Dual-Layer Collaborative Architecture for Knowledge and Physics Integration in PHM Large Models

Context of the research

The reliability of industrial systems is paramount for ensuring operational safety, minimizing economic losses, and maintaining competitive advantage in modern manufacturing environments. Equipment failures can lead to catastrophic consequences, including safety hazards, production disruptions, and substantial financial impacts. Prognostics and Health Management (PHM) emerges as a critical technology to address these challenges by providing capabilities for early failure detection, health assessment, and predictive maintenance planning. PHM integrates advanced sensing, data analytics, and prognostic algorithms to evaluate system reliability under actual operating conditions and enable condition-based maintenance strategies.

This thesis addresses the critical tension between physics-based models and data-driven approaches in PHM. While physics models offer interpretability and consistency, they struggle with novel fault patterns; conversely, data-driven models can identify new patterns but often lack physical consistency and interpretability. The research will develop a novel dual-layer architecture that effectively integrates physics principles with domain knowledge to create robust, explainable PHM models.

Objective of the research

- Developing a physics-informed neural network (PINN) architecture that incorporates multidisciplinary engineering equations and conservation laws;
- Creating knowledge enhancement modules that leverage large language models to interpret maintenance documents and expert knowledge;
- Designing mechanisms to allow "controlled deviation" from pure physics models when evidence suggests novel fault patterns;
- Implementing adaptive weighting mechanisms that dynamically balance physics constraints against empirical observations;
- Design a hybrid modeling framework that combines physics-informed neural architectures with knowledge-enhanced modules to simulate aircraft component degradation.

Expected Research Outcomes

The research will yield a comprehensive modeling framework that combines digital twin technology with large language models to create PHM systems with both high accuracy and explainability. The framework will include methods for dynamic confidence assessment, providing uncertainty quantification for different prediction types. Validation on industrial equipment will show that this approach significantly outperforms both pure physics-based and pure data-driven approaches, especially in scenarios with limited labeled fault data.

Composition of the research group

- 2 Full Professors
- 1 Associate Professor

Total thesis duration

- 8 to 12 months

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