Sensor-less control of a novel stepped hydraulic flow control valve

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Abstract

This paper aims to create a sensor-less feedback position detection for a flow control orifice actuated by a stepper motor. Nowadays, many applications such as hydraulic and pneumatic systems use a stepper motor as an actuator, instead of traditional mechanical or solenoid. In nonlinear environment such as hydraulic systems, a stepper motor may suffer from step losing and leads to poor controllability of the system. Mechanical sensors are usually used as a feedback of the position and speed, but at the same time the harsh environment of hydraulic applications prevents implementing this kind of sensing. On the other hand, a sensor-less technique based on Kalman filter was used to control a stepper motor in different applications. This research represents a primarily investigation of the performance of Kalman filter in these for the valve based on modelling and simulation.

Keywords: Hydraulic sensor-less control, Hydraulic stepper drive, Sensor-less position control, Stepper rotary valve, Mechatronics hydraulic systems, Extended kalman filter.

1. Introduction

In general, the classical electrohydraulic feedback servo systems rely on sensors to grant a precise position. Costs and reliability represent the main challenge for implementing new mechatronics electrohydraulic applications, and avoiding sensors in these systems reduces the cost and risk of failure. In literature, a control of the pneumatic system using stepped actuated valve was investigated by [1]. A reversible hydraulic pump controlled using a servo motor was developed for a forklift. The motor position feedback using sensor was attached to the system and some sensor-less techniques were suggested as an alternative [2]. A step unit based on two slave cylinders and three valves was designed for open-loop control of hydraulic drives to reduce the sensors numbers in hydraulic applications [3]. The system contains many components that increase the cost and the hardware size, which is the main drawback. A nonlinear sliding mode observer was developed for a linear brake-pressure control in the hydraulic control unit [4]. The observer is used to estimate the spool position based on the voltage and the current values on the solenoid coil. A sensor-less control of a rotary valve actuator for combustion engine was developed in a cooperation work between the German ministry of education (BMBF), the Institute of Automation and Computer Science Wernigerode in collaboration with the Harz University. The used sensor-less concept is based on the back-emf measurement [5]. However, a novel hydraulic rotary flow control orifice was designed by a research team at Bournemouth University in cooperation with HYRECO hydraulic Ltd [6]. This orifice combined with a stepper motor leads to a novel stepped rotary flow control valve. The valve can be used in different applications, especially high flow rate applications such as hydraulic independent metering for mobile machines. Selecting a stepper motor as a main actuator for this orifice requires a highly accurate positioning which usually relies on feedback sensors, but using sensors in this harsh environment increases the cost and the failure consequences. So, this paper aims to principally study a sensor-less technique for position control of this valve.

The sensor-less feedback control for electrical drives has been studied and evaluated by [(7)]. Several sensor-less methods for a stepper motor were reviewed by [(8)]. The techniques are standstill method, the back electromotive force method, high-frequency signal injection method, and the observers' methods. The standstill method is used for low-speed applications, and it's based on the inductance variation according to the rotor position. The high-frequency signal injection method can be used for low-speed application and it's able to detect the initial position of the rotor. The back-electromagnetic force is usually used because of its easy implementation. For the medium and low-speed applications, the observer is preferred. Different kind of observer can be implemented. For example, sliding mode observer is preferred because of its robustness [(9)]. The Kalman filter algorithm can be used to detect the speed and the position of a stepper motor rotor and it's most preferred for stepper motor because it relies on low pass filter, and its ability to detect under load fluctuation. Different types of Kalman filter which are Extended Kalman filter (EKF) and Unscented Kalman Filter (UKF) were analysed and reviewed by [(10)]. According to this comparison, the EKF showed a better performance as it's able to eliminate the measurement noises which are the main problem in a harsh environment such as hydraulic applications, so this observer was selected for this research. This paper represents an initial study for the sensor-less position detection on of a stepped rotary flow control valve. The investigation is based on modelling and simulation. The paper sections are as follows: In Section 2, the novel valve construction and performance is included. In Section 3, the extended Kalman filter concepts. In Section 4, performance analysis using modelling and simulation. In Section 5, the conclusion and the future work.

2. The proposed valve construction and work principle

The rotary flow control valve considered in this research is shown in Figure 1. The flow is controlled by the position of the rotor in the stepper motor. When the driving circuit of the motor starts feeding current into the coils, an electromagnetic force is produced in the stators [(11)]. The force rotates the stepper rotator which is connected to the valve spool. Consequently, the opening area of the orifice is changed. Figure 1Figure 2 illustrates the relation between the rotation angle and the produced flow under different pressure drops.

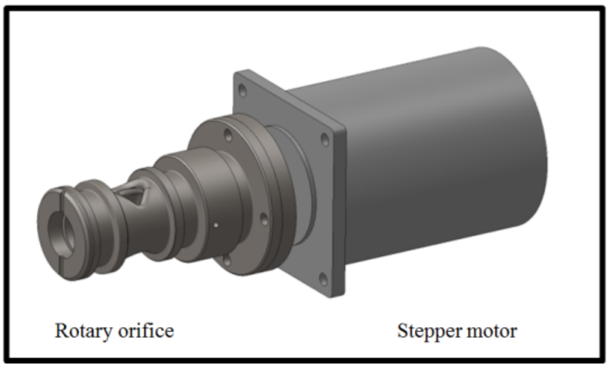

Figure 1. The novel stepped rotary flow control valve.

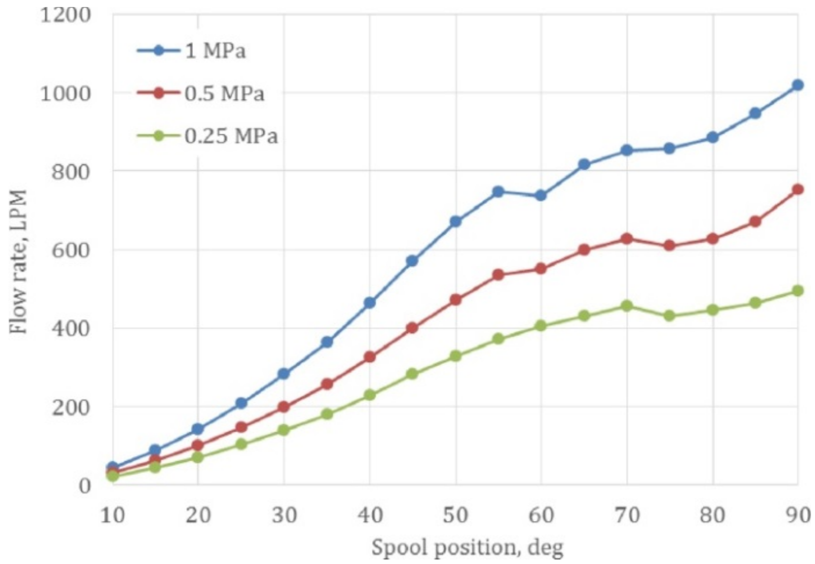

Figure 2. The fluid flow regime of the rotary orifice related to the opening areas with different pressure drops [6].

Regarding the stepper motor, it is usually used in industrial and manufacturing applications such as robotics and production lines. Main characteristics are as follows [12]:

1- Positional error isn't accumulative.
2- Can be used in open loop applications.

Main types of this motor are Variable Reluctance (VR), Permanent magnet (PM) and Hybrid [13]. Hybrid motor is a combination of the two previous types which are VR and PM, and it has two main forms, which are Unipolar and Bipolar [14]. The bipolar is usually preferred because it produces more torque despite required complex control techniques [11]. This was selected as a main actuator for the orifice to configure the flow control valve. Figure 3 shows the schematic construction of the motor and the orifice.

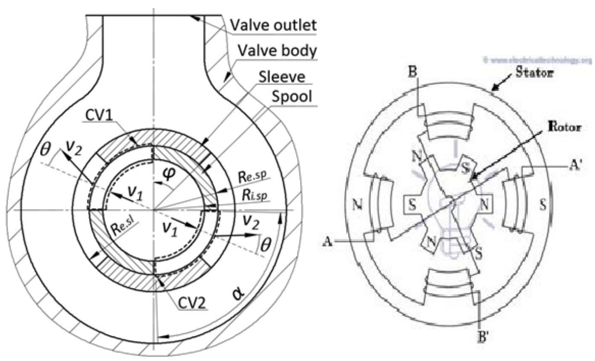

Figure 3. Construction of the two parts of the valve which are the rotary orifice and the stepper motor.

The bipolar hybrid stepper motor state space model is as follows:

$$\frac{d\varphi}{dt}=\omega$$

$$\frac{d\omega}{dt}=\frac{1}{J}[-K_m i_a \sin(N_r\varphi)+K_m i_b \sin(N_r\varphi)-B\omega-T_L] \quad \ldots\ldots(1)$$

$$\frac{di_a}{dt}=\frac{1}{L}[v_a-Ri_a+K_m \sin(N_r\varphi)]$$

$$\frac{di_b}{dt}=\frac{1}{L}[v_b-Ri_b-K_m \cos(N_r\varphi)]$$

where i_a, i_b and v_a, v_b are currents and voltages in phases A and B of the stepper motor, respectively; K_m – motor torque constant, N_r – number of rotor teeth; B – viscous friction coefficient; T_L – the load torque; L, R – inductance and resistance of the phase winding respectively.

3. Extended Kalman Filter (EKF)

Kalman filter is an algorithm that is used to estimate systems states of a linear system. It has many applications ranging from aerospace to biomedical engineering [9]. The standard Kalman filter should be used with a system described by linear stochastic difference equations as follows:

$$x_{(k+1)} = A(k)x(k) + B(k)u(k) + v(k) \quad \ldots\ldots(2)$$

$$z(k) = H(k)x(k) + w(k) \quad \ldots\ldots(3)$$

where the $(n * n)$ matrix A is the dynamic matrix that relates the state at time step k to the state at time step $k + 1$. The matrix $z(k)$ is the measured values as a function of a state corrupted by noises. $x(k)$ is the system state that is estimated, $v(k)$ is the process noise and $w(k)$ is the measurement noise.

$$v(k) = N\left(0, Q(k)\right) \quad \ldots\ldots(4)$$

$$w(k) = N\left(0, R(k)\right) \quad \ldots\ldots(5)$$

The Kalman filter can be expressed as a feedback estimation. It has two groups of equations which are the time update and the measurement update. The time update as shown in Figure 4. This part of the algorithm represents the projection of the state and the error covariance, or the priori estimates, according to the following equations:

$$\hat{x}^-_{(k+1)} = A\hat{x}_k + Bu_k \quad \ldots\ldots(6)$$

$$P^-_{(k+1)} = A_k P_k A_k^T + Q_k \quad \ldots\ldots(7)$$

The second stage of the Kalman Filter is the measurement update equations which are as follows:

$$K_k = P_K^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \quad \ldots\ldots(8)$$

$$\hat{x}_k = \hat{x}_k^- + K_k\,(z_k - H\hat{x}_k^-) \quad \ldots\ldots(9)$$

$$P_k = (1 - K_k H_k)P_k^- \quad \ldots\ldots(10)$$

The projection from period k to k+1 of state estimate and covariance. The Kalman gain which is the first step in the measurement update stage is calculated using Equation (8). In the second step, the posterior estimate is obtained based on the actual measurements and the estimated in Equation (4). The last step is to compute the error covariance as presented in Equation (8).

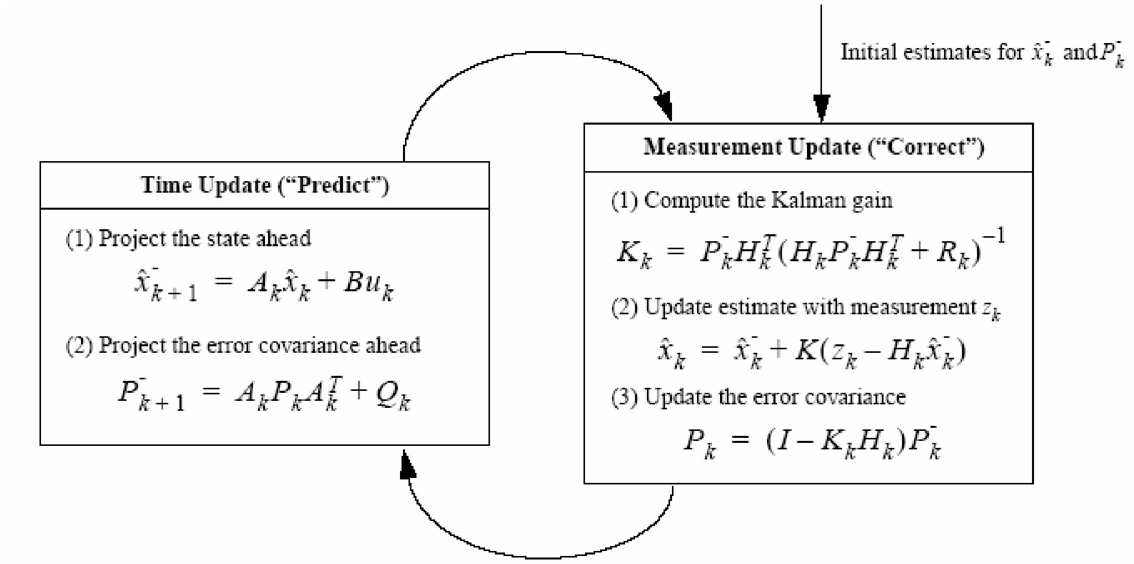

Figure 4 The Kalman filter algorithm.

To initialize Kalman filter, an initial estimation of the state $\hat{x}_k^-$ and the error covariance P_k^- that represents the uncertainty of the initial state estimation. The value of P_k^- is based on the confidant of the initial estimation. The main drawback of the Kalman filter is only applied to linear systems which are non-real. However, the filter tuning is an important factor in Kalman algorithm, and it is based on the plant noise $Q(k)$ and the measurement error $R(k)$.

The Extended Kalman Filter (EKF) is used for nonlinear systems. It can estimate the state and the parameters for a nonlinear dynamic system using noisy signals. The nonlinear system can be represented by nonlinear stochastic difference equations as follows:

$x_{(k+1)} = f(x(k), u(k), \xi(k))$ ……………………………………………(11)

$\mathrm{z(k)} = \mathrm{h(x(k)}, \eta\mathrm{(k))}$ …………………………………………(12)

where the random variable ξ_k and $\eta(k)$ are the plant and measurement noise, respectively. The nonlinear function $f(.)$ is a nonlinear function that relates the state of time step k into $(k+1)$.

The linearization of the estimation can be represented as follow:

$$x(k+1) = \hat{x}(k+1) + A\big(x(k) - \hat{x}(k)\big) + Ww(k) \quad \ldots\ldots(13)$$
$$z(k) = \hat{z}(k) + H\big(x(k) - \hat{x}(k)\big) + Vv(k) \quad \ldots\ldots(14)$$

$\hat{x}(k+1)$ and $\hat{z}(k)$ are the approximate and measurement vector. A is a Jacobian matrix of the partial derivative of $f(.)$ with respect to x .

$$A_{[i,j]} = \frac{\partial f_{[i]}}{\partial x_{[i]}}(\hat{x}(k), u(k), 0), \quad \ldots\ldots(15)$$

W is a Jacobian matrix of the partial derivative of $f(.)$ with respect to w .

$$W_{[i,j]} = \frac{\partial f_{[i]}}{\partial x_{[i]}}(\hat{x}(k), u(k), 0), \quad \ldots\ldots(16)$$

H is the Jacobian matrix of partial derivatives of $h(.)$ with respect to x

$$H_{[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[i]}}(\hat{x}(k), 0), \quad \ldots\ldots(17)$$

V is the Jacobian matrix of partial derivatives of $h(.)$ with respect to v

$$V_{[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[i]}}(\hat{x}(k), 0), \quad \ldots\ldots(18)$$

The EKF has two main stages which are the time update or predict and the measurement update as shown in Figure 5:

The time updates equations:

$$\hat{x}^{-}(k+1) = f\ (\hat{x}(k), u(k), 0) \quad \ldots\ldots(19)$$
$$p^{-}(k+1) = A(k)P(k)A^{T}(k) + W(k)Q(k)W^{T}(k) \quad \ldots\ldots(20)$$

The measurements update equation:

$$\hat{x}(k) = \hat{x}^{-}(k) + k(k)(z(k) - h(\hat{x}^{-}(k), 0)) \quad \ldots\ldots(21)$$
$$K(k) = p^{-}(k)H^{T}(k)\big(H(k)p^{-}(k)H^{T}(k) + V(k)R(K)V^{T}(K)\big)^{-1} \quad \ldots\ldots(22)$$

Where $A(k)$ is a plant jaccobian matrix, $H(k)$ is measurement noise, the priori estimate error covariance$p^{-}(k)$, a posteriori estimate error covariance$P(k)$, and the Kalman gain $k(k)$.

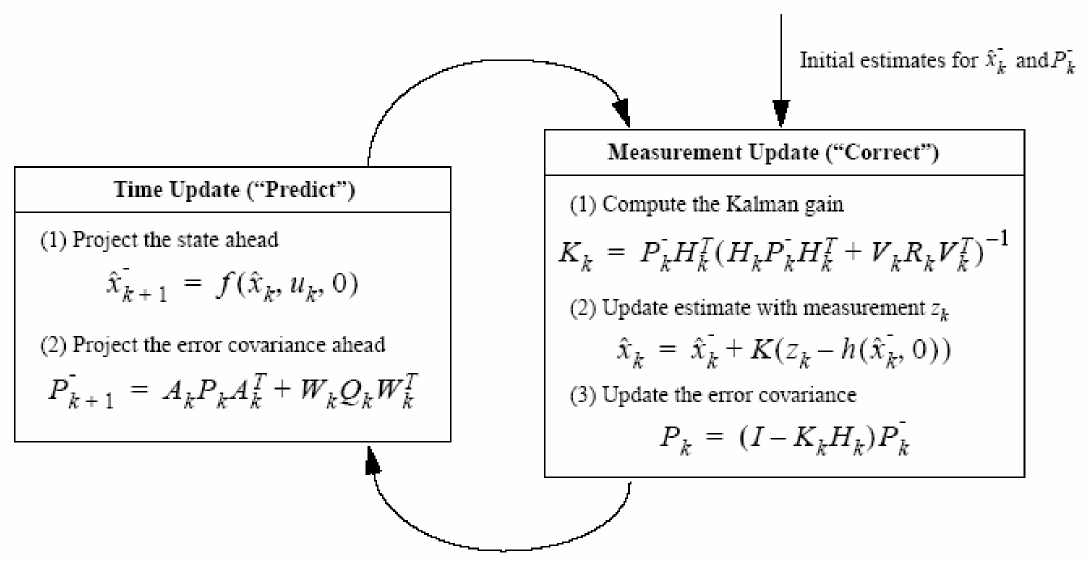

Figure 5 The main stages of extended Kalman filter

4. Modelling and Simulation

A Matlab code was developed to implement a model of the used stepper motor and the EKF algorithm [15]. The main parameters of the used stepper motor are listed in Table 1. Figures 6, 7, 8 and 9indicate the EKF is able to estimate the speed and the position of the rotator.

Table 1 Main stepper motor parameters.

Parameter	Symbols	Unit	Value
Inducatance	L	H	11.8e-3
Resistance	R	Ohm	3.07
Motor Constant	Km	V*S/rad	0.015
Viscosity	B	N*m*s/rad	1e-3
Rotor Inertia	J	N*m*s^2/rad	2.07e-6

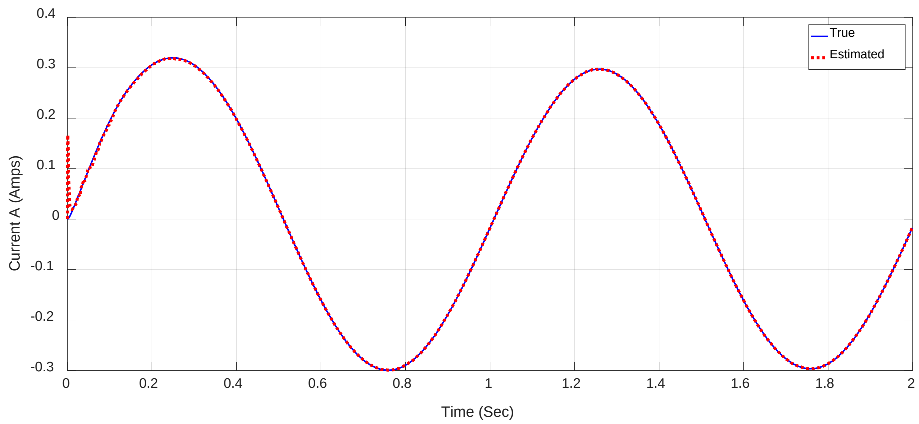

Figure 6 The true and the estimated signal for the Coil A.

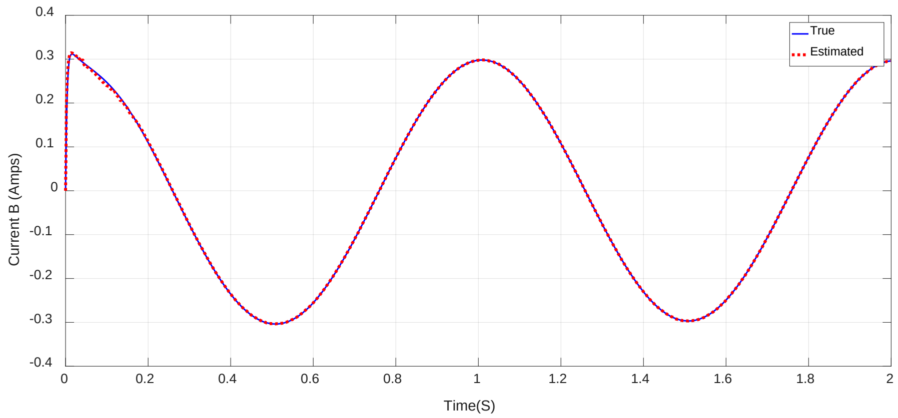

Figure 7 The ture and the estimated curret in the coil B.

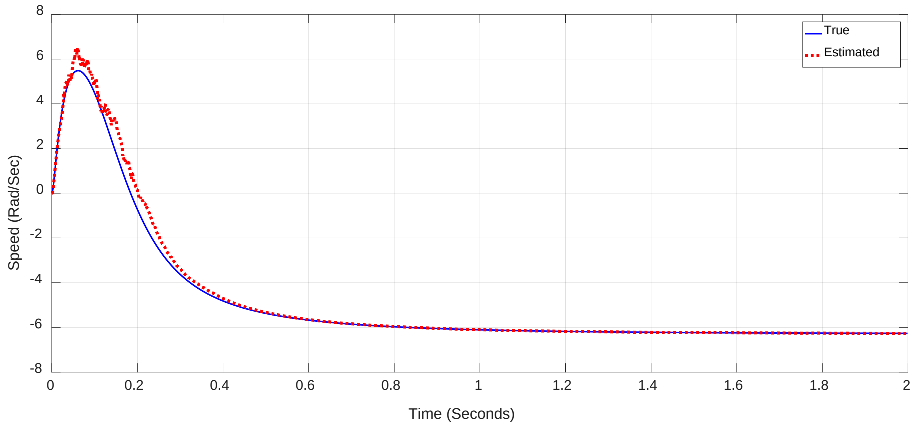

Figure 8 The speed true and estimation of the rotator.

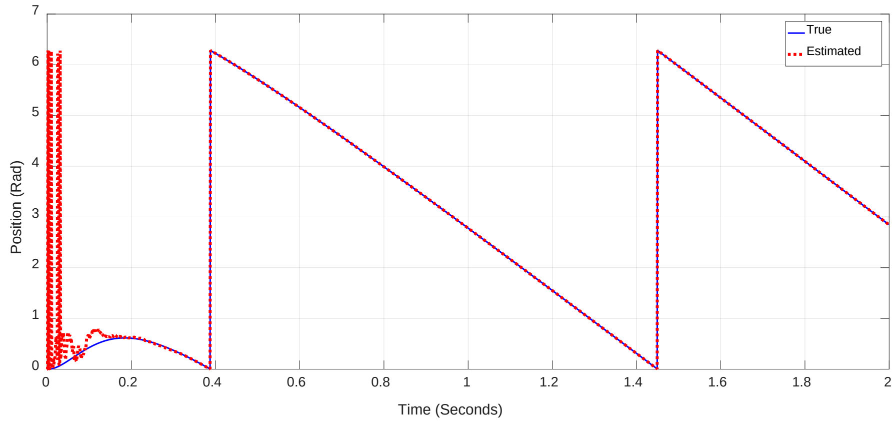

Figure 9 The rotator real and estimated position.

5. Conclusion and Future work

This paper represents an initial study for the sensor-less monitoring of a novel hydraulic flow control valve. According to the literature review, the extended Kalman filter is able to perform a suitable estimation under fluctuated load, and for medium and high-speed applications. Modelling and simulation for sensor-less estimation compared to the real calculation. The result showed that EKF is able to estimate the parameters which are the current, speed and position. Different initial assumptions have an effect on the performance such as the measurement and plant noises. For example, the initially assumed noises or the processing sampling time may lead to the ineffective estimator. Design the system hardware using dsPic Microchip and implement the algorithm with initial measurements values will be included as future work.

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