

Construction of DC-DC Converters Fuzzy Models

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1 Takagi-Sugeno Fuzzy Model

The design procedure begins with representing a given non-linear plant by the Takagi-Sugeno fuzzy model. This model is characterized by fuzzy IF-THEN rules which describe local linear input-output relations of a non-linear system. The TS Fuzzy model expresses the local dynamics of each fuzzy rule using a linear system model, while the global model is achieved by combining these linear system models

The i -th fuzzy rules for Continuous Fuzzy Systems (CFS) are of the following forms:

Model Rule i :

$$\begin{array}{ll} \text{IF } z_1(t) \text{ is } M_{i1} \text{ and } \dots \text{ and } z_p(t) \text{ is } M_{ip} \\ \text{THEN } \begin{cases} \dot{x} = A_i x(t) + B_i u(t) \\ y = C_i x, \end{cases} & , \quad i = 1, 2, \dots, r. \end{array}$$

Here, M_{ij} is the fuzzy set and r is the number of model rules; $x(t) \in \mathbb{R}^n$ is the state vector, $u(t) \in \mathbb{R}^m$ is the input vector, $y(t) \in \mathbb{R}^q$ is the output vector, $A_i \in \mathbb{R}^{n \times n}$, $B_i \in \mathbb{R}^{n \times m}$ and $C_i \in \mathbb{R}^{q \times n}$; $z_1(t), \dots, z_p(t)$ are known premise variables which may be functions of the state variables, external disturbances, and/or time.

Given a pair of $(x(t), u(t))$, the final outputs of the CFS are inferred as follows:

$$\dot{x} = \frac{\sum_{i=1}^r w_i(z(t)) \{A_i x(t) + B_i u(t)\}}{\sum_{i=1}^r w_i(z(t))} = \sum_{i=1}^r h_i(z(t)) \{A_i x(t) + B_i u(t)\} \quad (1)$$

$$y(t) = \frac{\sum_{i=1}^r w_i(z(t)) C_i x(t)}{\sum_{i=1}^r w_i(z(t))} = \sum_{i=1}^r h_i(z(t)) C_i x(t) \quad (2)$$

where $z(t) = [z_1(t), z_2(t), \dots, z_p(t)]$,

$$w_i(z(t)) = \prod_{j=1}^p M_{ij}(z_j(t)) \quad \text{and} \quad h_i(z(t)) = \frac{w_i(z(t))}{\sum_{j=1}^r w_i(z(t))}, \quad (3)$$

for all time t . The term $M_{ij}(z(t))$ is the grade of membership of $z_j(t)$ in M_{ij} . Since

$$\sum_{i=1}^r w_i(z(t)) > 0, \quad w_i(z(t)) \geq 0, \quad i = 1, 2, \dots, r, \quad (4)$$

we have

$$\sum_{i=1}^r h_i(z(t)) > 0, \quad h_i(z(t)) \geq 0, \quad i = 1, 2, \dots, r. \quad (5)$$

2 Buck Converter

The buck converter circuit is illustrated in Figure 1. In this circuit, $v_{in}(t)$ represents the input voltage, and D denotes the diode. The output voltage filter consists of an inductor with winding resistance R_L and inductance L , and a capacitor with capacitance C . Finally, two types of loads are supplied: a Constant Resistance Load with resistance $R(t)$ and a Constant Power Load (CPL) with power $P_\ell(t)$, represented by a controlled current source.

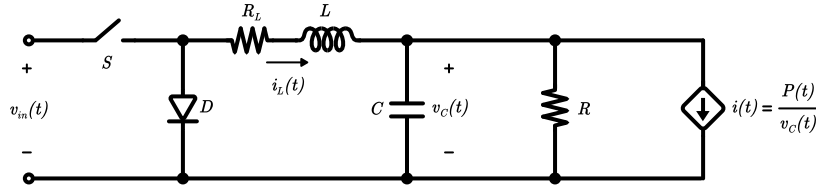


Fig. 1: Buck converter circuit.

2.1 Non-linear Buck Converter Model

When the switch S is in the off state for the duration t_{off} , the dynamic equations describing the circuit's behavior at this moment, derived from Kirchhoff's laws, are as follows:

$$\begin{cases} \dot{i}_L = -\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) \\ \dot{v}_C = \frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \end{cases} \quad (6)$$

And, when the switch S is in the on state for the duration t_{on} ,

$$\begin{cases} \dot{i}_L = -\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) + \frac{1}{L}v_{in}(t) \\ \dot{v}_C = \frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \end{cases} \quad (7)$$

Building on the equations (6) and (7), the average dynamic model that represents the behavior of the buck converter throughout its operation is:

$$\begin{cases} \dot{i}_L = \left[-\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) \right] \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} + \left[-\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) + \frac{1}{L}v_{\text{in}}(t) \right] \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} \\ \dot{v}_C = \left[-\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \right] \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} + \left[-\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \right] \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} \end{cases} \quad (8)$$

Defining the following expression:

$$d = \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}}, \quad (9)$$

yields,

$$\frac{t_{\text{off}} + t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} = 1 \Rightarrow \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} + \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} = 1 \Rightarrow \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} = 1 - \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} \Rightarrow \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} = 1 - d \quad (10)$$

Therefore, the equation (8) can be rewritten as follows:

$$\begin{cases} \dot{i}_L = \left[-\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) \right] (1 - d) + \left[-\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) + \frac{1}{L}v_{\text{in}}(t) \right] d \\ \dot{v}_C = \left[-\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \right] (1 - d) + \left[-\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \right] d \end{cases}$$

Then,

$$\begin{cases} \dot{i}_L = -\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) + \frac{1}{L}v_{\text{in}}(t)d \\ \dot{v}_C = -\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \end{cases} \quad (11)$$

The variable d is commonly known as the switching duty cycle, which plays a crucial role in controlling switch states. Its value can be determined based on the control input $u_d(t)$, defined by:

$$d(u_d(t)) = \max \{ \min \{ u_d(t), 1 \}, 0 \}. \quad (12)$$

Choosing the operation point $P^o = (i_L^o, v_C^o, u_d^o, v_{\text{in}}^o, P_\ell^o)$, where $u_d^o \in [0, 1]$, the following coordinate change can be performed:

$$\delta i_L(t) = i_L(t) - i_L^o, \quad \delta v_C(t) = v_C(t) - v_C^o, \quad \delta u_d(t) = u_d(t) - u_d^o \quad (13)$$

$$\delta v_{\text{in}}(t) = v_{\text{in}}(t) - v_{\text{in}}^o, \quad \delta P_\ell(t) = P_\ell(t) - P_\ell^o \quad (14)$$

Moreover, let the control input saturation be modeled by means of the function $\text{sat} : \mathbb{R} \rightarrow [-v, v]$ such that:

$$\delta d = \text{sat}(\delta u_d(t)) = \max \{ \min \{ \delta u_d(t), v \}, -v \} \quad (15)$$

$$v = \min \{ 1 - u_d^o, u_d^o \} \quad (16)$$

Thus, the following non-linear model is obtained:

$$\begin{cases} \delta \dot{i}_L = -\frac{R_L}{L} \delta i(t) - \frac{1}{L} \delta v_C(t) + \frac{v_{in}^o + \delta v_{in}(t)}{L} \text{sat}(\delta u_d(t)) + \frac{u_d^o}{L} \delta v_{in}(t) \\ \delta \dot{v}_C = \frac{1}{C} \delta i_L(t) + \left[-\frac{1}{CR} + \frac{P_\ell^o}{C v_C^o [v_C^o + \delta v_C(t)]} \right] \delta v_C(t) - \frac{1}{C [v_C^o + \delta v_C(t)]} \delta P_\ell(t) \end{cases} \quad (17)$$

where,

$$i_L^o = \frac{1}{R} v_C^o + \frac{1}{v_C^o} P_\ell^o, \quad u_d^o = \frac{R_L}{v_{in}^o} i_L^o + \frac{v_C^o}{v_{in}^o}.$$

Finally, the model (17) can be rewritten as:

$$\dot{x} = A(x)x(t) + B(w)\text{sat}(u(t)) + E(x, u)w(t) \quad (18)$$

where $x(t) = \begin{bmatrix} i_L(t) & v_C(t) \end{bmatrix}^T$, $u(t) = \delta u_d(t)$, $w(t) = \begin{bmatrix} \delta v_{in}(t) & \delta P_\ell(t) \end{bmatrix}^T$, and

$$A(x) = \begin{bmatrix} -\frac{R_L}{L} & -\frac{1}{L} \\ \frac{1}{C} & -\frac{1}{CR} + \frac{P_\ell^o}{C v_C^o [v_C^o + \delta v_C(t)]} \end{bmatrix} \quad B(w) = \begin{bmatrix} \frac{v_{in}^o + \delta v_{in}(t)}{L} \\ 0 \end{bmatrix}$$

$$E(x, u) = \begin{bmatrix} \frac{u_d^o}{L} & 0 \\ 0 & -\frac{1}{C [v_C^o + \delta v_C(t)]} \end{bmatrix} \quad (18)$$

2.2 Buck Converter Fuzzy Model

In order to address the nonlinearity introduced by saturation, an approach based on substituting $\text{sat}(\circ)$ with a dead-zone type nonlinearity is used. The dead-zone nonlinearity is defined as:

$$\psi(u(t)) \triangleq u(t) - \text{sat}(u(t)) \quad (19)$$

From the matrices presented in equation (18), it follows $\frac{1}{v_C^o + \delta v_C^o}$ and $v_{in}^o + \delta v_{in}(t)$ are non-linear terms. For the non-linear terms, are defined

$$z_0(t) \equiv \frac{1}{v_C^o + \delta v_C^o} \quad \text{and} \quad z_1(t) \equiv v_{in}^o + \delta v_{in}(t). \quad (20)$$

Thus, the equation (18) can be rewritten as:

$$\dot{x} = A(z(t))x(t) + B(z(t))u(t) - B(w)\psi(u(t)) + E(z(t))w(t), \quad (21)$$

where $z(t) = \begin{bmatrix} z_0(t) & z_1(t) \end{bmatrix}$, $A(z(t)) = \begin{bmatrix} -\frac{R_L}{L} & -\frac{1}{L} \\ \frac{1}{C} & -\frac{1}{CR} + \frac{P_\ell^o}{Cv_C^o} z_0(t) \end{bmatrix}$, $B(z(t)) = \begin{bmatrix} \frac{1}{L} z_1(t) \\ 0 \end{bmatrix}$ and $E(z(t)) = \begin{bmatrix} \frac{u_d^o}{L} & 0 \\ 0 & -\frac{1}{C} z_0(t) \end{bmatrix}$.

Next, the minimum and maximum values of $z_0(t)$ e $z_1(t)$ under $v_C(t) \in [v_C^{\min}, v_C^{\max}]$ and $v_{in}(t) \in [v_{in}^{\min}, v_{in}^{\max}]$, are obtained as follows:

$$\begin{cases} z_i^0 = \min_{v_C(t), v_{in}(t)} z_i(t) \\ z_i^1 = \max_{v_C(t), v_{in}(t)} z_i(t) \end{cases}, \quad i = 1, 2 \quad (22)$$

From the maximum and minimum values of $z_0(t)$ and $z_1(t)$, the membership functions can be calculated as:

$$z_i(t) = \sum_{j=0}^1 M_i^j(z_i(t)) z_i^j, \quad \text{where} \quad M_i^1 = \frac{z_i(t) - z_i^0}{z_i^1 - z_i^0} \quad \text{and} \quad M_i^0 = 1 - M_i^1, \quad \text{for } i = \{1, 2\}. \quad (23)$$

Therefore, the Takagi-Sugeno fuzzy model for the buck converter is:

$$\dot{x} = \sum_{i=0}^1 \sum_{j=0}^1 \prod_{k=1}^2 M_k^i(z_k(t)) \left[A(z^{\{i,j\}}) x(t) + B(z^{\{i,j\}}) u(t) - B(z^{\{i,j\}}) \psi(u(t)) + E(z^{\{i,j\}}) w(t) \right] \quad (24)$$

where $z^{\{i,j\}}(t)$ is a shorthand for $\begin{bmatrix} z_1^i(t) & z_2^j(t) \end{bmatrix}$.

The summations in (24) can be aggregated as one summations:

$$\dot{x} = \sum_{p=\{0,0\}}^{\{1,1\}} h_p(z(t)) \{A_p x(t) + B_p u(t) - B_p \psi(u(t)) + E_p w(t)\} \quad (25)$$

where $p = \{b_1, b_2\} \in \mathbb{B}^2$, $\mathbb{B} = \{0, 1\}$,

$$h_p(z(t)) = \prod_{k=1}^2 M_k^{b_k}(z_k(t)) \quad (26)$$

$$A_p = A(z^p) \quad B_p = B(z^p) \quad E_p = E(z^p) \quad (27)$$