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Modelling the Components of Livestock Stress for Precision Animal Management

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Abstract. *An individual animal's stress level is the summation of stresses from three areas: the environment, animal, and management. A model is being developed to summarize components of each of these three areas to determine the overall stress on the animal. The purpose of the model will be three-fold. First, the animal component will be used to identify animals at high risk for suffering from heat stress. This would allow producers to sort these animals and provide them with extra care. Second, the model could be used to monitor weather events to indicate extreme weather, so precautions could be taken. Third, producers could investigate different management strategies and impacts on stress. All three components could be used in conjunction to investigate management strategies under different weather events on animals with different risk factors. This paper documents the first component of the model—animal susceptibility. The details provided explain the type of model, method of integrating a prediction of ambiguity associated with each prediction made, and an initial validation of the animal susceptibility model.*

Keywords. *Modeling, Cattle, Heat Stress, Health, Temperament*

Introduction

Heat stress in feedlot cattle is a common summertime occurrence in cattle producing parts of the United States and Australia. The impact of heat stress on feedlot animals are quite varied, from little to no effect in a brief exposure, to causing reductions in feed intake, growth, and well-being of the cattle in a moderate event, and to death of vulnerable animals during a extreme event ((Hahn, 1999, Hahn and Mader, 1997). Vulnerable animals have been described as *Bos taurus* (instead of *Bos indicus* or a cross-bred) animal with dark or black hides (Busby and Loy, 1996; Hungerford et al., 2000), compromised immune systems, more fat cover, and animals with excitable temperament (Brown-Brandl et al., 2006).

The level of heat stress that an animal experiences is related to three main factors: the weather conditions that exist (Hahn, 1999), vulnerability of the animal in question (Brown-Brandl et al., 2006), and management protocols used (for example sprinkling, shades, dietary management, waterer space available [cm/animal], surface conditions, and many others). The interactions of these three components are unknown to date, and are very difficult to determine experimentally due to the complex nature of the question. However, to effectively manage animals using the fewest resources (precision animal management) requires some knowledge of these interactions.

The objective of the project was to develop a model to predict the overall stress of an individual animal given the animal vulnerability, environment, and management. This paper will document the development of the animal vulnerability portion of the model.

Materials and Methods

The fuzzy inference system models can be one of two general types, either a data-driven model or a knowledge-driven model. Because of the complex nature of this system and the number of variables needed to be included, a data-driven model became very difficult to develop. The data needed to create such a model is virtually impossible to collect. The knowledge-driven models are designed completely by a modeler in an attempt to describe the system based on inherent knowledge about the system that may not be obvious in a conventional data collection scheme.

In the knowledge-driven model, the modeler determines the arrangement of the model and the expression of input and output variables that best describe the system. The expression of the input and output variables are described by the number and shape of membership functions. The modeler also develops the rule structure, including how many rules need to be developed and what relationships are important. While the modeler names each of the membership functions, the names are immaterial to the model itself. The model sees the inputs as only numeric expressions, and generates an output of a value that is based on the membership functions and the rules associated with those functions.

While a knowledge-driven model allows the models of complex systems to be developed, the nature of this system was still too complex to describe effectively in a single model. To ensure the system was adequately and accurately described, it was subdivided into smaller more easily understood pieces of the system. The outputs of the smaller sub-models where then compiled together in a second layer of small models. The final model was developed with several layers of models in a hierarchal structure. The hierarchal nature of this model allows for numerous inputs into the model in an orderly and organized manner. Each “node” or sub-model was associated with a simple rule structure that organizes a limited number of inputs into a reasonable and recognizable arrangement. The lowest level models use input data to derive an output response, while the upper levels of models use the output responses from lower level models as inputs to generate an output.

One important piece of information that is often ignored in many models is the certainty or ambiguity associated with the prediction. The ambiguity associated with each sub-model is derived from one of three sources: missing data, poor quality data, and lack of certainty in the prediction (based on the lack of information in the literature). The ambiguity of the prediction was incorporated into this model by using two outputs – one for the parameter estimate and one for the ambiguity of that prediction. Figure 1 illustrates the relationship between the amount and quality of data known to the ambiguity in the final prediction.

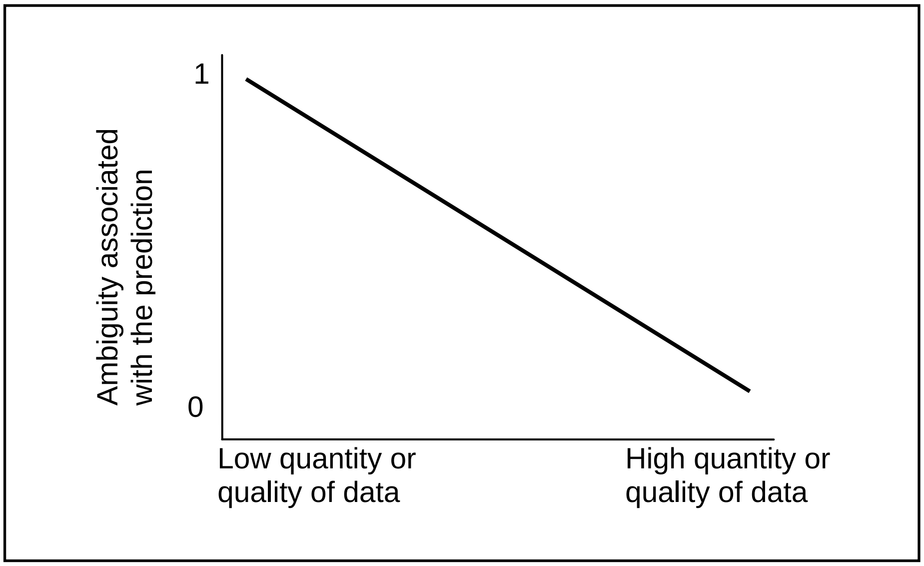

Figure 1. The relationship between ambiguity associated with a prediction and the quantity and/or quality of input data.

Results and Discussion

Model overview

A hierarchal knowledge-based fuzzy inference system model was developed using Matlab version 7.0, with the Fuzzy Logic Toolbox application package. A concept model was first developed to define the individual fuzzy inference models needing to be developed. Overall animal stress was first divided into three sub-sections: animal susceptibility, environmental conditions, and animal management (fig. 2).

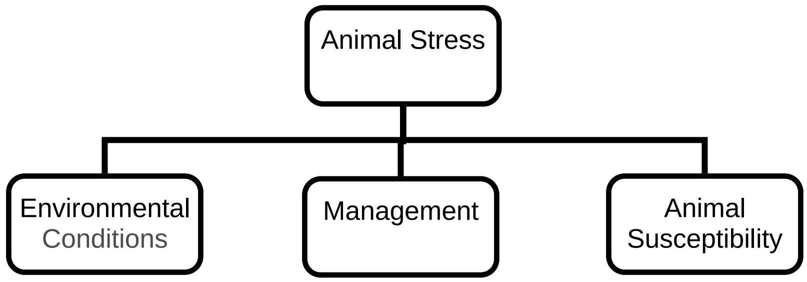

Figure 2. Overview of animal stress.

The objective of this paper was to describe the development of one of the three sections of the overall animal stress model—animal susceptibility. An overview of this section of the model is shown in Figure 3. Animal Susceptibility is first divided into two components: Inherent Animal Factors and Transient Animal Factors. The Inherent Animal Factors model includes the genetic components to animal susceptibility, which tend not to change over time. Components include Temperament and Genetics. The Genetics model has three inputs: Color, Species, and Sex. Transient Animal Factors model includes those factors that can change over time, and includes main components of Acclimation, Finish, and Health. The Acclimation model has two inputs Hair Thickness and Previous Exposure. The Finish model also has two inputs—Condition Score and Age. The Health model is broken into two sub-models: The Current Health model, which is a direct input, and the Previous Health model, which has two inputs—Number of Pneumonia Cases and Other Health Related Issues.

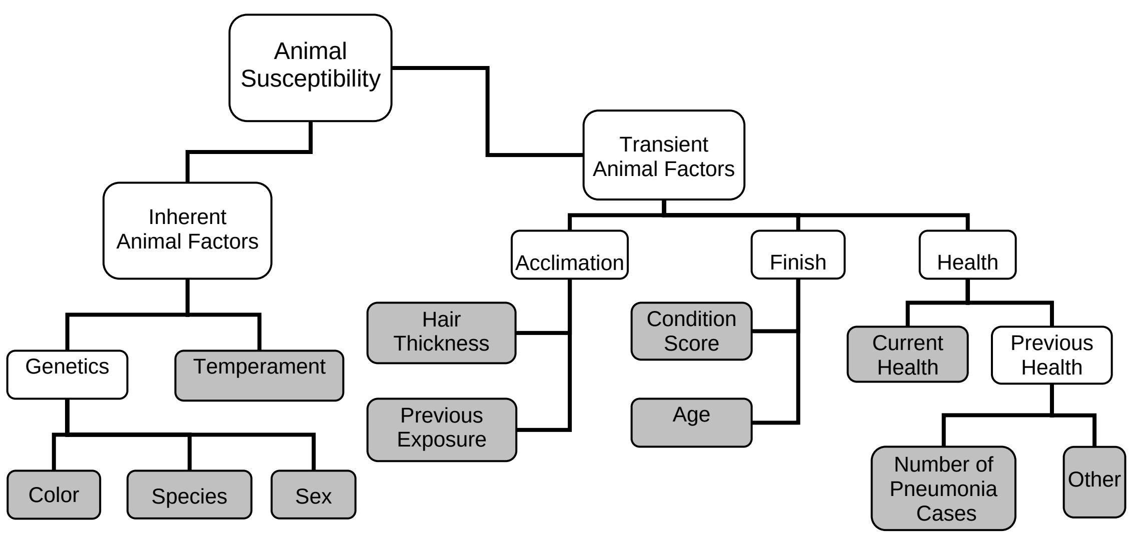

Figure 3. Schematic of overall animal susceptibility. Gray boxes indicate input boxes, while white boxes indicate knowledge-based fuzzy inference systems.

The knowledge-based model was developed using literature where available, and filling in with anecdotal evidence where needed. The genetics model was developed using the following information. Brown-Brandl et al. (2006) showed that darker colors of cattle were more impacted by hot weather than lighter colors. Hungerford et al. (2000) showed that black cattle are 5.7 times more likely to die from heat stress than all other colors. Busby and Loy (1996) also reported a higher death loss in dark-hided cattle after the 1995 heat wave in Western Iowa. Many researchers have shown the *Bos indicus* cattle are more tolerant to heat stress conditions than *Bos taurus* cattle (Gaughan et al., 1999). The response differences between heifers and steers was not well documented, and there is a little evidence presented in Busby and Loy (1996) that suggest heifers are more susceptible to heat stress than steers. The animal susceptibility model combines the output of the genetics model with the input of temperament. Temperament was shown to have a slight impact on stress level during hot weather, with higher temperament score leading to about a 3% increase in stress level (Brown-Brandl et al., 2006).

Less is known about the input to the Transient Animal Factors model than the inputs to the Inherent Animal Factors model. Cattle commonly grow a thick woolly coat over the winter months to increase its insulation from the environment. A thick wooly coat has greater insulatative properties; therefore, the animal with a thick woolly coat will have a more difficult time losing metabolic heat to the environment than an animal with a slick coat with little undercoat. Many authors have reported details on animal acclimation; Senft and Rittenhouse (1985) reported acclimation of beef cattle to take between 9 and 14 days. Those animals not acclimated to a hot environment will be more impacted by the increase in temperature than those that are sufficiently acclimated (Brown-Brandl et al., 2005). Brown-Brandl et al. (2006) reported an increase in respiration rate at a given temperature (a measure of stress) as cattle condition scores increased. Cattle that are just arriving in the feedlot and/or animals that are in poor condition for their age, are more likely to suffer from stress. Health issues are very difficult to quantify, but have been shown to increase the stress level. Brown-Brandl (2006) reported a 10% increase in respiration rate (stress) at temperatures above 25°C in animals treated for pneumonia either prior to the experiment, or during the experiment.

Early in the development it was determined that there was a need for a “degree of certainty” or ambiguity prediction with every prediction made. For example, the output of the model would be “low level of susceptibility with a high degree of certainty” or “moderate level of susceptibility with a low degree of certainty.” To accomplish this task the hierarchal fuzzy inference system was developed using multiple inputs and two outputs. One output was associated with the modeling parameter and one for ambiguity. This ambiguity factor was then transferred up the hierarchal structure, so the ultimate ambiguity output is a reflection of the total degree of certainty throughout the model. The ambiguity from one level is then one of the inputs to the next level.

The ambiguity output at the lowest level model is determined by the amount of data entered and the amount of literature data available during the original model development; this ambiguity output is then transferred up the hierarchy. For example, the genetics model has inputs of color, species, and sex and output of “genetics” and “ambiguity.” The ambiguity is based not only on missing information, but also on the degree of certainty of the prediction being made. The ambiguity is then transferred up the hierarch to the next model. Therefore, the Inherent Animal Factors model has three inputs of genetics, temperament, and genetic ambiguity.

Model output

The model Animal Susceptibility output was tested using the following method: inputs were set to lowest susceptibility input (*Bos indicus*, healthy, white, etc.), and then one by one the inputs were changed to maximum susceptibility input (*Bos taurus*, black, etc.) to ensure proper model response. The ambiguity output was tested by starting with all known values, then decreasing the known values by one, to ensure the ambiguity output responded correctly.

Results of the model Animal Susceptibility outputs test are shown in Table 1. The lowest perceived animal susceptibility would be calm, white, *Bos indicus* steer with thin hair, well acclimated, normal condition score, no previous cases of pneumonia, good previous and current health status. When this condition was tested in the model, the results equal a very low susceptibility (0.044 [0 to 1 scale, 0 is the lowest susceptibility and 1 is the highest susceptibility]). The tests 2, 3, and 4 all had one "risk" factor (*Bos taurus*, black, or excitable, respectively); the results for all three tests were 0.1662. Test 5 had two risk factors (black and *Bos taurus*), and had an output of 0.3333. Tests 6 and 7 each had three risk factors (excitable, black, and *Bos taurus*; black, *Bos taurus*, and fat condition score), and both had an output of 0.5000. Test 8 used a condition with five risk factors (excitable, black, *Bos taurus*, thick hair coat, and acute exposure); this condition resulted in a susceptibility output of 0.6667. Test 9 tested a case with six risk factors (excitable, black, *Bos taurus*, heifer, thick hair coat, acute exposure), and had a susceptibility output of 0.8333. The final test used the condition of eight risk factors (excitable, black, *Bos taurus*, steer, thick hair coat, acute exposure, many previous cases of pneumonia, poor previous and current health status), and had a susceptibility output of 0.9548.

The Animal Susceptibility output of the model seems to be working in a logical fashion—increases in the number of risk factors increased the animal susceptibility. The next typical step in model validation is to test the model using actual data. The difficulty with this model is that there is no direct measure of animal susceptibility. There are measures of animal stress, however, stress is influenced by the environment and management system to which that animal is subjected. A method of assessing susceptibility will need to be developed.

The results of the model Ambiguity output test are shown in Table 2. Like the Animal Susceptibility output test, 10 different scenarios are tested to ensure the logical function of the model's ambiguity output. Ambiguity output is given on a 0 to 1 scale, with 0 being certain of the result given, and 1 being completely uncertain of the result given. Ambiguity increases under several circumstances: first, if data is unknown or missing; second, the knowledge of the relationship between the inputs is lacking; or third, if the confidence of the input data is questioned. Test 1 was the case where all data is known, and the relationships between the input categories are well documented, so the ambiguity of this output was equal to 0.0747. In test 2, all the data are known, however the health data were entered as no previous or current health related issues. When there is no health related issue there are two possible circumstances that could have resulted in that outcome: the animal could be healthy, or poor or no records were taken or transferred to the current owner. In this case the ambiguity is slightly higher because of this question about the input data; ambiguity was equal to 0.275. Test 3 had one of 11 missing input data parameter (temperament), and also had an output ambiguity of 0.275. Test 4 had no health information data provided, and also had an output ambiguity of 0.275. Test 5 had two of 11 missing input data parameters (temperament and color), and had an output ambiguity of 0.525. Test 6 tested the condition with three missing parameters (temperament, color, and species), and has an output ambiguity of 0.775. Tests 7 and 8 had five and six missing input parameters, respectively, and both had an output ambiguity of 0.775. Test 9 had two known parameters, and Test 10 had no known parameters; both situations had an ambiguity output of 0.9999. While the output ambiguity seems to work logically, it could be more refined.

Conclusion

This paper documents the development of the Animal Susceptibility model. The model was developed as a knowledge-based hierarchal fuzzy inference system. The model was designed to not only predict the susceptibility of an individual animal to heat stress, but also document the certainty of the prediction made.

The model uses 11 input parameters (temperament, hair coat color, species [*Bos taurus or Bos Indicus*], sex, hair thickness, previous exposure to hot temperatures, condition score, age, previous cases of pneumonia, other previous health issues, and current health state. The output of Animal Susceptibility is created by the combination of eight smaller models that use either original input data, output data from a lower level model, or a combination of both to make knowledge-based decisions. The degree of certainty of the Animal Susceptibility prediction is based the knowledge of the combination of inputs, the certainty that the data is correct (in the case of health data), and the quantity of the input data.

In two preliminary tests, it appears the model's outputs (susceptibility and ambiguity) responds correctly. However, a method to validate the susceptibility output against actual data needs to be developed, and the ambiguity output needs further development so it responds in a more refined matter.

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Table 1. Results of the model output test.

Inputs	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9	Test 10
Temperament	Calm	Calm	Calm	Excitable	Calm	Excitable	Calm	Excitable	Excitable	Excitable
Color	White	White	Black	White	Black	Black	Black	Black	Black	Black
Species	*Bos indicus*	*Bos taurus*	*Bos indicus*	*Bos indicus*	*Bos taurus*	*Bos taurus*	*Bos taurus*	*Bos taurus*	*Bos taurus*	*Bos taurus*
Sex	Steer	Steer	Steer	Steer	Steer	Steer	Steer	Steer	Heifer	Steer
Hair Thickness	Thin	Thin	Thin	Thin	Thin	Thin	Thin	Thick	Thick	Thick
Previous Exposure	Acclimated	Acclimated	Acclimated	Acclimated	Acclimated	Acclimated	Acclimated	Acute	Acute	Acute
Condition Score	Normal	Normal	Normal	Normal	Normal	Normal	Fat	Normal	Normal	Normal
Age	Growing	Growing	Growing	Growing	Growing	Growing	Growing	Growing	Growing	Growing
Previous Pneumonia	None	None	None	None	None	None	None	None	None	Many
Previous Health	Good	Good	Good	Good	Good	Good	Good	Good	Good	Poor
Current Health	Good	Good	Good	Good	Good	Good	Good	Good	Good	Poor
Outputs										
Animal Susceptibility[1]	0.044	0.1662	0.1662	0.1662	0.3333	0.5000	0.5000	0.6667	0.8333	0.9548

[1] The output of “Animal Susceptibility” is a 0 to 1 scale, where 0 is the lowest susceptibility and 1 the highest.

Table 2. Results of the model ambiguity test. Ambiguity was determine by either the input values, or by missing values.

Inputs	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9	Test 10
Temperament	Calm	Calm	—	Excitable	—	—	—	—	—	—
Color	Black	Black	Black	Black	—	—	—	—	—	—
Species	*Bos taurus*	*Bos taurus*	*Bos taurus*	*Bos taurus*	*Bos taurus*	—	—	—	—	—
Sex	Steer	Steer	Steer	Steer	Steer	Steer	—	—	—	—
Hair Thickness	Thin	Thin	Thin	Thin	Thin	Thin	—	—	—	—
Previous Exposure	Acclimated	Acclimated	Acclimated	Acclimated	Acclimated	Acclimated	Acclimated	—	—	—
Condition Score	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	—	—
Age	Growing	Growing	Growing	Growing	Growing	Growing	Growing	Growing	—	—
Previous Pneumonia	Many	None	None	—	None	None	None	None	—	—
Previous Health	Poor	Good	Good	—	Good	Good	Good	Good	Good	—
Current Health	Poor	Good	Good	—	Good	Good	Good	Good	Good	—
Output										
Overall Ambiguity[1]	0.0747	0.275	0.275	0.275	0.525	0.775	0.775	0.775	0.9999	0.9999

[1] The output of "Overall Ambiguity" output is a 0 to 1 scale, where 0 is 100% certain or 0% ambiguity, and 1 is 0% certain or 100% ambiguous.