

Robust Intelligent Controller for Voltage Stabilization of dc-dc Boost Converters

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Abstract - Recently, dc-dc converters are increasingly employed for eliminating the output voltage variations of the intermittent generation resources in the power system. However, due to nonlinear dynamics of these converters and uncertainties induced from the load side, designing a robust controller for voltage tracking control of these converters is of paramount importance. In this paper, motivated by the learning capabilities of Brain Emotional Learning method, a robust intelligent controller for voltage stabilization of dc-dc boost converters is proposed. Moreover, the gains for Brain Emotional Learning Based Intelligent Controller (BELBIC) are optimally obtained using particle swarm optimization (PSO) algorithm by minimizing the cost function defined based on the system stabilization indices. Performance of the proposed method is investigated in presence of the system uncertainties. The results demonstrate the satisfactory performance of the proposed method.

Key Words: dc-dc boost converters, Brain Emotional Learning, system dynamics uncertainties, voltage stabilization.

1. INTRODUCTION

The deployment of advanced control and communication technologies in smart grids [1] has opened the door to clean generation technologies, such as wind turbines and photovoltaic panels [2]. Over the past fifty years, the earth average temperature has been increased by 0.6 Celsius degrees [3] and therefore, using these environmental-friendly power resources can be a very desirable substitute for conventional power sources such as gas-fired generators [4]. Recently, reliability and sustainability of these units have attracted lots of attention since their generation consistency greatly depends on the environmental parameters (e.g., wind speed and sun radiation) [5,6]. Increased penetration of intermittent, fluctuate and uncontrollable renewable generation leads to more generators idling, which may have an opposite effect environmentally and economically. Therefore, there

is a need to move from traditional reserve to considering an active role for controllable load through appropriate control strategies for grid operators such as demand respond [7-9]. Furthermore, the quality of delivered power and safety of the power system greatly depend on working at nominal voltage [10]. The output voltage can be easily affected by variations on the load side. Therefore, dc-dc converters such as dc-dc buck/boost converters are extensively employed to provide a robust output voltage against possible uncertainties. However, designing a robust control mechanism for these converters is challenging due to their nonlinear system dynamics. Hence, it is of paramount importance to develop a robust closed-loop control system to have a reliable and satisfactory performance.

There are several control strategies for controlling the power electronic elements used in power system [11]. Recently, many researchers spent tremendous efforts for designing the high-performance robust control strategies for dc-dc buck/boost converters. For example, the authors in [12] proposed a total sliding-mode control (TSMC) scheme for the voltage tracking control of a conventional dc-dc boost converter. An adaptive fuzzy-neural-network control scheme for the voltage tracking control of a conventional dc-dc boost converter has been investigated in [13-14]. Designing a robust adaptive sliding-mode controller for a dc-dc boost converter with an unknown resistive load and external input voltage has been addressed in [15-16]. The authors in [17] designed a robust controller for regulating a dc-dc boost converter capacitor output voltage. Closely related, a constrained near-time-optimal sliding-mode control of boost converters based on switched affine model analysis is studied in [18-19]. Most recently, parabolic-modulated sliding-mode voltage control of a buck converter has been proposed in [20]. However, most of these recent studies highly depend on the system dynamics. Moreover, the conventional PID controllers are not efficient to control non-linear systems since adjusting their gains according to the process dynamics is challenging [21]. In this regard, developing the control strategies,

which are not dependent to the system dynamics, is essential.

In recent years, learning based approaches have been taken into account for solving complex problems [22-30]. Among them, a new Brain Emotional Learning Based Intelligent Controller (BELBIC) has been introduced in [29] and successfully employed in many control applications with linear and non-linear systems such as control of a submarine, gas turbine generator [29], attitude control of a quadrotor [31], control of interior permanent-magnet synchronous motor drive [32], speed control of a digital servo [33], optimal bi-objective control of DVR [34], and flocking control of multi-agent systems [35-36]. The satisfactory performance of the BELBIC to control complex non-linear dynamic systems was demonstrated in these studies. Furthermore, implementation of the BELBIC controller is simpler compared to other intelligent and PID controllers since it has fewer parameters.

In this paper, motivated by the learning capabilities of brain emotional learning method, a robust intelligent controller for voltage stabilization of dc-dc boost converters is presented. Besides, particle swarm optimization (PSO) technique is utilized to optimally adjust the gains for BELBIC by simultaneously optimizing the overshoot, settling time and stability index of the system. Performance of the proposed method is evaluated in presence of the system uncertainties. The simulation results show the superior performance of the proposed method compared to PID controller.

This paper is organized as follows. The non-linear model of the dc-dc boost converter is presented in Section 2. PSO algorithm is introduced in Section 3. The BELBIC method is discussed in Section 4. The robust intelligent controller is proposed in Section 5. Simulation results are illustrated in Section 6. Finally, some conclusions are drawn from the outcomes of this paper in Section 7.

2. Boost Model

To evaluate the performance of the dc-dc boost converter, we need to model this converter to obtain an accurate transfer function, which comprise all complex and detailed features. There are various techniques for modelling circuits e.g., circuit averaging, current injected approach, and steady-state averaging. Reviewing the related work shows that steady-state averaging method is extensively employed for modelling dc-dc converters. The so-called dc-dc boost converter equivalent circuit, shown in Figure 1, will be the basis for modelling and

validating our intelligent controller. Consider the following continuous-time dynamical system:

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t) \tag{1}$$

$$\frac{dy(t)}{dt} = Cx(t) + Du(t) \tag{2}$$

where $x(t)$, $y(t)$ and $u(t)$ are system states, output and input vectors, respectively. A , B , C and D are state-space matrices. The performance of the boost converter should be evaluated in two modes. In the first mode, the MOSFET switch is on due to coming PWM signal. In this mode, the output voltage is equal to the voltage of the MOSFET. In the second mode when the MOSFET is off, the output voltage is equal to the voltage of the capacitor. According to Figure 1, the ideal average model of the dc-dc boost converter is proposed in the form of dynamical system equations in two modes.

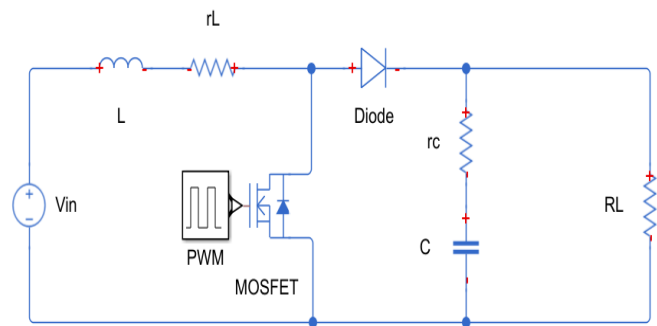


Figure 1. A dc-dc boost converter equivalent circuit.

i) when the MOSFET switch is on:

$$V_{in} - \left(v_c + r_c C \frac{dv_c}{dt} \right) = (r_t + r_L) i_L + L \left(\frac{di_L}{dt} \right) \tag{3}$$

$$i_L = C \frac{dv_c}{dt} + (v_c + r_c C \frac{dv_c}{dt}) / R_L \tag{4}$$

where all the parameters are defined in Figure 1. r_t is the thevenin equivalence resistor of the MOSFET switch. If we assume that all the system parameters are fixed over the time, then we can linearize the dynamic system of equations as follows:

$$\dot{X} = A_1 X + B_1 V_{in} \tag{5}$$

$$x_1 = i_L \quad , \quad x_2 = V_c \quad , \quad X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$A_1 = \begin{bmatrix} a_{11} & a_{12} \\ a_{13} & a_{14} \end{bmatrix}, \quad B_1 = \begin{bmatrix} b_{11} \\ b_{12} \end{bmatrix}$$

where X is the system state vector and A_1 and B_1 are obtained according to the following equations:

$$\begin{aligned} a_{11} &= -[r_L + r_t + \frac{(r_c R_L)/(r_c + R_L)}{L}] \\ a_{12} &= -R_L/[L(R_L + r_c)] \\ a_{13} &= R_L/[C(R_L + r_c)] \\ a_{14} &= -1/[C(R_L + r_c)] \\ b_{11} &= \frac{1}{L}, \quad b_{12} = 0 \end{aligned}$$

ii) when the MOSFET switch is off:

$$(r_L + r_d)i_L + L\left(\frac{di_L}{dt}\right) + v_c + r_c C \frac{dv_c}{dt} = 0 \tag{6}$$

$$i_L = C \frac{dv_c}{dt} + (v_c + r_c C \frac{dv_c}{dt})/R_L \tag{7}$$

Again, by linearizing the system equations, we can write:

$$\dot{X} = A_2 X + B_2 V_{in} \tag{8}$$

where A_2 and B_2 are the state-space matrices for the second mode and defined according to the following equations:

$$A_2 = \begin{bmatrix} a_{21} & a_{22} \\ a_{23} & a_{24} \end{bmatrix}, \quad B_2 = \begin{bmatrix} b_{21} \\ b_{22} \end{bmatrix}$$

where,

$$\begin{aligned} a_{21} &= -[r_L + r_t + \frac{(r_c R_L)/(r_c + R_L)}{L}] \\ a_{22} &= -R_L/[L(R_L + r_c)] \\ a_{23} &= R_L/[C(R_L + r_c)] \\ a_{24} &= -1/[C(R_L + r_c)] \end{aligned}$$

$$i_L = C \frac{dv_c}{dt} + (v_c + r_c C \frac{dv_c}{dt})/R_L$$

$$b_{21} = \frac{1}{L}, \quad b_{22} = 0$$

To show the effect of the alternative on-off conditions of the switch, we should calculate the average of the system state-space model as follows.

$$\dot{X} = AX + BV_{in} \tag{9}$$

where,

$$A = DA_1 + (1 - D)A_2$$

$$B = DB_1 + (1 - D)B_2$$

where D is the working period of the MOSFET switch which is calculated by the following equation:

Table 1. Parameters of a dc-dc boost converter.

Parameter	Value	
L	250	μH
R _L	25	Ω
C	1000	μF
r _L	50	Ωm
r _c	100	Ωm
V _{in}	5	V
D	0.59	-

$$D = \frac{t_{ON}}{T} \tag{10}$$

where T is the PWM switching cycle and t_{ON} is the time duration that switch is in the on mode.

Using the above-mentioned equations, and the parameters in Table 1, the state-space model of a dc-dc boost converter is obtained as follows.

$$X = \begin{bmatrix} i_L \\ V_c \end{bmatrix}, U = [V_{in}]$$

$$A = \begin{bmatrix} -4805.5 & -2357.41 \\ 68200.83 & -150.79 \end{bmatrix}$$

$$B = \begin{bmatrix} 59523.7 \\ 0 \end{bmatrix}, C = [0 \quad 1], D = [0].$$

Then, the transfer function of a dc-dc boost converter is acquired as follows.

$$\frac{V_{out}}{D(s)} = -\frac{V_{in}}{LCS^2 + S\left[\frac{L}{R_L} + r_L C\right] + \left[1 + \frac{r_L}{R_L}\right]} \tag{11}$$

$$\frac{V_{out}}{D(s)} = \frac{V_{in} \left(1 - S \frac{L_0}{R_L}\right) \left(S r_c C + \frac{r_c}{R_L} + 1\right)}{dcL_0(S^2 + b_1 S + b_2)} \tag{12}$$

where,

$$d = (1 - D)$$

$$L_0 = L/(1 - D)^2$$

$$b_1 = \frac{(R_L/D^2) + (r_c/D)}{L_0} + \frac{1}{r_c}$$

$$b_2 = \frac{(R_L/D^2) + (r_c/D)}{r_c L} + \frac{1}{LC}$$

Finally, the transfer function of the modeled dc-dc-boost converter is described as follows:

$$T(s) = \frac{-1.22s^2 + 8256s + 2.058 \times 10^8}{25s^2 + 10100s + 1.717 \times 10^7} \quad (13)$$

3. PSO Algorithm

Meta-heuristic approaches are powerful applications to find optimal solutions in optimization problems especially in nonlinear systems [37-39]. Along the same line, PSO [40-42] is a population-based evolutionary search algorithm which is initialized by a set of random solutions, called particles. PSO has many advantages over other optimization techniques. It is derivative free algorithm, which is less sensitive to the nature of the cost function. Besides, a key feature of the PSO algorithm is its easy implementation which consists of two equations [43-44]. Each particle is associated with two vectors, the position x_i^j and velocity v_i^j , which represent the possible solution. At each iteration, the particles (i.e., possible solutions) explore the solution space by updating their positions according to their best experience,

$$x_i^{j+1} = x_i^j + v_i^{j+1} \quad (14)$$

and velocity vector as follows:

$$v_i^{j+1} = w \cdot v_i^j + r_1 \cdot c_1 (x_i^{pbest} - x_i^j) + r_2 \cdot c_2 (x_i^{gbest} - x_i^j) \quad (15)$$

where c_1 and c_2 are two positive constants, r_1 and r_2 are two random numbers in the interval [0,1], w is the inertia weight, x_i^{pbest} is the best position particle achieved based on its own experience and x_i^{gbest} is the best particle position based on overall swarm's experience.

4. BELBIC Method

The Emotional Learning (EL) is mathematically modeled by Moren et. al. [45] in 2000 (see Figure 2). This model is mimicking the emotional learning process in mammalian limbic system. The main components of the limbic system are Thalamus, Sensory Cortex, Amygdala, Orbitofrontal Cortex, Hypothalamus, and Hippocampus. Learning happens in amygdala which is one of the important components of the mathematical model of the emotional learning. The other important component of the EL model is orbitofrontal cortex which is responsible for inhabitation of any inappropriate

learning happening in the amygdala. Lucas et. al. [29] introduced the Brain Emotional Learning Based Intelligent Controller (BELBIC) in 2004. There are two important inputs to the BELBIC model. The Sensory Input (S) and the Reward (Rew) which should be appropriately defined by the control designer where they could be defined as follows:

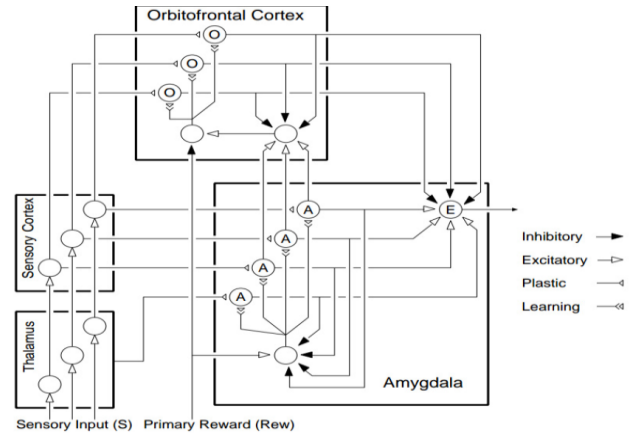


Figure 2. Mathematical model of emotional learning

$$Rew = F(u, e, y) \quad (16)$$

$$S = G(u, e, y) \quad (17)$$

where u is the control input, e is the system error and y is the output of the system to be controlled.

The output of a node in amygdala and the corresponding weight update are calculated by the following equations respectively.

$$A_i = S_i V_i \quad (18)$$

$$\Delta V_i = \alpha S_i \max \left(0, Rew - \sum_j A_j \right) \quad (19)$$

where α is the learning rate of the amygdala.

The output of a node in orbitofrontal cortex and the corresponding weight update are obtained by the following equations respectively.

$$O_i = S_i W_i \quad (20)$$

$$\Delta W_i = \beta S_i \left(\sum_j A_j - \sum_j O_j - Rew \right) \quad (21)$$

where β is the learning rate of the orbitofrontal cortex.

The output of the BELBIC model is computed as follows.

$$E = \sum_j A_j - \sum_j O_j \quad (22)$$

In this paper, motivated by the learning capabilities of BELBIC, a robust intelligent controller

for voltage stabilization of dc-dc boost converters is developed and described in Section 5.

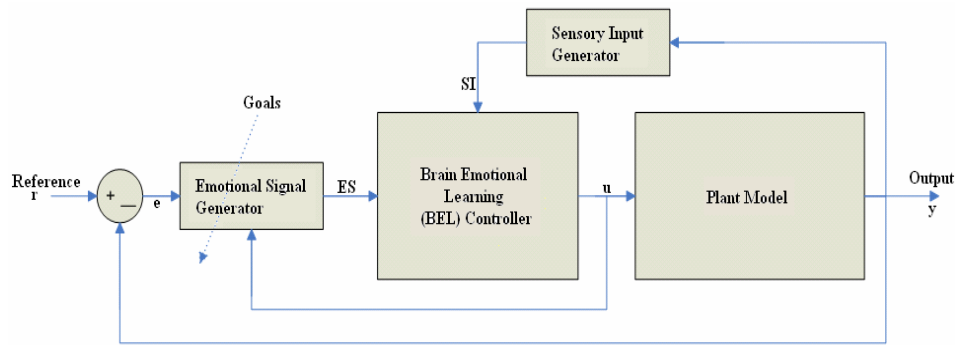


Figure 3. BELBIC model in a typical feedback control loop

5. Robust Intelligent Controller for Voltage Stabilization of dc-dc Boost Converters

The Brain Emotional Learning Based Intelligent Controller (BELBIC) is shown in a typical feedback control loop architecture in Figure 3.

To be able to design a BELBIC based controller, we should first define appropriate Sensory Input (*S*) and the Reward (*Rew*) functions. The following functions are used in this paper for this reason.

$$Rew = K_p e(t) + K_d \frac{de(t)}{dt} + K_i \int e(t) dt \quad (23)$$

$$S = e(t) \quad (24)$$

where $e(t)$ is the system error, K_p , K_d , and K_i are positive coefficients of the reward function. To obtain the best gains for PSO-BELBIC, we calculate the step response of the closed-loop system in each iteration of the optimization and the employed cost function is defined according to the following model:

$$C(M_p, t_s, P_0) = w_1 \times M_p + w_2 \times t_s + w_3 \times s.I. \quad (25)$$

where M_p is overshoot, t_s is settling time, P_0 is the smallest left-hand pole, and *s.I.* is stability index of feedback system, which is as follows:

$$s.I. = 1/\max(\text{real of } P_0) \quad (26)$$

For each particle at each iteration, the cost function is evaluated to update x_i^{pbest} . When the cost for all particles are calculated, the best cost is assigned as x^{gbest} . This process continues until the stopping criteria is met.

6. Simulation Results

This section presents the simulation results of applying a robust intelligent controller for voltage stabilization of dc-dc boost converters under the following two scenarios: voltage stabilization with no-uncertainty in the system parameters, and voltage stabilization in presence of the system uncertainty.

Scenario 1: voltage stabilization with no-uncertainty in the system parameters.

To study the performance of the proposed robust intelligent controller for voltage stabilization of dc-dc boost converters, we applied the PSO-BELBIC controller to the system model in Equation 13 and compared the results with the not optimally tuned BELBIC and PSO-PID controllers. Figure 4 shows the voltage response of the all controllers. It is shown that the proposed PSO_BELBIC controller can stabilize the system with lower overshoot, smaller settling time and faster than the other methods.

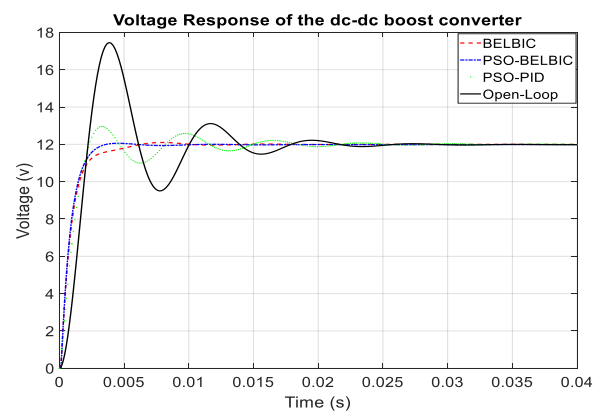


Figure 4. Voltage response of the dc-dc boost converter. The PSO-BELBIC controller is in BLUE while the BELBIC controller in RED. The PSO-PID is in GREEN and the Open-loop system in BLACK.

Scenario 2: voltage stabilization in presence of the system uncertainty.

In order to study the robustness of the proposed method in the presence of the system uncertainty we designed an experiment by changing the parameters in the Table 1 by $\pm 10\%$ of the original values. The new transfer function is obtained as follows.

$$T_{new}(s) = \frac{-3.59s^2 + 30636s + 5.02 \times 10^8}{73.7s^2 + 27526s + 4.189 \times 10^7} \quad (27)$$

We did the same experiment in scenario 1, but using the new system. The parameters of the all controllers remained the same as before. Figure 5 shows the output of the system by applying different controllers. Comparing the response of the new system with the old one shows that the proposed PSO-BELBIC controller can perfectly handle the system uncertainty and the response is almost as good as the old system.

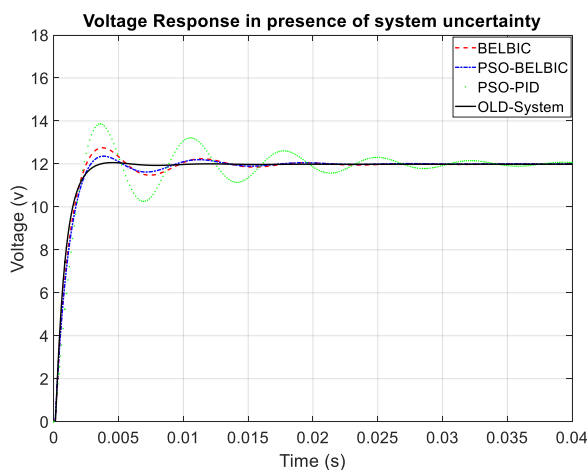


Figure 5. Voltage response of the dc-dc boost converter in presence of the system uncertainty. The PSO-BELBIC controller is in BLUE while the BELBIC controller in RED. The PSO-PID is in GREEN and the OLD system in BLACK.

7. CONCLUSIONS

In this paper, motivated by the learning capabilities of brain emotional learning method, a robust intelligent controller for voltage stabilization of dc-dc boost converters is proposed. The Brain Emotional Learning Based Intelligent Controller (BELBIC) gains are optimally attained using particle swarm optimization (PSO) technique in terms of the best overshoot, settling time and stability index of the system. Performance of the proposed method is evaluated in presence of the system dynamic

uncertainties. Comparing the results demonstrate the satisfactory performance of the PSO-BELBIC against other alternative methods.

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