Seasonal Broiler Growth Performance Prediction Based on Observational Study

Peijie Huang
College of Informatics, South China Agricultural University, Guangzhou 510642, P. R. China
pjhuang@scau.edu.cn

Piyuan Lin[1*], Shangwei Yan[1, 2], Meiyan Xiao[1]
[1]College of Informatics, South China Agricultural University, Guangzhou 510642, P. R. China
[2] Guangdong Wen's Foodstuffs Group Co., Ltd., Xinxing, 527439, P. R. China
pyuanlin@163.com, yswysw@21cn.com, maymayxiao@scau.edu.cn

***Abstract*—For the modern poultry breeding companies, it is worthwhile to predict the poultry growth performance parameters to help future production and management. Most of the existing literature of broiler growth performance is based on well designed experiment. However, for the farmers who carry on the large scale breeding all the year round, it is impractical to adjust all the ambient factors to suitable levels systematically like in the laboratory. In this case, it requires an observational study based on the massive historical data gradually cumulated in production. In this paper, observational study is proposed for seasonal broiler growth performance prediction. Systematic observational study with statistical analysis and data mining technology is adopted including macro analysis, exploratory data analysis, and modeling. Case study using the broiler growth dataset of the most famous poultry raising company in China shows the effectiveness of our approach.**

***Index Terms*—observational study, growth performance, seasonal influences, broiler breeding, data mining**

I. INTRODUCTION

Modern poultry breeding companies hope to extract valuable knowledge from the massive historical data to help future production and management. However, because of the complexity and uncertainty bring by the influence of environmental and physiological factors, data analysis and mining of poultry raising dataset is a challenge. In animal production, genotype and environment are two main factors that affect output. Ample research has demonstrated that meteorological factor is one of the ambient environmental factors that play important part in broiler production [1-6]. In broiler breeding, growth performance parameters have obvious seasonal variation.

Much existing relative literature deals with broiler growth performance under preselected ambient factor levels [1-4,6-10]. These works have a certain practical significance for broiler breeding. However, for the farmers who carry on the large scale breeding all the year round, it is impractical to adjust all the ambient factors to suitable levels systematically like in the laboratory. The levels of ambient environmental factors cannot be controlled and thus, much of the time it involves a situation in which the data structure can only be a monitoring of the data from the poultry house across time. In this case it may require an observational study. Based on the observational historical data, we try to uncover the seasonal growth rules hidden among the broiler data, which are regulated by both the natural law of seasons and the biological law of poultry upgrowth. Given a certain uncontrollable environmental condition, the knowledge about seasonal influences in broiler growth performance gained from our approach will provide valuable guidence for broiler farmers.

The rest of this paper is organized as follows. In the next section, we briefly discuss the distinctness between observational study and designed experiment, including literature review and methodology comparison. The technical framework of the proposed observational study is presented in Section III. Section IV gives detail introduction of seasonal broiler growth performance prediction based on observational study by a case study using the broiler growth dataset of the most famous poultry raising company in China. Finally, Section V lists some conclusions and discussion.

II. OBSERVATIONAL STUDY VS. DESIGNED EXPERIMENT

A. Literature Review

There are two methods for collecting and analyzing data, designed experiment and observational study [11].

Most of the existing literature of broiler growth performance is based on designed experiment. Donkoh [2] conducted an experiment to elucidate the influence of four constant ambient temperatures (20℃, 25℃, 30℃ and 35℃) on the performance and physiological

This paper is based on "Data Mining for Seasonal Influences in Broiler Breeding Based on Observational Study," by Peijie Huang, Piyuan Lin, Shangwei Yan, and Meiyan Xiao, which appeared in the conference proceedings for the 2nd International Conference on Information Computing and Applications (ICICA 2011) in Beidaihe Qinhuangdao, China October, 2011

* Corresponding author. Tel.: +86-13650761603.

doi:10.4304/jcp.7.8.1895-1902

reactions of male commercial broiler chicks from 3 to 7 weeks of age. The results indicated that continuous exposure of broiler chickens to high ambient temperatures markedly affects their performance and physiological response. Bonnet et al. [3] designed a study to estimate the direct effect of high ambient temperature on dietary ME value, feed digestibility and nitrogen and total mineral retentions. In their experiment, the broilers were distributed into three treatments from 4 weeks of age to 6 weeks of age: ad libitum feed consumption at 22℃ (22AL), ad libitum feed consumption at 32℃ (32AL), and pair-feeding chicks reared at 22℃ on the feed intake of the 32AL (22PF). The relative humidity was maintained at 55±5%. The lighting program was 23 h light: 1 h dark. Worse performance was reported in the controlled group with high temperature. Olanrewaju et al. [6] investigated the effects of ambient temperature, light intensity and their interaction on growth performance and carcass characteristics of broilers. 9 treatments consisted of 3 levels (Low=15.6℃, Moderate=21.1℃, High=26.7℃) of temperatures from 21-56 d of age and 3 levels (0.5, 3.0, 20 lx) of light intensities from 8-56 d of age at 50% relative humidity. Their experiment results indicated that exposure of modern heavy broilers to high ambient temperature in comparison with low and moderate ambient temperatures at 56 d old has a negative effect on growth performance and carcass characteristics. Aengwanich and Simaraks [7] investigated pathological changes in broilers under chronic heat stress. The broilers, twenty-eight days old were kept at 33±1℃ environmental temperature for 21 days. Relative humidity was set to 60-70%. Body temperature and respiratory rate and behavior were investigated and observed. 21 days after their heat exposure, fifteen birds were killed by cervical dislocation. Blahova et al. [4] investigated the effect of low environmental temperature on performance and selected biochemical and haematological indicators. In their experiment, broiler chickens since 22nd day to 42nd day of age were divided into control and experimental groups. The ambient temperature in the control groups decreased from 24 to 21℃. The temperature in the experimental groups was continually monitored and ranged between 4 and 13℃. They documented that during growth, the decrease in environmental temperature (cold stress) negatively influenced some indices of performance and blood system in broiler chickens. Actually, both low and high temperatures act in a negative way. The optimal temperature range for efficient production for broiler chickens over 4 weeks of age is reported as 18 - 21℃ [7]. While contrary to the adult chicken, chick is not accustomed in low temperature environment. Long duration with cold weather could cause high mortality of chick, especially in first week.

Some other designed experiments focus on the fitting of broiler growth curves. Aggrey [8] compared three non-linear growth models (Richards, Gompertz, and logistic) and the spline linear regression model to study how the shape parameter affects growth patterns, carcass yield, and composition. In the experiment of Roush et al. [9], temperature started at 32.2℃ and was reduced 2.8℃ degrees each week until 21.1℃ was attained. Dewpoint was constant at 10.0℃, and the lighting program was 23 L: 1 D. Comparison was made between the modeling by the Gompertz nonlinear regression equation and neural network modeling. Their experiment results shown that neural network had better ability to predict responses. Ahmad [10] continued the study based on the broiler data report by Roush et al. [9] to recognize data patterns and model growth curves by using various neural networks. Three neural networks, namely, BackPropagation-3 (3 layers of back propagation, with each layer connected to the previous layer), BackPropagation-5 (5 layers of back propagation, with each layer connected to the previous layer), and Ward-5 (5 hidden slabs with various activation functions, using NeuroShell 2 Ward software) were used. Back-Propagation-3 neural network gave the best fitting line in his report.

Few studies have dealt with the broiler growth performance by observational study. Akyuz [5] investigate the effects of Mediterranean climates and poultry house conditions on production performance of broilers. The meteorological factors he observed are temperiture, lighting and humidity. In our early work, we have dealt with the data preprocessing of the observated broiler production data [13], and proposed gradual advancing methods for broiler growth performance analysis [14]. In this paper, we extend our earlier work in order to support systematic observational study for seasonal broiler growth performance prediction.

B. Methodology Comparison

In designed experiment, researcher assigns the individuals in a study to a certain group, intentionally changes the value of the explanatory variable, and then records the value of the response variable for each group. In contrast, an observational study measures the value of the response variable without attempting to manipulate or influence the value of either the response of explanatory variables [11]. That is, in an observational study, the researcher has to find that group or the thing he wants to study occurring naturally.

The prominent characteristic of observational study is that factor levels could not be preselected. But for large scale poultry raising, it is not possible to conduct an well designed experiment, thus it should confront such challenge. When compared to designed experiments, the disadvantage in observational study is that unlike the former, observational studies are at the mercy of nature, environmental or other uncontrolled circumstances that impact the ranges of factors of interest [12]. Also, another potentially problem in observational study is that differences found in the fundamental response may be due to other lurking variables that are not considered in a study [11]. To tackle these problems, it is much in need of systematic analysis method and powerful technology.

III. Technical Framework of the Proposed Observational Study

We perform a systematic observational study for researching broiler growth performance prediction, from

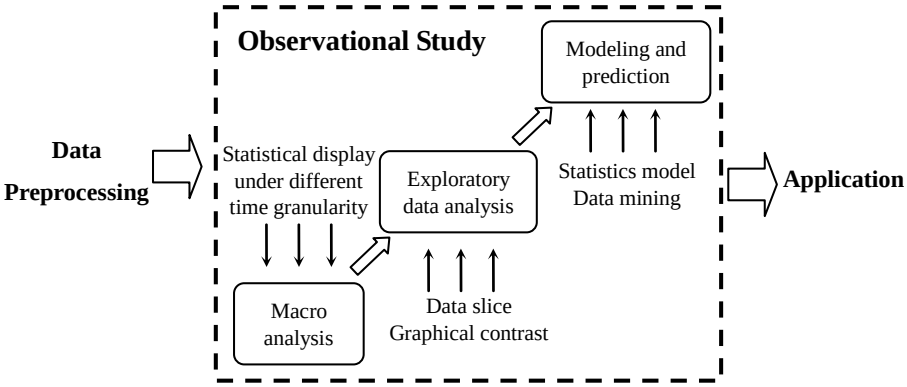


Figure 1. Technical framework of the proposed observational study.

macro analysis, exploratory data analysis, to modeling and prediction. The technical framework is shown in Fig. 1, where macro analysis is performed to validate the universality of seasonal influences in broiler breeding, exploratory data analysis is to maximize the analyst's insight into a data set and into the underlying structure of a data set, and modeling is an effective mean to provide prediction for better decision support.

Traditional statistical analyses are used in macro analysis and exploratory data analysis. Often a summary of a collection of data via data slice and graphical display can provide insight regarding the system from which the data were taken. Data mining technology is combined with traditional statistical model for modeling and prediction. It is worthwhile to note that, data preprocessing is an important issue for effective data mining, as real-world data tend to be incomplete, noisy, and inconsistent [15]. The detail about data preprocessing of the broiler production data can be found in our former work [12]. Base on it, this paper foucses on data analysis and mining in observational study perspective, the knowledge gained can be applied to large scale broiler breeding

IV. Seasonal Broiler Growth Performance Prediction Based on Observational Study

A. Materials

The broiler growth dataset is provided by Guangdong Wen's Foodstuffs Group Limited Company, which is the most famous poultry raising company in China. The dataset of *short-feet buff B* of the breeding area of Guangdong province of China, which is the breed with the largest numbers, is taken as case study to show the effectiveness of our approach, in which we use the hen growth data during 2004 to 2007 for macro analysis and the hen growth data of 2007 is selected for deeper studies of both exploratory data analysis and modeling. Each datum corresponds to the broilers raised by a certain farmer in one time period with the amount varying from several thousand to several tens of thousand. In modeling and prediction, we select 70% samples randomly for training, and the rest for testing. The dataset of meteorological factors is provided by Guangdong Provincial Climate and Agrometeorological Center.

B. Macro Analysis

At the first stage, the universality of seasonal influences in broiler breeding is validated by macro analysis. Broiler growth performance parameters including rate for sale, mean weight, feed conversion ratio, and mean drug cost of *short-feet buff B* of Guangdong province of China during 2004 to 2007 are shown in Fig.2.

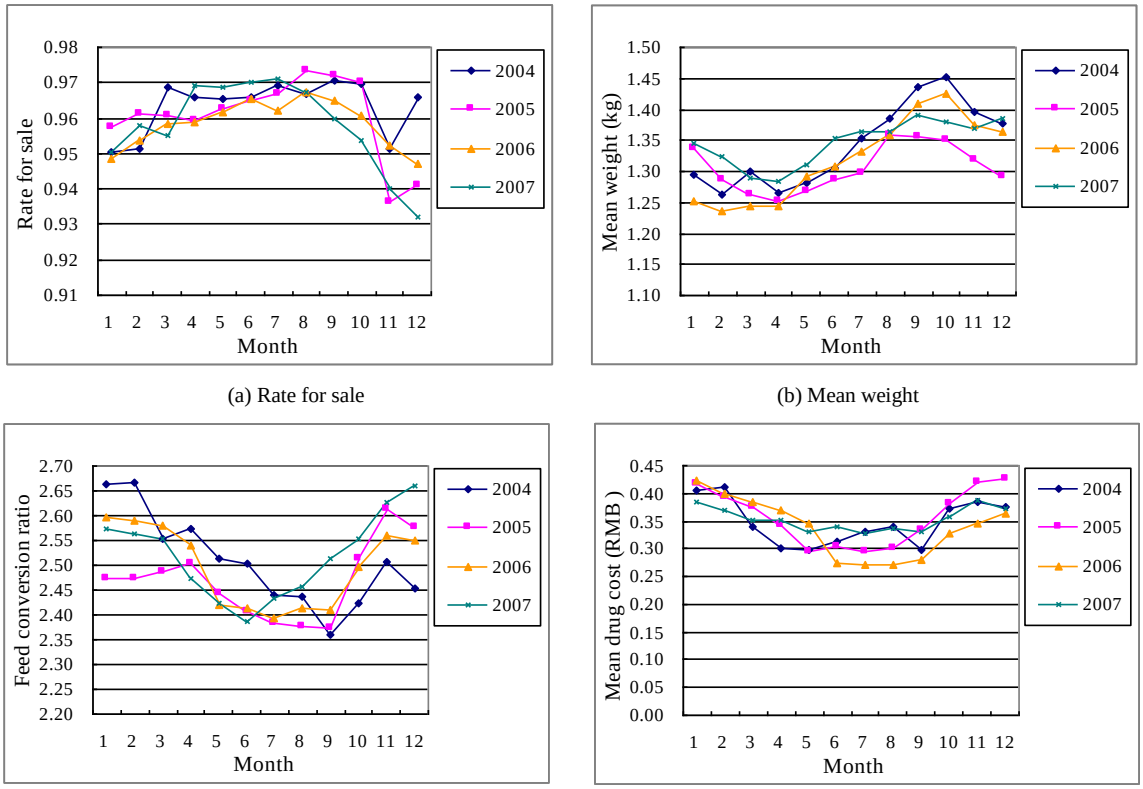
The data shown in Fig.2 is the mean of the broilers adopted in the same month. As we can see from Fig.2, all the observed growth performance parameters take on entirely seasonal fluctuations. The rate for sale increased steadily after January, reaches its peak at July or August, and then decreases gradually, with worst-case at November or December for possible influence of disease and low temperature environment. It can be observed that feed conversion ratio, and mean drug cost of broilers reach highest and lowest in summer and in winter respectively. That may be because high environmental temperatures depress food intake and body weight and also cause deterioration in the food conversion ratio. Mean weight found to be best in autumn, and worst in summer.

C. Exploratory Data Analysis

After the macro analysis, a deeper study can be done by exploratory data analysis [16, 17]. In our current research, only some fundamental graphical techniques are adopted for data detectives. Due to the validated universality of seasonal influences of all the growth performance parameters, we mainly take the influence of the meteorological factors include air temperature, relative humidity, precipitation, wind velocity, pressure, sunshine hours, etc to the rate for sale for example to show our further research. Many unique features contained in data are discovered in such deep analysis according to the observational data. The most representative ones are shown as follows:

- **Choose an appropriate time granularity**

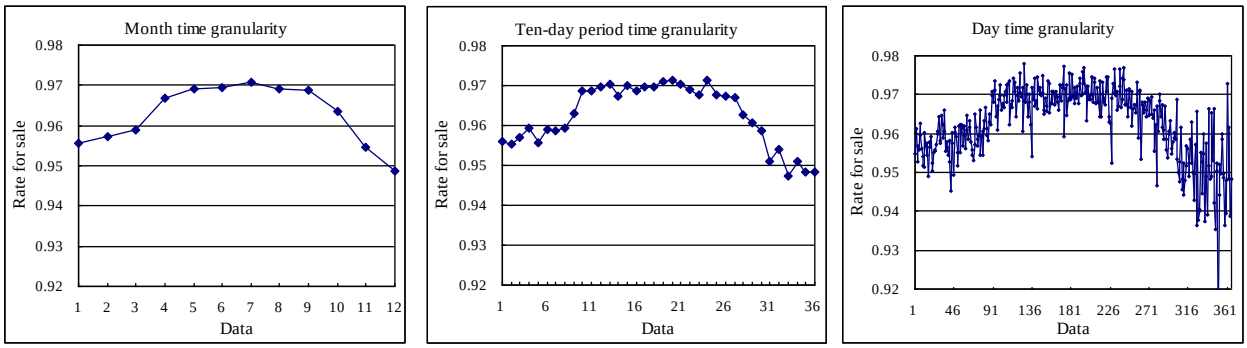
Time granularity is an important issue associated with the data analysis. In general, most people are accustomed to use monthly display, just as we take in the macro



(a) Rate for sale (b) Mean weight

(c) Feed conversion ratio (d) Mean drug cost

Figure 2. Growth performance parameters of short-feet buff B of Guangdong province of China.



(a) Month time granularity (b) Ten-day period time granularity (c) Day time granularity

Figure 3. Different time granularity in data display.

analysis above. However, as we can see in Fig. 3, the month time granularity is too large to catch the variety of meteorological factors. In contrast, the short time granularity such as day can reflect the daily change, but it often causes over fitting and leads to unreliable prediction results. As a compromise, we choose moderate time granularity such as ten-day period to make further study. One month is divided into three ten-day periods, i.e. early, middle and late.

- **Correlation analysis by scatterplot matrix**

The scatterplot matrix is one of the lesser known graphical tools beloved by statisticians, which is a great way for multivariate visualization. Each cell of the matrix contains a plot for a selected pair of variables. All plots in any given row have the same variable on the *Y* axis, while all plots in a given column have the same variable on the *X* axis. One of the benefits of a scatterplot matrix is that one can look across a row or column and see the scatterplots of a given variable against all other variables.

The scatterplot matrix for rate for sale and different relevant meteorological factors is shown in Fig. 4. The first row of the plots shows us a strong correlation between rate for sale and air temperature, with pressure followed. Moreover, due to the potential multicollinearity between air temperature and pressure, which is shown in row 2 and column 5 of Fig. 4., we only use air temperature for the modeling of rate for sale prediction in this case study.

- **Reveal underlying features in broiler growth**

Some other underlying features in broiler growth are found in the deep analysis according to the observational data. The most remarkable phenomenon is shown in Fig. 5. The data shown in Fig.5 is the mean of broilers with the mid dates of breeding period in the same ten-day period. As we can see in Fig. 5, two set of observational data, A (22.48 ℃) and B (22.81 ℃), in second and first half of year respectively, which have approximating mean air temperature in the entire growth period, have unbelievable different rate for sale and mean weight. The growth performance of second half of year is better than first half of year significantly, involving an extended span of time. Such phenomenon is in agreement with the experience in poultry science. In poultry science viewpoint, the full growing stage of broiler can be divided into chickling stage (the first 4 weeks) and adult chicken stage, and broiler of these two stages have

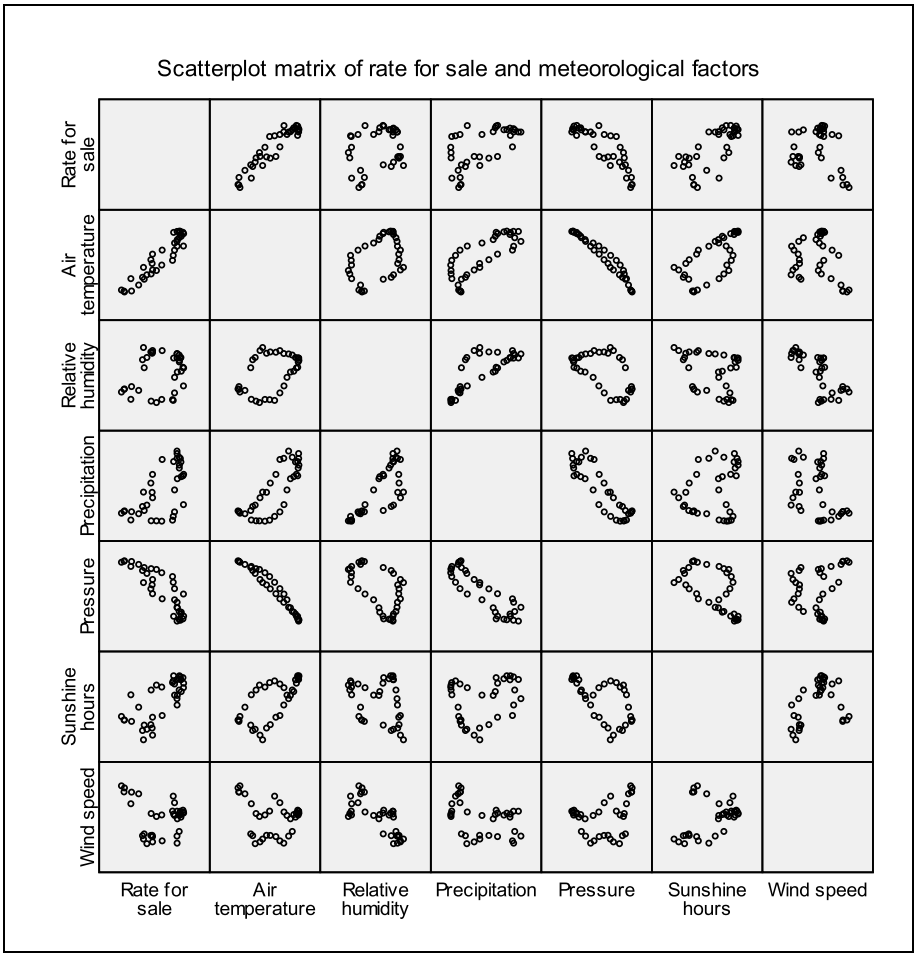
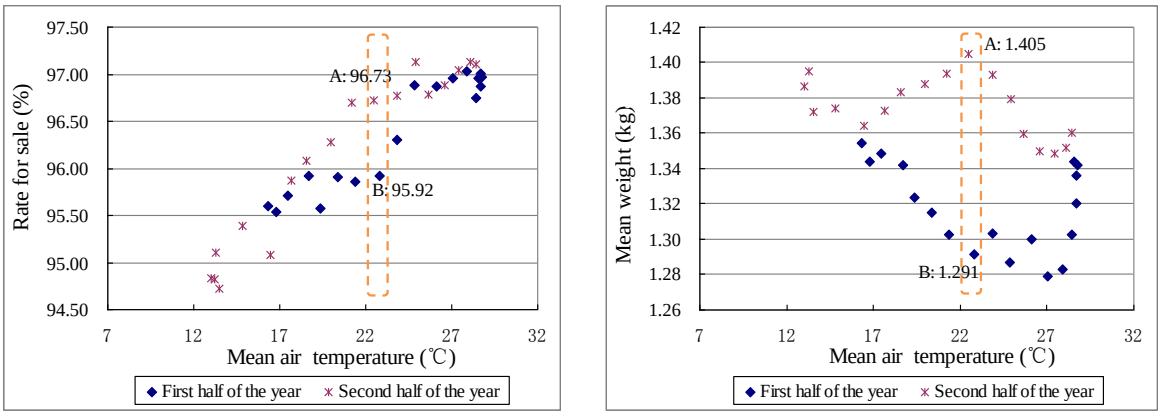


Figure 4. Correlation analysis between rate for sale and different meteorological factors.



(a) Rate for sale (b) Mean weight

Figure 5. Growth performance comparison of first and second half of year (sample data: short-feet buff B of Guangdong province of China, 2007).

different seasonal adaptability, that is "chickling fear of cold and adult chicken hot afraid". Replacing the mean air temperature of the entire growth period with the combination of chickling stage and adult chicken stage, we get that A (26.82 ℃, 20.17 ℃) and B(18.79 ℃, 24.80 ℃). The air temperature combination of datum A is more suit for both chickling and adult chicken, apparently, and thus gets better growth performance. So we use the meteorological factors of both chickling stage and adult chicken stage as explanatory variables when modeling.

D. Modeling and Prediction

The goal of our research topic is to determine if and how seasonal influences affect the broiler growth performance. In broiler growth performance prediction, broiler growth performance parameters are the response variables. Because seasonal factors only have partial linear influence on broiler growth performance, we adopt multiple linear regression (MLR) [18] and neural network [19] models to catch both linear and nonlinear correlations. In both MLR and neural network, we use the mean air temperature of chickling stage and adult chicken stage as inputs, and set the rate for sale as output. For each broiler datum, we compute the mid dates of chick stage and adult chicken stage, respectively, and record them in the form of the corresponding ten-day periods. Then, the broiler data with the same breeding ten-day period combination are aggregated into one input for modeling. In order to obtain reliable models, only those inputs with more than 20 original samples are adopted in training and more than 5 samples are used in testing.

- **Multiple linear regression**

The following MLR equation is fit for the training data:

$$y = 0.000711x_1 + 0.000618x_2 + 0.93422, \quad (1)$$

where y is the rate for sale, and x_1 and x_2 are the mean air temperature of chickling stage and adult chicken stage respectively.

The criterion commonly used to illustrate the adequacy of a fitted regression model is the coefficient of multiple determination, which is denoted by R^2,

$$R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \quad (2)$$

where y_i equals the observed value of input i, $\hat{y}_i$ equals the estimated value, n equals the number of observations, SST is the total corrected sum of squares, which represents the variation in the response values that ideally would be explained by the model, and SSR is the regression sum of squares, which is the variability explained.

R^2 of the fitted model is 0.8428, suggesting that the computed regression model can explain 84.28% of the total variance.

- **Neural network**

As an alternative to regression analysis for modeling, in our study, we choose the Back-Propagation (BP) neural network, which is a feed-forward multi-layer network based on the Back-Propagation algorithm developed by Rumelhart and McCelland [20] and has become one of the most widely used neural network in practice. The Activation Transfer Function (ATF) of a BP network, usually, is a differentiable Sigmoid (S-shape) function, which helps to apply non-linear mapping from inputs to outputs. A two-layer tansig/purelin BP network, and the one used in our study, is shown in Fig.6.

A BP neural network with a single hidden layer is adopted in the case study. And the number of hidden layer neurons is set to 5 according to the formula suggested by Hecht-Nielsen [21], that is

$$k = 2R + 1, \quad (3)$$

where R is the number of input neurons, and k is the number of neurons in the hidden layer

The training goal is set as 5e-6.

- **Prediction performance**

Fig. 7 shows the real observed values and predicted rate for sale for both MLR model and trained neural network (labeled as "NN" in Fig. 7) model, using the testing data.

The goodness of fits for the obtained MLR and neural network model was calculated by mean square error (MSE) and mean percentage error (MPE).

The MSE and MPE are computed as,

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}, \quad (4)$$

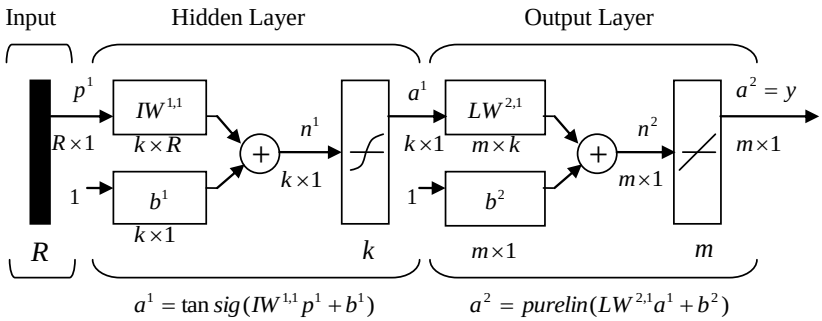


Figure 6. Two-layer BP network architecture.

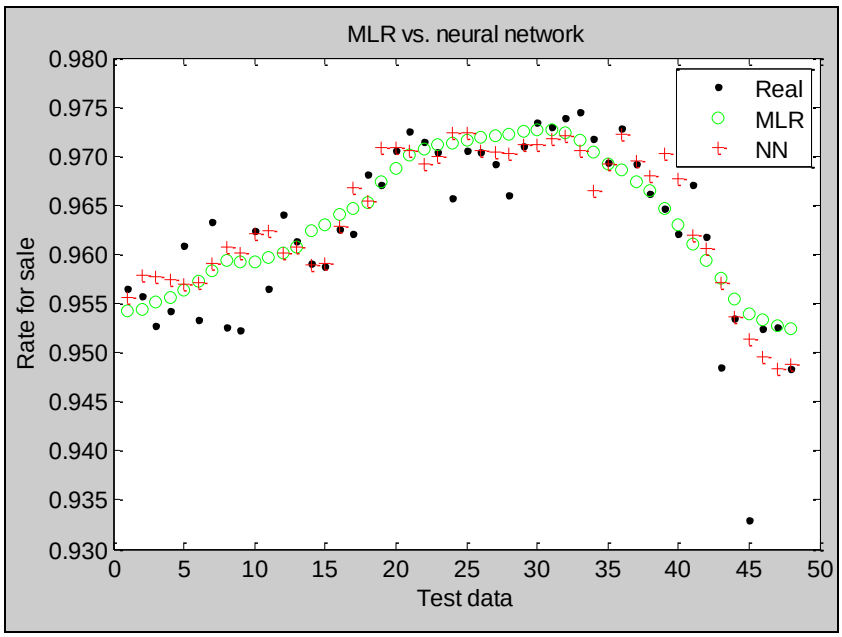


Figure 7. Comparison of MLR and neural network in prediction.

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{y}_i - y_i}{y_i}. \quad (5)$$

Table I shows the statistics for the MLR and neural network models for predicting broiler rate for sale using the testing data.

TABLE I.
MODEL STATISTICS FOR MLR AND NEURAL NETWORK FOR PREDICTING RATE FOR SALE

Model	Statistic	
	MSE	MPE
MLR	2.039E-05	0.10%
NN	2.034E-05	0.11%

As we can see from Table I, both neural network model and MLR model get good peformance in prediction, which are of comparable ability.

V. CONCLUSION

This paper presents systematic observational study, from macro analysis, exploratory data analysis, to modeling, for seasonal broiler growth performance prediction. Case study using the broiler growth dataset of the most famous poultry raising company in China shows the effectiveness of the proposed method.

Our approach validates some general concept of the experience from broiler farmers and industry experts. For example, the phenomenon found in exploratory data analysis supports the industry knowledge of "chickling fear of cold and adult chicken hot afraid". In addition, from the gained MLR model, we can found that the mean air temperature in chickling stage has greater influence to rate for sale than that of adult chicken stage, which validates that "higher mortality occur in chickling stage than adult chicken stage". Moreover, compare to the rough evaluation of growth performance based on "high" and "low" ambient temperature, the prediction models gained from systematic observational study can give better guiding for broiler farmers all the year round.

Regarding the prediction models, due to only partial linear correlation between seasonal factors and broiler growth performance, we adopt both linear regression and neural network model for nonlinear fitting. In the case study of this paper, neural network model and MLR model get comparable ability in testing. So combined prediction can be considered in actual application. Future work includes reseach on more computationally intensive methods in exploratory data analysis for pattern discovery and statistical visualization, more prediction technologies in modeling, such as Support Vector Machine (SVM) which is a learning technique based on the structural risk minimization principle, and making use of the advantage of fuzzy logical and rough set theory in dealing with uncertainty.

Due to the limited objective conditions, our research needs further improvement. Along with the development of Internet of Things (IOT), automatic monitoring condition of poultry breeding will get rapid promotion. Based on multiview and multilevel granularity observational data, the analysis and mining using systematic observational study proposed in this paper is expected to provide better decision support for large scale broiler breeding.

ACKNOWLEDGMENT

This work is supported by Science and Technology Planning Project of Guangdong Province, China under Grant No. 2007A020300010 and 2010B020315024, the

Foundation for Distinguished Young Talents in Higher Education of Guangdong, China under Grant No. LYM09034, and the Industry-Education-Research Cooperation Project of Guangdong Province and Ministry of Education under Grant No. 2011A090200072.

REFERENCES

[1] M. A. R. Howlider, S. P. Rose, "Temperature and the growth of broilers," *World's Poult. Sci. J.* vol. 43, no. 2, pp. 228–237, 1987

[2] A. Donkoh, "Ambient temperature: A Factor Affecting Performance and Physiological Response of Broiler Chickens," *International Journal of Biometeorology*, vol. 33, no. 4, pp. 259-265, 1989

[3] S. Bonnet, P. A. Greraert, M. Lessire, et al., "Effect of High Ambient Temperature on Feed Digestibility in Broiler," *Poult. Sci.*, vol. 76, no. 6, pp. 857−863, 1997

[4] J. Blahová, R. Dobšíková, E. Straková, et al., "Effect of Low Environmental Temperature on Performance and Blood System in Broiler Chickens (Gallus domesticus)," *Acta Vet. Brno*, vol. 76, pp. S17–S23, 2007

[5] A. Akyuz, "Effects of Some Climates Parameters of Environmentally Uncontrollable Broiler Houses on Broiler Performance," *J. Anim. Vet. Adv.*, vol. 8, no. 12, pp. 2608-2612, 2009

[6] H. A. Olanrewaju, J. L. Purswell, S. D. Collier, et al., "Effect of Ambient Temperature and Light Intensity on Growth Performance and Carcass Characteristics of Heavy Broiler Chickens at 56 Days of Age," *International Journal of Poultry Science*, vol. 9, no. 8, pp. 720-725, 2010

[7] W. Aengwanich, S. Simaraks, "Pathology of heart, lung, liver and kidney in broilers under chronic heat stress," *Songklanakarin J Sci Technol.*, vol. 26, no. 3, pp. 417-424, 2004

[8] S. E. Aggrey, "Comparison of Three Nonlinear and Spline Regression Models for Describing Chicken Growth Curves," *Poult. Sci.*, vol. 81, no. 12, pp. 1782-1788, 2002

[9] W. B. Roush, W. A. Dozier III, S.L. Branton, "Comparision of Gompertz and Neural Networks Models of Broiler Growth," *Poult. Sci.*, vol. 85, no. 4, pp. 794–797, 2006

[10] H. A. Ahmad, "Poultry growth modeling using neural networks and simulated data," J. Appl. Poult. Res., vol. 18, no. 3, pp. 440–446, 2009

[11] M. Sullivan, *Statistics: Informed Decisions Using Data*, 3rd ed., Pearson Prentice Hall, 2008

[12] R. E. Walpole, R.H. Myers, S.L. Myers, et al., *Probability & Statistics for Engineers & Scientists*, 9th ed., Pearson Prentice Hall, 2011

[13] M. Y. Xiao, P. Y. Lin, S. W. Yan, et al., "Data Preprocessing of Poultry Breeding Production Data," *Journal of Anhui Agricultural Sciences*, vol. 38, pp. 20707-20709, 2010

[14] M. Y. Xiao, P. J. Huang, P. Y. Lin, et al., "Broiler Growth Performance Analysis: from Correlation Analysis, Multiple Linear Regression, to Neural Network.," *Proceedings of the 4th International Conference on Bioinformatics and Biomedical Engineering (iCBBE2010)*, June, 2010

[15] J. W. Han, M. Kamber, *Data Mining: Concepts and Techniques*, 2nd ed., Morgan Kaufmann, 2006

[16] J. W. Tukey, *Exploratory Data Analysis*, New York: Addison-Wesley, 1977.

[17] T. J. Hastie, R. J. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference and Prediction*, 2nd ed., New York: Springer, 2009

[18] S. Weisberg, *Applied Linear Regression*, 3rd ed., New York: Wiley, 2005

[19] S. S. Haykin, *Neural Networks and Learning Machines*, 3rd ed., Pearson Prentice Hall, 2009

[20] D. E. Rumelhart, J. L. McCelland, "Learning representations by backpropagating errors," *Nature*, vol. 323, no.6188, pp.533-536, 1986

[21] R. Hecht-Nielsen, "Counter propagation networks," *Appl. Optics*, vol. 26, no. 23, pp. 4979-4984, 1987

Peijie Huang received his B.S. and Ph.D. degrees, both in computer science, from South China University of Technology in 2003 and 2008, respectively. He is now a lecturer at the College of Informatics, South China Agricultural University. His research interests include intelligent computing, Cloud computing and bioinformatics.

Piyuan Lin received his B.S. and M.S degrees, both in Computer Science, from University of Electronic Science and Technology of China in 1984 and 1989, respectively. He is currently a senior member of the China Computer Federation (CCF), a professor and the vice-dean of College of Informatics, South China Agricultural University. He has presided over and participated in 21 projects supported by the National Natural Science Foundation, the 863 Program, the Provincial High-tech Program of Guangdong, and some companies. His research interests include bioinformatics and data mining.

Shangwei Yan received his B.S. degrees in Computer software from Fudan University in 1984. He is currently an associate professor at the College of Informatics, South China Agricultural University. He is in charge of enterprise informatization of Guangdong Wen's Foodstuffs Group Limited Company since 1991. His research interests include software engineering and bioinformatics.

Meiyan Xiao received her B.S. and M.S degrees, both in Computer Science, from South China Agricultural University. She is now an intermediate experimentar at the College of Informatics, South China Agricultural University. Her research interests include intelligent computing and bioinformatics.