Predicting the Impact of Supplemental Phytase, Wheat and Phosphorus on the Performance of Layin Hen

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Abstract. A Genetic Fuzzy Rule Base System (GFRS) for modeling the response of laying hen hyline W36 performance to dietary supplemental phytase source, wheat and phosphorus level is described based on experimental data. Using data obtained via measurement of various characteristics of laying hens prepared with different levels of dosage of a commercial phytase source proteinase, (0, 500 and 1000 phytase (FTU)/kg of feed) at 0.0, 25, 50, 75, 100 percent of wheat with 0.22 and 0.28 percent available phosphorus (AP), it is concluded that construction of an optimized fuzzy model for evaluation of different dietary supplemental phytase, wheat and phosphorus level is a reliable procedure. A comparison has done between three statistically based regression models and one type of fuzzy inference systems.This qualitative fuzzy model may in fact help drive appropriate selection of combinations of potential feed parameters.

Keywords. Laying hen, Percent production, Feed conversion ratio, Modeling, Prediction, Fuzzy, Genetic algorithm.

Introduction

Phosphorus is a vital nonrenewable natural resource that is essential for growth and development (both structurally and metabolically). Despite the relatively high content of P in the cereal grains and oilseed meals, up to eighty percent of the P is present as phytic acid. Due to insufficient amount of intrinsic factor phytase, nonruminant animals can not hydrolyze the phytic acid complexes (Makkar and Becker, 1998).

Microbial phytase provides a practical solution for improving P availability in plants (Broz and Ward, 2007). The use of phytase in broiler feed is clearly established (Nelson et al., 1971; Denbow et al., 1998). Some studies have demonstrated that dietary supplemental phytase improves phytate P utilization in laying hens (Panda, et. al., 2005, Gordon and Roland, 1998; Carlos and Edwards, 1998), swine (Young et al., 1993), and turkeys (Ledoux et al., 1995; Qian et al., 1996). Although phytate may promote endogenous losses, recent studies indicate that phytase can help prevent those losses. Main effects of phytase addition are summarized as follows:

- Improved availability and utilization of phytate P.
- Improved availability of Zn and Ca as well as amino acids.
- Enhancement of performance parameters in comparison with respective controls receiving low levels of P.
- Reduction of P excretion and accordingly decreased environmental pollution.

This reserch and experience was conducted to evaluate and predict the utilization of different levels of phytase in diets including different levels of wheat with reduced phosphorus level for laying hens. In order to obtain the knowledge of optimal supplemental feed, the prediction ability of different behaviors of laying hen as the results of different supplemental feeds is essential which can be reached through modeling.

Two general types of modeling are the principles of system science, namely conventional and heuristic modeling. Conventional modeling techniques are difficult to model complex real systems like feed conversion ratio in laying hens due to their multivariable and non-linear nature, where there are complex interactions between the input and output channels. This provides justification for the use of heuristic modeling methods and mainly soft-computing techniques as a good alternative. Fuzzy rule-based model is soft-computing technique and is a set of fuzzy IF–THEN rules with the ability of taking advantages of both approaches with added bonus of ability to describe uncertainty, imprecision and vagueness in a nonprobabilistic framework (Klir and Yuan, 1995; Zimmerman, 1996). All modelling schemes, whether based on conventional mathematical principles or developed through heuristic techniques like soft-computing; represent mapping a set of inputs to a set of outputs.

While ability of fuzzy systems in solving different problems with various characteristics and complexity has been established, an increasing interest on enhancing them with machine learning procedures as genetic algorithms is developing. Genetic algorithms (GA) cover different levels of complexity from the simplest parameter optimization to the highest level of complexity of learning the rule set of a rule base system (Dejong, 1988). For optimization of fuzzy models, different techniques such as gradient based or neurofuzzy to evolutionary approaches are applied (Cordon, et al, 2001, Jang, et al, 1997). Different approaches such as Pittsburg and Michigan can be employed to learning different components of a fuzzy rule base system. While in Pittsburg approach an entire rule set is considered as members of the population, an individual rules are considered as genetic codes (chromosomes) in Michigan approach. (Herrera, et al., 1998)

It can be noted that since phytase source, wheat and phosphorus level are strong symbols of variation in laying hen performance and are crucial factors, modeling of its changes as the result of various impressive parameters seems necessary.

In the next section, the data preparation for modelling is presented. Fuzzy systems and fuzzy modeling are discussed in section 3. Following this, genetic fuzzy rule system is presented and discussed in section 4. Regression models are presented in section 5 and finally results and discussion in section 6 concludes this paper.

Material and Methods

This experience was conducted to evaluate utilization of different levels of phytase in diets including different levels of wheat with reduced phosphorus level for laying hens. All diets were isocaloric and isonitrogenous. The experiment is performed on the Ferdowsi University of Mashhad and is consisted of 31 diets with three replicates each containing 3 laying hens Hy-Line W36 from 53 to 64 week of age. The experiment was conducted as a 5 X 3 X 2 factorial arrangement of treatments with 5 levels of wheat at 0.0, 25, 50, 75, 100 percent of total corn of the control diet, 3 concentrations of enzyme (0, 500, 1000 ftu/kg Phytase) with 0.22 and 0.28 percent available phosphorus (AP) and a control diet.

The dataset is randomly divided into two subsets. Set 1 known as training set consisted of 24 (≈75 percent of 31) independent data points, and was used in the model development. Set 2 known as testing set consisted of the remaining 7 (≈25 percent of 31) data points, and the model evaluation was completed using this set. This ratio of data selection for developing and evaluation model was selected, as it is a common ratio to use.

Fuzzy Systems and Fuzzy Modeling

In the mid 1960, fuzzy logic (FL), fuzzy reasoning and fuzzy systems have been introduced in the field of control engineering as an extension to the classical set theory to use the expert knowledge in terms of vague concepts in this area (Zadeh, 1956, 1971). With its wide mathematical theory extensions, FL has some interesting properties that most of them will not cover at this point.

A typical fuzzy system consists of five basic components. The *fuzzification* and *defuzzification* elements are the interfaces of such system to the real world. The *fuzzy reasoning* is adopted using the remaining parts included *fuzzy rule* base and *fuzzy inference engine* using membership function (MF) of knowledge base. This system has many promising properties; just one of which we will deal here, i.e. non-linear mapping. The others are addressed in related text-books (Wang, 1997).

Here, the non-linear mapping property is used to design a fuzzy model. Designing a fuzzy model for multi-input single-output (MISO) system from input-output pairs (obtained experimentally), applied in this research involves 3 steps and can easily be extended to apply to multi-input multi-output (MIMO) system.

1- MF construction to cover each of input-output universes of discourse.

2- Generation of one rule from each input-output pair.

3- Creation of fuzzy rule base.

In most Fuzzy System applications, according to the knowledge of an expert, the structure of the system is chosen non-systematically. Nevertheless the system parameters are rich enough to ensure the desired behavior. Here, evolutionary algorithms are used in order to adjust the MFs and rules of fuzzy system. This approach will be useful in all complex systems with high nonlinearity especially in alive systems due to their multivariable and non-linear nature.

Genetic Fuzzy Rule Base System

Designing a fuzzy rule bases system is equivalent to find the optimal configuration of fuzzy sets and rules that can highly influence the modeling/prediction capabilities. So improvements can be made by setting up values of the parameters of the MFs and rules through optimization routines (Castro, 2005). Optimization procedures are mainly classified into to conventional methods like steepest descent and gradient methods, and global methods. While conventional search algorithms are likely to trap in local minimums, the advantages of using genetic algorithms (GA) as global optimization can be incorporated in genetic fuzzy rule base system (GFRS). Such systems have been successfully applied to modeling and optimization of complex systems with high nonlinearity, control system design, classification and information retrieval (Cintra, et al., 2007; Camargo, et al., 2004; Jang, et al., 1997).

Main approaches for chromosome representation in a GFRS includes: Michigan which considers individual rules as members of the population and Pittsburg, which considers the entire rule base as a genetic code. In other word in Pittsburg approach, there is a GA that maintains a population of strings each of which represents a candidate model.

In the present work, for consequence MFs (since are Gaussian and defuzzification is carried out with center of gravity (COG) method), their mean is required as unknown parameters. Unknown parameters are arranged in a chromosome. Number of defined MFs for the first, second and last inputs are 4, 2 and 2 respectively. So, there are totally 16 (4 X 2 X 2) rules, and so 16 consequents are needed to adjust. Accordingly, there are 8 (4+2+2) membership functions that are needed to define by 2 parameters, namely the spread and center of each MF. Hence 16 (8 X 2) parameter are added up to rule numbers. According to Pittsburg's approach, each chromosome contains all 32 (16 + 16) parameters. Low cost initial population is obtained by incorporating expert comments.

The GA routines utilized random initial populations, binary-coded chromosomes, mutation, fitness scaling, and an elitist stochastic universal sampling selection strategy. Also we have used single-point crossover. In these simulations, the probabilities of crossover (PCROSSOVER = 1) and mutation (PMUTATION = 0.01), population size is 100 and generation size is 100. Finally individual length in general is depends on the number of variables but each variable is allocated 8 bits (Forghany, et al.)..

Regression Models

The polynomial regression technique can easily be fitted to data using many approaches like least square approach. The theory of least square polynomial curve fitting is well documented to fit polynomials of arbitrary order to multi-dimensional input data (Wang, 1997). The coefficient vectors are estimated through minimizing the obtained least square error.

Here three multiple regression models were developed using the regression procedure in SAS package (SAS, 2004). The first model was a linear regression model and is described based dietary supplemental wheat (x1) and of AP (x2) and enzyme (x3) level. The second model was included interaction and the last model was a quadratic model and included three linear, interaction and quadratic terms itself (Forghany, et al.).

Results and Discussion

The goal of running model is to shape the nonlinearity that maps inputs to outputs. This nonlinearity is called the “control surface”. The output of fuzzy model is plotted against two of its inputs when the third input is considers constant. The benefit of the surface representation is its compact form for information representation in fuzzy model.

Based on experiment values, fuzzy models were designed using MATLAB 6.5. In the present work, inputs are fuzzified with Gaussian MF and defuzzification is carried out with center of gravity (CoG) method.

The metric, namely Mean-Square-Error (MSE) is used to measure the accuracy of the above four modelling method. One can select an input and compute the deviation between the actual response function and the model output. The root MSE (RMSE) is then used as another model validation metric. Similar to RMSE, mean-absolute-percentage-error (MAPE) is used to determine the accuracy of a meta-model. This is defined as mean percentage of the absolute error (absolute deviation of a meta-model from its original response function).

Performance of optimal fuzzy model after 1000 generations for experimental data set and of three regression models are summarized in table I and II. Figures 1 and 2 depicts the control surface plot for percent production and feed conversion ratio against wheat and AP respectively while the enzyme is considered as a constant parameter 0.01.

The outputs of the models were validated by selecting a certain number of data points, different from those 24 pointes used for model training. Each validated data points given in table I, was fed into the system. The predicted properties in addition to the actual values of those properties and the percentage error -for all four models- are presented in table I and II for feed conversion ratio and percent production respectively. The results indicate that the system is well-trained to predict the percent production and feed conversion ratio. Table I and II shows the MSE, RMSE and MAPE that obtained from different techniques, for 7 test experiments.

In this study, laying hens were randomly allocated in cages for 30 dietary treatments with arranged of 5 X 3 X 2 factorial experiment with three replicates each containing three hens plus one control group. The experimental period lasted 90 days, when the age of hen was 53 weeks; and the following conclusions can be drawn.

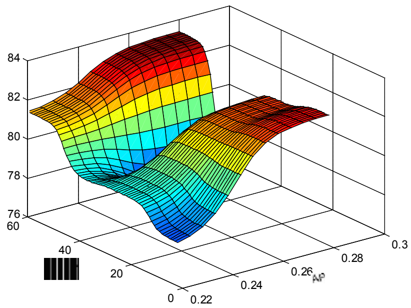

Figure 1: Control surface for percent production

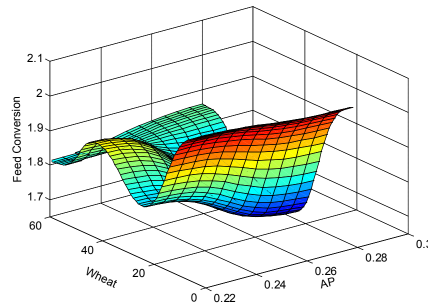

Figure 2: Control surface for feed conversion

This experience demonstrates that phytase enzyme supplementation can compensate the reduced AP levels in layer diets and significantly improved feed conversion of laying hens. Hens that fed the control diet (50%wheat, 500ftu/kg, 0.28%AP) resulted in higher percent production and feed conversion ratio ($p<0.05$). Besides, we concluded that supplementation of phytase at a level of 1000ftu/kg in the diet of laying hens can improve egg shell thickness and decrease the number of broken and soft eggs and P excretion.

Additionally, although phytase enzyme can compensate the reduced AP levels in layer diets, it provides an indication that the optimal levels of AP and enzyme are not the maximum. Based on the numerical results, enrichment of diets with high AP level does not increase egg weight. Probably the high level AP diet decrease egg weight.

The results of this study show that an optimized fuzzy model can be a reliable approach to interpolate the relation between different variables. This model can describe the working area for those involved with the prediction of a definite feature in a defined range of variables.

Fuzzy models achieved an average percent prediction error of output properties of only 3.6% in the worst case. The present study shows that fuzzy tools are a technique which can be use efficiently to predict animals response to different supplemental feed. It is believed that this approach can be applied to predict many other parameter and properties in livestock industry.

Table I: Simulation Results for Feed Conversion ratio

			Real Output	Regression I		Regression II		Regression III		Fuzzy	
				Output	%Error	Output	%Error	Output	%Error	Output	%Error
1	Wheat	0	82.1	78.7	4.1	81.2	1.1	79.4	3.3	80.1	2.4
	AP*	0.28									
	Enzyme	0.02									
2	Wheat	33.5	80.5	82.1	2	81.5	1.3	82.8	2.9	80.8	0.4
	AP*	0.28									
	Enzyme	0.0									
3	Wheat	50.0	84.3	82.7	1.9	82.2	2.5	82.8	1.8	81.3	3.6
	AP*	0.28									
	Enzyme	0.0									
4	Wheat	65.0	84.7	83.2	1.8	82.1	3.1	80.6	4.9	81.7	3.5
	AP*	0.28									
	Enzyme	0.02									
5	Wheat	17.0	84.3	81.3	3.6	81	3.9	81.6	3.2	86.3	2.4
	AP*	0.22									
	Enzyme	0									
6	Wheat	33.7	85.7	81.3	5.1	80.8	5.7	81.9	4.4	82.8	3.4
	AP*	0.22									
	Enzyme	0.02									
7	Wheat	66.0	76.7	84.1	9.6	84.6	10.4	83.6	9	84	9.5
	AP*	0.22									
	Enzyme	0.01									

Mean % Error	4.014	4	4.214	3.6
MSE	14.59	15.806	14.476	12.54
RMSE	3.82	3.976	3.805	3.541

*AP: Available Phosphorus

Table II: Simulation Results for Percent Production

			Real Output	Regression I		Regression II		Regression III		Fuzzy	
				Output	%Error	Output	%Error	Output	%Error	Output	%Error
1	Wheat	0	1.8	1.87	3.7	1.73	3.7	1.88	4.2	1.76	2.2
	AP*	0.28									
	Enzyme	0.02									
2	Wheat	33.5	1.8	1.82	1.2	1.81	0.7	1.75	2.8	1.66	7.8
	AP*	0.28									
	Enzyme	0.0									
3	Wheat	50.0	1.8	1.79	0.4	1.79	0.5	1.76	2	1.77	1.7
	AP*	0.28									
	Enzyme	0.0									
4	Wheat	65.0	1.8	1.75	2.6	1.9	5.6	2.03	13.1	1.8	0
	AP*	0.28									
	Enzyme	0.02									
5	Wheat	17.0	1.9	1.93	1.7	2.01	5.6	2	5.1	1.93	1.6
	AP*	0.22									
	Enzyme	0									
6	Wheat	33.7	1.8	1.89	5	1.87	4.1	1.83	1.6	1.89	5
	AP*	0.22									
	Enzyme	0.02									
7	Wheat	66.0	1.9	1.84	3.1	1.79	5.8	1.8	5	1.91	0.5
	AP*	0.22									
	Enzyme	0.01									
Mean % Error				2.529		3.714		4.829		2.686	
MSE				0.003		0.006		0.012		0.004	
RMSE				0.055		0.077		0.11		0.063	

*AP: Available Phosphorus

Conclusion

A novel approach in modeling the response of laying hen performance to dietary supplemental phytase source, combining FL modeling and incorporation of evolutionary algorithm learning ability in the model is presented in this work. The results indicated that while fuzzy modeling seems a promising method in alive systems, application of GFRS leads to better estimation of the output variable. Genetic programming (GP) which is generally referred to as direct evolution of programs or algorithms for the purpose of inductive reasoning, can be the following stage in optimization of a FL model obtained based on experimental input-output specially for reduction in the number of rules and faster convergence. Moreover it must be mentioned that no extrapolation can be made out of the particular range for which parameters and coefficients of the models are calculated.

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