Institute of Mechanical and Electrical Engineering

PhD Defense
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Title:	**“Digital Twins of Axial Piston Pumps (APPs) for Machine Learning-based Condition Monitoring”**
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Abstract

Axial piston pumps (APPs) are widely used in industrial hydraulic systems due to their high energy efficiency and compact design. In the era of smart systems and predictive maintenance, vibration-based *Condition Monitoring* (CM) is a critical enabler for operational efficiency and extended service life. However, the application of vibration-based CM in APPs remains underexplored in research, leaving significant gaps in monitoring practices.

The vibration response of APPs is characterized by a combination of structural and excitation effects. While structural vibrations can contain information about potential damage, they are often masked by harmonics generated by rotating components and fluid–structure interactions. These effects, combined with uncertainties from operational and environmental conditions, manufacturing variability, and nonlinear system behavior, make fault isolation challenging. Limitations in measurement techniques and the scarcity of failure data further hinder the development of reliable CM algorithms. Addressing these limitations requires a *Digital Twin* (DT) approach that integrates physics-based modeling with data-driven methods. This approach enables strategies to separate structural responses from harmonic content and mitigate uncertainty in assembly and measurement.

This thesis develops and validates a hybrid DT framework for APPs that integrates physics–based modeling with data obtained through experimental vibration testing. The work is divided into two main parts. The first part focuses on extensive experimental testing and the development of a base *Finite Element* (FE) model of the APP. System identification techniques, such as *Stochastic Subspace Identification* (SSI) and histogram-based *Frequency Stabilization Diagrams* (FSD), are used to identify the modal parameters from a sample of more than 1,000 datasets. This process yields an empirical distribution of the modal parameters, which forms the basis for quantifying the uncertainty introduced by manufacturing variability, boundary conditions, and tolerances in the APP. The base FE model and the identified modal parameters, including their variability, are subsequently used for modal updating in the second part.

The second part introduces a Bayesian *Finite Element Model Updating* (FEMU) approach based on the Gauss–Newton algorithm, which propagates the uncertainties of the modal parameters into the physical parameters of the system. While the calculations involved in FEMU are almost trivial for low-dimensional systems, these become a heavy computational burden when the number of *Degrees of Freedom* (DOF) is large. In such cases, it is more convenient to use a *Reduced Order Model* (ROM) that estimates the eigenvalues with minimal computational effort. Both physics-based ROM using *Component Mode Synthesis* (CMS) and data-driven *Response Surface Models* (RSMs) based on *Multi-Output Gaussian Processes* (MOGPs) are incorporated within the updating framework. The updated model serves as a high-fidelity DT capable of simulating a wide range of damage scenarios and operational conditions at a fraction of the computational cost. Synthetic data generated from the DT augments the experimental datasets, enabling robust training of machine learning models for damage detection. By combining empirical measurements with statistically informed synthetic data, the framework mitigates the scarcity of real-world damage cases and enhances the generalization capability of the predictive models.

The proposed methodology demonstrates that a hybrid model approach can provide a robust, scalable foundation for intelligent condition monitoring of APPs. The integration of Bayesian synthetic data generation, reduced-order modeling, and digital twin concepts provides a computationally efficient framework suitable for complex industrial systems such as the APP. The improved computational efficiency also makes the framework well-suited for potential future online deployment in industrial CM systems.