🎓Inlet Valve Wear Prediction using Machine Learning - Presentation for Mechanical Engineers

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🪠Slide 1: Introduction

Title: Predicting Inlet Valve Wear Using ML

- Objective: Predict wear on inlet valves based on operational and material parameters.
- Industry Need: Reduce testing cost and time by predicting outcomes with high accuracy.
- Approach: Use machine learning (ML), especially XGBoost, trained on synthetic data grounded in physics.

🔧Slide 2: Engineering Parameters (Inputs to Model)

Parameter	Description	Units / Type
Pressure	Peak combustion pressure	Pa
RPM	Engine revolutions per minute	rev/min
Temperature	Valve temperature (derived)	°C
Seat Angle	Valve seat cone angle	degrees
Insert Angle	Mating angle of insert	degrees
Mismatch	Angular difference (seat - insert)	degrees
Hardness	Surface material hardness	HV
Diameter	Valve head diameter	mm
Velocity	Valve motion velocity (derived)	m/s
Duration	Test duration	seconds
Face Width	Contact width of valve seating face	mm
Lubrication Index	Oil film quality	Unitless (0.5–1)
Coeff. Modifier	Friction coefficient modifier	Unitless (0.5–1.2)
Materials/Coating	Valve and insert materials, coating types	Categorical

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🧪Slide 3: Why Predict Wear?

- **Manual testing** is expensive and time-consuming.
- Want to **simulate wear behavior** under varying operating conditions.
- Allows **faster iterations** in design and testing.
- ML provides a data-driven way to predict wear without extensive physical testing.

🔦Slide 4: How Synthetic Data Was Generated

Pseudo-Algorithm Steps:

1. **Wear binning** – Define wear ranges and allocate data samples.
2. **Parameter scaling** – Adjust input ranges per bin (e.g., high pressure for high wear).
3. **Random sampling** – Choose inputs using uniform/normal distribution.
4. **Derived variables** – Temperature, velocity, mismatch, etc.
5. **Wear equation**:

```
wear = (P × V × t × T_mult × Material_mod × (1 + mismatch × k1)) / (Hardness × Width × Coeff_Mod)
```

1. **Noise and clamping** – Add randomness and restrict output within bounds (0.3–3.0).

⚙️Slide 5: Understanding the Wear Equation (Physics Basis)

- **Archard's Law** inspired: Wear proportional to Pressure × Velocity × Time.
- **Temperature Multiplier** – Accounts for heat-induced softening.
- **Mismatch** – Stress concentration from angular misalignment.
- **Hardness** – Inverse relation: harder materials wear less.
- **Lubrication & Coating** – Friction coefficient modifies wear.

  Equation reflects real-world physical wear mechanisms.

🪥Slide 6: What is XGBoost (Layman Terms)

- XGBoost = "Extreme Gradient Boosting"
- Learns in **small steps** by improving where previous guesses failed.

Analogy: Like fixing your answers in an exam after seeing your mistakes.

- Builds **decision trees** that ask YES/NO questions to split the data smartly.
- Each tree corrects the previous one's error (residual).

Slide 7: How XGBoost Learns

Step-by-step:

1. Predict initial values (average).
2. Calculate **residuals** = actual - predicted.
3. New tree learns to predict these residuals.
4. Update model: new prediction = old + learning × residual prediction.
5. Repeat until errors are minimized.

> **Residual = What model got wrong**

📊Slide 8: Evaluation Metrics (Performance)

Metric	Meaning	Our Model (Test)
R^2	Variance explained	0.9996
RMSE	Average large error penalty	0.0159
MAE	Average error magnitude	0.0124
MAPE	% deviation from true value	1.21%

✅All metrics show **very high accuracy**.

📉Slide 9: Understanding Residuals & Plot

- **Residual** = Predicted – Actual
- If close to 0: prediction was accurate

Graph Explained:

- X-axis: True wear
- Y-axis: Residuals (errors)
- Dots: predictions from validation (🔵) and test set (🟢)
- Flat cluster near 0: model isn't biased
- Few outliers = extreme or rare test cases

🔍Slide 10: Feature Importance

Shows which features most impact prediction.

- Pressure 🟢– highest contributor
- Velocity 🔵– significant sliding influence
- Hardness 🔴– strong negative impact (resistance)
- Duration, Mismatch – moderate effects

Helps engineers prioritize which design factors matter most.

🧰Slide 11: Summary & Why It Works

✅Wear modeling is grounded in physical reality. ✅Synthetic data ensures diverse training scenarios. ✅XGBoost handles complexity and noise well. ✅Residuals show no bias. ✅Ready to integrate in test benches or design loops.

📰Slide 12: Final Q&A

Ask your questions:

- About model usage
- Data preparation
- Integration with test rigs
- Extending to exhaust valves

Let me know if you'd like this exported to PowerPoint or Google Slides.