

# Artificial Neural Network with Hardware Chip Implementation

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**Abstract:** An Artificial Neural Network (ANN) system is based on a group of associated units or nodes in a biological brain called neurons. The signal is transferred from one neuron to another neuron. The ANN model accepts the input signal which are multiplied with their weights. The multiplied output is weighted sum with the bias component and processed with the nonlinear signals. In the research work we have considered the 8 inputs ANN signal which are multiplied with their corresponding weights. The hardware chip is designed to support the system functionality in Xilinx ISE 14.2 software. The designed chip is simulated with Modelsim 10.0 software for test cases. The designed chip is also synthesized on SPARTAN-3E FPGA and hardware and timing parameters are also analyzed.

**Keywords:** Artificial Neural Network (ANN), FPGA, Xilinx ISE software

## 1. Introduction

An Artificial Neural Network (ANN) [1, 2] is a computing system paradigm based on biological neuron networks [3, 4], such as the brain, process information. The main component of this paradigm is the innovative structure of the information processing system. The system consists of the extremely interrelated processing elements called neurons work in unison to resolve some explicit problems. The ANN is also learning system, as the people learn by the examples. The ANN based system is configured for a specific application, such as data classification or pattern recognition [5] with the help of learning process. The learning behavior in biological systems comprises changes to the synaptic connections that exist between the neurons. An ANN architecture is based on a gathering of associated neurons which forms a biological brain. The interconnected system can transmit the signal from one artificial neuron [7, 8] to another like synapses called artificial neurons which loosely model the neurons in a biological brain. Each connection of the biological brain [6] like the synapse that can transfer a signal from one artificial neuron to another artificial neuron. The artificial neuron that accepts these signals should be capable to process the signals and additionally signals of artificial neurons associated to it.

### 1.2 ANN Architecture

The neural architecture consists of the input signals, weight coefficients [2, 9, 10] and activation function. The fig.1 presents the architecture of neural network in which 8 inputs are given as  $P_1, P_2, P_3, P_4, P_5, P_6, P_7$  and  $P_8$ . The corresponding weights of the inputs are given as  $W_1, W_2, W_3, W_4, W_5, W_6, W_7$  and  $W_8$ . The inputs are multiplied with their weight confidents and weight sum [6, 11] is added with another bias input ( $b$ ) [12, 13]. In the same way the ANN architecture can be extended [14, 15] for 'N' inputs. For the activation function  $y = f(x)$  the output is expressed as,

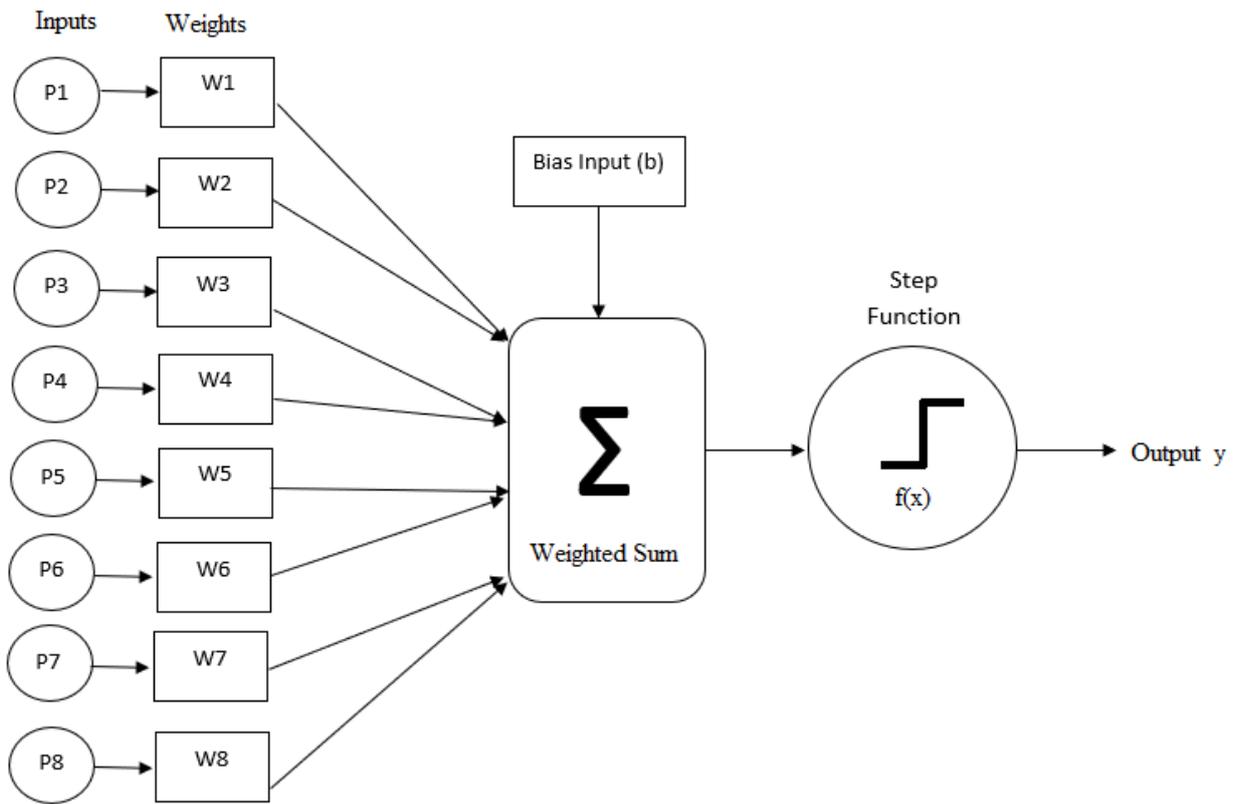


Fig. 1 Neural Network with 8 inputs

$$y = \sum_{i=1}^n P_i W_i + (bias) \quad (1)$$

For 8 inputs

$$y = \sum_{i=1}^8 P_i W_i + (b) \quad (2)$$

$$y = P_1 W_1 + P_2 W_2 + P_3 W_3 + P_4 W_4 + P_5 W_5 + P_6 W_6 + P_7 W_7 + P_8 W_8 \quad (3)$$

### 3. Results & Discussions

The Xilinx software simulation results for 8 input ANN Architecture is shown in Fig 2 that presents the RTL level view of the developed chip. The RTL provides the details of all the pins used for the design of the chip.

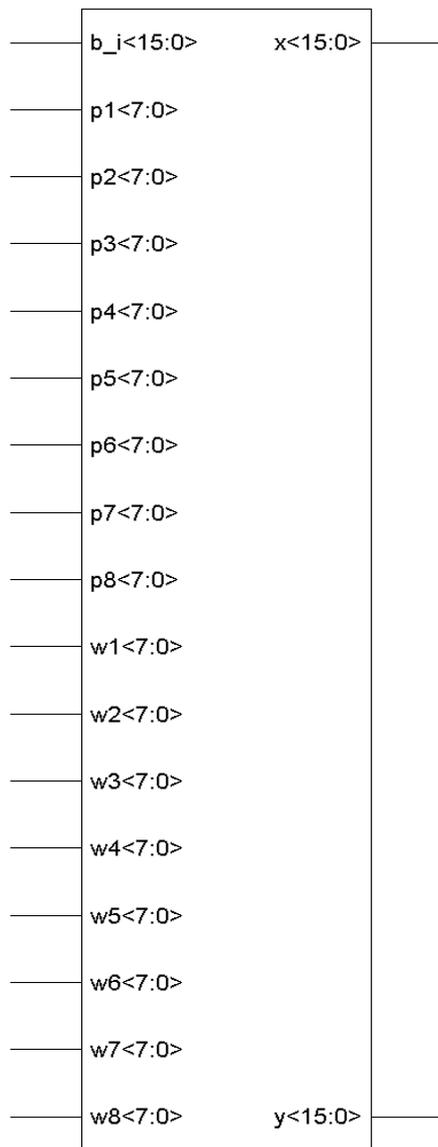


Fig. 2 RTL View of 8 point ANN Architecture Chip

**Test-1 :** P1<7:0> = “00000011” in binary = 3 in decimal, P2<7:0> = “00000100” in binary = 4 in decimal, P3<7:0> = “00000101” in binary = 5 in decimal, P4<7:0> = “00000110” = 6 in decimal, P5<7:0> = “00000101” in binary = 5 in decimal, P6<7:0> = “00000100” in binary = 4 in decimal, P7<7:0> = “00000011” in binary = 3 in decimal, P8<7:0> = “00000010” in binary = 2 in decimal, W1<7:0> = “00000001” in binary = 1 in decimal, W2<7:0> = “00000010” in binary = 2 in decimal, W3<7:0> = “00000011” in binary = 2 in decimal, W4<7:0> = “00000010” in binary = 2 in decimal, W5<7:0> = “00000010” = 2 in decimal, W6<7:0> = “00000001” = 1 in decimal, W7<7:0> = “00000001” = 1 in decimal, W8<7:0> = “00000010” = 2 in decimal, b\_j<15:0> = “00000000110111100” = 220 in decimal, Then output will be Y <15:0> = “0000000100010111” = 279 in decimal.

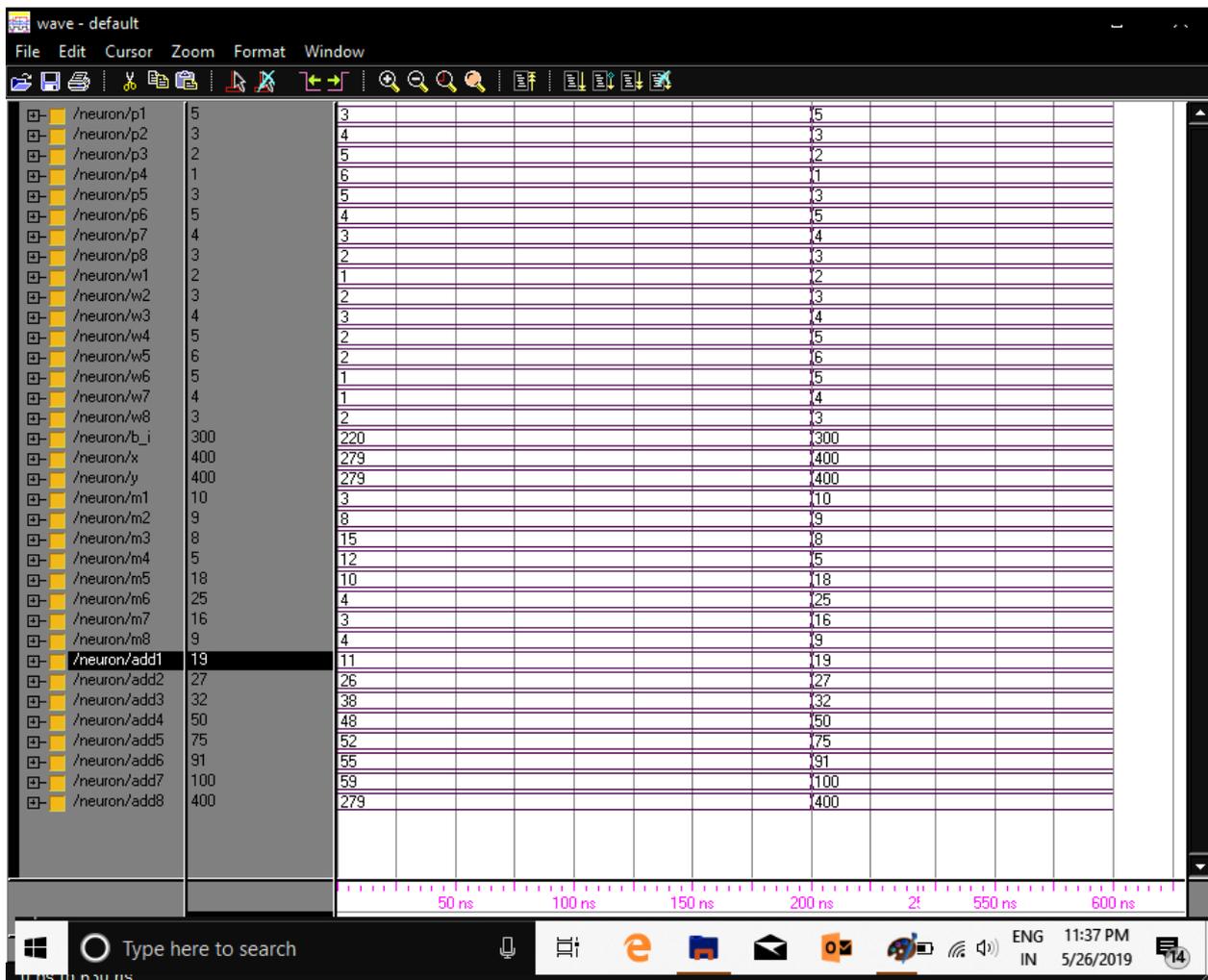


Fig. 3 Modelsim simulation of 8 input ANN with test-1 and test-2in integer

**Test-2 :** P1<7:0> = “00000101” in binary = 5 in decimal, P2<7:0>=“00000011” in binary = 3 in decimal, P3<7:0> = “00000010” in binary = 2 in decimal, P4<7:0> = “00000001” = 1 in decimal, P5<7:0> = “00000011” in binary = 3 in decimal, P6<7:0> = 00000101” in binary = 5 in decimal, P7<7:0> = “00000100” in binary = 4 in decimal, , P8<7:0> = “00000011” in binary = 3 in decimal , W1<7:0> = “00000010” in binary = 2 in decimal, W2<7:0> = “00000011” in binary = 3 in decimal W3<7:0> = “00000100” in binary = 4 in decimal, W4<7:0> = “00000101” in binary = 5 in decimal, W5<7:0> = “00000110” = 6 in decimal, W6<7:0> = “00000101” in binary = 5 in decimal, W7<7:0> = “00000100” in binary = 4 in decimal, W8<7:0> = “00000011” = 3 in decimal, b\_i<15:0> = “0000000100101100” = 300 in decimal, Then output will be Y <15:0> = “0000001100100000” =400 in decimal.

#### 4. Device Hardware Detail

The percentage of hardware that is used by the device is given by device utilization report for the implementation of chip. Device hardware includes No. of slices. of input LUTs, No. of bounded IOBs and No. of gated clocks (GCLKs) used in design implementation. Timing details provides the knowledge of maximum frequency and combinational delay. To complete the design, the total memory utilization required is also given. The Xilinx software gives the details of the hardware utilization for 8 input ANN. Table 1 presents the utilization report of the hardware parameters.

Table 1 Hardware summary for 8 input ANN for SPARTAN 3E FPGA

Parameter	ANN(8 input)
Number of Slices	355
Number of Slice flipflops	418
Number of LUTs	648
Number of IoBs	178
GCLKs	1
Memory Usage	116688 kB

Table 2 Timing Parameters for 8 input ANN for SPARTAN 3E FPGA

Parameter	ANN(8 input)
Frequency (MHz)	235 MHz
Min Period (ns)	1.921 ns
Min time before clock signal (ns)	1.982 ns
Max Time after clock signal(ns)	3.517 ns
Combinational Delay (ns)	4.518 ns

## 5. Conclusions

The hardware chip of 8 input ANN architecture is designed in Xilinx ISE 14.2 software successfully and simulated in Modelsim 10.0 software. The designed chip is synthesized on SPARTAN-3E FPGA. The designed chip support the frequency of 235 MHz. The timing detail parameters are minimum period (ns), minimum time before clock signal (ns), maximum time after clock signal (ns) and combinational delay (ns) which are estimated as 1.921 ns, 1.982 ns, 3.517 ns and 4.518 ns respectively.

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