

0.1 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 :

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

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 $M_{ij}(z_j(t))$ 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

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

Chapter 1

DC-DC Converters Modeling

1.1 Buck Converter

The buck converter circuit is illustrated in Figure 1.1. 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.

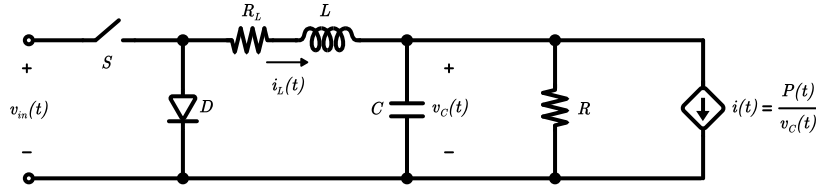


Figure 1.1: Buck converter circuit.

1.1.1 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:

$$\begin{cases} \dot{i}_L = -\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) \\ \dot{v}_C = \frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \end{cases} \quad (1.1)$$

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

$$\begin{cases} \dot{i}_L = -\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) + \frac{1}{L}v_{in}(t) \\ \dot{v}_C = \frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \end{cases} \quad (1.2)$$

Building on the equations (1.1) and (1.2), the average dynamic model that represents the behavior of the buck converter throughout its operation is:

$$\begin{cases} \dot{i}_L = \left[-\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) \right] \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} + \left[-\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) + \frac{1}{L}v_{\text{in}}(t) \right] \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} \\ \dot{v}_C = \left[-\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \right] \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} + \left[-\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \right] \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} \end{cases} \quad (1.3)$$

Defining the following expression:

$$d = \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}}, \quad (1.4)$$

yields,

$$\frac{t_{\text{off}} + t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} = 1 \Rightarrow \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} + \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} = 1 \Rightarrow \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} = 1 - \frac{t_{\text{on}}}{t_{\text{off}} + t_{\text{on}}} \Rightarrow \frac{t_{\text{off}}}{t_{\text{off}} + t_{\text{on}}} = 1 - d \quad (1.5)$$

Therefore, the equation (1.3) 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,

$$\begin{cases} \dot{i}_L = -\frac{R_L}{L}i(t) - \frac{1}{L}v_C(t) + \frac{1}{L}v_{\text{in}}(t)d \\ \dot{v}_C = -\frac{1}{C}i_L(t) - \frac{1}{CR}v_C(t) - \frac{1}{Cv_C(t)}P_\ell(t) \end{cases} \quad (1.6)$$

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:

$$d(u_d(t)) = \max \{ \min \{ u_d(t), 1 \}, 0 \}. \quad (1.7)$$

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:

$$\delta i_L(t) = i_L(t) - i_L^o, \quad \delta v_C(t) = v_C(t) - v_C^o, \quad \delta u_d(t) = u_d(t) - u_d^o \quad (1.8)$$

$$\delta v_{\text{in}}(t) = v_{\text{in}}(t) - v_{\text{in}}^o, \quad \delta P_\ell(t) = P_\ell(t) - P_\ell^o \quad (1.9)$$

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

$$\delta d = \text{sat}(\delta u_d(t)) = \max \{ \min \{ \delta u_d(t), v \}, -v \} \quad (1.10)$$

$$v = \min \{ 1 - u_d^o, u_d^o \} \quad (1.11)$$

Thus, the following non-linear model is obtained:

$$\begin{cases} \delta \dot{i}_L = -\frac{R_L}{L} \delta i(t) - \frac{1}{L} \delta v_C(t) + \frac{v_{in}^o + \delta v_{in}(t)}{L} \text{sat}(\delta u_d(t)) + \frac{u_d^o}{L} \delta v_{in}(t) \\ \delta \dot{v}_C = \frac{1}{C} \delta i_L(t) + \left[-\frac{1}{CR} + \frac{P_\ell^o}{C v_C^o [v_C^o + \delta v_C(t)]} \right] \delta v_C(t) - \frac{1}{C [v_C^o + \delta v_C(t)]} \delta P_\ell(t) \end{cases} \quad (1.12)$$

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 (1.12) can be rewritten as:

$$\dot{x} = A(x)x(t) + B(w)\text{sat}(u(t)) + E(x, u)w(t) \quad (1.13)$$

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

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

$$E(x, u) = \begin{bmatrix} \frac{u_d^o}{L} & 0 \\ 0 & -\frac{1}{C [v_C^o + \delta v_C(t)]} \end{bmatrix} \quad (1.13)$$

1.1.2 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:

$$\psi(u(t)) \triangleq u(t) - \text{sat}(u(t)) \quad (1.14)$$

From the matrices presented in equation (1.13), it follows $\frac{1}{v_C^o + \delta v_C}$ and $v_{in}^o + \delta v_{in}(t)$ are non-linear terms. For the non-linear terms, are defined

$$z_0(t) \equiv \frac{1}{v_C^o + \delta v_C} \quad \text{and} \quad z_1(t) \equiv v_{in}^o + \delta v_{in}(t). \quad (1.15)$$

Thus, the equation (1.13) can be rewritten as:

$$\dot{x} = A(z(t))x(t) + B(z(t))u(t) - B(w)\psi(u(t)) + E(z(t))w(t), \quad (1.16)$$

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:

$$\begin{cases} z_i^0 &= \min_{v_C(t), v_{in}(t)} z_i(t) \\ z_i^1 &= \max_{v_C(t), v_{in}(t)} z_i(t) \end{cases}, \quad i = 1, 2 \quad (1.17)$$

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

$$z_i(t) = \sum_{j=0}^1 M_i^j(z_i(t)) z_i^j, \quad \text{where} \quad M_i^1 = \frac{z_i(t) - z_i^0}{z_i^1 - z_i^0} \quad \text{and} \quad M_i^0 = 1 - M_i^1, \quad \text{for } i = \{1, 2\}. \quad (1.18)$$

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

$$\dot{x} = \sum_{i=0}^1 \sum_{j=0}^1 \prod_{k=1}^2 M_k^i(z_k(t)) \left[A(z^{\{i,j\}}) x(t) + B(z^{\{i,j\}}) u(t) - B(z^{\{i,j\}}) \psi(u(t)) + E(z^{\{i,j\}}) w(t) \right] \quad (1.19)$$

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

The summations in (1.19) can be aggregated as one summations:

$$\dot{x} = \sum_{p=\{0,0\}}^{\{1,1\}} h_p(z(t)) \{A_p x(t) + B_p u(t) - B_p \psi(u(t)) + E_p w(t)\} \quad (1.20)$$

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

$$h_p(z(t)) = \prod_{k=1}^2 M_k^{b_k}(z_k(t)) \quad (1.21)$$

$$A_p = A(z^p) \quad B_p = B(z^p) \quad E_p = E(z^p) \quad (1.22)$$

Chapter 2

Event-based Control for DC-DC Converters

2.1 Problem formulation

Dynamic system:

$$\dot{x} = \sum_{p \in \mathbb{B}^n} h_p(z(t)) \{A_p x(t) + B_p u(t) - B_p \psi(u(t)) + E_p w(t)\} \quad (2.1)$$

$$h_p(z(t)) = \prod_{k=1}^n M_k^{b_k}(z_k(t)) \quad (2.2)$$

$$A_p = A(z^p) \quad B_p = B(z^p) \quad E_p = E(z^p) \quad (2.3)$$

Control law:

$$u(t) = K(\hat{x})\hat{x}(t) + L(\hat{x})\hat{w}(t) \Rightarrow u(t) = \sum_{p \in \mathbb{B}^n} h_p(z(t)) \{K_p \hat{x}(t) + L_p \hat{w}(t)\} \quad (2.4)$$

Consider a vector $v \in \mathbb{R}^{n_u}$ such that the following set \mathcal{S} can be defined:

$$\mathcal{S} = \{u, v \in \mathbb{R}^{n_u} : |u_i - v_i| \leq u_{0i}, i = 1, \dots, n_u\} \quad (2.5)$$

If u and $v \in \mathcal{S}$, then the relation

$$\psi(u)^T T [\psi(u) - v] \leq 0 \quad (2.6)$$

is satisfied for any diagonal and positive definite matrix $T \in \mathbb{R}^{n_u \times n_u}$.

$$v = G(\hat{x})x(t) = \sum_{p \in \mathbb{B}^n} h_p(z(t)) \{G_p \hat{x}(t)\} \quad (2.7)$$

If $x \in \mathcal{S}$, such that

$$\mathcal{S} = \{x \in \mathbb{R}^n : |K(\hat{x})\hat{x}(t) + L(\hat{x})\hat{w}(t) - G(\hat{x})\hat{x}(t)| \leq u_{0i}, i = 1, \dots, n_u\} \quad (2.8)$$

$$\mathcal{S} = \{x \in \mathbb{R}^n : |[K(\hat{x}) - G(\hat{x})]\hat{x}(t) + L(\hat{x})\hat{w}(t)| \leq u_{0i}, i = 1, \dots, n_u\} \quad (2.9)$$

$$\mathcal{S} = \left\{ x \in \mathbb{R}^n : \left| \sum_{p \in \mathbb{B}^n} h_p(z(t)) \{ (K_p - G_p)\hat{x}(t) + L_p\hat{w}(t) \} \right| \leq u_{0i}, i = 1, \dots, n_u \right\} \quad (2.10)$$

then,

$$\psi^T(K(\hat{x})x(t) + L(\hat{x})\hat{w})T[\psi(K(\hat{x})\hat{x} + L(\hat{x})\hat{w}) - G(\hat{x})\hat{x}] \leq 0 \quad (2.11)$$

$$\psi^T(u(t))T[\psi(u(t)) - G(\hat{x})\hat{x}] \leq 0 \quad (2.12)$$

$$\psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x(t) + e_x(t))[x(t) + e_x(t)] \leq 0 \quad (2.13)$$

$$\begin{aligned} \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x(t))x(t) - \psi^T(u(t))TG(x(t))e_x(t) \\ - \psi^T(u(t))TG(e_x(t))x(t) - \psi^T(u(t))TG(e_x(t))e_x(t) \leq 0 \end{aligned} \quad (2.14)$$

$$\begin{aligned} \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x(t))x(t) - \psi^T(u(t))TG(x(t))e_x(t) \\ - \psi^T(u(t))T[G(x(t) + e_x(t)) - G(x)][x(t) + e_x(t)] \leq 0 \end{aligned} \quad (2.15)$$

$$\begin{aligned} \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x(t))x(t) - \psi^T(u(t))TG(x(t))e_x(t) - \psi^T(u(t))TG(e_x(t))[x(t) + e_x(t)] \leq 0 \\ (2.16) \end{aligned}$$

2.1.1 Sistema

Seja $e_x(t) = \hat{x}(t) - x(t)$ and $e_w(t) = \hat{w}(t) - w(t)$. Têm-se,

$$\dot{x} = A(x)x(t) + B(x)u(t) - B\psi(u(t)) + E(x)w(t) \quad (2.17)$$

$$\dot{x} = A(x)x(t) + B(x)[K(\hat{x})\hat{x}(t) + L(\hat{x})\hat{w}(t)] - B\psi(u(t)) + E(x)w(t) \quad (2.18)$$

$$\dot{x} = A(x)x(t) + B(x)K(\hat{x})\hat{x}(t) + B(x)L(\hat{x})\hat{w}(t) - B\psi(u(t)) + E(x)w(t) \quad (2.19)$$

$$\begin{aligned} \dot{x} = & A(x)x(t) + B(x)K(\hat{x}(t)) [e_x(t) + x(t)] \\ & + B(x)L(\hat{x}(t)) [e_w(t) + w(t)] - B\psi(u(t)) + E(x)w(t) \end{aligned} \quad (2.20)$$

$$\begin{aligned} \dot{x} = & [A(x) + B(x)K(x(t))] x(t) + B(x)K(x(t))e_x(t) + B(x)K(e_x(t)) [e_x(t) + x(t)] \\ & + [E(x) + B(x)L(x(t))] w(t) + B(x)L(x(t))e_w(t) + B(x)L(e_x(t)) [e_w(t) + w(t)] \\ & - B\psi(u(t)) \end{aligned} \quad (2.21)$$

ETM dinâmico:

$$t_0 = 0, t_{k+1} = \inf\{t > t_k : \eta(t) + \theta\Gamma(x(t), e_x(t), e_w(t)) < 0\}, \forall k \in \mathbb{N}. \quad (2.22)$$

Função de ativação:

$$\Gamma(x, e_x) = x^T(t)\Psi x(t) - e_x^T \Xi_x e_x - \zeta(x, e_x) \quad (2.23)$$

onde,

$$\zeta(x, e_x) = 2x^T P [B(x) (K(x + e_x) - x) (x + e_x)] \quad (2.24)$$

LMI de restrição,

$$\begin{bmatrix} \mathbf{He}(A_i X + B_i \tilde{K}_j) + (1 - \beta)I & E_i X + B_i \tilde{L}_j & B_i \tilde{K}_j & B_i \tilde{L}_j & -B_i X - \frac{1}{2} X T G_i X & X \\ \star & -(\mu - \alpha)I & 0 & 0 & 0 & 0 \\ \star & \star & -\tilde{\Xi} - \beta & 0 & -\frac{1}{2} X T G_i X & 0 \\ \star & \star & \star & \alpha I & 0 & 0 \\ \star & \star & \star & \star & \tilde{T} & 0 \\ \star & \star & \star & \star & \star & -\tilde{\Psi} \end{bmatrix} < 0 \quad (2.25)$$

Multiplicando por $\text{diag}(X^{-1}, X^{-1}, X^{-1}, X^{-1}, I)$, e fazendo as mudança de variáveis: $K_j = \tilde{K}_j X^{-1}$, $L_j = \tilde{L}_j X^{-1}$, $\Xi = X^{-1} \tilde{\Xi} X^{-1}$, $T = X^{-1} \tilde{T} X^{-1}$, $P = X^{-1}$

$$\begin{bmatrix} \Omega & P [E(x) + B(x)L(x)] & P B(x)K(x) & P B(x)L(x) & -P B(x) - \frac{1}{2} T G(x) & I \\ \star & -(\mu - \alpha)I & 0 & 0 & 0 & 0 \\ \star & \star & -\Xi - \beta & 0 & -\frac{1}{2} T G(x) & 0 \\ \star & \star & \star & \alpha I & 0 & 0 \\ \star & \star & \star & \star & T & 0 \\ \star & \star & \star & \star & \star & -\tilde{\Psi} \end{bmatrix} < 0 \quad (2.26)$$

onde $\Omega = P \mathbf{H}e(A(x) + B(x)K(x)) + (1 - \beta)I$. Pelo complemento de Schur,

$$\begin{bmatrix} \Omega + \Psi & P[E(x) + B(x)L(x)] & PB(x)K(x) & PB(x)L(x) & -PB(x) - \frac{1}{2}TG(x) \\ \star & -(\mu - \alpha)I & 0 & 0 & 0 \\ \star & \star & -\Xi - \beta & 0 & -\frac{1}{2}TG(x) \\ \star & \star & \star & \alpha I & 0 \\ \star & \star & \star & \star & T \end{bmatrix} < 0 \quad (2.27)$$

Considerando $v = [x^T(t) \ w^T(t) \ e_x^T(t) \ e_w^T(t) \ \psi(u)^T]^T$, pré e pós-multiplicando por v e v^T , respectivamente, obtêm-se:

$$\begin{aligned} & 2x^T(t)P\{[A(x) + B(x)K(x(t))]x(t) + [E(x) + B(x)L(x(t))]w(t) + B(x)K(x(t))e_x(t) + B(x)L(x(t))e_w(t) \\ & - B(x)\psi(u(t))\} - \psi^T(u(t))TG(x)x(t) + (1 - \beta)x^T(t)x(t) - (\mu - \alpha)w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) \\ & - \beta e_x^T(t)e_x(t) + \alpha e_w^T(t)e_w(t) + \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x)e_x(t) < 0 \end{aligned} \quad (2.28)$$

Onde $\alpha \in \mathbb{R}_{>0}$ é tal que:

$$2x^T(t)PB(x)L(e_x(t))[w(t) + e_w(t)] \leq \alpha^{-1}\|x^T(t)PB(x)L(e_x)\|^2 + \alpha\|w(t) + e_w(t)\|^2 \quad (2.29)$$

$$2x^T(t)PB(x)L(e_x(t))[w(t) + e_w(t)] \leq \alpha^{-1}\|x^T(t)PB(x)L(e_x)\|^2 + \alpha\|w(t)\|^2 + \alpha\|w(t)\|\|e_w(t)\| + \alpha\|e_w(t)\|^2 \quad (2.30)$$

$$-\alpha^{-1}\|x^T(t)PB(x)L(e_x)\|^2 - \alpha\|w(t)\|^2 - \alpha\|w(t)\|\|e_w(t)\| - \alpha\|e_w(t)\|^2 \leq -2x^T(t)PB(x)L(e_x(t))[w(t) + e_w(t)] \quad (2.31)$$

Assim,

$$\begin{aligned} & 2x^T(t)P\{[A(x) + B(x)K(x(t))]x(t) + [E(x) + B(x)L(x(t))]w(t) + B(x)K(x(t))e_x(t) + B(x)L(x(t))e_w(t) \\ & - B(x)\psi(u(t))\} - \psi^T(u(t))TG(x)x(t) + (1 - \beta)x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \beta e_x^T(t)e_x(t) \\ & + \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x)e_x(t) < -\alpha w^T(t)w(t) - \alpha e_w^T(t)e_w(t) \end{aligned} \quad (2.32)$$

$$\begin{aligned} & 2x^T(t)P\{[A(x) + B(x)K(x(t))]x(t) + [E(x) + B(x)L(x(t))]w(t) + B(x)K(x(t))e_x(t) + B(x)L(x(t))e_w(t) \\ & - B(x)\psi(u(t))\} - \psi^T(u(t))TG(x)x(t) + (1 - \beta)x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \beta e_x^T(t)e_x(t) \\ & + \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x)e_x(t) - \alpha\|w(t)\|\|e_w(t)\| - \alpha^{-1}\|x^T(t)PB(x)L(e_x)\|^2 \\ & < -\alpha w^T(t)w(t) - \alpha e_w^T(t)e_w(t) - \alpha\|w(t)\|\|e_w(t)\| - \alpha^{-1}\|x^T(t)PB(x)L(e_x)\|^2 \end{aligned} \quad (2.33)$$

$$\begin{aligned}
& 2x^T(t)P\{[A(x) + B(x)K(x(t))]x(t) + [E(x) + B(x)L(x(t))]w(t) + B(x)K(x(t))e_x(t) + B(x)L(x(t))e_w(t) \\
& - B(x)\psi(u(t))\} - \psi^T(u(t))TG(x)x(t) + (1 - \beta)x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \beta e_x^T(t)e_x(t) \\
& + \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x)e_x(t) - \alpha\|w(t)\|\|e_w(t)\| - \alpha^{-1}\|x^T(t)PB(x)L(e_x)\|^2 \\
& < -2x^T(t)PB(x)L(e_x(t))[w(t) + e_w(t)] \quad (2.34)
\end{aligned}$$

$$\begin{aligned}
& 2x^T(t)P\{[A(x) + B(x)K(x(t))]x(t) + [E(x) + B(x)L(x(t))]w(t) + B(x)K(x(t))e_x(t) + B(x)L(x(t))e_w(t) \\
& + B(x)L(e_x(t))[w(t) + e_w(t)] - B(x)\psi(u(t))\} - \psi^T(u(t))TG(x)x(t) + (1 - \beta)x^T(t)x(t) - \mu w^T(t)w(t) \\
& + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \beta e_x^T(t)e_x(t) + \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x)e_x(t) - \alpha\|w(t)\|\|e_w(t)\| \\
& - \alpha^{-1}\|x^T(t)PB(x)L(e_x)\|^2 < 0 \quad (2.35)
\end{aligned}$$

$$\begin{aligned}
& 2x^T(t)P\{[A(x) + B(x)K(x(t))]x(t) + [E(x) + B(x)L(x(t))]w(t) + B(x)K(x(t))e_x(t) + B(x)L(x(t))e_w(t) \\
& + B(x)L(e_x(t))[w(t) + e_w(t)] - B(x)\psi(u(t))\} - \psi^T(u(t))TG(x)x(t) + (1 - \beta)x^T(t)x(t) - \mu w^T(t)w(t) \\
& + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \beta e_x^T(t)e_x(t) + \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x)e_x(t) < 0 \quad (2.36)
\end{aligned}$$

Somando $\zeta(x(t), e_x(t))$, têm-se:

$$\begin{aligned}
& 2x^T(t)P\dot{x}(t) - \psi^T(u(t))TG(x)x(t) + (1 - \beta)x^T(t)x(t) - \mu w^T(t)w(t) \\
& + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \beta e_x^T(t)e_x(t) + \psi^T(u(t))T\psi(u(t)) - \psi^T(u(t))TG(x)e_x(t) < 0 \quad (2.37)
\end{aligned}$$

De forma semelhante, $\beta \in \mathbb{R}_{>0}$ é tal que,

$$\psi^T(u(t))G(e_x(t))[x(t) + e_x(t)] \leq \beta^{-1}\|\psi(u(t))G(e_x(t))\|^2 + \beta\|x(t) + e_x(t)\|^2 \quad (2.38)$$

$$\psi^T(u(t))G(e_x(t))[x(t) + e_x(t)] - \beta^{-1}\|\psi(u(t))G(e_x(t))\|^2 - \beta\|x(t)\|^2 - \beta\|x(t)\|\|e_x(t)\| - \beta\|e_x(t)\|^2 \leq 0 \quad (2.39)$$

Logo,

$$\begin{aligned}
& 2x^T(t)P\dot{x}(t) + x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \beta x^T(t)x(t) + \psi^T(u(t))T\psi(u(t)) \\
& - \psi^T(u(t))TG(x)x(t) - \psi^T(u(t))TG(x)e_x(t) - \psi^T(u(t))G(e_x(t))[x(t) + e_x(t)] \\
& + \psi^T(u(t))G(e_x(t))[x(t) + e_x(t)] - \beta e_x^T(t)e_x(t) < 0 \quad (2.40)
\end{aligned}$$

De ,

$$\begin{aligned}
& 2x^T(t)P\dot{x}(t) + x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) \\
& + \psi^T(u(t))G(e_x(t))[x(t) + e_x(t)] - \beta x^T(t)x(t) - \beta e_x^T(t)e_x(t) < 0 \quad (2.41)
\end{aligned}$$

$$\begin{aligned}
& 2x^T(t)P\dot{x}(t) + x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) + \psi^T(u(t))G(e_x(t)) [x(t) + e_x(t)] \\
& - \beta x^T(t)x(t) - \beta e_x^T(t)e_x(t) - \beta \|x(t)\| \|e_x(t)\| - \beta^{-1} \|\psi(u(t))G(e_x(t))\|^2 < 0 \quad (2.42)
\end{aligned}$$

$$2x^T(t)P\dot{x}(t) + x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) < 0 \quad (2.43)$$

Como $\lambda\eta(t) > 0$, então:

$$2x^T(t)P\dot{x}(t) + x^T(t)x(t) - \mu w^T(t)w(t) + x^T(t)\Psi x(t) - e_x^T(t)\Xi e_x(t) - \lambda\eta(t) < 0 \quad (2.44)$$

Logo,

$$\dot{x}^T(t)Px(t) + x^T(t)P\dot{x}(t) + \dot{\eta}(t) + x^T(t)x(t) - \mu w^T(t)w(t) < 0 \quad (2.45)$$

$$\dot{x}^T(t)Px(t) + x^T(t)P\dot{x}(t) + \dot{\eta}(t) < 0 \quad (2.46)$$

$$\dot{W}(x, \eta) < 0 \quad (2.47)$$

Portanto, a origem do sistema em malha fechada sob o ETM dinâmico é estável.