Intelligent Agent-Based Optimization for Multimodal PHM Model Training Under Uncertainty

Context of the research

Industrial systems worldwide face escalating challenges in maintaining reliability and operational efficiency, with equipment failures resulting in economic losses, safety risks, and production disruptions. The complexity of modern industrial equipment demands sophisticated approaches to health monitoring and failure prediction. Prognostics and Health Management (PHM) represents a transformative methodology that integrates detection, diagnosis, and prognosis capabilities to address these challenges proactively. PHM technologies enable the evaluation of system reliability under actual operating conditions, facilitating the transition from reactive maintenance to predictive and condition-based maintenance strategies that minimize downtime and optimize resource utilization.

This thesis explores decentralized training frameworks for complex multimodal PHM models with conflicting optimization requirements. Training large-scale multimodal models for industrial PHM presents unique challenges including high-dimensional hyperparameter spaces, multi-objective optimization conflicts, and imbalanced fault data distributions. Traditional approaches to model training often rely heavily on human expertise for parameter tuning and conflict resolution, leading to inefficient resource utilization and suboptimal model performance. The research will develop an innovative multi-agent collaborative framework that can autonomously coordinate the entire training process while balancing physical consistency constraints against empirical observations.

Objective of the research

- Designing a hierarchical multi-agent architecture comprising command, data processing, and optimization agents for autonomous model training coordination;
- Developing dynamic resource allocation strategies that can adaptively prioritize underrepresented fault scenarios in imbalanced datasets;
- Creating conflict arbitration mechanisms to resolve tensions between physical equation constraints and data-driven learning objectives;
- Implementing real-time monitoring and intervention protocols that can detect and address convergence issues or distribution shifts during training.

Expected Research Outcomes

The research will deliver a generalizable multi-agent training framework that significantly reduces dependence on human intervention while producing more robust and reliable PHM models. The hierarchical agent architecture will demonstrate capabilities for autonomous hyperparameter tuning, conflict resolution between physics constraints and data-driven learning, and adaptive handling of imbalanced data distributions. The framework will include real-time monitoring dashboards that provide transparent insight into training dynamics and decision processes, enabling both automated optimization and human oversight when needed. Performance metrics will show improved training efficiency (reduced time and computational resources), enhanced model generalization across diverse operating conditions, and more reliable uncertainty quantification compared to conventional training approaches. The work will also produce theoretical contributions to decentralized optimization in high-dimensional parameter spaces and an open-source toolkit that can be adapted to various industrial PHM applications beyond aviation.

Composition of the research group

- 2 Full Professors

- 1 Associate Professor

Total thesis duration

- 8 to 12 months

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