BAYESIAN INFERENCE FOR HIGH CONFIDENCE SIGNAL VALIDATION AND SENSOR CALIBRATION ASSESSMENT

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ABSTRACT

Online Monitoring (OLM) systems has been investigated for applications in the nuclear industry for the past two decades. These systems offer economic and technological advantages over the currently implemented time based testing methods for sensors and associated instrumentations. The advantages offered not only augment economic viability of current nuclear reactors but will be an inevitable change called for to suit the technologies of the advanced reactors (Gen III+). Irrespective, the acceptance of OLM into the regulatory structure in the U.S. is still hindered by technical and structural clarity on uncertainty quantification used by these systems. A Bayesian inference technique is implemented in the form of a residual model to quantify uncertainty in OLM predictions. The developed system used Gaussian processes to represent the OLM predictions and model inadequacy, the stationary representation of model based uncertainty. In addition, model selection techniques are used in conjunction with numerical methods such as Genetic Algorithm (GA) and Gibb's sampler to add robustness to the estimation model inadequacy, particularly in the presence of drifts and faulted conditions. The prediction model developed herein find applicability in fault detection, obtaining real values of processes after the onset of faults etc. Further development looks into the extension of current method for a multiple output scale implementation.

Keywords: Sensor Calibration, Bayesian hierarchical inference, OLM.

1 INTRODUCTION

The dynamics of the deregulated energy markets has over the years reflected greatly in the economics of the nuclear industry. With competing energy sources such as natural gas with its low initial plant capital, and operational and maintenance cost (O&M) which has become the preferred form of electricity generation both for base load and peaking functions, nuclear energy has had to reevaluate its cost structures [1]. 60-70% of the overall generation cost of nuclear power is attributed to O&M of which 80% accounts for labor cost [2,3,4]. Further to the Three-Mile Island, the NRC brought forth stringent and enhanced safety requirements, which along with preventive maintenance programs attributed to large staff sizes and higher labor costs. The second major contributor to O&M costs are outages, where the economics stem a combination of loss of energy generation and maintenance procedures carried out [4]. The revenue loss from halted energy production was estimated at about 1.25 million dollars per day of shutdown [2, NIE 2001].

NRC RG1.153 Criterion 13, dictates the requirements of appropriate instrumentation to support monitoring of variables under normal, anticipated operational occurrences and accident conditions to ascertain safety requisites. This also ascertains the definitions of predefined operating ranges for variables and instrumentations to meet safety standards. Maintenance testing plays an important role in characterizing and ensuring maximum utilization of instrument lifespan. Currently, in the nuclear industry testing and calibration of instrumentation is carried out in accordance to the Technical Specification (TS) on a time-directed manner, recurring every 18 to 24 months [5]. This method involves testing of instrumentation in an isolated environment, followed by appropriate recalibration to ensure its functionality over the next cycle. This process is time, economic and labor intensive. On average the cost of calibrating a single sensor stands between 3000-6000; with about 50-150 sensors that need recalibration procedure during any given cycle [6]. The calibration process being highly intrusive calls for extensive labor resources, which also contributes to ALARA [5].

Apart from economics, the calibration process brings in technical issues as well. The removal, handing and reinstallation of instrumentation leads to instrument wear and tear and fault introduction (e.g. disoriented valves etc.). Manual calibration causes wear on instrumentation block valve manifolds and on instrument root valves [7]. Maintenance procedure has been identified as one of several stressors for instrument aging. The extensive human element in the process also brings in possibilities of various forms of errors including but not limited to calibration errors, invariant damage due to transmitter pressure surge during calibration etc. On a larger scope, the legacy fleet is transitioning to extended licensing beyond initial specification (74 approved and 19 under review) and implementing power uprates [2]. This places significance on higher efficiency preventive maintenance procedures that incorporates operating experience to sustain optimized operations. With near-term implementation of advanced reactors such as AP1000 and long term interests in Gen IV reactors (molten salt/ liquid metal /gas cooled reactors), the dynamics of operations and maintenance needs are set to vary from current focuses. These reactor designs bring in harsher operating envelope, advanced sensor technologies and larger numbers of sensor with limited accessibility, completely digital instrumentation and interfaces, load following functions, and longer operating cycles [6]. These aspects call for maintenance objectives with focus on non-intrusive, higher frequency procedures to achieve health management of systems while still ensuring economic competitiveness.

Studies show that under the time directed maintenance regime, only 5-10% of sensors show notable shift in calibration [6,8], indicating that the current safety levels are attainable with lesser resource dedication. An alternative maintenance philosophy that draws attention is the condition based maintenance (CBM), where calibration is only initiated if the instrumentation health status calls for it. This procedure succeeds in compartmentalizing the calibration procedure into testing and recalibration. Here the systems and components can be tested more frequently for monitoring their health, leading to fewer calibration procedures while meeting safety standards. CBM in the form of online monitoring systems show great promise in facilitating frequent minimally intrusive calibration testing [9]. OLM offers many benefits both direct in the form of reduced calibration procedures and indirect ones including performance enhancement and equipment monitoring [9]. Its empirical structure yields to versatile models for various types and ranges of sensors with minimal loss of generalizability. It can be beneficial to O&M planning, reducing outage times and minimizing possibilities of unscheduled outages, a major cost factor to nuclear plant operations. In UK, implementation of OLM has shown certain common sensor types succeed to attain reliable outputs while maintaining calibration for a minimum of 8 years [12]. Analysis indicates possibilities of cost savings in the scale of 1 billion $ per year in through fleet wide implementation of PHM systems including OLM in US [2,11]. Current application of OLM in the Legacy fleet is constrained by regulatory and technical issues. Regulatory safety requisites translate into the nuclear plant operations in the form of set point calculation and associated acceptance criterion and drift limits. OLM's strengths as an analytically promising tool is limited by its capacity to show traceability of accuracy to meet currently established regulatory safety standards which the current time directed maintenance techniques achieve [9,13]. This primarily leads to technical issues concerning the estimation of uncertainty in process predictions made by OLM systems. Other concerns include the functional limitations of OLM in case of single-point monitoring (when plant processes progress with minimal change or variability), the effect of OLM on set point calculations and the assumptions associated with it [14]. Furthermore, how OLM compensates additional uncertainty brought in by common mode drift and non-simultaneous measurements needed to be addressed. An extensive overview of the requirements can be found in NRC's Safety Evaluation Report [13].

As USNRC moves towards risk-informed regulations based on the Backfit Rule, 10 CFR 50.109 [15, 16], the establishment of surveillance frequency is moved from the purview of the license technical specifications to licensee control through regulatory modifications such as TSTF-425 Rev.3 [13]. TSTF-425 can form the basis for calibration interval extension and relaxation of even limited periodic calibrations once the identified technical gaps are addressed [6].

1.1 Uncertainty in OLM Systems

As seen in Fig. 1, an OLM system there are various sources of uncertainty. The regulatory issues primarily focus on predictive uncertainty as a cumulative manifestation of all uncertainty processed by typical OLM system.

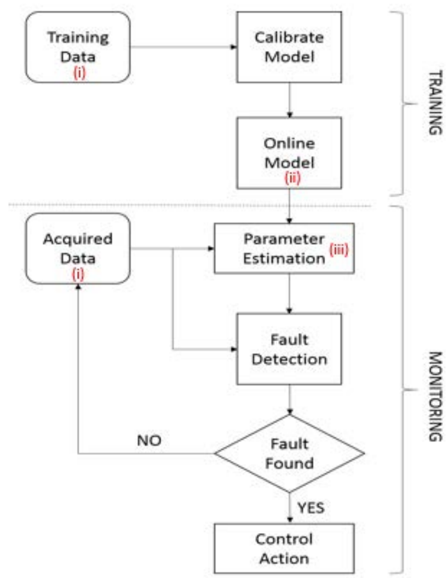

Figure 1. Generic OLM system with sources of uncertainty

The capacity of a given OLM system to detect faults relies heavily on two factors, namely predictive uncertainty and auto sensitivity [14]. Faults in calibration or process shift requires drift limit and acceptance criterion that delimits the allowed level of process variability and drift in the parameter as observed by the sensor. The residual calculated as the difference of the predicted estimate and the observed values with the 95% uncertainty envelope specifying the confidence in prediction. It can be inferred that the level of uncertainty in the predicted value is a limit to the capacity of the OLM system to sense faults at levels lesser than its inherent uncertainty. For example, if the predictive uncertainty of an OLM is 1.5% defined by a specific 95% certainty, then it will not detect drifts of 0.5% or less [14]. This can manifest as hindrance in multiple forms. Any drift that is initiated at a value that falls within the predictive uncertainty confidence will only be detected after it has grown to a value that violates the confidence levels. This leads to delay in fault detection capacities. Another issue occurs when the predictive uncertainty is locally greater than the associated drift limits. In this case, the validity of the OLM system to identify fault and calibration deviations becomes void. Further when OLM systems serve the purpose of health monitoring in addition to calibration assessment the expected sensitivity to drifts and faults can grow more stringent. This establishes the significance of minimizing predictive uncertainty of OLM systems and to quantify the remaining uncertainty effectively for taking decisions based on these systems with confidence [14,17].

The initial NRC review of OLM for sensor recalibration interval extension identified several aspects of the proposed approach that reduce the conservatism of the fault detection process [9,13]. OLM uses a model of the underlying process to provide error-corrected estimates of the true process parameter values; these predictions are assumed to be more accurate than sensor measurements that may be affected by sensor degradation. The credibility of the model predictions requires that the uncertainty in the process estimates be quantitatively bounded and accounted for in the fault detection process, thereby satiating regulatory demands. This is the objective the current model implementation undertakes using Bayesian inference techniques and will be further elaborated in the following section.

2 METHODOLOGY

The foundational method used for this work calibrates a computer model to the features and its operational range of the physical system [18]. In order to calibrate the model to the "true process," the calibration method attempts to capture and minimize elements of uncertainty both in the computer model and the observed process. A Bayesian inference model is used to gain knowledge about the posterior distribution of the calibrating parameters (hyper parameter learning), which uses Gaussian priors and the observed data as evidence [19]. Rasmussen used prediction intervals to quantify and bound parameter estimate uncertainty [20]. Sibert et al identified that measurement noise in most sensors was sufficient to cause prediction interval uncertainty estimate to exceed the drift limits even under normal conditions [21]. Hence, they proposed that confidence interval be applied to the filtered residuals to detect drift in sensors.

A residual model is used for this implementation for ease of explicit expression of prediction uncertainty and also as an effective structure for fault detection capacities. The model as seen in equation (1) forms the basis for the posterior distribution estimation of model based error.

$$r(z_i, \omega_i) = y(z_i, \omega_i) - z_i = \delta(z_i, \omega_i) + e_i + \rho\eta(\Delta t_i, l_i) \quad (1)$$

Where $r(z_i, \omega_i)$ represents the residual as a function of measured data, z_i and internal variable(s) of the OLM model, ω_i. The residual is defined as the difference between the OLM system, $y(z_i, \omega_i)$ and measured data. There are three; model inadequacy ($\delta(z_i, \omega_i)$), observational error (e_i) and sensor degradation error ($\eta(\Delta t_i, l_i)$). The characterization of the terms of this model is controlled by the following factors:

a. The measured data,z_i , which follows a non-stationary Gaussian distribution.

b. The empirical model used for error correction is predefined and static with pre-optimized internal variables. But the predictions themselves follow a non-stationary Gaussian distribution.

c. The model inadequacy,$\delta(z_i, \omega_i)$ and the observational error,e_i . They two together comprise the portion of the residual error present under both normal and faulted conditions. This consolidate is currently assumed to be stationary with respect to observed data,z_i.

d. The sensor degradation error,$\eta(\Delta t_i, l_i)$. It forms the non-stationary component of the residual and is modeled as a non-stationary Gaussian random variable which. The coefficient ρ characterizes the portion of the actual sensor degradation that appears in the model residual.

Modeling simplifications are made using assuming that (i) the data is treated as stationary, (ii) the parameters of the model is pre-optimized and held constant to meet regulatory conditions, (iii)the model used for this implementation will be an Auto Associative Kernel Regression (AAKR) [9], and (iv) Modeling the model predictions and model inadequacy as multivariate Gaussian Processes, while the non-stationary error is implicitly expressed as the difference between residuals and model inadequacy estimates.

This leads the simplification of the model in equation (1); a special case of the development seen in [23]:

$$Y_o(x) = Y_m(x) + \delta(x) + \varepsilon \quad (2)$$

Where Y_o is experimental data or observed data and Y_m represents the model output.

The two Gaussian processes are represented by mean variables $\mu_\delta = f_\delta * \beta_\delta$, and$\mu_m = f_m * \beta_m$,with the subscript of δ for model inadequacy and m for the model predictions. These mean variables are linear functions; a product of factor f, a function of the data and β ,an unknown characterized parameter. In this representation the f is assumed to be the data itself. Other possible representations for f include a weighted average of constants associated with each dimension of the data. The corresponding covariance of the GPs are represented by $\sigma_\delta\, R_\delta$ and $\sigma_m\, R_m$,with R taking the form:

$$R = \prod_{k=1}^{p} \exp\left(-\,\varphi\left(x_{i,k} - x_{j,k}\right)^{P}\right) \tag{3}$$

Such that $\varphi > 0$ and $0 \leq P \leq 2$

$$F_m = (f_{m,1}\, f_{m,2} \dots \dots .. f_{m,p})^T \tag{4a}$$

and

$$F_\delta = (f_{\delta,1}\, f_{\delta,2} \dots \dots .. f_{\delta,p})^T \tag{4b}$$

This results in a collective of parameters, which will be categorized on the basis of their origins. The two GPs are assumed to be independent of each other. Furthermore, the mean and covariance parameters of each of these GPs are also established to be independent. These assumptions help ease the process of integrating out the various parameters in multiple stages to attain closed form expression for the posterior distributions of interest. This, leads to the following group of hyper parameters:

$$\theta = \{\, \beta_m\,, \beta_\delta\,, \sigma_m\,, \sigma_\delta, \varphi_m, \varphi_\delta, P_m, P_\delta\} \tag{5}$$

2.1 Implementation

The posterior distributions of most variables can be inferred from the terms and distributions defined above. Here we represent a few key conditional distributions that are significant to the model uncertainty and the true process calculations. Given the presence of multiple hyper parameters that have non informative priors and the intricate dynamics of parameter interdependence, the integration of distributions become tedious with limited possibilities of closed formed solutions. This calls for the use of numerical techniques such as Gibbs sampler and Genetic Algorithms(GA) to draw insights into the distributional behaviors of such hyper parameters. The efficiency of these numerical methods have a bearing on the performance of the Bayesian framework under variable working conditions. Hence these techniques are used in conjunction with model selection criterions to maximize performance under faulty data conditions.

The process of estimation of parameters Bayesian systems go from the higher level less informative hyper parameters, which are then used to establish the distribution of more basic parameters of interest. Here the hyper parameters that persist are $\varphi_m, \varphi_\delta, P_m, P_\delta, \tau$. Given the data, The P_m, P_δ are set 2 in order to simplify the covariance structure to a second order radial basis function. These are calculated by maximizing as equation (6)

$$p\left(y^e, y^m | \varphi_m, \varphi_\delta, P_m, P_\delta, \tau\right) = p\left(y^e | y^m, \varphi_\delta, P_\delta, \tau,\right). p(y^m | \varphi_m, P_m) \tag{6}$$

The maximization process can be achieved in two steps. Firstly, estimate the distribution of φ_m and set the mode as the true value of this parameter. This can be achieved by minimizing equation (8) or as attempted here in using a Gibbs sampler. This value is then used to establish the maximum likelihood estimate (MLE) of φ_δ by minimizing equation (9). This is achieved using a GA augmented using a model selection criterion (see equation (10)).

$$\log(|R_m(D_m)|) - \log(|A_m|) + (n_m + 2\alpha_m).\log\,(2\gamma_m + (y^m)^T R_m^{-1}(D_m) y^m + b_m^T V_m^{-1} b_m - v_m^T A_m v_m) \tag{8}$$

$$\log(|R_\delta(D_e)|) - \log(|A_\delta|) + (n_e + 2\alpha_\delta).\log\,(2\gamma_\delta + \left(y^e - y_{n_e}^m\right)^T \left(R_\delta(D_m) + \tau I_{n_e}\right)^{-1} (y^e - y_{n_e}^m) + b_\delta^T V_\delta^{-1} b_\delta - v_\delta^T A_\delta v_\delta) \tag{9}$$

$$\text{MLE} = C(\Sigma(\varphi_\delta)) - [\log(|R_\delta(D_e)|) - \log(|A_\delta|) + (n_e + 2\alpha_\delta).\log\left(2\gamma_\delta + \left(y^e - y_{n_e}^m\right)^T \left(R_\delta(D_m) + \tau I_{n_e}\right)^{-1} \left(y^e - y_{n_e}^m\right) + b_\delta^T V_\delta^{-1} b_\delta - v_\delta^T A_\delta v_\delta\right)] \tag{10}$$

Where, $C(\Sigma(\varphi_\delta))$ is the information complexity criterion, an evolved form of the Akaike Information Criterion (AIC). Elaborate developments of these MLEs is available in [22,23]

The modes of $\varphi_m, \varphi_\delta$ are used to calculate the model inadequacy parameter using [23],

$$\delta(D)|y_o y_m \sim T_n(v_{\delta|o,m}, \mu_{\delta|o,m}(D), \Sigma_{\delta|o,m}(D)) \tag{11}$$

Where,

$$v_{\delta|o,m} = n + 2\alpha_\delta \tag{12a}$$

$$\mu_{\delta|o,m}(D) = H_\delta^T A_\delta v_\delta + [R_\delta(D, D_o)\left(R_\delta(D_o) + \tau I_p\right)^{-1} * \left(y_o - y_m(D_o)\right)] \tag{12b}$$

$$\Sigma_{\delta|o,m}(D) = \frac{Q_\delta}{v_{\delta|o,m}}\,[R_\delta(D) - R_\delta(D, D_o)\left(R_\delta(D_o) + \tau I_p\right)^{-1} * R_\delta(D_o, D) + H_\delta^T A_\delta H_\delta] \tag{12c}$$

The calculated posterior distribution is then used to establish prediction intervals.

3 RESULTS

The model was implemented on multiple data sets. The first data set consists of nuclear coolant data collected from an online nuclear power plant under load following conditions. This data consists of 13 sensors providing over 8000 data points. Eight correlated signals are used to build AAKR models whose predictions form input to the Bayesian inference implementation. The second data set is a flow loop data collected at the collaborator facility (AMS). The data captures the trends of 17 sensors (these include temperature, pressure and flow sensors) which is manipulated using temperature and pressure controls to simulate stationary and transient type behavior under both normal and faulted conditions. These signals are similarly used to obtain AAKR predictions that feed into the Bayesian module.

It has been observed that under normal stationary conditions the Bayesian inference system is capable of offering high confidence predictions (minimal mean error ranging from .8 % to 1.5%) for the model inadequacy term which accounts for most of the uncaptured uncertainty under stationary data behavior. This is captured in Fig. 2, where the model inadequacy predictions for sensor ten of the nuclear coolant data is seen.

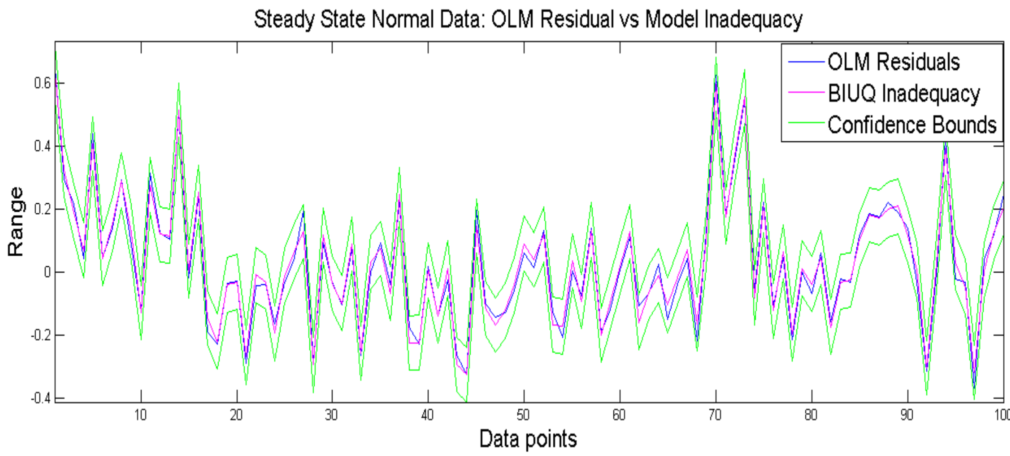

Figure 2. Model Inadequacy predictions for sensor 10 of nuclear coolant data

The second data set brings in transient dynamics, still under normal working conditions for the sensors. The sensor with the most distinct transience (sensor 7) is opted to be represented here. As seen in Fig.3 the AAKR predictions like any statistical system faces issues in regions of transience resulting in higher values and dynamics in prediction residuals. But the Bayesian system shows promise with consistent predictions in this region, which is the expected behavior given the model assumptions.

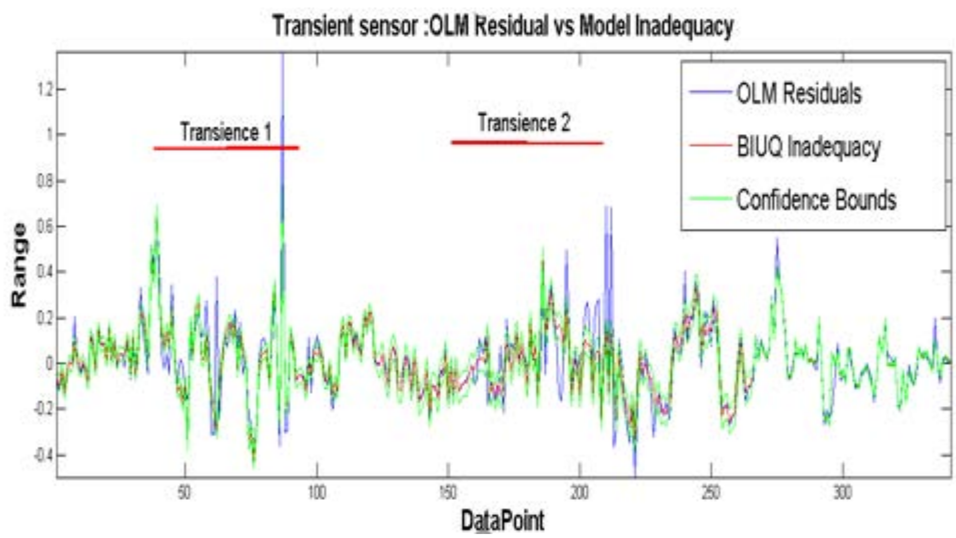

Figure 3. Model inadequacy prediction trends for sensor displaying transient behavior

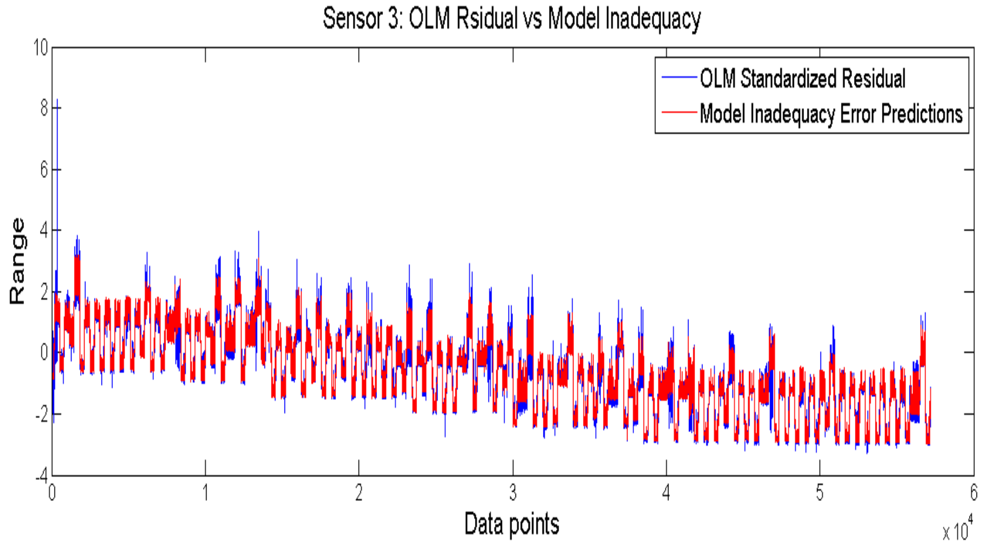

Figure 4. Model Inadequacy predictions for faulty sensor conditions

When tested under faulted behavior as seen in the second data set, the Bayesian model showed currently limited applicability due to the model inadequacy prediction showing sensitivity towards the prediction residual, as captured in Fig 4. This possess a limitation on the capacity of the current model in fault detection capacities; an objective of this research initiative.

4 CONCLUSION AND FUTURE WORK

The Bayesian based signal validation framework shows promising results in uncertainty quantification under normal conditions under stationary and transient behaviors. The tendency to follow drift while using the present model is currently believed to be due to the lack of a non-stationary term for the portion of the residual related to sensor degradation.

This sensitivity can be countered by improving model selection process that isolates appropriate hyper parameters, since once calculated these values are held constant. Under faulty condition such a hyper parameter estimation needs to be sensitive and more efficient to isolate under lying persistent trends. Model selection criterions of various complexities should be compared to establish the most efficient technique.

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