# Sensor Reliability-through Fault Diagnosis

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***Abstract*—Sensor Reliability is important for control system effectiveness. Knowing the health of sensor can allow early replacement before serious safety violations happen. Redundant measurements are used to generate measurements and comparison with threshold allows diagnosis. In this paper, a state space model of an Induction motor and sensor measurements is built upon which offset and drift faults are simulated. A diagnostic strategy is presented that also reports the offset and drift values. Simulation results are presented to quantify effectiveness of method. Similarly, another diagnostic system is built using Support Vector Machine for Air Traffic Controller Sensors. Simulations results show that larger offset and drift faults are detected with higher probability.**

***Index Terms*—diagnosis, threshold, offset, drift, Support Vector Machine**

## I. INTRODUCTION

In control intensive applications, the demand for reliable sensors is increasing. Effectiveness of control systems is heavily dependant upon feedback sensor measurements. In safety critical applications, multiple sensors are used and weighted average of measurements gives a value closer to true value (figure 1). However, sensors are prone to faults. By correctly identifying one or more sensors as faulty, they can be replaced or not used at all in calculations, thus increasing robustness. Hence, its important to study and evaluate the effectiveness of a diagnostic system for sensor health monitoring. International Standards require failure rates to be kept minimum for safety certification of a system, this results in having to live some false alarm. Hence, building effective diagnostic strategy with minimal false alarm and higher detection of faults is budding area of research.

The basic idea behind diagnosis is comparing the difference between two measurements (figure 1) with threshold as in [1], where theoretical method to calculate diagnostic coverage and false alarm rate is presented. Deciding the threshold itself presents a trade-off between false alarm rate and probability of fault detection. Lower threshold gives higher probability of detection but also higher alarm rate which is expensive. To illustrate this, let $X_0$ be the sensor measurement from an ideal sensor and a control intensive application requires reported measurement to be within some range $X_0 \pm \Delta X_s$. The ideal sensor cannot be realised but consider two non ideal sensors with measurements as $X_1$ and $X_2$. Suppose the systematic offset in $X_1$ and $X_2$ is $\Delta X_1$ and $\Delta X_2$ respectively. The systematic offset is caused due to imperfect calibration and quantisation error. However it is very small and generally not

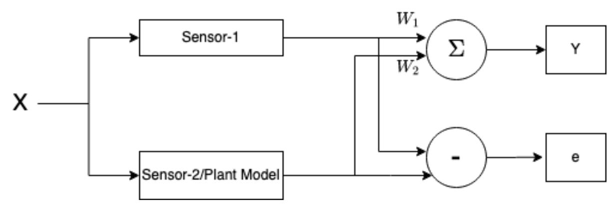


Fig. 1. Redundancy

a problem. In the analog circuitry of $X_1$, if a fault occurs, it would cause measurement $X_1$ to deviate from its value. Figure 2 illustrates this. Faults that cause reported measurements of $X_1$ beyond safe limits are classified as dangerous faults. Detection of these faults can initiate appropriate action before failure of system happens. The diagnostic strategy utilises measurement $X_2$ and flags a fault if the difference $|X_1 - X_2| > \epsilon$. [2] goes further on this approach of modelling faults by the probability distribution of deviations to calculate metrics of diagnostic system and effect of choosing thresholds. However, this approach is very theoretical and serves as a good start but one may still need experimental or simulation results to verify.

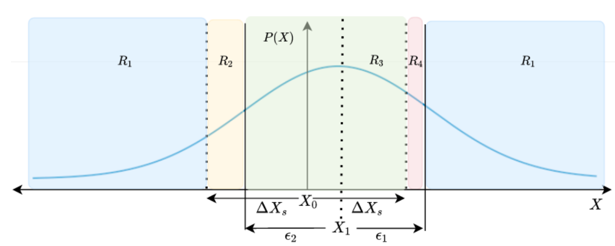


Fig. 2. Effect of choosing threshold on Alarm Rates

$$\begin{aligned} \epsilon_1 + \epsilon_2 &= 2\epsilon, \\ \epsilon_1 &= \epsilon + \Delta X_2 - \Delta X_1 \end{aligned} \tag{1}$$

In figure 2, Region $R_1$ refers to dangerous but detected faults. $R_2$ represents false alarm, $R_3$ represents safe faults that are not flagged as error, $R_4$ represents Faults that are dangerous and undetected. By tightening $\epsilon$, $R_4$ shrinks at the cost of expanding $R_2$.

The fault diagnostic methods can be broadly classified as analytical redundancy and data driven approach. In [3], a DC-

DC boost converter model is used to generate a redundant measurement of inductor current which is used to diagnose current sensor. However, the effects of noise on degrading performance of diagnosis were not considered. In [4], Kalman filter is used to generate redundant measurements. As the system becomes complex, it becomes difficult to model the system and effect of sensor faults analytically, hence some other data driven approaches have to be used. [5] employs support vector regression to generate redundant measurements based on other sensor data. [6] uses training data to train a Support Vector Classifier to diagnose sensor, and also provide experimental data about performance of the Classifier.

We study the two approaches with two case studies. In section 2, analytical redundancy is used to develop a diagnostic strategy on an Induction Motor State Space Model. In Section 3, data driven approach is used to build a Support Vector Classifier for Air Traffic Controller sensors.

## II. Induction Motor Sensor:Analytical Approach

A noisy state space and measurement model of an Induction Motor was built in python based on [7]. The motor model is simulated using RK-4th order method. The estimation of speed of motor is done by Extended Kalman filter.

$$\begin{aligned} \frac{dX}{dt} &= f(X,U) + W, \\ Y &= g(X) + V. \end{aligned} \tag{2}$$

$X$ is vector of states, $Y$ is measurment, $U$ is input and $Y$ is measurement. $W$, $V$ are zero mean Gaussian random variables that represent model uncertainty and measurement noise.

In this study we study two kinds of faults in sensors, Offset and Drift, which can be modelled as

$$\begin{aligned} Y_{offset} &= g(X) + Ku(t-t_0) + V, \\ Y_{drift} &= g(X) + mtu(t-t_0) + V \end{aligned} \tag{3}$$

$K$ is offset, $m$ is drift slope and $u(t)$ is unit step function. We consider fault in one sensor. The induction motor model is simulated with dynamic input i.e. varying $U$. Figure 3 Illustrates sensor measurements for three cases-(a) healthy sensor, (b) offset, (c) Drift

Such errors decrease accuracy of estimated states. To diagnose such faults, a diagnostic strategy is proposed as follows: In real time, run a noise free state space model in parallel with actual motor simply using Euler-Method and generate noise free measurements from the same using sensor model. This generates one error signal. Along with this, another error signal i.e. Kalman Prediction Error is utilised. Figure 4 illustrates the two error signals. The two error signals are smoothed by averaging last 400 samples and difference of the two smoothed error signals is generated (figure 5)

In real time, a zero cross detector measures the time since last zero crossing. If the time exceeds a limit of 40, then its flagged as fault. Further, after flagging fault, continuous average is taken and if it remains constant its reported as offset

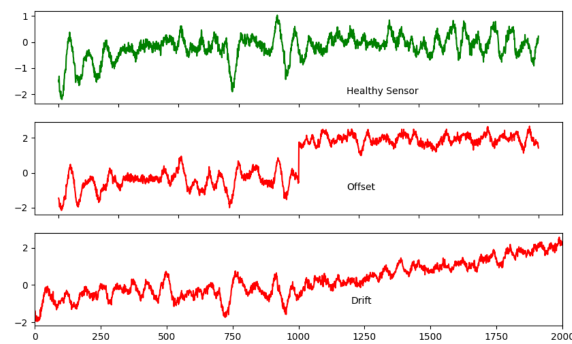


Fig. 3. Sensor Measurements

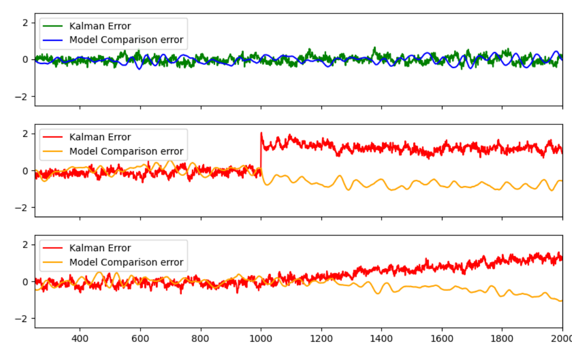


Fig. 4. Error Signals

otherwise we calculate its slope and report drift coefficient (figure 5). To verify the the performance, for some offset values, 100 simulations were done and average reported offset value was calculated and similarly was done for drift (Figure 6).

Though, the offset and drift may seem to be estimated very accurately, it is due to average of many measurements. Hence, to determine offset or drift very accurately, repeated analysis on the same sensor maybe required. The reported values are on average slightly lower than actual values. This is because, Kalman error prediction gives some weight to sensor measurement hence these error predictions would be biased slightly but this effect is negligible. It was observed that for lower offset values, rate of detection was lower (figure 7) and reported values had a larger deviation. This is expected since the random noise effect dominate at these values. Also, low detection rate for smaller values (figure 7) is consistent with figure 2, since faults that would cause $X_1$ to be deviated more (region $R_1$) are easier to detect than those causing $X$ to lie in region $R_4$. For no offset, 99 out of 100 times, flag wasn't raised. This process however is cumbersome, especially when having to decide thresholds but it is suitable where computational resources are constrained.

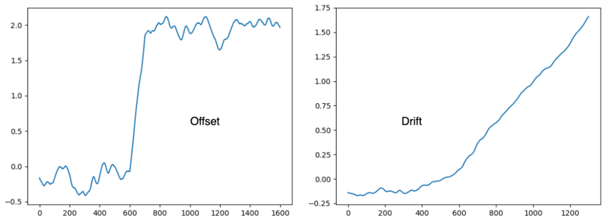


Fig. 5. Smoothed difference of error signals

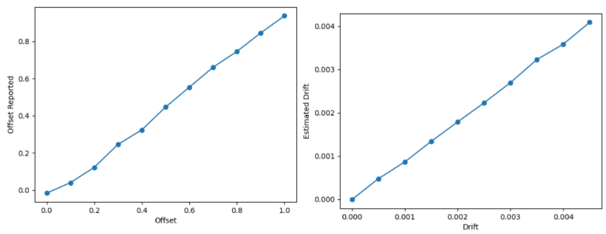


Fig. 6. Measured vs Actual Fault Values

## III. Air Traffic Controller

Computational resource are generally not constrained at an airport. However, safety standards are extremely stringent and lot of sensors are employed. For large number of sensors, the process of arriving at a diagnostic strategy manually becomes extremely difficult. Therefore, we shall deploy a Support Vector Classifier to identify if a sensor has gone bad. A state space model of a plane circling an airport and associated measurements of its distance, azimuth and elevation angles were made using a sensor model [8]. Similar to figure 3, faulty simulations were done for offset and drift. For a given offset, total of 100 simulations for healthy and 100 for faulty sensors was done, and error computed comparing with noise free state space simulation. On the error signal 10 features were extracted as was done in [6]. These features being -root mean square, square root of amplitude, kurtosis value, skewness value, peak to peak value, crest factor, impulse factor, marginal factor, shape factor , and kurtosis factor. The generated data was used to train a Support Vector Model with 60-40 train-test ratio. The last step was executed 1000 times, with different combinations of train-test data samples. In each step accuracy of the SVM was calculated and average of all 1000 accuracies was used to generate figure 8. The similar procedure was employed for drift faults.

From Figure 8, increasing fault value increases probability of detection. The sensor classified as faulty can be replaced with a healthier one before estimated state error exceeds the safe limits (Figure 2).

## IV. Conclusions

In this paper, analytical and data based diagnostic strategies were developed and their performance was evaluated. For applications that are restricted in resources, pre-determined analytical strategies can be employed which are computationally

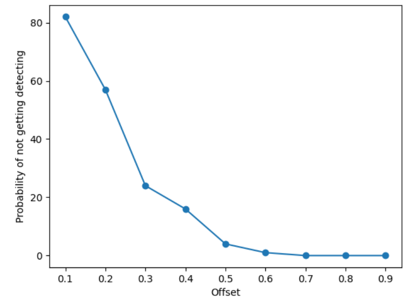


Fig. 7. Offset diagnosis detection probability

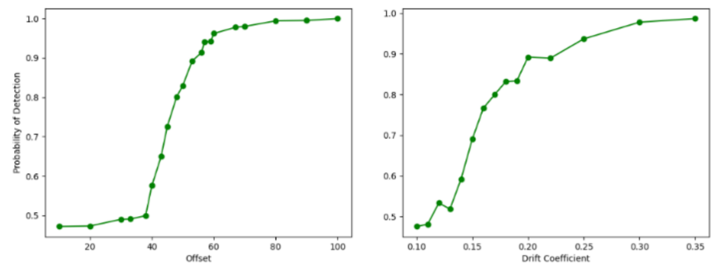


Fig. 8. Performance of Support Vector Classifier

light and happen in real time. They have a disadvantage of being very system specific and cumbersome to develop. On the other hand, data driven strategies, are easy to implement and are suitable for large complex systems where safety is much more critical than cost.

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