Estimation of Spring Torque in an Electronic Throttle Valve

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***Abstract*: This paper discusses the torque estimation of the spring which is internally connected between the motor shaft and the plate in an electronic throttle valve. In advanced engine control (such as EGR rate control), the throttle valve may need to be controlled in both opening and closing directions using a bidirectional driver in order to achieve more accurate and faster transient performance. The spring inside poses an additional force against the motor torque in opening direction, and an extra force that helps the valve to response faster in closing direction. Therefore the total torque acting on the valve plate is the sum of the motor torque, regulated by the motor drive controller, and the spring torque. Hence, it is important to estimate the spring torque and the information could then be used to improve the motor torque control. In this paper three different filters design are developed to estimate the spring torque while taking into account the model parameters uncertainty and/or the existence of white noise.**

I. INTRODUCTION

Estimation of disturbance torque on the DC motor shaft has been proposed and developed [1, 5, 6]. In [1], the disturbance torque acting on the motor shaft is assumed to be constant with respect to the dynamics of the filter and a Luenberger filter is proposed. In[5,6], the disturbance torque is treated as an uncertain variable input and a robust filter developed in [3] is applied to estimate the motor speed and current so that the estimation of the disturbance torque could be calculated from the current and speed estimation.

Electric throttle valves driven by DC motors have been used broadly in automotive engine control to improve engine performance so that emission standards could be satisfied [2, 7, 8]. Specifically, low temperature combustion is a hopeful mode that would facilitate low NOx emission while still keeping the engine efficiency high [2]. An important fact in such a mode is that the feasible combustion window is very narrow. This in general requires faster transient responses from controlling valves and, hence, calls for advanced control of valve operation that could allow faster and accurate performance. For example, in the EGR valve case, the accuracy requirement for the valve plate position (opening or closing) would be more stringent and the control must be more prompting in order to facilitate low temperature combustion. In an electric throttle valve, the total torque acting on the plate is actually the sum of the motor torque and a spring torque which goes against the plate during opening session and serves as an extra assisting torque during the closing session. Since this spring torque is not regulated by the motor drive controller, for faster and more accurate control of such a throttle valve it is important to estimate the spring torque so that the information could be used to further improve the motor torque control. In this paper, model based robust estimations are developed using the ideas in [3, 5, 6] to estimate the spring torque in a throttle valve. In particular, the spring torque is treated as a disturbance torque applied to the motor shaft and three filter designs, namely, Kalman, H_∞ , and, H_∞ Gaussian, are developed and compared to estimate the spring torque.

The paper is organized as follows, in Section II, a model for the throttle valve is summarized from [2] with the spring torque. In Section III, the design of the filters is presented for spring torque estimation. In Section IV the Hardware-in-Loop setup is shown and explained. Section V shows the experimental validation results while the paper is concluded in Section VI.

II. MODELLING THROTTLE VALVE

In this section, an electric throttle valve model is summarized which will be used in the next section to develop spring torque estimation. It is pointed out that the original model was presented in [2] where an identification method was proposed to derive the model and the model was then used in a model predictive control design validated with experimental results. It is noted that in [2], the spring torque was actually ignored in the control design. Since the spring torque is our interest in this paper, the throttle valve model is presented again with the spring effect and same model parameters used in [2] are applied here.

The throttle valve modeled in this development is a two plate butterfly valve driven by a DC motor. As can be seen in Fig. 1 the DC motor mounted on top of the plate body is connected to the plate shaft through two sets of gear. So the motor torque is magnified through these gears when applied on the plate shaft. The other side of the plate shaft is connected to a position sensor. This sensor is in fact a potentiometer converting the plate angular position into a DC voltage used for the plate position control. Also there is a spring connects internally the plate shaft to the motor shaft. This spring adds an extra torque to the plate which helps the valve in closing direction and acts against it in opening movement.

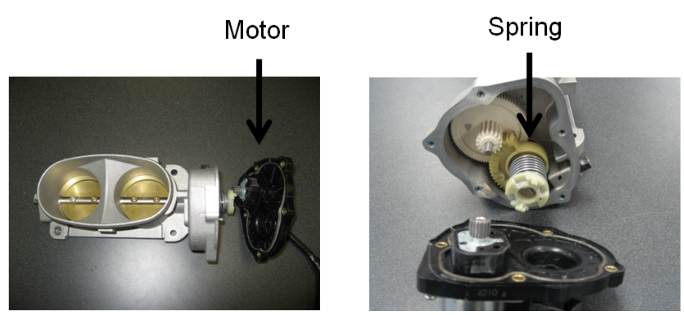

Figure 1. The throttle valve and spring connection to the plate shaft

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The armature controlled DC motor provides the motor torque to drive the plates. The following equations can be established to model the motor drive:

$$V = R_a i_a + L_a \frac{di_a}{dt} + K_e \dot{\theta}_m , \quad (1)$$

$$T_m = K_t i_a , \quad (2)$$

$$J_m \ddot{\theta}_m + D_m \dot{\theta}_m = T_m - T_f , \quad (3)$$

where R_a and L_a are resistance and inductance of the motor armature winding, i_a is the armature current; and K_e and K_t are the voltage and torque constants which in SI units have the same value [9], θ_m is the motor shaft angle, T_m is the motor torque and T_f is the counter balance torque on the motor shaft.

The plate structure is modeled by an inertial and a damping ratio:

$$J_p \ddot{\theta}_p + D_p \dot{\theta}_p = T'_f + T_s , \quad (4)$$

where, J_p and D_p are the plate moment of inertia and viscous damping factor, θ_p is the plate shaft angle, T'_f and T_s are the motor driving torque through the gearbox and the spring torque which will be estimated out in this paper. Also, it is known that $\theta_m = n\theta_p$ and n is the gear ratio.

With equations (1) to (4), the electric throttle valve can be modeled in single shaft as follows:

$$V = R_a i_a + L_a \frac{di_a}{dt} + K_e n \dot{\theta}_p , \quad (5)$$

$$T_m = K_t i_a , \quad (6)$$

$$T_m + T_s = \bar{J} \ddot{\theta}_p + \bar{D} \dot{\theta}_p , \quad (7)$$

where: $\bar{J} = (J_p + n^2 J_m)$ and $\bar{D} = (D_p + n^2 D_m)$ are the total moment of inertia and viscous damping factor of the system when considering both the motor and the plate.

It is noted that the accurate value of the motor armature resistance is very hard to obtain in practice [2]. Besides, this resistance could also vary during the life time of motor operation due to the friction erosion between the brush and the commutator. Therefore, such a parameter uncertainty should be considered and is modeled as $R_a + \Delta R_a$.

The state space model of the valve can then be derived by choosing armature current and plate angular speed as two state variables:

$$\dot{x} = Ax + Bu + B_1 w, \quad z = C_1 x, \quad y = C_2 x, \quad (8)$$

where $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} i_a \\ \omega_p \end{bmatrix}$, $u = V$ is the system input, y is the measured output, z is the desired output, A and B depend on the model parameters, A , B , C_1 and C_2 are derived as:

$$A = \begin{bmatrix} \frac{-R_a}{L_a} & \frac{-nK_e}{L_a} \\ \frac{K_t}{\bar{J}} & \frac{-\bar{D}}{\bar{J}} \end{bmatrix} , \quad B = \begin{bmatrix} \frac{1}{L_a} \\ 0 \end{bmatrix} ,$$

$$C_1 = [0 \quad 1] , \quad C_2 = [1 \quad 0] ,$$

The uncertainty disturbance signal $w = \begin{bmatrix} i_a \Delta R_a \\ T_s \end{bmatrix}$ includes both disturbance due to the uncertainty armature resistance and the spring torque T_s and will be considered in the H_∞ and H_∞ Gaussian filter designs but will not be considered in the Kalman filter design. The matrix B_1 depends on the weighting factors chosen in H_∞ and H_∞ Gaussian filters design and will be explained later.

Now that the throttle valve is modeled, the system parameters introduced in the above equations should be identified experimentally. In this paper the parameters identified and validated in [2] are used as system parameters in all the following sections. These parameters are chosen for the range of voltages (1-10*V*) applied to the system in the identification part (see Table I).

It is shown in equation (7) that the total torque acting on the plate shaft is the sum of motor and spring torque. So for a more accurate control of the valve the spring torque should be estimated and added to the motor control signal.

TABLE I. MODEL PARAMETERS

System Parameters	1 – 10 v range
$\bar{J}(kgm^{-1})$	2.94×10^{-4}
$\bar{D}(Nm/rad/s)$	0.0075
$R_a(\Omega)$	3
L_a(H)	0.0012
K_t(Nm/A)	0.019
n	17.54

III. FILTER DESIGN FOR SPRING TORQUE ESTIMATION

The filter model is as follows:

$$\begin{aligned}\dot{\hat{x}} &= A\hat{x} + L(\hat{y} - y) + Bu,\\ \hat{z} &= C_1\hat{x},\\ \hat{y} &= C_2\hat{x},\end{aligned} \qquad (9)$$

where $\hat{x} = \begin{bmatrix}\hat{x}_1\\ \hat{x}_2\end{bmatrix} = \begin{bmatrix}\hat{i}_a\\ \hat{\omega}_p\end{bmatrix}$ are the estimation of state variables, $\hat{z}$ is the desired output, $\hat{y}$ is measured output, L is the filter gain.

The required variable to be estimated is the spring torque which is treated as a disturbance torque acting on the motor shaft, and a law which relates it with the state variables is used:

$$\hat{T}_{disturbance} = \bar{J}_1 \frac{d\hat{\omega}_p}{dt} + \bar{D}_1\hat{\omega}_p - K_t i_a, \qquad (10)$$

In this case the $\bar{J}_1$ and $\bar{D}_1$ are the total inertia and viscose damping factor of the system and the estimated disturbance torque includes all the external disturbances as well as the spring torque. So the spring torque should be calculated out. For this purpose, the dynamometer inertia and viscous damping factor should be considered in the above model:

$$\hat{T}_s = (\bar{J}_1 - J_{dyno})\frac{d\hat{\omega}_p}{dt} + (\bar{B}_1 - B_{dyno})\hat{\omega}_p - K_t i_a, \quad (11)$$

Since, in this case the dynamometer parameters are unknown parameters, the spring torque is calculated by subtracting the data obtained in the two estimations: with and without the spring. The disturbance torque for the case with spring is in fact the sum of spring torque and the dynamometer disturbances, equation (12). When the spring is disconnected there is only the dynamometer torque, equation (13). In order to calculate the spring torque the data from these two experiments are subtracted and the result is considered as the spring torque (14):

$$T_{disturbances}(ws) = T_s + T_{dyno}, \qquad (12)$$

$$T_{disturbances}(wos) = T_{dyno}, \qquad (13)$$

$$T_s = T_{disturbances}(ws) - T_{disturbances}(wos), \qquad (14)$$

In order to estimate the spring torque, two state variables, motor armature current and plate speed, are considered in the filter model. Even though the filter gives the estimation of the current, the motor armature current is measured in practice and will be used to estimate the spring torque. Note that all three filters carry the same model structure and the only difference among them is the filter gain.

The filter gain is designed by different methods depending on the type of filters which are presented in Part A, B and C below.

A. Kalman Filter

Kalman filter is used to estimate the state variables for the system subjected to white noise. This filter estimates the state variables in a noisy environment by minimizing the variance of the estimation error.

For Kalman filter design, the state space model (8) of the valve system is modified by including noises in but not considering the disturbance signal w:

$$\begin{aligned}\dot{x} &= Ax + Bu + \zeta,\\ z &= C_1 x,\\ y &= C_2 x + \theta,\end{aligned} \qquad (15)$$

where:

$$x = \begin{bmatrix} i_a \\ \omega_p \end{bmatrix}, \quad A = \begin{bmatrix} \frac{-R_a}{L_a} & \frac{-nK_e}{L_a} \\ \frac{K_t}{\bar{J}} & \frac{-\bar{D}}{\bar{J}} \end{bmatrix}, \quad B = \begin{bmatrix} \frac{1}{L_a} \\ 0 \end{bmatrix},$$

$$C_1 = \begin{bmatrix} 0 & 1 \end{bmatrix}, \quad C_2 = \begin{bmatrix} 1 & 0 \end{bmatrix},$$

ζ and θ are the system noise and the measurement noise respectively. It is assumed that the average values of both the noises, ζ and θ, are zero and there is no correlation between them. These two noises are modeled by a white noise, vector w_0, with power spectrums: $\zeta = B_0 w_0$ and $\theta = D_{20} w_0$. In practice, B_0 and D_{20} are set by measuring the covariance of the measurment noise and process noise respectively. In this paper they are set as:

$$B_0 = \begin{bmatrix} 0.5 & 0.4 \\ 0.4 & 0.8 \end{bmatrix}, \quad D_{20} = \begin{bmatrix} 0.1 & 0 \end{bmatrix},$$

The filter gain is obtained by solving the Riccati equation:

$$\begin{aligned}&(A - B_0 D_{20}^T R_0^{-1} C_2)P + P(A - B_0 D_{20}^T R_0^{-1} C_2)^T \\ &- P C_2^T R_0^{-1} C_2 P + B_0(I - D_{20}^T R_0^{-1} D_{20})B_0^T = 0\end{aligned} \qquad (16)$$

So: $L = -(B_0 D_{20}^T + P C_2) R_0^{-1}$, where $R_0 = D_{20} D_{20}^T$.

B. H_∞ Filter

When the system model parameters are uncertain and bound to change with time or process, these uncertainty should be taken into account when the state variables are estimated. For such a system, H_∞ filter is designed to make the state estimation robust to changes in model parameters.

In the H_∞ filter design, the state space model (8) of the valve system is set as:

$$\begin{aligned}\dot{x} &= Ax + Bu + B_1 w,\\ z &= C_1 x,\\ y &= C_2 x,\end{aligned} \qquad (17)$$

where

$$B_1 = \begin{bmatrix} -\frac{1}{L_a} w_1 & 0 \\ 0 & -\frac{1}{J} w_2 \end{bmatrix},$$

The disturbance vector, w is taken as $\begin{bmatrix} \Delta R_a \\ T_s \end{bmatrix}$. T_s is considered as one of the uncertainties. B_1 is the weight given to the uncertainty disturbances, w, depending on its effect on the system performance. The weights w_1 and w_2 could be added to provide appropriate penalty on the particular uncertainty signals [4]. In this paper they are set as: $w_1 = 1$, $w_2 = 0.1$. The H_∞ filter gain is obtained by solving the Riccati equation [4]:

$$AP + PA^T + P(\gamma^{-2} C_1^T C_1 - C_2^T C_2)P + B_1 B_1^T = 0 \qquad (18)$$

and $L = -PC_2^T$

Here γ is the design parameter which decides the limit of uncertainty which could be tolerated by the filter for good performance.

C. H_∞ Gaussian Filter

A practical system is subjected to both white noise and parameter uncertainty. The Kalman filter is designed to achieve good performance against white noises while it is model dependant and sensitive to parameters variations. The H_∞ filter is designed to handle model parameters variation; however it does not give good performance against white noise. So the performance of these two filters conflict each other. So for the case when the system is subjected to both model parameters uncertainty and white noise, H_∞ Gaussian filter is designed based on constrained optimization result and H_∞ optimization design. This filter is also designed using the parameter γ which decides the weight which is given to the performance of each type of the filters, thus obtains a suitable balance between the performances of the two filters [3].

The valve system model (8) needs to be modified to accommodate the H_∞ Gaussian filter design:

$$\begin{aligned} \dot{x} &= Ax + Bu + B_0 w_0 + B_1 w, \\ z &= C_1 x, \\ y &= C_2 x + D_{20} w_0, \end{aligned} \qquad (19)$$

where w_0, w, B_0, and B_1 were introduced in part A and B.

For the H_∞ Gaussian filter design, the filter gain is obtained through solving two Riccati equations [3]:

$$\begin{aligned} &(A - P_2 C_2^T R_0^{-1} C_2 - B_0 D_{20}^T R_0^{-1} C_2)^T P_1 \\ &+ P_1 (A - P_2 C_2^T R_0^{-1} C_2 - B_0 D_{20}^T R_0^{-1} C_2) \\ &+ \gamma^{-2} P_1 B_1 B_1^T P_1 + C_1^T C_1 = 0 \end{aligned} \qquad (20)$$

$$\begin{aligned} &(A - B_0 D_{20}^T R_0^{-1} C_2 + \gamma^{-2} B_1 B_1^T P_1) P_2 \\ &+ P_2 (A - B_0 D_{20}^T R_0^{-1} C_2 + \gamma^{-2} B_1 B_1^T P_1)^T \\ &- P_2 C_2^T R_0^{-1} C_2 P_2 + B_0 (I - D_{20}^T R_0^{-1} D_{20}) B_0^T = 0 \end{aligned} \qquad (21)$$

$L = -(P_2 C_2^T + B_0 D_{20}^T) R_0^{-1}$ where $R_0 = D_{20} D_{20}^T$.

IV. Experiment Setup

In this section, the experiment setup to measure the spring torque is shown in Fig. 2. As can be seen, the valve is connected to a dynamometer through a torque sensor. The torque sensor measures the effective torque acting on the valve shaft. In the experiment, the dynamometer produces a torque of 0.5 $N \cdot m$ applied to one end of the torque sensor shaft, on the other end is the valve motor torque magnified through the gear box. Because the torque sensor measures the total torque on the valve shaft including the spring torque, so it is impossible to obtain the spring torque through direct measurement. Therefore, an indirect way is conducted by performing two sets of experiments in order to calculate the spring torque. In the first experiment the spring is connected between the motor and the plate shaft. In this case the total torque acting on the torque sensor shaft is $T_{ts} = T_{dyno} + T_p - T_s$, where T_{ts} is the torque measured by the torque sensor, T_{dyno} is the dynamometer torque, T_p and T_s are the plate (hence the valve motor) and the spring torque respectively. In the second experiment the spring is taken off so the torque measured by the torque sensor is $T_{ts} = T_{dyno} + T_p$. Clearly, the difference in the two readings of the torque sensor would be the spring torque. During the experiments, the filter estimation is executed at the same real time as the real experiment to keep the integrity of the transient process. All three filtering designs are validated this way and the results are shown in the next section.

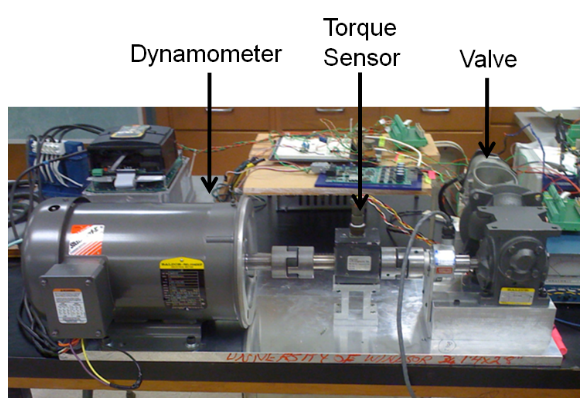

Figure 2. Hardware-in-Loop setup

V. VALIDATION OF RESULTS

In this section the experimental results are presented to show the validation of the filtering results (estimation of the spring torque). The performance of Kalman filter, H_∞ and H_∞ Gaussian filters are compared with the torque signal obtained from the experiment. The real valve operation (opening) and the filter estimation are conducted the same time. The recorded estimated spring torque through three design methods are then shown in comparison with the calculated spring torque from the torque sensor reading. The calculated gains are almost the same for the Kalman and H_∞ filter, so their results are so close to each other that the difference cannot be distinguished unless the figure is magnified.

The figures are plot for the opening period of the valve when the voltage is applied through the motor. The plate hits the block when it opens about 90 degrees, so only the data during this period is valid to use in estimation.

CASE 1: Spring torque estimation with parameters identified for the valve used for observer design

The spring torque estimation result is shown in Fig. 3 and its estimated error is shown in Fig. 4. Here, the weights used in the uncertainty matrix are $w_1 = 1$ and $w_2 = 0.1$. The value of the resistor is $R = 3\Omega$ and the weighting factor in the H_∞ and H_∞ Gaussian filter is chosen as $\gamma = 5.01$.

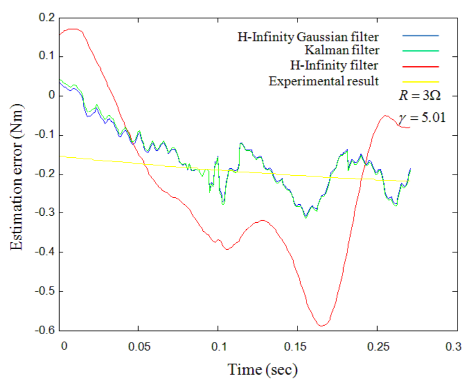

Figure 3. Estimation of spring torque, Case 1

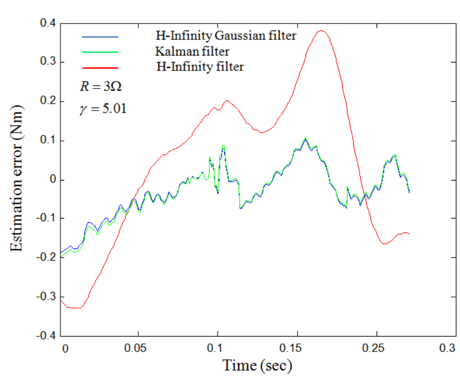

Figure 4. Estimation error, Case 1

Case 2: Spring torque estimation with parameters identified for the valve used for observer design when $\gamma = 99.8$.

When the value of γ is increased the H_∞ Gaussian and H_∞ filter gains slightly change. So there is only a very small difference in the estimation result. Fig. 5 shows the estimation result for this case and Fig. 6 shows its estimation error.

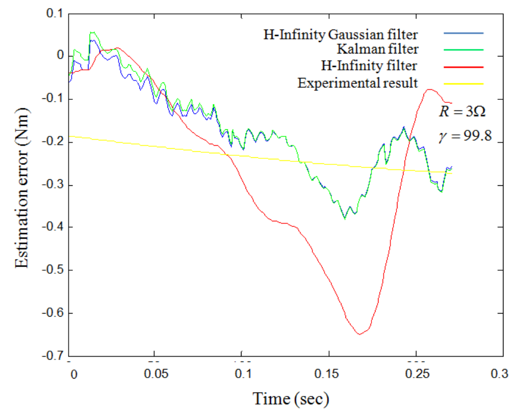

Figure 5. Estimation of spring torque, Case 2

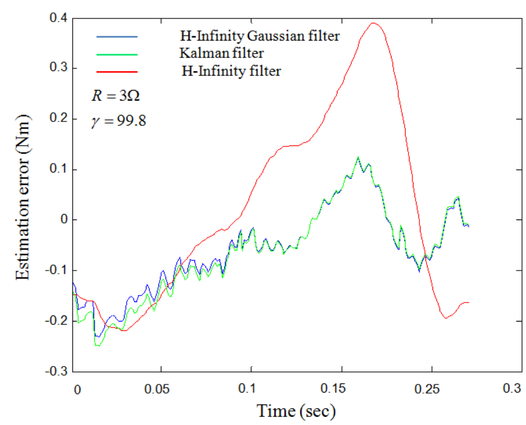

Figure 6. Estimation error, Case 2

Case 3: Spring torque estimation with identified parameters used for observer design and 33%parameter uncertainty in motor resistance.

Fig. 7 and Fig. 8 show the estimation of spring torque and the estimation error when there is a 33% decrease in motor resistance value from its nominal value.

As can be seen, the torque estimated by the Kalman and H_∞ Gaussian filters show a good consistency which validates the effectiveness of these two filtering designs. It is shown that the torque estimated with these two filters follow the real torque with less error than the estimated torque with H_∞ filter.

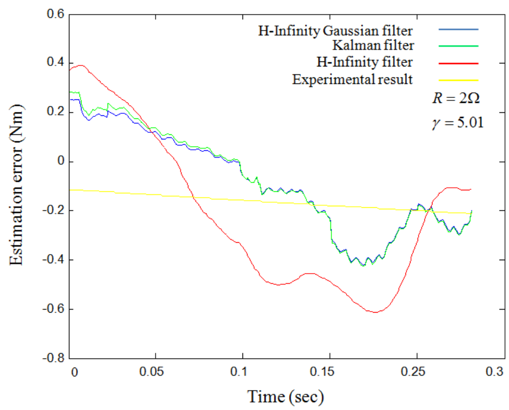

Figure 7. Estimation of spring torque, Case 3

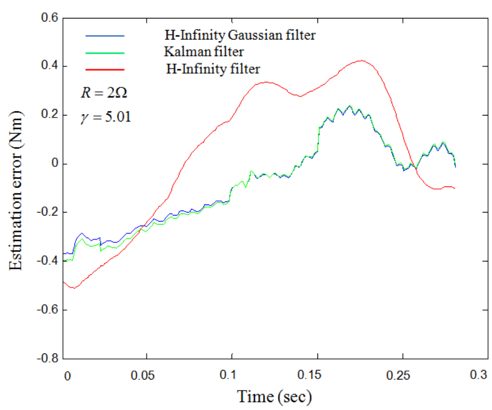

Figure 8. Estimation error, Case 3

VI. CONCOLUSION

In advanced engine control the throttle valve should be controlled as fast and accurate as possible in both opening and closing directions, so the total effective torque on the plate should be known considered in the control loop. Besides the motor torque which is provided by the controller, there is also the spring torque acting on the plate shaft. The purpose of this paper is to estimate this spring torque which is an step to a more accurate engine control. In this paper considering the spring effects and based on previous work the model of the throttle valve is derived. The spring torque is considered as a disturbance torque on the plate shaft and three filters, Kalman, H_∞ and H_∞ Gaussian, are used to estimate its value. It is seen from the experimental results the Kalman and H_∞ Gaussian filters give a better estimation of the spring torque than the H_∞ filter in the short period of opening of the valve.

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