Physics-Guided Gaussian Process for System Performance Prognosis

This project presented a physics-guided Gaussian process (PGGP) to integrate the complementary strength of model-based and data-driven methods to overcome their respective limitations. The objective of the research is to improve the accuracy of performance prognosis of dynamical systems, which provides the basis for predictive maintenance. Specifically, the integrated method, as shown in **Fig. 1**, is realized through:

1) embedding physical equations, such as *Arrhenius* equation and *Heaviside* function that model the degradation trend and abrupt performance changes, into the mean function of Gaussian process (GP) to guide the prognosis;
2) designing GP kernel functions that more realistically model the time-dependent variations and periodicity in the system performance degradation than the standard stationary kernel;
3) jointly optimizing the parameters of physical mean function and kernel functions through the maximum likelihood estimator.

This integration allows to calibrate the physical equations to the specific system conditions and enables GP to predict the residual between the prediction from the calibrated physical equations and the measured actual degradation to better account for degradation-related parameters not encapsulated in the physical knowledge (e.g., local variation in degradation rate and data variance).

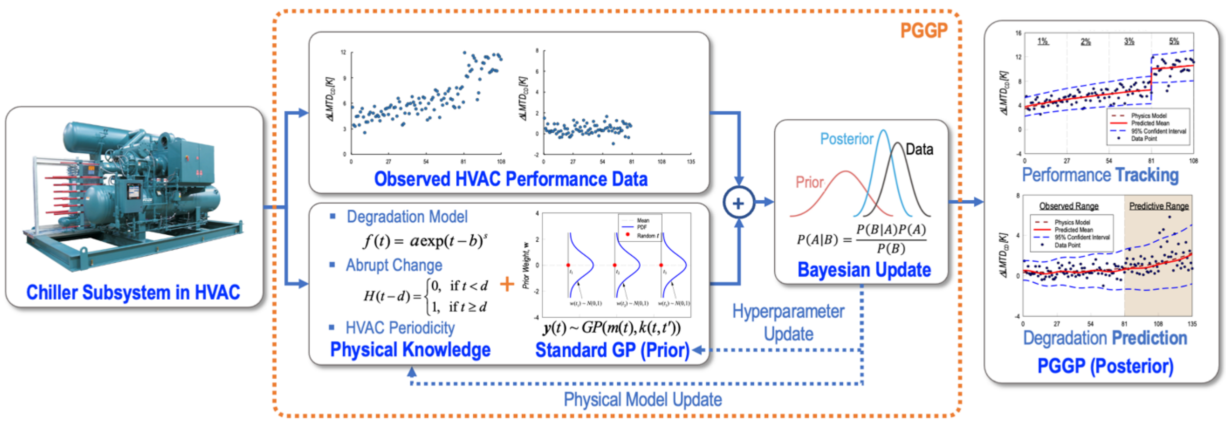

Fig. 1 PGGP for performance prognosis of dynamical system

The PGGP is evaluated using a building HVAC system and battery degradation prediction as case studies. Its performance is compared to machine learning methods without embedded physical knowledge, including support vector machines, recurrent neural network, convolutional neural network, deep Gaussian process, and deep ensembles. It is seen that, at the early degradation stage (e.g., at 40% of system service life), the PGGP outperformed other methods, improving the accuracy of remaining life prediction by up to 60%. This advantage decreases as degradation progresses. However, the PGGP still outperforms other methods by up to 39% when the system is at 80% of its service life. These findings confirm the effectiveness of incorporating physical knowledge into machine learning to improve performance prognosis of dynamical systems.

Related Publication

[1] J. Zhang, C. Liu and R. Gao, "Physics-guided Gaussian process for HVAC system performance prognosis," *Mechanical Systems and Signal Processing*, vol. 179, p. 109336, 2022. https://doi.org/10.1016/j.ymssp.2022.109336