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POSITION AND SPEED ESTIMATION OF A STEPPING MOTOR AS AN ACTUATOR OF DIESEL ENGINE FUEL RACK

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Summary

This paper illustrates one efficient method for permanent magnet synchronous motor - PMSM position and speed estimation using Extended Kalman filter - EKF. This is very important, especially in case of faulty sensors. The Extended Kalman Filter is an optimal recursive estimation algorithm for nonlinear systems. Marine diesel engine is a very complex, nonlinear dynamic system. Therefore, it is very important to control the engine shaft torque and power in all circumstances and working conditions. This paper, in short, includes a description of the standard Kalman Filter and its algorithm with the two main steps, the prediction step and the correction step. Furthermore the Extended Kalman Filter is discussed as a nonlinear system. The objective of this paper is to present implementation of Extended Kalman Filter for estimation of the PMSM rotor position and speed in case of faulty sensors by using measurements of the motor currents only. Simulation has been conducted in MATLAB programming environment. Achieved results of the simulation have shown that the PMSM rotor position and speed are estimated sufficiently well for the purpose of marine diesel engine fuel rack position control in the main engine speed control loop.

Key words: marine diesel engine, fuel actuator, PMSM, estimation, Kalman filter

1. Introduction

Marine diesel engine is a high-risk plant of the ship propulsion. Therefore, it is very important to control the engine shaft torque and power in all circumstances and working conditions. This can be realized by controlling the engine shaft speed using conventional or digital governors. Digital speed controllers of large marine diesel engines have been increasingly in use in combination with an electrical PMSM servo-motor as actuator of the fuel rack position. The output of the digital controller is a periodic pulse width modulated signal relative to the size of deviation of the actual speed from the desired speed. Such a signal is the input to the fuel rack positioning system actuated with the PMSM electrical motor, Fig 1. Good quality of the diesel engine fuel actuator control has key importance for maintaining the necessary engine power in different operating conditions, especially in cases of significant external disturbances (sea waves, currents, wind, etc.) and faulty sensors.

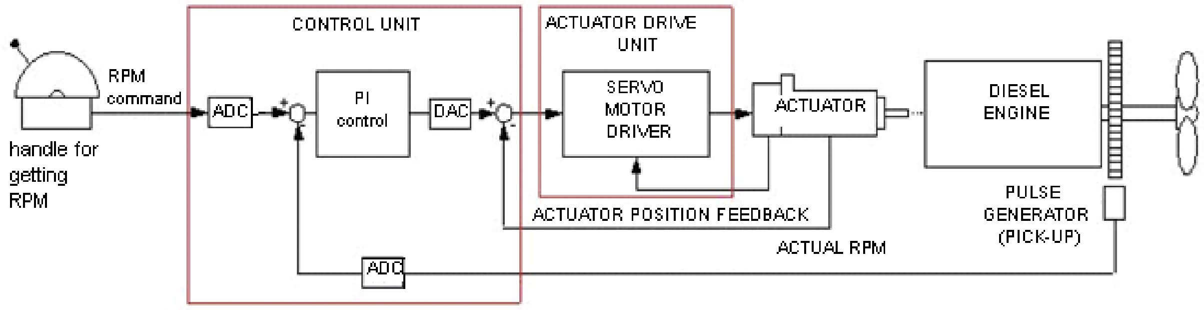

Fig. 1 Structural block diagram of the electrical actuator of fuel rack position within the diesel engine speed control [1]

The actuator functioning, Fig. 2 is controlled from the main position control loop and the local closed control loops (speed and current control loop).

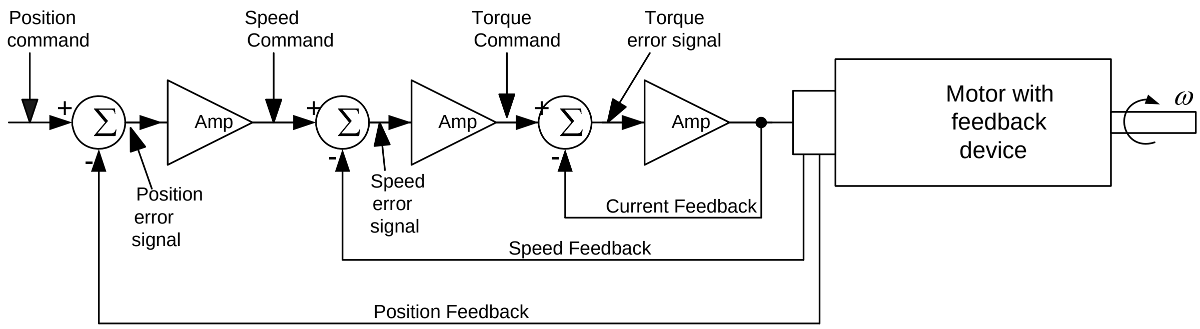

Fig. 2 Diagram of the electrical actuator control loop in the engine fuel positioning system [1]

The development and availability of very high energy permanent magnet materials have contributed to an increased use of the permanent magnet stepping motors – PMSM [2]. Due to its high efficiency, high power density, and robustness, permanent magnet stepping motors have been widely used, especially in systems that have demanding requirements on reliability, such as ship propulsion systems (see Fig. 1), robotic systems, process control systems, machine tools etc.

2. Dynamics of Stepping Motors

Stepping motor converts electronic pulses into proportionate mechanical movement. Each revolution of the stepping motor's shaft is made up of a series of discrete individual steps i.e. angular incremental movements. PMSM operates on the reaction between a permanent-magnet rotor and electromagnetic stator fields, Fig. 3.

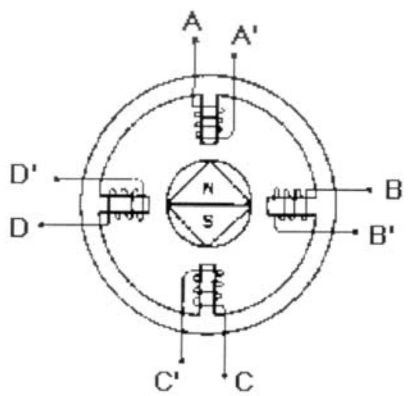

Fig. 2 Basic components of PMSM [3]

The essential property of the stepping motor is its ability to convert electronic pulses into precisely defined increments of rotor position [4].

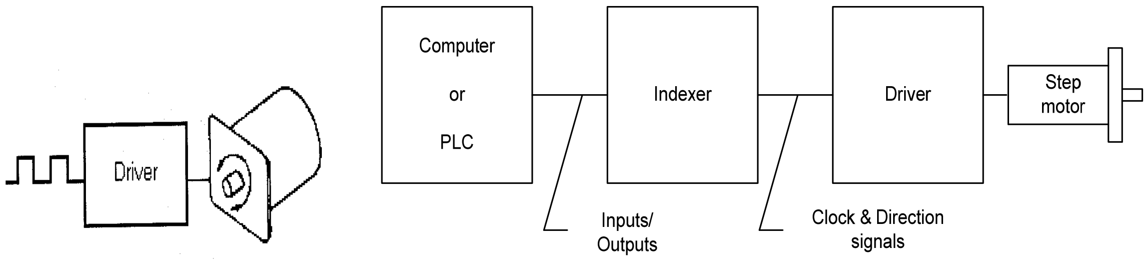

Fig. 4 Principle of stepping motor control [3]

Stepping motors are simple, robust and reliable and are well suited for open or close loop controlled actuators [5], Fig. 4. A more recent development in PM stepping motor technology is the thin-disk rotor. Fig. 5 shows the basic construction of a thin-disk rotor PMSM. This type of PMSM dissipates much less power in heat losses and is considerable more efficient.

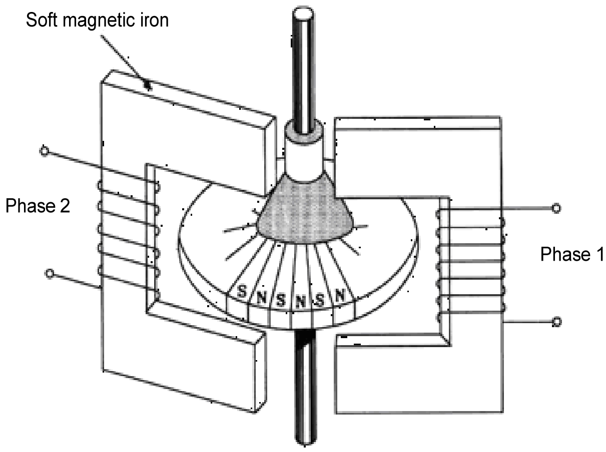

Fig. 5 Thin-disk rotor of PMSM [6]

Dynamics of PMSM, for the purpose in this paper, is analyzed with the condition that a sinusoidal characteristic of the magnetic field in the air gap (between rotor and stator segments) is assumed. The contribution of each phase on the motor torque T_{mj} can be written as [7]:

$$T_{mj} = k_m \cdot sin\left[n \times \theta(t) + \theta_0\right] \cdot I_j(t) \tag{1}$$

where is:

k_m - motor constant, depending on the design of the motor:

n – number of rotor pole pairs;

$\theta(t)$ - actual rotor position;

θ_0 - local field angle;

$I_j(t)$ - current in the coil as function of time.

The total torque T_m produced by stepping motor is [7]:

$$T_m = \sum_{j=1}^{m} T_{mj} \tag{2}$$

The equation of motion of the stepper motor is given as follows:

$$\sum_{j=1}^{m} T_{MJ} = J\frac{d\omega}{dt} + D\omega + T_F \tag{3}$$

where is:

J – inertia of the rotor and the load;

D – viscous damping constant;

T_F - frictional load torque.

In this paper Extended Kalman Filter is used to estimate the states of a two-phase PMSM. Dynamic model for this motor is as follows:

$$\begin{aligned}
i_a &= -\frac{R}{L}I_a + \frac{\lambda \cdot \omega}{L}\sin\Theta + \frac{u_a + \Delta u_b}{L} \\
i_b &= -\frac{R}{L}I_b + \frac{\lambda \cdot \omega}{L}\cos\Theta + \frac{u_b + \Delta u_b}{L} \\
\frac{d\omega}{dt} &= -\frac{3}{2}\cdot\frac{\lambda}{J}I_a\sin\Theta + \frac{3}{2}\cdot\frac{\lambda}{J}I_b\cos\Theta - \frac{B\cdot\omega}{J} + \Delta\alpha \\
\frac{d\Theta}{dt} &= \omega
\end{aligned} \tag{4}$$

where:

I_a and I_b are the currents in the two motor windings;

Θ and ω are the angular position and speed of the rotor;

R and L are the motor winding's resistance and inductance;

λ is the flux constant of the motor;

B is the coefficient of viscous friction that acts on the motor shaft and its load;

J is the moment of inertia of the motor shaft and its load;

u_a and u_b are the voltages that are applied across the two motor windings;

Δu_a and Δu_b are noise terms due to errors in u_a and u_b ;

$\Delta\alpha$ is a noise term due to uncertainly in the load torque;

The Extended Kalman Filter - EKF algorithm is an optimal recursive estimation algorithm for nonlinear system like PMSM is. EKF processes all available measurements to provide estimate of the variables of interest. The EKF approach is ideal for the state estimation of PMSM. Mathematical model, describing the motor dynamics is sufficiently well known and the motor winding currents can be measured and are suitable for the determination of the rotor position and speed of PMSM.

The purpose of this paper is to show the possibility to apply the mathematics of a Kalman Filter to a microcontroller to get i.e. estimate the PMSM rotor position and speed without using the faulty sensors, encoders.

3. Kalman Filter Estimator

Kalman filter is a linear, discrete time and finite dimensional system [8]. Fig. 6. illustrates the typical application context in which the Kalman filter is used.

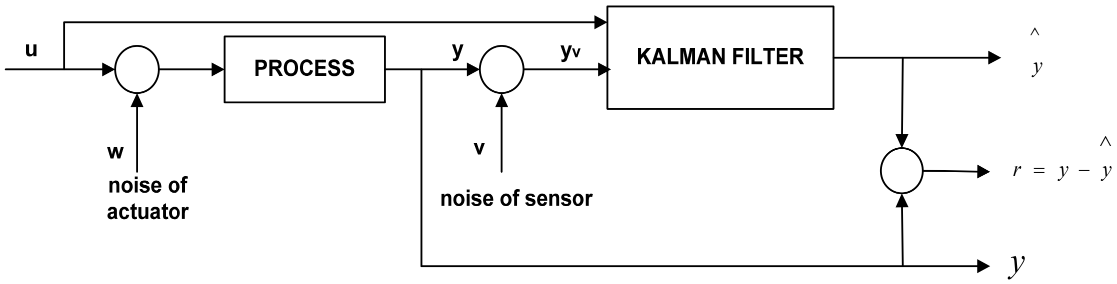

Fig. 6 Typical application of the Kalman filter [9]

The Kalman filter can incorporate all available information such as system's dynamics model, known control inputs, measurement errors, and any information about initial conditions of the variables of interest, to form an optimal estimate of the system state. It estimates the state of a dynamic system in each time instant working on-line.

Taking into account the noise of actuator and sensor, system with stationary noise covariance can be expressed in discrete form as [9]:

$$\begin{aligned} x(k+1) &= A\,x(k) + B\,u(k) + w(k) \\ y_v(k) &= C\,x(k) + v(k) \end{aligned} \tag{5}$$

Where w and v are independent incidental white noise processes: (w – actuator noise, input additive signal, v – sensor or measurement noise, output additive signal). A, B, C are matrix of states, matrix of inputs, matrix of outputs respectively. The basic problem in practical cases such as this, is the optimal state estimation $x(k)$ from the noise measurement data.

Estimated state is indexed with $\hat{x}(k\,|\,k)$. The optimal estimator class includes Minimum Mean Square Error Estimators - MMSE [10]. These minimize the expected minimum value of the minimum mean square error estimation. Recursive Kalman Filter algorithm consists of two parts [9]:

- prediction (one step in advance) of the state $\hat{x}(k+1)$ with known previous state $\hat{x}(k)$,

$$\hat{x}(k+1\,|\,k) = A\,\hat{x}(k\,|\,k) + B\,u(k) \tag{6}$$

- estimated state correction $\hat{x}(k+1)$ based on new measurement $y_v(k+1)$,

$$x(k\,|\,k) = x(k\,|\,k-1) + K(y(k) - C\,x(k\,|\,k-1)) \tag{7}$$

The value of the correction part is the function of the so called innovation that is discrepancy of the measured value and the predicted value.

$$y_v(k+1)-C\hat{x}(k+1|k)=C(x(k+1)-\hat{x}(k+1|k)) \tag{8}$$

Increased innovation matrix K (Kalman's gain) is selected in a way to minimize the estimation error in steady state for given actuator and sensor noise covariance.

$$Q=E\left(w(k)w(k)^T\right);\; R=E\left(v(k)v(k)^T\right) \tag{9}$$

By combining the equations above the recursive Kalman algorithm can be expressed as:

$$\hat{x}(k+1|k)=A(I-KC)\hat{x}(k|k-1)+\begin{bmatrix} B & AK \end{bmatrix}\begin{bmatrix} u(k) \\ y_v(k) \end{bmatrix} \tag{10}$$

$$\hat{y}(k|k)=C(I-KC)\hat{x}(k|k-1)+CKy_v(k) \tag{11}$$

Kalman Filter generates the optimal estimate $\hat{y}(k|k)$ for corresponding $y(k)$ and the filter state $\hat{x}(k|k-1)$. This algorithm represents the standard adaptive Kalman Filter. The measurement error is $(y-y_v)$ and the estimation error is $(y-\hat{y})$.

Kalman filter addresses the general problem of trying to estimate the state of a discrete time controlled process that is governed by a linear stochastic difference equation [11]. If the process to be estimated or the measurement relationship to the process is nonlinear in this purpose we use Extended Kalman Filter.

4. Extended Kalman Filter

Extended Kalman Filter - EKF is the nonlinear version of the Kalman Filter which linearizes an estimate of the current mean and covariance. The EKF for parameter estimation has a number of advantages such as [10]:

- it only uses the mean and covariance of the state, it is simple and computationally fast,
- it has close connection with the state-space theory,
- it has a unified formulation for both single variable and multivariable problems.

The nonlinear process model (from time k to time $k+1$) is described as [12]:

$$x(k+1)=f\left[x(k),u(k)\right]+w(k) \tag{12}$$

where is:

$x(k)$, $x(k+1)$ - the system state at time instant k, $k+1$;
$u(k)$ – the control;
$w(k)$ – the zero-mean Gaussian process noise.

The objective is to estimate at each time step by the process model and the observation. The observation model at time $k+1$ is give by [12]:

$$y(k+1)=C\left[x(k+1)\right]+v(k+1) \tag{13}$$

Where is:

C – the observation function;
$v(k+1)$ – the zero-mean Gaussian observation noise.

As with the original Kalman Filter, the Extended Kalman Filter uses a two step predictor – corrector algorithm. The first step involves projecting both the most recent state estimate and an estimate of the error covariance in forward instant time to compute a predicted estimate of the state at the current time. Predict using process model [12]:

$$\begin{aligned} \bar{x}(k+1) &= f(\hat{x}(k),u(k)) \\ \bar{P}(k+1) &= \nabla f(k)P(x)\nabla f^T(x)+Q \end{aligned} \tag{14}$$

where $\nabla f(x)$ is the Jacobian of function *f* with respect to *x* evaluated $\hat{x}(k)$.

The second step involves correcting the predicted state estimate calculated in the first step by incorporating the most recent process measurement to generate an update state estimate. Update using observation [12]:

$$\begin{aligned} \hat{x}(k+1) &= \bar{x}(k+1)+K\left[y(k+1)-C(\bar{x}(k+1)\right] \\ P(k+1) &= \bar{P}(k+1)-KSK^T \end{aligned} \tag{15}$$

Where P is the estimation error.

Where the innovation covariance *S* and the Kalman gain *K* are given by:

$$\begin{aligned} S &= \nabla C\bar{P}(k+1)\nabla C^T+R \\ K &= \bar{P}(k+1)\nabla C^T S^{-1} \end{aligned} \tag{16}$$

where ∇C is the Jacobian of function *C* evaluated at $\bar{x}(k+1)$, R is the covariance of the measurement noise.

5. SIMULATION CASE

We used here EKF to estimate position and speed of PMSM as the actuator of fuel rack position in diesel engine speed control process. Parameters values for PMSM model were as follows [13]:

R=0,7 Ω - winding resistance;

L=5 mH – winding inductance;

λ=0,193 Vs/rad – motor constant;

J=$9\cdot 10^{-5}$ kg/m² - moment of inertia;

B=0,001 Nms/rad – coefficient of viscous friction.

The goal of this paper was to estimate the rotor position and speed with the assumption that the motor winding currents can be measured continuously. The control inputs (winding voltages) are expressed as (17), according [14]:

$$\begin{aligned} u_a(t) &= \sin 2\pi\cdot t \\ u_b(t) &= \cos 2\pi\cdot t \end{aligned} \tag{17}$$

Equation (17) means that in discrete time, the control inputs are equal to [14]:

$$\begin{aligned} u_{ak} &= \sin 2\pi\cdot k\cdot T \\ u_{bk} &= \cos 2\pi\cdot k\cdot T \end{aligned} \tag{18}$$

where: k=0,1,2,..n; *T* – sampling period.

The voltages that are applied to the winding currents are equal to these values plus u_{ak} and u_{bk}, which are zero-mean variables with standard deviations equal to 1 mA. It is assumed that the speed noise due to load torque disturbance has a standard deviation of 0.05 rad/s².

In this paper Extended Kalman Filter simulation code in MATLAB has been used. The obtained results are presented graphically. Fig. 7a and 7b shows currents i_a and i_b through motor windings.

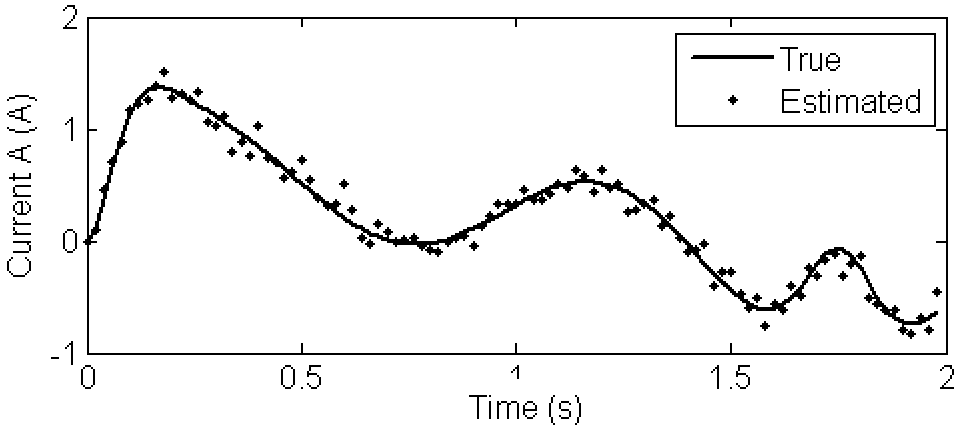

Fig. 7a Time dependence of true and estimated value of PMSM current in coil A

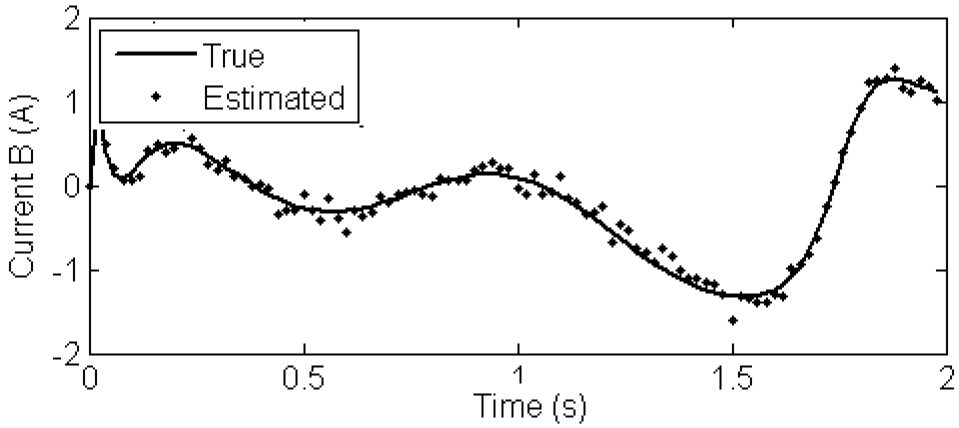

Fig. 7b Time dependence of true and estimated value of PMSM current in coil

The Fig. 7a and 7b clearly shows the true value and the estimated value of motor winding currents. Winding currents measurements are obtained once per millisecond. Even though the deviation of true value has appeared due to measurement noise v_a and v_b it is negligible. Measurement noise in this case is commonly caused by electric noise, quantization error in microcontroller, etc.

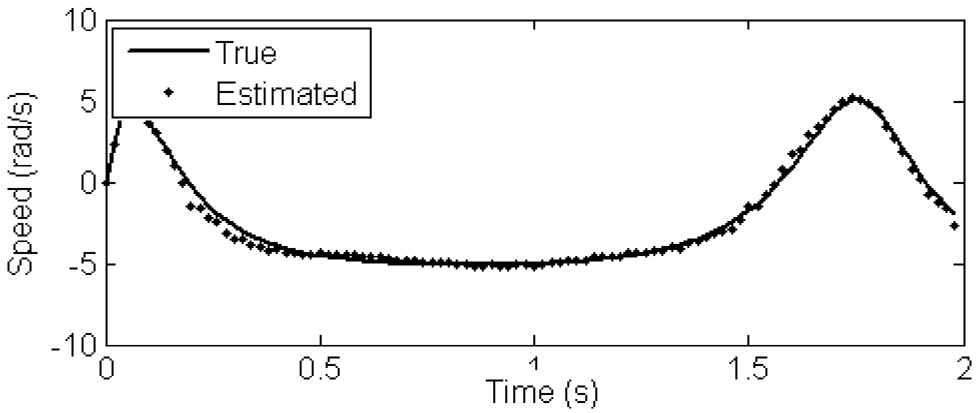

Fig. 8 Time dependence of true and estimated value of PMSM rotor speed

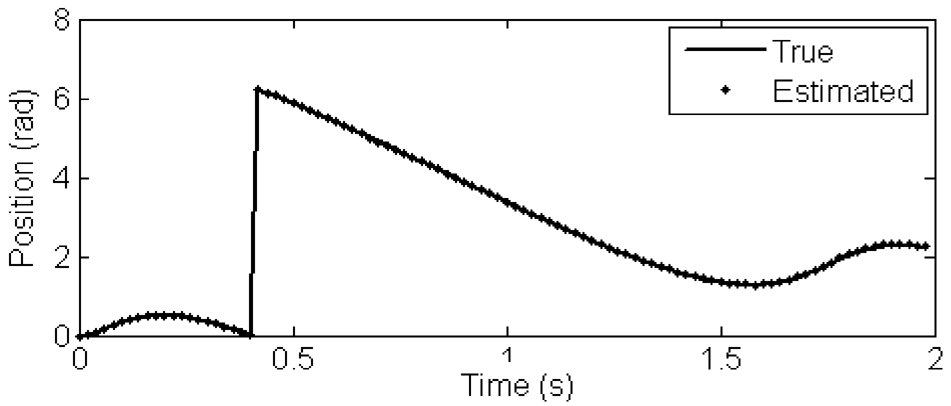

Fig. 9 Time dependence of true and estimated value of PMSM rotor position

Fig. 8 and 9 clearly show that the rotor position and speed are estimated quite well. The above results show that the Extended Kalman Filter can be efficiently implemented to estimate the speed and rotor position of the PMSM. These simulations have proved that it is possible to achieve the position and speed of PMSM rotor in case of faulty sensors.

6. CONCLUSION

In this paper, the design and implementation of an Extended Kalman Filter has been researched. The system considered is a permanent magnet synchronous motor – PMSM as a fuel rack position actuator. The Extended Kalman Filter is designed for estimation of the rotor position and speed in case of faulty sensor by using measurements of the PMSM motor currents only. In this paper PMSM has been investigated, because digital speed controllers of large marine diesel engines have been increasingly in use in combination with an electrical PMSM servo-motor as actuator of the fuel rack position.

Good quality of the diesel engine fuel actuator control has key importance for maintaining the necessary engine power in different operating conditions, especially in cases of significant external disturbances and faulty sensors.

In the paper MATLAB programming environment has been used to simulate and display the results of conducted simulations. Simulation results are presented to demonstrate the feasibility of this estimation process. The data analysis has showed that PMSM rotor position and speed are estimated quite well. The results of the simulations show that the Extended Kalman Filter can be efficiently implemented to estimate the rotor position and speed of PMSM for the purpose of marine diesel engine fuel rack position control in the main marine engine speed control loop.

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