Literature Review: Predictive Maintenance Using LSTM Methods

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1. A Deep Learning Model for Remaining Useful Life Prediction of Aircraft Turbofan Engine on C-MAPSS Dataset

Research Focus:
Accurate remaining useful life (RUL) prediction for turbofan engines using an LSTM-based deep learning model, with improved preprocessing and degradation modelling to enhance predictive accuracy on the NASA C-MAPSS dataset.

Methodology:

- Preprocessing steps: correlation analysis for sensor selection, moving median filter for denoising, and normalization.
- An improved piecewise linear degradation model is used to assign RUL target labels.
- Grid search is used for hyperparameter optimization of a multi-layer LSTM.
- The method is validated across all four C-MAPSS sub-datasets and benchmarked against previous methods.

Key Findings:

- The proposed model achieves state-of-the-art (or close to) performance on most C-MAPSS sub-datasets (lowest RMSE and score function on FD001 and FD003, second best on FD002 and FD004).
- Careful sensor selection and preprocessing significantly improve LSTM predictive power and generalization.
- Distinct models for different operational scenarios yield better results than a single one-size-fits-all model.

Relevance:
Addresses the challenge of reliable RUL estimation for critical aerospace components. Shows how tailored preprocessing and LSTM architectures outperform traditional and other deep learning approaches in PdM for aircraft engines.

Scope Comparison:
Outperforms SVMs, DNNs, CNNs, random forests, traditional model-based approaches, and even other advanced LSTM combinations, especially in RUL regression accuracy and robustness to noise.

2. Bearing Fault Predictive Maintenance using LSTM

Research Focus:

Application of LSTM networks to predict bearing faults in rotating industrial machinery, emphasizing forecasting the condition indicator (RMS) before failure.

Methodology:

- Extracts statistical features (maximum, std, kurtosis, RMS) from vibration acceleration signals (IMS dataset).
- Constructs a multivariate time-series for LSTM input; past 7 cycles used to predict the next RMS value.
- Performance compared to Kernel Ridge regression (classical ML approach).

Key Findings:

- LSTM achieves very low RMSE on training, validation, and test sets (0.0017, 0.0101, 0.0012), outperforming Kernel Ridge Regression.
- Demonstrates that effective LSTM-based forecasting is feasible even with a relatively small training set if features are chosen carefully.

Relevance:

Highlights LSTM's superiority for time-series health monitoring and predictive maintenance of rotating equipment.

Scope Comparison:

LSTM significantly outdoes SVM, ANN, Random Forest, and XGBoost in regression and forecasting tasks related to bearing health, demonstrating the advantage of deep sequence models for degradation prediction.

3. An Investigation of Exhaust Gas Temperature of Aircraft Engine Using LSTM

Research Focus:

Use of LSTM neural networks for monitoring, forecasting, and diagnosis of exhaust gas temperature (EGT) in aircraft engines for predictive maintenance.

Methodology:

- Real flight and borescope inspection data, including both healthy and fault conditions.
- Inputs include 12 sensor features selected for correlation with EGT.
- Evaluated LSTM with different batch sizes, validated against real engine data.

Key Findings:

- LSTM yields high predictive accuracy for EGT, with average errors as low as ~6°C (within acceptable tolerances for real-world usage).
- Predictive performance degrades mainly in the presence of severe mechanical faults (e.g., turbine blade cracks).
- Smaller batch sizes yield slightly better results.

Relevance:

Validates LSTM's utility for real flight data—outside simulation environments—making it a promising tool for direct in-flight diagnostics and early warning systems.

Scope Comparison:

Bridges the gap between simulation/test bench validation and true flight data. Prior approaches focused on steady-state/simulated data; this work tests LSTM on real-world, noisy sensor streams with direct operational consequences.

4. A Novel Remaining Useful Life Prediction Approach Combined XG Boosting and Multi-Quantile Recurrent Neural Network

Research Focus:
Development of a non-parametric RUL prediction framework combining XGBoost for feature selection and a Multi-Quantile RNN (MQ-RNN) for both point and interval prediction, enabling uncertainty quantification for predictive maintenance.

Methodology:

- XGBoost selects the most influential sensor features.
- MQ-RNN encodes temporal dependencies and outputs quantile-based (interval) predictions.
- Benchmarked on the C-MAPSS dataset and compared against LSTM, SVM, DBN, CNN, BiGRU-MMOE, and other advanced models.

Key Findings:

- Outperforms the baseline LSTM and other deep learning competitors in both point and interval prediction (lower RMSE, better PICP, PINAW, and CWC metrics).
- Interval prediction (quantile outputs) provides actionable uncertainty information for maintenance decision-making.
- Limitations include high computational and data demands.

Relevance:
Establishes new benchmarks for accuracy and uncertainty-aware decision support in predictive maintenance for high-value equipment.

Scope Comparison:
Improves upon classical LSTM and hybrid models by adding risk-quantification, essential for maintenance scheduling where uncertainty and reliability are critical.

5. A Data-based Expert System for Aero-Engine Gas Path Fault Diagnosis

Research Focus:

Unified data-driven system for monitoring and diagnosing aero-engine gas path faults, integrating LSTM-based time-series prediction with wavelet denoising and rough set attribute reduction.

Methodology:

- Wavelet transform denoising to improve signal quality.
- LSTM forecasts key parameters (e.g., high-pressure rotor speed).
- Rough set theory applied for knowledge extraction from labeled data, implementing an adaptive, continuously improving expert system.

Key Findings:

- LSTM and wavelet denoising yield robust predictions even on noisy, real flight data.
- System provides a scalable expert interface for aircraft maintenance technicians, with performance validated through real army test data.
- Identified instability in some prediction cases and need for further robustness improvements.

Relevance:

Demonstrates practical deployment of LSTM-based PdM in aviation, integrating traditional and deep learning methods in an operational expert system.

Scope Comparison:

Moves from algorithmic research to system-level implementation; addresses unique challenges of military aviation (data isolation, security, and compatibility) and applies LSTM prediction beyond individual sensors to full asset diagnosis.

6. Machine Learning-Based Predictive Maintenance Using CNN-LSTM Network

Research Focus:
Development and benchmarking of a hybrid deep learning architecture (CNN-LSTM) for predictive maintenance, evaluating its suitability for Remaining Useful Life (RUL) prediction of complex equipment (e.g., turbofan engines).

Methodology:

- Serially combines Convolutional Neural Networks (CNN) for spatial feature extraction with LSTM for temporal feature learning.
- Employs preprocessing to drop sensors with low relevance.
- Model hyperparameters: LSTM layers, ReLU activation, Adam optimizer, dropout.
- Benchmarked using NASA C-MAPSS FD003 dataset and compared to Random Forest, baseline LSTM, parallel CNN-LSTM, and other state-of-the-art methods.

Key Findings:

- Achieves RMSE of 15.31, not better than best available, but shows advantages for quick and lean training.
- Serial (not parallel) combination of CNN with LSTM enables fast training, supporting use in resource-constrained applications.
- Performance is slightly behind top literature models, but demonstrates potential if deeper networks and tuning are applied.

Relevance:
Validates deep learning (and, specifically, LSTMs) as a leading approach for predictive maintenance where temporal and spatial dependencies exist.

Scope Comparison:
Findings highlight benefits of serial CNN-LSTM versus complex parallel structures. While not outperforming state-of-the-art, it provides a feasible, computationally lean alternative, especially for quick prototyping and lower-resource applications.

7. On the Use of LSTM Networks for Predictive Maintenance in Smart Industries

Research Focus:

Comprehensive study of LSTM architectures for RUL estimation in jet engines—including the effect of hyperparameter tuning on predictive accuracy.

Methodology:

- NASA C-MAPSS dataset, with focus on regression of RUL.
- Grid search across hyperparameters: window size, number of LSTM layers, and layer units.
- Best architecture: 3 layers with 40, 15, and 15 units; window size 90; dropout 0.2/0.5.

Key Findings:

- Achieves RMSE of 11.42, outperforming SVM (RMSE 51.54) and DNN (RMSE 41.77), and surpasses prior deep learning approaches cited in literature.
- Model performance highly sensitive to hyperparameter tuning, especially window size and network depth.
- Model with variable hidden units per layer and large window achieves best results.

Relevance:

Demonstrates LSTM's clear superiority over traditional ML and shallow architectures for sequential degradation modeling—highlighting the importance of sequence length and network depth for capturing engine wear patterns.

Scope Comparison:

Establishes new benchmark for RUL prediction on C-MAPSS, outshining both shallow and other DNN models thanks to optimized LSTM architecture.

8. Fault Diagnosis and Remaining Useful Life Estimation of Aero Engine Using LSTM Neural Network

Research Focus:
Early fault detection and life prediction of aero engines using LSTM, with both labeling and preprocessing enhancements for better feature construction and model generalization.

Methodology:

- NASA C-MAPSS dataset used for training/test.
- Labels constructed using a sliding window for RUL; features normalized/scaled for effective network training.
- LSTM configuration tuned for maximum accuracy.

Key Findings:

- High correlation between LSTM-predicted and real RUL; life trend labeling supports interpretable and physically meaningful regression.
- LSTM accurately distinguishes between fault types and estimates RUL under various simulated degradation conditions.

Relevance:
Showcases LSTM's dual application for both ongoing health monitoring and root-cause-level fault diagnosis in PdM.

Scope Comparison:
Demonstrates LSTM's flexibility for both regression and classification, supporting both continuous monitoring and discrete fault prediction tasks—widely applicable in practical aircraft maintenance.

9. Quality of Service Forecasting Using Optimized LSTM Networks Based on EMD

Research Focus:

Application of an optimized LSTM-EMD model for time series forecasting in Quality of Service (QoS) analytics, providing insight into how decomposition and optimization can enhance LSTM performance.

Methodology:

- Time-series decomposition of QoS signals using Empirical Mode Decomposition (EMD).
- LSTM network then trained on each decomposed component, with parameters further optimized via Particle Swarm Optimization (PSO).
- Tests on public SERV1 dataset, benchmarking against ARIMA, Holt-Winters, base LSTM, and EMD-LSTM models.

Key Findings:

- EMD-PSO-LSTM outperforms benchmarks, achieving best RMSE, MAE, and MAPE for high-granularity QoS prediction.
- Layering EMD and PSO with LSTM provides much closer alignment of predicted time series to ground truth than standard LSTM or traditional statistical models.
- Model supports practical QoS forecasting and incident preemption in high-demand service environments.

Relevance:

Illustrates the extensibility of LSTM PdM models beyond traditional machinery, proving effective for service-based predictive analytics and digital infrastructure PdM.

Scope Comparison:

Shows LSTM is highly adaptable—combining with advanced decomposition (EMD) and metaheuristics (PSO) to achieve top performance in challenging, noisy series forecasting environments.

10. Explainable Predictive Maintenance: A Survey of Current Methods, Challenges, and Opportunities

Research Focus:

Systematic review of explainability methods for predictive maintenance, with a dedicated focus on their application to black-box models like LSTM.

Methodology:

- PRISMA-guided meta-analysis, grouping XAI and explainability methods as applied to PdM.
- Evaluation and taxonomy of model-agnostic (e.g., SHAP, LIME, LRP) and model-specific (e.g., GradCAM) approaches.
- Assessment of challenges for integrating explainability into PdM workflows.

Key Findings:

- XAI methods (SHAP, LIME, rule extraction, visual analytics) are crucial for LSTM-based PdM, increasing operator trust and auditability.
- Recommends user-centric explanation strategies tailored to various stakeholders (engineers, managers, regulators).
- Identifies research gap in standardized XAI/interpretability metrics for PdM.

Relevance:

The survey provides a foundation for safe deployment of LSTM and other deep models in PdM, guiding both modelers and end-users in the adoption of interpretable ML frameworks.

Scope Comparison:

Differentiates itself by bridging technical advances in black-box modeling (like LSTM) with practical, regulatory, and human-centered interpretation, essential for widespread PdM adoption.

11. Using LSTM Networks to Predict Engine Condition on Large Scale Data Processing Framework

Research Focus:
Development of a scalable predictive maintenance framework using LSTM networks to assess engine condition in real-time, leveraging big data technologies.

Methodology:

- Deploys LSTM neural networks to process multivariate, sequential sensor data from engine degradation simulations (NASA C-MAPSS).
- Implements feature selection to reduce noise and multicollinearity.
- Uses Apache Spark distributed cluster architecture with Python (Keras, Elephas) for training and inference at scale.
- Classifies engine states into "Healthy," "Caution," "Repair," and "Fail."

Key Findings:

- Training yields 85% accuracy for Remaining Useful Life (RUL) prediction and early alerts before system breakdowns.
- Scalable infrastructure allows rapid processing of massive streaming datasets, suitable for IoT and industrial environments.

Relevance:
Validates LSTM's practical application in streaming data environments and industrial IoT, offering reliable predictive maintenance with a high level of automation and scalability.

Scope Comparison:
Compared to traditional approaches like Hidden Markov Models and standard ANNs, the LSTM-based distributed framework demonstrates superior flexibility, scalability, and performance for big data-driven predictive maintenance and real-time asset health monitoring.

12. Remaining Useful Life Estimation in Prognostics Using Deep Reinforcement Learning

Research Focus:

Introduction of a novel Deep Reinforcement Learning (DRL) method for Remaining Useful Life (RUL) estimation in prognostics, extending predictive maintenance capabilities beyond conventional supervised learning.

Methodology:

- Reformulates RUL estimation as a Markov Decision Process (MDP) and employs Proximal Policy Optimization (PPO) as the DRL algorithm.
- Features: CNN-based neural network extracts key features from sensor data, FCN maps features to actions (RUL estimates).
- Data preprocessing includes z-score normalization and time window slicing across operational conditions (NASA C-MAPSS dataset).
- Benchmarks performance against state-of-the-art ML and deep learning methods (SVR, ANN, CNN, LSTM, BiGRU).

Key Findings:

- Achieves state-of-the-art performance on complex turbofan datasets (FD002, FD004), with significant RMSE and scoring metric improvement over leading supervised LSTM and CNN approaches.
- DRL framework demonstrates higher robustness and generalization, particularly on datasets with greater operational and fault-mode complexity.

Relevance:

Advances predictive maintenance by introducing RL for superior exploration, less overfitting, and better accuracy in real-world industrial prognostics; emphasizes adaptability to unseen data and changing operational profiles.

Scope Comparison:

DRL outperforms supervised learning approaches—including LSTM—on the most challenging scenarios, overcoming typical limitations of overfitting and static learning. While LSTM can learn temporal dependencies, DRL’s policy-based learning on sequential decision environments yields greater robustness and generalizability for RUL prediction.