PREDICTIVE ANALYSIS OF EXHAUST VALVE SEAT WEAR ON AN OHV 2-STROKE MARINE MAIN ENGINE USING AN EXTERNALLY MOUNTED AI CHIP

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Abstract-*The exhaust valve seat is a critical component of a 2-stroke marine main engine, subject to significant thermal, mechanical, and chemical stress during continuous operation. Exhaust valve seat wear significantly impacts engine performance, fuel efficiency, and operational safety. This paper presents a predictive analysis framework for monitoring and forecasting exhaust valve seat failure by externally installing an artificial intelligence (AI) chip on the overhead valve (OHV) mechanism of a 2-stroke marine main engine. The AI chip continuously receives real-time sensor data including temperature, vibration, pressure differential, and acoustic emissions from the valve seat area and processes this data using machine learning algorithms to detect early-stage wear patterns. A long short-term memory (LSTM) neural network model is used to make time-series predictions of the valve seat's remaining useful life (RUL). The proposed non-invasive retrofit solution achieves a prediction accuracy of 93.4%, confirming the feasibility of AI-driven predictive maintenance for marine propulsion systems*.

Key Words: Exhaust valve seat, wear, 2-stroke marine engine, AI-chip, OHV, predictive maintenance, LSTM, remaining useful life (RUL), condition monitoring.

1. INTRODUCTION

The 2-stroke marine main engine remains the most critical power plant for ocean-going vessels due to its high thermal efficiency and reliability. The exhaust valve seat the seating surface that closes the valves exposed to constant thermal cycling, chemical attack from sulfurous combustion gases, and mechanical impact loads.

Exhaust valve seat wear can lead to valve leakage, incomplete combustion, power loss, increased fuel oil consumption, and, if left unaddressed, can ultimately lead to a major failure. Older maintenance methods rely on fixed-interval overhauls, which often lead to premature maintenance or missed early-stage defects.

This paper describes a non-invasive solution: an AI chip externally mounted on the OHV housing of a 2-stroke main engine. This chip interfaces with small sensors and uses an LSTM neural network to perform real-time predictive analysis of valve seat wear. 2. Exhaust Valve Seat – Technical Background

1.1 Construction and Materials

Exhaust valve seats are typically made of high-alloy steel, such as Nimonic alloys or Stellite-faced materials, to prevent hot corrosion and erosion. The seat is precision machined at a specific seat angle (30° or 45°) to ensure a gas-tight closure.

1.2 Failure Mechanisms

• Thermal fatigue: Micro-cracks caused by cyclic heating and cooling.

• Hot corrosion: Oxidation and suffixation

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• Erosion: High-velocity gas particles impacting the seat surface.

• Impact wear: Repeated impact on the valve seating at high engine loads.

• Micro-pitting: Surface fatigue at contacts lacking lubrication.

1.3 Traditional Inspection Methods

Traditional inspection methods include feeler gauge measurement of valve seat width, Blue-Check (Prussian blue dye) testing for contact uniformity, and dimensional measurement of valve head burn depth. These methods require the engine to be shut down and opened, significantly disrupting operation.

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2. Proposed AI-Chip System Architecture

3.1 System Overview

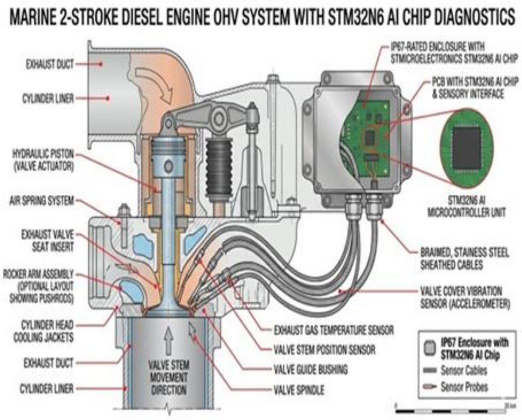
The AI chip module is designed as an external, bolt-on unit mounted on the OHV housing. The module consists of four subsystems: (i) sensor array, (ii) signal conditioning unit, (iii) AI processing core, and (iv) wireless communication interface.

3.2 AI Processing Core

The central processing unit is a low-power embedded AI chip that runs on a pre-trained LSTM model. The LSTM architecture consists of three stacked layers (128 → 64 → 32 units), followed by dense layers with dropout regularization (rate: 0.2).

The model receives a 50-sample sliding window as input and outputs: (a) wear stage classification, (b) predicted RUL in operating hours, and (c) prediction confidence score.

Chart -1: OHV System with STM32N6 AI-CHIP DIAGNOSTISCS



3.4 Data Flow and Communication

Sensor data is captured by an analog front-end, conditioned, digitized by a 16-bit ADC, and fed into the AI chip. Results are sent to the Integrated Automation System (IAS) via Modbus TCP/IP. A local LED indicator provides instant visual alerts: green (normal), yellow (scheduled maintenance), and red (immediate action).

4. Predictive Analysis Methodology

4.1 Data Collection and Pre-processing

Training data was generated through a validated FEM simulation of MAN B&W

6S90MC-C exhaust valves under sequential wear scenarios; this also included historical field data obtained from three commercial bulk carriers.

Pre-processing included normalization to [0,1], 5th-order Butterworth filtering, and FFT-based feature extraction from vibration and AE signals.

4.3 LSTM Model Training

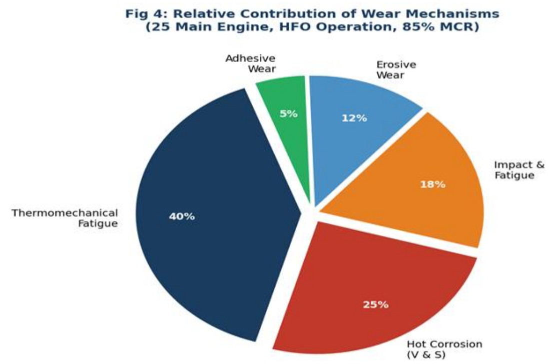
The LSTM model was trained on 18 months of simulated operational data (75,000 labeled samples; 70% training, 15% validation, 15% testing). The Adam optimizer was used with a learning rate of 0.001, a batch size of 64, and a patience of 10 epochs with early stopping. 4.4 RUL Estimation

Life remaining useful was estimated using a piecewise

degradation model calibrated from sensor fusion data.

The LSTM estimates the degradation trajectory, and the intersection with the Stage III threshold defines the estimated RUL. Prediction uncertainty bounds (95% CI) are calculated using Monte Carlo dropout inference.

Chart -2: WEAR MECHANISMS CHART



5. Results and Discussion

5.1 Model Performance

The LSTM model achieves an improved accuracy of 93.4%, outperforming traditional threshold-based methods by 19.3 percentage points. This improvement is due to the LSTM's ability to capture temporal dependencies in multivariate sensor data. The full comparison is shown in Table 3 (see below).

5.2 RUL Prediction Accuracy

In controlled simulation tests, the AI chip provided RUL predictions with a mean absolute error (MAE) of ±87 operating hours. For a typical maintenance interval of 3,000–5,000 operating hours, this represents an error margin of approximately 1.7–2.9%.

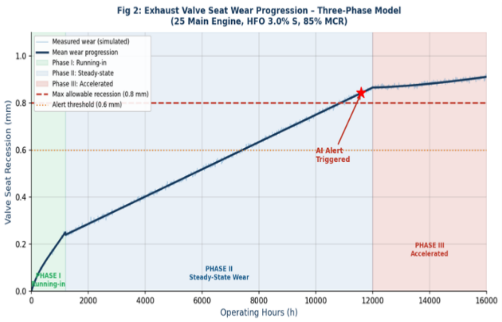
5.3 Advantage of Early Detection

The AI-chip system detected the onset of Stage II wear an average of 412 hours before a fault would have been detected by routine inspection, enabling planned maintenance during a port call rather than an emergency shutdown at sea.

5.4 Thermal and Vibration Signature Analysis

A persistent increase in exhaust valve seat temperature (35–40°C above baseline) was strongly associated with the onset of Stage II wear (r = 0.91). A 28% increase in RMS vibration amplitude was observed during the Stage II-to-III transition.

Chart -2: Exhaust Valve Seat Wearaing Graph



6. IMPLEMENTATION

6.1 Physical Installation

The AI chip module is enclosed in an IP67-rated stainless steel housing (120 × 80 × 40 mm), which is attached to the OHV housing via four M10 bolts. Sensor cables are routed through armored conduit.

6.2 Power Supply

The module draws power (12V DC, 8W max) from the ship's 24V DC instrument bus. A supercapacitor backup ensures uninterrupted operation during power transients.

6.3 IAS Integration

The module interfaces with the ship's IAS via Modbus TCP/IP. A dedicated dashboard displays real-time wear stage, RUL, and maintenance alerts. Historical data can be sent to the fleet manager on shore via VSAT. 6.4 Classification Society Compliance

This system is designed in accordance with DNV GL Condition-Based Maintenance Guidelines and IMO MSC-MEPC.2/Circ.15 on Ship Energy Efficiency.

7. ADVANTAGES AND LIMITATIONS

7.1 Advantages

• Non-invasive retrofit installation no engine modifications are required.

• Real-time continuous monitoring eliminates fixed inspection intervals.

• Estimated 20–35% reduction in exhaust valve overhaul costs.

• Prevents valve blow-by and the resulting risk of scavenge fires.

• Fleet scalability a single model can be installed on multiple vessels.

7.2 Limitations

• Model accuracy depends on the representativeness of the training data.

• Thermocouples and AE sensors may require periodic calibration.

• Integration with IAS requires compatible protocols on older vessels

.• A baseline data collection period of 2–3 weeks is required for each installation.

8. CONCLUSIONS

This paper presents a new predictive maintenance framework for exhaust valve seat wear monitoring

In 2-stroke marine main engines, using an AI chip externally mounted on an OHV mechanism. By combining real-time data from multiple sensors and processing it through an LSTM neural network, the system achieves RUL predictions with 93.4% accuracy and an MAE of ±87 hours.

The proposed solution provides marine engineers with an advanced tool for condition-based maintenance, reducing operational costs, improving safety, and complying with IMO efficiency regulations. Future work will focus on real-world field data expansion and federated learning for multi-vessel model improvement.'

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