PV BOOST CONVERTER CONDITIONING USING NEURAL NETWORK

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ABSTRACT

This master report presents a voltage control system for DC-DC boost converter integrated with Photovoltaic (PV) array using optimized feed-forward neural network controller. A specific output voltage of a boost converter is regulated at a constant value under input voltage variations caused by a sudden changes in irradiation for a purpose of supplying a stabilize dc voltage to Base Transceiver Station (BTS) telecommunication equipment that required a 48V dc input supply to be operated. For a given solar irradiance, the tracking algorithm changes the duty ratio of the converter such that the output voltage produced equals to 48V. This is done by the feed-forward loop, which generates an error signal by comparing converter output voltage and reference voltage. Depending on the error and change of error signals, the neural network controller generates a control signal for the pulse width-modulation generator which in turn adjusts the duty ratio of the converter. The effectiveness of the proposed method is verified by developing a simulation model in MATLAB-Simulink program. Tracking performance of the proposed controller is also compared with the conventional proportional-integral-differential (PID) controller. The simulation results show that the proposed neural network controller (NNC) produce an improvement of control performance compared to the PID controller.

ABSTRAK

Laporan ini membentangkan satu sistem kawalan voltan DC-DC penukar Boost yang memperolehi sumber voltan daripada sistem solar, dengan menggunakan kaedah jaringan tiruan (ANN). Voltan keluaran daripada penukar Boost ini akan dikawal supaya sentiasa berada pada nilai yang tetap walaupun pelbagai voltan masukkan dikenakan yang terjadi disebabkan oleh perubahan mendadak sinaran matahari, bagi tujuan membekalkan voltan arus terus yang stabil kepada Stesen Transceiver Base (BTS) iaitu suatu peralatan telekomunikasi yang memerlukan bekalan voltan masukkan arus terus 48V. Apabila sesuatu nilai sinaran matahari diberikan, jaringan tiruan (ANN) ini akan memastikan penukar Boost hanya mengeluarkan voltan arus terus bersamaan dengan 48V sahaja. Ini dilakukan dengan menggunakan kaedah gelung suapan ke hadapan, yang akan menjanakan isyarat ralat daripada hasil daripada perbandingan yang telah dibuat di antara voltan daripada penukar Boost dengan voltan rujukan yang ditetapkan. Bergantung kepada nilai ralat yang terhasil, pengawal jaringan tiruan ini akan menjanakan isyarat kawalan kepada penjana nadi lebar modulasi, yang seterusnya akan memberikan nilai nisbah duti penukar yang sesuai. Keberkesanan kaedah yang dicadangkan ini akan dikaji dengan membangunkan model simulasi menggunakan program MATLAB-Simulink. Prestasi daripada pengawal jaringan tiruan (ANN) yang dicadangkan ini akan dibandingkan dengan pengawal konvensional PID. Keputusan simulasi menunjukkan bahawa, pengawal jaringan tiruan (ANN) ini telah menghasilkan peningkatan prestasi berbanding dengan pengawal konvensional PID.

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LIST OF SYMBOLS AND ABBREVIATIONS

PV	-	Photovoltaic
DC	-	Direct Current
PWM	-	Pulse Width Modulation
PID	-	Proportional integral derivative Control
ANN	-	Artificial Neural Network
BTS	-	Base Transceiver Station
GSM	-	Global System for Mobile
CDMA	-	Code Division Multiple Access
WAN	-	Wide Area Network
AC	-	Alternate Current
CCM	-	Continuous Current Mode
DCM	-	Discontinuous Current Mode
V_L	-	Inductor Voltage
V_S	-	Supply Voltage
i_L	-	Inductor Current
Δ	-	Small Constant Value
T	-	Time
D	-	Duty Cycle
V_o	-	Output Voltage
I_o	-	Output Current
R	-	Resistance
L	-	Inductance
C	-	Capacitance

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CHAPTER 1

INTRODUCTION

1.1 Project background

Renewable energy has become a higher priority for both research and industry communities due to natural gas and pollution have increased, and considerable attempts to find sources of energy efficiency have been made extensively. Photovoltaic systems (PV), which convert sunlight into electricity, has been regarded as one of the potential alternative because there is no fuel costs, low maintenance costs, low operating costs and no sound. PV systems are classified into three types, namely, grid-connected systems, stand-alone and hybrid. All types require an electronic interface between the solar panel system for either direct current or alternating load [1].

In particular for stand-alone PV systems that produce constant and specific output voltage, the electronics interface system is required between the output of the PV system and the load. Typically, PV systems make use of a DC-DC boost converter, which is a category of switching power regulator that provides an output voltage greater than a received input voltage. Such a boost converter also fixes the output voltage even though the solar cells deliver unstable input voltage due to variations of irradiation intensity. In general, the boost converter operates at a certain duty cycle resulting in a specific output voltage value. In the case when the input voltage is changed while the duty cycle is still kept constant, the output voltage will vary. Most converters are controlled by a pulse width modulation (PWM) technique that regulates the constant output voltage through the change in the duty cycle in the control signal.

Traditional design techniques are based on Proportional-Integral-Derivative (PID) controllers in which parameters can be adjusted for appropriate settling-time, overshoot and specific output values according to Mohamed Elshaer [2]. However, the PID controller is not sufficient for non-linear systems. Hence, an Artificial Neural Network (ANN) has become proficient solution for non linear system controls [3], with the capability of learning problems and predicts the next solution.

In this project, the output voltage control system for boost converter integrated with PV model is studied with the purpose of controlling a specific output voltage under input voltage variation caused by changes in irradiation of the solar cells. The ANN control technique is used to regulate the output voltage. The application of this system is to supply a constant dc 48V to Base Transceiver Station (BTS) that used in telecommunication system according to P. A. Dahono [4].

1.2 Problem statement

Photovoltaic (PV) system, which converts sunlight into electricity is not always received an optimum sun irradiation everyday. The sudden changes in irradiation will cause the output voltage of the PV system varies. Therefore the stand-alone PV system without an electronics interface system between the output of the PV system and the load is not suitable to be used to supply power to an application that required a constant dc supply to be operated such as Base Transceiver Station (BTS) telecommunication equipment that required a 48V dc input supply.

1.3 Project objective

The objectives of this project are:

i. To develop a simulation of PV boost converter using Neural Network controller to control a specific output voltage under input voltage variation caused by changes in irradiation of the solar cells.
ii. To analyze the performance of boost converter in stabilizing the output voltage between the controlling scheme using PID and Neural Network controller.

1.4 Project scope

The scopes of this project is to simulate the proposed method of stabilize the output voltage of the Boost converter by using Neural Network Controller (NNC) with MATLAB Simulink software. Neural network controller will be design based on a two-layer feed-forward network with sigmoid hidden neurons and linear output neurons and train by using Levenberg-Marquardt back-propagation algorithm.

1.5 Thesis overview

This thesis is organized into five chapters. The structure and description of the thesis can be described as follows.

Chapter 1 describes about project background, problem statement, project objectives and project scope. Chapter 2 covers the literature review of previous case study based on neural network controller background and development. Besides, general information about renewable energy, Base Transceiver Station, Boost Converter and theoretical revision on neural network control system also described in this chapter. Chapter 3 presents the methodology used to design open loop Boost Converter and neural network controller.

Chapter 4 shows the analysis for open loop, closed loop using PID and Neural Network using boost converter circuit. Lastly, Chapter 5 will go through about the conclusion and future recommendation for future study.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature survey on existing model of neural network DC-DC converter

Since neural network controller can mimic human behaviour, many researchers applied neural network controller to control voltage output. A thorough literature overview was done on the usage of neural network controller as applied in DC-DC Boost Converter.

N. Jiteurtragool, C. Wannaboom and W. San-Um [1], proposed a power control system in DC-DC Boost converter integrated with photovoltaic arrays using optimized back propagation artificial neural network by using MATLAB simulink software. The simulation result shows the neural network controller possesses fast settling time of 6.4ms with low voltage ripples of approximately 0.625%.

Vasanth Subramaniam (2007) [5], proposed an evolution of artificial neural network controller for a boost converter by using MATLAB simulink software. The simulation result shows that the performance of the artificial neural network controller are comparable to the PI controllers and also some of the problems of the conventional linear control techniques for non-linear system have been mitigated, proving these AI based control techniques would be the future of controller design.

Ivan Petrović, Ante Magzan, Nedjeljko Perić and Jadranko Matuško [6], proposed a neural control of boost converter input current by using MATLAB simulink software. The simulation result shows that the neural network controller provides much better responses of the input current than PI controller: 15 times shorter settling time, 2 times better ripples attenuation and responses without overshoots in opposite to 35% overshoots. Besides, it is much easier to adjust neural network controller then the PI controller.

B. S. Dhivya, V. Krishnan and Dr. R. Ramaprabha [7], proposed a Neural Network Controller for Boost Converter by using MATLAB simulink software. The simulation result shows that the ANN based controller proves to have a fast response in tracking the desired output voltage and is also effective ill decreasing overshoot, oscillations and settling time.

2.2 Solar Energy

Solar energy is energy that is extracted from the radiation released from the sun in the form of heat and electricity. This energy is essential to all life on earth. It is a renewable source of clean, economical, and less pollution than other sources of energy [8]. Therefore, solar energy is rapidly gaining notoriety as an important means of expanding renewable energy resources. Therefore, it is important that people understand the technology of engineering associated with this area.

2.3 Photovoltaic Technology

Photovoltaic (PV) systems use cells to convert solar radiation into electricity. The cell consists of layers of a semi-conducting material. When light shines on the cell it creates an electric field across the layers, causing electricity to flow. The greater the intensity of the light, the greater the flow of electricity will. However, a PV system can also generate electricity on cloudy days; it does not need bright sunlight to operate. The performance of a solar cell is measured in terms of efficiency at turning sunlight into electricity. A typical commercial solar module has an efficiency of 15% -- in other words, about one-sixth of the sunlight striking the module is converted into electricity. Improving solar module efficiencies while holding down the cost per cell is an important goal of the PV industry.

Cristalline silicon (monocrystalline or polycristalline) and Thin Film are the two main photovoltaic technologies.

- **Crystalline silicon**
  Made from thin slices cut from a single crystal of silicon (monocrystalline) or from a block of silicon crystals polycrystalline), with an efficiency ranging between 11% and 20%. This technology represents about 85% of the market today

- **Thin Film**
  Made by depositing extremely thin layers of photosensitive materials onto a low-cost backing such as glass, stainless steel or plastic. Lower production costs counterbalance this technology's lower efficiency rates (from 5% to 13% average)

- **Other cell types**
  Several other types of PV technologies are being developed today or are starting to be commercialised, including concentrated photovoltaics (operates with concentrated sunlight, using a lens to focus the sunlight onto the cells) and flexible cells (similar production process to thin film cells, their flexibility opens the range of applications).

2.4 Base Transceiver Station

A base transceiver station (BTS) as shown in Figure 2.1 below is a piece of equipment that facilitates wireless communication between user equipment (UE) and a network which required dc 48V input power supply [4]. The location of the BTS is inside a BTS tower as per Figure 2.2. UEs are device like mobile phones, computers with wireless internet connectivity and others. The network can be that of any of the wireless communication technologies like GSM, CDMA, wireless local loop, WAN, WiFi, WiMAX and others.

Figure 2.1: Base Transceiver Station (BTS)

Figure 2.2: Base Transceiver Station tower

BTS conventional power system scheme is shown in Fig. 2.3. BTS is usually power-driven by utility lines. A diesel generator is typically used as back-up. Air conditioning and lighting systems are powered from the AC bus. By using rectifiers, AC power is converted into 48V dc power. Batteries and telecommunication equipment connected directly to 48V dc bus. These batteries are typically designed to provide at least 6 hours of back-up time. In rural areas, however, diesel generator is usually the main source. For small BTSs, around 2000 liters of diesel fuel needed each month. In rural areas or small islands, the main problem is how to deliver the fuel. Just in several years, the fuel cost may exceed the price of the BTS itself [4].

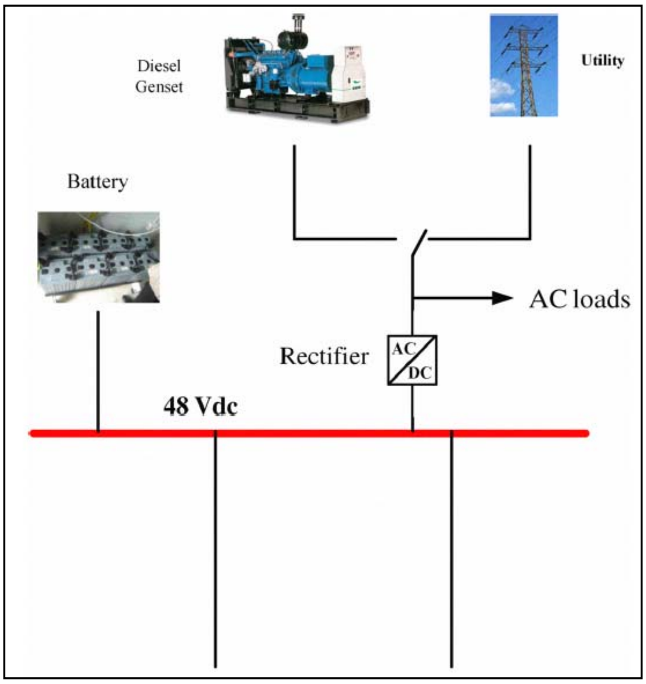

Figure 2.3: Scheme of conventional BTS [4]

Figure 2.4 below shows the proposed system that used a renewable energy as a power supply for the BTS to reduce the operating cost when using diesel. In this system, the wind and PV power plants produce dc voltage. For solar PV, each array is connected to the dc bus through a solar charge controller. The charge controller is basically a boost converter that operates according to the dc bus voltage. No maximum power point tracker is provided in this solar charge controller [4].

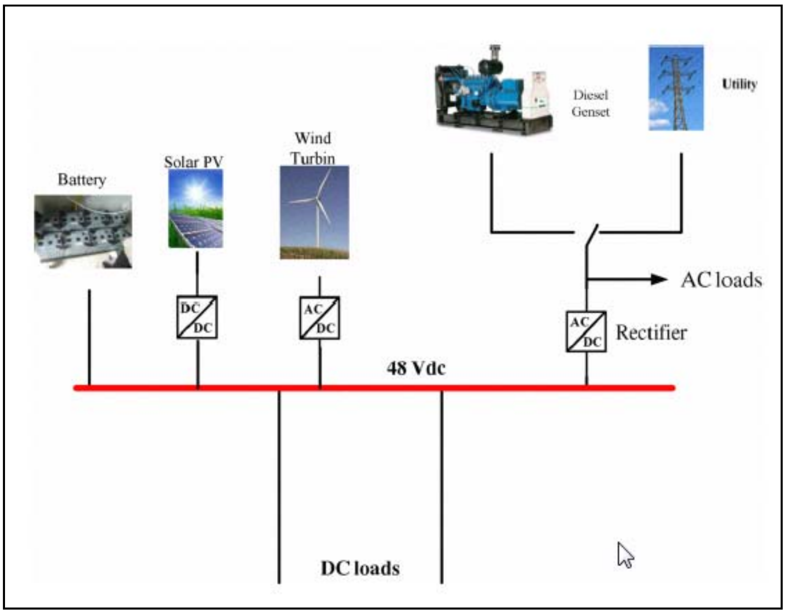

Figure 2.4: Base Transceiver Station using renewable energy
(P. A. Dahono et al,. 2009).

2.5 Boost converter

The boost converter is shown in Figure 2.5. This is a switching converter that operates by periodically opening and closing an electronic switch. It is called a boost converter because the output voltage is larger than the input [9].

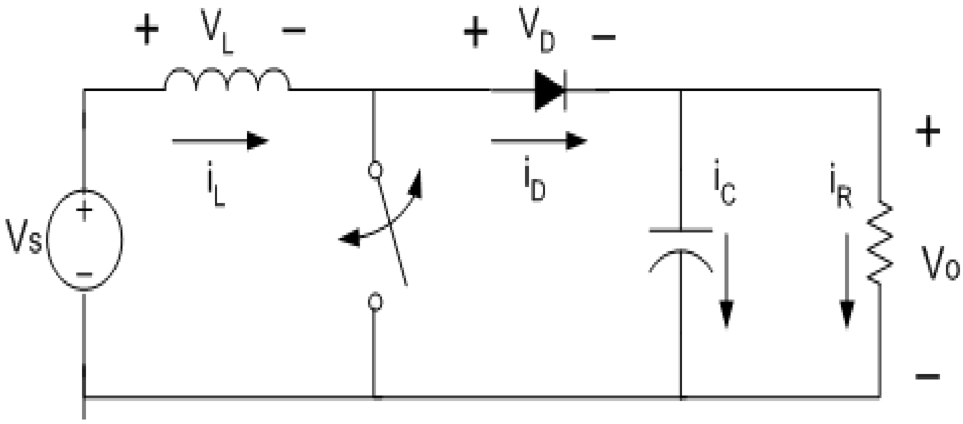

Figure 2.5: Boost converter

The boost converter is analysed in two condition which are during switch position is closed and switch position is opened. It is to be done before all the related formula of the boost converter can be derived.

2.5.1 Analysis for the Switch Closed

Figure 2.6 below shows the equivalent circuit of boost converter during the switch is closed.

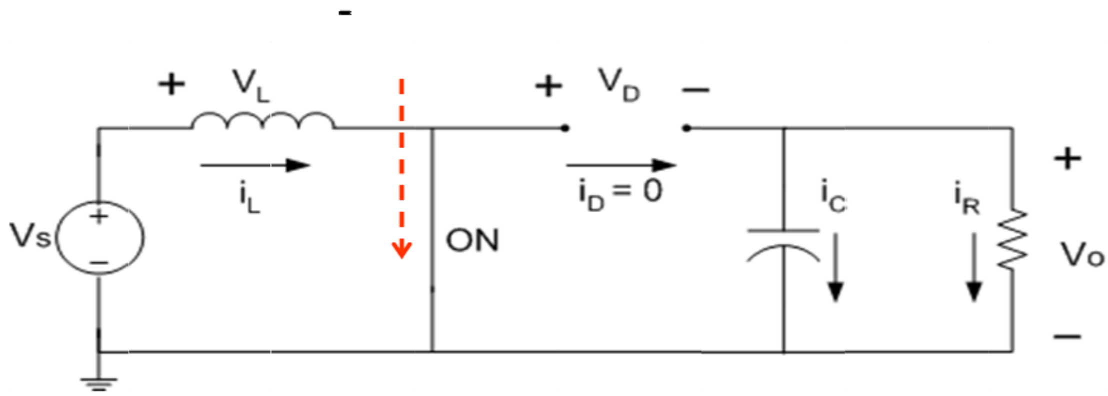

Figure 2.6: Boost equivalent circuit for the switch closed

When the switch is closed, the diode is reverse biased. Kirchhoff's voltage law around the path containing the source, inductor, and closed switch is

$$V_L = V_s = L\frac{di_L}{dt} \quad \text{or} \quad \frac{di_L}{dt} = \frac{V_s}{L} \tag{2.1}$$

The rate of change of current is a constant, so the current increases linearly while the switch is closed, as shown in Figure 2.7.

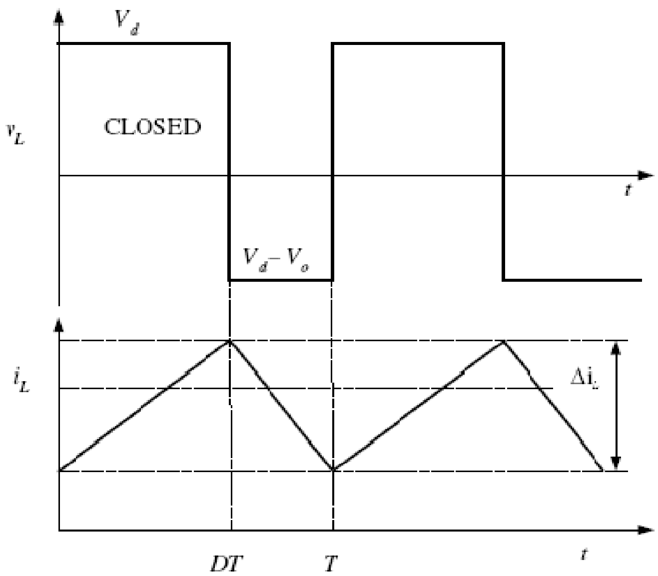

Figure 2.7: Waveforms for inductor voltage and current during switch closed

The change in inductor current is computed from

$$\frac{di_L}{dt} = \frac{\Delta i_L}{\Delta dt} = \frac{\Delta i_L}{T_{ON}} = \frac{\Delta i_L}{DT} = \frac{V_s}{L} \tag{2.2}$$

Solving for ΔiL for the switch closed,

$$(\Delta i_L)_{closed} = \left(\frac{V_s}{L}\right) \cdot DT \tag{2.3}$$

2.5.2 Analysis for the Switch Open

Figure 2.8 below shows the equivalent circuit of boost converter during the switch is opened.

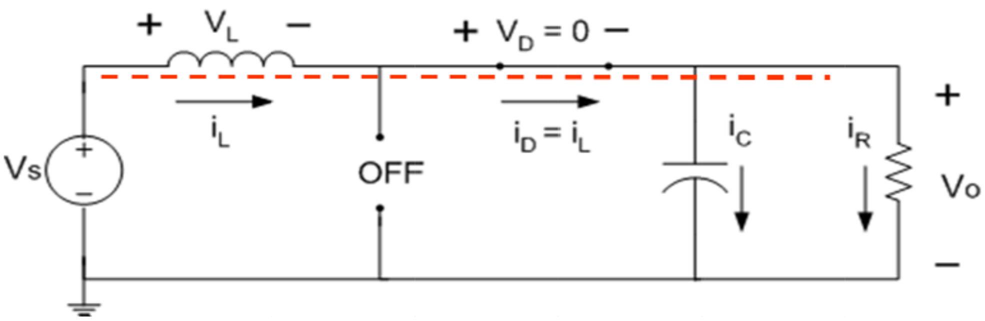

Figure 2.8: Boost equivalent circuit for the switch opened

Figure 2.9 below shows the inductor voltage and inductor current waveform during the switch is opened.

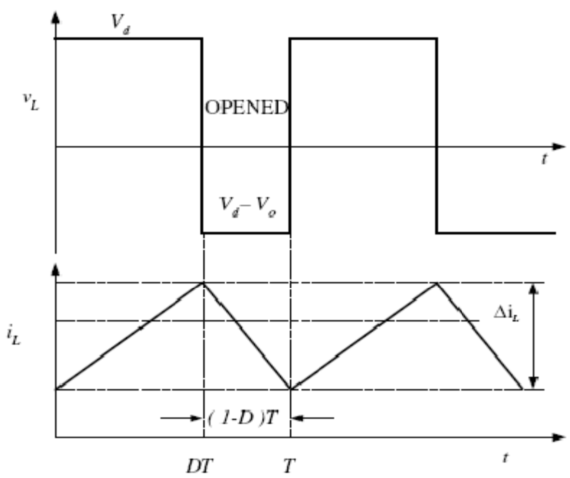

Figure 2.9: Waveforms for inductor voltage and current during switch opened

When the switch is opened, the inductor current cannot change instantaneously, so the diode becomes forward-biased to provide a path for inductor current. Assuming that the output voltage *Vo* is a constant, the voltage across the inductor is

$$V_L = V_s - V_o = L\frac{di_L}{dt}$$

$$\therefore \frac{di_L}{dt} = \frac{V_s - V_o}{L} \tag{2.4}$$

The rate of change of inductor current is a constant, so the current must change linearly while the switch is open. The change in inductor current while the switch is opened is

$$\frac{di_L}{dt} = \frac{\Delta i_L}{\Delta dt} = \frac{\Delta i_L}{T_{OFF}} = \frac{\Delta i_L}{(1-D)T} = \frac{V_s - V_o}{L} \tag{2.5}$$

Solving for ΔiL for the switch opened,

$$\left(\Delta i_L\right)_{opened} = \left(\frac{V_s - V_o}{L}\right)\cdot(1-D)T \tag{2.6}$$

2.5.3 Steady state operation

For steady-state operation, the net change in inductor current must be zero. Using Equation (2.3) and (2.6),

$$\left(\Delta i_L\right)_{closed} + \left(\Delta i_L\right)_{opened} = 0$$

$$\left(\frac{V_s}{L}\right)\cdot DT + \left(\frac{V_s - V_o}{L}\right)\cdot(1-D)T = 0$$

Solving for V_o

$$V_o = \frac{V_s}{1-D} \tag{2.7}$$

The average current in the inductor is determined by recognizing that the average power supplied by the source must be the same as the average power absorbed by the load resistor. Output power is

$$P_o = \frac{V_o^2}{R} = V_o I_o \tag{2.8}$$

and input power is *Vs Is* = *Vs IL*. Equating input and output powers and using Equation (2.7),

$$V_s I_L = \frac{\left(\frac{V_s}{1-D}\right)^2}{R} = \frac{V_s^2}{(1-D)^2 R} \tag{2.9}$$

By solving for average inductor current and making various substitutions, *IL* can be expressed as

$$I_L = \frac{V_s}{(1-D)^2 R} \tag{2.10}$$

Maximum and minimum inductor currents are determined by using the average value and the change in current from Equation (2.3).

$$I_{\mathrm{L(max)}} = I_L + \frac{\Delta i_L}{2} = \frac{V_s}{(1-D)^2 R} + \frac{V_s DT}{2\mathrm{L}} \tag{2.11}$$

$$I_{\mathrm{L(min)}} = I_L - \frac{\Delta i_L}{2} = \frac{V_s}{(1-D)^2 R} - \frac{V_s DT}{2\mathrm{L}} \tag{2.12}$$

2.5.4 Boost Converter modes of operation

The DC-DC converters can have two distinct modes of operation: Continuous conduction mode (CCM) and discontinuous conduction mode (DCM). In practice, a converter may operate in both modes, which have significantly different characteristics. However, this project only considers the DC-DC converters operated in CCM. CCM used for efficient power conversion and Discontinuous Conduction Mode DCM for low power or stand-by operation [10].

Figure 2.10 below shows the inductor current condition for CCM and DCM modes.

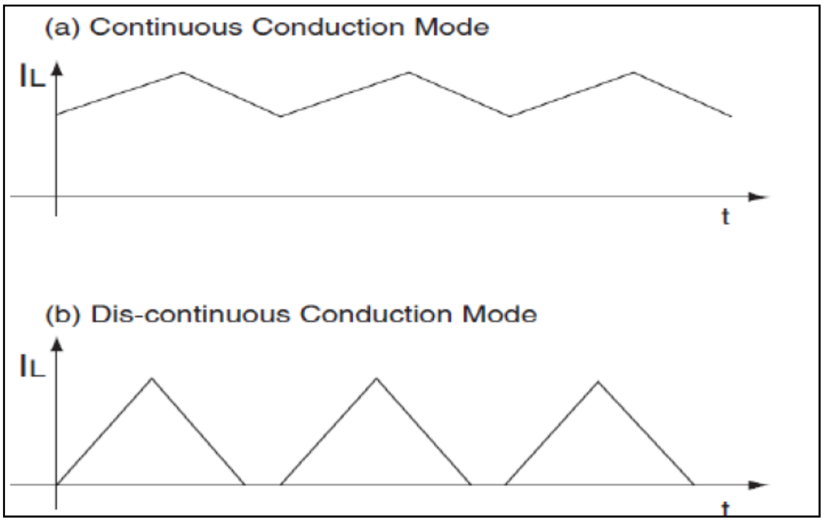

Figure 2.10: Inductor current waveform in CCM and DCM modes

2.6 Artificial Neural Network (ANN)

Artifical neural network are computational networks which attempt to simulate the network of biological central nervous system. The human brain is made of millions of individual processing elements that are highly interconnected. A schematic of single biological neurons is shown in Figure 2.11.

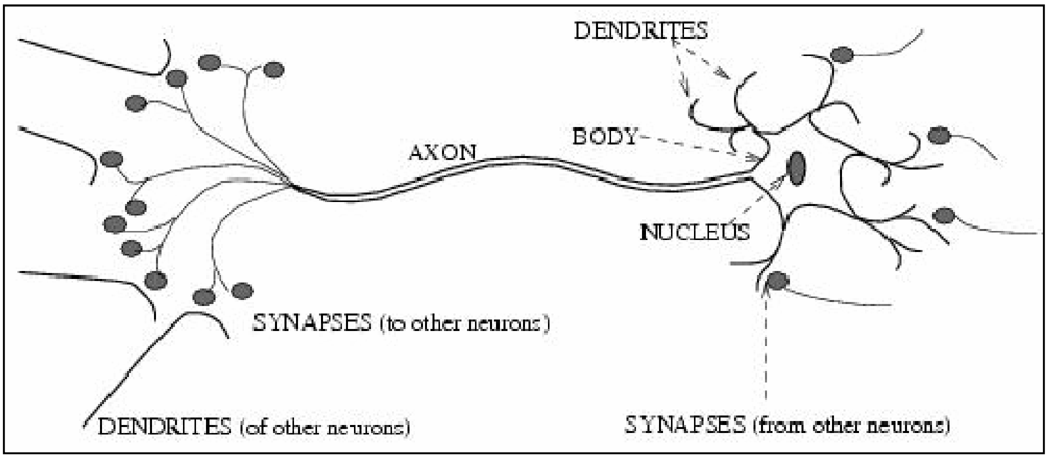

Figure 2.11: Schematic of a Biological Neuron

Information from the outputs of neurons, in the form of electrical pulses, is received by the cell at the connections called synapse. This mechanism of signal flow is not via electrical conduction but rather, attributed to charge exchange transported by the diffusion of ions. These synapses connect to the cell inputs, or dendrites and the single output of the neuron appears at the axon [5].

Artificial neural networks are made up of individual models of the biological neuron connected together to form a network. These neuron models are simplified versions of the actions of a real neuron. In simulating a biological neuron network, artificial neural networks allow using simple computational operations to solve complex, mathematical ill-defined and non-linear problems.

Another important feature of artificial neural networks is its learning capability. The learning mechanism is often achieved by appropriate adjustments of the weights in the synapses of the artificial neuron models. Training is done by non-linear mapping or pattern recognition. If an input set of data corresponds to a definitive signal pattern, the network can be trained to give correspondingly a desired pattern at the output. This capability to learn is due to the distributed intelligence contributed by the weights which can be done either online or offline. A properly trained neural network is able to generalize to new inputs by providing sensible outputs when presented with a set of input data that is has not been exposed to.

The simplest artificial neural network model is based on the McCulloch-Pitts neurons defined by Warren S. McCulloch and Walter Pitts in 1943. This neuron was static and did not include changing input weights. It dealt with variable inputs multiplied with fixed synaptic weight, with the product being summed. If this sum exceeded the neurons threshold, the neuron turned on or stayed on. If the sum was below the threshold of an inhibitory pulse was received, the neuron turned off or stayed off. The output of the neuron, y(i), is represented by:

$$y = \sum_{i=1}^{n} w_i x_i \tag{2.13}$$

Where w_i is the weight value, xi is the input and n represent the number of inputs.

In 1958, Frank Rosenblatt put together a learning machine, the perceptron by modifying the McCulloch-Pitts and Hebb models. This merged the concepts of synapse changes as a function of activity as well as the effects of combining multiple inputs to a single neuron. The perceptron is the simplest form of neural network consisting of a single neuron with adjustable synaptic weights and bias. This model is limited to performing pattern classification with only two linearly separable classes. The perceptron forms the basis of an adaline (adaptive linear neuron) proposed by B. Widrow in 1960. This is a single neuron model involving weight training according to the least square error algorithm, defined by the following equation:

$$W = \overline{W} + \eta \sum_i e(i)x(i) \tag{2.14}$$

Where W is the desired weight, $\overline{W}$ is the current weight, e(i) is the error term calculated by taking the difference between the desired and actual output, x(i) is the input to the neuron and η is the learning rate. The above mentioned can be generalized under a specific class known as the single layer perceptron (SLP). Another popular artificial neural network architecture is the multiple layer perceptron (MLP). This network consists of an input layer, a number of hidden layers and output layer as shown in Figure 2.12.

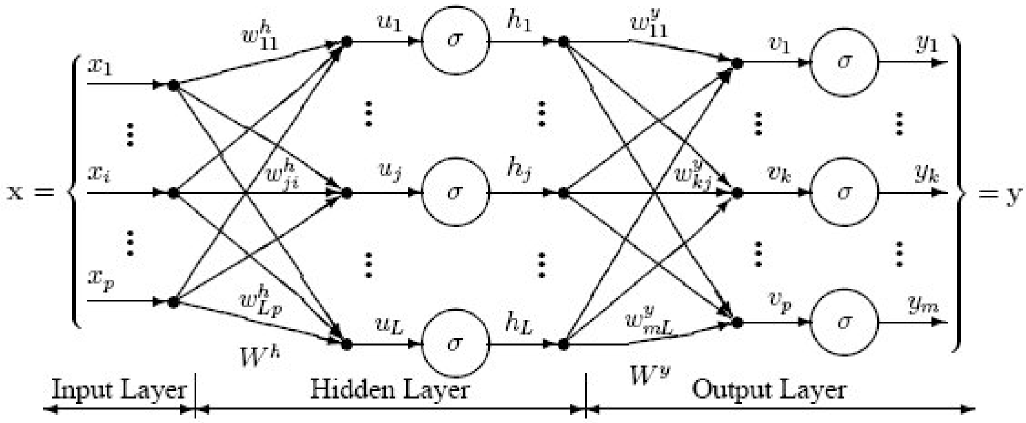

Figure 2.12: Multilayer perceptron

The output of each node is connected to the inputs of all the nodes in the subsequent layer. Data flows through the network in one direction from input to output. The network is trained in a supervised fashion involving both network inputs and target outputs.

Back-propagation (BP) is a supervised learning technique used for training artificial neural networks. It was first described by Paul Werbos in 1974 and further developed by David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams in 1986. As the algorithm's name implies, the errors (and therefore the learning) propagate backwards from the output nodes to the inner nodes. So technically, BP is used to calculate the gradient of the error of the network with respect to the network's modifiable weights. This gradient is almost always used in a simple stochastic gradient descent algorithm to find weight that minimizes the error. It is important to note that BP networks are necessarily multilayer (usually with one input, one hidden and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers, whereas a multilayer network using only linear activation functions is equivalent to a single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function and the Gaussian functions.

2.7 PID Controller

Most of the control techniques in industrial applications are embedded with the Proportional-Integral-Derivative (PID) controller. PID control is one of the oldest techniques. It uses one of its families of controllers including P, PD, PI and PID controllers. There are two reasons why nowadays it is still the majority and important in industrial applications. First, its popularity stems from the fact that the control engineer essentially only has to determine the best setting for proportional, integral and derivative control action needed to achieve a desired closed-loop performance that obtained from the well-known Ziegler-Nichols tuning procedure.

A proportional integral derivation controller (PID Controller) is a generic control loop feedback mechanism widely used in industrial control system. A PID is most commonly used feedback controller. Over 90% of the controllers in operation today are PID controllers (or at least some form of PID controller like a P or PI controller). This approach is often viewed as simple, reliable, and easy to understand.

Controllers respond to the error between a selected set point and the offset or error signal that is the difference between the measurement value and the set point. Optimum values can be computed based upon the natural frequency of a system. Too much feedback (positive feedback cause stability problems) causes increasing oscillation. With proportional (gain) only control the output increases or decreases to a new value that is proportional to the error. Higher gain makes the output change larger corresponding to the error. Integral can be added to the proportional action to ramp the output at a particular rate thus bring the error back toward zero. Derivative can be added as a momentary spike of corrective action that tails off. Derivative can be a bad thing with a noisy signal.

Typical steps for designing a PID controller are;

i. Determine what characteristics of the system need to be improved.

ii. Use KP to decrease the rise time.

iii. Use KD to reduce the overshoot and settling time.

iv. Use KI to eliminate the steady-state error.

Equation below shows the mathematical equation of designing a PID controller based on the Figure 2.13.

$$u = K_p e + K_I \int edt + \frac{de}{dt} \tag{2.15}$$

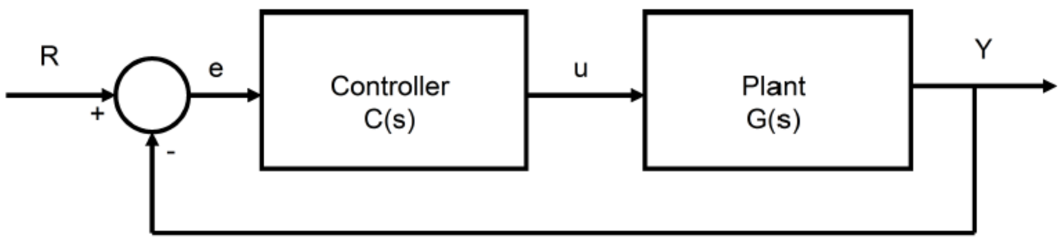

Figure 2.13: PID controller structure

The variable *e* denotes the tracking error, which is sent to the PID controller. The control signal *u* from the controller to the plant is equal to the proportional gain (K_P) times the magnitude of the error plus the integral gain (K_I) times the integral of the error plus the derivative gain (K_D) times the derivative of the error.

CHAPTER 3

METHODOLOGY

3.1 Project design

Figure 3.1 below shows a project block diagram. Photovoltaic (PV) will supply input voltage to the boost converter depending on the value of sun irradiation. The neural network controller function is to adjust the necessary duty cycle to ensure that the boost converter will produce output voltage that will equal to the reference voltage.

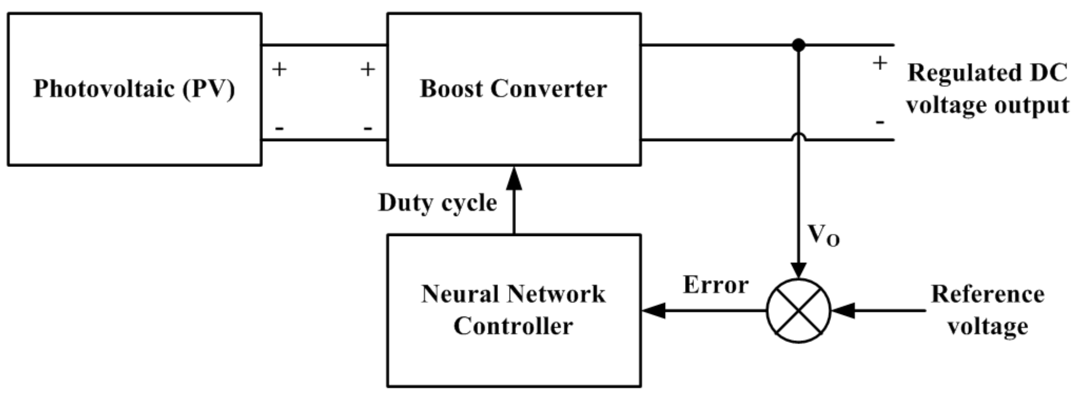

Figure 3.1: Block diagram of the proposed PV boost system control by neural network controller

3.2 Modelling of boost converter

3.2.1 Average State-Space representation for dc-dc boost converter

The ideal dynamics of the boost converter are derived by the state space averaging method. The boost converter of Figure 3.2 below with a switching period of T and a duty cycle of D is given. The converter will be operating in a continuous conduction mode (CCM) and the state space equations when the main switch is ON are shown by equation below [11].

$$\begin{cases} \dfrac{di_L}{dt} = \dfrac{1}{L}(V_{in}) \\ \dfrac{dv_o}{dt} = \dfrac{1}{C}(-\dfrac{v_o}{R}) \end{cases}, \quad 0 < t < dT, \quad Q:ON \tag{3.1}$$

State space equations when the main switch in OFF are shown by equation below.

$$\begin{cases} \dfrac{di_L}{dt} = \dfrac{1}{L}(v_o) \\ \dfrac{dv_o}{dt} = \dfrac{1}{C}(-i_L - \dfrac{v_o}{R}) \end{cases}, \quad dT < t < T, \quad Q:OFF \tag{3.2}$$

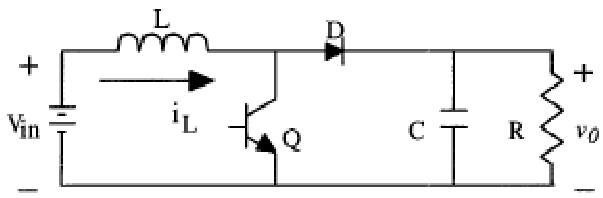

Figure 3.2: DC – DC Boost converter

The state space averaging model will result in the following equations [11].

$$\begin{cases} \dot{x}_1 = \dfrac{-1-d}{L}x_2 + \dfrac{1}{L}V_{in} \\ \dot{x}_2 = \dfrac{1-d}{C}x_1 - \dfrac{1}{RC}x_2 \end{cases} \tag{3.3}$$

Where x_1 and x_2 are the moving averages of i_L and V_o respectively.

In state space representation the averaging state space formula of the converter during turn-on and turn-off are given as

$$\dot{x} = Ax + Bu \tag{3.4}$$

where

$$x = \begin{bmatrix} i_L \\ V_o \end{bmatrix}$$

$$u = V_{in}$$

Therefore

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & \dfrac{-1-d}{L} \\ \dfrac{1-d}{C} & -\dfrac{1}{RC} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} \dfrac{1}{L} \\ 0 \end{bmatrix} V_{in} \tag{3.5}$$

where

$$A = \begin{bmatrix} 0 & \dfrac{-1-d}{L} \\ \dfrac{1-d}{C} & -\dfrac{1}{RC} \end{bmatrix}$$

$$B = \begin{bmatrix} \dfrac{1}{L} \\ 0 \end{bmatrix}$$

Figure 3.3 below shows the simulink diagram of the state space average model of the boost converter. The parameters which influence the operation of the boost converter are input voltage V_{in} , output voltage V_o, inductance L and capacitance C which are given in the Table 3.1.

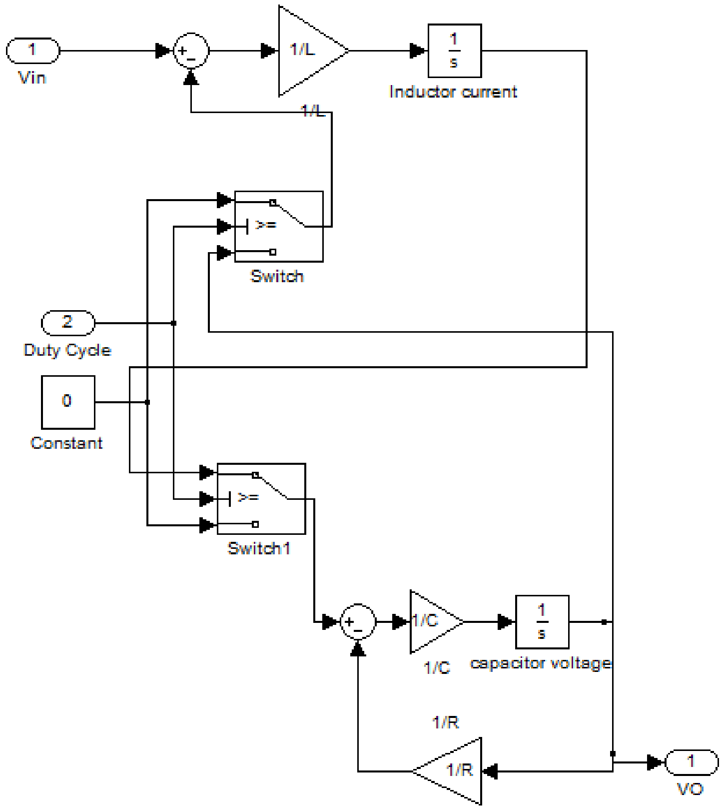

Figure 3.3: Simulink diagram of state space averaged model of the boost converter

Table 3.1: Parameters of the boost converter

Input voltage, Vin	6 – 20 V
Output voltage , Vo	46 V
Inductance, L	278 µH
Capacitance, C	2.5 mF
Resistance, R	13 Ω

3.3 Proposed neural network controller (NNC) architecture

This project will be using a two-layer feed-forward neural network with sigmoid hidden neurons and linear output neurons as shown in Figure 3.4 below. Two units of neurons will be used for hidden layer and a single neuron for output layer. Chapter 4 will explain in detail why only two neurons will be used for the neural network controller.

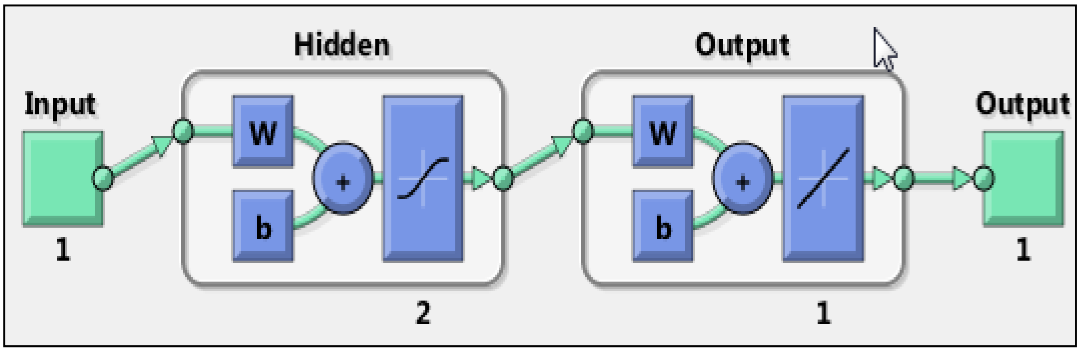

Figure 3.4: Proposed neural network structure

The input to the neural network controller (NNC) is the error values between the reference voltage and the feedback voltage as previously shown in the block diagram on Figure 3.1. NNC will analyse the resulted error values to produce an appropriate duty cycle signal as a switching signal for the boost converter. Figure 3.5 shows the neural network simulink subsystem block.

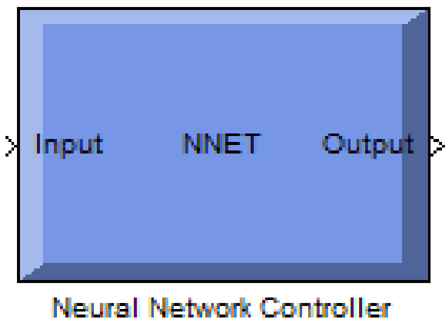

Figure 3.5: Simulink block of neural network controller

Figure 3.6 shows the neural network system inside the subsystem block where it shows that the neural network system consist of two neuron layers.

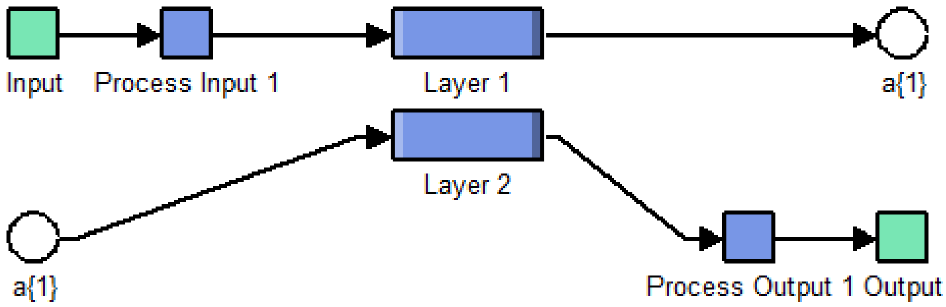

Figure 3.6: Look under mask block of neural network controller

Layer 1 is the hidden layer of the NNC. Figure 3.7 shows the hidden layer architecture where is shows the sum of the weight and bias of the neural network. The sigmoid transfer function is used for the hidden layer.

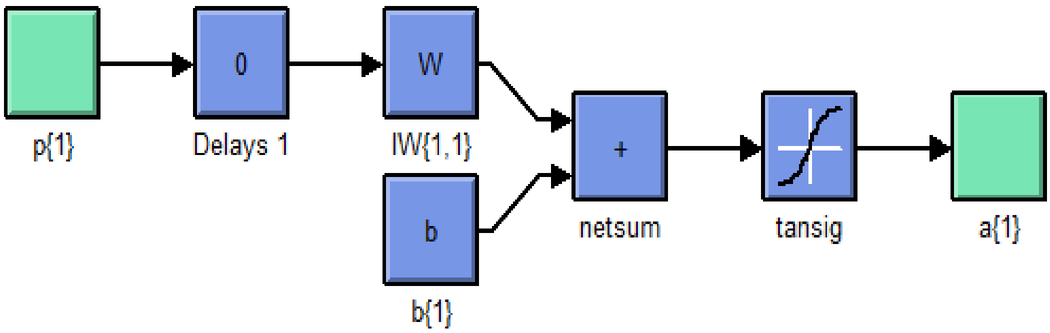

Figure 3.7: Hidden layer architecture of the neural network

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