Abstract— The Smart Hybrid Powerpack (SHP) is the electro-hydraulic system that combines the system of Electro Hydraulic Actuator (EHA) and advanced technologies such as Fault-tolerance. In the industry, the EHA system has been famous because that the EHA acts as a Power-Shift which shifts the power from high-speed electric motor to the high-force of hydraulic cylinder by bi-directional piston pump. If errors like sensor and plant noises occur in the EHA system, the system will cause serious malfunctions. To overcome this situation, this paper shows the motor fault tolerance algorithms about the kalman filter and threshold predictor, and compares with these methods for reducing sensor noises in the SHP. The simulation result shows better performance by the kalman filter than threshold predictor. Proposed Motor fault tolerance algorithms using the kalman filter has a time-delay. However, this time-delay is small enough to be ignored for measuring accuracy sensor signals in the SHP.

Keywords— Smart Hybrid Powerpack (SHP), Motor Sensor fault tolerance, Kalman filter, Threshold predictor.

I. INTRODUCTION

CONVENTIONAL hydraulic actuator systems (CHA) which consist of an electric motor, pump, various valves, hoses for transferring the working fluid, and actuator have been widely used as power units because they can generate very large power. [6] However, CHA systems have some problems such as the low energy efficiency, leakage of the working fluid, maintenance load, heavy weight, and limited installation space.

To overcome these shortcomings of CHA systems, electro-hydraulic actuator (EHA) systems have been developed, which have some advantages such as smaller size, higher energy efficiency, and faster response due to high stiffness than CHA systems.[1], [7]

Proposed smart hybrid powerpack (SHP) applied to the EHA system which directly is connected to the motor and the hydraulic pump, and controls by electric-motor directly to change direction and speed of cylinders without valves in the CHA system. Therefore, the electric-motor has very important role in the EHA system. Miniaturized system using only the electric motor control system to reduce the plant noise is also essential for the robust one. [8]. For SHP system, there are many motor fault tolerance algorithms including the Kalman filter, sliding mode observer (SMO), and adaptive fuzzy control. Motor (Hall, Encoder) fault tolerance and intelligent control structure is expressed as Fig.1

![Fig.1 The motor fault tolerance and intelligent control structure.](image)

In this paper, we designed the motor fault tolerance algorithm to reduce temporarily noises which can occur in the encoder and hall sensor, and to recover from wrong signals of sensors. This paper is organized into four sections including this introduction. Section 2 shows a comparison between the kalman filter and threshold predictor. Section 3 gives the result using MATLAB simulation model of the comparison between the kalman filter and threshold predictor. Section 4 gives the conclusion is given in Section 4.
II. COMPARISON BETWEEN THE KALMAN FILTER AND THRESHOLD PREDICTOR FOR MOTOR FAULT TOLERANCE

A. Motor Fault Tolerance Algorithm by Kalman Filter

The kalman filter is an adaptive least square error filter that provides an efficient computational recursive solution for estimating a signal in presence of Gaussian noises. It is an algorithm which makes optimal use of imprecise data on a linear system with Gaussian errors to continuously update the best estimate of the system's current state.

The kalman filter is a powerful method for reducing noise in measurements. The kalman filter equations consist of two parts such as the predict equations and correct equations. The predict equations are expressed as, (1) and (2), [2], [4], [9].

\[ \hat{x}_k = A\hat{x}_{k-1} \]  
\[ P_k = AP_{k-1}A^T + Q \]  

where \( \hat{x}_k \) is a priori state estimate value, and \( \hat{x}_{k-1} \) is a posteriori state estimate value, and \( P_{k-1} \) is estimation covariance of the error, and \( P_k \) is a covariance of the error in the state estimate and \( Q \) is the process noise covariance. The \( n \times n \) matrix \( A \) in the difference equation (1) means the conversion factor to be connected to the next step in the previous step. The predict equations output to \( \hat{x}_k \) and \( P_k \) using System model parameters \( A, Q \) and \( \hat{x}_{k-1}, P_{k-1} \) as input. The correct equations are shown as (3), (4) and (5), [2], [4], [9].

\[ K_k = P_k H^T (HP_k H^T + R)^{-1} \]  
\[ \hat{x}_k = \hat{x}_{k-1} + K_k (z_k - H\hat{x}_k) \]  
\[ P_k = P_{k-1} - K_k H P_{k-1} \]  

where \( K_k \) is a kalman gain, and \( z_k \) is actual measurement value, and \( R \) is a measurement covariance of error, and \( H \) is a measurement matrix relating state to measurement. In the (3), update \( K_k \) using output of (2) \( P_k \). After updating \( K, K \) is used in the (4) as a weight of prediction error of measurement value. The (4) updates State Estimate using \( Z_k \) and \( K_k \). In the (4), \( H\hat{x}_k \) means a measurement prediction and \( z_k - H\hat{x}_k \) means a prediction error of measurement value. In correct equations, the correct equations output to \( \hat{x}_k \) and \( P_k \) as final results using system model variable \( H, R \) and \( P_k, \hat{x}_k, z_k \) and \( z_k \) as input. After updating \( P_k \) using (5), \( \hat{x}_k \) and \( P_k \) are returned in the (1) and then repeated.

B. Motor Fault Tolerance Algorithm by Threshold predictor

Between the kalman filter and threshold predictor, the gain of weight value is the biggest difference. The threshold predictor is shown as (6), (7), (8) and (9), [3], [4], [5].

\[ FT^{[1]} = \alpha RT_k + (1 - \alpha) FT_k^{[1]} \]  
\[ RT = z_{k-1} - z_{k-2} \]  
\[ FT^{[3]} = aFT^{[1]} + (1 - a)FT_k^{[2]} \]  
\[ FT = (2 + \alpha / (1 - \alpha))FT_k^{[1]} - (1 + \alpha / (1 - \alpha))FT_k^{[2]} \]  

where \( z \) is actual measurement value, \( \alpha \) is the weight value of the threshold predictor used double exponential smoothing method to predict the threshold, \( FT \) is the forecast threshold, and \( RT \) is a deviation for output (k-1) cycle and (k-2) cycle. When error occurred the moment, this algorithm is used to correct the error by currently value \( RT \). \( FT \) is calculated by gain of weight value in the (9), the gain is constant of (k-1) cycle \( FT^{[1]} \) and (k-2) cycle \( FT^{[2]} \). \( RT \) will be output directly, when it confirmed to normal signal compare than \( FT \). On the other hand, in the estimates equation (4), the kalman filter is calculated by the kalman gain \( K \) that is variable on the cycle time situation. In section 3, this paper shows that algorithm will be applied for the motor fault tolerance in the SHP using MATLAB Simulink.

III. PERFORMANCE EVALUATION OF THE COMPARISON BETWEEN THE KALMAN FILTER AND THRESHOLD PREDICTOR

A. Performance of Fault Tolerance Algorithm

This section evaluates the performance of the comparison between the kalman filter and threshold predictor along with implementation details for the MATLAB simulink model. In the MATLAB simulink, the kalman filter and threshold predictor are implemented using the general function block of MATLAB simulink, as shown in Fig. 2 to 5.

![Fig.2 MATLAB Simulink model using the threshold predictor(Hall)](http://dx.doi.org/10.15242/IIE.E0214047)

![Fig.3 MATLAB Simulink model using the kalman filter(Hall)](http://dx.doi.org/10.15242/IIE.E0214047)
The model simulates motor fault tolerant algorithms about the hall sensor and encoder signals in the SHP. In the hall sensor, we assumed the motor speed is 1800rpm, the noise sampling time is 0.001s, the noise deviation is ±1V DC and the maximum output of sensor signal is 4V. In the encoder part, we also assumed the motor speed is 1800rpm, the noise sampling time is 0.000001s, the noise deviation is ±1V DC and the maximum output of encoder signal is 5V. The simulation model generated a fault signal artificially by adding noise value to the original sensor signal. The information of sensors are shown in Table I.

<table>
<thead>
<tr>
<th>Motor Sensor error simulation</th>
<th>Hall sensor</th>
<th>Encoder</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor speed</td>
<td>1800rpm</td>
<td>1800rpm</td>
</tr>
<tr>
<td>Sampling time</td>
<td>0.0001</td>
<td>0.00000001</td>
</tr>
<tr>
<td>Noise sample</td>
<td>0.001</td>
<td>0.0000001</td>
</tr>
<tr>
<td>Noise deviation</td>
<td>±1V</td>
<td>±1V</td>
</tr>
<tr>
<td>Output</td>
<td>4V</td>
<td>5V</td>
</tr>
<tr>
<td>Performance evaluation</td>
<td>0.25%</td>
<td>0.25%</td>
</tr>
</tbody>
</table>

B. Performance of Fault Tolerance Algorithm about Hall Sensor Comparison between The Kalman filter and Threshold Predictor

In the hall sensor part, the reference of the hall sensor in the SHP is shown in Fig. 6. The hall sensor signal is sine wave form which varies quickly. To generate the hall sensor signal with sensor noises, we use random noise signals using MATLAB simulink. The hall sensor signal with sensor noises in the SHP is shown in Fig. 7. In the same condition, we apply the kalman filter and threshold predictor as the motor fault tolerant algorithm. Estimates of the hall sensor outputs using the kalman filter and threshold predictor are shown in Fig. 6 and in Fig. 7. Comparing Fig. 8 with Fig. 9, the kalman filter is better performance than the threshold predictor. In this result of MATLAB simulation, the estimates of the hall sensor output using the kalman filter is almost same as the reference of the hall sensor. In this simulation, maximum sensor noise length is 1.032V, and recovered signal length is 0.0021V. Therefore, Percentage of maximum estimates error deviation by sensor noise using the kalman filter is about ±0.2%. That is small enough to be ignored because accuracy of proposed sensor is less than ±0.25%. The difference between estimates of the hall sensor and the reference signal is time-delay. On the other hand, a sensor noise in the SHP using threshold predictor algorithm is not small enough to be ignored because estimates by the threshold predictor cannot follow the rapid area in the reference. In Fig. 9, estimates of the hall sensor output using the threshold predictor do not follow the reference. Because the kalman filter algorithm calculates a new value for the kalman gain K through repeated. However, the threshold predictor algorithm calculates estimates using fixed value for weight through repeated. On the other hand, a sensor noise in the SHP using the threshold predictor algorithm is not small enough to be ignored because estimates by the threshold predictor cannot follow the rapid area in the reference.
C. Performance of Fault Tolerance Algorithm about Encoder Comparison between the Kalman filter and Threshold Predictor

We studied the kalman filter and threshold predictor in the hall sensor to reduce sensor noises. We also used the kalman filter and threshold predictor to correct noises in the encoder. In the encoder part, we also use random noise signals using MATLAB simulink to generate the encoder signal with sensor noise like the hall sensor. The reference of the encoder output in the SHP is shown in Fig. 10, and the encoder output with noise in the SHP is shown in Fig. 11. Estimates of the encoder output using the kalman filter and the threshold predictor is shown in Fig. 12 and in Fig. 13.

Comparing Fig. 12 with Fig. 13, we know that the kalman filter shows also better performance than the threshold predictor. In Fig. 12, estimates of the encoder output using the kalman filter follows the reference well. The ability of estimating using the kalman filter is more accurate than the threshold predictor in rapid areas because of the kalman gain \(K\). The maximum encoder noise length is 1.389V, and recovered signal length is 0.0034V. Therefore, percentage of maximum estimates error deviation by the encoder noise using the kalman filter is about \(\pm0.244\%\). That is also small enough to be ignored because accuracy of proposed encoder is less than \(\pm0.25\%\). In fig.13, estimates of the encoder output signals using the threshold predictor do not follow the reference because the weight \(\alpha\) cannot change when calculating using the threshold predictor. The encoder signal is digital signal. So this signal is more difficult to reduce noises by the threshold predictor using fixed weight a value than hall sensor signal. However, the kalman filter algorithm has the ability to recover sensor noises. The SHP system is controlled by the motor as changing directions rapidly. Therefore, the kalman filter can be more suitable than the threshold predictor.
D. Performance of Fault Tolerance Algorithm using Kalman filter about Time-Delay

We know that the kalman filter is more suitable than the threshold predictor in SHP from the previous results. In this section, we study time-delay caused by motor tolerance algorithm using the kalman filter. Time-delay is important to control the motor direction and torque by sensor. Comparison of sensor time-delay using the hall sensor and encoder is shown in Fig.14 and Fig.15. In Fig.14, the kalman filter algorithm has time-delay. In this result of MATLAB simulation, the reference of the hall sensor output is faster than estimates of the hall sensor output using the kalman filter. This time-delay is about 0.0002sec. This interval is small enough to be ignored for motor current control in the SHP. In Fig.15, this output result also has time-delay. The reference of the encoder output is 0.0001s, and estimate of the encoder output is 0.00013sec using the kalman filter. This time-delay is about 0.00003sec. This gap is also small enough to be ignored for motor direction and speed control in the SHP.
IV. CONCLUSIONS

In this paper, we apply the motor fault tolerant logic for SHP system using the kalman filter and threshold predictor algorithms. We analyze into the motor fault tolerant algorithms by comparison which is better as the motor fault tolerant ability based on the same condition in the SHP. In this simulation result, simulation results have good performances by the kalman filter comparing with the threshold predictor. In part of time-delay, the kalman filter has time-delay, but this time-delay has not influence to control a motor accurately. Therefore, we decide the motor fault tolerant algorithm in the SHP as the kalman filter.

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