PREDICTION OF POULTRY DEEP BODY TEMPERATURES USING ARTIFICIAL NEURAL NETWORKS

by

LIN LIU

(Under the Direction of Takoi Hamrita)

ABSTRACT

To understand the relationships among ambient temperature (AT), relative humidity (RH) and broiler deep body temperature (DBT), controlled experiments were conducted for different RH (50 and 80%) and AT (31, 34 and 37^{o}C) combinations. The DBT measurements were collected by a radio biotelemetry system. Three types of Artificial Neural Network (ANN) models have been developed to predict broiler's DBT. Type I models predict DBT responses of birds not used in training to AT×RH combinations used in training. Type II models predict DBT responses of birds used in training to AT×RH combinations not used in training. Type III models predict DBT response of birds not used in training to AT×RH combinations not used in training. These models capture the complex relationship among DBT, AT and RH very well. They could be applied in the future in the development of environmental control system for poultry housing.

INDEX WORDS: Artificial Neural Networks, Deep Body Temperature, Ambient Temperature, Relative Humidity, Broiler.

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LIN LIU

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LIN LIU

Major Professor: Takoi Hamrita

Committee: Ronald W. McClendon
Donald Nute

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
December 2002

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Chickens are homeothermic animals. They are able to maintain constant deep body temperature (DBT) within a thermoneutral zone through various mechanisms. The thermoneutral zone is a range of ambient temperatures (AT) within which birds can maintain a near constant DBT with minimum energy expenditure (Ernst, 1995). Van Kampen et al. (1979) defined this range as 32.2-37.7^{o}C in the light and 27.5-37.7^{o}C in the dark, whereas other researchers identified 24^{o}C as being thermoneutral (Teeter et al., 1992; Fulton et al., 1993; Smith, 1993). The DBT of unstressed chickens normally varies between 41.0 and 41.5^{o}C (Lacey, 1999). Usually, chickens are able to maintain this temperature through a complex combination of physiological and behavioral responses. Under higher temperature above the thermoneural zone (namely thermal stress environments), chickens try to regulate their DBT by other physiological and behavioral mechanisms, such as evaporative cooling and reduction of feeding. However, these regulation mechanisms are often ineffective, and frequently result in thermal imbalance and DBT increase. Such thermal imbalance and DBT increase are undesirable in poultry performance and production.

There have been numerous studies in understanding the physiological responses of poultry to thermal stress environments, and sometimes the findings are not consistent. Considering the complexity of the relevant biological system, such inconsistency seems to be understandable. As pointed out by Etches et al. (1995), the physiological responses to high temperature is affected complicatedly by many factors including relative humidity (RH), strain, age of bird, feed energy level, light intensity, previous exposure to high AT, and so on.

In the poultry industry, great efforts have been focused on increasing growth efficiency through the improvement of environmental control. However, the challenging fact is that many environmental factors, including ambient temperature (AT), relative humidity (RH), velocity of moving air, light intensity, temperature of water supply and so on, could affect poultry growth performance simultaneously (Etches, et. al, 1995; Yahav, et. al., 1995; Lott, et al., 1998; Furlan, et al., 2000). Physiological feedback such as respiration rate, heart rate, heat production or body temperature could provide good indication for the immediate condition and growth performance of housing animals, accounting for a complex interaction among different environmental factors (Lacey et al., 2000 a, b; Hamrita et al., 1997 a, b; Aerts et al., 1996, 1998; Moberg, 1985). The potential use of physiological feedback data to improve environmental control and management of animal housing is getting more and more research interest (Lacey et al., 2000 a, b; Hamrita et al., 1997 a,b; Aerts et al., 1998; Goedseels et al., 1992; Barnett and Hemsworth, 1990).

Deep Body Temperature (DBT) has been documented to be a useful indicator of stress in poultry (Mitchell, 1981; Hamrita et al., 1997b; Kettlewell et al., 1997; Lacey et al., 2000 a, 2000 b). Van Kampen (1979) found that the body temperature of domestic fowl is practically constant up to an AT of 27^{o}C, but rises with AT above this. Mitchell (1981) used a radio telemetry system to understand the effects of handling and temperature stress on heart rate of broiler, electrocardiogram and DBT. It was found that DBT was very sensitive to handling and a good candidate for a stress indicator. Kettlewell et al. (1997) also used a radio telemetry system to study chicken DBT and heart rate, and proved that chicken DBT vary measurably with stressful conditions (Ketlewell et al., 1997). Lacey (1999) reported that even small increases in AT, at a non-stressful level, resulted in a detectable response in DBT of broilers. Lacey et al. (2000 b) conducted 6-week experiments based on six pairs of broilers equipped with DBT sensing transmitters. The broilers were exposed to combinations of three ATs (31, 34 and 37^{o}C) and two RHs (50 and 80%). Based on the analysis of variance on DBT data, the authors found that DBT responses were consistent among all birds, and the changes of AT and RH significantly contributed to DBT changes in broilers. Definitely, DBT is an ideal physiological variable of chicken for us to study the physiological responses to environmental stress.

Many current efforts are aimed at developing models of predicting dynamic responses of physiological variables to environmental conditions (Aerts et al., 1996, 1998; Lacey 1999; Lacey et al., 2000b). Robust models for predicting these physical variables are indispensable for establishing dynamic and precise control systems for the poultry house environment in the future. Some research efforts in the literature have been focused on the study of predictability of physiological responses of poultry to environmental stress (Mitchell, 1981; Yahav et al., 1995; Aerts et al., 1996; Hamrita, 1997; Aerts et al., 1998; Lacey, 1999; Lacey et al., 2000b). Aerts et al. (1996) developed recursive regression models that predicted dynamic responses of broiler heat production to variations in ambient temperature and light-dark alternations. The recursive regression models had a relative prediction error of 3.4% for 1 step-ahead (4.5 min) prediction and 4.3% for 3 step-ahead predictions. Aerts et al. (1998) also developed a recursive regression model to predict heart rate responses of broilers to changes in ambient temperature and light-dark alternations with a 15 minute-ahead relative prediction error of 4.0%. Also, DBT responses to environmental variables seemed to be consistent enough to be modeled and predicted. Lacey (1999) developed ANNs using ambient temperature and on-line measurements of broiler DBT to predict future DBT under changing ambient temperature. The author concluded that longer-term (e.g. 50 min ahead) and short-term (e.g. 2 min ahead) predictions are possible with decreasing accuracy as the prediction distance increases. Short-term and longer-term predictions are considered in this research. DBT response predictions ranging from one step (10 minute) to 6 steps (60 minutes) ahead were performed. These predictions could ultimately be used to improve environmental control in poultry housing control systems in the future (Lacey, 1999). The short-term prediction model could be used as part of a model-based controller that continuously adjusts environmental conditions based on physiological responses of the birds. The longer-term predictions could be used as part of online expert systems that makes management decisions such as deciding an on set point for the environmental controller. Moreover, in another 5-day experiment to determine the response of broiler DBT to step changes in AT, Lacey et al. (2000 a) exposed three birds implanted with DBT sensing transmitter to five sequential schedules of AT steps spanning 13 hours a day. In this study, three different ANN models had been developed: the first one predicted DBT responses of a bird not used in training to AT schedules used in training, the second one predicted DBT responses of a bird used in training to AT schedules that were not used in training, and the third one predicted DBT responses of birds not used in training to AT schedules not used in training. All three models had used 10-minute prior DBT, AT and RH as input variables. Authors found that the first and second model displayed good prediction accuracy whereas the third model showed poor performance. They concluded that predicting DBT responses to step changes of AT using ANNs is a promising approach.

Artificial Neural Networks (ANNs) provide a computational intelligence technique for modeling that has become more and more popular in the study of biological systems. Artificial Neutral Networks are ideal for processing data in which the relationships between variables are not clear and nonlinear (Chester, 1993). The main objective of this research is to develop new ANN models that could capture the complex relationship among DBT, AT, RH and TIME and provide good predictions for real-time DBT. The specific goals of the research reported in this thesis are: (1) capture and quantify the relationships between DBT and combinations of multiple environmental factors (i.e., AT, RH and Time) using ANNs, and determine how well ANN models perform, (2) examine the generalization capability of the ANN models over longer experiment durations and for larger datasets and (3) determine how far ahead DBT could be predicted using prior DBT, AT or RH, and understand what is the model performance if none of any prior DBT, AT or RH was used in the ANN model at all.

CHAPTER 2

PREDICTION OF POULTRY DEEP BODY TEMPERATURES USING ARTIFICIAL NEURAL NETWORKS [1]

[1] L. Liu, T. K. Hamrita and B. Lacey. Submitted to *Computers and Electronics in Agriculture*, 2002/11/25.

2.1. Introduction

In the poultry industry, great efforts have been focused on increasing growth efficiency through the improvement of environmental control. However, the challenging fact is that many environmental factors, including ambient temperature (AT), relative humidity (RH), velocity of moving air, light intensity, temperature of water supply and so on, could affect poultry growth performance simultaneously (Yahav, et. al., 1995; Lott, et al., 1998; Furlan, et al., 2000). Physiological feedback such as respiration rate, heart rate, heat production or body temperature could provide good indication for the immediate condition and growth performance of housing animal, accounting for a complex interaction among different environmental factors (Lacey et al., 2000 a, b; Hamrita et al., 1997 a, b; Aerts et al., 1996, 1998; Moberg, 1985). The potential use of physiological feedback data to improve environmental control and management of animal housing is getting more and more research interests (Lacey et al., 2000 a, b; Hamrita et al., 1997 a,b; Aerts et al., 1998; Goedseels et al., 1992; Barnett and Hemsworth, 1990). Particularly, many current efforts are aimed at developing models of predicting dynamic responses of physiological variables to environmental conditions (Aerts et al., 1996, 1998; Lacey 1999; Lacey et al., 2000b). Robust models of predicting these physical variables are indispensable for establishing dynamic and precise control systems of the poultry house environment in the future.

Deep Body Temperature (DBT) has been documented to be a useful indicator of stress in poultry (Mitchell, 1981; Hamrita et al., 1997b; Kettlewell et al., 1997; Lacey et al., 2000 a, 2000 b). Poultry DBT has been proved to vary measurably with stressful conditions (Ketlewell et al., 1997). Lacey (1999) reported that even small increases in

AT, at a non-stressful level, resulted in a detectable response in DBT of broilers. Moreover, DBT responses to environmental variables seemed to be consistent enough to be modeled and predicted. In a 5-day experiment to determine the response of broiler DBT to step changes in AT, Lacey et al. (2000 a) exposed three birds implanted with DBT sensing transmitter to five sequential schedules of AT steps spanning 13 hours a day. In this study, three different ANN models had been developed: the first one predicted DBT responses of a bird not used in training to AT schedules used in training, the second one predicted DBT responses of a bird used in training to AT schedules that were not used in training, and the third one predicted DBT responses of birds not used in training to AT schedules not used in training. All three models had used 10-minute prior DBT, AT and RH as input variables. Authors found that the first and second model displayed good prediction accuracy whereas the third model showed poor performance. They concluded that predicting DBT responses to step changes of AT using ANNs is a promising approach.

In another independent experiment, Lacey et al. (2000 b) conducted 6-week experiments based on six pairs of broilers equipped with DBT sensing transmitters. The broilers were exposed to combinations of three ATs (31, 34 and 37^{o}C) and two RHs (50 and 80%). Based on the analysis of variance on DBT data, the authors found that DBT responses were consistent among all birds, and the changes of AT and RH significantly contributed to DBT changes in broilers. Using the same data set, we are developing ANNs model to predict broiler DBT responses as a function of changing AT and RH regimes. The specific goals of the research reported in this article are:

1. Capture and quantify the relationships between DBT and combinations of multiple environmental factors (i.e., AT, RH and Time) using ANNs, and determine how well ANN models perform.
2. Examine the generalization capability of the ANN models over longer experiment durations and for larger datasets, by (a) predicting DBT responses of birds not used in training to AT×RH combinations used in training, (b) predicting DBT responses of birds used in training to AT×RH combinations not used in training, and (c) predicting DBT responses of birds not used in training to AT×RH combinations not used in training.
3. Determine how far ahead DBT could be predicted using prior DBT, AT or RH, and understand what is the model performance if none of any prior DBT, AT or RH was used in ANN model at all.

2.2. Methodolody

2.2.1. Artificial Neutral Networks

Artificial Neutral Networks are ideal for processing data in which the relationships between variables are not clear and nonlinear (Chester, 1993). In our study, the relationship between bird physiological responses such as DBT and environmental variables such as AT and RH could be very complex, non-linear and time varying. For example, the same AT×RH combination could affect a broiler's DBT differently depending on the age of the bird and prior exposure to environmental stress (Lacey, 1999). Therefore, the characteristics of ANN could help us capture and quantify such complex interrelationship among these multiple variables accurately and efficiently.

Currently, the most general-purpose and widely used neural network architecture is the backpropagation network (BPN). The BPN uses the gradient-descent training algorithm to achieve its generality. The standard BPN usually consists of one input layer, one to many hidden layer(s), and one output layer. In this study, the standard BPN was used as one of ANN architectures for predicting broiler's DBT.

The second ANN architecture used in this study is the Elman-Jordan network. Essentially, the Elman-Jordan ANN is a recurrent backpropagation network in which predictions made for a pattern are fed back to the network's input layer and used to make subsequent predictions. Such distinguishing characteristics of this architecture made it ideal for processing time series data (Smith, 1996). Considering the time sequence nature of broiler physiological responses, we selected the Elman-Jordan network as one of the ANN architectures in our model development.

NeuroShell™ software package (Ward Systems Group, Inc., Frederic, Maryland) was used to develop the ANN models. As the recommended architecture by the software package, Ward Networks were also used as one of the ANN architectures in this study. As shown in Figures 2.1A and 2.1B, the distinguishing characteristic of the Ward Networks is that they consist of two or three hidden layers, each of which adopts a different activation function (e.g. Gaussian, Gaussian complement and hyperbolic tangent). Such characteristic could help to improve model performance by detecting different features hidden in the data patterns using different activation functions. For example, one hidden layer with Gaussian function can be used to detect features in the mid-range of the data whereas another hidden layer can use Gaussian complement to detect features from the upper and lower extremes of the data. The cooperation among different activation functions could enhance the model performance.

2.2.2. Experimental design and data collection

The experimental design was a 6×6 Latin square design for 3 AT × 2 RH. The three AT settings were 31, 34 and 37^{o}C while the two RH settings were 50 and 80% (see Table 2.1). Because only one climate control chamber was available for experimentation, each of the 3AT × 2RH combinations was scheduled in one day of each experimental week in terms of the Latin square design requirement. The total experimental duration was 6 weeks and within each week, six days (except Sundays) were used for experimentation. In each day, two commercial broilers were used as two replicates for each AT×RH combination. For each week, a different pair of broilers in the same age had been used for experimentation. The detailed description of the experimental design and procedure can be found in Lacey et al. (2000 a).

Both broiler physiological data (DBT) and environmental data (AT and RH) were collected simultaneously at a time interval of 10 minutes for 4 to 10 hours a day. As shown in Table 2.2, there were a total of 2916 experimentally observed data points and these data were distributed unevenly among different AT×RH combinations over different days and weeks. The lack of consistency in the data was due to occasional malfunction of the DBT transmitters. In the experimentally observed dataset, each data pattern includes the following 4 variables: TIME (0.00 – 24.00), AT (^{o} C), DBT (^{o} C) and

RH (%). In addition, we include 18 variables for each pattern. These variables are AT, DBT and RH recorded at 10, 20, 30, 40, 50 and 60 min prior. These variables are named by adding a prefix like “PREV10_” (e.g. PREV10_AT, PREV10_DBT and PREV10_RH), where the number indicates how many minutes ahead the value of a variable was recorded. When we adopted these variables, there were some data patterns that have missing values. Because missing values will cause bias in ANN model development and evaluation, we decided to remove these patterns from the dataset. Correspondingly, there are a total of 2484 data patterns used in ANN model, which are 432 patterns less than the experimentally observed dataset.

2.2.3. Model Development and Evaluation

Some research efforts in the literature have been focused on the study of predictability of physiological responses of poultry to environmental stress (Mitchell, 1981; Yahav et al., 1995; Aerts et al., 1996; Hamrita, 1997; Aerts et al., 1998; Lacey, 1999; Lacey et al., 2000b). Aerts et al. (1996) developed recursive regression models that predicted dynamic responses of broiler heat production to variations in ambient temperature and light-dark alternations. The recursive regression models had a relative prediction error of 3.4% for 1 step-ahead (4.5 min) prediction and 4.3% for 3 step-ahead predictions. Aerts et al. (1998) also developed a recursive regression model to predict heart rate responses of broilers to changes in ambient temperature and light-dark alternations with a 15 minute-ahead relative prediction error of 4.0%. Lacey (1999) developed ANNs using ambient temperature and on-line measurements of broiler’s DBT to predict future DBT under changing ambient temperature. The author concluded that longer-term (e.g. 50 min ahead) and short-term (e.g. 2 min ahead) predictions are possible with decreasing accuracy as the prediction distance increases.

Short-term and longer-term predictions are considered in this research. DBT response predictions ranging from one step (10 minute) to 6 steps (60 minutes) ahead were performed. These predictions could ultimately be used to improve environmental control in poultry housing control systems in the future (Vranken et al., 1998; Lacey, 1999). The short-term prediction model could be used as part of a model-based controller that continuously adjusts environmental conditions based on physiological responses of the birds. The longer-term predictions could be used as part of online expert systems that makes management decisions such as deciding an on set point for the environmental controller.

Three types of ANN models (i.e. Model Type I, II and III) were developed in this study for both the short-term and the longer-term prediction. Type I models predicted DBT responses of birds not used in training to AT×RH combinations used in training. Type II models predicted DBT responses of birds used in training to AT×RH combinations not used in training. Type III models predicted DBT responses of birds not used in training to AT×RH combinations not used in training. For all three types of model, the output variable is the DBT response whereas the input variables were varied depending on the different model types. Moreover, a great deal of effort had been focused on determining the best ANN architecture (BPN, Elman-Jordan or Ward networks) and its optimal parameter setting. For each ANN architecture, different data partitioning strategies, hidden node number, learning rate and momentum were used and compared to obtain the best model parameter settings.

When an ANN model is developed, data patterns are partitioned into training, testing and production sets. The training set is used to adjust the weights of the ANN model. The testing set is used to evaluate the model accuracy during training in order to determine when to stop training. During the ANN training, the weights of the model that performed best on the testing set are saved automatically. When the training is stopped, the production set is used to evaluate the saved network.

The partition strategy for obtaining the production set for our ANN models depended on the different types of models. For Type I models, the production set consisted of data patterns for birds not used in training. We selected one bird from week 4 and one bird from week 6, because the DBT differences between two replicate birds are intermediate among all 6 weeks. Within the dataset, there are 370 data patterns in the production set and 2114 in the training and testing sets. For Type II models, the production set consists of the data patterns present in one AT×RH combination not used in training. Among all 6 kinds of AT×RH combinations (A, B, C, D, E and F), we select F (AT=34^{o}C and RH=80%) as the production set because its ambient temperature is an intermediate value in comparison with 31 and 37 ^{o}C. Also because only two RH regimes (i.e. 50% and 80%) have been used in the experimental design, we just pick 80% RH and therefore we pick F as production set. Within the dataset, there are 430 data patterns in the production set and 2054 in training and testing sets. Type III models predicted DBT responses of birds not used in training to AT×RH combinations not used in training. We select all data patterns present in F from one replicate for all six weeks as the production set, whereas all data patterns of A, B, C, D and E from the other replicate for all six weeks consist of the training and testing data. Within the dataset, there are 215 data patterns in the production set and 1027 in training and testing sets whereas 1242 data patterns are not in used.

The partition strategies for separating training and testing sets are common for all three types of models. For both BPN and Ward networks, different random data partitioning strategies (i.e. 85% vs. 15%, 80% vs. 20%, 75% vs. 25%, 70% vs. 30%, 65% vs. 35% and 60% vs. 40%) have been adopted for separating the training and testing sets. Because the Elman-Jordan network needs the data represented in a time sequence, we adopted a nonrandom strategy for partitioning training and testing sets when we developed the DBT prediction model using the Elman-Jordan network architecture.

In addition to considering different ANN architectures (BPN, Elman-Jordan and Ward networks) and different data partition strategies, we also treated hidden node number, learning rate and momentum as model parameters that might improve model performance. To get the best setting for these model parameters, we used various hidden node numbers ranging from 1 to 60 nodes, and different values of (0.05, 0.1, 0.3, 0.6 and 0.9) for both learning rate and momentum. In order to understand the effect of a specific model parameter such as learning rate, models were developed using different values for that parameter while all other model parameters were unchanged. The accuracy of our ANN model is evaluated using the mean absolute error (MAE) and r^2 value of DBT. The higher the r^2 value and the lower the MAE value, the better the model performance.

2.3. Results and discussion

Table 2.3 shows model performance of the best ANN models developed for the three model types. It is clear that model accuracy decreases as the prediction interval increases. As shown in Table 2.3, for all three types of models, the r^2 values decreases linearly with the increase of the prediction intervals, while MAE values increases linearly with the increase of the prediction intervals. Particularly, all models using previous variables shows good prediction: r^2 values are greater than 0.79. The performance of these models seem to be much better than those reported by Lacey (1999). However, our best ANN models without using any previous variables displayed poor performance in DBT prediction (r^2 of 0.3818, 0.4085 and 0.3450 for Type I, II and III respectively). Considering the fact that there were only two replicates in each AT×RH combination and the differences between replicates were noticeably great in some cases, our model performance might have been degraded due to smaller sample population and larger data noises.

In order to get the best models displayed in Table 2.3, we have conducted extensive experimentation in determining the best ANN architecture and its relevant parameter settings, including data partition strategy, hidden node number, learning rate, momentum and input variables (i.e. different previous variables). Models shown in the Table 2.3 have some differences either in ANN architecture or in its parameter settings. For example, the best type II model using measurements from 60 minutes prior was a Ward (1B) ANN architecture, with hidden nodes of 22 in each hidden layer, random data partition strategy of 20/80 for test and training sets, and input variables of TIME, AT, RH, deep body temperature measured 60 minutes prior (PREV60_DBT), ambient temperature measured 60 minutes prior (PREV60_AT) and relative humidity measured 60 minutes prior (REV60_RH). In contrast, the best type I model using "PREV60_" variables was a Ward (1A) ANN architecture, with hidden node of 20 in each hidden layers, random data partition strategy of 20/80 for test and training sets, and input variables of TIME, AT, RH, PREV60_DBT, PREV60_AT, PREV60_RH.

In all cases Ward networks had much better prediction accuracy than both Elman-Jordan and standard BPN. Comparing with standard BPN, different activation functions (e.g. Gaussian and Gaussian complement) could be used simultaneously to detect different features in the data patterns in Ward networks. Comparing with Elman-Jordan, random data pattern strategy in Ward networks could bring network more representative data in training and test sets, especially in the case where only two replicates in each AT×RH combination are available. These reasons might provide an explanation why Ward networks performed better than both standard BPN and Elman-Jordan for all three types of models in this study.

Different data partition strategies have proved to dramatically influence ANN model performance, even for the same ANN architecture. As shown in the table 2.4, for type II model using "PREV60_" variables, random data partition strategy of 20/80 for test and training sets appear to have contributed the best model performance (r^2 of 0.8049, MAE of 0.202 and correlation coefficient r of 0.8972). However, this data partition strategy may not be the best one for other types of models.

Table 2.5 shows the effect of different hidden node numbers for Ward (1B) networks using "PREV60_" variables (Type II model). Clearly, model performance varied with the hidden node number in a non-linear way. We found that the hidden node number of 22 gave the best performance, with r^2 of 0.8049, correlation coefficient r of 0.8972 and MAE of 0.202. Similarly, different learning rates, momentum and initial weights were tested to develop the best models. After extensive experimentation with different values for learning rate and momentum, it was determined that the default values of 0.1 seemed to contribute to the best results in most cases.

Prediction accuracy of ANN networks is highly dependent on the quality of training data. Also there are only two replicates in each AT×RH combination and sometimes the data noises seem to be big, model performance revealed in this study seems to be very good in most cases. As shown in Figures 2.2A, 2.2B, 2.3A and 2.3B, the type I model using "PREV10_" variables displayed higher prediction accuracy than that using "PREV60_" variables. This can be further confirmed when we compared the relevant figures 2.11 and 2.12. For the type I model using "PREV10_" variables data points are gathering along the diagonal line (Figure 2.11) whereas for the type I model using "PREV60_" variables data points are much scattered (Figure 2.12). The diagonal line in each of these charts shows what would be produced by perfect predictions. Similarly, we had found the same trend for the type II model in Figures 2.5, 2.6, 2.14 and 2.15 and for the type III model in Figures 2.8, 2.9, 2.17 and 2.18. Obviously, it further confirms that ANN network is a very promising method for us to develop broiler DBT prediction model.

However in our study, all three types of models without using any previous variables displayed poor prediction accuracy as shown in Figures 2.4A, 2.4B, 2.7, 2.10, 2.13, 2.16 and 2.19. It seems that the prediction error mainly comes from the replicate differences within the AT×RH combination. For example as shown in Figure 2.4A and 2.4B, the week 4 seemed to have much better DBT prediction than the week 6 for type I model without using any previous variables. This is due to the fact that two replicates in week 4 displayed much less differences in DBT than the two replicates in week 6 (Figure 2.20 and 2.21). However, our study still suggests that it is possible to predict the broiler DBT only based on current AT and RH values, rather than using previously recorded values, if there were more replicates represented in each AT×RH combination. In our opinion, similar to the above-mentioned short-term and longer-term models, the models without using any information of previously measured variables will also have great potential in its application to the development of environmental control systems for poultry housing.

Table 2.1. Six AT×RH combinations

	Ambient Temperature	31^{o}C	34 ^{o}C	37 ^{o}C
Relative	50 %	A	C	E
Humidity	80 %	D	F	B

Table 2.2. Latin square design and data distribution

Day	Mon	Tues	Wed	Thur	Fri	Sat
Week 1	F(51)	C(51)	D(24)	A(43)	B(46)	E(44)
Week 2	A(45)	B(62)	E(52)	F(45)	C(52)	D(49)
Week 3	E(28)	F(42)	A(34)	C(35)	D(42)	B(39)
Week 4	C(35)	A(33)	B(43)	D(35)	E(34)	F(33)
Week 5	B(42)	D(33)	C(37)	E(40)	F(37)	A(43)
Week 6	D(35)	E(40)	F(43)	B(38)	A(35)	C(38)

* Each AT×RH combination had two birds as replicates, and the number in parenthesis indicates the number of data points available for each of the two replicates.

** Each week, a different pair of birds of the same age had been used for 6 days

Table 2.3. Artificial Neural Network (ANN) model performance for predicting broiler DBT

	Type I Model			Type II Model			Type III Model		
	r^2	MAE	r	r^2	MAE	r	r^2	MAE	r
1 step ahead	0.9783	0.085	0.9891	0.9708	0.086	0.9853	0.9760	0.080	0.9879
2 steps ahead	0.9534	0.126	0.9764	0.9421	0.140	0.9706	0.9472	0.110	0.9732
3 steps ahead	0.9255	0.164	0.9620	0.9109	0.157	0.9544	0.9008	0.143	0.9562
4 steps ahead	0.8941	0.198	0.9456	0.8775	0.172	0.9368	0.8747	0.170	0.9352
5 steps ahead	0.8568	0.228	0.9256	0.8395	0.191	0.9163	0.8307	0.199	0.9114
6 steps ahead	0.8263	0.239	0.9090	0.8049	0.202	0.8972	0.7898	0.216	0.8887
No previous variable	0.3818	0.692	0.6179	0.4085	0.269	0.6392	0.3450	0.322	0.5874

Note: 1 step ahead equals to 10 minutes in advance and correspondingly 6 steps ahead means 60 minutes in advance.

Table 2.4. Effect of different data partition strategies for Ward (B) networks of DBT prediction using "PREV60_" variables (Type II model)

Partition Strategy	**r^2**	**MAE**	**r**
10/90	0.7834	0.229	0.8851
15/85	0.7917	0.209	0.8898
20/80	0.8049	0.202	0.8972
25/75	0.7221	0.253	0.8498
30/70	0.7497	0.247	0.8658
35/65	0.7425	0.242	0.8617
40/60	0.6986	0.260	0.8359

Notation: the default parameter settings are following: Hidden Node Number=22, Learning Rate=0.1, Momentum=0.1, Initial Weights=0.3, Input variables=TIME, AT, RH, PREV60_AT, RREV60_RH, PREV60_DBT.

Table 2.5. Effect of different hidden node number for Ward (B) networks of DBT prediction using "PREV60_" variables (Type II model)

Hidden Node Number	r^2	MAE	r
12	0.8046	0.220	0.8970
14	0.7636	0.249	0.8738
16	0.7952	0.222	0.8917
18	0.8006	0.217	0.8948
20	0.8023	0.211	0.8957
22	0.8049	0.202	0.8972
24	0.8053	0.211	0.8974
26	0.7719	0.236	0.8786
28	0.8020	0.217	0.8956
30	0.7310	0.266	0.8550
32	0.7896	0.235	0.8886

Notation: the other default parameter settings are following: Data Partition Strategy (20/80 for test/training), Learning Rate=0.1, Momentum=0.1, Initial Weights=0.3, Input variables=TIME, AT, RH, PREV60_AT, RREV60_RH, PREV60_DBT.

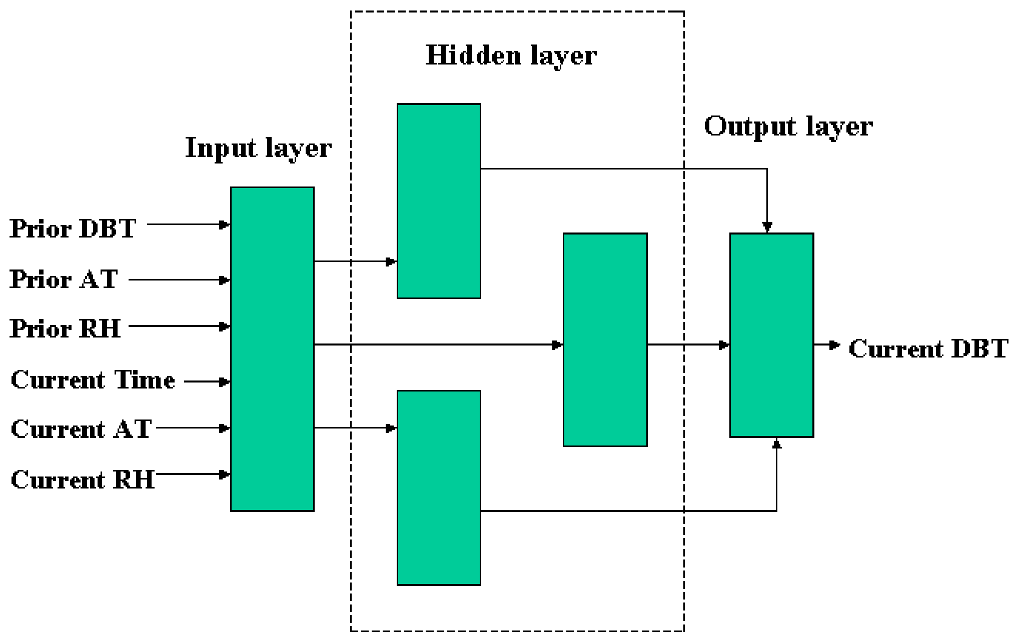

Figure 2.1 A. The Ward Network with one input layer, three hidden layers and one output layer

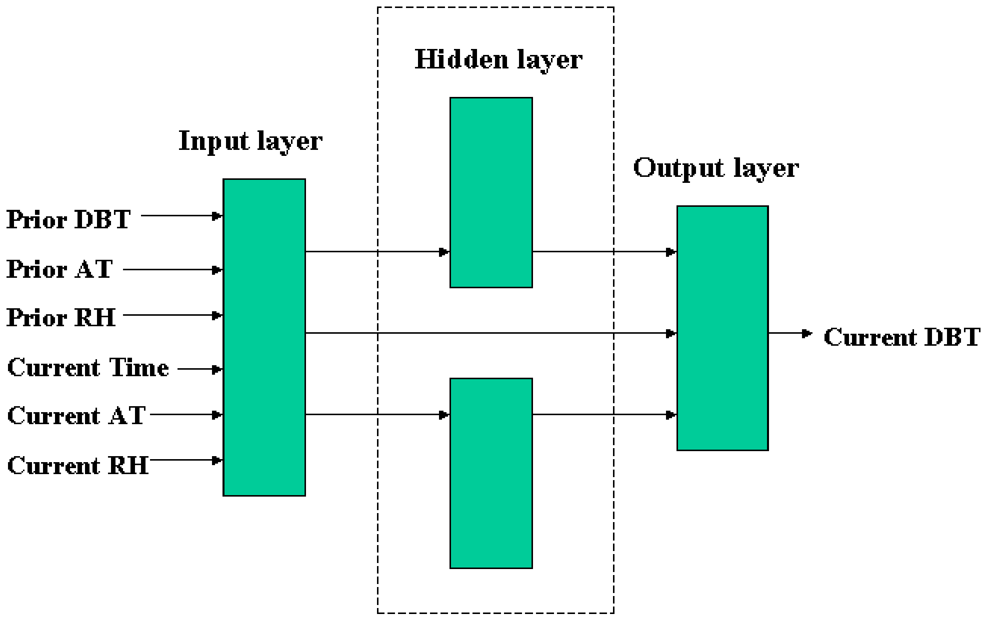

Figure 2.1 B. The Ward Network with one input layer, two hidden layers and one output layer

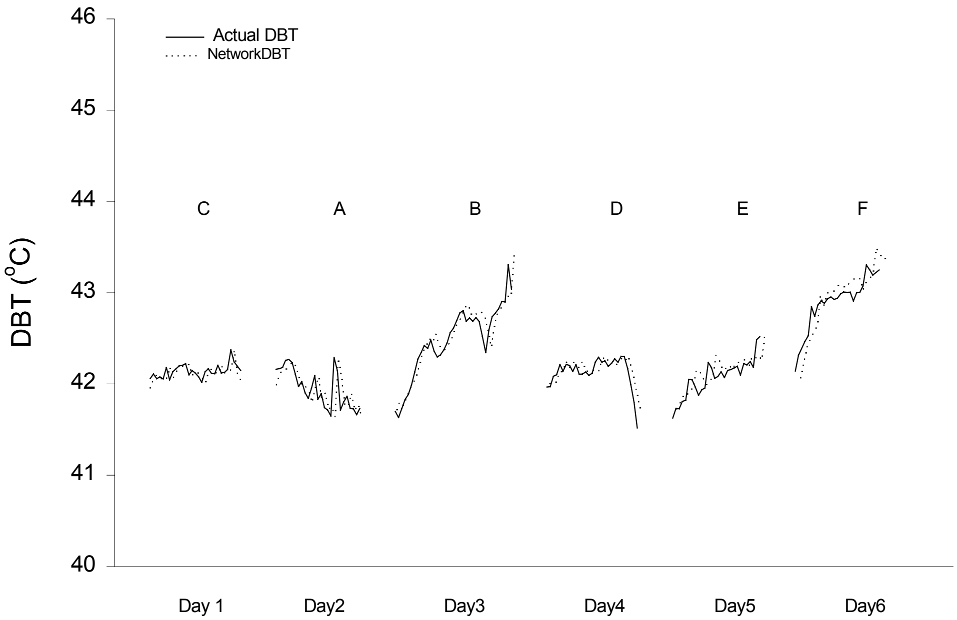

Figure 2.2 A. Comparison between actual data (Week 4) and one-step ahead network prediction of Type I model (Ward network A) (step size=10 minutes)

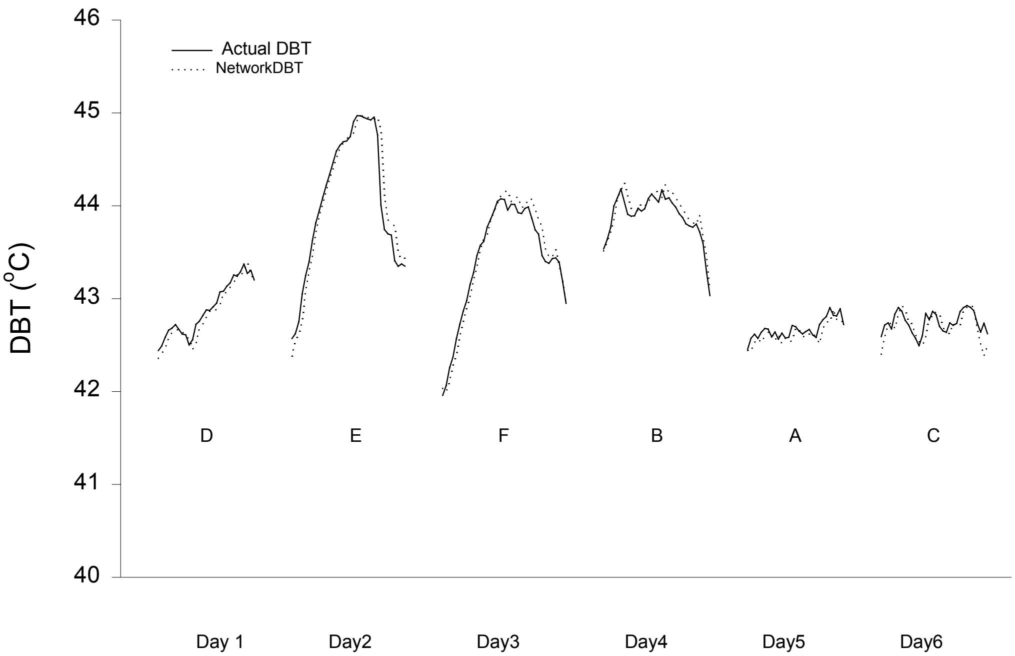

Figure 2.2 B. Comparison between actual data (Week 6) and one-step ahead network prediction of Type I model (Ward network A) (step size=10 minutes)

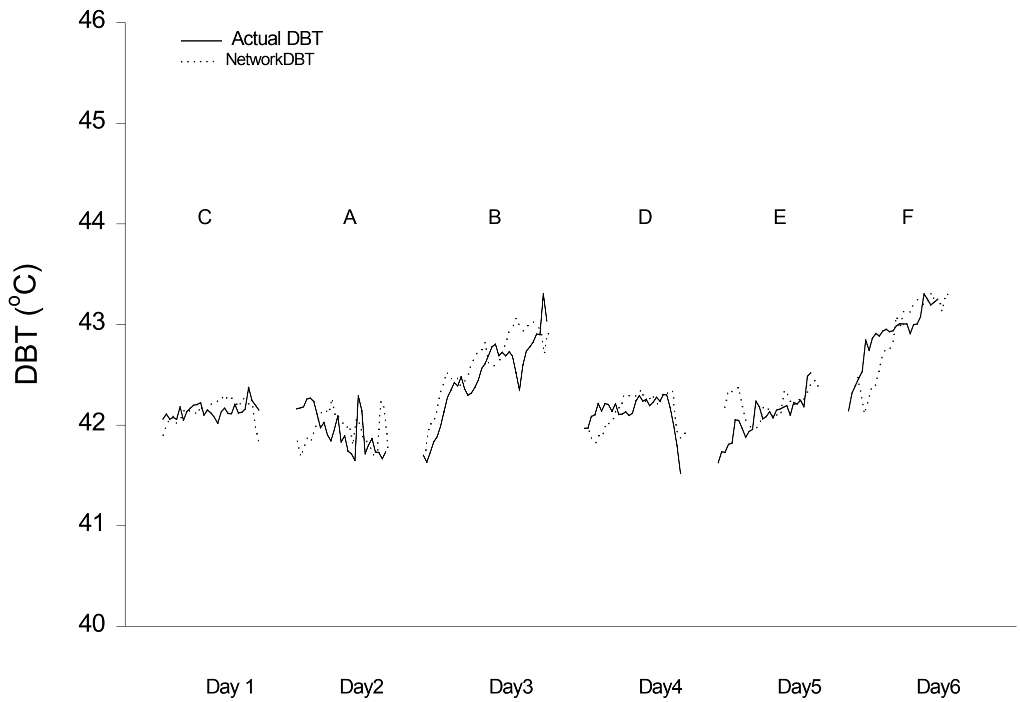

Figure 2.3 A. Comparison between actual data (Week 4) and six-step ahead network prediction of Type I model (Ward network A) (step size=10 minutes)

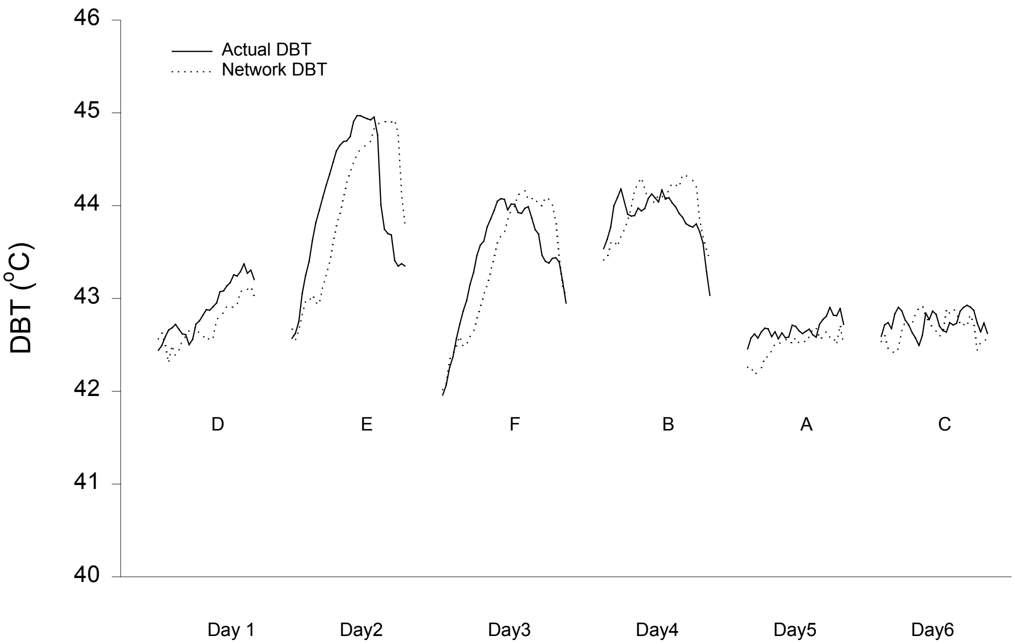

Figure 2.3 B. Comparison between actual data (Week 6) and six-step ahead network prediction of Type I model (Ward network A) (step size=10 minutes)

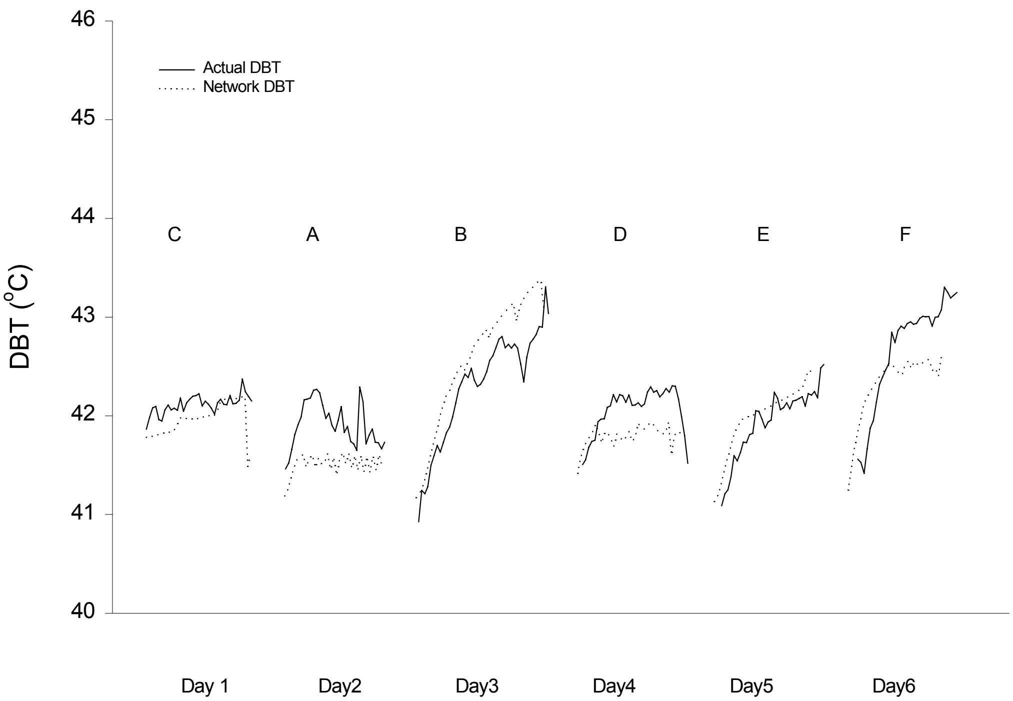

Figure 2.4 A. Comparison between actual data (Week 4) and network prediction of Type I model without using any previous variables (Ward network A)

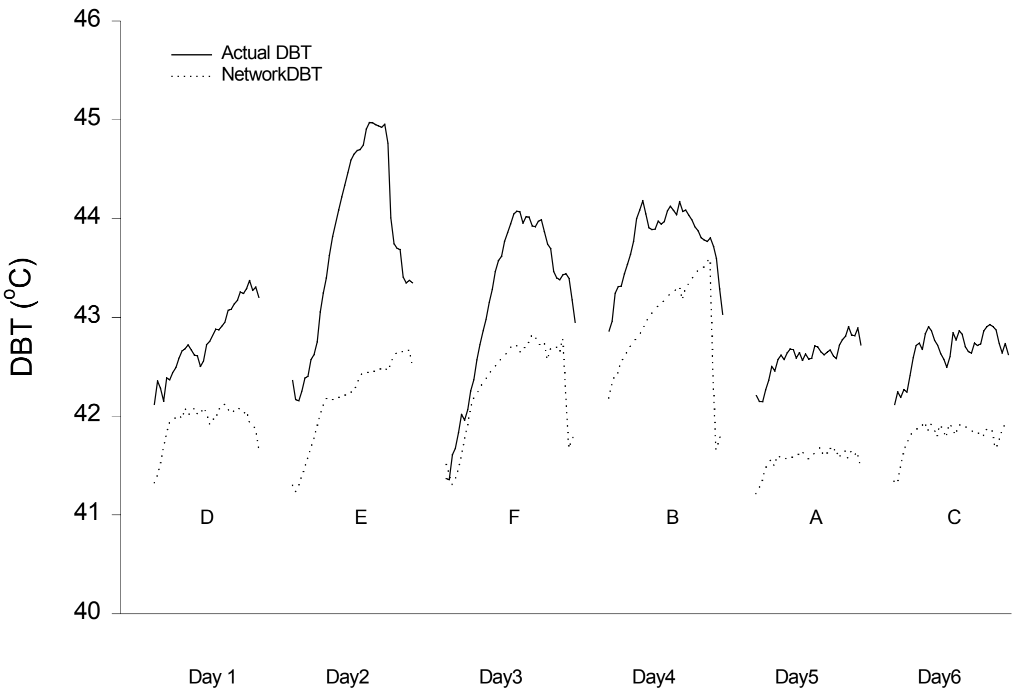

Figure 2.4 B. Comparison between actual data (Week 6) and network prediction of Type I model without using any previous variables (Ward network A)

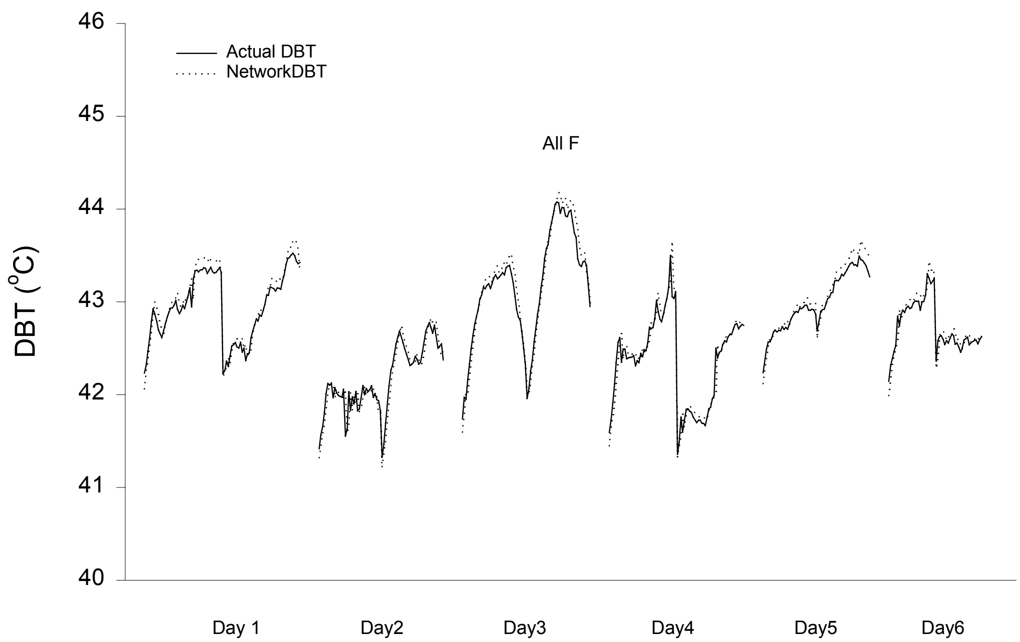

Figure 2.5. Comparison between actual data (all F) and one-step ahead network prediction of Type II model (Ward network A) (step size=10 minutes)

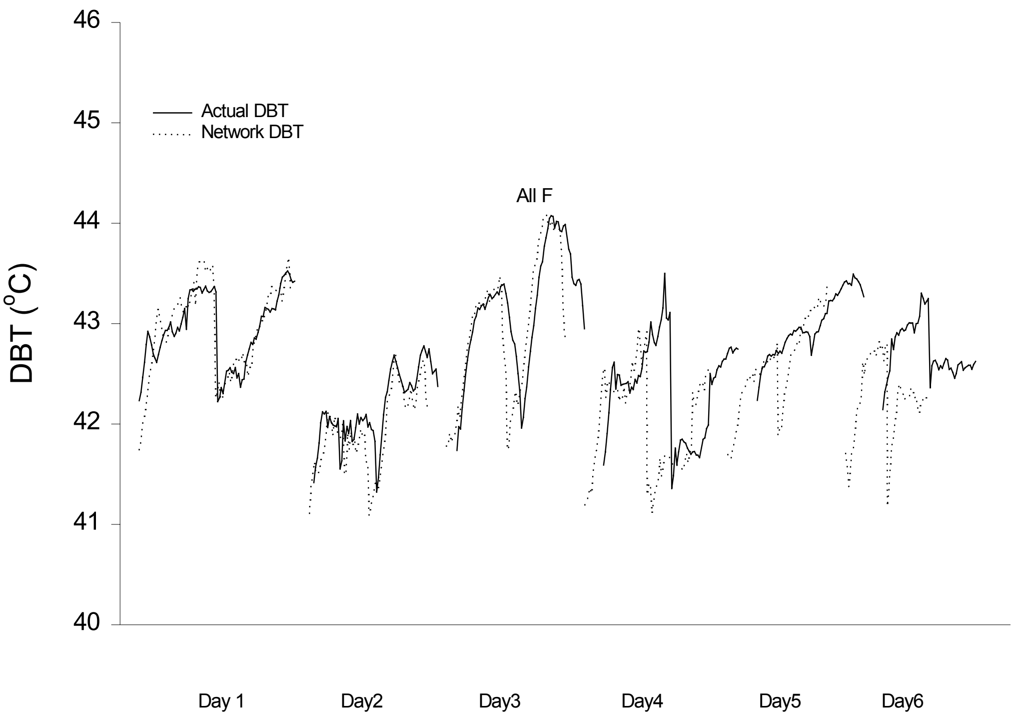

Figure 2.6. Comparison between actual data (all F) and six-step ahead network prediction of Type II model (Ward network B) (step size=10 minutes)

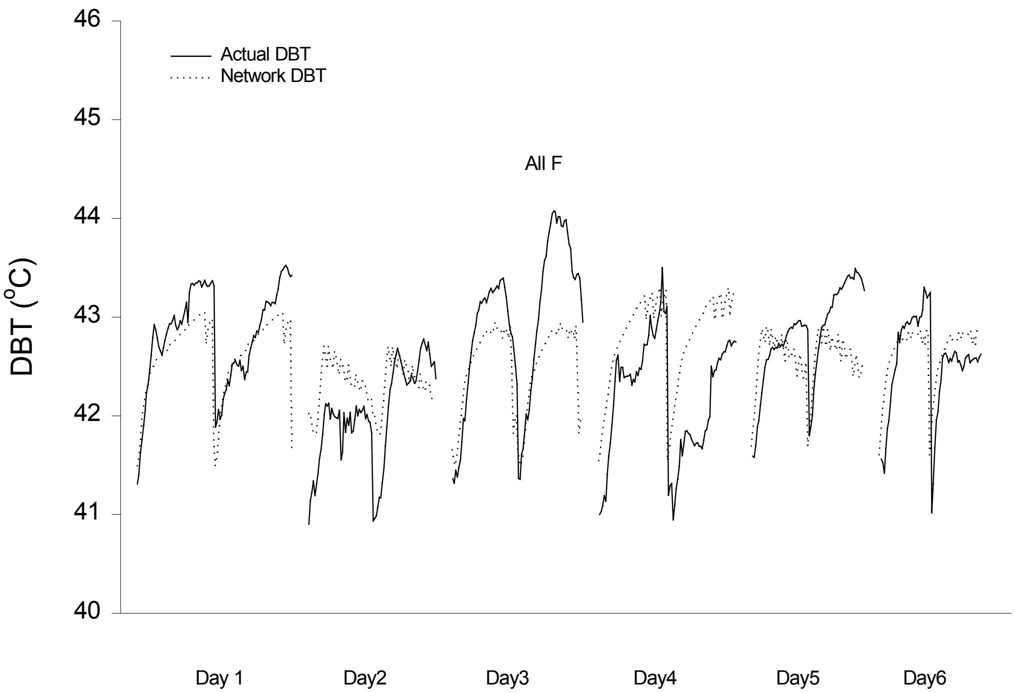

Figure 2.7. Comparison between actual data (all F) and network prediction of Type II model without using any previous variables (Ward network B)

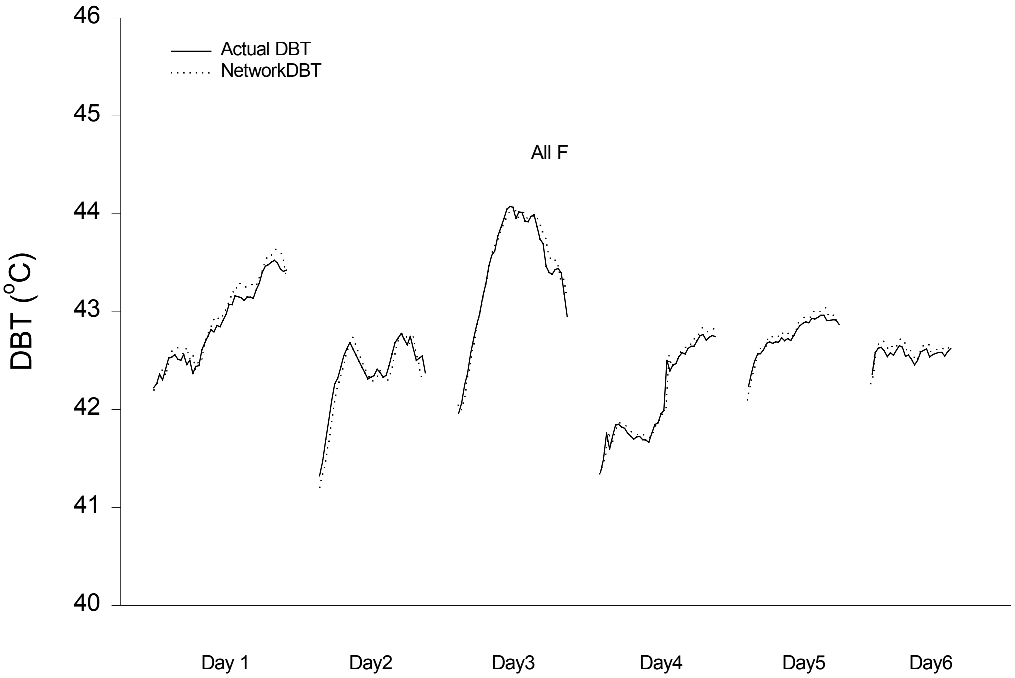

Figure 2.8. Comparison between actual data (all F) and one-step ahead network prediction of Type III model (Ward network A) (step size=10 minutes)

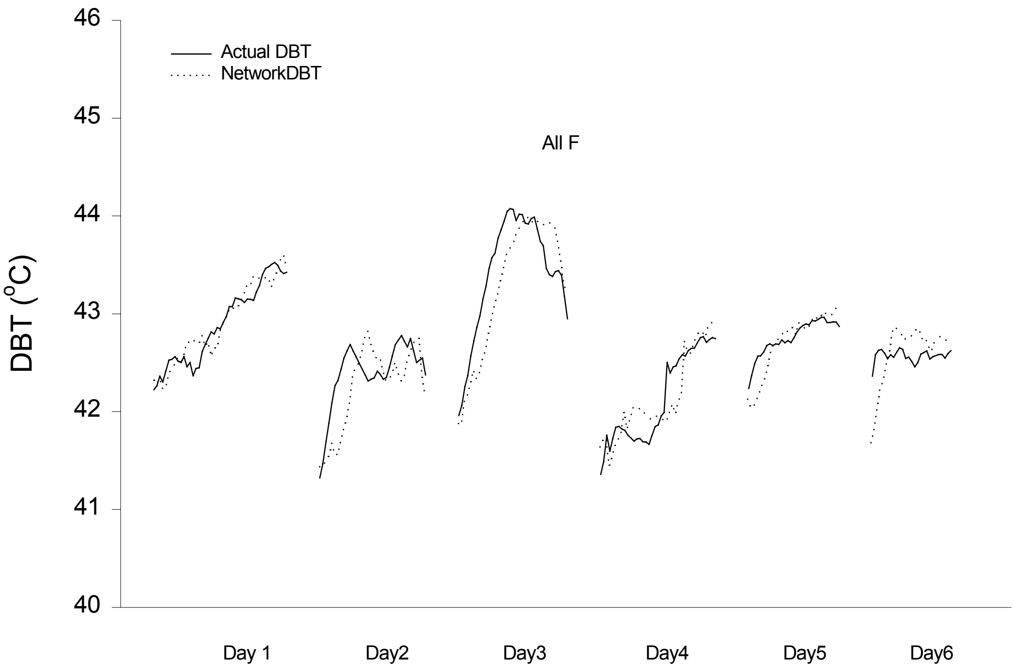

Figure 2.9. Comparison between actual data (all F) and six-step ahead network prediction of Type III model (Ward network A) (step size=10 minutes)

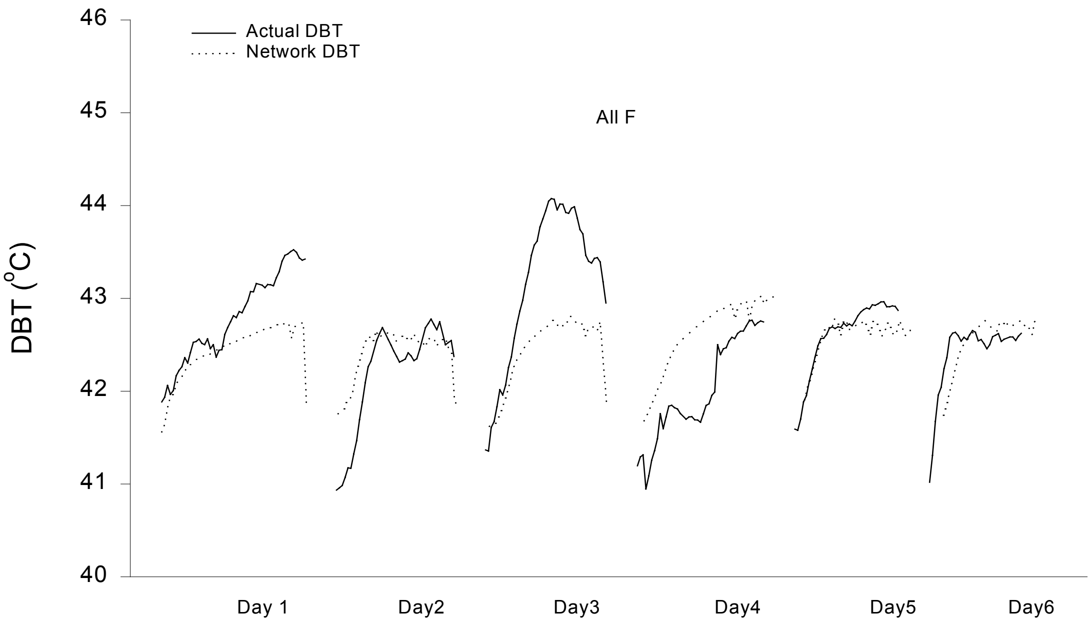

Figure 2.10. Comparison between actual data (all F) and network prediction of Type III model without using any previous variables (Ward network A)

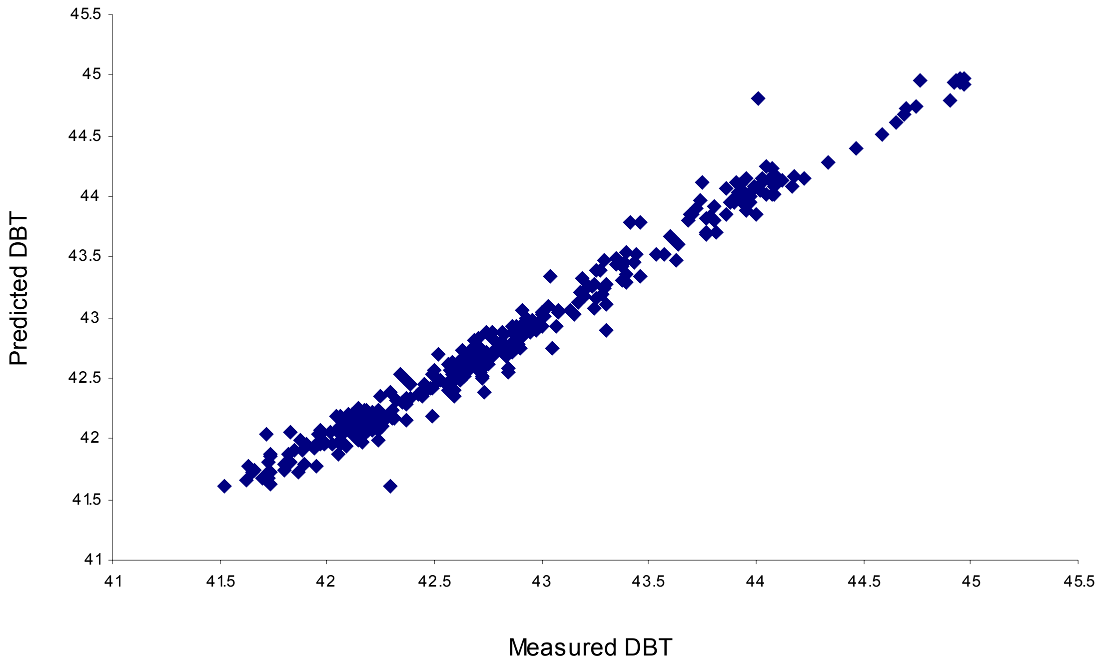

Figure 2.11. Measured versus one-step ahead predicted DBT for Type I model

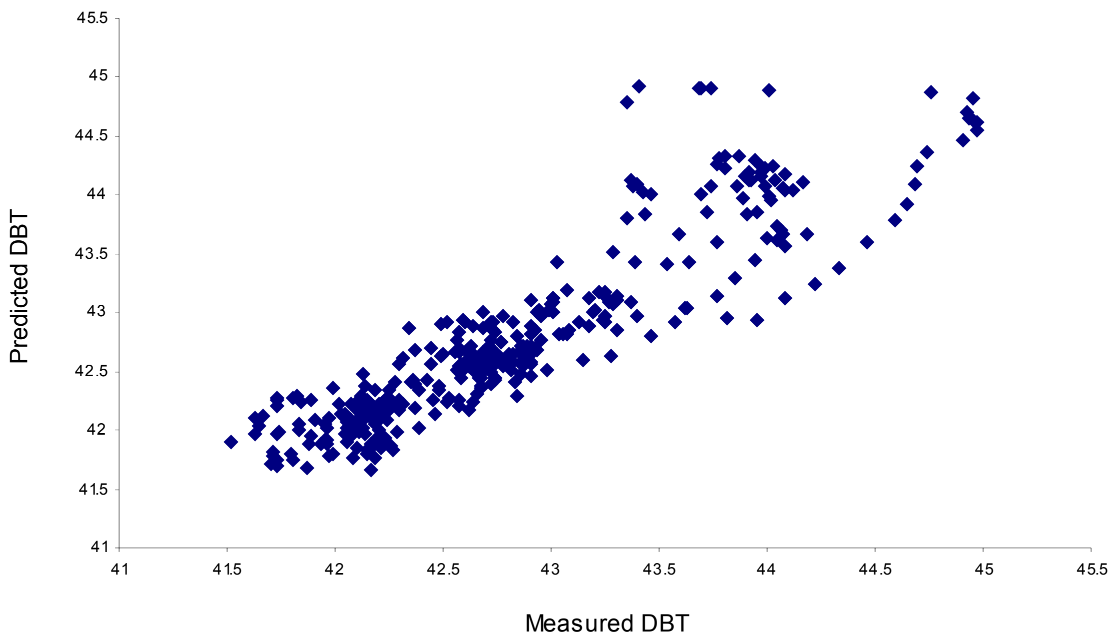

Figure 2.12. Measured versus six-step ahead predicted DBT for Type I model

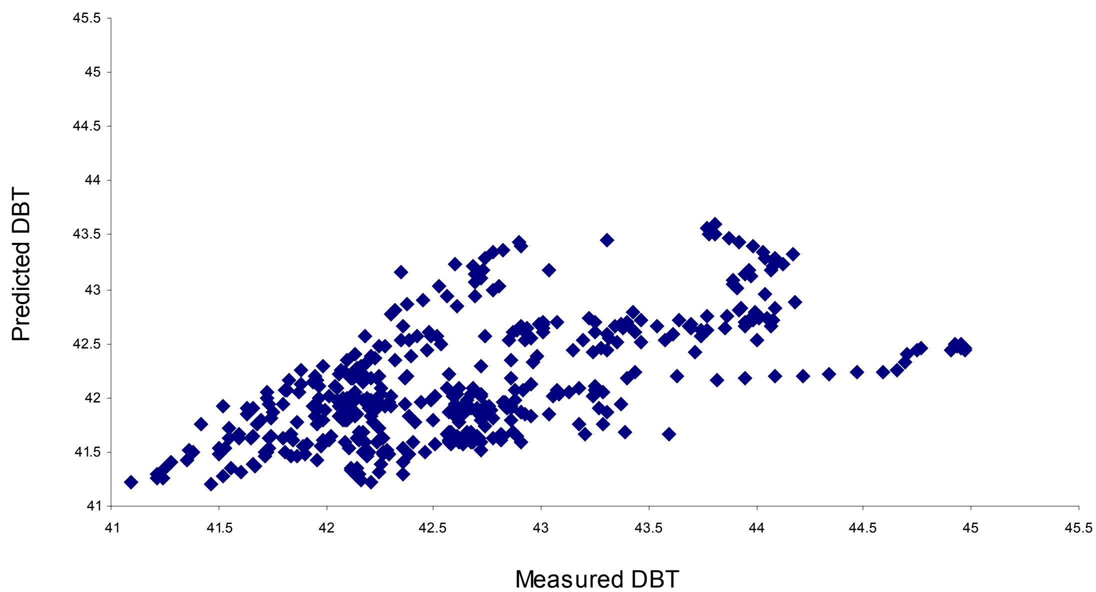

Figure 2.13. Measured versus predicted DBT for Type I model without using any previous variables

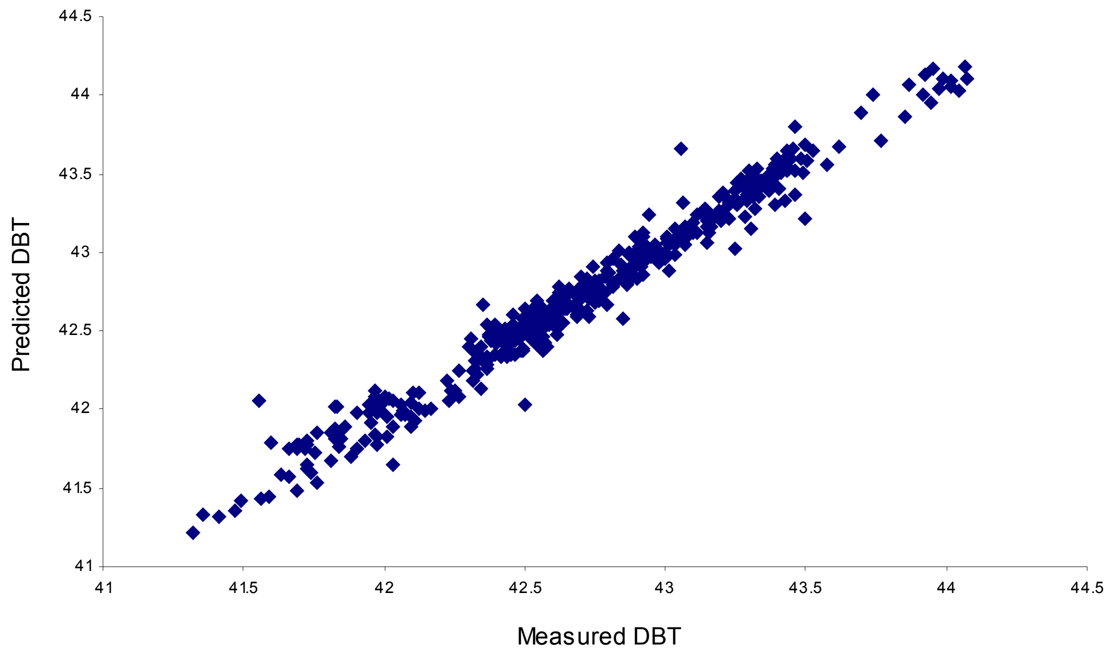

Figure 2.14. Measured versus one-step ahead predicted DBT for Type II model

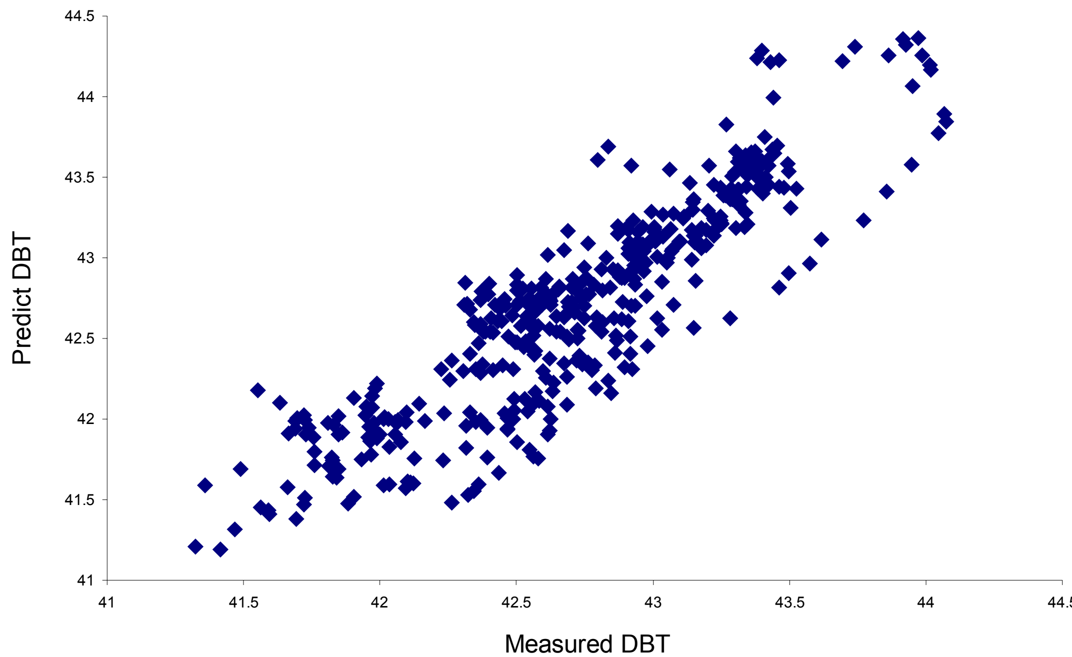

Figure 2.15. Measured versus six-step ahead predicted DBT for Type II model

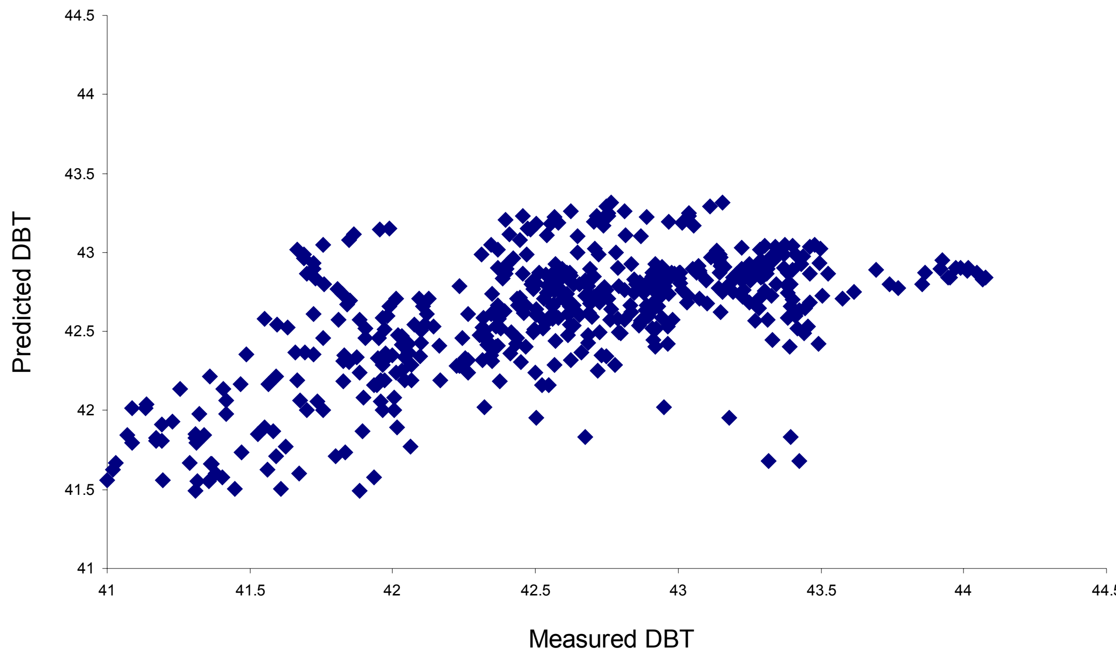

Figure 2.16. Measured versus predicted DBT for Type II model without using any previous variables

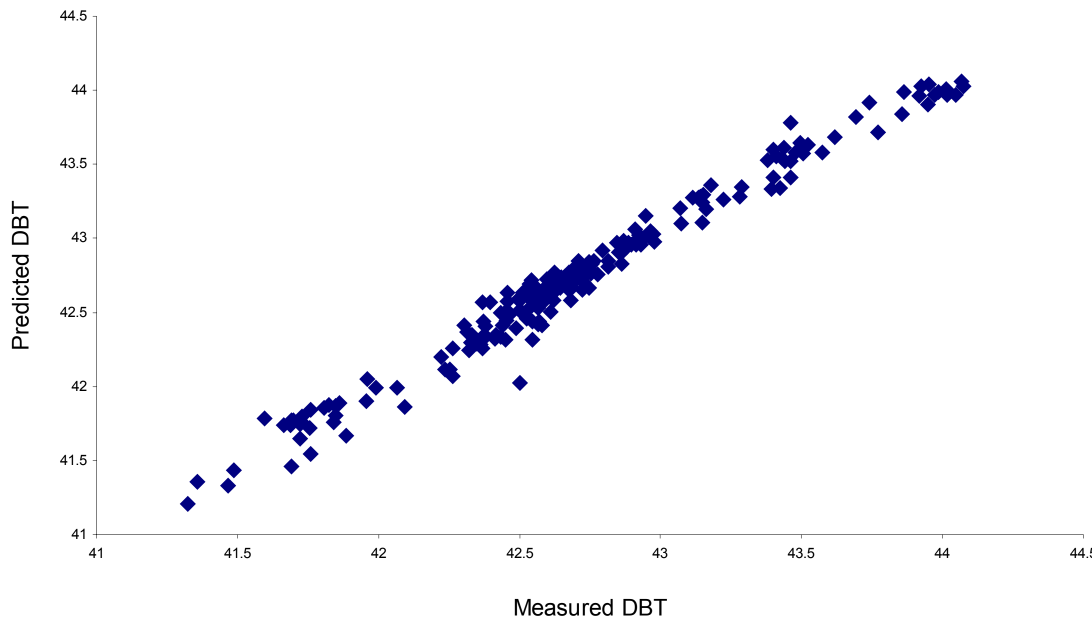

Figure 2.17. Measured versus one-step ahead predicted DBT for Type III model

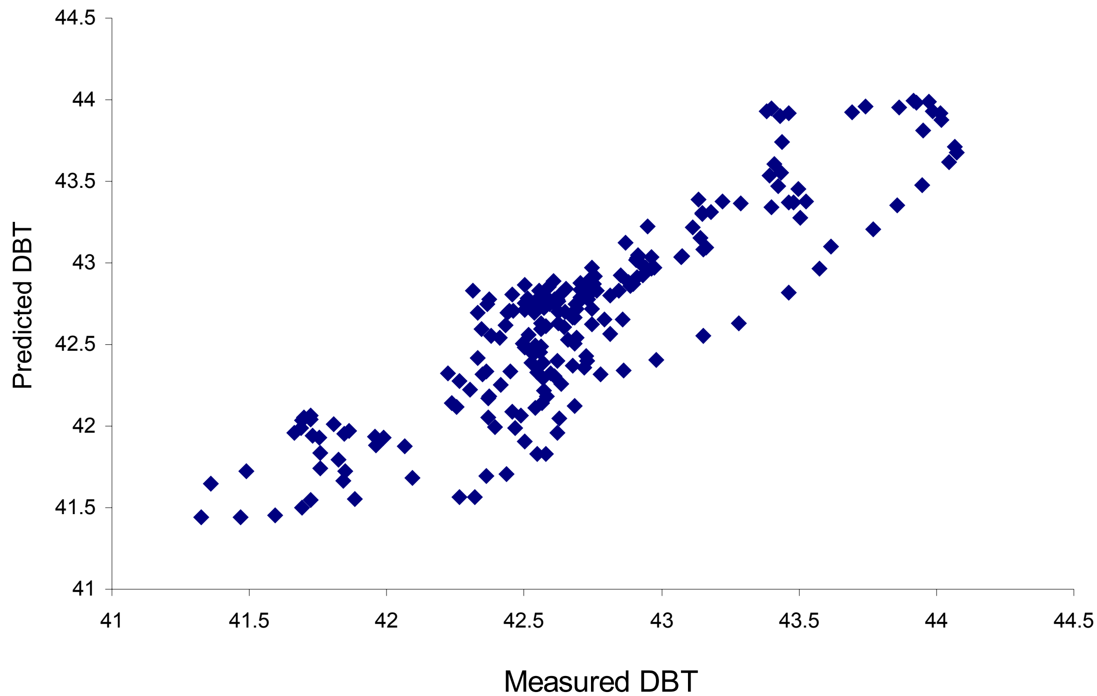

Figure 2.18. Measured versus six-step ahead predicted DBT for Type III model

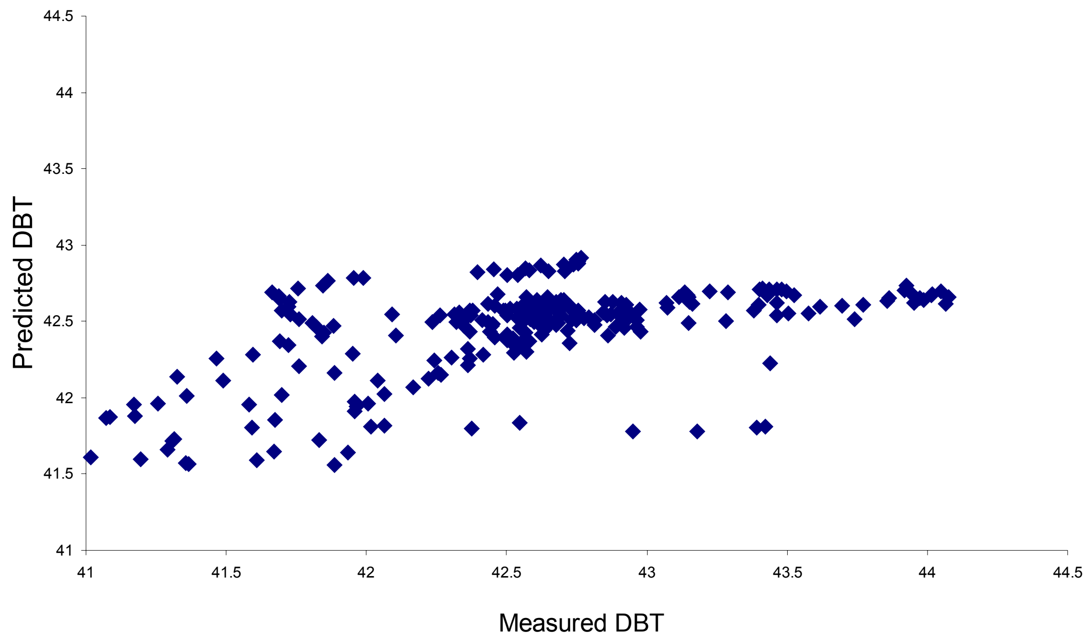

Figure 2.19. Measured versus predicted DBT for Type III model without using any previous variables

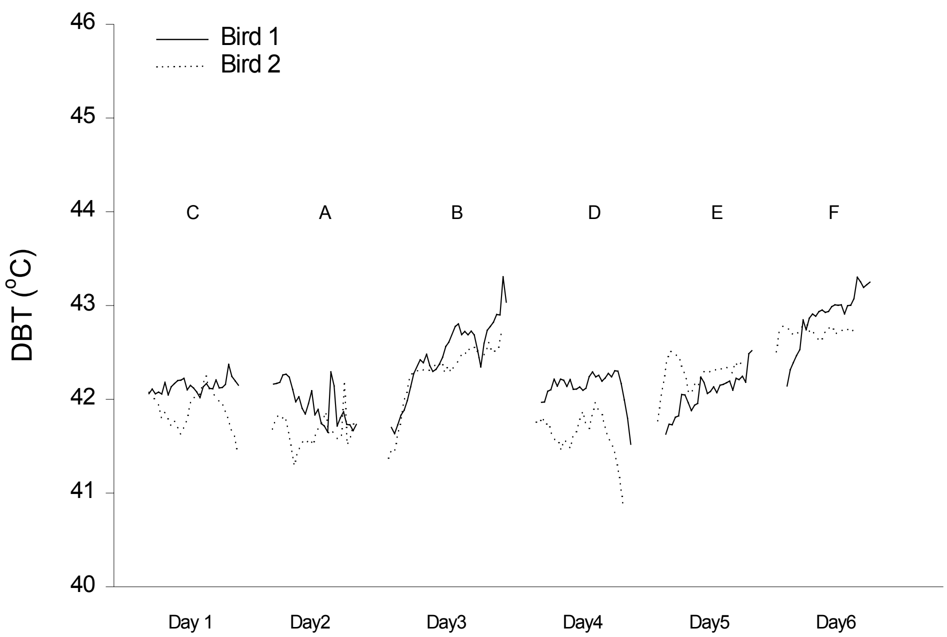

Figure 2.20. Comparison between actual DBT data of a pair of birds in Week 4

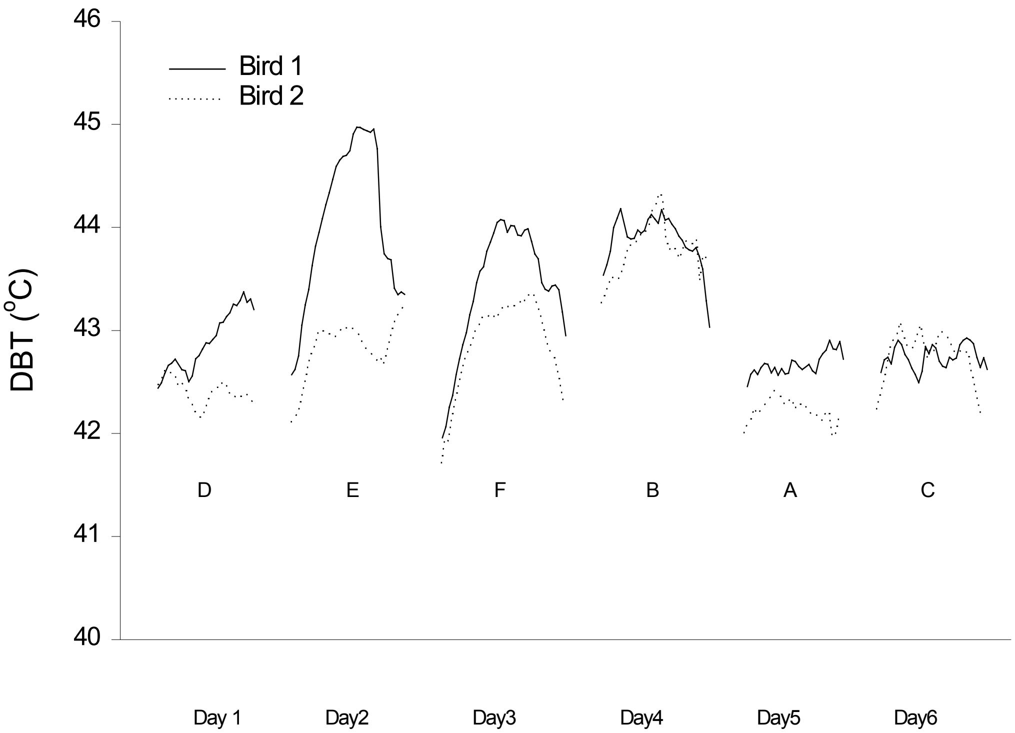

Figure 2.21. Comparison between actual DBT data of a pair of birds in Week 6

CHAPTER 3

CONCLUSION

The main objective of this research was to develop new ANN models that could capture the complex relationship among DBT, AT, RH and TIME and provide good predictions for real-time DBT.

Three types of ANN models were developed in this research. Type I model predicted DBT responses of birds not used in training to AT×RH combinations used in training. Type II model predicted DBT responses of birds used in training to AT×RH combinations not used in training. Type III model predicted DBT responses of birds not used in training to AT×RH combinations not used in training. For each type of model, we also developed short-term and longer-term prediction models based on using previous DBT, AT and RH measured in 1 to 6 steps ahead (1 step = 10 minutes). Moreover, for each type of model, we developed a DBT prediction model without using any previous DBT, AT and RH measurements. The short-term DBT prediction model could be used as part of a model-based controller that continuously adjusts environmental conditions based on physiological responses of the birds. The longer-term DBT prediction could be used as part of online expert systems that makes management decisions such as deciding an on set point for environmental controller. In addition, the DBT prediction model based only on current AT, RH and TIME without using any previous DBT, AT, RH measurements could provide a greater potential in its application to the development of environmental control systems for poultry housing.

The ANN models developed in this study seemed to capture the complex relationship between DBT and other environmental variables including AT, RH and TIME very well, and generally provided a good DBT predictions. Our data indicated clearly that ANN models displayed good generalization ability under unknown birds, unknown treatments and unknown birds with unknown treatments for both short-term and longer-term DBT prediction. All ANN models using previous DBT, AT and RH showed good model performance with r^2 great than 0.79. For all three types of models, the r^2 values decrease linearly with the increase of the prediction intervals, while MAE values increase linearly with the increase of the prediction intervals. This suggested that the accuracy of model prediction decreases as the prediction interval increases. However, our best ANN models without using any previous variables displayed poor model performance in DBT prediction (r^2 of 0.3818, 0.4085 and 0.3450 for Type I, II and III respectively). Considering the fact that there were only two replicates in each AT×RH combination and the differences between replicates were noticeably great in some cases, our model performance might have been degraded due to such smaller sample population and larger data noises. Obviously, in the future, the experiment with more replicates and therefore larger sample population are needed for developing more robust DBT prediction models.

ANN is a very promising approach in real-time DBT prediction, which provides new insight about how to model poultry physiological responses to environmental stress. The developed new types of models could be applied in the future in the development of environmental control systems for poultry housing.

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