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# Studying Generation Modes of Linearized Artificial Neurons Based on FPGA Architecture Hardware Implementation

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**Abstract**—This paper describes the development of embedded software for the implementation and testing of the artificial multistable neuron model's basic behavior with the help of the hardware architecture of programmable logic integrated circuits (FPGA). The real behavior and function of the biological neuron with linearized activation characteristics are investigated and implemented in the programming language VHD. The base model is a three-stable neuron with three asymmetric dendrites. To develop a hardware model, a computational mathematical model of a neuron is used, based on which a corresponding discrete model is synthesized. The model consists of the following modules: an input block, a timer, a clock generator, a threshold element, and an output signal generator. It is shown that the implemented system allows synthesizing a neural model with a predetermined number of stable discrete states, with the neuron changing its stable state depending on the input vector. Each stable state corresponds to the output function of the neuron. The developed model of artificial neurons was implemented on the DIGILENT BASYS II SPARTAN-3E XC3S100E FPGA kit in the WebPACKTM ISE 13.3 environment. Resulting neuron output generation modes relation from input sequences and structure parameters were studied. The results of the work allow investigating high-speed neural networks with a dynamic structure using FPGA, which can be used for a wide range of modern tasks such as recognition, classification of patterns and development of elements of artificial intelligence.

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## 1. PROBLEM BACKGROUND

Considerable work has been done on the development and implementation of hardware neurocomputers since the 2000s. However, most of these efforts can be considered unsuccessful: none of the systems was widely used. The lack of success is because the previous work was almost entirely focused on the development of neurocomputers [1] that are built on the application-specific integrated circuit (ASIC) technology. However, this technology has never been sufficiently developed and competitive for large-scale deployment [2] for areas such as neural networks.

The significant improvement of modern technologies has opened a new way. The potential and performance of existing FPGAs are such that they provide a much more realistic alternative. FPGA-based neurocomputers can be the basis for the mass implementation of parallel distributed data processing systems. The main task in all forms of parallel computing is to translate as many processes as possible into hardware for their rapid execution in parallel mode and with minimal energy costs.

Moreover, the model of a neuron or neural network is a dynamic structure where changes, even structural ones, can occur [3, 4]. The flexible FPGA structures become the most attractive for modeling neural networks and allow modeling the behavior of artificial neurons with biological similarity in real-time.

The main limitation of the software implementation of neurons, neural networks, and pattern recognition systems is the consecutive execution of calculations. Compared to any modern microcontroller, FPGAs have the reconfiguration property and very low power consumption while maintaining high power and small linear dimensions [5]. Delayed execution of an algorithm of several milliseconds can be significant for use, for example, in medical diagnostics.

Reconfigured FPGA-based computations are well-suited for the implementation of neural structures because they utilize parallelism and can be quickly reconfigured according to input weights and neuronal

## CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

## ADDITIONAL INFORMATION

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