INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI
SHORT ABSTRACT OF THESIS

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Thesis Title: **:** PROBABILISTIC MACHINE LEARNING APPROACHES TOWARDS DIAGNOSTIC AND PROGNOSTIC OF DEGRADING ENGINEERING SYSTEMS

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Thesis Submitted to the Department/ Center	:	Department of Civil Engineering
Date of completion of Thesis Viva-Voce Exam	:	16-04-2025
Key words for description of Thesis Work	:	Bayesian Filter, Diagnosis, Prognosis, Machine Learning

SHORT ABSTRACT

Damage detection and prognosis are critical to managing degrading systems in the engineering infrastructure. The damage detection relying on sensor data and prognosis on historical failure data, usually both are treated separately. However, a holistic approach is needed to capture degradation at initial stages and prognosis. When implementing a machine learning framework for remaining useful life (RUL) estimation, two primary scenarios emerge: (1) utilizing a complete run-to-failure dataset for training, and (2) relying on a partial dataset. The latter presents significant challenges due to the necessity for extrapolation. Furthermore, limited research has explored extending damage detection results to RUL estimation by modeling the underlying degradation process using a surrogate measure. Moreover, few studies extend damage detection results to remaining useful life (RUL) estimation by modeling the underlying degradation process using a surrogate measure. An integrated probabilistic machine learning framework that systematically undertakes diagnosis, prognosis, and RUL estimation is lacking in the literature. Additionally, parameters for the surrogate degradation model used for prognosis are often estimated using conjugate gradient methods, which often fall into local minima. These surrogate models also ignore general population trends.

The main objectives of this thesis are threefold: First, a comprehensive prognosis framework is developed that integrates Gaussian Process Regression (GPR) with a robust solution to address extrapolation challenges, ensuring accurate and reliable predictions beyond the training data range. Second, the set of GPR hyperparameters for achieving the global optimum value of maximum likelihood is obtained through the proposed entropy-assisted genetic algorithm. This incorporates Renyi's entropy to diversify the initial population, achieve global convergence, and mitigate the risk of premature optimization. Finally, the proposed probabilistic framework is applied to real-world scenarios, specifically the prognosis of elastomeric rubber bearings and fatigue crack monitoring in lap joints. The aim is to demonstrate the framework's practical applicability, effectiveness in predicting RUL, and ability to account for uncertainties in different engineering domains.

Damage initiation in these applications is often followed by a sudden change in the degradation path. With this shock, the degradation path changes its trajectory, leading to multi-stage degradation that requires shifting the adaptive mean function. Hence, this thesis attempts to locate change points through a Bayesian approach, presenting theoretical formulations for multi-functional forms in two phases (pre and post-change point) with damage detection in the context of structural health monitoring.

For case-specific surrogate measures, the development of a system identification tool using the two-stage constraint unscented Kalman filter (CUKF) is proposed for complex structural systems like elastomeric high damping rubber bearings. These are modeled through the Biaxial Bouc-Wen model to account for bidirectional effects observed in structures under seismic excitations. The effectiveness of the two-stage CUKF in parameter estimation is validated through numerical case studies and experimental validation, establishing a robust foundation for subsequent prognostics. Additionally, a case study from the aviation industry is investigated where a combination of automated wavelet feature extraction and a probabilistic Bayesian neural network directly correlates Lamb wave signatures with crack widths, addressing both aleatoric and epistemic uncertainties. This method provides probabilistic estimates of crack width and automates fatigue life prognosis, validated through extensive experimental data.

Results from numerical and experimental data show that the proposed surrogate degradation modeling framework is effective in performing prognosis. The analysis reveals that utilizing more degradation data post-change point leads to timely fault detection, improved model hyperparameter estimates, variance reduction, and reasonably accurate RUL predictions. Experimental validations underscore the robustness and reliability of the methods across diverse applications, paving the way for future innovations in the probabilistic machine learning diagnosis and prognosis of engineering systems.