Hybrid control methods for a Single Ended Primary Inductor Converter (SEPIC)

Mihai Bâja, Diego Patino, Hervé Cormerais, Pierre Riedinger and Jean Buisson

***Abstract*— This paper proposes two synthesis methods for controlling power converters. The first one is a stabilizing method in which a unique Lyapunov function is introduced and the second one is a new predictive control approach, which uses model predictive control to track a given optimal stable limit cycle. Moreover, the two methods can include the discontinuous conduction mode (DCM) in the formulation. The control laws are exemplified with a Single Ended Primary Inductor Converter (SEPIC) in simulation.**

***Index terms*— Stabilization, Predictive control, Limit cycle, Discontinuous Conduction Mode.**

I. INTRODUCTION

One advantage of the Single Ended Primary Inductor Converter (SEPIC) structure with respect to classical power converter, e.g. Cuk or boost converters, is that it can operate as a non-inverting step-up or step-down DC-DC converter. This property allows it to be used in many applications. The counterpart is that the control is not easy to compute because intrinsic oscillations naturally appear in the system. These oscillations are directly related to the value of the storage R-C elements [1], [2]. For example, in automotive or photovoltaic field, the SEPIC has an output capacitor with a big value leading to small oscillations in the output capacitor voltage. On the other hand, for DC-DC applications which require a low-power and/or wide input voltage range, the converter does have big oscillations (cell phones, battery interfaces, etc). Usually, existing solutions are based on the selection of passive components to prevent instability [1], [3] or sliding mode control [4]. Another characteristic of this converter is that, for some control objectives the system can operate in DCM (Discontinuous Conduction Mode) instead of CCM (Continuous Conduction Mode) [5].

In this paper, two original control strategies are introduced with the goal of reducing oscillations in steady state. The first one is a stabilization approach extended to the DCM case. It is based on energetic principles. The first step of the method consists in the definition of a common Lyapunov candidate function including a weight matrix. Its expression is directly related to the storage energy. This approach uses the Hamiltonian Port formalism. The control law which is under a static state feedback is chosen to ensure at each sample time the negativity of the time-derivative of the common Lyapunov candidate function. The second one is a predictive control approach. We propose to track an optimal limit cycle defined as a reference in the steady state. This cycle represents the best cycle in the sense given by a criterion. For instance, this criterion can be defined in order to reduce the quadratic norm of the tracking error or to avoid the undesired harmonic content in the the system. The tracking control is obtained using a predictive controller, which can take into account constraints on the switching frequency related to the devices in the design part. The solutions are learnt by a neural network (NN) that yields a state feedback control.

The paper is organized as follows : in section II, the physical model of the SEPIC is introduced in CCM and DCM. As most of the converters, it is shown that the model enters into the class of affine-switched system. Section III states the control problem and its constraints. In section IV, the two control methods are introduced. In section V, the two control strategies are applied on the particular case of the SEPIC with simulation results. Section VI provides some comparisons in term of performances and methodology between the two approaches. Finally, we reach some conclusions about the methods and propose some futur work.

II. PHYSICAL MODEL OF THE SEPIC

The SEPIC structure is shown in the Fig. 1. L_1 is the leakage inductance of the coupled inductor L_2. The ideal transformer (U voltage and J current) is used for modelling coupled inductor. Capacitors C_1 and C_2 are supposed to be ideal.

An equivalent representation of the converter is given in the Fig. 2.

In the Continuous Conduction Mode (CCM), two configurations or modes are available parameterized by ρ. $\rho = 0$ corresponds to the diode closed and the MOSFET open, $\rho = 1$ corresponds to the diode open and the MOSFET closed.

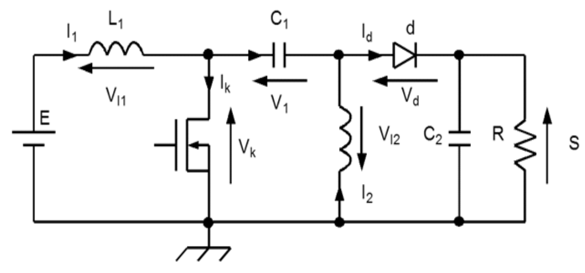

Fig. 1. The topology of the SEPIC

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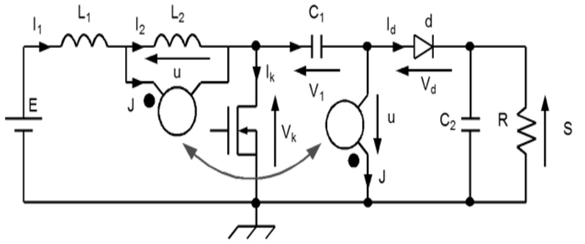

Fig. 2. Equivalent representation of the SEPIC

This system can be written as a hybrid system whose state vector is composed by $[p_{L_1}, p_{L_2}, q_{C_1}, q_{C_2}]^T$ and it represents the magnetic flux of each inductance and the charge of each capacitor. The corresponding generic state equation is:

$$\begin{bmatrix} \dot{p}_{L_1} \\ \dot{p}_{L_2} \\ \dot{q}_{C_1} \\ \dot{q}_{C_2} \end{bmatrix} = \begin{bmatrix} 0 & 0 & \frac{-1}{C_1} & 0 \\ 0 & 0 & \frac{\rho}{C_1} & \frac{\rho-1}{C_2} \\ \frac{1}{L_1} & \frac{-\rho}{L_2} & 0 & 0 \\ 0 & \frac{1-\rho}{L_2} & 0 & \frac{-1}{RC_2} \end{bmatrix} \begin{bmatrix} p_{L_1} \\ p_{L_2} \\ q_{C_1} \\ q_{C_2} \end{bmatrix} + \begin{bmatrix} E \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (1)$$

and for the current in the diode : $I_d = \frac{(1-\rho)p_{L_2}}{L_2}$

In DCM, a third mode corresponding to the case where the diode and the MOSFET are open occurs. In this configuration, the order of the system decreases from 4 to 3 and the state space equation is:

$$\begin{bmatrix} \dot{p}_{L_1} \\ \dot{q}_{C_1} \\ \dot{q}_{C_2} \end{bmatrix} = \begin{bmatrix} 0 & \frac{-1}{C_1} & 0 \\ \frac{1}{L_1} & 0 & 0 \\ 0 & 0 & \frac{-1}{RC_2} \end{bmatrix} \begin{bmatrix} p_{L_1} \\ q_{C_1} \\ q_{C_2} \end{bmatrix} + \begin{bmatrix} E \\ 0 \\ 0 \end{bmatrix} \quad (2)$$

with $I_d = 0$. The currents and voltages i_{L_1}, i_{L_2}, v_{C_1} and v_{C_2} are easily obtained from $i_{L_1} = p_{L_1}/L_1$, $i_{L_2} = p_{L_2}/L_2$, $v_{C_1} = q_{C_1}/C_1$ and $v_{C_2} = q_{C_2}/C_2$.

An equivalent state equation in an affine form with respect to the control will be:

$$\begin{bmatrix} \dot{i}_{L_1} \\ \dot{i}_{L_2} \\ \dot{v}_{C_1} \\ \dot{v}_{C_2} \end{bmatrix} = \begin{bmatrix} -\frac{v_{C_1}}{L_1} + \frac{E}{L_1} \\ -\frac{v_{C_2}}{L_2} \\ \frac{i_{L_1}}{C_1} \\ \frac{i_{L_2}}{C_2} - \frac{v_{C_2}}{RC_2} \end{bmatrix} + \rho \begin{bmatrix} 0 \\ \frac{v_{C_1}}{L_2} + \frac{v_{C_2}}{L_2} \\ -\frac{i_{L_2}}{C_1} \\ -\frac{i_{L_2}}{C_2} \end{bmatrix} \quad (3)$$

In DCM when the diode and the MOSFET are open, $i_{L_2} = 0$ and $\rho = 0$. In the following, for the construction of the methods, the stabilization control approach uses model (1) and the neural predictive approach deals with the state equation (3).

III. THE CONTROL PROBLEM

The physical parameters for this problem are : $E = 20V, R = 5\Omega, L_1 = 3\mu H, L_2 = 10\mu H, C_1 = C_2 = 6\mu F$. The capacitance value being quite small big oscillations could appear.

The two control laws presented in this paper will be evaluated for the following case : Start-up from zero initial conditions, the control objective is to regulate the output voltage around an average value of $V_s = 5V$ using nominal parameter values. The oscillations on the load voltage must be reduced as far as possible with no overshoot during transient.

IV. CONTROL APPROACHES

A. Stabilization Approach

1) Stabilization Approach in CCM: The matrix representation of a switching system in standard PCH (Port Control Hamiltonian) formulation has the following expression:

$$\dot{x} = [J(\rho) - R(\rho)] \frac{\partial H(x)}{\partial x} + G(\rho)u \quad (4)$$

where $x \in \mathbb{R}^n$ is the state vector, $\rho \in \{0,1\}^p$ is the boolean control variable and $u \in \mathbb{R}^m$ is the power input vector. Matrices J and R are called structure matrices. Matrix J is skew-symmetric, $J = -J^T$, it corresponds to the power interconnection in the model. Matrix R which is non-negative corresponds to the dissipating part of the system and G is the power input matrix. H represents the energy stored in the system, also called the Hamiltonian of the system.

If the constitutive relations of the storage elements are linear, which is most often the case of power converters, the Hamiltonian of the system is such that:

$$\frac{\partial H(x)}{\partial x} = Fx = z \quad (5)$$

where $F = F^T > 0$ and in the simple cases, it is a diagonal matrix. The Hamiltonian of the system can thus be represented as:

$$H(x) = \frac{1}{2} x^T F x \quad (6)$$

Furthermore, we assume that the matrices J, R and G are affine with respect to the boolean control variable [6].

It is important to note that (4) can also be interpreted as an average model provided that the control variables are not restricted to the set $\{0, 1\}$. Then, the equilibrium point for the average model can be easily determined by solving (4) for $\dot{x} = 0$.

The approach developed in this part consists in defining a point in which to stabilize the system. This point corresponds to the control objective and it is defined using the same approach as in the case of the average model. Indeed, this is the value $z_0 = Fx_0$, which must satisfy:

$$0 = (J(\rho_0) - R(\rho_0)) z_0 + G(\rho_0) u \quad (7)$$

if there is a $\rho_0 \in \mathbb{R}^p, 0 \leq \rho_{0j} \leq 1$, $1 < j \leq p$.

According to the properties of this equation and the respective dimension of x and ρ, for one ρ_0, the equilibrium point can be unique or not and for ρ_0 any point of the state space can be an equilibrium point or not [7].

Let us consider the following function V as a Lyapunov candidate function:

$$V(x, x_0) = \tfrac{1}{2}(x - x_0)^T F (x - x_0) \quad (8)$$

Because the matrix F is unique for all the modes of the system, V is positive and continuous for every x. V is also zero only in x_0. Using (4) and (7) the derivative of V is:

$$\dot{V} = -\left(z - z_0\right)^T R\left(\rho\right)\left(z - z_0\right) + \\ + \sum_{j=1}^{p} \left(z - z_0\right)^T \left(\left(J_j - R_j\right) z_0 + G_j u\right)\left(\rho_j - \rho_{0j}\right) \quad (9)$$

Due to the fact that $R(\rho)$ is a non-negative matrix, the first term is always negative. Because $0 \leq \rho_{0j} \leq 1$ the sum can be negative by choosing an appropriate value for each boolean ρ_j such that each product $(z - z_0)^T((J_j - R_j)z_0 + G_j u)(\rho_j - \rho_{0j}))$ be negative. If such control law is applied, then V is a Lyapunov function for the closed loop system which converges asymptotically toward x_0. Multiple state feedback control strategies can be considered for attaining this goal like maximum descent strategy or minimum switching strategy. Both strategies require an infinite bandwidth. In practice, switching frequency is limited.

2) Extension to the case of DCM: The stabilizing control approach can be formally extended to the case of DCM with the following assumptions

1) DCM only appears when one or more diodes are open (a Boolean ρ_{ci} is associated with the i_{th} diode equals to 0 when the diode opens and equals 1 otherwise). A generic state equation is also determined by the Boolean control ρ and the new Boolean ρ_c whose components are ρ_{ci}. Then, a generic state equation can be defined for the system in PCH form as function of boolean variables ρ and ρ_c.

$$\dot{x} = [J(\rho, \rho_c) - R(\rho, \rho_c)]\frac{\partial H(x)}{\partial x} + G(\rho, \rho_c)u \quad (10)$$

The matrices $J(\rho, \rho_c)$, $R(\rho, \rho_c)$ and $G(\rho, \rho_c)$ are affine with respect to the boolean variables ρ and ρ_c. In CCM, all components of ρ_c are equal to 1. In DCM, at least one component of ρ_c is equal to 0.
2) The equilibrium point only depends on the boolean control variable ρ like in CCM.
3) In DCM one or more lines of the generic state equation are equal to zero. It corresponds to the algebraic constraints resulting from the opening of some diodes.

Following these assumptions after the determination of an admissible reference corresponding to the control objective, a Lyapunov candidate function V is defined as in the CCM case with the following expression:

$$V\left(x, x_0\right) = \tfrac{1}{2}\left(x - x_0\right)^T F\left(x - x_0\right) \quad (11)$$

For any value of the boolean variable ρ_c, the system is defined by equation (10) and it corresponds to a switching physical system formulated under a PCH form. Therefore, the principle of stabilizing approach can be applied [7]. The Lyapunov candidate function derivative deduced from (11) is always negative by choosing an appropriate value of ρ. As previously in CCM, different strategies can be investigated, e.g. minimum switching strategy or maximum descent strategy [7].

In order to improve performances, a modified Lyapunov candidate function can be used

$$V\left(x, x_0\right) = \tfrac{1}{2}\left(x - x_0\right)^T WF\left(x - x_0\right) \quad (12)$$

where W is a weight positive definite matrix.

B. Neural Predictive Approach

1) Method Description: Classical control methods are usually designed with a constant reference which represents a mean value of the steady state. Consequently, the switches are not controlled around the equilibrium and the steady state shows unexpected harmonic content. In order to avoid this uncontrolled behavior, we propose to design a state feedback control law, which is able to track an optimal limit cycle near the operating point instead of a mean value. The predictive control has already been used as a control method for the power converters but not with the goal of optimizing the limit cycle [8].

Indeed, for a given operating point, an optimal cycle can optimize a criterion. Once the optimal cycle is defined, the tracking control is achieved using a predictive controller with two-stage strategies depending whether the system is in a transitory state or not.

In order to avoid excessive computation time, the real time implementation of the controller is ensured by the use of a Neural Network. Next, we will briefly present each point.

2) Closed loop design: Consider the class of affine switched systems described by:

$$\dot{z} = f\left(z\right) + g\left(z\right)\rho \quad (13)$$

where $f(z) : \mathbb{R}^n \rightarrow \mathbb{R}^n$, $g(z) = [g_1(z), \ldots, g_p(z)] \in \mathbb{R}^{n \times p}$, $g_i : \mathbb{R}^n \rightarrow \mathbb{R}^n$, $i = \{1, \ldots, p\}$. The system (13) is affine in the control signal ρ with a boolean control vector $\rho(t)$. Most of the power converters can be written in the form given by (13) when the switches are supposed to be ideals [6].

Once a relation between control values and operating modes is given (i.e. a one to one map from $\{0,1\}^p \rightarrow \{1, 2, \cdots, 2^p\}$), we can define:

Definition 1: A switching sequence is a finite sequence represented by:

$$(\mathcal{T}, \mathcal{I})^s = \{(t_1, i_1), (t_2, i_2), \ldots, (t_j, i_j), \ldots, (t_s, i_s)\} \quad (14)$$

where

- $\mathcal{T} = \{0 = t_1, t_2, \ldots, t_j, \ldots, t_s\}$ is a strictly increasing time sequence composed by the time values when a mode is switched on.
- $\mathcal{I} = \{i_1, i_2, \ldots, i_j, \ldots, i_s\}$, $i_j \in \{1, \ldots, 2^p\}$ for $j = 1, \ldots, s$ is the mode sequence. A mode i_j is switched on at time t_j, $j = 1, \ldots, s$.
- s is the (finite) length of the sequence.

The case for discontinuous conduction mode is exactly an autonomous mode depending on the state. This can be also included in the switching sequence.

a) Determination of the optimal steady state: The aim is to determine the best cycle in steady state. It means the best switching sequence $(\mathcal{T},\mathcal{I})^s$ $(1 < s < s_{max})$ which optimizes the quadratic criterion:

$$\mathcal{J}((\mathcal{T}^*,\mathcal{I}^*)^{s^*}) = \min_{s,\mathcal{T},\mathcal{I}} \int_0^{t_f} \parallel z - z_0 \parallel_Q^2 dt \qquad (15)$$

subject to the constraints:

$$z(0) = z(t_f) \text{ (periodic)} \qquad (16)$$

$$t_f \leq T_{p,max} \text{ (maximal duration)} \qquad (17)$$

$$\begin{aligned} \delta_k(t_j) \geq t_{min}|\rho_k(t_j) - \rho_k(t_{j+1})| \;\; \forall j = 1,\dots,s \\ \dot{\delta_k}(t_j) = 1 \;\; \forall k = 1,\dots,p \\ \delta_k(t_{j+1}) = 0 \;\; if \;\; |\rho_k(t_j) - \rho_k(t_{j+1})| \neq 0 \end{aligned} \qquad (18)$$

where $\| \cdot \|_Q^2$ is a quadratic norm associated to a symmetric positive definite matrix Q, z_0 is the average reference, t_f is a free final time ($t_f = t_{s+1}$) which is bounded by $T_{p,max}$. Equation (18) imposes a minimum duration equals to t_{min}, between two activations of the same switch. δ_k is the time elapsed from the last activation. This equations set is indeed an integrator with a reset for each switch.

With $(s,\mathcal{I})$ fixed, the length and the mode of the sequence, the solution of (15) is determined using nonlinear programming. The procedure is repeated until all admissibles values for $(s,\mathcal{I})$ are tested. This optimisation is obviously performed off-line and the solution of (15) gives an optimal sequence $(\mathcal{T}^*,\mathcal{I}^*)^{s^*}$ and the optimal reference $R_0(t)$ for the closed loop in steady state.

b) Neural Predictive Controller: As mentioned above, the design control and the data for training the neural network are obtained in the following two-stages:

- Far from the optimal limit cycle $R_0(t)$: since the behavior of the system is in a transitory phase, $(\mathcal{T},\mathcal{I})$ are optimized and we choose to fix s and the receding horizon t_f to (s^*, t_f^*). The following cost function is minimized on a grid:

$$J(z, z_0) = \min_{\mathcal{T},\mathcal{I}} \int_0^{t_f^*} \parallel z - z_0 \parallel_Q^2 dt \qquad (19)$$

  The first mode and its duration are used for training the network. The DCM is easily taken into account for this approach because it is introduced as part of the model in the optimization procedure.
- Near the limit cycle $R_0(t)$. $\mathcal{I}$ and s are fixed to the reference values $\mathcal{I}^*$ and s^*. The optimization is only done with respect to the time sequence. The cost function becomes:

$$\min_{\mathcal{T}} \int_0^{t_f} \|z - R_0\|_Q^2 dt \qquad (20)$$

The inputs for the NN are the tracking error ($\varepsilon(t) = z(t) - R(t)$) and the operating point reference z_0. The output is the optimal policy obtained from the optimization problem (19) or (20) with $R = z_0$ or $R = R_0$ respectively.

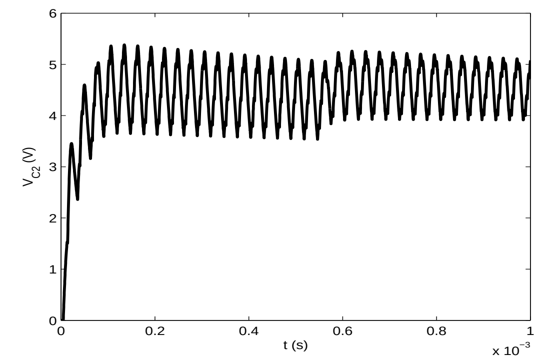

Fig. 3. Stabilization approach - Output voltage for the start-up test with the identity weight matrix of W

V. APPLICATION TO THE SEPIC

A. Stabilization Approach

It is easy to verify that the three assumptions described above hold. Thus, the principles of stabilization extended to DCM can be applied and a generic state equation under a PCH form (cf. (10)) can be established with the following expressions for the matrices $J(\rho,\rho_c)$, $R(\rho,\rho_c)$, $G(\rho,\rho_c)$ and the constitutive relation F:

$$J(\rho) = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & \rho_c\rho & \rho_c(1-\rho) \\ 1 & \rho_c\rho & 0 & 0 \\ 0 & -\rho_c(1-\rho) & 0 & 0 \end{bmatrix}, \qquad (21)$$

$$R(\rho) = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{R_{ch}} \end{bmatrix}, \; G(\rho) = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \qquad (22)$$

$$F = \begin{bmatrix} \frac{1}{L_1} & 0 & 0 & 0 \\ 0 & \frac{1}{L_2} & 0 & 0 \\ 0 & 0 & \frac{1}{C_1} & 0 \\ 0 & 0 & 0 & \frac{1}{C_2} \end{bmatrix} \qquad (23)$$

The Lyapunov candidate function extended to the DCM

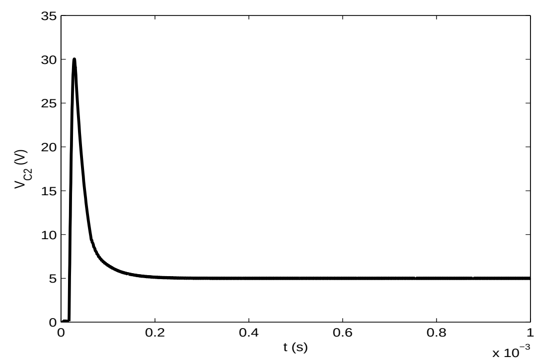

Fig. 4. Stabilization approach - Output voltage for the start-up test with a weight matrix of $W = diag[100, 1, 100, 1]$

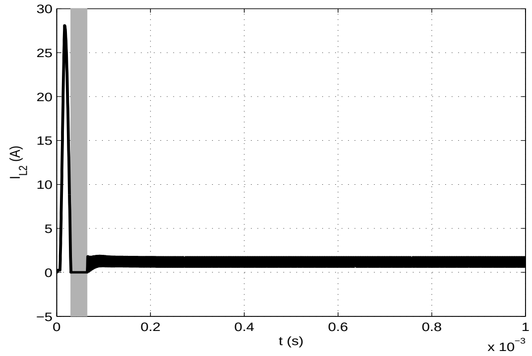

Fig. 5. Stabilization approach - Start-up response for the i_{L_2} current with a weight matrix of $W = diag[100, 1, 100, 1]$

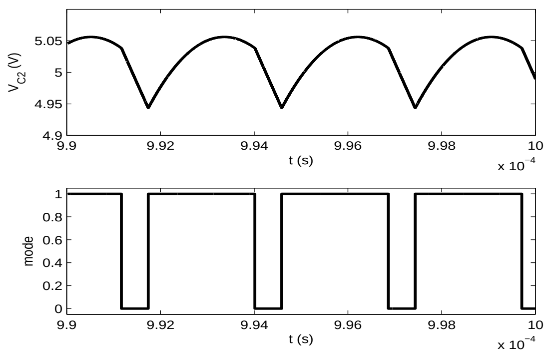

Fig. 6. Stabilization approach - Zoom on the limit cycle with a weight matrix of $W = diag[100, 1, 100, 1]$ - Evolution of the control ρ

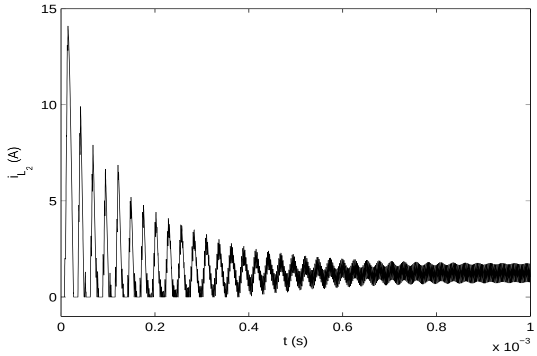

Fig. 7. Neural predictive approach - Start-up response for the i_{L_2} current with a weight matrix of $Q = diag[10, 10, 1, 10]$

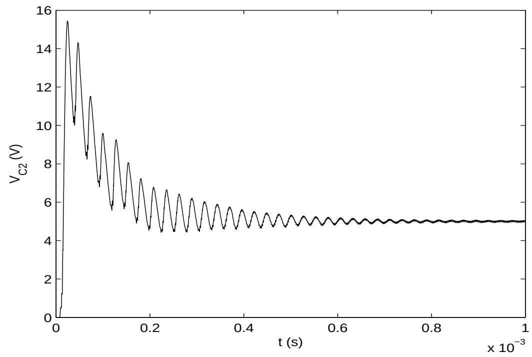

Fig. 8. Neural predictive approach - Output voltage for the start-up test with a weight matrix of $Q = diag[10, 10, 1, 10]$

is:

$$\dot{V} = \frac{(v_{C_2} - v_{C_20})}{R} + \\ + (i_{L_2}(v_{C_10} + v_{C_20})\rho_c - i_{L_20}(v_{C_10} + v_{C_20}))(\rho - \rho_0) \tag{24}$$

Two simulations are provided with the minimal switching strategy. The first one (cf. Fig. 3) has been established taking W as the identity matrix and the second one (cf. Fig. 4) with $W = diag[100, 1, 100, 1]$.

These figures show the evolution of the load voltage. A zoom in steady state (the limit cycle is established) and the mode used are shown in Fig. 6. As for Fig. 5, it shows that DCM occurs during transient.

B. Neural Predictive Approach

We consider the state equation given by (13) with $z = [i_{L_1}, i_{L_2}, v_{C_1}, v_{C_2}]^T$. $f(z)$ and $g(z)$ are directly deduced from (3)

We solve the optimization problem (15) with $T_{p,max} = 8\mu s$, $s_{max} = 4$. t_{min} is supposed to be the minimum time that the MOSFET needs to switch from 0 to 1 or from 1 to 0. It is supposed to be equal to $1\mu s$, $Q = diag[q_1, q_2, q_3, q_4] = diag[10, 10, 1, 10]$ and taking as operating point $z_0 = [0.25, 1.25, 20, 5]^T$, we find the following optimal sequence:

$$(\mathcal{T}^*, \mathcal{I}^*)^{s^*} = \{(1.9\mu s, 0), (2.9\mu s, 1)\} \tag{25}$$

with an initial condition $z(0) = [0.2750, 1.7190, 19.9608, 4.948]^T$. It can be noticed, from equation (25) that the optimal period which minimizes the oscillations is $T_p = 2.9\mu s$. The dwell time constraints t_{min} for the switch component is also verified.

The NN interpolates the solution with 40 neurones in the hidden layer with a back-propagation training algorithm and sigmoid functions. After training, the NN is tested with a set of known solutions not used for the training phase (Validation set). In the case when the error with the validation set is not acceptable, the number of neurons is increased in the hidden layer until all validation sets lead to a good result.

Fig. 7 shows i_{L_2}. It is observed the DCM ($i_{L_2} = 0$) occurs during the transient of the system. Fig. 8 shows the start-up response of the system (evolution of the voltage in the load) and Fig. 9 is a zoom in steady state showing the limit cycle and the time evolution of mode. Finally in order to reduce the overshoot in the output voltage, the matrix Q is changed by $Q = diag[10, 100, 1, 10]$. Fig. 10 shows the response. It is observed that the overshoot is almost eliminated but the stabilization time increases.

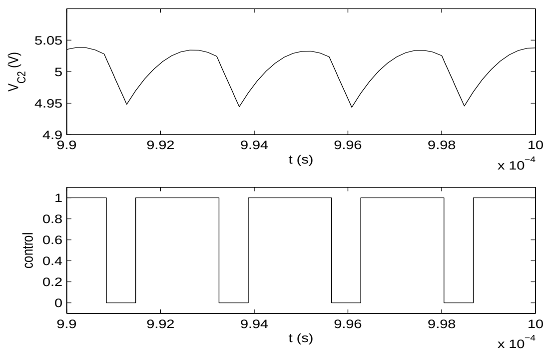

Fig. 9. Neural predictive approach - Zoom on the limit cycle with a weight matrix of $Q = diag[10, 10, 1, 10]$ - Evolution of the control ρ

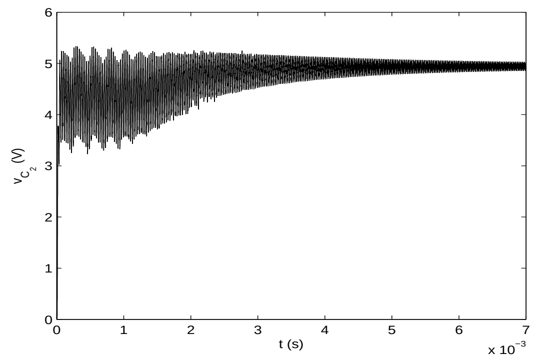

Fig. 10. Neural predictive approach - Output voltage for the start-up test with a weight matrix of $Q = diag[10, 100, 1, 10]$

VI. COMPARISON

Concerning the stabilization approach, simulation results with W as an identity matrix show that the oscillations are not damped. They slowly decrease. This yields variations for the load voltage around the control objective. However, common applications (cell phones, battery interfaces) require small variations. With the weight matrix $W = diag[100, 1, 100, 1]$, the oscillations are drastically damped but a high overshoot appears during transient ($V_{max} = 30V$).

For the neural predictive approach, the oscillations around the control objective are smaller, but an overshoot still exists during transient ($V_{max} = 15V$) (cf. Fig. 8). Nevertheless, changing the matrix Q, the overshoot can be reduced but with a higher stabilization time (cf. Fig. 10). From several modification of the matrix Q, it is observed that a big weight q_2 (The weight associated to the error $i_{L_2} - i_{L_2 ref}$) has a strong influence in the output voltage. Bigger value of q_2 allows to have less overshoot but higher stabilization time.

For the two strategies, the DCM appears during transient but when the steady state is reached only CCM occurs.

VII. CONCLUSION

In this paper two original control strategies have been implemented in simulation on a SEPIC.

The neural predictive approach allows tracking an optimal limit cycle and also controlling the waveform while the stabilization approach, based on energetic principles, determines the control values. This ensures the asymptotic stability of the system combined with a control objective. From a methodological point of view, the stabilization approach has the advantage of being easier to synthesize since at each sampling time, only a few functions have to be evaluated. For the predictive approach, although the synthesis takes some time, the implementation only require the evaluation of the activation functions in the neural network.

Currently, both strategies do not satisfy control objectives because of the overshoot during transient. However, from the predictive approach, it is shown that it must be a deal between overshoot and stabilization time.

Further works could consist to test the feasibility of commutation controllers in order to improve performances during transient. As a future work, robustness test (load variation, parameters variation and input source supply variations) must be carried out. Moreover, in a practical point of view, these two approaches should be evaluated on an experimental platform in order to validate their performances.

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