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Estimation of the remaining useful life of sensor and actuator component embedded in a complex mechanical system

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Abstract
In this paper, a Kalman Filter-based Bayesian model have been proposed for the estimation and simulation of the remaining useful life of a sensor and actuator components embedded in a complex mechanical system that is subjected to harsh operational and environmental conditions. Results from the simulations shows that, in the absence of process noise in the components, the output value for the remaining useful life decreases steadily over time. However, when the sensor and actuator components are exposed to a quantify process noise, the simulated results show a drastic shift from normal. It can therefore be concluded that when the sensor and actuator components are subjected to the harsh operational and environmental conditions their remaining useful life becomes irregular and sometime unpredictable, hence precaution should be taking to avoid process noise as much as possible in sensor and actuator component.

Keywords: *Kalman filter-based Bayesian model, Sensor and actuator component, Process noise, Remaining useful life*

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1. Introduction

The need to increase the competitiveness of industrial systems, demands that the maintenance cost is reduced, without compromising safety in the industrial system's operations (Aikhuele et al., 2020). Forecasting the future behavior of a component or systems allows more serious maintenance planning, cost savings, and the prevention of unexpected downtime and repairs. Although the cost of unexpected downtime is much higher than the cost of performing repairs and returning component or systems to its initial service condition (Tabikh, 2014). Generally, the prediction of future failures or system behavior, provides the important information needed for strategic decision-making in the industrial systems (Aikhuele, 2021b).

Condition-based maintenance (CBM) which is an effective maintenance model used for future system failure behavior evaluation, involves a real-time analysis of equipment sensor data, and could help in the maintenance and condition planning for the remaining useful life (Verbert et al., 2017). The maintenance activities which are performed on the basis of necessity (Aikhuele, 2021a), provide opportunities for authentic learning. These learning however, could be grouped into, failure learning where the root cause of failure of the system is determined through a special program where manufacturer learn from mistakes with the purpose of improving the overall system. And through a repetitive learning, which can be described from the point of the repetitive nature of preventive maintenance (PM) strategy, where manufacturer gains knowledge, experience and learns to perform the PM activities faster at a reduced cost (Tarakci, 2015).

In using the condition-based maintenance model, a deterioration indicator that correctly describes the dynamic nature of the failure process is evaluated and obtained. The evaluation is based on information collected on the various deterioration-related parameters of the system, which include, vibration, temperature, pressure, noise levels and the type of lubricating oil used (Liu et al., 2021). Although several studies have investigated the different modelling approaches for the deterioration indicator of industrial systems, however, there are still opportunity for the design of a progressive monitoring approach and model for systems with dynamic operating condition and a high monitoring cost. Based on this preposition, industrial systems can be efficiently monitored to track their real-time health status during operation, the gained data are then processed to extract relevant features associated with the degradation condition of the system/components (Biggio and Kastanis, 2020). Sensor and actuator which are a very important part of the industrial systems and with a dynamic operating condition, gives an interesting research problem (Valade et al., 2017). They are composed of electronic, electrical and mechanical subsystems which result in implicit failure effects and modes. Any fault leading to failure in these sub-systems needs to be efficiently identified, detected and isolated using a limited set of signals available (Coble, 2010; Hasan and Johansen, 2018), also it is important that their remaining useful life are estimated and monitored through a simple and cost effective predictive approach.

Sensors and actuators are essential elements of embedded system that are used for monitoring and measuring the continuous and discrete process variable and parameters of a system (Zyrianoff et al., 2020). They are located at the most remote part of a system and are mainly subjected to a very harsh operational and environmental conditions like high heat, freezing temperature, moisture, mechanical tire and wear and vibration (Moore et al., 2020). It is on this basis therefore, that this study seeks to evaluate the remaining useful life estimates of the actuators and sensors system by using Kalman Filter-based Bayesian model where the different harsh operational and environmental conditions are considered.

2. Materials and methods

2. Kalman filter-based Bayesian model

The Kalman filtering method which is based on statistics and control theory assumptions, can be referred to as a linear quadratic estimation (LQE) of a statistical and control systems (Baltieri and Buckley, 2020). Its algorithm uses a series of measurements that contain statistical noise and other inaccuracies taken over time to produce estimates of unknown variables that are more accurate than those that are based on a single measurement (Aditya et al., 2018). This is accomplished by calculating a joint probability distribution for each timeframe's variables. The Kalman filter works well for analyzing the behavior of systems that change or grow over time. It is useful in circumstances where we may have ambiguous information (e.g., statistical noise and other inaccuracies) regarding the current state of a system in order to estimate information about how the system will look in the future (say, in the next state) (Akram et al., 2019; Li et al., 2015).

It is possible to estimate the future state k, by capturing specific correlations in the processes relevant to the system based on its current state, say $t = k - 1$. If we assume that a quantity y is observed over time, and the observed quantity is represented with the data $y_1, y_1, \ldots, y_n$, it can therefore be said that it fits into a simple linear regression model as shown in Equation (1).

$$y_i = \theta_1 + \theta_2 t_i + \epsilon_i \tag{1}$$

where $\epsilon_i \sim N(0, v^2)$ and is given as the random noise that is added to the linear regression model, the epsilons are sampled independently from a normal distribution with a zero mean and variance v^2. The time of observation is given as $t_1 < t_2 \ldots t_n$. If a simple construct is consider such that the data is represented as H and the parameter as θ, then they can be defined as $H_i = [1, t_i]\ and\ \theta = \begin{bmatrix}\theta_1 \\ \theta_2\end{bmatrix}$ respectively, where the observed values of the quantity y is defined as being sampled from a normal distribution, $y_i \sim N(H_i\theta, v^2)$. If an independent and identically distributed observations are considered, the likelihood of y given the parameter θ, for which $i = (0,1,2, \ldots, n)$, follows the normal distribution as a joint condition over all the observations, this is given as a product (Equation (2)).

$$p(y|\theta) = \prod_{i=1}^{n} (2\pi v^2)^{-1/2} \exp\left(-\frac{1}{2v^2}\ (y_i - H_i\theta)\right) \tag{2}$$

Without loss of generality, $p(y|\theta)$ can be further extended, such that the dataset with n points are given using the matrix in the form of a Bayesian notations.

$$y|\theta \sim N_n(H\theta, v^2 I_n) \tag{3}$$

where I_n is an n-dimensional identity matrix that applies the likelihood approach of Bayesian model in the Kalman filter method, the Bayesian model is an intuitive technique that involves the improvement of prior understanding of a condition or system, to provides a more certain posterior probability estimate, in the light of new observations of the condition or system. Generally, the Bayesian model (Bayes theorem) can be represented by the formation:

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)} \tag{4}$$

On putting the above Bayesian model in perspective as it relates to the parameter (θ) presented above, then the model can be rewritten as:

$$\begin{matrix} Posterior \\ p(\theta|y) \end{matrix} = \frac{\overset{Likelihood}{p(y|\theta)} \quad . \quad \overset{Prior}{p(\theta)}}{\underset{Marginal\ likelihood}{\int_{\theta=0}^{\theta=1} p(y_i,\theta)d\theta}} \tag{5}$$

which is the intuitive Bayesian model, and can be related to the Kalman filter method. In this sense, the model parameter (θ) is assumed to be dynamic and evolves over time. The mathematical formation of the model parameter is given as:

$$\theta_k = A\theta_{k-1} + qk - 1, \qquad qk - 1 \sim N(0, Q) \tag{6}$$

where q is a random variable drawn from a normal distribution with a mean of zero and a variance of Q. The intuitive Bayesian model which is based on the Kalman filter method can therefore be represented as:

$$\left.\begin{matrix} yk = H_k\theta_k + \epsilon_k & Observation\ model \\ \theta_k = A\theta_{k-1} + r_{k-1} & Signal \end{matrix}\right\} \tag{7}$$

This is a linear state-space model in which the initial component of the signal is observed along with some process noise. This simple model which is used to develop intuition, can be extended to a more sophisticated models that do not have a linear relationship, if sample from the distribution of the system is considered which can be referred to as a filtering problem, then the first and second component of the signal can be reconstructed and estimated.

3. Results and discussion

In this section, the Kalman Filter-based Bayesian model is implemented for the evaluation of the remaining useful life of the sensors and actuator embedded in a complex mechanical system. To achieve the aim of the study, a number of simulations have been carried out to verify the effectiveness of the model. In measuring the performance and remaining useful life of the sensors and actuators systems, several scenarios of process noise (i.e. the harsh operational and environmental conditions in the system) are quantified and simulated, starting with a sensor and actuator component that is not affected with any operational and environmental conditions.

Scenarios 1 - No Process noise

A sensors and actuator component embedded in a mechanical system with no process noise (w) is evaluated using the Kalman Filter-based Bayesian model. If the component has a gain value a=0.85 which is derived from a maximum likelihood estimation, then the output value for the remaining useful life of the component can be simulated. The result of the output value for the remaining useful life of the component decreases steadily when the output gain (h) is set equal to 3, (i.e. h=3), when the measurement noise (v) and when the covariance (R) is set to 1, (i.e. R=1). The simulated result has been shown in the Fig. 1, where the upper left graph consists of the actual (exact) state values which have been heighted in red, the priori estimates in blue – (i.e. the predictor step) and the posteriori estimate in green – (i.e. the corrected step). The initial guess of the state is set at 1.5, while the initial estimate of the a posteriori covariance is set at 1. Similarly, the lower left part of the graph shows the actual error that is between the estimates of the systems and the actual state of the sensor and actuator systems. Finally, the graph on the upper right part shows the calculated covariance, while the graph at the lower right shows the Kalman filter gain.

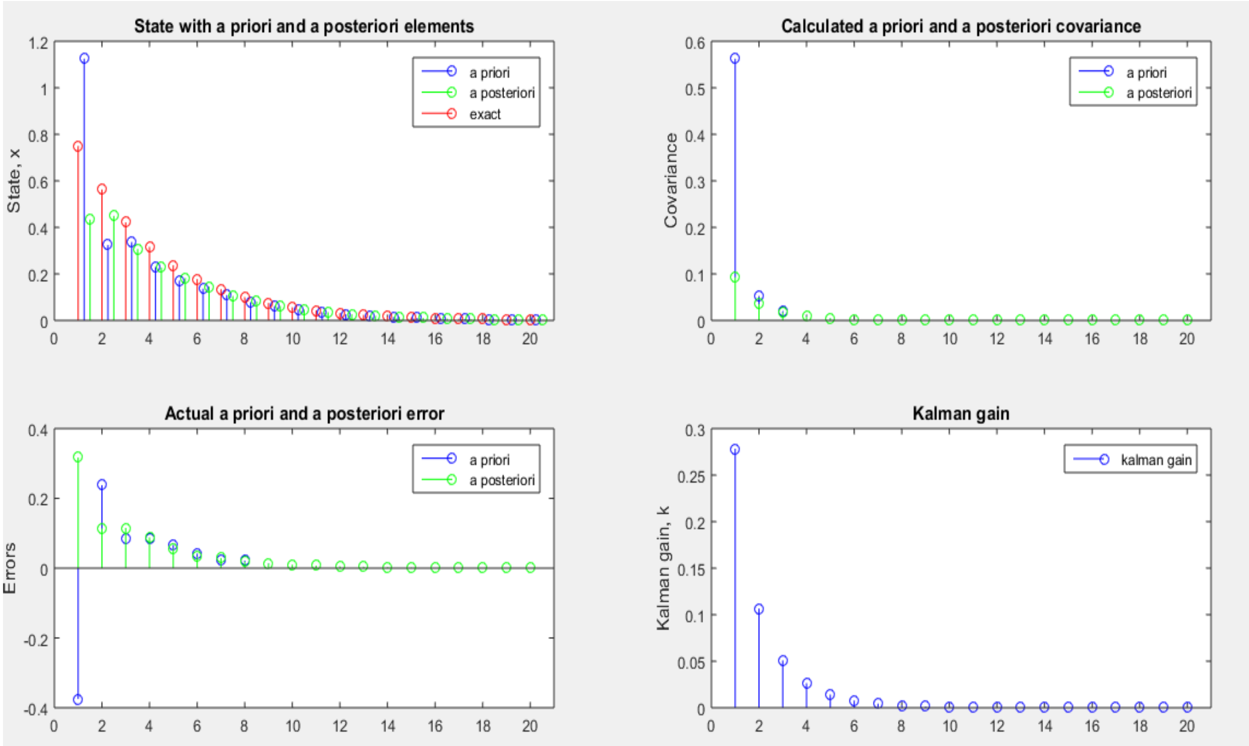

Fig. 1: Remaining useful life of sensor and actuator system with no noise (steady and normal)

Scenarios 2 - Process noise

In this case study, all the parameters associated with the sensor and actuator components are assumed to be constant and the process noise within the system is increased gradually to Q=0.01, such that the linear state-space model becomes dynamic. The simulated results from the dynamic state-space model which has been presented in Fig. 2, show that the present of process noise within the sensor and actuator components, will results in a steady shift from normal in the remaining useful life estimate of the sensor and actuator components. This however, has been captured in the figure as shown in the state with a priori and posteriori elements graph, actual priori and posteriori error, calculated priori and posteriori covariance and the Kalman gain graph.

Scenarios 3 – Increase in the process noise

If the process noise is gradually increased further, which could represent the continuous usage of the sensor and actuator systems over a period of time, when all other parameters associated with the sensor and actuator components are assumed to be constant. Then the results from the simulation, as shown in Fig. 3 is not surprising, as the remaining useful life is expected to further drift from normal when compare with Fig. 1 (no process noise) and Fig. 2 (with a process noise of Q=0.01). Again, from the figure, it is observed that, the posteriori estimate is closer to the exact value at each step than it is in the priori estimate. Also, the calculated priori and posteriori covariance started high, but drop immediately, while in the Kalman gain, it drops and balance up immediately. The remaining useful life estimate of the sensor and actuator components in this case study however, is determined from the priori estimate, since it does not drop as low as in the first case where process noise was removed, or in the second scenario with some amount of process noise.

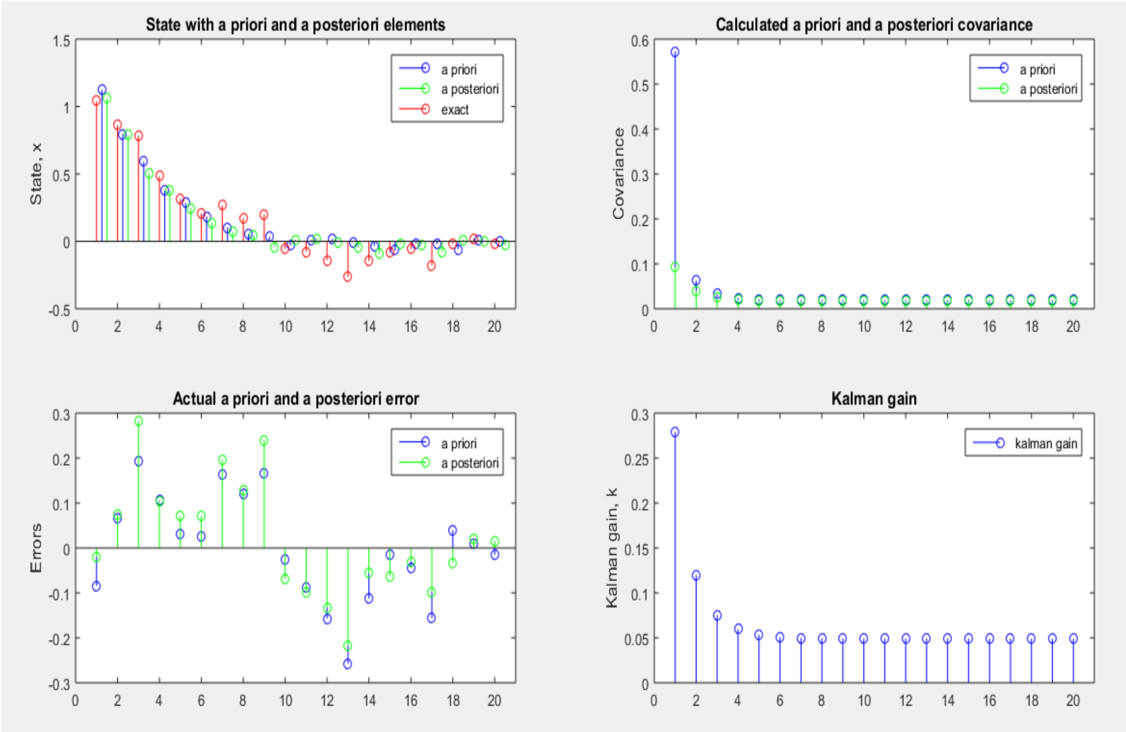

Fig. 2: Remaining useful life of sensor and actuator system with process noise of Q=0.01

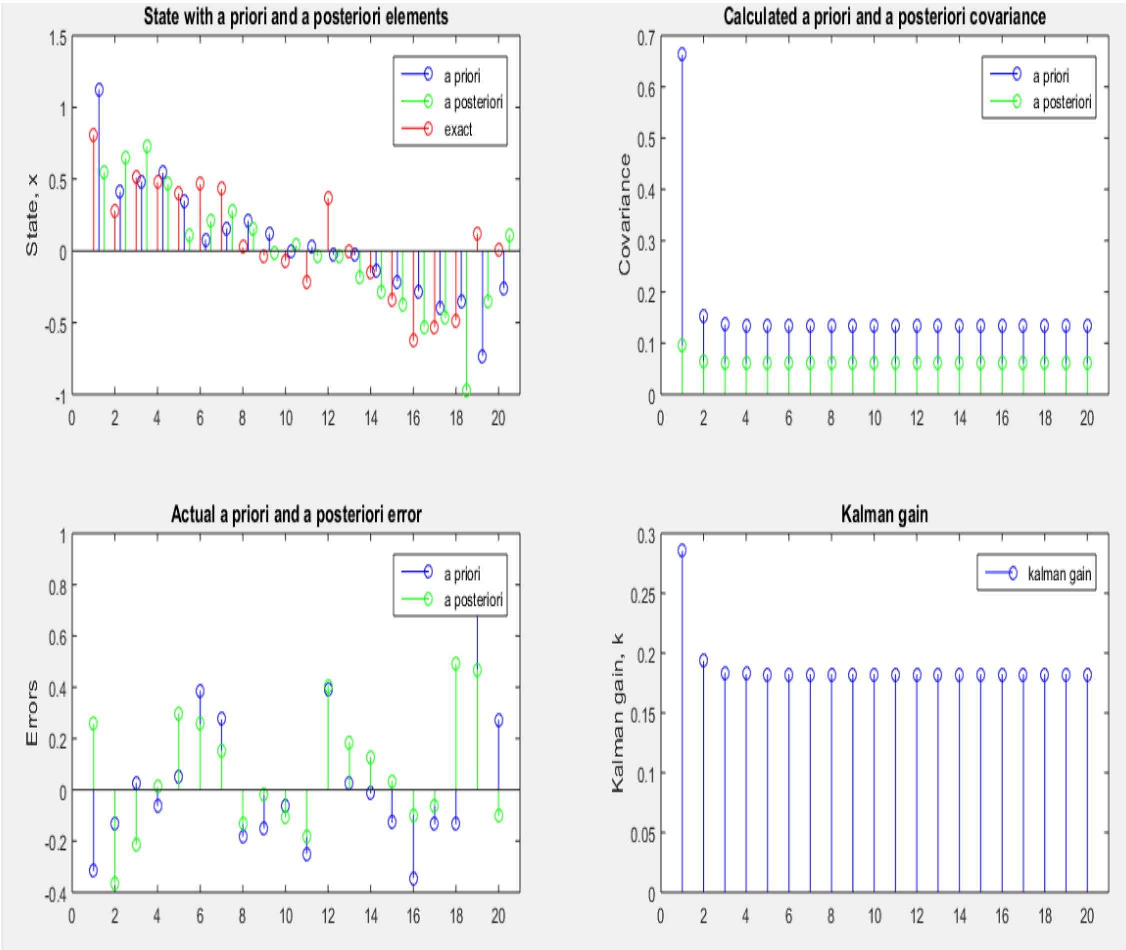

Fig 3: Remaining useful life of sensor and actuator system with process noise of Q=0.1

Scenarios 4 – Increase measurement noise

In this case study, unlike the previous scenarios, the process noise is increased to (Q=2) while the other parameters remain the same. This is mainly to check the flexibility of the parameters and to see if the process noise parameter also has effect on the simulated outcome. From the Fig. 4, it is not hard to see that, the process noise parameter has a lot of effect in the outcome of the remaining useful life simulation of the sensor and actuator system. This result could also be interpreted in the form; if the sensor and actuator components are maintained, monitored or serviced regularly, the remaining useful life of the system could improve.

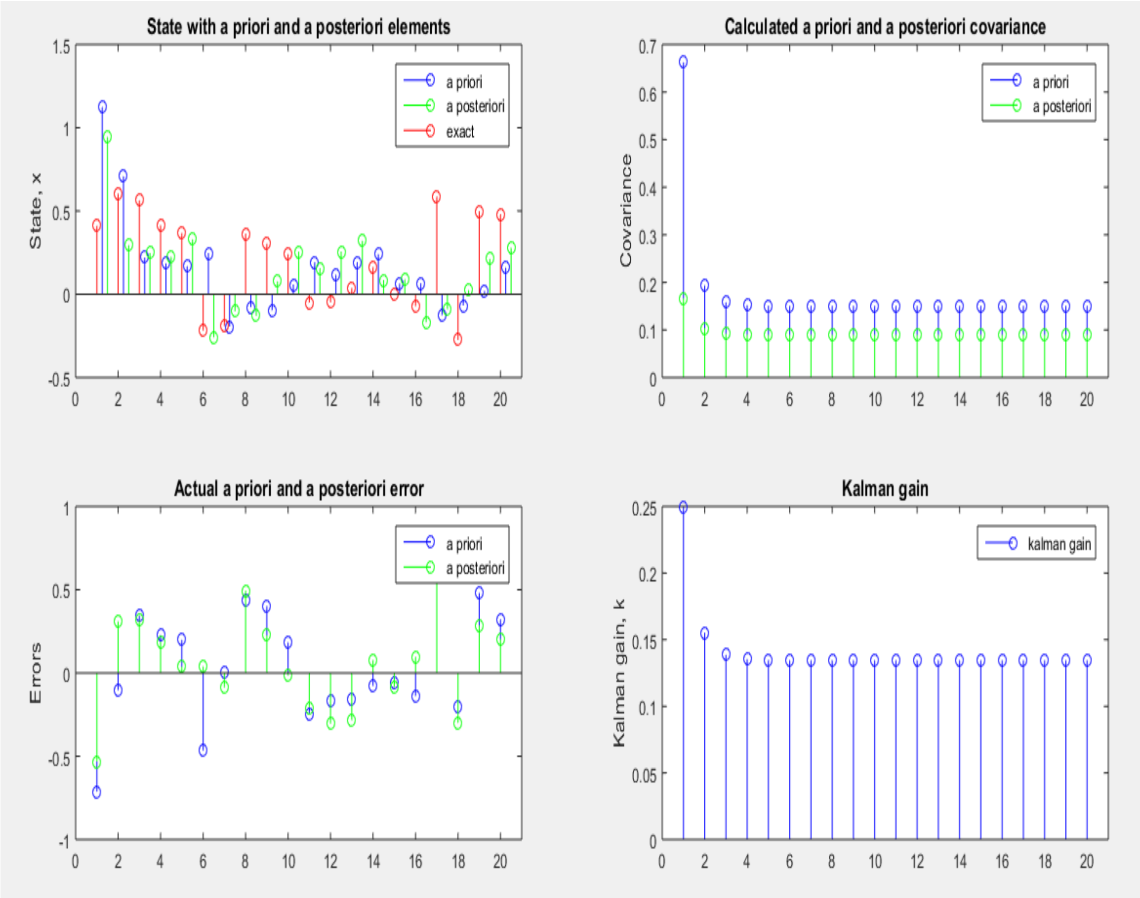

Fig. 4: Remaining useful life of sensor and actuator system with increased process noise Q=2

From the results of the case scenarios presented above, the study can conclude therefore that in the absences of process noise (harsh operational and environmental conditions), the output value for the remaining useful life of the sensor and actuator components decreases steadily over time. However, the results changes drastically when the components are subjected process noise. It can therefore be said that when the sensor and actuator components are subjected to the harsh operational and environmental conditions their remaining useful life becomes irregular and unpredictable as seen in the figures.

4. Conclusions

In this study, the remaining useful life estimate of sensor and actuator components have been studied using a Kalman Filter-based Bayesian model. Sensor and actuators which are essential elements that are usually embedded in complex mechanical systems, are used for monitoring and measuring the continuous and discrete process variable and parameters. They are often located at the most remote part of a system and are mostly subjected to very harsh operational and environmental conditions like high heat, freezing temperature, moisture, mechanical tire and wear and vibration. It is important therefore, that the remaining useful life of the sensor and actuator components are checked and estimated.

In implementing the Kalman Filter-based Bayesian model, a number of simulations have been undertaken, mainly to verify the effectiveness of the model for estimating the remaining useful life of the sensor and actuator components. This has been achieved by simulating several case scenarios of process noise (quantified harsh operational and environmental conditions) in a sensor and actuator components embedded in a complex mechanical system. Results from the simulations shows that, in the absence of process noise in the components, the output value for the remaining useful life decreases steadily over time. However, when the sensor and actuator components are exposed to a quantify process noise, the simulated results show a drastic shift from normal. It can therefore be concluded that when the sensor and actuator components are subjected to the harsh operational and environmental conditions their remaining useful life becomes irregular and sometime unpredictable as it is seen in the study.

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