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Development of Neuro-Fuzzy Based Temperature Control for Egg Hatchery

Elisha Adeleke Joseph, Henry Sunday Okeke, Michael A. Taiwo

Electrical Engineering Department, The Federal Polytechnic, Ilaro, Ogun State, Nigeria

ABSTRACT
Neuro-fuzzy have been successfully applied to extract knowledge from data in the form of fuzzy rules. This project describes the development of Adaptive Neuro-fuzzy system applied to the temperature variable of a thermal system with a range of 35 to 40°C for Egg Hatchery control. The system developed was based on heat transfer based on the principle of radiation to actualize the system. The generation of membership function is a challenging problem for fuzzy systems and the response of fuzzy systems depends mainly on the membership functions. The ANFIS based input-output model is used to tune the membership functions in neuro-fuzzy system. Experimental results were determiner. Processing the membership function the ANFIS was trained, tested and validated. The neuro-fuzzy controller used the neural network learning techniques to tune the membership functions while keeping the semantics of the fuzzy logic controller intact. Both the architecture and the learning algorithm are presented for a general neuro-fuzzy controller. In conclusion, a resulting effective system temperature control with energy conservation up to 100 eggs was achieved. The developed system finds application in egg incubation system industry.

KEYWORDS: *Neuro-fuzzy, Egg Hatchery, Heat Transfer, Membership Function, Incubation System Industry*

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INTRODUCTION

An incubator is the management of fertilized eggs to ensure satisfactory development of the embryo into a normal chick. **[1]**. In the last few years, egg incubation systems have experienced a technological, economic, and social revolution. Remarkable technological and scientific developments allowed the transition from manual incubation to large incubation machines and hatcheries, which incubate a much greater number of eggs using less labor, increasing chick production throughout the year. On the other hand, this incubation revolution generated costs related to the construction of more sophisticated facilities, as well as operational costs, such as energy and water expenses to maintain adequate incubation conditions. It also influenced social relations, creating two classes: producers and consumers.

An incubator should be able to regulate factors, such as temperature and humidity, and to allow air renewal and egg turning, providing the perfect environmental conditions for embryonic development, aiming at achieving high hatchability of healthy chicks, which is directly correlated with the survival and performance of individual chicks in the field. Currently, incubators capable of incubating different numbers of eggs of different species of birds are commercially available, with more or less sophisticated temperature, humidity, ventilation, and egg turning control systems. Modern state of the art commercial hatcheries are provided with automatic systems controlling all the physical factors of incubation: egg turning; environmental temperature set according to eggshell temperature determined by thermosensors; air relative humidity and egg water loss determined by egg tray weight using weight sensors; and air quality (O_2 and CO_2 levels). However, as already pointed out by [2], despite the technological advances of the modern incubation machines, the success of incubation still depends on the quality of labor both inside and outside the hatcheries, which requires training.

Nigeria population is growing at an alarming rate and so is the demand for white meat, a mastery of protein especially in all nook and crannies. Poultry is a good source of protein if it is affordable. The production level is limited with natural and the present artificial incubation system because the number of eggs an adult female bird lays in a year vary from none to 365 or one per day [3]. But a broody hen (a hen that wants to set and hatch eggs and raise the chicks) can hatch just about 10-12 eggs at once in 21 days [3]. This hatching method cannot hold this population unto its effectiveness. In order to sustain this population level, a better method of fast-hatching the eggs is required. For this reason, this research work comes in, to develop a neuro-fuzzy based temperature control for an effective hatching of the eggs in order to match with the population on ground.

Literature Review

Artificial egg incubation principle was established centuries ago. At that time, heat, moisture and air renewal of the incubation environment, well as the egg turning, were already taken into consideration. Based in historical records, [2]mentioned that, in ancient Egypt, eggs were incubated in mud-brick buildings (an "incubation house") divided in incubation chambers similar to ovens separated by a central hallway and accessible through manholes. In the upper part of the egg chambers, there were shelves for burning, straw, dung, or charcoal to heat the eggs below. Vents in the roof allowed the smoke from the fires to escape and provided some light. In this primitive incubation system, the temperature within the incubation chambers was managed by controlling fire intensity and opening the manholes, vents, and the hallway. Humidity was controlled by placing moistened jute on eggs, which were manually turned twice per day. Mechanical incubating was not invented until the year of 1749 by Reamur in Paris, France, and the first commercial incubator was manufactured by Hearson in 1881.

[4]In their paper used the advantages of neuro-fuzzy network techniques to develop an intelligent control system for cement kiln process. The NFC was able to learn to control the process by updating the fuzzy rules and membership functions. With a precise observation on the simulation results of the controller, it can be said that using the intelligent systems for learning the fuzzy networks definitely improve the controller functionality. However, some practical limitations and specifications should be considered for the controller design.

[5]Bolzanet'al (2008) in their study demonstrates the possibility of the use of artificial intelligence in agribusiness, specifically in broiler production. The representative and predictive capacity of ANN was compared to the multiple linear regression model. The results showed that the proposed ANN methodology was more efficient to predict hatchability, as compared to the MLR statistical model.

[6]Put up a work based on the increased stability and comfortable period of indoor temperature with the decreased number and ratio of overshoots and undershoots of temperature using Artificial Neural Network-based temperature control logic which was able to maintain the indoor temperature more comfortably and with more stability within the operating range due to the predictive and adaptive features of ANN models.

Modeling Analysis
The algorithm for this work is as analyzed below and shown in Figure 1, with inputs as Number of Eggs and Current, and output as temperature.

The following algorithm was developed for this work:
1. Input determination and customization
2. Output determination and customization
3. Membership degree determination for both inputs and outputs
4. Development of the rule base
5. Allocation of the rule strength
6. Rule combination

Simulation software
Matlab R2007a edition environment was used to carry out this work.

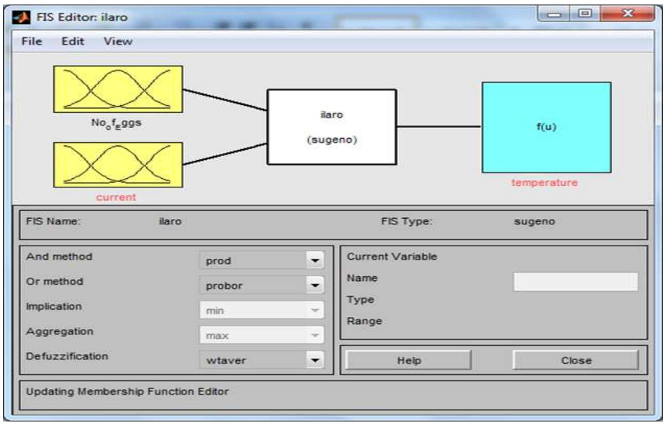

Figure 1: The algorithm used

The Research Input
The following are the required input of the research that was worked upon:

Using 100w bulb as the heating device, with the following data:

Input Voltage: 220V

Current: 0.45A

Average weight of an Egg: 56.7g,

Total number of eggs: 100 eggs

The output determination is:

The Temperature: 35°C – 40°C (a maximum temperature of 38.5°C was considered).

The Transfer function: $\phi_2/\phi_1 = 1/(120s+1)$

Where

ϕ_1 = temperature of eggs before they are placed in incubator

ϕ_2 = temperature of incubator after heat has been transferred from the law of heat transfer: temperature rise is proportional to heat added.

In this work, the membership functions were configured as shown in Figure 2

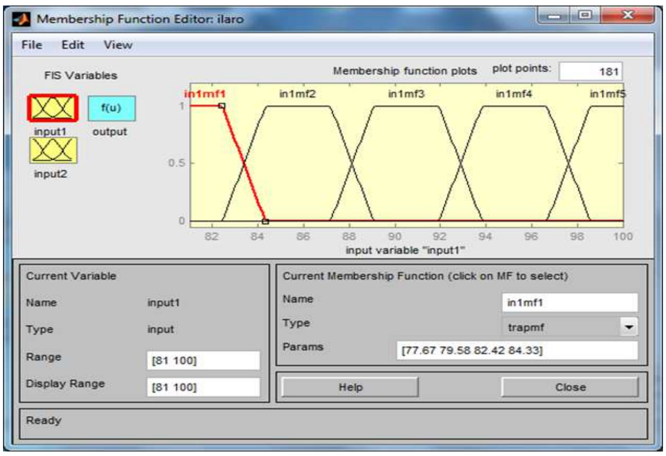

Figure 2: Membership Function Plot

The membership function of the inputs as shown in Figure 2 is as analyzed below:

Input 1: current = (0.35 - 0.45) Amps

Input 2: No of eggs = (1-100)

Output temperature = (35 – 40)°C

Current = Very Low (V_L), Low (L), Medium (M), High (H), Very High (V_H)

No of eggs = Very Small (V_S), Small (S), Medium (M), Moderate (M_O), Very Moderate (V_{MO})

Output (Temperature) = Very Low (V_L), Low (L), Moderate (M_O), High (H), Very High (V_H)

The controller rule base, which was gotten from the combination of the inputs and the output is as shown in Figure 3.

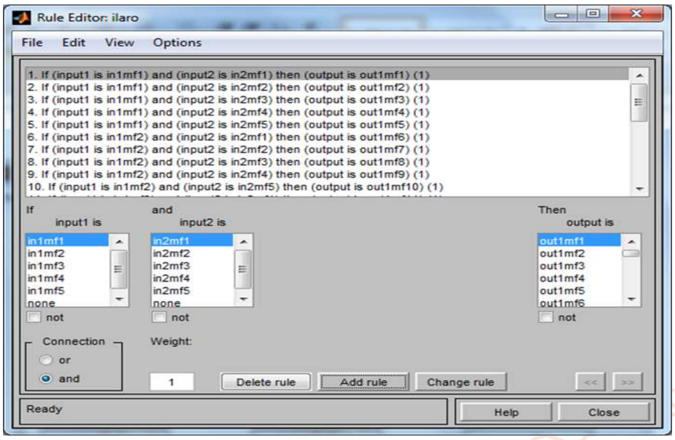

Figure 3: The Rule Base of the Controller

Table 1: The Controller Rule Base/Rule Combination

Noof Eggs / Current	V_S	S	M	M_O	V_{MO}
V_L	V_L	L	M_O	H	V_H
L	V_L	L	M_O	H	V_H
M	V_L	L	M_O	H	V_H
H	V_L	L	M_O	H	V_H
V_H	V_L	L	M_O	H	V_H

Controller Selection

Fuzzy Logic controller is selected as the actuator while Neuro-Fuzzy controller is selected as the network architecture since the proposed Neuro-fuzzy network has a suitable 5-layer feed-forward architecture (not fully connected) as shown in Figure 4. The layers are as analyzed:

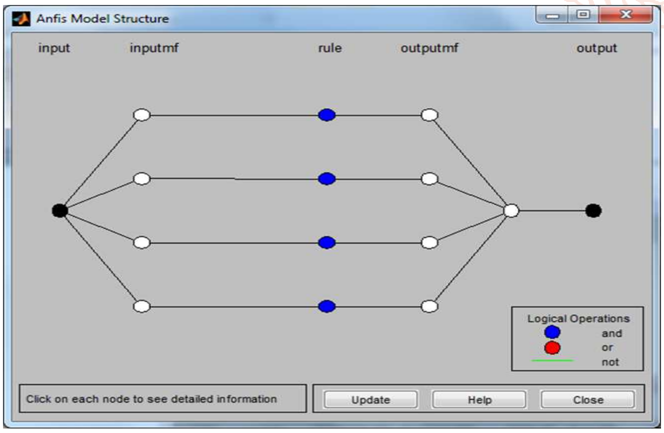

Figure 4: Architecture of four rule fuzzy controller

Input layer: it simply spreads the input signals to the membership layer's neurons, jumping the second layer:

T-layer: the nodes of such layer are grouped in n blocks, each corresponding to one input variable.

Membership Layer: Each neuron of this layer is connected with an input neuron and a pair of consecutive neurons of the T-Layer. These neurons compute membership values of each input to each fuzzy set of the corresponding axis. Given an input index I, the transfer function of a neuron of such layer is calculated. In this way function T was embodied in the network architecture. It is noteworthy to observe that these neurons are fixed, that is they do not have free parameters, which are the basic components of T. in this way the understand ability of fuzzy rules is maintained.

Rules layer: The neurons of this layer compute the truth value of each rule by making use of transfer functions. The function is implemented by the connections between the membership layer and the rule layer. Full connection between the rule layer and the membership layer is requested when grid partition of the input space is adopted. The neurons of this layer have no free parameters.

Output layers: This layer determines the system output via weighted method.

Double-input, single-output dynamic system whose states at any instant can be defined by "n" variables X_1, X_2,...,n was considered. The control action that derives the system to a desired state can be described by a well-known concept of "IF-THEN" rules, where input variables are first transformed into their respective linguistic variables, also called fuzzification. Then, conjunction of these rules, called inferencing process, determines the linguistic value for the output. This linguistic value of the output also called fuzzified output is then converted to a crisp value by using defuzzification scheme. All rules in this architecture are evaluated in parallel to generate the final output fuzzy set, which is then defuzzified to get the crisp output value.

The conjunction of fuzzified inputs is usually done by either min or product operation (product operation was used) and for generating the output max or sum operation is generally used. For defuzzification, The method of simplified reasoning was employed, also known as modified center of area method. For simplicity, triangular fuzzy sets was used for both input and output. The whole working and analysis of fuzzy controller is dependent on the following constraints, fuzzification, defuzzification and the knowledge base of an Fuzzy Logic Controller (FLC), which gives a linear approximation of most FLC implementations.

Result

The following results were gotten after simulation of the model, using Matlab R2007a edition environment and whose results were analyzed as shown in the Figures below.

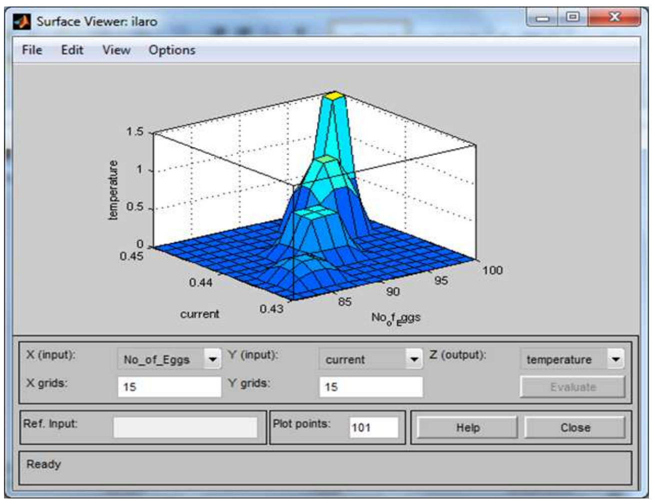

Figure 5: 3D Representation Showing the Relationship between the Inputs and the Output.

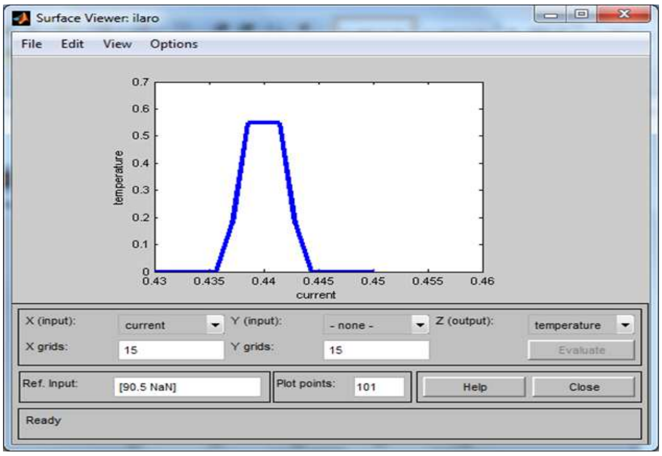

Figure 6: The Curve Showing the Relationship between Temperature and Current

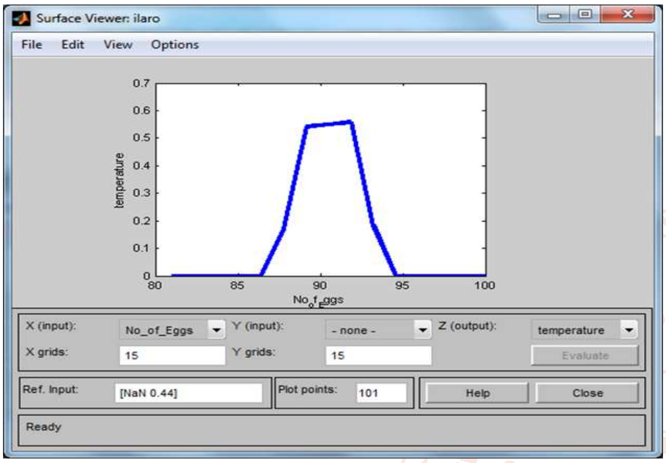

Figure 7: The curve showing the relationship between temperature and no of eggs

Discussion

Figure 5 shows the surface view of the three parameters. These surface view show the relationship between the two inputs and the output for the neuro-fuzzy system.

Figure 6 shows that the controller picks up at 0.435A rising steadily and remains constant between 0.435A and 0.445A before regulating the output temperature again. It shows that the controller behaves in that region like a thermostat or thermocouple. It therefore conserves energy while maintaining the needed temperature.

Figure 7 indicates that the controller effectively increases incubator temperature peaking between 85 eggs and 95 eggs before regulating the output incubator temperature in order to conserve energy and maintaining it up till 100 eggs. The graph also shows that the controller behaves like a thermostat or thermocouple.

Conclusion

The modeling and designing of an egg incubator system that is able to incubate various types of egg within the temperature range of 35 – 40^{0}C was achieved. Adaptive Network based Fussy Inference Systems (ANFIS) was used in modeling and identification of numerous systems and successful results have been achieved. The development of the temperature control model was executed using Neuro-fuzzy controller, which entails the combination of neural network that predict the functionality of the egg hatchery system and fuzzy logic that act as an actuator for the system.

Recommendation

It is recommended that this controller should be applied to egg hatchery operation for optimum performance.

Also recommended for quality product and mass production of chicks which will meet the country (Nigeria) economic demand.

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