**Wind Turbine Gearbox Temperature Prediction Report**

**Executive Summary**

This report presents a deep learning approach for predicting wind turbine gearbox temperatures 48 hours in advance to enable early failure detection. The model successfully achieves 80.86% accuracy with a recall of 58% for identifying potential overheating scenarios, representing a significant improvement from initial 20% recall through strategic threshold adjustment.

**Approach**

**Data Preprocessing and Aggregation**

The initial dataset contained 5-minute interval measurements, which proved too noisy for reliable prediction patterns. Through systematic testing of different aggregation intervals (5-min, 15-min, 30-min, 1-hour), **15-minute aggregation** was identified as optimal, providing sufficient smoothing of temperature fluctuations while preserving critical trend information for failure detection.

The 85th percentile threshold (70°C) was established based on domain knowledge as the critical temperature indicating potential gearbox failure risk.

**Feature Engineering Strategy**

Feature engineering was performed separately on train, validation, and test sets to prevent data leakage. Three categories of features were developed:

**1. Alarm-Based Features:**

* Hours since last alarm occurrence
* Recent alarm flags (within 6 hours)
* 24-hour alarm frequency
* Alarm system lags (0.5h, 2h)

These features capture the relationship between alarm events and temperature escalation patterns.

**2. Enhanced Lag Features:** Critical temperature sensors (gearbox bearing temperatures, main gearbox temperature) were engineered with multiple time lags (0.5h, 1h, 2h, 4h, 8h) and delta features (1h, 4h differences). This captures the temporal evolution of heating patterns that precede failures.

**3. Cyclic Time Features:**

* Hourly patterns (sine/cosine encoding)
* Daily patterns (day of week)
* Seasonal patterns (week/month encoding)

These features account for natural operational cycles and seasonal variations affecting turbine performance.

The final feature set was selected based on domain expertise from the problem statement and validated through XGBoost feature importance analysis and permutation importance testing.

**Model Architecture**

A hybrid deep learning architecture was implemented combining:

* **Conv1D layers**: Extract local temporal patterns and reduce noise
* **Bidirectional LSTM**: Capture long-term dependencies in both directions
* **Dense layers**: Final prediction mapping with regularization

The model predicts 192 time steps (48 hours) ahead using 384 historical time steps (96 hours lookback).

**Training Configuration:**

* Huber loss function (robust to outliers)
* Adam optimizer with gradient clipping
* Early stopping and learning rate reduction
* 70/15/15 train/validation/test split

**Key Findings**

**Model Performance**

| **Dataset** | **MAE (°C)** | **RMSE (°C)** | **R²** | **MAPE (%)** |
| --- | --- | --- | --- | --- |
| Training | 5.385 | 8.506 | 0.533 | 12.24 |
| Validation | 8.153 | 10.169 | 0.680 | 18.05 |
| Test | 5.911 | 8.163 | 0.738 | 14.76 |

**Failure Detection Performance**

**Threshold Analysis:**

* **Critical threshold: 70°C (85th percentile)**
* **Safe prediction limit: 65°C (threshold - MAE of 5°C)**
* **Total test samples: 14,865**
* **Test samples with actual failures: 5,029 (33.83%)**
* **Model-predicted high-risk samples: 3,680 (24.76%)**
* **Coverage rate: Model captures 2,932 out of 5,029 actual failures (58.3%)**
* **Prediction accuracy: Among 3,680 model predictions, 2,932 are correct (79.7%)**

**Classification Metrics:**

* **Precision: 80%** - When model predicts overheating, it's correct 4 out of 5 times
* **Recall: 58%** - Model successfully identifies 58% of actual overheating events
* **F1 Score: 67%** - Balanced performance measure
* **Accuracy: 80.86%** - Overall correctness

**Critical Improvement**

The strategic use of **MAE-adjusted threshold** (65°C instead of 70°C) improved recall from 20% to 58%, significantly enhancing the model's ability to detect potential failures while maintaining reasonable precision.

**Potential Improvements**

**1. Advanced Architectures**

* **Attention mechanisms**: Focus on critical time periods
* **Transformer models**: Better capture long-range dependencies
* **Ensemble methods**: Combine multiple model predictions

**2. Enhanced Feature Engineering**

* **Weather data integration**: External temperature, wind speed, humidity
* **Maintenance records**: Incorporate historical maintenance events
* **Operational mode features**: Power output categories, wind conditions

**3. Imbalanced Data Handling**

* **SMOTE techniques**: Synthetic overheating event generation
* **Focal loss**: Better handling of rare failure events
* **Cost-sensitive learning**: Penalize false negatives more heavily

**4. Real-time Implementation**

* **Streaming predictions**: Continuous model updates
* **Uncertainty quantification**: Confidence intervals for predictions
* **Alert system integration**: Automated maintenance scheduling

**5. Domain-Specific Enhancements**

* **Physics-informed constraints**: Incorporate thermodynamic principles
* **Multi-turbine learning**: Learn patterns across turbine fleet
* **Seasonal adaptation**: Dynamic model adjustment for weather patterns

**Conclusion**

The developed model demonstrates strong predictive capability for gearbox temperature forecasting with practical failure detection performance. The 58% recall rate means the system can proactively identify over half of potential overheating events 48 hours in advance, enabling preventive maintenance actions. The 80% precision ensures that maintenance resources are deployed efficiently with minimal false alarms.

The strategic combination of temporal aggregation, comprehensive feature engineering, and threshold adjustment has created a robust early warning system suitable for industrial deployment in wind turbine monitoring applications.