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A Novel BiGMM-HMM Framework for Predictive Maintenance in Naval Vessel Propulsion Equipment

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***Abstract*— Predictive maintenance plays a crucial role in ensuring the reliability and efficiency of naval vessel propulsion. Naval vessel propulsion systems generate intricate sensor data because each sensor exhibits multiple modes of distribution, and the collective sensing across sensors results in multivariate distributions that form a combination of each sensor's outputs. This intricacy poses challenges for conventional predictive maintenance approaches. This paper introduces a novel Bidirectional Gaussian Mixture Model - Hidden Markov Model (BiGMM-HMM) framework that addresses these challenges by integrating Gaussian Mixture Models (GMMs) with HMMs in a bidirectional architecture. The proposed framework explores two data preprocessing methods: feature generation with Principal Component Analysis (Method 1) and direct utilization of the raw dataset (Method 2). The results demonstrate the superiority of Method 1, highlighting the importance of feature engineering and dimensionality reduction in predictive maintenance applications. The BiGMM-HMM framework achieves effective concatenation of two GMMs to infer labels and to model the transition and emission probabilities of the HMM, thereby adeptly capturing the multimodal nature of the observed data. A systematic analysis reveals that incorporating up to 3 GMMs within HMM enhances the model's predictive capabilities while avoiding overfitting and optimizing computational resources. The comparative analysis of various configurations provides valuable insights into the robust predictive maintenance frameworks.**

Keywords—Predictive maintenance, Naval vessel propulsion, Gaussian Mixture Models, Hidden Markov Models, Multimodality, Multivariate distributions, Feature generation, Dimensionality reduction.

I. Introduction

Framing an effective predictive maintenance strategy is crucial for the success of any organization heavily reliant on physical assets. This technology enables them to execute Condition-Based Maintenance (CBM), a cornerstone of predictive maintenance. In data acquisition, sensors stand as the powerful bridges linking physical realities with digital landscapes, essential for predictive maintenance efforts. With the ability to transform diverse variables, from mechanical motions to electrical signals, sensors assume the interpreters' role, decoding the equipment conditions' language into observable states. This transformation is pivotal, as it allows for the early detection of potential failures and the optimization of maintenance schedules, thereby reducing downtime and extending the lifespan of assets.

The challenge that traditional predictive maintenance methodologies, such as HMMs, face in addressing the complicated and multimodal nature of sensor data from physical assets is notably significant. This issue arises from a critical oversight: the assumption of unimodality in HMMs [1] can lead to suboptimal performance when these methodologies are applied to intricate, real-world data that inherently exhibit multimodality within each sensor's data and undergo multimodal sensing [2, 3]. The sensor data from physical assets exhibits *multimodality* [4], where each sensor generates data with multiple modes of distribution, and the system undergoes multimodal sensing, leading to *multivariate distributions* that can be represented as a mixture of distributions from each sensor. Leveraging these characteristics to achieve more accurate predictive outcomes is a successful strategy because it provides complementary information. Incorporating multimodality into predictive models reduces information uncertainty and enhances model performance [5]. This approach allows for more generalized results than those obtained by models relying on a single data modality, thereby improving the effectiveness of predictive maintenance strategies [6].

Addressing this gap, our research introduces an advanced Bidirectional Gaussian Mixture Model - Hidden Markov Model (BiGMM-HMM) framework, meticulously engineered to navigate and exploit the multimodality within each sensor's data and the multivariate distributions arising from multimodal sensing. possible impact on predictive maintenance strategies for physical assets, with a focus on naval propulsion equipment in our case study. The core of our proposed framework is the synergistic integration of GMMs and HMMs in a bidirectional setup. This integration is pivotal, this fusion is crucial; GMMs excel in navigating the intricate, multimodal landscape of sensor data, adeptly capturing the nuanced variations in operational states with remarkable precision. When combined with the temporal sequencing capabilities of HMMs, the framework is uniquely positioned to accurately predict transitions between operational states, including the onset of potential failures. This dual-model approach allows for a nuanced understanding of equipment health, far surpassing the capabilities of traditional predictive maintenance models. Our research addresses varying