ADAPTIVE PARAMETER ESTIMATION FOR AN ENERGY MODEL OF BELT CONVEYOR WITH DC MOTOR

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ABSTRACT

In practice, design parameters of a belt conveyor likely drift away from their design values by maintenance, readjustment, retrofit, abrasion, and circumstance change. For the purpose of energy optimization, these parameters should be estimated through experiments. In this paper, a new energy model of a DC motor driven belt conveyor is presented. Then, based on an adaptive observer, a parameter estimation algorithm is derived. In addition, under a persistent excitation condition, the convergence of the parameters to the desired values can also be concluded. Compared with the existing methods, our methods can be implemented by measuring only the feed rate of the belt conveyor and the angular velocity of the rotor of the DC motor.

Key Words: Parameter estimation, energy model, belt conveyor, observer, DC motor.

I. INTRODUCTION

Belt conveyors have a high transfer capacity and a long transfer distance. They are widely used to transfer bulk material in the mining, metallurgical, and coal industries. According to the report in [1], about 10% of the total maximum power demand in South Africa is to handle materials, where up to 40% of the energy cost is borne by the operational cost of the belt conveyor systems [2]. Therefore, improving energy efficiency of belt conveyors by reducing the energy consumption of material handling is of great significance.

There are four levels where energy efficiency of a belt conveyor can be improved: performance, operation, equipment, and technology [3]. It is easy to achieve higher energy efficiency by introducing highly efficient equipment [4–8]. Nevertheless, extra investment is needed to retrofit or replace the equipment. At the operation level, many methods have been proposed to improve energy efficiency for the belt conveyors [9–18]. For example, the authors in [17] proposed an optimal switching control and a variable speed drive based optimal control to reduce the energy consumption of belt conveyors. In [18], an analytical energy model was proposed. This model had four coefficients that could be estimated through algorithms, such as least square (LSQ) [19] and recursive least square (RLSQ) [20]. After obtaining the energy model, an optimization was also done at the operational level with two performance indicators, energy cost and energy consumption. In order to estimate these four coefficients, however the power of the motor $P_M$, feed rate $T$, and belt speed $V$ should be measured. Recently, in order to estimate unknown states and unknown constant parameters, adaptive observers have made great progress [21–30].

In this paper, a new energy model of belt conveyor with a DC motor is introduced. Then, an adaptive observer is designed for the model. In order to identify the four coefficients of the energy model, the feed rate $T$ of the belt conveyor and the angular velocity $w_m$ of the rotor of the DC motor should be measured on-line. Then, based on the adaptive observer, a parameter estimation algorithm is derived. In addition, under a persistent excitation condition, the convergence of the parameters to the desired values can also be concluded. Simulation results show the validity of our methods.

This paper is organized as follows. The analytical energy model of belt conveyors in [18], the model of a DC motor, and the adaptive observers design are reviewed in Section II. In Section III, we present a new energy model of belt conveyors with DC motors, an adaptive observer for this model, and a parameter estimation algorithm. In Section IV, an example is given to show the validity of our new methods. Section V presents the conclusion.

II. PRELIMINARIES

2.1 An analytical energy model of belt conveyors

A typical belt conveyor is shown in Fig. 1. As in [18], an analytical energy model of the belt conveyor is given as follows:
where $P_T$ is the mechanical power; $V$ denotes the belt speed (m/s); $T$ is the feed rate (t/h); $\theta_1$, $\theta_2$, $\theta_3$, and $\theta_4$ are four parameters. In practice, the four parameters often drift away through maintenance, readjustment, retrofit, abrasion, and circumstance change. For the purpose of energy optimization, these four parameters are estimated by both off-line and on-line parameter estimation schemes, based on $P_T$, $V$, and $T$ measured on-line and off-line, respectively, in [18].

2.2 A DC motor

The dynamics of a DC motor are given by [31]:

\[
\begin{align*}
J_m \frac{d\omega_m}{dt} + b_m \omega_m &= k_i i_a - T_L, \\
L_f \frac{di_f}{dt} + R_f i_f &= e_f, \\
L_a \frac{di_a}{dt} + R_a i_a &= e_a - k_i i_f \omega_m,
\end{align*}
\]

where $J_m$ denotes the mass moment of inertia of the motor, $\omega_m$ is its angular velocity, $k_i$ is the torque constant, $b_m$ is the damping coefficient, $T_L$ is the presence of some external load, $L_a$ and $L_f$ are its inductances, $R_a$ and $R_f$ are its resistances, $i_a$ and $i_f$ are its currents, $k_i$ is a proportional constant to the flux and the angular velocity of the motor, and $e_a$ and $e_f$ are two separate potentials are used to power the armature and field, respectively. The corresponding circuit is shown in Fig. 2.

2.3 Adaptive observers

Adaptive observers can be used to estimate unknown parameters. Now, let us review the adaptive observers' design. Consider the following system in adaptive observer form [26]:

\[
\begin{align*}
\dot{\hat{z}} &= \tilde{A}_0 \hat{z} + \gamma(y, u) + \hat{\beta} \hat{Y}(y, u, t) \hat{\theta}, \\
y &= \tilde{C}_0 \hat{z},
\end{align*}
\]

where $z \in \mathbb{R}^n$, $y \in \mathbb{R}$, $u \in \mathbb{R}^m$, $\theta \in \mathbb{R}^p$, and $\gamma(y, u)$ are smooth function mapping $\mathbb{R} \times \mathbb{R}^m \to \mathbb{R}^n$; $\tilde{A}_0 = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$; $\tilde{B} = [\tilde{b}_1, \cdots, \tilde{b}_p] \in \mathbb{R}^n$ is given such that the polynomial $\tilde{b}_1 z^{p-1} + \cdots + \tilde{b}_p$ is Hurwitz and $\tilde{b}_1 > 0$; and $\tilde{C}_0 = [1 \ 0 \ \cdots \ 0]$, $\beta \in L^1 \times \mathbb{R}^m$, $\beta'(y, u, t) \theta = \sum_{i=1}^{p} \beta_i(y, u, t)$ are continuous functions and uniformly bounded for every $(y, u)$ bounded. A global adaptive observer with parameter convergence is designed in [26] as follows:

\[
\begin{align*}
\dot{\hat{z}} &= \tilde{A}_0 \hat{z} + \tilde{K} \tilde{C}_0 \hat{z} + e(y, u) + \hat{\beta} \hat{Y}(y, u, t) \hat{\theta}, \\
\dot{\hat{\theta}} &= \Gamma \beta(y, u, t) \tilde{C}_0 e, \\
\end{align*}
\]

where $\hat{\theta}$ is any symmetric positive definite matrix, $e = z - \hat{z}$, $\Gamma = \frac{1}{b_1} (\tilde{A}_0 + \lambda \tilde{B})$ with $\lambda$ being an arbitrary positive real. Since $(\tilde{A}_0, \tilde{B}, \tilde{C}_0)$ satisfies the strictly positive real condition, then, for any symmetric definite matrix $\tilde{Q}$, there exist a symmetric positive definite matrix $\tilde{P}$, a positive real $\lambda$ such that [26]:

\[\tilde{A}_0 + \tilde{K} \tilde{C}_0 \gamma \tilde{P} \tilde{P} + \tilde{P} (\tilde{A}_0 + \tilde{K} \tilde{C}_0) < -\tilde{d} \tilde{Q}, \quad \tilde{P} \tilde{B} = \tilde{C}^T.\]

III. A NEW ENERGY MODEL

In this section, we make the following assumption: the belt is non-slip. $T$ and $\omega_m$ are measured on-line. We shall also assume a constant potential $e_f$ and assume that the circuit is operating at steady state so that $e_f = i R_f$, yielding a constant field current $i_f$. Therefore, we have:
\[
\begin{aligned}
J_m \frac{d\omega_m}{dt} + b_m \omega_m &= k_f i_1 - T_c, \\
L_a \frac{di_a}{dt} + R_a i_a &= e_a - k_b \omega_m,
\end{aligned}
\] (4)

where \( k_f = k_f i_1, k_b = k_b i_1. \)

When the DC motor is employed to drive the conveyor belt, then,
\[
T_c = F_c r, \quad V = 2\pi r w_m,
\] (5)

where \( r \) is the radius of the rotor and \( F_c \) is the peripheral driving force of the belt conveyor and can be calculated by the following equation [18]:
\[
F_c = \frac{VT}{3.6} + \frac{T^2}{6.48 \rho b_i} + \left[ g L \cos \delta + L(1 - \cos \delta) \left(1 - \frac{2Q_b}{Q}\right) \right] + k_3 + C_f, \quad (6)
\]

\[
+ k_1 \frac{T^2}{r^2} + \left( \frac{gL \sin \delta + gL \cos \delta}{3.6} + k_2 \right) \frac{T}{2\pi r w_m},
\]

where \( f \) is the artificial friction factor; \( L \) is the center-to-center distance (m); \( Q = Q_{Rf} + Q_{Rg} + 2Q_b; Q_{Rf} \) is the unit mass of the rotating parts of the belt conveyor (kg/m), and \( Q_b \) is the unit mass of the belt of rotating parts of the return idler rollers (kg/m); \( \delta \) is the inclination angle (°); \( \rho \) is the bulk density of material (kg/m³); \( b_i \) is the width between the skirt boards (m); \( k_1, k_2, \) and \( k_3 \) are constant coefficients that relate to the structural parameters of the belt conveyor; and \( C_f \) is a constant. From (5) and (6), we have:
\[
T_c = \frac{2\pi r^2 T w_m}{3.6} = \frac{r T^2}{6.48 \rho b_i} + \left[ g L \cos \delta + L(1 - \cos \delta) \left(1 - \frac{2Q_b}{Q}\right) \right] + k_3 + C_f, \quad (7)
\]

\[
+ k_1 \frac{T^2}{4\pi^2 r^2 w_m^2} + \left( \frac{gL \sin \delta + gL \cos \delta}{3.6} + k_2 \right) \frac{T}{2\pi r w_m}.
\]

Let \( \theta_1 = \frac{r}{6.48 \rho b_i}, \quad \theta_2 = r \left[ g L \cos \delta + L(1 - \cos \delta) \left(1 - \frac{2Q_b}{Q}\right) \right] + k_3 + C_f, \quad \theta_3 = \frac{k_r \theta_1}{4\pi^2 r^2}, \quad \theta_4 = \left( \frac{gL \sin \delta + gL \cos \delta}{3.6} + k_2 \right), \quad \theta = \left[ \theta_1, \theta_2, \theta_3, \theta_4 \right]^T, \quad \psi(T, w_m) = \left[ T, \frac{T^2}{w_m^2}, \frac{T}{w_m} \right]^T.
\]

Then, a new energy model of the belt conveyor with a DC motor is given as follows:
\[
\begin{aligned}
J_m \frac{d\omega_m}{dt} + b_m \omega_m &= k_f i_1 - \frac{2\pi r^2 T w_m}{3.6} - \psi'(T, w_m) \theta, \\
L_a \frac{di_a}{dt} + R_a i_a &= e_a - k_b \omega_m,
\end{aligned}
\] (8)

or
\[
\dot{z} = \dot{\theta} z + \tilde{b} \psi'(T, w_m) \theta,
\] (9)

where \( \dot{\theta} = \frac{2\pi^2}{3.6 J_m} T w_m \).

For the conveyor with permanent instruments for \( T \) and \( w_m \), the real-time data can be accessed through the supervisory control and data acquisition system (SCADA). Therefore, let \( w_m \) be the output of the system (8), i.e.,
\[
y = w_m = C z,
\] (10)

where \( C = [1 \ 0] \). We obtain that
\[
\text{rank} \left[ \begin{array}{c} C \\ CA \end{array} \right] = \text{rank} \left[ \begin{array}{cc} 1 & 0 \\ -J_m & J_m \end{array} \right] = 2,
\]

which means that \((\dot{\theta}, C)\) is observable. Then, the coordinate transformation
\[
\ddot{z} = Q z + \left[ \begin{array}{c} 1 \\ 0 \\ -J_m \\ J_m \end{array} \right] z
\]

can transform (9), (10) into the following canonical form [32]:
\[
\begin{aligned}
\dot{z}_1 &= \dot{z}_2 + a_1 y - \frac{2\pi^2}{3.6 J_m} T w_m + \frac{1}{J_m} \psi'(T, y) \theta, \\
\dot{z}_2 &= a_2 y - \frac{2R_e \pi^2}{3.6 L_m J_m} T w_m + \frac{k_f}{J_m L_m} e_a + \frac{R_e}{L_m J_m} \psi'(T, y) \theta, \\
y &= \tilde{z}_1,
\end{aligned}
\] (11)

where \( a_1 = -\frac{b_m}{J_m}, \quad a_2 = -\frac{R_e b_m}{L_m J_m} \frac{k_f}{J_m}, \quad \tilde{b} = [1, b_3]^T \) be a vector such that

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is a Hurwitz polynomial. Consider the following filter transformation [26]:

\[
\begin{align*}
\dot{x}_1 &= \dot{z}_n, \\
\dot{x}_2 &= \dot{z}_2 - \sum_{i=1}^{4} \eta_i \theta_i, \\
\end{align*}
\]  
(12)

where

\[
\eta_i = -b_2 \eta_i - b_2 \dot{y}_i(T, \omega_m) + \frac{R_e}{L_w J_m} \dot{y}_i(T, \omega_m),
\]
(13)

where \(\eta(T, \omega_m)\) is the \(i\)th component of \(\psi(T, \omega_m)\) \((i = 1, \ldots, 4)\). This transforms (11) into the following system:

\[
\begin{align*}
\dot{x}_1 &= x_2 + a_1 \omega_m - \frac{2 \pi r^2}{3 J_m} \dot{W}_m + \left(\frac{1}{J_m} \psi(T, \omega_m) + \eta\right) \theta, \\
\dot{x}_2 &= \omega_m - \frac{2 R_e \pi r^2}{3 J_m L_w} \dot{W}_m + \frac{k_T}{J_m L_w} \dot{e}_a \\
&\quad + b_1 \left(\frac{1}{J_m} \psi(T, \omega_m) + \eta\right) \theta, \\
\end{align*}
\]  
(14)

and

\[
\dot{\theta} = -\Gamma \left(\frac{1}{J_m} \psi(T, \omega_m) + \eta\right) e_i,
\]
(18)

where \(e = x - \dot{z}_n\), \(\dot{\theta} = \theta - \dot{\theta}\).

Let us now state and prove the main results of this paper.

**Theorem 1.** For the energy model of belt conveyor with a DC motor (8), there exists a filter transformation (12), (13) to transform (8) into (14). Moreover, for the system (15), (16), if \(k_1\) and \(k_2\) are selected such that \((A, b, C)\) satisfies the strictly positive real condition, where \(A = A_0 + KC, K = [k_1, k_2]^T\), then \(\|\dot{\theta}(t) - \theta\|\) is uniformly bounded.

**Proof.** Using the same method as in [26], we can obtain the result.

In order to ensure that \(\dot{\theta}(t)\) converges to the desired value, the following result is needed.

**Lemma 1.** Consider the following system:

\[
\begin{align*}
\dot{\eta} &= A_1 \eta + B_1 \psi(T, \omega_m), \\
\dot{\psi} &= C_1 \eta + D_1 \psi(T, \omega_m),
\end{align*}
\]  
(19)

where \(A_1 = \text{diag}\{-b_2, -b_2, -b_2, -b_2\}, B_1 = \text{diag}\{-b_2, b_2, -b_2, -b_2\}, C_1 = I, D_1 = I\). If there exist \(T_0 > 0, k_0 > 0\) such that \(\psi(T, \omega_m)\) satisfies the following persistence excitation condition

\[
\int_{t_0}^{t_0 + T_0} \psi(T, \omega_m)^T (T, \omega_m) d\tau > k_0 I,
\]
(20)

then, there exists \(k_0' > 0\) such that

\[
\int_{t_0}^{t_0 + T_0} \psi(T, \omega_m)^T (T, \omega_m) d\tau > k_0' I.
\]
(21)

**Proof.** It follows from (19) that

\[
C_1 (S I - A_1) B_1 + D_1 = \left(\frac{R_e}{L_w} \right) \frac{I}{s + b_2}
\]

which implies that the system (19) is stable and minimal phase. By lemma 2.6.7 in [33], we obtain the result.
**Theorem 2.** For the energy model of the belt conveyor with a DC motor (8), there exists a filter transformation (12), (13) to transform (8) into (14). Moreover, for the system (15), (16), if $k_1$ and $k_2$ are selected such that $(A, B, C)$ satisfies the strictly positive real condition, and there exist $T_0 > 0$ and $k_p > 0$ such that the condition (20) holds, then, we have
\[
\lim_{t \to \infty} \| \hat{\theta} - \hat{\theta} \| = 0.
\]

**Proof.** From (13), we have:
\[
\eta(t) = e^{b_2 t} \int_{t_0}^{t} e^{b_2 \tau} \left( - \frac{b_2}{J_m} + \frac{R_n}{J_m} \right) \psi(T(\tau), \omega_n(\tau)) d\tau.
\]
One can see that $\psi(T, \omega_n)$ is bounded for every $(T, \omega_n)$ bounded. Therefore, $\eta(t)$ (i = 1, 2, 3, 4) are bounded for every $(T, \omega_n)$, which implies that \( \left( \frac{1}{J_m} \psi(T, \omega_n) + \eta \right) \) is bounded for every $(T, \omega_n)$ bounded. Along the trajectory of the system (17), (18), calculate the derivative of the following Lyapunov function:
\[
V(e) = e^T Pe + \hat{\theta}^T \Gamma^{-1} \hat{\theta}.
\]

We have
\[
\frac{dV(e)}{dt} \bigg|_{(17),(18)} = e^T (A^T P + PA) e + 2 e^T P b \left( \frac{1}{J_m} \psi(T, y) + \eta \right)^T \hat{\theta} - \hat{\theta}^T \left( \frac{1}{J_m} \psi(T, y) + \eta \right) e < -de^T Q e.
\]
Thus, $\|e(t)\|$ and $\|\hat{\theta}(t)\|$ are uniformly bounded for any $t > t_0$.

Moreover, \( \left( \frac{1}{J_m} \psi(T, y) + \eta \right) \) is uniformly bounded, then, $\|\hat{\theta}(t)\|$ is also uniformly bounded. Since $V(e)$ is a uniformly bounded non-increasing function
\[
\lim_{t \to \infty} e^T(t)Qe(t) = < V(t_0) - V(\infty),
\]
By Barbalat’s Lemma [26], we have:
\[
\lim_{t \to \infty} \|\hat{\theta}(t)\| = 0.
\]
(23)

From (18) and (23), we have:
\[
\lim_{t \to \infty} \hat{\theta}(t) = 0.
\]
Then, there exits a constant $\hat{\theta}^*$ such that
\[
\lim_{t \to \infty} \hat{\theta}(t) = \hat{\theta}^*.
\]
Therefore, for any $\varepsilon > 0$, there exists $t_1 > 0$ such that
\[
\| \hat{\theta}(t) - \hat{\theta}^* \| < \varepsilon, \forall t > t_1.
\]
(24)

Now, we will prove that $\hat{\theta}^* = 0$ by contradiction. Assume that $\hat{\theta}^* \neq 0$.

Consider the following function
\[
\varphi(\hat{\theta}(t), t) = \frac{1}{2} \left[ \hat{\theta}^T (t + T_0) \Gamma^{-1} \hat{\theta}(t + T_0) - \hat{\theta}^T (t) \Gamma^{-1} \hat{\theta}(t) \right],
\]
which is bounded. The time derivative of $\varphi(\hat{\theta}(t), t)$ is given as
\[
\frac{d\varphi(\hat{\theta}(t), t)}{dt} = \hat{\theta}^T (t + T_0) \Gamma^{-1} \hat{\theta}(t + T_0) - \hat{\theta}^T (t) \Gamma^{-1} \hat{\theta}(t)
\]
\[
= \int_{t}^{t + T_0} d \frac{d}{d\tau} (\hat{\theta}^T (\tau) \Gamma^{-1} \hat{\theta}(\tau)) d\tau
\]
\[
= -\int_{t}^{t + T_0} d \frac{d}{d\tau} (\hat{\theta}^T (\tau) \hat{\theta}(\tau)) + \eta^T (\tau) e_1(\tau) d\tau
\]
\[
= -\int_{t}^{t + T_0} \hat{\theta}^T (\tau) \hat{\theta}(\tau) + \eta^T (\tau) e_1(\tau) d\tau
\]
\[
= -\int_{t}^{t + T_0} \hat{\theta}^T (\tau) \hat{\theta}(\tau) + k_p e_1(\tau) d\tau
\]
\[
= -\int_{t}^{t + T_0} \hat{\theta}^T (\tau) \hat{\theta}(\tau) - k_p e_1(\tau) d\tau
\]
\[
< M \int_{t}^{t + T_0} (e_1^T (\tau) + e_1^2 (\tau) d\tau
\]
\[
- \int_{t}^{t + T_0} \hat{\theta}^T (\tau) \hat{\theta}(\tau) d\tau
\]
\[
- \int_{t}^{t + T_0} (\hat{\theta}(\tau) - \hat{\theta}^*)^T (\tau) \hat{\theta}(\tau) - \hat{\theta}^* d\tau
\]
\[
< M \int_{t}^{t + T_0} (e_1^T (\tau) + e_1^2 (\tau) d\tau
\]
\[
- \frac{k_p^2}{4} \hat{\theta}^* \hat{\theta}^* \eta^T (t) e_1(\tau) d\tau
\]
\[
- \frac{k_p^2}{4} \hat{\theta}^* \hat{\theta}^* \eta^T (t) e_1(\tau) d\tau
\]
\[
< 0
\]
which contradicts the boundedness of $\varphi(\hat{\theta}(t), t)$. Therefore, $\lim_{t \to \infty} \hat{\theta}(t) = 0$. The proof is completed.

**IV. SIMULATION RESULTS**

We test the proposed adaptive parameter estimation (13), (15), (16) by simulation with parameters $b_2 = 4.0, \lambda = 3,$ and $\Gamma = \text{diag}(180, 180, 180, 180)$ and with four coefficients $\theta_1 = 1, \theta_2 = 0.3, \theta_3 = 3.5,$ and $\theta_4 = 2.1$, for a DC motor, whose parameters are: $k_r = 0.1, k_i = 0.1, k_m = 0.4, J_m = 0.05 \text{ Kgm}^2, R_s = 15 \text{ Ohm}, L_s = 1.0 \text{ H}, r = 0.01 \text{ m},$ and $e_v = 380 \text{ V}$. The initial conditions of (14), (15), and (16) are given by (0.01, 0.7), (0.8, 0.2), and (0.1, 0.1, 0.1, 0.1), respectively. It should
be noted that it is difficult to check that inequality (20) holds. In practice, if the feed rate $T$ does not change much, a complete determination of all of the parameters is impossible. In order to estimate all of the parameters, one should sufficiently disturb the feed rate $T$ during the period of estimation. In this example, we choose the feed rate $T = 0.09(8 + 5\sin(10t + 1) + 2\cos(-5t + 2) + \sin(20t)) + 0.3(8.6 + 2\cos(-5t + 2) + \sin(15t + 0.4) + \sin(20t) + 4\sin(t)) | \sin(4t + 0.5)) | \text{kg/s} \ (0 \leq t \leq 60 \text{s}).$

The simulation results are shown in Fig. 3–Fig. 6. To test the algorithm against measurement noise, a band limited white noise is added to $y_1$. The results are demonstrated in Fig. 7–Fig. 10.

Fig. 3. Trajectory of $\hat{\theta}_1$.

Fig. 4. Trajectory of $\hat{\theta}_2$.

Fig. 5. Trajectory of $\hat{\theta}_3$. 
Practically, the parameters may drift away during the conveyor belt operation. For example, $\theta_1 = 1.2$, $\theta_2 = 0.3$, $\theta_3 = 3.5$, $\theta_4 = 2.3$, using the same initial conditions and the feed rate $T$, we implement the adaptive identifier for 30s. Figs 11–14 show the simulation results.

V. CONCLUSION

In this paper, a new energy model of a conveyor belt driven by a DC motor was presented, which lumped all the parameters into four coefficients. Then, an
adaptive observer was designed to estimate the unknown parameters. In addition, under a persistent excitation condition, the convergence of the parameters to the desired values could also be concluded. Compared with the existing methods, our methods could be implemented by measuring only the feed rate of the conveyor belt and the angular velocity of the rotor of the DC motor.
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Fig. 12. Trajectories of $\theta_2$ and $\hat{\theta}_2$.

Fig. 13. Trajectories of $\theta_3$ and $\hat{\theta}_3$.

Fig. 14. Trajectories of $\theta_4$ and $\hat{\theta}_4$. 

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