## CHAPTER 2

# **PRELIMINARIES**

In this chapter, we give some basic definitions, notations, lemmas and results which will be used in the later chapters.

#### 2.1 Notations

The following notations that will be used in this thesis:

 $\mathbb{R}^n$  – the n dimensional Euclidean space,

 $\mathbb{R}^{n \times n}$  – the set of all  $n \times n$  real matrices,

||x|| – the Euclidean norm of vector x,

I — the identity matrix,

 $A^T$  – the transpose of matrix A,

 $A>0, A\geq 0, A<0, A\leq 0$  — means that A is symmetric positive definite,

positive semi-definite, negative definite and negative semi-definite,

 $\lambda(A)$  – the set of all eigenvalues of matrix A,

 $\lambda_M(A)$  – maximum eigenvalue of matrix A,

 $\lambda_m(A)$  – minimum eigenvalue of matrix A,

$$||x|| = \sqrt{\sum_{i=1}^{n} x_i^2}$$
, for any  $x \in \mathbb{R}^n$ ,

 $C([-h_M,0],\mathbb{R}^n), h_M > 0$  — denotes the space of continuous functions mapping the interval  $[-h_M,0]$  into  $\mathbb{R}^n$ ,

 $x_t \in C([-h_M,0],\mathbb{R}^n)$  defined  $x_t(s) = x(t+s), s \in [-h_M,0]$  and

$$||x_t|| = \sup_{s \in [-h_M, 0]} ||x(t+s)||,$$

$$\begin{bmatrix} A & B \\ * & C \end{bmatrix} - * \text{ represents the symmetric form of matrix, namely } * = B^T.$$

### 2.2 Types of Matrix and Function

**Definition 2.2.1 (Symmetric Matrix)** A real  $n \times n$  matrix A is called *symmetric* if

$$A^T = A$$
.

**Definition 2.2.2 (Positive Definite Matrix)** A real  $n \times n$  matrix A is called *positive definite* if

$$x^T A x > 0$$

for all nonzero vectors  $x \in \mathbb{R}^n$ . It is called *positive semidefinite* if

$$x^T A x \ge 0.$$

**Definition 2.2.3 (Negative Definite Matrix)** A real  $n \times n$  matrix A is called *negative definite* if

$$x^T A x < 0$$

for all nonzero vectors  $x \in \mathbb{R}^n$ . It is called *negative semidefinite* if

$$x^T A x \le 0.$$

The follows result are well known.

**Lemma 2.2.1** A symmetric matrix is positive semidefinite (definite) matrix if all of its eigenvalues are nonnegative (positive).

**Lemma 2.2.2** A symmetric matrix is negative semidefinite (definite) matrix if all of its eigenvalues are nonpositive (negative).

**Definition 2.2.4 (Positive Definite Function)** A function  $f(x) \in \mathbb{R}^n$  is called *positive definite* if  $f(\bar{0}) = 0$ , f(x) > 0 for all  $x \in \mathbb{R}^n$ . It is called *positive semidefinite* if  $f(x) \geq 0$  for all  $x \in \mathbb{R}^n$ .

**Definition 2.2.5 (Negative Definite Function)** A function  $f(x) \in \mathbb{R}^n$  is called negative definite if  $f(\bar{0}) = 0$ , f(x) < 0 for all  $x \in \mathbb{R}^n$ . It is called negative semidefinite if  $f(x) \leq 0$  for all  $x \in \mathbb{R}^n$ .

#### 2.3 Lyapunov Function

Consider the system described by

$$\dot{x} = f(t, x), \ x(t_0) = x_0,$$
 (2.1)

where  $x = (x_1, x_2, ..., x_n) \in \mathbb{R}^n$ ,  $x_i = x_i(t)$ ,  $f = (f_1, f_2, ..., f_n) \in \mathbb{R}^n$  and  $f_i = f_i(t, x_1, x_2, ..., x_n)$  for i = 1, 2, ..., n.

**Definition 2.3.1 (Lyapunov Function)** Let D be a domain  $\mathbb{R}^n$  such that  $\overline{0} \in D$   $V: D \subseteq \mathbb{R}^n \to \mathbb{R}$ , we say that V(x) is a Lyapunov function of system (2.1) if the following conditions hold:

- (1) V(x) is continuous on  $D \subseteq \mathbb{R}^n$ .
- (2) V(x) is positive definite such that  $V(\bar{0}) = 0$  and V(x) > 0 for all  $x \neq \bar{0}$ .
- (3) the derivative of V with respect to (2.1) is negative semidefinite (i.e.,  $\dot{V}(0) = 0$ , and  $\dot{V}(x) \leq 0$  for all  $x \neq \bar{0}$ ).

### 2.4 Stability

**Definition 2.4.1** A point  $\bar{x}$  is called an *equilibrium point* of equation (2.1) if  $f(t,\bar{x})=0$  for all  $t\geq t_0$ . For all purposes of the stability theory we can assume that  $\bar{0}$  is an equilibrium of (2.1).

**Definition 2.4.2 (Stable)** The equilibrium point  $\bar{x}$  of equation (2.1) is called *stable* if, for each  $\epsilon > 0$ , there is  $\delta = \delta(\epsilon, t_0) > 0$  such that  $||x(t_0)|| < \delta$  implies  $||x(t)|| < \epsilon$  for all  $t \ge t_0 \ge 0$ .

**Definition 2.4.3 (Unstable)** The equilibrium point  $\bar{x}$  of equation (2.1) is called *unstable* if it is not stable.

**Definition 2.4.4 (Asymptotically Stable)** The equilibrium point  $\bar{x}$  of equation (2.1) is called asymptotically stable (denoted A.S.) if it is stable and  $||x(t)|| \to 0$  as  $t \to \infty$ .

The following Theorems and Lemmas will be used throughout this thesis.

**Theorem 2.4.1** [4] The equilibrium point  $\bar{x}$  of equation (2.1) is stable if there exists a Lyapunov function for system (2.1). Moreover, if there exists a Lyapunov function whose derivative is negative definite, then the equilibrium point  $\bar{x}$  is A.S.

**Lemma 2.4.1** [15] Given a positive definite matrix  $Q \in \mathbb{R}^{n \times n}$  and  $x \in \mathbb{R}^n$ , then

$$\lambda_m(Q)x^Tx \le x^TQx \le \lambda_M(Q)x^Tx.$$

**Lemma 2.4.2 [6]** For any  $x, y \in \mathbb{R}^n$ , matrices W, E, F, H with  $W > 0, F^T F \leq I$ , and scalar  $\varepsilon > 0$ , one has

$$(1.) EFH + H^T F^T E^T \le \varepsilon^{-1} E E^T + \varepsilon H^T H,$$

(2.) 
$$2x^Ty \le x^TW^{-1}x + y^TWy$$
.

**Lemma 2.4.3** [1] Let  $u:[t_0,\infty]\to\mathbb{R}$  satisfy the following delay differential inequality:

$$\dot{u}(t) \le \alpha u(t) + \beta \sup_{\theta \in [t-\tau,t]} u(\theta), \ t \ge t_0.$$

Assume that  $\alpha + \beta > 0$ . Then, there exist positive constant  $\xi$  and k such that

$$u(t) \le k e^{\xi(t-t_0)}, \ t \ge t_0$$

 $u(t) \le ke^{\xi(t-t_0)}, \ t \ge t_0,$  where  $\xi = \alpha + \beta$  and  $k = \sup_{\theta \in [t_0 - \tau, t_0]} u(\theta).$ 

**Lemma 2.4.4** [1] Let the following differential inequality

$$\dot{u} \le -\alpha u(t) + \beta \sup_{\theta \in [t-\tau,t]} u(\theta), \ t \ge t_0,$$

hold. If  $\alpha > \beta > 0$ , then there exist positive k and  $\zeta$  such that

$$u(t) \le ke^{-\zeta(t-t_0)}, \ t \ge t_0,$$

where  $\zeta = -\alpha + \beta$  and  $k = \sup_{\alpha \in \mathcal{A}} u(\theta)$ .

**Lemma 2.4.5** [5] (Schur Complement) Given constant symmetric Q, S and  $R \in$  $\mathbb{R}^{n \times n}$  where  $R > 0, Q = Q^T$  and  $R = R^T$  we have

$$\begin{bmatrix} Q & S \\ S^T & -R \end{bmatrix} < 0 \Leftrightarrow Q + SR^{-1}S^T < 0.$$