress. A replicated 4 x 4 Latin square was implemented and each group of six cows was fed a different experimental treatment diet over the four periods. Throughout each period, cows were fed increasing amounts of dietary net energy of lactation (NEL) intake from top dress. Two algorithms were then developed based on the training data that aimed to maximize individual cow feed efficiency. Eight cows were assigned to each algorithm and eight cows were assigned to an ad libitum TMR treatment to serve as the control group. During the 35-d testing period that followed the training period, algorithms were updated weekly in an attempt to make better predictions to positively affect individual cow feed efficiency.

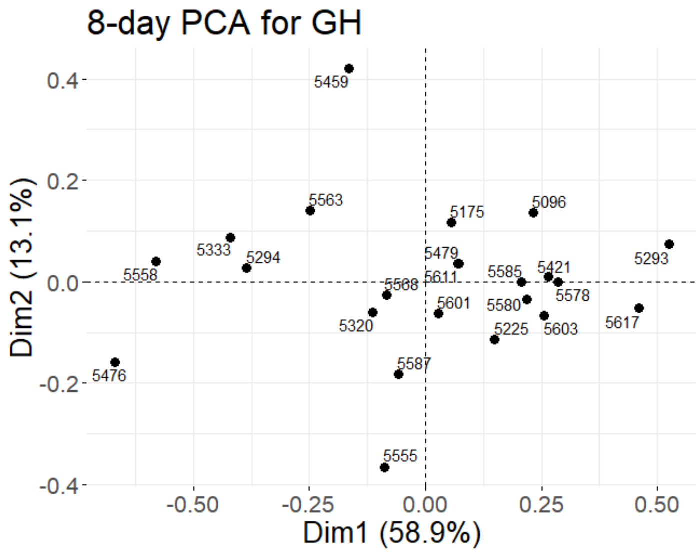

Figure 2-2. Principal components 1 (Dim1) and 2 (Dim2) derived from principal component analysis (PCA) of each cow's feed to milk conversion ratio response to the grass hay top dress (GH). Each cow is represented by one point on the scatterplot, with the cow's ID number appearing next to its respective point.

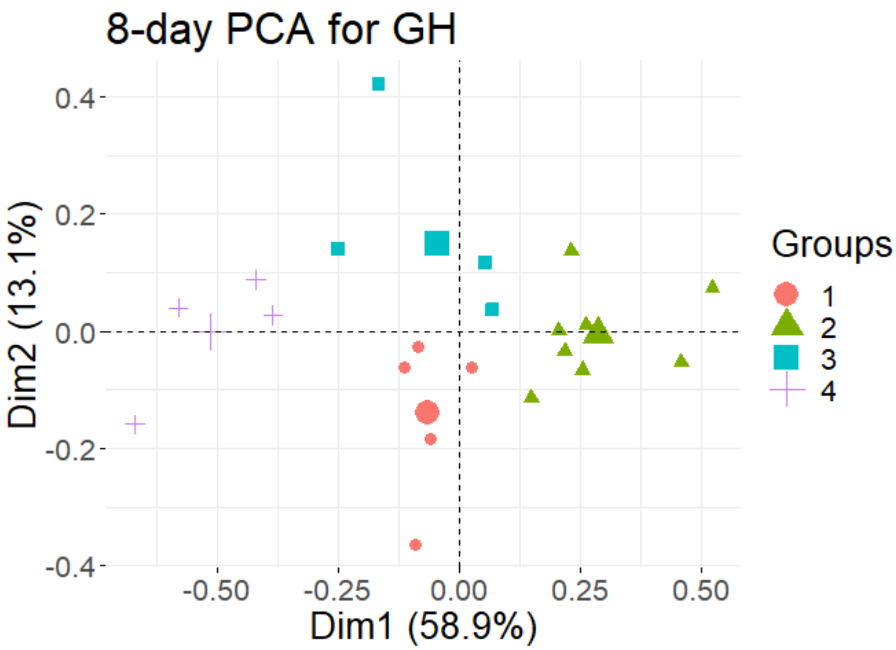

Figure 2-3. Scatterplot of principal components 1 (Dim1) and 2 (Dim2) for each cow based on the principal components analysis (PCA) of their response to grass hay top dress (GH). Four groups are divided based on k-means clustering of the Dim1 and Dim2 coordinates. The larger symbol plotted in each group represents the centroid coordinates of that group.

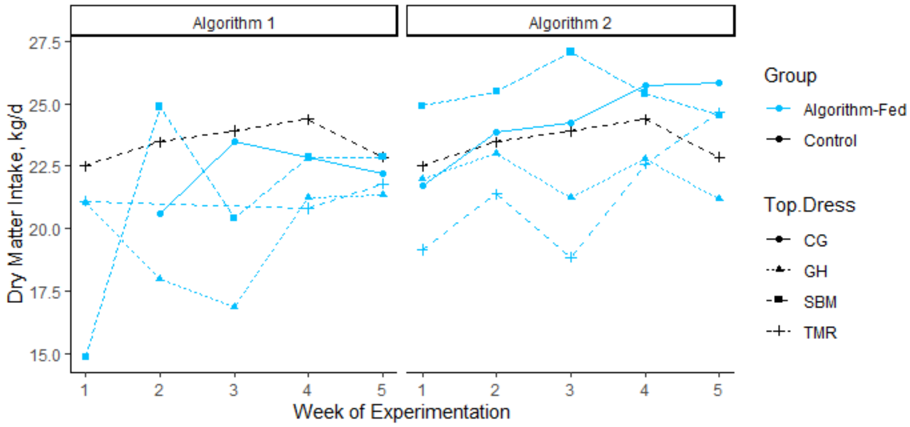

Figure 2-4. Least squares means (LSM) of dry matter intake (DMI) (kg/d) for each top dress predicted by each algorithm over the weeks of the experimental period.

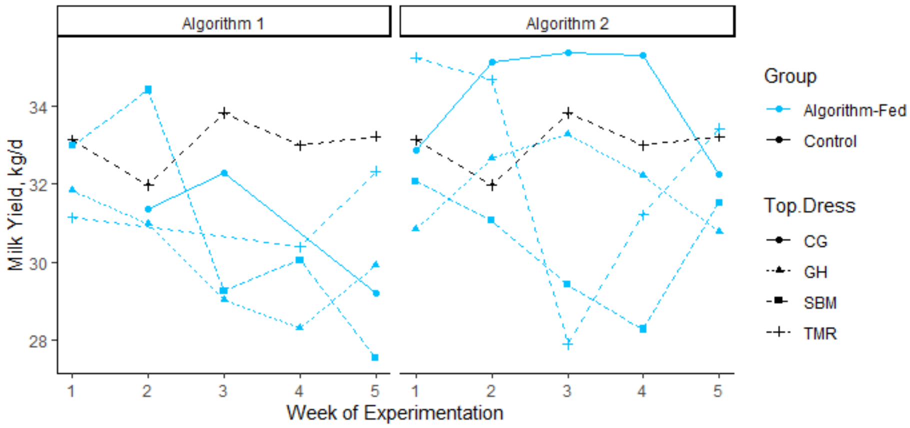

Figure 2-5. Least squares means (LSM) of milk yield (MY) (kg/d) for each top dress predicted by each algorithm over the weeks of the experimental period.

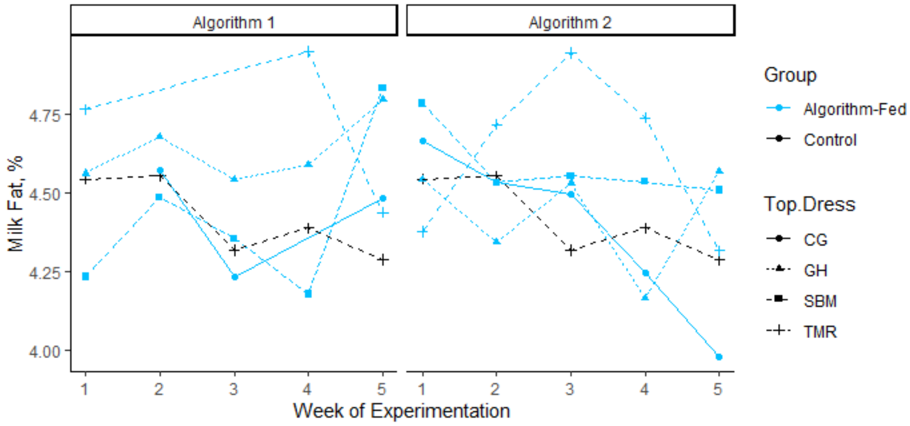

Figure 2-6. Least squares means (LSM) of milk fat percentage for each top dress predicted by each algorithm over the weeks of the experimental period.

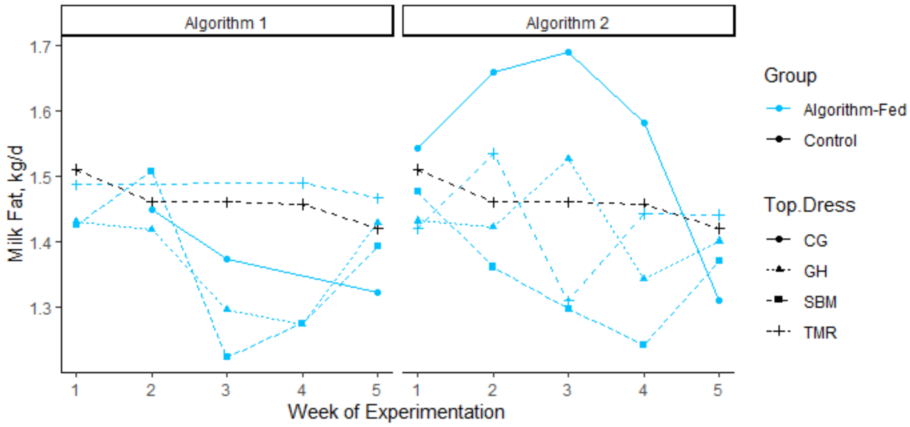

Figure 2-7. Least squares means (LSM) of milk fat yield (kg/d) for each top dress predicted by each algorithm over the weeks of the experimental period.

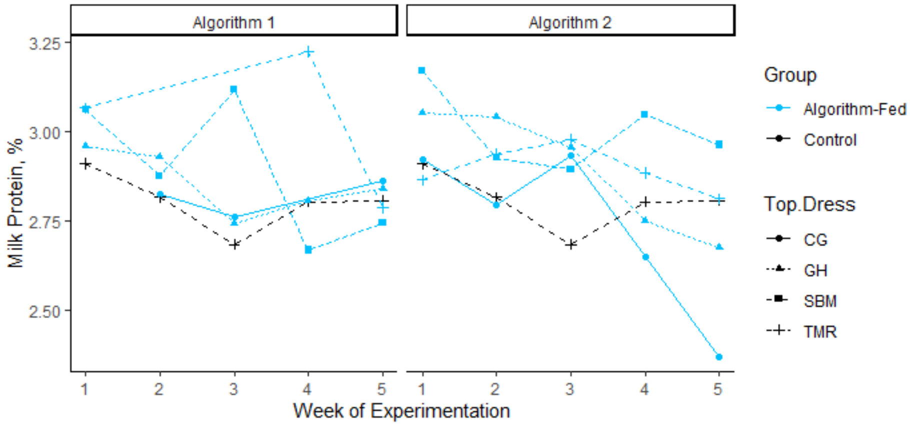

Figure 2-8. Least squares means (LSM) of milk protein percentage for each top dress predicted by each algorithm over the weeks of the experimental period.

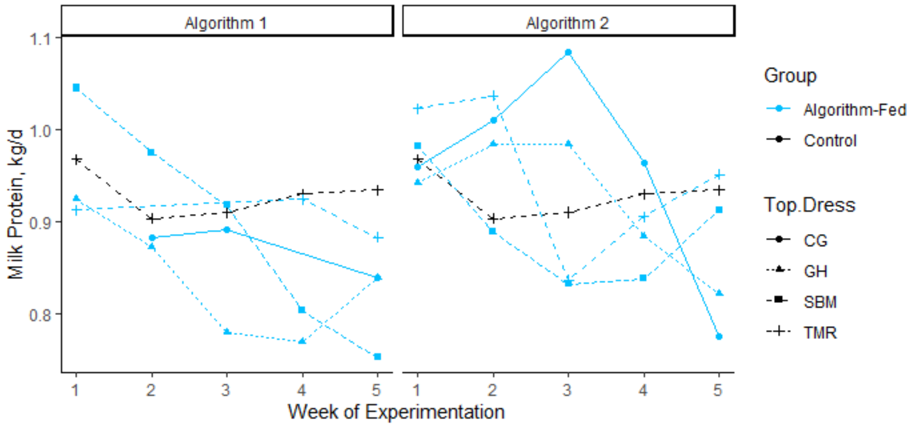

Figure 2-9. Least squares means (LSM) of milk protein yield (kg/d) for each top dress predicted by each algorithm over the weeks of the experimental period.

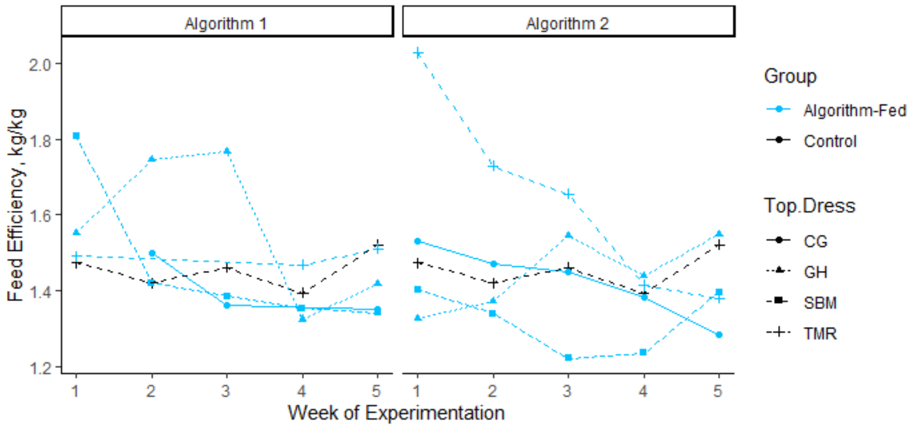

Figure 2-10. Least squares means (LSM) of feed efficiency (kg milk/kg feed) for each top dress predicted by each algorithm over the weeks of the experimental period.

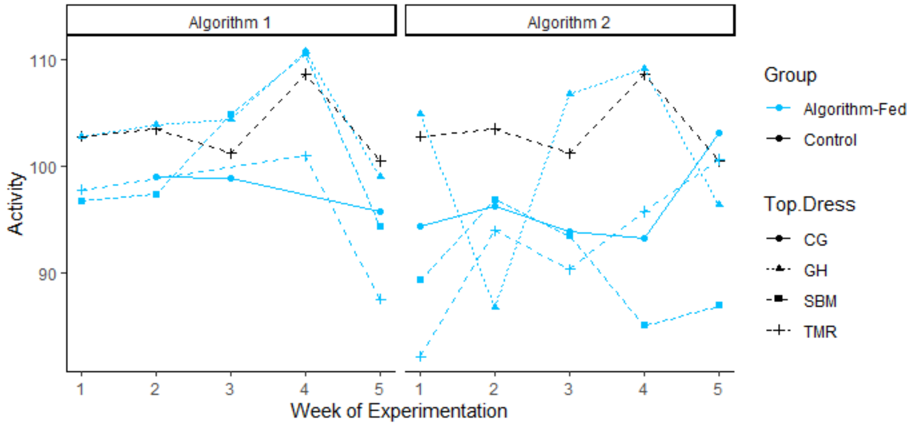

Figure 2-11. Least squares means (LSM) of activity (steps/h) for each top dress predicted by each algorithm over the weeks of the experimental period.

CHAPTER 5: CONCLUSIONS

Utilizing precision technologies to individually feed dairy cattle has the ability to increase profit for farmers and lower costs associated with feeding. In order to increase cow production and minimize feed expenses, maximizing feed efficiency through individualized ration recommendations may be of interest. Therefore, automated feeding systems (AFS) are necessary to individually feed dairy cattle with precision technologies in order to minimize on-farm labor increases associated with feeding animals independently. Automated feeding systems implemented on-farm must be compatible with current housing configurations on individual operations and capable of feeding a variety of feedstuffs. These systems require substantial initial investment, but economic returns from increased cow production and lower feed costs may outweigh these expenses.

Individual dairy cows elicit many unique production responses. As a result, individualized feeding is of interest to attempt to capitalize on these individual animal differences. Precision feeding through AFS is an approach likely capable of predicting ration recommendations tailored to individual animals. However, the type and quantity of feedstuffs to include in precision ration formulation need to be determined. Feeding only a portion of cattle diets through AFS is likely the most feasible approach. Therefore, various top dress supplements were fed to lactating cattle in an attempt to collect short-term response data on individual animals. These results highlight individual animal differences in many production parameters and suggest that individualized feeding, rather than group feeding, may have the potential to increase feed efficiency of dairy cattle. However, additional studies that utilize individualized feeding with various feedstuffs are needed to increase the available data for use in algorithm development.

Precision feeding algorithms based on individualized animal data are necessary for prediction of custom supplements for individual animals. Fortunately, developed algorithms may be based on individual cow data that many producers currently collect, but rarely utilized to make feed recommendations for enhanced productivity of individuals. As a result, two algorithms were designed to predict top dress supplementation to maximize feed efficiency of individual animals. Both algorithms were trained with short-term individual animal response data to various types and quantities of top dress feedstuffs. Training models for short periods of time will allow for maximum use of precision feeding throughout lactation for individual animals. Precision algorithms were designed to influence feed efficiency of individuals. However, future research of models utilizing alternative outputs, such as milk yield (MY), is of interest. Availability and cost of feedstuffs vary globally, and models should also be developed to account for producers' preferences of feed ingredients.

Utilizing precision feeding through top dress supplementation with the two algorithms presented in this work shows promise for individualized feeding to affect feed efficiency. However, the two algorithmic feeding strategies are not economically practical when compared to conventional total mixed ration (TMR) ad libitum feeding. Income from milk production over feed expenses was highest for conventionally fed animals. Therefore, future research is needed to investigate and develop more successful models capable of increasing feed efficiencies through economical ration recommendations for individual animals. This may require longer training periods, different model analytics, or alternative model inputs and outputs.

Overall, individualized feeding through precision technology shows promise to positively influence the dairy industry. However, current models for individualized feeding are inefficient and not worth the investment of AFS on many dairy operations. Future research is needed to determine if acceptable models for individualized dietary intervention can be developed. In conclusion, precision feeding in the dairy industry has potential to increase profit for farmers through greater productivity of cattle, and to decrease costs associated with daily feeding. Research involving the collection of individual cow production response data and development of efficient models are of interest to purse active precision feeding for dairy operations globally.