VOLTAGE TRACKING OF A DC-DC CUK CONVERTER USING NEURAL NETWORK CONTROL

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ABSTRACT

This paper presents a control scheme of a neural network for a DC-DC Cuk converter. The proposed neural network control (NNC) strategy is designed to produce regulated variable DC output voltage. The mathematical model of Cuk converter and artificial neural network algorithm is derived. Cuk converter has some advantages compared to other type of converters. However the nonlinearity characteristic of the Cuk converter due to the switching technique is difficult to be handled by conventional controller such as proportional-integral-derivative (PID) controller. To overcome this problem, a neural network controller with online learning back propagation algorithm is developed. The NNC designed tracked the converter voltage output and improve the dynamic performance regardless load disturbances and supply variations. The proposed controller effectiveness during dynamic transient response is then analyze and verified using MATLAB-Simulink. Simulation results confirm the excellent performance of the proposed NNC, exhibits better dynamic performance compared to the classical PID controller.

ABSTRAK

Kertas ini membentangkan satu skim kawalan jaringan saraf untuk penukar arus terus (AT-AT) jenis Cuk. Pengawal jaringan saraf yang dicadangkan (NNC) direkabentuk untuk menghasilkan keluaran voltan AT yang teratur. Model matematik bagi penukar Cuk dan algoritma jaringan saraf tiruan (ANN) diterbitkan. Penukar Cuk mempunyai beberapa kelebihan berbanding penukar AT yang lain. Bagaimanapun ciri-ciri ketidaklelurusan penukar Cuk disebabkan oleh teknik pensuisannya amat sukar ditangani oleh pengawal konvensional seperti pengawal jenis pembezaan–kamiran-berkadaran (PID). Untuk mengatasi masalah ini, pengawal jaringan saraf dengan teknik pembelajaran dalam talian berdasarkan algoritma penyebaran belakang dibangunkan. Pengawal jaringan saraf yang dibangunkan akan memperbaiki prestasi dinamik tanpa dipengaruhi oleh perubahan masukan atau gangguan beban. Keberkesanan pengawal yang dibangunkan semasa sambutan transient dinamik dianalisa dan disahkan menggunakan simulasi MATLAB-Simulink. Keputusan simulasi mengesahkan prestasi cemerlang pengawal jaringan saraf yang dibangunkan, mempamerkan prestasi dinamik yang lebih baik berbanding pengawal konvensional PID.

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SYMBOLS

Δ	Small constant value
C	capacitance
D	Duty cycle
Ds	Diode
f	Frequency
f_s	Switching frequency
i_C	Capacitor current
i_D	Diode current
i_L	Inductor current
k_p, k_I, k_d	Proportional gain and integral gain of PID controller
L	Inductance
Q	Charge
R	Load resistance
S	Controllable switch
T_S	Switching time
u	Control input
v_0	Output voltage
v_C	Capacitor voltage
v_{in}	Input voltage
v_L	Inductor voltage
V_{ref}	Reference voltage
x	State vector
ω	weight

ABBREVIATIONS

ANN	Artificial Neural Network
BPA	Back Propagation Algorithm
CCM	Continuous Conduction Mode
DC	Direct Current
DCM	Discontinuous Conduction Mode
EW	Error Weight
FNN	Feedforward Neural Network
FNNC	Fuzzy-Neural Network Controller
FNSM	Fuzzy-Neural Sliding Mode
HVDC	High Voltage Direct Current
KVL	Kirchoff Voltage Law
NNC	Neural Network Control
PD	Proportional Derivative
PI	Proportional Integral
PID	Proportional Integral Derivative
PWM	Pulse Width Modulation

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CHAPTER 1

INTRODUCTION

1.1 Project Background

The role of power conversion is to facilitate the transfer of power from the source to the load by converting voltages and currents from one magnitude and/or frequency to another. This function of power processing is performed through an analog power circuit known as the power converter. A controller is required for the management of this power transfer process. The ultimate aim of the entire conversion process is to have as high efficiency as possible, while achieving as closely as possible the desired conversion and control functions. Reliable and sustainable sources in power electronic are vital to adhere the continuous power supply.

Basic configurations of DC–DC converters, namely, the buck, boost, buck-boost, and Cuk converters. Cuk converters are widely used in many industries such as aerospace, electric trains and modern control in HVDC power supply. Cuk converter has many advantages which exhibit the characteristics of higher efficiency because of low input and output current ripple, minimal radio fequency interference, thus resulting smaller in size and weight. In fact, by careful adjustment of the inductor values, the ripple in either input or output can be nulled completely.

However, operation of the switching devices causes the Cuk converter inherent the nonlinear characteristics. Nonlinear system requires a controller with higher degree of dynamic response. In linear system model, the Proportional-Integral-Differential (PID) controller parameters are easy to determine and resulting good control performances. PID controllers commonly used in industries because of their simplicity verified by M.Y.Hassan & G. Khotapali (2010).

A study by Rubaai A., I. Burge & Garuba (2008) shows that PID controller is unable to adapt and approach the best performance when applied to nonlinear system. It will sufer from dynamic response, produces overshoot, longer rise time and settling time which in turn will influenced the output voltage regulation of the Cuk converter. In order to improve control performance of the Cuk converter, many studies on several intelligence controllers such as fuzzy logic control have been reported in (Rubaai, A. *et al.,* 2008) and Evgueniy Entchev & Libing Yang (2007), neural network controller by (Mahdavi, J. *et al.*, 2005) and hybrid neuro-fuzzy control methods for Cuk converter by K. Mehran, D. Giaouris & B. Zahawi (2010). Furthermore, the implementations of the neural network control (NNC) have been proposed recently in (Utomo, W. *et al.,* 2011).

In addition, the NNC also have been applied for several power sources applications such as solar photovoltaic (PV) modules with voltage tracking properties. A study by M. Vaigundamoorthi & R. Ramesh (2011) shows that Cuk converter resulting in high conversion efficiency at high-frequency operation, improved transient, steady state response without significant increase in voltage and current stresses on switches.

Some researchers have developed learning back propagation scheme to improve the effectiveness of nonlinear system. A study by (Utomo, W. *et al.,* 2011) shows that learning back propagation scheme improves the performance of the NNC by improving the dynamic response and minimizing the steady state error.

In this project, neural network controller (NNC) scheme with back propagation algorithm is proposed for the voltage tracking of a DC-DC Cuk Converter using MATLAB Simulink. The developed NNC reacted as an adaptive controller that has an ability to learn instantaneously and updated the control parameters based on external disturbance and internal variation of the converter with minimum steady state error, overshoot and rise time of the output voltage.

1.2 Problem Statement

Most of the common DC-DC converters such as Buck, Boost and Buck-Boost converter which is capable to step-up or step-down the output voltage produce higher current ripple. This will influenced and decreased the output voltage regulation and efficiency of the converter. These weaknesses can be overcomed by Cuk converter which exhibit low input and low output current ripple. Thus the efficiency of the converter will be increased. These factors will contribute to minimise the radio fequency interference, thus the converter size becomes smaller and lighter (compact).

However the switching technique of the Cuk converter causes the converter system to be nonlinear system. Nonlinear system requires a controller with higher degree of dynamic response. Proportional-Integral-Differential (PID) controllers has an advantages in term of simple structure and low cost. However, PID controllers unable to adapt to the external disturbances and internal variations parameters and suffer from dynamic response of the system. PID controllers will produce higher overshoot, longer rise time and settling time which in turn will decreased the output voltage regulation of the Cuk converter.

Since the Cuk converter is a nonlinear system, the neural network control (NNC) method will be developed to improve the voltage tracking of the converter. The developed NNC has the ability to learn instantaneuously and adapt its own controller parameters based on external disturbances and internal variation of the converter. Thus this NNC can overcome the problems stated to obtain the required output voltage with better performances; decreasing overshoot and oscillation, faster rise time, faster settling time and minimised steady state error of the system.

1.3 Project Objectives

The objectives of this project are;

i. To model and analyse a DC-DC Cuk converter and simulate using MATLAB Simulink.

ii. To develop voltage tracking of a DC-DC Cuk converter using Neural Network Control (NNC) method.

iii. To analyze the impact of Neural Network Controller (NNC) on voltage tracking DC-DC Cuk converter performances (reducing over shoot, rise time and steady state error).

1.4 Project Scopes

The scopes of this project is to simulate the proposed method of voltage tracking of non-isolated Cuk converter by using Neural Network Controller (NNC) with MATLAB Simulink software. The proposed NNC architecture with 1-3-1 neurons structure; the input layer consists of input neurons, three neurons at the hidden layer followed by an output layer. Analysis of the converter will be done for continuous current mode (CCM) only. Analysis in this mode of operation use a state-space averaged model of the Cuk converter with small signal analysis. The PID controller will be developed to compare the effectiveness of the proposed controller.

1.5 Thesis Organization

This thesis is organized as follows: Chapter 2 discusses the basic concept of a Cuk converter and describes the development of dynamic modelling. An introduction to concept and design of learning back propagation algorithm of neural network control is also detailed. Mathematical model of the Cuk converter is derived in Chapter 3 and the proposed Neural Network Controller for voltage tracking of a DC-DC Cuk converter is developed. Chapter 4 shows the simulation results of the NNC controller and the dynamical responses. Finally, conclusions are summarized in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Controller Development

Switching control techniques of the nonlinear DC-DC converter has been great issues in power conversion system. Usually, the control problem consists in defining the desired nominal operating conditions and regulating the circuit so that it stays close to the nominal, when the system is subject to external disturbances and internal variations. Modeling errors also can cause its operation to deviate from the nominal value. Many approaches for designing controller for Cuk converter has been deeply studied and conducted to obtain high quality and reliable power conversion system.

In the past decade, basically switching control enlightened towards the applications of Proportional-Integral (PI); enhanced to Proportional-Integral-Derivative (PID) controllers. A study by A.J. Forsyth and S.V. Mollow (1998) shows that these classical control methods are very efficient when the converter model is well-known; the working-point of the load is well defined. If the dynamics of the whole converter is more complex, varying and/or uncertain, advanced control laws have to be introduced.

The controller must keep the DC-DC converter within a certain percentage of the specified nominal operating points in the presence of disturbances and modeling errors.

Unfortunately, PID controller does not always fulfill the above mentioned control specifications, especially when disturbance rejection and transient response time requirements are concerned, due to the highly nonlinear characteristics of the converter. PID will suffer from dynamic transient time response; higher overshoot and longer rise time reported by Loic Michel, I. Cedric Join and Michel Fliess (2010).

A large number of possible intelligence controllers among others, fuzzy logic control, neural network control and hybrid neuro-fuzzy control have been reported in M. Milanovic and D. Gleich (2005). Many types of controllers have been proposed on the previous papers.

By referring to the (K.H. Cheng, *et al.*, 2007), the research focused on an efficient simulation model of Cuk converter by applying the fuzzy-neural sliding mode control (FNSM) as the controller. The simulation model of FNSM developed improved the dynamic characteristics of Cuk converter. The fuzzy logic controller is designed purposely to ensure the converter system is able to reach the steady state condition in a short time. The result obtained from fuzzy logic controller will compared with the PID controller. The result shows that the fuzzy logic controller is better performance compared with PID controller.

Development of Proportional-Derivative and Integral (PD-I) type Fuzzy-Neural Network Controller (FNNC) based on Takagi-Sugeno fuzzy model is proposed for Cuk converter to achieve satisfied performance under steady state and transients conditions presented in (K. Mehran. *et al.*, 2010). The PD-FNNC is activated during transient states and the PI-FNNC is activates in steady state region.

After the pioneering studies done by (Loic Michel, *et al.*, 2010), a great deal of research has been directed at developing techniques for averaged modeling of different classes of switching converters (S.R. Sanders, *et al.*, 2009) and for an automatic generation of the averaged models. The motivation of such studies was the simplest possible selection of continuous models adequate to capture all the main features of the switching converters in term of stability, dynamic characteristics, and effectiveness of the design.

Rapid technologies discover intelligent controls of neural network controllers (NNC) has great capability to adapt by updating its learning process using back propagation and sensitivity adjustment. Therefore it is suitable for nonlinear control system. NNC found to be improving the dynamic characteristic of the converter compared with the conventional method. Voltage tracking of Cuk converter using NNC demonstrates the results in achieving the minimum error between regulated DC output voltage and reference voltage injected to the system. This has been verified in (Utomo, W. *et al.,* 2011). From the simulation results, it shows that when the proposed NNC is trained with back propagation algorithm, the overshoot has been greatly decreased and the Cuk converter output voltage can reach its steady state faster. In the case of load disturbances, the NNC can shorten the settling time compared with ordinary PID control with a better tracking performance.

2.2 Cuk converter

The Cuk converter is a type of step-down/step-up converter based on a switching boost-buck topology. Essentially, the converter is composed of two sections, an input stage and an output stage. The schematic of the Cuk converter is presented in Figure 2.1, where V_{in} is input voltage source, V_o is output voltage, input inductor L_1, controllable switch S, energy transfer capacitor C_1, diode D_1, filter inductor L_2, filter capacitor C_2, and load resistance R. An important advantage of this topology is a continuous current at both the input and the output of the converter. Disadvantages of the Cuk converter are a high number of reactive components and high current stresses on the switch, the diode, and the capacitor C_1.

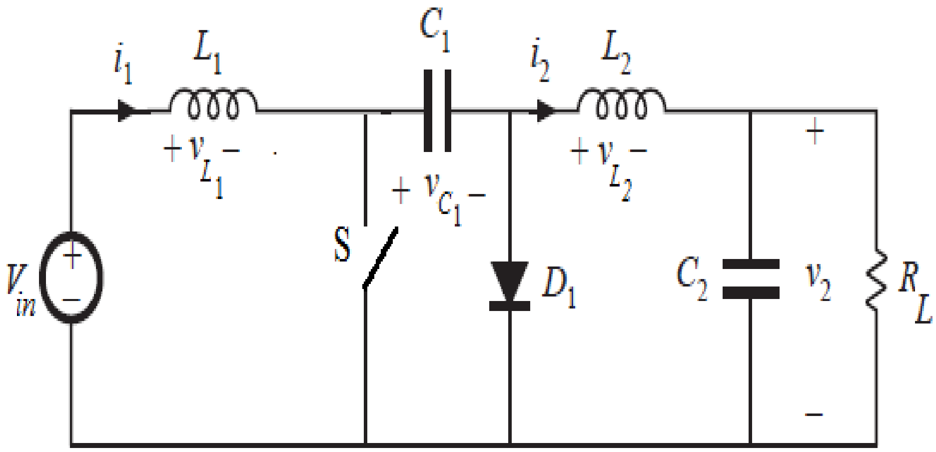

Figure 2.1: Cuk converter circuit

2.2.1 Cuk converter analysis

Analysis for Cuk converter operation using a state-space averaged model developed as described by the inventor, Slobodan M., Cuk, 1977. These analyses involve the use of steady-state and dynamic small signal models of the converter to determine the responses of the converter when operating in the operational continuous current mode (CCM). In the subsequent, parasitic resistances are negligibly small, and all elements are assumed ideal. During the operation, the switch S switches on and off by an externally applied control signal at a switching frequency 'f_S', and duty ratio 'D' within the period T. CCM operation implies that inductor currents do not fall to zero at any instant within the period. The operation of the converter within the period T can be divided into two states for CCM operation where duty cycle of the converter is $D = T_{on}/T$ and $D' = 1 - D$.

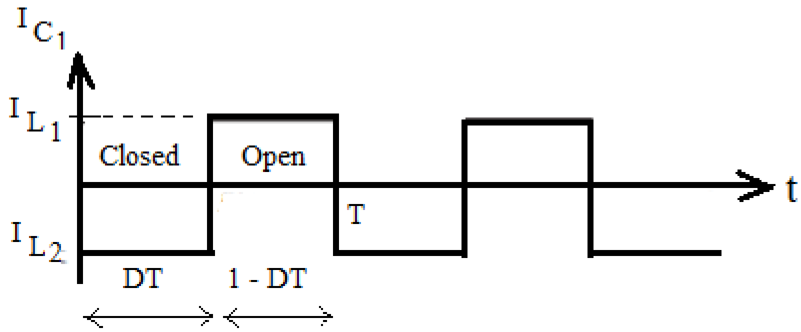

Figure 2.2: Current in inductor L

2.2.1.1 When switch S is 'on', 0 < t < DT

In the state switch S is on, the converter circuit takes the form shown in Figure 2.3. There are two separate meshes. In the left hand mesh the input inductor L_1 stores energy from the source over S during the time interval. The energy storage capacitor C_1 is now in the right hand mesh and it transfers stored energy, over S, to the load R, and energy storing elements L_2 and C_2. Due to the inappropriate voltage polarity of the charge on the capacitor C_1, diode D_1 is reverse biased and therefore off. The common path between the two meshes is provided by switch S this time.

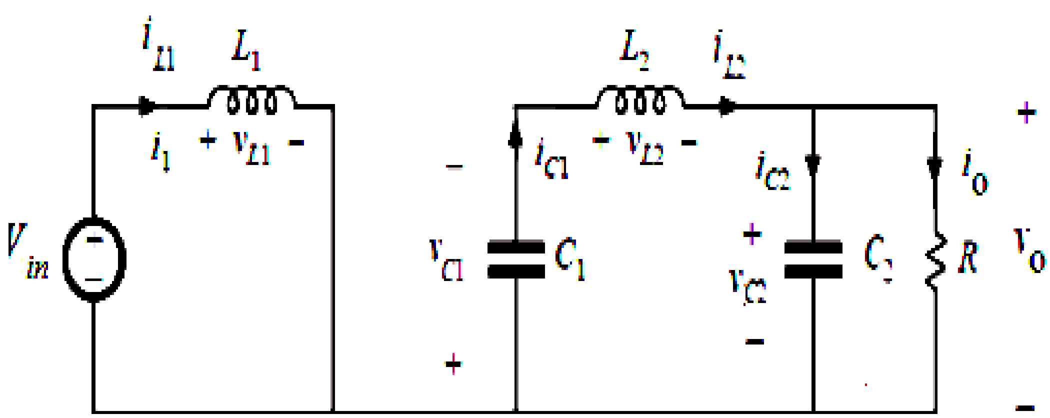

Figure 2.3: Cuk converter equivalent circuit when S is on

In the left hand mesh, $v_{L_1} = v_{in}$

$$L_1 \frac{di_{L_1}}{dt} = v_{in}$$

$$\frac{di_{L_1}}{dt} = \frac{1}{L_1}(v_{in}) \tag{2.1}$$

In the right hand mesh, $i_{C_1} = i_{L_2}$

$$\frac{dv_{C_1}}{dt} = \frac{i_{L_2}}{C_1} \tag{2.2}$$

$$v_{L_2} = -v_{C_1} - v_o$$

$$L_2 \frac{di_{L_2}}{dt} = -v_{C_1} - v_o$$

$$\frac{di_{L_2}}{dt} = \frac{-v_{C_1} - v_o}{L_2} \tag{2.3}$$

The current through capacitor C_2, $i_{C_2} = i_{L_2} - i_o$

$$\frac{dv_{C_2}}{dt} = \frac{i_{L_2}}{C_2} - \frac{v_o}{RC_2} \tag{2.4}$$

Current passing through S is the sum of input and output inductor currents:

$$i_s = i_{L_1} + i_{L_2} \tag{2.5}$$

2.2.1.2 When switch S is 'off', DT < t < T

The circuit is divided into two separate meshes as seen in Figure 2.4. When S is off, the energy storage capacitor C_1 in the left hand mesh is charged through L_1 and D_1 in this time interval. Diode D_1 common to both meshes is forward biased in this time interval. L_2 and C_2 in the right hand mesh transfer their stored energies, left from the previous time interval during the steady-state operation, to the load R over D_1 again.

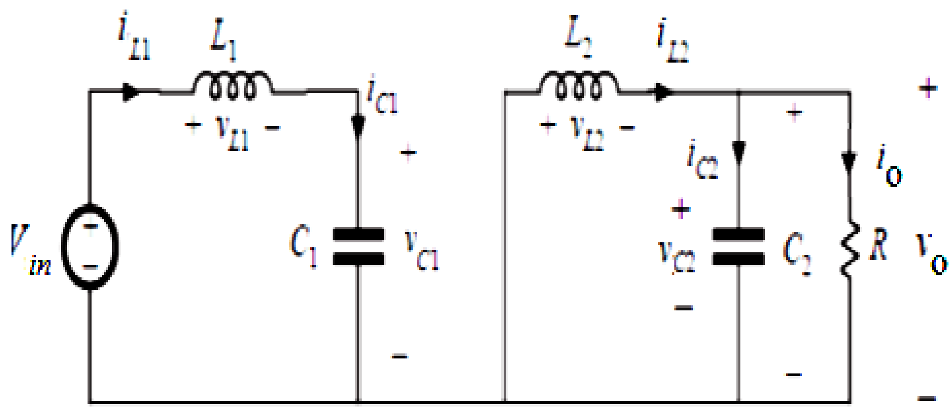

Figure 2.4: Cuk converter equivalent circuit when S is off

In the left hand mesh, by applying KVL;

$$v_{in} = v_{L_1} + v_{C_1} \tag{2.6}$$

$$v_{L_1} = v_{in} - v_{C_1}$$

$$L_1 \frac{di_{L_1}}{dt} = v_{in} - v_{C_1}$$

$$\frac{di_{L_1}}{dt} = \frac{1}{L_1}(v_{in} - v_{C_1}) \tag{2.7}$$

The current through capacitor C_1, $\quad i_{C_1} = i_{L_1}$

$$\frac{dv_{C_1}}{dt} = \frac{i_{L_1}}{C_1} \tag{2.8}$$

In the right hand mesh, by applying KVL;

$$v_{L_2} = -v_o$$

$$L_2 \frac{di_{L_2}}{dt} = -v_o$$

$$\frac{di_{L_2}}{dt} = \frac{-v_o}{L_2} \tag{2.9}$$

The current through capacitor C_2,

$$i_{C_2} = i_{L_2} - i_o$$

$$\frac{dv_{C_2}}{dt} = \frac{i_{L_2}}{C_2} - \frac{v_o}{RC_2} \tag{2.10}$$

Current passing through D_1 is the sum of input and output inductor currents:

$$i_{D_1} = i_{L_1} + i_{L_2} \tag{2.11}$$

2.2.2 Cuk waveforms

Based on the equations derived during the switching intervals, off and on state, the main waveforms of the voltage across inductor v_{L_1} and v_{L_2} and capacitor current i_{C_1} and i_{C_2} of Cuk converter are presented in Figure 2.5. (Rashid, 2004).

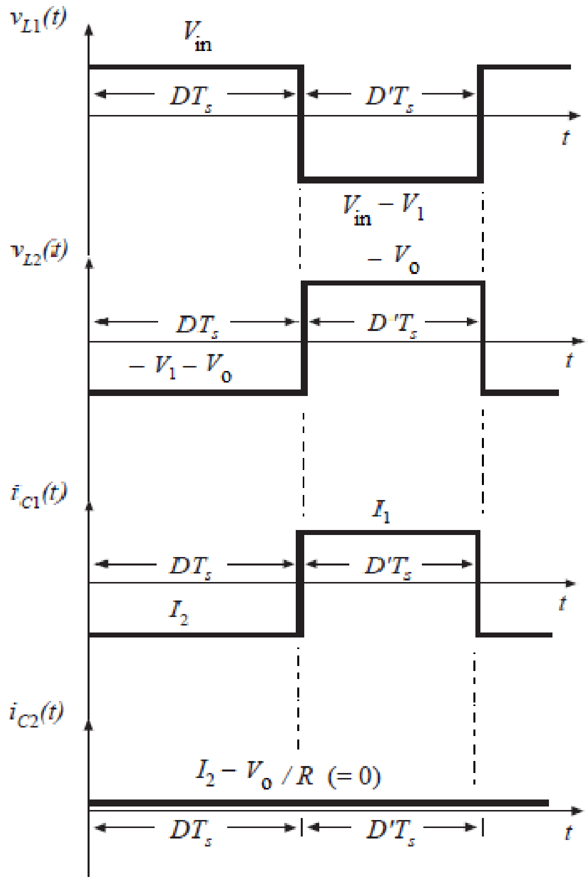

Figure 2.5: Cuk converter waveforms

In steady state, the transfer function can be determined by average current through capacitor in one period is zero. Therefore, by solving the linear equation during turn-on and turn-off, the average output voltage is derived as follows;

$$[(i_{C1})_{closed}]\mathrm{DT} + \left[(i_{C1})_{open}\right](1-D)T = 0$$

$$(-i_{L_2})\mathrm{DT} + (i_{L_1})(1-D)T = 0$$

$$\frac{i_{L_1}}{i_{L_2}} = \frac{D}{1-D} \tag{2.12}$$

$$\frac{i_{L_1}}{i_{L_2}} = -\frac{v_o}{v_{in}} \tag{2.13}$$

Combining equation (2.12 and (2.13), the relationship of output-input voltage function yields the transfer function as follows;

$$\frac{v_o}{v_{in}} = -\frac{D}{1-D} \tag{2.14}$$

Rearrange the transfer function equation in (2.14), the Cuk converter output voltage, v_o can be determined as;

$$v_o = -\frac{D}{1-D} v_{in} \tag{2.15}$$

The negative sign indicates a polarity reversal between output and input.

Based on equation (2.15), it is obviously shown that the output voltage of this converter is regulated according to the duty cycle (D) of the PWM input at fixed frequency. When the duty cycle (D) is less than 0.5, the output voltage of the converter is lower than the input voltage (step-down). If the duty cycle (D) is greater than 0.5, the output voltage of the converter is higher than the input voltage (step-up).

2.3 Operating Modes

The operation of DC-DC converters can be classified by two modes of operation: discontinuous current mode (DCM) and continuous current mode (CCM). In the DCM, the inductor current falls to zero during the time the switch is turned off. In the CCM, the current flowing through the inductor never falls to zero. A converter can be design in any mode of operation according to the requirement.

2.3.1 Discontinuous Conduction Mode (DCM)

When the inductor current has an interval of time staying at zero with no charge and discharge then it is said to be working in discontinuous conduction mode (DCM) operation and the waveform of inductor current is illustrated in Figure 2.5(a). At lighter load currents, converter operates in DCM. The regulated output voltage in DCM does not have a linear relationship with the input voltage as in CCM. In DCM, each switching cycle is divided into of three parts that is D_1T_S, D_2T_S and D_3T_S. During the third mode i.e in D_3T_S, inductor current stays at zero.

2.3.2 Continuous Conduction Mode (CCM)

When the inductor current flow is continuous of charge and discharge during a switching period, it is called continuous conduction mode (CCM). The inductor current waveform of CCM shown in Figure 2.5(b). The converter operating in CCM delivers larger current than in DCM. In CCM, each switching cycle T_s consists of two parts that is D_1T_S and D_2T_S. During D_1T_S inductor current increases linearly and then in D_2T_S it decreases linearly. In this thesis, only operation in the CCM is analysed.

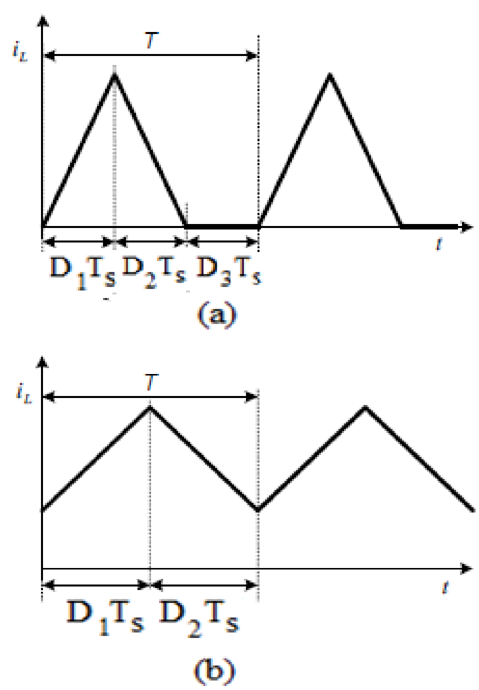

Figure 2.6: Inductor current waveform of converter: (a) DCM, (b) CCM

2.3.3 Steady State Operation

Steady-state operation requires that the inductor current at the end of the switching cycle be the same as that at the beginning, meaning that the net change in inductor current over one period is zero.

2.3.3.1 Component selection

It is a vital task to select the minimum value of components to ensure that the converter operates in CCM. In the preceding analysis, the capacitor was assumed to be very large to keep the output voltage constant. In practice, the output voltage cannot be kept perfectly constant with a finite capacitance. The variation in output voltage, or ripple, is computed from the voltage-current relationship of the capacitor. The current in the capacitor is;

$$i_{C_2} = i_L - i_o \tag{2.16}$$

The average voltage across C_2 is computed from KVL around the outermost loop. The average voltage across inductors is zero for steady-state operation, resulting in

$$v_{C_2} = v_o \tag{2.17}$$

While the capacitor current is positive, the capacitor is charging. From the definition of capacitance,

$$Q = C_2 V_o \tag{2.18}$$

$$\Delta Q = C_2 \Delta V_o \tag{2.19}$$

$$\Delta V_o = \frac{\Delta Q}{C_2} \tag{2.20}$$

The change in charge ΔQ is the area of the triangle above the time axis as shown in Figure 2.7.

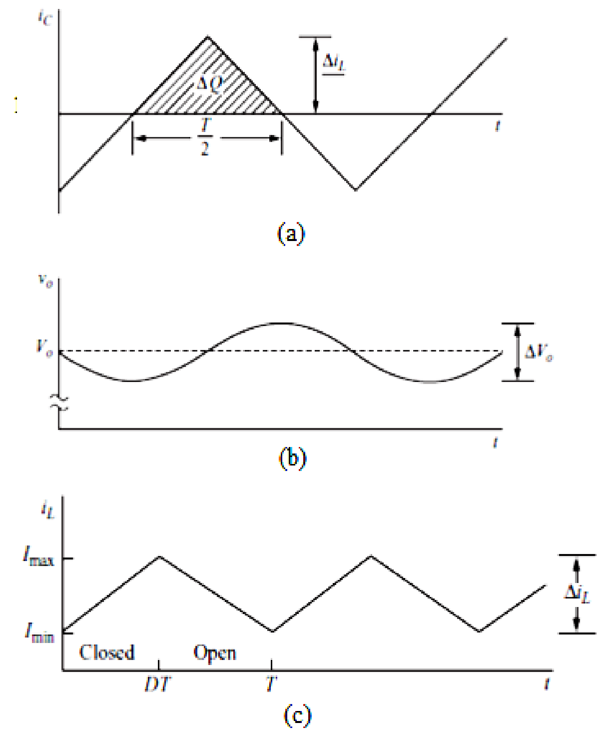

Figure 2.7: Cuk converter waveforms (a) Capacitor current
(b) Capacitor ripple voltage (c) Inductor current

$$\Delta Q = \frac{1}{2}\left(\frac{T}{2}\right)\left(\frac{\Delta i_L}{2}\right) = \frac{T\Delta i_L}{8} \tag{2.21}$$

resulting in

$$\Delta V_o = \frac{T\Delta i_L}{8C_2} \tag{2.22}$$

Substiting Δi_L into equation (2.22) yields;

$$\Delta V_o = \frac{TV_o}{8C_2L_2}(1-D)T \tag{2.23}$$

$$\Delta V_o = \frac{V_o(1-D)}{8C_2L_2f^2} \tag{2.24}$$

Since $\frac{V_o}{V_{in}} = \frac{D}{1-D}$, equation (2.24) can be rearranged as;

$$\Delta V_o = \frac{DV_{in}}{8C_2L_2f^2} \tag{2.25}$$

In this equation, ΔV_o is the peak-to-peak ripple voltage at the output, as shown in Figure 2.6 (b). The output voltage ripple is the ripple on the voltage of the capacitor C_2. It is also useful to express the ripple as a fraction of the output voltage,

$$\frac{\Delta V_o}{V_o} = \frac{1-D}{8C_2L_2f^2} \tag{2.26}$$

In design, it is useful to rearrange the preceding equation to express required capacitance in terms of specified voltage ripple,

$$C_2 = \frac{1-D}{8L_2(\Delta V_o/V_o)f^2} \tag{2.27}$$

Then ripple in C_1 can be estimated by computing the change in v_{C_1} in the interval when the switch is open and the currents i_{L_1} and i_{C_1} are the same. Assuming the current in L_1 to be constant at a level i_{L_1};

$$\Delta v_{C_1} \approx \frac{1}{C_1}\int_0^T i_{L_1}\, dt = \frac{i_{L_1}}{C_1}(1-D)T = \frac{V_{in}}{RC_1f}\left(\frac{D^2}{1-D}\right) \tag{2.28}$$

$$\Delta v_{C_1} \approx \frac{DV_o}{RC_1f} \tag{2.29}$$

Then fluctuations in inductor currents can be computed by examining the inductor voltage while the switch is close. The voltage across $\boldsymbol{L_1}$ with the switch close is;

$$v_{L_1} = v_{in}\, \frac{DV_o}{RC_1f} = L_1\frac{di_{L_1}}{dt} \tag{2.30}$$

In the time interval DT when the switch is closed, the change in inductor current is;

$$\frac{\Delta i_{L_1}}{DT} = \frac{v_{in}}{L_1} \tag{2.31}$$

$$\Delta i_{L_1} = \frac{v_{in}DT}{L_1} = \frac{v_{in}D}{L_1 f} \tag{2.32}$$

For inductor L_2, the voltage across it when the switch is closed is;

$$v_{L_2} = v_o + (v_{in} - v_o) = v_{in} = L_2 \frac{di_{L_2}}{dt} \tag{2.33}$$

The change in i_{L_2} is then;

$$\Delta i_{L_2} = \frac{v_{in}DT}{L_2} = \frac{v_{in}D}{L_2 f} \tag{2.34}$$

For continuous current in the inductors, the average current must be greater than one-half the change in current. Minimum inductor sizes for continuous current are;

$$L_{1,min} = \frac{(1-D)^2 R}{2Df} \tag{2.35}$$

$$L_{2,min} = \frac{(1-D)R}{2f} \tag{2.36}$$

2.4 Artificial Neural Network (ANN)

An artificial neural network (ANN), usually called neural network (NN), is a type of artificial intelligence technique that mimics the behavior of human brain. It can approximate a nonlinear relationship between the input and outputs variables of nonlinear, complex system without requiring explicit mathematical representations. In other word, it duplicate the mathematical model or computational model that inspired by the structure and/or functional aspects of biological nervous system, such as brain, process information (neural networks). A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. It is composed of a large number of highly interconnected processing elements working in unison to solve specific problems. Each of these processing elements, known as neuron, has a number of internal parameters called weights ($\boldsymbol{\omega}$). Changing the weights of a neuron alters not only the behavior of the neuron, but the behavior of the entire network. Hence, by means of a training process, the weight of each neuron is self-tuned to achieve a desired input-output relationship.

Feedforward Neural Networks (FNN's) are widely used to solve complex problems in pattern classification, system modeling and identification, and nonlinear signal processing. It is known that the learning process of a FNN is characterized by the rate of convergence to a solution and the possibility to reach an optimal solution.

Figure 2.8 illustrates a Feed-forward Multilayer Perceptron Neural Network architecture. “Feed forward” means that the values only move from input to hidden to output layers; no values are fed back to earlier layers. All neural networks have an input layer and an output layer, but the number of hidden layers may vary.

This network has an input layer ($\boldsymbol{x}$), one hidden layer and an output layer ($\boldsymbol{y}$); all with three neurons.

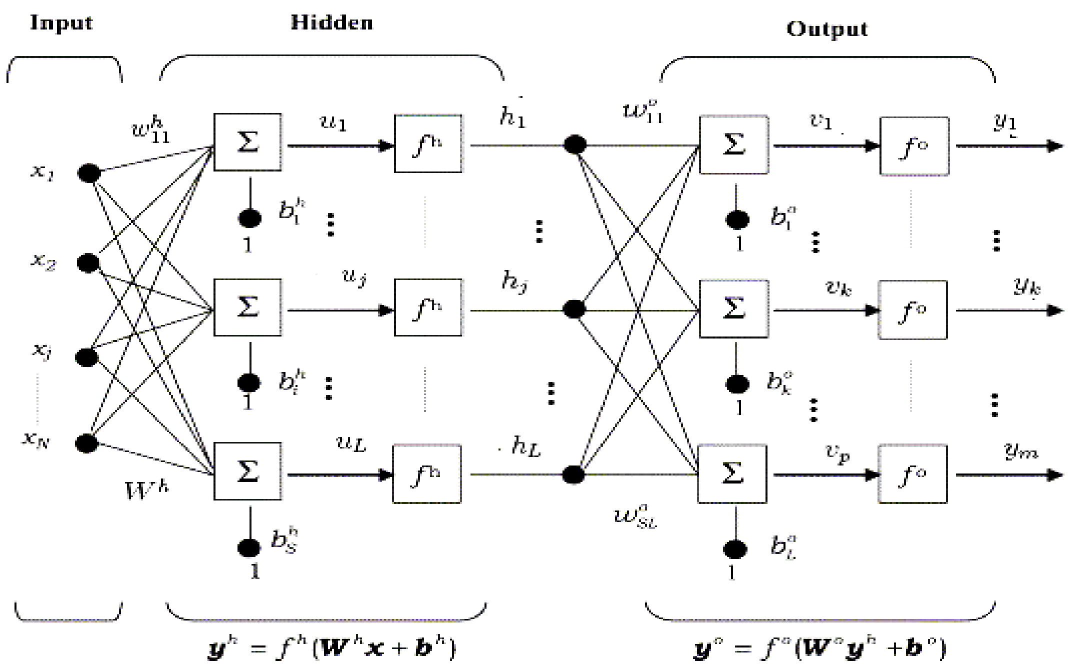

Figure 2.8: A feed-forward perceptron network with three layers

At the input Layer, a vector of predictor variable values ($x_1 \ldots x_p$) is presented to the input layer. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the *bias* that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron. Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (w_{ji}), and the resulting weighted values are added together producing a combined value u_j.

The weighted sum (u_j) is fed into a transfer function, σ, which outputs a value h_j. The outputs from the hidden layer are distributed to the output layer. Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (w_{kj}), and the resulting weighted values are added together producing a combined value v_j. The weighted sum (v_j) is fed into a transfer function, σ, which outputs a value y_k. The y values are the outputs of the network. Therefore, the main advantage of applying the ANN in the control of DC-DC converters lies in its intrinsic capabilities to learn and reproduce highly nonlinear transfer function that enables the control to be done effectively for small and large signal conditions.

2.4.1 Back Propagation Algorithm

In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way the error between the desired output and actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other word, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm (BPA) is the most widely used method for determining the EW.

Back Propagation Algorithm (BPA) is also known as generalized delta rule. BPA is based on the gradient descent optimization technique. As mentioned earlier, the NN proposed contains three layers; input, hidden and output layers. During the training phase, the training data is fed into the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the *forward pass* of the BPA. In forward pass, each node in hidden layer gets input from all the nodes from input layer, which are multiplied with appropriate weights and then summed. The output of the hidden node is the non-linear transformation of the resulting sum. Similarly each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights and then summed. The output of this node is the non-linear transformation of the resulting sum.

The output values of the output layer are compared with the target output values. The target output values are those that we attempt to teach our network. The error between actual the output values and target output values is calculated and propagated back toward hidden layer. This is called the *backward pass* of the BPA. The error is used to update the strengths between nodes, i.e weight matrices between input-hidden layers and hidden-output layers are updated.

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