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Control of chaos in an induction motor system with LMI predictive control and experimental circuit validation

M. Messadi*, A. Mellit

LER Laboratory, Jijel University, BP 98 Ouled Aissa, Jijel 18000,Algeria

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ABSTRACT

This paper concerns the control problems of an induction motor with chaotic behavior due to the defiance of indirect field oriented control applied with a proportional integral (PI) speed loop. The feedbacks predictive control is used to control this chaotic system owing to its simplicity of configuration and implementation. In general, the gain of the predictive control used in the literature is taken as a constant included in an interval, however, in this work, this gain is taken a matrix and Linear matrix inequality is using to calculate this gain. To highlight the efficiency and applicability of the proposed control scheme, simulations and experimental results are presented.

1. Introduction

In the scientific field, chaos could be defined as "the art of forming the complex from the simple". A chaotic system is therefore a deterministic and unpredictable system, but it is also and above all a nonlinear system [1]. The link between these two paradoxical notions, determinism and unpredictability, is the property of sensitivity to initial conditions. Indeed, two initial conditions that are infinitely close can lead to very different future states of the system. The theory of chaos is a discipline in its own right based on the theory of dynamic systems which results, in part, from the work of the mathematician Henri Poincar (1854–1912) at the end of the XIXth century.

In 1963, meteorologist Edward Lorenz [2] was experimenting with a method for predicting meteorological phenomena. It was by pure chance that he observed that a minimal modification of the initial data could considerably change his results. Lorenz had just discovered the phenomenon of sensitivity to the initial conditions. The systems corresponding to this property will be from 1975 denominated: chaotic systems. It was during the 1970s that the theory of chaos began to grow [3]. Since, The theory of chaos has applications in meteorology, sociology, physics, computer science, engineering, economics, biology and philosophy [3–7].

The incessant application of the permanent magnet synchronous machine (PMSM) in the industry is due to its many advantages, among which are [9]:–High start torque, –high power factor,–low inertia,–high torque and high efficiency and simple structure. However, the chaotic characteristics will appear in PMSG under certain specific parameters and working conditions [8]. This chaotic behavior will not only affect system stability, safety, and even endanger its system load. Therefore, based on the problems of damage caused by chaos in the system, it is imperative to adopt an effective control method, to eliminate the chaotic phenomena in the operation of the machine when the chaotic PMSM caused the instability of the engine system. The first mathematical model of the chaotic PMSM was established in 1994 by Hemanti [10]. In 2002, a more detailed study of the chaos in the PMSM at was completed by Zhong et al. [11] and Gao et al. [12]. Recently the fractional calculus is widely used in the fields of nonlinear dynamics [13] and recently Borah et al. [14] presented a new fractional-order model of a PMSG. Since then, the control of chaos in the PMSM has emerged as a new research axes and numerous theory and methods have been developed, such as the unidirectional correlation method [15], the indirect method of neural adaptive approximation [16] , Adaptive sliding methods associated with neural networks [17], high-order sliding mode [18], neural adaptive control [19], finite-time adaptive methods [20], Generalized predictive control [21], predictive control [14,22] and many other methods [23–27]. In the literature, there are many interesting methods for controlling the nonlinear system which have not been investigated to control the chaotic PMSM such as [28] [29] and other perspective

* Corresponding author.
E-mail addresses: messadi.manel@ensea.fr, messadi.manel@gmail.com (M. Messadi).

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for the application of controlling the chaotic PMSM such as in hydro-turbine [30] with modeling the hydro-turbine governing system in the process of load rejection transient with chaotic PMSM.

Recently, Chen et al. [31] proposed a new mathematical model of a chaotic induction motor, with the indirect field oriented control applied with a proportional integral (PI) speed loop and proposed sliding mode control to stabilize the system. In this paper, we are interested in the application of predictive control [32–35] for the control of a chaotic behavior induction motor because of its simplicity of configuration and implementation. It's a very used technique for the control of chaotic systems because of its advantages [34]. In general, the gain of the predictive control used in the literature is taken as a constant included in an interval and the control is applied to a single state of the system. The fist contribution of this work, is the consideration of this gain as a matrix and we propose a new approach to calculate it, this approach inspired from [36] is based on the linear matrix inequality (LMI). The second contribution of this work is the control of the chaotic induction motor with passive control and the comparison of the results obtained with those obtained by the LMI-predictive control to prove the effectiveness of the proposed approach and the third contribution of this work is the simulation of the circuit of the proposed controller using Multisim to valid the effectiveness of the approach presented. The work is organized as follows: in Section 2, the theory of LMI-predictive control is presented. In Section 3, the mathematical model of the chaotic induction system is describes. The performances of the proposed control approach is given and a comparison with passive control to demonstrate the performance of proposed approach in Section 4. In Section 5, the experimental results using Multisim to valid the effectiveness of the approach is presented. Finally, in Section 6, we give some concluding remarks.

2. The theory of the LMI-predictive feedback control

Consider the class of nonlinear systems described by the dynamic equation:

$$\begin{cases} \dot{x}(t) = f(x(t)) + u(t) \\ x(t_0) = x_0 \end{cases} \tag{1}$$

where: $x \in R^n$ the state of the system, $u \in R^n$ the control and $f : R^n \times R^+ \to R^n$ is a non-linear continuous function.

The objective of the predictive feedback control is to ensure that the system converges asymptotically to a stable fixed point or an unstable periodic orbit x_f.

The fixed point or equilibrium point of the system (1) is the point x_f such as:

$$\frac{dx}{dt} = \dot{x} = f(x_f) = 0, \tag{2}$$

As part of the predictive control, the form of the control $u(t)$ is chosen as proposed by Boukabou et al. [34] :

$$u(t) = K(x_p(t) - x(t)) \tag{3}$$

where: K the gain, $x(t)$ the state of the system and $x_p(t)$ the predicted state.

Using a one-step forward prediction, we obtain [34]:

$$u(t) = K(\dot{x}(t) - x(t)) \tag{4}$$

The references [33–35] suppose that the gain K as a constant included in an interval. In our work, we assume the gain as a matrix, which must be calculated from the LMI using the following theorem:

Theorem 1. *the system (1) is asymptotically stable under the control: $u(t) = [YX^{-1}]^T(\dot{x}(t) - x(t))$, if and only if there exists a positive definite symmetric matrix $X = X^T = P > 0$ and Y matrix for any symmetric matrix $Q = Q^T > 0$, Checking the inequality:*

$$\begin{vmatrix} A & I \\ I & -Q^{-1} \end{vmatrix} < 0 \tag{5}$$

with :

$$A = Df(x_f)^T X + Df(x_f)^T Y - Y + X \cdot Df(x_f) + Y^T \cdot Df(x_f) - Y^T \tag{6}$$

Proof Of Theorem 1. By linearizing the preceding system around the equilibrium point and using the first-order Taylor series expansion of $f(x)$, we get:

$$\dot{x}(t) = \left(Df(x_f) + K(Df(x_f) - I)\right)x(t) \tag{7}$$

We consider the Lyapunov function:

$$V(x(t)) = x^T(t)Px(t) \tag{8}$$

where: $P = P^T > 0$.

$$\begin{aligned} \dot{V}(x(t)) &= \dot{x}^T(t)Px(t) + x^T(t)P\dot{x}(t) \\ &= x(t)^T(Df(x_f)^T P + Df(x_f)^T [YP^{-1}]P \\ &\quad -[YP^{-1}]P)x(t) + x(t)^T(P \cdot Df(x_f) \\ &\quad +P \cdot [YP^{-1}]^T \cdot Df(x_f) - P \cdot [YP^{-1}]^T)x(t) \\ &= x(t)^T(Df(x_f)^T P + Df(x_f)^T Y - Y \\ &\quad +P \cdot Df(x_f) + Y^T \cdot Df(x_f) - Y^T)x(t) \end{aligned}$$

If the following LMI is checked:

$$\begin{aligned} &Df(x_f)^T P + Df(x_f)^T [YP^{-1}]P - [YP^{-1}]P \\ &+P \cdot Df(x_f) + P \cdot [YP^{-1}] \cdot Df(x_f) \\ &-P \cdot [YP^{-1}]^T + Q < 0 \end{aligned} \tag{9}$$

So $\dot{V}(x(t)) < -x(t)^T Q x(t) < 0$, Then the system is asymptotically stable.

□

Lemma 1. *Complement of Schur [37] Let a symmetric matrix $S = \begin{bmatrix} S_{11} & S_{12} \\ S_{12}^T & S_{22} \end{bmatrix} < 0$, avec $S_{ij}(i, j = 1, 2)$ have appropriate dimensions, the following inequalities are equivalent:*

1. $S < 0$.
2. $S_{11} < 0,\ S_{22} - S_{12}^T S_{11}^{-1} S_{12} < 0$.
3. $S_{22} < 0,\ S_{11} - S_{12} S_{22}^{-1} S_{12}^T < 0$.

From the Schur complement, the Eq. (9) is equivalent to

$$\begin{vmatrix} B & I \\ I & -Q^{-1} \end{vmatrix} < 0 \tag{10}$$

with:

$$\begin{aligned} B = &Df(x_f)^T P + Df(x_f)^T K^T P - K^T P \\ &+P \cdot Df(x_f) + P \cdot K \cdot Df(x_f) - P \cdot K \end{aligned} \tag{11}$$

By introducing a change of variable as follows:
$X = P$ et $Y = K^T P$
The matrix inequality (10) becomes:

$$\begin{vmatrix} A & I \\ I & -Q^{-1} \end{vmatrix} < 0 \tag{12}$$

with :

$$A = Df(x_f)^T X + Df(x_f)^T Y - Y + X \cdot Df(x_f) + Y^T \cdot Df(x_f) - Y^T \tag{13}$$

Which confirms the theorem.