

Article

Tracking Control with Zero Phase-difference for Linear Switched Reluctance Machines Network

Bo Zhang^{1,2}, J.F. Pan¹, Jianping Yuan^{2,*}, Wufeng Rao^{1,2}, Li Qiu¹, Jianjun Luo² and Honghua Dai²

¹ College of Mechatronics and Control Engineering, Shenzhen University, Shenzhen, 518060, China; zhangbo@szu.edu.cn (B.Z.); pfj@szu.edu.cn (J.F.P.); michaelmile@qq.com (W.R.); qili@szu.edu.cn;

² Laboratory of Advanced Unmanned Systems Technology, Northwestern Polytechnical University, Shenzhen, 518060, China; jjluo@nwpu.edu.cn (J.L.); hhdai@nwpu.edu.cn

* Correspondence: jianpingyuan@yeah.net; Tel.: +86-755-2653-1066

1 **Abstract:** This paper discusses about control of the linear switched reluctance machines (LSRMs)
2 network for the zero phase-difference tracking to a sinusoidal reference. The dynamics of each
3 LSRM is derived by online system identification and modeled as a second-order linear system.
4 Accordingly, based on the coupled harmonic oscillators synchronization manner, a distributed
5 control is proposed to synchronize each LSRM state to a virtual LSRM node representing the external
6 sinusoidal reference for tracking it with zero phase-difference. Subsequently, a simulation scenario
7 and an experimental platform with the identical parameter setup are designed to investigate the
8 tracking performance of the LSRMs network constructed by the proposed distributed control.
9 Finally, the simulation and experimental results verify the effectiveness of the proposed LSRMs
10 network controller, and also prove that the coupled harmonic oscillators synchronization method
11 can improve the synchronization tracking performance and precision.

12 **Keywords:** linear switched reluctance machine (LSRM); coordinated network; distributed control;
13 synchronization tracking

14 1. Introduction

15 Linear tracking control systems based on direct drive linear machines are vastly used in
16 manufacture industry, such as parts assembly, printed circuit boarding (PCB) drilling and chip
17 processing, etc. In addition, there are many tasks that require a cooperation of many linear machines
18 to work harmonically. For example, in a multi-station PCB drilling machine, each linear machine acts
19 as one working unit. The board being processed requires the linear machines to track the command
20 position precisely and coordinates with each other to finish the whole drilling work. Therefore, each
21 linear machine often demands the state information from other machines, so as to work cooperatively
22 and synchronously. The overall motion control performance can be improved such as faster operation
23 time, more efficiency and the annihilation of accumulated errors, etc., compared to a traditional
24 sequenced working manner [1]. Furthermore, if multiple linear machines can be organized as a
25 coordinated and distributed motion tracking network and each machine has the position controller,
26 sensor and driver of its own, the ultimate global tracking control goal can be emerged by local
27 communications among the independent linear machine nodes with local controllers, without the
28 necessity of any global supervision or decision [2].

29 Among different types of linear machines, a linear switched reluctance motor (LSRM) has the
30 advantages of a simple and robust mechanical structure, low cost, high reliability and free of frequent
31 maintenance or adjustments [3]. Current motion tracking research on LSRMs mainly focuses on the
32 control performance improvement for single machine based position control systems [4–7]. In [4], an

33 adaptive position controller is inspected to compensate uncertain behaviors of a double-sided LSRM.
34 A nonlinear proportional differential (PD) tracking controller based on the tracking differentiator is
35 proposed for a real-time LSRM suspension system, to achieve a better dynamic position response
36 [5]. A sliding mode position control technique is investigated in [6] and a passivity-based control
37 algorithm is proposed for the LSRM position tracking system to overcome the inherent nonlinear
38 characteristics and ameliorate system robustness against uncertainties and bounded disturbances
39 [7]. From the latest development on the tracking control performance of LSRMs, the ratio of an
40 absolute dynamic tracking error to full range of 5% can be achieved in single LSRM position control
41 applications.

42 As remarked above, by employing a multi-agent network formed by distributed control on
43 the same product line, all LSRMs can be coordinated to work together harmonically. Up till
44 now, the experiment and technique studies on the tracking control network based on LSRMs have
45 gained much attention, and related researches are increasing [8], [9]. Current analysis of motion
46 coordinated control of multi-agent network mainly focuses on distributed control methods with
47 multi-agent network [10–16], which provides a guidance to the LSRMs network. Ref. [10] primarily
48 investigates the consensus for coordinated control of multi-agent networks, and establishes the
49 connections between structural properties and the performance of networks. Cao [11] elaborates
50 the main results and the progress about coordinated control algorithms for multi-agent networks
51 and summarizes the future directions of the distributed coordination of multi-agent. At present,
52 multi-agent network study has been classified into several major aspects, which include constrained
53 or imperfect communication [12], delay or switching information linkage [13], [14], agent with
54 nonlinear dynamics [15], influence of noise [16], etc. Furthermore, the multi-agent network by
55 distributed control distributed control algorithms have been exploited in the regime of spacecraft
56 cluster [17], robots coordination [18], and unmanned aerial vehicle formation [19].

57 It can be concluded from the above analysis that current theoretical work mainly concentrates on
58 distributed control methods to achieve the network synchronization under some network topology
59 constraint condition. The ultimate goal is to form a stable synchronized motion among the
60 multiple agents within the network employing distributed and networked control algorithms. But
61 in most industry processes, multiple LSRMs as a multi-agent network is not only required to
62 motion synchronization but also to track some specific desired trajectory [20]. In practice, directly
63 control every agent in a multi-agent network with a number of agents might be impossible or
64 unnecessary. Therefore, pinning control is regarded as a desirable method [21]. Accordingly, the
65 multi-agent network formed by the pinning control is defined as the leader-following network
66 [2]. In leader-following network, a reference can be accessed directly by minority agents named
67 as leaders only, and then the rest of agents named as followers are steered to implement the
68 synchronized motion to the common reference by the effect of the distributed control. Wang
69 [22] reviews elaborately advances in pinning control approaches, including the feasibility, stability
70 and effectiveness of pinning control and pinning-based consensus and flocking control of mobile
71 multi-agent networked systems. One of the challenges with leader-following network is that the
72 reference possesses different dynamic characteristics from all agents. Cao [23] proposes a distributed
73 consensus tracking algorithm for second-order dynamics guarantees global exponential tracking
74 without acceleration measurements, and the dynamic reference is modeled as the virtual leader with
75 time-varying velocity. Especially, in industrial processes, for implementing much of repetitive work,
76 some periodic motion modes such as sinusoid always are as the desired motion. Wang [24] proposes
77 an internal model controller compensating the reference dynamics for output synchronization of
78 more general heterogeneous multi-agents systems. Wieland [25] proves that an internal model
79 principle is necessary and sufficient for exponential synchronizability of the group to some common,
80 non-trivial output trajectory, bounded by a polynomial function in time, and also notes that the
81 internal model components may give rise to the instability of the multi-agent network under the
82 influence of parametric uncertainties.

83 In this paper, the mathematical model of each LSRM is derived by the online system
 84 identification, which is essential modeled as a general second-order linear system. Second, inspired
 85 by coupled harmonic oscillators [26], [27], a distributed control is designed to track a sinusoidal
 86 reference with zero phase-difference among each LSRM and the reference as virtual node, so as
 87 to improve the tracking performance of the LSRMs network. Last, simulation and experimental
 88 verification is provided to prove the effectiveness of the network controller design scheme.

89 The main contributions of this paper are three folds. First, for the convenience of the coordinated
 90 motion control, the reference signal is modeled as a virtual LSRM node which has the same dynamic
 91 characteristics as three motor nodes based on the proposed distributed tracking control strategy.
 92 Second, three motor nodes and the virtual node can be realized the synchronization control by
 93 adopting the coupled harmonic oscillators method, so as to achieve for tracking the sinusoidal
 94 reference signal with zero phase-difference. Finally, the distributed tracking control performance
 95 for the LSRMs network is investigated by a simulation and experimental platform testing.

96 2. Model and Preliminaries

97 2.1. Mathematical Preliminaries

Notations: Let \mathbb{R}^n and $\mathbb{R}^{n \times m}$ indicate the n dimensional Euclidean space and the set of $n \times m$ real matrices, respectively. I_N represents a N -dimension unit matrix. The Kronecker product of matrices $A \in \mathbb{R}^{n \times m}$ and $B \in \mathbb{R}^{p \times q}$ satisfies the following properties as,

$$\begin{aligned}
 (A \otimes B)(C \otimes D) &= AC \otimes BD & (1) \\
 (A \otimes B)^T &= A^T \otimes B^T \\
 k(A \otimes B) &= (kA) \otimes B = A \otimes (kB) \\
 A \otimes (B_1 + B_2) &= A \otimes B_1 + A \otimes B_2
 \end{aligned}$$

98 The interaction topology of coordinated network building LSRMs network system is represented
 99 using a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, as shown in Fig. 1, which is characterized by an edge-linked node
 100 set \mathcal{V} . It denotes N local closed-loop LSRM systems termed as LSRM node $L_i, i = 1, \dots, N$, formed by
 101 each LSRM and its local controller individually. An edge set $\mathcal{E} \in \mathcal{V} \times \mathcal{V}$ represents M communication
 102 linkages among all LSRM nodes, where an edge exists from LSRM node L_j to L_i if $(j, i) \in \mathcal{E}$. If a set
 103 composed of LSRM nodes L_j satisfies $(j, i) \in \mathcal{E}$, it is named as the neighbor set \mathcal{N}_i associated with
 104 the LSRM node L_i . A directed graph contains a directed spanning tree if there exists a node called
 105 root such that there is one or more than one directed path from this node to every other node, such as
 106 L_1 in Fig. 1. A path from v_1 to v_k in \mathcal{G} is formed by the \mathcal{E} subset $\{(v_i, v_{i+1}) | i = 1, \dots, k-1\}$. \mathcal{A}, \mathcal{L}
 denote its adjacency matrix and Laplacian matrix of \mathcal{G} , respectively.

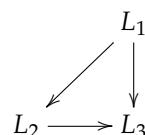


Figure 1. Topology of coodinated network

¹⁰⁸ 2.2. Model of the LSRM node

Any of the N three-phase LSRMs (indexed as i -th, $i = 1, \dots, N$) can be described in the voltage equation as [4],

$$u_{k,i} = R_{k,i}i_{k,i} + \frac{d\lambda_{k,i}}{dt}, k = a, b, c \quad (2)$$

where $u_{k,i}$, $R_{k,i}$ and $i_{k,i}$ are terminal voltage, coil resistance and current, respectively. $\lambda_{k,i}$ represents the flux-linkage of the k -th winding. Each LSRM can also be depicted as the second-order dynamics as follows,

$$m_i \frac{d^2x_i}{dt^2} + B_i \frac{dx_i}{dt} + fl_i = f_i \quad (3)$$

where x_i , B_i , m_i , f_i and fl_i represent position, friction coefficient, mass, total and load force of the i -th LSRM, respectively. The second-order system as Eq. (3) can be further represented in the discrete-time form as [5],

$$A(z^{-1})x_i = B(z^{-1})f_i + e_i \quad (4)$$

where $A(z^{-1})$ and $B(z^{-1})$ are polynomials to be determined, z is the discrete-time operator, and e_i denotes unknown disturbances of the i -th LSRM. The polynomials $A(z^{-1})$ and $B(z^{-1})$ correspond to the typical discrete-time form are depicted as,

$$\begin{cases} A(z^{-1}) = 1 + a_1z^{-1} + a_2z^{-2} \\ B(z^{-1}) = b_0 + b_1z^{-1} \end{cases} \quad (5)$$

The purpose of online system identification is to correctly estimate a_1 , a_2 , b_0 and b_1 that contain all dynamic information of each LSRM. For the n -th estimation, Eq. (4) can also be considered as a typical least square form as follows,

$$x_i(k) = \varphi^T(k-1)\theta + e_i(k) \quad (6)$$

where $x_i(k)$ is the i -th LSRM state including the position and velocity at time step k , and

$$\begin{cases} \theta = [a_1 \ a_2 \ b_0 \ b_1]^T \\ \varphi(k-1) = [-x_i(k-1) \ \dots \ -x_i(k-n) \ f_i(k) \ \dots \ f_i(k-n)]^T \end{cases} \quad (7)$$

The parameters described in Eq. (7) can be estimated by the recursive least square method as [29],

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + R(k)e_i(k) \\ R(k) = P(k-1)\varphi(k-1)[\rho + \varphi^T(k)P(k-1)\varphi(k)]^{-1} \\ P(k) = \rho^{-1}[I - K(k)\varphi^T(k)]P(k-1) \end{cases} \quad (8)$$

where P is the covariance matrix and R is the gain, K and I are respectively the gain matrix and an identity matrix with compatible dimensions, and $\hat{\theta}$ represents the estimated value of θ through the identification process. ρ is the forgetting factor that reflects the relationship between the converging rate and tracking ability and it falls into 0 and 1. For the LSRM, ρ is chosen as 0.98 for moderate converging ripples and a fast identification speed. For initial values, $P(0)$ can be chosen as $\eta \cdot I_4$ with η as a constant value of 50. Stochastic errors e_i can be represented as,

$$e_i(k) = x_i(k) - \varphi^T(k)\hat{\theta}(k-1) \quad (9)$$

If the relative error from the present to the last step is comparatively a small positive value ζ , it can be regarded that the present estimated value is correct. Then the termination criterion can be represented as,

$$\left| \frac{\hat{\theta}(k+1) - \hat{\theta}(k)}{\hat{\theta}(k)} \right| < \zeta \quad (10)$$

Any local LSRM control system is defined as a LSRM node in the LSRMs network. The control block diagram for any LSRM node can be depicted as shown in Fig. 2. The LSRM node L_i receives both the position feedback information from its linear encoder and the node L_j , and only the leader node (i.e. the node located at the root of a certain spanning tree in a coordinated network topology) accesses the external reference information, i.e the input signal of the LSRMs network from outside. Each LSRM node is composed of a local position controller, the multiphase excitation scheme with look-up table linearization, current controllers and a LSRM, and the control scheme conforms to the typical dual-loop architecture [28]. For the LSRM node L_i , position error is decided from the difference between reference (the leader only) and actual position ρ_i of the i -th LSRM, along with the position information ρ_j from the LSRM node L_j . The position controller then calculates the control input, and the multi-phase excitation with the look-up table linearization scheme determines the current command for the k -th phase of the i -th LSRM, according to the current position of the i -th LSRM. Then the current controller outputs the actual current to the k -th winding.

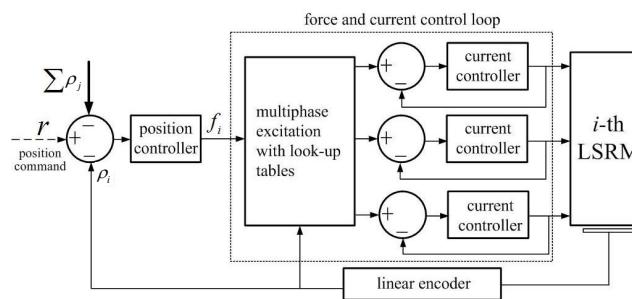


Figure 2. Control block diagram for the LSRM node.

Rearranging Eq. (3) in the state-space form, we have

$$\begin{bmatrix} \dot{\rho}_i \\ \ddot{\rho}_i \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -\frac{B_i}{m_i} \end{bmatrix} \begin{bmatrix} \rho_i \\ \dot{\rho}_i \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m_i} \end{bmatrix} u_i \quad (11)$$

where $u_i = f_i - fl_i$ is the control input of the i -th LSRM.

3. Synchronization Tracking Control Design

Since each LSRM is a mechatronic device fulfilling double-acting periodic line motion, some sinusoidal or its combinatorial patterns are often applied as the predefined trajectory planning some desired reciprocating motion for the LSRMs network. For this purpose, inspired by coupled harmonic oscillators synchronization proposed in [26], [27], the distributed control law can be formulated as,

$$u_i = -\alpha \rho_i + B_i \dot{\rho}_i - \sum_{j \in \mathcal{N}_i} K_{d,i} [\dot{\rho}_i(t) - \dot{\rho}_j(t)] \quad (12)$$

where α is a parameter associated with the angular frequency ω of the reference sinusoidal signal. Substituting Eq. (12) into Eq. (11), the LSRM node L_i can be depicted as,

$$\begin{bmatrix} \dot{\rho}_i \\ \ddot{\rho}_i \end{bmatrix} = \left\{ \begin{bmatrix} 0 & 1 \\ 0 & -\frac{B_i}{m_i} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ -\frac{\alpha}{m_i} & \frac{B_i}{m_i} \end{bmatrix} \right\} \begin{bmatrix} \rho_i \\ \dot{\rho}_i \end{bmatrix} - \sum_{j \in \mathcal{N}_i} \begin{bmatrix} 0 \\ \frac{K_{d,i}}{m_i} \end{bmatrix} [\dot{\rho}_i(t) - \dot{\rho}_j(t)]$$

$$= \begin{bmatrix} 0 & 1 \\ -\frac{\alpha}{m_i} & 0 \end{bmatrix} \begin{bmatrix} \rho_i \\ \dot{\rho}_i \end{bmatrix} - \sum_{j \in \mathcal{N}_i} \begin{bmatrix} 0 \\ \frac{K_{d,i}}{m_i} \end{bmatrix} \begin{bmatrix} \dot{\rho}_i(t) - \dot{\rho}_j(t) \end{bmatrix} \quad (13)$$

Let $\omega^2 = \frac{\alpha}{m_i}$, $k_b = \frac{K_{d,i}}{m_i}$, $\rho = [\rho_1, \dots, \rho_N]^T$, the model of LSRMs network can be derived as,

$$\begin{bmatrix} \dot{\rho} \\ \ddot{\rho} \end{bmatrix} = \underbrace{\begin{bmatrix} 0_N & I_N \\ -\omega^2 \cdot I_N & -k_b \cdot \mathcal{L}(\mathcal{G}) \end{bmatrix}}_{\mathcal{S}} \begin{bmatrix} \rho \\ \dot{\rho} \end{bmatrix} \quad (14)$$

According to Eq. (14), the LSRMs network can be reformulated as,

$$\dot{\tilde{X}} = \mathcal{S} \tilde{X} \quad (15)$$

where $\tilde{X} = [\rho^T, \dot{\rho}^T]^T$.

To prove the LSRMs network Eq. (15) has ability to track a sinusoidal reference signal $r = M \sin(\omega t + \theta)$ without phase disparity, the following lemma is provided.

Lemma 1. Let $\Psi_{l,i}, \Psi_{r,i}$ be the left and right eigenvectors of Laplacian matrix \mathcal{L} associated to the i -th eigenvalue ψ_i , $i = 1, \dots, N$, respectively. the eigenvalues of \mathcal{S} in Eq. (15) can thus be represented as,

$$\lambda_{i\pm} = \frac{k_b \psi_i \pm \sqrt{k_b^2 \psi_i^2 - 4\omega^2}}{2},$$

and its left and right eigenvectors can be denoted as the following,

$$\Lambda_{l,i\pm} = [\Psi_{l,i}^T, \lambda_{i\pm} \Psi_{l,i}^T]^T, \Lambda_{r,i\pm} = [\Psi_{r,i}^T, -\frac{\lambda_{i\pm}}{\omega^2} \Psi_{r,i}^T]^T.$$

Proof of Lemma 1. We divide $\Lambda_{l,i\pm}, \Lambda_{r,i\pm}$ in two parts, denoted as $\Lambda_{l,i\pm} = [\Lambda_{l,u}^T, \Lambda_{l,d}^T]^T$ and $\Lambda_{r,i\pm} = [\Lambda_{r,u}^T, \Lambda_{r,d}^T]^T$, respectively. For convenience, we omit the subscript index i or $i\pm$. For $\Lambda_{l,i\pm}$, we have,

$$\begin{bmatrix} \Lambda_{l,u}^T & \Lambda_{l,d}^T \end{bmatrix} \mathcal{S} = \lambda \begin{bmatrix} \Lambda_{l,u}^T & \Lambda_{l,d}^T \end{bmatrix} \quad (16)$$

Similarly, for $\Lambda_{r,i\pm}$, we have,

$$\mathcal{S} \begin{bmatrix} \Lambda_{r,u} \\ \Lambda_{r,d} \end{bmatrix} = \lambda \begin{bmatrix} \Lambda_{r,u} \\ \Lambda_{r,d} \end{bmatrix} \quad (17)$$

From Eq.(14), Eq.(16) can be derived as,

$$\Lambda_{l,d}^T = -\frac{\lambda}{\omega^2} \cdot \Lambda_{l,u}^T \quad (18a)$$

$$\Lambda_{l,u}^T - k_b \Lambda_{l,d}^T \cdot \mathcal{L} = \lambda \cdot \Lambda_{l,d}^T \quad (18b)$$

Likewise, we can obtain the equation as,

$$\Lambda_{r,d} = \lambda \cdot \Lambda_{r,u} \quad (19a)$$

$$-\omega^2 \cdot \Lambda_{r,u} - k_b \cdot \mathcal{L} \Lambda_{r,d} = \lambda \cdot \Lambda_{r,d} \quad (19b)$$

Substituting Eq. (18a) into Eq. (18b), we obtain

$$\Lambda_{l,u}^T + \frac{k_b}{\omega^2} \lambda \cdot \Lambda_{l,u}^T \cdot \mathcal{L} = -\frac{\lambda^2}{\omega^2} \cdot \Lambda_{l,u}^T \quad (20)$$

$$-\Lambda_{l,u}^T \cdot \mathcal{L} = \frac{\lambda^2 + \omega^2}{k_b \lambda} \Lambda_{l,u}^T$$

In addition, substituting Eq. (19a) into Eq. (19b), we have

$$-\omega^2 \cdot \Lambda_{r,u} - k_b \lambda \cdot \mathcal{L} \cdot \Lambda_{r,u} = \lambda^2 \cdot \Lambda_{r,u} \quad (21a)$$

$$-\mathcal{L} \cdot \Lambda_{r,u} = \frac{\lambda^2 + \omega^2}{k_b \lambda} \cdot \Lambda_{r,u} \quad (21b)$$

According to Eq. (21b), we notice $\psi = -\frac{\lambda^2 + \omega^2}{k_b \lambda}$, $\Psi_l = \Lambda_{r,u}$ are the eigenvalue and left eigenvector of Laplacian matrix \mathcal{L} , respectively. Therefore we have

$$\lambda^2 + k_b \psi \lambda + \omega^2 = 0 \quad (22)$$

Eq. (22) can thus be solved as

$$\lambda_{\pm} = \frac{k_b \psi \pm \sqrt{k_b^2 \psi^2 - 4\omega^2}}{2} \quad (23)$$

127 Besides, from (18a) and (19a), we know $\Lambda_{l,\pm} = [\Psi_l^T, -\frac{\lambda_{\pm}}{\omega^2} \Psi_l^T]$, $\Lambda_{r,\pm} = [\Psi_r^T, \lambda_{\pm} \Psi_r^T]^T$. Lemma 1 is
128 proved. \square

129 **Theorem 1.** If graph \mathcal{G} describing the coordinated network includes a directed spanning tree, and the root
130 node can access to the reference position as sinusoidal signal $r = \sin(\omega t + \theta)$ such as shown in Fig. 3a, the
131 LSRMs network Eq. (15) can track asymptotically the reference with zero difference-phase.



Figure 3. LSRMs network with virtual LSRM modeling reference.

Proof of Theorem 2. According to [29], for a directed graph \mathcal{G} with a spanning tree in the network topology, its Laplacian matrix $-\mathcal{L}(\mathcal{G})$ has the left eigenvector $\Psi_{l,1} = \mathbf{p}_N$ and the right eigenvector $\Psi_{r,1} = \mathbf{1}_N$. They correspond to a simple zero eigenvalue $\psi_1 = 0$ of \mathcal{L} , and all rest of eigenvalues $\psi_i, i = 2, \dots, N$ satisfy $\text{Re}(\psi_i) < 0$, where $\text{Re}(\cdot)$ is the real part of a complex number. Furthermore, \mathbf{p}_N satisfies

$$\begin{aligned} \mathbf{p}_N &\geq 0 \\ \mathbf{p}_N^T \mathbf{1}_N &= 1. \end{aligned} \quad (24)$$

According to Lemma 1, the first two eigenvalues of \mathcal{S} in Eq. (15) are $\lambda_{1,\pm} = \pm j\omega$, j is the imaginary unit. Accordingly, the left eigenvector and right eigenvector are $\Lambda_{l,1,\pm} = [\mathbf{p}_N^T, \pm j\omega \mathbf{p}_N^T]^T$, $\Lambda_{r,1,\pm} = [\mathbf{1}_N^T, \pm \frac{1}{j\omega} \mathbf{1}_N^T]^T$ respectively. We have

$$\mathcal{S} = \mathcal{P} \mathcal{M} \mathcal{P} \quad (25)$$

where

$$\mathcal{P} = \left[\begin{array}{c} \Lambda_{l,1\pm}, \dots, \Lambda_{l,N\pm} \end{array} \right], \mathcal{P}^{-1} = \left[\begin{array}{c} \Lambda_{r,1\pm}, \dots, \Lambda_{r,N\pm} \end{array} \right]^T, \mathcal{M} = \left[\begin{array}{ccc} j\omega & 0 & 0_{1 \times (2N-2)} \\ 0 & -j\omega & 0_{1 \times (2N-2)} \\ 0_{(2N-2) \times 1} & 0_{(2N-2) \times 1} & J(\lambda_k) \end{array} \right]$$

Here $J(\lambda_k)$ is the Jordan block matrix associated to $k = 2\pm, \dots, N\pm$.

Since $e^{\mathcal{S}t} = \mathcal{P}e^{\mathcal{M}t}\mathcal{P}^{-1}$, $\lim_{t \rightarrow \infty} J(\lambda_k) = 0_{(2N-2) \times (2N-2)}$, it follows that,

$$\begin{aligned} \lim_{t \rightarrow \infty} e^{\mathcal{S}t} &= [\Lambda_{l,1+}^T, \Lambda_{l,1-}^T] e^{\mathcal{M}_{1\pm}t} [\Lambda_{r,1+}^T, \Lambda_{r,1-}^T] \\ &= \frac{1}{2} e^{j\omega t} \left[\begin{array}{c} \mathbf{1}_N \\ j\omega \cdot \mathbf{1}_N \end{array} \right] \left[\begin{array}{c} \mathbf{p}_N \\ \frac{1}{j\omega} \mathbf{p}_N \end{array} \right]^T + \frac{1}{2} e^{-j\omega t} \left[\begin{array}{c} \mathbf{1}_N \\ -j\omega \cdot \mathbf{1}_N \end{array} \right] \left[\begin{array}{c} \mathbf{p}_N \\ \frac{-1}{j\omega} \mathbf{p}_N \end{array} \right]^T \\ &= \frac{[\cos(\omega t) + j \sin(\omega t)]}{2} \left[\begin{array}{c} \mathbf{1}_N \\ j\omega \cdot \mathbf{1}_N \end{array} \right] \left[\begin{array}{c} \mathbf{p}_N \\ \frac{1}{j\omega} \mathbf{p}_N \end{array} \right]^T \\ &\quad + \frac{[\cos(-\omega t) + j \sin(-\omega t)]}{2} \left[\begin{array}{c} \mathbf{1}_N \\ -j\omega \cdot \mathbf{1}_N \end{array} \right] \left[\begin{array}{c} \mathbf{p}_N \\ \frac{-1}{j\omega} \mathbf{p}_N \end{array} \right]^T \\ &= \left[\begin{array}{cc} \frac{\cos(\omega t) + j \sin(\omega t)}{2} & \frac{\cos(\omega t) + j \sin(\omega t)}{2\omega j} \\ \frac{\omega j[\cos(\omega t) + j \sin(\omega t)]}{2} & \frac{\cos(\omega t) + j \sin(\omega t)}{2} \end{array} \right] \otimes \mathbf{1}_N \mathbf{p}_N^T \\ &\quad + \left[\begin{array}{cc} \frac{\cos(\omega t) - j \sin(\omega t)}{2} & \frac{-\cos(\omega t) + j \sin(\omega t)}{2\omega j} \\ \frac{\omega j[-\cos(\omega t) + j \sin(\omega t)]}{2} & \frac{\cos(\omega t) - j \sin(\omega t)}{2} \end{array} \right] \otimes \mathbf{1}_N \mathbf{p}_N^T \\ &= \left[\begin{array}{cc} \cos(\omega t) & \frac{1}{\omega} \sin(\omega t) \\ -\omega \sin(\omega t) & \cos(\omega t) \end{array} \right] \otimes \mathbf{1}_N \mathbf{p}_N^T \end{aligned} \quad (26)$$

where $\mathcal{M}_{1\pm} = \begin{bmatrix} \omega j & 0 \\ 0 & -\omega j \end{bmatrix}$ is a block matrix of \mathcal{M} associated to $\lambda_{1\pm} = \pm\omega j$ and the simple zero eigenvalue of $-\mathcal{L}$.

Let $\tilde{X} = [\rho^T, \dot{\rho}^T]^T$, the solution of LSRMs network in Eq. (14) can be obtained as

$$\tilde{X}(t) = e^{\mathcal{S}t} \tilde{X}(0) \quad (27)$$

Moreover, according to Eq. (26),

$$\begin{aligned} \lim_{t \rightarrow \infty} \tilde{X}(t) &= \lim_{t \rightarrow \infty} e^{\mathcal{S}t} \cdot \tilde{X}(0) \\ &= \left\{ \left[\begin{array}{cc} \cos(\omega t) & \frac{1}{\omega} \sin(\omega t) \\ -\omega \sin(\omega t) & \cos(\omega t) \end{array} \right] \otimes \mathbf{1}_N \mathbf{p}_N^T \right\} \tilde{X}(0) \\ &= \left\{ \left[\begin{array}{cc} \cos(\omega t) & \frac{1}{\omega} \sin(\omega t) \\ -\omega \sin(\omega t) & \cos(\omega t) \end{array} \right] \otimes \mathbf{1}_N \right\} \cdot [\mathbf{1}_2 \otimes \mathbf{p}_N^T] \tilde{X}(0) \end{aligned} \quad (28)$$

According to Eq. (24), it can be seen that \mathbf{p}_N can be set as $[1, \mathbf{0}_{N-1}^T]^T$ in Eq. (28). Therefore, Eq. (28) is derived as

$$\lim_{t \rightarrow \infty} \tilde{X}(t) = \left\{ \left[\begin{array}{cc} \cos(\omega t) & \frac{1}{\omega} \sin(\omega t) \\ -\omega \sin(\omega t) & \cos(\omega t) \end{array} \right] \otimes \mathbf{1}_N \right\} x_1(0) \quad (29)$$

where $x_1(0)$ is the initial values of the LSRM node L_1 as the root of a directed spanning tree in the coordinated network topology \mathcal{G} , as shown in Fig. 1. In addition, the states of LSRM nodes $L_i, i = 2, \dots, N$ converge to the steady state as,

$$\begin{cases} \rho_i(t) = \cos(\omega t)\rho_1(0) + \frac{1}{\omega} \sin(\omega t)\dot{\rho}_1(0) \\ \dot{\rho}_i(t) = -\omega \sin(\omega t)\rho_1(0) + \cos(\omega t)\dot{\rho}_1(0) \end{cases} \quad (30)$$

Obviously, the steady state values are determined by the initial values $[\rho_1(0), \dot{\rho}_1(0)]$ of root node L_1 . Therefore, the states of other $N - 1$ LSRM nodes $L_i, i = 2, \dots, N$ converge to the state of root without phase disparity. The fact verifies under the effect of the coordinated control Eq. (12), the states of LSRMs network can track the state of root node L_1 represented as

$$\begin{cases} \rho_1(t) = \cos(\omega t)\rho_1(0) + \frac{1}{\omega} \sin(\omega t)\dot{\rho}_1(0) \\ \dot{\rho}_1(t) = -\omega \sin(\omega t)\rho_1(0) + \cos(\omega t)\dot{\rho}_1(0) \end{cases} \quad (31)$$

Let $\sin \theta = \rho_1(0)$, $\cos \theta = \frac{1}{\omega} \dot{\rho}_1(0)$, Eq. (31) is rewritten as,

$$\begin{cases} \rho_1(t) = \sin(\omega t + \theta) \\ \dot{\rho}_1(t) = \omega \cos(\omega t + \theta) \end{cases} \quad (32)$$

Accordingly, if the reference sinusoidal position signal $r = \sin(\omega t + \theta)$ in Fig. 3a and its derivative is regarded as the state $[\rho_r, \dot{\rho}_r]^T$ of a virtual root node L_r , as shown in Fig. 3b, the sinusoidal reference signal can be tracked asymptotically by the LSRMs network Eq. (15) in a coupled harmonic oscillators synchronization manner. *Theorem 2* is proved. \square

Remark 1. By selecting appropriate initial values of virtual root node L_r , the LSRMs network Eq. (15) can converge to the specified sinusoidal reference, which has phase $\theta = \arcsin(\rho_r(0))$ and angular frequency $\omega = \frac{\dot{\rho}_r(0)}{\cos \theta}$.

4. Illustrative examples

Example 1. The sinusoidal reference r is modeled as a virtual LSRM node L_r , and its initial phase and amplitude are $\frac{\pi}{2}, 30\text{mm}$, respectively. In addition, the angular frequency of L_r is set as 2π to investigate the system control feature tracking a higher frequency sine signal.

Each LSRM can be characterized by the second-order dynamics Eq. (11). According to the method proposed in [8], system matrices A_i and B_i ($i = 1, 2, 3$) can be obtained by the online least squares identification [4] with a sampling time of $T = 0.001$ s and they can be derived as

$$A_i = \begin{bmatrix} 0 & 1 \\ 0 & 0.3333 \end{bmatrix}, B_i = \begin{bmatrix} 0 \\ 0.6667 \end{bmatrix}.$$

The initial positions of three LSRM nodes are set as $\rho_1(0) = 0, \rho_2(0) = 0, \rho_3(0) = -12$, respectively, and all velocities of three LSRM nodes are 0. The control gain k_b is set as 0.25 empirically (according to some parameter tuning experience). The topology of the LSRMs network is depicted as Fig. 3.

The results of the state and position error responses are depicted in Figs. 4a and b, respectively. Fig. 4a illustrates that the LSRMs network Eq. (14) tracks the reference $r = \sin(2\pi t + \frac{\pi}{2})$ in a zero phase-difference and asymptotic manner by applying the proposed control law Eq. (12). the position error among all nodes including $\{L_r, L_1, L_2, L_3\}$ are illustrated in Fig. 4b. The disparity of position

errors are eliminated for all LSRM nodes after about 0.9s.

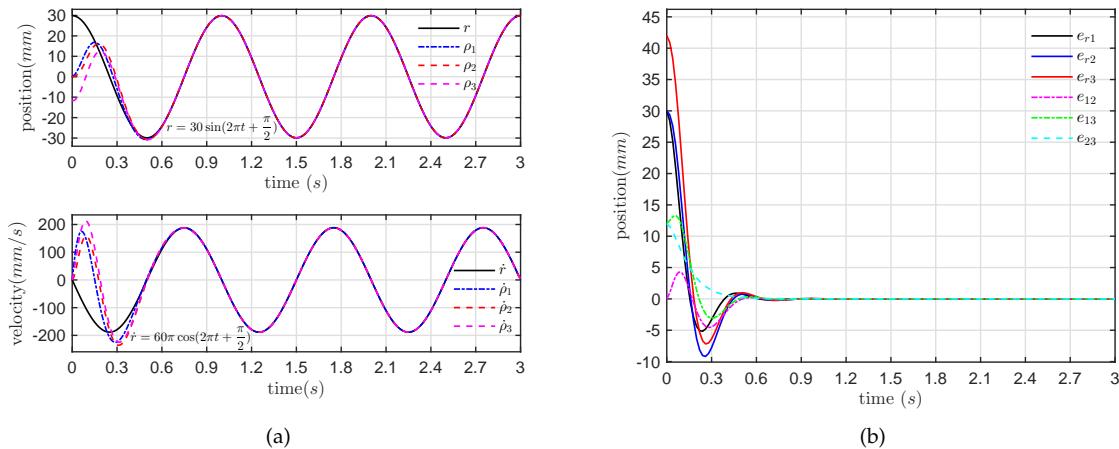


Figure 4. (a) Position and velocity response and (b) relative position error response.

150
151

152 **Example 2.** To further verify the effectiveness of the proposed control strategy, a comparative study with
153 Example 1 are addressed. We locate the initial positions of three LSRM nodes at $\rho_1(0) = 0, \rho_2(0) = 0, \rho_3(0) =$
154 12, respectively, and three LSRM nodes start work from static state. we set the reference r initial phase as $\frac{\pi}{2}$,
155 and the angular frequency are selected as $\frac{\pi}{4}$ to test the track feature to a lower frequency sine wave. The other
156 systems parameters, such as the control gain etc., are given the identical values as in Example 1.

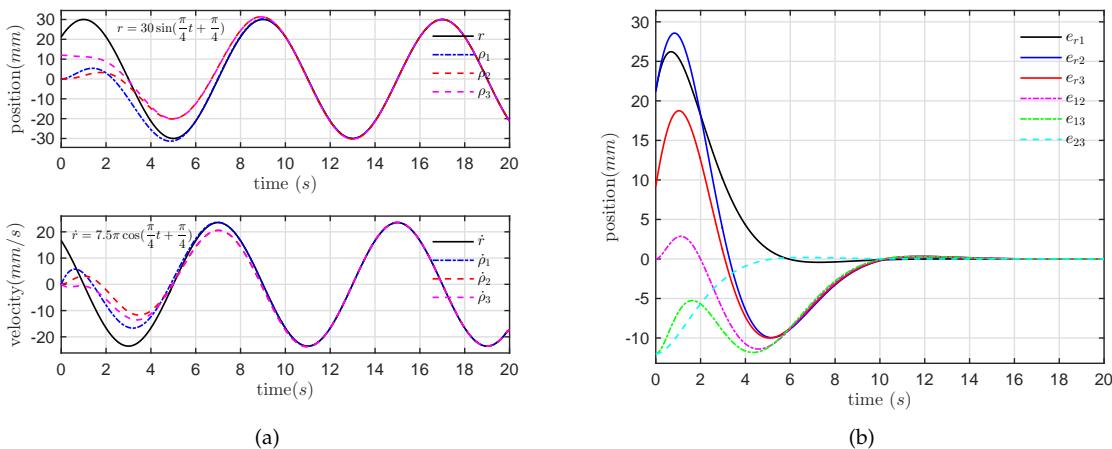


Figure 5. (a) Position and velocity response and (b) relative position error response.

157 The simulation results are shown in Figs. 5a and b, respectively. The control performance from
158 the proposed control method shows that a slower dynamic response can be achieved with a lower
159 frequency sinusoidal reference, compared to Example 1 for the same system without considering
160 uncertain parameters and external disturbances. The results also demonstrate that the LSRMs
161 network has successfully achieved the stable state without phase-difference after 10s. Therefore, the
162 proposed tracking control scheme has certain superior stability.

163 **Remark 2.** From two example comparative results, it is noted that the response effectiveness of Example 2 is
 164 counterintuitive, since the state consensus process of Example 2 takes longer time rather than Example 1 as
 165 with expected. The main cause is that the angular frequency of the reference sinusoidal signal strongly effects
 166 the response rate of each LSRM node through Eq. (12).

167 **5. System Construction and Experimental results**

168 **5.1. System Construction**

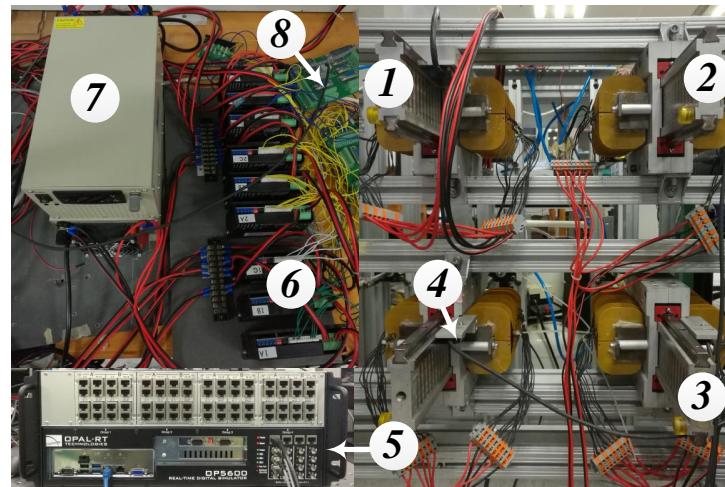


Figure 6. Experimental platform of LSRMs network. (1) LSRM 1, (2) LSRM 2, (3) LSRM 3, (4) Linear encoder, (5) RT-LAB, (6) Current amplifier, (7) Power supply, (8) Connection interface to RT-LAB

169 The experimental platform on the LSRMs network is exhibited in Fig. 6. The platform applies
 170 RT-LAB (OP5600) real-time digital simulator as the distributed controllers on each LSRM node, and
 171 builds a virtual LSRM node L_r modeling the specific sinusoidal reference r . The position state of each
 172 LSRM node is measured and collected by a linear magnetic encoder and inspected by the host PC
 173 which is the management terminal remotely. The sampling frequency of the position control loop is 1
 174 kHz. The current drivers of each LSRMs node are connected to RT-LAB through the analog-to-digital
 175 converters. The current control is realized by three commercial amplifiers that are capable of
 176 inner current regulation based on the proportional-integral-differential algorithm with a switching
 177 frequency of 20 kHz. The sampling frequency of the position control loop is 1 kHz. The proposed
 178 distributed tracking control algorithm Eq. (12) can be programmed under MATLAB/Simulink[®]
 179 environment, and the developed algorithm can be downloaded to the digital signal processor of
 180 RT-LAB. All control parameters can be modified on-line. The real time state response waveforms of
 181 all LSRM nodes of the LSRMs network are monitored and recorded by the host PC.

182 The control objects of three LSRM nodes are three identical LSRMs that conform to the
 183 6/4 switched reluctance machine structure. A double-sided machine arrangement guarantees a
 184 more stable and reliable output performance and the asymmetry of the stators ensures a higher
 185 force-to-volume ratio. The major specifications of the LSRM are demonstrated in [28]. LSRM
 186 parameters can be obtained as $a_1 = 0.3, a_2 = 0.315, b_0 = 0.026, b_1 = 0.014$, and through the online
 187 recursive least square parameter identification scheme.

188 **5.2. Experimental Results**

189 In order to validate the proposed control scheme based on coupled harmonic oscillators, the
 190 experiment of the tracking control is implemented for the LSRMs network based on the designed
 191 controller. Moreover, to compare with two aforementioned simulation example, system scenario and

192 its parameters, including initial states of the reference and LSRM nodes and its controller gain, are
 193 given the same values as in Example 1 and 2.

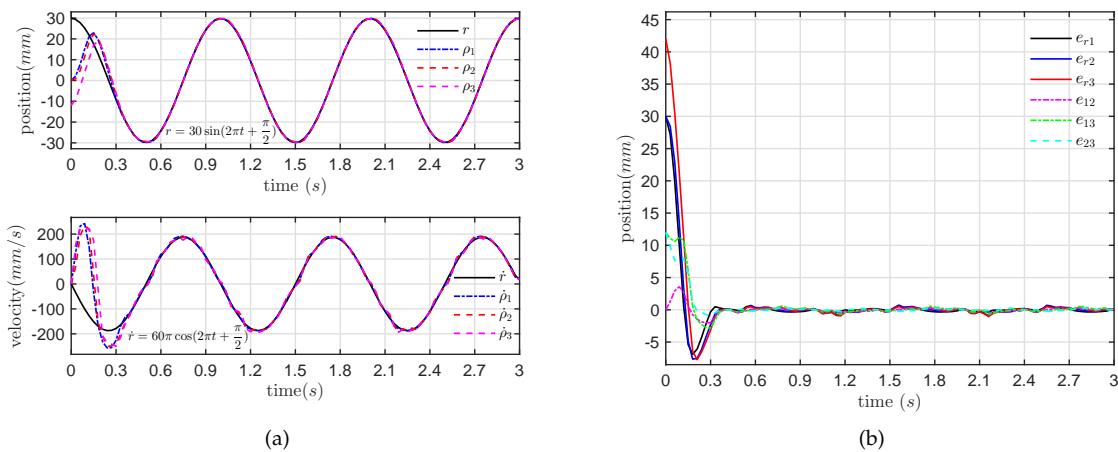


Figure 7. Position and velocity of reference and three LSRMs corresponding with Example 1.

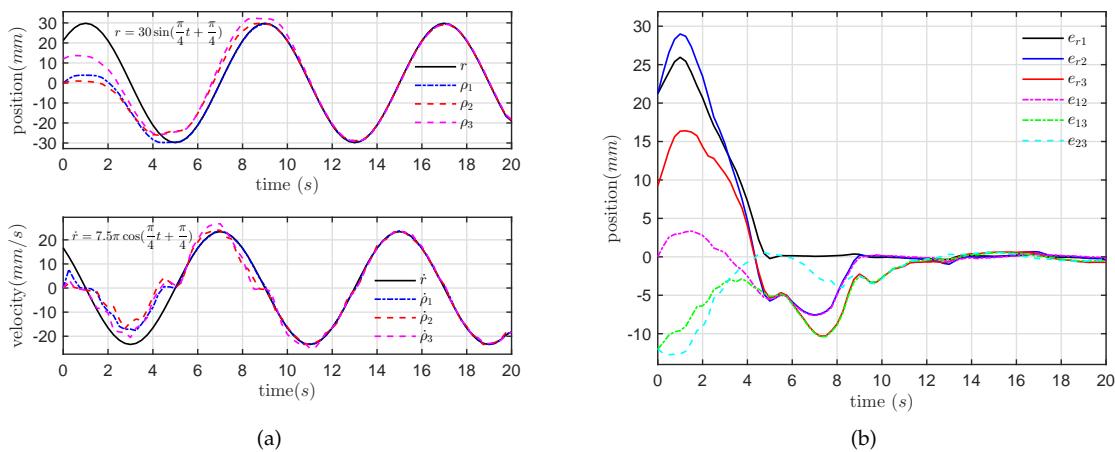


Figure 8. Position and velocity of reference and three LSRMs corresponding with Example 2.

194 The tracking response waveforms for the three LSRMs node are shown in Fig. 7 and Fig. 8.
 195

Fig. 7a illustrates the tracking control of three LSRM nodes takes the zero phase-difference effect
 196 at about the time of 0.4s. From Fig. 7b, the relative position errors among three LSRMs and the
 197 reference fall into 1.2mm in stable state after the transient time of 0.4s.

198 Fig. 8a illustrates the dynamic position and relative position error response waveforms under
 199 tracking control of three LSRM nodes. It is clear that the zero phase-difference effect is taken at about
 200 the time of 11s. From the dynamic error response profiles as Fig. 8b, it is clear that the maximum
 201 error values fall into 1.2mm.

202 According to the tracking profiles of the three LSRMs in Fig. 7 and Fig. 8, the LSRMs network
 203 has all capable of following the position reference signal in zero phase-difference manner. However,
 204 the control performance from the three LSRMs is disagreement and fluctuating slightly, especially at
 205 steady state. This is mainly because the imperfect manufacture and assembly of three LSRMs, which
 206 results in the asymmetric control performance from the positive and negative transitions. But from
 207 Figs. 4-5 and Figs. 7-8, it can be seen that the tracking control effect displays high similarity to the

208 aforementioned numerical simulative examples. It can be concluded that proposed control method is
209 effective.

210 **6. Conclusions**

211 A distributed control strategy of the LSRMs network is proposed for tracking to a sinusoidal
212 reference in a zero phase-difference manner. The dynamics of the LSRM nodes are modeled as
213 general second-order linear systems by online system identification. Subsequently, inspired by
214 the coupled harmonic oscillators synchronization, a distributed control is presented to track a
215 sinusoidal reference without the phase-difference among each LSRM and the reference. Simulation
216 and experimental results verify that the proposed control improves the synchronization and tracking
217 accuracy performance of the LSRMs network through eliminating the phase-difference among LSRM
218 nodes and virtual node modeling the sinusoidal reference. To further improve the tracking precision,
219 it is suggested that the advanced internal model compensation schemes are introduced to the
220 feedback control design of the LSRMs network. For the tracking control of some general periodical
221 reference signals, the combined frequency domain analysis is also recommended for better control
222 schemes.

223 **Acknowledgments:** This work was supported in part by the National Natural Science Foundation of China
224 under Grant 51577121, 11572248, 51477103, 61690211 and 61403258. The authors also would like to thank
225 Guangdong and Shenzhen Government under the code of S2014A030313564, 2015A010106017, 2016KZDXM007
226 and JCYJ20160308104825040 for support.

227 **Author Contributions:** Bo Zhang and Jianping Yuan conceived and wrote the paper main body and designed
228 the main body of study. J.F. Pan and Li Qiu guide the system designed, analyzed the data and revised the
229 manuscript. Wufeng Rao performed the simulations and experiments. Jianjun Luo and Honghua Dai helped to
230 revise the paper.

231 **Conflicts of Interest:** The authors declare no conflict of interest.

232 **Bibliography**

- 233 1. Leitao, P.; Marik, V.; Vrba, P. Past, Present, and Future of Industrial Agent Applications. *IEEE Transactions*
234 *on Industrial Informatics* **2013**, *9*, 2360–2372.
- 235 2. Qin, J.; Yu, C.; Gao, H. Coordination for Linear Multiagent Systems With Dynamic Interaction Topology
236 in the Leader-Following Framework. *IEEE Transactions on Industrial Electronics* **2014**, *61*, 2412–2422.
- 237 3. Amoros, J.; Andrada, P. Sensitivity Analysis of Geometrical Parameters on a Double-Sided Linear
238 Switched Reluctance Motor. *IEEE Transactions on Industrial Electronics* **2010**, *57*, 311–319.
- 239 4. Pan, J.F.; Zou, Y.; Cao, G. Adaptive controller for the double-sided linear switched reluctance motor based
240 on the nonlinear inductance modelling. *Iet Electric Power Applications* **2013**, *7*, 1–15.
- 241 5. Lin, J.; Cheng, K.W.E.; Zhang, Z.; Cheung, N.C.; Xue, X.D.; Ng, T.W. Active Suspension System Based
242 on Linear Switched Reluctance Actuator and Control Schemes. *IEEE Transactions on Vehicular Technology*
243 **2013**, *62*, 562–572.
- 244 6. Lin, J.; Cheng, K.W.E.; Zhang, Z.; Cheung, N.C.; Xue, X.D. Adaptive sliding mode technique-based
245 electromagnetic suspension system with linear switched reluctance actuator. *Iet Electric Power Applications*
246 **2015**, *9*, 50–59.
- 247 7. Zhao, S.; Cheung, N.C.; Gan, W.; Yang, J.M.; Zhong, Q. Passivity-based control of linear switched
248 reluctance motors with robustness consideration. *Iet Electric Power Applications* **2008**, *2*, 164–171.
- 249 8. Zhang, B.; Yuan, J.; Qiu, L.; Cheung, N.; Pan, J.F. Distributed Coordinated Motion Tracking of the Linear
250 Switched Reluctance Machine-Based Group Control System. *IEEE Transactions on Industrial Electronics*
251 **2016**, *63*, 1480–1489.
- 252 9. Qiu, L.; Shi, Y.; Pan, J.; Zhang, B.; Xu, G. Collaborative Tracking Control of Dual Linear Switched
253 Reluctance Machines Over Communication Network With Time Delays. *IEEE Transactions on Systems,
254 Man, and Cybernetics* **2016**, pp. 1–11.
- 255 10. Olfati-Saber, R.; Fax, J.A.; Murray, R.M. Consensus and Cooperation in Networked Multi-Agent Systems.
256 *Proceedings of the IEEE* **2007**, *95*, 215–233.

257 11. Cao, Y.; Yu, W.; Ren, W.; Chen, G. An Overview of Recent Progress in the Study of Distributed
258 Multi-Agent Coordination. *IEEE Transactions on Industrial Informatics* **2012**, *9*, 427–438.

259 12. Li, L.; Ho, D.W.C.; Lu, J. A Unified Approach to Practical Consensus with Quantized Data and Time
260 Delay. *IEEE Transactions on Circuits and Systems I Regular Papers* **2013**, *60*, 2668–2678.

261 13. Yu, W.; Chen, G.; Cao, M.; Ren, W. Delay-Induced Consensus and Quasi-Consensus in Multi-Agent
262 Dynamical Systems. *IEEE Transactions on Circuits and Systems I-regular Papers* **2013**, *60*, 2679–2687.

263 14. Wei, J.; Fang, H. Multi-agent consensus with time-varying delays and switching topologies. *Journal of
264 Systems Engineering and Electronics* **2014**, *25*, 489–495.

265 15. Wang, H. Consensus of Networked Mechanical Systems With Communication Delays: A Unified
266 Framework. *IEEE Transactions on Automatic Control* **2014**, *59*, 1571–1576.

267 16. Liu, K.; Zhu, H.; Lu, J. Bridging the Gap Between Transmission Noise and Sampled Data for Robust
268 Consensus of Multi-Agent Systems. *IEEE Transactions on Circuits and Systems I-regular Papers* **2015**,
269 *62*, 1836–1844.

270 17. Ning, X.; Yuan, J.; Yue, X. Uncertainty-based Optimization Algorithms in Designing Fractionated
271 Spacecraft. *Scientific Reports* **2016**, *6*, 22979.

272 18. Zhang, Q.; Lapierre, L.; Xiang, X. Distributed Control of Coordinated Path Tracking for Networked
273 Nonholonomic Mobile Vehicles. *IEEE Transactions on Industrial Informatics* **2013**, *9*, 472–484.

274 19. Dong, X.; Yu, B.; Shi, Z.; Zhong, Y. Time-Varying Formation Control for Unmanned Aerial Vehicles:
275 Theories and Applications. *IEEE Transactions on Control Systems and Technology* **2014**, *23*, 340–348.

276 20. Cheng, M.H.; Li, Y.J.; Bakhoum, E.G. Controller Synthesis of Tracking and Synchronization for Multiaxis
277 Motion System. *IEEE Transactions on Control Systems Technology* **2014**, *22*, 378–386.

278 21. Li, X.; Wang, X.; Chen, G. Pinning a complex dynamical network to its equilibrium. *Circuits and Systems
279 I Regular Papers IEEE Transactions on* **2004**, *51*, 2074–2087.

280 22. Wang, X.; Su, H. Pinning control of complex networked systems: A decade after and beyond. *Annual
281 Reviews in Control* **2014**, *38*, 103–111.

282 23. Cao, Y.; Ren, W. Distributed Coordinated Tracking With Reduced Interaction via a Variable Structure
283 Approach. *IEEE Transactions on Automatic Control* **2012**, *57*, 33–48.

284 24. Wang, X.; Hong, Y.; Huang, J.; Jiang, Z. A Distributed Control Approach to A Robust Output Regulation
285 Problem for Multi-Agent Linear Systems. *IEEE Transactions on Automatic Control* **2010**, *55*, 2891–2895.

286 25. Wieland, P.; Sepulchre, R.; Allgower, F. An internal model principle is necessary and sufficient for linear
287 output synchronization. *Automatica* **2011**, *47*, 1068–1074.

288 26. Su, H.; Wang, X.; Lin, Z. Synchronization of coupled harmonic oscillators in a dynamic proximity
289 network. *Automatica* **2009**, *45*, 2286–2291.

290 27. Ren, W. Synchronization of coupled harmonic oscillators with local interaction. *Automatica* **2008**,
291 *44*, 3195–3200.

292 28. Pan, J.F.; Zou, Y.; Cao, G. An Asymmetric Linear Switched Reluctance Motor. *IEEE Transactions on Energy
293 Conversion* **2013**, *28*, 444–451.

294 29. Mesbahi, M.; Egerstedt, M. *Graph theoretic methods in multiagent networks*; Princeton University Press, 2010;
295 pp. 399–403.