FPGA Implementation of Adaptive Neuro-Fuzzy Inference Systems Controller for Greenhouse Climate

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Abstract: This paper describes a Field-programmable Gate Array (FPGA) implementation of the Adaptive neuro-fuzzy inferences Systems (ANFIS) using the Very High speed integrated-circuit Hardware-Description Language (VHDL) for temperature and humidity control inside a horticultural greenhouse. The main advantages of using the HDL approach are rapid prototyping, and allowing usage of powerful synthesis controller through the use of the VHDL code. Use of the hardware description language (HDL) in the application is suitable for being implemented into an Application Specific Integrated Circuit (ASIC) and Field tools such as Quartus II 8.1. The system is built up with major modules namely fuzzification, inference, normalization of rules’s weights, identification of rules’ outputs and defuzzification. A neuro-fuzzy approach based on fuzzy clustering is proposed in control a greenhouse climate built up on the experimental data. The fuzzy rules were automatically generated by the ANFIS editor. Then, the cluster centers were trained by neural network and optimized using the backpropagation and the least square algorithm. The tests are made on a sequence of 48 days, the experimental data collected on the site BENOMOR, greenhouse horticulture, Plantation tomato, Guelma (Algeria). The system employs a fuzzy interface cascaded with a feed-forward neural network in order to obtain an optimum decision regarding the future thermal state of the greenhouse.

Key words: Neuro-Fuzzy; ANFIS; VHDL; FPGA; Quartus; Matlab Fuzzy Logic Toolbox

I. INTRODUCTION

Under greenhouse production, the climate control is a tool used for crop yield manipulation which maximise the entrepreneurial benefits. Once the objectives that optimise crop growth and development are defined, the control engineer must design and implement automatic control systems that make possible to obtain a maximum crop yield at minimum production costs. In this sense, control engineering has undergone a considerable development. Researchers have used many control techniques in different fields, from the conventional or classic strategies [proportional integral derivative (PID) control, cascade], artificial intelligence (AI) (fuzzy control, neural networks, genetic algorithms and neuro-fuzzy), advanced control techniques (predictive control, adaptive), to robust control strategies, non-linear and optimal control. Specifically, they have been applied in the area of greenhouse climatic control [1][2][3]. Conventional control techniques are difficult to implement in greenhouse systems due to their multi-variable and non-linear nature. Where interrelations between internal and external variables are complex (physical non-linear phenomena that govern these systems dynamics are complicated). This provides justification for the use of intelligent control techniques as a good alternative. In this way, fuzzy logic as part of AI techniques is an attractive and well-established approach to solve control problems [4]. We were brought to develop a Neuro-Fuzzy control of the humidity and temperature inside the greenhouse. This last characterises the operation of the complex system which the greenhouse constitutes. The identification which is in the center of this step is a process of search for a mathematical representation that minimises the variations of the real system compared to the modeled system. The development of the plant is influenced mainly by the environmental climatic variables. The greenhouse, which is a closed circle in which the climatic variables can be controlled, constitutes the ideal medium for the control of the plant’s growth. The greenhouse must not only create the favorable conditions with the growth of the plants, but it must moreover be able to ensure certain flexibility in the calendar of production: precocity and spreading out of the calendar. To carry out this objective a robust model using the Artificial Neural Networks and the fuzzy logic can be well adapted to control the nonlinear comportment of greenhouse climate accurately is more than necessary [5].

For the implementation of agricultural technologies (innovations in control systems, remote monitoring, information management), robustness, low-cost and real-time capabilities are needed. In this sense, field programmable gate arrays (FPGAs) present as a good option for greenhouse technology development and implementation, because FPGAs allow fast development of prototypes and the design of complex hardware systems. These devices have been used in
many real applications [6]. Through FPGAs, fast tests, modifications accomplishment, up-dates using single software modifications and an effective production cost (relation performance-price is very favorable) are obtained. In the same sense, reduction in development and commercialisation time is accomplished. On the other hand, for neuro-fuzzy control implementation, which can be based on software or hardware, FPGAs are an alternative that keep both benefits, hardware speed and software flexibility. Research made around these devices has experienced an enormous development, in the academic field as well as in the industrial area. There is a great number of contributions about FPGAs applications in different fields [7][8][9]. Also, there are some contributions reported about hardware implementations of neuro-fuzzy control [10]. Moreover, problems of digitzed neuro-fuzzy control have been studied [11]. The approach proposed here is focused on greenhouse technologies development, based on AI techniques, particularly fuzzy logic cascaded with a feed-forward neural network, and system-on-a-chip (SoC) applications using FPGA technology, with the purpose of obtaining complete engineering solutions on a single integrated circuit. In our case, an intelligent SoC was developed to carry out the complete functionality for the greenhouse climate control.

II. NEURONAL METHODS IN THE FUZZY SYSTEMS

A. Model of Comportment

The model of knowledge obtained is not easily controllable because it is at variable and nonlinear time [12]. The use of the methods neuro-fuzzy become very popular in the resolution of the complex problems [13], can apprehend the greenhouse in all its complexity by integrating qualitative empirical and expert concepts [14] and generate a model of comportment able for control. If there is a base of knowledge expressed in the form of linguistic rules, we can formulate a fuzzy inference system, and if one has experimental data we will use the artificial neurons. To build a fuzzy inference system, it is necessary to specify the fuzzy clustering, the fuzzy operators and the base of knowledge, and to build an artificial network of neurons, the user needs to specify the architecture and the algorithm of training. The analysis shows that these two approaches seem complementary, and the construction of a complete system must combine the two concepts. In the literature there is panoply of systems neuro-fuzzy like: the systems neuro-fuzzy cooperatives, competitors, and the systems say hybrid or adaptive neuro-fuzzy. In the latter the fuzzy systems are represented in the form of structure networks thus imitating the artificial neural networks (Ann) [15].

B. Adaptive Neuro-Fuzzy Inferences Systems

The Adaptive neuro-fuzzy inferences Systems (ANFIS) are hybrid systems using the fuzzy inference of Takagi Sugeno. The structure ANFIS makes up of five layers as shown by the “Fig. 1.”. The first hidden layer “fuzzified” the variables of inputs and the operators T-norm type calculate the premise part of the rules in the second hidden layer. The third hidden layer standardises the weights of the rules followed by the fourth hidden layer where the parameters of the conclusion parts of the rules are given. The layer of output calculates the sum of all the signals coming from the fourth stratum [16]. The adaptable parameters in the systems ANFIS are:

- Parameters of the function of membership of the premises part \([A, B, C, D]\).
- Polynomial parameters \([p, q, r]\), called parameters of the conclusion part.

Their training is achieved by the algorithm of the gradient descent (back propagation), for the optimization of the parameters of the parts premises, and the algorithm of least square for the resolution of the parameters of the conclusion parts. In order to reduce the error \(E\) [16],

\[
E = \frac{1}{2} \left( y - y' \right)^2
\]

(4)

The \(i\) rule of the fuzzy system type Sugeno constituted of \(m\) input and \(N\) rules \((i=1...N)\), is represented with the “Fig. 1.”. A Sugeno system of order zero is represented by the following equations:

\[
w_i = \prod_{j=1}^{m} \mu_{A_j}(x_j) \quad \text{and} \quad \overrightarrow{w_i} = \frac{w_i}{\sum_{i=1}^{n} w_i}
\]

(5)

\[
y = \sum_{i=1}^{n} \overrightarrow{w_i} f_i = \sum_{i=1}^{n} y_i
\]

(6)

Where \(f_i\) is a constant defined by:

\[
f_i = r_i
\]

(7)

In the presence of the target exits \((y^T)\), the network can be adjusted to reduce the measurement of error. The adjustable parameters are the functions of membership of input, and the output of the type singleton \(r_i\),

\[
r_i \left(t'+1 \right) = r_i \left(t' \right) - lr \frac{\partial E}{\partial r_i}
\]

(8)

\[\Leftrightarrow r_i \left(t' + 1 \right) = r_i \left(t' \right) - lr \frac{\mu^p}{\sum_{i=1}^{n} \mu^p} \left(y^p - y^p \right)\]

(9)

Fig. 1. Sugeno system of order one with \(n=3\) rules and \(m=6\) inputs
In the presence of the target exits \((y^T)\), the network can be adjusted to reduce the measurement of error. The adjustable parameters are the functions of membership of input, and the output of the type singleton \(r_i\).

\[
 r_i \left( t + 1 \right) = r_i \left( t \right) - lr \frac{\partial \varepsilon}{\partial r_i} \quad (8)
\]

\[
 \Leftrightarrow r_i \left( t + 1 \right) = r_i \left( t \right) - lr \frac{\partial E}{\partial \mu_i} (y^o - y^w) \quad (9)
\]

For a Sugeno system of first order parameters of conclusions \((p, q, r)\) of \(n\) rule are connected linearly by a polynomial of first order of form:

\[
f_n = p_n x_1 + q_n x_2 + r_n \quad (10)
\]

If the output of the nodes in each respective stratum is represented by: \(O_i\), where \(i\) is \(i\) \text{th} node of the stratum \(l\), then description sleeps by stratum of a Sugeno system of first order of 6 inputs and 3 rules is the following one:

- **Layer 1** generation of the degree of membership:
  \[
o_i^1 = \mu_{H_i} (x) \quad (11)
  \]

- **Layer 2** generation of the weight of rules \(i\):
  \[
o_i^2 = w_i = \prod_{j=1}^{m} \mu_{H_i} (x) \quad (12)
  \]

- **Layer 3** aggregation of the weights of the rule:
  \[
o_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad (13)
  \]

- **Layer 4** calculates output of the rules according to the parameters conclusions:
  \[
o_i^4 = y_i = \bar{w}_i \tilde{f}_i = \bar{w}_i (p_i x_1 + q_i x_2 + r_i) \quad (14)
  \]

- **Layer 5** to make the sum all inputs starting from the layer 4:
  \[
o_i^5 = \sum_i y_i = \sum_i \bar{w}_i \tilde{f}_i = \left( \bar{w}_1 x_1 \right) p_1 + \left( \bar{w}_1 x_2 \right) q_1 + \left( \bar{w}_2 x_2 \right) q_2 + \left( \bar{w}_2 x_2 \right) q_1 + \bar{w}_1 r_1 + \left( \bar{w}_2 x_2 \right) q_2 + w_2 r_2 \quad (15)
  \]

It is in this last layer that the parameters of the conclusions parts can be optimised using the algorithm of least squares. The above Equation becomes in the following form:

\[
o_i^6 = y = \left( \bar{w}_1 x_1 \right) p_1 + \left( \bar{w}_1 x_2 \right) q_1 + \left( \bar{w}_2 x_2 \right) q_2 + w_1 r_1 + \left( \bar{w}_2 x_2 \right) q_2 + w_2 r_2 \quad (16)
  \]

\[
y = \left[ \bar{w}_1 x_1 \bar{w}_1 x_2 \bar{w}_2 x_1 \bar{w}_2 x_2 \bar{w}_2 x_2 \bar{w}_2 x_2 \right] \left[ \begin{array}{c} p_1 \\ q_1 \\ q_2 \\ r_1 \\ r_2 \\ \end{array} \right] = XW \quad (17)
  \]

III. NEURO-FUZZY CLIMATE CONTROLLER

As is already known from neuro-fuzzy principles, a neuro fuzzy controller acts as a non-linear system capable of implementing expert reasoning for computation of the control values. Indeed, a neuro fuzzy controller which is defined by a set of linguistic rules, fuzzy sets and the cluster centers were trained by neural network and optimized using the back-propagation and the least square algorithm is able to compute appropriate values for greenhouse actuators (heating, ventilation) taking into account information data from the system for control proposes. In the experimental greenhouse, the temperature is controlled by means of heaters, while the humidity is controlled indirectly with the ventilation index regulation. That affects the temperature and the humidity. Using the physical model, a complete system simulator is shown in “Fig. 3.” With this simulator, a first experiment was carried out using a conventional controller (on-off) with a dead band of 2°C; this is based on a heating system that is activated or deactivated when the error exceeds the fixed regulation range. The humidity depends on the internal air temperature and the ventilation index. This variable is regulated by windows opening in the greenhouse according to the wind speed measurements.

In this case, a multiple inputs, multiple outputs (MIMO) non-linear controller for temperature regulation was used. A MIMO neuro fuzzy controller can be distributed in several multiple inputs, single output (MISO) controllers keeping the same performance. These controllers are independent and can be executed in parallel, which is advisable for the climate controller implementation in a FPGA. The Neuro Fuzzy Controller has six input variables and two output variables, characterized by three fuzzy sets in the universe of discourse. Input variables are: Inside and outside temperature (Ti, Text), inside-outside humidity (Hi, Hext), global radiation (Gr) and wind speed (Ws). Membership functions sets and their appropriate modifications were obtained following a test and error strategy by making exhaustive simulations in MATLAB until reaching a good performance through a careful tuning. “Fig. 4.” shows an example of a membership functions set for the input. For this one, three linguistic variables were used (MIN, minimum; MOY, medium; MAX, maximum). The set of fuzzy rules to develop the controller for each variable has been obtained from the expert grower. For tuning the fuzzy
rules as well as for membership functions sets a trial-and-error strategy (manual tuning) was used, this is modifying control rule sets until we reaching a good performance of the controller by using the ANFIS editor (simulation system). Each possible linguistic value of inputs is assigned to a consequential action.

The NEURO FUZZY CONTROLLER shown in “Fig. 5,” has been implemented on an FPGA. The hardware platform used is the Altera DE2 development and education board that is based on the Altera Cyclone II EP2C35F672C6 FPGA. In order to implement our application effectively the design is broken down into modules. The different building blocks are:

A. The de-multiplexer component:

The system should accept multiple inputs with 8-bits in total of 48-bits. In order to reduce the number of pins used in FPGA we have made a de-multiplexing as shown in “Fig. 6,” It has one input of 8-bits and three selection lines, in order to learn at each clock pulse one input and he settles it into a buffer. After six hologe top it will acquire all inputs. At the seventh clock pulse it delivers the enable signal and the values of multiples inputs to the rest of the system.

B. The Fuzzier module:

In this section we have realized six blocks, where each block is intended for one of memberships functions. The example of such block is presented in the figure it used for the external temperature given in “Fig. 7.”. The blocks transformed the numerical data to three linguistic variables (MIN, MOY, MAX). For easy implementation and as we have three cases two bits are used to materialize these case as follows (min => 10, mean => max = 00 and> 11).
C. The command module:

The following operation is the order of the ventilation and the heating. This component shown in “Fig. 8,” admits at the inputs the various decisions for the multiple inputs and it will computing the rules of our FIS structure obtained by Matlab Fuzzy Logic Toolbox. To reduce the use of the hardware resource, finite state machine (FSM) is adopted to model this computing process. Finally it will transform the linguistics values on the binary values.

V. RESULTS AND DISCUSSION

The next step is the simulation of the design to illustrate how it works. “Fig. 9,” shows the global simulation timing obtained by Quartus II version 8.1 SJ Web edition. ‘data’ is the input values information, (T_int, T_ext, H_int, H_int, W_s and R_g) are the values of the deferent parameters, (fuz_Tint, fuz_Text, fuz_Hint, fuz_Hext, fuz_Ws and fuz_Rg) are are the resultant of all the membership functions. ‘Cmd-H-W’ is the finally output value represent the ventilation and heater.

The table I shows the strong similarity between the results obtained by Matlab Fuzzy Logic Toolbox environment and those obtained in “Fig. 9,”. It shows the best operation of all modules. We can also see how the transformation of these data from the linguistics values to numerical values.

Table I Comparison of the results given by Matlab Fuzzy Logic Toolbox and those obtained with Quartus II.

<table>
<thead>
<tr>
<th>Meteorological data</th>
<th>Greenhouse data</th>
<th>Decision control</th>
</tr>
</thead>
<tbody>
<tr>
<td>T_ext</td>
<td>H_ext</td>
<td>G_r</td>
</tr>
<tr>
<td>MIN</td>
<td>10</td>
<td>00</td>
</tr>
<tr>
<td>MOV</td>
<td>MOV</td>
<td>MOV</td>
</tr>
<tr>
<td>00</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>MAX</td>
<td>11</td>
<td>10</td>
</tr>
</tbody>
</table>

Synthesis Of fuzzy neural network On FPGA:

We have implemented the design using the DE2 board, contain Cyclone®II 2C35Altera FPGA device, EP1C6Q240. The principal features of Cyclone II EP2C35 FPGA are as follows:

- 33216 Logic elements.
- 105 M 4K RAM blocks.
- 483,840 total RAM bits.
- 35 embedded 1818 multipliers.
- Four PLLs.
- 475 user I/O pins.

The summary of the hardware resource consumption result for the Neuro-Fuzzy Control Of A Greenhouse Internal Climate Fpga Is Given In Table II.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Top-Level Entity Name</td>
<td>climate control</td>
</tr>
<tr>
<td>Family</td>
<td>Cyclone II</td>
</tr>
<tr>
<td>Device</td>
<td>EP2C35F1206</td>
</tr>
<tr>
<td>Total logic elements</td>
<td>90 / 102,316 (+1 %)</td>
</tr>
<tr>
<td>Total combinational functions</td>
<td>90 / 35,216 (+1 %)</td>
</tr>
<tr>
<td>Total registers</td>
<td>70</td>
</tr>
<tr>
<td>Total inputs</td>
<td>17 / 475 (4 %)</td>
</tr>
<tr>
<td>Fmax restricted to</td>
<td>415 MHz</td>
</tr>
<tr>
<td>TDP (Dynamic Power Dissipation)</td>
<td>111.88 mW</td>
</tr>
<tr>
<td>TDP (Static Power Dissipation)</td>
<td>79.93 mW</td>
</tr>
<tr>
<td>TDP (Power Dissipation)</td>
<td>31.95 mW</td>
</tr>
</tbody>
</table>
VI. CONCLUSION

The current work focuses on the application of neuro-fuzzy control of a greenhouse internal climate. It successfully demonstrated the performance through co-simulation by using ANFIS and ModelSim. This implementation accurately reproduces the theoretical behavior of the system, thus is ready to be used. The future work will be integrated to improve the design of our work which will be intensify to widen the membership function.

References


