Interactive Multiple-Model Application for Hydraulic Servovalve Health Monitoring

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Abstract

Hydraulic systems are widely used as power source for several different applications. Servovalves are critical components and often subjected to failures. Estimating degradations from these components requires dynamic analysis of their behavior and consequently advanced monitoring techniques. This article proposes an on line monitoring method to estimate a degradation parameter of the servovalve using an interactive multiple-model technique considering a bank of Extended Kalman Filters that models not only the valve itself but also the degradation trend. A single failure mode was considered related to the nozzle line clogging. The degradation estimates and the likelihood of the correctness of each model were analyzed in order to evaluate the proposed method.

1. Introduction

Hydraulic servovalve health monitoring have been addressed in several works, including (Samadani., Kwuimy & Nataraj, 2014), (Borello, Vedova, Jacazio & Sorli, 2009), (Mussi & Góes 2009) and (Sepasi 2005). Most failure modes from these components require dynamic analysis of its behavior and consequently advanced monitoring techniques. One commonly used method is the Kalman filter applied as parameter identification and examples of application include (Hajiyev & Caliskan, 2003) and (Sepasi 2005). These applications consider an augmented state model including the variable of the model associated with the degradation. Eq. (1) and Eq. (2) give an example from (Hajiyev & Caliskan, 2003) where the parameter a of the system is the desired value to be estimated.

Linear system:

$$\begin{cases} x_k = a x_{k-1} + w_{k-1} \\ z_k = x_k + v_k \end{cases} \tag{1}$$

Augmented system:

$$\begin{cases} \begin{bmatrix} x_k \\ a_k \end{bmatrix} = \begin{bmatrix} a_{k-1} x_{k-1} \\ a_{k-1} \end{bmatrix} + \begin{bmatrix} w_{k-1} \\ 0 \end{bmatrix} \\ z_k = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_k \\ a_k \end{bmatrix} + v_k \end{cases} \tag{2}$$

This augmented state-space model considers the parameter a constant and may not address properly its estimation if the system presents variations of a specially when submitted to abrupt degradation variations and when quick decisions are required such as applications in reconfiguration systems. Alternatives include modeling the dynamic of the parameter being estimated and including it at the augmented state model. An example is given in (Keong, Lim & Mbab, 2014) where a Helicopter tail gearbox bearing is monitored considering three possible degradation dynamics: stationary trend, linear trend and polynomial trend. Figure 1 illustrates these dynamics.

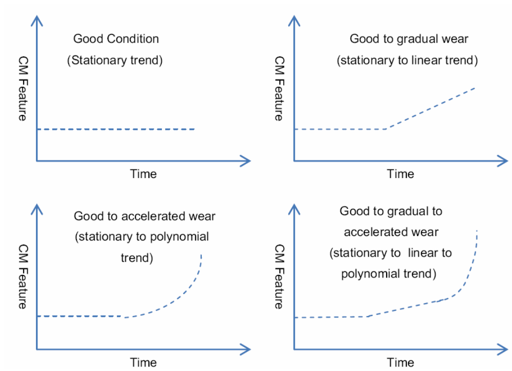

Figure 1: Degradation trends extracted from (Keong, Lim & Mbab, 2014)

Estimation of parameter a may be useful when it is related to a degradation, for example a friction or orifice diameter in hydraulic line whose variation may indicate clogging of the line.

Each possible degradation dynamic model included at the augmented state model result in a different Kalman Filter (KF) and consequently an estimation of the degradation parameter as well as other state variables. The technique that combines different models using KF are called Switching Kalman Filter (SKF). The methods used in SKF applications include Autonomous Multiple Model (AMM), Generalized Pseudo-Bayesian of first-order (GPB1), Generalized Pseudo-Bayesian of second-order (GPB2), Interacting MM (IMM) among others. An implementation and comparison of several of these method is presented in (Pitre, 2004) with application in Target Tracking. From these examples, the most popular one is the IMM (Pitre, 2004), whose main advantage is the lower computation cost (Chze & Inseok, 2008), but by using more complex "mixing techniques", it is more difficult to analyze its results (Chze & Inseok, 2008).

This paper proposes a method to monitor a hydraulic servovalve using an IMM algorithm combined with a bank of Extended Kalman Filter containing some augmented state-space models similar to Eq. (2), modeling not only the dynamics of the valve itself but also the dynamics of the degradation.

2. HYDRAULIC SERVOVALVE MODEL

This article considered a two stage servo valve as illustrated in Figure 2.

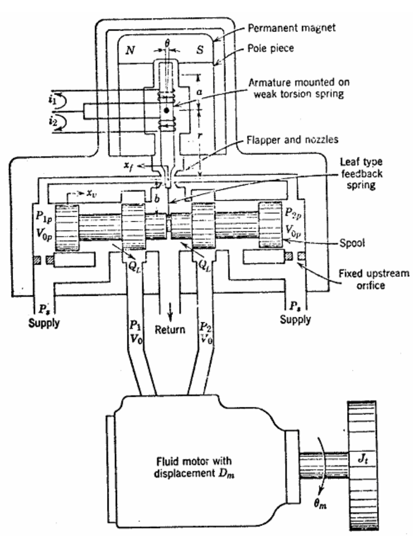

Figure 2. Schematic of a two stage electro hydraulic servovalve with force feedback (Merrit, 1976).

The first stage of the servo valve comprises the permanent magnet, pole piece, armature, flapper, nozzle, leaf type feedback spring and the spool. The equation relating the current input and the spool and flapper position is given by Eq. (3) (Merrit, 1976).

$$K_t \Delta i = J_a s^2 \frac{x_f}{r} + (r+b) K_f \left[(r+b) \frac{x_f}{r} + x_v \right] \qquad (3)$$

in which:

K_t is the torque constant of the torque motor;

Δi is the current input;

J_a is the inertia of armature;

x_f is the flapper position;

r is the distance between center of armature and flapper;

b is the distance between flapper and spool;

K_f is the spring constant feedback at free end;

x_v is the spool position.

The equation relating spool and flapper position is given by Eq. (4) (Merrit, 1976).

$$\frac{x_v}{x_f} = \frac{K_{qp} / A_v}{s\left(\frac{s^2}{\omega_{hp}^2} + \frac{2\delta_{hp}}{\omega_{hp}} + 1 \right)} \qquad (4)$$

In which:

K_{qp} is the flow gain of flapper valve;

A_v is the area of spool;

ω_{hp} is the hydraulic natural frequency of pilot stage.

δ_{hp} is the pilot stage damping ratio

The parameters values used in this work are:

$K_t = 0.025\ in.lbs/ma$;

$r = 0.015\, in$;

$b = 0.0012\, in$;

$A_v = 0.026\, in^2$;

$K_{qp} = 3.9\ in/in.\sec$;

$K_f = 93\ in.lbs/in$.

In order to simulate the time varying input current Δi, a sinusoidal wave form was adopted. The system response for this input is given in Figure 3.

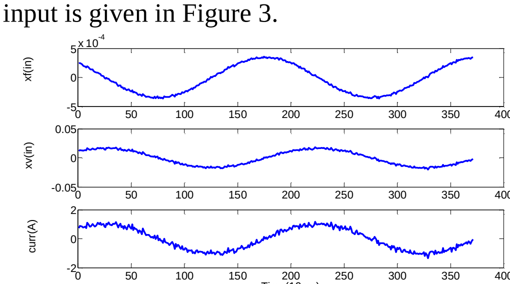

Figure 3: Model response to a sinusoidal input

3. BANK OF STATE-SPACE MODELS

The first step to build the bank of filters is to obtain the state space model of the first stage servovalve equations given in last topic. To accomplish that, discrete time domain equations based on Eq. (3) and Eq.(4) and simplifications described previously are built using the Euler discretization method and then put in the state space model. Eq. (5) shows the resulting model.

$$\begin{cases} x_k = Ax_{k-1} + Bu_k + w_{k-1} \\ z_k = Hx_k + v_k \end{cases} \tag{5}$$

in which:

$x_k = \begin{bmatrix} x_f & x_v & \dot{x}_v \end{bmatrix}^T$ is the state vector;

$u_k = [\Delta i]$ is the input;

$z_k = \begin{bmatrix} x_f & x_v \end{bmatrix}^T$ is the output;

$$A = \begin{bmatrix} 0 & -r/(r+b) & 0 \\ K_{qp} ts / 2A_v & 1 & ts/2 \\ K_{qp}/A_v & 0 & 0 \end{bmatrix};$$

$$B = \begin{bmatrix} rK_t/(K_f(r+b)^2) & 0 & 0 \end{bmatrix};$$

$$H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix};$$

ts is the sampling time;

and w_{k-1}, v_k are the process and measurement noise.

In order to present the proposed method, the procedures are illustrated using three augmented models similar to those in (Chze & Inseok, 2014) associated to stationary trend, linear trend and second order polynomial trend of the degradation parameter. The degradation parameter chosen to be evaluated is the flow gain of the flapper valve (K_{qp}) and its decrease relates to clogging of the nozzle line. In order to estimate this parameter, some augmented state space system are considered. Notice that by putting the degradation parameter in the state vector, the model becomes non linear, since this parameter multiplies a state parameter (x_f) requiring the implementation of a modified version of the Kalman Filter. To accomplish that a bank of Extended Kalman Filter was implemented. The three augmented models are given in what follows:

1) Stationary degradation ($K_{qp_k} = K_{qp_{k-1}}$):

$$x_{stat\,k} = \begin{bmatrix} x_f & x_v & \dot{x}_v & K_{qp} \end{bmatrix}^T$$

$$z_{stat\,k} = z_k$$

$$A_{stat\,k} = \begin{bmatrix} 0 & \frac{-r}{r+b} & 0 & 0 \\ \frac{K_{qp0} ts}{2A_v} & 1 & \frac{ts}{2} & 0 \\ \frac{K_{qp0}}{A_v} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_{stat\,k} = \begin{bmatrix} \frac{rK_t}{K_f(r+b)^2} & 0 & 0 & 0 \end{bmatrix}$$

$$H_{stat\,k} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

2) Linear degradation ($\dot{K}_{qp_k} = \dot{K}_{qp_{k-1}}$):

$$x_{lin\,k} = \begin{bmatrix} x_f & x_v & \dot{x}_v & K_{qp} & \dot{K}_{qp} \end{bmatrix}^T$$

$$z_{lin\,k} = z_k$$

$$A_{lin\,k} = \begin{bmatrix} 0 & \frac{-r}{r+b} & 0 & 0 & 0 \\ \frac{K_{qp0} ts}{2A_v} & 1 & \frac{ts}{2} & 0 & 0 \\ \frac{K_{qp0}}{A_v} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & ts \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_{lin\,k} = \begin{bmatrix} \frac{rK_t}{K_f(r+b)^2} & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$H_{lin\,k} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

3) Polynomial degradation ($\ddot{K}_{qp_k} = \ddot{K}_{qp_{k-1}}$):

$$x_{pol\,k} = \begin{bmatrix} x_f & x_v & \dot{x}_v & K_{qp} & \dot{K}_{qp} & \ddot{K}_{qp} \end{bmatrix}^T$$

$$z_{pol\,k} = z_k$$

$$A_{pol\,k} = \begin{bmatrix} 0 & \frac{-r}{r+b} & 0 & 0 & 0 & 0 \\ \frac{K_{qp0} ts}{2A_v} & 1 & \frac{ts}{2} & 0 & 0 & 0 \\ \frac{K_{qp0}}{A_v} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & ts & 0 \\ 0 & 0 & 0 & 0 & 1 & ts \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_{pol\,k} = \begin{bmatrix} \frac{rK_t}{K_f(r+b)^2} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$H_{lin_k} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The Jacobian matrices (required for the Extended Kalman Filter process) containing the partial derivatives of A are given below.

$$dA_{stat\,k} = \begin{bmatrix} 0 & \frac{-r}{r+b} & 0 & 0 \\ \frac{K_{qp0}ts}{2A_v} & 1 & \frac{ts}{2} & \frac{x_{f0}ts}{2A_v} \\ \frac{K_{qp0}}{A_v} & 0 & 0 & \frac{x_{f0}}{A_v} \\ 0 & 0 & 0 & 1 \end{bmatrix};$$

$$dA_{lin\,k} = \begin{bmatrix} 0 & \frac{-r}{r+b} & 0 & 0 & 0 \\ \frac{K_{qp0}ts}{2A_v} & 1 & \frac{ts}{2} & \frac{x_{f0}ts}{2A_v} & 0 \\ \frac{K_{qp0}}{A_v} & 0 & 0 & \frac{x_{f0}}{A_v} & 0 \\ 0 & 0 & 0 & 1 & ts \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix};$$

$$dA_{pol\,k} = \begin{bmatrix} 0 & \frac{-r}{r+b} & 0 & 0 & 0 & 0 \\ \frac{K_{qp0}ts}{2A_v} & 1 & \frac{ts}{2} & \frac{x_{f0}ts}{2A_v} & 0 & 0 \\ \frac{K_{qp0}}{A_v} & 0 & 0 & \frac{x_{f0}}{A_v} & 0 & 0 \\ 0 & 0 & 0 & 1 & ts & 0 \\ 0 & 0 & 0 & 0 & 1 & ts \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

4. INTERACTIVE MULTIPLE-MODEL ALGORITHM

The IMM algorithm (Blom & Bar-Shalom, 1988) reinitializes each model with a weighted sum of the updated estimates from every model based on probabilities estimations of each model. This process is called merging and it reduces its computational complexity to M where M is the number of models used in the algorithm, which in this case is 3. An illustration of the IMM model switching process is described in Figure 4. The interaction between the models depends on the switching probabilities and the likelihood of each of the model. The IMM result is a combined state vector that is the sum of the state vectors for each of the modes weighted by their model probabilities.

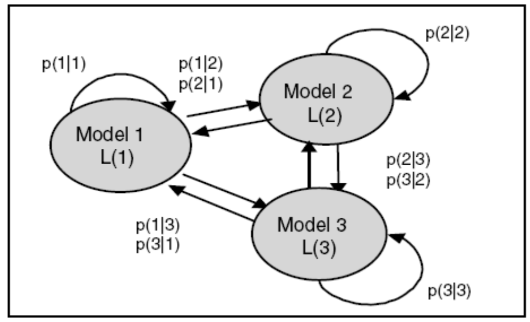

Figure 4: IMM model switching process (Farmer, Hsu & Jain, 2002).

The estimation of each switching probability and model likelihood is described below where a single cycle of the IMM algorithm is given (Eq.(6) to Eq.(14)). It consists of 4 steps: reinitialization where mixing estimates and variances are estimated for each model; the filtering process itself also for each model and considering the mixed estimates; probabilities and likelihood updates and finally estimate fusion resulting in a single state estimation.

1) Model-conditioned reinitialization (for $i = 1,2...M$):

1a. Predicted mode probability:

$$\mu^i_{k|k-1} = \sum_{j\in M} \pi_{ji}\mu^j_{k-1} \tag{6}$$

1b. Mixing weight

$$\mu^{j|i}_{k-1} = \frac{\pi_{ji}\mu^j_{k-1}}{\mu^i_{k|k-1}} \tag{7}$$

1c. Mixing estimate:

$$\bar{x}^i_{k-1|k-1} = \sum_{j\in M} \hat{x}^j_{k-1|k-1}\mu^{j|i}_{k-1} \tag{8}$$

1d. Mixing covariance:

$$\bar{P}^i_{k-1|k-1} = [\sum_{j\in M} P^j_{k-1|k-1} + (\bar{x}^i_{k-1|k-1} - \hat{x}^j_{k-1|k-1}) \\ - \hat{x}^j_{k-1|k-1})]'\mu^{j|i}_{k-1} \tag{9}$$

2)Model-conditioned filtering (for $i = 1,2...M$):

$$(\bar{x}^i_{k-1|k-1}, \bar{P}^i_{k-1|k-1}) \rightarrow (\hat{x}^i_{k|k}, P^i_{k|k}, \tilde{z}^i_k, S^i_k) \tag{10}$$

3)Mode probability update:

3a. Model likelihood:

$$L_k^i = N(\tilde{z}_k^i; 0, S_k^i) \tag{11}$$

3b. Model probability

$$\mu_k^i = \frac{\mu_{k|k-1}^i L_k^i}{\sum_{j \in M} \mu_{k|k-1}^j L_k^j} \tag{12}$$

4)Estimate fusion:

4a. Overall estimate:

$$\hat{x}_{k|k} = \sum_{i \in M} \hat{x}_{k|k}^i \mu_k^i \tag{13}$$

4b. Overall covariance:

$$P_{k|k} = \sum_{i \in M} \left[P_{k|k}^i + (\hat{x}_{k|k} - \hat{x}_{k|k}^i)(\hat{x}_{k|k} - \hat{x}_{k|k}^i)' \right] \mu_k^i \tag{14}$$

in which:

π_{ji} is the model transition probability;

μ_k is the probability of each model;

L_k is the likelihood of each model;

M is the number of models, which in this case is 3.

A summary of the IMM algorithm is illustrated in Figure 5.

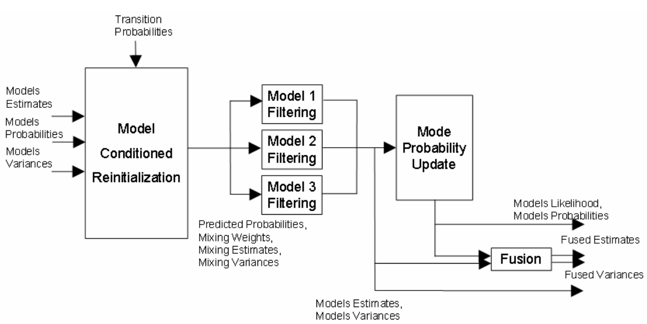

Figure 5: IMM process

Eq. (10) represents the Extended Kalman filter detailed by the following process:

1) Time Update:

$$\hat{x}^-_{aug\,k} = A_{aug\,k} \hat{x}_{aug\,k-1} + B_{aug\,k} u_k \tag{15}$$

$$P^-_{aug\,k} = dA_{aug\,k} P_{aug\,k-1} dA_{aug\,k}' + Q_{aug\,k} \tag{16}$$

2) Measurement Update:

$$S_{aug\,k} = H_{aug\,k} P^-_{aug\,k} H_{aug\,k}' + R_{aug\,k} \tag{17}$$

$$K_{aug\,k} = P^-_{aug\,k} H_{aug\,k}' \left(S_{aug\,k} \right)^{-1} \tag{18}$$

$$\hat{x}_{aug\,k} = \hat{x}^-_{aug\,k} + K_{aug\,k} \left(z_{aug\,k} - H_{aug\,k} \hat{x}^-_{aug\,k} \right) \tag{19}$$

$$P_{aug\,k} = \left(I - K_{aug\,k} H_{aug\,k} \right) P^-_{aug\,k} \tag{20}$$

in which:

$K_{aug\,k}$ is the Kalman gain;

$P_{aug\,k}$ is the covariance matrix of the state estimates.

As an example, the estimations of the EKF states with stationary trend of the degradation parameter and the same sinusoidal input current in Figure 3 is given in Figure 6.

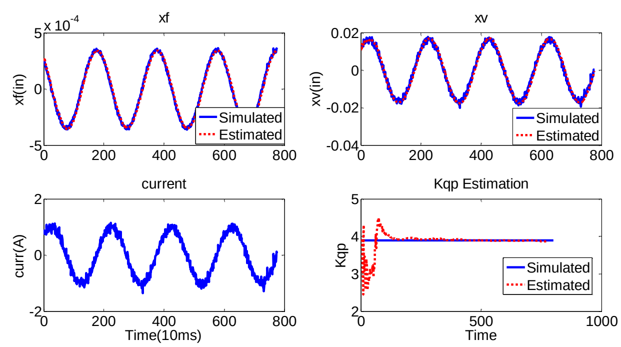

Figure 6: EKF estimations

5. RESULTS

In order to evaluate the IMM method, four degradation trends were evaluated, a stationary one, a linear one, a polynomial one and another containing a combination of the three last ones. Figure 7 shows these input trends.

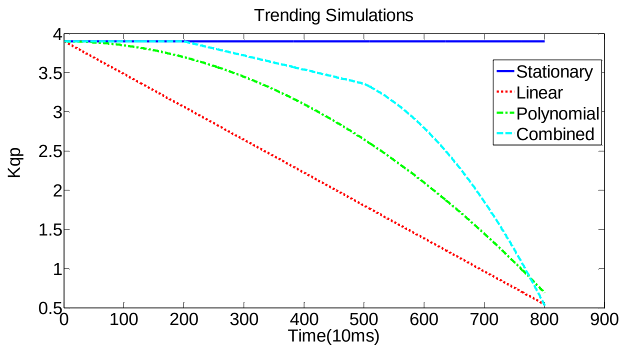

Figure 7: Degradation trends

All these trends were combined with the same sinusoidal current input from Figure 3 and submitted to all three filters (stationary, linear and polynomial) described previously using the conventional EKF as well as the IMM described in last topic. For all simulations the IMM transition probability matrix used is:

$$\pi = \begin{bmatrix} 0.998 & 0.001 & 0.001 \\ 0.001 & 0.998 & 0.001 \\ 0.001 & 0.001 & 0.998 \end{bmatrix}$$

The degradation parameter estimations are given in Figure 8, Figure 9 and Figure 10.

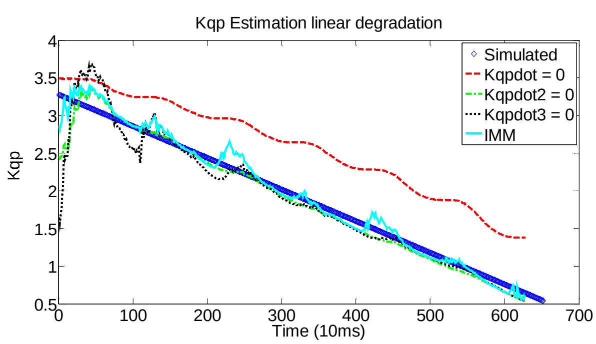

Figure 8: Estimations for linear degradation

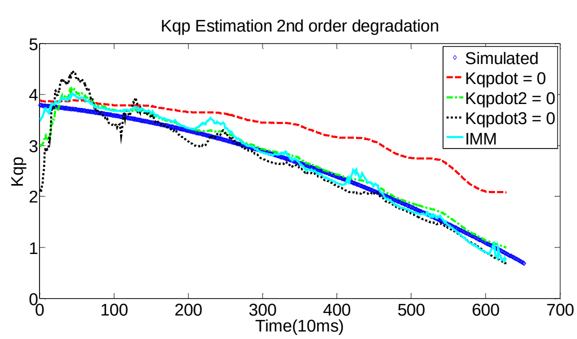

Figure 9: Estimations for polynomial degradation

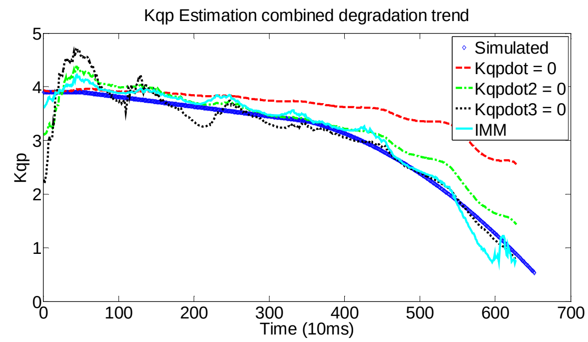

Figure 10: Estimations for combined degradation trends

It is possible to see from these results how lower order models could not estimate properly degradations submitted to higher order variations (i.e. red dashed line).

The probability of each trend estimated in the IMM method are given in Figure 11, Figure 12, Figure 13 and Figure 14. As mentioned before these probabilities are used in the IMM fusion step in Eq. (13) and Eq. (14) as weighting factors to estimate the resulting states from all three models estimations.

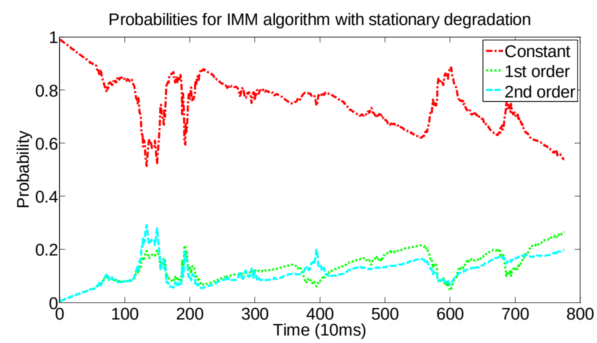

Figure11: Probabilities for stationary degradation simulation

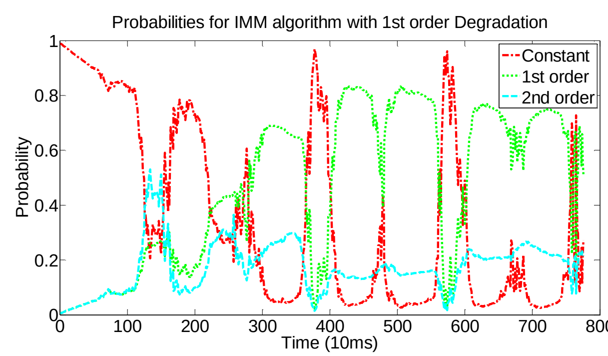

Figure 12: Probabilities for linear degradation simulation

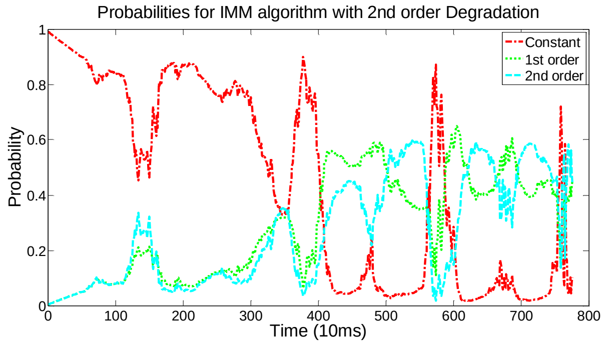

Figure 13: Probabilities for polynomial degradation simulation

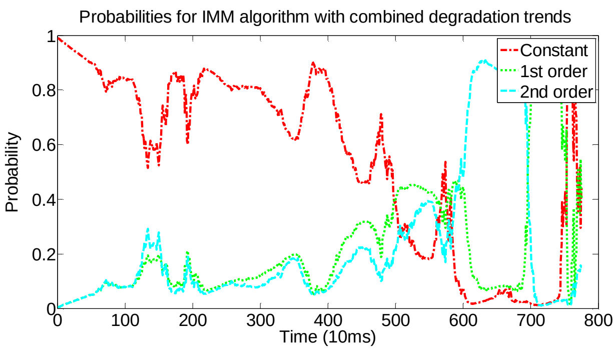

Figure 14: Probabilities for combined degradation simulation

Figure 11 (stationary simulation) shows as expected a predominance of the stationary model probability for stationary simulation. Figure 12 (linear degradation simulation) shows a predominance of the linear model, although during some small intervals the stationary model had higher probability. Figure 13 (2^{nd} order degradation simulation) could predict correctly the increased probability in only some intervals at the 2^{nd} half of the simulation. Figure 14 (combined trend) could predict correctly the stationary trend (higher probability for the initial interval) but could not distinguish properly between linear and polynomial trend for the 2^{nd} half of the simulation. From all these results it is possible to observe that higher the order of the degradation trend, more difficult is to distinguish between them.

In order to compare the precision of all filters from all degradation trends, the mean square error (MSE) between the simulated degradation parameter and its estimation from all simulation frame were estimated. Table 1 shows the results, where each row contain the filtering model (stationary, linear, polynomial and the IMM respectively) and each column the simulation performed (stationary, linear, polynomial and the combination trend as in Figure 6).

Table 1. MSE summary.

		Simulation			
		Stationary	Linear	Polynomial	Combined
Model	Stationary	0.0568	0.3865	0.4674	0.4498
	Linear	0.1011	0.0895	0.1014	0.1426
	Polynomial	0.1816	0.1602	0.0806	0.1832
	IMM	0.0643	0.0939	0.0929	0.0835

As expected, the MSE corresponding to the stationary trend was lower for the stationary model, the MSE of the linear trend for the linear model and the MSE of the polynomial trend for the polynomial model. For the combined trend, the IMM had the lowest MSE proving its effectiveness to deal with multiple evolutionary degradation trends. Also it performed well for the other non-combined trends.

6. CONCLUSIONS

The present work showed an application of an Interactive Multiple Model for on-line degradation estimation of a single failure (nozzle clogging) of the first stage of a two stage flapper nozzle hydraulic servovalve. To accomplish that, three augmented states models were built from the valve model considering stationary, linear and polynomial trend of the degradation parameter. After building these models the IMM could be implemented.

The evaluation of the IMM was done considering four different degradation trends: stationary, linear, polynomial and combination of all previous ones. Together with the IMM, conventional EKF was applied to all simulations considering all three models. Results showed that the IMM had a better estimation for the combination trend while the stationary model for the stationary trend, linear model for the linear trend and the polynomial model for polynomial trend.

It is possible to conclude from this work that the IMM algorithm successfully estimated degradations from the servovalve model relating correctly the probabilities of each model, specially when dealing to a combination of different degradation trends.

The main benefit of using the method proposed in this paper is the possibility to have an on line health monitoring of the component with fast response to degradation variations. Applications may include systems that requires quick decisions for fast degradation evolutions such as reconfiguration systems for transmission lines power grids, flight controls reconfiguration systems and launch vehicle abort trigger.

Improvements in this work includes investigating this method with different components (i.e. actuators) as well as other failure modes, also evaluating other multiple models algorithms such as the Generalized Pseudo-Bayesian of second-order (GPB2) and applications using field data.

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