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Artificial Neural Network Signal Routing Model: An Effective Solution to Telecommunication Networks Problems

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ABSTRACT

Artificial Neural Network signal is a neural network model that mimics the way a human brain works by selecting the best conditions that are reliable for reliable network propagation. This model will choose the best network route at a particular interval. It is made up of a number of nodes that are organized in several layers that must follow the Artificial neural network routing algorithm. The input layers of neurons feeds the input variables into the network through the hidden layers or processing elements which send the processed signal to the output layers. The routing algorithm will basically be applied on the input nodes of the neural network. We will analyze the network using node based packet tracers, in this work, we did manual routing with few nodes with the algorithm. This show that network will present various possible routes. This can be implemented on a real telecommunication network with billions of nodes[neural netwok input nodes]. If this is achieved, we will experience a more reliable networks on reliable secured protocols. This network will be more efficienct than the conventional network. There will not be signal lost on the network because of various signal routes of the same class of nodes. Network breakdown might be impossible with this because any breakdown on the network presents the next possible route on the same network[artificial intelligent learning].

Keywords – Artificial neural network, intelligent learning, artificial intelligent training, artificial intelligent signal routing, telecommunication network

1. INTRODUCTION

Examinations of humans' central nervous systems inspired the concept of artificial neural networks. In an artificial neural network, simple artificial nodes, known as "neurons", “processing elements” or “units”, are connected together to form a network which mimics a biological neural network(Hebb, 1949). The adaptive weights can be thought of as connection strengths between neurons, which are activated during training and prediction Werbos(1975). Artificial neural networks are similar to biological neural networks in the performing by its units of functions collectively and in parallel, rather than by a clear delineation of subtasks to which individual units are assigned. The term "neural network" usually refers to models employed in statistics, cognitive psychology and artificial intelligence. Neural network models which command the central nervous system and the rest of the brain are part of theoretical neuroscience and computational neuroscience.

In modern software implementations of artificial neural networks, the approach inspired by biology has been largely abandoned for a more practical approach based on statistics and signal processing. In some of these systems, neural networks or parts of neural networks (like artificial neurons) form components in larger systems that combine both adaptive and non-adaptive elements. While the more general approach of such systems is more suitable for real-world problem solving, it has little to do with the traditional, artificial intelligence connectionist models. What they do have in common, however, is the principle of non-linear, distributed, parallel and local processing and adaptation. Historically, the use of neural network models marked a directional shift in the late eighties from high-level (symbolic) artificial intelligence, characterized by expert systems with knowledge embodied in "*if then*" rules, to low-level (sub-symbolic) machine learning, characterized by knowledge embodied in the parameters of a dynamical system.

1.1 Problem Definition

In Nigeria presently, telecommunication services are just disaster, we have so many issues concerning network like no service issues, weak service issues, availability of both sender and receiver of the signals, inability to place calls at the right time when needed by the users, hanging of calls and SMS during session. In the security aspect, the present telecommunication might not handle these essential security properties;

i. **Authentication/access** of all parties and objects involved in a session.
ii. **Confidentiality** of services during sessions
iii. **Integrity** of services to the public

1.2 Research Objectives

i. To develop a network signal route algorithm that can generate all possible signal route of a network.
ii. To develop artificial neural network architecture that will be able to predict accurately the best network signal route at any given time.
iii. To develop an intelligent neural network model that can learn from past network sessions and present a secured network from the source to the destination.

2. ARTIFICIAL NEURAL NETWORK

Neural networks, as used in artificial intelligence, have traditionally been viewed as simplified models of neural processing in the brain *Behnke (2003)*, even though the relation between this model (see figure 1 and figure 2) and the biological architecture of the brain (see figure 3) is debated; it's not clear to what degree artificial neural networks mirror brain function. Support vector machines and other, much simpler methods such as linear classifiers gradually overtook neural networks in machine learning popularity. But the advent of deep learning in the late 2000s sparked renewed interest in neural networks.

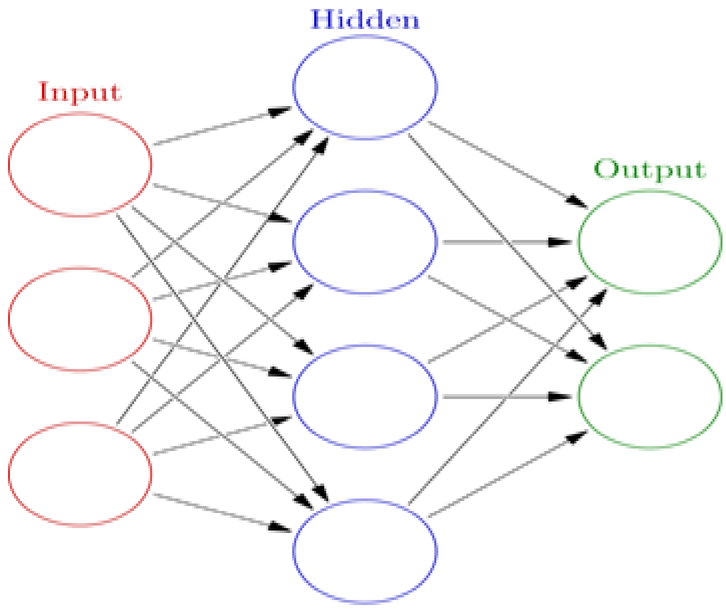

Figure 1: Artificial Neural Network model (one processing element region) *Behnke (2003).*

Artificial neural networks (**ANN**) or **connectionist systems** are computing systems that are inspired by, but not necessarily identical to, the biological neural networks that constitute animal brains *Behnke (2003)*. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any prior knowledge about cats, for example, that they have fur, tails, whiskers and cat-like faces. Instead, they automatically generate identifying characteristics from the learning material that they process.

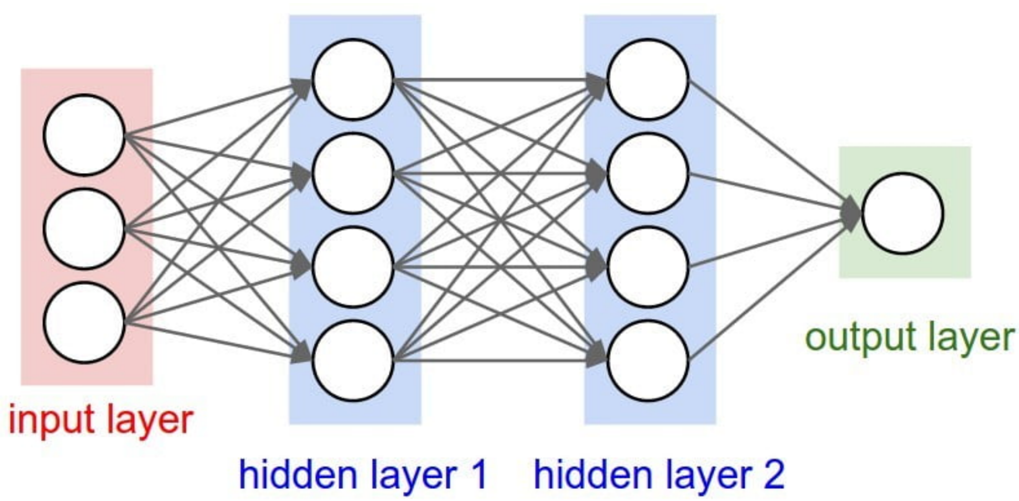

Figure 2: Artificial Neural Network model (two processing element region) *Behnke (2003).*

An ANN is based on a collection of connected units or nodes called artificial neurons (*Cireşan, 2010*), which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it. In common ANN implementations, the signals are a connection between artificial neurons which are real numbers, and the output of each artificial neuron is computed by some non-linear function of the sum of its inputs. The connections between artificial neurons are called 'edges'(*Cireşan, 2010*). Artificial neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Artificial neurons may have a threshold such that the signal is only sent if the aggregate signal crosses that threshold. Typically, artificial neurons are aggregated into layers. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

Neural networks are also an emerging artificial intelligence technology that imitates the human brain on the computer(*Cireşan, 2010*). These techniques are based on the parallel, distributed processing design. The parallel structure makes neural networks proficient at analyzing problems with many variables (Tafti, 1993 and Zhang, 2004). Scientists have been inspired by the capabilities of the human brain for information processing and problem solving. Therefore, neural networks designers try to put intelligence into these systems in the form of generalized ability to learn and recognize patterns to exhibit similar intelligent functionality like humans (Shachurove, 2002).

A neural network model is composed of a number of neurons that are organized in several layers: an input layer, a hidden layer(s), and an output layer (Malhotra and Malhotra, 2003). The input layer of neurons feeds the input variables into the network. The hidden layer is a bridge between the input layer and the output layer. The neurons in this layer are fundamentally hidden from view, and their number and arrangement can typically be treated as a black box to those who are carrying out the system. The function of the hidden layer is to process the input variables. This is achieved by summing up all weighted inputs, checking whether the sum meets the threshold value and applying the transformation function. The weights between the input neuron and hidden neurons determine when each unit in the hidden layer may fire or not and by modifying these weights, the hidden layer may fire or not (Zhang, 2004). In other words, the hidden layers learn the relationship between inputs and outputs in a way similar to that of the human brain by adjusting the weights during the training process (Peel and Wilson, 1996). The function of the output layer is similar to that of the hidden layer. Each input for this layer is possessed as in the hidden layer (Muller et.al, 2009). A specific neural network model is determined by its topology, learning paradigm and learning algorithm (Handzic et.al, 2003).

2.1 Biological Model of Artificial Neural Network

The original goal of the ANN approach was to solve problems in the same way that a human brain would. However, over time, attention moved to performing specific tasks, leading to deviations from biology. Artificial neural networks have been used on a variety of tasks, including computer vision, speech recognition, machine translation, social network filtering, playing board and video games and medical diagnosis. Artificial neural networks born after McCulloc and Pitts introduced a set of simplified neurons in 1943. These neurons were represented as models of biological networks into conceptual components for circuits that could perform computational tasks. The basic model of the artificial neuron is founded upon the functionality of the biological neuron. By definition, "Neurons are basic signaling units of the nervous system of a living being in which each neuron is a discrete cell whose several processes are from its cell body" (Ndinechi et al, 2011), see figure 3.

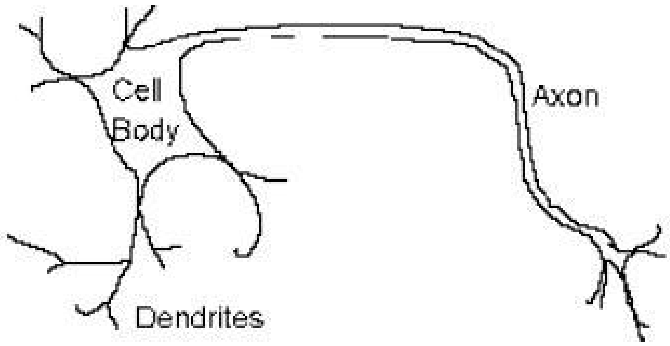

Figure 3: Artificial Neural Network biological model (Ndinechi et al, 2011).

The biological neuron has three main regions to its structure:

i. The cell body, or soma, has two offshoots from it.
ii. The dendrites and
iii. the axon end in pre-synaptic terminals.

The cell body is the heart of the cell. It contains the nucleolus and maintains protein synthesis. A neuron has many dendrites, which look like a tree structure, receives signals from other neurons. A single neuron usually has one axon, which expands off from a part of the cell body. This we called the axon hillock. The axon main purpose is to conduct electrical signals generated at the axon hillock down its length. These signals are called action potentials. The other end of the axon may split into several branches, which end in a pre-synaptic terminal. The electrical signals (action potential) that the neurons use to convey the information of the brain are all identical. The brain can determine which type of information is being received based on the path of the signal. The brain analyzes all patterns of signals sent, and from that information it interprets the type of information received. The myelin is a fatty issue that insulates the axon. The non-insulated parts of the axon area are called Nodes of Ranvier. At these nodes, the signal traveling down the axon is regenerated. This ensures that the signal travel down the axon to be fast and constant. The synapse is the area of contact between two neurons. They do not physically touch because they are separated by a cleft. The electric signals are sent through chemical interaction. The neuron sending the signal is called pre-synaptic cell and the neuron receiving the electrical signal is called postsynaptic cell. The electrical signals are generated by the membrane potential which is based on differences in concentration of sodium and potassium ions and outside the cell membrane. Biological neurons can be classified by their function or by the quantity of processes they carry out. When they are classified by processes, they fall into three categories(Ndinechi et al, 2011):

i. Unipolar neurons,
ii. bipolar neurons and
iii. multipolar neurons.

Unipolar neurons have a single process. Their dendrites and axon are located on the same stem. These neurons are found in invertebrates.

Bipolar neurons have two processes. Their dendrites and axon have two separated processes too.

Multipolar neurons: These are commonly found in mammals. Some examples of these neurons are spinal motor neurons, pyramidal cells and purkinje cells.

When biological neurons are classified by function they fall into three categories (Ndinechi et al, 2011).

i. The first group is sensory neurons. These neurons provide all information for perception and motor coordination.
ii. The second group provides information to muscles, and glands. There are called motor neurons.
iii. The last group, the interneuronal, contains all other neurons and has two subclasses. One group called relay or protection interneurons. They are usually found in the brain and connect different parts of it. The other group called local interneurons are only used in local circuits.

An artificial neuron mimics the working of a biophysical neuron with inputs and outputs, but is not a biological neuron model. Figure 4 shows the neuron and myelinated axon, with signal flow from inputs at dendrites to outputs at axon terminals. The *network* forms by connecting the output of certain neurons to the input of other neurons forming a directed, weighted graph. The weights as well as the functions that compute the activation can be modified by a process called *learning* which is governed by a *learning rule* (Russell and Norvig, 2010).

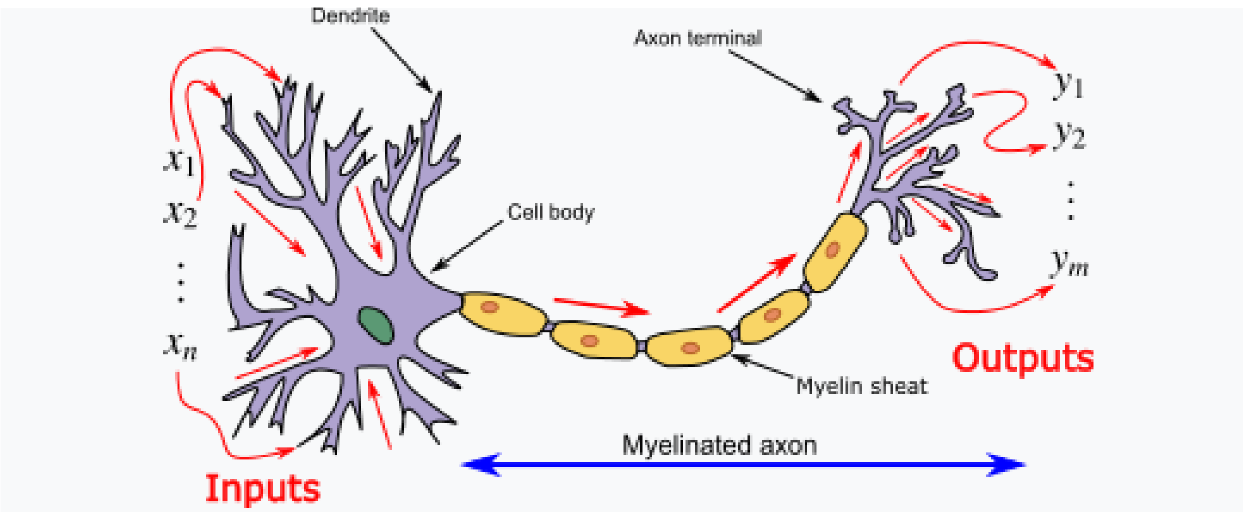

Figure 4: Neuron and myelinated axon, with signal flow from inputs at dendrites to outputs at axon terminals (en.wikipedia.org/neuron)

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it. In common ANN implementations, the signal at a connection between artificial neurons are a real number, and the output of each artificial neuron is computed by some non-linear function of the sum of its inputs.

The connections between artificial neurons are called 'edges' (Anyaeche and Ighravwe, 2013). Artificial neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Artificial neurons may have a threshold such that the signal is only sent if the aggregate signal crosses that threshold. Typically, artificial neurons are aggregated into layers. Different layers may perform different kinds of.

2.2 The Mathematical Model

Once modeling an artificial functional model from the biological neuron, we must take into account three basic components. First off, the synapses of the biological neuron are modeled as weights. Let's remember that the synapse of the biological neuron is the one which interconnects the neural network and gives the strength of the connection. For an artificial neuron, the weight is a number, and represents the synapse. A negative weight reflects an **inhibitory connection**, while positive values **designate excitatory connections** (Ndinechi et al, 2011). The following components of the model represent the actual activity of the neuron cell. All inputs are summed altogether and modified by the weights. This activity is referred as a linear combination. Finally, an activation function controls the amplitude of the output. For example, an acceptable range of output is usually between 0 and 1, or it could be -1 and 1.

Mathematically, this process is described in the figure 5

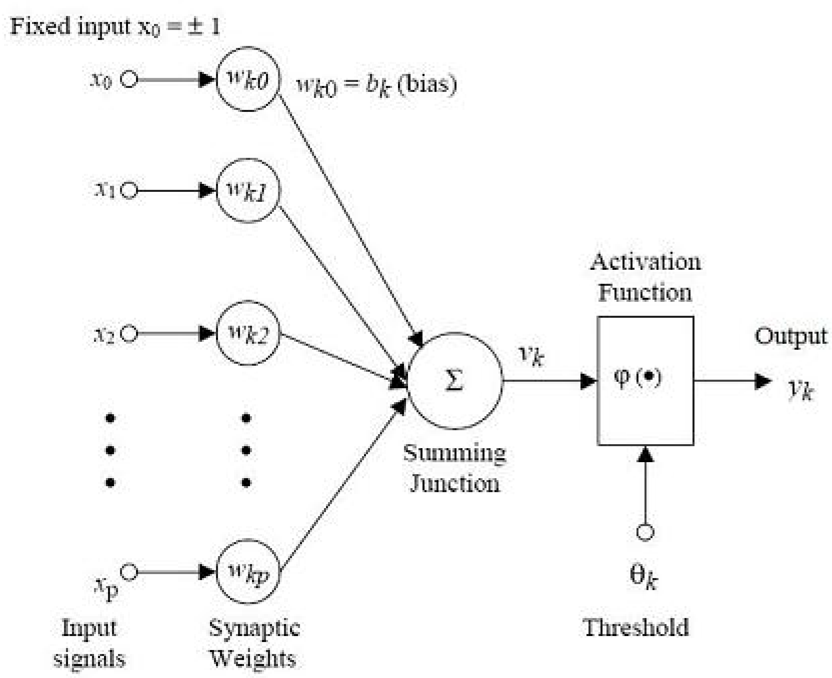

Figure 5: Mathematical Model(Ndinechi et al, 2011).

From this model the interval activity of the neuron can be shown to be:

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \qquad \text{.........................(1)}$$

The output of the neuron, y_k, would therefore be the outcome of some activation function on the value of v_k.

i. Activation functions

The activation function acts as a squashing function, such that the output of a neuron in a neural network is between certain values (usually 0 and 1, or -1 and 1). In general, there are three types of activation functions, denoted by Φ(.) . First, there is the Threshold Function which takes on a value of 0 if the summed input is less than a certain threshold value (v), and the value 1 if the summed input is greater than or equal to the threshold value.

$$\varphi(v)=\begin{cases}1 & \text{if } v\geq 0\\ 0 & \text{if } v<0\end{cases} \qquad \text{.........................(2)}$$

Secondly, there is the Piecewise-Linear function. This function again can take on the values of 0 or 1, but can also take on values between that depending on the amplification factor in a certain region of linear operation.

$$\varphi(v)=\begin{cases}1 & v\geq \frac{1}{2}\\ v & -\frac{1}{2}>v>\frac{1}{2}\\ 0 & v\leq -\frac{1}{2}\end{cases} \qquad \text{..................................(3)}$$

Thirdly, there is the sigmoid function. This function can range between 0 and 1, but it is also sometimes useful to use the -1 to 1 range. An example of the sigmoid function is the hyperbolic tangent function.

$$\varphi(v)=\tanh\left(\frac{v}{2}\right)=\frac{1-\exp(-v)}{1+\exp(-v)} \qquad \text{...................(4)}$$

ii. The network activation rate

During the training (supervised training) in the artificial neural network, the activation function also called the alpha must be present. This parameter helps to detemine the initial network weights called the initial weight (w_{i1} to w_{in}). The final weights (w_{f1} to w_{fn}) of the network is detemine by the initial weight in addition to the product of the network error vector and the chosen network input. the final weights (w_{f1} to w_{fn}) = the initial weight (w_{i1} to w_{in}) + (the network error vector)(the chosen network input)(alpha).

The the network error vector is determinmined from the differene between the actual output and the network output.

The network error vector = the actual output - the network output.

3. ARTIFICIAL INTELLIGENCE NEURAL NETWORK [AINN] TELECOMMUNICATION SIGNAL ROUTING

Presently, we are doing research on how to achieve this but we have arrived at a model that can handle the signal routing which is: [N-1]! Where N is the number of initial input nodes on the network. Assuming that a network has four initial input nodes. The routing will be [4-1]!= 3! = 3x2x1= 6 routes.
Assumming that the four nodes are $N_{a,}$ $N_{b,}$ N_c and N_d
The network routes will be

Route1
$N_{a,} \rightarrow N_{b,} \rightarrow N_c \rightarrow N_d \rightarrow N_a$

Route 2
$N_{a,} \rightarrow N_b \rightarrow N_{d,} \rightarrow N_c \rightarrow N_a$

Route 3
$N_{a,} \rightarrow N_{c,} \rightarrow N_b \rightarrow N_d \rightarrow N_a$

Route 4
$N_{a,} \rightarrow N_c \rightarrow N_d \rightarrow N_b \rightarrow N_a$

Route 5
$N_a \rightarrow N_{d,} \rightarrow N_{b,} \rightarrow N_c \rightarrow N_a$

Route 6
$N_a \rightarrow N_{d,} \rightarrow N_{c\,,} \rightarrow N_b \rightarrow N_a$

This can be carried out on a real telecommunication network with billions of nodes. I found out that the network will be more efficienct than the conventional network. There will not be signal lost on the network because of various signal routes. Network breakdown might be impossible with this because any breakdown on the network presents the next possible route on the same network. This makes it intelligent.

4. THE EXPECTED OUTCOMES/RESULTS

At the end of the research, we will be able to achieve intelligent neural network models that can effectively handle the telecommunication network signal routing with the proposed routing model. This can be implemented on a real telecommunication network with billions of nodes[neural netwok input nodes]. If this is achieved, we will experience a more reliable networks on reliable secured protocols. This network will be more efficienct than the conventional network. There will not be signal lost on the network because of various signal routes of the same class of nodes. Network breakdown might be impossible with this because any breakdown on the network presents the next possible route on the same network[artificial intelligent learning].

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