Control of PMSM chaos using backstepping-based adaptive fuzzy method in the presence of uncertainty and disturbance

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\textbf{ABSTRACT}

This paper presents a novel nonlinear control strategy based on a backstepping fuzzy adaptive approach to avoid chaos in a synchronous motor. In the controller design and stability proof, the parameter uncertainty and the system disturbance are taken into account. The matching condition is not satisfied in this model, and disturbances with an unknown upper bound are also exerted on the system. The disturbance and uncertainty are considered in one manifold with an unspecified upper bound. The system stability is verified using the Lyapunov method. The cuckoo optimization algorithm is employed to optimize the adaptive and backstepping control coefficients.

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1. Introduction

The permanent magnet synchronous motors (PMSMs) have gained growing importance for industrial applications, including wind turbines and renewable energies (Kim & Youn, 2001). They offer various advantages like low volume, light-weight, high power factor, fast dynamics, high efficiency, and large output torque. Their remarkable reliability makes them suitable for highly efficient applied programs such as industrial drive systems and electric vehicle batteries (Chi & Cheng, 2014; Zhang et al., 2010; Zhang & Li, 2015). Furthermore, the PMSMs serve as the preferred system to convert wind energy (Chi & Cheng, 2014). Ensuring the secure and stable performance of PMSMs, which is indispensable for industrial automation, faces many challenges. This is mostly due to the nonlinear and multi-variable nature of the PMSM dynamic model which might even exhibit bifurcation, limit cycles, and chaos behaviours in certain parameter values.

The chaotic PMSMs exhibit irregular motions which have the destructive impact on their performance stability. Such motions, including intermittent oscillation of torque and speed, unstable control performance, and electromagnetic noise (Kuroe & Hayashi, 1989; Wang & Chen, 2000; Li et al., 2002), are attributable to the external disturbances and system failure (Ren et al., 2003; Ren & Liu, 2006). The chaos has been frequently encountered with various synchronous motors, including reluctance motor (Harb, 2004), hysteresis motor (Zribi et al., 2009), brushless DC motor (Luo et al., 2007), and permanent magnet motor (Harb & Ahmad, 1999).

In recent years, the control and analysis of chaos have become a significant research topic due to its theoretical and practical significance (Cai et al., 2017; Li et al., 2002; Lin & Zhang, 2017; Sun, Wu, et al., 2016). Kuroe and Hayashi were the first to report chaos in motor drive systems in 1989. From then on, there have been numerous efforts at the detection and control of chaos in electrical machines operations (Ge & Huang, 2005; Harb, 2004; Li et al., 2002; Luo et al., 2007; Ren et al., 2003; Ren & Liu, 2006; Zribi et al., 2009). The chaos in PMSMs is associated with adverse outcomes such as instability and failure of the entire system (Souhail et al., 2019; Yu et al., 2016). Thus, chaos should be avoided in PMSMs using effective control schemes.

The performance of PMSM is lead to the nonlinear dynamic, system parameter, and external load disturbances. Several studies have indicated chaos in PMSMs for certain parameter values and under specific operational conditions (Li et al., 2014; Hu et al., 2016). Such dynamic behaviours will exert detrimental effects on the stable performance of PMSMs. The nonlinear analysis has emerged as the integral theory of modern technology and engineering and has found increasing significance in chaos control applications. Thus, further considerations are required for the analysis of nonlinear dynamic behaviour to ensure the effective and stable performance of PMSMs in the presence of parameter uncertainty and disturbance.
While the OGY (Ott, Grebogi, and Yorke) method has initially been considered a primary tool for chaos control (Rahimi et al., 2016), the adjustable parameter selection seems to be a sophisticated task. The feedback control of chaotic PMSMs has also faced challenges in real applications (Xie et al., 2018). The neuro-fuzzy control (NFC) shows superior performance in controlling these systems in the presence of uncertainties and nonlinearities (Wei et al., 2014). Despite self-learning capacity of NFC, its ability to achieve online learning is limited due to its expensive time cost (Li et al., 2017). Sliding mode control (SMC) also provides effective performance in tackling the effects of nonlinearity, uncertainty, and bounded disturbance. However, the chattering phenomenon in SMCs is a major drawback in the applications (Loria, 2008; Yang et al., 2018). A robust control scheme using SMC and backstepping was also designed (Sun, Shi, et al., 2016); however, the proposed method was restricted under some conditions; for instance, the control gain must be a unique constant, and the system’s exact values parameters should be known. The backstepping-based adaptive nonlinear scheme (Coban, 2019; Gopaluni et al., 2003; Karagiannis & Astolfi, 2008; Zhou & Wang, 2005) has been interested in controlling nonlinear uncertain systems, in which the uncertainties do not meet the matching conditions. As an example, in a recent study, the backstepping method has succeeded in controlling the PMSM drives. However, the ‘complexity explosion’ due to the repeated derivations of the virtual control function remains an inherent disadvantage to the standard backstepping method and needs to be avoided using appropriate schemes (Hou & Han, 2010; Sun & Zhu, 2013).

Considering the development of robust control methods in various applications (Zong et al., 2019, 2020, 2021), the primary objective of this study is to control and avoid chaos in PMSM in the presence of disturbance and parameter uncertainty. To this end, we develop a backstepping-based fuzzy adaptive nonlinear approach to suppress the chaotic behaviour in the PMSM system. In this study, the system is under the effect of a bounded disturbance with an unknown upper bound. Furthermore, the uncertainty and disturbance are taken into account in one manifold for which the upper bound is unspecified. We also apply the fuzzy logic in the controller design process to approximate the PMSM drive system’s nonlinearities. Covering the unmatched disturbances entering the system which have unknown upper bound is the most important feature of this study that distinguishes it from previous articles. In addition, despite the high sensitivity of the chaos phenomenon to the values of the parameters, the proposed method is able for regulatory and eliminating disturbances at high speed.

Furthermore, a robust nonlinear controller is utilized to ensure the system’s stability against parameter uncertainties, and disturbances exerted on the model. The model also employs the optimization algorithm to achieve the minimum value in the cost function. The adaptive rules optimization is performed through cuckoo optimization algorithm. Finally, the control system performance is evaluated by finding the optimal control and adaptive gains based on the optimization algorithm.

The organization of this paper is as follows. Sections 2 and 3 present the PMSM model and controller design, respectively. The cuckoo optimization algorithm used for control method optimization is introduced in Section 4, while Section 5 provides the simulation and comparative results for the proposed fuzzy adaptive method. Finally, the conclusions are given in Section 6.

2. Mathematical model of the chaotic PMSM drive system

The dimensionless mathematical model of a PMSM with a smooth air-gap can be described as follows (Li et al., 2002):

\[
\begin{align*}
\frac{d\omega}{dt} &= \sigma (i_q - \omega) - \tilde{I}_L, \\
\frac{di_q}{dt} &= -i_q - i_d \omega + \gamma \omega + \tilde{u}_q, \\
\frac{di_d}{dt} &= -i_d - i_p \omega + \tilde{u}_d,
\end{align*}
\]

(1)

where the state variables of \(\omega, i_d, i_q\) and \(\tilde{u}_d, \tilde{u}_q, \tilde{I}_L\) stand for the angular speed, the \(d-q\) axis currents, and the \(d-q\) axis voltages and load torque, respectively. \(\sigma\) and \(\gamma\) are the positive systems operating parameters. \(\tilde{u}_d, \tilde{u}_q, \tilde{I}_L\) stand for the \(d-q\) axis voltages and load torque, respectively. The external inputs for the system (1) are set to zero, i.e. \(\tilde{I}_L = \tilde{u}_d = \tilde{u}_q = 0\) (Li et al., 2002). Then, the system (1) becomes an unforced system:

\[
\begin{align*}
\frac{d\omega}{dt} &= \sigma (i_q - \omega), \\
\frac{di_q}{dt} &= -i_q - i_d \omega + \gamma \omega \\
\frac{di_d}{dt} &= -i_d - i_p \omega
\end{align*}
\]

(2)

PMSM drive system stability can be investigated using modern nonlinear theories such as bifurcation and chaos. In this study, the PMSM experiences chaotic behaviour when the operating parameters \(\sigma\) and \(\gamma\) fall in a certain range of values. For example, the PMSM displays chaos for \(\sigma = 5.45\) and \(\gamma = 20\). Figure 1 shows a typical chaotic attractor. These chaotic oscillations can disrupt the stabilization of the PMSM drive system. For elimination or control of chaos, we use \(u_d\) as an adjustable variable that
is suitable for real applications. An adaptive fuzzy control approach is proposed to control chaos in the PMSM drive system via the backstepping technique. For simplicity, the following notations are introduced: $x_1 = \omega, x_2 = i_d, x_3 = \Omega$. By using these notations, the dynamic model of the PMSM drive system can be expressed in the following differential equations:

$$
\begin{align*}
\dot{x}_1 &= \sigma (x_2 - x_1), \\
\dot{x}_2 &= -x_2 - x_1 x_3 + \gamma x_1, \\
\dot{x}_3 &= -x_3 + x_1 x_2 + u_d.
\end{align*}
$$

(3)

The control objective includes the design of an adaptive fuzzy controller so that the state variable $x_1$ follows the given reference signal $x_{d1}$ and all the closed-loop signals which are bounded. To this end, the singleton fuzzifier, product inference, and the centre-defuzzifier are adopted to deduce the following fuzzy logical rules:

$$
R_i : \text{IF } x_1 \text{ is } F_i^1 \text{ and } \ldots \text{ and } x_n \text{ is } F_i^n \text{ THEN } y \text{ is } B_i (i = 1, 2, \ldots, n) 
$$

(4)

where $x = [x_1, \ldots, x_n]^T \in \mathbb{R}^n$, and $y \in \mathbb{R}$ is the input and output of the fuzzy system, respectively. $F_i^j$ and $B_i$ are fuzzy sets in $\mathbb{R}$. The fuzzy inference engine performs a mapping from fuzzy sets in $\mathbb{R}$ to a fuzzy set in $\mathbb{R}$ based on the IF–THEN fuzzy rules and the compositional rule of inference. The fuzzifier maps a crisp point $x = [x_1, \ldots, x_n]^T \in \mathbb{R}^n$ into a fuzzy set $A_i$ in $\mathbb{R}$. The defuzzifier maps a fuzzy set in $\mathbb{R}$ to a crisp point in $\mathbb{R}$. Since the strategy of singleton fuzzification, centre-average defuzzification, and product inference is used, the output of the fuzzy system can be formulated as:

$$
y(x) = \frac{\sum_{j=1}^{N} W_j \prod_{i=1}^{n} \mu_j(x_i)}{\sum_{j=1}^{N} \prod_{i=1}^{n} \mu_j(x_i)},
$$

(5)

where $W_j$ is the point at which the fuzzy membership function $\mu_j(W_j)$ reaches its maximum value, and it is further assumed that $\mu_j(W_j) = 1$.

Let $p_j(x) = \sum_{i=1}^{n} W_j \prod_{i=1}^{n} \mu_j(x_i)$, $S(x) = [p_1(x), p_2(x), \ldots, p_N(x)]^T$, and $W = [W_1, \ldots, W_N]^T$, then the fuzzy logic system above can be rewritten as:

$$
y(x) = W^T S(x).
$$

(6)

If all memberships are taken as Gaussian functions, then the following lemma holds.

Lemma 1 (Wang & Mendel, 1992). Let $f(x)$ be a continuous function defined on a compact set $\Omega$. Then for any scalar $\varepsilon < 0$, there exists a fuzzy logic system in the form (3) such that

$$
\sup_{x \in \Omega} |f(x) - y(x)| \leq \varepsilon.
$$

(7)

### 3. The controller implementation

This section presents the backstepping-based nonlinear fuzzy adaptive method designed to suppress chaos in PMSM. The proposed method can deal with the impacts of uncertainties and bounded disturbances. The general schematic of the proposed controller is shown in Figure 1. The controller design process consists of the following steps. First, the system equations are rewritten, considering the control inputs and disturbances, as follows:

$$
\begin{align*}
\dot{x}_1 &= a(x_2 - x_1) + d_1(t) \\
\dot{x}_2 &= -x_2 - x_1 x_3 + bx_1 + u_q + d_2(t) \\
\dot{x}_3 &= -x_3 - x_1 x_2 + u_d + d_3(t)
\end{align*}
$$

(8)

In order to use the backstepping method to design the controller and prove the stability, it is first necessary to define the system error equations. The error is defined as:

$$
\begin{align*}
e_1 &= x_1 - x_{1d} \\
e_2 &= x_2 - x_{2d} \\
e_3 &= x_3 - x_{3d}
\end{align*}
$$

(9)

By differentiating (9), the dynamic equations of the error are obtained as follows:

$$
\begin{align*}
\dot{e}_1 &= \sigma (e_2 - e_1) + \sigma (x_2 - x_{1d}) + d_1(t) - \dot{x}_{1d} \\
\dot{e}_2 &= -\dot{e}_1 + \gamma e_1 - x_2 - x_{3d} - e_1 x_2 - x_1 x_3 \\
&\quad - x_1 d_{x3} + \gamma x_{1d} + u_q + d_2(t) - \dot{x}_{2d} \\
\dot{e}_3 &= -e_2 - e_1 e_2 - x_{3d} - e_1 x_{2d} - e_2 x_{1d} - x_1 d_{x2d} \\
&\quad + u_d + d_3(t) - \dot{x}_{3d}
\end{align*}
$$

(10)

The controller design steps are described below. The first step:

The first Lyapunov function candidate is as follows:

$$
\begin{align*}
V_1 &= 0.5 e_2^2 + \frac{1}{2\sigma} \tilde{D}_1^2 \\
\tilde{D}_1 &= D_1 - \dot{D}_1, |d_1(t)| < D_1
\end{align*}
$$

(11)

(12)

where $\tilde{D}_1$ is the upper bound estimate of $D_1$. An error between $D_1$ and $\tilde{D}_1$ is defined as $\hat{D}_1$. The derivative of the first Lyapunov function is:

$$
\begin{align*}
\dot{V}_1 &= e_1 \dot{e}_1 - \frac{1}{\lambda_1} \hat{D}_1 \hat{D}_1 + 1 \sigma (e_2 - e_1) + \sigma (x_{2d} - x_{1d}) \\
&\quad + d_1(t) - \dot{x}_{1d} - \frac{1}{\lambda_1} \hat{D}_1 \dot{D}_1
\end{align*}
$$

(13)

By selecting $e_2$ as the virtual controller, the rule $\varphi$ is obtained as follows:

$$
\begin{align*}
e_2 &= \varphi = x_{1d} - x_{2d} + \frac{1}{\sigma} \dot{x}_{1d} - k_1 e_1 \frac{\dot{D}_1}{\sigma} \text{sgn}(e_1)
\end{align*}
$$

(14)
Now by placing the relation $\psi$ in the derivative of the first Lyapunov function, it is obtained:

$$\dot{V}_1 = -(k_1 + \sigma)e_1^2 + e_1 d_1(t) - \dot{D}_1 e_1 \text{sgn}|e_1| - \frac{1}{\lambda_1} \dot{D}_1 \dot{D}_1$$

$$\leq -(k_1 + \sigma)e_1^2 + |e_1| D_1 - \dot{D}_1|e_1| - \frac{1}{\lambda_1} \dot{D}_1 \dot{D}_1$$

$$\leq -(k_1 + \sigma)e_1^2 + \dot{D}_1 \left(|e_1| - \frac{1}{\lambda_1} \dot{D}_1\right)$$

(15)

To ensure the stability of the first Lyapunov function, it is necessary to eliminate the $\dot{D}_1$ effect in Equation (15), so by selecting the following adaptive law:

$$\dot{\hat{D}}_1 = \lambda_1 |e_1|$$

(16)

And put it in (15), it is obtained:

$$\dot{V}_1 \leq -(k_1 + \sigma)e_1^2$$

(17)

which indicates the negativity of $\dot{V}_1$, the limitation of the $V_1$ function, and the stability of the first error dynamics under the virtual control (14).

The second step:

According to the law of backstepping, we define $z$ as follows:

$$z = e_2 - \varphi$$

(18)

The derivative of $z$ is obtained:

$$\dot{z} = \dot{e}_2 - \dot{\varphi} = -e_2 - e_1 e_3 + \gamma e_1 - x_{2d}$$

$$- e_1 x_{3d} - e_3 x_{1d} - x_{1d} x_{3d}$$

$$+ \gamma x_{1d} + u_q + d_2(t) - \dot{x}_{2d} - \dot{\varphi}$$

(19)

Now we rewrite $\dot{\varphi}$ by the fuzzy approximation method as follows:

$$\dot{\varphi} = W^T \hat{P} + \varepsilon$$

(20)

where $\varepsilon$ is the fuzzy approximation error. We also define $\psi(.)$ like this:

$$\psi(.) = d_2(t) + \varepsilon, |\psi(.)| \leq \Psi$$

(21)

which $\Psi$ is the upper bound of $\psi(.)$.

Now, the second Lyapunov function candidate is as follows:

$$V_2 = \frac{1}{2} z^2 + \frac{1}{2\lambda_2} \dot{\hat{\psi}}^2 + \frac{1}{2\lambda_3} W^T \hat{W}$$

(22)

wherein

$$\hat{W} = W - \hat{W}$$

(23)

$$\hat{\psi} = \psi - \hat{\psi}$$

(24)

Also $\hat{W}$ is the upper bound estimate of $W$ and $\hat{\psi}$ is the upper bound estimate of $\psi$.

The derivative of $V_2$ gives

$$\dot{V}_2 = zz - \frac{1}{\lambda_2} \dot{\hat{\psi}} \dot{\hat{\psi}} - \frac{1}{\lambda_3} W^T \hat{W}$$

$$= z(-e_2 - e_1 e_3 + \gamma e_1 - x_{2d} - e_1 x_{3d} - e_3 x_{1d})$$

$$- x_{1d} x_{3d} + \gamma x_{1d} - x_{2d} + u_q + \psi(.) + W^T P$$

$$- \frac{1}{\lambda_2} \dot{\hat{\psi}} \dot{\hat{\psi}} - \frac{1}{\lambda_3} \hat{W}^T \hat{W}$$

(25)

By selecting $u_q$ as follows:

$$u_q = e_2 + e_1 e_3 - \gamma e_1 + x_{2d} + e_1 x_{3d}$$

$$+ e_3 x_{1d} + x_{1d} x_{3d} - \gamma x_{1d} + \dot{x}_{2d} - k_2 z$$

$$- \frac{1}{\lambda_2} \dot{\hat{\psi}} \dot{\hat{\psi}} - \frac{1}{\lambda_3} W^T P$$

(26)
It is obtained
\[ \dot{V}_2 = -k_2 z^2 + z \psi(.) - \hat{\psi} z \text{sgn}(z) + \hat{W}^T Pz \]
\[- \frac{1}{\lambda_2} \hat{\psi} \dot{\psi} - \frac{1}{\lambda_3} \hat{W}^T \dot{\hat{W}} \]
\[ \dot{V}_2 \leq -k_2 z^2 + |z| \psi - \hat{\psi} |z| - \frac{1}{\lambda_2} \hat{\psi} \dot{\psi} + \hat{W}^T \left( Pz - \frac{1}{\lambda_3} \dot{\hat{W}} \right) \]
\( (27) \)

To ensure the stability of the second Lyapunov function, it is necessary to eliminate the \( W \) and \( \hat{W} \) effects in Equation (27), so by selecting \( \hat{W} \) as follows:
\[ \dot{\hat{W}} = \lambda_3 Pz \]
\( (28) \)

And put it in (27), it is obtained:
\[ \dot{V}_2 \leq -k_2 z^2 + \hat{\psi} \left( |z| - \frac{1}{\lambda_2} \dot{\psi} \right) \]
\( (29) \)

We now define the adaptive law to obtain \( \dot{\hat{\psi}} \) as follows:
\[ \dot{\hat{\psi}} = \lambda_2 |z| \]
\( (30) \)

It is obtained by placing in equation (29)
\[ \dot{V}_2 \leq -k_2 z^2 \]
\( (31) \)

which indicates the negativity of \( \dot{V}_2 \), the limitation of the \( V_2 \) function, and the stability of the second error dynamics under the control (26).

The third step:

The third Lyapunov function candidate is as follows:
\[ V_3 = \frac{1}{2} e_3^2 + \frac{1}{2} \lambda_4 \hat{D}_3^2 \]
\( (32) \)

wherein
\[ \hat{D}_3 = D_3 - \hat{D}_3, \ |d_3(t)| \leq D_3 \]
\( (33) \)

where \( D_3 \) indicates the upper bound of \( d_3(t) \), and \( \hat{D}_3 \) is the upper bound estimate of \( D_3 \). An error between \( D_3 \) and \( \hat{D}_3 \) is defined as \( \hat{D}_3 \). The derivative of \( V_3 \) gives
\[ \dot{V}_3 = e_3 \dot{e}_3 - \frac{1}{\lambda_4} \hat{D}_3 \dot{\hat{D}}_3 \]
\[ = e_3 (-e_3 - e_1 e_2 - x_{3d} - e_1 x_{2d} - e_2 x_{1d}) \]
\[ - x_{1d} x_{2d} + u_d + d_3(t) - \dot{x}_{3d} - \frac{1}{\lambda_4} \hat{D}_3 \dot{\hat{D}}_3 \]
\( (34) \)

By selecting \( u_d \) as follows:
\[ u_d = e_1 e_2 + x_{3d} + e_1 x_{2d} + e_2 x_{1d} + x_{1d} x_{2d} \]
\[ + \dot{x}_{3d} - k_3 e_3 - \hat{D}_3 \text{sgn}(e_3) \]
\( (35) \)

It is obtained
\[ \dot{V}_3 = -(k_3 + 1) e_3^2 + e_3 d_3(t) - \hat{D}_3 e_3 \text{sgn}(e_3) - \frac{1}{\lambda_4} \hat{D}_3 \dot{\hat{D}}_3 \]
\( (36) \)

\[ \dot{V}_3 \leq -(k_3 + 1) e_3^2 + |e_3| d_3 - \frac{1}{\lambda_4} \hat{D}_3 \dot{\hat{D}}_3 \]
\[ \leq -(k_3 + 1) e_3^2 + \hat{D}_3 \left( |e_3| - \frac{1}{\lambda_4} \hat{D}_3 \right) \]
\( (37) \)

To ensure the stability of the third Lyapunov function, it is necessary to eliminate the \( \hat{D}_3 \) effect in Equation (37), so by defining adaptive law in this way:
\[ \dot{\hat{D}}_3 = \lambda_4 |e_3| \]
\( (38) \)

And replacing in (37), it is obtained
\[ \dot{V}_3 \leq -(k_3 + 1) e_3^2 \]
\( (39) \)

which indicates the negativity of \( \dot{V}_3 \), the limitation of the \( V_3 \) function, and the stability of the third error dynamics under the control (35).

The last step:

The Lyapunov function candidate for the overall system is
\[ V_{\text{total}} = V_1 + V_2 + V_3 \]
\( (40) \)

The derivative of \( V_{\text{total}} \) gives
\[ V_{\text{total}} = \dot{V}_1 + \dot{V}_2 + \dot{V}_3 \]
\[ = -(k_1 + \sigma) e_1^2 - k_2 z^2 - (k_3 + 1) e_3^2 \]
\( (41) \)

Thus, Equation (41) guarantees the boundary asymptotic stability of the system under the proposed controller.

4. Optimization algorithm

Cuckoo optimization algorithm is one of the algorithms developed to solve 'non-linear optimization problems' and 'continuous optimization problems'. The algorithm is inspired by the life of a family of birds called the cuckoo. According to Rajabioun (2011), the cuckoo optimization algorithm is based on the optimal lifestyle and interesting features of this species, such as spawning and reproduction and it is employed to find the optimal parameter (\( k \)) that guarantees the system stability by ensuring the Lyapunov’s concept stability and suitable time response. The cost function below optimizes the controller in equation (8):
\[ f(e_1, e_2, \cdots, e_n) = \frac{1}{n} \sqrt{\sum_{i=1}^{n} e_i^2 dt} \]
\( (42) \)
5. Simulation

This section simulates the developed controller using three different scenarios to verify its effectiveness. The results are then compared to those of other controllers proposed in (Chen et al., 2012, August, 2015). The simulation parameters for PMSM are extracted from Yu et al. (2011).

In the first scenario, there is no disturbance, while in the second scenario, bounded disturbances are applied.
to the system in the following form:

\[
\begin{align*}
    d_1(t) &= 2x_1 \sin \left( \frac{3\pi}{2} t \right), \\
    d_2(t) &= 3x_2 \cos \left( \frac{4\pi}{3} t \right), \\
    d_3(t) &= 5x_3 \sin \left( \frac{5\pi}{4} t \right)
\end{align*}
\] (43)

Figures 2–4 depict the system states for various controllers. Moreover, the control signals obtained from the proposed approach, compared to the existing techniques, are provided in Figures 5–7. The comparative analysis of the system states for the designed controller demonstrates that it can achieve chaos suppression in
Figure 6. The $u_q$ curve of the controller in scenario 1.

Figure 7. The $u_d$ curve of the controller in scenario 1.

the PMSM system with fewer oscillations, minimum overshooting, and zero error. The proposed approach stabilizes the system faster than other existing methods (even the finite time method). More precisely, using the proposed method, first state in < 1 s, and the second and third states in less than half a second have reached their final value, while this has happened in about 5 s by using finite time method, and of course, the sliding
mode method is not able to guarantee the stability of the system at all. While the finite time and sliding mode methods also utilize the load torque $T_l$ to avoid chaos, in the presented fuzzy adaptive scheme, the control signals of $u_q$ and $u_d$ have smaller amplitude and can stabilize the system within a notably shorter time.

In the second scenario, the PMSM system is affected by disturbance as well. Figures 8–10 display the system states for this case. The obtained control signals from the various methods are available in Figures 11–13.

In this scenario, similar to the previous one, the proposed controller achieves a lower steady-state error.
and smoother oscillations. However, disturbance causes
the system states to experience more oscillations com-
pared to the previous simulation. These two scenar-
ios successfully demonstrated the proposed method’s
superiority from various aspects, including the response
speed, error magnitude, response oscillations, the con-
trol signal amplitude, and the overshooting amount.
The results of these two scenarios show well that
the proposed method is able to eliminate unmatched
disturbance effect without torque $T_L$, and stabilize

Figure 10. The $i_d$ curve of the chaotic PMSM under different controllers in scenario 2.

Figure 11. The $T_L$ curve of the controller in scenario 2.
To achieve a better control response, we optimize the adaptive controller using the cuckoo algorithm. The proposed controller is optimized in the third scenario with simulation conditions identical to the first scenario and to better understand the capabilities of the optimization method, we consider a situation in which the system speed undergoes a sudden change in the fifth second. The parameters of the cuckoo algorithm are given in

**Figure 12.** The $u_q$ curve of the controller in scenario 2.

**Figure 13.** The $u_d$ curve of the controller in scenario 2.
Table 1. Also, the optimal values of the control parameters obtained from the cuckoo algorithm are included in Table 2. The cost function diagram obtained from the implementation of the algorithm in each iteration is shown in Figure 14. Figures 15–19 provide the system states and control signals obtained from the optimization.
algorithm. As can be seen from the figures, using the optimization algorithm, the achievement of stable performance under new working conditions occurs in the shortest possible time, and despite the drastic changes that occur, the reliable performance of the system is persistent.
Figure 18. The $u_q$ curve of the controller under cuckoo optimization algorithm in scenario 3.

Figure 19. The $u_d$ curve of the controller under cuckoo optimization algorithm in scenario 3.

6. Conclusion

This article presents a novel control scheme based on the fuzzy adaptive method to avoid chaos phenomena in PMSMs. This method can successfully deal with the nonlinear dynamic effects, the parameter uncertainties, and disturbance exerted on the system. The employment of the Lyapunov method ensures the stability of the system under the above conditions. Our simulation results also indicated the superior performance of the presented approach in terms of speed, steady-state error response, and control signal amplitude. The Cuckoo optimization method is also applied and explored to achieve
the optimal control signal. The simulation results of the optimization algorithm suggest the effectiveness of the proposed method against rapid alterations in PMSM dynamics.

**Disclosure statement**

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| Parameters       | Values |
|------------------|--------|
| Number of initial population | 50     |
| Number of clusters    | 2      |
| Maximum iterations   | 80     |
| Maximum number of cuckoos | 100    |
| k search interval    | Kim and Youn (2001), Harb (2004) |

| Table 1. Cuckoo algorithm parameters. |

| Table 2. Optimal parameters of the controller. |

| k₁ | k₂ | k₃ | λ₁  | λ₂  | λ₃  | λ₄  |
|-----|----|----|-----|-----|-----|-----|
| 9.98 | 10 | 6.89 | 1   | 10  | 1   |

| Cuckoo number of initial population | Maximum number of cuckoos |
|-----------------------------------|----------------------------|
| 50                                | 100                        |

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