ABSTRACT

Development of expert systems for dairy herd management is now feasible due to recent advances in computer technology. Expert systems are special computer software applications that utilize inference and symbolic representation to carry out reasoning and analysis functions in contrast to the numerical approach of traditional programming. Applications that appear to have specific use in dairy management include interpretation of data collected automatically from specialized animal sensors, diagnosis and prescription of remedies for equipment malfunctions, analysis of current herd programs and recommendations for improvement in feeding, culling, mastitis control, selection of sires, and designation of specific service sires for individual cows.

INTRODUCTION

The use of electronics and computers is destined to have a significant impact on animal agriculture. This paper reviews one aspect of computer applications, that of expert systems (ES), and its potential use in dairy management. Expert systems is one of four major branches of artificial intelligence (AI). Other branches are natural language interpretation, computer vision, and robotics (2, 12). At present, a robotic milker is under development in Europe, but the authors are unaware of any major programs to apply computer vision or natural language interpretation to dairy management. However, ES appear to have a substantial role in future dairy management practices, especially with new electronic sensors (18).

Two requirements necessary for routine development of ES have been attained. The first is a decreasing price to performance ratio for computers. Development of ES was, until recently, restricted to expensive LISP machines and mainframe computers. Recent advances in hardware and software have made development of reasonably sized ES possible on microcomputers. The second component is an increase in ease with which ES can be “programmed”. Early advances in ES removed the necessity to program in LISP or Pascal; metalevels, in the form of ES shells, may now be used. These shells have reduced the task of developing ES to knowledge engineering.

EARLY SUCCESSFUL EXPERT SYSTEMS

One of the earliest and most widely cited ES is Mycin (3). Mycin was developed at Stanford University to diagnose infectious diseases in humans. Two other commonly cited ES are Prospector and R1. Prospector, developed at SRI International, predicts the location of molybdenum deposits (5); R1 (also known as XCON), developed at Carnegie-Mellon University, examines the configuration of VAX-11/780 computer systems to ensure the system is configured properly before being shipped to the customer (11).

Two ES developed in agriculture are noteworthy. The first, PLANT/ds, was developed at the University of Illinois to diagnose 17 soybean diseases (15). The second, COMAX, was developed by USDA for the management of cotton crop (10); COMAX serves as an expert by preparing input for Gossym, a Fortran simulation program, and interpreting the simulation output.

COMPONENTS OF EXPERT SYSTEMS

Expert systems are characterized by separation of knowledge from the program’s control...
structure; this feature also differentiates them from conventional software (4, 7, 24). Knowledge is stored in the knowledge base and the control structure is in the inference engine. Separation of these components into distinct entities began with research in AI and gives ES the necessary flexibility to draw conclusions for problems previously reserved for experts. In addition to the knowledge base and inference engine, several other AI components have become associated with ES.

Knowledge Base

The knowledge base contains assertions and knowledge relationships about the task at hand represented in a form the ES can interpret. Expert systems have been developed that use production rules (3), frames (1), and semantic nets (5) as knowledge representation schemes. Production rules are condition-action pairs in the form of if-then rules. Frames are a method of representing a collection of relevant facts together. Frames are very similar to records or structures used by Pascal and C programming languages. Decisions are made by matching the current facts to prototypical frames. Semantic nets are relational tree structures with the relationship between nodes being the arcs of the tree. Historically, production rules have been the representation of choice for diagnostic ES, as they have the advantage of being modular and declarative. Due to their widespread use, production rules will have the most impact on early dairy ES. However, the current trend in developing large ES is to use combinations of knowledge representation schemes; such systems are referred to as multiparadigm systems.

Building a knowledge base requires a knowledge engineer to extract and describe the opinions of the expert. The knowledge base grows and expands as it is fine tuned. Often the expert may not be able to explain exactly why he makes a decision in a particular situation but uses his intuition, rules of thumb and experience to obtain a solution to the problem which has been posed. One of the most challenging aspects of writing ES for dairy management applications is expression of a true expert's knowledge.

Inference Engine

The inference engine is charged with the role of performing and controlling inference on the knowledge base. Specific features of the inference engine depend on the knowledge representation scheme used for the knowledge base. Because the most common representation scheme is production rules, this inference engine will be exemplified.

Two types of inference are typically performed, deduction and plausible deduction. Deduction is usually modus ponens. That is, given if <antecedent> then <consequent> and <antecedent> it follows that <consequent> must be true. Plausible deduction is deduction under uncertainty and is not a formal logic [see (3) for a review of reasoning under uncertainty]. Assertions are annotated with a confidence or certainty factor that are propagated through the inference and reflected in the conclusions. Plausible deduction allows ES to reason with missing data, that is, data with a certainty of zero. The ability of ES to reason with uncertain data makes this technique attractive for wide use in dairy management.

The two most common control strategies for deductive inference engines are forward and backward chaining. Forward chaining is top-down or data driven; that is, it starts from observations and tries to reach a conclusion about the observations. The inference engine scans rules in the data base for those with antecedents that match the assertion. The inference engine “fires” rules meeting this criteria adding their results to the database. Backward chaining is bottom-up or goal driven; that is, it starts with a hypothesis and looks for data to support the hypothesis. Rules in the database are scanned for those with consequents that match the assertion. The inference engine “fires” rules meeting this criteria adding their results to the database. Backward chaining is bottom-up or goal driven; that is, it starts with a hypothesis and looks for data to support the hypothesis. Rules in the database are scanned for those with consequents that match the hypothesis. These rules are “fired”, with the inference engine trying to prove their antecedent. Forward chaining is appropriate for problems with many goals and limited data, whereas backward chaining is appropriate for situations with few goals and much data.

A less common control strategy is one used by Michalski et al. (13) for diagnosing soybean diseases. In this system each rule concludes a diagnosis and only the rule with the highest degree of evidence is “fired”. This approach requires a more structured knowledge base than the chaining control strategies.
Other Artificial Intelligence Subsystems

The ability of users to converse with a computer in natural language is one goal of AI research. This goal is particularly important for ES, as they need to explain their conclusions (6, 9). One example of natural language with ES is Mycin. Explanation capabilities were incorporated into Mycin in two forms (22). The first is a reasoning status checker used during the consultation. At each question the user can ask either “why” or “how”. “Why” displays the rule under consideration and “how” searches the history tree and displays the rules leading to the current question. The second form is a general question-answer subsystem based on simple pattern-matching of the input. This approach was successful due to the relatively unambiguous vocabulary used in the medical domain. Natural language interfaces that use pattern matching will probably have little application in an area with a diverse and ambiguous vocabulary such as dairy management.

Machine learning (13) is an area in AI that is beginning to receive much attention. Machine learning has been used in conjunction with ES to develop rules from examples through induction (14). In the example cited, machine-generated rules outperformed the experts’ rules. Machine learning has the potential to decrease greatly the knowledge acquisition process required in developing ES.

Expert System Shells

One of the major reasons for ES becoming a logical approach to applications such as dairy management is that ES shells are readily available. An ES shell is the skeleton of an ES after removal of the knowledge base. The shell resulting from Mycin is Emycin (25). Shells can be used with another knowledge base greatly reducing the time required to develop a new ES. Expert system shells for mainframes and LISP machines are reviewed by Richer (21) and for microcomputers by Whittaker et al. (26, 27). More recently, both type of shells have been summarized by Gevarter (7).

EXPERT SYSTEM BENEFITS AND LIMITATIONS

Certain situations in dairy herd management lend themselves to the ES approach. Such situations occur when information needed for the proper solution is incomplete, uncertain, subjective, inconsistent, or subject to change. In these situations a solution is necessary even though it may not be perfect; moreover, an answer of “no feasible solution”, as might occur in a linear programming approach, is simply not acceptable. Often the necessary solution or conclusion reached is uncertain although it should be the best one available (8, 24). An ES approach is also practical when many factors need to be considered in formulating a decision. Linear programming requires that the procedure to solve a large problem be known a priori. Expert systems choose appropriate rules from the data base as they are needed. This technique also leads to the feature that rules need not be ordered in the knowledge base of an ES. New rules can be entered without worry with regard to program semantics.

As with conventional software, ES have certain limitations. The old cliche, “garbage in, garbage out”, is still true for ES. The process of developing ES is not dissimilar from that of conventional software either. Development of an ES includes defining a suitable specific problem, collecting the necessary human and computer resources, finding and implementing the expert’s knowledge, then verifying, validating, and updating the resulting program (17). It is appropriate to point out that the mature ES discussed generally have been in developmental stages in excess of 5 years. Certainly ES should not be expected to revolutionize instantaneously the way in which dairy cattle are managed.

DAIRY HERD MANAGEMENT APPLICATION OF EXPERT SYSTEMS

There are three types of ES applications appropriate in dairy management. An advisory ES will model an expert and advise dairy farmers on management problems in a well-defined, narrowly scoped subject domain. A strategic planning ES will assist dairy farmers in making strategic management decisions. A diagnostic ES will diagnose equipment malfunctions or determine subnormal animal or herd performance.

Advisory Systems

In nearly every aspect of dairy herd management, expert knowledge is required. Experts
are often consulted for advice related to nutrition, breeding and genetics, and herd health. Expert systems are well-suited to such applications. In each situation, an ES could be used to deliver the advice currently being sought from the expert. The ES, however, would not replace the expert but rather would enhance his availability.

Linear programming and least cost ration balancing have gained widespread use assisting dairy farmers in developing a feeding program. However, this approach, taken alone, does not necessarily adhere to sound nutritional practices, nor do general programs incorporate on-farm constraints such as feed inventory, storage capacity, and feeding systems. An expert is often required to interpret the output and to make appropriate adjustments to the inputs and constraints to generate a nutritionally sound feeding program tailored to the situation on a specific farm. One needs only to look at the number of specialized feed consultants and the number of requests that extension nutritionists receive from the field to focus on the multitude of feeding problems that are present. Certainly such problems can only increase with the proliferation of new feed additives, the incorporation of bovine somatropin into routine use, and the many new methods for feed delivery still under development. An ES could embody the knowledge of these experts to assist dairy farmers in correctly and fully utilizing these technologies.

Another advisory application of ES for dairy management is that of the genetic program for the herd. This may be described as a two-stage process. The first step is the selection of service sires to be used in the herd; the second step is the selection of a specific service sire for each individual cow. At present, these decisions are made widely throughout the industry by so-called experts, some of whom use conventional computer programs as aids in making decisions. This application is one that seems ideally suited to the expert systems approach. At the same time it is important to keep in perspective that this task often falls into the category of being ill-structured and one that requires a decision being made with incomplete data. Many geneticists will argue that the scientific basis for deciding which bull should be mated to each cow is inadequate. Nevertheless, a specific bull must be selected by someone for each of the several million matings made each year. Many dairy farmers use professional consultants to assist in these decisions.

**Strategic Planning Systems**

An ES also is well-suited for use in strategic farm planning. For example, it could be used to predict the likely consequences of a given situation, such as that of cow or herd performance. This would include information currently provided by DHIA such as the predicted 305-d 2× mature equivalent milk, fat, and protein records. With an ES, a number of additional variables could be considered simultaneously and the results for predicting the cow’s future performance or economic worth to the herd could be fine tuned substantially.

A number of models have been put forth for culling decisions and certainly many of them serve as hand guides for culling aids (16). However, the aids available are incomplete. They typically do not consider such things as the value of a particular cow as a brood animal, her age, her health status, or how she fits into seasonal needs for milk.

**Diagnostic Systems**

One of the most logical situations for use of an ES is in the interpretation of animal sensor data that can be collected automatically on a daily or continuous basis. Many of these sensors are still in the developmental stages and certainly an expert’s opinion is required to interpret the results that come from sensors to monitor activity (19), tissue hydration (23), milk conductivity (20), or even to maximize the use of every-milking values for milk yield (Figure 1).

As new, more sophisticated equipment becomes available, the ability to detect and correct system malfunctions becomes much more important. One of the most widespread industrial applications of ES is to diagnose the problem and prescribe a remedy when a piece of equipment fails. Such diagnostic systems would be most welcome on the dairy to troubleshoot problems involved with our modern high technological approach to dairy farming.

**Examples**

As a final part of this report several approaches to the design of ES for specific dairy
management situations are presented. The first situation (Figure 2) is where the cow is in estrus and ready to be bred. The task for the ES could be to first diagnose that the animal is in estrus and then to recommend action to take as a result of that conclusion. Estrus may be monitored by some of the new sensors that are being developed, such as an activity sensor or a tissue hydration implant sensor, or by the use of monitoring feeding behavior, partial milk ejection, and body or milk temperature in association with each other. None of these last three variables are likely to be sufficient by themselves to justify declaring an animal in estrus. The combination of several events considered simultaneously may help to determine that the animal is in estrus on that particular day. If she stands to be mounted by other cows, then the probability of her being in estrus increases substantially. The recommended action may be to mate to a specific bull or the conclusion may not be sufficiently certain that mating should proceed without additional information. If the first screen for estrus is not sufficiently certain, the recommended action may be to confirm estrus by use of an on-farm test for milk progesterone before the decision for mating is made.

In another situation (Figure 3) a cow has subclinical mastitis; that is, she is infected with a primary mastitis pathogen but the infection has not progressed to the clinical stage. The expert system diagnosis responsible for the initial alert diagnosis may be either by electrical conductivity of the milk or by somatic cell counts. The question then becomes what should be done. There are a number of possibilities: she could be culled, she could be dried off, she could be treated (although the cost-benefit ratio is questionable in many cows), no action should be taken, or the cow should be sampled to obtain more information to determine what organisms are present. With
need to be made. However, the concept of having people that are well-versed enough to provide expert knowledge for programs designed for widespread use is not one to be taken lightly. Finally, substantial progress is occurring in the development of electronic communications of dairy management data (milk records, genetic evaluations, nonproduction traits), new electronic sensors, and in the various branches of AI. It is now suddenly feasible to develop ES for dairy management that should truly improve the management of most dairy herds. We expect that such developments will happen; but substantial time and resources will be required to develop the required cadre of knowledge engineers, to select or develop appropriate ES shells and inference engines, and to design appropriate knowledge bases and user interfaces.

CONCLUSIONS

Expert systems have the potential to exert a big impact on our dairy management practices. At the same time, the development of mature ES is a substantial task and elegant results are not to be expected in the short term. Many professional people in the industry are very knowledgeable about the specific decisions that additional information the recommended action may become much more clear, particularly if the organism is known to have a high or low probability of developing into a clinical infection.

A third situation is where an animal has substandard performance (Figure 4). This situation may be diagnosed by detection of a low daily milk yield, excessive body weight change, low concentrate consumption or substandard reproductive performance. An appropriate recommended action could be that the feeding program needs to be changed, the cow needs to be culled, or maybe none of these are apparent and she needs to be examined to obtain more information. If she has a reproductive problem, the ES could be of substantial value by diagnosing the situation early and recommending appropriate action.

REFERENCES


16 Mid-States Dairy Records Processing Center. 1986. Pages 10–11 in How to obtain and interpret the flexible management report.


