Output Voltage Regulation of the DC-to-DC C'uk Converter Using a New Brain Emotional Based Intelligence Controller

Alimorad khajehzadeh, Hamzeh Afzalineya, Reza Sayedi

Abstract—In this paper, a new approach for the design of an output voltage regulator for the DC-to-DC C'uk Converter using a new Brain Emotional Learning Based Intelligent Controller (BELBIC) is presented. The BELBIC is a new type of intelligent controller based on emotion processing mechanism in the brain. In the proposed method, a tuning system is applied to tune the BELBIC parameters dynamically during control procedure based on the system error and its derivative. To investigate the controller performance, some numerical results are presented on an averaged model of the DC-to-DC C'uk converter. The simulation studies show that the designed controller has good capability to solve the output voltage regulation problem for the DC-to-DC C'uk converter.

Index Terms— Brain Emotional Learning Based Intelligent Controller (BELBIC), Power converters, design, error, voltage, regulation.

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1 INTRODUCTION

R CENTLY, there has been an increasing interest for applications such as electric/hybrid electric vehicles, mobile phone, air and space vehicles, industrial systems, electric power transmission systems, photovoltaic cells, and etc because of their advantages in weight, price, size, capability, and efficiency to being tightly regulated. DC-DC converters are one of the important electronic devices, which associated to the conversion, control, and conditioning of electric power. DC-DC converters are employed to convert one DC voltage to other [1].

The inputs of DC-DC converter are unregulated DC voltage in and the required outputs should be a constant or fixed voltage irrespective of variation in load current or input voltage. One of the main limitations with operation of such converter is unregulated power supply of voltage and current, which leads to improper work of these converters. To overcome the above mentioned difficulties, there are various kinds of voltage regulators with a variety of analogue and digital control methods used in combination with DC-DC converters to enhance the efficiency of these devices [2].

Conventionally, power electronic circuits use fixedstructure classical PID or PI controllers because of its simple structure and ease of physical realization. The parameters of a conventional controller are normally fixed at values determined based on classical control theory. These classes of controllers are designed at one operating condition and always suffer from a poor

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performance due to the converter's nonlinear damped dynamics which are a function of load parameters, uncertainty in parameters, and wide range of operating conditions. So, the fixed-structure classical based control of the power converter may require additional algorithm modifications to achieve a combination of good transient and steady-state performance.

To overcome the shortcomings of conventional controllers, many control strategies applying various techniques based on optimal control, robust control and adaptive control have been proposed and developed by the researchers around the world over the last two decades. The works carried out in [3]-[6] are examples of such applied techniques. Each of these techniques has their own advantages and disadvantages.

More recently, the controllers based on Artificial Intelligence (AI) techniques, such as fuzzy logic control (FLC) [7] and Artificial Neural Network (ANN) [8] are applied to design of DC-DC converter regulators in a power electronic circuits to overcome the drawbacks of conventional controllers. But, due to the advancement in power electronics and improved technology a more severe requirement for accurate and reliable regulation is desired.

Brain Emotional Learning Based on Intelligent Controller (BELBIC) is a new type of artificial intelligent controller based on medial brain model and emotional processes. BELBIC is a direct adaptive controller with low on-line computation, simple structure and fast auto learning, which indicates good robustness and performance properties [9]. The Emotional learning controller has been applied for a lot of engineering systems such Permanent-Magnet Synchronous Motor (PMSM) Drive [10], washing machine [11], interior permanent magnet synchronous motor system [12], and power system stabilizer design [13] and so on.

In this paper, the BELBIC is proposed for output voltage regulation of the DC-to-DCC'uk converter, by

applying a signal function in Emotional Cue Function of the BELBIC model. Furthermore, in the proposed method, a tuning system is employed to tune the BELBIC parameters dynamically during control procedure based on the system error and its derivative. In order to show the effectiveness of proposed method, the numerical results are presented on a real model of DC-to-DC C´uk converter. The obtained results show the superiority and capability of the proposed BELBIC scheme in output voltage regulation of a DC-to-DC C´uk converter with strong nonlinearity.

The paper is organized as follows. Section II describes the average model of the DC-to-DC C'uk converter. To make a proper background, Section III gives a brief summary about the basic structure of the proposed intelligent BELBIC controller based on medial brain and its emotional learning. The control topology of BELBIC controller for the DC-to-DC Cuk converter is described in Section IV. The simulation results are presented in Section V. Finally, some conclusions are drawn in Section VI.

2 THE MODEL OF DC-TO-DC C UK CONVERTER

The DC-to-DC C'uk converter is one of the most widely used power converters which invert the polarity of the input voltage and step-up or step-down its absolute value. A schematic of the DC-to-DC C'uk converter is shown in Fig.1.

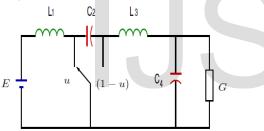


Fig .1. A schematic of DC-to-DC 'Cuk converter circuit.

The DC-to-DCC'uk converter model consists of ordinary differential equations as follows:

$$L_{1} \frac{d}{dt} i_{1} = -(1-u)v_{2} + E$$

$$C_{2} \frac{d}{dt} v_{2} = (1-u)i_{1} + ui_{3}$$

$$L_{3} \frac{d}{dt} i_{3} = -uv_{2} - v_{4}$$

$$C_{4} \frac{d}{dt} v_{4} = i_{3} - Gv_{4}$$
(1)

Where i_1 and i_3 are the currents in the inductances L_1 and L_3 , respectively. Also, v_2 and v_4 denote the voltages across the capacitors C_2 and C_4 , respectively. The constants L_1 , C_2 , L_3 and C_4 represent the values of the capacitance and of the inductances, respectively. Furthermore, parameters *G* and *E* stand for the load admittance and the value of the voltage source, respectively. Finally, *u* is a continuous control signal,

which represents the slew rate of a PWM circuit which employed to control the switch position in the converter. It is assumed that only the input capacitor voltage and the output inductor current are measured. A detailed analysis of DC-to-DC ′ Cuk converter has been discussed in the technical literature [14] and will not be undertaken in this paper.

3 MAIN EMOTIONAL CONTROLLER MODEL

The BELBIC (Brain Emotional Learning Based Intelligent Controller) is a biologically inspired control technique which is developed by Caro Lucas [9] and adopts the simple computational model of emotional learning that is developed by Moren and Balkenius [15] to mimic those parts of the limbic system of mammalian's brain which are known to produce emotion (namely, the Amygdala, Orbitofrontal cortex, Thalamus and Sensory input cortex). Fig. 2 shows the structure of the BELBIC.

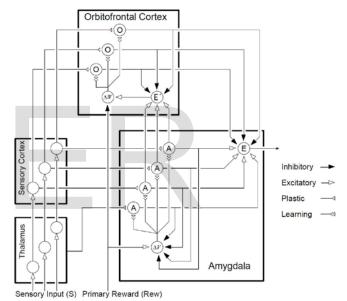


Fig. 2. A graphical depiction of the computational model of emotional learning.

As illustrated in Fig. 2, Amygdala receives inputs from the Thalamus and from cortical areas while the Orbitofrontal receives inputs from Amygdala and cortical areas (Orbitofrontal cortex and Sensory cortex). The system also receives a reinforcing signal (Primary Reward) in addition to Sensory Cortex inputs. The emotional learning takes place in the Amygdala part of the brain. There is one *A* node in the amygdale for each stimulus, *S*, including one for the thalamic stimulus (Ath). There is also one O node for each of the stimuli in the Orbitofrontal except for the thalamic node. The output node, E, simply sums the outputs from the A nodes and then subtracts the inhibitory outputs from the O nodes. The result is the output from the model. The E' node sums the outputs from A except A_{th} and then subtracts from inhibitory outputs from the O nodes [16].

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$$E = \sum_{i} A_{i} - \sum_{i} O_{i} \quad (including \ A_{th})$$
(2)

$$E' = \sum_{i} A_{i} - \sum_{i} O_{i} \quad (not \ including \ A_{th}) \tag{3}$$

The thalamic connection is calculated as the maximum of stimuli inputs (*S*):

$$A_{th} = \max(S_i) \tag{4}$$

Unlike other inputs to the Amygdala the thalamic input is not planned into the Orbitofrontal part and cannot be inhabited. There is a plastic connection weight V for each A node. Any input is multiplied by this weight to obtain the output of the node.

$$A_i = S_i V_i \tag{5}$$

The connection weights V_i are adjusted proportionally to the difference between the activation of the *A* nodes and the reinforcement signal Reward (*REW*). The learning rule of Amygdala is given as follow:

$$\Delta V_i = \alpha \left(S_i \max(0, REW - \sum_i A_i) \right)$$
(6)

where α is a standard learning rate parameter used to adjust the learning speed and set between 0 (no learning) and 1 (instant adaptation). The Orbitofrontal learning rule is very similar to the Amygdala rule but the Orbitofrontal connection weights can both increase and decrease as needed to track the required inhibition [16]. The learning rule in Orbitofrontal cortex is calculated as follows:

$$\Delta W_i = \beta(S_i(E' - REW)) \tag{7}$$

where ΔW_i is the change in the weight of Orbitofrontal connection and β is Orbitofrontal learning rate. The Orbitofrontal connection node values are then calculated as follows:

$$O_i = S_i W_i \tag{8}$$

The model of the proposed structure of Fig. 2 is illustrated as control blocks in Fig. 3. The BELBIC is fundamentally an action generation mechanism based on sensory inputs and emotional cues (*REW*). The reinforcing signal *REW* comes as a function of others signal. Similarly the sensory inputs must be a function of plant outputs and controller outputs. These functions should be defined for each application [17].

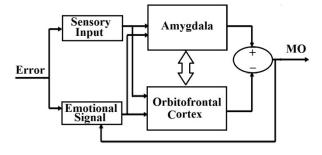


Fig .3.Basic block structure of the BELBIC emotional controller.

4 CONTROL TOPOLOGY OF DC-TO-DC ´CUK CONVERTER

There are several topologies for DC-to-DC 'Cuk converter that is depending on the selected application. In this paper we use an Asymmetric converter for this paper. The control system structure of th DC-to-DC 'Cuk converter is shown in Fig. 4.

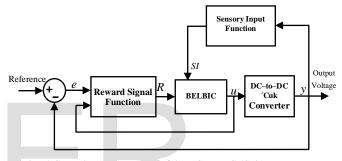


Fig . 4.Control system structure of the DC-to-DC 'Cuk converter.

In this figure, the sensory input (*SI*) and reward signal (*Rew*) can be arbitrary function of the reference, and the plant (converter circuit) input and output. It is all up to the designer to find a proper function for control. As can be seen from Fig.4, the emotional controller receives the reward signal (*Rew*) from Reward Signal Function block (which can be an arbitrary function of the reference) and sensory input (*SI*) from Sensory Input Function block (which can be an arbitrary function of the plant (converter circuit) input and output) as a part of inputs. Also, the error signal voltage between the desired voltage and the actual converter output voltage is considered as input to Reward Signal Function block.

As expressed in the previous section, the E node sums the outputs from the A nodes, then subtracts the inhibitory outputs from the O nodes. The result is the output from the model.

$$MO = E = \sum_{i} A_{output} \cdot i - \sum_{i} OC_{output} \cdot i$$
(9)

This equation include Ath where Ath=max (SI). The learning rule in amygdala is as follow:

$$\Delta K_a = K_1 \cdot \max(0, EC - A_{output}) \ge 0 \tag{10}$$

That K_a is the weight in amygdale connection K_1 is learning rate in Amygdala, and *EC* is Emotional Cue Function or reward signal. Also, the reinforce for the *O* nodes is calculated as the difference between the previous output *E* and the reinforcing signal *Rew*. The learning rule in orbitofrontal cortex is

$$\Delta K_{oc} = K_2 (MO - EC) \tag{11}$$

The learning rule in amygdale and orbitofrontal cortex is similar and OFC connection gain can be positive or negative to modify the inappropriate Amygdala's answer. If (10) and (11) are combined, we have

$$MO = (K_a - K_{oc}).SI = K(SI.EC).SI$$
(12)

where *SI* and *EC* are depending on several parameters. We can say the output of the controller is variable gain and act similar to PI self tune. The first suggestion for *SI* is

$$SI = K_p \cdot e_v + K_I \int_0^t e_v dt$$
⁽¹³⁾

in which

$$e_v = \left| V_{actual} - V_{desired} \right| \tag{14}$$

Where $V_{desired}$ and V_{actual} are the desired voltage and the actual converter output voltage, respectively. Emotional signal of *EC* indicates appropriate operation of system and it can tune for primitive and secondary goals of the system, for instance, reduction of torque ripple. In this work, we consider EC as follow:

$$EC = C_1 \cdot e_{\omega} + C_2 \cdot MO + F(output voltage ripple)$$
 (15)

That C_1 and C_2 are constant, where C_1 and C_2 are responsible for tuning the steady-state error and smoothing of the response. Since these BELBIC parameters have significant effects on the quality of the control performance, first the parameters in (15) must be set. In this work, a large number of experiments are performed by changing the range of variation for BELBIC coefficients, the best values are found. The Learning coefficients of BELBIC controller are given in Table I. It should be noted that, there is not an analytical way to prove stability of main controller, BELBIC.

TABLE 1

GAIN PARAMETERS FOR CONTROL SYSTEM

а	0.001
β	0.01
C_{I}	0.65
C_2	7.6

Where α is Amygdala learning step and β is Amygdala learning step of Orbitofrontal cortex for the BELBIC. Also C_1 and C_2 are constant coefficients in (15).

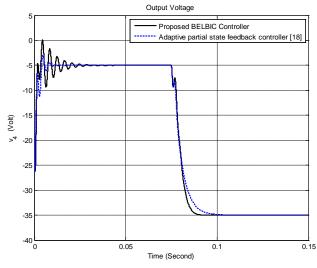
5 SIMULATION STUDIES

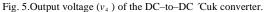
In this section, some numerical simulations are carried out to provide a reasonable dynamic performance for the proposed controller. The results obtained by the proposed method are compared with the adaptive partial state feedback control approach, which presented in [18].

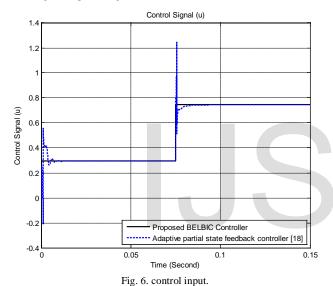
The values of the circuit parameters are adopted from [18]. Therefore, to make the results comparable, the same values of circuit parameters as literature are used, i.e. $L_1 = 10 \, mH$, $C_2 = 22 \, \mu F$, $L_3 = 10 \, mH$ and $C_4 = 22.9 \, \mu F$. Also, the nominal values for the load admittance and the) input voltage are considered $G_N = 0.0447 S$ and $E_N = 12 V$, respectively. Moreover, the initial conditions for all simulations are considered $x(0) = [0.6 \ 12 \ -2 \ -14]$. Additionally, the initial set point for the output voltage is set to -5V, and then this is changed at t = 0.075 to -35 V.

Figs 5 and 6, respectively, show the output voltage (v_4) and control input (u) for the proposed method and those approach which presented in [18]. These figures show that with both methods the output voltage converges to the desired value properly but the controller designed by BELBIC method improve the transient response characteristics and has a better performance in terms of settling time and output and control signal ripple to the controller designed by adaptive partial state feedback control approach.

To show the effectiveness of the designed controller under more severe condition, the same control goal as above is considered, *i.e.* output voltage regulation at -5V for t < 0.075, and at -35V, for $t \ge 0.075$. Furthermore, two step changes of the load admittance and the input voltage is considered in new operating condition: at t = 0.05 the load admittance G is decreased to 0.022 S and the input voltage E is decreased to 10 V; also, the load admittance G is increased to $0.066 S_{1}$ and the input voltage E is increased to 14 V, at t = 0.10. The obtained results are illustrated in Figs 7-10. Fig. 7 and 8 show the output voltage (v_4) and control input (u) for the proposed method and adaptive partial state feedback control approach. Moreover, the time histories of the output voltage and the control signal and of the estimation errors for the input voltage and the input current, for designed BELBIC regulator is shown in Fig 9.







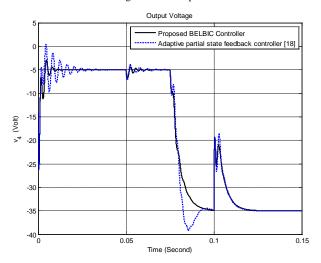
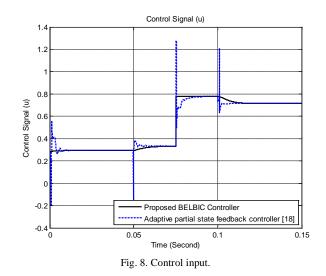


Fig .7. Output voltage (v_4) of the DC-to-DC 'Cuk converter.



nput voltage estimation error (continuous line) and input current estimation error (dashed line)

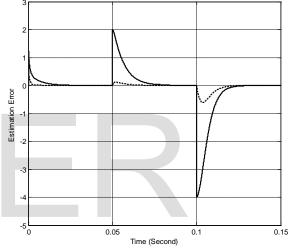


Fig. 9. Input voltage estimation error (continuous line) and input current estimation error (dashed line) for propsed BELBIC method.

6 CONCLUSION

In this paper a new control approach incorporating Brain Emotional Learning Based Intelligent Controller (BELBIC) is developed for output voltage regulation of a DC-to-DC C'uk converter. The proposed method is applied successfully to design of stabilizing controls for regulating the power electronic C'uk converter. The effectiveness and robustness of the proposed method is illustrated by considering various operating conditions. The results obtained by the proposed method are compared with the adaptive partial state feedback control approach, which presented in [18]. Simulation results are shown that both the proposed BELBIC controller and adaptive partial state feedback control approach satisfactorily regulate the output voltage of the converter. But, the suggested BELBIC controller has superiority and better performance in comparison with the designed by other method in improving the regulation of the output voltage of the system.

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